Practical security guidance for authentication-system designers

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To the Samwise Gamgees that have helped me on this journey

Abstract

Designers of authentication systems have a challenging task of balancing security requirements with organizational demands, including usability requirements and other practical constraints. They must design a system that is secure against modern attackers that are able to leverage increasingly large amounts of computational resources to undermine security protections. In some cases, system designers are subject to mandatory regulatory guidance that restricts that space of possible designs they are able to implement. Different organizations will have different levels of security requirements reflecting different threat models; designers must understand these requirements and design a solution specific to these requirements. Designers of authentication systems to be incorporated in consumer-facing products often must produce a solution that not only provides a given security level but that also does not undermine a high usability standard associated with the product brand. Different organizations will have different authentication needs; a single design solution will not work for all.

In designing an authentication system for an organization, system designers often rely on the guidance of security experts. Although system designers can often find security guidance on how to design an authentication system, this guidance may not always be applicable. For example, designers may be subject to regulatory requirements or usability constraints that preclude security solutions recommended by experts. In other cases, available security guidance may be incomplete, abstract, or incompatible with available resources. Security guidance for system designers should produce recommendations relevant for different scenarios; these recommendations should be both comprehensive and concrete.

In this thesis, I provide practical guidance for system designers tasked with designing an organizational password policy. This guidance is comprehensive, flexible to implementation requirements, concrete, and evaluated in experimental user studies considering both security and usability dimensions. Using a combination of machine-learning and statistical modeling methods, I explore techniques for expanding guidance available to system designers in the area of text feedback for password-creation meters. I also provide design recommendations for applications that incorporate public-key fingerprint comparison, using user studies that evaluate the effective security of solutions providing varying levels of usability.

Thesis statement: **The objective of this thesis is to provide practical, concrete, and actionable guidance for designing authentication systems that include text-based passwords or public-key fingerprint verification, for systems subject to practical, real-world constraints and requirements. This guidance provides design recommendations sensitive to systems with different targeted security levels, organizational implementation requirements, and human usability constraints.**

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Chapter 1

Introduction

Organizations in both the public and private sector often turn to security experts for guidance on how to design the authentication systems used for protecting their users. For example, system designers often implement protections based on the advice of NIST, in order to satisfy mandated regulatory compliance or as a means of adhering to an established set of best practices in the security realm. Given its potential impact on widespread adoption, it is important that the guidance provided by security experts is effective and optimal.

Providing effective and optimal security guidance for all organizations is a challenge because in practice these organizations often differ in the type of users they manage, business goals, and in regulatory compliance they are subject to. In the public sector, certain authentication components may be mandatory for regulatory compliance reasons and security-level requirements may vary greatly. In the private sector, usability considerations are often critical and place practical constraints on the type of security mechanisms users are subjected to for the sake of authentication. Thus, it is important that security guidance for organization not only be effective, but also practical given constraints and goals specific to an organization.

In this thesis, I use the results of experiments to provide practical guidance on how to design secure and usable authentication systems in the areas of passwords and end-to-end encrypted messaging applications. I demonstrate how guidance can be tailored to the different needs and requirements of organizations with respect to implementation requirements, targeted security level, and emphasis on usability.

I begin in Chapter 2 by providing background and summarizing related work on topics related to password policies, password-creation guidance, interpreting neural network predictions, and public-key fingerprints.

I next tackle guidance relevant for authentication system designs tasked with designing an organizational password policy, in Chapter 3. Using two large-scale experimental user studies, I perform a comprehensive investigation of password-policy requirements, including character-class requirements and blocklists. I also design and experiment with a new type of requirement—minimum-strength requirements—which require passwords to be above a configurable strength

threshold, where strength is estimated by a neural network. As result of this study, I provide recommendations that reflect the diversity of organizational needs and requirements. I provide concrete recommendations for blocklist configurations that balance usability and security that can be incorporated by organizations mandated to use them. For organizations with more implementation flexibility, I recommend specific configurations of minimum-strength requirements that achieve similar usability as top-tested blocklist configurations while providing stronger offline-attack protection.

Password policies are typically coupled with password meters, which can provide real-time feedback to users on which policy requirements have been met, as well as provide text-based advice to users on how choose a secure password. Text guidance is an important component of an authentication system that organizations can incorporate in password-creation interfaces; they can nudge users into creating stronger passwords, which helps increase account protection for the user base as a whole, and in consumer settings they can alleviate user annoyance that might otherwise harm business growth. Despite their proven usefulness, limited guidance is available to authentication system designers on the exact form that password guidance should take. While prior work has outlined heuristics for identifying predictable patterns in passwords, these heuristics are often based on intuition and may not be comprehensive in covering all relevant password patterns. In addition, certain implementation details relevant to system designers have not been explored, including whether and how feedback should communicate the relative importance of addressing individual text-feedback recommendations.

In Chapter 4 I describe how I applied machine-learning clustering and model-explanation techniques on sets of leaked passwords in order to explore the space of password patterns useful for inclusion in heuristic-driven text feedback. I also explore the relationship between known heuristics and guessability using statistical models in order to learn which heuristics should be prioritized in feedback. Results of this study did not ultimately lead to actionable guidance on how system designers should incorporate text feedback. I discuss potential ways that the techniques we explored could be modified in order to produce more fruitful results.

In secure messaging applications, public-key fingerprints are useful for authentication. By comparing fingerprints, users can ensure communication is secure and free of eavesdroppers. Fingerprint verification is effective defense against man-in-the-middle attacks and is often used in high-risk scenarios or when security is tantamount. Although many consumer-facing organizations are increasingly incorporating secure messaging as a privacy-enhancing feature of their applications, designers of these applications may be hesitant to surface fingerprint comparison as a security mechanism due to usability concerns; users tend to be confused by this type of security feature and often use them incorrectly, nullifying their security benefits.

In Chapter 5 I describe how I performed an experimentally designed user study to explore ways of improving the usability of fingerprint comparisons, using different fingerprint representations and comparison configurations. I pay special attention to simulating real life conditions. We find that textual fingerprint representations perform reasonably well. Given their security properties, we recommend textual representations for organizations deploying fingerprint comparisons in settings where security failure could have severe repercussion. We also identify graphical fingerprints as a potential design option for organizations in which high usability is an essential design

requirement.

I conclude in Chapter 6 with high-level findings and insights formed as a result of this work. I also outline ideas for future work that can extend the ideas in this thesis to potentially improve password-strength modeling, the presentation of and feedback shown for minimum-strength password-policy requirements, and password-creation usability guidance.

Chapter 2

Background and related work

This section first describes related work on password security, including the frequency and types of password reuse, metrics for quantifying the strength of a password against guessing attacks, and tools researchers have created to assist users in creating strong passwords. Next, we discuss prior work on learning interpretable text-based explanations for black-box machine-learning model predictions. Lastly, we provide an overview of public-key fingerprints, including actual application that use them, studies of their usability, and how entropy can be used to quantify the strength of fingerprint representations and attacks.

2.1 Passwords

2.1.1 Composition policies

Password composition policies aim to help users create more unique, less predictable passwords. Composition policies can be used at password-creation time to enforce a minimum number of character classes—uppercase letters, lowercase letters, symbols, and digits—and a minimum-length requirement.

Early work on composition policies focused on character-class requirements to increase password strength [55]. In general, policies that require more character classes have been found to produce overall stronger passwords [42, 46]. Later work explored policies that emphasized length over character-class composition. Researchers exploring length requirements have found that reducing the number of required character classes while increasing the minimum-length requirement could strengthen passwords without decreasing their memorability or making them more difficult to create [42, 46, 72, 73].

Although researchers and, more recently, NIST advise to avoid composition policies requiring a minimum number of character classes, this type of policy is still often used in practice [13, 50].

We include such policies in our studies to provide concrete recommendations to organizations that may continue to rely on them.

2.1.2 Blocklists

Even if password requirements are generally effective at improving strength, some users will fulfill them predictably. Thus, character-class and minimum-length rules are insufficient to prevent very weak passwords [72]. For example, *4class8* and *1class16* policies allow extremely predictable passwords such as "Password1!" and "passwordpassword." A common mitigation is to combine composition requirements with a blocklist check. For instance, NIST 800-63B recommends that passwords not be in a list of commonly-used, expected, or compromised values [56]. Properly configured blocklist checks can reject predictable, or easy-to-guess passwords.

A blocklist requirement uses a wordlist and a matching algorithm that checks whether a given password is prevented by that wordlist. Wordlists can contain common sequences of characters, as well as previously-leaked passwords. Matching algorithms range from exact match (a candidate password should not be in the wordlist), to more complicated rules—e.g., stripping symbols and digits from the password, making it case-insensitive, and checking that the resulting string does not match any wordlist entry.

Prior work found that blocklists used by major online service providers vary in architecture, including client-side, server-side, and hybrid approaches [13]. Blocklists differed in their wordlists and matching algorithms, e.g., whether and how symbols or digits were removed from passwords before matching. They also differed in whether they forbid, warned, or decreased a password-strength score if a blocklist check returned positive.

Initial password research focused on blocklists that forbid dictionary words in passwords. For example, many studies have examined policies that perform blocklist checks against the OpenWall wordlist [45]. These studies found that blocklist checks caused more annoyance compared to policies without them. More recently, blocklists based on ad-hoc cracking dictionaries were found to produce weaker passwords than when relying on larger wordlists gleaned from password leaks, such as the Xato password corpus [15]. Blocklists based on Xato were found to produce reasonably strong passwords [28, 87]; we will use this wordlist here.

By analyzing large leaked sets of passwords, Weir et al. found that larger blocklists strengthened passwords [95]. Kelley et al. tested three blocklists varying in size and similarly found that larger blocklists produced stronger passwords [42]. While blocklists might be effective against online attacks, Florêncio et al. questioned their practicality against offline attacks due to the required wordlist size or potential negative usability impact [22].

Despite these studies, our understanding of blocklist usability and security effects is incomplete, particularly for large blocklists or string-matching algorithms that remove non-alphanumeric characters. Prior work that uses retrospective policy analyses has limitations, e.g., subsetting policy-allowed passwords retroactively overestimates the impact of password policies on strength [50] and cannot account for users who replace blocklisted passwords with even weaker, but non-

blocklisted ones. Retrospective studies also cannot analyze many usability-related aspects of password policies.

Prior findings may also not apply to modern contexts. Conclusions on blocklist usability derived from studies that lack real-time feedback [42, 46] may lead to overly pessimistic usability results. For example, the largest cause of policy compliance failure in prior work was the dictionary check, which real-time feedback could alleviate [72]. Additionally, blocklists may differently impact password strength and usability depending on interactions between the wordlist, matching algorithm, and composition policy they augment. For instance, prior work has examined digit-and-symbol-stripping matching algorithms with *3class8* and *4class8* policies, and wordlists based on the OpenWall dictionary, which was found to be relatively ineffective [45,46].

2.1.3 Quantifying password strength

The strength of passwords produced under a particular password-creation policy can be quantified using guess numbers. Guess numbers can be computed by enumerating the passwords predicted by a particular guessing model, in decreasing probability, or according to the order that a commonly-configured password-cracking tool would output guesses. A password's guess number estimates the number of guesses an attacker need make before guessing that particular password. Guess numbers are parameterized by the particular tool used, as different tools and models guess passwords in different orders. Prior work recommends taking the minimum guess number across multiple automated guessing methods as a conservative proxy for an expert attacker's guessing capabilities [90].

The Password Guessability Service (PGS) [61] is a state-of-the-art tool for estimating password strength. PGS supports the popular password-cracking tools Hashcat and John the Ripper, as well as tools based on password-modeling approaches such as Probabilistic Context-Free Grammars (PCFG) and artificial neural networks. PGS also provides *min-auto* guess numbers, computed as the lowest guess number among the set of supported password-guessing methods. For probabilistic models, Monte Carlo sampling methods allow for estimation of guess numbers for low-probability passwords [15]. Probability-to-guess-number mappings can be precomputed, enabling client-side, real-time guess number estimates. We apply this method in our study, using a meter based on prior work [87].

Guess numbers do not paint a complete picture. The number and frequency of guesses an attacker can make depend on many factors, including whether it is an online or offline attack, the extent to which rate limiting is applied, and whether defenses such as iterated hashing are deployed. Florêncio et al. discuss the "online-offline chasm" between password-strength thresholds that may be relevant in practice [22]. They argue that offline attacks may not always be a threat, e.g., for service providers that reversibly encrypt passwords or store passwords in plaintext. When offline attacks are applicable, they argue that the user effort to create passwords that resist such attacks is usually wasted unless passwords can withstand attacks that make up to 10^{14} guesses.

2.1.4 Minimum-strength requirements

Minimum-strength password requirements have been explored less than other types of policy requirements. Accurate strength estimates for individual passwords are indeed difficult to perform in real-time. Password-strength heuristics can roughly estimate password strength, but the accuracy of these estimates may be insufficient. Prior work evaluating password meters has found that strength estimates from heuristic-based meters are often inconsistent [13] and contradict guess number estimations [52]. One of the more accurate password-strength estimators, zxcvbn [97], uses advanced heuristics to output quite reliable password strength estimates at low guess numbers typical of online attacks. Although zxcvbn can be configured to meet minimum password-strength thresholds, this has not been evaluated through user studies.

Recently, Melicher et al. designed a client-side recurrent neural network for modeling password strength [52]. This development has enabled minimum-strength requirements based on password-strength estimates that are both accurate and data driven, rather than heuristic driven. In our study, we explore minimum-strength requirements expressed as a minimum guess number estimated by a neural network. This is the first time we are aware of that this type of requirement has been incorporated into a password-creation policy and evaluated in a user study.

2.1.5 Password reuse

Prior work has found that users heavily rely on password reuse (both exact and partial reuse) in order to manage the large number of online accounts they accumulate over time [21, 25, 30, 94]. While this helps reduce memory burdens associated with having unique passwords for each account, it also can reduce the effective security of passwords against attackers.

Choong et al. studied the password management behaviors of U.S. Department of Commerce employees using an online survey [10]. They found that employees had an average of 9 work-related accounts that required login, with a median of 5 of those accounts being frequently used. Around 40% of employees wanted the workplace to transition to a SSO system to help them manage passwords. To reduce the burden of remembering or storing unique passwords for each workplace account, employees relied on a variety password reuse strategies: 67% made minor changes to existing passwords, 43% reused an existing password, 38% recycled a previously expired password, and 34% created new passwords by modifying a common "password root" (e.g., 2PwdRt&, PwdRt42%). When asked what an ideal login process would entail, employees did not show a strong preference for using PINs over passwords; although most employees preferred a system that used biometrics or the badges they already carried, employees mentioned passwords about as often as PINs, at approximately 5% in both cases.

Pearman et al. examined password reuse for online accounts in an in situ study of 154 participants [62]. In their study, the average participant used approximately ten unique passwords. Participants heavily relied on password reuse, with 40% of participants reusing 80-90% of passwords. For the average participant's unique passwords, 67% were exactly reused, 63% were partially reused, and 79% were reused in both ways (exactly and partially). Most of this partial

reuse involved simple changes to existing passwords (the most common reuse strategy involved changing a single character) and more than half of the time these changes were consolidated at the beginning and end of the reused passwords. Passwords for work-related accounts were approximately three times as likely to be reused compared to passwords for non-work-related accounts. Participants also reused passwords across categories of websites, often in unsafe ways. For example, 85% of passwords on financial sites were reused (either partially or exactly), and of these, 95% were reused for other types of websites.

Zhang et al. studied password reuse in the context of password expiration policies [102]. They developed an algorithm that would use knowledge of a user's previously expired passwords combined with a set of password transformation rules to guess that user's newer replacement password. They evaluated their algorithm by testing it against password histories associated with defunct university accounts. Their results confirm that many users create new passwords by modifying old ones, and that this information can be leveraged by attackers to improve password guessing success. Even when limiting password guesses to five attempts, an attacker with knowledge of a previously used account password could use their algorithm to successfully guess a future account password for an average of 17% of accounts.

Haque et al. examined how easily passwords created for a user's low-value accounts could be leveraged to crack passwords created by the same user for high-value accounts [29]. Participants in their study were asked to create passwords for different categories of websites. Website categories differed according to the degree with which a user might be incentivized to secure an account in that category. For example, participants were asked to create a banking account password, as well as a password for a weather forecasting website. They then attempted to use the John The Ripper (JTR) password cracking tool to guess participant's high-value account passwords, using only their low-value account passwords (i.e., no other cracking dictionary). Nearly 20% of high-value account passwords were able to be guessed in this way. This supports the idea that users partially reuse password across account categories, even in unsafe directions (reusing low-value account passwords for high-value accounts), and that a significant portion of unsafe partial password reuse can be guessed using a default configuration of a freely available password cracking tool.

2.1.6 Measuring resistance to guessing attacks

Security researchers have attempted to quantify the *guessability* of secrets, which is the resistance of secrets (e.g., passwords, PINs) to guessing attacks. Current metrics for quantifying the guessability of secrets fall into two categories: metrics based on statistical properties of the secret distribution and metrics based on using (or simulating) actual secret-cracking tools.

Statistic-based metrics can be further divided into entropy-based metrics and guess-based metrics. Among entropy-based metrics, Shannon entropy has seen the most use. NIST provided a heuristic for estimating the Shannon entropy of passwords, which studies have used and extended [75]. Shannon entropy can be interpreted in many ways. It characterizes the "uncertainty" of a secret distribution, or equivalently how many bits are needed to optimally compress a dis-

tribution. While this can be a useful metric of resistance to guessing attacks, especially in the case of cryptographic keys that are randomly generated, in general it has no direct relationship to guessability and can be significantly influenced by rare events (e.g., a small set of users that choose large randomly-generated cryptographic keys as their password) [6]. This limits its use for quantifying the guessability of user-chosen secrets. Another useful metric is min-entropy, which quantifies security based only on the most probable secret.

Guess-based statistical metrics more closely align with a model of an attacker that makes sequential guesses, e.g., an attacker that tries to guess common passwords to break into a set of accounts. *Guesswork* quantifies the expected number of guesses that would be required to correctly guess a set of secrets, assuming the attacker orders her guesses in an optimal way, i.e. guessing the most probable secret first, with subsequent guesses in order of decreasing probability. Bonneau argues that guesswork does not reflect resistance to actual attackers, since it averages the number of guesses needed to compromise all accounts, whereas in practice attackers may ignore harder-to-guess secrets and where they may be limited by a security policy in the number of guesses they can attempt [6]. Partial guesswork metrics can capture this. *Marginal success rate* or β*-success-rate* measures the expected fraction of accounts that can be compromised (or, equivalently, the expected probability of breaking an individual account) if an attacker is limited to β guesses per account. α*-guesswork* measures the number of guesses required by an attacker to compromise a proportion α of accounts (or, equivalently, to have an expected probability α of breaking an individual account) [6]. [1]

The other general category of guessability metrics are metrics based on actual secret-cracking tools. A variety of cracking tools exist, all of which are tailored to cracking passwords: oclHashcat and John the Ripper use wordlists and mangling rules to quickly generate guesses, probabilistic context-free grammar (PCFG) tools generate guesses according to a grammar-based model that represents passwords using character class terminals (e.g., letters, digits, symbols), and Markov model tools generate guesses according to a trained character-level Markov model. The most recent development in cracking tools is the modeling of passwords using artificial neural networks. The features used by a neural network are generated as a result of training and not easily interpreted.[2] By attacking a password dataset and observing the point (guess number) at which each password is guessed by a particular tool, a distribution of guess numbers can be generated. This can be translated into useful metrics such as the expected percentage of passwords guessed for a given number of guesses, similar to the marginal success rate metric. A refinement of this approach is to combine guess numbers for a set a popular password-cracking tools into a summary metric. For example, researchers have created Password Guessability Service (PGS), a service which allows other researchers to generate *min-auto* guess numbers for sets of passwords [90]. For a given password, that password's min-auto guess number is defined as the smallest guess number among five password-cracking tools: oclHashcat, John the Ripper, and three password models (Markov, PCFG, neural network). Min-auto guess numbers were found

[1] This improves upon a related metric, α*-work-factor* (also known as marginal guesswork), by modeling the fact that an intelligent attacker will stop guessing for an account once one of those guesses succeeds.

[2] The features learned by a neural network that models passwords could theoretically include the same features used by PCFG or Markov models, as long as those features are useful for accurately modeling passwords in the training set.

to approximate the guessing success typical of expert attackers [90].

Guess-based statistical metrics and tool-based guessability metrics are closely related; both attempt to characterize resistance to an attacker. The primary differences between them are the assumptions about the particular guesses made by an attacker, and the order in which they are made. Guess-based statistical metrics are useful for characterizing security against a best-case attacker who has complete knowledge of the distribution of secrets and orders guesses for an account starting with the most probable secret. This provides a worst-case-scenario security analysis, which may be appropriate for high-risk applications. Their weakness is that they may overestimate security concerns; no practical attacker will have complete knowledge of the secret distribution, and these distributions will differ based on many contextual factors, including the sub-population being attacked [6]. More realistic characterizations of security can be provided by tool-based metrics, but the ability to generalize conclusions from these metrics will necessarily be limited; cracking tools can be configured and trained in many different ways besides those that were used to calculate metric values.[3]

2.1.7 Password-creation guidance

Prior work by Ur et al. [87] demonstrated that data-driven password meters are useful for helping users create more guess-resistant passwords. Besides the standard password strength meter, the password meter in that work introduced text feedback intended to guide users toward stronger passwords, by explaining aspects of the user's current password that could be improved. In that study, text feedback was the result of a regression of min-auto guess numbers onto 21 heuristic features associated with guessable passwords. For each heuristic feature, the meter would detect if that heuristic was present in the current password. It would then display up to three pieces of text feedback describing any detected heuristics and how addressing them could strengthen the password. Results from a Mechanical Turk user study in which participants created passwords using a password meter incorporating such text feedback showed that the feedback helped participants create stronger passwords.

Concrete password suggestions were also explored. These suggested improvements were optional, and took the form of a slightly modified password that users could choose to replace their current password. The slightly modified password was the result of an algorithm that made modifications in a random manner to remove heuristic features commonly used in passwords. The modifications that were made included those addressing aspects besides those shown in the actual text feedback, in order to increase the space of possible modifications utilized in the suggested improvements [87].

User study results reported by that same work found most participants did not choose to explicitly show suggested improvements. Among those that did, most found it useful, and a slight majority reported that it helped make their password stronger, albeit not by choosing suggested

[3]Researchers attempt to mitigate this by using configurations and training data representative of a sophisticated attacker (e.g., configurations recommended by Hashcat, publicly leaked passwords). However, it is still possible that an attacker could use more effective configurations or additional training data to increase guessing effectiveness.

improvements verbatim, but more often by serving as inspiration for what to change in their existing password. Those that did not find the suggested improvement useful were either concerned about password memorability when using exact suggestions or about the trustworthiness of the algorithm creating those suggestions. Based on these results, Ur et al. recommended keeping concrete password improvements as optional [87].

2.2 Interpretable text-based model explanations

Prior work has produced neural-network-driven models for predicting password guessability that are both accurate and can be embedded in client-side password meters for providing users with real-time feedback on password strength. Another type of feedback that has been found beneficial for users is text feedback on how to improve passwords. Using neural network models of password strength for deriving text feedback is a challenge due to the complexity and opaqueness of neural-network predictions. Here we review prior work on interpretable model explanations relevant to interpretable password-strength text feedback.

2.2.1 Using interpretable models

A general approach for explaining complex models is to approximate the complex model using a simpler, more interpretable model. For example, Ur et al. utilize linear regression of password guessability using a set of 21 heuristic-derived features to approximate a more complex neural network [87]. Linear regression models provide a natural way of understanding contributions of individual features to a prediction, in terms of the product of features weights and input values.

A potential downside of using a simpler model to approximate a complex model is that the simpler model may not produce as accurate of predictions. Ribeiro et al. introduced LIME, a technique that uses simpler models to provide accurate predictions with a local region of the input space [67]. Although the simpler model may not be able to accurately model the output for all inputs, within a small region, e.g. for passwords similar to a specific candidate password, a sparse linear model may provide sufficiently accurate predictions. A drawback of LIME is that it can be expensive to implement for networks with a densely-populated input feature space [82]. In addition, finding a suitable simpler model (including its features) is a requirement for LIME. For a given complex model, not all linear models will be powerful enough to explain the complex model's predictions. Further, a linear model may not be sufficient to produce locally-faithful explanations under LIME if the complex model is highly non-linear even in the restricted local space [67].

Learning relative feature importance

Regression models are often used as a tool for understanding the relative importance of predictors in determining an outcome. For multiple regression models, this involves comparing the weights

of different features in a trained model. This can shed light on the relative importance of features in terms of association with the predicted outcome.[4]

Interpretation of regression feature coefficients in terms of relative importance is not always appropriate, depending on properties of the particular features used and their relationship to each other. If different features are measured in very different numerical scales, then their values are not directly comparable. In addition, if features are highly collinear, this severely limits our ability to separate out the contribution of each feature for predicting an outcome [17].

Certain techniques can be applied to regression feature sets in order to help with interpretability in terms of relative feature importance. Clustering of features, e.g. using principle component analysis (PCA) or by learning a latent space, can produce independent sets of features [17], although this creates challenges in understanding and describing what the resulting features represent. Another approach to handle feature collinearity is to use domain knowledge and feature collinearity estimates (e.g., pairwise correlation coefficients and variance inflation factors) to pre-select a set of features associated with multi-collinearity estimates below a rule-of-thumb-based threshold [17]. Lastly, regression features can be standardized by dividing by the standard deviation of the feature in the training data, which helps interpretability by placing features an similar scales [27]. In our work, we apply each of these approaches in order to understand the relative importance of heuristic-associated features on different outcomes.

2.2.2 Learning interpretable features from latent representations

Interpretable model explanations often require interpretable features. While intuition-derived features are often interpretable and can provide useful predictions, intuition does not always produce accurate features and useful but less obvious features may be missed. A systematic way of learning features that describe data is to use a latent representation. Latent representations of data represent that data in a lower dimensional space than the input space. Due to the way they are constructed, latent spaces often can capture abstract, semantically meaningful concepts that are useful for describing data; data points that are nearby to each other in a latent space often share similar high-level characteristics of that data.

A latent space can be learned using many different methods. Prior work has explored learning a latent representation of passwords using generative adversarial networks (GANs) and autoencoders. Hitaj et al. designed PassGAN, which uses a GAN-learned latent space to estimate the distribution of training-data passwords in order to make new, likely password guesses [31]. Pasquini et al. leverage latent representations of passwords learned by training GANs and autoencoders in order to generate two types of password guessing attacks. In the first type, guesses are generating by sampling from the latent space near a given template password. In the second type, password guesses are dynamically modified according to successful guessing attempts on a test set; password generation is performed using a Gaussian mixture model defined in the latent space, where each guessed password contributes a new mixture [60].

[4]Relative importance should generally not be interpreted in terms of causal effects, which is dependent on study design.

Although prior work has experimented with latent spaces in order to generate novel guess techniques [31,60], the focus of those works has been in more efficient and effective password guessing. In those works, the authors reported that similarity in the latent space seemed to primarily correspond to character-class structure and common substrings. However, those studies did not systematically analyze the learned latent space in order to learn how interpretable feedback could be extracted from it.

In our work, we explore latent representation of passwords with the goal of identifying features that can be reflected in heuristic-based text feedback on password strength. We accomplish this using three high-level steps: (1) use an autoencoder to learn a latent representation, (2) cluster passwords in that latent representation, and (3) analyze clusters in order to label them with high-level text useful for password-strength guidance. This general approach is most applicable when using a small-dimensionality latent space, otherwise distance in the latent space tends to be uninformative (an issue related to the curse of dimensionality) [59]. We discuss background related to the first two steps next, and afterwards describe background on the model-explanation technique Integrated Gradients, which we used to help accomplish the third step.

Autoencoders. Autoencoders are a type of neural network often used for performing unsupervised feature learning. They are composed an encoder and decoder; the input to the decoder is the output of the encoder, and the goal is reconstruct the encoder input while learning a latent representation that captures abstract, semantically meaningful data features. Given a sufficiently high capacity encoder or decoder, autoencoders can simply learn the identity function without learning any useful features of the input data. Autoencoders can be forced to learned a compressed representation by introducing different types of bottlenecks between the encoder and decoder. In this thesis, we use an under-complete autoencoder, which accomplishes this by having an innermost encoding layer that is smaller in dimensionality than the input layer.

Fuzzy clustering

A natural way to learn a small set of features is to cluster data in a latent space. Clustering in a latent space corresponds to grouping data based on similarity according to high-level, abstract concepts. Fuzzy c-means is a type of clustering model based on fuzzy logic that is especially suited for learning patterns in complex systems, where clusters form around imprecisely learned, approximated patterns [68]. In this thesis, we were interested in learning abstract patterns more complex than those identified in existing password-guidance heuristics, and were willing tolerate some degree of imprecision to achieve that.

Fuzzy c-means clusters data by assigning membership values for each data point to each cluster. Different data points will have different degrees of membership to clusters, indicating the level of precision or uncertainty for which that data point is estimated to belong to each cluster. Importantly, data points that are similar in the latent space will have similar cluster memberships [68].

The fuzzy c-means algorithm is parameterized by a scaling factor that determines how gradual ("fuzzy") the transition is from cluster membership to non-membership. In addition, fuzzy sets

can be turned into well-defined ("crisp") sets using different transformations. We use an approach that assigns a data point to the cluster for which the data point has the highest membership value [68] and denote the resulting memberships values as hard assignments (analogous to the soft-assignment output of a neural-network softmax layer).

t-SNE

t-distributed stochastic neighbor embedding (t-SNE) is machine-learning technique that can project multidimensional data onto a two-dimensional plot. t-SNE performs the transformation in such a way that close neighbors in the latent space appear close in the two-dimensional visualization. Although not a clustering algorithm, t-SNE data points often cluster in groups that align with clusterings of more formal clustering algorithms [43]. They are particularly useful in data exploration to help determine the number of clusters to experiment with in clustering models.

A limitation of t-SNE visualizations is that they do not always accurately depict the global structure of a latent space. Kobak et al. explored steps that can be taken to help maintain global structure in t-SNE visualizations, including initialization of t-SNE embeddings according to PCA components and increased learning rates. They also suggest a rule of thumb for configuring the t-SNE perplexity parameter, which controls the number of neighbors in the latent space used to compute data similarity [43]. We use configurations based on their recommendations when generating t-SNE visualizations for our data.

2.2.3 Interpretable cluster-membership predictions

Clusters of passwords in a latent representation can help reveal patterns, but this process still relies on intuition and manual inspection to identify patterns in passwords nearest to different clusters. This can be especially problematic when the patterns we would like to identify are complex and non-obvious. To assist in this process, we apply Integrated Gradients to highlight characters in password associated with a given cluster assignment, including their relative contributions to that assignment.

Predicting cluster membership using neural networks

In order to apply machine-learning model-explanation techniques to explain cluster-membership predictions, the clustering model must first be expressed in terms of neural-network-layer operations. Kauffman et al. describe how to explain k-means cluster-membership predictions in terms of input features using a two-step process. They explain different ways that the k-means algorithm can be expressed in a functionally equivalent neural network using standard detection and pooling layers. In their work they demonstrate how layerwise relevance propagation can be applied to these neural networks to explain cluster membership in terms of input features. In particular, this process does not require retraining the k-means clustering model [40].

Integrated Gradients

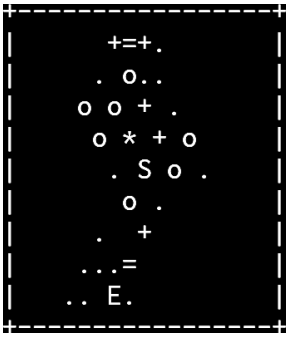
Sundararajan et al. proposed *Integrated Gradients* (IG), a technique for highlighting the relative importance of input features to a neural network prediction. This attribution method utilizes the gradients of a neural network prediction with respect to the input of the network. Specifically, it accumulates the attributions of input variables along the straightline path in the input space from an feature-uninformative baseline to the target input being explained. As features relevant to a prediction score are introduced along the path from the baseline to the target input, the gradients of the score with respect to each input dimension become non-zero; summing the stepwise gradients separately for each input dimension can therefore reveal which inputs affected the final prediction score [82]. IG explanations can help highlight characters associated with high-level patterns that determine a prediction score, however, these explanations have limitations. In particular, it cannot disentangle attributions for correlated input features and does not directly reveal feature interaction effects [81].

Baseline for attributions. IG attributions depend on the baseline that they are computed with respect to. For text applications, a commonly recommended baseline is the all-zero embedding vector [82]. For machine-learning models trained with sequence start and end tokens, a similar padding-based baseline using start and end tokens can be used. Prior work in image-classification explanations has found success using baselines consisting of randomly selected training data [80] and Gaussian noise centered at the target input. In order to smoothen attributions generated by such randomly-determined baselines, attributions are often averaged over many baseline instances [77, 80].

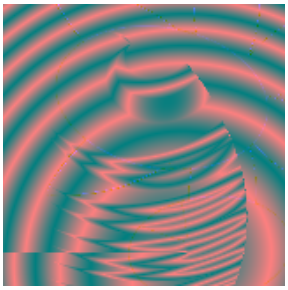
Visualizing attributions. IG attributions for text-based models often take the form a heatmap, which uses color to highlight the relative contribution of different characters (or words) to a network prediction. The exact way that visualizations are formed can lead to significantly different results for the same set of attributions [80]. Prior work provides some recommendations on how to visualize attributions, but also suggests that different modeling domains may be suited to different visualization configurations (e.g., how negative attributions are displayed) [2, 77, 83]. Recommendations for pre-processing IG attributions prior to visualization include capping attribution values above at a threshold and testing different ways of displaying (or suppressing) negative attributions. The faithfulness of IG visualizations in capturing all relevant attributions can be quantified by comparing the sum of estimated character-wise attributions to the theoretically-justified target of the delta in prediction scores for the baseline and input target [2, 80].

2.3 Public-key fingerprints

Public-key encryption can be used to secure communications such as email or instant messaging. For Alice to send a message to Bob that only Bob can read, she needs to encrypt the message with



(a) OpenSSH Visual Host Key



(b) Vash

(c) Unicorn

Figure 2.1: Examples of graphical fingerprint representations.

Bob's public key. Bob will use his private key to decrypt the message. One type of attack against such communications is a man-in-the-middle (MITM) attack, in which an attacker inserts himself or herself between the two communicating parties in such a way that neither party is aware of the attacker. Once inserted, the attacker can eavesdrop or actively manipulate communications.

In order to prevent MITM attacks, it is important that Alice encrypts her messages with the actual public key belonging to Bob (and vice versa). In many situations, there may not be a trusted and secure key server that Alice can use to obtain Bob's legitimate key online. In these cases, Bob can still host his public key online somewhere that Alice can retrieve it. Then, Bob only needs to provide Alice with his key *fingerprint*—a digest of the full key that makes manual key comparison feasible—through some secure channel (such as in person). By manually comparing fingerprints, both sides of the communication channel can detect when the other side has been replaced by an imposter.

2.3.1 Fingerprint applications

Well-known applications that make use of fingerprints include GnuPG [9], a tool for encrypting communications, and OpenSSH [23], commonly used for remote access to servers. Off-the-Record (OTR) Messaging applications provide multiple ways to authenticate message recipients, including fingerprint verification [84]. Many popular secure chat smartphone apps also use fingerprints, usually in a layered approach in which fingerprint comparison is optional [96, 99].

A variety of fingerprint representations and formats are used, the majority of which are textual. Examples of textual representations used in real systems are shown in Table 2.1. Graphical representations have seen limited use; examples include Peerio [54], which uses an avatar representation, and OpenSSH Visual Host Key, which resembles ASCII art (Figure 5.2).

GnuPG	`3A70 F9A0 4ECD B5D7 8A89` `D32C EDA0 A352 66E2 C53D`
OpenSSH	`ef:6d:bb:4c:25:3a:6d:f8:79:d3:a7:90:db:c9:` `b4:25`
bubblebabble	`xucef-masiv-zihyl-bicyr-zalot-cevyt-lusob-` `negul-biros-zuhal-cixex`
OTR	`4206EA15 1E029807 C8BA9366 B972A136 C6033804`

WhatsApp	`54040 65258 71972 73974`
	`10879 55897 71430 75600`
	`25372 60226 27738 71523`

Table 2.1: Examples of textual fingerprint representations used in actual applications.

2.3.2 Usability of fingerprints

Public key cryptography has long had usability and adoption issues [11, 24, 26, 70, 98]. Fingerprints have been part of the problem. In a user study on OTR messaging, participants were confused by fingerprints and struggled to verify them correctly [78]. In order to make fingerprint verification more usable, researchers have explored a variety of approaches.

One way to make comparison easier is to shorten fingerprints. This approach is used in Short Authentication Strings (SAS). SAS can provide reasonable security using only a 15-bit string [92], though they are primarily useful in synchronous environments. SAS-based methods are less useful for public-key fingerprint verification, which is traditionally asynchronous. Alternatively, the computational security of small fingerprints can be increased by slowing down the hashing algorithm using a stretching function.

Adding structure to a fingerprint representation may make it easier to compare. Textual fingerprint representations can be separated into smaller chunks. Representing fingerprints as pronounceable words or sentences may also facilitate comparison. For graphical representations, structured images resembling abstract art have been suggested for improving usability. These include Random Art [63] and OpenSSH Visual Host Key, which was inspired by Random Art [57]. Another way to add structure is to represent fingerprints as avatars, such as unicorns [91] or robots [12].

Different comparison modes have also been proposed, primarily for SAS-based device pairing or synchronous authentication [20, 76]. These include compare-and-confirm (compare two strings and indicate if they match), compare-and-select (compare one string to a set of others and select the matching option), and copy-and-enter (copy a string from one device to another and let the device itself perform the check). Compare-and-select has also been used for anti-phishing tools that ask users to select the website they want to visit from a list, rather than ask for a yes/no answer to whether users would like to proceed to a given website [100]. Prior work has postulated that compare-and-select may help prevent users from "verifying" fingerprints without actually comparing them [20, 85].

A number of usability studies on device pairing have explored different fingerprint represen-

tations and comparison modes [38, 44, 47]. They considered representations such as numbers, images of visual patterns, and phrases, as well as various comparison modes. In each of these studies, participants performed fingerprint comparison tasks in a lab setting. In some cases, participants were also subjected to a simulated MITM attack [38, 47]. These studies had mixed findings; for example, Kainda et al. conclude that compare-and-confirm and compare-and-select should not be used because it is subject to security failures [38], while Kumar et al. recommend that compare-and-confirm with numbers be used due to its low error rate and comparison speed [47]. An important note about the fingerprints tested in these lab studies is the size of fingerprints tested, which ranged from 15-20 bits; for traditional asynchronous public-key fingerprint verification, a larger fingerprint size would be needed.

In a 400-participant online study, Hsiao et al. examined the speed and accuracy of fingerprint comparisons under different representations [32]. In contrast to lab studies, their methodology enabled statistical testing. A specific fingerprint representation they tested was Random Art [63], which can encode bit sizes large enough to be suitable for use as cryptographic key fingerprints. In order to generate attacks against Random Art fingerprints, researchers selected visually similar fingerprint pairs from 2000 randomly-generated fingerprints. They found Random Art performed well in both accuracy and speed, recommending its use for color-display devices with sufficient computational power.

Scant research has tested representations suitable for key fingerprints. Dechand et al. conducted a large-scale, within-subjects experiment on Mechanical Turk (MTurk) in which participants compared fingerprints displayed in different textual representations, including hexadecimal, numbers, words, and sentences. They measured comparison speed and accuracy, and they also recorded whether participants correctly compared fingerprints for multiple simulated 2^{80} attacks. They found that hexadecimal performed significantly worse than numbers and sentences in both attack detection rates and usability ratings. In addition, they found that sentences had a significantly higher attack detection rate than numbers, while also being rated as more usable [14]. More recently, Azimpourkivi et al. describe CEAL, a method for generating graphical fingerprints in the form of nature landscape images, where fingerprints are generated using a GAN trained to produce realistic-appearing images that can easily be discriminated using an additional classifier network [4]. Future work is needed to understand the effective security provided by CEAL in realistic comparison settings.

2.3.3 Entropy as a security metric

Entropy can be used to measure the computational security afforded by different fingerprint representations. If users compare fingerprints fully, then the entropy of a fingerprint representation quantifies the average work needed to find a key whose fingerprint collides with the target fingerprint. If users do not compare fingerprints completely, but only compare certain aspects, then an intelligent attacker may attempt to only match the aspects he expects will be actually compared. This type of attack, in which the adversary attempts to find a visually similar fingerprint to the target fingerprint, has been explored for both the hexadecimal and graphical fingerprints used in

OpenSSH [49,64]. More recently, the previously mentioned study by Dechand et al. investigated users' ability to detect such attacks for different textual representations [14].

The reduction in entropy of the original representation (after fixing the matched aspects) can be used to quantify the work an attacker must spend to produce a key whose fingerprint matches specific aspects of the target fingerprint. This approach to quantifying attacker work has the added benefit of being independent of the particular binary encoding used for a fingerprint. A 2^{60} attack corresponds to an attacker that generates 2^{60} keys, computes the fingerprint for each, and then (manually or programmatically) selects the key whose fingerprint maximizes similarity according to some metric. Stevens et al. estimate the cost of renting CPU/GPU time from EC2 to find a SHA-1 collision, which requires resources similar to those to perform a 2^{60} attack on fingerprints. They estimate this cost to be between 75K and 120K USD, which they note is within the budget of criminal organizations [79].

Chapter 3

Practical recommendations for stronger, more usable passwords combining minimum-strength, minimum-length, and blocklist requirements

3.1 Introduction

In this chapter we use large-scale experiments to provide concrete password-policy recommendations for system designers. Our recommendations include designs applicable for systems under different implementation and security-level requirements.

To help users create stronger passwords, system administrators often require passwords to exceed a certain length, contain at least a specific number of character classes, or not appear on a blocklist [56]. Users are also often nudged to create stronger passwords by password meters that give feedback on the strength of candidate passwords and suggestions about how to improve them.

Early guidance for how to deploy these approaches relied mostly on common sense and experts' opinions [53, 55]. Over the past decade, a scientific basis has emerged for what requirements are most effective at encouraging users to create passwords that are strong but still memorable. For example, research has shown that increasing minimum length may increase password strength more than relying just on character class requirements [73]; that password meters can very effectively nudge users to create stronger passwords [87]; and that carefully configured blocklists can help prevent users from picking easily guessed passwords [28].

These early efforts shed light on which password requirements were more or less effective, but stopped short of providing empirically evaluated, definitive guidance for how to combine requirements. In this chapter, we seek to address this. Building on previous findings, we empirically examine combinations of length, character-class, blocklist, and password meter requirements—

all of which were previously individually studied—as well as minimum-strength requirements, which have been less studied. We consider practical implementions of minimum-strength requirements, using estimates from a neural network trained on leaked password data. Our research questions examine and compare the security and usability properties of differently configured blocklists and minimum-strength requirements, with careful attention to how the choice of underlying composition requirements affect these properties.

Our results, derived through two successive experiments that investigated a wide range of potential interactions between requirements, allow us to provide concrete, practical recommendations for how to combine and configure these mechanisms. We find that how users pick passwords has changed over time, and that this, in combination with advances in password guessing, implies that requiring passwords to have multiple character classes brings at best minor benefit to password strength. Although some blocklist configurations are more effective than others at eliminating weak passwords, policies that require passwords to have at least eight characters and that simultaneously prohibit passwords that can be guessed within 10^6 guesses perform better—in terms of encouraging password strength—than the best-performing blocklist policies we examine. Properly configured minimum-strength policies not only match our top tested blocklist policies in usability, but can also provide better security, especially against offline attacks that make up to 10^{14} guesses. For organizations that nevertheless require blocklists, we recommend blocklist policies that impose a minimum of eight characters and perform a fuzzy blocklist-matching check against either a subset of the most popular passwords found in password leaks, or that perform a fullstring-matching check against a very large database of publicly-leaked passwords.

A primary contribution of our work is to design, evaluate, and recommend configurations for minimum-strength requirements. These requirements build on the large body of password research conducted over the past 15 years. Conceptually, minimum-strength requirements represent the goal of other types of password-creation requirements that have been proposed and tested: to reject weak, easily-guessed passwords while permitting strong, hard-to-guess passwords. In this study, we present a concrete (neural-network-driven) implementation of minimum-strength requirements that both faithfully achieves password-strength goals and achieves comparable usability to the best competing blocklist-based policies we tested. Neural-network-driven minimum-strength requirements are easy to deploy, flexibly configurable, and can be easily retrained to reflect changing patterns in passwords over time.

3.2 Methodology

Here we present our experimental factors and conditions; the design of the user studies we used to collect data; and the statistical methods we applied to analyze that data. To limit the number of interactions between policies that we would have to simultaneously explore, we conducted two experiments (*Experiment 1* and *Experiment 2*), each involving independent data collection. Both were identical in terms of methodology and implementation—only the experimental conditions differed.

3.2.1 Experimental factors

Each of our user studies presented participants with password-creation policies that differed based on assigned treatment. The experimental factors consisted of three types of requirements that can be enforced by a password-creation policy: composition, blocklist, and minimum-strength requirements.

We performed retrospective analyses on randomly-selected subsets of leaked 000webhost passwords to help identify the parameters to explore in our user study for each type of experimental factor. This involved retroactively applying a password policy to a set of leaked passwords and observing the proportions and strengths of passwords that were allowed or rejected by that policy. Retrospective analyses and analyses relying on leaked data have inherent limitations discussed in Section 2.1.2. The overall findings we present are based on data collected from *experimentally* designed user studies, which avoids these limitations. In addition, results from Experiment 1 informed the parameters explored in Experiment 2.

Composition requirements All policies required passwords to be at least eight characters long. In addition, some policies required longer password lengths or required passwords to contain a minimum number of character classes. We abbreviate composition requirements using a notation that lists the required number of character classes followed by the minimum length, e.g., *3c12* corresponds to requirements that passwords contain at least three character classes and at least twelve characters. In Experiment 1, we tested *1c8*, *1c16*, *3c8*, *3c12*, and *4c8*, each of which has been explored in prior work [42, 46, 51, 55, 73, 74]. In Experiment 2, we explored additional longer-length one-class policies (*1c10* and *1c12*).

Blocklist requirements We tested policies incorporating a blocklist requirement, which rejected any password that matched an entry on a list of prohibited strings. We explored several wordlists and matching algorithms. The majority of our blocklist configurations followed previous work [28, 87, 97] in using the *Xato* wordlist, consisting of 96,480 passwords that appeared four or more times in the leaked Xato corpus of 10 million passwords [8].[1] This We also used a wordlist of 555 million unique passwords previously leaked in data breaches[2] that are accessed using the freely available *Pwned* Passwords API [36].[3] Last, we tested the wordlist (and matching algorithm) used at Carnegie Mellon University (CMU), which consisted of 630,034 English dictionary words [3, 58].

We tested four matching algorithms: case-insensitive full-string (*cifs*); case-sensitive full-string (*fs*); stripping digits and symbols and then performing a case-insensitive full-string comparison (*strip-cifs*); and checking whether any length-5 substring of any wordlist entry was a case-

[1]The Xato leak primarily includes passwords leaks that occurred between 2010 and 2015 [7].

[2]This includes password datasets leaked as early as 2007 (Foxy Bingo, gPotato) up until July 2019, and passwords for accounts created as early as 2004 (diet.com) [37].

[3]This API employs privacy-protecting mechanisms to protect the confidentiality of submitted passwords: it only accepts SHA-1 hashes of passwords and utilizes a k-anonymity range search to report matches [35].

insensitive substring of the candidate password (*ciss*). Each of these has been used in deployed password-creation policies [13]. The *ciss* algorithm has been explored by prior work [72], albeit with a much smaller wordlist than we considered.[4]

Minimum-strength requirements In addition to composition and blocklist requirements, we tested policies incorporating a minimum-strength requirement, expressed as the minimum number of guesses that passwords should withstand in a guessing attack. We used password-strength estimates computed by a client-side, JavaScript-based neural network, implemented and trained following the approach of Melicher et al. [52] (see Appendix A.1). We defined minimum-strength requirements in terms of a log-10 guess number threshold. For example, *NN6* required passwords to have password-strength estimates no weaker than 10^6 guesses.

We tested four minimum-strength thresholds, ranging from 10^6 to 10^{12} guesses. In Experiment 1 we tested policies that included *NN6* and *NN12* requirements. Results suggested that *NN6* requirements may be too lenient for protecting high-value accounts and that *NN12* requirements can make password-creation annoying or difficult for some users. Hence, we tested *NN8* and *NN10* in Experiment 2 to explore minimum-strength thresholds that might produce a better balance of both security and usability.

3.2.2 Research questions

We designed our experimental conditions to answer specific research questions. Some research questions explored the security and usability impacts of policies differing in a single experimental factor (e.g., blocklist configuration). We also investigated whether certain policy components impact password strength or usability differently depending on the configuration of other policy components (e.g., the same blocklist configuration used alongside different composition policies). Table 3.1 lists our research questions and the experimental conditions and comparisons used to answer them.

Experiment 1

We tested 15 experimental conditions designed to answer four high-level research questions. In order to both quantify the impact of blocklists relative to policies that only required composition requirements (*RQ1*) and to find blocklist requirements for use in *1c8* policies that performed well on both security and usability dimensions (*RQ2*) we tested blocklist configurations that were either commonly used or recommended by prior work. Our third high-level research question focused on the impact of character-class and minimum-length requirements on *NN6* minimum-strength policies (*RQ3*). The particular set of character-class and minimum-length combinations we explored included composition policies explored in prior work. Our fourth research question

[4]We use a computationally efficient *ciss* implementation that performs multiple substring searching via the Rabin-Karp algorithm [5].

Baseline	**Comparisons**	**Exp.**
*RQ1: What is the impact of **adding a blocklist** to 1c8 and 3c8?*		
1c8	1c8+Pwned-fs, 1c8+Xato-cifs, 1c8+Xato-strip-cifs, 1c8+Xato-ciss	1
3c8	3c8+Xato-cifs	1
*RQ2: What is the impact of varying **blocklist reqs.** on 1c8?*		
1c8+Xato-strip-cifs	1c8+Pwned-fs, 1c8+Xato-cifs, 1c8+Xato-ciss	1
1c8+Xato-strip-cifs	1c8+Pwned-fs	2
*RQ3: What is the impact of varying **char-class and min-length reqs.** on NN6?*		
3c8+NN6	1c8+NN6, 1c16+NN6, 2c12+NN6, 3c12+NN6	1
*RQ4: How do **min-strength reqs. compare with blocklists**?*		
1c8+NN6	1c8+Pwned-fs, 1c8+Xato-cifs, 1c8+Xato-strip-cifs, 1c8+Xato-ciss	1
1c8+Pwned-fs	1c8+NN8, 1c8+NN10	2
1c8+Xato-strip-cifs	1c8+NN8, 1c8+NN10	2
*RQ5: How do **min-strength reqs. interact with min-length reqs.**?*		
1c8+NN10	1c8+NN8, 1c10+NN10	2
1c10+NN8	1c8+NN8, 1c10+NN10	2
1c12+NN10	1c8+NN10, 1c10+NN10	2
*RQ6: How do **blocklist reqs. interact with char-class reqs.**?*		
1c8+Xato-strip-cifs	4c8+Xato-strip-cifs	2
1c8+Pwned-fs	4c8+Pwned-fs	2
4c8+Xato-strip-cifs	4c8+Pwned-fs	2

Table 3.1: Research questions and planned comparisons.

involved directly comparing blocklist and minimum-strength policies on both security and usability dimensions (*RQ4*). In Experiment 1, we explored this question by comparing a variety of blocklists with a *NN6* minimum-strength policy that we hypothesized would provide adequate protection against online attacks, withstanding at least 10^6 guesses (*RQ4.A*).

Experiment 2

The results of Experiment 1 raised additional research questions that could not be answered with the experimental data that had already been collected. Therefore, we conducted a second experiment, testing seven new conditions and re-testing three conditions from Experiment 1.[5] One goal of Experiment 2 was to explore how specific minimum-length requirements interacted with specific minimum-strength requirements to effect usability or security (*RQ5*). In particular, we hypothesized that longer minimum-length requirements could make minimum-strength requirements easier to satisfy. We explored this question using strength thresholds in-between those we tested in Experiment 1; results from that experiment had suggested *NN8* and *NN10* requirements may provide the level of offline protection needed for high-value accounts. Experiment 2 was also designed to test whether blocklist requirements impact password strength or policy usability differently depending on the particular character-class requirements they are combined with, and vice versa (*RQ6*). We hypothesized that fullstring blocklist checks against lists of leaked passwords might be less useful for policies requiring many character classes, since leaked passwords may be less likely to contain many character classes. We also hypothesized that the *strip-cifs* matching algorithm might be especially frustrating to users when combined with a *4c8* policy; compared to *1c8* passwords, 4c8 candidate passwords might be more likely to incorporate digits and symbols in ways that would be rejected by blocklist checks that first strip digits and symbols. Lastly, we revisited *RQ4* comparing top-performing blocklist policies from Experiment 1 with the additional *NN10* and *NN12* policies tested in Experiment 2 (*RQ4.B*).

3.2.3 User-study protocol

For each experiment we ran a user study on Amazon Mechanical Turk in which participants were tasked with creating and recalling a password under a randomly assigned password policy. The design of our user studies closely followed that of prior work [46, 73, 87]. In Part 1, participants were asked to role play, imagining that they needed to create a new password because their main email account provider had been breached. We emailed participants two days later asking them to participate in Part 2, in which they were asked to recall their password. We considered the data of only the participants who completed Part 2 between two and five days after Part 1. After each part, participants completed a survey that collected demographic and usability-related data. The survey materials are provided in Appendix A.6.

[5] We collected new data for each policy in Experiment 2, even if that policy had been previously tested in Experiment 1.

The password-creation task in Part 1 used a password meter developed in prior work, which incorporated real-time requirements feedback, a password-strength bar, and text feedback on improving password strength. Participants were shown feedback on improving password strength only after all composition, minimum-strength, and blocklist requirements were satisfied. The password meter's configuration was based on best practices empirically shown by prior work [87]. We communicated unmet minimum-strength and blocklist requirements as follows: for the *Xato* blocklist configurations the meter reported that the password must "not be an extremely common password;" for the *Pwned* blocklist configurations that the password must "not use a password found in previous security leaks;" and for the minimum-strength requirements that the password must "not be similar to common passwords" (Figure 3.1).

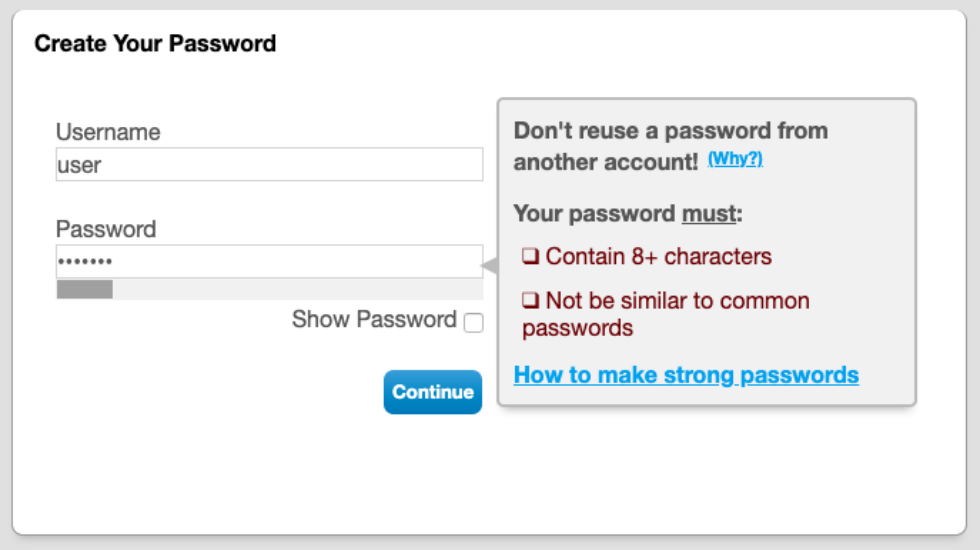


Figure 3.1: Password-creation meter displaying unmet password policy requirements.

We submitted the passwords created by participants to PGS [61], which computed guess numbers for each PGS-supported guessing approach using its recommended configuration. We additionally computed guess numbers using a set of neural networks (collectively referred to as the PGS3 NN) that we trained ourselves, closely following the design and implementation of password models in prior work [52]. When computing min-auto guess numbers, we selected each password's lowest guess number among all guessing approaches. For the NN guessing approach, we use PGS3 NN guess numbers in place of PGS-reported NN guess numbers, given the improved guessing performance of the PGS3 NN (see Appendix A.1).

In addition to evaluating the strength and objective usability (e.g., memorability) of passwords created under each policy, we wanted to understand their usability in terms of user difficulty or frustration when creating or recalling passwords. Participants' responses to surveys shown after both Part 1 and Part 2 shed light on this. Our surveys also asked questions such as whether participants reused a previous password or wrote their password down after creating it. In order to elicit truthful responses we told participants that they would receive compensation regardless of their answers.

We instrumented our study to record password-creation and recall keystrokes and whether participants copied and pasted their password during recall tasks. When analyzing password recall, we only analyze data for participants who: typed in their password from memory (as self-reported in the survey); said they didn't reuse their study password (as self-reported); and didn't copy and paste their password during the Part 2 recall task, either manually from a file or using a password manager/browser (based on keystroke data). Study participants who become frustrated with password-creation requirements may be more likely to drop out of our study. We record and analyze dropout rates between experimental conditions as potential evidence of usability issues for a given policy.

The full set of usability metrics we considered include both objective (creation/recall time, recall success, study dropout, copy/paste from storage/password managers) and subjective data (creation annoyance/difficulty, difficulty remembering).[6] Each of these metrics have been used in prior work to measure usability impacts of password-creation policies [71, 74, 87].

We recruited study participants from Mechanical Turk (MTurk). Workers were required to be located in the United States, have had at least 500 HITs approved, and have a HIT approval rate of 95% or higher. Workers were not allowed to participate in our study more than once. We paid 55 cents for Part 1 of our study and 70 cents for Part 2. Our study protocol was approved by our institutional review board and all participants completed online consent forms.

Experiment 1 participants were recruited in July and August 2019. Their ages ranged from 18 to 81 years, with a median of 35. 53% of participants were female and 47% male. Of the 5,099 participants who started the study, 4,317 finished Part 1 and 3,463 also finished Part 2. Most (81%) participants reported that they did not have a technical degree or work in an area related to computer science or information technology. Experiment 2 participants were recruited in October and November 2019. Their ages ranged from 18 to 90 years, with a median of 35. 56% of participants were female, 43% male, 1% reported their gender as "Other," and the remainder chose not to answer. Of the 4,817 participants who started the study, 4,005 finished Part 1 and 3,014 also finished Part 2. Our password-recall analysis includes data for 1,518 participants in Experiment 1 and 1,362 participants in Experiment 2, excluding those who reported reusing a password or not entering their password from memory.

3.2.4 Statistical analysis

Before running each experiment, we identified a set of hypothesis tests we planned to conduct to answer our research questions. We perform omnibus tests to compare three or more conditions as well as pairwise tests.[7] For each family of tests (the combination of test type and research question), we chose the baseline condition to be used in pairwise comparisons before collecting data.

[6] As we employ real-time feedback in our password meter, our study data do not include the notion of a password-creation attempt. However, this concept is closely related to creation time and creation annoyance/difficulty.

[7] We tried a Cox regression model to measure guessability differences but opted for pairwise hypothesis tests instead, due to poor fit of the linear model to our data.

To compare the overall strength of passwords created under different policies, we use an extension of the Log-rank test called the Peto-Peto test (PP). This test, used in prior work [50], weighs early-appearing differences in guess curves more heavily than later differences, corresponding to heavier weight for strength differences that resource-constrained or rate-limited attackers could exploit. The Peto-Peto test is also appropriate when many data points are censored. In our study, passwords with guess numbers past our offline attack threshold of 10^{14} were censored prior to the test (i.e., labeled as unguessed), as we wanted to compare password guessability only up to the number of guesses that a typical attacker could feasibly attempt in an offline attack.

To compare the vulnerability of passwords to guessing attacks of different magnitudes, we apply Chi-square tests of independence and Fisher's exact tests (FET) to the percent of passwords in each set that an attacker would guess within 10^6 and within 10^{14} attempts.[8] These thresholds have been used in prior work as estimates of how many guesses an online and an offline attacker could make [22], respectively. Unless otherwise noted, analyses that operate on guess numbers are based on min-auto guess number estimates.

We examine usability through statistical tests of Part 1 and Part 2 survey data (password-creation sentiment, post-creation actions) and behavioral data collected by our study framework (study dropout rates, password-creation time, Part 2 recall time, and Part 2 recall success). We bin categorical and Likert data before applying Chi-square tests and Fisher's tests (e.g., Likert agreement data is grouped into two bins: "Strongly agree" or "Agree" vs. otherwise). For comparing count data, we use the non-parametric Kruskal-Wallis (KW) and Mann-Whitney U (MWU) tests.

We record whether text entered into the password-creation field failed to meet requirements, but the real-time nature of requirements feedback in our meter means that even if a blocklist or minimum-strength requirement was unsatisfied at some point, the participant may not have intended to actually create that password—they may have had a different password in mind and hadn't finished typing it. To shed light on whether participants actually encountered one of these unmet requirements for a password, our survey asked "were any passwords you tried to create rejected for the specific reason shown above?" We interpret affirmative answers as evidence that those participants changed their password at least once due to the associated policy requirement.

Within each family of tests, we only perform pairwise tests if the corresponding omnibus test is statistically significant. We use the Holm-Bonferroni method to correct for multiple pairwise comparisons within each family and report adjusted p-values. All hypothesis tests use a significance level of 0.05. When comparing two policies, we only attribute differences to a particular policy dimension if all other dimensions in those policies are identical.

[8] Our conservative assumption is that the attacker knows the password distribution and makes guesses in order of decreasing probability. While we assume the attacker knows the length and character-class requirements when making guesses, we do not assume that the attacker knows which passwords would have been rejected by blocklist or minimum-strength requirements in order to avoid guessing those passwords.

3.2.5 Limitations

Our study has limitations common to user studies conducted on MTurk. Study participants may not have created passwords similar to those they would have created for actual high-value accounts, despite our role-playing instructions. However, prior work has shown that MTurk passwords collected in this way are similar to actual user passwords created for high-value accounts [19, 50]. More recently, Redmiles et al. performed an in-depth study examining how well results from MTurk studies on privacy and security generalize to the general population, in particular for self-reported behaviors, experiences, knowledge, and beliefs. They found that MTurk results were representative of the U.S. except for participants over the age of 50 and for those having only a high school education or lower. Although they did not directly examine how well MTurk-based user studies on security tasks such as password creation generalize to the broader public, their results suggest that MTurk participants—including those older and less educated—have similar self-reported knowledge of how to create strong passwords [66].

Our password-policy results and recommendations rely on passwords being created under the specific password meter we used in our study. This meter provided text feedback on how to improve passwords, a strength bar, and real-time requirements feedback, each of which was configured according to recommendations from prior studies [72,87,88]. Based on survey responses, the majority of participants found the meter to be informative, helpful, and influential. For example, most participants reported that they implemented changes suggested by text feedback and that it was important to them that the colored bar rated their password highly. Experiments using password meters with substantially different implementations may produce different results.

It is worth noting that our analysis and recommendations concerning blocklists do not apply to site-specific or user-specific blocklists, which are useful for preventing passwords based on user-associated data or contextual information that targeted guessing attacks could leverage (e.g., user IDs, words related to the service).

3.3 Results

The results we report here lead to our recommendation for password policies that include both minimum-length and minimum-strength requirements. In case an organization decides against minimum-strength requirements, we recommend two policies incorporating minimum-length and blocklist requirements. These policies provide less protection than minimum-strength policies against offline attacks, but provide adequate protection against online attacks while remaining usable during password creation.

Our results from Experiment 1 show that blocklists may not improve password strength substantially if the blocklist check uses a strict matching algorithm with an insufficiently large wordlist. However, when properly configured, either blocklist requirements or minimum-strength requirements can be combined with other requirements to provide adequate protection against online guessing attacks. In Experiment 2 we explore in more depth *1c8* minimum-strength policies that

provide strong protection against both online and offline guessing attacks. We also extensively analyze interaction effects between policy components. Experiment 2 results show that *NN8* and *NN10* policies can be just as usable as the blocklist policies we test, while also producing passwords more resistant to offline attacks. In this section, we describe the results from both experiments, organized by research question. P-values for each statistical test can be found in Appendix A.7.1.

Condition	# in Part 1	# in Part 2	Part 1 dropout	Creation time	Creation difficult	Creation annoying	Guessed @ 10^6	Guessed @ 10^{14}	Noticed reject	Stored pwd	Recall success	Recall time
Experiment 1												
CMU	290	228	14%	104 s	34%	42%	1.2%	36.3%	50%	57%	74%	26 s
3c8	284	235	15%	78 s	25%	37%	4.5%	44.8%	-	52%	80%	24 s
4c8	297	237	10%	84 s	31%	35%	5.4%	48.4%	-	44%	76%	27 s
1c8	318	250	13%	86 s	25%	28%	6.3%	48.2%	-	53%	78%	21 s
3c8+NN6	264	213	15%	92 s	33%	38%	0.4%	41.3%	22%	56%	79%	21 s
1c8+NN12	261	213	14%	100 s	36%	44%	0.4%	13%	46%	56%	75%	28 s
1c8+NN6	288	229	10%	73 s	22%	33%	1%	48.3%	20%	50%	79%	21 s
3c12+NN6	257	212	15%	99 s	31%	37%	0%	27.6%	16%	53%	75%	25 s
1c16+NN6	276	209	11%	97 s	37%	45%	0.4%	15.2%	16%	50%	82%	25 s
2c12+NN6	294	231	13%	86 s	26%	33%	0%	29.6%	20%	50%	66%	23 s
3c8+Xato-cifs	337	256	10%	81 s	25%	34%	3.8%	51.4%	23%	48%	76%	20 s
1c8+Xato-cifs	287	241	14%	70 s	26%	32%	4.5%	46.6%	32%	54%	77%	19 s
1c8+Pwned-fs	292	242	13%	85 s	24%	28%	0%	41.9%	23%	52%	86%	23 s
1c8+Xato-strip-cifs	311	267	12%	93 s	27%	35%	1%	41%	50%	53%	79%	25 s
1c8+Xato-ciss	261	200	26%	139 s	49%	47%	0%	24.4%	78%	65%	67%	23 s
Experiment 2												
CMU	429	333	13%	98 s	33%	42%	1.6%	37.9%	-	56%	81%	24 s
1c8+NN8	381	291	11%	86 s	30%	35%	0.8%	40.2%	27%	50%	72%	24 s
1c8+NN10	385	293	13%	109 s	33%	38%	0.5%	31.7%	34%	52%	80%	24 s
1c10+NN8	381	286	11%	89 s	32%	40%	0.8%	31%	25%	51%	77%	23 s
1c10+NN10	401	303	12%	92 s	32%	41%	0%	25.2%	30%	49%	75%	27 s
1c12+NN10	378	273	14%	95 s	28%	38%	0.3%	19.8%	22%	58%	73%	22 s
1c8+Pwned-fs	435	322	16%	83 s	25%	33%	0.7%	43%	-	47%	75%	25 s
1c8+Xato-strip-cifs	434	327	11%	97 s	29%	35%	2%	40.1%	-	55%	76%	21 s
4c8+Pwned-fs	378	287	16%	90 s	29%	33%	3.1%	50.6%	-	56%	71%	24 s
4c8+Xato-strip-cifs	403	299	14%	99 s	32%	41%	1.4%	41.7%	-	51%	81%	25 s

Table 3.2: Descriptive statistics for Experiments 1 and 2. Recall time and success rates are for Part 2. Median creation and recall times are shown. "Noticed reject" refers to rejection by a minimum-strength or blocklist requirement.

Figures 3.2 and 3.3 show participants' annoyance with and perceived difficulty of password-creation.

Figure 3.2: Experiment 1: Participants' level of agreement with the statement above each chart.

3.3.1 RQ1: Impact of blocklists

We compared each blocklist condition to its corresponding *1c8* or *3c8* baseline condition to quantify the impact of blocklists on guessability and usability. **We found blocklist configurations *1c8+Pwned-fs* and *1c8+Xato-strip-cifs* significantly improved password strength over their baseline without substantial harm to usability.**

As shown in Figure 3.4, passwords created under either *1c8+Xato-cifs* or *3c8+Xato-cifs* were neither stronger overall nor less likely to be guessed in online attacks than passwords created under the baseline policies that only contained composition requirements. While blocklist policies that use full-string matching can provide adequate protection against online guessing attacks (as demonstrated by *1c8+Pwned-fs*), our results suggest that this requires a much larger wordlist than the *Xato* wordlist we tested.

Of the policies with blocklists that improved password defense against online attacks, two policies did so without also making passwords substantially more difficult or time-consuming to create. Both *1c8+Pwned-fs* and *1c8+Xato-strip-cifs* passwords were much less likely to be guessed in online attacks (within 10^6 guesses) than *1c8* passwords (FET: 0% and 1% guessed, resp., vs.

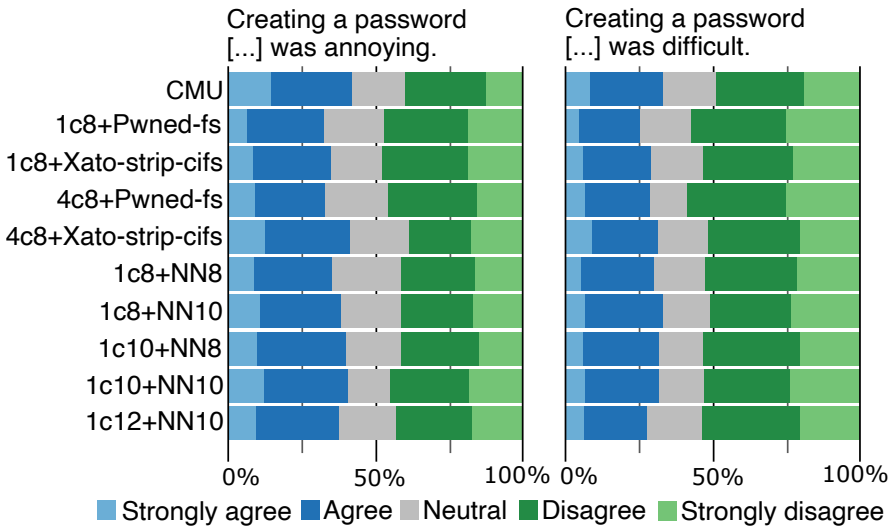


Figure 3.3: Experiment 2: Participants' level of agreement with the statement above each chart.

6% guessed). Yet, participants did not find either policy substantially more annoying or difficult relative to a *1c8* policy (see Figure 10 in Appendix).

3.3.2 RQ2: Blocklist reqs. for *1c8* policies

We next compared *1c8* blocklist policies. All pairwise comparisons were made with respect to *Xato-strip-cifs*, which was recommended in prior work [28]. We found that **case-sensitive, full-string matching against very large blocklists of leaked passwords leads to similarly usable and secure passwords as fuzzy matching against smaller blocklists of the most common leaked passwords.**

Prior work hypothesized that the *strip-cifs* algorithm would produce strong passwords by preventing simple modifications to blocklisted passwords that might pass the blocklist check without improving password strength [28]. Our user study confirms this. As shown in Figure 3.4, passwords created under the *1c8+Xato-cifs* policy, which did not strip digits and symbols before performing blocklist checks, were overall weaker and more susceptible to online guessing than passwords created under the *1c8+Xato-strip-cifs* policy, which stripped digits and symbols (PP, FET: 5% vs. 1% guessed). Furthermore, while the stricter matching algorithm used in *1c8+Xato-strip-cifs* led to slightly longer password-creation times compared to *1c8+Xato-cifs* (MWU: median of 93 s vs. 70 s), it did not make password creation more challenging or annoying.

Among blocklist configurations using the same *Xato* wordlist, only *1c8+Xato-ciss* produced overall stronger passwords that were more resistant to 10^{14} offline attacks than *1c8+Xato-strip-cifs* (PP, FET: 24% vs. 41% guessed). However, as shown in Figure 10 and Table 3.2, severe

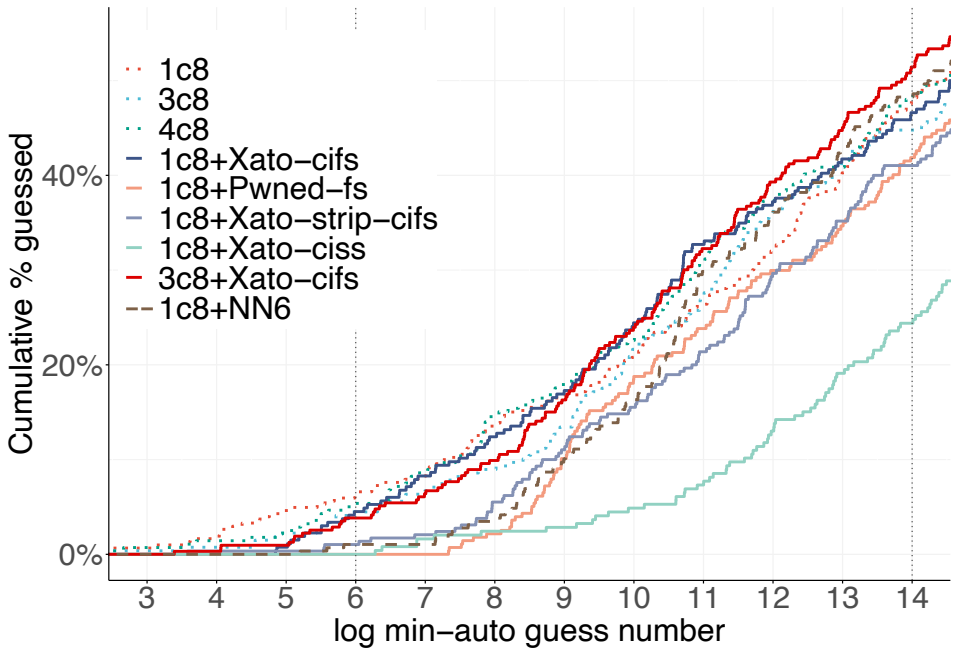


Figure 3.4: Min-auto guess numbers for Experiment 1 blocklist, composition-requirements-only, and *1c8+NN6* policies.

password-creation usability issues associated with *1c8+Xato-ciss* prevent us from recommending it in place of *1c8+Xato-strip-cifs*. Participants took longer to create passwords under *1c8+Xato-ciss* than under *1c8+Xato-strip-cifs* (MWU: median of 139 s vs. 93 s) and reported more annoyance (FET: 47% vs. 35%) and difficulty (FET: 49% vs. 27%). Compared to *1c8+Xato-strip-cifs* participants, *1c8+Xato-ciss* participants were also more likely to drop out before finishing Part 1 (FET: 26% vs. 12%) and to digitally store or write down their password after creating it (FET: 65% vs. 53%). These results lead us to conclude that while a *ciss* blocklist matching algorithm can provide strong security against guessing attacks, it also may severely harm password-creation usability if used alongside a wordlist as large as or larger than the *Xato* wordlist.

Besides *Xato*-based blocklists, we tested a blocklist configuration that used *fs* matching with the much larger *Pwned* wordlist. We found that *1c8+Pwned-fs* and *1c8+Xato-strip-cifs* led to passwords of similar strength, both in terms of overall password strength and in terms of resistance to online and offline guessing attacks. Participants also reported similar usability during password creation. Although *1c8+Xato-strip-cifs* participants were much more likely to report noticing a password they wanted to create being rejected by the blocklist requirement than *1c8+Pwned-fs* participants (FET: 50% vs. 23% noticed), they did not take substantially longer to create their password nor report more difficulty or annoyance. Thus, we conclude that blocklists that perform *fs* checking against the *Pwned* wordlist can provide comparable protections against guessing attacks and similar usability compared to blocklists that perform *strip-cifs* checking against the *Xato* wordlist.

3.3.3 RQ3: Composition requirements for min-strength policies

We examined whether certain combinations of minimum-strength and composition requirements would lead to stronger or easier-to-create passwords. As we had hypothesized that a *NN6* requirement would provide sufficient protection against 10^6 online attacks, we focused on *NN6* policies and varied composition requirements. All pairwise comparisons were made against the *3c8+NN6* baseline, as our initial retrospective analyses suggested the *3c8+NN6* policy would produce overall stronger passwords than other *NN6* policies. We find that **while minimum-strength policies can be strengthened against offline attacks by either increasing the minimum required length or the minimum number of character classes, increasing the minimum length accomplishes this at a lower usability cost, in terms of how long users need to create a compliant password and how annoying or challenging they find that task**.

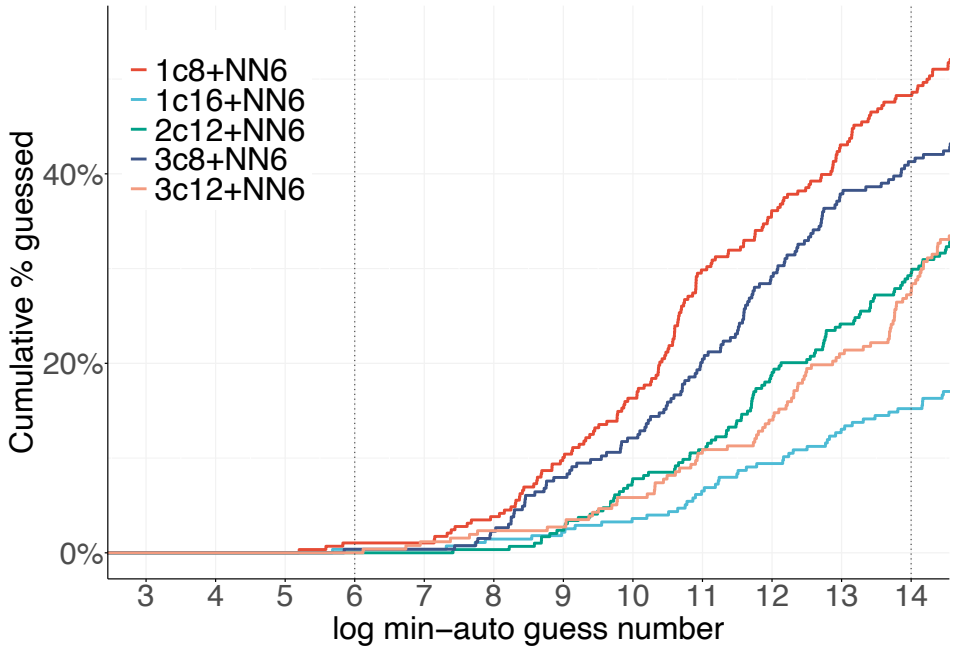


Figure 3.5: Min-auto guess numbers for policies containing *NN6* requirements and varying composition requirements.

As shown in Figure 3.5, combining a *NN6* minimum-strength requirement with different additional requirements led to passwords that differed substantially in overall guessability (PP). We did not find statistically significant differences in the number of *NN6* passwords guessed for online attacks (i.e., up to 10^6 guesses). However, against a 10^{14} offline attack, policies differed in their defensive effectiveness. While *1c8+NN6* provided similar protection to *3c8+NN6* (48% vs. 41% guessed, respectively), *1c16+NN6* (15% guessed), *2c12+NN6* (30% guessed), and *3c12+NN6* (28% guessed) all offered significantly more protection than *3c8+NN6* (FET).

Most of the *NN6* policies we tested showed similar usability properties relative to our *3c8+NN6* baseline; only *1c8+NN6* performed better on two of our usability metrics. Compared to *3c8+NN6*

participants, *1c8+NN6* participants reported password-creation to be less difficult (FET: 22% vs. 33% found difficult) and also took less time (MWU: median of 73 s vs. 92 s).

Overall, our results show that, for policies enforcing a particular minimum-strength requirement, more complex composition requirements can lead to passwords that are more resistant to guessing attacks, particularly for offline attack scenarios. While our results show that requiring more character classes or longer passwords both make passwords stronger, we found evidence that increasing the length requirement could produce larger security benefits than increasing character-class-count requirements, while also having less of a negative impact on password-creation usability (e.g., *1c8+NN6* vs. *3c8+NN6*, compared to *3c8+NN6* vs. *3c12+NN6*).

3.3.4 RQ4: Blocklists vs. min-strength policies

A high-level goal for both experiments was to compare *1c8* policies that incorporated a blocklist requirement to those that instead incorporated a minimum-strength requirement. In Experiment 1, we found that **a *1c8+NN6* minimum-strength policy can provide similar protection against online attacks and similar usability compared to the two best-performing blocklist policies we tested.** In Experiment 2, we compared those two blocklist policies to two additional minimum-strength policies, *1c8+NN8* and *1c8+NN10*. **Both *1c8+NN8* and *1c8+NN10* led to overall stronger passwords than the blocklist policies, while maintaining comparable usability.**

RQ4.A

As shown in Figure 3.4, neither *1c8+Xato-cifs* nor *1c8+Xato-ciss* resulted in passwords comparable in strength to those created under *1c8+NN6*. Compared to *1c8+NN6* passwords, *1c8+Xato-cifs* passwords were overall significantly weaker (PP). *1c8+Xato-ciss* resulted in passwords that were significantly stronger than those created under *1c8+NN6* (PP), but at the expense of the severe usability issues described in Section 3.3.2.

Two blocklist policies provided comparable security to *1c8+NN6*, in terms of general guessability as well as resistance to online guessing attacks: *1c8+Pwned-fs* and *1c8+Xato-strip-cifs*. We did not find any statistically significant differences between either blocklist policy and *1c8+NN6* for any of the usability metrics we measured. Thus these three policies appear to be suitable for preventing predictable passwords that might be compromised in online attacks.

RQ4.B

As shown in Figure 3.6, we found that both *1c8+NN8* and *1c8+NN10* policies produced passwords that were overall stronger when compared to either of *1c8+Pwned-fs* or *1c8+Xato-strip-cifs* passwords (PP). For attackers making 10^{14} guesses, *1c8+NN8* passwords would be guessed with similar success rates compared to either *1c8+Pwned-fs* or *1c8+Xato-strip-cifs* passwords.

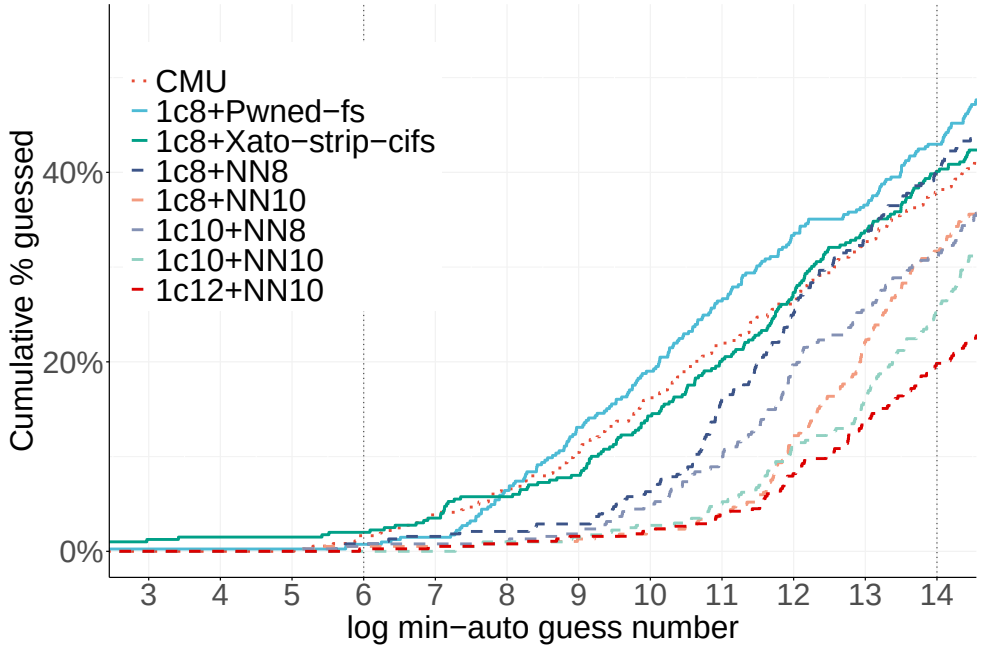


Figure 3.6: Min-auto guess numbers for Experiment 2 *1c8* and *CMU* policies.

In contrast, *1c8+NN10* passwords remained less likely to be guessed, even against the number of guesses possible in offline attacks: 32% of *1c8+NN10* passwords would be guessed within 10^{14} attempts, compared to 40% of *1c8+Xato-strip-cifs* passwords and 43% of *1c8+Pwned-fs* passwords (FET). Across our usability measurements, we did not find statistically significant differences between *1c8+NN8* or *1c8+NN10* and either blocklist policy, except when comparing *1c8+Pwned-fs* to *1c8+NN10*: *1c8+Pwned-fs* participants took less time to create their password than *1c8+NN10* participants (MWU: median of 83 s vs. 109 s) and were less likely to report password-creation as being difficult (FET: 25% vs. 33% found difficult).

These results demonstrate the value of minimum-strength requirements. While both blocklist and minimum-strength requirements can prevent users from picking common passwords that attackers are likely to try first, minimum-strength requirements can do so while also making passwords harder to guess for more determined attackers (see top half of Table 3.3).

3.3.5 RQ5: Min-strength and min-length requirement interactions

We tested additional minimum-strength policies with the goal of identifying configurations with more positive password-creation usability properties yet similarly strong offline attack protections as minimum-strength policies we had tested in Experiment 1. We focused our exploration of policies on those that only enforced minimum-strength and minimum-length requirements, without any character-class requirements. **Our results ultimately show that *NN10* requirements can provide stronger protection ag-ainst offline attacks than *NN8* requirements without introducing substantial usability harm, and that combining *NN10* requirements with a**

Condition	Peto-Peto	percent @ 10^6	percent @ 10^{14}	Creation time	Creation difficult
RQ4.B					
1c8+Pwned-fs		0.7%	43%	83 s	25%
1c8+NN8	p<.001	0.8%	40.2%	86 s	30%
1c8+NN10	p<.001	0.5%	31.7%	109 s	33%
1c8+Xato-strip-cifs		2%	40.1%	97 s	29%
1c8+NN8	p=.009	0.8%	40.2%	86 s	30%
1c8+NN10	p<.001	0.5%	31.7%	109 s	33%
RQ5					
1c10+NN8		0.8%	31%	89 s	32%
1c8+NN8	p=.628	0.8%	40.2%	86 s	30%
1c10+NN10	p=.002	0%	25.2%	92 s	32%
1c12+NN10	p=.925	0.3%	19.8%	95 s	28%
1c10+NN10		0%	25.2%	92 s	32%
1c8+NN10		0.5%	31.7%	109 s	33%
1c8+NN10		0.5%	31.7%	109 s	33%
1c10+NN10	p=.752	0%	25.2%	92 s	32%
1c8+NN8	p<.001	0.8%	40.2%	86 s	30%

Color key

Baseline for pairwise comparisons	
Pairwise test statistically significant (better than baseline)	
Pairwise test statistically significant (worse than baseline)	
Pairwise test not stat. sig.	Omnibus test not stat. sig.

Table 3.3: RQ4.B and RQ5 strength/usability comparison. Pairwise comparisons for non-baseline policies are for the baseline policy listed immediately above.

minimum length of 10 characters can help users create passwords more quickly.

Unsurprisingly, increasing the minimum-strength requirement while fixing the minimum password length was effective at increasing overall password strength (PP: *1c8+NN8* vs. *1c8+NN10*, *1c10+NN8* vs. *1c10+NN10*). We find evidence that increasing a policy's minimum-strength threshold from *NN8* to *NN10* also strengthened offline attack defenses, as shown in Figure 3.6. For example, 40% of *1c8+NN8* passwords would be guessed in a 10^{14} attacks compared to only 32% of *1c8+NN10* passwords, a difference which was statistically significant (FET). More interestingly, for the min-length-8 and min-length-10 policies we explored, participants did not find passwords substantially more difficult or annoying to create regardless of whether their policy included a *NN8* or *NN10* requirement. The only statistically significant usability difference we found between *NN8* and *NN10* policies was with respect to password-creation time: *1c8+NN8* passwords took slightly less time to create than *1c8+NN10* passwords (MWU: median of 86 s vs. 109 s).

We performed similar comparisons between minimum-strength policies with the same required strength threshold but varying minimum-length requirements. For policies enforcing the same minimum-strength requirement, increasing the minimum-length requirement tended to produce stronger passwords. As shown in Figure 3.6, for policies containing *NN8* or *NN10* minimum-strength requirements, passwords were less likely to be guessed in a 10^{14} offline attack if that policy imposed *1c10* rather than *1c8* requirements (FET). We did not find large differences in reported password-creation annoyance or difficulty between *NN8* and *NN10* policies depending on whether those policies required passwords to be at least 10 or 12 characters. While we find some support for our initial hypothesis that minimum-length requirements can make minimum-strength requirements easier to satisfy, the improvements were small (e.g., *1c10+NN10* passwords were created in 17 fewer seconds than *1c8+NN10* passwords, on average). Interestingly, only 22% of participants assigned to the *1c12+NN10* policy reported noticing a password they wanted to create being rejected by the minimum-strength requirement, a significantly lower percentage than we found for participants assigned to either *1c10+NN10* (FET: 30% noticed) or *1c8+NN10* (FET: 34% noticed). However, differences in proportions of participants who noticed a minimum-strength rejection did not translate to statistically significant differences in reported password-creation annoyance or difficulty (Figure 11). Table 3.3 (bottom half) summarizes these results.

Overall, we found little reason to prefer *NN8* policies over the stronger and similarly usable *NN10* policies. Among *NN10* policies, *1c12+NN10* appeared particularly attractive. Compared to *1c8+NN10* and *1c10+NN10*, *1c12+NN10* led to participants encountering minimum-strength rejections less often and improved resistance to offline guessing attacks.

3.3.6 RQ6: Blocklist and composition requirement interactions

We compared *1c8+Xato-strip-cifs*, *1c8+Pwned-fs*, *4c8+Xato-strip-cifs*, and *4c8+Pwned-fs* with each other in order to understand how blocklist requirements interacted with character-class requirements. Our results confirm that the choice of blocklist can impact usability and security

differently depending on whether it is included in a *1c8* or *4c8* policy. **While the choice of *1c8* or *4c8* composition requirements to combine with a given blocklist did not significantly impact usability, we found evidence that *4c8* requirements could *negatively* impact security relative to *1c8* requirements if combined with a very large blocklist and full-string matching.**

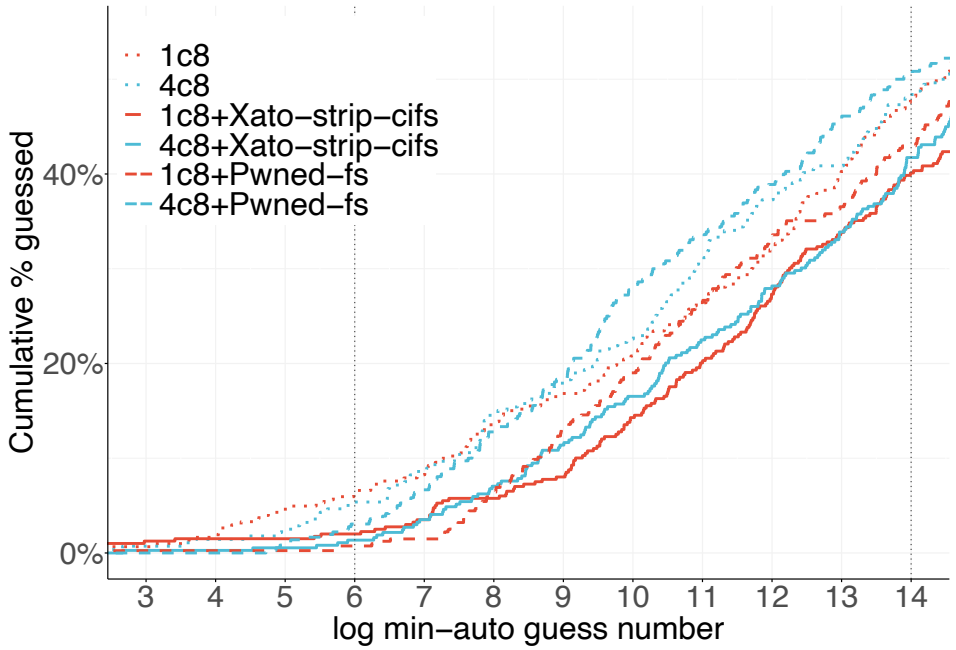


Figure 3.7: Blocklist/composition policy interaction effects. *1c8* and *4c8* curves are based on data collected from Experiment 1 and are shown only for reference.

As in Experiment 1, passwords created under *1c8+Pwned-fs* were not statistically significantly different in their guess-number distribution than those created under *1c8+Xato-strip-cifs*. However, we did find usability differences: *1c8+Pwned-fs* participants were more likely to drop out of our study before creating their password than *1c8+Xato-strip-cifs* participants (FET: 16% vs. 11% dropped out) and those who did not drop out took slightly longer to create their passwords (MWU: median of 97 s vs. 83 s).

We performed similar comparisons between our *4c8+Pwned-fs* and *4c8+Xato-strip-cifs* conditions. Unlike the case for *1c8* requirements, we found that *4c8+Pwned-fs* passwords were overall weaker than *4c8+Xato-strip-cifs* passwords (PP). Although this only translated to substantially higher likelihood of passwords being guessed for 10^{14} offline attacks (FET: 51% vs 42%) and not 10^{6} online attacks, Figure 3.7 suggests *4c8+Xato-strip-cifs* also may be preferable to *4c8+Pwned-fs* for online attack scenarios. In terms of usability, we found that—unlike for *1c8* policies—a higher proportion of participants were annoyed by *4c8+Xato-strip-cifs* compared to *4c8+Pwned-fs* (FET: 41% vs 33% annoyed).

We found support for our hypothesis that blocklists of large password leaks are more effective when combined with *1c8* requirements than with *4c8* requirements. Passwords created under

4c8+Pwned-fs were statistically significantly weaker than *1c8+Pwned-fs* passwords, both overall (PP) and in terms of resistance to 10^6 (FET: 3.1% vs. 0.7% guessed) and 10^{14} guessing attacks (FET: 50.6% vs. 43% guessed). We found less support for our hypothesis that *Xato-strip-cifs* makes password creation a more frustrating experience when combined with *4c8* requirements than with *1c8* requirements.

3.4 Discussion

3.4.1 Character-class requirements

Although prior work has repeatedly found that requiring more character classes decreases guessability [42, 52], researchers have shown that character-class requirements lead to frustration and difficulty for users [46, 65, 93]. Since other requirements, e.g., minimum-length or blocklist requirements, can strengthen passwords with less negative impact on usability research has advocated retiring character-class requirements [22, 73]. These recommendations have been standardized in recent NIST password-policy guidance [56].

Our experimental results provide the first concrete evidence that character-class requirements should be avoided not only because users tend to find them annoying, but also because they don't provide substantial benefit against attackers using state-of-the-art password-cracking tools: an expert attacker can guess *1c8*, *3c8*, and *4c8* passwords with equal success rates.[9] Experiment 2 also suggests that character-class requirements should be avoided for password-creation policies that include a blocklist or minimum-strength requirement. We find evidence that policies requiring all four character classes and a large blocklist check produce passwords that are, at best, as strong as passwords created under a policy that performed the same blocklist check without character-class requirements. Although Experiment 2 does show that a policy requiring more character classes does tend to produce stronger passwords under a minimum-strength requirement, it also shows that this strength improvement is much lower than the improvement that results from increasing either length requirements or minimum-strength threshold requirements.

Our new findings on character-class requirements seem to be caused by two factors. First, users tend to create passwords that are longer and contain more character classes than required; this was more pronounced in our experiments than in previous studies. In Appendix A.4, we examine passwords from studies conducted from 2010 to 2019 and observe that in more recent studies, and in those with a password meter, users were more likely to exceed length and character-class requirements. Second, password guessing has improved over time, and more so for passwords containing three or four character classes than for passwords containing one or two classes. We describe this in more detail in Appendix A.5.

[9] We assume passwords are created with feedback that includes a strength meter and text feedback, similar to our study.

3.4.2 Blocklist requirements

Blocklists can be useful, but only if carefully configured. Both the wordlist and matching algorithm can significantly affect password strength and usability. Our experiments show that some blocklist configurations are much more likely than others to make password creation a frustrating and time-consuming experience. Given a blocklist composed of passwords that appear at least four times in public password leaks, a blocklist policy configured to reject passwords that contain a five-character substring of any blocklisted password will strengthen resulting passwords, but with a severe impact on usability. We also find blocklist configurations that do not offer sufficient strength protections. Full-string matching against a list of roughly 10^5 commonly leaked passwords leads to a negligible improvement in defense against guessing attacks. However, a more fuzzy matching algorithm such as one that performs the same check ignoring non-alphabetic characters can improve password strength without requiring a larger set of leaked passwords to check against.

We recommend that policies containing blocklist requirements should not additionally require passwords to contain a minimum number of character classes, especially if the blocklist check is based on rejecting any password exactly matching one that has been previously compromised in a public leak. Although further research is needed to confirm this, our results suggests that passwords subjected to such a blocklist check may actually be weaker if additionally required to contain all four character classes. One explanation for this is that easily-guessed *4c8* passwords may be less likely to appear in public leaks than easily-guessed *1c8* passwords and so are less likely to be included in blocklists.

Two *1c8* blocklist configurations we tested performed well with respect to both security and usability: the *Xato* wordlist combined with *strip-cifs* matching and the *Pwned* blocklist combined with *fs* matching. The *Pwned-fs* blocklist configuration may be stronger against online attacks than the *Xato-strip-cifs* blocklist. Although the two configurations have similar usability in general, the higher dropout rate in Experiment 2 for *1c8+Pwned-fs* suggests that that policy may be more frustrating for some users. Unlike the easily-embedded *Xato-strip-cifs* blocklist, the *Pwned-fs* blocklist is less useful for fully client-side password checking.

System administrators incorporating a blocklist check should check for password-policy compliance remotely on the server, since clients collecting passwords can misbehave or lie. Password checks against externally controlled databases of leaked passwords involve some security risk, even if mitigated by transmitting partial password hashes. Concerned organizations can perform leaked-password checks locally, either against a large set of leaked passwords (30 GB uncompressed for a comprehensive set [36]) or against a Bloom filter, which substantially reduce storage space requirements at the expense of false positives (1.1 GB for a Bloom filter with a false positive rate of 0.1% for the same set). If using a large blocklist with a Bloom filter or a smaller blocklist with a *strip-cifs* matching, it may be useful to also check for policy compliance locally to facilitate real-time requirements feedback without network latency introduced by remote checks.

3.4.3 Minimum-strength requirements

Our results confirm that minimum-strength requirements can effectively guide users toward stronger passwords without significantly inhibiting password memorability or ease of password creation. The choice of minimum-strength threshold depends on security requirements; too low a threshold may not provide enough defense (particularly against online attacks) and too high a threshold may unacceptably inhibit usability.

When online attacks are a concern, we recommend setting the minimum-strength threshold to at least 10^6. We recommend using minimum-strength requirements alongside minimum-length requirements, but without blocklists or character-class requirements. While our results suggest that, when combined with a minimum-strength requirement, policies that require multiple character classes improve resistance against offline attacks, similar improvement can be achieved with less impact on password-creation usability by increasing the minimum-strength threshold or the minimum required length. For example, *1c8+NN12* had similar usability to *3c8+NN6* but led to much stronger passwords (post-hoc comparison, see Table 6 in Appendix).

Increasing the minimum-strength threshold improves the security of passwords, but too high a threshold can make creating passwords difficult and annoying. For example, for online services that prioritize a seamless user experience, usability impacts from a *1c8+NN12* policy may be unacceptable.

One might question why minimum-strength thresholds above 10^6 guesses but below 10^{14} guesses are useful; a 10^6 threshold will help avoid the most predictable passwords that might be guessed in an online attack, and in scenarios where attackers can make more than 10^6 guesses, any threshold below 10^{14} will not be enough to prevent account compromise in an offline guessing attack on a hashed and salted database of passwords [22]. Although resistance to guessing attacks between feasible online (10^6) and extensive offline (10^{14}) attacks may not always prevent account compromise, we note that policies with minimum-strength thresholds between 10^6 and 10^{14} resulted in significantly higher resistance to offline guessing attacks at a 10^{14} cutoff; a *NN8* minimum-strength policy not only prevents the most predictable 10^8 passwords, but also increases the proportion of created passwords with guess numbers above 10^{14} relative a *NN6* policy. In addition, the use of tunable, slow hashing algorithms and increased computational resources for guessing attacks over time means that guessing thresholds other than 10^6 and 10^{14} (including 10^8 and 10^{10}) can be relevant to protect against. As demonstrated in Experiment 2, by combining minimum-strength requirements with specific minimum-length requirements, we can achieve this benefit of increased resistance to offline guessing without incurring substantial negative impact on the ease of password creation.

In general, increasing length requirements for a given minimum-strength policy strengthened passwords produced under that policy against offline attacks, while maintaining strength against online attacks. Since we didn't find any significant usability differences between length variants of the *1c8* and *1c10* minimum-strength policies that we tested, this suggests that the longer-length versions of these policies should be preferred for their security benefits. However, we note that longer minimum-length requirements for a given minimum-strength requirement do

not always come without a usability hit; in Experiment 1, *1c16+NN6* led to noticeably higher levels of reported annoyance and difficulty during password creation than did *1c8+NN6*. This illustrates the importance of testing specific combinations of minimum-length and minimum-strength requirements before their deployment in a password policy.

Synthesizing these results, we recommend a password policy of *1c12+NN10* for security settings that need protection against offline attacks while still providing reasonable usability. Similar to blocklists, system administrators using a minimum-strength requirement should check that the requirement is met at both the client and at the remote server.

3.4.4 Blocklists vs. minimum-strength policies

A main goal of our study was to compare blocklist and minimum-strength policies while considering both security and usability. We find that both types of policies can protect well against 10^6 online attacks without unduly harming usability: both the *1c8+Xato-strip-cifs* and *1c8+Pwned-fs* blocklist policies achieve these goals, as does the minimum-strength *1c8+NN6* policy. However, we also find that minimum-strength policies can provide better protection than top-performing blocklist policies against offline attacks, while improving usability.

Why use minimum-strength policies if blocklists are adequate as a defense against online attacks and easy to deploy? Prior work has also suggested that protecting against guessing attacks beyond the threshold of effort possible in online attacks may be wasted effort, e.g., users suffer through a more painful password-creation process for no practical security gain [22]. We believe minimum-strength policies are a good alternative, for three reasons.[10] First, we believe minimum-strength policies can be deployed just as easily—if not more easily—than blocklist policies, particularly as the smaller blocklists we tested were not adequately effective. Our results are based on a client-side NN model that could be pre-trained and distributed to system administrators. Second, users often reuse passwords, including between high-value and low-value accounts [62,94]. Even if an organization is not concerned about offline attacks, e.g., due to sophisticated hashing, its users may reuse their passwords on less secure systems. In this case, resistance to offline attacks would still be relevant. Third, we showed that using minimum-strength policies can increase password strength without noticeable negative impact on user experience.

3.5 Conclusion

We explored in depth three types of requirements enforced in password policies: composition requirements, blocklists, and neural-network-driven minimum-strength requirements. Using two

[10] A fourth potential reason to use minimum-strength policies rather than blocklist-based policies is that some organizations may be barred from using data that has been unethically obtained and released by a third party, including blocklists constructed from password-database leaks [18]. It is unclear and perhaps organization-specific whether this reasoning would extend to tools and guidance indirectly derived from leaked data, e.g. neural networks pre-trained by a third party on leaked passwords and shared with an organization.

large-scale, experimentally designed user studies, we examined the security and usability of each type of requirement, and their combinations, when deployed in a modern password meter. Our results lead to concrete recommendations for configuring blocklist requirements. We recommend that blocklist requirements either check candidate passwords against a list of about 10^5 commonly leaked passwords using a fuzzy matching algorithm or perform a full-string check against a large list consisting of all known leaked passwords. Password policies incorporating blocklist requirements should not impose character-class requirements. We also find that minimum-strength policies, which we believe our work to be the first to closely investigate in a user study, can improve upon blocklist policies by increasing resilience to offline attacks without degrading usability. We recommend a *1c12+NN10* minimum-strength policy for organizations that wish to protect high-value accounts without a substantial negative usability impact.

Chapter 4

Text-based password feedback

4.1 Introduction

In the previous chapter, we provided guidance relevant to system designers tasked with incorporating a password policy. Password policies are often used alongside password meters, which are useful for displaying real-time feedback to users about which policy requirements have been met, and can provide feedback to users about why certain requirements are violated in a candidate password (e.g., the part of a password rejected by a blocklist requirement). In this way, password meters can make password-creation less difficult and time-consuming, by helping users understand necessary changes that will lead to an accepted, policy-compliant password.

In addition to providing text feedback that explains to users which parts of a candidate password violate a password policy, password meters can provide text feedback on how to improve the strength of a password, including for passwords that are already policy-compliant. This feedback can be tailored to the particular password candidate entered by a user in real-time, by using heuristics to check for predictable patterns in a password and notifying the user of the negative impact those patterns often have on guessability. Prior work has shown that incorporating this type of text feedback into a password meter is appreciated by users and can lead users to create stronger passwords [87]. In fact, in Chapter 3 we found support that text feedback can sometimes help accomplish a similar goal of composition policies—to strengthen passwords by rejecting weak passwords—without the negative usability cost associated with character-class requirements.

Unfortunately, there is little available guidance from security experts to guide system administrators in what kind of text feedback to provide to users. System designers may turn to recommendations from standards-setting bodies such as NIST. However, current NIST advice only specifies that a password meter should be provided to users when creating passwords and that this meter should provide feedback on why a candidate password violates policy requirements [56]; in particular, it does not provide guidance about how text feedback should be used for policy-compliant passwords. Prior work in the research community has provided useful guidance in this area, al-

beit guidance based largely on intuition and qualitative analyses. For example, both zxcvbn [97] and the password meter by Ur et al. [87] provide concrete password-meter implementations incorporating text feedback that advises users about any detected heuristic features in candidate passwords associated with weak passwords. While these meters are useful and provide examples that system designers can use for reference, the heuristics used in these meters are constructed based on intuition and may not be comprehensive or always correct; system designers may wish for more principled and systematically determined text feedback, which currently does not exist.

Besides guidance on the particular set of heuristics that should be used to derive feedback to be given to users, system designers may want guidance on how this feedback should be displayed to users, in terms of which heuristic-based text feedback to display in a space-limited interface when many patterns are simultaneously detected, and how to determine and display the relative priority of feedback for a set of detected patterns. Ur et al. provided a prioritized ordering of the heuristic features used in their password meter [86], determined using a combination of laboratory study results and expert intuition. This prioritization is useful for system designers, but if heuristic features have different impacts on password guessability for different set of passwords, then a static prioritization of heuristics will not be able to reflect this.

In this chapter we explore using machine-learning and statistical modeling techniques in order to expand the guidance available to system designers on how to incorporate text feedback into password-creation interfaces. Our exploration has two primary goals: to systematically learn patterns in passwords useful for text feedback, and to learn how to best prioritize existing heuristic-based text feedback for a specific candidate password.

In order to systematically learn patterns in passwords, we first used an autoencoder to compress a large set of leaked passwords, which produced a latent representation of passwords capturing high-level password features. We then clustered passwords with respect to these features in order to group passwords that exhibit similar patterns. In particular, we applied a fuzzy clustering algorithm to group passwords in terms of high-level patterns, including complex patterns that are learned in an imprecise manner. We then analyzed these groups of passwords in an attempt to intuitively understand and label the semantic concepts they represented. This analysis used both visual inspection of password clusters and application Integrated Gradients for explaining cluster-membership predictions.

In order to generate password-specific guidance for existing heuristic features, we leveraged our fuzzy clustering results. We modeled password guessability locally around each cluster and then used these cluster-local models to prioritize heuristic guidance specific to a candidate password, based on that password's cluster memberships. This generated guidance was of the form of numeric importance values for each heuristic, which could then be prioritized and optionally displayed to users in text feedback.

Unfortunately, our study was not successful at learning new high-level password patterns relevant for heuristic-based text feedback. The primary reason for this was that clusters of passwords did not demonstrate high-level patterns useful for text feedback. Although clusters of passwords sometimes contained consistent patterns, these patterns either appeared to be related to character-class structure or were low-level, e.g. related to the position of particular characters

in a password.

Our study was also not successful in learning a useful prioritization of existing heuristic feedback for a given password. Local models of guessability for each cluster are useful for learning how password strength relates to predictable patterns for passwords nearest to each cluster. By quantifying this relationship we can create a cluster-specific ordering of heuristics based on their associated impact on guessability. Our technique for providing prioritized text feedback was ultimately not successful due to characteristics of the password clusters learned by our clustering model. Cluster-specific orderings of heuristics are useful for text feedback when that feedback should guide users to strengthen a candidate password without changing certain characteristics of that candidate password, in particular those characteristics associated with the nearest cluster. In our work, the semantic concepts associated with clusters did not represent desirable attributes of passwords, leading to inappropriate prioritization of heuristics.

Section 4.2 describes the methods we applied for this study, including autoencoder training, clustering, and regression analyses. Section 4.3 describes characteristics of clusters learned in the latent space, the relationship between clusters and guessability, and our exploration applying cluster-membership-weighed feature importance to actual passwords. In Section 4.4, we discuss the potential usefulness of each of the primary techniques used in this study. We conclude in Section 4.5.

4.2 Methodology

Here we describe the steps we took to learn a latent representation of passwords, cluster passwords in that latent space, and leverage those clustering results with the goal of improving text feedback. A significant effort was placed on understanding high-level concepts associated with clusters. This involved multiple types of regression analyses, visualization of the latent space, projection of new data onto existing clusters, and model-prediction explanation techniques. We also perform an exploratory evaluation of the explored techniques by applying them to user study passwords that were previously collected for a separate study.

4.2.1 Learning a latent representation

We chose to learn a latent representation of passwords by training an autoencoder on leaked password data. In order to limit the size of the latent space learned, we used a deep undercomplete autoencoder, which forced the model to learn a compact representation of training-data passwords by having the size of encoding layer dimensions be smaller than that of the input layer. The latent representation for a given password corresponded to the output of the encoding layers for that password input.

We experimented with a variety of training parameters, including the length of passwords in the training data, the number and size of encoder layers, training batch size, and whether dropout

was applied in LSTM layers. Table 4.1 lists details of the model architecture and training configuration that we report results for.

Password lengths	8-12 characters
Character-level embedding dim.	32
Encoder layers	Bi-directional LSTM (32), LSTM (16), LSTM (8)
Decoder layer	LSTM (8), LSTM (16), LSTM (32)
LSTM dropout ratios	0.2 (input), 0.2 (recurrent)
Batch size	4096
Number of train epochs	400
Optimizer	Adam
Loss	Categorical cross-entropy
Train/validation data ratio	0.9
Train backwards	True

Table 4.1: Autoencoder model and training details

We trained our model on a single NVIDIA Tesla P100 GPU over a period of 20 days. The training data for our model was sourced from the subset of *PGS3* passwords having lengths between 8 and 12 characters (denoted *PGS3max12*), a total of approximately 29 million passwords. Appendix B.1 provides additional detail on this dataset.

t-SNE visualizations

We use t-SNE to visualize passwords in the 8-dimensional password-encoding space. Besides showing the global structure of the latent space, t-SNE visualizations were also useful for comparing how clusters in the t-SNE projection corresponded to password strength and fuzzy c-means clustering results (described next, in Section 4.2.2).

Visualizing t-SNE projections for the full set of *PGS3max12* passwords was too computationally expensive given our resources, so we instead visualized subsets of this dataset. In order to visualize a wide range of types of passwords , these subsets were selected via random stratified sampling, described in Section 4.2.5. This also has the benefit of ensuring that the password samples shown in t-SNE visualizations reflect the proportions of password-strength and cluster-locality distributions of passwords in *PGS3max12*.

t-SNE results can be sensitive to the chosen perplexity parameter and may differ across multiple runs due its stochastic nature. To address this, we experimented with various perplexity parameters and run t-SNE five times for each visualization, selecting the t-SNE run with lowest final KL divergence.

We used the scikit-learn Python implementation of t-SNE.[1] In general, we used the default settings in their implementation, including use of the Barnes-Hut optimization algorithm and use of Euclidean distance as the distance metric. Based on the recommendations of prior work [43],

[1] https://scikit-learn.org/stable/index.html

we applied some modifications the default settings. For a given t-SNE sample size n, the learning rate was set to $n/12$ and t-SNE embeddings were initialized according to the first two PCA components. The majority of our visualizations also used a perplexity setting of 1% of n. When plotting t-SNE visualizations, both axes are set to the same scale in order to avoid stretching the resulting visualization, which can bias visual interpretation.

4.2.2 Clustering passwords in the latent space

In order to group passwords based on their similarity in the learned latent space, we applied *fuzzy c-means* to passwords encodings (produced by the encoding layers of the autoencoder). Our choice of a fuzzy clustering algorithm rather than a hard clustering algorithm, such as k-means clustering, was motivated by the idea that passwords can often contain multiple different types of patterns and these patterns may appear in a noisy fashion. Our goal was to learn separate clusters for each pattern, such that a password would be viewed in terms of membership to multiple clusters, with the degree of membership related to how strongly that pattern was manifested in a password.

We used an implementation of fuzzy c-means provided by the scikit-fuzzy Python package.[2]. Fuzzy c-means parameters include the fuzzifier m, determining how crisp of a partitioning to learn, and the number of clusters to use. We experimented with fuzzifier values of $m = 2$ and $m = 3$, using models having between 2 and 30 clusters. The results we report here are for the model using $m = 2$ and 30 clusters. Appendix B.3 provides additional detail on our experiments using other parameters.

We applied clustering on all passwords in *PGS3max12*. Cluster predictions for new passwords not part of the training data were made by running the fuzzy c-means algorithm with the coordinates of each cluster center (centroid) fixed.

4.2.3 Conceptualizing clusters

While fuzzy c-means is useful for clustering passwords, the algorithm itself does not provide an intuitive explanation for why passwords belong more or less to a given cluster. We attempt to uncover this explanation in two ways: by visually examining sets of passwords nearest to each cluster, and by applying Integrated Gradients (IG) explanations to an augmented version of the password encoder NN.

Explaining why passwords are drawn to particular clusters is tantamount to describing high-level concepts (patterns in passwords) associated with each cluster. Understanding the patterns associated with clusters is important since our end goal was to provide text feedback based on the membership of passwords to those clusters.

[2]https://pythonhosted.org/scikit-fuzzy/

Analysis of cluster hard-assignments

We attempted to characterize clusterings based on visual inspection of clustering results on *PGS3max12* passwords. We transformed the fuzzy membership values of passwords into hard membership values (*hard-assignments*) and analyze each cluster's set of hard-assigned passwords with respect to summary statistics on (soft) membership scores, *PGS3* NN guess numbers, length, and character-class structure. We also visually analyze the top 1,000 nearest hard-assigned passwords for each cluster and attempt to use human intuition to recognize consistent patterns in that set. In addition, we examine the centroid of each cluster reconstructed in the (plaintext) input space, which we refer to as the reconstructed cluster *prototype*.

Explaining cluster assignments using Integrated Gradients

Manually identifying patterns in passwords using visual inspection can be difficult, especially when the patterns captured by a cluster are complex or non-intuitive. Thus we supplement our analysis of cluster concepts based on visual inspection with cluster-membership explanations provided by Integrated Gradients (IG). In this chapter, we focus on IG explanations for hard-assigned passwords nearest to each cluster, which correspond to passwords that most exhibit patterns associated with that cluster. In Appendix B.5.1, we test IG explanations of cluster assignment for *1c8* passwords collected in the user study described in Chapter 3.

Neuralizing fuzzy c-means predictions. A key requirement needed in order to obtain IG explanations of cluster membership is that the clustering step is implemented in the form of one or more neural network layers. We accomplish this by implementing fuzzy c-means in terms of densely connected layers with password-specific weights, which are connected to the output of the NN password encoder (see Appendix B.2 for details). This end-to-end clustering model enabled IG explanations of clustering results in terms of character-level input features.

IG parameters. When applied to our cluster-prediction NN model, IG attributions can be used to explain which characters in a password are most responsible for each of that password's cluster assignments. These explanations are parameterized by the baseline that is compared to when computing IG attributions; different choices of a baseline can produce different results. We experimented with a variety of types of baselines, including an all-zero embedding vector, padding-based baselines, randomly generated passwords, and Gaussian noise centered at the input password. For the randomly generated passwords and Gaussian noise baselines, we experimented with smoothing IG attributions by averaging over many baseline instances. Appendix B.5 provides details on these experiments. In this chapter we present results for a padding baseline that performed well in terms of providing overall intuitive and consistent explanations, while also explaining a large proportion of the baseline-to-input prediction-score delta.

Visualization parameters. In order to be useful for understanding high-level patterns, IG attributions need to be visualized. For text-based models, attributions are often visualized in the form of a colored heatmap, where high-intensity-colored characters correspond to those that have high importance for explaining a model prediction. The exact manner in which numeric attribution values are converted into colors can have a large impact on the resulting visualization. We experimented with many ways of capping IG values at an upper percentile threshold to prevent a small set of attributions from dominating the colorspace, and ways of handling negative-valued attributions indicating negative support for a prediction. Appendix B.5 provides details on a subset of these experiments. In this chapter we present visualization results for two configurations that visualize positive attributions only and that produced overall intuitive and consistent explanations.

4.2.4 Exploring relationship between cluster membership and heuristics

In the previous section, we described methods to explain cluster membership in terms of patterns appearing in password, where patterns were identified manually by visual inspection or by reverse engineering the computational graph that a neural network uses for predicting cluster membership. A limitation of these approaches is that the patterns appearing in passwords may not be easy to describe in terms of high-level patterns, which is the ideal goal for text-based password guidance. Therefore we conducted additional analyses to understand the association between cluster membership and heuristic features identified by prior work.

As discussed in Section 4.3.2, visual inspection of cluster hard-assignments and prototypes suggested there might be some relationship between cluster membership and the appearance of certain patterns captured by heuristic features. To quantify this relationship, we performed a set of linear regressions. We note that the goal of these regressions was not to create a model that could be used to *predict* cluster membership from known heuristic features; in practice for a given password, we could just predict cluster membership directly, using either the fuzzy c-means model or the cluster-prediction of a neural network that implemented the fuzzy c-means prediction logic. Rather, the regressions described in this section are useful for understanding whether and how cluster membership related to a particular heuristic feature.[3]

Furthermore, even if our clustering model clustered passwords in a way that proved difficult to intuitively label, if clusters correlated to password strength, then we could potentially still use our clustering results for password-strength guidance. The idea is that the neural network clustering model may cluster passwords based on non-intuitive features, but if clusters correlate with password strength and we can find a relationship between cluster membership and some independent set of features (not directly determining clustering, but nonetheless associated with those determining factors), then we could potentially still leverage our clustering results to present password-strength feedback in terms of that independent set of features.

[3]The relationship between cluster membership and combinations of multiple heuristic features is also interesting, but would not be captured in our case since our model did not include interaction terms.

Cluster-local sampling

We created a separate regression model for each cluster. The independent and dependent variables were the same for each regression model. The only differences between the models were the samples used to train those models.

Since we used fuzzy c-means to produce clusters, our clusters did not have a natural set of associated passwords. One option for creating cluster-specific training samples would be to use a subset of hard-assigned passwords for a each cluster as the training data for that cluster. Instead, we chose to create each cluster-specific training sample using weighted randomly sampling of *PGS3max12* passwords, where selection weights corresponded to the distance of a password to a given cluster. This approach for constructing localized sets of training samples has been used in prior work for generating locally interpretable model explanations [67]. In contrast to training each cluster using only cluster-hard-assigned passwords, locally weighed sample selection has the benefit of producing more robust regression results, since models are trained on the full dataset; there is a chance that passwords nearer to other clusters are still included in the training data, with that chance proportional to password membership in a cluster.

Preparing heuristic features for regression

We considered a set of 21 heuristics identified by prior work [87] as candidates for the predictor features in our model. Appendix B.6 lists each of these heuristics. We refer to each heuristic rule by their order in this list, e.g. "h1" for the first listed heuristic feature.

As mentioned previously, the goal of our regressions was not to understand how well the set of all 21 heuristics could be used to predict cluster membership. Rather, we were interested in the importance of an individual heuristic feature for determining cluster membership. Given this goal, it was necessary that the heuristic features included as predictors in our model were not substantially correlated and that they were transformed to be on similar numerical scales. These two conditions are important prerequisites for being able to interpret coefficients of regression model features in terms of relative importance for the prediction.

As is often the case in many real-life applications, the set of model features we considered contained varying levels of multicollinearity (see Figure B.23 in Appendix). For example, password length was correlated to the number of symbols, digits, uppercase, and lowercase letters in a password. Even when using a subset of these features, there was still some degree of collinearity between features. Our goal was select a subset of features that would eliminate the most severe cases of collinearity between features. This was accomplished by using domain knowledge, feature-correlation heatmaps, and Variation Influence Factor (VIF) values.

In their original form, many of the heuristic features differed in numerical scale. For example, *Predictable uppercase (h8)* was measured as a binary variable, *Longest dictionary token (h18)* could range from 0 to the maximum password length of 12, and *Character-class predictability (h7)* could range from 0 to 2,124. We scaled all feature values by standardizing them to have unit norm, without centering. Standardization by dividing feature values by the standard deviation

of the training data places features on a similar scale, and lack of centering helped ensure that the sign of coefficients could be compared between models trained on different samples with the results having the same directional meaning.

Linear regression of cluster membership on heuristics

We selected a total of nine heuristic features with low levels of multicollinearity and scaled them as previously described:

- Duplicated characters (h3)
- Repeated characters (h4)
- Keyboard patterns (h5)
- Repeated sections (h6)
- Character-class structure predictability (h7)
- Use of dates (h15)
- Alphabetic/numeric sequences (h16)
- Dictionary (longest token) (h18)
- Common password (h21)

We used a training set size of 100,000 passwords locally sampled for each cluster. When using a large sample such as this, we expected the majority of feature coefficients learned by our model to be statistically significant (i.e. nonzero); we therefore focus on effect size and the relative ordering of features.

Formally, we constructed a linear regression model for each cluster m. Let $p_m(x) \in [0, 1]$ denote the c-means-computed membership of password x to cluster m and let N denote the total number of heuristics (here, $N = 9$). The dependent variable was the logit-transformed c-means membership,[4] which can be interpreted as the log-odds of cluster assignment. Let h_j denote the numeric feature value corresponding to heuristic j and $s_{j,m}$ denote the standard deviation of feature j in the training data for the cluster-m model. The general form of each model was the following:

$$\text{logit}(p_m(x)) = \beta_{0,m} + \beta_{1,m}\frac{h_1(x)}{s_{1,m}} + \ldots + \beta_{N,m}\frac{h_N(x)}{s_{N,m}} \tag{4.1}$$

The coefficients $\beta_{j,m}$ for each feature in each cluster-specific model were determined via OLS estimation. The baseline for this model is a password where all heuristics features have the value zero, which allows for coefficients to be interpreted with respect to a password for which no

[4]This type of transformation is appropriate when the dependent variable is a proportion, which was the case for fuzzy c-means membership.

heuristic-associated patterns are detected. The coefficient estimates in this model are in units of log-odds estimates. In particular, since we scaled features values to have a unit norm, each learned coefficient corresponds to the estimated increase/decrease in log-odds corresponding to a one standard deviation increase in the feature value holding all other feature values constant, relative to a password for which no heuristic-associated patterns were detected.

In our analysis of regression results, the quantities we were most interested in were $\beta_{j,m}$, which we can interpret as the average relative importance of heuristic j in determining cluster membership of a password to cluster m. In particular, we compared how the relative importance of heuristics differed between different clusters.

4.2.5 Exploring relationship between cluster membership and guessability

In the previous two sections, we described the methods we used to conceptualize patterns associated with clusters, and to quantify relationships between prior-work-identified heuristics and cluster membership. The results of these methods are sets of patterns that relate to cluster membership and the degree of these relationships, which can potentially be used for real-time feedback during password creation to alert users of predictable patterns found in candidate passwords.

In order for cluster membership to be directly useful for providing password-strength guidance, cluster membership should have a close relationship password strength. If no relationship exists or if the relationship is very weak, then the relationship between guessability and any patterns associated with cluster membership may also not exist or be very weak.[5] While in theory any password pattern has (or could be targeted to have) some influence on password guessability, some patterns may describe high-level patterns that users instantiate in many different ways, as opposed to in the same general, predictable way.

Logistic regression of guessability on cluster membership

We explored the relationship between cluster membership and guessability using a logistic regression. Specifically, we performed a logistic regression where the dependent variable was the binned password strength[6] (based on log10 guess numbers reported by the PGS3 NN), and where the independent variables were fuzzy c-means cluster memberships for a given password (i.e., 30 membership values in the range $[0, 1]$). Our goal for this model was to experimentally determine how well cluster membership could be used to *predict* password strength, rather than to understand the relative importance of cluster-membership features for predicting password strength.

[5]Even if cluster-associated patterns could be instantiated in passwords of varying guessability, cluster membership could be potentially useful for password-strength feedback if that feedback was conditionally shown only for weak passwords, based on guessability estimates from an external model, such as the NN-based strength estimator from prior work [52].

[6]We represented binned password strength as a categorical variable, rather than ordinal. This means our prediction accuracy will be conservative. We could potentially achieve better performance by retaining information about strength-bin ordering during model training.

Hence, in contrast to previous regression models, we included all two-way interactions between cluster assignments.[7] Our password-strength bins consisted of five levels from *very weak* to *strong* (Table 4.2).

Strength bin	**Threshold(s)**
Very weak	$x \leq 10^3$
Weak	$10^3 < x \leq 10^6$
Fair	$10^6 < x \leq 10^9$
Good	$10^9 < x \leq 10^{14}$
Strong	$x > 10^{14}$

Table 4.2: Criteria used to classify passwords into strength bins based on their guess number x.

We used multinomial logistic regression models with L2 regularization. Formally, the optimization problem for our model was to learn a set of coefficient weights that minimized the following, where $w = [\beta_0, \beta_1, ..., \beta_{21,21}]$ are the weights for predictor features, y_i is the strength bin for password i, C determines the degree of L2 regularization, and X_i represents the numeric heuristic-feature values for password i:

$$\min_{w,c} \frac{1}{2} w^T w + C \sum_{i=1}^{n} \log(\exp(-y_i(X_i^T w + c)) + 1) \tag{4.2}$$

We implemented our model using the scikit-learn library with 10-fold cross validation and a maximum of 250 iterations per optimization loop. We used the SAGA solver and our scoring function was defined as the class-weighted F1 score.

Stratified sampling An important goal of this regression was to understand the relationship between cluster membership and guessability separately for individual cluster. We also wanted to understand this relationship for passwords across the full range of possible strengths. Therefore, we performed random stratified sampling to generate the logistic regression training data. Our strata were composed of the combination of strength bin and hard-assigned cluster. This sampling method results in a training set as diverse in cluster membership and strength distribution as the *PGS3max12* dataset from which we sampled: it generates a set of passwords for which each strength bin and nearest-cluster combination are in the same proportion as in *PGS3max12*. This was important given the unbalanced distribution of password strengths near each cluster. Our random sampling approach maintains this imbalance while still providing data that can help explain relationships between guessability and membership for different classes of password strength.

We trained our logistic regression model on a sample of 2.9 million passwords (10% of *PGS3max12*) and tested its predictions on a held-out sample of 10,000 passwords, which were also selected

[7] This introduces severe multicollinearity which would hinder interpretation of coefficients as feature importance.

via random stratified sampling. Our model was trained on an 8-core machine containing AMD Opteron 6274 CPUs and 126GB of RAM, with a separate concurrent worker for each CPU, which took approximately four days to finish.

4.2.6 Prioritizing feedback using cluster-membership-weighed importance

In this section, we discuss our technique combining clustering results with regression results of cluster membership onto heuristic features in order to learn password-specific heuristic importance. The set of heuristics we considered are the nine heuristics described in Section 4.2.4, though the same approach could be extended to other sets of heuristics features, as long as features in that set are scaled similarly and do not exhibit severe multicollinearity.

The technique we detail in this section produces password guidance in the form of quantified relative importance for a set of nine heuristics, which can be presented in a text feedback format.[8] Importance values for different text-feedback items could be incorporated into a password meter by an interface that denotes the relative importance of each detected heuristic (e.g., similar to Figure 4.9), or by an interface that presents feedback for detected heuristic features according to their relative importance, without indicating numerical importance.

The prioritization of heuristics described in this section is password-specific in the sense that the relative importance of heuristics for a candidate password are specific to passwords with similar cluster assignments to that candidate password. Since clusters correspond to password patterns, this prioritization will be specific to passwords containing similar patterns as the candidate password. Furthermore, assuming that the importance of a heuristic features for determining password strength differs for differently clustered passwords, passwords with different patterns will be associated with different heuristic priorities, which can be reflected in user feedback.

In order to learn heuristic priorities for each individual cluster, we train cluster-specific regression models that predict guess numbers from heuristics. In order to determine the relative importance of features for a new candidate password, we calculate the cluster-membership-weighted sum of importance values associated with each cluster-specific model, separately for each feature.

Linear regression of guessability on heuristics

We constructed regression models where the dependent variable was a password's log10-transformed PGS3 NN guess number and the independent variables were the following 14 heuristic features:

- Repeated characters (h4)
- Keyboard patterns (h5)
- Repeated sections (h6)

[8]The specific text associated a heuristic feature could be the same as or similar to text feedback provided a password meter from prior work (e.g, [87]).

- Predictable uppercase (h8)
- Predictable digits (h9)
- Predictable symbols (h10)
- Uppercase count (h11)
- Lowercase count (h12)
- Digits count (h13)
- Symbols count (h14)
- Use of dates (h15)
- Alphabetic/numeric sequences (h16)
- Common substrings (h17)
- Dictionary (longest token) (h18)

The heuristic features we included in this model differed from those included in the models described in Section 4.2.4. Our reasoning for selecting a different subset was to include heuristics that were more amenable to actionable advice by users. For example, rather than include *Character-class structure (h7)*, we chose to include heuristic features that captured the number characters in the password of each class type (*h8–h12*) along with features denoting whether a password contained predictable use of uppercase, digits, or symbols (*h8–h10*). We ensured that the modified set of heuristic features did not exhibit strong multicollinearity and used the same scaling approach described previously, in order to interpret learned weights in terms of feature importance.

Formally, let $g_m(x)$ denote the log10 guess number of password x for the regression model specific to cluster m. Other formal parameters are defined as in previous regression models. The general formula for our model is then:

$$g_m(x) = \beta_{0,m} + \beta_{1,m}\frac{h_1(x)}{s_{1,m}} + \ldots + \beta_{N,m}\frac{h_N(x)}{s_{N,m}} \tag{4.3}$$

As for the regression described in Section 4.2.4, in this model we were interested in understanding the relative importance of heuristic features, only in this case for predicting guessability rather than cluster membership. In addition, the particular quantity we were interested in was not the average relative importance denoted by heuristic feature coefficients $\beta_{j,m}$, but rather the product of that coefficient and the corresponding scaled feature value for a given password, $\beta_{j,m}\frac{h_j(x)}{s_{j,m}}$.

Our reasoning for multiplying feature coefficients by scaled heuristic feature values was to learn password-specific, heuristic importance that reflected both the importance of that heuristic in similarly-clustered passwords as well as the extent to which that heuristic-associated pattern was actually exhibited in the candidate password. For example, even if *Predictable uppercase*

(h8) was found to be generally important for determining the strength of passwords with similar clustering memberships as the candidate password, if the candidate password did not exhibit predictable uppercase then the password-specific importance for this heuristic would be zero, as desired. This modification was useful given the fuzzy nature of patterns in passwords, heuristic-associated patterns generally appearing in passwords strongly assigned to a cluster were not always present.

Each cluster-specific model was trained using a set 100,000 passwords locally sampled around each cluster, as described in Section 4.2.4.

Comparison to global regression model

For the sake of understanding how much cluster-membership-weighted heuristic importance differed from heuristic importance for the average password, we also trained a global regression model that was trained using 100,000 passwords randomly sampled from *PGS3max12*. The general structure of this model was the same as for the cluster-specific models:

$$g^*(x) = \beta_0^* + \beta_1^* \frac{h_1(x)}{s_1^*} + \ldots + \beta_N^* \frac{h_N(x)}{s_N^*} \tag{4.4}$$

In our analyses, we compare the impact of heuristic-feature importance based on a global regression to heuristic-feature importance based on cluster-membership-weighed feature importance. Concretely, we compare the password-specific, global importance values $\beta_j^* \frac{h_j(x)}{s_j^*}$ to the password-specific, cluster-membership-weighed importance values $\left\langle \beta_{j,m} \frac{h_j(x)}{s_{j,m}}, p_m(x) \right\rangle$.

Evaluation on user study and leaked passwords

In order to evaluate our technique for providing password-specific text feedback, we predicted the importance values of heuristics for passwords in two different sets. The first set consisted of 185 *1c8* passwords collected for the user study described in Chapter 3. The second set consisted of 600 password comprised of the 20 *weak* passwords from *PGS3max12* nearest to each cluster.[9] Heuristic importance values for these two sets were computed using both the cluster-local and global regression models and their results compared.

4.2.7 Limitations

The experiments discussed in this chapter and their results are subject to limitations. Our autoencoder model was trained to minimize the reconstruction error of input passwords. If passwords

[9] We chose to analyze *weak* password because we hypothesized those passwords might contain multiple heuristic-associated patterns for which prioritized text-based guidance might be especially relevant.

are similar in many ways and some of those ways are correlated with each other, then it can be arbitrary which similar characteristics within a correlated set of characteristics an autoencoder learns to eventually model. This limitation also affects IG explanations of cluster NN model predictions, since those predictions depend on the abstract patterns learned by the autoencoder during training.

Another limitation of our autoencoder model is that it is only trained to model the subset of passwords in the length range of 8–12 characters that use the ASCII subset of PGS-supported characters. Although the majority (88%) of passwords in *PGS3* are contained in this subset, our autoencoder modeling results, as well as analyses that depend on them, may differ when modeling passwords with other structural restrictions.

We performed an initial evaluation of techniques by testing them on passwords collected in user studies. However, we are not able to determine the usability or impact on effective security for actual tools incorporating those techniques. Determining these aspects would require an experimental user study of the type performed in Chapter 3, which due to time constraints we did not perform.

4.3 Results

We first describe the distribution of cluster membership for *PGS3max12* passwords and visualize the global structure of the latent space using t-SNE plots. We then describe patterns in passwords identified using visual inspection, IG explanations, and a regression of cluster membership onto known heuristic features. Next, we quantify the relationship between cluster membership and guessability using a logistic regression. The relationship between cluster membership and heuristic features, combined with the relationship between cluster membership and guessability, provide support for our hypothesis that cluster-membership-weighed heuristic importance can learn a prioritization of heuristic features specific to the patterns found in a given password. We describe results in which computed cluster-membership-weighed heuristic importance for sets of test passwords and compared these results to heuristic importance for passwords in general.

4.3.1 Distribution of passwords among clusters

We found that membership values of passwords nearest to each cluster varied in magnitude across clusters. Table 4.3 displays the seven nearest passwords to each cluster. We see that for some clusters (e.g., Cluster 0 and Cluster 1), the nearest passwords to those clusters have high cluster-assignment scores, indicating strong membership. We examined the top 1,000 hard-assigned passwords nearest to each cluster and observed similar findings among clusters in the extent to which cluster-nearby passwords belonged to those clusters. For example, the 1,000th nearest password to Cluster 0 had a membership score of 97% for that cluster. In contrast, the 1,000th nearest password to Cluster 10 only had a membership score of 52% for the cluster. This sug-

gests that for some clusters, the patterns in passwords near those clusters are more dominantly displayed relative to the patterns of other clusters.

Some clusters had majority ownership of passwords more frequently than others. We examined the percentages of hard-assigned passwords in the training data for each cluster. Cluster 27 had the largest percentage of hard-assigned passwords at 5% (1.46 million). In contrast, Cluster 8 had the lowest percentage of hard-assigned passwords at 1.4% (400 thousand). Another way of stating this is that some clusters are the dominant pattern more frequently than others; more passwords are nearest to that cluster than is the case for other clusters.

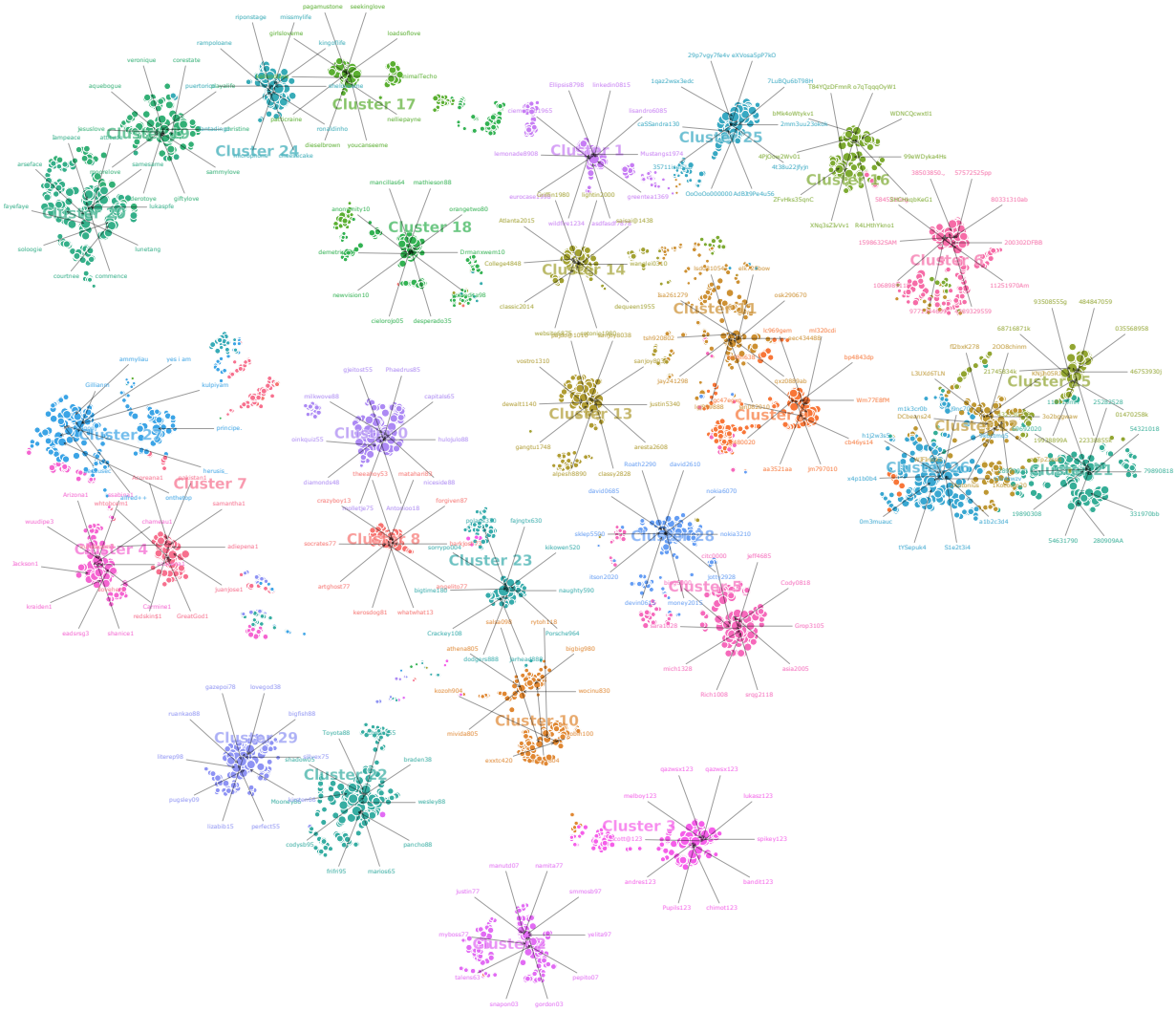


Figure 4.1: t-SNE visualization for 5,000 passwords. Passwords data points are colored according to their nearest fuzzy c-means cluster, with the size of those points proportional to their membership to that cluster.

t-SNE plots are useful for visually summarizing the distribution of password samples in the latent space learned by the password autoencoder. Figure 4.1 shows the t-SNE visualization for a sample of 5,000 passwords, sampled from *PGS3max12* using random stratified sampling

with respect to hard-assignment and strength-bin strata. In this visualization, each password is visualized as a circle-shaped data point.

Colored t-SNE plots such as the one shown in Figure 4.1 show information about clustering in the latent space using two separate, but related methods. The spatial positioning of each data point in the plot is determined by the t-SNE algorithm, which places each data point relative to other data points such that the distance between points (i.e. similarity between passwords) in the eight-dimensional latent space is maintained in the two-dimensional projection. The other way that clustering information is shown in Figure 4.1 is through the coloring of data points, which map to the hard-assigned cluster for each password, as determined by the fuzzy c-means clustering algorithm. Additionally, the size in radius of each circular data point reflects the membership score for that password to its hard assigned cluster.

We see that t-SNE-determined spatial clusters of passwords generally are of the same color, i.e. have the same fuzzy c-means hard assignment. This is not too surprising given that both algorithms operate on Euclidean distances between latent representation of passwords, but is a good sanity check that both algorithms have been implemented correctly. It is also not surprising that we see passwords hard-assigned to each fuzzy c-means cluster appearing in the t-SNE plot; one of the goals of stratified sampling with respect to cluster hard assignment is to ensure passwords near each fuzzy c-means cluster appear in the t-SNE plot. More interesting is to observe how the size of password data points corresponds to spatial placement in the t-SNE plot and whether any clusters not strongly captured by a fuzzy c-means cluster appear. For example, in Figure 4.1 we observe some small groups of passwords that lie spatially distant from other larger clusters (i.e. are distant from other passwords in the latent space), that have generally small size (i.e. low membership to the nearest fuzzy c-means cluster), and that sometimes contain data points of multiple colors (i.e. are comprised of passwords nearest to multiple different fuzzy c-means clusters). Such sets of passwords may indicate a pattern that is dissimilar from the primary fuzzy-c-means-associated patterns, which could potentially be captured by performing fuzzy c-means with a larger number of clusters.

4.3.2 Patterns associated with clusters

We applied a few different methods to help understand high-level patterns associated with each individual cluster: looking at the prototypes of each cluster reconstructed in the plaintext password space, visually inspecting each cluster's nearest hard-assigned passwords, and applying Integrated Gradients to explain cluster-membership predictions.

Cluster prototypes and hard-assignments

As shown in Table 4.3, we find that the text-reconstructed prototype of a cluster can provide a useful template of patterns associated with that cluster, in particular with respect to character-class structural patterns. For example, the prototype of Cluster 0, "saaeanen85", has a structure of eight lowercase letters followed by two digits, which the majority of passwords hard-assigned

Cluster 0		**Cluster 1**		**Cluster 2**		**Cluster 3**		**Cluster 4**	
saaeanen85		saaeeden1364		sanned641		sanned123		saanedo1	
suzanneg75	(.98)	tremuned1160	(.97)	HaageB53	(.70)	otoxeh113	(.87)	juvgexn1	(.91)
Mayaguez75	(.98)	abhishek1390	(.97)	sinned53	(.70)	igebeh113	(.87)	damnedn1	(.90)
nunucaem85	(.98)	mohammed1390	(.97)	powned53	(.70)	osameh113	(.87)	kmpuehn1	(.90)
nimajneb85	(.98)	martinez1780	(.97)	dodge.53	(.70)	jammeh113	(.86)	ecgfedn1	(.90)
dadadaeu85	(.98)	abhishek1890	(.97)	yodjek53	(.70)	rushed113	(.86)	jaydedn1	(.90)
enriquez75	(.98)	steelhed1660	(.97)	lynne@53	(.70)	wicked113	(.86)	sladeqn1	(.90)
partanen75	(.98)	lemozney1060	(.97)	byczek53	(.70)	enivez113	(.86)	Linkedn1	(.90)
Cluster 5		**Cluster 6**		**Cluster 7**		**Cluster 8**		**Cluster 9**	
aoia6108		2002291aow		sananedr1		saaaaroh63		aa100eo5	
yll@5978	(.92)	859216Js25	(.98)	cubanezu1	(.97)	marooned63	(.85)	bo638cnT	(.89)
kirk5578	(.92)	405M369iv5	(.98)	Hackneyn1	(.97)	cultdyed63	(.85)	Kw4K7urU	(.89)
lala5978	(.92)	1989GMCs15	(.97)	teamaedn1	(.97)	martinez63	(.85)	<=)-Hi@>	(.88)
golf5578	(.92)	170397AkHw	(.96)	Celinedu1	(.96)	clubcued63	(.85)	<d415ie>	(.88)
nery5278	(.92)	571356YahI	(.95)	rstunedn1	(.96)	SanzaWeb63	(.85)	Gm4ORlnM	(.88)
mark5278	(.92)	290887IcfB	(.95)	Whitneyn1	(.96)	uynbdqez63	(.85)	bu453rnT	(.88)
alex5578	(.92)	130573DjTj	(.95)	tyronebu1	(.96)	jwdzkgeb63	(.85)	ty32LerC	(.88)
Cluster 10		**Cluster 11**		**Cluster 12**		**Cluster 13**		**Cluster 14**	
aaeraa990		arn120208y		2da1a122g		santen0980		saaedon0994	
shilo#97#	(.60)	clk500LIN	(.70)	5c2Igee5$	(.85)	jayden5580	(.98)	Evilken5060	(.99)
damian90t	(.60)	Xia0109HC	(.70)	3#Megan4$	(.85)	linked0980	(.98)	realped5960	(.99)
pocong90t	(.60)	bob04JOHN	(.70)	4hJpb9bNt	(.85)	nguyen8880	(.98)	Hellyea8960	(.99)
Jonesy90#	(.59)	srw0711NH	(.70)	4n99ymbot	(.85)	wolfey5080	(.98)	kebumen8390	(.99)
Maxim_22#	(.59)	Ken082958	(.70)	M1k3cusi$	(.85)	Cmoney5190	(.98)	shithed8360	(.99)
Damian23#	(.59)	lea994138	(.69)	3j1buy*&$	(.85)	DanyeL8990	(.98)	stephen5060	(.99)
matron98#	(.59)	Brk5346cN	(.69)	w1P9krot$	(.84)	Gracey5590	(.98)	iclozem8080	(.99)
Cluster 15		**Cluster 16**		**Cluster 17**		**Cluster 18**		**Cluster 19**	
122229Aam		ARA33aa112x		saneeadodno		saneeamon64		sanewoane	
102537Mom	(.98)	CDo04npsXBh	(.95)	dili_que-no	(.96)	rajeshaec60	(.96)	OctaneOne	(.85)
277007Tgm	(.98)	OGHABbash1!	(.95)	cinzialegno	(.96)	iyvotqaem60	(.96)	UniqueOne	(.85)
318818Agm	(.97)	H2O*R@tt72!	(.95)	ladynotekno	(.96)	rodriguez60	(.96)	IamTheOne	(.84)
109607Sam	(.96)	ALPHAmale1!	(.94)	www.kake.no	(.96)	onurbilen60	(.96)	I@mTheOne	(.84)
314159Hxj	(.96)	O4mLUph2qfx	(.94)	gumbletekno	(.96)	iupgacqew60	(.95)	hnehnehne	(.84)
119688Fpj	(.96)	SMILEnow76!	(.94)	nesogorengo	(.96)	ayvmotnek60	(.95)	kneknekne	(.84)
303161Tom	(.96)	ALPHAbeat1!	(.94)	dualcoreduo	(.96)	agvumxpeq60	(.95)	AspireOne	(.84)
Cluster 20		**Cluster 21**		**Cluster 22**		**Cluster 23**		**Cluster 24**	
soasshni		2000105N		sannen68		saaeroa794		saaeemohne	
fursidni	(.95)	332211BB	(.91)	linnea88	(.94)	vedeven390	(.94)	jalinkedne	(.96)
sumeshni	(.94)	112176GC	(.91)	beaney88	(.94)	kavuwew390	(.94)	hate@me@ne	(.96)
mukeshni	(.94)	170558AB	(.91)	denney88	(.94)	sekibep390	(.94)	jangadeyne	(.96)
rajeshni	(.94)	112152TC	(.91)	penney88	(.94)	luxicen390	(.94)	sorenhejne	(.96)
bolishni	(.94)	170845GT	(.90)	kenney88	(.94)	qilivem490	(.94)	iluvcheyne	(.96)
periodni	(.94)	160886RC	(.90)	zeynep88	(.94)	qiloxew790	(.94)	dhagaweyne	(.96)
darsshni	(.94)	120788AB	(.90)	Linnea88	(.94)	fijihek390	(.94)	liveonedge	(.96)
Cluster 25		**Cluster 26**		**Cluster 27**		**Cluster 28**		**Cluster 29**	
2R113aen110j		s0s4ne05		iloveminy		aanen0070		saaemon85	
R4T4*pasad4*	(.96)	cDD1dw1N	(.95)	jackedu^	(.74)	jozek0070	(.97)	rfhfxey85	(.99)
4H0P2ewpv4Uw	(.96)	wJH1zn1T	(.95)	Tybalt<>	(.74)	ahmed0180	(.97)	whamfey85	(.99)
OGq71eljcKxb	(.96)	m4a1colT	(.95)	martini*	(.70)	mike&0480	(.97)	babyfed85	(.99)
GFAC0mp0nent	(.96)	7c0cca4B	(.95)	zjgvednv	(.70)	coded0070	(.97)	oakaped85	(.99)
FD102<>csjob	(.96)	qHG1pj1H	(.95)	nintendo*	(.70)	numec0770	(.97)	soliyen85	(.99)
JHG65drtl&3%	(.96)	z6n2zcqB	(.95)	matienzo*	(.69)	ahmed0770	(.97)	ada_deh85	(.99)
4z355jocupub	(.96)	k3v0subB	(.95)	ashleynv	(.69)	ruben0580	(.97)	hershey85	(.99)

Table 4.3: Seven closest hard-assigned passwords to each cluster. Cluster prototypes are listed immediately below cluster label. Cluster assignment scores are shown in parentheses.

to Cluster 0 also exhibit. The extent to which the reconstructed prototype represents patterns associated with nearby passwords to a given cluster appears to be related to the cluster membership of those nearby passwords. While the reconstructed prototype of Cluster 0 has a character-class structure matching that of nearby passwords, the character-class structure found in the reconstructed prototype of Cluster 10 often does not match that of passwords near to Cluster 10, especially for the nearest set of passwords.

We find instances where prototypes appear less useful for demonstrating cluster-associated patterns, even when nearby passwords have high cluster membership (e.g., Cluster 26). We investigated the cluster membership predictions for the reconstructed prototype "s0s4ne05" and found that, unlike other clusters, it was assigned a relatively low cluster membership score to its associated cluster. While "saaeanen85" was assigned to Cluster 0 with a membership score of 98%, "s0s4ne05" was assigned to Cluster 26 with a membership score of 49%. This demonstrates a limitation of reconstructed cluster prototypes. While a cluster prototype represents a latent data point that has a membership score of 100% to its associated cluster, the decoder neural network may introduce reconstruction error when transforming that cluster prototype back into a plaintext format.

Visual examination of hard-assigned passwords for each cluster show patterns related to password length, character-class structure, and the particular substrings that passwords end in. The similarity in password endings is especially evident when viewing a large number of hard-assigned passwords, e.g. as provided in Appendix B.3.2. For example, passwords near Cluster 4 often end in "u1", "n1", "c1", or "a1". The beginning substrings of passwords near a given cluster were much more varied, which we hypothesize may reflect higher similarity of password endings than password beginnings in general among leaked passwords.

Character-class structural patterns often appear in a fuzzy fashion. If we only examine the most frequent character-class structure in hard-assigned passwords to Cluster 8, we find that this structure, nine lowercase letters followed by two digits, accounts for approximately 8% of all hard-assigned passwords, a relatively low proportion. However, if we consider the top ten character-class structures found in all hard-assigned passwords to Cluster 8, we see that the general pattern of lowercase letters followed by digits accounts for 83% of passwords. Expanding that pattern to include passwords that additionally begin with a single uppercase letter accounts for 92% of passwords. We note that some clusters share similar character-class-structure patterns, yet remain separate entities in our clustering results. In these cases, we found that such clusters could often be differentiated by patterns appearing in the particular substrings that passwords ended in. While both Cluster 22 and Cluster 29 have high membership of passwords beginning with all lowercase characters and ending in two digits, passwords hard-assigned to Cluster 22 tend to be eight character long and often end with "68" or "78"; in contrast, passwords for Cluster 29 tend to be nine characters long and often end with "85" or "75".

Lastly, it is worth mentioning that although we often find consistent patterns in passwords hard-assigned to a given cluster, this was not the case for all clusters. For example, it is difficult to discern any consistent pattern in the hard-assigned passwords of Cluster 25, either with respect to the presence of particular substrings or to character-class structure.

Cluster-assignment explanations using Integrated Gradients

Here we describe our results applying IG explanations for understanding cluster-associated patterns in terms of individual characters in passwords. We experimented with many different IG configurations that differed in the IG baseline used to generate explanations, the number of IG approximation steps, and how numeric attributions were visualized. In this chapter, we show results for one of the more promising configurations that used a padding-based baseline, which we found provided intuitive cluster-assignment explanations.

In Figures 4.2 and 4.3 we show IG cluster-assignment explanations for a subset of clusters. Both figures show positive attributions for the nearest 20 passwords to each cluster. Figure 4.2 highlights all positive-attributed characters in a given password associated with that password's cluster assignment, without distinguishing relative differences in the magnitude of positive attributions. In contrast, the attributions visualized in Figure 4.3 are first capped above at the 95th percentile, and then displayed such that the intensity in color of each red-colored character corresponds to the relative magnitude of that character's attribution value, where the character with the largest attribution value is displayed in the largest-intensity red color and characters with non-positive attributions are colored grey.[10] We found both types of visualizations useful for explaining cluster assignments. Highlighting all positive attributions without distinguishing relative magnitudes was useful for showing all relevant characters in the password, and showing relative importance of characters as different shades of red was useful for understanding which characters were most important for explaining cluster membership among the set of all relevant characters.

Both visualization configurations we tested seemed to highlight patterns we expected to be associated with cluster membership based on visual examination of cluster prototypes and hard-assigned passwords. For example, Cluster 1, Cluster 7, and Cluster 21 appear to highlight characters associated with character-class structure. In general, attributions that appeared to be associated with character-class structure tended to highlight a particular character-class sequence in the overall structure, such as trailing digits in Cluster 1. IG explanations also sometimes highlighted patterns in passwords where a particular character consistently appeared in a particular location, especially for characters located at the end of a password. This was most evident for visualizations that showed relative character importance, e.g. Cluster 7 in Figure 4.3.

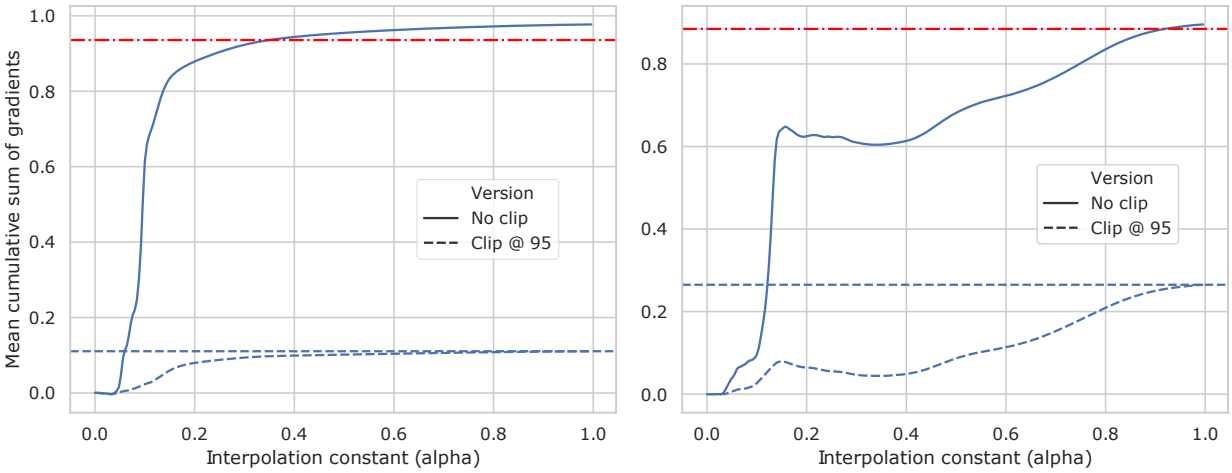
For the visualization configuration that highlighted the relative importance of characters, some character attributions dominated others such that explanations focused on single character, despite our attempts to limit this behavior by capping attribution values (e.g., Cluster 17 in Figure 4.3). However, this configuration was sometimes successful at highlighting less obvious patterns in cluster-assigned passwords. For example, IG explanations for Cluster 7 and 17 highlighted the letter "e" near the ends of passwords, which we found to be a consistent pattern when examining the top 1,000 hard-assigned passwords. Similarly, IG attributions for Cluster 26 in the same figure often highlight a capital letter at the end of the password, a pattern which we found less obvious to detect based on visual inspection. Despite their overall usefulness, for some clus-

[10] Absent clipping, a large attribution value for a single character tended to dominate the attribution color scheme (see Figure B.13 in the Appendix).

Figure 4.2: Visualization of IG attributions where positive attributions are highlighted equally. IG attributions are with respect to the padding baseline approximated over 250 steps.

Figure 4.3: Visualization of IG attributions where positive attributions are shown in red with intensity relative to the magnitude of attributions across all characters. IG attributions are with respect to the padding baseline approximated over 250 steps and have been clipped above at the 95 percentile.

ters neither type of IG visualization configuration was able to shed light on consistent patterns in passwords that might explain cluster membership, e.g. Cluster 25.



(a) Cluster 1

(b) Cluster 21

Figure 4.4: Cluster-assignment attribution accumulated over the interpolation path from the baseline to the input password. IG attributions are with respect to the padding baseline and approximated over 250 steps. Attribution values were clipped stepwise at the 95th percentile. These plots have been averaged over the 50 nearest hard-assigned passwords to each respective cluster.

Clipping attribution values above at the 95th percentile has an impact on the total sum of attributions that are visualized. In order to quantify how much of an impact this procedure had on IG visualizations such as those in Figure 4.3, we compared the sum of attributions visualized by IG after performing clipping to the total sum of attributions associated with a given cluster-assignment prediction, equal to the difference in cluster-assignment prediction for the input password and the IG baseline. Figure 4.4 shows this comparison. In this figure, the sum of attributions (cumulative sum of gradients of the cluster-assignment prediction with respect to the character-level embedding tensors) is shown on the y-axis. The x-axis shows how this sum changes as we interpolate from the baseline to the input password (i.e. alpha corresponds to the fraction of the path from the baseline to the input that has been traversed in the latent space). The dot-dashed red line corresponds to the total sum of attributions, equal to the delta in prediction scores between the input and baseline. The dashed blue line shows the effect of clipping gradient values stepwise; the horizontal dashed blue line shows the final sum of attributions after clipping.

As shown in Figure 4.4, while the unclipped IG approximation often produced a set of attributions that summed near to the theoretical target of input-baseline prediction-score delta (see the solid blue line at $\alpha = 1$), capping attribution values at the 95th percentile had a substantial effect on the proportion of total attributions that were visualized. The impact of capping reduced the proportion of attributions visualized by an approximate average of 75% to 90%. While we do not notice a direct relationship between the amount of IG attributions visualized and the clarity or consistency of patterns appearing in visualizations of those attributions (e.g., when comparing Cluster 1 and Cluster 21 in Figure 4.3), this does suggest that our visualizations may not reveal all patterns associated with cluster membership.

Relationship between cluster membership and heuristics

Here we present an overview of our results on quantifying the relationship between cluster membership and prior-work-identified heuristic features using linear regressions, as described in Section 4.2.4. Detailed tables for each set of regression results can be found in Appendix B.6.2.

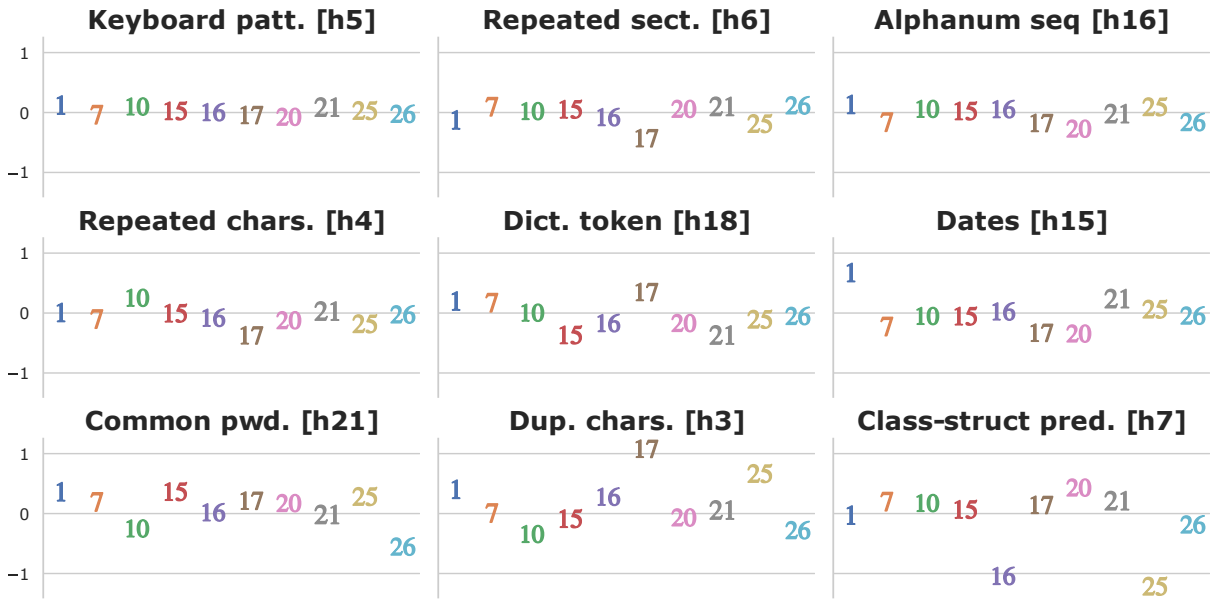


Figure 4.5: Visualization of a feature importance for determining membership to a subset of clusters, as determined by cluster-specific regressions of cluster-assignment scores onto nine heuristic features. The y-axis is in units of log-odds.

We confirmed that the nine heuristic features we examined are not useful for accurate predictions of cluster membership. Based on adjusted R^2 values, our models explained an average 15% of the total variation in log-odds of cluster assignment, with a maximum of 35% for Cluster 16 and a minimum of 3% for Cluster 11. Nonetheless, our models can still be used for understanding the relative importance of heuristics features, in terms of which features raise or lower the odds of assignment to a given cluster. This information is useful for further understanding concepts each cluster is associated with, by shedding light on password patterns associated with those concepts.

As shown in Figure 4.5, the presence of some heuristics-associated patterns in passwords had little associated effect on likelihood of cluster assignment for any clusters. This was most apparent for keyboard patterns, which based on informal observation seemed to frequently appear in passwords that were both strongly and weakly assigned to a given cluster. For some clusters, such as Cluster 7, none of the nine heuristic features we explored demonstrated a substantial association with cluster membership. In contrast, for some clusters certain heuristics were more strongly associated with likelihood of cluster membership than others, e.g. *Dictionary token (h18)* and Cluster 17.

4.3.3 Relationship between cluster membership and guessability

Besides understanding the patterns associated with cluster membership, an important determining factor in how that membership can be used for generating password-strength guidance is the relationship between cluster membership and guessability. We explored this relationship using a logistic regression, as described in Section 4.2.5, and further probe this relationship by examining the passwords nearest to each cluster separately for each strength bin.

Logistic regression of strength bin onto cluster-assignment scores

Here we present the results of a logistic regression of password strength onto cluster membership. Strength was binned according to Table 4.2 and all two-way interactions between cluster-assignment scores were considered.

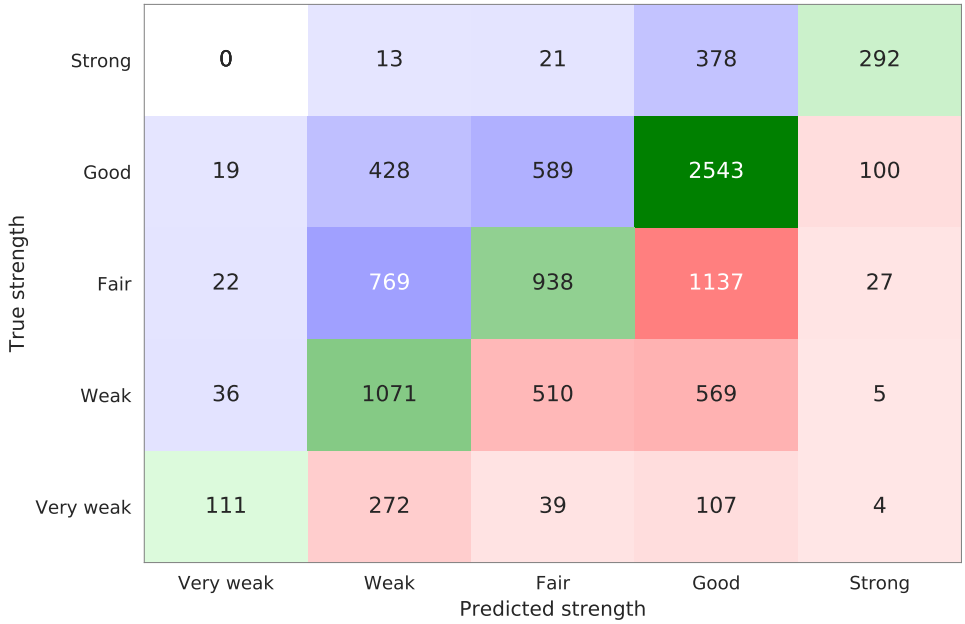


Figure 4.6: Confusion matrix for the logistic regression of cluster-assignment scores onto strength bin. Results are based on a test set of 10,000 passwords.

In Figure 4.6 we show a confusion matrix that summarizes the performance of our trained logistic regression classifier on held-out test data. We found that our classifier performed reasonably well at predicting *good* and *strong* passwords. It performed less well at predicting *fair* or weaker passwords. In particular, the large number of unsafe errors (i.e. predicting a strength stronger than the true strength) for *very weak* and *weak* passwords imply this classifier would not be appropriate for estimating strength in password meter.

Table 4.4 shows summary statistics describing our test results. As shown in the F1-scores for each strength bin, performance was best for *good* passwords, which constituted the majority of test

Strength bin	Precision	Recall	F1-Score	Support
Very weak	0.59	0.23	0.33	533
Weak	0.42	0.48	0.45	2191
Fair	0.43	0.32	0.37	2893
Good	0.53	0.69	0.60	3679
Strong	0.75	0.41	0.53	704
Accuracy	-	-	0.49	10000
Weighted Avg.	0.50	0.49	0.48	10000

Table 4.4: Precision, recall, and other performance metrics for the logistic regression of cluster-assignment scores onto strength bin.

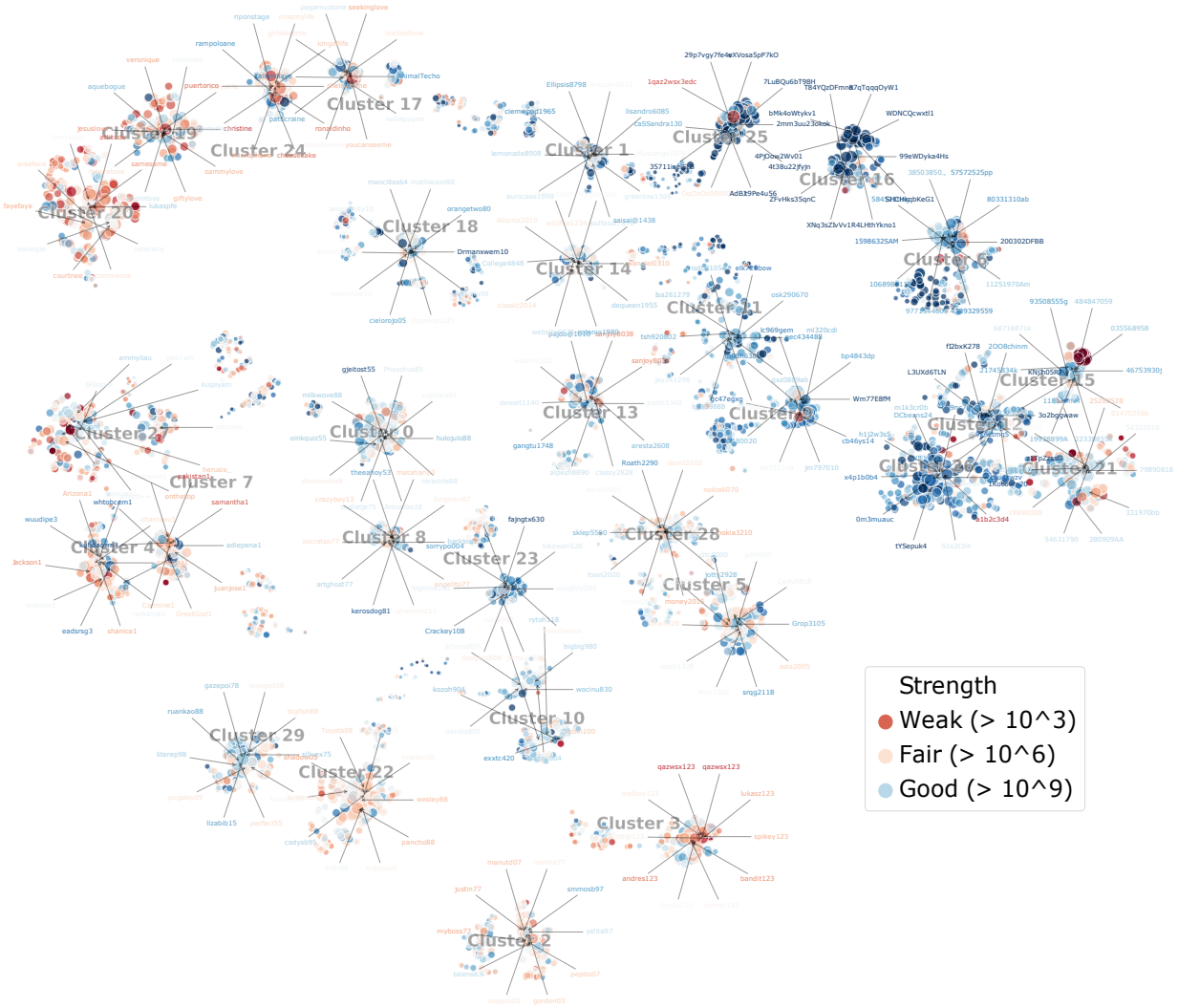


Figure 4.7: t-SNE visualization for 5,000 passwords colored by log10 PGS3 NN guess number. The size in radius of each data point is proportional to cluster membership for the associated password's fuzzy c-means hard-assigned cluster.

passwords. The classifier struggled with predicting *very weak* and *fair* passwords, in particular with respect to recall. The t-SNE visualization in Figure 4.7 illustrates why recall for *very weak* passwords may have been particularly challenging. We see that clusters often are relatively homogeneous in the strength of passwords they comprise, e.g. Cluster 20 is mainly composed of *weak* and *very weak* passwords. However, in predominately *strong* password clusters, e.g. Cluster 15, we see a substantial amount of strongly-assigned *very weak* passwords, which limit the usefulness of cluster membership for predicting that strength bin.

We attempted to explore characteristics of passwords within each cluster associated with password strength. Table 4.5 shows a subset of the passwords nearest to each cluster for each strength bin. Across clusters, *very weak* and *weak* passwords tended to contain predictable phrases, common passwords, keyboard patterns, and dictionary words with and without "leet" character substitutions (e.g., "4" for "a"). *Weak* passwords often contained names and dates that might correspond to birth years. *Strong* passwords often contained less predictable combinations of words and strings that do not appear to be variations of a dictionary word. While none of this is new information—each of these pattern types are captured in heuristic features we use in this chapter—it underlines how the presence of commonly known heuristic-associated patterns is often negatively associated with password guessability, even when passwords are of a complex character-class structure, as shown for Cluster 25 and Cluster 26.

While we see in Table 4.5 that passwords near to a cluster can be of many different strengths, we notice that the nearest passwords in some strength bins for some clusters have a low assignment score, e.g. the nearest *very weak* and *strong* passwords to Cluster 21 have relatively low membership. In contrast, Cluster 26 has the highest assignment scores for nearby *good* and *strong* passwords. These varied password-strength distributions for clusters are evident when examining guessability curves plotted for each cluster's hard-assigned passwords (Figures B.2-B.4 in the Appendix), and illustrate relationships the logistic regression was trained to learn.

4.3.4 Cluster-membership-weighed vs. global importance

In Section 4.3.2 we showed that a linear relationship exists between cluster membership and heuristics. While the extent of this relationship was insufficient for prediction purposes, our models provide some information about when one heuristic was more relevant than another for determining membership of a password to a given cluster. In Section 4.3.3 we demonstrated a linear relationship between cluster membership and the binned strength of a password. Although the performance of this model is not high enough for applications such as estimating strength in a password meter, its performance may be reasonable for other types of applications. In this section we model the relationship between heuristic features and guessability using a linear regression of log10 guess numbers onto a set of heuristic features. Our goal for this model is to learn the relative importance of heuristics on determining guessability in a way that leverages the locality provided by cluster memberships for a given password. We formulate a method for weighing heuristic-feature importance based on cluster-assignment scores and investigate the extent to which cluster-membership-weighed heuristic importance differs from heuristic importance learned by a single, global regression model.

Very weak	Weak	Fair	Good	Strong
Cluster 1				
password1234 (.69)	getmoney1000 (.96)	abhishek1390 (.97)	steelhed1660 (.97)	tremuned1160 (.97)
jamesbond007 (.24)	kingsley1990 (.95)	mohammed1390 (.97)	bermudez1190 (.97)	lemozney1060 (.97)
zxcasdqwe123 (.18)	gonzalez1990 (.95)	martinez1780 (.97)	MissyBen1170 (.97)	pugboyed1680 (.97)
qazwsxedc123 (.17)	kingsley1980 (.95)	abhishek1890 (.97)	Shadowed1360 (.97)	leicched1370 (.97)
asdfghjkl123 (.17)	hayabusa1300 (.95)	muhammed1770 (.97)	mitabrev1490 (.97)	thioulea1760 (.97)
Howareyou123 (.17)	Hayabusa1300 (.95)	gretchen1700 (.97)	Adminweb1580 (.97)	Uzituxez1800 (.97)
qweasdzxc123 (.15)	gonzalez1980 (.95)	abhishek1100 (.97)	bloodren1360 (.97)	hurdspec1090 (.97)
qwerty123456 (.13)	martinez1990 (.95)	startrek1060 (.97)	astrazen1370 (.97)	nistgwen1060 (.97)
Cluster 7				
samantha1 (.77)	anjaneya1 (.94)	Hackneyn1 (.97)	cubanezu1 (.97)	pauheu1 (.95)
pakistan1 (.72)	Anjaneya1 (.94)	Celinedu1 (.96)	teamaedn1 (.97)	SfdkJeza1 (.93)
jennifer1 (.61)	peoplepc1 (.94)	Whitneyn1 (.96)	rstunedn1 (.96)	Ba^ilena1 (.92)
whatever1 (.61)	arboleda1 (.93)	quequequ1 (.96)	tyronebu1 (.96)	UhjfreEc1 (.92)
sunshine1 (.58)	rezareza1 (.93)	delaneyc1 (.96)	Tyronebu1 (.96)	Fpspweqv1 (.91)
iloveyou1 (.56)	kalarepa1 (.93)	ihackedu1 (.96)	mapireku1 (.96)	woywdewa1 (.91)
computer1 (.50)	maitreya1 (.93)	trainedu1 (.96)	cutoneku1 (.96)	zmkSteam1 (.84)
princess1 (.47)	redareda1 (.93)	desalegn1 (.95)	hadileyn1 (.96)	Abzuweqq1 (.82)
Cluster 17				
ilovemylife (.91)	tranquilino (.95)	dualcoreduo (.96)	cinzialegno (.96)	dili_que-no (.96)
mississippi (.90)	alejandrino (.95)	rodriguezco (.95)	ladynotekno (.96)	Teana@teano (.95)
information (.71)	germanteamo (.95)	yesyesyesno (.95)	www.kake.no (.96)	•jdubfresno (.95)
nolongthing (.64)	monicateamo (.95)	leggomyeggo (.95)	gumbletekno (.96)	noe&jose.co (.95)
justlooking (.64)	silviateamo (.95)	lilianalino (.95)	nesogorengo (.96)	itanisrexmo (.95)
firefighter (.62)	sandrateamo (.95)	silvestrino (.95)	numenoreano (.96)	ohmadatehgo (.95)
sweetmother (.61)	martinteamo (.95)	chilindrino (.95)	medicarehmo (.96)	yuuuupleggo (.95)
christopher (.56)	mamitateamo (.95)	giancarlino (.95)	alexisleano (.95)	kusprayetno (.95)
Cluster 21				
22241610 (.58)	91589158 (.83)	332211BB (.91)	112176GC (.91)	10sZ375B (.76)
69696969 (.54)	01470258 (.83)	120788AB (.90)	170558AB (.91)	11n46Ic5 (.72)
10101010 (.52)	00580058 (.83)	102030RM (.90)	112152TC (.91)	68!4)))) (.69)
19861986 (.49)	02580258 (.82)	102030IM (.89)	170845GT (.90)	1029%&qm (.68)
88888888 (.45)	01480148 (.82)	112211MM (.88)	160886RC (.90)	2198.5-+ (.67)
00000000 (.44)	99289928 (.82)	121212BB (.86)	120558JH (.89)	12d08EBH (.66)
12280202 (.43)	92289228 (.82)	99230458 (.84)	120903CB (.89)	!9228$1B (.65)
12qw23we (.43)	08280828 (.81)	00316158 (.84)	141600CC (.89)	81Z517nF (.65)
Cluster 25				
1qaz2wsx3edc (.80)	!QAZ2wsx3edc (.91)	%TGB6yhn7ujm (.94)	3EDC5tgb7ujm (.95)	R4T4*pasad4* (.96)
q1w2e3r4t5y6 (.78)	5t6y7u8i9o0p (.89)	!QAZ2wsx9ol. (.94)	v1r35account (.95)	4H0P2ewpv4Uw (.96)
19761968Serg (.55)	GOODman12345 (.88)	OLUWAtobi008 (.94)	MPW10network (.95)	GFAC0mp0nent (.96)
123a123a123a (.52)	!QAZ2wsx#EDC (.86)	HAPPYdays100 (.93)	IT461project (.95)	FD102<>csjob (.96)
123qweasdzxc (.51)	1QAZ2wsx3EDC (.86)	UNDERtaker10 (.93)	YAHOOmail12w (.95)	JHG65drtl&3% (.96)
123456789abc (.51)	KWAMEtus1234 (.86)	KWABEna12345 (.92)	NFL72perfect (.95)	4z355jocupub (.96)
123456qwerty (.43)	LOVEyou12345 (.85)	ZXCVBnm12345 (.92)	2+3=5correct (.94)	FD143<>cshob (.95)
111111111111 (.18)	1m2m3m4m5m6m (.85)	ABCDEfg12345 (.92)	5m4n8mataram (.94)	3uy27gbltkob (.95)
Cluster 26				
q1w2e3r4 (.73)	f3d3ric0 (.87)	b4j1ng4N (.91)	cDD1dw1N (.95)	z6n2zcqB (.95)
a1a2a3a4 (.67)	q1w3e4r5 (.85)	7uv3ntu5 (.90)	wJH1zn1T (.95)	a6w9pgkH (.93)
a1s2d3f4 (.67)	s4y4lup4 (.84)	v3r4cru5 (.90)	m4a1colT (.95)	p7W6km2C (.93)
a1b2c3d4 (.67)	c4U2amew (.82)	C3l3ste8 (.90)	7c0cca4B (.95)	d4g2aK1C (.93)
p4ssw0rd (.53)	q1w2e3t5 (.82)	s4y4ngkU (.89)	qHG1pj1H (.95)	Q2u3ee4N (.93)
4rfv5tgb (.43)	q1w2e3r5 (.81)	pR1nce55 (.89)	k3v0subB (.95)	K7E8p0oM (.93)
LqFg4HWt (.34)	Q2w3e4r5 (.81)	R3b3ccaM (.89)	kCt1xn2T (.94)	6l2aby0N (.92)
a123456a (.24)	S4m4nth4 (.81)	m4m3luc0 (.89)	rVG0pg1T (.94)	r{J8im5T (.92)

Table 4.5: Nearest passwords in *PGS3max12* to each cluster, separately for each of five strength bins.

We trained cluster-specific and global regression models as described in Section 4.2.6. Detailed results of each regression are shown in Appendix B.6.1. Our results show that cluster-local models of guessability assigned different weights to heuristic features compared to a globally trained model. The predictive power of these models was limited: the average adjusted R^2 value for the global model was 0.49 and the average across all cluster-specific models was 0.47 (min: 0.35 for Clusters 17 and 24, max: 0.67 for Cluster 16). Prior work has performed a similar regression using 21 heuristic features values [87]. Although that work does not report details about model fit, we expect that our model fit was substantially reduced by the fact that we used a subset of 14 of the heuristic features that they used. However, since we carefully selected these heuristic features in order to minimize multicollinearity between features and because we transformed numeric feature values to be on the same scale, we can interpret the coefficients for heuristic features in each model as an indicator of relative importance of those heuristic features for determining guessability. In particular, while the global model learned the relative importance of heuristics features for the average password (sampled randomly from *PGS3max12*), each cluster-specific model learned the relative importance of heuristic features in the local vicinity of those clusters.

We highlight a few examples where a cluster-local model learned different priorities for the same set of heuristic features. While *Common substrings [h17]* was universally associated as having the largest negative impact on password strength for both global and cluster-local models, in Cluster 3 *Alphanumeric sequences [h16]* was associated with nearly twice as much of a negative impact on strength compared to in the global model. On the other hand, *Repeated sections [h6]* in Cluster 24 was less important for determining guessability compared to in the global model by an approximate factor of two. In Figure 4.8, we illustrate differences between feature weights learned in the global model and in Clusters 1 and 7. Although many parameter estimates are similar in the three models, we observe larger differences in estimates for heuristics related to use of dates, predictable digits, and use of common substrings.

Evaluation on user study and leaked passwords

We tested out whether cluster-membership-weighed heuristic importance produced different heuristic priorities than heuristic importance determined by a single, globally trained model. We did this by applying both approaches to two password sets: *1c8* user study passwords from Chapter 3 and *weak*-classified passwords nearest to each cluster from *PGS3max12*.

Weighing feature importance by cluster membership did not produce different heuristic priorities for the majority in password in both sets (Table 4.6). Furthermore, for a given password in our test sets, there were usually between one and three out of 14 heuristics-associated patterns that were detected, with a maximum of four. In practice, a meter could show up to four feedback items without an overly cluttered interface. Therefore, in terms of both deciding which text feedback to show and in which particular order, cluster-membership-weighed heuristic-feature importance had limited impact.

We examined test passwords for which cluster-membership-weighed heuristic importance did

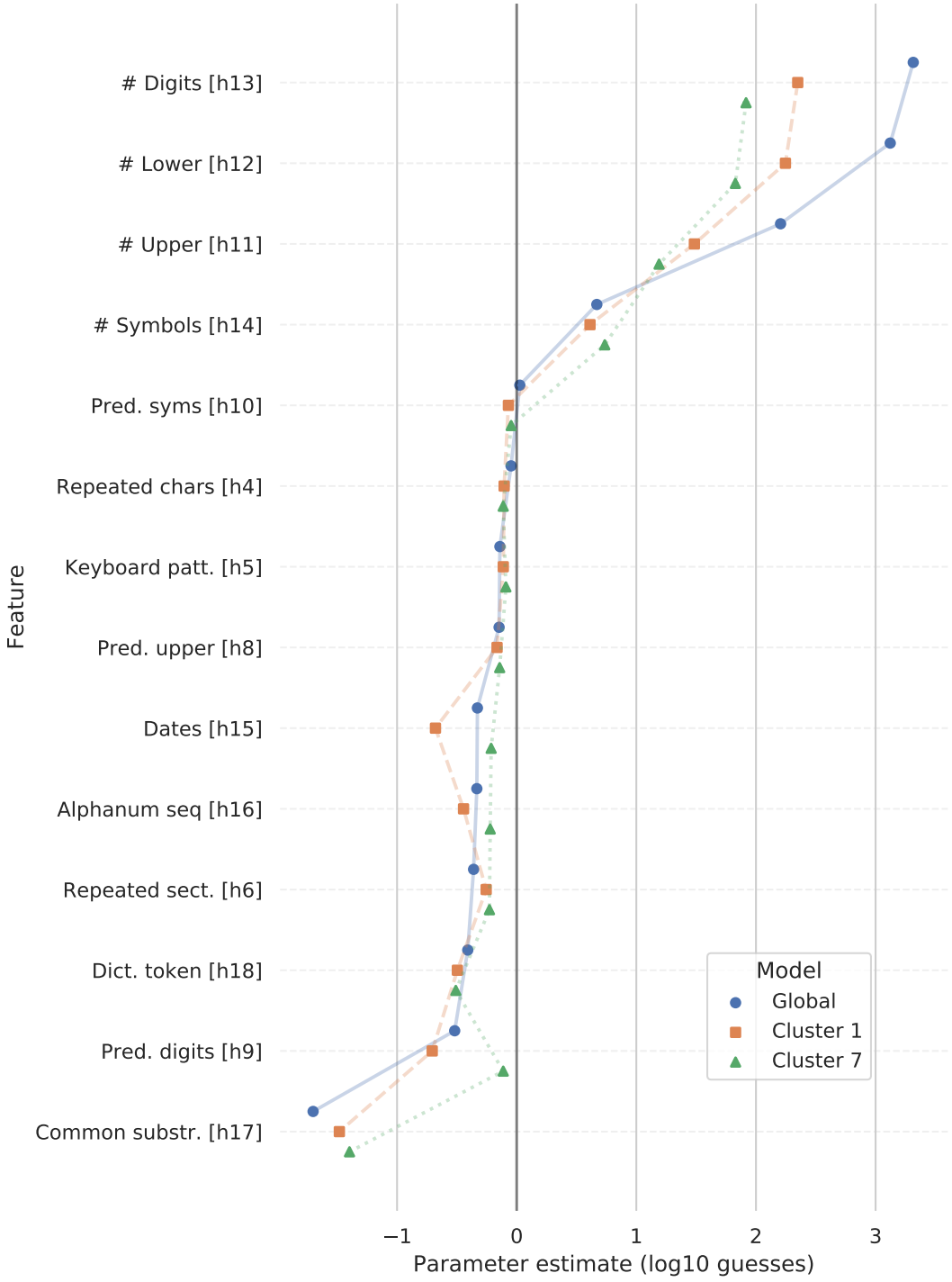
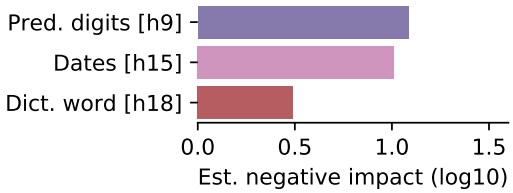


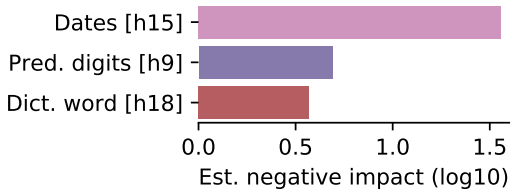
Figure 4.8: Comparison of heuristic importance learned by three models: a global regression model and two regression models learned locally around Cluster 1 and Cluster 7. Parameter estimates for each feature depict the expected change in log10 guessability corresponding to a one-standard-deviation increase in the feature value, holding all else equal.

Feedback items	CCS20 1c8	Nearby weak
0 items	24 (13%)	30 (5%)
1 item	52 (28%)	270 (45%)
2 items	45 (24%)	115 (19%)
3 items	45 (24%)	183 (31%)
4 items	19 (10%)	2 (<1%)
Total	185	600
Diff. than global	80 (43%)	205 (34%)

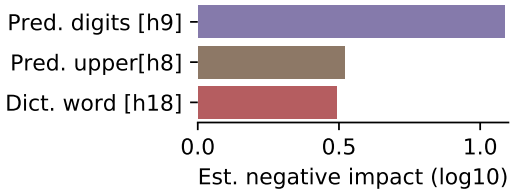
Table 4.6: Summary of feedback. "Diff. than global" is a count of passwords that differed in cluster-weighed and global feedback importance. This includes difference in the particular items predicted to negatively impact guessability and in the order of those items. "Nearby weak" consists of 20 *weak* passwords nearest to each cluster from *PGS3max12*.



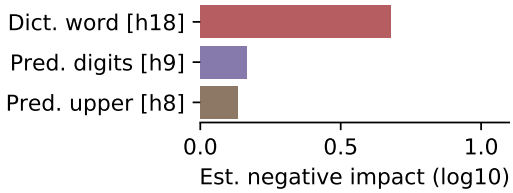
(a) Global feedback for "kingsley1990"



(b) Local feedback for "kingsley1990"



(c) Global feedback for "Sunshine1"



(d) Local feedback for "Sunshine1"

Figure 4.9: Global and local feedback for two test passwords: "kingsley1990" (closest to Cluster 1) and "Sunshine1" (closest to Cluster 7).

impact resulting heuristic priorities. As shown in Figure 4.9 cluster-membership-weighed heuristic importance does intuitively convey the relative importance of heuristic features associated with making a particular password more guessable, *relative to similarly clustered passwords*.

The majority of differences between cluster-membership-weighed heuristic importance and globally determined importance reflected patterns observed in hard-assigned passwords of test passwords primary-assigned cluster. For example, the password "kingsley1990" had the largest membership to Cluster 1 (95%). We see that Cluster 1 contained many passwords ending in four digits (Table 4.3), that *Dates [h15]* has an larger negative impact on guessability for the Cluster 1 model compared to the global model, and that this difference is larger than the difference for *Predictable digits [h9]* for the same two models. Given this, we might expect *Dates [h15]* to have a higher importance in the password "kingsley1990" when importance is weighed by cluster-membership compared to when it is determined globally, which is what we find in Figures 4.9a and 4.9b. Another example is shown in 4.9c and 4.9d for the password "Sunshine1". The majority of passwords in the hard-assigned cluster of "Sunshine1", Cluster 7, contain predictable digits, but a smaller proportion contains dictionary words. Even though *Predictable digits [h9]* may be more harmful to guessability in general, for passwords similar to "Sunshine1", *Dictionary token (h18)* is associated with a larger guessability impact.

These examples emphasize that cluster-membership-weighed importance shows local importance with respect to similarly clustered passwords. This also demonstrates a critical weakness of using cluster-membership-weighted heuristic importance with clusters that contain predominantly weak passwords. If the majority of similarly clustered passwords are predictable and exhibit the pattern X to a similar degree, then local heuristic importance will determine heuristic X to have little relative impact on guessability, even if that heuristic X does have a large impact from a global perspective. Unfortunately, this observation severely limits the usefulness of cluster-membership-weighed feature importance for the clustering model we trained.

4.4 Discussion

Here we evaluate the three primary techniques we applied in terms of their usefulness for providing users with password-creation guidance: clustering passwords in a latent space, using Integrated Gradients to explain patterns associated with cluster membership, and learning the relative importance of heuristic features for determining guessability based on cluster membership. Our specific application of these techniques in our study did not prove fruitful for expanding guidance for users on how to design text-based password feedback. We discuss reasons why this was the case and potential ways to improve the usefulness of those techniques.

4.4.1 Usefulness of clustering passwords

Clustering methods can be used to assist in pattern recognition. Clustering a latent representation can learn patterns in passwords based on their latent-representation similarity. Patterns in

passwords should have some relationship with guessability, since the existence of a pattern can be used by attackers to improve guessing effectiveness.

Our goal was to learn previously unknown patterns relevant to text feedback. As users typed candidate passwords, cluster-associated patterns could be detected in real-time and associated text feedback could be provided in a password-creation meter. The way we envisioned this working was the following: Say we learn Clusters A, B, C, and D by performing fuzzy clustering on the latent representations of leaked passwords. Using visual inspection and IG explanations, we determine that Clusters A, B, and C are associated with Patterns A, B, and C, respectively. Perhaps for Cluster D we were not able to infer a consistent pattern associated with membership to that cluster; we decide to discard that cluster from consideration and focus on the remaining clusters.

Assume that we perform a regression of guessability onto cluster-assignment scores for Cluster A, B, and C, including two-way interactions between these scores. Say that results of this regression show that (1) memberships to Clusters A and B are both individually associated with slight increases in guessability, (2) Cluster C is associated with a moderate increase in guessability, and (3) the interaction between Clusters A and B is synergistic, such that when a password has strong membership to both of these clusters then this results in a severe increase in password guessability. In terms of cluster-associated patterns, we could interpret these results as saying that (1) Pattern C has a moderate negative effect on password guessability (independent of whether other patterns are present), (2) Patterns A and B have slight negative effects on password guessability when only one or the other is present in a password, and (3) whenever Patterns A and B are both present in a password then the net result is a severe negative effect on password guessability (perhaps these patterns are especially likely to appear together in leaked passwords).

Next assume that we create four text feedback items: Feedback A ("Pattern A tends to make passwords slightly more predictable"), Feedback B (similar to Feedback A), Feedback C ("Pattern C tends to make passwords more predictable"), and Feedback AB ("Patterns A and B are often used together and make your password extremely predictable"). Given this hypothetical scenario, we could then provide text feedback to users in real-time. As users type candidate passwords, we could generate cluster memberships for that password. If a password had high membership to both Clusters A and B (but not Cluster C), then we might infer that the candidate password is likely to contain Patterns A and B.[11] Our hypothetical password meter could then present the user with the text for Feedback AB.

The hypothetical scenario described above would provide text feedback specific to a candidate password, in terms of patterns found in that candidate. Using cluster-identified patterns would not be necessary for providing feedback, since we could model guessability with heuristic features from prior work (another technique we ultimately tried). However, the clustering model might provide benefits: it might identify new types of patterns with respect to unsupervised-learned features, and pattern detection could accommodate noise in how users instantiate different types of patterns.

[11]This pattern detection is with respect to fuzzy-cluster membership, and may be more likely to detect the general presence of a given pattern compared to standard regular-expression-matching approaches.

In our study, we were not able to learn high-level patterns that differed from prior work based on clustering results. Fuzzy c-means seemed to group passwords with similar patterns, but those groups of passwords were either similar with respect to combinations of character-class structure and password endings. While theoretically this could be used to define a new low-level type of heuristic, the problem with this was that patterns were *too fuzzy* for us to generate concise high-level text feedback for. For example, the majority of passwords with high membership to Cluster 7 passwords end in similar-appearing substrings. However these substrings vary greatly; among the top 1000 training-data passwords with highest membership to Cluster 7, the only consistent commonality is that passwords end in the digit "1". A password meter could detect if a candidate password is both weak and has high membership to Cluster 7, e.g. "Sunshine1" (Figure 4.9), and provide text feedback explaining that the majority of passwords ending in "1" tend to be weak, but this feedback doesn't seem particularly more useful than the existing heuristic guidance captured by the *Predictable digits (h9)* heuristic from prior work.

Potential changes to the clustering algorithm or the autoencoder used to generate the latent space might help make the clustering technique we explored more useful for generating text feedback. The fuzzy nature of cluster-associated patterns we encountered made generating text feedback difficult. Using a larger number of clusters might potentially help by separating related but semantically separate concepts associated with clusters in our model. Another change that may help is to use a hard-clustering algorithm instead of fuzzy c-means, e.g. k-means.

Certain modifications to the training and architecture of the autoencoder may help. We found that passwords near to clusters were not always of the same strength, which limits the applicability of text feedback based on cluster membership. To address this, the loss function used to train the autoencoder could be changed to not only reflect reconstruction error, but also error with respect to the input password strength and the reconstructed password strength. It may be useful to increase the dimensionality of the latent space in the autoencoder. In our work, clustering on the latent space seemed to group passwords with respect to character-class structure and password endings. Perhaps this reflects the most predictable parts of a password, and so the most useful aspects to learn as features for the sake of reconstruction. However, it may be useful for the autoencoder to learn less predictable patterns, which a larger latent space could help with. A risk in doing so is that the autoencoder may be more likely to memorize the training data, and thus not generalize as well. To counter this, dropout could be increased in the network. An alternative is to train an entirely different model, e.g., using an architecture and training method similar to BERT [16], a language model trained to produce a deep bi-directional representation by predicting masked tokens in the input.

4.4.2 Usefulness of IG-based cluster-membership explanations

In our work, IG cluster-membership explanations had limited usefulness for detecting patterns associated with cluster membership that were not immediately obvious based on visual inspection. Furthermore, in those cases where we could not discern consistent patterns based on visual inspection of cluster-associated passwords, IG explanations did not provide additional enlightenment.

We hypothesize that limitations in identifying patterns might be improved using different visualization techniques. In our work, we applied clipping to IG attributions at the 95th percentile, which helped in identifying visually consistent patterns at the expense of significantly reducing the proportion of cluster-assignment attributions that was visualized. Different, non-linear techniques for transforming attribution values into colors for visualization may help reveal patterns with less impact on the space of visualized attributions. Besides the extent of attributions that were visualized, in many cases visualizations of IG attributions were noisy. Applying different variants of IG explanations may improve this, e.g. BlurIG [101], a recently proposed model-explanation technique that can avoid the introduction of spurious attributions using a baseline-input path defined by a Gaussian blur filter.

We experimented with applying IG explanations to user study passwords in order to understand whether visualization of IG attributions could potentially be useful for highlighting cluster-associated patterns in candidate passwords entered by users (Appendix B.5.1). Unlike the hard-assigned training-data passwords that we used to learn cluster-associated patterns in our work, user-study passwords were often not assigned a high membership value to any particular cluster, with membership much more spread out. We hypothesize that this difference may have led to poor results in the highlighting of cluster-associated patterns of user study passwords. Thus we conclude, for the IG implementation and clustering model we used, IG explanations would not be useful for real-time pattern visualization. It is unclear whether a different clustering model or a different type of model explanation technique would make this type of feedback feasible for real-time use in a password meter.

4.4.3 Usefulness of cluster-membership-weighed heuristic importance

We attempted to expand guidance on heuristic-based text feedback using the concept of cluster-membership-weighed feature importance, which computes heuristic priorities for a candidate password based on a weighted sum of heuristic importance learned locally for each cluster. By computing heuristic priorities in this way, we implicitly assume that the priority that users should eliminate patterns in a candidate password should be based on heuristics most strongly associated with decreased guessability among similarly clustered passwords. We discovered that this assumption may not always hold, depending on the clustering model that is used, including for the particular clustering model we applied in our experiments.

Cluster-membership-weighed feature importance is useful when text feedback should reflect the importance of heuristic features on guessability for similar passwords more so than for passwords as a whole. It makes sense when there is a valid reason that experts (or users themselves) would like guidance on ways to improve the strength of a candidate password without changing aspects of that candidate determining its cluster membership. This requires that clusters of passwords form around more meaningful concepts than similarity in patterns useful for compression, as was the case for our clustering model.

An example in which cluster-membership-weighed feature importance might be more useful for generating relevant heuristic-based text feedback is when clusters form around passwords having

similar usability properties, where passwords exhibiting that property vary in predictability. In this case, guidance can prioritize the particular text-feedback items presented to users in way that is contrary to guidance that would be provided for passwords in general, but which will still tend to strengthen passwords in the password domain that the user wishes to adhere to. In practice, it is difficult to imagine a type of usability property that would benefit from being represented as a cluster in a latent space of passwords. For example, in some cases users may want to create a password that is pronounceable (e.g., for easy of copying between devices) or that excludes specific character classes (e.g., for easy entry on mobile devices). It is feasible that heuristic priorities would differ for these subsets of passwords compared to the global case. For example, feedback on *Duplicated characters (h3)*—non-consecutive use of the same character—may be de-prioritized for the set of pronounceable passwords relative to passwords in general, since vowels are more likely to be reused to facilitate pronunciation. However, in these cases it would likely be simpler to forgo clustering and simply train model on a leaked passwords satisfying a specific constraint, e.g. passwords containing alternative consonants and vowels.

Lastly, the usefulness of cluster-membership-weighed feature importance ultimately depends on whether it impacts password-creation for actual users, in terms of usability aspects (creation time, annoyance) and the strength of created passwords. When we applied this technique to user-study passwords, it often had no effect on the resulting order of heuristic importance. We also only hypothesize that ordering heuristic-based guidance or denoting the magnitude of estimated importance for individual text-feedback items will have a measurable impact on behavior. These aspects have not been explicitly studied in prior work, and therefore need to be formally tested in a user study.

4.5 Conclusion

In this chapter we explored ways of improving guidance available to authentication system designers on how to incorporate text feedback into password meters. We experimented with two techniques for expanding available guidance.

First, we used an autoencoder to learn a latent representation of passwords and performed fuzzy clustering with respect to the latent representation, as a means of systematically learning high-level features that could be incorporated into heuristic-based text feedback. Results from this experiment ultimately did not lead to knowledge of high-level patterns that augmented patterns captured by previously known password heuristics.

Second, we investigated a technique for prioritizing text feedback for a set of heuristic features identified by prior work. Although application of this technique to user study passwords sometimes produced cluster-membership-weighed heuristic priorities for candidate passwords that differed from globally determined heuristic priorities, we found that cluster-membership-weighed heuristic prioritization did not reflect a meaningful or desirable goal, since our clusters did not represent password properties that should be maintained after changes made by users to follow guidance.

Chapter 5

Public-key fingerprint representations that help users detect MITM attacks

5.1 Introduction

In the previous two chapters we provide guidance for system designers of password-based authentication systems. In addition to password-based systems, system designers may be tasked with designing security features for public-key authentication systems. For example, secure-messaging applications are becoming increasingly popular among businesses that offer communication software to consumers. Secure messaging based on end-to-end encryption can provide communication software with a privacy-enhancing feature useful to distinguish a software product from the offerings of competitors.

Thus, system designers may be tasked with designing a secure messaging system. Although off-the-shelf products and libraries can be leveraged to accomplish this, one component that system designers have less guidance on is how to implement identity verification tasks associated with secure messaging. In this chapter, we provide concrete guidance on different ways to design the security components users interact in identity verification tasks. Our guidance includes consideration of practical constraints that system designers may face.

To protect the privacy of communications like email and instant messaging, users can encrypt messages using public-key encryption. For Alice to send a message to Bob that only Bob can read, she needs to encrypt the message with Bob's public key. Bob will use his private key to decrypt the message.

While this method of securing communication is believed to be technically sound, it hinges on Alice knowing Bob's public key. To learn Bob's key, Alice would typically look it up on a web site (e.g., a public key server) that publishes such information. Unfortunately, an attacker seeking to intercept Alice's communications to Bob might try to add his own key to the key server under Bob's name. When trying to find Bob's public key, Alice would then unwittingly download the attacker's key. Any messages she composed for Bob would then be readable by the attacker, and

not by Bob.

A more reliable method would be for Bob to deliver his public key to Alice in person. Because public keys are long strings of arbitrary bits, this approach is unfortunately unwieldy and impractical. A common alternative is for Bob to give Alice a *fingerprint* of his key, which is a short digest (hash) of the key. Alice then manually compares (e.g., looks at them side by side) the fingerprint received from Bob to the fingerprint computed from the key she downloaded from the key server. Fingerprints are by design long enough for it to be exceedingly unlikely that two different keys will have the same fingerprint, yet short enough for manual comparison to be feasible.

Fingerprint verification is only useful, however, if Alice is able to determine easily and successfully whether the fingerprint she obtained from Bob matches the one she computed. If Alice is only comparing the first part of the two fingerprints, for example, this opens the door to attackers who try to create a public key whose fingerprint will be *similar* to Bob's key's fingerprint, in the hope that Alice's (cursory) examination will not distinguish it from the real fingerprint.

Fingerprints can be represented in many ways, which may impact the efficiency and accuracy with which users compare them. Besides the commonly used hexadecimal format [9, 23], other representations used in practice include ASCII art [57], numbers [96], pronouncable strings [34], and avatars [54]. Additional representations have been proposed, including abstract art [63], sentences [1], snowflakes [48], and fractal flames [69].

In this chapter we report on the results of a 661-participant online study through which we compare the usability and efficacy of a range of fingerprint representations and configurations. We test eight different representations and examine how likely users are to notice fingerprint mismatches caused by an attacker who creates public keys whose fingerprints are similar to the authentic key's fingerprint. We include fingerprint representations used in practice (e.g., hexadecimal strings, ASCII art) as well as ones hypothesized to be good alternatives (e.g., randomly generated images of unicorns). We also examine different approaches used to compare fingerprints (seeing two fingerprints side by side versus selecting the correct fingerprint from a list) and the effect on security against differently powerful attackers. We pay special attention to our experiment's realism, simulating time pressure that users may feel in practice when performing security tasks, accounting for the fact that attacks are rare rather than the typical case, and simulating other practical challenges (e.g., comparing a fingerprint on a business card to one on a screen).

Our results include findings important for designing systems that involve comparing fingerprints. We find that graphical representations, thought promising [32], have mixed success. Although all allowed quick comparisons, some were much more susceptible to attack than more standard representations. We also find that the compare-and-select method of comparing fingerprints resulted in many users failing to detect mismatches, to the point where its use for fingerprint comparison should be strongly discouraged. Echoing prior work [14], we find that non-hexadecimal textual representations have promise, especially for usability. The traditional hexadecimal representation, however, overall fares surprisingly well.

These findings lead to a set of suggestions for when a fingerprint representation may be appro-

priate. When security is paramount, none of the representations tested seem adequate. When the risk and impact of attack is low but usability is paramount, visual representations excel. For casual use, when security and usability need to be balanced, textual representations, including hexadecimal, seem to be the most appropriate.

5.2 Methodology

We conducted a between-subjects experiment to evaluate and compare the usability and security of fingerprint representations and configurations. We recruited participants from MTurk in August 2016. We required participants be 18 years or older and live in the United States. Our protocol was approved by our university's IRB.

We advertised the study as a "role-playing activity involving technology and communication in the workplace" that would take about 20 minutes. We compensated participants $3, with the opportunity to earn a $1 bonus. As our activity was not designed for use on tablets or smartphones, we asked that participants use a desktop or laptop computer. Participants were randomly assigned to a condition, which determined the fingerprint representation and configuration they saw.

We asked participants to imagine they worked as an accountant at a company that was updating its employee database. To perform this update, participants had to retrieve the social security numbers (SSNs) for 30 employees and enter them into a database. We chose SSNs to motivate the need for secure communication. In the U.S., SSNs are highly sensitive because knowing an individual's SSN can enable identity theft and have other financial ramifications. Our activity web page divided the browser window into two sections that mimicked the appearance of a computer screen and a desk (Figure 5.1). The computer screen section displayed a spreadsheet-like database where participants would need to fill in missing SSN details for employees. Several business cards were sitting on the desk. A stopwatch and information about the participant's progress completing the task appeared in the top right corner.

We provided the instructions for the activity via an interactive tutorial. Participants could repeat the tutorial any number of times until they were comfortable proceeding, and the on-screen stopwatch did not begin until after the tutorial ended.

At the start of a task, a chat window appeared on the simulated computer screen informing participants of an incoming message from one of the 30 employees. To proceed, they had to perform a security check. Shortly afterward, a dialog box was displayed on the computer screen containing a fingerprint and instructions to compare it to the fingerprint on the employee's business card, which appeared simultaneously on the desk.

For our baseline configuration, a security check involved comparing two fingerprints (one in the security check dialog box and one on the business card) and pressing a button to indicate if they were the same. We informed participants that this check was needed to ensure a secure chat session and avoid potential eavesdroppers. Depending on which fingerprint representation was

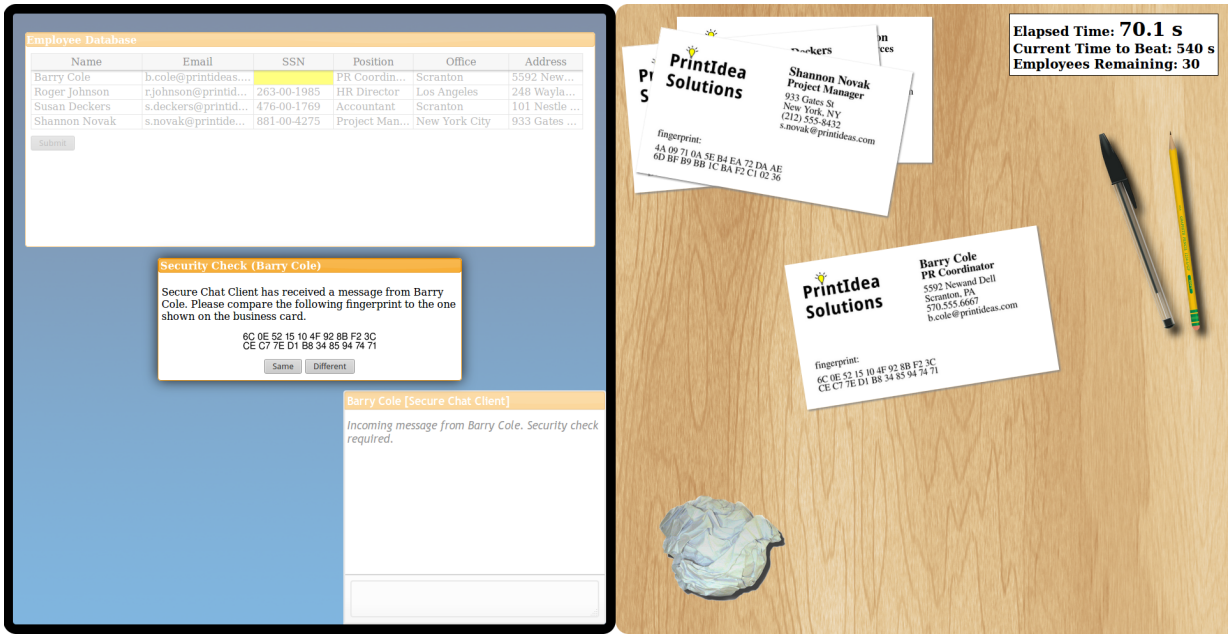


Figure 5.1: Screenshot of the task. This example is the compare-and-confirm, simultaneously visible, hexadecimal condition.

shown, we provided guidance on what differences participants should look for when comparing fingerprints.

If the participant indicated that the fingerprints matched, the chat window displayed a message from the employee with her SSN. The participant was instructed to type the SSN into the database. If the participant instead indicated that fingerprints did not match, the chat message instructed the participant to instead enter "ERROR" in the database. Each participant repeated this task for 30 employees.

We instrumented our activity to record participants' database entries, security-task decisions, and detailed timing information. We also recorded their browser user agent strings to determine whether participants used a tablet or smartphone. For one condition in which users had to toggle between two views, we recorded the number and timing of toggles.

Afterwards, participants filled out a survey. In this survey, we told participants whether they had missed our attack and asked them to explain why they thought they missed or detected that attack. To aid in memory, we showed the fingerprint pair corresponding to the attack alongside these questions. We asked participants to describe their strategy for comparing fingerprints, respond on a Likert scale to statements about the fingerprints they saw, and provide general demographic data.

5.2.1 Security-task design considerations

Security tasks are rarely performed for their own sake. Fingerprint comparisons are secondary to a primary purpose, such as communicating with someone. Combined with the pressures and stresses of everyday life, this state of affairs often results in users performing security tasks while distracted or otherwise not fully attentive. In addition, few users will have previously been the target of a MitM attack and might have little reason to believe they would become such a target. Users asked to compare fingerprints might only encounter mismatching fingerprints due to device misconfiguration, the acquisition of a new device, or security software re-installation. Many design decisions for our activity reflect these real-world factors.

To increase distraction and stress, we incentivized participants to perform the task both quickly and correctly by informing them that the "15% fastest participants with the fewest mistakes" would receive an additional $1 bonus. We considered a mistake to be entering an incorrect SSN into the database or failing the security check for an employee. The interface contained both a persistent reminder of this bonus and a timer showing the elapsed time, a target time participants should try to beat, and the number of employees remaining. We also highlighted this box in the tutorial. To avoid cases where participants felt under-pressured due to exceeding the target time, we noted that beating the target time did not guarantee the bonus as future participants could lower or raise it.

We expected most participants would have little to no experience comparing key fingerprints and thus would lack the expectations typically held by users who frequently compare fingerprints. In an effort to ingrain these expectations quickly, we sacrificed realism with respect to the role-playing activity. To habituate participants to benign situations, 28 of the 30 comparison tasks involved matching fingerprints. One fingerprint comparison task involved obviously different fingerprints, reflecting what would commonly be seen by users in benign situations (e.g., misconfigurations). This task was shown in a randomly determined position between the second and fifth pairs, inclusive. We also used this task to filter out participants who mindlessly clicked through the entire activity.

5.2.2 Threat model and simulated attack

In our threat model, an adversary attempts a MitM attack on a specific user in the context of a fingerprint comparison task. We assume preimage attacks on the user's fingerprint are infeasible. Instead, an adversary attempts to present a key whose fingerprint is similar to the target user's fingerprint. We assume the adversary has finite resources, limiting how similar the attack fingerprint can be to the target. Participants were shown a single simulated attack according to this threat model. The comparison task in which the attack appeared was randomly chosen from between the 25th and 29th pairs, inclusive. To minimize bias, we generated three attack instances for each configuration and randomly selected one of these three for each participant. Since we tested attack strengths requiring computational resources not available to us, we simulated these attacks; we generated a 2^{60} attack by creating a version of the target fingerprint whose similarity was such that it would take 2^{60} bruteforce attempts on average to produce.

Hexadecimal	`BAAA 9AE6 7B8B 0D41 BD83` `05E7 5209 8EDF 1058 41F6`
Alt vow./cons.	`bunu difu tura wefi wiwe haqe` `tano haco qevu cori qife nufi`

Words	`learning equal education bent`
	`collar religion new shelf`
	`angle table train sad`
	`keep meal thing punishment`

Numbers	`7748 5689 7453 6977 5604 5939` `2765 8791 5022 4957 3805 0309`

Sentences	`The basket ends your right cat on his linen.`
	`Her range repeats her nerve.`
	`The smile tells secretly.`
	`My clean cake pulls your waiting pocket.`

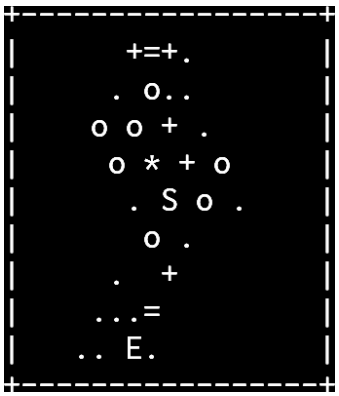
Table 5.1: Textual fingerprint representations used for experiments. For hexadecimal, we tested both uppercase and lowercase variations.

Applications can optionally use key stretching to increase resistance to brute-force attacks. WhatsApp implements this approach using iterated hashing [96]. The simulated attacks in our study assume that hash strengthening techniques are not applied. Thus, our attack detection results directly apply to applications such as GnuPG and OpenSSH, which do not currently implement such defenses. However, the attack strengths we test can be translated to applications that do use hash strengthening. Specifically, if a fingerprint scheme employs hash strengthening to require an additional 2^{20} work per generated fingerprint (reasonable even on mobile devices), then our results for 2^{60} attacks on fingerprints without strengthening translate to 2^{80} attacks on fingerprints with strengthening.

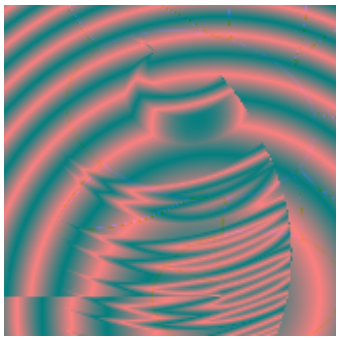
5.2.3 Experimental factors

Representations

For textual representations, we chose to target a fingerprint security level of 160 bits. This is the same fingerprint security provided by current implementations of GnuPG, which uses SHA-1 for its hash function. Where applicable, textual representations were chunked in groups of four, with chunks separated by spaces. This chunk size performed well in prior work [14]. For our graphical representations, we evaluate the representation implementation in its original form, leaving the fingerprint security as is. Table 5.1 demonstrates our textual representations and Figure 5.2 our graphical representations. As we introduce the representations, we note the number of bits representing the space of possibilities that can be generated using that representation with those parameters. For all representations, both textual and graphical, the number of possibilities that a human can distinguish can only be determined empirically, which is implicit in the rate at which participants in our study detect attacks.



(a) OpenSSH Visual Host Key



(b) Vash

(c) Unicorn

Figure 5.2: Visual fingerprint representations.

For textual representations, we tested hexadecimal (uppercase and lowercase), alternating vowels/consonants, words, numbers, and sentences. Hexadecimal was 40 characters long (160 bits), numbers was 48 digits long (159.5 bits), alternating was 48 characters long (161.1 bits), and words was 16 words long (155.7 bits). We selected words from Ogden's Basic English word list.[1] For sentences, we used an implementation based on a deterministic sentence generator [1] (159.8 bits). For this representation, the average number of sentences is 3.6 (max: 7) and the average length of the longest sentence is 9 words (max: 12). Each of hex, numbers, and alternating vowels/consonants was equally spread over two lines. Words were spread over 4 lines. For the sentences representation, each sentence began on a separate line, wrapping where necessary.

For graphical representations, we test OpenSSH Visual Host Key ($\leq$ 128 bits), Vash ($\approx$ 5,438 bits), and unicorns [91] ($\approx$ 2,854 bits).[2] Visual Host Key was included because it is widely deployed in SSH software. Prior work explored Random Art fingerprints [63], of which Vash is an open-source implementation. We included unicorns to test fingerprints that use avatar-like representations. We limited consideration to those representations whose entropy was large enough for use as cryptographic fingerprints in asynchronous settings (i.e., at least 128 bits). Unicorn fingerprints were generated by a program in which unicorn attributes were set according to numbers drawn from a pseudorandom number generator. The key to be hashed served as the seed to the generator. For Vash fingerprints, which can viewed abstractly as a graph, a similar process was used to determine graph node types and properties, which uniquely determine the fingerprint appearance.

For all representations, we allowed the fingerprint to take up a maximum of 50% of the card, horizontal or vertical. For sentences, this required formatting the fingerprint using a slightly smaller font size than for the other textual formats. For textual representations, we advised participants that they should ignore differences in font size or type. In addition, for words and sentences, we

[1] http://ogden.basic-english.org/words.html

[2] Given the computational difficulty of an exact calculation, for our graphical representations we roughly estimate security.

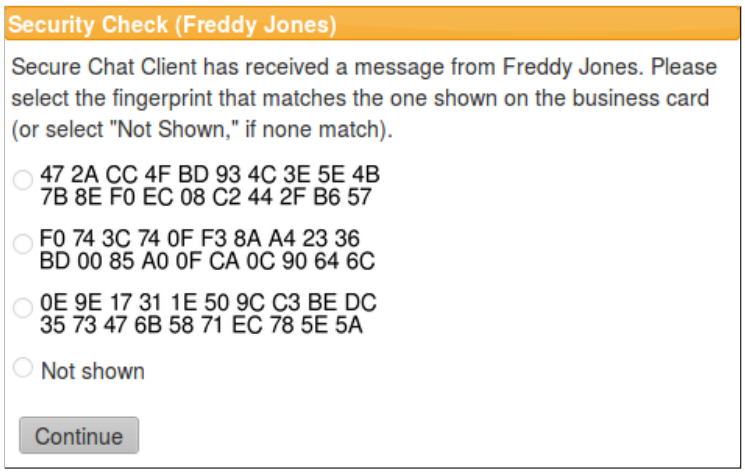


Figure 5.3: Security task dialog for participants in the compare-and-select, hexadecimal condition.

informed participants that differences in fingerprints due to misspelled words would not occur.

For each representation, we thus needed to pick the specific aspects that would be matched and ensure that the reduction in entropy matched the assumed attacker strength. Our overall strategy was to match the aspects we expected users would focus on during comparisons. For textual representations, we primarily matched the beginning and end of lines. For graphical representations, we mainly attempted to match "big picture" elements, such as overall pattern and color. For Vash, we matched node types up to a certain depth. For unicorns, we chose to roughly match many aspects, such as background hue and horn length. Images of each attack used in our experiment are included as supplementary material.

Comparison mode

We tested both compare-and-confirm and compare-and-select, as previously described. While compare-and-confirm is the traditional method of fingerprint comparison, we were interested in the performance of compare-and-select, given its potential benefits for inattentive users. An example of compare-and-select is shown in Figure 5.3. Our implementation is similar to that used in SafeSlinger [20]; three fingerprints are shown in a random order, with two fingerprints randomly generated and one fingerprint corresponding to the received fingerprint.

Visibility mode

In most cases, participants tasked with comparing fingerprints are able to see both fingerprints simultaneously. For example, to compare a fingerprint on a business card to one on a computer screen, the user can simply hold the business card up to the screen to place the fingerprints side-by-side. However, in certain use cases, it may not be possible or easy to view both fingerprints simultaneously in order to compare. As an example, many versions of Android do not have

any easy way to view two applications in a split-screen view. In this case, if the user needs to compare fingerprints shown in two applications (say, a fingerprint shown in a secure chat app and one shown on a website), the user will need to toggle back and forth in order to compare.

We tested situations in which fingerprints are both visible simultaneously as well as situations in which the user must toggle between them. We expected the need to toggle to affect representations differently, as it may be easier to place certain representations in short-term memory than others.

Attack strength

We considered three different attack strengths: 2^{40}, 2^{60}, and 2^{80}. These strengths correspond to the estimated capabilities of an attack performed on commodity hardware, an attack performed by a well-funded criminal organization, and an attack performed by a state-sponsored actor.

Other factors

We included two other experimental factors. For hexadecimal, we tested the impact of letter case on performance. We were interested in this because both types have been used for real security applications (e.g., lowercase in OpenSSH and uppercase in GnuPG). We also tested a variation of our activity in which the target time-to-beat was doubled, from 540 seconds to 1080 seconds. We tested this to provide insight into the extent to which our results depend on the specific target time that was used.

5.2.4 Experimental conditions

Participants were randomly assigned to one of 17 experimental conditions, which determined the specific fingerprint representation, configuration, and attacker strength used for that participant in the activity. Eight of our conditions assumed an attacker strength of 2^{60} and varied only according to fingerprint representation. To explore the effect of different attacker strength assumptions, we tested four additional conditions: 2^{40} attacks on uppercase hexadecimal and unicorns and 2^{80} attacks on uppercase hexadecimal and Visual Host Key.

The four remaining experimental conditions were designed to be compared with our baseline hexadecimal condition, namely uppercase hex using the compare-and-confirm configuration in which both fingerprints to be compared were simultaneously visible, with an assumed attacker strength of 2^{60}. These conditions varied from the baseline condition with respect to only one factor: compare-and-select (comparison mode), toggle (visibility mode), lowercase (hex letter case), and twice the target time-to-beat.

We performed some modifications to test fingerprint comparisons under adverse conditions. In all conditions, fingerprints were displayed in different font types and sizes. The business cards were presented randomly tilted up to 10 degrees. For the Vash and unicorn representations, we

applied a random gamma correction to the fingerprint shown on the computer screen section in the range [0.8, 1.2], in order to simulate the effect of an improperly calibrated display. For sentences, we showed fingerprint pairs formatted such that line breaks occurred in different places.

5.2.5 Statistical analysis

We performed hypothesis tests for each metric we measured. To test for significant effects with respect to the proportion of security failures across conditions, we used Pearson's chi-squared test (for omnibus tests) and Fisher's exact test (to compare two conditions). To test for significant effects for median comparison time, number of false positives, and Likert ratings, we used the Kruskal-Wallis test (for omnibus tests) and the Mann-Whitney-Wilcoxon test (to compare two conditions). Given the large number of comparisons we made, we applied the Holm-Bonferonni method and report corrected p-values. All hypothesis tests used a significance value of $\alpha = 0.05$.

5.2.6 Limitations

For each representation, we used an attack strategy to maximize similarity to the target fingerprint for particular aspects (or in particular locations) of that fingerprint. Our goal was to find the most effective attack given a fixed computational budget. Nonetheless, it is unlikely that we selected the best possible attack for each representation. Given this limitation, we believe that our statistical power, sufficient to detect only large differences in attack detection rate, is appropriate. Such large differences, if they exist, may indicate weakness intrinsic to a representation or configuration, not only in our attack strategy.

Our participants were recruited from MTurk, which is not representative of the general U.S. population; MTurk workers have been found to be younger and better educated [39].

To habituate participants to benign security scenarios in a short amount of time, we had to sacrifice some realism. However, feedback from participants indicates that we achieved our goal of recreating the types of conditions under which people would likely perform fingerprint comparisons as a security task.

Since the primary goal of most MTurk users is to get paid, and since we tied the bonus payment to participants' performance on the security tasks in our activity, the security tasks were not secondary to some other task, as would be the case in the real world. However, as previously explained, we believe we captured the desirable characteristics intrinsic to security as a secondary task.

5.2.7 Participants

A total of 677 participants completed our MTurk HIT. We excluded 16: 3 participants used an Android or iOS device, 3 encountered technical issues, and 10 failed an attention check. The

average time spent on our HIT was 14 minutes and 12 seconds. We paid all workers that accepted our HIT.

Our reduced sample consisted of 661 participants. Participants' ages ranged from 18 to 74 with an average of 33 years ($\sigma = 9.7$). Participants were 44% female and 55% male, with 1% choosing not to specify. The two most common education levels were a four-year college degree (35%) and some years of college without finishing (27%). The most frequently reported occupations were service (16%); business, management, or financial (13%); and computer engineering or IT professional (12%). We considered participants as technical if two out of three of the following were true: they listed their occupation type as computer engineering or IT professional, they knew a programming language, or they indicated that people often asked them for computer-related advice. According to this definition, 18% of participants qualified as technical.

5.3 Results

We first describe the performance of different fingerprint representations. We then describe the effects of different ways of eliciting confirmation (compare-and-confirm vs. compare-and-select) and varying whether users could see the two fingerprints they were comparing one at a time or both at once. Finally, we discuss participants' self-reported strategies for comparing fingerprints. An overview of our results is provided in Table 5.2.

5.3.1 Representations

Attack detection rate

The fraction of participants who failed to notice a simulated 2^{60} attack varied significantly by condition ($\chi^2 = 131.93$, $df = 16$, $p < .001$). The best performing representation was sentences, causing participants to miss just 6% of attacks; unicorns, surprisingly, were worst, with participants missing 54% of attacks. Our baseline, the hexadecimal representation, was roughly in the middle, with 21% of participants missing the attack. The uppercase and lowercase variants of hexadecimal had an attack success rate within 1% of each other. Figure 5.4 summarizes these results.

The difference in attack success rate between hexadecimal (21%) and unicorns (54%) was borderline significant ($p = .052$). Unicorns performed significantly worse than both Vash ($p = .003$) and Visual Host Key ($p < .001$). In contrast to related work by Dechand et al. [14], we did not observe any statistically significant differences in attack success rate between textual representations.

We also tested whether participants who fell under our definition of technical were more successful at detecting attacks than those who did not. Technical users were better at detecting attacks (80% to 69%), but this difference was not statistically significant after correction ($p = .08$).

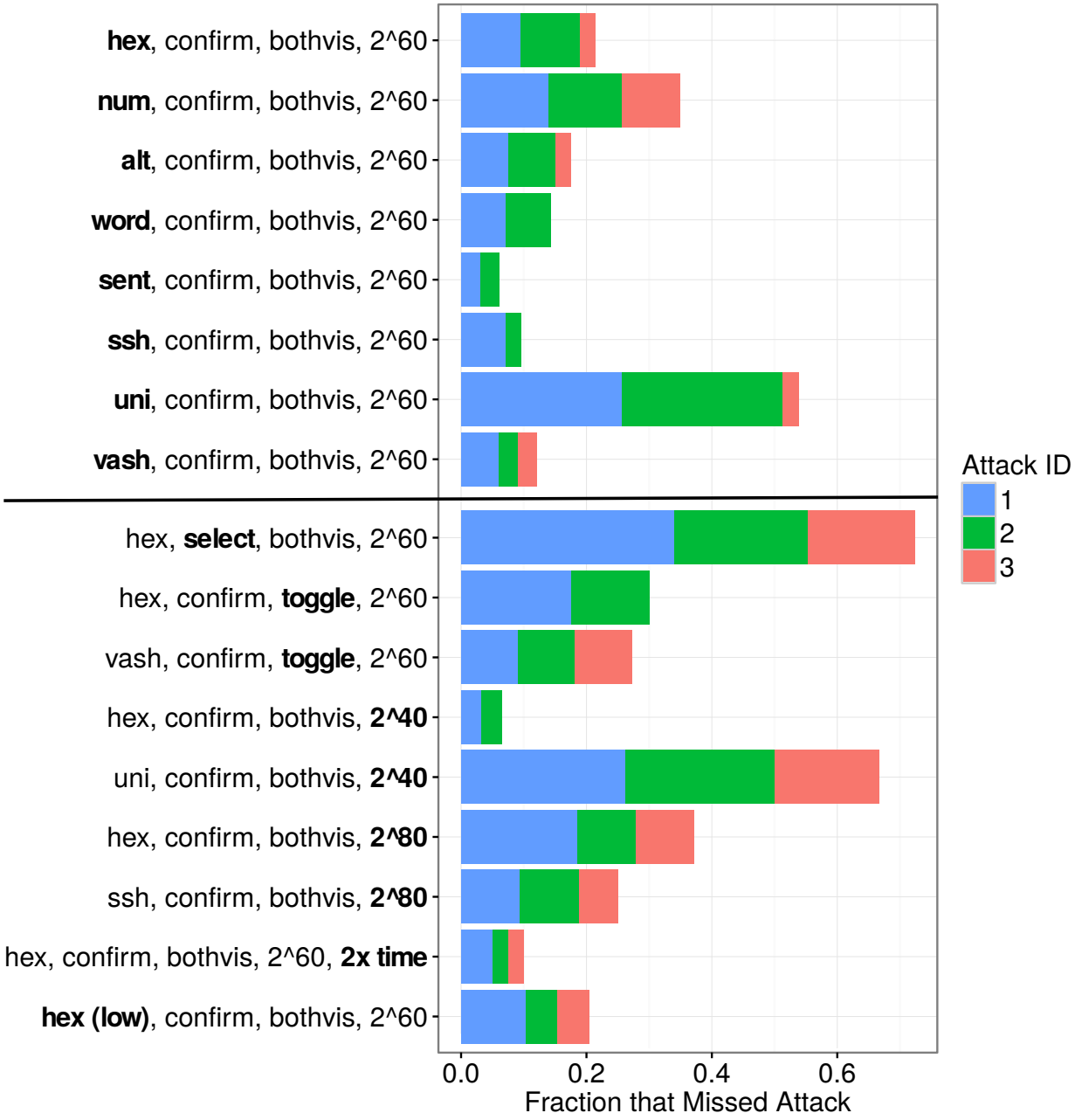


Figure 5.4: Fraction of participants in each condition that missed the attack, grouped by condition and attack instance. The attack IDs correspond to three different attacks we generated for each configuration.

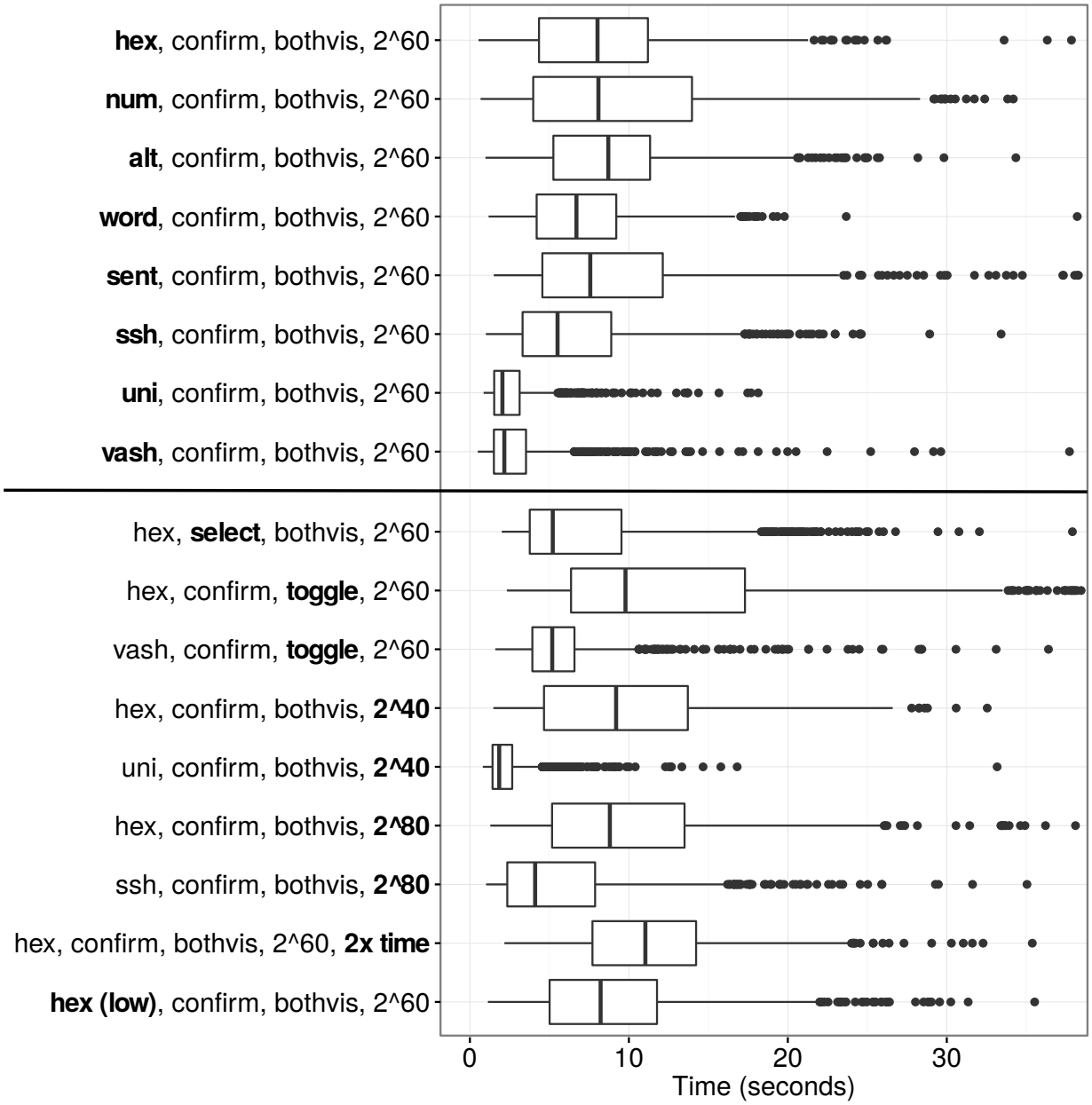


Figure 5.5: Median comparison time by condition.

Condition	Frac. Missed	M(comp)	# Part.
hex, confirm, bothvis, 2^60	0.21	8.03	42
num, confirm, bothvis, 2^60	0.35	8.09	43
alt, confirm, bothvis, 2^60	0.17	8.71	40
word, confirm, bothvis, 2^60	0.14	6.70	42
sent, confirm, bothvis, 2^60	0.06	7.57	33
ssh, confirm, bothvis, 2^60	0.10	5.51	42
uni, confirm, bothvis, 2^60	0.54	2.04	39
vash, confirm, bothvis, 2^60	0.12	2.17	33
hex, **select**, bothvis, 2^60	0.72	5.21	47
hex, confirm, **toggle**, 2^60	0.30	9.79	40
vash, confirm, **toggle**, 2^60	0.27	5.18	33
hex, confirm, bothvis, **2^40**	0.06	9.20	31
uni, confirm, bothvis, **2^40**	0.67	1.84	42
hex, confirm, bothvis, **2^80**	0.37	8.80	43
ssh, confirm, bothvis, **2^80**	0.25	4.10	32
hex, confirm, bothvis, 2^60, **2x time**	0.10	11.04	40
hex (low), confirm, bothvis, 2^60	0.21	8.22	39

Table 5.2: Summary statistics by condition, including median comparison time (*M(comp)*), fraction of participants that missed the attack, and total number of participants.

Similarly, for the three representations in which we varied attack strength (Visual Host Key, uppercase hexademical, unicorns), we did not observe any statsticically significant differences in the fraction of participants that missed an attack between attacks of different strengths.

Comparison time

The median time spent comparing fingerprints[3] ranged from 2.0 seconds for the unicorns representation to 8.7 seconds for the alternating vowels/consonants representation. Graphical representations were generally faster to compare than textual ones. The median comparison times for each representation are shown in Figure 5.5.

Differences in comparison time between conditions were significant ($\chi^2 = 289.39$, $df = 16$, $p < .001$). Looking at individual conditions, the median comparison time was significantly lower for unicorns (2.0 s) compared to both hexadecimal (8.0 s; $p < .001$) and Visual Host Key (5.51 s; $p < .001$). In contrast to related work by Dechand et al. [14], we did not observe any statistically significant differences in comparison time between textual representations.

[3]For participants in experimental conditions where the time to beat was set at 540 seconds.

Subjective ratings

We asked participants for their subjective ratings before we revealed whether they had missed the attack. For all representations, most participants (70% for alternating to 91% for Vash) believed that the time it took to compare fingerprints was reasonable for a security check. The majority also thought that it was easy to compare fingerprints and were confident that they could do so correctly. We did not observe statistically significant differences in ratings by condition for confidence ($p = .386$), ease of use ($p = .102$), or reasonableness of comparison time ($p = .117$). Detailed summaries of subjective ratings for each experimental condition are shown in Appendix C.3.

5.3.2 Compare-and-select

Compare-and-select participants did not spend much time comparing fingerprints. Of the configurations involving textual representations, the compare-and-select configuration had the lowest median comparison time (5.2 seconds), though this difference was not statistically significant.

Across all experimental conditions, the compare-and-select condition had the lowest attack detection rate; 72% of participants missed the simulated attack. The difference in attack detection rate between our baseline compare-and-confirm hexadecimal condition and the compare-and-select hexadecimal condition was statistically significant ($p < .001$).

5.3.3 Toggle use case

Our toggle use case explored the effect of requiring users to toggle back and forth between fingerprints in order to make comparisons, as opposed to being able to view both simultaneously. For hexadecimal, we did not observe statistically significant differences in attack detection rate or comparison time between toggle and simultaneously visible configurations. For Vash, only the difference in comparison time between toggle and simultaneously visible configurations was statistically significant (median time of 5.2 seconds when toggling, compared to 2.2 seconds when not; $p < .001$).

While it is not surprising that participants would take longer to compare fingerprints when they have to toggle between two views to perform that comparison, it is interesting to compare the interaction between visibility mode and representation. While participants did not take significantly longer comparing hexadecimal fingerprints when they had to toggle (median toggle: 9.8 s; both visible: 8.0 s), they did take significantly longer comparing Vash fingerprints when they had to toggle (median toggle: 5.2 s; both visible: 2.2 s). One explanation for this is that fingerprints based on abstract art are difficult to commit to memory, and so require more toggles (and thus more time) to compare than textual representations like hexadecimal.

5.3.4 Target time-to-beat

We set the time-to-beat to 1080 seconds in one condition, which allowed approximately 36 seconds per task. All participants finished before the time-to-beat, with a median elapsed activity time (reflected in the on-screen stopwatch) of 716 seconds. The median comparison time for participants in the 2x time configuration was significantly different from those in the comparable configuration where the time-to-beat was 540 seconds (11.03 compared to 8.02 s; $p = .005$). The difference in the fraction of attacks missed was not significantly different between the 2x time configuration (10% missed) and the corresponding regular configuration (21% missed).

5.3.5 Comparison strategies

Participants had a variety of strategies for comparing fingerprints. For textual fingerprints, participants often compared some subset of the beginning, middle, and end of fingerprints. Some participants also chose to compare random parts of the fingerprint, including one participant who was shown the hexadecimal representation, who said: "I first checked the last set of numbers, then randomly glanced at other sections until I felt I had verified enough values."

Other participants compared fingerprints in reading order, and instead focused on methods for efficiently doing so. For example, some participants had a strategy similar to the one described by a participant shown uppercase hexadecimal: "I would quickly read a segment and shift my eyes over as I repeated it, then compare and immediately/cross over into reading the next set from the other card to myself as I shifted back and compared to the next set of numbers, etc. - constant crossovers, but not having to cross over without going towards the next step to reduce time." Interestingly, one participant chose to compare hexadecimal fingerprints in reverse reading order: "I started with the rightmost set of numbers on the first line of the card, found one of the offered fingerprints that matched, then compared numbers back and forth in reverse reading order. I thought it would be easier to be accurate if using a technique that wouldn't make me fall into an easy 'reading' mode."

For all textual fingerprint representations besides sentences, fingerprints were presented in chunks of a fixed size, which provide a natural unit of comparison.[4] Indeed, many participants reported comparing fingerprints chunk-by-chunk. However, some participants chose to devise their own chunking strategy, a strategy prior work in the area of system-generated PINs has observed [33]. Many participants chose to compare multiple hexadecimal chunks at a time. Other reported units of comparison for textual representations included sentences, rows, and columns. Participants also described chunking strategies for graphical representations, such as comparing fingerprints by quadrant. Interestingly, more than one participant treated the visual host key representation more akin to textual representations, and compared in units of lines of text.

Although some participants compared graphical representations according to a chunking strategy, more commonly participants mentioned comparing particular features or characteristics of

[4]For the sentence representation, individual sentences served a similar purpose, though the way we presented it made it difficult to immediately discern sentences as individual units.

the specific fingerprints shown. One participant shown Vash said they tried "to pick out a couple things that might be different between pictures and then alternate between them to see if they are different." For Visual Host Key, one participant's strategy was to "look at general cues like the placement of the dots or big letters like B or S or E."

Participants strategies sometimes distinguished between the size of differences they looked for when performing comparisons, particularly for graphical representations. Some participants only checked for large differences. Others adopted a layered approach in which they looked for large differences first, followed by a search for more subtle differences. For example, one participant described this strategy for comparing Visual Host Key fingerprints: "The first thing I did was to try and glance at the whole fingerprint and see if anything jumped out at me. If I saw no difference by looking at the basic overview of it then I looked with a little more detail. If I was still unsure of its validity then I examined each line as quickly and accurately as possible."

5.4 Discussion

5.4.1 Impact of methodology

A main difference between our study and closely related work [14] was our focus on examining practical effects such as habituation, stress, and difficulties in comparison caused by variations in color, font, and position of the two fingerprints relative to each other. Based on both quantitative and qualitative data, we believe we successfully simulated some of these practical constraints, which we show do affect user behavior.

For example, in practice, attacks are likely to be few and far between. We simulated this by asking users to perform many comparisons of matching fingerprints before exposing them to an attack. Failing to find differences after several comparisions, most participants refined their strategy to compare only selected parts of fingerprints, which in turn increased the chance that they would miss attacks. Our experiment appeared to successfully simulate situations where users feel pressed for time. When asked what the hardest thing about the activity was, many participants responded that they felt stressed, pressured, distracted, or in a rush.

To verify that results weren't unduly driven by participants' need to finish tasks quickly, we included a condition in which participants had twice the time to complete the activity. In this condition, participants took only about 37% more time for each comparison, suggesting that time pressure was no longer a significant factor. These participants did make fewer mistakes (though the difference was not significant) but continued to miss attacks, suggesting both that time pressure in the study was at least partly successful at simulating real-life stress and that this stress was not the only factor which lead to mistakes.

5.4.2 Compare-and-select vs. compare-and-confirm

We were surprised by how susceptible the compare-and-select method of verifying fingerprints was to attacks. Compare-and-select seeks to ease comparisons by offering users multiple options from which to select a fingerprint that matches another one that they are looking at. Over time, however, the compare-and-select approach appears to train users that one of the options is always correct (since some options always aren't). More specifically, at the end of the study we asked participants to report their concern about false negatives (saying that the fingerprints did not match when in fact they did) and false positives (saying that two fingerprints matched when they did not). While there was no significant difference in the rate at which compare-and-confirm and compare-and-select participants reported concern about false negatives ($p = .657$), compare-and-select participants were significantly less worried about false positives, i.e., failing to detect an attack ($p < .001$).

At the same time, while current implementations of compare-and-select appear to be a poor fit at least for fingerprint comparisions, there has been discussion of a compare-and-select approach where the options are chosen to be visually similar. A potential benefit of this approach is that users would be forced to focus on small details (since through a cursory comparison all options would look alike), leading to more effective security. A potential downside is the usability cost of performing detailed comparisions between all the options that need to be compared.

5.4.3 Desirable properties and tradeoffs

For both textual and graphical representations, participants struggled to decide how detailed a comparison to perform. For graphical representations, participants noted slight differences in color (as could potentially be caused by comparing a fingerprint printed on a business card to one on a computer screen) that caused uncertainties.

Participants shown graphical fingerprints tended to look at the big picture more often. While this is fine if small differences do not exist, it may be feasible for a determined attacker to find a key whose fingerprint is overall similar to the target fingerprint but different in small details, as was the case for our unicorn condition.

One advantage of textual formats like hexadecimal over image-based formats like Vash is that the former allow a user to know for certain whether two fingerprints are the same. For textual formats, a motivated user can check each digit and compare. For Vash, manual human comparison can only go so far; the user cannot confirm each pixel value through just visual inspection, and the representation does not convey what the smallest difference the user should look for is.

Another advantage of textual representations relates to the fact that they easily lend themself to being segmented into a particular structure, e.g., chunks of four characters, lines of text, etc. This structure seems to offer participants a useful reference point at semantically arbitrary locations within a fingerprint. Participants reported (unknowingly) taking advantage of this structure by making multiple detailed comparisons between various parts of corresponding fingerprints. This kind of behavior seems likely to make successful attacks less likely.

5.4.4 Recommendations

Overall, all the representations and configurations we experimented with exhibited higher rates of successful attack than seems desirable for high-risk situations. This strongly suggest that additional effort should be put towards removing the human in the loop, e.g., by using a smartphone camera to capture a printed fingerprint and having smartphone software make the comparison. When manual fingerprint comparison is necessary, the right choice likely depends on the context, since the different fingerprint representations we experimented with showed substantially different security and usability properties.

For all representations we tested, we observed participants making rational (if not always well informed) assumptions about how to go about comparing fingerprints. Graphical representations in general seemed to be more susceptible to comparison strategies that ignored fine details; at the same time, they allowed seemingly easy and quick comparisons. Consequently, unless the representation is accompanied by measures to help the user compare small details between two fingerprints, graphical representations appear not to be well suited for high-risk situations, but could be of benefit in low-risk environments, when attackers are not likely to be strong and usability is paramount.

When security is paramount, the best option is likely one we did not test: manually copying a printed fingerprint into a device and having software on that device make the comparison. This virtually eliminates the possibility of missing an attack, but at a high usability cost. For situations in which risk is not high and there is a need to balance security and usability, textual representations like hex (but also others like ASCII art and sentences) may be appropriate.

Chapter 6

Conclusions and future work

In this chapter we discuss high-level conclusions resulting from the studies described in this thesis. We also discuss how future work can extend the ideas we explored in order to improve guidance available to designers of password-based authentication systems.

6.1 Conclusions

6.1.1 Guidance on password-policy requirements

Prior work has shown that composition requirements [42,46,72,73], blocklists [22,28,42,45,46, 50,72,87,95], strength meters [88], real-time requirements feedback [72] and text feedback [87] are all useful elements of an effective password-authentication system design. A primary goal of this thesis was to build on the knowledge provided by prior work in order to provide practical, actionable guidance to system designers of password-authentication systems.

In Chapter 3 we perform a comprehensive study of password-policy requirements. In experimentally designed user studies using a password-creation interface configured according to prior-work recommendations (i.e., incorporating a strength meter, real-time requirements, and heuristic-driven text feedback), we measured the security and usability provided by character-class, length, and blocklists requirements. The specific configurations of character-class, length, and blocklist requirements that we tested were based on the results and recommendations of prior work. Importantly, we not only test the recommended configurations for each type of requirement, but also ways that different types of requirements can be combined in a password policy. We find that attention to combinations of policy requirements is important for a comprehensive password-policy evaluation, as specific combinations of requirements can lead to significantly different security outcomes. As a result of our study, we provide improved guidance for system designers on effective combinations of length, character-class, and blocklist requirements. In addition, we provide concrete, experimentally-tested guidance on particular implementations of

blocklist requirements that designers can use, which before our study was a missing aspect of system design guidance.

Our study of password-policy requirements provides practical and actionable guidance that is flexible to the different constraints and priorities that system designers must abide by. In some settings, system designers may be required to use certain types of authentication requirements for regulatory compliance reasons. An example of this is use of blocklist requirements in organizations mandated to follow NIST recommendations [56]. In such cases, our concrete recommendations of blocklist configurations can be used by system designers. In other settings, system designers may have more implementation flexibility. In these cases, we provide guidance on concrete minimum-strength requirements that not only offer increased security benefits against attackers able to attempt many password guesses, but is also actionable. System designers can incorporate minimum-strength requirements that can be implemented in client-side password-creation interfaces using minimal JavaScript and a pre-trained neural-network model requiring as little as 5MB in storage.

The implementation of minimum-strength requirements that we recommend are flexible to system designers with different levels of security requirements. Designers can modify the minimum-strength-requirement threshold to produce passwords resistant against adversaries with different attack capabilities. Neural-network-driven minimum-strength requirements can also be updated to incorporate passwords compromised in new data breaches by simply retraining the underlying neural network on the newly leaked password data.

6.1.2 Guidance on text feedback for password meters

Results of the study described in Chapter 3 echo findings of prior work [45, 87, 89] on the usefulness of providing users with heuristic-driven guidance on predictable patterns in passwords. We therefore recommend this type of guidance be presented to users in password meters. System designers should use implementations that have been vetted by the research community as guiding references, including the password meter designed by Ur et al [89] and zxcvbn [97].

Our results provide support that heuristics are a useful tool for helping users create stronger passwords even when presented to users in terms of optional guidance on changes that would strengthen passwords. Although heuristics can be formally incorporated into a password policy as hard requirements, we find support that this is not always necessary in order for users follow heuristic guidance, and when presented as a hard requirement rather than a suggested change heuristic guidance may lead to increased user annoyance. For example, study participants in Chapter 3 created passwords using a meter that provided heuristic guidance on adding characters of different classes if a participant entered a weak candidate password. We found that participants in that study were likely to create passwords that exceeded the character-class requirements of the policy they were assigned to, a trend which we partially attribute to the password meter (and associated guidance) used by participants. However, when a policy required those additional character classes, participants created passwords that were not statistically significantly stronger than those created under optional character-class guidance, and were also more annoyed with the

password-creation process.

6.1.3 Guidance on public-key fingerprint-verification designs

In Chapter 5 we investigated ways of improving the usability of fingerprint verification using different fingerprint representations and comparison techniques. We provide concrete recommendations for system designers that incorporate fingerprint comparison for identity verification. In particular, we recommend that visual comparison be avoided whenever automated comparison methods are available, such as QR-scanning approaches. These methods avoid security failure due to human error and are can be as easy to use as it is for users to take a picture using a smartphone.

System designers may face implementation requirements that prevent automated methods. For example, they made need to design a system that uses fingerprints and does not rely on the availability of camera hardware. In this case, we provide alternative design guidance. For designers of systems that have high security-level requirements, we recommend using a *compare-and-confirm* comparison technique using a textual key-fingerprint representation, such as a numerical or hexadecimal format. We also provide recommendations for designers of systems in which users have less stringent security requirements, or in which organizational constraints demand a high usability standard for any security tasks that system designers might introduce. In particular, we recommend visual comparison of abstract-art fingerprints as a practical design for providing a quick and user-friendly method of identity verification.

6.2 Future work

In this section we describe how future work on text-based password-strength feedback might help provide more comprehensive guidance to system designers of password-authentication systems, including for systems that incorporate a minimum-strength password policy. We also outline an application of Integrated Gradients that could potentially provide a different kind of password-strength feedback, in the form of suggested changes to individual password characters that are attributed with a weak password-strength prediction.

6.2.1 Improving text-based password-strength feedback

In Chapter 4 we explored ways of improving text feedback shown to users in the context of heuristics associated with making a password weaker. Here we describe avenues of research that could potentially lead to more effective and comprehensive system-design guidance on ways to incorporate text feedback in password-creation interfaces.

Prior work in the area of heuristic-driven password-strength guidance has focused on providing recommendations to users about ways to change a password by removing some predictable

component of that password. For example, among the set of advanced heuristics provided by prior work [87], the majority are used for feedback on removing predictable patterns from a password. Besides describing heuristics for identifying predictable patterns, text feedback can be used to suggest heuristic-based modifications associated with increasing password strength. The distinction between these two types of feedback is nuanced; feedback on predictable parts of a password can often be viewed in terms of a suggested change to increase password strength, by removing those predictable parts. However, in some cases heuristic guidance on ways to improve password strength cannot be naturally cast in terms of eliminating an existing password pattern. A good example of this is heuristic-driven text feedback on how to make passwords stronger for users trying to satisfy a minimum-strength requirement. Often a user may not have any explicit patterns in their password initially as they construct it, but nonetheless would like real-time, password-specific suggestions for creating a strong password.

Text feedback on heuristics for both adding and removing characters from a password may be useful. Security experts are understandably more cautious about developing heuristics for suggesting changes to increase password strength; if a suggested change is overly prescriptive or users tend to implement that change in a predictable way, such heuristic-based suggestions may not ultimately help improve the strength of passwords, and worse, could actually lead users to create weaker, more predictable passwords. We believe this risk is mitigated, however, for password policies incorporating a minimum strength requirement.[1] Results in this thesis suggest a baseline heuristic: feedback that suggests users create a longer password. Prior work suggests more-specific variants may also be helpful, e.g. a recommendation that users add a digit or symbol someplace in a password besides at the beginning or end position [74]. Future work could explore other types of positive-action heuristic guidance and apply them in user studies to evaluate their effective impact on security.

Another avenue that future work could investigate is learning a larger set of password patterns associated with decreased password guessability. In particular, it may be useful to learn lower-level, more complex patterns. One reason for this is to be able to model the relationship between heuristic features and guessability more accurately. In our work, after transforming a set of 21 heuristic features to use in regressions for understanding the relative importance of patterns on determining guessability, we were left with a reduced set of heuristic features that explained a relatively small amount of variation in guessability. Being able to model guessability using a more comprehensive set of non-overlapping heuristic features could facilitate more detailed and prioritized feedback on patterns to eliminate in passwords. User studies could then evaluate whether certain prioritization of heuristics and different ways of displaying that prioritization ultimately helps users create stronger passwords.

Lastly, researchers could investigate ways of better modeling guessability using heuristics already identified by the research community. This could involve improving how heuristic features are detected in passwords (e.g., detection of keyboard patterns could be improved), how detected patterns are transformed into numeric values for use in statistical models (e.g., predictable use of symbols could be made more granular), and how guessability is modeled using heuristic-feature

[1] In such cases, users are prevented from making weaker passwords and in the worst case users may be annoyed and learn to ignore text feedback; this is also undesirable, but not a security failure.

values (e.g., modeling interactions between heuristic features could identify pairs of patterns that are particularly likely to be used together).

6.2.2 Text-based guidance for minimum-strength requirements

In this thesis, we use experiments to recommend password policies combining minimum-strength and minimum-length requirements. An aspect we did not explore in our experiments was how text-based heuristic guidance could be used to make password creation easier for users. In our study, we provided real-time feedback on whether participants had satisfied a minimum-strength requirement. General tips on creating stronger passwords were made available in the password meter, but few participants actually viewed these.[2]

Researchers could explore how using heuristic guidance affects the usability of password-creation under minimum-strength requirements. This guidance could take the form of suggested ways to add to a candidate password, as well as real-time heuristic guidance for any predictable patterns detected in that password. In contrast to general guidance for making passwords stronger, this type of guidance could be made more visible to users and made specific to any password characters entered by users. In Chapter 3 we found that minimum-length requirements can help make it easier for users to satisfy minimum-strength requirements. Heuristic guidance in the form of suggestions to users that they can voluntarily choose to implement may accomplish a similar goal of improving the usability of minimum-strength requirements. This could be particularly helpful for ease of password creation under high-threshold minimum-strength requirements.

6.2.3 IG-based guidance on predictable password characters

In Chapter 4 we explored using Integrated Gradients to highlight patterns in passwords with the goal of learning new heuristics that feedback could reflect. Although we found limited success in applying IG for identifying patterns, future research could explore ways to use alternative, simpler clustering models for highlighting patterns. Our clustering model predicted 30 cluster membership values for each password. A model trained to predict membership to a single cluster might produce better results than we observed. Furthermore, if researchers are able to learn clusters associated with patterns that can be described in text feedback, that text feedback could be shown to users alongside IG-based character highlighting of the pattern described by that feedback, potentially making it easier for users to implement feedback.

The focus on password-strength guidance in this thesis was for text-based feedback. In addition to text-based feedback, IG may be useful for a different type of visual feedback that highlights characters associated with a given password-strength prediction. This type of feedback could be used for real-time password-creation guidance and might be especially useful for highlighting complex, non-intuitive patterns. It may not be necessary to describe these patterns in words in

[2]This involved an extra mouse click in order to be viewed.

order for this type of feedback to help users; they might simply be told that the highlighted characters are associated with weak passwords and thus modifying those characters might improve password strength. Researchers could explore applying IG techniques to end-to-end neural-network models that predict a strength-bin categorization and experimentally test the usefulness of this new kind of feedback.

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Appendix A

Additional details for password-policy study

A.1 Neural network training

Here we present additional tables and plots related to the training and evaluation of the PGS3 NN models used in our user studies.

Prior to conducting our user study, we trained neural network models for predicting password strength. Our models were created using code based on prior work by Melicher et al. [52]. Similar to their work, we trained a large Tensorflow-based Keras model containing three recurrent layers and two densely connected layers. Each recurrent layer contained 512 LSTM units and each dense layer contained 1,000 units. Our models used a vocabulary of 96 characters, including lowercase, uppercase, digits, and symbols. The minimum and maximum lengths of passwords predicted by our model were 8 and 30 characters, and the context length was 10 characters wide. We did not apply rare character or lettercase optimizations, nor dropout. Our base *1c8* model was trained using two NVIDIA Tesla P100 GPUs and a batch size of 1024 samples for 20 epochs over a period of 11 days. For each large Keras model, we also trained a smaller version containing 200 units in both the LSTM and dense network layers. We then created a model that could be included in a client-side password meter by converting the smaller Keras model into a TensorflowJS model. While the size of the large NN models were around 100MB, each TensorflowJS NN model was approximately 4.7MB uncompressed, including the precomputed probability-to-guess-number mapping file.

We experimented with transfer learning in order to train policy-specific NN models, which prior work had found improved *1c16* guessing performance, particularly for large guess numbers [52].[1]

A primary difference between the PGS++ NN models used in prior work [52] and our PGS3

[1] We only trained composition-requirements-specific NN models for Experiment 1. These models were also used for Experiment 2.

Policy	PGS++ (old)	PGS3 (new)
1c8	73.4 million	32.8 million
1c16	2.5 million	1.5 million
2c12	13.3 million	5.4 million
3c8	13.6 million	5.7 million
3c12	4.1 million	1.8 million
4c8	311 thousand	599 thousand

Table A.1: Training data used for PGS3 and PGS++ [52] NN models. Each PGS3 model other than the *1c8* model was trained using transfer learning, initialized according to model weights for a superset policy (e.g., the *3c8* model was trained starting from the trained *1c8* model).

models is that our models contained a character-level embedding layer. The embedding size was set to eight dimensions. Another difference between the prior PGS++ models and our PGS3 models is the training data used for each set of models, which consisted of of PGS-compliant passwords in the LinkedIn, Mate1, RockYou, and 000webhost datasets. As shown in Table A.1, our training data contains many fewer *1c8* passwords, but slightly more *4c8* passwords.

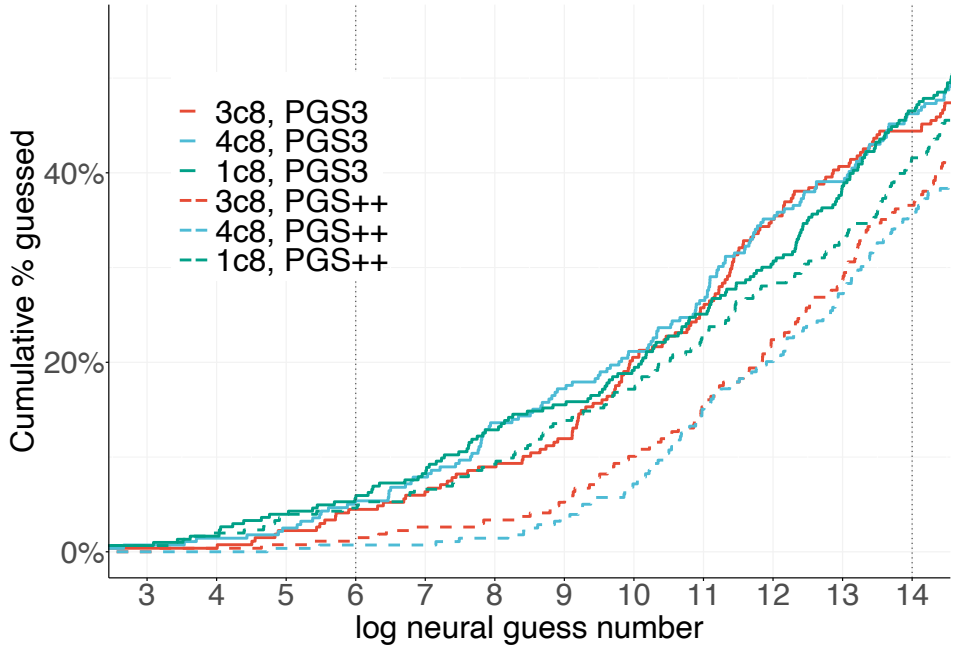


Figure A.1: Guessing performance of the PGS++ and PGS3 NN models for passwords collected in Experiment 1. In contrast to the previous PGS++ model, the PGS3 model guesses *1c8*, *3c8*, and *4c8* passwords at similar rates.

We compared the guessing effectiveness of our PGS3 NN models and the prior PGS++ model for *1c8*, *3c8*, and *4c8* passwords collected in Experiment 1. As demonstrated in Figure A.1, the PGS3 models guessed passwords from each of these policies more effectively than the PGS++ model. Furthermore, we find that the improvement in guessing performance is largest for *4c8*, followed by *3c8*, and then by *1c8*. While we do notice a small increase in guessing performance

for *1c8* passwords, this increase was not statistically significant. For *3c8* and *4c8* passwords, the increase was statistically significant (PP; *3c8*: χ=11.9, p=.001; *4c8*: χ=18.2, p<.001). We experimented with many model variations in order to understand which differences between the PGS3 and PGS++ models led to these results. We found that the majority of the guessing improvement of PGS3 over PGS++ could be attributed to the inclusion of the embedding layer in the PGS3 model. On the other hand, the PGS3 training data and the application of policy-specific transfer learning produced only slight improvements in guessing performance.

A.2 Minimum-strength-requirement attackers

For a minimum-strength policy, the underlying NN used to estimate password strength and allow or reject passwords can be leveraged by attackers to improve guessing effectiveness. As a rough analysis of how much benefit this kind of attacker knowledge provides, we plot and compare guess curves for both situations. To simplify analysis, we plot the password guessability under each policy according to browser-NN guess numbers. These guess numbers are similar to PGS3-NN guess numbers that we primarily report, modulo artifacts introduced during NN compression.

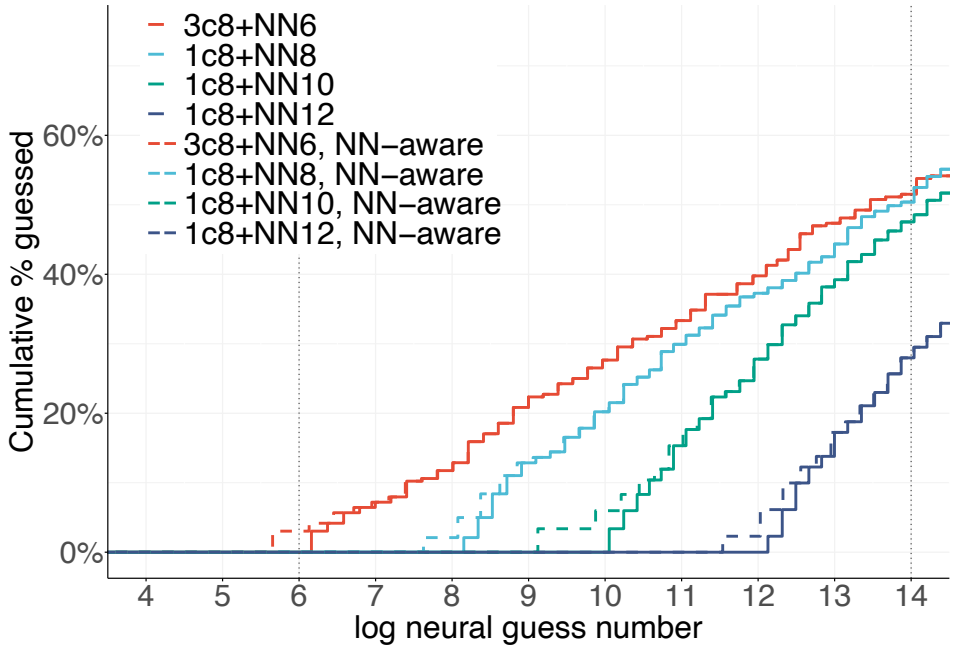


Figure A.2: Password guessability against minimum-strength-aware and minimum-strength-oblivious attackers. Both types of attackers order password guesses from most probable to least probable. The minimum-strength-aware attacker additionally avoids making guesses that the minimum-strength requirement would have rejected. The *NN8* and *NN10* conditions are from Experiment 2. This plot shows browser-NN guess numbers.

As illustrated in Figure A.2, a minimum-strength-aware attacker does gain a noticeable increase in guessing effectiveness, equivalent to those passwords able to be guessed in the head start

afforded by skipping minimum-strength-rejected passwords (e.g., skipping 10^6 passwords for a *NN6* policy). However, this benefit quickly fades within an order of magnitude or fewer guesses.

A.3 Policies enforcing composition requirements only

Our initial research questions did not focus on analyzing password-creation policies consisting of only composition requirements (minimum character-class-count and length requirements). Prior work has examined these policies and found them to be insufficient for preventing the creation of easily-guessed passwords. However, as our experimental design included simple composition policies to serve as baselines in certain planned comparisons, we also chose to compare between such policies as a sanity check for our experimental results. Our baseline policy for pairwise comparisons was *3c8*, since retrospective analyses suggested this would produce the most guess-resistant passwords.

As shown in Figure 3.4, our results on the sufficiency of simple composition policies remain the same as reported by prior work; each of *1c8*, *3c8*, *4c8* allow a non-negligible amount of weak passwords that can be guessed by a 10^6 online attack. *1c8* passwords were also reported as less annoying to create than *3c8* passwords (FET). However, we found all three simple composition policies produced passwords that were equally resistant to guessing attacks.

A.4 How have passwords changed?

Results from our experiments related to the impact of character-class requirements on password guessability differed from those reported in prior work. Prior work has found that policies requiring more character classes tend to produce overall stronger passwords. In contrast, in our study participants assigned to *1c8*, *3c8*, and *4c8* policies created passwords that did not significantly differ in strength. As noted in Section 3.4.1, this change appeared to be in part due to the fact that participants in our study were more likely to exceed composition requirements than participants from prior work. To investigate further, we compared how password lengths and character-class compositions have changed across both prior work and in our study.

We focused our comparisons on passwords collected in three separate studies under a *1c8* policy with no other restrictions, which used a similar methodology to ours (i.e., Mechanical Turk participants and use of role playing to create an email account password) [42, 87, 88]. Although these passwords were collected under similar methods to ours, some differences exist. We identified primary differences that could have potentially impacted participants' passwords, which included when data was collected and the password-creation interface that participants created passwords under. We attempted to understand how these differences related to our new findings by comparing the character-class composition and length of passwords collected in each study.

We find that more passwords contain multiple character classes over time. Part of this appears to be due to the password meter used to collect passwords in each study. Comparing 2016 study

	Without meter			With meter	
	2010	**2012**	**2016**	**2016**	**2019**
One class	38%	14%	11%	7%	4%
Two classes	46%	20%	39%	26%	18%
Three classes	12%	49%	32%	35%	30%
Four classes	4%	16%	19%	32%	48%

Table A.2: Number of character classes contained in *1c8* passwords collected in studies that were conducted in 2010 [46], 2012 [88], 2016 [87], and 2019 (our study).

passwords collected without a meter to passwords from the same study collected using a meter (similar to ours), we see a 13% jump in the percentage of passwords containing four classes. We also find increases in the number of character classes contained in passwords over time that are not attributable to use of a meter. As shown in Table A.2, 2016 passwords collected without a meter had 27% fewer passwords containing exactly one class and 15% more passwords containing four classes compared to 2010 passwords collected without a meter. Similarly, *1c8* passwords collected in our study contained 16% more passwords containing four classes compared to passwords collected in 2016 using the same meter.

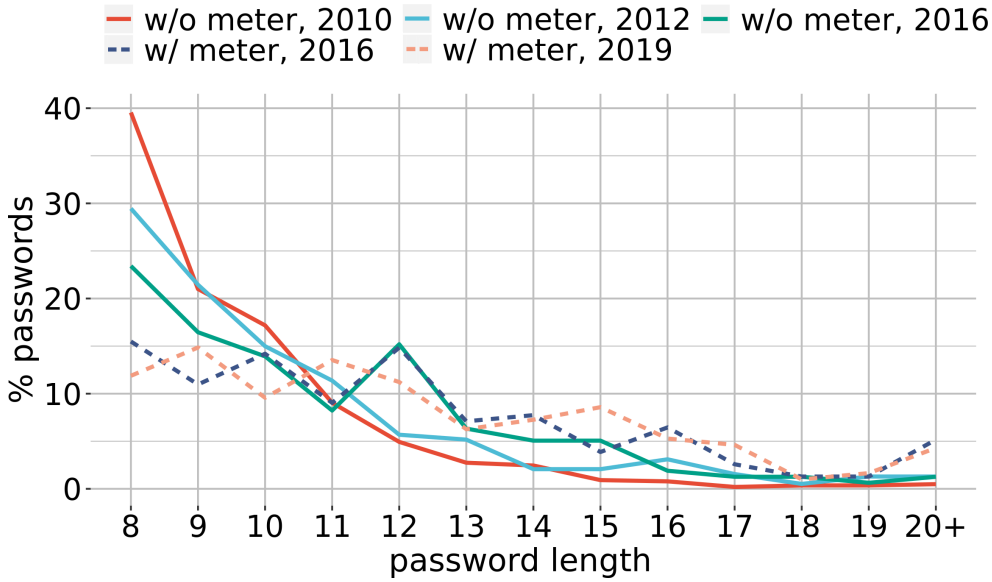


Figure A.3: Length distribution for *1c8* passwords collected in studies over time.

Besides containing more character classes, we find that passwords have become longer over time. As illustrated in Figure A.3, both the year of the study and the use of a password meter appear to be associated with this change. For example, *1c8* passwords collected without a meter in 2016 had roughly 15% fewer passwords that were exactly eight characters long compared to passwords collected without a meter in 2010. We also see evidence that the password meter played a role in lengthening passwords; 2016 passwords collected with a meter had approximately 10% fewer passwords that were exactly eight characters long compared to passwords collected in the same study without a meter. We observe similar password-length distributions for passwords collected

in 2016 and 2019 using the same password meter.

A.5 Character classes and guessability

In our study we find that character-class requirements are not only annoying, but provide little security benefit in terms of defending against guessing attacks. As mentioned in Appendix A.4, this result applies to character-class requirements in a policy deployed using a password meter similar to the one we use. Here we show support that a rough relationship still exists between the number of character classes actually contained in a password and password guessability, for passwords collected via a *1c8* policy.

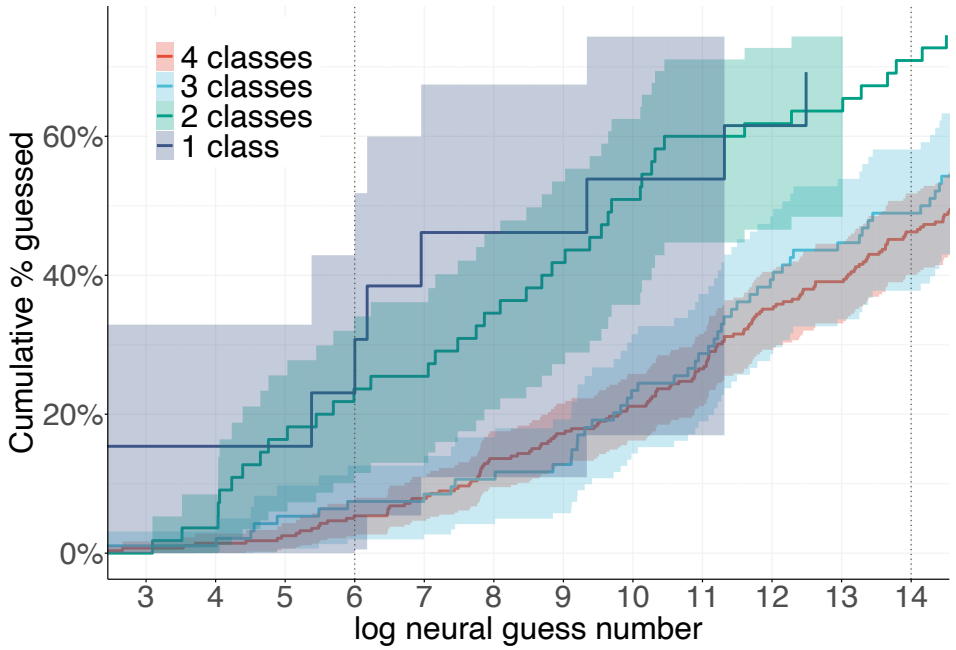


Figure A.4: PGS3 NN guess numbers for passwords containing exactly one, two, three, and four class(es), subsetted from passwords created under *1c8*, *3c8*, and *4c8* policies in Experiment 1. Each of these sets contains differing number of passwords; we plot confidence intervals to reflect how this impacts guess curve estimations. The 95% confidence interval for passwords containing exactly one class is large due to the small number of *1c8* passwords that contained exactly one class.

In Figure A.4 we plot guess curves for passwords containing an exact number of character classes.[2] We see that the PGS3 NN guesses passwords containing exactly three characters or

[2]We chose to subset passwords created under different policies, rather than subset only *1c8* passwords, in order to focus on passwords created by participants who may tend to satisfy minimum requirements only. If we had performed a similar analysis on only *1c8* passwords, then comparisons between passwords containing exactly one class versus four classes might also implicitly compare passwords created by participants who naturally put different levels of effort into creating strong passwords.

four characters at around the same rate, but guesses passwords containing exactly one or two classes at a much faster rate. In other words, we find evidence that passwords containing three or four character classes tend to be stronger than those containing one or two classes. Similarly, in Experiment 1 we found that character-class requirements, when combined with minimum-strength requirements, do impact resulting password guessability.

Nonetheless, we still recommend avoiding character-class requirements. Users tend to find these requirements annoying and, given an effectively designed password meter, many will incorporate multiple classes anyway of their own accord. Other types of policy requirements, including minimum-strength and minimum-length requirements, annoy users less, have a larger potential effect on resulting password guessability, and can be configured more granularly to achieve a desired security level. Character-class requirements also hinder the ability of users to create passphrases, which can be a memorable alternative to passwords [41] and additionally can avoid issues in legacy systems that differ in which particular special characters are allowed.

A.6 Study instructions and Survey protocols

Here we include the study instructions shown to participants on Mechanical Turk and in the user study activity. We also include the questions shown to participants in the Part 1 and Part 2 surveys. Placeholder text is shown inside [brackets].

A.6.1 User study instructions

0. MTurk HIT instructions
Please visit the study link below to continue this HIT. After completing the study, you will be provided a completion code, which will be required in order to receive payment. *Make sure to leave this window open as you complete the study.* When you are finished, return to this page to paste the completion code into the box.
[text box for completion code]

1. Participant consent
[consent form]

2. Part 1 instructions
In this study you will be asked to create a password and fill out a 3-minute survey for a 55 cent payment. We will contact you to come back a few days later to try to use your password to log in again and fill out another survey for a 70 cent bonus payment.
Imagine that an online *account that you care a lot about*, such as your main email account, is requiring that all users change their passwords. We will ask you to use this password in a few days to log in again, so it is important that you remember your new password. Please take the

steps you would normally take to create and remember your important passwords, and protect this password as you normally would protect your important passwords. Please behave as you would if this was your real password! *NOTE: This password is only being used for the purpose of this study and you should not use a password that you use for your actual email account.*

3. Password-creation task
[password meter used to create password]

4. Part 1 password-recall task
[password entry form]

5. Part 1 survey
[see Appendix A.6.2]

6. Instructions after completing Part 1 survey
Thank you! You have finished Part 1 of the study. Please enter the following completion code on MTurk: [study completion code]
Please expect an email a few days from now to return for Part 2 of the study, for which you will receive an additional 70 cent bonus payment.

7. Part 2 password-recall task
[password entry form]

8. Part 2 survey
[see Appendix A.6.3]

9. Instructions after completing Part 2 survey
Thank you! You have finished Part 2 of this study about the memorability and security of passwords. Please expect a 70 cent bonus payment on Mechanical Turk within the next few days.

A.6.2 Part 1 survey

Thank you for creating a password. Next, we would like you to answer some survey questions.

Creating a password during this study was annoying
○ [Strongly disagree to Strongly agree] (5-point scale)

Creating a password during this study was fun
○ [Strongly disagree to Strongly agree] (5-point scale)

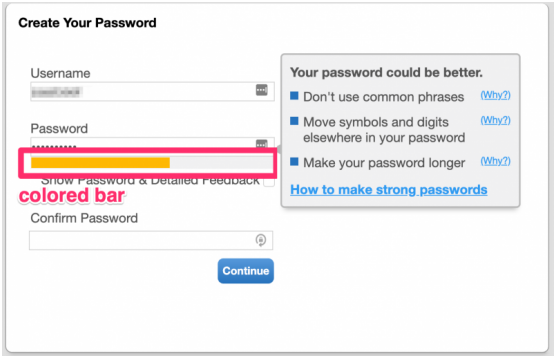
Creating a password during this study was difficult
○ [Strongly disagree to Strongly agree] (5-point scale)

Please explain why creating a password during this study was/was not difficult.
[text box input]

Which of the following best describes your approach to creating your password in this study?
○ I reused a password that I currently use, or previously have used, for a different account.
○ I modified a password that I currently use, or previously have used, for a different account.
○ I created an entirely new password, but I used the same general approach that I normally do.
○ I created an entirely new password, and I used a different approach than I normally do.

In general, I am confident in my ability to create strong passwords.
○ [Strongly disagree to Strongly agree] (5-point scale)

The following questions refer only to the colored bar that measures the strength of your password (highlighted inside pink box).



The colored bar helped me create a stronger password.
○ [Strongly disagree to Strongly agree] (5-point scale)

The colored bar was informative.
○ [Strongly disagree to Strongly agree] (5-point scale)

Because of the colored bar, I created a different password than I would have otherwise.

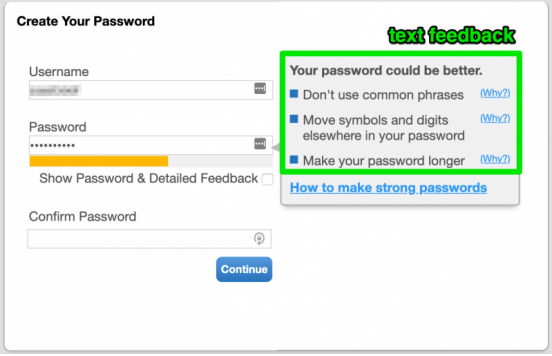
○ [Strongly disagree to Strongly agree] (5-point scale)

It's important to me that the colored bar gives my password a high score.
○ [Strongly disagree to Strongly agree] (5-point scale)

What is your opinion of the accuracy of the colored bar's rating?
○ The colored bar's rating accurately reflected the strength of my password.
○ The colored bar's rating did not accurately reflect the strength of my password; the colored bar gave my password a lower score than it deserved.
○ The colored bar's rating did not accurately reflect the strength of my password; the colored bar gave my password a higher score than it deserved.
○ I don't remember how the colored bar rated my password.

Do you have any other thoughts about the colored bar?
[text box input]

The following questions refer only to the text feedback that measures the strength of your password (highlighted inside green box).



The text feedback helped me create a stronger password.
○ [Strongly disagree to Strongly agree] (5-point scale)

The text feedback was informative.
○ [Strongly disagree to Strongly agree] (5-point scale)

Because of the text feedback, I created a different password than I would have otherwise.
○ [Strongly disagree to Strongly agree] (5-point scale)

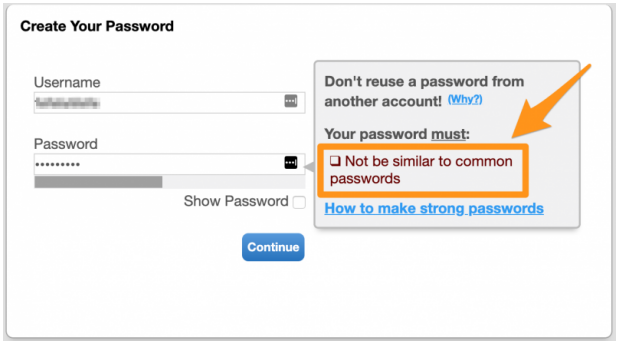
It's important to me that I follow the suggested changes to my password provided by the text feedback.

○ [Strongly disagree to Strongly agree] (5-point scale)

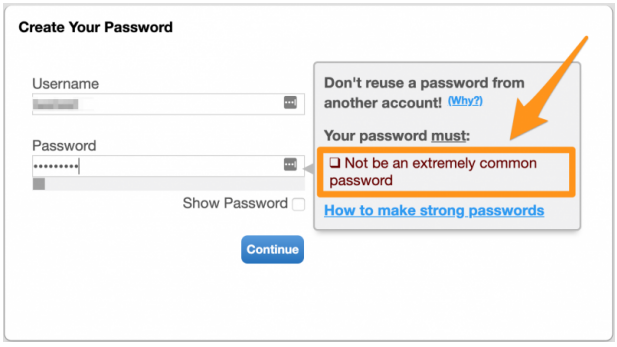
What is your opinion of the appropriateness of the text feedback?
○ The text feedback was appropriate for my password; the suggested changes improved the strength of my password.
○ The text feedback was not appropriate for my password; the suggested changes had no effect on the strength of my password.
○ The text feedback was not appropriate for my password; the suggested changes weakened the strength of my password.
○ I don't remember whether the text feedback was appropriate for my password.

Do you have any other thoughts about the text feedback?
[text box input]

[if assigned to a minimum-strength condition]
The following feedback was shown if you attempted to create a common password:

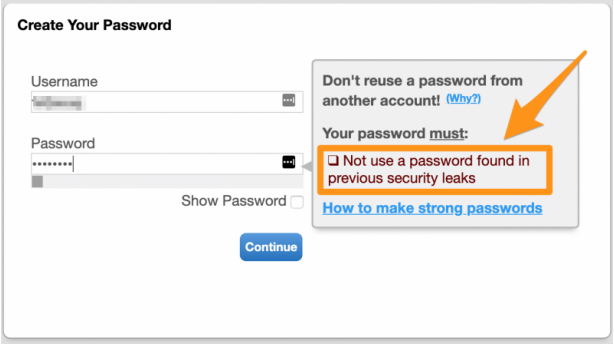


[if assigned to a Xato-based blocklist condition]
The following feedback was shown if you attempted to create a common password:



[if assigned to the Pwned blocklist condition]
The following feedback was shown if you attempted to create a password found in previous

security leaks:



[if assigned to a minimum-strength or blocklist condition]
Were any passwords you tried to create rejected for the specific reason shown above (highlighted in orange)?
○ Yes, I remember these passwords were rejected for that specific reason (list rejected passwords in box)

[optional text box input]
○ Yes, but I don't remember which passwords were rejected / ○ No / ○ I don't remember

With what gender do you identify?
○ Male / ○ Female / ○ Other / ○ I prefer not to answer

How old are you?
[numeric text box input]

Are you majoring in or do you have a degree or job in computer science, computer engineering, information technology, or a related field?
○ Yes / ○ No / ○ I prefer not to answer

A.6.3 Part 2 survey

Which of the following statements best reflects *how you entered your password on the previous screen?*
○ My password was automatically entered for me by a password manager or by my browser
○ I typed my password in entirely from memory
○ I had written my password down on paper, and I typed it in after looking it up
○ I had saved my password electronically (e.g., in a file or on my phone), and I typed it in after looking it up

○ I had written down or electronically stored a hint (not the password itself) to help me remember my password for this study, and I typed the password in after looking at the hint
○ Other [text box input]

It was difficult for me to remember the password I entered on the previous screen
○ [Strongly disagree to Strongly agree] (5-point scale) / ○ I did not recall the password from memory

Which of the following statements reflect *how you normally enter passwords in your daily life?* (Choose all that apply)
□ My passwords are automatically entered for me by a password manager or by my browser
□ I type my passwords in entirely from memory
□ I write my passwords down on paper, and I type them in after looking them up
□ I save my passwords electronically (e.g., in a file or on my phone), and I type them in after looking them up
□ I write down or electronically store hints to help me remember my passwords, and I type my passwords in after looking at those hints
□ Other

[text box input]

Regardless of how you entered your password on the previous screen, did you do any of the following after you created your password? (Choose all that apply)
□ I stored my password for this study in a password manager or in my browser
□ I wrote my password for this study down on paper
□ I took steps to memorize my password
□ I stored my password for this study electronically (e.g., in a file or on my phone)
□ I wrote down or electronically stored hints to help me remember my password for this study, but not my password itself
□ I did not do any of the above
□ Other [text box input]

What would you have done differently in creating, protecting, and remembering your password if this password were used for an account you use outside this study?
[text box input]

Do you use the password you created for this study for any other account?
○ Yes / ○ No / ○ I prefer not to answer

A.7 Additional details of experimental results

A.7.1 Strength/usability summary tables

Tables 6 and 7 show the results of omnibus and pairwise statistical tests for both experiments. Table 3.3 explains how to read these tables. We report Holm-Bonferroni-adjusted p-values. See Table 3.2 for descriptive statistics explaining effect sizes.

Condition	Peto-Peto	percent @ 10^6	percent @ 10^{14}	Noticed rejection	Creation time	Creation difficult	Creation annoying	Stored password	Part 1 dropout	Part 2 dropout	Recall time	Recall success	Remember difficult
Impact of blocklists													
3c8													
3c8+Xato-cifs	p=.842	p=.835	p=.114	N/A	p=.895	p=.926	p=.449	p=.941	p=.07	p=.047	p=.101	p=.524	p=.176
1c8												p=.076	
1c8+Xato-cifs	p=.54	p=.46	p=.737	N/A	p=.114	p>.999	p=.574	p>.999	p>.999	p=.29	p=.57		p>.999
1c8+Pwned-fs	p=.54	p<.001	p=.267	N/A	p=.722	p>.999	p>.999	p>.999	p>.999	p=.436	p=.418		p=.645
1c8+Xato-strip-cifs	p=.54	p=.001	p=.25	N/A	p=.558	p>.999	p=.215	p>.999	p>.999	p=.086	p=.29		p>.999
1c8+Xato-ciss	p=.002	p<.001	p<.001	N/A	p<.001	p<.001	p<.001	p=.038	p<.001	p=.616	p=.57		p=.931
Blocklist requirements for *1c8* policies													
1c8+Xato-strip-cifs													p=.064
1c8+Xato-cifs	p=.017	p=.048	p=.399	p=.051	p=.003	p=.808	p=.544	p>.999	p=.988	p=.738	p=.016	p=.745	
1c8+Xato-ciss	p=.013	p=.498	p<.001	p<.001	p<.001	p<.001	p=.011	p=.031	p<.001	p=.015	p>.999	p=.31	
1c8+Pwned-fs	p=.8	p=.498	p=.865	p<.001	p=.142	p=.808	p=.161	p>.999	p=.988	p=.738	p>.999	p=.332	
Composition requirements for minimum-strength policies													
3c8+NN6		p=.224		p=.436				p=.705	p=.272	p=.385	p=.084	p=.071	p=.163
1c8+NN6	p=.586		p=.104		p=.021	p=.022	p=.636						
1c16+NN6	p=.586		p<.001		p=.38	p=.643	p=.467						
2c12+NN6	p=.119		p=.009		p=.38	p=.281	p=.636						
3c12+NN6	p=.061		p=.004		p=.212	p=.643	p=.928						
Blocklists vs minimum-strength policies													
1c8+NN6												p=.074	p=.156
1c8+Xato-cifs	p=.007	p=.065	p=.734	N/A	p=.609	p=.66	p>.999	p>.999	p=.45	p=.585	p=.279		
1c8+Pwned-fs	p>.999	p=.747	p=.747	N/A	p=.609	p=.66	p=.724	p>.999	p=.654	p=.678	p=.683		
1c8+Xato-strip-cifs	p>.999	p>.999	p=.282	N/A	p=.054	p=.47	p>.999	p>.999	p=.654	p=.203	p=.658		
1c8+Xato-ciss	p=.005	p=.747	p<.001	N/A	p<.001	p<.001	p=.003	p=.01	p<.001	p=.678	p=.683		
Policies enforcing composition requirements only													
3c8	p=.558	p=.639	p=.635		p=.891	p=.124		p=.157	p=.174	p=.414	p=.102	p=.711	p=.103
4c8				N/A			p=.604						
1c8				N/A			p=.037						
***3c8+NN6* vs *1c8+NN12* (post-hoc comparison)**													
3c8+NN6													
1c8+NN12	p=.001	p=.343	p<.001	p<.001	p=.036	p=.464	p=.184	p=.821	p=.37	p=.426	p=.076	p=.125	p=.052

Table A.3: Experiment 1 policy comparisons

Condition	Peto-Peto	percent @ 10^6	percent @ 10^{14}	Noticed rejection	Creation time	Creation difficult	Creation annoying	Stored password	Part 1 dropout	Part 2 dropout	Recall time	Recall success	Remember difficult
Blocklists vs. minimum-strength policies													
1c8+Pwned-fs		p=.89					p=.223	p=.987	p=.062	p=.689	p=.629	p=.257	p=.7
1c8+NN8	p<.001		p=.427	N/A	p=.648	p=.136							
1c8+NN10	p<.001		p=.002	N/A	p<.001	p=.027							
1c8+Xato-strip-cifs		p=.107				p=.409	p=.551	p>.999	p=.247	p=.937	p=.3	p=.261	p=.25
1c8+NN8	p=.009		p>.999	N/A	p=.122								
1c8+NN10	p<.001		p=.034	N/A	p=.066								
Minimum-strength and minimum-length requirement interactions													
1c10+NN8		p=.205		p=.318	p=.197	p=.827	p=.26	p=.865	p=.68	p=.913	p=.319	p=.644	p=.756
1c8+NN8	p=.628		p=.02										
1c10+NN10	p=.002		p=.08										
1c12+NN10	p=.925	p=.356			p=.1	p=.234	p=.66	p=.213	p=.67	p=.41	p=.285	p=.349	p=.982
1c10+NN10			p=.086	p=.009									
1c8+NN10			p<.001	p<.001									
1c8+NN10		p=.229		p=.076		p=.659	p=.323	p>.999	p=.38	p=.963	p=.46	p=.262	p=.829
1c10+NN10	p=.752		p=.048		p=.045								
1c8+NN8	p<.001		p=.032		p=.001								
Blocklist and composition requirement interactions													
1c8+Xato-strip-cifs													
4c8+Xato-strip-cifs	p=.855	p=.582	p=.66	N/A	p=.301	p=.452	p=.064	p=.758	p=.094	p=.75	p=.131	p=.459	p=.054
1c8+Pwned-fs													
4c8+Pwned-fs	p=.039	p=.027	p=.042	N/A	p=.206	p=.268	p=.94	p=.069	p=.93	p=.57	p=.775	p=.505	p=.699
1c8+Pwned-fs													
1c8+Xato-strip-cifs	p=.067	p=.141	p=.431	N/A	p=.04	p=.223	p=.474	p=.1	p=.015	p=.697	p=.263	p=.786	p=.061
4c8+Pwned-fs													
4c8+Xato-strip-cifs	p=.003	p=.135	p=.018	N/A	p=.062	p=.436	p=.018	p=.564	p=.408	p=.62	p=.898	p=.085	p=.789

Table A.4: Experiment 2 policy comparisons

A.7.2 Details of statistical tests

Tables 8-11 contain the detailed results of each statistical test. For Fisher's exact tests, the odds ratio estimate (OR) and its 95% confidence interval are listed. For Mann-Whitney U tests, the μ location parameter estimate and its 95% confidence interval are listed.

Comparison	Family	Details	Adj. p
Tests on guessability curves (Peto-Peto)			
Experiment 1			
3c8 v. 3c8+Xato-cifs	Impact of bl. (3c8)	χ^2=0, df=1	0.842
1c8 v. 1c8+Xato-cifs	Impact of bl. (1c8)	χ^2=1.8, df=1	0.54
1c8 v. 1c8+Pwned-fs	Impact of bl. (1c8)	χ^2=1.8, df=1	0.54
1c8 v. 1c8+Xato-scifs	Impact of bl. (1c8)	χ^2=1.2, df=1	0.54
1c8 v. 1c8+Xato-ciss	Impact of bl. (1c8)	χ^2=12, df=1	0.002
1c8+Xato-scifs v. 1c8+Xato-cifs	Bl. reqs. for 1c8	χ^2=6.9, df=1	0.017
1c8+Xato-scifs v. 1c8+Xato-ciss	Bl. reqs. for 1c8	χ^2=8.2, df=1	0.013
1c8+Xato-scifs v. 1c8+Pwned-fs	Bl. reqs. for 1c8	χ^2=0.1, df=1	0.8
3c8+NN6 v. 1c8+NN6	Comp. reqs. for min-str.	χ^2=1.1, df=1	0.586
3c8+NN6 v. 1c16+NN6	Comp. reqs. for min-str.	χ^2=0.9, df=1	0.586
3c8+NN6 v. 2c12+NN6	Comp. reqs. for min-str.	χ^2=4.2, df=1	0.119
3c8+NN6 v. 3c12+NN6	Comp. reqs. for min-str.	χ^2=5.9, df=1	0.061
1c8+NN6 v. 1c8+Xato-cifs	Bl. v. min-str.	χ^2=9.2, df=1	0.007
1c8+NN6 v. 1c8+Xato-scifs	Bl. v. min-str.	χ^2=0, df=1	$>$.999
1c8+NN6 v. 1c8+Xato-ciss	Bl. v. min-str.	χ^2=10.3, df=1	0.005
1c8+NN6 v. 1c8+Pwned-fs	Bl. v. min-str.	χ^2=0, df=1	$>$.999
3c8 (PGS3 NN) v. 3c8 (PGS++ NN)	PGS3 NN v. PGS++ NN	χ^2=11.9, df=1	0.001
4c8 (PGS3 NN) v. 4c8 (PGS++ NN)	PGS3 NN v. PGS++ NN	χ^2=18.2, df=1	$<$.001
1c8 (PGS3 NN) v. 1c8 (PGS++ NN)	PGS3 NN v. PGS++ NN	χ^2=0.3, df=1	0.56
Omnibus	Comp. reqs. only	χ^2=1.2, df=2	0.558
3c8NN6 vs 1c8NN12	Comp. reqs. for min-str. (post-hoc)	χ^2=10.8, df=1	0.001
Experiment 2			
1c8+Pwned-fs v. 1c8+NN8	Bl. v. min-str. (Pwned)	χ^2=24.1, df=1	$<$.001
1c8+Pwned-fs v. 1c8+NN10	Bl. v. min-str. (Pwned)	χ^2=64.6, df=1	$<$.001
1c8+Xato-scifs v. 1c8+NN8	Bl. v. min-str. (Xato)	χ^2=6.8, df=1	0.009
1c8+Xato-scifs v. 1c8+NN10	Bl. v. min-str. (Xato)	χ^2=40.7, df=1	$<$.001
1c10+NN8 v. 1c8+NN8	Min-str./len. req. ia. (1c10)	χ^2=0.2, df=1	0.628
1c10+NN8 v. 1c10+NN10	Min-str./len. req. ia. (1c10)	χ^2=11.1, df=1	0.002
Omnibus	Min-str./len. req. ias. (1c12)	χ^2=0.2, df=2	0.925
1c8+NN10 v. 1c10+NN10	Min-str./len. req. ias. (1c8)	χ^2=0.1, df=1	0.752
1c8+NN8 v. 1c8+NN10	Min-str./len. req. ias. (1c8)	χ^2=24.8, df=1	$<$.001
1c8+Xato-scifs v. 4c8+Xato-scifs	Bl./comp. req. ias. (Xato)	χ^2=0, df=1	0.855
1c8+Pwned-fs v. 4c8+Pwned-fs	Bl./comp. req. ias. (Pwned)	χ^2=4.3, df=1	0.039
1c8+Pwned-fs v. 1c8+Xato-scifs	Bl./comp. req. ias. (1c8)	χ^2=3.4, df=1	0.067
4c8+Pwned-fs v. 4c8+Xato-scifs	Bl./comp. req. ias. (4c8)	χ^2=9.1, df=1	0.003
Tests on the proportions of participants that noticed bl./min-str. rejection (Chi-square, FET)			
Experiment 1			
1c8+Xato-scifs v. 1c8+Xato-cifs	Bl. reqs. for 1c8	OR=0.48 ([0.21, 1.05])	0.051
1c8+Xato-scifs v. 1c8+Xato-ciss	Bl. reqs. for 1c8	OR=0.28 ([0.15, 0.50])	$<$.001
1c8+Xato-scifs v. 1c8+Pwned-fs	Bl. reqs. for 1c8	OR=0.31 ([0.16, 0.59])	$<$.001
Omnibus	Comp. reqs. for min-str.	χ^2=3.8, df=4	0.436
3c8NN6 vs 1c8NN12	Comp. reqs. for min-str. (post-hoc)	OR=0.33 ([0.21, 0.50])	$<$.001
Experiment 2			
Omnibus	Min-str./len. req. ia. (1c10)	χ^2=2.3, df=2	0.318
1c12+NN10 v. 1c10+NN10	Min-str./len. req. ias. (1c12)	OR=1.54 ([1.10, 2.16])	0.009
1c12+NN10 v. 1c8+NN10	Min-str./len. req. ias. (1c12)	OR=1.88 ([1.35, 2.64])	$<$.001
Omnibus	Min-str./len. req. ias. (1c8)	χ^2=5.2, df=2	0.076

Table A.5: Detailed statistical test results (1)

Comparison	Family	Details	Adj. p
Tests on the proportions of password guessed at 10^6 guess cutoff (Chi-square, FET)			
Experiment 1			
3c8 v. 3c8+Xato-cifs	Impact of bl. (3c8)	OR=1.18 ([0.47, 2.92])	0.835
1c8 v. 1c8+Xato-cifs	Impact of bl. (1c8)	OR=0.71 ([0.31, 1.57])	0.46
1c8 v. 1c8+Pwned-fs	Impact of bl. (1c8)	OR=0 ([0.00, 0.22])	$<$.001
1c8 v. 1c8+Xato-scifs	Impact of bl. (1c8)	OR=0.16 ([0.03, 0.54])	0.001
1c8 v. 1c8+Xato-ciss	Impact of bl. (1c8)	OR=0 ([0.00, 0.25])	$<$.001
1c8+Xato-scifs v. 1c8+Xato-cifs	Bl. reqs. for 1c8	OR=4.51 ([1.20, 25.17])	0.048
1c8+Xato-scifs v. 1c8+Xato-ciss	Bl. reqs. for 1c8	OR=Inf ([0.35, Inf])	0.498
1c8+Xato-scifs v. 1c8+Pwned-fs	Bl. reqs. for 1c8	OR=0 ([0.00, 2.53])	0.498
Omnibus	Comp. reqs. for min-str.	χ^2=5.7, df=4	0.224
1c8+NN6 v. 1c8+Xato-cifs	Bl. v. min-str.	OR=4.48 ([1.19, 25.00])	0.065
1c8+NN6 v. 1c8+Xato-scifs	Bl. v. min-str.	OR=0.99 ([0.13, 7.48])	$>$.999
1c8+NN6 v. 1c8+Xato-ciss	Bl. v. min-str.	OR=0 ([0.00, 2.83])	0.747
1c8+NN6 v. 1c8+Pwned-fs	Bl. v. min-str.	OR=0 ([0.00, 2.51])	0.747
Omnibus	Comp. reqs. only	χ^2=0.9, df=2	0.639
Omnibus	Comp. reqs. for min-str. (post-hoc)	χ^2=5.6, df=5	0.343
Experiment 2			
Omnibus	Bl. v. min-str. (Pwned)	χ^2=0.2, df=2	0.89
Omnibus	Bl. v. min-str. (Xato)	χ^2=4.5, df=2	0.107
Omnibus	Min-str./len. req. ia. (1c10)	χ^2=3.2, df=2	0.205
Omnibus	Min-str./len. req. ias. (1c12)	χ^2=2.1, df=2	0.356
Omnibus	Min-str./len. req. ias. (1c8)	χ^2=3, df=2	0.229
1c8+Xato-scifs v. 4c8+Xato-scifs	Bl./comp. req. ias. (Xato)	OR=1.49 ([0.42, 5.84])	0.582
1c8+Pwned-fs v. 4c8+Pwned-fs	Bl./comp. req. ias. (Pwned)	OR=0.24 ([0.04, 0.91])	0.027
1c8+Pwned-fs v. 1c8+Xato-scifs	Bl./comp. req. ias. (1c8)	OR=0.37 ([0.06, 1.54])	0.141
4c8+Pwned-fs v. 4c8+Xato-scifs	Bl./comp. req. ias. (4c8)	OR=2.29 ([0.73, 8.50])	0.135
Tests on the proportions of password guessed at 10^14 guess cutoff (Chi-square, FET)			
Experiment 1			
3c8 v. 3c8+Xato-cifs	Impact of bl. (3c8)	OR=0.77 ([0.54, 1.08])	0.114
1c8 v. 1c8+Xato-cifs	Impact of bl. (1c8)	OR=0.94 ([0.67, 1.32])	0.737
1c8 v. 1c8+Pwned-fs	Impact of bl. (1c8)	OR=0.78 ([0.55, 1.09])	0.267
1c8 v. 1c8+Xato-scifs	Impact of bl. (1c8)	OR=0.75 ([0.53, 1.05])	0.25
1c8 v. 1c8+Xato-ciss	Impact of bl. (1c8)	OR=0.35 ([0.24, 0.51])	$<$.001
1c8+Xato-scifs v. 1c8+Xato-cifs	Bl. reqs. for 1c8	OR=1.25 ([0.88, 1.78])	0.399
1c8+Xato-scifs v. 1c8+Xato-ciss	Bl. reqs. for 1c8	OR=2.15 ([1.46, 3.20])	$<$.001
1c8+Xato-scifs v. 1c8+Pwned-fs	Bl. reqs. for 1c8	OR=1.04 ([0.73, 1.47])	0.865
3c8+NN6 v. 1c8+NN6	Comp. reqs. for min-str.	OR=0.75 ([0.53, 1.07])	0.104
3c8+NN6 v. 1c16+NN6	Comp. reqs. for min-str.	OR=3.91 ([2.56, 6.05])	$<$.001
3c8+NN6 v. 2c12+NN6	Comp. reqs. for min-str.	OR=1.67 ([1.16, 2.41])	0.009
3c8+NN6 v. 3c12+NN6	Comp. reqs. for min-str.	OR=1.84 ([1.26, 2.71])	0.004
1c8+NN6 v. 1c8+Xato-cifs	Bl. v. min-str.	OR=0.94 ([0.66, 1.33])	0.734
1c8+NN6 v. 1c8+Xato-scifs	Bl. v. min-str.	OR=0.75 ([0.53, 1.05])	0.282
1c8+NN6 v. 1c8+Xato-ciss	Bl. v. min-str.	OR=0.35 ([0.23, 0.51])	$<$.001
1c8+NN6 v. 1c8+Pwned-fs	Bl. v. min-str.	OR=0.77 ([0.55, 1.09])	0.282
Omnibus	Comp. reqs. only	χ^2=0.9, df=2	0.635
3c8NN6 vs 1c8NN12	Comp. reqs. for min-str. (post-hoc)	OR=4.68 ([2.98, 7.49])	$<$.001
Experiment 2			
1c8+Pwned-fs v. 1c8+NN8	Bl. v. min-str. (Pwned)	OR=1.12 ([0.84, 1.51])	0.427
1c8+Pwned-fs v. 1c8+NN10	Bl. v. min-str. (Pwned)	OR=1.62 ([1.2, 2.2])	0.002
1c8+Xato-scifs v. 1c8+NN8	Bl. v. min-str. (Xato)	OR=1 ([0.74, 1.34])	$>$.999
1c8+Xato-scifs v. 1c8+NN10	Bl. v. min-str. (Xato)	OR=1.44 ([1.06, 1.96])	0.034
1c10+NN8 v. 1c8+NN8	Min-str./len. req. ia. (1c10)	OR=1.49 ([1.10, 2.04])	0.02
1c10+NN8 v. 1c10+NN10	Min-str./len. req. ia. (1c10)	OR=1.33 ([0.96, 1.85])	0.08
1c12+NN10 v. 1c10+NN10	Min-str./len. req. ias. (1c12)	OR=1.36 ([0.96, 1.94])	0.086
1c12+NN10 v. 1c8+NN10	Min-str./len. req. ias. (1c12)	OR=1.87 ([1.33, 2.65])	$<$.001
1c8+NN10 v. 1c10+NN10	Min-str./len. req. ias. (1c8)	OR=1.38 ([1.00, 1.91])	0.048
1c8+NN8 v. 1c8+NN10	Min-str./len. req. ias. (1c8)	OR=1.45 ([1.06, 1.97])	0.032
1c8+Xato-scifs v. 4c8+Xato-scifs	Bl./comp. req. ias. (Xato)	OR=0.93 ([0.69, 1.26])	0.66
1c8+Pwned-fs v. 4c8+Pwned-fs	Bl./comp. req. ias. (Pwned)	OR=0.74 ([0.55, 0.99])	0.042
1c8+Pwned-fs v. 1c8+Xato-scifs	Bl./comp. req. ias. (1c8)	OR=1.12 ([0.84, 1.50])	0.431
4c8+Pwned-fs v. 4c8+Xato-scifs	Bl./comp. req. ias. (4c8)	OR=1.43 ([1.05, 1.93])	0.018

Table A.6: Detailed statistical test results (2)

Comparison	Family	Details	Adj. p
Tests on password-creation time (KW, MWU)			
Experiment 1			
3c8 v. 3c8+Xato-cifs	Impact of bl. (3c8)	W=48150, μ=0.6 ([-7.8, 9.2])	0.895
1c8 v. 1c8+Xato-cifs	Impact of bl. (1c8)	W=50088, μ=9.2 ([0.5, 18.2])	0.114
1c8 v. 1c8+Pwned-fs	Impact of bl. (1c8)	W=47202, μ=1.5 ([-7.4, 10.8])	0.722
1c8 v. 1c8+Xato-scifs	Impact of bl. (1c8)	W=46983, μ=-5.1 ([-15.1, 4.3])	0.558
1c8 v. 1c8+Xato-ciss	Impact of bl. (1c8)	W=28044, μ=-46.3 ([-61.5, -32.1])	$<$.001
1c8+Xato-scifs v. 1c8+Xato-cifs	Bl. reqs. for 1c8	W=37932, μ=-15.2 ([-25.1, -5.7])	0.003
1c8+Xato-scifs v. 1c8+Xato-ciss	Bl. reqs. for 1c8	W=29159, μ=-41.0 ([-56.4, -26.9])	$<$.001
1c8+Xato-scifs v. 1c8+Pwned-fs	Bl. reqs. for 1c8	W=42266, μ=-7.4 ([-17.0, 2.2])	0.142
3c8+NN6 v. 1c8+NN6	Comp. reqs. for min-str.	W=43247, μ=13.2 ([3.9, 22.5])	0.021
3c8+NN6 v. 1c16+NN6	Comp. reqs. for min-str.	W=34605, μ=-4.9 ([-14.3, 4.5])	0.38
3c8+NN6 v. 2c12+NN6	Comp. reqs. for min-str.	W=41301, μ=6.2 ([-3.1, 15.6])	0.38
3c8+NN6 v. 3c12+NN6	Comp. reqs. for min-str.	W=30818, μ=-9.2 ([-19.5, 0.8])	0.212
1c8+NN6 v. 1c8+Xato-cifs	Bl. v. min-str.	W=43028, μ=3.4 ([-4.5, 11.6])	0.609
1c8+NN6 v. 1c8+Xato-scifs	Bl. v. min-str.	W=39777, μ=-11.6 ([-21.7, -2.0])	0.054
1c8+NN6 v. 1c8+Xato-ciss	Bl. v. min-str.	W=23233, μ=-52.5 ([-67.8, -38.6])	$<$.001
1c8+NN6 v. 1c8+Pwned-fs	Bl. v. min-str.	W=39974, μ=-4.6 ([-13.5, 4.2])	0.609
Omnibus	Comp. reqs. only	χ^2=0.231, df=2	0.891
3c8NN6 vs 1c8NN12	Comp. reqs. for min-str. (post-hoc)	W=30801, μ=-11.6 ([-23.1, -0.8])	0.036
Experiment 2			
1c8+Pwned-fs v. 1c8+NN8	Bl. v. min-str. (Pwned)	W=81334, μ=-1.8 ([-9.4, 5.8])	0.648
1c8+Pwned-fs v. 1c8+NN10	Bl. v. min-str. (Pwned)	W=69655, μ=-18.4 ([-27.7, -9.6])	$<$.001
1c8+Xato-scifs v. 1c8+NN8	Bl. v. min-str. (Xato)	W=87868, μ=6.5 ([-1.8, 15.2])	0.122
1c8+Xato-scifs v. 1c8+NN10	Bl. v. min-str. (Xato)	W=76348, μ=-10.1 ([-19.5, -0.8])	0.066
Omnibus	Min-str./len. req. ia. (1c10)	χ^2=3.25, df=2	0.197
Omnibus	Min-str./len. req. ias. (1c12)	χ^2=4.61, df=2	0.1
1c8+NN10 v. 1c10+NN10	Min-str./len. req. ias. (1c8)	W=83571, μ=9.4 ([0.2, 18.8])	0.045
1c8+NN8 v. 1c8+NN10	Min-str./len. req. ias. (1c8)	W=62294, μ=-16.6 ([-26.4, -7.5])	0.001
1c8+Xato-scifs v. 4c8+Xato-scifs	Bl./comp. req. ias. (Xato)	W=83838, μ=-4.7 ([-13.7, 4.2])	0.301
1c8+Pwned-fs v. 4c8+Pwned-fs	Bl./comp. req. ias. (Pwned)	W=77992, μ=-5.0 ([-12.8, 2.9])	0.206
1c8+Pwned-fs v. 1c8+Xato-scifs	Bl./comp. req. ias. (1c8)	W=86778, μ=-8.4 ([-16.7, -0.4])	0.04
4c8+Pwned-fs v. 4c8+Xato-scifs	Bl./comp. req. ias. (4c8)	W=70276, μ=-8.3 ([-17.4, 0.4])	0.062
Tests on password-creation difficulty (Chi-square, FET)			
Experiment 1			
3c8 v. 3c8+Xato-cifs	Impact of bl. (3c8)	OR=1.02 ([0.7, 1.5])	0.926
1c8 v. 1c8+Xato-cifs	Impact of bl. (1c8)	OR=0.94 ([0.64, 1.38])	$>$.999
1c8 v. 1c8+Pwned-fs	Impact of bl. (1c8)	OR=1.01 ([0.69, 1.49])	$>$.999
1c8 v. 1c8+Xato-scifs	Impact of bl. (1c8)	OR=0.86 ([0.59, 1.25])	$>$.999
1c8 v. 1c8+Xato-ciss	Impact of bl. (1c8)	OR=0.34 ([0.23, 0.49])	$<$.001
1c8+Xato-scifs v. 1c8+Xato-cifs	Bl. reqs. for 1c8	OR=0.92 ([0.63, 1.35])	0.808
1c8+Xato-scifs v. 1c8+Xato-ciss	Bl. reqs. for 1c8	OR=0.39 ([0.27, 0.56])	$<$.001
1c8+Xato-scifs v. 1c8+Pwned-fs	Bl. reqs. for 1c8	OR=0.85 ([0.58, 1.25])	0.808
3c8+NN6 v. 1c8+NN6	Comp. reqs. for min-str.	OR=1.72 ([1.16, 2.56])	0.022
3c8+NN6 v. 1c16+NN6	Comp. reqs. for min-str.	OR=0.83 ([0.57, 1.19])	0.643
3c8+NN6 v. 2c12+NN6	Comp. reqs. for min-str.	OR=1.38 ([0.95, 2.03])	0.281
3c8+NN6 v. 3c12+NN6	Comp. reqs. for min-str.	OR=1.11 ([0.75, 1.63])	0.643
1c8+NN6 v. 1c8+Xato-cifs	Bl. v. min-str.	OR=0.82 ([0.55, 1.23])	0.66
1c8+NN6 v. 1c8+Xato-scifs	Bl. v. min-str.	OR=0.76 ([0.51, 1.12])	0.47
1c8+NN6 v. 1c8+Xato-ciss	Bl. v. min-str.	OR=0.3 ([0.20, 0.44])	$<$.001
1c8+NN6 v. 1c8+Pwned-fs	Bl. v. min-str.	OR=0.89 ([0.59, 1.33])	0.66
Omnibus	Comp. reqs. only	χ^2=4.2, df=2	0.124
3c8NN6 vs 1c8NN12	Comp. reqs. for min-str. (post-hoc)	OR=0.87 ([0.60, 1.27])	0.464
Experiment 2			
1c8+Pwned-fs v. 1c8+NN8	Bl. v. min-str. (Pwned)	OR=0.78 ([0.57, 1.08])	0.136
1c8+Pwned-fs v. 1c8+NN10	Bl. v. min-str. (Pwned)	OR=0.68 ([0.50, 0.93])	0.027
Omnibus	Bl. v. min-str. (Xato)	χ^2=1.8, df=2	0.409
Omnibus	Min-str./len. req. ia. (1c10)	χ^2=0.4, df=2	0.827
Omnibus	Min-str./len. req. ias. (1c12)	χ^2=2.9, df=2	0.234
Omnibus	Min-str./len. req. ias. (1c8)	χ^2=0.8, df=2	0.659
1c8+Xato-scifs v. 4c8+Xato-scifs	Bl./comp. req. ias. (Xato)	OR=0.89 ([0.65, 1.21])	0.452
1c8+Pwned-fs v. 4c8+Pwned-fs	Bl./comp. req. ias. (Pwned)	OR=0.84 ([0.61, 1.15])	0.268
1c8+Pwned-fs v. 1c8+Xato-scifs	Bl./comp. req. ias. (1c8)	OR=0.83 ([0.61, 1.13])	0.223
4c8+Pwned-fs v. 4c8+Xato-scifs	Bl./comp. req. ias. (4c8)	OR=0.88 ([0.64, 1.21])	0.436

Table A.7: Detailed statistical test results (3)

Comparison	Family	Details	Adj. p
Tests on password-creation annoyance (Chi-square, FET)			
Experiment 1			
3c8 v. 3c8+Xato-cifs	Impact of bl. (3c8)	OR=1.15 ([0.82, 1.62])	0.449
1c8 v. 1c8+Xato-cifs	Impact of bl. (1c8)	OR=0.82 ([0.57, 1.19])	0.574
1c8 v. 1c8+Pwned-fs	Impact of bl. (1c8)	OR=1 ([0.69, 1.44])	>.999
1c8 v. 1c8+Xato-scifs	Impact of bl. (1c8)	OR=0.73 ([0.51, 1.04])	0.215
1c8 v. 1c8+Xato-ciss	Impact of bl. (1c8)	OR=0.44 ([0.31, 0.63])	<.001
1c8+Xato-scifs v. 1c8+Xato-cifs	Bl. reqs. for 1c8	OR=0.89 ([0.62, 1.26])	0.544
1c8+Xato-scifs v. 1c8+Xato-ciss	Bl. reqs. for 1c8	OR=0.61 ([0.43, 0.86])	0.011
1c8+Xato-scifs v. 1c8+Pwned-fs	Bl. reqs. for 1c8	OR=0.73 ([0.51, 1.05])	0.161
3c8+NN6 v. 1c8+NN6	Comp. reqs. for min-str.	OR=1.26 ([0.87, 1.81])	0.636
3c8+NN6 v. 1c16+NN6	Comp. reqs. for min-str.	OR=0.76 ([0.53, 1.09])	0.467
3c8+NN6 v. 2c12+NN6	Comp. reqs. for min-str.	OR=1.24 ([0.86, 1.78])	0.636
3c8+NN6 v. 3c12+NN6	Comp. reqs. for min-str.	OR=1.02 ([0.71, 1.48])	0.928
1c8+NN6 v. 1c8+Xato-cifs	Bl. v. min-str.	OR=1.03 ([0.71, 1.48])	>.999
1c8+NN6 v. 1c8+Xato-scifs	Bl. v. min-str.	OR=0.91 ([0.64, 1.30])	>.999
1c8+NN6 v. 1c8+Xato-ciss	Bl. v. min-str.	OR=0.55 ([0.38, 0.79])	0.003
1c8+NN6 v. 1c8+Pwned-fs	Bl. v. min-str.	OR=1.24 ([0.86, 1.80])	0.724
3c8 v. 4c8	Comp. reqs. only	OR=1.1 ([0.78, 1.57])	0.604
3c8 v. 1c8	Comp. reqs. only	OR=1.53 ([1.07, 2.19])	0.037
3c8NN6 vs 1c8NN12	Comp. reqs. for min-str. (post-hoc)	OR=0.79 ([0.55, 1.13])	0.184
Experiment 2			
Omnibus	Bl. v. min-str. (Pwned)	χ^2=3, df=2	0.223
Omnibus	Bl. v. min-str. (Xato)	χ^2=1.2, df=2	0.551
Omnibus	Min-str./len. req. ia. (1c10)	χ^2=2.7, df=2	0.26
Omnibus	Min-str./len. req. ias. (1c12)	χ^2=0.8, df=2	0.66
Omnibus	Min-str./len. req. ias. (1c8)	χ^2=2.3, df=2	0.323
1c8+Xato-scifs v. 4c8+Xato-scifs	Bl./comp. req. ias. (Xato)	OR=0.76 ([0.57, 1.02])	0.064
1c8+Pwned-fs v. 4c8+Pwned-fs	Bl./comp. req. ias. (Pwned)	OR=0.98 ([0.72, 1.33])	0.94
1c8+Pwned-fs v. 1c8+Xato-scifs	Bl./comp. req. ias. (1c8)	OR=0.9 ([0.67, 1.20])	0.474
4c8+Pwned-fs v. 4c8+Xato-scifs	Bl./comp. req. ias. (4c8)	OR=0.7 ([0.52, 0.94])	0.018
Tests on password storage after creation (Chi-square, FET)			
Experiment 1			
3c8 v. 3c8+Xato-cifs	Impact of bl. (3c8)	OR=1.15 ([0.79, 1.66])	0.941
Omnibus	Impact of bl. (1c8)	χ^2=10.4, df=4	0.07
1c8 v. 1c8+Xato-cifs	Impact of bl. (1c8)	OR=0.97 ([0.67, 1.41])	>.999
1c8 v. 1c8+Pwned-fs	Impact of bl. (1c8)	OR=1.05 ([0.72, 1.52])	>.999
1c8 v. 1c8+Xato-scifs	Impact of bl. (1c8)	OR=1 ([0.70, 1.43])	>.999
1c8 v. 1c8+Xato-ciss	Impact of bl. (1c8)	OR=0.6 ([0.4, 0.9])	0.038
1c8+Xato-scifs v. 1c8+Xato-cifs	Bl. reqs. for 1c8	OR=1.03 ([0.72, 1.48])	>.999
1c8+Xato-scifs v. 1c8+Xato-ciss	Bl. reqs. for 1c8	OR=0.6 ([0.41, 0.89])	0.031
1c8+Xato-scifs v. 1c8+Pwned-fs	Bl. reqs. for 1c8	OR=0.95 ([0.66, 1.37])	>.999
Omnibus	Comp. reqs. for min-str.	χ^2=2.2, df=4	0.705
1c8+NN6 v. 1c8+Xato-cifs	Bl. v. min-str.	OR=0.88 ([0.60, 1.28])	>.999
1c8+NN6 v. 1c8+Xato-scifs	Bl. v. min-str.	OR=0.9 ([0.62, 1.30])	>.999
1c8+NN6 v. 1c8+Xato-ciss	Bl. v. min-str.	OR=0.54 ([0.36, 0.82])	0.01
1c8+NN6 v. 1c8+Pwned-fs	Bl. v. min-str.	OR=0.94 ([0.65, 1.38])	>.999
Omnibus	Comp. reqs. only	χ^2=5.1, df=2	0.157
Omnibus	Comp. reqs. for min-str. (post-hoc)	χ^2=3.6, df=5	0.821
Experiment 2			
Omnibus	Bl. v. min-str. (Pwned)	χ^2=1.4, df=2	0.987
Omnibus	Bl. v. min-str. (Xato)	χ^2=1.4, df=2	>.999
Omnibus	Min-str./len. req. ia. (1c10)	χ^2=0.3, df=2	0.865
Omnibus	Min-str./len. req. ias. (1c12)	χ^2=4.5, df=2	0.213
Omnibus	Min-str./len. req. ias. (1c8)	χ^2=0.4, df=2	>.999
1c8+Xato-scifs v. 4c8+Xato-scifs	Bl./comp. req. ias. (Xato)	OR=1.15 ([0.83, 1.60])	0.758
1c8+Pwned-fs v. 4c8+Pwned-fs	Bl./comp. req. ias. (Pwned)	OR=0.7 ([0.50, 0.98])	0.069
1c8+Pwned-fs v. 1c8+Xato-scifs	Bl./comp. req. ias. (1c8)	OR=0.73 ([0.53, 1.01])	0.1
4c8+Pwned-fs v. 4c8+Xato-scifs	Bl./comp. req. ias. (4c8)	OR=1.2 ([0.86, 1.69])	0.564

Table A.8: Detailed statistical test results (4)

Comparison	Family	Details	Adj. p
Tests on Part 1 participant dropout rate (Chi-square, FET)			
Experiment 1			
3c8 v. 3c8+Xato-cifs	Impact of bl. (3c8)	OR=1.52 ([0.95, 2.45])	0.07
1c8+Xato-scifs v. 1c8+Xato-cifs	Bl. reqs. for 1c8	OR=1.19 ([0.74, 1.91])	0.988
1c8+Xato-scifs v. 1c8+Xato-ciss	Bl. reqs. for 1c8	OR=0.38 ([0.25, 0.58])	$<$.001
1c8+Xato-scifs v. 1c8+Pwned-fs	Bl. reqs. for 1c8	OR=1.06 ([0.66, 1.73])	0.988
Omnibus	Comp. reqs. for min-str.	χ^2=5.1, df=4	0.272
1c8+NN6 v. 1c8+Xato-cifs	Bl. v. min-str.	OR=0.69 ([0.41, 1.14])	0.45
1c8+NN6 v. 1c8+Xato-scifs	Bl. v. min-str.	OR=0.82 ([0.49, 1.36])	0.654
1c8+NN6 v. 1c8+Xato-ciss	Bl. v. min-str.	OR=0.31 ([0.20, 0.49])	$<$.001
1c8+NN6 v. 1c8+Pwned-fs	Bl. v. min-str.	OR=0.77 ([0.46, 1.28])	0.654
Omnibus	Comp. reqs. only	χ^2=3.5, df=2	0.174
Omnibus	Comp. reqs. for min-str. (post-hoc)	χ^2=5.4, df=5	0.37
Experiment 2			
Omnibus	Bl. v. min-str. (Pwned)	χ^2=5.6, df=2	0.062
Omnibus	Bl. v. min-str. (Xato)	χ^2=2.8, df=2	0.247
Omnibus	Min-str./len. req. ia. (1c10)	χ^2=0.8, df=2	0.68
Omnibus	Min-str./len. req. ias. (1c12)	χ^2=0.8, df=2	0.67
Omnibus	Min-str./len. req. ias. (1c8)	χ^2=1.9, df=2	0.38
1c8+Xato-scifs v. 4c8+Xato-scifs	Bl./comp. req. ias. (Xato)	OR=0.71 ([0.47, 1.07])	0.094
1c8+Pwned-fs v. 4c8+Pwned-fs	Bl./comp. req. ias. (Pwned)	OR=0.97 ([0.68, 1.40])	0.93
1c8+Pwned-fs v. 1c8+Xato-scifs	Bl./comp. req. ias. (1c8)	OR=1.59 ([1.08, 2.36])	0.015
4c8+Pwned-fs v. 4c8+Xato-scifs	Bl./comp. req. ias. (4c8)	OR=1.17 ([0.8, 1.7])	0.408
Tests on Part 2 participant dropout rate (Chi-square, FET)			
Experiment 1			
3c8 v. 3c8+Xato-cifs	Impact of bl. (3c8)	OR=0.66 ([0.43, 1.00])	0.047
1c8 v. 1c8+Xato-cifs	Impact of bl. (1c8)	OR=1.42 ([0.92, 2.21])	0.290
1c8 v. 1c8+Pwned-fs	Impact of bl. (1c8)	OR=1.32 ([0.86, 2.02])	0.436
1c8 v. 1c8+Xato-scifs	Impact of bl. (1c8)	OR=1.65 ([1.07, 2.57])	0.086
1c8 v. 1c8+Xato-ciss	Impact of bl. (1c8)	OR=0.89 ([0.59, 1.35])	0.616
1c8+Xato-scifs v. 1c8+Xato-cifs	Bl. reqs. for 1c8	OR=1.16 ([0.72, 1.86])	0.738
1c8+Xato-scifs v. 1c8+Xato-ciss	Bl. reqs. for 1c8	OR=0.54 ([0.34, 0.85])	0.015
1c8+Xato-scifs v. 1c8+Pwned-fs	Bl. reqs. for 1c8	OR=1.25 ([0.79, 2.00])	0.738
Omnibus	Comp. reqs. for min-str.	χ^2=4.2, df=4	0.385
1c8+NN6 v. 1c8+Xato-cifs	Bl. v. min-str.	OR=1.35 ([0.86, 2.12])	0.585
1c8+NN6 v. 1c8+Xato-scifs	Bl. v. min-str.	OR=1.56 ([1.00, 2.46])	0.203
1c8+NN6 v. 1c8+Xato-ciss	Bl. v. min-str.	OR=0.84 ([0.55, 1.29])	0.678
1c8+NN6 v. 1c8+Pwned-fs	Bl. v. min-str.	OR=1.25 ([0.80, 1.94])	0.678
Omnibus	Comp. reqs. only	χ^2=1.8, df=2	0.414
Omnibus	Comp. reqs. for min-str. (post-hoc)	χ^2=4.9, df=5	0.426
Experiment 2			
Omnibus	Bl. v. min-str. (Pwned)	χ^2=0.7, df=2	0.689
Omnibus	Bl. v. min-str. (Xato)	χ^2=0.1, df=2	0.937
Omnibus	Min-str./len. req. ia. (1c10)	χ^2=0.2, df=2	0.913
Omnibus	Min-str./len. req. ias. (1c12)	χ^2=1.8, df=2	0.41
Omnibus	Min-str./len. req. ias. (1c8)	χ^2=0.1, df=2	0.963
1c8+Xato-scifs v. 4c8+Xato-scifs	Bl./comp. req. ias. (Xato)	OR=0.94 ([0.68, 1.30])	0.75
1c8+Pwned-fs v. 4c8+Pwned-fs	Bl./comp. req. ias. (Pwned)	OR=1.11 ([0.80, 1.54])	0.570
1c8+Pwned-fs v. 1c8+Xato-scifs	Bl./comp. req. ias. (1c8)	OR=1.07 ([0.78, 1.47])	0.697
4c8+Pwned-fs v. 4c8+Xato-scifs	Bl./comp. req. ias. (4c8)	OR=0.91 ([0.65, 1.28])	0.62
Tests on password-recall time in Part 2 (KW, MWU)			
Experiment 1			
3c8 v. 3c8+Xato-cifs	Impact of bl. (3c8)	W=4512, μ=3.3 ([-0.8, 7.3])	0.101
1c8 v. 1c8+Xato-cifs	Impact of bl. (1c8)	W=3703, μ=1.8 ([-1.9, 5.5])	0.570
1c8 v. 1c8+Pwned-fs	Impact of bl. (1c8)	W=3655, μ=-2.8 ([-6.8, 0.9])	0.418
1c8 v. 1c8+Xato-scifs	Impact of bl. (1c8)	W=3541, μ=-4.0 ([-8.5, 0.3])	0.290
1c8 v. 1c8+Xato-ciss	Impact of bl. (1c8)	W=1629, μ=-2.8 ([-8.3, 2.2])	0.570
1c8+Xato-scifs v. 1c8+Xato-cifs	Bl. reqs. for 1c8	W=2649, μ=-5.7 ([-10.4, -1.6])	0.016
1c8+Xato-scifs v. 1c8+Xato-ciss	Bl. reqs. for 1c8	W=1957, μ=0.8 ([-4.6, 6.5])	$>$.999
1c8+Xato-scifs v. 1c8+Pwned-fs	Bl. reqs. for 1c8	W=4194, μ=-0.7 ([-5.3, 3.3])	$>$.999
Omnibus	Comp. reqs. for min-str.	χ^2=8.23, df=4	0.084
1c8+NN6 v. 1c8+Xato-cifs	Bl. v. min-str.	W=3809, μ=3.0 ([-0.2, 6.4])	0.279
1c8+NN6 v. 1c8+Xato-scifs	Bl. v. min-str.	W=3573, μ=-2.6 ([-7.1, 1.4])	0.658
1c8+NN6 v. 1c8+Xato-ciss	Bl. v. min-str.	W=1629, μ=-1.6 ([-6.6, 3.1])	0.683
1c8+NN6 v. 1c8+Pwned-fs	Bl. v. min-str.	W=3669, μ=-1.7 ([-5.4, 2.0])	0.683
Omnibus	Comp. reqs. only	χ^2=4.57, df=2	0.102
Omnibus	Comp. reqs. for min-str. (post-hoc)	χ^2=9.98, df=5	0.076
Experiment 2			
Omnibus	Bl. v. min-str. (Pwned)	χ^2=0.927, df=2	0.629
Omnibus	Bl. v. min-str. (Xato)	χ^2=2.41, df=2	0.3
Omnibus	Min-str./len. req. ia. (1c10)	χ^2=2.28, df=2	0.319
Omnibus	Min-str./len. req. ias. (1c12)	χ^2=2.51, df=2	0.285
Omnibus	Min-str./len. req. ias. (1c8)	χ^2=1.55, df=2	0.46
1c8+Xato-scifs v. 4c8+Xato-scifs	Bl./comp. req. ias. (Xato)	W=4798, μ=-3.0 ([-7.1, 0.9])	0.131
1c8+Pwned-fs v. 4c8+Pwned-fs	Bl./comp. req. ias. (Pwned)	W=5188, μ=-0.6 ([-5.0, 4.1])	0.775
1c8+Pwned-fs v. 1c8+Xato-scifs	Bl./comp. req. ias. (1c8)	W=6514, μ=2.4 ([-1.5, 6.9])	0.263
4c8+Pwned-fs v. 4c8+Xato-scifs	Bl./comp. req. ias. (4c8)	W=4790, μ=-0.3 ([-4.7, 4.2])	0.898

Table A.9: Detailed statistical test results (5)

Comparison	Family	Details	Adj. p
Tests on recall success in Part 2 (Chi-square, FET)			
Experiment 1			
3c8 v. 3c8+Xato-cifs	Impact of bl. (3c8)	OR=1.28 ([0.65, 2.54])	0.524
Omnibus	Impact of bl. (1c8)	χ^2=8.5, df=4	0.076
1c8+Xato-scifs v. 1c8+Xato-cifs	Bl. reqs. for 1c8	OR=0.89 ([0.44, 1.78])	0.745
1c8+Xato-scifs v. 1c8+Xato-ciss	Bl. reqs. for 1c8	OR=1.81 ([0.85, 3.83])	0.31
1c8+Xato-scifs v. 1c8+Pwned-fs	Bl. reqs. for 1c8	OR=1.66 ([0.79, 3.63])	0.332
Omnibus	Comp. reqs. for min-str.	χ^2=8.6, df=4	0.071
Omnibus	Bl. v. min-str.	χ^2=8.5, df=4	0.074
Omnibus	Comp. reqs. only	χ^2=0.7, df=2	0.711
Omnibus	Comp. reqs. for min-str. (post-hoc)	χ^2=8.6, df=5	0.125
Experiment 2			
Omnibus	Bl. v. min-str. (Pwned)	χ^2=2.7, df=2	0.257
Omnibus	Bl. v. min-str. (Xato)	χ^2=2.7, df=2	0.261
Omnibus	Min-str./len. req. ia. (1c10)	χ^2=0.9, df=2	0.644
Omnibus	Min-str./len. req. ias. (1c12)	χ^2=2.1, df=2	0.349
Omnibus	Min-str./len. req. ias. (1c8)	χ^2=2.7, df=2	0.262
1c8+Xato-scifs v. 4c8+Xato-scifs	Bl./comp. req. ias. (Xato)	OR=0.78 ([0.41, 1.46])	0.459
1c8+Pwned-fs v. 4c8+Pwned-fs	Bl./comp. req. ias. (Pwned)	OR=1.2 ([0.69, 2.11])	0.505
1c8+Pwned-fs v. 1c8+Xato-scifs	Bl./comp. req. ias. (1c8)	OR=0.93 ([0.52, 1.64])	0.786
4c8+Pwned-fs v. 4c8+Xato-scifs	Bl./comp. req. ias. (4c8)	OR=0.6 ([0.32, 1.11])	0.085
Tests on password-remembrance difficulty (Chi-square, FET)			
Experiment 1			
3c8 v. 3c8+Xato-cifs	Impact of bl. (3c8)	OR=0.65 ([0.34, 1.25])	0.176
Omnibus	Impact of bl. (1c8)	χ^2=6.3, df=4	0.179
Omnibus	Bl. reqs. for 1c8	χ^2=5.5, df=2	0.064
Omnibus	Comp. reqs. for min-str.	χ^2=6.5, df=4	0.163
Omnibus	Bl. v. min-str.	χ^2=6.6, df=4	0.156
Omnibus	Comp. reqs. only	χ^2=4.5, df=2	0.103
Omnibus	Comp. reqs. for min-str. (post-hoc)	χ^2=10.9, df=5	0.052
Experiment 2			
Omnibus	Bl. v. min-str. (Pwned)	χ^2=0.7, df=2	0.7
Omnibus	Bl. v. min-str. (Xato)	χ^2=2.8, df=2	0.25
Omnibus	Min-str./len. req. ia. (1c10)	χ^2=0.6, df=2	0.756
Omnibus	Min-str./len. req. ias. (1c12)	χ^2=0, df=2	0.982
Omnibus	Min-str./len. req. ias. (1c8)	χ^2=0.4, df=2	0.829
1c8+Xato-scifs v. 4c8+Xato-scifs	Bl./comp. req. ias. (Xato)	OR=0.580 ([0.32, 1.03])	0.054
1c8+Pwned-fs v. 4c8+Pwned-fs	Bl./comp. req. ias. (Pwned)	OR=0.9 ([0.53, 1.55])	0.699
1c8+Pwned-fs v. 1c8+Xato-scifs	Bl./comp. req. ias. (1c8)	OR=1.72 ([0.98, 3.05])	0.061
4c8+Pwned-fs v. 4c8+Xato-scifs	Bl./comp. req. ias. (4c8)	OR=1.1 ([0.63, 1.92])	0.789

Table A.10: Detailed statistical test results (6)

Appendix B

Additional details for text-based password feedback study

B.1 Leaked-password datasets

PGS3 data

```
Total pwds: 32,869,155
Total unique pwds: 21,471,379

Password lengths:
        Length 8: 10843079 (32.99%)
        Length 9: 7067953 (21.50%)
        Length 10: 5677190 (17.27%)
        Length 11: 3214704 (9.78%)
        Length 12: 2137620 (6.50%)
        Length 13: 1157739 (3.52%)
        Length 14: 779533 (2.37%)
        Length 15: 484495 (1.47%)
        Length 16: 858979 (2.61%)
        Length 17: 154326 (0.47%)
        Length 18: 109365 (0.33%)
        Length 19: 80230 (0.24%)
        Length 20: 73158 (0.22%)
        Length 21: 51318 (0.16%)
        Length 22: 42628 (0.13%)
        Length 23: 33886 (0.10%)
        Length 24: 29191 (0.09%)
        Length 25: 19401 (0.06%)
        Length 26: 14553 (0.04%)
        Length 27: 10217 (0.03%)
        Length 28: 7354 (0.02%)
        Length 29: 5169 (0.02%)
        Length 30+: 17067 (0.05%)

Character classes:
        4 classes: 559083 (1.70%)
        3 classes: 5223347 (15.89%)
                lower/upper/symbol: 72611 (1.39%)
                lower/upper/number: 4153038 (79.51%)
                lower/symbol/number: 961512 (18.41%)
                upper/symbol/number: 36186 (0.69%)
        2 classes: 20542395 (62.50%)
                lower/upper: 286586 (1.40%)
                lower/number: 19295750 (93.93%)
                lower/symbol: 488963 (2.38%)
                upper/number: 380017 (1.85%)
                upper/symbol: 12253 (0.06%)
                number/symbol: 78826 (0.38%)
        1 class: 6544330 (19.91%)
                lower: 5236833 (80.02%)
                upper: 104021 (1.59%)
                symbol: 1359 (0.02%)
                number: 1202117 (18.37%)
```

PGS3max12 data (autoencoder training data)

```
Total pwds: 28,940,546
Total unique pwds: 18,187,327 (62.84%)

Password lengths:
        Length 8: 10843079 (37.47%)
        Length 9: 7067953 (24.42%)
        Length 10: 5677190 (19.62%)
        Length 11: 3214704 (11.11%)
        Length 12: 2137620 (7.39%)

Character classes:
        4 classes: 456689 (1.58%)
        3 classes: 3894954 (13.46%)
                lower/upper/symbol: 57024 (1.46%)
                lower/upper/number: 3120665 (80.12%)
                lower/symbol/number: 687212 (17.64%)
                upper/symbol/number: 30053 (0.77%)
        2 classes: 18393148 (63.55%)
                lower/upper: 233278 (1.27%)
                lower/number: 17477814 (95.02%)
                lower/symbol: 269701 (1.47%)
                upper/number: 341798 (1.86%)
                upper/symbol: 9413 (0.05%)
                number/symbol: 61144 (0.33%)
        1 class: 6195755 (21.41%)
                lower: 4915637 (79.34%)
                upper: 98239 (1.59%)
                symbol: 1221 (0.02%)
                number: 1180658 (19.06%)

Strength bins:
        Very weak: 1538322 (5.32%) [unique: 987 (0.01%)]
        Weak: 6342759 (21.92%) [unique: 780562 (4.29%)]
        Fair: 8381087 (28.96%) [unique: 6297008 (34.62%)]
        Good: 10646592 (36.79%) [unique: 9222816 (50.71%)]
        Strong: 2031786 (7.02%) [unique: 1885954 (10.37%)]
```

B.2 Fuzzy c-means predictions using neural network layers

Here we describe how we implemented fuzzy c-means cluster-membership predictions as a series of neural network layers.

We first fit a fuzzy c-means clustering model to the *PGS3max12* dataset as described in Section 4.2.2. The output of this step is a set of centroids, one for each fuzzy c-means cluster.

We create a new neural network model for each password. This is fast and can be done in real-time because there is no additional training needed once the password encoder has been trained and the fuzzy c-means clustering model has been fit. For a given input password, we augment the trained password encoder neural network with additional layers for computing cluster memberships. These layers compute the Euclidean distance of the input password encoding to each cluster centroid and then turns those distances into soft assignments via a normalization step. We compute squared Euclidean distances of the input password to each cluster centroid using Keras dense, lambda, and merge layers that implement the linear transformation $Wx + b$, where x is the password encoding for the input, $W = -2 * centroids$ and $b = L2(centroids)^2 + L2(encode(x))^2$.

We compared the cluster memberships output by the clustering neural network model to those reported by our scikit-fuzzy fuzzy c-means implementation. We verified both approaches produced the same clustering predictions, modulo small differences due to numerical rounding.

B.3 Clustering

We experimented with clustering models that differed in the number of clusters and the configured fuzzification parameter. As shown in Figure B.1, the fuzzy partition coefficient (FPC) metric did not lead to useful insights for selecting a particular number of clusters. We did not observe an "elbow" that would indicate an optimal number of clusters for separating the data; rather, FPC values continued to decrease as the number of clusters was increased.

B.3.1 Summary of clustering results

Hard-assignment distribution:

```
Cluster 0: 858790 (2.97%)
Cluster 1: 787485 (2.72%)
Cluster 2: 1028605 (3.55%)
Cluster 3: 1097077 (3.79%)
Cluster 4: 1014120 (3.50%)
Cluster 5: 1311330 (4.53%)
Cluster 6: 1014019 (3.50%)
Cluster 7: 994983 (3.44%)
Cluster 8: 400130 (1.38%)
Cluster 9: 1007341 (3.48%)
Cluster 10: 1011484 (3.50%)
Cluster 11: 1135410 (3.92%)
Cluster 12: 840012 (2.90%)
Cluster 13: 904104 (3.12%)
Cluster 14: 663690 (2.29%)
Cluster 15: 676601 (2.34%)
Cluster 16: 801397 (2.77%)
Cluster 17: 739729 (2.56%)
Cluster 18: 1368455 (4.73%)
Cluster 19: 957397 (3.31%)
Cluster 20: 1252495 (4.33%)
Cluster 21: 1069204 (3.69%)
Cluster 22: 1453659 (5.02%)
Cluster 23: 819021 (2.83%)
Cluster 24: 654336 (2.26%)
Cluster 25: 659544 (2.28%)
Cluster 26: 1118178 (3.86%)
Cluster 27: 1461674 (5.05%)
Cluster 28: 817916 (2.83%)
Cluster 29: 1022360 (3.53%)
```

Strength-bin overview:

```
In the following, clusters are sorted in ascending order according to
the percentage of weak/very weak hard-assigned passwords.
```

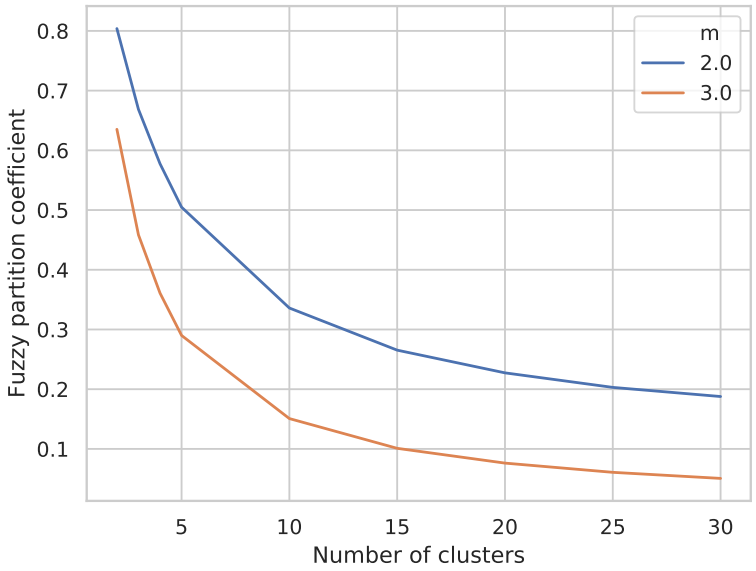


Figure B.1: Fuzzy partition coefficient for models with varying numbers of clusters and fuzzification configurations.

1. Cluster 20 (4.33% of total)
62.01% very weak or weak
12.54% good or strong
Very weak: 260320 (20.78%)
Weak: 516411 (41.23%)
Fair: 318742 (25.45%)
Good: 154564 (12.34%)
Strong: 2458 (0.20%)

2. Cluster 19 (3.31% of total)
55.20% very weak or weak
17.05% good or strong
Very weak: 144240 (15.07%)
Weak: 384248 (40.13%)
Fair: 265766 (27.76%)
Good: 160457 (16.76%)
Strong: 2686 (0.28%)

3. Cluster 4 (3.50% of total)
50.75% very weak or weak
20.71% good or strong
Very weak: 89446 (8.82%)
Weak: 425267 (41.93%)
Fair: 289302 (28.53%)
Good: 207226 (20.43%)
Strong: 2879 (0.28%)

4. Cluster 3 (3.79% of total)
48.66% very weak or weak
19.35% good or strong
Very weak: 80453 (7.33%)
Weak: 453421 (41.33%)
Fair: 350966 (31.99%)
Good: 210198 (19.16%)
Strong: 2039 (0.19%)

5. Cluster 27 (5.05% of total)
45.98% very weak or weak
26.09% good or strong
Very weak: 231131 (15.81%)
Weak: 440933 (30.17%)
Fair: 408287 (27.93%)
Good: 359101 (24.57%)
Strong: 22222 (1.52%)

6. Cluster 15 (2.34% of total)
41.41% very weak or weak
41.84% good or strong
Very weak: 216986 (32.07%)
Weak: 63220 (9.34%)
Fair: 113295 (16.74%)
Good: 272859 (40.33%)
Strong: 10241 (1.51%)

7. Cluster 22 (5.02% of total)
39.97% very weak or weak
20.82% good or strong
Very weak: 14700 (1.01%)
Weak: 566357 (38.96%)
Fair: 570018 (39.21%)
Good: 297937 (20.50%)
Strong: 4647 (0.32%)

8. Cluster 7 (3.44% of total)
39.75% very weak or weak
28.75% good or strong
Very weak: 50639 (5.09%)
Weak: 344877 (34.66%)
Fair: 313352 (31.49%)
Good: 267585 (26.89%)
Strong: 18530 (1.86%)

9. Cluster 2 (3.55% of total)
38.0% very weak or weak
23.11% good or strong
Very weak: 10542 (1.02%)
Weak: 380345 (36.98%)
Fair: 399997 (38.89%)
Good: 235173 (22.86%)
Strong: 2548 (0.25%)

10. Cluster 24 (2.26% of total)
37.04% very weak or weak
31.88% good or strong
Very weak: 32362 (4.95%)
Weak: 209978 (32.09%)
Fair: 203406 (31.09%)
Good: 196811 (30.08%)
Strong: 11779 (1.80%)

11. Cluster 21 (3.69% of total)
34.21% very weak or weak
34.63% good or strong
Very weak: 96037 (8.98%)
Weak: 269724 (25.23%)
Fair: 333154 (31.16%)
Good: 366041 (34.23%)
Strong: 4248 (0.40%)

12. Cluster 29 (3.53% of total)
29.66% very weak or weak
34.41% good or strong
Very weak: 7821 (0.76%)
Weak: 295416 (28.90%)
Fair: 367333 (35.93%)
Good: 343572 (33.61%)
Strong: 8218 (0.80%)

13. Cluster 17 (2.56% of total)
22.32% very weak or weak
47.72% good or strong
Very weak: 16886 (2.28%)
Weak: 148231 (20.04%)
Fair: 221583 (29.95%)
Good: 310193 (41.93%)
Strong: 42836 (5.79%)

14. Cluster 5 (4.53% of total)
22.05% very weak or weak
31.52% good or strong
Very weak: 26335 (2.01%)
Weak: 262837 (20.04%)
Fair: 608850 (46.43%)
Good: 402467 (30.69%)
Strong: 10841 (0.83%)

15. Cluster 28 (2.83% of total)
21.88% very weak or weak
29.68% good or strong
Very weak: 11295 (1.38%)
Weak: 167657 (20.50%)
Fair: 396170 (48.44%)
Good: 235333 (28.77%)
Strong: 7461 (0.91%)

16. Cluster 8 (1.38% of total)
19.87% very weak or weak
46.36% good or strong
Very weak: 3486 (0.87%)
Weak: 76016 (19.00%)

Fair: 135121 (33.77%)
Good: 165042 (41.25%)
Strong: 20465 (5.11%)

17. Cluster 23 (2.83% of total)
17.84% very weak or weak
54.54% good or strong
Very weak: 9195 (1.12%)
Weak: 136966 (16.72%)
Fair: 226221 (27.62%)
Good: 407428 (49.75%)
Strong: 39211 (4.79%)

18. Cluster 13 (3.12% of total)
17.71% very weak or weak
39.12% good or strong
Very weak: 12808 (1.42%)
Weak: 147286 (16.29%)
Fair: 390281 (43.17%)
Good: 332810 (36.81%)
Strong: 20919 (2.31%)

19. Cluster 0 (2.97% of total)
17.68% very weak or weak
50.55% good or strong
Very weak: 2493 (0.29%)
Weak: 149383 (17.39%)
Fair: 272824 (31.77%)
Good: 378350 (44.06%)
Strong: 55740 (6.49%)

20. Cluster 18 (4.73% of total)
16.95% very weak or weak
51.47% good or strong
Very weak: 25663 (1.88%)
Weak: 206228 (15.07%)
Fair: 432338 (31.59%)
Good: 554981 (40.56%)
Strong: 149245 (10.91%)

21. Cluster 6 (3.50% of total)
16.76% very weak or weak
66.33% good or strong
Very weak: 80788 (7.97%)
Weak: 89114 (8.79%)
Fair: 171515 (16.91%)
Good: 515354 (50.82%)
Strong: 157248 (15.51%)

22. Cluster 14 (2.29% of total)
14.08% very weak or weak
51.42% good or strong
Very weak: 5469 (0.82%)
Weak: 88009 (13.26%)
Fair: 228933 (34.49%)
Good: 292779 (44.11%)
Strong: 48500 (7.31%)

23. Cluster 10 (3.50% of total)
12.92% very weak or weak
50.78% good or strong
Very weak: 28306 (2.80%)
Weak: 102385 (10.12%)
Fair: 367096 (36.29%)
Good: 502135 (49.64%)
Strong: 11562 (1.14%)

24. Cluster 12 (2.90% of total)
12.63% very weak or weak
63.11% good or strong
Very weak: 19912 (2.37%)
Weak: 86181 (10.26%)
Fair: 203757 (24.26%)
Good: 389024 (46.31%)
Strong: 141138 (16.80%)

25. Cluster 1 (2.72% of total)
11.94% very weak or weak
61.99% good or strong
Very weak: 8452 (1.07%)
Weak: 85612 (10.87%)
Fair: 205261 (26.07%)
Good: 359320 (45.63%)
Strong: 128840 (16.36%)

26. Cluster 11 (3.92% of total)
6.95% very weak or weak
77.9% good or strong
Very weak: 10978 (0.97%)
Weak: 67950 (5.98%)
Fair: 171986 (15.15%)
Good: 728044 (64.12%)
Strong: 156452 (13.78%)

27. Cluster 9 (3.48% of total)
6.70% very weak or weak
76.32% good or strong
Very weak: 7106 (0.71%)
Weak: 60376 (5.99%)
Fair: 171078 (16.98%)
Good: 722692 (71.74%)
Strong: 46089 (4.58%)

28. Cluster 26 (3.86% of total)
6.65% very weak or weak
81.61% good or strong
Very weak: 16286 (1.46%)
Weak: 57994 (5.19%)
Fair: 131277 (11.74%)
Good: 763656 (68.29%)
Strong: 148965 (13.32%)

29. Cluster 25 (2.28% of total)
6.44% very weak or weak
85.97% good or strong
Very weak: 12358 (1.87%)
Weak: 30137 (4.57%)
Fair: 50080 (7.59%)
Good: 233467 (35.40%)
Strong: 333502 (50.57%)

30. Cluster 16 (2.77% of total)
4.5% very weak or weak
87.63% good or strong
Very weak: 5829 (0.73%)
Weak: 30200 (3.77%)
Fair: 63098 (7.87%)
Good: 281993 (35.19%)
Strong: 420277 (52.44%)

B.3.2 Cluster hard-assignments

In the following, [space] characters are depicted using "●". The numbers in parenthesis after each password correspond to (cluster assignment score, log10 PGS3 NN guess number). Guess numbers have been capped above at 10^14.

Cluster 0

Prototype: saaeanen85

Hard-assigned pwds: 858790 (2.97% of total)
Unique hard-assigned pwds: 631416 (26.48% of cluster total)

Cluster-assignment scores:
- Min: 0.060
- Max: 0.985
- Mean: 0.412
- SD: 0.215

Strength bins:
- Very weak: 2493 (0.29%)
- Weak: 149383 (17.39%)
- Fair: 272824 (31.77%)
- Good: 378350 (44.06%)
- Strong: 55740 (6.49%)

Password lengths:
- Length 9: 2251 (0.26%)
- Length 10: 856539 (99.74%)

Character classes:
- 4 classes: 10445 (1.22%)
- 3 classes: 108305 (12.61%)
  - lower/upper/symbol: 262 (0.24%)
  - lower/upper/number: 87811 (81.08%)
  - lower/symbol/number: 20232 (18.68%)
  - upper/symbol/number: 0 (0.00%)
- 2 classes: 740039 (86.17%)
  - lower/upper: 3 (0.00%)
  - lower/number: 738919 (99.85%)
  - lower/symbol: 1117 (0.15%)
  - upper/number: 0 (0.00%)
  - upper/symbol: 0 (0.00%)
  - number/symbol: 0 (0.00%)
- 1 class: 1 (0.00%)
  - lower: 1 (100.00%)
  - upper: 0 (0.00%)
  - symbol: 0 (0.00%)
  - number: 0 (0.00%)

Most frequent char-class structures:
- LLLLLLLLDD: 619159 (72.1%)
- LLLLLLLLD: 110795 (12.9%)
- ULLLLLLLDD: 58718 (6.8%)
- ULLLLLLLD: 12284 (1.4%)
- LLLLLLSDD: 8822 (1.0%)
- LLLLLLLLDL: 7023 (0.8%)
- ULLLLLLSDD: 3902 (0.5%)
- LLLLLLLDS: 3380 (0.4%)
- ULLLULLLDD: 2889 (0.3%)
- LLLLLLLSD: 2327 (0.3%)

1,000 nearest passwords

0. suzanneg75	(0.98, 9.1)	46. moniquea75	(0.98, 8.9)
1. Mayaguez75	(0.98, 8.1)	47. pyafdcen85	(0.98, 14.0)
2. nunucaem85	(0.98, 11.3)	48. loftsued85	(0.98, 9.1)
3. nimajneb85	(0.98, 7.9)	49. qvcfzdep85	(0.98, 14.0)
4. dadadaeu85	(0.98, 12.3)	50. luwamfev85	(0.98, 13.1)
5. enriquez75	(0.98, 7.3)	51. geldanew85	(0.98, 10.8)
6. partanen75	(0.98, 10.3)	52. gleecued75	(0.98, 9.9)
7. henjune-75	(0.98, 13.5)	53. profired75	(0.98, 11.2)
8. pimphued85	(0.98, 9.7)	54. intowhey75	(0.98, 10.2)
9. Huttunen75	(0.98, 9.8)	55. zkmajfec85	(0.98, 13.8)
10. drubknew85	(0.98, 9.5)	56. vetowhen85	(0.98, 10.5)
11. mtshknez85	(0.98, 13.8)	57. voteanew75	(0.98, 9.8)
12. brandnew85	(0.98, 6.8)	58. dwpcuqej75	(0.98, 13.7)
13. brittney85	(0.98, 5.9)	59. quizired75	(0.98, 11.8)
14. Brittney85	(0.98, 6.7)	60. fortwhen75	(0.98, 9.8)
15. martinez85	(0.98, 5.3)	61. surfired75	(0.98, 10.3)
16. bwhoxued85	(0.98, 14.0)	62. jaymoney85	(0.98, 7.0)
17. courtney85	(0.98, 5.4)	63. awaycued88	(0.98, 10.4)
18. Martinez85	(0.98, 6.1)	64. Vaughnez78	(0.98, 12.0)
19. xxkyqhem85	(0.98, 14.0)	65. edgycued78	(0.98, 10.0)
20. dxnguyen85	(0.98, 10.0)	66. ohanquez78	(0.98, 12.3)
21. wishknew75	(0.98, 8.8)	67. antichew75	(0.98, 10.6)
22. Eveline_75	(0.98, 9.9)	68. sahsenem75	(0.98, 11.7)
23. brittney75	(0.98, 6.2)	69. zomvmae.88	(0.98, 14.0)
24. textanew85	(0.98, 10.6)	70. tyroque$88	(0.98, 12.4)
25. martinez75	(0.98, 5.4)	71. designed88	(0.98, 7.3)
26. Martinez75	(0.98, 6.1)	72. adrianeb88	(0.98, 9.6)
27. ichange@75	(0.98, 11.5)	73. crunched85	(0.98, 9.7)
28. calhaney85	(0.98, 10.4)	74. nfhf[ney88	(0.98, 14.0)
29. macroney75	(0.98, 11.4)	75. uytomheq75	(0.98, 14.0)
30. kourtney75	(0.98, 6.9)	76. newmoney85	(0.98, 6.5)
31. courtney75	(0.98, 5.6)	77. muhammed75	(0.98, 6.0)
32. draganec75	(0.98, 9.5)	78. nimajneb88	(0.98, 7.5)
33. joltwhey85	(0.98, 9.5)	79. unhinged85	(0.98, 9.9)
34. gieschen85	(0.98, 11.3)	80. duckapex85	(0.98, 10.4)
35. itlcpneb75	(0.98, 14.0)	81. Gizachew75	(0.98, 13.3)
36. molsonex75	(0.98, 8.7)	82. ploptrek75	(0.98, 9.2)
37. brclonej85	(0.98, 13.1)	83. takethem85	(0.98, 8.0)
38. domecued85	(0.98, 9.2)	84. danhquen88	(0.98, 9.4)
39. jablonec75	(0.98, 10.5)	85. nimajneb78	(0.98, 7.8)
40. sagehued75	(0.98, 9.7)	86. jvasquez88	(0.98, 8.3)
41. dykehued75	(0.98, 9.7)	87. skinhaed88	(0.98, 10.5)
42. propanew85	(0.98, 8.7)	88. martinez88	(0.98, 4.9)
43. iawukped85	(0.98, 14.0)	89. tiffaney88	(0.98, 7.6)
44. zuemzuem75	(0.98, 10.4)	90. Squidney88	(0.98, 9.4)
45. semrinec75	(0.98, 12.7)	91. jasesney88	(0.98, 12.2)
92. flakwhey75	(0.98, 10.0)		
93. Martinez88	(0.98, 5.8)		
94. abhishek85	(0.98, 6.3)		
95. martdyed88	(0.98, 10.3)		
96. raptcued78	(0.98, 10.6)		
97. nyimcaem88	(0.98, 12.8)		
98. headsued85	(0.98, 9.5)		
99. dorothey85	(0.98, 9.5)		
100. assholez75	(0.98, 8.6)		
101. brandnew88	(0.97, 6.4)		
102. marcinek85	(0.97, 7.3)		
103. maidcued88	(0.97, 9.1)		
104. Chopsuey85	(0.97, 8.6)		
105. xgcqtyen85	(0.97, 14.0)		
106. snagknew78	(0.97, 10.6)		
107. TylerBen85	(0.97, 10.2)		
108. rzhimgep75	(0.97, 14.0)		
109. getmoney85	(0.97, 5.4)		
110. wokeurea75	(0.97, 10.8)		
111. ZebraRed75	(0.97, 11.0)		
112. newmaned78	(0.97, 10.7)		
113. Aveitneg88	(0.97, 14.0)		
114. tushchew85	(0.97, 10.5)		
115. brittney88	(0.97, 5.6)		
116. hintthen85	(0.97, 9.6)		
117. punyanew78	(0.97, 10.2)		
118. vivasued75	(0.97, 9.5)		
119. martinez78	(0.97, 5.3)		
120. Martinez78	(0.97, 6.1)		
121. grayhued78	(0.97, 9.8)		
122. fmtjpuey78	(0.97, 13.9)		
123. ammowhey75	(0.97, 10.0)		
124. courtney88	(0.97, 5.1)		
125. tacoahem85	(0.97, 10.3)		
126. schnafen75	(0.97, 12.2)		
127. Courtney88	(0.97, 6.0)		
128. avowitem75	(0.97, 11.6)		
129. GreenSea75	(0.97, 10.3)		
130. clewstew75	(0.97, 10.0)		
131. gushanew88	(0.97, 10.3)		
132. chewurea75	(0.97, 10.1)		
133. Sindayen75	(0.97, 12.4)		
134. duelwhen85	(0.97, 9.6)		
135. siddhdey85	(0.97, 12.6)		
136. kingknew78	(0.97, 9.4)		
137. leakwhew75	(0.97, 9.6)		

138. brittney78 (0.97, 6.0)
139. tuhkanen78 (0.97, 11.9)
140. lynxtrek75 (0.97, 9.8)
141. boimunex88 (0.97, 13.2)
142. Sky-chen88 (0.97, 14.0)
143. Tuin#jeS75 (0.97, 14.0)
144. huyquyen88 (0.97, 6.9)
145. tikecued88 (0.97, 10.2)
146. dykesued88 (0.97, 9.0)
147. drumchew75 (0.97, 9.7)
148. thuhuyen88 (0.97, 7.0)
149. Primagen85 (0.97, 11.2)
150. dataknew78 (0.97, 10.3)
151. mutewhey75 (0.97, 9.1)
152. metethem85 (0.97, 11.2)
153. ragaahem88 (0.97, 10.4)
154. mohammed85 (0.97, 5.7)
155. courtney78 (0.97, 5.5)
156. khmfnzev75 (0.97, 14.0)
157. shedsled75 (0.97, 9.4)
158. needstem75 (0.97, 9.9)
159. divewhen85 (0.97, 10.2)
160. refinnej78 (0.97, 7.9)
161. abhishek75 (0.97, 6.3)
162. revbayem75 (0.97, 13.2)
163. ibgotpey85 (0.97, 13.7)
164. xiaoyuef88 (0.97, 11.4)
165. Csi.Jnec88 (0.97, 14.0)
166. ilovesex75 (0.97, 6.7)
167. zpbgywex85 (0.97, 13.9)
168. dareanew88 (0.97, 8.7)
169. Getmoney75 (0.97, 6.7)
170. hartaped75 (0.97, 9.9)
171. hardened75 (0.97, 8.7)
172. honewhew85 (0.97, 10.8)
173. mireanew88 (0.97, 11.3)
174. sramzden85 (0.97, 12.7)
175. getmoney75 (0.97, 5.6)
176. youngCed88 (0.97, 12.7)
177. dolecued78 (0.97, 9.5)
178. cytrynek88 (0.97, 11.1)
179. Inloggen88 (0.97, 8.1)
180. eijzxgez88 (0.97, 14.0)
181. gawkthen85 (0.97, 9.9)
182. smutsped85 (0.97, 9.9)
183. sedanten75 (0.97, 10.4)
184. MadhuBen88 (0.97, 11.3)
185. wifethem75 (0.97, 9.2)
186. anhyeuem85 (0.97, 5.3)
187. skewtrek85 (0.97, 10.6)
188. gullknew88 (0.97, 10.6)
189. vjimenez75 (0.97, 10.1)
190. cozydyed88 (0.97, 9.7)
191. ikbengek75 (0.97, 8.2)
192. Queensea75 (0.97, 10.2)
193. scudthem85 (0.97, 9.8)
194. votethey75 (0.97, 9.9)
195. riskstem75 (0.97, 10.0)
196. njnhhjep88 (0.97, 14.0)
197. tuberued75 (0.97, 9.8)
198. forsaken75 (0.97, 6.8)
199. hugechef75 (0.97, 10.2)
200. niggajew85 (0.97, 9.3)
201. Khachweb75 (0.97, 12.4)
202. wickkked75 (0.97, 12.8)
203. children75 (0.97, 6.8)
204. wagewhen75 (0.97, 9.9)
205. kingsley75 (0.97, 6.4)
206. muhammed88 (0.97, 5.8)
207. pinkwhey88 (0.97, 9.7)
208. katethea75 (0.97, 11.2)
209. passagem88 (0.97, 8.4)
210. harkonen75 (0.97, 8.6)
211. unefcaen78 (0.97, 13.8)
212. notingem88 (0.97, 11.3)
213. RetroWeb78 (0.97, 10.4)
214. hsanchez88 (0.97, 8.4)
215. indabzez88 (0.97, 13.6)
216. anbwluez75 (0.97, 14.0)
217. advanced88 (0.97, 6.4)
218. greygrey75 (0.97, 7.9)
219. sbbetmen85 (0.97, 12.5)
220. dealgrew75 (0.97, 9.6)
221. babazmeg88 (0.97, 12.2)
222. ziomalek85 (0.97, 8.0)
223. hanksled75 (0.97, 9.4)
224. fuckeneh88 (0.97, 9.5)
225. iconanew78 (0.97, 11.1)
226. snitsued78 (0.97, 9.8)
227. casiopea85 (0.97, 7.1)
228. pactired75 (0.97, 10.8)
229. takeoxen85 (0.97, 9.1)
230. narkwhey75 (0.97, 10.4)
231. mohammed75 (0.97, 5.7)
232. prayshed85 (0.97, 10.5)
233. Hawksley75 (0.97, 9.3)
234. kajakken88 (0.97, 10.1)
235. Advance@88 (0.97, 9.3)
236. awshalem75 (0.97, 12.6)
237. yuckchef78 (0.97, 9.2)
238. uzbrdhen75 (0.97, 14.0)
239. gridrued85 (0.97, 10.3)
240. stanchek88 (0.97, 10.2)
241. dhextrez85 (0.97, 12.8)
242. Brigate_75 (0.97, 10.6)
243. college.85 (0.97, 8.7)
244. summoned88 (0.97, 8.6)
245. tabrenea88 (0.97, 12.6)
246. Koljanek78 (0.97, 12.3)
247. wavysled75 (0.97, 9.9)
248. nookired78 (0.97, 10.5)
249. mcguffey78 (0.97, 9.1)
250. Gammoned88 (0.97, 11.2)
251. FleaFlea!5 (0.97, 12.7)
252. glibwhew75 (0.97, 9.6)
253. Pinkwhen88 (0.97, 11.6)
254. extensen75 (0.97, 11.1)
255. rriveneq75 (0.97, 14.0)
256. breybrey75 (0.97, 8.6)
257. campaped88 (0.97, 11.8)
258. sfatized85 (0.97, 12.9)
259. jaymoney88 (0.97, 6.6)
260. seresped85 (0.97, 9.7)
261. timechef75 (0.97, 10.5)
262. somechef75 (0.97, 10.1)
263. schinken85 (0.97, 8.2)
264. stunstew75 (0.97, 10.4)
265. ilovesex85 (0.97, 6.6)
266. chrisken85 (0.97, 8.8)
267. barkflex75 (0.97, 9.4)
268. camaguey65 (0.97, 6.8)
269. Anicole^78 (0.97, 12.8)
270. blocflea75 (0.97, 9.4)
271. mienslew85 (0.97, 10.5)
272. Chuanyen78 (0.97, 12.2)
273. gainrued75 (0.97, 9.7)
274. feltipen85 (0.97, 11.8)
275. lewdchef88 (0.97, 8.6)
276. gs@nchez78 (0.97, 12.6)
277. SuperRep78 (0.97, 10.8)
278. sweetpea85 (0.97, 5.8)
279. luckahem78 (0.97, 10.9)
280. examahem78 (0.97, 11.7)
281. okraslew85 (0.97, 10.6)
282. minisped85 (0.97, 11.1)
283. elenalex85 (0.97, 10.0)
284. f.i.n.e.88 (0.97, 10.8)
285. Fre_they85 (0.97, 14.0)
286. theatre*85 (0.97, 9.8)
287. onceshed88 (0.97, 10.6)
288. cloggrey75 (0.97, 10.0)
289. gonzalez75 (0.97, 5.8)
290. ziabolek78 (0.97, 11.1)
291. luckyme#88 (0.97, 8.8)
292. haltslew75 (0.97, 10.5)
293. anhyeuem75 (0.97, 6.4)
294. newmoney88 (0.97, 6.1)
295. wolfwhew75 (0.97, 10.6)
296. prelude_85 (0.97, 8.8)
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298. Newlife_85 (0.97, 8.6)
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300. barfthen85 (0.97, 9.8)
301. liardyed75 (0.97, 9.7)
302. tummybed78 (0.97, 7.0)
303. yeahchef88 (0.97, 9.8)
304. menditem85 (0.97, 10.4)
305. shawnken88 (0.97, 9.2)
306. iambshed75 (0.97, 10.8)
307. millipen85 (0.97, 9.8)
308. Thenprem75 (0.97, 12.4)
309. seanchen88 (0.97, 8.4)
310. snejsnej78 (0.97, 10.8)
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312. lanespec75 (0.97, 10.3)
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314. autoopen75 (0.97, 10.9)
315. peachbed75 (0.97, 7.1)
316. minhuyen88 (0.97, 7.3)
317. toiyeuem85 (0.97, 6.8)
318. luvmoney78 (0.97, 8.2)
319. pimpslew85 (0.97, 8.6)
320. agogstew85 (0.97, 10.0)
321. gentibex85 (0.97, 11.4)
322. kirkwhen75 (0.97, 10.0)
323. duyjacey78 (0.97, 12.6)
324. zhaizhen88 (0.97, 10.0)
325. BigDaveJ85 (0.97, 11.0)
326. pintamen85 (0.97, 8.7)
327. slawrued75 (0.97, 9.9)
328. nikolaev88 (0.97, 6.9)
329. mehemmed85 (0.97, 8.4)
330. pactahem88 (0.97, 10.8)
331. flaxarea85 (0.97, 9.8)
332. vineoxen85 (0.97, 10.3)
333. Jessalex75 (0.97, 9.3)
334. balmclef75 (0.97, 9.4)
335. Fisngtez75 (0.97, 14.0)
336. Skindred75 (0.97, 9.5)
337. slabstew85 (0.97, 8.6)
338. abhishek88 (0.97, 6.0)
339. sumpaped78 (0.97, 11.0)
340. szpaczek78 (0.97, 10.6)
341. Abhishek88 (0.97, 7.3)
342. sectaxed85 (0.97, 10.5)
343. hazegrey75 (0.97, 9.6)
344. failflea75 (0.97, 9.6)
345. rovetrek75 (0.97, 9.4)
346. troubleg75 (0.97, 9.1)
347. zonecrew75 (0.97, 8.8)
348. Jsemckey85 (0.97, 13.3)
349. gretchen78 (0.97, 6.7)
350. lolmoney88 (0.97, 8.2)
351. haulcrew75 (0.97, 10.0)
352. floreseb75 (0.97, 10.7)
353. Lilmoney88 (0.97, 8.2)
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356. billoxen85 (0.97, 9.5)
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358. slipcrew75 (0.97, 9.0)
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366. getmoney88 (0.97, 4.9)
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372. trimblew75 (0.97, 10.0)
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382. Miloncef88 (0.97, 12.4)
383. Nijmegen85 (0.97, 8.1)
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435. earlstep75 (0.97, 9.8)
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438. chupirex88 (0.97, 11.8)
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463. avowgrew85 (0.97, 10.4)
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466. Shuriken75 (0.97, 7.8)
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764. drewdrew78 (0.96, 7.2)
765. petoskey78 (0.96, 8.1)
766. axelalex88 (0.96, 9.8)
767. defeated65 (0.96, 8.9)
768. mafiamex88 (0.96, 10.1)
769. anhyeuem78 (0.96, 5.7)
770. liceamen75 (0.96, 9.8)
771. delircem75 (0.96, 12.2)
772. children65 (0.96, 6.8)
773. foamapex78 (0.96, 10.9)
774. Myibanez68 (0.96, 10.9)
775. seedglen65 (0.96, 10.2)
776. auntpled75 (0.96, 11.4)
777. Beemobey85 (0.96, 12.2)
778. unonaren88 (0.96, 11.6)
779. perkwren65 (0.96, 9.6)
780. Blackpen78 (0.96, 9.1)
781. thugstep78 (0.96, 8.8)
782. womensex78 (0.96, 9.6)
783. leptamen88 (0.96, 10.6)
784. Nitrogen78 (0.96, 7.9)
785. brengsek88 (0.96, 6.4)
786. fdssrney65 (0.96, 14.0)
787. benhumea88 (0.96, 11.4)
788. roarwren78 (0.96, 9.8)
789. maniczek78 (0.96, 9.5)
790. buddyjen65 (0.96, 9.8)
791. swatowed88 (0.96, 10.7)
792. siloomen88 (0.96, 10.9)
793. moneykev88 (0.96, 9.7)
794. pantblew75 (0.96, 9.5)
795. komitmen88 (0.96, 8.1)
796. aridgrew78 (0.96, 9.9)
797. honkfled85 (0.96, 10.2)
798. savlovey88 (0.96, 11.9)
799. heineken85 (0.96, 6.7)
800. loseabed88 (0.96, 9.8)
801. amarahen78 (0.96, 11.7)
802. aleyfred88 (0.96, 11.1)
803. dollbled78 (0.96, 10.8)
804. waveaxed88 (0.96, 9.3)
805. bozoired65 (0.96, 10.4)
806. suckeven85 (0.96, 9.0)
807. wineplea78 (0.96, 8.9)
808. tornamen75 (0.96, 10.4)
809. gunkdrew75 (0.96, 9.9)
810. bredchef78 (0.96, 9.8)
811. forgeten88 (0.96, 8.1)
812. costcrew85 (0.96, 10.0)
813. ben=trev65 (0.96, 13.1)
814. coilaped88 (0.96, 10.7)
815. bredflew78 (0.96, 9.3)
816. sohorney65 (0.96, 8.5)
817. editfled75 (0.96, 9.9)
818. housebed75 (0.96, 6.6)
819. cornidea85 (0.96, 10.3)
820. vanhalen85 (0.96, 6.3)
821. goldchef78 (0.96, 10.9)
822. weldclew78 (0.96, 9.1)
823. muhammed65 (0.96, 6.6)
824. knewstep68 (0.96, 9.5)
825. jfygmxen65 (0.96, 14.0)
826. dareclef85 (0.96, 10.0)
827. mrtinyeg65 (0.96, 12.4)
828. daisyred78 (0.96, 9.0)
829. elisaven88 (0.96, 10.5)
830. RiderRed65 (0.96, 10.1)
831. chanalex85 (0.96, 9.7)
832. Alizadeh88 (0.96, 8.4)
833. samiilea65 (0.96, 11.1)
834. melendez88 (0.96, 6.6)
835. klmrolex85 (0.96, 12.7)
836. tdsystem88 (0.96, 10.2)
837. chidubem88 (0.96, 6.9)
838. derffred88 (0.96, 8.3)
839. wenenweg85 (0.96, 12.6)
840. dofusdex88 (0.96, 10.5)
841. coldaced88 (0.96, 10.2)
842. earlykey78 (0.96, 10.1)
843. chugused75 (0.96, 11.9)
844. tonydrea78 (0.96, 10.2)
845. uwaiclez75 (0.96, 14.0)
846. planthem78 (0.96, 10.7)
847. feelflex78 (0.96, 9.8)
848. kingsley65 (0.96, 6.2)
849. sweetpea78 (0.96, 5.7)
850. nijmegen88 (0.96, 7.2)
851. redmegen88 (0.96, 10.8)
852. permbrew88 (0.96, 11.0)
853. drgxtaef65 (0.96, 13.8)
854. obeyidea85 (0.96, 9.7)
855. dunraven75 (0.96, 8.7)
856. fbgorkem75 (0.96, 11.7)
857. hulladek88 (0.96, 11.0)
858. senkisem78 (0.96, 10.0)
859. tideplea78 (0.96, 9.1)
860. smsystem88 (0.96, 9.9)
861. sweattea68 (0.96, 8.2)
862. brewbred88 (0.96, 10.3)
863. kehinde@78 (0.96, 8.9)
864. guweiwen88 (0.96, 11.3)
865. wcgtmyea65 (0.96, 13.8)
866. educated85 (0.96, 8.2)
867. soondrew78 (0.96, 10.4)
868. sealgrew65 (0.96, 8.4)
869. farzaneh68 (0.96, 8.5)
870. windobey75 (0.96, 9.4)
871. joelopez78 (0.96, 8.7)
872. rumpsled65 (0.96, 8.7)
873. drewdrew88 (0.96, 6.8)
874. bolawren65 (0.96, 10.4)
875. geoffrey78 (0.96, 6.6)
876. nickobey75 (0.96, 9.7)
877. kingsley88 (0.96, 5.6)
878. clamsped88 (0.96, 10.1)
879. sloeglen78 (0.96, 8.6)
880. pkcowtev75 (0.96, 14.0)
881. petersen85 (0.96, 7.5)
882. peedgrew65 (0.96, 9.1)
883. scowprey78 (0.96, 8.9)
884. demontez88 (0.96, 9.5)
885. mythThem78 (0.96, 9.4)
886. Pedersen85 (0.96, 8.2)
887. ventsled88 (0.96, 9.2)
888. landskew88 (0.96, 8.2)
889. Laraine@65 (0.96, 11.1)
890. jillfred88 (0.96, 9.5)
891. jackbred75 (0.96, 9.9)
892. tendobey75 (0.96, 11.3)
893. rearblew78 (0.96, 9.6)
894. crazyred88 (0.96, 7.4)
895. martasek85 (0.96, 9.8)
896. tungsten78 (0.96, 7.8)
897. ruskaxed88 (0.96, 10.2)
898. pongulec78 (0.96, 12.4)
899. simonmec88 (0.96, 11.2)
900. gonzalez88 (0.96, 5.4)
901. Ceridwen78 (0.96, 9.7)
902. pigculec78 (0.96, 13.3)
903. startrek78 (0.96, 6.2)
904. dotedrew88 (0.96, 10.1)
905. wordgrey88 (0.96, 9.9)
906. terhemen85 (0.96, 8.5)
907. fressnek68 (0.96, 11.6)
908. wrengrew88 (0.96, 10.1)
909. moatflea85 (0.96, 9.7)
910. jwharden88 (0.96, 10.6)
911. omitclef75 (0.96, 9.7)
912. bitepled78 (0.96, 10.4)
913. linksdeb88 (0.96, 10.7)
914. schoenen68 (0.96, 8.7)
915. GodGiven85 (0.96, 9.7)
916. warestep78 (0.96, 10.4)
917. bilkcrew65 (0.96, 9.8)
918. goryomen85 (0.96, 11.4)
919. pokewren78 (0.96, 10.1)
920. nicodrea65 (0.96, 12.0)
921. murphley78 (0.96, 9.4)
922. Drewdrew88 (0.96, 7.5)
923. homeave.75 (0.96, 12.7)
924. konradek88 (0.96, 8.6)
925. kedvesem88 (0.96, 10.2)
926. diregrew88 (0.96, 10.9)
927. buzzarea78 (0.96, 9.3)
928. confused78 (0.96, 6.5)
929. laquesea78 (0.96, 7.5)
930. conegrew65 (0.96, 9.0)
931. siteprey65 (0.96, 10.0)
932. peakthem78 (0.96, 10.0)
933. tuxtepec88 (0.96, 9.0)
934. curlibex78 (0.96, 10.2)
935. centsled65 (0.96, 9.0)
936. tvholden88 (0.96, 9.3)
937. silenced78 (0.96, 8.5)
938. thanexec75 (0.96, 9.7)
939. hkholden88 (0.96, 9.2)
940. binladen88 (0.96, 6.5)
941. pallawed75 (0.96, 10.8)
942. sillasen88 (0.96, 11.1)
943. poppyrex88 (0.96, 9.1)
944. dachosen78 (0.96, 8.3)
945. uiramzey78 (0.96, 13.7)
946. tniwlmec75 (0.96, 14.0)
947. lifenfen88 (0.96, 9.9)

948. dmhciwen85 (0.96, 13.5)
949. Jatordez88 (0.96, 13.7)
950. jembuten88 (0.96, 9.0)
951. modeglen78 (0.96, 9.7)
952. fairired85 (0.96, 11.5)
953. wildahem78 (0.96, 9.0)
954. Bleedred88 (0.96, 9.8)
955. drewtrek68 (0.96, 10.3)
956. asenasen88 (0.96, 9.4)
957. Jaexksen78 (0.96, 14.0)
958. coatstep88 (0.96, 8.6)
959. tirmizey85 (0.96, 13.6)
960. winebrew65 (0.96, 8.9)
961. dcunited65 (0.96, 8.7)
962. cibertec85 (0.96, 7.1)
963. Sebastec88 (0.96, 10.9)
964. henrike@78 (0.96, 11.2)
965. miststem65 (0.96, 9.1)
966. hoaxstew68 (0.96, 9.5)
967. steelbed88 (0.96, 6.1)
968. rinkitem68 (0.96, 10.7)
969. gonzalez65 (0.96, 6.1)
970. newtclef85 (0.96, 9.7)
971. schatten78 (0.96, 9.0)
972. Gonsalez88 (0.96, 7.8)
973. bensalem65 (0.96, 8.5)
974. sashskew88 (0.96, 9.2)
975. Magikweb78 (0.96, 12.3)
976. wildtrek68 (0.96, 10.1)
977. lynxbrew75 (0.96, 9.9)
978. ihncvreq75 (0.96, 14.0)
979. LinkBren68 (0.96, 10.2)
980. notestep65 (0.96, 10.9)
981. chepemex85 (0.96, 10.2)
982. bicastef88 (0.96, 11.2)
983. Trustren88 (0.96, 10.7)
984. brewcrew65 (0.96, 7.2)
985. fudpimev75 (0.96, 13.3)
986. gungaden65 (0.96, 8.9)
987. Secooley65 (0.96, 12.4)
988. bulkblew65 (0.96, 10.1)
989. omkbjdev68 (0.96, 14.0)
990. lieuaced78 (0.96, 11.3)
991. confused65 (0.96, 6.4)
992. viatamea78 (0.96, 8.6)
993. gobigred88 (0.96, 6.8)
994. fleaflex88 (0.96, 9.9)
995. keppeke@75 (0.96, 12.7)
996. slopbrew88 (0.96, 9.6)
997. lieubrew65 (0.96, 9.7)
998. kearsley85 (0.96, 9.0)
999. mckinley78 (0.96, 6.8)

Cluster 1

Prototype: saaeeden1364

Hard-assigned passwords: 787485 (2.72% of total)
Unique hard-assigned passwords: 579496 (26.41% of cluster total)

Cluster-assignment scores:
        Min: 0.067
        Max: 0.974
        Mean: 0.347
        SD: 0.235

Strength bins:
        Very weak: 8452 (1.07%)
        Weak: 85612 (10.87%)
        Fair: 205261 (26.07%)
        Good: 359320 (45.63%)
        Strong: 128840 (16.36%)

Password lengths:
        Length 12: 787485 (100.00%)

Character classes:
        4 classes: 19594 (2.49%)
        3 classes: 123142 (15.64%)
                lower/upper/symbol: 246 (0.20%)
                lower/upper/number: 84104 (68.30%)
                lower/symbol/number: 38791 (31.50%)
                upper/symbol/number: 1 (0.00%)
        2 classes: 644747 (81.87%)
                lower/upper: 0 (0.00%)
                lower/number: 643834 (99.86%)
                lower/symbol: 900 (0.14%)
                upper/number: 0 (0.00%)
                upper/symbol: 1 (0.00%)
                number/symbol: 12 (0.00%)
        1 class: 2 (0.00%)
                lower: 0 (0.00%)
                upper: 0 (0.00%)
                symbol: 2 (100.00%)
                number: 0 (0.00%)

Most frequent char-class structures:
        LLLLLLLLDDDD: 259198 (32.9%)
        LLLLLLLLLDDD: 207652 (26.4%)
        LLLLLLDDDDDD: 86945 (11.0%)
        LLLLLLLDDDDD: 35539 (4.5%)
        ULLLLLLLDDDD: 32117 (4.1%)
        ULLLLLLLLDDD: 16985 (2.2%)
        LLLLLLLDLLLL: 7999 (1.0%)
        ULLLLLDDDDDD: 7444 (0.9%)
        LLLLLLLSDDDD: 6711 (0.9%)
        LLLLLLLLSDDD: 6676 (0.8%)

1,000 nearest passwords

  0. tremuned1160 (0.97, 14.0)
  1. abhishek1390 (0.97, 7.6)
  2. mohammed1390 (0.97, 7.4)
  3. martinez1780 (0.97, 7.9)
  4. abhishek1890 (0.97, 7.8)
  5. steelhed1660 (0.97, 11.8)
  6. lemozney1060 (0.97, 14.0)
  7. bermudez1190 (0.97, 9.2)
  8. pugboyed1680 (0.97, 14.0)
  9. MissyBen1170 (0.97, 12.6)
 10. muhammed1770 (0.97, 8.9)
 11. leicched1370 (0.97, 14.0)
 12. Shadowed1360 (0.97, 10.7)
 13. mitabrev1490 (0.97, 12.7)
 14. Adminweb1580 (0.97, 11.0)
 15. bloodren1360 (0.97, 11.6)
 16. thioulea1760 (0.97, 14.0)
 17. astrazen1370 (0.97, 11.1)
 18. necochea1080 (0.97, 10.1)
 19. taymoney1400 (0.97, 10.5)
 20. gretchen1700 (0.97, 8.1)
 21. abhishek1100 (0.97, 7.6)
 22. startrek1060 (0.97, 8.3)
 23. windstep1080 (0.97, 10.3)
 24. Uzituxez1800 (0.97, 14.0)
 25. vanhalen1090 (0.97, 8.7)
 26. hurdspec1090 (0.97, 14.0)
 27. nistgwen1060 (0.97, 14.0)
 28. hempdsep1180 (0.97, 14.0)
 29. oakhaven1600 (0.97, 11.1)
 30. Mouhamed1400 (0.97, 10.2)
 31. lacdcaec1710 (0.97, 14.0)
 32. attorney4460 (0.97, 9.8)
 33. sheetfed1300 (0.97, 13.9)
 34. Brittney6190 (0.97, 9.6)
 35. dunguyen1310 (0.97, 10.0)
 36. lynguyen1410 (0.97, 10.4)
 37. courtney1310 (0.97, 6.9)
 38. destiney1000 (0.97, 7.3)
 39. anhyeuem6990 (0.97, 8.5)
 40. stevchen4360 (0.97, 12.3)
 41. realoveu1090 (0.97, 12.5)
 42. mohammed6060 (0.97, 7.1)
 43. Mohammed6060 (0.97, 8.0)
 44. Jaymoney1000 (0.97, 8.0)
 45. anhyeuem1810 (0.97, 6.3)
 46. Startnew4680 (0.97, 12.3)
 47. gonzalez1070 (0.97, 7.9)
 48. advanced1000 (0.96, 7.7)
 49. riffage@1000 (0.96, 13.9)
 50. gotmoney1000 (0.96, 7.1)
 51. histprej1470 (0.96, 13.9)
 52. getmoney1000 (0.96, 5.8)
 53. winerden4490 (0.96, 13.2)
 54. Getmoney1000 (0.96, 6.7)
 55. yedsakev1710 (0.96, 14.0)
 56. reloaded1710 (0.96, 8.3)
 57. aishudev1310 (0.96, 12.3)
 58. elcarmen4060 (0.96, 10.8)
 59. mohammed1000 (0.96, 6.0)
 60. sramirez1110 (0.96, 9.7)
 61. Milegyen1000 (0.96, 14.0)
 62. internew1520 (0.96, 11.9)
 63. wolfalex1000 (0.96, 10.4)
 64. krueshey1000 (0.96, 13.1)
 65. abasaleh1300 (0.96, 10.7)
 66. give_me.1310 (0.96, 13.0)
 67. martinez1010 (0.96, 6.4)
 68. Buggyben1720 (0.96, 13.2)
 69. startrec1070 (0.96, 10.5)
 70. Martinez4770 (0.96, 9.5)
 71. courtney4970 (0.96, 8.3)
 72. snirojeh4180 (0.96, 14.0)
 73. massagem1010 (0.96, 9.5)
 74. mohsine-1010 (0.96, 11.3)
 75. gerente,1510 (0.96, 11.9)
 76. enhanced4570 (0.96, 10.6)
 77. linkzrex1100 (0.96, 13.7)
 78. staridea1110 (0.96, 12.2)
 79. greentea4490 (0.96, 9.4)
 80. comparex1000 (0.96, 10.3)
 81. papashea6970 (0.96, 13.0)
 82. startrek1400 (0.96, 8.1)
 83. jefyevef1610 (0.96, 14.0)
 84. gobigred1000 (0.96, 8.0)
 85. osabohen1000 (0.96, 13.0)
 86. Stainley1000 (0.96, 10.9)
 87. crisadem6870 (0.96, 12.7)
 88. queteden1000 (0.96, 8.7)
 89. children1810 (0.96, 8.4)
 90. CuhaElex1310 (0.96, 14.0)
 91. deadprez1000 (0.96, 9.0)
 92. pervflex1610 (0.96, 13.3)
 93. archimed1000 (0.96, 10.6)
 94. mckinney4200 (0.96, 8.6)
 95. sweetpea1420 (0.96, 7.9)
 96. bohaggen4200 (0.96, 13.5)
 97. lberkley1000 (0.96, 11.4)
 98. startrek1000 (0.96, 6.7)
 99. topcoben6870 (0.96, 14.0)
100. rhaporen4980 (0.96, 14.0)
101. nicaalex1710 (0.96, 12.3)
102. ivansaez6800 (0.96, 13.3)
103. gonzalez6390 (0.96, 8.9)
104. cepasweb1320 (0.96, 13.1)
105. aezpgrev1510 (0.96, 14.0)
106. contgren1810 (0.96, 12.3)
107. semdfwed1010 (0.96, 14.0)
108. breathef1010 (0.96, 11.1)
109. benjimen1420 (0.96, 11.3)
110. nomensen1310 (0.96, 12.3)
111. courtney1020 (0.96, 6.4)
112. ilovepez1120 (0.96, 11.4)
113. kingsley1010 (0.96, 6.3)
114. nickdrew6060 (0.96, 11.2)
115. Omarobed1010 (0.96, 13.5)
116. eramirez1020 (0.96, 10.0)
117. farzaneh1330 (0.96, 10.0)
118. bercpref1320 (0.96, 14.0)
119. mohammed1020 (0.96, 6.4)
120. abohaseh1420 (0.96, 13.9)
121. hijacked1330 (0.96, 10.3)
122. canthpep1430 (0.96, 14.0)
123. hatecrew1420 (0.96, 10.3)
124. kennyken1330 (0.96, 9.6)
125. thumbmen1440 (0.96, 13.5)
126. jhayarec1820 (0.96, 12.7)
127. martinez3090 (0.96, 8.0)
128. rankinec7860 (0.96, 13.4)
129. mjhunnem3090 (0.96, 14.0)
130. natalied1180 (0.96, 11.3)
131. grounded1020 (0.96, 8.4)
132. cadence@1130 (0.96, 10.5)
133. Reyhaneh1350 (0.96, 11.4)
134. opjoched3590 (0.96, 14.0)
135. lavishe-7890 (0.96, 12.7)
136. Lismore@1830 (0.96, 12.6)
137. Abhishek3060 (0.96, 9.7)
138. inverted1620 (0.96, 9.6)
139. singtzed1830 (0.96, 14.0)
140. JaminFen7080 (0.96, 14.0)
141. courtney1030 (0.96, 6.5)
142. meenaben1530 (0.96, 12.0)
143. christen1020 (0.96, 8.4)
144. mcbumped7880 (0.96, 14.0)
145. Linkedeb1330 (0.96, 12.7)
146. Anferney4220 (0.96, 11.5)
147. jasonrey1020 (0.96, 10.7)
148. consudec1350 (0.96, 13.6)
149. fuckchef4120 (0.96, 12.1)
150. Trysome.6110 (0.96, 14.0)
151. lilmoney1030 (0.96, 8.8)
152. redseven1330 (0.96, 11.7)
153. alkencen1850 (0.96, 14.0)
154. jbezsbez1540 (0.96, 14.0)
155. xiaochen4520 (0.96, 8.8)
156. reloaded7980 (0.96, 9.3)
157. olietvev1340 (0.96, 14.0)
158. nutriweb6510 (0.96, 12.5)
159. Welcome.7890 (0.96, 8.8)
160. billchen1030 (0.96, 10.2)
161. Hydrogen6020 (0.96, 10.6)

162. sassysex6670 (0.96, 12.5)
163. nitrogen6020 (0.96, 10.1)
164. sweetpea4720 (0.96, 9.0)
165. mohammed7070 (0.96, 7.2)
166. mnsystem4800 (0.96, 12.4)
167. Marantec4500 (0.96, 12.8)
168. mikealex1030 (0.96, 10.0)
169. schoolep1640 (0.96, 12.3)
170. moemoney7570 (0.96, 10.4)
171. anointed1340 (0.95, 9.1)
172. dlatjdeh3570 (0.95, 14.0)
173. Berkesey1850 (0.95, 12.9)
174. bigcase●1030 (0.95, 13.4)
175. Poseidon1390 (0.95, 9.4)
176. awesome-7070 (0.95, 10.1)
177. daddydon1580 (0.95, 10.8)
178. gonzalez1030 (0.95, 7.0)
179. miconred1650 (0.95, 13.3)
180. Patricia1190 (0.95, 8.4)
181. schenjeu1050 (0.95, 14.0)
182. machine@3000 (0.95, 10.0)
183. CindyLou1360 (0.95, 11.2)
184. alauddin1390 (0.95, 9.8)
185. discomen7070 (0.95, 9.5)
186. Liversen6500 (0.95, 13.8)
187. lollipop1890 (0.95, 8.2)
188. jaymoney3000 (0.95, 7.8)
189. ooooooned3000 (0.95, 13.2)
190. BigMoney3000 (0.95, 8.2)
191. kingsley?910 (0.95, 11.6)
192. benladen1050 (0.95, 10.1)
193. lilmoney3000 (0.95, 7.9)
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657. startrek3500 (0.94, 8.4)
658. academia1000 (0.94, 7.2)
659. concepta4000 (0.94, 10.1)
660. koteczek1980 (0.94, 7.6)
661. ilyasbek8700 (0.94, 13.9)
662. abhishek3440 (0.94, 8.7)
663. firoozeh5160 (0.94, 12.9)
664. Abhishek3440 (0.94, 10.2)
665. loverboy6900 (0.94, 7.5)
666. sargeboy6200 (0.94, 11.7)
667. loverboy6700 (0.94, 8.2)
668. intrepid1000 (0.94, 7.0)
669. stefanix1810 (0.94, 11.2)
670. fountain1000 (0.94, 7.5)
671. mountain1000 (0.94, 6.3)
672. kennyboy1520 (0.94, 9.3)
673. piketdog1000 (0.94, 11.4)
674. onthetop1370 (0.94, 10.1)
675. rasempek1970 (0.94, 12.9)
676. pandadog1010 (0.94, 9.1)
677. babumita4080 (0.94, 13.8)
678. martinez5060 (0.94, 7.8)
679. pedrodsa7590 (0.94, 13.9)
680. jonnyboy1000 (0.94, 7.7)
681. Zangetsu6190 (0.94, 10.9)
682. autarkic3290 (0.94, 14.0)
683. toolshed5780 (0.94, 10.3)
684. phylsden1794 (0.94, 13.6)
685. security1690 (0.94, 7.5)
686. linkedin1120 (0.94, 6.6)
687. sondavid1000 (0.94, 9.7)
688. strange#3540 (0.94, 12.1)
689. wiggstip1160 (0.94, 14.0)
690. kushkush4200 (0.94, 8.1)
691. sweetpea1960 (0.94, 6.2)
692. arlequin6000 (0.94, 9.9)
693. whiteboy1000 (0.94, 6.8)
694. iloveyou1070 (0.94, 7.1)
695. cashcash4000 (0.94, 8.7)
696. rgwadmin1010 (0.94, 11.6)
697. bautista6480 (0.94, 10.0)
698. jakaruta3060 (0.94, 13.4)
699. oghomwen1104 (0.94, 10.7)
700. wevelgem8500 (0.94, 13.8)
701. blackcod1000 (0.94, 8.5)

702. mischief1020 (0.94, 8.3)
703. dtfadmin1000 (0.94, 11.4)
704. thiarhex1704 (0.94, 14.0)
705. granteed1310 (0.94, 13.0)
706. linkedin7090 (0.94, 7.5)
707. kittymon7960 (0.94, 12.4)
708. Deurknop6000 (0.94, 12.7)
709. demonfog6900 (0.94, 13.0)
710. anhyeuem1260 (0.94, 8.2)
711. casacasa1320 (0.94, 9.1)
712. protect#6600 (0.94, 12.0)
713. debrakem1104 (0.94, 12.5)
714. linkedin7690 (0.94, 7.5)
715. hornymen1980 (0.94, 9.2)
716. linkedin7890 (0.94, 6.4)
717. blackboy1000 (0.94, 6.8)
718. asgfrdew1980 (0.94, 14.0)
719. xuwenwen1990 (0.94, 10.2)
720. Linkedin3090 (0.94, 8.0)
721. revoluta6000 (0.94, 12.1)
722. Billyboy1120 (0.94, 8.9)
723. helinked1970 (0.94, 11.0)
724. linkedin1820 (0.94, 6.8)
725. haitrieu1980 (0.94, 8.6)
726. sweetpea1980 (0.94, 6.2)
727. Sparkie#4270 (0.94, 12.6)
728. Mydomain1000 (0.94, 9.2)
729. svdragon1000 (0.94, 10.4)
730. kaprizen1990 (0.94, 10.8)
731. IamMatec1910 (0.94, 14.0)
732. firsania6710 (0.94, 13.5)
733. teamidea1990 (0.94, 10.9)
734. framloed4920 (0.94, 14.0)
735. Sweetpea1980 (0.94, 7.1)
736. brownsea1910 (0.94, 10.2)
737. Tasmania1000 (0.94, 8.4)
738. nitrogen1304 (0.94, 8.9)
739. dixiedog1000 (0.94, 8.1)
740. boesmith1180 (0.94, 12.2)
741. cliobleu6440 (0.94, 14.0)
742. bensalem1910 (0.94, 9.6)
743. pleasusn6200 (0.94, 14.0)
744. porchboy1420 (0.94, 10.8)
745. Colorboy1000 (0.94, 9.9)
746. radioweb1980 (0.94, 9.1)
747. linkedin3460 (0.94, 7.5)
748. Boxerdog1000 (0.94, 9.3)
749. cheatyou1000 (0.94, 10.4)
750. kaicorey1404 (0.94, 12.2)
751. sautpasa1000 (0.94, 13.7)
752. ngoanhtu7890 (0.94, 11.3)
753. dannyboy4420 (0.94, 8.4)
754. linkedin1000 (0.94, 5.8)
755. ystarley1020 (0.94, 12.0)
756. gonzalez1200 (0.94, 7.4)
757. El_Loco_1620 (0.94, 14.0)
758. golinked11!# (0.94, 12.5)
759. aguilas.1000 (0.94, 9.2)
760. rahulash1000 (0.94, 11.1)
761. dothedew1960 (0.94, 7.7)
762. lakeshia1010 (0.94, 9.2)
763. wolseley6110 (0.94, 11.2)
764. kwameata1000 (0.94, 9.7)
765. martinez5580 (0.94, 8.2)
766. :omlrfom3360 (0.94, 14.0)
767. alisaleh1910 (0.94, 9.5)
768. gooseboy1000 (0.94, 8.5)
769. Osvaldo_1000 (0.94, 9.9)
770. hyacinth1000 (0.94, 7.8)
771. benjamin1000 (0.94, 6.1)
772. farnoosh1370 (0.94, 9.8)
773. gogmagog7980 (0.94, 12.6)
774. Yloveyou1120 (0.94, 12.0)
775. billyboy1000 (0.94, 7.1)
776. Benjamin1000 (0.94, 6.9)
777. illbeatz4200 (0.94, 12.9)
778. youngdog4610 (0.94, 11.3)
779. skorpion6390 (0.94, 9.7)
780. nenengsu7490 (0.94, 13.7)
781. alihamed1394 (0.94, 10.6)
782. ilovemom1120 (0.94, 8.2)
783. deviljin1000 (0.94, 8.8)
784. ngochien1990 (0.94, 7.5)
785. teleajen1970 (0.94, 12.0)
786. gholston1300 (0.94, 11.5)
787. drcarmen1980 (0.94, 10.1)
788. iloveyou3490 (0.94, 7.5)
789. invinity6780 (0.94, 12.1)
790. webrahim7890 (0.94, 10.5)
791. versedon1000 (0.94, 11.2)
792. orquidea3950 (0.94, 10.6)
793. briangta4500 (0.94, 12.4)
794. patricia1010 (0.94, 6.3)
795. pokerwin1000 (0.94, 10.9)
796. jhonjhon1000 (0.94, 7.8)
797. kleeuwen1504 (0.94, 12.3)
798. dreampop1620 (0.94, 11.3)
799. iwelomen7650 (0.94, 13.6)
800. khorshid1330 (0.94, 9.7)
801. sarneson1690 (0.94, 13.1)
802. linkedin7180 (0.94, 7.6)
803. kianokia3280 (0.94, 10.7)
804. Kingsmen1980 (0.94, 9.3)
805. palencia1000 (0.94, 8.5)
806. stickmen1970 (0.94, 8.9)
807. colombia1010 (0.94, 6.5)
808. airindia1010 (0.94, 8.6)
809. supergod1010 (0.94, 9.1)
810. NetSoft@1520 (0.94, 13.6)
811. Gromoboy7890 (0.94, 12.9)
812. linkedin7980 (0.94, 7.4)
813. schenley1694 (0.94, 11.0)
814. jesusweb5380 (0.94, 12.4)
815. ghorizon1010 (0.94, 11.2)
816. pokeydog1000 (0.94, 9.3)
817. adedoyin1000 (0.94, 8.1)
818. avinnash7860 (0.94, 12.9)
819. cleveden1990 (0.94, 10.8)
820. ahmedasd1000 (0.94, 9.6)
821. parisboy7070 (0.94, 10.1)
822. sixseven8000 (0.94, 10.0)
823. illusion1890 (0.94, 9.0)
824. Joesipe●1980 (0.94, 14.0)
825. locksley1734 (0.94, 10.9)
826. martinez4584 (0.94, 8.5)
827. rubyanto1360 (0.94, 11.6)
828. tomasito1360 (0.94, 9.2)
829. Jackass@1310 (0.94, 10.1)
830. mauyjesi1690 (0.94, 14.0)
831. batalion1190 (0.94, 10.0)
832. cursoweb1604 (0.94, 9.4)
833. hayabusa1340 (0.94, 8.0)
834. irlandia3360 (0.94, 10.5)
835. superpig1010 (0.94, 8.6)
836. greentea1494 (0.94, 8.8)
837. plymouth1620 (0.94, 8.8)
838. jayaduta1010 (0.94, 11.3)
839. linkedin6410 (0.94, 7.3)
840. Hayabusa1340 (0.94, 8.1)
841. contprem1174 (0.94, 11.7)
842. nycperez3280 (0.94, 13.3)
843. linkedin4510 (0.94, 7.5)
844. snoopdog6020 (0.94, 9.2)
845. filetito1360 (0.94, 12.5)
846. Saiarkin4110 (0.94, 14.0)
847. cursoweb1304 (0.94, 9.5)
848. Waterdog1010 (0.94, 9.1)
849. favoured1194 (0.94, 9.4)
850. sujiasif6960 (0.94, 13.4)
851. Kingfish1500 (0.94, 9.4)
852. louisdog1010 (0.94, 10.4)
853. ironaven1980 (0.94, 11.7)
854. davidson1470 (0.94, 8.5)
855. Housebed1970 (0.94, 8.9)
856. jonathon1010 (0.94, 7.2)
857. Iloveyou1000 (0.94, 7.0)
858. iloveyou1000 (0.94, 5.5)
859. mountain7370 (0.94, 8.8)
860. mauricio1790 (0.94, 8.3)
861. througin1640 (0.94, 13.7)
862. indokush1000 (0.94, 10.2)
863. heineken1980 (0.94, 7.0)
864. popzyboy1010 (0.94, 7.7)
865. Popzyboy1010 (0.94, 9.2)
866. napattem1734 (0.94, 14.0)
867. tucachon1020 (0.94, 11.2)
868. huangbin1020 (0.94, 8.4)
869. tomilysh1000 (0.94, 13.3)
870. mauricio1190 (0.94, 8.0)
871. goldrush7180 (0.94, 9.7)
872. befrozen1980 (0.94, 9.4)
873. reostato1190 (0.94, 13.2)
874. Maglite*1844 (0.94, 14.0)
875. muhammed6264 (0.94, 8.4)
876. Muhammed6264 (0.94, 9.7)
877. getmoney8810 (0.94, 8.3)
878. Morrison6190 (0.94, 9.8)
879. bobssnow1630 (0.94, 13.0)
880. basatneh6784 (0.94, 14.0)
881. anhnhoem1990 (0.94, 6.4)
882. ataneata1000 (0.94, 11.1)
883. stavista1700 (0.94, 11.9)
884. robinson6890 (0.94, 8.7)
885. Bolleke@1980 (0.94, 10.3)
886. ilovepsp1000 (0.94, 9.8)
887. postspid1830 (0.94, 12.8)
888. pulguita6680 (0.94, 10.8)
889. davidson6060 (0.94, 8.0)
890. serenity1300 (0.94, 7.9)
891. nadjidou4720 (0.94, 14.0)
892. bushbush1000 (0.94, 9.0)
893. triomnia1010 (0.94, 12.0)
894. hardyweb1970 (0.94, 10.6)
895. dannyboy7000 (0.94, 8.0)
896. toilatoi1590 (0.94, 9.0)
897. alimaloo1360 (0.94, 12.2)
898. abrathod1010 (0.94, 12.0)
899. contstep1704 (0.94, 11.2)
900. ouistiti1380 (0.94, 12.2)
901. giangcoi1190 (0.94, 9.1)
902. courtney1004 (0.94, 6.7)
903. mechanic1010 (0.94, 7.4)
904. Roheisen7920 (0.94, 14.0)
905. weymouth1000 (0.94, 8.0)
906. blackboy1010 (0.94, 6.9)
907. GbczJdth7000 (0.94, 14.0)
908. kostebek1970 (0.94, 10.0)
909. mariposa1300 (0.94, 7.8)
910. onelove_1980 (0.94, 8.9)
911. forgiven1990 (0.94, 6.6)
912. wanabros1160 (0.94, 12.8)
913. onlydied6190 (0.94, 12.7)
914. icandoit1560 (0.94, 9.8)
915. almighty1000 (0.94, 6.5)
916. cablegod3370 (0.94, 12.4)
917. Monarrez1990 (0.94, 9.8)
918. underdog1130 (0.94, 8.0)
919. impressa1700 (0.94, 10.8)
920. persvest1190 (0.94, 12.4)
921. mudsrets1590 (0.94, 14.0)
922. yonacien1990 (0.94, 7.9)
923. dirtydog1540 (0.94, 9.9)
924. hotlive.1990 (0.94, 11.9)
925. urologia6420 (0.94, 12.6)
926. winslett1190 (0.94, 11.1)
927. longview1100 (0.94, 8.9)
928. benjamin7070 (0.94, 7.3)
929. loverboy1010 (0.94, 6.4)
930. charmcom1730 (0.94, 11.8)
931. ghislain1340 (0.94, 10.3)
932. almaazon1010 (0.94, 13.0)
933. whitesox1470 (0.94, 8.7)
934. Hayabusa3000 (0.94, 7.9)
935. ryrpvytm1000 (0.94, 14.0)
936. next-gen8510 (0.94, 14.0)
937. aseptata4910 (0.94, 13.9)
938. sixseven8910 (0.94, 10.6)
939. cherimea1970 (0.94, 11.2)
940. arnelyon7070 (0.94, 12.7)
941. lucrecia4020 (0.94, 9.6)
942. peladito1690 (0.94, 10.2)
943. linkedin1010 (0.94, 5.8)
944. linkedin1730 (0.94, 7.3)
945. phpclass1390 (0.94, 11.5)
946. bensatou1870 (0.94, 13.7)
947. frankie-1960 (0.94, 9.3)
948. Linkedin1010 (0.94, 6.5)
949. casioctk3000 (0.94, 11.5)
950. danykaty3000 (0.94, 11.6)
951. thebeast1490 (0.94, 8.7)
952. benjamin1010 (0.94, 6.1)
953. kisskiss1190 (0.94, 9.4)
954. pitchsis1590 (0.94, 13.0)
955. marinatu1010 (0.94, 10.4)
956. gustavo@3000 (0.94, 9.2)
957. benjimen6064 (0.94, 12.3)
958. cessbest1660 (0.94, 12.4)
959. moonpie/1990 (0.94, 11.7)
960. sarabasa1000 (0.94, 10.4)
961. semifusa1000 (0.94, 10.7)
962. thinkbig1010 (0.94, 8.0)
963. alvernia1330 (0.94, 10.7)
964. tormenta1000 (0.94, 7.6)
965. StaniceK1980 (0.94, 12.9)
966. Freecash1000 (0.94, 9.1)
967. economia7470 (0.94, 10.1)
968. mashroob1370 (0.94, 11.7)
969. ghostboy3000 (0.94, 8.7)
970. princess1590 (0.94, 7.5)
971. khalimoh3200 (0.94, 12.5)

972. idiotbob3000 (0.94, 11.1)
973. Vendetta1500 (0.94, 9.1)
974. anhyeuem1004 (0.94, 7.1)
975. benjamin1340 (0.94, 7.8)
976. chilehot1660 (0.94, 13.9)
977. gosergio1590 (0.94, 13.0)
978. minhdien1990 (0.94, 7.5)
979. marokkia3000 (0.94, 11.7)
980. linkedin6620 (0.94, 7.5)
981. kakaroto1180 (0.94, 9.1)
982. wordfrec1920 (0.94, 12.0)
983. linkedin4020 (0.94, 7.3)
984. Heineken6464 (0.94, 9.8)
985. redeemed8010 (0.94, 9.7)
986. linkedin1740 (0.94, 7.5)
987. abhishek1004 (0.94, 7.5)
988. unityasa1630 (0.94, 13.0)
989. coolchop1010 (0.94, 10.4)
990. gumakasa1020 (0.94, 13.4)
991. asesino_3000 (0.94, 9.9)
992. linkedin6120 (0.94, 7.6)
993. linkedin6520 (0.94, 7.3)
994. dinkedin6120 (0.94, 11.4)
995. linkedin1130 (0.94, 6.5)
996. johnmiss1660 (0.94, 12.0)
997. mischief1980 (0.94, 7.4)
998. shebadog1010 (0.94, 8.4)
999. phamdiem1990 (0.94, 8.1)

Cluster 2

Prototype: sanned641

Hard-assigned passwords: 1028605 (3.55% of total)
Unique hard-assigned passwords: 575293 (44.07% of cluster total)

Cluster-assignment scores:
        Min: 0.070
        Max: 0.700
        Mean: 0.274
        SD: 0.125

Strength bins:
        Very weak: 10542 (1.02%)
        Weak: 380345 (36.98%)
        Fair: 399997 (38.89%)
        Good: 235173 (22.86%)
        Strong: 2548 (0.25%)

Password lengths:
        Length 8: 649149 (63.11%)
        Length 9: 379456 (36.89%)

Character classes:
        4 classes: 15184 (1.48%)
        3 classes: 142425 (13.85%)
                lower/upper/symbol: 400 (0.28%)
                lower/upper/number: 119874 (84.17%)
                lower/symbol/number: 22150 (15.55%)
                upper/symbol/number: 1 (0.00%)
        2 classes: 870992 (84.68%)
                lower/upper: 30 (0.00%)
                lower/number: 869841 (99.87%)
                lower/symbol: 1120 (0.13%)
                upper/number: 0 (0.00%)
                upper/symbol: 0 (0.00%)
                number/symbol: 1 (0.00%)
        1 class: 4 (0.00%)
                lower: 0 (0.00%)
                upper: 0 (0.00%)
                symbol: 4 (100.00%)
                number: 0 (0.00%)

Most frequent char-class structures:
        LLLLLLDD: 547314 (53.2%)
        LLLLLLLDD: 316676 (30.8%)
        ULLLLLDD: 67223 (6.5%)
        ULLLLLLDD: 39743 (3.9%)
        LLLLLLSDD: 6767 (0.7%)
        LLLLLSDD: 5979 (0.6%)
        LLLLLLDL: 4681 (0.5%)
        ULLLLLSDD: 3398 (0.3%)
        ULLLLSDD: 3111 (0.3%)
        ULLLLLDS: 2890 (0.3%)

1,000 nearest passwords

0.	HaageB53	(0.70, 12.5)	54.	sowded33	(0.69, 9.3)	108.	xokuef67	(0.69, 12.2)
1.	sinned53	(0.70, 6.5)	55.	flamez53	(0.69, 7.5)	109.	tianen87	(0.69, 8.4)
2.	powned53	(0.70, 7.9)	56.	ardnek67	(0.69, 9.2)	110.	robnew67	(0.69, 9.4)
3.	dodge.53	(0.70, 9.1)	57.	claneb33	(0.69, 9.7)	111.	mennen87	(0.69, 7.9)
4.	yodjek53	(0.70, 11.3)	58.	hamzeh33	(0.69, 7.3)	112.	ShuFen87	(0.69, 11.2)
5.	lynne@53	(0.70, 9.0)	59.	powned67	(0.69, 7.6)	113.	jaraed33	(0.69, 9.3)
6.	byczek53	(0.70, 9.0)	60.	played33	(0.69, 6.8)	114.	slane#67	(0.69, 10.7)
7.	fucked53	(0.70, 6.6)	61.	phone#33	(0.69, 8.1)	115.	patyek33	(0.69, 7.9)
8.	bruceh53	(0.70, 8.5)	62.	wicked33	(0.69, 5.4)	116.	PippeN33	(0.69, 9.0)
9.	jacked53	(0.70, 7.6)	63.	krunek67	(0.69, 9.8)	117.	mannen87	(0.69, 7.3)
10.	issued53	(0.69, 9.8)	64.	rodhej33	(0.69, 10.7)	118.	bibyen87	(0.69, 10.3)
11.	Noyneb53	(0.69, 12.1)	65.	Jadded33	(0.69, 9.8)	119.	sachek67	(0.69, 9.2)
12.	linked53	(0.69, 6.0)	66.	Tanned67	(0.69, 9.0)	120.	Mjrmed53	(0.69, 12.0)
13.	mihaek33	(0.69, 10.7)	67.	damned67	(0.69, 6.6)	121.	labwed33	(0.69, 8.8)
14.	nevaeh33	(0.69, 5.6)	68.	kejaeg67	(0.69, 11.1)	122.	Disney67	(0.69, 6.4)
15.	loaded53	(0.69, 6.3)	69.	jimmed33	(0.69, 8.6)	123.	waynec67	(0.69, 7.9)
16.	aehaeh33	(0.69, 10.5)	70.	sidney67	(0.69, 5.8)	124.	muggen87	(0.69, 8.5)
17.	rednek33	(0.69, 6.9)	71.	iojnep67	(0.69, 11.9)	125.	hanyen87	(0.69, 8.2)
18.	graced53	(0.69, 7.9)	72.	stpney67	(0.69, 10.3)	126.	oakwed33	(0.69, 9.8)
19.	Payne_33	(0.69, 8.8)	73.	hejhej33	(0.69, 6.0)	127.	disney67	(0.69, 5.7)
20.	Notneb53	(0.69, 9.6)	74.	rodney67	(0.69, 5.7)	128.	penbed33	(0.69, 6.0)
21.	amazed53	(0.69, 7.7)	75.	Lanced33	(0.69, 8.6)	129.	nguyen87	(0.69, 5.4)
22.	dodgeb53	(0.69, 7.9)	76.	fucked33	(0.69, 5.9)	130.	thuyen87	(0.69, 6.7)
23.	penbed53	(0.69, 6.6)	77.	sonney67	(0.69, 7.4)	131.	runnef87	(0.69, 10.6)
24.	urthek53	(0.69, 11.3)	78.	hacked33	(0.69, 5.4)	132.	chuyen87	(0.69, 7.1)
25.	sinned33	(0.69, 6.0)	79.	owquex67	(0.69, 11.9)	133.	tioneb33	(0.69, 9.2)
26.	toshed53	(0.69, 9.6)	80.	chaney67	(0.69, 7.1)	134.	dohjeh67	(0.69, 10.4)
27.	pigwed53	(0.69, 10.4)	81.	buzzed33	(0.69, 7.0)	135.	kangen87	(0.69, 7.1)
28.	Brucej53	(0.69, 9.4)	82.	jenney67	(0.69, 7.9)	136.	irenej33	(0.68, 8.3)
29.	boyjeb53	(0.69, 10.4)	83.	blaney67	(0.69, 7.8)	137.	gr@$e#33	(0.68, 12.7)
30.	rugged33	(0.69, 6.2)	84.	Sydney67	(0.69, 6.4)	138.	Rangep67	(0.68, 10.0)
31.	hemdeb53	(0.69, 9.5)	85.	sydney67	(0.69, 5.6)	139.	duhhen87	(0.68, 11.0)
32.	dogged33	(0.69, 7.3)	86.	punked33	(0.69, 7.2)	140.	mmhpeh67	(0.68, 11.7)
33.	Mendez53	(0.69, 7.1)	87.	redfed33	(0.69, 8.1)	141.	Kingem87	(0.68, 9.4)
34.	bighed33	(0.69, 7.7)	88.	tiaweb53	(0.69, 9.3)	142.	linnea87	(0.68, 7.0)
35.	Duwveb53	(0.69, 13.2)	89.	rotpeg53	(0.69, 8.9)	143.	heyhey67	(0.68, 6.4)
36.	raghed33	(0.69, 10.1)	90.	cyvpex53	(0.69, 12.6)	144.	gunhed67	(0.68, 10.0)
37.	serge@53	(0.69, 8.9)	91.	Linked33	(0.69, 6.2)	145.	redhen87	(0.68, 8.0)
38.	ibanez33	(0.69, 5.6)	92.	funaeq67	(0.69, 10.6)	146.	CaydeN33	(0.68, 9.1)
39.	babyej33	(0.69, 8.7)	93.	warped53	(0.69, 7.3)	147.	shahen87	(0.68, 7.6)
40.	nevaeh67	(0.69, 5.9)	94.	sukkeL33	(0.69, 9.7)	148.	teagen87	(0.68, 7.7)
41.	shaneh67	(0.69, 8.1)	95.	yahveh33	(0.69, 9.2)	149.	mechef87	(0.68, 8.9)
42.	kanneh67	(0.69, 9.2)	96.	wayne.67	(0.69, 8.2)	150.	lamhew87	(0.68, 10.3)
43.	majaeb33	(0.69, 9.5)	97.	grabek33	(0.69, 8.3)	151.	reagen87	(0.68, 7.0)
44.	sacweb53	(0.69, 8.9)	98.	linked33	(0.69, 5.6)	152.	sexyew87	(0.68, 8.6)
45.	timmeh33	(0.69, 8.6)	99.	shane.67	(0.69, 8.3)	153.	gabhem87	(0.68, 10.0)
46.	devdek33	(0.69, 9.9)	100.	tinbed33	(0.69, 5.6)	154.	mayhem87	(0.68, 6.2)
47.	dianeb33	(0.69, 8.2)	101.	peace.33	(0.69, 7.7)	155.	Ertneb67	(0.68, 11.3)
48.	KbaceS33	(0.69, 12.4)	102.	ragheb33	(0.69, 8.4)	156.	rooney67	(0.68, 5.6)
49.	inmced33	(0.69, 10.9)	103.	nowpeg33	(0.69, 10.6)	157.	looney67	(0.68, 6.3)
50.	klidek53	(0.69, 10.3)	104.	nambe@33	(0.69, 10.7)	158.	dooney67	(0.68, 6.7)
51.	sudnek67	(0.69, 10.9)	105.	bagged67	(0.69, 6.9)	159.	mooney67	(0.68, 6.3)
52.	tapped33	(0.69, 8.7)	106.	rifhek67	(0.69, 11.3)	160.	ptuyen87	(0.68, 9.2)
53.	EmineM33	(0.69, 7.9)	107.	stonep53	(0.69, 8.5)	161.	Henney87	(0.68, 8.7)

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163. ginhew87 (0.68, 10.4)
164. bowhey87 (0.68, 9.9)
165. morneg33 (0.68, 9.6)
166. sioned67 (0.68, 8.4)
167. fibgem67 (0.68, 9.9)
168. bonnex87 (0.68, 8.5)
169. rodgey87 (0.68, 9.1)
170. najmeh67 (0.68, 9.2)
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172. hodgey87 (0.68, 7.4)
173. Sidney87 (0.68, 7.0)
174. cejceb33 (0.68, 11.2)
175. Godden87 (0.68, 9.4)
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183. pugdeb33 (0.68, 10.4)
184. lahpen87 (0.68, 10.0)
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186. michem67 (0.68, 8.1)
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188. Jayden87 (0.68, 6.6)
189. MwaGeN33 (0.68, 12.6)
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203. alonew87 (0.68, 9.2)
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207. stoney67 (0.68, 5.9)
208. Nooney87 (0.68, 9.3)
209. jampev87 (0.68, 10.1)
210. jewden87 (0.68, 9.9)
211. hadden87 (0.68, 7.7)
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274. lexmen87 (0.68, 9.4)
275. Luckey67 (0.68, 7.4)
276. minden87 (0.68, 7.3)
277. KrameR33 (0.68, 9.3)
278. Keeney67 (0.68, 8.9)
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286. Benneh87 (0.68, 10.8)
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438. ripken67 (0.68, 7.0)	528. dancex33 (0.68, 7.9)	618. luckey53 (0.68, 6.9)
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443. hamzeh87 (0.68, 7.0)	533. sailed33 (0.68, 7.6)	623. traveb67 (0.68, 9.9)
444. pigpen67 (0.68, 6.7)	534. pitted33 (0.68, 9.2)	624. lackey53 (0.68, 7.5)
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446. jayden67 (0.68, 6.0)	536. kraken67 (0.68, 7.1)	626. hookem87 (0.68, 6.1)
447. ledzep67 (0.68, 6.4)	537. penpen67 (0.68, 6.2)	627. putzen87 (0.68, 8.4)
448. hayden67 (0.68, 5.9)	538. sefteR33 (0.68, 10.5)	628. foiled33 (0.68, 7.9)
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450. loaded87 (0.68, 6.4)	540. rashed67 (0.68, 6.5)	630. hawkey53 (0.68, 7.9)
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452. mendez87 (0.68, 5.7)	542. ZenFeb33 (0.68, 11.7)	632. Anthem67 (0.68, 7.8)
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454. roddev67 (0.68, 8.9)	544. Shoyeb87 (0.68, 8.7)	634. maiden87 (0.68, 6.1)
455. dokken67 (0.68, 6.7)	545. voitek67 (0.68, 10.0)	635. glrgej67 (0.68, 11.9)
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463. hendek67 (0.68, 8.0)	553. looney53 (0.68, 6.6)	643. holden87 (0.68, 5.1)
464. althea87 (0.68, 6.3)	554. rooney53 (0.68, 6.3)	644. sankey53 (0.68, 7.5)
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469. rhuben67 (0.68, 9.0)	559. cutyea67 (0.68, 9.4)	649. shiken87 (0.68, 8.3)
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471. jjireh33 (0.68, 8.6)	561. bmmheh43 (0.68, 11.5)	651. smoked33 (0.68, 6.4)
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474. tenbed87 (0.68, 8.4)	564. heyhey53 (0.68, 6.7)	654. arsfeb87 (0.68, 10.7)
475. igorek33 (0.68, 7.3)	565. meiden87 (0.68, 8.2)	655. anteeL67 (0.68, 11.5)
476. mathew87 (0.68, 5.9)	566. jusben87 (0.68, 9.6)	656. montez53 (0.68, 7.0)
477. pempek87 (0.68, 7.7)	567. United33 (0.68, 6.0)	657. jorden87 (0.68, 6.6)
478. penbed87 (0.68, 6.5)	568. wasted33 (0.68, 5.9)	658. St@cey53 (0.68, 8.8)
479. chavez67 (0.68, 6.0)	569. boskey87 (0.68, 8.9)	659. Andre^67 (0.68, 10.4)
480. mdpweb67 (0.68, 9.6)	570. fasted33 (0.68, 7.0)	660. dotled33 (0.68, 8.9)
481. cashew87 (0.68, 6.8)	571. inokek33 (0.68, 9.6)	661. Wildey87 (0.68, 8.9)
482. Grape$67 (0.68, 9.2)	572. united33 (0.68, 5.1)	662. mathew67 (0.68, 5.8)
483. tekken67 (0.68, 6.4)	573. llaved67 (0.68, 8.9)	663. AndreV87 (0.68, 9.0)
484. sonney53 (0.68, 8.0)	574. joered33 (0.68, 7.9)	664. bladex33 (0.68, 8.2)
485. ninney53 (0.68, 9.1)	575. kwsleW53 (0.68, 13.1)	665. pinkey53 (0.68, 7.0)
486. nonney53 (0.68, 8.6)	576. elimed33 (0.68, 9.0)	666. stacey53 (0.68, 6.0)
487. Femmen67 (0.68, 10.3)	577. primed33 (0.68, 7.8)	667. xtacey53 (0.68, 11.0)
488. joaney53 (0.68, 8.9)	578. texmex33 (0.68, 6.4)	668. norbey87 (0.68, 8.8)
489. jurgen87 (0.68, 6.8)	579. matted33 (0.68, 7.4)	669. monkey53 (0.68, 5.0)
490. funvex87 (0.68, 10.5)	580. wiskey87 (0.68, 7.0)	670. florez33 (0.68, 6.7)
491. lanney53 (0.68, 8.2)	581. rainey53 (0.68, 7.4)	671. Tanzey53 (0.68, 9.9)
492. rodney53 (0.68, 6.1)	582. wenweb87 (0.68, 9.4)	672. szeged67 (0.67, 7.6)
493. hanney53 (0.68, 8.6)	583. aliben87 (0.68, 8.1)	673. garden87 (0.67, 5.8)
494. sidney53 (0.68, 6.3)	584. sergey67 (0.68, 6.4)	674. Gurdev87 (0.67, 8.4)
495. webweb87 (0.68, 6.8)	585. meoden87 (0.68, 7.9)	675. lieben87 (0.67, 7.6)
496. chavez87 (0.68, 5.7)	586. serged87 (0.68, 8.3)	676. brucey53 (0.67, 7.3)
497. tenney53 (0.68, 8.0)	587. Nickey53 (0.68, 8.0)	677. passed33 (0.67, 6.3)
498. penney53 (0.68, 7.4)	588. trydex33 (0.68, 9.3)	678. leuven67 (0.67, 7.8)
499. matuek87 (0.68, 9.0)	589. ayuwek87 (0.68, 10.7)	679. permen87 (0.67, 7.6)
500. rekweb87 (0.68, 8.6)	590. stoney53 (0.68, 6.7)	680. trozen87 (0.67, 8.7)
501. Rospen87 (0.68, 9.2)	591. amore@33 (0.68, 8.2)	681. heuven67 (0.67, 8.9)
502. aliced33 (0.68, 7.5)	592. stacex33 (0.68, 8.3)	682. smilez33 (0.67, 6.3)
503. tinpen67 (0.68, 6.1)	593. teqwen67 (0.68, 10.9)	683. lutbeh87 (0.67, 11.7)
504. Sergey87 (0.68, 7.1)	594. windex33 (0.68, 6.6)	684. spidey87 (0.67, 6.1)
505. sinden67 (0.68, 8.8)	595. dotpeg87 (0.68, 9.4)	685. grimey87 (0.67, 7.0)
506. wonpen67 (0.68, 9.7)	596. Torben87 (0.68, 8.4)	686. darcey87 (0.67, 7.2)
507. krazed67 (0.68, 8.7)	597. Maskey87 (0.68, 9.3)	687. llopez33 (0.67, 8.0)
508. tatfed33 (0.68, 9.7)	598. yeslek33 (0.68, 7.9)	688. carmex53 (0.67, 7.4)
509. Jorgeg33 (0.68, 9.2)	599. Baskey87 (0.68, 9.9)	689. anipeg33 (0.67, 9.1)
510. redmen67 (0.68, 6.9)	600. shakep33 (0.68, 8.8)	690. mircea87 (0.67, 7.0)
511. zedvex67 (0.68, 10.8)	601. Tatted33 (0.68, 8.2)	691. Moose@33 (0.67, 8.0)
512. denjev67 (0.68, 10.9)	602. noogen67 (0.68, 8.1)	692. torpez87 (0.67, 8.9)
513. sydney53 (0.68, 6.1)	603. gutfeu87 (0.68, 11.1)	693. Koose@33 (0.67, 10.2)
514. phile#33 (0.68, 9.9)	604. mickey53 (0.68, 5.5)	694. flopez33 (0.67, 8.3)
515. dusted53 (0.68, 7.8)	605. dmoney53 (0.68, 6.5)	695. carmen87 (0.67, 5.2)
516. sholeh33 (0.68, 7.7)	606. dickey53 (0.68, 7.1)	696. sliven87 (0.67, 7.4)
517. uswnej43 (0.68, 12.3)	607. odiseh33 (0.68, 9.6)	697. klopez87 (0.67, 7.7)
518. noumea67 (0.68, 7.0)	608. lowkey53 (0.68, 6.9)	698. heaven67 (0.67, 5.8)
519. weired33 (0.68, 8.8)	609. Golden87 (0.68, 6.3)	699. draven67 (0.67, 6.4)
520. blazed87 (0.68, 6.3)	610. Holden87 (0.68, 6.1)	700. tolken87 (0.67, 8.1)
521. gercek33 (0.68, 7.9)	611. ChaseR33 (0.68, 8.4)	701. lilken87 (0.67, 7.5)

702. Quebec87 (0.67, 7.0)
703. merve_33 (0.67, 8.4)
704. moodeh87 (0.67, 9.1)
705. rlopez87 (0.67, 7.9)
706. montez33 (0.67, 6.3)
707. nutmeg87 (0.67, 6.7)
708. glmteJ33 (0.67, 13.3)
709. MableB67 (0.67, 10.3)
710. Smokey87 (0.67, 5.7)
711. garcea87 (0.67, 7.8)
712. rvelez33 (0.67, 9.4)
713. helmey87 (0.67, 9.0)
714. onose@33 (0.67, 10.5)
715. W@nted33 (0.67, 7.9)
716. zoltek33 (0.67, 8.9)
717. stomey87 (0.67, 8.7)
718. quebec87 (0.67, 6.3)
719. smokey87 (0.67, 4.6)
720. jermey87 (0.67, 7.5)
721. dantek33 (0.67, 7.9)
722. mgrjej33 (0.67, 11.2)
723. wanted33 (0.67, 5.4)
724. earken87 (0.67, 9.4)
725. joshep33 (0.67, 8.2)
726. bergen67 (0.67, 6.9)
727. jurgen67 (0.67, 7.0)
728. puskey67 (0.67, 8.7)
729. poopey67 (0.67, 7.8)
730. outleg33 (0.67, 9.4)
731. bluzep33 (0.67, 9.9)
732. opemed33 (0.67, 10.1)
733. canvey53 (0.67, 8.7)
734. ratbex67 (0.67, 10.0)
735. wenwen67 (0.67, 7.2)
736. rersed53 (0.67, 10.6)
737. aapje_43 (0.67, 9.6)
738. Puskey67 (0.67, 9.4)
739. Wanted33 (0.67, 6.9)
740. jarred33 (0.67, 6.0)
741. rutfez67 (0.67, 10.4)
742. wilven87 (0.67, 9.7)
743. bremen87 (0.67, 7.0)
744. SteveS87 (0.67, 9.0)
745. Joyce&43 (0.67, 10.3)
746. leike-67 (0.67, 11.0)
747. kelbeh87 (0.67, 9.7)
748. ilovec87 (0.67, 7.3)
749. iloveu87 (0.67, 5.3)
750. piesek33 (0.67, 7.2)
751. ddavey53 (0.67, 9.5)
752. wojtek33 (0.67, 6.1)
753. lyemen87 (0.67, 9.8)
754. sgtpep67 (0.67, 8.6)
755. valdez87 (0.67, 6.3)
756. egemen87 (0.67, 6.9)
757. gifted33 (0.67, 6.3)
758. sidney33 (0.67, 5.7)
759. Rodney33 (0.67, 6.4)
760. crikey67 (0.67, 7.6)
761. paired67 (0.67, 9.1)
762. rodney33 (0.67, 5.5)
763. dafney33 (0.67, 7.7)
764. mookey67 (0.67, 7.5)
765. kolkea87 (0.67, 9.4)
766. shaney33 (0.67, 6.5)
767. chaney33 (0.67, 6.6)
768. turkey87 (0.67, 5.6)
769. Chaney33 (0.67, 7.4)
770. sydney33 (0.67, 5.5)
771. steve_33 (0.67, 8.1)
772. Duece@33 (0.67, 9.3)
773. Helvem87 (0.67, 10.8)
774. barkey87 (0.67, 7.6)
775. liemem87 (0.67, 10.1)
776. thered67 (0.67, 7.9)
777. vianey33 (0.67, 6.9)
778. jacked43 (0.67, 7.3)
779. hacked43 (0.67, 6.3)
780. monney33 (0.67, 6.8)
781. slopey67 (0.67, 8.1)
782. Hooked67 (0.67, 8.5)
783. marzec87 (0.67, 7.4)
784. inimeg87 (0.67, 9.6)
785. Steven87 (0.67, 6.1)
786. jlopez67 (0.67, 7.4)
787. jobzed43 (0.67, 10.4)
788. matwea87 (0.67, 9.8)
789. penney33 (0.67, 6.7)
790. kenney33 (0.67, 6.7)
791. aliceb67 (0.67, 7.9)
792. tesweb87 (0.67, 8.5)
793. fcimeg33 (0.67, 10.7)
794. kissez33 (0.67, 7.8)
795. warped67 (0.67, 7.3)
796. leszek87 (0.67, 7.0)
797. redted33 (0.67, 7.3)
798. Naimeh87 (0.67, 10.5)
799. vetrep67 (0.67, 10.7)
800. steven87 (0.67, 5.0)
801. durmex87 (0.67, 9.5)
802. Owedeb87 (0.67, 10.5)
803. spicey67 (0.67, 6.8)
804. ayehey67 (0.67, 9.4)
805. aitken67 (0.67, 7.9)
806. sirbed67 (0.67, 8.6)
807. disweb33 (0.67, 8.7)
808. kuicek87 (0.67, 11.1)
809. agomez87 (0.67, 7.4)
810. linked43 (0.67, 5.9)
811. lilred33 (0.67, 6.0)
812. haolep67 (0.67, 10.2)
813. matrex67 (0.67, 7.1)
814. masmex67 (0.67, 10.1)
815. iloveg87 (0.67, 7.9)
816. stated67 (0.67, 7.9)
817. garvey87 (0.67, 7.1)
818. miodek67 (0.67, 10.0)
819. kolked87 (0.67, 9.9)
820. spidey67 (0.67, 6.0)
821. harvey87 (0.67, 5.4)
822. turbed67 (0.67, 9.2)
823. potted67 (0.67, 8.0)
824. harxex87 (0.67, 11.5)
825. eissej67 (0.67, 9.8)
826. whited67 (0.67, 7.6)
827. aneleh67 (0.67, 9.0)
828. nutmeg67 (0.67, 6.4)
829. busted67 (0.67, 6.5)
830. hooten67 (0.67, 8.0)
831. ayevex53 (0.67, 11.2)
832. stevev87 (0.67, 8.4)
833. zedzed43 (0.67, 7.8)
834. turkeg33 (0.67, 9.7)
835. spiked67 (0.67, 7.4)
836. primex67 (0.67, 7.9)
837. leibeu67 (0.67, 11.1)
838. united67 (0.67, 5.3)
839. therev67 (0.67, 7.3)
840. valdez67 (0.67, 6.7)
841. go-red53 (0.67, 10.7)
842. woiken67 (0.67, 9.6)
843. michey33 (0.67, 7.3)
844. Currej33 (0.67, 11.4)
845. galvez87 (0.67, 6.8)
846. leewen87 (0.67, 8.5)
847. kitten67 (0.67, 5.2)
848. yorled53 (0.67, 10.4)
849. system67 (0.67, 5.8)
850. hookem67 (0.67, 6.4)
851. chevey87 (0.67, 7.3)
852. killed33 (0.67, 6.6)
853. simsek33 (0.67, 7.4)
854. santez33 (0.67, 7.9)
855. Piewey87 (0.67, 11.2)
856. smokey67 (0.67, 4.7)
857. connex43 (0.67, 7.9)
858. Disney33 (0.67, 6.0)
859. Lilmex67 (0.67, 9.4)
860. disney33 (0.67, 5.3)
861. fratem67 (0.67, 9.9)
862. Smokey67 (0.67, 5.8)
863. Chase_53 (0.67, 8.7)
864. promex67 (0.67, 8.2)
865. spotey67 (0.67, 8.4)
866. Awtrey67 (0.67, 11.0)
867. daizey67 (0.67, 8.4)
868. ohofez67 (0.67, 11.6)
869. physed33 (0.67, 9.0)
870. weiney33 (0.67, 8.9)
871. korpen67 (0.67, 9.4)
872. rellek67 (0.67, 8.3)
873. jkhbec97 (0.67, 11.3)
874. milkey67 (0.67, 7.4)
875. smiley67 (0.67, 5.3)
876. frowed87 (0.67, 9.8)
877. batmen67 (0.67, 7.4)
878. corkey67 (0.67, 7.1)
879. abcdef97 (0.67, 6.5)
880. easyed43 (0.67, 9.3)
881. awtrey67 (0.67, 10.0)
882. bailey67 (0.67, 5.1)
883. heyhey33 (0.67, 6.0)
884. hailey67 (0.67, 5.9)
885. rooney33 (0.67, 5.5)
886. looney33 (0.67, 6.0)
887. groden67 (0.67, 8.9)
888. booney33 (0.67, 6.7)
889. tooney33 (0.67, 6.9)
890. mooney33 (0.67, 5.9)
891. ediveb33 (0.67, 10.2)
892. raidem67 (0.67, 9.8)
893. carmex67 (0.67, 7.4)
894. qempev97 (0.67, 12.0)
895. hoekey67 (0.67, 9.6)
896. garcea67 (0.67, 8.3)
897. turkey67 (0.67, 5.5)
898. Smile@67 (0.67, 7.6)
899. kemfez43 (0.67, 11.0)
900. unitec67 (0.67, 7.0)
901. vialek33 (0.67, 9.4)
902. hommem97 (0.67, 10.1)
903. haeley67 (0.67, 8.1)
904. yepwed43 (0.67, 10.0)
905. torrez33 (0.67, 6.6)
906. Unitef67 (0.67, 8.9)
907. talked67 (0.67, 9.4)
908. juqzeb97 (0.67, 12.4)
909. lainey33 (0.67, 6.8)
910. raiden67 (0.67, 7.2)
911. joepea67 (0.67, 9.1)
912. maiden67 (0.67, 6.2)
913. parlez33 (0.67, 9.0)
914. dueley67 (0.67, 8.8)
915. Buffey33 (0.67, 8.5)
916. laffey33 (0.67, 8.1)
917. Stoney33 (0.67, 6.8)
918. bbhdez43 (0.67, 11.8)
919. Pompey33 (0.67, 6.7)
920. nielen67 (0.67, 9.5)
921. decfeb43 (0.67, 10.3)
922. pompey33 (0.67, 5.7)
923. grisen67 (0.67, 7.5)
924. Holden67 (0.67, 6.3)
925. Bontey67 (0.67, 8.3)
926. stoney33 (0.67, 5.9)
927. redred33 (0.67, 5.6)
928. nettek43 (0.67, 9.6)
929. golden67 (0.67, 5.6)
930. holden67 (0.67, 5.4)
931. Jorden67 (0.67, 7.6)
932. poppey33 (0.67, 7.5)
933. whitey67 (0.67, 6.0)
934. ianfeb97 (0.67, 9.3)
935. horsea67 (0.67, 8.6)
936. united43 (0.67, 5.7)
937. jensen67 (0.67, 6.4)
938. huskey53 (0.67, 7.6)
939. Mickey33 (0.67, 5.8)
940. Nickey33 (0.67, 7.5)
941. Chosen67 (0.67, 7.6)
942. jorden67 (0.67, 6.9)
943. pookey53 (0.67, 6.8)
944. elecea67 (0.67, 11.8)
945. Lowkey33 (0.67, 7.4)
946. moose-43 (0.67, 8.8)
947. waimea67 (0.67, 7.1)
948. poepen67 (0.67, 6.2)
949. nickey33 (0.67, 6.6)
950. mouled53 (0.67, 9.5)
951. mickey33 (0.67, 4.8)
952. mayhem97 (0.67, 6.3)
953. halden67 (0.67, 8.1)
954. larkej67 (0.67, 10.6)
955. awlhex33 (0.67, 9.7)
956. kmoney33 (0.67, 6.0)
957. dickey33 (0.67, 6.7)
958. rickey33 (0.67, 6.3)
959. Waimea67 (0.67, 8.2)
960. dmoney33 (0.67, 5.8)
961. fecfec97 (0.67, 9.2)
962. jmdsed53 (0.67, 11.0)
963. lickey33 (0.67, 7.7)
964. jmoney33 (0.67, 5.7)
965. bigred53 (0.67, 5.5)
966. eegle#33 (0.67, 11.2)
967. zmoney33 (0.67, 6.8)
968. gmoney33 (0.67, 5.4)
969. saucey33 (0.67, 6.6)
970. tandem97 (0.67, 7.4)
971. owedeb67 (0.67, 10.0)

972. cmoney33 (0.67, 6.2)	982. Mikkey33 (0.67, 7.8)	992. bigred33 (0.67, 4.8)
973. muncey33 (0.67, 8.7)	983. papdew97 (0.67, 10.4)	993. garden67 (0.67, 5.8)
974. Hockey33 (0.67, 5.4)	984. tmoney33 (0.67, 5.3)	994. smpkey33 (0.67, 9.9)
975. raise}43 (0.67, 12.8)	985. wszhev97 (0.67, 11.9)	995. hockey33 (0.67, 4.2)
976. emoney33 (0.67, 6.5)	986. pockey33 (0.67, 7.6)	996. jackey33 (0.67, 6.7)
977. nlbcec97 (0.67, 11.5)	987. nibpew97 (0.67, 10.1)	997. brycem97 (0.67, 8.1)
978. galvez67 (0.67, 6.8)	988. newbey33 (0.67, 9.1)	998. colbey53 (0.67, 7.6)
979. Garden67 (0.67, 6.7)	989. harvey67 (0.67, 5.3)	999. anstey67 (0.67, 8.5)
980. edoben67 (0.67, 9.3)	990. alfred33 (0.67, 5.7)	
981. mutley67 (0.67, 6.4)	991. rockey33 (0.67, 6.2)	

Cluster 3

Prototype: sanned123

Hard-assigned passwords: 1097077 (3.79% of total)
Unique hard-assigned passwords: 493542 (55.01% of cluster total)

Cluster-assignment scores:
	Min: 0.066
	Max: 0.867
	Mean: 0.288
	SD: 0.177

Strength bins:
	Very weak: 80453 (7.33%)
	Weak: 453421 (41.33%)
	Fair: 350966 (31.99%)
	Good: 210198 (19.16%)
	Strong: 2039 (0.19%)

Password lengths:
	Length 8: 477488 (43.52%)
	Length 9: 570548 (52.01%)
	Length 10: 49041 (4.47%)

Character classes:
	4 classes: 13586 (1.24%)
	3 classes: 116843 (10.65%)
		lower/upper/symbol: 49 (0.04%)
		lower/upper/number: 89450 (76.56%)
		lower/symbol/number: 27342 (23.40%)
		upper/symbol/number: 2 (0.00%)
	2 classes: 966648 (88.11%)
		lower/upper: 0 (0.00%)
		lower/number: 966477 (99.98%)
		lower/symbol: 165 (0.02%)
		upper/number: 0 (0.00%)
		upper/symbol: 0 (0.00%)
		number/symbol: 6 (0.00%)
	1 class: 0 (0.00%)

Most frequent char-class structures:
	LLLLLLDDD: 498184 (45.4%)
	LLLLLDDD: 420332 (38.3%)
	LLLLLLLDDD: 42814 (3.9%)
	ULLLLLDDD: 41924 (3.8%)
	ULLLLDDD: 38748 (3.5%)
	LLLLLSDDD: 10196 (0.9%)
	LLLLSDDD: 8576 (0.8%)
	ULLLLSDDD: 4406 (0.4%)
	ULLLLLLDDD: 2946 (0.3%)
	ULLLLLDDS: 2759 (0.3%)

1,000 nearest passwords

0. otoxeh113	(0.87, 10.0)	55. rozbeh123	(0.86, 6.4)	110. Sayyed123	(0.85, 7.5)
1. igebeh113	(0.87, 10.2)	56. pompek123	(0.86, 7.8)	111. saadeh123	(0.85, 6.9)
2. osameh113	(0.87, 10.7)	57. playek123	(0.86, 8.1)	112. munkeh123	(0.85, 7.8)
3. jammeh113	(0.86, 9.9)	58. lacbeh123	(0.86, 9.0)	113. buthek123	(0.85, 9.6)
4. rushed113	(0.86, 9.1)	59. sakpek123	(0.86, 8.1)	114. spacek123	(0.85, 6.5)
5. wicked113	(0.86, 6.9)	60. tempek123	(0.86, 6.0)	115. rugged123	(0.85, 5.5)
6. enivez113	(0.86, 10.6)	61. cehceh123	(0.86, 8.6)	116. ragged123	(0.85, 6.6)
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23. gornek123	(0.86, 8.7)	78. behbeh123	(0.85, 6.1)	133. mekmek123	(0.85, 6.0)
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980. wummex123 (0.84, 9.0)
981. sammex123 (0.84, 6.7)
982. maddex123 (0.84, 6.6)
983. weqweq123 (0.84, 6.6)
984. floweb123 (0.84, 7.5)
985. niujex123 (0.84, 10.9)
986. aleweb123 (0.84, 7.2)
987. sajmex123 (0.84, 9.1)
988. aaacex123 (0.84, 10.5)
989. sexmex123 (0.84, 7.3)
990. paigex123 (0.84, 7.6)
991. texmex123 (0.84, 5.8)
992. rexmex123 (0.84, 6.9)
993. mexmex123 (0.84, 6.4)
994. Brucex123 (0.84, 8.7)
995. dexmex123 (0.84, 7.4)
996. danyep123 (0.84, 8.1)
997. mapzex123 (0.83, 9.7)
998. yandex123 (0.83, 6.0)
999. landex123 (0.83, 7.2)

Cluster 4

Prototype: saanedo1

Hard-assigned passwords: 1014120 (3.50% of total)
Unique hard-assigned passwords: 442263 (56.39% of cluster total)

Cluster-assignment scores:
        Min: 0.081
        Max: 0.906
        Mean: 0.342
        SD: 0.179

Strength bins:
        Very weak: 89446 (8.82%)
        Weak: 425267 (41.93%)
        Fair: 289302 (28.53%)
        Good: 207226 (20.43%)
        Strong: 2879 (0.28%)

Password lengths:
        Length 8: 970936 (95.74%)
        Length 9: 43184 (4.26%)

Character classes:
        4 classes: 10708 (1.06%)
        3 classes: 130604 (12.88%)
                lower/upper/symbol: 2924 (2.24%)
                lower/upper/number: 109290 (83.68%)
                lower/symbol/number: 18382 (14.07%)
                upper/symbol/number: 8 (0.01%)
        2 classes: 720476 (71.04%)
                lower/upper: 5069 (0.70%)
                lower/number: 704701 (97.81%)
                lower/symbol: 10700 (1.49%)
                upper/number: 0 (0.00%)
                upper/symbol: 0 (0.00%)
                number/symbol: 6 (0.00%)
        1 class: 152332 (15.02%)
                lower: 152326 (100.00%)
                upper: 0 (0.00%)
                symbol: 6 (0.00%)
                number: 0 (0.00%)

Most frequent char-class structures:
        LLLLLLLD: 669196 (66.0%)
        LLLLLLLL: 152326 (15.0%)
        ULLLLLLD: 91902 (9.1%)
        LLLLLLLLD: 35426 (3.5%)
        LLLLLLSD: 12880 (1.3%)
        LLLLLLLS: 7638 (0.8%)
        ULLLLLSD: 6548 (0.6%)
        ULLLLLLLD: 4751 (0.5%)
        ULLLLLLL: 3840 (0.4%)
        LLLLLLUD: 2078 (0.2%)

1,000 nearest passwords

0.	juvgexn1	(0.91, 11.9)	54.	gwhuedc1	(0.87, 11.6)	108.	sonne+a1	(0.87, 10.4)
1.	damnedn1	(0.90, 8.6)	55.	iluvedu1	(0.87, 7.5)	109.	sinuema1	(0.87, 9.0)
2.	kmpuehn1	(0.90, 11.1)	56.	Irenebc1	(0.87, 9.6)	110.	bongeda1	(0.87, 8.7)
3.	ecgfedn1	(0.90, 11.5)	57.	btbpegc1	(0.87, 11.7)	111.	dongeda1	(0.87, 8.1)
4.	jaydedn1	(0.90, 9.8)	58.	whymeyu1	(0.87, 9.4)	112.	gadheda1	(0.87, 9.4)
5.	sladeqn1	(0.90, 10.7)	59.	nogueda1	(0.87, 7.7)	113.	scfuefa1	(0.87, 11.1)
6.	Linkedn1	(0.90, 7.4)	60.	esqueda1	(0.87, 5.6)	114.	hacheka1	(0.87, 8.4)
7.	Graceyn1	(0.89, 8.8)	61.	minneda1	(0.87, 9.3)	115.	booneha1	(0.87, 7.8)
8.	PlaceOn1	(0.89, 10.2)	62.	niqueda1	(0.87, 8.4)	116.	crwaema1	(0.87, 11.2)
9.	v@lje@n1	(0.89, 10.0)	63.	luckepc1	(0.87, 9.3)	117.	anmgeca1	(0.87, 11.6)
10.	hognegu1	(0.89, 10.5)	64.	lahueda1	(0.87, 8.1)	118.	Sitnexa1	(0.87, 11.8)
11.	Vonnegu1	(0.89, 8.0)	65.	alqaeda1	(0.87, 5.7)	119.	rudgeja1	(0.87, 10.8)
12.	ftswezn1	(0.88, 12.0)	66.	akaneda1	(0.87, 7.7)	120.	saabexc1	(0.87, 11.3)
13.	deonequ1	(0.88, 9.7)	67.	zhaneka1	(0.87, 8.6)	121.	mnbkejc1	(0.87, 11.2)
14.	Sinaedu1	(0.88, 10.1)	68.	alcaeda1	(0.87, 6.1)	122.	nevaeva1	(0.87, 7.1)
15.	japaeju1	(0.88, 10.3)	69.	donneka1	(0.87, 7.2)	123.	xfwneza1	(0.87, 11.5)
16.	betaeju1	(0.88, 9.4)	70.	shaneka1	(0.87, 5.8)	124.	munyeca1	(0.87, 10.1)
17.	ahaneku1	(0.88, 9.1)	71.	wayneda1	(0.87, 6.8)	125.	shaheda1	(0.87, 6.9)
18.	juanedu1	(0.88, 7.4)	72.	Winneba1	(0.87, 7.4)	126.	labaeza1	(0.87, 8.3)
19.	Anx_edu1	(0.88, 11.4)	73.	winneba1	(0.87, 6.6)	127.	henneyc1	(0.87, 9.5)
20.	T@muedu1	(0.88, 13.1)	74.	dlawedu1	(0.87, 10.0)	128.	jpineda1	(0.87, 6.4)
21.	ttvkequ1	(0.88, 12.0)	75.	migueba1	(0.87, 7.4)	129.	rudjedc1	(0.87, 12.0)
22.	Stccebu1	(0.88, 12.4)	76.	komaeda1	(0.87, 10.1)	130.	bbmaeva1	(0.87, 10.0)
23.	cbwpegu1	(0.88, 11.6)	77.	cihneba1	(0.87, 10.6)	131.	gingewa1	(0.87, 9.6)
24.	imageku1	(0.88, 9.1)	78.	riqueza1	(0.87, 5.8)	132.	euphema1	(0.87, 8.2)
25.	itsmeRn1	(0.88, 10.7)	79.	sunnepa1	(0.87, 2.9)	133.	dodgeva1	(0.87, 8.9)
26.	Chinedu1	(0.88, 5.2)	80.	Mojaewa1	(0.87, 10.3)	134.	adanena1	(0.87, 8.2)
27.	chinedu1	(0.88, 3.5)	81.	lanueva1	(0.87, 5.7)	135.	zevyefa1	(0.87, 11.4)
28.	gjineku1	(0.88, 8.2)	82.	ipanema1	(0.87, 5.8)	136.	rpagefa1	(0.87, 10.8)
29.	LetMeIn1	(0.88, 4.7)	83.	vinueza1	(0.87, 7.4)	137.	asdfedc1	(0.87, 4.8)
30.	LetmeIn1	(0.88, 5.8)	84.	esquema1	(0.87, 7.8)	138.	Aruneya1	(0.87, 9.7)
31.	ycomeyn1	(0.88, 11.2)	85.	jtoheku1	(0.87, 11.9)	139.	Kongepa1	(0.87, 10.1)
32.	hfccedu1	(0.88, 10.4)	86.	Rayneja1	(0.87, 9.8)	140.	donneya1	(0.87, 8.7)
33.	haccedu1	(0.88, 11.1)	87.	layneba1	(0.87, 8.5)	141.	kimuena1	(0.87, 9.3)
34.	Vtvvebu1	(0.88, 13.0)	88.	daaneva1	(0.87, 8.3)	142.	mawuena1	(0.87, 7.1)
35.	ychceku1	(0.88, 11.4)	89.	incuema1	(0.87, 11.0)	143.	Sisneyc1	(0.87, 11.7)
36.	Nondeju1	(0.88, 10.6)	90.	danneva1	(0.87, 8.6)	144.	Mawuena1	(0.87, 7.2)
37.	heguepc1	(0.88, 10.7)	91.	shaneza1	(0.87, 7.1)	145.	gusnepa1	(0.87, 9.3)
38.	usydedu1	(0.88, 11.2)	92.	annaeva1	(0.87, 6.8)	146.	amineka1	(0.87, 7.3)
39.	vincedu1	(0.88, 7.8)	93.	Sopueva1	(0.87, 10.1)	147.	ripnena1	(0.87, 7.8)
40.	hackedu1	(0.88, 6.4)	94.	bdcueza1	(0.87, 11.6)	148.	aloneka1	(0.87, 6.9)
41.	Daiveyn1	(0.88, 10.5)	95.	apaneca1	(0.87, 8.1)	149.	elchema1	(0.87, 8.5)
42.	saraedu1	(0.88, 8.0)	96.	mgaueca1	(0.87, 10.8)	150.	pequena1	(0.87, 5.2)
43.	ruapehu1	(0.88, 9.9)	97.	lacueva1	(0.87, 5.6)	151.	Pequena1	(0.87, 6.6)
44.	bendezu1	(0.88, 9.8)	98.	fennema1	(0.87, 8.7)	152.	monyeka1	(0.87, 8.3)
45.	heyheyu1	(0.87, 6.9)	99.	raynema1	(0.87, 8.0)	153.	Bengeza1	(0.87, 9.7)
46.	renaejc1	(0.87, 8.7)	100.	Jenneva1	(0.87, 8.2)	154.	Pufjeka1	(0.87, 11.6)
47.	VsvNeku1	(0.87, 13.5)	101.	babyeva1	(0.87, 6.5)	155.	Dataeba1	(0.87, 9.1)
48.	nahuexc1	(0.87, 10.6)	102.	Senneca1	(0.87, 8.2)	156.	alinepa1	(0.87, 8.2)
49.	Menzedu1	(0.87, 11.1)	103.	matneda1	(0.87, 8.7)	157.	xyzfeda1	(0.87, 9.9)
50.	cfvceyu1	(0.87, 8.1)	104.	vicyeka1	(0.87, 9.9)	158.	bappeda1	(0.87, 6.6)
51.	Cfvceyu1	(0.87, 8.5)	105.	samneha1	(0.87, 7.3)	159.	Myhyena1	(0.87, 10.3)
52.	blake.c1	(0.87, 9.2)	106.	Sinuema1	(0.87, 9.3)	160.	fdvxehc1	(0.87, 11.9)
53.	mashehu1	(0.87, 8.6)	107.	nevaeha1	(0.87, 5.9)	161.	Gfdyena1	(0.87, 12.2)

162. peguena1 (0.87, 8.5)
163. luvyeya1 (0.87, 10.3)
164. stoneka1 (0.87, 6.8)
165. sidneyc1 (0.87, 7.0)
166. aninеja1 (0.87, 10.1)
167. cambeda1 (0.87, 8.7)
168. kengeja1 (0.87, 9.5)
169. zhaneya1 (0.87, 8.8)
170. palcebu1 (0.87, 10.4)
171. Disneya1 (0.87, 7.7)
172. Tanaeya1 (0.87, 10.1)
173. yengema1 (0.87, 8.9)
174. disneya1 (0.87, 6.8)
175. comheya1 (0.87, 9.7)
176. eroneja1 (0.87, 8.8)
177. eminema1 (0.87, 6.0)
178. hpzgena1 (0.87, 11.2)
179. paigepc1 (0.87, 7.7)
180. trimebu1 (0.87, 9.6)
181. Aapjeba1 (0.87, 10.3)
182. shoteNn1 (0.87, 13.3)
183. sanjeda1 (0.87, 7.6)
184. sauceda1 (0.87, 5.3)
185. jeppeha1 (0.87, 8.4)
186. cjdjeva1 (0.87, 11.1)
187. shayena1 (0.87, 6.9)
188. kimzeda1 (0.87, 10.5)
189. bakkeka1 (0.87, 8.9)
190. SkyDeva1 (0.87, 10.1)
191. nbxfeza1 (0.87, 11.8)
192. alizebu1 (0.87, 8.3)
193. placekc1 (0.87, 9.6)
194. baccega1 (0.87, 8.8)
195. mizzeka1 (0.87, 8.6)
196. mojmeda1 (0.87, 9.1)
197. oohyeaa1 (0.87, 9.9)
198. oyabeda1 (0.87, 8.1)
199. motueka1 (0.87, 7.4)
200. cheneka1 (0.87, 8.3)
201. xzonema1 (0.87, 10.0)
202. irvdeba1 (0.87, 11.3)
203. nxdbeza1 (0.87, 11.4)
204. azadeha1 (0.87, 7.1)
205. Hildegu1 (0.87, 8.7)
206. candeda1 (0.87, 8.2)
207. Whymedc1 (0.87, 9.5)
208. Snakeda1 (0.86, 8.6)
209. Domdeja1 (0.86, 10.2)
210. mzlpeku1 (0.86, 11.4)
211. khubeka1 (0.86, 9.8)
212. Hiddema1 (0.86, 8.3)
213. Josueba1 (0.86, 8.7)
214. Huckeba1 (0.86, 10.4)
215. dxmueyc1 (0.86, 11.8)
216. rickema1 (0.86, 8.6)
217. abcdefa1 (0.86, 6.5)
218. pankeka1 (0.86, 7.8)
219. qtmdega1 (0.86, 11.6)
220. Sikkema1 (0.86, 8.9)
221. archena1 (0.86, 7.7)
222. rebbeka1 (0.86, 7.3)
223. djeneba1 (0.86, 8.5)
224. spadeka1 (0.86, 8.8)
225. whakeka1 (0.86, 11.0)
226. sephena1 (0.86, 8.3)
227. roxdeja1 (0.86, 10.3)
228. jackeva1 (0.86, 6.9)
229. Bimmega1 (0.86, 10.9)
230. Zheneva1 (0.86, 9.2)
231. Tammeca1 (0.86, 9.5)
232. spykepa1 (0.86, 9.6)
233. shadeka1 (0.86, 7.0)
234. bruceda1 (0.86, 6.9)
235. ndapewa1 (0.86, 10.7)
236. cienega1 (0.86, 7.1)
237. ggeneva1 (0.86, 7.6)
238. anumeha1 (0.86, 7.5)
239. ikeneva1 (0.86, 8.6)
240. mixmega1 (0.86, 8.1)
241. grajeda1 (0.86, 7.9)
242. ipajepa1 (0.86, 10.0)
243. pompeya1 (0.86, 6.4)
244. sheneva1 (0.86, 8.0)
245. Chenega1 (0.86, 9.8)
246. doddema1 (0.86, 9.0)
247. recdepa1 (0.86, 10.3)
248. sewmega1 (0.86, 9.0)
249. tboneya1 (0.86, 9.6)
250. tdavexc1 (0.86, 11.5)
251. ccabeza1 (0.86, 8.4)
252. xcabeza1 (0.86, 9.9)
253. shydeja1 (0.86, 9.3)
254. Chupepa1 (0.86, 9.8)
255. nandeza1 (0.86, 8.1)
256. agapema1 (0.86, 8.6)
257. Gweneva1 (0.86, 7.8)
258. akudewa1 (0.86, 5.9)
259. punkeva1 (0.86, 8.6)
260. munkeva1 (0.86, 9.4)
261. szczepa1 (0.86, 8.3)
262. evenema1 (0.86, 7.5)
263. Gankema1 (0.86, 9.8)
264. sydneyc1 (0.86, 6.2)
265. ebadeba1 (0.86, 8.0)
266. mickeya1 (0.86, 6.7)
267. nickeya1 (0.86, 7.6)
268. Gundega1 (0.86, 9.5)
269. rebbeca1 (0.86, 6.9)
270. gionena1 (0.86, 7.6)
271. sindeka1 (0.86, 8.0)
272. orimedu1 (0.86, 9.5)
273. puakepa1 (0.86, 8.3)
274. evadeva1 (0.86, 7.1)
275. iaukepa1 (0.86, 11.4)
276. shakema1 (0.86, 7.5)
277. Wauzeka1 (0.86, 10.9)
278. iecyebf1 (0.86, 12.1)
279. blakeda1 (0.86, 7.8)
280. Shameka1 (0.86, 6.7)
281. jagmega1 (0.86, 9.4)
282. mickeyc1 (0.86, 6.5)
283. feddema1 (0.86, 9.5)
284. heddema1 (0.86, 9.1)
285. shameka1 (0.86, 5.6)
286. adakeja1 (0.86, 8.8)
287. amadeja1 (0.86, 7.6)
288. redbema1 (0.86, 9.2)
289. adi&eva1 (0.86, 10.3)
290. rikveda1 (0.86, 10.6)
291. waynedf1 (0.86, 7.8)
292. placeka1 (0.86, 9.1)
293. Vinkega1 (0.86, 11.1)
294. Khadeja1 (0.86, 7.6)
295. majveda1 (0.86, 9.5)
296. $araeva1 (0.86, 10.0)
297. piubega1 (0.86, 10.4)
298. Diadema1 (0.86, 7.2)
299. zaqwedc1 (0.86, 6.4)
300. sinbeva1 (0.86, 9.1)
301. TeubeMa1 (0.86, 12.1)
302. diadema1 (0.86, 6.3)
303. wondema1 (0.86, 9.4)
304. osadeba1 (0.86, 6.8)
305. condega1 (0.86, 7.7)
306. iracema1 (0.86, 6.6)
307. shamema1 (0.86, 8.0)
308. Fuckena1 (0.86, 7.8)
309. rigveda1 (0.86, 9.7)
310. gracema1 (0.86, 6.8)
311. fuckena1 (0.86, 6.5)
312. schweda1 (0.86, 8.1)
313. mackena1 (0.86, 6.6)
314. Dogveda1 (0.86, 9.2)
315. trapeza1 (0.86, 7.1)
316. Jorgejc1 (0.86, 8.6)
317. diazeka1 (0.86, 9.4)
318. ikkkena1 (0.86, 10.4)
319. Azucena1 (0.86, 5.9)
320. siameka1 (0.86, 8.2)
321. azucena1 (0.86, 5.1)
322. Schweda1 (0.86, 8.8)
323. cybvega1 (0.86, 10.7)
324. jaydena1 (0.86, 6.5)
325. samvega1 (0.86, 7.8)
326. rozweba1 (0.86, 10.1)
327. haydena1 (0.86, 6.5)
328. beukema1 (0.86, 8.0)
329. lilnena1 (0.86, 6.1)
330. pende\a1 (0.86, 14.0)
331. bigweda1 (0.86, 10.0)
332. Kwabena1 (0.86, 6.2)
333. Alameda1 (0.86, 5.9)
334. kwabena1 (0.86, 5.0)
335. Landena1 (0.86, 8.0)
336. Flukeyc1 (0.86, 10.0)
337. bandena1 (0.86, 7.1)
338. megmega1 (0.86, 8.7)
339. alameda1 (0.86, 4.9)
340. Pendeja1 (0.86, 6.5)
341. anakena1 (0.86, 6.2)
342. uwecedu1 (0.86, 11.3)
343. pendeja1 (0.86, 5.4)
344. acadena1 (0.86, 7.6)
345. reycena1 (0.86, 7.7)
346. lesheka1 (0.86, 7.5)
347. Chameya1 (0.86, 9.2)
348. donmega1 (0.86, 6.0)
349. joncena1 (0.86, 6.1)
350. frameka1 (0.86, 7.5)
351. boacena1 (0.86, 9.4)
352. edaweda1 (0.86, 7.8)
353. rasheda1 (0.86, 5.9)
354. uutbepc1 (0.86, 12.4)
355. ubaveca1 (0.86, 10.3)
356. Ilyfeaa1 (0.86, 12.0)
357. wnlveju1 (0.86, 11.7)
358. acuzena1 (0.86, 9.5)
359. jenjena1 (0.86, 7.5)
360. olumega1 (0.86, 9.1)
361. exavega1 (0.86, 8.9)
362. melaena1 (0.86, 7.8)
363. netheya1 (0.86, 10.1)
364. ghbnekf1 (0.86, 9.9)
365. ilovedu1 (0.86, 7.0)
366. benzema1 (0.86, 5.1)
367. iloveku1 (0.86, 6.8)
368. lprueba1 (0.86, 7.3)
369. ontheba1 (0.86, 7.4)
370. masheka1 (0.86, 7.3)
371. nuraena1 (0.86, 8.1)
372. DonMega1 (0.86, 8.7)
373. tasheka1 (0.86, 7.6)
374. chasejn1 (0.86, 8.7)
375. wenzega1 (0.86, 9.6)
376. Dysheka1 (0.86, 9.5)
377. jorgeha1 (0.86, 8.2)
378. Tasheba1 (0.86, 9.0)
379. tasheba1 (0.86, 8.0)
380. blazeya1 (0.86, 8.4)
381. Jarhepc1 (0.86, 11.9)
382. mysheba1 (0.86, 6.5)
383. casheca1 (0.86, 8.8)
384. kashema1 (0.86, 8.3)
385. noruega1 (0.86, 6.7)
386. Rwigema1 (0.86, 11.4)
387. tashema1 (0.86, 8.2)
388. bradena1 (0.86, 7.0)
389. owogeka1 (0.86, 10.8)
390. wesdedc1 (0.86, 9.4)
391. Fonteyn1 (0.86, 10.7)
392. Natjedc1 (0.86, 11.7)
393. lemaejv1 (0.86, 11.1)
394. chezeku1 (0.86, 9.1)
395. barneyf1 (0.86, 7.3)
396. Abrgeza1 (0.86, 11.9)
397. zryuebv1 (0.86, 11.5)
398. aethena1 (0.86, 8.6)
399. cruzena1 (0.86, 7.9)
400. shuwena1 (0.86, 8.0)
401. awoyefa1 (0.86, 8.6)
402. burgepa1 (0.86, 9.1)
403. Norgeja1 (0.86, 10.1)
404. jenveyc1 (0.86, 10.4)
405. semLena1 (0.86, 11.9)
406. roryeva1 (0.86, 9.4)
407. plsbeda1 (0.86, 10.6)
408. tosjewa1 (0.86, 10.4)
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410. wathena1 (0.86, 8.0)
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412. mathena1 (0.86, 6.4)
413. zvigena1 (0.86, 10.4)
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415. haiyena1 (0.86, 7.5)
416. kashena1 (0.86, 7.3)
417. SrgFena1 (0.86, 12.9)
418. shegema1 (0.86, 8.7)
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420. tyshena1 (0.86, 7.7)
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422. iloveyu1 (0.86, 5.8)
423. kesbewa1 (0.86, 9.3)
424. adeSewa1 (0.86, 10.0)
425. CisBeka1 (0.86, 12.8)
426. awsxedc1 (0.86, 6.4)
427. Setdefa1 (0.86, 9.9)
428. cravena1 (0.86, 6.8)
429. heavena1 (0.86, 6.8)
430. ssbaean1 (0.86, 10.9)
431. tzidegc1 (0.86, 11.3)

432. slavena1	(0.86, 7.6)	
433. kynnean1	(0.86, 9.3)	
434. juice-a1	(0.86, 10.8)	
435. Vergena1	(0.86, 8.9)	
436. Elifeda1	(0.86, 10.4)	
437. AnimeEu1	(0.86, 12.0)	
438. ffttepu1	(0.86, 11.8)	
439. etspeua1	(0.86, 11.4)	
440. gurgena1	(0.86, 6.7)	
441. Nevaehv1	(0.86, 8.2)	
442. Aliceva1	(0.86, 8.2)	
443. melheba1	(0.85, 8.3)	
444. rodneyv1	(0.85, 7.4)	
445. ericeva1	(0.85, 7.9)	
446. Sorbeda1	(0.85, 9.7)	
447. Sidneyv1	(0.85, 8.3)	
448. alicepa1	(0.85, 7.6)	
449. Adryena1	(0.85, 8.7)	
450. seryena1	(0.85, 8.4)	
451. Merceda1	(0.85, 7.3)	
452. Cerceda1	(0.85, 9.1)	
453. juskeya1	(0.85, 9.9)	
454. diodeka1	(0.85, 7.3)	
455. Patfema1	(0.85, 9.9)	
456. tribeca1	(0.85, 5.8)	
457. salceda1	(0.85, 6.4)	
458. ilovepc1	(0.85, 5.8)	
459. yasmeka1	(0.85, 9.2)	
460. oropeza1	(0.85, 6.7)	
461. lookepa1	(0.85, 8.1)	
462. artpena1	(0.85, 8.3)	
463. akdxepv1	(0.85, 11.8)	
464. dulceka1	(0.85, 8.7)	
465. ilovebc1	(0.85, 6.0)	
466. kolbeva1	(0.85, 9.7)	
467. olateju1	(0.85, 6.8)	
468. njideka1	(0.85, 9.0)	
469. hdymexv1	(0.85, 11.6)	
470. gilbema1	(0.85, 8.8)	
471. itskeaa1	(0.85, 10.4)	
472. ajhvekf1	(0.85, 10.9)	
473. kentebu1	(0.85, 8.9)	
474. Sangean1	(0.85, 7.8)	
475. onobeka1	(0.85, 9.7)	
476. jaideva1	(0.85, 7.5)	
477. sangean1	(0.85, 6.8)	
478. EdiZeka1	(0.85, 11.7)	
479. Llccedv1	(0.85, 12.6)	
480. Merdeka1	(0.85, 5.4)	
481. zuidema1	(0.85, 9.0)	
482. Ilovejc1	(0.85, 6.6)	
483. talbepa1	(0.85, 10.3)	
484. ilovejc1	(0.85, 5.4)	
485. merdeka1	(0.85, 4.3)	
486. ilovegc1	(0.85, 6.4)	
487. alizeba1	(0.85, 7.4)	
488. obscena1	(0.85, 7.9)	
489. ktejeda1	(0.85, 10.7)	
490. brijena1	(0.85, 7.3)	
491. aingean1	(0.85, 8.6)	
492. Mordeca1	(0.85, 6.7)	
493. pastequ1	(0.85, 9.2)	
494. abeceda1	(0.85, 5.4)	
495. raifema1	(0.85, 8.9)	
496. Baileyn1	(0.85, 7.0)	
497. marceya1	(0.85, 8.2)	
498. morcega1	(0.85, 7.6)	
499. enghean1	(0.85, 8.2)	
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501. Karjeva1	(0.85, 9.0)	
502. goomega1	(0.85, 8.4)	
503. voiNena1	(0.85, 12.0)	
504. trimega1	(0.85, 8.6)	
505. Brikena1	(0.85, 7.3)	
506. Gracebv1	(0.85, 9.4)	
507. baileyn1	(0.85, 6.4)	
508. orinean1	(0.85, 10.5)	
509. jarmeka1	(0.85, 9.3)	
510. itsmeaa1	(0.85, 8.0)	
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512. alebeka1	(0.85, 9.4)	
513. oldme.v1	(0.85, 11.6)	
514. Aardema1	(0.85, 10.0)	
515. reeceva1	(0.85, 8.2)	
516. gytbepf1	(0.85, 11.7)	
517. wilmepa1	(0.85, 10.3)	
518. Roszena1	(0.85, 9.2)	
519. aldhean1	(0.85, 8.0)	
520. brikena1	(0.85, 6.7)	
521. piomega1	(0.85, 8.4)	
522. hookena1	(0.85, 8.7)	
523. zardeya1	(0.85, 8.9)	
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525. jktdepf1	(0.85, 11.1)	
526. ilovedc1	(0.85, 6.0)	
527. iloveha1	(0.85, 6.7)	
528. crebeca1	(0.85, 8.4)	
529. ofisegu1	(0.85, 10.3)	
530. grozema1	(0.85, 10.0)	
531. precepa1	(0.85, 8.8)	
532. smokeya1	(0.85, 6.4)	
533. iamjean1	(0.85, 7.1)	
534. latvega1	(0.85, 8.2)	
535. sirmega1	(0.85, 9.3)	
536. tomjean1	(0.85, 7.5)	
537. lasvega1	(0.85, 6.8)	
538. jmsmena1	(0.85, 9.5)	
539. miedema1	(0.85, 8.5)	
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541. alefema1	(0.85, 8.2)	
542. oredeca1	(0.85, 8.7)	
543. Ewizeba1	(0.85, 11.0)	
544. nkomeza1	(0.85, 9.5)	
545. Lasvega1	(0.85, 8.0)	
546. Rowdean1	(0.85, 9.5)	
547. iloveba1	(0.85, 6.6)	
548. verbena1	(0.85, 6.4)	
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550. primena1	(0.85, 7.0)	
551. SamDean1	(0.85, 7.4)	
552. gercena1	(0.85, 7.5)	
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557. ajmbean1	(0.85, 9.3)	
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559. ivyjean1	(0.85, 7.1)	
560. byxbean1	(0.85, 10.1)	
561. amyjean1	(0.85, 6.0)	
562. BudBean1	(0.85, 9.1)	
563. jimdean1	(0.85, 6.5)	
564. iloveca1	(0.85, 6.2)	
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566. micdean1	(0.85, 7.7)	
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569. mizbean1	(0.85, 9.0)	
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572. ilovema1	(0.85, 6.0)	
573. buddean1	(0.85, 7.2)	
574. micfean1	(0.85, 9.4)	
575. jimbean1	(0.85, 6.1)	
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587. danjean1	(0.85, 7.1)	
588. annjean1	(0.85, 7.4)	
589. adeteju1	(0.85, 7.8)	
590. edomega1	(0.85, 8.1)	
591. emybean1	(0.85, 8.4)	
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609. Avabean1	(0.85, 6.9)	
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611. univega1	(0.85, 7.3)	
612. profebf1	(0.85, 9.1)	
613. zeqdean1	(0.85, 10.4)	
614. mjimena1	(0.85, 7.4)	
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623. topmean1	(0.85, 7.2)	
624. unitedu1	(0.85, 7.2)	
625. Daymean1	(0.85, 8.5)	
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628. DooleIn1	(0.85, 11.2)	
629. soybean1	(0.85, 5.0)	
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631. redbean1	(0.85, 5.4)	
632. Iloveaa1	(0.85, 7.7)	
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647. Zerweja1	(0.85, 11.7)	
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650. dgeqedf1	(0.85, 11.9)	
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653. efemena1	(0.85, 7.0)	
654. cervena1	(0.85, 6.6)	
655. blubean1	(0.85, 6.8)	
656. Neapean1	(0.85, 9.6)	
657. slezena1	(0.85, 9.4)	
658. marvena1	(0.85, 8.0)	
659. saepedf1	(0.85, 9.6)	
660. blakean1	(0.85, 7.8)	
661. sylvena1	(0.85, 7.5)	
662. dradean1	(0.84, 7.7)	
663. keadean1	(0.84, 7.7)	
664. mr.bean1	(0.84, 7.5)	
665. smokeyf1	(0.84, 6.9)	
666. trevena1	(0.84, 8.1)	
667. sethean1	(0.84, 7.8)	
668. alamean1	(0.84, 7.4)	
669. weareyn1	(0.84, 9.6)	
670. futrebu1	(0.84, 10.1)	
671. rashean1	(0.84, 8.1)	
672. harveyf1	(0.84, 7.0)	
673. Kaeseku1	(0.84, 9.7)	
674. Mousepc1	(0.84, 7.8)	
675. pruneau1	(0.84, 6.6)	
676. Bruneau1	(0.84, 7.1)	
677. bonneau1	(0.84, 6.1)	
678. baatezu1	(0.84, 11.0)	
679. choteja1	(0.84, 9.0)	
680. panneau1	(0.84, 7.4)	
681. saiteja1	(0.84, 6.2)	
682. ilegean1	(0.84, 9.3)	
683. bottega1	(0.84, 7.8)	
684. desjean1	(0.84, 8.3)	
685. lenteja1	(0.84, 6.7)	
686. piscean1	(0.84, 5.2)	
687. hotbean1	(0.84, 7.2)	
688. austeja1	(0.84, 7.7)	
689. maitena1	(0.84, 6.4)	
690. sporega1	(0.84, 9.6)	
691. Fostena1	(0.84, 8.6)	
692. nxftequ1	(0.84, 11.4)	
693. whitepa1	(0.84, 7.9)	
694. Mairena1	(0.84, 6.8)	
695. Netbean1	(0.84, 7.8)	
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698. mairena1	(0.84, 5.9)	
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700. statepa1	(0.84, 7.9)	
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848. misseda1 (0.83, 7.2)
849. unitedf1 (0.83, 6.9)
850. chameau1 (0.83, 5.9)
851. Trudeau1 (0.83, 6.3)
852. irasema1 (0.83, 7.1)
853. Thebean1 (0.83, 6.3)
854. csndrsn1 (0.83, 10.7)
855. nursena1 (0.83, 6.7)
856. trudeau1 (0.83, 5.6)
857. bsksrsn1 (0.83, 11.2)
858. drivean1 (0.83, 8.5)
859. luversu1 (0.83, 9.5)
860. thebean1 (0.83, 5.2)
861. Ewejean1 (0.83, 9.6)
862. Chazeau1 (0.83, 8.7)
863. mantena1 (0.83, 6.7)
864. mooreda1 (0.83, 7.3)
865. kantega1 (0.83, 8.8)
866. bassema1 (0.83, 7.7)
867. oytsefa1 (0.83, 11.4)
868. andersc1 (0.83, 7.3)
869. drapeau1 (0.83, 6.6)
870. fonseca1 (0.83, 5.0)
871. Morteza1 (0.83, 6.3)
872. timorsu1 (0.83, 8.8)
873. tlaseca1 (0.83, 9.8)
874. tasteya1 (0.83, 7.7)
875. biltema1 (0.83, 8.5)
876. adesewa1 (0.83, 5.7)
877. caureyn1 (0.83, 10.2)
878. ihatega1 (0.83, 6.9)
879. raedean1 (0.83, 7.5)
880. maedean1 (0.83, 7.6)
881. taedean1 (0.83, 8.0)
882. morteza1 (0.83, 5.5)
883. Shanepm1 (0.83, 9.3)
884. thedean1 (0.83, 6.0)
885. shedean1 (0.83, 7.6)
886. ratwean1 (0.83, 9.2)
887. Abedean1 (0.83, 9.7)
888. donregu1 (0.83, 9.7)
889. wojtepa1 (0.83, 10.1)
890. Nantena1 (0.83, 8.5)
891. rocgexm1 (0.83, 11.6)
892. powersc1 (0.83, 7.8)
893. culzean1 (0.83, 7.4)
894. kortefa1 (0.83, 7.8)
895. riversc1 (0.83, 8.3)
896. jesseca1 (0.83, 6.4)
897. moexean1 (0.83, 9.6)
898. tarrega1 (0.83, 6.9)
899. tesseva1 (0.83, 9.8)
900. cottean1 (0.83, 8.2)
901. lopersc1 (0.83, 9.2)
902. aesseda1 (0.83, 7.8)
903. alpersu1 (0.83, 8.8)
904. bustean1 (0.83, 8.4)
905. ilusema1 (0.83, 9.7)
906. albertn1 (0.83, 6.6)
907. vperezc1 (0.83, 9.8)
908. robertn1 (0.83, 6.2)
909. plumeau1 (0.83, 7.3)
910. tolteca1 (0.83, 6.9)
911. barrena1 (0.83, 6.4)
912. abmsedu1 (0.83, 10.7)
913. Karrena1 (0.83, 8.5)
914. meuseka1 (0.83, 9.1)
915. certeza1 (0.83, 6.1)
916. hotlema1 (0.83, 9.6)
917. kojteba1 (0.83, 9.8)
918. shanedm1 (0.83, 7.9)
919. sugarsu1 (0.83, 8.9)
920. Nhatexa1 (0.83, 12.2)
921. huntlsu1 (0.83, 9.3)
922. Wegregu1 (0.83, 12.3)
923. hdfxrsc1 (0.83, 11.7)
924. themean1 (0.83, 6.2)
925. fissеha1 (0.83, 9.5)
926. Nouveau1 (0.83, 6.2)
927. kastean1 (0.83, 7.8)
928. kiyarsu1 (0.83, 10.5)
929. fjgurtn1 (0.83, 11.0)
930. selersu1 (0.83, 10.1)
931. Nictema1 (0.83, 9.3)
932. Shateka1 (0.83, 9.7)
933. nouveau1 (0.83, 5.4)
934. Aliseya1 (0.83, 9.5)
935. ojyelsc1 (0.83, 11.7)
936. jobprsc1 (0.83, 10.9)
937. nursema1 (0.83, 7.1)
938. jerrena1 (0.83, 8.4)
939. nerrena1 (0.83, 8.7)
940. Mohsena1 (0.83, 8.1)
941. anatema1 (0.83, 6.5)
942. Moyseca1 (0.83, 8.3)
943. matheau1 (0.83, 8.2)
944. quwertu1 (0.83, 10.6)
945. aszqrsu1 (0.83, 13.0)
946. Marsema1 (0.83, 9.0)
947. kwateva1 (0.83, 8.7)
948. %dinrsn1 (0.83, 14.0)
949. dc,eltn1 (0.83, 13.2)
950. shatema1 (0.83, 8.6)
951. siktebf1 (0.83, 11.4)
952. manteca1 (0.83, 5.2)
953. npaqezm1 (0.83, 11.3)
954. skateda1 (0.83, 7.4)
955. Crwceac1 (0.83, 11.9)
956. stuartn1 (0.83, 7.4)
957. hayalsu1 (0.83, 9.5)
958. sherean1 (0.83, 6.7)
959. borrega1 (0.83, 6.2)
960. Manteca1 (0.83, 6.4)
961. gmpalsu1 (0.83, 10.4)
962. carlena1 (0.83, 6.3)
963. marlena1 (0.83, 5.6)
964. whateva1 (0.83, 5.0)
965. aputeca1 (0.83, 9.4)
966. Whateva1 (0.83, 6.1)
967. redtema1 (0.83, 9.5)
968. gallega1 (0.83, 6.7)
969. ultreYa1 (0.83, 11.4)
970. Ballena1 (0.83, 6.7)
971. Kallena1 (0.83, 7.7)

972. Suerean1 (0.83, 10.2)	982. linklsu1 (0.83, 8.0)	992. rpffedm1 (0.83, 11.6)
973. carreca1 (0.83, 7.4)	983. amisean1 (0.83, 8.1)	993. tearepa1 (0.83, 9.9)
974. grasean1 (0.83, 8.0)	984. lzdfeym1 (0.83, 11.5)	994. zippedm1 (0.83, 9.3)
975. ballena1 (0.83, 5.8)	985. Turgeau1 (0.83, 9.6)	995. aeslehc1 (0.83, 6.9)
976. fallena1 (0.83, 7.2)	986. mickeym1 (0.83, 5.8)	996. fellena1 (0.83, 8.6)
977. mallena1 (0.83, 6.6)	987. bergeau1 (0.83, 8.4)	997. zoqsrtu1 (0.83, 11.9)
978. consean1 (0.83, 7.9)	988. tnvoltc1 (0.83, 10.1)	998. calleja1 (0.83, 6.0)
979. Bullena1 (0.83, 8.2)	989. verlena1 (0.83, 7.7)	999. estreya1 (0.83, 6.3)
980. Arielsc1 (0.83, 9.5)	990. letreya1 (0.83, 9.2)	
981. benseanl (0.83, 7.2)	991. ultreya1 (0.83, 8.1)	

Cluster 5

Prototype: aoia6108

Hard-assigned passwords: 1311330 (4.53% of total)
Unique hard-assigned passwords: 880678 (32.84% of cluster total)

Cluster-assignment scores:
	Min: 0.085
	Max: 0.922
	Mean: 0.331
	SD: 0.182

Strength bins:
	Very weak: 26335 (2.01%)
	Weak: 262837 (20.04%)
	Fair: 608850 (46.43%)
	Good: 402467 (30.69%)
	Strong: 10841 (0.83%)

Password lengths:
	Length 8: 1132046 (86.33%)
	Length 9: 179283 (13.67%)
	Length 10: 1 (0.00%)

Character classes:
	4 classes: 24203 (1.85%)
	3 classes: 185259 (14.13%)
		lower/upper/symbol: 308 (0.17%)
		lower/upper/number: 138766 (74.90%)
		lower/symbol/number: 46130 (24.90%)
		upper/symbol/number: 55 (0.03%)
	2 classes: 1101855 (84.03%)
		lower/upper: 53 (0.00%)
		lower/number: 1100929 (99.92%)
		lower/symbol: 808 (0.07%)
		upper/number: 0 (0.00%)
		upper/symbol: 4 (0.00%)
		number/symbol: 61 (0.01%)
	1 class: 13 (0.00%)
		lower: 0 (0.00%)
		upper: 0 (0.00%)
		symbol: 13 (100.00%)
		number: 0 (0.00%)

Most frequent char-class structures:
	LLLLDDDD: 776808 (59.2%)
	LLLLLDDDD: 112230 (8.6%)
	ULLLDDDD: 80146 (6.1%)
	LLLLDLLL: 56157 (4.3%)
	LLLDDDDD: 49233 (3.8%)
	LLLLDDLL: 22406 (1.7%)
	LLLLDDDDD: 15091 (1.2%)
	ULLLLDDDD: 14109 (1.1%)
	LLLSDDDD: 13848 (1.1%)
	LLLLDLLD: 12935 (1.0%)

1,000 nearest passwords

0.	yll@5978	(0.92, 12.4)	54.	dark5678	(0.92, 6.1)	108.	jmrm0478	(0.92, 10.3)
1.	kirk5578	(0.92, 8.3)	55.	marc5678	(0.92, 6.6)	109.	lulu5288	(0.92, 7.5)
2.	lala5978	(0.92, 8.4)	56.	lulu5878	(0.92, 7.7)	110.	sben8778	(0.92, 10.1)
3.	golf5578	(0.92, 7.4)	57.	Alex5178	(0.92, 7.8)	111.	Bren5908	(0.92, 9.3)
4.	nery5278	(0.92, 9.2)	58.	yhrg5178	(0.92, 10.9)	112.	hieu0978	(0.92, 7.9)
5.	mark5278	(0.92, 7.0)	59.	surf5678	(0.92, 6.6)	113.	rain8978	(0.92, 8.2)
6.	alex5578	(0.92, 6.8)	60.	joey5678	(0.92, 6.2)	114.	kaia5878	(0.92, 9.2)
7.	lkr@5678	(0.92, 10.0)	61.	*llw5678	(0.92, 11.7)	115.	ploy5678	(0.92, 7.1)
8.	ajlp5978	(0.92, 10.4)	62.	golf5678	(0.92, 5.7)	116.	klop5678	(0.92, 7.5)
9.	warn5378	(0.92, 9.7)	63.	greg5678	(0.92, 6.2)	117.	silv0678	(0.92, 9.9)
10.	Mula5678	(0.92, 8.9)	64.	yarm5678	(0.92, 9.1)	118.	Rrld5588	(0.92, 11.3)
11.	Flr$5678	(0.92, 11.2)	65.	fred5678	(0.92, 6.0)	119.	pwrb8878	(0.92, 10.9)
12.	jrrT5778	(0.92, 12.6)	66.	seed5678	(0.92, 8.1)	120.	troy5678	(0.92, 6.4)
13.	Mary5678	(0.92, 7.3)	67.	qweq5678	(0.92, 8.3)	121.	urla5988	(0.92, 10.6)
14.	Gold5678	(0.92, 7.2)	68.	trev5678	(0.92, 6.9)	122.	alex8878	(0.92, 6.9)
15.	Zerg5678	(0.92, 9.5)	69.	xtep5678	(0.92, 10.2)	123.	lora5588	(0.92, 8.0)
16.	Hulk5678	(0.92, 7.5)	70.	stew5678	(0.92, 7.1)	124.	lion5678	(0.92, 6.4)
17.	Spen5678	(0.92, 8.7)	71.	acex5678	(0.92, 9.2)	125.	amin0278	(0.92, 8.5)
18.	lulu5678	(0.92, 6.3)	72.	pweb5678	(0.92, 8.9)	126.	bren5908	(0.92, 8.5)
19.	reed5478	(0.92, 8.5)	73.	mfib5578	(0.92, 10.7)	127.	Chep0478	(0.92, 11.0)
20.	tmrb5478	(0.92, 10.4)	74.	noly8478	(0.92, 9.8)	128.	july0678	(0.92, 6.8)
21.	korn5678	(0.92, 6.7)	75.	smod5678	(0.92, 9.9)	129.	cjej8778	(0.92, 10.4)
22.	Calv5678	(0.92, 9.4)	76.	eded8278	(0.92, 9.9)	130.	smeg5208	(0.92, 9.2)
23.	ser.5678	(0.92, 9.7)	77.	ipod5678	(0.92, 7.2)	131.	sara5088	(0.92, 7.9)
24.	burn5678	(0.92, 7.2)	78.	alex0278	(0.92, 6.6)	132.	alex0378	(0.92, 6.8)
25.	mark5078	(0.92, 7.4)	79.	emoh5678	(0.92, 9.3)	133.	gary5988	(0.92, 7.8)
26.	lala5678	(0.92, 6.7)	80.	hboy5678	(0.92, 9.2)	134.	tory5088	(0.92, 9.2)
27.	Germ5678	(0.92, 8.4)	81.	kara0278	(0.92, 8.2)	135.	greg5508	(0.92, 7.5)
28.	tora5678	(0.92, 7.7)	82.	lyla0278	(0.92, 9.1)	136.	ally5088	(0.92, 8.6)
29.	hola5678	(0.92, 6.3)	83.	alex8278	(0.92, 6.9)	137.	oloz8278	(0.92, 10.2)
30.	nola5678	(0.92, 7.2)	84.	aslh8078	(0.92, 10.8)	138.	Alex5588	(0.92, 7.2)
31.	nila5678	(0.92, 7.6)	85.	mnop5678	(0.92, 8.7)	139.	eric5578	(0.92, 7.5)
32.	Step5678	(0.92, 8.1)	86.	syin5678	(0.92, 9.3)	140.	yueh5588	(0.92, 9.9)
33.	lily5678	(0.92, 6.5)	87.	mark8678	(0.92, 7.4)	141.	arif5278	(0.92, 8.6)
34.	Hoez5678	(0.92, 10.4)	88.	wira8178	(0.92, 9.6)	142.	lily0178	(0.92, 8.0)
35.	sara5678	(0.92, 6.2)	89.	hiep0978	(0.92, 9.4)	143.	mark5588	(0.92, 6.6)
36.	drew5478	(0.92, 7.7)	90.	spiv5678	(0.92, 9.3)	144.	July0978	(0.92, 7.8)
37.	open5678	(0.92, 6.4)	91.	jeep0978	(0.92, 8.0)	145.	gary5408	(0.92, 7.9)
38.	porn5178	(0.92, 8.5)	92.	akiv5178	(0.92, 10.3)	146.	roey5588	(0.92, 9.2)
39.	lsea5678	(0.92, 9.6)	93.	pmem8078	(0.92, 11.2)	147.	oblf5588	(0.92, 11.5)
40.	ally5678	(0.92, 6.9)	94.	vvof8378	(0.92, 12.0)	148.	joey5588	(0.92, 6.9)
41.	spen5678	(0.92, 8.0)	95.	oplk0978	(0.92, 10.4)	149.	Room5678	(0.92, 8.3)
42.	reen5678	(0.92, 8.1)	96.	torj8178	(0.92, 10.6)	150.	fred5588	(0.92, 6.8)
43.	khen5678	(0.92, 7.9)	97.	clog5678	(0.92, 8.0)	151.	golf5408	(0.92, 7.5)
44.	burg5678	(0.92, 7.9)	98.	maia5678	(0.92, 7.4)	152.	barb0878	(0.91, 7.9)
45.	rhea5678	(0.92, 7.7)	99.	marf0978	(0.92, 9.6)	153.	bury0778	(0.91, 9.6)
46.	Alex5678	(0.92, 6.5)	100.	zaia5678	(0.92, 8.9)	154.	wolf0878	(0.91, 8.0)
47.	mary5678	(0.92, 6.4)	101.	jrod5978	(0.92, 9.1)	155.	gary0878	(0.91, 7.8)
48.	turk5678	(0.92, 7.2)	102.	ghij5678	(0.92, 8.8)	156.	geof5678	(0.91, 8.5)
49.	milk5678	(0.92, 6.8)	103.	morg0978	(0.92, 9.6)	157.	alex5588	(0.91, 6.3)
50.	xery5678	(0.92, 9.1)	104.	kain5678	(0.92, 7.6)	158.	slex5588	(0.91, 9.5)
51.	mark5678	(0.92, 5.7)	105.	stop5678	(0.92, 7.0)	159.	pard0778	(0.91, 9.5)
52.	jord5678	(0.92, 7.3)	106.	mrob5678	(0.92, 9.1)	160.	Sbou5408	(0.91, 12.0)
53.	lilj5678	(0.92, 7.9)	107.	july0478	(0.92, 6.9)	161.	ecla5488	(0.91, 9.8)

162. gdog0678 (0.91, 9.8)
163. chop8778 (0.91, 8.9)
164. lily5488 (0.91, 7.6)
165. gard5608 (0.91, 9.5)
166. snow0378 (0.91, 9.4)
167. ruru5108 (0.91, 9.4)
168. Nlln8008 (0.91, 12.4)
169. boom5678 (0.91, 6.6)
170. uuea5488 (0.91, 9.9)
171. doom5678 (0.91, 7.0)
172. noom5678 (0.91, 7.5)
173. poop5678 (0.91, 6.4)
174. kyla5108 (0.91, 8.4)
175. sala5688 (0.91, 8.6)
176. owen5808 (0.91, 7.9)
177. mulg5808 (0.91, 11.2)
178. thom5208 (0.91, 8.6)
179. wood5678 (0.91, 6.6)
180. Work8008 (0.91, 8.5)
181. mary5688 (0.91, 7.5)
182. pooh5678 (0.91, 6.8)
183. erin5678 (0.91, 7.0)
184. herb0208 (0.91, 8.3)
185. Erin5178 (0.91, 9.0)
186. corb5808 (0.91, 10.4)
187. Pulp5!08 (0.91, 12.3)
188. look5678 (0.91, 6.9)
189. joey0208 (0.91, 6.3)
190. Bird8288 (0.91, 8.7)
191. palm5808 (0.91, 8.4)
192. skij0178 (0.91, 10.5)
193. icon5308 (0.91, 8.8)
194. quik0478 (0.91, 9.9)
195. ijrm0078 (0.91, 11.1)
196. fury8208 (0.91, 9.7)
197. kola8208 (0.91, 9.1)
198. sara8508 (0.91, 7.8)
199. julz0208 (0.91, 8.6)
200. Erik5678 (0.91, 8.1)
201. ariv5678 (0.91, 8.8)
202. loek0208 (0.91, 9.5)
203. wirk0208 (0.91, 9.8)
204. july0208 (0.91, 6.6)
205. jhrh8208 (0.91, 10.2)
206. jeon8478 (0.91, 10.1)
207. help5688 (0.91, 7.7)
208. tory0208 (0.91, 8.0)
209. mark0208 (0.91, 6.4)
210. Vfr$0178 (0.91, 10.7)
211. oila8908 (0.91, 9.8)
212. ugly8908 (0.91, 9.7)
213. mila0208 (0.91, 7.0)
214. marc0208 (0.91, 6.5)
215. guru8288 (0.91, 8.1)
216. phen8908 (0.91, 9.3)
217. maru5788 (0.91, 9.1)
218. hold5888 (0.91, 9.0)
219. greg0208 (0.91, 6.9)
220. serg0208 (0.91, 7.6)
221. sten8408 (0.91, 9.0)
222. alex0208 (0.91, 5.6)
223. sara0208 (0.91, 6.6)
224. ayla8008 (0.91, 8.9)
225. dora0208 (0.91, 7.4)
226. slim5878 (0.91, 8.0)
227. kara8008 (0.91, 7.8)
228. rfid5288 (0.91, 10.8)
229. chen8008 (0.91, 7.3)
230. lela0208 (0.91, 7.8)
231. kara8988 (0.91, 8.5)
232. elom0478 (0.91, 10.6)
233. tueb8508 (0.91, 11.9)
234. pprd8908 (0.91, 10.2)
235. lara8088 (0.91, 7.8)
236. hela8988 (0.91, 9.4)
237. syrk8288 (0.91, 11.1)
238. yyey8008 (0.91, 9.7)
239. aden0208 (0.91, 6.9)
240. marg8088 (0.91, 8.6)
241. kola8308 (0.91, 8.8)
242. ablp0288 (0.91, 10.9)
243. Erik5878 (0.91, 9.4)
244. alex8208 (0.91, 6.9)
245. alex5888 (0.91, 6.7)
246. tbow5488 (0.91, 10.3)
247. mark8088 (0.91, 7.0)
248. ford8088 (0.91, 6.9)
249. bird8288 (0.91, 7.8)
250. exlu0208 (0.91, 11.2)
251. xbox5488 (0.91, 8.2)
252. kar~0208 (0.91, 11.3)
253. oiey5788 (0.91, 9.5)
254. owen0078 (0.91, 7.6)
255. zord8588 (0.91, 10.4)
256. werk8088 (0.91, 8.9)
257. mee@8488 (0.91, 10.6)
258. chow5488 (0.91, 8.6)
259. mjib5408 (0.91, 10.7)
260. dboy5388 (0.91, 8.9)
261. alex8908 (0.91, 6.5)
262. erik5878 (0.91, 8.4)
263. zeek8008 (0.91, 8.7)
264. lion8878 (0.91, 7.8)
265. fila0288 (0.91, 9.3)
266. wolf8588 (0.91, 7.4)
267. Hira8808 (0.91, 10.0)
268. Shin5608 (0.91, 9.7)
269. alex8408 (0.91, 6.9)
270. ford5188 (0.91, 7.3)
271. golf8088 (0.91, 7.5)
272. trey8308 (0.91, 7.9)
273. ngoc0208 (0.91, 7.1)
274. rain5088 (0.91, 8.4)
275. alex8988 (0.91, 6.7)
276. wilu8488 (0.91, 10.5)
277. balu8488 (0.91, 8.5)
278. alex8288 (0.91, 6.6)
279. alex5788 (0.91, 6.9)
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283. broz5508 (0.91, 10.5)
284. Galp8808 (0.91, 11.0)
285. milk0908 (0.91, 7.7)
286. Eden0208 (0.91, 8.2)
287. croc5588 (0.91, 9.0)
288. Para0208 (0.91, 8.3)
289. norm0908 (0.91, 7.8)
290. valu0078 (0.91, 9.3)
291. kala8388 (0.91, 8.6)
292. dil@8888 (0.91, 8.9)
293. cdog5788 (0.91, 9.1)
294. ydoc8588 (0.91, 10.5)
295. cblb0508 (0.91, 9.8)
296. yml●8888 (0.91, 11.1)
297. reed0908 (0.91, 7.5)
298. Alex8808 (0.91, 7.5)
299. odin5108 (0.91, 8.6)
300. trev0908 (0.91, 7.6)
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302. jhon0078 (0.91, 8.0)
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305. mark0908 (0.91, 6.3)
306. aley8388 (0.91, 9.5)
307. join5678 (0.91, 7.4)
308. golf0508 (0.91, 6.6)
309. hern8708 (0.91, 9.6)
310. zara8808 (0.91, 7.9)
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314. fery0908 (0.91, 9.0)
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316. greg8388 (0.91, 7.3)
317. Holy8188 (0.91, 9.5)
318. alex0908 (0.91, 5.7)
319. area8808 (0.91, 8.8)
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321. woof8878 (0.91, 9.0)
322. gary8688 (0.91, 7.4)
323. shea0908 (0.91, 7.1)
324. zeek0408 (0.91, 7.9)
325. wiem0408 (0.91, 9.7)
326. mary8708 (0.91, 7.7)
327. fred8388 (0.91, 7.4)
328. joey0408 (0.91, 6.4)
329. wald0988 (0.91, 9.2)
330. skin8008 (0.91, 8.3)
331. stew0408 (0.91, 7.7)
332. trey0408 (0.91, 7.1)
333. spry0408 (0.91, 8.8)
334. ctek8808 (0.91, 10.3)
335. fdlg0908 (0.91, 10.6)
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339. nark0988 (0.91, 9.4)
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343. prem0408 (0.91, 7.7)
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347. holy0408 (0.91, 8.1)
348. odin8408 (0.91, 8.8)
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351. tjrj0408 (0.91, 9.5)
352. uaoy0288 (0.91, 10.2)
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354. julu8888 (0.91, 8.1)
355. xbox0908 (0.91, 7.6)
356. faru8888 (0.91, 8.5)
357. kalu8888 (0.91, 7.2)
358. Cold!578 (0.91, 11.1)
359. uioa0678 (0.91, 9.2)
360. drew8488 (0.91, 7.5)
361. Parm8888 (0.91, 8.6)
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363. soef0308 (0.91, 9.7)
364. golf0608 (0.91, 6.8)
365. july0508 (0.91, 6.2)
366. dark0508 (0.91, 7.2)
367. alex8808 (0.91, 6.4)
368. whrk0408 (0.91, 10.7)
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370. alex0508 (0.91, 5.6)
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372. bblu8888 (0.91, 8.6)
373. jeep8808 (0.91, 7.3)
374. heru8888 (0.91, 7.0)
375. wboy0908 (0.91, 9.7)
376. luo●8708 (0.91, 12.0)
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378. lily8888 (0.91, 6.0)
379. burn8888 (0.91, 7.3)
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382. marc0508 (0.91, 6.6)
383. hard0408 (0.91, 8.2)
384. ldob0408 (0.91, 9.8)
385. Plok5688 (0.91, 10.1)
386. ally8888 (0.91, 6.5)
387. golf0308 (0.91, 6.6)
388. cory8888 (0.91, 6.5)
389. holy8888 (0.91, 6.9)
390. leen8888 (0.91, 7.4)
391. ageb0708 (0.91, 9.9)
392. wolf0608 (0.91, 7.0)
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394. sven8888 (0.91, 7.1)
395. ahia0208 (0.91, 9.4)
396. kory8888 (0.91, 7.4)
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407. veid5778 (0.91, 11.4)
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410. mary8888 (0.91, 5.9)
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417. gmen8888 (0.91, 7.8)
418. vara8888 (0.91, 7.5)
419. aura8888 (0.91, 7.4)
420. hila8888 (0.91, 7.6)
421. para8888 (0.91, 6.6)
422. nala8888 (0.91, 6.6)
423. sara8888 (0.91, 5.8)
424. folk8888 (0.91, 7.4)
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427. herb0708 (0.91, 8.2)
428. kera8888 (0.91, 7.5)
429. crea8888 (0.91, 7.3)
430. tark8888 (0.91, 7.9)
431. joey0708 (0.91, 6.3)

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436. trey0308	(0.91, 6.9)	
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438. mark8888	(0.91, 5.4)	
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440. mary0608	(0.91, 6.7)	
441. milf0588	(0.91, 9.4)	
442. dark8888	(0.91, 6.0)	
443. ford8888	(0.91, 5.7)	
444. dirk8888	(0.91, 6.8)	
445. marc8888	(0.91, 6.2)	
446. kdsj5678	(0.91, 9.8)	
447. sieg8888	(0.91, 8.2)	
448. joey3578	(0.91, 6.9)	
449. gold8888	(0.91, 6.0)	
450. ebru3278	(0.91, 9.3)	
451. bard8888	(0.91, 7.3)	
452. narf3578	(0.91, 9.3)	
453. yml+8888	(0.91, 11.3)	
454. #jlm0608	(0.91, 11.2)	
455. word8888	(0.91, 6.4)	
456. fern0908	(0.91, 8.0)	
457. joey8888	(0.91, 5.8)	
458. chef0108	(0.91, 7.4)	
459. balj8888	(0.91, 9.2)	
460. elec8888	(0.91, 7.7)	
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465. carp0608	(0.91, 7.9)	
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470. adog0908	(0.91, 8.8)	
471. mery0708	(0.91, 8.3)	
472. gary0108	(0.91, 6.8)	
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474. drob5108	(0.91, 9.9)	
475. bork0308	(0.91, 8.9)	
476. alec0308	(0.91, 7.4)	
477. surf8888	(0.91, 6.7)	
478. pain8088	(0.91, 8.4)	
479. fred0608	(0.91, 6.6)	
480. pilz8888	(0.91, 8.2)	
481. lily0608	(0.91, 6.8)	
482. busy5678	(0.91, 7.9)	
483. paru3578	(0.91, 9.0)	
484. cyrq3478	(0.91, 11.7)	
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486. alex0308	(0.91, 5.6)	
487. loly0608	(0.91, 8.6)	
488. wolf8888	(0.91, 5.8)	
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492. garv8888	(0.91, 8.4)	
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495. fglm8888	(0.91, 9.3)	
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497. fred8888	(0.91, 5.7)	
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499. tara0508	(0.91, 6.9)	
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505. liem0108	(0.91, 7.9)	
506. nara8188	(0.91, 8.6)	
507. But@5678	(0.91, 10.4)	
508. shin8608	(0.91, 8.9)	
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510. help8888	(0.91, 6.5)	
511. lily0308	(0.91, 6.6)	
512. ipek0108	(0.91, 9.4)	
513. mark3478	(0.91, 7.0)	
514. greg0708	(0.91, 6.9)	
515. huey0808	(0.91, 7.7)	
516. wera8788	(0.91, 9.6)	
517. mala0608	(0.91, 7.7)	
518. lara0408	(0.91, 6.9)	
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520. gold0808	(0.91, 6.7)	
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522. prem0108	(0.91, 7.6)	
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562. greg0108	(0.91, 6.9)	
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570. mary0808	(0.91, 6.5)	
571. pooh5988	(0.91, 8.3)	
572. djsm8578	(0.91, 10.3)	
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574. July0908	(0.91, 7.0)	
575. adem0808	(0.91, 7.5)	
576. berg0708	(0.91, 7.9)	
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581. sara0308	(0.91, 6.5)	
582. Nerd0908	(0.91, 9.2)	
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584. wasd5678	(0.91, 6.5)	
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586. owen0708	(0.91, 6.7)	
587. dork0808	(0.91, 7.8)	
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593. zara0108	(0.91, 7.6)	
594. alex8788	(0.91, 6.6)	
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596. aziz0908	(0.91, 7.5)	
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598. perk0808	(0.91, 8.1)	
599. hyin8108	(0.91, 11.1)	
600. jklq3678	(0.91, 11.2)	
601. greg0808	(0.91, 6.7)	
602. mark0808	(0.91, 6.0)	
603. tata5678	(0.91, 6.8)	
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607. Cora0908	(0.91, 8.3)	
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610. trey0388	(0.91, 7.9)	
611. Tutu5678	(0.91, 8.3)	
612. tara0108	(0.91, 6.8)	
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626. Marx3378	(0.91, 10.0)	
627. bren0308	(0.91, 7.2)	
628. alok8288	(0.91, 8.9)	
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633. kirk0808	(0.91, 7.1)	
634. eric5088	(0.91, 7.5)	
635. kyra0308	(0.91, 7.4)	
636. kora0308	(0.91, 8.1)	
637. flea0808	(0.91, 7.9)	
638. kasu5678	(0.91, 8.1)	
639. pien0808	(0.91, 8.6)	
640. july0388	(0.91, 6.6)	
641. ally7278	(0.91, 8.2)	
642. owen7578	(0.91, 7.9)	
643. bily7278	(0.91, 10.2)	
644. july3178	(0.91, 6.2)	
645. Alex0608	(0.91, 6.5)	
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647. Leeh7578	(0.91, 10.6)	
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661. zhou8888	(0.91, 7.2)	
662. cory3178	(0.91, 8.1)	
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664. alex7578	(0.91, 6.8)	
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667. fera0808	(0.91, 8.5)	
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673. july3078	(0.91, 6.6)	
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678. stew0788	(0.91, 8.2)	
679. trey7578	(0.91, 8.0)	
680. deep7978	(0.91, 8.4)	
681. vera0808	(0.91, 7.0)	
682. eren0808	(0.91, 7.3)	
683. corn0108	(0.91, 8.0)	
684. shop0808	(0.91, 7.9)	
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686. daly7578	(0.91, 9.1)	
687. alex0008	(0.91, 6.6)	
688. gerb7978	(0.91, 9.6)	
689. mark0788	(0.91, 7.1)	
690. rioc8288	(0.91, 10.1)	
691. tara3178	(0.91, 7.8)	
692. lily7578	(0.91, 7.6)	
693. bsia5488	(0.91, 10.2)	
694. Prlj0708	(0.91, 10.9)	
695. lulu0708	(0.91, 6.6)	
696. Gold!878	(0.91, 10.3)	
697. odin8888	(0.91, 7.1)	
698. twin8888	(0.91, 6.9)	
699. Maeh0608	(0.91, 10.2)	
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701. caem0888	(0.91, 9.5)	

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704. biru0108 (0.91, 8.3)
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723. vern0808 (0.91, 7.8)
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726. aciz0608 (0.91, 10.4)
727. lmok0808 (0.91, 9.5)
728. Olof8888 (0.91, 9.6)
729. trob0408 (0.91, 9.5)
730. awin8888 (0.91, 8.4)
731. chef7178 (0.91, 8.3)
732. biru7478 (0.91, 9.4)
733. good5388 (0.91, 7.7)
734. silk7378 (0.91, 9.0)
735. July0608 (0.91, 6.9)
736. gold7478 (0.91, 7.3)
737. Deej0808 (0.91, 9.8)
738. mark0888 (0.91, 6.8)
739. lord0088 (0.91, 7.6)
740. hood0878 (0.91, 9.0)
741. lulu0308 (0.91, 6.7)
742. azin8888 (0.91, 7.9)
743. duru3878 (0.91, 9.6)
744. iory0008 (0.91, 10.3)
745. beef3778 (0.91, 8.7)
746. vwin0408 (0.91, 10.4)
747. jeep0188 (0.91, 7.9)
748. nata5778 (0.91, 8.0)
749. vira7478 (0.91, 9.0)
750. Abod7978 (0.91, 10.5)
751. Park3778 (0.91, 8.8)
752. leon8408 (0.91, 8.2)
753. July0308 (0.91, 7.0)
754. njiu3278 (0.91, 10.7)
755. jhiv0608 (0.91, 10.3)
756. Shea3778 (0.91, 9.4)
757. C@ra0408 (0.91, 10.1)
758. okeg0008 (0.91, 11.3)
759. swim8888 (0.91, 6.8)
760. acid8888 (0.91, 6.8)
761. khen0888 (0.91, 9.4)
762. nmrb3778 (0.91, 10.6)
763. Vira7478 (0.91, 10.0)
764. ally7378 (0.91, 8.3)
765. jhon0108 (0.91, 7.3)
766. njoy0088 (0.91, 9.6)
767. mbsa0678 (0.91, 10.3)
768. enta8478 (0.91, 10.1)
769. Work0108 (0.91, 7.7)
770. cola3878 (0.91, 8.6)
771. Hrog0208 (0.91, 11.6)
772. karu0808 (0.91, 8.1)
773. golf7178 (0.91, 7.4)
774. paia8888 (0.91, 8.2)
775. Furm0808 (0.91, 10.4)
776. rory3778 (0.91, 8.7)
777. eric0078 (0.91, 6.9)
778. kioc8608 (0.91, 10.7)
779. jfia0608 (0.91, 10.2)
780. Alok!978 (0.91, 10.3)
781. Fred0808 (0.91, 7.5)
782. frog8888 (0.91, 6.4)
783. lulu0808 (0.91, 6.3)
784. rain8888 (0.91, 6.3)
785. adik8888 (0.91, 7.6)
786. Paeu0708 (0.91, 10.7)
787. uwog7478 (0.91, 11.1)
788. Sara0608 (0.91, 7.7)
789. Ottf5678 (0.91, 10.8)
790. chip8888 (0.91, 6.6)
791. Hola0308 (0.91, 8.1)
792. Mery0308 (0.91, 8.9)
793. Lism5678 (0.91, 10.0)
794. moop0288 (0.91, 10.1)
795. Ford0808 (0.91, 7.3)
796. tira0008 (0.91, 9.2)
797. alex7678 (0.91, 6.8)
798. Cora0108 (0.91, 8.2)
799. shih0608 (0.91, 8.9)
800. zoe@0108 (0.91, 9.4)
801. kook0208 (0.91, 8.7)
802. boob8008 (0.91, 8.5)
803. yiea7678 (0.91, 9.8)
804. asif5888 (0.91, 8.1)
805. moon8308 (0.91, 7.8)
806. jaen0008 (0.91, 9.2)
807. wpij0808 (0.91, 11.1)
808. khen0088 (0.91, 8.3)
809. olik0208 (0.91, 9.1)
810. yoey7678 (0.91, 9.4)
811. maix0708 (0.91, 9.6)
812. Peru0908 (0.91, 8.5)
813. Lion8888 (0.91, 7.1)
814. mura0088 (0.91, 9.0)
815. sook0208 (0.91, 9.3)
816. snow7478 (0.91, 7.7)
817. skin0108 (0.91, 8.2)
818. kjid0708 (0.91, 10.8)
819. chip8788 (0.91, 7.9)
820. unic8888 (0.91, 8.0)
821. troy0408 (0.91, 6.9)
822. faiy8888 (0.91, 9.3)
823. iuiu3278 (0.91, 9.5)
824. mrtg5678 (0.91, 8.9)
825. koik0178 (0.91, 10.9)
826. tara7678 (0.91, 7.7)
827. pooh8288 (0.91, 8.3)
828. eric8908 (0.91, 7.1)
829. wood8008 (0.91, 7.4)
830. lisa5678 (0.91, 6.2)
831. jasp8178 (0.91, 9.3)
832. rain0508 (0.91, 7.1)
833. good8588 (0.91, 7.7)
834. drof0308 (0.91, 9.0)
835. Alex0088 (0.91, 7.4)
836. kkid0808 (0.91, 9.5)
837. cain0508 (0.91, 7.6)
838. cvl-0008 (0.91, 11.0)
839. alta5678 (0.91, 7.4)
840. Alex0008 (0.91, 7.5)
841. grom8888 (0.91, 7.6)
842. Tien0808 (0.91, 8.1)
843. Lily0388 (0.91, 8.5)
844. look8008 (0.91, 8.0)
845. lark7878 (0.91, 8.2)
846. Par-0708 (0.91, 10.4)
847. khen7878 (0.91, 8.3)
848. zulu0008 (0.91, 8.8)
849. belu0188 (0.91, 9.8)
850. asep7878 (0.91, 8.3)
851. geof8108 (0.91, 9.7)
852. wsex7878 (0.91, 10.1)
853. blew7878 (0.91, 9.2)
854. spec7778 (0.91, 8.4)
855. moon8388 (0.91, 7.6)
856. hisX5678 (0.91, 11.7)
857. urty5678 (0.91, 9.2)
858. Work7878 (0.91, 7.8)
859. Aaia0908 (0.91, 10.4)
860. zion8888 (0.91, 6.4)
861. boon8488 (0.91, 8.5)
862. clem7878 (0.91, 8.3)
863. lion8888 (0.91, 6.0)
864. grey7878 (0.91, 7.4)
865. trey7878 (0.91, 7.2)
866. mark7778 (0.91, 6.6)
867. fish5678 (0.91, 6.0)
868. koey7878 (0.91, 9.0)
869. Alex7878 (0.91, 7.2)
870. amen7778 (0.91, 9.0)
871. good5188 (0.91, 7.7)
872. Ebok0008 (0.91, 10.8)
873. djlj7878 (0.91, 9.4)
874. july7878 (0.91, 6.5)
875. golf7878 (0.91, 6.4)
876. Grey7878 (0.91, 8.4)
877. fred7778 (0.91, 6.8)
878. Lmik0108 (0.91, 10.8)
879. bulu0008 (0.91, 9.2)
880. sss@5678 (0.91, 8.7)
881. alen7778 (0.91, 8.6)
882. harw7878 (0.91, 9.7)
883. dold7878 (0.91, 9.5)
884. lulu7878 (0.91, 7.0)
885. gold7878 (0.91, 6.8)
886. mliv8488 (0.91, 10.7)
887. srey7778 (0.91, 9.9)
888. rish5678 (0.91, 7.3)
889. uiiy8208 (0.91, 9.8)
890. troy0308 (0.91, 6.9)
891. Htop3178 (0.91, 11.8)
892. Porn0808 (0.91, 8.2)
893. Fren7778 (0.91, 9.4)
894. wiox8888 (0.91, 9.2)
895. eloy8188 (0.91, 9.4)
896. hula7878 (0.91, 8.6)
897. bala7878 (0.91, 7.5)
898. Naia0908 (0.91, 9.2)
899. brog0708 (0.91, 9.4)
900. kbld7778 (0.91, 10.6)
901. fila7878 (0.91, 8.5)
902. hola7878 (0.91, 6.7)
903. bola7878 (0.91, 7.7)
904. tmia0888 (0.91, 10.4)
905. zulu7778 (0.91, 8.2)
906. elin8388 (0.91, 8.8)
907. lulu7778 (0.91, 7.4)
908. gold7778 (0.91, 7.3)
909. Wilk0088 (0.91, 10.4)
910. blog0308 (0.91, 8.0)
911. mcsh5008 (0.91, 9.8)
912. Boom8888 (0.91, 7.4)
913. odin0788 (0.91, 8.9)
914. Kneh0088 (0.91, 10.9)
915. gosf5178 (0.91, 10.8)
916. Sera7878 (0.91, 9.0)
917. ayou7078 (0.91, 9.6)
918. iron0908 (0.91, 7.7)
919. nesc5178 (0.91, 11.2)
920. brod0708 (0.91, 8.6)
921. Caim0108 (0.91, 10.1)
922. rush5508 (0.91, 8.2)
923. cash8778 (0.91, 7.9)
924. cain0808 (0.91, 7.4)
925. boog8888 (0.91, 6.8)
926. ccth5908 (0.91, 11.2)
927. json0708 (0.91, 8.7)
928. Erin5/98 (0.91, 11.9)
929. jctv5288 (0.91, 10.3)
930. book0988 (0.91, 8.0)
931. lisa5778 (0.91, 7.5)
932. plow0808 (0.91, 8.2)
933. wood0908 (0.91, 7.5)
934. troy0808 (0.91, 6.7)
935. grim8108 (0.91, 8.8)
936. lith5678 (0.91, 8.6)
937. Chou0708 (0.91, 8.7)
938. eliw0908 (0.91, 10.0)
939. tity5678 (0.91, 8.1)
940. loop0988 (0.91, 7.4)
941. wood8808 (0.91, 7.6)
942. eric8108 (0.91, 7.1)
943. eliz0908 (0.91, 8.1)
944. Lui$0308 (0.91, 9.7)
945. leon8888 (0.91, 6.1)
946. Odin0308 (0.91, 8.4)
947. acoh7878 (0.91, 10.3)
948. Kaia0708 (0.91, 8.6)
949. aloa0108 (0.91, 8.4)
950. kish5878 (0.91, 9.2)
951. wric0408 (0.91, 10.0)
952. josh5678 (0.91, 6.0)
953. slim8688 (0.91, 8.0)
954. meth5678 (0.91, 7.8)
955. moon8888 (0.91, 5.8)
956. hrod0808 (0.91, 9.3)
957. troy7278 (0.91, 7.8)
958. beth5678 (0.91, 7.0)
959. yash5008 (0.91, 8.4)
960. greg!988 (0.91, 9.7)
961. nwtx5208 (0.91, 11.4)
962. krom7578 (0.91, 9.4)
963. goon8888 (0.91, 6.7)
964. oeiu5688 (0.91, 9.8)
965. Kath5908 (0.91, 9.4)
966. blik8808 (0.91, 10.2)
967. mmek3208 (0.91, 10.2)
968. bitu5678 (0.91, 8.4)
969. deoc8888 (0.91, 9.0)
970. kjeg3288 (0.91, 10.5)
971. wood0408 (0.91, 7.3)

972.	clim8888	(0.91, 7.8)	982.	doom8888	(0.91, 6.7)	992.	sai@0508	(0.91, 8.5)
973.	eric0988	(0.91, 7.1)	983.	skip7878	(0.91, 7.4)	993.	kirk5098	(0.91, 8.6)
974.	grig8888	(0.91, 7.9)	984.	FaiZ7878	(0.91, 10.3)	994.	rita8478	(0.91, 8.2)
975.	dion0708	(0.91, 7.6)	985.	cbsc5688	(0.91, 10.2)	995.	aiea3288	(0.91, 9.5)
976.	msej3288	(0.91, 10.8)	986.	rain7178	(0.91, 8.2)	996.	mary3208	(0.90, 7.7)
977.	leoj8888	(0.91, 7.9)	987.	lion0508	(0.91, 6.9)	997.	ori@8888	(0.90, 9.9)
978.	owen3288	(0.91, 7.7)	988.	olia8888	(0.91, 8.2)	998.	soon8888	(0.90, 6.9)
979.	wood0508	(0.91, 7.3)	989.	boop8888	(0.91, 7.1)	999.	lion7278	(0.90, 7.8)
980.	roof0708	(0.91, 8.7)	990.	Laia0308	(0.91, 9.2)			
981.	drew3208	(0.91, 7.6)	991.	murf3208	(0.91, 9.1)			

Cluster 6

Prototype: 2002291aow

Hard-assigned passwords: 1014019 (3.50% of total)
Unique hard-assigned passwords: 706290 (30.35% of cluster total)

Cluster-assignment scores:
	Min: 0.092
	Max: 0.979
	Mean: 0.356
	SD: 0.151

Strength bins:
	Very weak: 80788 (7.97%)
	Weak: 89114 (8.79%)
	Fair: 171515 (16.91%)
	Good: 515354 (50.82%)
	Strong: 157248 (15.51%)

Password lengths:
	Length 10: 962487 (94.92%)
	Length 11: 51532 (5.08%)

Character classes:
	4 classes: 16162 (1.59%)
	3 classes: 169462 (16.71%)
		lower/upper/symbol: 1296 (0.76%)
		lower/upper/number: 144753 (85.42%)
		lower/symbol/number: 18177 (10.73%)
		upper/symbol/number: 5236 (3.09%)
	2 classes: 501774 (49.48%)
		lower/upper: 2349 (0.47%)
		lower/number: 417817 (83.27%)
		lower/symbol: 235 (0.05%)
		upper/number: 63316 (12.62%)
		upper/symbol: 1770 (0.35%)
		number/symbol: 16287 (3.25%)
	1 class: 326621 (32.21%)
		lower: 0 (0.00%)
		upper: 15491 (4.74%)
		symbol: 141 (0.04%)
		number: 310989 (95.21%)

Most frequent char-class structures:
	DDDDDDDDDD: 294037 (29.0%)
	DDDDDDDDDL: 38029 (3.8%)
	DDDDDDLLLL: 37886 (3.7%)
	DDDDLLLLLL: 35193 (3.5%)
	DDDDDDDDLL: 34320 (3.4%)
	DDDDLLLLL: 29071 (2.9%)
	LDDDDDDDDD: 26786 (2.6%)
	DDDLLLLLLL: 25624 (2.5%)
	DDLLLLLLLL: 24367 (2.4%)
	DDDDDDDLLL: 19701 (1.9%)

1,000 nearest passwords

0.	859216Js25	(0.98, 14.0)	54.	400887Drew	(0.89, 12.8)	108.	11X14CbbD5	(0.87, 14.0)
1.	405M369iv5	(0.98, 14.0)	55.	23B24C7d^^	(0.89, 14.0)	109.	150300JOCC	(0.87, 13.6)
2.	1989GMCs15	(0.97, 13.6)	56.	250410YcGg	(0.89, 14.0)	110.	84207330Bb	(0.87, 12.8)
3.	170397AkHw	(0.96, 13.9)	57.	101684KIKI	(0.89, 11.8)	111.	70949151LI	(0.87, 13.6)
4.	571356YahI	(0.95, 14.0)	58.	332010Kkab	(0.89, 14.0)	112.	8940078mgw	(0.87, 13.8)
5.	290887IcfB	(0.95, 14.0)	59.	10609SDrew	(0.88, 13.9)	113.	88222081EU	(0.87, 13.9)
6.	130573DjTj	(0.95, 14.0)	60.	2651173Cem	(0.88, 13.1)	114.	80992773CM	(0.87, 14.0)
7.	591782BoiN	(0.95, 14.0)	61.	241201@@NI	(0.88, 13.7)	115.	140285ARBI	(0.87, 12.7)
8.	11y3T67ppU	(0.94, 14.0)	62.	100193HSII	(0.88, 13.0)	116.	1315293FPF	(0.87, 14.0)
9.	666*666dbp	(0.94, 13.4)	63.	24y2LKPsK5	(0.88, 14.0)	117.	150962BALT	(0.87, 13.5)
10.	7422143Erw	(0.94, 14.0)	64.	12R2$*D2@~	(0.88, 14.0)	118.	9924241sh5	(0.87, 13.6)
11.	219260Rfmj	(0.94, 14.0)	65.	72298162JM	(0.88, 13.5)	119.	111205DRAC	(0.87, 12.9)
12.	17107V9uNI	(0.94, 14.0)	66.	16F06A98RM	(0.88, 14.0)	120.	07241994EC	(0.87, 11.4)
13.	1h84EJ4fgU	(0.94, 14.0)	67.	191191MCAI	(0.88, 13.5)	121.	78241200EB	(0.87, 13.1)
14.	1504EP93ep	(0.93, 14.0)	68.	2014K&knew	(0.88, 14.0)	122.	22222.Ali.	(0.87, 12.5)
15.	1ja96F0lGM	(0.93, 14.0)	69.	100871YANI	(0.88, 12.5)	123.	292A460C1F	(0.87, 14.0)
16.	26xAA26xAF	(0.93, 14.0)	70.	05271991PM	(0.88, 10.8)	124.	271099HAJI	(0.87, 12.1)
17.	052100Jksj	(0.93, 14.0)	71.	48057746JC	(0.88, 13.8)	125.	9824156dup	(0.87, 13.7)
18.	1q2w3E4r%T	(0.93, 8.3)	72.	101979BETU	(0.88, 12.6)	126.	0332110yzw	(0.87, 13.8)
19.	589113Ping	(0.93, 12.8)	73.	170186KIMI	(0.88, 11.9)	127.	2060063ASH	(0.87, 12.8)
20.	6292009Bam	(0.93, 12.9)	74.	181186THOM	(0.88, 12.6)	128.	8822605xsw	(0.87, 12.1)
21.	270782Jing	(0.93, 11.1)	75.	26wD691TdF	(0.88, 14.0)	129.	0123456dow	(0.87, 9.4)
22.	2841990M●m	(0.93, 13.7)	76.	20qIB0Uq80	(0.88, 14.0)	130.	7131897ypw	(0.87, 14.0)
23.	317Z358a18	(0.93, 14.0)	77.	2091377ALI	(0.88, 12.3)	131.	9661503wow	(0.87, 12.3)
24.	220686_FsT	(0.92, 14.0)	78.	160402KAFI	(0.88, 13.6)	132.	231991NACI	(0.87, 12.4)
25.	792091Kiev	(0.92, 13.9)	79.	73501505TM	(0.88, 12.9)	133.	261096MALU	(0.87, 12.0)
26.	320973Frog	(0.92, 12.7)	80.	130499BATU	(0.88, 11.9)	134.	110495AMAT	(0.87, 11.7)
27.	15B9LR2ol5	(0.92, 14.0)	81.	747A84226b	(0.88, 14.0)	135.	147/20/8KN	(0.87, 14.0)
28.	230262Olib	(0.92, 14.0)	82.	887115Adam	(0.88, 12.0)	136.	250795KOPF	(0.87, 14.0)
29.	220690Romm	(0.91, 12.9)	83.	170198JUAN	(0.87, 10.6)	137.	12......ab	(0.87, 10.0)
30.	18eNV019uB	(0.91, 14.0)	84.	9241942dfw	(0.87, 13.1)	138.	171970JOHN	(0.87, 11.1)
31.	3023214Jtm	(0.91, 13.7)	85.	181092ORYM	(0.87, 13.7)	139.	231063GISI	(0.87, 13.9)
32.	1q2w3E$R%T	(0.91, 8.1)	86.	130987CARI	(0.87, 12.4)	140.	7871930zgw	(0.87, 13.7)
33.	1E2L3B7elb	(0.91, 14.0)	87.	251025MNSF	(0.87, 14.0)	141.	170659Thom	(0.87, 12.7)
34.	504-34-1jv	(0.91, 14.0)	88.	180380JAVI	(0.87, 11.7)	142.	2011QOProm	(0.86, 14.0)
35.	31gS58CvY5	(0.91, 14.0)	89.	08311998BM	(0.87, 10.9)	143.	50253008Ep	(0.86, 13.4)
36.	4098196Dem	(0.91, 13.8)	90.	110794WAFI	(0.87, 13.0)	144.	1508467RBH	(0.86, 13.8)
37.	5605746Kim	(0.91, 13.4)	91.	190292VIRI	(0.87, 11.7)	145.	1025177Gsj	(0.86, 14.0)
38.	7181967CaM	(0.91, 13.4)	92.	240062ASDF	(0.87, 11.6)	146.	9581919wow	(0.86, 12.2)
39.	240575Irek	(0.91, 13.3)	93.	210186VYOM	(0.87, 14.0)	147.	562141SEgm	(0.86, 14.0)
40.	6722067kDv	(0.91, 14.0)	94.	101704VICT	(0.87, 12.9)	148.	16azZJe76T	(0.86, 14.0)
41.	132105WCjm	(0.90, 14.0)	95.	1q2w#E$R%T	(0.87, 8.0)	149.	9437111pjp	(0.86, 13.3)
42.	320785Link	(0.90, 11.3)	96.	360350Dsb.	(0.87, 14.0)	150.	201713KAGT	(0.86, 14.0)
43.	2129055BgH	(0.90, 14.0)	97.	1yDM80Do1C	(0.87, 14.0)	151.	9370919jkw	(0.86, 13.0)
44.	03B7699wi8	(0.90, 14.0)	98.	201198MIKI	(0.87, 11.5)	152.	8228961gt5	(0.86, 14.0)
45.	252141.Job	(0.90, 14.0)	99.	18013FE1DC	(0.87, 14.0)	153.	8063082s45	(0.86, 14.0)
46.	885-4539tv	(0.90, 14.0)	100.	280996Link	(0.87, 10.2)	154.	825120.taw	(0.86, 14.0)
47.	262610Simp	(0.89, 13.2)	101.	131290MasH	(0.87, 13.3)	155.	08611156AB	(0.86, 12.7)
48.	633-4508vw	(0.89, 14.0)	102.	161084SALT	(0.87, 12.6)	156.	261281MANU	(0.86, 11.4)
49.	762100Adcb	(0.89, 14.0)	103.	052008Jack	(0.87, 10.1)	157.	75611657CT	(0.86, 14.0)
50.	314F8810dC	(0.89, 14.0)	104.	4429510Sam	(0.87, 12.6)	158.	290892GOKU	(0.86, 12.9)
51.	1505F43CA5	(0.89, 14.0)	105.	2522134MAN	(0.87, 12.0)	159.	809174Asif	(0.86, 12.8)
52.	1mRh75SazM	(0.89, 14.0)	106.	130913Room	(0.87, 12.7)	160.	1121975ABC	(0.86, 10.0)
53.	432112HGhg	(0.89, 13.4)	107.	102027Aa-+	(0.87, 14.0)	161.	8189020tsw	(0.86, 13.1)

162. 9229169tOA (0.86, 14.0)
163. 210682DANI (0.86, 11.2)
164. 9831617abm (0.86, 13.2)
165. 291295HJpp (0.86, 13.4)
166. 1I7eX0Ctk0 (0.86, 14.0)
167. 210889DENI (0.86, 12.0)
168. 291102FHET (0.86, 13.7)
169. 241012VCPC (0.86, 14.0)
170. 210972JUAN (0.86, 10.4)
171. 220484Lili (0.86, 11.3)
172. 250376Gigi (0.86, 11.9)
173. 280194EUAN (0.86, 12.6)
174. 291132kiTT (0.86, 14.0)
175. 161511LSmL (0.86, 14.0)
176. 6831028((8 (0.86, 14.0)
177. 06261996Bm (0.86, 10.2)
178. 08220066AB (0.86, 12.4)
179. 61285Gg208 (0.86, 14.0)
180. 8181978Kjk (0.86, 13.1)
181. 211-37WHAT (0.86, 14.0)
182. 62230167Dj (0.86, 13.3)
183. 37904Kjp65 (0.86, 14.0)
184. 110968DIAH (0.86, 12.4)
185. 1OhzR5q1k5 (0.86, 14.0)
186. 290507YESI (0.86, 12.9)
187. 0025672tip (0.86, 12.8)
188. 110789KCMB (0.86, 13.0)
189. 9142501srj (0.86, 13.5)
190. 210981IVAN (0.86, 10.8)
191. 0343909f85 (0.86, 14.0)
192. 512142Mani (0.86, 12.2)
193. 84222431ap (0.86, 12.8)
194. 160877JAVI (0.86, 11.9)
195. 3660011TNT (0.86, 13.5)
196. 61289786ON (0.86, 13.8)
197. 1619800NHC (0.86, 13.3)
198. 230896NIKI (0.86, 12.0)
199. 141287ENC+ (0.86, 14.0)
200. 9252008avb (0.86, 12.9)
201. 270899Dani (0.86, 10.2)
202. 6060842bjw (0.86, 12.8)
203. 9937021ram (0.86, 11.5)
204. 07261993Jp (0.86, 10.5)
205. 28DEG06qiB (0.86, 14.0)
206. 1314520CXH (0.86, 10.8)
207. 2020250AbC (0.85, 12.2)
208. 0032230wap (0.85, 12.6)
209. 1v2P2G34jU (0.85, 14.0)
210. 131072KBok (0.85, 14.0)
211. 87916057Ob (0.85, 13.8)
212. 250960STAN (0.85, 11.7)
213. 8381590wow (0.85, 12.1)
214. !!11QAzxsw (0.85, 9.1)
215. 160554Dick (0.85, 12.2)
216. 150397Dalm (0.85, 13.0)
217. 8024513bbb (0.85, 12.2)
218. 1302468CLB (0.85, 13.8)
219. 86915631jp (0.85, 12.6)
220. 21qB788RVM (0.85, 14.0)
221. 0123456ghj (0.85, 7.9)
222. 05502151ap (0.85, 13.5)
223. 0130367jcb (0.85, 12.5)
224. 04301997Lj (0.85, 11.0)
225. 9940213ram (0.85, 11.2)
226. 4229043mOH (0.85, 14.0)
227. 8251994mlb (0.85, 11.6)
228. 0123469abb (0.85, 7.9)
229. 08313111xm (0.85, 13.1)
230. 8961610web (0.85, 11.2)
231. 8522522alp (0.85, 12.1)
232. 250000KLUB (0.85, 13.2)
233. !)@(#*$&%^ (0.85, 14.0)
234. 0123456web (0.85, 6.2)
235. 842036&web (0.85, 14.0)
236. 230598Fati (0.85, 11.1)
237. 23FFZ99odg (0.85, 14.0)
238. 9892751sam (0.85, 11.7)
239. 6241998irw (0.85, 12.7)
240. 7142128ipm (0.85, 13.2)
241. 0123589abb (0.85, 7.0)
242. 0952010tpp (0.85, 12.8)
243. 131064JhGg (0.85, 14.0)
244. 9141955tsb (0.85, 12.5)
245. 18M404N17N (0.85, 14.0)
246. 6761761akw (0.85, 14.0)
247. 118118.COM (0.85, 11.0)
248. 0123456adm (0.85, 7.1)
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250. 9134290rbw (0.85, 14.0)
251. 5408466FFF (0.85, 13.0)
252. 9341077oob (0.85, 13.6)
253. 6531514dew (0.85, 12.9)
254. 76913895Ab (0.85, 12.2)
255. 7895123aqw (0.85, 8.6)
256. 06301979XH (0.85, 12.6)
257. 200302DFBB (0.85, 13.9)
258. 0125689abb (0.85, 7.8)
259. 9976191chm (0.85, 12.7)
260. 7925025top (0.85, 12.2)
261. 9970177mdb (0.85, 12.8)
262. 3291979GLC (0.85, 12.9)
263. 250909_FAN (0.85, 13.8)
264. 270892ZIAH (0.85, 12.3)
265. 9131962gbw (0.85, 12.6)
266. 560053Snap (0.85, 13.2)
267. 0251933bgb (0.85, 13.8)
268. 7261206hjb (0.85, 13.0)
269. 9827184wzm (0.85, 13.4)
270. 03912351BB (0.85, 13.1)
271. 5103OC4y00 (0.85, 14.0)
272. 2991616SjT (0.85, 14.0)
273. 9379992www (0.85, 8.7)
274. 0463118a2m (0.85, 14.0)
275. 2145EC124C (0.85, 14.0)
276. 6123156Tn. (0.85, 14.0)
277. 9469155sjb (0.85, 13.3)
278. 8124258pop (0.85, 12.1)
279. 1026493Gab (0.85, 13.8)
280. 7531240gdm (0.85, 13.6)
281. 0722721obb (0.85, 13.4)
282. 0031258mhm (0.85, 12.3)
283. 7561086mom (0.85, 12.1)
284. 6431901aAb (0.85, 13.6)
285. 331612BATU (0.85, 12.9)
286. 2412618MOM (0.85, 12.7)
287. 8371078web (0.85, 11.1)
288. 9251934edm (0.85, 13.0)
289. 8072005mam (0.85, 11.6)
290. 6661999cop (0.85, 11.8)
291. 9223059deb (0.85, 12.7)
292. 20000AZX** (0.85, 13.0)
293. 47203047LC (0.85, 14.0)
294. 9496107akm (0.85, 12.7)
295. 7532159dwp (0.85, 10.8)
296. 240966JACB (0.85, 13.3)
297. 31x2FWJqb5 (0.85, 14.0)
298. 6641232tgm (0.85, 13.1)
299. 0072007kgb (0.85, 11.7)
300. 8150629www (0.85, 11.9)
301. 0632291tom (0.85, 12.1)
302. 270895DEVI (0.85, 11.5)
303. 9632147web (0.85, 7.7)
304. 1504089VMH (0.85, 14.0)
305. 171009_JAB (0.85, 13.7)
306. 8851978mlw (0.85, 13.1)
307. 80715942tw (0.85, 13.4)
308. 7493024jvm (0.85, 13.9)
309. 3222426Web (0.85, 12.2)
310. 97318246a5 (0.85, 12.7)
311. 280428Cab& (0.85, 14.0)
312. 112233Fuck (0.85, 8.4)
313. 98414542pp (0.85, 11.8)
314. 9851912mum (0.85, 12.4)
315. 50925092Pp (0.85, 11.1)
316. 33B8E4fb75 (0.85, 14.0)
317. 612259Njkz (0.85, 14.0)
318. 99501157LI (0.85, 13.3)
319. 6990577wdw (0.85, 13.1)
320. 0179812seb (0.85, 13.1)
321. 3221322ZXC (0.85, 13.3)
322. 450905Ludw (0.85, 14.0)
323. 1181915SDM (0.85, 14.0)
324. 2861927Jim (0.85, 12.8)
325. 9898731sam (0.85, 11.4)
326. 82320296pw (0.85, 13.1)
327. 50gF92AtAC (0.85, 14.0)
328. 1qaz2WSX** (0.85, 10.1)
329. 2223939Tom (0.85, 12.0)
330. 494G2604MF (0.85, 14.0)
331. 98390086y5 (0.85, 14.0)
332. 511445Reem (0.85, 13.4)
333. 88990325Jb (0.85, 12.9)
334. 100878HeVi (0.85, 13.8)
335. 0071420aym (0.85, 12.1)
336. 21232321BB (0.85, 12.0)
337. 1hQ26Vze0B (0.84, 14.0)
338. 8950227jjj (0.84, 11.4)
339. 101658GWPJ (0.84, 14.0)
340. 7895123sbm (0.84, 9.9)
341. 9928408dab (0.84, 13.1)
342. 261724Pack (0.84, 12.8)
343. 88890810aw (0.84, 12.4)
344. 0032238g18 (0.84, 14.0)
345. 0595000web (0.84, 10.7)
346. 6242000rnm (0.84, 12.5)
347. 112209ZLHM (0.84, 14.0)
348. 0041980mkm (0.84, 11.9)
349. 09233801rw (0.84, 12.9)
350. 5290426Ani (0.84, 13.2)
351. 06241220Pb (0.84, 12.7)
352. 92771234sw (0.84, 12.3)
353. 8790654+mb (0.84, 13.9)
354. 7183015tom (0.84, 11.8)
355. 7792881hjm (0.84, 13.0)
356. 0123690dbj (0.84, 12.0)
357. 10FK41nZ58 (0.84, 14.0)
358. 7462081bjm (0.84, 13.1)
359. 8524163plm (0.84, 12.2)
360. 92531520dj (0.84, 11.9)
361. 8186000web (0.84, 9.8)
362. 6661954now (0.84, 11.7)
363. 8332142rwb (0.84, 13.0)
364. 84267139qw (0.84, 10.7)
365. 221069REAH (0.84, 14.0)
366. 1qaz1QAZ** (0.84, 10.2)
367. 6442113sem (0.84, 12.2)
368. 9731916adg (0.84, 12.5)
369. 301187MACH (0.84, 12.2)
370. 4315991MNM (0.84, 13.7)
371. 0425245nsm (0.84, 13.5)
372. 9940421djg (0.84, 12.3)
373. 1w0qE5GoZ0 (0.84, 14.0)
374. 8198716tjj (0.84, 13.2)
375. 132033Grip (0.84, 13.4)
376. 8235110mom (0.84, 11.6)
377. 8359105akm (0.84, 12.6)
378. 21977051Wm (0.84, 13.8)
379. 1@2#$%^&*((0.84, 12.6)
380. 1990252MOH (0.84, 13.3)
381. 7532159qpm (0.84, 11.0)
382. 9790804kej (0.84, 13.5)
383. 24801553LI (0.84, 13.1)
384. 819974.new (0.84, 14.0)
385. 7470900mgm (0.84, 12.6)
386. 8945000map (0.84, 11.9)
387. 189189AaA? (0.84, 13.1)
388. 0994280jsj (0.84, 13.5)
389. 6342143skp (0.84, 12.7)
390. 85420912xw (0.84, 13.6)
391. 06281993Rm (0.84, 10.6)
392. 6260044mmb (0.84, 12.4)
393. 6881249zzb (0.84, 13.4)
394. 9929126@aB (0.84, 14.0)
395. 1F0348GjCB (0.84, 14.0)
396. 7750977jjb (0.84, 12.6)
397. 53wPU37ltj (0.84, 14.0)
398. 8861973jsj (0.84, 12.8)
399. 9589251new (0.84, 12.8)
400. 1021TAsb50 (0.84, 14.0)
401. 220985VINI (0.84, 11.8)
402. 780074Hang (0.84, 13.4)
403. 7581419arj (0.84, 13.4)
404. 6162097mjb (0.84, 12.6)
405. 1E32D7c10M (0.84, 14.0)
406. 5417707LoL (0.84, 13.1)
407. 7125471svv (0.84, 13.2)
408. 7040598jim (0.84, 12.3)
409. 97238152rj (0.84, 13.0)
410. 100986CEpg (0.84, 14.0)
411. 8770260iub (0.84, 12.6)
412. 51303891Vb (0.84, 13.7)
413. 7789711xhj (0.84, 13.1)
414. 70719901im (0.84, 10.9)
415. 9354221sum (0.84, 12.6)
416. 33rQ4Jq9u5 (0.84, 14.0)
417. 6792491mmm (0.84, 11.3)
418. 0351027sgb (0.84, 12.9)
419. 9051988bpv (0.84, 12.4)
420. 9031434-dj (0.84, 13.5)
421. 79500900@om (0.84, 13.9)
422. 99421524mm (0.84, 11.7)
423. 95419541mp (0.84, 9.8)
424. 02884012rw (0.84, 7.1)
425. 4171966Mlg (0.84, 13.5)
426. 2411995THT (0.84, 12.6)
427. 51504948Ab (0.84, 11.7)
428. 170707NorA (0.84, 13.0)
429. 6127598mmp (0.84, 13.0)
430. 2702199JON (0.84, 12.4)
431. 82400757ip (0.84, 13.1)

432. 89808980mw (0.84, 10.1)
433. 150578Work (0.84, 11.6)
434. 31255973Dm (0.84, 13.3)
435. 77941483wp (0.84, 13.3)
436. 180394LMKL (0.84, 13.0)
437. 75315982qw (0.84, 8.6)
438. 7051965www (0.84, 12.1)
439. 6961441sam (0.84, 11.4)
440. 7271983jmb (0.84, 10.7)
441. 10101AMEEN (0.84, 11.7)
442. 251292Yoni (0.84, 11.4)
443. 9028794avv (0.84, 13.9)
444. 6651409smm (0.84, 12.7)
445. 1q2w3E4R5T (0.84, 6.6)
446. 012589●ahv (0.84, 14.0)
447. 7282711rhm (0.84, 13.0)
448. 7361342sup (0.84, 13.4)
449. 80267791aw (0.84, 12.6)
450. 9832132_uv (0.84, 14.0)
451. 5020952ABC (0.84, 12.0)
452. 1422009Tam (0.84, 11.6)
453. 6699619aop (0.84, 13.0)
454. 350350pmPM (0.84, 13.8)
455. 97302465ab (0.84, 11.8)
456. 76281742lp (0.84, 12.3)
457. 9077912jjj (0.84, 12.5)
458. 1800015ABC (0.84, 11.2)
459. 6360290csj (0.84, 13.1)
460. 7261978sjm (0.84, 11.6)
461. 85690133cp (0.84, 12.7)
462. 7781255com (0.84, 11.4)
463. 953151_scm (0.84, 14.0)
464. 0820580iub (0.84, 13.1)
465. 7870988bjp (0.84, 13.2)
466. 03221980TT (0.84, 10.6)
467. 08585111op (0.84, 12.4)
468. 71503191am (0.84, 11.9)
469. 6097935caw (0.84, 13.2)
470. 94254043pp (0.83, 12.2)
471. 95591525nb (0.83, 13.4)
472. 63296274jw (0.83, 13.0)
473. 86540711dp (0.83, 12.5)
474. 6371070ttj (0.83, 13.2)
475. 101292AASL (0.83, 12.0)
476. 75351023bp (0.83, 13.1)
477. 4352W4352w (0.83, 12.7)
478. 41414141SB (0.83, 9.9)
479. 98406813mm (0.83, 11.8)
480. 8551213kaM (0.83, 13.9)
481. 07833701mw (0.83, 12.9)
482. 94513372ab (0.83, 12.1)
483. 1991828GXH (0.83, 11.9)
484. 1qNh7B8mLO (0.83, 14.0)
485. 92415942am (0.83, 12.1)
486. 7895123qqw (0.83, 9.4)
487. 0067072zim (0.83, 13.8)
488. 7895123arg (0.83, 8.8)
489. 87507193sj (0.83, 13.2)
490. 4105516ABC (0.83, 11.6)
491. 3371D0951v (0.83, 14.0)
492. 88415000aj (0.83, 11.6)
493. 7880371iim (0.83, 13.4)
494. 101064LVDL (0.83, 13.7)
495. 1192246Bhb (0.83, 14.0)
496. 49PK01SDn8 (0.83, 14.0)
497. 7558181mmm (0.83, 11.5)
498. 015121-lsm (0.83, 13.4)
499. 81276411ap (0.83, 12.6)
500. 8059076t00 (0.83, 13.6)
501. 90505356sb (0.83, 12.6)
502. 5121472ALI (0.83, 10.7)
503. 88440022pp (0.83, 10.7)
504. 6022746vdv (0.83, 13.8)
505. 80331310ab (0.83, 11.6)
506. 49186SGndc (0.83, 14.0)
507. 96740062jp (0.83, 12.0)
508. 89631139n5 (0.83, 12.0)
509. 2101959DLM (0.83, 13.3)
510. 9280431nmg (0.83, 13.9)
511. 76413955qw (0.83, 13.0)
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513. 7831699mom (0.83, 12.4)
514. 88316006rm (0.83, 12.3)
515. 2014214KDM (0.83, 13.2)
516. 83982185mw (0.83, 13.3)
517. 88315052zj (0.83, 12.7)
518. 8629953ddg (0.83, 14.0)
519. 03300060Mm (0.83, 12.0)
520. 80690986tp (0.83, 13.2)
521. 05281984Tw (0.83, 10.8)
522. 6096924adm (0.83, 12.5)
523. 271988Kiki (0.83, 10.6)
524. 07319992kw (0.83, 13.0)
525. 91822332op (0.83, 12.7)
526. 9380000deb (0.83, 12.7)
527. 99514802pm (0.83, 12.6)
528. 05341901nm (0.83, 12.7)
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531. 83315961rm (0.83, 12.7)
532. 230494JDLB (0.83, 13.5)
533. 08231994Hb (0.83, 10.6)
534. 9126419gr8 (0.83, 13.8)
535. 6224932kim (0.83, 12.0)
536. 95517292mj (0.83, 12.6)
537. 01599510qw (0.83, 9.6)
538. 84998499mw (0.83, 10.9)
539. 251397YBR* (0.83, 14.0)
540. 80406420am (0.83, 12.8)
541. 88319383cb (0.83, 12.5)
542. 97259281zw (0.83, 13.2)
543. 0196362ssg (0.83, 13.4)
544. 2702008LMH (0.83, 13.3)
545. 8880852kjw (0.83, 13.0)
546. 7758521a6w (0.83, 10.9)
547. 7895123c++ (0.83, 10.0)
548. 9490935dom (0.83, 13.1)
549. 0225689abb (0.83, 9.5)
550. 10HN1A0458 (0.83, 14.0)
551. 78985200tw (0.83, 10.4)
552. 7241987amj (0.83, 11.6)
553. 02527192tj (0.83, 13.0)
554. 016099,com (0.83, 12.8)
555. 88321897dm (0.83, 12.7)
556. 63613273qw (0.83, 12.4)
557. 71514343mm (0.83, 11.6)
558. 9096942jlg (0.83, 13.0)
559. 6152142adg (0.83, 12.5)
560. 07298830mw (0.83, 12.6)
561. 88508319gm (0.83, 12.8)
562. 78259625pp (0.83, 11.8)
563. 7294193rgg (0.83, 13.3)
564. 7179922mcb (0.83, 13.0)
565. 05551341fb (0.83, 12.1)
566. 78451210bb (0.83, 9.7)
567. 97570962mj (0.83, 13.0)
568. 62516251ab (0.83, 9.0)
569. 7845120rr0 (0.83, 11.6)
570. 531980DRUM (0.83, 13.3)
571. 86631202ib (0.83, 12.9)
572. 88890615ab (0.83, 11.2)
573. 8134060tom (0.83, 12.1)
574. 140266MRKL (0.83, 13.8)
575. 03916893mM (0.83, 13.3)
576. 08521456op (0.83, 11.5)
577. 01431364tb (0.83, 12.5)
578. 620894Tmtm (0.83, 14.0)
579. 97319731ab (0.83, 9.5)
580. 75580011t% (0.83, 14.0)
581. 88861995kw (0.83, 12.4)
582. 6261955rlb (0.83, 12.6)
583. 80923634ap (0.83, 12.9)
584. 9492100aA* (0.83, 13.4)
585. 88269651hb (0.83, 12.6)
586. 02884012wp (0.83, 7.5)
587. 39u%9C!7KB (0.83, 14.0)
588. 9889188oo8 (0.83, 12.8)
589. 7254915m4m (0.83, 14.0)
590. 84230383jb (0.83, 12.7)
591. 300379IVAN (0.83, 11.3)
592. 99731193ab (0.83, 11.2)
593. 05442110dj (0.83, 11.7)
594. 00284871jw (0.83, 12.7)
595. 110902AvL* (0.83, 14.0)
596. 20c-.,xz<> (0.83, 14.0)
597. 96515241dj (0.83, 11.7)
598. 6223222adg (0.83, 11.7)
599. 7831298tag (0.83, 12.7)
600. 01304595np (0.83, 12.8)
601. 81944430dj (0.83, 12.4)
602. 780326Ajgg (0.83, 14.0)
603. 6786700o6p (0.83, 14.0)
604. 9948571a9w (0.83, 14.0)
605. 77621176dm (0.83, 12.4)
606. 95962232ap (0.83, 12.3)
607. 34A208XC1U (0.83, 14.0)
608. 98322432ab (0.83, 11.6)
609. 23IBA82Dv0 (0.83, 14.0)
610. 1205MCGrow (0.83, 12.9)
611. 96631319mm (0.83, 11.7)
612. 82405891kj (0.83, 13.1)
613. 850721Deng (0.83, 12.4)
614. 8252138mom (0.83, 12.0)
615. 96545612sp (0.83, 11.5)
616. 6953016xam (0.83, 13.6)
617. 1212&*(&*((0.83, 12.8)
618. 80979325ab (0.83, 12.3)
619. 67350211jm (0.83, 12.4)
620. 02860402gp (0.83, 12.9)
621. 01551530ww (0.83, 12.2)
622. 65318186zj (0.83, 13.1)
623. 91740959ab (0.83, 11.7)
624. 01245566ab (0.83, 10.3)
625. 01241964DB (0.83, 10.9)
626. 147/258/*- (0.83, 10.0)
627. 29220697GC (0.83, 13.8)
628. 01234567ab (0.83, 6.1)
629. 1A2b3C4d@. (0.83, 11.4)
630. 8050750inv (0.83, 13.4)
631. 112793#Cpf (0.83, 14.0)
632. 05407962jj (0.83, 12.1)
633. 86971386gj (0.83, 13.3)
634. 63509333pp (0.83, 12.0)
635. 44mD1BRwf8 (0.83, 14.0)
636. 0571632sav (0.83, 12.9)
637. 00235666bb (0.83, 11.3)
638. 63316331ap (0.83, 9.5)
639. 02884012cp (0.83, 8.1)
640. 6768190u70 (0.83, 13.9)
641. 6532812sam (0.83, 11.2)
642. 6592840now (0.83, 12.5)
643. 300405IIOI (0.83, 13.4)
644. 1mAU$100rb (0.83, 14.0)
645. 64590270sj (0.83, 13.1)
646. 00316200rj (0.83, 11.6)
647. 44m8T0qzH8 (0.83, 14.0)
648. 87421991qw (0.83, 12.0)
649. 24BF82F7EF (0.83, 14.0)
650. 91827391ab (0.83, 10.5)
651. 220797Luli (0.83, 10.9)
652. 04274519sb (0.83, 12.5)
653. 92691204vp (0.83, 12.9)
654. 6141747vip (0.83, 11.9)
655. 200690ARIJ (0.83, 12.9)
656. 01234567bb (0.82, 6.7)
657. 61496149dj (0.82, 9.6)
658. 94259425bb (0.82, 9.4)
659. 00550055mm (0.82, 8.4)
660. 07261996aN (0.82, 11.3)
661. 00272826iI (0.82, 14.0)
662. 21720884LI (0.82, 13.4)
663. 102053JOHN (0.82, 11.0)
664. 96319631jj (0.82, 9.8)
665. 7895123-xp (0.82, 9.3)
666. 92421505ev (0.82, 13.2)
667. 78415937sp (0.82, 13.0)
668. 99761311mm (0.82, 11.4)
669. 78932145pm (0.82, 10.0)
670. 7351110K5N (0.82, 14.0)
671. 91237255aT (0.82, 13.6)
672. 95717261●8 (0.82, 14.0)
673. 96283819jm (0.82, 12.2)
674. 5832690f15 (0.82, 13.2)
675. 66821963db (0.82, 12.2)
676. 88608420dj (0.82, 12.4)
677. 64323015rw (0.82, 13.1)
678. 66504494mp (0.82, 12.7)
679. 81840936tb (0.82, 13.3)
680. 92702689ab (0.82, 7.3)
681. 02884012wb (0.82, 7.5)
682. 88321384qw (0.82, 11.9)
683. 50400767Mm (0.82, 12.7)
684. 81927506em (0.82, 13.0)
685. 20512406GC (0.82, 13.2)
686. 01247889ab (0.82, 7.5)
687. 160888T@nA (0.82, 14.0)
688. 0226600eng (0.82, 12.2)
689. 78528121gm (0.82, 12.4)
690. 959640001j (0.82, 12.6)
691. 290583IREN (0.82, 13.0)
692. 1A2S3S4O5U (0.82, 13.2)
693. 92963791wj (0.82, 13.0)
694. 66340881q8 (0.82, 14.0)
695. 8294600bmp (0.82, 12.9)
696. 99953275pp (0.82, 11.9)
697. 74817481jp (0.82, 10.0)
698. 01234569ab (0.82, 7.3)
699. 76770104mb (0.82, 12.5)
700. 00998877pp (0.82, 7.5)
701. 01236889ab (0.82, 6.5)

702. 01235689ab (0.82, 6.5)
703. 03614081jp (0.82, 12.1)
704. 111222asDF (0.82, 10.6)
705. 88890025dj (0.82, 12.4)
706. 8047023com (0.82, 12.2)
707. 99691720ab (0.82, 11.8)
708. 84616800xm (0.82, 12.8)
709. 01237889ab (0.82, 6.0)
710. 93332134vm (0.82, 12.6)
711. 606180831m (0.82, 12.9)
712. 02884012rp (0.82, 6.6)
713. 8189409jjj (0.82, 12.5)
714. 70922645ab (0.82, 12.0)
715. 13G1I60C6J (0.82, 14.0)
716. 803313101v (0.82, 13.2)
717. 01236779ab (0.82, 7.7)
718. 96983100ab (0.82, 11.1)
719. 0182322arv (0.82, 13.3)
720. 01236789ab (0.82, 5.9)
721. 06433019hm (0.82, 12.5)
722. 07980797rm (0.82, 11.5)
723. 02884012rm (0.82, 6.6)
724. 66233401mm (0.82, 11.8)
725. 90944575hm (0.82, 12.8)
726. 01954485dm (0.82, 13.0)
727. 50517212Up (0.82, 13.9)
728. 02908860Mm (0.82, 13.0)
729. 8271952aug (0.82, 11.9)
730. 04281962mM (0.82, 10.9)
731. 62248185dj (0.82, 12.0)
732. 6227790mum (0.82, 12.0)
733. 01430143bb (0.82, 9.3)
734. 70288250am (0.82, 12.8)
735. 78561245pp (0.82, 10.6)
736. 96321525yg (0.82, 12.5)
737. 94516452ab (0.82, 11.6)
738. 66661212cm (0.82, 11.0)
739. 8169930alp (0.82, 12.5)
740. 89622125ab (0.82, 11.5)
741. 01257889ab (0.82, 7.8)
742. 75560612jj (0.82, 12.4)
743. 282811Jeff (0.82, 11.2)
744. 02884012sb (0.82, 7.8)
745. 6271936klb (0.82, 13.0)
746. 7159927sam (0.82, 11.4)
747. 71289465fN (0.82, 14.0)
748. 9347811mpb (0.82, 13.2)
749. 02884012dm (0.82, 7.5)
750. 98252221qw (0.82, 12.1)
751. 04301975Sm (0.82, 10.7)
752. 03243107bm (0.82, 12.4)
753. 908049081b (0.82, 13.0)
754. 171934jaRM (0.82, 14.0)
755. 6060842a10 (0.82, 12.7)
756. 01235677np (0.82, 11.4)
757. 02884012rb (0.82, 6.7)
758. 04252007sj (0.82, 10.2)
759. 111111ALEL (0.82, 11.3)
760. 06293030jw (0.82, 12.0)
761. 78602417rm (0.82, 12.4)
762. 02884012db (0.82, 7.3)
763. 6027147elb (0.82, 13.6)
764. 8861287alp (0.82, 12.2)
765. 6550713●zm (0.82, 14.0)
766. 68260370ab (0.82, 12.1)
767. 290498Etec (0.82, 13.1)
768. 01256789bb (0.82, 8.1)
769. 32279622AF (0.82, 13.6)
770. 7340985cxm (0.82, 13.6)
771. 7884120ryj (0.82, 13.2)
772. 04276509mb (0.82, 12.6)
773. 78963214im (0.82, 9.7)
774. 0370423zag (0.82, 13.6)
775. 91470172db (0.82, 12.9)
776. 92772000dj (0.82, 11.7)
777. 20155Champ (0.82, 11.2)
778. 01236788ab (0.82, 6.5)
779. 69712850jb (0.82, 12.5)
780. 332030Raj$ (0.82, 13.9)
781. 06671800im (0.82, 12.6)
782. 102192MHS? (0.82, 13.8)
783. 05262007cw (0.82, 10.6)
784. 94280464dm (0.82, 12.9)
785. 11111HHHHH (0.82, 10.6)
786. 9379992mmm (0.82, 8.6)
787. 21233638Dj (0.82, 12.5)
788. 05465113zb (0.82, 13.1)
789. 3421876DGM (0.82, 14.0)
790. 7285**11** (0.82, 13.0)
791. 66233917jj (0.82, 12.1)
792. 95882391mm (0.82, 12.2)
793. 68937009ab (0.82, 12.2)
794. 01470147bb (0.82, 8.2)
795. 91285630am (0.82, 12.4)
796. 7127340xdg (0.82, 13.8)
797. 07831505qw (0.82, 12.1)
798. 01234567mp (0.82, 8.0)
799. 11223344NM (0.82, 8.7)
800. 420012Kopp (0.82, 13.4)
801. 1I2S3L4A5m (0.82, 12.4)
802. 06270704sp (0.82, 11.5)
803. 7865090taj (0.82, 12.4)
804. 09216544Jb (0.82, 12.7)
805. 84760052mb (0.82, 12.8)
806. 732781281p (0.82, 12.3)
807. 00861972bb (0.82, 12.0)
808. 8724602sgg (0.82, 13.4)
809. 6199420njw (0.82, 13.0)
810. 71932846gb (0.82, 12.6)
811. 08569931hb (0.82, 12.3)
812. 80978797qw (0.82, 12.5)
813. 7498243sam (0.82, 11.6)
814. 71570277cp (0.82, 12.9)
815. 89272265dv (0.82, 13.0)
816. 0688214map (0.82, 12.7)
817. 73731515mm (0.82, 11.7)
818. 01233210Ew (0.82, 10.3)
819. 78963214mm (0.82, 7.7)
820. 3520112PP% (0.82, 14.0)
821. 1b3j327tFN (0.82, 14.0)
822. 96312184cv (0.82, 12.4)
823. 1.2.3.Inti (0.82, 11.8)
824. 88552211bj (0.82, 10.6)
825. 70637071tb (0.82, 12.5)
826. 1qazWSXedc (0.82, 6.1)
827. 01235840nj (0.82, 11.5)
828. 8259524a70 (0.82, 13.6)
829. 79641213kv (0.82, 13.0)
830. 08261996aB (0.82, 10.1)
831. 61740955wb (0.82, 13.3)
832. 421977Tiff (0.82, 12.6)
833. 78945612pp (0.82, 7.7)
834. 271297Golf (0.82, 11.1)
835. 8892239llj (0.82, 13.1)
836. 46mUS29cLM (0.82, 14.0)
837. 00245678ab (0.82, 8.0)
838. 30271070AN (0.82, 13.3)
839. 112233GAVC (0.82, 11.5)
840. 7799420mcg (0.82, 12.2)
841. 1011-Salem (0.82, 11.1)
842. 24902815VC (0.82, 14.0)
843. 94415152rg (0.82, 12.5)
844. 050568ppDM (0.82, 14.0)
845. 79513258dv (0.82, 12.0)
846. 6830920eng (0.82, 12.3)
847. 6523567q58 (0.82, 14.0)
848. 06671021bm (0.82, 12.4)
849. 01274506jj (0.82, 12.0)
850. 77923901wm (0.82, 13.0)
851. 7552411jlm (0.82, 12.7)
852. 06280704ej (0.82, 12.1)
853. 250196STIL (0.82, 12.2)
854. 6529354slj (0.82, 13.2)
855. 9494949bow (0.82, 12.1)
856. 92709270ym (0.82, 11.5)
857. 012148Rigw (0.82, 14.0)
858. 260282Cowi (0.82, 13.6)
859. 85309791jp (0.82, 12.3)
860. 37kMC046M8 (0.82, 14.0)
861. 21F44Nf07M (0.82, 14.0)
862. 73371991av (0.82, 12.6)
863. 95279537vb (0.82, 13.1)
864. 86560323jw (0.82, 12.7)
865. 76232087lp (0.82, 12.5)
866. 96964200jv (0.82, 12.0)
867. 86235324hj (0.82, 13.0)
868. 28f9CNrAh0 (0.82, 14.0)
869. 270892LCCL (0.82, 13.1)
870. 69993255x8 (0.82, 14.0)
871. 112233QQqq (0.82, 8.5)
872. 003500751m (0.82, 12.6)
873. 60302041tT (0.82, 13.5)
874. 74761234hp (0.82, 11.8)
875. 65600696nN (0.82, 13.7)
876. 231259Riki (0.82, 11.8)
877. 2071979Mr. (0.82, 12.9)
878. 78982500ab (0.82, 11.0)
879. 3522926YMC (0.82, 13.8)
880. 01278899ab (0.82, 8.4)
881. 290892(Ii) (0.82, 13.3)
882. 10162ABFAB (0.82, 13.8)
883. 0684912jww (0.82, 13.6)
884. 9870450ham (0.82, 13.1)
885. 6942069alv (0.82, 12.0)
886. 04883110ab (0.82, 11.4)
887. 1qazXSWedc (0.82, 7.4)
888. 98806141rv (0.82, 13.2)
889. 17L03A87G. (0.82, 14.0)
890. 62462511mb (0.82, 11.8)
891. 09851218gv (0.82, 13.0)
892. 66906372em (0.82, 13.1)
893. 69712361tT (0.82, 13.5)
894. 86542121gj (0.82, 12.6)
895. 87940510SC (0.82, 13.4)
896. 99882020mm (0.82, 10.8)
897. 213112ANEL (0.81, 13.1)
898. 140697Vivi (0.81, 11.2)
899. 1fY5S7jso5 (0.81, 14.0)
900. 73612033jb (0.81, 12.7)
901. 02850900mm (0.81, 11.4)
902. 02440244dv (0.81, 10.6)
903. 06323492pp (0.81, 12.0)
904. 02241993Pw (0.81, 10.9)
905. 88599107bb (0.81, 12.1)
906. 8996252hjg (0.81, 13.3)
907. 54518129IC (0.81, 14.0)
908. 98319754sb (0.81, 12.8)
909. 140713Didi (0.81, 11.9)
910. 71977256mm (0.81, 12.4)
911. 321997@HOT (0.81, 13.2)
912. 95617694av (0.81, 13.1)
913. 05232004cm (0.81, 10.2)
914. 072722.mom (0.81, 12.8)
915. 62618269dv (0.81, 13.4)
916. 4122476JAM (0.81, 13.3)
917. 10G24E13LA (0.81, 14.0)
918. 01720714ab (0.81, 11.4)
919. 9530199alv (0.81, 13.4)
920. 142016King (0.81, 10.9)
921. 31249755Ak (0.81, 13.1)
922. 9624206mt* (0.81, 14.0)
923. 01840363dm (0.81, 12.9)
924. 250757ELAN (0.81, 12.9)
925. 99999999AF (0.81, 9.3)
926. 7779311gtb (0.81, 10.6)
927. 9099513keg (0.81, 13.8)
928. 08229633sp (0.81, 12.3)
929. 99829440mm (0.81, 11.9)
930. 6031412nqm (0.81, 13.9)
931. 2381977RRM (0.81, 12.9)
932. 114013Anum (0.81, 13.4)
933. 151515LARA (0.81, 10.5)
934. 08242009nb (0.81, 10.6)
935. 53203340RA (0.81, 13.4)
936. 99521046og (0.81, 12.9)
937. 591278LILI (0.81, 12.6)
938. 0857222waw (0.81, 12.8)
939. 999123Jeff (0.81, 11.0)
940. 07251997Dk (0.81, 10.5)
941. 91332569cp (0.81, 12.8)
942. 99252303zj (0.81, 12.5)
943. 130397Dani (0.81, 10.2)
944. 1009878ABC (0.81, 11.6)
945. 24hPT6bB2F (0.81, 14.0)
946. 245XC34h68 (0.81, 14.0)
947. 1R4mJW8w9J (0.81, 14.0)
948. 05261965Rv (0.81, 11.3)
949. 39A16A88BC (0.81, 14.0)
950. 8592536szw (0.81, 13.7)
951. 94813221dv (0.81, 13.1)
952. 6339223tom (0.81, 12.3)
953. 2251982LKL (0.81, 12.5)
954. 170509Yoni (0.81, 12.1)
955. 1qhYA9R5uF (0.81, 14.0)
956. 01520152rH (0.81, 11.4)
957. 02876182sp (0.81, 12.6)
958. 81258788dj (0.81, 11.7)
959. 0125678*.0 (0.81, 13.4)
960. 92769016am (0.81, 12.4)
961. 74655112zp (0.81, 13.1)
962. 6281627cmj (0.81, 12.8)
963. 150635N$$$ (0.81, 14.0)
964. 190214DADA (0.81, 12.7)
965. 1aqwZSXedc (0.81, 8.0)
966. 00962799bm (0.81, 12.3)
967. 141002DETA (0.81, 12.9)
968. 88224646sb (0.81, 10.7)
969. 60327916rm (0.81, 12.9)
970. 893124.com (0.81, 10.6)
971. 5014475TYT (0.81, 14.0)

972. 6760370++0 (0.81, 14.0)	982. 05300530jj (0.81, 9.3)	992. 81756129hb (0.81, 12.9)
973. 111213NIKA (0.81, 10.8)	983. 06701805Aw (0.81, 13.3)	993. 301327RAAJ (0.81, 14.0)
974. 52030KkK38 (0.81, 14.0)	984. 8126800zzj (0.81, 11.9)	994. 01421023Sk (0.81, 13.1)
975. 5723004alp (0.81, 12.1)	985. 84551320dj (0.81, 11.8)	995. 81417602bg (0.81, 12.8)
976. 7654321imb (0.81, 9.4)	986. 0198354esb (0.81, 13.1)	996. 2620527Jc* (0.81, 14.0)
977. 78255230am (0.81, 12.2)	987. 62351298dm (0.81, 12.6)	997. 05420542ap (0.81, 9.5)
978. 2030250AAA (0.81, 11.4)	988. 07231979Ab (0.81, 9.9)	998. 07970797mm (0.81, 9.3)
979. 75412648cp (0.81, 12.6)	989. 5202603ABC (0.81, 11.8)	999. 00818148kb (0.81, 13.4)
980. 77441100bg (0.81, 9.8)	990. 62552711lp (0.81, 12.2)	
981. 83917733qw (0.81, 11.9)	991. 5973271a15 (0.81, 13.3)	

Cluster 7

Prototype: sananedr1

Hard-assigned passwords: 994983 (3.44% of total)
Unique hard-assigned passwords: 517755 (47.96% of cluster total)

Cluster-assignment scores:
- Min: 0.063
- Max: 0.970
- Mean: 0.306
- SD: 0.172

Strength bins:
- Very weak: 50639 (5.09%)
- Weak: 344877 (34.66%)
- Fair: 313352 (31.49%)
- Good: 267585 (26.89%)
- Strong: 18530 (1.86%)

Password lengths:
- Length 8: 403 (0.04%)
- Length 9: 620868 (62.40%)
- Length 10: 373697 (37.56%)
- Length 11: 15 (0.00%)

Character classes:
- 4 classes: 11929 (1.20%)
- 3 classes: 145090 (14.58%)
  - lower/upper/symbol: 3361 (2.32%)
  - lower/upper/number: 121385 (83.66%)
  - lower/symbol/number: 20344 (14.02%)
  - upper/symbol/number: 0 (0.00%)
- 2 classes: 705437 (70.90%)
  - lower/upper: 5545 (0.79%)
  - lower/number: 685227 (97.14%)
  - lower/symbol: 14664 (2.08%)
  - upper/number: 0 (0.00%)
  - upper/symbol: 0 (0.00%)
  - number/symbol: 1 (0.00%)
- 1 class: 132527 (13.32%)
  - lower: 132527 (100.00%)
  - upper: 0 (0.00%)
  - symbol: 0 (0.00%)
  - number: 0 (0.00%)

Most frequent char-class structures:
- LLLLLLLLD: 460261 (46.3%)
- LLLLLLLLD: 223764 (22.5%)
- LLLLLLLLL: 82635 (8.3%)
- ULLLLLLLD: 69189 (7.0%)
- LLLLLLLL: 49880 (5.0%)
- ULLLLLLLD: 36306 (3.6%)
- LLLLLLLSD: 9077 (0.9%)
- LLLLLLLS: 6913 (0.7%)
- LLLLLLLSD: 5771 (0.6%)
- ULLLLLLSD: 4958 (0.5%)

1,000 nearest passwords

0. cubanezu1	(0.97, 9.5)	53. alpinekc1	(0.94, 8.6)
1. Hackneyn1	(0.97, 8.9)	54. idiotequ1	(0.94, 8.8)
2. teamaedn1	(0.97, 10.5)	55. fedufedu1	(0.94, 7.9)
3. Celinedu1	(0.96, 8.5)	56. Jocamegu1	(0.94, 12.0)
4. rstunedn1	(0.96, 13.1)	57. coastehc1	(0.94, 11.5)
5. Whitneyn1	(0.96, 8.1)	58. diddledu1	(0.94, 10.4)
6. tyronebu1	(0.96, 9.1)	59. ailopeyu1	(0.94, 10.3)
7. Tyronebu1	(0.96, 9.7)	60. mimiseku1	(0.94, 10.1)
8. mapireku1	(0.96, 10.4)	61. watdaepf1	(0.94, 12.0)
9. quequequ1	(0.96, 6.7)	62. mohadebn1	(0.94, 11.4)
10. cutoneku1	(0.96, 11.7)	63. googledc1	(0.94, 8.0)
11. delaneyc1	(0.96, 7.3)	64. redcredc1	(0.94, 9.4)
12. ihackedu1	(0.96, 6.7)	65. ckmatebn1	(0.94, 12.1)
13. hadileyn1	(0.96, 10.7)	66. peoplepc1	(0.94, 5.5)
14. trainedu1	(0.96, 8.0)	67. oraclejc1	(0.94, 8.8)
15. pauheu1	(0.95, 14.0)	68. tobateku1	(0.94, 9.6)
16. desalegn1	(0.95, 8.4)	69. tonydehn1	(0.94, 10.4)
17. omoarebu1	(0.95, 7.7)	70. noensehn1	(0.94, 11.3)
18. hzctnepc1	(0.95, 13.2)	71. kukareku1	(0.94, 6.8)
19. ladupedu1	(0.95, 10.4)	72. brookeyc1	(0.94, 8.4)
20. louchejc1	(0.95, 11.7)	73. Kukareku1	(0.94, 7.5)
21. Helenebu1	(0.95, 9.3)	74. pickleqn1	(0.94, 10.4)
22. josenegu1	(0.95, 10.2)	75. qhfmaekf1	(0.94, 13.0)
23. littlegu1	(0.95, 7.8)	76. britneya1	(0.94, 7.1)
24. rachmeyn1	(0.95, 11.0)	77. Innatedc1	(0.94, 12.0)
25. heyuheyu1	(0.95, 7.1)	78. vfwbgehf1	(0.94, 12.9)
26. kanapepu1	(0.95, 10.2)	79. Akindeju1	(0.94, 7.9)
27. umichedu1	(0.95, 10.3)	80. sanhueza1	(0.94, 8.2)
28. orvahedc1	(0.95, 12.9)	81. qrnpmeku1	(0.94, 12.8)
29. unnamedn1	(0.95, 8.7)	82. tierneyf1	(0.94, 8.7)
30. Adsfqeyc1	(0.95, 13.8)	83. mamayeya1	(0.94, 9.6)
31. bvfpweju1	(0.95, 13.6)	84. Urmaseku1	(0.94, 11.9)
32. NicoleMc1	(0.95, 9.3)	85. Zangredu1	(0.94, 11.9)
33. ryanfehn1	(0.95, 10.2)	86. blessedn1	(0.94, 7.0)
34. lakesebu1	(0.95, 10.5)	87. jeromedc1	(0.94, 8.3)
35. rpkuaebf1	(0.95, 12.9)	88. bmonkeyc1	(0.94, 10.5)
36. Diakcehc1	(0.95, 13.6)	89. noodlekc1	(0.93, 9.5)
37. pekuleku1	(0.95, 9.7)	90. zulubebu1	(0.93, 10.3)
38. reynreyn1	(0.94, 7.6)	91. jeromehu1	(0.93, 9.0)
39. sazukeku1	(0.94, 9.7)	92. veduvedu1	(0.93, 7.8)
40. louisepc1	(0.94, 8.5)	93. simoreda1	(0.93, 8.9)
41. omoijebu1	(0.94, 6.7)	94. cipaneza1	(0.93, 9.4)
42. Googledu1	(0.94, 8.6)	95. upslpedu1	(0.93, 12.0)
43. wdzineku1	(0.94, 12.3)	96. CodyKeya1	(0.93, 10.2)
44. musicedu1	(0.94, 7.9)	97. dreizehn1	(0.93, 10.2)
45. doodlebn1	(0.94, 9.5)	98. hcanrehc1	(0.93, 11.4)
46. etamfehc1	(0.94, 12.2)	99. arboleda1	(0.93, 5.9)
47. bojaxezu1	(0.94, 11.9)	100. taracepu1	(0.93, 10.7)
48. Gretrepu1	(0.94, 12.7)	101. ucenmedu1	(0.93, 11.9)
49. anuaneya1	(0.94, 9.8)	102. lahmtedn1	(0.93, 12.8)
50. anjaneya1	(0.94, 5.8)	103. Poboleda1	(0.93, 10.4)
51. Anjaneya1	(0.94, 5.9)	104. strknepf1	(0.93, 12.4)
52. mydaneya1	(0.94, 11.5)	105. illsueya1	(0.93, 12.6)
106. godfreyc1	(0.93, 8.5)		
107. ywuacebf1	(0.93, 13.0)		
108. chuckeya1	(0.93, 8.6)		
109. iyaijebu1	(0.93, 9.7)		
110. whoareya1	(0.93, 7.1)		
111. shealeya1	(0.93, 8.9)		
112. sancheza1	(0.93, 6.7)		
113. vasqueza1	(0.93, 6.8)		
114. i●love●u1	(0.93, 6.0)		
115. paramedc1	(0.93, 8.0)		
116. iubireaa1	(0.93, 8.6)		
117. Qawsxedc1	(0.93, 7.4)		
118. qawsxedc1	(0.93, 6.2)		
119. radioedu1	(0.93, 8.4)		
120. pfbtxequ1	(0.93, 13.1)		
121. aliireza1	(0.93, 9.5)		
122. lukasekn1	(0.93, 8.3)		
123. dkxjlepu1	(0.93, 13.2)		
124. nahvaeaa1	(0.93, 11.3)		
125. bradleyc1	(0.93, 6.5)		
126. tyroneda1	(0.93, 7.4)		
127. fakorewa1	(0.93, 9.6)		
128. Metareza1	(0.93, 10.6)		
129. ashareya1	(0.93, 8.8)		
130. onamaeha1	(0.93, 10.4)		
131. maybheda1	(0.93, 10.3)		
132. Mosqueda1	(0.93, 7.1)		
133. manuneha1	(0.93, 8.4)		
134. xccihehc1	(0.93, 13.9)		
135. natureza1	(0.93, 6.6)		
136. fesqueda1	(0.93, 9.3)		
137. pesqueda1	(0.93, 7.9)		
138. rezareza1	(0.93, 5.6)		
139. mylovekc1	(0.93, 7.9)		
140. bulavezu1	(0.93, 9.8)		
141. subhnewa1	(0.93, 12.8)		
142. asiqueda1	(0.93, 10.0)		
143. naciremа1	(0.93, 7.1)		
144. Maitreya1	(0.93, 6.7)		
145. thealexa1	(0.93, 8.0)		
146. Advicedu1	(0.93, 10.4)		
147. kalarepa1	(0.93, 5.9)		
148. milarepa1	(0.93, 6.5)		
149. Milarepa1	(0.93, 7.4)		
150. maitreya1	(0.93, 5.9)		
151. rafireva1	(0.93, 9.6)		
152. heyaheya1	(0.93, 7.1)		
153. tonibegu1	(0.93, 11.2)		
154. BenAlexa1	(0.93, 9.3)		
155. AshAlexa1	(0.93, 10.9)		
156. titcheya1	(0.93, 10.6)		
157. evakneva1	(0.93, 11.0)		
158. ortareda1	(0.93, 10.5)		

159. petcheya1 (0.93, 10.1)
160. cataleya1 (0.93, 6.1)
161. iwudneva1 (0.93, 11.6)
162. Sachaeva1 (0.93, 8.9)
163. lindseyn1 (0.93, 7.4)
164. antareja1 (0.93, 8.0)
165. ryosaeba1 (0.93, 11.1)
166. azuqueca1 (0.93, 9.8)
167. milaneza1 (0.93, 6.9)
168. panqueca1 (0.93, 6.6)
169. sadageba1 (0.93, 10.4)
170. Jeannepa1 (0.93, 9.0)
171. babageba1 (0.93, 8.8)
172. sutileza1 (0.93, 10.3)
173. redareda1 (0.93, 5.4)
174. babyheba1 (0.93, 7.9)
175. moraleda1 (0.93, 8.2)
176. mamanema1 (0.93, 8.0)
177. onlinepa1 (0.93, 7.3)
178. Pesonepa1 (0.93, 10.4)
179. SfdkJeza1 (0.93, 14.0)
180. qazwsedc1 (0.93, 6.5)
181. nwanneka1 (0.93, 6.2)
182. nicoleca1 (0.93, 7.3)
183. Akpaneka1 (0.93, 10.9)
184. lamuneka1 (0.93, 8.1)
185. Nicoleca1 (0.93, 8.3)
186. buwaneka1 (0.93, 8.9)
187. Med+rexa1 (0.93, 13.8)
188. xinoreca1 (0.93, 10.9)
189. nofacegf1 (0.92, 11.3)
190. kutineha1 (0.92, 10.5)
191. rgaedegc1 (0.92, 13.1)
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193. Oceguеda1 (0.92, 12.0)
194. higareda1 (0.92, 6.9)
195. regarega1 (0.92, 7.3)
196. icravejc1 (0.92, 12.1)
197. slaineza1 (0.92, 9.9)
198. hirameku1 (0.92, 8.6)
199. Higareda1 (0.92, 7.6)
200. patarepa1 (0.92, 7.3)
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203. simbaeva1 (0.92, 8.0)
204. linkmeya1 (0.92, 8.0)
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207. royalexa1 (0.92, 9.0)
208. mamorena1 (0.92, 7.3)
209. tdsbjeya1 (0.92, 13.2)
210. Lamorena1 (0.92, 6.3)
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213. maewaeha1 (0.92, 12.6)
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215. Elvilena1 (0.92, 10.5)
216. dubstepv1 (0.92, 8.6)
217. codykeya1 (0.92, 9.0)
218. codecedc1 (0.92, 10.3)
219. kjpxsehc1 (0.92, 13.1)
220. Savageha1 (0.92, 9.4)
221. Myeureka1 (0.92, 10.2)
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224. jeboteja1 (0.92, 8.0)
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226. nancyeva1 (0.92, 6.9)
227. NacBreda1 (0.92, 10.4)
228. mundyema1 (0.92, 10.7)
229. widenegv1 (0.92, 12.3)
230. jihaneka1 (0.92, 8.3)
231. bontreva1 (0.92, 11.6)
232. lucilena1 (0.92, 7.4)
233. Angilena1 (0.92, 9.3)
234. Celineca1 (0.92, 8.6)
235. polinema1 (0.92, 5.3)
236. ladupeda1 (0.92, 10.5)
237. abrateja1 (0.92, 10.0)
238. wincheja1 (0.92, 10.3)
239. koknaeva1 (0.92, 10.6)
240. muhabeda1 (0.92, 10.4)
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248. yaequepa1 (0.92, 11.4)
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256. olpineda1 (0.92, 7.5)
257. UhjfreEc1 (0.92, 14.0)
258. mamanena1 (0.92, 6.3)
259. miafreja1 (0.92, 9.2)
260. raviteja1 (0.92, 5.8)
261. lalanega1 (0.92, 9.8)
262. minfreja1 (0.92, 9.8)
263. teyateya1 (0.92, 8.5)
264. kqktueza1 (0.92, 13.3)
265. turuleca1 (0.92, 9.4)
266. Joenaeha1 (0.92, 11.6)
267. odraleva1 (0.92, 11.7)
268. St.Elena1 (0.92, 10.4)
269. bradleya1 (0.92, 6.9)
270. jayaxeda1 (0.92, 11.5)
271. delarena1 (0.92, 7.5)
272. lamoneda1 (0.92, 7.5)
273. jumaxeda1 (0.92, 12.1)
274. tavareza1 (0.92, 7.4)
275. alkaheda1 (0.92, 9.4)
276. Majabeba1 (0.92, 8.1)
277. suraneha1 (0.92, 10.1)
278. majabeba1 (0.92, 7.1)
279. bankmega1 (0.92, 9.6)
280. laparеja1 (0.92, 8.6)
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282. lunadeja1 (0.92, 7.7)
283. matareka1 (0.92, 9.0)
284. wanareja1 (0.92, 9.2)
285. camahema1 (0.92, 8.6)
286. kayagefa1 (0.92, 11.5)
287. azfareza1 (0.92, 10.8)
288. lemalema1 (0.92, 7.4)
289. onesheba1 (0.92, 7.5)
290. dajadeja1 (0.92, 8.6)
291. zigfreda1 (0.92, 10.7)
292. kjjadeja1 (0.92, 10.8)
293. littlema1 (0.92, 6.6)
294. qcojueka1 (0.92, 13.1)
295. valsheda1 (0.92, 8.9)
296. iniakeya1 (0.92, 9.9)
297. osbureka1 (0.92, 11.3)
298. masquefa1 (0.92, 9.3)
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301. Toenneaa1 (0.92, 12.1)
302. Odobleja1 (0.92, 11.3)
303. tedvaena1 (0.92, 11.0)
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305. dujajeha1 (0.92, 11.6)
306. desirena1 (0.92, 7.1)
307. Forsheda1 (0.92, 10.9)
308. Evealena1 (0.92, 10.4)
309. eldaleka1 (0.92, 10.0)
310. kubakepa1 (0.92, 11.3)
311. alexlega1 (0.92, 9.0)
312. jukabeqa1 (0.92, 11.1)
313. dodoseba1 (0.92, 9.4)
314. jinotega1 (0.92, 7.9)
315. Drogheda1 (0.92, 6.2)
316. lamaleza1 (0.92, 8.5)
317. complexa1 (0.92, 7.4)
318. tejateja1 (0.92, 6.7)
319. frocheda1 (0.92, 10.5)
320. vasileva1 (0.92, 7.5)
321. Littleka1 (0.92, 8.6)
322. Mademeku1 (0.92, 11.8)
323. scumpeca1 (0.92, 10.5)
324. hejaheja1 (0.92, 6.9)
325. tristeza1 (0.92, 6.6)
326. drogheda1 (0.92, 5.6)
327. akwameba1 (0.92, 10.5)
328. tiabuena1 (0.92, 7.5)
329. escajeda1 (0.92, 8.7)
330. mojateja1 (0.92, 7.6)
331. renarena1 (0.92, 6.4)
332. Cocaleca1 (0.92, 8.8)
333. fpsarena1 (0.92, 9.7)
334. mayaleja1 (0.92, 8.5)
335. passlema1 (0.92, 8.8)
336. ginanena1 (0.92, 9.6)
337. pasarena1 (0.92, 7.5)
338. gegagega1 (0.92, 7.0)
339. Seikleja1 (0.92, 13.4)
340. hliymegf1 (0.92, 13.2)
341. tetraeda1 (0.92, 9.2)
342. alfaMega1 (0.91, 9.8)
343. fepixeku1 (0.91, 12.3)
344. kostrena1 (0.91, 8.6)
345. oursheba1 (0.91, 10.5)
346. trizteza1 (0.91, 10.8)
347. sexynena1 (0.91, 6.7)
348. Khesjeda1 (0.91, 12.0)
349. mrssheba1 (0.91, 8.4)
350. nyambeka1 (0.91, 8.1)
351. borinena1 (0.91, 8.8)
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355. ygtbcekf1 (0.91, 12.7)
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357. moraaeva1 (0.91, 10.2)
358. SekaSeka1 (0.91, 9.1)
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362. monoseba1 (0.91, 9.0)
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364. sachdeva1 (0.91, 6.1)
365. fozzbeba1 (0.91, 10.9)
366. lysalena1 (0.91, 9.4)
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368. Lenalena1 (0.91, 6.9)
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371. albulena1 (0.91, 6.6)
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373. cezaceza1 (0.91, 6.5)
374. iwoogema1 (0.91, 12.3)
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376. doubleda1 (0.91, 7.8)
377. hehaheha1 (0.91, 6.5)
378. catalena1 (0.91, 7.0)
379. stokdejv1 (0.91, 12.3)
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381. tandmeka1 (0.91, 10.7)
382. Mamagena1 (0.91, 8.5)
383. newdrema1 (0.91, 9.9)
384. purpleha1 (0.91, 7.9)
385. weivreca1 (0.91, 11.1)
386. sexydeda1 (0.91, 8.4)
387. sendreka1 (0.91, 9.4)
388. armoredm1 (0.91, 8.4)
389. Kevineha1 (0.91, 9.0)
390. safyrepa1 (0.91, 11.3)
391. EitileDa1 (0.91, 13.5)
392. lisaseba1 (0.91, 8.8)
393. mahadewa1 (0.91, 5.8)
394. capttepa1 (0.91, 12.0)
395. Poohreva1 (0.91, 11.4)
396. nasslena1 (0.91, 8.8)
397. Sweeneka1 (0.91, 11.7)
398. thandeka1 (0.91, 6.2)
399. Hugfreya1 (0.91, 11.6)
400. SebyBeca1 (0.91, 12.2)
401. anomteja1 (0.91, 10.6)
402. rhasheda1 (0.91, 10.7)
403. tekoteka1 (0.91, 8.7)
404. doubleaa1 (0.91, 7.5)
405. adeshewa1 (0.91, 6.5)
406. HolaBeba1 (0.91, 8.8)
407. jakabeka1 (0.91, 6.7)
408. makmreza1 (0.91, 11.7)
409. mamaweba1 (0.91, 9.5)
410. Thoopeba1 (0.91, 13.5)
411. mahadeva1 (0.91, 5.7)
412. sexylena1 (0.91, 6.2)
413. manurewa1 (0.91, 5.9)
414. tomnlena1 (0.91, 10.8)
415. gemagema1 (0.91, 6.7)
416. Andafema1 (0.91, 11.2)
417. tehenega1 (0.91, 10.3)
418. rriquena1 (0.91, 11.8)
419. karateca1 (0.91, 6.7)
420. carateca1 (0.91, 6.9)
421. Bjorneva1 (0.91, 9.6)
422. charneca1 (0.91, 8.1)
423. Karateca1 (0.91, 7.3)
424. ortopeda1 (0.91, 8.7)
425. Kambreya1 (0.91, 8.9)
426. nedabeda1 (0.91, 9.1)
427. Sebaseba1 (0.91, 6.8)
428. lxaisexa1 (0.91, 13.5)

429. medabeda1 (0.91, 6.4)
430. rawrheya1 (0.91, 10.7)
431. sebaseba1 (0.91, 5.9)
432. bobabeba1 (0.91, 8.1)
433. marblena1 (0.91, 8.2)
434. sedaseda1 (0.91, 5.6)
435. gatubeda1 (0.91, 9.0)
436. mariceda1 (0.91, 7.0)
437. franseba1 (0.91, 9.2)
438. lamarema1 (0.91, 8.5)
439. BabyXena1 (0.91, 8.9)
440. dedadeda1 (0.91, 6.6)
441. nedmnedm1 (0.91, 8.2)
442. softkeya1 (0.91, 9.4)
443. joseseba1 (0.91, 7.5)
444. Jejajeja1 (0.91, 8.3)
445. karateka1 (0.91, 5.5)
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911. Kristean1 (0.88, 7.7)
912. qeyofena1 (0.88, 12.8)
913. dalunean1 (0.88, 10.6)
914. ozoemena1 (0.88, 5.9)
915. wewewepa1 (0.88, 8.7)
916. Meeuwena1 (0.88, 9.4)
917. savecena1 (0.88, 8.0)
918. gauvreau1 (0.88, 7.6)
919. Mopopena1 (0.88, 11.1)
920. adamdean1 (0.88, 6.6)
921. ladyjean1 (0.88, 6.9)
922. lucyjean1 (0.88, 6.7)
923. macyjean1 (0.88, 7.5)
924. rubyjean1 (0.88, 6.0)
925. babyjean1 (0.88, 6.5)
926. simoneau1 (0.88, 6.8)
927. treysean1 (0.88, 7.2)
928. repelega1 (0.88, 9.8)
929. Treysean1 (0.88, 8.0)
930. Dimodena1 (0.88, 11.1)
931. abbyjean1 (0.88, 6.5)
932. snapbean1 (0.88, 7.9)
933. fernleaf1 (0.88, 7.8)
934. RubyJean1 (0.88, 7.4)
935. weergehm1 (0.88, 11.5)
936. gregsean1 (0.88, 7.6)
937. elmodena1 (0.88, 7.8)
938. Mazizena1 (0.88, 10.0)
939. fenomena1 (0.88, 6.4)
940. putrieku1 (0.88, 10.0)
941. deansean1 (0.88, 6.9)
942. seansean1 (0.88, 5.1)
943. annajean1 (0.88, 6.6)
944. iliadebm1 (0.88, 10.8)
945. Danajean1 (0.88, 7.4)
946. danajean1 (0.88, 6.8)
947. mungbean1 (0.88, 6.7)
948. Jazzmean1 (0.88, 9.1)
949. bensiena1 (0.88, 8.7)
950. genowefa1 (0.88, 7.2)
951. andybean1 (0.88, 6.7)
952. chapleau1 (0.88, 7.2)
953. dawnjean1 (0.88, 7.8)
954. Mamajean1 (0.88, 6.8)
955. parksean1 (0.88, 8.3)
956. mamajean1 (0.88, 6.0)
957. Emmajean1 (0.88, 5.6)
958. emmajean1 (0.88, 5.0)
959. blog.ean1 (0.88, 11.2)
960. ciansean1 (0.88, 8.2)
961. Babybean1 (0.88, 7.0)
962. lucybean1 (0.88, 6.9)
963. mgbemena1 (0.88, 10.6)
964. Emmybean1 (0.88, 8.0)
965. oberzena1 (0.88, 10.5)
966. babydean1 (0.88, 6.5)
967. beanleaf1 (0.88, 7.6)
968. sexysean1 (0.88, 5.9)

969. shaylean1 (0.88, 7.0)
970. livedena1 (0.88, 9.8)
971. lottieda1 (0.88, 8.7)
972. bboyleaf1 (0.88, 8.8)
973. Lilexena1 (0.88, 9.7)
974. rezimena1 (0.88, 8.1)
975. onlymejm1 (0.88, 9.2)
976. ryandean1 (0.88, 6.3)
977. lilexena1 (0.88, 9.2)
978. coolsean1 (0.88, 7.4)
979. bugnbean1 (0.88, 8.3)
980. Lynnbean1 (0.88, 7.9)
981. shervena1 (0.88, 8.1)
982. jothsean1 (0.88, 9.2)
983. annadean1 (0.88, 7.3)
984. Ryandean1 (0.88, 6.8)
985. aspnleaf1 (0.88, 11.2)
986. Jinusean1 (0.88, 10.2)
987. yuyubean1 (0.88, 10.0)
988. Andereya1 (0.88, 9.6)
989. solewefa1 (0.88, 12.5)
990. jujubean1 (0.88, 5.3)
991. remizena1 (0.88, 9.0)
992. tayabean1 (0.88, 9.3)
993. jadabean1 (0.88, 6.9)
994. Janevena1 (0.88, 10.0)
995. emmabean1 (0.88, 6.4)
996. javabean1 (0.88, 5.7)
997. PoknBean1 (0.88, 11.7)
998. Emmadean1 (0.88, 7.2)
999. Goldleaf1 (0.88, 6.1)

Cluster 8

```
Prototype: saaaaroh63

Hard-assigned passwords: 400130 (1.38% of total)
Unique hard-assigned passwords: 284832 (28.82% of cluster total)

Cluster-assignment scores:
        Min: 0.060
        Max: 0.853
        Mean: 0.418
        SD: 0.208

Strength bins:
        Very weak: 3486 (0.87%)
        Weak: 76016 (19.00%)
        Fair: 135121 (33.77%)
        Good: 165042 (41.25%)
        Strong: 20465 (5.11%)

Password lengths:
        Length 9: 14409 (3.60%)
        Length 10: 368649 (92.13%)
        Length 11: 17072 (4.27%)

Character classes:
        4 classes: 7181 (1.79%)
        3 classes: 56157 (14.03%)
                lower/upper/symbol: 516 (0.92%)
                lower/upper/number: 45171 (80.44%)
                lower/symbol/number: 10470 (18.64%)
                upper/symbol/number: 0 (0.00%)
        2 classes: 336791 (84.17%)
                lower/upper: 0 (0.00%)
                lower/number: 334867 (99.43%)
                lower/symbol: 1924 (0.57%)
                upper/number: 0 (0.00%)
                upper/symbol: 0 (0.00%)
                number/symbol: 0 (0.00%)
        1 class: 1 (0.00%)
                lower: 0 (0.00%)
                upper: 0 (0.00%)
                symbol: 1 (100.00%)
                number: 0 (0.00%)

Most frequent char-class structures:
        LLLLLLLLDD: 275543 (68.9%)
        LLLLLLLLD: 31185 (7.8%)
        ULLLLLLLDD: 30972 (7.7%)
        LLLLLLLDD: 12784 (3.2%)
        LLLLLLLDDD: 11804 (3.0%)
        LLLLLLSDD: 4198 (1.0%)
        ULLLLLLLD: 3941 (1.0%)
        ULLLLLLDS: 2363 (0.6%)
        ULLLLLSDD: 2179 (0.5%)
        LLLLLLLLDD: 2146 (0.5%)
```

1,000 nearest passwords

```
  0. marooned63   (0.85,  7.8)
  1. cultdyed63   (0.85, 10.4)
  2. martinez63   (0.85,  5.6)
  3. clubcued63   (0.85,  9.2)
  4. SanzaWeb63   (0.85, 13.4)
  5. uynbdqez63   (0.85, 14.0)
  6. jwdzkgeb63   (0.85, 14.0)
  7. nosyhued63   (0.85,  9.7)
  8. shunwhey63   (0.85,  9.1)
  9. banghued63   (0.85, 10.2)
 10. muhammed63   (0.85,  6.5)
 11. covecued63   (0.85,  9.5)
 12. advanced63   (0.85,  7.4)
 13. courtney63   (0.85,  5.9)
 14. sgaqayeq63   (0.85, 14.0)
 15. luckyme/63   (0.85, 11.1)
 16. yrbstnen63   (0.85, 14.0)
 17. crapdyed63   (0.85,  9.5)
 18. spanaxed63   (0.85,  8.9)
 19. paulinen63   (0.85,  9.3)
 20. numbapex63   (0.85, 12.1)
 21. smackdef63   (0.85, 11.5)
 22. lustshed63   (0.85,  9.7)
 23. shawnfeb63   (0.85,  9.8)
 24. nestwhew63   (0.85, 10.0)
 25. ductthey63   (0.85,  9.7)
 26. qlrnwyeg63   (0.85, 14.0)
 27. lpbuzwey63   (0.85, 13.4)
 28. lacethem63   (0.85,  9.1)
 29. nczfgaem63   (0.85, 13.5)
 30. tummypen63   (0.85,  7.0)
 31. njzlwuea63   (0.85, 13.8)
 32. xuhdfnec63   (0.85, 13.8)
 33. panddweb63   (0.85, 13.2)
 34. baldsued63   (0.85,  9.8)
 35. Mohammed63   (0.85,  7.0)
 36. nameiced63   (0.85, 10.7)
 37. antithen63   (0.85, 11.0)
 38. cakerued63   (0.85,  9.5)
 39. codeaged63   (0.85,  9.5)
 40. vvfzNxez63   (0.85, 14.0)
 41. muffamen63   (0.85, 10.4)
 42. dadochef63   (0.85, 10.7)
 43. fromaged63   (0.85,  8.9)
 44. getmoney63   (0.85,  5.8)
 45. mashwhen63   (0.85, 10.7)
 46. bardaged63   (0.85,  9.9)
 47. shoechef63   (0.85, 10.0)
 48. peachbed63   (0.85,  7.1)
 49. gonerued63   (0.85,  9.2)
 50. lameskew63   (0.85, 10.3)
 51. beerthey63   (0.85, 11.2)
 52. coalthem63   (0.85, 10.8)
 53. wishrued63   (0.85,  9.1)
 54. nagicxez63   (0.85, 13.8)
 55. janechen63   (0.85, 10.8)
 56. roilsped63   (0.85,  9.1)
 57. acmeeyed63   (0.85, 10.7)
 58. transgen63   (0.85,  9.6)
 59. rillwhew63   (0.85, 10.4)
 60. likespew63   (0.85,  9.4)
 61. koolshen63   (0.85,  9.9)
 62. opalobey63   (0.85, 11.4)
 63. denyabed63   (0.85, 10.7)
 64. pupasped63   (0.85,  9.4)
 65. studaxed63   (0.85, 10.4)
 66. lifewhen63   (0.85,  8.9)
 67. tykeaced63   (0.85, 10.3)
 68. goldchew63   (0.85, 10.2)
 69. pramthey63   (0.85, 10.0)
 70. acmeidea63   (0.85, 11.3)
 71. meteobey63   (0.85, 10.4)
 72. lostskew63   (0.85, 10.3)
 73. bodyeyed63   (0.85, 10.4)
 74. sweetpea63   (0.85,  5.7)
 75. tarpthey63   (0.85,  9.4)
 76. agblcmez63   (0.85, 13.1)
 77. pixysped63   (0.85, 10.4)
 78. doteaced63   (0.85,  8.4)
 79. Unbroken63   (0.85,  8.3)
 80. mareopen63   (0.85, 11.1)
 81. highsped63   (0.85,  9.0)
 82. woveowed63   (0.85,  9.9)
 83. turnaped63   (0.85,  9.1)
 84. tatuaje@63   (0.85, 11.2)
 85. wiseabed63   (0.85, 10.1)
 86. trmlzkej63   (0.85, 13.9)
 87. latahzen63   (0.85, 10.5)
 88. shzzsfex63   (0.85, 14.0)
 89. icedabed63   (0.85,  9.7)
 90. toutamen63   (0.85, 10.3)
 91. lankspew63   (0.85,  9.6)
 92. Imagine>33   (0.85,  9.5)
 93. violidea63   (0.85, 11.4)
 94. lostoven63   (0.85,  8.7)
 95. MikeRhea63   (0.85, 11.5)
 96. pintoven63   (0.85,  8.5)
 97. kfirlheq63   (0.85, 13.7)
 98. Alkounek33   (0.85, 13.5)
 99. winnipeg63   (0.84,  7.3)
100. lashawed63   (0.84, 10.2)
101. swumibex63   (0.84, 10.8)
102. lindiped63   (0.84, 10.7)
103. chitrhea63   (0.84, 10.8)
104. betaawed63   (0.84,  9.7)
105. idlerhea63   (0.84, 10.9)
106. aksarben63   (0.84,  8.7)
107. steelpen63   (0.84,  6.1)
108. pillrhea63   (0.84,  9.9)
109. uhudekeg63   (0.84, 13.6)
110. moreamen63   (0.84,  9.9)
111. cipithek33   (0.84, 12.7)
112. pjharvey63   (0.84, 10.2)
113. hypoexec63   (0.84,  8.9)
114. bonyeked63   (0.84, 10.6)
115. samoaned33   (0.84, 10.3)
116. rolighed33   (0.84, 11.3)
117. rearrhea63   (0.84,  9.4)
118. zazzopen63   (0.84, 11.6)
119. tummybed33   (0.84,  6.7)
120. StoRage-33   (0.84, 12.8)
121. corkcued33   (0.84,  9.6)
122. puckexec63   (0.84, 10.1)
123. gaffaped33   (0.84, 10.3)
124. ikbengek33   (0.84,  8.2)
125. moandyed33   (0.84,  8.9)
126. palmeked63   (0.84, 11.8)
127. pramired63   (0.84, 12.4)
128. imatrueG33   (0.84, 12.8)
129. haloexec63   (0.84,  9.7)
130. savanmed33   (0.84, 12.7)
131. doffopen63   (0.84, 10.0)
132. stadsgek33   (0.84, 12.9)
133. ltrduvem63   (0.84, 13.5)
134. maquened33   (0.84, 11.3)
135. Cordobez63   (0.84, 10.7)
136. roxanne.33   (0.84,  8.9)
137. slitexec63   (0.84, 10.2)
138. willexec63   (0.84,  9.5)
139. pitaidea63   (0.84, 11.3)
140. varieTek33   (0.84, 13.8)
141. bethoben63   (0.84,  9.3)
142. dingoxen63   (0.84,  9.8)
143. iglinked33   (0.84, 10.0)
144. tramsued33   (0.84,  9.4)
145. typedyed33   (0.84,  9.1)
146. martinez33   (0.84,  5.0)
147. bragowed63   (0.84, 10.5)
148. lazyawed33   (0.84, 10.4)
149. locoaged33   (0.84, 10.3)
150. luvyame●33   (0.84, 12.4)
151. JayWade.33   (0.84, 12.8)
152. hulaoxen63   (0.84, 11.6)
153. hushoven63   (0.84, 10.0)
154. mohammed33   (0.84,  5.9)
155. sladoled63   (0.84,  7.0)
156. bang●me●33   (0.84, 13.0)
157. dodoiced33   (0.84, 11.7)
158. iambored63   (0.84,  7.6)
159. lornaged33   (0.84,  9.8)
160. tiadorey63   (0.84, 12.3)
161. unzipped33   (0.84,  9.4)
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162. Abilene#33 (0.84, 9.6)
163. isaahmed33 (0.84, 10.9)
164. beenomen63 (0.84, 9.4)
165. cruxeven63 (0.84, 10.8)
166. balmaged33 (0.84, 9.8)
167. nucicfed33 (0.84, 13.6)
168. doordyed33 (0.84, 9.3)
169. soldowed63 (0.84, 10.9)
170. careiced33 (0.84, 10.3)
171. Chifire#63 (0.84, 13.3)
172. dsanchez33 (0.84, 7.9)
173. konfyzed33 (0.84, 12.5)
174. hawgeye_33 (0.84, 12.2)
175. hivearea63 (0.84, 9.5)
176. acreage#33 (0.84, 11.4)
177. tarqtrek63 (0.84, 12.7)
178. Monique@33 (0.84, 8.1)
179. propsled63 (0.84, 8.7)
180. konfuzed33 (0.84, 8.6)
181. rodrigez33 (0.84, 8.2)
182. ChrisWeb33 (0.84, 10.1)
183. H@wkeye_33 (0.84, 10.9)
184. reelarea63 (0.84, 10.5)
185. justswed33 (0.84, 11.6)
186. leadaxed33 (0.84, 9.8)
187. saphire@63 (0.84, 9.8)
188. godspwed33 (0.84, 11.4)
189. ariaarea63 (0.84, 9.9)
190. jdmbluez33 (0.84, 12.4)
191. boonslew63 (0.84, 10.5)
192. ChemaWeb33 (0.84, 12.0)
193. Awesome#33 (0.84, 7.9)
194. chewaced33 (0.84, 10.8)
195. qazwsxed33 (0.84, 7.1)
196. whizurea63 (0.84, 10.6)
197. edylopez33 (0.84, 10.5)
198. lionsped33 (0.84, 9.3)
199. barnsley63 (0.84, 6.8)
200. dlttired63 (0.84, 12.9)
201. marlopez33 (0.84, 8.8)
202. softone-73 (0.84, 11.5)
203. poutine-73 (0.84, 9.5)
204. isolated63 (0.84, 8.7)
205. heelbred63 (0.84, 9.0)
206. favoured63 (0.84, 7.4)
207. Habahbeh73 (0.84, 11.6)
208. divorced33 (0.84, 6.6)
209. thegtheg33 (0.84, 10.2)
210. devinrex63 (0.84, 9.9)
211. rnubfmeh73 (0.84, 13.9)
212. ywnmvbek73 (0.84, 14.0)
213. dushizeh33 (0.84, 13.7)
214. Camguyey73 (0.84, 14.0)
215. swabwhey73 (0.84, 9.8)
216. meeksped33 (0.84, 9.4)
217. rumpchef73 (0.84, 9.8)
218. garymred63 (0.84, 12.2)
219. martinez73 (0.84, 5.5)
220. silodyed73 (0.84, 10.9)
221. advanced73 (0.84, 7.0)
222. dcazvcec73 (0.84, 14.0)
223. uhnwqbec73 (0.84, 13.9)
224. rakethem73 (0.84, 9.7)
225. children63 (0.84, 7.0)
226. hypothem73 (0.84, 9.3)
227. stripped73 (0.84, 7.5)
228. ristonen73 (0.84, 11.8)
229. frogeye#33 (0.84, 10.2)
230. knitchef73 (0.84, 9.7)
231. Angelme$33 (0.84, 11.4)
232. famished73 (0.84, 9.6)
233. ripethem73 (0.84, 9.0)
234. snitwhew73 (0.84, 9.4)
235. hartaped73 (0.84, 9.8)
236. nsanchez73 (0.84, 8.9)
237. gonzalez63 (0.84, 6.1)
238. Mrbruney73 (0.84, 12.2)
239. adejokeF33 (0.84, 11.5)
240. futzhued73 (0.84, 9.5)
241. shanapea73 (0.84, 10.8)
242. talcplea63 (0.84, 9.9)
243. weltabed73 (0.84, 9.6)
244. refinnej73 (0.84, 8.0)
245. pramanew73 (0.84, 11.3)
246. My.Life.33 (0.84, 11.4)
247. sandine_73 (0.84, 9.9)
248. sadigheh73 (0.84, 11.9)
249. tiirawed33 (0.84, 11.8)
250. noseanew73 (0.84, 9.4)
251. pokysued73 (0.84, 10.0)
252. veldanew73 (0.84, 11.3)
253. bareanew73 (0.84, 9.8)
254. valeprep63 (0.84, 10.2)
255. ForgoteN63 (0.84, 11.9)
256. tiltaxed73 (0.84, 11.0)
257. dudespec73 (0.84, 9.6)
258. scabawed73 (0.84, 10.4)
259. bigmoney73 (0.84, 6.4)
260. mesastep63 (0.84, 11.2)
261. duneobey73 (0.84, 10.2)
262. dickeked33 (0.84, 10.2)
263. fareeked33 (0.84, 10.9)
264. richzhea73 (0.84, 12.7)
265. tarebred63 (0.84, 10.5)
266. zbqojyew73 (0.84, 14.0)
267. teenglen63 (0.84, 9.4)
268. maimwhey73 (0.84, 11.0)
269. nopebrew63 (0.84, 9.1)
270. dashwhew73 (0.84, 8.8)
271. raregrew63 (0.84, 9.1)
272. soldblew63 (0.84, 9.7)
273. fressme@33 (0.84, 11.6)
274. iotachew73 (0.84, 10.3)
275. tarppled63 (0.84, 10.0)
276. quayhued73 (0.84, 8.6)
277. getmoney73 (0.84, 5.7)
278. pastsped73 (0.84, 9.4)
279. puffhued73 (0.84, 9.7)
280. funlove@33 (0.84, 10.3)
281. onehoneb73 (0.84, 11.2)
282. pikespec73 (0.84, 9.0)
283. benichef73 (0.84, 10.7)
284. luauowed33 (0.83, 12.1)
285. execwhey73 (0.83, 9.9)
286. mohammed73 (0.83, 5.8)
287. darkened73 (0.83, 7.6)
288. safechef73 (0.83, 10.3)
289. gwpbquea73 (0.83, 14.0)
290. kuglinek43 (0.83, 12.3)
291. latrobe$73 (0.83, 11.5)
292. brattley63 (0.83, 9.3)
293. citespec73 (0.83, 9.5)
294. otisapex73 (0.83, 11.4)
295. flatobey73 (0.83, 10.5)
296. mazewhew73 (0.83, 9.9)
297. tropflex63 (0.83, 9.4)
298. jasmine@73 (0.83, 7.9)
299. ylwbzdeg73 (0.83, 13.9)
300. drumstem63 (0.83, 9.9)
301. zramdbey73 (0.83, 14.0)
302. frogeked33 (0.83, 11.6)
303. casiopea73 (0.83, 7.4)
304. cookwren63 (0.83, 8.4)
305. visewhew73 (0.83, 8.9)
306. mileiced73 (0.83, 11.1)
307. krzaczek73 (0.83, 10.0)
308. tinyshed73 (0.83, 9.9)
309. waveoxen73 (0.83, 9.6)
310. meetibex73 (0.83, 11.7)
311. stunabed73 (0.83, 9.4)
312. mosesben73 (0.83, 10.0)
313. tsvbmken73 (0.83, 14.0)
314. blurspew73 (0.83, 10.5)
315. sellblew63 (0.83, 8.6)
316. sweetpea73 (0.83, 5.8)
317. brchwzeg73 (0.83, 14.0)
318. gaingrew63 (0.83, 8.9)
319. cockabed73 (0.83, 10.3)
320. ivjlszen73 (0.83, 14.0)
321. joltskew73 (0.83, 9.2)
322. ovalbled63 (0.83, 10.2)
323. lockshed73 (0.83, 9.6)
324. beauowed33 (0.83, 9.5)
325. seatopen73 (0.83, 10.0)
326. glutrued73 (0.83, 9.3)
327. kaleopen73 (0.83, 10.8)
328. kamyczek83 (0.83, 9.9)
329. mydogrex63 (0.83, 8.6)
330. Branorek33 (0.83, 12.2)
331. soudabeH73 (0.83, 13.6)
332. abhishek83 (0.83, 6.2)
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374. Eibergen73 (0.83, 10.4)
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805. dingtrek83 (0.82, 10.6)
806. winifred73 (0.82, 7.4)
807. msunited73 (0.82, 9.1)
808. computek73 (0.82, 9.9)
809. confused43 (0.82, 6.9)
810. chinasea73 (0.82, 9.0)
811. lockwhey43 (0.82, 10.7)
812. deckgrey73 (0.82, 9.4)
813. flakbrew73 (0.82, 8.8)
814. bormaley33 (0.82, 11.9)
815. housebed53 (0.82, 6.1)
816. xrslaieh63 (0.82, 14.0)
817. zatsegeg53 (0.82, 12.5)
818. gapethey43 (0.82, 10.1)
819. cimcime_53 (0.82, 13.7)
820. doomibex43 (0.81, 10.8)
821. hornysex33 (0.81, 8.6)
822. editthey43 (0.81, 9.7)
823. Slikotej83 (0.81, 13.2)
824. krslalex43 (0.81, 13.4)
825. newmoney43 (0.81, 7.2)
826. Ozbailey33 (0.81, 11.1)
827. fistthey43 (0.81, 9.4)
828. concave#53 (0.81, 11.3)
829. flayflex73 (0.81, 9.3)
830. titansex73 (0.81, 10.4)
831. lliaxtep73 (0.81, 14.0)
832. maclaren83 (0.81, 7.5)
833. opaleked53 (0.81, 11.7)
834. poseawed53 (0.81, 10.7)
835. wiststep73 (0.81, 9.5)
836. tongeked53 (0.81, 11.3)
837. johnplea73 (0.81, 9.7)
838. getmoney43 (0.81, 6.1)
839. viewstew83 (0.81, 8.3)
840. levyarea83 (0.81, 10.2)
841. wrapclew73 (0.81, 10.3)
842. sendclew73 (0.81, 9.0)
843. Supreme*53 (0.81, 10.0)
844. rollbred83 (0.81, 9.7)
845. startrek73 (0.81, 6.4)
846. kingsley83 (0.81, 6.1)
847. prefuse.73 (0.81, 11.0)
848. gentstem73 (0.81, 9.7)
849. sandslew83 (0.81, 9.3)
850. brantley83 (0.81, 7.0)
851. impresed43 (0.81, 9.7)
852. banistew73 (0.81, 11.3)
853. bongflew73 (0.81, 9.7)
854. avczkbex53 (0.81, 14.0)
855. cordtoed33 (0.81, 9.5)
856. robinred83 (0.81, 9.2)
857. manoplex33 (0.81, 9.2)
858. kingsley33 (0.81, 6.1)
859. vesttied63 (0.81, 8.9)
860. riucxjeq53 (0.81, 14.0)
861. ilovesex83 (0.81, 6.6)
862. ilkvetek83 (0.81, 12.6)
863. yawntied63 (0.81, 9.2)
864. ductcrew73 (0.81, 8.5)
865. ploydrew83 (0.81, 9.8)
866. jerkstep43 (0.81, 9.1)
867. tarpstew83 (0.81, 9.7)
868. Tanksley83 (0.81, 9.9)
869. ccjensen73 (0.81, 10.5)
870. Release_73 (0.81, 10.6)
871. gonzalez83 (0.81, 5.7)
872. fociobey43 (0.81, 11.5)
873. hentesek73 (0.81, 11.6)
874. moldblew83 (0.81, 9.8)
875. berbice#53 (0.81, 13.2)
876. Epresley73 (0.81, 9.4)
877. nfqwmkep53 (0.81, 14.0)
878. lopestep33 (0.81, 9.9)
879. theeobey43 (0.81, 12.9)
880. kralfrey33 (0.81, 11.2)
881. Gonzalez83 (0.81, 6.6)
882. emaildeb53 (0.81, 12.1)
883. yelpfled83 (0.81, 10.3)
884. extremeg53 (0.81, 8.5)
885. thwaitey73 (0.81, 11.1)
886. slatused73 (0.81, 10.4)
887. Ambrose#43 (0.81, 9.4)
888. longitea83 (0.81, 10.0)
889. cbswireh53 (0.81, 13.5)
890. jordwsep73 (0.81, 13.8)
891. idolitem73 (0.81, 11.8)
892. Elevated83 (0.81, 9.0)
893. chantley33 (0.81, 9.2)
894. restitem73 (0.81, 12.2)
895. leakstep83 (0.81, 10.9)
896. Rambasek43 (0.81, 13.0)
897. adminweb53 (0.81, 8.1)
898. gutesten73 (0.81, 12.7)
899. avowbrew83 (0.81, 10.0)
900. vetoflea73 (0.81, 10.1)
901. braxsten83 (0.81, 11.4)
902. robinlen83 (0.81, 10.5)
903. ramstien63 (0.81, 9.8)
904. pailstew73 (0.81, 9.8)
905. katestep73 (0.81, 9.7)
906. lanedrew83 (0.81, 8.8)
907. clodowed53 (0.81, 9.9)
908. geoffrey83 (0.81, 6.5)
909. sellbled83 (0.81, 9.3)
910. weanstep83 (0.81, 9.0)
911. Geoffrey83 (0.81, 7.2)
912. Glenglen83 (0.81, 9.2)
913. zmkytseg73 (0.81, 14.0)
914. orgygrew83 (0.81, 9.8)
915. Crippled83 (0.81, 9.2)
916. wageprey33 (0.81, 10.2)
917. patchrex83 (0.81, 10.7)
918. aqasaleh83 (0.81, 12.1)
919. sqzluiev63 (0.81, 13.6)
920. cwrnatey83 (0.81, 14.0)
921. pourfled83 (0.81, 9.2)
922. bollflex83 (0.81, 10.1)
923. lynxgrew73 (0.81, 9.8)
924. anglesey73 (0.81, 8.6)
925. fuzeused73 (0.81, 11.0)
926. ladestem73 (0.81, 10.7)
927. failglen83 (0.81, 10.0)
928. Linkstef83 (0.81, 10.2)
929. belgutey83 (0.81, 13.6)
930. hgwcloeq63 (0.81, 14.0)
931. goutdrew83 (0.81, 9.7)
932. wavecrew83 (0.81, 9.3)
933. mckinley33 (0.81, 6.5)
934. tendbrew83 (0.81, 9.8)
935. ntzpiley43 (0.81, 13.7)
936. grizzley33 (0.81, 6.8)
937. goreblew83 (0.81, 11.0)
938. micaobey43 (0.81, 10.9)
939. beampled83 (0.81, 9.8)
940. hvqyloex63 (0.81, 13.9)
941. bumpstep83 (0.81, 9.7)
942. dumbobey43 (0.81, 10.4)
943. yqaudftx63 (0.81, 14.0)
944. yeahflex83 (0.81, 9.8)
945. babakrek73 (0.81, 11.2)
946. steakley33 (0.81, 8.7)
947. supersex33 (0.81, 7.0)
948. pitaclef83 (0.81, 10.5)
949. Kneutsen83 (0.81, 12.0)
950. vnyajqtg63 (0.81, 14.0)
951. sodacrew83 (0.81, 8.0)
952. howlired83 (0.81, 11.8)
953. trayfled83 (0.81, 10.3)
954. finktied33 (0.81, 9.0)
955. rkwbxjtf63 (0.81, 13.9)
956. pikeflew83 (0.81, 8.1)
957. nbqckvth63 (0.81, 13.9)
958. puttgrew83 (0.81, 9.4)
959. tiltgrey73 (0.81, 9.3)
960. ifbdxctp63 (0.81, 13.7)
961. girltied63 (0.81, 9.1)
962. hljensen83 (0.81, 11.0)
963. gamesled83 (0.81, 9.8)
964. dzybalex43 (0.81, 13.6)
965. iambfled73 (0.81, 11.7)
966. vqycxmtp63 (0.81, 14.0)
967. Dccursed73 (0.81, 12.9)
968. Elimelek33 (0.81, 10.8)
969. brinkley33 (0.81, 7.0)
970. soporteb43 (0.81, 9.9)
971. poolstep83 (0.81, 9.5)

972. pomphrey33 (0.81, 10.7)
973. kiwibled83 (0.81, 9.0)
974. hoedibex53 (0.81, 9.9)
975. eastgrey83 (0.81, 9.7)
976. liedibex53 (0.81, 11.2)
977. Tomadre_83 (0.81, 11.7)
978. ruedtrek53 (0.81, 9.5)
979. houseted83 (0.81, 11.2)
980. curtbrew73 (0.81, 10.3)
981. dorytrek53 (0.81, 8.9)
982. hartstem83 (0.81, 8.7)
983. Gilmore#53 (0.81, 9.7)
984. mullinix63 (0.81, 9.2)
985. roboclem83 (0.81, 9.9)
986. tanzania63 (0.81, 6.8)
987. perktied43 (0.81, 9.7)
988. veeplied63 (0.81, 7.9)
989. tjpvmcsb63 (0.81, 14.0)
990. jeannie*63 (0.81, 9.6)
991. kingsley43 (0.81, 6.7)
992. ovalstew83 (0.81, 9.5)
993. daubwhey53 (0.81, 9.3)
994. moldgrey43 (0.80, 10.0)
995. alumlied63 (0.80, 10.1)
996. autotoed33 (0.80, 8.7)
997. luckgain63 (0.80, 8.9)
998. snagvain63 (0.80, 9.7)
999. yfnhjxsv63 (0.80, 14.0)

Cluster 9

```
Prototype: aa100eo5

Hard-assigned passwords: 1007341 (3.48% of total)
Unique hard-assigned passwords: 786622 (21.91% of cluster total)

Cluster-assignment scores:
        Min: 0.091
        Max: 0.890
        Mean: 0.323
        SD: 0.157

Strength bins:
        Very weak: 7106 (0.71%)
        Weak: 60376 (5.99%)
        Fair: 171078 (16.98%)
        Good: 722692 (71.74%)
        Strong: 46089 (4.58%)

Password lengths:
        Length 8: 884506 (87.81%)
        Length 9: 122832 (12.19%)
        Length 10: 3 (0.00%)

Character classes:
        4 classes: 23496 (2.33%)
        3 classes: 173372 (17.21%)
                lower/upper/symbol: 674 (0.39%)
                lower/upper/number: 140951 (81.30%)
                lower/symbol/number: 30907 (17.83%)
                upper/symbol/number: 840 (0.48%)
        2 classes: 810442 (80.45%)
                lower/upper: 1101 (0.14%)
                lower/number: 805538 (99.39%)
                lower/symbol: 957 (0.12%)
                upper/number: 2406 (0.30%)
                upper/symbol: 21 (0.00%)
                number/symbol: 419 (0.05%)
        1 class: 31 (0.00%)
                lower: 0 (0.00%)
                upper: 0 (0.00%)
                symbol: 31 (100.00%)
                number: 0 (0.00%)

Most frequent char-class structures:
        LLDDDDDD: 163628 (16.2%)
        LLLDDLLL: 61303 (6.1%)
        LLLDLLLL: 58274 (5.8%)
        LLLDDDDD: 52047 (5.2%)
        LLLDLLLD: 26713 (2.7%)
        LLDDDDLL: 26578 (2.6%)
        LLDLLLLL: 24496 (2.4%)
        LLDDLLDD: 23249 (2.3%)
        ULDDDDDD: 22398 (2.2%)
        LDDDDDDD: 21755 (2.2%)
```

1,000 nearest passwords

```
  0. bo638cnT     (0.89, 13.6)
  1. Kw4K7urU     (0.89, 14.0)
  2. <=)-Hi@>     (0.88, 14.0)
  3. <d415ie>     (0.88, 14.0)
  4. Gm4ORlnM     (0.88, 14.0)
  5. bu453rnT     (0.88, 13.6)
  6. ty32LerC     (0.88, 13.5)
  7. Co475miC     (0.88, 13.2)
  8. t@14J@dN     (0.88, 14.0)
  9. nk66KenT     (0.88, 13.9)
 10. mp718uo5     (0.88, 12.1)
 11. xl79YsoM     (0.88, 14.0)
 12. tg496fw5     (0.88, 12.4)
 13. fy7FSptC     (0.88, 14.0)
 14. wq4BGhmM     (0.88, 14.0)
 15. bp7+6rqC     (0.88, 14.0)
 16. Hs754niM     (0.88, 13.6)
 17. Jf47IbwT     (0.88, 14.0)
 18. Jc300olT     (0.88, 13.4)
 19. Ca32SepT     (0.88, 11.9)
 20. Pm481ghT     (0.88, 13.5)
 21. Di69SigN     (0.88, 12.7)
 22. Cq6MOluH     (0.88, 14.0)
 23. au42EebB     (0.88, 14.0)
 24. An!M8ioN     (0.88, 14.0)
 25. Rw7FKttN     (0.88, 14.0)
 26. wi678uc5     (0.88, 11.7)
 27. Jg65UbdT     (0.88, 14.0)
 28. ie3G4kdC     (0.88, 14.0)
 29. Dx41KgfH     (0.88, 14.0)
 30. qa379vo5     (0.88, 11.8)
 31. Fs34XarB     (0.88, 14.0)
 32. Iy{TPkoN     (0.88, 14.0)
 33. se722daN     (0.88, 12.8)
 34. pd799uv5     (0.88, 12.3)
 35. pr!42esT     (0.88, 14.0)
 36. pe727acH     (0.88, 13.1)
 37. Ma76_jaN     (0.88, 13.2)
 38. Ja786miN     (0.88, 11.2)
 39. St324geT     (0.88, 13.1)
 40. sb3R4bjM     (0.88, 14.0)
 41. zv168vm5     (0.88, 12.2)
 42. mr488fc5     (0.88, 12.7)
 43. jy71PjbN     (0.88, 14.0)
 44. df35OkbT     (0.88, 14.0)
 45. ca786fc5     (0.88, 10.9)
 46. sc62DxdB     (0.88, 14.0)
 47. ew7Q7eyB     (0.88, 14.0)
 48. Kz34RvzT     (0.88, 14.0)
 49. za320ttB     (0.88, 13.0)
 50. Ea731khT     (0.88, 14.0)
 51. Ey787iyT     (0.88, 13.6)
 52. et6P.4gT     (0.88, 14.0)
 53. Je4U2qsT     (0.88, 14.0)
 54. ds647cw5     (0.88, 11.9)
 55. Xa7DSipB     (0.88, 14.0)
 56. Fr33ShiT     (0.88, 10.8)
 57. Jg45YfsT     (0.88, 14.0)
 58. Ec308zzN     (0.88, 14.0)
 59. Ln4Z2atH     (0.88, 14.0)
 60. lj76TvfI     (0.88, 14.0)
 61. kc6MHctT     (0.88, 14.0)
 62. fa37JncC     (0.88, 14.0)
 63. Ky67RgyI     (0.88, 14.0)
 64. Jg65RvsU     (0.88, 14.0)
 65. bq6Z9aUC     (0.88, 14.0)
 66. wp1OMdaN     (0.88, 14.0)
 67. tt470vsI     (0.88, 14.0)
 68. im1GAstC     (0.88, 14.0)
 69. Dd3!NahH     (0.88, 14.0)
 70. Lh7TVedI     (0.88, 14.0)
 71. np3S5rGC     (0.88, 14.0)
 72. Pr11AedT     (0.88, 13.5)
 73. nn7KJnrU     (0.87, 14.0)
 74. ck48LiHN     (0.87, 14.0)
 75. va7T)feH     (0.87, 14.0)
 76. do34Lm-M     (0.87, 14.0)
 77. ^#)!)^$^     (0.87, 13.0)
 78. ve172@MN     (0.87, 14.0)
 79. zz6FCzEC     (0.87, 14.0)
 80. ts642tTT     (0.87, 13.2)
 81. Kw321cUC     (0.87, 14.0)
 82. Kc3H8vCC     (0.87, 14.0)
 83. sr32GxWM     (0.87, 14.0)
 84. wj69RmgF     (0.87, 14.0)
 85. mu74LcGN     (0.87, 14.0)
 86. ri462fo5     (0.87, 12.2)
 87. yr61BhQB     (0.87, 14.0)
 88. Fr4X0tDB     (0.87, 14.0)
 89. gg7KRxUN     (0.87, 14.0)
 90. Au78YdRN     (0.87, 14.0)
 91. Dp3B4sCT     (0.87, 14.0)
 92. Bk390gRT     (0.87, 14.0)
 93. zb3ALCuM     (0.87, 14.0)
 94. jm49AtLI     (0.87, 13.8)
 95. Kd1C7fxN     (0.87, 14.0)
 96. bl389ty8     (0.87, 12.1)
 97. Nc!17xBT     (0.87, 14.0)
 98. xe36FcUT     (0.87, 14.0)
 99. S@!LF@ST     (0.87, 12.3)
100. ur3PQv_T     (0.87, 14.0)
101. nn480pLI     (0.87, 13.5)
102. ki607pi8     (0.87, 12.4)
103. ge411iu8     (0.87, 12.0)
104. Pn4*LupF     (0.87, 14.0)
105. mn3M0n!C     (0.87, 13.7)
106. pw4JJ@LI     (0.87, 12.8)
107. lk319@WH     (0.87, 13.2)
108. pe774ma8     (0.87, 12.0)
109. cs376uo8     (0.87, 12.1)
110. wx793yb8     (0.87, 11.8)
111. oz701mx8     (0.87, 12.3)
112. hj364vw5     (0.87, 12.1)
113. at11&al8     (0.87, 13.3)
114. Pe43StLI     (0.87, 13.8)
115. fp364uy8     (0.87, 12.4)
116. er312mJH     (0.87, 13.8)
117. Gt4C7v5C     (0.87, 14.0)
118. ej674ax8     (0.87, 12.1)
119. tl675tg8     (0.87, 12.0)
120. uw176tu8     (0.87, 12.8)
121. cv602ro5     (0.87, 12.2)
122. hw684mz8     (0.87, 12.1)
123. Sj69HKcH     (0.87, 14.0)
124. up686uj8     (0.87, 11.4)
125. rq175mq8     (0.87, 12.2)
126. ku682sg8     (0.87, 12.5)
127. aj154@DH     (0.87, 13.5)
128. zj462pt8     (0.87, 12.7)
129. Th1SNoaH     (0.87, 13.2)
130. ry614an8     (0.87, 11.7)
131. Bi69!r0N     (0.87, 14.0)
132. Be!80dfF     (0.87, 14.0)
133. sz346yo8     (0.87, 12.3)
134. Cn42PqYU     (0.87, 14.0)
135. sa463db8     (0.87, 11.3)
136. uh752iw8     (0.87, 12.6)
137. le650oi8     (0.87, 11.6)
138. Gd3SMb8C     (0.87, 14.0)
139. cf476af8     (0.87, 11.5)
140. aj179vo8     (0.87, 12.4)
141. hm370pg8     (0.87, 12.0)
142. Wm6WQa6T     (0.87, 14.0)
143. of167ps8     (0.87, 11.9)
144. zn662pu8     (0.87, 12.5)
145. mk786oi8     (0.87, 11.2)
146. od7SVtg8     (0.87, 14.0)
147. ll402co5     (0.87, 12.4)
148. ua323aw8     (0.87, 12.5)
149. Sa7R5iKI     (0.87, 14.0)
150. gm771sc8     (0.87, 12.0)
151. mc636tt8     (0.87, 12.1)
152. ca737ab8     (0.87, 10.9)
153. kv17Pou8     (0.87, 14.0)
154. xr4BPvy8     (0.87, 14.0)
155. vm785ux8     (0.87, 12.6)
156. jt425gx8     (0.87, 12.5)
157. Bu115h1T     (0.87, 12.9)
158. ss393tt8     (0.87, 11.8)
159. Ba77Ag1N     (0.87, 12.9)
160. im35GuWI     (0.87, 14.0)
161. tp476vd8     (0.87, 12.0)
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162. fv465bt8 (0.87, 12.0)
163. du780pt8 (0.87, 12.6)
164. dy677oc8 (0.87, 12.1)
165. ty74GrLI (0.87, 14.0)
166. ae774mc8 (0.87, 12.2)
167. bd339ai8 (0.87, 12.1)
168. jp728uz8 (0.87, 12.3)
169. cg724uj8 (0.87, 12.3)
170. fn350zTT (0.87, 14.0)
171. Ni304oCU (0.87, 14.0)
172. uu487gz8 (0.87, 12.3)
173. wb75WcSU (0.87, 14.0)
174. ea676xt8 (0.87, 11.9)
175. zt643bl8 (0.87, 12.5)
176. Gs100muC (0.87, 13.2)
177. ad610tf8 (0.87, 11.9)
178. xj612xk8 (0.87, 12.3)
179. ak47Was8 (0.87, 11.9)
180. Ph68HPa8 (0.87, 14.0)
181. ln314no8 (0.87, 11.9)
182. sc491wv5 (0.87, 12.5)
183. Ya761p9M (0.87, 14.0)
184. Bd4KLaw8 (0.87, 14.0)
185. Xf7A1cTN (0.87, 14.0)
186. ya761p9M (0.87, 14.0)
187. xy73/vm8 (0.87, 14.0)
188. ec709pv8 (0.87, 12.1)
189. rr373vp8 (0.87, 12.4)
190. Je74Rt3N (0.87, 13.4)
191. fa346tu8 (0.87, 11.6)
192. mx766tu8 (0.87, 12.4)
193. lq402do8 (0.87, 12.6)
194. Ls743c0C (0.87, 14.0)
195. cw636ri8 (0.87, 12.1)
196. vm705nq8 (0.87, 12.6)
197. dr74Rb2T (0.87, 13.8)
198. db6PXx5T (0.87, 14.0)
199. lf11●eb8 (0.87, 14.0)
200. ne111jo8 (0.87, 12.6)
201. ck3BNjpF (0.87, 14.0)
202. ko423rf5 (0.87, 12.3)
203. gv48Ex1M (0.87, 14.0)
204. Bm39Afy8 (0.87, 14.0)
205. mv491lo5 (0.87, 12.7)
206. vt3N1yAI (0.87, 14.0)
207. nq143ev5 (0.87, 12.5)
208. vz412fz8 (0.87, 12.4)
209. rl364oc8 (0.87, 12.1)
210. yu615vu8 (0.87, 11.9)
211. iz6XBd4T (0.87, 14.0)
212. pc318nq8 (0.87, 12.5)
213. my355ou8 (0.87, 11.9)
214. tw347bu8 (0.87, 12.3)
215. zb170ru5 (0.87, 12.3)
216. dd329ge8 (0.87, 12.0)
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669. rj112siv (0.86, 11.7)
670. kf3NWsVJ (0.86, 14.0)
671. hg3N4UnH (0.86, 14.0)
672. ec416muw (0.86, 12.5)
673. zi800on8 (0.85, 11.9)
674. cd682e18 (0.85, 11.2)
675. fn438q18 (0.85, 12.2)
676. ps118v28 (0.85, 11.6)
677. xg640k28 (0.85, 12.1)
678. nv730k18 (0.85, 11.9)
679. Al76Ge78 (0.85, 11.6)
680. ss484fmv (0.85, 12.3)
681. ya7A2PaN (0.85, 14.0)
682. Ln8RWfGT (0.85, 14.0)
683. pn145lvv (0.85, 12.6)
684. Qr4FGzY5 (0.85, 14.0)
685. ln8MMso8 (0.85, 14.0)
686. Km1705mC (0.85, 12.9)
687. dx4QWDtM (0.85, 14.0)
688. lv639lIJ (0.85, 14.0)
689. pb114div (0.85, 11.6)
690. Jm323nov (0.85, 11.9)
691. co445bSJ (0.85, 14.0)
692. wc536teH (0.85, 14.0)
693. qv168cQ5 (0.85, 14.0)
694. Bv1301mM (0.85, 13.1)
695. zc118fmm (0.85, 12.7)
696. Me100niT (0.85, 11.5)
697. op317now (0.85, 10.5)
698. Lk7IPeBJ (0.85, 14.0)
699. wk118com (0.85, 10.6)
700. xw189owv (0.85, 12.8)
701. jd666mcm (0.85, 10.7)

702. go177now (0.85, 10.1)
703. xi586grB (0.85, 14.0)
704. mx666z18 (0.85, 11.3)
705. ro56**BN (0.85, 13.4)
706. sl158kx5 (0.85, 12.1)
707. pk305w18 (0.85, 11.7)
708. hc130nav (0.85, 11.6)
709. lm6UE5yT (0.85, 14.0)
710. rr169ij5 (0.85, 12.3)
711. Dd7531cC (0.85, 12.2)
712. vn776iuv (0.85, 12.6)
713. cu36BReC (0.85, 14.0)
714. Fm4865fM (0.85, 12.1)
715. ew827vp5 (0.85, 12.5)
716. my786num (0.85, 10.2)
717. Or45!StC (0.85, 14.0)
718. mh7MUxK5 (0.85, 14.0)
719. xt827hr8 (0.85, 12.2)
720. jg399ruv (0.85, 12.2)
721. qx6E7fU5 (0.85, 14.0)
722. yl812ga8 (0.85, 12.5)
723. cc183c08 (0.85, 10.8)
724. hn5AEuqT (0.85, 14.0)
725. yj329uvw (0.85, 12.4)
726. it490now (0.85, 10.1)
727. my350n55 (0.85, 11.9)
728. ou812gr8 (0.85, 6.2)
729. wh7OINrI (0.85, 14.0)
730. De13Be08 (0.85, 11.0)
731. Hy73Cq28 (0.85, 13.5)
732. Dt3V8pU5 (0.85, 14.0)
733. ds175wcv (0.85, 12.4)
734. ss454z28 (0.85, 11.7)
735. ga491inv (0.85, 13.0)
736. Ou812ou8 (0.85, 7.5)
737. nn437tnv (0.85, 12.2)
738. il147b68 (0.85, 11.8)
739. oe888jc8 (0.85, 11.8)
740. fs655gov (0.85, 12.4)
741. mw499www (0.85, 11.7)
742. fh175viv (0.85, 12.5)
743. fg491ivv (0.85, 12.8)
744. zz409z28 (0.85, 12.2)
745. li837qn8 (0.85, 11.7)
746. no420luv (0.85, 10.2)
747. tq649GiN (0.85, 14.0)
748. hb4E2zTJ (0.85, 14.0)
749. An62Nn85 (0.85, 12.4)
750. Vs375PyN (0.85, 14.0)
751. te359vmw (0.85, 12.6)
752. kj442ucv (0.85, 12.4)
753. Gd6973pN (0.85, 13.6)
754. oj328oiv (0.85, 12.3)
755. Cd4017aC (0.85, 12.9)
756. ip450luv (0.85, 11.2)
757. ag147jrv (0.85, 11.4)
758. Am3388aM (0.85, 11.8)
759. sc7855sM (0.85, 12.5)
760. pb452oyv (0.85, 12.4)
761. bh845nz5 (0.85, 12.2)
762. kx435lmv (0.85, 12.5)
763. ar458fiv (0.85, 11.7)
764. Jo15Ka18 (0.85, 10.2)
765. in142huv (0.85, 12.1)
766. jw321scv (0.85, 11.4)
767. uc179gev (0.85, 12.2)
768. dx32TEwI (0.85, 14.0)
769. rp428pav (0.85, 12.0)
770. dz302z28 (0.85, 12.3)
771. Do872sWI (0.85, 14.0)
772. tj737luv (0.85, 11.1)
773. an172viv (0.85, 11.2)
774. Hb678RcH (0.85, 13.9)
775. sx106vy8 (0.85, 12.0)
776. mg796bfv (0.85, 12.7)
777. rx300suv (0.85, 11.6)
778. jn330niv (0.85, 12.4)
779. lt646dfv (0.85, 11.8)
780. Mj3482oH (0.85, 13.6)
781. jt336@wv (0.85, 13.8)
782. x_8_3y2H (0.85, 14.0)
783. eq470oav (0.85, 12.2)
784. kj3Q07aM (0.85, 14.0)
785. vs17KCtC (0.85, 14.0)
786. ku649lmv (0.85, 12.5)
787. El10WttC (0.85, 14.0)
788. yt615nev (0.85, 12.5)
789. Km512uwM (0.85, 14.0)
790. be320oiv (0.85, 12.7)
791. mo119lpv (0.85, 12.7)
792. Xm16-l18 (0.85, 14.0)
793. ck829du5 (0.85, 12.1)
794. hm144fbv (0.85, 12.4)
795. Do17Ke18 (0.85, 11.4)
796. sy486mzv (0.85, 12.2)
797. ct733pwv (0.85, 12.6)
798. Jg45CVsT (0.85, 14.0)
799. Ze8JWn4N (0.85, 14.0)
800. ee366com (0.85, 11.5)
801. kw728rav (0.85, 12.1)
802. wl8WXnYH (0.85, 14.0)
803. Sl3584nB (0.85, 13.5)
804. jb308viv (0.85, 11.8)
805. wp3NAu2J (0.85, 14.0)
806. Ug8AZoSU (0.85, 14.0)
807. tm4SGdA5 (0.85, 14.0)
808. br549mc5 (0.85, 8.7)
809. gp336siv (0.85, 12.4)
810. db63XDdM (0.85, 14.0)
811. Wg66E6pT (0.85, 14.0)
812. hj134hyv (0.85, 12.8)
813. fr330n35 (0.85, 9.5)
814. gl886nov (0.85, 11.8)
815. kx7836bC (0.85, 13.8)
816. Iw14JDaT (0.85, 14.0)
817. Wx73T1vT (0.85, 14.0)
818. em867ag5 (0.85, 12.6)
819. Kj1HVvDJ (0.85, 14.0)
820. wu136wav (0.85, 12.7)
821. ht30BUaM (0.85, 14.0)
822. bk6VBf2J (0.85, 14.0)
823. Jb655xcv (0.85, 13.3)
824. ca358iqv (0.85, 12.9)
825. wy673viv (0.85, 12.2)
826. az485yxv (0.85, 12.5)
827. bn411brv (0.85, 12.2)
828. cs601ybv (0.85, 12.4)
829. wb101zi8 (0.85, 12.2)
830. bi114qnv (0.85, 12.7)
831. Nc476u45 (0.85, 13.6)
832. wu113qqv (0.85, 13.5)
833. jr6TTa85 (0.85, 14.0)
834. nm575sd8 (0.85, 11.8)
835. px861sq5 (0.85, 12.1)
836. vw654u45 (0.85, 12.2)
837. my429com (0.85, 8.9)
838. hj816dg5 (0.85, 11.9)
839. af827oh5 (0.85, 12.4)
840. wi414rpv (0.85, 12.6)
841. yv847rd5 (0.85, 12.5)
842. At6436aT (0.85, 11.7)
843. fj687cev (0.85, 12.4)
844. kn553fi8 (0.85, 12.3)
845. ch113LaB (0.85, 13.0)
846. Li3528iN (0.85, 12.3)
847. Lf)6SL@B (0.85, 14.0)
848. Ma15Fr28 (0.85, 11.2)
849. er468u85 (0.85, 11.7)
850. hk798o05 (0.85, 11.8)
851. Mv3OPRdT (0.85, 14.0)
852. Ya69Na75 (0.85, 11.9)
853. Er10JuaN (0.85, 11.2)
854. ge32Rubv (0.85, 14.0)
855. jk326Ec5 (0.85, 13.9)
856. Gb8QUrFT (0.85, 14.0)
857. b@35Q1aT (0.85, 14.0)
858. nj370grv (0.85, 12.3)
859. yo790dcv (0.85, 12.7)
860. pv676s05 (0.85, 11.9)
861. my301grv (0.85, 11.8)
862. uz550mu8 (0.85, 12.4)
863. eb6196eB (0.85, 12.6)
864. ha420kev (0.85, 10.6)
865. kl631pjv (0.85, 12.3)
866. wh790hmv (0.85, 12.3)
867. Cl3M3nT5 (0.85, 11.2)
868. gp448cbv (0.85, 12.8)
869. nq755wrv (0.85, 12.6)
870. jr358crm (0.85, 11.6)
871. ln370kwv (0.85, 12.7)
872. Kc8HIyYB (0.85, 14.0)
873. po671lsv (0.85, 12.1)
874. v$3Z8q1F (0.85, 14.0)
875. rk762lrv (0.85, 12.4)
876. cz537ms8 (0.85, 12.2)
877. xe609pgv (0.85, 12.5)
878. fk335ozv (0.85, 12.5)
879. zr547ww5 (0.85, 12.7)
880. Ac3420dC (0.85, 12.2)
881. rl167t98 (0.85, 12.2)
882. dp384kwv (0.85, 12.4)
883. jg621m75 (0.85, 12.1)
884. vd871hp5 (0.85, 12.3)
885. zm889fj5 (0.85, 12.3)
886. ah317sdv (0.85, 11.7)
887. rb525sn8 (0.85, 12.1)
888. br340div (0.85, 11.7)
889. Jo79Ho75 (0.85, 10.9)
890. mq791lgv (0.85, 12.8)
891. aq639psv (0.85, 12.4)
892. pc185tlv (0.85, 12.3)
893. Ta3275wN (0.85, 13.3)
894. yw59WuTM (0.85, 14.0)
895. ad608a75 (0.85, 11.3)
896. jy887y68 (0.85, 11.9)
897. mm331rtv (0.85, 12.5)
898. Re411y75 (0.85, 13.1)
899. kn862dd5 (0.85, 12.5)
900. ha187cev (0.85, 11.8)
901. lc882gp5 (0.85, 11.9)
902. pf7MY4wB (0.85, 14.0)
903. jl352ppv (0.85, 12.3)
904. ef627f85 (0.85, 11.3)
905. zb305esv (0.85, 12.7)
906. ge894@g5 (0.85, 14.0)
907. pi688ctv (0.85, 12.5)
908. Cv1412eB (0.85, 13.2)
909. bf534ti8 (0.85, 12.0)
910. gk688ghv (0.85, 12.0)
911. am761eqv (0.85, 12.8)
912. bk798wrm (0.85, 11.8)
913. ft73EEqT (0.85, 14.0)
914. pe726u05 (0.85, 12.2)
915. qq575br8 (0.85, 12.5)
916. cy110com (0.85, 10.1)
917. gq586pl8 (0.85, 12.2)
918. rx869kb5 (0.85, 12.4)
919. ly316tlv (0.85, 12.6)
920. nw1J9$s5 (0.85, 14.0)
921. no744s05 (0.85, 12.1)
922. hp384y85 (0.85, 11.9)
923. xk101jm5 (0.85, 11.9)
924. Mb3212xT (0.85, 13.6)
925. Oz1719aN (0.85, 13.6)
926. L@357thv (0.85, 13.4)
927. Nu7N17rI (0.85, 14.0)
928. jw305bgv (0.85, 12.5)
929. su333r05 (0.85, 11.2)
930. qv4UHqpv (0.85, 14.0)
931. my337com (0.85, 10.0)
932. Jk579brB (0.85, 13.8)
933. gc883i18 (0.85, 12.3)
934. Pl31Ku75 (0.85, 13.4)
935. qu749edv (0.85, 12.3)
936. yt478l75 (0.85, 12.0)
937. wb740bgv (0.85, 12.4)
938. zg712szv (0.85, 12.6)
939. ks462jrv (0.85, 12.0)
940. fm533xi8 (0.85, 12.2)
941. kn659kav (0.85, 12.3)
942. kh457qtv (0.85, 12.1)
943. Ws46Jb75 (0.85, 13.1)
944. im)))com (0.85, 13.1)
945. Xk6GJ3dH (0.85, 14.0)
946. Le14Na05 (0.85, 10.6)
947. bb693b75 (0.85, 10.6)
948. mt47Eb85 (0.85, 13.7)
949. Bz472cpv (0.85, 14.0)
950. qu739tlv (0.85, 12.1)
951. rb475jxv (0.85, 12.7)
952. an716u05 (0.85, 12.1)
953. Mc7755sB (0.85, 13.0)
954. Da33St85 (0.85, 12.0)
955. Ts76Cp75 (0.85, 13.0)
956. zs3NMdpv (0.85, 14.0)
957. Ed7IR1jM (0.85, 14.0)
958. al717znv (0.85, 12.4)
959. Yz450f05 (0.85, 10.8)
960. sk311y75 (0.85, 11.4)
961. Vy3PH2zM (0.85, 14.0)
962. **789dav (0.85, 11.4)
963. aw342krv (0.85, 12.3)
964. pg821v38 (0.85, 12.4)
965. Th1515iT (0.85, 12.0)
966. qo734r85 (0.85, 12.1)
967. tr4D7DpU (0.85, 14.0)
968. Ca6329aU (0.85, 13.5)
969. Dh74Ir75 (0.85, 13.2)
970. yk530mg8 (0.85, 12.3)
971. id3Z2CgI (0.85, 14.0)

972. ia401x75 (0.85, 12.0)
973. rh7240xN (0.85, 14.0)
974. pp523ew8 (0.85, 12.1)
975. tk323dhv (0.85, 11.9)
976. it168com (0.85, 10.2)
977. ro614kjv (0.85, 12.5)
978. rs789vtv (0.85, 11.9)
979. ln157clv (0.85, 12.1)
980. Mc373FbB (0.85, 14.0)
981. xb38#*AJ (0.85, 14.0)
982. cs835tz5 (0.85, 12.2)
983. go414cjv (0.85, 12.3)
984. Kv4615pH (0.85, 13.8)
985. rj450com (0.85, 10.0)
986. jk854a48 (0.85, 11.5)
987. ll390www (0.85, 11.6)
988. rc891u48 (0.85, 12.6)
989. cv602g75 (0.85, 12.2)
990. oz820d38 (0.85, 12.3)
991. bl832fc5 (0.85, 12.3)
992. fc863d98 (0.85, 11.1)
993. St17Br05 (0.85, 11.1)
994. yc583ar8 (0.85, 12.3)
995. Ev1511wM (0.85, 13.9)
996. ou812me5 (0.85, 7.4)
997. gg488v45 (0.85, 11.8)
998. ke849ee5 (0.85, 11.7)
999. nv56EcxU (0.85, 14.0)

Cluster 10

Prototype: aaeraa990

Hard-assigned passwords: 1011484 (3.50% of total)
Unique hard-assigned passwords: 779922 (22.89% of cluster total)

Cluster-assignment scores:
	Min: 0.069
	Max: 0.598
	Mean: 0.231
	SD: 0.082

Strength bins:
	Very weak: 28306 (2.80%)
	Weak: 102385 (10.12%)
	Fair: 367096 (36.29%)
	Good: 502135 (49.64%)
	Strong: 11562 (1.14%)

Password lengths:
	Length 8: 604828 (59.80%)
	Length 9: 401861 (39.73%)
	Length 10: 4795 (0.47%)

Character classes:
	4 classes: 30220 (2.99%)
	3 classes: 119621 (11.83%)
		lower/upper/symbol: 843 (0.70%)
		lower/upper/number: 79261 (66.26%)
		lower/symbol/number: 39492 (33.01%)
		upper/symbol/number: 25 (0.02%)
	2 classes: 861639 (85.19%)
		lower/upper: 728 (0.08%)
		lower/number: 859039 (99.70%)
		lower/symbol: 1837 (0.21%)
		upper/number: 0 (0.00%)
		upper/symbol: 21 (0.00%)
		number/symbol: 14 (0.00%)
	1 class: 4 (0.00%)
		lower: 0 (0.00%)
		upper: 0 (0.00%)
		symbol: 4 (100.00%)
		number: 0 (0.00%)

Most frequent char-class structures:
	LLLLLDDD: 449906 (44.5%)
	LLLLLLDDD: 323787 (32.0%)
	LLLLLDLL: 33592 (3.3%)
	ULLLLDDD: 31216 (3.1%)
	ULLLLLDDD: 18908 (1.9%)
	LLLLLDDL: 17499 (1.7%)
	LLLLLLDLL: 10501 (1.0%)
	LLLLLDLD: 9471 (0.9%)
	LLLLLLDDS: 8310 (0.8%)
	LLLLLDDS: 7526 (0.7%)

1,000 nearest passwords

0.	shilo#97#	(0.60, 12.0)	54.	rollin26s	(0.56, 9.0)	108.	xejipa280	(0.56, 10.3)
1.	damian90t	(0.60, 9.7)	55.	Alnech01#	(0.56, 13.4)	109.	mafomy280	(0.56, 10.8)
2.	pocong90t	(0.60, 10.7)	56.	Romesa04#	(0.56, 12.6)	110.	hupixy280	(0.56, 10.4)
3.	Jonesy90#	(0.59, 10.0)	57.	ganesh07$	(0.56, 8.8)	111.	tivoga280	(0.56, 10.1)
4.	Maxim_22#	(0.59, 11.2)	58.	rdcozu26s	(0.56, 14.0)	112.	hyhixa270	(0.56, 10.6)
5.	Damian23#	(0.59, 8.4)	59.	Romesa05#	(0.56, 12.3)	113.	dopidu280	(0.56, 10.2)
6.	matron98#	(0.59, 10.8)	60.	shiloh07$	(0.56, 9.1)	114.	rexoga280	(0.56, 10.3)
7.	regina21#	(0.59, 8.7)	61.	Marlin01$	(0.56, 8.5)	115.	qumidy280	(0.56, 10.0)
8.	Willow99#	(0.59, 8.3)	62.	Philip03$	(0.56, 8.7)	116.	Tedium06#	(0.56, 13.1)
9.	Dillon93#	(0.59, 8.9)	63.	jenlin09#	(0.56, 11.3)	117.	woxoka270	(0.56, 10.3)
10.	Devind21#	(0.59, 10.7)	64.	mahoma290	(0.56, 9.9)	118.	voxowy280	(0.56, 10.1)
11.	qwerty22#	(0.59, 7.4)	65.	jaqoza290	(0.56, 10.5)	119.	jamify280	(0.56, 10.3)
12.	matrix99#	(0.59, 7.7)	66.	moneyg96$	(0.56, 10.8)	120.	qipiza270	(0.56, 10.0)
13.	azerty92$	(0.59, 8.2)	67.	vagima290	(0.56, 10.4)	121.	rowofu270	(0.56, 10.3)
14.	barliz24$	(0.59, 12.3)	68.	vagipa290	(0.56, 10.8)	122.	dydony290	(0.56, 10.9)
15.	Joseoj94$	(0.59, 13.4)	69.	angeam27$	(0.56, 12.4)	123.	defiwu270	(0.56, 10.7)
16.	merlin92$	(0.59, 8.8)	70.	mekezy990	(0.56, 10.1)	124.	nypicy280	(0.56, 10.7)
17.	yefin#29#	(0.59, 13.4)	71.	Deploy09$	(0.56, 11.2)	125.	sewiga270	(0.56, 10.6)
18.	gloria25t	(0.59, 8.6)	72.	badiwy290	(0.56, 10.3)	126.	fipozu270	(0.56, 10.4)
19.	winsab20#	(0.59, 11.9)	73.	hizizu290	(0.56, 10.4)	127.	kogoby280	(0.56, 10.8)
20.	matrix21$	(0.58, 7.9)	74.	vixepu990	(0.56, 10.2)	128.	wahihu280	(0.56, 9.7)
21.	Sweetu23#	(0.58, 9.8)	75.	NokiaN900	(0.56, 6.8)	129.	vfhecz980	(0.56, 11.7)
22.	sahima26$	(0.58, 11.8)	76.	nokiaN900	(0.56, 6.8)	130.	gshock270	(0.56, 9.0)
23.	racing24t	(0.58, 8.8)	77.	giwepa990	(0.56, 10.1)	131.	zozecu970	(0.56, 10.1)
24.	alaska22#	(0.58, 8.5)	78.	Majesa03$	(0.56, 13.0)	132.	cibony290	(0.56, 10.2)
25.	matrix95$	(0.58, 8.5)	79.	bozicu290	(0.56, 10.4)	133.	hotrod23t	(0.56, 9.5)
26.	florin23$	(0.58, 8.7)	80.	wapona290	(0.56, 9.7)	134.	dododa07$	(0.56, 11.7)
27.	yayonk21$	(0.58, 12.0)	81.	Ballin06$	(0.56, 8.9)	135.	dahoam02$	(0.56, 13.5)
28.	Maktag28#	(0.58, 11.9)	82.	xunodu290	(0.56, 10.6)	136.	byconu990	(0.56, 11.1)
29.	Annick21$	(0.58, 9.6)	83.	jamekv990	(0.56, 12.1)	137.	cocogc270	(0.55, 11.3)
30.	bsprom20$	(0.58, 12.8)	84.	hexiby290	(0.56, 10.2)	138.	zuniga01$	(0.55, 9.3)
31.	bells@21#	(0.58, 11.6)	85.	wajicy290	(0.56, 9.9)	139.	robepu970	(0.55, 11.0)
32.	Aneesh26#	(0.58, 9.9)	86.	jahijy290	(0.56, 11.0)	140.	cifivy270	(0.55, 10.2)
33.	Indian29$	(0.58, 8.9)	87.	hehody290	(0.56, 10.2)	141.	gynony290	(0.55, 10.3)
34.	kidimk96#	(0.58, 14.0)	88.	remend21$	(0.56, 11.8)	142.	piveku960	(0.55, 10.2)
35.	qwerty21$	(0.58, 7.1)	89.	damian22t	(0.56, 8.8)	143.	sapinu270	(0.55, 10.8)
36.	DevinB01$	(0.58, 10.8)	90.	amdiaz09#	(0.56, 12.6)	144.	reming270	(0.55, 9.1)
37.	qwerty25$	(0.58, 7.5)	91.	kevin@990	(0.56, 8.9)	145.	gijoba260	(0.55, 10.7)
38.	Ganesh21#	(0.58, 8.4)	92.	Damian01$	(0.56, 7.7)	146.	Sajid@970	(0.55, 10.5)
39.	nbnsux97#	(0.57, 14.0)	93.	roheya05$	(0.56, 12.9)	147.	mubeca970	(0.55, 10.3)
40.	nimiyA01$	(0.57, 13.4)	94.	pagoda280	(0.56, 8.5)	148.	muneca01$	(0.55, 8.5)
41.	Kruidn00t	(0.57, 12.2)	95.	tumodu280	(0.56, 10.9)	149.	iydoUk0Ut	(0.55, 14.0)
42.	Kbctja99$	(0.57, 13.9)	96.	suhima280	(0.56, 10.6)	150.	yugiOH900	(0.55, 11.8)
43.	yellow01#	(0.57, 8.2)	97.	vahemy990	(0.56, 10.7)	151.	typefy960	(0.55, 10.6)
44.	Geheim01$	(0.57, 8.7)	98.	shaina02#	(0.56, 9.8)	152.	jykevu960	(0.55, 10.1)
45.	Arleta01$	(0.57, 10.0)	99.	fivewy980	(0.56, 10.0)	153.	hiveku900	(0.55, 10.3)
46.	Teresa01$	(0.57, 8.3)	100.	zomevu980	(0.56, 10.3)	154.	Rikih^910	(0.55, 14.0)
47.	Philou01$	(0.57, 9.3)	101.	cukofu280	(0.56, 10.0)	155.	ledeqy900	(0.55, 10.7)
48.	sweety02$	(0.57, 9.1)	102.	puwiba270	(0.56, 10.2)	156.	dflesh990	(0.55, 10.5)
49.	Dagrim01$	(0.57, 10.6)	103.	nozima280	(0.56, 10.0)	157.	temiga260	(0.55, 10.0)
50.	Gehivd07t	(0.57, 14.0)	104.	vuhixu280	(0.56, 10.2)	158.	necepa960	(0.55, 10.3)
51.	athlon01#	(0.57, 9.6)	105.	kejedy980	(0.56, 10.0)	159.	zuwedu900	(0.55, 9.9)
52.	Shiloh07$	(0.57, 9.0)	106.	nebejy980	(0.56, 10.3)	160.	mrbean900	(0.55, 8.2)
53.	ztiroM02#	(0.57, 14.0)	107.	tobozu280	(0.56, 10.3)	161.	fabian990	(0.55, 7.2)

162. puseta990 (0.55, 9.8)	252. ksnecn24$ (0.55, 14.0)	342. redeon900 (0.54, 9.9)
163. nohebu960 (0.55, 10.4)	253. samona200 (0.55, 8.4)	343. udyrib990 (0.54, 10.5)
164. zumema960 (0.55, 9.5)	254. cajixu980 (0.55, 10.3)	344. Yellow900 (0.54, 7.2)
165. dedeva900 (0.55, 9.8)	255. echina970 (0.55, 10.6)	345. junekw900 (0.54, 11.6)
166. kucing990 (0.55, 7.6)	256. myqika980 (0.55, 10.3)	346. ekoriw980 (0.54, 10.3)
167. jitesh990 (0.55, 9.1)	257. zijepa290 (0.55, 10.3)	347. hixipa980 (0.54, 10.2)
168. lopez.900 (0.55, 9.0)	258. jiniha990 (0.55, 10.3)	348. qohogy970 (0.54, 10.1)
169. zupehy900 (0.55, 10.1)	259. nokiax200 (0.55, 4.5)	349. jaconn200 (0.54, 10.6)
170. sweety980 (0.55, 8.0)	260. nokian900 (0.55, 5.5)	350. afarox270 (0.54, 10.0)
171. medina260 (0.55, 7.8)	261. janick200 (0.55, 8.6)	351. sonicx200 (0.54, 7.2)
172. namibm200 (0.55, 11.1)	262. Magick200 (0.55, 8.4)	352. zacoky210 (0.54, 10.3)
173. fyqiby260 (0.55, 10.2)	263. Kigoma200 (0.55, 10.3)	353. jivogy970 (0.54, 10.6)
174. Vaishu27$ (0.55, 10.0)	264. davidb210 (0.55, 7.9)	354. pebetu900 (0.54, 9.9)
175. gabevx900 (0.55, 12.4)	265. lipiam200 (0.55, 11.3)	355. xekiqy200 (0.54, 10.2)
176. gudexx900 (0.55, 11.7)	266. ezylib280 (0.55, 10.7)	356. pacipy210 (0.54, 9.9)
177. tywiju990 (0.55, 10.4)	267. kucing200 (0.55, 6.7)	357. ryqidy900 (0.54, 10.0)
178. maxima200 (0.55, 6.6)	268. yxulom290 (0.55, 10.6)	358. knjiga900 (0.54, 11.9)
179. hamoda200 (0.55, 8.1)	269. merlin990 (0.55, 7.2)	359. gaming210 (0.54, 7.9)
180. sajova200 (0.55, 10.5)	270. lahodu900 (0.55, 11.4)	360. Fleety50$ (0.54, 12.4)
181. mayowa200 (0.55, 6.5)	271. dyqiha980 (0.55, 10.1)	361. didima220 (0.54, 9.7)
182. manina260 (0.55, 9.0)	272. iweliw280 (0.55, 10.3)	362. sadocy210 (0.54, 10.4)
183. siziqu990 (0.55, 10.1)	273. kadian200 (0.55, 8.1)	363. kaqema280 (0.54, 10.3)
184. cezivy260 (0.55, 10.2)	274. azulip990 (0.55, 10.2)	364. bacong210 (0.54, 9.1)
185. legend900 (0.55, 6.4)	275. gasron290 (0.55, 11.4)	365. junozu210 (0.54, 9.7)
186. kuwovu990 (0.55, 10.2)	276. myking200 (0.55, 7.4)	366. indian210 (0.54, 6.5)
187. ryjijy990 (0.55, 10.1)	277. folria990 (0.55, 12.5)	367. ajasaq290 (0.54, 10.6)
188. jonezy980 (0.55, 9.0)	278. nokiac200 (0.55, 6.1)	368. regina200 (0.54, 6.7)
189. tuhecu900 (0.55, 10.2)	279. mohoxa210 (0.55, 10.7)	369. fywefy270 (0.54, 10.3)
190. ruwimu200 (0.55, 10.6)	280. caseih270 (0.55, 9.0)	370. dykeba280 (0.54, 10.0)
191. kifoga990 (0.55, 10.4)	281. gebeny910 (0.55, 10.4)	371. phuong960 (0.54, 8.4)
192. pubomu990 (0.55, 10.6)	282. caseih280 (0.55, 8.9)	372. makiah220 (0.54, 8.5)
193. racoka200 (0.55, 10.2)	283. daylin290 (0.55, 9.1)	373. rofesu970 (0.54, 10.3)
194. mivida200 (0.55, 6.6)	284. qaneju960 (0.55, 10.4)	374. vuvoxu970 (0.54, 10.3)
195. azerty990 (0.55, 6.3)	285. samijy980 (0.55, 10.0)	375. legend090 (0.54, 7.0)
196. rudich200 (0.55, 9.9)	286. hopofy980 (0.55, 9.8)	376. pamifu900 (0.54, 10.4)
197. tiwofa200 (0.55, 10.0)	287. fijian900 (0.55, 8.5)	377. qojohy970 (0.54, 10.3)
198. akkiAA000 (0.55, 11.0)	288. hollow290 (0.55, 8.3)	378. jukemy910 (0.54, 10.8)
199. regowd200 (0.55, 11.6)	289. udatyj290 (0.55, 10.7)	379. zofimy210 (0.54, 10.0)
200. qwerty990 (0.55, 5.4)	290. satrix990 (0.55, 9.9)	380. haxopy220 (0.54, 10.1)
201. zicina980 (0.55, 10.1)	291. nfuikc200 (0.55, 13.4)	381. nadomn970 (0.54, 13.6)
202. werrty990 (0.55, 10.4)	292. kimian900 (0.55, 8.5)	382. zidoha900 (0.54, 10.3)
203. askoda200 (0.55, 10.2)	293. indian200 (0.55, 6.1)	383. Nokiax200 (0.54, 5.9)
204. Xenonn270 (0.55, 13.3)	294. wicoka210 (0.55, 10.1)	384. suresh960 (0.54, 8.3)
205. cudimy990 (0.55, 10.5)	295. mamoha210 (0.55, 10.7)	385. cipewa910 (0.54, 10.4)
206. aldova200 (0.55, 9.8)	296. buvoxy980 (0.55, 10.5)	386. zehixy210 (0.54, 9.6)
207. dunozy990 (0.55, 10.3)	297. magica210 (0.55, 8.1)	387. nokiaq200 (0.54, 8.0)
208. cusesy980 (0.55, 10.4)	298. kejofy980 (0.55, 10.6)	388. enurox280 (0.54, 10.3)
209. mimikk200 (0.55, 10.1)	299. kevinm200 (0.55, 8.0)	389. jayona210 (0.54, 9.2)
210. tayima200 (0.55, 10.7)	300. ehyrif270 (0.55, 10.3)	390. willow270 (0.54, 7.2)
211. nicozy990 (0.55, 9.0)	301. uviloj280 (0.55, 10.7)	391. pohevy910 (0.54, 10.7)
212. damimu990 (0.55, 10.4)	302. Optimx21# (0.55, 12.7)	392. opuloz280 (0.54, 10.4)
213. numodu980 (0.55, 10.5)	303. efilig280 (0.55, 9.9)	393. naresh960 (0.54, 8.4)
214. ikilim290 (0.55, 10.2)	304. duwegy910 (0.55, 10.0)	394. ruxipu970 (0.54, 10.5)
215. tahiby990 (0.55, 10.5)	305. hiking900 (0.55, 8.0)	395. zunoca900 (0.54, 10.5)
216. uthsam01# (0.55, 13.2)	306. nexian900 (0.55, 9.1)	396. zowiqa220 (0.54, 10.6)
217. levoby990 (0.55, 10.5)	307. yjytav290 (0.55, 10.6)	397. beqiwu220 (0.54, 10.8)
218. Zenoah260 (0.55, 11.7)	308. zipogu970 (0.55, 10.1)	398. vakofy220 (0.54, 10.5)
219. Therin990 (0.55, 10.8)	309. muneka960 (0.55, 9.8)	399. kagogu220 (0.54, 10.7)
220. admin@270 (0.55, 8.3)	310. radeon900 (0.55, 7.2)	400. Louiza200 (0.54, 9.0)
221. sens#^900 (0.55, 13.9)	311. mekepy910 (0.55, 11.3)	401. jynipu210 (0.54, 10.8)
222. Padova200 (0.55, 8.7)	312. nikond200 (0.55, 5.0)	402. omaloq270 (0.54, 10.9)
223. revica990 (0.55, 10.2)	313. wassup23$ (0.55, 9.2)	403. bojina960 (0.54, 9.6)
224. wexopy990 (0.55, 10.5)	314. jaxiah210 (0.55, 10.9)	404. tewovu970 (0.54, 10.1)
225. oxirod990 (0.55, 9.8)	315. afusyp280 (0.55, 10.8)	405. xyqidy220 (0.54, 10.3)
226. puwipy200 (0.55, 10.2)	316. ebilox270 (0.55, 10.5)	406. newink210 (0.54, 9.6)
227. marlon990 (0.55, 7.6)	317. teresa900 (0.55, 7.1)	407. Matrix57# (0.54, 9.1)
228. wizoha200 (0.55, 10.3)	318. Qwerty900 (0.55, 6.3)	408. vahozy970 (0.54, 10.6)
229. sneet@900 (0.55, 11.3)	319. ecilop270 (0.55, 10.3)	409. nikipy900 (0.54, 10.2)
230. wealth990 (0.55, 8.3)	320. qacima220 (0.55, 10.4)	410. Nokiac200 (0.54, 7.4)
231. waylon990 (0.55, 8.2)	321. tamiya220 (0.55, 8.2)	411. wuaimm990 (0.54, 13.8)
232. Mayowa200 (0.55, 7.7)	322. tacovu900 (0.55, 9.5)	412. microZOFt (0.54, 14.0)
233. merlon990 (0.55, 9.4)	323. sharon290 (0.55, 7.3)	413. wujing220 (0.54, 9.5)
234. hafody200 (0.55, 10.4)	324. labokh220 (0.55, 11.7)	414. qwertY990 (0.54, 8.5)
235. sidiny970 (0.55, 11.3)	325. tiqoxy980 (0.55, 10.6)	415. tabsum260 (0.54, 11.5)
236. Meisha99# (0.55, 10.5)	326. tajevu290 (0.55, 11.1)	416. gyweza260 (0.54, 10.1)
237. anbtcw08$ (0.55, 14.0)	327. marlin270 (0.55, 7.8)	417. shorty900 (0.54, 6.7)
238. raheim280 (0.55, 9.6)	328. kehomu210 (0.55, 10.8)	418. ytutyz290 (0.54, 10.2)
239. omaroj990 (0.55, 9.9)	329. liping200 (0.55, 8.5)	419. cypopa970 (0.54, 10.4)
240. qxgsym280 (0.55, 14.0)	330. almond900 (0.55, 7.1)	420. Sodium200 (0.54, 8.5)
241. xevoza990 (0.55, 10.5)	331. tuning900 (0.55, 7.8)	421. wibigu220 (0.54, 10.1)
242. monika990 (0.55, 7.4)	332. cocozu900 (0.55, 9.9)	422. Jediah210 (0.54, 10.5)
243. ewiroj990 (0.55, 10.2)	333. anying200 (0.55, 9.0)	423. @laska270 (0.54, 10.8)
244. nagoxa210 (0.55, 9.7)	334. zifigu970 (0.54, 10.0)	424. almond210 (0.54, 7.5)
245. ganeza970 (0.55, 10.7)	335. woviwa220 (0.54, 10.6)	425. willow900 (0.54, 6.7)
246. hotrod990 (0.55, 7.2)	336. vocizu210 (0.54, 10.8)	426. olasmm01# (0.54, 13.3)
247. wagojy980 (0.55, 10.3)	337. manima210 (0.54, 8.9)	427. goniga900 (0.54, 10.0)
248. bixemu290 (0.55, 10.5)	338. arnica200 (0.54, 8.5)	428. fefoda970 (0.54, 10.4)
249. Lovida200 (0.55, 10.5)	339. bewoby210 (0.54, 10.4)	429. viking210 (0.54, 6.3)
250. chhidc990 (0.55, 12.8)	340. yfelib990 (0.54, 10.3)	430. uwerig980 (0.54, 10.3)
251. vitetu900 (0.55, 10.6)	341. india@260 (0.54, 8.6)	431. alaska270 (0.54, 7.3)

432. ovasaw280 (0.54, 10.1)
433. ncueng50$ (0.54, 14.0)
434. danika900 (0.54, 7.5)
435. okuloj900 (0.54, 9.7)
436. yellow900 (0.54, 6.2)
437. azerty900 (0.54, 6.1)
438. Sufian210 (0.54, 9.0)
439. zyfopa970 (0.54, 10.2)
440. zynoku220 (0.54, 10.4)
441. flying200 (0.54, 6.8)
442. loving220 (0.54, 7.1)
443. xokowa900 (0.54, 10.0)
444. jajiwa294 (0.54, 10.9)
445. zavewa994 (0.54, 10.5)
446. xiqexy994 (0.54, 10.1)
447. fullon900 (0.54, 8.6)
448. qwerty900 (0.54, 5.3)
449. jopiqa900 (0.54, 10.2)
450. isaiah200 (0.54, 6.6)
451. jodipy220 (0.54, 10.9)
452. zserty900 (0.54, 9.6)
453. alirsk270 (0.54, 12.3)
454. typeha994 (0.54, 10.2)
455. biziku960 (0.54, 10.6)
456. kevinc210 (0.54, 8.4)
457. mumepa260 (0.54, 10.3)
458. vumiwy900 (0.54, 9.9)
459. pkllsx900 (0.54, 12.8)
460. xikoky960 (0.54, 10.5)
461. egytpy280 (0.54, 13.9)
462. sewiha970 (0.54, 10.6)
463. pazihy220 (0.54, 10.2)
464. voketa900 (0.54, 10.0)
465. aqasum280 (0.54, 10.1)
466. oniriv970 (0.54, 10.2)
467. izaiah210 (0.54, 7.6)
468. apolon900 (0.54, 8.2)
469. cgbrth900 (0.54, 12.2)
470. ujelof900 (0.54, 10.3)
471. myziwy970 (0.54, 10.5)
472. regina220 (0.54, 7.1)
473. matron900 (0.54, 8.5)
474. vyfixa970 (0.54, 10.5)
475. marlon280 (0.54, 7.7)
476. demoza294 (0.54, 10.4)
477. muyiwa900 (0.54, 6.4)
478. freeiz900 (0.54, 8.7)
479. behoxa900 (0.54, 11.8)
480. heyong210 (0.54, 8.8)
481. amzoqq900 (0.54, 13.6)
482. mauroB57$ (0.54, 13.3)
483. puziju960 (0.54, 10.9)
484. cofoxa970 (0.54, 10.2)
485. hotrod900 (0.54, 6.7)
486. qwerty270 (0.54, 6.0)
487. ufyroq900 (0.54, 9.8)
488. afasub270 (0.54, 9.9)
489. david@200 (0.54, 7.8)
490. elgigc900 (0.54, 12.2)
491. nujifu960 (0.54, 10.2)
492. admin+210 (0.54, 9.3)
493. tuning210 (0.54, 7.3)
494. gubiga294 (0.54, 10.6)
495. legend080 (0.54, 7.2)
496. sonovy210 (0.54, 10.6)
497. lifojy960 (0.54, 10.6)
498. gebiby294 (0.54, 10.6)
499. merlin900 (0.54, 6.6)
500. tuneha900 (0.54, 10.1)
501. ikirix900 (0.54, 9.6)
502. SimonL000 (0.54, 9.6)
503. qoveda260 (0.54, 10.4)
504. neniju220 (0.54, 10.6)
505. pablog970 (0.54, 10.1)
506. cokecy290 (0.54, 10.0)
507. dofipu294 (0.54, 10.0)
508. matrix900 (0.54, 6.1)
509. Lefou*210 (0.54, 11.5)
510. ziqocy960 (0.54, 10.0)
511. athlon900 (0.54, 7.5)
512. esasuv280 (0.54, 9.8)
513. peteta280 (0.54, 10.1)
514. logofa960 (0.54, 9.8)
515. qwerty280 (0.54, 6.2)
516. uvusyh260 (0.54, 10.3)
517. locoqp294 (0.54, 12.9)
518. daksh@900 (0.54, 8.9)
519. venom●210 (0.54, 9.9)
520. tocomy294 (0.54, 11.2)
521. ipalow960 (0.54, 9.7)
522. fenix●200 (0.54, 9.3)
523. almomd900 (0.54, 11.7)
524. pybigu294 (0.54, 10.5)
525. finipu960 (0.54, 10.9)
526. xafoqa960 (0.54, 10.1)
527. olyrob970 (0.54, 10.1)
528. xodiha960 (0.54, 10.2)
529. italia900 (0.54, 6.4)
530. otilia900 (0.54, 9.0)
531. isaiah210 (0.54, 6.6)
532. stalin900 (0.54, 7.1)
533. devepy920 (0.54, 11.0)
534. evatup270 (0.54, 10.2)
535. jevewy920 (0.54, 10.3)
536. damsam200 (0.54, 8.4)
537. ximena920 (0.54, 8.3)
538. umasyd260 (0.54, 10.3)
539. isorin970 (0.54, 10.5)
540. makeCA010 (0.54, 11.5)
541. dukegu280 (0.54, 11.2)
542. callo@910 (0.54, 11.8)
543. logivy294 (0.54, 10.4)
544. admin●210 (0.54, 8.4)
545. tweety270 (0.54, 7.3)
546. ridewu920 (0.54, 11.1)
547. piqinu910 (0.54, 9.9)
548. himinu910 (0.54, 10.5)
549. radexu260 (0.54, 10.6)
550. qibiva960 (0.54, 10.4)
551. afylid260 (0.54, 10.4)
552. sanron960 (0.54, 10.4)
553. sazsaz200 (0.54, 9.1)
554. Yellow55# (0.54, 8.4)
555. tahsan200 (0.54, 8.4)
556. cbvtyc990 (0.54, 13.0)
557. vucewy920 (0.54, 10.2)
558. montay990 (0.54, 9.2)
559. arysug260 (0.54, 10.2)
560. xeqeva920 (0.54, 10.3)
561. bihequ280 (0.54, 10.2)
562. piersw260 (0.54, 11.3)
563. kinifa294 (0.54, 10.3)
564. rollin22s (0.54, 8.4)
565. refsc-200 (0.54, 12.7)
566. fohohy294 (0.54, 10.2)
567. ktmexc200 (0.54, 7.8)
568. achema080 (0.54, 11.2)
569. Azerty910 (0.54, 7.6)
570. nabina910 (0.54, 9.5)
571. ravenn000 (0.54, 8.2)
572. aqalog260 (0.54, 10.6)
573. dillon93d (0.54, 9.3)
574. hibesa960 (0.54, 10.4)
575. vipehy270 (0.54, 10.5)
576. qwerty57$ (0.54, 7.9)
577. lovenk000 (0.54, 8.9)
578. rohihy294 (0.54, 10.2)
579. ytatyb260 (0.54, 10.4)
580. arion@28# (0.54, 11.9)
581. miasia97# (0.54, 11.1)
582. ianian910 (0.54, 9.1)
583. rynoqy294 (0.54, 10.6)
584. jovenp000 (0.54, 10.3)
585. wemean000 (0.54, 9.6)
586. yufeng000 (0.54, 8.1)
587. clutch260 (0.54, 8.2)
588. ipusyk200 (0.54, 10.6)
589. vivek_000 (0.54, 7.9)
590. vujexy260 (0.54, 10.3)
591. lukesy900 (0.54, 10.6)
592. dagohy994 (0.54, 9.9)
593. matrix200 (0.54, 5.5)
594. xahepu920 (0.54, 10.3)
595. yaslim200 (0.54, 9.9)
596. Maxima910 (0.54, 8.3)
597. gomezz200 (0.54, 8.5)
598. geneva910 (0.54, 7.9)
599. tomek_000 (0.54, 8.6)
600. rapigu994 (0.54, 9.9)
601. biqena290 (0.54, 10.5)
602. sajlin960 (0.54, 11.7)
603. pabohy994 (0.54, 10.8)
604. ohirif200 (0.54, 10.4)
605. athena000 (0.54, 6.8)
606. livoqu994 (0.54, 10.6)
607. exilim200 (0.54, 8.7)
608. ridoqu994 (0.54, 10.7)
609. zyjevy260 (0.54, 10.4)
610. orutum260 (0.54, 10.9)
611. retlob54# (0.54, 12.4)
612. Ahmedw000 (0.54, 10.2)
613. bodega000 (0.54, 7.6)
614. MattiP01# (0.54, 12.6)
615. shorty910 (0.54, 7.0)
616. qwerty260 (0.54, 6.0)
617. zuciqu910 (0.54, 10.1)
618. onslow910 (0.54, 9.4)
619. court_920 (0.54, 10.7)
620. acheny000 (0.54, 10.0)
621. pedocy994 (0.54, 10.1)
622. cpvenu87$ (0.54, 14.0)
623. matrix220 (0.54, 6.2)
624. shorty260 (0.54, 7.0)
625. badegg000 (0.54, 9.5)
626. wonoku994 (0.54, 10.7)
627. mivicu910 (0.54, 10.7)
628. obirod910 (0.54, 10.3)
629. aqolig200 (0.54, 10.4)
630. qeteta260 (0.54, 10.0)
631. kamon@200 (0.54, 10.5)
632. shalom910 (0.54, 7.7)
633. pyjijy994 (0.54, 10.0)
634. cwarim200 (0.54, 11.7)
635. sherif220 (0.54, 7.3)
636. memedy000 (0.54, 9.4)
637. mahsaz980 (0.54, 10.6)
638. cepenu290 (0.54, 10.5)
639. jopeby260 (0.54, 11.1)
640. dudoby994 (0.54, 10.8)
641. syarif200 (0.54, 7.6)
642. madrid200 (0.54, 5.9)
643. khalsa910 (0.54, 8.3)
644. khalid200 (0.54, 6.2)
645. byzomu994 (0.54, 10.3)
646. zynipu994 (0.54, 10.6)
647. ttslip200 (0.54, 11.4)
648. jiweja000 (0.54, 10.4)
649. rebeca000 (0.54, 6.7)
650. kozlov910 (0.54, 9.7)
651. Wklein80# (0.54, 12.7)
652. givovu994 (0.54, 10.4)
653. ryfejv000 (0.54, 12.6)
654. almeja000 (0.54, 8.3)
655. tuarik200 (0.54, 11.1)
656. nuwovy994 (0.54, 9.9)
657. qejigy910 (0.54, 10.2)
658. orelof910 (0.54, 9.3)
659. navey$000 (0.53, 12.0)
660. hotrod910 (0.53, 7.2)
661. cixipu910 (0.53, 10.2)
662. baleia910 (0.53, 9.3)
663. mensha200 (0.53, 9.2)
664. mehedy000 (0.53, 8.3)
665. Godiva54# (0.53, 10.4)
666. madrid220 (0.53, 7.3)
667. emilia200 (0.53, 7.4)
668. dinesh270 (0.53, 8.0)
669. prasad990 (0.53, 7.5)
670. muslim210 (0.53, 7.2)
671. bchezz210 (0.53, 11.4)
672. rideon22s (0.53, 10.5)
673. danopa910 (0.53, 11.0)
674. fyninu920 (0.53, 10.5)
675. kypida994 (0.53, 10.6)
676. jibivu994 (0.53, 10.8)
677. mensah200 (0.53, 4.6)
678. zydopa994 (0.53, 10.6)
679. rbbtmb220 (0.53, 12.5)
680. qowika910 (0.53, 10.2)
681. ofiroh220 (0.53, 9.9)
682. elilip220 (0.53, 9.6)
683. ramrod200 (0.53, 7.4)
684. flying994 (0.53, 8.6)
685. qwerty99z (0.53, 7.7)
686. rameya000 (0.53, 8.7)
687. fefesa290 (0.53, 10.4)
688. zopeva210 (0.53, 10.3)
689. bigsby220 (0.53, 9.0)
690. wupiha994 (0.53, 10.5)
691. ycelom200 (0.53, 10.5)
692. agatha200 (0.53, 7.0)
693. sowrov200 (0.53, 11.5)
694. johoja994 (0.53, 11.3)
695. barrow200 (0.53, 7.4)
696. matrix910 (0.53, 6.7)
697. ekarip910 (0.53, 10.5)
698. daniya994 (0.53, 9.2)
699. tictac900 (0.53, 7.5)
700. ugelin910 (0.53, 10.7)
701. gensan200 (0.53, 9.7)

702. mantha92s	(0.53, 10.6)	
703. peqoja910	(0.53, 10.4)	
704. utyroq910	(0.53, 10.1)	
705. madrid210	(0.53, 7.1)	
706. anglia200	(0.53, 7.3)	
707. enilog200	(0.53, 10.2)	
708. joqexa210	(0.53, 10.4)	
709. astrix210	(0.53, 8.4)	
710. ceprom200	(0.53, 10.3)	
711. whatup990	(0.53, 8.3)	
712. dapova994	(0.53, 10.2)	
713. henrik200	(0.53, 7.1)	
714. zorrow200	(0.53, 9.2)	
715. derric210	(0.53, 8.5)	
716. sallom200	(0.53, 8.4)	
717. mdbehd200	(0.53, 12.7)	
718. mikegb220	(0.53, 9.9)	
719. yellow200	(0.53, 5.4)	
720. osyedd000	(0.53, 11.5)	
721. alaska210	(0.53, 6.5)	
722. gloria200	(0.53, 6.3)	
723. jarrod200	(0.53, 7.3)	
724. montha200	(0.53, 9.3)	
725. timtam220	(0.53, 8.4)	
726. admind96d	(0.53, 10.8)	
727. raxoba994	(0.53, 10.2)	
728. teoria200	(0.53, 7.9)	
729. willow200	(0.53, 6.0)	
730. hotrod200	(0.53, 6.3)	
731. fovowa994	(0.53, 10.6)	
732. pillow200	(0.53, 7.3)	
733. patron220	(0.53, 7.3)	
734. Mensah200	(0.53, 4.6)	
735. monica910	(0.53, 7.1)	
736. kedlin55$	(0.53, 12.1)	
737. cabron220	(0.53, 7.5)	
738. ddsltd200	(0.53, 11.3)	
739. heniff24d	(0.53, 12.3)	
740. italia910	(0.53, 7.0)	
741. yratyf990	(0.53, 10.3)	
742. lovegg200	(0.53, 8.1)	
743. iperok210	(0.53, 10.4)	
744. viclog200	(0.53, 8.8)	
745. samsam900	(0.53, 6.8)	
746. soniaf910	(0.53, 10.2)	
747. pstein220	(0.53, 10.5)	
748. tahron220	(0.53, 9.9)	
749. inysup210	(0.53, 10.6)	
750. qupemy210	(0.53, 10.3)	
751. pujesa270	(0.53, 10.0)	
752. aputaw980	(0.53, 10.7)	
753. Syarif200	(0.53, 9.3)	
754. patron200	(0.53, 6.5)	
755. ocutac200	(0.53, 10.2)	
756. piolin200	(0.53, 6.8)	
757. linea.994	(0.53, 12.2)	
758. ninety090	(0.53, 9.6)	
759. zubikh994	(0.53, 13.2)	
760. sharon200	(0.53, 6.4)	
761. Bonenk000	(0.53, 10.5)	
762. Roniag51$	(0.53, 13.2)	
763. hotrod210	(0.53, 6.7)	
764. carlin200	(0.53, 7.7)	
765. yellow210	(0.53, 6.0)	
766. kofing920	(0.53, 10.7)	
767. gaylon200	(0.53, 9.1)	
768. nikesb910	(0.53, 9.5)	
769. jayron210	(0.53, 8.8)	
770. rodri.210	(0.53, 10.0)	
771. jerrod210	(0.53, 8.0)	
772. zefiwa994	(0.53, 10.2)	
773. rfvthf900	(0.53, 10.8)	
774. merlin200	(0.53, 6.1)	
775. Nairod200	(0.53, 10.0)	
776. obatux200	(0.53, 9.8)	
777. berlin200	(0.53, 6.4)	
778. pakoda920	(0.53, 10.2)	
779. gogeta994	(0.53, 8.8)	
780. isaiah910	(0.53, 7.3)	
781. iaglsd210	(0.53, 12.8)	
782. tdersa210	(0.53, 12.2)	
783. Admin@200	(0.53, 7.6)	
784. izutak900	(0.53, 9.8)	
785. mewlon210	(0.53, 11.0)	
786. hinsky220	(0.53, 10.5)	
787. rebeca200	(0.53, 6.7)	
788. corroa210	(0.53, 10.3)	
789. collin200	(0.53, 6.7)	
790. Ahih90*	(0.53, 13.5)	
791. Eresic03#	(0.53, 13.6)	
792. pymizu920	(0.53, 10.3)	
793. seatac200	(0.53, 8.9)	
794. ryythy200	(0.53, 12.4)	
795. yxusum210	(0.53, 10.4)	
796. ezasup980	(0.53, 10.5)	
797. bogoka920	(0.53, 11.4)	
798. citron200	(0.53, 7.4)	
799. prueba000	(0.53, 5.5)	
800. fujesy910	(0.53, 10.5)	
801. qwerty220	(0.53, 5.6)	
802. anaegy000	(0.53, 10.5)	
803. caneca000	(0.53, 8.0)	
804. willow920	(0.53, 7.2)	
805. vuzepu200	(0.53, 10.2)	
806. tamtam294	(0.53, 8.4)	
807. bohihy920	(0.53, 10.7)	
808. shorty220	(0.53, 6.5)	
809. azerty220	(0.53, 6.1)	
810. Fleetw00d	(0.53, 6.8)	
811. Sweetw00d	(0.53, 7.4)	
812. ricibu920	(0.53, 10.1)	
813. truson92#	(0.53, 12.4)	
814. puerta210	(0.53, 8.4)	
815. ulerow920	(0.53, 10.3)	
816. zunibu920	(0.53, 10.7)	
817. shveta090	(0.53, 9.6)	
818. gideon200	(0.53, 6.5)	
819. stelth210	(0.53, 10.0)	
820. dillon200	(0.53, 6.4)	
821. ulatyv210	(0.53, 10.3)	
822. milroy27d	(0.53, 11.0)	
823. shutup900	(0.53, 7.4)	
824. djflow920	(0.53, 11.0)	
825. moutaz200	(0.53, 8.7)	
826. DeweyM020	(0.53, 12.1)	
827. ilasug220	(0.53, 10.4)	
828. kipety920	(0.53, 10.4)	
829. uzasyg294	(0.53, 10.6)	
830. adytza900	(0.53, 9.2)	
831. mavoba920	(0.53, 11.0)	
832. rodeca220	(0.53, 10.5)	
833. alaska900	(0.53, 6.3)	
834. qwerty210	(0.53, 5.5)	
835. Goblin210	(0.53, 8.6)	
836. ronron200	(0.53, 7.8)	
837. tociza920	(0.53, 10.4)	
838. Anotpw29t	(0.53, 14.0)	
839. Avalon210	(0.53, 7.5)	
840. ynelid920	(0.53, 10.6)	
841. fleetw00d	(0.53, 6.2)	
842. monica22*	(0.53, 8.1)	
843. zomega200	(0.53, 9.0)	
844. shorty210	(0.53, 6.1)	
845. justin98$	(0.53, 7.8)	
846. tiqeba200	(0.53, 10.3)	
847. hotrod920	(0.53, 7.3)	
848. govecy220	(0.53, 10.6)	
849. qwerty200	(0.53, 5.3)	
850. pharty200	(0.53, 9.5)	
851. Sillsw00d	(0.53, 10.5)	
852. Qwerty090	(0.53, 6.4)	
853. ballou200	(0.53, 7.3)	
854. Starsp200	(0.53, 10.1)	
855. egataw960	(0.53, 10.3)	
856. vinroy200	(0.53, 10.3)	
857. Sizeon87$	(0.53, 12.2)	
858. ihalin920	(0.53, 10.5)	
859. azerty200	(0.53, 5.8)	
860. dacefu220	(0.53, 10.3)	
861. Avalon200	(0.53, 7.1)	
862. wakeup010	(0.53, 7.8)	
863. usuriw920	(0.53, 10.8)	
864. quartz090	(0.53, 8.4)	
865. ahmed●010	(0.53, 7.7)	
866. pajeda200	(0.53, 10.3)	
867. Admin@000	(0.53, 6.1)	
868. teresa210	(0.53, 6.8)	
869. clutch900	(0.53, 7.7)	
870. ajirim994	(0.53, 10.2)	
871. dakota97t	(0.53, 9.0)	
872. aqelij920	(0.53, 10.1)	
873. qudepu200	(0.53, 10.2)	
874. Smartf00d	(0.53, 8.2)	
875. nifty@920	(0.53, 11.4)	
876. BossBR900	(0.53, 12.8)	
877. kamrin920	(0.53, 9.5)	
878. Tallow00d	(0.53, 10.5)	
879. pereta200	(0.53, 9.0)	
880. tefegy904	(0.53, 10.4)	
881. italia920	(0.53, 7.3)	
882. puzena210	(0.53, 10.2)	
883. hselin82#	(0.53, 11.9)	
884. Taytay200	(0.53, 7.7)	
885. Reset_000	(0.53, 8.7)	
886. yralop994	(0.53, 10.1)	
887. otatup220	(0.53, 9.8)	
888. fakeby200	(0.53, 9.4)	
889. garlic25z	(0.53, 10.3)	
890. ufytyf960	(0.53, 10.1)	
891. ruboka230	(0.53, 10.7)	
892. Anton@09#	(0.53, 10.9)	
893. wamesa920	(0.53, 11.3)	
894. dobecy220	(0.53, 10.3)	
895. okyrib920	(0.53, 10.4)	
896. mohemd010	(0.53, 10.5)	
897. login@080	(0.53, 8.5)	
898. ahmeda010	(0.53, 8.2)	
899. smartf00d	(0.53, 7.7)	
900. ryweda904	(0.53, 10.1)	
901. qehenu260	(0.53, 10.4)	
902. maxima230	(0.53, 7.7)	
903. whatup960	(0.53, 8.8)	
904. hollow27*	(0.53, 9.8)	
905. nkatmp900	(0.53, 12.4)	
906. Ajalon82$	(0.53, 12.8)	
907. qwerty090	(0.53, 5.9)	
908. Spurs.210	(0.53, 10.3)	
909. bazena904	(0.53, 10.8)	
910. italia27*	(0.53, 8.3)	
911. migegy260	(0.53, 10.7)	
912. camoqa230	(0.53, 10.2)	
913. bededa904	(0.53, 10.0)	
914. janeth200	(0.53, 7.0)	
915. bazixy230	(0.53, 10.5)	
916. youth●200	(0.53, 9.7)	
917. nybidy230	(0.53, 10.4)	
918. anvinh230	(0.53, 10.7)	
919. Jugend270	(0.53, 11.2)	
920. Micron81$	(0.53, 9.9)	
921. dyxoxa240	(0.53, 10.5)	
922. xaboqu230	(0.53, 9.9)	
923. mideoz000	(0.53, 10.5)	
924. nilesh000	(0.53, 6.7)	
925. gazofa240	(0.53, 10.6)	
926. pacony904	(0.53, 10.1)	
927. cexiga230	(0.53, 10.2)	
928. ohatah294	(0.53, 10.4)	
929. Berlin89#	(0.53, 9.5)	
930. azerty92*	(0.53, 7.8)	
931. cycevu904	(0.53, 10.2)	
932. qwerty27z	(0.53, 7.8)	
933. ytysud294	(0.53, 10.4)	
934. Sobika23*	(0.53, 11.1)	
935. geheim2)*	(0.53, 11.4)	
936. bazika240	(0.53, 9.4)	
937. D@lton90$	(0.53, 10.9)	
938. vipin@000	(0.53, 8.0)	
939. qwaszx900	(0.53, 7.8)	
940. Ahfinn20*	(0.53, 13.3)	
941. cykepa904	(0.53, 10.4)	
942. nokian97*	(0.53, 7.2)	
943. lyqigu230	(0.53, 10.4)	
944. myciqu230	(0.53, 10.8)	
945. cobro_200	(0.53, 10.5)	
946. sohody230	(0.53, 10.1)	
947. sweety200	(0.53, 6.4)	
948. lucian090	(0.53, 8.0)	
949. dajica240	(0.53, 10.4)	
950. tweety200	(0.53, 6.2)	
951. kafocu240	(0.53, 10.7)	
952. cimopy230	(0.53, 10.1)	
953. guponu230	(0.53, 10.7)	
954. Qwerty210	(0.53, 6.7)	
955. wyhecy904	(0.53, 10.0)	
956. cuheny904	(0.53, 9.7)	
957. Mmbiac230	(0.53, 13.3)	
958. dipejy200	(0.53, 10.3)	
959. fahihu230	(0.53, 10.5)	
960. suvozy240	(0.53, 10.7)	
961. pepidy230	(0.53, 10.5)	
962. diwevu984	(0.53, 10.1)	
963. gefehy200	(0.53, 9.8)	
964. Amelia24*	(0.53, 8.3)	
965. squeak010	(0.53, 8.0)	
966. appiah240	(0.53, 8.2)	
967. mimou.090	(0.53, 11.1)	
968. mitesh000	(0.53, 7.0)	
969. toyota98$	(0.53, 8.3)	
970. tugiju240	(0.53, 10.2)	
971. sobedy984	(0.53, 10.1)	

972. money@010 (0.52, 7.9)	982. piolin92* (0.52, 9.3)	992. xikexu984 (0.52, 10.2)
973. Darrin21d (0.52, 10.9)	983. teresa000 (0.52, 6.5)	993. jagoba274 (0.52, 10.4)
974. kegiqa230 (0.52, 10.2)	984. pociva29* (0.52, 12.1)	994. kikinh090 (0.52, 10.2)
975. Wipro@000 (0.52, 7.5)	985. jejeby974 (0.52, 10.5)	995. ganesh000 (0.52, 5.8)
976. xiviby240 (0.52, 10.3)	986. nadeau210 (0.52, 8.5)	996. ygysak910 (0.52, 10.2)
977. babijn21g (0.52, 13.9)	987. junesh000 (0.52, 9.4)	997. pihedu220 (0.52, 10.6)
978. rokeku984 (0.52, 10.6)	988. sayoyu84$ (0.52, 13.2)	998. sejeha984 (0.52, 9.9)
979. qicifu240 (0.52, 10.6)	989. zicojy240 (0.52, 9.9)	999. login_000 (0.52, 7.3)
980. pijong090 (0.52, 11.4)	990. sweetu000 (0.52, 7.2)	
981. depimu240 (0.52, 10.3)	991. abhi@$000 (0.52, 9.5)	

Cluster 11

Prototype: arn120208y

Hard-assigned passwords: 1135410 (3.92% of total)
Unique hard-assigned passwords: 852221 (24.94% of cluster total)

Cluster-assignment scores:
	Min: 0.068
	Max: 0.700
	Mean: 0.221
	SD: 0.115

Strength bins:
	Very weak: 10978 (0.97%)
	Weak: 67950 (5.98%)
	Fair: 171986 (15.15%)
	Good: 728044 (64.12%)
	Strong: 156452 (13.78%)

Password lengths:
	Length 8: 503 (0.04%)
	Length 9: 404876 (35.66%)
	Length 10: 468834 (41.29%)
	Length 11: 243357 (21.43%)
	Length 12: 17840 (1.57%)

Character classes:
	4 classes: 30959 (2.73%)
	3 classes: 209923 (18.49%)
		lower/upper/symbol: 497 (0.24%)
		lower/upper/number: 154271 (73.49%)
		lower/symbol/number: 54656 (26.04%)
		upper/symbol/number: 499 (0.24%)
	2 classes: 894512 (78.78%)
		lower/upper: 277 (0.03%)
		lower/number: 892630 (99.79%)
		lower/symbol: 1251 (0.14%)
		upper/number: 44 (0.00%)
		upper/symbol: 11 (0.00%)
		number/symbol: 299 (0.03%)
	1 class: 16 (0.00%)
		lower: 0 (0.00%)
		upper: 0 (0.00%)
		symbol: 16 (100.00%)
		number: 0 (0.00%)

Most frequent char-class structures:
	LLLDDDDDD: 157800 (13.9%)
	LLLLDDDDDD: 116918 (10.3%)
	LLLLLDDDDD: 73356 (6.5%)
	LLDDDDDDDD: 43661 (3.8%)
	LLLDDDDDDD: 39825 (3.5%)
	LLLLDDDDD: 33563 (3.0%)
	LLDDDDDDD: 31620 (2.8%)
	LLLDDDDDDDD: 30531 (2.7%)
	LLLLDDDDDD: 24979 (2.2%)
	LLLLDLLLL: 20140 (1.8%)

1,000 nearest passwords

0.	clk500LIN	(0.70, 12.3)	52.	clb061158	(0.69, 9.7)	104.	cr.523728	(0.69, 12.7)
1.	Xia0109HC	(0.70, 14.0)	53.	niu945848	(0.69, 11.4)	105.	mob976538	(0.69, 11.7)
2.	bob04JOHN	(0.70, 10.6)	54.	srk050758	(0.69, 10.0)	106.	iru920318	(0.69, 10.9)
3.	srw0711NH	(0.70, 14.0)	55.	hlm060858	(0.69, 10.3)	107.	jrw005548	(0.69, 11.7)
4.	Ken082958	(0.70, 10.2)	56.	ita091058	(0.69, 10.0)	108.	bla800348	(0.69, 11.6)
5.	lea994138	(0.69, 11.0)	57.	Cld561748	(0.69, 12.6)	109.	ply585858	(0.69, 9.3)
6.	Brk5346cN	(0.69, 14.0)	58.	drj020658	(0.69, 9.8)	110.	asd992148	(0.69, 10.2)
7.	hrv50YKHT	(0.69, 14.0)	59.	cou064658	(0.69, 12.0)	111.	usu010458	(0.69, 11.2)
8.	lin5401GT	(0.69, 12.8)	60.	rod962258	(0.69, 11.0)	112.	son0427^^	(0.69, 11.9)
9.	slc83PITT	(0.69, 14.0)	61.	jon90RACH	(0.69, 12.1)	113.	ria077558	(0.69, 11.7)
10.	jek961948	(0.69, 11.3)	62.	jrc081658	(0.69, 9.5)	114.	rod010458	(0.69, 9.6)
11.	Feb081958	(0.69, 8.4)	63.	yra504348	(0.69, 12.5)	115.	new089638	(0.69, 10.9)
12.	kla014048	(0.69, 11.3)	64.	lou041258	(0.69, 9.7)	116.	cem585858	(0.69, 7.8)
13.	sln052648	(0.69, 11.1)	65.	crb070458	(0.69, 9.9)	117.	Osa5603M8	(0.69, 14.0)
14.	tru092248	(0.69, 10.9)	66.	alh071258	(0.69, 10.1)	118.	tsn004038	(0.69, 11.4)
15.	sep021958	(0.69, 7.9)	67.	ven315KAT	(0.69, 12.9)	119.	btu071438	(0.69, 11.9)
16.	sra072358	(0.69, 11.5)	68.	drh081158	(0.69, 9.7)	120.	prg831948	(0.69, 11.2)
17.	jlu5323LI	(0.69, 13.5)	69.	hey555YOU	(0.69, 12.1)	121.	sed534458	(0.69, 11.3)
18.	Sid0690WH	(0.69, 13.3)	70.	rlj022258	(0.69, 10.4)	122.	mia050358	(0.69, 9.4)
19.	jea010648	(0.69, 10.7)	71.	jla985928	(0.69, 11.7)	123.	arp911228	(0.69, 10.3)
20.	kla029348	(0.69, 12.0)	72.	rlh071158	(0.69, 10.1)	124.	psb918758	(0.69, 11.7)
21.	lek963258	(0.69, 9.6)	73.	web074248	(0.69, 10.2)	125.	Ilu061318	(0.69, 12.2)
22.	beg022758	(0.69, 10.5)	74.	Msa017258	(0.69, 11.8)	126.	few087338	(0.69, 12.2)
23.	kem990048	(0.69, 11.3)	75.	erb060148	(0.69, 10.7)	127.	don013438	(0.69, 10.4)
24.	keb915648	(0.69, 11.9)	76.	Il<3ALLAH	(0.69, 13.1)	128.	Rob011758	(0.69, 10.0)
25.	win888WIN	(0.69, 9.1)	77.	sef021248	(0.69, 10.7)	129.	kon520AYU	(0.69, 14.0)
26.	peg090658	(0.69, 10.3)	78.	red33FAST	(0.69, 10.3)	130.	jsp945348	(0.69, 11.6)
27.	@rc922038	(0.69, 13.3)	79.	jsu93019M	(0.69, 14.0)	131.	Rlb927218	(0.69, 12.7)
28.	feb031958	(0.69, 7.4)	80.	dlj012258	(0.69, 9.9)	132.	ksa012358	(0.69, 10.0)
29.	jsj076LHC	(0.69, 14.0)	81.	win94.6FM	(0.69, 14.0)	133.	mlp541258	(0.69, 11.2)
30.	aek958448	(0.69, 11.7)	82.	ssg963258	(0.69, 10.0)	134.	ely548548	(0.69, 10.3)
31.	jeg056048	(0.69, 11.9)	83.	ned378MEH	(0.69, 14.0)	135.	fsg062058	(0.69, 10.9)
32.	lex001WHI	(0.69, 13.5)	84.	stu020038	(0.69, 11.1)	136.	lin032358	(0.69, 9.3)
33.	srd092158	(0.69, 10.8)	85.	won082948	(0.69, 10.9)	137.	etk998738	(0.69, 12.3)
34.	prp031858	(0.69, 10.7)	86.	you012358	(0.69, 9.1)	138.	slv910928	(0.69, 11.0)
35.	rom923958	(0.69, 11.5)	87.	arm552958	(0.69, 10.5)	139.	Mom062258	(0.69, 10.2)
36.	mrg005638	(0.69, 11.4)	88.	klc051358	(0.69, 10.1)	140.	mi@524048	(0.69, 12.1)
37.	ysn923648	(0.69, 12.0)	89.	Roy052048	(0.69, 10.8)	141.	joy038538	(0.69, 11.3)
38.	arh013UTM	(0.69, 14.0)	90.	rta040458	(0.69, 10.5)	142.	roy030138	(0.69, 10.0)
39.	crh093058	(0.69, 10.1)	91.	ksa020858	(0.69, 10.1)	143.	noa941128	(0.68, 10.6)
40.	jlj031958	(0.69, 9.8)	92.	jed584558	(0.69, 10.9)	144.	den908618	(0.68, 10.7)
41.	slb050958	(0.69, 9.5)	93.	you040148	(0.69, 10.0)	145.	asd011938	(0.68, 9.8)
42.	Ita091058	(0.69, 10.8)	94.	Don082838	(0.69, 10.7)	146.	nov011958	(0.68, 7.6)
43.	Dog8763JC	(0.69, 13.5)	95.	rlb551958	(0.69, 10.2)	147.	Zrf007228	(0.68, 13.1)
44.	dec021958	(0.69, 7.1)	96.	rlm5427.C	(0.69, 14.0)	148.	lsd020158	(0.68, 9.8)
45.	ktm520EXC	(0.69, 8.9)	97.	yek930228	(0.69, 11.1)	149.	lia940728	(0.68, 9.8)
46.	jeg032158	(0.69, 10.4)	98.	jr@080818	(0.69, 11.1)	150.	stu936228	(0.68, 11.6)
47.	ren924928	(0.69, 11.4)	99.	ron090548	(0.69, 9.7)	151.	crx950728	(0.68, 10.7)
48.	crk074758	(0.69, 12.1)	100.	grw082048	(0.69, 11.0)	152.	drd045228	(0.68, 11.6)
49.	hex962148	(0.69, 11.8)	101.	ala810458	(0.69, 11.0)	153.	mom081158	(0.68, 8.9)
50.	clh081858	(0.69, 9.7)	102.	psu021448	(0.69, 10.5)	154.	krd080128	(0.68, 10.8)
51.	reg031448	(0.69, 10.6)	103.	asa012938	(0.69, 10.9)	155.	web8HOSt8	(0.68, 12.8)

156. jrh542848 (0.68, 11.0)
157. reh395REH (0.68, 11.7)
158. med887358 (0.68, 10.8)
159. isa541958 (0.68, 9.9)
160. Sep041918 (0.68, 10.0)
161. dob092748 (0.68, 9.2)
162. pop050848 (0.68, 9.8)
163. rob031358 (0.68, 9.3)
164. csd070758 (0.68, 10.1)
165. cid001248 (0.68, 10.8)
166. rez540958 (0.68, 11.5)
167. llf931018 (0.68, 10.6)
168. oiu987OIU (0.68, 12.6)
169. reg872458 (0.68, 11.1)
170. krw586858 (0.68, 10.7)
171. jin920628 (0.68, 9.3)
172. rof031648 (0.68, 11.7)
173. flc558558 (0.68, 10.8)
174. mtg032258 (0.68, 10.2)
175. dew999328 (0.68, 11.0)
176. Moa950128 (0.68, 11.7)
177. dlx564738 (0.68, 11.6)
178. asj0319JU (0.68, 14.0)
179. jth082958 (0.68, 9.6)
180. ben514028 (0.68, 10.0)
181. Ft@001218 (0.68, 12.5)
182. mon585858 (0.68, 8.0)
183. ptm093048 (0.68, 11.0)
184. wlb960318 (0.68, 10.2)
185. lip050158 (0.68, 10.4)
186. god900728 (0.68, 10.5)
187. grb524338 (0.68, 11.3)
188. bsb062758 (0.68, 10.0)
189. ftb031948 (0.68, 10.6)
190. ara560328 (0.68, 10.7)
191. bob042"*B (0.68, 14.0)
192. alc589358 (0.68, 11.1)
193. liu520558 (0.68, 9.0)
194. tim020758 (0.68, 9.1)
195. ssv080958 (0.68, 10.4)
196. srq581158 (0.68, 11.8)
197. mrv021128 (0.68, 11.0)
198. blf964318 (0.68, 12.1)
199. crf050428 (0.68, 10.5)
200. alb904318 (0.68, 11.4)
201. dsd990928 (0.68, 10.5)
202. mlz941218 (0.68, 11.1)
203. Jon808858 (0.68, 11.5)
204. arx828758 (0.68, 12.0)
205. you073528 (0.68, 11.2)
206. jrh987118 (0.68, 11.2)
207. lra951108 (0.68, 10.5)
208. nsb071748 (0.68, 10.9)
209. rrb241958 (0.68, 10.4)
210. Den571618 (0.68, 11.4)
211. jtk040358 (0.68, 10.2)
212. ash050558 (0.68, 9.2)
213. Mod006628 (0.68, 11.8)
214. ssn591248 (0.68, 11.2)
215. geb221058 (0.68, 10.3)
216. feb221958 (0.68, 6.4)
217. mia940118 (0.68, 9.4)
218. miu547548 (0.68, 11.6)
219. cec847658 (0.68, 11.5)
220. rrp5657#8 (0.68, 14.0)
221. msh041558 (0.68, 9.9)
222. ten580128 (0.68, 10.4)
223. ben944108 (0.68, 10.4)
224. ita080228 (0.68, 10.4)
225. niu990518 (0.68, 10.3)
226. tea916708 (0.68, 11.3)
227. qiu910518 (0.68, 9.6)
228. cew818258 (0.68, 12.2)
229. asd987528 (0.68, 9.1)
230. crg943508 (0.68, 11.7)
231. Ola960108 (0.68, 11.1)
232. qiu970618 (0.68, 10.5)
233. Lea050508 (0.68, 9.4)
234. jth032248 (0.68, 9.8)
235. dec777DEC (0.68, 10.6)
236. pop585858 (0.68, 7.5)
237. Ben061008 (0.68, 9.1)
238. Wed091908 (0.68, 9.9)
239. eru031208 (0.68, 10.5)
240. asd988128 (0.68, 10.0)
241. kim845KIM (0.68, 11.3)
242. me_860328 (0.68, 11.3)
243. yip930128 (0.68, 10.8)
244. red911008 (0.68, 9.0)
245. mia857658 (0.68, 10.9)
246. msu832458 (0.68, 11.6)
247. ilc7254BN (0.68, 14.0)
248. psn040628 (0.68, 11.0)
249. Wed041908 (0.68, 10.5)
250. red514428 (0.68, 10.1)
251. Wld832328 (0.68, 12.7)
252. min024228 (0.68, 11.1)
253. Yln841218 (0.68, 12.0)
254. tom811958 (0.68, 9.5)
255. rsp972128 (0.68, 11.3)
256. mtn052328 (0.68, 10.7)
257. cla020108 (0.68, 9.3)
258. min970118 (0.68, 9.9)
259. din579248 (0.68, 11.2)
260. mln020508 (0.68, 10.0)
261. fsc032458 (0.68, 10.7)
262. liz010758 (0.68, 9.5)
263. jsd502448 (0.68, 11.4)
264. mom052028 (0.68, 9.9)
265. mlm540828 (0.68, 10.7)
266. bob303BOB (0.68, 10.3)
267. Lin042428 (0.68, 10.4)
268. llc030918 (0.68, 10.5)
269. red811028 (0.68, 9.0)
270. web522828 (0.68, 9.8)
271. gsc030358 (0.68, 10.0)
272. xsq005038 (0.68, 12.7)
273. mra071808 (0.68, 10.2)
274. Srw548928 (0.68, 13.0)
275. dec221958 (0.68, 6.6)
276. min099128 (0.68, 11.1)
277. big32CENT (0.68, 11.5)
278. job999((((0.68, 11.9)
279. jln050508 (0.68, 9.6)
280. gep232658 (0.68, 11.2)
281. dec241948 (0.68, 7.2)
282. rsj980628 (0.68, 10.7)
283. cty901018 (0.68, 10.0)
284. meh3711MM (0.68, 12.7)
285. dob241058 (0.68, 8.9)
286. asd051628 (0.68, 9.6)
287. rsn888.r8 (0.68, 14.0)
288. ken011108 (0.68, 8.6)
289. den007008 (0.68, 8.6)
290. Mr.328358 (0.68, 12.0)
291. wlj565828 (0.68, 11.5)
292. dsm50-148 (0.68, 13.7)
293. Meb061408 (0.68, 10.5)
294. gsm513648 (0.68, 11.1)
295. wed021608 (0.68, 9.3)
296. lsf920818 (0.68, 10.2)
297. bec920408 (0.68, 10.4)
298. aew532028 (0.68, 11.8)
299. wed020208 (0.68, 8.8)
300. Drm012508 (0.68, 10.5)
301. kea080808 (0.68, 8.6)
302. mid564448 (0.68, 11.2)
303. Llb062908 (0.68, 10.6)
304. lea238258 (0.68, 11.0)
305. wrd062508 (0.68, 10.7)
306. wsj510958 (0.68, 11.8)
307. jin921208 (0.68, 8.7)
308. jlb227748 (0.68, 10.8)
309. ard008008 (0.68, 9.3)
310. sin042618 (0.68, 10.1)
311. ded050408 (0.68, 9.6)
312. tim910518 (0.68, 9.5)
313. dec231938 (0.68, 7.6)
314. lin741ABC (0.68, 11.0)
315. aom3R06cT (0.68, 14.0)
316. wlp850628 (0.68, 10.5)
317. alc597328 (0.68, 11.5)
318. jlm551818 (0.68, 10.7)
319. aej906508 (0.68, 12.2)
320. red234738 (0.68, 10.2)
321. gth930818 (0.68, 10.4)
322. Alk080708 (0.68, 10.2)
323. mrg012308 (0.68, 10.3)
324. Dlb030308 (0.68, 10.4)
325. joy940208 (0.68, 9.8)
326. dec241148 (0.68, 9.9)
327. Lex050908 (0.68, 9.6)
328. hlm518518 (0.68, 10.1)
329. com722LIN (0.68, 11.6)
330. you908908 (0.68, 9.9)
331. lly512518 (0.68, 11.0)
332. Clp080808 (0.68, 9.5)
333. Ss.587818 (0.68, 12.9)
334. web892228 (0.68, 10.0)
335. feb291948 (0.68, 7.4)
336. jt%032108 (0.68, 12.3)
337. Dev062508 (0.68, 10.0)
338. arm291058 (0.68, 9.7)
339. jlb580218 (0.68, 10.4)
340. atm040928 (0.68, 10.3)
341. psy001218 (0.68, 11.1)
342. tom818748 (0.68, 10.4)
343. vip062228 (0.68, 9.9)
344. Lev082908 (0.68, 10.3)
345. mlp061308 (0.68, 9.5)
346. joy990408 (0.68, 9.9)
347. boy932008 (0.68, 10.0)
348. Cec011508 (0.68, 11.0)
349. Mef008008 (0.68, 10.2)
350. clb092208 (0.68, 9.3)
351. Lej088308 (0.67, 12.8)
352. lrp032208 (0.67, 10.1)
353. clp050908 (0.67, 9.3)
354. Bob080818 (0.67, 10.1)
355. bry010708 (0.67, 9.3)
356. dsg831138 (0.67, 11.2)
357. alp060508 (0.67, 9.3)
358. nsn996908 (0.67, 11.8)
359. nov231958 (0.67, 6.5)
360. loc882658 (0.67, 11.3)
361. web090508 (0.67, 8.1)
362. meg070708 (0.67, 8.7)
363. dom060718 (0.67, 10.0)
364. lly881818 (0.67, 10.4)
365. rem000308 (0.67, 11.0)
366. jia519028 (0.67, 10.6)
367. jim221948 (0.67, 9.0)
368. trk020408 (0.67, 9.5)
369. mem050608 (0.67, 9.1)
370. som228358 (0.67, 11.0)
371. non248048 (0.67, 11.2)
372. lin78JPPT (0.67, 14.0)
373. nim531148 (0.67, 10.8)
374. mlm033008 (0.67, 9.8)
375. hsn537228 (0.67, 11.6)
376. hou850528 (0.67, 10.3)
377. len230558 (0.67, 10.1)
378. feb082008 (0.67, 6.9)
379. feb012008 (0.67, 6.6)
380. csd024118 (0.67, 11.3)
381. doc809658 (0.67, 11.1)
382. ven349858 (0.67, 12.0)
383. lsd944208 (0.67, 11.4)
384. lin520528 (0.67, 9.5)
385. ns@070208 (0.67, 11.1)
386. liu811028 (0.67, 7.7)
387. rlw980108 (0.67, 10.5)
388. srf510318 (0.67, 11.2)
389. dec271958 (0.67, 6.7)
390. web010408 (0.67, 8.0)
391. ron860828 (0.67, 9.5)
392. aly888818 (0.67, 10.7)
393. clj840328 (0.67, 10.6)
394. nov231938 (0.67, 7.5)
395. jsb012328 (0.67, 10.2)
396. jek210958 (0.67, 10.9)
397. hek062808 (0.67, 11.2)
398. nov231948 (0.67, 7.1)
399. lin891028 (0.67, 8.4)
400. ken552508 (0.67, 10.1)
401. kim526%@^ (0.67, 13.8)
402. yoj870258 (0.67, 12.0)
403. mlm040608 (0.67, 9.0)
404. rob236148 (0.67, 10.6)
405. mic910318 (0.67, 9.8)
406. plj880428 (0.67, 10.7)
407. zek030808 (0.67, 10.2)
408. dec261958 (0.67, 6.6)
409. prf060408 (0.67, 10.3)
410. kim876358 (0.67, 11.0)
411. lex052008 (0.67, 9.1)
412. lek030708 (0.67, 9.6)
413. rrh002108 (0.67, 10.8)
414. wew890828 (0.67, 10.2)
415. dex008008 (0.67, 9.3)
416. den329258 (0.67, 10.2)
417. eta081208 (0.67, 9.5)
418. wsq930318 (0.67, 10.7)
419. liu839028 (0.67, 10.2)
420. alf010908 (0.67, 9.0)
421. deh040508 (0.67, 9.5)
422. liu516618 (0.67, 10.2)
423. vlc836128 (0.67, 11.6)
424. Ron053008 (0.67, 10.0)
425. mef080908 (0.67, 9.6)

426. rof227348 (0.67, 12.0)
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894. Sen000888 (0.66, 10.6)
895. Meg031588 (0.66, 10.3)
896. Asd332448 (0.66, 10.6)
897. mla090588 (0.66, 9.7)
898. gsg031778 (0.66, 10.4)
899. wtp091078 (0.66, 10.8)
900. toj013178 (0.66, 11.3)
901. web787828 (0.66, 9.6)
902. joa656SUN (0.66, 14.0)
903. Alf884578 (0.66, 12.1)
904. rta231708 (0.66, 11.1)
905. msp052478 (0.66, 10.2)
906. mtp292518 (0.66, 11.3)
907. den041988 (0.66, 8.5)
908. him286518 (0.66, 11.1)
909. six55B&@H (0.66, 14.0)
910. dim091278 (0.66, 9.5)
911. rsp042478 (0.66, 10.2)
912. feb212008 (0.66, 6.3)
913. rob070778 (0.66, 8.7)
914. eid282418 (0.66, 11.8)
915. bln020988 (0.66, 10.1)
916. lea081688 (0.66, 9.2)
917. bsm093078 (0.66, 10.4)
918. nid252518 (0.66, 10.7)
919. tox020878 (0.66, 10.4)
920. red770918 (0.66, 9.3)
921. feb292008 (0.66, 6.4)
922. box808808 (0.66, 9.7)
923. vrn202128 (0.66, 11.6)
924. etv369258 (0.66, 10.6)
925. ^sn21001^ (0.66, 14.0)
926. gex951988 (0.66, 11.4)
927. Sep205558 (0.66, 11.5)
928. sec316918 (0.66, 10.5)
929. kig284818 (0.66, 11.7)
930. pla281208 (0.66, 9.8)
931. sep212008 (0.66, 7.2)
932. mtm051078 (0.66, 9.7)
933. Feb282828 (0.66, 10.1)
934. Asm359348 (0.66, 12.3)
935. Feb021988 (0.66, 7.3)
936. cih301158 (0.66, 11.5)
937. Bea20139^ (0.66, 13.9)
938. msb081978 (0.66, 9.3)
939. asb081978 (0.66, 9.6)
940. ped091988 (0.66, 9.9)
941. tod230608 (0.66, 10.3)
942. asm860408 (0.66, 10.5)
943. lo.817178 (0.66, 12.7)
944. Mom230328 (0.66, 10.7)
945. hsp820608 (0.66, 10.1)
946. lsh251228 (0.66, 10.4)
947. moh880908 (0.66, 9.1)
948. feb282008 (0.66, 6.4)
949. ush891208 (0.66, 10.8)
950. sra030688 (0.66, 9.9)
951. feb262008 (0.66, 6.3)
952. ztg225508 (0.66, 12.1)
953. ben062488 (0.66, 9.0)
954. Lem091688 (0.66, 10.6)
955. rtn242108 (0.66, 11.5)
956. Jim042178 (0.66, 9.9)
957. csy783848 (0.66, 11.4)
958. lim880908 (0.66, 10.0)
959. wen081188 (0.66, 8.8)
960. med024088 (0.66, 10.2)
961. tim821008 (0.66, 9.4)
962. nea090188 (0.66, 10.0)
963. zen000888 (0.66, 10.0)
964. csx215118 (0.66, 11.3)
965. mom307928 (0.66, 10.6)

966. alg022988 (0.66, 10.1)
967. rey041288 (0.66, 8.9)
968. feb241978 (0.66, 6.3)
969. Nov201958 (0.66, 7.5)
970. kia201518 (0.66, 10.3)
971. Crc774828 (0.66, 12.5)
972. red718718 (0.66, 8.3)
973. ysb808308 (0.66, 11.4)
974. Jtw081478 (0.66, 10.6)
975. ben251108 (0.66, 8.4)
976. web968188 (0.66, 10.0)
977. lea221078 (0.66, 9.1)
978. jea072188 (0.66, 10.2)
979. jlf883078 (0.66, 11.4)
980. mey011088 (0.66, 10.1)
981. ken040488 (0.66, 8.6)
982. Mef954388 (0.66, 12.7)
983. feb221978 (0.66, 6.3)
984. glu290208 (0.66, 10.5)
985. csc510808 (0.66, 10.1)
986. sep252008 (0.66, 7.3)
987. Ns@041288 (0.66, 11.3)
988. mic566408 (0.66, 11.2)
989. mif081278 (0.66, 10.4)
990. web731018 (0.66, 8.9)
991. brd071388 (0.66, 10.1)
992. jrp021988 (0.66, 9.5)
993. asd331628 (0.66, 9.4)
994. rem786818 (0.66, 11.4)
995. isn552178 (0.66, 11.6)
996. crc774828 (0.66, 11.3)
997. sed325008 (0.66, 11.1)
998. dec212008 (0.66, 6.4)
999. yen241078 (0.66, 9.7)

Cluster 12

```
Prototype: 2da1a122g

Hard-assigned passwords: 840012 (2.90% of total)
Unique hard-assigned passwords: 628215 (25.21% of cluster total)

Cluster-assignment scores:
        Min: 0.090
        Max: 0.855
        Mean: 0.280
        SD: 0.088

Strength bins:
        Very weak: 19912 (2.37%)
        Weak: 86181 (10.26%)
        Fair: 203757 (24.26%)
        Good: 389024 (46.31%)
        Strong: 141138 (16.80%)

Password lengths:
        Length 8: 352573 (41.97%)
        Length 9: 404470 (48.15%)
        Length 10: 82969 (9.88%)

Character classes:
        4 classes: 28934 (3.44%)
        3 classes: 210786 (25.09%)
                lower/upper/symbol: 2801 (1.33%)
                lower/upper/number: 177499 (84.21%)
                lower/symbol/number: 26949 (12.79%)
                upper/symbol/number: 3537 (1.68%)
        2 classes: 566408 (67.43%)
                lower/upper: 7557 (1.33%)
                lower/number: 525831 (92.84%)
                lower/symbol: 947 (0.17%)
                upper/number: 29807 (5.26%)
                upper/symbol: 1691 (0.30%)
                number/symbol: 575 (0.10%)
        1 class: 33884 (4.03%)
                lower: 0 (0.00%)
                upper: 33854 (99.91%)
                symbol: 30 (0.09%)
                number: 0 (0.00%)

Most frequent char-class structures:
        DDLLLLLL: 57738 (6.9%)
        DLLLLLLL: 39900 (4.7%)
        DLLLLLL: 35914 (4.3%)
        DDLLLLLL: 34111 (4.1%)
        UUUUUUUU: 30621 (3.6%)
        DDLLLLDD: 22181 (2.6%)
        DLLLLLD: 18044 (2.1%)
        DDDLLLLL: 17629 (2.1%)
        DLDLDLDL: 14846 (1.8%)
        DDLLLLLDD: 14815 (1.8%)
```

1,000 nearest passwords

```
  0. 5c2Igee5$    (0.85, 14.0)
  1. 3#Megan4$    (0.85, 11.5)
  2. 4hJpb9bNt    (0.85, 14.0)
  3. 4n99ymbot    (0.85, 14.0)
  4. M1k3cusi$    (0.85, 14.0)
  5. 3j1buy*&$    (0.85, 14.0)
  6. w1P9krot$    (0.84, 14.0)
  7. 4Me2find$    (0.84, 10.1)
  8. 5kyLine1$    (0.84, 14.0)
  9. 5am8ghert    (0.84, 13.6)
 10. 4nsRhus4t    (0.82, 14.0)
 11. yIN7slm2g    (0.82, 14.0)
 12. !#Mango!#    (0.82, 11.3)
 13. 5r6gzfplg    (0.82, 14.0)
 14. 4me2talk*    (0.82, 10.8)
 15. 4u2mechat    (0.82,  8.6)
 16. 4nj0solit    (0.82, 11.4)
 17. m1n3craft    (0.82,  5.5)
 18. l1v3@tru#    (0.82, 12.5)
 19. 2g2bbtwat    (0.82, 13.5)
 20. 4ku●t4kut    (0.82, 12.9)
 21. s1b3rkurt    (0.82, 10.8)
 22. 2na2bydet    (0.82, 13.6)
 23. s1g4nteng    (0.82,  8.2)
 24. 4u2xpctit    (0.81, 14.0)
 25. 4kr8chtig    (0.81, 13.5)
 26. 5l5qkubjg    (0.81, 14.0)
 27. 4k42kvygg    (0.81, 14.0)
 28. L1f2short    (0.81, 10.8)
 29. 4me2swing    (0.81, 10.2)
 30. 3nd3rwigg    (0.81, 10.5)
 31. B1k3rguy#    (0.81, 11.3)
 32. rUw0rking    (0.81, 10.9)
 33. 5ia7yjyrg    (0.81, 14.0)
 34. 2k22shirt    (0.81, 11.3)
 35. 5s7UpWa0$    (0.80, 14.0)
 36. 2Fr0ggle$    (0.80, 13.1)
 37. 4r6tdkfcg    (0.80, 14.0)
 38. !br4kskit    (0.80, 14.0)
 39. M1n3craft    (0.80,  5.9)
 40. 4s55dling    (0.80, 13.0)
 41. 5l4kuqlct    (0.80, 14.0)
 42. BBSykes7$    (0.80, 13.4)
 43. GBUNdmq7t    (0.80, 14.0)
 44. 5TR1ng8Ag    (0.80, 14.0)
 45. 4yLRkaq5b    (0.80, 14.0)
 46. ERPokk3n$    (0.80, 14.0)
 47. rIy8hLz2t    (0.80, 14.0)
 48. 2be2benot    (0.80,  9.7)
 49. !L10nking    (0.80,  9.5)
 50. 5u5anGr3g    (0.80, 12.8)
 51. PV96rajat    (0.80, 13.2)
 52. S1r0g@lIt    (0.80, 14.0)
 53. 3tt3cker*    (0.79, 13.0)
 54. 2k9samrat    (0.79, 11.1)
 55. 4x4carpet    (0.79,  8.1)
 56. 4me2young    (0.79,  8.5)
 57. 3g0nblant    (0.79, 13.5)
 58. WDGis2hot    (0.79, 13.4)
 59. 4p0gnaaet    (0.79, 14.0)
 60. 3d3nswift    (0.79, 10.0)
 61. 4bP2yuQ4g    (0.79, 14.0)
 62. HP87elect    (0.79, 12.6)
 63. 5s@4y@4ng    (0.79, 14.0)
 64. MB21subat    (0.79, 12.5)
 65. 5u48wufyb    (0.79, 14.0)
 66. 2p2MsB8pt    (0.79, 14.0)
 67. DF02kuls$    (0.79, 14.0)
 68. MY02girl$    (0.79, 10.9)
 69. 5wx6biytb    (0.79, 14.0)
 70. w1y7doxut    (0.78, 13.1)
 71. TRAiner4$    (0.78, 11.4)
 72. PRIvate8*    (0.78, 10.8)
 73. tI5qnwEwg    (0.78, 14.0)
 74. N1c0l@s*#    (0.78, 10.3)
 75. 2k7ukgrrt    (0.78, 14.0)
 76. HGSrnpw2#    (0.78, 14.0)
 77. 5h8FqtS3b    (0.78, 14.0)
 78. 2s18dki##    (0.78, 14.0)
 79. U4tBsaa9b    (0.78, 14.0)
 80. 3k4s@y4ng    (0.78, 12.9)
 81. .1M0nday$    (0.78, 12.7)
 82. 2G0lf_nut    (0.78, 13.5)
 83. QWERt!@#$    (0.78,  8.0)
 84. lInPasi10    (0.78, 13.1)
 85. UC3MbtD7t    (0.78, 14.0)
 86. d1o2wning    (0.78, 12.1)
 87. w1l8urcat    (0.78, 13.1)
 88. RM23yrvet    (0.78, 14.0)
 89. !@12grunt    (0.78, 11.3)
 90. 3s3sil3nt    (0.78, 13.1)
 91. DH88comet    (0.78, 11.8)
 92. 2sx3dc%tg    (0.77, 14.0)
 93. f1f1kereg    (0.77, 14.0)
 94. 2x2=empat    (0.77, 11.7)
 95. 3k7Trcqdg    (0.77, 14.0)
 96. 4ty9ersfb    (0.77, 12.5)
 97. 2H7Ox4pkt    (0.77, 14.0)
 98. $13Sm1le$    (0.77, 12.3)
 99. 4x4mudbog    (0.77, 10.7)
100. TB61sport    (0.77, 11.8)
101. 4p39pmtat    (0.77, 14.0)
102. 5jy4yemxb    (0.77, 14.0)
103. 5fa5tian*    (0.77, 13.2)
104. MK92fcs##    (0.77, 14.0)
105. ZBc3zdTwg    (0.77, 14.0)
106. b1o1ogic$    (0.77, 14.0)
107. 99s1lver$    (0.77, 13.0)
108. HD73sport    (0.77, 11.5)
109. !am2smart    (0.77, 12.0)
110. ABCdef!@#    (0.77,  7.3)
111. 3l3phant#    (0.77,  7.2)
112. EVIL@!dog    (0.77, 12.6)
113. GR33nport    (0.77,  9.4)
114. gOOdbye10    (0.77, 10.6)
115. 4xvDlnq60    (0.77, 14.0)
116. sAZ9m4Avg    (0.77, 14.0)
117. SRQpr0fit    (0.77, 14.0)
118. !GHpass00    (0.77, 12.0)
119. RR30maret    (0.77, 11.4)
120. 2i2cexpfg    (0.77, 14.0)
121. 5ce9sxjut    (0.77, 14.0)
122. DM4wzuzyg    (0.77, 14.0)
123. KCHam1let    (0.77, 13.5)
124. CV_pswd_#    (0.77, 14.0)
125. 5anKalp10    (0.77, 14.0)
126. EP4misu5t    (0.77, 14.0)
127. 2+2=empat    (0.77, 10.5)
128. 2jy9rtezg    (0.77, 14.0)
129. iUK1sn2Q0    (0.77, 14.0)
130. 5P0ngeB0b    (0.76, 10.8)
131. CG23pabs*    (0.76, 14.0)
132. 2k4mumsag    (0.76, 13.0)
133. 2b||not2b    (0.76, 11.0)
134. 4PP3lfl4p    (0.76, 12.7)
135. s1o2ghrat    (0.76, 13.3)
136. s1m0nsay$    (0.76,  8.5)
137. SPI@cc3$$    (0.76, 13.3)
138. GRh0sting    (0.76, 10.0)
139. c1v1lblog    (0.76, 12.1)
140. 2●2=empat    (0.76, 10.9)
141. 4l13n@Bug    (0.76, 14.0)
142. 4n20years    (0.76, 12.5)
143. CW21stmsg    (0.76, 14.0)
144. r1p3m@ng0    (0.76, 11.7)
145. ABCabc!@#    (0.76,  6.2)
146. vI1avrO90    (0.76, 14.0)
147. 2t00sweet    (0.76,  9.2)
148. 3d71rohit    (0.76, 12.4)
149. AU02elect    (0.76, 11.6)
150. CHeFove3*    (0.76, 14.0)
151. BP94stang    (0.76, 11.9)
152. 4gl1eoyzp    (0.76, 14.0)
153. KM10ezzat    (0.76, 11.9)
154. NY99minit    (0.76, 13.4)
155. CPPch3ung    (0.76, 13.4)
156. 3s4banget    (0.76,  9.9)
157. 3b3nsal0t    (0.76, 11.1)
158. GQqLbd7*$    (0.76, 14.0)
159. 2k10loong    (0.76, 12.1)
160. t6A*n22L#    (0.76, 14.0)
161. 4by4turb0    (0.76, 12.2)
```

162. 4Me2cn2it (0.76, 12.3)
163. 5p0ngeB0b (0.76, 9.7)
164. 4zj4yyep0 (0.76, 14.0)
165. s1p1lblog (0.76, 12.2)
166. w1a8ledeb (0.76, 13.1)
167. 4b3ghmdf0 (0.76, 14.0)
168. k1k1maret (0.76, 10.1)
169. 5T3enb3rg (0.76, 13.0)
170. AD81mo$** (0.76, 14.0)
171. 4l3jandr0 (0.76, 5.9)
172. t1g3rlink (0.76, 7.8)
173. 3uT2pbhm0 (0.76, 14.0)
174. 2zg4dunkb (0.76, 14.0)
175. w1d3ruins (0.76, 10.2)
176. 4u2bsweet (0.76, 9.2)
177. pA1$nting (0.76, 14.0)
178. 2CLoyvd40 (0.75, 14.0)
179. 5bk5rdep0 (0.75, 14.0)
180. 4ss2hole0 (0.75, 14.0)
181. EX83llent (0.75, 13.5)
182. RQ2brpgat (0.75, 14.0)
183. l1k3ntrip (0.75, 12.4)
184. B1u3stars (0.75, 9.1)
185. 3ng1neers (0.75, 7.6)
186. b1i9ubplg (0.75, 14.0)
187. sEEcret40 (0.75, 12.2)
188. bAiLiw1ck (0.75, 14.0)
189. x1x2ardit (0.75, 13.3)
190. NUMbers8* (0.75, 11.4)
191. l1c3umxl0 (0.75, 14.0)
192. RSGspr1ng (0.75, 11.5)
193. 3ph3sians (0.75, 8.8)
194. CF46pitjt (0.75, 14.0)
195. 4e5htujgp (0.75, 14.0)
196. N7bJvU2wg (0.75, 14.0)
197. 2w6fnervg (0.75, 14.0)
198. PU09saint (0.75, 12.6)
199. 3c01mpact (0.75, 12.3)
200. 3l3ph@nt* (0.75, 9.6)
201. G1v3andg0 (0.75, 12.3)
202. 3m3coaqe0 (0.75, 14.0)
203. 2EZ2f0get (0.75, 14.0)
204. 4O77n8je0 (0.75, 14.0)
205. eO35nofP0 (0.75, 14.0)
206. 3cl3ttic0 (0.75, 11.6)
207. a1n2gaKok (0.75, 14.0)
208. yIRvmmx00 (0.75, 14.0)
209. 5m2Sfbsj0 (0.75, 14.0)
210. !alBert10 (0.75, 10.6)
211. TR3bl3nu$ (0.75, 13.9)
212. 4u2seey2k (0.75, 11.9)
213. 2y06tfIng (0.75, 14.0)
214. 4W00dlink (0.75, 10.8)
215. D3vNull00 (0.75, 13.5)
216. 4zt8gwrnt (0.75, 14.0)
217. SF49eratb (0.75, 13.7)
218. 2K2ismyct (0.75, 14.0)
219. m1m1reang (0.75, 12.4)
220. 4v0fzariz (0.75, 14.0)
221. 2r1dablbb (0.75, 13.9)
222. 5v4kytzab (0.75, 14.0)
223. 2NuStrt10 (0.75, 14.0)
224. l1c2adsfg (0.75, 13.3)
225. REDhat!@# (0.75, 8.6)
226. m1h0sting (0.75, 8.0)
227. 3d3sxdxdt (0.75, 14.0)
228. L1o2ulink (0.75, 11.3)
229. CC40mrcmt (0.75, 14.0)
230. NHpOy4qeb (0.75, 14.0)
231. 3yy2rmnop (0.75, 14.0)
232. 4r1efpunk (0.75, 12.2)
233. 3v1lzpunk (0.75, 12.7)
234. LD15inebg (0.75, 14.0)
235. F4kGfx8ek (0.75, 14.0)
236. 3d0ardit0 (0.75, 12.1)
237. f14Tomcat (0.75, 6.4)
238. 3ft4lbhdk (0.75, 14.0)
239. VRX5fj5Jg (0.75, 14.0)
240. 3/1gowers (0.75, 13.0)
241. n1c3shooz (0.75, 13.3)
242. 4<d*h%R8$ (0.74, 14.0)
243. l1l1ana** (0.74, 10.9)
244. 3@1oceans (0.74, 11.1)
245. A3EIx7z0g (0.74, 14.0)
246. w1n4erers (0.74, 13.1)
247. $1m3trick (0.74, 10.2)
248. 5g85zSEjt (0.74, 14.0)
249. 4b1gkdmsk (0.74, 13.9)
250. 4n4ksehat (0.74, 9.1)
251. 3ad3rains (0.74, 12.2)
252. WENdell1$ (0.74, 9.3)
253. LI50benit (0.74, 12.7)
254. PREimr4ab (0.74, 14.0)
255. 3ff1cient (0.74, 11.4)
256. 5a55yzack (0.74, 13.2)
257. JETking1* (0.74, 11.0)
258. 5mm9zvnit (0.74, 14.0)
259. w1d5dmiE0 (0.74, 14.0)
260. k1w1fruit (0.74, 11.3)
261. 3on1break (0.74, 11.1)
262. yA9plkY1z (0.74, 14.0)
263. qEVVq7l70 (0.74, 14.0)
264. ODArtc9bg (0.74, 14.0)
265. #17Dewalt (0.74, 10.8)
266. 3e2cjezfk (0.74, 14.0)
267. #15Tebowt (0.74, 14.0)
268. m1m1ngcat (0.74, 10.6)
269. 3@9ljbmaz (0.74, 14.0)
270. 3ur0pian0 (0.74, 11.5)
271. 4vk4rdstk (0.74, 14.0)
272. 4o4vtztfz (0.74, 14.0)
273. *EDCrfv3* (0.74, 11.4)
274. 5oh7seong (0.74, 13.5)
275. 4me2qwert (0.74, 9.6)
276. 3NQXrzs4z (0.74, 14.0)
277. LTw4mlatb (0.74, 14.0)
278. REC0nnect (0.74, 9.4)
279. 2bo2prosp (0.74, 12.1)
280. GODisgr8t (0.74, 6.4)
281. 3ks8bmlnk (0.74, 14.0)
282. 2h6ngb5et (0.74, 14.0)
283. 4c9tercap (0.74, 13.5)
284. VQ1Ia0Abg (0.74, 14.0)
285. 2s72iyufb (0.74, 14.0)
286. JQoKooq9g (0.74, 14.0)
287. AA22the$$ (0.74, 12.8)
288. 6i88sijlb (0.74, 14.0)
289. 4r3maind0 (0.74, 13.2)
290. 3jj3bbxit (0.74, 14.0)
291. s1h0mbing (0.74, 10.4)
292. 2l0ckU0ut (0.74, 14.0)
293. K!LLmyw3b (0.74, 12.3)
294. 5yk3srock (0.74, 12.8)
295. 3n7fgikbz (0.74, 14.0)
296. 5m6nqatrk (0.74, 14.0)
297. 2an6eles$ (0.74, 13.9)
298. v1p3rpunk (0.74, 9.9)
299. k11Unepab (0.74, 14.0)
300. 3z37niejk (0.74, 14.0)
301. ZX81cs$** (0.74, 14.0)
302. SPaGast20 (0.74, 13.8)
303. 4k0oxhmzt (0.74, 14.0)
304. 4b2bfrank (0.74, 10.7)
305. CMPdown2p (0.74, 14.0)
306. vAL7o2Qd0 (0.74, 14.0)
307. Z6jRkMc0g (0.74, 14.0)
308. ASMDt_6dg (0.74, 14.0)
309. VINli!@#$ (0.74, 12.4)
310. ?Y3go4lez (0.74, 14.0)
311. r1g0lett0 (0.74, 8.8)
312. 3g,5la,ek (0.74, 14.0)
313. 2n5exqxpp (0.74, 14.0)
314. 3st3rians (0.74, 9.9)
315. 3l3arning (0.74, 7.1)
316. BOBjeff1$ (0.74, 11.9)
317. ZH5Atwo7b (0.74, 14.0)
318. 4w0hkhpas (0.74, 14.0)
319. SETking1* (0.74, 12.9)
320. VMYay2d2t (0.74, 14.0)
321. RXFdqdo5b (0.74, 14.0)
322. RR1borT0b (0.74, 14.0)
323. m1k3knapp (0.74, 10.4)
324. 3po2vgijk (0.73, 14.0)
325. 5t1menmaz (0.73, 13.2)
326. 4i2dzonbt (0.73, 14.0)
327. ONGara=90 (0.73, 14.0)
328. 2p1hxbmsg (0.73, 14.0)
329. DZsMxl9yp (0.73, 14.0)
330. M1x3ll3nt (0.73, 11.4)
331. 5t4lker_0 (0.73, 12.9)
332. 4TjKm3gbw (0.73, 14.0)
333. 3to6stars (0.73, 10.8)
334. $1b3rpunk (0.73, 12.5)
335. LMKiger00 (0.73, 12.1)
336. uA6PwX3wp (0.73, 14.0)
337. 3r05amu5t (0.73, 13.9)
338. TY06ajJbb (0.73, 14.0)
339. LVTking90 (0.73, 12.1)
340. 4a20bbiap (0.73, 14.0)
341. WHOOpia10 (0.73, 11.9)
342. 5q0kuyep0 (0.73, 14.0)
343. SWEmflu20 (0.73, 14.0)
344. PA66word* (0.73, 9.3)
345. FFFlare20 (0.73, 11.4)
346. BCAemma20 (0.73, 12.2)
347. HPBJxqq00 (0.73, 14.0)
348. MFSuper90 (0.73, 11.4)
349. KBSvood00 (0.73, 13.8)
350. c12Llea8z (0.73, 14.0)
351. 5wt5wtswt (0.73, 14.0)
352. R!d#ab!k# (0.73, 14.0)
353. FREEdom10 (0.73, 6.8)
354. G3t-a-J0b (0.73, 14.0)
355. k1a7zitag (0.73, 12.7)
356. ZBvLumk60 (0.73, 14.0)
357. 5l4ntoo0b (0.73, 14.0)
358. KRCheck90 (0.73, 11.8)
359. SFJHerr80 (0.73, 14.0)
360. 3f8rykv6$ (0.73, 14.0)
361. GMBvyln30 (0.73, 14.0)
362. 3st3spark (0.73, 10.4)
363. WHItton10 (0.73, 11.5)
364. 4n4ks3mut (0.73, 8.7)
365. BNRdoiu10 (0.73, 14.0)
366. SKPBoct10 (0.73, 14.0)
367. VMFArva4$ (0.73, 14.0)
368. CNGpost20 (0.73, 12.8)
369. 3j7rqhm8t (0.73, 14.0)
370. SJ4ever** (0.73, 10.4)
371. TLtJecv50 (0.73, 14.0)
372. AQStage20 (0.73, 13.3)
373. THOmas@70 (0.73, 11.1)
374. SHArone00 (0.73, 11.0)
375. dAgReP000 (0.73, 14.0)
376. ARAlast20 (0.73, 13.1)
377. 3sd3pyxaz (0.73, 14.0)
378. SWEvids20 (0.73, 14.0)
379. 2b1like2b (0.73, 10.7)
380. AKAalan80 (0.73, 12.4)
381. AI7=xiang (0.73, 14.0)
382. MACclub1$ (0.73, 11.9)
383. r1v0lett0 (0.73, 11.0)
384. PZzYc2yhp (0.73, 14.0)
385. OHMerch20 (0.73, 14.0)
386. a1a1@kmbg (0.73, 14.0)
387. JDBooty10 (0.73, 10.8)
388. !ps2notok (0.73, 14.0)
389. 2/3din@#$ (0.73, 14.0)
390. THEcape20 (0.73, 9.7)
391. SCMlink10 (0.73, 9.5)
392. THEgame20 (0.73, 4.3)
393. 4cZpba6Pw (0.73, 14.0)
394. 5v5rawxyz (0.73, 14.0)
395. OSXlion10 (0.73, 12.5)
396. 3l9nvpytk (0.73, 14.0)
397. JRmHirq40 (0.73, 14.0)
398. 5rq1pkpvg (0.73, 14.0)
399. INFairy40 (0.73, 13.1)
400. CDQRpiw20 (0.73, 14.0)
401. GGGunit50 (0.73, 9.4)
402. RMDavis60 (0.73, 10.9)
403. ADVAmed10 (0.73, 13.3)
404. KLHealy10 (0.73, 12.1)
405. 4l4ign4nt (0.73, 11.0)
406. ASShole00 (0.73, 7.3)
407. APOllo@10 (0.73, 11.1)
408. LM2make$$ (0.73, 13.2)
409. NRxLetx30 (0.73, 14.0)
410. 4st7lbkek (0.73, 14.0)
411. WZWVr4kpp (0.73, 14.0)
412. MSLNana10 (0.73, 12.8)
413. CHDNapa80 (0.73, 14.0)
414. ACDCfan80 (0.73, 11.4)
415. LLLwhos40 (0.73, 13.7)
416. DWMyogi10 (0.73, 13.5)
417. AKKelly10 (0.73, 11.1)
418. LM7Oijk40 (0.73, 14.0)
419. 2B41spock (0.73, 13.2)
420. 4gu$t1nu$ (0.73, 13.4)
421. USAgigi20 (0.73, 11.1)
422. EVAunit00 (0.73, 11.8)
423. UMNcell30 (0.73, 13.5)
424. AYOdeji20 (0.73, 10.1)
425. 5l86ddzkk (0.73, 14.0)
426. MTBfuel90 (0.73, 13.4)
427. vIp4kids* (0.73, 13.4)
428. DKKrehn60 (0.73, 14.0)
429. ASCDsns10 (0.73, 13.9)
430. D6I6v6Ln0 (0.73, 14.0)
431. IMeMine30 (0.73, 12.3)

432. k1k1nwang	(0.73, 10.7)	
433. LFCindo20	(0.73, 13.0)	
434. TCLCmyx70	(0.73, 14.0)	
435. LZsWubb80	(0.73, 14.0)	
436. JLCBuff10	(0.73, 13.2)	
437. vIwUrdJ90	(0.73, 14.0)	
438. KDK5kwang	(0.73, 13.8)	
439. 4p4rtm3nt	(0.73, 9.2)	
440. A1w2koihk	(0.73, 14.0)	
441. DJDesil10	(0.73, 12.1)	
442. 4qu4sh0rt	(0.73, 9.6)	
443. MPtLigr10	(0.73, 14.0)	
444. EYEbuck20	(0.73, 13.5)	
445. HGWells30	(0.73, 11.5)	
446. NBGkino40	(0.73, 14.0)	
447. AW05axdfg	(0.73, 14.0)	
448. pI6BvWg40	(0.73, 14.0)	
449. SWELbml20	(0.73, 14.0)	
450. S10NeczK0	(0.73, 13.9)	
451. 5hYQx8jDw	(0.73, 14.0)	
452. NTAdmin00	(0.73, 10.4)	
453. EKMLink10	(0.73, 11.2)	
454. q123qwert	(0.72, 7.3)	
455. LNTouti00	(0.72, 13.2)	
456. 001Tecnet	(0.72, 11.5)	
457. WKZrefk70	(0.72, 14.0)	
458. gU1tar1ng	(0.72, 14.0)	
459. 4d3sayang	(0.72, 8.7)	
460. 4aDodge*#	(0.72, 14.0)	
461. QAZwsx!@#	(0.72, 5.2)	
462. L1c4nonnk	(0.72, 14.0)	
463. 4sr1sm4rt	(0.72, 11.3)	
464. DRBaker70	(0.72, 10.4)	
465. MSOphia00	(0.72, 12.5)	
466. RKBlive70	(0.72, 13.2)	
467. 3fl1ghts*	(0.72, 12.1)	
468. WJSmith50	(0.72, 10.4)	
469. 2nw6yozk0	(0.72, 14.0)	
470. GBColor30	(0.72, 11.6)	
471. 2b4acting	(0.72, 10.5)	
472. MTPilot40	(0.72, 11.1)	
473. z1i5kegoz	(0.72, 12.5)	
474. 2bc2think	(0.72, 11.5)	
475. CUi5pldbg	(0.72, 14.0)	
476. CVGldkx90	(0.72, 14.0)	
477. KWSxjan60	(0.72, 14.0)	
478. 2tq2pock#	(0.72, 14.0)	
479. QWE_iop10	(0.72, 11.1)	
480. 4u00nxyzg	(0.72, 14.0)	
481. 3m3ronm4g	(0.72, 11.8)	
482. 4r15venuz	(0.72, 13.9)	
483. SSGmfrl70	(0.72, 14.0)	
484. XMa.gue20	(0.72, 14.0)	
485. 07tRoll10	(0.72, 12.1)	
486. BSMatt3rs	(0.72, 12.1)	
487. SHOWnow90	(0.72, 11.3)	
488. SCMSves30	(0.72, 14.0)	
489. 4JA7u60M0	(0.72, 14.0)	
490. a1k5kaunp	(0.72, 14.0)	
491. !m0nitor0	(0.72, 10.3)	
492. WTF8wrong	(0.72, 12.7)	
493. 3or4ontop	(0.72, 12.6)	
494. 4me2bgr8t	(0.72, 9.5)	
495. KCCclub10	(0.72, 11.5)	
496. FLOrenz30	(0.72, 10.8)	
497. JMKCar98*	(0.72, 14.0)	
498. 5r2fjegcw	(0.72, 14.0)	
499. 3r3dxvwwg	(0.72, 14.0)	
500. QAZasd!@#	(0.72, 8.2)	
501. PARtner1#	(0.72, 10.5)	
502. TM0zquGq0	(0.72, 14.0)	
503. 3x/jwepM#	(0.72, 14.0)	
504. 2BSoulm8s	(0.72, 14.0)	
505. INC0rr3ct	(0.72, 7.9)	
506. zO4Yy1Hs0	(0.72, 14.0)	
507. AMORmio30	(0.72, 9.3)	
508. OJQueen50	(0.72, 11.9)	
509. 3DOnpN140	(0.72, 14.0)	
510. !x0eogl5k	(0.72, 14.0)	
511. xE62avC4b	(0.72, 14.0)	
512. ARIelle20	(0.72, 10.3)	
513. ACVZasw20	(0.72, 14.0)	
514. 4v9yzkfbw	(0.72, 14.0)	
515. JH$$nnl60	(0.72, 14.0)	
516. qIJcg1jKw	(0.72, 14.0)	
517. NWyNpy9i0	(0.72, 14.0)	
518. TH3_tang0	(0.72, 11.6)	
519. GMbY14jmz	(0.72, 14.0)	
520. 3l3@rning	(0.72, 9.1)	
521. ZAQwsx!@#	(0.72, 6.9)	
522. p1c0bell0	(0.72, 9.3)	
523. d1d1erlag	(0.72, 13.3)	
524. ABC_@_!@#	(0.72, 12.8)	
525. QH0jy6Alb	(0.72, 14.0)	
526. nOM8fK3c0	(0.72, 14.0)	
527. MPiKxq2ek	(0.72, 14.0)	
528. 5b8lasdog	(0.72, 13.3)	
529. 5ma6depok	(0.72, 13.1)	
530. HUNter!@#	(0.72, 9.6)	
531. KVDRh2pdk	(0.72, 14.0)	
532. 5c4jhplzw	(0.72, 14.0)	
533. 4im8or8rt	(0.72, 14.0)	
534. IR8kpvQ6g	(0.72, 14.0)	
535. SGZGedw50	(0.72, 14.0)	
536. 5yp2ihrzg	(0.72, 14.0)	
537. 5PH1j2vYz	(0.72, 14.0)	
538. MDSGoct30	(0.72, 13.8)	
539. ASDFjkl10	(0.72, 8.1)	
540. VT18ls6St	(0.72, 14.0)	
541. GGDaizi10	(0.72, 12.6)	
542. US)Navy80	(0.72, 14.0)	
543. BGU4rghrg	(0.72, 14.0)	
544. TDSlink10	(0.72, 9.8)	
545. LIJet7ing	(0.72, 14.0)	
546. 4j0deeye0	(0.72, 14.0)	
547. CR4zyj$zz	(0.72, 14.0)	
548. 4me2youok	(0.72, 9.3)	
549. CJCQedb70	(0.72, 14.0)	
550. KNJwhit10	(0.72, 13.0)	
551. 5uP3rG33k	(0.72, 9.6)	
552. KMGjune10	(0.72, 11.4)	
553. 4u22ylink	(0.72, 11.8)	
554. PKJ8yPh8b	(0.72, 14.0)	
555. EGBdfa$$$	(0.72, 13.8)	
556. JLSchai10	(0.72, 13.0)	
557. !M0rph1n$	(0.72, 10.3)	
558. 4m0uss0u$	(0.72, 11.6)	
559. 3o2bggwaw	(0.72, 14.0)	
560. QSWApio80	(0.72, 14.0)	
561. STApler0+	(0.72, 12.6)	
562. 5f4ozffvw	(0.72, 14.0)	
563. 3dh3rb3rt	(0.72, 9.6)	
564. 6as2mrhg*	(0.72, 14.0)	
565. ZLDWatc0z	(0.72, 14.0)	
566. 2mg7tmokk	(0.72, 14.0)	
567. 2b4bears*	(0.72, 11.7)	
568. OLUmide80	(0.72, 9.1)	
569. 5t33ld4rt	(0.72, 11.9)	
570. DC2gisL80	(0.72, 14.0)	
571. ALT0clar0	(0.72, 11.6)	
572. 4ss4ssins	(0.72, 7.8)	
573. 4w4kening	(0.72, 11.1)	
574. KB47jdanb	(0.72, 14.0)	
575. 5q4yeuqlw	(0.72, 14.0)	
576. VGY7ujmnb	(0.72, 10.0)	
577. OSUgirl10	(0.72, 10.2)	
578. MR1mancub	(0.72, 12.0)	
579. JJu0askd0	(0.71, 14.0)	
580. 2EGRx74D0	(0.71, 14.0)	
581. CJh0rhins	(0.71, 14.0)	
582. SMOucmd00	(0.71, 14.0)	
583. JBOkids10	(0.71, 12.8)	
584. !@East3rd	(0.71, 12.2)	
585. TWY8v3Bjg	(0.71, 14.0)	
586. M1a2tnkrs	(0.71, 13.4)	
587. z13Vj5pJp	(0.71, 14.0)	
588. NX5Wq8sTp	(0.71, 14.0)	
589. 4me2cumup	(0.71, 9.6)	
590. AZ8sharpp	(0.71, 14.0)	
591. LVGkedw50	(0.71, 14.0)	
592. 5t3amb0at	(0.71, 11.7)	
593. PWDsito50	(0.71, 13.2)	
594. 3q09craig	(0.71, 12.6)	
595. 3e8jkkplw	(0.71, 14.0)	
596. 3h6hdvf4t	(0.71, 14.0)	
597. bAk2watas	(0.71, 14.0)	
598. R3dSpr1ng	(0.71, 9.8)	
599. 3zm4ev7nt	(0.71, 14.0)	
600. TR1plet50	(0.71, 10.9)	
601. 2kd2dg4ct	(0.71, 14.0)	
602. W3CKzw000	(0.71, 14.0)	
603. SG4Ri0jD0	(0.71, 14.0)	
604. 2dp2dppdg	(0.71, 12.9)	
605. s1g4nt3ng	(0.71, 7.8)	
606. NGOwork10	(0.71, 11.6)	
607. PZKseqs40	(0.71, 14.0)	
608. TRP@kqf90	(0.71, 14.0)	
609. VKVVtl9e0	(0.71, 14.0)	
610. p1y2bylub	(0.71, 13.6)	
611. RGIdeas10	(0.71, 12.9)	
612. OPOMee8fz	(0.71, 14.0)	
613. MDS1mmons	(0.71, 12.0)	
614. KTl7j9FQb	(0.71, 14.0)	
615. v1z1sell0	(0.71, 12.8)	
616. RU2busy2p	(0.71, 14.0)	
617. TQiEwx9R0	(0.71, 14.0)	
618. DH7qdhSy0	(0.71, 14.0)	
619. #PaRijn10	(0.71, 14.0)	
620. 5w79fCM20	(0.71, 14.0)	
621. v1v4cious	(0.71, 11.1)	
622. KDFadam00	(0.71, 13.4)	
623. UJStime10	(0.71, 12.4)	
624. F14Tomcat	(0.71, 6.0)	
625. 2gr8tkidz	(0.71, 10.0)	
626. 2d2dbbxyz	(0.71, 13.6)	
627. NSWdifd30	(0.71, 14.0)	
628. DCPrime10	(0.71, 11.3)	
629. r1v3rb0at	(0.71, 7.3)	
630. r1m1ndeep	(0.71, 10.2)	
631. 2Qaz+2Qaz	(0.71, 13.6)	
632. 4MhPxna8w	(0.71, 14.0)	
633. 5t1nkyB00	(0.71, 11.8)	
634. ZXCasd*90	(0.71, 11.1)	
635. 4ng3licAz	(0.71, 13.1)	
636. MSWgrad10	(0.71, 10.9)	
637. LKYffe33$	(0.71, 14.0)	
638. 2xr2ndVf0	(0.71, 14.0)	
639. 5l4dekfbw	(0.71, 14.0)	
640. MQ4hobbit	(0.71, 13.1)	
641. 3ez0jpj4t	(0.71, 14.0)	
642. 3we4er5rt	(0.71, 10.0)	
643. 5qRgiqdqt	(0.71, 14.0)	
644. PJBfaqh60	(0.71, 14.0)	
645. YM7KkrZ90	(0.71, 14.0)	
646. TOPiim!@#	(0.71, 13.7)	
647. 3at3at3at	(0.71, 8.2)	
648. PMPart1$t	(0.71, 14.0)	
649. ODTechw3b	(0.71, 12.8)	
650. 4QwGr5nrj	(0.71, 14.0)	
651. RLKpass10	(0.71, 11.1)	
652. 4g6jfkh4t	(0.71, 14.0)	
653. jENLink10	(0.71, 12.2)	
654. BLSwave40	(0.71, 12.6)	
655. s133hwUK#	(0.71, 14.0)	
656. OMAMp3K0t	(0.71, 14.0)	
657. AY39ki%Sp	(0.71, 14.0)	
658. fEi9lgVv0	(0.71, 14.0)	
659. 3n0barbus	(0.71, 11.9)	
660. 5tr1pp1ng	(0.71, 8.8)	
661. p1k1jakob	(0.71, 12.4)	
662. PWPmate10	(0.71, 11.6)	
663. I3R5tsMig	(0.71, 14.0)	
664. MHCPmay00	(0.71, 13.5)	
665. 4my2girls	(0.71, 5.9)	
666. JJP6bpzfz	(0.71, 14.0)	
667. 2xh6rndoz	(0.71, 14.0)	
668. BIGjohn1%	(0.71, 11.5)	
669. 5p0mcsi4g	(0.71, 14.0)	
670. 85AUu4zng	(0.71, 14.0)	
671. IQ69yayup	(0.71, 14.0)	
672. t1g3r-lnk	(0.71, 12.1)	
673. WMHxevw00	(0.71, 14.0)	
674. 2r1dk!@#$	(0.71, 13.4)	
675. PV29mou++	(0.71, 14.0)	
676. WQn3mxD5t	(0.71, 14.0)	
677. FR65td3St	(0.71, 14.0)	
678. JMUduke10	(0.71, 11.8)	
679. CS3elmcnp	(0.71, 14.0)	
680. NGwOa7xBz	(0.71, 14.0)	
681. b1w6ejjup	(0.71, 14.0)	
682. ASHton21#	(0.71, 10.5)	
683. WLYccmq5z	(0.71, 14.0)	
684. JBH2nai10	(0.71, 14.0)	
685. vUJ3na1Cz	(0.71, 14.0)	
686. ATLanta10	(0.71, 7.9)	
687. gA8vhxydw	(0.71, 14.0)	
688. 2$2isknck	(0.71, 14.0)	
689. 5g0uld1ng	(0.71, 10.6)	
690. 3fk_drift	(0.71, 13.3)	
691. WHTdwrf50	(0.71, 14.0)	
692. 3f3ysoozg	(0.71, 14.0)	
693. 3m3wyaeez	(0.71, 14.0)	
694. INJSion70	(0.71, 14.0)	
695. VM22jmbcp	(0.71, 14.0)	
696. NVGiagp2w	(0.71, 14.0)	
697. 2d7Oi2D3t	(0.71, 14.0)	
698. NYYanks00	(0.71, 8.3)	
699. ARSenal10	(0.71, 7.1)	
700. FV03oC8Sg	(0.71, 14.0)	
701. CC41mrcmt	(0.71, 14.0)	

702. fUYioj9qw (0.71, 14.0)
703. SP29eel30 (0.71, 13.9)
704. KXvBte3c0 (0.71, 14.0)
705. 2bElink3d (0.71, 11.0)
706. 2f53wmvkg (0.71, 14.0)
707. CL4udn4V0 (0.71, 14.0)
708. 2l84afuck (0.71, 12.5)
709. AETank3rs (0.71, 13.5)
710. 2sw5uipez (0.71, 14.0)
711. JC12lig7g (0.71, 14.0)
712. VA3vanang (0.71, 13.8)
713. GOhXzy7tg (0.71, 14.0)
714. AQ!sw2DE# (0.71, 12.2)
715. MSUspar10 (0.71, 12.4)
716. aON1k2rVd (0.71, 14.0)
717. UJc0rback (0.71, 14.0)
718. LRXvoMt80 (0.71, 14.0)
719. ESPinar10 (0.71, 11.1)
720. ONSpass10 (0.71, 10.4)
721. HVTbuff80 (0.71, 13.7)
722. STB8gUf70 (0.71, 14.0)
723. fE95slgF0 (0.71, 14.0)
724. 3du1s1mpt (0.71, 14.0)
725. SLbRjLc0t (0.71, 14.0)
726. 4g0tpaswd (0.71, 12.3)
727. 4x4fordtk (0.71, 10.3)
728. VANessa4$ (0.71, 9.7)
729. F18Hornet (0.71, 7.0)
730. 2@Support (0.70, 9.0)
731. FL1bugout (0.70, 13.4)
732. TCAgrad10 (0.70, 11.5)
733. UNCgrad10 (0.70, 10.4)
734. 4xETavC1g (0.70, 14.0)
735. 02f1zGhd0 (0.70, 14.0)
736. GRP_grp70 (0.70, 12.6)
737. SF49iners (0.70, 13.4)
738. 4f56ahmed (0.70, 11.7)
739. 2h3zqjscg (0.70, 14.0)
740. 2vf9jdgbg (0.70, 14.0)
741. 3ekWdi5bw (0.70, 14.0)
742. PPa$$w0rt (0.70, 10.0)
743. 4LUNbw1wd (0.70, 14.0)
744. 4gr8girls (0.70, 7.4)
745. sOlorR600 (0.70, 14.0)
746. 3l34rn1ng (0.70, 11.5)
747. THEsame10 (0.70, 10.0)
748. 2mt2lo2mt (0.70, 12.6)
749. 5h3epd0g$ (0.70, 12.8)
750. 3xc3ll3nt (0.70, 6.0)
751. n1n1hell0 (0.70, 11.1)
752. 2f7ishing (0.70, 11.5)
753. MBMslm*80 (0.70, 14.0)
754. SLUHigh00 (0.70, 12.7)
755. USFrach80 (0.70, 12.6)
756. DCLink*80 (0.70, 12.5)
757. 4aBreg7l0 (0.70, 14.0)
758. 4g1SvvzUb (0.70, 14.0)
759. JCAcce55* (0.70, 13.0)
760. g1f3zzzvb (0.70, 14.0)
761. SA31scout (0.70, 10.9)
762. SPR0glet0 (0.70, 12.4)
763. 2c75rm0rt (0.70, 14.0)
764. LW0lfp@ck (0.70, 12.0)
765. VKL1vik2b (0.70, 14.0)
766. ZGOQqu1mp (0.70, 14.0)
767. SNOver86* (0.70, 13.0)
768. DK24black (0.70, 10.6)
769. 6wo2tyzap (0.70, 14.0)
770. 4b74nptkd (0.70, 14.0)
771. HPNfsrE10 (0.70, 14.0)
772. 2ez2pleez (0.70, 11.7)
773. 5JDkivu9z (0.70, 14.0)
774. H1s5hadow (0.70, 12.6)
775. PE26jdgfb (0.70, 14.0)
776. QWE!@#qaz (0.70, 8.3)
777. 4nt0jusup (0.70, 12.6)
778. 2/18dclnp (0.70, 14.0)
779. DSI#h3ll0 (0.70, 13.9)
780. JCCrrjr10 (0.70, 13.6)
781. B1g5uckY0 (0.70, 14.0)
782. ADLeach80 (0.70, 12.1)
783. GSNewaQ90 (0.70, 14.0)
784. 3sl1pkn0t (0.70, 9.1)
785. W4MStl4u0 (0.70, 14.0)
786. 4my3girls (0.70, 6.7)
787. GH2Va6cC0 (0.70, 14.0)
788. 4MEko5wF0 (0.70, 14.0)
789. LAKshmi5$ (0.70, 11.0)
790. YW0RcHx80 (0.70, 14.0)
791. 4u2killl# (0.70, 13.2)
792. 4u2nvmeok (0.70, 8.8)
793. fli1xidip (0.70, 13.3)
794. UEYded52# (0.70, 14.0)
795. B1u3blood (0.70, 11.5)
796. 5sAFcVl4t (0.70, 14.0)
797. kll4o5um* (0.70, 14.0)
798. TW14years (0.70, 10.3)
799. vU02pHXvp (0.70, 14.0)
800. 4lYae4P20 (0.70, 14.0)
801. 5c4Hh5Gi0 (0.70, 14.0)
802. BL47hnaik (0.70, 14.0)
803. OKMokm$$$ (0.70, 12.9)
804. I3KFm8n10 (0.70, 14.0)
805. gIg9lefit (0.70, 14.0)
806. M1N3twork (0.70, 10.7)
807. E3dEn_23# (0.70, 14.0)
808. l1l9rosqz (0.70, 14.0)
809. 4n4lbe4d$ (0.70, 14.0)
810. MRB4kucr* (0.70, 14.0)
811. 4Jt5jGwhz (0.70, 14.0)
812. AQ!2wsDE# (0.70, 10.8)
813. b3nTheD0g (0.70, 9.9)
814. 2ez4u2get (0.70, 8.4)
815. 3x3enadiz (0.70, 13.7)
816. 4m2lic2dg (0.70, 14.0)
817. RKEzjuhwp (0.70, 14.0)
818. JIM2zackb (0.70, 14.0)
819. WRK4end10 (0.70, 14.0)
820. d1m4ztwap (0.70, 13.6)
821. 4d4my0ung (0.70, 9.1)
822. 4p3sepu5b (0.70, 14.0)
823. OVERton20 (0.70, 10.8)
824. FBSucks10 (0.70, 10.3)
825. #1p.i.m.p (0.70, 12.6)
826. 2b4racing (0.70, 8.5)
827. VESMad13# (0.70, 14.0)
828. 3Bl4e5web (0.70, 14.0)
829. 2b2xfeN20 (0.70, 14.0)
830. LEL6aBv1b (0.70, 14.0)
831. 4SOhkX220 (0.70, 14.0)
832. 4x4fordtw (0.70, 10.0)
833. 3sAcrowd$ (0.70, 14.0)
834. GTAgta48$ (0.70, 12.2)
835. l1f3guard (0.70, 7.6)
836. oOu7blFLt (0.70, 14.0)
837. h1x3rsasd (0.70, 13.0)
838. KWxZyZt80 (0.70, 14.0)
839. AUCRad13# (0.70, 14.0)
840. Y123ellow (0.70, 11.7)
841. F17Loveit (0.70, 12.3)
842. 3nt3rlink (0.70, 6.9)
843. 3a11t7mug (0.70, 14.0)
844. jO5vuYmpp (0.70, 14.0)
845. j123sleep (0.70, 9.8)
846. m1n3cr4ft (0.70, 5.6)
847. k1w1blink (0.70, 10.9)
848. $Un5and6s (0.70, 14.0)
849. JP0sada20 (0.70, 13.5)
850. ZAQ1wasx# (0.69, 11.6)
851. 2pe5fcotw (0.69, 14.0)
852. 3e5tgf6yg (0.69, 12.9)
853. BEEfast00 (0.69, 12.1)
854. dAd1gMpok (0.69, 14.0)
855. 4v1erpxmp (0.69, 14.0)
856. 3*Babolat (0.69, 11.6)
857. WB12sleuk (0.69, 13.5)
858. 2bXci9qnp (0.69, 14.0)
859. 2n4robert (0.69, 9.6)
860. cAAsey000 (0.69, 13.2)
861. MVr6z0AEp (0.69, 14.0)
862. 4g9ac1wHp (0.69, 14.0)
863. FM1GhY7k0 (0.69, 14.0)
864. A6W8jilXb (0.69, 14.0)
865. 3sm6zrbbb (0.69, 14.0)
866. GZ1pkcB6k (0.69, 14.0)
867. JM10gomez (0.69, 10.8)
868. FTAfta38$ (0.69, 13.8)
869. DFL4dfl20 (0.69, 13.0)
870. d1n0saurs (0.69, 6.6)
871. ASOdis33* (0.69, 14.0)
872. 4(r1bB3mp (0.69, 14.0)
873. m1n0taur0 (0.69, 7.4)
874. 4u7prlvjd (0.69, 14.0)
875. 4rz4xnv1b (0.69, 14.0)
876. MR.fix-it (0.69, 14.0)
877. RB0sdet00 (0.69, 14.0)
878. HWNmeHr30 (0.69, 14.0)
879. 4n35t4bdg (0.69, 13.9)
880. 3-9aezihw (0.69, 14.0)
881. SAN0xiang (0.69, 12.1)
882. 84FDs@0&d (0.69, 14.0)
883. LQsYex7Z0 (0.69, 14.0)
884. LID4craft (0.69, 11.3)
885. AXJEguz9w (0.69, 14.0)
886. SAIram!@# (0.69, 8.8)
887. RKn4tdZxz (0.69, 14.0)
888. 3c2jsivad (0.69, 14.0)
889. 5tf7eazej (0.69, 14.0)
890. xOrPhc0I0 (0.69, 14.0)
891. NW05dbsap (0.69, 14.0)
892. LUZvero10 (0.69, 12.7)
893. eAk3rPbpj (0.69, 14.0)
894. KSXMqv3Q0 (0.69, 14.0)
895. 2io9rlhiz (0.69, 14.0)
896. ZC1fukop0 (0.69, 14.0)
897. RZ27h3JEb (0.69, 14.0)
898. NEPats@80 (0.69, 11.1)
899. ZXSDer45% (0.69, 12.6)
900. CC71trick (0.69, 12.5)
901. 5r5hdjuyj (0.69, 14.0)
902. 5P1umb1ng (0.69, 14.0)
903. cEm5nJObb (0.69, 14.0)
904. CW.drum70 (0.69, 14.0)
905. 3r7oojw2b (0.69, 14.0)
906. aA1@ritik (0.69, 12.8)
907. TENasin10 (0.69, 11.9)
908. 4v0gqbcjp (0.69, 14.0)
909. CUNning50 (0.69, 11.0)
910. GWdHpG720 (0.69, 14.0)
911. 5h6hk0ff* (0.69, 14.0)
912. e1s3nb3rg (0.69, 10.2)
913. KDbUp9Tjg (0.69, 14.0)
914. GG88thunk (0.69, 13.3)
915. JSvTlLo90 (0.69, 14.0)
916. 4M6sb1if* (0.69, 14.0)
917. 4my4kids4 (0.69, 7.9)
918. YB4hgQ3J0 (0.69, 14.0)
919. EMOvfcmg0 (0.69, 14.0)
920. QGjZsO700 (0.69, 14.0)
921. GH1zpapX0 (0.69, 14.0)
922. 3L3ment4L (0.69, 10.4)
923. LXMYl3umw (0.69, 14.0)
924. LNu5nDb40 (0.69, 14.0)
925. 3d3comsep (0.69, 13.6)
926. 4U9js1LAd (0.69, 14.0)
927. ALIcia41$ (0.69, 11.6)
928. GG85truck (0.69, 11.2)
929. NW1iv1VXp (0.69, 14.0)
930. POIson!@# (0.69, 9.8)
931. MC5upp0rt (0.69, 10.6)
932. XD4rkZ3r0 (0.69, 13.7)
933. bOb4mbird (0.69, 14.0)
934. NL6el8mY0 (0.69, 14.0)
935. NTMjhD0jk (0.69, 14.0)
936. K!KLa89#p (0.69, 14.0)
937. 3VeNtPr0d (0.69, 14.0)
938. GILbert40 (0.69, 9.0)
939. 4u2seexyz (0.69, 11.3)
940. 3yPokB430 (0.69, 14.0)
941. 4VA1w8hTs (0.69, 14.0)
942. w1f1rulez (0.69, 9.9)
943. MHd3aPH00 (0.69, 14.0)
944. 5m5kcsxdj (0.69, 14.0)
945. BIGdogg80 (0.69, 9.5)
946. 6m2krsep0 (0.69, 14.0)
947. DT1forget (0.69, 10.9)
948. 5i55kek0t (0.69, 14.0)
949. p1i7ahoyz (0.69, 14.0)
950. 4Gr4moN94 (0.69, 14.0)
951. MS4getnot (0.69, 11.6)
952. BW52vhsfp (0.69, 14.0)
953. 4c1qhdvbp (0.69, 14.0)
954. m1k3child (0.69, 9.5)
955. 5d80kHcud (0.69, 14.0)
956. STPauL390 (0.69, 12.5)
957. NRQKaZl90 (0.69, 14.0)
958. w1h2y3not (0.69, 11.3)
959. UR8Mupp3t (0.69, 12.8)
960. b1b1atriz (0.69, 11.6)
961. 4U2linkjg (0.69, 12.7)
962. 3rdSite14 (0.69, 11.6)
963. DPVthe3rd (0.69, 12.7)
964. ABC.abc.0 (0.69, 8.9)
965. AL31@work (0.69, 11.5)
966. X6kYjH0tp (0.69, 14.0)
967. SRIsri87* (0.69, 12.9)
968. 4nt4riks4 (0.69, 7.7)
969. FBHthe3rd (0.69, 11.5)
970. 3cv3n5lA0 (0.69, 14.0)
971. WEBhost00 (0.69, 7.2)

972. SIKness10 (0.69, 10.6)	982. STBRois20 (0.69, 13.3)	992. 4tl4ntik4 (0.69, 9.1)
973. 3Vn7rRG3z (0.69, 14.0)	983. 6m65mykob (0.69, 14.0)	993. bI2mmZtn0 (0.69, 14.0)
974. MFSSec420 (0.69, 12.7)	984. LI#manu20 (0.69, 13.2)	994. 5q4eefj5b (0.69, 14.0)
975. LEOgirl10 (0.69, 9.6)	985. 5qu1d8urg (0.69, 14.0)	995. 3h97ufm2p (0.69, 14.0)
976. 4Me2nonow (0.69, 10.9)	986. 4k8xanhod (0.69, 14.0)	996. 3ViMi1zv. (0.69, 14.0)
977. b1j1busuk (0.69, 11.5)	987. 5b5cuabcd (0.69, 14.0)	997. HCC1hD3P0 (0.69, 14.0)
978. !nc0nt3xt (0.69, 10.6)	988. 2Zc5oZX3k (0.69, 14.0)	998. YRZje3=id (0.69, 14.0)
979. t1q1krejt (0.69, 14.0)	989. +BMWix330 (0.69, 14.0)	999. LINplop00 (0.69, 11.6)
980. 3hx7zxzbt (0.69, 14.0)	990. 4o1nh3cjt (0.69, 14.0)	
981. 5MOdq96Wz (0.69, 14.0)	991. a113love$ (0.69, 12.1)	

Cluster 13

Prototype: santen0980

Hard-assigned passwords: 904104 (3.12% of total)
Unique hard-assigned passwords: 635986 (29.66% of cluster total)

Cluster-assignment scores:
	Min: 0.066
	Max: 0.982
	Mean: 0.319
	SD: 0.190

Strength bins:
	Very weak: 12808 (1.42%)
	Weak: 147286 (16.29%)
	Fair: 390281 (43.17%)
	Good: 332810 (36.81%)
	Strong: 20919 (2.31%)

Password lengths:
	Length 9: 6124 (0.68%)
	Length 10: 897980 (99.32%)

Character classes:
	4 classes: 18942 (2.10%)
	3 classes: 143976 (15.92%)
		lower/upper/symbol: 141 (0.10%)
		lower/upper/number: 112141 (77.89%)
		lower/symbol/number: 31692 (22.01%)
		upper/symbol/number: 2 (0.00%)
	2 classes: 741184 (81.98%)
		lower/upper: 3 (0.00%)
		lower/number: 740644 (99.93%)
		lower/symbol: 530 (0.07%)
		upper/number: 0 (0.00%)
		upper/symbol: 0 (0.00%)
		number/symbol: 7 (0.00%)
	1 class: 2 (0.00%)
		lower: 0 (0.00%)
		upper: 0 (0.00%)
		symbol: 2 (100.00%)
		number: 0 (0.00%)

Most frequent char-class structures:
	LLLLLLDDDD: 628834 (69.6%)
	ULLLLLDDDD: 84776 (9.4%)
	LLLLLDDDDD: 62039 (6.9%)
	LLLLLSDDDD: 12368 (1.4%)
	LLLLLDLLLL: 12315 (1.4%)
	LLLLLLDLLL: 10587 (1.2%)
	ULLLLDDDDD: 7744 (0.9%)
	ULLLLSDDDD: 6533 (0.7%)
	LLLLLLDDDS: 5942 (0.7%)
	LLLLLDDDD: 5266 (0.6%)

1,000 nearest passwords

0.	jayden5580	(0.98, 8.1)	54.	elguey0370	(0.97, 12.8)	108.	radhey0000	(0.97, 8.8)
1.	linked0980	(0.98, 7.2)	55.	stimey8080	(0.97, 10.1)	109.	abcdef0000	(0.97, 7.1)
2.	nguyen8880	(0.98, 8.4)	56.	steven5570	(0.97, 8.2)	110.	rodney7890	(0.97, 7.6)
3.	wolfey5080	(0.98, 10.7)	57.	lutfen0090	(0.97, 12.1)	111.	hichem0000	(0.97, 7.8)
4.	Cmoney5190	(0.98, 10.2)	58.	rodney0670	(0.97, 9.0)	112.	webweb0000	(0.97, 7.9)
5.	DanyeL8990	(0.98, 11.9)	59.	steven0760	(0.97, 8.1)	113.	gddgek7890	(0.97, 13.0)
6.	Gracey5590	(0.98, 10.0)	60.	cookey5960	(0.97, 10.3)	114.	stgbed0000	(0.97, 12.0)
7.	Davyev5660	(0.98, 13.7)	61.	iloveu8080	(0.97, 7.3)	115.	dabkeh5200	(0.97, 12.8)
8.	gmoney5570	(0.98, 8.6)	62.	mickey8560	(0.97, 7.9)	116.	hayden3480	(0.97, 8.2)
9.	Monke@5390	(0.98, 12.8)	63.	dalken8790	(0.97, 11.1)	117.	hockey0000	(0.97, 6.7)
10.	linked8080	(0.98, 7.2)	64.	spidey8990	(0.97, 8.7)	118.	sydney5800	(0.97, 8.2)
11.	tlfced5870	(0.98, 13.6)	65.	smokey8990	(0.97, 7.1)	119.	eminem0000	(0.97, 7.1)
12.	hayden5190	(0.98, 8.1)	66.	quebec5560	(0.97, 9.0)	120.	kenken8000	(0.97, 8.8)
13.	disney5370	(0.98, 8.8)	67.	steven0860	(0.97, 8.1)	121.	spicec5300	(0.97, 11.8)
14.	kungen0290	(0.98, 9.8)	68.	Smokey5460	(0.97, 8.8)	122.	donkey8800	(0.97, 8.2)
15.	Steven5980	(0.98, 9.0)	69.	hscheh3880	(0.97, 13.6)	123.	heaven0200	(0.97, 7.8)
16.	jockey0770	(0.98, 9.8)	70.	manneh7580	(0.97, 11.5)	124.	monkey0000	(0.97, 5.9)
17.	stacey5870	(0.98, 8.6)	71.	keykey5500	(0.97, 9.2)	125.	moamed0000	(0.97, 9.1)
18.	Tbone-5560	(0.98, 11.9)	72.	donkey5500	(0.97, 7.9)	126.	sydney5400	(0.97, 8.1)
19.	hacked8080	(0.98, 7.6)	73.	monkey5500	(0.97, 7.1)	127.	turkey0300	(0.97, 8.3)
20.	otabek0770	(0.98, 12.6)	74.	Kuchen5000	(0.97, 10.7)	128.	golden0300	(0.97, 8.2)
21.	nguyen0590	(0.98, 8.4)	75.	ficken5000	(0.97, 7.6)	129.	nedned5000	(0.97, 9.2)
22.	vezvez8080	(0.98, 10.8)	76.	bigcep5400	(0.97, 12.3)	130.	drajea0000	(0.97, 10.9)
23.	yeayea0870	(0.98, 10.8)	77.	stoney5000	(0.97, 7.7)	131.	merced0000	(0.97, 8.7)
24.	jayden0990	(0.98, 7.3)	78.	gmoney5000	(0.97, 7.1)	132.	sophea0000	(0.97, 8.4)
25.	kommen0190	(0.98, 11.0)	79.	jayden5000	(0.97, 7.1)	133.	donkey8300	(0.97, 8.4)
26.	smokey5280	(0.98, 7.6)	80.	donkey5000	(0.97, 6.9)	134.	ibanez8000	(0.97, 8.1)
27.	ficken0190	(0.98, 9.4)	81.	monkey5000	(0.97, 6.1)	135.	wiskey0000	(0.97, 8.3)
28.	acumen5760	(0.98, 10.5)	82.	linked5000	(0.97, 6.6)	136.	hickey7890	(0.97, 8.9)
29.	snakey5770	(0.98, 10.3)	83.	smokey8360	(0.97, 7.8)	137.	Mickey0000	(0.97, 7.2)
30.	barney0060	(0.98, 8.7)	84.	eminem5000	(0.97, 6.7)	138.	wicked3060	(0.97, 8.4)
31.	holden8380	(0.98, 8.2)	85.	ahoney7080	(0.97, 11.2)	139.	wil-em3190	(0.97, 13.6)
32.	linked0570	(0.98, 7.6)	86.	steven8960	(0.97, 7.9)	140.	masked5200	(0.96, 9.7)
33.	gayven5670	(0.98, 11.5)	87.	linked5900	(0.97, 7.2)	141.	iloveu5000	(0.96, 7.0)
34.	aachen5270	(0.98, 10.4)	88.	Holden5000	(0.97, 7.4)	142.	Linked0000	(0.96, 7.0)
35.	jayden0660	(0.98, 8.3)	89.	tasnem5000	(0.97, 9.8)	143.	monkey3890	(0.96, 7.5)
36.	monkey5960	(0.98, 7.4)	90.	buckey5000	(0.97, 8.8)	144.	Monkey0000	(0.96, 7.0)
37.	tmoney5360	(0.98, 9.7)	91.	bimpea7680	(0.97, 12.4)	145.	looney0000	(0.96, 7.6)
38.	Jrice$8080	(0.98, 12.6)	92.	trabex5000	(0.97, 9.6)	146.	golfen8800	(0.96, 9.9)
39.	carmen5670	(0.98, 7.8)	93.	torben5700	(0.97, 10.1)	147.	hinzep3280	(0.96, 14.0)
40.	chaney8760	(0.98, 9.8)	94.	linked0800	(0.97, 7.4)	148.	cathey7890	(0.96, 9.7)
41.	stacey8890	(0.98, 7.9)	95.	babaey3280	(0.97, 11.9)	149.	kraken0000	(0.96, 8.2)
42.	zimbem8090	(0.98, 12.7)	96.	tundex5000	(0.97, 10.0)	150.	linkeD!280	(0.96, 11.6)
43.	ElyNev8860	(0.98, 14.0)	97.	bryjen7680	(0.97, 11.9)	151.	mathew7890	(0.96, 7.2)
44.	Heaven0890	(0.98, 8.9)	98.	linked0400	(0.97, 7.6)	152.	boiken8500	(0.96, 12.2)
45.	hayden8890	(0.98, 7.4)	99.	barney0100	(0.97, 7.9)	153.	linked7890	(0.96, 6.2)
46.	sydney5160	(0.98, 7.9)	100.	maiden5000	(0.97, 7.7)	154.	monkey7890	(0.96, 6.3)
47.	trane_0890	(0.98, 11.4)	101.	smokey5500	(0.97, 7.3)	155.	linked3690	(0.96, 7.2)
48.	linked5160	(0.98, 7.4)	102.	Grace@8600	(0.97, 10.5)	156.	steven0900	(0.96, 7.6)
49.	jayden8670	(0.98, 7.9)	103.	jmoney5200	(0.97, 8.3)	157.	raiden0000	(0.96, 8.4)
50.	linked0070	(0.97, 7.4)	104.	gmoney7890	(0.97, 7.3)	158.	carmen0000	(0.96, 6.9)
51.	harvey0170	(0.97, 8.1)	105.	yasmen5700	(0.97, 10.5)	159.	hickey3570	(0.96, 9.7)
52.	Steven5790	(0.97, 8.9)	106.	broken5000	(0.97, 7.1)	160.	Snake#0000	(0.96, 10.5)
53.	izegem8870	(0.97, 12.6)	107.	linked5200	(0.97, 7.0)	161.	monkey7760	(0.96, 8.0)

162. linKen3660 (0.96, 12.7)
163. rahmed7890 (0.96, 9.0)
164. wolfeN7980 (0.96, 11.7)
165. chevey0000 (0.96, 9.0)
166. yahweh8800 (0.96, 8.6)
167. stacey3490 (0.96, 8.5)
168. nvidea8400 (0.96, 12.1)
169. juiceb3080 (0.96, 11.1)
170. colmed7180 (0.96, 12.1)
171. hayden3190 (0.96, 7.9)
172. Linked7670 (0.96, 8.2)
173. coljen3280 (0.96, 11.7)
174. Pushey3070 (0.96, 11.7)
175. umadem3570 (0.96, 12.6)
176. eminem7260 (0.96, 8.9)
177. jayden7390 (0.96, 8.5)
178. linked3270 (0.96, 7.5)
179. steven8400 (0.96, 7.9)
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181. rueben7890 (0.96, 9.0)
182. heaven7860 (0.96, 8.1)
183. golden7470 (0.96, 8.0)
184. karmen7570 (0.96, 9.4)
185. Nutmeg7860 (0.96, 9.8)
186. carmen7070 (0.96, 7.7)
187. mlopez7560 (0.96, 10.6)
188. steven3660 (0.96, 7.8)
189. frozen3960 (0.96, 9.0)
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191. epuyen5410 (0.96, 13.0)
192. pionex3100 (0.96, 9.8)
193. yibyeb7700 (0.96, 11.9)
194. mathew5510 (0.96, 8.7)
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198. Tienen3300 (0.96, 11.5)
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203. hughey5110 (0.95, 11.0)
204. rugged3000 (0.95, 7.9)
205. hckhex0110 (0.95, 13.0)
206. alone_3000 (0.95, 9.1)
207. payne_3000 (0.95, 9.8)
208. mayhem3000 (0.95, 7.3)
209. heyhey0110 (0.95, 8.3)
210. monkey0410 (0.95, 7.1)
211. linked3700 (0.95, 7.6)
212. linked0510 (0.95, 6.9)
213. kayden5810 (0.95, 8.5)
214. bigkev0110 (0.95, 9.5)
215. kamdev0110 (0.95, 9.9)
216. oxygen3200 (0.95, 8.8)
217. mickey7800 (0.95, 7.7)
218. dandev0410 (0.95, 10.3)
219. rowdev0310 (0.95, 11.6)
220. jaydev0610 (0.95, 9.7)
221. nephew0810 (0.95, 8.7)
222. mathew3100 (0.95, 8.1)
223. donkey0610 (0.95, 7.8)
224. monkey0610 (0.95, 7.0)
225. hockey7700 (0.95, 7.7)
226. oxygen0710 (0.95, 8.6)
227. zednem3000 (0.95, 10.0)
228. malbek9790 (0.95, 12.9)
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230. linked0710 (0.95, 6.9)
231. linked0110 (0.95, 6.7)
232. rruben0410 (0.95, 10.4)
233. hendec0710 (0.95, 10.8)
234. abcde_3600 (0.95, 10.7)
235. webdev0910 (0.95, 8.2)
236. shoney5010 (0.95, 10.0)
237. wicked0310 (0.95, 8.0)
238. momden0210 (0.95, 11.0)
239. braden0510 (0.95, 7.9)
240. Herbey0510 (0.95, 11.1)
241. landen0510 (0.95, 7.9)
242. jayden0110 (0.95, 6.9)
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245. reuben0110 (0.95, 8.1)
246. texmex3000 (0.95, 8.1)
247. jeshea3400 (0.95, 12.2)
248. ArtKen8710 (0.95, 13.0)
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254. Imogen0210 (0.95, 8.9)
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262. Bighem0910 (0.95, 11.6)
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277. kaiden0610 (0.95, 7.7)
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279. carmen9280 (0.95, 8.4)
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287. ownbey5210 (0.95, 13.6)
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297. ferney8910 (0.95, 9.2)
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308. kinney4180 (0.95, 10.4)
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310. raiXen0410 (0.95, 13.2)
311. bbsbec7500 (0.95, 13.2)
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313. valdez3000 (0.95, 7.4)
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327. Coquen0610 (0.95, 11.2)
328. GooneR4780 (0.95, 12.7)
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335. Huizen3000 (0.95, 9.5)
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337. Larven7500 (0.95, 11.6)
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551. steven6590 (0.93, 8.0)
552. united7780 (0.93, 8.1)
553. smoke@7210 (0.93, 10.4)
554. monkey4700 (0.93, 7.7)
555. rlhdez0930 (0.93, 13.7)
556. driven3210 (0.93, 8.8)
557. cortez3290 (0.93, 8.5)
558. linked6500 (0.93, 7.1)
559. steven3210 (0.93, 6.9)
560. jensen7980 (0.93, 8.8)
561. golden5830 (0.93, 8.5)
562. stevem4760 (0.93, 10.3)
563. vivkev6000 (0.93, 11.2)
564. whitey3390 (0.93, 8.7)
565. stacey0040 (0.93, 8.7)
566. steven3010 (0.93, 6.9)
567. plovep3010 (0.93, 11.3)
568. monkey4600 (0.93, 7.6)
569. rooney9090 (0.93, 7.0)
570. iloveu7610 (0.93, 8.1)
571. lowkey4200 (0.93, 8.2)
572. jayden0930 (0.93, 6.6)
573. caiden0730 (0.93, 8.1)
574. cagney9600 (0.93, 9.8)
575. tracey5440 (0.93, 9.2)
576. mickey4200 (0.93, 6.8)
577. Mayhem8840 (0.93, 10.3)
578. jockey4200 (0.93, 8.6)
579. golden0630 (0.93, 7.8)
580. Mon$ey9200 (0.93, 12.8)
581. jayden0540 (0.93, 8.6)
582. netref8490 (0.93, 12.7)
583. nucmed6600 (0.93, 11.3)
584. lilmen0630 (0.93, 9.7)
585. Jayden0930 (0.93, 7.4)
586. mickey0530 (0.93, 7.0)
587. jersey0790 (0.93, 8.4)
588. mickey0130 (0.93, 7.1)
589. mendez9000 (0.93, 7.7)
590. sergey8740 (0.93, 9.7)
591. grejef9110 (0.93, 13.6)
592. linked0340 (0.93, 7.8)
593. massey5480 (0.93, 8.8)
594. mtndew6000 (0.93, 8.7)
595. monkey4200 (0.93, 6.2)
596. linked0530 (0.93, 7.0)
597. luckey0430 (0.93, 8.7)
598. Daxten5890 (0.93, 12.3)
599. mathew0330 (0.93, 8.0)
600. aayden4200 (0.93, 10.2)
601. eminem0330 (0.93, 7.9)
602. Sydney5830 (0.93, 9.3)
603. barney0430 (0.93, 7.7)
604. scubed4200 (0.93, 9.7)
605. linkin0280 (0.93, 8.6)
606. steven6960 (0.93, 7.7)
607. steven0830 (0.93, 7.4)
608. oxygen8440 (0.93, 9.6)
609. goncia0580 (0.93, 11.8)
610. chosen7860 (0.93, 8.9)
611. mayaev9000 (0.93, 11.5)
612. holden0530 (0.93, 7.0)
613. ahamed6600 (0.93, 9.0)
614. taymon0070 (0.93, 11.0)
615. telsey3180 (0.93, 11.9)
616. caiden0530 (0.93, 8.0)
617. stone_0430 (0.93, 10.3)
618. carmen0530 (0.93, 7.4)
619. linked9410 (0.93, 7.6)
620. jayden0330 (0.93, 6.9)
621. dragon0080 (0.93, 7.4)
622. lilced4900 (0.93, 10.2)
623. steven0240 (0.93, 7.7)
624. Blazed4200 (0.93, 7.9)
625. eminem5230 (0.93, 8.2)
626. steven6560 (0.93, 8.0)
627. Amaze●0430 (0.93, 12.6)
628. tinfe@5050 (0.93, 12.2)
629. barney0295 (0.93, 8.5)
630. ahnne.0330 (0.93, 14.0)
631. linked8530 (0.93, 7.6)
632. ghanou0770 (0.93, 10.9)
633. Mickey5050 (0.93, 7.5)
634. abcdef9910 (0.93, 8.5)
635. cayden9410 (0.93, 9.0)
636. bosley5580 (0.93, 9.7)
637. playem5050 (0.93, 10.6)
638. wicked5850 (0.93, 8.6)
639. mickey5050 (0.93, 6.4)
640. beabea5050 (0.93, 9.2)
641. rugged5050 (0.93, 8.4)
642. ilovef0530 (0.93, 10.4)
643. heaven4300 (0.93, 8.3)
644. pimpin0180 (0.93, 9.4)
645. golden4000 (0.93, 7.0)
646. mohsen3090 (0.93, 8.2)
647. carmen6700 (0.93, 7.9)
648. donfed5050 (0.93, 10.6)
649. Cmoney3420 (0.93, 10.4)
650. chidex4000 (0.93, 10.7)
651. daisey8390 (0.93, 9.4)
652. Aljaem8030 (0.93, 13.6)
653. tbonez0395 (0.93, 11.1)
654. catdog0180 (0.93, 8.6)
655. DelRey0140 (0.93, 12.7)
656. ferdek4000 (0.93, 10.1)
657. garden4200 (0.93, 7.3)
658. YngveN4200 (0.93, 13.8)
659. bolden6000 (0.93, 9.3)
660. broken8930 (0.93, 8.8)
661. tsiken5050 (0.93, 11.3)
662. mohsen8180 (0.93, 8.7)
663. ibanez9000 (0.93, 7.8)
664. donkey9000 (0.93, 7.0)
665. hrubec0195 (0.93, 13.4)
666. monkey9000 (0.93, 6.2)
667. broken5050 (0.93, 7.3)
668. wesley8990 (0.93, 7.6)
669. sydney0330 (0.93, 7.5)
670. payten3170 (0.93, 9.6)
671. golden0850 (0.93, 8.8)
672. GabDob0460 (0.93, 13.6)
673. Iloveu0430 (0.93, 8.7)
674. hitmen5050 (0.93, 8.4)
675. junaid0170 (0.93, 8.9)
676. taufiq0590 (0.93, 9.5)
677. dragon0570 (0.93, 7.5)
678. smokey5050 (0.93, 6.2)
679. menyou0070 (0.93, 9.5)
680. Ibanez7620 (0.93, 9.4)
681. OnediN0000 (0.93, 9.4)
682. Massey3080 (0.93, 9.4)
683. Wisdom0080 (0.93, 8.7)
684. shaney5195 (0.93, 9.9)
685. kayden9000 (0.93, 8.2)
686. dragon0070 (0.93, 6.7)
687. sabzi/9980 (0.93, 14.0)
688. monkey3420 (0.93, 7.5)
689. bailey8390 (0.93, 7.9)
690. linked8230 (0.93, 7.6)
691. Cayden3520 (0.93, 9.3)
692. thimen6300 (0.93, 12.2)
693. janaen0750 (0.93, 11.5)
694. Hayden5150 (0.93, 7.4)
695. linked0050 (0.93, 7.7)
696. poyzen5150 (0.93, 12.0)
697. linked!420 (0.93, 8.3)
698. spidey8330 (0.93, 9.4)
699. plamen9000 (0.93, 8.7)
700. hockey5150 (0.93, 6.3)
701. dragon0890 (0.93, 7.3)

702. locked5150 (0.93, 7.3)
703. donkey5150 (0.93, 6.7)
704. kayden5150 (0.93, 6.9)
705. jayden5150 (0.93, 6.5)
706. hayden5150 (0.93, 6.4)
707. linked5150 (0.93, 6.6)
708. mayhem5150 (0.93, 7.4)
709. monkey7520 (0.93, 7.7)
710. MapJoy5560 (0.93, 14.0)
711. tracey0150 (0.93, 9.1)
712. bigben0095 (0.93, 9.3)
713. Spacey5150 (0.93, 9.2)
714. awaken5150 (0.93, 8.8)
715. monkey0795 (0.93, 7.7)
716. looney5150 (0.93, 7.3)
717. matvey6000 (0.93, 9.3)
718. maicon0690 (0.93, 9.0)
719. sackey9810 (0.93, 10.5)
720. holden5150 (0.93, 6.4)
721. mickey5350 (0.93, 7.9)
722. Calvin0290 (0.93, 8.8)
723. bigdog0690 (0.93, 7.6)
724. iloled7890 (0.93, 11.3)
725. QazWsx0990 (0.93, 9.9)
726. maddog5180 (0.93, 8.2)
727. crazed5150 (0.93, 8.6)
728. mashed3120 (0.93, 9.7)
729. allyou0070 (0.93, 11.1)
730. hockey0895 (0.93, 8.2)
731. carmen8230 (0.93, 8.2)
732. sydney5750 (0.93, 8.4)
733. Hayden5895 (0.93, 9.2)
734. peavey5150 (0.93, 7.7)
735. stupid0290 (0.93, 8.4)
736. linked3020 (0.93, 7.3)
737. sydney5025 (0.93, 8.5)
738. Ggomez9710 (0.93, 11.8)
739. smokey5150 (0.93, 5.8)
740. langtu0780 (0.93, 9.5)
741. ibanez5150 (0.93, 7.5)
742. Smokey9000 (0.93, 7.7)
743. Sophia0860 (0.93, 9.0)
744. massey7460 (0.93, 9.4)
745. Jccjec5250 (0.93, 14.0)
746. eight_0880 (0.93, 11.4)
747. window0990 (0.93, 7.9)
748. looney5250 (0.93, 9.0)
749. marvin0990 (0.93, 7.8)
750. stevep4200 (0.92, 9.5)
751. window0770 (0.92, 8.9)
752. draken8995 (0.92, 9.9)
753. mathew7020 (0.92, 8.7)
754. svgmeg5595 (0.92, 13.3)
755. jazmin5670 (0.92, 8.3)
756. smiley7860 (0.92, 7.9)
757. uniled7890 (0.92, 9.9)
758. bailey3090 (0.92, 7.5)
759. prazem7720 (0.92, 12.8)
760. darvid0380 (0.92, 12.0)
761. Kelvin0490 (0.92, 9.3)
762. Sydney9070 (0.92, 9.1)
763. spyboy5590 (0.92, 10.0)
764. shanem9610 (0.92, 10.6)
765. nunney5450 (0.92, 11.5)
766. steven5150 (0.92, 6.4)
767. premey5150 (0.92, 10.2)
768. cjbmeb5250 (0.92, 13.3)
769. hayden8150 (0.92, 8.5)
770. iloveu9210 (0.92, 7.9)
771. brybey7220 (0.92, 12.6)
772. mendez8995 (0.92, 8.5)
773. united0100 (0.92, 7.6)
774. ramji@0000 (0.92, 9.2)
775. Panzon0000 (0.92, 9.2)
776. landen7120 (0.92, 9.0)
777. Massey8270 (0.92, 10.1)
778. stiven0995 (0.92, 9.7)
779. eminem3940 (0.92, 8.5)
780. grafiz0770 (0.92, 11.4)
781. qazwsx0990 (0.92, 7.8)
782. iloveu0250 (0.92, 8.7)
783. taakin8080 (0.92, 11.2)
784. zaphod5590 (0.92, 9.4)
785. system8100 (0.92, 8.1)
786. storex8500 (0.92, 10.6)
787. raydon0000 (0.92, 8.9)
788. mosmon5580 (0.92, 11.8)
789. Rodney5150 (0.92, 7.9)
790. disney7740 (0.92, 8.9)
791. michin5570 (0.92, 10.6)
792. smiley0160 (0.92, 8.4)
793. sidney5150 (0.92, 7.1)
794. bigjim5580 (0.92, 9.2)
795. kayvon0900 (0.92, 9.8)
796. signin5060 (0.92, 9.0)
797. ctkbiz0490 (0.92, 13.3)
798. united4960 (0.92, 8.4)
799. disney4410 (0.92, 8.5)
800. united4290 (0.92, 8.2)
801. nutmeg7720 (0.92, 9.3)
802. Linked0275 (0.92, 8.7)
803. alexey0595 (0.92, 9.3)
804. shahin0000 (0.92, 7.0)
805. acacia8080 (0.92, 8.0)
806. Bremen3720 (0.92, 10.3)
807. badboy0360 (0.92, 8.1)
808. bruno/0000 (0.92, 9.7)
809. Eminem8185 (0.92, 9.2)
810. horney6910 (0.92, 8.0)
811. sachin0000 (0.92, 6.9)
812. gamboa0500 (0.92, 9.5)
813. Maddog0000 (0.92, 8.2)
814. judge_4510 (0.92, 11.3)
815. amazon0000 (0.92, 7.4)
816. mickey3040 (0.92, 7.3)
817. carmen7320 (0.92, 8.3)
818. pestey7000 (0.92, 11.5)
819. shadow5470 (0.92, 7.5)
820. awakeN0130 (0.92, 12.5)
821. langtu0190 (0.92, 9.4)
822. Beacon5390 (0.92, 9.7)
823. revsev8170 (0.92, 12.6)
824. monkey5025 (0.92, 7.9)
825. monkey0085 (0.92, 7.9)
826. akdmia0000 (0.92, 11.7)
827. calvin5480 (0.92, 8.5)
828. layden9910 (0.92, 9.6)
829. bailey7770 (0.92, 7.5)
830. steven5695 (0.92, 7.8)
831. lizben8385 (0.92, 11.6)
832. jayden9810 (0.92, 7.9)
833. kayden9810 (0.92, 8.7)
834. smokey8995 (0.92, 7.6)
835. iamgod0500 (0.92, 9.8)
836. brewok0270 (0.92, 10.5)
837. qawsed7890 (0.92, 7.5)
838. cuncon9180 (0.92, 10.3)
839. lunney3140 (0.92, 10.6)
840. hotsex6980 (0.92, 8.3)
841. jonkea3040 (0.92, 12.3)
842. alopez7920 (0.92, 9.8)
843. shabih9290 (0.92, 10.8)
844. heaven5385 (0.92, 8.6)
845. gundog0200 (0.92, 10.3)
846. inkgod0000 (0.92, 10.0)
847. wesley7070 (0.92, 7.6)
848. maddog0000 (0.92, 7.0)
849. SummiT8800 (0.92, 10.5)
850. cowdew3140 (0.92, 12.9)
851. wooten3000 (0.92, 8.0)
852. ripped3030 (0.92, 8.9)
853. steven3320 (0.92, 7.5)
854. maddog8180 (0.92, 8.8)
855. Oztash0480 (0.92, 14.0)
856. vernon5280 (0.92, 8.8)
857. hockey3030 (0.92, 6.8)
858. london8580 (0.92, 7.9)
859. eminem5585 (0.92, 8.0)
860. giggog9480 (0.92, 11.4)
861. london0000 (0.92, 5.6)
862. monkey5075 (0.92, 8.1)
863. disney3530 (0.92, 8.4)
864. bigdog5470 (0.92, 7.7)
865. rodney3540 (0.92, 8.7)
866. bigdog5060 (0.92, 7.5)
867. hidden4710 (0.92, 9.2)
868. Darcey0085 (0.92, 11.2)
869. bardia9280 (0.92, 9.9)
870. bmchen0375 (0.92, 11.9)
871. JenJen8485 (0.92, 11.0)
872. Sammeg0485 (0.92, 11.8)
873. camden8385 (0.92, 8.8)
874. anthon0000 (0.92, 8.4)
875. sandip0000 (0.92, 7.1)
876. mamaia0000 (0.92, 7.4)
877. ramsey7290 (0.92, 9.4)
878. comvia5190 (0.92, 11.8)
879. navyen5175 (0.92, 11.4)
880. whodey0985 (0.92, 9.6)
881. anabia0300 (0.92, 10.5)
882. mickey5785 (0.92, 7.8)
883. Mickey5685 (0.92, 8.6)
884. Fatboy0000 (0.92, 7.6)
885. system5000 (0.92, 6.5)
886. wayneg0485 (0.92, 10.9)
887. dondon8080 (0.92, 8.1)
888. lennon0000 (0.92, 7.5)
889. edtrek8500 (0.92, 12.2)
890. pannik0000 (0.92, 10.0)
891. mentex5000 (0.92, 10.2)
892. sachin8090 (0.92, 8.5)
893. rgukt@8080 (0.92, 14.0)
894. sydney0725 (0.92, 7.3)
895. doaken4110 (0.92, 12.0)
896. Hayden7940 (0.92, 9.3)
897. jasmin5890 (0.92, 8.6)
898. alicia5980 (0.92, 8.5)
899. Fucked3030 (0.92, 9.1)
900. jlshen3540 (0.92, 13.1)
901. shovon5060 (0.92, 9.6)
902. linked0025 (0.92, 7.3)
903. segata0080 (0.92, 11.2)
904. boobea8895 (0.92, 11.7)
905. pigpen8985 (0.92, 9.9)
906. kiaden3030 (0.92, 9.9)
907. demdem3530 (0.92, 10.1)
908. mildew3840 (0.92, 11.0)
909. suinon0000 (0.92, 10.2)
910. asdasd0980 (0.92, 7.9)
911. bigboy5170 (0.92, 7.7)
912. nguyen0075 (0.92, 8.9)
913. shadow0000 (0.92, 5.9)
914. bassem0000 (0.92, 7.2)
915. shakey3030 (0.92, 8.1)
916. dragon0000 (0.92, 5.7)
917. canvix0000 (0.92, 11.4)
918. minmin0000 (0.92, 7.6)
919. shahid0300 (0.92, 7.2)
920. rodney9000 (0.92, 7.8)
921. hayden4110 (0.92, 7.5)
922. rramon0500 (0.92, 10.9)
923. london8880 (0.92, 7.8)
924. weeksy0570 (0.92, 11.6)
925. luckey3440 (0.92, 9.8)
926. mancow0000 (0.92, 9.0)
927. reymon0000 (0.92, 9.3)
928. hotsex8100 (0.92, 9.1)
929. tagnew8275 (0.92, 11.8)
930. mhekim0660 (0.92, 12.4)
931. pimpin0000 (0.92, 7.2)
932. jayden6510 (0.92, 8.0)
933. muhaim9270 (0.92, 12.2)
934. Calhou0000 (0.92, 10.6)
935. lakaoa8090 (0.92, 13.1)
936. london0300 (0.92, 7.3)
937. Meahev5775 (0.92, 14.0)
938. landen0585 (0.92, 9.1)
939. bigboy5490 (0.92, 7.7)
940. holden5585 (0.92, 8.2)
941. united5000 (0.92, 6.4)
942. skyden6810 (0.92, 11.6)
943. bhojia9290 (0.92, 12.3)
944. csuboy0000 (0.92, 9.4)
945. bigdog8080 (0.92, 7.1)
946. kitten3000 (0.92, 6.5)
947. Kelvin5190 (0.92, 9.3)
948. kayden8985 (0.92, 8.8)
949. tarsem0000 (0.92, 9.2)
950. cruzin0600 (0.92, 10.2)
951. catdog0000 (0.92, 7.0)
952. barney8975 (0.92, 8.5)
953. tracey8275 (0.92, 9.3)
954. educom5560 (0.92, 11.8)
955. Mickey5575 (0.92, 8.7)
956. gordon9780 (0.92, 8.8)
957. bigboy0000 (0.92, 5.9)
958. bigboy5390 (0.92, 7.8)
959. hacked3340 (0.92, 8.6)
960. Nguyen0075 (0.92, 10.2)
961. Mordia5790 (0.92, 11.8)
962. AyumiL0910 (0.92, 12.4)
963. spikey9010 (0.92, 8.8)
964. jelnem7295 (0.92, 12.8)
965. medved0775 (0.92, 10.5)
966. sachin9970 (0.92, 8.5)
967. markic9780 (0.92, 11.3)
968. samyia8690 (0.92, 11.5)
969. lukasz0090 (0.92, 8.4)
970. linked6010 (0.92, 7.2)
971. zipdog0000 (0.92, 9.7)

972. Pompey8885 (0.92, 9.9)	982. loczek8585 (0.92, 10.1)	992. toyboy9370 (0.92, 9.8)
973. sachin9760 (0.92, 8.4)	983. madden8585 (0.92, 8.5)	993. tannic8690 (0.92, 11.6)
974. steven8695 (0.92, 7.9)	984. valdez3030 (0.92, 7.8)	994. Linked0875 (0.92, 8.6)
975. touhou8780 (0.92, 11.1)	985. reddog0000 (0.92, 7.3)	995. system3000 (0.92, 7.1)
976. olivia0260 (0.92, 8.1)	986. glade_3130 (0.92, 11.8)	996. Darwin0800 (0.92, 9.0)
977. garcia9180 (0.92, 8.2)	987. redred3060 (0.92, 9.0)	997. moncoz0000 (0.92, 11.1)
978. Tinkey6210 (0.92, 11.5)	988. omani-9090 (0.92, 11.1)	998. denjen8975 (0.92, 11.4)
979. hardik9880 (0.92, 8.5)	989. djicey3030 (0.92, 10.7)	999. bojboj0000 (0.92, 10.0)
980. shamim0300 (0.92, 7.8)	990. landen8585 (0.92, 8.8)	
981. horsey8400 (0.92, 10.2)	991. Alice@3940 (0.92, 10.8)	

Cluster 14

Prototype: saaedon0994

Hard-assigned passwords: 663690 (2.29% of total)
Unique hard-assigned passwords: 482590 (27.29% of cluster total)

Cluster-assignment scores:
        Min: 0.066
        Max: 0.986
        Mean: 0.349
        SD: 0.214

Strength bins:
        Very weak: 5469 (0.82%)
        Weak: 88009 (13.26%)
        Fair: 228933 (34.49%)
        Good: 292779 (44.11%)
        Strong: 48500 (7.31%)

Password lengths:
        Length 11: 661063 (99.60%)
        Length 12: 2627 (0.40%)

Character classes:
        4 classes: 18839 (2.84%)
        3 classes: 118943 (17.92%)
                lower/upper/symbol: 119 (0.10%)
                lower/upper/number: 85672 (72.03%)
                lower/symbol/number: 33151 (27.87%)
                upper/symbol/number: 1 (0.00%)
        2 classes: 525907 (79.24%)
                lower/upper: 20 (0.00%)
                lower/number: 525476 (99.92%)
                lower/symbol: 407 (0.08%)
                upper/number: 0 (0.00%)
                upper/symbol: 1 (0.00%)
                number/symbol: 3 (0.00%)
        1 class: 1 (0.00%)
                lower: 0 (0.00%)
                upper: 0 (0.00%)
                symbol: 1 (100.00%)
                number: 0 (0.00%)

Most frequent char-class structures:
        LLLLLLLDDDD: 357474 (53.9%)
        LLLLLLDDDDD: 63810 (9.6%)
        LLLLLLLLDD: 50721 (7.6%)
        ULLLLLLDDDD: 48082 (7.2%)
        LLLLLDDDDDD: 15746 (2.4%)
        LLLLLLLLLL: 11784 (1.8%)
        LLLLLSDDDD: 11316 (1.7%)
        ULLLLLDDDDD: 8953 (1.3%)
        ULLLLSDDDD: 5245 (0.8%)
        ULLLLLLLDD: 4446 (0.7%)

1,000 nearest passwords

0.	Evilken5060	(0.99, 13.4)	54.	mohamed5200	(0.98, 7.3)	108.	stephen0400	(0.97, 7.9)
1.	realped5960	(0.99, 14.0)	55.	mohamed5000	(0.98, 6.3)	109.	Whiskey0000	(0.97, 8.4)
2.	Hellyea8960	(0.99, 11.2)	56.	matthew8300	(0.98, 7.5)	110.	citizen0000	(0.97, 7.9)
3.	kebumen8390	(0.99, 9.9)	57.	stenden8900	(0.98, 11.5)	111.	chicken8910	(0.97, 8.0)
4.	shithed8360	(0.99, 14.0)	58.	dukezen0470	(0.98, 13.4)	112.	sanchez0500	(0.97, 8.3)
5.	stephen5060	(0.99, 7.5)	59.	integea8400	(0.98, 13.0)	113.	papamoa5180	(0.97, 10.7)
6.	iclozem8080	(0.99, 13.3)	60.	vrancea5300	(0.98, 11.9)	114.	stephen5510	(0.97, 7.7)
7.	krisbek5080	(0.98, 12.9)	61.	zellnew6660	(0.98, 12.9)	115.	sangcom5780	(0.97, 12.3)
8.	matthew5280	(0.98, 7.6)	62.	chancey5000	(0.98, 8.7)	116.	aboodi-8080	(0.97, 11.6)
9.	chicken8380	(0.98, 8.8)	63.	zgplnep4890	(0.98, 14.0)	117.	langfen0000	(0.97, 10.8)
10.	rygsaek8260	(0.98, 14.0)	64.	P@tche$4590	(0.98, 12.8)	118.	rentgen0000	(0.97, 10.8)
11.	markheg5980	(0.98, 13.1)	65.	Chicken5100	(0.98, 8.8)	119.	justasc5280	(0.97, 12.2)
12.	Brenden5080	(0.98, 10.0)	66.	chicken5000	(0.97, 6.8)	120.	Chargen0000	(0.97, 10.5)
13.	stephen5280	(0.98, 7.9)	67.	sparkey0070	(0.97, 9.2)	121.	Jmalmin5890	(0.97, 14.0)
14.	learned8090	(0.98, 10.1)	68.	ibrahem5000	(0.97, 8.6)	122.	sampath8080	(0.97, 8.5)
15.	matthew3660	(0.98, 8.0)	69.	lifenew8000	(0.97, 10.1)	123.	cantata8660	(0.97, 11.6)
16.	nokiyem3660	(0.98, 11.7)	70.	salahef4580	(0.97, 13.4)	124.	matthew4500	(0.97, 7.6)
17.	Apache:8080	(0.98, 12.9)	71.	Missbea6060	(0.97, 12.8)	125.	chicken4800	(0.97, 7.9)
18.	stephen7760	(0.98, 8.4)	72.	branden6380	(0.97, 9.4)	126.	Avenged0000	(0.97, 7.2)
19.	chicken7890	(0.98, 7.3)	73.	Iphone_5800	(0.97, 11.3)	127.	phoenix5580	(0.97, 8.0)
20.	hershey3460	(0.98, 9.2)	74.	tierney6780	(0.97, 10.0)	128.	dariush5760	(0.97, 10.7)
21.	charmed7990	(0.98, 9.1)	75.	baloney5300	(0.97, 8.7)	129.	matthew4200	(0.97, 6.5)
22.	jotoxen7990	(0.98, 12.9)	76.	moloney5000	(0.97, 8.3)	130.	hrgrgew4500	(0.97, 14.0)
23.	blitzen3190	(0.98, 10.1)	77.	beloved6980	(0.97, 9.3)	131.	matthew6200	(0.97, 7.4)
24.	kartmen7460	(0.98, 12.6)	78.	emahmed3600	(0.97, 11.5)	132.	kasecey7410	(0.97, 13.5)
25.	tinhyeu3190	(0.98, 9.0)	79.	matthew3000	(0.97, 6.3)	133.	Brayden3110	(0.97, 8.4)
26.	rauchen7890	(0.98, 10.3)	80.	andrzej3400	(0.97, 9.6)	134.	brayden7410	(0.97, 8.2)
27.	Bibike,3990	(0.98, 14.0)	81.	griffen7800	(0.97, 10.1)	135.	mohamed3210	(0.97, 6.9)
28.	cajtped5470	(0.98, 14.0)	82.	funckey3000	(0.97, 11.5)	136.	rkmenon8290	(0.97, 13.5)
29.	mymoney3090	(0.98, 9.4)	83.	chicken3000	(0.97, 6.7)	137.	stopped6000	(0.96, 9.9)
30.	klrowen7890	(0.98, 13.0)	84.	unique.8800	(0.97, 10.6)	138.	nhimcon5790	(0.96, 12.2)
31.	vgracea7580	(0.98, 14.0)	85.	rouzbeh3000	(0.97, 11.9)	139.	whiskey7210	(0.96, 9.0)
32.	chicken7780	(0.98, 8.4)	86.	nolove@3800	(0.97, 10.9)	140.	chicken6200	(0.96, 8.1)
33.	santhej3080	(0.98, 13.2)	87.	shoppen3000	(0.97, 10.4)	141.	mohamed6200	(0.96, 7.8)
34.	Matthew5570	(0.98, 8.5)	88.	jimenez3500	(0.97, 8.4)	142.	pumpkin0880	(0.96, 8.7)
35.	stephen3480	(0.98, 8.0)	89.	momoney7400	(0.97, 9.1)	143.	Captain0780	(0.96, 9.3)
36.	scorpey5070	(0.98, 12.3)	90.	momoney3000	(0.97, 7.2)	144.	Woorden3210	(0.96, 10.9)
37.	stephen7480	(0.98, 8.3)	91.	unnamed0700	(0.97, 10.4)	145.	stephen7-10	(0.96, 9.7)
38.	Matthew8070	(0.98, 8.5)	92.	journey3000	(0.97, 7.3)	146.	rauchen6200	(0.96, 11.1)
39.	makubex0260	(0.98, 10.8)	93.	Matthew6670	(0.97, 8.3)	147.	shelvia5260	(0.96, 11.8)
40.	brunnen5690	(0.98, 11.3)	94.	firsweb0000	(0.97, 10.3)	148.	fahimeh6600	(0.96, 10.8)
41.	munchen3580	(0.98, 9.8)	95.	jtmoney4570	(0.97, 9.7)	149.	hostbew0510	(0.96, 12.3)
42.	sanchez7980	(0.98, 8.4)	96.	hostweb0000	(0.97, 6.5)	150.	glasgow5660	(0.96, 9.3)
43.	matthew0960	(0.98, 8.2)	97.	citizen0900	(0.97, 9.5)	151.	gfhbdtn0880	(0.96, 12.2)
44.	przemek0880	(0.98, 10.1)	98.	Whitney3000	(0.97, 8.3)	152.	_zvone_0000	(0.96, 14.0)
45.	touched0790	(0.98, 11.2)	99.	Mirage@6270	(0.97, 11.6)	153.	caedmon5560	(0.96, 13.0)
46.	jtmoney0690	(0.98, 9.3)	100.	Mohamed0100	(0.97, 7.8)	154.	rongxin8260	(0.96, 11.7)
47.	chicken3170	(0.98, 8.1)	101.	kianne●5000	(0.97, 13.0)	155.	wanphen3010	(0.96, 11.9)
48.	lanekey3170	(0.98, 12.0)	102.	murkaev3000	(0.97, 12.8)	156.	phoenix0290	(0.96, 8.0)
49.	stephen0880	(0.98, 8.2)	103.	Almazen0100	(0.97, 11.8)	157.	freedom5060	(0.96, 7.5)
50.	Krimpen0180	(0.98, 12.3)	104.	abandon5490	(0.97, 10.8)	158.	nhokkon8490	(0.96, 12.7)
51.	actifed5000	(0.98, 11.1)	105.	matthew5610	(0.97, 7.3)	159.	thathea0210	(0.96, 11.9)
52.	beloved5000	(0.98, 7.6)	106.	mohamed0000	(0.97, 6.5)	160.	vicchou0990	(0.96, 11.7)
53.	novocef5000	(0.98, 13.1)	107.	kagome_8910	(0.97, 11.8)	161.	moondog5780	(0.96, 9.2)

162. Ablegod8080 (0.96, 10.6)
163. Matthew0710 (0.96, 7.2)
164. matthew0810 (0.96, 6.7)
165. freeweb6000 (0.96, 8.1)
166. digimon8890 (0.96, 8.8)
167. billben0110 (0.96, 10.1)
168. avinash5460 (0.96, 9.7)
169. freedom5780 (0.96, 7.9)
170. shownow8080 (0.96, 9.6)
171. mailbox8880 (0.96, 9.6)
172. tallboy0660 (0.96, 10.1)
173. ibrahim8990 (0.96, 8.2)
174. prakash8480 (0.96, 8.6)
175. braiden0310 (0.96, 8.7)
176. brandon5770 (0.96, 8.0)
177. donavin0390 (0.96, 10.5)
178. Sullys@0780 (0.96, 13.4)
179. organic5670 (0.96, 9.3)
180. bandaid0470 (0.96, 10.4)
181. mohaned0000 (0.96, 9.2)
182. stripey8520 (0.96, 9.9)
183. croacia8080 (0.96, 10.7)
184. claudia5270 (0.96, 8.4)
185. hotchef0910 (0.96, 9.9)
186. kickbox0160 (0.96, 10.3)
187. mohamed8520 (0.96, 6.9)
188. fekakea0510 (0.96, 13.5)
189. Farmboy0690 (0.96, 10.0)
190. ffubhsf7890 (0.96, 14.0)
191. fuckyou3760 (0.96, 7.9)
192. farmboy0690 (0.96, 8.9)
193. matthew8520 (0.96, 7.4)
194. babyboy3690 (0.96, 8.0)
195. farmboy8560 (0.96, 9.3)
196. hungbon7890 (0.96, 11.7)
197. lucamia7790 (0.96, 11.2)
198. congjia8970 (0.96, 12.3)
199. Stephen0210 (0.96, 8.0)
200. griffin8960 (0.96, 9.3)
201. jimenez0310 (0.96, 7.9)
202. fgarcia0360 (0.96, 11.5)
203. chicken0510 (0.96, 7.9)
204. Fuckyou3880 (0.96, 9.0)
205. matthew5920 (0.96, 8.0)
206. mujahid3480 (0.96, 9.7)
207. brayden0910 (0.96, 7.3)
208. Lenovoy5070 (0.96, 10.5)
209. candytm7190 (0.96, 13.1)
210. kazyboy3680 (0.96, 12.3)
211. Teecash8080 (0.96, 12.9)
212. dominik5870 (0.96, 9.0)
213. dynamic3460 (0.96, 9.5)
214. danlkin8070 (0.96, 14.0)
215. juanyou7280 (0.96, 12.2)
216. sandbox7560 (0.96, 10.1)
217. Antonoa7890 (0.96, 13.5)
218. sexyboy8770 (0.96, 9.3)
219. getajob5570 (0.96, 10.7)
220. lefujiS5000 (0.96, 14.0)
221. gmackin5000 (0.96, 10.8)
222. igotyou7890 (0.96, 8.8)
223. creepin0360 (0.96, 10.6)
224. harshiv3690 (0.96, 11.5)
225. mamamia5000 (0.96, 7.2)
226. islamic5470 (0.96, 9.3)
227. fartboy7890 (0.96, 9.4)
228. lucknow5000 (0.96, 8.1)
229. hussain5000 (0.96, 6.5)
230. hongyen0510 (0.96, 8.5)
231. journey0910 (0.96, 7.8)
232. abinash0160 (0.96, 10.4)
233. plowboy5170 (0.96, 9.8)
234. qouqqou7890 (0.96, 13.0)
235. babyboy5300 (0.96, 7.9)
236. Farshid3380 (0.96, 10.7)
237. Marivi@7660 (0.96, 13.0)
238. Pinguin5100 (0.96, 10.3)
239. tinyboy7290 (0.96, 9.9)
240. pamapta8000 (0.96, 13.8)
241. Donagen5220 (0.96, 13.9)
242. wjsfkeh3520 (0.96, 14.0)
243. otisdog7890 (0.96, 10.1)
244. graphix7890 (0.96, 9.8)
245. sexyboy3390 (0.96, 8.9)
246. kjouved3320 (0.96, 14.0)
247. Indigo-7090 (0.96, 12.5)
248. zeenath0190 (0.96, 10.3)
249. brayden7520 (0.96, 8.9)
250. hazimi@7490 (0.96, 12.7)
251. brandon7890 (0.96, 6.5)
252. iluvdik7890 (0.96, 11.9)
253. babyboy8600 (0.96, 8.2)
254. gamewiz0070 (0.96, 11.1)
255. roaddog3080 (0.96, 9.6)
256. felicia5000 (0.96, 8.1)
257. julius.5000 (0.96, 9.9)
258. jerrytu0970 (0.96, 12.2)
259. Phoenix3090 (0.96, 8.2)
260. george-4110 (0.96, 10.3)
261. jayadev3220 (0.96, 12.0)
262. biggdog5000 (0.96, 9.1)
263. jiangsu5800 (0.96, 10.1)
264. Dazent.3290 (0.96, 14.0)
265. soroush7980 (0.96, 9.9)
266. pumpkin7470 (0.96, 8.3)
267. Jasonty8000 (0.96, 12.0)
268. brandon5000 (0.96, 6.4)
269. molodoy5800 (0.96, 13.1)
270. temujin!!60 (0.96, 14.0)
271. playboy3960 (0.96, 8.2)
272. babyboy7470 (0.96, 8.1)
273. phoenix3080 (0.96, 7.9)
274. tfsmbtj7480 (0.96, 14.0)
275. Keithtj5000 (0.96, 12.8)
276. fsfchop5600 (0.96, 14.0)
277. Snowden3220 (0.96, 11.2)
278. helpme_4710 (0.96, 11.9)
279. harobed0420 (0.96, 10.4)
280. fastmon8300 (0.96, 12.3)
281. freedom0070 (0.96, 7.0)
282. phiwdon3490 (0.96, 14.0)
283. laplata7980 (0.96, 10.3)
284. hemant@3880 (0.96, 10.6)
285. suprkid3980 (0.96, 12.9)
286. sherwin7680 (0.96, 9.8)
287. rossdiv5000 (0.96, 12.1)
288. bulldog3380 (0.96, 8.1)
289. Venkat@3690 (0.96, 10.1)
290. bulldog5000 (0.96, 6.7)
291. Spurath7280 (0.96, 14.0)
292. ebrahim7890 (0.96, 7.9)
293. silent@0770 (0.96, 10.7)
294. iseeyou5000 (0.96, 9.1)
295. taochin5000 (0.96, 10.7)
296. menkata7660 (0.96, 12.5)
297. ramirez3480 (0.96, 8.5)
298. mierdon3090 (0.96, 12.2)
299. matthew0620 (0.96, 6.9)
300. playboy5700 (0.96, 7.9)
301. verizon8500 (0.96, 8.7)
302. Sweeney3820 (0.96, 11.2)
303. Loveyou7890 (0.96, 8.3)
304. pravat_7780 (0.96, 12.2)
305. bulldog5700 (0.96, 7.7)
306. freedom3390 (0.96, 7.7)
307. matthew0320 (0.96, 6.8)
308. olympic5000 (0.96, 7.6)
309. horndog0070 (0.96, 9.1)
310. georgia7890 (0.96, 7.2)
311. logicon5500 (0.96, 10.3)
312. fookyou7990 (0.96, 11.5)
313. ttotheg0220 (0.96, 13.2)
314. klingon3190 (0.96, 9.4)
315. jilldog5100 (0.96, 11.2)
316. chrissy5280 (0.96, 8.9)
317. pokemon5000 (0.96, 6.1)
318. ramirez5580 (0.96, 8.6)
319. freedom3780 (0.96, 7.8)
320. Melissa8190 (0.96, 9.1)
321. goliath5000 (0.96, 8.3)
322. Freedom3560 (0.96, 8.5)
323. mateusz5200 (0.96, 8.8)
324. kakanik0000 (0.96, 11.2)
325. daphney0810 (0.96, 9.9)
326. bamaboy0000 (0.96, 7.9)
327. Drewbon5000 (0.96, 12.6)
328. Hussain0300 (0.96, 7.8)
329. fantasy7070 (0.96, 7.8)
330. minokia5300 (0.96, 6.7)
331. Freedom5000 (0.96, 6.3)
332. malaweb9890 (0.96, 12.1)
333. hawazik0000 (0.96, 12.1)
334. doorgod5000 (0.96, 9.9)
335. checkin5300 (0.96, 9.8)
336. claudia8800 (0.96, 8.0)
337. genevia5500 (0.96, 10.3)
338. mamamia0000 (0.96, 7.0)
339. umuahia0000 (0.96, 11.1)
340. alicvia3190 (0.96, 13.5)
341. fuckyou0000 (0.96, 6.3)
342. quynhon0000 (0.96, 8.9)
343. boredom5000 (0.96, 8.9)
344. Golabek0320 (0.96, 13.1)
345. lidawen0620 (0.96, 12.1)
346. catfish5890 (0.96, 8.4)
347. sadukov0000 (0.96, 11.4)
348. golfdog5000 (0.96, 9.5)
349. nokiyem5130 (0.96, 11.5)
350. hossain7070 (0.96, 8.5)
351. kajinth8700 (0.96, 14.0)
352. caugney0910 (0.96, 13.2)
353. freedom5000 (0.96, 5.8)
354. Fuckyou0000 (0.96, 7.7)
355. organic8200 (0.96, 9.7)
356. coolpix5000 (0.96, 8.1)
357. griffin7980 (0.96, 8.7)
358. brendon5300 (0.96, 8.9)
359. johnboy7970 (0.96, 8.7)
360. fodete*?690 (0.96, 14.0)
361. madison5680 (0.96, 7.9)
362. liandin7070 (0.96, 11.7)
363. zutipsg0000 (0.96, 14.0)
364. coolpix5700 (0.96, 9.6)
365. komodo$8000 (0.96, 12.1)
366. higuita8080 (0.96, 10.1)
367. leticia3070 (0.95, 8.9)
368. coolpix5200 (0.95, 8.9)
369. kolobok0000 (0.95, 7.9)
370. bigshow3470 (0.95, 9.2)
371. fbmoney0220 (0.95, 11.4)
372. pokemon8400 (0.95, 8.1)
373. jdmoney0420 (0.95, 9.7)
374. lolipop0000 (0.95, 6.4)
375. batavia3070 (0.95, 10.1)
376. bigfish8080 (0.95, 8.2)
377. vanessa8480 (0.95, 8.1)
378. pongosa5290 (0.95, 12.3)
379. wendysx7170 (0.95, 12.5)
380. johnson5980 (0.95, 8.5)
381. blanton8760 (0.95, 11.2)
382. dennis_0690 (0.95, 10.2)
383. verizon0000 (0.95, 7.0)
384. venessa5190 (0.95, 10.6)
385. almgnon0500 (0.95, 14.0)
386. udarain0000 (0.95, 11.1)
387. ikramsj8500 (0.95, 13.9)
388. mierdix8700 (0.95, 12.4)
389. ebrahim8400 (0.95, 9.3)
390. pacific0000 (0.95, 7.7)
391. segovia8300 (0.95, 9.7)
392. quentin5260 (0.95, 9.0)
393. hamodeh9990 (0.95, 10.7)
394. jackson5280 (0.95, 7.5)
395. sexyboy0000 (0.95, 7.2)
396. kirsten3260 (0.95, 9.3)
397. coolpix8800 (0.95, 9.2)
398. goatboy0000 (0.95, 8.8)
399. jtmoney0320 (0.95, 9.4)
400. retired5960 (0.95, 9.2)
401. rainbow7070 (0.95, 7.4)
402. ibrahim0200 (0.95, 7.7)
403. brayton5280 (0.95, 10.3)
404. headjob0000 (0.95, 9.0)
405. whiskey5050 (0.95, 7.8)
406. russpen7040 (0.95, 12.7)
407. matthew3030 (0.95, 6.6)
408. playboy0000 (0.95, 6.5)
409. trinity5580 (0.95, 8.5)
410. jtmoney0920 (0.95, 9.4)
411. yulissa0490 (0.95, 10.5)
412. mohamed3030 (0.95, 6.6)
413. bilemok0500 (0.95, 13.7)
414. opennow7070 (0.95, 8.8)
415. meramec5050 (0.95, 11.4)
416. albania0000 (0.95, 7.1)
417. lschmid0000 (0.95, 12.1)
418. mademen3040 (0.95, 9.7)
419. Herraiz0500 (0.95, 14.0)
420. Charas_0000 (0.95, 10.8)
421. spenceR5230 (0.95, 11.2)
422. braymeR5040 (0.95, 14.0)
423. Arcadia0000 (0.95, 8.5)
424. jnguyen0520 (0.95, 10.0)
425. Meinken0120 (0.95, 11.7)
426. demonea0920 (0.95, 11.6)
427. zanchez8330 (0.95, 11.9)
428. penguin0000 (0.95, 7.4)
429. analisa8890 (0.95, 9.7)
430. fuckyou5210 (0.95, 7.3)
431. Klassen3060 (0.95, 11.6)

432. homeboy3470 (0.95, 9.6)
433. mamamia5410 (0.95, 8.8)
434. toolbox3470 (0.95, 9.7)
435. access-0560 (0.95, 10.7)
436. brotheR7030 (0.95, 12.0)
437. fungaim7000 (0.95, 11.9)
438. fuckyou3000 (0.95, 6.2)
439. babyboy5410 (0.95, 8.3)
440. gogetta5360 (0.95, 10.4)
441. Hundai-3000 (0.95, 12.9)
442. takabow3100 (0.95, 11.7)
443. cityboy0000 (0.95, 7.8)
444. almoaid0000 (0.95, 12.4)
445. mdrakib7270 (0.95, 12.6)
446. titanic0000 (0.95, 7.1)
447. Shannon7300 (0.95, 9.0)
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449. thomas.7070 (0.95, 9.7)
450. nanahoj5910 (0.95, 13.5)
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455. PnhBgtk!700 (0.95, 14.0)
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461. melissa0390 (0.95, 8.1)
462. melissa8470 (0.95, 8.3)
463. chenmin0000 (0.95, 8.2)
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465. Godinez7930 (0.95, 11.4)
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467. delaney0420 (0.95, 8.1)
468. sampath7800 (0.95, 8.9)
469. AirbusA3570 (0.95, 9.5)
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471. amc@jec5150 (0.95, 14.0)
472. hellyea5150 (0.95, 8.2)
473. police/0430 (0.95, 10.9)
474. igmamex5450 (0.95, 14.0)
475. prince●5150 (0.95, 9.0)
476. griffin0000 (0.95, 7.3)
477. themask0000 (0.95, 8.3)
478. corndog0000 (0.95, 8.1)
479. directx0000 (0.95, 8.7)
480. augusta7890 (0.95, 8.1)
481. pugsley3690 (0.95, 9.2)
482. Dynasty3190 (0.95, 9.9)
483. chunyeu7240 (0.95, 11.7)
484. captain3000 (0.95, 6.5)
485. quepasa0000 (0.95, 8.8)
486. wrnmiop8980 (0.95, 14.0)
487. sonate_7780 (0.95, 12.8)
488. mcmahon0210 (0.95, 9.5)
489. RitaMia5710 (0.95, 13.0)
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491. majesty0960 (0.95, 10.0)
492. anhkhoa0210 (0.95, 8.0)
493. hershey0130 (0.95, 8.0)
494. cuqyhek6520 (0.95, 14.0)
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496. turiboy3000 (0.95, 10.4)
497. goldmen4120 (0.95, 10.6)
498. mynokia5310 (0.95, 6.2)
499. Fantasy7000 (0.95, 8.8)
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506. piripin7500 (0.95, 11.8)
507. Extensa5210 (0.95, 8.8)
508. ushuaia3000 (0.95, 8.8)
509. horizon3000 (0.95, 7.3)
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511. kiannia3300 (0.95, 11.5)
512. matthew0430 (0.95, 6.5)
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516. ramirez0190 (0.95, 8.1)
517. Rockboy3000 (0.95, 10.0)
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530. footjob7000 (0.95, 9.2)
531. mahoney5150 (0.95, 8.3)
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533. Rozane@3030 (0.95, 12.8)
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539. saushic0410 (0.95, 14.0)
540. Julissa7380 (0.95, 10.5)
541. Shannon0310 (0.95, 8.3)
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569. puppyta0110 (0.95, 11.4)
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572. Freedom0!!0 (0.95, 11.1)
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574. clerkty5010 (0.95, 12.6)
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889. thomson3290 (0.94, 9.2)
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906. wukevin6270 (0.94, 14.0)
907. desktop5000 (0.94, 4.8)
908. younyoa0620 (0.94, 12.9)
909. Misotta0000 (0.94, 12.5)
910. carwash4560 (0.94, 8.9)
911. johnboy9980 (0.94, 8.7)
912. zhicity0000 (0.94, 12.3)
913. melissa5410 (0.94, 8.0)
914. brandon!!10 (0.94, 8.8)
915. Mesetom5000 (0.94, 12.8)
916. jarvis@0000 (0.94, 10.2)
917. gweedog4270 (0.94, 11.2)
918. Mehwish0300 (0.94, 10.4)
919. adilson3660 (0.94, 10.0)
920. saksith0000 (0.94, 9.6)
921. bradley7890 (0.94, 7.3)
922. nubcaik5830 (0.94, 14.0)
923. loandoc0420 (0.94, 12.5)
924. bharath9160 (0.94, 9.5)
925. kristen0590 (0.94, 9.0)
926. lebanon0420 (0.94, 8.3)
927. preston0400 (0.94, 8.2)
928. lokomia8520 (0.94, 10.5)
929. palani.3710 (0.94, 12.0)
930. sampson0000 (0.94, 7.3)
931. rachnon5130 (0.94, 12.2)
932. suennia3010 (0.94, 11.8)
933. dominic3010 (0.94, 7.5)
934. jeffrey6990 (0.94, 8.5)
935. tinokia7610 (0.94, 9.0)
936. xeriseD7870 (0.94, 14.0)
937. chrissy3000 (0.94, 7.3)
938. BabyBoy5050 (0.94, 8.8)
939. novipin7510 (0.94, 12.4)
940. mertlem4490 (0.94, 11.5)
941. freedom7610 (0.94, 7.6)
942. mipopon7710 (0.94, 13.5)
943. fuckyou6600 (0.94, 7.3)
944. Paragon4770 (0.94, 11.1)
945. Braydon0620 (0.94, 8.8)
946. bradley4260 (0.94, 8.2)
947. ●mannix6000 (0.94, 13.3)
948. tarpley3570 (0.94, 11.7)
949. sampath0320 (0.94, 9.4)
950. paladin3210 (0.94, 8.1)
951. goodgod3310 (0.94, 8.2)
952. lolypop3110 (0.94, 9.3)
953. freedom3010 (0.94, 6.9)
954. rumania4000 (0.94, 9.7)
955. fuckyou4200 (0.94, 6.0)
956. simpson7370 (0.94, 9.4)
957. farmboy6670 (0.94, 9.2)
958. jackson0000 (0.94, 6.4)
959. georgia0220 (0.94, 7.4)
960. LiamRob0620 (0.94, 12.2)
961. clapton0300 (0.94, 9.2)
962. sainath3010 (0.94, 8.7)
963. loveyou3010 (0.94, 7.5)
964. melissa3000 (0.94, 6.5)
965. kinnita3600 (0.94, 11.2)
966. pumpkin4400 (0.94, 7.8)
967. clinton0500 (0.94, 8.6)
968. claudia0620 (0.94, 7.8)
969. ladydog9090 (0.94, 8.9)
970. logitec3300 (0.94, 9.9)
971. melissa8510 (0.94, 7.9)

972. hightop0000 (0.94, 9.2)	982. mclovin9090 (0.94, 8.6)	992. radchea1460 (0.94, 13.1)
973. kaution0300 (0.94, 10.7)	983. madison5210 (0.94, 7.5)	993. vanessa3000 (0.94, 6.7)
974. roximia8720 (0.94, 13.2)	984. dominic0420 (0.94, 7.0)	994. narotsy0710 (0.94, 13.3)
975. blossem8770 (0.94, 13.2)	985. Jacinta0720 (0.94, 9.5)	995. digimon0920 (0.94, 8.6)
976. Verizon9590 (0.94, 9.9)	986. freedom0220 (0.94, 7.0)	996. trungtv9890 (0.94, 12.1)
977. whiskey9500 (0.94, 9.0)	987. loveboy0420 (0.94, 8.5)	997. FuckYou5150 (0.94, 7.6)
978. mission5000 (0.94, 6.8)	988. fcvujtq9980 (0.94, 14.0)	998. mission3060 (0.94, 8.4)
979. shunko$5230 (0.94, 14.0)	989. marcus@3810 (0.94, 10.6)	999. prochex1480 (0.94, 12.7)
980. freedom8320 (0.94, 7.9)	990. srmintu3010 (0.94, 13.7)	
981. solomon9060 (0.94, 7.9)	991. Ceramic4370 (0.94, 11.6)	

Cluster 15

Prototype: 122229Aam

Hard-assigned passwords: 676601 (2.34% of total)
Unique hard-assigned passwords: 328670 (51.42% of cluster total)

Cluster-assignment scores:
        Min: 0.094
        Max: 0.980
        Mean: 0.413
        SD: 0.151

Strength bins:
        Very weak: 216986 (32.07%)
        Weak: 63220 (9.34%)
        Fair: 113295 (16.74%)
        Good: 272859 (40.33%)
        Strong: 10241 (1.51%)

Password lengths:
        Length 8: 24048 (3.55%)
        Length 9: 652553 (96.45%)

Character classes:
        4 classes: 2777 (0.41%)
        3 classes: 33421 (4.94%)
                lower/upper/symbol: 75 (0.22%)
                lower/upper/number: 20755 (62.10%)
                lower/symbol/number: 9720 (29.08%)
                upper/symbol/number: 2871 (8.59%)
        2 classes: 327779 (48.44%)
                lower/upper: 341 (0.10%)
                lower/number: 255275 (77.88%)
                lower/symbol: 4 (0.00%)
                upper/number: 60313 (18.40%)
                upper/symbol: 1782 (0.54%)
                number/symbol: 10064 (3.07%)
        1 class: 312624 (46.21%)
                lower: 0 (0.00%)
                upper: 20820 (6.66%)
                symbol: 51 (0.02%)
                number: 291753 (93.32%)

Most frequent char-class structures:
        DDDDDDDDD: 283209 (41.9%)
        DDDDDDLLL: 60571 (9.0%)
        DDDDDDDDL: 60245 (8.9%)
        DDDDLLLLL: 47176 (7.0%)
        DDDLLLLLL: 23549 (3.5%)
        UUUUUUUUU: 20820 (3.1%)
        DDDDDDDLL: 17599 (2.6%)
        DDDDDLLLL: 13910 (2.1%)
        UUUUUUUDD: 12753 (1.9%)
        UUUUUUDDD: 9226 (1.4%)

1,000 nearest passwords

0.	102537Mom	(0.98, 10.8)	54.	7925667mm	(0.93, 10.8)	108.	8953301hv	(0.92, 12.4)
1.	277007Tgm	(0.98, 12.7)	55.	7478361mm	(0.93, 11.1)	109.	6652719im	(0.92, 11.8)
2.	318818Agm	(0.97, 12.8)	56.	8489661jj	(0.93, 11.3)	110.	8581886vv	(0.91, 11.9)
3.	109607Sam	(0.96, 11.2)	57.	7294893pm	(0.93, 12.0)	111.	9749187rm	(0.91, 11.9)
4.	314159Hxj	(0.96, 11.2)	58.	6378710mm	(0.93, 10.8)	112.	0546321mm	(0.91, 10.6)
5.	119688Fpj	(0.96, 13.4)	59.	8350358hj	(0.93, 11.9)	113.	7824469mw	(0.91, 12.2)
6.	303161Tom	(0.96, 11.6)	60.	7324446cm	(0.93, 11.7)	114.	102354Mlb	(0.91, 11.2)
7.	19292-Lpv	(0.96, 14.0)	61.	7654321pj	(0.93, 8.2)	115.	7644205mm	(0.91, 11.1)
8.	112635Cow	(0.96, 12.5)	62.	3189178Zj	(0.93, 13.0)	116.	7854201av	(0.91, 11.5)
9.	219356Nh5	(0.96, 14.0)	63.	8245600mm	(0.93, 10.4)	117.	0139942em	(0.91, 12.1)
10.	513512Sxj	(0.95, 13.5)	64.	7763032cj	(0.93, 11.8)	118.	9676771mm	(0.91, 11.1)
11.	227127Jr^	(0.95, 14.0)	65.	7436901jm	(0.93, 11.5)	119.	122992Clj	(0.91, 11.5)
12.	102505Tom	(0.95, 9.9)	66.	8883096tj	(0.93, 11.7)	120.	7849138km	(0.91, 11.9)
13.	2230841Am	(0.94, 11.8)	67.	6753093mm	(0.93, 10.6)	121.	8335521jj	(0.91, 11.3)
14.	122399Tim	(0.94, 10.7)	68.	7075401jm	(0.93, 11.6)	122.	7879761aw	(0.91, 11.9)
15.	8726480bm	(0.94, 11.9)	69.	8675309mj	(0.93, 7.3)	123.	7777771sw	(0.91, 9.7)
16.	7632452sm	(0.94, 11.4)	70.	65414801v	(0.93, 11.8)	124.	5233502dv	(0.91, 12.0)
17.	6455004rm	(0.94, 12.0)	71.	7248045tj	(0.93, 11.6)	125.	8678612dw	(0.91, 11.3)
18.	7896732mm	(0.94, 11.1)	72.	8675309rm	(0.93, 7.4)	126.	8072790bw	(0.91, 12.4)
19.	419440Cd5	(0.94, 14.0)	73.	4341135Bj	(0.92, 12.5)	127.	149149Ccm	(0.91, 12.1)
20.	7899877nm	(0.94, 9.9)	74.	6236315zm	(0.92, 12.1)	128.	7173233tj	(0.91, 11.7)
21.	252402Kcj	(0.94, 13.1)	75.	6633259jm	(0.92, 11.4)	129.	8675309jj	(0.91, 6.4)
22.	6262623am	(0.94, 10.1)	76.	3142155Nm	(0.92, 12.5)	130.	7145946mv	(0.91, 11.8)
23.	7435291km	(0.94, 11.6)	77.	103172Rcw	(0.92, 12.2)	131.	5726527jm	(0.91, 11.5)
24.	8934241am	(0.94, 11.6)	78.	7788521gj	(0.92, 9.6)	132.	7824482dw	(0.91, 11.8)
25.	7347942mm	(0.94, 11.2)	79.	7654321rj	(0.92, 7.9)	133.	5254302aj	(0.91, 11.3)
26.	7363913bm	(0.94, 12.0)	80.	8742919um	(0.92, 12.8)	134.	7844331ww	(0.91, 11.4)
27.	7654321dm	(0.94, 7.4)	81.	6133692kv	(0.92, 12.2)	135.	5861666bm	(0.91, 11.7)
28.	6831553bm	(0.94, 11.8)	82.	5852123Dj	(0.92, 11.8)	136.	102565M@b	(0.91, 13.2)
29.	8675309mm	(0.94, 6.5)	83.	7227432mm	(0.92, 10.9)	137.	8675309mw	(0.91, 7.8)
30.	8883702jm	(0.94, 11.4)	84.	8793482pv	(0.92, 12.6)	138.	8883729xj	(0.91, 11.9)
31.	6151664cm	(0.94, 12.1)	85.	6754321tw	(0.92, 10.3)	139.	7157095ew	(0.91, 12.4)
32.	8982434hm	(0.94, 12.4)	86.	7287352nm	(0.92, 11.6)	140.	9959818dj	(0.91, 11.1)
33.	2522568Vm	(0.94, 12.5)	87.	9635821bm	(0.92, 11.7)	141.	9965492am	(0.91, 11.2)
34.	8254137am	(0.94, 11.5)	88.	6248302rv	(0.92, 12.3)	142.	6782571tv	(0.91, 12.5)
35.	5050725Mm	(0.94, 11.5)	89.	7982693av	(0.92, 11.8)	143.	2472006Om	(0.91, 11.9)
36.	662244-lm	(0.93, 12.6)	90.	9923566nm	(0.92, 11.5)	144.	5276510mm	(0.91, 10.7)
37.	8443061gm	(0.93, 11.9)	91.	112864Csf	(0.92, 12.2)	145.	7758521zw	(0.91, 7.9)
38.	6462254mm	(0.93, 10.7)	92.	8853525sm	(0.92, 11.7)	146.	2250406Jw	(0.91, 11.9)
39.	7235921@m	(0.93, 12.2)	93.	7758521gj	(0.92, 7.8)	147.	8871793sm	(0.91, 11.6)
40.	8383402am	(0.93, 11.3)	94.	1327985Am	(0.92, 12.0)	148.	0246810aj	(0.91, 8.0)
41.	7758521mj	(0.93, 7.7)	95.	4851223Jj	(0.92, 12.0)	149.	2089906Mm	(0.91, 12.0)
42.	6463232fm	(0.93, 11.8)	96.	7261366av	(0.92, 11.5)	150.	102795Knm	(0.91, 11.8)
43.	7537143mm	(0.93, 11.3)	97.	9643214rm	(0.92, 11.5)	151.	6954095pw	(0.91, 12.6)
44.	7357713mj	(0.93, 11.8)	98.	103008Mmj	(0.92, 12.0)	152.	8947041cj	(0.91, 12.0)
45.	7163323jj	(0.93, 11.2)	99.	112358Fib	(0.92, 10.9)	153.	6823244nm	(0.91, 11.6)
46.	6543210aj	(0.93, 8.1)	100.	7594621rj	(0.92, 12.0)	154.	7069320qw	(0.91, 11.3)
47.	8264593sm	(0.93, 11.5)	101.	6985152vm	(0.92, 12.4)	155.	4541297Rv	(0.91, 12.7)
48.	7295429em	(0.93, 11.6)	102.	7241984cm	(0.92, 10.1)	156.	7654321vw	(0.91, 8.7)
49.	8877125um	(0.93, 12.2)	103.	8337223gj	(0.92, 12.2)	157.	0881567fj	(0.91, 12.6)
50.	6623526jj	(0.93, 10.8)	104.	8598235cj	(0.92, 11.6)	158.	6868420sm	(0.91, 11.1)
51.	6753739sm	(0.93, 11.6)	105.	242424Ham	(0.92, 10.2)	159.	6827938km	(0.91, 11.9)
52.	262266&*^	(0.93, 12.7)	106.	6789123Nj	(0.92, 11.2)	160.	8064202bw	(0.91, 12.1)
53.	7930448cj	(0.93, 11.5)	107.	102587Beb	(0.92, 11.4)	161.	5855034cm	(0.91, 12.0)

162. 5785302mm (0.91, 11.0)
163. 6448619fw (0.91, 12.4)
164. 7580757av (0.91, 12.2)
165. 9482394cj (0.91, 11.9)
166. 7132476sm (0.91, 11.3)
167. 5677899sm (0.90, 9.7)
168. 6682957ww (0.90, 11.3)
169. 6395363mm (0.90, 10.9)
170. 7531594mM (0.90, 10.3)
171. 272297Sci (0.90, 13.1)
172. 7824208gm (0.90, 11.5)
173. 8135513ev (0.90, 12.3)
174. 8675309jv (0.90, 7.3)
175. 8067369jj (0.90, 11.4)
176. 7926985jm (0.90, 11.1)
177. 5064945sm (0.90, 11.6)
178. 7892864mm (0.90, 10.9)
179. 5174369pm (0.90, 11.7)
180. 7352611cM (0.90, 12.6)
181. 232515Rob (0.90, 11.0)
182. 5686262mm (0.90, 10.8)
183. 0277214rm (0.90, 12.8)
184. 9880587dm (0.90, 11.9)
185. 5554980wm (0.90, 11.9)
186. 6344410sw (0.90, 12.1)
187. 6675900qw (0.90, 11.1)
188. 7060757dj (0.90, 11.9)
189. 4558639om (0.90, 12.6)
190. 5346140am (0.90, 11.4)
191. 9693640tv (0.90, 12.5)
192. 8596267p/ (0.90, 13.6)
193. 5867045pm (0.90, 11.9)
194. 7145004ev (0.90, 11.0)
195. 8992853dj (0.90, 11.3)
196. 6941265E5 (0.90, 14.0)
197. 0548935mm (0.90, 11.3)
198. 1992345Mm (0.90, 10.4)
199. 87654321m (0.90, 5.2)
200. 0289354tj (0.90, 12.3)
201. 4623553am (0.90, 11.1)
202. 116900Sbj (0.90, 12.7)
203. 7878312kw (0.90, 11.7)
204. 7429457sm (0.90, 11.7)
205. 6173223oj (0.90, 12.5)
206. 3263126Aj (0.90, 12.3)
207. 0943032gm (0.90, 12.4)
208. 7951570jm (0.90, 11.5)
209. 8730327bj (0.90, 12.0)
210. 8640531am (0.90, 11.3)
211. 6294567dm (0.90, 11.5)
212. 6364270nm (0.90, 11.6)
213. 5537481um (0.90, 12.3)
214. 5423337am (0.90, 11.0)
215. 9962234am (0.90, 11.3)
216. 5653511kv (0.90, 12.5)
217. 5664991cj (0.90, 11.6)
218. 9782713cj (0.90, 11.6)
219. 5876098zj (0.90, 11.5)
220. 9867210+m (0.90, 12.8)
221. 5357613gj (0.90, 12.0)
222. 4535127nm (0.90, 10.7)
223. 5578006mm (0.90, 10.5)
224. 7246058mm (0.90, 11.1)
225. 4223867gm (0.90, 11.6)
226. 77265409m (0.90, 11.0)
227. 103093Eli (0.90, 10.8)
228. 7979661.v (0.90, 12.9)
229. 5875823jm (0.90, 11.3)
230. 6866053cw (0.90, 12.1)
231. 7896810oj (0.90, 12.5)
232. 5294750jj (0.90, 11.2)
233. 6789212Rj (0.90, 13.0)
234. 4032733bm (0.90, 11.6)
235. 8971602Bj (0.89, 12.7)
236. 1570009II (0.89, 12.0)
237. 7778042z- (0.89, 13.4)
238. 8899469jj (0.89, 10.6)
239. 202483Zh- (0.89, 14.0)
240. 85561284m (0.89, 10.9)
241. 4440535nm (0.89, 11.3)
242. 7036761qw (0.89, 11.0)
243. 6955054tw (0.89, 12.3)
244. 81725343m (0.89, 11.4)
245. 9152779aj (0.89, 11.7)
246. 419875Hjj (0.89, 13.2)
247. 8522456mm (0.89, 8.9)
248. 717717/*- (0.89, 9.8)
249. 8261897dj (0.89, 10.8)
250. 4662482mm (0.89, 10.6)
251. 7047053jf (0.89, 12.0)
252. 0159456pw (0.89, 11.1)
253. 1171768Rm (0.89, 12.7)
254. 0034229jj (0.89, 11.3)
255. 7725516jj (0.89, 11.1)
256. 6836281af (0.89, 11.5)
257. 3263899mm (0.89, 10.7)
258. 63796379m (0.89, 8.2)
259. 5157058fm (0.89, 11.7)
260. 6747111om (0.89, 12.2)
261. 8352770ww (0.89, 10.9)
262. 82780838m (0.89, 11.2)
263. 80543911v (0.89, 12.5)
264. 6656317fm (0.89, 12.1)
265. 12046LCLI (0.89, 13.9)
266. 813263Oq5 (0.89, 14.0)
267. 6392950M? (0.89, 14.0)
268. 8748149rf (0.89, 12.4)
269. 509507Z@% (0.89, 14.0)
270. 75743502v (0.89, 11.4)
271. 6994065dm (0.89, 12.8)
272. 3632247cm (0.89, 11.7)
273. 7297154mM (0.89, 12.3)
274. 8742801fw (0.89, 12.2)
275. 82338136m (0.89, 11.1)
276. 6725552hf (0.89, 12.2)
277. 4076623mj (0.89, 11.5)
278. 6184050cm (0.89, 11.6)
279. 8347135df (0.89, 11.8)
280. 8471729pw (0.89, 12.2)
281. 88772832v (0.89, 10.8)
282. 5678980r5 (0.89, 12.0)
283. 7296995mj (0.89, 11.8)
284. 4658791jj (0.89, 10.9)
285. 8266088pj (0.89, 11.9)
286. 789789mmm (0.89, 7.4)
287. 7898520ff (0.89, 8.6)
288. 6184562mf (0.89, 11.8)
289. 3352872mm (0.89, 10.4)
290. 8675309kj (0.89, 7.3)
291. 62633525m (0.89, 10.7)
292. 4052336nm (0.89, 11.4)
293. 5977320mm (0.89, 10.8)
294. 8269219jj (0.89, 10.8)
295. 7471628sf (0.89, 11.7)
296. 40973531m (0.89, 11.6)
297. 9262953ym (0.89, 12.6)
298. 8577200mf (0.89, 11.6)
299. 4444815rm (0.89, 11.8)
300. 66567891v (0.89, 10.9)
301. 3760845jm (0.89, 11.7)
302. 85431585m (0.89, 10.8)
303. 7435359of (0.89, 12.6)
304. 3779605bm (0.89, 11.9)
305. !8730411m (0.89, 14.0)
306. 5331553hj (0.89, 13.0)
307. 84418441j (0.89, 8.3)
308. 7572143aj (0.89, 11.5)
309. 3157248jm (0.89, 11.4)
310. 60566056m (0.89, 8.1)
311. 6885019km (0.89, 12.0)
312. 1051976HI (0.89, 11.8)
313. 72946491v (0.89, 11.6)
314. 8960751mm (0.89, 11.1)
315. 4255943dj (0.89, 11.1)
316. 8787513kw (0.89, 11.7)
317. 0072424am (0.89, 11.2)
318. 5966980jj (0.89, 11.0)
319. 8359670hj (0.89, 11.7)
320. 9543190_m (0.89, 12.3)
321. 70370681m (0.89, 11.3)
322. 6138594vf (0.89, 12.8)
323. 0054839am (0.89, 11.9)
324. 8289930yf (0.89, 12.6)
325. 5579227mj (0.89, 11.8)
326. 74661877m (0.89, 11.0)
327. 62549494j (0.89, 11.0)
328. 122400Cmw (0.89, 12.1)
329. 3244233tj (0.89, 11.5)
330. 5476051gm (0.89, 12.1)
331. 66843700m (0.89, 10.7)
332. 5624505aw (0.89, 11.4)
333. 5363572nv (0.89, 12.2)
334. 6823752mf (0.89, 12.0)
335. 69762562m (0.88, 11.1)
336. 6888095m/ (0.88, 13.2)
337. 4665899am (0.88, 10.6)
338. 7178769if (0.88, 12.3)
339. 87654321j (0.88, 5.7)
340. 3256321pj (0.88, 11.6)
341. 102477(*) (0.88, 11.7)
342. 8289914av (0.88, 12.1)
343. 5559355fm (0.88, 11.4)
344. 8260348mf (0.88, 12.2)
345. 402866Jpm (0.88, 12.9)
346. 7466303tj (0.88, 12.0)
347. 122266JHM (0.88, 11.4)
348. 1132050Sm (0.88, 12.0)
349. 85625780m (0.88, 10.7)
350. 8087403mf (0.88, 12.1)
351. 98346949m (0.88, 11.2)
352. 5124854sm (0.88, 11.4)
353. 88432416j (0.88, 10.9)
354. 5256231qw (0.88, 10.6)
355. 7128338kj (0.88, 11.7)
356. 5876852ww (0.88, 11.3)
357. 5566123am (0.88, 9.3)
358. 4033976jm (0.88, 11.4)
359. 4324825cm (0.88, 11.6)
360. 64858911m (0.88, 11.6)
361. 7972369ff (0.88, 11.6)
362. 63438809j (0.88, 11.7)
363. 7365196wf (0.88, 12.0)
364. 2785532nm (0.88, 11.4)
365. 97423561m (0.88, 10.9)
366. 2024527Mm (0.88, 11.7)
367. 129129UUU (0.88, 11.8)
368. 4958953dj (0.88, 11.3)
369. 9696420jv (0.88, 11.7)
370. 78966987m (0.88, 10.6)
371. 5627705ev (0.88, 11.8)
372. 3563179cm (0.88, 11.5)
373. 3939494mm (0.88, 10.7)
374. 94862236m (0.88, 11.1)
375. 5677899dj (0.88, 8.9)
376. 5559579vv (0.88, 11.7)
377. 3239058am (0.88, 11.3)
378. 9132769mm (0.88, 10.9)
379. 2574425nm (0.88, 11.0)
380. 7463002mw (0.88, 12.1)
381. 296104Fei (0.88, 12.6)
382. 233232Amm (0.88, 11.1)
383. 8675309cw (0.88, 7.5)
384. 5725254mm (0.88, 10.6)
385. 8867216qw (0.88, 11.1)
386. 4568923jj (0.88, 8.9)
387. 7884078cm (0.88, 11.6)
388. 112803CyF (0.88, 13.1)
389. 8524248jf (0.88, 12.2)
390. 65787051m (0.88, 11.3)
391. 9155580sm (0.88, 11.8)
392. 3834511qw (0.88, 10.8)
393. 2694455jm (0.88, 11.0)
394. 5789309bj (0.88, 12.1)
395. 2793447jm (0.88, 11.4)
396. 87654321~ (0.88, 7.7)
397. 3641709Pw (0.88, 13.0)
398. 4152699Nm (0.88, 12.4)
399. 7654321qw (0.88, 6.2)
400. 3344611mm (0.88, 10.5)
401. 4738482dj (0.88, 11.1)
402. 2255178bm (0.88, 11.3)
403. 2335410jm (0.88, 11.0)
404. 9436124km (0.88, 11.9)
405. 78673069m (0.88, 10.6)
406. 81889264m (0.88, 11.5)
407. 5628897*v (0.88, 13.1)
408. 77723560m (0.88, 10.4)
409. 4576220nj (0.88, 11.8)
410. 3389334mm (0.88, 11.0)
411. 7274723bj (0.88, 11.9)
412. 6528724jw (0.88, 11.8)
413. 7457332bj (0.88, 12.3)
414. 5693769j5 (0.88, 13.8)
415. 7057202df (0.88, 12.1)
416. 86898689j (0.88, 8.0)
417. 88855511m (0.88, 8.7)
418. 4894389tj (0.88, 11.9)
419. 97393454m (0.88, 11.0)
420. 6634104mM (0.88, 12.0)
421. 3456789nm (0.88, 7.8)
422. 84625156m (0.88, 10.7)
423. 7642155qw (0.88, 11.3)
424. 3386439mm (0.88, 11.0)
425. 60245844w (0.88, 11.8)
426. 1230.+-*/ (0.88, 9.5)
427. 2236423sm (0.88, 11.1)
428. 778089mom (0.88, 10.8)
429. 7440656am (0.88, 11.7)
430. 2426557mm (0.88, 10.2)
431. 77573941j (0.88, 11.4)

432. 81475539v (0.88, 11.3)
433. 7779311aw (0.88, 9.0)
434. 5245195Hm (0.88, 12.9)
435. 2249882jm (0.88, 10.9)
436. 2634803mm (0.88, 10.8)
437. 2765595jm (0.88, 11.2)
438. 78856943v (0.88, 11.5)
439. 2867720fm (0.88, 11.7)
440. 66688800j (0.88, 9.4)
441. 2684669mm (0.88, 9.8)
442. 95725694m (0.88, 11.3)
443. 68624550m (0.88, 10.7)
444. 3236232mv (0.88, 11.7)
445. 86899665m (0.88, 10.9)
446. 5223803rm (0.88, 11.5)
447. 208820MaU (0.88, 12.6)
448. 2939308pm (0.88, 11.8)
449. 4568927mm (0.88, 7.5)
450. 65759926m (0.88, 10.8)
451. 3524356dj (0.88, 11.1)
452. 42334233j (0.88, 8.1)
453. 62652703m (0.88, 10.8)
454. 64243534j (0.88, 11.1)
455. 5467711mj (0.88, 11.5)
456. 265168Kww (0.88, 13.7)
457. 7123456jj (0.88, 9.0)
458. 6971336ww (0.88, 11.3)
459. 6430558ff (0.88, 11.4)
460. 5864113mm (0.88, 10.4)
461. 122491Mjf (0.88, 11.7)
462. 2983298lm (0.88, 11.4)
463. 2644814em (0.88, 11.7)
464. 8259606ym (0.88, 12.2)
465. 5566039jw (0.87, 11.6)
466. 6566729zw (0.87, 11.9)
467. 66576101m (0.87, 11.8)
468. 93967405m (0.87, 11.1)
469. 1694949DI (0.87, 13.4)
470. 99663300m (0.87, 8.4)
471. 9894515*/ (0.87, 12.5)
472. 6251413mj (0.87, 11.0)
473. 8347502qw (0.87, 10.9)
474. 61438532m (0.87, 11.1)
475. 4842726dm (0.87, 11.7)
476. 02783930m (0.87, 10.7)
477. 9258915pw (0.87, 11.7)
478. 6541055Am (0.87, 12.0)
479. 5448173a? (0.87, 12.5)
480. 3169652gj (0.87, 12.0)
481. 74665135m (0.87, 11.1)
482. 9998877mw (0.87, 10.9)
483. 5796833ym (0.87, 12.4)
484. 7873123&& (0.87, 12.9)
485. 2872383am (0.87, 11.2)
486. 2441979Ni (0.87, 11.5)
487. 8439897tm (0.87, 11.9)
488. 5574026a5 (0.87, 12.2)
489. 08255878m (0.87, 11.0)
490. 2493983bm (0.87, 12.0)
491. 2545961vm (0.87, 12.3)
492. 38969591v (0.87, 12.4)
493. 87453232j (0.87, 11.0)
494. 75884722v (0.87, 11.5)
495. 2227466pj (0.87, 11.4)
496. 3598705.m (0.87, 12.1)
497. 99460358m (0.87, 10.7)
498. 2872190NM (0.87, 12.6)
499. 102508Lam (0.87, 10.7)
500. 876211Zz) (0.87, 14.0)
501. 2269517km (0.87, 11.4)
502. 4361848sv (0.87, 11.9)
503. 2928673cj (0.87, 11.3)
504. 2597758mm (0.87, 10.5)
505. 3457244dj (0.87, 11.0)
506. 6178082av (0.87, 12.0)
507. 2256324jj (0.87, 10.7)
508. 2943882nj (0.87, 12.4)
509. 3858906wj (0.87, 12.5)
510. 7770777mf (0.87, 10.1)
511. 2349327dj (0.87, 11.2)
512. 7654196fi (0.87, 11.6)
513. 77666145m (0.87, 10.7)
514. 2752420mm (0.87, 10.5)
515. 2572598jj (0.87, 10.7)
516. 6583216jf (0.87, 10.7)
517. 9239650mm (0.87, 11.0)
518. 5287520dj (0.87, 11.1)
519. 2624680aj (0.87, 11.3)
520. 63471988m (0.87, 10.4)
521. 366711_mm (0.87, 12.6)
522. 6558058tj (0.87, 11.5)
523. 052759mom (0.87, 9.9)
524. 7527541ab (0.87, 10.8)
525. 1571998Ai (0.87, 10.8)
526. 78624394w (0.87, 11.2)
527. 123123Mjm (0.87, 9.5)
528. 9548941nw (0.87, 13.0)
529. 3324327dj (0.87, 10.8)
530. 84463091m (0.87, 11.1)
531. 4842426jj (0.87, 10.8)
532. 01475963m (0.87, 8.2)
533. 6034225bb (0.87, 11.2)
534. 5050725Bb (0.87, 11.6)
535. 99898411m (0.87, 10.5)
536. 5399344Jj (0.87, 12.5)
537. 87543052m (0.87, 11.0)
538. 6541235cm (0.87, 10.0)
539. 80739706j (0.87, 11.7)
540. 0070646nf (0.87, 12.7)
541. 78998764j (0.87, 10.8)
542. 87879404j (0.87, 10.9)
543. 8189980Hw (0.87, 13.0)
544. 97467395m (0.87, 11.0)
545. 2677582jj (0.87, 11.1)
546. 293907RcM (0.87, 14.0)
547. 85866310m (0.87, 10.6)
548. 52316458j (0.87, 10.9)
549. 85482452v (0.87, 11.1)
550. 342808B6M (0.87, 14.0)
551. 73532626m (0.87, 11.1)
552. 5529975Jb (0.87, 12.7)
553. 3993456tw (0.87, 12.0)
554. 72974778w (0.87, 11.6)
555. 8068966qw (0.87, 11.5)
556. 3172560cj (0.87, 11.3)
557. 96803741jj (0.87, 11.2)
558. 3682223nm (0.87, 11.6)
559. 2952605cj (0.87, 11.6)
560. 823514.1m (0.87, 13.0)
561. 3439372sj (0.87, 12.0)
562. 5045150tj (0.87, 11.2)
563. 5572004Mj (0.87, 12.0)
564. 7424782ab (0.87, 11.6)
565. 6861458db (0.87, 11.6)
566. 54265426m (0.87, 7.1)
567. 5836232ff (0.87, 11.6)
568. 2956963km (0.87, 11.8)
569. 6559272qq (0.87, 10.6)
570. 75977597v (0.87, 8.4)
571. 3322394Aj (0.87, 12.9)
572. 6893690bb (0.87, 10.7)
573. 6665401ab (0.87, 11.1)
574. 6167213pw (0.87, 11.8)
575. 7779311jw (0.87, 8.9)
576. 71547154m (0.87, 8.5)
577. 7480410Jm (0.87, 12.5)
578. 78527852j (0.87, 8.0)
579. 6865153qq (0.87, 10.4)
580. 8898258bb (0.87, 11.2)
581. 6341536qq (0.87, 10.2)
582. 537121Job (0.87, 12.4)
583. 8962722qq (0.87, 10.6)
584. 7753191vv (0.87, 7.7)
585. 7758521qf (0.87, 9.2)
586. 76543210m (0.87, 6.5)
587. 77850385v (0.87, 11.4)
588. 79469490m (0.87, 11.6)
589. 112358Aa. (0.87, 8.6)
590. 2340640ev (0.87, 11.4)
591. 96423980m (0.87, 10.6)
592. 6341649ki (0.87, 12.0)
593. 42354242v (0.87, 11.4)
594. 108317Ram (0.87, 11.7)
595. 6930637ab (0.87, 11.4)
596. 75853611j (0.87, 11.2)
597. 4371353cj (0.87, 11.5)
598. 3632850ww (0.87, 11.6)
599. 68984495m (0.87, 11.0)
600. 61647260j (0.87, 11.3)
601. 42330420m (0.87, 10.6)
602. 0556722ff (0.87, 11.8)
603. 8185825sb (0.87, 11.8)
604. 61326081p (0.87, 10.2)
605. 52455245v (0.87, 8.6)
606. 2557881cv (0.87, 12.2)
607. 2532892mm (0.87, 10.6)
608. 0187285pw (0.87, 12.4)
609. 02315868m (0.87, 10.5)
610. 2737006wm (0.87, 12.0)
611. 4165519tj (0.87, 11.4)
612. 2084762dj (0.87, 10.9)
613. 7624432ab (0.87, 10.6)
614. 3430333tm (0.87, 12.0)
615. 6196676mb (0.87, 11.7)
616. 192525Ms, (0.87, 13.3)
617. 67525881m (0.87, 11.3)
618. 88836922m (0.87, 10.9)
619. 8143234ab (0.87, 10.8)
620. 3380588vv (0.87, 11.7)
621. 96885271j (0.87, 11.2)
622. 5680428mm (0.87, 10.9)
623. 3792843tw (0.87, 12.1)
624. 2889463cj (0.87, 11.4)
625. 92475821m (0.87, 11.0)
626. 5775725jj (0.87, 11.3)
627. 05350535m (0.87, 7.9)
628. 4165414aw (0.87, 11.4)
629. 112666Htc (0.87, 12.0)
630. 6441338kb (0.86, 11.7)
631. 72583592j (0.86, 11.0)
632. 07880375j (0.86, 10.9)
633. 3687154ev (0.86, 11.8)
634. 1230.●-*/ (0.86, 9.1)
635. 568071_ew (0.86, 13.4)
636. 3139850mj (0.86, 11.5)
637. 2480466bj (0.86, 11.5)
638. 112233Moi (0.86, 8.8)
639. 8863166yj (0.86, 12.2)
640. 6677212yi (0.86, 12.7)
641. 8787900ab (0.86, 10.3)
642. 8343413mb (0.86, 11.7)
643. 76627055w (0.86, 11.5)
644. 75553150j (0.86, 11.3)
645. 6242317ab (0.86, 10.8)
646. 5044084tj (0.86, 11.8)
647. 48454251j (0.86, 10.7)
648. 8580585bb (0.86, 11.1)
649. 71777037v (0.86, 11.5)
650. 87654321w (0.86, 5.7)
651. 8675309cf (0.86, 7.3)
652. 87653099j (0.86, 9.8)
653. 8258772ib (0.86, 12.4)
654. 8963701ab (0.86, 10.9)
655. 03655323j (0.86, 11.1)
656. 6225713mm (0.86, 10.7)
657. 83303891i (0.86, 11.3)
658. 8325656pw (0.86, 11.9)
659. 2659160CF (0.86, 13.0)
660. 55326632m (0.86, 10.2)
661. 2387551av (0.86, 12.0)
662. 6699786bb (0.86, 10.6)
663. 24422461v (0.86, 11.7)
664. 52588082m (0.86, 11.0)
665. 73324428m (0.86, 11.1)
666. 7831635cb (0.86, 11.6)
667. 3236145ev (0.86, 11.7)
668. 7753191bv (0.86, 9.5)
669. 5850355qw (0.86, 10.9)
670. 83542629- (0.86, 12.6)
671. 2356925wj (0.86, 12.0)
672. 0624855jj (0.86, 11.2)
673. 7788321pq (0.86, 11.4)
674. 3323529mm (0.86, 10.5)
675. 7682713$q (0.86, 14.0)
676. 2142689ev (0.86, 11.6)
677. 6232752jq (0.86, 12.4)
678. 68956895j (0.86, 8.9)
679. 83433173m (0.86, 11.2)
680. 68696968m (0.86, 10.4)
681. 61360361p (0.86, 10.9)
682. 86753099j (0.86, 7.2)
683. 8878126ab (0.86, 10.4)
684. 64506450j (0.86, 8.7)
685. 2362402mm (0.86, 10.4)
686. 8042417db (0.86, 12.1)
687. 56578234j (0.86, 11.1)
688. 2242533cv (0.86, 11.3)
689. 2989494mm (0.86, 10.9)
690. 88692256m (0.86, 10.7)
691. 328222%%% (0.86, 12.4)
692. 89265471m (0.86, 12.0)
693. 84312861i (0.86, 11.2)
694. 6423987ab (0.86, 10.6)
695. 5361493cm (0.86, 11.6)
696. 91585985m (0.86, 10.7)
697. 66792066j (0.86, 11.0)
698. 7993266Dj (0.86, 12.7)
699. 0587929q8 (0.86, 13.2)
700. 69936081p (0.86, 10.3)
701. 82528253m (0.86, 10.8)

702. 6352410., (0.86, 10.3)
703. 102865Tac (0.86, 11.0)
704. 8381666af (0.86, 12.1)
705. 87654321f (0.86, 5.7)
706. 72872148m (0.86, 11.0)
707. 63523803v (0.86, 12.3)
708. 7869217mi (0.86, 10.7)
709. 8665618bj (0.86, 11.9)
710. 78343395w (0.86, 11.8)
711. 87769652j (0.86, 11.1)
712. 9174304fj (0.86, 12.5)
713. 767231__? (0.86, 13.9)
714. 5898252kj (0.86, 12.0)
715. 7734922cb (0.86, 11.6)
716. 52737821v (0.86, 11.8)
717. 4567890am (0.86, 8.2)
718. 2493820aj (0.86, 11.6)
719. 96496033j (0.86, 10.9)
720. 726060-bb (0.86, 12.7)
721. 59804511m (0.86, 11.6)
722. 8143503db (0.86, 12.3)
723. 8426499gb (0.86, 11.9)
724. 8057803nb (0.86, 12.3)
725. 4095578jj (0.86, 11.2)
726. 7654321zb (0.86, 8.1)
727. 69696969m (0.86, 5.7)
728. 60450271p (0.86, 10.7)
729. 4568927jj (0.86, 7.9)
730. 76265987j (0.86, 11.3)
731. 4779225dw (0.86, 12.2)
732. 53425342m (0.86, 7.6)
733. 5644110av (0.86, 11.6)
734. 72498256w (0.86, 11.6)
735. 74862035w (0.86, 11.7)
736. 4452511am (0.86, 10.7)
737. 3698741qw (0.86, 7.0)
738. 42649345m (0.86, 10.8)
739. 7041653ab (0.86, 10.9)
740. 73967928m (0.86, 11.2)
741. 2228373mj (0.86, 11.1)
742. 71452863m (0.86, 10.9)
743. 75365620m (0.86, 11.2)
744. 7996963jb (0.86, 11.9)
745. 112413Jim (0.86, 10.5)
746. 84286285m (0.86, 10.7)
747. 6144320fb (0.86, 11.5)
748. 2174935pm (0.86, 11.6)
749. 6173959mi (0.86, 11.7)
750. 86442324v (0.86, 10.7)
751. 7931634sb (0.86, 11.8)
752. 50568088m (0.86, 10.8)
753. 82790461p (0.86, 10.8)
754. 72397239m (0.86, 8.6)
755. 569987/*- (0.86, 10.5)
756. 6472232qq (0.86, 10.2)
757. 56784321m (0.86, 9.1)
758. 88626691m (0.86, 10.5)
759. 69696969j (0.86, 6.1)
760. 2247963hm (0.86, 11.7)
761. 83404251p (0.86, 10.5)
762. 44542444m (0.86, 10.6)
763. 88332126j (0.86, 10.8)
764. 6262619ab (0.86, 10.3)
765. 84427729I (0.86, 12.9)
766. 2532549ww (0.86, 11.0)
767. 87570669j (0.86, 11.5)
768. 5224828qw (0.86, 10.9)
769. 7964214mb (0.86, 11.4)
770. 4567231dw (0.86, 11.7)
771. 86680886w (0.86, 11.4)
772. 69430061p (0.86, 10.9)
773. 2832809mm (0.86, 10.7)
774. 7654321ab (0.86, 6.2)
775. 89226634m (0.86, 11.2)
776. 6066202eb (0.86, 11.7)
777. 67233451p (0.86, 10.7)
778. 2230345Vv (0.86, 11.9)
779. 68403591p (0.86, 10.0)
780. 2255225cw (0.86, 10.8)
781. 7564023fi (0.86, 12.2)
782. 2488090pm (0.86, 11.9)
783. 6534015of (0.86, 12.5)
784. 7788999qq (0.86, 8.3)
785. 5278000oj (0.86, 12.1)
786. 3540539cj (0.86, 11.8)
787. 5985089sw (0.86, 11.9)
788. 61360541p (0.86, 10.6)
789. 86495315j (0.86, 11.4)
790. 84640161p (0.86, 10.8)
791. 7078515fq (0.86, 12.8)
792. 7758521bb (0.86, 7.0)
793. 7325310mm (0.86, 10.6)
794. 2747826mm (0.86, 10.7)
795. 78776097m (0.86, 11.1)
796. 7654321mp (0.86, 7.2)
797. 9549049+- (0.86, 12.3)
798. 80569038m (0.86, 11.1)
799. 77853316j (0.86, 11.3)
800. 6640486bb (0.86, 10.9)
801. 8642038-- (0.86, 11.6)
802. 1042003Mv (0.86, 11.2)
803. 67525091p (0.86, 10.5)
804. 408060Rob (0.86, 11.4)
805. 4544124●- (0.86, 12.3)
806. 8231965pj (0.86, 10.8)
807. 7758990ai (0.86, 11.6)
808. 677091Eni (0.86, 12.7)
809. 96522987m (0.86, 10.7)
810. 8223445bb (0.86, 11.1)
811. 3471987am (0.86, 10.5)
812. 8460507ab (0.86, 10.9)
813. 2244300jw (0.86, 11.2)
814. 4561508mm (0.86, 11.0)
815. 9877118aw (0.86, 12.0)
816. 81468146m (0.86, 8.6)
817. 6330598qq (0.86, 10.2)
818. 77666145M (0.86, 11.5)
819. 9880732am (0.86, 11.7)
820. 1998V70T5 (0.86, 13.6)
821. 8435810hb (0.86, 11.6)
822. 7661337ab (0.86, 10.6)
823. 2540842km (0.86, 11.7)
824. 4928805am (0.86, 11.5)
825. 418146Abc (0.86, 11.4)
826. 61275671p (0.86, 10.6)
827. 5160566sm (0.86, 11.6)
828. 57428603j (0.86, 11.2)
829. 9898798sf (0.86, 10.9)
830. 46545323j (0.86, 10.7)
831. 4046711wm (0.86, 11.9)
832. 68327911p (0.86, 10.4)
833. 7736251kb (0.86, 11.6)
834. 159801Phi (0.86, 12.3)
835. 7496888mf (0.86, 12.3)
836. 3065910am (0.86, 11.2)
837. 5632522Tm (0.86, 12.4)
838. 2345413qw (0.86, 10.2)
839. 64549056m (0.86, 11.1)
840. 022796_pv (0.86, 13.0)
841. 82324957w (0.86, 11.7)
842. 8825252tw (0.86, 11.6)
843. 8831863db (0.86, 11.3)
844. 55656234w (0.86, 11.3)
845. 51627542v (0.86, 11.2)
846. 73382942v (0.86, 11.3)
847. 2137385dj (0.86, 11.2)
848. 48817344m (0.86, 11.2)
849. 3267420dj (0.86, 11.0)
850. 74454890m (0.86, 11.0)
851. 2179538jj (0.86, 11.0)
852. 2661888kv (0.86, 11.7)
853. 7654321pp (0.86, 6.6)
854. 8675309hi (0.86, 7.1)
855. 6440901GM (0.86, 12.9)
856. 5286705rm (0.86, 11.5)
857. 8876820pw (0.86, 11.9)
858. 82647193m (0.86, 11.0)
859. 3569381mv (0.86, 12.3)
860. 49542581m (0.86, 11.1)
861. 5649969sf (0.86, 11.6)
862. 84650948m (0.86, 11.1)
863. 2552446+m (0.86, 12.1)
864. 4568908nm (0.86, 11.4)
865. 70571681p (0.86, 10.9)
866. 1200IIIep (0.86, 13.4)
867. 7753191Bv (0.86, 10.3)
868. 53479246j (0.86, 11.3)
869. 5285416cj (0.86, 11.6)
870. 3531873ew (0.86, 12.0)
871. 7530419mm (0.86, 11.2)
872. 486153+cv (0.86, 13.3)
873. 6885625ti (0.86, 12.0)
874. 8898560kb (0.86, 11.7)
875. 83232831p (0.86, 10.4)
876. 69770201i (0.86, 11.1)
877. 8324206Vj (0.86, 12.8)
878. 4581620Rf (0.86, 12.9)
879. 8051356cv (0.86, 12.1)
880. 36347954m (0.86, 11.0)
881. 55663502v (0.86, 11.5)
882. 123123Alf (0.86, 8.6)
883. 2938793kw (0.86, 12.3)
884. 88641268m (0.86, 10.8)
885. 75395146v (0.86, 7.5)
886. 7641461qw (0.86, 10.9)
887. 4397293cm (0.86, 12.0)
888. 2337600qw (0.86, 10.6)
889. 112233Wii (0.86, 10.4)
890. 8794077ab (0.86, 10.9)
891. 68699304v (0.86, 11.5)
892. 30666965m (0.85, 11.0)
893. 8551316Kj (0.85, 12.8)
894. 0456123mm (0.85, 9.6)
895. 3846080ev (0.85, 12.3)
896. 48644323j (0.85, 10.8)
897. 112233Tem (0.85, 9.1)
898. 60963361p (0.85, 10.9)
899. 89898989j (0.85, 7.1)
900. 82474254v (0.85, 11.5)
901. 8675309vb (0.85, 7.6)
902. 462246fnm (0.85, 12.4)
903. 6192864sm (0.85, 11.6)
904. 71387244m (0.85, 11.2)
905. 199220Dec (0.85, 9.9)
906. 7654312pp (0.85, 9.8)
907. 23783100m (0.85, 12.9)
908. 639068unm (0.85, 12.3)
909. 2260567pj (0.85, 11.5)
910. 4568927ww (0.85, 8.3)
911. 57678167j (0.85, 11.4)
912. 70471271p (0.85, 10.8)
913. 94462582m (0.85, 10.9)
914. 9089751yf (0.85, 13.1)
915. 61469101p (0.85, 10.7)
916. 84488999+ (0.85, 12.4)
917. 166933AJ? (0.85, 13.8)
918. 6650808●- (0.85, 12.6)
919. 68899901p (0.85, 10.8)
920. 6282270p8 (0.85, 13.5)
921. 6561404u+ (0.85, 14.0)
922. 5050725Pp (0.85, 11.8)
923. 81873590j (0.85, 11.5)
924. 5753572af (0.85, 11.4)
925. 5327779jf (0.85, 11.6)
926. 8262023rj (0.85, 11.8)
927. 8228563jp (0.85, 11.2)
928. 7894568dj (0.85, 9.8)
929. 87654321` (0.85, 7.3)
930. 9087819mm (0.85, 11.2)
931. 8675309ab (0.85, 6.2)
932. 88618331i (0.85, 11.5)
933. 55378008m (0.85, 10.9)
934. 2473116ev (0.85, 11.6)
935. 102803Ali (0.85, 9.8)
936. 73393347w (0.85, 11.4)
937. 5162985gf (0.85, 11.7)
938. 83580951p (0.85, 10.7)
939. 2547689dw (0.85, 11.6)
940. 8474519ab (0.85, 10.9)
941. 5669147jj (0.85, 10.8)
942. 5256054kv (0.85, 12.2)
943. 66571565M (0.85, 12.3)
944. 47253685m (0.85, 10.4)
945. 70441301p (0.85, 10.8)
946. 2380632ev (0.85, 11.7)
947. 79449592M (0.85, 12.2)
948. 342524Jpm (0.85, 12.7)
949. 6956958cm (0.85, 11.0)
950. 85263987j (0.85, 10.3)
951. 7784231mp (0.85, 11.6)
952. 38938470m (0.85, 11.1)
953. 3245902ev (0.85, 11.9)
954. 8537947pm (0.85, 12.1)
955. 2689423cw (0.85, 11.7)
956. 8668714ap (0.85, 11.9)
957. 55717775m (0.85, 11.1)
958. 83275701p (0.85, 10.5)
959. 4226531mm (0.85, 10.4)
960. 74625028M (0.85, 11.8)
961. 79760730m (0.85, 11.1)
962. 6638609pp (0.85, 11.2)
963. 2575112AM (0.85, 12.4)
964. 49525533m (0.85, 10.9)
965. 8069954qq (0.85, 11.0)
966. 28626061w (0.85, 11.9)
967. 1212IRAQI (0.85, 12.9)
968. 9055952qi (0.85, 13.1)
969. 6947513ci (0.85, 12.6)
970. 2358760jm (0.85, 11.2)
971. 77624302m (0.85, 11.0)

972. 78936078v (0.85, 10.7)
973. 2747816gw (0.85, 11.8)
974. 122557Alp (0.85, 11.2)
975. 626141-ff (0.85, 13.0)
976. 5688006bf (0.85, 11.7)
977. 5839126Cb (0.85, 12.6)
978. 7533500ab (0.85, 10.9)
979. 3139593gj (0.85, 12.2)
980. 06622485w (0.85, 11.2)
981. 309398-Mv (0.85, 14.0)
982. 8399866tp (0.85, 12.0)
983. 82739182M (0.85, 12.0)
984. 77318446j (0.85, 11.0)
985. 6831473m; (0.85, 13.6)
986. 87424813m (0.85, 11.0)
987. 62826282v (0.85, 8.9)
988. 31564423m (0.85, 10.7)
989. 528031Saw (0.85, 12.3)
990. 7758521qq (0.85, 5.9)
991. 51535759m (0.85, 8.3)
992. 6138817lp (0.85, 10.6)
993. 8996460jp (0.85, 11.9)
994. 123123SEM (0.85, 9.0)
995. 8442729qq (0.85, 10.6)
996. 193168Arm (0.85, 11.3)
997. 159263Rap (0.85, 9.9)
998. 1131462Ci (0.85, 13.2)
999. 8675309!M (0.85, 9.4)

Cluster 16

Prototype: ARA33aa112x

Hard-assigned passwords: 801397 (2.77% of total)
Unique hard-assigned passwords: 682240 (14.87% of cluster total)

Cluster-assignment scores:
        Min: 0.069
        Max: 0.949
        Mean: 0.351
        SD: 0.154

Strength bins:
        Very weak: 5829 (0.73%)
        Weak: 30200 (3.77%)
        Fair: 63098 (7.87%)
        Good: 281993 (35.19%)
        Strong: 420277 (52.44%)

Password lengths:
        Length 10: 68201 (8.51%)
        Length 11: 731186 (91.24%)
        Length 12: 2010 (0.25%)

Character classes:
        4 classes: 19711 (2.46%)
        3 classes: 400522 (49.98%)
                lower/upper/symbol: 1429 (0.36%)
                lower/upper/number: 375877 (93.85%)
                lower/symbol/number: 19745 (4.93%)
                upper/symbol/number: 3471 (0.87%)
        2 classes: 340076 (42.44%)
                lower/upper: 2031 (0.60%)
                lower/number: 295383 (86.86%)
                lower/symbol: 455 (0.13%)
                upper/number: 35728 (10.51%)
                upper/symbol: 1138 (0.33%)
                number/symbol: 5341 (1.57%)
        1 class: 41088 (5.13%)
                lower: 0 (0.00%)
                upper: 7994 (19.46%)
                symbol: 19 (0.05%)
                number: 33075 (80.50%)

Most frequent char-class structures:
        DDDDDDDDDDD: 33075 (4.1%)
        DDDDDDLLLLL: 19239 (2.4%)
        DDDDDDDDLLL: 18697 (2.3%)
        LDDDDDDDDDD: 18000 (2.2%)
        DDDDLLLLLLL: 16188 (2.0%)
        LLLDDDDDDDD: 15671 (2.0%)
        LLDDDDDDDDD: 12347 (1.5%)
        DDDLLLLLLLL: 11529 (1.4%)
        DLLLLLLLLLL: 11442 (1.4%)
        DDLLLLLLLLL: 10879 (1.4%)

1,000 nearest passwords

0.	CDo04npsXBh	(0.95, 14.0)	54.	oAj7UjTt0rY	(0.91, 14.0)	108.	RSM90fgyXVG	(0.90, 14.0)
1.	OGHABbash1!	(0.95, 14.0)	55.	XNM9Zge4qrG	(0.91, 14.0)	109.	7TJDPeNl1ay	(0.90, 14.0)
2.	H2O*R@tt72!	(0.95, 14.0)	56.	7dR2Ndw8prx	(0.91, 14.0)	110.	KCI37adgZPh	(0.90, 14.0)
3.	ALPHAmale1!	(0.94, 10.6)	57.	VSk14zRXxes	(0.91, 14.0)	111.	Q7d8IunHhws	(0.90, 14.0)
4.	O4mLUph2qfx	(0.94, 14.0)	58.	GNg71nnUcWG	(0.91, 14.0)	112.	!REW#mate1!	(0.90, 14.0)
5.	SMILEnow76!	(0.94, 12.6)	59.	GVeMXr35eFh	(0.91, 14.0)	113.	7xnOTsw0xKs	(0.90, 14.0)
6.	ALPHAbeat1!	(0.94, 10.4)	60.	YVx37hvzWWG	(0.91, 14.0)	114.	RY4nQz17YUY	(0.90, 14.0)
7.	CHUTIdope1!	(0.94, 14.0)	61.	4SxEEo1x5Ix	(0.91, 14.0)	115.	MSDBEdwards	(0.90, 13.7)
8.	5q7rIgooh7h	(0.94, 14.0)	62.	ILOVEmymom!	(0.91, 8.5)	116.	8xI6Yt1nQWx	(0.90, 14.0)
9.	VGN7Kkb9gUh	(0.94, 14.0)	63.	HQF2jiayou!	(0.91, 14.0)	117.	ARAI4family	(0.90, 13.4)
10.	DHF89ipMhxx	(0.93, 14.0)	64.	7Q8I2d25GPx	(0.91, 14.0)	118.	7I2nVm0Sxms	(0.90, 14.0)
11.	7yXgHcrbm4s	(0.93, 14.0)	65.	fIq36glPMny	(0.91, 14.0)	119.	5SeU5pmWe1Y	(0.90, 14.0)
12.	6kQo7jltlqh	(0.93, 14.0)	66.	6PpYPkf2znh	(0.91, 14.0)	120.	h2sA9cBGQLx	(0.89, 14.0)
13.	JJJdPfqvs1!	(0.93, 14.0)	67.	GMC46sjdsay	(0.91, 14.0)	121.	8T4xHrl7P2y	(0.89, 14.0)
14.	FPL4Asf3sXh	(0.93, 14.0)	68.	5iYSIhmq70x	(0.91, 14.0)	122.	MMbKHd32pQY	(0.89, 14.0)
15.	ITyQRtbr1es	(0.93, 14.0)	69.	TVh58hlWYjh	(0.91, 14.0)	123.	WF7l1uIFkKh	(0.89, 14.0)
16.	DQm07ugXees	(0.93, 14.0)	70.	ITS@Sa0P0l!	(0.91, 14.0)	124.	p4s5.linked	(0.89, 9.7)
17.	TRn5Vbf8tJs	(0.93, 14.0)	71.	KVO82lppLXh	(0.91, 14.0)	125.	W3bH0stpasS	(0.89, 10.6)
18.	hEi19chSTAh	(0.93, 14.0)	72.	+100Cheese!	(0.91, 13.0)	126.	tPB08hZKunx	(0.89, 14.0)
19.	V3RY}b00st!	(0.93, 14.0)	73.	4DGp6eoOa6x	(0.91, 14.0)	127.	7e2h7gqvXQG	(0.89, 14.0)
20.	SLKQ5g2oZbx	(0.93, 14.0)	74.	7IH8Zh9tZ2x	(0.91, 14.0)	128.	HPsTZq79lfy	(0.89, 14.0)
21.	kEEp1ntouch	(0.92, 12.7)	75.	8ik77opalos	(0.91, 14.0)	129.	n35LJdpgwux	(0.89, 14.0)
22.	OKY8Qoo9iuY	(0.92, 14.0)	76.	k6sRVb5F2bx	(0.91, 14.0)	130.	ANTIMetid0s	(0.89, 14.0)
23.	8o162ybyloh	(0.92, 14.0)	77.	KGTjLf45hOy	(0.91, 14.0)	131.	7w8lEcacaqs	(0.89, 14.0)
24.	6e0r6efaris	(0.92, 14.0)	78.	UJMJUjmju7!	(0.91, 14.0)	132.	7wVeXqf8rDG	(0.89, 14.0)
25.	7G6uOj0kdes	(0.92, 14.0)	79.	7gz5VfBLe0s	(0.91, 14.0)	133.	7TZj5juLL7s	(0.89, 14.0)
26.	8L3W2vdkxKh	(0.92, 14.0)	80.	hEH55vuySXs	(0.91, 14.0)	134.	8AK31bOj1dG	(0.89, 14.0)
27.	rDn1Kmh1FKh	(0.92, 14.0)	81.	7XmQ3sawh4x	(0.91, 14.0)	135.	l123●nus_ed	(0.89, 14.0)
28.	iAH88jwtskx	(0.92, 14.0)	82.	VPq35siPPxh	(0.91, 14.0)	136.	ZNR64vdBHzs	(0.89, 14.0)
29.	SFxEIm47rcy	(0.92, 14.0)	83.	KMG80rqksMY	(0.91, 14.0)	137.	yHd9Txd5JSs	(0.89, 14.0)
30.	PBY17bdOoaY	(0.92, 14.0)	84.	lKJ88=>;.yx	(0.91, 14.0)	138.	ZQV7Zap7snd	(0.89, 14.0)
31.	ZMZDTc94ddx	(0.92, 14.0)	85.	RHETTnp123!	(0.90, 14.0)	139.	7m0gJvU5x8y	(0.89, 14.0)
32.	FXS68ibrLex	(0.92, 14.0)	86.	IDf5Sfq5nXy	(0.90, 14.0)	140.	7E9l8cTjAxs	(0.89, 14.0)
33.	FCZ10uerich	(0.92, 14.0)	87.	QNf12ukQTKs	(0.90, 14.0)	141.	6f4u4c8k^ux	(0.89, 14.0)
34.	JR233series	(0.92, 11.9)	88.	5qXx8bgRZ9x	(0.90, 14.0)	142.	AHMEDaloun!	(0.89, 14.0)
35.	7G2fSeRqz4x	(0.92, 14.0)	89.	yX9j4wiaRJs	(0.90, 14.0)	143.	kRA93qfvWVx	(0.89, 14.0)
36.	7dP44cSb26h	(0.92, 14.0)	90.	m1256lafg.h	(0.90, 14.0)	144.	7UzM8hxz7ds	(0.89, 14.0)
37.	4kWwWemgd7x	(0.92, 14.0)	91.	7ns6Wga9GHh	(0.90, 14.0)	145.	s7LS9ql<U9S	(0.89, 14.0)
38.	P360RaKUSUx	(0.92, 14.0)	92.	7y1IIlx2sEy	(0.90, 14.0)	146.	6f01Wahck9y	(0.89, 14.0)
39.	BYSySeo1qdx	(0.92, 14.0)	93.	RX9nRdrqlpx	(0.90, 14.0)	147.	8oUL9vk8C4G	(0.89, 14.0)
40.	7yB1Uz8yrFx	(0.92, 14.0)	94.	5dLXJrtz6jY	(0.90, 14.0)	148.	7oHd9cdZGrh	(0.89, 14.0)
41.	7qmCEys1kQx	(0.91, 14.0)	95.	7TzUJcni7uy	(0.90, 14.0)	149.	HZJ8Do79NlG	(0.89, 14.0)
42.	hKL3Es@n45!	(0.91, 14.0)	96.	8fcV4vP56xY	(0.90, 14.0)	150.	SMY22months	(0.89, 12.2)
43.	SWo59mfzYDG	(0.91, 14.0)	97.	bDm38uUsxbY	(0.90, 14.0)	151.	6XaE3bARr7Y	(0.89, 14.0)
44.	7c6aNwChh9h	(0.91, 14.0)	98.	6R7m2wN4ksG	(0.90, 14.0)	152.	m!50Ndus3ps	(0.89, 14.0)
45.	WLu75aybFRY	(0.91, 14.0)	99.	zASVZdat55h	(0.90, 14.0)	153.	ACLC_thesis	(0.89, 14.0)
46.	8gqXRmqw0fy	(0.91, 14.0)	100.	8wo51tYVraY	(0.90, 14.0)	154.	aQF4Yuwrc5Y	(0.89, 14.0)
47.	G311Marines	(0.91, 11.3)	101.	7mVw3pW4qMs	(0.90, 14.0)	155.	dQL52ngspdx	(0.89, 14.0)
48.	SYz00gJbtry	(0.91, 14.0)	102.	8BXNLr1sR5h	(0.90, 14.0)	156.	4in!Linked!	(0.89, 11.9)
49.	ALp92grZgbx	(0.91, 14.0)	103.	TYO12ueTpwG	(0.90, 14.0)	157.	yAh00things	(0.89, 13.3)
50.	8A0X2atzsZx	(0.91, 14.0)	104.	VZo22csdaws	(0.90, 14.0)	158.	gIE47bYVO8x	(0.89, 14.0)
51.	8-1/4inches	(0.91, 14.0)	105.	T65U9xZDsGh	(0.90, 14.0)	159.	bCp66pOUhzx	(0.89, 14.0)
52.	ZDUkMr58YQx	(0.91, 14.0)	106.	7AWkKxk11gY	(0.90, 14.0)	160.	7kRzDn71tBs	(0.89, 14.0)
53.	cEx25ukLLNY	(0.91, 14.0)	107.	WH*j0keritt	(0.90, 14.0)	161.	ZBcWRx45jph	(0.89, 14.0)

162. 4o79QghY7ry (0.89, 14.0)
163. 5u0D0ozel3Y (0.88, 14.0)
164. h3P8Wjxd2DS (0.88, 14.0)
165. 7F5c9kzRLws (0.88, 14.0)
166. wCPb9hyqiXx (0.88, 14.0)
167. 8Nj71pytJsS (0.88, 14.0)
168. Y2LA3p4XrPy (0.88, 14.0)
169. ADk94qwpzuY (0.88, 14.0)
170. BREAKneg1Q! (0.88, 14.0)
171. QXN55uxtutG (0.88, 14.0)
172. GVZqWq84NJs (0.88, 14.0)
173. ZHI90rasQxd (0.88, 14.0)
174. aLTIMa1895! (0.88, 14.0)
175. S263IodI9gh (0.88, 14.0)
176. 6xXjHvnt7pS (0.88, 14.0)
177. bVoM0priWes (0.88, 14.0)
178. CHL34bzvXqS (0.88, 14.0)
179. GKo68pcAvLS (0.88, 14.0)
180. 7s2D1rw6xCx (0.88, 14.0)
181. 4dSE1a1eoHx (0.88, 14.0)
182. 7mMM0uF5ciG (0.88, 14.0)
183. IL0VEh0ckey (0.88, 10.8)
184. AF193martis (0.88, 14.0)
185. 8lAH9f6vygS (0.88, 14.0)
186. 7Xz5Kuq7qGd (0.88, 14.0)
187. gARrAgIe42! (0.88, 14.0)
188. 7B9h7yprDfd (0.88, 14.0)
189. 6kbCAmu1qgS (0.88, 14.0)
190. NHb09qLCGph (0.88, 14.0)
191. jTh5Ilj8nmG (0.88, 14.0)
192. r2d24matrix (0.88, 9.9)
193. WRVPVyt9edd (0.88, 14.0)
194. xTn43gnikpY (0.88, 14.0)
195. iJR00znWAmh (0.88, 14.0)
196. sOH41tokuTG (0.88, 14.0)
197. TRIADrocks! (0.88, 11.9)
198. 4UjUSog82ls (0.88, 14.0)
199. RVA0Zkc8bHG (0.88, 14.0)
200. 7u1bVpJ1OAx (0.88, 14.0)
201. BMW3-series (0.88, 11.4)
202. AGGROlites! (0.88, 14.0)
203. ARM_Strongs (0.88, 12.1)
204. c21Z4gsDits (0.88, 14.0)
205. iMk2>sd^7Ch (0.88, 14.0)
206. TCh03yyQcdS (0.88, 14.0)
207. GR!TInfoway (0.88, 14.0)
208. MSQLEpri10! (0.88, 14.0)
209. gAYV0jG7W6x (0.88, 14.0)
210. 7m34Xy2UtUx (0.88, 14.0)
211. 7hMg9auMazd (0.88, 14.0)
212. TSN9Gfx9oAd (0.88, 14.0)
213. XWx32quhNWd (0.88, 14.0)
214. VS76-linked (0.88, 12.7)
215. vFz7QhxqzMY (0.88, 14.0)
216. L3sC0t3@ux! (0.88, 14.0)
217. 5deF2pzhhRh (0.88, 14.0)
218. 7kBrZf5gaTy (0.88, 14.0)
219. tRJDJs9h7YG (0.88, 14.0)
220. 7Wd2Zpp0wkx (0.88, 14.0)
221. QH01AeN2q7Y (0.88, 14.0)
222. PVg64rgBgBS (0.88, 14.0)
223. bII14dbIIls (0.88, 14.0)
224. sVVk2scYJry (0.88, 14.0)
225. WBH5Xte1JKG (0.88, 14.0)
226. 7TH19aMQcbs (0.88, 14.0)
227. 9faHUbzm9ax (0.88, 14.0)
228. ALA05linked (0.88, 10.5)
229. KGk46qgQAVd (0.88, 14.0)
230. LJQGDz41ACh (0.88, 14.0)
231. 8Af90pJDUbs (0.88, 14.0)
232. D1148@pass! (0.88, 14.0)
233. 8qt98zVlVjd (0.88, 14.0)
234. 5sl44z7ZOaY (0.87, 14.0)
235. d4n131Jones (0.87, 11.9)
236. 2MOkOxj0xgs (0.87, 14.0)
237. 6vJ50tsnr5S (0.87, 14.0)
238. VMc0Jhg2Agd (0.87, 14.0)
239. vE6HUzQylfG (0.87, 14.0)
240. WXX44mNzMeY (0.87, 14.0)
241. 5d4ATtDns0y (0.87, 14.0)
242. 8UZqFup6ijY (0.87, 14.0)
243. QWt08jiQKFd (0.87, 14.0)
244. X4c2Yx5IxeS (0.87, 14.0)
245. 5yp40gYWwRx (0.87, 14.0)
246. rEa27linked (0.87, 12.6)
247. 6Cz36uwhMAG (0.87, 14.0)
248. 7xB13sQfoXY (0.87, 14.0)
249. @131Oakland (0.87, 12.4)
250. oUxM0sIiajy (0.87, 14.0)
251. BTS@Company (0.87, 12.9)
252. JJ928linked (0.87, 11.1)
253. TRM99linked (0.87, 10.7)
254. 8g4AAjUevcx (0.87, 14.0)
255. 7whT2pSI7gh (0.87, 14.0)
256. UMN97hockey (0.87, 13.6)
257. B3n51nmurah (0.87, 14.0)
258. rBCa7yB8YMy (0.87, 14.0)
259. 7hk41gJWLDh (0.87, 14.0)
260. QQb1BrF3JoY (0.87, 14.0)
261. 3ovOQjdw0qy (0.87, 14.0)
262. 3jcI7jzEC7h (0.87, 14.0)
263. UHwMFc90Y9G (0.87, 14.0)
264. tVC93tSDPux (0.87, 14.0)
265. eAG29wwiuUS (0.87, 14.0)
266. OGL06fXVttt (0.87, 14.0)
267. 8lDnPe41Tzh (0.87, 14.0)
268. dER38ntt3ny (0.87, 14.0)
269. JGST6svejhG (0.87, 14.0)
270. XRhCMv49XUy (0.87, 14.0)
271. AMG-Germany (0.87, 11.8)
272. JPE8Fw7ZtRh (0.87, 14.0)
273. 7WQzBbt8wzd (0.87, 14.0)
274. #1994@yosoy (0.87, 14.0)
275. 3U1MKrcvl2s (0.87, 14.0)
276. 7a1uIfSqlLx (0.87, 14.0)
277. NH510jGoo4s (0.87, 14.0)
278. qHH99kVRkkh (0.87, 14.0)
279. lXmPKkOqo0S (0.87, 14.0)
280. RHf98ffXTCd (0.87, 14.0)
281. lYOkVdik4CY (0.87, 14.0)
282. 6rI0Er7IU7h (0.87, 14.0)
283. yZw20nkCEmy (0.87, 14.0)
284. wPiXDwcV35s (0.87, 14.0)
285. 7DEm5wTvlkG (0.87, 14.0)
286. 9Gc0Xuzsf6y (0.87, 14.0)
287. UYPTJk68EQh (0.87, 14.0)
288. THT!4linked (0.87, 11.9)
289. dKDp9tBO6zs (0.87, 14.0)
290. rAL34vGUPQx (0.87, 14.0)
291. 5wjP1x5PAvy (0.87, 14.0)
292. 7tHiVlwax8Y (0.87, 14.0)
293. L411Jeffrey (0.87, 11.8)
294. 6HRh5snMhgh (0.87, 14.0)
295. oTB5Pqc3AQh (0.87, 14.0)
296. 7n7f9hiMX3S (0.87, 14.0)
297. 6sEV8fbm8jy (0.87, 14.0)
298. 8oI0YwX4qHx (0.87, 14.0)
299. HD@97linked (0.87, 12.0)
300. 3PNfFa7xwaY (0.87, 14.0)
301. 7xGuBjEe5tt (0.87, 14.0)
302. TLB22linked (0.87, 10.9)
303. X2SJNl69wDS (0.87, 14.0)
304. 3Zd5MkT9pqy (0.87, 14.0)
305. iLOVEmy15@! (0.86, 13.4)
306. TRB62linked (0.86, 11.6)
307. cC91QtG5ylY (0.86, 14.0)
308. QCC12linked (0.86, 11.0)
309. IMh07iHQQGh (0.86, 14.0)
310. cOr1anDeer! (0.86, 14.0)
311. cQZ2Ae3XeOh (0.86, 14.0)
312. 6n347niddsd (0.86, 14.0)
313. 5d/40mosely (0.86, 14.0)
314. @Un#1linked (0.86, 12.7)
315. SJo0Fl6Wi3d (0.86, 14.0)
316. SYDchetS24! (0.86, 14.0)
317. GHKGdyu3df! (0.86, 14.0)
318. QVP52giMhuS (0.86, 14.0)
319. o26IYe8y0KS (0.86, 14.0)
320. TKC67linked (0.86, 11.3)
321. 8ARaQq4uFwh (0.86, 14.0)
322. OMGhelp4me! (0.86, 12.3)
323. 6vWBXg6mzyS (0.86, 14.0)
324. 7CyNOw704uG (0.86, 14.0)
325. qEb0bkjCfix (0.86, 14.0)
326. OYL2fdA3iiy (0.86, 14.0)
327. EXJ53exXOih (0.86, 14.0)
328. gSJPCq79MOh (0.86, 14.0)
329. 7eNS7deWwfx (0.86, 14.0)
330. 5DLJ1f8Awkd (0.86, 14.0)
331. NHL11devils (0.86, 13.4)
332. 7JUaUdfol3G (0.86, 14.0)
333. !aUm$hanti! (0.86, 14.0)
334. IRY26hlAkGY (0.86, 14.0)
335. tJP80zQWwHY (0.86, 14.0)
336. l18MUr9EaNh (0.86, 14.0)
337. UZy5wyy0CBx (0.86, 14.0)
338. BSN-Liblary (0.86, 14.0)
339. dE39EfhWhns (0.86, 14.0)
340. j3u45yif7uh (0.86, 14.0)
341. gKY14odwmSS (0.86, 14.0)
342. 6u661icious (0.86, 14.0)
343. 7ojShev1Vhx (0.86, 14.0)
344. 6GqRajl5m6h (0.86, 14.0)
345. uTTtSo89Zwx (0.86, 14.0)
346. A425Diamond (0.86, 11.6)
347. DS344eVH21G (0.86, 14.0)
348. c3c62vettes (0.86, 13.6)
349. 6jb5Vs6J9cS (0.86, 14.0)
350. 8yjFFfzH7gY (0.86, 14.0)
351. UXo91sLQPUY (0.86, 14.0)
352. 8UI31layO7yd (0.86, 14.0)
353. WWcTBk08ddS (0.86, 14.0)
354. 7fvY7znzwnS (0.86, 14.0)
355. WGy4lib2Zgx (0.86, 14.0)
356. HD66Panhead (0.86, 11.8)
357. 0dXUXe19Sds (0.86, 14.0)
358. 7BzL6sH1a7y (0.86, 14.0)
359. EZ!2ba/Pvt! (0.86, 14.0)
360. V3r0!nit@ly (0.86, 14.0)
361. ZPH04rzqhly (0.86, 14.0)
362. SBSIr3land! (0.86, 14.0)
363. eG146ozSTwy (0.86, 14.0)
364. 7jJBAo3qtTG (0.86, 14.0)
365. DRJP+knight (0.86, 14.0)
366. 5rUCZch25dd (0.86, 14.0)
367. 7pX19nikcpD (0.86, 14.0)
368. YT7ruid5Igs (0.86, 14.0)
369. 7F1vrHn5kuh (0.86, 14.0)
370. 7zCS5r84ATs (0.86, 14.0)
371. VKbVtp69STh (0.86, 14.0)
372. uCL6EaT8pPx (0.86, 14.0)
373. ZW99Usk5TVS (0.86, 14.0)
374. f3s22sgas3G (0.86, 14.0)
375. xYFWKk33lkh (0.86, 14.0)
376. BRJ65linked (0.86, 11.6)
377. 8wuVKiat8Ix (0.86, 14.0)
378. ALWbXr60pCy (0.86, 14.0)
379. CHG8kcm4Ygs (0.86, 14.0)
380. D3v1lMayCry (0.86, 10.7)
381. RMV57linked (0.86, 11.5)
382. S1%53@Fpoux (0.86, 14.0)
383. IRE76linked (0.86, 12.0)
384. MXq66yvEWIS (0.86, 14.0)
385. 5NeZ4uF5Q4s (0.86, 14.0)
386. d2m93d-bus! (0.86, 14.0)
387. vHGXZo8gW2s (0.86, 14.0)
388. mPc9EuZ2dFY (0.86, 14.0)
389. S3DPEm8cpeh (0.86, 14.0)
390. 8yVE6axiEqx (0.86, 14.0)
391. 7bKT4rwWlqy (0.86, 14.0)
392. 7dY12wyeifD (0.86, 14.0)
393. qJY36fviOPx (0.86, 14.0)
394. MT_km5xlaZ! (0.85, 14.0)
395. ALMA●xvirus (0.85, 14.0)
396. YM626tptest (0.85, 14.0)
397. dM138fwYsSx (0.85, 14.0)
398. 8B3Xe1olyrh (0.85, 14.0)
399. 6dnKlfUnr4x (0.85, 14.0)
400. E26ULc85SHd (0.85, 14.0)
401. NGNhOdwdj24 (0.85, 14.0)
402. 6nWea1ktzKx (0.85, 14.0)
403. 7m2YRp44gfx (0.85, 14.0)
404. SSXTricky1! (0.85, 13.1)
405. 7SIbPn5bqcS (0.85, 14.0)
406. 5e5fFuyfyxY (0.85, 14.0)
407. OR30Cook13S (0.85, 14.0)
408. 2ByLLuih94Y (0.85, 14.0)
409. 7JUcVsznnnx (0.85, 14.0)
410. oAZ57pjpghd (0.85, 14.0)
411. SQM59gVFEKh (0.85, 14.0)
412. 7f68sn6yYJh (0.85, 14.0)
413. n4k37xyzBDP (0.85, 14.0)
414. 7vMXAve28WS (0.85, 14.0)
415. bVqS5bnLXPs (0.85, 14.0)
416. 0i042etipod (0.85, 14.0)
417. ECRv2xioN5D (0.85, 14.0)
418. 7L7zMqi3eYS (0.85, 14.0)
419. 2Q8f0barLjs (0.85, 14.0)
420. 8-50z-hitch (0.85, 14.0)
421. EGK7Lwd2NHG (0.85, 14.0)
422. BMS9vTb4uex (0.85, 14.0)
423. WqQ47dIyzAh (0.85, 14.0)
424. 7fLpLq9ZBbY (0.85, 14.0)
425. AKAthe3kids (0.85, 12.2)
426. H2SO4linked (0.85, 11.4)
427. 9pWv8tLxlvG (0.85, 14.0)
428. #1000vortex (0.85, 12.1)
429. wHZ56hgupKS (0.85, 14.0)
430. 7guYLdJzrvd (0.85, 14.0)
431. 3fhQ1vo4aQh (0.85, 14.0)

432. U4P6kd7VDQx (0.85, 14.0)
433. ERn37cBtIWy (0.85, 14.0)
434. SDF1Macross (0.85, 13.5)
435. rT76BhY76Vx (0.85, 14.0)
436. MNE18always (0.85, 13.4)
437. 6T7Z1pwjURG (0.85, 14.0)
438. PWd37faAwzD (0.85, 14.0)
439. rBIFVo32QmY (0.85, 14.0)
440. dDYwTp45JUs (0.85, 14.0)
441. PLU0nAmjG9x (0.85, 14.0)
442. 6Yv87hd1uOP (0.85, 14.0)
443. NC08Raleigh (0.85, 13.6)
444. 8uAhDxb6i0d (0.85, 14.0)
445. 5AnDUb1h8Ed (0.85, 14.0)
446. 7VHtxf3myOh (0.85, 14.0)
447. FVGtMj53oCS (0.85, 14.0)
448. 6StG2iuxgrS (0.85, 14.0)
449. jA131flaiSS (0.85, 14.0)
450. AZC0Bc44mBy (0.85, 14.0)
451. VROLVx14ers (0.85, 14.0)
452. JXl1Pvm9ysK (0.85, 14.0)
453. sDW76vESQ1t (0.85, 14.0)
454. PBf08rurgAd (0.85, 14.0)
455. 7Y9O5mm4wfP (0.85, 14.0)
456. 8ig34pbwuds (0.85, 14.0)
457. uHCWLq70nXY (0.85, 14.0)
458. H26Siris99! (0.85, 14.0)
459. EHp49vyEsxX (0.85, 14.0)
460. 7LOC1f5Bfed (0.85, 14.0)
461. 7Tu3Ydf0aYh (0.85, 14.0)
462. e4y99ujbiwx (0.85, 14.0)
463. NQb74jpmZbD (0.85, 14.0)
464. ILUV2likpus (0.85, 12.5)
465. p3p4Lacl34! (0.85, 14.0)
466. 6gDyHxYeivs (0.85, 14.0)
467. NYGiants#4x (0.85, 12.0)
468. G2124regory (0.85, 14.0)
469. 7ODC2i9L8Ys (0.85, 14.0)
470. JDL.Webhost (0.85, 11.4)
471. JXm8ylA6tvh (0.85, 14.0)
472. 8Eq3Jh01iXx (0.85, 14.0)
473. 2dKoNaqw7dY (0.85, 14.0)
474. FSEF#gsdfed (0.85, 14.0)
475. tRNrFq90plG (0.85, 14.0)
476. EDC3_linked (0.85, 11.8)
477. KMR0ObyzSDD (0.85, 14.0)
478. r4f43lgom3s (0.85, 11.8)
479. YVd5dhO3Amx (0.85, 14.0)
480. n7p42usu8uh (0.85, 14.0)
481. 7X91GrjgzKy (0.85, 14.0)
482. qHl8YjP8BXs (0.85, 14.0)
483. JJDolfan92! (0.85, 14.0)
484. 7buI4rjmivS (0.85, 14.0)
485. HMS_Victory (0.85, 12.4)
486. IFv2Zvf6ihD (0.85, 14.0)
487. WRz5bpg3FYY (0.85, 14.0)
488. 5HP9Uelzuex (0.85, 14.0)
489. TR1Xar4kids (0.85, 14.0)
490. 5Jt8GcbQ1eG (0.85, 14.0)
491. z6I7wgwPPGx (0.85, 14.0)
492. 8hGt4nLN8Ds (0.85, 14.0)
493. 7i6o5a7yryx (0.85, 14.0)
494. wBQYv9dRg8h (0.85, 14.0)
495. J1m1Hendrix (0.85, 11.3)
496. 3n3lDe4tras (0.85, 14.0)
497. MLQ13linked (0.85, 11.7)
498. 4a6u9ilJSHh (0.85, 14.0)
499. ETr8mcm6KJY (0.85, 14.0)
500. eEA00exSsiV (0.85, 14.0)
501. ghPgDfJ8F9h (0.85, 14.0)
502. 7EnAWo8rgUy (0.84, 14.0)
503. aCeQ6ppU2ZS (0.84, 14.0)
504. SFZ4tnx2Ruy (0.84, 14.0)
505. jOB13linked (0.84, 12.4)
506. 3N1NEew01es (0.84, 14.0)
507. UWe7prP2nbY (0.84, 14.0)
508. ID0n'tKnow! (0.84, 14.0)
509. OMV8Crs74wG (0.84, 14.0)
510. ZNJ72dgERBG (0.84, 14.0)
511. U668LviCVPD (0.84, 14.0)
512. QBQ29oDLuqy (0.84, 14.0)
513. TJj68pdYmfK (0.84, 14.0)
514. 2T2TVvws6Oy (0.84, 14.0)
515. IKUZkw55FZh (0.84, 14.0)
516. 3MDzWt9f1Gy (0.84, 14.0)
517. CSp39ayBgdK (0.84, 14.0)
518. CXp6hjI9XAx (0.84, 14.0)
519. 7aVtVzbleyd (0.84, 14.0)
520. 9aj2Oxr1vTd (0.84, 14.0)
521. 7qLk5rmiHUd (0.84, 14.0)
522. ELSislief1! (0.84, 12.7)
523. eFf4syi2RCh (0.84, 14.0)
524. 3mOZ8n58eZx (0.84, 14.0)
525. TT2fly2day! (0.84, 13.1)
526. UPX60orywbD (0.84, 14.0)
527. DZF5nGq7pux (0.84, 14.0)
528. nT3sWeMzwSh (0.84, 14.0)
529. N3wPas2danG (0.84, 14.0)
530. 4NNz6pVtmTy (0.84, 14.0)
531. SR-sev2.isx (0.84, 14.0)
532. dC6cPl2PGWh (0.84, 14.0)
533. P1948ssword (0.84, 12.0)
534. 7pzQGx3hRad (0.84, 14.0)
535. AQUAland11! (0.84, 14.0)
536. MYj9jzI9RBh (0.84, 14.0)
537. 0e3b6zonkmh (0.84, 14.0)
538. aOwEBvf8vUx (0.84, 14.0)
539. 7wpX7gq7uEP (0.84, 14.0)
540. HLt41oqhfis (0.84, 14.0)
541. 6gn5p7gktPs (0.84, 14.0)
542. d2w3hoaWoWx (0.84, 14.0)
543. G5PREsSe3@! (0.84, 14.0)
544. lU1s7hffJjh (0.84, 14.0)
545. RQbAyO08Tuh (0.84, 14.0)
546. hQ7oOqO372x (0.84, 14.0)
547. GYfZy72SHnh (0.84, 14.0)
548. NGg39aMnxnV (0.84, 14.0)
549. URLP4ssw0rd (0.84, 11.6)
550. YN12IrPe7vD (0.84, 14.0)
551. 7toL5anht4X (0.84, 14.0)
552. 8lMx5dorF7K (0.84, 14.0)
553. 9w0bCkqtt3S (0.84, 14.0)
554. JVV1phZ8boY (0.84, 14.0)
555. 0neM1leH1gh (0.84, 13.0)
556. wNjKXb39hxS (0.84, 14.0)
557. IHg26pCmZKd (0.84, 14.0)
558. EVx1hRa6Xvx (0.84, 14.0)
559. k6o5wyxefah (0.84, 14.0)
560. 7HH8xO1nf1x (0.84, 14.0)
561. CJM14linked (0.84, 10.4)
562. b1978spaces (0.84, 12.4)
563. CKK25fdtpgK (0.84, 14.0)
564. O7270yYUS8S (0.84, 14.0)
565. lBh42qzJbiS (0.84, 14.0)
566. OMOgbehin1! (0.84, 14.0)
567. tKSmJx3tkCd (0.84, 14.0)
568. 7B4r6jzTtPd (0.84, 14.0)
569. 3q200mpTIXs (0.84, 14.0)
570. QNfEkx83pBY (0.84, 14.0)
571. TSProvost1! (0.84, 13.5)
572. 7N7m1v3nhRP (0.84, 14.0)
573. 6AHfGvec4pS (0.84, 14.0)
574. 6WdI7aT6Qny (0.84, 14.0)
575. 7e7aligy6es (0.84, 14.0)
576. z133IfC5dyd (0.84, 14.0)
577. 2MSj2dsSv0Y (0.84, 14.0)
578. j1659french (0.84, 12.3)
579. 4MyNetw0rk! (0.84, 9.6)
580. QRi4pYX4cqh (0.84, 14.0)
581. MFy3Zcd5vCD (0.84, 14.0)
582. 6pbXCxx2q4h (0.84, 14.0)
583. HST49eiders (0.84, 14.0)
584. 8mo6Yeyl2pZ (0.84, 14.0)
585. 2hN1Zj3k7MY (0.84, 14.0)
586. 4B0mfktj0Nx (0.84, 14.0)
587. 7OHuGu1nz4P (0.84, 14.0)
588. 8d6zGf9qR8x (0.84, 14.0)
589. QZV20bdXoxP (0.84, 14.0)
590. 6VA8utYi9qh (0.84, 14.0)
591. gKwIKqGw16G (0.84, 14.0)
592. 6YnK0jrd7dZ (0.84, 14.0)
593. YT9PIm5w01S (0.84, 14.0)
594. 9yD37angdys (0.84, 14.0)
595. 7IM9SxF3atY (0.84, 14.0)
596. M34GtuBhd6Y (0.84, 14.0)
597. RLGgerila!! (0.84, 14.0)
598. a4eB5c8sX1G (0.84, 14.0)
599. 3CIH7iDs6fs (0.84, 14.0)
600. hFs47dQQQPy (0.84, 14.0)
601. 5GMXjwG830x (0.84, 14.0)
602. FBb56beVxwV (0.84, 14.0)
603. 5h51VnZAoMx (0.84, 14.0)
604. HSs58uxyATK (0.84, 14.0)
605. UNJ8dr@ud3! (0.84, 14.0)
606. 4Y62Iqr2yYd (0.84, 14.0)
607. CVGengine1! (0.84, 14.0)
608. z1346idoxeh (0.84, 14.0)
609. JLWABt51riD (0.84, 14.0)
610. 6a3a6ugeq4s (0.84, 14.0)
611. ILo5Oly7aaV (0.84, 14.0)
612. 8Xu2QejyuFx (0.84, 14.0)
613. @1793carlos (0.84, 12.2)
614. sTaJRk11cnS (0.84, 14.0)
615. 6ni15cux5ry (0.84, 14.0)
616. VYn1jwe9TRY (0.84, 14.0)
617. 8hAtb9l3NzY (0.84, 14.0)
618. EXSGyD4w1a! (0.84, 14.0)
619. 7qjZ3aj4Z4P (0.84, 14.0)
620. KYGeorge23! (0.84, 13.5)
621. LHC@Utrecht (0.84, 14.0)
622. CZB48zdEMJy (0.84, 14.0)
623. 5hGtany7tQx (0.84, 14.0)
624. CQd4viH2ueh (0.84, 14.0)
625. 9w65Fk7iqJS (0.84, 14.0)
626. SR71BlkBird (0.84, 14.0)
627. l1553sdenis (0.84, 14.0)
628. MHg1Wmz2mWV (0.84, 14.0)
629. LQ5system5! (0.84, 14.0)
630. YWt63rejCMD (0.84, 14.0)
631. dBO41wZNLFY (0.84, 14.0)
632. 4LrU9qPgtmG (0.84, 14.0)
633. nT5kwdc5GKh (0.84, 14.0)
634. 7hDnHxSJ68x (0.84, 14.0)
635. 7fIhKrmxikY (0.84, 14.0)
636. PVF9agm7wFG (0.84, 14.0)
637. 8V92Fsks4lP (0.84, 14.0)
638. OHw30hdNyzd (0.84, 14.0)
639. ORb62uTxgMD (0.84, 14.0)
640. 5Q04Lro8G5P (0.84, 14.0)
641. HRConnect5! (0.84, 12.7)
642. 5GOLDbricks (0.84, 11.0)
643. 7C1Oc6qules (0.84, 14.0)
644. 7Z2m1axGazP (0.84, 14.0)
645. 7S7qSsz3ALS (0.84, 14.0)
646. ZGQ89oBLchS (0.84, 14.0)
647. uYKbUpifB14 (0.84, 14.0)
648. iMFwftic4e! (0.84, 14.0)
649. CMLinkPass! (0.84, 11.9)
650. SMPhilips1! (0.84, 11.9)
651. 7uqW7ijZ26K (0.84, 14.0)
652. GCZ3Swr1zIK (0.84, 14.0)
653. 7XBTc3p7jAy (0.84, 14.0)
654. TDB27swWpSS (0.84, 14.0)
655. 7uB3Rqc73gD (0.84, 14.0)
656. 4j4PDaCvsnd (0.84, 14.0)
657. 3xkGYg4V0dh (0.83, 14.0)
658. IMI7rKE7ggs (0.83, 14.0)
659. DKSlinked1! (0.83, 10.3)
660. BMv1fZR3vXx (0.83, 14.0)
661. ACG4ericb1! (0.83, 14.0)
662. fQS9Of5oJcs (0.83, 14.0)
663. 7v90YizN0YS (0.83, 14.0)
664. WH0GCaracas (0.83, 14.0)
665. 6jA5vBl54lY (0.83, 14.0)
666. 6YQeQaq4t0P (0.83, 14.0)
667. MJBlovesu2! (0.83, 13.5)
668. 4fGyNuh75Qd (0.83, 14.0)
669. 7iAVTf7bgDx (0.83, 14.0)
670. 6nYaen74uFG (0.83, 14.0)
671. NVu37iAqyiV (0.83, 14.0)
672. 98DHSigf!!! (0.83, 14.0)
673. n1117briggs (0.83, 13.1)
674. 7hoXKg2n2uP (0.83, 14.0)
675. s18K9eLW5tG (0.83, 14.0)
676. KTGBaby-87! (0.83, 14.0)
677. 7fPuhd3ypuY (0.83, 14.0)
678. k2rMHwPkaYx (0.83, 14.0)
679. 4i3y6oti8os (0.83, 14.0)
680. 8uYXVn1Zg2G (0.83, 14.0)
681. 3LQLZo6c4jd (0.83, 14.0)
682. 8szVb7kb4Dy (0.83, 14.0)
683. xDp1wwk5TeY (0.83, 14.0)
684. gIH31jAyiez (0.83, 14.0)
685. eH3ld@3Yhc! (0.83, 14.0)
686. 6lP68nsb3TK (0.83, 14.0)
687. USMCusmc55! (0.83, 14.0)
688. WSV07kgZjdy (0.83, 14.0)
689. LGT77mwJtsD (0.83, 14.0)
690. JMN58bsHedD (0.83, 14.0)
691. BCP1wiQ8iih (0.83, 14.0)
692. 7Vb6to6lsVy (0.83, 14.0)
693. 5dGmNp56GIS (0.83, 14.0)
694. SLAMSslams! (0.83, 12.9)
695. yuR58cnEJvx (0.83, 14.0)
696. 7kLc5iEk2KS (0.83, 14.0)
697. kLeIntjen!! (0.83, 14.0)
698. NCNJCw51rzD (0.83, 14.0)
699. AQz3Jqh5xyX (0.83, 14.0)
700. 6q6NrQ7K68y (0.83, 14.0)
701. 6hAN6b2cY3P (0.83, 14.0)

702. 7j6br1U1GuY (0.83, 14.0)
703. 6K3N7ha7Y7X (0.83, 14.0)
704. 3Me23\\]e3G (0.83, 14.0)
705. 6uCyJjj26IX (0.83, 14.0)
706. 7u0aktxn6nx (0.83, 14.0)
707. LLDRh9W5baY (0.83, 14.0)
708. LKi77rPQLey (0.83, 14.0)
709. 5lCvjQDs9ay (0.83, 14.0)
710. 2TPi0lkzEwY (0.83, 14.0)
711. 5fd1DdPhxpy (0.83, 14.0)
712. bPk41rOIerY (0.83, 14.0)
713. RR123oilers (0.83, 12.5)
714. NPB4sYz0yJs (0.83, 14.0)
715. 5t6nd0tDMwx (0.83, 14.0)
716. R3s3archGuy (0.83, 10.6)
717. 8V5cWfu8cqV (0.83, 14.0)
718. 6j6G6yL71RD (0.83, 14.0)
719. OTf83ptyXKZ (0.83, 14.0)
720. DWBracing2x (0.83, 14.0)
721. QTHEBl59fpD (0.83, 14.0)
722. 3Ft23i8B4Xy (0.83, 14.0)
723. 7aTiDuqe40d (0.83, 14.0)
724. VGBHnjmk8wh (0.83, 14.0)
725. 9l0yMn4xV2d (0.83, 14.0)
726. PB4ugo2bed! (0.83, 14.0)
727. 7QiOQft4qKS (0.83, 14.0)
728. SJD82nikbcV (0.83, 14.0)
729. 7tuAHv3Ew2G (0.83, 14.0)
730. DMEJ_linked (0.83, 12.9)
731. 5Us5a3n4CQx (0.83, 14.0)
732. tNB5Ldq9HWx (0.83, 14.0)
733. HaTaDaBa01! (0.83, 14.0)
734. GR82balive! (0.83, 11.5)
735. UBK4uQs04AY (0.83, 14.0)
736. 8fLw1p8GeUD (0.83, 14.0)
737. HRG1iht9sXG (0.83, 14.0)
738. t3l3futur@! (0.83, 12.8)
739. 7vABRg0n8mK (0.83, 14.0)
740. 5JDrScoV0eY (0.83, 14.0)
741. 8UXw2a2ZLPd (0.83, 14.0)
742. 7I62Yi71Yjd (0.83, 14.0)
743. 6CXzTtxJ0jG (0.83, 14.0)
744. JXQdov67ZJY (0.83, 14.0)
745. JXt84rawRJZ (0.83, 14.0)
746. 3bbV4gIa2md (0.83, 14.0)
747. 5qZAgW3vl3s (0.83, 14.0)
748. v1CB9emyvjx (0.83, 14.0)
749. DjOvYz9tBox (0.83, 14.0)
750. FTB46yxoVSS (0.83, 14.0)
751. RCInumber1! (0.83, 11.6)
752. iKV80ogsKFd (0.83, 14.0)
753. 7vFQLg67aiX (0.83, 14.0)
754. N3wR3dMon3y (0.83, 13.4)
755. HGBXTp75mqD (0.83, 14.0)
756. DYLANbell14 (0.83, 10.5)
757. AM828wats!! (0.83, 14.0)
758. UQpYrm79KBy (0.83, 14.0)
759. GLN5bAjft4G (0.83, 14.0)
760. BRIghton93! (0.83, 11.9)
761. 7bSdcgO74EY (0.83, 14.0)
762. yD13l8buYTY (0.83, 14.0)
763. 5zDmoYx7J2x (0.83, 14.0)
764. 7n2rd00Vloh (0.83, 14.0)
765. ZLB1Hershey (0.83, 14.0)
766. 7id58u57xMD (0.83, 14.0)
767. whCtTg02OTx (0.83, 14.0)
768. tTu03meguDK (0.83, 14.0)
769. 5uCKm35illy (0.83, 14.0)
770. ZYG22hZ4heP (0.83, 14.0)
771. 7ig5nepo3ih (0.83, 14.0)
772. LJ70vwOj9TG (0.83, 14.0)
773. aTl43eaGles (0.83, 14.0)
774. GZU6pwH3fnG (0.83, 14.0)
775. 9jOe1jsnH3S (0.83, 14.0)
776. P4SSvordd!! (0.83, 14.0)
777. 0FsV6o6ey8s (0.83, 14.0)
778. m4h4dsunnah (0.83, 14.0)
779. 8T2vg5gV0Ny (0.83, 14.0)
780. 7bjRs46XuxY (0.83, 14.0)
781. 6nBwWq7gut4 (0.83, 14.0)
782. 5RUMMbrvr2z (0.83, 14.0)
783. 3TL0Zvhb4Is (0.83, 14.0)
784. iEy9hoK9DCY (0.83, 14.0)
785. ZThWcl43KTY (0.83, 14.0)
786. 7ysWn8cquoy (0.83, 14.0)
787. S3l4lusalah (0.83, 13.9)
788. KCd58eypasZ (0.83, 14.0)
789. IJNMKo0p●24 (0.83, 14.0)
790. CZc3Kos7dMV (0.83, 14.0)
791. OZfB7fkfcU4 (0.83, 14.0)
792. SGGuitar22! (0.83, 13.1)
793. oRl44soXejy (0.83, 14.0)
794. ZSp3zbJ8Bih (0.83, 14.0)
795. tNI39fmCNss (0.83, 14.0)
796. WDEbeg01GQy (0.83, 14.0)
797. FPPsId22fqP (0.83, 14.0)
798. 7iz2Lt0ziDZ (0.83, 14.0)
799. EDL99bsRCHS (0.83, 14.0)
800. 8hN5orWg2mh (0.83, 14.0)
801. 7h47Zd3b8lS (0.83, 14.0)
802. 4KqYi14Gffx (0.83, 14.0)
803. 7nhYRmgC8yY (0.83, 14.0)
804. D3T3mp0rary (0.83, 10.7)
805. xTQ46jeqYfP (0.83, 14.0)
806. 5TJx9c2nqKX (0.83, 14.0)
807. HBY44osSCGh (0.83, 14.0)
808. 6cuZrozer9x (0.83, 14.0)
809. ANNIEpots14 (0.83, 14.0)
810. 0go05ltqpDK (0.83, 14.0)
811. 70EX3xzr32x (0.83, 14.0)
812. w34HKbs8cvP (0.83, 14.0)
813. 6BLhd0bAg9h (0.83, 14.0)
814. 7joVEn0sWGY (0.83, 14.0)
815. RPmQDi79vNK (0.83, 14.0)
816. 7cXC2jWu08D (0.83, 14.0)
817. C2o2l3dplay (0.83, 14.0)
818. 7Pu77yn5rCV (0.83, 14.0)
819. y2k12asdfgh (0.83, 11.9)
820. 4y4h4gustus (0.83, 13.8)
821. LHc33knZCiX (0.83, 14.0)
822. GJI248esilh (0.83, 14.0)
823. NRKUav38rHG (0.83, 14.0)
824. 7Yh0iTM7k7Y (0.83, 14.0)
825. 7ZVs8hENwkY (0.83, 14.0)
826. 9o0YAzwWe5y (0.83, 14.0)
827. bR7bRandyTS (0.83, 14.0)
828. lOA9QzB3kts (0.83, 14.0)
829. VFwWKo23gDX (0.83, 14.0)
830. m4m4kadalah (0.83, 12.1)
831. 7Fk1Fil9x5K (0.83, 14.0)
832. bV5TGqwZxeY (0.83, 14.0)
833. SGT6Dragons (0.83, 13.1)
834. WZMzlX59vfx (0.83, 14.0)
835. r1957chusid (0.83, 14.0)
836. dNVsOstJd24 (0.83, 14.0)
837. 5ImPl1c!tLY (0.83, 14.0)
838. 7YPnw3N6ily (0.83, 14.0)
839. 0UpY0urBum! (0.82, 14.0)
840. g4B1OzpotaZ (0.82, 14.0)
841. DXG9lsK3zmG (0.82, 14.0)
842. 3n19Tf1oMaS (0.82, 14.0)
843. OJ13lSCY1bY (0.82, 14.0)
844. 7RaF8o3zJDS (0.82, 14.0)
845. CDN5hkp9rnG (0.82, 14.0)
846. 7M2hc3MpsIh (0.82, 14.0)
847. D2920lUigwG (0.82, 14.0)
848. 7x90kXQt0rx (0.82, 14.0)
849. 7f5J5t0QqhZ (0.82, 14.0)
850. uFQftW26pDh (0.82, 14.0)
851. 7s2uoA7l2DY (0.82, 14.0)
852. 7s50u2ymaly (0.82, 14.0)
853. 5lPH1yMVM5h (0.82, 14.0)
854. 7sModfb2HQh (0.82, 14.0)
855. VKPoao58SVs (0.82, 14.0)
856. uMX1lh4QyAx (0.82, 14.0)
857. zY2dbSs5Gqx (0.82, 14.0)
858. ML23Hawkins (0.82, 12.7)
859. BVG41ixyCQX (0.82, 14.0)
860. AR52m_0STr! (0.82, 14.0)
861. 5OLfb3ajT6G (0.82, 14.0)
862. THErider#@! (0.82, 13.6)
863. 7KIhSmih6h4 (0.82, 14.0)
864. 4myWHaccess (0.82, 14.0)
865. 2jaUKfp8d8G (0.82, 14.0)
866. ZQU7KqwldBZ (0.82, 14.0)
867. DYMDYd1983! (0.82, 14.0)
868. 7bG72t1QbCX (0.82, 14.0)
869. 7PFcl7y5FtY (0.82, 14.0)
870. jVR86ngMWXd (0.82, 14.0)
871. r3b0rt@oke! (0.82, 14.0)
872. 5g9qJwGVB3x (0.82, 14.0)
873. ESGUoo04QWh (0.82, 14.0)
874. 8q0Sf5Uax7G (0.82, 14.0)
875. SHM1lussg!! (0.82, 14.0)
876. RXwDBg34alV (0.82, 14.0)
877. l2o8riwasuh (0.82, 14.0)
878. mTAhRd36AKx (0.82, 14.0)
879. 7twHIg7bEPy (0.82, 14.0)
880. qTA53rdfZWS (0.82, 14.0)
881. 4ss3ssm3nT! (0.82, 13.5)
882. AKHaxG58zIY (0.82, 14.0)
883. 7Oa9PwMu5bS (0.82, 14.0)
884. EXP09dlDrID (0.82, 14.0)
885. CHCPupil99! (0.82, 14.0)
886. 4w3ktiE3m3Y (0.82, 14.0)
887. 8FGaf05hdvY (0.82, 14.0)
888. LEV60mbfKAx (0.82, 14.0)
889. 6z54w8GLH5Y (0.82, 14.0)
890. IM!s5theLBK (0.82, 14.0)
891. 7DT09zGqvoz (0.82, 14.0)
892. 5wDzSy2tIOG (0.82, 14.0)
893. XNb95saGuGQ (0.82, 14.0)
894. P7B1Om3vtW4 (0.82, 14.0)
895. JG3w5sL0jDD (0.82, 14.0)
896. 7cBWf81lOdax (0.82, 14.0)
897. 6xOcYp06ApX (0.82, 14.0)
898. 7iFxPc04vkD (0.82, 14.0)
899. 7kFnyUyvrnh (0.82, 14.0)
900. NQX22kqZbaK (0.82, 14.0)
901. TVuAHt91WQX (0.82, 14.0)
902. 6zQ5eN28TEy (0.82, 14.0)
903. 7I5gBx69yyX (0.82, 14.0)
904. aRy12f6tgAS (0.82, 14.0)
905. 8w65gbqOP2s (0.82, 14.0)
906. TJSexyBitch (0.82, 12.3)
907. l2e6k6Jeff! (0.82, 14.0)
908. 7F2sgaAltzx (0.82, 14.0)
909. SUr98lLugnh (0.82, 14.0)
910. 7rVr9qFx5hZ (0.82, 14.0)
911. 7PKO2m5n5JX (0.82, 14.0)
912. HKxKVs48PhX (0.82, 14.0)
913. 6m90NsBwAdd (0.82, 14.0)
914. LYgEFa80fgV (0.82, 14.0)
915. D24HisGlory (0.82, 13.5)
916. KHB5xsy6GpG (0.82, 14.0)
917. t4t1kurlat! (0.82, 14.0)
918. 3W2i5l6GzIs (0.82, 14.0)
919. 7pXLVut47xZ (0.82, 14.0)
920. ETKjBs95gKZ (0.82, 14.0)
921. 7pwNg0O7B9Y (0.82, 14.0)
922. VYp64mEQmeD (0.82, 14.0)
923. yY23ZqbihiG (0.82, 14.0)
924. vCi07ozSTAS (0.82, 14.0)
925. STOPp33pin! (0.82, 14.0)
926. CYj6GzY5er4 (0.82, 14.0)
927. RYYHtmjug0h (0.82, 14.0)
928. pYFwRakvu94 (0.82, 14.0)
929. 7A1Fk7Mdj7G (0.82, 14.0)
930. 7F3K7m2TkTS (0.82, 14.0)
931. EMOtion$#@! (0.82, 11.9)
932. n3wPasSw0rd (0.82, 9.3)
933. NBqTRt44tWZ (0.82, 14.0)
934. 8qZiGjh1zA4 (0.82, 14.0)
935. 7y2M1nCbF3K (0.82, 14.0)
936. m1995marcos (0.82, 9.3)
937. d4y5nurukuh (0.82, 14.0)
938. eTlBjt4WE7Y (0.82, 14.0)
939. RDTDuck4mtt (0.82, 14.0)
940. gDc5fTgfd5h (0.82, 14.0)
941. mO05Lk2bBeX (0.82, 14.0)
942. p4$$w0rd$$! (0.82, 10.6)
943. bRH83ciPPVx (0.82, 14.0)
944. 7S5fjAdbcpx (0.82, 14.0)
945. USScable24! (0.82, 13.4)
946. 6Vp7vsK3wQY (0.82, 14.0)
947. b2i4qibyzyx (0.82, 14.0)
948. TNFhty16osY (0.82, 14.0)
949. qHI4hks6tqh (0.82, 14.0)
950. 7gsN8bQ1RjK (0.82, 14.0)
951. W4yOfDsT1ny (0.82, 14.0)
952. 6vS0ZrgVznG (0.82, 14.0)
953. jAzGuitar1! (0.82, 13.8)
954. 8bJc2eeR5XD (0.82, 14.0)
955. ZPQrsr21HOG (0.82, 14.0)
956. 8mm4yfSl5Gs (0.82, 14.0)
957. UqPA3gV6P8h (0.82, 14.0)
958. i4uFx8zODMs (0.82, 14.0)
959. FREE$legend (0.82, 11.7)
960. k1989khalid (0.82, 10.4)
961. BCl9dYl3lkh (0.82, 14.0)
962. 8uzFvw3ioDY (0.82, 14.0)
963. 7iS6csylj8Y (0.82, 14.0)
964. 7gJVt6odOfh (0.82, 14.0)
965. 6LF5Ksd0VlY (0.82, 14.0)
966. N3wOrleans! (0.82, 8.7)
967. PJO23vcEofP (0.82, 14.0)
968. lcDlGn92Vsx (0.82, 14.0)
969. 7lJhwLm9pnY (0.82, 14.0)
970. 7y4PnD01WOy (0.82, 14.0)
971. KSAKOl10WUD (0.82, 14.0)

972. 7YZs3e4N6rX (0.82, 14.0)
973. o77HHwrtg6V (0.82, 14.0)
974. 4RPbIg9lSzG (0.82, 14.0)
975. 7T6I3d0obVD (0.82, 14.0)
976. SFSqId1Yn14 (0.82, 14.0)
977. 7N46mj7He4x (0.82, 14.0)
978. 5k4U5zKEB4h (0.82, 14.0)
979. n4e5xitutax (0.82, 14.0)
980. xDm52z8Dalh (0.82, 14.0)
981. 2EwSScq11NG (0.82, 14.0)
982. fYKk9uip4GP (0.82, 14.0)
983. 3aS80juQaFY (0.82, 14.0)
984. 5kXqFmzocfS (0.82, 14.0)
985. nqR7Yio0MAy (0.82, 14.0)
986. NQtCkW33xfG (0.82, 14.0)
987. ENOShK92xBy (0.82, 14.0)
988. ZHa9saRxvnY (0.82, 14.0)
989. TLP/1w2e/DZ (0.82, 14.0)
990. 6cV94rCwqrQ (0.82, 14.0)
991. CLG89bMrHKS (0.82, 14.0)
992. 7vLvsIqvl2s (0.82, 14.0)
993. 6uIiPhV6mes (0.82, 14.0)
994. 4IGB6mt2miD (0.82, 14.0)
995. 7CsDPz7yhuY (0.82, 14.0)
996. 6ZHjwa98REy (0.82, 14.0)
997. 7gUeCe61wLZ (0.82, 14.0)
998. 3X4xCtfbDay (0.82, 14.0)
999. hIr6ntR7HjY (0.82, 14.0)

Cluster 17

Prototype: saneeadodno

Hard-assigned passwords: 739729 (2.56% of total)
Unique hard-assigned passwords: 486165 (34.28% of cluster total)

Cluster-assignment scores:
	Min: 0.063
	Max: 0.964
	Mean: 0.422
	SD: 0.224

Strength bins:
	Very weak: 16886 (2.28%)
	Weak: 148231 (20.04%)
	Fair: 221583 (29.95%)
	Good: 310193 (41.93%)
	Strong: 42836 (5.79%)

Password lengths:
	Length 11: 429907 (58.12%)
	Length 12: 309822 (41.88%)

Character classes:
	4 classes: 0 (0.00%)
	3 classes: 7673 (1.04%)
		lower/upper/symbol: 7673 (100.00%)
		lower/upper/number: 0 (0.00%)
		lower/symbol/number: 0 (0.00%)
		upper/symbol/number: 0 (0.00%)
	2 classes: 89604 (12.11%)
		lower/upper: 31621 (35.29%)
		lower/number: 0 (0.00%)
		lower/symbol: 57978 (64.70%)
		upper/number: 0 (0.00%)
		upper/symbol: 5 (0.01%)
		number/symbol: 0 (0.00%)
	1 class: 642452 (86.85%)
		lower: 642389 (99.99%)
		upper: 0 (0.00%)
		symbol: 63 (0.01%)
		number: 0 (0.00%)

Most frequent char-class structures:
	LLLLLLLLLL: 377949 (51.1%)
	LLLLLLLLLLL: 264440 (35.7%)
	ULLLLLLLLL: 10910 (1.5%)
	ULLLLLLLLLL: 6778 (0.9%)
	LLLLLSLLLL: 6715 (0.9%)
	LLLLLSLLLLL: 4637 (0.6%)
	LLLLLLSLLLL: 4290 (0.6%)
	LLLLLLSLLLL: 4240 (0.6%)
	LLLLSLLLLL: 3766 (0.5%)
	LLLLLLLLLS: 2413 (0.3%)

1,000 nearest passwords

0.	dili_que-no	(0.96, 14.0)	54.	tayrigolino	(0.95, 12.1)	108.	pinpirulino	(0.95, 11.3)
1.	cinzialegno	(0.96, 12.1)	55.	narditorino	(0.95, 10.5)	109.	stamboulino	(0.95, 10.7)
2.	ladynotekno	(0.96, 11.6)	56.	gran●torino	(0.95, 9.2)	110.	alejandrino	(0.95, 5.5)
3.	www.kake.no	(0.96, 13.0)	57.	grandtorino	(0.95, 6.6)	111.	chinyereugo	(0.95, 9.5)
4.	gumbletekno	(0.96, 12.2)	58.	magomerlino	(0.95, 6.7)	112.	linkkiseppo	(0.95, 11.1)
5.	nesogorengo	(0.96, 11.9)	59.	legmomyegmo	(0.95, 14.0)	113.	newcentexpo	(0.95, 12.8)
6.	dualcoreduo	(0.96, 8.0)	60.	fiascherino	(0.95, 10.0)	114.	otsoporligo	(0.95, 14.0)
7.	numenoreano	(0.96, 11.8)	61.	saraimerino	(0.95, 9.8)	115.	teterodrigo	(0.95, 10.0)
8.	medicarehmo	(0.96, 11.2)	62.	choocherino	(0.95, 9.3)	116.	rojorodrigo	(0.95, 6.8)
9.	Teana@teano	(0.95, 14.0)	63.	fornaiolino	(0.95, 12.8)	117.	roverttrigo	(0.95, 10.7)
10.	alexisleano	(0.95, 10.8)	64.	irraavelino	(0.95, 10.8)	118.	longtimeago	(0.95, 7.5)
11.	tutagalevao	(0.95, 13.6)	65.	bobmajorino	(0.95, 13.2)	119.	luisrodrigo	(0.95, 6.2)
12.	ciaranseano	(0.95, 10.4)	66.	sanceferino	(0.95, 9.8)	120.	marcos.rigo	(0.95, 10.5)
13.	loismasengo	(0.95, 12.7)	67.	brissoslino	(0.95, 12.5)	121.	axelrodrigo	(0.95, 7.2)
14.	●jdubfresno	(0.95, 14.0)	68.	mikauselino	(0.95, 12.1)	122.	nyamachenpo	(0.95, 11.6)
15.	noe&jose.co	(0.95, 14.0)	69.	montevelino	(0.95, 7.8)	123.	juanrodrigo	(0.95, 6.8)
16.	gmartinengo	(0.95, 11.3)	70.	giuggiolino	(0.95, 8.4)	124.	gabyrodrigo	(0.95, 8.1)
17.	euamofresno	(0.95, 10.4)	71.	kiwancirino	(0.95, 12.7)	125.	r@dioheligo	(0.95, 13.7)
18.	itanisrexmo	(0.95, 14.0)	72.	mannyfelino	(0.95, 11.4)	126.	seamussligo	(0.95, 11.6)
19.	thedamiesno	(0.95, 13.2)	73.	caxxxxolino	(0.95, 13.6)	127.	archipeligo	(0.95, 10.9)
20.	rodriguezco	(0.95, 8.0)	74.	ospazzolino	(0.95, 11.5)	128.	piergiorigo	(0.95, 11.0)
21.	ohmadatehgo	(0.95, 14.0)	75.	ramandolino	(0.95, 9.0)	129.	fuckperrigo	(0.95, 10.6)
22.	micunpleano	(0.95, 12.7)	76.	patyavelino	(0.95, 10.4)	130.	helioburigo	(0.95, 12.0)
23.	samojejedno	(0.95, 11.3)	77.	tuutamelino	(0.95, 11.5)	131.	wbyeatsligo	(0.95, 14.0)
24.	changchehao	(0.95, 11.9)	78.	tranquilino	(0.95, 5.8)	132.	tuttiatempo	(0.95, 11.7)
25.	yesyesyesno	(0.95, 7.6)	79.	sandycarino	(0.95, 9.3)	133.	superverigo	(0.95, 10.6)
26.	yuuuupleggo	(0.95, 14.0)	80.	elwicholino	(0.95, 10.4)	134.	te●amo●rigo	(0.95, 9.7)
27.	kusprayetno	(0.95, 14.0)	81.	pupattolino	(0.95, 9.9)	135.	steventrigo	(0.95, 9.1)
28.	leggomyeggo	(0.95, 7.7)	82.	dannymarino	(0.95, 7.8)	136.	efsaeopekwo	(0.95, 14.0)
29.	fuckface●fo	(0.95, 11.2)	83.	nebuddilino	(0.95, 12.9)	137.	tapatiorigo	(0.95, 10.9)
30.	chakabwengo	(0.95, 11.7)	84.	cayang●rino	(0.95, 11.4)	138.	noshowdeano	(0.95, 12.9)
31.	poiuytrewpo	(0.95, 10.1)	85.	anntapolino	(0.95, 11.8)	139.	agusoderigo	(0.95, 11.1)
32.	mujroenejwo	(0.95, 14.0)	86.	axelsobrino	(0.95, 9.0)	140.	bobbonarigo	(0.95, 12.0)
33.	LuceroHenao	(0.95, 12.2)	87.	sambufalino	(0.95, 12.2)	141.	schoolsligo	(0.95, 7.6)
34.	free.aleppo	(0.95, 11.5)	88.	frankcarino	(0.95, 8.4)	142.	erindoreamo	(0.95, 10.7)
35.	pietroerino	(0.95, 12.0)	89.	elanamarino	(0.95, 9.0)	143.	smartfortwo	(0.95, 8.7)
36.	kojoagyengo	(0.95, 13.1)	90.	mabilijengo	(0.95, 13.7)	144.	nnanyereugo	(0.95, 8.0)
37.	elpoblerino	(0.95, 12.5)	91.	grandtarino	(0.95, 10.0)	145.	rosesfortwo	(0.95, 9.3)
38.	wayuptheygo	(0.95, 12.5)	92.	ilovemarino	(0.95, 6.3)	146.	goldenrembo	(0.95, 9.0)
39.	lilianalino	(0.95, 8.3)	93.	stevemarino	(0.95, 8.3)	147.	chiaweiliao	(0.95, 10.6)
40.	pesciollino	(0.95, 9.5)	94.	nurialuengo	(0.95, 12.1)	148.	madalailiao	(0.95, 12.2)
41.	silvestrino	(0.95, 6.9)	95.	santamarino	(0.95, 6.5)	149.	gianguieago	(0.95, 13.6)
42.	licooterino	(0.95, 12.4)	96.	crusasulino	(0.95, 11.8)	150.	kaarloheino	(0.95, 13.0)
43.	mocciollino	(0.95, 10.1)	97.	TonyPaulino	(0.95, 10.9)	151.	petrumbengo	(0.95, 12.4)
44.	chilindrino	(0.95, 6.8)	98.	smscatarino	(0.95, 11.2)	152.	aiyuyudemao	(0.95, 14.0)
45.	corsotorino	(0.95, 11.2)	99.	montemarino	(0.95, 7.1)	153.	dancefortwo	(0.95, 8.8)
46.	clau,merino	(0.95, 12.2)	100.	theelmarino	(0.95, 10.9)	154.	transfertwo	(0.95, 9.8)
47.	frankferino	(0.95, 9.8)	101.	denise●rino	(0.95, 10.8)	155.	apairfortwo	(0.95, 11.7)
48.	quitrillino	(0.95, 10.0)	102.	patopaulino	(0.95, 9.2)	156.	totwofortwo	(0.95, 10.1)
49.	pieritolino	(0.95, 10.9)	103.	huhhuhheyyo	(0.95, 13.6)	157.	pampukpempo	(0.95, 14.0)
50.	rinocarlino	(0.95, 11.0)	104.	pinkopalino	(0.95, 11.8)	158.	explorertwo	(0.95, 9.1)
51.	giancarlino	(0.95, 7.9)	105.	kawaimalino	(0.95, 10.5)	159.	loverfortwo	(0.95, 8.9)
52.	donceferino	(0.95, 11.4)	106.	diaspaulino	(0.95, 9.2)	160.	gbogbotegbo	(0.95, 10.4)
53.	chriscerino	(0.95, 9.3)	107.	roxana_lino	(0.95, 11.3)	161.	soloiltempo	(0.95, 13.1)

162. zdravobosno (0.95, 14.0)
163. foxridersco (0.95, 9.2)
164. twodivertwo (0.95, 10.3)
165. providertwo (0.95, 8.9)
166. aroundertwo (0.95, 10.3)
167. shantelltwo (0.95, 8.7)
168. oneentertwo (0.95, 10.9)
169. fivefourtwo (0.95, 7.6)
170. tuanlovebao (0.95, 10.0)
171. fourfourtwo (0.95, 6.0)
172. worldwartwo (0.95, 10.6)
173. marshalltwo (0.95, 7.8)
174. resomeeltwo (0.95, 13.3)
175. stockportco (0.95, 9.1)
176. getitalltwo (0.95, 9.5)
177. mexicoteamo (0.95, 6.6)
178. emmanuelsco (0.95, 9.8)
179. elvirateamo (0.95, 7.6)
180. brendateamo (0.95, 6.4)
181. Baseballtwo (0.95, 8.4)
182. baseballtwo (0.95, 7.2)
183. alianateamo (0.95, 8.8)
184. arianateamo (0.95, 6.9)
185. virginteamo (0.95, 7.1)
186. estelateamo (0.95, 7.1)
187. aids.marsco (0.95, 13.6)
188. jehovateamo (0.95, 7.5)
189. erickateamo (0.95, 7.1)
190. renatoursao (0.95, 12.1)
191. ximenateamo (0.95, 7.3)
192. aileenteamo (0.95, 8.5)
193. bourbonstno (0.95, 12.0)
194. rhinohartco (0.95, 11.4)
195. jobienteamo (0.95, 11.3)
196. selenateamo (0.95, 6.9)
197. revecateamo (0.95, 10.9)
198. karnivaltwo (0.95, 11.9)
199. germanteamo (0.95, 6.0)
200. lorenateamo (0.95, 6.4)
201. HedwigHeino (0.95, 12.4)
202. reginateamo (0.95, 6.5)
203. heinzmtembo (0.95, 14.0)
204. monicateamo (0.95, 5.7)
205. leeslyteamo (0.95, 11.5)
206. elprincepyo (0.95, 10.9)
207. karllateamo (0.95, 8.5)
208. greciateamo (0.95, 7.4)
209. javibiteamo (0.95, 11.8)
210. mininateamo (0.95, 8.4)
211. mireyateamo (0.95, 8.1)
212. oneydateamo (0.95, 11.5)
213. virgenteamo (0.95, 7.6)
214. mibebeteamo (0.95, 8.3)
215. plechalenjo (0.95, 14.0)
216. alyssarenzo (0.95, 9.1)
217. silviateamo (0.95, 5.9)
218. delflamengo (0.95, 9.8)
219. zafirateamo (0.95, 9.8)
220. nacirateamo (0.95, 10.5)
221. yadirateamo (0.95, 9.5)
222. camilateamo (0.95, 6.1)
223. angelateamo (0.95, 6.7)
224. Hilaryteamo (0.95, 8.6)
225. anhelateamo (0.95, 10.7)
226. samirateamo (0.95, 7.5)
227. blancateamo (0.95, 6.9)
228. tamarateamo (0.95, 6.9)
229. c.figueroao (0.95, 13.8)
230. karen.teamo (0.95, 8.7)
231. david●teamo (0.95, 7.2)
232. lorensteamo (0.95, 9.1)
233. blankateamo (0.95, 7.6)
234. abuelateamo (0.95, 8.0)
235. getlinkedyo (0.95, 8.4)
236. oliviateamo (0.95, 7.1)
237. sandrateamo (0.95, 5.9)
238. daianateamo (0.95, 7.7)
239. yohelyteamo (0.95, 11.4)
240. ekoprayitno (0.95, 11.0)
241. pamailalsco (0.95, 14.0)
242. Jorge.teamo (0.95, 9.8)
243. dileryteamo (0.95, 11.3)
244. ibironkeayo (0.95, 9.9)
245. karen_teamo (0.95, 8.7)
246. marieuteamo (0.95, 6.7)
247. susanateamo (0.95, 6.9)
248. thomasteamo (0.95, 6.7)
249. carmenteamo (0.95, 6.7)
250. ondinateamo (0.95, 9.0)
251. myloveteamo (0.95, 7.7)
252. conchateamo (0.95, 7.5)
253. andreateamo (0.95, 6.4)
254. roxanateamo (0.95, 7.4)
255. antropologo (0.95, 6.4)
256. majomafemao (0.95, 13.9)
257. alexisteamo (0.95, 6.4)
258. belkisteamo (0.95, 10.5)
259. saraeuteamo (0.95, 8.5)
260. sergioteamo (0.95, 6.0)
261. gobrewersgo (0.95, 10.5)
262. magalyteamo (0.95, 9.5)
263. tinaeuteamo (0.95, 8.5)
264. darlynteamo (0.95, 9.1)
265. j_luisteamo (0.95, 12.1)
266. evelynteamo (0.95, 7.1)
267. vianeyteamo (0.95, 8.4)
268. tania_teamo (0.95, 8.4)
269. goraidersgo (0.95, 7.4)
270. mwananyembo (0.95, 14.0)
271. fredlorenzo (0.95, 7.8)
272. kinesiologo (0.95, 8.8)
273. brissateamo (0.95, 8.8)
274. kazukikeigo (0.95, 13.4)
275. megaloalogo (0.95, 11.8)
276. aliifaalogo (0.95, 14.0)
277. elsitateamo (0.95, 8.3)
278. melisateamo (0.95, 6.9)
279. cositateamo (0.95, 6.9)
280. gladisteamo (0.95, 7.9)
281. ivonneteamo (0.95, 8.2)
282. lorolorenzo (0.95, 7.8)
283. rositateamo (0.95, 6.5)
284. appollologo (0.95, 10.0)
285. martinteamo (0.95, 5.9)
286. palentologo (0.95, 10.8)
287. oftalmologo (0.95, 11.9)
288. colitateamo (0.95, 8.9)
289. flavioteamo (0.95, 7.4)
290. toritateamo (0.95, 7.8)
291. desilorenzo (0.95, 7.4)
292. neonatologo (0.95, 11.5)
293. plhktrologo (0.95, 14.0)
294. nielsenexpo (0.95, 13.1)
295. obeylorenzo (0.95, 10.0)
296. fofolorenzo (0.95, 9.1)
297. panchiteamo (0.95, 8.4)
298. meteorologo (0.95, 7.4)
299. maritateamo (0.95, 6.5)
300. i’m●a●lezbo (0.95, 13.0)
301. forzatrento (0.95, 10.2)
302. strong.enzo (0.95, 10.5)
303. ginolorenzo (0.95, 7.5)
304. gastonteamo (0.95, 7.9)
305. mamitateamo (0.95, 5.9)
306. bucitateamo (0.95, 10.8)
307. bonitoteamo (0.95, 7.5)
308. mastrolembo (0.95, 10.9)
309. lupitateamo (0.95, 6.3)
310. nickietembo (0.95, 11.8)
311. possibletwo (0.95, 8.2)
312. terribletwo (0.95, 8.4)
313. onethreetwo (0.95, 7.7)
314. piolinteamo (0.94, 8.2)
315. ednitateamo (0.94, 9.3)
316. mijuliteamo (0.94, 10.9)
317. neyretteamo (0.94, 12.8)
318. berlinteamo (0.94, 8.2)
319. mimoreteamo (0.94, 9.2)
320. gatitateamo (0.94, 6.7)
321. ratitateamo (0.94, 7.3)
322. Carlosteamo (0.94, 7.4)
323. mositoteamo (0.94, 8.7)
324. dorlinteamo (0.94, 9.9)
325. carlosteamo (0.94, 6.2)
326. smileralogo (0.94, 11.2)
327. Dorianteamo (0.94, 8.4)
328. angpangetmo (0.94, 6.3)
329. yutineteamo (0.94, 11.8)
330. sempreteamo (0.94, 8.7)
331. caritoteamo (0.94, 7.8)
332. lalitoteamo (0.94, 8.2)
333. palomateamo (0.94, 6.7)
334. nguoivietco (0.94, 10.5)
335. berthateamo (0.94, 8.1)
336. giuliateamo (0.94, 7.0)
337. marizateamo (0.94, 7.5)
338. osangelesmo (0.94, 11.8)
339. deniseteamo (0.94, 7.1)
340. judelorenzo (0.94, 7.2)
341. rafalorenzo (0.94, 8.7)
342. lucalorenzo (0.94, 7.7)
343. marinateamo (0.94, 5.8)
344. teoditrento (0.94, 12.7)
345. karinateamo (0.94, 5.6)
346. marthateamo (0.94, 6.8)
347. san●lorenzo (0.94, 8.1)
348. nikkionetwo (0.94, 8.9)
349. yanyanteamo (0.94, 9.2)
350. Malcontento (0.94, 11.3)
351. sucksometwo (0.94, 9.1)
352. andresteamo (0.94, 7.2)
353. janayateamo (0.94, 10.9)
354. patitoteamo (0.94, 6.2)
355. silmarteamo (0.94, 10.1)
356. jacky,teamo (0.94, 11.9)
357. smoochmetwo (0.94, 10.1)
358. coachonetwo (0.94, 9.8)
359. oueatonetwo (0.94, 10.9)
360. loveronetwo (0.94, 7.9)
361. tyleronetwo (0.94, 8.8)
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367. Rjulianteamo (0.94, 11.2)
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386. willytresco (0.94, 10.6)
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397. derickteamo (0.94, 8.0)
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533. Puerto●rico (0.94, 7.7)
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543. felipeprimo (0.94, 8.4)
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562. wigancasino (0.94, 10.4)
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588. Samuelalibo (0.94, 11.8)
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598. babycallico (0.94, 9.3)
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686. Chicolatino (0.94, 7.5)
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724. grayinglobo (0.94, 11.5)
725. Anthonyespo (0.94, 10.7)
726. abdou+nejmi (0.94, 14.0)
727. ireneopezzo (0.94, 11.4)
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734. jesseorosco (0.94, 10.0)
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736. marlborotwo (0.94, 9.2)
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743. vitonprisco (0.94, 11.5)
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747. frankprisco (0.94, 8.7)
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793. nincsjelszo (0.94, 10.2)
794. jacobtwotwo (0.94, 9.3)
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823. fastonestwo (0.94, 11.7)
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825. nazukaetsuo (0.94, 14.0)
826. pajaro●rojo (0.94, 8.2)
827. jeannebosco (0.94, 7.7)
828. tuckerbosco (0.94, 8.6)
829. meualimento (0.94, 11.6)
830. BondMabenjo (0.94, 12.6)
831. leonnacosmo (0.94, 11.1)
832. kjrtimestwo (0.94, 13.7)
833. otaviodiogo (0.94, 10.9)
834. sempertegui (0.94, 10.5)
835. deusconosco (0.94, 9.4)
836. Dadtimestwo (0.94, 11.9)
837. chief●bosco (0.94, 11.1)
838. arafemorojo (0.94, 13.5)
839. twotimestwo (0.94, 8.5)
840. eltigrerojo (0.94, 8.2)
841. emmanuelojo (0.94, 7.0)
842. maridaje.mi (0.94, 13.6)
843. perroterojo (0.94, 9.9)
844. camaronrojo (0.94, 8.3)
845. diabloyrojo (0.94, 11.0)
846. holuwarsogo (0.94, 10.7)
847. oktubrerojo (0.94, 11.2)
848. sadeeqmosco (0.94, 10.6)
849. uncarrorojo (0.94, 9.3)
850. octubrerojo (0.94, 7.8)
851. tiburonrojo (0.94, 8.3)
852. pescadorojo (0.94, 8.8)
853. elcarrorojo (0.94, 7.7)
854. ferrarirojo (0.94, 8.1)
855. micarrorojo (0.94, 6.6)
856. demoniorojo (0.94, 9.1)
857. onolinkeado (0.94, 11.3)
858. Boraberengi (0.94, 13.1)
859. cineargento (0.94, 11.7)
860. eagleeyeato (0.94, 10.4)
861. tractorrojo (0.94, 7.9)
862. gondessekui (0.94, 13.8)
863. lekanbolojo (0.94, 11.4)
864. marisolrojo (0.94, 8.2)
865. fuckmelesbo (0.94, 9.4)
866. paintamento (0.94, 9.9)
867. pompiliotao (0.94, 12.3)
868. delrastrojo (0.94, 10.6)
869. malbororojo (0.94, 7.2)
870. danielhento (0.94, 10.5)
871. pepeargento (0.94, 9.9)
872. esperimento (0.94, 5.8)
873. no●entiendo (0.94, 9.8)
874. mustangrojo (0.94, 7.2)
875. discutiendo (0.94, 12.0)
876. copihuerojo (0.94, 13.2)
877. aionambenjo (0.94, 14.0)
878. heyholetsgo (0.94, 6.1)
879. troubletogo (0.94, 8.4)
880. wento.wento (0.94, 9.5)
881. pasquapezzo (0.94, 13.4)
882. dragon●rojo (0.94, 7.4)
883. tuntuniento (0.94, 10.4)
884. girasolrojo (0.94, 10.5)
885. xitaraposao (0.94, 13.6)
886. hottielesbo (0.94, 8.7)
887. zachaypegui (0.94, 13.5)
888. blancoyrojo (0.94, 10.0)
889. ifuckshituo (0.94, 9.9)
890. ojoconelojo (0.94, 13.1)
891. halconrrojo (0.94, 12.9)
892. sentra●rojo (0.94, 9.9)
893. creolelesbo (0.94, 11.5)
894. papichulojo (0.94, 8.5)
895. gonzomustgo (0.94, 12.3)
896. tylashbrojo (0.94, 14.0)
897. patriotstwo (0.94, 8.7)
898. ghanamostgo (0.94, 5.0)
899. yemdo@yemdo (0.94, 13.4)
900. sherlynlojo (0.94, 11.3)
901. toylinkeado (0.94, 11.7)
902. corazonrojo (0.94, 7.9)
903. gonuggetsgo (0.94, 11.1)
904. ghanamustgo (0.94, 4.8)
905. rubytodisco (0.94, 10.6)
906. radio@diogo (0.94, 10.7)
907. blackopstwo (0.94, 6.6)
908. cazaquistao (0.94, 12.9)
909. brutiscisco (0.94, 10.2)
910. realmatismo (0.94, 11.4)
911. lovelylesbo (0.94, 7.2)
912. BriscoDisco (0.94, 10.7)
913. felipediogo (0.94, 8.5)
914. marcogreppi (0.94, 10.8)
915. narcosistao (0.94, 10.0)
916. Nina-Ovisco (0.94, 14.0)
917. mistrzostwo (0.94, 11.9)
918. cocoandenzo (0.94, 11.8)
919. sexocontigo (0.94, 8.4)
920. noeslomismo (0.94, 8.6)
921. diogo=diogo (0.94, 10.1)
922. tomcatcisco (0.94, 10.0)
923. friscodisco (0.94, 8.3)
924. yoranentigo (0.94, 14.0)
925. grandmastwo (0.94, 9.1)
926. SaturnCisco (0.94, 11.1)
927. sanfrasisco (0.94, 10.6)
928. femaledisco (0.94, 9.4)
929. dziuginenai (0.94, 13.0)
930. nicolasisao (0.94, 9.8)
931. mobiledisco (0.94, 8.5)
932. chiscodisco (0.94, 9.1)
933. nowiletitgo (0.94, 13.1)
934. petrolcitgo (0.94, 11.9)
935. pussyobisco (0.94, 10.5)
936. casilomismo (0.94, 11.3)
937. dontletitgo (0.94, 11.6)
938. briantatsuo (0.94, 10.8)
939. fattratttwo (0.94, 11.9)
940. xoxoredtogo (0.94, 13.9)
941. fiveplustwo (0.94, 9.2)
942. dejoelmismo (0.94, 11.6)
943. psychocisco (0.94, 8.5)
944. migueldiogo (0.94, 8.3)
945. prekletstvo (0.94, 14.0)
946. judiescisco (0.94, 12.6)
947. shakeebenzo (0.94, 10.0)
948. fivefoottwo (0.94, 10.7)
949. almudenismo (0.94, 11.4)
950. antesgastao (0.94, 13.1)
951. grandevisao (0.94, 11.5)
952. iloveapisco (0.94, 9.3)
953. tobilodisco (0.94, 11.5)
954. Trainedtogo (0.94, 11.1)
955. trainedtogo (0.94, 9.9)
956. iheartdisco (0.94, 8.1)
957. hitech@itmo (0.94, 11.7)
958. gobobcatsgo (0.94, 10.4)
959. linkedgismo (0.94, 8.7)
960. danielbeygi (0.94, 10.2)
961. istam@cisco (0.94, 12.4)
962. cisco$cisco (0.94, 9.6)
963. Danielbeygi (0.94, 11.2)
964. atthecdisco (0.94, 11.5)
965. Restlesstwo (0.94, 10.1)
966. mickeydisco (0.94, 8.7)
967. josephfisco (0.94, 9.7)
968. sincretismo (0.94, 12.9)
969. solocontogo (0.94, 9.4)
970. qidaozhenai (0.94, 13.1)
971. veryhottogo (0.94, 10.6)

972. freowaytogo (0.94, 11.1)	982. danielwebbo (0.94, 8.4)	992. isreadytogo (0.94, 8.2)
973. Dcybercisco (0.94, 13.2)	983. kadidjaismo (0.94, 13.8)	993. aylinbreijo (0.94, 13.2)
974. sanfrncisco (0.94, 10.8)	984. kpalimetogo (0.94, 13.4)	994. chingamento (0.94, 9.7)
975. arcadiatogo (0.94, 10.8)	985. anaformento (0.94, 11.1)	995. haregeweyni (0.94, 14.0)
976. whatwaytogo (0.94, 10.7)	986. aafrancisco (0.94, 8.0)	996. irenetolido (0.94, 11.0)
977. shortypequi (0.94, 11.2)	987. nissannismo (0.94, 7.5)	997. smokinhendo (0.94, 9.3)
978. Longwaytogo (0.94, 7.9)	988. alreadytogo (0.94, 7.3)	998. luannenisco (0.94, 12.1)
979. elfrancisco (0.94, 7.0)	989. easywaytogo (0.94, 8.6)	999. hidrocalido (0.94, 9.0)
980. longwaytogo (0.94, 6.6)	990. sffrancisco (0.94, 9.0)	
981. riquelme.jo (0.94, 10.7)	991. victorbitco (0.94, 10.2)	

Cluster 18

Prototype: saneeamon64

Hard-assigned passwords: 1368455 (4.73% of total)
Unique hard-assigned passwords: 959842 (29.86% of cluster total)

Cluster-assignment scores:
	Min: 0.063
	Max: 0.956
	Mean: 0.264
	SD: 0.187

Strength bins:
	Very weak: 25663 (1.88%)
	Weak: 206228 (15.07%)
	Fair: 432338 (31.59%)
	Good: 554981 (40.56%)
	Strong: 149245 (10.91%)

Password lengths:
	Length 11: 1004299 (73.39%)
	Length 12: 364156 (26.61%)

Character classes:
	4 classes: 25656 (1.87%)
	3 classes: 231974 (16.95%)
		lower/upper/symbol: 2971 (1.28%)
		lower/upper/number: 179998 (77.59%)
		lower/symbol/number: 49005 (21.13%)
		upper/symbol/number: 0 (0.00%)
	2 classes: 1034467 (75.59%)
		lower/upper: 4621 (0.45%)
		lower/number: 1019048 (98.51%)
		lower/symbol: 10785 (1.04%)
		upper/number: 0 (0.00%)
		upper/symbol: 0 (0.00%)
		number/symbol: 13 (0.00%)
	1 class: 76358 (5.58%)
		lower: 76357 (100.00%)
		upper: 0 (0.00%)
		symbol: 1 (0.00%)
		number: 0 (0.00%)

Most frequent char-class structures:
	LLLLLLLLLD: 369021 (27.0%)
	LLLLLLLLDD: 214451 (15.7%)
	LLLLLLLLLD: 185937 (13.6%)
	LLLLLLLLLD: 151276 (11.1%)
	LLLLLLLLLD: 87750 (6.4%)
	LLLLLLLLLL: 70883 (5.2%)
	ULLLLLLLLD: 45587 (3.3%)
	ULLLLLLLLD: 28066 (2.1%)
	ULLLLLLLLD: 26267 (1.9%)
	ULLLLLLLDD: 20724 (1.5%)

1,000 nearest passwords

0. rajeshaec60 (0.96, 13.0)	54. bajvhxgew70 (0.94, 14.0)	108. manhatten70 (0.94, 8.5)
1. iyvotqaem60 (0.96, 14.0)	55. meramirez70 (0.94, 10.7)	109. hillside-80 (0.94, 10.1)
2. rodriguez60 (0.96, 6.5)	56. hodfvpneq70 (0.94, 14.0)	110. kosmossen70 (0.94, 10.7)
3. onurbilen60 (0.96, 13.0)	57. pqdgrinev70 (0.94, 14.0)	111. Savemoney80 (0.94, 9.4)
4. iupgacqew60 (0.95, 14.0)	58. lqcjghsey60 (0.94, 14.0)	112. handsome_80 (0.94, 9.0)
5. ayvmotnek60 (0.95, 14.0)	59. wishiknew70 (0.94, 10.2)	113. teremoney80 (0.94, 10.0)
6. agvumxpeq60 (0.95, 14.0)	60. gmdxqckez70 (0.94, 14.0)	114. tarnished80 (0.94, 11.1)
7. killarney60 (0.95, 7.8)	61. Leeyanne@70 (0.94, 13.0)	115. cairouwen80 (0.94, 12.6)
8. KeatonGen60 (0.95, 13.6)	62. fpbgqxced70 (0.94, 14.0)	116. huqpyvrek70 (0.94, 14.0)
9. tbgcdzveh60 (0.95, 14.0)	63. girmaynew70 (0.94, 14.0)	117. silverpen70 (0.94, 6.8)
10. qszacjhef60 (0.95, 14.0)	64. sunshine@70 (0.94, 7.9)	118. zekierdem70 (0.94, 13.6)
11. truckined60 (0.95, 11.9)	65. oldebroek60 (0.94, 11.4)	119. promyczek70 (0.94, 10.7)
12. ladyinred60 (0.95, 8.2)	66. patomoney70 (0.94, 10.9)	120. cinquecen70 (0.94, 10.9)
13. makemoney60 (0.95, 7.5)	67. capqtwhef70 (0.94, 14.0)	121. MonkeyGem80 (0.94, 11.8)
14. kbtzphlev60 (0.95, 14.0)	68. Nortcele-60 (0.94, 14.0)	122. clairehen70 (0.94, 10.6)
15. staticpen60 (0.95, 7.1)	69. tarbswgem70 (0.94, 14.0)	123. Xovinraez80 (0.94, 14.0)
16. emadzaref60 (0.95, 14.0)	70. bacafluey70 (0.94, 14.0)	124. ivklqtgez80 (0.94, 14.0)
17. ifixtchen60 (0.95, 14.0)	71. goodmoney70 (0.94, 7.8)	125. fhqcsbxek80 (0.94, 14.0)
18. kralbenem60 (0.95, 10.0)	72. iarnagrea70 (0.94, 13.6)	126. gqytbnkew80 (0.93, 14.0)
19. bigapple-60 (0.95, 10.5)	73. alekhine_70 (0.94, 10.9)	127. mukhairez80 (0.93, 13.2)
20. gilupzqey60 (0.95, 14.0)	74. narutogen70 (0.94, 10.1)	128. gsikcnrem80 (0.93, 14.0)
21. teawasted60 (0.95, 11.5)	75. jerusalem70 (0.94, 6.9)	129. crgknabem80 (0.93, 14.0)
22. trueblue$60 (0.95, 10.1)	76. zrscfpyea70 (0.94, 14.0)	130. maimaiyeu80 (0.93, 8.4)
23. gjsbohpew60 (0.95, 14.0)	77. htfixpyec70 (0.94, 14.0)	131. uramonkey80 (0.93, 10.6)
24. DaviDSieM60 (0.95, 14.0)	78. markinley70 (0.94, 11.3)	132. hernandeZ70 (0.93, 9.3)
25. bigmonkey60 (0.95, 8.3)	79. hdjlucgen70 (0.94, 14.0)	133. ykqswudeh80 (0.93, 14.0)
26. bgizxnqep60 (0.95, 14.0)	80. zodcsmpef70 (0.94, 14.0)	134. Amohammed80 (0.93, 7.6)
27. grannydeb60 (0.95, 10.5)	81. pthwcqbea70 (0.94, 14.0)	135. smartfren70 (0.93, 8.4)
28. Pendrive@60 (0.95, 10.5)	82. Rodriguez80 (0.94, 7.0)	136. Rgonzalez80 (0.93, 9.5)
29. tdnbhrpex60 (0.95, 14.0)	83. raxzwkueg80 (0.94, 14.0)	137. lonelymen80 (0.93, 9.2)
30. hazelnke●60 (0.95, 14.0)	84. wareagle$70 (0.94, 10.2)	138. trskboxeh70 (0.93, 14.0)
31. multiplex60 (0.95, 8.3)	85. aortlsxec70 (0.94, 14.0)	139. icjnwflez70 (0.93, 14.0)
32. elerande@60 (0.95, 14.0)	86. pajkungen80 (0.94, 12.4)	140. Goodtime@80 (0.93, 10.0)
33. elioruben60 (0.95, 12.7)	87. whyiloveu70 (0.94, 10.4)	141. dodytarek80 (0.93, 12.1)
34. browneyed60 (0.95, 8.6)	88. ktkbnkmek70 (0.94, 14.0)	142. virginred80 (0.93, 10.5)
35. desc@rte$60 (0.95, 13.0)	89. Scarface@70 (0.94, 9.1)	143. nickelpen80 (0.93, 6.8)
36. gukylrcep60 (0.95, 14.0)	90. ybrgofnez80 (0.94, 14.0)	144. dermanbey80 (0.93, 11.9)
37. Chantzley60 (0.95, 12.4)	91. mybeloved70 (0.94, 8.6)	145. dendenden80 (0.93, 8.5)
38. tjacobsen60 (0.95, 10.7)	92. kboxmunec80 (0.94, 14.0)	146. rajabokep80 (0.93, 10.7)
39. copperbed60 (0.95, 7.2)	93. qwlurknex80 (0.94, 14.0)	147. Summertex70 (0.93, 10.9)
40. hernandez60 (0.95, 6.2)	94. ariglvxeu70 (0.94, 14.0)	148. oceancrew80 (0.93, 9.2)
41. walnutpen60 (0.95, 7.2)	95. velazquez80 (0.94, 6.9)	149. Glendive#70 (0.93, 11.5)
42. walnutbed60 (0.95, 7.0)	96. fifthave'70 (0.94, 12.0)	150. hernandez80 (0.93, 5.6)
43. daouykvep60 (0.95, 14.0)	97. rnoxlaiey60 (0.94, 14.0)	151. kuiacgvep80 (0.93, 14.0)
44. yuclzihef60 (0.95, 14.0)	98. kinkychef80 (0.94, 10.4)	152. silverbed80 (0.93, 6.9)
45. newjersey60 (0.95, 7.0)	99. pattenden70 (0.94, 10.7)	153. groovyred80 (0.93, 10.5)
46. paginaweb60 (0.94, 6.9)	100. penkitten70 (0.94, 7.4)	154. doaralmeu80 (0.93, 14.0)
47. optimized60 (0.94, 9.6)	101. ndvaugwej80 (0.94, 14.0)	155. paulmikey80 (0.93, 9.3)
48. peruraven60 (0.94, 12.9)	102. Sunshine$80 (0.94, 8.8)	156. ubongedem80 (0.93, 12.7)
49. fqaydzuep70 (0.94, 14.0)	103. nickelpen70 (0.94, 6.9)	157. rancaekek80 (0.93, 12.4)
50. lorianne&70 (0.94, 11.7)	104. staticpen80 (0.94, 6.8)	158. votqzclen80 (0.93, 14.0)
51. mccartney70 (0.94, 7.5)	105. uzlhiraef80 (0.94, 14.0)	159. deakatten80 (0.93, 13.6)
52. Rodriguez70 (0.94, 7.0)	106. hernandez70 (0.94, 6.0)	160. chayanne#45 (0.93, 10.5)
53. rodriguez70 (0.94, 6.3)	107. makemoney80 (0.94, 7.1)	161. coganglen80 (0.93, 8.3)

162. Rodriquez40 (0.93, 9.5)
163. Lovehelen70 (0.93, 9.8)
164. NoviBecej80 (0.93, 14.0)
165. rodriguez40 (0.93, 6.4)
166. vxfkjhuew65 (0.93, 14.0)
167. protected80 (0.93, 7.7)
168. sophietex80 (0.93, 10.4)
169. mentioned40 (0.93, 10.7)
170. DanAndrew80 (0.93, 10.5)
171. nwqmbvjec40 (0.93, 14.0)
172. cvkhxbdey40 (0.93, 14.0)
173. sirkoune-40 (0.93, 13.7)
174. jgldpwseu80 (0.93, 14.0)
175. azjpnqrew80 (0.93, 14.0)
176. jjsquared45 (0.93, 10.4)
177. carlosseg80 (0.93, 11.0)
178. rodriguez68 (0.93, 6.4)
179. votmdnjem!0 (0.93, 14.0)
180. nrcqpbued45 (0.93, 14.0)
181. Chelmalex40 (0.93, 11.6)
182. ducatired45 (0.93, 10.7)
183. mjvditgef40 (0.93, 14.0)
184. omerguney68 (0.93, 11.5)
185. Rodriguez65 (0.93, 7.2)
186. kellytrev40 (0.93, 9.4)
187. rodriguez65 (0.93, 6.5)
188. lsmnvhoez60 (0.93, 14.0)
189. vanreenen40 (0.93, 13.0)
190. Ilovealex40 (0.93, 8.3)
191. aurelalex68 (0.93, 11.7)
192. ibironke@40 (0.93, 10.8)
193. Earl.Grey65 (0.93, 13.7)
194. Neophyle@40 (0.93, 13.4)
195. NitroWren68 (0.93, 13.1)
196. cjggoshen40 (0.93, 13.7)
197. Rodriguez45 (0.93, 7.0)
198. rodriguez45 (0.93, 6.3)
199. mccartney65 (0.93, 7.4)
200. hzvlxqrea40 (0.93, 14.0)
201. jerusalem40 (0.93, 6.8)
202. dominguez68 (0.93, 6.9)
203. alpdehuez68 (0.93, 13.3)
204. mamanolen68 (0.93, 11.3)
205. velazquez68 (0.93, 7.1)
206. HofGarten80 (0.93, 13.8)
207. Panamared45 (0.93, 9.2)
208. wuixmsteh45 (0.93, 14.0)
209. killarney68 (0.93, 7.6)
210. cherished40 (0.93, 8.6)
211. dwqyfkmeh45 (0.93, 14.0)
212. submursed80 (0.93, 14.0)
213. velasquez65 (0.93, 7.2)
214. moremoney40 (0.93, 6.8)
215. jerosaren40 (0.93, 13.4)
216. staticbed40 (0.93, 7.8)
217. crashcrew68 (0.93, 9.3)
218. imsotired68 (0.93, 10.1)
219. mrntitley68 (0.93, 13.3)
220. lovemoney40 (0.93, 7.8)
221. vpjnxuceq65 (0.93, 14.0)
222. wickedred40 (0.93, 10.4)
223. cheyenne$65 (0.93, 10.0)
224. ultr@plex40 (0.93, 14.0)
225. babyahmed68 (0.93, 10.0)
226. lohyvyreg68 (0.93, 14.0)
227. selassie_70 (0.93, 10.2)
228. Mortgage_65 (0.93, 10.0)
229. Lakeside@40 (0.93, 9.3)
230. prettyred40 (0.93, 9.0)
231. cashmoney68 (0.93, 6.7)
232. vuofphren40 (0.92, 14.0)
233. arwouiegk70 (0.92, 14.0)
234. jennycreg45 (0.92, 12.5)
235. annaisgek68 (0.92, 10.7)
236. plkamyneh65 (0.92, 14.0)
237. truesfred45 (0.92, 13.1)
238. jsdcfoewb70 (0.92, 14.0)
239. fordzetec40 (0.92, 10.9)
240. dqbatiewv60 (0.92, 14.0)
241. elefante.40 (0.92, 9.2)
242. nellanaed65 (0.92, 13.3)
243. bayebaye#40 (0.92, 12.1)
244. Dominguez45 (0.92, 7.4)
245. fyoatqueh65 (0.92, 14.0)
246. ThonFahey68 (0.92, 14.0)
247. Gafuschen68 (0.92, 14.0)
248. surtogpek45 (0.92, 14.0)
249. smashkrew68 (0.92, 12.1)
250. kwfdlngem65 (0.92, 14.0)
251. huhlinked68 (0.92, 11.2)
252. tyjokxceq40 (0.92, 14.0)
253. sundance_65 (0.92, 9.6)
254. Driebanen65 (0.92, 13.8)
255. manunited45 (0.92, 5.9)
256. teabagged45 (0.92, 8.6)
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258. lzaghvwey65 (0.92, 14.0)
259. encrypted45 (0.92, 7.6)
260. mychoice_68 (0.92, 10.6)
261. soulmate@68 (0.92, 9.0)
262. Testcase●68 (0.92, 12.3)
263. Destroyed68 (0.92, 8.4)
264. Darkside#40 (0.92, 9.6)
265. lqbvkmzed65 (0.92, 14.0)
266. gzyangwen68 (0.92, 13.9)
267. unleashed40 (0.92, 7.7)
268. marquise%40 (0.92, 11.3)
269. sexybabe@40 (0.92, 9.2)
270. Elefante.65 (0.92, 10.2)
271. sedsedsed45 (0.92, 8.6)
272. staticbed68 (0.92, 7.7)
273. Maximusex68 (0.92, 12.1)
274. wiesbaden68 (0.92, 8.6)
275. SisTecWeb65 (0.92, 12.5)
276. babeloued65 (0.92, 9.8)
277. zaoptuqev65 (0.92, 14.0)
278. codyriley68 (0.92, 9.1)
279. iybdvnkez45 (0.92, 14.0)
280. yfhvmrgep68 (0.92, 14.0)
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283. ashlinked45 (0.92, 9.2)
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285. easymoney65 (0.92, 6.9)
286. madmonkey68 (0.92, 7.9)
287. sachinten40 (0.92, 9.4)
288. snaketrex40 (0.92, 11.1)
289. Emelendez40 (0.92, 10.6)
290. Bishesari60 (0.92, 13.5)
291. unlimited65 (0.92, 7.0)
292. makemoney65 (0.92, 6.6)
293. jamesstef65 (0.92, 9.7)
294. sajjadali60 (0.92, 8.6)
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296. harshanem30 (0.92, 11.7)
297. glcrjftek65 (0.92, 14.0)
298. IchLiebeC40 (0.92, 11.6)
299. rodriguez30 (0.92, 5.8)
300. goodmoney65 (0.92, 6.4)
301. Iamanobed40 (0.92, 11.9)
302. afkropnej30 (0.92, 14.0)
303. kiavrugex65 (0.92, 14.0)
304. staticpen65 (0.92, 7.0)
305. nickelpen40 (0.92, 6.6)
306. alwoodley68 (0.92, 10.8)
307. vigurdsen65 (0.92, 13.9)
308. Mathiasen68 (0.92, 10.9)
309. rvjsdpceh68 (0.92, 14.0)
310. Mikeperez80 (0.92, 10.6)
311. srialone@30 (0.92, 12.5)
312. paatabbey65 (0.92, 13.4)
313. Vela$queZ30 (0.92, 13.8)
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316. Phaseonep45 (0.92, 13.2)
317. sexyabbed68 (0.92, 11.9)
318. shitfaced68 (0.92, 8.4)
319. uncharted45 (0.92, 7.1)
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330. vkpzncdea30 (0.92, 14.0)
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333. staticbed65 (0.92, 7.7)
334. JuneJune.30 (0.92, 11.0)
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339. cytujcneg30 (0.92, 14.0)
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344. contacted65 (0.92, 9.1)
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372. purplepen40 (0.92, 8.1)
373. rodroqpen30 (0.92, 14.0)
374. Vanrooyen30 (0.92, 11.8)
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376. johnmiked40 (0.92, 10.1)
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386. driversed65 (0.92, 10.6)
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388. joebidden68 (0.92, 11.2)
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413. Goldmine.30 (0.92, 10.0)
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421. lovemoney30 (0.92, 7.0)
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717. hznywxpio60 (0.91, 14.0)
718. palmtrees60 (0.91, 7.3)
719. lolaboyes60 (0.91, 12.9)
720. khemisset60 (0.91, 9.0)
721. heartless60 (0.91, 6.9)
722. qkhyofteb30 (0.91, 14.0)
723. dimnjgbot60 (0.91, 14.0)
724. sexyveena70 (0.91, 10.7)
725. Schoolboy60 (0.91, 7.8)
726. dgmxwilen78 (0.91, 14.0)
727. LitleFoot60 (0.91, 12.0)
728. mohdshoeb70 (0.91, 12.9)
729. minchiuso60 (0.91, 12.2)
730. shameless60 (0.91, 7.6)
731. Autoparts60 (0.91, 8.5)
732. bgnjrizox60 (0.91, 14.0)
733. goodiskey45 (0.91, 11.0)
734. sweetnest60 (0.91, 8.9)
735. tkrghsney75 (0.91, 14.0)
736. GolfRules60 (0.91, 9.7)
737. sugarfoot60 (0.91, 7.4)
738. daddymort70 (0.91, 10.9)
739. willsboro70 (0.91, 9.0)
740. zsfhyqneu78 (0.91, 14.0)
741. willrene⋆75 (0.91, 13.4)
742. ntacvdqeu75 (0.91, 14.0)
743. gogokaren78 (0.91, 10.5)
744. muxgzrpov60 (0.91, 14.0)
745. redmonkey45 (0.91, 7.9)
746. bucknaked75 (0.91, 7.8)
747. tomomiweb45 (0.91, 11.6)
748. tkszydfoi60 (0.91, 14.0)
749. sweetness60 (0.91, 6.6)
750. cherryred75 (0.91, 7.8)
751. CondoKess60 (0.91, 14.0)
752. Happiness60 (0.91, 7.2)
753. happiness60 (0.91, 6.8)
754. sgyavrned75 (0.91, 14.0)
755. whatamess60 (0.91, 9.7)
756. scarindex75 (0.91, 12.9)
757. otumiseng60 (0.91, 14.0)
758. garamanli70 (0.91, 11.1)
759. hogdoggin60 (0.91, 11.1)
760. guttamess60 (0.91, 11.6)
761. umrpxvgli70 (0.91, 14.0)
762. fevrovers70 (0.91, 12.4)
763. Medodream60 (0.91, 13.0)
764. tigerjets60 (0.91, 11.0)
765. gojackets60 (0.91, 9.2)
766. newechoes60 (0.91, 12.4)
767. ibanezgsa60 (0.91, 11.2)
768. mandretta60 (0.91, 10.4)
769. friargreg75 (0.91, 12.5)
770. yankeeboy60 (0.91, 7.6)
771. Zimbabwe@35 (0.91, 9.7)
772. yuqmrdksp60 (0.91, 14.0)
773. darkalien65 (0.91, 10.5)
774. desaduren78 (0.91, 11.3)
775. ijcvaybef78 (0.91, 14.0)
776. nyakbabeh75 (0.91, 13.7)
777. NumanEren78 (0.91, 13.2)
778. dwcgkqert70 (0.91, 14.0)
779. Mikefoley35 (0.91, 11.2)
780. umutturem75 (0.91, 14.0)
781. OysterBed75 (0.91, 12.3)
782. brigfried65 (0.91, 11.1)
783. akhesamen75 (0.91, 12.9)
784. eduamcweb75 (0.91, 14.0)
785. Davichito60 (0.91, 11.7)
786. sperandio60 (0.91, 11.2)
787. Disturbed35 (0.91, 7.7)
788. deedarali70 (0.91, 11.4)
789. xirmlgneo60 (0.91, 14.0)
790. mksdjsmss60 (0.91, 14.0)
791. jeffdavis60 (0.91, 9.0)
792. anekbanek75 (0.91, 12.8)
793. gaspesien40 (0.91, 9.5)
794. cornbread60 (0.91, 7.2)
795. Geronimo^60 (0.91, 10.8)
796. Theydidit60 (0.91, 13.2)
797. fiatpunto60 (0.91, 7.7)
798. tlhkugjew75 (0.91, 14.0)
799. Economist60 (0.91, 8.9)
800. sitepluto60 (0.91, 12.2)
801. pitroipin60 (0.91, 13.2)
802. lsutigers70 (0.91, 7.1)
803. tenndalen78 (0.91, 12.3)
804. Katowice_35 (0.91, 11.1)
805. toilamain60 (0.91, 12.3)
806. swisskiss60 (0.91, 10.1)
807. shaunalex35 (0.91, 10.4)
808. bobmarley80 (0.91, 6.4)
809. zbptutsts60 (0.91, 14.0)
810. cskasofia60 (0.91, 11.2)
811. vpuqylseh30 (0.91, 14.0)
812. moremoney75 (0.91, 7.2)
813. kylemoney75 (0.91, 10.3)
814. ofbgszwit60 (0.91, 14.0)
815. Alleycatt60 (0.91, 10.2)
816. caballero70 (0.91, 6.4)
817. adomingez75 (0.91, 12.8)
818. mumbaigoa60 (0.91, 12.8)
819. quentinth60 (0.91, 10.8)
820. kralbenim60 (0.91, 8.1)
821. ulknights60 (0.91, 12.4)
822. silverbed35 (0.91, 7.2)
823. harleypig60 (0.91, 10.7)
824. hoqmvaxsp60 (0.91, 14.0)
825. pauldenis60 (0.91, 10.1)
826. rinneett●60 (0.91, 14.0)
827. owbjqlcst60 (0.91, 14.0)
828. nqjombits60 (0.91, 14.0)
829. pmckinnon60 (0.91, 11.0)
830. ethellost60 (0.91, 11.3)
831. metaleiro70 (0.91, 10.3)
832. mlclinked75 (0.91, 10.3)
833. prospekta60 (0.91, 10.1)
834. misionero70 (0.91, 7.4)
835. eujizoksm60 (0.91, 14.0)
836. gsktvxcip60 (0.91, 14.0)
837. xnygjbvef78 (0.91, 14.0)
838. rmhogxjsv60 (0.91, 14.0)
839. wxrpzvgim60 (0.91, 14.0)
840. jegfqipta60 (0.91, 14.0)
841. delivered35 (0.91, 8.5)
842. silvestro70 (0.91, 8.4)
843. vawsiumog60 (0.91, 14.0)
844. qpxzjiwom60 (0.91, 14.0)
845. byronalex35 (0.91, 10.0)
846. anitaholt70 (0.91, 11.2)
847. psixsixty60 (0.91, 11.9)
848. oothooney78 (0.91, 12.4)
849. higvmfcsq60 (0.91, 14.0)
850. Stuttgart70 (0.91, 8.3)
851. koliberek35 (0.91, 11.6)
852. gprdclbtn60 (0.91, 14.0)
853. rosecorey78 (0.91, 9.6)
854. goldshirt70 (0.91, 7.6)
855. sbbbetmen75 (0.91, 14.0)
856. Goodagain60 (0.91, 11.8)
857. glcnbzhsu60 (0.91, 14.0)
858. twinakers70 (0.91, 10.5)
859. frcmpewiu60 (0.91, 14.0)
860. swmyzrgep75 (0.91, 14.0)
861. sibmrokev75 (0.91, 14.0)
862. wayneross60 (0.91, 9.3)
863. xnlkqrehc60 (0.91, 14.0)
864. pinknails70 (0.91, 8.9)
865. naxhtgwro70 (0.91, 14.0)
866. yztakisew75 (0.91, 14.0)
867. liomathew75 (0.91, 11.1)
868. getinnnow60 (0.91, 11.5)
869. dialgirex78 (0.91, 13.4)
870. azulcrema60 (0.91, 9.3)
871. jerusalem78 (0.91, 6.5)
872. browneyez35 (0.91, 8.1)
873. integrity60 (0.91, 7.2)
874. apibnseqh70 (0.91, 14.0)
875. Islanders70 (0.91, 8.0)
876. pachnidlo70 (0.91, 13.0)
877. Testarolo70 (0.91, 12.6)
878. taladrero70 (0.91, 11.8)
879. lowlights60 (0.91, 10.3)
880. wlanjzpsv60 (0.91, 14.0)
881. ztkxheuop60 (0.91, 14.0)
882. yahlateef70 (0.91, 8.2)
883. chicosolo70 (0.91, 9.5)
884. krqszxbev75 (0.91, 14.0)
885. Labyrinth70 (0.91, 8.3)
886. razdjpweu78 (0.91, 14.0)
887. finncrisp60 (0.91, 12.1)
888. krjueyqth60 (0.91, 14.0)
889. dybrwmfeu75 (0.91, 14.0)
890. masterkey45 (0.91, 6.6)
891. fcxndogey75 (0.91, 14.0)
892. mymandiri80 (0.91, 9.8)
893. jobel@nob60 (0.91, 14.0)
894. tunacarey75 (0.91, 13.0)
895. raikkonen78 (0.91, 7.7)
896. trocadero70 (0.91, 8.4)
897. lushaikey45 (0.91, 13.0)
898. Ben_Goten78 (0.91, 13.8)
899. quavlihek75 (0.91, 14.0)
900. selvallen40 (0.91, 10.6)
901. brigittec75 (0.91, 10.0)
902. travisboy60 (0.91, 9.2)
903. sadecesen75 (0.91, 7.4)
904. scottydog60 (0.91, 8.2)
905. misiaczek75 (0.91, 7.0)
906. johnnyboy60 (0.91, 6.6)
907. jrwuidzoy60 (0.91, 14.0)
908. peterbilt70 (0.91, 6.4)
909. zapotillo70 (0.91, 10.2)
910. nakedchef78 (0.91, 9.3)
911. jaypandey78 (0.91, 10.1)
912. kglevuxiz60 (0.91, 14.0)
913. juliakatz70 (0.91, 11.7)
914. shitballs70 (0.91, 8.2)
915. rumykitty60 (0.91, 11.9)
916. harleyboy60 (0.91, 7.4)
917. hnmuircev75 (0.91, 14.0)
918. pmstigueq78 (0.91, 14.0)
919. pierpaolo70 (0.91, 9.2)
920. melodisen75 (0.91, 10.7)
921. Bobgeldof60 (0.91, 12.5)
922. devillish60 (0.91, 9.1)
923. justdoit.60 (0.91, 10.3)
924. rodriguez50 (0.91, 6.1)
925. rodriguez78 (0.91, 6.1)
926. manengkey75 (0.91, 12.9)
927. ojkxzylem75 (0.91, 14.0)
928. dpramirez78 (0.91, 10.9)
929. dmartinez50 (0.91, 7.8)
930. akbulopsf70 (0.91, 14.0)
931. acidbytez75 (0.91, 12.8)
932. adegbenro70 (0.91, 8.4)
933. wanakitri80 (0.91, 12.7)
934. paunmxfth70 (0.91, 14.0)
935. Buthelezi70 (0.91, 14.0)
936. skoobydew78 (0.91, 11.7)
937. jeanfritz60 (0.91, 10.4)
938. belacasey75 (0.91, 11.9)
939. mxtlkvgeu78 (0.91, 14.0)
940. jasperdog60 (0.91, 8.7)
941. mullarkey1B (0.91, 12.9)
942. Hugeballs70 (0.91, 10.8)
943. takemenow60 (0.91, 9.2)
944. boagente@75 (0.91, 14.0)
945. lifeisnew88 (0.91, 8.9)
946. amartinez78 (0.91, 7.8)
947. trashyboy60 (0.91, 9.5)
948. chelliedw40 (0.91, 13.1)
949. meetmenow60 (0.91, 8.3)
950. gratismed75 (0.91, 12.4)
951. ptocdievk45 (0.91, 14.0)
952. Spartans#70 (0.91, 9.4)
953. cslhjgbeu75 (0.91, 14.0)
954. radixlemu70 (0.91, 13.9)
955. rtyukxben78 (0.91, 14.0)
956. qsrpadhef78 (0.91, 14.0)
957. lgjtchnez78 (0.91, 14.0)
958. snprockex50 (0.91, 14.0)
959. cqbvhrlef65 (0.91, 14.0)
960. vzijcgdtp60 (0.91, 14.0)
961. ecsqvyulo70 (0.91, 14.0)
962. Alehandro70 (0.91, 9.5)
963. dnlpvsxiy60 (0.91, 14.0)
964. mcdlinkin70 (0.91, 11.3)
965. logopedia60 (0.91, 10.4)
966. pkybvdlex35 (0.91, 14.0)
967. wpyfujxed50 (0.91, 14.0)
968. loenlyboy60 (0.91, 12.9)
969. LinkAlexa60 (0.91, 11.4)
970. JackWiley78 (0.91, 11.5)
971. umewbvfty60 (0.91, 14.0)

972. tinkitten75 (0.91, 6.9)
973. Acciaroli80 (0.91, 12.8)
974. bigsmokey45 (0.91, 8.1)
975. Vainatori80 (0.91, 13.2)
976. mickeymez75 (0.91, 11.2)
977. sharonnia80 (0.91, 9.9)
978. lisabelen30 (0.91, 9.9)
979. chocballs70 (0.91, 11.1)
980. zhangzhen88 (0.91, 7.6)
981. okanlawon60 (0.91, 8.4)
982. lilmonkey75 (0.91, 8.2)
983. avyxwfutp70 (0.91, 14.0)
984. douggiemd40 (0.91, 12.1)
985. Barcaccia60 (0.91, 11.9)
986. tomboonen88 (0.91, 9.1)
987. xsmawtezf80 (0.91, 14.0)
988. manjarrez68 (0.91, 9.3)
989. mgdebjhlt70 (0.91, 14.0)
990. gjznbhuep85 (0.91, 14.0)
991. blueballs70 (0.91, 6.9)
992. Berrymasn60 (0.91, 13.9)
993. canoneosd60 (0.91, 12.0)
994. sethjered30 (0.91, 11.8)
995. uyvtzlgek75 (0.91, 14.0)
996. violetdog60 (0.91, 10.0)
997. pzgylikew78 (0.91, 14.0)
998. anldogpsw60 (0.91, 14.0)
999. byrswjvex50 (0.91, 14.0)

Cluster 19

Prototype: sanewoane

Hard-assigned passwords: 957397 (3.31% of total)
Unique hard-assigned passwords: 370194 (61.33% of cluster total)

Cluster-assignment scores:
	Min: 0.134
	Max: 0.846
	Mean: 0.405
	SD: 0.126

Strength bins:
	Very weak: 144240 (15.07%)
	Weak: 384248 (40.13%)
	Fair: 265766 (27.76%)
	Good: 160457 (16.76%)
	Strong: 2686 (0.28%)

Password lengths:
	Length 8: 245200 (25.61%)
	Length 9: 712197 (74.39%)

Character classes:
	4 classes: 0 (0.00%)
	3 classes: 2490 (0.26%)
		lower/upper/symbol: 2490 (100.00%)
		lower/upper/number: 0 (0.00%)
		lower/symbol/number: 0 (0.00%)
		upper/symbol/number: 0 (0.00%)
	2 classes: 54229 (5.66%)
		lower/upper: 35328 (65.15%)
		lower/number: 0 (0.00%)
		lower/symbol: 18901 (34.85%)
		upper/number: 0 (0.00%)
		upper/symbol: 0 (0.00%)
		number/symbol: 0 (0.00%)
	1 class: 900678 (94.08%)
		lower: 900678 (100.00%)
		upper: 0 (0.00%)
		symbol: 0 (0.00%)
		number: 0 (0.00%)

Most frequent char-class structures:
	LLLLLLLLL: 666469 (69.6%)
	LLLLLLLL: 234209 (24.5%)
	ULLLLLLLL: 20908 (2.2%)
	ULLLLLLL: 6871 (0.7%)
	LLLLSLLLL: 5850 (0.6%)
	LLLSLLLLL: 2642 (0.3%)
	LLLLLSLLL: 2369 (0.2%)
	ULLLLULLL: 1851 (0.2%)
	ULLLULLLL: 1782 (0.2%)
	LLSLLLLLL: 1388 (0.1%)

1,000 nearest passwords

0.	OctaneOne	(0.85, 8.9)	54.	metaledge	(0.81, 7.3)	108.	leadwedge	(0.80, 8.6)
1.	UniqueOne	(0.85, 8.2)	55.	sandwedge	(0.81, 5.6)	109.	middleage	(0.80, 5.5)
2.	IamTheOne	(0.84, 6.6)	56.	crensedge	(0.81, 10.8)	110.	portledge	(0.80, 7.0)
3.	I@mTheOne	(0.84, 8.3)	57.	garyledge	(0.81, 8.5)	111.	privledge	(0.80, 10.4)
4.	hnehnehne	(0.84, 8.2)	58.	hsffbedge	(0.81, 13.8)	112.	rockledge	(0.80, 5.8)
5.	kneknekne	(0.84, 7.2)	59.	mossledge	(0.81, 8.2)	113.	Rockledge	(0.80, 7.0)
6.	AspireOne	(0.84, 6.8)	60.	renosedge	(0.81, 10.3)	114.	femdrenge	(0.80, 12.2)
7.	DivineOne	(0.84, 7.6)	61.	demonedge	(0.81, 7.6)	115.	lisamedge	(0.80, 9.5)
8.	MatureOne	(0.84, 8.1)	62.	ravenedge	(0.81, 7.6)	116.	Olespenge	(0.80, 12.5)
9.	dopoledne	(0.84, 12.1)	63.	satireage	(0.81, 11.0)	117.	Stonhenge	(0.80, 10.5)
10.	IamtheOne	(0.84, 6.6)	64.	leonlegge	(0.81, 9.9)	118.	knowlexge	(0.80, 12.6)
11.	UnsafeOne	(0.83, 10.6)	65.	chakdenge	(0.81, 9.4)	119.	babylegge	(0.80, 7.7)
12.	NeoTheOne	(0.83, 8.6)	66.	mediaedge	(0.81, 7.9)	120.	Knowledge	(0.80, 5.0)
13.	novadeyne	(0.82, 10.1)	67.	jamesedge	(0.81, 7.0)	121.	knowledge	(0.80, 3.3)
14.	budepekne	(0.82, 12.1)	68.	marbledge	(0.81, 8.5)	122.	nadanehme	(0.80, 11.9)
15.	okltrebne	(0.82, 13.2)	69.	blackedge	(0.81, 6.1)	123.	kniwledge	(0.80, 7.2)
16.	puzzle@ne	(0.82, 10.7)	70.	beddbedge	(0.81, 11.5)	124.	footwedge	(0.80, 7.5)
17.	bubbaedge	(0.82, 8.0)	71.	stretedge	(0.81, 10.3)	125.	chocwedge	(0.80, 8.6)
18.	mommaedge	(0.82, 8.8)	72.	soundedge	(0.81, 7.2)	126.	flugzeuge	(0.80, 8.2)
19.	mcvane.ge	(0.82, 11.7)	73.	roundedge	(0.81, 6.8)	127.	ruudkeane	(0.80, 9.3)
20.	gumbyedge	(0.82, 8.7)	74.	standedge	(0.81, 8.1)	128.	babydeane	(0.80, 8.0)
21.	puppyedge	(0.82, 7.4)	75.	chandenge	(0.81, 9.1)	129.	knowleage	(0.80, 9.3)
22.	hoganedge	(0.82, 8.4)	76.	castleage	(0.81, 6.3)	130.	ryankeane	(0.80, 6.3)
23.	masonedge	(0.82, 7.9)	77.	thenyedge	(0.81, 9.6)	131.	change*me	(0.80, 7.5)
24.	SandWedge	(0.82, 8.4)	78.	tshitenge	(0.81, 10.5)	132.	kumasenge	(0.80, 8.8)
25.	setonedge	(0.82, 9.8)	79.	woodsedge	(0.81, 7.0)	133.	change.me	(0.80, 6.7)
26.	fawnhedge	(0.81, 9.3)	80.	kongfegge	(0.81, 10.9)	134.	Change.me	(0.80, 8.0)
27.	razoredge	(0.81, 4.9)	81.	flangenge	(0.81, 9.1)	135.	rosehedge	(0.80, 7.7)
28.	oceanedge	(0.81, 7.9)	82.	prestedge	(0.81, 9.3)	136.	saesaehme	(0.80, 11.3)
29.	zandhegge	(0.81, 9.8)	83.	crossedge	(0.81, 7.1)	137.	change_me	(0.80, 5.9)
30.	PresSedge	(0.81, 11.0)	84.	Kelstedge	(0.81, 10.4)	138.	mmaduekwe	(0.80, 10.5)
31.	cleanedge	(0.81, 6.2)	85.	broodedge	(0.81, 9.9)	139.	fieldedge	(0.80, 8.4)
32.	ergoledge	(0.81, 9.5)	86.	emesledge	(0.81, 10.7)	140.	worldedge	(0.80, 7.7)
33.	loamhedge	(0.81, 10.2)	87.	bloodedge	(0.81, 6.1)	141.	change&me	(0.80, 7.7)
34.	roughedge	(0.81, 6.6)	88.	longledge	(0.80, 8.1)	142.	rescue●me	(0.80, 8.0)
35.	longhedge	(0.81, 8.0)	89.	thesledge	(0.80, 6.0)	143.	change●me	(0.80, 5.8)
36.	alcaneuge	(0.81, 11.7)	90.	darkledge	(0.80, 6.8)	144.	mypage&me	(0.80, 9.3)
37.	Plainedge	(0.81, 7.3)	91.	solidedge	(0.80, 7.2)	145.	balowenge	(0.80, 9.8)
38.	chanbedge	(0.81, 9.9)	92.	iglide.ge	(0.80, 13.0)	146.	pepsiedge	(0.80, 8.9)
39.	plainedge	(0.81, 6.0)	93.	tofthedge	(0.80, 9.4)	147.	rickkeane	(0.80, 8.3)
40.	bigsledge	(0.81, 7.7)	94.	cliffedge	(0.80, 7.9)	148.	change@me	(0.80, 7.3)
41.	trutledge	(0.81, 7.7)	95.	bigpledge	(0.80, 7.8)	149.	taraleane	(0.80, 8.8)
42.	routledge	(0.81, 6.9)	96.	mudhwenge	(0.80, 12.6)	150.	nakededge	(0.80, 7.8)
43.	sabinedge	(0.81, 8.2)	97.	newoneage	(0.80, 9.7)	151.	karaleane	(0.80, 8.4)
44.	bubuyenge	(0.81, 10.9)	98.	ura_renge	(0.80, 12.7)	152.	bronzeage	(0.80, 8.4)
45.	moniaedge	(0.81, 9.9)	99.	bono_edge	(0.80, 10.9)	153.	dukehegge	(0.80, 8.4)
46.	cedaredge	(0.81, 6.9)	100.	engetenge	(0.80, 8.8)	154.	nicole&me	(0.80, 8.2)
47.	alldredge	(0.81, 9.6)	101.	ndingenge	(0.80, 11.0)	155.	littleane	(0.80, 7.5)
48.	yogi@edge	(0.81, 10.4)	102.	google.ge	(0.80, 4.6)	156.	iluvkeane	(0.79, 7.4)
49.	Kittredge	(0.81, 10.9)	103.	tripleage	(0.80, 6.4)	157.	Kn@wledge	(0.79, 10.3)
50.	gavinedge	(0.81, 8.7)	104.	dawnsedge	(0.80, 7.9)	158.	nyanpehme	(0.79, 11.2)
51.	duralegge	(0.81, 10.7)	105.	hairyedge	(0.80, 8.2)	159.	fuckme●me	(0.79, 6.6)
52.	greyledge	(0.81, 8.7)	106.	Cartledge	(0.80, 8.2)	160.	can-be-me	(0.79, 11.8)
53.	Terbregge	(0.81, 12.0)	107.	cartledge	(0.80, 7.1)	161.	marijeane	(0.79, 7.7)

162. fastkeane (0.79, 8.8)
163. warsteane (0.79, 12.4)
164. kfuckedme (0.79, 9.6)
165. ubuckedme (0.79, 9.7)
166. Nagymedve (0.79, 10.8)
167. tyjake&me (0.79, 12.2)
168. nagymedve (0.79, 9.6)
169. missjeane (0.79, 8.2)
170. hazezegge (0.79, 11.2)
171. alankeane (0.79, 7.0)
172. lonibenge (0.79, 10.1)
173. gamehenge (0.79, 8.8)
174. Brisbeane (0.79, 11.2)
175. future&me (0.79, 8.7)
176. mamace-ce (0.79, 10.2)
177. urdopeage (0.79, 13.1)
178. marcjeane (0.79, 9.4)
179. paintedme (0.79, 6.7)
180. please•me (0.79, 5.7)
181. dalewedge (0.79, 8.1)
182. little•me (0.79, 6.4)
183. secure_me (0.79, 7.5)
184. manosekme (0.79, 10.2)
185. Escape_me (0.79, 9.0)
186. elsadeane (0.79, 9.9)
187. please_me (0.79, 6.6)
188. toastedme (0.79, 7.7)
189. babsdeane (0.79, 10.1)
190. awsome.me (0.79, 8.3)
191. segemenge (0.79, 10.6)
192. ubustedme (0.79, 9.3)
193. delete•me (0.79, 7.6)
194. tarakeane (0.79, 7.9)
195. frostedme (0.79, 7.8)
196. tizisezme (0.79, 12.6)
197. myrevenge (0.79, 6.4)
198. twistedme (0.79, 6.6)
199. delete_me (0.79, 7.9)
200. twiztedme (0.79, 7.6)
201. BlmGleHme (0.79, 14.0)
202. opinsezme (0.79, 9.6)
203. opensezme (0.79, 4.4)
204. lordledme (0.79, 10.6)
205. Jesuse@me (0.79, 9.9)
206. fuckmeqwe (0.79, 7.8)
207. ketivetne (0.79, 11.9)
208. jerome_me (0.79, 9.1)
209. Madeleyne (0.79, 10.8)
210. i.love.me (0.79, 6.3)
211. i*love*me (0.79, 7.1)
212. staple•me (0.79, 9.2)
213. krestedme (0.79, 9.5)
214. choose•me (0.79, 5.9)
215. cheese_me (0.79, 7.4)
216. mosomedve (0.79, 11.9)
217. I_love_me (0.79, 6.6)
218. i_love_me (0.79, 5.7)
219. umissedme (0.79, 8.6)
220. chrouesne (0.79, 10.9)
221. uplayedme (0.79, 9.7)
222. lovesexme (0.79, 6.6)
223. thensexme (0.79, 10.5)
224. simple_me (0.79, 6.5)
225. hcehcehce (0.79, 8.2)
226. belive_me (0.79, 8.4)
227. aaaqweqwe (0.79, 7.9)
228. i-love-me (0.79, 5.9)
229. djkniegge (0.79, 12.9)
230. rayejeane (0.79, 10.2)
231. I•love•me (0.79, 5.7)
232. kmekmekme (0.79, 7.7)
233. i•love•me (0.79, 4.4)
234. single-me (0.79, 7.1)
235. poweredge (0.79, 5.4)
236. poesjegwe (0.79, 11.7)
237. wadebeane (0.79, 10.0)
238. riveredge (0.79, 6.7)
239. belive•me (0.79, 8.4)
240. blessedme (0.78, 5.0)
241. compiegne (0.78, 9.5)
242. singleQwe (0.78, 10.2)
243. helovedme (0.78, 7.8)
244. zexzsedwe (0.78, 13.3)
245. ttheredge (0.78, 9.9)
246. etheredge (0.78, 7.5)
247. jjaskedme (0.78, 11.2)
248. manquehue (0.78, 10.8)
249. choose/me (0.78, 7.5)
250. sexysexme (0.78, 7.3)
251. sheacedme (0.78, 11.5)
252. blindedme (0.78, 7.9)
253. ulinkedme (0.78, 9.1)
254. allowedme (0.78, 7.1)
255. wreckedme (0.78, 8.8)
256. sagekeane (0.78, 7.9)
257. demideane (0.78, 9.7)
258. kweslebwe (0.78, 13.0)
259. cubaneate (0.78, 9.1)
260. see_me_me (0.78, 9.7)
261. meonme@me (0.78, 10.2)
262. jcejcejce (0.78, 8.1)
263. cocokeane (0.78, 8.5)
264. la•puente (0.78, 9.0)
265. royrkeane (0.78, 10.2)
266. Picklebme (0.78, 11.1)
267. raceredge (0.78, 8.0)
268. keverenge (0.78, 9.8)
269. lceadejme (0.78, 12.7)
270. brookeqwe (0.78, 8.2)
271. mimquente (0.78, 10.6)
272. hesavedme (0.78, 6.2)
273. saddle•me (0.78, 7.3)
274. stchuente (0.78, 10.9)
275. shikwekwe (0.78, 8.5)
276. menike+me (0.78, 11.0)
277. marfyeyme (0.78, 12.3)
278. mymike&me (0.78, 10.0)
279. remanente (0.78, 7.5)
280. panqueque (0.78, 5.8)
281. chindebwe (0.78, 8.7)
282. openzezme (0.78, 12.4)
283. rapeme_me (0.78, 10.7)
284. mywife&me (0.78, 8.8)
285. knuppehue (0.78, 10.2)
286. lottieane (0.78, 9.2)
287. bonqueque (0.78, 8.6)
288. uneededme (0.78, 9.6)
289. unteregge (0.78, 9.6)
290. iconnecte (0.78, 6.9)
291. outeredge (0.78, 7.9)
292. wateredge (0.78, 7.0)
293. dwedwedwe (0.78, 6.0)
294. m@kepe@ce (0.78, 10.5)
295. bamerenge (0.78, 10.1)
296. hevilegue (0.78, 11.8)
297. bfebfebfe (0.78, 8.7)
298. jojoreape (0.78, 11.7)
299. frecuente (0.78, 8.4)
300. trickeyme (0.78, 8.8)
301. aribwebwe (0.78, 11.5)
302. mcudhedpe (0.78, 14.0)
303. paycheque (0.78, 7.9)
304. mikepe@ce (0.78, 11.0)
305. T@lpuente (0.78, 11.2)
306. kampfente (0.78, 10.1)
307. vigilente (0.78, 9.4)
308. knoeledge (0.78, 9.8)
309. mukelenge (0.78, 9.6)
310. osiqueque (0.78, 9.6)
311. gladheate (0.78, 8.7)
312. paulneate (0.78, 9.9)
313. pussyeate (0.78, 6.9)
314. ilmpleyme (0.78, 12.5)
315. gueguegue (0.78, 6.8)
316. ateateate (0.78, 6.5)
317. qweqweqwe (0.78, 3.8)
318. quequeque (0.78, 5.2)
319. nchelenge (0.78, 10.1)
320. ryannemae (0.78, 7.3)
321. garaneque (0.78, 10.6)
322. zackmezue (0.78, 11.8)
323. inpotente (0.78, 8.7)
324. Penitente (0.77, 9.5)
325. sanamente (0.77, 7.9)
326. delasente (0.77, 9.7)
327. sugamente (0.77, 10.2)
328. dirigente (0.77, 8.2)
329. uteuteute (0.77, 7.9)
330. dazzleqwe (0.77, 9.8)
331. robynemae (0.77, 9.1)
332. mojebebce (0.77, 11.1)
333. molqueque (0.77, 8.4)
334. indomexme (0.77, 12.7)
335. lucsteppe (0.77, 11.0)
336. nicolebae (0.77, 8.2)
337. the•seppe (0.77, 10.6)
338. ginoseppe (0.77, 8.8)
339. kaekaekae (0.77, 5.8)
340. sexnaenae (0.77, 10.1)
341. krjnaenae (0.77, 12.1)
342. NaeNaeNae (0.77, 10.4)
343. mayabeque (0.77, 8.7)
344. maemaemae (0.77, 5.6)
345. mwakyembe (0.77, 11.0)
346. Trynaenae (0.77, 10.7)
347. purplehue (0.77, 7.4)
348. cgiuseppe (0.77, 11.7)
349. giusseppe (0.77, 6.8)
350. purpleape (0.77, 8.0)
351. nutsleppe (0.77, 10.9)
352. jemine&pe (0.77, 12.8)
353. liuyueyue (0.77, 7.6)
354. asistente (0.77, 6.0)
355. aremaegbe (0.77, 10.0)
356. mongoedge (0.77, 8.7)
357. hottie_me (0.77, 8.0)
358. jeffmente (0.77, 9.1)
359. RedGlente (0.77, 11.8)
360. crescente (0.77, 6.7)
361. procreate (0.77, 7.2)
362. chamhembe (0.77, 10.5)
363. buonleute (0.77, 9.8)
364. existente (0.77, 7.6)
365. ngempe-te (0.77, 13.9)
366. pinckewte (0.77, 12.9)
367. ana•wente (0.77, 10.5)
368. tararenae (0.77, 7.6)
369. ianchembe (0.77, 12.2)
370. kyrarenae (0.77, 8.6)
371. Erotheque (0.77, 10.8)
372. qweQweqwe (0.77, 8.3)
373. lulhaejae (0.77, 11.7)
374. tyiyteque (0.77, 13.1)
375. descreate (0.77, 6.6)
376. Mesatempe (0.77, 11.8)
377. meesbente (0.77, 10.2)
378. twocreate (0.77, 8.2)
379. namagembe (0.77, 8.8)
380. namirembe (0.77, 8.6)
381. uaeuaeuae (0.77, 7.7)
382. elausente (0.77, 9.9)
383. alducente (0.77, 9.5)
384. delchente (0.77, 9.7)
385. battleaxe (0.77, 4.8)
386. onesteppe (0.77, 8.3)
387. aziarenae (0.77, 10.6)
388. decapente (0.77, 8.0)
389. kemilembe (0.77, 10.3)
390. batoleyte (0.77, 10.7)
391. vivamente (0.77, 8.5)
392. purpleute (0.77, 7.2)
393. ritarenae (0.77, 9.4)
394. yvettejae (0.77, 9.8)
395. naenaenae (0.77, 6.9)
396. juscreate (0.77, 9.7)
397. shenaenae (0.77, 9.4)
398. abissegue (0.77, 11.1)
399. eteuseque (0.77, 11.7)
400. GeorgeSte (0.77, 8.8)
401. biggiehge (0.77, 11.0)
402. siribente (0.77, 9.3)
403. singsegue (0.77, 11.5)
404. cactaecae (0.77, 14.0)
405. residente (0.77, 5.4)
406. concreate (0.77, 6.1)
407. rodalebae (0.77, 10.2)
408. kutakente (0.77, 10.0)
409. lampleyme (0.77, 10.3)
410. ninarenae (0.77, 6.9)
411. grandefte (0.77, 9.8)
412. i•mite•be (0.77, 13.1)
413. fuckmebae (0.77, 7.6)
414. markpeate (0.77, 9.2)
415. syntheque (0.77, 8.1)
416. annaseppe (0.77, 8.9)
417. malomente (0.77, 7.4)
418. jodyrenae (0.77, 8.5)
419. emergente (0.77, 6.2)
420. issajeyte (0.77, 12.3)
421. celeteque (0.77, 8.6)
422. lilnaenae (0.77, 7.8)
423. solomente (0.77, 7.3)
424. jvincente (0.77, 7.2)
425. niggaeaye (0.77, 10.6)
426. acclaempe (0.77, 13.2)
427. corodegue (0.77, 8.9)
428. allorente (0.77, 8.4)
429. ccjbyebye (0.77, 13.2)
430. idioteque (0.77, 7.4)
431. elainemae (0.77, 6.1)

432. joshtebbe	(0.77, 9.7)	
433. pletjeppe	(0.77, 12.1)	
434. lilbremae	(0.77, 11.0)	
435. securedbe	(0.77, 8.6)	
436. xantheppe	(0.77, 9.2)	
437. subabebbe	(0.77, 11.7)	
438. cantrembe	(0.77, 8.8)	
439. stockente	(0.77, 10.7)	
440. i●love●ue	(0.77, 8.1)	
441. just_embe	(0.77, 11.5)	
442. minnie●me	(0.77, 7.3)	
443. ideoteque	(0.77, 10.8)	
444. polopeque	(0.77, 8.2)	
445. toonbeute	(0.77, 10.4)	
446. noorledge	(0.77, 9.2)	
447. malajente	(0.77, 9.0)	
448. denisemae	(0.77, 6.8)	
449. ofumwegbe	(0.77, 10.2)	
450. leahrenae	(0.77, 6.1)	
451. veradehue	(0.77, 11.1)	
452. netamente	(0.77, 7.8)	
453. altamente	(0.77, 7.9)	
454. tembleque	(0.77, 7.6)	
455. rushrenae	(0.77, 9.0)	
456. reginemae	(0.77, 8.1)	
457. igoylecxe	(0.77, 13.7)	
458. alexsebbe	(0.77, 9.0)	
459. jasirembe	(0.77, 10.4)	
460. jomamexpe	(0.77, 13.4)	
461. aimtoeaae	(0.77, 13.6)	
462. dessvente	(0.77, 10.2)	
463. parapente	(0.77, 6.0)	
464. palomeque	(0.77, 6.0)	
465. dortheabe	(0.77, 10.2)	
466. tanarenae	(0.77, 9.0)	
467. pflorenxe	(0.77, 11.4)	
468. caradente	(0.77, 8.2)	
469. petopepue	(0.77, 12.3)	
470. tworledge	(0.77, 9.5)	
471. minnie_me	(0.77, 7.9)	
472. teleteube	(0.77, 8.6)	
473. fauxtexte	(0.77, 12.3)	
474. jaycreate	(0.77, 7.7)	
475. carstenbe	(0.77, 9.5)	
476. andraemae	(0.77, 9.8)	
477. emekaenye	(0.77, 9.4)	
478. malamente	(0.77, 7.6)	
479. mtrujeque	(0.77, 13.7)	
480. aiwonegbe	(0.77, 4.9)	
481. BattleAxe	(0.77, 8.1)	
482. Solamente	(0.77, 6.3)	
483. lakasegbe	(0.77, 8.0)	
484. solamente	(0.77, 4.6)	
485. mkanyenye	(0.77, 10.6)	
486. Karypeque	(0.77, 11.5)	
487. delamente	(0.77, 6.5)	
488. veramente	(0.77, 9.2)	
489. osomhegbe	(0.77, 8.3)	
490. mhaibente	(0.77, 12.3)	
491. chinaenye	(0.76, 8.8)	
492. fismylige	(0.76, 11.3)	
493. innocente	(0.76, 5.6)	
494. Innocente	(0.76, 7.3)	
495. woodbrige	(0.76, 8.7)	
496. pheobemae	(0.76, 10.0)	
497. leahdenae	(0.76, 9.4)	
498. pparmente	(0.76, 9.8)	
499. ariekrige	(0.76, 10.8)	
500. mynrwlige	(0.76, 13.6)	
501. flintrige	(0.76, 9.7)	
502. walugembe	(0.76, 9.7)	
503. Walugembe	(0.76, 10.8)	
504. shiralige	(0.76, 10.2)	
505. eliselige	(0.76, 10.4)	
506. leeskemae	(0.76, 11.4)	
507. indobrige	(0.76, 10.8)	
508. DenGirige	(0.76, 12.3)	
509. petfcecae	(0.76, 13.8)	
510. engsalige	(0.76, 11.2)	
511. dimitrige	(0.76, 7.9)	
512. wolvorine	(0.76, 6.7)	
513. asgaelige	(0.76, 12.5)	
514. janesembe	(0.76, 11.0)	
515. elfitrine	(0.76, 8.2)	
516. kongelige	(0.76, 10.6)	
517. ipiptrine	(0.76, 11.5)	
518. fielmente	(0.76, 10.4)	
519. koskorine	(0.76, 10.0)	
520. biomarine	(0.76, 9.1)	
521. jeonarine	(0.76, 10.5)	
522. deonarine	(0.76, 9.0)	
523. armarrige	(0.76, 10.9)	
524. k.ostrige	(0.76, 12.5)	
525. clemarine	(0.76, 8.2)	
526. deiparine	(0.76, 10.7)	
527. chrodebae	(0.76, 12.4)	
528. joekarine	(0.76, 8.1)	
529. delzarine	(0.76, 9.5)	
530. tremarine	(0.76, 7.7)	
531. simawehbe	(0.76, 12.5)	
532. zoemarine	(0.76, 7.0)	
533. welverine	(0.76, 5.5)	
534. hlrmarine	(0.76, 10.3)	
535. wolvarine	(0.76, 6.0)	
536. wolferine	(0.76, 6.2)	
537. Wolvarine	(0.76, 7.5)	
538. Volvarine	(0.76, 9.9)	
539. lilmarine	(0.76, 6.4)	
540. Margarine	(0.76, 6.5)	
541. wilverine	(0.76, 6.2)	
542. margarine	(0.76, 5.2)	
543. wolwerine	(0.76, 6.1)	
544. volverine	(0.76, 5.0)	
545. wolverine	(0.76, 2.3)	
546. qolverine	(0.76, 8.4)	
547. eolverine	(0.76, 9.9)	
548. Wolverine	(0.76, 4.1)	
549. jyrkarine	(0.76, 11.7)	
550. markarine	(0.76, 7.7)	
551. hectorine	(0.76, 7.1)	
552. boogerine	(0.76, 7.4)	
553. margerine	(0.76, 5.7)	
554. nicoleuye	(0.76, 9.7)	
555. cathirine	(0.76, 7.7)	
556. profiline	(0.76, 7.1)	
557. themarine	(0.76, 5.4)	
558. barberine	(0.76, 7.0)	
559. victorine	(0.76, 5.6)	
560. retmarine	(0.76, 8.6)	
561. Sylverine	(0.76, 9.5)	
562. walverine	(0.76, 5.7)	
563. Victorine	(0.76, 6.9)	
564. bteghrine	(0.76, 10.6)	
565. maladrine	(0.76, 7.5)	
566. daleslige	(0.76, 10.4)	
567. sosmarine	(0.76, 8.9)	
568. Hitnarine	(0.76, 10.8)	
569. CathArine	(0.76, 8.3)	
570. Bteghrine	(0.76, 11.8)	
571. occidente	(0.76, 6.4)	
572. blessedbe	(0.76, 4.6)	
573. frontline	(0.76, 3.8)	
574. gerarrine	(0.76, 8.8)	
575. trentline	(0.76, 8.1)	
576. Dexidrine	(0.76, 12.5)	
577. cisserine	(0.76, 10.5)	
578. lisserine	(0.76, 8.1)	
579. listerine	(0.76, 5.0)	
580. Frontline	(0.76, 5.6)	
581. msflorine	(0.76, 8.6)	
582. semadegbe	(0.76, 10.0)	
583. printline	(0.76, 6.4)	
584. zephirine	(0.76, 7.7)	
585. Authorine	(0.76, 8.1)	
586. authorine	(0.76, 6.7)	
587. marybrine	(0.76, 8.1)	
588. Listerine	(0.76, 6.7)	
589. Cathorine	(0.76, 8.5)	
590. burnsline	(0.76, 7.3)	
591. crinoline	(0.76, 7.9)	
592. carmiline	(0.76, 7.4)	
593. tischrine	(0.76, 10.4)	
594. lechirine	(0.76, 9.9)	
595. tricoline	(0.76, 7.6)	
596. necterine	(0.76, 8.2)	
597. dexedrine	(0.76, 9.8)	
598. cheatline	(0.76, 6.3)	
599. dalarrine	(0.76, 10.2)	
600. VeraEline	(0.76, 9.5)	
601. marysline	(0.76, 7.9)	
602. BioOnline	(0.76, 9.3)	
603. emtmarine	(0.76, 9.3)	
604. peregrine	(0.76, 4.4)	
605. sweptline	(0.76, 9.7)	
606. Peregrine	(0.76, 6.0)	
607. margoline	(0.76, 6.8)	
608. gargoline	(0.76, 7.3)	
609. Katharine	(0.76, 5.9)	
610. catharine	(0.76, 4.0)	
611. Satnarine	(0.76, 10.4)	
612. catmarine	(0.76, 7.0)	
613. katharine	(0.76, 4.5)	
614. w.vicente	(0.76, 9.3)	
615. gwenoline	(0.76, 8.7)	
616. marcoline	(0.76, 5.6)	
617. Narcoline	(0.76, 9.4)	
618. nectarine	(0.76, 4.9)	
619. carvoline	(0.76, 7.2)	
620. parvoline	(0.76, 7.7)	
621. annalevae	(0.76, 10.6)	
622. valvoline	(0.76, 5.0)	
623. Valvoline	(0.76, 6.5)	
624. globaline	(0.76, 6.6)	
625. avonoline	(0.76, 9.0)	
626. econoline	(0.76, 5.7)	
627. djecoline	(0.76, 10.5)	
628. jeonjedae	(0.76, 12.0)	
629. dropaline	(0.76, 8.2)	
630. c@therine	(0.76, 6.2)	
631. bellarine	(0.76, 7.1)	
632. viovaline	(0.76, 9.8)	
633. rexosline	(0.76, 10.6)	
634. zillarine	(0.76, 8.2)	
635. stenaline	(0.76, 7.2)	
636. blumarine	(0.76, 8.6)	
637. LisaEline	(0.76, 8.6)	
638. bkessedbe	(0.76, 11.9)	
639. olamarine	(0.76, 9.4)	
640. drenaline	(0.76, 6.8)	
641. seamarine	(0.76, 5.7)	
642. flow●line	(0.76, 9.5)	
643. zepherine	(0.76, 6.5)	
644. crownline	(0.76, 4.9)	
645. seafarine	(0.76, 7.9)	
646. cathyrine	(0.76, 7.6)	
647. maxtheaxe	(0.76, 9.0)	
648. fernaline	(0.76, 8.0)	
649. amiboline	(0.76, 9.0)	
650. lamourine	(0.76, 6.6)	
651. millerine	(0.76, 6.6)	
652. seunarine	(0.76, 8.2)	
653. fredaline	(0.76, 6.5)	
654. kookaline	(0.76, 7.8)	
655. glycerine	(0.76, 5.0)	
656. gremaline	(0.76, 8.3)	
657. trevaline	(0.76, 7.1)	
658. betzuline	(0.76, 10.1)	
659. oldmarine	(0.76, 7.3)	
660. wrongline	(0.76, 6.8)	
661. casperine	(0.76, 6.1)	
662. lingerine	(0.76, 8.3)	
663. allkaline	(0.76, 8.6)	
664. catgerine	(0.76, 9.0)	
665. claudrine	(0.76, 7.3)	
666. lozzerine	(0.76, 8.1)	
667. siljaline	(0.76, 8.0)	
668. broadline	(0.76, 6.8)	
669. ballerine	(0.76, 6.1)	
670. virmaline	(0.76, 8.7)	
671. normaline	(0.76, 6.8)	
672. monderine	(0.76, 8.5)	
673. vonderine	(0.76, 8.8)	
674. tomgerine	(0.76, 9.2)	
675. brookemae	(0.76, 5.5)	
676. latherine	(0.76, 6.2)	
677. Derepente	(0.76, 8.3)	
678. patherine	(0.76, 6.7)	
679. autherine	(0.76, 6.9)	
680. Katherine	(0.76, 4.4)	
681. mescaline	(0.76, 5.3)	
682. Matherine	(0.76, 7.7)	
683. Passerine	(0.76, 8.7)	
684. catherine	(0.76, 2.9)	
685. passerine	(0.76, 7.0)	
686. meskaline	(0.76, 6.5)	
687. stoneline	(0.76, 3.9)	
688. Catherine	(0.76, 4.5)	
689. ●atherine	(0.76, 8.6)	
690. breadline	(0.76, 6.2)	
691. marvaline	(0.76, 6.7)	
692. droffline	(0.76, 7.5)	
693. kasserine	(0.76, 5.5)	
694. katherine	(0.76, 2.9)	
695. rhodaline	(0.76, 7.3)	
696. chicaline	(0.76, 7.9)	
697. hollyrine	(0.76, 7.9)	
698. phinaline	(0.76, 7.7)	
699. nigouline	(0.76, 10.7)	
700. berajline	(0.76, 11.1)	
701. victprine	(0.76, 10.1)	

702. xenadrine (0.76, 7.9)
703. sergeline (0.76, 7.2)
704. treadline (0.76, 6.5)
705. terjeline (0.76, 8.2)
706. ferdeline (0.76, 7.7)
707. verdeline (0.76, 6.5)
708. gerdeline (0.76, 8.2)
709. zitsarine (0.76, 9.9)
710. ferceline (0.76, 8.2)
711. fredeline (0.76, 7.4)
712. sewnarine (0.76, 9.3)
713. trendline (0.76, 6.8)
714. nassirine (0.76, 8.7)
715. derepente (0.76, 6.6)
716. carlorine (0.76, 8.5)
717. steamline (0.76, 6.1)
718. slifeline (0.76, 8.4)
719. brassline (0.76, 6.6)
720. forceline (0.76, 6.7)
721. gremeline (0.76, 6.7)
722. vibesline (0.76, 7.8)
723. strapline (0.76, 6.6)
724. priceline (0.76, 5.9)
725. herveline (0.76, 7.2)
726. slimeline (0.76, 5.8)
727. slideline (0.76, 6.0)
728. dioceline (0.76, 6.7)
729. ephedrine (0.76, 7.4)
730. Hermeline (0.76, 7.4)
731. Mrincline (0.76, 10.9)
732. primeline (0.76, 6.3)
733. lilfeline (0.76, 8.2)
734. dogmarine (0.76, 6.8)
735. newmarine (0.76, 6.9)
736. swingline (0.76, 4.2)
737. cirkeline (0.76, 6.2)
738. dreamline (0.76, 5.1)
739. creamline (0.76, 6.9)
740. griveline (0.76, 7.3)
741. valueline (0.76, 6.4)
742. snow●line (0.76, 8.3)
743. Sirkeline (0.76, 9.1)
744. cougarine (0.76, 7.0)
745. driveline (0.76, 5.6)
746. Cirkeline (0.76, 7.4)
747. redonline (0.76, 6.7)
748. listarine (0.76, 8.1)
749. meninline (0.76, 7.8)
750. wascoline (0.76, 7.1)
751. Sexonline (0.76, 7.6)
752. adeuxline (0.76, 10.8)
753. Swingline (0.76, 6.0)
754. crew-line (0.76, 8.3)
755. peconline (0.76, 7.9)
756. clponline (0.76, 8.7)
757. dexonline (0.76, 8.7)
758. newonline (0.76, 6.1)
759. rexonline (0.76, 7.8)
760. purzeline (0.76, 8.7)
761. sexonline (0.76, 5.3)
762. sthonline (0.76, 8.6)
763. dexadrine (0.76, 8.9)
764. lsdonline (0.76, 8.1)
765. ftponline (0.76, 7.9)
766. ventoline (0.76, 6.6)
767. jobonline (0.76, 6.9)
768. bobonline (0.76, 6.7)
769. tozonline (0.76, 9.0)
770. kidmarine (0.76, 7.3)
771. Wokonline (0.76, 9.7)
772. boxonline (0.76, 7.1)
773. gardeline (0.76, 6.9)
774. saracline (0.76, 7.6)
775. bigmarine (0.76, 6.9)
776. par●eline (0.76, 10.1)
777. viponline (0.76, 7.3)
778. memealine (0.76, 9.0)
779. pofonline (0.76, 8.5)
780. maryeline (0.76, 6.9)
781. logonline (0.76, 6.8)
782. parceline (0.76, 6.1)
783. marceline (0.76, 5.2)
784. Marceline (0.76, 6.0)
785. kofonline (0.76, 5.9)
786. patjoline (0.76, 8.8)
787. gsmonline (0.76, 8.5)
788. bluonline (0.76, 8.0)
789. tomonline (0.76, 7.6)
790. menonline (0.76, 6.8)
791. parkeline (0.76, 7.8)
792. markeline (0.76, 5.7)
793. masculine (0.76, 5.7)
794. mwclorine (0.76, 10.4)
795. ninepente (0.76, 9.7)
796. neyonline (0.76, 7.7)
797. carmeline (0.76, 5.8)
798. trainline (0.76, 5.7)
799. Trineline (0.76, 8.1)
800. mrskyline (0.76, 7.0)
801. closeline (0.76, 6.6)
802. slickline (0.76, 6.6)
803. markcline (0.76, 8.0)
804. pizdurine (0.76, 9.4)
805. brickline (0.76, 6.3)
806. coastline (0.76, 5.2)
807. trnonline (0.76, 8.6)
808. trickline (0.76, 7.5)
809. niskyline (0.76, 7.8)
810. aiuonline (0.76, 8.8)
811. stumbrine (0.76, 9.7)
812. mtnonline (0.76, 8.7)
813. tryonline (0.76, 6.9)
814. breakline (0.76, 6.0)
815. reddiline (0.76, 9.4)
816. dipnarine (0.76, 9.1)
817. nasszeige (0.76, 13.1)
818. garycline (0.76, 7.7)
819. pinonline (0.76, 6.9)
820. readiline (0.76, 8.9)
821. opiumline (0.76, 9.4)
822. metteline (0.76, 8.0)
823. csaonline (0.76, 8.3)
824. nsaonline (0.76, 8.0)
825. pascaline (0.76, 4.5)
826. fredkline (0.76, 7.8)
827. endocrine (0.76, 5.8)
828. rifleline (0.76, 7.9)
829. penciline (0.76, 7.7)
830. Pascaline (0.76, 5.9)
831. wesseline (0.76, 6.5)
832. yesceline (0.76, 9.0)
833. ketteline (0.76, 7.7)
834. life●line (0.76, 7.2)
835. strenline (0.76, 9.6)
836. civmarine (0.76, 9.9)
837. joshcline (0.76, 7.6)
838. love●line (0.76, 7.0)
839. ultraline (0.76, 6.7)
840. fitteline (0.76, 9.0)
841. uml-vente (0.76, 14.0)
842. greenline (0.76, 5.5)
843. realmente (0.76, 6.6)
844. crossline (0.76, 6.1)
845. rino●line (0.76, 10.4)
846. sisseline (0.76, 7.9)
847. heartline (0.76, 6.5)
848. microline (0.76, 5.5)
849. spineline (0.76, 6.8)
850. drumsline (0.76, 9.5)
851. josieline (0.76, 7.5)
852. phoneline (0.76, 5.8)
853. georeline (0.76, 9.1)
854. Greenline (0.76, 6.9)
855. johnprine (0.76, 8.4)
856. fleetline (0.76, 6.0)
857. Nikieline (0.76, 10.8)
858. weaseline (0.76, 7.1)
859. frostline (0.76, 5.9)
860. sofieline (0.76, 7.6)
861. Transline (0.76, 7.1)
862. josseline (0.76, 5.8)
863. petroline (0.76, 6.5)
864. metroline (0.76, 5.8)
865. adrenline (0.76, 9.2)
866. maniyembe (0.76, 9.6)
867. craftline (0.76, 6.1)
868. jihnprine (0.76, 10.8)
869. dicipline (0.76, 6.5)
870. stateline (0.76, 5.2)
871. maineline (0.76, 7.5)
872. motorline (0.76, 7.5)
873. epipeline (0.76, 8.5)
874. Tosseline (0.76, 8.8)
875. Ipipeline (0.76, 9.8)
876. Stateline (0.76, 6.7)
877. shearline (0.76, 7.9)
878. guideline (0.76, 5.0)
879. lessoline (0.76, 8.7)
880. life*line (0.76, 7.9)
881. Josceline (0.76, 8.0)
882. gottiline (0.76, 8.3)
883. spiruline (0.76, 6.6)
884. Astaeline (0.76, 11.1)
885. myskyline (0.76, 6.1)
886. youseline (0.76, 7.8)
887. tayapeige (0.76, 11.9)
888. nxskyline (0.76, 9.2)
889. smskyline (0.76, 7.5)
890. bossoline (0.76, 6.7)
891. toyseline (0.76, 9.9)
892. moneyline (0.76, 5.5)
893. colorline (0.76, 7.1)
894. spreeline (0.76, 9.0)
895. terraline (0.76, 6.4)
896. threeline (0.76, 6.3)
897. falteline (0.76, 8.8)
898. TinaKline (0.76, 9.8)
899. etherline (0.76, 7.7)
900. mejerline (0.76, 9.4)
901. cederline (0.76, 6.8)
902. apeapeape (0.76, 10.0)
903. nextnline (0.76, 10.0)
904. life_line (0.76, 7.6)
905. lepolline (0.76, 8.4)
906. msherline (0.76, 8.7)
907. girolline (0.76, 8.7)
908. rathcline (0.76, 8.9)
909. love_line (0.76, 7.8)
910. Mikerline (0.76, 10.7)
911. fiberline (0.76, 6.4)
912. loucoline (0.76, 8.4)
913. sewerline (0.76, 7.5)
914. keverline (0.76, 8.4)
915. schosline (0.76, 10.0)
916. peterline (0.76, 6.1)
917. sopholine (0.76, 8.7)
918. tightline (0.76, 5.6)
919. audisline (0.76, 8.6)
920. viggoline (0.76, 8.3)
921. nightline (0.76, 6.4)
922. pressline (0.76, 7.2)
923. ekaterine (0.76, 5.9)
924. colecline (0.76, 7.2)
925. adrieline (0.76, 7.6)
926. powerline (0.76, 4.7)
927. kolecline (0.76, 9.9)
928. cacouline (0.76, 8.2)
929. deazaline (0.76, 9.4)
930. marieline (0.76, 6.7)
931. towerline (0.76, 6.6)
932. frugaline (0.76, 8.4)
933. babouline (0.76, 7.8)
934. Powerline (0.76, 6.7)
935. nassarine (0.76, 7.6)
936. picholine (0.76, 8.2)
937. myhotline (0.76, 6.7)
938. drum@line (0.76, 8.7)
939. FraGreEye (0.76, 11.6)
940. kassarine (0.76, 7.6)
941. hendaline (0.76, 7.8)
942. trootline (0.76, 8.3)
943. storyline (0.76, 7.2)
944. sweetline (0.76, 6.4)
945. goccoline (0.76, 10.3)
946. sheraline (0.76, 6.8)
947. speedline (0.76, 5.3)
948. nikkoline (0.76, 7.4)
949. esterline (0.76, 7.0)
950. versoline (0.76, 8.6)
951. eliobembe (0.76, 10.6)
952. bruneline (0.76, 7.2)
953. micarline (0.76, 7.8)
954. bikokline (0.76, 11.0)
955. olau_line (0.76, 12.9)
956. audioline (0.76, 6.3)
957. carolline (0.76, 5.7)
958. denneline (0.76, 9.0)
959. whoseline (0.76, 6.3)
960. daisyrine (0.76, 6.3)
961. alphaline (0.76, 7.5)
962. qqpraline (0.76, 10.0)
963. braceline (0.76, 6.7)
964. ++fonline (0.76, 11.9)
965. mecheline (0.76, 6.3)
966. emmenline (0.76, 9.2)
967. whiteline (0.76, 5.2)
968. crestline (0.76, 5.4)
969. infraline (0.76, 7.9)
970. bjkenline (0.76, 11.6)
971. Lapraline (0.76, 9.3)

972. jhoseline (0.76, 7.4)	982. jumonline (0.76, 7.6)	992. djponline (0.76, 9.6)
973. jemmaline (0.76, 7.1)	983. edfonline (0.76, 10.3)	993. zeppeline (0.76, 6.9)
974. brakeline (0.76, 6.6)	984. ccponline (0.76, 8.9)	994. zaponline (0.76, 8.2)
975. kidaeline (0.76, 10.8)	985. childline (0.76, 6.9)	995. jchonline (0.76, 9.0)
976. swissline (0.76, 7.2)	986. budonline (0.76, 8.1)	996. vcgonline (0.76, 10.0)
977. finalline (0.76, 6.8)	987. kbconline (0.76, 9.4)	997. willcline (0.76, 7.5)
978. thirdline (0.76, 6.4)	988. dbzonline (0.76, 9.0)	998. ncgonline (0.76, 9.3)
979. stageline (0.76, 6.9)	989. mkzonline (0.76, 10.1)	999. bkdonline (0.76, 8.2)
980. tcconline (0.76, 8.9)	990. mhponline (0.76, 9.5)	
981. graveline (0.76, 5.8)	991. iamonline (0.76, 5.1)	

Cluster 20

Prototype: soasshni

Hard-assigned passwords: 1252495 (4.33% of total)
Unique hard-assigned passwords: 415075 (66.86% of cluster total)

Cluster-assignment scores:
	Min: 0.087
	Max: 0.947
	Mean: 0.431
	SD: 0.143

Strength bins:
	Very weak: 260320 (20.78%)
	Weak: 516411 (41.23%)
	Fair: 318742 (25.45%)
	Good: 154564 (12.34%)
	Strong: 2458 (0.20%)

Password lengths:
	Length 8: 1149593 (91.78%)
	Length 9: 99600 (7.95%)
	Length 10: 3302 (0.26%)

Character classes:
	4 classes: 0 (0.00%)
	3 classes: 3428 (0.27%)
		lower/upper/symbol: 3428 (100.00%)
		lower/upper/number: 0 (0.00%)
		lower/symbol/number: 0 (0.00%)
		upper/symbol/number: 0 (0.00%)
	2 classes: 62732 (5.01%)
		lower/upper: 41029 (65.40%)
		lower/number: 0 (0.00%)
		lower/symbol: 21703 (34.60%)
		upper/number: 0 (0.00%)
		upper/symbol: 0 (0.00%)
		number/symbol: 0 (0.00%)
	1 class: 1186335 (94.72%)
		lower: 1186335 (100.00%)
		upper: 0 (0.00%)
		symbol: 0 (0.00%)
		number: 0 (0.00%)

Most frequent char-class structures:
	LLLLLLLL: 1093359 (87.3%)
	LLLLLLLLL: 90080 (7.2%)
	ULLLLLLL: 29701 (2.4%)
	LLLSLLLL: 4555 (0.4%)
	LLLLSLLL: 4057 (0.3%)
	ULLLULLL: 3268 (0.3%)
	LLLLLLLLLL: 2896 (0.2%)
	ULLLLLLLL: 2340 (0.2%)
	LLLLSLLLL: 2079 (0.2%)
	LLSLLLLL: 1737 (0.1%)

1,000 nearest passwords

0.	fursidni	(0.95, 10.9)	54.	above.no	(0.90, 9.9)	108.	no●no●no	(0.88, 6.9)
1.	sumeshni	(0.94, 8.3)	55.	svejedno	(0.90, 6.3)	109.	beppigno	(0.88, 10.5)
2.	mukeshni	(0.94, 7.3)	56.	bozoohno	(0.90, 10.7)	110.	smokeyno	(0.88, 6.5)
3.	rajeshni	(0.94, 7.5)	57.	socoohno	(0.90, 12.2)	111.	pitrigno	(0.88, 9.5)
4.	bolishni	(0.94, 11.0)	58.	letmekno	(0.90, 6.9)	112.	fumkegno	(0.88, 11.2)
5.	periodni	(0.94, 7.2)	59.	ohnoohno	(0.90, 5.9)	113.	alizeyno	(0.88, 8.1)
6.	darsshni	(0.94, 10.6)	60.	seriozno	(0.90, 9.9)	114.	calligno	(0.88, 8.5)
7.	bunvegni	(0.94, 11.8)	61.	mycheyni	(0.90, 10.3)	115.	ferrigno	(0.88, 7.0)
8.	ritoshni	(0.94, 10.0)	62.	hercegno	(0.90, 6.3)	116.	maxgobno	(0.88, 11.4)
9.	gerdepni	(0.94, 10.9)	63.	josjedno	(0.90, 10.1)	117.	baddogno	(0.88, 8.8)
10.	linkedni	(0.94, 7.0)	64.	morbegno	(0.90, 9.6)	118.	cordigno	(0.88, 9.9)
11.	ejkntdni	(0.93, 12.3)	65.	loopezno	(0.90, 10.0)	119.	slobodno	(0.88, 7.3)
12.	samashni	(0.93, 7.6)	66.	lisethno	(0.90, 9.3)	120.	Fredigno	(0.88, 10.6)
13.	s-gushni	(0.93, 13.2)	67.	menotkno	(0.90, 9.8)	121.	svobodno	(0.88, 8.6)
14.	degbegni	(0.93, 11.1)	68.	delsogno	(0.90, 8.3)	122.	m@rci@no	(0.88, 8.3)
15.	maxsigni	(0.93, 10.9)	69.	shnoshno	(0.90, 7.2)	123.	vosmogno	(0.88, 11.4)
16.	freweyni	(0.93, 11.4)	70.	LneesUno	(0.90, 12.7)	124.	kiidogno	(0.88, 11.5)
17.	kereshni	(0.93, 8.3)	71.	to●ti●no	(0.90, 9.3)	125.	kokosyno	(0.88, 9.7)
18.	consigni	(0.93, 8.1)	72.	likeohno	(0.89, 8.7)	126.	p@mpe@no	(0.88, 12.7)
19.	KubusAni	(0.93, 11.7)	73.	mmamehno	(0.89, 11.8)	127.	tulsiani	(0.88, 8.2)
20.	abbjsjni	(0.93, 13.0)	74.	AmigoUno	(0.89, 10.2)	128.	mykasyno	(0.88, 10.6)
21.	nivashni	(0.93, 7.4)	75.	oggiogno	(0.89, 10.4)	129.	trpripno	(0.87, 11.1)
22.	Vikashni	(0.93, 9.4)	76.	yukaohno	(0.89, 11.0)	130.	multiani	(0.87, 6.4)
23.	vikashni	(0.93, 7.9)	77.	jrbeijno	(0.89, 11.7)	131.	lovesani	(0.87, 6.4)
24.	machikni	(0.93, 6.5)	78.	uaintkno	(0.89, 10.3)	132.	catvixno	(0.87, 11.1)
25.	sobashni	(0.93, 9.2)	79.	idont●no	(0.89, 7.7)	133.	chattyno	(0.87, 7.9)
26.	nimitzni	(0.93, 8.5)	80.	c_h.i,no	(0.89, 14.0)	134.	jejetani	(0.87, 8.6)
27.	lotashni	(0.93, 10.7)	81.	agniogno	(0.89, 9.4)	135.	beautyno	(0.87, 7.3)
28.	ysmmsgni	(0.93, 12.6)	82.	udontkno	(0.89, 6.1)	136.	mahesani	(0.87, 8.0)
29.	terashni	(0.93, 9.4)	83.	idontkno	(0.89, 5.5)	137.	kassiani	(0.87, 7.0)
30.	vilashni	(0.93, 10.2)	84.	Idontkno	(0.89, 7.0)	138.	Cassiani	(0.87, 7.4)
31.	p@r@s@ni	(0.92, 9.1)	85.	babyohno	(0.89, 6.5)	139.	iuriigai	(0.87, 10.9)
32.	fharshni	(0.92, 10.0)	86.	crarsdno	(0.89, 12.9)	140.	neritani	(0.87, 8.9)
33.	dharshni	(0.92, 8.3)	87.	vegsobno	(0.89, 12.3)	141.	coritani	(0.87, 8.1)
34.	hehcexni	(0.92, 13.0)	88.	haydi_no	(0.89, 11.2)	142.	kilitani	(0.87, 7.9)
35.	quefikni	(0.92, 11.0)	89.	mactogno	(0.89, 9.7)	143.	xoriixai	(0.87, 10.6)
36.	campogni	(0.92, 8.0)	90.	yeahikno	(0.89, 6.6)	144.	restiani	(0.87, 7.8)
37.	olatogni	(0.92, 11.3)	91.	hesaidno	(0.89, 8.9)	145.	JamesOne	(0.87, 6.9)
38.	bm.togni	(0.92, 13.1)	92.	camjohno	(0.89, 8.7)	146.	orsotani	(0.87, 9.9)
39.	inxssxni	(0.92, 12.4)	93.	maxjohno	(0.89, 8.3)	147.	alliikai	(0.87, 10.3)
40.	mhrmohni	(0.92, 11.6)	94.	onlyikno	(0.89, 5.8)	148.	britiani	(0.87, 7.3)
41.	tinlikni	(0.92, 10.4)	95.	tifpidno	(0.89, 11.2)	149.	donjiyno	(0.87, 11.5)
42.	jirnepni	(0.92, 11.7)	96.	amycigno	(0.89, 9.7)	150.	SweetOne	(0.87, 6.9)
43.	anivodni	(0.92, 10.6)	97.	cachodno	(0.88, 10.3)	151.	ristiani	(0.87, 7.4)
44.	ingridni	(0.92, 8.6)	98.	kevjohno	(0.88, 9.2)	152.	kanetani	(0.87, 7.8)
45.	miszo●ni	(0.92, 13.0)	99.	silvihno	(0.88, 10.2)	153.	allotuai	(0.87, 11.0)
46.	ronrodni	(0.92, 10.3)	100.	bigjohno	(0.88, 6.4)	154.	leeithne	(0.87, 10.2)
47.	febri@ni	(0.92, 9.1)	101.	youridno	(0.88, 7.7)	155.	aartijai	(0.87, 9.0)
48.	cgicogni	(0.92, 11.1)	102.	tabasqno	(0.88, 9.8)	156.	newotani	(0.87, 9.3)
49.	arirokni	(0.92, 10.4)	103.	svabodno	(0.88, 9.3)	157.	kokotani	(0.87, 6.9)
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51.	gnawoyni	(0.91, 11.6)	105.	elghigno	(0.88, 11.0)	159.	tirsikci	(0.87, 11.5)
52.	Joeropni	(0.91, 13.3)	106.	sauvigno	(0.88, 6.4)	160.	tudeskci	(0.87, 11.0)
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522. tagliani (0.86, 7.2)
523. nyassmai (0.86, 10.4)
524. cagliani (0.86, 7.6)
525. thilogne (0.86, 8.5)
526. kanzekai (0.86, 9.5)
527. wendegai (0.86, 9.8)
528. Cipriani (0.86, 7.8)
529. febriani (0.86, 6.9)
530. kayliani (0.86, 7.4)
531. cipriani (0.86, 6.1)
532. chinthui (0.86, 7.7)
533. shitokai (0.86, 6.1)
534. latrogne (0.86, 9.1)
535. fengshui (0.86, 4.7)
536. ruffigne (0.86, 9.9)
537. indriani (0.86, 5.6)
538. andriani (0.86, 5.8)
539. sexysani (0.86, 6.8)
540. italiani (0.86, 5.3)
541. ardpiVai (0.86, 14.0)
542. deshtani (0.86, 7.1)
543. shintani (0.86, 6.8)
544. amariani (0.86, 6.6)
545. jmariani (0.86, 8.3)
546. carmeyne (0.86, 8.7)
547. shotokai (0.86, 6.4)
548. udontani (0.86, 9.2)
549. JimboOne (0.86, 7.8)
550. ottathai (0.86, 8.9)
551. ukpaizne (0.86, 11.4)
552. gachiani (0.86, 9.9)
553. kauaigai (0.86, 9.4)
554. oudjiani (0.86, 10.4)
555. aglethai (0.86, 9.4)
556. dnmniaai (0.86, 12.0)
557. kisutcai (0.86, 11.1)
558. moshehai (0.86, 9.0)
559. sabaijai (0.86, 8.7)
560. thanigai (0.86, 6.7)
561. holatani (0.86, 8.3)
562. travthai (0.86, 8.6)
563. baratani (0.86, 7.3)
564. sshaiani (0.86, 10.2)
565. grantkai (0.86, 8.0)
566. vajaijai (0.86, 8.3)
567. $$jaijai (0.86, 10.1)
568. arsusani (0.86, 8.9)
569. suzciani (0.86, 10.3)
570. toiyeuai (0.86, 6.1)
571. DiojiOne (0.86, 12.5)
572. ra-mo-ne (0.86, 12.1)
573. dapaocai (0.86, 11.1)
574. alhashmi (0.86, 6.8)
575. jajaizai (0.86, 9.0)
576. jambiani (0.86, 7.9)
577. noanshai (0.86, 10.3)
578. artliani (0.86, 8.9)
579. pacciani (0.86, 8.1)
580. gabbiani (0.86, 6.5)
581. ajanikai (0.86, 8.8)
582. emiliani (0.86, 6.2)
583. ailatnai (0.86, 11.2)
584. pilatnai (0.86, 9.7)
585. fitriani (0.86, 5.8)
586. kauaikai (0.86, 7.4)
587. nandiani (0.86, 8.0)
588. pandiani (0.86, 6.1)
589. candiani (0.86, 6.9)
590. LaxmiBai (0.86, 10.1)
591. seinthci (0.86, 10.4)
592. aryashai (0.85, 8.4)
593. iraniani (0.85, 7.1)
594. kingshai (0.85, 7.3)
595. vetriani (0.85, 7.6)
596. sutriani (0.85, 7.1)
597. satriani (0.85, 4.7)
598. Satriani (0.85, 6.3)
599. thanikai (0.85, 8.8)
600. floriani (0.85, 6.3)
601. maggimai (0.85, 7.2)
602. mokashfi (0.85, 10.5)
603. csiriani (0.85, 9.4)
604. tangiwai (0.85, 8.2)
605. blumeani (0.85, 9.9)
606. odpiszmi (0.85, 12.4)
607. migas.fi (0.85, 10.6)
608. jemashci (0.85, 10.9)
609. spaziani (0.85, 8.7)
610. rangiwai (0.85, 8.2)
611. yangsbui (0.85, 9.8)
612. confidne (0.85, 9.8)
613. laumenai (0.85, 8.8)
614. aroythai (0.85, 9.4)
615. lockshmi (0.85, 10.4)
616. milesmai (0.85, 7.8)
617. adamiani (0.85, 6.1)
618. xdamiani (0.85, 10.1)
619. pdamiani (0.85, 9.6)
620. udonthai (0.85, 8.1)
621. riyasjai (0.85, 9.8)
622. tejashwi (0.85, 8.3)
623. julliani (0.85, 6.6)
624. lalliani (0.85, 7.4)
625. machikne (0.85, 5.4)
626. galliani (0.85, 7.2)
627. kalliani (0.85, 6.7)
628. langogne (0.85, 8.6)
629. ingiingi (0.85, 8.0)
630. lloyedmi (0.85, 11.2)
631. marliani (0.85, 7.2)
632. shamiani (0.85, 7.3)
633. chiktani (0.85, 9.1)
634. Kawpimai (0.85, 12.0)
635. keenthai (0.85, 8.7)
636. klakshmi (0.85, 7.3)
637. TraLoOne (0.85, 12.6)
638. ilakshmi (0.85, 8.3)
639. jlakshmi (0.85, 8.4)
640. alakshmi (0.85, 6.4)
641. dlakshmi (0.85, 8.8)
642. salathai (0.85, 6.7)
643. rlakshmi (0.85, 7.2)
644. slakshmi (0.85, 6.0)
645. Vlakshmi (0.85, 7.4)
646. hlakshmi (0.85, 7.8)
647. glakshmi (0.85, 7.1)
648. bachigai (0.85, 8.3)
649. vlakshmi (0.85, 6.3)
650. tarathai (0.85, 7.7)
651. mlakshmi (0.85, 6.7)
652. maruthai (0.85, 7.6)
653. brastagi (0.85, 7.3)
654. jerriani (0.85, 8.5)
655. abbatzvi (0.85, 11.1)
656. delespai (0.85, 7.8)
657. harasani (0.85, 7.3)
658. karasani (0.85, 7.3)
659. barasani (0.85, 8.2)
660. dilasani (0.85, 8.5)
661. surasani (0.85, 8.8)
662. khensani (0.85, 8.6)
663. greathai (0.85, 8.9)
664. bandikui (0.85, 8.8)
665. mtmaimai (0.85, 9.2)
666. howaiwai (0.85, 8.4)
667. Rancogne (0.85, 11.1)
668. rangipai (0.85, 8.2)
669. lizhihui (0.85, 7.2)
670. sexioggi (0.85, 10.0)
671. monainai (0.85, 9.6)
672. jazminai (0.85, 7.9)
673. webhsgui (0.85, 11.2)
674. parathvi (0.85, 9.4)
675. kpruthvi (0.85, 9.4)
676. mandicai (0.85, 8.2)
677. Rugnidfi (0.85, 12.9)
678. nielshui (0.85, 8.4)
679. bermthai (0.85, 9.2)
680. lalaigne (0.85, 8.2)
681. umbuibui (0.85, 12.3)
682. ruchikai (0.85, 7.3)
683. chudiwai (0.85, 9.9)
684. khassdgi (0.85, 11.2)
685. jrcdsgui (0.85, 11.5)
686. tagitagi (0.85, 7.8)
687. rkustagi (0.85, 10.8)
688. sweetjai (0.85, 7.5)
689. reggiani (0.85, 6.4)
690. shadihai (0.85, 8.6)
691. Edort.fi (0.85, 14.0)
692. kambigai (0.85, 9.0)
693. mezzegai (0.85, 10.2)
694. yanzimai (0.85, 8.8)
695. reenigne (0.85, 10.1)
696. yahnowai (0.85, 11.1)
697. LiuLiTai (0.85, 11.5)
698. yorkthai (0.85, 8.5)
699. luinswai (0.85, 10.7)
700. sirtongi (0.85, 9.4)
701. sweetbai (0.85, 6.8)

702. quduodui (0.85, 12.0)
703. peniskne (0.85, 12.5)
704. OneToOne (0.85, 9.7)
705. hai&shai (0.85, 10.2)
706. ajadenai (0.85, 9.0)
707. isalibne (0.85, 10.5)
708. sanmihai (0.85, 7.8)
709. lazdijai (0.85, 10.7)
710. aicaijai (0.85, 9.6)
711. Alavigne (0.85, 7.6)
712. kyakenai (0.85, 10.8)
713. alavigne (0.85, 5.8)
714. ouofthci (0.85, 13.2)
715. luansbci (0.85, 11.7)
716. kunjibai (0.85, 8.2)
717. umutingi (0.85, 8.8)
718. shonshai (0.85, 8.7)
719. mikciani (0.85, 9.5)
720. ramkijai (0.85, 7.2)
721. obenohne (0.85, 11.2)
722. skvlshai (0.85, 11.8)
723. nandejai (0.85, 9.8)
724. ericshai (0.85, 8.3)
725. zihaigui (0.85, 11.1)
726. ivyhohui (0.85, 11.6)
727. lebaizai (0.85, 11.5)
728. pomaikai (0.85, 6.8)
729. santiagi (0.85, 6.5)
730. iamaokai (0.85, 10.9)
731. marashmi (0.85, 7.1)
732. imrashmi (0.85, 8.5)
733. brattygi (0.85, 9.2)
734. dilysmai (0.85, 11.1)
735. makcibai (0.85, 10.2)
736. kyrashai (0.85, 9.5)
737. Avi_shai (0.85, 11.5)
738. wshaikgi (0.85, 11.9)
739. sarashai (0.85, 8.2)
740. jizhihai (0.85, 8.8)
741. wp-mihmi (0.85, 12.8)
742. ikeashai (0.85, 9.6)
743. l.akszmi (0.85, 13.9)
744. shupikai (0.85, 9.1)
745. lekaikai (0.85, 9.4)
746. chimengi (0.85, 8.3)
747. caucibai (0.85, 10.5)
748. cruciani (0.85, 7.9)
749. ziguigui (0.85, 7.3)
750. figuigui (0.85, 5.8)
751. Rhymijai (0.85, 12.5)
752. roopspai (0.85, 11.5)
753. jonnikgi (0.85, 10.6)
754. naywejvi (0.85, 12.6)
755. berzengi (0.85, 10.0)
756. huzhouai (0.85, 9.3)
757. brucefai (0.85, 7.2)
758. hpl]shvi (0.85, 9.7)
759. kichigai (0.85, 7.5)
760. ponziani (0.85, 8.0)
761. targiani (0.85, 8.4)
762. sucuokai (0.85, 9.4)
763. mervigne (0.85, 8.2)
764. kschojne (0.85, 10.6)
765. zaghofai (0.85, 11.5)
766. podhigai (0.85, 9.6)
767. graziani (0.85, 6.8)
768. avivshai (0.85, 9.2)
769. muthiani (0.85, 6.7)
770. klujikne (0.85, 12.0)
771. alexshai (0.85, 7.6)
772. daiyihui (0.85, 8.5)
773. machomai (0.85, 8.0)
774. kaigiani (0.85, 8.4)
775. rvekshmi (0.85, 11.9)
776. shivohne (0.85, 8.9)
777. boueidai (0.85, 11.3)
778. sinjimai (0.85, 9.0)
779. qwertzui (0.85, 4.8)
780. saymehai (0.85, 10.4)
781. ninisqui (0.85, 9.0)
782. gascogne (0.85, 9.3)
783. cpvnizvi (0.85, 12.3)
784. ensespci (0.85, 12.6)
785. aeneidai (0.85, 10.3)
786. porco.ne (0.85, 10.1)
787. woshikui (0.85, 7.5)
788. mandovai (0.85, 8.5)
789. narusdai (0.85, 10.1)
790. voddihai (0.85, 11.1)
791. wwwdomai (0.85, 10.6)
792. gedgibne (0.85, 12.3)
793. janvijai (0.85, 8.3)
794. balbiani (0.85, 8.0)
795. liquidfi (0.85, 9.1)
796. sarbiani (0.85, 7.7)
797. ceelthvi (0.85, 12.1)
798. gordiani (0.85, 8.4)
799. kristyne (0.85, 6.2)
800. merdiani (0.85, 8.1)
801. slatspne (0.85, 12.3)
802. mahwihwi (0.85, 12.4)
803. owthsgmi (0.85, 11.7)
804. perciani (0.85, 7.9)
805. mardiani (0.85, 6.4)
806. keyviani (0.85, 10.0)
807. Dordogne (0.85, 9.8)
808. dordogne (0.85, 8.2)
809. bhavikai (0.85, 8.0)
810. lethimai (0.85, 8.1)
811. manutagi (0.85, 8.5)
812. detrigui (0.85, 9.8)
813. kaivskai (0.85, 10.6)
814. aborthai (0.85, 8.8)
815. fisgi.ai (0.85, 13.3)
816. chelskai (0.85, 9.0)
817. marksbai (0.85, 8.7)
818. marziani (0.85, 6.4)
819. yhgfihgi (0.85, 11.1)
820. guhuozai (0.85, 10.5)
821. suspiani (0.85, 8.0)
822. basaidai (0.85, 7.1)
823. mankedai (0.85, 9.8)
824. pedrogui (0.85, 8.3)
825. caspiani (0.85, 6.2)
826. Rusciani (0.85, 9.1)
827. nemosyne (0.85, 7.6)
828. sxfisxfi (0.85, 10.3)
829. hochofai (0.85, 10.9)
830. Hushihai (0.85, 11.1)
831. bourogui (0.85, 9.2)
832. abershai (0.85, 10.4)
833. overshai (0.85, 10.3)
834. sagisagi (0.85, 6.0)
835. lex_i%ci (0.85, 14.0)
836. biyaobai (0.85, 10.9)
837. tribiani (0.85, 6.0)
838. hindijai (0.85, 8.3)
839. eronibai (0.85, 10.0)
840. shijiani (0.85, 5.9)
841. ppmatqmi (0.85, 12.5)
842. klodiani (0.85, 6.9)
843. paklojui (0.85, 10.4)
844. dondijai (0.85, 9.4)
845. nomisugi (0.85, 9.6)
846. uyfniygi (0.85, 12.9)
847. goldengi (0.85, 6.7)
848. Hunmoani (0.85, 11.8)
849. plortpai (0.85, 11.2)
850. rinkibai (0.85, 8.6)
851. rughokvi (0.85, 12.8)
852. trobiani (0.85, 8.4)
853. maiaiyai (0.85, 9.6)
854. rongomai (0.85, 7.8)
855. rimcofai (0.85, 10.8)
856. barbengi (0.85, 8.9)
857. makwikwi (0.85, 10.8)
858. sahjobai (0.85, 10.8)
859. dorasbui (0.85, 10.4)
860. pequegno (0.85, 9.4)
861. isadiyai (0.85, 9.9)
862. genkikai (0.85, 8.7)
863. maeciani (0.85, 9.9)
864. Chibiani (0.85, 8.5)
865. qwettyui (0.85, 7.2)
866. mahligai (0.85, 7.7)
867. hkjdifgi (0.85, 11.7)
868. louisxvi (0.85, 9.8)
869. cczysyne (0.85, 12.9)
870. woshibai (0.85, 7.8)
871. tangodai (0.85, 8.4)
872. kalaikai (0.85, 7.4)
873. nyadodui (0.85, 10.6)
874. yogioygi (0.85, 10.3)
875. malaikai (0.85, 7.2)
876. primiani (0.85, 8.0)
877. yoshikai (0.85, 6.7)
878. mordicai (0.85, 8.7)
879. kishikai (0.85, 9.0)
880. athlopne (0.85, 11.5)
881. lancebai (0.85, 9.6)
882. emixihui (0.85, 11.0)
883. speziani (0.85, 8.4)
884. yyhlikai (0.85, 12.1)
885. sugisugi (0.85, 6.5)
886. laquiqui (0.85, 7.3)
887. wauasyne (0.85, 11.3)
888. dawntyne (0.85, 8.4)
889. feahidfi (0.85, 11.9)
890. zopsiyfi (0.85, 12.9)
891. genkidai (0.85, 8.2)
892. myadonai (0.85, 6.5)
893. dianokai (0.85, 9.3)
894. drubidai (0.85, 10.2)
895. brunokai (0.85, 7.2)
896. maycejai (0.85, 10.1)
897. ShrLiKai (0.85, 14.0)
898. zorrogui (0.85, 8.6)
899. banatyne (0.85, 9.9)
900. Mopbsdgi (0.85, 13.5)
901. Laptopmi (0.85, 9.0)
902. deijiwai (0.85, 10.5)
903. uhuatyne (0.85, 12.3)
904. chantyne (0.85, 7.4)
905. emalikai (0.85, 9.0)
906. arunodai (0.85, 8.2)
907. shurikai (0.85, 7.8)
908. krystyne (0.85, 6.1)
909. losmiwai (0.85, 11.4)
910. mainomai (0.85, 7.9)
911. mercimai (0.85, 8.7)
912. saypokai (0.85, 10.3)
913. wansongi (0.85, 9.8)
914. dadweyne (0.85, 9.7)
915. fkccicgi (0.85, 13.0)
916. sandokai (0.85, 6.6)
917. jundokai (0.85, 10.0)
918. rambodai (0.85, 7.6)
919. getvinai (0.85, 9.4)
920. cidcidci (0.85, 7.2)
921. terlikci (0.85, 10.5)
922. lilbigai (0.85, 9.5)
923. shukokai (0.85, 5.3)
924. dhulibai (0.85, 9.9)
925. oaraomai (0.85, 11.0)
926. henribai (0.85, 8.9)
927. bhuribai (0.85, 9.6)
928. juthequi (0.85, 10.3)
929. mateiwai (0.85, 8.6)
930. robrijai (0.85, 9.6)
931. jhaztyne (0.85, 10.7)
932. tu/usagi (0.85, 13.6)
933. ooshomai (0.85, 9.2)
934. kallikai (0.85, 8.5)
935. mallikai (0.85, 6.6)
936. teamoyai (0.85, 7.6)
937. farzihai (0.85, 11.2)
938. putlibai (0.85, 10.3)
939. Koerikai (0.85, 10.4)
940. Leycegui (0.85, 12.2)
941. alnjoani (0.85, 11.0)
942. mitzikai (0.85, 7.9)
943. dracohmi (0.85, 9.9)
944. malligai (0.85, 6.4)
945. daskijai (0.85, 9.4)
946. baryomai (0.85, 9.9)
947. tompohci (0.85, 10.7)
948. ggaktugi (0.85, 12.9)
949. timronai (0.85, 9.7)
950. alijibai (0.85, 8.6)
951. lachiqui (0.85, 6.3)
952. rongopai (0.85, 8.8)
953. egoeimai (0.85, 10.1)
954. stiroqai (0.85, 11.1)
955. leycegui (0.85, 11.0)
956. noslohci (0.85, 10.1)
957. l_chiqui (0.85, 10.4)
958. ebruezgi (0.85, 12.4)
959. misaodai (0.85, 9.3)
960. lefriqui (0.85, 9.4)
961. seirijai (0.85, 10.6)
962. kekhodai (0.85, 10.3)
963. kirribai (0.85, 8.7)
964. dumgoyne (0.85, 10.6)
965. chikipai (0.85, 8.4)
966. osaliqui (0.85, 11.0)
967. jesusqui (0.85, 7.2)
968. mallihai (0.85, 8.2)
969. teamoani (0.85, 6.8)
970. nii●okai (0.85, 11.8)
971. vancezai (0.85, 10.4)

972. mundozai (0.85, 9.6)	982. sherizai (0.85, 8.4)	992. jerrijai (0.85, 9.7)
973. necropai (0.85, 9.9)	983. sharifai (0.85, 7.0)	993. shikibai (0.85, 7.8)
974. shadozai (0.85, 8.6)	984. bunzozai (0.85, 8.9)	994. baleiwai (0.85, 10.4)
975. draconai (0.85, 7.7)	985. difmokfi (0.85, 12.1)	995. puleivai (0.85, 9.1)
976. nicatyne (0.85, 9.6)	986. shalopai (0.85, 9.0)	996. boudokai (0.85, 7.4)
977. marlijai (0.85, 8.0)	987. cherijai (0.85, 8.4)	997. sevmekmi (0.85, 9.5)
978. Talvi.fi (0.85, 13.7)	988. rosdengi (0.85, 10.7)	998. chiriqui (0.85, 5.9)
979. fiamodui (0.85, 11.2)	989. bascomai (0.85, 9.7)	999. zendokai (0.85, 7.3)
980. khodijai (0.85, 8.3)	990. maicibai (0.85, 9.5)	
981. kempokai (0.85, 8.1)	991. saddiqui (0.85, 7.4)	

Cluster 21

Prototype: 2000105N

Hard-assigned passwords: 1069204 (3.69% of total)
Unique hard-assigned passwords: 628002 (41.26% of cluster total)

Cluster-assignment scores:
        Min: 0.092
        Max: 0.909
        Mean: 0.377
        SD: 0.137

Strength bins:
        Very weak: 96037 (8.98%)
        Weak: 269724 (25.23%)
        Fair: 333154 (31.16%)
        Good: 366041 (34.23%)
        Strong: 4248 (0.40%)

Password lengths:
        Length 8: 995644 (93.12%)
        Length 9: 73560 (6.88%)

Character classes:
        4 classes: 4040 (0.38%)
        3 classes: 46126 (4.31%)
                lower/upper/symbol: 8 (0.02%)
                lower/upper/number: 29422 (63.79%)
                lower/symbol/number: 12851 (27.86%)
                upper/symbol/number: 3845 (8.34%)
        2 classes: 493933 (46.20%)
                lower/upper: 15 (0.00%)
                lower/number: 409558 (82.92%)
                lower/symbol: 13 (0.00%)
                upper/number: 64951 (13.15%)
                upper/symbol: 443 (0.09%)
                number/symbol: 18953 (3.84%)
        1 class: 525105 (49.11%)
                lower: 0 (0.00%)
                upper: 4 (0.00%)
                symbol: 34 (0.01%)
                number: 525067 (99.99%)

Most frequent char-class structures:
        DDDDDDDD: 502793 (47.0%)
        DDDDDDLL: 96016 (9.0%)
        DDDDLLLL: 87811 (8.2%)
        DDDDDDDL: 51839 (4.8%)
        DDDLLLLL: 24989 (2.3%)
        DDDDDDDDD: 22274 (2.1%)
        DDDDDLLL: 20506 (1.9%)
        UUUUUUDD: 15014 (1.4%)
        DDLLDDLL: 13065 (1.2%)
        UUUUDDDD: 12567 (1.2%)

1,000 nearest passwords

0.	332211BB	(0.91, 8.1)	54.	120289DM	(0.88, 10.0)	108.	8040095F	(0.86, 11.5)
1.	112176GC	(0.91, 10.1)	55.	170454EM	(0.88, 10.7)	109.	130009CH	(0.86, 11.2)
2.	170558AB	(0.91, 9.9)	56.	121591CN	(0.88, 10.8)	110.	052619#5	(0.86, 11.5)
3.	112152TC	(0.91, 10.2)	57.	209020MH	(0.87, 11.5)	111.	120474MI	(0.86, 10.2)
4.	170845GT	(0.90, 10.2)	58.	112191JT	(0.87, 9.8)	112.	292299EC	(0.86, 11.7)
5.	160886RC	(0.90, 10.2)	59.	120210MN	(0.87, 10.1)	113.	110903BC	(0.86, 10.3)
6.	120788AB	(0.90, 8.9)	60.	6821477B	(0.87, 11.3)	114.	774101nC	(0.85, 12.2)
7.	102030RM	(0.90, 7.7)	61.	151266EB	(0.87, 11.0)	115.	50K7820T	(0.85, 13.1)
8.	120558JH	(0.89, 10.3)	62.	121498BJ	(0.87, 10.3)	116.	7025821M	(0.85, 11.0)
9.	102030IM	(0.89, 8.6)	63.	019168wH	(0.87, 11.7)	117.	092193sH	(0.85, 10.9)
10.	120903CB	(0.89, 10.1)	64.	121267JH	(0.87, 9.5)	118.	14?510JC	(0.85, 13.9)
11.	141600CC	(0.89, 9.8)	65.	151690AH	(0.87, 10.9)	119.	110849YH	(0.85, 11.5)
12.	120707HH	(0.89, 10.1)	66.	0159195I	(0.87, 12.1)	120.	121622LF	(0.85, 11.3)
13.	160510DB	(0.89, 10.6)	67.	140789RF	(0.87, 10.7)	121.	131994JB	(0.85, 10.1)
14.	190486EM	(0.89, 10.3)	68.	121357DH	(0.87, 10.5)	122.	140812PC	(0.85, 10.3)
15.	170990AT	(0.89, 9.8)	69.	121088BB	(0.87, 9.2)	123.	237100MC	(0.85, 10.7)
16.	180386GM	(0.89, 10.4)	70.	181226RN	(0.87, 11.3)	124.	181594TI	(0.85, 11.6)
17.	140504MT	(0.89, 10.5)	71.	140564MI	(0.87, 10.7)	125.	110877DI	(0.85, 10.7)
18.	121386UC	(0.89, 10.9)	72.	110253BB	(0.87, 10.5)	126.	219621HC	(0.85, 11.3)
19.	362012KB	(0.89, 11.1)	73.	131990HH	(0.87, 9.9)	127.	6696122C	(0.85, 11.3)
20.	0825199T	(0.89, 10.4)	74.	120797MJ	(0.87, 9.6)	128.	171721HN	(0.85, 11.3)
21.	130246EH	(0.89, 11.3)	75.	150793AC	(0.87, 9.8)	129.	120131RB	(0.85, 10.4)
22.	120348PM	(0.89, 10.7)	76.	8070932C	(0.87, 11.9)	130.	171988FF	(0.84, 10.5)
23.	120667AB	(0.89, 9.5)	77.	122100DC	(0.87, 9.3)	131.	7160320M	(0.84, 11.0)
24.	121503KC	(0.89, 10.5)	78.	242012LF	(0.87, 11.6)	132.	7760047C	(0.84, 11.3)
25.	120953MC	(0.89, 10.3)	79.	150948PH	(0.87, 10.8)	133.	6061491I	(0.84, 11.5)
26.	121484MC	(0.89, 9.8)	80.	121799JH	(0.87, 9.7)	134.	280880DM	(0.84, 10.1)
27.	121409RH	(0.89, 10.4)	81.	170610MF	(0.87, 10.9)	135.	99230458	(0.84, 9.0)
28.	112010ZM	(0.89, 10.9)	82.	120160JH	(0.87, 10.0)	136.	120007JJ	(0.84, 10.7)
29.	152009GT	(0.89, 10.5)	83.	171841DB	(0.87, 11.5)	137.	7820268N	(0.84, 11.3)
30.	160910DC	(0.88, 10.4)	84.	170308IU	(0.87, 11.3)	138.	77521158	(0.84, 9.1)
31.	112211MM	(0.88, 8.1)	85.	809215aB	(0.87, 11.0)	139.	23P539k5	(0.84, 13.4)
32.	333&888B	(0.88, 12.9)	86.	280695AB	(0.87, 9.1)	140.	8320524C	(0.84, 11.3)
33.	190345SC	(0.88, 10.7)	87.	110596MC	(0.86, 9.7)	141.	131080CB	(0.84, 9.8)
34.	121409ZH	(0.88, 11.0)	88.	19118DkH	(0.86, 12.1)	142.	180277MI	(0.84, 10.3)
35.	140270AB	(0.88, 9.5)	89.	171717EC	(0.86, 9.5)	143.	91959558	(0.84, 9.4)
36.	112113JH	(0.88, 9.6)	90.	119998^^	(0.86, 13.1)	144.	110499GB	(0.84, 10.2)
37.	0150178M	(0.88, 10.5)	91.	130461JN	(0.86, 10.8)	145.	170914JM	(0.84, 10.8)
38.	0521742C	(0.88, 11.5)	92.	8491418F	(0.86, 11.5)	146.	942509v8	(0.84, 11.7)
39.	7090387N	(0.88, 11.4)	93.	6329913C	(0.86, 11.2)	147.	150599SC	(0.84, 9.8)
40.	110668HH	(0.88, 10.5)	94.	150200RF	(0.86, 10.4)	148.	5061998N	(0.84, 10.7)
41.	131364BM	(0.88, 10.8)	95.	161982IC	(0.86, 10.6)	149.	102898AM	(0.84, 9.6)
42.	112225SI	(0.88, 10.9)	96.	121579AF	(0.86, 10.4)	150.	5721375B	(0.84, 11.3)
43.	120999MB	(0.88, 9.9)	97.	121212BB	(0.86, 7.3)	151.	668011gB	(0.84, 12.2)
44.	8571026B	(0.88, 11.3)	98.	150601HB	(0.86, 10.8)	152.	120795^^	(0.84, 10.1)
45.	8226141M	(0.88, 10.8)	99.	9320955H	(0.86, 11.5)	153.	93512158	(0.84, 9.2)
46.	180997TC	(0.88, 10.4)	100.	214201AC	(0.86, 10.6)	154.	91621958	(0.84, 9.0)
47.	9421658I	(0.88, 11.7)	101.	120587DJ	(0.86, 10.1)	155.	00316158	(0.84, 8.5)
48.	110584AN	(0.88, 9.8)	102.	160283FF	(0.86, 10.3)	156.	93801648	(0.84, 9.4)
49.	110499RB	(0.88, 10.2)	103.	112509CT	(0.86, 10.4)	157.	940566nN	(0.84, 12.4)
50.	121066AB	(0.88, 9.4)	104.	141000CB	(0.86, 10.1)	158.	94400948	(0.84, 9.2)
51.	110866JB	(0.88, 10.0)	105.	10036JfC	(0.86, 12.0)	159.	112233MM	(0.84, 6.5)
52.	180249DN	(0.88, 11.3)	106.	180280MJ	(0.86, 10.0)	160.	5550123T	(0.84, 8.3)
53.	150978ON	(0.88, 11.1)	107.	110678MC	(0.86, 9.7)	161.	90244948	(0.84, 9.6)

162. 5122482M (0.84, 10.5)
163. 94908438 (0.84, 9.6)
164. 91257048 (0.84, 9.1)
165. 94501538 (0.84, 9.6)
166. 99319948 (0.84, 9.0)
167. 131296KM (0.84, 10.1)
168. 92960048 (0.83, 9.2)
169. 302002CH (0.83, 10.2)
170. 06231538 (0.83, 8.5)
171. 99591958 (0.83, 8.5)
172. 160689^^ (0.83, 10.0)
173. 99318158 (0.83, 9.1)
174. 91274038 (0.83, 9.4)
175. 97961758 (0.83, 9.4)
176. 2128714C (0.83, 10.8)
177. 002330f8 (0.83, 9.8)
178. 96407158 (0.83, 9.1)
179. 130860TL (0.83, 10.8)
180. 190199MB (0.83, 10.2)
181. 110760SH (0.83, 10.4)
182. 98321358 (0.83, 8.6)
183. 97322958 (0.83, 9.1)
184. 91316858 (0.83, 9.1)
185. 01608158 (0.83, 9.1)
186. 90276358 (0.83, 9.5)
187. 97254158 (0.83, 9.1)
188. 270461JM (0.83, 10.5)
189. 97631258 (0.83, 8.7)
190. 98258358 (0.83, 8.8)
191. 120890TL (0.83, 10.2)
192. 91386158 (0.83, 9.1)
193. 06904838 (0.83, 8.9)
194. 01245948 (0.83, 8.2)
195. 191000AB (0.83, 9.3)
196. 98613258 (0.83, 9.2)
197. 92681958 (0.83, 9.0)
198. 02239148 (0.83, 8.9)
199. 483001Mw (0.83, 11.3)
200. 99717258 (0.83, 9.0)
201. 98502938 (0.83, 9.3)
202. 00233938 (0.83, 8.6)
203. 98741258 (0.83, 6.1)
204. 98505658 (0.83, 9.2)
205. 98851258 (0.83, 8.9)
206. 92603958 (0.83, 9.4)
207. 100895BB (0.83, 9.4)
208. 90267858 (0.83, 9.5)
209. 5151970M (0.83, 9.9)
210. 99255058 (0.83, 8.9)
211. 96661358 (0.83, 8.9)
212. 01935958 (0.83, 9.2)
213. 140774KF (0.83, 11.0)
214. 95851858 (0.83, 9.2)
215. 96494158 (0.83, 9.6)
216. 90253638 (0.83, 9.4)
217. 247C216M (0.83, 13.0)
218. 112233GM (0.83, 8.0)
219. 122087Aw (0.83, 9.8)
220. 8670137M (0.83, 11.1)
221. 91751358 (0.83, 9.2)
222. 90604458 (0.83, 9.5)
223. 76906438 (0.83, 9.4)
224. 05251848 (0.83, 8.7)
225. 90979048 (0.83, 9.3)
226. 8231993v (0.83, 9.1)
227. 98715358 (0.83, 9.2)
228. 97970938 (0.83, 8.9)
229. 06519258 (0.83, 8.9)
230. 3722173N (0.83, 11.3)
231. 95954258 (0.83, 9.3)
232. 9699086v (0.83, 10.7)
233. 96970858 (0.83, 9.3)
234. 93949758 (0.83, 9.2)
235. 91589158 (0.83, 5.8)
236. 90589058 (0.83, 6.2)
237. 94922248 (0.83, 9.3)
238. 90860058 (0.83, 9.3)
239. 91958858 (0.83, 9.2)
240. 122185Jv (0.83, 9.5)
241. 99599958 (0.83, 7.7)
242. 92650258 (0.83, 9.3)
243. 94818758 (0.83, 9.7)
244. 11111ABC (0.83, 7.0)
245. 97940048 (0.83, 8.9)
246. 94992658 (0.83, 9.6)
247. 81881948 (0.83, 8.6)
248. 7193+858 (0.83, 12.9)
249. 3921684H (0.83, 11.1)
250. 01681148 (0.83, 8.7)
251. 453011JB (0.83, 11.3)
252. 91985458 (0.83, 9.2)
253. 03431958 (0.83, 8.6)
254. 4131971N (0.83, 10.1)
255. 09239358 (0.83, 9.1)
256. 110797OM (0.83, 10.5)
257. 180889GU (0.83, 11.1)
258. 61316048 (0.83, 9.0)
259. 98999248 (0.83, 9.0)
260. 97992238 (0.83, 9.5)
261. 239097PJ (0.83, 12.0)
262. 07309958 (0.83, 9.1)
263. 9023524v (0.83, 10.5)
264. 79712048 (0.83, 9.2)
265. 112233TT (0.83, 6.6)
266. 98441048 (0.83, 9.0)
267. 08276958 (0.83, 9.3)
268. 08491958 (0.83, 9.3)
269. 03237958 (0.83, 9.0)
270. 111002DB (0.83, 10.2)
271. 09609148 (0.83, 9.2)
272. 96250738 (0.83, 9.1)
273. 00942658 (0.83, 9.4)
274. 60491258 (0.83, 9.3)
275. 012499e5 (0.83, 9.8)
276. 03471158 (0.83, 8.8)
277. 98551048 (0.83, 8.7)
278. 98571048 (0.83, 8.9)
279. 91461638 (0.83, 9.5)
280. 03260658 (0.83, 8.8)
281. 02980048 (0.83, 9.1)
282. 00520038 (0.83, 8.3)
283. 06417558 (0.83, 8.7)
284. 95326148 (0.83, 9.3)
285. 07934158 (0.83, 8.9)
286. 90451238 (0.83, 9.5)
287. 032194tJ (0.83, 11.0)
288. 99691238 (0.83, 9.0)
289. 181818YH (0.83, 9.7)
290. 98581738 (0.83, 9.3)
291. 00339458 (0.83, 9.2)
292. 08621058 (0.83, 9.2)
293. 01255558 (0.83, 8.5)
294. 87712958 (0.83, 9.1)
295. 06810538 (0.83, 8.7)
296. 99461438 (0.83, 9.0)
297. 9231993v (0.83, 9.1)
298. 151992TM (0.83, 10.0)
299. 752206a5 (0.83, 10.8)
300. 5199601B (0.83, 10.8)
301. 97404148 (0.83, 9.1)
302. 76224258 (0.83, 9.2)
303. 100468PN (0.83, 10.7)
304. 99451338 (0.83, 9.1)
305. 02418758 (0.83, 9.9)
306. 07410638 (0.83, 9.0)
307. 09278658 (0.83, 9.0)
308. 90264838 (0.83, 9.5)
309. 95306538 (0.83, 9.4)
310. 130176AH (0.83, 10.1)
311. 04259058 (0.83, 9.1)
312. 93312838 (0.83, 9.3)
313. 91937338 (0.83, 9.2)
314. 95861938 (0.83, 9.3)
315. 03420658 (0.83, 8.8)
316. 94414438 (0.83, 9.3)
317. 05933858 (0.83, 9.0)
318. 93771148 (0.83, 9.0)
319. 06661658 (0.83, 8.6)
320. 05325158 (0.83, 8.5)
321. 98831448 (0.83, 9.1)
322. 01470258 (0.83, 4.7)
323. 00285858 (0.83, 8.5)
324. 92541448 (0.83, 9.2)
325. 91680138 (0.83, 9.4)
326. 96603948 (0.83, 9.1)
327. 95504638 (0.83, 9.6)
328. 03370258 (0.83, 9.0)
329. 08592958 (0.83, 9.8)
330. 95603948 (0.83, 9.4)
331. 03308858 (0.83, 8.8)
332. 97861448 (0.83, 8.9)
333. 95263438 (0.83, 9.2)
334. 03914458 (0.83, 9.1)
335. 00815238 (0.83, 9.6)
336. 222101HM (0.83, 11.0)
337. 99821838 (0.83, 9.2)
338. 280497WF (0.83, 11.1)
339. 11111ZUB (0.83, 11.5)
340. 95530048 (0.83, 9.1)
341. 00580058 (0.83, 5.6)
342. 04225758 (0.83, 9.1)
343. 90275538 (0.83, 9.5)
344. 01809848 (0.83, 9.5)
345. 90305738 (0.83, 9.5)
346. 03597158 (0.83, 8.9)
347. 100594AB (0.83, 9.0)
348. 91284648 (0.83, 9.4)
349. 92924448 (0.83, 8.9)
350. 93831538 (0.83, 9.5)
351. 112696NH (0.83, 10.9)
352. 100805NC (0.83, 10.2)
353. 94803948 (0.83, 9.0)
354. 95552148 (0.83, 9.3)
355. 97923548 (0.82, 9.2)
356. 95505148 (0.82, 9.5)
357. 3423199B (0.82, 11.2)
358. 342216Mm (0.82, 10.3)
359. 95259838 (0.82, 9.5)
360. 0070010F (0.82, 10.2)
361. 323-4528 (0.82, 10.1)
362. 110691AH (0.82, 9.6)
363. 280482AB (0.82, 9.2)
364. 06814758 (0.82, 8.9)
365. 90389038 (0.82, 6.6)
366. 00416248 (0.82, 9.0)
367. 91489148 (0.82, 6.1)
368. 91841848 (0.82, 9.2)
369. 91389138 (0.82, 6.1)
370. 08981738 (0.82, 9.2)
371. 93806538 (0.82, 9.4)
372. 08223348 (0.82, 9.0)
373. 99680138 (0.82, 9.1)
374. 97850048 (0.82, 8.8)
375. 92252848 (0.82, 9.1)
376. 97659138 (0.82, 9.3)
377. 77719038 (0.82, 8.7)
378. 02580258 (0.82, 4.6)
379. 93399148 (0.82, 9.3)
380. 5731138M (0.82, 10.7)
381. 97996838 (0.82, 9.4)
382. 00246638 (0.82, 9.2)
383. 91287648 (0.82, 9.4)
384. 120581MI (0.82, 10.1)
385. 7891960F (0.82, 10.3)
386. 91539838 (0.82, 9.3)
387. 05959258 (0.82, 9.0)
388. 99760038 (0.82, 8.8)
389. 03608558 (0.82, 9.0)
390. 07708058 (0.82, 8.9)
391. 02279558 (0.82, 9.0)
392. 94660238 (0.82, 9.3)
393. 306090AB (0.82, 9.1)
394. 07761558 (0.82, 8.9)
395. 91529348 (0.82, 9.4)
396. 04232938 (0.82, 9.1)
397. 102699Tm (0.82, 9.9)
398. 90822448 (0.82, 9.3)
399. 97829438 (0.82, 9.4)
400. 99697038 (0.82, 9.3)
401. 02806758 (0.82, 9.3)
402. 08237138 (0.82, 8.7)
403. 07341938 (0.82, 9.1)
404. 06707358 (0.82, 9.5)
405. 07230548 (0.82, 8.7)
406. 100559RJ (0.82, 10.3)
407. 07481948 (0.82, 8.8)
408. 90798038 (0.82, 9.2)
409. 06612238 (0.82, 8.4)
410. 78321028 (0.82, 9.0)
411. 99692238 (0.82, 9.2)
412. 112672Em (0.82, 10.3)
413. 01517638 (0.82, 9.0)
414. 88500858 (0.82, 8.9)
415. 02970458 (0.82, 9.5)
416. 9595013v (0.82, 10.4)
417. 04310548 (0.82, 8.8)
418. 03531048 (0.82, 8.7)
419. 5620332C (0.82, 11.1)
420. 08413538 (0.82, 9.6)
421. 03419948 (0.82, 9.0)
422. 90829838 (0.82, 9.8)
423. 08403838 (0.82, 9.8)
424. 02246338 (0.82, 8.5)
425. 06252948 (0.82, 8.5)
426. 01253938 (0.82, 8.5)
427. 250795AB (0.82, 9.0)
428. 06404138 (0.82, 9.4)
429. 02412648 (0.82, 9.0)
430. 08802858 (0.82, 9.3)
431. 80407238 (0.82, 9.3)

432. 01238448 (0.82, 7.9)
433. 2751080T (0.82, 10.9)
434. 05233538 (0.82, 9.1)
435. 03933938 (0.82, 9.0)
436. 161510CL (0.82, 10.6)
437. 06797158 (0.82, 9.5)
438. 01256748 (0.82, 8.3)
439. 09255048 (0.82, 9.1)
440. 03690258 (0.82, 8.7)
441. 07315548 (0.82, 8.9)
442. 03999238 (0.82, 9.3)
443. 442159TB (0.82, 11.4)
444. 02951958 (0.82, 8.8)
445. 83300648 (0.82, 9.2)
446. 04801848 (0.82, 9.0)
447. 08540038 (0.82, 9.3)
448. 04243238 (0.82, 9.1)
449. 09380938 (0.82, 6.1)
450. 04274938 (0.82, 9.0)
451. 112491DF (0.82, 10.2)
452. 03370948 (0.82, 9.1)
453. 00380038 (0.82, 6.2)
454. 09841048 (0.82, 8.8)
455. 08270448 (0.82, 9.3)
456. 2791888B (0.82, 10.8)
457. 05600638 (0.82, 9.1)
458. 09480948 (0.82, 6.2)
459. 03245238 (0.82, 9.0)
460. 00851238 (0.82, 9.2)
461. 00480048 (0.82, 6.3)
462. 01480148 (0.82, 5.6)
463. 2182002H (0.82, 9.9)
464. 260797JJ (0.82, 9.9)
465. 00559038 (0.82, 9.1)
466. 07650148 (0.82, 9.0)
467. 240496AM (0.82, 9.5)
468. 04263538 (0.82, 8.9)
469. 73812238 (0.82, 9.4)
470. 07818148 (0.82, 8.9)
471. 04549148 (0.82, 9.6)
472. 270890WT (0.82, 10.8)
473. 03661038 (0.82, 8.8)
474. 04300848 (0.82, 8.8)
475. 100524TJ (0.82, 11.0)
476. 03891258 (0.82, 8.6)
477. 03490048 (0.82, 9.2)
478. 02380238 (0.82, 6.1)
479. 05730138 (0.82, 9.7)
480. 02480248 (0.82, 7.0)
481. 022061jM (0.82, 10.9)
482. 06262238 (0.82, 8.3)
483. 04701338 (0.82, 9.2)
484. 112594Jm (0.82, 9.4)
485. 06609048 (0.82, 9.1)
486. 97295138 (0.82, 9.7)
487. 97265538 (0.82, 9.1)
488. 8431203w (0.82, 10.3)
489. 0629021H (0.82, 11.4)
490. 71620048 (0.82, 9.2)
491. 2961999M (0.82, 9.3)
492. 02399048 (0.82, 9.4)
493. 02861938 (0.82, 9.4)
494. 04275338 (0.82, 9.1)
495. 03942248 (0.82, 9.2)
496. 98225148 (0.82, 8.9)
497. 240608CJ (0.82, 10.4)
498. 5450032N (0.82, 11.3)
499. 83510348 (0.82, 9.2)
500. 03269838 (0.82, 8.9)
501. 03279248 (0.82, 9.1)
502. 99289928 (0.82, 5.9)
503. 91616228 (0.82, 9.1)
504. 00732248 (0.82, 9.4)
505. 01706538 (0.82, 9.4)
506. 151739MJ (0.82, 11.0)
507. 07863138 (0.82, 9.0)
508. 059416z8 (0.82, 12.1)
509. 96710628 (0.82, 9.2)
510. 94257458 (0.82, 9.3)
511. 160894RR (0.82, 9.7)
512. 9271993v (0.82, 9.0)
513. 01603848 (0.82, 9.3)
514. 07969438 (0.82, 9.2)
515. 4791283M (0.82, 10.8)
516. 08282538 (0.82, 8.4)
517. 100489OJ (0.82, 10.8)
518. 09951628 (0.82, 9.3)
519. 038118mv (0.82, 10.8)
520. 4592150M (0.82, 10.6)
521. 06987248 (0.82, 9.4)
522. 100767MH (0.82, 10.0)
523. 00724138 (0.82, 8.8)
524. 7070178L (0.82, 10.9)
525. 81320328 (0.82, 9.4)
526. 90928628 (0.82, 9.4)
527. 170176AM (0.82, 9.9)
528. 102030JR (0.82, 7.7)
529. 01686248 (0.82, 8.8)
530. 01652348 (0.82, 8.8)
531. 082962-5 (0.82, 10.9)
532. 07730048 (0.82, 8.9)
533. 112793JJ (0.82, 9.1)
534. 668106n5 (0.82, 11.7)
535. 86282158 (0.82, 9.1)
536. 07300728 (0.82, 8.1)
537. 07805338 (0.82, 8.8)
538. 11111JJJ (0.82, 8.4)
539. 100694KF (0.82, 10.4)
540. 5051392M (0.82, 11.0)
541. 112597Jm (0.82, 9.5)
542. 05720238 (0.82, 9.8)
543. 98710528 (0.82, 8.8)
544. 09564138 (0.82, 9.0)
545. 93941428 (0.82, 8.8)
546. 0140933v (0.82, 11.2)
547. 02972948 (0.82, 9.3)
548. 03250728 (0.82, 8.0)
549. 92289228 (0.82, 5.9)
550. 189018AB (0.82, 10.5)
551. 250897PH (0.82, 9.9)
552. 235112&J (0.82, 13.7)
553. 03803838 (0.82, 8.0)
554. 121399CL (0.82, 10.4)
555. 58T5502v (0.82, 13.1)
556. 66402258 (0.81, 9.3)
557. 75809238 (0.81, 9.5)
558. 92906438 (0.81, 9.3)
559. 8994133w (0.81, 10.8)
560. 00502728 (0.81, 8.8)
561. 01868238 (0.81, 9.4)
562. 90982428 (0.81, 9.2)
563. 111099CC (0.81, 9.4)
564. 07892948 (0.81, 9.4)
565. 772299e5 (0.81, 11.0)
566. 92241858 (0.81, 9.1)
567. 191199AB (0.81, 9.4)
568. 92992328 (0.81, 9.4)
569. 111661BB (0.81, 9.7)
570. 3328099M (0.81, 10.7)
571. 73225438 (0.81, 9.1)
572. 8461215w (0.81, 10.2)
573. 05829948 (0.81, 9.7)
574. 6299215J (0.81, 11.2)
575. 91988228 (0.81, 9.2)
576. 01795638 (0.81, 9.4)
577. 2142004M (0.81, 9.5)
578. 160980CR (0.81, 10.3)
579. 71284038 (0.81, 9.2)
580. 69421958 (0.81, 8.5)
581. 70721858 (0.81, 9.6)
582. 08280828 (0.81, 5.0)
583. 332200Sm (0.81, 10.5)
584. 05300328 (0.81, 8.0)
585. 839815h8 (0.81, 11.8)
586. 3691230B (0.81, 10.0)
587. 218900RN (0.81, 11.2)
588. 45N8844v (0.81, 13.3)
589. 06230428 (0.81, 7.7)
590. 05240328 (0.81, 7.6)
591. 07899238 (0.81, 9.3)
592. 020483sB (0.81, 10.5)
593. 6842100w (0.81, 9.4)
594. 00819538 (0.81, 9.9)
595. 08331658 (0.81, 9.0)
596. 15042Oo5 (0.81, 12.1)
597. 110384LI (0.81, 9.5)
598. 818200mv (0.81, 10.3)
599. 170199MJ (0.81, 10.3)
600. 2250168M (0.81, 10.3)
601. 238116JM (0.81, 11.3)
602. 9392298w (0.81, 10.4)
603. 96509928 (0.81, 9.1)
604. 04250428 (0.81, 7.3)
605. 569131SU (0.81, 11.2)
606. 03280328 (0.81, 5.1)
607. 84260528 (0.81, 8.5)
608. 03907428 (0.81, 9.1)
609. 85301358 (0.81, 9.0)
610. 218069Ep (0.81, 11.6)
611. 01962728 (0.81, 9.4)
612. 07280728 (0.81, 5.3)
613. 99331628 (0.81, 8.7)
614. 09250628 (0.81, 7.8)
615. 100897RF (0.81, 10.3)
616. 02899948 (0.81, 10.0)
617. 964401z8 (0.81, 11.8)
618. 93351728 (0.81, 9.2)
619. 77223348 (0.81, 9.2)
620. 03906328 (0.81, 9.1)
621. 100889KT (0.81, 10.3)
622. 78971328 (0.81, 9.4)
623. 99993128 (0.81, 8.7)
624. 9231995w (0.81, 9.4)
625. 97247228 (0.81, 9.1)
626. 92341928 (0.81, 9.0)
627. 96516728 (0.81, 9.0)
628. 85821948 (0.81, 9.0)
629. 98342028 (0.81, 9.0)
630. 9889123v (0.81, 9.9)
631. 05280528 (0.81, 5.4)
632. 140603YR (0.81, 11.4)
633. 4224007F (0.81, 10.5)
634. 98294828 (0.81, 9.3)
635. 8241994m (0.81, 8.8)
636. 68418138 (0.81, 9.2)
637. 769908mv (0.81, 11.0)
638. 9392202m (0.81, 9.8)
639. 92317828 (0.81, 9.2)
640. 11111.LN (0.81, 10.7)
641. 06280628 (0.81, 5.2)
642. 0981207w (0.81, 11.0)
643. 98267028 (0.81, 9.0)
644. 7798140w (0.81, 10.4)
645. 98330128 (0.81, 9.0)
646. 03941428 (0.81, 9.0)
647. 9829898m (0.81, 9.8)
648. 98471228 (0.81, 8.5)
649. 95340928 (0.81, 9.5)
650. 96306828 (0.81, 8.8)
651. 8141441w (0.81, 10.4)
652. 7040603m (0.81, 9.8)
653. 190888DR (0.81, 10.3)
654. 141404MW (0.81, 10.9)
655. 97614128 (0.81, 9.0)
656. 230598MT (0.81, 10.3)
657. 08960128 (0.81, 8.8)
658. 60232848 (0.81, 9.2)
659. 03941028 (0.81, 8.9)
660. 98287928 (0.81, 8.8)
661. 252510JB (0.81, 10.7)
662. 3081996I (0.81, 9.8)
663. 9623032m (0.81, 9.7)
664. 7062009v (0.81, 9.7)
665. 77721958 (0.81, 8.3)
666. 0725202v (0.81, 10.6)
667. 04280428 (0.81, 5.2)
668. 99714128 (0.81, 8.9)
669. 9881941m (0.81, 10.2)
670. 80256148 (0.81, 9.3)
671. 052400cv (0.81, 9.3)
672. 2132013B (0.81, 9.2)
673. 04239028 (0.81, 8.9)
674. 8825042m (0.81, 9.7)
675. 91570928 (0.81, 9.3)
676. 98282828 (0.81, 8.4)
677. 8098817w (0.81, 10.6)
678. 11902Mav (0.81, 11.4)
679. 99420828 (0.81, 9.2)
680. 94245628 (0.81, 9.4)
681. 94550928 (0.81, 9.4)
682. 123*123W (0.81, 9.6)
683. 99502128 (0.81, 8.6)
684. 95504128 (0.81, 9.4)
685. 97922528 (0.81, 9.2)
686. 0051303m (0.81, 9.8)
687. 73289038 (0.81, 9.3)
688. 9295059m (0.81, 10.0)
689. 99495028 (0.81, 8.9)
690. 98289828 (0.81, 5.8)
691. 06223328 (0.81, 8.3)
692. 93289328 (0.81, 6.0)
693. 97259328 (0.81, 9.3)
694. 616000AB (0.81, 10.0)
695. 92719628 (0.81, 8.9)
696. 120718ER (0.81, 10.9)
697. 96289628 (0.81, 6.2)
698. 191024RU (0.81, 11.4)
699. 81303938 (0.81, 9.5)
700. 070687aB (0.81, 9.5)
701. 98274428 (0.81, 9.1)

702. 0623089m (0.81, 9.8)
703. 82620148 (0.81, 9.2)
704. 816095hH (0.81, 11.4)
705. 073071w8 (0.81, 11.0)
706. 91942038 (0.81, 9.2)
707. 962272f5 (0.81, 11.4)
708. 8429761m (0.81, 10.1)
709. 5060238M (0.81, 10.7)
710. 0630143m (0.81, 9.9)
711. 7150562v (0.81, 10.3)
712. 81988258 (0.81, 9.2)
713. 0293901w (0.81, 11.0)
714. 97705828 (0.81, 9.2)
715. 91339428 (0.81, 9.4)
716. 66802258 (0.81, 9.3)
717. 06318128 (0.81, 8.6)
718. 100989AC (0.81, 9.6)
719. 98608428 (0.81, 9.4)
720. 95289528 (0.81, 6.3)
721. 89420018 (0.81, 9.1)
722. 98985128 (0.81, 8.7)
723. 93580428 (0.81, 9.3)
724. 76230048 (0.81, 9.4)
725. 60721738 (0.81, 9.5)
726. 290678IM (0.81, 10.8)
727. 9065116w (0.81, 10.9)
728. 92705128 (0.81, 9.7)
729. 72701358 (0.81, 9.3)
730. 60969938 (0.81, 9.4)
731. 306141#M (0.81, 13.0)
732. 280481JM (0.81, 9.8)
733. 0225145v (0.80, 11.0)
734. 9161949R (0.80, 11.1)
735. 03253028 (0.80, 8.8)
736. 90850528 (0.80, 9.1)
737. 07232628 (0.80, 8.3)
738. 2141976J (0.80, 9.4)
739. 90898128 (0.80, 9.5)
740. 8351227m (0.80, 9.7)
741. 8781292m (0.80, 9.9)
742. 859086a5 (0.80, 11.3)
743. 270884MM (0.80, 9.6)
744. 96678138 (0.80, 9.3)
745. 6793143w (0.80, 10.5)
746. 7138199m (0.80, 9.6)
747. 95822328 (0.80, 9.1)
748. 71451248 (0.80, 8.9)
749. 63800738 (0.80, 9.5)
750. 05332028 (0.80, 8.7)
751. 03307028 (0.80, 8.6)
752. 00710458 (0.80, 8.8)
753. 00486028 (0.80, 9.0)
754. 02266728 (0.80, 8.7)
755. 100517TH (0.80, 10.4)
756. 06402628 (0.80, 8.9)
757. 230300VF (0.80, 11.3)
758. 04430028 (0.80, 8.7)
759. 0123456w (0.80, 5.1)
760. 06250928 (0.80, 7.8)
761. 171824FW (0.80, 11.2)
762. 6127499v (0.80, 10.5)
763. 013058t8 (0.80, 10.9)
764. 05516328 (0.80, 9.0)
765. 03313328 (0.80, 8.7)
766. 09272728 (0.80, 8.7)
767. 9148139v (0.80, 10.7)
768. 0079009w (0.80, 9.7)
769. 00364128 (0.80, 9.1)
770. 02318828 (0.80, 8.9)
771. 08232428 (0.80, 8.2)
772. 04340028 (0.80, 8.9)
773. 77819658 (0.80, 9.2)
774. 8730053M (0.80, 11.0)
775. 07371428 (0.80, 8.9)
776. 9195829m (0.80, 10.0)
777. 07262728 (0.80, 8.1)
778. 190107AJ (0.80, 10.7)
779. 06930528 (0.80, 8.8)
780. 843000av (0.80, 10.1)
781. 07496128 (0.80, 9.1)
782. 132187PC (0.80, 11.0)
783. 92989528 (0.80, 9.4)
784. 03609028 (0.80, 8.9)
785. 05451228 (0.80, 8.8)
786. 93621118 (0.80, 8.9)
787. 01380228 (0.80, 8.1)
788. 06408328 (0.80, 9.0)
789. 04258228 (0.80, 8.6)
790. 161193KH (0.80, 10.3)
791. 9999999m (0.80, 6.0)
792. 02641128 (0.80, 9.1)
793. 96612018 (0.80, 8.8)
794. 13018MMM (0.80, 10.7)
795. 03297828 (0.80, 8.9)
796. 82228048 (0.80, 9.1)
797. 60761138 (0.80, 9.5)
798. 293_8748 (0.80, 11.8)
799. 102682Nw (0.80, 10.6)
800. 02492028 (0.80, 8.3)
801. 00986728 (0.80, 9.8)
802. 7428052w (0.80, 10.6)
803. 90489048 (0.80, 6.3)
804. 7860905m (0.80, 9.5)
805. 03490928 (0.80, 9.3)
806. 8495152m (0.80, 10.2)
807. 04926928 (0.80, 9.4)
808. 05751828 (0.80, 9.5)
809. 9861228m (0.80, 9.9)
810. 01254418 (0.80, 11.2)
811. 162210Jv (0.80, 10.4)
812. 00391718 (0.80, 9.1)
813. 212158HH (0.80, 10.5)
814. 112358Am (0.80, 8.0)
815. 08322428 (0.80, 8.8)
816. 22N6000N (0.80, 12.3)
817. 7395159m (0.80, 10.1)
818. 890820tM (0.80, 11.3)
819. 07706828 (0.80, 8.9)
820. 7451922m (0.80, 9.5)
821. 73421958 (0.80, 8.8)
822. 09322328 (0.80, 8.8)
823. 91861818 (0.80, 8.9)
824. 06389128 (0.80, 8.7)
825. 00528528 (0.80, 8.2)
826. 159007Mm (0.80, 10.1)
827. 9962021m (0.80, 9.7)
828. 04943128 (0.80, 9.2)
829. 03838128 (0.80, 9.0)
830. 102266Hm (0.80, 10.4)
831. 04252528 (0.80, 8.1)
832. 04262628 (0.80, 7.9)
833. 919444f5 (0.80, 10.8)
834. 95924118 (0.80, 9.2)
835. 8281989m (0.80, 8.5)
836. 87717118 (0.80, 9.1)
837. 93811338 (0.80, 9.2)
838. 141809IL (0.80, 11.3)
839. 7552181w (0.80, 10.1)
840. 4041324N (0.80, 11.3)
841. 00244718 (0.80, 8.8)
842. 072990bv (0.80, 9.9)
843. 209591Tj (0.80, 11.1)
844. 112001SL (0.80, 9.8)
845. 02419018 (0.80, 9.1)
846. 06950918 (0.80, 8.5)
847. 545015a8 (0.80, 10.5)
848. 60276238 (0.80, 9.0)
849. 005049a5 (0.80, 10.8)
850. 01984628 (0.80, 9.4)
851. 418016kI (0.80, 11.8)
852. 01978628 (0.80, 9.3)
853. 05985728 (0.80, 8.9)
854. 03928328 (0.80, 9.1)
855. 249079Pj (0.80, 11.7)
856. 121307IR (0.80, 10.7)
857. 01517718 (0.80, 8.7)
858. 03691228 (0.80, 8.4)
859. 03283428 (0.80, 8.8)
860. 9026356w (0.80, 10.8)
861. 9293929w (0.80, 9.0)
862. 04240518 (0.80, 7.8)
863. 05225818 (0.80, 8.9)
864. 512572/8 (0.80, 11.8)
865. 91303818 (0.80, 9.1)
866. 02259718 (0.80, 9.0)
867. 83319718 (0.80, 8.9)
868. 329170FM (0.80, 12.0)
869. 122162ML (0.80, 9.8)
870. 04301948 (0.80, 6.8)
871. 07690528 (0.80, 9.0)
872. 06685128 (0.80, 8.7)
873. 9629233v (0.80, 10.7)
874. 71234158 (0.80, 9.0)
875. 788021a5 (0.80, 10.8)
876. 9231985w (0.80, 8.9)
877. 6822806m (0.80, 9.9)
878. 01505318 (0.80, 9.3)
879. 7970812m (0.80, 9.8)
880. 04250618 (0.80, 7.6)
881. 687102LH (0.80, 12.0)
882. 718191ST (0.80, 10.2)
883. 06271958 (0.80, 6.2)
884. 04282828 (0.80, 7.7)
885. 075210a5 (0.80, 10.6)
886. 92612818 (0.80, 9.2)
887. 554100LN (0.80, 11.3)
888. 7895123w (0.80, 5.7)
889. 230964sB (0.80, 11.2)
890. 04241958 (0.80, 6.1)
891. 321456tT (0.80, 8.6)
892. 00873228 (0.80, 9.8)
893. 290588KH (0.80, 10.3)
894. 502050jB (0.80, 11.0)
895. 60581028 (0.80, 9.2)
896. 00680528 (0.80, 8.8)
897. 71741018 (0.80, 8.8)
898. 69690128 (0.80, 8.3)
899. 369123AB (0.80, 8.9)
900. 8381228m (0.80, 10.0)
901. 6092675v (0.80, 10.4)
902. 170291BR (0.80, 10.2)
903. 01672728 (0.80, 8.9)
904. 7989120m (0.80, 9.8)
905. 754017nm (0.80, 10.6)
906. 240678JJ (0.80, 10.0)
907. 97281728 (0.80, 8.9)
908. 2061997B (0.80, 9.2)
909. 07270518 (0.80, 7.9)
910. 318131cC (0.80, 10.9)
911. 88294858 (0.80, 9.4)
912. 023911a5 (0.80, 11.0)
913. 06230318 (0.80, 7.8)
914. 602860vv (0.80, 10.2)
915. 8560214m (0.80, 9.7)
916. 77927018 (0.80, 9.1)
917. 250687RC (0.80, 10.2)
918. 274199SH (0.80, 10.9)
919. 9032918w (0.80, 10.7)
920. 06260028 (0.80, 8.1)
921. 83250058 (0.80, 9.3)
922. 60939328 (0.80, 9.2)
923. 7297154m (0.80, 10.0)
924. 4781038F (0.80, 11.2)
925. 13116JAT (0.80, 11.8)
926. 102631DB (0.80, 11.0)
927. 100982BM (0.80, 10.2)
928. 97510428 (0.80, 9.1)
929. 00331918 (0.80, 9.0)
930. 0171751m (0.80, 9.5)
931. 862313qw (0.80, 9.6)
932. 0749010w (0.80, 10.4)
933. 269N627C (0.80, 13.5)
934. 191417AI (0.80, 11.4)
935. 8424005m (0.80, 10.0)
936. 81248738 (0.80, 9.2)
937. 6729861m (0.80, 10.2)
938. 8781256v (0.80, 10.4)
939. 180197TU (0.79, 10.6)
940. 62521128 (0.79, 8.9)
941. 96811348 (0.79, 9.1)
942. 789319dw (0.79, 11.0)
943. 08472028 (0.79, 9.0)
944. 02249418 (0.79, 8.8)
945. 11J98B2C (0.79, 13.9)
946. 272900FR (0.79, 10.9)
947. 522084Kw (0.79, 11.5)
948. 3971251T (0.79, 11.2)
949. 7326186m (0.79, 9.9)
950. 88233118 (0.79, 9.1)
951. 60286028 (0.79, 6.4)
952. 2381249C (0.79, 11.2)
953. 072068aw (0.79, 9.5)
954. 96302518 (0.79, 8.9)
955. 61315638 (0.79, 9.5)
956. 99620218 (0.79, 8.7)
957. 98246218 (0.79, 9.0)
958. 74312358 (0.79, 8.3)
959. 99351018 (0.79, 8.5)
960. 57321158 (0.79, 9.0)
961. 06261958 (0.79, 6.2)
962. 9951617m (0.79, 9.8)
963. 8172002W (0.79, 10.5)
964. 120412FR (0.79, 10.2)
965. 08951318 (0.79, 8.9)
966. 74800748 (0.79, 8.3)
967. 92282418 (0.79, 9.0)
968. 9326904m (0.79, 10.1)
969. 9880312m (0.79, 9.9)
970. 68971728 (0.79, 9.7)
971. 111853LB (0.79, 10.9)

972. 7592514v (0.79, 10.4)	982. 98521418 (0.79, 8.9)	992. 892959mm (0.79, 10.0)
973. 94371018 (0.79, 9.0)	983. 007007mm (0.79, 5.8)	993. 97934018 (0.79, 9.2)
974. 092270bw (0.79, 9.8)	984. 88272028 (0.79, 8.9)	994. 97467018 (0.79, 9.0)
975. 6722728m (0.79, 9.8)	985. 290355AC (0.79, 10.6)	995. 93771718 (0.79, 9.1)
976. 22B3671B (0.79, 12.3)	986. 7161498m (0.79, 10.1)	996. 91822918 (0.79, 9.2)
977. 7862197m (0.79, 9.2)	987. 7188123m (0.79, 9.4)	997. 9824511w (0.79, 10.5)
978. 290677MJ (0.79, 10.4)	988. 90533218 (0.79, 9.4)	998. 7893070m (0.79, 9.4)
979. 90687058 (0.79, 9.4)	989. 151126JB (0.79, 11.0)	999. 91741418 (0.79, 8.7)
980. 9125767m (0.79, 10.0)	990. 102323Tj (0.79, 10.5)	
981. 08312718 (0.79, 8.6)	991. 97403318 (0.79, 9.0)	

Cluster 22

Prototype: sannen68

Hard-assigned passwords: 1453659 (5.02% of total)
Unique hard-assigned passwords: 783056 (46.13% of cluster total)

Cluster-assignment scores:
        Min: 0.074
        Max: 0.942
        Mean: 0.331
        SD: 0.184

Strength bins:
        Very weak: 14700 (1.01%)
        Weak: 566357 (38.96%)
        Fair: 570018 (39.21%)
        Good: 297937 (20.50%)
        Strong: 4647 (0.32%)

Password lengths:
        Length 8: 1442308 (99.22%)
        Length 9: 11351 (0.78%)

Character classes:
        4 classes: 15634 (1.08%)
        3 classes: 187038 (12.87%)
                lower/upper/symbol: 452 (0.24%)
                lower/upper/number: 159103 (85.06%)
                lower/symbol/number: 27482 (14.69%)
                upper/symbol/number: 1 (0.00%)
        2 classes: 1250981 (86.06%)
                lower/upper: 191 (0.02%)
                lower/number: 1249696 (99.90%)
                lower/symbol: 1084 (0.09%)
                upper/number: 0 (0.00%)
                upper/symbol: 0 (0.00%)
                number/symbol: 10 (0.00%)
        1 class: 6 (0.00%)
                lower: 0 (0.00%)
                upper: 0 (0.00%)
                symbol: 6 (100.00%)
                number: 0 (0.00%)

Most frequent char-class structures:
        LLLLLLDD: 1113241 (76.6%)
        ULLLLLDD: 121189 (8.3%)
        LLLLLLD: 97212 (6.7%)
        LLLLLLDL: 30148 (2.1%)
        LLLLLSDD: 12299 (0.8%)
        ULLLLLD: 11242 (0.8%)
        LLLLLLDD: 8554 (0.6%)
        ULLLLSDD: 5724 (0.4%)
        LLLLLLDS: 5550 (0.4%)
        ULLULLDD: 4826 (0.3%)

1,000 nearest passwords

0.	linnea88	(0.94, 6.5)	54.	looney88	(0.94, 5.9)	108.	Eminem88	(0.94, 5.8)
1.	beaney88	(0.94, 7.8)	55.	Giggey88	(0.94, 10.5)	109.	Modhej88	(0.94, 11.4)
2.	denney88	(0.94, 7.0)	56.	cooney88	(0.94, 6.5)	110.	laugen88	(0.94, 8.6)
3.	penney88	(0.94, 6.6)	57.	navyew88	(0.94, 8.8)	111.	bagged88	(0.94, 6.5)
4.	kenney88	(0.94, 6.6)	58.	notneb88	(0.94, 7.5)	112.	kungen88	(0.94, 6.3)
5.	zeynep88	(0.94, 6.2)	59.	Mainey88	(0.94, 8.5)	113.	cangen88	(0.94, 8.4)
6.	Linnea88	(0.94, 7.1)	60.	sydney88	(0.94, 5.3)	114.	knugen88	(0.94, 9.0)
7.	fennec88	(0.94, 7.8)	61.	richey88	(0.94, 6.7)	115.	yewhew88	(0.94, 9.1)
8.	sonnen88	(0.94, 6.9)	62.	Sydney88	(0.94, 6.1)	116.	hemhem88	(0.94, 7.5)
9.	Beaney88	(0.94, 8.9)	63.	Stoney88	(0.94, 6.9)	117.	carney88	(0.94, 6.5)
10.	hennep88	(0.94, 8.7)	64.	cudyep88	(0.94, 10.6)	118.	eboney88	(0.94, 7.0)
11.	tennej88	(0.94, 8.8)	65.	zeineb88	(0.94, 8.1)	119.	Birney88	(0.94, 8.3)
12.	connex88	(0.94, 7.1)	66.	Jochen88	(0.94, 8.2)	120.	eminem88	(0.94, 4.6)
13.	finney88	(0.94, 6.9)	67.	lichen88	(0.94, 6.9)	121.	skined88	(0.94, 8.2)
14.	jihaej88	(0.94, 10.5)	68.	fudgey88	(0.94, 7.2)	122.	keagen88	(0.94, 7.8)
15.	sinned88	(0.94, 6.1)	69.	duinen88	(0.94, 9.0)	123.	slagen88	(0.94, 8.6)
16.	aebaeb88	(0.94, 10.1)	70.	jibyep88	(0.94, 9.5)	124.	barney88	(0.94, 5.1)
17.	kidnep88	(0.94, 9.2)	71.	Zingen88	(0.94, 8.6)	125.	meagen88	(0.94, 7.6)
18.	Necnec88	(0.94, 9.1)	72.	sochen88	(0.94, 8.3)	126.	stoned88	(0.94, 6.0)
19.	newnew88	(0.94, 6.4)	73.	yschen88	(0.94, 9.2)	127.	horney88	(0.94, 5.6)
20.	rodney88	(0.94, 5.4)	74.	cunyeu88	(0.94, 7.3)	128.	forney88	(0.94, 6.8)
21.	kidney88	(0.94, 6.5)	75.	jochen88	(0.94, 7.3)	129.	sachen88	(0.94, 7.5)
22.	shaneb88	(0.94, 7.1)	76.	Glwgew88	(0.94, 12.2)	130.	lachen88	(0.94, 7.1)
23.	sidney88	(0.94, 5.6)	77.	Muggen88	(0.94, 9.4)	131.	spngem88	(0.94, 10.4)
24.	wayneb88	(0.94, 6.8)	78.	stoney88	(0.94, 5.9)	132.	hughey88	(0.94, 7.6)
25.	ibanez88	(0.94, 5.1)	79.	dhoney88	(0.94, 8.3)	133.	pache●88	(0.94, 9.4)
26.	Rodney88	(0.94, 6.5)	80.	rezhen88	(0.94, 9.1)	134.	nvpqeu88	(0.94, 12.5)
27.	shaney88	(0.94, 6.4)	81.	jhoney88	(0.94, 8.0)	135.	cheney88	(0.94, 6.6)
28.	banned88	(0.94, 6.7)	82.	keygen88	(0.94, 7.0)	136.	arkhew88	(0.94, 8.7)
29.	canned88	(0.94, 6.8)	83.	tingen88	(0.94, 7.9)	137.	vonyea88	(0.94, 9.9)
30.	funney88	(0.94, 8.2)	84.	heyhey88	(0.94, 5.8)	138.	Mayhem88	(0.94, 6.9)
31.	hunney88	(0.94, 7.4)	85.	nguyen88	(0.94, 5.2)	139.	uruhed88	(0.94, 10.9)
32.	wayned88	(0.94, 7.0)	86.	Cmoney88	(0.94, 6.8)	140.	hachem88	(0.94, 7.1)
33.	payned88	(0.94, 8.3)	87.	chuyen88	(0.94, 6.9)	141.	bronek88	(0.94, 7.5)
34.	Mannen88	(0.94, 7.7)	88.	Ngage.88	(0.94, 9.9)	142.	mayhem88	(0.94, 5.7)
35.	jibneh88	(0.94, 10.4)	89.	phuyen88	(0.94, 7.6)	143.	uswjec88	(0.94, 11.4)
36.	Sidney88	(0.94, 6.6)	90.	Dmoney88	(0.94, 6.6)	144.	verneJ88	(0.94, 10.8)
37.	ekanem88	(0.94, 8.0)	91.	richem88	(0.94, 7.7)	145.	sughex88	(0.94, 10.6)
38.	lannem88	(0.94, 8.2)	92.	Pionex88	(0.94, 8.1)	146.	truyen88	(0.94, 6.5)
39.	downey88	(0.94, 6.8)	93.	oxygen88	(0.94, 6.2)	147.	yenyen88	(0.94, 7.0)
40.	waynev88	(0.94, 8.0)	94.	Pmoney88	(0.94, 7.3)	148.	machew88	(0.94, 8.0)
41.	disney88	(0.94, 5.1)	95.	stoneh88	(0.94, 7.4)	149.	hekhek88	(0.94, 7.6)
42.	Boone@88	(0.94, 8.9)	96.	Jmoney88	(0.94, 6.5)	150.	anuhea88	(0.94, 9.4)
43.	cagney88	(0.94, 6.9)	97.	redgem88	(0.94, 7.5)	151.	CorneE88	(0.94, 10.8)
44.	damned88	(0.94, 6.3)	98.	dmoney88	(0.94, 5.6)	152.	MadSen88	(0.94, 10.0)
45.	nevaeh88	(0.94, 5.5)	99.	ciphex88	(0.94, 9.7)	153.	atenea88	(0.94, 6.3)
46.	Looney88	(0.94, 6.8)	100.	jmoney88	(0.94, 5.5)	154.	pompey88	(0.94, 5.4)
47.	aacaed88	(0.94, 9.6)	101.	lochem88	(0.94, 8.7)	155.	punhem88	(0.94, 8.7)
48.	Nevaeh88	(0.94, 6.7)	102.	gmoney88	(0.94, 5.3)	156.	shahed88	(0.94, 6.9)
49.	Rooney88	(0.94, 6.0)	103.	cmoney88	(0.94, 6.0)	157.	vimpen88	(0.94, 8.8)
50.	Anhyeu88	(0.94, 7.5)	104.	Barney88	(0.94, 6.1)	158.	pimpen88	(0.94, 5.8)
51.	anhyeu88	(0.94, 6.0)	105.	lesaew88	(0.94, 10.8)	159.	MadMen88	(0.94, 9.1)
52.	cydney88	(0.94, 6.5)	106.	rugged88	(0.94, 6.3)	160.	Mickey88	(0.94, 5.8)
53.	rooney88	(0.94, 5.1)	107.	shoney88	(0.94, 6.9)	161.	bowden88	(0.94, 6.7)

162. kobpey88	(0.94, 10.5)	
163. emenem88	(0.94, 7.9)	
164. wicced88	(0.94, 8.4)	
165. liffey88	(0.94, 6.8)	
166. Hockey88	(0.94, 5.6)	
167. pizdec88	(0.94, 6.4)	
168. mickey88	(0.94, 4.8)	
169. goffey88	(0.94, 8.1)	
170. dickey88	(0.94, 6.6)	
171. rickey88	(0.94, 6.1)	
172. Ficken88	(0.94, 7.1)	
173. hickey88	(0.94, 6.7)	
174. fockey88	(0.94, 7.7)	
175. jockey88	(0.93, 6.6)	
176. rockey88	(0.93, 6.1)	
177. Ripken88	(0.93, 7.8)	
178. hoppen88	(0.93, 7.4)	
179. hockey88	(0.93, 4.4)	
180. kiffen88	(0.93, 8.1)	
181. Robben88	(0.93, 7.5)	
182. Tommey88	(0.93, 8.8)	
183. ficken88	(0.93, 6.1)	
184. wicken88	(0.93, 7.3)	
185. hidden88	(0.93, 6.1)	
186. mopden88	(0.93, 8.6)	
187. Pigpen88	(0.93, 7.5)	
188. huffey88	(0.93, 7.7)	
189. doffen88	(0.93, 8.1)	
190. Waffen88	(0.93, 8.8)	
191. dampea88	(0.93, 9.0)	
192. laffen88	(0.93, 8.2)	
193. bodden88	(0.93, 7.6)	
194. ripken88	(0.93, 6.8)	
195. likken88	(0.93, 7.3)	
196. ushkey88	(0.93, 9.4)	
197. waffen88	(0.93, 7.3)	
198. wicked88	(0.93, 5.3)	
199. tippex88	(0.93, 7.7)	
200. tomdeb88	(0.93, 8.1)	
201. lumpex88	(0.93, 8.3)	
202. joyced88	(0.93, 8.0)	
203. Sockem88	(0.93, 9.9)	
204. sokken88	(0.93, 8.3)	
205. redpen88	(0.93, 7.0)	
206. somfeb88	(0.93, 9.6)	
207. dokken88	(0.93, 6.6)	
208. ripkea88	(0.93, 9.6)	
209. comdex88	(0.93, 8.5)	
210. locked88	(0.93, 5.6)	
211. modded88	(0.93, 6.8)	
212. grace@88	(0.93, 7.4)	
213. beffen88	(0.93, 8.6)	
214. brycen88	(0.93, 6.2)	
215. Stacey88	(0.93, 6.1)	
216. siucen88	(0.93, 10.2)	
217. hamden88	(0.93, 7.6)	
218. caraeg88	(0.93, 9.5)	
219. kemben88	(0.93, 8.4)	
220. Donkey88	(0.93, 6.4)	
221. Monkey88	(0.93, 5.4)	
222. bigben88	(0.93, 5.8)	
223. nadben88	(0.93, 9.5)	
224. Magben88	(0.93, 10.0)	
225. spydey88	(0.93, 8.1)	
226. madden88	(0.93, 5.5)	
227. luckey88	(0.93, 6.2)	
228. debken88	(0.93, 9.0)	
229. behdeh88	(0.93, 9.5)	
230. youcef88	(0.93, 6.7)	
231. tekken88	(0.93, 6.0)	
232. Hawken88	(0.93, 7.6)	
233. pinkey88	(0.93, 6.4)	
234. Kayden88	(0.93, 6.6)	
235. abcdef88	(0.93, 5.7)	
236. sinkey88	(0.93, 8.4)	
237. hogben88	(0.93, 8.7)	
238. oinkey88	(0.93, 8.8)	
239. atmmez88	(0.93, 10.8)	
240. dekken88	(0.93, 7.9)	
241. duckey88	(0.93, 7.2)	
242. stacey88	(0.93, 5.1)	
243. magben88	(0.93, 8.7)	
244. Cayden88	(0.93, 6.9)	
245. monkey88	(0.93, 4.1)	
246. donkey88	(0.93, 5.3)	
247. jackey88	(0.93, 6.8)	
248. yemmen88	(0.93, 8.9)	
249. ravmed88	(0.93, 9.9)	
250. anykey88	(0.93, 8.1)	
251. behbeh88	(0.93, 7.2)	
252. bryden88	(0.93, 6.8)	
253. bigkev88	(0.93, 6.7)	
254. bakken88	(0.93, 7.0)	
255. skyden88	(0.93, 8.6)	
256. cayden88	(0.93, 6.1)	
257. Grape_88	(0.93, 8.3)	
258. jayden88	(0.93, 5.1)	
259. kayden88	(0.93, 5.8)	
260. Linked88	(0.93, 6.3)	
261. wacken88	(0.93, 7.4)	
262. hayden88	(0.93, 5.2)	
263. orbfew88	(0.93, 10.4)	
264. kacken88	(0.93, 7.7)	
265. tracey88	(0.93, 5.7)	
266. bedbed88	(0.93, 7.9)	
267. Hawked88	(0.93, 8.3)	
268. Munden88	(0.93, 9.0)	
269. BobBec88	(0.93, 11.0)	
270. fdgdec88	(0.93, 10.6)	
271. donkeh88	(0.93, 8.8)	
272. jenjen88	(0.93, 6.1)	
273. monken88	(0.93, 8.0)	
274. Mankey88	(0.93, 8.3)	
275. deajeh88	(0.93, 9.5)	
276. kdubey88	(0.93, 8.3)	
277. Tankey88	(0.93, 8.7)	
278. sunjem88	(0.93, 8.8)	
279. joycek88	(0.93, 8.0)	
280. madmen88	(0.93, 6.8)	
281. bandey88	(0.93, 7.7)	
282. linden88	(0.93, 6.1)	
283. Landen88	(0.93, 7.0)	
284. dandey88	(0.93, 7.9)	
285. flukey88	(0.93, 7.0)	
286. wincep88	(0.93, 10.0)	
287. mahjek88	(0.93, 10.0)	
288. redmen88	(0.93, 6.1)	
289. tankey88	(0.93, 7.6)	
290. lunden88	(0.93, 7.1)	
291. pigmen88	(0.93, 7.8)	
292. linked88	(0.93, 5.6)	
293. hacked88	(0.93, 5.5)	
294. fuckem88	(0.93, 6.5)	
295. landen88	(0.93, 6.1)	
296. doncex88	(0.93, 8.6)	
297. banden88	(0.93, 7.4)	
298. Diadev88	(0.93, 9.9)	
299. nanden88	(0.93, 7.8)	
300. maykeg88	(0.93, 8.9)	
301. cauden88	(0.93, 9.3)	
302. drakey88	(0.93, 7.0)	
303. brubey88	(0.93, 9.0)	
304. eeacec88	(0.93, 10.0)	
305. shakey88	(0.93, 6.2)	
306. agapea88	(0.93, 7.9)	
307. tinbed88	(0.93, 5.8)	
308. clydew88	(0.93, 8.7)	
309. texmex88	(0.93, 6.7)	
310. shakeu88	(0.93, 7.5)	
311. dekdek88	(0.93, 7.8)	
312. traced88	(0.93, 7.3)	
313. Dance*88	(0.93, 8.7)	
314. dembek88	(0.93, 8.5)	
315. mexmex88	(0.93, 7.4)	
316. meymey88	(0.93, 6.9)	
317. vanpep88	(0.93, 10.6)	
318. condev88	(0.93, 8.2)	
319. budmep88	(0.93, 10.0)	
320. caymen88	(0.93, 7.8)	
321. adadeh88	(0.93, 6.5)	
322. kwaken88	(0.93, 9.9)	
323. bladey88	(0.93, 7.5)	
324. windex88	(0.93, 6.7)	
325. achmed88	(0.93, 6.9)	
326. nyapew88	(0.93, 11.4)	
327. penpen88	(0.93, 6.1)	
328. benben88	(0.93, 6.1)	
329. dandeb88	(0.93, 8.1)	
330. Mtndew88	(0.93, 7.1)	
331. methey88	(0.93, 8.8)	
332. sandep88	(0.93, 8.6)	
333. sotheu88	(0.93, 11.2)	
334. Seabed88	(0.93, 9.5)	
335. braden88	(0.93, 6.4)	
336. nekzej88	(0.93, 12.0)	
337. ledzep88	(0.93, 5.8)	
338. mladen88	(0.93, 6.1)	
339. raymeg88	(0.93, 9.1)	
340. ilufea88	(0.93, 9.6)	
341. snakep88	(0.93, 8.4)	
342. phabej88	(0.93, 10.1)	
343. mendez88	(0.93, 5.4)	
344. abluez88	(0.93, 9.9)	
345. mtndew88	(0.93, 6.0)	
346. wyczek88	(0.93, 9.0)	
347. amadej88	(0.93, 9.1)	
348. sothea88	(0.93, 6.5)	
349. Mishea88	(0.93, 9.4)	
350. gradev88	(0.93, 8.3)	
351. tradem88	(0.93, 7.8)	
352. evamen88	(0.93, 8.5)	
353. ciapek88	(0.93, 7.4)	
354. hatyep88	(0.93, 9.6)	
355. mundek88	(0.93, 8.3)	
356. rendex88	(0.93, 8.1)	
357. bethed88	(0.93, 8.9)	
358. althea88	(0.93, 6.1)	
359. lakven88	(0.93, 8.7)	
360. MeaMea88	(0.93, 9.6)	
361. diamed88	(0.93, 9.0)	
362. ChaveS88	(0.93, 10.2)	
363. Cedwey88	(0.93, 11.7)	
364. szymek88	(0.93, 7.3)	
365. maiyeu88	(0.93, 6.3)	
366. haiyen88	(0.93, 6.1)	
367. cedwey88	(0.93, 10.4)	
368. sergey88	(0.93, 5.9)	
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370. Medved88	(0.93, 7.8)	
371. puthen88	(0.93, 7.8)	
372. chigem88	(0.93, 9.2)	
373. anthea88	(0.93, 7.1)	
374. brazen88	(0.93, 6.8)	
375. acthen88	(0.93, 8.6)	
376. plamen88	(0.93, 6.6)	
377. blazen88	(0.93, 6.1)	
378. nedved88	(0.93, 6.3)	
379. medved88	(0.93, 6.9)	
380. hayven88	(0.93, 7.4)	
381. tumweb88	(0.93, 9.2)	
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383. kathem88	(0.93, 8.7)	
384. bergen88	(0.93, 6.5)	
385. imogen88	(0.93, 6.1)	
386. lashea88	(0.93, 7.1)	
387. dogwen88	(0.93, 8.9)	
388. jorgec88	(0.93, 7.3)	
389. Mathew88	(0.93, 6.8)	
390. Jorgeb88	(0.93, 9.0)	
391. adamek88	(0.93, 6.9)	
392. KatKev88	(0.93, 9.9)	
393. erjwex88	(0.93, 13.0)	
394. yahweh88	(0.93, 5.9)	
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396. mathew88	(0.93, 5.6)	
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401. Reaven88	(0.93, 8.3)	
402. gravey88	(0.93, 6.7)	
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404. sergej88	(0.93, 6.4)	
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406. sueyen88	(0.92, 8.9)	
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410. ciawen88	(0.92, 9.2)	
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413. Ronney78	(0.92, 8.5)	
414. ninney78	(0.92, 8.6)	
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433. shyne@78 (0.92, 9.4)	523. spidey88 (0.92, 5.6)	613. Sweden88 (0.91, 7.1)
434. kitjen88 (0.92, 8.9)	524. Plauen78 (0.92, 9.2)	614. Darken88 (0.91, 7.5)
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439. GerDen88 (0.92, 10.3)	529. terbea88 (0.92, 8.8)	619. notwen88 (0.91, 7.7)
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448. misdec88 (0.92, 9.6)	538. cheney78 (0.92, 7.0)	628. locked78 (0.91, 6.2)
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450. bricey88 (0.92, 7.6)	540. caiden88 (0.92, 6.4)	630. sweden88 (0.91, 6.1)
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452. soiden88 (0.92, 8.0)	542. zaiden88 (0.92, 6.7)	632. conyeu78 (0.91, 7.8)
453. roquem78 (0.92, 9.4)	543. raiden88 (0.92, 6.6)	633. darken88 (0.91, 6.7)
454. poopey88 (0.92, 7.2)	544. Juicem88 (0.92, 8.9)	634. waimea88 (0.91, 6.6)
455. roiben88 (0.92, 9.6)	545. spikey88 (0.92, 5.6)	635. Stacey78 (0.91, 6.5)
456. rooney78 (0.92, 5.6)	546. aspgem78 (0.92, 9.3)	636. tomkeg78 (0.91, 9.2)
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459. tooney78 (0.92, 7.0)	549. nuijep88 (0.92, 11.0)	639. ruebeg88 (0.91, 10.0)
460. paskey88 (0.92, 8.7)	550. yaocen88 (0.92, 9.5)	640. eyebeg88 (0.91, 10.8)
461. pudgey78 (0.92, 7.6)	551. alszeg88 (0.92, 10.9)	641. Monkey78 (0.91, 6.0)
462. bukaen78 (0.92, 9.9)	552. kdopey88 (0.92, 9.0)	642. driven88 (0.91, 6.6)
463. Rennef78 (0.92, 10.8)	553. garcea88 (0.92, 7.5)	643. carmex88 (0.91, 6.9)
464. gainey78 (0.92, 7.7)	554. jlpqeg78 (0.92, 11.9)	644. berxew88 (0.91, 11.6)
465. alicen88 (0.92, 7.4)	555. whodey88 (0.92, 6.4)	645. winkey78 (0.91, 7.1)
466. colbey88 (0.92, 6.9)	556. niecey88 (0.92, 7.2)	646. alexey88 (0.91, 6.5)
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469. bookey88 (0.92, 7.4)	559. spiced88 (0.92, 7.5)	649. lance$78 (0.91, 8.7)
470. pookey88 (0.92, 6.2)	560. durden88 (0.92, 7.3)	650. stiven88 (0.91, 6.5)
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472. Looped88 (0.92, 9.1)	562. yarden88 (0.92, 7.0)	652. stacey78 (0.91, 5.6)
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474. tulpen88 (0.92, 6.9)	564. Corkey88 (0.92, 7.9)	654. steken88 (0.91, 8.1)
475. wooden88 (0.92, 6.3)	565. Shahed78 (0.92, 8.7)	655. Harvey88 (0.91, 6.0)
476. serpen88 (0.92, 7.7)	566. garden88 (0.92, 5.4)	656. kjopek88 (0.91, 11.3)
477. sayyed78 (0.92, 8.8)	567. harden88 (0.92, 6.8)	657. donkey78 (0.91, 5.8)
478. soidem88 (0.92, 9.4)	568. shahed78 (0.92, 7.3)	658. ziomek88 (0.91, 6.4)
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480. lichex78 (0.92, 10.1)	570. goldeg88 (0.92, 8.7)	660. jugbed78 (0.91, 9.9)
481. hdsdec88 (0.92, 10.6)	571. normen88 (0.92, 7.4)	661. duckez78 (0.91, 10.3)
482. wolfen88 (0.92, 6.8)	572. nutmeg88 (0.92, 6.4)	662. wolven88 (0.91, 7.5)
483. Bugged78 (0.92, 8.9)	573. valdez88 (0.92, 6.0)	663. sikcek78 (0.91, 10.2)
484. Badge:78 (0.92, 10.7)	574. acokey88 (0.92, 9.6)	664. dyrdek88 (0.91, 8.0)
485. betmen88 (0.92, 6.9)	575. Diffey78 (0.92, 9.1)	665. Munkey78 (0.91, 8.0)
486. Broken88 (0.92, 6.5)	576. berke.88 (0.92, 7.8)	666. markez88 (0.91, 7.5)
487. Solfeg88 (0.92, 9.8)	577. Haldex88 (0.92, 10.7)	667. iloveu88 (0.91, 4.7)
488. altmen88 (0.92, 8.5)	578. gamgen78 (0.92, 10.1)	668. tracey78 (0.91, 6.1)
489. alicem88 (0.92, 7.6)	579. flixed88 (0.92, 9.9)	669. ilived88 (0.91, 8.7)
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491. kmoney78 (0.92, 6.6)	581. fermen88 (0.92, 7.8)	671. hammed78 (0.91, 6.8)
492. Holden88 (0.92, 5.7)	582. liffey78 (0.92, 7.3)	672. fucked78 (0.91, 6.5)
493. vexyea78 (0.92, 10.5)	583. Mickey78 (0.92, 6.1)	673. cepbep78 (0.91, 10.7)
494. briceb88 (0.92, 8.4)	584. holmez88 (0.92, 7.7)	674. hamzeh78 (0.91, 7.3)
495. jmoney78 (0.92, 6.1)	585. Turkey88 (0.92, 6.2)	675. Flukey78 (0.91, 8.5)
496. mntdew88 (0.92, 9.0)	586. goldej88 (0.92, 9.6)	676. weekev88 (0.91, 8.9)
497. gmoney78 (0.92, 5.8)	587. sieben88 (0.92, 7.2)	677. bazmeg78 (0.91, 10.0)
498. Jorden88 (0.92, 7.1)	588. mickey78 (0.92, 5.1)	678. marzec88 (0.91, 7.1)
499. fmoney78 (0.92, 7.4)	589. pimped78 (0.92, 7.2)	679. serven88 (0.91, 7.7)
500. Norden88 (0.92, 8.1)	590. Nguyen78 (0.92, 6.8)	680. harvey88 (0.91, 4.9)
501. carped88 (0.92, 7.5)	591. [live]88 (0.92, 11.1)	681. linked78 (0.91, 5.6)
502. emoney78 (0.92, 6.8)	592. spiked88 (0.92, 6.8)	682. delvec88 (0.91, 8.0)
503. mttaep78 (0.92, 11.3)	593. eminem78 (0.92, 5.6)	683. feiwen88 (0.91, 8.3)
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518. Burden88 (0.92, 8.2)	608. atenea78 (0.92, 6.5)	698. zedzed78 (0.91, 7.7)
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828. poopey78 (0.90, 7.7)
829. wolfe@78 (0.90, 9.2)
830. eggyen68 (0.90, 9.9)
831. twoten88 (0.90, 7.6)
832. Rostek88 (0.90, 9.7)
833. wolfey78 (0.90, 7.7)
834. heaven78 (0.90, 5.4)
835. braven78 (0.90, 7.1)
836. juicey78 (0.90, 6.6)
837. harbey78 (0.90, 7.8)
838. disney68 (0.90, 5.7)
839. dostep88 (0.90, 9.8)
840. josdec78 (0.90, 9.6)
841. Fittej88 (0.90, 9.6)
842. viggen68 (0.90, 7.3)
843. matney68 (0.90, 8.4)
844. knine_68 (0.90, 10.4)
845. trawen78 (0.90, 8.7)
846. platex88 (0.90, 8.4)
847. lotpen78 (0.90, 8.8)
848. RalDeb78 (0.90, 12.0)
849. leonen68 (0.90, 8.7)
850. michey68 (0.90, 7.6)
851. Merced78 (0.90, 8.1)
852. boggey68 (0.90, 8.7)
853. Obsfed78 (0.90, 12.8)
854. rooney68 (0.90, 5.8)
855. looney68 (0.90, 6.5)
856. juiced78 (0.90, 7.0)
857. cooney68 (0.90, 6.8)
858. edibey78 (0.90, 9.3)
859. naike_78 (0.90, 10.6)
860. mooney68 (0.90, 6.5)
861. marpeg78 (0.90, 9.0)
862. asspen78 (0.90, 8.9)
863. zephen68 (0.90, 7.4)
864. listen88 (0.90, 6.5)
865. Spidey78 (0.90, 7.0)
866. witten88 (0.90, 5.7)
867. stonec68 (0.90, 8.4)
868. lainey68 (0.90, 7.2)
869. system88 (0.90, 4.8)
870. sachem68 (0.90, 8.1)
871. titten88 (0.90, 7.7)
872. scoRea78 (0.90, 10.7)
873. valdez78 (0.90, 6.3)
874. cuchem68 (0.90, 9.8)
875. wasdef78 (0.90, 8.1)
876. smitec88 (0.90, 8.8)
877. kitten88 (0.90, 5.3)
878. eminem68 (0.90, 5.9)
879. snipe●78 (0.90, 10.5)
880. rotten88 (0.90, 6.1)
881. nutmeg78 (0.90, 6.3)
882. mayhem68 (0.90, 6.1)
883. posted88 (0.90, 7.1)
884. v@lcea78 (0.89, 10.2)
885. justen88 (0.89, 6.6)
886. radhey68 (0.89, 7.9)
887. ajchey68 (0.89, 10.7)
888. relpek78 (0.89, 9.9)
889. kaiten88 (0.89, 8.0)
890. stoney68 (0.89, 6.2)
891. staten88 (0.89, 7.3)
892. smokey78 (0.89, 4.9)
893. frage@68 (0.89, 11.0)
894. knotek78 (0.89, 9.8)
895. ledhed68 (0.89, 9.1)
896. littez88 (0.89, 9.1)
897. hookem78 (0.89, 6.4)
898. rusted88 (0.89, 6.7)
899. icetea88 (0.89, 6.1)
900. jessek88 (0.89, 7.5)
901. Smokey78 (0.89, 6.0)
902. budhed68 (0.89, 10.5)
903. Corkey78 (0.89, 8.2)
904. Seiken78 (0.89, 8.9)
905. tetten88 (0.89, 7.6)
906. Kitten88 (0.89, 6.5)
907. dmoney68 (0.89, 6.2)
908. kostek78 (0.89, 7.2)
909. wasted88 (0.89, 5.9)
910. Witten88 (0.89, 6.5)
911. tsedey78 (0.89, 10.6)
912. gmoney68 (0.89, 5.7)
913. biomed78 (0.89, 7.5)
914. tenten88 (0.89, 6.3)
915. shonen68 (0.89, 8.2)
916. HeaveN78 (0.89, 9.0)
917. spirek88 (0.89, 9.5)
918. masken78 (0.89, 8.1)
919. emoney68 (0.89, 6.7)
920. pooneh68 (0.89, 8.8)
921. tmoney68 (0.89, 6.4)
922. tainep68 (0.89, 10.2)
923. stoned68 (0.89, 6.7)
924. jhosep88 (0.89, 7.2)
925. barney68 (0.89, 5.7)
926. burkey78 (0.89, 7.3)
927. crimea78 (0.89, 7.6)
928. bastek78 (0.89, 7.5)
929. Sistem88 (0.89, 7.1)
930. united88 (0.89, 4.7)
931. burney68 (0.89, 7.7)
932. turkey78 (0.89, 5.7)
933. gfahey68 (0.89, 11.2)
934. dented88 (0.89, 7.5)
935. earkey78 (0.89, 9.7)
936. horney68 (0.89, 6.4)
937. torney68 (0.89, 8.3)
938. wolfen78 (0.89, 7.1)
939. promex78 (0.89, 8.4)
940. United88 (0.89, 5.8)
941. holdem78 (0.89, 5.9)
942. saetex88 (0.89, 10.0)
943. seebeg78 (0.89, 9.6)
944. bowden68 (0.89, 6.9)
945. Gerben78 (0.89, 8.2)
946. twomey78 (0.89, 9.3)
947. Busted88 (0.89, 6.9)
948. bartek88 (0.89, 5.8)
949. berben78 (0.89, 8.1)
950. sussex88 (0.89, 6.3)
951. hurben78 (0.89, 9.9)
952. Lvicek78 (0.89, 12.1)
953. pompey68 (0.89, 7.2)
954. marben78 (0.89, 7.6)
955. parked78 (0.89, 8.0)
956. jasmen78 (0.89, 7.7)
957. puffen68 (0.89, 8.1)
958. hotsex88 (0.89, 5.7)
959. broken78 (0.89, 6.1)
960. vgomez78 (0.89, 9.0)
961. chosen88 (0.89, 6.1)
962. kenyez68 (0.89, 9.8)
963. kresek88 (0.89, 8.0)
964. Golden78 (0.89, 6.2)
965. waffen68 (0.89, 7.5)
966. uniden78 (0.89, 6.4)
967. pantek88 (0.89, 5.7)
968. soeneg68 (0.89, 10.2)
969. abcdef68 (0.89, 6.6)
970. gurtej88 (0.89, 7.1)
971. jaiden78 (0.89, 6.4)

972. Kelden78 (0.89, 9.5)	982. doffen68 (0.89, 8.0)	992. vortex88 (0.89, 5.8)
973. golden78 (0.89, 5.3)	983. decdef68 (0.89, 9.7)	993. mickey68 (0.89, 5.2)
974. holden78 (0.89, 5.2)	984. labben68 (0.89, 8.9)	994. gossen88 (0.89, 7.7)
975. whitey88 (0.89, 5.6)	985. wfozez78 (0.89, 11.8)	995. feirex88 (0.89, 9.6)
976. raiden78 (0.89, 7.0)	986. helden78 (0.89, 8.2)	996. Pigpen68 (0.89, 8.2)
977. bubben68 (0.89, 8.9)	987. survey78 (0.89, 6.5)	997. herden78 (0.89, 8.3)
978. maiden78 (0.89, 5.8)	988. Mickey68 (0.89, 6.2)	998. cortex88 (0.89, 6.8)
979. iloveh78 (0.89, 7.7)	989. nabben68 (0.89, 9.2)	999. wojtek88 (0.89, 5.7)
980. grisen88 (0.89, 7.1)	990. syolek88 (0.89, 10.9)	
981. adisen88 (0.89, 8.4)	991. harvey78 (0.89, 5.4)	

Cluster 23

```
Prototype: saaeroa794

Hard-assigned passwords: 819021 (2.83% of total)
Unique hard-assigned passwords: 595276 (27.32% of cluster total)

Cluster-assignment scores:
        Min: 0.060
        Max: 0.938
        Mean: 0.254
        SD: 0.178

Strength bins:
        Very weak: 9195 (1.12%)
        Weak: 136966 (16.72%)
        Fair: 226221 (27.62%)
        Good: 407428 (49.75%)
        Strong: 39211 (4.79%)

Password lengths:
        Length 9: 57607 (7.03%)
        Length 10: 692027 (84.49%)
        Length 11: 69387 (8.47%)

Character classes:
        4 classes: 16405 (2.00%)
        3 classes: 87986 (10.74%)
                lower/upper/symbol: 357 (0.41%)
                lower/upper/number: 58720 (66.74%)
                lower/symbol/number: 28909 (32.86%)
                upper/symbol/number: 0 (0.00%)
        2 classes: 714629 (87.25%)
                lower/upper: 219 (0.03%)
                lower/number: 713332 (99.82%)
                lower/symbol: 1076 (0.15%)
                upper/number: 0 (0.00%)
                upper/symbol: 0 (0.00%)
                number/symbol: 2 (0.00%)
        1 class: 1 (0.00%)
                lower: 0 (0.00%)
                upper: 0 (0.00%)
                symbol: 1 (100.00%)
                number: 0 (0.00%)

Most frequent char-class structures:
        LLLLLLLDDD: 591887 (72.3%)
        LLLLLLLDDD: 54173 (6.6%)
        LLLLLLDDD: 50057 (6.1%)
        ULLLLLLDDD: 38494 (4.7%)
        LLLLLLSDDD: 12427 (1.5%)
        LLLLLLLDLL: 7139 (0.9%)
        LLLLLLLDDS: 6184 (0.8%)
        ULLLLLLDDS: 5023 (0.6%)
        ULLLLLSDDD: 4767 (0.6%)
        LLLLLLLDDL: 4325 (0.5%)
```

1,000 nearest passwords

```
  0. vedeven390   (0.94, 13.0)
  1. kavuwew390   (0.94, 12.2)
  2. sekibep390   (0.94, 11.3)
  3. luxicen390   (0.94, 12.6)
  4. qilivem490   (0.94, 11.6)
  5. qiloxew790   (0.94, 11.3)
  6. fijihek390   (0.94, 11.0)
  7. cstkwem390   (0.94, 13.7)
  8. wikiqeg390   (0.94, 11.8)
  9. qoceheh390   (0.94, 11.7)
 10. xerevep790   (0.94, 11.3)
 11. bygipew790   (0.94, 12.0)
 12. vekecec790   (0.94, 11.5)
 13. wevepec790   (0.94, 11.1)
 14. giceden790   (0.94, 11.6)
 15. sicohef490   (0.93, 11.6)
 16. lejohef490   (0.93, 11.6)
 17. lirupec390   (0.93, 11.8)
 18. fadedex490   (0.93, 11.4)
 19. kisuxep390   (0.93, 12.1)
 20. vahejed790   (0.93, 11.6)
 21. kelydex390   (0.93, 11.5)
 22. jenawew690   (0.93, 12.8)
 23. lifufem490   (0.93, 11.2)
 24. citizen690   (0.93,  8.7)
 25. mobabex390   (0.93, 11.9)
 26. duqopef690   (0.93, 11.7)
 27. sparkey490   (0.93,  9.0)
 28. mzrpkef490   (0.93, 13.6)
 29. myqubec490   (0.93, 11.4)
 30. zsteven360   (0.93, 10.2)
 31. faqajew490   (0.93, 11.8)
 32. genuzed790   (0.93, 11.2)
 33. hoqivew890   (0.93, 11.4)
 34. wukupez390   (0.93, 12.7)
 35. hoboken360   (0.93,  7.7)
 36. honuzez790   (0.93, 11.2)
 37. jawuvej690   (0.93, 11.9)
 38. xucegev690   (0.93, 11.5)
 39. vyxycek490   (0.93, 11.5)
 40. peteweb360   (0.93, 10.4)
 41. liniden360   (0.93, 10.2)
 42. vuciqem360   (0.93, 11.6)
 43. zilivez890   (0.93, 11.5)
 44. jefyzen690   (0.93, 11.4)
 45. pitajeh490   (0.93, 11.0)
 46. xonufed790   (0.93, 11.8)
 47. megucev690   (0.93, 11.1)
 48. vihyceq390   (0.93, 11.3)
 49. biloveb760   (0.93, 11.4)
 50. pibidep360   (0.93, 11.3)
 51. xksoceu360   (0.93, 13.8)
 52. ockeyed690   (0.93, 13.6)
 53. lezefeh360   (0.93, 11.6)
 54. zebikef890   (0.93, 11.7)
 55. tamabez790   (0.93, 11.5)
 56. geochem390   (0.93, 11.5)
 57. nkdozem794   (0.93, 13.8)
 58. dococew794   (0.93, 11.9)
 59. qixecep890   (0.93, 11.6)
 60. blksfen760   (0.93, 13.0)
 61. nakemeh890   (0.93, 11.6)
 62. pirudev360   (0.93, 10.9)
 63. brenden360   (0.93,  7.7)
 64. stvuceg690   (0.93, 13.4)
 65. suxocef764   (0.93, 11.6)
 66. wohizew460   (0.93, 10.9)
 67. nodemen764   (0.93, 11.1)
 68. cuxoveg794   (0.93, 11.5)
 69. jekidem460   (0.93, 11.6)
 70. waqyqew490   (0.93, 11.3)
 71. kaweceq760   (0.93, 11.3)
 72. desicem460   (0.93, 11.4)
 73. reroceb794   (0.93, 11.1)
 74. dyjexez764   (0.93, 11.8)
 75. taviwep590   (0.93, 11.2)
 76. sufydeg690   (0.93, 11.6)
 77. qylizeg460   (0.93, 11.5)
 78. xboxweb360   (0.93,  9.9)
 79. cexibej764   (0.93, 11.4)
 80. frnikex794   (0.93, 13.4)
 81. mohamed360   (0.93,  6.1)
 82. xylodew590   (0.93, 11.4)
 83. wawadef360   (0.93, 11.3)
 84. matthew360   (0.93,  6.2)
 85. deqiveh380   (0.93, 11.8)
 86. hewawew660   (0.93, 12.1)
 87. gyzikew380   (0.93, 11.3)
 88. cebofed764   (0.93, 11.5)
 89. xozomen660   (0.93, 12.0)
 90. womoced794   (0.93, 11.7)
 91. whiskey360   (0.93,  7.1)
 92. sigoweb364   (0.93, 11.7)
 93. puhicev660   (0.93, 11.4)
 94. kaduken360   (0.93, 10.2)
 95. pygoweh660   (0.93, 11.5)
 96. wiwojef660   (0.93, 12.1)
 97. cijaxem460   (0.93, 11.5)
 98. freemen660   (0.93,  9.9)
 99. chicken360   (0.93,  6.4)
100. jezyweg890   (0.93, 12.1)
101. vigawen660   (0.93, 11.3)
102. xiremeq460   (0.93, 11.8)
103. camepef660   (0.93, 12.1)
104. taxipeh764   (0.93, 10.9)
105. cihohez890   (0.93, 11.8)
106. anhiuem360   (0.93,  8.3)
107. guhofez460   (0.93, 11.5)
108. legyhed390   (0.93, 11.4)
109. rylizez590   (0.93, 12.0)
110. hokonew690   (0.93, 11.7)
111. tywiqeh460   (0.93, 11.2)
112. nextgen360   (0.93,  7.6)
113. sobimed660   (0.93, 12.2)
114. qacezev394   (0.93, 11.1)
115. rilimep364   (0.93, 11.7)
116. sixomez590   (0.93, 12.6)
117. lanamec460   (0.93, 12.3)
118. spanjew360   (0.93, 11.6)
119. asppwed890   (0.93, 13.1)
120. hershey360   (0.93,  7.0)
121. lomxzew760   (0.93, 14.0)
122. bixageb490   (0.93, 11.5)
123. myrypef460   (0.93, 11.7)
124. beckhem690   (0.93, 11.3)
125. saracen460   (0.93,  9.4)
126. kyhopex660   (0.93, 11.9)
127. rijaxef794   (0.93, 11.7)
128. hadekeq660   (0.93, 11.7)
129. kawiveq694   (0.93, 11.8)
130. romigef764   (0.93, 10.8)
131. sezebec364   (0.93, 12.6)
132. qeqiwez694   (0.93, 11.5)
133. ruligew660   (0.93, 11.8)
134. qavokex590   (0.93, 11.7)
135. luvedeq660   (0.93, 12.1)
136. rirakex760   (0.93, 12.5)
137. dinoxek780   (0.93, 11.8)
138. mohamed890   (0.93,  6.3)
139. cyfehew590   (0.93, 11.8)
140. boqaced360   (0.93, 11.7)
141. sawoceb364   (0.93, 11.3)
142. princew890   (0.93, 10.1)
143. korymez764   (0.93, 11.3)
144. kyfafeq360   (0.93, 11.2)
145. dopuhed690   (0.93, 11.6)
146. kidykep360   (0.93, 12.1)
147. glenken794   (0.93, 12.1)
148. qobekew784   (0.93, 11.4)
149. xygohef380   (0.93, 11.3)
150. kywemeg364   (0.93, 11.3)
151. ugvmqed490   (0.93, 13.8)
152. gyluqek360   (0.93, 11.6)
153. basygek690   (0.93, 12.1)
154. wysabed760   (0.93, 11.1)
155. vuqehez660   (0.93, 11.4)
156. mupafek660   (0.93, 12.5)
157. cipaxez890   (0.93, 11.4)
158. wehogeb764   (0.93, 11.2)
159. chicken760   (0.93,  7.5)
160. dofyzep460   (0.93, 11.7)
161. jugyxen760   (0.93, 11.9)
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162. lygexex664 (0.93, 11.8)
163. xynocek780 (0.93, 11.6)
164. moqocez694 (0.93, 11.7)
165. qeqigec764 (0.93, 11.3)
166. zifijew480 (0.93, 11.8)
167. jujubek660 (0.93, 10.0)
168. wopyfev890 (0.93, 11.6)
169. femubec764 (0.93, 12.5)
170. dacafej760 (0.93, 11.5)
171. fiatmef480 (0.93, 14.0)
172. sufihev394 (0.93, 12.1)
173. Matthew890 (0.93, 7.0)
174. qtyzcew760 (0.93, 13.3)
175. kehuded890 (0.93, 11.3)
176. nynikez590 (0.93, 11.9)
177. veticev780 (0.93, 11.3)
178. gudiben780 (0.93, 11.2)
179. woodbed460 (0.93, 8.0)
180. zykupef890 (0.93, 12.0)
181. canyjev460 (0.93, 12.1)
182. sewiqeh590 (0.93, 11.8)
183. dijohex590 (0.93, 12.3)
184. hawiheb664 (0.93, 11.7)
185. luriwed464 (0.93, 11.4)
186. momezek394 (0.93, 12.3)
187. gorajew364 (0.93, 11.0)
188. nilejeg664 (0.93, 12.2)
189. xatyvep664 (0.93, 11.4)
190. kegideb784 (0.93, 11.9)
191. fedeqeq464 (0.93, 11.6)
192. tutozeh590 (0.93, 12.6)
193. zaqyfem794 (0.93, 11.2)
194. pozomem680 (0.93, 12.2)
195. rerikeg860 (0.93, 12.1)
196. mizozem680 (0.93, 11.8)
197. byqudeq460 (0.93, 10.9)
198. kikocen464 (0.93, 12.0)
199. trgmzeb794 (0.93, 13.8)
200. quxohew784 (0.93, 11.5)
201. cygohen694 (0.93, 11.1)
202. sutodep394 (0.93, 12.0)
203. wamamep380 (0.93, 12.2)
204. mofuceg460 (0.93, 11.8)
205. rudyxeg460 (0.93, 11.3)
206. juxfmew764 (0.93, 13.2)
207. dicajep890 (0.93, 11.5)
208. vunywep664 (0.93, 11.2)
209. tesoweq864 (0.93, 11.1)
210. nejyfej660 (0.93, 11.5)
211. nobiheg664 (0.93, 12.3)
212. pedeceh464 (0.93, 11.7)
213. dovydeb764 (0.93, 10.9)
214. fatemeh784 (0.93, 8.5)
215. wolfden380 (0.93, 9.6)
216. mczdqey690 (0.93, 13.7)
217. nusykeh460 (0.93, 11.9)
218. neredeh784 (0.93, 11.7)
219. csogweh780 (0.92, 14.0)
220. junozec894 (0.92, 11.4)
221. kinonej690 (0.92, 11.8)
222. tihoxeg680 (0.92, 11.9)
223. wyfipev384 (0.92, 11.6)
224. fimafen364 (0.92, 11.7)
225. burlpen394 (0.92, 9.2)
226. tocyvef494 (0.92, 11.4)
227. pavujec764 (0.92, 11.7)
228. julozec384 (0.92, 12.0)
229. sikekeq680 (0.92, 12.9)
230. chicken890 (0.92, 6.7)
231. wabobec494 (0.92, 11.3)
232. pusigev890 (0.92, 11.7)
233. hydehej464 (0.92, 10.5)
234. livedeg680 (0.92, 14.0)
235. lykoxem684 (0.92, 11.5)
236. xecafen694 (0.92, 11.8)
237. sanchez690 (0.92, 7.6)
238. plumkey664 (0.92, 10.2)
239. baqybeh760 (0.92, 11.2)
240. jyjywez464 (0.92, 11.6)
241. kojapev394 (0.92, 12.2)
242. symojeg680 (0.92, 11.5)
243. vesufej364 (0.92, 11.4)
244. hupacev380 (0.92, 11.2)
245. amsuxef480 (0.92, 14.0)
246. bawywex464 (0.92, 11.8)
247. wyduxeh380 (0.92, 11.7)
248. cukygeb790 (0.92, 11.5)
249. jovehed680 (0.92, 12.0)
250. msidden364 (0.92, 13.3)
251. zixewef560 (0.92, 11.5)
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709. zmukjty764 (0.91, 13.8)
710. necsae_860 (0.91, 14.0)
711. prakash890 (0.91, 7.5)
712. satymif590 (0.91, 11.5)
713. killkop890 (0.91, 10.6)
714. gigimon890 (0.91, 10.2)
715. zinumeg474 (0.91, 11.5)
716. juxadif894 (0.91, 11.3)
717. dufygem560 (0.91, 11.4)
718. nubygim894 (0.91, 11.1)
719. ovtxhsq790 (0.91, 13.6)
720. ruxazof894 (0.91, 11.0)
721. rymyhiq794 (0.91, 11.6)
722. thuggin794 (0.91, 9.0)
723. jaxfgsz794 (0.91, 14.0)
724. pokemon890 (0.91, 6.0)
725. dafanej660 (0.91, 11.3)
726. linejed874 (0.91, 12.7)
727. opogata890 (0.91, 11.4)
728. Namhui$894 (0.91, 14.0)
729. dokykeg564 (0.91, 11.9)
730. agykhsc894 (0.91, 13.6)
731. desyhep370 (0.91, 11.2)
732. sotukej474 (0.91, 11.8)
733. jitynec380 (0.91, 11.7)
734. iqyjatu794 (0.91, 11.3)
735. lavysod390 (0.91, 11.6)
736. justyou360 (0.91, 8.4)
737. pymacon894 (0.91, 11.4)
738. qapyveg584 (0.91, 11.5)
739. nipohod890 (0.91, 11.6)
740. vyjosox390 (0.91, 11.8)
741. efywuta794 (0.91, 11.1)
742. ducyhig794 (0.91, 11.6)
743. qacapik380 (0.91, 11.8)
744. fakamop794 (0.91, 12.5)
745. freedom890 (0.91, 6.3)
746. Woofkin890 (0.91, 11.4)
747. lebogen584 (0.91, 11.5)
748. kapajon490 (0.91, 12.1)
749. osimjep674 (0.91, 14.0)
750. kavujeh674 (0.91, 11.6)
751. ijewyta890 (0.91, 11.0)
752. babayev594 (0.91, 11.2)
753. fuckyoy360 (0.91, 9.1)
754. vajusih890 (0.91, 12.4)
755. hfxbqiv490 (0.91, 13.4)
756. dydybiq894 (0.91, 11.1)
757. mevenem564 (0.91, 12.3)
758. qoqujek774 (0.91, 11.3)
759. pumpkin760 (0.91, 7.5)
760. vosazem870 (0.91, 11.9)
761. corazon890 (0.91, 7.0)
762. fuckyou760 (0.91, 6.5)
763. scbwqtx894 (0.91, 13.9)
764. asususy590 (0.91, 12.2)
765. idigysy890 (0.91, 10.8)
766. ebrahim890 (0.91, 7.4)
767. ibrahim890 (0.91, 6.6)
768. qyqyfon860 (0.91, 11.4)
769. tuqupop490 (0.91, 11.4)
770. dalamia890 (0.91, 10.9)
771. qunyxoc860 (0.91, 11.7)
772. kesenib890 (0.91, 12.9)
773. naughty360 (0.91, 6.7)
774. kalkuta890 (0.91, 9.6)
775. wdxmvin860 (0.91, 13.6)
776. jynagof764 (0.91, 11.9)
777. bazuhix894 (0.91, 11.7)
778. turoktv360 (0.91, 12.0)
779. mawaqoh490 (0.91, 11.9)
780. ydbxnsu860 (0.91, 13.4)
781. Yesenia590 (0.91, 9.5)
782. ejixasu590 (0.91, 11.2)
783. tywymog760 (0.91, 11.8)
784. renjith390 (0.91, 9.6)
785. dubadid894 (0.91, 11.5)
786. cynthia360 (0.91, 7.1)
787. toqivov590 (0.91, 11.6)
788. hujacoj760 (0.91, 10.9)
789. goonkid890 (0.91, 9.6)
790. pdnaftv860 (0.91, 13.8)
791. sumaqow860 (0.91, 11.8)
792. oghxvtj760 (0.91, 13.9)
793. pyzgdev584 (0.91, 13.6)
794. stephen674 (0.91, 7.6)
795. kohaqef474 (0.91, 11.4)
796. jgkfvic380 (0.91, 14.0)
797. nuxadib760 (0.91, 11.4)
798. toluboy890 (0.91, 9.5)
799. rimjhim360 (0.91, 9.3)
800. sijyzek374 (0.91, 11.8)
801. kerecic590 (0.91, 11.9)
802. vuxayoz490 (0.91, 14.0)
803. bjntzsh360 (0.91, 13.9)
804. ngefaij790 (0.91, 13.6)
805. ndbymsa490 (0.91, 14.0)
806. fotunex494 (0.91, 11.3)
807. xguvaif380 (0.91, 14.0)
808. cbwumsp380 (0.91, 13.7)
809. chsinth894 (0.91, 13.5)
810. omygosu590 (0.91, 11.4)
811. tukomej570 (0.91, 11.8)
812. mududeq474 (0.91, 12.7)
813. Directv590 (0.91, 10.0)
814. wuzyniz860 (0.91, 11.7)
815. esofysu890 (0.91, 10.7)
816. uqdbzsf860 (0.91, 13.2)
817. iqitasu794 (0.91, 11.0)
818. hopocib790 (0.91, 12.0)
819. fahadip380 (0.91, 11.8)
820. shitbox360 (0.91, 7.2)
821. ZagaZig490 (0.91, 14.0)
822. kushtia890 (0.91, 8.5)
823. pusawek874 (0.91, 11.1)
824. lixkyou360 (0.91, 12.8)
825. ydevutu590 (0.91, 11.1)
826. asapkok360 (0.91, 11.7)
827. nunycix380 (0.91, 11.9)
828. gunizok360 (0.91, 11.4)
829. hokyzem870 (0.91, 11.8)
830. mackgod380 (0.91, 11.2)
831. vyfwbta380 (0.91, 13.5)
832. yfeogij360 (0.91, 13.4)
833. yjacosa790 (0.91, 11.0)
834. zerugev474 (0.91, 10.8)
835. eynzpik794 (0.91, 14.0)
836. reedgid890 (0.91, 12.8)
837. hfdqyiv394 (0.91, 13.5)
838. udisuty864 (0.91, 11.0)
839. jzxkysg764 (0.91, 13.2)
840. bapfhtx860 (0.91, 13.5)
841. yxezasa590 (0.91, 11.2)
842. wirymip890 (0.91, 11.2)
843. bdrckop590 (0.91, 13.7)
844. fantasy594 (0.91, 8.6)
845. ebavata764 (0.91, 10.9)
846. caquhoq380 (0.91, 11.9)
847. puraqog590 (0.91, 11.6)
848. takvcsq860 (0.91, 14.0)
849. ywqtaiz794 (0.91, 13.8)
850. cacadiq380 (0.91, 12.8)
851. weqidoq590 (0.91, 11.3)
852. mamypif394 (0.91, 11.9)
853. dapyhiq380 (0.91, 11.7)
854. dujyjeg674 (0.91, 11.9)
855. pypuqiq380 (0.91, 11.5)
856. Pacific360 (0.91, 8.5)
857. dymuheh594 (0.91, 11.4)
858. enopasy790 (0.91, 11.7)
859. roofdog590 (0.91, 10.4)
860. idufusy860 (0.91, 10.7)
861. zylagej674 (0.91, 11.7)
862. pukenec670 (0.91, 11.9)
863. fuckyou864 (0.91, 6.9)
864. myvipof360 (0.91, 11.2)
865. cewoqox590 (0.91, 11.7)
866. chinita890 (0.91, 7.8)
867. britton390 (0.91, 9.1)
868. ezywata490 (0.91, 11.4)
869. ihavata490 (0.91, 11.2)
870. godebez570 (0.91, 11.1)
871. hegyqej674 (0.91, 11.5)
872. ricxbox360 (0.91, 9.5)
873. tymupow690 (0.91, 11.7)
874. ucycasy784 (0.91, 11.1)
875. nypukem874 (0.91, 11.4)
876. ywuhysa864 (0.91, 11.0)
877. cupodin360 (0.91, 11.2)
878. ngactid590 (0.91, 14.0)
879. kubaney360 (0.91, 11.2)
880. sahepof360 (0.91, 11.4)
881. ticydig360 (0.91, 11.5)
882. lufuziq394 (0.91, 11.6)
883. kagjwsn394 (0.91, 13.5)
884. yxynysy884 (0.91, 10.9)
885. wilodov794 (0.91, 11.5)
886. gqxwzoh394 (0.91, 13.8)
887. knoxmew870 (0.91, 12.5)
888. qybadif594 (0.91, 11.6)
889. pspxbox360 (0.91, 7.9)
890. xadaboh394 (0.91, 11.2)
891. lqpsxok860 (0.91, 13.6)
892. hasopij760 (0.91, 11.8)
893. ocyqusu394 (0.91, 11.0)
894. ejubaty380 (0.91, 11.3)
895. sogabog360 (0.91, 12.0)
896. watovim860 (0.91, 12.3)
897. Dolphin!60 (0.91, 9.3)
898. kabanov690 (0.91, 9.4)
899. winxbox360 (0.91, 7.7)
900. gxtcvsn360 (0.91, 13.6)
901. jpricok860 (0.91, 13.9)
902. tacymoc560 (0.91, 12.1)
903. wujucic394 (0.91, 11.6)
904. dynamic690 (0.91, 8.5)
905. Fantasy360 (0.91, 8.1)
906. maqydif690 (0.91, 11.8)
907. txkdbin394 (0.91, 13.9)
908. tuvaboh690 (0.91, 11.5)
909. ofnxwek584 (0.91, 13.6)
910. gacaped584 (0.91, 11.2)
911. onyputu394 (0.91, 10.8)
912. donuheq674 (0.91, 11.9)
913. bibadic894 (0.91, 12.4)
914. aqikisu390 (0.91, 11.2)
915. rixusip390 (0.91, 11.8)
916. nikitin890 (0.91, 9.1)
917. ysuhata894 (0.91, 11.2)
918. brretta390 (0.91, 11.9)
919. diggity890 (0.91, 8.3)
920. moxaqiw894 (0.91, 11.2)
921. difafen874 (0.91, 11.2)
922. beretta390 (0.91, 8.7)
923. Ibarhim360 (0.91, 14.0)
924. Coyxbox360 (0.91, 10.8)
925. bfpmxsn690 (0.91, 13.5)
926. elztgow360 (0.91, 13.8)
927. xidyviq360 (0.91, 11.2)
928. jupuhid690 (0.91, 11.8)
929. xamyqop394 (0.91, 11.6)
930. jidyjiw894 (0.91, 11.7)
931. xlytweq574 (0.91, 13.5)
932. gangsta894 (0.91, 8.3)
933. gadonen674 (0.91, 11.6)
934. vzfbcej374 (0.91, 13.8)
935. sapinih894 (0.91, 10.9)
936. tikubef870 (0.91, 11.5)
937. kupibox360 (0.91, 11.3)
938. yqarusy794 (0.91, 11.0)
939. qeliweg574 (0.91, 11.7)
940. hampton360 (0.91, 6.2)
941. kevxbox360 (0.91, 9.9)
942. kcmntsc794 (0.91, 14.0)
943. xcmpksa594 (0.91, 13.9)
944. cehynif894 (0.91, 11.5)
945. qazawov560 (0.91, 11.7)
946. qantasa380 (0.91, 11.6)
947. wofukog794 (0.91, 11.8)
948. bajacek374 (0.91, 11.1)
949. lalidin490 (0.91, 12.8)
950. mzpxwsg690 (0.91, 13.5)
951. jybanon364 (0.91, 10.8)
952. ldmgjop594 (0.91, 14.0)
953. nuxyzoz864 (0.91, 11.5)
954. Gdrive(300 (0.91, 14.0)
955. lazujiq690 (0.91, 11.3)
956. dunumow780 (0.91, 11.9)
957. gijahon490 (0.91, 11.6)
958. tsubasa360 (0.91, 7.6)
959. caxacoj864 (0.91, 11.7)
960. xazukek870 (0.91, 11.7)
961. sazehif794 (0.91, 11.6)
962. kctayoq360 (0.91, 13.9)
963. basegod360 (0.91, 8.3)
964. hjfcktx690 (0.91, 14.0)
965. ebylyta894 (0.91, 11.1)
966. rulicod860 (0.91, 11.2)
967. cijykod894 (0.91, 12.0)
968. pibmnsa794 (0.91, 13.6)
969. hugafom780 (0.91, 11.9)
970. gopukof760 (0.91, 11.5)
971. cuwydoc780 (0.91, 11.5)

972. swjhatq364 (0.91, 13.0)	982. redxbox360 (0.91, 6.7)	992. gubomeh574 (0.91, 11.6)
973. zewasog590 (0.91, 11.2)	983. crooked570 (0.91, 9.3)	993. fadygof780 (0.91, 11.8)
974. moisheb870 (0.91, 12.4)	984. naxugoh364 (0.91, 11.1)	994. opuntia360 (0.91, 10.3)
975. bangsta360 (0.91, 9.0)	985. JukeBox360 (0.91, 9.9)	995. Spindoc360 (0.91, 9.5)
976. rainbow360 (0.91, 5.6)	986. wocghsa860 (0.91, 13.4)	996. cheezey734 (0.91, 10.7)
977. gangsta360 (0.91, 6.7)	987. duqevej574 (0.91, 11.4)	997. duducop364 (0.91, 11.2)
978. riricow860 (0.91, 11.6)	988. ipycusa364 (0.91, 11.0)	998. cekubif794 (0.91, 11.1)
979. rusipoh594 (0.91, 11.4)	989. nezuzin894 (0.91, 11.5)	999. omiedog360 (0.91, 11.4)
980. zydepeg570 (0.91, 12.0)	990. ohmgxsc784 (0.91, 13.6)	
981. kovunek764 (0.91, 11.2)	991. samaqeb474 (0.91, 11.6)	

Cluster 24

Prototype: saaeemohne

Hard-assigned passwords: 654336 (2.26% of total)
Unique hard-assigned passwords: 351082 (46.35% of cluster total)

Cluster-assignment scores:
        Min: 0.085
        Max: 0.964
        Mean: 0.474
        SD: 0.218

Strength bins:
        Very weak: 32362 (4.95%)
        Weak: 209978 (32.09%)
        Fair: 203406 (31.09%)
        Good: 196811 (30.08%)
        Strong: 11779 (1.80%)

Password lengths:
        Length 9: 9981 (1.53%)
        Length 10: 644355 (98.47%)

Character classes:
        4 classes: 0 (0.00%)
        3 classes: 3168 (0.48%)
                lower/upper/symbol: 3168 (100.00%)
                lower/upper/number: 0 (0.00%)
                lower/symbol/number: 0 (0.00%)
                upper/symbol/number: 0 (0.00%)
        2 classes: 53018 (8.10%)
                lower/upper: 26980 (50.89%)
                lower/number: 0 (0.00%)
                lower/symbol: 26038 (49.11%)
                upper/number: 0 (0.00%)
                upper/symbol: 0 (0.00%)
                number/symbol: 0 (0.00%)
        1 class: 598150 (91.41%)
                lower: 598150 (100.00%)
                upper: 0 (0.00%)
                symbol: 0 (0.00%)
                number: 0 (0.00%)

Most frequent char-class structures:
        LLLLLLLLL: 588870 (90.0%)
        ULLLLLLLL: 17830 (2.7%)
        LLLLLLLL: 9280 (1.4%)
        LLLLLSLLL: 5926 (0.9%)
        LLLLSLLLL: 5356 (0.8%)
        ULLLLULLL: 3010 (0.5%)
        LLLLLLSLL: 2874 (0.4%)
        LLLSLLLLL: 2564 (0.4%)
        ULLLLLULL: 1690 (0.3%)
        ULLLULLLL: 1624 (0.2%)

1,000 nearest passwords

0. jalinkedne	(0.96, 10.1)	54. dhegaweyne	(0.95, 13.2)	108. ebakoleane	(0.94, 11.1)
1. hate@me@ne	(0.96, 12.8)	55. blackledge	(0.95, 6.2)	109. wertemenge	(0.94, 11.3)
2. jangadeyne	(0.96, 11.1)	56. dennybenge	(0.95, 10.3)	110. enterretne	(0.94, 10.2)
3. sorenhejne	(0.96, 13.3)	57. lurnigegge	(0.95, 14.0)	111. fuck•me•me	(0.94, 6.2)
4. iluvcheyne	(0.96, 8.9)	58. citirsedge	(0.95, 11.7)	112. badrevenge	(0.94, 8.7)
5. dhagaweyne	(0.96, 12.6)	59. riversedge	(0.95, 5.8)	113. pamyatesne	(0.94, 13.1)
6. liveonedge	(0.96, 10.4)	60. liversedge	(0.95, 8.0)	114. ranasresne	(0.94, 13.6)
7. priviledge	(0.96, 9.6)	61. Liversedge	(0.95, 9.0)	115. jasmine_me	(0.94, 8.3)
8. arrowhedge	(0.96, 9.5)	62. desertedge	(0.95, 8.4)	116. jamesdeane	(0.94, 5.9)
9. spardaedge	(0.96, 11.2)	63. majomsegge	(0.95, 12.5)	117. Pserevenge	(0.94, 11.0)
10. ansonhedge	(0.96, 10.2)	64. rasorsedge	(0.95, 10.8)	118. marmitedme	(0.94, 9.6)
11. teejcheyne	(0.95, 12.9)	65. shadyledge	(0.95, 9.1)	119. promise•me	(0.94, 7.4)
12. miojorenge	(0.95, 12.6)	66. leverhedge	(0.95, 10.3)	120. fellate_me	(0.94, 11.3)
13. myohorenge	(0.95, 9.5)	67. racersedge	(0.95, 7.2)	121. ahuabuebue	(0.94, 12.2)
14. fuckinedge	(0.95, 8.4)	68. razersedge	(0.95, 7.1)	122. nanabuebue	(0.94, 11.0)
15. globaledge	(0.95, 8.3)	69. camofledge	(0.95, 10.8)	123. finishedme	(0.94, 8.0)
16. scbmileage	(0.95, 13.4)	70. flyerhedge	(0.95, 10.0)	124. GetRevenge	(0.94, 8.6)
17. smoothedge	(0.95, 7.9)	71. watersedge	(0.95, 5.3)	125. Ketibhetne	(0.94, 14.0)
18. advanceage	(0.95, 8.2)	72. Razorsedge	(0.95, 7.0)	126. skittle•me	(0.94, 10.0)
19. parisreyne	(0.95, 9.2)	73. razorsedge	(0.95, 5.9)	127. defulaetne	(0.94, 14.0)
20. racingedge	(0.95, 7.9)	74. sweetsedge	(0.95, 7.7)	128. you•ate•me	(0.94, 8.2)
21. brownledge	(0.95, 7.3)	75. razorsefge	(0.95, 13.2)	129. kirihaehae	(0.94, 11.7)
22. talentedge	(0.95, 6.7)	76. up.jeje.ge	(0.95, 13.8)	130. takabwebwe	(0.94, 10.9)
23. Drewskepne	(0.95, 13.3)	77. petersenge	(0.95, 9.1)	131. chrisdeane	(0.94, 7.3)
24. Nelebreyne	(0.95, 12.6)	78. horsehedge	(0.95, 8.5)	132. just•me•me	(0.94, 7.0)
25. HugoPledge	(0.95, 11.1)	79. ruggededge	(0.95, 7.0)	133. eazydaedae	(0.94, 9.9)
26. livingedge	(0.95, 7.1)	80. raggededge	(0.95, 7.3)	134. beauchesne	(0.94, 6.3)
27. bellasedge	(0.95, 8.5)	81. jaggededge	(0.95, 5.4)	135. mm.love.me	(0.94, 10.3)
28. bobisledge	(0.95, 9.1)	82. jerrywedge	(0.95, 7.7)	136. orsonneque	(0.94, 9.6)
29. slightedge	(0.95, 9.1)	83. backswedge	(0.95, 8.3)	137. ayoodaedae	(0.94, 10.9)
30. cantagenge	(0.95, 10.3)	84. texaswedge	(0.95, 7.5)	138. titouleane	(0.94, 10.6)
31. winzaledge	(0.95, 11.0)	85. jedgejedge	(0.95, 9.1)	139. pontguegue	(0.94, 11.3)
32. nyanjwenge	(0.95, 12.1)	86. erinspenge	(0.95, 9.9)	140. ElmdaleAve	(0.94, 13.0)
33. chal[lenge	(0.95, 13.4)	87. aknowledge	(0.94, 8.0)	141. courchesne	(0.94, 8.4)
34. thomasedge	(0.95, 8.3)	88. lemonwedge	(0.94, 7.3)	142. lavonce&me	(0.94, 11.9)
35. tenjotenge	(0.95, 10.6)	89. stonehedge	(0.94, 5.9)	143. kathykeane	(0.94, 7.5)
36. bladesedge	(0.95, 8.7)	90. chadiceage	(0.94, 11.2)	144. castanedae	(0.94, 7.7)
37. baladweyne	(0.95, 9.2)	91. mangepenge	(0.94, 8.2)	145. missmaemae	(0.94, 7.7)
38. stevenedge	(0.95, 8.5)	92. djknowedge	(0.94, 11.0)	146. sarahjeane	(0.94, 7.0)
39. averyhedge	(0.95, 9.1)	93. hirutmenge	(0.94, 12.9)	147. troublebme	(0.94, 9.0)
40. energyedge	(0.95, 8.2)	94. taterwedge	(0.94, 9.1)	148. confusedme	(0.94, 6.6)
41. minedrenge	(0.95, 10.7)	95. stillbenge	(0.94, 9.6)	149. godloveSme	(0.94, 8.0)
42. baaraweyne	(0.95, 13.0)	96. dizinuehve	(0.94, 14.0)	150. kinkiregae	(0.94, 13.7)
43. chiapledge	(0.95, 11.6)	97. anya•keane	(0.94, 10.6)	151. Elvamaemae	(0.94, 11.3)
44. worldsedge	(0.95, 6.9)	98. massage•me	(0.94, 8.7)	152. juanpuente	(0.94, 7.7)
45. scottlenge	(0.95, 10.2)	99. hengepenge	(0.94, 8.5)	153. iaminkeane	(0.94, 10.2)
46. tylergedge	(0.95, 7.8)	100. shadowedge	(0.94, 5.7)	154. uramdaedae	(0.94, 11.8)
47. fulangenge	(0.95, 9.6)	101. mdmkmkekme	(0.94, 13.7)	155. technoedge	(0.94, 7.3)
48. grandledge	(0.95, 6.4)	102. peagepeage	(0.94, 11.6)	156. dagbenegni	(0.94, 12.7)
49. cutandedge	(0.95, 11.3)	103. yakupbekce	(0.94, 11.7)	157. djshade+me	(0.94, 12.1)
50. hamarweyne	(0.95, 11.6)	104. stonehenge	(0.94, 4.5)	158. deliquente	(0.94, 8.3)
51. citiesedge	(0.95, 10.4)	105. johnemenge	(0.94, 10.7)	159. euthadeane	(0.94, 13.0)
52. wobblyedge	(0.95, 10.0)	106. andrewedge	(0.94, 7.1)	160. bananaeate	(0.94, 8.8)
53. anthadedge	(0.95, 11.0)	107. sengemenge	(0.94, 7.4)	161. heslimedme	(0.94, 11.6)

162. Expectedme (0.94, 10.0)
163. boobssexme (0.94, 10.2)
164. expectedme (0.94, 8.2)
165. tbyaskedme (0.94, 13.6)
166. titopuente (0.94, 7.4)
167. roxannemae (0.94, 7.3)
168. pitopuente (0.94, 7.9)
169. lovable•me (0.94, 8.6)
170. zonaquente (0.94, 10.7)
171. ariabaebae (0.94, 10.5)
172. vhiemaemae (0.94, 9.6)
173. jangsaehae (0.94, 13.1)
174. godlovedme (0.94, 7.1)
175. simonkeane (0.94, 8.2)
176. sexmesexme (0.94, 7.2)
177. bakanyente (0.94, 10.3)
178. jellybeane (0.94, 6.8)
179. fellype.fe (0.94, 14.0)
180. continente (0.94, 5.7)
181. papaoceane (0.94, 9.0)
182. greenkeane (0.94, 7.3)
183. Land&Leute (0.94, 14.0)
184. normajeane (0.94, 6.6)
185. hopeusexme (0.94, 12.8)
186. dellarenae (0.94, 7.1)
187. testnmeqwe (0.94, 13.6)
188. carlyrenae (0.94, 8.2)
189. emilyrenae (0.94, 7.5)
190. laracuente (0.94, 6.9)
191. kaylarenae (0.94, 7.2)
192. delafuente (0.94, 5.3)
193. jaforcedme (0.94, 12.4)
194. tasharenae (0.93, 8.4)
195. juaneneque (0.93, 10.4)
196. yousavedme (0.93, 6.2)
197. miv,ckeywe (0.93, 14.0)
198. kadancemae (0.93, 10.3)
199. cowsarebae (0.93, 9.9)
200. jennarenae (0.93, 7.6)
201. aesif+eate (0.93, 14.0)
202. jaceyrenae (0.93, 9.4)
203. godsavedme (0.93, 4.5)
204. shanajente (0.93, 9.9)
205. idiotheque (0.93, 10.1)
206. fenerbehce (0.93, 8.8)
207. muitagente (0.93, 9.9)
208. emirateuae (0.93, 12.0)
209. modetheque (0.93, 11.5)
210. permanente (0.93, 5.9)
211. norskjente (0.93, 11.5)
212. belvadeane (0.93, 9.5)
213. barnamedve (0.93, 10.7)
214. meresmehue (0.93, 12.7)
215. Netheredge (0.93, 10.5)
216. AnitaBeate (0.93, 10.4)
217. worknaenae (0.93, 11.3)
218. e_dlfuente (0.93, 14.0)
219. samsonekpe (0.93, 10.1)
220. delaFuente (0.93, 8.7)
221. mrganrenae (0.93, 11.4)
222. divorcedme (0.93, 7.6)
223. abigalemae (0.93, 10.5)
224. danicheque (0.93, 8.3)
225. stoneledge (0.93, 7.2)
226. myspaceqwe (0.93, 8.0)
227. conordeane (0.93, 9.6)
228. RedesGente (0.93, 11.9)
229. tunethebae (0.93, 10.9)
230. chotenente (0.93, 11.3)
231. darlenemae (0.93, 7.5)
232. dongaledae (0.93, 12.4)
233. prudolente (0.93, 12.1)
234. fundamente (0.93, 6.1)
235. ampukyekye (0.93, 12.8)
236. liliyfente (0.93, 12.0)
237. asiankexme (0.93, 13.6)
238. gracelegge (0.93, 8.9)
239. tweedledue (0.93, 8.0)
240. jaimedeane (0.93, 8.7)
241. keanekeane (0.93, 6.7)
242. BoynameSue (0.93, 13.2)
243. seanekeane (0.93, 8.9)
244. componente (0.93, 6.3)
245. kobiekeane (0.93, 9.3)
246. fingeredge (0.93, 7.4)
247. cybersexme (0.93, 8.2)
248. leiacreque (0.93, 12.5)
249. casagreque (0.93, 10.5)
250. sweetsexme (0.93, 7.9)
251. peterkeane (0.93, 7.3)
252. wannasexme (0.93, 8.2)
253. ahmaftehfe (0.93, 14.0)
254. livannebye (0.93, 11.8)
255. rangeredge (0.93, 6.8)
256. kejizhexue (0.93, 14.0)
257. teaebwebwe (0.93, 12.5)
258. jasminebae (0.93, 8.0)
259. justicemae (0.93, 7.5)
260. erikssteppe (0.93, 11.4)
261. ademsteate (0.93, 12.7)
262. seymonebae (0.93, 10.9)
263. matinrezae (0.93, 11.6)
264. believe#me (0.93, 9.4)
265. bryantente (0.93, 9.8)
266. nikatsekpe (0.93, 13.1)
267. izzythebae (0.93, 10.7)
268. sita_tente (0.93, 11.7)
269. rudythebae (0.93, 10.8)
270. welcome@me (0.93, 6.8)
271. stijnseppe (0.93, 10.6)
272. desmuteate (0.93, 12.2)
273. phoe•te•te (0.93, 13.9)
274. andromedae (0.93, 6.5)
275. vozsilente (0.93, 12.5)
276. Silkeseppe (0.93, 11.7)
277. ilovekeane (0.93, 7.0)
278. elinosente (0.93, 11.8)
279. bonn_bente (0.93, 13.0)
280. cameogedye (0.93, 12.8)
281. bellsrenae (0.93, 9.9)
282. kuntakente (0.93, 7.0)
283. mauribente (0.93, 9.6)
284. giousseppe (0.93, 10.3)
285. testamente (0.93, 5.6)
286. outlewedme (0.93, 12.0)
287. Presidente (0.93, 6.2)
288. daweaweqwe (0.93, 12.3)
289. prettyekpe (0.93, 12.1)
290. iloveme=me (0.93, 8.3)
291. femkeseppe (0.93, 10.9)
292. parafrente (0.93, 10.0)
293. cettamente (0.93, 8.6)
294. masteredge (0.93, 6.9)
295. presidente (0.93, 5.0)
296. mimoypeque (0.93, 11.7)
297. forgive•me (0.93, 7.9)
298. bhongjemae (0.93, 13.2)
299. routeledge (0.93, 8.5)
300. katrinebbe (0.93, 10.0)
301. insurgente (0.93, 6.2)
302. trungmente (0.93, 11.0)
303. tattooedme (0.93, 7.5)
304. rubenseppe (0.93, 9.6)
305. architecte (0.93, 5.8)
306. mybestemae (0.93, 11.9)
307. ill•create (0.93, 9.8)
308. tatabyebye (0.93, 7.8)
309. WelcomeAve (0.93, 9.3)
310. s.giuseppe (0.93, 9.8)
311. iluvthebae (0.93, 8.9)
312. sentimente (0.93, 6.4)
313. sakkareppe (0.93, 10.4)
314. cadencemae (0.93, 7.9)
315. justamemte (0.93, 11.3)
316. detergente (0.93, 6.9)
317. gattopeppe (0.93, 10.5)
318. audradepue (0.93, 11.6)
319. deprimente (0.93, 10.3)
320. lentamente (0.93, 9.2)
321. pubparehni (0.93, 14.0)
322. represente (0.93, 5.7)
323. elpresente (0.93, 6.5)
324. obuathekpe (0.93, 14.0)
325. mipresente (0.93, 7.9)
326. sempesempe (0.93, 8.2)
327. cindykeppe (0.93, 9.9)
328. Lotteseppe (0.93, 10.4)
329. olisahenye (0.93, 12.4)
330. eliaspeque (0.93, 9.2)
331. passtheaxe (0.93, 8.8)
332. buenajente (0.93, 10.3)
333. rudytheape (0.93, 10.6)
334. atsaguegbe (0.93, 13.5)
335. bogonkente (0.93, 13.6)
336. lingayeaye (0.93, 11.6)
337. BeppeBeppe (0.93, 8.8)
338. adewaleabe (0.93, 7.7)
339. JetztHeute (0.93, 14.0)
340. maryjblige (0.93, 11.0)
341. trondbeate (0.93, 12.0)
342. harbedeyme (0.93, 14.0)
343. chalybeate (0.93, 11.1)
344. sarukalige (0.93, 10.4)
345. thevillige (0.93, 7.7)
346. hrlryglige (0.93, 14.0)
347. karenbente (0.93, 8.5)
348. cedar•rige (0.93, 10.5)
349. Angeldepue (0.93, 9.8)
350. icotepeque (0.93, 10.1)
351. aprendente (0.93, 7.6)
352. southbrige (0.93, 9.6)
353. arowosegbe (0.93, 9.8)
354. kevyntedye (0.93, 13.4)
355. igualmente (0.93, 7.8)
356. ocotepeque (0.93, 9.2)
357. citripeppe (0.93, 11.8)
358. mediamente (0.93, 7.8)
359. wskgcreate (0.93, 13.0)
360. kvindelige (0.93, 11.0)
361. hollamedae (0.93, 10.8)
362. singlelige (0.93, 8.3)
363. coatepeque (0.93, 6.6)
364. pfwvalente (0.93, 12.5)
365. maodejegue (0.93, 13.2)
366. georgbeate (0.93, 10.8)
367. hejsverige (0.93, 10.3)
368. SanVicente (0.93, 7.2)
369. pequepeque (0.93, 7.1)
370. lostinlige (0.93, 9.3)
371. urqdabewte (0.93, 14.0)
372. womaamewte (0.93, 11.7)
373. gonebyebye (0.93, 8.2)
374. hentehente (0.93, 8.3)
375. archibeque (0.93, 9.2)
376. ballislige (0.93, 9.8)
377. gpnutwente (0.93, 13.4)
378. adaralegbe (0.93, 8.5)
379. eironkeige (0.93, 14.0)
380. trecapente (0.93, 10.7)
381. eoligoeige (0.93, 13.2)
382. acctcreate (0.93, 9.5)
383. violamente (0.93, 8.0)
384. bullsprige (0.93, 10.5)
385. senyesenye (0.93, 9.2)
386. snilljente (0.93, 12.3)
387. elserpente (0.93, 9.5)
388. bekesmegye (0.93, 12.9)
389. tantebeate (0.93, 9.1)
390. rampejente (0.93, 11.3)
391. tahu•tempe (0.93, 11.8)
392. chatoneige (0.93, 10.5)
393. keniabeige (0.93, 9.9)
394. privateEye (0.93, 9.2)
395. usualmente (0.93, 8.8)
396. sanvicente (0.93, 5.5)
397. tobulmente (0.93, 13.1)
398. juliaseige (0.93, 8.8)
399. finalmente (0.93, 6.8)
400. pasdeneige (0.93, 10.5)
401. Arschgeige (0.93, 11.5)
402. lifyafejye (0.93, 14.0)
403. lornabeige (0.93, 10.3)
404. bogengeige (0.93, 12.5)
405. totalmente (0.93, 6.7)
406. demonseige (0.93, 6.2)
407. jonaspeppe (0.93, 10.1)
408. neigeneige (0.93, 7.0)
409. babyporige (0.93, 12.1)
410. dundjerige (0.93, 13.3)
411. perceneige (0.93, 11.2)
412. underseige (0.93, 8.0)
413. witsebente (0.93, 11.3)
414. Lottejente (0.93, 11.0)
415. superneige (0.93, 8.3)
416. kefirbeige (0.93, 12.2)
417. colorbeige (0.92, 11.6)
418. julieweyme (0.92, 11.8)
419. sofiabeppe (0.92, 10.3)
420. korismegye (0.92, 12.4)
421. matdaveate (0.92, 11.6)
422. podermente (0.92, 8.7)
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425. sanvizente (0.92, 11.9)
426. chopiyroge (0.92, 13.7)
427. suavemente (0.92, 6.3)
428. linkedente (0.92, 7.4)
429. sauvemente (0.92, 8.0)
430. birolpempe (0.92, 13.0)
431. openPleaze (0.92, 9.6)

432. Suavemente (0.92, 7.9)
433. solardente (0.92, 9.0)
434. petnjoroge (0.92, 12.9)
435. khloebloge (0.92, 11.5)
436. presedente (0.92, 7.6)
437. psychologe (0.92, 7.2)
438. insiemeate (0.92, 11.8)
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440. pneumologe (0.92, 10.1)
441. prosedente (0.92, 8.4)
442. ponteveque (0.92, 10.3)
443. tonydeloge (0.92, 9.6)
444. chesarebbe (0.92, 11.2)
445. dinside.no (0.92, 12.7)
446. coolbreaze (0.92, 6.5)
447. wolfverine (0.92, 6.8)
448. wolfwerine (0.92, 10.1)
449. trinetrine (0.92, 5.8)
450. Wolfverine (0.92, 8.0)
451. xglycerine (0.92, 12.9)
452. ainecerine (0.92, 10.9)
453. greeniebae (0.92, 9.5)
454. deofavente (0.92, 14.0)
455. woolverine (0.92, 6.3)
456. narrairine (0.92, 11.5)
457. bleumarine (0.92, 8.4)
458. Inepetrine (0.92, 12.4)
459. anepetrine (0.92, 11.0)
460. u.s.marine (0.92, 9.2)
461. breesveyye (0.92, 14.0)
462. siebebente (0.92, 10.0)
463. baldomeque (0.92, 9.9)
464. greymarine (0.92, 6.7)
465. saovicente (0.92, 6.2)
466. RealMarine (0.92, 8.1)
467. Gripmarine (0.92, 10.5)
468. aaiwonegbe (0.92, 8.4)
469. wolfvarine (0.92, 9.4)
470. jaiwonegbe (0.92, 10.0)
471. ticomarine (0.92, 8.2)
472. bluemarine (0.92, 5.3)
473. Nicemarine (0.92, 9.0)
474. palmmarine (0.92, 8.7)
475. the•marine (0.92, 7.2)
476. lovemarine (0.92, 5.9)
477. hellverine (0.92, 8.1)
478. ncexmarine (0.92, 10.6)
479. shivnarine (0.92, 9.3)
480. willverine (0.92, 8.3)
481. Iloveleane (0.92, 9.6)
482. Iamjane;;e (0.92, 14.0)
483. profitline (0.92, 9.1)
484. trempoline (0.92, 8.3)
485. mwolverine (0.92, 6.5)
486. xzelverine (0.92, 11.7)
487. esbenoline (0.92, 11.2)
488. matumbembe (0.92, 11.4)
489. flightline (0.92, 5.8)
490. tourmiline (0.92, 10.3)
491. wrightline (0.92, 7.3)
492. vimoutline (0.92, 10.9)
493. kemozoline (0.92, 11.7)
494. brinksline (0.92, 8.8)
495. fionamrine (0.92, 10.7)
496. freyabrine (0.92, 9.4)
497. el-nasrine (0.92, 11.2)
498. georgoline (0.92, 7.7)
499. knekkoline (0.92, 11.8)
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501. FragMarine (0.92, 8.8)
502. gwendoline (0.92, 5.1)
503. adreniline (0.92, 10.0)
504. kathyzehno (0.92, 11.0)
505. rattlerine (0.92, 10.5)
506. directline (0.92, 6.7)
507. morenoline (0.92, 8.4)
508. katenarine (0.92, 9.7)
509. evenimente (0.92, 10.7)
510. methadrine (0.92, 9.9)
511. sunsheeine (0.92, 11.1)
512. satxmarine (0.92, 10.3)
513. maiherrine (0.92, 11.0)
514. hutamarine (0.92, 10.9)
515. oyalmarine (0.92, 10.3)
516. joarceline (0.92, 9.2)
517. annecarine (0.92, 7.5)
518. elineeline (0.92, 7.0)
519. ellaceline (0.92, 8.8)
520. knightline (0.92, 6.1)
521. omarmarine (0.92, 7.8)
522. sofhqoehge (0.92, 14.0)
523. marcheline (0.92, 6.5)
524. flickaline (0.92, 8.8)
525. brendaline (0.92, 6.6)
526. gilvicente (0.92, 10.5)
527. kyraceline (0.92, 8.5)
528. esmeceline (0.92, 9.2)
529. slytherine (0.92, 5.3)
530. finefeline (0.92, 9.4)
531. heidibente (0.92, 9.5)
532. kathherine (0.92, 9.2)
533. qfdafaeawe (0.92, 14.0)
534. remiceline (0.92, 9.7)
535. smellarine (0.92, 9.6)
536. prosperine (0.92, 7.5)
537. JodyMarine (0.92, 9.3)
538. lenaperine (0.92, 10.0)
539. furadeline (0.92, 10.8)
540. larrysline (0.92, 8.3)
541. canomarine (0.92, 9.1)
542. princeline (0.92, 6.7)
543. flowerline (0.92, 6.2)
544. circleline (0.92, 7.7)
545. gigifeline (0.92, 10.2)
546. techmerine (0.92, 11.7)
547. mezkmarine (0.92, 11.7)
548. sexymarine (0.92, 5.6)
549. edegbeline (0.92, 10.9)
550. yarnoeline (0.92, 11.5)
551. leiafeline (0.92, 11.1)
552. oopipeline (0.92, 10.0)
553. Aventurine (0.92, 8.6)
554. hildaaline (0.92, 8.9)
555. diclemente (0.92, 8.8)
556. venogeline (0.92, 11.7)
557. parketline (0.92, 9.9)
558. aventurine (0.92, 7.4)
559. blogonline (0.92, 8.6)
560. gwendaline (0.92, 6.8)
561. murrabrine (0.92, 10.6)
562. journaline (0.92, 8.8)
563. stefonline (0.92, 8.0)
564. centreline (0.92, 6.4)
565. tullycrine (0.92, 9.9)
566. fiskfaline (0.92, 11.5)
567. sliverline (0.92, 7.0)
568. bodhnarine (0.92, 13.0)
569. libremente (0.92, 8.0)
570. alexonline (0.92, 7.0)
571. ibruznline (0.92, 14.0)
572. aikaterine (0.92, 9.4)
573. kappejeppe (0.92, 10.1)
574. alimonline (0.92, 8.8)
575. jordanline (0.92, 7.3)
576. peeponline (0.92, 8.1)
577. btangerine (0.92, 7.7)
578. benyagrine (0.92, 12.6)
579. leoninline (0.92, 10.6)
580. tourmaline (0.92, 4.9)
581. lionoonline (0.92, 7.3)
582. declemente (0.92, 9.2)
583. mobileline (0.92, 9.4)
584. Tourmaline (0.92, 6.8)
585. lauraoline (0.92, 8.3)
586. bergerline (0.92, 8.1)
587. by_levente (0.92, 11.5)
588. Sri@online (0.92, 9.5)
589. maroleline (0.92, 9.4)
590. viewonline (0.92, 8.8)
591. beluonline (0.92, 10.8)
592. alinealine (0.92, 6.4)
593. chepalline (0.92, 8.7)
594. fredraline (0.92, 9.9)
595. secureline (0.92, 6.9)
596. borderline (0.92, 5.2)
597. silverline (0.92, 4.7)
598. brokenline (0.92, 6.1)
599. Adrenaline (0.92, 5.9)
600. Mervonline (0.92, 11.0)
601. formerline (0.92, 7.3)
602. marieeline (0.92, 8.1)
603. adrenaline (0.92, 4.5)
604. workonline (0.92, 5.8)
605. tjinceline (0.92, 10.8)
606. Hurdonline (0.92, 11.1)
607. gssfonline (0.92, 11.0)
608. coohonline (0.92, 8.8)
609. maraonline (0.92, 7.3)
610. bestmarine (0.92, 7.7)
611. malaonline (0.92, 8.2)
612. realseline (0.92, 8.2)
613. talkonline (0.92, 8.5)
614. warnerline (0.92, 8.3)
615. frenchline (0.92, 6.4)
616. vikingline (0.92, 6.8)
617. rockmarine (0.92, 7.3)
618. thijseline (0.92, 9.2)
619. adexonline (0.92, 7.6)
620. dueponline (0.92, 8.9)
621. bpcoltrine (0.92, 12.5)
622. lalalaline (0.92, 8.5)
623. sertraline (0.92, 10.0)
624. clear@line (0.92, 10.7)
625. shoponline (0.92, 5.9)
626. Ecovonline (0.92, 11.9)
627. neveraline (0.92, 8.3)
628. usmcmarine (0.92, 7.7)
629. studioline (0.92, 7.5)
630. goldenline (0.92, 6.0)
631. keeskleppe (0.92, 11.5)
632. Franciline (0.92, 9.6)
633. cruiseline (0.92, 8.3)
634. marcelline (0.92, 5.8)
635. misterline (0.92, 7.3)
636. kokiroline (0.92, 10.8)
637. loversline (0.92, 6.3)
638. meshonline (0.92, 8.6)
639. mimiseline (0.92, 9.2)
640. fishonline (0.92, 6.5)
641. banjeurine (0.92, 13.2)
642. secondline (0.92, 6.4)
643. pierreline (0.92, 7.8)
644. maebelline (0.92, 7.9)
645. trampoline (0.92, 4.3)
646. signeoline (0.92, 10.5)
647. usovicente (0.92, 10.4)
648. gmeuroline (0.92, 11.7)
649. brite•line (0.92, 9.5)
650. gaiaonline (0.92, 6.5)
651. Trampoline (0.92, 5.8)
652. paschaline (0.92, 7.0)
653. adernaline (0.92, 8.4)
654. utdrumline (0.92, 9.5)
655. willtoexce (0.92, 10.6)
656. qtcaroline (0.92, 9.8)
657. robincline (0.92, 8.3)
658. technoline (0.92, 7.6)
659. merctaline (0.92, 10.4)
660. megaroline (0.92, 8.5)
661. mascueline (0.92, 9.6)
662. micaroline (0.92, 7.3)
663. patchaline (0.92, 8.1)
664. watchaline (0.92, 9.7)
665. ventevente (0.92, 7.5)
666. hicaroline (0.92, 8.8)
667. centerline (0.92, 5.2)
668. sgt_online (0.92, 9.7)
669. TeamOnline (0.92, 7.8)
670. Centerline (0.92, 6.7)
671. romuloline (0.92, 9.3)
672. boubacrine (0.92, 10.7)
673. nonnopeppe (0.92, 10.1)
674. nastraline (0.92, 8.1)
675. Poetryline (0.92, 10.2)
676. michealine (0.92, 7.0)
677. nonnobeppe (0.92, 10.5)
678. natureline (0.92, 7.0)
679. Tambourine (0.92, 7.3)
680. thirdnline (0.92, 11.6)
681. duskonline (0.92, 9.2)
682. tambourine (0.92, 6.3)
683. streamline (0.92, 4.9)
684. redskyline (0.92, 5.6)
685. sytleseine (0.92, 13.0)
686. kobbybrine (0.92, 10.4)
687. Streamline (0.92, 6.2)
688. gmcsirrine (0.92, 12.6)
689. k.atherine (0.92, 8.6)
690. kevinkline (0.92, 6.6)
691. palletline (0.92, 8.1)
692. amalkaline (0.92, 9.3)
693. dennerline (0.92, 9.7)
694. prayerline (0.92, 8.1)
695. playonline (0.92, 6.7)
696. clinecline (0.92, 8.3)
697. jeanneline (0.92, 7.7)
698. kenwalline (0.92, 10.8)
699. redairline (0.92, 7.8)
700. winnerline (0.92, 8.3)
701. irahonline (0.92, 10.3)

702. mexxonline (0.92, 9.5)
703. fingerline (0.92, 6.9)
704. gingerline (0.92, 7.2)
705. fashonline (0.92, 7.2)
706. tangerrine (0.92, 7.9)
707. boubouline (0.92, 6.5)
708. lawperrine (0.92, 10.2)
709. toptheline (0.92, 8.2)
710. gnomeseine (0.92, 9.1)
711. sexyonline (0.92, 5.9)
712. ionredline (0.92, 8.8)
713. mousseline (0.92, 5.8)
714. richonline (0.92, 7.9)
715. toyinbenye (0.92, 10.3)
716. rubenrenze (0.92, 10.1)
717. timberline (0.92, 4.6)
718. linkonline (0.92, 6.8)
719. copperline (0.92, 5.6)
720. Tannourine (0.92, 8.1)
721. cockerline (0.92, 7.5)
722. kimberline (0.92, 5.9)
723. grayfeline (0.92, 9.9)
724. carrolline (0.92, 6.7)
725. c●atherine (0.92, 8.6)
726. pimponline (0.92, 6.8)
727. rockonline (0.92, 6.3)
728. justherine (0.92, 6.9)
729. Timberline (0.92, 6.1)
730. tannourine (0.92, 7.4)
731. michelline (0.92, 5.9)
732. Mousseline (0.92, 7.1)
733. myarayline (0.92, 10.3)
734. sonyonline (0.92, 7.8)
735. leahceline (0.92, 7.7)
736. discipline (0.92, 3.7)
737. claudeline (0.92, 6.2)
738. donnelline (0.92, 8.0)
739. missyteine (0.92, 9.6)
740. pastmarine (0.92, 7.7)
741. srm@online (0.92, 9.7)
742. kryptoline (0.92, 7.6)
743. rammsteine (0.92, 6.3)
744. soncelline (0.92, 10.4)
745. tinaonline (0.92, 6.6)
746. ojpipeline (0.92, 9.0)
747. Mikkelline (0.92, 9.4)
748. octomarine (0.92, 7.6)
749. Discipline (0.92, 5.5)
750. lease-line (0.92, 9.3)
751. almaonline (0.92, 8.6)
752. mrgasoline (0.92, 8.3)
753. ptianceyye (0.92, 14.0)
754. finurjeppe (0.92, 13.7)
755. possieline (0.92, 9.1)
756. putzerline (0.92, 9.9)
757. hotsexline (0.92, 8.0)
758. sexyfeline (0.92, 9.6)
759. smytherine (0.92, 8.0)
760. topadiline (0.92, 12.1)
761. khatherine (0.92, 6.8)
762. sandyreine (0.92, 9.5)
763. denesoline (0.92, 9.8)
764. Streemline (0.92, 10.4)
765. aifaonline (0.92, 9.8)
766. thedecline (0.92, 7.3)
767. shitnurine (0.92, 11.8)
768. ekatherine (0.92, 6.7)
769. marie-line (0.92, 8.9)
770. methodline (0.92, 7.6)
771. thnbluline (0.92, 13.6)
772. clothsline (0.92, 10.1)
773. bettyaline (0.92, 8.1)
774. grooveline (0.92, 6.9)
775. m@gdouline (0.92, 11.7)
776. hijdarline (0.92, 12.4)
777. cathycline (0.92, 7.4)
778. chatraline (0.92, 8.8)
779. busterline (0.92, 7.6)
780. redboyline (0.92, 9.8)
781. casterline (0.92, 6.9)
782. saydedeoge (0.92, 13.3)
783. front.line (0.92, 8.1)
784. tickmoline (0.92, 10.2)
785. wadeacline (0.92, 10.2)
786. sandraline (0.92, 7.0)
787. whose_line (0.92, 11.4)
788. reneekline (0.92, 8.2)
789. sbcoffline (0.92, 10.5)
790. prezidente (0.92, 7.1)
791. tomatoline (0.92, 7.0)
792. katherline (0.92, 7.8)
793. apolloline (0.92, 7.7)
794. tonboyline (0.92, 11.0)
795. bryancline (0.92, 8.3)
796. magedreine (0.92, 11.2)
797. kellykline (0.92, 7.1)
798. elsiekline (0.92, 9.4)
799. linkedline (0.92, 6.8)
800. gtsskyline (0.92, 8.6)
801. chateleine (0.92, 10.0)
802. front_line (0.92, 8.1)
803. pchelpline (0.92, 9.7)
804. megancline (0.92, 8.1)
805. bobpauline (0.92, 7.7)
806. johnbeline (0.92, 9.9)
807. m.caroline (0.92, 8.2)
808. michaeline (0.92, 6.5)
809. quijemeute (0.92, 13.7)
810. Kathykline (0.92, 8.8)
811. beckycline (0.92, 8.4)
812. magdeleine (0.92, 8.3)
813. made.leine (0.92, 11.3)
814. cicoebeppe (0.92, 13.4)
815. tramopline (0.92, 10.4)
816. sacredline (0.92, 7.1)
817. michaaline (0.92, 9.5)
818. yemonkeyye (0.92, 13.7)
819. alleyseine (0.92, 10.8)
820. averyreine (0.92, 9.5)
821. ringopeppe (0.92, 10.5)
822. mylifeline (0.92, 6.4)
823. qqchotline (0.92, 12.1)
824. tyriqueawe (0.92, 11.4)
825. cccaroline (0.92, 8.8)
826. s@@bo@line (0.92, 13.5)
827. invhotline (0.92, 10.3)
828. eastmoline (0.92, 7.5)
829. myloveline (0.92, 6.9)
830. sisicaline (0.92, 9.6)
831. kilomarine (0.92, 8.0)
832. marjoleine (0.92, 6.2)
833. larobeline (0.92, 10.1)
834. fafcherine (0.92, 10.9)
835. papaverine (0.92, 8.5)
836. scamonline (0.92, 8.9)
837. thunderine (0.92, 7.5)
838. jadmouline (0.92, 10.7)
839. maakonline (0.92, 9.4)
840. chamonline (0.92, 7.0)
841. taffonline (0.92, 7.6)
842. oc.donline (0.92, 12.5)
843. fuckonline (0.92, 5.7)
844. majdouline (0.92, 6.6)
845. Hawgonline (0.92, 10.5)
846. rxpgonline (0.92, 11.3)
847. sda-online (0.92, 10.0)
848. partharine (0.92, 10.3)
849. designline (0.92, 7.2)
850. hopaofline (0.92, 13.1)
851. madyonline (0.92, 7.9)
852. j@cqueline (0.92, 6.3)
853. chaulkline (0.92, 8.9)
854. babyonline (0.92, 5.9)
855. sibcycline (0.92, 11.4)
856. tcb-online (0.92, 10.8)
857. acm-online (0.92, 10.2)
858. Andjerline (0.92, 12.2)
859. mplsmoline (0.92, 11.4)
860. khanonline (0.92, 7.0)
861. mdc.online (0.92, 10.3)
862. badgerline (0.92, 7.6)
863. startnline (0.92, 9.5)
864. bumperline (0.92, 7.6)
865. humberline (0.92, 9.1)
866. denesuline (0.92, 10.0)
867. lokionline (0.92, 7.4)
868. magaonline (0.92, 7.9)
869. kikionline (0.92, 7.6)
870. kiwionline (0.92, 8.3)
871. theomarine (0.92, 7.9)
872. calabrenze (0.92, 11.2)
873. bariciline (0.92, 12.9)
874. kafaonline (0.92, 8.6)
875. Maybelline (0.92, 7.1)
876. maybelline (0.92, 5.6)
877. sexoonline (0.92, 8.2)
878. Sportsline (0.92, 8.4)
879. pickupline (0.92, 7.0)
880. sadaonline (0.92, 8.0)
881. vegetaline (0.92, 7.7)
882. omoyeyeoge (0.92, 6.2)
883. hksskyline (0.92, 9.9)
884. geneonline (0.92, 7.9)
885. peppepeppe (0.92, 6.5)
886. jojoonline (0.92, 7.4)
887. gogoonline (0.92, 8.3)
888. loveonline (0.92, 5.1)
889. comeonline (0.92, 5.9)
890. J@cqueline (0.92, 6.3)
891. Patsycline (0.92, 8.4)
892. patsycline (0.92, 7.0)
893. Shanecline (0.92, 9.7)
894. zanakwenze (0.92, 12.2)
895. countyline (0.92, 6.5)
896. roseonline (0.92, 6.5)
897. capitoline (0.92, 6.6)
898. nextinline (0.92, 8.2)
899. cristaline (0.92, 6.1)
900. krystaline (0.92, 6.7)
901. switchline (0.92, 6.9)
902. jeppejeppe (0.92, 7.2)
903. chasekline (0.92, 7.4)
904. fedsonline (0.92, 9.9)
905. rehmerehme (0.92, 10.8)
906. pastycline (0.92, 9.4)
907. nileonline (0.92, 8.6)
908. annaarline (0.92, 10.4)
909. ribsonline (0.92, 9.2)
910. jobsonline (0.92, 8.5)
911. finishline (0.92, 5.0)
912. Randalline (0.92, 8.2)
913. westonline (0.92, 7.2)
914. Finishline (0.92, 6.6)
915. @herobrine (0.92, 9.3)
916. cessonline (0.92, 9.5)
917. jessonline (0.92, 8.9)
918. X@ccharine (0.92, 13.7)
919. scotchline (0.92, 7.5)
920. kissonline (0.92, 6.8)
921. healthline (0.92, 7.9)
922. liesonline (0.92, 8.8)
923. antoncline (0.92, 9.1)
924. naphtaline (0.92, 7.5)
925. sellonline (0.92, 8.7)
926. wilsonline (0.92, 7.2)
927. zeroonline (0.92, 6.7)
928. datingline (0.92, 6.1)
929. billonline (0.92, 7.2)
930. treoonline (0.92, 8.7)
931. Jacqueline (0.92, 4.5)
932. jacqueline (0.92, 3.3)
933. yacqueline (0.92, 8.8)
934. Avangeline (0.92, 8.8)
935. Evangeline (0.92, 5.2)
936. edieonline (0.92, 8.2)
937. evangeline (0.92, 4.1)
938. mymadeline (0.92, 7.7)
939. carsonline (0.92, 8.0)
940. magdheline (0.92, 11.4)
941. adamceline (0.92, 7.8)
942. epiemzembe (0.92, 13.8)
943. danaceline (0.92, 7.9)
944. fallinline (0.92, 7.3)
945. mayaceline (0.92, 8.1)
946. fawnfeline (0.92, 10.2)
947. shadowline (0.92, 5.9)
948. smukkeline (0.92, 7.6)
949. chandeline (0.92, 7.1)
950. euroonline (0.92, 7.7)
951. gtrskyline (0.92, 6.7)
952. staticline (0.92, 6.3)
953. edisonline (0.92, 7.5)
954. wwiionline (0.92, 11.2)
955. marthaline (0.92, 6.8)
956. mateonline (0.92, 6.0)
957. maryepeppe (0.92, 10.6)
958. Dateonline (0.92, 7.3)
959. amoronline (0.92, 8.3)
960. dateonline (0.92, 5.9)
961. smithkline (0.92, 8.4)
962. babbygeace (0.92, 10.0)
963. Aquamarine (0.92, 6.3)
964. faltapeine (0.92, 11.9)
965. stringline (0.92, 6.4)
966. muzionline (0.92, 9.7)
967. andycarine (0.92, 8.2)
968. aquamarine (0.92, 4.4)
969. babionline (0.92, 8.4)
970. gyrskyline (0.92, 9.0)
971. juancarine (0.92, 9.3)

972. papavarine (0.92, 10.3)	982. phauwarine (0.92, 14.0)	992. Jacquiline (0.92, 6.8)
973. paulonline (0.92, 7.6)	983. duckmarine (0.92, 6.7)	993. lustonline (0.92, 8.3)
974. buzzmarine (0.92, 8.5)	984. saccharine (0.92, 8.0)	994. scandiline (0.92, 8.3)
975. kaylonline (0.92, 10.9)	985. sharonline (0.92, 7.2)	995. gottageine (0.92, 11.6)
976. amandarine (0.92, 7.4)	986. daveonline (0.92, 7.6)	996. jacquiline (0.92, 5.8)
977. duplonline (0.92, 10.3)	987. kadoonline (0.92, 9.3)	997. dayoonline (0.92, 8.7)
978. ladymarine (0.92, 6.3)	988. danionline (0.92, 9.3)	998. sammysline (0.92, 8.0)
979. hawkmarine (0.92, 7.4)	989. waveonline (0.92, 7.2)	999. actionline (0.92, 6.6)
980. Safeonline (0.92, 8.9)	990. dppcholine (0.92, 13.1)	
981. deofevente (0.92, 11.3)	991. opsosaline (0.92, 10.5)	

Cluster 25

Prototype: 2R113aen110j

Hard-assigned passwords: 659544 (2.28% of total)
Unique hard-assigned passwords: 530564 (19.56% of cluster total)

Cluster-assignment scores:
        Min: 0.069
        Max: 0.964
        Mean: 0.425
        SD: 0.221

Strength bins:
        Very weak: 12358 (1.87%)
        Weak: 30137 (4.57%)
        Fair: 50080 (7.59%)
        Good: 233467 (35.40%)
        Strong: 333502 (50.57%)

Password lengths:
        Length 11: 5864 (0.89%)
        Length 12: 653680 (99.11%)

Character classes:
        4 classes: 16774 (2.54%)
        3 classes: 147640 (22.39%)
                lower/upper/symbol: 1115 (0.76%)
                lower/upper/number: 123549 (83.68%)
                lower/symbol/number: 20410 (13.82%)
                upper/symbol/number: 2566 (1.74%)
        2 classes: 470690 (71.37%)
                lower/upper: 1240 (0.26%)
                lower/number: 436706 (92.78%)
                lower/symbol: 454 (0.10%)
                upper/number: 23861 (5.07%)
                upper/symbol: 914 (0.19%)
                number/symbol: 7515 (1.60%)
        1 class: 24440 (3.71%)
                lower: 0 (0.00%)
                upper: 4630 (18.94%)
                symbol: 36 (0.15%)
                number: 19774 (80.91%)

Most frequent char-class structures:
        LLLLDDDDDDDD: 34017 (5.2%)
        DDDDDDDDDDD: 19395 (2.9%)
        DDDDDDDLLLL: 19362 (2.9%)
        DDDDDLLLLLL: 19226 (2.9%)
        LLLDDDDDDDD: 14246 (2.2%)
        DDDDDDDDLLL: 12642 (1.9%)
        DDDDLLLLLLL: 11635 (1.8%)
        LLLLLDDDDDD: 10724 (1.6%)
        DDDDDDDDDLL: 10613 (1.6%)
        DDDDDDDDDDL: 10528 (1.6%)

1,000 nearest passwords

  0. R4T4*pasad4* (0.96, 14.0)
  1. 4H0P2ewpv4Uw (0.96, 14.0)
  2. OGq71eljcKxb (0.96, 14.0)
  3. GFAC0mp0nent (0.96, 14.0)
  4. FD102<>csjob (0.96, 14.0)
  5. JHG65drtl&3% (0.96, 14.0)
  6. 4z355jocupub (0.96, 14.0)
  7. FD143<>cshob (0.95, 14.0)
  8. 3uy27gbltkob (0.95, 14.0)
  9. CHJ32nbf3TPk (0.95, 14.0)
 10. 2c3f6zickmkb (0.95, 14.0)
 11. 5AVk1tmk6aXg (0.95, 14.0)
 12. s1y24lnocnrt (0.95, 14.0)
 13. DBZ20xl*work (0.95, 14.0)
 14. COC&Gr8ful2b (0.95, 14.0)
 15. 2MQs6gneqhzb (0.95, 14.0)
 16. 4pRa2lgs9sYm (0.95, 14.0)
 17. 2z8g6cbfkodb (0.95, 14.0)
 18. 3EDC5tgb7ujm (0.95, 9.5)
 19. C(Q/7ag@xXdw (0.95, 14.0)
 20. 5u974mpmbcxk (0.95, 14.0)
 21. TJ7VXro7rvrj (0.95, 14.0)
 22. v1r35account (0.95, 12.1)
 23. 2JgM5idai9dm (0.95, 14.0)
 24. 5Ia48oz9wKpk (0.95, 14.0)
 25. x4A63ordy3Zb (0.95, 14.0)
 26. 3fz37goobpuk (0.95, 14.0)
 27. t1u44b9dljwk (0.95, 14.0)
 28. vAn34sChaick (0.95, 14.0)
 29. B10-Hazard15 (0.95, 14.0)
 30. OOM00mgood** (0.95, 14.0)
 31. 4y468wmpiepg (0.95, 14.0)
 32. MSs6Nd5jbibp (0.95, 14.0)
 33. DZNEOe8i0ahb (0.95, 14.0)
 34. 5h9k3ueankvk (0.95, 14.0)
 35. 3n9d6fpseuj5 (0.95, 14.0)
 36. AREVAnet12** (0.95, 14.0)
 37. MCaDSfnr5rcg (0.95, 14.0)
 38. HMOL6vLsrz7p (0.95, 14.0)
 39. 4c4c4connect (0.95, 11.4)
 40. JDG24@dori25 (0.95, 14.0)
 41. DQO90yku3mok (0.95, 14.0)
 42. ZBA63erj0APw (0.95, 14.0)
 43. 5o711of7kwrt (0.95, 14.0)
 44. MPW10network (0.95, 11.7)
 45. 5k163yyzwjat (0.95, 14.0)
 46. uIC66scr5QXm (0.95, 14.0)
 47. IT461project (0.95, 13.0)
 48. LHE2Iaq67leb (0.95, 14.0)
 49. MYG29tiv2uug (0.95, 14.0)
 50. YAHOOmail12w (0.95, 12.3)
 51. M1A1*tanker* (0.95, 14.0)
 52. NF3EKrwi5K15 (0.95, 14.0)
 53. sAlD7mmvW46b (0.95, 14.0)
 54. PVE09oMt9uVb (0.95, 14.0)
 55. NFL72perfect (0.95, 13.7)
 56. ZKv43sjl7UZt (0.95, 14.0)
 57. SR2u3kxhjH9F (0.94, 14.0)
 58. lE7XWq5cwS25 (0.94, 14.0)
 59. 2+3=5correct (0.94, 12.9)
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 89. 3r5t9ewluyhm (0.94, 14.0)
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 91. GP6F8lifSo30 (0.94, 14.0)
 92. CHE30bebotqm (0.94, 14.0)
 93. 5GPE2tvq0cG0 (0.94, 14.0)
 94. mOmT1p5hgAKj (0.94, 14.0)
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179. Z3r0Saneck15 (0.94, 14.0)
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186. OLUWAtobi008 (0.94, 7.1)
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433. 2qUP8ef4mm9k (0.93, 14.0)
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440. NN7K4ghLgC80 (0.93, 14.0)
441. DIB50kBD2fkw (0.93, 14.0)
442. DIB35njM1iSM (0.93, 14.0)
443. SSH30wtH4awU (0.93, 14.0)
444. LLCC0duM3P4j (0.93, 14.0)
445. OCPb3stcrypt (0.93, 14.0)
446. 2tv00wvdqtqm (0.93, 14.0)
447. AGC8Vte81gMp (0.93, 14.0)
448. 4r3b6mwl3i6k (0.93, 14.0)
449. MJx6Ewc05lFM (0.93, 14.0)
450. 2a6k3qvcn0om (0.93, 14.0)
451. N2CXAazlx8xg (0.93, 14.0)
452. TBL17iyE9smj (0.93, 14.0)
453. 2ty42mbvbuv5 (0.93, 14.0)
454. MKd4Lrt08Fgw (0.93, 14.0)
455. D2Q22hOeA1jb (0.93, 14.0)
456. PGZ2Wvb21gsM (0.93, 14.0)
457. YHV1Myr9zrgN (0.93, 14.0)
458. KDHY3zDq7E8g (0.93, 14.0)
459. KILL_mak8895 (0.93, 14.0)
460. zIkZ2vXcyzg8 (0.93, 14.0)
461. S4v0Na8gvlL8 (0.93, 14.0)
462. EC2hXzukdT95 (0.93, 14.0)
463. 3pz83wv2tybg (0.93, 14.0)
464. YJv85nxi2NEN (0.93, 14.0)
465. CANDYhard120 (0.93, 13.1)
466. CVK2Fno75LIw (0.93, 14.0)
467. MDo65kKU9pFg (0.93, 14.0)
468. 4vSF3yu9G29U (0.93, 14.0)
469. BNCH1newyork (0.92, 13.4)
470. 3ty26blokxjv (0.92, 14.0)
471. bIr89szl5acN (0.92, 14.0)
472. 3ih17azuz1m5 (0.92, 14.0)
473. JNU4Lph76LPj (0.92, 14.0)
474. XLk87xff5HjI (0.92, 14.0)
475. S3F^9qaodD5- (0.92, 14.0)
476. 3xCAQx07lE2j (0.92, 14.0)
477. SNGI4pzE9v1M (0.92, 14.0)
478. HTi6Puv02zeM (0.92, 14.0)
479. LEw61rrk7atb (0.92, 14.0)
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481. IDFkJzx6htfF (0.92, 14.0)
482. JMt34lgm6mvg (0.92, 14.0)
483. PUZ3Kaqq79g0 (0.92, 14.0)
484. MVT-W@rr10r$ (0.92, 14.0)
485. 00a38rebobev (0.92, 14.0)
486. MANOJ@cse505 (0.92, 14.0)
487. QTs27zzM6lsw (0.92, 14.0)
488. 6j3c9yloel2m (0.92, 14.0)
489. MBJ84ssH2qgv (0.92, 14.0)
490. 79s4Pg2Gw09w (0.92, 14.0)
491. CHUPAchups90 (0.92, 14.0)
492. 5j004log7fo5 (0.92, 14.0)
493. ENBx8rwwed55 (0.92, 14.0)
494. MXx32gWd4LlF (0.92, 14.0)
495. 8b6a4ewyhfxw (0.92, 14.0)
496. OFN9Mdm16gsM (0.92, 14.0)
497. LTS_*mypass* (0.92, 14.0)
498. SQG74uvL9Muv (0.92, 14.0)
499. 6ni02fpkg7vb (0.92, 14.0)
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501. qZIlVilra935 (0.92, 14.0)
502. 8h9r8uatapkk (0.92, 14.0)
503. 4w8y0zkrawev (0.92, 14.0)
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505. 5S8u0s0lRoav (0.92, 14.0)
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508. 2mFX0l6iSkhv (0.92, 14.0)
509. KWABEna12345 (0.92, 8.2)
510. 5g892zis6lzm (0.92, 14.0)
511. Z4D4Oocy8848 (0.92, 14.0)
512. 3nz82czfknzv (0.92, 14.0)
513. U4q0Dxz3s6MU (0.92, 14.0)
514. 5xj53yca6y3j (0.92, 14.0)
515. LQE21pyG7ifC (0.92, 14.0)
516. REm96kra7DTC (0.92, 14.0)
517. UBg80isD7YSI (0.92, 14.0)
518. 4vr72ceo3c2k (0.92, 14.0)
519. cUTe4hosting (0.92, 14.0)
520. MZJe9tjPqgIk (0.92, 14.0)
521. 5yv02es1yx7g (0.92, 14.0)
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523. XDl3Pnl43UgF (0.92, 14.0)
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525. 92/*-rawr22- (0.92, 14.0)
526. UIV81pyi6ivt (0.92, 14.0)
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528. 2BL04gJVe3Db (0.92, 14.0)
529. SJYO8u3gCu6g (0.92, 14.0)
530. D1dN0tD0ITok (0.92, 14.0)
531. 4u2u0qcvouf0 (0.92, 14.0)
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533. 7aw77tgucbow (0.92, 14.0)
534. 2iu0TsO14IDk (0.92, 14.0)
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537. WSKz9lnCSsfj (0.92, 14.0)
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539. MKO)9ijnBHU* (0.92, 12.5)
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542. UCQ20zPnkB88 (0.92, 14.0)
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544. 2x0r1obq4i9g (0.92, 14.0)
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546. BT1d4cJ6oCKt (0.92, 14.0)
547. 5w8e8tbgmfe0 (0.92, 14.0)
548. 5e0p5succhy8 (0.92, 14.0)
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550. 4ni52ze3avym (0.92, 14.0)
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552. 4kuC1nt4k4mU (0.92, 11.1)
553. MDY78riH3hsU (0.92, 14.0)
554. 5X696dukRx5k (0.92, 14.0)
555. XYL00zpm5esg (0.92, 14.0)
556. CGu37ddd6vdU (0.92, 14.0)
557. zIe93ltR2BUI (0.92, 14.0)
558. PFAvTx48Y7tw (0.92, 14.0)
559. FQReCeoeZl20 (0.92, 14.0)
560. HAj07bon9tut (0.92, 14.0)
561. 5q0f5ztddil8 (0.92, 14.0)
562. VD657megFaI0 (0.92, 14.0)
563. 0815Killer88 (0.92, 12.9)
564. ,A%c8^vZL%7> (0.92, 14.0)
565. OQYdFi4o1ovT (0.92, 14.0)
566. 5e2llobwbwu8 (0.92, 14.0)
567. 2tj22dzq4ebm (0.92, 14.0)
568. 2f4l2p8mck3j (0.92, 14.0)
569. GNM79aMA7zSm (0.92, 14.0)
570. W3bH0st_Mem0 (0.92, 14.0)
571. 5zt25nmaxje0 (0.92, 14.0)
572. 5gv33io2twq5 (0.92, 14.0)
573. D2R1Danna420 (0.92, 14.0)
574. 2P3k7y2crk.. (0.92, 14.0)
575. AWr08rsB3fvI (0.92, 14.0)
576. XU37NappG01C (0.92, 14.0)
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578. 2db32wkk8zgm (0.92, 14.0)
579. LHP4Bnx70rOU (0.92, 14.0)
580. YMCMBmmg0208 (0.92, 14.0)
581. 6fyP9sokvF70 (0.92, 14.0)
582. MQG32hoh6YBI (0.92, 14.0)
583. 5kn10pwdiyy8 (0.92, 14.0)
584. m1t97guxjpr8 (0.92, 14.0)
585. RCTIDimg30$$ (0.92, 14.0)
586. 5t0n3cutt3r5 (0.92, 14.0)
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588. HTOX0gp1XeOp (0.92, 14.0)
589. 3c323aprfij8 (0.92, 14.0)
590. 4xl20pewnin8 (0.92, 14.0)
591. PTx16t5wIuRv (0.92, 14.0)
592. 3l2l5kdpbxf8 (0.92, 14.0)
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594. CG464onG6bOC (0.92, 14.0)
595. 3x381p3bnkp5 (0.92, 14.0)
596. 3a253o5nfw8m (0.92, 14.0)
597. 5t0d6kmdvrk0 (0.92, 14.0)
598. AJ1KCp9iplZ0 (0.92, 14.0)
599. ABBASaa12345 (0.92, 12.4)
600. O4kIMueIlb75 (0.92, 14.0)
601. DWu3Evq92ONF (0.92, 14.0)
602. m1w14mxsl5uj (0.92, 14.0)
603. LWn65dup5Jkm (0.92, 14.0)
604. FBCR0s3m0unt (0.92, 14.0)
605. IEUw1pr0dfKH (0.92, 14.0)
606. PUI73pvy5MZI (0.92, 14.0)
607. CRg16diz8qIB (0.92, 14.0)
608. j1227rrdtrxm (0.92, 14.0)
609. ER7l1rGEni70 (0.92, 14.0)
610. IDP50ulo8QQM (0.92, 14.0)
611. 4m7bZcvjbf2q (0.92, 14.0)
612. DLFz4k7MDiqk (0.92, 14.0)
613. 4v7n4r4do5ab (0.92, 14.0)
614. VANYAlun2015 (0.92, 14.0)
615. e6d44x6AeTew (0.92, 14.0)
616. UCCCIlam2468 (0.92, 14.0)
617. 5s5f6fdgd6d5 (0.92, 14.0)
618. TURBOflag400 (0.92, 14.0)
619. BMk35rpi1siN (0.92, 14.0)
620. 65y76ba5epup (0.92, 14.0)
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622. xIxJWuHcSe90 (0.92, 14.0)
623. 3ur49avbf90g (0.92, 14.0)
624. ILOVEyou1290 (0.92, 10.0)
625. 3XmG6oP0j7kU (0.92, 14.0)
626. LYqWPqVFe2kg (0.92, 14.0)
627. FRqPMeV5v765 (0.92, 14.0)
628. 5l1s2thnrdu8 (0.92, 14.0)
629. 7913Zogge258 (0.92, 14.0)
630. HAGS4now3550 (0.92, 14.0)
631. 2rz93bsm3o7k (0.92, 14.0)
632. LOo36ann9bzw (0.92, 14.0)
633. 6Ya73bxCba90 (0.92, 14.0)
634. 3yw91utrev0v (0.92, 14.0)
635. FNc6Yte45zJT (0.92, 14.0)
636. 3sl23lj0lgw5 (0.92, 14.0)
637. gE010gyrock5 (0.92, 14.0)
638. XZT17jmad8v5 (0.92, 14.0)
639. UNI55center% (0.92, 14.0)
640. oOOqYb7cTe70 (0.92, 14.0)
641. 3y1q4guorhu8 (0.92, 14.0)
642. GQfMUg77Y1qk (0.92, 14.0)
643. 8t9e5ioyd9K5 (0.92, 14.0)
644. KO3g3baxgB4T (0.92, 14.0)
645. SKU99fyELe4U (0.92, 14.0)
646. 2L138z6K8tZw (0.92, 14.0)
647. 3h055ylrogj8 (0.92, 14.0)
648. EDv4BgW54zjg (0.92, 14.0)
649. 3Sw9BqDlpsu5 (0.92, 14.0)
650. 7z5n8mitgpop (0.92, 14.0)
651. UNSATeam2015 (0.92, 11.9)
652. 2m523fzncnov (0.92, 14.0)
653. 3hs55wqceig8 (0.92, 14.0)
654. 6t6h7razera0 (0.92, 14.0)
655. i4N1Tvi4N1Tv (0.92, 14.0)
656. 5ys83a8uhol5 (0.92, 14.0)
657. ICO1Mdx69bkU (0.92, 14.0)
658. 3be10i5juiav (0.92, 14.0)
659. JVe9JpF78PPw (0.92, 14.0)
660. SRp69eJ8UGHj (0.92, 14.0)
661. ZXCVBnm12345 (0.92, 6.4)
662. 4jj82diecoaf (0.92, 14.0)
663. 5d3oAh2Ak5tm (0.92, 14.0)
664. ZSASDrf856i5 (0.92, 14.0)
665. c6xIRvKr5y78 (0.92, 14.0)
666. 5i7x3kh1nu8p (0.92, 14.0)
667. AMD64solteck (0.92, 14.0)
668. VAu17sTL4bJj (0.92, 14.0)
669. 3o6x7edzcv90 (0.92, 14.0)
670. 5u3u3jkwbk30 (0.92, 14.0)
671. d3]!$y]bzbQ. (0.92, 14.0)
672. DZV29zJT8vwm (0.92, 14.0)
673. 6bu65dpax3tb (0.92, 14.0)
674. CBo01xnC4QAM (0.92, 14.0)
675. EJAZ1nish!@# (0.92, 14.0)
676. f1493norbert (0.92, 13.5)
677. BXg98tVM9PFw (0.92, 14.0)
678. SXHD2n3YdbJk (0.92, 14.0)
679. 2rw60lvkyfm0 (0.92, 14.0)
680. ABCDEfg12345 (0.92, 6.9)
681. 3cx50v7yf3fk (0.92, 14.0)
682. QEc03gAv4LlM (0.92, 14.0)
683. 2oy96bfv67nt (0.92, 14.0)
684. EBC7Jy6FW54j (0.92, 14.0)
685. YZHIAk39Z56w (0.92, 14.0)
686. IRISEufall88 (0.92, 14.0)
687. 5cr35w0dul7k (0.92, 14.0)
688. 4x2d0gdr2l0p (0.92, 14.0)
689. 3x1kLhnOS125 (0.92, 14.0)
690. EPt4AqF71kWF (0.92, 14.0)
691. 0241Jcze5640 (0.92, 14.0)
692. OAXX9vLlr748 (0.92, 14.0)
693. 0904Twenty10 (0.92, 12.5)
694. TVx64nkB23CI (0.92, 14.0)
695. 6e288lbdj7s5 (0.92, 14.0)
696. GOy0Adxh6w4C (0.92, 14.0)
697. JMwI8vxvrGZg (0.92, 14.0)
698. 5a2B4cogteob (0.92, 14.0)
699. 81a31bvndd9j (0.92, 14.0)
700. n4nN2u9clEdv (0.92, 14.0)
701. HPG2cwP62rbw (0.92, 14.0)

702. PBRV4tq0WWep (0.92, 14.0)
703. 3nd!3ssdr34m (0.92, 14.0)
704. URE89qCk1RFm (0.92, 14.0)
705. YFH92ykB4mFM (0.92, 14.0)
706. 3k58Oo9E2cU5 (0.92, 14.0)
707. wBY88uftw42k (0.92, 14.0)
708. SHATAjah1980 (0.92, 14.0)
709. 3a1y5qislch8 (0.92, 14.0)
710. 4a908j1osgq5 (0.92, 14.0)
711. ICKw1aImhqsF (0.92, 14.0)
712. 4WAwMv8yntp0 (0.92, 14.0)
713. UEw05smo3Ppp (0.92, 14.0)
714. 8gv73gtawxnw (0.92, 14.0)
715. NRJ74osy5LdH (0.92, 14.0)
716. O6SZZff99545 (0.92, 14.0)
717. YIP70xWZ4vIm (0.92, 14.0)
718. 73t34piayehv (0.92, 14.0)
719. LOL12zxcvbnm (0.92, 10.1)
720. h3Y9ZhCaw768 (0.92, 14.0)
721. 688IJcEo0g70 (0.92, 14.0)
722. GTS3Nnr36aGv (0.92, 14.0)
723. 3c1z1zye5o6p (0.92, 14.0)
724. 3g3l5jiqi7uv (0.92, 14.0)
725. OAh57ssd6qvI (0.92, 14.0)
726. D{f),;%s=heB (0.92, 14.0)
727. 5jg52yf4je9p (0.92, 14.0)
728. 4di50m4g4tut (0.92, 14.0)
729. 4y9p7a3qtp9m (0.92, 14.0)
730. nE89DfO80DY5 (0.92, 14.0)
731. 4pdDFs6Z2e5v (0.92, 14.0)
732. YP1JVc3rW4it (0.92, 14.0)
733. 2q2z6zcxzwl8 (0.92, 14.0)
734. 5yd4ll0lh4up (0.92, 14.0)
735. 5gj88polxm18 (0.92, 14.0)
736. TIV61xrF5MiM (0.92, 14.0)
737. UNDERtaker38 (0.92, 9.0)
738. ZJ8G8tJyQvhw (0.92, 14.0)
739. 5vr46aan5x0m (0.92, 14.0)
740. S6uSDb9wC240 (0.92, 14.0)
741. NYd8Nwm83Omg (0.92, 14.0)
742. BY88Yb4iAMHj (0.92, 14.0)
743. RBR1Rrp83YX0 (0.92, 14.0)
744. DH77RpMoD85v (0.92, 14.0)
745. KDr9ClT6jl78 (0.92, 14.0)
746. 5bb07i2sufh0 (0.92, 14.0)
747. o18A1zbHEi9k (0.92, 14.0)
748. f7mIYy1ygd55 (0.92, 14.0)
749. SUPERted2008 (0.92, 10.7)
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751. USq09rfV8NON (0.92, 14.0)
752. 45aYUa7v3v0w (0.92, 14.0)
753. 4xt87hvj6gi5 (0.92, 14.0)
754. e1s17sbw6izp (0.92, 14.0)
755. 5m971zodmv58 (0.92, 14.0)
756. 5YOeBaf38u1k (0.92, 14.0)
757. 3e2p3elm5lhv (0.92, 14.0)
758. 4dr14nhut0m0 (0.92, 11.6)
759. 2qx98np4nbhv (0.92, 14.0)
760. JRUTQcup6118 (0.92, 14.0)
761. 2wv01wiwq6i5 (0.92, 14.0)
762. 2hqZ4ejUo6Bj (0.92, 14.0)
763. CHE76miha!@# (0.92, 14.0)
764. 3i724bhi5bi5 (0.92, 14.0)
765. JSTgLto6G888 (0.92, 14.0)
766. YLLx2yvg6K6w (0.92, 14.0)
767. GBm17pcj9mJj (0.92, 14.0)
768. 5e7x0ww8dn5g (0.92, 14.0)
769. 8iy55hsrhosm (0.92, 14.0)
770. NSASEl9ct10N (0.92, 14.0)
771. AGn02dED2jcp (0.92, 14.0)
772. GHOSTrider90 (0.92, 8.8)
773. 4x4p0k3rk1ng (0.92, 13.1)
774. kI6o1ciuJC70 (0.92, 14.0)
775. 5k3y2rpbj3b8 (0.92, 14.0)
776. QTYq6qABp3Zb (0.92, 14.0)
777. h7h7Fgba6aq5 (0.92, 14.0)
778. GROUPscout25 (0.92, 12.9)
779. 5b7d7y7hetbv (0.92, 14.0)
780. GGe83gCI9yev (0.92, 14.0)
781. 4l0n3inky0t0 (0.92, 14.0)
782. MN1UJfR42315 (0.92, 14.0)
783. 2dv22ouwiqu0 (0.92, 14.0)
784. 5i993dp4zbzv (0.92, 14.0)
785. 7vj92xgcy7ab (0.92, 14.0)
786. 61u17fagebyw (0.92, 14.0)
787. 5pr99avmoetf (0.92, 14.0)
788. oAH05zFT3xap (0.92, 14.0)
789. 4t4l7sxo6wk0 (0.92, 14.0)
790. SHANErfc1690 (0.92, 14.0)
791. 5y253z6yzom5 (0.92, 14.0)
792. VOi67sgK6AXU (0.92, 14.0)
793. nEnE9xAg#6Q8 (0.92, 14.0)
794. pAVT6wzirum8 (0.92, 14.0)
795. 4j7r9k6eezv5 (0.92, 14.0)
796. o1o20vn4otg5 (0.92, 14.0)
797. VDq22lRP3Brt (0.92, 14.0)
798. SBHGUy552015 (0.92, 14.0)
799. AWA99waqdani (0.92, 14.0)
800. $1993pete325 (0.92, 14.0)
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802. 7ww82urjlfyb (0.92, 14.0)
803. *IK<.lo9)P:? (0.92, 14.0)
804. r6cHIklx4R38 (0.92, 14.0)
805. KOp16etT7onH (0.92, 14.0)
806. t1j47z2hxevg (0.92, 14.0)
807. 67k75xzutqwp (0.92, 14.0)
808. rT68DcYfE75k (0.92, 14.0)
809. a189XnsHxTm8 (0.92, 14.0)
810. NWW13oos6sEL (0.92, 14.0)
811. 5fy45dn9svfv (0.92, 14.0)
812. SMITH@151615 (0.92, 13.2)
813. 6s402rjvjuft (0.92, 14.0)
814. SCRUMhalle15 (0.92, 14.0)
815. NMB33pgN5jYM (0.92, 14.0)
816. 2Ay43nvpS860 (0.92, 14.0)
817. 86x46fwqk2ip (0.92, 14.0)
818. MVQ05wsz5vzN (0.92, 14.0)
819. 3fRB6r01KG3p (0.92, 14.0)
820. YMm5Eym47TIF (0.92, 14.0)
821. SHINEbrite08 (0.92, 13.3)
822. BQ8z9veReTmp (0.92, 14.0)
823. VOL75ppu9svv (0.92, 14.0)
824. WJPT8czQ0MEb (0.92, 14.0)
825. 4u3j1ue0brt5 (0.92, 14.0)
826. 6bn25ofscgrp (0.92, 14.0)
827. 2pL24rFd0vd0 (0.92, 14.0)
828. 7k4l5pcwskog (0.92, 14.0)
829. g1503aoi7oz5 (0.92, 14.0)
830. OLN55wjX0kit (0.92, 14.0)
831. 5t5x5zvd3lj5 (0.92, 14.0)
832. TK8LQqsq5WQk (0.92, 14.0)
833. 2ggGLtS54885 (0.92, 14.0)
834. 7y579ilqf3ej (0.92, 14.0)
835. CAPPYeagle05 (0.92, 14.0)
836. 2ze22unbmy38 (0.91, 14.0)
837. 2s8a8olk26uw (0.91, 14.0)
838. ZBC95svx95zb (0.91, 14.0)
839. 6uk29jip3fog (0.91, 14.0)
840. T4uQQmJ39225 (0.91, 14.0)
841. eE8v0ys0BMX8 (0.91, 14.0)
842. CHENGhua2008 (0.91, 11.2)
843. BFG45enivbyv (0.91, 14.0)
844. KZY02kyZ5hyB (0.91, 14.0)
845. 4DxH1mM1yK4p (0.91, 14.0)
846. 9410Wedding% (0.91, 13.5)
847. 2tw51s0crwuv (0.91, 14.0)
848. E6r0Aqr7QKsg (0.91, 14.0)
849. 79wMBtM38935 (0.91, 14.0)
850. TWj92rmA4UWN (0.91, 14.0)
851. MSiD8yG8CU7t (0.91, 14.0)
852. MOHANkumar18 (0.91, 11.3)
853. 2wsXVfr46yhN (0.91, 14.0)
854. HVu41xjw9VhN (0.91, 14.0)
855. WGI47mXt0soB (0.91, 14.0)
856. LNQN7l2Oq7a5 (0.91, 14.0)
857. KCoU9xZ1SsfF (0.91, 14.0)
858. 86a12qlze3tw (0.91, 14.0)
859. 4s0f1x8qq5wg (0.91, 14.0)
860. AO099rxu6l3w (0.91, 14.0)
861. WHAITboy1488 (0.91, 14.0)
862. FP3e3xDlVsgm (0.91, 14.0)
863. CK4W9wCn0vH8 (0.91, 14.0)
864. SAYANtan15.. (0.91, 14.0)
865. 4ku80py4ep7t (0.91, 14.0)
866. 3jh84q6sn5vg (0.91, 14.0)
867. 2od54e0bj5pp (0.91, 14.0)
868. 4xCNKpG16830 (0.91, 14.0)
869. 6vk28dbsfn65 (0.91, 14.0)
870. UEK26uaI2ySM (0.91, 14.0)
871. TEa88gzs6fJw (0.91, 14.0)
872. x6U5CpmEj1vv (0.91, 14.0)
873. 5qo83saqekxf (0.91, 14.0)
874. KHTC8wNCrg78 (0.91, 14.0)
875. RED44ellen** (0.91, 13.6)
876. GO123tab1reN (0.91, 14.0)
877. 5o880xdeoz28 (0.91, 14.0)
878. R1v2Iqd2PD60 (0.91, 14.0)
879. RSt4JtA88ETb (0.91, 14.0)
880. 5as39miyesci (0.91, 14.0)
881. 8c337lac7cub (0.91, 14.0)
882. G6G6Rjhv6Fuj (0.91, 14.0)
883. 3fm29ogyr1s8 (0.91, 14.0)
884. 7b779q7jkbsg (0.91, 14.0)
885. 3g4r4rbdn4of (0.91, 14.0)
886. 6pc80tu6ruxm (0.91, 14.0)
887. JBP5PaJc4t45 (0.91, 14.0)
888. 7qZaIa1arfjm (0.91, 14.0)
889. 16i4,is]hkKk (0.91, 14.0)
890. 4yk49ha2peiv (0.91, 14.0)
891. vUAp4vHNhT40 (0.91, 14.0)
892. VALISpaok888 (0.91, 14.0)
893. 2a3c3hil4jhv (0.91, 14.0)
894. CAPSLock1580 (0.91, 11.9)
895. 5uTS8yNSyt90 (0.91, 14.0)
896. 1m4g5muus2yj (0.91, 14.0)
897. WHITEb0y3690 (0.91, 13.7)
898. l1t0Webhost) (0.91, 13.8)
899. MXtA5z4A3bZt (0.91, 14.0)
900. 6vk63pv5vwej (0.91, 14.0)
901. 60k83sre3zzp (0.91, 14.0)
902. KZC59xXC6Fqg (0.91, 14.0)
903. 2c1t8rmfbl4v (0.91, 14.0)
904. 8ql37rqezc4w (0.91, 14.0)
905. g1v97wgr5bfw (0.91, 14.0)
906. KLLS9duV4Dfm (0.91, 14.0)
907. h1037rnceua5 (0.91, 14.0)
908. 06F12asawcat (0.91, 14.0)
909. z4s35dwarvb5 (0.91, 14.0)
910. xEF26uxv7wGA (0.91, 14.0)
911. SAMAIabdul40 (0.91, 14.0)
912. 5rd13lyzeaek (0.91, 14.0)
913. 4g216rq1uvs8 (0.91, 14.0)
914. 8dc29obtdusj (0.91, 14.0)
915. BIa2LxY7fox5 (0.91, 14.0)
916. 8sy30mtzxtgk (0.91, 14.0)
917. 7u8f1htsrikw (0.91, 14.0)
918. 02n24jexczot (0.91, 14.0)
919. 0sd87viijwib (0.91, 14.0)
920. 7mz16poqtack (0.91, 14.0)
921. 2x234dz5kb0g (0.91, 14.0)
922. 2dy21rtvmsk8 (0.91, 14.0)
923. XXIVMaggio35 (0.91, 14.0)
924. SCUBAsteve05 (0.91, 11.9)
925. ND%N1aezakmi (0.91, 14.0)
926. v1w73s3fkgzm (0.91, 14.0)
927. 4fr33h0st!ng (0.91, 9.9)
928. EVANSrle2565 (0.91, 14.0)
929. 5IDr1fE6hQ7g (0.91, 14.0)
930. 3ap51l4w8hnw (0.91, 14.0)
931. SUFODdofus25 (0.91, 14.0)
932. 6b5i3xibtttv (0.91, 14.0)
933. QCu68sip6vxv (0.91, 14.0)
934. SP.K(tyson)8 (0.91, 14.0)
935. 4AMC2network (0.91, 13.3)
936. 7hg93txsa0nw (0.91, 14.0)
937. GCJ41moa6ylO (0.91, 14.0)
938. 41ULHnt940ik (0.91, 14.0)
939. 4s6z1r7u9xqw (0.91, 14.0)
940. n1i06llbamkf (0.91, 14.0)
941. 5v746kq7yxb0 (0.91, 14.0)
942. HBZ62qzb1glv (0.91, 14.0)
943. w7S5IasgdO58 (0.91, 14.0)
944. 70CCCuo3i6vi (0.91, 14.0)
945. C1C1Qkoqlew5 (0.91, 14.0)
946. 6d426jijaz5p (0.91, 14.0)
947. SQWERzxpm985 (0.91, 14.0)
948. PAVLEpavle10 (0.91, 13.2)
949. VYI24qAf7rXU (0.91, 14.0)
950. OOL9Gzi36leB (0.91, 14.0)
951. 3z0k5f1hmcn0 (0.91, 14.0)
952. 6l729badc80p (0.91, 14.0)
953. 90126tj84TPN (0.91, 14.0)
954. 8xc69ipogf2w (0.91, 14.0)
955. $1976silver$ (0.91, 13.9)
956. 6tw34mfkumd5 (0.91, 14.0)
957. bAb1ZwbF0p98 (0.91, 14.0)
958. vOX84aTe8pIH (0.91, 14.0)
959. HE994moon145 (0.91, 14.0)
960. 2hc85dogjl70 (0.91, 14.0)
961. MFn29mID0Gwt (0.91, 14.0)
962. 3sy38z6te5up (0.91, 14.0)
963. 3ZL98xU55g8C (0.91, 14.0)
964. CMoRGaN1957% (0.91, 14.0)
965. ASE64mwV5XOt (0.91, 14.0)
966. FDNYSquad288 (0.91, 14.0)
967. ALEX4dm1n... (0.91, 14.0)
968. THV22wdM1mFH (0.91, 14.0)
969. NRN7Rtx60pvB (0.91, 14.0)
970. 4jxUKrQ35720 (0.91, 14.0)
971. 8l6u8fvvmk8t (0.91, 14.0)

972. 6i8r4t7xrptk (0.91, 14.0)
973. 5kTr7mLd0FeF (0.91, 14.0)
974. TSINGhua2970 (0.91, 14.0)
975. 5w9v4kb7jmm0 (0.91, 14.0)
976. 8o7b6tgiqa2j (0.91, 14.0)
977. f12I5caFranN (0.91, 14.0)
978. a4DYQlZ83108 (0.91, 14.0)
979. aASsDcQ36465 (0.91, 14.0)
980. ILYSMidc1508 (0.91, 14.0)
981. 6O83Xps45hZm (0.91, 14.0)
982. iIhQ8r4SQsrj (0.91, 14.0)
983. 7a3l3cgiqgs0 (0.91, 14.0)
984. 5vj13pk53nuj (0.91, 14.0)
985. SWEETanu2078 (0.91, 13.4)
986. GUx7Kx3Lri78 (0.91, 14.0)
987. rUrCLmIteb0g (0.91, 14.0)
988. e1t96vunkiji (0.91, 14.0)
989. 7x657ghoqp25 (0.91, 14.0)
990. 5i8f0qdj0qc0 (0.91, 14.0)
991. TVj12uUr4VTM (0.91, 14.0)
992. T4uQQmJ24790 (0.91, 14.0)
993. 6s992appnlj8 (0.91, 14.0)
994. 4ow69z1m8vck (0.91, 14.0)
995. 3@7PYr46$db8 (0.91, 14.0)
996. 3qn42hjsf5n8 (0.91, 14.0)
997. 61b73pz5zu8p (0.91, 14.0)
998. 8hn91hbztusw (0.91, 14.0)
999. rIES3pBjxy90 (0.91, 14.0)

Cluster 26

Prototype: s0s4ne05

Hard-assigned passwords: 1118178 (3.86% of total)
Unique hard-assigned passwords: 893674 (20.08% of cluster total)

Cluster-assignment scores:
	Min: 0.089
	Max: 0.954
	Mean: 0.365
	SD: 0.149

Strength bins:
	Very weak: 16286 (1.46%)
	Weak: 57994 (5.19%)
	Fair: 131277 (11.74%)
	Good: 763656 (68.29%)
	Strong: 148965 (13.32%)

Password lengths:
	Length 8: 975724 (87.26%)
	Length 9: 130022 (11.63%)
	Length 10: 12432 (1.11%)

Character classes:
	4 classes: 44150 (3.95%)
	3 classes: 306445 (27.41%)
		lower/upper/symbol: 4240 (1.38%)
		lower/upper/number: 269608 (87.98%)
		lower/symbol/number: 25505 (8.32%)
		upper/symbol/number: 7092 (2.31%)
	2 classes: 751969 (67.25%)
		lower/upper: 12529 (1.67%)
		lower/number: 673986 (89.63%)
		lower/symbol: 943 (0.13%)
		upper/number: 61372 (8.16%)
		upper/symbol: 1594 (0.21%)
		number/symbol: 1545 (0.21%)
	1 class: 15614 (1.40%)
		lower: 0 (0.00%)
		upper: 15446 (98.92%)
		symbol: 168 (1.08%)
		number: 0 (0.00%)

Most frequent char-class structures:
	LDDDDDDD: 45284 (4.0%)
	LDLDLDLD: 41939 (3.8%)
	LDDDDDDDD: 39630 (3.5%)
	DLLLLLLL: 30490 (2.7%)
	LDLLLLLL: 28997 (2.6%)
	LDDDDDDL: 16238 (1.5%)
	UUUUUUUU: 15446 (1.4%)
	DLDLDLDL: 14305 (1.3%)
	LDDLLLLL: 11596 (1.0%)
	LDLLLDLL: 11343 (1.0%)

1,000 nearest passwords

0.	cDD1dw1N	(0.95, 12.9)	54.	hDv8gr7N	(0.92, 13.0)	108.	n1c5n@t8	(0.91, 13.4)
1.	wJH1zn1T	(0.95, 13.3)	55.	T1m3pas5	(0.92, 9.6)	109.	8e2aafb8	(0.91, 11.2)
2.	m4a1colT	(0.95, 12.6)	56.	i6s2ouw5	(0.92, 12.4)	110.	pTv6tK1T	(0.91, 13.3)
3.	7c0cca4B	(0.95, 13.6)	57.	8r96klt5	(0.92, 12.6)	111.	7ny6vui8	(0.91, 12.6)
4.	qHG1pj1H	(0.95, 13.2)	58.	t3h9ela5	(0.92, 11.8)	112.	rJl7mK1T	(0.91, 13.4)
5.	z6n2zcqB	(0.95, 14.0)	59.	B4m8o0sH	(0.92, 14.0)	113.	r4c3car5	(0.91, 10.0)
6.	k3v0subB	(0.95, 12.7)	60.	6mNLg16J	(0.92, 14.0)	114.	7eu9pls5	(0.91, 12.5)
7.	kCt1xn2T	(0.94, 13.6)	61.	G4g3siz5	(0.92, 13.2)	115.	rTj4rS3B	(0.91, 13.1)
8.	rVG0pg1T	(0.94, 13.3)	62.	qXD6ww1B	(0.92, 13.2)	116.	sTe9xv0T	(0.91, 14.0)
9.	cNw1kn1T	(0.94, 13.3)	63.	7hCww2mH	(0.91, 14.0)	117.	8r3arvt5	(0.91, 12.9)
10.	hCR6jc1C	(0.94, 13.2)	64.	j6o4mfj5	(0.91, 13.2)	118.	7qg6vko5	(0.91, 12.7)
11.	a6w9pgkH	(0.93, 14.0)	65.	l1v3ant5	(0.91, 10.2)	119.	e4d3eyj5	(0.91, 13.0)
12.	p7W6km2C	(0.93, 14.0)	66.	8wb3yed5	(0.91, 12.7)	120.	b1e6eee8	(0.91, 11.1)
13.	rTg4ks9T	(0.93, 13.2)	67.	c4p9fz5N	(0.91, 14.0)	121.	hTx9nd1B	(0.91, 13.1)
14.	d4g2aK1C	(0.93, 14.0)	68.	tBk9sp1J	(0.91, 13.1)	122.	7ts6gub5	(0.91, 12.5)
15.	prN1pd2J	(0.93, 13.2)	69.	k4h8t8GF	(0.91, 13.9)	123.	j4j9jjJJ	(0.91, 13.4)
16.	h3j1ngLN	(0.93, 13.2)	70.	6N5qdc2T	(0.91, 14.0)	124.	lCx1hn0M	(0.91, 13.5)
17.	qDW1mg6N	(0.93, 12.9)	71.	b4j1ng4N	(0.91, 7.8)	125.	m7z*t5kL	(0.91, 14.0)
18.	Q2u3ee4N	(0.93, 14.0)	72.	h3w%pi!M	(0.91, 14.0)	126.	bRc6nb1C	(0.91, 12.8)
19.	rVz7dX1N	(0.93, 13.1)	73.	7d4qbvi5	(0.91, 12.7)	127.	kHk1nG7H	(0.91, 13.1)
20.	K7E8p0oM	(0.93, 14.0)	74.	sGK1nd9H	(0.91, 13.2)	128.	7xu0nio5	(0.91, 12.4)
21.	7nn3mxo5	(0.92, 12.7)	75.	$GAmec05	(0.91, 13.0)	129.	7d9kimv8	(0.91, 12.4)
22.	6l2aby0N	(0.92, 14.0)	76.	tBg4cw9T	(0.91, 13.2)	130.	7l35yhy5	(0.91, 12.4)
23.	r{J8im5T	(0.92, 14.0)	77.	8Bd8wxk5	(0.91, 14.0)	131.	8P9xrg7N	(0.91, 14.0)
24.	gVH1jq0C	(0.92, 12.8)	78.	r!(4rd0(	(0.91, 14.0)	132.	z7gFam85	(0.91, 14.0)
25.	Q2X7m3nC	(0.92, 14.0)	79.	f6g3lhc5	(0.91, 12.5)	133.	7O9Wc7v5	(0.91, 14.0)
26.	8c6ccbc5	(0.92, 11.1)	80.	rTz7fS6H	(0.91, 13.4)	134.	yQBme98J	(0.90, 14.0)
27.	8p8hnpv5	(0.92, 12.9)	81.	lBm3sd5B	(0.91, 13.0)	135.	T6v8cnoN	(0.90, 14.0)
28.	b3m2w8IC	(0.92, 14.0)	82.	8o6uexb8	(0.91, 12.5)	136.	nTd1zg5N	(0.90, 13.0)
29.	M!g0toe5	(0.92, 13.5)	83.	cH5wnn3B	(0.91, 14.0)	137.	rGk9xx2N	(0.90, 13.2)
30.	kCq2sv6N	(0.92, 13.3)	84.	8g6hfjo8	(0.91, 12.5)	138.	wLP1hp5B	(0.90, 13.4)
31.	R3d4l3rT	(0.92, 10.3)	85.	8ly0hoo5	(0.91, 12.7)	139.	u4s5syr8	(0.90, 12.4)
32.	tDj5nv2N	(0.92, 13.1)	86.	A7G7qwg5	(0.91, 14.0)	140.	c4r1du1T	(0.90, 11.1)
33.	tNh5qs9N	(0.92, 13.2)	87.	v6p7e-aN	(0.91, 14.0)	141.	7n0ldda8	(0.90, 12.9)
34.	E4n0amsB	(0.92, 14.0)	88.	M3l3nky5	(0.91, 12.5)	142.	8s4xoxg5	(0.90, 12.6)
35.	8mk2yld5	(0.92, 12.8)	89.	i6o3bca5	(0.91, 12.2)	143.	n3u7ghaL	(0.90, 13.8)
36.	bZH7wf1T	(0.92, 13.3)	90.	g6o2xcn5	(0.91, 12.6)	144.	w4i9aukC	(0.90, 14.0)
37.	7v5zygf5	(0.92, 12.7)	91.	7p5xtaj5	(0.91, 12.7)	145.	n3o6hdv5	(0.90, 12.3)
38.	vWc1qJ1C	(0.92, 13.0)	92.	8l2qfty5	(0.91, 12.7)	146.	7bZsot08	(0.90, 14.0)
39.	C3l3gan5	(0.92, 11.0)	93.	8q8ujhu5	(0.91, 12.7)	147.	o3y5gnf5	(0.90, 12.4)
40.	rGk6bL1N	(0.92, 13.2)	94.	xDc5hC1N	(0.91, 13.1)	148.	iR21h1tH	(0.90, 14.0)
41.	8Q@0d9*C	(0.92, 14.0)	95.	A7eYac45	(0.91, 14.0)	149.	7s2rymp8	(0.90, 12.6)
42.	6k2vwoz5	(0.92, 12.7)	96.	M3x6ktj5	(0.91, 14.0)	150.	pR71xy8B	(0.90, 14.0)
43.	8o9bbhm5	(0.92, 12.6)	97.	c3s4rpc5	(0.91, 11.1)	151.	hSg8vV1C	(0.90, 13.1)
44.	8it7jsn5	(0.92, 12.6)	98.	a6u4xdu5	(0.91, 12.2)	152.	h4dCh64B	(0.90, 14.0)
45.	8l5jjsp5	(0.92, 12.7)	99.	8e5rtqk5	(0.91, 12.4)	153.	w1n9nut5	(0.90, 10.5)
46.	dXb1tj6T	(0.92, 13.0)	100.	8p8deca8	(0.91, 12.4)	154.	W3l0v3SF	(0.90, 11.2)
47.	dSs1dd6T	(0.92, 12.9)	101.	kGw4vn9H	(0.91, 13.4)	155.	wCn6hv9N	(0.90, 13.3)
48.	m4y3g5BT	(0.92, 14.0)	102.	fCJ1cc4J	(0.91, 13.5)	156.	8YZ0h0uF	(0.90, 14.0)
49.	lVq8sw1N	(0.92, 13.2)	103.	u6h6eva5	(0.91, 12.2)	157.	7n0Pp9zI	(0.90, 14.0)
50.	v4i3zov5	(0.92, 12.9)	104.	8x7lndv5	(0.91, 12.7)	158.	c4f9ecf5	(0.90, 11.5)
51.	A3d4stu5	(0.92, 12.6)	105.	j7H6o8bF	(0.91, 14.0)	159.	r4u3yaf5	(0.90, 12.2)
52.	v3n3ac3F	(0.92, 12.8)	106.	8s6xykw5	(0.91, 12.6)	160.	j3t3voi5	(0.90, 12.5)
53.	7l3cjaf5	(0.92, 12.5)	107.	o4i9reh5	(0.91, 12.5)	161.	e6c9aea5	(0.90, 11.0)

162. vDP0sr1N (0.90, 13.2)
163. 7b7cygm5 (0.90, 12.6)
164. f1c5etr8 (0.90, 12.3)
165. 7t7rgrs5 (0.90, 12.2)
166. 8r8xlec8 (0.90, 12.6)
167. 8O8$c0tT (0.90, 14.0)
168. g4r3s9KL (0.90, 13.8)
169. r4n4cyu5 (0.90, 11.2)
170. 8i8gknx8 (0.90, 12.3)
171. sB1ind25 (0.90, 13.0)
172. s3q3ryx5 (0.90, 12.1)
173. cNt6sk8N (0.90, 13.1)
174. d1e8bbe5 (0.90, 10.7)
175. 7uv3ntu5 (0.90, 8.6)
176. f4i3wuw8 (0.90, 12.6)
177. 7l2yhdu8 (0.90, 12.6)
178. rTz9wS7B (0.90, 13.2)
179. hrQ1gl3T (0.90, 13.2)
180. tNIGw89B (0.90, 14.0)
181. 7b0ygyd5 (0.90, 12.5)
182. 8p5kcdt5 (0.90, 12.6)
183. 8i5aeuq8 (0.90, 12.4)
184. t1e6hai5 (0.90, 12.5)
185. 6v4ugam8 (0.90, 12.7)
186. cPMcr67F (0.90, 14.0)
187. s6u5efh8 (0.90, 12.5)
188. cDQ3jj0T (0.90, 13.3)
189. 7q5ekvy5 (0.90, 12.6)
190. yK18idjM (0.90, 14.0)
191. u2I8i74T (0.90, 14.0)
192. 6ZiQq3g5 (0.90, 14.0)
193. tRaNex15 (0.90, 11.1)
194. wDx3jT7B (0.90, 13.2)
195. 7dt8aq7N (0.90, 14.0)
196. rHd9qg8N (0.90, 13.1)
197. c3m2u2LI (0.90, 12.6)
198. v3r4cru5 (0.90, 7.7)
199. gTt7rx1B (0.90, 13.1)
200. lVh4hP8B (0.90, 13.1)
201. tHL4hx1M (0.90, 13.1)
202. c7Z4tz7U (0.90, 14.0)
203. 6WN3h03T (0.90, 14.0)
204. mMw4mS1H (0.90, 12.9)
205. b1q5rst5 (0.90, 12.2)
206. 8f0dkfl5 (0.90, 12.7)
207. 7m9vsve5 (0.90, 12.6)
208. a4t2gcu8 (0.90, 12.5)
209. kTc3nd0N (0.90, 13.1)
210. d4o4bjl5 (0.90, 12.8)
211. 8z3wolw5 (0.90, 12.8)
212. jBr9zn1B (0.90, 13.1)
213. xRs0pm9C (0.90, 13.3)
214. S2D3f4g5 (0.90, 9.2)
215. b4m5mun5 (0.90, 12.0)
216. pDx4xd0N (0.90, 13.0)
217. sHB1acb8 (0.90, 14.0)
218. dGh9bn7N (0.90, 12.9)
219. e6x4ljv5 (0.90, 12.5)
220. t6q5oyfw (0.90, 12.7)
221. wKlRj16H (0.90, 14.0)
222. rNq3mH8M (0.90, 13.5)
223. bDeSq25C (0.90, 14.0)
224. tKM0nd8N (0.90, 13.5)
225. yGZ0r8kN (0.90, 14.0)
226. 8m6heyj5 (0.90, 12.6)
227. o3h3oeh5 (0.90, 11.1)
228. nTf7pC8C (0.90, 13.1)
229. v6i7di55 (0.90, 12.5)
230. 6m7gplh5 (0.90, 12.8)
231. C3l3ste8 (0.90, 9.0)
232. n6c5k9^^ (0.90, 14.0)
233. t6d9fey5 (0.90, 12.7)
234. r4g1tzu5 (0.90, 10.1)
235. 8n06p4lH (0.90, 14.0)
236. kZc8nc2C (0.89, 13.3)
237. q3o6tag5 (0.89, 12.6)
238. 8r00kly^ (0.89, 13.2)
239. jDD7jk7N (0.89, 13.0)
240. a4m6rgd5 (0.89, 12.3)
241. E2V5ol25 (0.89, 13.8)
242. vSw6dr1N (0.89, 13.1)
243. iNUtb91B (0.89, 14.0)
244. n7Q3tK5H (0.89, 14.0)
245. c7r3th9B (0.89, 14.0)
246. 8t31c9BN (0.89, 14.0)
247. h3b3knh5 (0.89, 12.1)
248. v4a2eyf5 (0.89, 12.5)
249. l2aKe4a5 (0.89, 13.8)
250. R2Y8a1n5 (0.89, 12.8)
251. wRN6wl1H (0.89, 13.2)
252. l4t0bhc5 (0.89, 13.5)
253. zDm4nP8C (0.89, 12.9)
254. bDt3hd3N (0.89, 12.9)
255. b4d6abc8 (0.89, 11.2)
256. d6e4efd5 (0.89, 10.9)
257. sXS0jt1B (0.89, 13.4)
258. 6t4pzxyw (0.89, 12.6)
259. wWn4fd1B (0.89, 13.6)
260. 8m8rett8 (0.89, 12.2)
261. jPM1fm2T (0.89, 13.4)
262. 7j8shtbw (0.89, 12.8)
263. 7k0saby5 (0.89, 12.5)
264. s4y4ngkU (0.89, 6.6)
265. 7g8ksvt5 (0.89, 12.5)
266. fDc0sM5N (0.89, 13.1)
267. f1r3@nt5 (0.89, 10.7)
268. zNb7nM9C (0.89, 13.2)
269. 6f3rwahw (0.89, 13.1)
270. k3p6vrj5 (0.89, 12.7)
271. r6h6ykz5 (0.89, 12.4)
272. n6i4nkdw (0.89, 12.9)
273. tHC1mf7L (0.89, 13.0)
274. 7ed5gne5 (0.89, 12.1)
275. mBc3mW6T (0.89, 13.2)
276. 8y4pnyj5 (0.89, 12.8)
277. b7lLod38 (0.89, 14.0)
278. sVm6fT0N (0.89, 13.5)
279. xBc9ss9N (0.89, 13.1)
280. u4i1snd8 (0.89, 12.3)
281. kXc3wb6T (0.89, 13.4)
282. a4b4ycc0 (0.89, 11.2)
283. e4d3qgg5 (0.89, 12.4)
284. tDRmac78 (0.89, 12.7)
285. pWGbiv45 (0.89, 13.4)
286. b4t4tof0 (0.89, 11.8)
287. 7k5kbnp5 (0.89, 12.4)
288. u6t8sgaw (0.89, 12.6)
289. Y6h0qvJF (0.89, 14.0)
290. hCd7fl8T (0.89, 13.2)
291. dRk3bv2J (0.89, 12.9)
292. hV+2m6jT (0.89, 14.0)
293. 7RTbf82B (0.89, 14.0)
294. y7bBnl7w (0.89, 14.0)
295. 8s7foej8 (0.89, 12.6)
296. 8fGIj6x5 (0.89, 14.0)
297. y1s3bitw (0.89, 12.9)
298. 8oy7udf0 (0.89, 12.5)
299. m4r7inu5 (0.89, 10.3)
300. 6uvFv03U (0.89, 14.0)
301. x6o5ooqw (0.89, 12.5)
302. g7#%kf45 (0.89, 14.0)
303. x3u7dch5 (0.89, 12.4)
304. lNt7jl8B (0.89, 13.2)
305. m1l4nel0 (0.89, 10.0)
306. f4r1d●m5 (0.89, 13.7)
307. mVd3mW7T (0.89, 13.2)
308. fLq2fm9T (0.89, 13.4)
309. p4m3lacw (0.89, 11.1)
310. l4e3afn8 (0.89, 12.7)
311. y4o1ues8 (0.89, 12.4)
312. i3h6eyw5 (0.89, 12.4)
313. n4n0b0TT (0.89, 12.0)
314. pR1nce55 (0.89, 7.6)
315. m4i3hvq8 (0.89, 11.9)
316. kQz8mT3N (0.89, 13.2)
317. cKv9sx5T (0.89, 13.5)
318. n6m8jefR (0.89, 14.0)
319. H3l3nlaw (0.89, 9.9)
320. kCb0cD7N (0.89, 13.1)
321. 8i5wcmkw (0.89, 12.8)
322. 8f8xixi5 (0.89, 12.8)
323. z2X3c4v5 (0.89, 10.2)
324. fYSrss15 (0.89, 14.0)
325. cVp4nm6T (0.89, 13.2)
326. 8g2zvlzw (0.89, 13.1)
327. 8a1cecn0 (0.89, 12.1)
328. n1k0lce5 (0.89, 11.1)
329. 6y4sgyx5 (0.89, 12.7)
330. bGH3wq6N (0.89, 13.3)
331. kKw7tl9B (0.89, 13.6)
332. xDt6xd9B (0.89, 12.8)
333. 0w3sbux5 (0.89, 11.6)
334. oVCJg13C (0.89, 14.0)
335. 7d9ywdjw (0.89, 13.1)
336. cCd3hl1B (0.89, 13.3)
337. pHh3rM8B (0.89, 13.3)
338. 6of4dezw (0.89, 12.8)
339. bKN0lw7N (0.89, 13.2)
340. e1d9cie8 (0.89, 13.1)
341. gGTbtx05 (0.89, 13.9)
342. 6jaTje65 (0.89, 13.9)
343. l4r1llww (0.89, 13.7)
344. 8oi0lnc8 (0.89, 12.4)
345. s1p6cxl5 (0.89, 12.7)
346. 8p6wrqy5 (0.89, 12.6)
347. kFD8j5dN (0.89, 14.0)
348. j3r4ch0J (0.89, 11.3)
349. 7i26gutw (0.89, 12.9)
350. jPL0lz0C (0.89, 13.6)
351. dDv5xm5B (0.89, 13.2)
352. gND1rn2w (0.89, 13.2)
353. q7F5n1JU (0.89, 14.0)
354. rJh1fk7J (0.89, 13.1)
355. M3y3nii5 (0.89, 13.5)
356. b1n3mro0 (0.89, 12.7)
357. $H0bhna0 (0.89, 14.0)
358. 7mx3qiU5 (0.89, 14.0)
359. L!a6ty⋆0 (0.89, 14.0)
360. 7AdLbw0w (0.89, 14.0)
361. b7w3tpTT (0.89, 14.0)
362. 6a2rkgp5 (0.89, 12.6)
363. c4s4rrfw (0.89, 12.0)
364. t4t3rs55 (0.89, 10.5)
365. i4d2yzc0 (0.89, 12.5)
366. t6t0sco5 (0.89, 12.7)
367. d3N0npr0 (0.89, 12.6)
368. j6w2gka5 (0.89, 12.5)
369. d1e8nyl0 (0.89, 12.0)
370. xXHre69F (0.89, 14.0)
371. o1r0jti5 (0.89, 13.1)
372. 8d3ywam0 (0.89, 12.6)
373. iTN1yg3w (0.89, 14.0)
374. p3G0fV0F (0.89, 14.0)
375. j6y1eot8 (0.89, 12.2)
376. e6o2vvbw (0.89, 12.9)
377. q6v6zyu5 (0.89, 12.5)
378. r3W0rk#8 (0.89, 13.0)
379. 8q3ybucw (0.89, 13.0)
380. p3c6sWew (0.89, 14.0)
381. hJh6xx1H (0.89, 13.1)
382. wQQ9gx1T (0.89, 13.4)
383. p4r6ohp5 (0.89, 12.5)
384. 7t43jla0 (0.89, 12.6)
385. rRhHtr65 (0.89, 13.9)
386. s3j2syv8 (0.89, 12.4)
387. z4g2nmk5 (0.89, 12.5)
388. 8f9pqia8 (0.89, 12.4)
389. k3v3naGM (0.89, 12.6)
390. sNl8nL7C (0.89, 13.0)
391. zTN1ng6L (0.89, 13.1)
392. R3b3ccaM (0.89, 8.1)
393. D4r1ndnw (0.89, 13.9)
394. hJk6zf9H (0.89, 13.2)
395. fZd1tH7B (0.89, 13.1)
396. 8f62kah5 (0.89, 12.4)
397. eMAvt68C (0.89, 14.0)
398. m4m3luc0 (0.89, 8.0)
399. d1d4riy0 (0.89, 11.6)
400. t6m9d2RJ (0.89, 14.0)
401. I7eMp1uw (0.89, 14.0)
402. z6x6obv8 (0.89, 12.9)
403. s4o7jzw8 (0.89, 12.6)
404. d3l1lah8 (0.88, 10.5)
405. f3t9kBqH (0.88, 14.0)
406. b4u2ajv8 (0.88, 12.6)
407. L3u4hzv8 (0.88, 14.0)
408. p4t3tic0 (0.88, 9.8)
409. 8g22briw (0.88, 12.6)
410. qMt7dd9H (0.88, 13.0)
411. bZq3gzwC (0.88, 14.0)
412. wPd0nH0H (0.88, 13.2)
413. 6w4cgtj5 (0.88, 12.7)
414. 8wk3ynb5 (0.88, 12.6)
415. pKm3xj1N (0.88, 13.2)
416. wVd7dg1H (0.88, 12.8)
417. cNd3cL3N (0.88, 13.1)
418. n3d2kn3L (0.88, 14.0)
419. d6s9r3^^ (0.88, 14.0)
420. pZq1gJ5T (0.88, 13.3)
421. q1w2aqsw (0.88, 8.3)
422. kHz9cl8H (0.88, 13.4)
423. b1u0uit8 (0.88, 12.4)
424. 7sSNi6q5 (0.88, 14.0)
425. dTH6vb7H (0.88, 13.3)
426. 8uy2iej5 (0.88, 12.8)
427. o3g3bhk5 (0.88, 12.6)
428. o6s8bkr5 (0.88, 12.7)
429. x6a9qya5 (0.88, 12.3)
430. 7e3dbm1T (0.88, 14.0)
431. fDl1tW9C (0.88, 13.4)

432. rX5Fy12M (0.88, 14.0)
433. m4c4b6e((0.88, 13.4)
434. sTd1erv0 (0.88, 13.7)
435. xNJ5nv1M (0.88, 13.4)
436. 8c45awe0 (0.88, 12.6)
437. 8q3oatw8 (0.88, 12.7)
438. kNw8zg8C (0.88, 13.2)
439. 8u3thgd5 (0.88, 12.7)
440. mBj0dj1H (0.88, 13.0)
441. d4j3rg45 (0.88, 12.1)
442. 7maXim00 (0.88, 11.6)
443. 8d7rqykw (0.88, 12.9)
444. g4t5gt45 (0.88, 11.2)
445. i6o4cbm0 (0.88, 12.7)
446. sQR3gh6C (0.88, 13.1)
447. s4g5keh0 (0.88, 12.8)
448. 7P1km1n> (0.88, 14.0)
449. eK6yqlx5 (0.88, 14.0)
450. v4l9ul25 (0.88, 12.3)
451. a3i9ft7L (0.88, 14.0)
452. m1f5qbiw (0.88, 13.0)
453. g1d6pto0 (0.88, 12.7)
454. nXp0rl9N (0.88, 13.9)
455. bC_mtl05 (0.88, 14.0)
456. 0d5eltx8 (0.88, 12.5)
457. j4l5mlqw (0.88, 12.9)
458. w4f1hhv5 (0.88, 12.2)
459. mV7Tm99N (0.88, 14.0)
460. m4l3bug5 (0.88, 11.7)
461. u3x0bca5 (0.88, 12.5)
462. b2b3tt3T (0.88, 12.6)
463. qCc6zv6B (0.88, 13.1)
464. 6oWVx1aw (0.88, 14.0)
465. k4t9yxpw (0.88, 13.0)
466. lWX8bm6T (0.88, 13.2)
467. z3y8grkw (0.88, 12.9)
468. 8r0uwer5 (0.88, 12.2)
469. j6a4venw (0.88, 12.2)
470. pR0Mn34B (0.88, 14.0)
471. gNk5gd0N (0.88, 13.0)
472. d7A2b9E5 (0.88, 13.2)
473. M3n5@j35 (0.88, 12.4)
474. 8mt4uh3W (0.88, 14.0)
475. _K8nz8_U (0.88, 14.0)
476. x6u6gyf0 (0.88, 12.1)
477. 8v59nq3N (0.88, 14.0)
478. u3a8mgOM (0.88, 14.0)
479. uBJNh7g5 (0.88, 14.0)
480. r3z4b9cT (0.88, 13.5)
481. p3t3rkr8 (0.88, 10.2)
482. qRh0kv7T (0.88, 13.4)
483. h4i1ako8 (0.88, 11.7)
484. d3F4j3T5 (0.88, 13.2)
485. iP80uc3N (0.88, 14.0)
486. K4m4ngr8 (0.88, 11.8)
487. hKm7ds1J (0.88, 13.0)
488. P11Mik75 (0.88, 13.0)
489. 7t7zvL75 (0.88, 14.0)
490. s1k4ndr0 (0.88, 9.6)
491. j3i8iqqw (0.88, 12.7)
492. H6d7srg8 (0.88, 13.8)
493. kRN1xd2H (0.88, 13.2)
494. c6o8rxx8 (0.88, 12.3)
495. r1c4rdo0 (0.88, 8.0)
496. aPOcan10 (0.88, 12.1)
497. jKX7vw4B (0.88, 13.5)
498. pCCazo85 (0.88, 14.0)
499. 7p9icua8 (0.88, 12.5)
500. D3s1ert0 (0.88, 11.4)
501. n4c9dlgw (0.88, 12.7)
502. cCTpv37F (0.88, 14.0)
503. q4p7zyx5 (0.88, 12.5)
504. mKv8bh2N (0.88, 13.2)
505. jT57gN1M (0.88, 14.0)
506. s4z3kol0 (0.88, 12.3)
507. aPPels10 (0.88, 9.5)
508. nD07jP6J (0.88, 14.0)
509. lKn0pD6N (0.88, 13.0)
510. x3f2oe45 (0.88, 12.4)
511. s4a2ngrw (0.88, 12.4)
512. M4t4s4rI (0.88, 10.3)
513. gHf1hM2N (0.88, 13.6)
514. z4c7gsc0 (0.88, 12.4)
515. tR#let55 (0.88, 12.9)
516. rBS4pn6J (0.88, 13.4)
517. m6m5m4@M (0.88, 13.6)
518. dNb7dk6H (0.88, 12.9)
519. K2i7vk9I (0.88, 14.0)
520. mVf4gd5C (0.88, 12.9)
521. rBx9dQ6B (0.88, 13.1)
522. w6w3ypn8 (0.88, 12.8)
523. $LExus08 (0.88, 10.7)
524. z1z4jwt8 (0.88, 12.0)
525. cPj8fM4N (0.88, 13.2)
526. H2D1m9t5 (0.88, 13.4)
527. 7t5trpr5 (0.88, 12.4)
528. 8ie3kdlw (0.88, 13.0)
529. 8g4jgvy0 (0.88, 12.8)
530. m1a7mpl8 (0.88, 11.4)
531. l3g6xtc8 (0.88, 12.6)
532. X3v4ffy8 (0.88, 13.6)
533. d4s3apr0 (0.88, 11.4)
534. jMp7jC3T (0.88, 13.3)
535. zD09eo0C (0.88, 14.0)
536. dVC6cg7J (0.88, 13.1)
537. T!a9q3@C (0.88, 14.0)
538. vV_Ft09H (0.88, 14.0)
539. 0cTopu55 (0.88, 11.6)
540. 8n4nenv5 (0.88, 12.8)
541. kHN0qs8J (0.88, 13.2)
542. fP2epm1I (0.88, 14.0)
543. A7c9qbAT (0.88, 14.0)
544. yT1mje55 (0.88, 14.0)
545. hGr9ch7T (0.88, 13.2)
546. 7in1blow (0.88, 10.8)
547. 6f6dkwu8 (0.88, 12.4)
548. 8t8mvusw (0.88, 12.7)
549. u4o1vuw8 (0.88, 12.3)
550. dMm0kS3T (0.88, 13.2)
551. zCt0nt5N (0.88, 13.7)
552. 8es5nA38 (0.88, 13.6)
553. rCg5kz9M (0.88, 13.2)
554. vHj1mJ7M (0.88, 13.2)
555. fNG3qs6N (0.88, 13.3)
556. j3m5tyu5 (0.88, 12.4)
557. sVH5mw5N (0.88, 13.0)
558. sNd2jc3H (0.88, 13.1)
559. s4l4ctm5 (0.88, 11.9)
560. xSf0wN7T (0.88, 13.3)
561. 7thSon00 (0.88, 11.1)
562. t4o6gfwp (0.88, 12.6)
563. jQm6jt1B (0.88, 13.2)
564. d3m0cle5 (0.88, 10.6)
565. 7a3qlnd0 (0.88, 12.6)
566. v3s3ljk0 (0.88, 11.0)
567. u3q6acc0 (0.88, 12.4)
568. 8qg4yxa5 (0.88, 12.6)
569. H2bWn1wN (0.88, 14.0)
570. q2W#e4r5 (0.88, 8.4)
571. 6y8kjhf5 (0.88, 12.7)
572. rSr1tm7C (0.88, 13.3)
573. V3g1tt@0 (0.88, 11.5)
574. 8ke2yep0 (0.88, 12.5)
575. f1v3dad5 (0.88, 10.9)
576. 8a5tard5 (0.88, 11.6)
577. pRw3bf7C (0.88, 13.6)
578. b6g0stew (0.88, 12.8)
579. 8mb5yalw (0.88, 12.7)
580. pWq3kV8H (0.88, 13.3)
581. s3d4mkh8 (0.88, 12.2)
582. dCc1zt9L (0.88, 13.3)
583. eCSpar55 (0.88, 13.2)
584. 8o3kfckw (0.88, 12.7)
585. 6r8okfq5 (0.88, 12.4)
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606. pX8zuD25 (0.88, 14.0)
607. b6f4bfc8 (0.88, 11.2)
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616. n4b4azu0 (0.88, 12.7)
617. pBClin15 (0.88, 12.8)
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621. 7iz7jilp (0.88, 13.0)
622. i4n4vspw (0.88, 12.8)
623. 0c9fmrs5 (0.88, 12.5)
624. gF32a1qN (0.88, 14.0)
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626. 7a3jgji0 (0.88, 12.4)
627. f4v4mbr5 (0.88, 12.3)
628. 8r5wire8 (0.88, 12.4)
629. i1r9abg5 (0.88, 12.7)
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631. 0ft6sbo5 (0.88, 12.8)
632. j2s1g3BF (0.88, 14.0)
633. 7x6axwv5 (0.88, 12.7)
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876. c4b4ll05 (0.87, 8.1)
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879. K4p4lol0 (0.87, 11.2)
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884. 7i63ymgw (0.87, 12.6)
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995. cKf1vD0H (0.87, 13.8)
996. 7o34zkrw (0.87, 12.7)
997. 7h0gbhkw (0.87, 12.9)
998. dKH9hn1w (0.87, 13.1)
999. 7g56hom5 (0.87, 12.1)

Cluster 27

Prototype: iloveminy

Hard-assigned passwords: 1461674 (5.05% of total)
Unique hard-assigned passwords: 686661 (53.02% of cluster total)

Cluster-assignment scores:
	Min: 0.062
	Max: 0.739
	Mean: 0.269
	SD: 0.119

Strength bins:
	Very weak: 231131 (15.81%)
	Weak: 440933 (30.17%)
	Fair: 408287 (27.93%)
	Good: 359101 (24.57%)
	Strong: 22222 (1.52%)

Password lengths:
	Length 8: 799450 (54.69%)
	Length 9: 492260 (33.68%)
	Length 10: 168942 (11.56%)
	Length 11: 1022 (0.07%)

Character classes:
	4 classes: 773 (0.05%)
	3 classes: 23199 (1.59%)
		lower/upper/symbol: 14808 (63.83%)
		lower/upper/number: 6912 (29.79%)
		lower/symbol/number: 1479 (6.38%)
		upper/symbol/number: 0 (0.00%)
	2 classes: 210238 (14.38%)
		lower/upper: 54323 (25.84%)
		lower/number: 64130 (30.50%)
		lower/symbol: 91765 (43.65%)
		upper/number: 0 (0.00%)
		upper/symbol: 17 (0.01%)
		number/symbol: 3 (0.00%)
	1 class: 1227464 (83.98%)
		lower: 1226874 (99.95%)
		upper: 0 (0.00%)
		symbol: 590 (0.05%)
		number: 0 (0.00%)

Most frequent char-class structures:
	LLLLLLL: 693520 (47.4%)
	LLLLLLLL: 399342 (27.3%)
	LLLLLLLLL: 133209 (9.1%)
	LLLLLLLLD: 30693 (2.1%)
	LLLLLLD: 27149 (1.9%)
	ULLLLLL: 17723 (1.2%)
	LLLLLLS: 13665 (0.9%)
	ULLLLLLL: 11780 (0.8%)
	LLLLLLLLS: 10810 (0.7%)
	LLLLLLLLD: 6288 (0.4%)

1,000 nearest passwords

0.	jackedu^	(0.74, 11.8)	53.	*awesome*	(0.68, 7.0)	106.	wathithik	(0.67, 12.1)
1.	Tybalt<>	(0.74, 10.6)	54.	kislotnik	(0.68, 9.7)	107.	clerecnik	(0.67, 11.3)
2.	*martini*	(0.70, 7.7)	55.	zollitnik	(0.68, 11.0)	108.	thiksthik	(0.67, 8.5)
3.	zjgvednv	(0.70, 13.7)	56.	handsome*	(0.67, 6.4)	109.	koliasnik	(0.67, 9.3)
4.	nintendo*	(0.70, 6.9)	57.	panasonik	(0.67, 5.7)	110.	iepuroaik	(0.67, 11.8)
5.	matienzo*	(0.69, 9.5)	58.	reshotnik	(0.67, 10.8)	111.	lifeoopik	(0.67, 12.4)
6.	ashleynv	(0.69, 7.4)	59.	raspotnik	(0.67, 7.8)	112.	gantengok	(0.67, 8.1)
7.	czyzeski*	(0.69, 12.5)	60.	gafootnik	(0.67, 11.0)	113.	skillinc	(0.67, 6.3)
8.	dumplinv	(0.69, 9.4)	61.	gorgeous*	(0.67, 6.7)	114.	cuillinc	(0.67, 8.9)
9.	joselinv	(0.69, 8.3)	62.	umirisnik	(0.67, 10.4)	115.	gofijigo*	(0.67, 11.9)
10.	ganteng^	(0.69, 8.7)	63.	huizesnik	(0.67, 10.5)	116.	ecsputnik	(0.67, 9.0)
11.	suudiigi*	(0.69, 14.0)	64.	idahosaik	(0.67, 10.8)	117.	LizalizA	(0.67, 9.6)
12.	hazuri~^	(0.69, 12.0)	65.	kasjesnik	(0.67, 9.1)	118.	ezaitshik	(0.67, 12.6)
13.	samsebnik	(0.69, 9.8)	66.	broksonik	(0.67, 9.9)	119.	linnhtaik	(0.67, 13.1)
14.	santehnik	(0.69, 9.8)	67.	tecktonik	(0.67, 5.6)	120.	kraputnik	(0.67, 10.3)
15.	labteknik	(0.69, 7.1)	68.	kapustnik	(0.67, 9.7)	121.	tonicece*	(0.67, 11.7)
16.	shareinv	(0.69, 9.5)	69.	kiwikiwi*	(0.67, 7.0)	122.	sidred*^	(0.67, 12.4)
17.	oldteknik	(0.69, 8.3)	70.	gemkosnik	(0.67, 10.7)	123.	dechooxik	(0.67, 12.8)
18.	polteknik	(0.69, 6.9)	71.	grijesnik	(0.67, 10.0)	124.	mortenask	(0.66, 10.3)
19.	elliemae*	(0.69, 8.0)	72.	woshione*	(0.67, 11.5)	125.	novimenik	(0.66, 10.5)
20.	baba*sai*	(0.69, 11.0)	73.	exitosas*	(0.67, 9.9)	126.	shaolinc	(0.66, 6.0)
21.	sistemas*	(0.68, 6.0)	74.	gnagetaik	(0.67, 10.8)	127.	agairinc	(0.66, 9.5)
22.	andrebaik	(0.68, 9.1)	75.	negative*	(0.67, 7.0)	128.	stematnik	(0.66, 9.0)
23.	navarin(	(0.68, 10.7)	76.	kronosnik	(0.67, 7.9)	129.	phatloan$	(0.66, 11.1)
24.	varshini*	(0.68, 8.4)	77.	lapaezhik	(0.67, 10.9)	130.	adidasnik	(0.66, 6.6)
25.	siureduik	(0.68, 12.7)	78.	Sonytipo*	(0.67, 12.8)	131.	dezekenik	(0.66, 10.8)
26.	violence*	(0.68, 8.3)	79.	smile^_^	(0.67, 8.1)	132.	whitemask	(0.66, 7.4)
27.	mojseacik	(0.68, 11.7)	80.	onthe^&^	(0.67, 12.2)	133.	lentooz>	(0.66, 12.4)
28.	lgrrlsnc	(0.68, 11.9)	81.	eddie*je*	(0.67, 13.2)	134.	alaosodik	(0.66, 10.6)
29.	amoremio*	(0.68, 6.8)	82.	Kuznechik	(0.67, 9.2)	135.	skopusnik	(0.66, 9.8)
30.	*friends*	(0.68, 7.1)	83.	Steven@^	(0.67, 10.3)	136.	karisibik	(0.66, 10.3)
31.	kadrushi*	(0.68, 10.9)	84.	kuznechik	(0.67, 7.8)	137.	parecido*	(0.66, 10.4)
32.	lokiloki*	(0.68, 7.1)	85.	liebevj>	(0.67, 13.1)	138.	aramsidik	(0.66, 9.3)
33.	andreynik	(0.68, 8.5)	86.	krajisnik	(0.67, 7.0)	139.	kreavenik	(0.66, 12.7)
34.	YtpJescA	(0.68, 14.0)	87.	Hamletnc	(0.67, 10.0)	140.	logodenik	(0.66, 9.1)
35.	attsecbr*	(0.68, 14.0)	88.	duecesAok	(0.67, 13.5)	141.	alwaysme*	(0.66, 8.1)
36.	<ballin>	(0.68, 9.2)	89.	naplesnc	(0.67, 9.2)	142.	monaksnik	(0.66, 10.7)
37.	plavooko*	(0.68, 10.9)	90.	Obsidi@n*	(0.67, 13.4)	143.	sportskik	(0.66, 8.3)
38.	lakeside*	(0.68, 7.3)	91.	pamietnik	(0.67, 8.1)	144.	nirvasnik	(0.66, 10.7)
39.	robertnc	(0.68, 7.4)	92.	busted%(	(0.67, 11.1)	145.	magazine*	(0.66, 7.5)
40.	tasevski*	(0.68, 10.7)	93.	myhrithik	(0.67, 8.5)	146.	roxulinc	(0.66, 10.5)
41.	zecarias*	(0.68, 9.4)	94.	juburtaik	(0.67, 10.8)	147.	devilinc	(0.66, 7.7)
42.	fabolous*	(0.68, 6.9)	95.	radklinik	(0.67, 10.3)	148.	*terence*	(0.66, 8.2)
43.	svetionik	(0.68, 9.2)	96.	gevortnik	(0.67, 11.9)	149.	whitemusk	(0.66, 7.1)
44.	monchiki*	(0.68, 10.4)	97.	mamelinik	(0.67, 10.6)	150.	sbiplinc	(0.66, 10.4)
45.	ickerous*	(0.68, 12.5)	98.	paperinik	(0.67, 6.4)	151.	ossaiikik	(0.66, 13.5)
46.	Getleads*	(0.68, 11.6)	99.	Chillout*	(0.67, 7.7)	152.	honorinc	(0.66, 7.7)
47.	louahidi*	(0.68, 13.2)	100.	krablonik	(0.67, 10.8)	153.	elcolinc	(0.66, 9.5)
48.	mamamixi*	(0.68, 11.0)	101.	rahulsaik	(0.67, 8.5)	154.	meatlinc	(0.66, 7.8)
49.	cartoons*	(0.68, 7.4)	102.	pamjatnik	(0.67, 10.6)	155.	dirtbike*	(0.66, 7.2)
50.	pastotnik	(0.68, 10.7)	103.	lexezece*	(0.67, 14.0)	156.	mojprinc	(0.66, 9.0)
51.	paprotnik	(0.68, 8.9)	104.	jamjasnik	(0.67, 8.2)	157.	arfprinc	(0.66, 10.0)
52.	asteriks*	(0.68, 8.4)	105.	kyawhtaik	(0.67, 9.8)	158.	linclinc	(0.66, 6.3)

159. chineduik (0.66, 10.3)
160. sunshine* (0.66, 5.5)
161. Atmynine* (0.66, 14.0)
162. geu#linc (0.66, 12.6)
163. rincrinc (0.66, 7.0)
164. Neethone* (0.66, 11.0)
165. mahintas* (0.66, 12.5)
166. arjanonik (0.66, 11.7)
167. labelinc (0.66, 8.7)
168. robertho* (0.66, 10.0)
169. sidelinc (0.66, 8.2)
170. mgqufonik (0.66, 14.0)
171. rebelinc (0.66, 7.2)
172. dcsolinc (0.66, 10.4)
173. paumlinc (0.66, 11.0)
174. amsolinc (0.66, 9.1)
175. makrainik (0.66, 10.6)
176. jewelinc (0.66, 8.5)
177. caitlinc (0.66, 6.2)
178. kaitlinc (0.66, 7.0)
179. jaszmine* (0.66, 9.8)
180. iluvmike* (0.66, 7.5)
181. *clemens* (0.66, 9.3)
182. zeynepcik (0.66, 9.0)
183. mujprinc (0.66, 10.2)
184. ninenine* (0.66, 8.6)
185. scotrinc (0.66, 9.4)
186. morenonik (0.66, 9.9)
187. bradhome* (0.66, 10.8)
188. bonafide* (0.66, 8.2)
189. dynalinc (0.66, 8.4)
190. besiktas* (0.66, 7.2)
191. andzlinc (0.66, 10.0)
192. *welcome* (0.66, 6.2)
193. grisepjok (0.66, 11.2)
194. juventus* (0.66, 7.4)
195. samerinc (0.66, 8.5)
196. lorenice* (0.66, 11.2)
197. cymerinc (0.66, 9.9)
198. sifremyok (0.66, 7.0)
199. *heavens* (0.66, 8.9)
200. riverinc (0.66, 7.5)
201. powerinc (0.66, 6.7)
202. pasikonik (0.66, 10.0)
203. asstasyik (0.66, 10.8)
204. SharefaA (0.66, 10.5)
205. Spahrinc (0.66, 11.5)
206. katniskik (0.66, 10.4)
207. Armywife* (0.66, 9.0)
208. antimonik (0.66, 7.0)
209. hardbone* (0.66, 9.2)
210. DoneGone* (0.66, 10.7)
211. sumanthik (0.66, 7.7)
212. freevone* (0.66, 11.0)
213. feromonik (0.66, 9.5)
214. marujope* (0.66, 12.3)
215. vaseline* (0.66, 7.7)
216. juliepask (0.66, 10.3)
217. cyantifik (0.66, 10.6)
218. sckaushik (0.66, 9.5)
219. trasconik (0.66, 10.7)
220. nanisivik (0.66, 10.8)
221. ursuline* (0.66, 9.2)
222. nataliav (0.66, 7.1)
223. paradinik (0.66, 9.2)
224. ceciliav (0.66, 6.7)
225. bem@stmik (0.66, 11.9)
226. aikipiaik (0.66, 11.0)
227. haileynm (0.66, 8.0)
228. kinikinik (0.66, 8.5)
229. fineline* (0.66, 8.2)
230. Thenewme* (0.66, 8.8)
231. brestovik (0.66, 8.4)
232. eko.stmik (0.66, 11.9)
233. flikmonik (0.66, 10.5)
234. mazoltav (0.66, 10.3)
235. kirKlinc (0.66, 11.0)
236. Pietwins* (0.66, 10.6)
237. tussefisk (0.66, 8.1)
238. *semaias* (0.66, 11.3)
239. saltefisk (0.66, 9.1)
240. Manorika$ (0.66, 9.9)
241. chrissy> (0.66, 8.7)
242. aborushik (0.66, 9.0)
243. hranushik (0.66, 10.0)
244. kkkoushik (0.66, 9.4)
245. dhiyashik (0.66, 11.0)
246. omambiyik (0.66, 11.5)
247. soosbons* (0.66, 14.0)
248. gorenshik (0.66, 11.5)
249. sofiashik (0.66, 9.9)
250. mishyshik (0.66, 9.8)
251. sunchips* (0.66, 9.1)
252. mazeltav (0.66, 8.4)
253. altynshik (0.66, 12.1)
254. coolashik (0.66, 9.7)
255. lovemedik (0.66, 8.1)
256. valyashik (0.66, 10.1)
257. derviscik (0.66, 10.8)
258. vlkoushik (0.66, 10.2)
259. Godblsme* (0.66, 11.6)
260. magomedik (0.66, 10.1)
261. vedritwik (0.66, 13.0)
262. Ammaisgr* (0.66, 13.5)
263. tylersav (0.66, 7.9)
264. i@gowshik (0.66, 12.1)
265. shisenbok (0.66, 10.3)
266. cayodejik (0.66, 12.4)
267. *monkeys* (0.66, 7.9)
268. bulldogs* (0.66, 6.6)
269. JkawenaA (0.66, 12.7)
270. mermaids* (0.66, 8.3)
271. sukdatdik (0.66, 12.1)
272. themboys* (0.66, 9.1)
273. pobjednik (0.66, 8.8)
274. aznpride* (0.66, 7.8)
275. kissesxo* (0.66, 12.0)
276. snowlove* (0.66, 9.3)
277. palabiyik (0.66, 9.7)
278. sueprice* (0.66, 12.2)
279. kjlglove* (0.66, 13.0)
280. denemecik (0.66, 8.7)
281. iminlove* (0.66, 6.9)
282. fucklove* (0.66, 6.4)
283. nintendo$ (0.66, 7.5)
284. thuglife* (0.66, 7.0)
285. jloveinc (0.66, 8.9)
286. tamilove* (0.66, 10.4)
287. vitoriav (0.66, 7.9)
288. oscarsav (0.66, 7.9)
289. primeinc (0.66, 6.3)
290. crimeinc (0.66, 6.0)
291. Primeinc (0.66, 7.8)
292. hatelove* (0.66, 7.2)
293. steveinc (0.66, 6.6)
294. ghj,tk<> (0.66, 11.4)
295. Penelope* (0.66, 7.4)
296. penelope* (0.66, 6.7)
297. theresaA (0.66, 8.6)
298. blazeinc (0.66, 6.9)
299. iamleshik (0.66, 10.5)
300. kadawtbik (0.66, 12.2)
301. kristinv (0.66, 6.8)
302. hersheys* (0.66, 7.7)
303. casarsav (0.66, 8.9)
304. riversav (0.66, 8.8)
305. beatrice* (0.66, 6.6)
306. flamengo* (0.66, 8.1)
307. peaceinc (0.66, 6.5)
308. thomasdik (0.66, 7.8)
309. couriousk (0.66, 9.3)
310. lostlife* (0.66, 9.4)
311. pendrive* (0.66, 7.6)
312. lovelife* (0.66, 6.5)
313. livelife* (0.66, 6.9)
314. lovelove* (0.66, 6.3)
315. wickednik (0.66, 8.6)
316. truelove* (0.66, 6.6)
317. aalovekik (0.66, 10.7)
318. aloreinc (0.66, 9.4)
319. spireinc (0.66, 9.3)
320. agustinv (0.66, 7.1)
321. woodysdik (0.66, 10.0)
322. torreinc (0.66, 10.3)
323. bamoutfik (0.66, 12.1)
324. bollebuik (0.66, 10.7)
325. lilseanc (0.66, 7.8)
326. raymatmik (0.66, 10.3)
327. sungroyA (0.66, 11.9)
328. dhunatmik (0.66, 12.0)
329. outlooksk (0.66, 9.4)
330. smileinc (0.66, 6.6)
331. KayRenae* (0.66, 13.0)
332. francehik (0.66, 10.6)
333. spazmodik (0.66, 10.8)
334. vortexnw (0.66, 9.5)
335. KidalipO (0.66, 13.1)
336. tungesvik (0.66, 10.6)
337. jamjasmik (0.66, 9.4)
338. cheneinc (0.66, 9.6)
339. bmkarthik (0.65, 8.8)
340. vpkarthik (0.65, 9.3)
341. tasseanm (0.65, 9.8)
342. Kraken&((0.65, 11.8)
343. micpatmik (0.65, 11.4)
344. msofronsk (0.65, 12.9)
345. appleinc (0.65, 6.6)
346. spaceinc (0.65, 6.3)
347. pixiedusk (0.65, 7.6)
348. repwetcik (0.65, 12.6)
349. brkaltnsk (0.65, 12.8)
350. gambeinc (0.65, 8.6)
351. cobleinc (0.65, 9.2)
352. sistemas$ (0.65, 6.8)
353. chrumemik (0.65, 12.4)
354. ashleynm (0.65, 6.9)
355. amnarinm (0.65, 9.6)
356. hovhasmik (0.65, 12.8)
357. haimbodik (0.65, 11.8)
358. mehmetcik (0.65, 6.4)
359. movement* (0.65, 8.0)
360. kaytlinm (0.65, 8.1)
361. madelinm (0.65, 8.1)
362. cecilsask (0.65, 9.9)
363. kokikokik (0.65, 7.0)
364. devilinm (0.65, 7.6)
365. enceeinc (0.65, 9.4)
366. Montezz^ (0.65, 11.0)
367. crateinc (0.65, 7.8)
368. stateinc (0.65, 7.3)
369. yoselinm (0.65, 7.4)
370. taeseanm (0.65, 9.5)
371. acikkecik (0.65, 12.3)
372. bgfskevik (0.65, 13.0)
373. gobeeinc (0.65, 9.1)
374. kikikikik (0.65, 6.4)
375. laxskibik (0.65, 12.7)
376. ademkidik (0.65, 10.2)
377. kaitlinm (0.65, 6.1)
378. caitlinm (0.65, 5.5)
379. houseinc (0.65, 6.6)
380. tristonsk (0.65, 9.4)
381. angelica$ (0.65, 6.4)
382. hobyjibik (0.65, 12.1)
383. chillinm (0.65, 7.3)
384. jellosask (0.65, 9.8)
385. dancechik (0.65, 8.5)
386. lolipopik (0.65, 8.6)
387. parovozik (0.65, 9.6)
388. changeme* (0.65, 6.4)
389. minusinsk (0.65, 10.3)
390. mbolenzok (0.65, 12.5)
391. innocent* (0.65, 6.3)
392. multitask (0.65, 6.1)
393. Do-qtsb((0.65, 14.0)
394. peacechik (0.65, 7.6)
395. jeeofizik (0.65, 11.9)
396. gooseinc (0.65, 7.8)
397. snekkevik (0.65, 11.7)
398. diimooxsk (0.65, 13.3)
399. Broucicik (0.65, 12.4)
400. rhinotusk (0.65, 10.8)
401. jdarrinf (0.65, 10.2)
402. mindtoask (0.65, 10.3)
403. srisatwik (0.65, 9.8)
404. sterlinf (0.65, 8.3)
405. Puceaovik (0.65, 13.8)
406. cmu.bovik (0.65, 13.6)
407. Mraxis@^ (0.65, 13.5)
408. kikdedkik (0.65, 12.0)
409. gjeldsvik (0.65, 11.1)
410. taralinm (0.65, 9.0)
411. fightinv (0.65, 7.8)
412. bopowomik (0.65, 12.6)
413. witte●gek (0.65, 10.1)
414. marylinm (0.65, 7.9)
415. anniemaek (0.65, 7.2)
416. ssososksk (0.65, 11.4)
417. limpeddik (0.65, 9.0)
418. menshevik (0.65, 9.5)
419. whitetusk (0.65, 6.3)
420. marie_nc (0.65, 9.3)
421. relrefpik (0.65, 13.1)
422. achref&((0.65, 11.1)
423. suchet@v (0.65, 10.7)
424. grundevik (0.65, 9.5)
425. hodvednik (0.65, 11.9)
426. watchout* (0.65, 8.0)
427. acrapovik (0.65, 10.6)
428. dek●dewik (0.65, 11.8)

429. fiuteczek (0.65, 10.1)
430. needtoask (0.65, 7.7)
431. bolszewik (0.65, 9.0)
432. bosseczek (0.65, 9.7)
433. plateczek (0.65, 9.8)
434. Sturmovik (0.65, 7.7)
435. sturmovik (0.65, 6.2)
436. marieinc (0.65, 7.5)
437. adriennek (0.65, 7.3)
438. samfezzik (0.65, 11.6)
439. yorktonsk (0.65, 10.5)
440. koeiengek (0.65, 9.8)
441. blackout* (0.65, 7.1)
442. eva●ridA (0.65, 14.0)
443. siderinf (0.65, 9.6)
444. tomgdowik (0.65, 14.0)
445. polinowik (0.65, 10.0)
446. Maxelias$ (0.65, 11.4)
447. boonetav (0.65, 9.3)
448. cheyenne* (0.65, 6.7)
449. sathishsk (0.65, 8.1)
450. hou$dini$ (0.65, 13.0)
451. juleesnw (0.65, 11.1)
452. dgfxeanm (0.65, 12.4)
453. babalonv (0.65, 8.7)
454. divecoat* (0.65, 10.9)
455. waeelsksk (0.65, 13.0)
456. yelrebmik (0.65, 11.8)
457. perotinv (0.65, 11.0)
458. streetav (0.65, 9.0)
459. steraspr* (0.65, 12.9)
460. tobiloba$ (0.65, 7.6)
461. pridesav (0.65, 7.6)
462. letmeinm (0.65, 6.9)
463. donkeydik (0.65, 7.7)
464. akilegnA (0.65, 10.0)
465. fucked●ok (0.65, 9.9)
466. Barnegut* (0.65, 12.6)
467. camerons$ (0.65, 8.3)
468. bolshevik (0.65, 6.9)
469. truerednek (0.65, 10.3)
470. novalojik (0.65, 10.0)
471. oldrednek (0.65, 8.4)
472. ilyseanf (0.65, 9.8)
473. konfetka$ (0.65, 10.7)
474. apple#&((0.65, 9.9)
475. luanjian* (0.65, 8.5)
476. sundewcik (0.65, 11.2)
477. canadian* (0.65, 7.3)
478. ramkesav (0.65, 9.3)
479. theresav (0.65, 7.0)
480. scalpthi$ (0.65, 12.9)
481. yeshevav (0.65, 9.9)
482. kraweznik (0.65, 10.2)
483. tundemav (0.65, 9.6)
484. deujeanc (0.65, 11.0)
485. florence$ (0.65, 6.6)
486. mousesav (0.65, 7.3)
487. deeremav (0.65, 10.0)
488. mimulous$ (0.65, 12.2)
489. $uckit%^ (0.65, 9.4)
490. VsuvRtwA (0.65, 14.0)
491. luckytask (0.65, 8.0)
492. linkedmik (0.65, 6.7)
493. Octavian* (0.65, 7.8)
494. nyjstiutk (0.65, 14.0)
495. oladeinf (0.65, 8.9)
496. hjornevik (0.65, 11.3)
497. ilovejnm (0.65, 7.0)
498. ihatecav (0.65, 7.4)
499. Namodevi$ (0.65, 12.5)
500. bibelocik (0.65, 11.1)
501. yaadeinf (0.65, 9.7)
502. bmufsgnv (0.64, 12.9)
503. plzdntask (0.64, 13.0)
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506. hayastan$ (0.64, 8.2)
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510. bnjutjnv (0.64, 12.6)
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512. lawrence$ (0.64, 6.7)
513. $russian$ (0.64, 8.7)
514. dailytask (0.64, 8.7)
515. vidaloca$ (0.64, 8.5)
516. phoneinf (0.64, 8.8)
517. parkechik (0.64, 10.1)
518. genieinf (0.64, 9.3)
519. uriantask (0.64, 10.1)
520. gorgeous$ (0.64, 7.1)
521. domerikik (0.64, 11.5)
522. fenoeinf (0.64, 12.5)
523. time&task (0.64, 9.5)
524. ludidensk (0.64, 11.6)
525. pak-tiyok (0.64, 11.4)
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531. hairmensk (0.64, 10.5)
532. tboydtnsk (0.64, 13.3)
533. mvmdekav (0.64, 12.6)
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535. climecnik (0.64, 9.9)
536. goodnews* (0.64, 7.2)
537. togaloks$ (0.64, 12.4)
538. stereo.tk (0.64, 8.9)
539. bdhfhsksk (0.64, 12.5)
540. hellesvik (0.64, 10.1)
541. glenntusk (0.64, 8.6)
542. blacktusk (0.64, 7.1)
543. miaomiao* (0.64, 8.3)
544. Lobowski$ (0.64, 10.8)
545. pkkbksksk (0.64, 11.9)
546. ebcqipnv (0.64, 13.1)
547. kauaiian* (0.64, 9.9)
548. aaroniusk (0.64, 10.0)
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558. rayrhehsk (0.64, 14.0)
559. imindian$ (0.64, 8.8)
560. arianemik (0.64, 9.0)
561. LaurenzO (0.64, 8.9)
562. sorryiask (0.64, 10.2)
563. cardenas* (0.64, 7.5)
564. CarolinA (0.64, 5.9)
565. Zinnedav (0.64, 10.8)
566. juliesav (0.64, 7.9)
567. C@rolinA (0.64, 7.2)
568. iamrepmek (0.64, 13.2)
569. snezhinsk (0.64, 11.8)
570. rjpociask (0.64, 13.8)
571. julissatk (0.64, 9.2)
572. spsk@spsk (0.64, 9.5)
573. kelseygib (0.64, 8.8)
574. stevenaik (0.64, 7.7)
575. penmegmik (0.64, 12.0)
576. pakistan* (0.64, 5.6)
577. eastside$ (0.64, 6.8)
578. jsjsksksk (0.64, 8.8)
579. nortesav (0.64, 8.8)
580. boynedav (0.64, 9.5)
581. ushagopi$ (0.64, 12.8)
582. w,j.shf^ (0.64, 12.6)
583. loveyousk (0.64, 8.3)
584. dulsejav (0.64, 11.0)
585. barabinsk (0.64, 8.9)
586. rolltide$ (0.64, 6.5)
587. iloveunik (0.64, 7.3)
588. westside$ (0.64, 6.8)
589. carbrimik (0.64, 11.6)
590. cherooke$ (0.64, 10.6)
591. AngelinA (0.64, 6.5)
592. adoupeusk (0.64, 13.0)
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594. mambithok (0.64, 10.8)
595. sukudipsk (0.64, 13.1)
596. Alwaysmsk (0.64, 11.3)
597. hafidovi$ (0.64, 12.5)
598. everione$ (0.64, 12.0)
599. iloveanik (0.64, 6.9)
600. Testtobi# (0.64, 13.1)
601. egodkodsk (0.64, 13.8)
602. portside$ (0.64, 9.1)
603. newprint$ (0.64, 9.5)
604. alanious$ (0.64, 11.1)
605. precious$ (0.64, 6.3)
606. Svs-Tomsk (0.64, 14.0)
607. LinkedIn$ (0.64, 6.4)
608. MacaronI (0.64, 7.8)
609. sadatshok (0.64, 10.9)
610. maddside$ (0.64, 11.2)
611. ulyanovsk (0.64, 9.7)
612. ImoleayO (0.64, 8.8)
613. ctrhaicsk (0.64, 13.8)
614. tashishok (0.64, 10.5)
615. blossomO (0.64, 8.6)
616. smartone$ (0.64, 8.2)
617. daijho.ok (0.64, 14.0)
618. daggemask (0.64, 9.2)
619. cristian* (0.64, 6.6)
620. lasvegas* (0.64, 6.3)
621. hoestokok (0.64, 10.7)
622. texasokok (0.64, 8.7)
623. dsicrimI (0.64, 14.0)
624. slaweknc (0.64, 10.3)
625. CaterinA (0.64, 7.2)
626. vassenav (0.64, 8.1)
627. mandhini# (0.64, 11.2)
628. artemovsk (0.64, 10.2)
629. nipgedav (0.64, 11.0)
630. Semfront$ (0.64, 11.9)
631. StellinA (0.64, 8.1)
632. ebb_tide$ (0.64, 14.0)
633. bioset*** (0.64, 9.9)
634. deejezmik (0.64, 12.9)
635. RomiromI (0.64, 9.3)
636. valleyhi$ (0.64, 11.1)
637. mariefav (0.64, 8.8)
638. lubirizi# (0.64, 12.4)
639. showtime$ (0.64, 8.0)
640. bhavipnv (0.64, 10.8)
641. bambionek (0.64, 10.0)
642. sireesha$ (0.64, 8.8)
643. poustinek (0.64, 9.6)
644. aku@yoyok (0.64, 12.4)
645. stagedav (0.64, 9.1)
646. bo\\utyok (0.64, 14.0)
647. treftokok (0.64, 11.7)
648. tomtotbok (0.64, 11.0)
649. dovbenav (0.64, 10.7)
650. shahashok (0.64, 8.9)
651. s.akashok (0.64, 12.5)
652. jh-benav (0.64, 11.5)
653. remonejsk (0.64, 10.8)
654. Asma_smA (0.64, 13.8)
655. aallstar* (0.64, 11.3)
656. Manuashok (0.64, 10.1)
657. anjuashok (0.64, 8.1)
658. umnyashok (0.64, 11.9)
659. phytstar* (0.64, 13.3)
660. cellstar* (0.64, 9.3)
661. sukses_ok (0.64, 8.6)
662. cibyashok (0.64, 12.1)
663. Dini@thok (0.64, 13.0)
664. artiashok (0.64, 9.5)
665. Kwietocek (0.64, 11.7)
666. phantome$ (0.64, 9.1)
667. staszegok (0.64, 10.9)
668. lornedav (0.64, 9.3)
669. ajalashok (0.64, 9.4)
670. pennashok (0.64, 10.3)
671. lonestar* (0.64, 7.2)
672. truestar* (0.64, 8.8)
673. chhapthok (0.64, 11.3)
674. cushtibok (0.64, 11.6)
675. fivestar* (0.64, 7.4)
676. yourstar* (0.64, 8.5)
677. $episode$ (0.64, 11.1)
678. sai●ashok (0.64, 9.3)
679. glnahsntk (0.64, 14.0)
680. thisisaek (0.64, 9.8)
681. skubisnek (0.64, 10.9)
682. lax*star* (0.64, 12.2)
683. rockstar* (0.64, 6.3)
684. pinkstar* (0.64, 7.6)
685. kesetian* (0.64, 9.5)
686. roadstar* (0.64, 8.3)
687. Iamastar* (0.64, 9.4)
688. lipiashok (0.64, 11.1)
689. fabulous# (0.64, 7.8)
690. marysinek (0.64, 8.9)
691. *imastar* (0.64, 10.0)
692. limsoogek (0.63, 12.0)
693. bright.tk (0.63, 8.6)
694. gdsathnv (0.63, 12.4)
695. lucien%((0.63, 10.2)
696. swethintk (0.63, 11.3)
697. kippenhok (0.63, 7.6)
698. wangzi.tk (0.63, 9.9)

699. murufegok (0.63, 11.9)
700. kieliszek (0.63, 9.1)
701. bartoszek (0.63, 6.1)
702. lrakgogok (0.63, 12.9)
703. genccs.tk (0.63, 12.9)
704. Mohdsidek (0.63, 12.3)
705. *mekstar* (0.63, 11.6)
706. barlosbek (0.63, 11.1)
707. cheptoyek (0.63, 10.3)
708. bqbylon((0.63, 14.0)
709. putyiszok (0.63, 12.7)
710. goldstar* (0.63, 7.4)
711. binnegnu (0.63, 9.5)
712. rieles*** (0.63, 11.4)
713. positivek (0.63, 7.1)
714. rutsisgek (0.63, 11.3)
715. justisgek (0.63, 10.3)
716. priestmek (0.63, 9.9)
717. pudgefisk (0.63, 8.9)
718. dkebsodek (0.63, 12.7)
719. dooleajib (0.63, 12.0)
720. Camilo*** (0.63, 7.7)
721. snotisgek (0.63, 10.2)
722. harlemusk (0.63, 9.9)
723. videothek (0.63, 9.9)
724. martekvib (0.63, 12.3)
725. guchtimek (0.63, 12.0)
726. lasvgsnv (0.63, 12.7)
727. suusisgek (0.63, 10.9)
728. carOlinA (0.63, 9.0)
729. famwitgek (0.63, 12.9)
730. miesisgek (0.63, 11.2)
731. jfzpedcsk (0.63, 14.0)
732. aspirinw (0.63, 8.8)
733. kokoticek (0.63, 8.9)
734. kaffekask (0.63, 10.3)
735. skaanevik (0.63, 11.4)
736. szovoszek (0.63, 10.4)
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738. clovisnm (0.63, 10.1)
739. tacoisgek (0.63, 9.0)
740. kriboinc (0.63, 10.2)
741. suavejav (0.63, 9.7)
742. barneyutk (0.63, 9.7)
743. adidasdok (0.63, 9.3)
744. discothek (0.63, 10.3)
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746. babhishek (0.63, 8.2)
747. intekoktk (0.63, 13.4)
748. a@bhishek (0.63, 8.0)
749. Mprpcsw^ (0.63, 14.0)
750. arceli*** (0.63, 10.2)
751. domowekek (0.63, 11.9)
752. trynet*** (0.63, 9.9)
753. unionokok (0.63, 8.6)
754. kakakodok (0.63, 8.0)
755. kamukodok (0.63, 10.9)
756. rosalina$ (0.63, 8.5)
757. fabguijok (0.63, 12.4)
758. braciszek (0.63, 8.9)
759. biofitbek (0.63, 12.2)
760. sairutne$ (0.63, 12.7)
761. Sydneyav (0.63, 9.3)
762. susilo*** (0.63, 9.1)
763. dongetme$ (0.63, 11.3)
764. iluvgodok (0.63, 9.3)
765. blektopek (0.63, 10.9)
766. omahpojok (0.63, 11.6)
767. overbemtk (0.63, 13.9)
768. isscoinc (0.63, 9.3)
769. linkedcsk (0.63, 7.6)
770. $sabrina$ (0.63, 7.4)
771. kikdedkok (0.63, 12.5)
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773. saliptnek (0.63, 13.1)
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775. keat•taek (0.63, 13.8)
776. winnishek (0.63, 9.2)
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782. Civasoft$ (0.63, 11.8)
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784. sexilexi* (0.63, 8.3)
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786. wakokokok (0.63, 7.5)
787. okcomokok (0.63, 11.1)
788. wypwefgok (0.63, 14.0)
789. carebear* (0.63, 7.0)
790. jofneznu (0.63, 12.5)
791. lerkecav (0.63, 11.3)
792. ertekekek (0.63, 10.3)
793. korekekek (0.63, 10.3)
794. GerTzedek (0.63, 11.9)
795. guduli@c (0.63, 11.1)
796. juliejav (0.63, 8.3)
797. cheekokok (0.63, 8.8)
798. chucksuek (0.63, 9.8)
799. ilovejnc (0.63, 7.5)
800. radimecek (0.63, 9.0)
801. placuszok (0.63, 11.3)
802. atlassi^ (0.63, 11.3)
803. colitiaok (0.63, 11.9)
804. bearbear* (0.63, 6.9)
805. footwear* (0.63, 8.0)
806. madelonc (0.63, 8.9)
807. shivaivtk (0.63, 11.0)
808. gustoinc (0.63, 9.3)
809. covkoinc (0.63, 10.8)
810. jaylenav (0.63, 8.6)
811. andrzejek (0.63, 6.6)
812. borokokok (0.63, 6.8)
813. sunshine$ (0.63, 6.0)
814. Sunshine$ (0.63, 6.4)
815. nascoinc (0.63, 8.4)
816. lorrainek (0.63, 7.3)
817. pirebebek (0.63, 12.0)
818. whocoinc (0.63, 11.0)
819. cynamonek (0.63, 9.8)
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821. metebebek (0.63, 9.3)
822. tmmastaok (0.63, 11.9)
823. mattyibok (0.63, 10.8)
824. limabean* (0.63, 7.8)
825. tremainek (0.63, 8.7)
826. european* (0.63, 8.6)
827. tupixigo$ (0.63, 13.5)
828. stukutpok (0.63, 12.8)
829. chan@shek (0.63, 9.6)
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831. inovendA (0.63, 12.2)
832. flablonc (0.63, 9.8)
833. Misamigo$ (0.63, 9.5)
834. giobotaA (0.63, 13.0)
835. bunnyshek (0.63, 9.7)
836. deosoinc (0.63, 10.0)
837. aavalonc (0.63, 9.5)
838. luckyone$ (0.63, 7.4)
839. Wache$aw (0.63, 13.5)
840. biggythek (0.63, 9.4)
841. iamthekok (0.63, 8.1)
842. stuckinek (0.63, 11.0)
843. sankatcek (0.63, 10.6)
844. askacinek (0.63, 10.6)
845. emmajean$ (0.63, 8.6)
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847. bidouspok (0.63, 11.5)
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849. darajeyek (0.63, 10.9)
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851. aryaisaok (0.63, 11.4)
852. tacrtsnm (0.63, 12.2)
853. dinithnv (0.63, 10.6)
854. presioni. (0.63, 10.6)
855. abhi.shek (0.63, 8.6)
856. ilovem@v (0.63, 8.4)
857. Bhushido$ (0.63, 12.5)
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859. murrythek (0.63, 10.6)
860. jiricenek (0.63, 10.8)
861. tjlgqsuek (0.63, 14.0)
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863. bentbinek (0.63, 11.1)
864. twilliam (0.63, 6.1)
865. swilliam (0.63, 5.4)
866. wlilliam (0.63, 8.2)
867. owilliam (0.63, 7.4)
868. nevaminek (0.63, 8.2)
869. rwilliam (0.63, 5.7)
870. whilliam (0.63, 6.4)
871. kwilliam (0.63, 5.5)
872. uwilliam (0.63, 7.5)
873. karabinek (0.63, 7.8)
874. stelliam (0.63, 8.3)
875. philliam (0.63, 6.0)
876. nwilliam (0.63, 6.3)
877. awilliam (0.63, 6.4)
878. dwilliam (0.63, 5.6)
879. gwilliam (0.63, 5.5)
880. .william (0.63, 6.7)
881. jwilliam (0.63, 4.7)
882. cwilliam (0.63, 5.4)
883. FlamengO (0.63, 7.9)
884. mwilliam (0.63, 6.0)
885. bwilliam (0.63, 5.3)
886. zwilliam (0.63, 5.8)
887. pwilliam (0.63, 5.9)
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889. wuilliam (0.63, 7.8)
890. quilliam (0.63, 7.0)
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892. jgilliam (0.63, 6.9)
893. noelliam (0.63, 7.5)
894. mgilliam (0.63, 7.1)
895. mediathek (0.63, 9.3)
896. Swilliam (0.63, 7.0)
897. thisisme# (0.63, 7.2)
898. wailliam (0.63, 7.1)
899. sadekonek (0.63, 10.7)
900. islsmthek (0.63, 13.5)
901. mailliam (0.63, 7.0)
902. masspike$ (0.63, 10.3)
903. shelltam (0.63, 8.1)
904. jimboinc (0.63, 7.1)
905. hekhekhek (0.63, 7.1)
906. w_illiam (0.63, 9.4)
907. pingwinek (0.63, 9.4)
908. dallaice$ (0.63, 11.9)
909. sirspike$ (0.63, 11.1)
910. abelliam (0.63, 8.7)
911. ikg.lihnk (0.63, 14.0)
912. broucinek (0.63, 11.1)
913. dummefisk (0.63, 9.1)
914. mariuszek (0.63, 5.9)
915. Optimize$ (0.63, 9.2)
916. Mariuszek (0.63, 7.5)
917. iloveone$ (0.63, 8.3)
918. guinaouek (0.63, 11.3)
919. daycoinc (0.63, 8.1)
920. ilovecav (0.63, 6.6)
921. dreamemek (0.63, 11.3)
922. willliam (0.63, 4.9)
923. avjnisus# (0.63, 14.0)
924. ewe@memek (0.63, 12.6)
925. pietaszek (0.63, 8.3)
926. smalliaw (0.63, 9.0)
927. oincoinc (0.63, 8.1)
928. sihot$n^ (0.63, 14.0)
929. michaszek (0.63, 8.7)
930. lihessnm (0.63, 11.6)
931. miklashek (0.63, 11.0)
932. fistaszek (0.63, 8.1)
933. chlapecek (0.63, 12.2)
934. wialliam (0.63, 8.8)
935. Mateuszek (0.63, 7.2)
936. stromecek (0.63, 9.1)
937. mateuszek (0.63, 5.4)
938. pempuszek (0.63, 10.4)
939. mordegav (0.63, 9.5)
940. misiaszek (0.63, 9.5)
941. Wojt@szek (0.63, 13.0)
942. ghitataib (0.63, 11.5)
943. Loudpipe$ (0.63, 10.7)
944. henryice$ (0.63, 10.3)
945. sarpbebek (0.63, 10.5)
946. poohbear* (0.63, 6.6)
947. hudcoinc (0.63, 10.0)
948. $lutwive$ (0.63, 11.3)
949. tekefonek (0.63, 10.8)
950. slawuszek (0.63, 9.4)
951. tabcoinc (0.63, 10.5)
952. shophive$ (0.63, 12.0)
953. mayabean* (0.63, 9.7)
954. tempoinc (0.63, 8.1)
955. gananidek (0.63, 10.3)
956. orientbek (0.63, 9.9)
957. hansjepek (0.63, 9.6)
958. rafcoinc (0.63, 8.4)
959. cieluszek (0.63, 8.7)
960. aksijspek (0.63, 13.1)
961. sroubecek (0.63, 12.6)
962. miniaszek (0.63, 9.4)
963. ilovednc (0.63, 7.6)
964. ilovliam (0.63, 7.5)
965. kociaszek (0.63, 8.3)
966. tobiaszek (0.63, 7.2)
967. gumcoinc (0.63, 9.4)
968. boydliam (0.63, 8.7)

969. mathhome$ (0.63, 10.2)
970. camcoinc (0.63, 8.6)
971. liamliam (0.63, 4.4)
972. evasnopek (0.63, 11.6)
973. Filipecek (0.63, 10.8)
974. tallmikek (0.63, 10.3)
975. carlaspek (0.63, 10.1)
976. iluvliam (0.63, 6.1)
977. alanisnm (0.63, 9.8)
978. romanicek (0.63, 9.0)
979. spinzone$ (0.63, 9.9)
980. Gotrdone$ (0.63, 10.1)
981. finabobek (0.63, 10.3)
982. bobabobek (0.63, 10.7)
983. nintendo. (0.63, 6.6)
984. johnkijek (0.63, 10.1)
985. alexliam (0.63, 5.6)
986. saricicek (0.63, 9.9)
987. tomcoinc (0.63, 7.7)
988. matejicek (0.63, 10.4)
989. Bestcode$ (0.63, 9.1)
990. sbojnicek (0.63, 12.3)
991. jacekicek (0.63, 10.6)
992. qekejogek (0.63, 13.2)
993. ccssaint$ (0.63, 11.6)
994. mehboobA (0.63, 9.0)
995. ema.toni. (0.63, 11.5)
996. sitkaidek (0.63, 11.9)
997. sxobliam (0.63, 12.1)
998. sumruipek (0.63, 12.5)
999. IloveyoU (0.63, 7.2)

Cluster 28

Prototype: aanen0070

Hard-assigned passwords: 817916 (2.83% of total)
Unique hard-assigned passwords: 554229 (32.24% of cluster total)

Cluster-assignment scores:
- Min: 0.067
- Max: 0.970
- Mean: 0.281
- SD: 0.161

Strength bins:
- Very weak: 11295 (1.38%)
- Weak: 167657 (20.50%)
- Fair: 396170 (48.44%)
- Good: 235333 (28.77%)
- Strong: 7461 (0.91%)

Password lengths:
- Length 8: 68853 (8.42%)
- Length 9: 731696 (89.46%)
- Length 10: 17367 (2.12%)

Character classes:
- 4 classes: 15471 (1.89%)
- 3 classes: 121914 (14.91%)
  - lower/upper/symbol: 161 (0.13%)
  - lower/upper/number: 95744 (78.53%)
  - lower/symbol/number: 26009 (21.33%)
  - upper/symbol/number: 0 (0.00%)
- 2 classes: 680531 (83.20%)
  - lower/upper: 75 (0.01%)
  - lower/number: 680172 (99.95%)
  - lower/symbol: 277 (0.04%)
  - upper/number: 0 (0.00%)
  - upper/symbol: 0 (0.00%)
  - number/symbol: 7 (0.00%)
- 1 class: 0 (0.00%)

Most frequent char-class structures:
- LLLLLDDDD: 536438 (65.6%)
- ULLLLDDDD: 69802 (8.5%)
- LLLLDDDD: 57680 (7.1%)
- LLLLDDDDD: 36947 (4.5%)
- LLLLLDLLL: 13030 (1.6%)
- LLLLSDDDD: 9900 (1.2%)
- LLLLLLDDDD: 7597 (0.9%)
- ULLLDDDD: 6138 (0.8%)
- LLLLLDDLL: 5109 (0.6%)
- ULLLSDDDD: 4945 (0.6%)

1,000 nearest passwords

0.	jozek0070	(0.97, 9.8)	55.	Camin0370	(0.95, 10.2)	110.	pokey8280	(0.95, 8.7)
1.	ahmed0180	(0.97, 7.1)	56.	kane$0580	(0.95, 11.9)	111.	alpib9090	(0.95, 10.8)
2.	mike&0480	(0.97, 10.9)	57.	ramin9070	(0.95, 8.5)	112.	jacob0970	(0.95, 7.9)
3.	coded0070	(0.97, 8.7)	58.	M@jid0570	(0.95, 11.7)	113.	lydia9900	(0.95, 7.7)
4.	numec0770	(0.97, 12.6)	59.	Noviy9680	(0.95, 12.7)	114.	Alcon0000	(0.95, 9.5)
5.	ahmed0770	(0.97, 7.6)	60.	robi@0970	(0.95, 11.5)	115.	tania9090	(0.95, 7.5)
6.	ruben0580	(0.97, 8.1)	61.	nagem0000	(0.95, 8.5)	116.	saxon9500	(0.95, 8.6)
7.	ethen0070	(0.96, 9.7)	62.	sonic9480	(0.95, 8.6)	117.	raven5500	(0.95, 7.0)
8.	gomez0990	(0.96, 7.9)	63.	devon9880	(0.95, 8.5)	118.	habib9700	(0.95, 8.1)
9.	hamed0590	(0.96, 8.0)	64.	vivek9770	(0.95, 8.4)	119.	mejia9090	(0.95, 6.9)
10.	mrmen0990	(0.96, 10.7)	65.	robin9070	(0.95, 7.7)	120.	david9100	(0.95, 7.2)
11.	keven0000	(0.96, 7.4)	66.	majid0070	(0.95, 7.3)	121.	canon0000	(0.95, 6.8)
12.	seven0000	(0.96, 6.9)	67.	afyon0670	(0.95, 11.3)	122.	engin0000	(0.95, 7.7)
13.	bowen0900	(0.96, 8.9)	68.	David0880	(0.95, 8.1)	123.	simon9900	(0.95, 7.1)
14.	coven0000	(0.96, 8.4)	69.	women8080	(0.95, 8.8)	124.	magic9900	(0.95, 7.2)
15.	HomeG5570	(0.96, 12.6)	70.	lopez5590	(0.95, 7.7)	125.	nokia9300	(0.95, 5.2)
16.	yemem0000	(0.96, 9.9)	71.	ahmed0660	(0.95, 7.9)	126.	Bohem8180	(0.95, 12.0)
17.	tymed0000	(0.96, 10.0)	72.	radon9200	(0.95, 9.9)	127.	lydia0000	(0.94, 6.8)
18.	fedex0000	(0.96, 6.8)	73.	Kevin9080	(0.95, 8.4)	128.	mkkim0280	(0.94, 11.9)
19.	mtdew0000	(0.96, 8.5)	74.	Haken8080	(0.95, 10.8)	129.	abdou0000	(0.94, 6.6)
20.	raven0000	(0.96, 6.4)	75.	Jakob0170	(0.95, 9.4)	130.	Admin0890	(0.94, 7.7)
21.	cedec0000	(0.96, 8.7)	76.	jahon0770	(0.95, 10.8)	131.	mafia9800	(0.94, 7.6)
22.	bokep0000	(0.96, 8.2)	77.	mike.8580	(0.95, 10.3)	132.	Admin0690	(0.94, 7.8)
23.	asdef0000	(0.96, 8.6)	78.	raden5890	(0.95, 9.4)	133.	sumon0000	(0.94, 7.0)
24.	ahmed0000	(0.96, 5.3)	79.	huyen0000	(0.95, 7.5)	134.	nokia9900	(0.94, 5.8)
25.	ahmed0100	(0.96, 5.6)	80.	ahmed5790	(0.95, 7.8)	135.	india0000	(0.94, 6.2)
26.	sameh0000	(0.96, 7.6)	81.	Abdou0000	(0.95, 8.1)	136.	majid9800	(0.94, 8.0)
27.	aymen0000	(0.96, 7.2)	82.	safia9090	(0.95, 8.0)	137.	newed0310	(0.94, 10.5)
28.	lopez0000	(0.96, 6.1)	83.	sumon9090	(0.95, 7.4)	138.	tuhin0000	(0.94, 7.2)
29.	aiden0100	(0.96, 7.6)	84.	radek5790	(0.95, 9.5)	139.	Nokia9300	(0.94, 6.3)
30.	Love_0000	(0.96, 8.2)	85.	Pazon0000	(0.95, 10.3)	140.	codex5000	(0.94, 7.7)
31.	ahmed0200	(0.96, 7.3)	86.	navid9090	(0.95, 8.0)	141.	edwin0000	(0.94, 6.7)
32.	Ahmed0300	(0.96, 7.8)	87.	David9990	(0.95, 7.6)	142.	ayzsa9980	(0.94, 12.4)
33.	hopey0000	(0.96, 8.3)	88.	david9090	(0.95, 6.0)	143.	Kevin9090	(0.94, 7.3)
34.	daded0000	(0.96, 9.2)	89.	hamed5290	(0.95, 8.4)	144.	maui@9400	(0.94, 10.8)
35.	Ahmed0100	(0.96, 7.1)	90.	India0000	(0.95, 7.0)	145.	nadia0000	(0.94, 6.4)
36.	beben5580	(0.96, 10.2)	91.	rapid0580	(0.95, 9.0)	146.	mikey5000	(0.94, 6.5)
37.	poke-0900	(0.96, 11.6)	92.	admin9090	(0.95, 5.6)	147.	dldog9590	(0.94, 11.9)
38.	Cakep0000	(0.96, 8.8)	93.	edwin9090	(0.95, 7.0)	148.	amped8870	(0.94, 10.1)
39.	dewey5980	(0.96, 9.1)	94.	damo●0000	(0.95, 10.2)	149.	david9000	(0.94, 6.3)
40.	Ahmed0000	(0.96, 6.6)	95.	Admin0000	(0.95, 6.1)	150.	admin0000	(0.94, 4.8)
41.	ilhem0000	(0.96, 9.5)	96.	david9890	(0.95, 6.8)	151.	ahmed5000	(0.94, 5.9)
42.	lovex9370	(0.96, 10.6)	97.	mike-8580	(0.95, 10.1)	152.	mafia0000	(0.94, 6.2)
43.	simon9480	(0.96, 8.0)	98.	kcvin9590	(0.95, 12.4)	153.	javed9990	(0.94, 8.3)
44.	caden0000	(0.96, 7.1)	99.	dozey8280	(0.95, 11.0)	154.	nghia0000	(0.94, 7.3)
45.	nokia9480	(0.96, 8.2)	100.	Raven5000	(0.95, 7.2)	155.	nokia9500	(0.94, 4.4)
46.	jacob9780	(0.96, 7.9)	101.	fuji_9600	(0.95, 10.8)	156.	Ruben5300	(0.94, 8.7)
47.	Nokia0070	(0.95, 8.6)	102.	raven5000	(0.95, 6.3)	157.	siwek5200	(0.94, 11.2)
48.	simon9970	(0.95, 7.9)	103.	jamin9100	(0.95, 9.0)	158.	admin9000	(0.94, 6.1)
49.	david9680	(0.95, 7.3)	104.	wagon9900	(0.95, 8.6)	159.	Nokia9600	(0.94, 6.9)
50.	david9880	(0.95, 7.3)	105.	sobov0080	(0.95, 12.7)	160.	cawin9000	(0.94, 10.2)
51.	gavin0070	(0.95, 7.3)	106.	godin9090	(0.95, 8.1)	161.	tania0000	(0.94, 6.7)
52.	damon0080	(0.95, 8.1)	107.	nokia9090	(0.95, 6.6)	162.	nokia9800	(0.94, 5.9)
53.	magic9870	(0.95, 7.8)	108.	Rice-8880	(0.95, 11.4)	163.	donia9090	(0.94, 8.6)
54.	zahed0000	(0.95, 7.8)	109.	admin9900	(0.95, 6.3)	164.	dunia0000	(0.94, 7.5)

165. aphid9000	(0.94, 10.3)	
166. pikon0000	(0.94, 9.0)	
167. kopek5800	(0.94, 10.4)	
168. djdev5000	(0.94, 9.9)	
169. enjoy0000	(0.94, 7.4)	
170. login0000	(0.94, 6.4)	
171. eldon9800	(0.94, 9.3)	
172. vshih0480	(0.94, 13.1)	
173. bijou0000	(0.94, 7.4)	
174. Novik0000	(0.94, 9.7)	
175. endep5000	(0.94, 10.1)	
176. repox0980	(0.94, 11.3)	
177. raven5200	(0.94, 7.1)	
178. taqim9000	(0.94, 9.9)	
179. suvo@9800	(0.94, 10.8)	
180. ripon0000	(0.94, 8.1)	
181. alkon0000	(0.94, 8.5)	
182. simon0000	(0.94, 6.0)	
183. maxem9100	(0.94, 10.5)	
184. vivek0110	(0.94, 7.1)	
185. nixon9000	(0.94, 7.9)	
186. alden0560	(0.94, 9.9)	
187. Brain0000	(0.94, 8.1)	
188. loveu9980	(0.94, 9.3)	
189. pimiu0000	(0.94, 10.4)	
190. nokia9000	(0.94, 6.5)	
191. nokia0000	(0.94, 6.1)	
192. gomez8390	(0.94, 8.5)	
193. raven0410	(0.94, 7.0)	
194. Sibiu9090	(0.94, 10.8)	
195. Nokia9500	(0.94, 5.5)	
196. mono●9600	(0.94, 11.0)	
197. nbveh0010	(0.94, 12.5)	
198. yudik0000	(0.94, 9.5)	
199. sanoj0000	(0.94, 7.4)	
200. craig9090	(0.94, 7.2)	
201. kevin0000	(0.94, 5.9)	
202. alvin0000	(0.94, 6.8)	
203. david0000	(0.94, 5.2)	
204. Sonic0000	(0.94, 7.8)	
205. mawen0710	(0.94, 9.9)	
206. lidia9000	(0.94, 7.8)	
207. remek0110	(0.94, 9.5)	
208. hamid0000	(0.94, 5.8)	
209. rtdtn9270	(0.94, 12.8)	
210. mafia0690	(0.94, 8.0)	
211. magic0000	(0.94, 6.5)	
212. media0000	(0.94, 6.5)	
213. Dukey8390	(0.94, 10.4)	
214. coben0310	(0.94, 9.6)	
215. jaxon0100	(0.94, 8.5)	
216. tuzic0000	(0.94, 10.2)	
217. lopez8890	(0.94, 7.5)	
218. Lezen0810	(0.94, 11.0)	
219. sonia9800	(0.94, 8.0)	
220. tania0900	(0.94, 8.3)	
221. yemen9570	(0.94, 9.4)	
222. lopez0310	(0.94, 7.2)	
223. sonia0000	(0.94, 6.5)	
224. redea0610	(0.94, 10.7)	
225. lydia0700	(0.94, 8.1)	
226. admin0490	(0.94, 7.3)	
227. vaqif0000	(0.94, 11.5)	
228. admin0400	(0.94, 7.3)	
229. hakim0000	(0.94, 6.5)	
230. jacob0000	(0.94, 6.1)	
231. rahim0000	(0.94, 6.9)	
232. jjwiz0000	(0.94, 10.4)	
233. denon9000	(0.94, 8.4)	
234. jamed0710	(0.94, 9.2)	
235. kenia0000	(0.94, 7.4)	
236. mikey0510	(0.94, 7.2)	
237. david0890	(0.94, 7.1)	
238. midou0190	(0.94, 9.4)	
239. aiden0810	(0.94, 6.6)	
240. Lenox0990	(0.94, 10.2)	
241. lcmeh0210	(0.94, 12.5)	
242. david0990	(0.94, 6.9)	
243. bebek9090	(0.94, 7.6)	
244. dawid0890	(0.94, 8.4)	
245. jaden0310	(0.94, 7.1)	
246. magic0290	(0.94, 7.9)	
247. aiden0910	(0.94, 6.6)	
248. money0990	(0.94, 6.9)	
249. Nsaim0000	(0.94, 11.7)	
250. bopek0910	(0.94, 10.6)	
251. Honey0390	(0.94, 9.1)	
252. kaden0410	(0.94, 7.1)	
253. vivek8600	(0.94, 8.3)	
254. lomik0000	(0.94, 8.7)	
255. mcpep8190	(0.94, 12.2)	
256. haney0000	(0.94, 8.2)	
257. romij0000	(0.94, 10.7)	
258. nikop0000	(0.94, 8.5)	
259. rajen0110	(0.94, 8.4)	
260. kaden0510	(0.94, 7.1)	
261. ymmij0500	(0.94, 10.8)	
262. lukey0110	(0.94, 8.5)	
263. zahid0300	(0.94, 7.1)	
264. abbey0610	(0.94, 7.6)	
265. KeviN0210	(0.94, 9.8)	
266. Aiden0810	(0.94, 7.3)	
267. wajid0300	(0.94, 8.0)	
268. jaden0810	(0.94, 6.9)	
269. popop0000	(0.94, 7.0)	
270. kevin0390	(0.94, 7.6)	
271. deven9590	(0.94, 9.5)	
272. hopey0210	(0.94, 9.1)	
273. david0100	(0.94, 6.8)	
274. Edfeb0210	(0.94, 11.9)	
275. ancoc0100	(0.94, 11.2)	
276. hamid0300	(0.94, 7.1)	
277. jaden0710	(0.94, 6.9)	
278. david0490	(0.94, 7.2)	
279. jacob0500	(0.94, 7.3)	
280. Fenix9000	(0.94, 8.8)	
281. rafiq0300	(0.94, 7.9)	
282. deden8600	(0.94, 9.5)	
283. lacey0610	(0.94, 7.6)	
284. mixed9800	(0.94, 9.8)	
285. myboy0700	(0.94, 8.8)	
286. widow0000	(0.94, 8.2)	
287. sonic0000	(0.94, 6.6)	
288. venom0000	(0.94, 6.9)	
289. pwned0000	(0.94, 7.9)	
290. hafiz0300	(0.94, 7.1)	
291. robin0700	(0.94, 8.0)	
292. dideu9870	(0.94, 11.7)	
293. IlwiS0810	(0.94, 13.2)	
294. train0290	(0.94, 8.7)	
295. lopez9090	(0.94, 6.5)	
296. bugsy9090	(0.94, 8.4)	
297. ihnen0000	(0.94, 11.2)	
298. mikey8900	(0.94, 7.6)	
299. madey8000	(0.94, 10.1)	
300. hchen0310	(0.94, 10.2)	
301. Mpzs@9690	(0.94, 14.0)	
302. kuben8800	(0.94, 10.2)	
303. baden8900	(0.94, 9.4)	
304. bunty9870	(0.93, 8.6)	
305. kaveh5960	(0.93, 10.4)	
306. money0000	(0.93, 5.1)	
307. nactx0270	(0.93, 13.3)	
308. dsusa9780	(0.93, 11.4)	
309. rehim0500	(0.93, 10.3)	
310. gomez9000	(0.93, 7.4)	
311. sahej0010	(0.93, 10.8)	
312. Isaev0000	(0.93, 10.9)	
313. kamen9100	(0.93, 9.7)	
314. softy0870	(0.93, 10.0)	
315. mikek5560	(0.93, 9.8)	
316. money5280	(0.93, 7.8)	
317. jlcsd0170	(0.93, 11.8)	
318. lewi@9760	(0.93, 11.6)	
319. eljem5160	(0.93, 12.6)	
320. pansy9090	(0.93, 8.8)	
321. sahev8500	(0.93, 11.7)	
322. anath0080	(0.93, 11.0)	
323. mikey9090	(0.93, 6.9)	
324. NokiA5800	(0.93, 9.0)	
325. Jobs#9800	(0.93, 10.9)	
326. honey5970	(0.93, 8.0)	
327. sluty9870	(0.93, 10.5)	
328. santu0870	(0.93, 9.5)	
329. edwin9210	(0.93, 7.5)	
330. luyen0410	(0.93, 8.6)	
331. jvas.0880	(0.93, 13.0)	
332. Tbusu0000	(0.93, 12.2)	
333. Money8080	(0.93, 7.4)	
334. m@noj9210	(0.93, 10.2)	
335. cinta0980	(0.93, 8.5)	
336. Pepon9210	(0.93, 10.7)	
337. nokia9210	(0.93, 5.8)	
338. Jacob9110	(0.93, 7.9)	
339. Nokia9210	(0.93, 7.0)	
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342. gavin9110	(0.93, 7.6)	
343. vixen9800	(0.93, 8.7)	
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347. ruben9900	(0.93, 7.8)	
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349. abbey9000	(0.93, 7.2)	
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354. momon9610	(0.93, 9.7)	
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357. domin9110	(0.93, 9.1)	
358. nokia9110	(0.93, 6.1)	
359. david9510	(0.93, 7.0)	
360. dave●9070	(0.93, 10.7)	
361. nokia5070	(0.93, 6.0)	
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363. David9810	(0.93, 7.7)	
364. lovey5410	(0.93, 9.2)	
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366. India0910	(0.93, 7.9)	
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368. daasn0000	(0.93, 10.2)	
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370. Saheb9100	(0.93, 10.4)	
371. Bebo@0710	(0.93, 10.5)	
372. flash0580	(0.93, 7.9)	
373. Canon5590	(0.93, 9.0)	
374. pensa9900	(0.93, 10.1)	
375. dhush9700	(0.93, 11.0)	
376. Lydia0810	(0.93, 8.0)	
377. mafia5980	(0.93, 8.8)	
378. Gavin0810	(0.93, 7.3)	
379. Denty9090	(0.93, 10.8)	
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383. Myko$0210	(0.93, 12.0)	
384. bayoh0660	(0.93, 11.3)	
385. ivhsm0900	(0.93, 12.8)	
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388. jhdez9260	(0.93, 12.9)	
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410. miked7070	(0.92, 8.5)	
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785. hafiz8890 (0.91, 8.4)
786. dania0520 (0.91, 8.2)
787. ayush0610 (0.91, 7.9)
788. david8290 (0.91, 7.5)
789. mafia8800 (0.91, 7.8)
790. jazon0320 (0.91, 9.6)
791. mahsa5600 (0.91, 8.9)
792. kevin8390 (0.91, 7.7)
793. fryta0510 (0.91, 9.7)
794. gl@s$5870 (0.91, 13.4)
795. nokia8390 (0.91, 7.9)
796. waysw0810 (0.91, 12.7)
797. ouvom8490 (0.90, 13.4)
798. kent@5000 (0.90, 9.6)
799. tavia0820 (0.90, 8.9)
800. kazin5010 (0.90, 10.7)
801. bugsy5190 (0.90, 9.4)
802. fanta5000 (0.90, 7.3)
803. money9700 (0.90, 6.8)
804. Truth0410 (0.90, 8.7)
805. admin0320 (0.90, 6.5)
806. tufty5500 (0.90, 9.9)
807. codec3160 (0.90, 10.4)
808. david5760 (0.90, 7.3)
809. sofia8490 (0.90, 8.7)
810. tibia8500 (0.90, 9.2)
811. jovon0920 (0.90, 9.3)
812. avcom8400 (0.90, 11.3)
813. nokia8890 (0.90, 6.7)
814. yanez0320 (0.90, 9.1)
815. money9070 (0.90, 7.4)
816. edyth0210 (0.90, 10.5)
817. Flash0110 (0.90, 7.7)
818. dixon8100 (0.90, 9.2)
819. nono@5160 (0.90, 10.5)
820. chain0420 (0.90, 8.4)
821. nokia8600 (0.90, 6.0)
822. Death0610 (0.90, 8.5)
823. sonia8690 (0.90, 8.1)
824. sh@on5310 (0.90, 11.9)
825. save$3.00 (0.90, 12.5)
826. elfin0920 (0.90, 9.3)
827. truth5680 (0.90, 8.3)
828. binta0110 (0.90, 8.7)
829. axat$0210 (0.90, 13.5)
830. boken7160 (0.90, 10.6)
831. sofia0920 (0.90, 7.5)
832. Rahim0720 (0.90, 9.6)
833. david0820 (0.90, 6.6)
834. hojin0320 (0.90, 11.1)
835. jonty0310 (0.90, 8.8)
836. Nokia5610 (0.90, 6.6)
837. David5560 (0.90, 7.8)
838. devon0320 (0.90, 7.6)
839. devon0420 (0.90, 7.1)
840. nokia8800 (0.90, 5.1)
841. Nokia5310 (0.90, 5.3)
842. pobox8000 (0.90, 8.0)
843. monty0410 (0.90, 7.5)
844. david0120 (0.90, 6.3)
845. tyboc0620 (0.90, 11.1)
846. david0420 (0.90, 6.3)
847. gavin5510 (0.90, 7.8)
848. Flash0710 (0.90, 7.8)
849. kevin0320 (0.90, 6.6)
850. janey7100 (0.90, 9.7)
851. sofia0820 (0.90, 7.6)
852. life@8520 (0.90, 8.7)
853. novia0820 (0.90, 9.5)
854. fhneh8410 (0.90, 11.1)
855. novia0120 (0.90, 9.3)
856. rabsj8570 (0.90, 12.4)
857. yrasa0810 (0.90, 11.1)
858. india8060 (0.90, 8.1)
859. anaid0320 (0.90, 9.0)
860. kevin5010 (0.90, 7.4)
861. magic0420 (0.90, 6.9)
862. miyon0220 (0.90, 10.0)
863. robin0220 (0.90, 7.3)
864. Slash5000 (0.90, 8.1)
865. navin5610 (0.90, 9.2)
866. Nokia5110 (0.90, 6.4)
867. jacob0920 (0.90, 6.6)
868. cocoa5860 (0.90, 8.5)
869. megty5000 (0.90, 10.1)
870. cinta5000 (0.90, 7.3)
871. gavin5310 (0.90, 7.8)
872. cohen3360 (0.90, 8.8)
873. Liden3260 (0.90, 12.1)
874. llysa5190 (0.90, 11.8)
875. youth0210 (0.90, 8.7)
876. cunty5000 (0.90, 8.4)
877. money9090 (0.90, 5.7)
878. truth0910 (0.90, 7.8)
879. elvia0220 (0.90, 9.3)
880. vanek3000 (0.90, 8.3)
881. cp_sk8670 (0.90, 14.0)
882. Sanek3000 (0.90, 9.4)
883. aymen8520 (0.90, 8.3)
884. Akash8080 (0.90, 8.4)
885. jacob0120 (0.90, 6.6)
886. panic0420 (0.90, 7.9)
887. cami$5160 (0.90, 11.3)
888. jacob0420 (0.90, 6.2)
889. Dude*8420 (0.90, 11.4)
890. money!200 (0.90, 9.4)
891. Bebop5010 (0.90, 9.9)
892. spatz0610 (0.90, 9.4)
893. fdnec7700 (0.90, 11.7)
894. nikon5560 (0.90, 8.6)
895. info$5360 (0.90, 11.3)
896. honey0120 (0.90, 6.9)
897. erdem8520 (0.90, 8.1)
898. money7000 (0.90, 6.0)
899. money7500 (0.90, 6.1)
900. devin5960 (0.90, 8.6)
901. money0420 (0.90, 6.6)
902. simon5560 (0.90, 7.7)
903. kekeu0740 (0.90, 12.2)
904. death0910 (0.90, 7.4)
905. cocoa5560 (0.90, 8.3)
906. lamed0030 (0.90, 10.9)
907. hamed8020 (0.90, 8.4)
908. KastA0000 (0.90, 10.5)
909. arash0810 (0.90, 7.9)
910. jakob5960 (0.90, 8.6)
911. akmed8520 (0.90, 10.5)
912. ahmed8520 (0.90, 6.5)
913. lscom8700 (0.90, 11.1)
914. monic0520 (0.90, 9.4)
915. nokia5510 (0.90, 5.7)
916. conex3400 (0.90, 9.6)
917. honey3200 (0.90, 7.3)
918. Money3900 (0.90, 8.2)
919. david5510 (0.90, 7.0)
920. momon8060 (0.90, 10.2)
921. sodom0120 (0.90, 9.6)
922. kodim0620 (0.90, 9.4)
923. pepey0730 (0.90, 9.5)
924. money3400 (0.90, 7.1)
925. bonty5000 (0.90, 8.9)
926. santu5400 (0.90, 9.3)
927. nokia5610 (0.90, 4.7)
928. raven0130 (0.90, 7.3)
929. chaim0720 (0.90, 9.6)
930. tofik5860 (0.90, 10.3)
931. nokia5310 (0.90, 4.2)
932. money3000 (0.90, 5.4)
933. money3800 (0.90, 7.0)
934. fifty5060 (0.90, 7.5)
935. david5310 (0.90, 7.2)
936. vivec0330 (0.90, 10.9)
937. crush5000 (0.90, 7.1)
938. enaid5360 (0.90, 11.0)
939. david5410 (0.90, 7.1)
940. kevin5310 (0.90, 7.3)
941. jacob5160 (0.90, 7.3)
942. venom0420 (0.90, 7.8)
943. zsain0220 (0.90, 11.5)
944. flash0710 (0.90, 7.0)
945. david5360 (0.90, 7.3)
946. Mubsy0020 (0.90, 12.6)
947. dubin5210 (0.90, 10.0)
948. robin5110 (0.90, 7.9)
949. jacey0830 (0.90, 8.8)
950. nokia5110 (0.90, 4.8)
951. Fede*3110 (0.90, 11.0)
952. myken0630 (0.90, 9.4)
953. lakey0930 (0.90, 8.9)
954. dogen7260 (0.90, 10.6)
955. gaken0630 (0.90, 10.8)
956. janta8670 (0.90, 10.7)
957. devin5110 (0.90, 8.2)
958. erdem7410 (0.90, 8.6)
959. weken7810 (0.90, 10.5)
960. eawiw5410 (0.90, 12.9)
961. loden7110 (0.90, 9.9)
962. shcs@8600 (0.90, 11.8)
963. Elden7910 (0.90, 11.0)
964. aiden0130 (0.90, 7.3)
965. Luke_0830 (0.90, 9.7)
966. t@deu7410 (0.90, 12.6)
967. mazen3210 (0.90, 8.1)
968. hamed7410 (0.90, 7.6)
969. ramez7410 (0.90, 9.1)
970. nice=3210 (0.90, 11.7)
971. aiden3310 (0.90, 7.7)
972. death5000 (0.90, 6.3)
973. ahmed3510 (0.90, 7.5)
974. tadeu7410 (0.90, 9.4)

975. Romey3710 (0.90, 10.4)
976. affen3210 (0.90, 9.3)
977. mike-0130 (0.90, 9.0)
978. aiden3810 (0.90, 8.0)
979. maxeg3010 (0.90, 11.4)
980. Jaco@8910 (0.90, 10.9)
981. Aspen3310 (0.90, 8.6)
982. hajek9520 (0.90, 11.1)
983. jacek3410 (0.90, 9.2)
984. aaden7610 (0.90, 10.0)
985. addem3110 (0.90, 10.1)
986. Aiden0130 (0.90, 8.0)
987. reus.9320 (0.90, 12.1)
988. lacek3710 (0.90, 10.5)
989. david5210 (0.90, 7.0)
990. David8760 (0.90, 8.1)
991. nokia5210 (0.90, 5.1)
992. mobic5410 (0.90, 11.2)
993. jvcsw8890 (0.90, 12.3)
994. bims@8400 (0.90, 12.2)
995. Addey3910 (0.90, 11.7)
996. nupe@0140 (0.90, 12.4)
997. money9000 (0.89, 5.5)
998. Daksh0320 (0.89, 10.2)
999. linea3960 (0.89, 10.0)

Cluster 29

Prototype: saaemon85

Hard-assigned passwords: 1022360 (3.53% of total)
Unique hard-assigned passwords: 645476 (36.86% of cluster total)

Cluster-assignment scores:
	Min: 0.062
	Max: 0.989
	Mean: 0.335
	SD: 0.196

Strength bins:
	Very weak: 7821 (0.76%)
	Weak: 295416 (28.90%)
	Fair: 367333 (35.93%)
	Good: 343572 (33.61%)
	Strong: 8218 (0.80%)

Password lengths:
	Length 8: 69827 (6.83%)
	Length 9: 946964 (92.63%)
	Length 10: 5569 (0.54%)

Character classes:
	4 classes: 14916 (1.46%)
	3 classes: 138022 (13.50%)
		lower/upper/symbol: 212 (0.15%)
		lower/upper/number: 110578 (80.12%)
		lower/symbol/number: 27232 (19.73%)
		upper/symbol/number: 0 (0.00%)
	2 classes: 869421 (85.04%)
		lower/upper: 0 (0.00%)
		lower/number: 868758 (99.92%)
		lower/symbol: 663 (0.08%)
		upper/number: 0 (0.00%)
		upper/symbol: 0 (0.00%)
		number/symbol: 0 (0.00%)
	1 class: 1 (0.00%)
		lower: 0 (0.00%)
		upper: 0 (0.00%)
		symbol: 1 (100.00%)
		number: 0 (0.00%)

Most frequent char-class structures:
	LLLLLLLDD: 709218 (69.4%)
	LLLLLLLD: 82231 (8.0%)
	ULLLLLLDD: 77565 (7.6%)
	LLLLLLD: 37746 (3.7%)
	LLLLLLDD: 22973 (2.2%)
	LLLLLSDD: 14042 (1.4%)
	LLLLLLLDL: 11871 (1.2%)
	ULLLLLLLD: 9691 (0.9%)
	ULLLLSDD: 6143 (0.6%)
	LLLLLLLDS: 5140 (0.5%)

1,000 nearest passwords

0.	rfhfxey85	(0.99, 12.1)	54.	jtmoney85	(0.99, 6.8)	108.	azizbek85	(0.99, 8.9)
1.	whamfey85	(0.99, 10.0)	55.	meadken85	(0.99, 9.0)	109.	anasjeb85	(0.99, 12.6)
2.	babyfed85	(0.99, 8.9)	56.	rlvgbep85	(0.99, 12.9)	110.	saidbek85	(0.99, 10.6)
3.	oakaped85	(0.99, 10.6)	57.	bumthen85	(0.99, 10.2)	111.	bjnhyen85	(0.99, 12.1)
4.	soliyen85	(0.99, 11.8)	58.	troygen85	(0.99, 9.3)	112.	marquez85	(0.99, 6.1)
5.	ada_deh85	(0.99, 11.6)	59.	awewhen85	(0.99, 10.9)	113.	rolodex85	(0.99, 7.3)
6.	hershey85	(0.99, 6.0)	60.	grubdew85	(0.99, 9.7)	114.	fieoven85	(0.99, 11.1)
7.	mufffed85	(0.99, 9.6)	61.	Daboney85	(0.99, 10.5)	115.	glopbed85	(0.99, 9.5)
8.	maxamed85	(0.99, 7.0)	62.	gaitfen85	(0.99, 9.1)	116.	barnnew85	(0.99, 10.0)
9.	worthen85	(0.99, 8.4)	63.	dashyea85	(0.99, 10.9)	117.	garacey85	(0.99, 10.6)
10.	makubex85	(0.99, 7.9)	64.	skinhem85	(0.99, 9.2)	118.	chefken85	(0.98, 8.5)
11.	fzjdpeq85	(0.99, 13.1)	65.	sumenep85	(0.99, 8.4)	119.	princef85	(0.98, 8.9)
12.	nilthem85	(0.99, 10.4)	66.	heathen85	(0.99, 8.0)	120.	glibkev85	(0.98, 11.3)
13.	Buttgen85	(0.99, 10.7)	67.	wickweb85	(0.99, 9.8)	121.	gadsden85	(0.98, 8.3)
14.	babywed85	(0.99, 10.1)	68.	fjyouen85	(0.99, 12.0)	122.	taraneh85	(0.98, 7.7)
15.	izdnweh85	(0.99, 12.9)	69.	Changed85	(0.99, 7.3)	123.	chesney85	(0.98, 6.9)
16.	riyjceh85	(0.99, 12.6)	70.	avenged85	(0.99, 6.3)	124.	bragwen85	(0.98, 9.4)
17.	alethea85	(0.99, 7.9)	71.	sanchez85	(0.99, 5.3)	125.	Passnew85	(0.98, 9.4)
18.	matthew85	(0.99, 5.1)	72.	stephen85	(0.99, 5.3)	126.	obeypeg85	(0.98, 9.8)
19.	fizzpeg85	(0.99, 9.5)	73.	Franken85	(0.99, 8.3)	127.	mrcaven85	(0.98, 10.8)
20.	Matthew85	(0.99, 6.0)	74.	tinhyeu85	(0.99, 5.9)	128.	sueanep85	(0.98, 12.1)
21.	wostyew85	(0.99, 10.1)	75.	snitfed85	(0.99, 9.6)	129.	ironbed85	(0.98, 6.3)
22.	combfed85	(0.99, 10.4)	76.	kelpyen85	(0.99, 10.0)	130.	beloved85	(0.98, 6.5)
23.	cladhey85	(0.99, 9.4)	77.	codapew85	(0.99, 9.7)	131.	rgindex85	(0.98, 12.3)
24.	nyasgem85	(0.99, 11.8)	78.	grinyew85	(0.99, 11.0)	132.	safeyea85	(0.98, 10.1)
25.	hindpeg85	(0.99, 10.0)	79.	Mohamed85	(0.99, 6.5)	133.	beliveu85	(0.98, 9.5)
26.	vihuyen85	(0.99, 8.7)	80.	jenshen85	(0.99, 9.4)	134.	jogeyed85	(0.98, 9.9)
27.	loadhen85	(0.99, 9.3)	81.	journey85	(0.99, 6.4)	135.	Tur&nen85	(0.98, 13.4)
28.	foambed85	(0.99, 9.1)	82.	mojamed85	(0.99, 9.2)	136.	garabed85	(0.98, 9.3)
29.	cubsued85	(0.99, 9.8)	83.	mohamed85	(0.99, 5.5)	137.	hheaded85	(0.98, 11.9)
30.	rumphey85	(0.99, 10.3)	84.	jimenez85	(0.99, 6.1)	138.	branwen85	(0.98, 8.4)
31.	sinkhen85	(0.99, 10.7)	85.	bojymex85	(0.99, 13.0)	139.	volumen85	(0.98, 8.0)
32.	dresden85	(0.99, 7.0)	86.	orbthen85	(0.99, 9.7)	140.	askeyed85	(0.98, 10.2)
33.	humayed85	(0.99, 10.4)	87.	broome@85	(0.99, 10.3)	141.	dopeyep85	(0.98, 9.4)
34.	jambhew85	(0.99, 9.6)	88.	taskfew85	(0.99, 9.6)	142.	ideapew85	(0.98, 10.2)
35.	bcfagew85	(0.99, 12.9)	89.	woodpen85	(0.99, 5.8)	143.	zbyszek85	(0.98, 8.0)
36.	plumpep85	(0.99, 10.5)	90.	clipped85	(0.99, 8.8)	144.	sectfen85	(0.98, 8.9)
37.	kitchen85	(0.99, 6.6)	91.	Woodpen85	(0.99, 7.3)	145.	hopeyea85	(0.98, 10.5)
38.	ganghex85	(0.99, 10.2)	92.	yelphew85	(0.99, 10.3)	146.	funobey85	(0.98, 10.7)
39.	whiskey85	(0.99, 6.2)	93.	boopceg85	(0.99, 12.6)	147.	wellfed85	(0.98, 9.8)
40.	mitchem85	(0.99, 8.8)	94.	chicken85	(0.99, 5.6)	148.	ChickeN85	(0.98, 9.2)
41.	uhvcqex85	(0.99, 12.6)	95.	legshed85	(0.99, 10.1)	149.	vasquez85	(0.98, 6.1)
42.	fieopen85	(0.99, 11.4)	96.	knowmew85	(0.99, 9.6)	150.	udaidev85	(0.98, 10.9)
43.	ahughed85	(0.99, 12.4)	97.	bergyep85	(0.99, 10.4)	151.	jayiden85	(0.98, 10.2)
44.	rickgem85	(0.99, 9.5)	98.	trowden85	(0.99, 9.4)	152.	dcnlmek85	(0.98, 12.7)
45.	devake_85	(0.99, 11.5)	99.	menaxed85	(0.99, 10.5)	153.	meramec85	(0.98, 10.2)
46.	beayjeg85	(0.99, 12.6)	100.	sweeney85	(0.99, 7.3)	154.	dierbeb85	(0.98, 11.9)
47.	dziobek85	(0.99, 10.1)	101.	benamen85	(0.99, 9.1)	155.	shelbea85	(0.98, 9.8)
48.	prydyed85	(0.99, 10.6)	102.	marine.85	(0.99, 8.4)	156.	vswtkea85	(0.98, 12.9)
49.	foxymen85	(0.99, 9.0)	103.	pertzed85	(0.99, 9.7)	157.	poolpea85	(0.98, 10.0)
50.	songyew85	(0.99, 10.0)	104.	woodkey85	(0.99, 8.2)	158.	arpynek85	(0.98, 12.2)
51.	tmonhey85	(0.99, 11.4)	105.	soldhex85	(0.99, 10.3)	159.	Trouwen85	(0.98, 8.8)
52.	ruespew85	(0.99, 10.0)	106.	mildhex85	(0.99, 10.4)	160.	olyuaev85	(0.98, 13.6)
53.	jrmoney85	(0.99, 8.0)	107.	roofpew85	(0.99, 10.2)	161.	bourben85	(0.98, 9.9)

162. arjuned85 (0.98, 10.6)
163. gainwed85 (0.98, 9.6)
164. icyidea85 (0.98, 10.8)
165. CheezeO85 (0.98, 12.6)
166. ramiced85 (0.98, 9.7)
167. Quarken85 (0.98, 10.4)
168. yepcued85 (0.98, 9.6)
169. ako@web85 (0.98, 11.3)
170. ilniked85 (0.98, 11.9)
171. taleden85 (0.98, 10.0)
172. txgjjek75 (0.98, 13.8)
173. madehew85 (0.98, 10.2)
174. cznjpek75 (0.98, 12.9)
175. fcdmzek75 (0.98, 12.7)
176. jelonek75 (0.98, 8.7)
177. panefew85 (0.98, 9.5)
178. wilepew85 (0.98, 11.0)
179. yoeemen85 (0.98, 10.9)
180. cokeben85 (0.98, 10.4)
181. hopefey85 (0.98, 9.7)
182. tahabey75 (0.98, 10.9)
183. fenomen85 (0.98, 8.3)
184. hyucdep75 (0.98, 12.6)
185. dinepew85 (0.98, 11.0)
186. taxifez85 (0.98, 11.1)
187. jackdez75 (0.98, 10.2)
188. cavemen85 (0.98, 7.9)
189. znazzen75 (0.98, 12.8)
190. handken75 (0.98, 9.8)
191. dkzxqep75 (0.98, 12.9)
192. jpwkdef75 (0.98, 12.9)
193. fuckme●75 (0.98, 8.7)
194. nagaped75 (0.98, 9.4)
195. nibwhey75 (0.98, 10.4)
196. dnguyen75 (0.98, 8.1)
197. Schagen75 (0.98, 10.2)
198. shothey75 (0.98, 9.5)
199. baloney75 (0.98, 7.1)
200. maloney75 (0.98, 7.5)
201. change_75 (0.98, 8.2)
202. togepea85 (0.98, 8.9)
203. cmbhxej75 (0.98, 12.9)
204. munchen75 (0.98, 7.1)
205. yjbxhea75 (0.98, 13.5)
206. krmche@75 (0.98, 13.0)
207. thychef75 (0.98, 9.8)
208. sanchez75 (0.98, 5.8)
209. mogahed75 (0.98, 11.6)
210. kjfmgen75 (0.98, 12.7)
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217. wigchef75 (0.98, 10.0)
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693. belepek88 (0.96, 9.0)
694. hazefey88 (0.96, 9.5)
695. braiden88 (0.96, 7.0)
696. sumobeg88 (0.96, 10.4)
697. andrzej88 (0.96, 6.6)
698. mobikey88 (0.95, 11.2)
699. H@doken88 (0.95, 10.7)
700. BreydeN88 (0.95, 11.3)
701. amrekey88 (0.95, 10.4)

702. Loveme_88 (0.95, 8.5)
703. ahaomen88 (0.95, 10.2)
704. Waeezey88 (0.95, 13.8)
705. tubefen88 (0.95, 8.8)
706. waeezey88 (0.95, 12.6)
707. jeremey88 (0.95, 7.3)
708. Raceme⋆88 (0.95, 10.9)
709. orhidea88 (0.95, 8.3)
710. gafffed78 (0.95, 10.3)
711. hunkfed78 (0.95, 9.9)
712. campbed78 (0.95, 9.1)
713. ridebeg88 (0.95, 9.6)
714. bangbeg78 (0.95, 9.9)
715. m.ahmed78 (0.95, 10.0)
716. ananzeh78 (0.95, 10.6)
717. adzezed88 (0.95, 9.8)
718. ownaped78 (0.95, 9.3)
719. spankey78 (0.95, 7.5)
720. blesSed78 (0.95, 10.1)
721. leptweb88 (0.95, 9.6)
722. hoboken88 (0.95, 6.9)
723. padanew88 (0.95, 9.2)
724. Sanchez78 (0.95, 6.7)
725. sanchez78 (0.95, 5.7)
726. tunahey78 (0.95, 10.2)
727. avanged78 (0.95, 8.8)
728. swumhex78 (0.95, 9.4)
729. spayyea78 (0.95, 12.5)
730. lewdyea78 (0.95, 10.1)
731. vastyea78 (0.95, 10.2)
732. cacafea78 (0.95, 9.5)
733. vazquez88 (0.95, 6.2)
734. hypomew88 (0.95, 11.1)
735. dabsued78 (0.95, 9.8)
736. ownhued88 (0.95, 10.0)
737. VoyageS78 (0.95, 9.9)
738. rdkived88 (0.95, 12.5)
739. hershey78 (0.95, 5.8)
740. anyoven88 (0.95, 10.7)
741. Alethea78 (0.95, 9.2)
742. hikekeg88 (0.95, 10.8)
743. _shemek88 (0.95, 13.2)
744. lemone_78 (0.95, 10.6)
745. AtotheK88 (0.95, 11.5)
746. qwrkneg78 (0.95, 12.8)
747. jimenez78 (0.95, 6.3)
748. reggae_88 (0.95, 8.5)
749. momoney78 (0.95, 6.3)
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752. journey78 (0.95, 6.1)
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760. Fofonek78 (0.95, 12.0)
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762. manguey88 (0.95, 8.8)
763. ninaked78 (0.95, 9.4)
764. cortney78 (0.95, 6.9)
765. racynew88 (0.95, 9.6)
766. delaney78 (0.95, 6.4)
767. plumkey78 (0.95, 7.8)
768. lagawed78 (0.95, 10.8)
769. mosevej88 (0.95, 9.1)
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771. saxawed78 (0.95, 10.7)
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773. krochea78 (0.95, 10.4)
774. steeven88 (0.95, 7.2)
775. endowed88 (0.95, 7.4)
776. klseven88 (0.95, 10.5)
777. fuckued88 (0.95, 8.8)
778. bigdaeh88 (0.95, 10.4)
779. fanchew78 (0.95, 9.7)
780. dorkyep78 (0.95, 9.5)
781. winshey78 (0.95, 10.0)
782. kurtbey78 (0.95, 9.2)
783. warsped78 (0.95, 8.1)
784. whiskey78 (0.95, 6.0)
785. matthew78 (0.95, 4.9)
786. Vasquez78 (0.95, 7.0)
787. millueg78 (0.95, 11.5)
788. Matthew78 (0.95, 5.8)
789. voidfez78 (0.95, 9.2)
790. crushed78 (0.95, 7.4)
791. whamhem78 (0.95, 9.8)
792. M@rije_78 (0.95, 11.6)
793. gaitbeg78 (0.95, 9.9)
794. mcamden78 (0.95, 10.1)
795. mohamed78 (0.95, 5.7)
796. funkken78 (0.95, 10.2)
797. passmeh78 (0.95, 10.3)
798. untokeg78 (0.95, 11.6)
799. chicpea78 (0.95, 8.6)
800. warynew78 (0.95, 9.9)
801. icbnmev78 (0.95, 12.4)
802. juminem78 (0.95, 10.4)
803. fatdhem78 (0.95, 11.2)
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806. arathea78 (0.95, 9.0)
807. treewen88 (0.95, 9.0)
808. lochhen78 (0.95, 9.3)
809. Tlicue.78 (0.95, 12.8)
810. qongvez78 (0.95, 13.6)
811. kajeweb88 (0.95, 12.4)
812. roodgem78 (0.95, 9.6)
813. freeweb88 (0.95, 5.5)
814. joseweb88 (0.95, 7.5)
815. gaweweb88 (0.95, 11.5)
816. seamhen78 (0.95, 9.9)
817. siteweb88 (0.95, 6.6)
818. betibex78 (0.95, 10.8)
819. elmahen78 (0.95, 9.6)
820. sininen78 (0.95, 8.7)
821. riffpen78 (0.95, 9.4)
822. blocked78 (0.95, 7.5)
823. yukamen78 (0.95, 10.8)
824. untamed78 (0.95, 7.1)
825. Volguen78 (0.95, 11.7)
826. kjernen78 (0.95, 11.3)
827. yvonnew78 (0.95, 9.2)
828. micadem78 (0.95, 9.5)
829. axonnew78 (0.95, 9.9)
830. iluvjen78 (0.95, 7.7)
831. korggem78 (0.95, 11.7)
832. abuthem78 (0.95, 10.0)
833. glamkem78 (0.95, 11.8)
834. Belize@78 (0.95, 8.6)
835. kitchen78 (0.95, 6.4)
836. swingen78 (0.95, 8.4)
837. tikadec78 (0.95, 10.9)
838. larkdeb78 (0.95, 9.7)
839. ironbed78 (0.95, 6.3)
840. wushuem78 (0.95, 11.6)
841. methuen78 (0.95, 8.4)
842. pieaced78 (0.95, 9.8)
843. princek78 (0.95, 7.9)
844. goodnew78 (0.95, 7.3)
845. longden78 (0.95, 8.5)
846. Rmendez78 (0.95, 9.6)
847. agoowed78 (0.95, 11.2)
848. yawsped78 (0.95, 9.6)
849. slowfew78 (0.95, 9.3)
850. bracken78 (0.95, 7.3)
851. poiknew78 (0.95, 10.5)
852. Stephen78 (0.95, 6.3)
853. whoknew78 (0.95, 8.8)
854. roanken78 (0.95, 9.7)
855. nounden78 (0.95, 9.8)
856. Nomaden78 (0.95, 8.8)
857. Flatbed78 (0.95, 8.2)
858. pumawen78 (0.95, 9.8)
859. stephen78 (0.95, 5.2)
860. duoopen78 (0.95, 11.2)
861. wloczek78 (0.95, 9.0)
862. beayden78 (0.95, 10.7)
863. brayden78 (0.95, 6.3)
864. callgem78 (0.95, 10.0)
865. slopdew78 (0.95, 10.4)
866. homymen78 (0.95, 10.2)
867. smogdew78 (0.95, 10.0)
868. pubthen78 (0.95, 10.3)
869. hailyew78 (0.95, 10.7)
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871. hackney88 (0.95, 6.5)
872. tcxpueg78 (0.95, 12.9)
873. moutmez78 (0.95, 12.0)
874. RobyneC88 (0.95, 11.8)
875. polaxed78 (0.95, 10.9)
876. sclnze.78 (0.95, 14.0)
877. chivken78 (0.95, 10.4)
878. dokumen78 (0.95, 9.4)
879. chicken78 (0.95, 5.4)
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881. burlbed78 (0.95, 6.3)
882. camaney78 (0.95, 7.7)
883. bestweb78 (0.95, 7.7)
884. sitoweb78 (0.95, 8.1)
885. Sefigec78 (0.95, 12.5)
886. batebed78 (0.95, 9.4)
887. fordmew78 (0.95, 10.5)
888. pinkney78 (0.95, 6.7)
889. shyobey78 (0.95, 11.5)
890. ivlpcen78 (0.95, 13.0)
891. giftzed78 (0.95, 10.1)
892. sanane.78 (0.95, 7.4)
893. Montjeu78 (0.95, 11.8)
894. harmden78 (0.95, 9.5)
895. msogden78 (0.95, 11.6)
896. islegen78 (0.95, 10.7)
897. steffen78 (0.95, 7.1)
898. shedden78 (0.95, 9.1)
899. pwayne●78 (0.95, 11.5)
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902. sharkey78 (0.94, 7.0)
903. tornfew78 (0.94, 10.1)
904. heedken78 (0.94, 9.6)
905. itrsven78 (0.94, 12.5)
906. nullkey78 (0.94, 9.3)
907. cakedeb78 (0.94, 9.7)
908. posebeg78 (0.94, 10.7)
909. repobey78 (0.94, 10.2)
910. corehew78 (0.94, 10.2)
911. tonefed78 (0.94, 9.4)
912. hivehex78 (0.94, 9.9)
913. pnvidek78 (0.94, 12.4)
914. Dawidek78 (0.94, 8.4)
915. roilzed78 (0.94, 10.6)
916. starkey78 (0.94, 7.4)
917. sandnew78 (0.94, 8.7)
918. kelebek78 (0.94, 7.1)
919. jokepeg78 (0.94, 10.5)
920. hackney78 (0.94, 7.0)
921. pierfen78 (0.94, 9.7)
922. lchlweb78 (0.94, 12.4)
923. lurezed78 (0.94, 10.8)
924. Woerden78 (0.94, 9.6)
925. moulden78 (0.94, 9.8)
926. Freeveb78 (0.94, 11.8)
927. yeniben78 (0.94, 8.9)
928. dekidem78 (0.94, 11.2)
929. mojoben78 (0.94, 10.5)
930. cabaweb05 (0.94, 9.6)
931. mitemen78 (0.94, 9.4)
932. freeweb78 (0.94, 6.0)
933. iloinen65 (0.94, 11.0)
934. hershey05 (0.94, 5.7)
935. cwtmuen65 (0.94, 13.1)
936. online@65 (0.94, 8.3)
937. qfryjeb05 (0.94, 13.3)
938. chutney65 (0.94, 7.6)
939. clooney65 (0.94, 7.4)
940. mmadden65 (0.94, 9.3)
941. sanchez65 (0.94, 5.9)
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943. whitney65 (0.94, 6.1)
944. zsliaeq65 (0.94, 13.3)
945. hummped65 (0.94, 11.8)
946. czxgjev65 (0.94, 12.6)
947. filipek05 (0.94, 7.3)
948. woosued65 (0.94, 9.7)
949. yomayen65 (0.94, 11.8)
950. jockyea65 (0.94, 10.7)
951. ekeeven78 (0.94, 11.0)
952. kalibex05 (0.94, 7.9)
953. ayoube.05 (0.94, 8.8)
954. herbnew65 (0.94, 9.1)
955. topchef65 (0.94, 7.0)
956. jntmueb65 (0.94, 13.5)
957. pillwen78 (0.94, 10.9)
958. rungken65 (0.94, 9.2)
959. dddjbeg65 (0.94, 13.5)
960. malikey05 (0.94, 9.2)
961. Sweeney65 (0.94, 8.4)
962. Apache⋆65 (0.94, 9.2)
963. sexyhen65 (0.94, 9.4)
964. chancey65 (0.94, 7.3)
965. juanjep65 (0.94, 10.8)
966. bailnew65 (0.94, 9.7)
967. smahmed65 (0.94, 9.6)
968. waitgem65 (0.94, 10.1)
969. papadec05 (0.94, 9.5)
970. whiskey05 (0.94, 5.9)
971. artifex05 (0.94, 7.7)

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972. seleneT65    (0.94, 10.8)
973. zeromen05    (0.94,  9.4)
974. busigep05    (0.94, 11.1)
975. mytobey05    (0.94, 10.0)
976. sosomed05    (0.94,  9.4)
977. journey65    (0.94,  6.3)
978. lgstvea05    (0.94, 12.2)
979. rolodex05    (0.94,  7.4)
980. slztfev05    (0.94, 12.8)
981. magamed05    (0.94,  9.8)
982. chimney65    (0.94,  7.0)
983. jgypfek65    (0.94, 13.0)
984. sxvbcej05    (0.94, 13.1)
985. vcwypex05    (0.94, 13.3)
986. saidyep65    (0.94, 10.1)
987. matthew05    (0.94,  4.4)
988. kamine_65    (0.94, 10.4)
989. eugene.65    (0.94,  8.9)
990. mugaxed65    (0.94, 12.3)
991. Leschen65    (0.94,  9.5)
992. momoney65    (0.94,  5.9)
993. crashed05    (0.94,  7.1)
994. catthem65    (0.93,  9.6)
995. blooded05    (0.93,  7.9)
996. beauyea65    (0.93,  9.9)
997. crushed05    (0.93,  7.1)
998. matthew65    (0.93,  5.3)
999. cljqaed65    (0.93, 12.8)
```

B.3.3 Guessability curves

Figures B.2-B.4 show guess curves for each cluster's set of hard-assigned passwords. PGS3 NN guess numbers are shown.

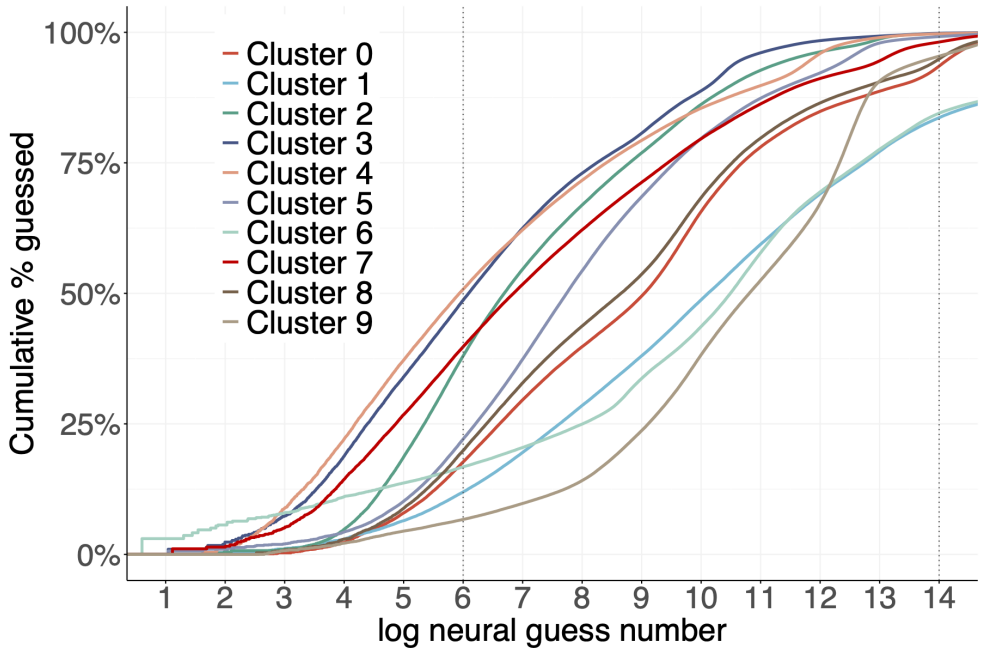


Figure B.2: Guess curves for passwords hard-assigned to clusters 0-9.

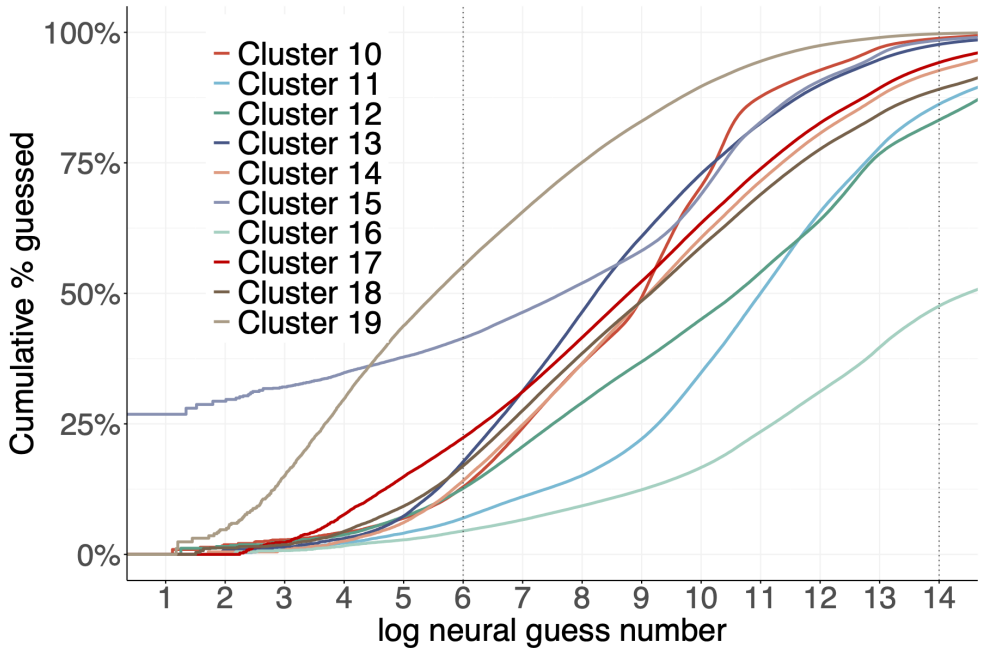


Figure B.3: Guess curves for passwords hard-assigned to clusters 10-19.

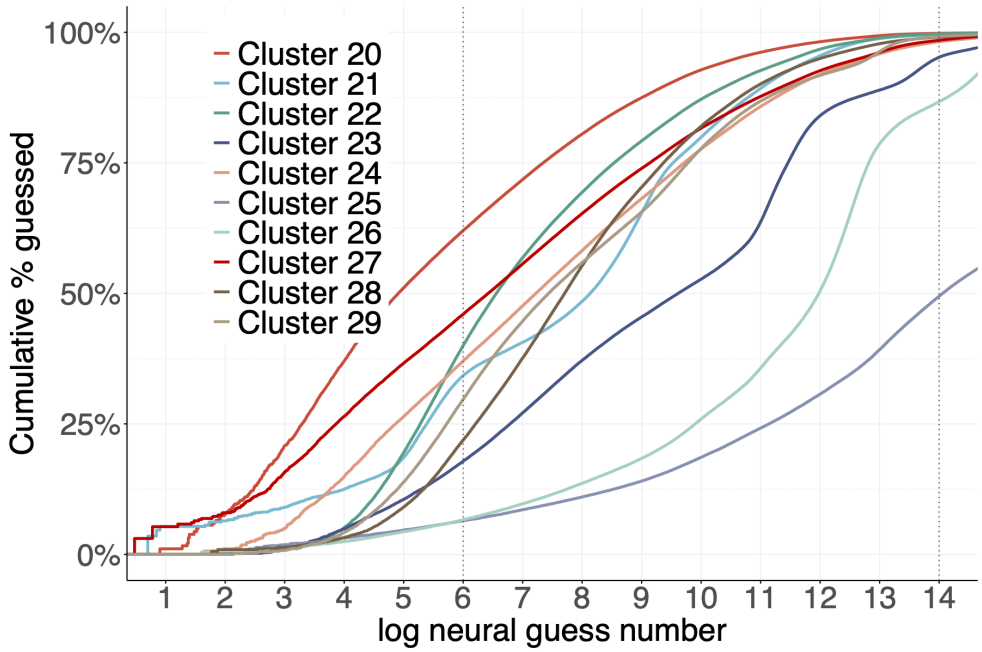


Figure B.4: Guess curves for passwords hard-assigned to clusters 20-29.

B.4 t-SNE plots

Figure B.5 shows a t-SNE plot of 5,000 passwords with the plot grid included. The axes for both embedding dimensions have displayed using the same scale, which is important in order for avoid distorting visualization of global structure in the password-encoding latent space.

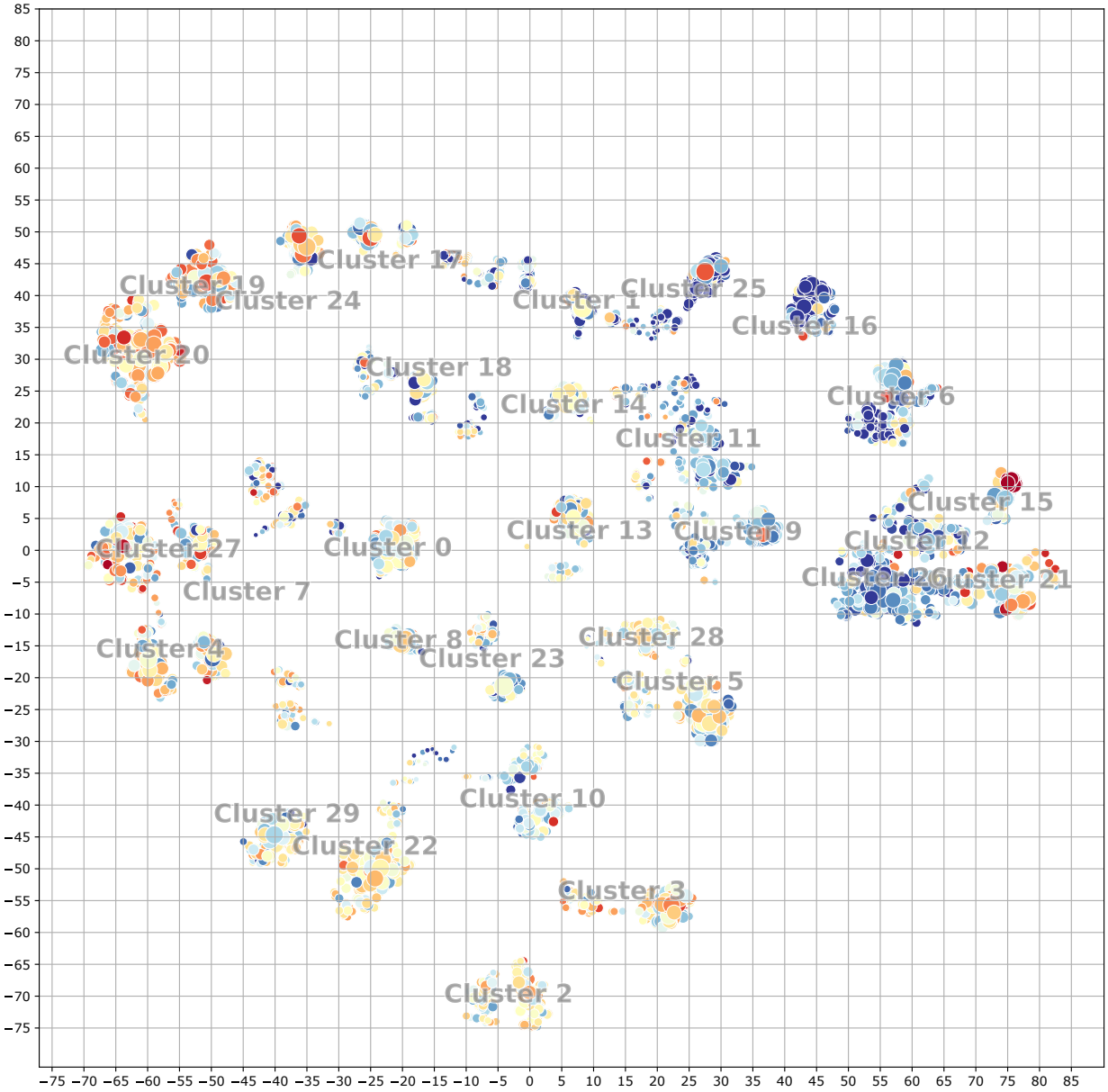


Figure B.5: t-SNE visualization that includes axes and tick marks for the t-SNE embedding dimensions

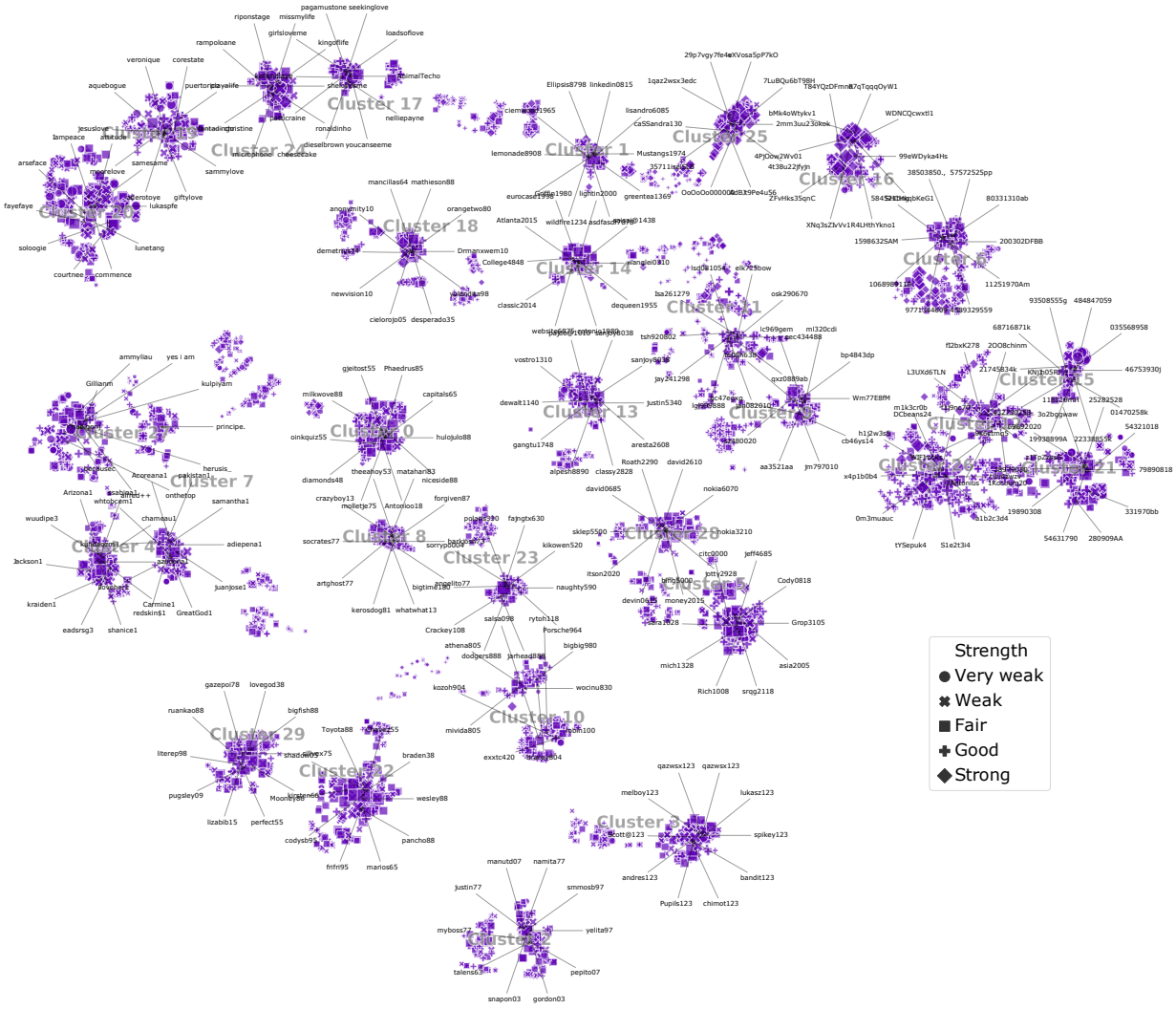


Figure B.6: t-SNE visualization for 5,000 passwords, where the binned password strength of each password data point is depicted using different marker styles.

B.4.1 Cluster relationship to guessability

Cluster membership for randomly generated passwords

We revisited the question of cluster relationship to guessability by observing how randomly generated passwords were clustered by fuzzy c-means and where they were projected to in t-SNE visualizations.

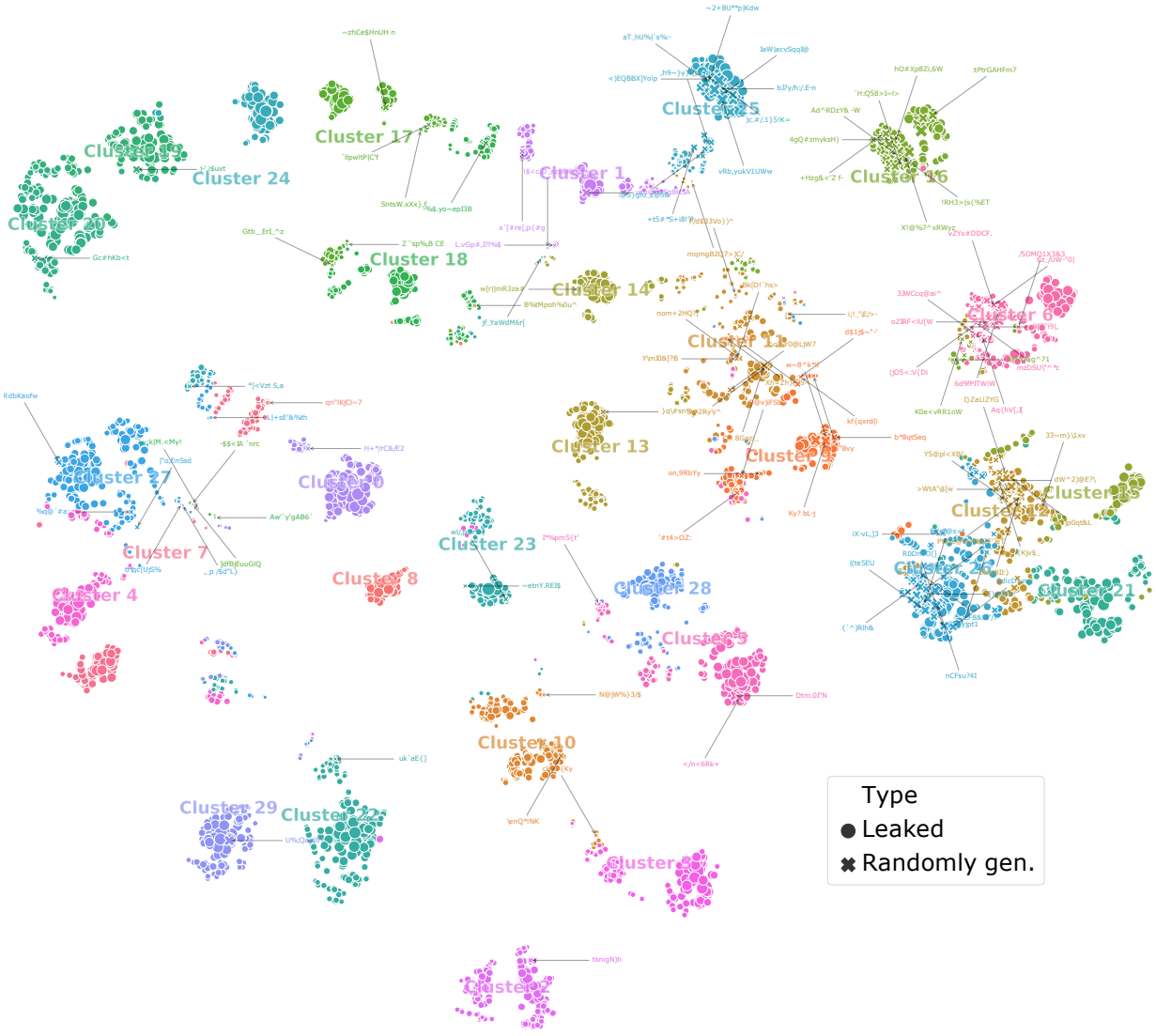


Figure B.7: t-SNE visualization for 5,000 passwords and 300 randomly generated passwords. Cluster membership is depicted using marker colors.

Our results show that some cluster-associated patterns are much more likely to exist in randomly generated passwords than others. As shown in Figure B.7, the majority of randomly generated passwords were projected near to a specific few clusters (e.g., Clusters 16, 25, and 26). Figure B.8 verifies that these randomly generated passwords were associated with low guessability,

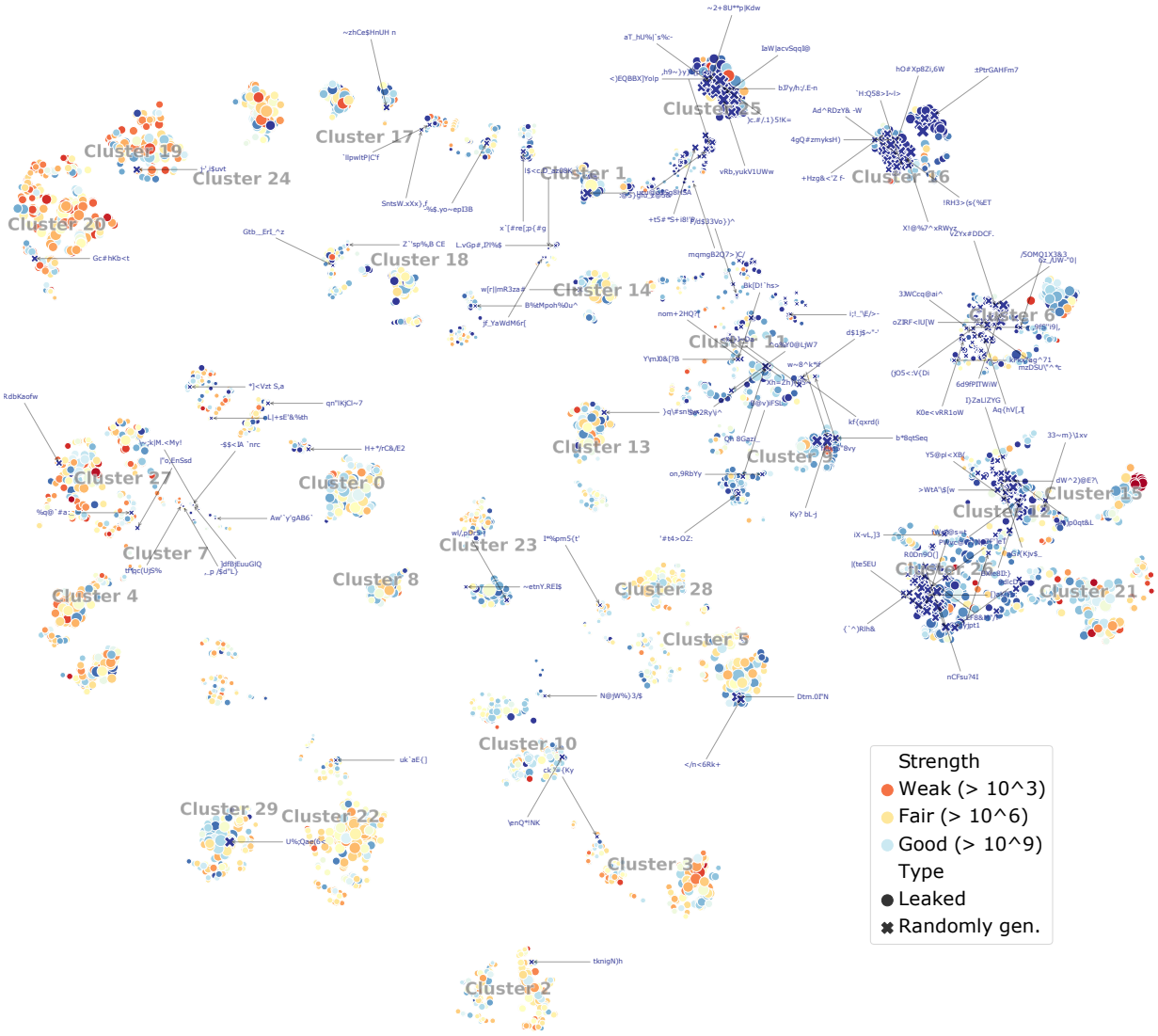
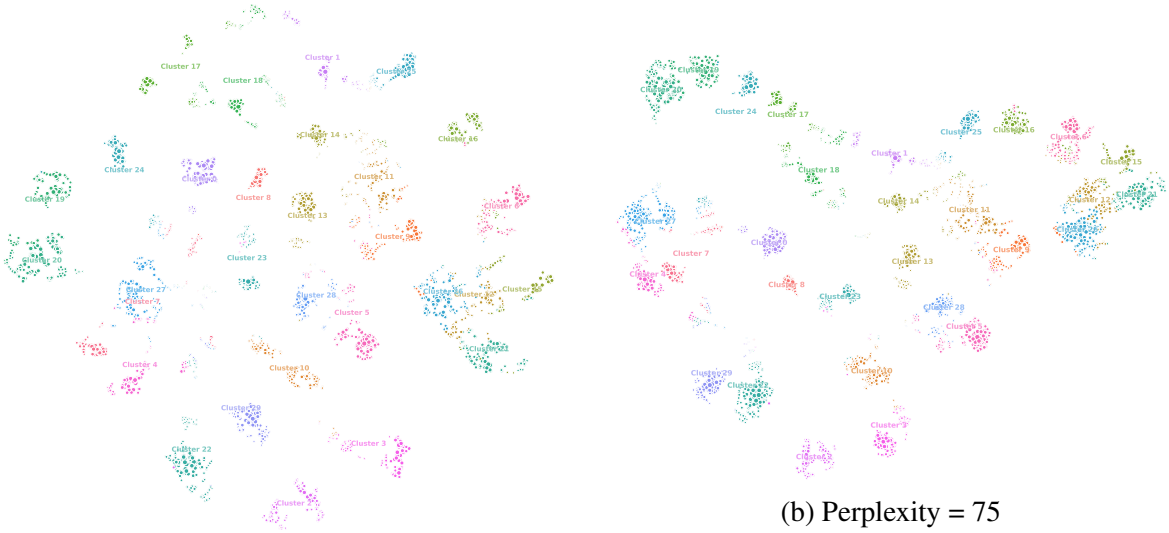


Figure B.8: t-SNE visualization for 5,000 passwords and 300 randomly generated passwords. PGS3 NN guess numbers are depicted using marker colors.

but nonetheless were distributed among clusters of predominantly weak passwords, limiting the utility of cluster membership for predicting guessability.

B.4.2 Effect of varying perplexity

Figure B.9 illustrates how t-SNE visualizations of the latent space change as a function of the perplexity parameter.



(a) Perplexity = 25

(b) Perplexity = 75

(c) Perplexity = 200

(d) Perplexity = 400

Figure B.9: t-SNE plots for 5,000 passwords and varying values of the perplexity parameter.

B.4.3 t-SNE with IG cluster-assignment explanations

Figure B.10 shows a t-SNE visualization with Integrated-Gradients cluster-assignment explanations for the hard assignments of the ten passwords nearest to each cluster.

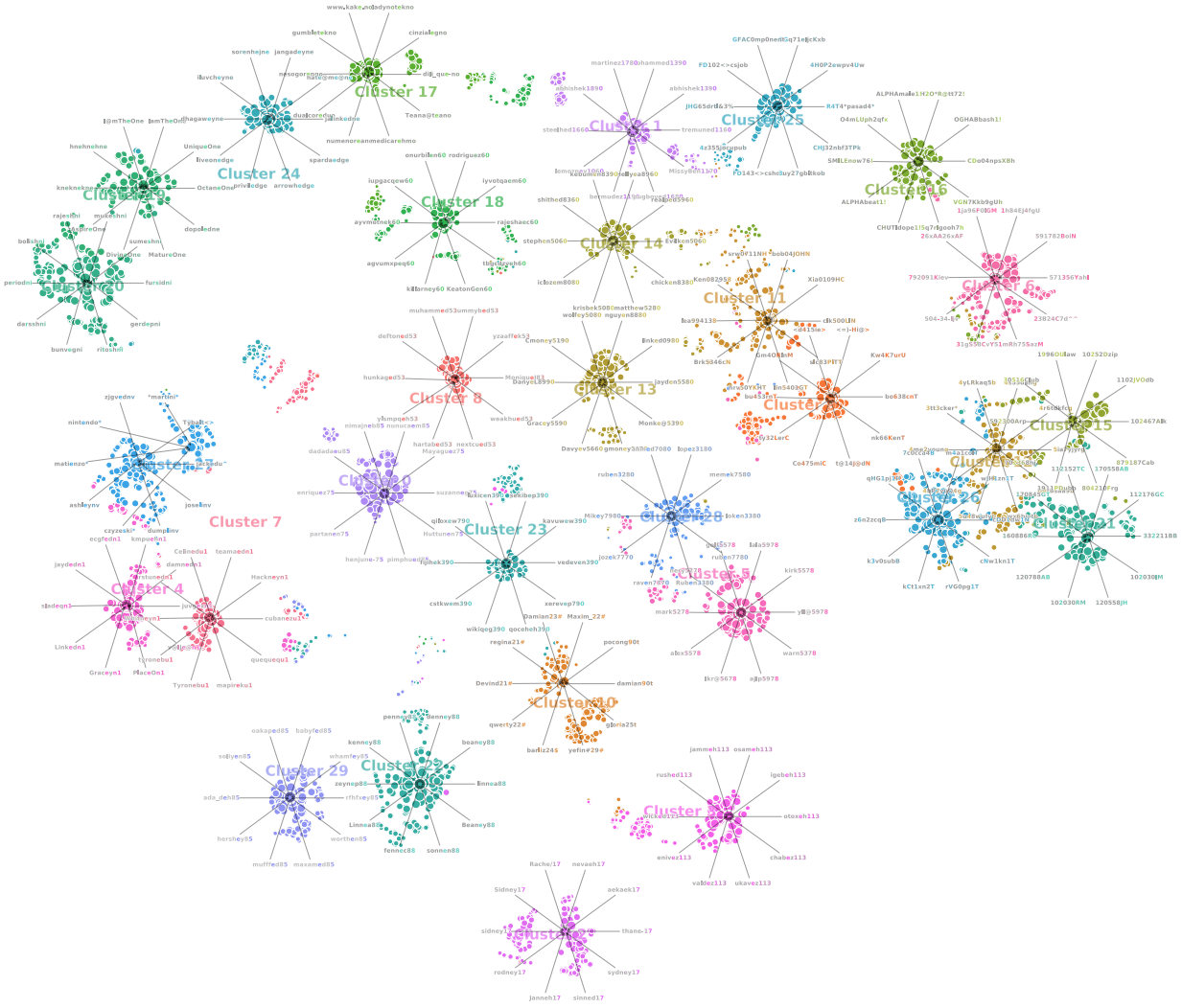


Figure B.10: t-SNE visualization with IG cluster-membership explanations for the nearest passwords to each cluster. IG attributions were computed using the padding baseline over 250 approximation steps.

B.4.4 t-SNE embeddings for 90,000 passwords

In Figures B.11 and B.12 we show t-SNE visualization for 90,000 passwords selected from *PGS3max12* using random stratified sampling.

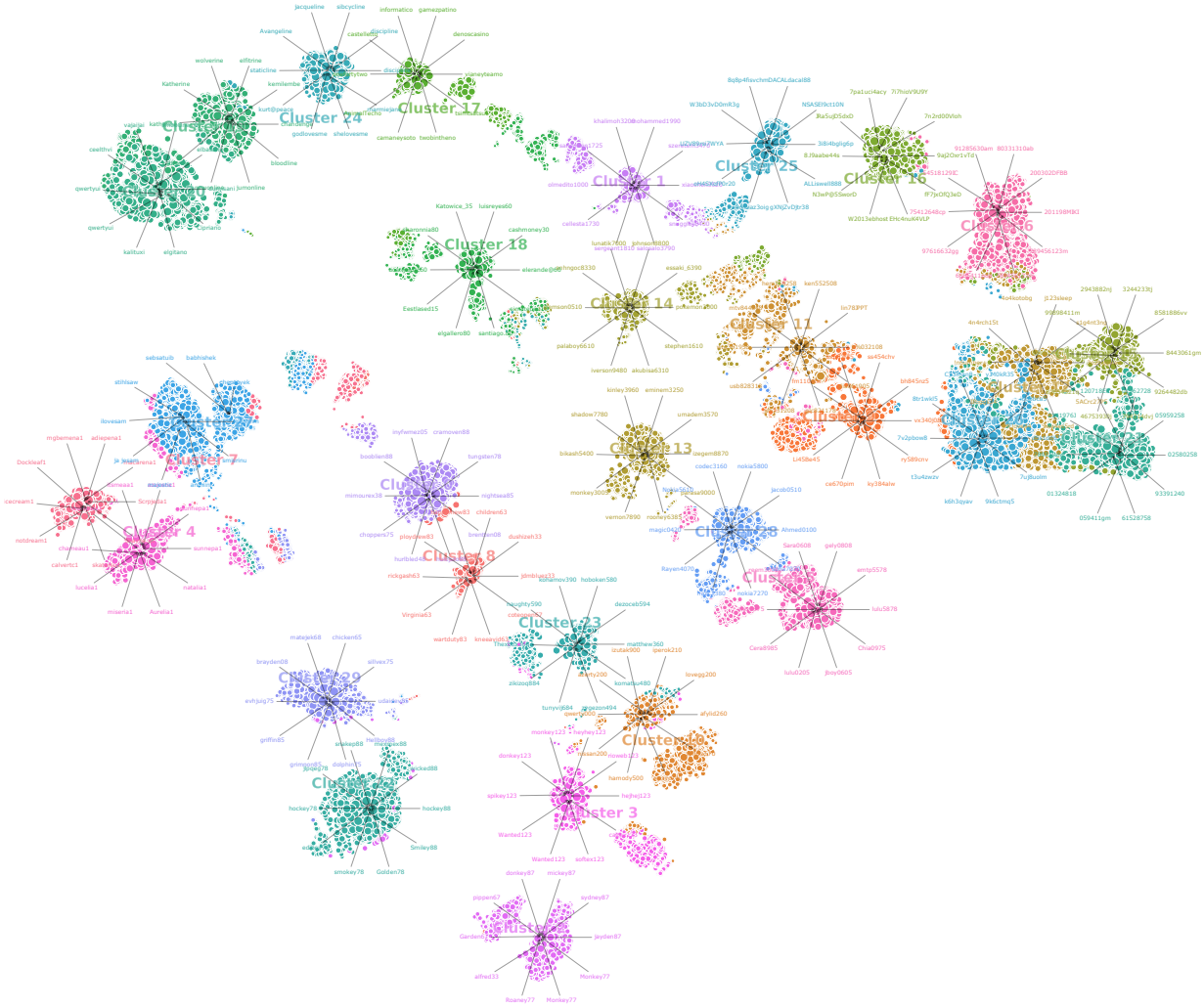


Figure B.11: t-SNE visualization for 90,000 passwords. Cluster membership is depicted using marker colors.

A benefit of viewing t-SNE with large sample sizes is that it can help reveal new clusters of passwords appearing in the t-SNE embedding plot that are heterogeneous in terms of fuzzy c-means hard-assignments. These grouping of passwords could potentially be captured in a distinct cluster if we re-run fuzzy c-means with a larger number of clusters.

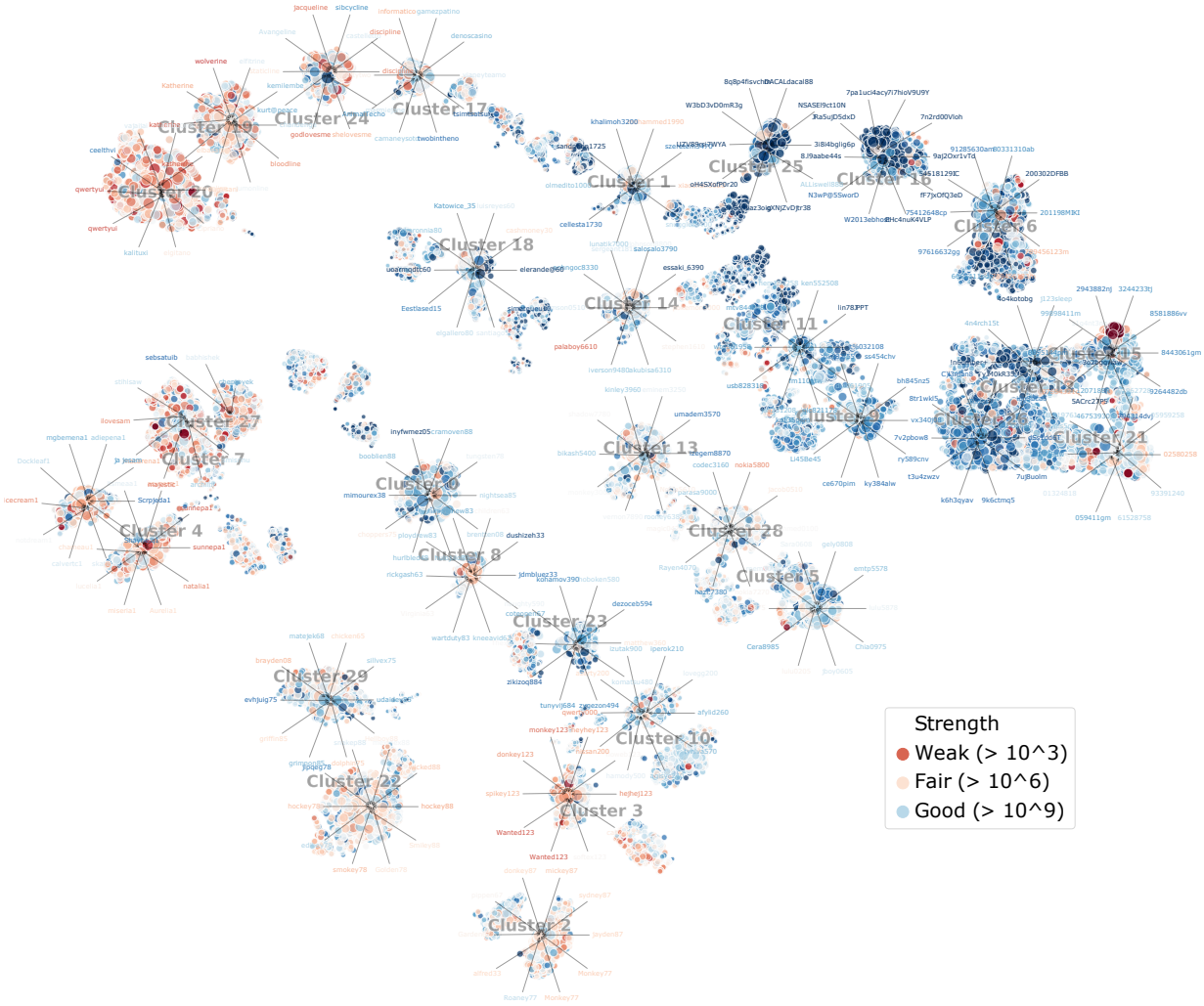


Figure B.12: t-SNE visualization for 90,000 passwords. PGS3 NN guess numbers are depicted using marker colors.

B.5 IG experiments

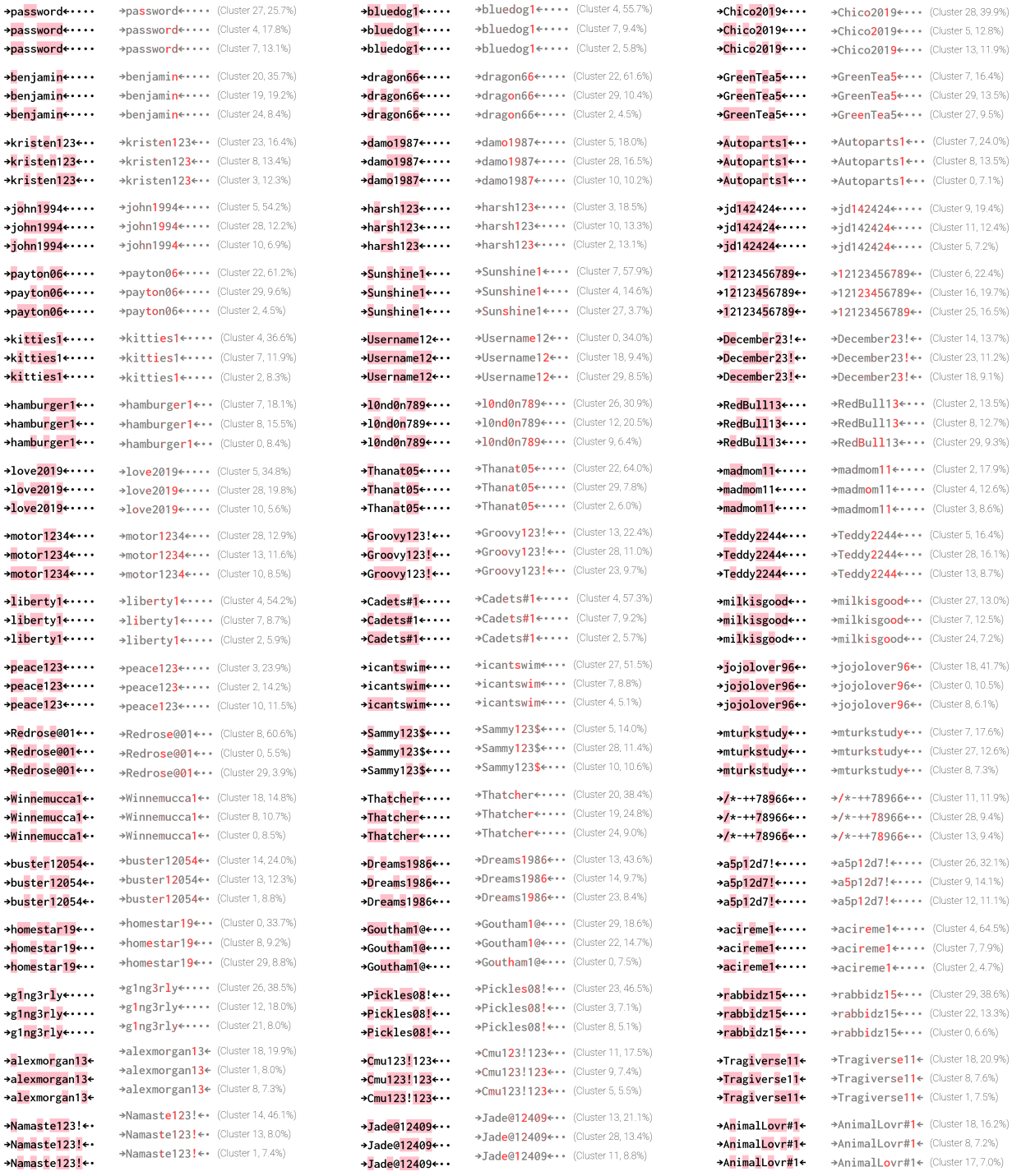
B.5.1 Padding baseline

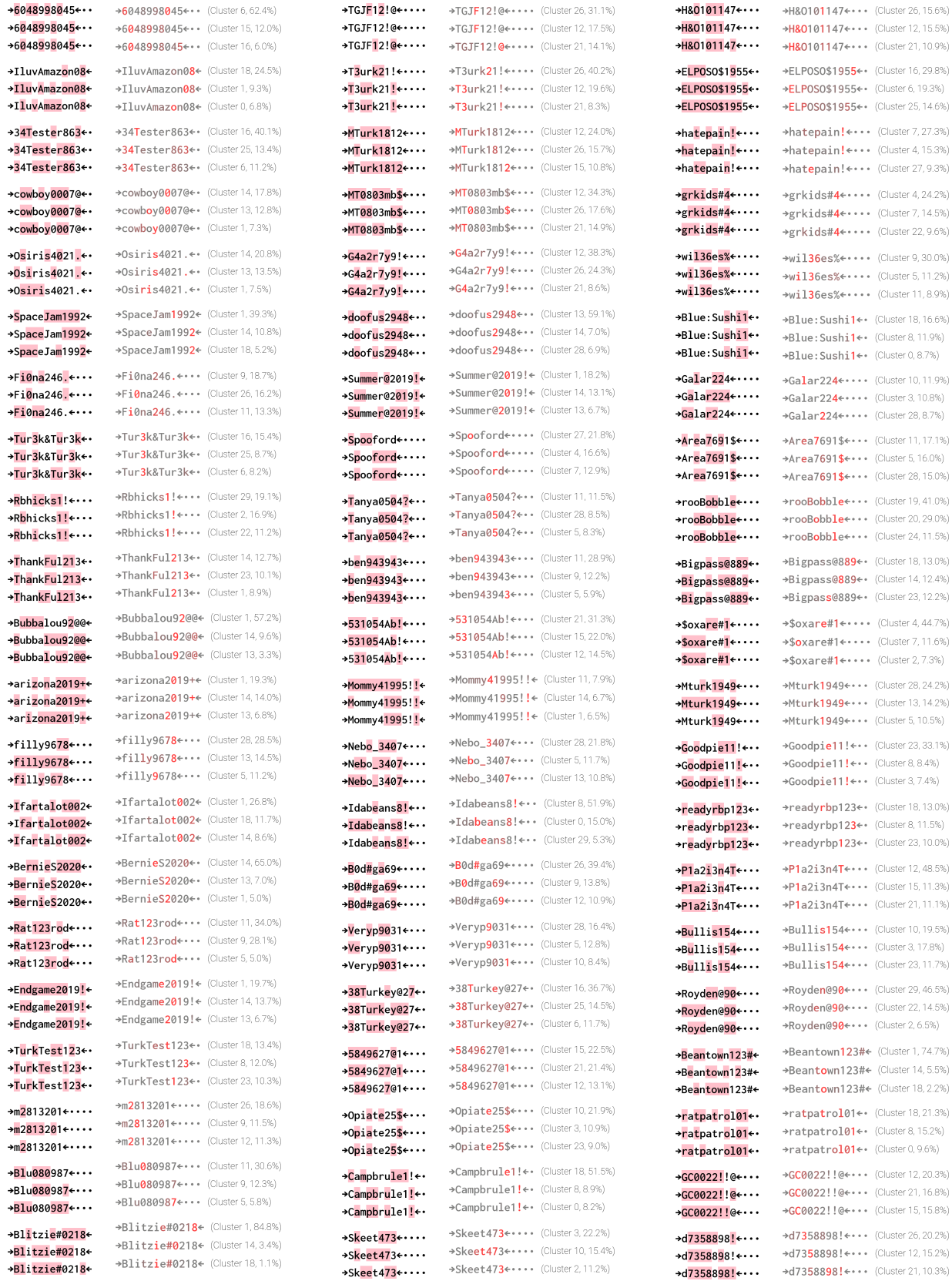
We experimented with a few variations of padding-based baselines, including: the embedding produced by a sequence of eight PAD tokens (the minimum training-data password length); the embedding produced by a sequence of PAD tokens of the same length as the input password (the maximum training-data password length was twelve characters); an all-zero embedding vector; and the embedding corresponding to a right-padded START and END token (with no padding in-between). The baseline that produced the overall clearest and most consistent saliency maps was the embedding for a sequence of PAD tokens of the same length as the input password, including START and END tokens.

Figure B.13: Visualization of positive IG attributions with respect to the padding baseline, approximated over 250 steps. Attribution values have not been clipped in this visualization.

Attributions for *1c8* user-study passwords (CCS 2020)

Here we show padding-baseline IG attributions for two visualization configurations: all positive attributions highlighted equally (left) and attributions clipped at the 95th percentile with color intensity proportional to the clipped attribution magnitude (right).




→6048998045←•• →6048998045←•• (Cluster 6, 62.4%)
→6048998045←•• →6048998045←•• (Cluster 15, 12.0%)
→6048998045←•• →6048998045←•• (Cluster 16, 6.0%)
→IluvAmazon08← →IluvAmazon08← (Cluster 18, 24.5%)
→IluvAmazon08← →IluvAmazon08← (Cluster 1, 9.3%)
→IluvAmazon08← →IluvAmazon08← (Cluster 0, 6.8%)
→34Tester863←•• →34Tester863←•• (Cluster 16, 40.1%)
→34Tester863←•• →34Tester863←•• (Cluster 25, 13.4%)
→34Tester863←•• →34Tester863←•• (Cluster 6, 11.2%)
→cowboy0007@←• →cowboy0007@←• (Cluster 14, 17.8%)
→cowboy0007@←• →cowboy0007@←• (Cluster 13, 12.8%)
→cowboy0007@←• →cowboy0007@←• (Cluster 1, 7.3%)
→Osiris4021.←• →Osiris4021.←• (Cluster 14, 20.8%)
→Osiris4021.←• →Osiris4021.←• (Cluster 13, 13.5%)
→Osiris4021.←• →Osiris4021.←• (Cluster 1, 7.5%)
→SpaceJam1992← →SpaceJam1992← (Cluster 1, 39.3%)
→SpaceJam1992← →SpaceJam1992← (Cluster 14, 10.8%)
→SpaceJam1992← →SpaceJam1992← (Cluster 18, 5.2%)
→Fi0na246.←••• →Fi0na246.←••• (Cluster 9, 18.7%)
→Fi0na246.←••• →Fi0na246.←••• (Cluster 26, 16.2%)
→Fi0na246.←••• →Fi0na246.←••• (Cluster 11, 13.3%)
→Tur3k&Tur3k←• →Tur3k&Tur3k←• (Cluster 16, 15.4%)
→Tur3k&Tur3k←• →Tur3k&Tur3k←• (Cluster 25, 8.7%)
→Tur3k&Tur3k←• →Tur3k&Tur3k←• (Cluster 6, 8.2%)
→Rbhicks1!←••• →Rbhicks1!←••• (Cluster 29, 19.1%)
→Rbhicks1!←••• →Rbhicks1!←••• (Cluster 2, 16.9%)
→Rbhicks1!←••• →Rbhicks1!←••• (Cluster 22, 11.2%)
→ThankFul213←• →ThankFul213←• (Cluster 14, 12.7%)
→ThankFul213←• →ThankFul213←• (Cluster 23, 10.1%)
→ThankFul213←• →ThankFul213←• (Cluster 1, 8.9%)
→Bubbalou92@@← →Bubbalou92@@← (Cluster 1, 57.2%)
→Bubbalou92@@← →Bubbalou92@@← (Cluster 14, 9.6%)
→Bubbalou92@@← →Bubbalou92@@← (Cluster 13, 3.3%)
→arizona2019+← →arizona2019+← (Cluster 1, 19.3%)
→arizona2019+← →arizona2019+← (Cluster 14, 14.0%)
→arizona2019+← →arizona2019+← (Cluster 13, 6.8%)
→filly9678←••• →filly9678←••• (Cluster 28, 28.5%)
→filly9678←••• →filly9678←••• (Cluster 13, 14.5%)
→filly9678←••• →filly9678←••• (Cluster 5, 11.2%)
→Ifartalot002← →Ifartalot002← (Cluster 1, 26.8%)
→Ifartalot002← →Ifartalot002← (Cluster 18, 11.7%)
→Ifartalot002← →Ifartalot002← (Cluster 14, 8.6%)
→BernieS2020←• →BernieS2020←• (Cluster 14, 65.0%)
→BernieS2020←• →BernieS2020←• (Cluster 13, 7.0%)
→BernieS2020←• →BernieS2020←• (Cluster 1, 5.0%)
→Rat123rod←••• →Rat123rod←••• (Cluster 11, 34.0%)
→Rat123rod←••• →Rat123rod←••• (Cluster 9, 28.1%)
→Rat123rod←••• →Rat123rod←••• (Cluster 5, 5.0%)
→Endgame2019!← →Endgame2019!← (Cluster 1, 19.7%)
→Endgame2019!← →Endgame2019!← (Cluster 14, 13.7%)
→Endgame2019!← →Endgame2019!← (Cluster 13, 6.7%)
→TurkTest123←• →TurkTest123←• (Cluster 18, 13.4%)
→TurkTest123←• →TurkTest123←• (Cluster 8, 12.0%)
→TurkTest123←• →TurkTest123←• (Cluster 23, 10.3%)
→m2813201←•••• →m2813201←•••• (Cluster 26, 18.6%)
→m2813201←•••• →m2813201←•••• (Cluster 9, 11.5%)
→m2813201←•••• →m2813201←•••• (Cluster 12, 11.3%)
→Blu080987←••• →Blu080987←••• (Cluster 11, 30.6%)
→Blu080987←••• →Blu080987←••• (Cluster 9, 12.3%)
→Blu080987←••• →Blu080987←••• (Cluster 5, 5.8%)
→Blitzie#0218← →Blitzie#0218← (Cluster 1, 84.8%)
→Blitzie#0218← →Blitzie#0218← (Cluster 14, 3.4%)
→Blitzie#0218← →Blitzie#0218← (Cluster 18, 1.1%)
→TGJF12!@←••••• →TGJF12!@←••••• (Cluster 26, 31.1%)
→TGJF12!@←••••• →TGJF12!@←••••• (Cluster 12, 17.5%)
→TGJF12!@←••••• →TGJF12!@←••••• (Cluster 21, 14.1%)
→T3urk21!←••••• →T3urk21!←••••• (Cluster 26, 40.2%)
→T3urk21!←••••• →T3urk21!←••••• (Cluster 12, 19.6%)
→T3urk21!←••••• →T3urk21!←••••• (Cluster 21, 8.3%)
→MTurk1812←•••• →MTurk1812←•••• (Cluster 12, 24.0%)
→MTurk1812←•••• →MTurk1812←•••• (Cluster 26, 15.7%)
→MTurk1812←•••• →MTurk1812←•••• (Cluster 15, 10.8%)
→MT0803mb$←•••• →MT0803mb$←•••• (Cluster 12, 34.3%)
→MT0803mb$←•••• →MT0803mb$←•••• (Cluster 26, 17.6%)
→MT0803mb$←•••• →MT0803mb$←•••• (Cluster 21, 14.9%)
→G4a2r7y9!←•••• →G4a2r7y9!←•••• (Cluster 12, 38.3%)
→G4a2r7y9!←•••• →G4a2r7y9!←•••• (Cluster 26, 24.3%)
→G4a2r7y9!←•••• →G4a2r7y9!←•••• (Cluster 21, 8.6%)
→doofus2948←•• →doofus2948←•• (Cluster 13, 59.1%)
→doofus2948←•• →doofus2948←•• (Cluster 14, 7.0%)
→doofus2948←•• →doofus2948←•• (Cluster 28, 6.9%)
→Summer@2019!← →Summer@2019!← (Cluster 1, 18.2%)
→Summer@2019!← →Summer@2019!← (Cluster 14, 13.1%)
→Summer@2019!← →Summer@2019!← (Cluster 13, 6.7%)
→Spoofor d←••••• →Spoofor d←••••• (Cluster 27, 21.8%)
→Spoofor d←••••• →Spoofor d←••••• (Cluster 4, 16.6%)
→Spoofor d←••••• →Spoofor d←••••• (Cluster 7, 12.9%)
→Tanya0504?←•• →Tanya0504?←•• (Cluster 11, 11.5%)
→Tanya0504?←•• →Tanya0504?←•• (Cluster 28, 8.5%)
→Tanya0504?←•• →Tanya0504?←•• (Cluster 5, 8.3%)
→ben943943←•••• →ben943943←•••• (Cluster 11, 28.9%)
→ben943943←•••• →ben943943←•••• (Cluster 9, 12.2%)
→ben943943←•••• →ben943943←•••• (Cluster 5, 5.9%)
→531054Ab!←•••• →531054Ab!←•••• (Cluster 21, 31.3%)
→531054Ab!←•••• →531054Ab!←•••• (Cluster 15, 22.0%)
→531054Ab!←•••• →531054Ab!←•••• (Cluster 12, 14.5%)
→Mommy41995!!← →Mommy41995!!← (Cluster 11, 7.9%)
→Mommy41995!!← →Mommy41995!!← (Cluster 14, 6.7%)
→Mommy41995!!← →Mommy41995!!← (Cluster 1, 6.5%)
→Nebo_3407←•••• →Nebo_3407←•••• (Cluster 28, 21.8%)
→Nebo_3407←•••• →Nebo_3407←•••• (Cluster 5, 11.7%)
→Nebo_3407←•••• →Nebo_3407←•••• (Cluster 13, 10.8%)
→Idabeans8!←••• →Idabeans8!←••• (Cluster 8, 51.9%)
→Idabeans8!←••• →Idabeans8!←••• (Cluster 0, 15.0%)
→Idabeans8!←••• →Idabeans8!←••• (Cluster 29, 5.3%)
→B0d#ga69←••••• →B0d#ga69←••••• (Cluster 26, 39.4%)
→B0d#ga69←••••• →B0d#ga69←••••• (Cluster 9, 13.8%)
→B0d#ga69←••••• →B0d#ga69←••••• (Cluster 12, 10.9%)
→Veryp9031←•••• →Veryp9031←•••• (Cluster 28, 16.4%)
→Veryp9031←•••• →Veryp9031←•••• (Cluster 5, 12.8%)
→Veryp9031←•••• →Veryp9031←•••• (Cluster 10, 8.4%)
→38Turkey@27←• →38Turkey@27←• (Cluster 16, 36.7%)
→38Turkey@27←• →38Turkey@27←• (Cluster 25, 14.5%)
→38Turkey@27←• →38Turkey@27←• (Cluster 6, 11.7%)
→5849627@1←•••• →5849627@1←•••• (Cluster 15, 22.5%)
→5849627@1←•••• →5849627@1←•••• (Cluster 21, 21.4%)
→5849627@1←•••• →5849627@1←•••• (Cluster 12, 13.1%)
→Opiate25$←•••• →Opiate25$←•••• (Cluster 10, 21.9%)
→Opiate25$←•••• →Opiate25$←•••• (Cluster 3, 10.9%)
→Opiate25$←•••• →Opiate25$←•••• (Cluster 23, 9.0%)
→Campbrule1!←• →Campbrule1!←• (Cluster 18, 51.5%)
→Campbrule1!←• →Campbrule1!←• (Cluster 8, 8.9%)
→Campbrule1!←• →Campbrule1!←• (Cluster 0, 8.2%)
→Skeet473←••••• →Skeet473←••••• (Cluster 3, 22.2%)
→Skeet473←••••• →Skeet473←••••• (Cluster 10, 15.4%)
→Skeet473←••••• →Skeet473←••••• (Cluster 2, 11.2%)
→H&O101147←•••• →H&O101147←•••• (Cluster 26, 15.6%)
→H&O101147←•••• →H&O101147←•••• (Cluster 12, 15.5%)
→H&O101147←•••• →H&O101147←•••• (Cluster 21, 10.9%)
→ELPOSO$1955←• →ELPOSO$1955←• (Cluster 16, 29.8%)
→ELPOSO$1955←• →ELPOSO$1955←• (Cluster 6, 19.3%)
→ELPOSO$1955←• →ELPOSO$1955←• (Cluster 25, 14.6%)
→hatepain!←•••• →hatepain!←•••• (Cluster 7, 27.3%)
→hatepain!←•••• →hatepain!←•••• (Cluster 4, 15.3%)
→hatepain!←•••• →hatepain!←•••• (Cluster 27, 9.3%)
→grkids#4←••••• →grkids#4←••••• (Cluster 4, 24.2%)
→grkids#4←••••• →grkids#4←••••• (Cluster 7, 14.5%)
→grkids#4←••••• →grkids#4←••••• (Cluster 22, 9.6%)
→wil36es%←••••• →wil36es%←••••• (Cluster 9, 30.0%)
→wil36es%←••••• →wil36es%←••••• (Cluster 5, 11.2%)
→wil36es%←••••• →wil36es%←••••• (Cluster 11, 8.9%)
→Blue:Sushi1←• →Blue:Sushi1←• (Cluster 18, 16.6%)
→Blue:Sushi1←• →Blue:Sushi1←• (Cluster 8, 11.9%)
→Blue:Sushi1←• →Blue:Sushi1←• (Cluster 0, 8.7%)
→Galar224←••••• →Galar224←••••• (Cluster 10, 11.9%)
→Galar224←••••• →Galar224←••••• (Cluster 3, 10.8%)
→Galar224←••••• →Galar224←••••• (Cluster 28, 8.7%)
→Area7691$←•••• →Area7691$←•••• (Cluster 11, 17.1%)
→Area7691$←•••• →Area7691$←•••• (Cluster 5, 16.0%)
→Area7691$←•••• →Area7691$←•••• (Cluster 28, 15.0%)
→rooBobble←•••• →rooBobble←•••• (Cluster 19, 41.0%)
→rooBobble←•••• →rooBobble←•••• (Cluster 20, 29.0%)
→rooBobble←•••• →rooBobble←•••• (Cluster 24, 11.5%)
→Bigpass@889←• →Bigpass@889←• (Cluster 18, 13.0%)
→Bigpass@889←• →Bigpass@889←• (Cluster 14, 12.4%)
→Bigpass@889←• →Bigpass@889←• (Cluster 23, 12.2%)
→$oxare#1←••••• →$oxare#1←••••• (Cluster 4, 44.7%)
→$oxare#1←••••• →$oxare#1←••••• (Cluster 7, 11.6%)
→$oxare#1←••••• →$oxare#1←••••• (Cluster 2, 7.3%)
→Mturk1949←•••• →Mturk1949←•••• (Cluster 28, 24.2%)
→Mturk1949←•••• →Mturk1949←•••• (Cluster 13, 14.2%)
→Mturk1949←•••• →Mturk1949←•••• (Cluster 5, 10.5%)
→Goodpie11!←•• →Goodpie11!←•• (Cluster 23, 33.1%)
→Goodpie11!←•• →Goodpie11!←•• (Cluster 8, 8.4%)
→Goodpie11!←•• →Goodpie11!←•• (Cluster 3, 7.4%)
→readyrbp123←• →readyrbp123←• (Cluster 18, 13.0%)
→readyrbp123←• →readyrbp123←• (Cluster 8, 11.5%)
→readyrbp123←• →readyrbp123←• (Cluster 23, 10.0%)
→P1a2i3n4T←•••• →P1a2i3n4T←•••• (Cluster 12, 48.5%)
→P1a2i3n4T←•••• →P1a2i3n4T←•••• (Cluster 15, 11.3%)
→P1a2i3n4T←•••• →P1a2i3n4T←•••• (Cluster 21, 11.1%)
→Bullis154←•••• →Bullis154←•••• (Cluster 10, 19.5%)
→Bullis154←•••• →Bullis154←•••• (Cluster 3, 17.8%)
→Bullis154←•••• →Bullis154←•••• (Cluster 23, 11.7%)
→Royden@90←••• →Royden@90←••• (Cluster 29, 46.5%)
→Royden@90←••• →Royden@90←••• (Cluster 22, 14.5%)
→Royden@90←••• →Royden@90←••• (Cluster 2, 6.5%)
→Beantown123#← →Beantown123#← (Cluster 1, 74.7%)
→Beantown123#← →Beantown123#← (Cluster 14, 5.5%)
→Beantown123#← →Beantown123#← (Cluster 18, 2.2%)
→ratpatrol01←• →ratpatrol01←• (Cluster 18, 21.3%)
→ratpatrol01←• →ratpatrol01←• (Cluster 8, 15.2%)
→ratpatrol01←• →ratpatrol01←• (Cluster 0, 9.6%)
→GC0022!!@←••• →GC0022!!@←••• (Cluster 12, 20.3%)
→GC0022!!@←••• →GC0022!!@←••• (Cluster 21, 16.8%)
→GC0022!!@←••• →GC0022!!@←••• (Cluster 15, 15.8%)
→d7358898!←•••• →d7358898!←•••• (Cluster 26, 20.2%)
→d7358898!←•••• →d7358898!←•••• (Cluster 12, 15.2%)
→d7358898!←•••• →d7358898!←•••• (Cluster 21, 10.3%)

→Un!corn23←····	→Un!corn23←···· (Cluster 9, 14.5%)	
→Un!corn23←····	→Un!corn23←···· (Cluster 11, 13.1%)	
→Un!corn23←····	→Un!corn23←···· (Cluster 26, 12.4%)	
→Fi8r&iSL67@←··	→Fi8r&iSL67@←·· (Cluster 16, 18.4%)	
→Fi8r&iSL67@←··	→Fi8r&iSL67@←·· (Cluster 25, 11.4%)	
→Fi8r&iSL67@←··	→Fi8r&iSL67@←·· (Cluster 6, 9.7%)	
→hlab27!1988←·	→hlab27!1988←· (Cluster 11, 14.8%)	
→hlab27!1988←·	→hlab27!1988←· (Cluster 16, 6.9%)	
→hlab27!1988←·	→hlab27!1988←· (Cluster 9, 6.0%)	
→xdk302GO21←···	→xdk302GO21←··· (Cluster 11, 18.5%)	
→xdk302GO21←···	→xdk302GO21←··· (Cluster 9, 7.8%)	
→xdk302GO21←···	→xdk302GO21←··· (Cluster 26, 5.5%)	
→1a^M3omSTQBt←	→1a^M3omSTQBt← (Cluster 25, 75.3%)	
→1a^M3omSTQBt←	→1a^M3omSTQBt← (Cluster 16, 7.6%)	
→1a^M3omSTQBt←	→1a^M3omSTQBt← (Cluster 6, 3.4%)	
→ti@wuhukw!d←·	→ti@wuhukw!d←· (Cluster 18, 9.3%)	
→ti@wuhukw!d←·	→ti@wuhukw!d←· (Cluster 0, 7.8%)	
→ti@wuhukw!d←·	→ti@wuhukw!d←· (Cluster 8, 7.8%)	
→$FLchihaw←····	→$FLchihaw←···· (Cluster 12, 48.6%)	
→$FLchihaw←····	→$FLchihaw←···· (Cluster 26, 19.3%)	
→$FLchihaw←····	→$FLchihaw←···· (Cluster 15, 7.0%)	
→919egBls!←····	→919egBls!←···· (Cluster 12, 34.9%)	
→919egBls!←····	→919egBls!←···· (Cluster 15, 12.8%)	
→919egBls!←····	→919egBls!←···· (Cluster 21, 12.5%)	
→XcvL1$Linky2←	→XcvL1$Linky2← (Cluster 25, 9.8%)	
→XcvL1$Linky2←	→XcvL1$Linky2← (Cluster 16, 8.0%)	
→XcvL1$Linky2←	→XcvL1$Linky2← (Cluster 11, 7.5%)	
→!m0806TURK!←·	→!m0806TURK!←· (Cluster 16, 46.6%)	
→!m0806TURK!←·	→!m0806TURK!←· (Cluster 6, 15.9%)	
→!m0806TURK!←·	→!m0806TURK!←· (Cluster 25, 10.4%)	
→Toenail0304%←	→Toenail0304%← (Cluster 1, 21.7%)	
→Toenail0304%←	→Toenail0304%← (Cluster 14, 13.7%)	
→Toenail0304%←	→Toenail0304%← (Cluster 13, 6.5%)	
→qLoA5!6mAzL←·	→qLoA5!6mAzL←· (Cluster 16, 54.1%)	
→qLoA5!6mAzL←·	→qLoA5!6mAzL←· (Cluster 6, 11.9%)	
→qLoA5!6mAzL←·	→qLoA5!6mAzL←· (Cluster 25, 10.7%)	
→jaBlowme14!←·	→jaBlowme14!←· (Cluster 16, 74.1%)	
→jaBlowme14!←·	→jaBlowme14!←· (Cluster 25, 5.5%)	
→jaBlowme14!←·	→jaBlowme14!←· (Cluster 6, 5.3%)	
→R0ux&yZ8←·····	→R0ux&yZ8←····· (Cluster 26, 42.3%)	
→R0ux&yZ8←·····	→R0ux&yZ8←····· (Cluster 12, 13.6%)	
→R0ux&yZ8←·····	→R0ux&yZ8←····· (Cluster 9, 8.9%)	
→JAM70#48def←·	→JAM70#48def←· (Cluster 16, 30.7%)	
→JAM70#48def←·	→JAM70#48def←· (Cluster 6, 19.8%)	
→JAM70#48def←·	→JAM70#48def←· (Cluster 25, 16.3%)	
→mTn^3er$←·····	→mTn^3er$←····· (Cluster 26, 54.4%)	
→mTn^3er$←·····	→mTn^3er$←····· (Cluster 12, 13.1%)	
→mTn^3er$←·····	→mTn^3er$←····· (Cluster 21, 6.4%)	
→Lacra*Mioana←	→Lacra*Mioana← (Cluster 17, 19.1%)	
→Lacra*Mioana←	→Lacra*Mioana← (Cluster 18, 9.9%)	
→Lacra*Mioana←	→Lacra*Mioana← (Cluster 24, 7.3%)	
→my!wayOquery←	→my!wayOquery← (Cluster 25, 20.7%)	
→my!wayOquery←	→my!wayOquery← (Cluster 16, 15.1%)	
→my!wayOquery←	→my!wayOquery← (Cluster 6, 7.2%)	
→823excite#48←	→823excite#48← (Cluster 25, 55.9%)	
→823excite#48←	→823excite#48← (Cluster 16, 11.9%)	
→823excite#48←	→823excite#48← (Cluster 6, 5.7%)	
→mo1Lago1+ra←·	→mo1Lago1+ra←· (Cluster 16, 17.7%)	
→mo1Lago1+ra←·	→mo1Lago1+ra←· (Cluster 25, 11.4%)	
→mo1Lago1+ra←·	→mo1Lago1+ra←· (Cluster 6, 9.7%)	
→tsimmcuwap←···	→tsimmcuwap←··· (Cluster 27, 12.1%)	
→tsimmcuwap←···	→tsimmcuwap←·· (Cluster 24, 8.7%)	
→tsimmcuwap←···	→tsimmcuwap←·· (Cluster 7, 7.6%)	
→Wn4yz879!56←·	→Wn4yz879!56←· (Cluster 16, 13.2%)	
→Wn4yz879!56←·	→Wn4yz879!56←· (Cluster 25, 10.1%)	
→Wn4yz879!56←·	→Wn4yz879!56←· (Cluster 6, 8.3%)	
→E1plmn8qR←····	→E1plmn8qR←···· (Cluster 12, 46.6%)	
→E1plmn8qR←····	→E1plmn8qR←···· (Cluster 26, 11.8%)	
→E1plmn8qR←····	→E1plmn8qR←···· (Cluster 15, 9.7%)	
→4kabzJ#962uF←	→4kabzJ#962uF← (Cluster 25, 64.2%)	
→4kabzJ#962uF←	→4kabzJ#962uF← (Cluster 16, 10.4%)	
→4kabzJ#962uF←	→4kabzJ#962uF← (Cluster 6, 4.3%)	
→50rp3RMg←·····	→50rp3RMg←····· (Cluster 12, 33.6%)	
→50rp3RMg←·····	→50rp3RMg←····· (Cluster 26, 20.5%)	
→50rp3RMg←·····	→50rp3RMg←····· (Cluster 21, 15.0%)	
→Loo#43Bb$←····	→Loo#43Bb$←···· (Cluster 5, 16.9%)	
→Loo#43Bb$←····	→Loo#43Bb$←···· (Cluster 11, 16.7%)	
→Loo#43Bb$←····	→Loo#43Bb$←···· (Cluster 28, 15.0%)	
→2327.Teddy!←·	→2327.Teddy!←· (Cluster 16, 51.4%)	
→2327.Teddy!←·	→2327.Teddy!←· (Cluster 6, 14.2%)	
→2327.Teddy!←·	→2327.Teddy!←· (Cluster 25, 10.8%)	
→Ba7H3Qzx9y47←	→Ba7H3Qzx9y47← (Cluster 25, 21.9%)	
→Ba7H3Qzx9y47←	→Ba7H3Qzx9y47← (Cluster 16, 15.3%)	
→Ba7H3Qzx9y47←	→Ba7H3Qzx9y47← (Cluster 6, 7.3%)	
→A@B71^7Yb←····	→A@B71^7Yb←···· (Cluster 26, 24.2%)	
→A@B71^7Yb←····	→A@B71^7Yb←···· (Cluster 12, 20.1%)	
→A@B71^7Yb←····	→A@B71^7Yb←···· (Cluster 21, 10.4%)	
→ate4Seven1!←·	→ate4Seven1!←· (Cluster 16, 15.3%)	
→ate4Seven1!←·	→ate4Seven1!←· (Cluster 11, 9.8%)	
→ate4Seven1!←·	→ate4Seven1!←· (Cluster 25, 7.9%)	
→RjbRwb2012@←·	→RjbRwb2012@←· (Cluster 14, 9.4%)	
→RjbRwb2012@←·	→RjbRwb2012@←· (Cluster 11, 9.2%)	
→RjbRwb2012@←·	→RjbRwb2012@←· (Cluster 13, 8.9%)	
→parS1monious←	→parS1monious← (Cluster 25, 12.7%)	
→parS1monious←	→parS1monious← (Cluster 16, 11.1%)	
→parS1monious←	→parS1monious← (Cluster 11, 6.7%)	
→869!GDY*omj←·	→869!GDY*omj←· (Cluster 16, 39.1%)	
→869!GDY*omj←·	→869!GDY*omj←· (Cluster 6, 18.2%)	
→869!GDY*omj←·	→869!GDY*omj←· (Cluster 25, 14.3%)	
→0m0Rr0w$7←····	→0m0Rr0w$7←···· (Cluster 12, 22.6%)	
→0m0Rr0w$7←····	→0m0Rr0w$7←···· (Cluster 26, 18.7%)	
→0m0Rr0w$7←····	→0m0Rr0w$7←···· (Cluster 21, 10.0%)	
→JaNeWaY1701@←	→JaNeWaY1701@← (Cluster 25, 72.0%)	
→JaNeWaY1701@←	→JaNeWaY1701@← (Cluster 16, 7.6%)	
→JaNeWaY1701@←	→JaNeWaY1701@← (Cluster 6, 3.5%)	
→Gci0042!g00d←	→Gci0042!g00d← (Cluster 25, 23.8%)	
→Gci0042!g00d←	→Gci0042!g00d← (Cluster 16, 15.3%)	
→Gci0042!g00d←	→Gci0042!g00d← (Cluster 6, 7.1%)	
→LMNOP201965←·	→LMNOP201965←· (Cluster 16, 30.7%)	
→LMNOP201965←·	→LMNOP201965←· (Cluster 6, 19.4%)	
→LMNOP201965←·	→LMNOP201965←· (Cluster 25, 14.5%)	
→2owJaifrcy!←·	→2owJaifrcy!←· (Cluster 16, 72.2%)	
→2owJaifrcy!←·	→2owJaifrcy!←· (Cluster 25, 6.6%)	
→2owJaifrcy!←·	→2owJaifrcy!←· (Cluster 6, 6.6%)	
→hoWrt94J←·····	→hoWrt94J←····· (Cluster 26, 67.1%)	
→hoWrt94J←·····	→hoWrt94J←····· (Cluster 12, 8.9%)	
→hoWrt94J←·····	→hoWrt94J←····· (Cluster 9, 4.9%)	
→TLimf4k3!←····	→TLimf4k3!←···· (Cluster 12, 39.0%)	
→TLimf4k3!←····	→TLimf4k3!←···· (Cluster 26, 20.4%)	
→TLimf4k3!←····	→TLimf4k3!←···· (Cluster 21, 8.8%)	
→M0r3$Pl3453←·	→M0r3$Pl3453←· (Cluster 16, 50.4%)	
→M0r3$Pl3453←·	→M0r3$Pl3453←· (Cluster 25, 9.7%)	
→M0r3$Pl3453←·	→M0r3$Pl3453←· (Cluster 6, 8.8%)	
→doelkk9@9←····	→doelkk9@9←···· (Cluster 10, 15.1%)	
→doelkk9@9←····	→doelkk9@9←···· (Cluster 23, 10.6%)	
→doelkk9@9←····	→doelkk9@9←···· (Cluster 28, 7.8%)	
→!#%135qeT←····	→!#%135qeT←···· (Cluster 12, 29.4%)	
→!#%135qeT←····	→!#%135qeT←···· (Cluster 15, 16.9%)	
→!#%135qeT←····	→!#%135qeT←···· (Cluster 21, 16.6%)	
→Cr8p3#Myrtle←	→Cr8p3#Myrtle← (Cluster 25, 37.4%)	
→Cr8p3#Myrtle←	→Cr8p3#Myrtle← (Cluster 16, 14.7%)	
→Cr8p3#Myrtle←	→Cr8p3#Myrtle← (Cluster 6, 6.5%)	
→Ded4aFigL22&←	→Ded4aFigL22&← (Cluster 25, 19.5%)	
→Ded4aFigL22&←	→Ded4aFigL22&← (Cluster 16, 12.8%)	
→Ded4aFigL22&←	→Ded4aFigL22&← (Cluster 6, 6.8%)	
→P00P20#19#!←·	→P00P20#19#!←· (Cluster 16, 38.7%)	
→P00P20#19#!←·	→P00P20#19#!←· (Cluster 6, 13.1%)	
→P00P20#19#!←·	→P00P20#19#!←· (Cluster 25, 10.2%)	
→Anyman70&&&L←	→Anyman70&&&L← (Cluster 1, 7.8%)	
→Anyman70&&&L←	→Anyman70&&&L← (Cluster 14, 7.8%)	
→Anyman70&&&L←	→Anyman70&&&L← (Cluster 11, 6.8%)	
→7/24Remus19←·	→7/24Remus19←· (Cluster 16, 42.4%)	
→7/24Remus19←·	→7/24Remus19←· (Cluster 25, 15.3%)	
→7/24Remus19←·	→7/24Remus19←· (Cluster 6, 13.7%)	
→1D0ok3r$l0←···	→1D0ok3r$l0←··· (Cluster 6, 34.4%)	
→1D0ok3r$l0←···	→1D0ok3r$l0←··· (Cluster 16, 14.9%)	
→1D0ok3r$l0←···	→1D0ok3r$l0←··· (Cluster 15, 12.9%)	
→!TiIr5787!←···	→!TiIr5787!←··· (Cluster 6, 21.7%)	
→!TiIr5787!←···	→!TiIr5787!←··· (Cluster 16, 17.0%)	
→!TiIr5787!←···	→!TiIr5787!←··· (Cluster 12, 15.0%)	
→AZwolF!140←··	→AZwolF!140←·· (Cluster 6, 17.6%)	
→AZwolF!140←··	→AZwolF!140←·· (Cluster 12, 17.3%)	
→AZwolF!140←··	→AZwolF!140←·· (Cluster 16, 16.4%)	
→J52!aLP0$e#←·	→J52!aLP0$e#←· (Cluster 16, 62.3%)	
→J52!aLP0$e#←·	→J52!aLP0$e#←· (Cluster 6, 8.0%)	
→J52!aLP0$e#←·	→J52!aLP0$e#←· (Cluster 25, 7.8%)	
→FT7CM8W@←·····	→FT7CM8W@←····· (Cluster 26, 29.7%)	
→FT7CM8W@←·····	→FT7CM8W@←····· (Cluster 12, 19.4%)	
→FT7CM8W@←·····	→FT7CM8W@←····· (Cluster 21, 13.9%)	
→!12Gam256!ST←	→!12Gam256!ST← (Cluster 25, 82.0%)	
→!12Gam256!ST←	→!12Gam256!ST← (Cluster 16, 5.4%)	
→!12Gam256!ST←	→!12Gam256!ST← (Cluster 6, 2.3%)	
→ksP@1@1%99M←·	→ksP@1@1%99M←· (Cluster 16, 46.2%)	
→ksP@1@1%99M←·	→ksP@1@1%99M←· (Cluster 25, 13.1%)	
→ksP@1@1%99M←·	→ksP@1@1%99M←· (Cluster 6, 11.6%)	
→ploetysyyg←··	→ploetysyyg←·· (Cluster 24, 63.8%)	
→ploetysyyg←··	→ploetysyyg←·· (Cluster 19, 9.2%)	
→ploetysyyg←··	→ploetysyyg←·· (Cluster 17, 6.8%)	
→4Vf6Z7**EupV←	→4Vf6Z7**EupV← (Cluster 25, 59.7%)	
→4Vf6Z7**EupV←	→4Vf6Z7**EupV← (Cluster 16, 11.6%)	
→4Vf6Z7**EupV←	→4Vf6Z7**EupV← (Cluster 6, 5.3%)	
→Myickie085←··	→Myickie085←·· (Cluster 23, 44.8%)	
→Myickie085←··	→Myickie085←·· (Cluster 0, 6.2%)	
→Myickie085←··	→Myickie085←·· (Cluster 13, 5.8%)	
→#7ern19&)H*w←	→#7ern19&)H*w← (Cluster 25, 61.3%)	
→#7ern19&)H*w←	→#7ern19&)H*w← (Cluster 16, 11.2%)	
→#7ern19&)H*w←	→#7ern19&)H*w← (Cluster 6, 4.5%)	
→!@wesdxc#$T←·	→!@wesdxc#$T←· (Cluster 16, 41.9%)	
→!@wesdxc#$T←·	→!@wesdxc#$T←· (Cluster 25, 15.4%)	
→!@wesdxc#$T←·	→!@wesdxc#$T←· (Cluster 6, 11.2%)	
→visby1958SJR←	→visby1958SJR← (Cluster 1, 7.7%)	
→visby1958SJR←	→visby1958SJR← (Cluster 11, 7.6%)	
→visby1958SJR←	→visby1958SJR← (Cluster 14, 7.6%)	
→Kels1202773@←	→Kels1202773@← (Cluster 25, 11.1%)	
→Kels1202773@←	→Kels1202773@← (Cluster 16, 9.0%)	
→Kels1202773@←	→Kels1202773@← (Cluster 11, 7.1%)	
→k!ngst0ntr1o←	→k!ngst0ntr1o← (Cluster 25, 59.7%)	
→k!ngst0ntr1o←	→k!ngst0ntr1o← (Cluster 16, 10.8%)	
→k!ngst0ntr1o←	→k!ngst0ntr1o← (Cluster 6, 4.8%)	

B.6 Regressions using heuristic features

The heuristic features we used for regression models in Chapter 4 were selected from the set of advanced heuristics used in prior work [87]. Heuristic features for a password were converted into numeric values using the TypeScript implementation provided by the authors.[1] For two heuristics (*h5* and *h16*), we used pattern-detection code provided by zxcvbn;[2] however, the scoring function used to convert detected patterns into numeric values was not modified from the original scoring function.

The full set of heuristic features from prior work that we consider were the following:

- Length (h1)
- Character-class count (h2)
- Duplicated chars (h3)
- Repeated characters (h4)
- Keyboard patterns (h5)
- Repeated sections (h6)
- Character-class structure predictability (h7)
- Predictable uppercase (h8)
- Predictable digits (h9)
- Predictable symbols (h10)
- Uppercase count (h11)
- Lowercase count (h12)
- Digits count (h13)
- Symbols count (h14)
- Use of dates (h15)
- Alphabetic/numeric sequences (h16)
- Common substrings (h17)
- Dictionary (longest token) (h18)
- Dictionary (number of wordlist entries) (h19)
- Dictionary (substitution commonness) (h20)
- Common password (h21)

[1] `https://github.com/cupslab/password_meter`
[2] `https://github.com/dropbox/zxcvbn`

Figure B.23 shows the correlation of numeric heuristic-feature values for password data globally sampled from *PGS3max12*.

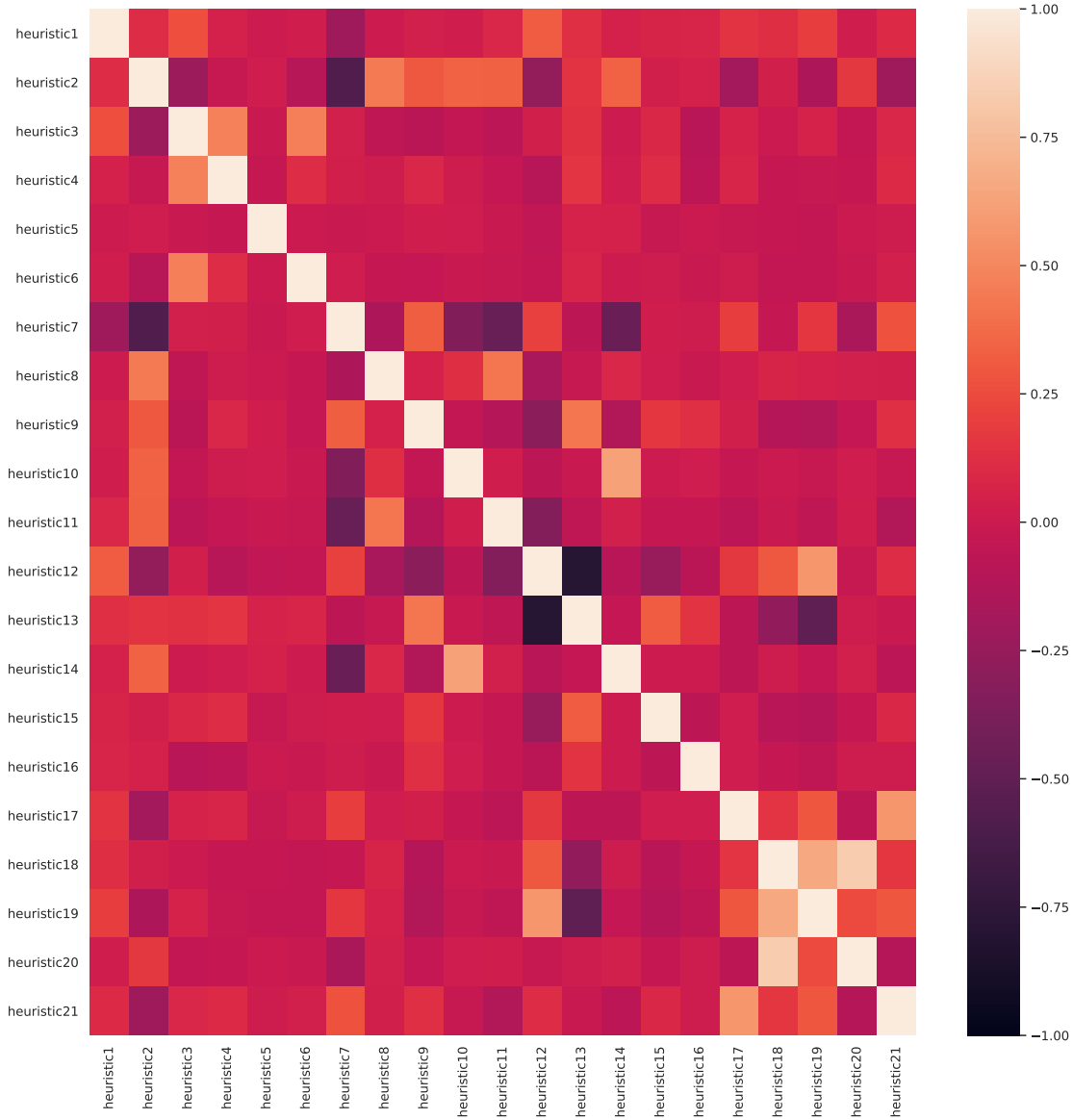


Figure B.23: Correlation of the 21 heuristic features from prior work [87], computed using a sample of *PGS3max12* passwords.

B.6.1 Regression of guessability onto heuristic features

Single global model

Dep. Variable:	log_guess_num	**R-squared:**	0.491
Model:	OLS	**Adj. R-squared:**	0.491
Method:	Least Squares	**F-statistic:**	6884.
Date:	Thu, 20 Aug 2020	**Prob (F-statistic):**	0.00
Time:	17:38:51	**Log-Likelihood:**	-2.4062e+05
No. Observations:	100000	**AIC:**	4.813e+05
Df Residuals:	99985	**BIC:**	4.814e+05
Df Model:	14		

	coef	**std err**	**t**	**P> |t|**	**[0.025**	**0.975]**
Intercept	-0.2885	0.063	-4.545	0.000	-0.413	-0.164
heuristic4	-0.0472	0.009	-5.406	0.000	-0.064	-0.030
heuristic5	-0.1404	0.009	-16.453	0.000	-0.157	-0.124
heuristic6	-0.3603	0.009	-41.920	0.000	-0.377	-0.343
heuristic8	-0.1472	0.010	-15.333	0.000	-0.166	-0.128
heuristic9	-0.5183	0.010	-53.720	0.000	-0.537	-0.499
heuristic10	0.0260	0.011	2.390	0.017	0.005	0.047
heuristic11	2.2057	0.012	189.911	0.000	2.183	2.228
heuristic12	3.1223	0.019	167.097	0.000	3.086	3.159
heuristic13	3.3147	0.018	182.418	0.000	3.279	3.350
heuristic14	0.6698	0.011	60.461	0.000	0.648	0.691
heuristic15	-0.3283	0.009	-36.305	0.000	-0.346	-0.311
heuristic16	-0.3331	0.009	-38.170	0.000	-0.350	-0.316
heuristic17	-1.7018	0.009	-193.723	0.000	-1.719	-1.685
heuristic18	-0.4089	0.009	-45.169	0.000	-0.427	-0.391

Omnibus:	3563.622	**Durbin-Watson:**	2.011
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	4007.308
Skew:	-0.461	**Prob(JB):**	0.00
Kurtosis:	3.335	**Cond. No.**	28.5

Table B.1: Guessability regression results for single global model.

Increase guessability:

Feature	**Estimate**
Common substrings [h17]	-1.702
Predictable digits [h9]	-0.518
Dictionary (longest token) [h18]	-0.409
Repeated sections [h6]	-0.360
Alphabetic/numeric sequences [h16]	-0.333
Dates [h15]	-0.328
Predictable uppercase [h8]	-0.147
Keyboard patterns [h5]	-0.140
Repeated chars [h4]	-0.047

Decrease guessability:

Feature	**Estimate**
Digits count [h13]	3.315
Lowercase count [h12]	3.122
Uppercase count [h11]	2.206
Symbols count [h14]	0.670
Predictable symbols [h10]	0.026

Cluster 0 model

Dep. Variable:	log_guess_num	**R-squared:**	0.396
Model:	OLS	**Adj. R-squared:**	0.396
Method:	Least Squares	**F-statistic:**	4677.
Date:	Thu, 20 Aug 2020	**Prob (F-statistic):**	0.00
Time:	18:40:18	**Log-Likelihood:**	-2.3258e+05
No. Observations:	100000	**AIC:**	4.652e+05
Df Residuals:	99985	**BIC:**	4.653e+05
Df Model:	14		

	coef	**std err**	**t**	**P> |t|**	**[0.025**	**0.975]**
Intercept	-0.0801	0.071	-1.133	0.257	-0.219	0.058
heuristic4	-0.1694	0.008	-21.197	0.000	-0.185	-0.154
heuristic5	-0.0827	0.008	-10.488	0.000	-0.098	-0.067
heuristic6	-0.2145	0.008	-27.187	0.000	-0.230	-0.199
heuristic8	-0.1573	0.009	-16.637	0.000	-0.176	-0.139
heuristic9	-0.2539	0.009	-27.805	0.000	-0.272	-0.236
heuristic10	-0.0211	0.011	-1.965	0.049	-0.042	-5.22e-05
heuristic11	1.1810	0.010	117.450	0.000	1.161	1.201
heuristic12	1.8670	0.013	146.525	0.000	1.842	1.892
heuristic13	1.8234	0.013	137.258	0.000	1.797	1.849
heuristic14	0.6152	0.011	56.191	0.000	0.594	0.637
heuristic15	-0.2809	0.008	-33.781	0.000	-0.297	-0.265
heuristic16	-0.2931	0.008	-36.281	0.000	-0.309	-0.277
heuristic17	-1.4008	0.008	-172.489	0.000	-1.417	-1.385
heuristic18	-0.4443	0.008	-54.899	0.000	-0.460	-0.428

Omnibus:	444.372	**Durbin-Watson:**	1.991
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	452.813
Skew:	-0.157	**Prob(JB):**	4.71e-99
Kurtosis:	3.098	**Cond. No.**	51.0

Table B.2: Guessability regression results for Cluster 0 model.

Increase guessability:

Feature	**Estimate**
Common substrings [h17]	-1.401
Dictionary (longest token) [h18]	-0.444
Alphabetic/numeric sequences [h16]	-0.293
Dates [h15]	-0.281
Predictable digits [h9]	-0.254
Repeated sections [h6]	-0.214
Repeated chars [h4]	-0.169
Predictable uppercase [h8]	-0.157
Keyboard patterns [h5]	-0.083
Predictable symbols [h10]	-0.021

Decrease guessability:

Feature	**Estimate**
Lowercase count [h12]	1.867
Digits count [h13]	1.823
Uppercase count [h11]	1.181
Symbols count [h14]	0.615

Cluster 1 model

Dep. Variable:	log_guess_num	**R-squared:**	0.421
Model:	OLS	**Adj. R-squared:**	0.421
Method:	Least Squares	**F-statistic:**	5203.
Date:	Thu, 20 Aug 2020	**Prob (F-statistic):**	0.00
Time:	18:40:19	**Log-Likelihood:**	-2.4265e+05
No. Observations:	100000	**AIC:**	4.853e+05
Df Residuals:	99985	**BIC:**	4.855e+05
Df Model:	14		

	coef	**std err**	**t**	**P> |t|**	**[0.025**	**0.975]**
Intercept	0.9120	0.068	13.441	0.000	0.779	1.045
heuristic4	-0.1049	0.009	-11.768	0.000	-0.122	-0.087
heuristic5	-0.1120	0.009	-12.842	0.000	-0.129	-0.095
heuristic6	-0.2551	0.009	-29.300	0.000	-0.272	-0.238
heuristic8	-0.1641	0.010	-16.572	0.000	-0.184	-0.145
heuristic9	-0.7061	0.010	-69.063	0.000	-0.726	-0.686
heuristic10	-0.0694	0.012	-5.763	0.000	-0.093	-0.046
heuristic11	1.4854	0.011	135.509	0.000	1.464	1.507
heuristic12	2.2463	0.014	163.316	0.000	2.219	2.273
heuristic13	2.3492	0.014	164.627	0.000	2.321	2.377
heuristic14	0.6129	0.012	49.862	0.000	0.589	0.637
heuristic15	-0.6790	0.009	-72.454	0.000	-0.697	-0.661
heuristic16	-0.4444	0.009	-49.619	0.000	-0.462	-0.427
heuristic17	-1.4823	0.009	-163.504	0.000	-1.500	-1.465
heuristic18	-0.4958	0.009	-54.721	0.000	-0.514	-0.478

Omnibus:	1905.739	**Durbin-Watson:**	2.019
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	2044.620
Skew:	-0.328	**Prob(JB):**	0.00
Kurtosis:	3.244	**Cond. No.**	40.4

Table B.3: Guessability regression results for Cluster 1 model.

Increase guessability:

Feature	**Estimate**
Common substrings [h17]	-1.482
Predictable digits [h9]	-0.706
Dates [h15]	-0.679
Dictionary (longest token) [h18]	-0.496
Alphabetic/numeric sequences [h16]	-0.444
Repeated sections [h6]	-0.255
Predictable uppercase [h8]	-0.164
Keyboard patterns [h5]	-0.112
Repeated chars [h4]	-0.105
Predictable symbols [h10]	-0.069

Decrease guessability:

Feature	**Estimate**
Digits count [h13]	2.349
Lowercase count [h12]	2.246
Uppercase count [h11]	1.485
Symbols count [h14]	0.613

Cluster 2 model

Dep. Variable:	log_guess_num	**R-squared:**	0.423
Model:	OLS	**Adj. R-squared:**	0.423
Method:	Least Squares	**F-statistic:**	5229.
Date:	Thu, 20 Aug 2020	**Prob (F-statistic):**	0.00
Time:	18:40:19	**Log-Likelihood:**	-2.2497e+05
No. Observations:	100000	**AIC:**	4.500e+05
Df Residuals:	99985	**BIC:**	4.501e+05
Df Model:	14		

	coef	**std err**	**t**	**P> |t|**	**[0.025**	**0.975]**
Intercept	0.1256	0.066	1.911	0.056	-0.003	0.254
heuristic4	-0.1243	0.007	-16.782	0.000	-0.139	-0.110
heuristic5	-0.0798	0.007	-10.931	0.000	-0.094	-0.065
heuristic6	-0.1894	0.007	-25.852	0.000	-0.204	-0.175
heuristic8	-0.1185	0.009	-13.167	0.000	-0.136	-0.101
heuristic9	-0.3391	0.008	-40.481	0.000	-0.356	-0.323
heuristic10	-0.0166	0.011	-1.580	0.114	-0.037	0.004
heuristic11	1.1615	0.010	121.809	0.000	1.143	1.180
heuristic12	1.7508	0.012	145.571	0.000	1.727	1.774
heuristic13	1.8547	0.012	154.325	0.000	1.831	1.878
heuristic14	0.6097	0.011	56.669	0.000	0.589	0.631
heuristic15	-0.2540	0.008	-32.689	0.000	-0.269	-0.239
heuristic16	-0.3861	0.008	-50.912	0.000	-0.401	-0.371
heuristic17	-1.3019	0.008	-172.881	0.000	-1.317	-1.287
heuristic18	-0.4097	0.007	-54.657	0.000	-0.424	-0.395

Omnibus:	782.874	**Durbin-Watson:**	2.003
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	925.353
Skew:	-0.158	**Prob(JB):**	1.15e-201
Kurtosis:	3.350	**Cond. No.**	48.5

Table B.4: Guessability regression results for Cluster 2 model.

Increase guessability:

Feature	**Estimate**
Common substrings [h17]	-1.302
Dictionary (longest token) [h18]	-0.410
Alphabetic/numeric sequences [h16]	-0.386
Predictable digits [h9]	-0.339
Dates [h15]	-0.254
Repeated sections [h6]	-0.189
Repeated chars [h4]	-0.124
Predictable uppercase [h8]	-0.119
Keyboard patterns [h5]	-0.080
Predictable symbols [h10]	-0.017

Decrease guessability:

Feature	**Estimate**
Digits count [h13]	1.855
Lowercase count [h12]	1.751
Uppercase count [h11]	1.161
Symbols count [h14]	0.610

Cluster 3 model

Dep. Variable:	log_guess_num	**R-squared:**	0.446
Model:	OLS	**Adj. R-squared:**	0.446
Method:	Least Squares	**F-statistic:**	5759.
Date:	Thu, 20 Aug 2020	**Prob (F-statistic):**	0.00
Time:	18:40:19	**Log-Likelihood:**	-2.2769e+05
No. Observations:	100000	**AIC:**	4.554e+05
Df Residuals:	99985	**BIC:**	4.555e+05
Df Model:	14		

	coef	**std err**	**t**	**P> |t|**	**[0.025**	**0.975]**
Intercept	0.6356	0.068	9.355	0.000	0.502	0.769
heuristic4	-0.0986	0.008	-12.829	0.000	-0.114	-0.084
heuristic5	-0.0952	0.008	-12.666	0.000	-0.110	-0.080
heuristic6	-0.2351	0.008	-31.270	0.000	-0.250	-0.220
heuristic8	-0.1130	0.009	-12.452	0.000	-0.131	-0.095
heuristic9	-0.5151	0.009	-59.342	0.000	-0.532	-0.498
heuristic10	-0.0323	0.011	-2.967	0.003	-0.054	-0.011
heuristic11	1.1714	0.010	120.712	0.000	1.152	1.190
heuristic12	1.7832	0.013	142.386	0.000	1.759	1.808
heuristic13	1.9085	0.013	151.511	0.000	1.884	1.933
heuristic14	0.5604	0.011	50.284	0.000	0.539	0.582
heuristic15	-0.2998	0.008	-37.513	0.000	-0.315	-0.284
heuristic16	-0.6470	0.008	-81.595	0.000	-0.663	-0.631
heuristic17	-1.3468	0.008	-174.155	0.000	-1.362	-1.332
heuristic18	-0.3569	0.008	-46.331	0.000	-0.372	-0.342

Omnibus:	2238.046	**Durbin-Watson:**	1.995
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	2693.850
Skew:	-0.311	**Prob(JB):**	0.00
Kurtosis:	3.509	**Cond. No.**	48.5

Table B.5: Guessability regression results for Cluster 3 model.

Increase guessability:

Feature	**Estimate**
Common substrings [h17]	-1.347
Alphabetic/numeric sequences [h16]	-0.647
Predictable digits [h9]	-0.515
Dictionary (longest token) [h18]	-0.357
Dates [h15]	-0.300
Repeated sections [h6]	-0.235
Predictable uppercase [h8]	-0.113
Repeated chars [h4]	-0.099
Keyboard patterns [h5]	-0.095
Predictable symbols [h10]	-0.032

Decrease guessability:

Feature	**Estimate**
Digits count [h13]	1.909
Lowercase count [h12]	1.783
Uppercase count [h11]	1.171
Symbols count [h14]	0.560

Cluster 4 model

Dep. Variable:	log_guess_num	**R-squared:**	0.437
Model:	OLS	**Adj. R-squared:**	0.437
Method:	Least Squares	**F-statistic:**	5539.
Date:	Thu, 20 Aug 2020	**Prob (F-statistic):**	0.00
Time:	18:40:20	**Log-Likelihood:**	-2.3038e+05
No. Observations:	100000	**AIC:**	4.608e+05
Df Residuals:	99985	**BIC:**	4.609e+05
Df Model:	14		

	coef	**std err**	**t**	**P> |t|**	**[0.025**	**0.975]**
Intercept	-1.1174	0.070	-16.066	0.000	-1.254	-0.981
heuristic4	-0.1121	0.008	-14.274	0.000	-0.127	-0.097
heuristic5	-0.0708	0.008	-9.179	0.000	-0.086	-0.056
heuristic6	-0.1976	0.008	-25.502	0.000	-0.213	-0.182
heuristic8	-0.1140	0.010	-11.920	0.000	-0.133	-0.095
heuristic9	-0.1210	0.009	-13.236	0.000	-0.139	-0.103
heuristic10	0.0039	0.010	0.371	0.711	-0.017	0.024
heuristic11	1.2103	0.010	120.069	0.000	1.191	1.230
heuristic12	1.8200	0.013	143.755	0.000	1.795	1.845
heuristic13	1.9758	0.013	156.347	0.000	1.951	2.001
heuristic14	0.6807	0.011	64.068	0.000	0.660	0.701
heuristic15	-0.2026	0.008	-24.636	0.000	-0.219	-0.187
heuristic16	-0.2386	0.008	-29.978	0.000	-0.254	-0.223
heuristic17	-1.4210	0.008	-178.666	0.000	-1.437	-1.405
heuristic18	-0.4573	0.008	-57.946	0.000	-0.473	-0.442

Omnibus:	7.831	**Durbin-Watson:**	1.996
Prob(Omnibus):	0.020	**Jarque-Bera (JB):**	8.025
Skew:	-0.009	**Prob(JB):**	0.0181
Kurtosis:	3.040	**Cond. No.**	49.7

Table B.6: Guessability regression results for Cluster 4 model.

Increase guessability:

Feature	**Estimate**
Common substrings [h17]	-1.421
Dictionary (longest token) [h18]	-0.457
Alphabetic/numeric sequences [h16]	-0.239
Dates [h15]	-0.203
Repeated sections [h6]	-0.198
Predictable digits [h9]	-0.121
Predictable uppercase [h8]	-0.114
Repeated chars [h4]	-0.112
Keyboard patterns [h5]	-0.071

Decrease guessability:

Feature	**Estimate**
Digits count [h13]	1.976
Lowercase count [h12]	1.820
Uppercase count [h11]	1.210
Symbols count [h14]	0.681
Predictable symbols [h10]	0.004

Cluster 5 model

Dep. Variable:	log_guess_num	**R-squared:**	0.478
Model:	OLS	**Adj. R-squared:**	0.478
Method:	Least Squares	**F-statistic:**	6536.
Date:	Thu, 20 Aug 2020	**Prob (F-statistic):**	0.00
Time:	18:40:20	**Log-Likelihood:**	-2.2068e+05
No. Observations:	100000	**AIC:**	4.414e+05
Df Residuals:	99985	**BIC:**	4.415e+05
Df Model:	14		

	coef	**std err**	**t**	**P> |t|**	**[0.025**	**0.975]**
Intercept	2.7944	0.061	46.071	0.000	2.676	2.913
heuristic4	-0.0868	0.007	-12.126	0.000	-0.101	-0.073
heuristic5	-0.1034	0.007	-14.776	0.000	-0.117	-0.090
heuristic6	-0.2887	0.007	-41.014	0.000	-0.302	-0.275
heuristic8	-0.0777	0.008	-9.643	0.000	-0.093	-0.062
heuristic9	-0.9519	0.009	-111.074	0.000	-0.969	-0.935
heuristic10	-0.0083	0.010	-0.865	0.387	-0.027	0.010
heuristic11	1.2315	0.009	136.416	0.000	1.214	1.249
heuristic12	1.7206	0.013	132.764	0.000	1.695	1.746
heuristic13	1.9450	0.013	149.425	0.000	1.920	1.971
heuristic14	0.4847	0.010	49.137	0.000	0.465	0.504
heuristic15	-0.5730	0.007	-77.624	0.000	-0.587	-0.559
heuristic16	-0.3066	0.007	-42.994	0.000	-0.321	-0.293
heuristic17	-1.1746	0.007	-160.323	0.000	-1.189	-1.160
heuristic18	-0.4643	0.007	-64.129	0.000	-0.478	-0.450

Omnibus:	9679.356	**Durbin-Watson:**	1.992
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	16592.811
Skew:	-0.690	**Prob(JB):**	0.00
Kurtosis:	4.442	**Cond. No.**	39.5

Table B.7: Guessability regression results for Cluster 5 model.

Increase guessability:

Feature	**Estimate**
Common substrings [h17]	-1.175
Predictable digits [h9]	-0.952
Dates [h15]	-0.573
Dictionary (longest token) [h18]	-0.464
Alphabetic/numeric sequences [h16]	-0.307
Repeated sections [h6]	-0.289
Keyboard patterns [h5]	-0.103
Repeated chars [h4]	-0.087
Predictable uppercase [h8]	-0.078
Predictable symbols [h10]	-0.008

Decrease guessability:

Feature	**Estimate**
Digits count [h13]	1.945
Lowercase count [h12]	1.721
Uppercase count [h11]	1.232
Symbols count [h14]	0.485

Cluster 6 model

Dep. Variable:	log_guess_num	**R-squared:**	0.582
Model:	OLS	**Adj. R-squared:**	0.582
Method:	Least Squares	**F-statistic:**	9963.
Date:	Thu, 20 Aug 2020	**Prob (F-statistic):**	0.00
Time:	18:40:20	**Log-Likelihood:**	-2.4833e+05
No. Observations:	100000	**AIC:**	4.967e+05
Df Residuals:	99985	**BIC:**	4.968e+05
Df Model:	14		

	coef	**std err**	**t**	**P> |t|**	**[0.025**	**0.975]**
Intercept	0.1557	0.084	1.855	0.064	-0.009	0.320
heuristic4	0.1997	0.010	20.548	0.000	0.181	0.219
heuristic5	-0.1106	0.009	-11.980	0.000	-0.129	-0.093
heuristic6	-0.4144	0.010	-43.595	0.000	-0.433	-0.396
heuristic8	-0.5817	0.012	-46.942	0.000	-0.606	-0.557
heuristic9	-0.7925	0.011	-72.457	0.000	-0.814	-0.771
heuristic10	0.1109	0.011	10.163	0.000	0.090	0.132
heuristic11	4.0753	0.021	197.619	0.000	4.035	4.116
heuristic12	4.1427	0.025	163.794	0.000	4.093	4.192
heuristic13	3.9173	0.028	140.324	0.000	3.863	3.972
heuristic14	0.6342	0.011	55.422	0.000	0.612	0.657
heuristic15	-0.0283	0.009	-2.999	0.003	-0.047	-0.010
heuristic16	-0.3721	0.009	-39.717	0.000	-0.390	-0.354
heuristic17	-2.1308	0.010	-222.333	0.000	-2.150	-2.112
heuristic18	-0.5925	0.010	-57.030	0.000	-0.613	-0.572

Omnibus:	8483.237	**Durbin-Watson:**	1.993
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	11301.479
Skew:	-0.728	**Prob(JB):**	0.00
Kurtosis:	3.770	**Cond. No.**	32.6

Table B.8: Guessability regression results for Cluster 6 model.

Increase guessability:

Feature	**Estimate**
Common substrings [h17]	-2.131
Predictable digits [h9]	-0.793
Dictionary (longest token) [h18]	-0.592
Predictable uppercase [h8]	-0.582
Repeated sections [h6]	-0.414
Alphabetic/numeric sequences [h16]	-0.372
Keyboard patterns [h5]	-0.111
Dates [h15]	-0.028

Decrease guessability:

Feature	**Estimate**
Lowercase count [h12]	4.143
Uppercase count [h11]	4.075
Digits count [h13]	3.917
Symbols count [h14]	0.634
Repeated chars [h4]	0.200
Predictable symbols [h10]	0.111

Cluster 7 model

Dep. Variable:	log_guess_num	**R-squared:**	0.406
Model:	OLS	**Adj. R-squared:**	0.405
Method:	Least Squares	**F-statistic:**	4873.
Date:	Thu, 20 Aug 2020	**Prob (F-statistic):**	0.00
Time:	18:40:21	**Log-Likelihood:**	-2.3423e+05
No. Observations:	100000	**AIC:**	4.685e+05
Df Residuals:	99985	**BIC:**	4.686e+05
Df Model:	14		

	coef	**std err**	**t**	**P> |t|**	**[0.025**	**0.975]**
Intercept	-0.6313	0.071	-8.952	0.000	-0.769	-0.493
heuristic4	-0.1126	0.008	-13.838	0.000	-0.129	-0.097
heuristic5	-0.0903	0.008	-11.267	0.000	-0.106	-0.075
heuristic6	-0.2277	0.008	-28.381	0.000	-0.243	-0.212
heuristic8	-0.1424	0.010	-14.354	0.000	-0.162	-0.123
heuristic9	-0.1124	0.009	-11.866	0.000	-0.131	-0.094
heuristic10	-0.0463	0.011	-4.268	0.000	-0.068	-0.025
heuristic11	1.1902	0.010	114.265	0.000	1.170	1.211
heuristic12	1.8277	0.013	138.853	0.000	1.802	1.854
heuristic13	1.9172	0.014	140.379	0.000	1.890	1.944
heuristic14	0.7361	0.011	66.324	0.000	0.714	0.758
heuristic15	-0.2136	0.009	-25.050	0.000	-0.230	-0.197
heuristic16	-0.2214	0.008	-26.738	0.000	-0.238	-0.205
heuristic17	-1.3976	0.008	-168.248	0.000	-1.414	-1.381
heuristic18	-0.5087	0.008	-61.556	0.000	-0.525	-0.493

Omnibus:	104.214	**Durbin-Watson:**	1.996
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	90.982
Skew:	-0.021	**Prob(JB):**	1.75e-20
Kurtosis:	2.858	**Cond. No.**	48.5

Table B.9: Guessability regression results for Cluster 7 model.

Increase guessability:

Feature	**Estimate**
Common substrings [h17]	-1.398
Dictionary (longest token) [h18]	-0.509
Repeated sections [h6]	-0.228
Alphabetic/numeric sequences [h16]	-0.221
Dates [h15]	-0.214
Predictable uppercase [h8]	-0.142
Repeated chars [h4]	-0.113
Predictable digits [h9]	-0.112
Keyboard patterns [h5]	-0.090
Predictable symbols [h10]	-0.046

Decrease guessability:

Feature	**Estimate**
Digits count [h13]	1.917
Lowercase count [h12]	1.828
Uppercase count [h11]	1.190
Symbols count [h14]	0.736

Cluster 8 model

Dep. Variable:	log_guess_num	**R-squared:**	0.405
Model:	OLS	**Adj. R-squared:**	0.405
Method:	Least Squares	**F-statistic:**	4868.
Date:	Thu, 20 Aug 2020	**Prob (F-statistic):**	0.00
Time:	18:40:21	**Log-Likelihood:**	-2.3359e+05
No. Observations:	100000	**AIC:**	4.672e+05
Df Residuals:	99985	**BIC:**	4.673e+05
Df Model:	14		

	coef	**std err**	**t**	**P> |t|**	**[0.025**	**0.975]**
Intercept	0.0241	0.068	0.353	0.724	-0.110	0.158
heuristic4	-0.1616	0.008	-19.983	0.000	-0.177	-0.146
heuristic5	-0.1037	0.008	-13.022	0.000	-0.119	-0.088
heuristic6	-0.2166	0.008	-27.160	0.000	-0.232	-0.201
heuristic8	-0.1465	0.010	-15.326	0.000	-0.165	-0.128
heuristic9	-0.2485	0.009	-27.137	0.000	-0.266	-0.231
heuristic10	-0.0581	0.011	-5.285	0.000	-0.080	-0.037
heuristic11	1.2241	0.010	121.216	0.000	1.204	1.244
heuristic12	1.9062	0.013	148.292	0.000	1.881	1.931
heuristic13	1.9107	0.013	141.788	0.000	1.884	1.937
heuristic14	0.6548	0.011	58.320	0.000	0.633	0.677
heuristic15	-0.2756	0.008	-32.682	0.000	-0.292	-0.259
heuristic16	-0.4093	0.008	-49.532	0.000	-0.425	-0.393
heuristic17	-1.4099	0.008	-171.303	0.000	-1.426	-1.394
heuristic18	-0.4613	0.008	-56.219	0.000	-0.477	-0.445

Omnibus:	316.105	**Durbin-Watson:**	2.000
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	319.070
Skew:	-0.137	**Prob(JB):**	5.19e-70
Kurtosis:	3.032	**Cond. No.**	47.1

Table B.10: Guessability regression results for Cluster 8 model.

Increase guessability:

Feature	**Estimate**
Common substrings [h17]	-1.410
Dictionary (longest token) [h18]	-0.461
Alphabetic/numeric sequences [h16]	-0.409
Dates [h15]	-0.276
Predictable digits [h9]	-0.249
Repeated sections [h6]	-0.217
Repeated chars [h4]	-0.162
Predictable uppercase [h8]	-0.146
Keyboard patterns [h5]	-0.104
Predictable symbols [h10]	-0.058

Decrease guessability:

Feature	**Estimate**
Digits count [h13]	1.911
Lowercase count [h12]	1.906
Uppercase count [h11]	1.224
Symbols count [h14]	0.655

Cluster 9 model

Dep. Variable:	log_guess_num	**R-squared:**	0.498
Model:	OLS	**Adj. R-squared:**	0.498
Method:	Least Squares	**F-statistic:**	7074.
Date:	Thu, 20 Aug 2020	**Prob (F-statistic):**	0.00
Time:	18:40:21	**Log-Likelihood:**	-2.2674e+05
No. Observations:	100000	**AIC:**	4.535e+05
Df Residuals:	99985	**BIC:**	4.537e+05
Df Model:	14		

	coef	**std err**	**t**	**P> |t|**	**[0.025**	**0.975]**
Intercept	2.8419	0.060	47.281	0.000	2.724	2.960
heuristic4	-0.0955	0.008	-12.358	0.000	-0.111	-0.080
heuristic5	-0.1566	0.007	-21.104	0.000	-0.171	-0.142
heuristic6	-0.4756	0.008	-63.344	0.000	-0.490	-0.461
heuristic8	-0.1532	0.008	-18.595	0.000	-0.169	-0.137
heuristic9	-1.1206	0.009	-121.914	0.000	-1.139	-1.103
heuristic10	-0.0548	0.009	-5.900	0.000	-0.073	-0.037
heuristic11	1.8846	0.011	173.129	0.000	1.863	1.906
heuristic12	2.3690	0.016	143.841	0.000	2.337	2.401
heuristic13	2.6020	0.017	151.678	0.000	2.568	2.636
heuristic14	0.5912	0.010	61.575	0.000	0.572	0.610
heuristic15	-0.3429	0.008	-44.060	0.000	-0.358	-0.328
heuristic16	-0.3326	0.008	-43.864	0.000	-0.347	-0.318
heuristic17	-1.3357	0.008	-164.358	0.000	-1.352	-1.320
heuristic18	-0.5970	0.008	-75.147	0.000	-0.613	-0.581

Omnibus:	15171.657	**Durbin-Watson:**	1.996
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	28609.780
Skew:	-0.960	**Prob(JB):**	0.00
Kurtosis:	4.784	**Cond. No.**	29.0

Table B.11: Guessability regression results for Cluster 9 model.

Increase guessability:

Feature	**Estimate**
Common substrings [h17]	-1.336
Predictable digits [h9]	-1.121
Dictionary (longest token) [h18]	-0.597
Repeated sections [h6]	-0.476
Dates [h15]	-0.343
Alphabetic/numeric sequences [h16]	-0.333
Keyboard patterns [h5]	-0.157
Predictable uppercase [h8]	-0.153
Repeated chars [h4]	-0.096
Predictable symbols [h10]	-0.055

Decrease guessability:

Feature	**Estimate**
Digits count [h13]	2.602
Lowercase count [h12]	2.369
Uppercase count [h11]	1.885
Symbols count [h14]	0.591

Cluster 10 model

Dep. Variable:	log_guess_num	**R-squared:**	0.450
Model:	OLS	**Adj. R-squared:**	0.450
Method:	Least Squares	**F-statistic:**	5837.
Date:	Thu, 20 Aug 2020	**Prob (F-statistic):**	0.00
Time:	18:40:22	**Log-Likelihood:**	-2.2478e+05
No. Observations:	100000	**AIC:**	4.496e+05
Df Residuals:	99985	**BIC:**	4.497e+05
Df Model:	14		

	coef	**std err**	**t**	**P> |t|**	**[0.025**	**0.975]**
Intercept	1.2125	0.063	19.171	0.000	1.089	1.336
heuristic4	-0.1820	0.007	-24.457	0.000	-0.197	-0.167
heuristic5	-0.0939	0.007	-12.862	0.000	-0.108	-0.080
heuristic6	-0.2384	0.007	-32.579	0.000	-0.253	-0.224
heuristic8	-0.1249	0.009	-14.456	0.000	-0.142	-0.108
heuristic9	-0.5898	0.008	-69.820	0.000	-0.606	-0.573
heuristic10	0.0554	0.010	5.526	0.000	0.036	0.075
heuristic11	1.2307	0.009	132.442	0.000	1.212	1.249
heuristic12	1.8288	0.012	146.988	0.000	1.804	1.853
heuristic13	1.9979	0.012	159.996	0.000	1.973	2.022
heuristic14	0.4856	0.010	46.930	0.000	0.465	0.506
heuristic15	-0.3922	0.008	-50.450	0.000	-0.407	-0.377
heuristic16	-0.4089	0.007	-54.531	0.000	-0.424	-0.394
heuristic17	-1.3396	0.008	-176.989	0.000	-1.354	-1.325
heuristic18	-0.4516	0.008	-60.047	0.000	-0.466	-0.437

Omnibus:	4085.874	**Durbin-Watson:**	2.011
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	5204.448
Skew:	-0.441	**Prob(JB):**	0.00
Kurtosis:	3.685	**Cond. No.**	43.2

Table B.12: Guessability regression results for Cluster 10 model.

Increase guessability:

Feature	**Estimate**
Common substrings [h17]	-1.340
Predictable digits [h9]	-0.590
Dictionary (longest token) [h18]	-0.452
Alphabetic/numeric sequences [h16]	-0.409
Dates [h15]	-0.392
Repeated sections [h6]	-0.238
Repeated chars [h4]	-0.182
Predictable uppercase [h8]	-0.125
Keyboard patterns [h5]	-0.094

Decrease guessability:

Feature	**Estimate**
Digits count [h13]	1.998
Lowercase count [h12]	1.829
Uppercase count [h11]	1.231
Symbols count [h14]	0.486
Predictable symbols [h10]	0.055

Cluster 11 model

Dep. Variable:	log_guess_num	**R-squared:**	0.506
Model:	OLS	**Adj. R-squared:**	0.506
Method:	Least Squares	**F-statistic:**	7306.
Date:	Thu, 20 Aug 2020	**Prob (F-statistic):**	0.00
Time:	18:40:22	**Log-Likelihood:**	-2.3187e+05
No. Observations:	100000	**AIC:**	4.638e+05
Df Residuals:	99985	**BIC:**	4.639e+05
Df Model:	14		

	coef	**std err**	**t**	**P> |t|**	**[0.025**	**0.975]**
Intercept	1.8586	0.062	29.855	0.000	1.737	1.981
heuristic4	-0.0211	0.008	-2.606	0.009	-0.037	-0.005
heuristic5	-0.1773	0.008	-22.698	0.000	-0.193	-0.162
heuristic6	-0.4699	0.008	-59.532	0.000	-0.485	-0.454
heuristic8	-0.1490	0.009	-17.186	0.000	-0.166	-0.132
heuristic9	-1.1227	0.010	-116.596	0.000	-1.142	-1.104
heuristic10	-0.0468	0.010	-4.626	0.000	-0.067	-0.027
heuristic11	2.0084	0.011	181.431	0.000	1.987	2.030
heuristic12	2.6241	0.017	157.876	0.000	2.592	2.657
heuristic13	2.9997	0.017	176.887	0.000	2.966	3.033
heuristic14	0.6055	0.010	58.088	0.000	0.585	0.626
heuristic15	-0.4185	0.008	-51.174	0.000	-0.434	-0.402
heuristic16	-0.3961	0.008	-49.730	0.000	-0.412	-0.381
heuristic17	-1.3775	0.008	-165.950	0.000	-1.394	-1.361
heuristic18	-0.5341	0.008	-63.788	0.000	-0.550	-0.518

Omnibus:	12143.418	**Durbin-Watson:**	2.007
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	20038.023
Skew:	-0.846	**Prob(JB):**	0.00
Kurtosis:	4.395	**Cond. No.**	30.0

Table B.13: Guessability regression results for Cluster 11 model.

Increase guessability:

Feature	**Estimate**
Common substrings [h17]	-1.377
Predictable digits [h9]	-1.123
Dictionary (longest token) [h18]	-0.534
Repeated sections [h6]	-0.470
Dates [h15]	-0.418
Alphabetic/numeric sequences [h16]	-0.396
Keyboard patterns [h5]	-0.177
Predictable uppercase [h8]	-0.149
Predictable symbols [h10]	-0.047
Repeated chars [h4]	-0.021

Decrease guessability:

Feature	**Estimate**
Digits count [h13]	3.000
Lowercase count [h12]	2.624
Uppercase count [h11]	2.008
Symbols count [h14]	0.605

Cluster 12 model

Dep. Variable:	log_guess_num	**R-squared:**	0.537
Model:	OLS	**Adj. R-squared:**	0.537
Method:	Least Squares	**F-statistic:**	8285.
Date:	Thu, 20 Aug 2020	**Prob (F-statistic):**	0.00
Time:	18:40:22	**Log-Likelihood:**	-2.4171e+05
No. Observations:	100000	**AIC:**	4.834e+05
Df Residuals:	99985	**BIC:**	4.836e+05
Df Model:	14		

	coef	**std err**	**t**	**P> |t|**	**[0.025**	**0.975]**
Intercept	1.4793	0.071	20.812	0.000	1.340	1.619
heuristic4	0.0650	0.009	7.227	0.000	0.047	0.083
heuristic5	-0.3628	0.009	-42.052	0.000	-0.380	-0.346
heuristic6	-0.5020	0.009	-56.937	0.000	-0.519	-0.485
heuristic8	-0.5377	0.011	-49.170	0.000	-0.559	-0.516
heuristic9	-0.7806	0.010	-80.949	0.000	-0.800	-0.762
heuristic10	0.0262	0.010	2.576	0.010	0.006	0.046
heuristic11	3.4052	0.018	188.712	0.000	3.370	3.441
heuristic12	3.3533	0.022	154.633	0.000	3.311	3.396
heuristic13	3.0853	0.022	139.418	0.000	3.042	3.129
heuristic14	0.7441	0.011	69.743	0.000	0.723	0.765
heuristic15	-0.2603	0.009	-28.385	0.000	-0.278	-0.242
heuristic16	-0.3082	0.009	-35.180	0.000	-0.325	-0.291
heuristic17	-1.8824	0.009	-205.891	0.000	-1.900	-1.864
heuristic18	-0.5484	0.009	-58.964	0.000	-0.567	-0.530

Omnibus:	10792.207	**Durbin-Watson:**	2.000
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	15504.810
Skew:	-0.836	**Prob(JB):**	0.00
Kurtosis:	3.964	**Cond. No.**	27.5

Table B.14: Guessability regression results for Cluster 12 model.

Increase guessability:

Feature	**Estimate**
Common substrings [h17]	-1.882
Predictable digits [h9]	-0.781
Dictionary (longest token) [h18]	-0.548
Predictable uppercase [h8]	-0.538
Repeated sections [h6]	-0.502
Keyboard patterns [h5]	-0.363
Alphabetic/numeric sequences [h16]	-0.308
Dates [h15]	-0.260

Decrease guessability:

Feature	**Estimate**
Uppercase count [h11]	3.405
Lowercase count [h12]	3.353
Digits count [h13]	3.085
Symbols count [h14]	0.744
Repeated chars [h4]	0.065
Predictable symbols [h10]	0.026

Cluster 13 model

Dep. Variable:	log_guess_num	**R-squared:**	0.451
Model:	OLS	**Adj. R-squared:**	0.451
Method:	Least Squares	**F-statistic:**	5876.
Date:	Thu, 20 Aug 2020	**Prob (F-statistic):**	0.00
Time:	18:40:22	**Log-Likelihood:**	-2.2782e+05
No. Observations:	100000	**AIC:**	4.557e+05
Df Residuals:	99985	**BIC:**	4.558e+05
Df Model:	14		

	coef	**std err**	**t**	**P> |t|**	**[0.025**	**0.975]**
Intercept	1.7103	0.065	26.157	0.000	1.582	1.838
heuristic4	-0.0747	0.008	-9.729	0.000	-0.090	-0.060
heuristic5	-0.1004	0.008	-13.350	0.000	-0.115	-0.086
heuristic6	-0.2690	0.008	-35.742	0.000	-0.284	-0.254
heuristic8	-0.1377	0.009	-15.802	0.000	-0.155	-0.121
heuristic9	-0.7527	0.009	-84.635	0.000	-0.770	-0.735
heuristic10	-0.0581	0.011	-5.382	0.000	-0.079	-0.037
heuristic11	1.3184	0.010	136.472	0.000	1.299	1.337
heuristic12	1.8578	0.013	143.805	0.000	1.832	1.883
heuristic13	2.0964	0.013	160.180	0.000	2.071	2.122
heuristic14	0.5719	0.011	51.633	0.000	0.550	0.594
heuristic15	-0.6364	0.008	-79.638	0.000	-0.652	-0.621
heuristic16	-0.3771	0.008	-49.080	0.000	-0.392	-0.362
heuristic17	-1.2920	0.008	-166.021	0.000	-1.307	-1.277
heuristic18	-0.4454	0.008	-57.034	0.000	-0.461	-0.430

Omnibus:	4198.505	**Durbin-Watson:**	2.002
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	5508.367
Skew:	-0.439	**Prob(JB):**	0.00
Kurtosis:	3.743	**Cond. No.**	43.6

Table B.15: Guessability regression results for Cluster 13 model.

Increase guessability:

Feature	**Estimate**
Common substrings [h17]	-1.292
Predictable digits [h9]	-0.753
Dates [h15]	-0.636
Dictionary (longest token) [h18]	-0.445
Alphabetic/numeric sequences [h16]	-0.377
Repeated sections [h6]	-0.269
Predictable uppercase [h8]	-0.138
Keyboard patterns [h5]	-0.100
Repeated chars [h4]	-0.075
Predictable symbols [h10]	-0.058

Decrease guessability:

Feature	**Estimate**
Digits count [h13]	2.096
Lowercase count [h12]	1.858
Uppercase count [h11]	1.318
Symbols count [h14]	0.572

Cluster 14 model

Dep. Variable:	log_guess_num	**R-squared:**	0.433
Model:	OLS	**Adj. R-squared:**	0.433
Method:	Least Squares	**F-statistic:**	5455.
Date:	Thu, 20 Aug 2020	**Prob (F-statistic):**	0.00
Time:	18:40:23	**Log-Likelihood:**	-2.3550e+05
No. Observations:	100000	**AIC:**	4.710e+05
Df Residuals:	99985	**BIC:**	4.712e+05
Df Model:	14		

	coef	**std err**	**t**	**P> |t|**	**[0.025**	**0.975]**
Intercept	1.2868	0.067	19.325	0.000	1.156	1.417
heuristic4	-0.0744	0.008	-8.957	0.000	-0.091	-0.058
heuristic5	-0.0981	0.008	-12.087	0.000	-0.114	-0.082
heuristic6	-0.2348	0.008	-28.901	0.000	-0.251	-0.219
heuristic8	-0.1593	0.009	-17.037	0.000	-0.178	-0.141
heuristic9	-0.7190	0.009	-75.733	0.000	-0.738	-0.700
heuristic10	-0.0618	0.011	-5.537	0.000	-0.084	-0.040
heuristic11	1.4142	0.010	136.645	0.000	1.394	1.434
heuristic12	2.0356	0.013	152.737	0.000	2.009	2.062
heuristic13	2.2442	0.014	164.681	0.000	2.218	2.271
heuristic14	0.6079	0.011	53.180	0.000	0.586	0.630
heuristic15	-0.6559	0.009	-75.566	0.000	-0.673	-0.639
heuristic16	-0.4281	0.008	-51.385	0.000	-0.444	-0.412
heuristic17	-1.3652	0.008	-162.236	0.000	-1.382	-1.349
heuristic18	-0.4602	0.008	-54.684	0.000	-0.477	-0.444

Omnibus:	2920.903	**Durbin-Watson:**	2.008
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	3427.473
Skew:	-0.381	**Prob(JB):**	0.00
Kurtosis:	3.492	**Cond. No.**	41.7

Table B.16: Guessability regression results for Cluster 14 model.

Increase guessability:

Feature	**Estimate**
Common substrings [h17]	-1.365
Predictable digits [h9]	-0.719
Dates [h15]	-0.656
Dictionary (longest token) [h18]	-0.460
Alphabetic/numeric sequences [h16]	-0.428
Repeated sections [h6]	-0.235
Predictable uppercase [h8]	-0.159
Keyboard patterns [h5]	-0.098
Repeated chars [h4]	-0.074
Predictable symbols [h10]	-0.062

Decrease guessability:

Feature	**Estimate**
Digits count [h13]	2.244
Lowercase count [h12]	2.036
Uppercase count [h11]	1.414
Symbols count [h14]	0.608

Cluster 15 model

Dep. Variable:	log_guess_num	**R-squared:**	0.645
Model:	OLS	**Adj. R-squared:**	0.645
Method:	Least Squares	**F-statistic:**	1.300e+04
Date:	Thu, 20 Aug 2020	**Prob (F-statistic):**	0.00
Time:	18:40:23	**Log-Likelihood:**	-2.4416e+05
No. Observations:	100000	**AIC:**	4.883e+05
Df Residuals:	99985	**BIC:**	4.885e+05
Df Model:	14		

	coef	**std err**	**t**	**P> |t|**	**[0.025**	**0.975]**
Intercept	0.6737	0.080	8.389	0.000	0.516	0.831
heuristic4	0.3978	0.009	42.790	0.000	0.380	0.416
heuristic5	-0.1791	0.009	-20.252	0.000	-0.196	-0.162
heuristic6	-0.4650	0.009	-50.681	0.000	-0.483	-0.447
heuristic8	-0.4841	0.013	-38.053	0.000	-0.509	-0.459
heuristic9	-0.6651	0.010	-63.997	0.000	-0.685	-0.645
heuristic10	0.1313	0.011	12.337	0.000	0.110	0.152
heuristic11	3.4648	0.020	173.834	0.000	3.426	3.504
heuristic12	3.8349	0.024	159.521	0.000	3.788	3.882
heuristic13	3.3309	0.027	124.663	0.000	3.279	3.383
heuristic14	0.5871	0.011	52.822	0.000	0.565	0.609
heuristic15	0.0092	0.009	1.021	0.307	-0.009	0.027
heuristic16	-0.2680	0.009	-29.990	0.000	-0.286	-0.250
heuristic17	-2.7094	0.009	-286.357	0.000	-2.728	-2.691
heuristic18	-0.4229	0.010	-42.136	0.000	-0.443	-0.403

Omnibus:	5144.347	**Durbin-Watson:**	2.000
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	6578.746
Skew:	-0.517	**Prob(JB):**	0.00
Kurtosis:	3.715	**Cond. No.**	33.6

Table B.17: Guessability regression results for Cluster 15 model.

Increase guessability:	
Feature	**Estimate**
Common substrings [h17]	-2.709
Predictable digits [h9]	-0.665
Predictable uppercase [h8]	-0.484
Repeated sections [h6]	-0.465
Dictionary (longest token) [h18]	-0.423
Alphabetic/numeric sequences [h16]	-0.268
Keyboard patterns [h5]	-0.179

Decrease guessability:	
Feature	**Estimate**
Lowercase count [h12]	3.835
Uppercase count [h11]	3.465
Digits count [h13]	3.331
Symbols count [h14]	0.587
Repeated chars [h4]	0.398
Predictable symbols [h10]	0.131
Dates [h15]	0.009

Cluster 16 model

Dep. Variable:	log_guess_num	**R-squared:**	0.667
Model:	OLS	**Adj. R-squared:**	0.667
Method:	Least Squares	**F-statistic:**	1.431e+04
Date:	Thu, 20 Aug 2020	**Prob (F-statistic):**	0.00
Time:	18:40:23	**Log-Likelihood:**	-2.4635e+05
No. Observations:	100000	**AIC:**	4.927e+05
Df Residuals:	99985	**BIC:**	4.929e+05
Df Model:	14		

	coef	**std err**	**t**	**P> |t|**	**[0.025**	**0.975]**
Intercept	-0.5384	0.079	-6.803	0.000	-0.694	-0.383
heuristic4	-0.0065	0.010	-0.684	0.494	-0.025	0.012
heuristic5	-0.1725	0.009	-19.054	0.000	-0.190	-0.155
heuristic6	-0.4906	0.009	-53.009	0.000	-0.509	-0.472
heuristic8	-0.6352	0.010	-61.215	0.000	-0.656	-0.615
heuristic9	-0.9467	0.010	-90.842	0.000	-0.967	-0.926
heuristic10	0.0505	0.010	4.839	0.000	0.030	0.071
heuristic11	4.9618	0.019	262.828	0.000	4.925	4.999
heuristic12	4.2836	0.022	191.451	0.000	4.240	4.327
heuristic13	4.1508	0.023	176.754	0.000	4.105	4.197
heuristic14	0.7201	0.011	65.985	0.000	0.699	0.741
heuristic15	-0.1979	0.009	-20.963	0.000	-0.216	-0.179
heuristic16	-0.3721	0.009	-40.449	0.000	-0.390	-0.354
heuristic17	-1.9298	0.010	-198.333	0.000	-1.949	-1.911
heuristic18	-0.6575	0.010	-67.406	0.000	-0.677	-0.638

Omnibus:	17979.887	**Durbin-Watson:**	2.010
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	38753.649
Skew:	-1.057	**Prob(JB):**	0.00
Kurtosis:	5.197	**Cond. No.**	29.3

Table B.18: Guessability regression results for Cluster 16 model.

Increase guessability:

Feature	**Estimate**
Common substrings [h17]	-1.930
Predictable digits [h9]	-0.947
Dictionary (longest token) [h18]	-0.658
Predictable uppercase [h8]	-0.635
Repeated sections [h6]	-0.491
Alphabetic/numeric sequences [h16]	-0.372
Dates [h15]	-0.198
Keyboard patterns [h5]	-0.173
Repeated chars [h4]	-0.007

Decrease guessability:

Feature	**Estimate**
Uppercase count [h11]	4.962
Lowercase count [h12]	4.284
Digits count [h13]	4.151
Symbols count [h14]	0.720
Predictable symbols [h10]	0.050

Cluster 17 model

Dep. Variable:	log_guess_num	**R-squared:**	0.346
Model:	OLS	**Adj. R-squared:**	0.346
Method:	Least Squares	**F-statistic:**	3783.
Date:	Thu, 20 Aug 2020	**Prob (F-statistic):**	0.00
Time:	18:40:24	**Log-Likelihood:**	-2.4387e+05
No. Observations:	100000	**AIC:**	4.878e+05
Df Residuals:	99985	**BIC:**	4.879e+05
Df Model:	14		

	coef	**std err**	**t**	**P> |t|**	**[0.025**	**0.975]**
Intercept	-1.0641	0.074	-14.462	0.000	-1.208	-0.920
heuristic4	-0.0244	0.009	-2.748	0.006	-0.042	-0.007
heuristic5	-0.1292	0.009	-14.579	0.000	-0.147	-0.112
heuristic6	-0.2222	0.009	-25.132	0.000	-0.240	-0.205
heuristic8	-0.0244	0.010	-2.434	0.015	-0.044	-0.005
heuristic9	-0.0389	0.013	-3.038	0.002	-0.064	-0.014
heuristic10	-0.0143	0.010	-1.442	0.149	-0.034	0.005
heuristic11	1.1051	0.011	105.156	0.000	1.085	1.126
heuristic12	2.4205	0.016	155.230	0.000	2.390	2.451
heuristic13	1.9356	0.017	114.235	0.000	1.902	1.969
heuristic14	0.8095	0.010	80.143	0.000	0.790	0.829
heuristic15	-0.1914	0.010	-20.142	0.000	-0.210	-0.173
heuristic16	-0.1171	0.009	-12.901	0.000	-0.135	-0.099
heuristic17	-1.1932	0.009	-126.992	0.000	-1.212	-1.175
heuristic18	-0.7203	0.010	-74.818	0.000	-0.739	-0.701

Omnibus:	166.543	**Durbin-Watson:**	1.997
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	167.226
Skew:	-0.099	**Prob(JB):**	4.87e-37
Kurtosis:	2.969	**Cond. No.**	45.9

Table B.19: Guessability regression results for Cluster 17 model.

Increase guessability:

Feature	**Estimate**
Common substrings [h17]	-1.193
Dictionary (longest token) [h18]	-0.720
Repeated sections [h6]	-0.222
Dates [h15]	-0.191
Keyboard patterns [h5]	-0.129
Alphabetic/numeric sequences [h16]	-0.117
Predictable digits [h9]	-0.039
Repeated chars [h4]	-0.024
Predictable uppercase [h8]	-0.024
Predictable symbols [h10]	-0.014

Decrease guessability:

Feature	**Estimate**
Lowercase count [h12]	2.420
Digits count [h13]	1.936
Uppercase count [h11]	1.105
Symbols count [h14]	0.810

Cluster 18 model

Dep. Variable:	log_guess_num	**R-squared:**	0.387
Model:	OLS	**Adj. R-squared:**	0.386
Method:	Least Squares	**F-statistic:**	4501.
Date:	Thu, 20 Aug 2020	**Prob (F-statistic):**	0.00
Time:	18:40:24	**Log-Likelihood:**	-2.4184e+05
No. Observations:	100000	**AIC:**	4.837e+05
Df Residuals:	99985	**BIC:**	4.839e+05
Df Model:	14		

	coef	**std err**	**t**	**P> |t|**	**[0.025**	**0.975]**
Intercept	-0.1655	0.071	-2.336	0.019	-0.304	-0.027
heuristic4	-0.1837	0.009	-20.932	0.000	-0.201	-0.166
heuristic5	-0.1129	0.009	-13.058	0.000	-0.130	-0.096
heuristic6	-0.2166	0.009	-25.042	0.000	-0.234	-0.200
heuristic8	-0.1939	0.010	-19.042	0.000	-0.214	-0.174
heuristic9	-0.2560	0.010	-25.106	0.000	-0.276	-0.236
heuristic10	-0.0513	0.012	-4.331	0.000	-0.074	-0.028
heuristic11	1.2880	0.011	119.416	0.000	1.267	1.309
heuristic12	2.1618	0.014	154.458	0.000	2.134	2.189
heuristic13	2.0207	0.015	135.328	0.000	1.991	2.050
heuristic14	0.7063	0.012	58.526	0.000	0.683	0.730
heuristic15	-0.3058	0.009	-33.505	0.000	-0.324	-0.288
heuristic16	-0.3734	0.009	-41.914	0.000	-0.391	-0.356
heuristic17	-1.4231	0.009	-157.965	0.000	-1.441	-1.405
heuristic18	-0.5359	0.009	-59.632	0.000	-0.554	-0.518

Omnibus:	628.421	**Durbin-Watson:**	2.003
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	639.651
Skew:	-0.195	**Prob(JB):**	1.26e-139
Kurtosis:	2.956	**Cond. No.**	44.5

Table B.20: Guessability regression results for Cluster 18 model.

Increase guessability:

Feature	**Estimate**
Common substrings [h17]	-1.423
Dictionary (longest token) [h18]	-0.536
Alphabetic/numeric sequences [h16]	-0.373
Dates [h15]	-0.306
Predictable digits [h9]	-0.256
Repeated sections [h6]	-0.217
Predictable uppercase [h8]	-0.194
Repeated chars [h4]	-0.184
Keyboard patterns [h5]	-0.113
Predictable symbols [h10]	-0.051

Decrease guessability:

Feature	**Estimate**
Lowercase count [h12]	2.162
Digits count [h13]	2.021
Uppercase count [h11]	1.288
Symbols count [h14]	0.706

Cluster 19 model

Dep. Variable:	log_guess_num	**R-squared:**	0.396
Model:	OLS	**Adj. R-squared:**	0.396
Method:	Least Squares	**F-statistic:**	4691.
Date:	Thu, 20 Aug 2020	**Prob (F-statistic):**	0.00
Time:	18:40:24	**Log-Likelihood:**	-2.3375e+05
No. Observations:	100000	**AIC:**	4.675e+05
Df Residuals:	99985	**BIC:**	4.677e+05
Df Model:	14		

	coef	**std err**	**t**	**P> |t|**	**[0.025**	**0.975]**
Intercept	-1.9893	0.074	-26.810	0.000	-2.135	-1.844
heuristic4	-0.0196	0.008	-2.446	0.014	-0.035	-0.004
heuristic5	-0.0866	0.008	-10.842	0.000	-0.102	-0.071
heuristic6	-0.1625	0.008	-20.361	0.000	-0.178	-0.147
heuristic8	0.0415	0.009	4.428	0.000	0.023	0.060
heuristic9	0.0652	0.012	5.481	0.000	0.042	0.089
heuristic10	-0.0695	0.009	-7.652	0.000	-0.087	-0.052
heuristic11	0.9932	0.010	100.946	0.000	0.974	1.013
heuristic12	1.7040	0.012	141.472	0.000	1.680	1.728
heuristic13	1.6487	0.015	109.358	0.000	1.619	1.678
heuristic14	0.7718	0.009	83.672	0.000	0.754	0.790
heuristic15	-0.1541	0.009	-17.906	0.000	-0.171	-0.137
heuristic16	-0.0431	0.008	-5.277	0.000	-0.059	-0.027
heuristic17	-1.0779	0.008	-129.031	0.000	-1.094	-1.062
heuristic18	-0.7520	0.008	-88.510	0.000	-0.769	-0.735

Omnibus:	250.949	**Durbin-Watson:**	2.000
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	272.303
Skew:	0.091	**Prob(JB):**	7.41e-60
Kurtosis:	3.180	**Cond. No.**	63.4

Table B.21: Guessability regression results for Cluster 19 model.

Increase guessability:

Feature	**Estimate**
Common substrings [h17]	-1.078
Dictionary (longest token) [h18]	-0.752
Repeated sections [h6]	-0.163
Dates [h15]	-0.154
Keyboard patterns [h5]	-0.087
Predictable symbols [h10]	-0.070
Alphabetic/numeric sequences [h16]	-0.043
Repeated chars [h4]	-0.020

Decrease guessability:

Feature	**Estimate**
Lowercase count [h12]	1.704
Digits count [h13]	1.649
Uppercase count [h11]	0.993
Symbols count [h14]	0.772
Predictable digits [h9]	0.065
Predictable uppercase [h8]	0.042

Cluster 20 model

Dep. Variable:	log_guess_num	**R-squared:**	0.421
Model:	OLS	**Adj. R-squared:**	0.421
Method:	Least Squares	**F-statistic:**	5189.
Date:	Thu, 20 Aug 2020	**Prob (F-statistic):**	0.00
Time:	18:40:25	**Log-Likelihood:**	-2.3058e+05
No. Observations:	100000	**AIC:**	4.612e+05
Df Residuals:	99985	**BIC:**	4.613e+05
Df Model:	14		

	coef	**std err**	**t**	**P> |t|**	**[0.025**	**0.975]**
Intercept	-2.1933	0.073	-30.050	0.000	-2.336	-2.050
heuristic4	-0.0440	0.008	-5.654	0.000	-0.059	-0.029
heuristic5	-0.0559	0.008	-7.242	0.000	-0.071	-0.041
heuristic6	-0.1712	0.008	-22.166	0.000	-0.186	-0.156
heuristic8	0.0365	0.009	3.963	0.000	0.018	0.055
heuristic9	0.0818	0.012	7.038	0.000	0.059	0.105
heuristic10	-0.0544	0.009	-6.250	0.000	-0.072	-0.037
heuristic11	0.9614	0.010	100.375	0.000	0.943	0.980
heuristic12	1.6473	0.012	142.682	0.000	1.625	1.670
heuristic13	1.6520	0.015	111.522	0.000	1.623	1.681
heuristic14	0.7750	0.009	87.504	0.000	0.758	0.792
heuristic15	-0.1359	0.008	-16.261	0.000	-0.152	-0.120
heuristic16	-0.0577	0.008	-7.289	0.000	-0.073	-0.042
heuristic17	-1.0935	0.008	-135.157	0.000	-1.109	-1.078
heuristic18	-0.7712	0.008	-93.786	0.000	-0.787	-0.755

Omnibus:	703.212	**Durbin-Watson:**	2.000
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	907.413
Skew:	0.118	**Prob(JB):**	9.07e-198
Kurtosis:	3.403	**Cond. No.**	65.7

Table B.22: Guessability regression results for Cluster 20 model.

Increase guessability:

Feature	**Estimate**
Common substrings [h17]	-1.093
Dictionary (longest token) [h18]	-0.771
Repeated sections [h6]	-0.171
Dates [h15]	-0.136
Alphabetic/numeric sequences [h16]	-0.058
Keyboard patterns [h5]	-0.056
Predictable symbols [h10]	-0.054
Repeated chars [h4]	-0.044

Decrease guessability:

Feature	**Estimate**
Digits count [h13]	1.652
Lowercase count [h12]	1.647
Uppercase count [h11]	0.961
Symbols count [h14]	0.775
Predictable digits [h9]	0.082
Predictable uppercase [h8]	0.036

Cluster 21 model

Dep. Variable:	log_guess_num	**R-squared:**	0.556
Model:	OLS	**Adj. R-squared:**	0.556
Method:	Least Squares	**F-statistic:**	8934.
Date:	Thu, 20 Aug 2020	**Prob (F-statistic):**	0.00
Time:	18:40:25	**Log-Likelihood:**	-2.3876e+05
No. Observations:	100000	**AIC:**	4.776e+05
Df Residuals:	99985	**BIC:**	4.777e+05
Df Model:	14		

	coef	**std err**	**t**	**P> |t|**	**[0.025**	**0.975]**
Intercept	1.6102	0.075	21.551	0.000	1.464	1.757
heuristic4	0.2394	0.009	27.469	0.000	0.222	0.256
heuristic5	-0.5133	0.008	-61.119	0.000	-0.530	-0.497
heuristic6	-0.6686	0.009	-77.250	0.000	-0.686	-0.652
heuristic8	-0.4682	0.012	-39.683	0.000	-0.491	-0.445
heuristic9	-0.6436	0.010	-65.574	0.000	-0.663	-0.624
heuristic10	0.0943	0.010	9.337	0.000	0.075	0.114
heuristic11	2.9158	0.018	163.249	0.000	2.881	2.951
heuristic12	3.2740	0.022	147.163	0.000	3.230	3.318
heuristic13	2.9782	0.024	122.221	0.000	2.930	3.026
heuristic14	0.5645	0.011	53.579	0.000	0.544	0.585
heuristic15	-0.2794	0.009	-31.523	0.000	-0.297	-0.262
heuristic16	-0.3150	0.008	-37.176	0.000	-0.332	-0.298
heuristic17	-1.9293	0.009	-220.988	0.000	-1.946	-1.912
heuristic18	-0.3965	0.009	-42.113	0.000	-0.415	-0.378

Omnibus:	7358.581	**Durbin-Watson:**	2.000
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	9436.760
Skew:	-0.673	**Prob(JB):**	0.00
Kurtosis:	3.673	**Cond. No.**	33.2

Table B.23: Guessability regression results for Cluster 21 model.

Increase guessability:

Feature	**Estimate**
Common substrings [h17]	-1.929
Repeated sections [h6]	-0.669
Predictable digits [h9]	-0.644
Keyboard patterns [h5]	-0.513
Predictable uppercase [h8]	-0.468
Dictionary (longest token) [h18]	-0.396
Alphabetic/numeric sequences [h16]	-0.315
Dates [h15]	-0.279

Decrease guessability:

Feature	**Estimate**
Lowercase count [h12]	3.274
Digits count [h13]	2.978
Uppercase count [h11]	2.916
Symbols count [h14]	0.564
Repeated chars [h4]	0.239
Predictable symbols [h10]	0.094

Cluster 22 model

Dep. Variable:	log_guess_num	**R-squared:**	0.432
Model:	OLS	**Adj. R-squared:**	0.432
Method:	Least Squares	**F-statistic:**	5430.
Date:	Thu, 20 Aug 2020	**Prob (F-statistic):**	0.00
Time:	18:40:25	**Log-Likelihood:**	-2.2178e+05
No. Observations:	100000	**AIC:**	4.436e+05
Df Residuals:	99985	**BIC:**	4.437e+05
Df Model:	14		

	coef	**std err**	**t**	**P> |t|**	**[0.025**	**0.975]**
Intercept	0.1669	0.066	2.523	0.012	0.037	0.297
heuristic4	-0.1332	0.007	-18.629	0.000	-0.147	-0.119
heuristic5	-0.0549	0.007	-7.765	0.000	-0.069	-0.041
heuristic6	-0.2037	0.007	-28.752	0.000	-0.218	-0.190
heuristic8	-0.1156	0.009	-13.163	0.000	-0.133	-0.098
heuristic9	-0.3570	0.008	-43.641	0.000	-0.373	-0.341
heuristic10	0.0107	0.010	1.073	0.283	-0.009	0.030
heuristic11	1.1426	0.009	122.757	0.000	1.124	1.161
heuristic12	1.6616	0.012	144.344	0.000	1.639	1.684
heuristic13	1.7528	0.011	154.066	0.000	1.730	1.775
heuristic14	0.6034	0.010	59.368	0.000	0.583	0.623
heuristic15	-0.2562	0.007	-34.259	0.000	-0.271	-0.242
heuristic16	-0.2842	0.007	-39.087	0.000	-0.298	-0.270
heuristic17	-1.2865	0.007	-176.714	0.000	-1.301	-1.272
heuristic18	-0.3924	0.007	-54.093	0.000	-0.407	-0.378

Omnibus:	963.595	**Durbin-Watson:**	1.998
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	1256.789
Skew:	-0.151	**Prob(JB):**	1.24e-273
Kurtosis:	3.459	**Cond. No.**	52.0

Table B.24: Guessability regression results for Cluster 22 model.

Increase guessability:

Feature	**Estimate**
Common substrings [h17]	-1.286
Dictionary (longest token) [h18]	-0.392
Predictable digits [h9]	-0.357
Alphabetic/numeric sequences [h16]	-0.284
Dates [h15]	-0.256
Repeated sections [h6]	-0.204
Repeated chars [h4]	-0.133
Predictable uppercase [h8]	-0.116
Keyboard patterns [h5]	-0.055

Decrease guessability:

Feature	**Estimate**
Digits count [h13]	1.753
Lowercase count [h12]	1.662
Uppercase count [h11]	1.143
Symbols count [h14]	0.603
Predictable symbols [h10]	0.011

Cluster 23 model

Dep. Variable:	log_guess_num	**R-squared:**	0.443
Model:	OLS	**Adj. R-squared:**	0.443
Method:	Least Squares	**F-statistic:**	5673.
Date:	Thu, 20 Aug 2020	**Prob (F-statistic):**	0.00
Time:	18:40:26	**Log-Likelihood:**	-2.3063e+05
No. Observations:	100000	**AIC:**	4.613e+05
Df Residuals:	99985	**BIC:**	4.614e+05
Df Model:	14		

	coef	**std err**	**t**	**P> |t|**	**[0.025**	**0.975]**
Intercept	0.6787	0.066	10.299	0.000	0.550	0.808
heuristic4	-0.2371	0.008	-29.986	0.000	-0.253	-0.222
heuristic5	-0.1296	0.008	-16.733	0.000	-0.145	-0.114
heuristic6	-0.2259	0.008	-29.143	0.000	-0.241	-0.211
heuristic8	-0.1217	0.009	-13.237	0.000	-0.140	-0.104
heuristic9	-0.4917	0.009	-55.170	0.000	-0.509	-0.474
heuristic10	-0.0389	0.011	-3.573	0.000	-0.060	-0.018
heuristic11	1.2149	0.010	123.393	0.000	1.196	1.234
heuristic12	1.9347	0.013	154.639	0.000	1.910	1.959
heuristic13	2.0761	0.013	161.591	0.000	2.051	2.101
heuristic14	0.5742	0.011	51.631	0.000	0.552	0.596
heuristic15	-0.4245	0.008	-51.526	0.000	-0.441	-0.408
heuristic16	-0.4792	0.008	-60.083	0.000	-0.495	-0.464
heuristic17	-1.4232	0.008	-177.825	0.000	-1.439	-1.407
heuristic18	-0.4503	0.008	-56.377	0.000	-0.466	-0.435

Omnibus:	2759.028	**Durbin-Watson:**	2.006
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	3294.045
Skew:	-0.360	**Prob(JB):**	0.00
Kurtosis:	3.521	**Cond. No.**	45.0

Table B.25: Guessability regression results for Cluster 23 model.

Increase guessability:

Feature	**Estimate**
Common substrings [h17]	-1.423
Predictable digits [h9]	-0.492
Alphabetic/numeric sequences [h16]	-0.479
Dictionary (longest token) [h18]	-0.450
Dates [h15]	-0.424
Repeated chars [h4]	-0.237
Repeated sections [h6]	-0.226
Keyboard patterns [h5]	-0.130
Predictable uppercase [h8]	-0.122
Predictable symbols [h10]	-0.039

Decrease guessability:

Feature	**Estimate**
Digits count [h13]	2.076
Lowercase count [h12]	1.935
Uppercase count [h11]	1.215
Symbols count [h14]	0.574

Cluster 24 model

Dep. Variable:	log_guess_num	**R-squared:**	0.347
Model:	OLS	**Adj. R-squared:**	0.346
Method:	Least Squares	**F-statistic:**	3788.
Date:	Thu, 20 Aug 2020	**Prob (F-statistic):**	0.00
Time:	18:40:26	**Log-Likelihood:**	-2.4086e+05
No. Observations:	100000	**AIC:**	4.818e+05
Df Residuals:	99985	**BIC:**	4.819e+05
Df Model:	14		

	coef	**std err**	**t**	**P> |t|**	**[0.025**	**0.975]**
Intercept	-1.4533	0.075	-19.264	0.000	-1.601	-1.305
heuristic4	-0.0587	0.009	-6.812	0.000	-0.076	-0.042
heuristic5	-0.1157	0.009	-13.476	0.000	-0.133	-0.099
heuristic6	-0.1676	0.009	-19.569	0.000	-0.184	-0.151
heuristic8	0.0019	0.010	0.186	0.853	-0.018	0.021
heuristic9	0.0497	0.013	3.922	0.000	0.025	0.074
heuristic10	-0.0428	0.010	-4.429	0.000	-0.062	-0.024
heuristic11	1.0206	0.010	98.145	0.000	1.000	1.041
heuristic12	1.9720	0.014	142.087	0.000	1.945	1.999
heuristic13	1.7369	0.016	106.384	0.000	1.705	1.769
heuristic14	0.8213	0.010	83.242	0.000	0.802	0.841
heuristic15	-0.1633	0.009	-17.725	0.000	-0.181	-0.145
heuristic16	-0.0866	0.009	-9.880	0.000	-0.104	-0.069
heuristic17	-1.0725	0.009	-119.092	0.000	-1.090	-1.055
heuristic18	-0.7022	0.009	-76.613	0.000	-0.720	-0.684

Omnibus:	51.730	**Durbin-Watson:**	2.003
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	52.025
Skew:	-0.052	**Prob(JB):**	5.04e-12
Kurtosis:	3.042	**Cond. No.**	54.0

Table B.26: Guessability regression results for Cluster 24 model.

Increase guessability:

Feature	**Estimate**
Common substrings [h17]	-1.073
Dictionary (longest token) [h18]	-0.702
Repeated sections [h6]	-0.168
Dates [h15]	-0.163
Keyboard patterns [h5]	-0.116
Alphabetic/numeric sequences [h16]	-0.087
Repeated chars [h4]	-0.059
Predictable symbols [h10]	-0.043

Decrease guessability:

Feature	**Estimate**
Lowercase count [h12]	1.972
Digits count [h13]	1.737
Uppercase count [h11]	1.021
Symbols count [h14]	0.821
Predictable digits [h9]	0.050
Predictable uppercase [h8]	0.002

Cluster 25 model

Dep. Variable:	log_guess_num	**R-squared:**	0.622
Model:	OLS	**Adj. R-squared:**	0.622
Method:	Least Squares	**F-statistic:**	1.177e+04
Date:	Thu, 20 Aug 2020	**Prob (F-statistic):**	0.00
Time:	18:40:26	**Log-Likelihood:**	-2.5636e+05
No. Observations:	100000	**AIC:**	5.128e+05
Df Residuals:	99985	**BIC:**	5.129e+05
Df Model:	14		

	coef	**std err**	**t**	**P> |t|**	**[0.025**	**0.975]**
Intercept	-0.4942	0.084	-5.865	0.000	-0.659	-0.329
heuristic4	0.1114	0.010	10.660	0.000	0.091	0.132
heuristic5	-0.2274	0.010	-22.686	0.000	-0.247	-0.208
heuristic6	-0.6209	0.010	-60.932	0.000	-0.641	-0.601
heuristic8	-0.5676	0.012	-48.413	0.000	-0.591	-0.545
heuristic9	-1.1774	0.012	-100.638	0.000	-1.200	-1.154
heuristic10	0.0355	0.012	3.083	0.002	0.013	0.058
heuristic11	4.5292	0.019	238.284	0.000	4.492	4.566
heuristic12	4.5835	0.024	190.706	0.000	4.536	4.631
heuristic13	4.3588	0.023	185.519	0.000	4.313	4.405
heuristic14	0.7413	0.012	61.419	0.000	0.718	0.765
heuristic15	-0.3415	0.010	-32.692	0.000	-0.362	-0.321
heuristic16	-0.4132	0.010	-40.656	0.000	-0.433	-0.393
heuristic17	-2.0164	0.011	-188.810	0.000	-2.037	-1.995
heuristic18	-0.7442	0.011	-69.821	0.000	-0.765	-0.723

Omnibus:	16720.470	**Durbin-Watson:**	1.999
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	31484.654
Skew:	-1.048	**Prob(JB):**	0.00
Kurtosis:	4.780	**Cond. No.**	29.0

Table B.27: Guessability regression results for Cluster 25 model.

Increase guessability:

Feature	**Estimate**
Common substrings [h17]	-2.016
Predictable digits [h9]	-1.177
Dictionary (longest token) [h18]	-0.744
Repeated sections [h6]	-0.621
Predictable uppercase [h8]	-0.568
Alphabetic/numeric sequences [h16]	-0.413
Dates [h15]	-0.341
Keyboard patterns [h5]	-0.227

Decrease guessability:

Feature	**Estimate**
Lowercase count [h12]	4.584
Uppercase count [h11]	4.529
Digits count [h13]	4.359
Symbols count [h14]	0.741
Repeated chars [h4]	0.111
Predictable symbols [h10]	0.036

Cluster 26 model

Dep. Variable:	log_guess_num	**R-squared:**	0.505
Model:	OLS	**Adj. R-squared:**	0.505
Method:	Least Squares	**F-statistic:**	7284.
Date:	Thu, 20 Aug 2020	**Prob (F-statistic):**	0.00
Time:	18:40:27	**Log-Likelihood:**	-2.3692e+05
No. Observations:	100000	**AIC:**	4.739e+05
Df Residuals:	99985	**BIC:**	4.740e+05
Df Model:	14		

	coef	**std err**	**t**	**P> |t|**	**[0.025**	**0.975]**
Intercept	2.2732	0.069	33.132	0.000	2.139	2.408
heuristic4	0.0188	0.009	2.169	0.030	0.002	0.036
heuristic5	-0.3191	0.008	-38.828	0.000	-0.335	-0.303
heuristic6	-0.4856	0.008	-57.770	0.000	-0.502	-0.469
heuristic8	-0.4430	0.010	-45.228	0.000	-0.462	-0.424
heuristic9	-0.7729	0.009	-81.675	0.000	-0.791	-0.754
heuristic10	0.0016	0.010	0.173	0.863	-0.017	0.020
heuristic11	2.9637	0.017	176.785	0.000	2.931	2.997
heuristic12	2.8868	0.020	144.425	0.000	2.848	2.926
heuristic13	2.6714	0.020	130.438	0.000	2.631	2.712
heuristic14	0.7357	0.010	73.120	0.000	0.716	0.755
heuristic15	-0.2505	0.009	-28.513	0.000	-0.268	-0.233
heuristic16	-0.2667	0.008	-31.795	0.000	-0.283	-0.250
heuristic17	-1.7347	0.009	-194.759	0.000	-1.752	-1.717
heuristic18	-0.5942	0.009	-68.138	0.000	-0.611	-0.577

Omnibus:	16164.285	**Durbin-Watson:**	2.002
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	29204.752
Skew:	-1.036	**Prob(JB):**	0.00
Kurtosis:	4.648	**Cond. No.**	27.7

Table B.28: Guessability regression results for Cluster 26 model.

Increase guessability:

Feature	**Estimate**
Common substrings [h17]	-1.735
Predictable digits [h9]	-0.773
Dictionary (longest token) [h18]	-0.594
Repeated sections [h6]	-0.486
Predictable uppercase [h8]	-0.443
Keyboard patterns [h5]	-0.319
Alphabetic/numeric sequences [h16]	-0.267
Dates [h15]	-0.250

Decrease guessability:

Feature	**Estimate**
Uppercase count [h11]	2.964
Lowercase count [h12]	2.887
Digits count [h13]	2.671
Symbols count [h14]	0.736
Repeated chars [h4]	0.019
Predictable symbols [h10]	0.002

Cluster 27 model

Dep. Variable:	log_guess_num	**R-squared:**	0.433
Model:	OLS	**Adj. R-squared:**	0.433
Method:	Least Squares	**F-statistic:**	5452.
Date:	Thu, 20 Aug 2020	**Prob (F-statistic):**	0.00
Time:	18:40:27	**Log-Likelihood:**	-2.3756e+05
No. Observations:	100000	**AIC:**	4.752e+05
Df Residuals:	99985	**BIC:**	4.753e+05
Df Model:	14		

	coef	**std err**	**t**	**P> |t|**	**[0.025**	**0.975]**
Intercept	-1.3888	0.070	-19.854	0.000	-1.526	-1.252
heuristic4	-0.0817	0.008	-9.741	0.000	-0.098	-0.065
heuristic5	-0.0917	0.008	-11.084	0.000	-0.108	-0.075
heuristic6	-0.2419	0.008	-29.086	0.000	-0.258	-0.226
heuristic8	-0.0681	0.010	-6.955	0.000	-0.087	-0.049
heuristic9	0.0906	0.012	7.849	0.000	0.068	0.113
heuristic10	0.0465	0.010	4.501	0.000	0.026	0.067
heuristic11	1.1890	0.010	116.058	0.000	1.169	1.209
heuristic12	1.9318	0.013	144.941	0.000	1.906	1.958
heuristic13	1.9419	0.015	126.228	0.000	1.912	1.972
heuristic14	0.8429	0.011	78.877	0.000	0.822	0.864
heuristic15	-0.1827	0.009	-20.577	0.000	-0.200	-0.165
heuristic16	-0.1575	0.009	-18.476	0.000	-0.174	-0.141
heuristic17	-1.4159	0.009	-163.370	0.000	-1.433	-1.399
heuristic18	-0.6306	0.009	-72.729	0.000	-0.648	-0.614

Omnibus:	57.120	**Durbin-Watson:**	1.994
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	54.351
Skew:	-0.037	**Prob(JB):**	1.58e-12
Kurtosis:	2.913	**Cond. No.**	47.5

Table B.29: Guessability regression results for Cluster 27 model.

Increase guessability:

Feature	**Estimate**
Common substrings [h17]	-1.416
Dictionary (longest token) [h18]	-0.631
Repeated sections [h6]	-0.242
Dates [h15]	-0.183
Alphabetic/numeric sequences [h16]	-0.157
Keyboard patterns [h5]	-0.092
Repeated chars [h4]	-0.082
Predictable uppercase [h8]	-0.068

Decrease guessability:

Feature	**Estimate**
Digits count [h13]	1.942
Lowercase count [h12]	1.932
Uppercase count [h11]	1.189
Symbols count [h14]	0.843
Predictable digits [h9]	0.091
Predictable symbols [h10]	0.047

Cluster 28 model

Dep. Variable:	log_guess_num	**R-squared:**	0.472
Model:	OLS	**Adj. R-squared:**	0.472
Method:	Least Squares	**F-statistic:**	6374.
Date:	Thu, 20 Aug 2020	**Prob (F-statistic):**	0.00
Time:	18:40:27	**Log-Likelihood:**	-2.2370e+05
No. Observations:	100000	**AIC:**	4.474e+05
Df Residuals:	99985	**BIC:**	4.476e+05
Df Model:	14		

	coef	**std err**	**t**	**P> |t|**	**[0.025**	**0.975]**
Intercept	2.0133	0.062	32.435	0.000	1.892	2.135
heuristic4	-0.0844	0.007	-11.439	0.000	-0.099	-0.070
heuristic5	-0.0777	0.007	-10.768	0.000	-0.092	-0.064
heuristic6	-0.2830	0.007	-39.058	0.000	-0.297	-0.269
heuristic8	-0.1096	0.008	-13.123	0.000	-0.126	-0.093
heuristic9	-0.8797	0.009	-101.785	0.000	-0.897	-0.863
heuristic10	-0.0185	0.010	-1.828	0.068	-0.038	0.001
heuristic11	1.2971	0.009	138.991	0.000	1.279	1.315
heuristic12	1.8473	0.013	143.039	0.000	1.822	1.873
heuristic13	2.0897	0.013	161.078	0.000	2.064	2.115
heuristic14	0.5195	0.010	50.085	0.000	0.499	0.540
heuristic15	-0.5960	0.008	-78.158	0.000	-0.611	-0.581
heuristic16	-0.3445	0.007	-46.744	0.000	-0.359	-0.330
heuristic17	-1.2356	0.008	-164.590	0.000	-1.250	-1.221
heuristic18	-0.4504	0.007	-60.303	0.000	-0.465	-0.436

Omnibus:	6488.350	**Durbin-Watson:**	1.983
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	9453.824
Skew:	-0.556	**Prob(JB):**	0.00
Kurtosis:	4.015	**Cond. No.**	40.6

Table B.30: Guessability regression results for Cluster 28 model.

Increase guessability:

Feature	**Estimate**
Common substrings [h17]	-1.236
Predictable digits [h9]	-0.880
Dates [h15]	-0.596
Dictionary (longest token) [h18]	-0.450
Alphabetic/numeric sequences [h16]	-0.344
Repeated sections [h6]	-0.283
Predictable uppercase [h8]	-0.110
Repeated chars [h4]	-0.084
Keyboard patterns [h5]	-0.078
Predictable symbols [h10]	-0.018

Decrease guessability:

Feature	**Estimate**
Digits count [h13]	2.090
Lowercase count [h12]	1.847
Uppercase count [h11]	1.297
Symbols count [h14]	0.520

Cluster 29 model

Dep. Variable:	log_guess_num	**R-squared:**	0.416
Model:	OLS	**Adj. R-squared:**	0.416
Method:	Least Squares	**F-statistic:**	5083.
Date:	Thu, 20 Aug 2020	**Prob (F-statistic):**	0.00
Time:	18:40:28	**Log-Likelihood:**	-2.2705e+05
No. Observations:	100000	**AIC:**	4.541e+05
Df Residuals:	99985	**BIC:**	4.543e+05
Df Model:	14		

	coef	**std err**	**t**	**P> |t|**	**[0.025**	**0.975]**
Intercept	-0.1428	0.069	-2.072	0.038	-0.278	-0.008
heuristic4	-0.1445	0.008	-19.107	0.000	-0.159	-0.130
heuristic5	-0.0770	0.007	-10.333	0.000	-0.092	-0.062
heuristic6	-0.2075	0.007	-27.714	0.000	-0.222	-0.193
heuristic8	-0.1502	0.009	-16.313	0.000	-0.168	-0.132
heuristic9	-0.2779	0.009	-32.189	0.000	-0.295	-0.261
heuristic10	0.0097	0.010	0.939	0.348	-0.011	0.030
heuristic11	1.1775	0.010	120.900	0.000	1.158	1.197
heuristic12	1.7798	0.012	146.765	0.000	1.756	1.804
heuristic13	1.7811	0.012	143.708	0.000	1.757	1.805
heuristic14	0.6232	0.011	58.590	0.000	0.602	0.644
heuristic15	-0.2430	0.008	-30.623	0.000	-0.259	-0.227
heuristic16	-0.2640	0.008	-34.476	0.000	-0.279	-0.249
heuristic17	-1.3662	0.008	-178.174	0.000	-1.381	-1.351
heuristic18	-0.4202	0.008	-55.017	0.000	-0.435	-0.405

Omnibus:	589.250	**Durbin-Watson:**	2.000
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	635.823
Skew:	-0.158	**Prob(JB):**	8.57e-139
Kurtosis:	3.229	**Cond. No.**	51.8

Table B.31: Guessability regression results for Cluster 29 model.

Increase guessability:

Feature	**Estimate**
Common substrings [h17]	-1.366
Dictionary (longest token) [h18]	-0.420
Predictable digits [h9]	-0.278
Alphabetic/numeric sequences [h16]	-0.264
Dates [h15]	-0.243
Repeated sections [h6]	-0.207
Predictable uppercase [h8]	-0.150
Repeated chars [h4]	-0.144
Keyboard patterns [h5]	-0.077

Decrease guessability:

Feature	**Estimate**
Digits count [h13]	1.781
Lowercase count [h12]	1.780
Uppercase count [h11]	1.177
Symbols count [h14]	0.623
Predictable symbols [h10]	0.010

B.6.2 Regression of cluster assignment onto heuristic features

Cluster 0 model

Dep. Variable:	logit(soft_assign)	**R-squared:**	0.064
Model:	OLS	**Adj. R-squared:**	0.064
Method:	Least Squares	**F-statistic:**	756.6
Date:	Fri, 21 Aug 2020	**Prob (F-statistic):**	0.00
Time:	17:40:15	**Log-Likelihood:**	-1.9340e+05
No. Observations:	100000	**AIC:**	3.868e+05
Df Residuals:	99990	**BIC:**	3.869e+05
Df Model:	9		

	coef	**std err**	**t**	**P> |t|**	**[0.025**	**0.975]**
Intercept	-3.0570	0.024	-129.780	0.000	-3.103	-3.011
heuristic3	-0.0328	0.007	-4.880	0.000	-0.046	-0.020
heuristic4	-0.0304	0.006	-5.047	0.000	-0.042	-0.019
heuristic5	-0.0950	0.005	-17.922	0.000	-0.105	-0.085
heuristic6	-0.0224	0.006	-3.734	0.000	-0.034	-0.011
heuristic7	0.2070	0.005	38.864	0.000	0.197	0.217
heuristic15	-0.2689	0.005	-50.509	0.000	-0.279	-0.258
heuristic16	-0.1712	0.005	-32.171	0.000	-0.182	-0.161
heuristic18	0.1746	0.005	32.038	0.000	0.164	0.185
heuristic21	0.0462	0.006	8.407	0.000	0.035	0.057

Omnibus:	6293.452	**Durbin-Watson:**	1.998
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	7341.251
Skew:	0.651	**Prob(JB):**	0.00
Kurtosis:	2.746	**Cond. No.**	21.8

Table B.32: Cluster-assignment regression results for Cluster 0 model.

Raise odds of assignment:

Feature	**Odds ratio estimate**
Char-class structure [h7]	1.230
Dictionary (longest token) [h18]	1.191
Common password [h21]	1.047

Lower odds of assignments:

Feature	**Odds ratio estimate**
Dates [h15]	0.764
Alphabetic/numeric sequences [h16]	0.843
Keyboard patterns [h5]	0.909
Duplicated chars [h3]	0.968
Repeated chars [h4]	0.970
Repeated sections [h6]	0.978

Cluster 1 model

Dep. Variable:	logit(soft_assign)	**R-squared:**	0.150
Model:	OLS	**Adj. R-squared:**	0.150
Method:	Least Squares	**F-statistic:**	1957.
Date:	Fri, 21 Aug 2020	**Prob (F-statistic):**	0.00
Time:	17:40:15	**Log-Likelihood:**	-2.1202e+05
No. Observations:	100000	**AIC:**	4.241e+05
Df Residuals:	99990	**BIC:**	4.242e+05
Df Model:	9		

	coef	**std err**	**t**	**P> |t|**	**[0.025**	**0.975]**
Intercept	-3.5086	0.022	-159.109	0.000	-3.552	-3.465
heuristic3	0.3567	0.008	44.219	0.000	0.341	0.372
heuristic4	-0.0386	0.007	-5.261	0.000	-0.053	-0.024
heuristic5	0.0763	0.006	11.919	0.000	0.064	0.089
heuristic6	-0.1712	0.007	-23.952	0.000	-0.185	-0.157
heuristic7	-0.0743	0.007	-11.370	0.000	-0.087	-0.061
heuristic15	0.6275	0.007	95.322	0.000	0.615	0.640
heuristic16	0.0869	0.007	13.349	0.000	0.074	0.100
heuristic18	0.1528	0.007	23.305	0.000	0.140	0.166
heuristic21	0.3157	0.007	46.716	0.000	0.302	0.329

Omnibus:	3815.624	**Durbin-Watson:**	2.001
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	3216.317
Skew:	0.369	**Prob(JB):**	0.00
Kurtosis:	2.523	**Cond. No.**	14.4

Table B.33: Cluster-assignment regression results for Cluster 1 model.

Raise odds of assignment:

Feature	**Odds ratio estimate**
Dates [h15]	1.873
Duplicated chars [h3]	1.429
Common password [h21]	1.371
Dictionary (longest token) [h18]	1.165
Alphabetic/numeric sequences [h16]	1.091
Keyboard patterns [h5]	1.079

Lower odds of assignments:

Feature	**Odds ratio estimate**
Repeated sections [h6]	0.843
Char-class structure [h7]	0.928
Repeated chars [h4]	0.962

Cluster 2 model

Dep. Variable:	logit(soft_assign)	**R-squared:**	0.141
Model:	OLS	**Adj. R-squared:**	0.141
Method:	Least Squares	**F-statistic:**	1827.
Date:	Fri, 21 Aug 2020	**Prob (F-statistic):**	0.00
Time:	17:40:16	**Log-Likelihood:**	-1.5758e+05
No. Observations:	100000	**AIC:**	3.152e+05
Df Residuals:	99990	**BIC:**	3.153e+05
Df Model:	9		

	coef	**std err**	**t**	**P> |t|**	**[0.025**	**0.975]**
Intercept	-3.1593	0.017	-182.095	0.000	-3.193	-3.125
heuristic3	-0.3879	0.005	-80.882	0.000	-0.397	-0.379
heuristic4	0.1387	0.004	31.941	0.000	0.130	0.147
heuristic5	-0.0504	0.004	-13.591	0.000	-0.058	-0.043
heuristic6	0.0760	0.004	18.231	0.000	0.068	0.084
heuristic7	0.2573	0.004	68.717	0.000	0.250	0.265
heuristic15	-0.2142	0.004	-57.517	0.000	-0.222	-0.207
heuristic16	-0.0873	0.004	-23.403	0.000	-0.095	-0.080
heuristic18	-0.0267	0.004	-7.021	0.000	-0.034	-0.019
heuristic21	-0.0070	0.004	-1.811	0.070	-0.015	0.001

Omnibus:	1358.984	**Durbin-Watson:**	2.002
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	1415.134
Skew:	0.288	**Prob(JB):**	5.10e-308
Kurtosis:	3.088	**Cond. No.**	23.9

Table B.34: Cluster-assignment regression results for Cluster 2 model.

Raise odds of assignment:

Feature	**Odds ratio estimate**
Char-class structure [h7]	1.293
Repeated chars [h4]	1.149
Repeated sections [h6]	1.079

Lower odds of assignments:

Feature	**Odds ratio estimate**
Duplicated chars [h3]	0.678
Dates [h15]	0.807
Alphabetic/numeric sequences [h16]	0.916
Keyboard patterns [h5]	0.951
Dictionary (longest token) [h18]	0.974
Common password [h21]	0.993

Cluster 3 model

Dep. Variable:	logit(soft_assign)	**R-squared:**	0.274
Model:	OLS	**Adj. R-squared:**	0.273
Method:	Least Squares	**F-statistic:**	4183.
Date:	Fri, 21 Aug 2020	**Prob (F-statistic):**	0.00
Time:	17:40:16	**Log-Likelihood:**	-1.6266e+05
No. Observations:	100000	**AIC:**	3.253e+05
Df Residuals:	99990	**BIC:**	3.254e+05
Df Model:	9		

	coef	**std err**	**t**	**P> |t|**	**[0.025**	**0.975]**
Intercept	-3.2168	0.017	-186.705	0.000	-3.251	-3.183
heuristic3	-0.3165	0.005	-62.189	0.000	-0.326	-0.307
heuristic4	0.1580	0.005	34.047	0.000	0.149	0.167
heuristic5	0.0986	0.004	25.202	0.000	0.091	0.106
heuristic6	0.0768	0.004	17.655	0.000	0.068	0.085
heuristic7	0.2128	0.004	53.854	0.000	0.205	0.221
heuristic15	-0.1226	0.004	-31.065	0.000	-0.130	-0.115
heuristic16	0.6014	0.004	149.656	0.000	0.594	0.609
heuristic18	-0.0674	0.004	-16.913	0.000	-0.075	-0.060
heuristic21	-0.0068	0.004	-1.689	0.091	-0.015	0.001

Omnibus:	3615.839	**Durbin-Watson:**	2.006
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	5711.560
Skew:	0.338	**Prob(JB):**	0.00
Kurtosis:	3.957	**Cond. No.**	21.4

Table B.35: Cluster-assignment regression results for Cluster 3 model.

Raise odds of assignment:

Feature	**Odds ratio estimate**
Alphabetic/numeric sequences [h16]	1.825
Char-class structure [h7]	1.237
Repeated chars [h4]	1.171
Keyboard patterns [h5]	1.104
Repeated sections [h6]	1.080

Lower odds of assignments:

Feature	**Odds ratio estimate**
Duplicated chars [h3]	0.729
Dates [h15]	0.885
Dictionary (longest token) [h18]	0.935
Common password [h21]	0.993

Cluster 4 model

Dep. Variable:	logit(soft_assign)	**R-squared:**	0.147
Model:	OLS	**Adj. R-squared:**	0.147
Method:	Least Squares	**F-statistic:**	1916.
Date:	Fri, 21 Aug 2020	**Prob (F-statistic):**	0.00
Time:	17:40:16	**Log-Likelihood:**	-1.8158e+05
No. Observations:	100000	**AIC:**	3.632e+05
Df Residuals:	99990	**BIC:**	3.633e+05
Df Model:	9		

	coef	**std err**	**t**	**P> |t|**	**[0.025**	**0.975]**
Intercept	-3.2480	0.024	-138.015	0.000	-3.294	-3.202
heuristic3	-0.3168	0.006	-52.876	0.000	-0.329	-0.305
heuristic4	-0.0703	0.005	-13.256	0.000	-0.081	-0.060
heuristic5	-0.0955	0.005	-20.294	0.000	-0.105	-0.086
heuristic6	0.0569	0.005	10.522	0.000	0.046	0.067
heuristic7	0.2807	0.005	58.882	0.000	0.271	0.290
heuristic15	-0.2860	0.005	-60.538	0.000	-0.295	-0.277
heuristic16	-0.2653	0.005	-56.233	0.000	-0.275	-0.256
heuristic18	0.0211	0.005	4.370	0.000	0.012	0.031
heuristic21	0.1430	0.005	29.219	0.000	0.133	0.153

Omnibus:	2323.060	**Durbin-Watson:**	2.000
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	1758.955
Skew:	0.235	**Prob(JB):**	0.00
Kurtosis:	2.552	**Cond. No.**	27.1

Table B.36: Cluster-assignment regression results for Cluster 4 model.

Raise odds of assignment:

Feature	**Odds ratio estimate**
Char-class structure [h7]	1.324
Common password [h21]	1.154
Repeated sections [h6]	1.059
Dictionary (longest token) [h18]	1.021

Lower odds of assignments:

Feature	**Odds ratio estimate**
Duplicated chars [h3]	0.728
Dates [h15]	0.751
Alphabetic/numeric sequences [h16]	0.767
Keyboard patterns [h5]	0.909
Repeated chars [h4]	0.932

Cluster 5 model

Dep. Variable:	logit(soft_assign)	**R-squared:**	0.137
Model:	OLS	**Adj. R-squared:**	0.137
Method:	Least Squares	**F-statistic:**	1758.
Date:	Fri, 21 Aug 2020	**Prob (F-statistic):**	0.00
Time:	17:40:17	**Log-Likelihood:**	-1.8830e+05
No. Observations:	100000	**AIC:**	3.766e+05
Df Residuals:	99990	**BIC:**	3.767e+05
Df Model:	9		

	coef	**std err**	**t**	**P> |t|**	**[0.025**	**0.975]**
Intercept	-2.2274	0.018	-123.747	0.000	-2.263	-2.192
heuristic3	-0.3801	0.006	-58.507	0.000	-0.393	-0.367
heuristic4	0.2586	0.006	42.563	0.000	0.247	0.271
heuristic5	0.0611	0.005	12.088	0.000	0.051	0.071
heuristic6	-0.0286	0.006	-5.183	0.000	-0.039	-0.018
heuristic7	0.2434	0.005	46.806	0.000	0.233	0.254
heuristic15	0.3433	0.005	65.845	0.000	0.333	0.354
heuristic16	-0.1084	0.005	-21.233	0.000	-0.118	-0.098
heuristic18	-0.0025	0.005	-0.483	0.629	-0.013	0.008
heuristic21	-0.3310	0.005	-62.187	0.000	-0.341	-0.321

Omnibus:	1936.870	**Durbin-Watson:**	1.991
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	1485.013
Skew:	0.212	**Prob(JB):**	0.00
Kurtosis:	2.580	**Cond. No.**	15.0

Table B.37: Cluster-assignment regression results for Cluster 5 model.

Raise odds of assignment:

Feature	**Odds ratio estimate**
Dates [h15]	1.410
Repeated chars [h4]	1.295
Char-class structure [h7]	1.276
Keyboard patterns [h5]	1.063

Lower odds of assignments:

Feature	**Odds ratio estimate**
Duplicated chars [h3]	0.684
Common password [h21]	0.718
Alphabetic/numeric sequences [h16]	0.897
Repeated sections [h6]	0.972
Dictionary (longest token) [h18]	0.998

Cluster 6 model

Dep. Variable:	logit(soft_assign)	**R-squared:**	0.123
Model:	OLS	**Adj. R-squared:**	0.123
Method:	Least Squares	**F-statistic:**	1560.
Date:	Fri, 21 Aug 2020	**Prob (F-statistic):**	0.00
Time:	17:40:17	**Log-Likelihood:**	-1.8179e+05
No. Observations:	100000	**AIC:**	3.636e+05
Df Residuals:	99990	**BIC:**	3.637e+05
Df Model:	9		

	coef	**std err**	**t**	**P> |t|**	**[0.025**	**0.975]**
Intercept	-2.2420	0.012	-189.297	0.000	-2.265	-2.219
heuristic3	0.5202	0.007	79.021	0.000	0.507	0.533
heuristic4	-0.0951	0.006	-16.583	0.000	-0.106	-0.084
heuristic5	0.0367	0.005	7.760	0.000	0.027	0.046
heuristic6	-0.1985	0.005	-36.245	0.000	-0.209	-0.188
heuristic7	-0.2180	0.005	-40.096	0.000	-0.229	-0.207
heuristic15	-0.0368	0.005	-7.566	0.000	-0.046	-0.027
heuristic16	0.1529	0.005	32.041	0.000	0.144	0.162
heuristic18	-0.2875	0.005	-59.394	0.000	-0.297	-0.278
heuristic21	0.2766	0.005	51.745	0.000	0.266	0.287

Omnibus:	5415.009	**Durbin-Watson:**	2.002
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	6496.413
Skew:	-0.571	**Prob(JB):**	0.00
Kurtosis:	3.504	**Cond. No.**	8.40

Table B.38: Cluster-assignment regression results for Cluster 6 model.

Raise odds of assignment:

Feature	**Odds ratio estimate**
Duplicated chars [h3]	1.682
Common password [h21]	1.319
Alphabetic/numeric sequences [h16]	1.165
Keyboard patterns [h5]	1.037

Lower odds of assignments:

Feature	**Odds ratio estimate**
Dictionary (longest token) [h18]	0.750
Char-class structure [h7]	0.804
Repeated sections [h6]	0.820
Repeated chars [h4]	0.909
Dates [h15]	0.964

Cluster 7 model

Dep. Variable:	logit(soft_assign)	**R-squared:**	0.105
Model:	OLS	**Adj. R-squared:**	0.105
Method:	Least Squares	**F-statistic:**	1303.
Date:	Fri, 21 Aug 2020	**Prob (F-statistic):**	0.00
Time:	17:40:17	**Log-Likelihood:**	-1.7520e+05
No. Observations:	100000	**AIC:**	3.504e+05
Df Residuals:	99990	**BIC:**	3.505e+05
Df Model:	9		

	coef	**std err**	**t**	**P> |t|**	**[0.025**	**0.975]**
Intercept	-3.1042	0.021	-148.317	0.000	-3.145	-3.063
heuristic3	-0.0413	0.006	-7.349	0.000	-0.052	-0.030
heuristic4	-0.1505	0.005	-30.654	0.000	-0.160	-0.141
heuristic5	-0.0865	0.004	-19.580	0.000	-0.095	-0.078
heuristic6	0.0465	0.005	9.025	0.000	0.036	0.057
heuristic7	0.1494	0.004	33.497	0.000	0.141	0.158
heuristic15	-0.2750	0.004	-62.056	0.000	-0.284	-0.266
heuristic16	-0.2110	0.004	-47.623	0.000	-0.220	-0.202
heuristic18	0.1226	0.005	26.888	0.000	0.114	0.131
heuristic21	0.1442	0.005	31.360	0.000	0.135	0.153

Omnibus:	2652.097	**Durbin-Watson:**	2.005
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	2867.092
Skew:	0.413	**Prob(JB):**	0.00
Kurtosis:	3.084	**Cond. No.**	24.6

Table B.39: Cluster-assignment regression results for Cluster 7 model.

Raise odds of assignment:

Feature	**Odds ratio estimate**
Char-class structure [h7]	1.161
Common password [h21]	1.155
Dictionary (longest token) [h18]	1.130
Repeated sections [h6]	1.048

Lower odds of assignments:

Feature	**Odds ratio estimate**
Dates [h15]	0.760
Alphabetic/numeric sequences [h16]	0.810
Repeated chars [h4]	0.860
Keyboard patterns [h5]	0.917
Duplicated chars [h3]	0.960

Cluster 8 model

Dep. Variable:	logit(soft_assign)	**R-squared:**	0.051
Model:	OLS	**Adj. R-squared:**	0.051
Method:	Least Squares	**F-statistic:**	593.6
Date:	Fri, 21 Aug 2020	**Prob (F-statistic):**	0.00
Time:	17:40:18	**Log-Likelihood:**	-1.7444e+05
No. Observations:	100000	**AIC:**	3.489e+05
Df Residuals:	99990	**BIC:**	3.490e+05
Df Model:	9		

	coef	**std err**	**t**	**P> |t|**	**[0.025**	**0.975]**
Intercept	-3.2584	0.019	-170.532	0.000	-3.296	-3.221
heuristic3	0.0152	0.006	2.733	0.006	0.004	0.026
heuristic4	-0.0298	0.005	-5.974	0.000	-0.040	-0.020
heuristic5	-0.0629	0.004	-14.338	0.000	-0.071	-0.054
heuristic6	-0.0390	0.005	-7.845	0.000	-0.049	-0.029
heuristic7	0.1479	0.004	33.522	0.000	0.139	0.157
heuristic15	-0.2221	0.004	-50.397	0.000	-0.231	-0.213
heuristic16	-0.0333	0.004	-7.540	0.000	-0.042	-0.025
heuristic18	0.1282	0.005	28.389	0.000	0.119	0.137
heuristic21	0.0577	0.005	12.669	0.000	0.049	0.067

Omnibus:	9337.508	**Durbin-Watson:**	1.985
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	12239.944
Skew:	0.811	**Prob(JB):**	0.00
Kurtosis:	3.554	**Cond. No.**	21.1

Table B.40: Cluster-assignment regression results for Cluster 8 model.

Raise odds of assignment:

Feature	**Odds ratio estimate**
Char-class structure [h7]	1.159
Dictionary (longest token) [h18]	1.137
Common password [h21]	1.059
Duplicated chars [h3]	1.015

Lower odds of assignments:

Feature	**Odds ratio estimate**
Dates [h15]	0.801
Keyboard patterns [h5]	0.939
Repeated sections [h6]	0.962
Alphabetic/numeric sequences [h16]	0.967
Repeated chars [h4]	0.971

Cluster 9 model

Dep. Variable:	logit(soft_assign)	**R-squared:**	0.148
Model:	OLS	**Adj. R-squared:**	0.148
Method:	Least Squares	**F-statistic:**	1926.
Date:	Fri, 21 Aug 2020	**Prob (F-statistic):**	0.00
Time:	17:40:18	**Log-Likelihood:**	-1.8843e+05
No. Observations:	100000	**AIC:**	3.769e+05
Df Residuals:	99990	**BIC:**	3.770e+05
Df Model:	9		

	coef	**std err**	**t**	**P> |t|**	**[0.025**	**0.975]**
Intercept	-1.4057	0.013	-107.728	0.000	-1.431	-1.380
heuristic3	-0.1438	0.007	-21.302	0.000	-0.157	-0.131
heuristic4	0.1061	0.006	17.683	0.000	0.094	0.118
heuristic5	-0.0272	0.005	-5.384	0.000	-0.037	-0.017
heuristic6	0.0443	0.006	7.687	0.000	0.033	0.056
heuristic7	0.0077	0.005	1.443	0.149	-0.003	0.018
heuristic15	-0.0420	0.005	-8.046	0.000	-0.052	-0.032
heuristic16	-0.1181	0.005	-23.085	0.000	-0.128	-0.108
heuristic18	-0.1690	0.005	-33.134	0.000	-0.179	-0.159
heuristic21	-0.5841	0.006	-105.538	0.000	-0.595	-0.573

Omnibus:	1751.944	**Durbin-Watson:**	2.005
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	992.793
Skew:	-0.042	**Prob(JB):**	2.62e-216
Kurtosis:	2.519	**Cond. No.**	8.65

Table B.41: Cluster-assignment regression results for Cluster 9 model.

Raise odds of assignment:

Feature	**Odds ratio estimate**
Repeated chars [h4]	1.112
Repeated sections [h6]	1.045
Char-class structure [h7]	1.008

Lower odds of assignments:

Feature	**Odds ratio estimate**
Common password [h21]	0.558
Dictionary (longest token) [h18]	0.845
Duplicated chars [h3]	0.866
Alphabetic/numeric sequences [h16]	0.889
Dates [h15]	0.959
Keyboard patterns [h5]	0.973

Cluster 10 model

Dep. Variable:	logit(soft_assign)	**R-squared:**	0.154
Model:	OLS	**Adj. R-squared:**	0.154
Method:	Least Squares	**F-statistic:**	2021.
Date:	Fri, 21 Aug 2020	**Prob (F-statistic):**	0.00
Time:	17:40:18	**Log-Likelihood:**	-1.4411e+05
No. Observations:	100000	**AIC:**	2.882e+05
Df Residuals:	99990	**BIC:**	2.883e+05
Df Model:	9		

	coef	**std err**	**t**	**P> |t|**	**[0.025**	**0.975]**
Intercept	-2.7629	0.013	-213.620	0.000	-2.788	-2.738
heuristic3	-0.3425	0.004	-80.936	0.000	-0.351	-0.334
heuristic4	0.2539	0.004	65.336	0.000	0.246	0.262
heuristic5	0.0995	0.003	30.626	0.000	0.093	0.106
heuristic6	0.0225	0.004	6.245	0.000	0.015	0.030
heuristic7	0.1746	0.003	53.199	0.000	0.168	0.181
heuristic15	-0.0501	0.003	-15.257	0.000	-0.057	-0.044
heuristic16	0.0597	0.003	18.160	0.000	0.053	0.066
heuristic18	0.0053	0.003	1.601	0.109	-0.001	0.012
heuristic21	-0.2495	0.003	-73.613	0.000	-0.256	-0.243

Omnibus:	87.120	**Durbin-Watson:**	1.992
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	91.980
Skew:	-0.050	**Prob(JB):**	1.06e-20
Kurtosis:	3.109	**Cond. No.**	17.8

Table B.42: Cluster-assignment regression results for Cluster 10 model.

Raise odds of assignment:

Feature	**Odds ratio estimate**
Repeated chars [h4]	1.289
Char-class structure [h7]	1.191
Keyboard patterns [h5]	1.105
Alphabetic/numeric sequences [h16]	1.062
Repeated sections [h6]	1.023
Dictionary (longest token) [h18]	1.005

Lower odds of assignments:

Feature	**Odds ratio estimate**
Duplicated chars [h3]	0.710
Common password [h21]	0.779
Dates [h15]	0.951

Cluster 11 model

Dep. Variable:	logit(soft_assign)	**R-squared:**	0.029
Model:	OLS	**Adj. R-squared:**	0.029
Method:	Least Squares	**F-statistic:**	334.3
Date:	Fri, 21 Aug 2020	**Prob (F-statistic):**	0.00
Time:	17:40:19	**Log-Likelihood:**	-1.7766e+05
No. Observations:	100000	**AIC:**	3.553e+05
Df Residuals:	99990	**BIC:**	3.554e+05
Df Model:	9		

	coef	**std err**	**t**	**P> |t|**	**[0.025**	**0.975]**
Intercept	-2.2175	0.012	-182.934	0.000	-2.241	-2.194
heuristic3	0.0260	0.006	4.337	0.000	0.014	0.038
heuristic4	0.0574	0.005	10.748	0.000	0.047	0.068
heuristic5	0.0210	0.005	4.630	0.000	0.012	0.030
heuristic6	0.0258	0.005	4.978	0.000	0.016	0.036
heuristic7	-0.1459	0.005	-30.106	0.000	-0.155	-0.136
heuristic15	0.0854	0.005	18.273	0.000	0.076	0.095
heuristic16	0.0444	0.005	9.633	0.000	0.035	0.053
heuristic18	-0.0385	0.005	-8.394	0.000	-0.048	-0.030
heuristic21	-0.1489	0.005	-30.150	0.000	-0.159	-0.139

Omnibus:	5888.182	**Durbin-Watson:**	2.012
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	2179.820
Skew:	0.018	**Prob(JB):**	0.00
Kurtosis:	2.278	**Cond. No.**	9.26

Table B.43: Cluster-assignment regression results for Cluster 11 model.

Raise odds of assignment:

Feature	**Odds ratio estimate**
Dates [h15]	1.089
Repeated chars [h4]	1.059
Alphabetic/numeric sequences [h16]	1.045
Duplicated chars [h3]	1.026
Repeated sections [h6]	1.026
Keyboard patterns [h5]	1.021

Lower odds of assignments:

Feature	**Odds ratio estimate**
Common password [h21]	0.862
Char-class structure [h7]	0.864
Dictionary (longest token) [h18]	0.962

Cluster 12 model

Dep. Variable:	logit(soft_assign)	**R-squared:**	0.084
Model:	OLS	**Adj. R-squared:**	0.083
Method:	Least Squares	**F-statistic:**	1013.
Date:	Fri, 21 Aug 2020	**Prob (F-statistic):**	0.00
Time:	17:40:19	**Log-Likelihood:**	-1.6369e+05
No. Observations:	100000	**AIC:**	3.274e+05
Df Residuals:	99990	**BIC:**	3.275e+05
Df Model:	9		

	coef	**std err**	**t**	**P> |t|**	**[0.025**	**0.975]**
Intercept	-1.3991	0.009	-158.297	0.000	-1.416	-1.382
heuristic3	-0.1680	0.005	-30.824	0.000	-0.179	-0.157
heuristic4	0.0147	0.005	3.115	0.002	0.005	0.024
heuristic5	0.0088	0.004	2.228	0.026	0.001	0.017
heuristic6	0.0756	0.005	16.394	0.000	0.067	0.085
heuristic7	-0.2280	0.004	-52.064	0.000	-0.237	-0.219
heuristic15	-0.0140	0.004	-3.402	0.001	-0.022	-0.006
heuristic16	-0.0813	0.004	-20.496	0.000	-0.089	-0.073
heuristic18	-0.0142	0.004	-3.540	0.000	-0.022	-0.006
heuristic21	-0.1420	0.004	-32.318	0.000	-0.151	-0.133

Omnibus:	19057.395	**Durbin-Watson:**	2.004
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	34260.802
Skew:	-1.217	**Prob(JB):**	0.00
Kurtosis:	4.517	**Cond. No.**	6.94

Table B.44: Cluster-assignment regression results for Cluster 12 model.

Raise odds of assignment:

Feature	**Odds ratio estimate**
Repeated sections [h6]	1.079
Repeated chars [h4]	1.015
Keyboard patterns [h5]	1.009

Lower odds of assignments:

Feature	**Odds ratio estimate**
Char-class structure [h7]	0.796
Duplicated chars [h3]	0.845
Common password [h21]	0.868
Alphabetic/numeric sequences [h16]	0.922
Dictionary (longest token) [h18]	0.986
Dates [h15]	0.986

Cluster 13 model

Dep. Variable:	logit(soft_assign)	**R-squared:**	0.114
Model:	OLS	**Adj. R-squared:**	0.114
Method:	Least Squares	**F-statistic:**	1432.
Date:	Fri, 21 Aug 2020	**Prob (F-statistic):**	0.00
Time:	17:40:19	**Log-Likelihood:**	-1.8168e+05
No. Observations:	100000	**AIC:**	3.634e+05
Df Residuals:	99990	**BIC:**	3.635e+05
Df Model:	9		

	coef	**std err**	**t**	**P> |t|**	**[0.025**	**0.975]**
Intercept	-3.0390	0.017	-176.504	0.000	-3.073	-3.005
heuristic3	-0.1237	0.006	-20.468	0.000	-0.136	-0.112
heuristic4	0.1302	0.006	23.319	0.000	0.119	0.141
heuristic5	0.0480	0.005	10.148	0.000	0.039	0.057
heuristic6	-0.0427	0.005	-8.168	0.000	-0.053	-0.032
heuristic7	0.0789	0.005	16.273	0.000	0.069	0.088
heuristic15	0.4399	0.005	90.073	0.000	0.430	0.449
heuristic16	-0.0182	0.005	-3.794	0.000	-0.028	-0.009
heuristic18	0.0037	0.005	0.767	0.443	-0.006	0.013
heuristic21	0.1333	0.005	26.846	0.000	0.124	0.143

Omnibus:	6067.211	**Durbin-Watson:**	2.002
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	7287.160
Skew:	0.626	**Prob(JB):**	0.00
Kurtosis:	3.424	**Cond. No.**	15.7

Table B.45: Cluster-assignment regression results for Cluster 13 model.

Raise odds of assignment:

Feature	**Odds ratio estimate**
Dates [h15]	1.553
Common password [h21]	1.143
Repeated chars [h4]	1.139
Char-class structure [h7]	1.082
Keyboard patterns [h5]	1.049
Dictionary (longest token) [h18]	1.004

Lower odds of assignments:

Feature	**Odds ratio estimate**
Duplicated chars [h3]	0.884
Repeated sections [h6]	0.958
Alphabetic/numeric sequences [h16]	0.982

Cluster 14 model

Dep. Variable:	logit(soft_assign)	**R-squared:**	0.132
Model:	OLS	**Adj. R-squared:**	0.132
Method:	Least Squares	**F-statistic:**	1689.
Date:	Fri, 21 Aug 2020	**Prob (F-statistic):**	0.00
Time:	17:40:20	**Log-Likelihood:**	-1.9142e+05
No. Observations:	100000	**AIC:**	3.829e+05
Df Residuals:	99990	**BIC:**	3.830e+05
Df Model:	9		

	coef	**std err**	**t**	**P> |t|**	**[0.025**	**0.975]**
Intercept	-3.2799	0.018	-177.642	0.000	-3.316	-3.244
heuristic3	0.0846	0.007	12.930	0.000	0.072	0.097
heuristic4	0.0518	0.006	8.526	0.000	0.040	0.064
heuristic5	0.0563	0.005	10.797	0.000	0.046	0.067
heuristic6	-0.1570	0.006	-27.530	0.000	-0.168	-0.146
heuristic7	-0.0318	0.005	-5.963	0.000	-0.042	-0.021
heuristic15	0.5123	0.005	95.279	0.000	0.502	0.523
heuristic16	0.0416	0.005	7.851	0.000	0.031	0.052
heuristic18	0.0655	0.005	12.314	0.000	0.055	0.076
heuristic21	0.2459	0.005	44.824	0.000	0.235	0.257

Omnibus:	6104.069	**Durbin-Watson:**	2.002
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	7298.512
Skew:	0.637	**Prob(JB):**	0.00
Kurtosis:	3.357	**Cond. No.**	15.0

Table B.46: Cluster-assignment regression results for Cluster 14 model.

Raise odds of assignment:

Feature	**Odds ratio estimate**
Dates [h15]	1.669
Common password [h21]	1.279
Duplicated chars [h3]	1.088
Dictionary (longest token) [h18]	1.068
Keyboard patterns [h5]	1.058
Repeated chars [h4]	1.053
Alphabetic/numeric sequences [h16]	1.042

Lower odds of assignments:

Feature	**Odds ratio estimate**
Repeated sections [h6]	0.855
Char-class structure [h7]	0.969

Cluster 15 model

Dep. Variable:	logit(soft_assign)	**R-squared:**	0.151
Model:	OLS	**Adj. R-squared:**	0.151
Method:	Least Squares	**F-statistic:**	1970.
Date:	Fri, 21 Aug 2020	**Prob (F-statistic):**	0.00
Time:	17:40:20	**Log-Likelihood:**	-1.7520e+05
No. Observations:	100000	**AIC:**	3.504e+05
Df Residuals:	99990	**BIC:**	3.505e+05
Df Model:	9		

	coef	**std err**	**t**	**P> |t|**	**[0.025**	**0.975]**
Intercept	-2.2271	0.012	-180.530	0.000	-2.251	-2.203
heuristic3	-0.0839	0.007	-12.773	0.000	-0.097	-0.071
heuristic4	-0.0013	0.005	-0.228	0.819	-0.012	0.010
heuristic5	0.0287	0.004	6.490	0.000	0.020	0.037
heuristic6	0.0554	0.005	10.280	0.000	0.045	0.066
heuristic7	0.0709	0.005	14.057	0.000	0.061	0.081
heuristic15	-0.0504	0.005	-11.024	0.000	-0.059	-0.041
heuristic16	0.0276	0.004	6.229	0.000	0.019	0.036
heuristic18	-0.3636	0.005	-80.157	0.000	-0.372	-0.355
heuristic21	0.3673	0.005	72.743	0.000	0.357	0.377

Omnibus:	16065.279	**Durbin-Watson:**	2.006
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	32384.496
Skew:	-0.981	**Prob(JB):**	0.00
Kurtosis:	4.980	**Cond. No.**	9.76

Table B.47: Cluster-assignment regression results for Cluster 15 model.

Raise odds of assignment:

Feature	**Odds ratio estimate**
Common password [h21]	1.444
Char-class structure [h7]	1.073
Repeated sections [h6]	1.057
Keyboard patterns [h5]	1.029
Alphabetic/numeric sequences [h16]	1.028

Lower odds of assignments:

Feature	**Odds ratio estimate**
Dictionary (longest token) [h18]	0.695
Duplicated chars [h3]	0.919
Dates [h15]	0.951
Repeated chars [h4]	0.999

Cluster 16 model

Dep. Variable:	logit(soft_assign)	**R-squared:**	0.351
Model:	OLS	**Adj. R-squared:**	0.351
Method:	Least Squares	**F-statistic:**	5998.
Date:	Fri, 21 Aug 2020	**Prob (F-statistic):**	0.00
Time:	17:40:20	**Log-Likelihood:**	-1.7233e+05
No. Observations:	100000	**AIC:**	3.447e+05
Df Residuals:	99990	**BIC:**	3.448e+05
Df Model:	9		

	coef	**std err**	**t**	**P> |t|**	**[0.025**	**0.975]**
Intercept	-1.1098	0.008	-132.362	0.000	-1.126	-1.093
heuristic3	0.2814	0.006	48.320	0.000	0.270	0.293
heuristic4	-0.0780	0.005	-15.242	0.000	-0.088	-0.068
heuristic5	0.0071	0.004	1.641	0.101	-0.001	0.015
heuristic6	-0.0764	0.005	-15.473	0.000	-0.086	-0.067
heuristic7	-1.0409	0.005	-201.151	0.000	-1.051	-1.031
heuristic15	0.0274	0.004	6.133	0.000	0.019	0.036
heuristic16	0.0563	0.004	12.958	0.000	0.048	0.065
heuristic18	-0.1679	0.004	-38.620	0.000	-0.176	-0.159
heuristic21	0.0212	0.005	4.119	0.000	0.011	0.031

Omnibus:	4066.012	**Durbin-Watson:**	1.997
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	4535.959
Skew:	-0.516	**Prob(JB):**	0.00
Kurtosis:	2.842	**Cond. No.**	5.87

Table B.48: Cluster-assignment regression results for Cluster 16 model.

Raise odds of assignment:

Feature	**Odds ratio estimate**
Duplicated chars [h3]	1.325
Alphabetic/numeric sequences [h16]	1.058
Dates [h15]	1.028
Common password [h21]	1.021
Keyboard patterns [h5]	1.007

Lower odds of assignments:

Feature	**Odds ratio estimate**
Char-class structure [h7]	0.353
Dictionary (longest token) [h18]	0.845
Repeated chars [h4]	0.925
Repeated sections [h6]	0.926

Cluster 17 model

Dep. Variable:	logit(soft_assign)	**R-squared:**	0.273
Model:	OLS	**Adj. R-squared:**	0.273
Method:	Least Squares	**F-statistic:**	4171.
Date:	Fri, 21 Aug 2020	**Prob (F-statistic):**	0.00
Time:	17:40:21	**Log-Likelihood:**	-2.0818e+05
No. Observations:	100000	**AIC:**	4.164e+05
Df Residuals:	99990	**BIC:**	4.165e+05
Df Model:	9		

	coef	**std err**	**t**	**P> |t|**	**[0.025**	**0.975]**
Intercept	-4.8105	0.030	-159.180	0.000	-4.870	-4.751
heuristic3	1.0814	0.008	142.646	0.000	1.067	1.096
heuristic4	-0.3710	0.007	-56.628	0.000	-0.384	-0.358
heuristic5	-0.0404	0.006	-6.553	0.000	-0.052	-0.028
heuristic6	-0.4268	0.007	-59.923	0.000	-0.441	-0.413
heuristic7	0.1453	0.006	23.243	0.000	0.133	0.158
heuristic15	-0.3282	0.006	-53.131	0.000	-0.340	-0.316
heuristic16	-0.1738	0.006	-28.112	0.000	-0.186	-0.162
heuristic18	0.3517	0.007	53.255	0.000	0.339	0.365
heuristic21	0.2154	0.007	32.625	0.000	0.202	0.228

Omnibus:	1283.414	**Durbin-Watson:**	2.006
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	1085.420
Skew:	0.194	**Prob(JB):**	2.01e-236
Kurtosis:	2.668	**Cond. No.**	27.5

Table B.49: Cluster-assignment regression results for Cluster 17 model.

Raise odds of assignment:

Feature	**Odds ratio estimate**
Duplicated chars [h3]	2.949
Dictionary (longest token) [h18]	1.421
Common password [h21]	1.240
Char-class structure [h7]	1.156

Lower odds of assignments:

Feature	**Odds ratio estimate**
Repeated sections [h6]	0.653
Repeated chars [h4]	0.690
Dates [h15]	0.720
Alphabetic/numeric sequences [h16]	0.840
Keyboard patterns [h5]	0.960

Cluster 18 model

Dep. Variable:	logit(soft_assign)	**R-squared:**	0.062
Model:	OLS	**Adj. R-squared:**	0.062
Method:	Least Squares	**F-statistic:**	731.4
Date:	Fri, 21 Aug 2020	**Prob (F-statistic):**	0.00
Time:	17:40:21	**Log-Likelihood:**	-1.9862e+05
No. Observations:	100000	**AIC:**	3.973e+05
Df Residuals:	99990	**BIC:**	3.974e+05
Df Model:	9		

	coef	**std err**	**t**	**P> |t|**	**[0.025**	**0.975]**
Intercept	-2.8511	0.022	-127.091	0.000	-2.895	-2.807
heuristic3	0.2499	0.007	35.554	0.000	0.236	0.264
heuristic4	-0.1560	0.006	-24.981	0.000	-0.168	-0.144
heuristic5	-0.0640	0.006	-11.452	0.000	-0.075	-0.053
heuristic6	-0.1322	0.006	-20.845	0.000	-0.145	-0.120
heuristic7	0.0138	0.006	2.448	0.014	0.003	0.025
heuristic15	-0.2706	0.006	-48.180	0.000	-0.282	-0.260
heuristic16	-0.0919	0.006	-16.342	0.000	-0.103	-0.081
heuristic18	0.1833	0.006	31.554	0.000	0.172	0.195
heuristic21	0.1137	0.006	19.439	0.000	0.102	0.125

Omnibus:	4616.235	**Durbin-Watson:**	2.003
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	5116.529
Skew:	0.540	**Prob(JB):**	0.00
Kurtosis:	2.753	**Cond. No.**	18.2

Table B.50: Cluster-assignment regression results for Cluster 18 model.

Raise odds of assignment:

Feature	**Odds ratio estimate**
Duplicated chars [h3]	1.284
Dictionary (longest token) [h18]	1.201
Common password [h21]	1.120
Char-class structure [h7]	1.014

Lower odds of assignments:

Feature	**Odds ratio estimate**
Dates [h15]	0.763
Repeated chars [h4]	0.856
Repeated sections [h6]	0.876
Alphabetic/numeric sequences [h16]	0.912
Keyboard patterns [h5]	0.938

Cluster 19 model

Dep. Variable:	logit(soft_assign)	**R-squared:**	0.137
Model:	OLS	**Adj. R-squared:**	0.137
Method:	Least Squares	**F-statistic:**	1768.
Date:	Fri, 21 Aug 2020	**Prob (F-statistic):**	0.00
Time:	17:40:21	**Log-Likelihood:**	-1.8386e+05
No. Observations:	100000	**AIC:**	3.677e+05
Df Residuals:	99990	**BIC:**	3.678e+05
Df Model:	9		

	coef	**std err**	**t**	**P> |t|**	**[0.025**	**0.975]**
Intercept	-4.1097	0.032	-130.057	0.000	-4.172	-4.048
heuristic3	0.1029	0.006	16.830	0.000	0.091	0.115
heuristic4	-0.1195	0.005	-22.610	0.000	-0.130	-0.109
heuristic5	-0.0783	0.005	-16.219	0.000	-0.088	-0.069
heuristic6	-0.0713	0.006	-12.550	0.000	-0.082	-0.060
heuristic7	0.3742	0.005	76.342	0.000	0.365	0.384
heuristic15	-0.3140	0.005	-64.996	0.000	-0.323	-0.305
heuristic16	-0.2163	0.005	-44.750	0.000	-0.226	-0.207
heuristic18	-0.0288	0.005	-5.552	0.000	-0.039	-0.019
heuristic21	0.1582	0.005	30.237	0.000	0.148	0.168

Omnibus:	6896.806	**Durbin-Watson:**	2.005
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	8402.854
Skew:	-0.697	**Prob(JB):**	0.00
Kurtosis:	3.268	**Cond. No.**	45.5

Table B.51: Cluster-assignment regression results for Cluster 19 model.

Raise odds of assignment:

Feature	**Odds ratio estimate**
Char-class structure [h7]	1.454
Common password [h21]	1.171
Duplicated chars [h3]	1.108

Lower odds of assignments:

Feature	**Odds ratio estimate**
Dates [h15]	0.731
Alphabetic/numeric sequences [h16]	0.805
Repeated chars [h4]	0.887
Keyboard patterns [h5]	0.925
Repeated sections [h6]	0.931
Dictionary (longest token) [h18]	0.972

Cluster 20 model

Dep. Variable:	logit(soft_assign)	**R-squared:**	0.156
Model:	OLS	**Adj. R-squared:**	0.156
Method:	Least Squares	**F-statistic:**	2056.
Date:	Fri, 21 Aug 2020	**Prob (F-statistic):**	0.00
Time:	17:40:22	**Log-Likelihood:**	-1.9087e+05
No. Observations:	100000	**AIC:**	3.818e+05
Df Residuals:	99990	**BIC:**	3.819e+05
Df Model:	9		

	coef	**std err**	**t**	**P> |t|**	**[0.025**	**0.975]**
Intercept	-3.9741	0.036	-111.462	0.000	-4.044	-3.904
heuristic3	-0.0656	0.007	-9.823	0.000	-0.079	-0.053
heuristic4	-0.1210	0.006	-21.302	0.000	-0.132	-0.110
heuristic5	-0.0727	0.005	-14.056	0.000	-0.083	-0.063
heuristic6	0.0598	0.006	9.638	0.000	0.048	0.072
heuristic7	0.4329	0.005	82.159	0.000	0.423	0.443
heuristic15	-0.3430	0.005	-66.204	0.000	-0.353	-0.333
heuristic16	-0.2702	0.005	-52.176	0.000	-0.280	-0.260
heuristic18	-0.1680	0.006	-30.083	0.000	-0.179	-0.157
heuristic21	0.1740	0.006	30.827	0.000	0.163	0.185

Omnibus:	8312.139	**Durbin-Watson:**	1.991
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	10526.893
Skew:	-0.779	**Prob(JB):**	0.00
Kurtosis:	3.314	**Cond. No.**	49.8

Table B.52: Cluster-assignment regression results for Cluster 20 model.

Raise odds of assignment:

Feature	**Odds ratio estimate**
Char-class structure [h7]	1.542
Common password [h21]	1.190
Repeated sections [h6]	1.062

Lower odds of assignments:

Feature	**Odds ratio estimate**
Dates [h15]	0.710
Alphabetic/numeric sequences [h16]	0.763
Dictionary (longest token) [h18]	0.845
Repeated chars [h4]	0.886
Keyboard patterns [h5]	0.930
Duplicated chars [h3]	0.937

Cluster 21 model

Dep. Variable:	logit(soft_assign)	**R-squared:**	0.154
Model:	OLS	**Adj. R-squared:**	0.153
Method:	Least Squares	**F-statistic:**	2015.
Date:	Fri, 21 Aug 2020	**Prob (F-statistic):**	0.00
Time:	17:40:22	**Log-Likelihood:**	-1.7823e+05
No. Observations:	100000	**AIC:**	3.565e+05
Df Residuals:	99990	**BIC:**	3.566e+05
Df Model:	9		

	coef	**std err**	**t**	**P> |t|**	**[0.025**	**0.975]**
Intercept	-2.2217	0.013	-173.343	0.000	-2.247	-2.197
heuristic3	0.0605	0.007	8.899	0.000	0.047	0.074
heuristic4	0.0343	0.006	6.204	0.000	0.023	0.045
heuristic5	0.0913	0.005	19.954	0.000	0.082	0.100
heuristic6	0.1028	0.006	18.007	0.000	0.092	0.114
heuristic7	0.2160	0.005	42.010	0.000	0.206	0.226
heuristic15	0.2419	0.005	49.886	0.000	0.232	0.251
heuristic16	-0.0172	0.005	-3.743	0.000	-0.026	-0.008
heuristic18	-0.3650	0.005	-77.891	0.000	-0.374	-0.356
heuristic21	-0.0140	0.005	-2.725	0.006	-0.024	-0.004

Omnibus:	14322.100	**Durbin-Watson:**	1.985
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	22747.414
Skew:	-0.999	**Prob(JB):**	0.00
Kurtosis:	4.210	**Cond. No.**	10.2

Table B.53: Cluster-assignment regression results for Cluster 21 model.

Raise odds of assignment:

Feature	**Odds ratio estimate**
Dates [h15]	1.274
Char-class structure [h7]	1.241
Repeated sections [h6]	1.108
Keyboard patterns [h5]	1.096
Duplicated chars [h3]	1.062
Repeated chars [h4]	1.035

Lower odds of assignments:

Feature	**Odds ratio estimate**
Dictionary (longest token) [h18]	0.694
Alphabetic/numeric sequences [h16]	0.983
Common password [h21]	0.986

Cluster 22 model

Dep. Variable:	logit(soft_assign)	**R-squared:**	0.165
Model:	OLS	**Adj. R-squared:**	0.165
Method:	Least Squares	**F-statistic:**	2199.
Date:	Fri, 21 Aug 2020	**Prob (F-statistic):**	0.00
Time:	17:40:22	**Log-Likelihood:**	-1.7921e+05
No. Observations:	100000	**AIC:**	3.584e+05
Df Residuals:	99990	**BIC:**	3.585e+05
Df Model:	9		

	coef	**std err**	**t**	**P> |t|**	**[0.025**	**0.975]**
Intercept	-2.8500	0.022	-128.823	0.000	-2.893	-2.807
heuristic3	-0.5097	0.006	-85.497	0.000	-0.521	-0.498
heuristic4	0.1570	0.005	29.108	0.000	0.146	0.168
heuristic5	-0.0927	0.005	-20.158	0.000	-0.102	-0.084
heuristic6	0.1322	0.005	25.458	0.000	0.122	0.142
heuristic7	0.3167	0.005	68.080	0.000	0.308	0.326
heuristic15	-0.2637	0.005	-57.105	0.000	-0.273	-0.255
heuristic16	-0.2520	0.005	-54.698	0.000	-0.261	-0.243
heuristic18	-0.0479	0.005	-10.138	0.000	-0.057	-0.039
heuristic21	-0.0215	0.005	-4.497	0.000	-0.031	-0.012

Omnibus:	2271.573	**Durbin-Watson:**	2.011
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	2197.658
Skew:	0.329	**Prob(JB):**	0.00
Kurtosis:	2.691	**Cond. No.**	25.0

Table B.54: Cluster-assignment regression results for Cluster 22 model.

Raise odds of assignment:

Feature	**Odds ratio estimate**
Char-class structure [h7]	1.373
Repeated chars [h4]	1.170
Repeated sections [h6]	1.141

Lower odds of assignments:

Feature	**Odds ratio estimate**
Duplicated chars [h3]	0.601
Dates [h15]	0.768
Alphabetic/numeric sequences [h16]	0.777
Keyboard patterns [h5]	0.912
Dictionary (longest token) [h18]	0.953
Common password [h21]	0.979

Cluster 23 model

Dep. Variable:	logit(soft_assign)	**R-squared:**	0.062
Model:	OLS	**Adj. R-squared:**	0.061
Method:	Least Squares	**F-statistic:**	728.5
Date:	Fri, 21 Aug 2020	**Prob (F-statistic):**	0.00
Time:	17:40:23	**Log-Likelihood:**	-1.6630e+05
No. Observations:	100000	**AIC:**	3.326e+05
Df Residuals:	99990	**BIC:**	3.327e+05
Df Model:	9		

	coef	**std err**	**t**	**P> |t|**	**[0.025**	**0.975]**
Intercept	-2.8771	0.016	-177.206	0.000	-2.909	-2.845
heuristic3	-0.0823	0.005	-15.882	0.000	-0.092	-0.072
heuristic4	0.1009	0.005	21.230	0.000	0.092	0.110
heuristic5	0.1165	0.004	28.701	0.000	0.109	0.124
heuristic6	-0.0671	0.004	-14.913	0.000	-0.076	-0.058
heuristic7	0.1367	0.004	33.558	0.000	0.129	0.145
heuristic15	-0.0835	0.004	-20.365	0.000	-0.092	-0.075
heuristic16	0.1439	0.004	35.090	0.000	0.136	0.152
heuristic18	0.0101	0.004	2.418	0.016	0.002	0.018
heuristic21	-0.1874	0.004	-44.114	0.000	-0.196	-0.179

Omnibus:	14693.346	**Durbin-Watson:**	1.997
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	26244.919
Skew:	0.957	**Prob(JB):**	0.00
Kurtosis:	4.624	**Cond. No.**	18.0

Table B.55: Cluster-assignment regression results for Cluster 23 model.

Raise odds of assignment:

Feature	**Odds ratio estimate**
Alphabetic/numeric sequences [h16]	1.155
Char-class structure [h7]	1.147
Keyboard patterns [h5]	1.124
Repeated chars [h4]	1.106
Dictionary (longest token) [h18]	1.010

Lower odds of assignments:

Feature	**Odds ratio estimate**
Common password [h21]	0.829
Dates [h15]	0.920
Duplicated chars [h3]	0.921
Repeated sections [h6]	0.935

Cluster 24 model

Dep. Variable:	logit(soft_assign)	**R-squared:**	0.153
Model:	OLS	**Adj. R-squared:**	0.153
Method:	Least Squares	**F-statistic:**	2011.
Date:	Fri, 21 Aug 2020	**Prob (F-statistic):**	0.00
Time:	17:40:23	**Log-Likelihood:**	-2.0209e+05
No. Observations:	100000	**AIC:**	4.042e+05
Df Residuals:	99990	**BIC:**	4.043e+05
Df Model:	9		

	coef	**std err**	**t**	**P> |t|**	**[0.025**	**0.975]**
Intercept	-4.4297	0.033	-132.571	0.000	-4.495	-4.364
heuristic3	0.5809	0.007	80.410	0.000	0.567	0.595
heuristic4	-0.2376	0.006	-37.919	0.000	-0.250	-0.225
heuristic5	-0.0544	0.006	-9.386	0.000	-0.066	-0.043
heuristic6	-0.2123	0.007	-31.463	0.000	-0.226	-0.199
heuristic7	0.2967	0.006	50.492	0.000	0.285	0.308
heuristic15	-0.3273	0.006	-56.414	0.000	-0.339	-0.316
heuristic16	-0.1853	0.006	-31.914	0.000	-0.197	-0.174
heuristic18	0.1727	0.006	28.068	0.000	0.161	0.185
heuristic21	0.1263	0.006	20.363	0.000	0.114	0.138

Omnibus:	1239.261	**Durbin-Watson:**	1.997
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	840.407
Skew:	0.101	**Prob(JB):**	3.22e-183
Kurtosis:	2.599	**Cond. No.**	36.3

Table B.56: Cluster-assignment regression results for Cluster 24 model.

Raise odds of assignment:

Feature	**Odds ratio estimate**
Duplicated chars [h3]	1.788
Char-class structure [h7]	1.345
Dictionary (longest token) [h18]	1.189
Common password [h21]	1.135

Lower odds of assignments:

Feature	**Odds ratio estimate**
Dates [h15]	0.721
Repeated chars [h4]	0.789
Repeated sections [h6]	0.809
Alphabetic/numeric sequences [h16]	0.831
Keyboard patterns [h5]	0.947

Cluster 25 model

Dep. Variable:	logit(soft_assign)	**R-squared:**	0.283
Model:	OLS	**Adj. R-squared:**	0.283
Method:	Least Squares	**F-statistic:**	4393.
Date:	Fri, 21 Aug 2020	**Prob (F-statistic):**	0.00
Time:	17:40:23	**Log-Likelihood:**	-2.0280e+05
No. Observations:	100000	**AIC:**	4.056e+05
Df Residuals:	99990	**BIC:**	4.057e+05
Df Model:	9		

	coef	**std err**	**t**	**P> |t|**	**[0.025**	**0.975]**
Intercept	-1.4105	0.012	-113.548	0.000	-1.435	-1.386
heuristic3	0.6692	0.008	85.312	0.000	0.654	0.685
heuristic4	-0.1780	0.007	-26.162	0.000	-0.191	-0.165
heuristic5	0.0341	0.006	5.858	0.000	0.023	0.046
heuristic6	-0.1834	0.007	-26.786	0.000	-0.197	-0.170
heuristic7	-1.2114	0.007	-181.500	0.000	-1.225	-1.198
heuristic15	0.0657	0.006	10.856	0.000	0.054	0.078
heuristic16	0.0966	0.006	16.364	0.000	0.085	0.108
heuristic18	-0.1031	0.006	-17.443	0.000	-0.115	-0.091
heuristic21	0.2859	0.007	42.434	0.000	0.273	0.299

Omnibus:	2934.265	**Durbin-Watson:**	2.001
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	1406.779
Skew:	0.017	**Prob(JB):**	3.33e-306
Kurtosis:	2.420	**Cond. No.**	6.56

Table B.57: Cluster-assignment regression results for Cluster 25 model.

Raise odds of assignment:

Feature	**Odds ratio estimate**
Duplicated chars [h3]	1.953
Common password [h21]	1.331
Alphabetic/numeric sequences [h16]	1.101
Dates [h15]	1.068
Keyboard patterns [h5]	1.035

Lower odds of assignments:

Feature	**Odds ratio estimate**
Char-class structure [h7]	0.298
Repeated sections [h6]	0.832
Repeated chars [h4]	0.837
Dictionary (longest token) [h18]	0.902

Cluster 26 model

Dep. Variable:	logit(soft_assign)	**R-squared:**	0.224
Model:	OLS	**Adj. R-squared:**	0.224
Method:	Least Squares	**F-statistic:**	3200.
Date:	Fri, 21 Aug 2020	**Prob (F-statistic):**	0.00
Time:	17:40:24	**Log-Likelihood:**	-1.7859e+05
No. Observations:	100000	**AIC:**	3.572e+05
Df Residuals:	99990	**BIC:**	3.573e+05
Df Model:	9		

	coef	**std err**	**t**	**P> |t|**	**[0.025**	**0.975]**
Intercept	-0.7017	0.010	-71.578	0.000	-0.721	-0.682
heuristic3	-0.2766	0.006	-43.818	0.000	-0.289	-0.264
heuristic4	-0.0224	0.005	-4.092	0.000	-0.033	-0.012
heuristic5	-0.0219	0.005	-4.786	0.000	-0.031	-0.013
heuristic6	0.1198	0.005	22.449	0.000	0.109	0.130
heuristic7	-0.1820	0.005	-36.508	0.000	-0.192	-0.172
heuristic15	-0.0421	0.005	-8.795	0.000	-0.052	-0.033
heuristic16	-0.1592	0.005	-34.568	0.000	-0.168	-0.150
heuristic18	-0.0485	0.005	-10.501	0.000	-0.058	-0.039
heuristic21	-0.5507	0.005	-107.722	0.000	-0.561	-0.541

Omnibus:	5963.019	**Durbin-Watson:**	2.007
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	7214.116
Skew:	-0.610	**Prob(JB):**	0.00
Kurtosis:	3.495	**Cond. No.**	6.41

Table B.58: Cluster-assignment regression results for Cluster 26 model.

Raise odds of assignment:

Feature	**Odds ratio estimate**
Repeated sections [h6]	1.127

Lower odds of assignments:

Feature	**Odds ratio estimate**
Common password [h21]	0.577
Duplicated chars [h3]	0.758
Char-class structure [h7]	0.834
Alphabetic/numeric sequences [h16]	0.853
Dictionary (longest token) [h18]	0.953
Dates [h15]	0.959
Repeated chars [h4]	0.978
Keyboard patterns [h5]	0.978

Cluster 27 model

Dep. Variable:	logit(soft_assign)	**R-squared:**	0.111
Model:	OLS	**Adj. R-squared:**	0.111
Method:	Least Squares	**F-statistic:**	1388.
Date:	Fri, 21 Aug 2020	**Prob (F-statistic):**	0.00
Time:	17:40:24	**Log-Likelihood:**	-1.7415e+05
No. Observations:	100000	**AIC:**	3.483e+05
Df Residuals:	99990	**BIC:**	3.484e+05
Df Model:	9		

	coef	**std err**	**t**	**P> |t|**	**[0.025**	**0.975]**
Intercept	-3.2124	0.022	-146.354	0.000	-3.255	-3.169
heuristic3	0.0685	0.006	12.181	0.000	0.057	0.080
heuristic4	-0.1323	0.005	-27.396	0.000	-0.142	-0.123
heuristic5	-0.0658	0.004	-15.047	0.000	-0.074	-0.057
heuristic6	0.0255	0.005	4.919	0.000	0.015	0.036
heuristic7	0.1936	0.004	43.550	0.000	0.185	0.202
heuristic15	-0.3039	0.004	-69.375	0.000	-0.312	-0.295
heuristic16	-0.2265	0.004	-51.685	0.000	-0.235	-0.218
heuristic18	-0.0852	0.005	-18.533	0.000	-0.094	-0.076
heuristic21	0.1456	0.005	31.339	0.000	0.136	0.155

Omnibus:	3091.696	**Durbin-Watson:**	1.992
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	1563.967
Skew:	-0.098	**Prob(JB):**	0.00
Kurtosis:	2.420	**Cond. No.**	27.5

Table B.59: Cluster-assignment regression results for Cluster 27 model.

Raise odds of assignment:

Feature	**Odds ratio estimate**
Char-class structure [h7]	1.214
Common password [h21]	1.157
Duplicated chars [h3]	1.071
Repeated sections [h6]	1.026

Lower odds of assignments:

Feature	**Odds ratio estimate**
Dates [h15]	0.738
Alphabetic/numeric sequences [h16]	0.797
Repeated chars [h4]	0.876
Dictionary (longest token) [h18]	0.918
Keyboard patterns [h5]	0.936

Cluster 28 model

Dep. Variable:	logit(soft_assign)	**R-squared:**	0.127
Model:	OLS	**Adj. R-squared:**	0.127
Method:	Least Squares	**F-statistic:**	1615.
Date:	Fri, 21 Aug 2020	**Prob (F-statistic):**	0.00
Time:	17:40:24	**Log-Likelihood:**	-1.6835e+05
No. Observations:	100000	**AIC:**	3.367e+05
Df Residuals:	99990	**BIC:**	3.368e+05
Df Model:	9		

	coef	**std err**	**t**	**P> |t|**	**[0.025**	**0.975]**
Intercept	-2.7231	0.015	-182.356	0.000	-2.752	-2.694
heuristic3	-0.3045	0.005	-57.150	0.000	-0.315	-0.294
heuristic4	0.2222	0.005	44.838	0.000	0.213	0.232
heuristic5	0.0457	0.004	11.048	0.000	0.038	0.054
heuristic6	-0.0236	0.005	-5.179	0.000	-0.033	-0.015
heuristic7	0.1385	0.004	32.541	0.000	0.130	0.147
heuristic15	0.3473	0.004	81.272	0.000	0.339	0.356
heuristic16	-0.0542	0.004	-12.931	0.000	-0.062	-0.046
heuristic18	0.0118	0.004	2.808	0.005	0.004	0.020
heuristic21	-0.0757	0.004	-17.417	0.000	-0.084	-0.067

Omnibus:	3292.796	**Durbin-Watson:**	1.996
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	4159.255
Skew:	0.384	**Prob(JB):**	0.00
Kurtosis:	3.640	**Cond. No.**	15.3

Table B.60: Cluster-assignment regression results for Cluster 28 model.

Raise odds of assignment:

Feature	**Odds ratio estimate**
Dates [h15]	1.415
Repeated chars [h4]	1.249
Char-class structure [h7]	1.149
Keyboard patterns [h5]	1.047
Dictionary (longest token) [h18]	1.012

Lower odds of assignments:

Feature	**Odds ratio estimate**
Duplicated chars [h3]	0.737
Common password [h21]	0.927
Alphabetic/numeric sequences [h16]	0.947
Repeated sections [h6]	0.977

Cluster 29 model

Dep. Variable:	logit(soft_assign)	**R-squared:**	0.105
Model:	OLS	**Adj. R-squared:**	0.105
Method:	Least Squares	**F-statistic:**	1306.
Date:	Fri, 21 Aug 2020	**Prob (F-statistic):**	0.00
Time:	17:40:25	**Log-Likelihood:**	-1.7557e+05
No. Observations:	100000	**AIC:**	3.512e+05
Df Residuals:	99990	**BIC:**	3.513e+05
Df Model:	9		

	coef	**std err**	**t**	**P> |t|**	**[0.025**	**0.975]**
Intercept	-2.8588	0.020	-139.841	0.000	-2.899	-2.819
heuristic3	-0.2837	0.006	-50.224	0.000	-0.295	-0.273
heuristic4	0.0577	0.005	11.236	0.000	0.048	0.068
heuristic5	-0.0831	0.004	-18.742	0.000	-0.092	-0.074
heuristic6	-0.0059	0.005	-1.197	0.231	-0.016	0.004
heuristic7	0.2243	0.004	50.175	0.000	0.216	0.233
heuristic15	-0.2601	0.004	-58.410	0.000	-0.269	-0.251
heuristic16	-0.1968	0.004	-44.243	0.000	-0.206	-0.188
heuristic18	0.0350	0.005	7.686	0.000	0.026	0.044
heuristic21	0.0245	0.005	5.331	0.000	0.016	0.034

Omnibus:	6634.897	**Durbin-Watson:**	1.996
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	8058.405
Skew:	0.667	**Prob(JB):**	0.00
Kurtosis:	3.396	**Cond. No.**	23.2

Table B.61: Cluster-assignment regression results for Cluster 29 model.

Raise odds of assignment:

Feature	**Odds ratio estimate**
Char-class structure [h7]	1.251
Repeated chars [h4]	1.059
Dictionary (longest token) [h18]	1.036
Common password [h21]	1.025

Lower odds of assignments:

Feature	**Odds ratio estimate**
Duplicated chars [h3]	0.753
Dates [h15]	0.771
Alphabetic/numeric sequences [h16]	0.821
Keyboard patterns [h5]	0.920
Repeated sections [h6]	0.994

Appendix C

Additional details for public-key fingerprint study

C.1 Activity tutorial

(hex version)

Scenario: Imagine that you work as an accountant at Print Idea Solutions and that your company is in the process of updating its employee database.

Your task is to retrieve the SSN for 30 different employees and enter them into the database.

Each employee will send you a message with his or her SSN.

Before you can read the chat message, you'll need to perform a security check. To ensure the chat session is secure, you will need to compare a pair of text strings, which are called "fingerprints."

[if compare-and-confirm] One fingerprint will be displayed on your computer. The other fingerprint is printed on the employee's business card, located on your desk. If these two fingerprints are the same, your chat session is secure. If they are different, your session is not secure; someone else could be eavesdropping on your communications.

[if compare-and-select] Three fingerprints will be displayed on your computer. Another fingerprint is printed on the employee's business card, located on your desk. If one of the fingerprints on your computer matches the one on the business card, your chat session is secure. If none match, your session is not secure; someone could be eavesdropping on your communications.

Check for differences in the letters or numbers shown. The font size and type do not matter.

[if compare-and-confirm] Since the two fingerprints shown here are the same, you should click the 'Same' button.

[if compare-and-select] Since the first fingerprint shown here matches the one on the business card, you should select it and click Continue.

After performing the security check, you will need to enter the information shown in the chatbox into the highlighted database field.

You may enter the SSN with or without dashes or spaces ("123-45-678," "12345678," and "123 45 678" are all valid). You will need to manually type the SSN into the database, since copy/paste will not work.

For a $1 bonus, complete your task both quickly and correctly. The 15% fastest participants with the fewest mistakes will receive an additional $1 bonus.

This stopwatch will show you the current time to beat. Please note that beating this time does not guarantee the bonus; future participants may lower (or raise) the time to beat.

This is the end of the tutorial. If you need more practice, you can restart the tutorial. Otherwise, if you've got the hang of things, you may proceed to the actual activity.

C.2 Post-activity survey

Please fill out this short survey on the activity you just performed. At the end of the survey, you will receive a code that can be used for payment on Mechanical Turk.

Rank the following in terms of what you thought was most important while performing this activity (1 = most important): ***(dropdown containing 1-4)***
□ Responding to employees in the chatbox
□ Completing the activity as fast as possible
□ Entering the correct SSN into the database
□ Correctly comparing [representation]s

What was the hardest thing about this activity?

[textbox]

The following questions ask about the [representation] comparisons you just made. We've included an example below, as a reminder:

[image of comparison dialog]

It was easy was to determine if [representation]s were the same or different.
◯ Strongly agree
◯ Agree
◯ Somewhat agree
◯ Neither agree nor disagree
◯ Somewhat disagree
◯ Disagree
◯ Strongly disagree

The amount of time it took to compare [representation]s is reasonable for a security check.
◯ Strongly agree
◯ Agree
◯ Somewhat agree
◯ Neither agree nor disagree
◯ Somewhat disagree
◯ Disagree
◯ Strongly disagree

I feel confident that I could correctly compare [representation]s as a security check.
◯ Strongly agree
◯ Agree
◯ Somewhat agree
◯ Neither agree nor disagree
◯ Somewhat disagree
◯ Disagree
◯ Strongly disagree

I was worried about incorrectly choosing "Same" when two [representation]s were different.
◯ Strongly agree
◯ Agree
◯ Neither agree nor disagree
◯ Disagree
◯ Strongly disagree

I was worried about incorrectly choosing "Different" when two [representation]s were the same.
◯ Strongly agree
◯ Agree
◯ Neither agree nor disagree
◯ Disagree
◯ Strongly disagree

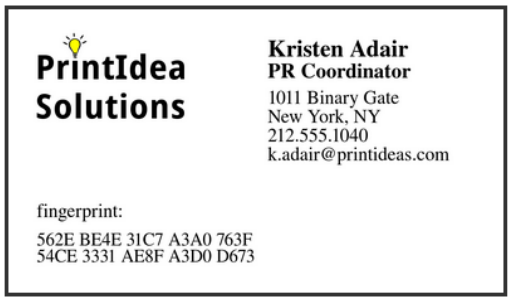
[if missed attack]

You incorrectly answered the following security check.

Security Check

Please compare the following fingerprint to the one shown on the business card.

562E C7BF 77C7 BA6E 8B3F
541E 0BB2 09B0 69EC 1973



Why do you think you failed to notice that the fingerprint shown on the business card did not match the one shown in the security check dialog?

[textbox]

[if caught attack]

You correctly answered the following security check.

[image of comparison dialog for attack instance]

What tipped you off that the fingerprint shown on the business card did not match the one shown in the security check dialog?

[textbox]

Please describe your strategy for comparing fingerprints to determine if they are the same or different.

[textbox]

What is the highest level of education you have completed?
◯ Elementary school only
◯ Some high school but did not finish
◯ Graduated from high school
◯ Some college but did not finish
◯ Two year college degree or A.A. or A.S.
◯ Four year college degree or B.A. or B.S.
◯ Some graduate school
◯ Graduate degree
◯ Prefer not to answer

What is your age (optional)?

What is your gender?
◯ Male
◯ Female
◯ Prefer not to answer

Which of the following best describes your primary occupation?
◯ Administrative Support (e.g. secretary, assistant)
◯ Art, Writing, or Journalism (e.g. author, reporter, sculptor)
◯ Business, Management, or Financial (e.g. manager, accountant, banker)
◯ Education or Science (e.g. teacher, professor, scientist)
◯ Legal (e.g. lawyer)
◯ Medical (e.g. doctor, nurse, dentist)
◯ Computer Engineering or IT Professional (e.g. programmer, IT consultant)
◯ Engineer in other field (e.g. Civil or bio engineer)
◯ Service (e.g. retail clerk, server)
◯ Skilled Labor (e.g. electrician, plumber, carpenter)

◯ Unemployed
◯ Retired
◯ College student
◯ Graduate student
◯ Prefer not to answer

Do you know any programming languages?
◯ Yes (list languages) [textbox]
◯ No

People often ask me for computer-related advice.
◯ Strongly agree
◯ Agree
◯ Neither agree nor disagree
◯ Disagree
◯ Strongly disagree

Did you encounter any technical issues while completing this HIT?

[textbox]

Please provide any additional feedback you have about this HIT.

[textbox]

C.3 Subjective ratings for fingerprint comparison tasks

Figures C.1, C.2, and C.3 summarize participants responses to usability-related survey questions about the fingerprint comparison task.

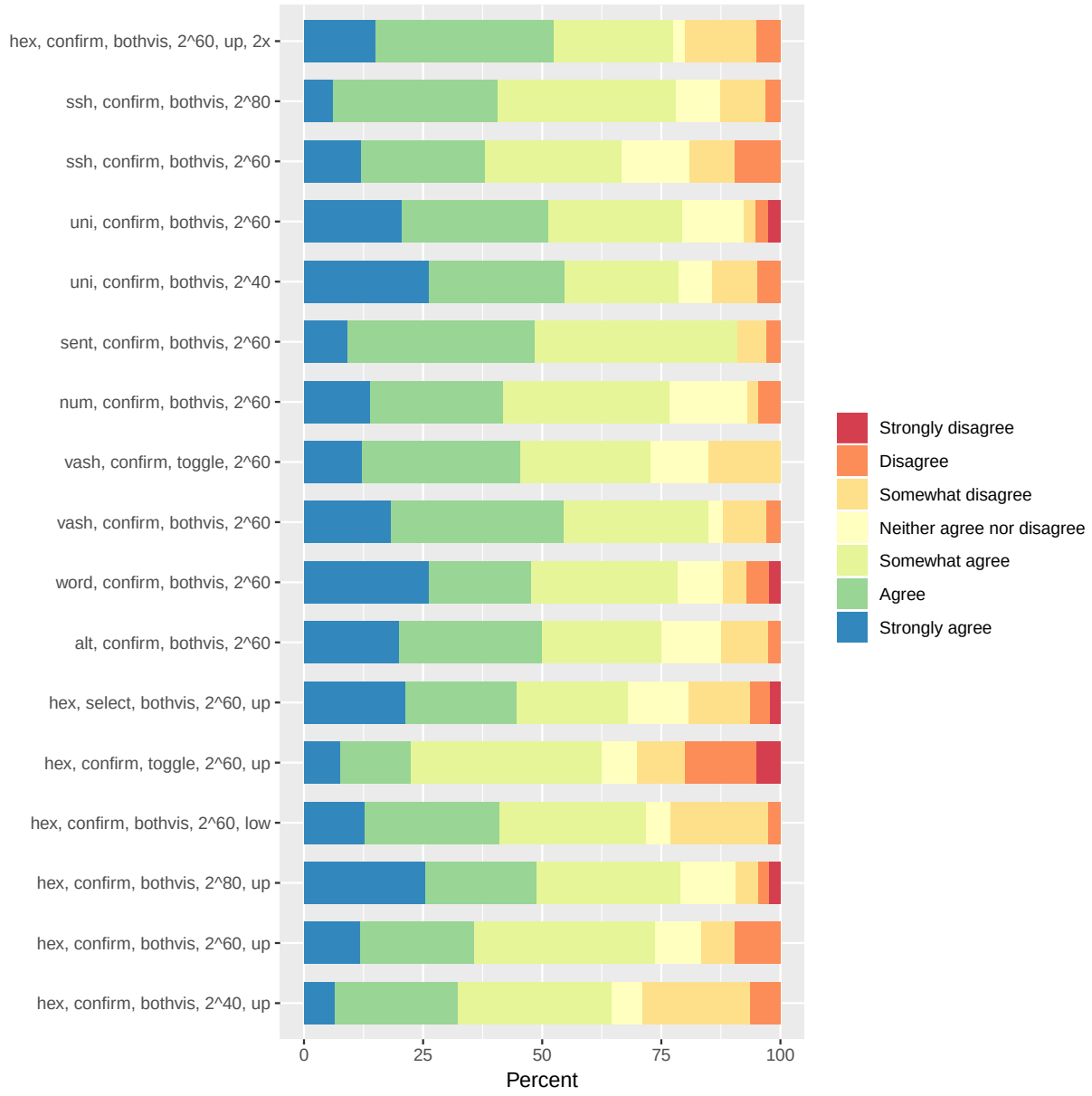


Figure C.1: Responses to the statement "It was easy to determine if fingerprints were the same or different."

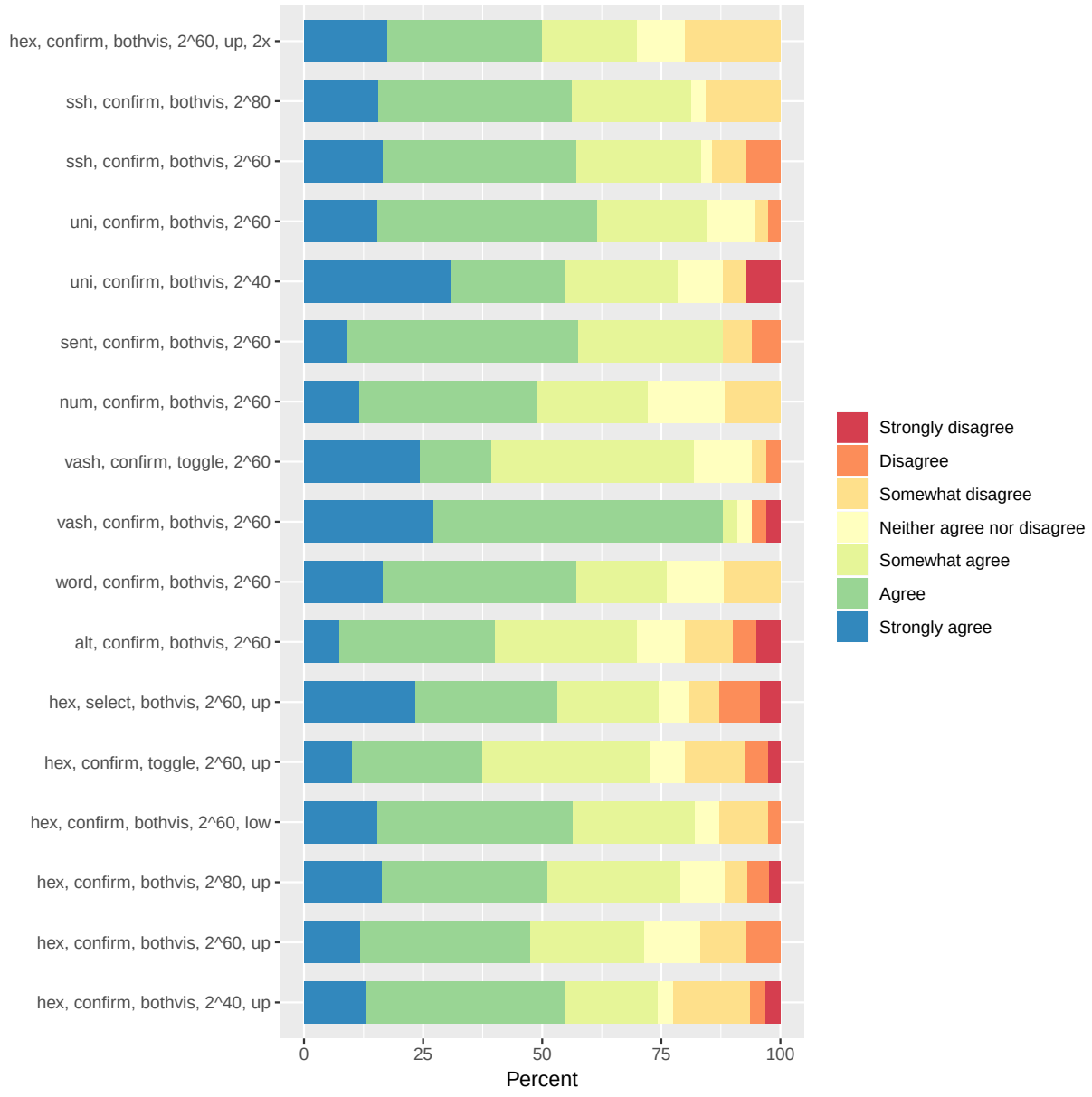


Figure C.2: Responses to the statement "The amount of time it took to compare fingerprints is reasonable for a security check."

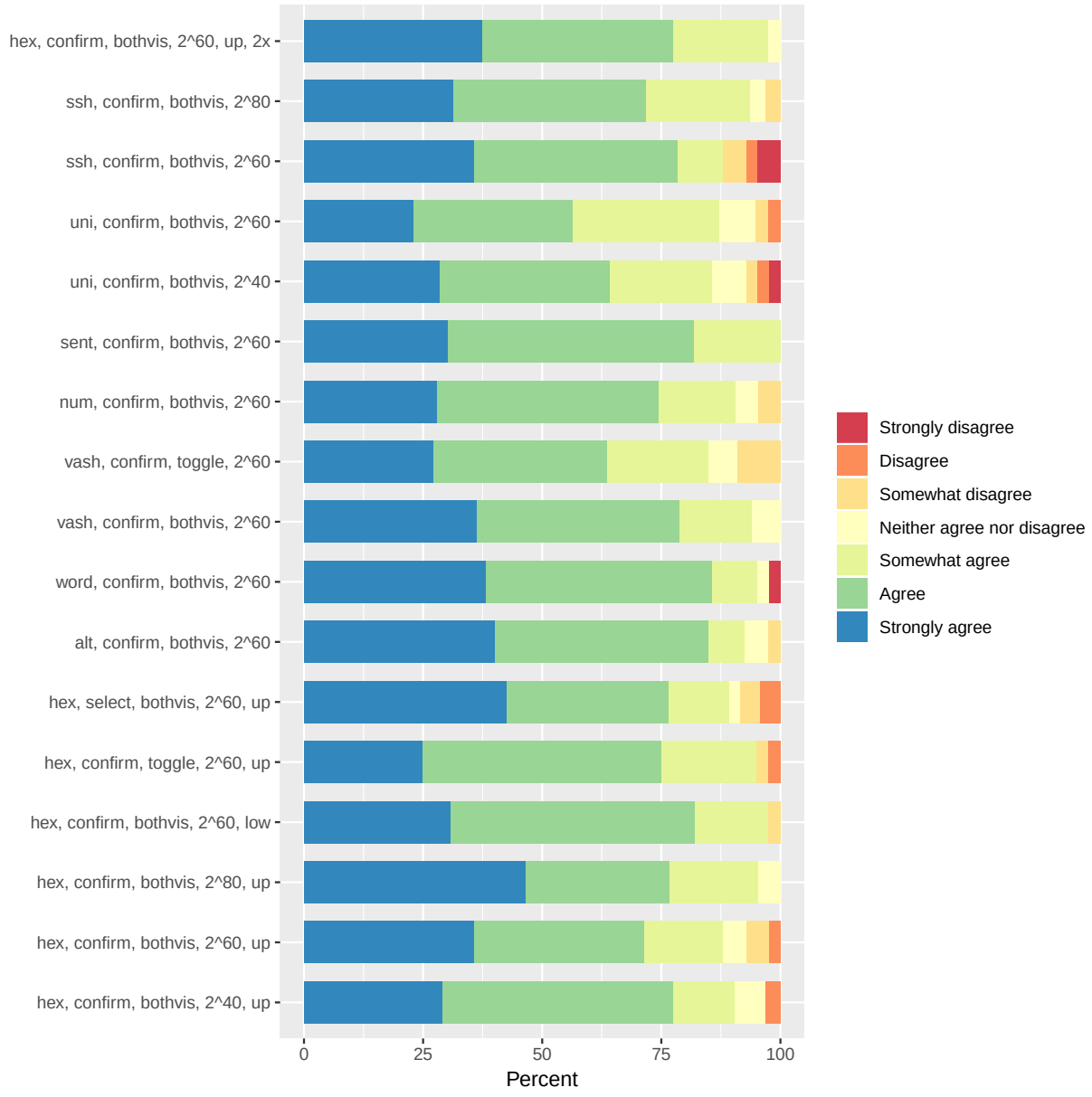


Figure C.3: Responses to the statement "I feel confident that I could correctly compare fingerprints for a security check."

C.4 Attacks

Here are the attacks used in our experiment. Attack #'s appearing in captions correspond to the attack IDs shown in Figure 4 of the paper.

Figure C.4: **hex**, confirm, bothvis, 2^{60}: Attack #1

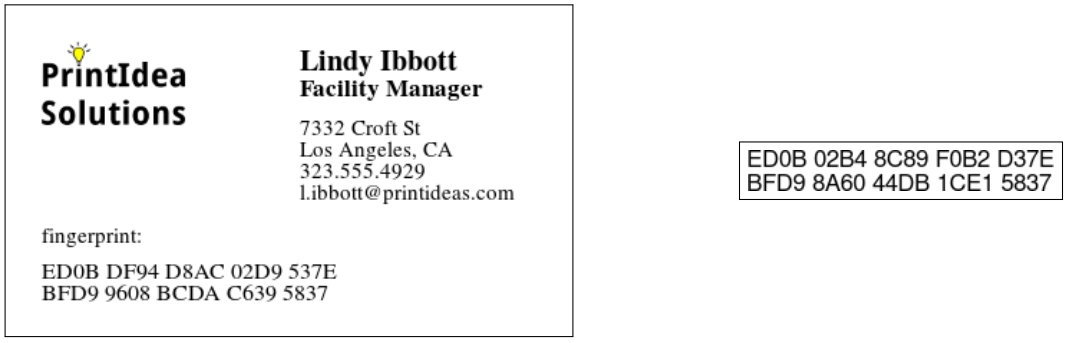


Figure C.5: **hex**, confirm, bothvis, 2^{60}: Attack #2

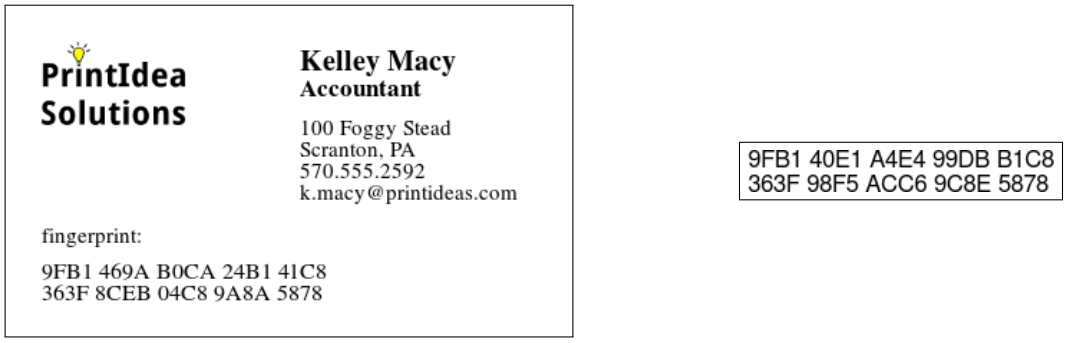


Figure C.6: **hex**, confirm, bothvis, 2^{60}: Attack #3

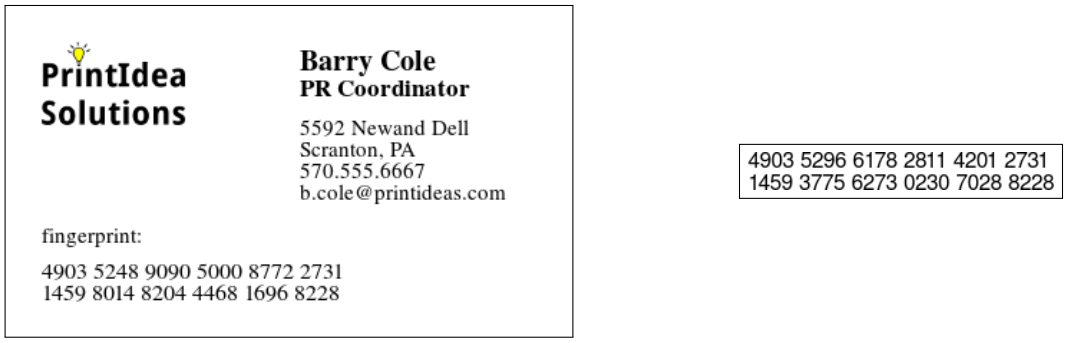


Figure C.7: **num**, confirm, bothvis, 2^{60}: Attack #1

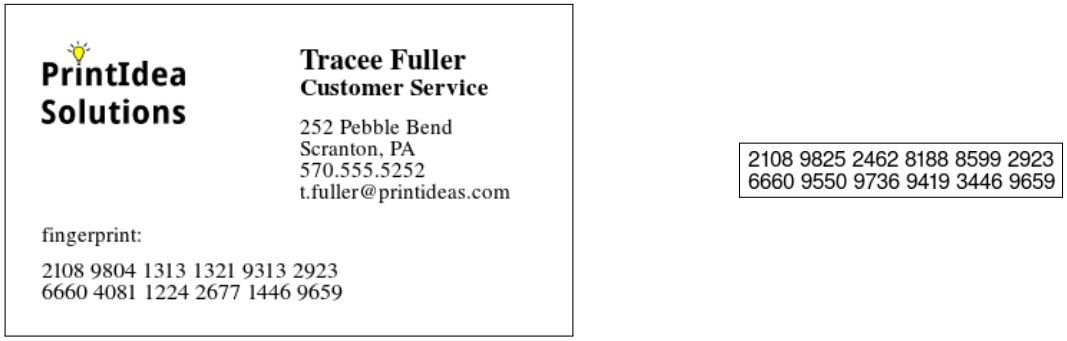


Figure C.8: **num**, confirm, bothvis, 2^{60}: Attack #2

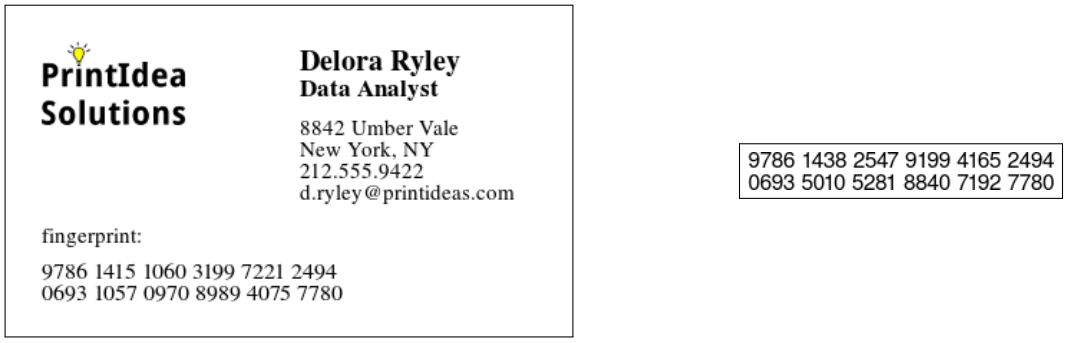


Figure C.9: **num**, confirm, bothvis, 2^{60}: Attack #3

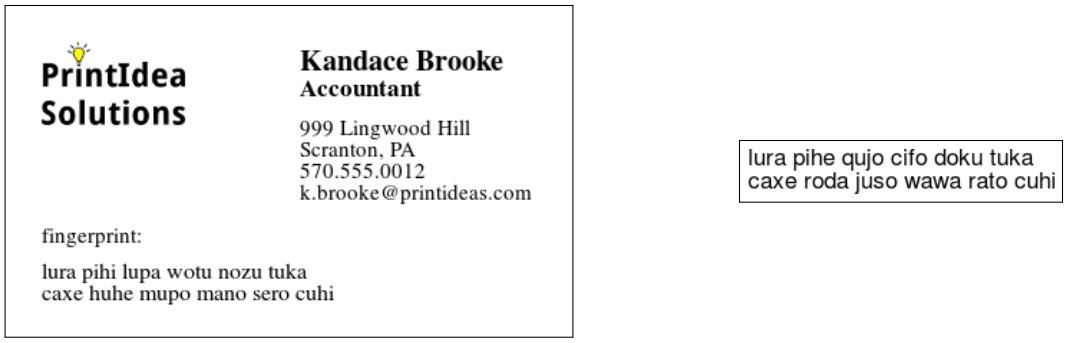


Figure C.10: **alt**, confirm, bothvis, 2^{60}: Attack #1

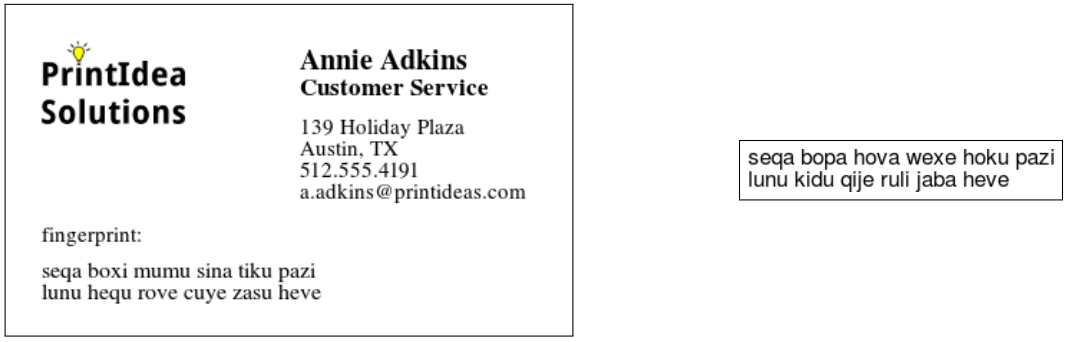


Figure C.11: **alt**, confirm, bothvis, 2^{60}: Attack #2

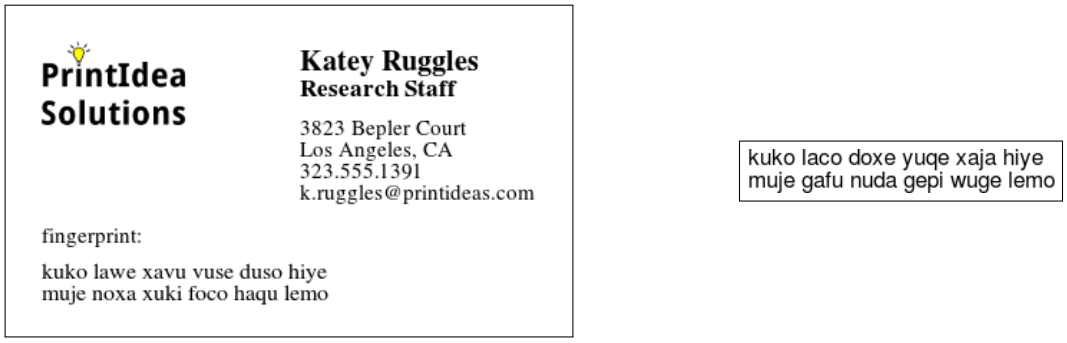


Figure C.12: **alt**, confirm, bothvis, 2^{60}: Attack #3

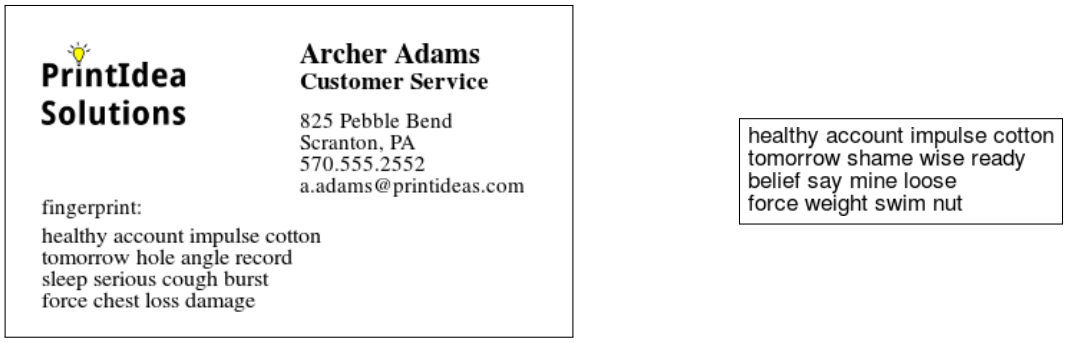


Figure C.13: **word**, confirm, bothvis, 2^{60}, Attack #1

Figure C.14: **word**, confirm, bothvis, 2^{60}: Attack #2

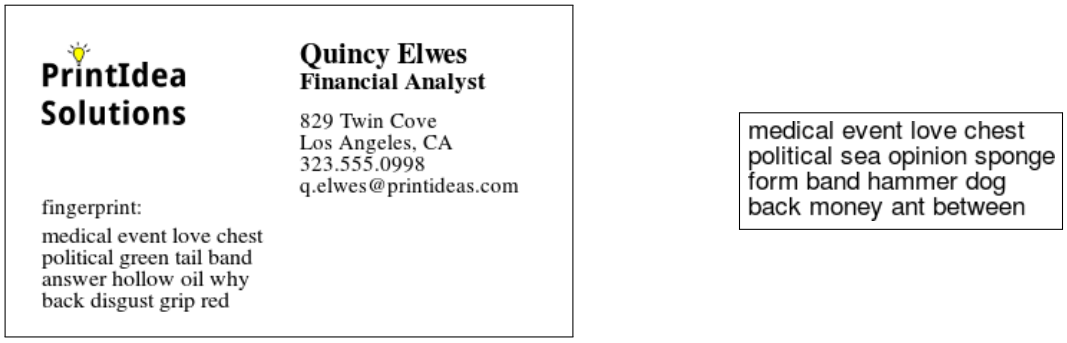


Figure C.15: **word**, confirm, bothvis, 2^{60}: Attack #3

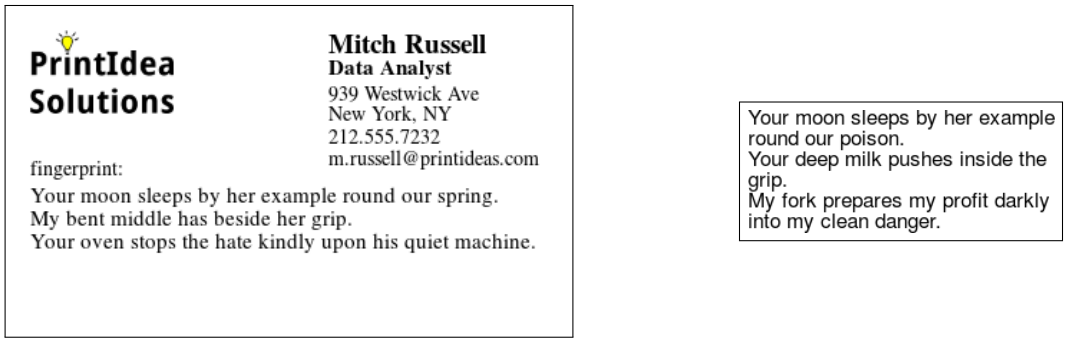


Figure C.16: **sent**, confirm, bothvis, 2^{60}: Attack #1

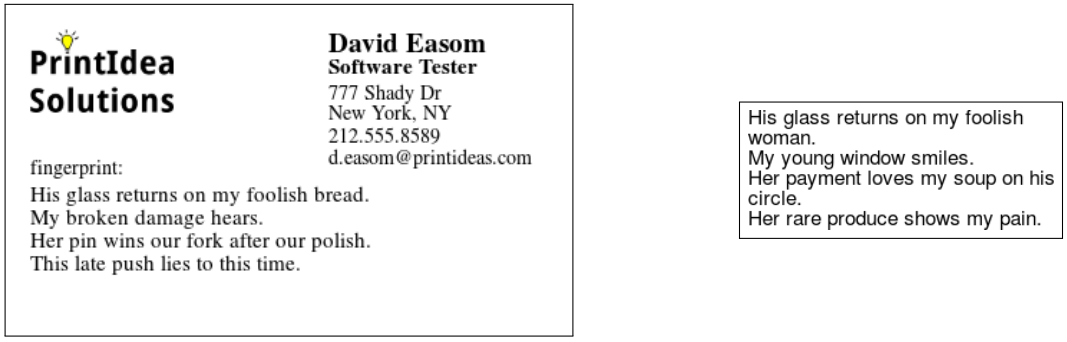


Figure C.17: **sent**, confirm, bothvis, 2^{60}: Attack #2

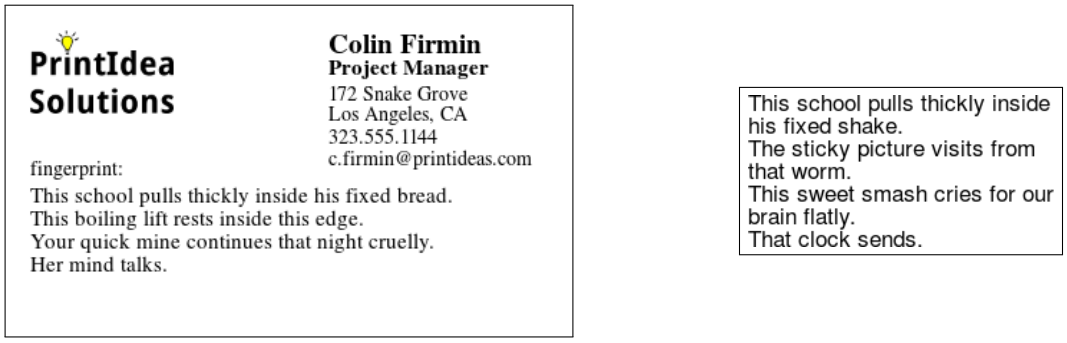


Figure C.18: **sent**, confirm, bothvis, 2^{60}: Attack #3

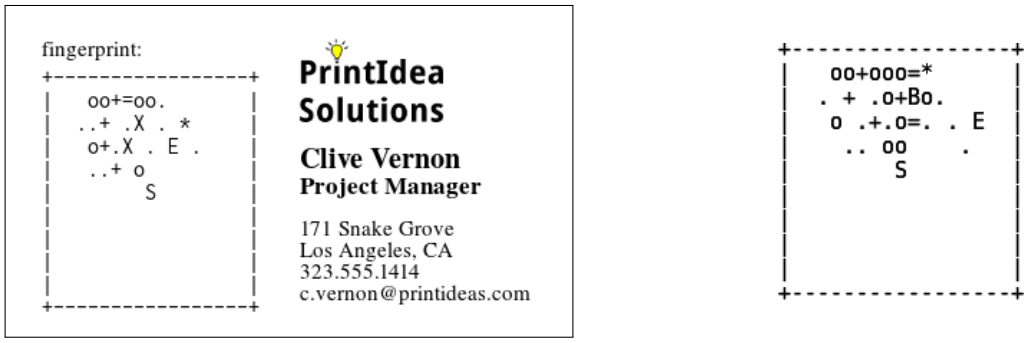


Figure C.19: **ssh**, confirm, bothvis, 2^{60}: Attack #1

Figure C.20: **ssh**, confirm, bothvis, 2^{60}: Attack #2

Figure C.21: **ssh**, confirm, bothvis, 2^{60}: Attack #3

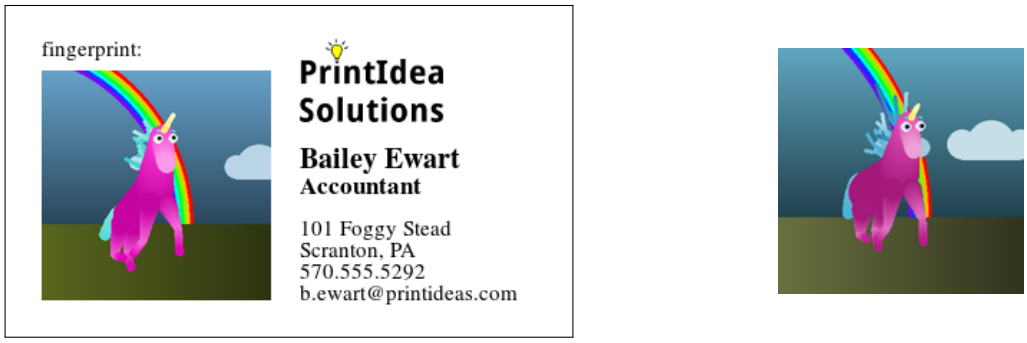


Figure C.22: **uni**, confirm, bothvis, 2^{60}: Attack #1

Figure C.23: **uni**, confirm, bothvis, 2^{60}: Attack #2

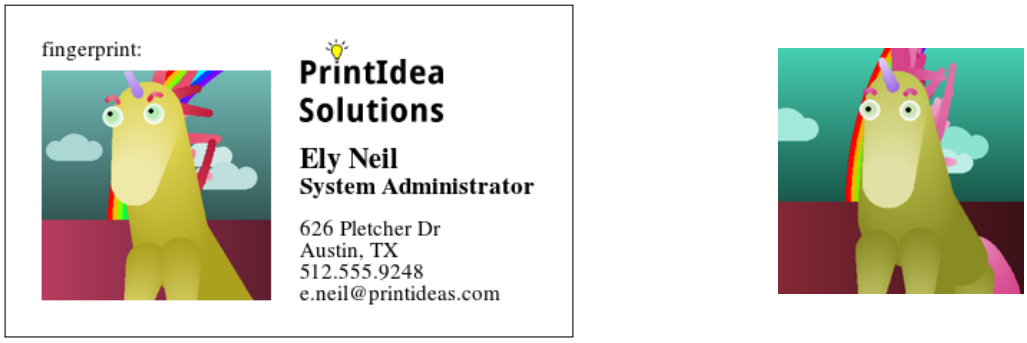


Figure C.24: **uni**, confirm, bothvis, 2^{60}: Attack #3

Figure C.25: **vash**, confirm, bothvis, 2^{60}: Attack #1

Figure C.26: **vash**, confirm, bothvis, 2^{60}: Attack #2

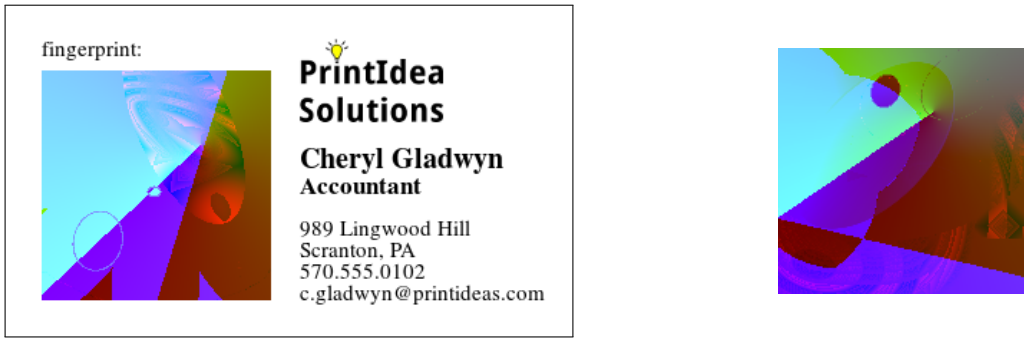


Figure C.27: **vash**, confirm, bothvis, 2^{60}: Attack #3

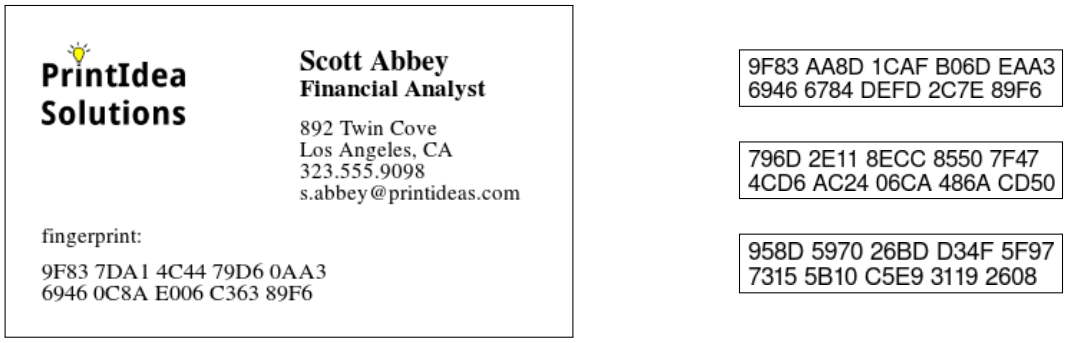


Figure C.28: hex, **select**, bothvis, 2^{60}: Attack #1

Figure C.29: hex, **select**, bothvis, 2^{60}: Attack #2

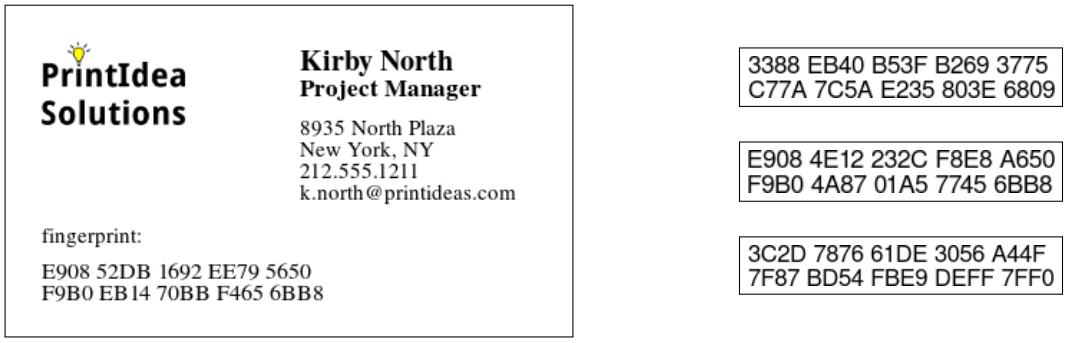


Figure C.30: hex, **select**, bothvis, 2^{60}: Attack #3

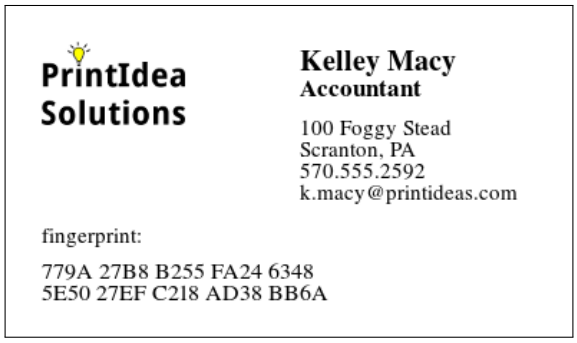


Figure C.31: hex, confirm, **toggle**, 2^{60}: Attack #1

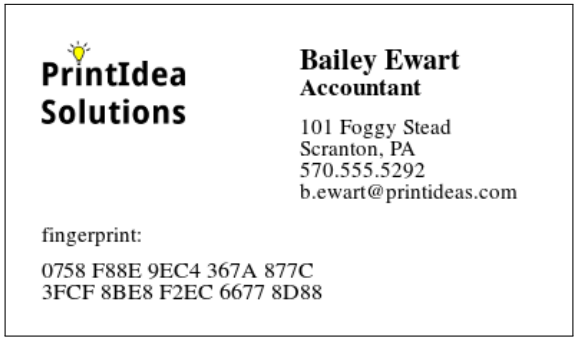


Figure C.32: hex, confirm, **toggle**, 2^{60}: Attack #2

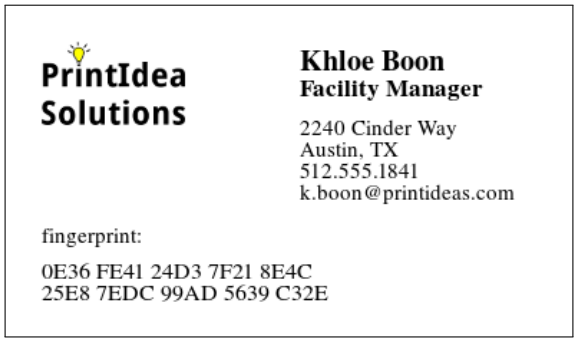


Figure C.33: hex, confirm, **toggle**, 2^{60}: Attack #3

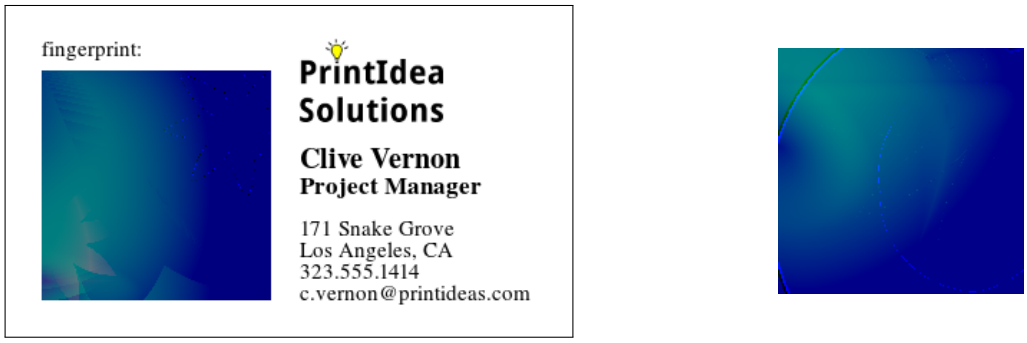


Figure C.34: vash, confirm, **toggle**, 2^{60}: Attack #1

Figure C.35: vash, confirm, **toggle**, 2^{60}: Attack #2

Figure C.36: vash, confirm, **toggle**, 2^{60}: Attack #3

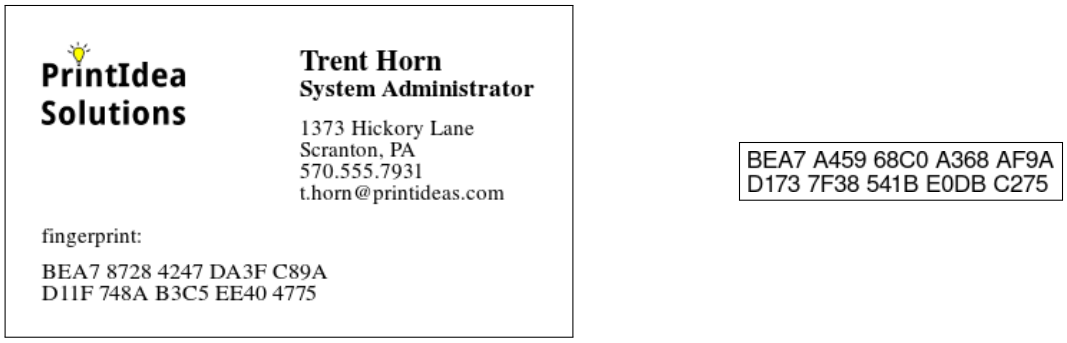


Figure C.37: hex, confirm, bothvis, $\mathbf{2^{40}}$: Attack #1

Figure C.38: hex, confirm, bothvis, $\mathbf{2^{40}}$: Attack #2

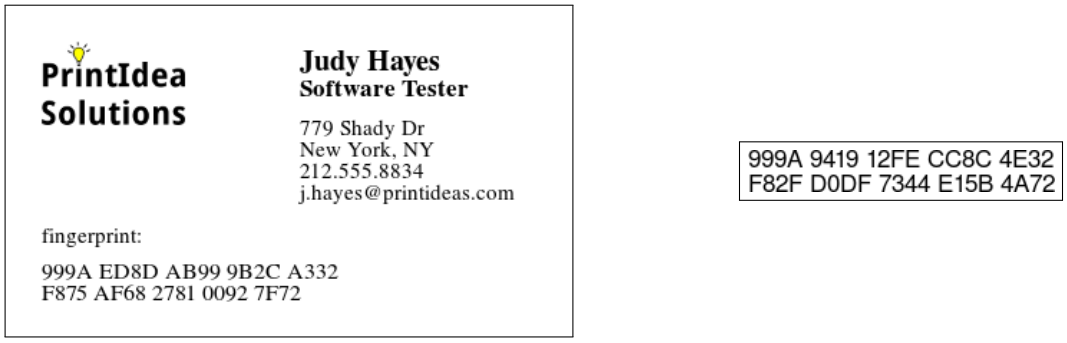


Figure C.39: hex, confirm, bothvis, $\mathbf{2^{40}}$: Attack #3

Figure C.40: uni, confirm, bothvis, $\mathbf{2^{40}}$: Attack #1

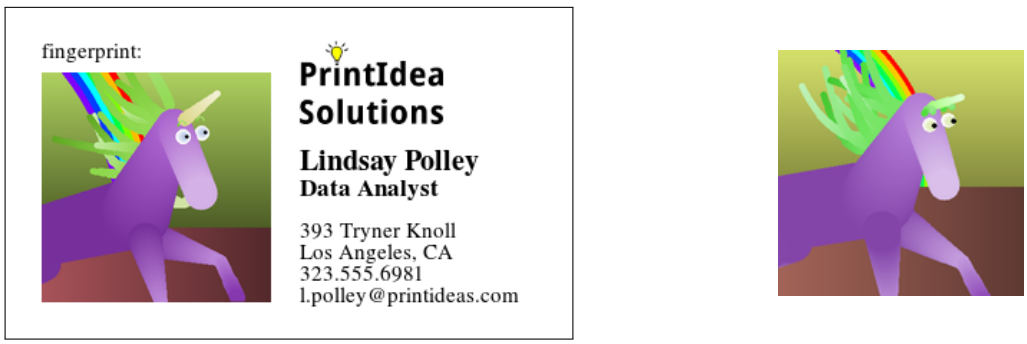


Figure C.41: uni, confirm, bothvis, $\mathbf{2^{40}}$: Attack #2

Figure C.42: uni, confirm, bothvis, $\mathbf{2^{40}}$: Attack #3

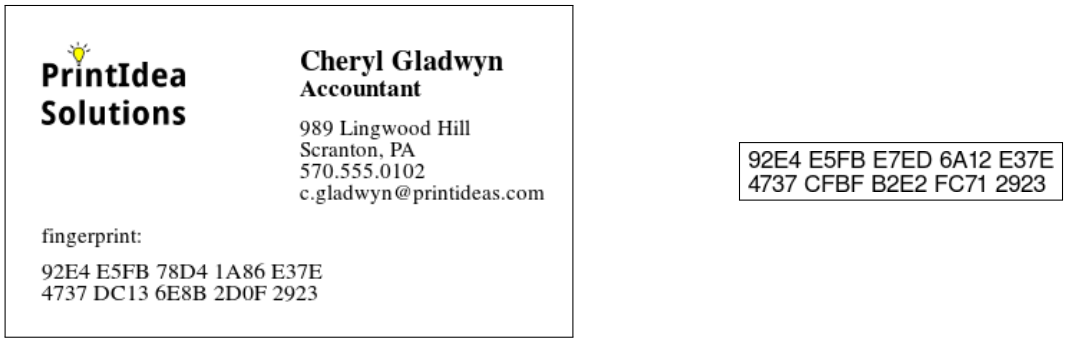


Figure C.43: hex, confirm, bothvis, $\mathbf{2^{80}}$: Attack #1

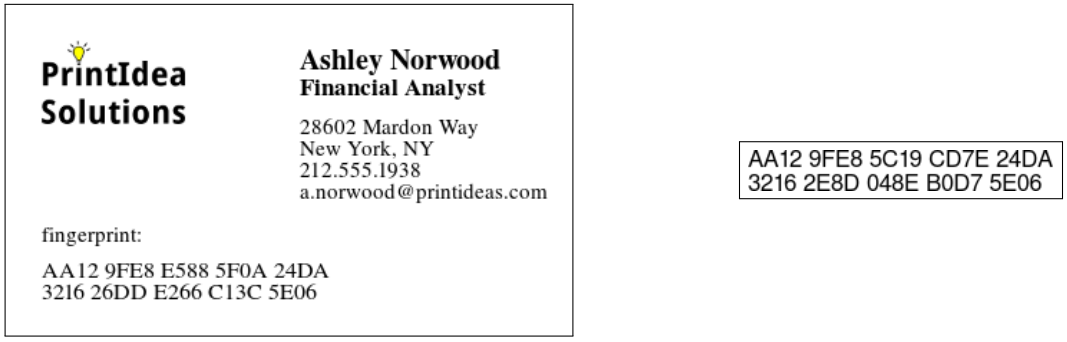


Figure C.44: hex, confirm, bothvis, $\mathbf{2^{80}}$: Attack #2

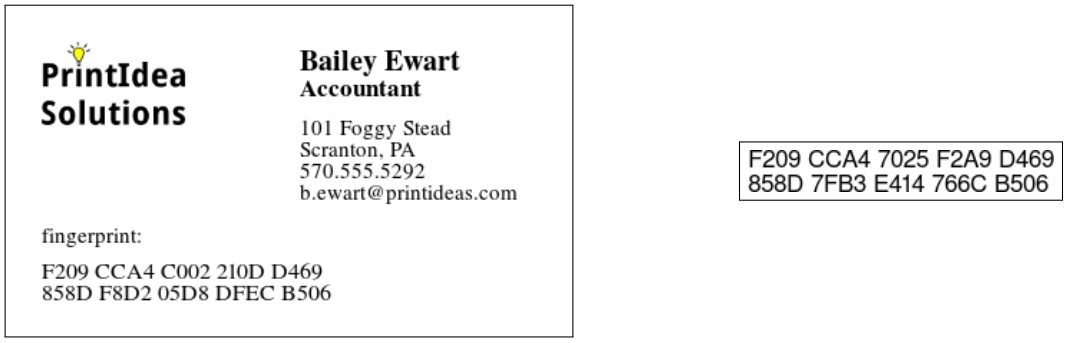


Figure C.45: hex, confirm, bothvis, $\mathbf{2^{80}}$: Attack #3

Figure C.46: ssh, confirm, bothvis, $\mathbf{2^{80}}$: Attack #1

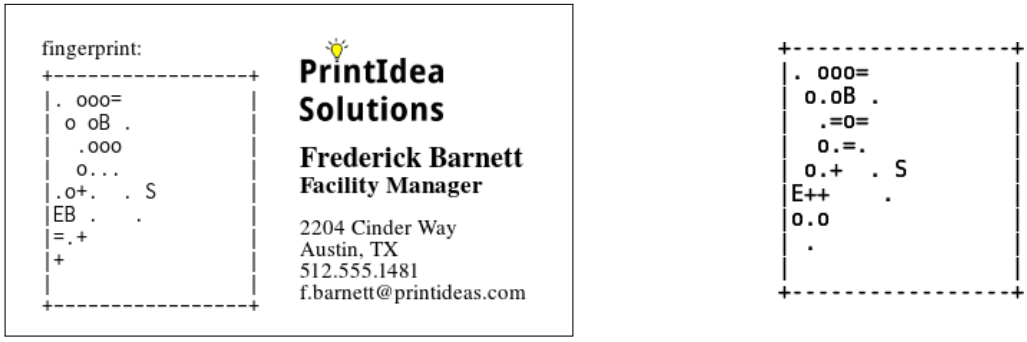


Figure C.47: ssh, confirm, bothvis, $\mathbf{2^{80}}$: Attack #2

Figure C.48: ssh, confirm, bothvis, $\mathbf{2^{80}}$: Attack #3

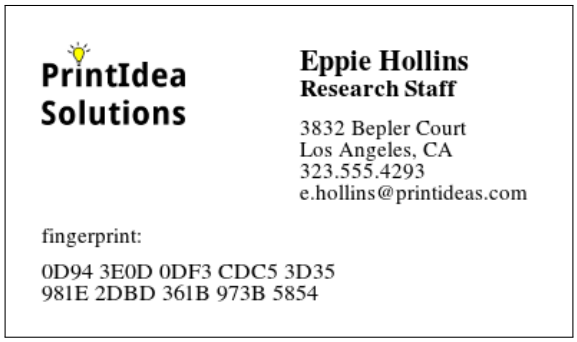


Figure C.49: hex, confirm, bothvis, 2^{60}, **2x time**: Attack #1

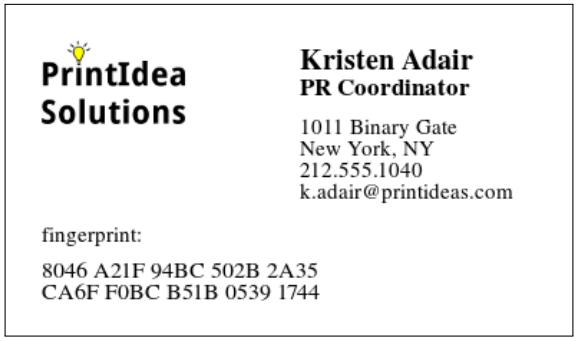


Figure C.50: hex, confirm, bothvis, 2^{60}, **2x time**: Attack #2

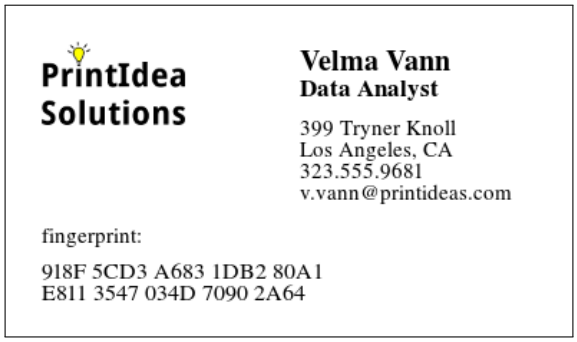


Figure C.51: hex, confirm, bothvis, 2^{60}, **2x time**: Attack #3

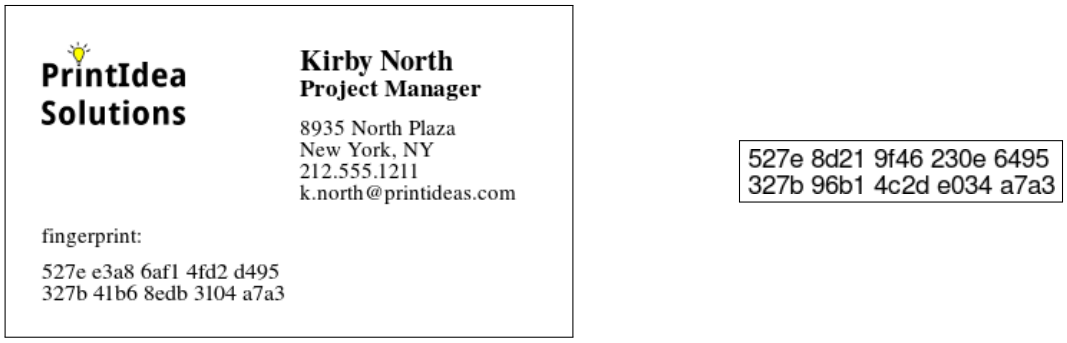


Figure C.52: **hex (low)**, confirm, bothvis, 2^{60}: Attack #1

Figure C.53: **hex (low)**, confirm, bothvis, 2^{60}: Attack #2

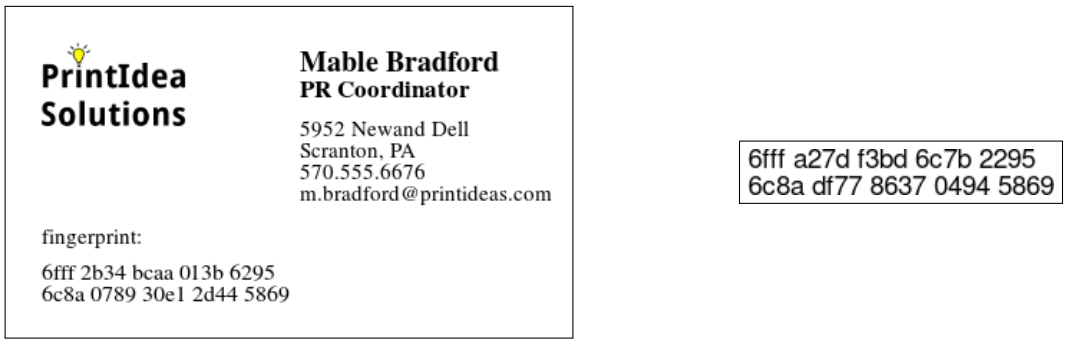


Figure C.54: **hex (low)**, confirm, bothvis, 2^{60}: Attack #3