Statistical Text Analysis for Social Science

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MACHINE LEARNING
DEPARTMENT

Carnegie Mellon

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Abstract

What can text corpora tell us about society? How can automatic text analysis algorithms efficiently and reliably analyze the social processes revealed in language production?

This work develops statistical text analyses of dynamic social and news media datasets to extract indicators of underlying social phenomena, and to reveal how social factors guide linguistic production. This is illustrated through three case studies: first, examining whether sentiment expressed in social media can track opinion polls on economic and political topics (Chapter 3); second, analyzing how novel online slang terms can be very specific to geographic and demographic communities, and how these social factors affect their transmission over time (Chapters 4 and 5); and third, automatically extracting political events from news articles, to assist analyses of the interactions of international actors over time (Chapter 6).

We demonstrate a variety of computational, linguistic, and statistical tools that are employed for these analyses, and also contribute *MiTextExplorer*, an interactive system for exploratory analysis of text data against document covariates, whose design was informed by the experience of researching these and other similar works (Chapter 2). These case studies illustrate recurring themes toward developing text analysis as a social science methodology: computational and statistical complexity, and domain knowledge and linguistic assumptions.

Acknowledgments

This work has been made possible only through rich collaborations and conversations with a wide variety of colleagues at both Carnegie Mellon (including the Noah's ARK lab and the Machine Learning Department) and many other institutions. Thanks to everyone for all the support and learning that influenced this work, from people including but not limited to: Yisong Yue, Dani Yogatama, Tae Yano, Min Xu, Eric Xing, Matt Wytock, Hanna Wallach, Johan Ugander, Dustin Tingley, Ryan Tibshirani, Sam Thomson, Andrew Thomas, Eric Sun, Brandon Stewart, Rion Snow, Alex Smola, Noah Smith, Yanchuan Sim, Cosma Shalizi, Phil Schrodt, Nathan Schneider, Aaron Schein, Bryan Routledge, Molly Roberts, Philip Resnik, Joseph Reisinger, Dan Ramage, Patrick Perry, Olutobi Owoputi, John Myles White, Burt Monroe, Tom Mitchell, Brendan Meeder, Andre Martins, Cameron Marlow, Yucheng Low, Michael Love, Jayant Krishnamurthy, Michel Krieger, Lingpeng Kong, Gary King, Rob Kass, Venky Iyer, Muhammed Idris, Qirong Ho, Michael Heilman, Alex Hanna, Aria Haghighi, Forest Gregg, Joey Gonzalez, Kevin Gimpel, Matt Gardner, Alona Fyshe, Seth Flaxman, Jeffrey Flanigan, Jenny Finkel, Khalid El-Arini, Jacob Eisenstein, Chris Dyer, Jesse Dodge, Dipanjan Das, Justin Cranshaw, Fred Conrad, William Cohen, Shay Cohen, Jonathan Chang, Andrew Carlson, Dallas Card, Lukas Biewald, Justin Betteridge, John Beieler, David Bamman, Ramnath Balasubramanyan, Erin Baggott, Lars Backstrom, Waleed Ammar, and David Ahn. My apologies for any omissions. Thanks most of all to my family and friends for all their support and encouragement.

Contents

Chapter 1

Text analysis for the social sciences

(Parts of this chapter were originally published as O'Connor et al. (2011).)

1.1 Introduction

Corpora of news, books, and social media encode human beliefs and culture. While labor-intensive manual content analysis is a well-established method in the social sciences—going back decades or even centuries (Krippendorff, 2012)—interest in automated text analysis has exploded in recent years, since it is impossible for a person to read all of these rapidly growing archives. Automated methods can help measure and discover patterns and themes described in text corpora: records of opinions, events, and ideas held by participants. Recent reviews, tutorials and workshops on automated text analysis range from political science (Grimmer and Stewart, 2013) to the humanities (Shaw, 2012), with a presence at meetings including *New Directions in Analyzing Text as Data*, *Digital Humanities*, and many computer science conferences such as *ACL, EMNLP, CIKM, ICWSM*, etc.

Researchers have considered a great breadth of questions. Just within academic research, there exist many examples from political science to literature analysis (Figure 1.2). In these works, text analysis is a methodological tool used in service of social science or humanistic questions, where the textual data has been created as the outcome of a socially embedded generation process. This is illustrated in Figure 1.1. A text generation process (*Generator*), constrained by variables of social context (*SocialAttributes*), produces linguistic text data (*Text*). This can be thought of as a stochastic function,

$$\text{Generator(SocialAttributes)} \mapsto \text{Text}$$

This thesis develops several case studies that are instances of analyzing this process. For example, Chapter 4 studies geographic lexical variation, in which an author's social context is represented as their geographic location. The parameters of the text generation process represent how people in different locations choose to talk about different topics or use different words to talk about them. (Maybe this is due to local topics of interest, or to geographic locality of social communities, which guide people's interests and vocabulary.)

Given observed text data, researchers would like to conduct inference to reverse the text generation process and learn about either social variables or the parameters of the generation process (how social context turns into language). For the geographic example, if we have a dataset of authors with both locations and text, we can learn the parameters of the text generation process,

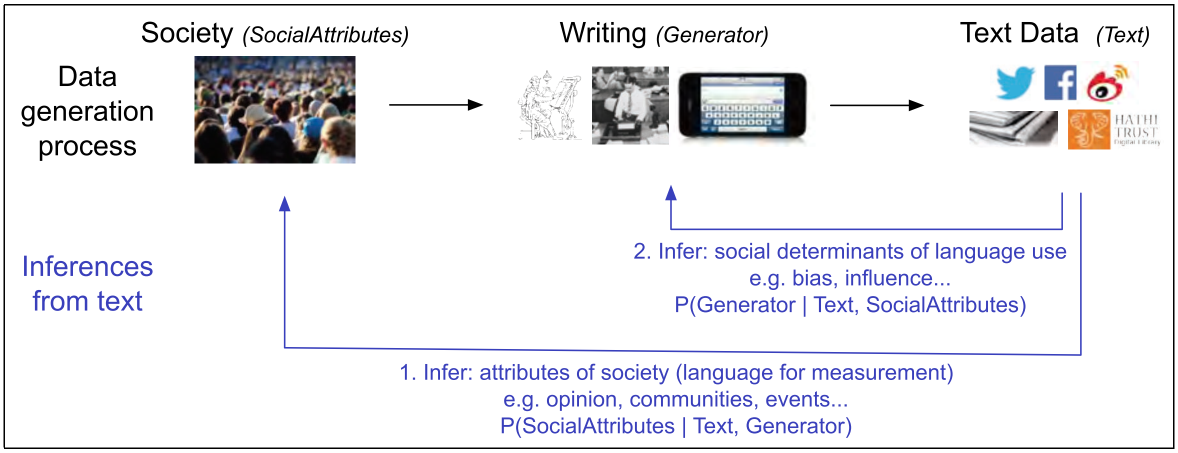

Society (SocialAttributes)
Writing (Generator)
Text Data (Text)
Data generation process
HATHI TRUST
Inferences from text
2. Infer: social determinants of language use
e.g. bias, influence...
P(Generator | Text, SocialAttributes)
1. Infer: attributes of society (language for measurement)
e.g. opinion, communities, events...
P(SocialAttributes | Text, Generator)

Figure 1.1: Overview: social production of text and the possibilities of text analysis.

which describe the differences in word and topic usage in different locations. We could also compare different hypotheses about this process. Furthermore, given such an inferred model, we can also infer the locations for new authors by analyzing their text.

Using a Bayesian notation for inference among these three groups of variables (*Text, Generator, SocialAttributes*), there exist two broader classes of text analyses in light of social questions:

1. **Language for social measurement:** $P(\text{SocialAttributes} \mid \text{Text}, \text{Generator})$

   The goal here is to infer attributes of society or individuals that are reliably discernible in textual content. For use in such a measurement instrument, text data might have useful properties; for example, it may be cheaper to acquire than surveys or interview methods. This typically requires assumptions about the the text generation process. For example, we might take Associated Press articles at their word and extract political events that they are reporting on, and use this as a measurement of how real-world politics changes over time (Chapter 6).

2. **Language generation as social mechanism:** $P(\text{Generator} \mid \text{Text}, \text{SocialAttributes})$

   It is critical to understand where the text comes from—the parameters of the text generation process. Language production is deeply embedded in social factors and subject to their biases and influence. Understanding how these factors shape the text is a question in itself. For example, instead of taking news articles at their word, we might analyze how different news sources report things differently—perhaps this is biased by media ownership or political perspectives.

Both types of analysis assume the existence of a statistical relationship between text and social context variables. Text variables may include words, phrases, named entities, or semantic argument structures; social context variables may include the author's community, characteristics, opinions, or a document's embedding in time and space. The parameters of the text generation process encompass social behavior and linguistic production, from individual-level psychological effects (e.g. people's mood might affect how they write), to macro-level trends (e.g. the popularity of topics over time within an academic community) or organizational effects (e.g. economic pressures on publishing companies might affect news coverage).

- Political Science: How do U.S. Senate speeches reflect agendas and attention? How are Senate institutions changing (Quinn et al., 2010)? What are the agendas expressed in Senators' press releases (Grimmer, 2010)? Do U.S. Supreme Court oral arguments predict justices' voting behavior (Black et al., 2011)? Does social media reflect public political opinion, or forecast elections (O'Connor et al., 2010a; Metaxas et al., 2011; Gayo-Avello, 2012)? What determines international conflict and cooperation (Schrodt et al., 1994; King and Lowe, 2003; Shellman, 2008; O'Connor et al., 2013)? How much did racial attitudes affect voting in the 2008 U.S. presidential election (Stephens-Davidowitz, 2012)?

- Economics: How does sentiment in the media affect the stock market (Tetlock, 2007; Lavrenko et al., 2000)? Does sentiment in social media associate with stocks (Gilbert and Karahalios, 2010; Das and Chen, 2007; Bollen et al., 2010)? Do a company's SEC filings predict aspects of stock performance (Kogan et al., 2009; Loughran and McDonald, 2011)? What determines a customer's trust in an online merchant (Archak et al., 2011)? How can we measure macroeconomic variables with search queries and social media text (Askitas and Zimmermann, 2009; Kahn and Kotchen, 2010; O'Connor et al., 2010a)? Can Internet data forecast consumer demand for movies (Asur and Huberman, 2010; Joshi et al., 2010)?

- Psychology: How does a person's mental and affective state manifest in their language (Tausczik and Pennebaker, 2009)? Are diurnal and seasonal mood cycles cross-cultural (Golder and Macy, 2011)?

- Sociology of Science: What are influential topics within a scientific community (Gerrish and Blei, 2010)? What determines a paper's citations (Bethard and Jurafsky, 2010; Ramage et al., 2011; Yogatama et al., 2011)?

- Sociolinguistics: How do geography (Labov et al., 2006; Nerbonne, 2009; Eisenstein et al., 2010), gender (Bamman et al., 2014), class, race, and other social factors (Tagliamonte, 2006; O'Connor et al., 2010b; Eisenstein et al., 2011c) influence linguistic variation, and the lexical diffusion process?

- Public Health: How can search queries and social media help measure levels of the flu and better understand other public health issues (Ginsberg et al., 2009; Culotta, 2010; Paul and Dredze, 2011; Broniatowski et al., 2013)?

- History: How did modern English legal institutions develop over the 17th to 20th centuries (Cohen et al., 2011)? When did concepts of religion, secularism, and social institutions develop over two millennia of Latin literature (Bamman and Crane, 2011)? What do topic labels in a historical encyclopeda reveal about contemporary ways of thought (Horton et al., 2009)?

- Literature: How do demographic determinants of fictional characters affect their language use (Argamon et al., 2009)? Who is the true author of a work of literature or historical documents (Holmes, 1998); for example, Shakespeare (Craig and Kinney, 2009) or the Federalist Papers (Mosteller and Wallace, 1964)?

Figure 1.2: A small sample of social scientific and humanistic questions to which automated text analysis methods have been applied.

While it is useful to distinguish these two types of analysis goals, they are also complementary and can sometimes reuse the same analysis methods. If a model of text can predict social variables (the measurement goal), this gives predictive validity to its text generation parameters (the parameter understanding goal).

1.2 Text analysis methods

How should we actually do these analyses, quantitatively speaking? One attractive framework, implied by the notation and description used above, is probabilistic generative modeling: test and develop models of the data-generating process, and use Bayes rule to invert them to infer the quantities of interest. Some of the work in this thesis directly uses this approach for specific aspects of social text generation, like the geographic and demographic topic model in Section 4.2. In the long-term, our research program should strive for this ambitious goal: develop a unified model of human social and linguistic behavior, from which many interesting inferences and predictions can be derived.

At the same time, social science and linguistics are vast and complex fields, and scientific progress must proceed by deductive process of developing and exploring hypotheses concerning many different scientific questions.[1] There exist many fascinating social questions, and a tangle of interesting but often messy text data to query for clues to their answers. Therefore social text analysis should proceed under a *data analytic* approach, incorporating a variety tools from statistics, social science methods, machine learning, and natural language processing. Since these are still early times in the study of language and social behavior, we need to explore a wide variety of methods, and better understand which of them are useful and when. A useful view is to think of automated text analysis as quantitative tools for social science investigations: quantitative methods, alongside traditional qualitative methods, are just another set of tools to investigate core questions of sociology, political science, and economics, and other areas (King et al., 1994).

There are easily dozens of automated text analysis methods that have been used in previous work or could be useful in future social analysis work. In order to help organize this area for practitioners, we suggest thinking about them on three dimensions:

1. Computational and statistical complexity
   (e.g. summary statistics, convex optimization, latent variable learning),

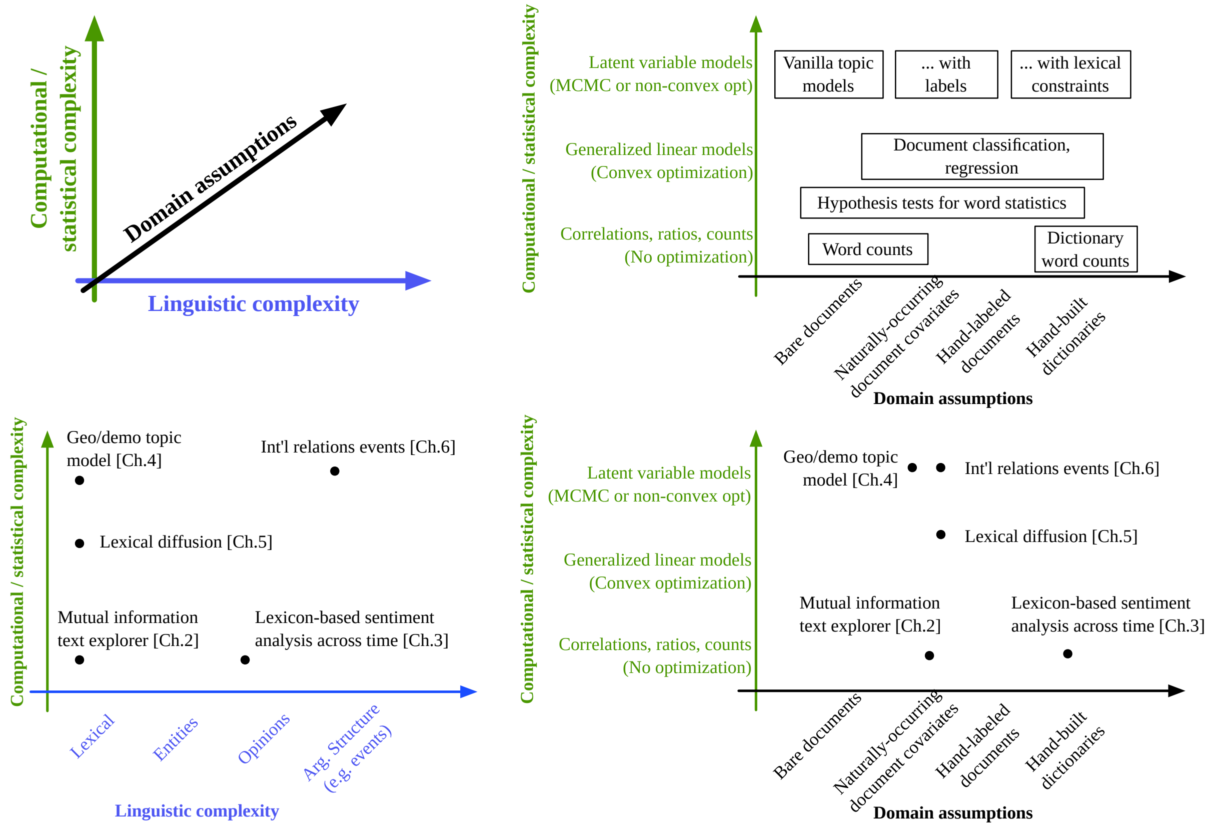
2. Amount of domain assumptions as input
   (e.g. document covariates, hand-built labels, hand-built dictionaries), and

3. Complexity of linguistic representation used in the analysis
   (e.g. word and phrases, entities, opinions, argument structure)

Figure 1.3 schematically illustrates these dimensions. The chapters of this thesis, consisting of tools and case studies, are shown on these dimensions; all of the studies listed at the start of this chapter could be placed on these dimensions as well.

Domain assumptions refer to how much knowledge of the substantive issue in question is used in the analysis.

[1] While Bayesian notation is useful to describe inferences among broad classes of variables, even if particular statistical techniques are Bayesian, scientific progress may proceed under deductive, not inductive, lines in any case (Gelman and Shalizi, 2013).


Computational / statistical complexity
Domain assumptions
Linguistic complexity
Computational / statistical complexity
Latent variable models (MCMC or non-convex opt)
Generalized linear models (Convex optimization)
Correlations, ratios, counts (No optimization)
Vanilla topic models
... with labels
... with lexical constraints
Document classification, regression
Hypothesis tests for word statistics
Word counts
Dictionary word counts
Bare documents
Naturally-occurring document covariates
Hand-labeled documents
Hand-built dictionaries
Domain assumptions
Computational / statistical complexity
Geo/demo topic model [Ch.4]
Int'l relations events [Ch.6]
Lexical diffusion [Ch.5]
Mutual information text explorer [Ch.2]
Lexicon-based sentiment analysis across time [Ch.3]
Lexical
Entities
Opinions
Arg. Structure (e.g. events)
Linguistic complexity
Computational / statistical complexity
Latent variable models (MCMC or non-convex opt)
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Lexicon-based sentiment analysis across time [Ch.3]
Bare documents
Naturally-occurring document covariates
Hand-labeled documents
Hand-built dictionaries
Domain assumptions

Figure 1.3: **Top:** Taxonomy of analysis methods, with some examples. **Bottom Left:** Work described in this thesis, compared on computation vs. linguistic complexity. **Bottom Right:** Compared on computation vs. domain assumptions.

- A **"bare documents"** analysis only considers the words of documents; for example, examining the most common words in a corpus, or co-occurrence patterns among words.
- **Document covariates** refer to non-textual metadata about the documents, which may have an interesting statistical relationship to the words. Typically this information takes the form of continuous, discrete, or ordinal variables associated with documents or segments of them.

  The examples in this thesis make extensive use of document covariates that represent social variables, such as time, geography, and demographics. From a strictly computational/statistical perspective, all covariates are not necessarily straightforwardly representative of social processes (for example, in Chapter 2 we use the book of the Bible as a covariate); therefore we use the term *covar* in the rest of this section.
- **Manually labeled documents** may be created in order to better understand particular quantities of interest; for example, annotating news articles with topics or perspectives they describe. Creating and evaluating the codebook (that carefully defines the semantics of the annotations a coder will produce) can be a laborious and iterative process, but is essential to understand the problem and create a reliable coding standard (Krippendorff, 2012). A traditional content analysis project uses manual labeling for all analysis, it can also be combined by computational techniques by relating the labels to textual data. From a strict computational/statistical perspective, a manual label is just another document covariate; the differ-

ence is that these are produced as part of the research process, as opposed to being part of the object under study. (This distinction is not always clear, of course; for example, correcting coding errors may be an essential data cleaning step.)

- Finally, another source of domain information can take the form of **dictionaries**: lists of terms of interest to the analysis, such as names, emotion-indicating words, event-indicating phrases, topic-specific keywords, etc. Ideally, they may be custom-built for the problem (if done manually, a labor-intensive task similar to coding documents), or they may be reused or adapted from already-existing dictionaries (e.g., Freebase (Bollacker et al., 2008) for names or LIWC (Tausczik and Pennebaker, 2009) for affect, though see Grimmer and Stewart (2013)'s critical comments on the naïve use of affect dictionaries). Useful information can be revealed with just a handful of terms; for example, Stephens-Davidowitz (2012) analyzes the Google search query frequencies of one highly charged racial epithet as a proxy for racial attitudes.

The second dimension is the complexity of the **linguistic representation**. Since natural language processing is inherently very difficult, these representations can only be identified imperfectly from text. For more complex representations, NLP systems tend to be less accurate and more computationally expensive. It is useful to catalogue important linguistic phenomena in text, since they comprise the potential objects of analysis.

- **Word and phrase** frequencies, ignoring their order in documents, is the most basic and essential linguistic representation—the "bag of words" representation. Word frequencies capture lexical variation, which is extremely important since words are most basic linguistic units of meaning in text. They are also practical, since words and phrases can often be identified through relatively simple programs for text tokenization.[2] All chapters in this thesis make extensive use of word and phrase frequencies; and they are the primary linguistic representation for Chapters 2–4.

- **Entities** are people, places, or organizations that the text refers to, typically when mentioned by name (a *named entity*). Often, particular actors or entities are the interesting subjects of analysis. Chapter 3, for example, analyzes messages that mention particular of political candidates, and Chapter 6 analyzes news articles' mentions of actors that represent different countries. Depending on the problem, entities might actually *not* be of interest: in Section 5 we seek to analyze the diffusion of novel slang terms, and actually exclude names from the analysis.

- **Opinions** about a topic are held by an opinion holder—perhaps the author of the document (for example, in a product review), or another entity mentioned in the text (Wiebe et al., 2005). One important aspect of an opinion might be a positive or negative opinion. Extracting opinions from text is often called *sentiment analysis*. Opinions are important for many social analysis problems, but are often difficult to reliably extract. Much work in this area uses word frequency approaches, which we apply in Chapter 3, though ongoing work in structured sentiment analysis will be important going forward.

- **Predicate-argument structures** represent the semantic relationships between words in a sentence or document. For example, adjectives modify nouns, representing attributes or aspects

[2] Exceptions: some languages, such as Chinese, have a standard orthographic convention that does not use spaces between words, which makes word segmentation a difficult problem. Furthermore, even in a language such as English that usually puts spaces and punctuation between words, in social media and casual text, the orthography is much more complicated, and tokenizers for standard text genres do not work well. We developed and use the tokenization system of O'Connor et al. (2010c); Owoputi et al. (2013) to tackle this. (These works are not part of this thesis.)

of a concept; and verbs have subjects and objects, which sometimes represent entites that initiate and receive the action described by the verb.

A bag-of-words representations fails to describe the interactions between words in a docment, whereas argument structures are inherenctly *relational*, a more complex representation. There are many possible levels of linguistic argument structure to extract from text, such as syntactic dependencies, semantic roles, frame semantics, discourse structure, and events. Chapter 6 uses a syntactic dependencies approach to extract basic event argument structures from text in order to analyze political events described in the news, relating them to social variables of who the actors are and the temporal context of the action.

Finally, the third dimension is **computational and statistical complexity**. Some methods only involve counting words and reporting summary statistics of them; Chapter 2's *MiTextExplorer* tool is interactive software within that paradigm, and Chapter 3's sentiment analysis of Twitter utilizes this level of complexity as well. Other approaches involve more computationally intensive activity such as learning latent semantic representations of words or more complex linguistic units. Chapters 4 and 6 pursue this approach. Many considerations may guide which methods are useful at different stages of an analysis; §4.4 contains some discussion.

In the following chapters, we make use of a wide variety of methods across these dimensions. Easy-to-interpret and computationally cheap methods are often very useful at the start of a project, when iterative exploration of a dataset is essential to gain a basic understanding; but more elaborate models can give further insights, or better target more refined hypotheses. And some questions simply require more computational or linguistic complexity to reach the questions of interest. Further discussion is contained within the chapters themselves and the conclusion (Chapter 7).

1.3 Thesis statement

We claim that automatic analysis of text corpora can reveal important attributes of society, through statistical analysis and modeling of linguistic data. Text data can be used to predict or measure social variables, and it can also demonstrate how socially embedded processes guide language production. This is illustrated through several case studies addressing questions in sociolinguistics and political science. While a variety of methods are necessary to accomplish this type of data analysis, we find that latent variable models, probabilistic graphical models, and natural language processing are all crucial tools.

The conclusion chapter contains a summary of contributions in this thesis.

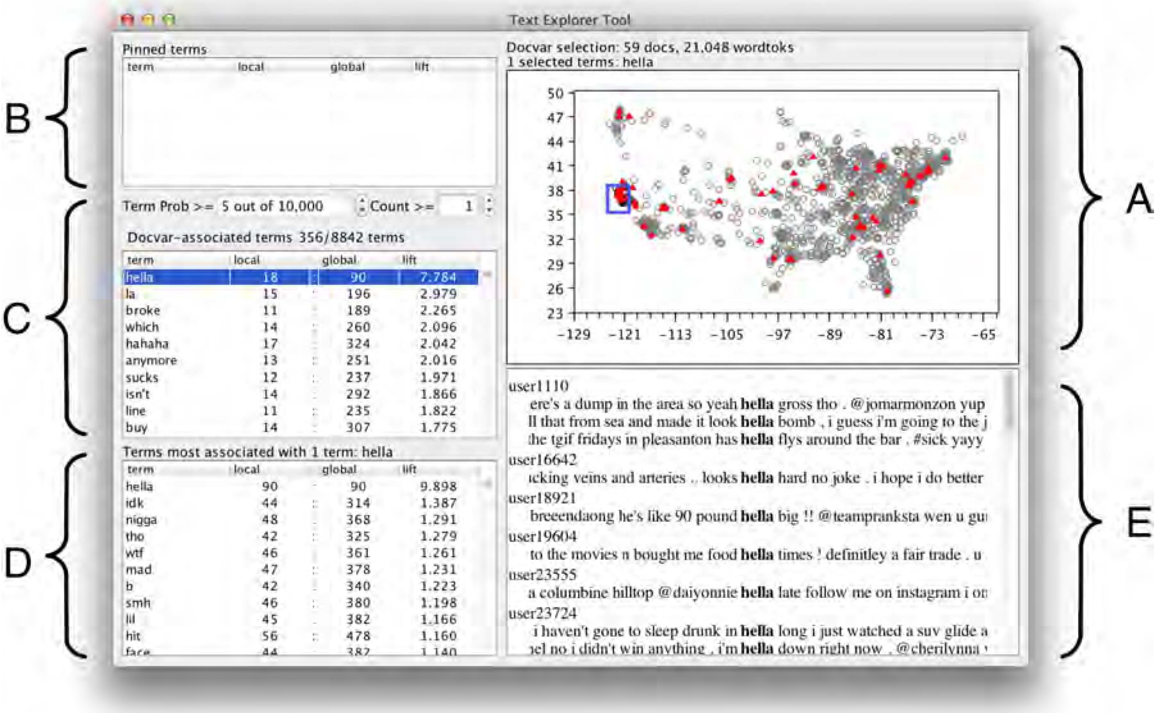
Chapter 2

MiTextExplorer: Interactive exploratory text and covariate analysis

(This chapter was originally published as O'Connor (2014).)

2.1 Introduction

In this chapter we describe a preliminary experimental system, MiTextExplorer, for *textual linked brushing*, which allows an analyst to interactively explore statistical relationships between (1) terms, and (2) document metadata (covariates). An analyst can graphically select documents



Pinned terms

term	local	global	lift

Term Prob >= 5 out of 10,000 Count >= 1

Docvar-associated terms 356/8842 terms

term	local	global	lift
hella	18	90	7.784
la	15	196	2.979
broke	11	189	2.265
which	14	260	2.096
hahaha	17	324	2.042
anymore	13	251	2.016
sucks	12	237	1.971
isn't	14	292	1.866
line	11	235	1.822
buy	14	307	1.775

Terms most associated with 1 term: hella

term	local	global	lift
hella	90	90	9.898
idk	44	314	1.387
nigga	48	368	1.291
tho	42	325	1.279
wtf	46	361	1.261
mad	47	378	1.231
b	42	340	1.223
smh	46	380	1.198
lil	45	382	1.166
hit	56	478	1.160
face	44	382	1.140

Docvar selection: 59 docs, 21,048 wordtoks
1 selected terms: hella

user1110
ere's a dump in the area so yeah **hella** gross tho . @jomarmonzon yup
ll that from sea and made it look **hella** bomb , i guess i'm going to the j
the tgif fridays in pleasanton has **hella** flys around the bar . #sick yayy
user16642
ıcking veins and arteries .. looks **hella** hard no joke . i hope i do better
user18921
breeendaong he's like 90 pound **hella** big !! @teamprankstа wen u gu
user19604
to the movies n bought me food **hella** times ! definitley a fair trade . u
user23555
a columbine hilltop @daiyonnie **hella** late follow me on instagram i on
user23724
i haven't gone to sleep drunk in **hella** long i just watched a suv glide a
ɔel no i didn't win anything . i'm **hella** down right now . @cherilynna

Figure 2.1: Screenshot of MiTextExplorer, analyzing geolocated tweets.

embedded in a temporal, spatial, or other continuous space, and the tool reports terms with strong statistical associations for the region. The user can then drill down to specific term and term groupings, viewing further associations, and see how terms are used in context. The goal is to rapidly compare language usage across interesting document covariates.

We illustrate examples of using the tool on several datasets, including geo-located Twitter messages, which are more extensively investigated in Chapter 4. We leave a more extensive evaluation for future work.

2.2 Motivation: Can we “just look” at statistical text data?

Exploratory data analysis (EDA) is an approach to extract meaning from data, which emphasizes learning about a dataset through an iterative process of many analyses which suggest and refine possible hypotheses. It is vital in early stages of a data analysis for data cleaning and sanity checks, which are crucial to help ensure a dataset will be useful. Exploratory techniques can also suggest possible hypotheses or issues for further investigation.

The classical approach to EDA, as pioneered in works such as Tukey (1977) and Cleveland (1993) (and other work from the Bell Labs statistics group during that period) emphasizes visual analysis under nonparametric, model-free assumptions, in which visual attributes are a fairly direct reflection of numerical or categorical aspects of data. As a simple example, consider the well-known Anscombe Quartet (1973), a set of four bivariate example datasets. The Pearson correlation, a very widely used measure of dependence that assumes a linear Gaussian model of the data, finds that each dataset has an identical amount of dependence ($r = 0.82$). However, a scatterplot instantly reveals that very different dependence relationships hold in each dataset (Figure 2.2). The scatterplot is possibly the simplest visual analysis tool for investigating the relationship between two variables, in which the variables’ numerical values are mapped to horizontal and vertical space. While the correlation coefficient is a model-based analysis tool, the scatterplot is model-free (or at least, it is effective under an arguably wider range of data generating assumptions), which is crucial for this example.

This nonparametric, visual approach to EDA has been encoded into many data analysis packages, including the now-ubiquitous R language (R Core Team, 2013), which descends from earlier software by the Bell Labs statistics group (Becker and Chambers, 1984). In R, tools such as histograms, boxplots, barplots, dotplots, mosaicplots, etc. are built-in, basic operators in the language. (Wilkinson (2006)’s grammar of graphics more extensively systematizes this approach; see also Wickham (2010); Bostock et al. (2011).)

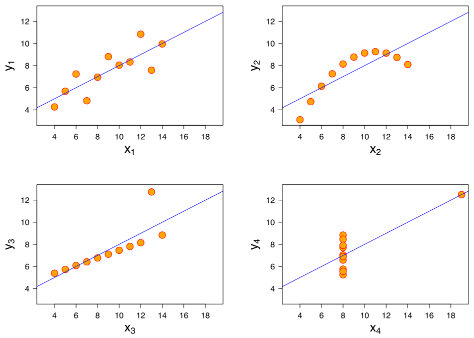


Figure 2.2: Anscombe Quartet. (Source: Wikipedia)

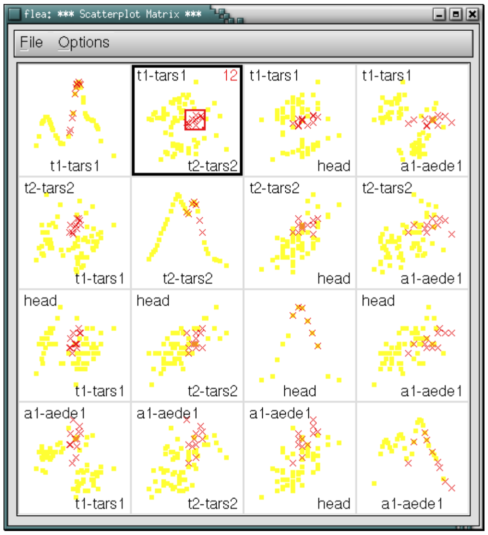


Figure 2.3: Linked brushing with the analysis software *GGobi*. More references at source: http://www.infovis-wiki.net/index.php?title=Linking_and_Brushing

In the meantime, *textual data* has emerged as a resource of increasing interest for many scientific, business, and government data analysis applications. Consider the use case of automated content analysis (a.k.a. text mining) as a tool for investigating social scientific and humanistic questions (Grimmer and Stewart, 2013; Jockers, 2013; Shaw, 2012; O'Connor et al., 2011). The content of the data is under question: analysts are interested in what/when/how/by-whom different concepts, ideas, or attitudes are expressed in a corpus, and the trends in these factors across time, space, author communities, or other document-level covariates (often called metadata). Comparisons of word statistics across covariates are essential to many interesting questions or social measurement problems, such as

- What topics tend to get censored by the Chinese government online, and why (Bamman et al., 2012; King et al., 2013)? *Covariates*: whether a message is deleted by censors, time/location of message.

- What drives media bias? Do newspapers slant their coverage in response to what readers want (Gentzkow and Shapiro, 2010)? *Covariates*: political preferences of readers, competitiveness of media markets.

In this work, we focus on the question: What should be the baseline exploratory tools for textual data, to discover important statistical associations between *text* and *document covariates*? Ideally, we'd like to "just look" at the data, in the spirit of scatterplotting the Anscombe Quartet. An analysis tool to support this should not require any statistical model assumptions, and should display the data in as direct a form as possible.

For low-dimensional, non-textual data, the base functionality of R prescribes a broad array of useful defaults: one-dimensional continuous data can be histogrammed (*hist(x)*), or kernel density plotted (*plot(density(x))*), while the relationship between two dimensions of continuous variables can be viewed as a scatterplot (*plot(x,y)*); or perhaps a boxplot for discrete x and continous y (*boxplot(x,y)*); and so on. Commercial data analysis systems such as Excel, Stata, Tableau, JMP, StatWing, etc., have similar functionality.

These visual tools can be useful for analyzing derived content statistics from text—for example, showing a high-level topic or sentiment frequency trending over time—but they cannot visualize the text itself. Text data consists of a linear sequence of high-dimensional discrete variables (words). The most aggressive and common analysis approach, bag-of-words, eliminates the problematic sequential structure, by reducing a document to a high-dimensional discrete counts over words. But still, none of the above visual tools makes sense for visualizing a word distribution; many popular tools simply crash or become very slow when given word count data. And besides the issues of discrete high-dimensionality, text is unique in that it has to be manually *read* in order to more reliably understand its meaning. Natural language processing tools can sometimes extract partial views of text meaning, but full understanding is a long ways off; and the quality of available NLP tools varies greatly across corpora and languages. A useful exploratory tool should be able to work with a variety of levels of sophistication in NLP tooling, and allow the user to fall back to manual reading when necessary. The tool should support Shneiderman (1996)'s recommendation of *overview first, zoom and filter, then details-on-demand*; the most detailed view of text data, of course, is to support reading of individual snippets and documents

2.3 MITEXTEXPLORER: linked brushing for text and covariate correlations

The analysis tool presented here, MITEXTEXPLORER, is designed for exploratory analysis of relationships between document covariates—such as time, space, or author community—against textual variables—words, or other units of meaning, that can be counted per document. Unlike topic model approaches to analyzing covariate-text relationships (Mimno, 2012; Roberts et al., 2013), there is no dimension reduction of the terms. Instead, interactivity allows a user to explore more of the high-dimensional space, by specifying a *document selection* (Q) and/or a *term selection* (T). We are inspired by the *linking and brushing* family of techniques in interactive data visualization, in which an analyst can select a group of data points under a query in one covariate space, and see the same data selection in a different covariate space (Figure 2.3; see Buja et al. (1996), and e.g. Becker and Cleveland (1987); Buja et al. (1991); Martin and Ward (1995); Cook and Swayne (2007)). In our case, one of the variables is text.

The interface consists of several *linked views*, which contain:

(A) a view of the documents in a two-dimensional covariate space (e.g. scatterplot),

(B) an optional list of pinned terms,

(C) *document-associated terms*: a view of the relatively most frequent terms for the current document selection,

(D) *term-associated terms*: a view of terms that relatively frequently co-occur with the current term selection; and

(E) a keyword-in-context (KWIC) display of textual passages for the current term selection.

Figure 2.1 shows the interface viewing a corpus of 201,647 geo-located Twitter messages from 2,000 users during 2009-2012, which have been tagged with their author's spatial coordinates through a mobile phone client and posted publicly; for data analysis, their texts have been lowercased and tokenized appropriately (Owoputi et al., 2013; O'Connor et al., 2010c). Since this type of corpus contains casual, everyday language, it is a dataset that may illuminate geographic patterns of slang and lexical variation in local dialects (Eisenstein et al., 2012, 2010).

The document covariate display (A) uses (longitude, latitude) positions as the 2D space. The corpus has been preprocessed to define a document as the concatenation of messages from a single author, with its position the average location of the author's messages. When the interface loads, all points in (A) are initially gray, and all other panels are blank.

2.3.1 Covariate-driven queries

A core interaction, *brushing*, consists of using the mouse to select a rectangle in the (x,y) covariate space. Figure 2.1 shows a selection around the Bay Area metropolitan area (blue rectangle). Upon selection, the document-driven term display (C) is updated to show the relatively most frequent terms in the document selection. Let Q denote the set of documents that are selected by the current covariate query. The tool ranks terms w by their (exponentiated) pointwise mutual information, a.k.a. *lift*, for Q:

$$\text{lift}(w;Q) = \frac{p(w|Q)}{p(w)} \quad \left(= \frac{p(w,Q)}{p(w)p(Q)} \right) \tag{2.1}$$

This quantity measures how much more frequent the term is in the queryset, compared to the baseline global probability in the corpus ($p(w)$). Probabilities are calculated with simple MLE relative frequencies, i.e.

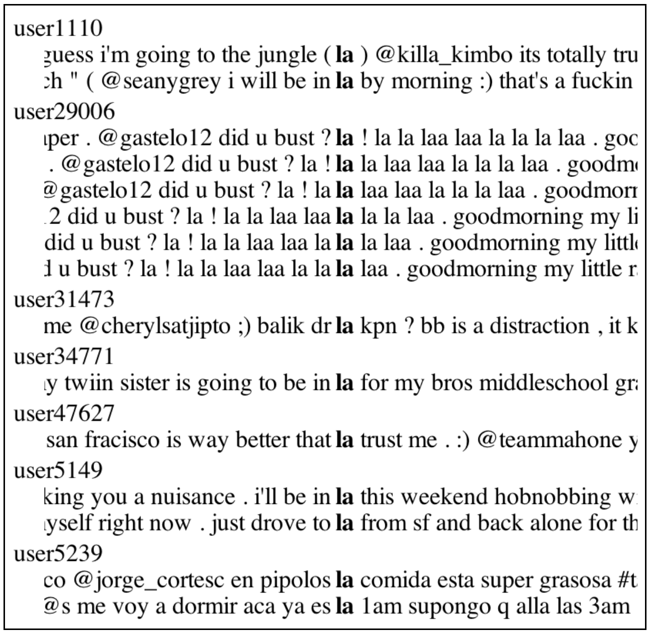
$$\frac{p(w|Q)}{p(w)} = \frac{\sum_{d \in Q} n_{dw}}{\sum_{d \in Q} n_d} \, \frac{N}{n_w} \tag{2.2}$$

where d denotes a document ID, n_{dw} the count of word w in document d, and N the number of tokens in the corpus. PMI gives results that are much more interesting than results from ranking w on raw probability within the query set ($p(w|Q)$), since that simply shows grammatical function words or other terms that are common both in the queryset and across the corpus, and not distinctive for the queryset.[1]

A well-known weakness of PMI is over-emphasis on rare terms; terms that appear only in the queryset, even if they appear only once, will attain the highest PMI value. One way to address this is through a smoothing prior/pseudocounts/regularization, or through statistical significance ranking (see §2.4). For simplicity, we use a minimum frequency threshold filter. The user interface allows minimums for either local or global term frequencies, and to easily adjust them, which naturally shifts the emphasis between specific and generic language. All methods to protect against rare probabilistic events necessarily involve such a tradeoff parameter that the user ought to experiment with; given this situation, we might prefer a transparent mechanism instead of mathematical priors (though see also §2.4).

Figure 2.1 shows that *hella* is the highest ranked term for this spatial selection (and freqency threshold), occurring 7.8 times more frequently compared to the overall corpus; this comports with surveyed intuitions of Californian English speakers (Bucholtz et al., 2007). For full transparency to the user, the local and global term counts are shown in the table. (Since *hella* occurred 18 times in the queryset and 90 times globally, this implies the simple conditional probability $p(Q|w) = 18/90$; and indeed, ranking on $p(Q|w)$ is equivalent to ranking on PMI, since exponentiated PMI is $p(Q|w)/p(Q)$.) The user can also sort by local count to see the raw most-frequent

[1] The term "lift" is used in business applications (Provost and Fawcett, 2013), while PMI has been used in many NLP applications to measure word associations.



```
user1110
   guess i'm going to the jungle ( la ) @killa_kimbo its totally tru
   ch " ( @seanygrey i will be in la by morning :) that's a fuckin
user29006
   per . @gastelo12 did u bust ? la ! la la laa laa la la la laa . goc
    . @gastelo12 did u bust ? la ! la la laa laa la la la laa . goodm
   @gastelo12 did u bust ? la ! la la laa laa la la la laa . goodmorn
   2 did u bust ? la ! la la laa laa la la la laa . goodmorning my li
   did u bust ? la ! la la laa laa la la la laa . goodmorning my littl
   d u bust ? la ! la la laa laa la la la laa . goodmorning my little r
user31473
   me @cherylsatjipto ;) balik dr la kpn ? bb is a distraction , it k
user34771
   y twiin sister is going to be in la for my bros middleschool gr
user47627
    san fracisco is way better that la trust me . :) @teammahone y
user5149
   king you a nuisance . i'll be in la this weekend hobnobbing w
   yself right now . just drove to la from sf and back alone for th
user5239
   co @jorge_cortesc en pipolos la comida esta super grasosa #t
   @s me voy a dormir aca ya es la 1am supongo q alla las 3am
```

Figure 2.4: KWIC examples of "la" usage in tweets selected in Figure 2.1.

term report for the document selection. As the user reshapes the query box, or drags it around the space, the terms in panel (C) are updated.

Not shown are options to change the term frequency representation. For exposition here, probabilities are formulated as counts of tokens, but this can be problematic for social media data, since a single user might use a term a very large number of times. The above analysis is conducted with an indicator representation of terms per user, so all frequencies refer to the probability that a user uses the term at least once. However, the other examples in this paper use token-level frequencies, which seem to work fine. It is an interesting statistical analysis question how to derive a single range of methods to work across these situations.

2.3.2 Term selection and KWIC views

Terms in the table (C) can be clicked and selected, forming a term selection as a set of terms T. This action drives several additional views:

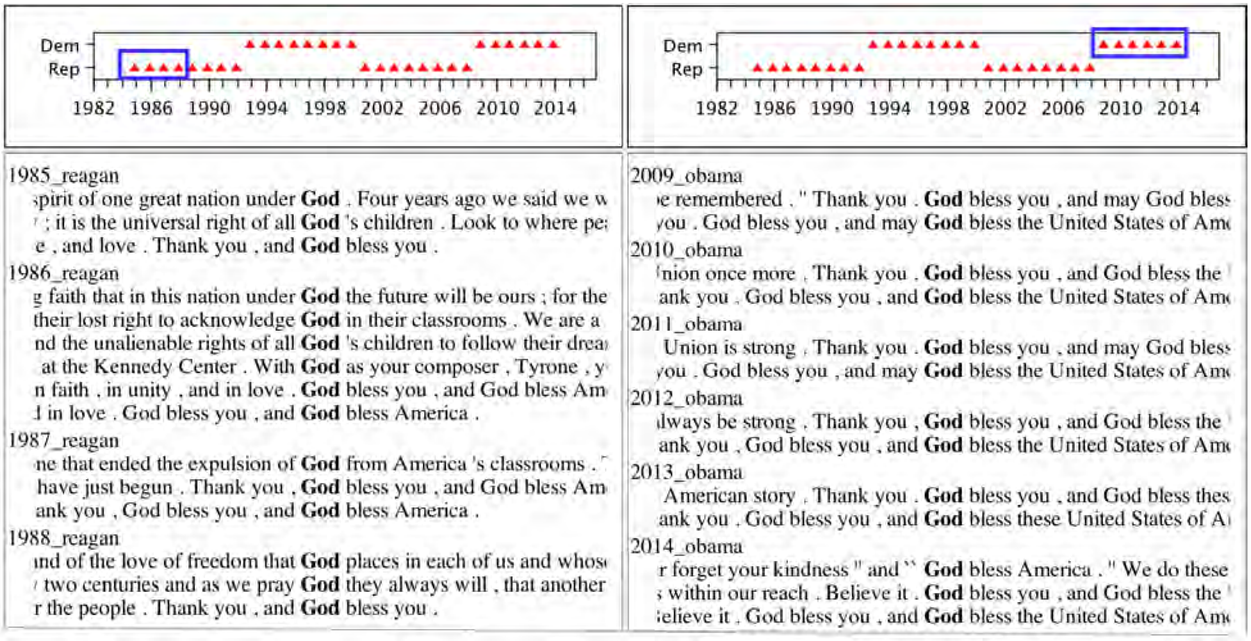
(A) documents containing the term are highlighted in the document covariate display (here, in red),

(E) examples of the term's usage, in Keyword-in-Context style with vertical alignment for the query term; and

(D) other terms that frequently co-occur with T (§2.3.3).

The KWIC report in (E) shows examples of term's usage. For example, why is the term "la" in the PMI list? My initial thought was that this was an example of "LA", short for "Los Angeles". But clicking on "la" instantly disproves this hypothesis—Figure 2.4, showing the Los Angeles sense, but also the "la la la" sense, as well as the Spanish function word.

The KWIC alignment makes it easier to rapidly browse examples, and think about a rough assessment of their word sense or how they are used. Figure 2.5 compares how the term "God"



```
1985_reagan
  spirit of one great nation under God . Four years ago we said we w
  ; it is the universal right of all God 's children . Look to where pe:
  e , and love . Thank you , and God bless you .
1986_reagan
  g faith that in this nation under God the future will be ours ; for the
  their lost right to acknowledge God in their classrooms . We are a
  nd the unalienable rights of all God 's children to follow their drea
   at the Kennedy Center . With God as your composer , Tyrone , y
  n faith , in unity , and in love . God bless you , and God bless Am
  l in love . God bless you , and God bless America .
1987_reagan
  ne that ended the expulsion of God from America 's classrooms .
  have just begun . Thank you , God bless you , and God bless Am
  ank you , God bless you , and God bless America .
1988_reagan
  ınd of the love of freedom that God places in each of us and whos
  two centuries and as we pray God they always will , that another
  r the people . Thank you , and God bless you .
```

```
2009_obama
  ıe remembered . " Thank you . God bless you , and may God bless
  you . God bless you , and may God bless the United States of Am
2010_obama
  nion once more . Thank you . God bless you , and God bless the
  ank you . God bless you , and God bless the United States of Am
2011_obama
   Union is strong . Thank you . God bless you , and may God bless
  you . God bless you , and may God bless the United States of Am
2012_obama
  ılways be strong . Thank you , God bless you , and God bless the
  ank you , God bless you , and God bless the United States of Am
2013_obama
   American story . Thank you . God bless you , and God bless thes
  ank you . God bless you , and God bless these United States of A
2014_obama
  r forget your kindness " and `` God bless America . " We do these
  s within our reach . Believe it . God bless you , and God bless the
  elieve it . God bless you , and God bless the United States of Am
```

Figure 2.5: KWIC examples of “God” in speeches by Reagan versus Obama.

is used by U.S. presidents Ronald Reagan and Barack Obama, in a corpus of State of the Union speeches, from two different displays of the tool. The predominant usage is the invocation of “God bless America” or similar, nearly ornamental, expressions, but Reagan also has substantive usages, such as references to the role of religion in schools. The vertical alignments of the right-side context words makes it easy to see the “God bless” word sense. We initially found this example simply by browsing the covariate space, and noticing “god” as a frequent term for Reagan, though still occurring for other presidents; the KWIC drilldown better illuminated these distinctions, and suggests differences in political ideologies between the presidents.

In many exploratory text analysis works, especially when utilizing topic models (see Chapter 5), it is common to look at word lists produced by a statistical analysis method and think about what they might mean. At least in our experience doing this, We have often found that seeing examples of words in context has disproved my initial intuitions—for example, in the social media topic models of Chapter 4, it was sometimes difficult to understand the words since we were unfamiliar with the idioms and dialects they came from. Chapter 5 notes the word “ion”, when it appears on Twitter, almost always is a shortened form of “I don’t”, as opposed to the scientific term. The word clusterings induced by a topic model help with this analysis, but reading examples in context is necessary to attain a more complete understanding. Hopefully, supporting this activity in an interactive user interface might make exploratory analysis more effective. Currently, the interface simply shows a sample of in-context usages from the document queryset; it would be interesting to perform grouping and stratified sampling based on local contextual statistics. Summarizing local context by frequencies could be done as a trie visualization (Wattenberg and Viégas, 2008); see §2.5.

2.3.3 Term-association queries

When a term is selected, its interaction with covariates is shown by highlighting documents in (B) that contain the term. This can be thought of as another document query: instead of being specified as a region in the covariate space, is specified as a fragment of the discrete lexical space. As illustrated in much previous work (e.g. Church and Hanks (1990); Turney (2001, 2002)), word-to-word PMI scores can find other terms with similar meanings, or having interesting semantic relationships, to the target term.[2]

This panel ranks terms u by their association with the query term v. The simplest method is to analyze the relative frequencies of terms in documents that contain v,

$$\text{bool-tt-epmi}(u, v) = \frac{p(w_i = u | v \in \text{supp}(d_i))}{p(w_i = u)}$$

Here, the subscript i denotes a token position in the entire corpus, for which there is a wordtype w_i and a document ID d_i. In this notation, the covariate PMI in 2.3.1 would be $p(w_i = u|d_i \in Q)/p(w_i = u)$. supp$(d_i)$ denotes the set of terms that occur at least once in document d_i.

This measure is a very simple extension of the document covariate selection mechanism, and easy to understand. However, it is less satisfying for longer documents, since a larger number of occurrences of v do not lead to a stronger association score. A possible extension is to consider the joint random event of selecting two tokens i and j in the corpus, and ask if the two tokens being in the same document is informative for whether the tokens are the words (u, v); that is, measure PMI$[(w_i, w_j) = (u, v); d_i = d_j]$,

$$\text{freq-tt-epmi}(u, v) = \frac{p(w_i = u, w_j = v | d_i = d_j)}{p(w_i = u, w_j = v)}$$

In terms of word counts, this expression has the form

$$\text{freq-tt-epmi}(u, v) = \frac{\sum_d n_{du} n_{dv}}{n_u n_v} \frac{N^2}{\sum_d n_d^2}$$

The right-side term is a normalizing constant invariant to u and v. The left-side term is interesting: it can be viewed as a similarity measure, where the numerator is the inner product of the inverted term-document vectors $n_{\cdot,u}$ and $n_{\cdot,v}$, and the denominator is the product of their ℓ_1 norms. This is a very similar form as cosine similarity, which is another normalized inner product, except its denominator is the product of the vectors' ℓ_2 norms.

Term-to-term associations allow navigation of the term space, complementing the views of terms driven by document covariates. This part of the tool is still at a more preliminary stage of development. One important enhancement would be adjustment of the context window size allowed for co-occurrences; the formulations above assume a context window the size of the document. Medium sized context windows might capture more focused topical content, especially in very long discourses such as speeches; and the smallest context windows, of size 1, should be more like collocation detection (though see §2.4; this is arguably better done with significance tests, not PMI).

2.3.4 Pinned terms

The term PMI views of (C) and (D) are very dynamic, which can cause interesting terms to disappear when their supporting query is changed. It is often useful to select terms to be constantly viewed when the document covariate queries change.

[2] For finding terms with similar semantic meaning, distributional similarity may be more appropriate (Turney and Pantel, 2010); this could be interesting to incorporate into the software.

Any term can be double-clicked to be moved to the the table of *pinned terms* (B). The set of terms here does not change as the covariate query is changed; a user can fix a set of terms and see how their PMI scores change while looking at different parts of the covariate space. One possible use of term pinning is to manually build up clusters of terms—for example, topical or synonymous term sets—whose aggregate statistical behavior (i.e. as a disjunctive query) may be interesting to observe. Manually built sets of keywords are a very useful form of text analysis; in fact, the WordSeer corpus analysis tool has explicit support to help users create them (Shrikumar, 2013).

2.4 Statistical term association measures

There exist many measures to measure the statistical strength of an association between a term and a document covariate, or between two terms. A number of methods are based on significance testing, looking for violations of a null hypothesis that term frequencies are independent. For collocation detection, which aims to find meaningful non-compositional lexical items through frequencies of neighboring words, likelihood ratio (Dunning, 1993) and chi-square tests have been used (see review in Manning and Schütze (1999)). For term-covariate associations, chi-square tests were used by Gentzkow and Shapiro (2010) to find politically loaded phrases often used by members of one political party; this same method is often used as a feature selection method for supervised learning (Guyon and Elisseeff, 2003).

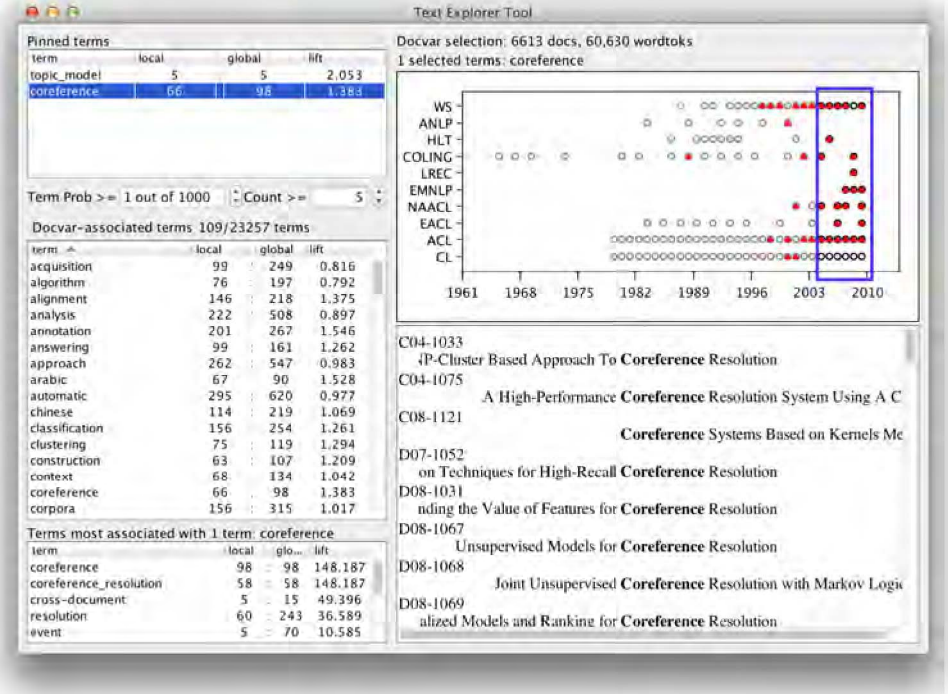
The approach we take here is somewhat different, being a point estimate approach, analyzing the estimated difference (and giving poor results when counts are small). Some related work for topic model analysis, looking at statistical associations between words and latent topics (as opposed to between words and observed covariates in this work) includes Chuang et al. (2012), whose term saliency function measures one word's associations against all topics; a salient term tends to have most of its probability mass in a small set of topics. The measure is a form of mutual information,[3] and may be useful for our purposes here if the user wishes to see a report of distinctive terms for a group of several different observed covariate values at once. Blei and Lafferty (2009) ranks words per topic by a measure inspired by TFIDF, which like PMI downweights words that are generically common across all topics.

Finally, hierarchical priors and regularizers can also be used; for example, by penalizing the log-odds parameterization of term probabilities (Eisenstein et al., 2011b; Taddy, 2013). These methods are better in that they incorporate both protection against small count situations, while paying attention to effect size, as well as allowing overlapping covariates and regression control variables; but unfortunately, they are more computationally intensive, as opposed to the above measures which all work directly from sufficient count statistics. An association measure that fulfilled all these desiderata would be very useful. For term-covariate analysis, Monroe et al. (2008) contains a review of many different methods, from both political science as well as computer science; they also propose a hierarchical prior method, and to rank by statistical significance via the asymptotic standard error of the terms' odds ratios. Kilgarriff (2001) reviews word comparison

[3] This is apparent as follows, using notation from their section 3.1:

$$\text{saliency}(w) = p(w) \sum_T p(T|w) \log[p(T|w)/p(T)] = \sum_T p(w,T) \log[p(w,T)/[p(w)p(T)]]$$

This might be called a "half-pointwise" mutual information: between a specific word w and the topic random variable T. Mutual information is $\sum_w \text{saliency}(w)$.



Pinned terms

term	local	global	lift
topic_model	5	5	2.053
coreference	66	98	1.383

Term Prob >= 1 out of 1000 Count >= 5

Docvar-associated terms 109/23257 terms

term	local	global	lift
acquisition	99	249	0.816
algorithm	76	197	0.792
alignment	146	218	1.375
analysis	222	508	0.897
annotation	201	267	1.546
answering	99	161	1.262
approach	262	547	0.983
arabic	67	90	1.528
automatic	295	620	0.977
chinese	114	219	1.069
classification	156	254	1.261
clustering	75	119	1.294
construction	63	107	1.209
context	68	134	1.042
coreference	66	98	1.383
corpora	156	315	1.017

Terms most associated with 1 term: coreference

term	local	glo...	lift
coreference	98	98	148.187
coreference_resolution	58	58	148.187
cross-document	5	15	49.396
resolution	60	243	36.589
event	5	70	10.585

Docvar selection: 6613 docs, 60,630 wordtoks
1 selected terms: coreference

C04-1033
IP-Cluster Based Approach To **Coreference** Resolution
C04-1075
A High-Performance **Coreference** Resolution System Using A C
C08-1121
Coreference Systems Based on Kernels Mc
D07-1052
on Techniques for High-Recall **Coreference** Resolution
D08-1031
nding the Value of Features for **Coreference** Resolution
D08-1067
Unsupervised Models for **Coreference** Resolution
D08-1068
Joint Unsupervised **Coreference** Resolution with Markov Logic
D08-1069
alized Models and Ranking for **Coreference** Resolution

Figure 2.6: MITEXTEXPLORER for paper titles in the ACL Anthology (Radev et al., 2009). Y-axis is venue (conference or journal name), X-axis is year of publication. Unlike the other figures, docvar-associated terms are sorted alphabetically.

methods as well. The Zeta methods from stylometry (Burrows, 2007; Craig and Kinney, 2009) calculates a word's distinctiveness based on its variability across a corpus.

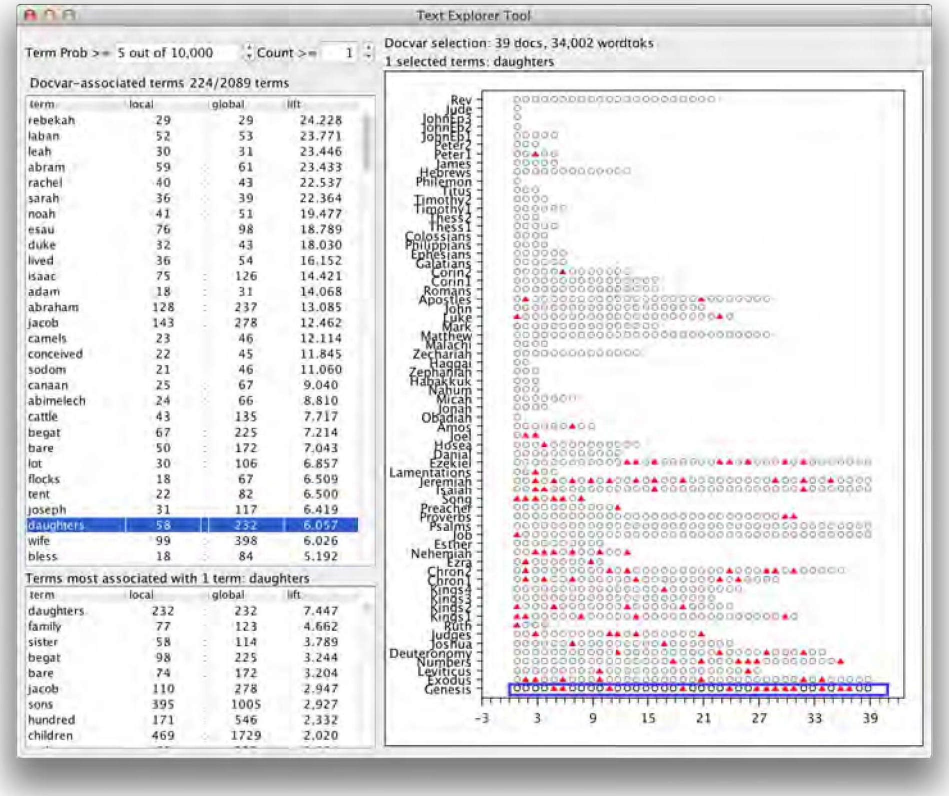
Given the large amount of previous work using the significance approach, it merits further exploration for this system.

2.5 Related work: Exploratory text analysis

Many systems and techniques have been developed for interactive text analysis. Two such systems, WordSeer and Jigsaw, have been under development for several years, each having had a series of user experiments and feedback. Recent and interesting review papers and theses are available for both of them.

The WordSeer system (Shrikumar, 2013)[4] contains many different interactive text visualization tools, including syntax-based search, and was initially designed for the needs of text analysis in the humanities; the WordSeer 3.0 system includes a word frequency analysis component that can compare word frequencies along document covariates. Interestingly, Shrikumar found in user studies with literary experts that data comparisons and annotation/note-taking support were very important capabilities to add to the system. Unique to the work in this paper is the emphasis on conditioning on document covariates to analyze relative word frequencies, and encouraging the user to change the statistical parameters that govern text correlation measurements. (The

[4] http://wordseer.berkeley.edu/



Term Prob >= 5 out of 10,000 Count >= 1

Docvar selection: 39 docs, 34,002 wordtoks
1 selected terms: daughters

Docvar-associated terms 224/2089 terms

term	local	global	lift
rebekah	29	29	24.228
laban	52	53	23.771
leah	30	31	23.446
abram	59	61	23.433
rachel	40	43	22.537
sarah	36	39	22.364
noah	41	51	19.477
esau	76	98	18.789
duke	32	43	18.030
lived	36	54	16.152
isaac	75	126	14.421
adam	18	31	14.068
abraham	128	237	13.085
jacob	143	278	12.462
camels	23	46	12.114
conceived	22	45	11.845
sodom	21	46	11.060
canaan	25	67	9.040
abimelech	24	66	8.810
cattle	43	135	7.717
begat	67	225	7.214
bare	50	172	7.043
lot	30	106	6.857
flocks	18	67	6.509
tent	22	82	6.500
joseph	31	117	6.419
daughters	58	232	6.057
wife	99	398	6.026
bless	18	84	5.192

Terms most associated with 1 term: daughters

term	local	global	lift
daughters	232	232	7.447
family	77	123	4.662
sister	58	114	3.789
begat	98	225	3.244
bare	74	172	3.204
jacob	110	278	2.947
sons	395	1005	2.927
hundred	171	546	2.332
children	469	1729	2.020

Figure 2.7: MiTextExplorer for the King James Bible. Y-axis is book, X-axis is chapter (truncated to 39).

term pinning and term-to-term association techniques are certainly less developed than previous work.)

Another text analysis system is Jigsaw (Görg et al., 2013),[5] originally developed for investigative analysis (as in law enforcement or intelligence), which again has many features. It emphasizes visualizations based on entity extractions, such as for names, places, and dates. Görg et al. note that errors in entity extraction were a major problem for users; this might be a worthwhile argument to focus on getting something to first work with simple words/phrases before tackling more complex units of meaning. A section of the review paper is entitled "Reading the documents still matters", pointing out that analysts did not want just to visualize high-level relationships, but also wanted to read documents in context; this capability was added to later versions of Jigsaw, and supports the emphasis here on the KWIC display.

Both these systems also use variants of Wattenberg and Viégas (2008)'s word tree visualization, which gives a sequential word frequencies as a tree (i.e., what computational linguists might call a trie representation of a high-order Markov model). The "God bless" word sense example from §2.3 indicates that such statistical summarization of local contextual information may be useful to integrate; it is worth thinking how to integrate this against the important need of document covariate analysis, while being efficient with the use of space.

Many other systems, especially ones designed for literary content analysis, emphasize concor-

[5] http://www.cc.gatech.edu/gvu/ii/jigsaw/

dances and keyword searches within a text; for example, Voyeur/Voyant (Rockwell et al., 2010),[6] which also features some document covariate analysis through temporal trend analyses for individual terms. Another class of approaches emphasizes the use of document clustering or topic models (Gardner et al., 2010; Newman et al., 2010; Grimmer and King, 2011; Chaney and Blei, 2013), while Overview[7] emphasizes hierarchical document clustering paired with manual tagging.

Finally, considerable research has examined exploratory visual interfaces for information retrieval, in which a user specifies an information need in order to find relevant documents or passages from a corpus (Hearst (2009), Ch. 10). Information retrieval problems have some similarities to text-as-data analysis in the need for an exploratory process of iterative refinement, but the text-as-data perspective differs in that it requires an analyst to understand content and contextual factors across multiple or many documents.

2.6 Future work

The current MiTextExplorer system is an extremely simple prototype to explore what sorts of "bare words" text-and-covariates analyses are possible. Several major changes will be necessary for more serious use.

First, essential basic capabilities must be added, such as a search box the user can use to search and filter the term list.

Second, the document covariate display needs to support more than just scatterplots. When there are hundreds or more documents, summarization is necessary in the form of histograms, kernel density plots, or other tools. For example, for a large corpus of documents over time, a lineplot or temporal histogram is more appropriate, where each timestep has a document count. The ACL Anthology scatterplot (Figure 2.6, Radev et al. (2009)), which has hundreds of overplotted points at each (year,venue) position, makes clear the limitations of the current approach.

Better visual feedback for term selections here could be useful—for example, sizing document points monotonically with the term's frequency (rather than just presence/absence), or using stacked line plots—though certain visual depictions of frequency may be difficult given the Zipfian distribution of word frequencies.

Furthermore, document structures may be thought of as document covariates. A single book has interesting internal variation that could be analyzed itself. Figure 2.7 shows the King James Bible, which has a hierarchical structure of book, chapter, and verse. Here, the (y,x) coordinates represent books and chapters. A more specialized display for book-level structures, or other discourse structures, may be appropriate for book-length texts.

Finally, a major goal of this work is to use analysis methods that can be computed on the fly, but the current prototype only works with small datasets. Hierarchical spatial indexing techniques (e.g. r-trees), may make it possible to interactively compute sums for covariate PMI scoring over very large numbers of documents. Text indexing is also important for term-driven queries and KWIC views. Techniques from ad-hoc data querying systems may be necessary for further scale (e.g. Melnik et al. (2010)).

Many other directions are possible. The prototype tool, as described in §2.3, is available as open-source software at: http://brenocon.com/mte/. It is a desktop application written in Java.

[6] http://voyant-tools.org/,
http://hermeneuti.ca/voyeur

[7] https://www.overviewproject.org/ http://overview.ap.org/

Chapter 3

Text sentiment and opinion polling

(This chapter was originally published as O'Connor et al. (2010a).)

3.1 Introduction

If we want to know, say, the extent to which the U.S. population likes or dislikes Barack Obama, a good approach is to ask a random sample of people—that is, take a poll. Survey and polling methodology, extensively developed through the 20th century (Krosnick et al., 2005), gives numerous tools and techniques to accomplish representative public opinion measurement.

With the dramatic rise of text-based social media, millions of people broadcast their thoughts and opinions on a great variety of topics. Can we analyze publicly available data to infer population attitudes in the same manner that public opinion pollsters query a population? If so, then mining public opinion from freely available text content could be a faster and less expensive alternative to traditional polls. Such analysis would also permit us to consider a greater variety of polling questions, limited only by the scope of topics and opinions people broadcast. Extracting the public opinion from social media text provides a challenging and rich context to explore computational models of natural language, motivating new research in computational linguistics.

In this chapter, we connect measures of public opinion derived from polls with sentiment measured from analysis of text from the popular microblogging site Twitter. We explicitly link measurement of textual sentiment in microblog messages through time, comparing to contemporaneous polling data. Surprisingly, summary statistics derived from extremely simple text analysis techniques are demonstrated to correlate with polling data on consumer confidence and political opinion. We find that temporal smoothing is a critically important issue to support a successful model, since the data is highly variable. This suggests there are many future challenges for using social media analysis for opinion tracking.

3.2 Data

We begin by discussing the data used in this study: Twitter for the text data, and public opinion surveys from multiple polling organizations.

3.2.1 Twitter Corpus

Twitter is a popular microblogging service in which users post messages that are very short: less than 140 characters, averaging 11 words per message. It is convenient for research because there are a very large number of messages, many of which are publicly available, and obtaining them is technically simple compared to scraping blogs from the web.

We use 1 billion Twitter messages posted over the years 2008 and 2009, collected by querying the Twitter API,[1] as well as archiving the "Gardenhose" real-time stream. This comprises a roughly uniform sample of public messages, in the range of 100,000 to 7 million messages per day. (The primary source of variation is growth of Twitter itself; its message volume increased by a factor of 50 over this two-year time period.)

Most Twitter users appear to live in the U.S., but we made no systematic attempt to identify user locations or even message language, though our analysis technique should largely ignore non-English messages.

There probably exist many further issues with this text sample; for example, the demographics and communication habits of the Twitter user population probably changed over this time period, which should be adjusted for given our desire to measure attitudes in the general population. There are clear opportunities for better preprocessing and stratified sampling to exploit these data.

3.2.2 Public Opinion Polls

We consider several measures of consumer confidence and political opinion, all obtained from telephone surveys to participants selected through random-digit dialing, a standard technique in traditional polling (Chang and Krosnick, 2003).

Consumer confidence refers to how optimistic the public feels, collectively, about the health of the economy and their personal finances. It is thought that high consumer confidence leads to more consumer spending, and further relationships with economic activity have been studied (Ludvigson, 2004; Wilcox, 2007). Knowing the public's consumer confidence is of great utility for economic policy making as well as business planning.

Two well-known surveys that measure U.S. consumer confidence are the Consumer Confidence Index from the Consumer Board, and the Index of Consumer Sentiment (ICS) from the Reuters/University of Michigan Surveys of Consumers.[2] We use the latter, as it is more extensively studied in economics, having been conducted since the 1950s. The ICS is derived from answers to five questions administered monthly in telephone interviews with a nationally representative sample of several hundred people; responses are combined into the index score. Two of the questions, for example, are:

> "We are interested in how people are getting along financially these days. Would you say that you (and your family living there) are better off or worse off financially than you were a year ago?"
>
> "Now turning to business conditions in the country as a whole—do you think that during the next twelve months we'll have good times financially, or bad times, or what?"

We also use another poll, the Gallup Organization's "Economic Confidence" index,[3] which is derived from answers to two questions that ask interviewees to to rate the overall economic health

[1] This scraping effort was conducted by Brendan Meeder.

[2] Downloaded from http://www.sca.isr.umich.edu/.

[3] Downloaded from http://www.gallup.com/poll/122840/gallup-daily-economic-indexes.aspx.

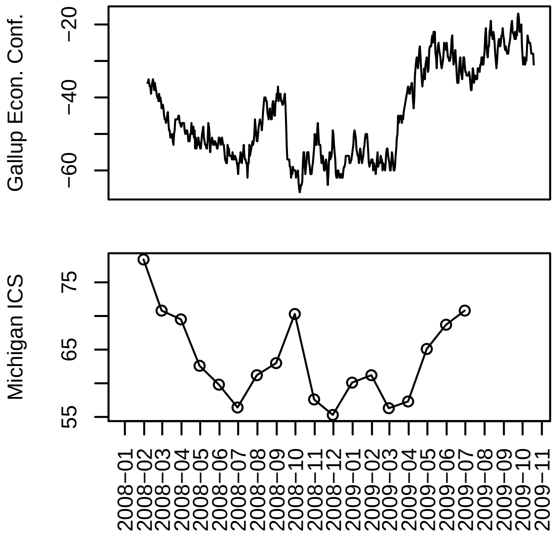


Figure 3.1: Monthly Michigan ICS and daily Gallup consumer confidence poll.

of the country. This only addresses a subset of the issues that are incorporated into the ICS. We are interested in it because, unlike the ICS, it is administered daily (reported as three-day rolling averages). Frequent polling data are more convenient for our comparison purpose, since we have fine-grained, daily Twitter data, but only over a two-year period. Both datasets are shown in Figure 3.1.

For **political opinion**, we use two sets of polls. The first is Gallup's daily tracking poll for the presidential job approval rating for Barack Obama over the course of 2009, which is reported as 3-day rolling averages.[4] These data are shown in Figure 3.2.

The second is a set of tracking polls during the 2008 U.S. presidential election cycle, asking potential voters whether they would vote for Barack Obama or John McCain. Many different organizations administered them throughout 2008; we use a compilation provided by Pollster.com, consisting of 491 data points from 46 different polls.[5] The data are shown in Figure 3.3.

3.3 Text Analysis

From text, we are interested in assessing the population's aggregate opinion on a topic. Immediately, the task can be broken down into two subproblems:

1. Message retrieval: identify messages relating to the topic.

2. Opinion estimation: determine whether these messages express positive or negative opinions or news about the topic.

If there is enough training data, this could be formulated as a topic-sentiment model (Mei et al., 2007), in which the topics and sentiment of documents are jointly inferred. Our dataset, however,

[4] Downloaded from http://www.gallup.com/poll/113980/Gallup-Daily-Obama-Job-Approval.aspx.

[5] Downloaded from http://www.pollster.com/polls/us/08-us-pres-ge-mvo.php

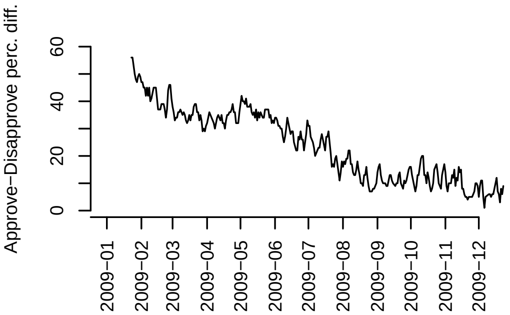


Figure 3.2: 2009 presidential job approval (Barack Obama).

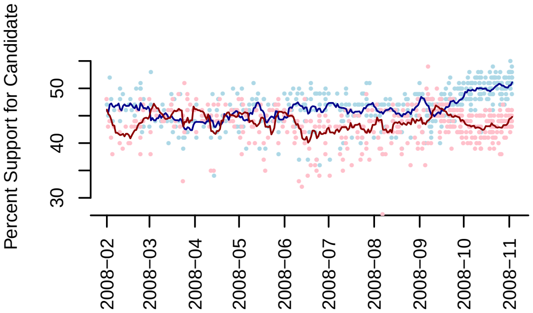


Figure 3.3: 2008 presidential elections, Obama vs. McCain (blue and red). Each poll provides separate Obama and McCain percentages (one blue and one red point); lines are 7-day rolling averages.

is asymmetric, with millions of text messages per day (and millions of distinct vocabulary items) but only a few hundred polling data points in each problem. It is a challenging setting to estimate a useful model over the vocabulary and messages. The signal-to-noise ratio is typical of information retrieval problems: we are only interested in information contained in a small fraction of all messages.

We therefore opt to use a transparent, deterministic approach based on prior linguistic knowledge, counting instances of positive-sentiment and negative-sentiment words in the context of a topic keyword.

3.3.1 Message Retrieval

We only use messages containing a topic keyword, manually specified for each poll:

- For consumer confidence, we use *economy*, *job*, and *jobs*.
- For presidential approval, we use *obama*.
- For elections, we use *obama* and *mccain*.

Each topic subset contained around 0.1–0.5% of all messages on a given day, though with occasional spikes, as seen in Figure 3.4. These appear to be driven by news events. All terms have

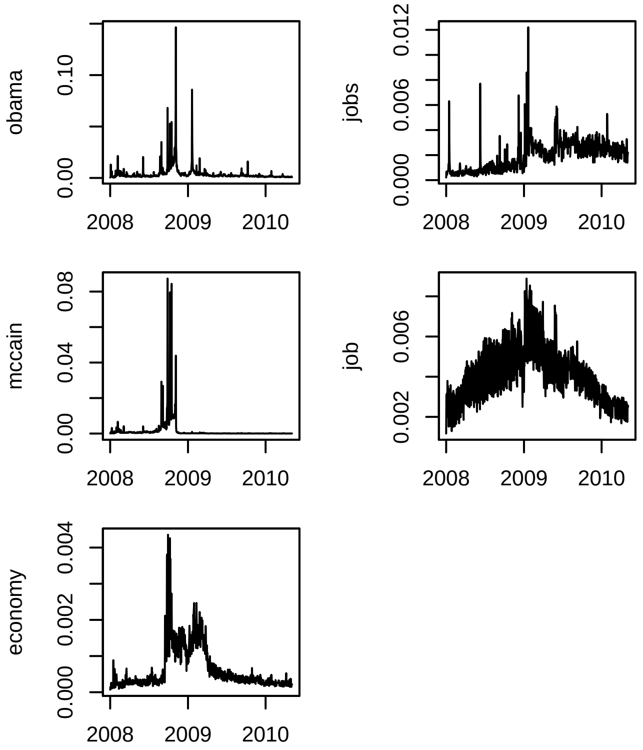


Figure 3.4: Fraction of Twitter messages containing various topic keywords, per day.

a weekly cyclical structure, occurring more frequently on weekdays, especially in the middle of the week, compared to weekends. (In the figure, this is most apparent for the term *job* since it has fewer spikes.) Nonetheless, these fractions are small. In the earliest and smallest part of our dataset, the topic samples sometimes come out just several hundred messages per day; but by late 2008, there are thousands of messages per day for most datasets.

3.3.2 Opinion Estimation

We derive day-to-day sentiment scores by counting positive and negative messages. Positive and negative words are defined by the subjectivity lexicon from OpinionFinder, a word list containing about 1,600 and 1,200 words marked as positive and negative, respectively (Wilson et al.).[6] We do not use the lexicon's distinctions between weak and strong words.

A message is defined as positive if it contains any positive word, and negative if it contains any negative word. (This allows for messages to be both positive and negative.) This gives similar results as simply counting positive and negative words on a given day, since Twitter messages are so short (about 11 words).

We define the sentiment score x_t on day t as the ratio of positive versus negative messages on the topic, counting from that day's messages:

$$\begin{aligned} x_t &= \frac{\text{count}_t(\text{pos. word} \wedge \text{topic word})}{\text{count}_t(\text{neg. word} \wedge \text{topic word})} \qquad (3.1) \\ &= \frac{p(\text{pos. word} \mid \text{topic word}, t)}{p(\text{neg. word} \mid \text{topic word}, t)} \end{aligned}$$

[6] Available at http://www.cs.pitt.edu/mpqa.

where the likelihoods are estimated as relative frequencies.

We performed casual inspection of the detected messages and found many examples of falsely detected sentiment. For example, the lexicon has the noun *will* as a weak positive word, but since we do not use a part-of-speech tagger, this causes thousands of false positives when it matches the verb sense of *will*.[7] Furthermore, recall is certainly very low, since the lexicon is designed for well-written standard English, but many messages on Twitter are written in an informal social media dialect of English, with different and alternately spelled words, and emoticons as potentially useful signals. Creating a more comprehensive lexicon with distributional similarity techniques could improve the system; Velikovich et al. (2010) find that such a web-derived lexicon substantially improves a lexicon-based sentiment classifier.

3.3.3 Comparison to Related Work

The sentiment analysis literature often focuses on analyzing individual documents, or portions thereof (for a review, see Pang and Lee (2008)). Our problem is related to work on sentiment information retrieval, such as the TREC Blog Track competitions that have challenged systems to find and classify blog posts containing opinions on a given topic (Ounis et al., 2008).

The sentiment feature we consider, presence or absence of sentiment words in a message, is one of the most basic ones used in the literature. If we view this system in the traditional light—as subjectivity and polarity detection for individual messages—it makes many errors, like all natural language processing systems. However, we are only interested in *aggregate* sentiment. A high error rate implies the sentiment detector is a noisy measurement instrument. If we have a large number of measurements, and the cause of sentiment errors is not confounded with the substantive comparisons we want to make (see §3.6), these errors will cancel out relative to the quantity of interest: aggregate public opinion as it changes over time. Furthermore, as Hopkins and King (2010) demonstrate, it can actually be inaccurate to naïvely use standard text analysis techniques, which are usually designed to optimize per-document classification accuracy, when the goal is to assess aggregate population proportions.

Many studies have estimated and made use of aggregated text sentiment. In earlier work, the informal study by Lindsay (2008) focused on lexical induction in building a sentiment classifier for a proprietary dataset of Facebook wall posts (a web conversation/microblog medium broadly similar to Twitter), and demonstrated correlations to several polls conducted during part of the 2008 presidential election. Other earlier uses of aggregate text sentiment time series include analyzing stock behavior based on text from blogs (Gilbert and Karahalios, 2010), news articles (Lavrenko et al., 2000; Koppel and Shtrimberg, 2004) and investor message boards (Antweiler and Frank, 2004; Das and Chen, 2007). Bollen et al. (2010) tried to predict stocks from Twitter, but see the critique by Anonymous (2012). Dodds and Danforth (2009) use an emotion word counting technique for purely exploratory analysis of several corpora.

3.4 Moving Average Aggregate Sentiment

Day-to-day, the sentiment ratio is volatile. Just like in the topic volume plots (Figure 3.4), the sentiment ratio rapidly rises and falls each day. In order to derive a more consistent signal, and following the same methodology used in public opinion polling, we *smooth* the sentiment ratio with one of the simplest possible temporal smoothing techniques, a moving average over a win-

[7] We tried manually removing this and several other frequently mismatching words, but it had little effect.

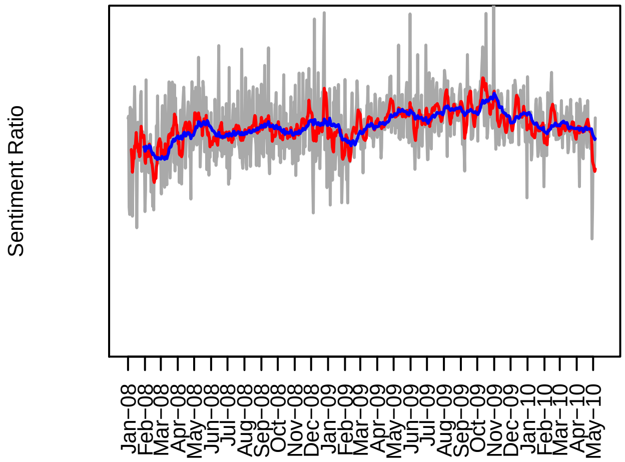


Figure 3.5: Moving average MA_t of sentiment ratio for *jobs*, under different windows $k \in \{1, 7, 30\}$: no smoothing (gray), past week (magenta), and past month (blue). The unsmoothed version spikes as high as 10, omitted for space.

dow of the past k days:

$$MA_t = \frac{1}{k}\left(x_{t-k+1} + x_{t-k+2} + ... + x_t\right)$$

Smoothing is a critical issue. It causes the sentiment ratio to respond more slowly to recent changes, thus forcing consistent behavior to appear over longer periods of time. Too much smoothing, of course, makes it impossible to see fine-grained changes to aggregate sentiment. See Figure 3.5 for an illustration of different smoothing windows for the *jobs* topic.

3.5 Correlation Analysis: Is text sentiment a leading indicator of polls?

Figure 3.6 shows the *jobs* sentiment ratio compared to the two different measures of consumer confidence, Gallup Daily and Michigan ICS. It is apparent that the sentiment ratio captures the broad trends in the survey data. With 15-day smoothing, it is reasonably correlated with Gallup at $r = 0.731$. The most glaring difference is a region of high positive sentiment in May-June 2008. But otherwise, the sentiment ratio seems to pick up on the downward slide of consumer confidence through 2008, and the rebound in February/March of 2009.

When consumer confidence changes, can this first be seen in the text sentiment measure, or in polls? If text sentiment responds faster to news events, a sentiment measure may be useful for economic researchers and policymakers. We can test this by looking at leading versions of text sentiment.

First note that the text-poll correlation reported above is the goodness-of-fit metric for fitting slope and bias parameters a, b in a one variable linear least-squares model:

$$y_t = b + a\left(\frac{1}{k}\sum_{j=0}^{k-1} x_{t-j}\right) + \epsilon_t$$

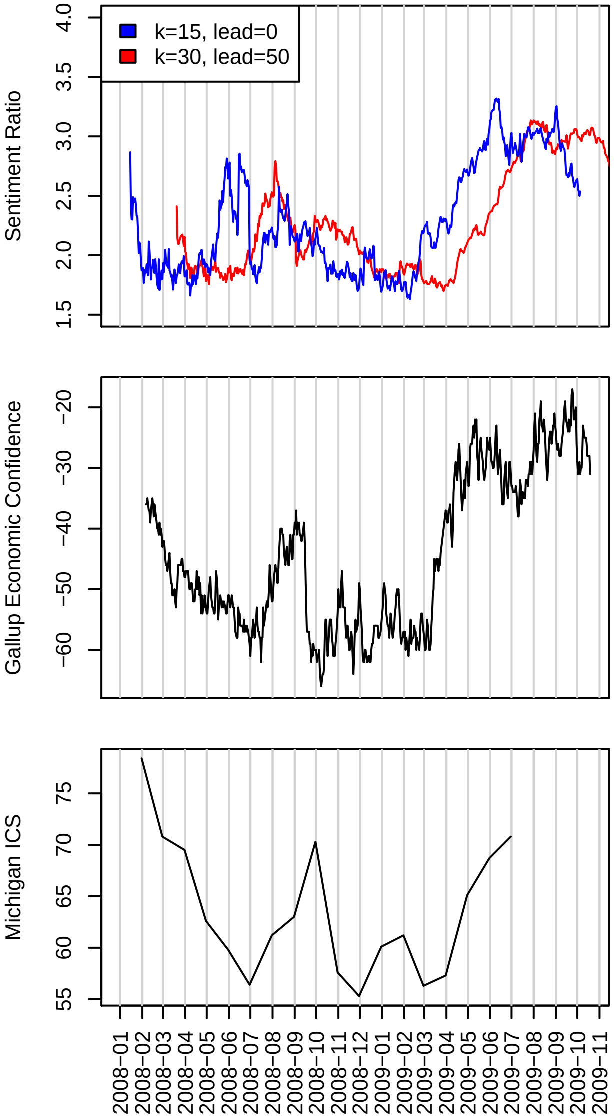


Figure 3.6: Sentiment ratio and consumer confidence surveys. Sentiment information captures broad trends in the survey data.

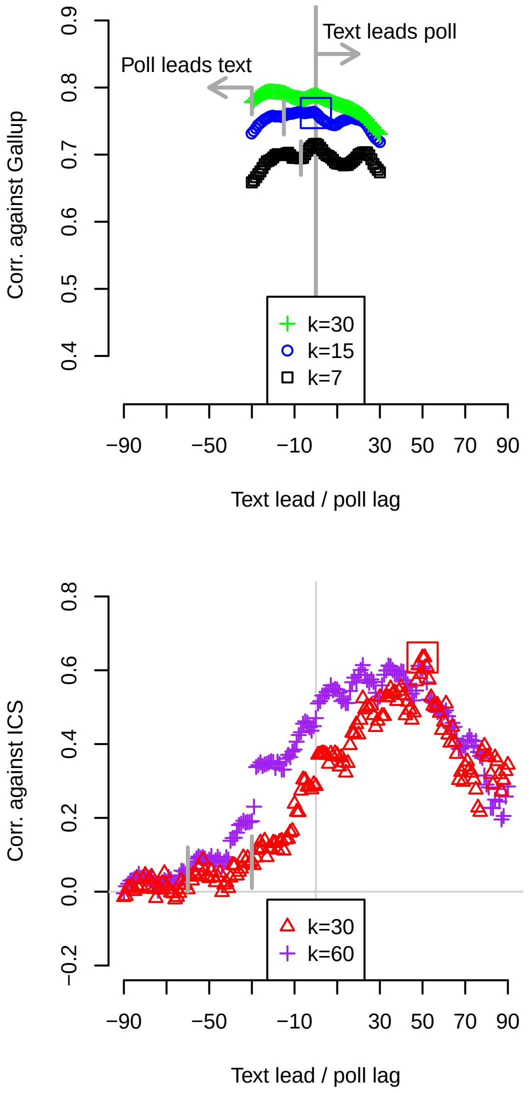


Figure 3.7: Cross-correlation plots: sensitivity to lead and lag for different smoothing windows. $L > 0$ means the text window completely precedes the poll, and $L < -k$ means the poll precedes the text. (The window straddles the poll for $L < -k < 0$.) The $L = -k$ positions are marked on each curve. The two parameter settings shown in Figure 3.6 are highlighted with boxes.

for poll outcomes y_t, daily sentiment ratios x_j, Gaussian noise ϵ_t, and a fixed hyperparameter k. A poll outcome is compared to the k-day text sentiment window that ends on the same day as the poll.

The lagged analysis results from introducing a lag hyperparameter L into the model, so the poll is compared against the text window ending L days before the poll outcome.

$$y_{t+L} = b + a \left(\frac{1}{k} \sum_{j=0}^{k-1} x_{t-j} \right) + \epsilon_t$$

Graphically, this is equivalent to taking one of the text sentiment lines on Figure 3.6 and shifting it to the right by L days, then examining the correlation against the consumer confidence polls below.

Polls are typically administered over an interval of time. The ICS is reported once per month (at the end of the month), and Gallup is reported for 3-day windows. We always consider the last day of the poll's window to be the poll date, which is the earliest possible day that the information could be used. Therefore, we would expect both daily measures, Gallup and text sentiment, to always lead ICS, since it measures phenomena occurring over the previous month.

The sensitivity of text-poll correlation to smoothing window and lag parameters (k, L) is shown in Figure 3.7. The regions corresponding to text preceding or following the poll are marked. Correlation is higher for text leading the poll and not the other way around, so text seems to be a leading indicator. Gallup correlations fall off faster for poll-leads-text than text-leads-poll, and the ICS has similar properties.

If text and polls moved at random relative to each other, these cross-correlation curves would stay close to 0. The fact they have peaks at all strongly suggests that the text sentiment measure captures information related to the polls.

Also note that more smoothing increases the correlation: for Gallup, 7-, 15-, and 30-day windows peak at $r = 0.716$, 0.763, and 0.794 respectively. The 7-day and 15-day windows have two local peaks for correlation, corresponding to shifts that give alternate alignments of two different humps against the Gallup data, but the better-correlating 30-day window smooths over these entirely. Furthermore, for the ICS, a 60-day window often achieves higher correlation than the 30-day window. These facts imply that the text sentiment information is volatile, and if polls are believed to be a gold standard, then it is best used to detect long-term trends.

It is also interesting to consider ICS a gold standard and compare correlations with Gallup and text sentiment. ICS and Gallup are correlated (best correlation is $r = 0.864$ if Gallup is given its own smoothing and alignment at $k = 30, L = 20$), which supports the hypothesis that they are measuring similar things, and that Gallup is a leading indicator for ICS. Fixed to 30-day smoothing, the sentiment ratio only achieves $r = 0.635$ under optimal lead $L = 50$. So it is a weaker indicator than Gallup.

Finally, we also experimented with sentiment ratios for the terms *job* and *economy*, which both correlate very poorly with the Gallup poll: 0.10 and 0.07 respectively (with the default $k = 15, L = 0$).[8]

This is a cautionary note on the common practice of stemming words, which in information retrieval can have mixed effects on performance (Manning et al., 2008, Chapter 2). Here, stemming would have conflated *job* and *jobs*, greatly degrading results (to $r = 0.40$).

[8] We inspected some of the matching messages to try to understand this result, but since the sentiment detector is very noisy at the message level, it was difficult to understand what was happening.

3.5.1 Obama 2009 Job Approval and 2008 Elections

We analyze the sentiment ratio for *obama* and compared it to two series of polls, presidential job approval in 2009, and presidential election polls in 2008, as seen in Figure 3.8. The job approval poll is the most straightforward, being a steady decline since the start of the Obama presidency, perhaps with some stabilization in September or so. The sentiment ratio also generally declines during this period, with $r = 0.725$ for $k = 15$.

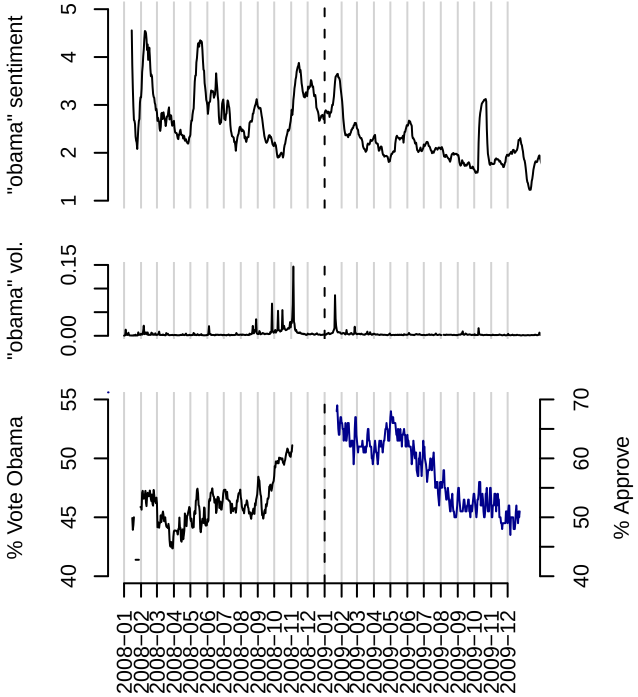


Figure 3.8: The sentiment ratio for *obama* (15-day window), and fraction of all Twitter messages containing *obama* (day-by-day, no smoothing), compared to election polls (2008) and job approval polls (2009).

However, in 2008 the sentiment ratio does not substantially correlate to the election polls ($r = -0.08$); we compare to the percent of support for Obama, averaged over a 7-day window of tracking polls: the same information displayed in Figure 3.3). Lindsay (2008) found that his daily sentiment score was a leading indicator to one particular tracking poll (Rasmussen) over a 100-day period from June-October 2008. Our measure also roughly correlates to the same data ($r = 0.44$ versus Lindsay's $r = 0.57$), and only at different lag parameters.

The elections setting may be structurally more complex than presidential job approval. In many of the tracking polls, people can choose to answer any *Obama*, *McCain*, *undecided*, *not planning to vote*, and third-party candidates. Furthermore, the name of every candidate has its own sentiment ratio scores in the data. We might expect the sentiment for *mccain* to be vary inversely with *obama*, but they in fact slightly correlate. It is also unclear how they should interact as part of a model of voter preferences.

Another question is to what how topic frequencies relate to polls. This is a complex question. First note that the message volume for *obama*, shown in Figure 3.8, has the usual daily spikes like other words on Twitter shown in Figure 3.4. Some of these spikes are very dramatic; for example, on November 5th, nearly 15% of all Twitter messages in our sample mentioned the word *obama*.

Furthermore, the *obama* message volume substantially correlates to the poll numbers. Even the raw volume has a 0.52 correlation to the polls, and the 15-day window version is up to $r = 0.79$ (basically stronger than the sentiment ratio's correlation!). This naïvely seems to indicate that media attention is associated with popularity. But the converse is not true for *mccain*; this word's 15-day message volume *also* correlates to higher Obama ratings in the polls ($r = 0.74$). This contradicts an "any press is good press" idea that media attention toward a candidate causes more popularity. There are many possible explanations; relative frequency, for example, may be a better measurement to investigate.

3.6 Measurement bias and inference goals

We do not focus on name frequency analysis, but other work has investigated this more thoroughly in other contexts. Tumasjan et al. (2010) analyzed relative name frequency for the 2009 German parliamentary elections, in Twitter messages over several weeks before the election. They found that the proportions of name frequencies of the six major political parties at the time were very similar to the parties' vote shares, reporting a mean absolute difference of less than 2%. Jungherr et al. (2012) replicated and critiqued this work, noting some sensitivity to details of data collection and name selection (among the six parties their replication found a lower correlation; see also Tumasjan et al. (2012)). Furthermore, they also found a remarkable sensitivity to party selection: the upstart Pirate Party, which was not included in the original study, actually had a far higher name frequency than any of the six major parties, but received a smaller vote share than any of them. We show their results in Figure 3.9. This may not be surprising since the Pirate Party was founded on a platform of of online civil liberties issues and had an especially active Internet presence; thus its name frequency was not comparable to the mainstream political parties, at least as an indicator of political preferences of the entire voting population.

This episode highlights a major issue of opinion analysis in social media: are the users representative of the greater population in question? A possible explanation for this result is that Twitter was overrepresented with Pirate-supporting users, compared to the greater population. A related issue is possible differences in platform-specific outreach and communication by political parties; in 2009, it may have been the case that mainstream parties were less effective at online engagement, and thus communications concerning them were relatively less frequent.

Generally speaking, the issue of measurement bias depends on the inference goal. If the goal is to assess the relative strengths of political parties, a relative name frequency analysis requires that the causes of party name mentions be similar across parties. This apparently was not the case for the Pirate Party, as might be expected since it was an outlier in many ways: it was founded just a few years before the election; it was not among the major parties commonly assessed by German polling firms; and it had no representation in the parliament at the time. On the other hand, among the six mainstream parties, the correlation to name frequency is quite remarkable; perhaps the process of their communication strategies and media coverage were comparable enough such that there was some mechanism to produce similar frequencies as voters' preferences—maybe users talked about the ones they liked, or maybe media coverage focused on parties in proportion to their support. These and other hypotheses are important to investigate in future work.

Tumasjan et al., 2010, Jungherr et al., 2012, and many other subsequent works such as Metaxas et al. (2011); Gayo-Avello (2012); Huberty (2013) focus on comparisons of popularity between parties, as a way to predict elections. The work in this chapter instead focuses on temporal correlations to tracking polls over time, where the key comparisons are popularity levels between timesteps. This suggests a number of possible reasons for non-correlations. If properties of the

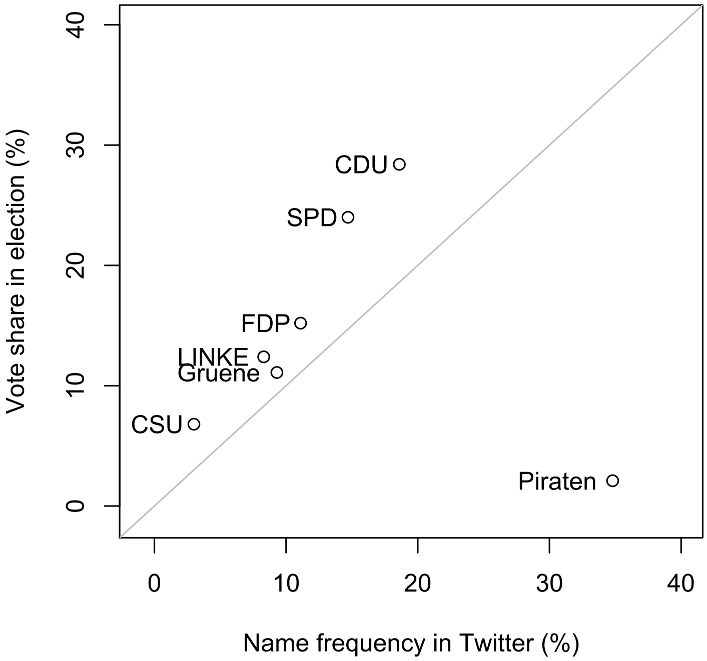


Figure 3.9: Jungherr et al. (2012)'s re-analysis of Tumasjan et al. (2010). *Grüne*=Green Party; *Piraten*=Pirate Party.

user population, such as demographic skew, or how different subpopulations use Twitter (for example, how heavily they use it), changed over time, that would render comparisons across time less meaningful. Even without such change, it could still be problematic since the proportions may not match the overall population; a small shift in opinion in an overrepresented subpopulation will cause an overly large shift to the averaged text measurement.

Besides population representativeness, the process by which the user population generates messages is also fraught: do certain populations write more or less under certain circumstances? Are the messages being observed sent by accounts controlled by personal users, or are they news media or other broadcast-like outlets? Are messages copies or retweets of those; if so, do they still indicate the sender's opinion? (And what about the gray area cases between personal use and broadcasting, such as "microcelebrities" like modestly popular bloggers, or previously unknown people whose messages go viral?) And since social media is monitored as a sign of importance or popularity, interested parties often attempt to manipulate Internet systems to gain apparent popularity (Metaxas and Mustafaraj, 2012).

We have already mentioned issues in the accuracy of the natural language processing techniques. Some of these issues may be invariant to the temporal or other substantively interesting comparisons: for example, if sentiment analyzer fails when negations are used, hopefully the probability of linguistic negation use does not change between timesteps. But linguistic issues may interact with user representativeness: if certain subpopulations or media sources use longer sentences, for example, NLP accuracy may be differentially affected. Chapters 4 and 5 show that certain demographics, such as minorities and youth, often use non-standard English online, and traditional NLP methods do not adequately capture them.

3.7 Conclusion

In the paper we find that a relatively simple sentiment detector based on Twitter data shares some common temporal signal with consumer confidence and presidential job approval polls. While the results do not come without caution, it is encouraging that expensive and time-intensive polling might be supplemented with the simple-to-gather text data that is generated from online social networking. The results suggest that more advanced NLP techniques to improve opinion estimation may be useful.

In this work, we treat polls as a gold standard. Of course, they are also noisy indicators of the truth, subject to biases or variability from question wording, low response rates, cell phone versus landline reachability (AAPOR, 2010), etc. Eventually, future work should seek to understand how these different signals reflect public opinion either as a hidden variable, or as measured from more reliable sources like face-to-face interviews—though currently the sources of measurement error are much better understood for polls than for social media sentiment analysis.

There exist many challenges in trying to derive opinion estimates similar to telephone polling of a more general population. At the very least, poststratification and weighting of the user population should be used: treating opinion analysis of social media data as conditional on user demographics, geography, or other subpopulations which can be reweighted to form an overall picture of the greater population. Wang et al. (2014) use a weighting model of non-representative online polls (from the Microsoft Xbox gaming service) to accurately forecast 2012 U.S. elections. More work is necessary to additionally address issues of variability in communication and linguistic behaviors mentioned in the previous section. A potentially useful technique, when there is enough data, is to use polls as a signal to learn better linguistic representations for classifiers; Beauchamp (2013) finds terms on Twitter that correlate to trends across many U.S. state polls.

Eventually, we see this research progressing to align with the more general goal of query-driven sentiment analysis where one can ask more varied questions of what people are thinking based on text they are already writing. Looking for correspondences with traditional survey data is a potential useful application of sentiment analysis. But it is also a stepping stone toward more complex applications.

Chapter 4

Mixed-membership analysis of geographic and demographic lexical variation in social media

4.1 Introduction

Even within a single language community, speakers from different backgrounds demonstrate substantial linguistic variation. Salient speaker characteristics include geography (Labov et al., 2006; Kurath, 1949), race (Rickford, 1999), and socioeconomic status (Labov, 1966; Eckert, 1989); they impact language at the phonological, lexical, and morphosyntactic levels (Wolfram and Schilling-Estes, 2005).

Sociolinguistics and dialectology feature a strong quantitative tradition of studying the relationship between language and social and geographical identity (e.g., Labov (1980); Tagliamonte (2006)). In general, these approaches begin by identifying both the communities of interest and the relevant linguistic dimensions of variability; for example, a researcher might identify the term "yinz" as characteristic of Pittsburgh dialect (Dressman, 1979), and then statistically model its relationship to the socioeconomic status of the speaker. This approach requires extensive fieldwork and linguistic expertise to identify the inputs that are to be analyzed. This is particularly challenging in the case of lexical variation, as a large amount of data must be analyzed in order to find demographic patterns for rare lexical items. In terms of Chapter 1's taxonomy of textual social analysis methods, this approach requires a high amount of domain assumptions—a preselected set of terms or other linguistic markers of dialect.

Given the massive quantities of everyday language that are now available in social media data, a new approach is possible: automatically discover terms that statistically associate with authors' social variables. In this chapter we develop a model-based, latent variable approach for exploratory analysis of geotagged social media, relating language to geography and demographics. Specifically, we use topic models, which are mixed-membership statistical models of text (Blei et al., 2003; Erosheva et al., 2004). Our model of Twitter users' language hypothesizes a number of latent topics, each of which is a soft cluster of words, and that each user tends to talk about a subset of these topics. The goal is to learn which words tend to belong to which topics, as well as which topics that individual users tend to use; the model learns both of these latent variables to best explain the data.

The specific model we develop here assumes another latent variable for a user—a community membership variable—that explains the users' geographic position (or demographic makeup of their neighborhood), which are tied to community-specific variants of topics. The model thus learns groups of users and terms that are jointly coherent across both linguistic and social data. Besides illustrating the model for exploratory analysis, we additionally validate the geographic model by applying Bayesian inference on its spatio-linguistic representations to predict a user's geographic location based on the text of their messages. We were surprised by some of the findings in this chapter—in particular, the huge variety of creative neologisms, sometimes very specific to certain geographies or demographics, which are rapidly evolving—which led to, among other work, Chapter 5 on the temporal diffusion of terms.

§4.2 explains our data and model as applied to geography, §4.3 presents an extension to analyze demographics, and §4.4 concludes with reflections and lessons for textual social data analysis.

4.2 Geographic topic model and lexical variation

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4.2.1 Synopsis

The rapid growth of geotagged social media raises new computational possibilities for investigating geographic linguistic variation. In this section, we present a multi-level generative model that reasons jointly about latent topics and geographical regions. High-level topics such as "sports" or "entertainment" are rendered differently in each geographic region, revealing topic-specific regional distinctions. Applied to a new dataset of geotagged microblogs, our model recovers coherent topics and their regional variants, while identifying geographic areas of linguistic consistency. The model also enables prediction of an author's geographic location from raw text, outperforming both text regression and supervised topic models.

Introduction

Sociolinguistics and dialectology study how language varies across social and regional contexts. Quantitative research in these fields generally proceeds by counting the frequency of a handful of previously-identified linguistic *variables*: pairs of phonological, lexical, or morphosyntactic features that are semantically equivalent, but whose frequency depends on social, geographical, or other factors (Paolillo, 2002; Chambers, 2009). It is left to the experimenter to determine which variables will be considered, and there is no obvious procedure for drawing inferences from the distribution of multiple variables. In this paper, we present a method for identifying geographically-aligned lexical variation directly from raw text. Our approach takes the form of a probabilistic graphical model capable of identifying both geographically-salient terms and coherent linguistic communities.

One challenge in the study of lexical variation is that term frequencies are influenced by a variety of factors, such as the topic of discourse. We address this issue by adding latent variables that allow us to model topical variation explicitly. We hypothesize that geography and topic interact, as "pure" topical lexical distributions are corrupted by geographical factors; for example, a sports-related topic will be rendered differently in New York and California. Each author is imbued with a latent "region" indicator, which both selects the regional variant of each topic, and generates the author's observed geographical location. The regional corruption of topics is modeled through a cascade of logistic normal priors—a general modeling approach which we call *cascading* topic models. The resulting system has multiple capabilities, including: (i) analyzing lexical variation by both topic and geography; (ii) segmenting geographical space into coherent linguistic communities; (iii) predicting author location based on text alone.

This research is only possible due to the rapid growth of social media. Our dataset is derived from the microblogging website Twitter,[1] which permits users to post short messages to the public. Many users of Twitter also supply exact geographical coordinates from GPS-enabled devices (e.g., mobile phones),[2] yielding *geotagged* text data. Text in computer-mediated communication is often more vernacular (Tagliamonte and Denis, 2008), and as such it is more likely to reveal the influence of geographic factors than text written in a more formal genre, such as news text (Labov, 1966).

We evaluate our approach both qualitatively and quantitatively. We investigate the topics and regions that the model obtains, showing both common-sense results (place names and sports teams are grouped appropriately), as well as less-obvious insights about slang. Quantitatively, we apply our model to predict the location of unlabeled authors, using text alone. On this task, our model outperforms several alternatives, including both discriminative text regression and related latent-variable approaches.

4.2.2 Data

The main dataset in this research is gathered from the microblog website Twitter, via its official API. We use an archive of messages collected over the first week of March 2010 from the "Gardenhose" sample stream,[3] which then consisted of 15% of all public messages, totaling millions per day. This short timeframe was chosen in order to obtain a conveniently sized sample that facilitated ease of experimentation. We aggressively filter this stream, using only messages that are tagged with physical (latitude, longitude) coordinate pairs from a mobile client, and whose authors wrote at least 20 messages over this period. We also filter to include only authors who follow fewer than 1,000 other people, and have fewer than 1,000 followers. Kwak et al. (2010) find dramatic shifts in behavior among users with social graph connectivity outside of that range; such users may be marketers, celebrities with professional publicists, news media sources, etc. We also remove messages containing URLs to eliminate bots posting information such as advertising or weather conditions. For interpretability, we restrict our attention to authors inside a bounding box around the contiguous U.S. states, yielding a final sample of about 9,500 users and 380,000 messages, totaling 4.7 million word tokens. We have made this dataset available online.[4]

Informal text from mobile phones is challenging to tokenize; we adapt a publicly available tokenizer[5] originally developed for Twitter (O'Connor et al., 2010c), which preserves emoticons and blocks of punctuation and other symbols as tokens. For each user's Twitter feed, we combine all messages into a single "document." We remove word types that appear in fewer than 40 feeds, yielding a vocabulary of 5,216 words. Of these, 1,332 do not appear in the English, French, or Spanish dictionaries of the spell-checking program `aspell`.

Every message is tagged with a location, but most messages from a single individual tend to come from nearby locations (as they go about their day); for modeling purposes we use only a single geographic location for each author, simply taking the location of the first message in the sample.

The authors in our dataset are fairly heavy Twitter users, posting an average of 40 messages per day (although we see, on average, only 15% of this total). We have little information about

[1] http://www.twitter.com

[2] User profiles also contain self-reported location names, but we do not use that information in this work.

[3] http://dev.twitter.com/pages/streaming_api

[4] http://www.ark.cs.cmu.edu/GeoText

[5] https://github.com/brendano/tweetmotif

their demographics, though from the text it seems likely that this user set skews towards teens and young adults. The dataset covers each of the 48 contiguous United States and the District of Columbia.

4.2.3 Model

We develop a model that incorporates two sources of lexical variation: topic and geographical region. We treat the text and geographic locations as outputs from a generative process that incorporates both topics and regions as latent variables.[6] During inference, we seek to recover the topics and regions that best explain the observed data.

At the base level of model are "pure" topics (such as "**sports**", "**weather**", or "**slang**"); these topics are rendered differently in each region. We call this general modeling approach a *cascading* topic model; we describe it first in general terms before moving to the specific application to geographical variation.

Cascading Topic Models

Cascading topic models generate text from a chain of random variables. Each element in the chain defines a distribution over words, and acts as the mean of the distribution over the subsequent element in the chain. Thus, each element in the chain can be thought of as introducing some additional corruption. All words are drawn from the final distribution in the chain.

At the beginning of the chain are the priors, followed by unadulerated base topics, which may then be corrupted by other factors (such as geography or time). For example, consider a base "**food**" topic that emphasizes words like *dinner* and *delicious*; the corrupted "**food-California**" topic would place weight on these words, but might place extra emphasis on other words like *sprouts*.

The path through the cascade is determined by a set of indexing variables, which may be hidden or observed. As in standard latent Dirichlet allocation (Blei et al., 2003), the base topics are selected by a per-token hidden variable z. In the geographical topic model, the next level corresponds to regions, which are selected by a per-author latent variable r.

Formally, we draw each level of the cascade from a normal distribution centered on the previous level; the final multinomial distribution over words is obtained by exponentiating and normalizing. To ensure tractable inference, we assume that all covariance matrices are uniform diagonal, i.e., $a\mathbf{I}$ with $a > 0$; this means we do not model interactions between words.

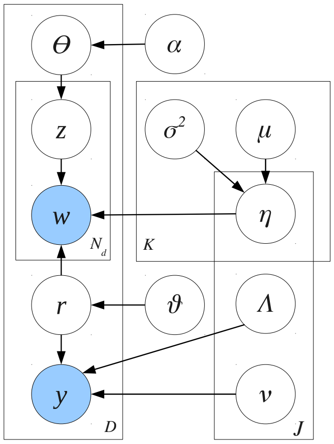
(§4.2.8 discusses this modeling approach in comparison to related work.)

The Geographic Topic Model

The application of cascading topic models to geographical variation is straightforward. Each document corresponds to the entire Twitter feed of a given author during the time period covered by our corpus. For each author, the latent variable r corresponds to the geographical region of the author, which is not observed. As described above, r selects a corrupted version of each topic: the kth basic topic has mean $\boldsymbol{\mu}_k$, with uniform diagonal covariance σ_k^2; for region j, we can draw the regionally-corrupted topic from the normal distribution, $\boldsymbol{\eta}_{jk} \sim \mathcal{N}(\boldsymbol{\mu}_k, \sigma_k^2\mathbf{I})$.

Because $\boldsymbol{\eta}$ is normally-distributed, it lies not in the simplex but in $\mathbb{R}^W$. We deterministically compute multinomial parameters $\boldsymbol{\beta}$ by exponentiating and normalizing: $\boldsymbol{\beta}_{jk} = \exp(\boldsymbol{\eta}_{jk}) / \sum_i \exp(\eta_{jk}^{(i)})$.

[6] The region could be observed by using a predefined geographical decomposition, e.g., political boundaries. However, such regions may not correspond well to linguistic variation.



$\boldsymbol{\mu}_k$	log of base topic k's distribution over word types
σ_k^2	variance parameter for regional variants of topic k
$\boldsymbol{\eta}_{jk}$	region j's variant of base topic $\boldsymbol{\mu}_k$
$\boldsymbol{\theta}_d$	author d's topic proportions
r_d	author d's latent region
$\boldsymbol{y}_d$	author d's observed GPS location
$\boldsymbol{\nu}_j$	region j's spatial center
Λ_j	region j's spatial precision
z_n	token n's topic assignment
w_n	token n's observed word type
$\boldsymbol{\alpha}$	global prior over author-topic proportions
$\boldsymbol{\vartheta}$	global prior over region classes

Figure 4.1: Plate diagram for the geographic topic model, with a table of all random variables. Priors (besides α) are omitted for clarity, and the document indices on z and w are implicit.

This normalization could introduce identifiability problems, as there are multiple settings for $\boldsymbol{\eta}$ that maximize $P(\boldsymbol{w}|\boldsymbol{\eta})$ (Blei and Lafferty, 2006a). However, this difficulty is obviated by the priors: given $\boldsymbol{\mu}$ and σ^2, there is only a single $\boldsymbol{\eta}$ that maximizes $P(\boldsymbol{w}|\boldsymbol{\eta})P(\boldsymbol{\eta}|\boldsymbol{\mu},\sigma^2)$; similarly, only a single $\boldsymbol{\mu}$ maximizes $P(\boldsymbol{\eta}|\boldsymbol{\mu})P(\boldsymbol{\mu}|\boldsymbol{a},b^2)$.

The observed latitude and longitude, denoted $\boldsymbol{y}$, are normally distributed and conditioned on the region, with mean $\boldsymbol{\nu}_r$ and precision matrix Λ_r indexed by the region r. The region index r is itself drawn from a single shared multinomial $\boldsymbol{\vartheta}$. The model is shown as a plate diagram in Figure 4.1.

Given a vocabulary size W, the generative story is as follows:

- **Generate base topics**: for each topic $k < K$
  - Draw the base topic from a normal distribution with uniform diagonal covariance: $\boldsymbol{\mu}_k \sim \mathcal{N}(\boldsymbol{a}, b^2\mathbf{I})$,
  - Draw the regional variance from a Gamma distribution: $\sigma_k^2 \sim \mathcal{G}(c, d)$.
  - **Generate regional variants**: for each region $j < J$,
    - Draw the region-topic $\boldsymbol{\eta}_{jk}$ from a normal distribution with uniform diagonal covariance: $\boldsymbol{\eta}_{jk} \sim \mathcal{N}(\boldsymbol{\mu}_k, \sigma_k^2\mathbf{I})$.
    - Convert $\boldsymbol{\eta}_{jk}$ into a multinomial distribution over words by exponentiating and normalizing: $\boldsymbol{\beta}_{jk} = \exp\left(\boldsymbol{\eta}_{jk}\right) / \sum_i^W \exp(\eta_{jk}^{(i)})$, where the denominator sums over the vocabulary.
- **Generate regions**: for each region $j < J$,
  - Draw the spatial mean $\boldsymbol{\nu}_j$ from a normal distribution.
  - Draw the precision matrix Λ_j from a Wishart distribution.
- Draw the distribution over regions $\boldsymbol{\vartheta}$ from a symmetric Dirichlet prior, $\boldsymbol{\vartheta} \sim \text{Dir}(\alpha_{\vartheta}\mathbf{1})$.
- **Generate text and locations**: for each document d,
  - Draw topic proportions from a symmetric Dirichlet prior, $\boldsymbol{\theta} \sim \text{Dir}(\alpha\mathbf{1})$.
  - Draw the region r from the multinomial distribution $\boldsymbol{\vartheta}$.
  - Draw the location $\boldsymbol{y}$ from the bivariate Gaussian, $\boldsymbol{y} \sim \mathcal{N}(\boldsymbol{\nu}_r, \Lambda_r)$.
  - For each word token,
    - Draw the topic indicator $z \sim \boldsymbol{\theta}$.
    - Draw the word token $w \sim \boldsymbol{\beta}_{rz}$.

4.2.4 Inference

We apply mean-field variational inference: a fully-factored variational distribution Q is chosen to minimize the Kullback-Leibler divergence from the true distribution. Mean-field variational inference with conjugate priors is described in detail elsewhere (Bishop, 2006; Wainwright and Jordan, 2008); we restrict our focus to the issues that are unique to the geographic topic model.

We place variational distributions over all latent variables of interest: $\boldsymbol{\theta}, \boldsymbol{z}, \boldsymbol{r}, \boldsymbol{\vartheta}, \boldsymbol{\eta}, \boldsymbol{\mu}, \sigma^2, \boldsymbol{\nu}$, and Λ, updating each of these distributions in turn, until convergence. The variational distributions over $\boldsymbol{\theta}$ and $\boldsymbol{\vartheta}$ are Dirichlet, and have closed form updates: each can be set to the sum of the expected counts, plus a term from the prior (Blei et al., 2003). The variational distributions $q(z)$ and $q(r)$ are categorical, and can be set proportional to the expected joint likelihood—to set $q(z)$ we marginalize over r, and vice versa.[7] The updates for the multivariate Gaussian spatial parameters $\boldsymbol{\nu}$ and Λ are described by Penny (2001).

Regional Word Distributions

The variational region-topic distribution $\boldsymbol{\eta}_{jk}$ is normal, with uniform diagonal covariance for tractability. Throughout we will write $\langle x \rangle$ to indicate the expectation of x under the variational distribution Q. Thus, the vector mean of the distribution $q(\boldsymbol{\eta}_{jk})$ is written $\langle \boldsymbol{\eta}_{jk} \rangle$, while the variance (uniform across i) of $q(\boldsymbol{\eta})$ is written $\mathcal{V}(\boldsymbol{\eta}_{jk})$.

To update the mean parameter $\langle \boldsymbol{\eta}_{jk} \rangle$, we maximize the contribution to the variational bound L from the relevant terms:

$$L_{[\langle \eta_{jk}^{(i)} \rangle]} = \langle \log p(\boldsymbol{w} | \boldsymbol{\beta}, \boldsymbol{z}, \boldsymbol{r}) \rangle + \langle \log p(\eta_{jk}^{(i)} | \mu_k^{(i)}, \sigma_k^2) \rangle, \tag{4.1}$$

with the first term representing the likelihood of the observed words (recall that $\boldsymbol{\beta}$ is computed deterministically from $\boldsymbol{\eta}$) and the second term corresponding to the prior. The likelihood term requires the expectation $\langle \log \boldsymbol{\beta} \rangle$, but this is somewhat complicated by the normalizer $\sum_i^W \exp(\eta^{(i)})$, which sums over all terms in the vocabulary. As in previous work on logistic normal topic models, we use a Taylor approximation for this term (Blei and Lafferty, 2006a).

The prior on $\boldsymbol{\eta}$ is normal, so the contribution from the second term of the objective (Equation 4.1) is $-\frac{1}{2\langle \sigma_k^2 \rangle} \langle (\eta_{jk}^{(i)} - \mu_k^{(i)})^2 \rangle$. We introduce the following notation for expected counts: $N(i, j, k)$ indicates the expected count of term i in region j and topic k, and $N(j, k) = \sum_i N(i, j, k)$. After some calculus, we can write the gradient $\partial L / \partial \langle \eta_{jk}^{((i))} \rangle$ as

$$N(i, j, k) - N(j, k) \langle \beta_{jk}^{(i)} \rangle - \langle \sigma_k^{-2} \rangle (\langle \eta_{jk}^{(i)} \rangle - \langle \mu_k^{(i)} \rangle), \tag{4.2}$$

which has an intuitive interpretation. The first two terms represent the difference in expected counts for term i under the variational distributions $q(z, r)$ and $q(z, r, \beta)$: this difference goes to zero when $\beta_{jk}^{(i)}$ perfectly matches $N(i, j, k) / N(j, k)$. The third term penalizes $\eta_{jk}^{(i)}$ for deviating from its prior $\mu_k^{(i)}$, but this penalty is proportional to the expected inverse variance $\langle \sigma_k^{-2} \rangle$. We apply gradient ascent to maximize the objective L. A similar set of calculations gives the gradient for the variance of $\boldsymbol{\eta}$; these are described in an online appendix (Eisenstein, 2010).

[7] Thanks to the mean field assumption, we can marginalize over $\boldsymbol{z}$ by first decomposing across all N_d words and then summing over $q(z)$.

Base Topics

The base topic parameters are $\boldsymbol{\mu}_k$ and σ_k^2; in the variational distribution, $q(\boldsymbol{\mu}_k)$ is normally distributed and $q(\sigma_k^2)$ is Gamma distributed. Note that $\boldsymbol{\mu}_k$ and σ_k^2 affect only the regional word distributions $\boldsymbol{\eta}_{jk}$. An advantage of the logistic normal is that the variational parameters over $\boldsymbol{\mu}_k$ are available in closed form,

$$\begin{aligned}\langle \mu_k^{(i)} \rangle &= \frac{b^2 \sum_j^J \langle \eta_{jk}^{(i)} \rangle + \langle \sigma_k^2 \rangle a^{(i)}}{b^2 J + \langle \sigma_k^2 \rangle} \\ \mathcal{V}(\boldsymbol{\mu}_k) &= (b^{-2} + J \langle \sigma_k^{-2} \rangle)^{-1},\end{aligned}$$

where J indicates the number of regions. The expectation of the base topic μ incorporates the prior and the average of the generated region-topics—these two components are weighted respectively by the expected variance of the region-topics $\langle \sigma_k^2 \rangle$ and the prior topical variance b^2. The posterior variance $\mathcal{V}(\boldsymbol{\mu})$ is a harmonic combination of the prior variance b^2 and the expected variance of the region topics.

The variational distribution over the region-topic variance σ_k^2 has Gamma parameters. These parameters cannot be updated in closed form, so gradient ascent optimization is again required. The derivation of these updates is more involved; see appendix.

4.2.5 Implementation

Variational scheduling and initialization are important aspects of any hierarchical generative model, and are often under-discussed. In our implementation, the variational updates are scheduled as follows: given expected counts, we iteratively update the variational parameters on the region-topics $\boldsymbol{\eta}$ and the base topics $\boldsymbol{\mu}$, until convergence. We then update the geographical parameters $\boldsymbol{\nu}$ and Λ, as well as the distribution over regions $\boldsymbol{\vartheta}$. Finally, for each document we iteratively update the variational parameters over $\boldsymbol{\theta}, \boldsymbol{z}$, and r until convergence, obtaining expected counts that are used in the next iteration of updates for the topics and their regional variants. We iterate an outer loop over the entire set of updates until convergence.

We initialize the model in a piecewise fashion. First we train a Dirichlet process mixture model on the locations $\boldsymbol{y}$, using variational inference on the truncated stick-breaking approximation (Blei and Jordan, 2006). This automatically selects the number of regions J, and gives a distribution over each region indicator r_d from geographical information alone. We then run standard latent Dirichlet allocation to obtain estimates of $\boldsymbol{z}$ for each token (ignoring the locations). From this initialization we can compute the first set of expected counts, which are used to obtain initial estimates of all parameters needed to begin variational inference in the full model.

The prior $\boldsymbol{a}$ is the expected mean of each topic $\boldsymbol{\mu}$; for each term i, we set $a^{(i)} = \log N(i) - \log N$, where $N(i)$ is the total count of i in the corpus and $N = \sum_i N(i)$. The variance prior b^2 is set to 1, and the prior on σ^2 is the Gamma distribution $\mathcal{G}(2, 200)$, encouraging minimal deviation from the base topics. The symmetric Dirichlet prior on $\boldsymbol{\theta}$ is set to $\frac{1}{2}$, and the symmetric Dirichlet parameter on ϑ is updated from weak hyperpriors (Minka, 2003). Finally, the geographical model takes priors that are linked to the data: for each region, the mean is very weakly encouraged to be near the overall mean, and the covariance prior is set by the average covariance of clusters obtained by running K-means.

4.2.6 Evaluation

For a quantitative evaluation of the estimated relationship between text and geography, we assess our model's ability to predict the geographic location of unlabeled authors based on their text alone.[8] This task may also be practically relevant as a step toward applications for recommending local businesses or social connections. A randomly-chosen 60% of authors are used for training, 20% for development, and the remaining 20% for final evaluation.

Systems

We compare several approaches for predicting author location; we divide these into latent variable generative models and discriminative approaches.

Geographic Topic Model This is the full version of our system, as described in this paper. To predict the unseen location $\boldsymbol{y}_d$, we iterate until convergence on the variational updates for the hidden topics $\boldsymbol{z}_d$, the topic proportions $\boldsymbol{\theta}_d$, and the region r_d. From r_d, the location can be estimated as $\hat{\boldsymbol{y}}_d = \arg\max_{\boldsymbol{y}} \sum_j^J p(\boldsymbol{y}|\boldsymbol{\nu}_j, \Lambda_j) q(r_d = j)$. The development set is used to tune the number of topics and to select the best of multiple random initializations.

Mixture of Unigrams A core premise of our approach is that modeling topical variation will improve our ability to understand geographical variation. We test this idea by fixing $K = 1$, running our system with only a single topic. This is equivalent to a Bayesian mixture of unigrams in which each author is assigned a single, regional unigram language model that generates all of his or her text. The development set is used to select the best of multiple random initializations.

Supervised Latent Dirichlet Allocation In a more subtle version of the mixture-of-unigrams model, we model each author as an admixture of regions. Thus, the latent variable attached to each author is no longer an index, but rather a vector on the simplex. This model is equivalent to supervised latent Dirichlet allocation (Blei and McAuliffe, 2008): each topic is associated with equivariant Gaussian distributions over the latitude and longitude, and these topics must explain both the text and the observed geographical locations. For unlabeled authors, we estimate latitude and longitude by estimating the topic proportions and then applying the learned geographical distributions. This is a linear prediction

$$f(\bar{\boldsymbol{z}}_d; \boldsymbol{a}) = (\bar{\boldsymbol{z}}_d^{\mathsf{T}} \boldsymbol{a}^{\text{lat}},\ \bar{\boldsymbol{z}}_d^{\mathsf{T}} \boldsymbol{a}^{\text{lon}})$$

for an author's topic proportions $\bar{\boldsymbol{z}}_d$ and topic-geography weights $\boldsymbol{a} \in \mathbb{R}^{2K}$.

Text Regression We perform linear regression to discriminatively learn the relationship between words and locations. Using term frequency features $\boldsymbol{x}_d$ for each author, we predict locations with word-geography weights $\boldsymbol{a} \in \mathbb{R}^{2W}$:

$$f(\boldsymbol{x}_d; \boldsymbol{a}) = (\boldsymbol{x}_d^{\mathsf{T}} \boldsymbol{a}^{\text{lat}},\ \boldsymbol{x}_d^{\mathsf{T}} \boldsymbol{a}^{\text{lon}})$$

[8] Alternatively, one might evaluate the attributed regional memberships of the words themselves. While the Dictionary of American Regional English (Cassidy and Hall, 1985) attempts a comprehensive list of all regionally-affiliated terms, it is based on interviews conducted from 1965-1970, and the final volume (covering Si–Z) is not yet complete.

	Regression		Classification accuracy (%)	
System	Mean Dist. (km)	Median Dist. (km)	Region (4-way)	State (49-way)
Geographic topic model	**900**	**494**	**58**	24
Mixture of unigrams	947	644	53	19
Supervised LDA	1055	728	39	4
Text regression	948	712	41	4
K-nearest neighbors	1077	853	37	2
Mean location	1148	1018		
Most common class			37	**27**

Table 4.1: Location prediction results; lower scores are better on the regression task, higher scores are better on the classification task. Distances are in kilometers. Mean location and most common class are computed from the test set. Both the geographic topic model and supervised LDA use the best number of topics from the development set (10 and 5, respectively).

Weights are trained to minimize the sum of squared Euclidean distances, subject to L_1 regularization:

$$\sum_d (\boldsymbol{x}_d^\top \boldsymbol{a}^{\text{lat}} - y_d^{\text{lat}})^2 + (\boldsymbol{x}_d^\top \boldsymbol{a}^{\text{lon}} - y_d^{\text{lon}})^2$$
$$+ \lambda_{\text{lat}} ||\boldsymbol{a}^{\text{lat}}||_1 + \lambda_{\text{lon}} ||\boldsymbol{a}^{\text{lon}}||_1$$

The minimization problem decouples into two separate latitude and longitude models, which we fit using the `glmnet` elastic net regularized regression package (Friedman et al., 2010) which has obtained good results on other text-based prediction tasks (Joshi et al., 2010). Regularization parameters were tuned on the development set. The L_1 penalty outperformed L_2 and mixtures of L_1 and L_2.

Note that for both word-level linear regression here, and the topic-level linear regression in SLDA, the choice of squared Euclidean distance dovetails with our use of spatial Gaussian likelihoods in the geographic topic models, since optimizing $\boldsymbol{a}$ is equivalent to maximum likelihood estimation under the assumption that locations are drawn from equivariant circular Gaussians centered around each $f(\boldsymbol{x}_d; \boldsymbol{a})$ linear prediction. We experimented with decorrelating the location dimensions by projecting $\boldsymbol{y}_d$ into the principal component space, but this did not help text regression.

***K*-Nearest Neighbors** Linear regression is a poor model for the multimodal density of human populations. As an alternative baseline, we applied supervised K-nearest neighbors to predict the location $\boldsymbol{y}_d$ as the average of the positions of the K most similar authors in the training set. We computed term-frequency inverse-document frequency features and applied cosine similarity over their first 30 principal components to find the neighbors. The choices of principal components, IDF weighting, and neighborhood size $K = 20$ were tuned on the development set.

Metrics

Our principle error metrics are the mean and median distance between the predicted and true location in kilometers.[9] Because the distance error may be difficult to interpret, we also report

[9] For convenience, model training and prediction use latitude and longitude as a naïvely projected 2D Euclidean space. However, properly measuring the physical distance between points on the Earth's surface requires calculating

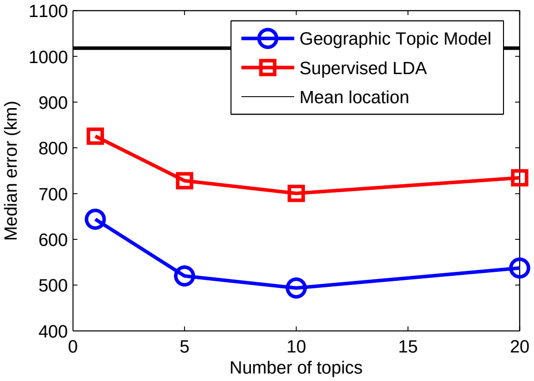


Figure 4.2: The effect of varying the number of topics on the median regression error (lower is better).

accuracy of classification by state and by region of the United States. Our data includes the 48 contiguous states plus the District of Columbia; the U.S. Census Bureau divides these states into four regions: West, Midwest, Northeast, and South.[10] Note that while major population centers straddle several state lines, most region boundaries are far from the largest cities, resulting in a clearer analysis.

Results

As shown in Table 4.1, the geographic topic model achieves the strongest performance on all metrics. All differences in performance between systems are statistically significant ($p < .01$) using the Wilcoxon-Mann-Whitney test for regression error and the χ^2 test for classification accuracy. Figure 4.2 shows how performance changes as the number of topics varies.

Note that the geographic topic model and the mixture of unigrams use identical code and parametrization – the only difference is that the geographic topic model accounts for topical variation, while the mixture of unigrams sets $K = 1$. These results validate our basic premise that it is important to model the interaction between topical and geographical variation.

Text regression and supervised LDA perform especially poorly on the classification metric. Both methods make predictions that are averaged across each word in the document: in text regression, each word is directly multiplied by a feature weight; in supervised LDA the word is associated with a latent topic first, and then multiplied by a weight. For these models, all words exert an influence on the predicted location, so uninformative words will draw the prediction towards the center of the map. This yields reasonable distance errors but poor classification accuracy. We hypothesized that K-nearest neighbors would be a better fit for this metric, but its performance is poor at all values of K. Of course it is always possible to optimize classification accuracy directly, but such an approach would be incapable of predicting the exact geographical location, which is the focus of our evaluation (given that the desired geographical partition

the great circle distance, for which we use the Haversine formula (Sinnott, 1984). For the continental U.S., degree-space is a reasonable approximation for modeling. While the dimensions are are differently sized—in the geographical center of the U.S., latitude is about 111 km/degree while longitude is about 85 km/degree—since our model includes spatial covariance, it effectively stretches and rotates as much as necessary. Extending the model to a continental scale would require a more sophisticated approach.

[10] http://www.census.gov/geo/www/us_regdiv.pdf

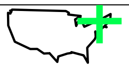
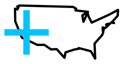
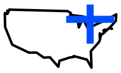
	“basketball”	**“popular music”**	**“daily life”**	**“emoticons”**	**“chit chat”**
	PISTONS KOBE LAKERS game DUKE NBA CAVS STUCKEY JETS KNICKS	album music beats artist video #LAKERS ITUNES tour produced vol	tonight shop weekend getting going chilling ready discount waiting iam	:) haha :d :(;) :p xd :/ hahaha hahah	lol smh jk yea wyd coo ima wassup somethin jp
Boston	CELTICS victory BOSTON CHARLOTTE	playing daughter PEARL alive war comp	BOSTON	;p gna loveee	*ese* exam suttin sippin
N. California	THUNDER KINGS GIANTS pimp trees clap	SIMON dl mountain seee	6am OAKLAND	*pues* hella koo SAN fckn	hella flirt hut iono OAKLAND
New York 	NETS KNICKS	BRONX	iam cab	oww	wasssup nm
Los Angeles 	#KOBE #LAKERS AUSTIN	#LAKERS load HOLLYWOOD imm MICKEY TUPAC	omw tacos hr HOLLYWOOD	af *papi* raining th bomb coo HOLLYWOOD	wyd coo af *nada* tacos messin fasho bomb
Lake Erie 	CAVS CLEVELAND OHIO BUCKS od COLUMBUS	premiere prod joint TORONTO onto designer CANADA village burr	stink CHIPOTLE tipsy	;d blvd BIEBER hve OHIO	foul WIZ salty excuses lames officer lastnight

Table 4.2: Example base topics (top line) and regional variants. For the base topics, terms are ranked by log-odds compared to the background distribution. The regional variants show words that are strong compared to both the base topic and the background. Foreign-language words are shown in *italics*, while terms that are usually in proper nouns are shown in SMALL CAPS. See Table 4.3 for definitions of slang terms; see Section 4.2.7 for more explanation and details on the methodology.

is unknown). Note that the geographic topic model is also not trained to optimize classification accuracy.

4.2.7 Analysis

Our model permits analysis of geographical variation in the context of topics that help to clarify the significance of geographically-salient terms. Table 4.2 shows a subset of the results of one randomly-initialized run, including five hand-chosen topics (of 50 total) and five regions (of 13, as chosen automatically during initialization). Terms were selected by log-odds comparison. For the base topics we show the ten strongest terms in each topic as compared to the background word distribution. For the regional variants, we show terms that are strong both regionally and topically: specifically, we select terms that are in the top 100 compared to both the background distribution and to the base topic. The names for the topics and regions were chosen by the authors.

Nearly all of the terms in column 1 (“**basketball**”) refer to sports teams, athletes, and place names—encouragingly, terms tend to appear in the regions where their referents reside. Column

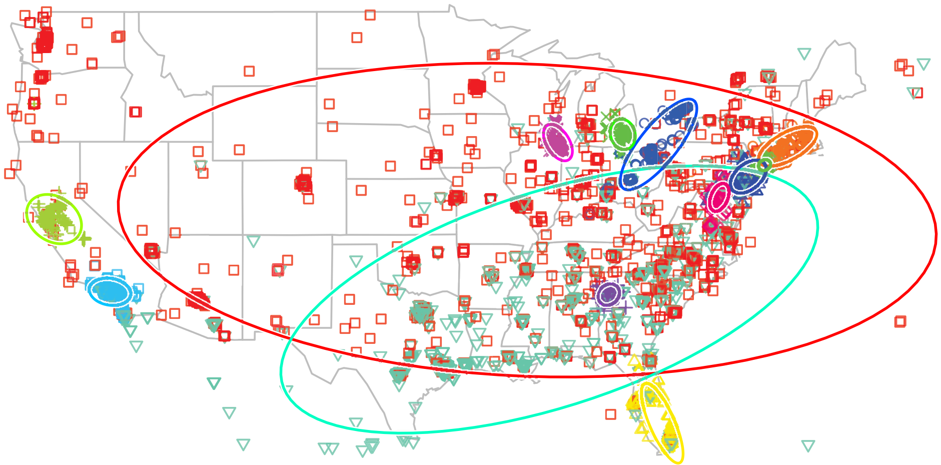


Figure 4.3: Regional clustering of the training set obtained by one randomly-initialized run of the geographical topic model. Each point represents one author, and each shape/color combination represents the most likely cluster assignment. Ellipses represent the regions' spatial means and covariances. The same model and coloring are shown in Table 4.2.

2 contains several proper nouns, mostly referring to popular music figures (including PEARL from the band Pearl Jam).[11] Columns 3–5 are more conversational. Spanish-language terms (*papi, pues, nada, ese*) tend to appear in regions with large Spanish-speaking populations—it is also telling that these terms appear in topics with emoticons and slang abbreviations, which may transcend linguistic barriers. Other terms refer to people or subjects that may be especially relevant in certain regions: *tacos* appears in the southern California region and *cab* in the New York region; TUPAC refers to a rap musician from Los Angeles, and WIZ refers to a rap musician from Pittsburgh, not far from the center of the "Lake Erie" region.

A large number of slang terms are found to have strong regional biases, suggesting that slang may depend on geography more than standard English does. The terms *af* and *hella* display especially strong regional affinities, appearing in the regional variants of multiple topics (see Table 4.3 for definitions). While research in perceptual dialectology does confirm the link of *hella* to Northern California (Bucholtz et al., 2007), we caution that our findings are merely suggestive, and a more extensive analysis must be undertaken before making definitive statements about the regional membership of individual terms. We view the geographic topic model as an exploratory tool that may be used to facilitate such investigations.

Figure 4.3 shows the regional clustering on the training set obtained by one run of the model. Each point represents an author, and the ellipses represent the bivariate Gaussians for each region. There are nine compact regions for major metropolitan areas, two slightly larger regions that encompass Florida and the area around Lake Erie, and two large regions that partition the country roughly into north and south.

[11] This analysis is from an earlier version of our dataset that contained some Twitterbots, including one from a Boston-area radio station. The bots were removed for the evaluation in Section 4.2.6, though the numerical results are nearly identical.

term	definition
af	as fuck (very)
coo	cool
dl	download
fasho	for sure
gna	going to
hella	very
hr	hour
iam	I am
ima	I'm going to
imm	I'm
iono	I don't know
lames	lame (not cool) people
jk	just kidding
jp	just playing (kidding)
koo	cool
lol	laugh out loud
nm	nothing much
od	overdone (very)
omw	on my way
smh	shake my head
suttin	something
wassup	what's up
wyd	what are you doing?

Table 4.3: A glossary of non-standard terms from Table 4.2. Definitions are obtained by manually inspecting the context in which the terms appear, and by consulting www.urbandictionary.com.

4.2.8 Related Work

The relationship between language and geography has been a topic of interest to linguists since the nineteenth century (Johnstone, 2010). An early work of particular relevance is Kurath's *Word Geography of the Eastern United States* (1949), in which he conducted interviews and then mapped the occurrence of equivalent word pairs such as *stoop* and *porch*. The essence of this approach—identifying variable pairs and measuring their frequencies—remains a dominant methodology in both dialectology (Labov et al., 2006) and sociolinguistics (Tagliamonte, 2006). Within this paradigm, computational techniques are often applied to post hoc analysis: logistic regression (Sankoff et al., 2005) and mixed-effects models (Johnson, 2009) are used to measure the contribution of individual variables, while hierarchical clustering and multidimensional scaling enable aggregated inference across multiple variables (Nerbonne, 2009). However, in all such work it is assumed that the relevant linguistic variables have already been identified—a time-consuming process involving considerable linguistic expertise. We view our work as complementary to this tradition: we work directly from raw text, identifying both the relevant features and coherent linguistic communities.

An active recent literature concerns geotagged information on the web, such as search queries (Backstrom et al., 2008) and tagged images (Crandall et al., 2009). This research identifies the geographic distribution of individual queries and tags, but does not attempt to induce any structural organization of either the text or geographical space, which is the focus of our research. More relevant is the work of Mei et al. (2006), in which the distribution over latent topics in blog posts is conditioned on the geographical location of the author. This is somewhat similar to the supervised LDA model that we consider, but their approach assumes that a partitioning of geographical space into regions is already given. The dataset we released with the published version of this paper has been used for several studies investigating the geolocation task. Wing and Baldridge (2011); Roller et al. (2012) focus just on the geolocation task, Eisenstein et al. (2011b) present a variant of the model here, and Hong et al. (2012); Ahmed et al. (2013) also discover geographical topics using different models.

Methodologically, our cascading topic model is designed to capture multiple dimensions of variability: topics and geography. Mei et al. (2007) include sentiment as a second dimension in a topic model, using a switching variable so that individual word tokens may be selected from either the topic or the sentiment. However, our hypothesis is that individual word tokens reflect both the topic and the geographical aspect. Sharing this intuition, Paul and Girju (2010) build topic-aspect models for the cross product of topics and aspects. They do not impose any regularity across multiple aspects of the same topic, so this approach may not scale when the number of aspects is large (they consider only two aspects). We address this issue using cascading distributions; when the observed data for a given region-topic pair is low, the model falls back to the base topic. The use of cascading logistic normal distributions in topic models follows earlier work on dynamic topic models (Blei and Lafferty, 2006b; Xing, 2005). Paul and Dredze (2012) present an alternative Dirichlet approach to combining multiple factors into topic-word distributions. (There has also been previous work with hierarchical Dirichlets and their generalizations for n-gram models of differing prefix lengths (MacKay and Peto, 1995; Teh, 2006) and interpolating against document-level topics (Wallach, 2008, §3.4).) Eisenstein et al. (2011b) extend the additive cascading topics approach here to have sparse deviations, and Roberts et al. (2013) embed them in a more general covariate-influenced topic model.

4.3 Demographic lexical variation through U.S. Census data

(This section was originally published as O'Connor et al. (2010b).)

4.3.1 Introduction

In this study, we apply the model of §4.2 to discover demographic language variation from text and metadata, in order to explain both linguistic variation and demographic features through a set of generative distributions, each of which is associated with a (latent) community of speakers. Thus, our model is capable of discovering both the relevant sociolinguistic communities, as well as the key dimensions of lexical variation.

4.3.2 Data

We start with the same dataset used in Section 4.2, focusing on a randomly-selected subset of 4875 authors. For this research, we have extended the corpus with detailed demographic metadata. While it is difficult to identify the demographic attributes of individual speakers, we can cross-reference speaker locations against U.S. Census data to extract aggregate demographic statistics of each user's geographic location.[12] We use the Zip Code Tabulation Areas (ZCTA) level of granularity, which partitions the U.S. into 33,178 geographic features (typically polygons). Using a standard geospatial tool,[13] we match each author's location to the area that contains it, and use the area's demographics as that author's demographic metadata. The set of features that we consider are shown in Table 4.4. To give a rough view of word association, for each variable we show the top five words ranked by the sample-corrected average demographic value among authors who use them at least once.[14] Some terms are telling by themselves, though some aspects are obviously issues with the relatively small sample and narrow timeframe (e.g. *mangoville*); based in part on this experience, in Chapter 5 we focus on longer-term data.

[12] We use year 2000 data from Summary Files 1 and 3: http://www.census.gov/support/cen2000.html

[13] PostGIS: http://postgis.net/

[14] We rank by the lower bound of the 95% confidence interval for the mean: $\hat{\mu} - 1.96\,\hat{\sigma}/\sqrt{n}$. Using the raw average always places rare words in the top ranks, which is often due to statistical noise.

Demographic Variable	Mean	SD	Words with Highest Average
Percent White	52.1%	29.0	leno, fantastic, holy, military, review
Percent African-American	32.2%	29.1	lml, momz, midterms, bmore, fuccin
Percent Hispanic	15.7%	18.3	cuando, estoy, pero, eso, gracias
Percent English speakers	73.7%	18.4	#lowkey, porter, #ilovefamu, nc, atlanta
Percent population in urban areas	95.1%	14.3	odeee, thatt, m2, maddd, mangoville
Percent family households	64.1%	14.4	mangoville, lightskin, iin, af, aha
Median annual income†	$39,045	(26k, 59k)	mangoville, tuck, itunes, jim, dose

Figure 4.4: List of demographic variables used, selected from 2000 U.S. Census data, along with their mean and standard deviation among authors in the data, and the words with the highest sample-adjusted average values. The procedure for selecting words is described in Section 4.3.2; some analysis appears in Section 4.3.4. (Income is shown in dollars, but the model uses log-dollars. The SD column shows $(\hat{\mu} \pm \hat{\sigma})$ computed on the log scale.)

While geographical aggregate statistics are frequently used to proxy for individual socioeconomic status in research fields such as public health (e.g., Rushton, 2008), it is clear that interpretation must proceed with caution. Consider an author from a zip code in which 60% of the residents are Hispanic:[15] we do not know the likelihood that the author is Hispanic, because the set of Twitter users is not a representative sample of the overall population. Polling research suggests that users of both Twitter (Smith and Rainie, 2010) and geolocation services (Zickuhr and Smith, 2010) are much more diverse with respect to age, gender, race and ethnicity than the general population of Internet users. Nonetheless, at present we can only use aggregate statistics to make inferences about the geographic communities in which our authors live, and not the authors themselves.

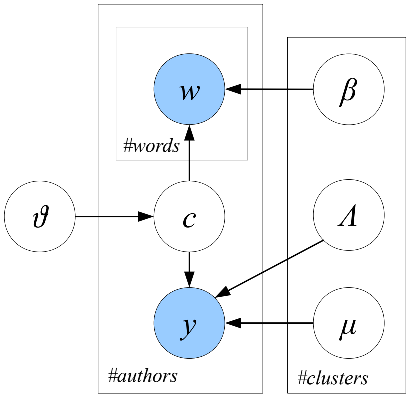
4.3.3 Model

Our latent variable model combines demographic metadata with microblog text. The goal is to extract a set of latent sociolinguistic communities which are coherent with respect to both data sources. Our model combines a multinomial distribution over text with a multivariate Gaussian over the demographic statistics; these generative components are unified in a Dirichlet process mixture, in which each speaker has a latent "community" index. The model corresponds to the single-membership, "mixture of unigrams" version of Section 4.2's Geographic Topic Model, where $K = 1$. For clarity, we give a complete description of this version of the model as follows.

We hypothesize a generative stochastic process that produces the text and the demographic data for each author. This generative process includes a set of latent variables; we will recover a variational distribution over these latent variables using a mean field representation. The plate diagram for this model is shown in Figure 4.5. The key latent variable is the community membership of each author, which we write c_d; this variable selects a distribution over both the metadata and the text. Each distribution over metadata is a multivariate Gaussian with parameters $\boldsymbol{\mu}$ and Λ; each distribution over text is a multinomial with parameter $\boldsymbol{\beta}$. Overall, we can describe the generative process as:

- Draw the community proportions $\boldsymbol{\vartheta}$ from a stick-breaking prior,
- **Generate the community distributions.** For each community i,

[15] In the U.S. Census, the official ethnonym is *Hispanic or Latino*; for brevity we use *Hispanic* in the rest of this thesis.



$w_n^{(d)}$	the observed word type for token n of document d
y_d	metadata vector for author d
c_d	the community membership for author d
$\boldsymbol{\mu}_i$	mean metadata vector for community i
Λ_i	precision matrix over metadata for community i
$\boldsymbol{\beta}_i$	word distribution for community i
$\boldsymbol{\alpha}$	global prior over topic proportions
$\boldsymbol{\vartheta}$	global prior over communities

Figure 4.5: Plate diagram for our model of text and demographics, with a table of all random variables. The document indices in the figure are implicit, as are the priors on $\boldsymbol{\mu}, \boldsymbol{\Lambda}, \boldsymbol{\beta}$.

  - Draw the metadata mean $\boldsymbol{\mu}_i$ from a multivariate Normal prior,
  - Draw the metadata precision matrix Λ_i from a Wishart prior,
  - Draw the word distribution $\boldsymbol{\beta}_i$ from a Dirichlet prior,

- **Generate the text and metadata.** For each author d,
  - Draw the community c_d from the distribution $\boldsymbol{\vartheta}$,
  - Draw the metadata $\boldsymbol{y}_d$ from a Gaussian with mean $\boldsymbol{\mu}_{c_d}$ and precision Λ_{c_d},
  - Draw the bag of words $\boldsymbol{w}_d$ from the multinomial $\boldsymbol{\beta}_{c_d}$,

We apply mean field variational inference to recover a posterior distribution over the random variables in this model (Bishop, 2006), as described in §4.2.4. For efficiency, we initialized by running the Dirichlet process mixture model on the demographic data alone. The number of active clusters from this initialization was used as the fixed number of clusters when running the full model on both text and demographics data.

4.3.4 Analysis

Figure 4.4 shows the words associated with large values for each demographic feature, ranked by sample-corrected averages (described above). This is informative and should be viewed as an exploratory method in its own right; however, correlations between demographic variables make it difficult to disentangle the underlying relationships between demography and lexical frequencies.

In contrast, Figure 4.3.3 summarizes all of the sociolinguistic clusters identified by our model. All clusters are shown. Each row shows a cluster that corresponds to a distribution over demographic information, along with a set of characteristic terms as chosen by likelihood ratio. This cluster analysis allows us to associate each term with a complete demographic profile.

Several of the top terms refer to subjects which attracted only an ephemeral interest, and would likely not appear in a dataset taken from a longer timespan. The term *19th* refers to an event on March 19, 2010 that was a frequent subject of conversation in this dataset. The term *olive* usually refers to the Olive Garden restaurant; *mangoville* refers to a restaurant in New York City. Florida

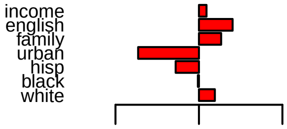
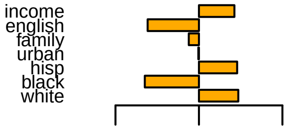
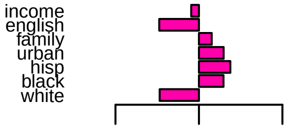
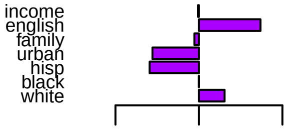
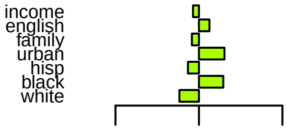
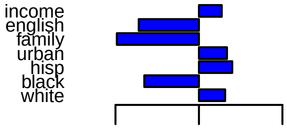
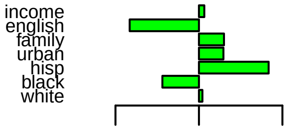
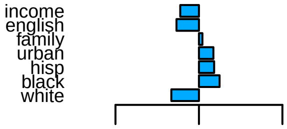
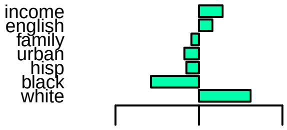
	Mean Vector	Top Words
Cluster 1		rsvp, ent, guest, blvd, broadcasting, details, bash, lls, retweet, ——, #free, —-, hosting, pow, vibe, 31, vol, —–, feat, 2nite
Cluster 2		en, de, el, que, es, por, se, un, los, pero, una, como, para, lo, del, te, si, eso, la, tu
Cluster 3		ii, dha, yu, uu, yuu, dhat, lols, lolss, lml, qo, qot, w—, myy, iim, qet, yuh, smhh, niqqa, buh, &&
Cluster 4		#ilovefamu, lmbo, grind, official, awards, #lowkey, #famusextape, jake, track, spirit, #thatisall, mental, famu, praying, studying, you're, bible, midterm, joy, awesome
Cluster 5		lls, jawn, neighbors, joints, nivea, #famusextape, sextape, #epicfail, cuddle, broad, midterms, jeezy, #thatisall, basic, nigga, waited, tmobile, menu, bcuz, famu
Cluster 6		gimmie, hosted, —, download, b-day, dl, limit, drake, mix, dj, mc, salute, //, #unotfromthehoodif, ft, exclusive, birthday, models, -, lab
Cluster 7		:], ;], -_-, ^, bahaha, :d, papi, ^_^, ily, aha, =], fck, hahah, lovee, ew, yess, :/, #urparentsever, mangoville, jamaica
Cluster 8		dats, dat, dis, wat, da, watz, dey, wats, den, gud, wen, gravity, niggaz, jus, der, fuk, rite, dem, tha, dese
Cluster 9		rare, 19th, olive, simply, adam, agent, coffee, obama, awesome, 400, hockey, leno, thomas, worked, pentagon, #fb, tone, presents, larry, peppers

Figure 4.6: Demographic mean vectors and most salient words per cluster. Demographic variables are shown on a normalized scale; zero indicates the population mean, and the axis tick marks denote ±1 standard deviation; see Table 4.4 for their values. For each cluster k, words shown are the top-20 most highly ranked by the ratio of topic probability against background probability: $\frac{\beta_k[w]}{\hat{p}(w)}$.

A&M, a historically-black university, appears in the terms *#ilovefamu* and *#famusextape*. Terms that start with hashtags (e.g., *#epicfail*, *#thatisall*) often represent "trends" that are shown on all users' Twitter pages; many users participate by adding their own commentary on such tags (Kwak et al., 2010). The topic lists also contain several names, including *leno*, *obama*, and the musicians *drake* and *jeezy*.

One cluster (number 2) contains exclusively Spanish words. These words exhibit a strong mutual association, as many authors will use only Spanish words and few if any words in English. This cluster is relatively diffuse with regard to demographic data, and thus we would not expect it to be detected without recourse to the linguistic properties of the speakers. Note that while this cluster contains a high proportion of Hispanics, it also appears to contain an above-average number of white speakers. We see two potential explanations: the speakers in this cluster may come from mixed white-Hispanic neighborhoods, or the individual authors may identify as both ethnicities.

We see a number of phenomena which are characteristic of computer-mediated communication, including emoticons, phonetic spelling, and abbreviations (Tagliamonte and Denis, 2008). Emoticons (e.g., *:]*) are grouped in cluster 7, which contains many Hispanics and is above-average with respect to income. Phonetic spelling is used in clusters 3 and 8, which are the two lowest-income clusters and contain the fewest whites. The other group with an above-average number of blacks is cluster 5, and the associated language is somewhat more standardized. Relative to clusters 3 and 8, cluster 5 is wealthier, more urban, and contains more whites and fewer Hispanics.

Clusters 1, 4, and 9 are substantially less urban than the other clusters, and they contain the most standard English words. Of particular interest is cluster 4, which is the only non-urban cluster with lower-than-average income; the fact that this cluster is still relatively standard may provide hint to the relative importance of urbanity and wealth with respect to relative frequency of standard and "vernacular" language. These findings are better thought of as provisional, given the complexities and limitations of the data, such as age and demographic skew of Twitter versus the full population the Census considers, and the small timeframe of the dataset.

4.4 Conclusion and reflections on textual social data analysis

The relationship between language, geography, and social identity has traditionally been studied with respect to micro-level phenomena, such as phonological features or individual words, that have been manually identified by researchers. In this work, we take a more holistic approach to discovering groups of words whose variation is associated with social factors, using a generative model that operates on authors' microblog texts. In §4.2 our model extracts geographic-linguistic communities that are coherent with respect to geographic location and text, while in §4.3 we discover sociolinguistic communities that are coherent with respect to both demographic metadata and text. This model also identifies individual terms that are especially characteristic of these communities in social media.

The overwhelming prevalence of non-standard and novel words was a surprise to us, and made evident that new forms of language are apparently being invented in the medium of online discussions. While the one-week dataset was convenient for getting started with analysis and model development, it is apparent that many aspects of language in social media might be ephemeral, and the results in this chapter are sometimes very specific to the dates the dataset was gathered. One lesson is that, in order to collect data for general linguistic analysis, it is important to use data from over a long timespan; we do this in support of a part-of-speech tagging system in Owoputi et al. (2013) (not included in this thesis). But also, this suggests that the temporal aspect of how geography, demographics, and language interact—that is, the social determinants of language change—is interesting in itself. This is the focus of the next chapter.

Finally, within the range of computational methods pursued in this thesis, this work stands at a particular position: it consists of a fairly complex, latent variable model used for exploratory analysis. The mixed-membership clustering is very useful for understanding broader groups of terms and authors, and it helped us get a sense that there exist large and widely used vocabularies—entire linguistic worlds—that are very divergent from standard English.

However, latent variable approaches have some practical issues for exploratory data analysis (EDA). For one, on large datasets, they can be computationally intensive to run, which runs counter to the need of rapid iterative data analytic experimentation when doing EDA. Newer research since this work has found ways to improve inference speed for topic models (such as stochastic variational approximations (Hoffman et al., 2013), or more specialized moment-based methods (Anandkumar et al., 2012; Arora et al., 2012)), but given the intractability of either posterior or maximum likelihood inference, runtimes may always be much slower than simpler count-based methods, such as the pointwise mutual information approach described in Chapter 2. In fact, after finishing the published version of Section 4.2, we experimented further with spatial density plots of individual terms, yielding fascinating patterns shown in the next chapter (Figure 5.1), and further investigated there. The experience of doing direct analysis of words against spatial coordinates also informed the *MiTextExplorer* tool, which attempts to better automated and make more interactive this type of exploratory text data analysis (Chapter 2).

Also, in work outside this thesis, we found PMI methods useful to summarize geographically-specific terms in Chinese social media (Bamman et al., 2012), to better understand the nature of government censorship of that medium. There, regions were pre-defined by the data (for example, some are provinces in China), and thus are a discrete variable amenable to measuring PMI against word frequencies. If there is access to coordinate-level location data, the geographic topic model developed in this chapter is more powerful in some respects because it discovers spatial regions, instead of pre-defining them; but this can also make analysis more difficult, since it requires effort to understand and verify that the inferred regions are meaningful for a particular analysis.

Still, latent variable models have many uses. The next chapter utilizes latent variables not for grouping terms, but for understanding temporal and diffusion dynamics of individual words. And Chapter 6, which investigates textually described events between political actors, makes extensive use of a topic model in order to infer latent classes of events.

Chapter 5

Social determinants of linguistic diffusion in social media

(An earlier version of this work was published as Eisenstein et al. (2012).)

5.1 Synopsis

Computer-mediated communication is driving fundamental changes in the nature of written language. We investigate these changes by statistical analysis of a dataset comprising 107 million Twitter messages (authored by 2.7 million unique user accounts). Using a latent vector autoregressive model to aggregate across thousands of words, we identify high-level patterns in diffusion of linguistic change over the United States. Our model is robust to unpredictable changes in Twitter's sampling rate, and provides a probabilistic characterization of the relationship of macro-scale linguistic influence to a set of demographic and geographic predictors. The results of this analysis offer support for prior arguments that focus on geographical proximity and population size. However, demographic similarity – especially with regard to race – plays an even more central role, as cities with similar racial demographics are far more likely to share linguistic influence. Rather than moving towards a single unified "netspeak" dialect, language evolution in computer-mediated communication reproduces existing fault lines in spoken American English.

5.2 Introduction

An increasing proportion of informal communication is conducted in written form, mediated by technology such as smartphones and social media platforms. Written language has been forced to adapt to meet the demands of synchronous conversation, resulting in a creative burst of new forms, such as emoticons, abbreviations, phonetic spellings, and other neologisms (Androutsopoulos, 2000; Anis, 2007; Herring, 2012). Such changes have often been considered as a single, uniform dialect — both by researchers (Crystal, 2006; Squires, 2010) and throughout the popular press (Thurlow, 2006; Squires, 2010). But despite the fact that social media facilitates instant communication between distant corners of the earth, the adoption of new written forms is often sharply delineated by geography and demographics (Eisenstein et al., 2010, 2011c; Schwartz et al., 2013). For example: the abbreviation *ikr* (*I know, right?*) occurs six times more frequently in the Detroit area than in the United States overall; the emoticon ˆ-ˆ occurs four times more frequently in Southern California; the phonetic spelling *suttin* (*something*) occurs five times more frequently in New York City.

These differences raise questions about how language change spreads in online communication. What groups are influential, and which communities evolve together? Is written language moving toward global standardization or increased fragmentation? As language is a crucial constituent of personal and group identity, examination of the competing social factors that drive language change can shed new light on the hidden structures that shape our society. This chapter offers a new technique for inducing networks of linguistic influence and co-evolution from raw word counts. We then seek explanations for this network in a set of demographic and geographic predictors.

A wave of recent research has shown how social media datasets can enable large-scale analysis of patterns of communication (Lotan et al., 2011; Wu et al., 2011), sentiment (Dodds et al., 2011; Thelwall, 2009; Mitchell et al., 2013), and influence (Lazer et al., 2009; Aral and Walker, 2012; Bond et al., 2012; Gomez-Rodriguez et al., 2012; Bakshy et al., 2012). Such work has generally focused on tracking the spread of discrete behaviors, such as using a piece of software (Aral and Walker, 2012), reposting duplicate or near-duplicate content (Leskovec et al., 2009; Cha et al., 2010; Lotan et al., 2011), voting in political elections (Bond et al., 2012), or posting a hyperlink to online content (Gomez-Rodriguez et al., 2012; Bakshy et al., 2012). Tracking linguistic changes poses a significant additional challenge, as we are concerned not with the first appearance of a word, but with the bursts and lulls in its popularity over time (Altmann et al., 2009). In addition, the well known "long-tail" nature of both word counts and city sizes (Zipf, 1949/2012) ensures that most counts for words and locations will be sparse, rendering simple frequency-based methods inadequate.

Language change has long been an active area of research, and a variety of theoretical models have been proposed. In the **wave** model, linguistic innovations spread through interactions over the course of an individual's life, so the movement of linguistic innovation from one region to another depends on the density of interactions (Bailey, 1973). In the simplest version of this model, the probability of contact between two individuals depends on their distance, so linguistic innovations should diffuse continuously through space. The **gravity** and **cascade** models refine this view, arguing that the likelihood of contact between individuals from two cities depends on the size of the cities as well as their distance; thus, linguistic innovations should be expected to travel between large cities first (Trudgill, 1974; Labov, 2003). However, Nerbonne and Heeringa find little evidence that population size impacts diffusion of pronunciation differences in dialects of the Netherlands (Nerbonne and Heeringa, 2007).

Cultural factors also play an important role in both the diffusion of, and resistance to, language change. Many words and phrases have entered the standard English lexicon from minority dialects (Lee, 1999); conversely, there is evidence that minority groups in the United States resist regional sound changes associated with European American speakers (Gordon, 2000), and that racial differences in speech persist even in conditions of very frequent social contact (Rickford, 1985). At present there are few quantitative sociolinguistic accounts of how geography and demographics interact; nor are their competing roles explained in the menagerie of theoretical models of language change, such as evolutionary biology (Zhang and Gong, 2013; Baxter et al., 2006), dynamical systems (Niyogi and Berwick, 1997), Nash equilibria (Trapa and Nowak, 2000), Bayesian learners (Reali and Griffiths, 2010), and agent-based simulations (Fagyal et al., 2010). In general, such research is concerned with demonstrating that a proposed theoretical framework can account for observed phenomena like geographical distribution of linguistic features and their rate of adoption over time. In contrast, this chapter is concerned with fitting a model to a large corpus of text data from individual language users, and analyzing the social meaning of the resulting parameters.

Research on reconstructing language phylogenies from cognate tables is more closely related (Gray and Atkinson, 2003; Gray et al., 2009; Bouckaert et al., 2012; Dunn et al., 2011), but rather than a phylogenetic process in which languages separate and then develop in relative independence, we have closely-related varieties of a single language, which are in constant interaction. Other researchers have linked databases of typological linguistic features (such as morphological complexity) with geographical and social properties of the languages' speech communities (Lupyan and Dale, 2010; Daumé III, 2009). Again, our interest is in more subtle differences within the same language, rather than differences across the entire set of world languages. The typological atlases and cognate tables that are the basis such work are inapplicable to our problem, requiring us to take a corpus-based approach (Szmrecsanyi, 2011), estimating an influence network directly from raw text.

The overall aim of this work is to build a computational model capable of identifying the demographic and geographic factors that drive the spread of newly popular words in online text. To this end, we construct a statistical procedure for recovering networks of linguistic diffusion from raw word counts, even as the underlying social media sampling rate changes unaccountably. We present a procedure for Bayesian inference in this model, capturing uncertainty about the induced diffusion network. We then consider a range of demographic and geographic factors which might explain the networks induced from this model, using a logistic regression analysis. This lends support to prior work on the importance of population and geography, but reveals a strong role for racial homophily at the level of city-to-city linguistic influence.

5.3 Materials and methods

We conducted a statistical analysis of a corpus of public data from the microblog site Twitter, from 2009–2012. The corpus includes 107 million messages, mainly in English, from more than 2.7 million unique user accounts. Each message contains GPS coordinates to locations in the continental United States. The data was temporally aggregated into 165 week-long bins. After taking measures to remove marketing-oriented accounts, each user account was associated with one of the 200 largest Metropolitan Statistical Areas (MSA) in the United States, based on their geographical coordinates. The 2010 United Census provides detailed demographics for MSAs. By linking this census data to changes in word frequencies, we can obtain an aggregate picture of the role of demographics in the diffusion of linguistic change in social media.

Empirical research suggests that Twitter's user base is younger, more urban, and more heavily composed of ethnic minorities, in comparison with the overall United States population (Mislove et al., 2011; Duggan and Smith, 2013). Our analysis does *not* assume that Twitter users are a representative demographic sample of their geographic areas. Rather, we assume that on a macro scale, the diffusion of words between metropolitan areas depends on the overall demographic properties of those areas, and not on the demographic properties specific to the Twitter users that those areas contain. Alternatively, the use of population-level census statistics can be justified on the assumption that the demographic skew introduced by Twitter — for example, towards younger individuals — is approximately homogeneous across cities. Table 5.1 shows the average demographics for the 200 MSAs considered in our study.

Linguistically, our analysis begins with the 100,000 most frequent terms overall. We narrow this list to 4,854 terms whose frequency changed significantly over time. The excluded terms have little dynamic range; they would therefore not substantially affect the model parameters, but would increase the computational cost if included. We then manually further refine the list to

	mean	st. dev
Population	1,170,000	2,020,000
Log Population	13.4	0.9
% Urbanized	77.1	12.9
Median Income	61,800	11,400
Log Median Income	11.0	0.2
Median age	36.8	3.9
% Renter	34.3	5.2
% Af. Am	12.9	10.6
% Hispanic	15.0	17.2

Table 5.1: Statistics of metropolitan statistical areas. Mean and standard deviation for demographic attributes of the 200 Metropolitan Statistical Areas (MSAs) considered in this study, from 2010 Census data.

2,603 English words, by excluding names, hashtags, and foreign language terms. Both a complete list of terms and more detailed procedures for data acquisition are given in §5.6.

Figure 5.1 shows the geographical distribution of six words over time. The first row shows the word *ion*, which is a shortened form of *I don't*, as in *ion even care*. Systematically coding a random sample of 300 occurrences of the string *ion* in our dataset revealed two cases of the traditional chemistry sense of *ion*, and 294 cases that clearly matched *I don't*. This word displays increasing popularity over time, but remains strongly associated with the Southeast. In contrast, the second row shows the emoticon -__- (indicating annoyance), which spreads from its initial bases in coastal cities to nationwide popularity. The third row shows the abbreviation *ctfu*, which stands for *cracking the fuck up* (i.e., laughter). At the beginning of the sample it is active mainly in the Cleveland area; by the end, it is widely used in Pennsylvania and the mid-Atlantic, but remains rare in the large cities to the west of Cleveland, such as Detroit and Chicago. What explains the non-uniform spread of this term's popularity?

While individual examples are intriguing, we seek an aggregated account of the spatiotemporal dynamics across many words, which we can correlate against geographic and demographic properties of metropolitan areas. Due to the complexity of drawing inferences about influence and demographics from raw word counts, we perform this process in stages. (A block diagram of the procedure is shown in Figure 5.2.) First, we model word frequencies as a dynamical system, using Bayesian inference over the latent spatiotemporal activation of each word. We use sequential Monte Carlo (Godsill et al., 2004) to approximate the distribution over spatiotemporal activations with a set of samples. Within each sample, we induce a model of the linguistic dynamics between metropolitan areas, which we then discretize into a set of pathways. Finally, we perform logistic regression to identify the geographic and demographic factors that correlate with the induced linguistic pathways. By aggregating across samples, we can estimate the confidence intervals of the resulting logistic regression parameters.

5.3.1 Modeling spatiotemporal lexical dynamics in social media data

This section describes our approach for modeling lexical dynamics in our data. We represent our data as counts $c_{w,r,t}$, which is the number of individuals who used the word w at least once in MSA r at time t (i.e., one week). (Mathematical notation is summarized in Table 5.2. We do not consider the total number of times a word is used, since there are many cases of a single

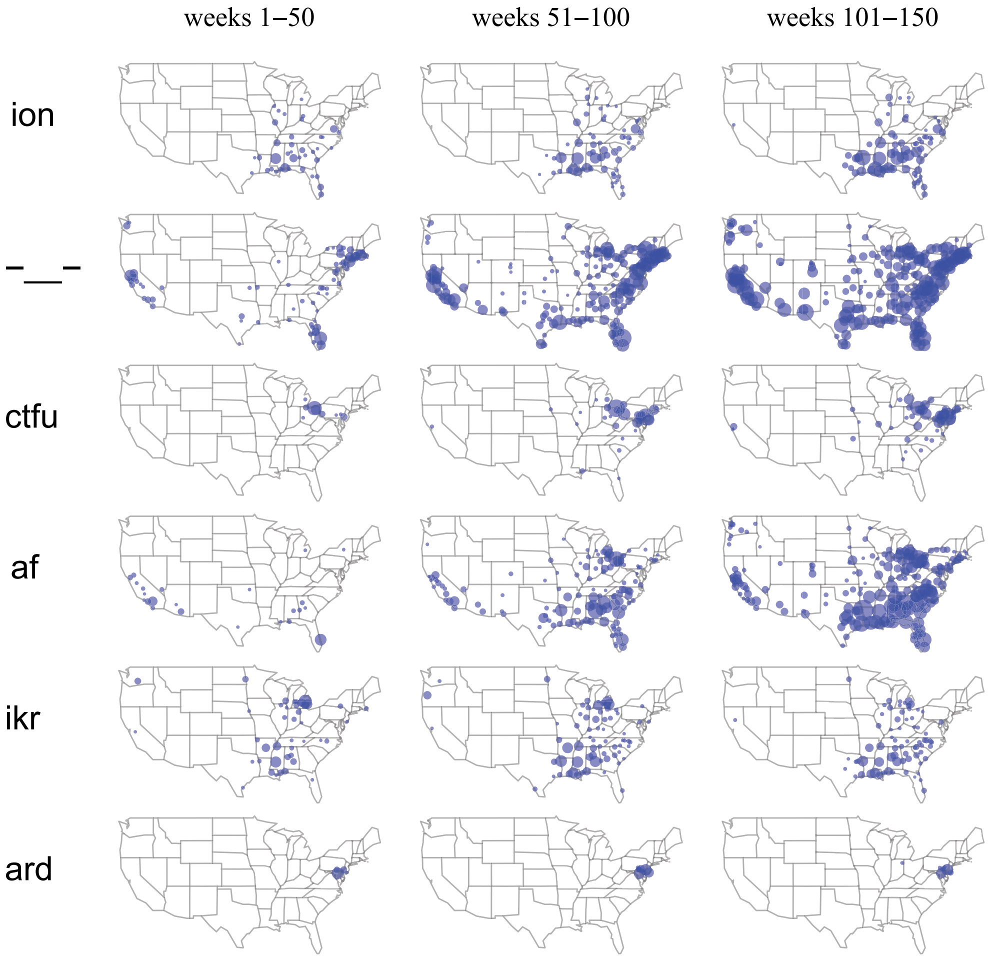


Figure 5.1: Change in frequency for six words: *ion*, -__-, *ctfu*, *af*, *ikr*, *ard*. Blue circles indicate cities where on average, at least 0.1% of users use the word during a week. A circle's area is proportional to the word's probability.

individual using a single word hundreds or thousands of times.) To capture the dynamics of these counts, we employ a latent vector autoregressive model, based on the binomial distribution with a logistic link function. The use of latent variable modeling is motivated by properties of the data that are problematic for simpler autoregressive models that operate directly on word counts and frequencies (without a latent variable). We begin by briefly summarizing these problems; we then present our model, describe the details of inference and estimation, and offer some examples of the inferences that our model supports.

Challenges for direct autoregressive models

The simplest modeling approach would be an autoregressive model that operates directly on the word counts or frequencies (Wei, 1994). A major challenge for such models is that Twitter offers only a sample of all public messages, and the sampling rate can change in unclear ways (Morstatter et al., 2013). For example, for much of the timespan of our data, Twitter's documentation

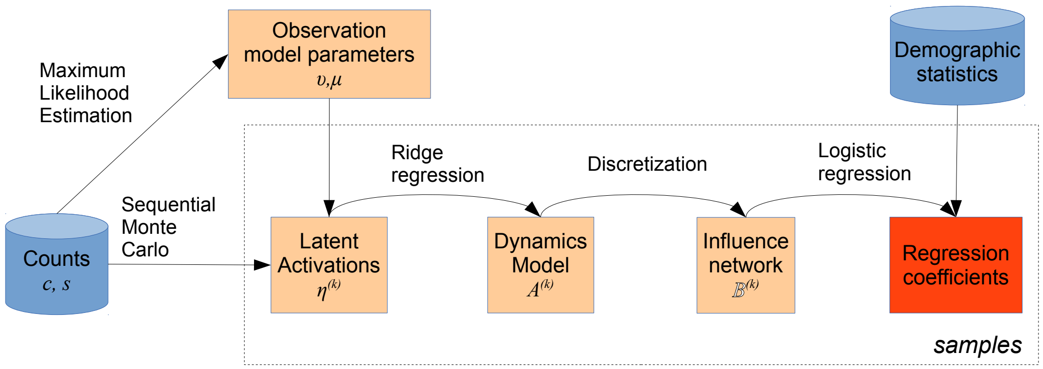


Figure 5.2: Block diagram for our statistical modeling procedure. The dotted outline indicates repetition across samples drawn from sequential Monte Carlo.

$c_{w,r,t}$	Number of individuals who used word w in metropolitan area r during week t.
$s_{r,t}$	Number of individuals who posted messages in metropolitan area r at time t.
$p_{w,r,t}$	Empirical probability that an individual from metropolitan area r will use word w during week t.
$\eta_{w,r,t}$	Latent spatiotemporal activation for word w in metropolitan area r at time t.
$\nu_{w,t}$	Global activation for word w at time t.
$\mu_{r,t}$	Regional activation ("verbosity") for metropolitan area r at time t.
a_{r_1,r_2}	Autoregressive coefficient from metropolis r_1 to r_2.
$A = \{a_{r_1,r_2}\}$	Complete autoregressive dynamics matrix.
$\sigma^2_{w,r}$	Autoregressive variance for $\eta_{w,r,t}$, for all times t.
λ	Variance of zero-mean Gaussian prior over each a_{r_1,r_2}.
$\omega^{(k)}_{w,r,t}$	Weight of sequential Monte Carlo hypothesis k for word w, metropolis r, and time t.
z_{r_1,r_2}	z-score of a_{r_1,r_2}, computed from empirical distribution over Monte Carlo samples.
$\overline{\mathbb{B}}$	Set of ordered city pairs for whom a_{r_1,r_2} is significantly greater than zero, computed over all samples.
$\mathbb{B}^{(k)}$	Top L ordered city pairs, as sorted by the bottom of the 95% confidence interval on $\{a^{(k)}_{r_1,r_2}\}$.
Q	Random distribution over discrete networks, designed so that the marginal frequencies for "sender" and "receiver" metropolises are identical to their empirical frequencies in the model-inferred network.

Table 5.2: Table of mathematical notation.

implies that the sampling rate is approximately 10%; but in 2010 and earlier, the sampling rate appears to be 15% or 5%.[1] After 2010, the volume growth in our data is relatively smooth, implying that the sampling is fair (unlike the findings of Morstatter et al., which focus on a more problematic case involving query filters, which we do not use).

Raw counts are not appropriate for analysis, because the MSAs have wildly divergent numbers of users and messages. New York City has four times as many active users as the 10th largest MSA

[1] This estimate is based on inspection of message IDs modulo 100, which appears to be how sampling was implemented at that time.

(San Francisco-Oakland, CA), twenty times as many as the 50th largest MSA (Oklahoma City, OK), and 200 times as many as the 200th largest MSA (Yakima, WA); these ratios are substantially larger when we count messages instead of active users. This necessitates normalizing the counts to frequencies $p_{w,r,t} = c_{w,r,t}/s_{r,t}$, where $s_{r,t}$ is the number of individuals who have written at least one message in region r at time t. The resulting frequency $p_{w,r,t}$ is the empirical probability that a random user in (r, t) used the word w. Word frequencies treat large and small cities more equally, but suffer from several problems:

- The frequency $p_{w,r,t}$ is *not* invariant to a change in the sampling rate: if, say, half the messages are removed, the probability of seeing a user use any particular word goes down, because $s_{r,t}$ will decrease more slowly than $c_{w,r,t}$ for any w. The changes to the global sampling rate in our data drastically impact $p_{w,r,t}$.

- Users in different cities can be more or less actively engaged with Twitter: for example, the average New Yorker contributed 55 messages to our dataset, while the average user within the San Francisco-Oakland MSA contributed 21 messages. Most cities fall somewhere in between these extremes, but again, this "verbosity" may change over time.

- Word popularities can be driven by short-lived global phenomena, such as holidays or events in popular culture (e.g., TV shows, movie releases), which are not interesting from the perspective of persistent changes to the lexicon. We manually removed terms that directly refer to such events (as described in Section 5.6), but there may be unpredictable second-order phenomena, such as an emphasis on words related to outdoor cooking and beach trips during the summer, and complaints about boredom during the school year.

- Due to the long-tail nature of both word counts and city populations (Clauset et al., 2009), many word counts in many cities are zero at any given point in time. This floor effect means that least squares models, such as Pearson correlations or the Kalman smoother, are poorly suited for this data, in either the $c_{w,r,t}$ or $p_{w,r,t}$ representations.

A latent vector autoregressive model

To address these issues, we build a latent variable model that controls for these confounding effects, yielding a better view of the underlying frequency dynamics for each word. Instead of working with raw frequencies $p_{w,r,t}$, we perform inference over latent variables $\eta_{w,r,t}$, which represent the underlying *activation* of word w in MSA r at time t. This latent variable parameterizes a distribution for the count data $c_{w,r,t}$ via a binomial distribution with the number of trials $s_{r,t}$. A binomial distribution requires a frequency parameter, which we attain by passing η through the logistic function, where $\text{Logistic}(\eta) = 1/(1 + e^{-\eta})$.

An η-only model, therefore, would be

$$c_{w,r,t} \sim \text{Binomial}(s_{r,t}, \text{Logistic}(\eta_{w,r,t})) \tag{5.1}$$

This is a very simple generalized linear model with a logit link function (Gelman and Hill, 2006), in which the maximum likelihood estimate of η would simply be a log-odds reparameterization of the probability of a user using the word, $\hat{\eta}_{w,r,t} = \log(p_{w,r,t}/(1 - p_{w,r,t}))$. By itself, this model corresponds to directly using $p_{w,r,t}$, and has all the same problems as noted in the previous section; in addition, the estimate $\hat{\eta}_{w,r,t}$ goes to negative infinity when $c_{w,r,t} = 0$.

The advantage of the logistic binomial parameterization is that it allows an additive combination of effects to control for confounds. The η variables still represent differences in log-odds, but after controlling for “base rate” effects. To this end, we include two additional parameters $\nu_{w,t}$ and $\mu_{r,t}$:

$$c_{w,r,t} \sim \text{Binomial}(s_{r,t}, \text{Logistic}(\eta_{w,r,t} + \nu_{w,t} + \mu_{r,t})). \tag{5.2}$$

The parameter $\nu_{w,t}$ represents the overall activation of the word w at time t, thus accounting for non-geographical changes, such as when a word becomes more popular everywhere at once. The parameter $\mu_{r,t}$ represents the “verbosity” of MSA r at time t, which varies for the reasons mentioned above. These parameters control for global effects due to t, such as changes to the API sampling rate. (Because $\mu_{r,t}$ and $\nu_{w,t}$ both interact with t, it is unnecessary to introduce a main effect for t.) These parameters subtract out nuisance effects, enabling a more stable estimate of η.

We can now measure lexical dynamics in terms of the latent variable η rather than the raw counts c. We take the simplest possible approach, modeling η as a first-order linear dynamical system with Gaussian noise (Gelb, 1974),

$$\eta_{w,r,t} \sim N\left(\sum_{r'} a_{r',r}\eta_{w,r',t-1}, \sigma^2_{w,r}\right). \tag{5.3}$$

The dynamics matrix $A = \{a_{r_1,r_2}\}$ is shared over both words and time; we also assume homogeneity of variance within each metropolitan area (per word), using the variance parameter $\sigma^2_{w,r}$. These simplifying assumptions are taken to facilitate statistical inference, by keeping the number of parameters at a reasonable size. If it is possible to detect clear patterns of linguistic diffusion under this linear homoscedastic model, then more flexible models should show even stronger effects, if they can be estimated successfully. We leave this investigation for future work. It is important to observe that this model *does* differentiate directionality: in general, $a_{r_1,r_2} \neq a_{r_2,r_1}$. The coefficient a_{r_1,r_2} reflects the extent to which $\eta_{r_1,t}$ predicts $\eta_{r_2,t+1}$, and vice versa for a_{r_2,r_1}. In the extreme case that r_1 ignores r_2, while r_2 imitates r_1 perfectly, we will have $a_{r_1,r_2} = 1$ and $a_{r_2,r_1} = 0$. Note that both coefficients can be positive, in the case that η_{r_1} and η_{r_2} evolve smoothly and synchronously; indeed, such mutual connections appear frequently in the induced networks.

Equation 5.2 specifies the *observation* model, and Equation 5.3 specifies the *dynamics* model; together, they specify the joint probability distribution,

$$P(\eta, c \mid s; A, \sigma^2, \mu, \nu) = P(c \mid \eta, s; \mu, \nu)P(\eta; A). \tag{5.4}$$

Because the observation model is non-Gaussian, the standard Kalman smoother cannot be applied. Inference under non-Gaussian distributions is often handled via second-order Taylor approximation, as in the extended Kalman filter (Gelb, 1974), but a second-order approximation to the Binomial distribution is unreliable when the counts are small. In contrast, sequential Monte Carlo sampling permits arbitrary parametric distributions for both the observations and system dynamics (Cappe et al., 2007). Forward-filtering backward sampling (Godsill et al., 2004) gives smoothed samples from the distribution $P(\eta_{w,1:R,1:T} \mid c_{w,1:R,1:T}, s_{1:R,1:T}, A)$, so for each word w, we obtain a set of sample trajectories $\eta^{(k)}_{w,1:R,1:T}$ for $k \in \{1, \ldots, K = 100\}$.

Inference and estimation

The total dimension of η is equal to the product of the number of MSAs (200), words (2,603), and time steps (165), requiring inference over 85 million interrelated random variables. To facilitate inference and estimation, we adopt a stagewise procedure. First we make estimates of the parameters ν (overall activation for each word) and μ (region-specific verbosity), assuming $\eta_{w,r,t} = 0, \forall w, r, t$. Next, we perform inference over η, assuming a simplified dynamics matrix $\tilde{A}$, which is diagonal. Last, we perform inference over the full dynamics matrix A, from samples from this distribution. See Figure 5.2 for a block diagram of the inference and estimation procedure.

The parameters ν (global word activation) and μ (region-specific verbosity) are estimated first. We begin by computing a simplified $\overline{\nu}_w$ as the inverse logistic function of the total frequency of word w, across all time steps. Next, we compute the maximum likelihood estimates of each $\mu_{r,t}$ via gradient descent. We then hold μ fixed, and compute the maximum likelihood estimates of each $\nu_{w,t}$. Inference over the latent spatiotemporal activations $\eta_{w,r,t}$ is performed via Monte Carlo Expectation Maximization (MCEM) (Wei and Tanner, 1990). For each word w, we construct a diagonal dynamics matrix $\tilde{A}_w$. Given estimates of $\tilde{A}_w$ and σ^2_w, we use the sequential Monte Carlo (SMC) algorithm of forward-filtering backward sampling (FFBS) (Godsill et al., 2004) to draw samples of $\eta_{w,1:R,1:T}$; this constitutes the E-step of the MCEM process. Next, we apply maximum-likelihood estimation to update $\tilde{A}_w$ and σ^2_w; this constitutes the M-step. These updates are repeated until either the parameters converge or we reach a limit of twenty iterations. We describe each step in more detail:

- **E-step**. The E-step consists of drawing samples from the posterior distribution over η. FFBS appends a backward pass to any SMC filter that produces a set of hypotheses and weights $\{\eta^{(k)}_{w,r,t}, \omega^{(k)}_{w,r,t}\}_{1 \leq k \leq K}$. The role of the backward pass is to reduce variance by resampling the hypotheses according to the joint smoothing distribution. Our forward pass is a standard bootstrap filter (Cappe et al., 2007): by setting the proposal distribution $q(\eta_{w,r,t} \mid \eta_{w,r,t-1})$ equal to the transition distribution $P(\eta_{w,r,t} \mid \eta_{w,t-1}; A_w, \sigma^2_{w,r})$, the forward weights are equal to the recursive product of the observation likelihoods,

$$\omega^{(k)}_{w,r,t} = \omega^{(k)}_{w,r,t-1} P(c_{w,r,t} \mid \eta_{w,r,t}, s_{w,t}; \nu_{w,t}, \mu_{r,t}). \tag{5.5}$$

  The backward pass uses these weights, and returns a set of unweighted hypotheses that are drawn directly from $P(\eta_{w,r,t} \mid c_{w,r,t}, s_{r,t}; \nu_{w,t}, \mu_{r,t})$. More complex SMC algorithms — such as resampling, annealing, and more accurate proposal distributions — did not achieve higher likelihood than the bootstrap filter.

- **M-step**. The M-step consists of computing the average of the maximum likelihood estimates of $\tilde{A}_w$ and σ^2_w. Within each sample, maximum likelihood estimation is straightforward: the dynamics matrix $\tilde{A}_w$ is obtained by least squares, and $\sigma^2_{w,r}$ is set to the empirical variance $\frac{1}{T}\sum_t^T (\eta_{w,r,t} - \tilde{a}_{w,r}\eta_{w,r,t-1})^2$.

Examples

Figure 5.3 shows the result of this modeling procedure for several example words. In the right panel, each sample of η is shown with a light dotted line. In the left panel, the empirical word frequencies are shown with circles, and the smoothed frequencies for each sample are shown with dotted lines. Large cities generally have a lower variance over samples, because the variance of the maximum *a posteriori* estimate of the binomial decreases with the total event count. For example, in Figure 5.3(c), the samples of η are tightly clustered for Philadelphia (the sixth-largest MSA in the United States), but are diffuse for Youngstown (the 95th largest MSA). Note also that the relationship between frequency and η is not monotonic — for example, the frequency of *ion* increases in Memphis over the duration of the sample, but the value of η decreases. This is because of the parameter for background word activation, $\nu_{w,t}$, which increases as the word attains more general popularity. The latent variable model is thus able to isolate MSA-specific activation from nuisance effects that include the overall word activation and Twitter's changing sampling rate.

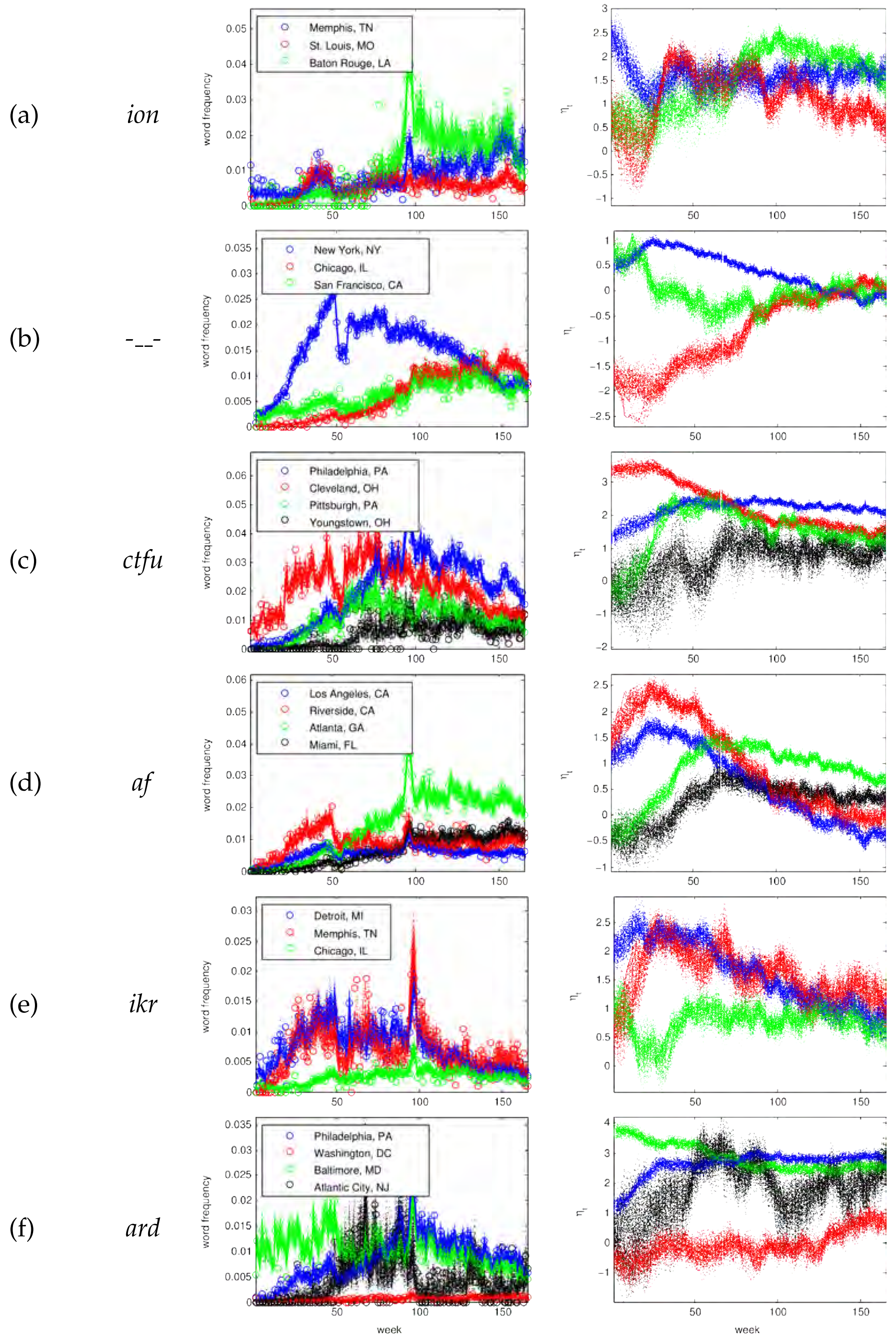


Figure 5.3: Left: empirical term frequencies (circles) and their Monte Carlo smoothed estimates (dotted lines); Right: Monte Carlo smoothed estimates of η.

5.3.2 Constructing a network of linguistic diffusion

Having obtained samples from the distribution $P(\eta \mid c, s)$ over latent spatiotemporal activations, we now move to estimate the system dynamics, which describes the pathways of linguistic diffusion. Given the simple Gaussian form of the dynamics model (Equation 5.3), the coefficients A can be obtained by ordinary least squares. We perform this estimation separately within each of the K sequential Monte Carlo samples $\eta^{(k)}$, obtaining K dense matrices $A^{(k)}$, for $k \in \{1, \ldots, K\}$.

The coefficients of $A^{(k)}$ are not in meaningful units, and their relationship to demographics and geography will therefore be difficult to interpret, model, and validate. Instead, we prefer to use a binarized, *network* representation, $\mathbb{B}$. Given such a network, we can directly compare the properties of linked MSAs with the properties of randomly selected pairs of MSAs not in $\mathbb{B}$, offering face validation of the proposed link between macro-scale linguistic influence and the demographic and geographic features of cities.

Specifically, we are interested in a set of pairs of MSAs, $\mathbb{B} = \{\langle r_1, r_2 \rangle\}$, for which we are confident that $a_{r_1,r_2} > 0$, given the uncertainty inherent in estimation across sparse word counts. Monte Carlo inference enables this uncertainty to be easily quantified: we compute z-scores z_{r_1,r_2} for each ordered city pair, using the empirical mean and standard deviation of $a^{(k)}_{r_1,r_2}$ across samples $k \in \{1, \ldots, K\}$. We select pairs whose z-score exceeds a threshold $z^{(\text{thresh})}$, denoting the selected set $\overline{\mathbb{B}} = \{\langle r_i, r_j \rangle : z_{i,j} > z^{(\text{thresh})}\}$. To compute uncertainty around a large number of coefficients, we apply the Benjamini-Hochberg False Discovery Rate (FDR) correction for multiple hypothesis testing (Benjamini and Hochberg, 1995), which controls the expected proportion of false positives in $\overline{\mathbb{B}}$ as

$$\text{FDR}(z^{(\text{thresh})}) = \frac{P_{null}(z_{i,j} > z^{(\text{thresh})})}{\tilde{P}(z_{i,j} > z^{(\text{thresh})})} = \frac{1 - \Phi(z^{(\text{thresh})})}{[R(R-1)]^{-1} \sum_{i \neq j} 1\{z_{i,j} > z^{(\text{thresh})}\}}, \tag{5.6}$$

where the null probability is a one-sided hypothesis that z exceeds $z^{(\text{thresh})}$ under a standard normal distribution, which we would expect if $a_{i,j}$ values were random; this has probability $1 - \Phi(z^{(\text{thresh})})$, where Φ is the Gaussian CDF. $\tilde{P}$ is the simulation-generated empirical distribution over $z(a_{i,j})$ values. If high z-scores occur much more often under the model ($\tilde{P}$) than we would expect by chance (P_{null}), only a small proportion should be expected to be false positives; the Benjamini-Hochberg ratio is an upper bound on the expected proportion of false positives in $\mathbb{B}$. To obtain FDR < 0.05, the individual test threshold is approximately $z^{(\text{thresh})} = 3.2$, or in terms of p-values, $p < 6 \times 10^{-4}$. We see 510 dynamics coefficients survive this threshold; these indicate high-probability pathways of linguistic diffusion. The associated set of city pairs is denoted $\overline{\mathbb{B}}_{0.05}$.

Figure 5.4 shows a sparser network $\overline{\mathbb{B}}_{0.001}$, induced using a more stringent threshold of FDR $<$ 0.001. The role of geography is apparent from the figure: there are dense connections within regions such as the Northeast, Midwest, and West Coast, and relatively few cross-country connections. For example, we observe many connections among the West Coast cities of San Diego, Los Angeles, San Jose, San Francisco, Portland, and Seattle (from bottom to top on the left side of the map), but few connections from these cities to other parts of the country.

Practical details. To avoid overfitting and degeneracy in the estimation of $A^{(k)}$, we place a zero-mean Gaussian prior on each element $a^{(k)}_{r_1,r_2}$, tuning the variance λ by grid search on the log-likelihood of a held-out subset of time slices within $\eta_{1:T}$. The maximum *a posteriori* estimate of A can be computed in closed form via ridge regression. Lags of length greater than one are accounted for by regressing the values of η_t against the moving average from the previous ten time steps. Results without this smoothing are broadly similar.

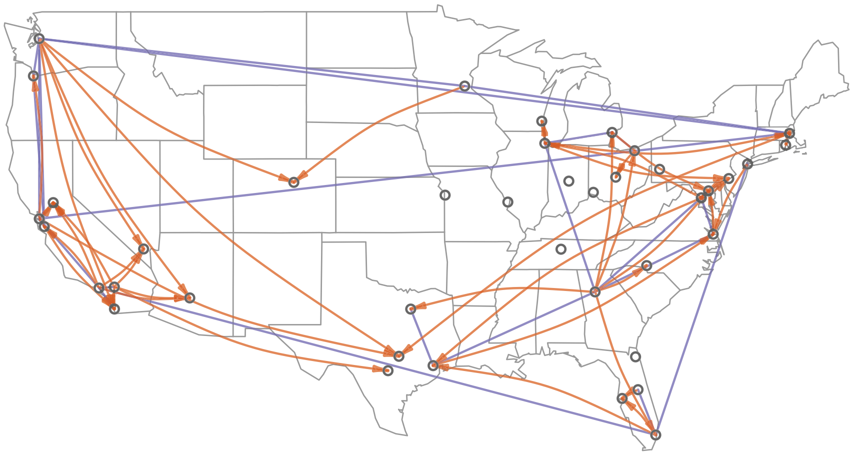


Figure 5.4: Induced network, showing significant coefficients among the 40 most populous MSAs (using an FDR < 0.001 threshold, yielding 254 links). Blue edges represent bidirectional influence, when there are directed edges in both directions; orange links are unidirectional.

5.3.3 Geographic and demographic correlates of linguistic diffusion

By analyzing the properties of pairs of metropolitan areas that are connected in the network $\mathbb{B}$, we can quantify the geographic and demographic drivers of online language change. Specifically, we construct a logistic regression to identify the factors that are associated with whether a pair of cities have a strong linguistic connection. The positive examples are pairs of MSAs with strong transmission coefficients a_{r_1,r_2}; an equal number of negative examples is sampled randomly from a distribution Q, which is designed to maintain the same empirical distribution of MSAs that appears in the positive examples. This ensures that each MSA appears with roughly the same frequency in the positive and negative pairs, eliminating a potential confound.

The independent variables in this logistic regression include geographic and demographic properties of pairs of MSAs. We include the following demographic attributes: median age, log median income, and the proportions of, respectively, African Americans, Hispanics, individuals who live in urbanized areas, and individuals who rent their homes. The proportion of European Americans was omitted because of a strong negative correlation with the proportion of African Americans; the proportion of Asian Americans was omitted because it is very low for the overwhelming majority of the 200 largest MSAs. These raw attributes are then converted into both asymmetric and symmetric predictors, using the raw difference and its absolute value. The symmetric predictors indicate pairs of cities that are likely to share influence; besides the demographic attributes, we include geographical distance and, as a control, the log of the sum of populations. The asymmetric predictors are properties that may make an MSA likely to be the driver of online language change. Besides the raw differences of the six demographic attributes, we include the log difference in population. For a given demographic attribute, a negative regression coefficient for the absolute difference would indicate that similarity is important; a positive regression coefficient for the (asymmetric) raw difference would indicate that regions with large values of this attribute tend to be senders rather than receivers of linguistic innovations. All variables are standardized.

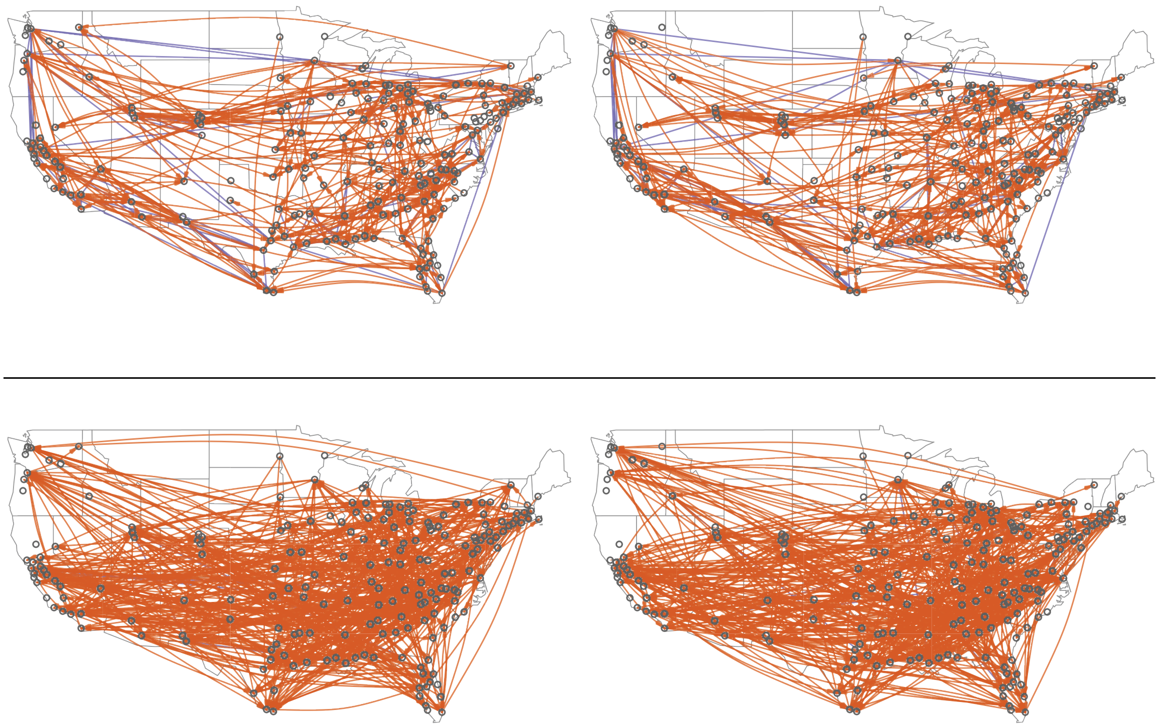


Figure 5.5: Top: two sample networks inferred by the model. (Unlike Figure 5.4, all 200 cities are shown.) Bottom: two "negative" networks, sampled from Q; these are samples from the non-linked pair distribution Q, which is constructed to have the same marginal distributions over senders and receivers as in the inferred network. A blue line indicates directed edges in both directions between the pair of cities; orange lines are unidirectional.

To visually verify the geographic distance properties of our model, Figure 5.5 compares networks obtained by discretizing $A^{(k)}$ against networks of randomly-selected MSA pairs, sampled from Q. Histograms of these distances are shown in Figure 5.6, and their average values are shown in Table 5.3. The networks induced by our model have many more short-distance connections as compared to chance. Table 5.3 also shows that many other demographic attributes are more similar among cities that are linked in our model's network.

A logistic regression can show the extent to which each of the above predictors relates to the dependent variable, the binarized linguistic influence. However, the posterior uncertainty of the estimates of the logistic regression coefficients depends not only on the number of instances (MSA pairs), but principally on the variance in the Monte Carlo-based estimates for $A^{(k)}$, which in turn depends on the sampling variance and the size of the observed spatiotemporal word counts. To properly account for this complex variance, we run the logistic regression separately within each Monte Carlo sample k, and report the empirical standard errors of the logistic coefficients across the samples.

Practical details This procedure requires us to discretize the dynamics network *within* each sample, which we will write $\mathbb{B}^{(k)}$. One solution would be simply take the L largest values; alterna-

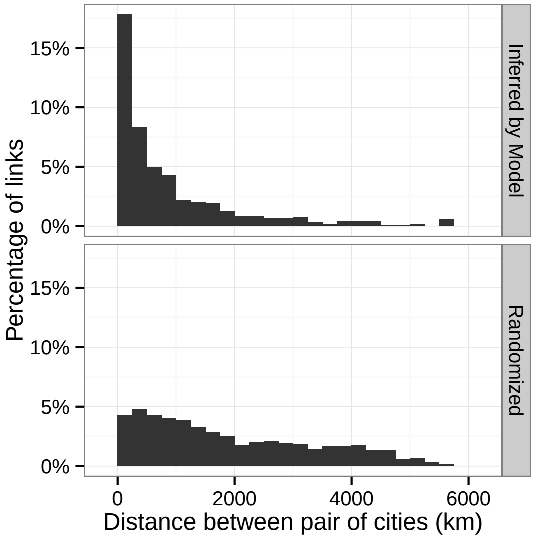


Figure 5.6: Histograms of distances between pairs of connected cities, in model-inferred networks (top), versus "negative" networks from Q (bottom).

tively, we could take the L coefficients for which we are most confident that $a^{(k)}_{r_1,r_2} > 0$. We strike a balance between these two extremes by sorting the dynamics coefficients according to the lower bound of their 95% confidence intervals. This ensures that we get city pairs for which $a^{(k)}_{r_1,r_2}$ is significantly distinct from zero, but that we also emphasize large values rather than small values with low variance. Per-sample confidence intervals are obtained by computing the closed form solution to the posterior distribution over each dynamics coefficient, $P(a^{(k)}_{r_1,r_2} \mid \eta^{(k)}_{r_1}, \eta^{(k)}_{r_2}, \lambda)$, which, in ridge regression, is normally distributed. We can then compute the 95% confidence interval of the coefficients in each $A^{(k)}$, and sort them by the bottom of this confidence interval, $\tilde{a}^{(k)}_{i,j} = \mu_{a^{(k)}_{i,j}} - Z_{(.975)}\sigma^2_{a^{(k)}_{i,j}}$, where $Z_{(.975)}$ is the inverse Normal cumulative density function evaluated at 0.975, $Z_{(.975)} = 1.96$. We select L by the number of coefficients that pass the $p < 0.05$ false discovery rate threshold in the aggregated network ($L = 510$), as described in the previous section. This procedure yields $K = 100$ different discretized influence networks $\mathbb{B}^{(k)}$, each with identical density to the aggregated network $\overline{\mathbb{B}}$. By comparing the logistic regression coefficients obtained within each of these K networks, it is possible to quantify the effect of uncertainty about η on the substantive inferences that we would like to draw about the diffusion of language change.

5.4 Results

Figure 5.7 shows the resulting logistic regression coefficients. While geographical distance is prominent, the absolute difference in the proportion of African Americans is the strongest predictor: the more similar two metropolitan areas are in terms of this demographic, the more likely that linguistic influence is transmitted between them. Absolute difference in the proportion of Hispanics, residents of urbanized areas, and median income are also strong predictors. This indicates that while language change does spread geographically, demographics play a central role, and nearby cities may remain linguistically distinct if they differ demographically, particularly in

	linked mean	linked s.e.	nonlinked mean	nonlinked s.e.
geography				
distance (km)	919	36.5	1940	28.6
symmetric				
abs diff % urbanized	9.09	0.246	13.2	0.215
abs diff log median income	0.163	0.00421	0.224	0.00356
abs diff median age	2.79	0.0790	3.54	0.0763
abs diff % renter	4.72	0.132	5.38	0.103
abs diff % af. am	6.19	0.175	14.7	0.232
abs diff % hispanic	10.1	0.375	20.2	0.530
asymmetric				
raw diff log population	0.247	0.0246	-0.0127	0.00961
raw diff % urbanized	1.77	0.389	-0.0912	0.112
raw diff log median income	0.0320	0.00654	-0.00166	0.00187
raw diff median age	-0.198	0.113	-0.00449	0.0296
raw diff % renter	0.316	0.195	-0.00239	0.0473
raw diff % af. am	0.00292	0.244	0.00712	0.109
raw diff % hispanic	0.0327	0.472	0.0274	0.182

Table 5.3: Differences between linked and (sampled) non-linked pairs of cities, summarized by their mean and its standard error.

terms of race. African American English differs more substantially from other American varieties than any regional dialect (Wolfram and Schilling-Estes, 2005); our analysis suggests that such differences persist in the virtual and disembodied realm of social media. Examples of linguistically linked city pairs that are distant but demographically similar include Washington D.C. and New Orleans (high proportions of African-Americans), Los Angeles and Miami (high proportions of Hispanics), and Boston and Seattle (relatively few minorities, compared with other large cities).

Of the asymmetric features, population is the most informative, as larger cities are more likely to transmit to smaller ones. In the induced network of linguistic influence $\overline{\mathbb{B}}_{0.05}$, the three largest metropolitan areas – New York, Los Angeles, and Chicago – have 40 outgoing connections and only fifteen incoming connections. Wealthier and younger cities are also significantly more likely to lead than to follow. While this may seem to conflict with earlier findings that language change often originates from the working class, wealthy *cities* must be differentiated from wealthy *individuals*: wealthy cities may indeed be the home to the upwardly-mobile working class that Labov associates with linguistic creativity (Labov, 2001), even if they also host a greater-than-average number of very wealthy individuals.

Additional validation for the logistic regression is obtained by measuring its cross-validated predictive accuracy. For each of the K samples, we randomly select 10% of the instances (positive or negative city pairs) as a held-out test set, and fit the logistic regression on the other 90%. For each city pair in the test set, the logistic regression predicts whether a link exists, and we check the prediction against whether the directed pair is present in $\mathbb{B}^{(k)}$. Results are shown in Table 5.4. Since the number of positive and negative instances are equal, a random baseline would achieve 50% accuracy. A classifier that uses only geography and population (the two components of the gravity model) gives 66.5% predictive accuracy. The addition of demographic features (both asymmetric and symmetric) increases this substantially, to 74.4%. While symmetric features obtain the most

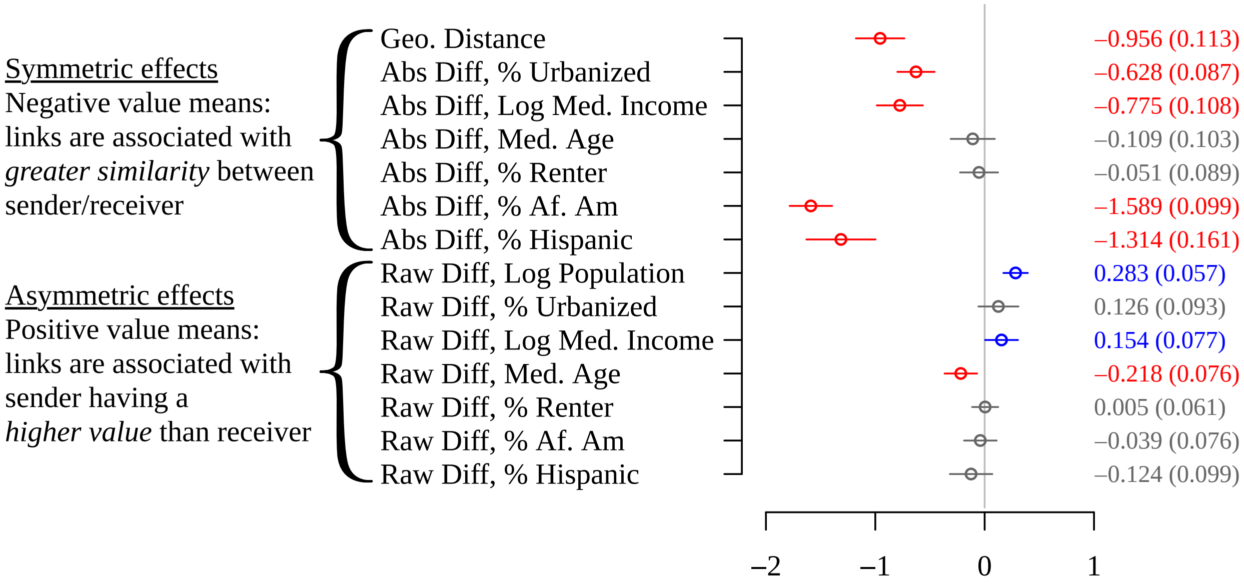


Figure 5.7: Logistic regression coefficients for predicting links between city (MSA) pairs. 95% confidence intervals are plotted; standard errors are in parentheses. Coefficient values are from standardized inputs; the mean and standard deviations are shown to the right.

robust regression coefficients, adding the asymmetric features increases the predictive accuracy from 74.1% to 74.4%, a small but statistically significant difference.

	mean acc	std. err
geography + symmetric + asymmetric	74.37	0.08
geography + symmetric	74.09	0.07
symmetric + asymmetric	73.13	0.08
geography + population	67.33	0.08
geography	66.48	0.09

Table 5.4: Average accuracy predicting links between MSA pairs, and its Monte Carlo standard error (calculated from $K = 100$ simulation samples). The feature groups are defined in Table 5.3; "population" refers to "raw diff log population."

5.5 Discussion

Language continues to evolve in social media. By tracking the popularity of words over time and space, we can harness large-scale data to uncover the hidden structure of language change. We find a remarkably strong role for demographics, particularly as our analysis is centered on a geographical grouping of individual users. Language change is significantly more likely to be transmitted between demographically-similar areas, especially with regard to race — although demographic properties such as socioeconomic class may be more difficult to assess from census statistics.

Language change spreads across social network connections, and it is well known that the social networks that matter for language change are often strongly homophilous in terms of both demographics and geography (Milroy, 1991; Labov, 2001). This chapter approaches homophily from a macro-level perspective: rather than homophily between individual speakers (Kwak et al., 2010), we identify homophily between geographical communities as an important factor driving the observable diffusion of lexical change. Individuals who are geographically proximate will indeed be more likely to share social network connections (Sadilek et al., 2012), so the role of geography in our analysis is not difficult to explain. But more surprising is the role of demographics, since it is unclear whether individuals who live in cities that are geographically distant but demographically similar will be likely to share a social network connection. Previous work has shown that friendship links on Facebook are racially homophilous (Chang et al., 2010), but to our knowledge the interaction with geography has not been explored. In principle, a large-scale analysis of social network links on Twitter or some other platform could shed light on this question. Such sites impose restrictions that make social networks difficult to acquire, but one possible approach would be to try to link the "reply trees" considered by Gonçalves et al. (2011) with the geographic and demographic metadata considered here; while intriguing, this is outside the scope of the present chapter. A major methodological contribution is that similar macro-scale social phenomena can be inferred directly from spatiotemporal word counts, even without access to individual social networks.

Our approach can be refined in several ways. We gain robustness by choosing metropolitan areas as the basic units of analysis, but measuring word frequencies among sub-communities or individuals could shed light on linguistic diversity *within* metropolitan areas. Similarly, estimation is facilitated by fitting a single first-order dynamics matrix across all words, but some regions may exert more or less influence for different types of words, and a more flexible model of temporal dynamics might yield additional insights. Finally, language change occurs at many different levels, ranging from orthography to syntax and pragmatics. This work pertains only to word frequencies, but future work might consider structural changes, such as the phonetical process resulting in the transcription of *i don't* into *ion*.

It is inevitable that the norms of written language must change to accommodate the new ways in which writing is used. As with all language changes, innovation must be transmitted between real language users, ultimately grounding out in countless individual decisions — conscious or not — about whether to use a new linguistic form. Traditional sociolinguistics has produced many insights from the close analysis of a relatively small number of variables. Analysis of large-scale social media data offers a new, complementary methodology by aggregating the linguistic decisions of millions of individuals.

5.6 Appendix: Data processing

We perform several preprocessing steps to prepare the raw Twitter feed for analysis, described in this section: (1) a message preprocessing pipeline, and (2) a selection procedure for the words to analyze. Supplementary files are available at:
`http://brenocon.com/DiffusionOfLexicalChangeInSocialMedia`

Filenames in this section refer to paths within this resource.

5.6.1 Messages

Our initial dataset is of Twitter Gardenhose/Decahose messages from August 2009 through September 2012, containing approximately 17 billion tweets. 721 million were found to have a geotag, and 171 million were located in the United States. After MSA and content filtering, 107 million messages (from 2.7 million unique user accounts) remained for the analysis. The preprocessing software is available at `https://github.com/brendano/twitter_geo_preproc/` and a copy is archived as supplementary information file *preprocessing_pipeline.zip*.

Geotags The Twitter API's structured data includes a field for latitude and longitude coordinates from users who have enabled geo-location; typically, these come from messages authored on mobile phones. Besides that field, there are also informal geotags in the *user.location* field, from clients that insert coordinates as a string; for example, *ÜT: 40.043883,-88.275849* is a geotag from the ÜberTwitter client. These informal geotags are more common in earlier data, and are the only source of coordinates before Twitter added official support for coordinate geotags in late 2009. A regular expression extracts this type of coordinates; there were about twice as many messages with informal coordinates as messages with official API coordinates. We use both types of messages.

Location We use only messages from the continental USA, locating the latitude and longitude coordinates to a county or county-equivalent, according to the U.S. Census Bureau's 2010 TIGER/Line Shapefiles. (`http://www.census.gov/geo/maps-data/data/tiger-line.html`). The United States Office of Management and Budget defines a set of Metropolitan Statistical Areas (MSAs), which are not legal administrative divisions, but rather, geographical regions centered around a single urban core (Office of Management and Budget (USA), 2010); every MSA is defined as a set of counties. We consider the 200 most populous MSAs in the lower 48 U.S. states. The most populous MSA is centered on New York City (population 19 million); the 200th most populous is Fargo, North Dakota (population 200,000). We retain messages whose location belongs to one of these MSAs. According to the 2010 census, the 200 largest MSAs include 76% of all US residents in the lower 48 states; however, we find that these MSAs contain 89% of all Twitter messages sent from within the lower 48 states, which coheres with recent work showing that geotagged Tweets are more likely to come from urban areas (Hecht and Stephens, 2014).

For each MSA, demographic attributes are computed from the 2010 U.S. Census. The following demographic attributes are included: log population, log median income, % residents in urbanized areas, media age, % renters, % African American; % Hispanic. We did not consider % European American because it has a strong negative correlation with % African American, $r = -0.71$; we did not consider % Asian American because it is much smaller, with a median value of 2.8%. Mean and standard deviations of all demographic attributes are shown in Table 2 of the main text.

Content and Follower Filtering Several additional processing steps were then performed to remove marketing-oriented and spam accounts. We remove all messages written by users who have more than 1000 followers, or who follow more than 1000 people. This helps to eliminate automated accounts, particularly content polluters (Lee et al., 2011). We remove all messages that are retweets—either marked as such in the API's structured data, or any message containing the word *RT* (in either lowercase or uppercase). While retweeting could be a useful linguistic signal in its own right, we prefer to focus on original text. Finally, any message containing a URL is removed; this acts as a filter to remove automated and marketing-oriented content, which is typically designed to draw the reader to a page elsewhere on the web. Of course, these filters also eliminate some legitimate messages, but since there is no shortage of data, we prefer to focus on a subsample that is more likely to contain original, non-automated content.

Time Each Twitter message includes a timestamp. We aggregate messages into seven-day intervals, which facilitates computation and removes any day-of-week effects. Each interval starts on Monday at UTC 0800, corresponding to 12am PST and 4am EDT.

5.6.2 Words

To select the set of words to analyze, we begin with the 100,000 most frequent terms, excluding hashtags and usernames. We further require that each term must be used more than more than twenty times in ten different metropolitan areas. We compute the variance of the word's log probability over time ($\nu_{w,t}$ in Equation 2 of the main text, estimated in a standalone step, as described there), and require that the variance be greater than three. This cutoff was chosen so that roughly 5,000 words would be selected; we end up with 4,854 words. From this subset, we manually eliminate all named entities and non-English words. This determination is ambiguous because some strings can reference both names and words (e.g. *homer*, a dictionary word that often references the character *Homer Simpson*) or multiple languages (e.g. *y*, which can mean *and* in Spanish, and *why* in informal English). For each term, we randomly select twenty example messages and manually determine from context whether the usage is as an English word. We retain terms that are used as English non-name words in at least 80% of the examples.

The final word set contains 2,603 words. Our annotation decisions for all 4,854 words can be seen in our supplementary information file, *name_annotations.tsv*, and the selected words can be seen in Figure 5.8 (or the file *wordlist_table.pdf*). The usage examples we inspected are available in *word_examples_for_annotation_in_cluster_order.html*.

The overall results of our analysis are broadly similar when we do not perform manual word filtering, but this filtering enables us to focus on changes in (English) language rather than in the popularity of entities or in the overall multilingual composition of American Twitter users.

All text was tokenized using the *Twokenize.java* program, which can be downloaded at http://www.ark.cs.cmu.edu/TweetNLP/. *Twokenize* is designed to be robust to social media phenomena that confuse other tokenizers, such as emoticons (O'Connor et al., 2010c; Owoputi et al., 2013). Repetition of the same character two or more times was normalized to just two (e.g. *sooooo* → *soo*). No other preprocessing (e.g., stemming) was performed.

hheeyy
niiccee
oommgg
yyaayy
bomb.com
=d
=p
=o
gooaall
gooll
shee
uve
u've
jut
jux
jus
jsut
iaint
ain't
aint
ainn
aiint
couldve
wulda
shulda
wouldve
shouldve
wudda
shudda
wuda
shuda
mustve
nevr
neva
eva
evr
evar
onli
evn
eem
realli
alrdy
cuda
allready
alreadyy
offically
finaly
ion
uma
casually
deadass
obvi
alwayz
alwys
definitly
defiantly
definetly
definately
qonna
bouta
fina
gne
trynaa
fenna
letss
letz

u'd
iwanna
imaa
u'll
culd
cld
cud
shud
shuld
shld
mite
wud
wuld
wld
iont
dn't
wldnt
wuldnt
shudnt
wudnt
shldnt
cudnt
kant
culdnt
cldnt
hafta
qotta
knoo
noe
warmers
excite
beleive
gaf
4get
rememba
memba
luvv
luv
nominate
h8
thnk
thght
4got
thk
quess
gotchuu
swea
hav
qot
favorited
hadd
pre-ordered
copped
preordered
aced
missd
askd
tol
bbm'd
calld
startd
sed
knos
knws
luvs
forgives

warms
heats
wlk
plow
re-up
swerve
beez
hangout
livee
workin
wrking
wrkn
wrkin
workn
sittin
standin
stayn
stayin
layin
sittn
chattin
dealin
steppin
otp
relaxin
checkn
cashin
cuddling
checkin
flirtin
grillin
mackin
arguin
mobbin
chillaxin
wakin
gearing
waken
snuggled
turnt
fukked
racked
chk
checc
shouts
matata
d/l
preorder
occupy
pre-order
nano
sync
conditioned
shun
twug
slander
scramble
punt
flee
draw
sweep
spill
sabotage
reboot
wobble
swim

twerk
tango
dougie
pik
mute
twit
twitt
twitvid
shovel
fite
knit
dribble
fling
subtweet
fuxx
hitt
bodied
toot
mow
go2
kall
sext
textt
fugg
gtf
fcuk
wink
smooches
shrugs
sniffles
faints
kanyeshrug
squee
pouts
sideeye
winks
shruggs
grins
shrug
ahem
mjb
sadface
pause
cosign
syh
fwm
holla
hmu
co-sign
laff
likey
muero
clinch
reinstall
install
decorate
transform
tackle
discover
violate
deactivate
followback
qet
takee
makee
giv

qo
kum
kome
waiit
elses
happn
i`m
iim
u're
something's
iits
itz
nothing's
everything's
thatz
datz
thas
dass
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whts
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whatss
whatz
wutchu
watchu
nobody's
smellin
feeln
feelin
soundin
dressin
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waz
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izz
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buhh
pero
esp
i.e.
i.e
iwant
gimmie
whys
imiss
ilovee
sumtimes
evrytime
iguess
mayb
altho
methinks
becuase
b/c
kause
wheneva
becuz
bcuz
eventhough
what're
iif

it-
thiis
dhis
thys
dhat
thiz
whr
wut
waht
wher
whut
weneva
wha
yy
veryy
absolutly
completly
awkwardly
legitimately
uber
f*ckin
fuggin
f-ing
fukkin
fuccin
effn
mf'n
flippin
f'n
f'in
effin
s0
liike
liek
lk
boutt
havin
havn
beinq
get'n
gettn
followin
followin
callin
treatin
helpin
lettn
ignorin
judgin
lettin
unfollowin
testin
killn
answerin
teachin
stalkin
calln
askn
askin
bbm'n
telln
stoppin
losin
changin
updating
payin

leavn
droppin
chargin
skippin
leavin
guarding
stealin
sendin
pushin
usin
catchin
breakin
bringin
cuttin
pickin
carryin
clockin
keepn
holdin
throwin
feedin
showin
puttn
hittn
shuttin
addin
scratchin
switchin
choppin
tearin
givin
rubbin
puttin
settin
lickin
postin
hittin
touchin
tackling
installing
takin
expectin
wearin
takn
despicable
buyin
makin
makn
watchinq
watch'n
watchn
watchin
hearin
findin
likin
surfin
blastin
luvin
enjoyin
readin
downloadin
rockn
celebratin
draggin
grabbin
coppin

Figure 5.8: (Page 1 of 6): All 2,603 words used in our main analysis. They are ordered by the hierarchical word clusters of (Owoputi et al., 2013) (http://www.ark.cs.cmu.edu/TweetNLP/) which tends to group words with similar syntactic or semantic properties. The lowercased forms are shown, which sometimes is not the most common form; for example, ":d" is usually written as ":D".

smashin
duin
doinn
doiin
doin
doinq
eatin
grilling
cookn
eattin
bakin
cookin
drinkn
cravin
drinkin
mert
mehh
mhe
urself
yaself
yurself
hym
ypu
yall
ya'll
y'all
yeen
iget
yhuu
yhu
y0u
juu
yoy
iht
iit
yurs
urs
evrything
everythin
everythng
nuttn
nutn
nuffin
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nothn
nuthing
nuthn
nthn
nun
sumtin
sumthn
sumthing
somethn
smthn
summin
sumthin
suttin
anythin
nething
nebody
any1
ne1
sumone
sum1

some1
evryone
evry1
every1
evrybdy
everyonee
evrybody
oomf
oomfs
meeka
no1
whoeva
waitn
waitin
rootin
feenin
searchin
lookn
look'n
commin
comin
comn
cummin
upgrading
startn
startin
plannin
omw
headin
enroute
s\o
s/o
shoutouts
s|o
s/0
qoinq
fixin
crackn
jumpin
shakin
rushin
crackin
goiin
movin
qoin
stickin
listenin
willin
sposed
refering
cooled
mowed
deactivated
spendin
wastin
violated
dvr'd
muted
graduated
bugged
swept
walkd
rained
fouled
biked
ducked

swagged
dunked
lookd
swam
sacked
bullied
benched
nominated
ranked
snowed
installed
launched
unplugged
leaked
hosted
stung
playd
hoed
subtweeted
sampled
wantd
4ward
starvin
singlee
outtie
preggers
siick
sauced
faded
preg
sunburned
sunburnt
tite
odee
maad
od
madd
embarassed
appalled
dissapointed
suprised
butthurt
dgaf
xcited
talm
talk'n
tlkn
bitching
talkn
braggin
talkinq
complainin
speakin
thinkin
thnkn
talmbout
jokin
forgettin
claimin
dunno
wonderin
debatin
pondering
guessin
hopin
knowin

bak
bakk
baq
bacc
bac
riqht
righ
riite
rite
rght
ritee
rii
ryte
schemin
hydrated
storming
rainin
poppin
snowing
poppington
happenin
goodie
poppn
snowin
popin
hailing
wronq
premieres
rox
suxx
sux
snows
wrks
tackles
scrolls
presents
mower
toasty
cozy
warm
rigged
postponed
trendin
undefeated
deadd
saucer
2go
bk
tangled
doobies
sweatin
slackin
chirping
thuggin
partyin
lien
wildin
knockin
buzzin
cheatin
frontin
buggin
dyin
speedin
preachin
coughin

dancin
ringin
sleepn
beastin
snitchin
cryin
hollin
flopping
breathin
twerkin
choosin
laffin
twerking
laughn
laughin
stylin
swaggin
trickin
performin
pumpin
flexin
starin
hooping
spinnin
blazin
jerkin
tweetin
planking
cuffin
packin
studyin
trolling
writin
subtweeting
twittering
protesting
grindin
bbming
chokin
fightin
texting
fasting
twitting
recordin
graduating
sexin
spellin
studying
blockin
singin
mixin
sharin
slammin
twatchin
datin
cuffing
typin
smackin
subtweetin
scheming
hidin
flexing
twatching
learnin
uploading
writting

editing
blogging
unpacking
syncing
scanning
grading
decorating
knitting
coding
designing
pitching
flooding
marvins
marvin's
openin
mowing
shoveling
cleanin
stocking
cooling
finishin
signin
fillin
wrapping
washin
cashing
passin
peeling
drivin
travelling
dunking
walkn
beaming
walkin
shuffling
up-
uhp
uprt
owt
0ut
out-
ova
ovr
ovaa
ovah
arnd
outsidee
w/u
w/me
2gether
2getha
2morro
2morrow
tomar
2mrw
2mor
2mrrw
2moro
2maro
toma
2morow
2day
2nite
tonite
tnite
2night

aqain
l8r
lata
sumtime
nomo
2u
tbh
ftl
afterall
mehn
nshit
jor
neways
leh
anywayz
nemore
neway
2me
lah
4me
2m
yest
4u
lastnite
evryday
errday
rn
tmo
yesturday
doee
thoe
doe
thoo
thoee
thoughh
now-
ther
heaa
4eva
4ever
sumwhere
forsure
manually
4sure
lyrically
eitha
,.
;;
);
,?
??..
.?
.??
?!..
.!!
,!
.!
!!..
ndd
&'
&&'
(&
be4
b4
witout
aftr

Figure 5.8. Page 2 of 6.

afta
t0
0f
4the
w/a
w/my
w/the
w/this
widd
w|
unda
wiit
frum
frm
4rm
n2
in2
btwn
durin
w/in
0n
iin
i'n
tge
thaa
dha
onna
inda
2my
yhur
urr
beyonces
yurr
ure
nicki's
somebodys
google's
rihanna's
beyonce's
hiz
year's
blog
headlines
downloads
chronicle
q&a
index
cc
fw
sn
psa
attn
sidenote
np
wts
null
cont
via
itrt
urt
nfb
swine
-*
punya
cade
pow

mem
supp
vox
nit
ren
ff
det
sk
aff
lat
stu
rm
wr
hu
int
rb
ent
thr
u's
gz
sp
baken
ft
fah
fir
ov
w/that
w/her
mos
hurd
derp
lml
lbvs
lolx
lolss
lls
l0l
lolzz
lols
wkwk
me2
rft
rotflmao
yessirr
rofl
kml
sheeshh
ctfu
ctfuu
leggoo
roflmao
legoo
rotfl
kmsl
bol
sheesshh
hyfr
yezzir
4sho
lma0
rotf
bwahahahaha
jajajajaja
jajajaja
aha
tqm

heehee
jaja
ahaa
jajaja
hihi
jajajajajaja
wkwkwk
jajajaj
jajaj
inshallah
yuup
yehh
nawl
noes
werd
iknow
nawh
yh
wordd
ikr
ayye
yuupp
asdfghjkl
omo
ooww
waahh
wheww
oww
owee
wooww
zomg
ayee
uugghh
wheeww
ggrr
omq
p.s.
awee
awhh
imy2
oow
oke
aaww
awh
wahh
tuhh
awl
uumm
huuhh
hhmm
kthx
brr
sheesh
whew
nbd
arghh
argh
geezz
uughh
wheew
blech
geesh
ick
arrgghh
arg
ewh

whelp
hmph
hmp
uugh
uqhh
urghh
urgh
hmmph
welp
uuggh
uqh
grr
wowzers
arrgh
thanxx
thankx
thnx
thankz
thanx
saludos
thanxs
thnxx
srry
sry
felicidades
grats
congratz
twugs
booyah
hooray
whoohoo
yummyy
yipee
woo-hoo
hoo
whee
leggo
ftw
huzzah
woot
yuumm
muah
tgif
w00t
gobble
rah
burr
meow
gudda
ayo
cmon
gmorning
brb
g'morning
laters
g'nite
gnight
ilyy
ilh
gnite
iloveyou
imy
goodnite
g'night
goodmorningg
ttyl

imyy
toodles
imu
hbd
plzz
hunh
abi
hbu
wbu
wby
whassup
wassupp
wussup
goodlookin
wydd
tf
wusup
df
wzup
waddup
wadup
wattup
4real
wuddup
watup
whattup
wyd
wya
whatup
wsup
ik
iono
idek
iknw
becareful
idgaf
amo
amoo
whatev
ig
wuteva
busta
whateva
gtfo
aiight
aiite
ard
iite
ookk
s2
<3333333
<333
<333333
<3<3<3
<33
<33333
<3<3
<3
<3333
b-)
;3
-
u.u
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;]
;-d

8-)
>:d
;-p
>:)
:3
(;
toort
^.^
=)
=]]
:}
(':
(:
^_^
=]
:')
^-^
((;
^__^
((:
;))
:))
cx
._.
haga
o__0
u_u
o__o
0_0
:-o
o_0
0__o
o.o
(-__-)
o_o
0_o
x_x
o:
:oo
/:
:"(
</3
)':
;-(
:-|
.__.
:-/
://
='(
-.-"
=|
--__--
:-\
>.<
=/
-_-"
=(
-__-
d;
;/
>:o
-,-
-.-
x__x
/;
<_<

:'/
:*(
=[
-__-"
:,(
-_-
>_<
:((
>__<
""
lok
hakuna
love-
(*
*)
chuuch
gnr
foh
smhh
tyna
smfhh
fyl
kmt
j/k
guhh
rns
goodtimes
frfr
iswear
ijs
j/p
(:<
<<"
<
<-
{
[[
<~~
<==
`
<<
lol-
\3
^_
|3
^
np-
drake-
viendo
>
voice)
}
>>"
->
::
>>
merry
jagged
/mi
sportacular
]
)):
[
f/
yg
ng

Figure 5.8. Page 3 of 6.

/via
/cc
hahart
smhrt
lolrt
lmaort
oan
inches
chainz
wks
loko
lokos
tds
rebounds
assists
innings
td's
pts
yards
flags
yds
km
min/mile
ln
utc
pst
hunnit
veces
yd
cpl
baybee
hommie
hunnie
hunni
hunn
sandz
homey
booskie
brahh
hun
siss
dawgg
booski
mamacita
sweety
famo
sonn
hon
soror
baee
meng
bestiee
cuhh
lovie
babez
bae
bruhh
bby
ddub
bbs
tete
bb
tunechi
todos
babii
lul

humps
boobie
tweep
jeezy
9700
heffa
nigha
bih
nikka
nicca
nukka
nucca
bihh
twigga
wuss
g6
spammer
slacker
bish
mfer
groupie
bumb
cornball
nupe
heaux
dubb
thugg
dweeb
hoee
mf
qirl
gyal
grl
dag
wrd
guh
kellz
shid
shiid
bwoy
manee
b-day
bdayy
gabba
gambino
axx
asx
arenas
daddys
neos
roomates
homegirls
exs
eyez
sideburns
jammies
talents
grades
cockiness
butthole
momz
cuzzin
novio
bestfriend
homeboi
cuzzos

timeline
cuzzins
homegirl
tl
boothang
homegurl
bestfriendd
besty
twifey
meech
roomate
co-worker
followerss
follwers
fren
bff's
bestfriends
thngs
ladys
lass
girlz
nupes
gurls
ratchets
refs
shorties
gurlz
bruhs
sistas
grls
niccas
mf's
suckas
heffas
heauxs
shyts
mfs
mofo's
hoes
bishes
nighas
nikkas
chics
guyz
twitfam
pplz
guise
twitterworld
twitters
twitches
twitts
ya'll!!
tweople
girlies
twamily
tweeples
twiggas
tweeps
peeps
tweethearts
twitterville
tweeties
lovies
twitterland
hunnies
sorors

tweoples
twits
tweeple
twitterverse
twam
twiggaz
tworld
ya'll!
bloggers
troops
commentators
grads
promoters
miners
interns
graduates
travelers
execs
crews
riots
dj's
bots
unions
shoppers
users
tablets
djs
producers
qbs
mc's
stans
candidates
developers
receivers
accts
haitians
republicans
hackers
libras
leos
protesters
jamaicans
scorpios
celebs
virgos
bikers
mosquitos
crooks
tornadoes
roads
lasers
fireworks
barbies
mosquitoes
turkeys
tt's
tts
c's
midterms
sigmas
professors
earthquakes
kiddies
deltas
bats
subliminals

cookouts
alphas
spammers
spiders
macs
savages
tornados
bigs
seniors
vampires
turntables
fakers
referees
allergies
jumpers
blisters
brackets
sacks
snapbacks
bikinis
weaves
dunks
helmets
scarves
mints
beatz
quizzes
exams
wigs
toys
stockings
sweatpants
textbooks
hoodies
boots
sweaters
coats
cd's
uniforms
mixtapes
dollaz
lacefronts
fitteds
pins
pumps
dreds
cargos
tees
blankets
tights
sandals
essays
boyshorts
joints
hitters
costumes
emojis
leggins
laptops
gloves
cleats
trunks
grenades
lighters
trax
snuggies

foams
nudes
subtweets
timelines
mentions
twitpics
e-mails
twitcons
avi's
skillz
viruses
piles
pix
wrds
vowels
disappointments
turnovers
fouls
leagues
tryouts
meetings
medals
pools
camps
penalties
pitches
finals
touchdowns
vids
billboards
lists
cribs
badges
dvd's
files
avatars
hashtags
blogs
ringtones
functionality
mixes
beaches
presentations
debates
podcasts
icons
polls
dvds
forums
quo
feedback
updates
tix
gifts
tixs
invites
suggestions
remedies
takers
predictions
nites
niight
nyte
nite
nitee

niqht
moorning
mornin
mornting
mawnin
morninq
morn
day-semester
wk
decade
wkend
wknd
shidd
shytt
schoolwork
taxes
hw
homework
hmwk
errands
enuf
enuff
hickies
matta
tyme
tiime
thng
thinq
werk
dreamland
k.o
multitask
intermission
midnite
soundcheck
fantasy
halftime
h.s.
tims
regionals
skewl
skoo
skool
twitterjail
recital
class
exam
orientation
midterm
homeroom
klass
rehersal
tamales
wedges
gumbo
crawfish
blueberries
smoothies
pumpkin
chowder
cherries
casserole
ice-cream
barbecue
sandwhich

Figure 5.8. Page 4 of 6.

canes
bbq
locos
turkey
veg
chilli
watermelon
ceasar
choc
frap
frappe
butta
smores
popsicles
potatoe
pina
chix
pneumonia
bronchitis
libra
terrorism
bullying
tsunami
qualifying
3-d
detention
3d
hd
trainin
threes
persuasion
nightlife
defense
amusement
comm
psychology
accounting
anatomy
mojito
chardonnay
merlot
moscato
eggnog
joose
martini
cider
patron
liqour
mojitos
latte
nuvo
lipgloss
guestlist
sunscreen
lint
radiation
bandwidth
drilling
tide
h20
randomness
autotune
climax
sunburn
applause
thirst

warmth
capitalism
ambition
ridiculousness
sucess
snow
pollen
sleet
flurries
thunder
lightening
thunderstorm
s
storms
willies
fog
leopard
showers
perf
ratchetness
goody
coonery
fiyah
shiznit
bitchassness
bullshyt
piff
lrt
ping
autocorrect
twitted
twitterr
deck
campus
racks
hoarders
rss
dsl
a/c
apocalypse
physics
calc
astronomy
sociology
calculus
omega
geometry
algebra
math
pc
psych
thesis
chem
quince
biology
creole
lte
tablet
froyo
jailbroken
desktop
gametime
bfast
poolside
tailgating
fishing

sledding
swimming
golfing
h.a.m
snowboarding
biking
shoppin
skiing
tanning
bowlin
fishin
swimmin
clubbin
kayaking
camping
tubing
kickback
potluck
cookout
bane
begining
weeknd
wrld
abyss
motto
creator
miz
crazies
buzzer
sideline
ballpark
caf
hosp
sidelines
dancefloor
beachh
moviess
bookstore
supermarket
pool
bachelor
endzone
studio
dugout
carwash
in-laws
fireplace
holidays
internets
library
patio
syllabus
buildin
itis
bizness
grinch
wackness
juiceman
porch
sunroof
bizz
lawn
krib
babyshower
dorm
stepfather

mamba
sleigh
crackberry
comp
trampoline
vm
router
trackball
bberry
fone
fne
fones
backround
avi
icon
avii
twiticon
avatar
background
acct
acc
layout
default
twitcon
gamertag
namee
tethering
firmware
widget
api
browser
site
homepage
plugin
earthquake
assassin
umpire
outburst
essay
e-mail
mms
addy
spam
interception
emoji
allergy
alchy
icee
wave
muzik
musik
bootleg
disk
webcam
batt
antenna
lab
modem
cpu
netbook
adapter
gift
promo
swagga
wasp
quickie

concussion
smut
tux
badger
peacock
slime
broom
bootz
reindeer
firework
tings
tt
snowball
snowman
cooter
mosquito
beeper
fitted
hipster
monsta
rockstar
jumpoff
ting
b+
lacefront
bikini
mink
guido
d*ck
choppa
professor
ump
prof
pin
fams
bottoms
ribbon
lite
coat
hoody
trench
cardigan
snapback
jacket
sweatshirt
gown
stylist
sundress
scarf
hoodie
v-neck
sweater
hammock
mound
parade
maze
licker
cabin
tree
recession
volcano
storm
breeze
resturant
swimsuit
thunderstorm

banga
tornado
shutout
fumble
grenade
layup
lapdance
touchdown
homerun
showerr
spliff
salts
texter
snippet
screenshot
vid
hitter
3some
mixtape
cypher
joint
sextape
sonq
bullpen
playoffs
tournament
matchup
lockout
redzone
ballgame
topic
af
texters
a'f
asf
mgr
coordinator
commerical
pact
forum
prototype
sidebar
nomination
cache
flyer
software
wiki
scandal
portfolio
database
newsletter
interference
savings
decor
elections
svc
processor
panels
outage
rankings
themes
supplies
workflow
developer
tutoring

documentatic
n
conversion
exp
integration
ui
interface
auditorium
bldg
blitz
conditioning
heater
fest
festival
klub
medal
computing
disasters
bases
scorer
beatdown
afterparty
presentation
banquet
sesh
gala
conf
keynote
tweetup
photoshoot
webinar
ceremony
finale
demo
premiere
catalog
opener
photog
kicker
goalie
quarterback
bracket
receiver
o-line
pitcher
officiating
qb
dictator
promoter
hoax
client
vaccine
producer
refill
study
setup
plank
file
rebound
dunk
lecture
scrimmage
turnover
protest
check-in
revolt

Figure 5.8. Page 5 of 6.

tailgate
rally
timeout
shootout
wrkout
kickoff
tutor
retreat
meanin
scope
launch
bundle
disclaimer
s/n
verdict
ques
url
vow
hashtag
tribute
refund
meetin
mtg
qtr
inning
quater
warranty
resolution
costume
roulette
decorations
resolutions
gully
dutty
wavy
trendy
matchin
ratchet
sexii
rachet
dtf
beastly
funnel
peppermint
corned
tanned
bizzy
chapped
collard
clutch
intresting
interestin
ode
ez
prosperous
diff
dif
seperate
ppl's
subliminal
ppls
winky
foul
futuristic
shameless
festive

low-key
quik
krazy
wackk
cray
crazi
crazii
crazzy
crzy
smoove
nutz
fancy
wack
trill
trippy
stoopid
wreckless
wak
grimey
judgmental
rediculous
annoyin
borin
awk
embarassing
spooky
hopeless
debatable
irrelevant
hala
hillarious
unforgettable
amazin
halarious
truue
truu
nicee
kewl
niccee
hott
kute
gudd
gd
qood
guud
gr8
grreat
kickass
niice
doobie
precious
2much
betta
bettr
bettah
colder
warmer
hotter
sharper
lonq
tardy
windy
dreary
cold
rainy
freezing

foggy
humid
snowy
coldd
muggy
chilly
thundering
coold
freezin
tamed
swizz
linen
flannel
camo
suede
pajama
fleece
jingle
swamp
gingerbread
blck
blk
haunted
geaux
twitterless
balloon
atta
olympic
women's
iconic
unsung
womens
mens
upscale
celeb
freelance
prepaid
wireless
touchscreen
seasonal
mindless
xtra
external
batting
static
curved
mp3
torrent
pdf
rbi
offical
infamous
domain
dr's
parkin
secondary
grad
flu
quake
couture
farmers
rack
powerhouse
renegade
xxl
blogger

rnb
kick-ass
burlesque
horror
snowboard
glam
camp
dubstep
sci-fi
hiphop
lotus
harvest
mvp
hip-hop
westcoast
soca
vamp
fg
bronze
shark
lightning
lib
football
pre-season
crossfit
b-ball
triathlon
allstar
frisbee
spades
gameday
lacrosse
multiplayer
preseason
soccer
baseball
varsity
golf
pep
fball
vball
f1
softball
derby
playoff
volleyball
ski
kickball
postseason
stimulus
healthcare
hc
voter
immigration
reform
web
cust
biz
gadget
baskets
skating
quiz
overcast
wackest
flyest
deadliest

nighty
nitey
lst
nxt
nex
farmer's
awkward
neww
wittle
biig
biq
teeny
24hr
womans
meteor
uur
otha
othr
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tew
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Figure 5.8. Page 6 of 6.

Chapter 6

International Events from the News

(This chapter was originally published as O'Connor et al. (2013).)

6.1 Synopsis

The previous chapters described a text analysis tool, as well as opinion and sociolinguistic analyses of social media, that operate at the level of word frequencies, which are a fundamental unit of linguistic representation. However, for analyzing many social questions, the objects of interest may involve more complex objects such as relationships among entities. This chapter specifically looks at textual descriptions of events, which typically engage more complex linguistic structures indicating the semantic relationships between words in a sentence. While more extensive natural language processing techniques are used, similar analysis techniques can be applied—latent variable models, Bayesian inference, and comparisons to previously established social science measurements and data—can be applied.

In this chapter we describe a new probabilistic model for extracting events between major political actors from news corpora. Our unsupervised model brings together familiar components in natural language processing (like parsers and topic models) with contextual political information—temporal and dyad dependence—to infer latent event classes. We quantitatively evaluate the model's performance on political science benchmarks: recovering expert-assigned event class valences, and detecting real-world conflict. We also conduct a small case study based on our model's inferences.

6.2 Introduction

The digitization of large news corpora has provided an unparalleled opportunity for the systematic study of international relations. Since the mid-1960s political scientists have used political *events data*, records of public micro-level interactions between major political actors of the form "someone does something to someone else" as reported in the open press (Schrodt, 2012), to study the patterns of interactions between political actors and how they evolve over time. Scaling this data effort to modern corpora presents an information extraction challenge: can a structured collection of accurate, politically relevant events between major political actors be extracted automatically and efficiently? And can they be grouped into meaningful event types with a low-dimensional structure useful for further analysis?

We present an unsupervised approach to event extraction, in which political structure and linguistic evidence are combined. A political context model of the relationship between a pair of political actors imposes a prior distribution over types of linguistic events. Our probabilistic model infers latent frames, each a distribution over textual expressions of a kind of event, as well as a representation of the relationship between each political actor pair at each point in time. We use syntactic preprocessing and a logistic normal topic model, including latent temporal smoothing on the political context prior.

We apply the model in a series of comparisons to benchmark datasets in political science. First, we compare the automatically learned verb classes to a pre-existing ontology and hand-crafted verb patterns from TABARI,[1] an open-source and widely used rule-based event extraction system for this domain. Second, we demonstrate correlation to a database of real-world international conflict events, the Militarized Interstate Dispute (MID) dataset (Jones et al., 1996). Third, we qualitatively examine a prominent case not included in the MID dataset, Israeli-Palestinian relations, and compare the recovered trends to the historical record.

We outline the data used for event discovery (§6.3), describe our model (§6.4), inference (§6.5), evaluation (§6.6), and comment on related work (§6.7).

6.3 Data

The model we describe in §6.4 is learned from a corpus of 6.5 million newswire articles from the English Gigaword 4th edition (1994–2008, Parker et al., 2009). We also supplement it with a sample of data from the *New York Times* Annotated Corpus (1987–2007, Sandhaus, 2008).[2] The Stanford CoreNLP system,[3] under default settings, was used to POS-tag and parse the articles, to eventually produce event tuples of the form

$$\langle s, r, t, w_{\text{predpath}} \rangle$$

where s and r denote "source" and "receiver" arguments, which are political actor entities in a predefined set $\mathcal{E}$, t is a timestep (i.e., a 7-day period) derived from the article's published date, and w_{predpath} is a textual predicate expressed as a dependency path that typically includes a verb (we use the terms "predicate-path" and "verb-path" interchangeably). For example, on January 1, 2000, the AP reported "Pakistan promptly accused India," from which our preprocessing extracts the tuple ⟨PAK, IND, 678, $\textit{accuse} \xleftarrow{\text{dobj}}$ ⟩. (The path excludes the first source-side arc.) Entities and verb paths are identified through the following sets of rules.

Named entity recognition and resolution is done deterministically by finding instances of country names from the *CountryInfo.txt* dictionary from TABARI,[4] which contains proper noun and adjectival forms for countries and administrative units. We supplement these with a few entries for international organizations from another dictionary provided by the same project, and clean up a few ambiguous names, resulting in a final actor dictionary of 235 entities and 2,500 names.

Whenever a name is found, we identify its entity's mention as the minimal noun phrase that contains it; if the name is an adjectival or noun-noun compound modifier, we traverse any such

[1] Available from the Penn State Event Data Project: http://eventdata.psu.edu/

[2] For arbitrary reasons this portion of the data is much smaller (we only parse the first five sentences of each article, while Gigaword has all sentences parsed), resulting in less than 2% as many tuples as from the Gigaword data.

[3] http://nlp.stanford.edu/software/corenlp.shtml

[4] http://eventdata.psu.edu/software.dir/dictionaries.html.

amod and *nn* dependencies to the noun phrase head. Thus *NATO bombing*, *British view*, and *Palestinian militant* resolve to the entity codes IGONAT, GBR, and PSE respectively.

We are interested in identifying actions initiated by agents of one country targeted towards another, and hence concentrate on verbs, analyzing the "CCprocessed" version of the Stanford Dependencies (de Marneffe and Manning, 2008). Verb paths are identified by looking at the shortest dependency path between two mentions in a sentence. If one of the mentions is immediately dominated by a *nsubj* or *agent* relation, we consider that the Source actor, and the other mention is the Receiver. The most common cases are simple direct objects and prepositional arguments like $\textit{talk} \xleftarrow{\text{prep\_with}}$ and $\textit{fight} \xleftarrow{\text{prep\_alongside}}$ ("S talk with R," "S fight alongside R") but many interesting multiword constructions also result, such as $\textit{reject} \xleftarrow{\text{dobj}} \textit{allegation} \xleftarrow{\text{poss}}$ ("S rejected R's allegation") or verb chains as in $\textit{offer} \xleftarrow{\text{xcomp}} \textit{help} \xleftarrow{\text{dobj}}$ ("S offered to help R").

We wish to focus on instances of directly reported events, so attempt to remove factively complicated cases such as indirect reporting and hypotheticals by discarding all predicate paths for which any verb on the path has an off-path governing verb with a non-*conj* relation. (For example, the verb at the root of a sentence always survives this filter.) Without this filter, the $\langle s, r, w \rangle$ tuple $\langle$USA, CUB, $\textit{want} \xleftarrow{\text{xcomp}} \textit{seize} \xleftarrow{\text{dobj}}$ $\rangle$ is extracted from the sentence "Parliament Speaker Ricardo Alarcon said the United States wants to seize Cuba and take over its lands"; the filter removes it since *wants* is dominated by an off-path verb through $\textit{say} \xleftarrow{\text{ccomp}} \textit{wants}$. The filter was iteratively developed by inspecting dozens of output examples and their labelings under successive changes to the rules.

Finally, only paths length 4 or less are allowed, the final dependency relation for the receiver may not be *nsubj* or *agent*, and the path may not contain any of the dependency relations *conj*, *parataxis*, *det*, or *dep*. We use lemmatized word forms in defining the paths.

Several document filters are applied before tuple extraction. Deduplication removes 8.5% of articles.[5] For topic filtering, we apply a series of keyword filters to remove sports and finance news, and also apply a text classifier for diplomatic and military news, trained on several hundred manually labeled news articles (using ℓ_1-regularized logistic regression with unigram and bigram features). Other filters remove non-textual junk and non-standard punctuation likely to cause parse errors.

For experiments we remove tuples where the source and receiver entities are the same, and restrict to tuples with dyads that occur at least 500 times, and predicate paths that occur at least 10 times. This yields 365,623 event tuples from 235,830 documents, for 421 dyads and 10,457 unique predicate paths. We define timesteps to be 7-day periods, resulting in 1,149 discrete timesteps (1987 through 2008, though the vast majority of data starts in 1994).

6.4 Model

We design two models to learn linguistic event classes over predicate paths by conditioning on real-world contextual information about international politics, $p(w_{\text{predpath}} \mid s, r, t)$, leveraging the fact there tends to be dyadic and temporal coherence in international relations: the types of actions that are likely to occur between nations tend to be similar within the same dyad, and usually their distribution changes smoothly over time.

[5] We use a simple form of shingling (ch. 3, Rajaraman and Ullman, 2011): represent a document signature as its $J = 5$ lowercased bigrams with the lowest hash values, and reject a document with a signature that has been seen before within the same month. J was manually tuned, as it affects the precision/recall tradeoff.

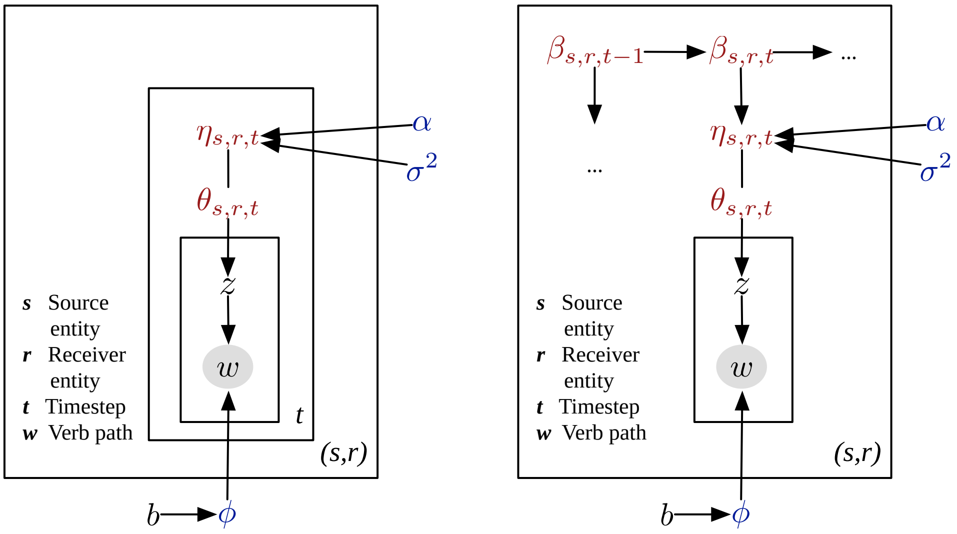


Figure 6.1: Directed probabilistic diagram of the independent timestep model (left) and the smoothed model (right).

Our model decomposes into two submodels: a Context submodel, which encodes how political context affects the probability distribution over event types, and a Language submodel, for how those events are manifested as textual predicate paths (Figure 6.1). The overall generative process is as follows. We color global parameters for a frame blue, and local context parameters red, and use the term "frame" as a synonym for "event type." The fixed hyperparameter K denotes the number of frames.

- The **context model** generates a frame prior $\theta_{s,r,t}$ for every context (s, r, t).
- **Language model:**
  - Draw lexical sparsity parameter b from a diffuse prior (see §6.10.4).
  - For each frame k, draw a multinomial distribution of dependency paths, $\phi_k \sim \text{Dir}(b/V)$ (where V is the number of dependency path types).
  - For each (s, r, t), for every event tuple i in that context,
    - Sample its frame $z^{(i)} \sim \text{Mult}(\theta_{s,r,t})$.
    - Sample its predicate realization $w^{(i)}_{\text{predpath}} \sim \text{Mult}(\phi_{z^{(i)}})$.

Thus the language model is very similar to a topic model's generation of token topics and wordtypes.

We use structured logistic normal distributions to represent contextual effects. The simplest is the **vanilla** (**V**) context model,

- For each frame k, draw global parameters from diffuse priors: prevalence α_k and variability σ^2_k.
- For each (s, r, t),

- Draw $\eta_{k,s,r,t} \sim N(\alpha_k,\ \sigma_k^2)$ for each frame k.
- Apply a softmax transform,

$$\theta_{k,s,r,t} = \frac{\exp \eta_{k,s,r,t}}{\sum_{k'=1}^{K} \exp \eta_{k',s,r,t}}$$

Thus the vector $\eta_{*,s,r,t}$ encodes the relative log-odds of the different frames for events appearing in the context (s, r, t). This simple logistic normal prior is, in terms of topic models, analogous to the asymmetric Dirichlet prior version of LDA in Wallach et al. (2009), since the α_k parameter can learn that some frames tend to be more likely than others. The variance parameters σ_k^2 control admixture sparsity, and are analogous to a Dirichlet's concentration parameter.

6.4.1 Smoothing Frames Across Time

The vanilla model is capable of inducing frames through dependency path co-occurences, when multiple events occur in a given context. However, many dyad-time slices are very sparse; for example, most dyads (all but 18) have events in fewer than half the time slices in the dataset. One solution is to increase the bucket size (e.g., to months); however, previous work in political science has demonstrated that answering questions of interest about reciprocity dynamics requires recovering the events at weekly or even daily granularity (Shellman, 2004), and in any case wide buckets help only so much for dyads with fewer events or less media attention. Therefore we propose a **smoothed frames** (**SF**) model, in which the frame distribution for a given dyad comes from a latent parameter $\beta_{*,s,r,t}$ that smoothly varies over time. For each (s, r), draw the first timestep's values as $\beta_{k,s,r,1} \sim N(0, 100)$, and for each context $(s, r, t > 1)$,

- Draw $\beta_{k,s,r,t} \sim N(\beta_{k,s,r,t-1},\ \tau^2)$
- Draw $\eta_{k,s,r,t} \sim N(\alpha_k + \beta_{k,s,r,t},\ \sigma_k^2)$

Other parameters (α_k, σ_k^2) are same as the vanilla model. This model assumes a random walk process on β, a variable which exists even for contexts that contain no events. Thus inferences about η will be smoothed according to event data at nearby timesteps. This is an instance of a linear Gaussian state-space model (also known as a linear dynamical system or dynamic linear model), and is a convenient formulation because it has well-known exact inference algorithms. Dynamic linear models have been used elsewhere in machine learning and political science to allow latent topic frequencies (Blei and Lafferty, 2006b; Quinn et al., 2010) and ideological positions (Martin and Quinn, 2002) to smoothly change over time, and thus share statistical strength between timesteps.

6.5 Inference

After randomly initializing all $\eta_{k,s,r,t}$, inference is performed by a blocked Gibbs sampler, alternating resamplings for three major groups of variables: the language model (z,ϕ), context model (α, γ, β, p), and the η, θ variables, which bottleneck between the submodels.

The **language model** sampler sequentially updates every $z^{(i)}$ (and implicitly ϕ via collapsing) in the manner of Griffiths and Steyvers (2004): $p(z^{(i)}|\theta, w^{(i)}, b) \propto \theta_{s,r,t,z}(n_{w,z}+b/V)/(n_z+b)$, where counts n are for all event tuples besides i.

For the **context model**, α is conjugate resampled as a normal mean. The random walk variables β are sampled with the forward-filtering-backward-sampling algorithm (FFBS; Harrison and

West, 1997; Carter and Kohn, 1994). There is one slight modification of the standard dynamic linear model that the zero-count weeks have no η observation; the Kalman filter implementation is appropriately modified to handle this.

The η update step is challenging since it is a nonconjugate prior to the z counts. Logistic normal distributions were introduced to text modeling by Blei and Lafferty (2007), who developed a variational approximation; however, we find that experimenting with different models is easier in the Gibbs sampling framework. While Gibbs sampling for logistic normal priors is possible using auxiliary variable methods (Mimno et al., 2008; Holmes and Held, 2006; Polson et al., 2012), it can be slow to converge. We opt for the more computationally efficient approach of Zeger and Karim (1991) and Hoff (2003), using a Laplace approximation to $p(\eta \mid \bar{\eta}, \Sigma, z)$, which is a mode-centered Gaussian having inverse covariance equal to the unnormalized log-posterior's negative Hessian (§8.4 in Murphy, 2012). We find the mode with the linear-time Newton algorithm from Eisenstein et al. (2011b), and sample in linear time by only using the Hessian's diagonal as the inverse covariance (i.e., an axis-aligned normal), since a full multivariate normal sample requires a cubic-time-to-compute Cholesky root of the covariance matrix. This η^* sample is a proposal for a Metropolis-within-Gibbs step, which is moved to according to the standard Metropolis-Hastings acceptance rule. Acceptance rates differ by K, ranging approximately from 30% ($K = 100$) to nearly 100% (small K).

Finally, we use diffuse priors on all global parameters, conjugate resampling variances τ^2, σ_k once per iteration, and slice sampling (Neal, 2003) the Dirichlet concentration b every 100 iterations. Automatically learning these was extremely convenient for model-fitting; the only hyperparameter we set manually was K. It also allowed us to monitor the convergence of dispersion parameters to help debug and assess MCMC mixing. For other modeling and implementation details, see the appendix section (§6.10).

6.6 Experiments

We fit the two models on the dataset described in §6.3, varying the number of frames K, with 8 or more separate runs for each setting. Posteriors are saved and averaged from 11 Gibbs samples (every 100 iterations from 9,000 to 10,000) for analysis.

We present intrinsic (§6.6.1) and extrinsic (§6.6.2) quantitative evaluations, and a qualitative case study (§6.6.4).

6.6.1 Lexical Scale Impurity

In the international relations literature, much of the analysis of text-based events data makes use of a unidimensional conflict to cooperation scale. A popular event ontology in this domain, CAMEO, consists of around 300 different event types, each given an expert-assigned scale in the range from -10 to $+10$ (Gerner et al., 2002), derived from a judgement collection experiment in Goldstein (1992). The TABARI pattern-based event extraction program comes with a list of almost 16,000 manually engineered verb patterns, each assigned to one CAMEO event type.

It is interesting to consider the extent to which our unsupervised model is able to recover the expert-designed ontology. Given that many of the categories are very fine-grained (e.g. "Express intent to de-escalate military engagement"), we elect to measure model quality as *lexical scale purity*: whether all the predicate paths within one automatically learned frame tend to have similar gold-standard scale scores. (This measures cluster cohesiveness against a one-dimensional continuous scale, instead of measuring cluster cohesiveness against a gold-standard clustering as in VI (Meilă, 2007), Rand index (1971), or cluster purity.) To calculate this, we construct a mapping between our corpus-derived verb path vocabulary and the TABARI verb patterns, many of which contain one to several word stems that are intended to be matched in surface order. Many of our dependency paths, when traversed from the source to receiver direction, also follow surface order, due to English's SVO word order.[6] Therefore we convert each path to a word sequence and match against the TABARI lexicon—plus a few modifications for differences in infinitives and stemming—and find 528 dependency path matches. We assign each path w a gold-standard scale $g(w)$ by resolving through its matching pattern's CAMEO code.

We formalize *lexical scale impurity* as the average absolute difference of scale values between two predicate paths under the same frame. Specifically, we want a token-level posterior expectation

$$\mathbb{E}(|g(w_i) - g(w_j)| \mid z_i = z_j, w_i \neq w_j) \tag{6.1}$$

which is taken over pairs of path instances (i, j) where both paths w_i, w_j are in M, the set of verb paths that were matched between the lexicons. This can be reformulated at the type level as:[7]

$$\frac{1}{N} \sum_k \sum_{\substack{w,v \in M \\ w \neq v}} n_{w,k}\, n_{v,k}\, |g(w) - g(v)| \tag{6.2}$$

where n refers to the averaged Gibbs samples' counts of event tuples having frame k and a particular verb path,[8] and N is the number of token comparisons (i.e. the same sum, but with a 1 replacing the distance). The worst possible impurity is upper bounded at 20 ($= \max(g(w)) - \min(g(w))$) and the best possible is 0. We also compute a randomized null hypothesis to see how low impurity can be by chance: each of ∼1000 simulations randomly assigns each path in M to one of K frames (all its instances are exclusively assigned to that frame), and computes the impurity. On average the impurity is same at all K, but variance increases with K (since small clusters might by chance get a highly similar paths in them), necessitating this null hypothesis analysis. We report the 5th percentile over simulations.

6.6.2 Conflict Detection

Political events data has shown considerable promise as a tool for crisis early warning systems (O'Brien, 2010; Brandt et al., 2011). While conflict forecasting is a potential application of our model, we conduct a simpler prediction task to validate whether the model is learning something useful: based on news text, tell whether or not an armed conflict is *currently* happening. For a gold standard, we use the Militarized Interstate Dispute (MID) dataset (Jones et al., 1996; Ghosn et al., 2004), which documents historical international disputes. While not without critics, the MID data is the most prominent dataset in the field of international relations. We use the Dyadic MIDs, each of which ranks hostility levels between pairs of actors on a five point scale over a date interval; we define conflict to be the top two categories "Use of Force" (4) and "War" (5). We convert the data into a variable $y_{s,r,t}$, the highest hostility level reached by actor s directed towards receiver r in the dispute that overlaps with our 7-day interval t, and want to predict the binary indicator $\mathbf{1}\{y_{s,r,t} \geq 4\}$. For the illustrative examples (USA to Iraq, and the Israel-Palestine example below) we use results from a smaller but more internally comparable dataset consisting of the 2 million Associated Press articles within the Gigaword corpus.

[6] There are exceptions where a Source-to-Receiver path traversal can have a right-to-left move, such as dependency edges for posessives, in e.g. $S \xrightarrow{\text{nsubj}} \textit{partner} \xleftarrow{\text{poss}} R$, as in "*S* is *R*'s partner". This approach can not match them.

[7] Derivation in §6.9.1.

[8] Results are nearly identical whether we use counts averaged across samples (thus giving posterior marginals), or simply use counts from a single sample (i.e., iteration 10,000).

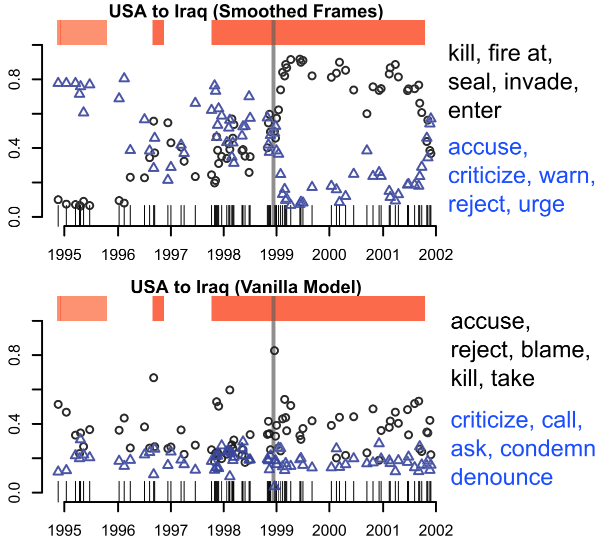


Figure 6.2: The USA→Iraq directed dyad, analyzed by smoothed (above) and vanilla (below) models, showing (1) gold-standard MID values (red intervals along top), (2) weeks with non-zero event counts (vertical lines along x-axis), (3) posterior $E[\theta_{k,\text{USA},\text{IRQ},t}]$ inferences for two frames chosen from two different $K = 5$ models, and (4) most common verb paths for each frame (right). Frames corresponding to material and verbal conflict were chosen for display. Vertical line indicates Operation Desert Fox (see §6.6.2).

For an example of the MID data, see Figure 6.2, which depicts three disputes between the US and Iraq in this time period. The MID labels are marked in red.

The first dispute is a "display of force" (level 3), cataloguing the U.S. response to a series of troop movements along the border with Kuwait. The third dispute (10/7/1997 to 10/10/2001) begins with increasing Iraqi violations of the no-fly zone, resulting in U.S. and U.K. retaliation, reaching a high intensity with Operation Desert Fox, a four-day bombing campaign from December 16 to 19, 1998—which is not shown in MID. These cases highlight MID's limitations—while it is well regarded in the political science literature, its coarse level of aggregation can fail to capture variation in conflict intensity.

Figure 6.2 also shows model inferences. Our smoothed model captures some of these phenomena here, showing clear trends for two relevant frames, including a dramatic change in December 1998. The vanilla model has a harder time, since it cannot combine evidence between different timesteps.

The MID dataset overlaps with our data for 470 weeks, from 1993 through 2001. After excluding dyads with actors that the MID data does not intend to include—Kosovo, Tibet, Palestine, and international organizations—we have 267 directed dyads for evaluation, 117 of which have at least one dispute in the MID data. (Dyads with no dispute in the MID data, such as Germany-France, are assumed to have $y = 0$ throughout the time period.) About 7% of the dyad-time contexts have a dispute under these definitions.

We split the dataset by time, training on the first half of the data and testing on the second half, and measure area under the receiver operating characteristic curve (AUC).[9] For each model, we

[9] AUC can be interpreted as follows: given a positive and negative example, what is the probability that the classifier's confidences order them correctly? Random noise or predicting all the same class both give AUC 0.5.

train an ℓ_1-regularized logistic regression[10] with the K elements of $\theta_{*,s,r,t}$ as input features, tuning the regularization parameter within the training set (by splitting it in half again) to optimize held-out likelihood. We weight instances to balance positive and negative examples. Training is on all individual θ samples at once (thus accounting for posterior uncertainty in learning), and final predicted probabilities are averaged from individual probabilities from each θ test set sample, thus propagating posterior uncertainty into the predictions. We also create a baseline ℓ_1-regularized logistic regression that uses normalized dependency path counts as the features (10,457 features). For both the baseline and vanilla model, contexts with no events are given a feature vector of all zeros.[11] (We also explored an alternative evaluation setup, to hold out by dyad; however, the performance variance is quite high between different random dyad splits.)

6.6.3 Results

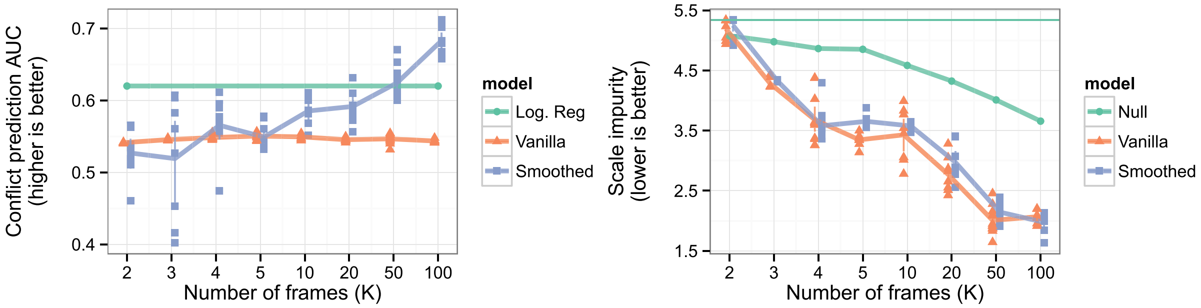


Figure 6.3: Evaluation results. Each point indicates one model run. Lines show the average per K, with vertical lines indicating the 95% bootstrapped interval. **Left:** Conflict detection AUC for different models (§6.6.2). Green line is the verb-path logistic regression baseline. **Right:** Lexical scale impurity (§6.6.1). Top green line indicates the simple random baseline $E(|g(w_i) - g(w_j)|) = 5.33$; the second green line is from the random assignment baseline.

Results are shown in Figure 6.3.[12]

The verb-path logistic regression performs strongly at AUC 0.62; it outperforms all of the vanilla frame models. This is an example of individual lexical features outperforming a topic model for predictive task, because the topic model's dimension reduction obscures important indicators from individual words. Similarly, Gerrish and Blei (2011) found that word-based regression outperformed a customized topic model when predicting Congressional bill passage, and Chapter 4 found word-based regression outperformed Supervised LDA for geolocation, and we have noticed this phenomenon for other text-based prediction problems.

However, adding smoothing to the model substantially increases performance, and in fact outperforms the verb-path regression at $K = 100$. It is unclear why the vanilla model fails to increase performance in K. Note also, the vanilla model exhibits very little variability in prediction performance between model runs, in comparison to the smoothed model which is much more variable (presumably due to the higher number of parameters in the model); at small values of K, the smoothed model can perform poorly. It would also be interesting to analyze the smoothed model with higher values of K and find where it peaks.

[10] Using the R *glmnet* package (Friedman et al., 2010).

[11] For the vanilla model, this performed better than linear interpolation (about 0.03 AUC), and with less variance between runs.

[12] Due to an implementation bug, the model put the vast majority of the probability mass only on $K - 1$ frames, so these settings might be better thought of as $K = 1, 2, 3, 4, 9, \ldots$; see the appendix for details.

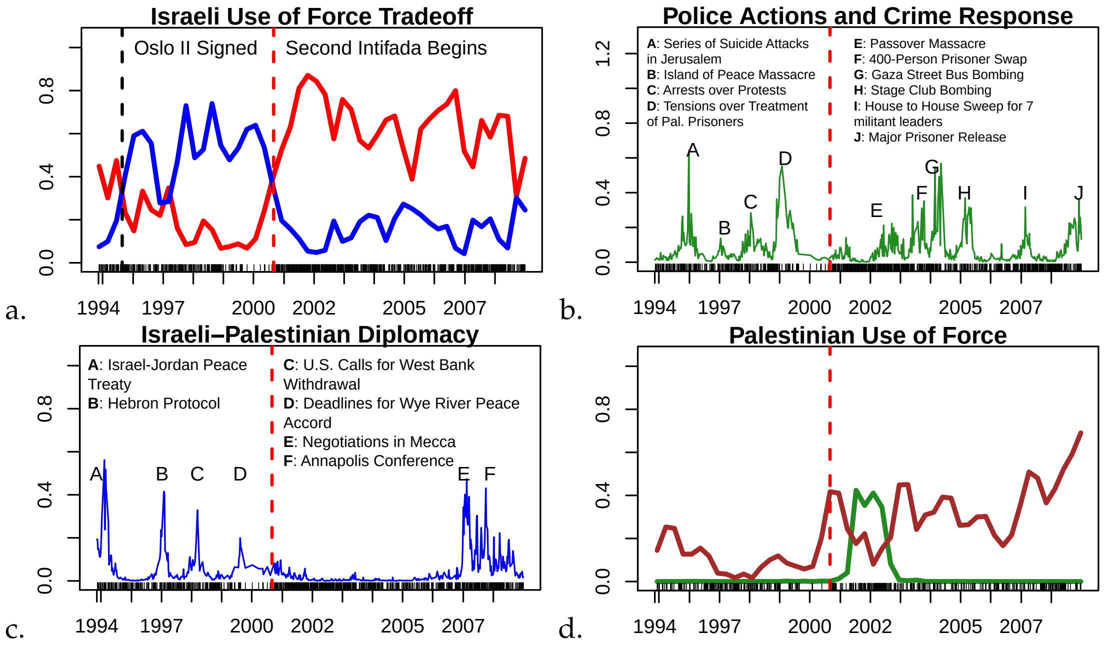


Figure 6.4: For Israel-Palestinian directed dyads, plots of $E[\theta]$ (proportion of weekly events in a frame) over time, annotated with historical events. (a): Words are 'kill, fire at, enter, kill, attack, raid, strike, move, pound, bomb' and 'impose, seal, capture, seize, arrest, ease, close, deport, close, release' (b): 'accuse, criticize, reject, tell, hand to, warn, ask, detain, release, order' (c): 'meet with, sign with, praise, say with, arrive in, host, tell, welcome, join, thank' (d): again the same 'kill, fire at' frame in (a), plus the erroneous frame (see text) 'include, join, fly to, have relation with, protest to, call, include bomber $\xleftarrow{\text{appos}}$ informer for'. Figures (b) and (c) use linear interpolation for zero-count weeks (thus relying exclusively on the model for smoothing); (a) and (d) apply a lowess smoother. (a-c) are for the ISR→PSE direction; (d) is PSE→ISR.

We view the conflict detection task only as one of several validations, and thus turn to lexical evaluation of the induced frames. For lexical scale purity (right side of Figure 6.3), the models perform about the same, with the smoothed model a little bit worse at some values of K (though sometimes with better stability of the fits—opposite of the conflict detection task). This suggests that semantic coherence does not benefit from the longer-range temporal dependencies.

In general, performance improves with higher K, but not beyond $K = 50$. This suggests the model reaches a limit for how fine-grained of semantics it can learn.

6.6.4 Case study

Here we qualitatively examine the narrative story between the dyad with the highest frequency of events in our dataset, the Israeli-Palestinian relationship, finding qualitative agreement with other case studies of this conflict (Brandt et al., 2012; Goldstein et al., 2001; Schrodt and Gerner, 2004). (The MID dataset does not include this conflict because the Palestinians are not considered a state actor.) Using the Associated Press subset, we plot the highest incidence frames from one run of the $K = 20$ smoothed frame models, for the two directed dyads, and highlight some of the interesting relationships.

Figure 6.4(a) shows that tradeoffs in the use of military vs. police action by Israel towards the

Palestinians tracks with major historical events. The first period in the data where police actions ('impose, seal, capture, seize, arrest') exceed military actions ('kill, fire, enter, attack, raid') is with the signing of the "Interim Agreement on the West Bank and the Gaza Strip," also known as the Oslo II agreement. This balance persists until the abrupt breakdown in relations that followed the unsuccessful Camp David Summit in July of 2000, which generally marks the starting point of the wave of violence known as the Second Intifada.

In Figure 6.4(b) we show that our model produces a frame which captures the legal aftermath of particular events ('accuse, criticize,' but also 'detain, release, extradite, charge'). Each of the major spikes in the data coincides with a particular event which either involves the investigation of a particular attack or series of attacks (as in A,B,E) or a discussion about prisoner swaps or mass arrests (as in events D, F, J).

Our model also picks up positive diplomatic events, as seen in Figure 6.4(c), a frame describing Israeli diplomatic actions towards Palestine ('meet with, sign with, praise, say with, arrive in'). Not only do the spikes coincide with major peace treaties and negotiations, but the model correctly characterizes the relative lack of positively valenced action from the beginning of the Second Intifada until its end around 2005–2006.

In Figure 6.4(d) we show the relevant frames depicting use of force from the Palestinians towards the Israelis (brown trend line). At first, the drop in the use of force frame immediately following the start of the Second Intifada seems inconsistent with the historical record. However, there is a concucrrent rise in a different frame driven by the word 'include', which actually appears here due to an NLP error compounded with an artifact of the data source. A casualties report article, containing variants of the text "The Palestinian figure includes... 13 Israeli Arabs...", is repeated 27 times over two years. "Palestinian figure" is erroneously identified as the PSE entity, and several noun phrases in a list are identified as separate receivers. This issue causes 39 of all 86 PSE→ISR events during this period to use the word 'include', accounting for the rise in that frame. (This highlights how better natural language processing could help the model, and the dangers of false positives for this type of data analysis, especially in small-sample drilldowns.) Discounting this erroneous inference, the results are consistent with heightened violence during this period.

We conclude that the frame extractions for the Israeli-Palestinian case are consistent with the historical record over the period of study.

6.7 Related Work

6.7.1 Events Data in Political Science

Projects using hand-collected events data represent some of the earliest efforts in the statistical study of international relations, dating back to the 1960s (Rummel, 1968; Azar and Sloan, 1975; McClelland, 1970). Beginning in the mid-1980s, political scientists began experimenting with automated rule-based extraction systems (Schrodt and Gerner, 1994). These efforts culminated in the open-source program, TABARI, which uses pattern matching from extensive hand-developed phrase dictionaries, combined with basic part of speech tagging (Schrodt, 2001); a rough analogue in the information extraction literature might be the rule-based, finite-state FASTUS system for MUC IE (Hobbs et al., 1997), though TABARI is restricted to single sentence analysis. Later proprietary work has apparently incorporated more extensive NLP (e.g., sentence parsing) though few details are available (King and Lowe, 2003). The most recent published work we know of, by Boschee et al. (2013), uses a proprietary parsing and coreference system (BBN SERIF, Ramshaw et al., 2011), and directly compares to TABARI, finding significantly higher accuracy. The original TABARI system is still actively being developed, including just-released work on a new 200 million event dataset, GDELT (Schrodt and Leetaru, 2013).[13] All these systems crucially rely on hand-built pattern dictionaries.

It is extremely labor intensive to develop these dictionaries. Schrodt (2006) estimates 4,000 trained person-hours were required to create dictionaries of political actors in the Middle East, and the phrase dictionary may have taken even longer; the comments in TABARI's phrase dictionary indicate some of its 15,789 entries were created as early as 1991. Ideally, any new events data solution would incorporate the extensive work already completed by political scientists in this area while minimizing the need for further dictionary development. In this work we use the actor dictionaries, and hope to incorporate the verb patterns in future work.

6.7.2 Events in Natural Language Processing

Political event extraction from news has also received considerable attention within natural language processing in part due to research programs such as MUC-3 and MUC-4 (Lehnert, 1994), which focused on the extraction of terrorist events, as well as the more recent ACE program. The work in this paper is inspired by unsupervised approaches that seek to discover types of relations and events, instead of assuming them to be pre-specified; this includes research under various headings such as template/frame/event learning (Cheung et al., 2013; Modi et al., 2012; Chambers and Jurafsky, 2011; Li et al., 2010; Bejan, 2008), script learning (Regneri et al., 2010; Chambers and Jurafsky, 2009), relation learning (Yao et al., 2011), open information extraction (Banko et al., 2007; Carlson et al., 2010), verb caseframe learning (Rooth et al., 1999; Gildea, 2002; Grenager and Manning, 2006; Lang and Lapata, 2010; Ó Séaghdha, 2010; Titov and Klementiev, 2012), and a version of frame learning called "unsupervised semantic parsing" (Titov and Klementiev, 2011; Poon and Domingos, 2009). Unlike much of the previous literature, we do not learn latent roles/slots. Event extraction is also a large literature, including supervised systems targeting problems similar to MUC and political events (Piskorski and Atkinson, 2011; Piskorski et al., 2011; Sanfilippo et al., 2008).

One can also see this work as a relational extension of co-occurence-based methods such as Gerrish (2013; ch. 4), Diesner and Carley (2005), Chang et al. (2009), or Newman et al. (2006), which perform bag-of-words-style analysis of text fragments containing co-occurring entities. (Gerrish also analyzed the international relations domain, using supervised bag-of-words regression to assess the expressed valence between a pair of actors in a news paragraph, using the predictions as observations in a latent temporal model, and compared to MID.) We instead use parsing to get a much more focused and interpretable representation of the relationship between textually co-occurring entities; namely, that they are the source and target of an action event. This is more in line with work in relation extraction on biomedical scientific articles (Friedman et al., 2001; Rzhetsky et al., 2004) which uses parsing to extracting a network of how different entities, like drugs or proteins, interact.

6.8 Conclusion

Large-scale information extraction can dramatically enhance the study of political behavior. Here we present a novel unsupervised approach to an important data collection effort in the social sciences. We see international relations as a rich and practically useful domain for the development of text analysis methods that jointly infer events, relations, and sociopolitical context. There are numerous areas for future work, such as: using verb dictionaries as semi-supervised seeds or priors;

[13] http://eventdata.psu.edu/data.dir/GDELT.html

interactive learning between political science researchers and unsupervised algorithms; building low-dimensional scaling, or hierarchical structure, into the model; and learning the actor lists to handle changing real-world situations and new domains. In particular, adding more supervision to the model will be crucial to improve semantic quality and make it useful for researchers.

6.9 Appendix: Evaluation

All references to software and data files are for the materials available at http://brenocon.com/irevents/. File names below are linked to URLs, but should be usable with any downloaded version of the software and data.

6.9.1 Type-level calculation of lexical scale impurity

As noted in §6.6.1, the measure we want is a posterior expectation defined for instance pairs, which we can reformulate at the type level as follows. Let i and j index over instances, and w and v index over types. Consider an expectation using a single sample to represent the posterior,

$$E\left[\, |g(w_i) - g(w_j)| \mid z_i = z_j \;\&\; w_i \neq w_j \;\&\; w_i, w_j \in M\right] = \frac{Q}{N} \tag{6.3}$$

where N is the number of instance pair comparisons satisfying the conditional, and Q is,

$$\begin{aligned}
Q &= \sum_{ij} 1\{z_i = z_j\}\; 1\{w_i \in M\}\; 1\{w_j \in M\}\; 1\{w_i \neq w_j\}\; d_{ij} &(6.4)\\
&= \sum_k \sum_{ij} 1\{z_i = k\}\; 1\{z_j = k\}\; 1\{w_i \in M\}\; 1\{w_j \in M\}\; 1\{w_i \neq w_j\}\; d_{ij} &(6.5)\\
&= \sum_k \sum_i 1\{z_i = k\}\; 1\{w_i \in M\} \sum_j 1\{z_j = k\}\; 1\{w_j \in M\}\;\; 1\{w_i \neq w_j\}\; d_{ij} &(6.6)\\
&= \sum_k \sum_{w \in M, v \in M, w \neq v} n_{wk}\; n_{vk}\; d_{wv} &(6.7)
\end{aligned}$$

where $d_{ij} = |g(w_i) - g(w_j)|$, $d_{wv} = |g(w) - g(v)|$, and n_{wk} and n_{vk} are from the collapsed Gibbs sampling count tables, i.e. $n_{wk} = \sum_i 1\{w_i = w\}\; 1\{z_i = k\}$.

The denominator is

$$N = \sum_k \sum_{w \in M, v \in M, w \neq v} n_{w,k} n_{v,k}$$

To properly compute a posterior expectation using multiple samples, Q/N should be re-evaluated on several complete samples and then averaged. However, we found little variation between samples so used only one. We also tried evaluating a single Q/N where n_{wk} and n_{vk} are *averaged* counts from multiple samples—using this corresponds to a factored, mean-field-like approximation to the posterior—but it also was very similar to using a single sample.

The implementation is in *verbdict/score.py*.

6.9.2 TABARI lexicon matching

Two additional notes:

1. There were a number of patterns in the TABARI lexicon that had multiple conflicting codes. See *verbdict/contradictory_codes.txt*.

2. As described in the paper, the dependency paths are traversed from source to receiver, creating the corresponding word sequence. Prepositions are un-collapsed and put into the sequence. There is special handling of *xcomp*'s, which sometimes represent an infinitival 'to' and sometimes do not; we generate two versions, with and without 'to'; if either one matches to a TABARI pattern then that counts as a match.

The implementation is in *verbdict/match.py*.

6.10 Appendix: Details on Inference

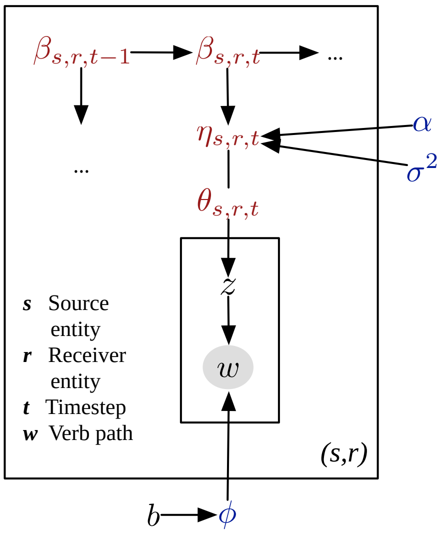
The full smoothed model is:

Context model (smoothed frames):

$$\begin{aligned}
\tau^2 &\sim \text{InvGamma} \\
\sigma_k^2 &\sim \text{InvGamma} \\
\alpha_k &\sim \text{Normal} \\
\beta_{s,r,1,k} &\sim N(0, 100) \\
\beta_{s,r,t>1,k} &\sim N(\beta_{k,s,r,t-1}, \tau^2) \\
\eta_{s,r,t,k} &\sim N(\alpha_k + \beta_{k,s,r,t}, \sigma_k^2) \\
\theta_{s,r,t,*} &= \text{Softmax}(\eta_{s,r,t,*})
\end{aligned}$$

Language model:

$$\begin{aligned}
b &\sim \text{ImproperUniform} \\
\phi_k &\sim \text{Dir}(b/V) \\
z &\sim \theta_{s,r,t} \\
w &\sim \phi_z
\end{aligned}$$



The blocked Gibbs sampler proceeds on the following groups of variables. These conditionals also implicitly condition on w, s, r, t.

- Context (Politics) submodel
  - $[\alpha \mid \eta, \beta, \sigma^2]$: Exact
  - $[\beta \mid \eta, \alpha, \sigma^2]$: Exact, FFBS algorithm
- Context/Language bridge
  - $[\eta \mid \beta, \alpha, z]$: Laplace approximation Metropolis-within-Gibbs step
- Language submodel
  - $[z|\eta]$: Exact, collapsing out ϕ

- Dispersions (variances and concentrations)
  - $[\tau^2|\beta]$, $[\sigma^2|\eta,\alpha]$, $[b|z,w]$

The key step is sampling instantiations of η, which is the bottleneck between the politics and language models; given that, inference proceeds on either side of the model via well-known conjugate posterior resampling updates, each described as follows.

6.10.1 Language Submodel $[z \mid \eta]$

This is the most straightforward step in light of previous work in Bayesian language modeling. Dirichlet-Multinomial conjugacy allows Gibbs sampling to proceed on individual z's for individual tuples, collapsing out ϕ (as in Griffiths and Steyvers (2004), though unlike that work we condition on θ):

$$p(z_i = k \mid s, r, t, w, z_{-i}, \theta, b) \;\; \propto \;\; \theta_{s,r,t} \, \frac{\#\{z = k, w\} + b/V}{\#\{z = k\} + b} \tag{6.8}$$

where the counts are taken from the current z setting in all corpus tuples, except tuple i. b is the Dirichlet concentration parameter, and V is the number of verb-path types.

6.10.2 Context Submodel $[\alpha, \beta \mid \eta]$

The α update is just a conjugate normal sample; see any standard Bayesian reference, e.g. §4.4.2.1 of Murphy (2012), or Gelman et al. (2003). Let the all-but-α residual be $r_{s,r,t,k} = \eta_{s,r,t,k} - \beta_{s,r,t,k}$, so $r \sim N(\alpha, \sigma_k^2)$. With prior $p(\alpha) \sim N(0, 100)$, then

$$p(\alpha_k \mid \eta, \beta, \sigma_k^2) = N\left(\frac{n/\sigma_k^2}{n/\sigma_k^2 + 1/100} \bar{r}_k, \;\; [1/100 + n/\sigma_k^2]^{-1} \right)$$

where $\bar{r}_k$ is the current residual empirical mean: $\bar{r}_k = \sum_{s,r,t} (\eta_{s,r,t,k} - \beta_{s,r,t,k})$, and n is the number of η emissions for this frame (i.e. the number contexts). η only exists for contexts with at least one event tuple (otherwise it is vacuous variable), the sums over (s, r, t) are only over those contexts. Still, n is very large (hundreds of thousands) so the posterior is very peaked; updating α is basically the same as an maximum likelihood estimate and the prior is irrelvant.

The β update is dynamic linear model inference. Because of the emissions' diagonal covariance $diag(\sigma_1^2 \ldots \sigma_K^2)$, it decomposes into conditional independence for each frame's time series for each dyad. A single joint sample of one of these time series,

$$(\hat{\beta}_{s,r,1,k} \ldots \hat{\beta}_{s,r,T,k}) \sim p(\beta_{s,r,1,k} \ldots \beta_{s,r,T,k} \mid \alpha, \eta, \sigma_k^2, \tau^2)$$

can be drawn exactly with dynamic programming, via the forward filter, backward sampling algorithm (FFBS; Harrison and West, 1997; Carter and Kohn, 1994). We leave out $\alpha, \sigma_k^2, \tau^2$ in the following equations for clarity. Here, FFBS proceeds in two steps: (1) run a Kalman filter, successively computing each $p(\beta_t \mid \eta_1 \ldots \eta_t)$ (each of which is normal), and (2) run a sampling variant of the RTS smoother, to sample successively each $\hat{\beta}_t \sim p(\beta_t \mid \hat{\beta}_{t+1}, \eta_1 \ldots \eta_t)$ (each of which is also normal). The final sequence of sampled $\hat{\beta}_t$ values is a sample from the joint sequence posterior, since $p(\beta_1 \ldots \beta_T | \eta_{1:T}) = p(\beta_T | \eta_{1:T}) \; p(\beta_{T-1} | \beta_T, \eta_{1:T-1}) \; \ldots \; p(\beta_1 | \beta_2, \eta_1)$.

We use μ and Σ to denote posterior beliefs about β. Let $N(\mu_{t|t-1}, \Sigma_{t|t-1})$ denote $p(\beta_t \mid \eta_1 \dots \eta_{t-1})$, and $N(\mu_t, \Sigma_t)$ denote $p(\beta_t \mid \eta_1 \dots \eta_t)$ (where Σ is just a scalar variance). The full Kalman filter is defined for much more general Gaussian state-space models: (Murphy, 2012 §18.3 notation)

$$\begin{aligned} z_t &= Az_{t-1} &+ \quad Bu_t &\quad + \quad N(0,Q) \\ y_t &= Cz_t &+ \quad Du_t &\quad + \quad N(0,R) \end{aligned}$$

Which for us is just

$$\begin{aligned} \beta_t &= \beta_{t-1} & & \quad + \quad N(0,\tau^2) \\ \eta_t &= \beta_t &+ \quad \alpha & \quad + \quad N(0,\sigma^2) \end{aligned}$$

The algorithm is[14]

- Filter, which takes $\eta_{1:T}$ as input.

  Initialize $\mu_{1|0} := 0,\ \Sigma_{1|0} := 100$ (and skip the prediction step on the first iteration).

  For $t = 1..T$,

  - Prediction step (infer $p(\beta_t \mid \eta_1 \dots \eta_{t-1})$):
    $\mu_{t|t-1} := \mu_{t-1}$
    $\Sigma_{t|t-1} := \Sigma_{t-1} + \tau^2$
  - Measurement step (infer $p(\beta_t \mid \eta_1 \dots \eta_t)$):
    $r := \eta_t - (\mu_{t|t-1} + \alpha)$ (residual)
    $K := \Sigma_{t|t-1}(\Sigma_{t|t-1} + \sigma^2)^{-1}$ (Kalman gain)
    $\mu_t := \mu_{t|t-1} + Kr$
    $\Sigma_t := \Sigma_{t|t-1}(1 - K)$

- Backward-sampler, which uses the filtered quantities μ_t, Σ_t as input.

  Initially sample $\hat{\beta}_T \sim N(\mu_T, \Sigma_T)$.

  For $t = (T-1)..1$,

  - Sample $\hat{\beta}_t \sim N(\mu_t + L(\hat{\beta}_{t+1} - \mu_{t+1|t}),\ \Sigma_t - L^2\Sigma_{t+1|t})$
    where $L = \Sigma_t(\Sigma_{t+1|t})^{-1}$

We have one modification to the standard linear dynamical system model: while a β exists for all timesteps, there are many zero-count contexts without any event tuples. The Kalman filter is modified to skip the measurement step for those timesteps, so simply $\mu_t := \mu_{t|t-1}$ and $\Sigma_t := \Sigma_{t|t-1}$. We do not store η variables at those timesteps, since they are unnecessary for inference; but we do simulate them when creating posterior samples for analysis in the conflict detection task. (The time-series plots of $E[\theta]$ in section 5 of the paper do not show these samples.)

We use a custom implementation of the filter and sampler that was tested via simulation in two ways: (1) comparing its inferences on simulated data to those from the *dlm* package in R (Petris, 2010), and (2) using the Cook et al. (2006) Bayesian software validation technique of checking the simulation distribution of inferred posterior quantiles of simulated parameters. The latter was useful for tesing other samplers as well. In fact, the softmax bug in the logistic normal inference procedure (§6.10.5) resulted from a case where the validation tests were not used.

[14] See also `http://www.gatsby.ucl.ac.uk/~turner/Notes/1DKalmanFilter/1d_kalman_filter.pdf`.

6.10.3 Logistic Normal $[\eta \mid z, \bar{\eta}]$

Next, we must resample the η variables; for every context, sample from the posterior density

$$p(\eta \mid \bar{\eta}, z) \;\propto\; N(\eta \mid \bar{\eta}, \Sigma)\;\; Mult(z \mid \theta(\eta)) \tag{6.9}$$

where $\bar{\eta} = \beta + \alpha$ denotes η's prior mean. This has an unnormalized log posterior density function

$$\ell(\eta) = \sum_k \left(-\frac{1}{2\sigma_k^2}(\eta_k - \bar{\eta}_k)^2 + n_k \log \theta(\eta)_k \right) \tag{6.10}$$

where n_k is the number of tuples in this context having frame k, and $\theta(\eta)$ is the value of θ deterministically associated with η via the softmax function.

Unfortunately, unlike the Dirichlet, a logistic normal prior on a multinomial is not conjugate; Equation 6.10 describes the unnormalized density, but there is no closed form for the normalized posterior (and more to the point, no known exact sampling algorithm).

As described in the paper, we use a Laplace approximation proposal—a Gaussian approximation centered at the mode, which can be justified as the second-order approximation to the log-posterior there—taking a proposed sample η^* via the steps

(1) Solve MAP $\hat{\eta} = \arg\max_\eta \ell(\eta)$

(2) Sample $\eta^* \sim N(\hat{\eta}, [H(-\ell(\hat{\eta}))]^{-1})$

where $H(-\ell(\hat{\eta}))$ denotes Hessian of the negative unnormalized log-posterior at $\hat{\eta}$.

Step #1 could be solved in a number of ways. We use a fast linear-time Newton algorithm from Eisenstein et al. (2011b), which was faster than gradient descent methods we tried; we reproduce it below. The Newton step is

$$\eta := \eta - \lambda H^{-1} g$$

where the gradient of $-\ell$ is

$$g(\eta)_k = n\theta_k - n_k + \frac{1}{\sigma_k^2}(\eta_k - \bar{\eta}_k)$$

and the Hessian has diagonal and off-diagonal elements

$$H_{kk} = n\theta_k(1 - \theta_k) + 1/\sigma_k^2, \qquad H_{jk} = -n\theta_j\theta_k$$

where n is the number of event tuples in the context (i.e. number of individual z's). Matrix inversion is in general a cubic time algorithm, but we apply the Sherman-Morrison formula to only have to invert a diagonal matrix. For any invertible square matrix A and vectors u,v, the Sherman-Morrison formula gives an alternate expression for $(A + uv^\mathsf{T})^{-1}$ in terms of A^{-1}. For a diagonal matrix A and vectors u, v, w, we apply the Sherman-Morrison formula and configure the order of operations to avoid creating any non-diagonal matrices:

$$Z = (A + uv^\mathsf{T})^{-1} w \tag{6.11}$$

$$Z = A^{-1}w - [1 + v^\mathsf{T} A^{-1} u]^{-1} (A^{-1}u)(v^\mathsf{T} A^{-1} w) \tag{6.12}$$

$$Z_j = (A_{jj}^{-1} w_j) - \frac{1}{1 + \sum_k A_{kk}^{-1} v_k u_k} (A_{jj}^{-1} u_j) \sum_k A_{kk}^{-1} v_k w_k \tag{6.13}$$

where the last line shows the resulting vector for one element j.

The Hessian can be rewritten as a sum of diagonal and rank-1 matrix as $H = diag[n\theta_k + 1/\sigma_k^2] - n\theta\theta^\mathsf{T}$, thus the Newton step direction $H^{-1}g$ can be calculated in linear time by applying Eq. 6.12 with $A_{kk}^{-1} = (n\theta_k + 1/\sigma_k^2)^{-1},\ w = g,\ u = \sqrt{n}\theta,\ v = -\sqrt{n}\theta.$

Eisenstein et al. (2011a) present this technique in the context of a variational inference algorithm, but actually it applies to any MAP logistic normal inference problem under diagonal covariance. We find it usually converges to an $\hat{\eta}$ estimate in only several iterations (using a line search,[15] first taking a step sized $\lambda = 1$, and if it's not an improvement, halving λ until it is.)

Step #2 is to sample from the multivariate normal $N(\hat{\eta}, H^{-1})$. The simplest MVN sampling algorithm is to take K samples from $N(0, 1)$ and multiply that vector by the Cholesky root of the covariance (and add the mean). But it takes cubic time to compute a Cholesky root (in the general case), which is too expensive for large values of K. Instead, we only invert the diagonal of the Hessian (linear time), resulting in a diagonal covariance (thus each $\eta^*_k \sim N(\bar{\eta}_k,\ 1/H_{kk})$); this is only an axis-aligned MVN approximation to the posterior.[16]

So this gives a η^{new} proposal. It is possible to simply update to it directly; but it is more accurate to use it as a Metropolis-Hastings proposal. Calculate the acceptance probability

$$a = \frac{p(\eta^{\text{new}}|\bar{\eta}, z)}{p(\eta^{\text{old}}|\bar{\eta}, z)} \frac{N(\eta^{\text{old}}; \hat{\eta}, H^{-1})}{N(\eta^{\text{new}}; \hat{\eta}, H^{-1})}$$

and accept the proposal at probability $\min(a, 1)$. The ratio of true posterior densities can be calculated with the unnormalized form in Equation 6.10.

See also Wang and Blei (2012) which develops a Laplace approximation for variational inference for several nonconjugate models, including a logistic normal topic model; this approach is also applied in Roberts et al. (2013). The Metropolis-Hastings approach we use here is similar to Hoff (2003).

6.10.4 Learning concentrations and variances

There are several parameters that control the overall variability of the above quantities. The Dirichlet concentration parameter b controls the similarity between the frames' predicate-path distributions; the autoregressive variance τ^2 controls how similar a dyad's latent positions are between timesteps; and the emission variances σ^2_k controls how similar the frame distributions are for two contexts with identical latent states.

All these prior parameters are learned, thus naturally leading the model to learn highly likely levels of sparsity and variability. This is tremendously convenient in practice, since there are no hyperparameters that need to be tuned (beyond K and data preprocessing decisions). It also helps the model learn better solutions; for example, Asuncion et al. (2009) finds that Dirichlet concentration learning gives much better solutions for LDA.

The symmetric Dirichlet parameter b is learned with slice sampling (Neal, 2003), under an improper uniform prior for b. (In other experiments we have found different diffuse priors for b make little difference.) Slice sampling only requires an (unnormalized) posterior density function; with a uniform prior it's just the Dirichlet-multinomial likelihood, which is, integrating out ϕ,

$$L(b) = p(w \mid z, b) = \prod_{k=1}^{K} \frac{\Gamma(b)}{\Gamma(b + n_k)} \prod_{w=1}^{V} \frac{\Gamma(b/V + n_{k,w})}{\Gamma(b/V)} \tag{6.14}$$

where V is the verb-path vocbaulary size, n_k is the number of event tuples having $z = k$, and $n_{k,w}$ the number having frame k and verb-path w. An implementation speedup is possible noting that

[15] e.g. http://www.cs.cmu.edu/~ggordon/10725-F12/slides/11-matrix-newton-annotated.pdf

[16] In fact, this is not even the factored marginals of $N(\hat{\eta}, H^{-1})$, since the diagonal of a Hessian inverse is different than the inverse of a Hessian diagonal.

each frame's lexical count vector $(n_{k,1}..n_{k,V})$ is usually very sparse with mostly 0's, so those terms can be skipped in the innermost loop. (Also draw out the $\Gamma(b/V)$ denominator.) This sparsity during Gibbs sampling is a natural consequence of the sparsity of language; it can be exploited in other ways to improve sampling efficiency, e.g. Yao et al. (2009).

The context model's variance terms are also learned. We use a conjugate inverse-Wishart prior, in inverse chi-squared parameterization (e.g. Murphy, 2012 §4.6.2.2) of $\chi^{-2}(\text{prior strength}, \text{ prior value})$, using diffuse prior $\chi^{-2}(1,1)$. However, since the amount of data is very high, the posterior intervals are very small (often less than 10^{-3}), and sampling is nearly equivalent to ML inference.

Technically, the conjugate sampling equations are

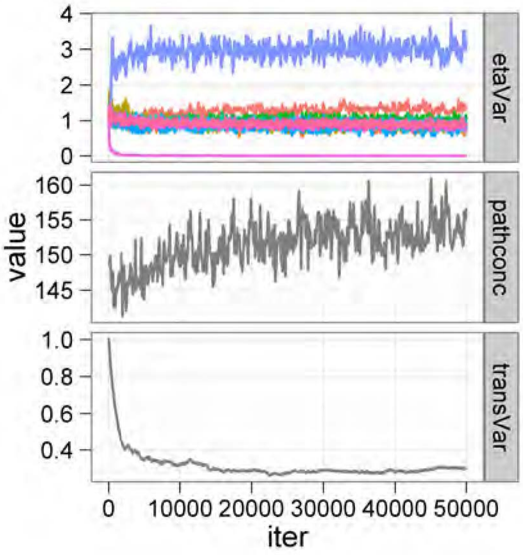
$$\tau^2 \sim \chi^{-2}\left(1+N,\ \frac{1}{1+N}\left[1+\sum_{s,r,t>1,k}(\beta_{s,r,t,k}-\beta_{s,r,t-1,k})^2\right]\right)$$

where N is $(K-1)\times$ NumDyads $\times$ (NumTimesteps-1), and

$$\sigma_k^2 \sim \chi^{-2}\left(1+N,\ \frac{1}{1+N}\left[1+\sum_{(s,r,t)\text{ where }n_{s,r,t}>0}(\eta_{s,r,t,k}-\bar{\eta}_{s,r,t,k})^2\right]\right)$$

where N is the number of contexts with non-zero events. In both cases N is hundreds of thousands to millions, swamping the prior pseudocount value of 1.

Here is a plot of the dispersion parameters over one Gibbs sampling run (all 10 σ_k^2's, b, then τ^2). The fact that dispersions are still drifting in early iterations is an indicator the sampler has not mixed. (Indeed, even though we attained useful results at iteration 10,000, and changing the number of iterations to higher numbers made little difference to the evaluation metrics, these plots clearly indicate mixing has not been achieved at that point. The inferences can be justified only as approximations (but useful ones) of the posterior.)



6.10.5 Softmax bug

The results in §6.6.3 have an anomaly where one frame often has a very low probability mass, so it is essentially has only $K-1$ latent classes. (This is why the $K=2$ models essentially learn only one class, and thus have a similar lexical scale purity as the random choice baseline that would come from one big cluster of all words.) This was later discovered to be due to a bug in the implementation: it clamped the K'th element of η to 0 (attempting to implement an alternate version of softmax with better identifiability), but only the first $K-1$ elements of θ were used in the posterior density evaluation for the MH step, so counts of $z = K$ were ignored in the likelihood. Thus the model would eventually shift θ_K to zero and put all the probability mass on the first $K-1$ elements. (It takes a while for the bug to cause this to happen, since the MAP optimum and Laplace approximation for η, given a fixed θ, is computed correctly. But the density ratio for the MH step prefers assigning low θ_K values, and in the limit the Markov chain should give zero probability for non-zero θ_K.) If $\theta_K = 0$, then the model is exactly the same as a fully parameterized $K-1$ model; since it is close to zero, it is very similar to that.

Chapter 7

Conclusion

7.1 Summary of contributions

We have presented a series of tools and case studies that analyze social phenomena and text: examining whether text analysis can help measure or predict social variables, and exploring hypotheses about how social factors guide the text generation process. These hold promise to shed light on a variety of areas of human society where the content of ideas, opinions, events, and other linguistically expressible concepts are crucial for how people behave. As textual and other digital records of human behavior keep growing at a rapid pace, these types of techniques will be key parts of the emerging discipline of computational social science (Lazer et al., 2009).

Specific contributions of this work include:

- The *MiTextExplorer* interactive data analysis system, for exploring the statistical relationship between document text and covariates (Chapter 2). It uses pointwise mutual information, a basic and useful technique for identifying phenomena worthy of further exploration. This is useful for many social text data analysis problems, which typically see document covariates as indicators of social attributes. (The other chapters of this thesis use these and other methods to get at these relationships.) An experimental prototype of this system is open source and available at `http://brenocon.com/mte/`.
- An analysis of public opinion polls compared to opinion experessed in social media, on several economic and political topics (Chapter 3). Some moderate correlations over time are observed, indicating the potential of sentiment analysis as an alternative to polling, but many challenges also exist, and are discussed.
- A mixed-membership model of geography, demographics, and lexical variation (Chapter 4), which infers geographically coherent linguistic communities, characterized by both spatial and word clusters. Applied to geotagged messages in social media, it reveals surprising patterns of geographically specific terms. The model also allows inference of a user's location based on the text of their messages. This model and dataset are also applied to learning demographically-based word groupings, by using U.S. Census data. The exploratory findings here motivate the next chapter:
- A study of linguistic diffusion (Chapter 5), which analyzes how novel terms spread across different cities in the U.S. over several years, as evidenced in social media. Our model for this statistical analysis is robust to confounds in data sampling rates and ephemeral trends.

We find that geography and population size are important drivers of diffusion, but also, demographic similarity—especially with regards to race—is a crucial determinant.

- We present a method to extract events in international relations from a corpus of news articles (Chapter 6), which unlike previous work automatically infers the latent classes of events, as well as their variation across time for different pairs of actors. The models' inferences are evaluated on their ability to reconstruct previous databases of international conflict, as well as pre-existing phrase dictionaries that have been engineered for this information extraction task. This illustrates the usefulness of natural language processing techniques such as syntactic parsing and the use of semantic arguments in probabilistic modeling.

7.2 Recurring themes

Some recurring themes in this work include the following.

Exploratory analysis. Many approaches are useful for exploring these types of social text data in light of different questions. Chapter 2 focuses on computationally cheap and fast count-based techniques, which are fast enough to allow rapid iteration and interactive refinement of hypotheses about the relationship of text and document covariates. Chapter 3 also uses count-based techniques for analyzing textual sentiment, but based on pre-existing linguistic dictionaries. In contrast, Chapter 4 develops a more expensive topic model approach, which infers groupings of terms, and Chapter 6 applies similar statistical models to a very different linguistic structure, syntactic dependencies describing events between actors. In all cases, these models allow exploration of social variables against text variables; there is a tradeoff between richness of representation and speed and simplicity of analysis.

Social science. An understanding of social science is crucial for useful social text data analysis. When analyzing Twitter data against time and space, many insights from the areas of sociolinguistics and dialectology are important to help interpret what is going on, and computational data analysis can shed light on important hypotheses in this area (Chapters 4 and 5). Sentiment analysis on Twitter is useful to think about in comparison to traditional polling methods (Chapter 3); there are of course many differences in how these measurement methods work. In some cases, previous work additionally provides rich datasets to work with; for example, the area of international relations has seen much work that we use to help validate and understand what our new event extraction methods methods are doing (Chapter 6), and in future work they may be integrated in new approaches to yield better analysis techniques.

Probabilistic machine learning. The framework of probabilistic graphical models and statistical modeling is used throughout. This gives a rich set of formal and computational tools to represent, infer, and learn important relationships in the data. Even when very simple techniques are used, it is enlightening to keep in mind statistical and machine learning interpretations of them—as in Chapter 2's use of pointwise mutual information for word analysis. Optimization, variational inference, and Markov chain Monte Carlo methods allow for flexible and useful inferences for a very wide variety of problems. A few other important techniques used in this thesis include false discovery rate control, dynamic programming, and distributed computation. These all have important uses in the social sciences.

A little bit of NLP can go a long way. Techniques for text analysis (i.e., natural language processing) are quite imperfect given the incredible complexity of language and human intelligence, but they can extract partial views of sentiment, entities, and events, which have many important applications in understanding social phenomena revealed in text data.

7.3 Directions for future work

Much of this work has a heavily exploratory nature. This is appropriate for early stages of gaining understanding, especially as we are still coming to grips with the remarkable possibilities of new social data produced by online systems.

However, the real gains will be made through deeper integration with substantive issues in the social sciences. One relatively simple approach is to leverage data and resources from previous social science research to guide the development of new algorithms and techniques. Chapter 3 explores to what extent traditional polling data might correlate to sentiment measured in social media, and Chapter 6 seeks to reconstruct traditional international event data from latent syntactic analysis techniques. This type of research has the attraction of a relatively simple framework—the researcher checks whether a new computational method correlates to an older, established method. In the longer term, it allows a relatively loose interaction between new computational research and more substantive research efforts: the computational researchers run algorithms to generate new data, then hand it off to others for further analysis. Many examples of this pattern exist: previous work in international event data, for example, follows this approach (King and Lowe, 2003; Schrodt, 2012), and a future version of our international events model could take a similar path. In political science, the well-known NOMINATE scores, a latent variable model of legislator partisanship (Poole and Rosenthal, 1997), are similarly inferred by a small set of researchers, and then made available for download; and they have indeed been used very widely.[1]

A more involved, in-depth integration of computation and social science is to directly engage substantive questions as part of the computational analysis. One avenue is by developing general-purpose text analysis tools that are directly used by researchers—methods such as keyword queries, dictionary frequencies, document classifiers, and topic models have all been widely used—and new methods such as the interactive explorer of Chapter 2 may help as well. Here, the computational research has substantive researchers as users; an iterative process of feedback and refinement is crucial for future progress.

Another approach is to develop customized, computationally-heavy analysis for a particular question, such as a statistical model of text conditioned on certain types of social variables (as in the generative process described in §1.1). In the course of our research on sociolinguistics and Twitter, we found that a latent variable, temporal model was necessary to investigate questions about linguistic diffusion (Chapter 5). To support this form of development, contributions from the computational, statistical, and linguistic sciences include the fundamental primitives of model building (such as probabilistic graphical models), and defining the linguistic objects of analysis. General advances in these areas, such as automatic statistical modeling frameworks like BUGS (Lunn et al., 2009) or Stan (Stan Development Team, 2014), or more robust natural language processing tools, can make the process of model development easier.

An exciting frontier is to incorporate ideas of measurement, causal inference, and other core social science topics into text analysis models. As mentioned in §3.6, the process by which opinions become expressed in social media is subject to a large number of complicated behavioral factors. In order to formulate more effective opinion measurement methods, a promising approach is to

[1] http://www.voteview.com/

model the data generating process, where latent variables of user and population opinions drive a process resulting in frequencies of different types of messages in social media. For international events data generated by traditional rule-based systems, Lowe (2012) examines the problem of statistical aggregation by positing a latent variable measurement model, where event counts are generated based on the dyadic relationsip; from this a scaling of event classes is inferred. Our event class model may benefit from an approach like this, or other alternative models of international actors and their dynamics. These can be combined with sophisicated linguistic representations. Researchers have also started to examine causal inference with text data (Roberts et al., 2014); this is a critical area for future work. Indeed, as many interesting "big data" possibilities emerge from digital records of human behavior from sensors or online environments, we will see more and more need for social analysis; as Grimmer (2014) puts it, "we're all social scientists now."

In terms of methodology, it might be useful to think of the following goal: make text analysis as widespread and useful as linear regression, the workhorse of much applied statistical analysis. Though it is not always thought of in this way, linear regression is a completely computational methodology—before computers, it was impossible to fit the types of linear regressions that are now commonplace. Since linear regressions and related statistical analysis methods are well understood, and widely implemented and straightforward to run, their use is usually not considered "computational social science" in the way that, say, topic models or network analyses sometimes are. But this is only because the methodology of linear regression is more mature than many text analysis models.

Finally, this line of research should not just provide better social science methodology, but feed back to natural language and artificial intelligence research as well. Language and cognition are deeply embedded in social processes: communities and their shared norms and ideas are key to giving language meaning. The social context for an utterance is an important piece of knowledge that should be integrated into models of language production and understanding. Research into analysis of social text data will reveal important considerations and insights for computational intelligence more generally.

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