

AutoMap1.2 – Extract, analyze, represent, and compare mental models from texts^{*}

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Abstract

AutoMap1.2 is a network text analysis tool that extracts, analyzes, represents, and compares mental models from texts. Network text analysis is a specific text analysis method that encodes links between words in a text and builds a network of the linked words.

Computational analysis of networks pulled out of textual data is a growing area of research for the following reasons:

- The large and still growing number of electronically available texts requires the investigation of appropriate methods and tools to analyze large scale collections of texts effectively and efficiently.
- Today's communication theories are oriented towards complex, large-scale systems, and therefore require methods that provide multi-level access to the meaning of textual data.

AutoMap helps users to analyze textual data according to the current requirements.

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Keywords: text analysis, network text analysis, computer-supported text analysis, machine coding, content analysis, maps

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1. Motivation

The large and still growing number of electronically available texts requires appropriate tools and methods for analyzing large scale texts effectively and efficiently (Alexa, 1997; Batagelj, Mrvar and Zaveršnik, 2002; Bernard and Ryan, 2000; Corman et al., 2002). Furthermore, today's communication theories are oriented towards complex, large-scale systems. Thus, analysts need powerful tools and methods in order to gain multi-level access to the meaning of textual data (Corman et al., 2002; Monge and Contractor, 2003). However, Corman et al. (2002) summarize the status quo of existing tools for classical text analysis as limited in the range and scope of techniques they provide in order to analyze data according to the today's requirements. Network Text Analysis (NTA) tools are an emerging branch of software that supports both, effective and efficient analysis of quantitative characteristics of large-scale textual data (Ryan and Bernard, 2000) as well as the extraction of meaning from texts (Carley, 1997b). Therefore, NTA software has the potential to compensate weaknesses of classical text analysis tools.

This technical report describes AutoMap1.2, a tool that extracts, analyzes, represents and compares mental models from texts. With AutoMap we hope to make a contribution towards the effective and efficient analysis of the network structure and meaning of textual data.

For illustrating AutoMap's functionalities and providing examples for the procedures describes in this paper, we use two newspaper articles about power outages in Denmark and the USA in 2003 (see the Appendix). The articles were shortened and reorganized for demonstration purposes.

2. Method and model

AutoMap1.2 performs map analysis and two sub types of map analysis called Meta-matrix analysis and Sub-matrix analysis. Map analysis is a specific type of NTA (Diesner, Lewis and Carley, 2003). NTA is a recently established method that encodes links among words in a text and constructs networks of the linked words (Popping, 2000). Besides map analysis (Carley, 1988; Carley and Palmquist, 1992) multiple other NTA techniques exist (for an overview see Popping, 2000; Popping and Roberts, 1997), such as Centering Resonance Analysis (Corman et al., 2002), Functional Depiction (Popping and Roberts, 1997), Knowledge Graphing (Bakker, 1987; James, 1992), Map Analysis and Network Evaluation (Kleinnijenhuis, Ridder and Rietberg, 1996). Network analysis of texts is based on the assumption that language and knowledge can be modeled as networks of words and the relations between them (Sowa, 1984). Thus, NTA analyzes the existence, frequencies, and covariance of terms and themes, and also derives the meaning of terms and themes by analyzing the relations between them. NTA methodologically originates from traditional techniques for indexing the relations between concepts, syntactic grouping of words, and the hierarchical and non-hierarchical linking of words (Kelle, 1997).

Map analysis systematically extracts and analyzes the ties between words in a text in order to model the authors "mental map" as a network of ties (Carley, 1997b; Carley and Palmquist 1992). Maps are a cognitively motivated representation of knowledge (Carley, 1988). In map analysis, a concept is a single idea represented by a single word or a phrase. A statement is two concepts and the relation between them. A map is the network of statements (Carley, 1997b).

3. Input

AutoMap takes raw, free flowing, and unmarked texts as input. This makes AutoMap very flexible with respect to the type of texts it can analyze: input texts can be, for example, news paper articles, e-mails, texts from individuals like award recommendations, or organizations like mission statements or annual reports.

When the input texts are loaded into AutoMap, the program automatically creates a concept list. A concept list is a two columned table that contains all concepts per text and the related frequencies. The user needs a concept list to get a first, quantitative overview of the concepts appearing in the texts and to make further data processing decisions (Section 4.1). When the user performs text processing operations that affect the text level concepts the concept list is automatically updated. The user can also request a union concept list that denotes all concepts appearing across all input texts and the related, cumulative frequencies. The union concept list can be refreshed after each step of text processing in order to visualize the impact of processing operations on the union of concepts. The concept list and the union concept list can be sorted alphabetically or by frequency. Both lists can be saved.

Figure 1 (page 3) and 2 (page 4) show parts of AutoMap's graphical user interface. These parts provide an example for the displayed part of a concept list and a union concept list, ordered by concept's frequency. The text corpus used for this example consists of two sub sample text from the sample texts (see the Appendix). Sub sample text one (from Denmark.txt) and two (from USA.txt) are displayed on the "1. Input Text" panel on the "Text Pre-processing" panel in Figure 1 and 2, respectively.

4. How AutoMap codes texts as maps

AutoMap encodes the links between concepts in a text and builds a network of the linked concepts. Coding in AutoMap is computer-assisted. Computer-assisted coding means that the machine applies a set of coding rules that were defined by a human in order to index the input texts and code them as networks (Ryan and Bernard, 2000, p.786; Kelle, 1997 p. 6; Klein, 1997, p. 256). The coding rules that the user needs to specify in AutoMap are about text pre-processing and statement formation (Carley, 1993; Alexa, 1997):

- Text pre-processing condenses the data to the concepts that capture the features of the texts that are relevant to the user. Therefore, pre-processing simplifies the task of making meaningful interpretations and comparisons across texts (Ryan and Bernard, 2000).
- Statement formation rules determine how to link concepts into statements. The procedure of statement formation is specific to NTA.

The pre-processing (section 4.1) rules and the statement formation rules together form the coding scheme. In the following, we describe the coding choices offered in AutoMap in detail, and their impact on the analysis results (for a more detailed description of the impact of coding choices on map analysis results see Diesner, Lewis and Carley, 2003).

Figure 1: Concept list

AutoMap 1.2

File Run Analysis CompareMap Help

< < 1 / 2 > >| Go to: OK File name: C:\Documents and Settings

Text Pre-processing

4. Meta-Matrix Thesaurus 5. Sub-Matrix Text

1. Input Text 2. Delete List 3. Generalization Thesaurus

Reporters said hundreds of people emerged from shops in Copenhagen city centre to see what was happening, and used their mobile phones to contact their families.

Pre-processing Settings and Analysis Settings

6. Sub-Matrix Selection 7. Analysis Settings 8. Output Options

4. Generalization Thesaurus 5. Meta-Matrix Thesaurus

1. Concept List 2. Union Concept List 3. Delete List

Concept	Frequency
their	2
to	2
and	1
centre	1
city	1
contact	1
copenhagen	1
emerged	1
families	1
from	1
happening	1
hundreds	1
in	1
mobile	1
of	1
people	1
phones	1
reporters	1
said	1
see	1
shops	1
used	1
was	1

Figure 2: Union concept list

AutoMap 1.2

File Run Analysis CompareMap Help

< < 2 / 2 > >| Go to: OK File name: C:\Documents and Settings\...

Text Pre-processing

4. Meta-Matrix Thesaurus 5. Sub-Matrix Text

1. Input Text 2. Delete List 3. Generalization Thesaurus

The New York City Police Department said a number of people were trapped in elevators for awhile. Thousands of people left buildings and walked into the streets.

Pre-processing Settings and Analysis Settings

6. Sub-Matrix Selection 7. Analysis Settings 8. Output Options

4. Generalization Thesaurus 5. Meta-Matrix Thesaurus

1. Concept List 2. Union Concept List 3. Delete List

Concept	Frequency
of	3
people	3
and	2
city	2
in	2
said	2
the	2
their	2
to	2
a	1
awhile	1
buildings	1
centre	1
contact	1
copenhagen	1
department	1
elevators	1
emerged	1
families	1
for	1
from	1
happening	1
hundreds	1

4.1 Text pre-processing

Unlike the explicit ties between people or organizations in social networks, ties between concepts in a text are implicit. These ties must be extracted based on the semantic, syntactic, and contextual information given in the text (Carley, 1986; Carley, 1988; Popping, 2003). Pre-processing is a semi-automated, iterative process. There are no scientific standards for determining an optimal pre-processing strategy; the user has to determine the most appropriate level of data reduction based on his or her research question. The two most general types of text pre-processing are the elimination of non-content bearing words (Alexa, 1997, p. 23, Corman et al., 2002), and the translation of specific words into more general concepts (Carley, 1997b). We refer to these techniques as deletion and generalization.

Deletion removes non-content bearing concepts from texts. Such concepts are, for example, proper names, conjunctions, articles, and prepositions (Carley, 1993). AutoMap registers these words in a delete list. When AutoMap applies a delete list, it searches the texts for the concepts specified in the delete list, deletes matches from the texts, and displays the resulting texts. After applying the delete list, the pre-processed texts or the analysis results would be evaluated to decide if further concepts should be deleted. Constructing a delete list tailored for a specific text set can begin with creating a union concept list, sorting it by the decreasing frequency of concepts, and entering the highest frequent concepts to the delete list. This procedure is based on the assumption that a words' frequency of occurrence is inversely related to its importance (Baeza-Yates and Ribeiro-Neto, 1999). The delete list can then be extended and re-applied to the texts. In AutoMap, the user does not have to create a new delete list for each text analysis session. AutoMap allows the user to load his or her own delete list or a pre-defined delete list provided in AutoMap. The two pre-defined delete lists that AutoMap offers were provided by David Kaufer from the Department of English, CMU, and reflect sub-sets of most frequently terms used in English. The pre-defined delete lists can be customized. The usage of delete lists is optional in AutoMap. A delete list can be used before any type of analysis. The customized delete list and the texts after the application of the delete list can be saved. Table 1 provides an example for the application of a delete list:

Table 1: Delete list application

Input text (from Denmark.txt)	Reporters said hundreds of people emerged from shops in Copenhagen city centre to see what was happening, and used their mobile phones to contact their families. Railway and underground train services ground to a halt. Hospitals switched to be using emergency generators. The (nuclear) security systems worked just as they should.
Self-created delete list	a, and, as, be, from, in, just, of, the, their, they, to, was, what
Resulting text after application of delete list	Reporters said hundreds people emerged shops Copenhagen city centre see happening, used mobile phones contact families. Railway underground train services ground halt. Hospitals switched using emergency generators. (nuclear) security systems worked should.

Generalization means applying a thesaurus. A thesaurus is a two-columned collection that lists all concepts that represent the content of the data set and the corresponding higher-level concepts that represent the text-level concepts in a generalized way (Burkart, 1997; Klein, 1997, p. 256; Popping and Roberts, 1997, p. 382). A single higher level concept typically has multiple entries in the thesaurus. When applying a thesaurus, AutoMap searches the text for the concepts

specified in the thesaurus, translates matches into the associated higher level concepts, and displays the modified texts. The terminology of a thesaurus depends on the content and the subject of the data set (Burkart, 1997, p.163; Zuell and Alexa, 2001, p.313). In AutoMap the user needs to provide a manually created thesaurus. The thesaurus can be created within AutoMap or with an external text editor. A thesaurus is created by reading a set of texts and/ or using pre-defined material and/ or deriving concepts and higher-level concepts from theory (Burkart, 1997; Kelle, 1997, p.5; Klein, 1997, p.356; Kuckartz, 1997, p. 364; Zuell and Alexa, 2001, p.13). AutoMap supports the user in building a thesaurus by displaying the union of concepts and the concepts per text. This helps the user to decide what concepts to enter in the thesaurus as text level concepts. Analogous to the delete list, an optimal thesaurus is created through an iterative process of testing and modifying.

When applying a thesaurus in AutoMap, the user must decide if he wants to:

- Maintain only the higher level concepts that match the text level concepts specified in the thesaurus while dropping the rest of the original input text. This option is called “thesaurus content only”;
- Generate pre-processed texts that maintain concepts not matching entries in the thesaurus while translating matching concepts into related high-level concepts.

Figure 3 shows how a generalization thesaurus is entered into AutoMap:

Figure 3: Entering a generalization thesaurus into AutoMap

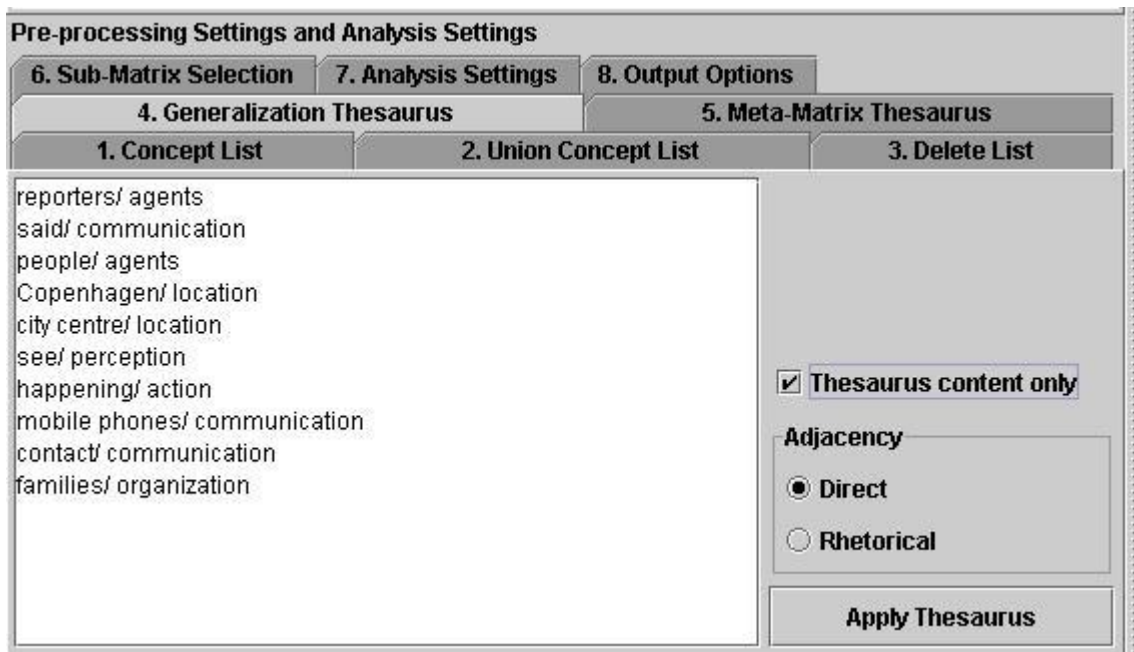


Table 2 shows the resulting texts after applying the thesaurus shown above with and without the “thesaurus content only” to a text. A delete list was not used prior to applying the thesaurus.

Table 2: Generalization

Input text, pre-processed with delete list (see Table 1)	Setting	Resulting text
Reporters said hundreds of people emerged from shops in Copenhagen city centre to see what was happening, and used their mobile phones to contact their families.	Thesaurus content only	agents communication agents location location perception action, communication communication organization.
	Not Thesaurus content only (default)	agents communication hundreds of agents emerged from shops in location location to perception what was action, and used their communication to communication their organization.

In AutoMap the usage of a thesaurus is optional. A generalization thesaurus can be used before any type of analysis. The customized thesaurus and the texts after the application of the thesaurus can be saved.

4.2 Impact of text pre-processing on the data

In a previous study, we investigated the impact of various pre-processing strategies available in AutoMap on map analysis results (Diesner, Lewis and Carley, 2003). The data set that we analyzed contained 172 texts. Each original input text on average had 372 total concepts; half of them were unique concepts. The number of unique concepts considers each concept only once, whereas the number of total concepts also considers repetitions of concepts. From our study we learned the following:

- Using a customized delete list removes 26 percent of the total concepts and 8 percent of unique concepts.
- Data reduction achieved by applying a thesaurus, but not using the “thesaurus content only” option is only a side-effect of this procedure. The main purpose of the usage of a thesaurus is the qualitative effect of translating text-level concepts into higher-level concepts. Data reduction after thesaurus application only occurs when N-grams are translated into shorter higher level concept (e.g. top market position into leading). In our study, the data reduction rates after applying a thesaurus were 2.4 percent for total concepts and 4.3 percent for unique concepts.
- The application can result in a significant quantitative data reduction if the “thesaurus content only” option is chosen. In our study, this strategy removed over 90% of the unique and total concepts. The remaining less than 10 percent of concepts form a highly stylized and reduced representation of the input texts. Furthermore, our results showed very similar reduction rates for unique and total concepts for this strategy. This indicates that with this pre-processing technique redundancy is strongly filtered out of the texts.

4.3 Statement formation

A second set of coding choices are statement formation options. In AutoMap, statement formation choices are implemented as various operationalizations of the distance between concepts (Carley, 1993). These operationalizations reflect different approaches of the windowing method (Danowski, 1993). Windowing defines the size of a window as the length of a string of adjacent concepts that get linked into statements if they match the statement formation criteria. When performing statement formation, AutoMap slides a fictitious window over the text and links concepts within that window according to the coding rules. The statement formation choices in AutoMap are:

1. Text Unit: The user specifies the text portion in which statements can be formed. These text units are either sentences, paragraphs or the entire text.
2. Window Size: By specifying the window size the user defines how distant concepts can be from each other and still have a relationship. The window size is then applied to the specified text unit. For example, with a window size of three and sentence as text unit, every pair of concepts that is separated by one concept and that is not divided by a period is linked into a statement.
3. Directionality: Directionality can be either unidirectional or bidirectional. If unidirectionality is chosen, texts are searched for statements from the beginning to the end. If bidirectional is selected, statements can be formed from the left to the right and reverse.
4. Adjacency: When forming statements, classic text analysis tools treat all concepts in a pre-processed text as directly adjacent to each other. This strategy ignores concepts that intervened the maintained concepts in the original input text, but were removed during pre-processing. AutoMap also supports this approach and calls it “direct adjacency.” In addition to that we introduced a novel statement formation approach in AutoMap1.1, which serves as a logical complement to the direct adjacency. This new approach takes the original distance of concepts as they appear in the original input text into consideration. In AutoMap this approach is called “rhetorical adjacency”. Adjacency is only applicable if a delete list or a thesaurus with the “thesaurus content only” option are applied. Using rhetorical adjacency for pre-processing text level concepts matching entries of the delete list or not matching entries of the thesaurus will be replaced by imaginary placeholders. These placeholders ensure that only concepts, which occurred within a window before pre-processing, can form statements. In contrast, with the direct adjacency, concepts that do not appear within a window size in the original text can though form statements when concepts specified in the delete list and concepts not included in the thesaurus are deleted from the text. As a result, concepts, that were located far away from each other in the original text, are brought closer together.

Table 3 shows the impact of the selection of the various text units, two different window sizes, and both directionality options on statement formation. For each cell in Table 3 one varied statement formation option was used in combination with AutoMap’s default statement formation settings, which are:

- Text Unit: text
- Window Size: 2
- Directionality: uni-directional

Input text, pre-processed with delete list (see Table one):
 Railway underground train services ground halt. Hospitals switched using emergency generators.
 (nuclear) security systems worked should.

Note: This text sample contains two paragraphs.

Table 3: Resulting statements after using various values for text unit, window size, and directionality for statement formation

Text Unit		
Sentence	Paragraph	Text
1 emergency, generators	1 emergency, generators	1 emergency, generators
1 ground, halt	1 ground, halt	1 generators, nuclear
1 hospitals, switched	1 halt, hospitals	1 ground, halt
1 nuclear, security	1 hospitals, switched	1 halt, hospitals
1 railway, underground	1 nuclear, security	1 hospitals, switched
1 security, systems	1 railway, underground	1 nuclear, security
1 services, ground	1 security, systems	1 railway, underground
1 switched, using	1 services, ground	1 security, systems
1 systems, worked	1 switched, using	1 services, ground
1 train, services	1 systems, worked	1 switched, using
1 underground, train	1 train, services	1 systems, worked
1 using, emergency	1 underground, train	1 train, services
1 worked, should	1 using, emergency	1 underground, train
	1 worked, should	1 using, emergency
		1 worked, should
		(same map as generated window-size 2 and uni-directionality)
Window Size		
2	3	
1 emergency, generators	1 emergency, generators	1 emergency, generators
1 generators, nuclear	1 emergency, nuclear	1 emergency, nuclear
1 ground, halt	1 generators, nuclear	1 generators, nuclear
1 halt, hospitals	1 generators, security	1 generators, security
1 hospitals, switched	1 ground, halt	1 ground, halt
1 nuclear, security	1 ground, hospitals	1 ground, hospitals
1 railway, underground	1 halt, hospitals	1 halt, hospitals
1 security, systems	1 halt, switched	1 halt, switched
1 services, ground	1 hospitals, switched	1 hospitals, switched
1 switched, using	1 hospitals, using	1 hospitals, using
1 systems, worked	1 nuclear, security	1 nuclear, security
1 train, services	1 nuclear, systems	1 nuclear, systems
1 underground, train	1 railway, train	1 railway, train
1 using, emergency	1 railway, underground	1 railway, underground
1 worked, should	1 security, systems	1 security, systems
	1 security, worked	1 security, worked
	1 services, ground	1 services, ground
	1 services, halt	1 services, halt
	1 switched, emergency	1 switched, emergency
	1 switched, using	1 switched, using
	1 systems, should	1 systems, should
	1 systems, worked	1 systems, worked
	1 train, ground	1 train, ground
	1 train, services	1 train, services
	1 underground, services	1 underground, services
(same map as generated with text unit and uni-directionality)		

	1 underground, train 1 using, emergency 1 using, generators 1 worked, should
Directionality	
Uni-directional	Bi-directional
1 emergency, generators 1 generators, nuclear 1 ground, halt 1 halt, hospitals 1 hospitals, switched 1 nuclear, security 1 railway, underground 1 security, systems 1 services, ground 1 switched, using 1 systems, worked 1 train, services 1 underground, train 1 using, emergency 1 worked, should (same map as generated with text unit and window-size 2)	1 emergency, generators 1 emergency, using 1 generators ,emergency 1 generators, nuclear 1 ground, halt 1 ground, services 1 halt, ground 1 halt, hospitals 1 hospitals, halt 1 hospitals, switched 1 nuclear, generators 1 nuclear, security 1 railway, underground 1 security, nuclear 1 security, systems 1 services, ground 1 services, train 1 should, worked 1 switched, hospitals 1 switched, using 1 systems, security 1 systems, worked 1 train, services 1 train, underground 1 underground, railway 1 underground, train 1 using, emergency 1 using, switched 1 worked, should 1 worked, systems

Table 4 and 5 illustrate the impact of the direct and rhetorical adjacency applied to a delete list and thesaurus:

Input text:
Reporters said hundreds of people emerged from shops in Copenhagen city centre to see what was happening, and used their mobile phones to contact their families.

Table 4: Statement formation: Adjacency applied to the delete list

Delete list (self-designed)	Adjacency option	Resulting text	Resulting statements
and from in of their to	Direct (default)	reporters said hundreds people emerged shops copenhagen city centre see happening , used mobile phones contact families .	1 centre, see 1 city, centre 1 contact, families 1 copenhagen, city 1 emerged , hops 1 happening, used

was what			1	hundreds, people
			1	mobile, phones
			1	people, emerged
			1	phones, contact
			1	reporters, said
			1	said, hundreds
			1	see, happening
			1	shops, copenhagen
			1	used, mobile
	Rhetorical	reporters said hundreds xxx people emerged xxx shops xxx copenhagen city centre xxx see xxx xxx happening , xxx used xxx mobile phones xxx contact xxx families	1	city, centre
			1	copenhagen, city
			1	mobile, phones
			1	people, emerged
			1	reporters, said
			1	said, hundreds

Table 5: Statement formation: Adjacency applied to the thesaurus

Thesaurus	Setting	Resulting text	Resulting statements
reporters/ agents said/ communication people/ agents Copenhagen/ location city centre/ location see/ perception happening/ action mobile phones/ communication contact/ communication families/ organization	Thesaurus content only, direct adjacency (default if Thesaurus content only is chosen)	agents communication agents location location perception action, communication communication organization.	1 action, communication 1 agents, communication 1 agents, location 1 communication, agents 1 communication, communication 1 communication, organization 1 location, location 1 location, perception 1 perception, action
	Thesaurus content only, rhetorical adjacency	agents communication xxx xxx agents xxx xxx xxx xxx location location xxx perception xxx xxx action, xxx xxx xxx communication xxx communication xxx organization.	1 agents, communication 1 location, location

Table 6 summarizes the coding choices offered in AutoMap:

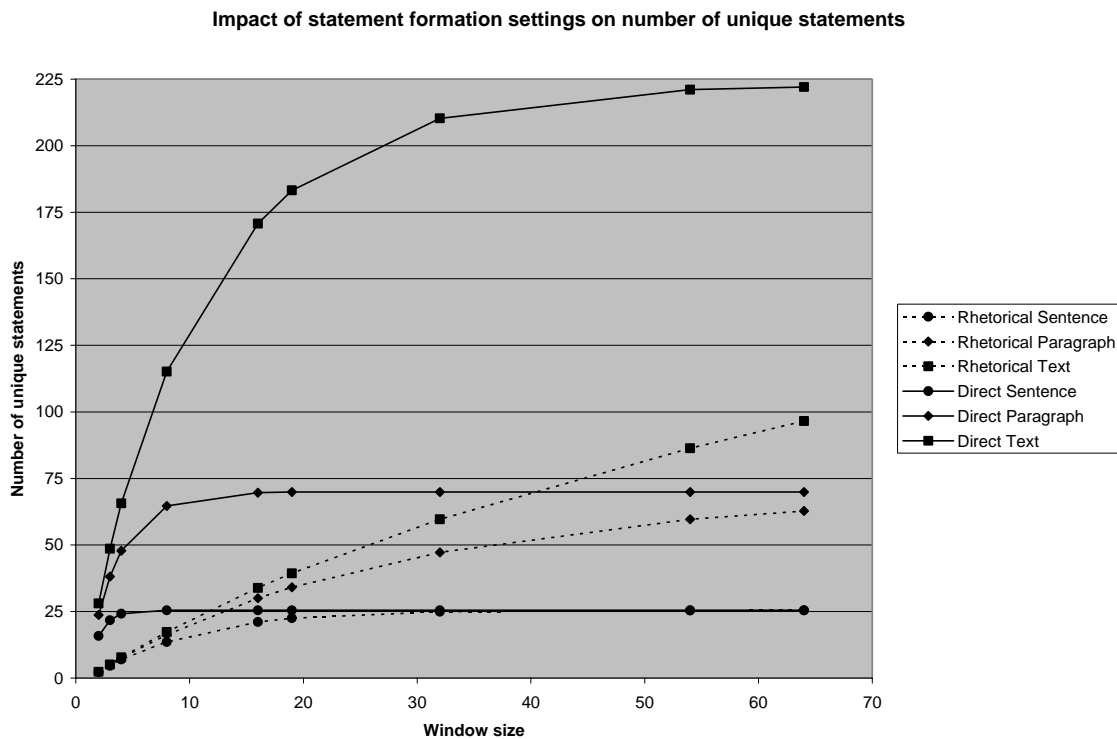
Table 6: Coding choices in AutoMap

Coding Choices	Explanation
Pre-processing	Delete irrelevant (non-content bearing) concepts from original input text
Deletion	Delete highly frequent, but not content bearing concepts
Generalization	Translate concepts into higher level concepts
Statement formation	Define distance of concepts that can form statements
Text unit	Consider end of sentences, paragraphs or texts as border for statement formation
Window size	Define number of adjacent words that can link into statements
Directionality	Treat statements as being directed from left to right or non directed
Adjacency	Decide whether to consider (rhetorical adjacency) or neglect (direct adjacency) original distance of concepts as they occur in original input text. Applicable when applying delete list and/or thesaurus.

4.4 Impact of statement formation on analysis results

The tables presented in the previous section indicate that different statement formations choices result in statements that differ in number and content. In a previous study (Diesner, Lewis and Carley, 2003) we tested the impact of various text units, window sizes, and adjacency options on map analysis results. Figure 4 shows the number of statements in dependence of the statement formation settings.

Figure 4: Impact of statement formation choices on AutoMap results



We learned the following:

- With direct adjacency, more statements and denser networks are found than with rhetorical adjacency. This trend declines and finally disappears with increasing window sizes: in coding settings, where only the adjacency is varied, the graphs that represent the size and density of the networks identified with rhetorical adjacency converge, and finally intersect the graphs produced with direct adjacency. The smaller the text unit is, the lower is the window size at which the graphs for rhetorical adjacency intersect the graph for direct adjacency. This means graphs showing the number of statements found with rhetorical and direct adjacency will first intersect on sentence level, then on paragraph level and then on text level. Furthermore, we learned that the window size at which the graphs will merge is bigger than the average size of the involved text unit.
- In a whole text, more statements and denser networks are found than in paragraphs, and in paragraphs more statements and denser networks are found than in sentences. This trend also decreases with increasing window sizes: The number of statements and the network's densities stabilize from a certain window size on. For both adjacency options, this stabilization first occurs on sentence level, then on paragraph level, and then on text

level. For settings including rhetorical adjacency the window sizes at which results stabilize are bigger than those for direct adjacency.

This section has described the coding choices provided in AutoMap. Furthermore, we showed that the user’s coding choices are critical, because they influence the analysis results (Carley, 1997a; Diesner, Lewis and Carley, 2003). Therefore, Carley (1997a) strongly recommends returning to the data several times and analyzing them with different coding schemes.

5. Outputs

AutoMap generates maps as representations of the author’s mental model that he or she had in mind when producing the text. AutoMap represents the extracted mental models as a map file and a stat file per text. A map file contains one coded statement per line (Figure 6, page 14, upper right panel). Depending on the user’s choice the map is binary or count. A stat file contains various measures that quantify the size and density of the network of each text (Figure 6, lower right panel). If multiple texts were analyzed the user can browse through the results on the AutoMap graphical user interface (GUI, Figure 6, browsing bar below the menu bar). For both, single and multiple analyses, the user can concurrently see the results, the related (pre-processed) input texts, and the pre-processing tools applied to the data (Figure 6).

Figure 5 briefly explains the entries in the stat file:

Figure 5: Stat file

Stat entry	Stat Entry	Explanation
File:		Name of the analyzed text file.
# of concepts	unique:	The number of unique concepts considers each concept only once, whereas the number of total statements also considers repetitions of concepts.
	total:	
# of statements:	unique:	The number of unique statements considers each concept only once, whereas the number of total statements also considers repetitions of statements.
	total:	
density (based on statements)	unique:	Unique density is the density of the resulting network based on unique statements, total density respectively is the density of the resulting network based on the total number of statements.
	total:	
Analysis Settings	Punctuation:	The punctuation option chosen by the user (text, paragraph, or sentence).
	Window Size:	The window size chosen by the user (2 to 100).
	Directionality:	The directionality option chosen by the user (uni-directional or bi-directional).

In addition to the map and stat files, the user can request various term distribution lists and matrices in comma separated value (csv) format from AutoMap. According to the user’s choice, these lists and matrices are binary or count. Table 7 (page 15) provides an overview of the types and contents of the term distribution lists and matrices.

Figure 6: AutoMap GUI

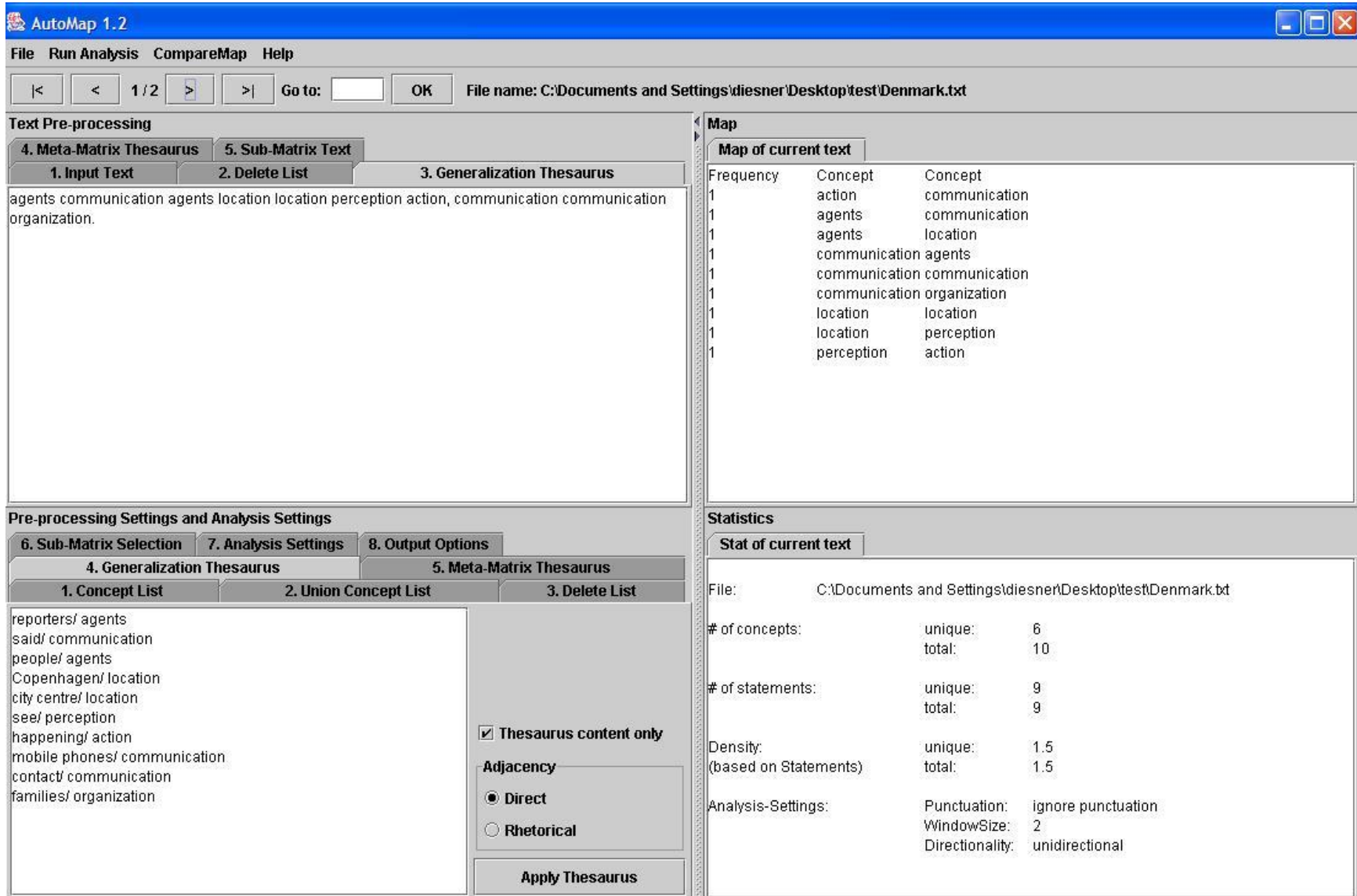


Table 7: Term distribution lists and matrices

Output type	Output files	Content of output files
Term Distribution Lists	List and statistics of concepts analyzed	Headers of columns in List: - Concepts - Name of texts that concept appears in - If count was chosen: Frequency with that concept appears in the texts
	List and statistics of concepts in statements and of isolates	Headers of columns in Statistics: - Concepts - If count was chosen: Cumulated sum of appearance of concept across text set
	List and statistics of statements	- Number of texts that concept appears in - Percentage of texts that concept appears in - Name of text files that concept appears in
Term Distribution Matrices	Matrix of concepts in statements	Matrix of concepts in statements by concepts in statements
	Matrix of concept analyzed	Matrix of concepts or statements by texts
	Matrix of concept in statements	
	Matrix of statements	

Table 8 shows an example for a term distribution matrix that denotes the concepts in statements by concepts in statements. The type of the matrix is count.

Input texts:

Denmark.txt:

Reporters said hundreds of people emerged from shops in Copenhagen city centre to see what was happening, and used their mobile phones to contact their families.

USA.txt:

The New York City Police Department said a number of people were trapped in elevators for awhile. Thousands of people left buildings and walked into the streets.

Delete list:

a, and, as, awhile, be, for, from, in, into, just, of, the, their, they, to, was, were, what

Thesaurus:

buildings/ location	city centre/ location
contact/ communication	copenhagen/ location
families/ organization	happening/ action
left/ action	mobile phones/ communication
new york city police department/ nypd	nypd/ agents
people/ agents	reporters/ agents
said/ communication	see/ perception
walked/ action	

Resulting texts after pre-processing (not “thesaurus content only” option):

Denmark.txt:

agents communication hundreds agents emerged shops location location perception action, used communication communication organization.

USA.txt:

agents communication number agents trapped elevators. thousands agents action location action streets.

Table 8: Term distribution matrix of concepts by concepts

	perception	action	elevators	agents	thousands	communication	emerged	location	streets	trapped	shops	used	number	hundreds
location	1	1	0	0	0	0	0	1	0	0	0	0	0	0
trapped	0	0	1	0	0	0	0	0	0	0	0	0	0	0
hundreds	0	0	0	1	0	0	0	0	0	0	0	0	0	0
elevators	0	0	0	0	1	0	0	0	0	0	0	0	0	0
perception	0	1	0	0	0	0	0	0	0	0	0	0	0	0
communication	0	0	0	0	0	1	0	0	0	0	0	0	1	1
agents	0	1	0	0	0	2	1	0	0	1	0	0	0	0
thousands	0	0	0	1	0	0	0	0	0	0	0	0	0	0
action	0	0	0	0	0	0	0	1	1	0	0	1	0	0
number	0	0	0	1	0	0	0	0	0	0	0	0	0	0
emerged	0	0	0	0	0	0	0	0	0	0	1	0	0	0
used	0	0	0	0	0	1	0	0	0	0	0	0	0	0
shops	0	0	0	0	0	0	0	1	0	0	0	0	0	0

All maps and term distribution matrices can additionally be stored in the DL format for UCINET. This enables the user to import AutoMap outputs into UCINET in order to:

1. Perform UCINET analysis on AutoMap results.
2. Visualize AutoMap results with the visualizations tools launched through UCINET.

What do the various outputs of AutoMap tell the user? AutoMap outputs represent mental models and therefore can help to answer the following questions:

- What words do people use?
- How do people link the words they use?
- What words to people use in order to refer to more abstract themes?
- What themes do people evoke?
- How do people link the themes they evoke?

The outputs that AutoMap generates reflect the complexity of the semantic and syntactical structure of the original input texts and the author’s mental maps. Therefore, map analysis as performed in AutoMap allows the user to stay close to the data and the research question, and to represent data in a rich network structure.

6. Types of analysis

AutoMap offers three different types of analysis:

1. Map Analysis
2. Meta-Matrix Analysis
3. Sub-Matrix Analysis

Each type of analysis generates the same types of outputs, as described in section 5, but takes texts after different stages of data pre-processing as an input.

Map analysis can be run on original input texts, or after deletion and/or generalization. The statements shown in the previous tables are results from map analysis. Table 9 shows an example for map analysis results. The analysis was run on texts that were pre-processed with the same delete list and generalization thesaurus as used for the example shown in Table 8.

Table 9: Map analysis results

Denmark.txt	USA.txt
Maps	
1 action, used	1 action, location
1 agents, communication	1 action, streets
1 agents, emerged	1 agents, action
1 communication, communication	1 agents, communication
1 communication, hundreds	1 agents, trapped
1 communication, organization	1 communication, number
1 emerged, shops	1 elevators, thousands
1 hundreds, agents	1 location, action
1 location, location	1 number, agents
1 location, perception	1 thousands, agents
1 perception, action	1 trapped, elevators
1 shops, location	
1 used, communication	
Stats	
File: C:\Denmark.txt	File: C:\USA.txt
# of concepts: unique: 10 total: 14	# of concepts: unique: 9 total: 12
# of statements: unique: 13 total: 13	# of statements: unique: 11 total: 11
Density (based on Statements): unique: 1.3 total: 1.3	Density (based on Statements): unique: 1.22 total: 1.22
Analysis-Settings: Punctuation: ignore punctuation Window Size: 2 directionality: unidirectional	Analysis-Settings: Punctuation: ignore punctuation Window Size: 2 directionality: unidirectional

The meta-matrix approach (Carley, 2003; Carley and Ren, 2001; Krackhardt and Carley, 1998) provides a representational framework and a set of methods for analyzing multi-dimensional data. The idea of the meta-matrix originates from the combination of knowledge management, operations research, and social network analytic techniques and measures. This model enables the classification of nodes in a network as one of the categories: agents, knowledge, resources, tasks, and organizations. In AutoMap meta-matrix analysis can be run on texts that were pre-processed with a meta-matrix thesaurus. A meta-matrix thesaurus associates concepts with meta-matrix categories. In AutoMap the meta-matrix thesaurus automatically loads the union of concepts after the highest level of pre-processing applied in its most left column. The right columns denote the meta-matrix categories, which are:

- Agent
- Knowledge
- Resource
- Task-event
- Organization
- Any user-defined categories

When applying a meta-matrix thesaurus, AutoMap searches the texts for the entries specified in the meta-matrix thesaurus and translates matches into the corresponding meta-matrix categories. A concept can be translated into one, multiple or none meta-matrix categories. A delete list and/or a generalization thesaurus can be applied before the meta-matrix thesaurus is applied. The meta-matrix thesaurus can be built within AutoMap or with an external text editor. Pre-defined meta-matrix thesauri can be imported into AutoMap, even if they match only partially the concepts in the left most column of the meta-matrix thesaurus. The meta-matrix thesaurus and the texts after the application of the meta-matrix thesaurus can be saved. Figure 7 (page 19) shows an example for the application of a meta-matrix thesaurus. Location was defined as a new category.

Input texts:

Denmark.txt:

Reporters said hundreds of people emerged from shops in Copenhagen city centre to see what was happening, and used their mobile phones to contact their families.

USA.txt:

The New York City Police Department said a number of people were trapped in elevators for awhile. Thousands of people left buildings and walked into the streets.

Delete list:

a, and, as, awhile, be, for, from, in, into, just, of, the, their, they, to, was, were, what

Thesaurus:

new york city police department/ nypd

Figure 7: Meta-matrix thesaurus

Pre-processing Settings and Analysis Settings

6. Sub-Matrix Selection 7. Analysis Settings 8. Output Options

4. Generalization Thesaurus 5. Meta-Matrix Thesaurus

1. Concept List 2. Union Concept List 3. Delete List

Concept	agent	knowledge	resource	task-event	organization	User-defined
buildings	<input type="checkbox"/>	<input type="checkbox"/>	<input checked="" type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	location
centre	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	location
city	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	location
contact	<input type="checkbox"/>	<input checked="" type="checkbox"/>	<input type="checkbox"/>	<input checked="" type="checkbox"/>	<input type="checkbox"/>	
copenhagen	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	location
elevators	<input type="checkbox"/>	<input type="checkbox"/>	<input checked="" type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	
emerged	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input checked="" type="checkbox"/>	<input type="checkbox"/>	
families	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input checked="" type="checkbox"/>	
hundreds	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	
left	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input checked="" type="checkbox"/>	<input type="checkbox"/>	
mobile	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	
number	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	
nypd	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input checked="" type="checkbox"/>	
people	<input checked="" type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	
phones	<input type="checkbox"/>	<input type="checkbox"/>	<input checked="" type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	
reporters	<input checked="" type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	
said	<input type="checkbox"/>	<input checked="" type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	
see	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input checked="" type="checkbox"/>	<input type="checkbox"/>	
shops	<input type="checkbox"/>	<input type="checkbox"/>	<input checked="" type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	location

Thesaurus content only Adjacency: Direct Rhetorical **Apply Meta-Matrix Thesaurus**

Applying the meta-matrix thesaurus to the data with the “thesaurus content only” option and rhetorical adjacency results in the following output texts:

Denmark.txt:

```
< agent> < knowledge> xxx < agent> < task-event> < resource location> < location> < location> < location> < task-event> xxx xxx xxx < resource> < knowledge task-event> < organization>
```

USA.txt:

```
< organization> < knowledge> xxx < agent> xxx < resource> . xxx < agent> < task-event> < resource location> < task-event> < location> .
```

When AutoMap performs a meta-matrix analysis, it links the concepts in the pre-processed texts according to statement formation settings specified by the user. Table 10 (page 20) shows the results of a meta-matrix analysis run on the texts, which were pre-processed as shown in Figure 7 and with AutoMap’s default statement formation settings.

Table 10: Meta-matrix analysis results

Denmark.txt		USA.txt	
Maps			
1	agent, knowledge	1	agent, task-event
1	agent, task-event	1	location, task-event
1	knowledge, organization	1	organization, knowledge
3	location, location	1	resource, task-event
1	location, task-event	2	task-event, location
1	resource, knowledge	1	task-event, resource
1	resource, location		
1	resource, task-event		
1	task-event, location		
1	task-event, organization		
1	task-event, resource		
Stats			
File:	C:\Denmark.txt	File:	C:\USA.txt
# of concepts:		# of concepts:	
unique:	6	unique:	6
total:	14	total:	10
# of statements:		# of statements:	
unique:	11	unique:	6
total:	13	total:	7
Density (based on Statements):		Density (based on Statements):	
unique:	1.83	unique:	1.0
total:	2.17	total:	1.17
Analysis-Settings:		Analysis-Settings:	
Punctuation:	ignore punctuation	Punctuation:	ignore punctuation
Window Size:	2	Window Size:	2
Directionality:	unidirectional	Directionality:	unidirectional

Sub-matrix analysis distills sub-network from the meta-matrix. This routine enables a more thorough analysis of particular sections of the meta-matrix, like e.g., agent by knowledge networks, or resource by organization networks. In order to run sub-matrix analysis the user has to select one or multiple meta-matrix categories on the AutoMap GUI. These categories will be retranslated into the concepts used as input for the meta-matrix thesaurus. Thus, sub-matrix analysis can only be run on texts that were pre-processed with a meta-matrix thesaurus. The “thesaurus content only” option automatically applies to the sub-matrix selection. The texts after the application of the sub-matrix selection can be saved. For the following sub-matrix analysis we chose the categories “agent”, “knowledge”, “resource”, and “location”. “Task-event” and “organization” we did not select. Applying the sub-matrix selection to the text resulting from the example shown in Figure 7 with the “thesaurus content only” option and direct adjacency results in the following texts:

Denmark.txt:
reporters said people shops copenhagen city centre, phones contact.

USA.txt:
said people elevators. people buildings streets.

When running sub-matrix analysis, AutoMap links the concepts in the pre-processed texts according to statement formation settings specified by the user. Table 11 shows the results of a

sub-matrix analysis run on the texts pre-processed as shown above with AutoMap's default statement formation settings.

Table 11: Sub-matrix analysis results

Denmark.txt	USA.txt
Maps	
1 centre, phones	1 buildings, streets
1 city, centre	1 elevators, people
1 copenhagen, city	1 people, buildings
1 people, shops	1 people, elevators
1 phones, contact	1 said, people
1 reporters, said	
1 said, people	
1 shops, copenhagen	
Stats	
File: C:\Denmark.txt	File: C:\USA.txt
# of concepts:	# of concepts:
unique: 9	unique: 5
total: 9	total: 6
# of statements:	# of statements:
unique: 8	unique: 5
total: 8	total: 5
Density (based on Statements):	Density (based on Statements):
unique: 0.89	unique: 1.0
total: 0.89	total: 1.0
Analysis-Settings:	Analysis-Settings:
Punctuation: ignore punctuation	Punctuation: ignore punctuation
Window Size: 2	Window Size: 2
Directionality: unidirectional	Directionality: unidirectional

7. Compare mental models

If any type of multiple analyses was run, the user might want to know:

- Do different people use the same words and themes in the same way?
- Do different people link concepts and themes in the same way?
- Do different people share the same knowledge?
- How similar or different are the analyzed texts?

AutoMap helps the user to answer these questions by providing:

1. Various term distribution lists and matrices as described in section 4.
2. CompareMap, a map comparison tool launched through AutoMap.

CompareMap can load maps generated with after any type of pre-processing. The outputs from the map comparison are verbal sets and stat files. The verbal sets can be binary or count and denote:

- The union of compared statements.
- The consensus between maps, which is represented by the intersection of statements.
- The dissension between maps, which is represented as the difference.

Table 12 compares the maps generated after meta-matrix analysis (Table 10).

Table 12: Map comparison results

Verbal sets		
Union of statements	Consensus	Dissension
1 agent, knowledge	1 agent, task-event	agent, knowledge
2 agent, task-event	1 location, task-event	knowledge, organization
1 knowledge, organization	1 resource, task-event	location, location
3 location, location	2 task-event, location	organization, knowledge
2 location, task-event	1 task-event, resource	resource, knowledge
1 organization, knowledge		resource, location
1 resource, knowledge		task-event, organization
1 resource, location		
2 resource, task-event		
3 task-event, location		
1 task-event, organization		
2 task-event, resource		
Stats for verbal sets		
# of statements in union: unique: 12 total: 20		
# of statements in consensus: unique: 5 total: 6		
# of statements in dissension: unique: 7		

8. Performance aspects

Table 13 shows the time that AutoMap's needs to perform map analysis on different numbers of texts and texts of different length. The tests were run on a 2 GHz, Pentium 4 processor, under Windows XP.

Table 13: Analysis duration (in seconds)

Number of words per text	Number of texts			
	10	100	500	1000
10	1	1	2	2.5
100	3	2	4.5	6.5
500	6.5	8	12	29
1000	12	15	34	59

9. Future development

In the near future, we plan to implement natural language processing techniques and social network analytic measures into AutoMap. The natural language processing features are sentence boundary detection and stemming. Sentence boundary detection should enhance the accuracy of text unit detection. Stemming enables the reduction of inflected concepts to morphemes. This makes the generation of the delete list and the thesaurus easier, because only the morpheme of a concepts needs to be entered in order to catch all inflected version of this word appearing in the texts. In a map, concepts form the nodes of the network of statements. For each concept social network analytic measures such as centrality, distance and betweenness can be calculated in order to determine the importance of a concept in a network.

10. Hardware and software requirements

AutoMap1.2 has been implemented in Java 1.4. The system has been validated for Windows. The installer for AutoMap1.2 for Windows and a help file that includes examples of all AutoMap1.2 functionalities are available online under <http://www.casos.cs.cmu.edu/projects/automap/software.html> at no charge. More information about AutoMap, such as publications, sponsors, and contact information is provided under <http://www.casos.cs.cmu.edu/projects/automap/index.html>. For information on all CASOS projects, including AutoMap, please use the general CASOS web site <http://www.casos.cs.cmu.edu>.

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Appendix

Sample text files:

Article 1 (Denmark.txt), Story from BBC NEWS, Published: 2003/09/23 © BBC MMIII , Title: Danish capital loses power:

The Danish capital, Copenhagen, and parts of Sweden have been hit by massive power cuts. Around four million homes and businesses lost supplies. Engineers restored most power by late afternoon, but the exact cause of the cuts remained unclear.

Electricity officials said the power cuts started when a main transmission line connecting Sweden and Denmark was affected. Reports said a storm which swept through the area, bringing down trees, may have been a factor, but electricity officials said it was impossible to confirm whether the timing was a coincidence.

The blackout follows similar incidents in London earlier this month, and in a huge swathe of North America in August. Sabotage was not suspected, police said, but some residents said their first thoughts were of a possible terrorist connection.

At least two Swedish nuclear plants - Oskarshamn and Ringhals - appear to have then developed problems and had to shut down production units. Copenhagen airport and the Oeresund bridge and tunnel, linking the capital to Sweden, were closed, with scenes of traffic chaos in Copenhagen centre. Railway and underground train services ground to a halt. Officials said passengers on at least two new driverless underground trains were evacuated without incident.

Reporters said hundreds of people emerged from shops in Copenhagen city centre to see what was happening, and used their mobile phones to contact their families. Hospitals switched to be using emergency generators.

The (nuclear) security systems worked just as they should. Nuclear power officials insisted that there was no safety threat from the shutdowns, which happened if there were big imbalances in the network and pressure suddenly fell.

Article 2 (USA.txt), Story from CNN, Thursday, August 14, 2003, Title: Major power outage hits New York, other large cities:

The outage occurred quickly and rippled across a large area. Cities affected included New York, Cleveland, Ohio, Detroit, Michigan, and Toronto and Ottawa, Canada. 21 plants went off line because when the grid is down there is no place for the power output to go. By 6 p.m. the power was being restored in parts of the affected area.

It was unclear what caused the outage, although state and federal officials agreed that it was not terrorism. One possibility was a lightning strike in the Niagara region on the U.S. side of the border, according to the Canadian Department of National Defense. Canadian Defense Minister John McCallum blamed an outage at a nuclear power plant in Pennsylvania, but the state's Emergency Management Agency said there had been no problems at any of the state's five nuclear plants and that all were operating normally.

The outage stopped trains, elevators and the normal flow of traffic and life. Airports across the affected region experienced delays and some shut down temporarily. The New York City Police Department said a number of people were trapped in elevators for awhile. Thousands of people left buildings and walked into the streets. The outage did slow the Internet. The New York Stock Exchange announced plans to open on schedule Friday, using emergency power if necessary.

Bloomberg mobilized 40,000 police officers and the entire fire department overnight to maintain order. President Bush said communication between local, state and federal officials was "quick and thorough. "We're better organized today than we were two and a half years ago to deal with an emergency and the system responded well," he said.