A Language-Based Approach to Categorical Analysis

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Abstract

With the digitization of media, computers can be employed to help us with the process of classification, both by learning from our behavior to perform the task for us and by exposing new ways for us to think about our information. Given that most of our media comes in the form of electronic text, research in this area focuses on building automatic text classification systems. The standard representation employed by these systems, known as the bag-of-words approach to information retrieval, represents documents as collections of words. As a byproduct of this model, automatic classifiers have difficulty distinguishing between different meanings of a single word.

This research presents a new computational model of electronic text, called a *synchronic imprint*, which uses structural information to contextualize the meaning of words. Every concept in the body of a text is described by its relationships with other concepts in the same text, allowing classification systems to distinguish between alternative meanings of the same word. This representation is applied to both the standard problem of text classification and also to the task of enabling people to better identify large bodies of text. The latter is achieved through the development of a visualization tool named *flux* that models synchronic imprints as a spring network.

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1 Introduction

The invention of the printing press revolutionized the way we think about media, creating an explosion in the amount of information that an individual could obtain, resulting in a more educated and well-connected society. The continued exponential growth of online resources is posing a similar revolution; as the scale and speed of the Internet increases, our capacity to consume media is expanded even more. Whereas a person fifty years ago would read only the local town's newspaper, people today can pay attention to thousands of newspapers from around the world that are updated by the minute, not by the day. One mitigating circumstance in this exciting new resource is our ability to organize and remember the media that we consume. In the era of the printed word we had librarians to depend on to perform this task for us, but the size and rapid change of the Internet precludes even all the world's librarians from creating orderliness. Instead lay people are left to their own devices to arrange their bookmarks, documents, and email.

The general way in which we organize our personal information is through classification. When we read a book or paper, we connect the concepts it contains to the things we already know. Our understanding of that information can be reflected by how we classify it, namely what other things we think it is related to, and how the categories we put it in relate to the rest of our understanding. This process of integrating a new piece of information takes some contemplation; in a study conducted at Xerox PARC before the explosion of personal computers, subjects related a difficulty in categorizing the personal information collected in their office space (Malone, 1983). Whenever possible, people tended to prefer unstructured information, because it allowed them to push off the cognitive chore of integrating the items into a coherent organization.

The digitization of media creates a new realm of possibilities. The complexity of classifying personal information can be diminished with intervening help from computers. Computer systems can observe the media that we consume and use an understanding of that information to help us classify it in two respects:

1. Based on the structure of our already existent organizational system, computers can perform classification of new material automatically.
2. Using new representations of our media, computers could allow us to explore new ways of looking at information, leading us to create classifications with less work than before.

This thesis explores computer-aided classification for the media of electronic text, also known as written natural language in digital form. Computer systems, such as email clients, web browsers, and file systems would all be much easier to use if some of the organizational burden was taken off of our shoulders. Why then, are our information systems devoid of such tools? The answer lies in the way in which computers typically represent our information, a representation that is in need of innovation.

1.1 A new representation

Most of the systems that people use today to search, navigate, and organize information utilize a simplistic model of language; while this representation has its limitations, it provides the efficiency and speed needed to search billions of documents of the web with sufficient results. This representation is known as the *vector-space model* for information retrieval, where documents are represented by the frequencies of the words they contain. Any person who has used a search engine has interacted with some form of this model, using individual words to locate documents that contain them.

The limitations of the vector-space model can be seen in the frustrations of an average Internet search: when looking for documents about the O.J. Simpson trial, the word "Simpson" returns web pages about Simpson college, Jessica Simpson, the Simpson's cartoon, and Simpson car-racing products. These documents are all considered equivalent in the eyes of the search engine because the term "Simpson" is merely a constituent part of each of them.

Automatic text classification, as performed by computers, typically uses the vector-space model to represent documents. The classification process involves taking a computer representation and having a system learn some quality of a particular class of information that allows it to make decisions about future cases. The automatic classification community has focused on innovating the methods for learning, depending on the standard representations of information retrieval. The scenario noted above has a similar effect on the functionality of these classification systems. While people typically classify information by its concepts, computers are restricted to the words. When a word can have many different meanings, as with "Simpson" above, the resulting ambiguity usually results in either some misclassification, or in the classifier ignoring that term, despite its relative importance.

This thesis introduces a new representation for electronic text for the purpose of classification. Similar to the way that people use context to disambiguate a word's meaning, this new representation contextualizes each word by the words that surround it. Based on the assumption that sentences provide semantic connections between words, a network of associations is built up from the co-occurrences of words in sentences. This representation, known as a *synchronic imprint*, allows a computer to understand the difference between the alternative meanings of words by recording the explicit context that they are being used in. In the example above, every instance of "Simpson" is connected to the surrounding words; in the case of O.J., terms such as "murder" and "trial" provide one context for a murder trial, while "Homer" and "Bart" provide another for the cartoon.

Another side of computer-aided classification is also investigated, utilizing synchronic imprints to help people understand electronic text in new ways. A visual tool for exploring the conceptual network described by synchronic imprints is introduced, called *flux*. Using the metaphor of a spring model, flux builds a visual representation of electronic text that reduces the text to its most important features. In this fashion people can recognize the important concepts and themes of a large body of text in a fraction of the time it would require to read and understand it. By focusing on a local region of the model, a user can explore the relationships of an individual word, providing the explicit context necessary to interpret the specific meaning implied in the text. The tool is offered as a general explorative interface to synchronic imprints, allowing people to utilize the same tools that computers use to perform classification.

1.2 An overview of the thesis

Chapter 2, "Example", presents an example exploring the three different representations of language compared in this thesis: the vector space model, synchronic imprints, and the flux visualization. The content of this thesis is represented in each of these forms, examining the qualities and assumptions of each model, while simultaneously providing a sneak-preview of some of the words and concepts integral to the thesis.

Chapter 3, "Theory", outlines the theoretical backdrop for this research. At the heart of classification lies the human conceptual system, serving as an outline of the problems passed on to computers. The standard approach and representations of information retrieval are presented and compared to the theories of mind already described. Finally, the relevant field of *information visualization* is introduced, including important systems and related work to this thesis.

Chapter 4, "Design", describes the development of synchronic imprints and the parallel construction of the flux visualization tool. The methodology for creating a new relational model of language is introduced, in addition to the explicit design criteria that influenced development are discussed.

Chapter 5, "Evaluation", presents two evaluations of this work. First, a formal evaluation based on the standards set down by the information-retrieval community was conducted. The results of these tests, in addition to an analysis of the successes and failures of synchronic imprints are discussed. Second, the flux visualization tool is assessed, using the parameters of design to understand the process of building visual explorative tools.

Chapter 6, "Conclusion", describes the major contributions and conclusions of this thesis. It also introduces possible future work, and synergies with other topics.

2 Example

This thesis is about representations—four to be exact. The first and foremost representation is electronic text, natural language in its digital form. This could be the news, a web page, or some notes in your PDA. In order for computers to make use of electronic text, it must be converted into a form optimized for a given task; here we concentrate on the task of automatic text classification, which is the process of separating electronic texts into a set of pre-arranged categories. Two representations are explored for automatic classification; one is the undefeated heavyweight champion for the task, and the other is introduced for the first time here. The final representation is visual, investigating how we can employ these computer models to help people better recognize, understand and classify electronic text.

To introduce the issues undertaken by this research, a good starting point is a brief introduction to each of these representations. Taking one body of electronic text, the respective characteristics of each representation will be extracted through comparison. With the goal of providing a good preface to the content of this thesis, the thesis itself will be used as this body of text; an earlier draft was taken and transformed into the other three forms mentioned above. This way, if you are unsure of what this thesis is about after this example, not only is the example bad, but also the representations.

2.1 Vector space

We begin with the most standard representation employed by computer systems for manipulating text, also known as the *vector-space model* for information retrieval. Most people have unknowingly interacted with the vector-space model in one form or another, at least anyone who has utilized an Internet search engine to locate a document on the web. This model represents documents by the frequencies of the words contained within them. The left-hand table below shows the 25 most frequent words along with the number of occurrences (from an older draft, of course); certain very common words, such as "the" and "to" are removed due to the lack of definition they provide.

Table 1: Frequencies of words and relationships in this thesis

word	frequency
term	147
word	140
representation	126
visualization	119
model	115
feature	103
information	102
system	98
set	94
document	91
imprint	79
synchronic	74
classification	73
categorization	65
text	64
number	62
spring	62
relationship	56
structure	54
import	51
perform	51
network	51
figure	50
data	46
evaluation	44

relation	frequency
term-word	29
imprint-word	26
information-retrieval	26
feature-word	19
space-vector	19
imprint-term	18
model-representation	17
feature-list	17
length-spring	17
document-word	17
feature-imprint	16
text-word	16
representation-system	16
information-system	15
number-term	15
information-representation	15
model-term	15
categorization-feature	15
classification-system	14
model-spring	14
number-word	13
body-text	13
document-information	13
document-set	13
imprint-representation	13

For the task of classification, the vector-space model uses the frequencies of words in a document to determine whether or not it belongs to a certain class. Automatic classification systems use these frequencies to build models that describe the given category. The features of new documents are compared to this model in order to decide whether or not they belong in the class. For instance, if this thesis were being compared to the class of theses on particle physics, the lack of such words as "physics" or "particle" would be good signifiers that this text is not about that subject.

One of the problems with the vector-space model comes from the fact that words on their own can often be ambiguous. This problem is called *polysemy*: when a word with more than one meaning is removed from it context, it is impossible to determine which sense was intended. An example can be seen in the term "model" which appears frequently in this document; if this thesis were being considered for the class of hobbyist's documents, e.g. those related to model airplanes, the high frequency of the term "model" might lead to this document being considered hobbyist material. In reality, models of language are not very similar to models of aircraft, and this classification would be illogical.

Given enough examples, the classifier mentioned might be able to adjust for this problem. If the set of documents used to train the classifier included some negative instances similar to this thesis, perhaps the existence of the term "model" would not be considered so highly. Instead, it might use other features such as "airplane" or "jet" to deduce the classification. However, the problems of ambiguity cannot always be avoided by providing more examples. Consider the case of this thesis and another document with all of the same words, but arranged in a totally different order; despite the fact that the meaning could be entirely different, both of these documents would appear *exactly* the same in the view of the vector-space model.

2.2 Synchronic imprints

A different model for representing text, introduced in this thesis is the *synchronic imprint*. The impetus of the last example let to the realization that structure of language is important in defining meaning; instead of merely using words, a new representation was built with the goal of capturing characteristics related to the arrangement of words, in addition to the words themselves. This structure is explicitly the intra-sentence relation of two nouns. In the previous sentence, "structure," "relation" and "nouns" are all nouns related to each other by the coherent meaning of that sentence. In a synchronic imprint, that sentence would be represented by three structural links: "structure-relation," "structure-noun" and "relation-noun." Each of these symbolizes a semantic link between the words, which could also be seen as a contextual feature for interpreting the word.

The right hand side of Table 1 shows the 25 most frequent semantic links in this thesis. In the example of the hobbyist category, the structure imparted by the synchronic imprint is enough to disambiguate the term "model:" in the case of documents about model airplanes, relations such as "model-glue," "model-airplane," and "model-kit" will be frequent, as opposed to the "model-representation," "model-term," and "model-spring" found in this thesis. The synchronic imprint provides higher-level structures for determining the features of a document, using the syntactic structure of the sentence to constrain the context of a given word.

2.3 A visual interpretation

Both the vector-space and synchronic-imprint models are built with a computer in mind; understanding the table above requires quite a bit of time and patience for a person. However, these representations are merely general tools for extracting relevant information from electronic text, providing a quantitative characteristic to a medium that is typically difficult to compare. The problem lies in the *presentation*, as

the human perceptual apparatus is not honed for making quick observations among large tables of numbers; that is an aptitude of computers. To make the representation more palpable to human reasoning, another visual representation can be constructed, which translates the features of the computer models into visual structures that are simple to interpret.

Figure 1 is an image from the *flux* visualization system, showing a visual interpretation of this thesis. The system uses a physical model of springs to represent the links between words specified by synchronic imprints; the more frequently a link occurs, the stronger the link is assumed to be, which translates into a spring with shorter length in the system. The system starts in a random state, and using the information from the interrelationships, moves around in search of equilibrium. At any time, a user can interact with the system by controlling the position of a word with the mouse. By observing how the system reacts to this movement, i.e., which words are pulled with the word, and which words are not, a person can quickly understand higher structures in how the words are connected. For instance, in the figure below, moving the word "model" has little effect on the word "set," while it is highly connected to "vector" and "space." Another feature, shown on the right, allows a user to focus on the connections of a given word. In the case shown, the word "model" is selected, highlighting its relations to "information," "words," and "classification," projecting a very different context than one might be shown for a remote-control club magazine.

The size of the words in the system is related to frequency information derived from the vector-space model. This allows a person to quickly recognize the important characteristics of the system before exploring the relationships. Within a few seconds of interaction, a user can recognize the defining concepts and their interrelations of this long document (over 20,000 words). Using two representations that are built for automatic classification, flux enables people to make classificatory decisions about electronic text that would otherwise be arduous and time-consuming.

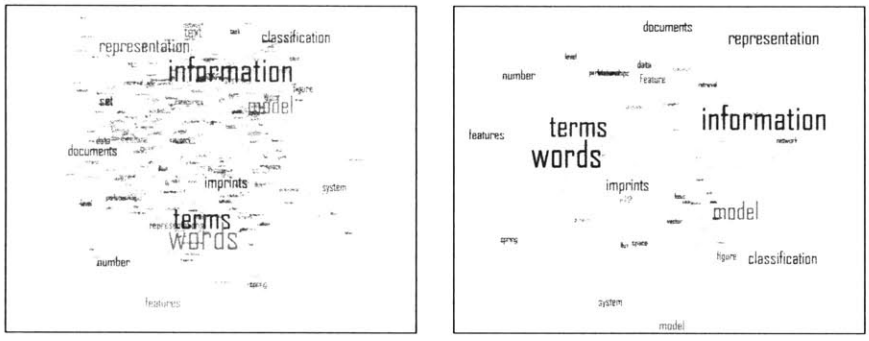


Figure 1: A visual interpretation of this thesis

3 Theory

This research is about *classification*, the process of deciding the inclusion of a given instance in a given class. Classification is fundamental to the way that people think; as we interact with the external world, classification is the apparatus through which we order the things that we perceive. Research in cognitive psychology has tried to model human classification for decades, and it has by no means converged on any general theory of the process or representations used. Furthermore the studies conducted are built on the assumption that simple concepts should be easier to model, so most of the research focuses on everyday objects, such as birds, boats or shoes. As noted in (Komatsu, 1992), it is unclear whether or not these theories can scale to more abstract concepts.

However, this research is not motivated by the urge to build computer programs that mimic the human classification system; rather it is focused on reproducing the cognitive faculty employed in this system, using whatever representations work best. Making automatic classification systems that work in real applications is an entirely different proposition than creating a general theory of mind; the former is evaluated by broad performance measures, the latter by specific studies. This impetus to build working artifacts is related most closely to fields with the same goal, namely information retrieval and artificial intelligence. Information retrieval provides the basic data structures commonly used for automatic classification. Artificial intelligence research in the domain of machine learning provides techniques for building models of these data that support classification. Sections 3.1 and 3.2 of this chapter introduce these topics, providing a framework for the construction of automatic classifiers.

This research is also about expressing a given representation visually to evoke a human understanding of its contents. For any given data structure, there are a near infinite number of mappings to visual form that could be chosen; the field of information visualization is devoted to understanding which of these mappings are most efficient in evoking understanding. Section 3.3 provides a foundation for experimenting in the domain of data visualizations, based on an array of examples from the past 10 years.

3.1 Information retrieval

In 1945, Vannevar Bush predicted the information revolution in an article sounding more like science fiction than science (Bush, 1945). He did so without the help of the conception of digital storage, using completely analog technologies to describe what today is known as the World Wide Web. His theoretical device, the "memex," consists of a desk containing thousands of pages of microfilm, all indexed for immediate retrieval by typing on a keyboard. Pages of this massive library can be linked together to create a trail of semantic connections, similar to a hyperlink on the web. This conception, fifty years ahead of its time, is the goal of information-retrieval researchers, and although the tools and techniques have evolved considerably, the problem has not been solved. Bush set the stage for future research by isolating the important problems of information science: finding and relating relevant documents.

The ambition of information retrieval is to create machine-optimized representations of electronic text, giving tasks such as retrieval, navigation and classification a much simpler interface to manipulate documents. This simplicity comes at the expense of expression, and one could argue that the operations performed by information-retrieval systems are far from the complexity of human thought; however, they provide a resource that our mind cannot compete with. As a brief introduction to the field, I will present four important representations that constitute the basis of most information systems today and some techniques for optimizing these representations for the task of classification.

The following models are often collectively called the *bag-of-words* approach, because they reduce the understanding of a document down to the constituent words of the document, ignoring the order, or any other relationships that they might have with each other. The bag-of-words approach has two canonical negative side-effects:

- Word-sense ambiguity (polysemy): given that one word may have many different meanings (senses), all senses are considered equivalent.
- Synonymy: distinct words with the same meaning are considered not equivalent.

Despite these disadvantages, the bag-of-words approach is used for most applications, because the algorithms utilized have been iterated and optimized for decades. However these systems often utilize features from other approaches to refine results in an intelligent fashion.

The inverted index

The simplest representation for locating documents, the *inverted index* is analogous to the index that is found in the back of most modern books. This technique has been employed as the basic tool for

searching for information in a set, or *corpus*, of documents. Given such a collection, each document is cataloged by every term that appears within its text. To find a document, a person can guess a set of words that might be contained within the documents, known as a *query*, which is translated into sets of documents that contain those words. The intersection of those sets, termed the *result set* is returned to the inquirer. A simple optimization is to store the frequencies of words in a document with the inverted index, and to sort the sets based on the number of times each word occurs, giving precedence to those documents with more occurrences.

The vector space model

An alternate representation for the inverted index is an *n*x*m* matrix, where *n* is the number of distinct words in all of the documents, and *m* is the number of documents. Each location a_{ij} corresponds the number of times that word *i* occurs in document *j*. This representation is known as the *vector-space model*, as each word can be thought of as a dimension in an *n*-dimensional vector space; in this model, a document is represented by a vector where the length along any dimension corresponds to the frequency of the word associated with that dimension. This technique was introduced by Gerard Salton (Salton & McGill, 1983), often referred to as the father of modern information retrieval due to its influence as a general model of language.

Representing documents as vectors gives rise to many operations borrowed from linear algebra. First, different properties of a document collection can be stressed when searching for a document. To find documents related to a set of words, the words are translated into a vector in the space. Similarity to other documents is computed in one of two ways: the *dot-product* calculates the Euclidean distance between the two vectors, and the *cosine-similarity* is a measure of the angle between the vectors, de-emphasizing the lengths of the vectors. In some corpora, the directions of vectors are a better indicator of semantic similarity than the distance between them.

Second, given these similarity measures, one can also find the distances between documents already contained in the collection. The technique of looking for arbitrary groupings using these distances is known as *clustering*. The assumption is that documents with similar semantic foci will be close together because they share similar words. For instance, documents containing the word "Saturn" fall into four neatly distinct groupings: some about the car, some about the planet, some about the rocket, and some about the console gaming system. The most popular algorithms, *k-means* and *hierarchical clustering*, both take as input the assumed number of clusters and return groups of documents.

Feature selection

Many algorithms that look at information as sets of features are often held up by unimportant features. For instance, most automatic classification systems perform optimally when only features important to classification are considered. To accommodate these requirements, *feature selection* algorithms are used to focus the structure of representation on the given task. For most IR systems, two approaches to feature selection are universally used as pre-processing steps: *stop listing* and *stemming*. Both of these techniques are based on simple understandings of language that allow a system to focus on the important linguistic components of a text. More aggressive feature-selection algorithms come in two types: those that remove non-informative features based on some measure of importance, and those that combine low-level features into higher-level orthogonal dimensions. Of the first type there are two popular methods designed with classification in mind, *information gain* and *chi-squared* (χ^2), which have stood out in comparative evaluations (Yang & Pedersen, 1997). The second type is a largely unexplored space, but one technique stands out as highly successful, *latent-semantic indexing* (LSI).

Stop listing

Most languages are full of structural words that provide little meaning to the text. For this reason, lists of substantially frequent words, called *stop lists*, are created and checked at the first stages of representation. Any occurrences of these *stop words* are removed from the body of the text to focus the representation on the other words. Stop lists can be generated automatically for a given corpus using statistical method, but for most systems, general lists constructed from such analysis over a large corpus of English text provide a sufficient resource for the task.

Stemming

Another popular step in pre-processing words is their conversion into a morphologically unique form through a technique called *stemming*. This process helps with the problem of synonymy, given that one concept may have many morphological forms; for example, the words "aviator," "aviating" and "aviation" will all be converted into the form "aviat," a term which has no significance to people, but represents the concept of flying. As long as all new words introduced to the system are stemmed first, any form of "aviation" will be transformed into the term "aviat" which will match other forms. The most popular method, known as the Porter stemmer, does a very effective job of combining different forms of the same word (Porter, 1980).

χ^2 (chi-squared) statistic

The χ^2 statistic is a measurement of lack of independence between term t and category c, based on the assumption that normal distributions do accurately describe terms in most sets of documents (Dunning, 1993); the χ^2 statistic instead view a corpus as a distribution of rare events. To simplify notation, consider that $f_{t,c}$ is the number of documents in c which contain the term t and $f_{!t,!c}$ is the number of documents not in category c which do not contain term t. Then the χ^2 statistic for each term and category is calculated with the following equation (Yang & Pedersen, 1997):

$$\chi^2(t,c) = \frac{n \times (f_{t,c} f_{!t,!c} - f_{!t,c} f_{t,!c})^2}{(f_{t,c} + f_{!t,c}) \times (f_{t,!c} + f_{!t,!c}) \times (f_{t,c} + f_{t,!c}) \times (f_{!t,c} + f_{!t,!c})}.$$

If t and c are statistically independent, then the χ^2 measure will have a value of zero. The χ^2 value is normalized over the entire corpus, providing information about a term's relation to the category in the context of the entire set of documents.

Information gain

Information gain is a popular technique for determining the importance of a term in the field of machine learning (Mitchell, 1997). It is a measurement of the number of bits of information gained by knowing a term in the process of classifying a document (Yang & Pedersen, 1997). For all categories c_i, this quantity can be calculated with the following equation:

$$G(t) = -\sum P(c_i) \log P(c_i) + P(t) \sum P(c_i \mid t) \log P(c_i \mid t) + P(!t) \sum P(c_i \mid !t) \log P(c_i \mid !t)$$

Using either a predetermined threshold of information gain or a target number of terms, these values can be used to determine a refined set of dimensions. In a comparative analysis of feature selection techniques, information gain was shown to have a highly correlated output to χ^2, despite a relatively different approach (Yang & Pedersen, 1997).

Latent semantic indexing

Since the invention of the vector space model, there have been very few divergently new representations. A recent technique, *latent semantic indexing* (LSI), was introduced in the early 90's by Sue Dumais, George Furnas and Michael Berry (Scott Deerwester, Susan T. Dumais, George W. Furnas, Thomas K. Landauer, & Harshman, 1990) as a technique to improve upon the vector space model. The core idea behind LSI is that many of the dimensions of a typical corpus vector space are not orthogonal, meaning that some of the dimensions are related to each other. Using the method of *singular-value decomposition* (SVD), the vector space is reduced into a space where each dimension has maximal meaning. This is not

the process of removing "unnecessary" dimensions, but rather creating new, orthogonal dimensions that represent combinations of words that were considered related.

The claim of LSI is that by using this standard matrix dimensionality-reduction technique, each dimension is representative of a semantic feature. It is particularly good at dealing with synonymy, as words that have a similar meaning will represent highly correlated dimensions in the vector space. It still suffers from the other problems of the standard vector space model, namely polysemy and a loss of syntactic features, because it is derived from the same basic representation.

3.2 Automatic classification

Having computers perform classification on text documents has been a long-standing goal of information-retrieval research, as it was considered by Salton early on to be one of the important tasks to be addressed by the field (Salton, 1968). The problem is specified as a *supervised-learning problem*, meaning that a computer system is expected to learn to recognize a set of specified classifications from a set of pre-classified examples. This problem can be distinguished from the problem of automatic categorization, which would be equivalent, but unsupervised (which could be equated with the method of *clustering* mentioned earlier). AI provides a variety of learning techniques that have been applied to the problem, all of which are optimized for different numbers and types of features. As a result, automatic classification has been reduced to two areas of concern: feature selection, or creating an appropriate representation for classification, and learning the specified classes. Feature selection was introduced in the discussion of information retrieval, so I will focus on classification here.

Learning has always been fundamental to AI; without learning, an intelligent computer would have to be explicitly programmed for each possible piece of knowledge represented. Learning enables programmers to build necessary representations by example, a process that is much less time consuming. Because of its centrality to the field, a well-developed community has formed around the topic, known as *machine learning*. In relation to the problem of text classification, popular methods include rule-induction systems, nearest neighbor, neural networks, Bayesian belief networks, and support-vector machines, which all differ by the types of representations created to support classification.

The well-defined mission of automatic classification has invited a number of different techniques into competition; the standard method of evaluating these competitors is by comparing them to their human counterpart. In other words, automatic classifiers are tested against human classification, usually by separating some human-classified set of documents into two sets, and then using one to train the classifier, and the other to test it.

Rule-induction and decision trees

One method for describing a category is to determine all of the important attributes of category members, make a list, and simply check this list every time a classification is made. If the rules are assumed to have dependence on each other, then they can be organized into a hierarchical chain, known as a *decision tree.* Every node of a decision tree is connected to another set of mutually exclusive possibilities. Performing classification in a decision tree is merely a matter of following the path that holds true. Popular systems include Quinlan's C4.5 (Quinlan, 1993), for decision-tree induction and Cohen's RIPPER (Cohen, 1995) for rule induction.

Nearest neighbor

A straightforward solution to the classification problem is to look for the most similar example that has already been encountered. This approach is known as *nearest-neighbor* classification (Cover & Hart, 1967), the simplicity of which has always made it popular. The algorithm is simple: for each classification task, compare the entity in question to example instances, and use the class of the most similar case. For example, if features are represented as dimensions in a vector space, the distance between two entities can be described as either the Euclidian distance between them, or the angle in between them (as with the vector space model for information retrieval). Difficulty comes in organizing the examples such that the most similar instance can be obtained efficiently. The most popular method, known as the *k-nearest neighbor* algorithm, looks for the *k*-nearest instances in all categories, and chooses the most frequent category of that set (Friedman, 1994).

Neural networks

Artificial neural networks (ANN) are a general method modeled after pattern-recognition systems of the mammalian brain. They consist of a large number of processing units, analogous to neurons, tied together by weighted connections, analogous to synapses. Given a large enough set of training data, they perform precise recognition, able to withstand a considerable amount of noise. Being a general approach, they have been applied to a number of problems, including computer vision, financial-data prediction, and speech recognition. Trained neural networks predict recognition and provide an associated expected error, so classification is performed by merely passing a test example to the network.

One of the discriminating attributes of neural networks is that they are not a comprehensible representation; the only information available after training a network is the weights of the connections, which are simply numerical values. Neural networks can have a number of intermediate representations,

in the form of extra "layers" of nodes. These nodes amalgamate the patterns of first level nodes into a higher-level representation (determined by the model of attachment).

Bayesian methods

Bayesian networks are a general technique for representing causality, which have recently gained wide appeal for various applications in the AI community. For this model, it is easiest to start with an example: assume you walk outside your house one morning, and the grass is wet. You know by deduce that one of two events has occurred: either your sprinkler was left on overnight, or it has just recently rained. You can ascertain one more piece of information by merely looking up to see whether or not it is cloudy; this fact could be very informative. We can represent this situation graphically as a network of dependencies:

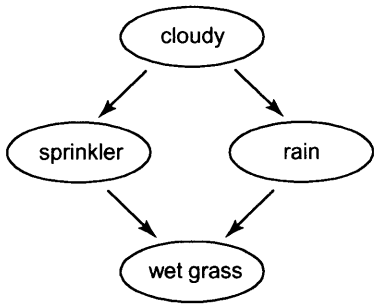


Figure 2: A simple causality network

We know that the grass is wet, which is dependent on either rain, or the sprinkler, and the probability of those events is influenced by whether or not the sky is cloudy. Thomas Bayes, an 18th century mathematician, conceived of a method for describing conditional probabilities such as this scenario. Bayes theorem states that for a random event r and some evidence e that we can predict the probability of r given e if we know the conditional probability between them. Mathematically, this is represented in the following equation:

$$P(R = r \mid e) = \frac{P(e \mid R = r)P(r)}{P(e)}$$

If we understand the causality of a system, which in our example would mean the probabilities of it being cloudy, the sprinkler being on, it raining, and the grass being wet, we can make reverse predictions about the state of the world. In other words, if the grass is wet, we can predict whether or not the sprinkler was on.

Learning in the case of Bayesian networks is a process of calculating the conditional probabilities based on a set of examples. This process makes the assumption that a model has already been constructed (i.e.

nodes laid out in a causal network, as above); otherwise, the model must also be learned (Heckerman, Geiger, & Chickering, 1994). Classification performed by checking the state of the example in question, and determining the probability of membership; above some probabilistic threshold instances are considered part of the class.

Support-vector machines

Support-vector machines (SVMs) are another learning method that has gained a significant following in the past few years. They are based on Vladimir Vapnik's theory of *structural-risk minimization* (Vapnik, 1995), which is a model for building theories about distributions of data. The goal of this principle is to find a hypothesis *h* for a set of data that minimizes error, where error is the probability of an incorrect prediction made by *h* for a randomly-selected test example

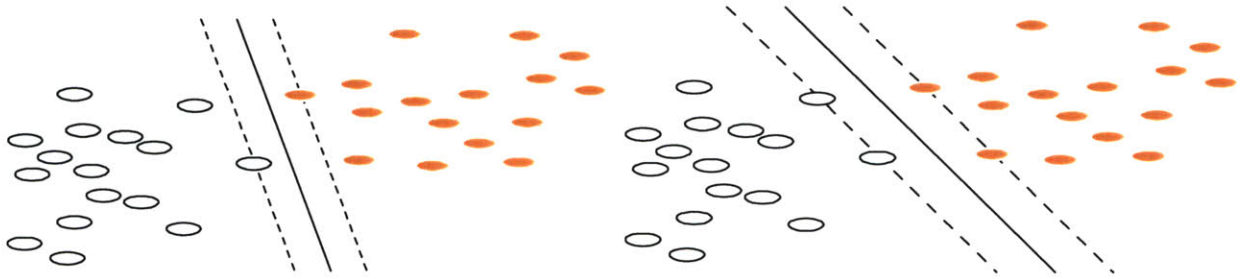


Figure 3: Two possible decision lines, with different margins of error

SVMs are an application of structural risk minimization to classification in a vector-space representation of data. The hypothesis is a partitioning of the vector space into class and non-class areas. Figure 3 shows two representations of such a partition for some data, where the dashed-lines are a margin where the decision line can be moved without causing a misclassification. The SVM problem is reduced to maximizing this margin (Joachims, 1998). The decision line is represented as a hyperplane that is written in the form:

$$\vec{w} \cdot \vec{x} - b = 0$$

Where $\vec{w}$ and b are learned from the training data. This partition can be described by a higher-order function (i.e. a second-order polynomial), but the hyperplane has been shown experimentally to be the most effective (Yang & Liu, 1999). The vectors $\vec{w}$ are called the *support vectors*, and are shown in Figure 3 by the points resting on dashed lines. An interesting property of this representation is that the only necessary instances are the support vectors; if we remove all of the rest of the examples from training set, the same model would be built (Yang & Liu, 1999). This distinguishes the SVM technique from the more general nearest-neighbor systems, which maintain a set of all examples.

3.3 Information visualization

The term *visualization* was first introduced to computing in 1987 in a report to the National Science Foundation (Defanti, Brown, & McCormick, 1987). The report outlined the possible synergies between many scientific fields and the new instrument of computer visual modeling. They proposed computers as a new scientific instrument that allowed for an understanding of scientific data that was not possible otherwise:

> "Visualization is a method of computing. It transforms the symbolic into the geometric, enabling researchers to observe their simulations and computations. Visualization offers a method for seeing the unseen. It enriches the process of scientific discovery and fosters profound and unexpected insights. In many fields it is already revolutionizing the way scientists do science." (Defanti et al., 1987)

The term *information visualization* refers to the field working explicitly on the general problem of visualization. It assumes the existence of particular types of data, and attempts to find solutions that extract a relevant analysis visually. In other words, "using vision to think" (Card, Mackinlay, & Shneiderman, 1999).

Visualizations fall into two categories: task-oriented and exploratory interfaces. The first takes a specific task, and presents a new solution based on a novel way of presenting the information necessary. The other type might be best described as representational experiments, where a type of data is presented along with a method for translating the data into a visual representation; the goal of the system is simply to explore the data in a novel way, with possible application in a number of tasks. This thesis presents a new representation for corpora, and seeks to explore possible interfaces for interacting with it. As an introduction to related work, an overview of visualization techniques will be presented, in addition to some recent related systems.

Techniques for visualization

The field of information visualization is very new, as research has been highly controlled by the availability of sufficient hardware. Despite its relative infancy, there have been a number of defining papers, many of which are collected in (Card et al., 1999); this collection is one of the first to establish a framework for describing the field. Using their structure, I will introduce some of the major components of visualization techniques.

Visual representations

Clearly the most important innovation in the field is in the uniqueness of methods employed to map raw data to visual form. This goal of such a process is to exploit the skills of human perception to provide a richer understanding of the data than would be possible by merely sifting through it. There are an infinite number of visual mappings that could be used to explore data, but a few patterns have emerged based on the familiarity they provide to our analysis. First, the use of Cartesian space is a popular focus, based on our physical expertise in interacting with the world. Second, different types of visual metaphors, such as trees and networks are both structures that evoke an analytical strategy that people can relate to.

Space

Much of visualization has to do with the extraction of *features*, namely the attributes of the data that are necessary for comparative analysis. This technique is familiar to most scientists, whose data analysis skills are related to their ability to choose the right variables to observe. Most scientists today are dependent on scientific visualization and mathematics programs that allow them to plot data in three dimensions, a facility that was generally unavailable before computer graphics.

In the case where the amount of visual space is a major concern, only one dimension can be used, allowing for the most minimal representation possible. Marti Hearst's TileBars, seen in Figure 4, describe the structural makeup of a document as a series of pixels whose color is determined by the importance of each passage to an information retrieval query (Hearst, 1994). As the output of most computer displays, two-dimensional representations are the most ubiquitous use of space for visualization; typical applications of two-dimensions are charts and other 2D structures (included in the next section).

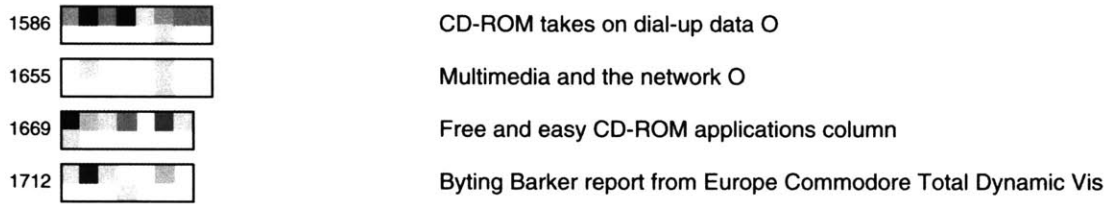


Figure 4: TileBars relates the structural relevance of a document to a query

Three-dimensional space is the limit of our perceptual apparatus, and also the most familiar environment for interaction. The *Galaxy of News* system pictured in Figure 5 uses three dimensions to represent the topical structure of news (Rennison, 1994), mapping the dimensions of the screen to similar topics, and depth to the level of detail (i.e. moving into the screen moves towards more detailed topics, until eventually stories are reached).

Figure 5: The *Galaxy of News* is an interactive 3D topical arrangement of news

Adding a third dimension to a visualization can introduce some challenges; the typical computer displays two, necessitating the addition of shadows and lighting to create the effect of three dimensions. This perceptual trick can cause *occlusion*, the obscuring of certain objects behind other, larger objects.

In many visualization tasks, the source of data is some high-dimensional data, demanding that some features be left out, or re-represented to fit into the dimensionality of the output device. Steven Feiner defines a method for interacting with higher than 3-dimensional spaces (Feiner & Beshers, 1990). His system, *n-Vision* represents a number of three-dimensional spaces simultaneously to represent higher-dimensionality, allowing interaction with any 3D space at a time.

Structural metaphors

Despite the ability to represent many dimensions visually, dimensionality problems will still always pose a problem. For instance, in the vector space model for information retrieval the number of dimensions is equal to the number of unique words in the represented documents, a number usually in the thousands. In these cases, sometimes another metaphor can be used to represent the crucial information through structure. Two data structures from computer science are commonly used for this task: networks and trees.

Networks are a visual structure corresponding to a set of relationships. Visually, instances are represented by nodes (points) connected by edges (lines). Edges can have weights or distances associated with them, which is reflected in the visual model. Figure 6 shows *Valence*, a three-dimensional network visualization created by Ben Fry of the MIT Media Laboratory (Fry, 2000). In the images shown, the system is displaying the network created by web traffic, where the distance of each edge relates to the amount of traffic between two web pages. *Valence* uses a physical model of springs to spatially lay out network points, a popular technique which creates a complex and informative behavior from simple physical rules.

A common technique to visualize high-dimensional spaces utilizes the network as a representation. For any vector space, if a scalar relation between two vectors can be defined (such as distance, or angle), the space can be mapped into a network. The *Bead* system (Chalmers & Chitson, 1992), covered later in detail, uses this method.

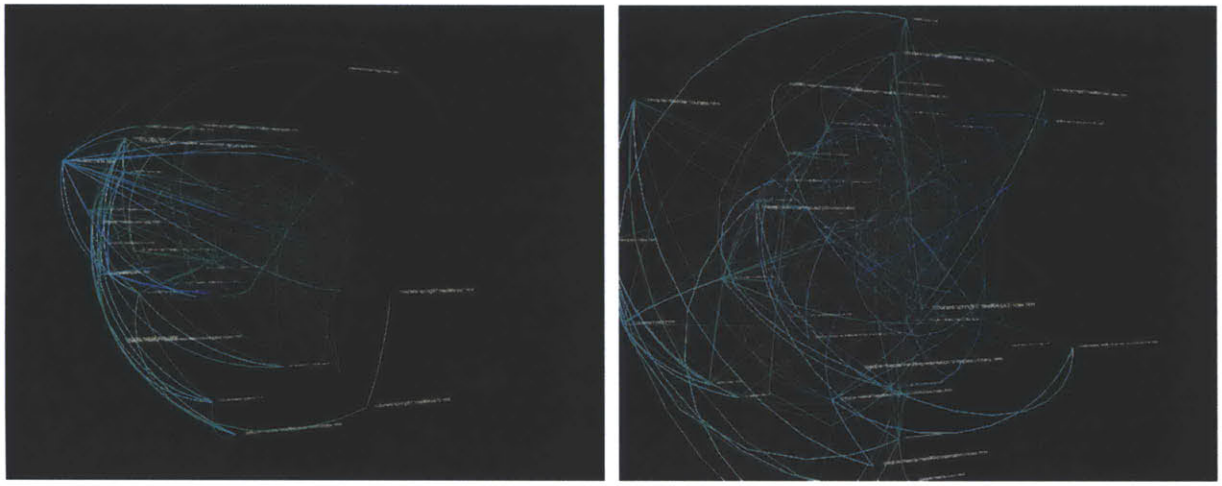


Figure 6: Two views of *Valence*, a three-dimensional network visualization

For data that has some hierarchical component, trees are a natural data structure for visual display. Trees are typically visualized in one of two ways: either as a network as described, or using the method of containment. The tree data structure is special case of a network, where a starting node is defined (root), with all nodes can be reached from this point, with no cyclic connections. The endpoints of this network are known as *leaves*, and for any given node, the node directly above is known as its *parent*, and nodes below it are referred to as *children*. The structure of trees makes them natural to layout, as opposed to the general case of networks, which are not. Containment is an efficient two-dimensional visualization of a tree that uses the size of the leaves to determine the area of a node. Figure 7 shows the containment visualization *Tree-maps*, a representation of a common directory tree.

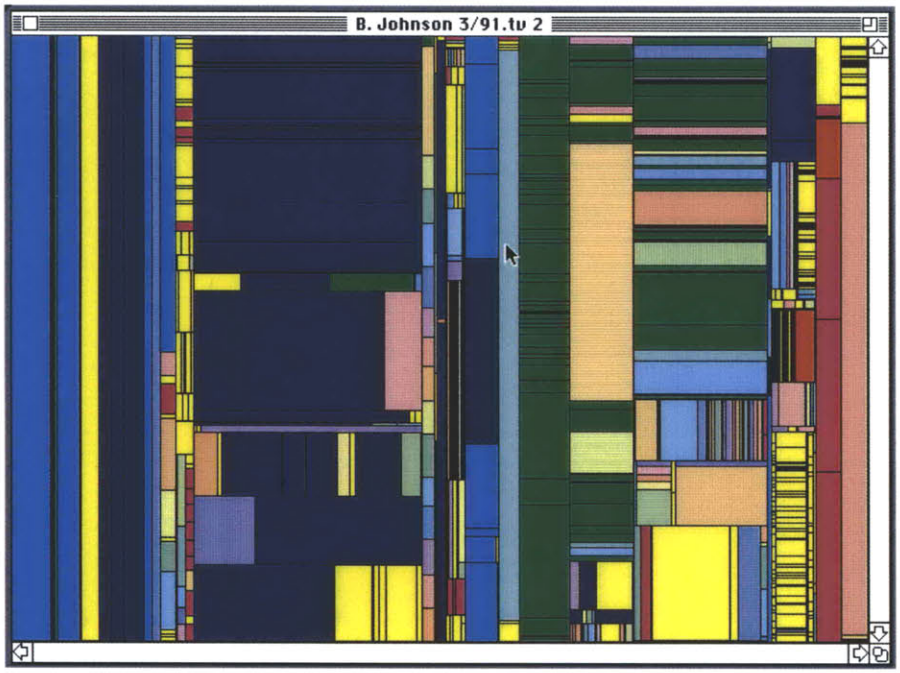


Figure 7: *Tree-maps*, a containment visualization, here showing a directory tree

Interaction

One of the key characteristics of computer-aided visualization is the possibility for interaction. Static visualizations must be carefully designed to evoke the intended understanding of a set of information, but interaction allows a user to actually manipulate the data at some level, leaving more room for interpretation. The analysis of interaction in (Card et al., 1999), represented in Figure 8 highlights all of the important types of interaction available to a visualization designer. At the lowest level, users can manipulate the initial data transformation, by selecting which instances to view, the variables to stress, or the actual metric for transformation. At the next level, the visual forms of the data can be manipulated, changing the appearance of the data without actually affecting the data itself. At the highest level a user can interact with the visual model itself, by selecting, moving, or adjusting focus on an object in the model. Using the analogy of a word processor, data transformations would be the manipulation of the text, visual mappings changing visual attributes of the text, such as font or color, and view transformations would be the selection of text, scrolling, or changing the zoom.

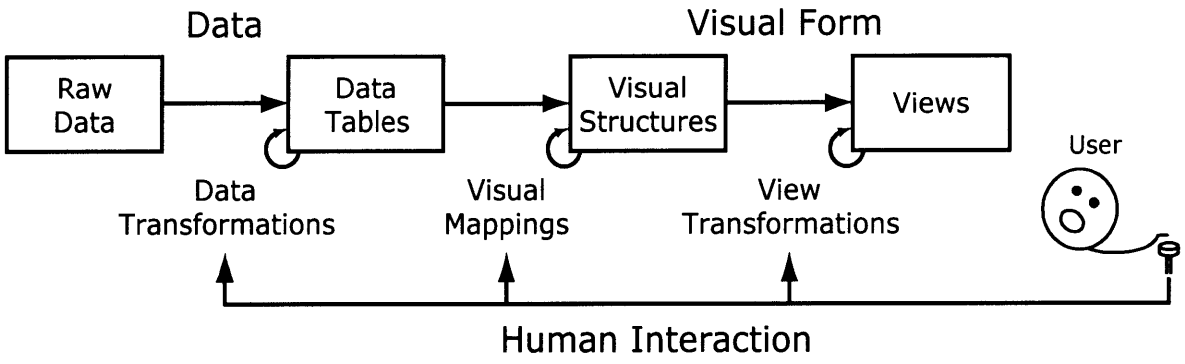


Figure 8: Parameters for interaction

Focus

Sometimes data sets are excessively large and complex. Even if a visualization is successful in accurately describing such data, it is often impossible for a user to recognize the significant message amidst the density of the representation. A seminal contribution to information visualization was the invention of the fisheye convention for focus (Furnas, 1981). A fisheye lens is a special optical device that performs two transformations to an image: it shows things in the center of the image with high magnification and detail while simultaneously showing the whole image, with decreasing magnification and detail progressing away from the center. This technique allows for a detailed look at a complex structure while simultaneously showing the larger context; Furnas introduced an algorithm for applying this method to the visualization of a tree (Furnas, 1981), which has become a popular tool for dealing with complicated tree-like structures. *IndiVideo*, a tool for creating video sequences on the web uses a fisheye perspective to arrange a tree of connected video sequences (Seo, 2001). A user can scroll through the sequences maintaining a focus on the current sequence, while still displaying the larger context.

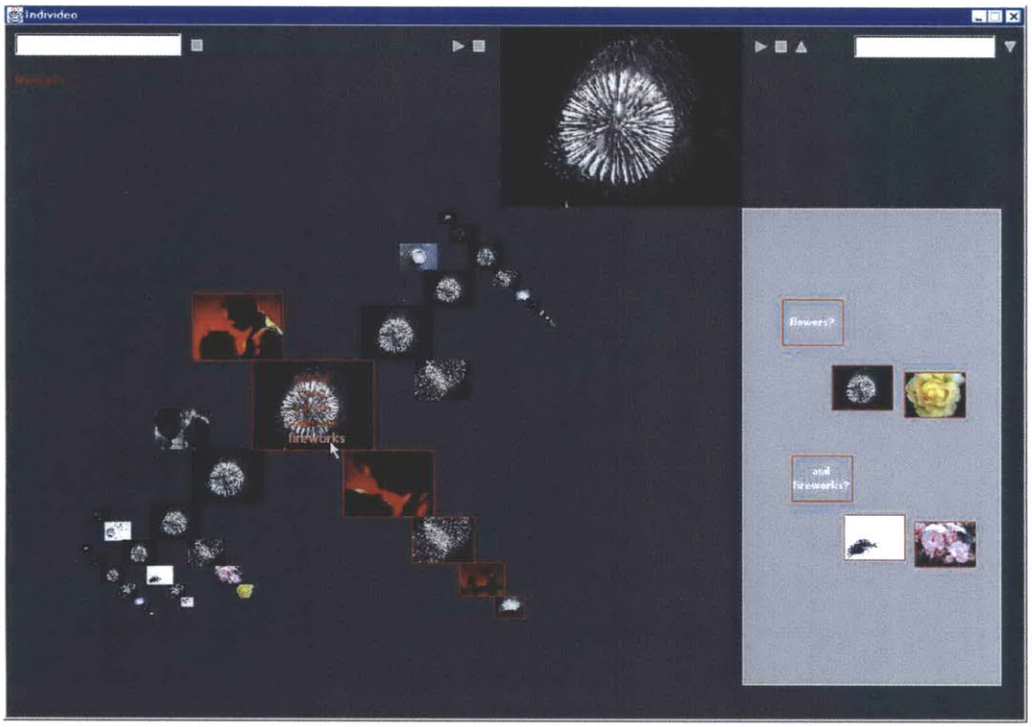


Figure 9: *IndiVideo*, a video editing tool uses a fisheye perspective to arrange movie sequences

Explorative interfaces

Many of the examples of systems referenced in this section are visualizations with a set function, such as reading news, browsing video sequences, or searching for a document. In these cases the visualization focuses the user by providing relevant information in a quickly comprehensible format. Some of the other examples, such as *Tree-map* are novel visualizations that are applied to an array of different data sets. Somewhere in between task-specific and technique-centered visualizations is a set of applications that are built around a specific representation, but not constrained to performing an explicit process; these applications can be termed *explorative interfaces*. I will introduce two related projects, *Bead* and *Conversation Map*, both of which are built as systems for interpreting a specific representation.

Bead

Information systems typically represent documents visually as lists sorted by some heuristic of relevance to a given query. This representation is closed to interpretation, and typically even the heuristic is not exposed to the user. In this respect, interpreting results from an IR system can be difficult, usually involving a person's reverse engineering of how the system works.

Bead is an alternative display for documents that uses the vector space model of information retrieval to create a dynamic display of the similarities between documents (Chalmers & Chitson, 1992). *Bead* uses the technique of physically modeling a network of springs to create a dynamic display of relationships; each document is connected to all other documents by springs whose desired length is related to the Euclidean distance between those documents in the original vector space (spring models are discussed at length in chapter 4). Figure 10 is a snapshot in time of the simulation. The model is constantly updated, giving an approximate view of relationships between the documents.

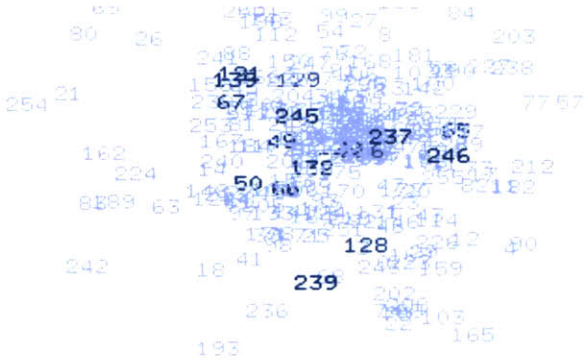


Figure 10: A document space in *Bead*

Users can then make queries to the system, as a standard information retrieval query. The results of the query are exposed in the visualization, show in Figure 10 as darker numbers in the field. By using queries to select documents, a user can explore the relationship between these documents; despite the reduction of many dimensions down to only three, through interaction a user can come to understand the dynamics of the documents in the original representation

Conversation Map

Sometimes a given representation or set of representations can convey a large number of analyses; instead of describing the information through a simple visual mapping, several different views of the information can be provided simultaneously. Warren Sack's *Conversation Map* presents a number of linguistic and social-dynamics representations in a single user interface (Sack, 2000). The domain of the visualization is what Sack terms *very large-scale conversations* (VLSC), discussions with hundreds or thousands of participants (i.e., newsgroups). Often these discussions have a specialized language and mode of interacting, all of which can be found somewhere the body of the discussion. Sack takes the discussion and parses it into a number of representations, including a semantic network of topics discussed, a network of social interactions, sets of important themes, and trees for each individual thread of

conversation. Underneath each of these representations lies some set of linguistic or socio-analytic tools used to build the representation, which is provided to the user at another level within the system.

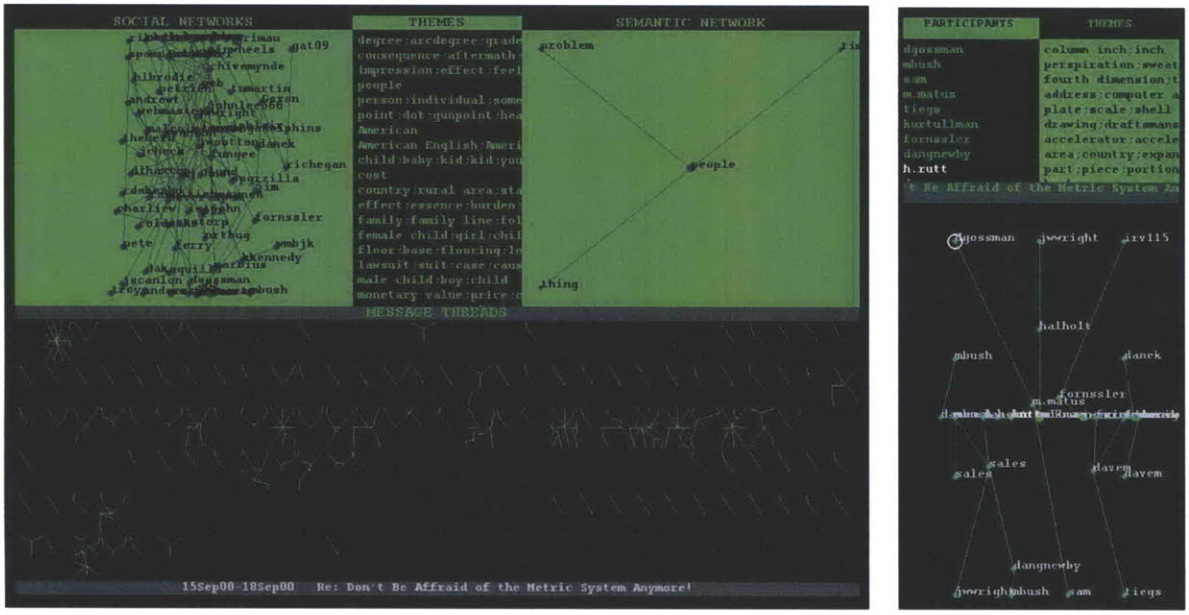


Figure 11: Two levels of detail in the *Conversation Map* interface

The interface to the visualization is divided initially into 4 separate areas, shown in the first diagram of Figure 11. In the top left corner is a spring-model visualization of the social interaction, i.e. who has conversed with whom. In the center are general themes that have been extracted from the text, and in the top right is a more distilled representation of the semantics of these themes. At the bottom of the interface is a set of tiny visualizations of each thread of discussion within the entire group conversation. By clicking on any individual thread, or set of threads, a similar style detail interface, as shown on the right, is displayed.

In a fashion similar to *n-Views*, *Conversation Map* shows many different interconnected representations simultaneously. As an explorative tool, the system provides an interesting form of interaction: when a user clicks on a visual object, that object is analogously selected in other representations. For example, if a set of people in the social network is selected, then every thread, theme and term in the semantic network that those individuals have contributed to is highlighted. This allows a user of the system to impose his or her own structure on the representations presented, integrating this structure with the rest of the visualization. This type of interaction, which might be labeled *expressive interaction*, allows the exploration of different theories about the representations through a system of expression and feedback.

Conclusion

Visualizing a representation is an easy way to understand it, given that the correct methodology is observed in creating the visualization. Computers allow us to see data in new ways, extending the possibilities of how we could visually represent things in the past; through space, interaction, and the simple ease of manipulation, information visualization is a whole new paradigm for research. For this thesis, the two systems presented in detail embody the sentiment of the explorative interface, using visual techniques to create a general tool for understanding the nature of an unexplored representation.

4 Design

4.1 Motivation

Structuralism

Decentralized systems have become a subject of great interest in recent times, due to the recognition that they play an important role in describing many natural phenomena. This trend comes from the realization that some natural systems are difficult to model from the perspective of central control, but are simple to understand from the viewpoint of an individual entity in the system (for a discussion and host of examples, see (Resnick, 1994)). One of the most influential shifts in linguistics came from the introduction of decentralized thinking now labeled *structuralism*. This theory, constructed from the lectures of Ferdinand de Saussure, purports that the meaning of a word is not defined by a dictionary, or its previous meaning, but instead by its relationships to other words in language usage.

Saussure divides the study of semantics into two fields of study: *synchronic*, focusing on understanding the meaning of words at a given point in time, and *diachronic*, looking at how this meaning evolves. Until his lectures in the early twentieth century (recounted in (Saussure, Bally, Sechehaye, & Reidlinger, 1983)), linguistics researchers had generally focused on diachronic analysis, using the history of a single word to derive its current meaning. Saussure realized that there is no intentionality in language and that changes in meaning usually occurred because usage changed, not because of other intervening consequences. He advocated the use of structural analysis for synchronic study, focusing on understanding words through their interrelationships with other words in a body of language.

Polysemy in classification

Most text classification systems' performance is mitigated by the ambiguity of words. Standard classifiers achieve the best performance when the features of the different categories are mutually exclusive; in this

case, it is easy to partition the space of instances with clear-cut boundaries. In the case that two categories share similar important words, classifiers will commonly make mistakes unless the feature selection algorithms place a higher emphasis on other features.

These faults are related to the canonical problem of polysemy, resulting from a lack of description by the standard features of information retrieval. For people, this issue is resolved by looking at the surrounding context of a word; when a word appears ambiguously, the words around it provide a finer detail of definition in its interpretation. The fundamental hypothesis of this thesis is that this contextual information should be part of the representation used by information systems associated with the task of classification. This new set of features can be used by both computers and people to disambiguate the vague and unclear cases that exist in typical information

In the following sections, I will retell the design process for creating a new representation for categorical analysis, influenced by the tradition of structuralism. The semantic links that result from the coherence of different concepts form the basis of this structural information necessary to disambiguate words; this structure is extracted from the co-occurrence of concepts in a sentence, a lexical structure that guarantees coherence between its terms. This new model of language was also fundamentally influential in the construction of a visual tool for exploring relationships in large bodies of text. Although they are described independently, these two undertakings were part of the same design cycle, with the goal of presenting a new description for electronic text, both to computers as a new extensible structure and to humans for visual investigation.

4.2 Synchronic imprints

Influence

The inability of automatic classifiers to understand different senses of the same term has a representational basis; to these systems, the word "model" in the context of a model airplane instruction manual has essentially the same meaning as the word "model" in this thesis. To address this problem, a representation that accounts not only for terms, but the relationships of the terms to each other seemed like an appropriate solution. The initial attempts at building this model were inspired theoretically by structuralist writings of Saussure, and also instrumentally by the representation used in the *Galaxy of News*.

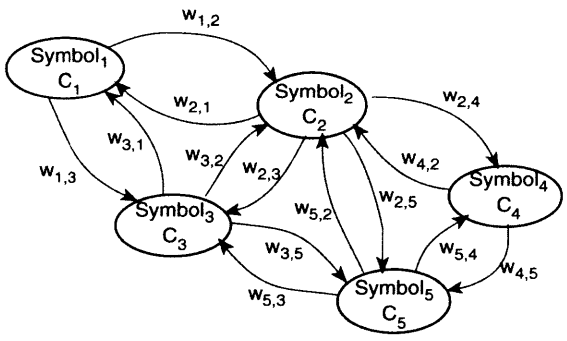


Figure 12: A simple Associative Relation Network

To understand the structure of news, Rennison constructed a model of relationships between terms in stories. This structure, called an *Associative Relation Network* (ARN), was built by looking at the co-occurrences of terms in news stories. Every term in the news is considered to be a node in an undirected weighted graph. The weight between any two words in the graph corresponds to the number of times that these words co-occur in a story together. Figure 12 shows a simple ARN for terms C_i and relationships $w_{i,j}$.

The method described above is a simple way to construct a *semantic network*, a set of relationships between concepts. In addition to the constituent terms, a semantic network also encodes information about the structure of language. This structural information could be a crucial resource for disambiguating the sense of a given word in the process of classification, but the network described by the ARN is too broad for this task. Within one sentence, two different meanings of a given word can be expressed; when these two meanings are connected, the structural information provided by their semantic link becomes ambiguous. For example, consider a news story reporting the recent weather events in America. When rain in California and snow in New England are associated together, the meaning of these two events is lost, with New England being associated with rain, and California with snow. A new representation was constructed in the image of the ARN, which accounts for semantics at a finer level of detail, as hypothesized in the following section.

A snapshot of language

An evaluation of second-order features, or higher-level features generated from words was conducted for the task of search by Mittendorf, et al. (Mittendorf, Mateev, & Schäuble, 2000). The features they used for representing documents were co-occurrences of words contained within a given window. Their results show that when a window of 10 words is used, around the average length of a sentence, the best

performance is achieved. Why this is the case, they do not posit. To explain this phenomenon, I offer the following hypothesis:

> *The sentence-semantics hypothesis: sentences are the largest lexical structure that guarantees semantic coherence.*

This conjecture is based on the observation that sentences are made up of one or more syntactic structures that are intentionally arranged to provide a higher-level meaning. While it is easy to find documents or paragraphs with conflicting or incoherent semantics, it is very difficult to find a sentence that has this attribute. Furthermore, a sentence that has this quality will merely sound nonsensical, so it can be considered outside the realm of natural language. Consider the following examples:

"George W. Bush is a man. George W. Bush is a woman."

"George W. Bush is a man and George W. Bush is a woman."

In the first example, the author of the sentences is assumed to have a problem deciding the sex of George Bush, implying contradictory semantics. However, in the second example, the semantic connection of these two facts implies the inference that George Bush is, in fact, a hermaphrodite. Under this assumption, the optimal window for building structural features is the sentence; this window maximizes the amount of structural information while simultaneously assuring coherence.

A new representation of relational information based on this hypothesis and the method outlined by Rennison was created. The purpose of this structure is to create a precise synchronic representation, such that diachronic analysis may be performed by comparing different instances. This model is called a *synchronic imprint* (SI); synchronic for its structural basis, and imprint referring to the fact that the actual meaning has been removed. For instance, a connection between the terms "Simpson" and "guilty" does not imply that O.J. Simpson murdered his wife, but simply that the two terms are structurally related in some way (in this case, that O.J. is *not* guilty).

The process of creating synchronic imprints is outlined in the following paragraphs. First, the document structure is broken into sentences. The concepts are then extracted by identifying the nouns in these sentences. A few stages of information retrieval processing techniques to improve performance are completed, and then finally the storage in one of two representations.

Sentence tokenization

The general algorithm for creating synchronic imprints starts with tokenizing the given text into sentences. It has been shown that in the case of the Brown corpus, the simplest algorithm for finding

sentence boundaries, namely breaking at periods and question marks, is at least 90 percent effective (Riley, 1989). For a first pass of evaluation, this performance is satisfactory, so a regular expression written in Perl is used to break the text into sentences.

Tagging

Next, concepts are extracted from the sentence by looking for nouns. This is accomplished by using a *part-of-speech* (POS) *tagger*, an analytical system that uses statistical data derived from typical sentences to decide the part of speech for each word in a body of text. I use Oliver Mason's freely available java-based tagger QTAG from the University of Birmingham (Mason, 1997), which employs the statistical method of Hidden Markov Models (Rabiner, 1989) to probabilistically determine each word's part of speech, based on a model built from human-tagged sentences.

Pre-processing

Before the final representation, two stages of standard IR pre-processing techniques are completed: stop-listing and stemming. A general stop-list roughly 500 terms long is used to remove common words, mostly pronouns, simple adjectives, conjunctions and prepositions. While there are very few nouns in the list, this process acts as a safety catch for uninformative terms that might slip through the POS tagger. The remaining terms are then stemmed to obtain a morphologically unique set of features, using the technique outlined by Porter (Porter, 1980). I use an implementation in Perl created by Daniel van Balen (Balen, 1999).

Representation

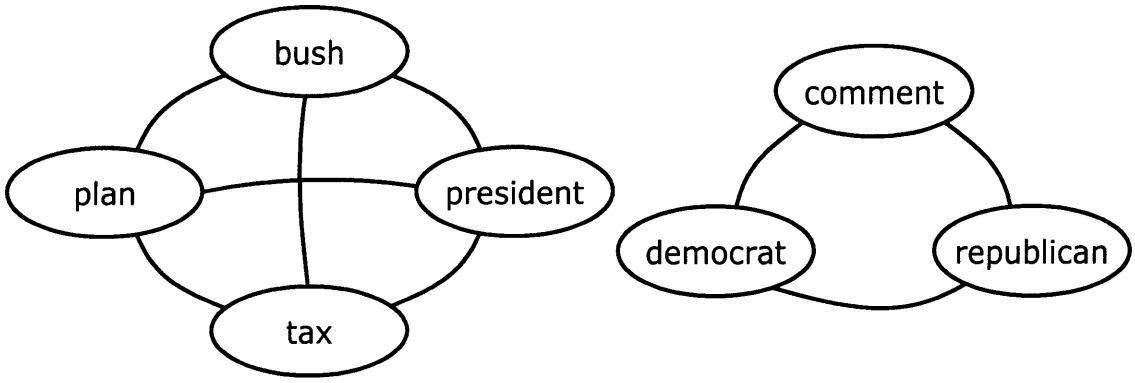
Finally, a set of the unique, stemmed, stop-listed terms for each sentence is constructed. The relationships between them can be modeled in two ways. First, using the same approach as the ARN, an undirected, weighted graph can be constructed, where the weight of each edge corresponds to the number of sentences in which those terms co-occur.

Alternatively, the text can be re-represented as word pairs corresponding to the relations. For each sentence we can replace the lexical features with relational features by taking these noun lists and generating pairs for each co-occurring word. For instance the pair Gorbachev and Reagan would be converted to "gorbachev-reagan" every time they occurred in a sentence together. Because the lexical structures of a sentence can be rearranged, the order of co-occurrences is considered not significant, so as a convention, lesser strings are always placed on the left. A couple of examples will illustrate these two representations:

Text: "President Bush announced his tax plan yesterday. Both Democrats and Republicans released disapproving comments."

Pairs: bush-president president-tax plan-president bush-tax bush-plan plan-tax democrat-republican democrat-comment republican-comment

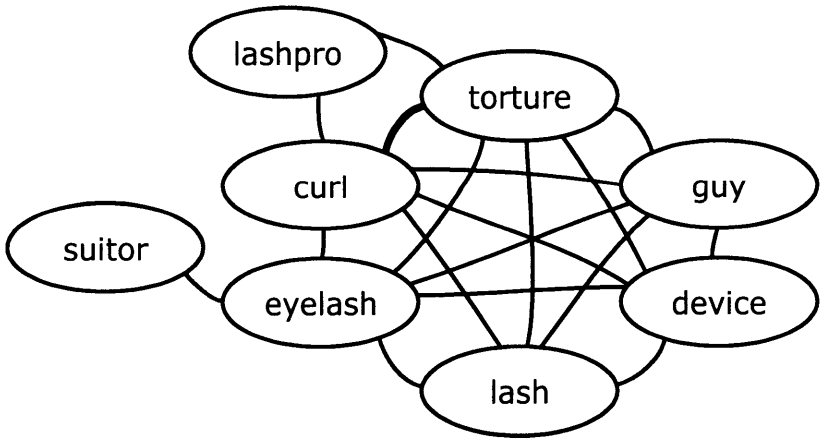
Network: (lines indicate edges with weight 1)



Text: "Not only do eyelash curlers look like torture devices, but after one of these little guys pinches you by the lash, you know they really are. Spare yourself the painful torture with standard curlers and try Lashpro. Now you can bat your eyelashes at your suitor guys instead of wincing and sniveling."

Pairs: curl-eyelash eyelash-torture device-eyelash eyelash-guy eyelash-lash curl-torture curl-device curl-guy curl-lash device-torture guy-torture lash-torture device-guy device-lash guy-lash curl-torture torture-lashpro curl-lashpro eyelash-suitor

Network: (thin lines indicate edges with weight 1, thick with weight 2)



Both of these representations covey the pair-wise relationships of concepts in a body of text. For sentences relating many concepts, an even higher-level structure might be imparted by trinary, quaternary, or even larger combinations. For these features, other representations, such as another undirected network or separate terms could be constructed. These extra features might provide yet another level of detail to

categorical comparison; this detail comes at the expense of a substantial increase in the number of features necessary to represent language. As a first pass at relating structural information, only second-order features were used. The addition of third and higher-level features is a platform for future experimentation.

The network model shown above is a spatially optimized version of the pairs representation; they are equivalent, as one can easily be generated from the other. The only advantage of the pairs is that they can be seen as words in the context of standard information systems (more so if the dashes are removed). This means that for in any existing information system, the structural information of synchronic imprints can be added to the functionality by simply replacing the standard terms with SI terms. In the following chapter, synchronic imprints will be evaluated as an alternative and added feature for automatic classification systems.

Word sense disambiguation

Computational linguistics research defines polysemy as the task of *word sense disambiguation* (WSD). Given a word with different possible meanings, the goal of WSD is to determine the given sense from the surrounding context of the word. A number of different approaches to this problem are outlined in (Ide & Veronis, 1998). The general methodology for addressing this problem is to break it into two stages:

1. Determine all of the possible senses for every relevant word to the text
2. Assign each occurrence of these words with the appropriate sense

An approach very similar to synchronic imprints is found in Marti Hearst's system *CatchWord* (Hearst, 1991). Hearst uses a number of surrounding features, including words and syntactic structures to provide a context for polysems. However, there is a fundamental difference between the WSD problem and this thesis research, found in the formulation of the problem: WSD looks to build systems that very accurately assign the correct meaning to a set of ambiguous words, typically looking for a mapping between dictionary definitions and words in a body of text. A typical example would be the word "bass," which can represent both fish and instruments.

Synchronic imprints on the other hand, look to provide a general context to all words, regardless of their level of ambiguity. Instead of senses, imprints may be seen as providing context for *uses*, the more general case of word meanings. Although they refer to the same sense, "bass" in terms of fishing guides will have a very different usage than from Sierra Club literature. The difference between these two cases could be an important factor in distinguishing documents about the topic of bass, which would be crucial to their classification.

4.3 Flux

The network representation of a synchronic imprint inspired development in the space of information visualization. Given the simplicity of the examples above, and the difficulty of understanding the relationships between terms by looking at the pair lists, it was a natural conclusion to build a system to help explore the relationships contained in an imprint. At the same time, such a system could used to explore how such relational information might be used to better describe documents in comparison to, or unison with the standard features of the text.

Motivation

A good starting point for visualizing text is an exploration of the standard vector-space model. The goal of visualizing synchronic imprints is to provide an alternative interface to the sometimes-cumbersome representation of electronic text. Many visualizations have used the vector-space model to show discrepancies *between* documents, but few have addressed using this representation at the level of one document.

Table 2: A simple visualization of terms from and issue of *Time* magazine

#	term	Frequency
1	bush	98
2	school	97
3	abortion	92
4	people	71
5	work	69
6	state	67
7	drug	67
8	american	63
9	women	63
10	doctor	60
...	...	...

Table 2 shows the simplest visualization of a body of text, as seen through the vector space model. The data is presented as a rank-ordered list of terms, sorted by the frequency of their co-occurrence. One could also imagine using a plot to show the quantitative discrepancies in the data. Both of these visual representations show the popular terms in a document, which can sometimes be important in discerning the important subjects. In the case shown, taken from an issue of *Time* magazine which covered the topics of political campaigns, school health, and an abortion drug, parts of each of these stories is conveyed in the top 10 terms. What is missing is the structure: how does each of these terms interact to create a larger story? This was motivating evidence that synchronic imprints could provide important information to visually representing large bodies of text.

Methodology

The general design methodology for visualizing the information presented in synchronic imprints comes from the pioneering work of Cleveland and McGill on the accuracy of perceptual tasks (Cleveland & McGill, 1984). Based on a number of tests visualizing statistical data, Cleveland showed a marked difference between the performances of subjects depending on the type of data and its graphical presentation. From these results, they created a mapping between data types and presentation which maximizes accuracy:

1. Quantitative: position, length, angle, slope, area, volume, density, color saturation, color hue, texture, connection containment, shape
2. Ordinal: position, density, color saturation, color hue, texture, connection, containment, length, angle, slope, area, volume, shape
3. Nominal: position, color hue, texture, connection, containment, density, color saturation, shape, length, angle, slope, area, volume

These rank ordered lists were used to decide the visual mappings employed in flux, always using the most accurate, unused presentation when a new mapping was constructed.

Physical modeling

In interactive interfaces, physical modeling is a popular technique for representing information; this is because people have an astounding amount of experience with the physical interfaces, and much less so with computer ones. By making computer interfaces act more like things encountered in the physical world, people bring an aptitude to the interaction that they otherwise would not have.

As mentioned, springs are a popular choice for interactive information displays; they were originally introduced as a simple method for constructing a spatial layout of weighted networks (Eades, 1984). A network is becomes a system of sprints simply by assuming that the edges are springs whose length or tension is correlated with the weight of the edge connecting those nodes. The force on any one of the springs is determined by how far it is from its resting state, described by Hooke's Law:

$$F = -kx,$$

where k is the natural property of the spring that determine its strength. An important attribute of this force is that it affects the spring both when the spring is compressed (shorter than its desired length) and when it is stretched (longer that its desired length). This means that at equilibrium, the ends of a spring are some distance apart. Thus a system of springs at equilibrium will have nodes generally set apart from each other, in a motionless state. This can be contrasted with other physical models, such as gravitation,

for which force only applies in one direction, and which varies at the square of the distance. In such a model equilibrium occurs when all entities either collide or fall into some oscillatory motion (such as the rotation of the earth around the sun).

Another important feature of spring models is that there are efficient algorithms for approximating spring motion, which make them simple to implement and very fast. Such an algorithm was included as an example program in an early version of the Java Developer's Kit (Sun Microsystems, 1998), and has inspired a number of spring-based interfaces, including Plumb Design's Visual Thesaurus (Plumb Design, 1998) among others. The algorithm works as follows: for each spring *s* in the set of all springs *S*, adjust the position of the two endpoints of that spring based on the current force on the spring. In this manner, the system is iteratively updated, one spring at a time, indefinitely, or until some level of entropy has been reached. This model has the side effect of creating unnatural oscillations; in a real spring system, all springs would move concurrently, but as each spring is updated independently in this iterative model, extra motion is introduced into the system, which causes nodes to overshoot their desired location regularly. This side effect can be fixed by adjusting the constant on the springs, and adding a small amount of dampening.

Visualizing synchronic imprints

A prototype visualization named *flux* was built using springs to model the relationships described by synchronic imprints. The prototype was built in OpenGL and c++ for speed and efficiency. Initially, a font rendering system from the Aesthetics and Computation Group (Aesthetics and Computation Group, 2001) was used to render the text of words at nodes; in later iterations, this was replaced by the FreeType system (FreeType Project, 2000), an open source font-rendering library, for considerations of efficiency and the ability to use TrueType fonts.

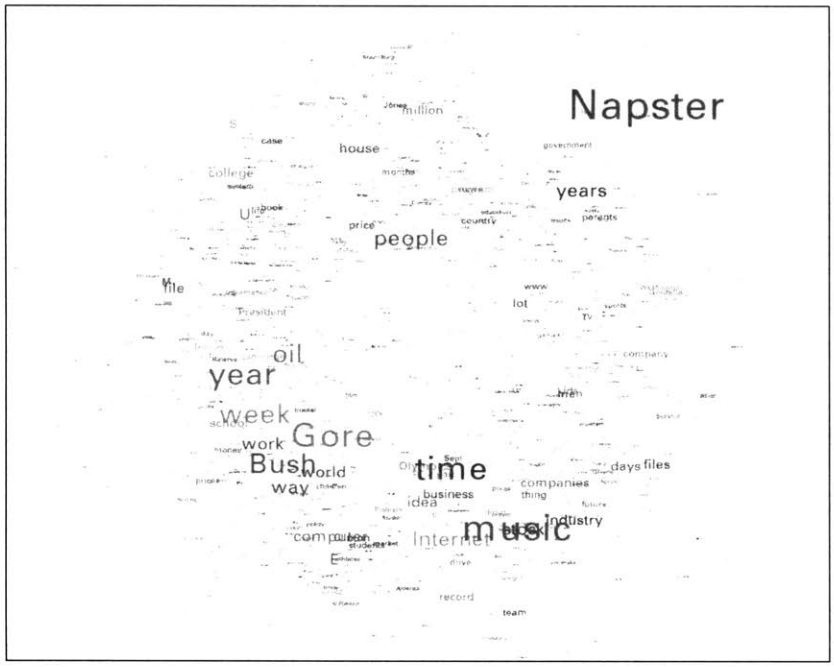


Figure 13: An early prototype of flux

Nodes in the network of synchronic imprints are words, and in the physical model of flux are considered to be massless points. An immediate thought was to use frequency information about the words to set the size of each term in the display. This allows attention to be drawn to the most important words in the system, but gives a false impression of mass (i.e. large words look heavy). However, for large bodies of text, it was necessary to place focus on some words, to bring some sense out of the mass. Using equal sizes for the terms, in addition to using the relational information of the synchronic imprint to determine size are were both considered later, and are included in the evaluation. The variance of term sizes gave an appearance of depth to the system, which initially it did not have. Since the comparative advantage of having interaction in the third dimension conflicted with the need for focus by different term sizes, the model was constrained to a two-dimensional plane.

Co-occurring terms would be connected by massless springs, but two values would need to be decided for each spring: both the strength of the spring, and the desired length. Three options were immediately apparent:

1. Normalize the spring length. Make all springs a set length, and vary the strength of the spring based on the relationships of the words. At equilibrium (if such a state exists), all words would be

equidistant from connected words, and only in movement of the system would the relationships become apparent.

2. Normalize the spring strength. Give all of the springs the same constant, and vary the length of the spring based on relationships. At equilibrium, the distance between words would predict information about relationships.

3. Vary both values. Use information about co-occurrences to manipulate both the spring constant and the length of the spring. These values could be either negatively or positively correlated, depending on whether one wanted short springs to be stronger, or longer ones.

Since the goal of the visualization is to understand the relational structure of synchronic imprints, the second option was implemented first, with the other two evaluated at a later time, and considered in the evaluation. The first iteration of this model, as depicted in Figure 13, used a spring length inversely related to the number of co-occurrences (i.e. more frequently co-occurring words would be pulled closer together than less frequent ones), normalized by the maximum number of co-occurrences. The initial layout of the nodes would be random, letting the springs move the system towards equilibrium.

After considerations to be discussed in the evaluation, it was realized that the spring length needed to be normalized by the frequency of the connected terms, so the final model was based on the following equation:

$$L_{a,b} = \frac{\min(f_a, f_b)}{cof_{a,b}},$$

where *f* refers to the frequency of a term in the original text, and *cof* refers to the frequency of two terms co-occurrence. When this modification was made to the model, the terms went from being equidistant (as seen in Figure 13), to having their distance correlated more closely by relation (as in Figure 14). This effect is discussed at length in the evaluation.

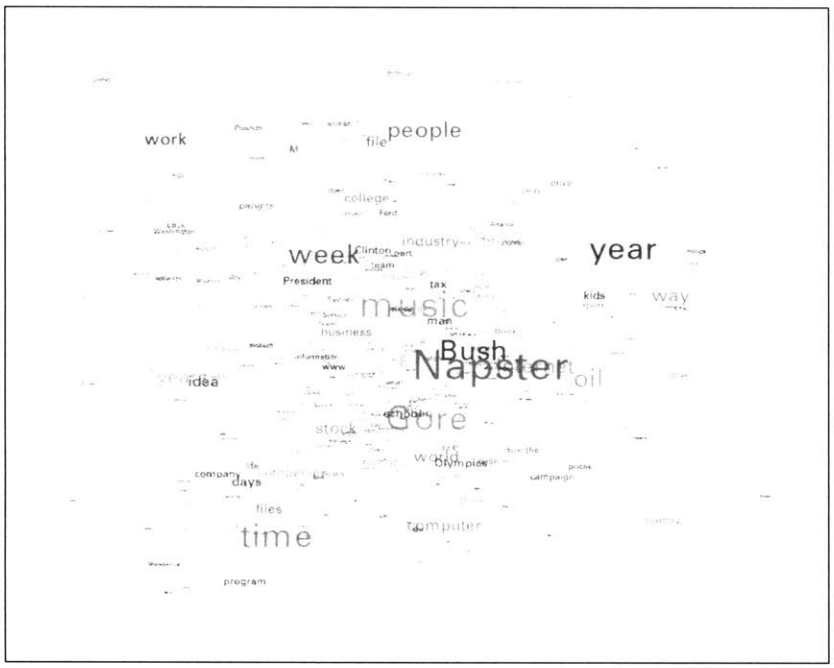


Figure 14: Flux with a new spring distance model

Visualizing connections

A crucial component of the flux visualization is the ability to recognize the existence, and additionally the state of the springs. To facilitate this, edges are drawn in between connected terms, the color saturation of which is determined by one of three models, corresponding to the order of images shown below:

1. Saturation is a polynomial function of the tension of the spring, brighter values corresponding to higher tensions. Below a certain threshold, the edge is invisible. This tends to place stress on only the springs in motion, as at a typical local equilibrium, most edges will be below the threshold.
2. Saturation is a linear function of the tension, and invisible below a threshold. This places emphasis on both the springs in motion, and those that are locked in a high-energy state, as the threshold is lowered.
3. Saturation is a constant function, unrelated to tension. This focuses attention on the complexity of the network, showing even those relations that are at their desired length.

Saturation was chosen since the information conveyed by the springs falls under the class of ordinal data, as specified by (Cleveland & McGill, 1984).

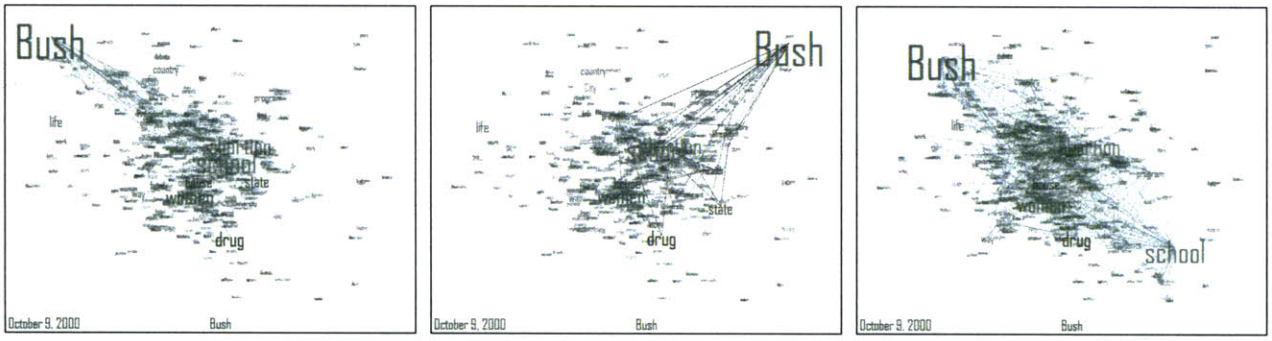


Figure 15: Three models for edge brightness: polynomial, linear, and constant

Interactivity

Given the number of springs in the model, and its constraint to a two-dimensional space, it became quickly evident that the system would never reach a perfect equilibrium. Furthermore, the intended purpose of the visualization was to enable the exploration of relationships, which necessitated some level of interactivity. After many iterations of design, three types of interactivity were implemented:

1. Local model control: using the mouse, a user could manipulate the model at a local level by fixing one of the terms to the mouse, and allowing them to move the term anywhere on the screen, and see how their local change affects the model as a whole.
2. Global model control: using various keys, a user can manipulate the global constants controlling the model.
3. Data model control: also using keys, a user can change the current data model to compare features between different bodies of text.

A complete users manual for flux is included as an appendix to this thesis, but some of the global features available to the user include: adjusting the general spring constant, re-randomizing the model, pausing the model update, and adjusting the maximum spring length.

Focus

One final feature that was added to flux recently was the ability to focus attention on a piece of the model. This is accomplished by highlighting the word currently in mouse focus, and all words connected to that word. In some sense, this is the most important feature, because it allows a user to truly explore the relationships in complex set of associations that is otherwise difficult to parse. By adding the ability to expand the focus to two or three connections from the focus word, the user is enabled to explore not just the relationships that could be processed by merely listing all of the connected features for a word, but

how generally connected the word is to the rest of the network, the branching factor, and other curious attributes.

4.4 Conclusion

Both elements of design for this thesis, the development of synchronic imprints and flux, were heavily influenced by the task at hand. In the case of the synchronic imprints, this was the process of automatic categorization, with the goal of achieving a level of accuracy comparable to a human counterpart. For flux the problem being addressed was creating a metaphor for exploring these same categorizations visually. While the development of both representations had a strong influence on the other, the most influential source of guidance came from the evaluation and reiteration of design that came from benchmarking synchronic imprints in automatic categorization, and actually using flux to explore visual categorization.

5 Evaluation

Synchronic imprints were built to provide a new level of detail to the analysis of electronic text; the focus of this chapter is to establish the effectiveness of this representation. Separate evaluations were performed for each part of the design, one evaluating the usefulness of synchronic imprints in existing information-system infrastructure, and the other investigating the value of imprints as an analytical tool for people to visually explore text. The computational evaluation takes a standard metric for analyzing information systems, namely the measures of *precision* and *recall*, to compare synchronic imprints to the customary word features in the context of the well-specified text categorization problem. The human evaluation is a set of lessons learned while developing and displaying the flux visualization tool in its effectiveness for understanding synchronic imprints and their functionality.

5.1 Synchronic imprints and automatic classification

Like many open problems in computer science, classification has become a rigorously defined topic space with a comprehensive set of evaluation metrics. Over the past twenty years, the creation of standard corpora and techniques for analyzing systems has allowed the performance bar for classification to be iteratively raised. While the second half of my evaluation focuses on what the gain might be for people interacting with synchronic imprints, this section adheres to the standards set down by the information-retrieval community to understand the net return of this new representation.

Experimental setup

The most classic categorization test setup revolves around the Reuters-21578 corpus, as it is one of the oldest and most challenging data sets available; for these reasons, variants of the corpus have been the benchmark for evaluating text categorization systems in the past 10 years. In the past few years, popularity of support vector machines (SVM) for classification tasks has unleashed a set of papers benchmarking the new competitor against other systems (Joachims, 1998; Yang & Liu, 1999), all of

which have proclaimed SVMs a winner. In this section, I will introduce the experimental apparatus, namely the support vector machine system SVM^{light}, the Reuters-21578 corpus, and the preparation of synchronic imprints for the task of classification.

Reuters-21578

The Reuters-21578 corpus is a set of news stories that originally appeared on the Reuters newswire over the course of 1987. The documents were hand categorized by employees of Reuters, formatted by David Lewis and Peter Shoemaker, and released to the public in 1993 as the "Reuters-22173 distribution 1.0" (the numbers refer to the number of total documents in the corpus). After a few years of testing and evaluation, the corpus was reformatted to be less ambiguous, and exact duplicate stories removed, establishing the Reuters-21578 distribution (Lewis, 1994).

Within this collection, there are a few different types of classes, but the standard set used for classification research is one set of categories titled *topics*, a collection of economic subjects. Every classification corpus is divided into two sets: one for training classification systems, and one for testing. I use the most popular *split*, or division, of the Reuters-21578, known as the ModApte split (Apte, Damerau, & Weiss, 1994). The training set contains 9603 documents and the test set contains 3299, with the additional 8676 documents being unused.

After removing categories that do not contain at least one training and one test document, there are a total of 90 categories in the ModApte split. Figure 16 shows the distribution of training documents among these categories. This graph tells the story of the skewed nature of the Reuters collection. As noted in (Yang & Liu, 1999), the largest category has 2877 test documents, while 82 percent of the categories have less than 100. Most of these categories are related to commodity industries, such as corn, soybeans, and natural gas, while a few represent more abstract classifications such as earnings reports, trade, and acquisitions.

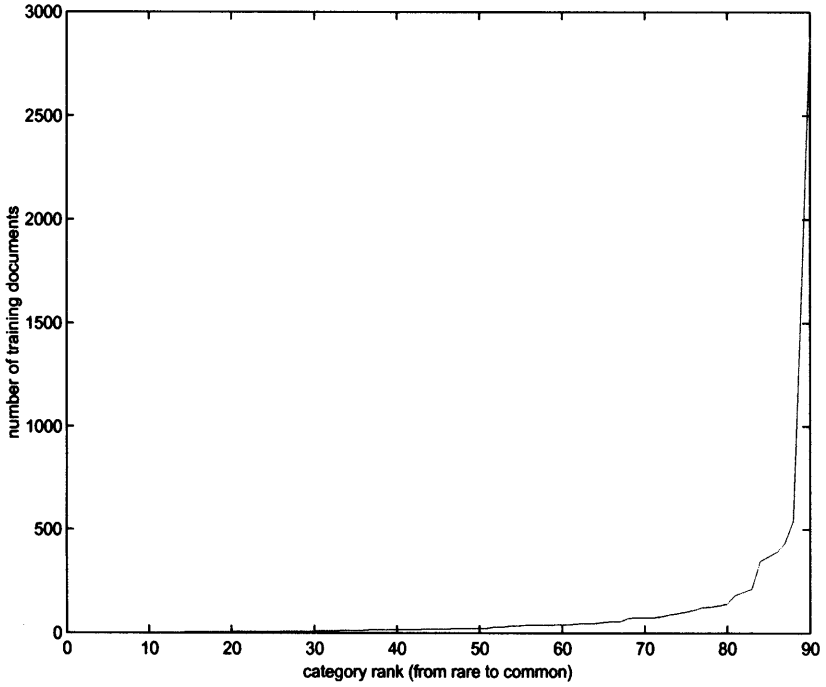


Figure 16: Training set sizes for Reuters-21578 ModApte split

Support vector machines

The focus of my evaluation is not related explicitly to the learning approach, so the choice of a classifier is mainly to provide a good basis for comparison. Support vector machines have outperformed most other techniques in recent evaluations (Joachims, 1998; Yang & Liu, 1999), and are highly optimized for a varying number of features. Since the dimensionality of synchronic imprints could possibly require these performance characteristics, SVMs were the natural choice. For regularity with other tests, I will be using the popular SVM package SVM^{light} written by Thorsten Joachims (Joachims, 2000).

Binary vs. m-ary

The problem of classification can be stated in two ways: first, it can be treated as *binary*, where each classification task is deciding true or false for one given document in one given class. It can also be viewed as *m-ary*, where for each document classification is deciding *all* classes for that document at once. Both of these approaches require different representations; for the binary method each class is represented individually, whereas the m-ary model assumes one representation for the entire set of classes. Learning systems are built under the assumption of one of these models and differ depending on what information they use to perform classification.

The choice of a classification model is determined by the goal of the evaluation. If the goal is to compare different learning techniques, such as some of the benchmarks used for this thesis, then the m-ary model is chosen. In some senses, the m-ary model subsumes the binary, as binary classifiers can be used in an m-ary representation, but not the reverse. If the evaluation's goal is to focus on an individual learning approach, the binary model is typically used (Lewis & Ringuette, 1994; Moulinier, Raskinis, & Ganascia, 1996), as each classification problem is mutually exclusive from the rest; this provides a better experimental setup for comparison between classes. Since this thesis is not concentrating on approaches to learning, with only one system being tested, the binary model will be assumed. Using this technique, separate vector spaces will be constructed for each class, depending on the features important to that class. The comparison of these feature spaces will be one metric for understanding the strengths and weaknesses of each representation.

Document preparation

The Reuters-21578 collection is packaged as a set of SGML files tagged with appropriate information regarding divisions, classes, and other attributes. The first stage of development for this evaluation was the re-representation of the corpus into various formats necessary for testing. For the standard words representation (*words*), terms in the documents were stop listed and stemmed, and for synchronic imprints (*SI*), the documents were represented as SI-pairs using the algorithm described in chapter 4. A third, hybrid representation (*hybrid*) was created to amalgamate both models, where each document was simply constructed from the concatenation of terms in the same document in both other representations.

The next stage of development was to determine the features for each category. The χ^2 feature-selection algorithm was employed, based on its performance in evaluations of feature selection for the task of text categorization (Yang & Pedersen, 1997). For each class, a list of terms was created from the training documents, rank-ordered by the χ^2 algorithm, including the dual representation of the hybrid model. These *feature lists* were recorded to disk for use in the learning and classification tasks, and for reference in analyzing the features important to each class.

The final stage of data transformation was in the conversion of test and training documents to the representation used by SVM^{light}. For each class, the classifier was trained at different dimensionalities, or using different numbers of terms to represent the documents. If the specified number of dimensions is n, then the first n terms from the given category's feature list was used to represent the document. As suggested in (Joachims, 1998), the *inverse document* frequency, a value based on the frequency of a word in other documents, was used to scale the dimensions. For each term t_i, the document frequency $DF(t_i)$ is

the number of documents in the corpus that t_i appears in. From this value the inverse document frequency, is defined by:

$$IDF(t_i) = \log\left(\frac{n}{DF(t_i)}\right).$$

This value, first introduced by Salton (Salton & Buckley, 1988) is typically used for stressing important terms in other applications of the vector-space model. The representation created for the classifier was simply a list of the frequencies of its terms, scaled by this factor.

Evaluating text categorization

Precision and recall

The standard means for evaluating information retrieval algorithms are the measures of *precision* and *recall*. These two statistics represent the tradeoff between specificity and coverage. Figure 17 is a representation of this measurement applied to the domain of classification.

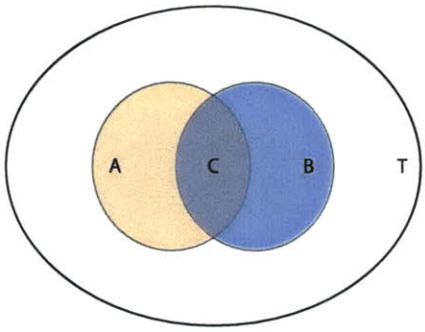


Figure 17: Precision and recall. T is the set of all test documents, B is the set in a given class, A the set predicted by a classifier, and C is the intersection of A and B.

In the diagram, T is the set of all test documents, B is a set of documents in a given class, A is the set returned by the classifier, and C is the set of correctly classified documents (the intersection of A and B). If the cardinality of set A, or the number of elements in A is denoted by $|A|$, then we can define precision p and recall r by the following equations:

$$p = \frac{|C|}{|A|} \qquad r = \frac{|C|}{|B|}.$$

Since C is at most the size of the smaller of A or B, then precision and recall fall in the range of $[0,1]$. In most information retrieval systems, these two values can be changed by adjusting parameters within the

system; in most cases, these variables have an affect on the scope of the returned documents. Figure 18 shows the tradeoff between precision and recall, where in the first case a system is adjusted to provide high precision and the other high recall.

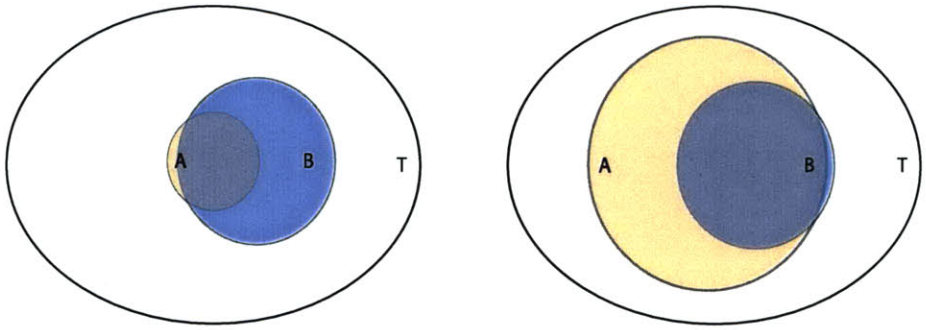


Figure 18: High precision vs. high recall

Combining the two

Because of this variability, precision and recall are not usually considered good measurements by themselves. Instead, two alternatives have become popular: the precision-recall breakeven and the F-measure. In the case where there is a clear correlation between some variability in the system and a performance/recall tradeoff, the precision-recall breakeven point is usually used. This is the point at which precision and recall are the same, providing a single score that relates the two values together. Sometimes variability of precision and recall is not a simple task, in this case, an alternate measurement known as the F-measure has been created to relate precision and recall:

$$F = \frac{2rp}{p+r}$$

This measurement was introduced by van Rijsbergen (van Rijsbergen, 1979) in reference to the problem of search but has become a popular metric for evaluating classification systems.

For my evaluation, I will use the F-measure as a metric for effectiveness of classification. My evaluation is comparative, and my benchmark is Yang's comparative analysis that also uses this measure (Yang & Liu, 1999). Since the feature spaces of both words and synchronic imprints vary widely, I am testing different size feature spaces for each class, with the final measure being designated as the feature space that produced the maximum F-measure. Further testing could be done to determine the precision-recall breakeven point at this number of features, but for a comparative analysis, the F-measure will suffice.

Averaging over many categories

Typically the evaluation of classification systems is done over a set of categories, and thus the results from each category must be merged into a global measurement of overall performance. There are two standard ways of combining the results: *micro-* and *macro-averaging*. The first measurement looks at the performance of the system globally, considering all of the categories as one set of decisions. From these decisions, the overall precision, recall and F-measure are calculated. The second method is simply to calculate each category performance individually, and then average those scores into one value.

For most corpora, the set of categories is not distributed uniformly, and the Reuters-21578 corpus demonstrates such skewing. In this distribution of category sizes, the micro and macro averages produce very different scores. If the micro-average is used, a weight is placed on the performance on the larger categories, and if the macro-average is used, a weight is placed on the smaller ones. For this evaluation, each class is an example, and thus micro-averaging the results in a loss of information. Macro-averaging is used whenever comparisons are made, but results are usually broken into groupings based on the size of categories, so that overall results are not skewed.

SI-space

What does the space of synchronic imprints look like? Before jumping into a comparative analysis of results, I will explore the fundamental differences between imprints and words. Building synchronic imprints involves a combinatorial explosion in the number of terms associated with a document; each set of nouns in a sentence is replaced by all combinations of those nouns in two-word pairs. In the Reuters-21578 corpus, after the initial preparation (stemming and stop listing), there are 13,821 unique nouns in the training set, which accounts for 67.5 percent of all terms. If the set of features for representing documents included every pair of these nouns, there would be roughly

$$\binom{13{,}821}{2} = \frac{13{,}821!}{2!13{,}819!} = 95{,}503{,}110$$

dimensions to represent the documents. Simply accounting for all of the strings associated with these dimensions would take a considerable amount of storage. Thankfully, the actual number of dimensions in the synchronic imprint representation is 459,055, over two orders of magnitude smaller than the upper bound. As with the normal words, nearly half of these dimensions go away if we remove the terms that have only one instance in the corpus.

The fact that only 0.5 percent of the possible dimensions are accounted for experimentally points to a key feature of synchronic imprints. Every possible pair of nouns that is not represented as a feature represents a semantic connection that does not exist. While the initial explosion of 20,000 by a factor of 20 seems

expansive, it is tiny in comparison to the set of all possible combinations. Each of these combinations results in a new feature whose meaning is more specific than the sum of its constituents. For instance, take the words "scandal" and "Clinton," each of which is a general term that might appear in many news stories, but together form a feature very specific to Bill Clinton's private life. This increase in specificity creates a reduction in the average frequency of a term, down from 33 times in the Reuters corpus using words to 3 times using synchronic imprints.

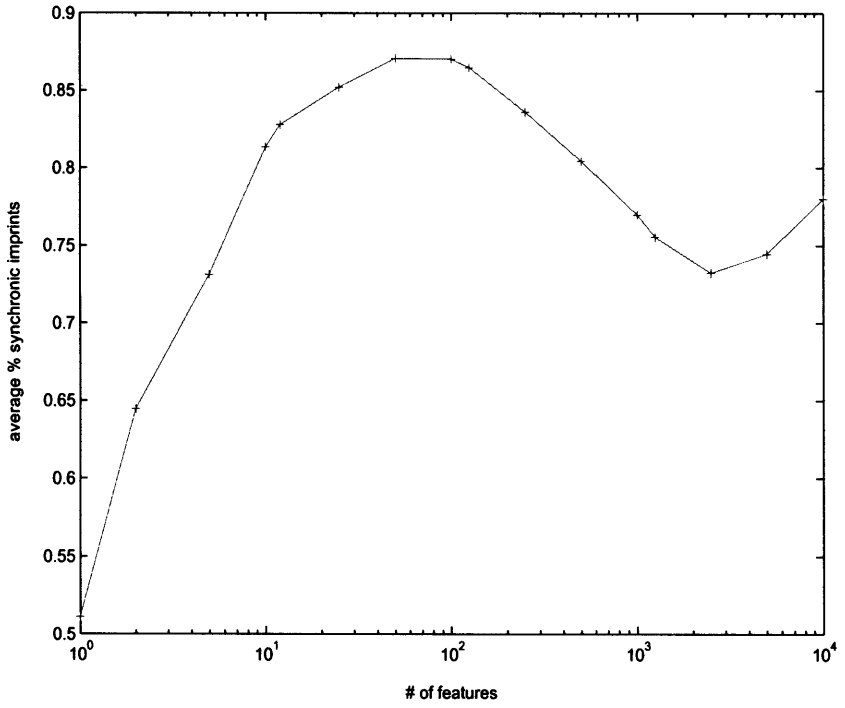


Figure 19: SI features selected in the hybrid model

Given that these two representations, words and synchronic imprints, have very different distributions and numbers of terms, what then does the hybrid model look like? As noted earlier, the hybrid is simply a combination of both sets of terms, and thus the complete vector space is merely the sum of the two separate vector spaces. Before classification is performed though, this hybrid space is reduced to the necessary number of dimensions by the feature selection algorithm, choosing some subset of words and synchronic imprints. This selection is made without regard to the origin of the words; instead it is defined by the importance of each term to the task of classification. One interesting measurement that falls out of this model is the relative importance of each feature type to the importance of the class, which can be measured by the percentage of terms from that type in the feature list.

Figure 19 shows the distribution of synchronic imprints in the hybrid model. For a given number of features *n*, the percentage of synchronic imprints in the top *n* terms averaged across all feature lists is recorded. Over the entire set of lists, the smallest average percentage of imprints is 50 percent, recorded with only one feature. As we follow the values towards 100 features, the plot increases. It then decreases between 100 and 2500 terms. This phenomenon, "tiers" of terms, is related to the χ^2 feature-selection algorithm (remember that the χ^2 value of a term is related to the dependence of that term on a given category). As shown in Figure 19, the overall dependence of words terms and synchronic imprints terms appears to oscillate, starting with words, shifting to imprints, and then back to words again.

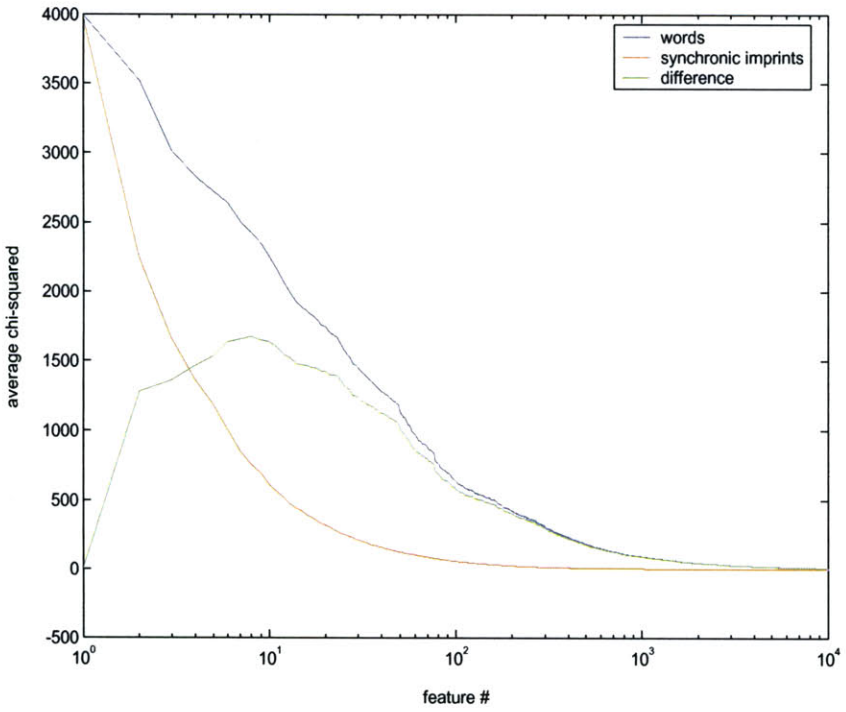


Figure 20: Average χ^2 by feature list number

This effect can be described by the relationship between the χ^2 feature-selection algorithm and both methods. Figure 20 shows the average χ^2 values for the feature lists of words and imprints, i.e. feature 10 corresponds to the average value across all categories for the 10^{th} item in the χ^2 feature list. This plot, which is shown on a logarithmic scale, shows an order of magnitude difference between the fall off of values in the models. This difference can be described by the number of features associated with each category. The baseline for χ^2 values is very close to zero, which typically results from a term not occurring in the given category. Due to the explosion of terms created by SIs, each category will have

around twenty times the number of unique terms, causing the χ^2 value to fall off much more slowly, reaching the baseline an order of magnitude later than with words.

Results

Classification tests were run for spaces of dimensionality 25, 50, 100, 250, 500, 1000, 2500, 5000, and 10000. The maximum F-measure for each category was recorded, and in the case that the same F-measure was found for multiple dimensionalities, the smallest was logged. These results were macro-averaged to obtain an overall performance measure for each technique, and are logged in Table 3.

Table 3: Performance summary of different methods

representation	macro-*p*	macro-*r*	**macro-F**	macro-*p* 60	macro-*r* 60	**macro-F 60**
benchmark			**0.5251**			
words	0.4961	0.6071	**0.5460**	0.5862	0.7331	**0.6515**
synchronic imprints	0.5830	0.5184	**0.5488**	0.7676	0.6844	**0.7236**
hybrid	0.6350	0.5387	**0.5829**	0.8067	0.6828	**0.7396**

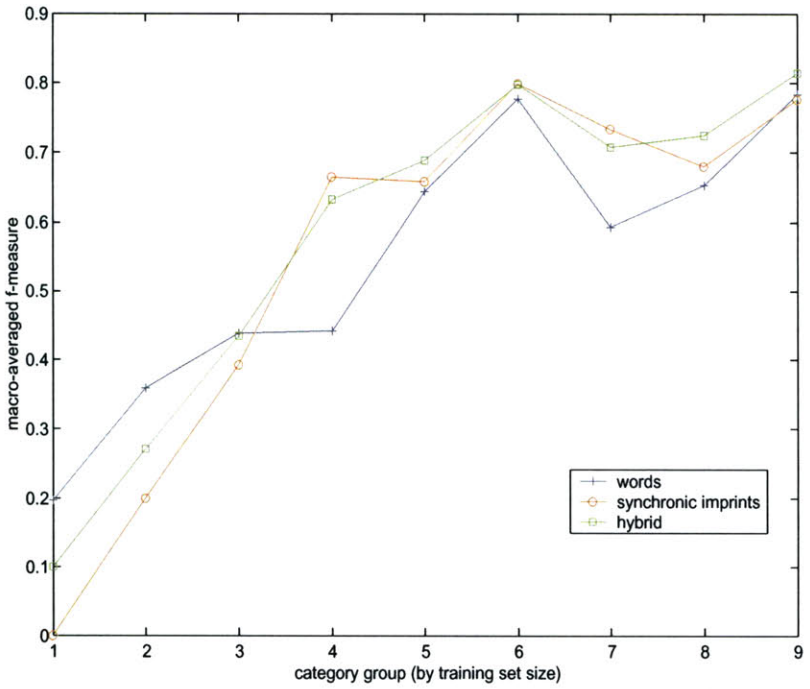


Figure 21: macro-averaged f-measure in groups of 10 (from rare to common)

The results shown in Table 3 show a words macro f-measure slightly higher than Yang (Yang & Liu, 1999), recorded in the table as "benchmark." This can probably be accounted for by either the use of a binary classification model or by slight differences in the feature preparation process. The first f-measure

accounts for all 90 categories and shows a marked performance difference between words and hybrid. Synchronic imprints performed very poorly in categories that had very few documents (< 10 training documents), usually scoring zero correct positive classifications. In many of these cases, there was no overlap between the synchronic terms in the training set and in the test set, which is inevitable with a more descriptive representation. For this reason, the macro f-measure was calculated for only the top 60 categories, or those with at least 10 training documents. This statistic shows a large gap in performance between the standard word representation and synchronic imprints.

To get a feeling for how the frequency of documents affects the success of the different models, Figure 21 shows the macro-averaged f-measures for groups of 10, arranged from the smallest categories to the largest. Once the threshold of 10 training documents is crossed, both synchronic imprint and hybrid models outperform words in every group.

Analysis

The results of the Reuters-21578 corpus are easy to distinguish but have yet to be substantiated. Why, in some cases, do synchronic imprints outperform words, and why in others is the reverse true? To analyze the representations, three categories were isolated for both cases by finding the bounds of the following equation for category *C*:

$$diff = |C| \times (F_w(C) - F_{si}(C))$$

where F_{method} denotes the f-measure for *method.* At the bounds of this value are large categories with a significant performance differences between synchronic imprints and words. The top three and bottom three categories are listed in tables 2-7, showing the top 15 terms ranked by χ^2 for each representation, the maximum f-measure, and number of features used for the maximum. While these features (terms, f-measure, optimal dimensionality) are not guaranteed to explain the results, they will be used to create a hypothesis. It is worthwhile to note that these tables expose some of the errors propagated in the creation of synchronic imprints, such as the misconstrual of "rose" as a noun in table 5, but they are nonetheless a useful tool for analyzing the results.

In each of the following tables, the maximum f-measure is displayed beneath the category title. This measure was achieved at some number of dimensions between 25 and 10,000. However, the dimensionality of the categories did not have a significant impact on the performances in comparison. In each case, the f-measure at the smallest number of dimensions (25) was comparable to the one listed, but for consistency, the maximum is shown.

The constraints of concepts

Synchronic imprints are constructed from the relationships between concepts in a body of text, and as one might expect, some categories have important features that are not concepts. The two weakest categories for synchronic imprints come at the expense of focusing on concepts (nouns). Tables 2 and 3 report a poor performance for imprints in the categories *earn* and *acq*; it is first important to note that both the words and hybrid models achieved similar f-measures with very few features (25), despite the fact that their highest performance was with a large dimensionality. On this measure, the top 15 terms should be good discriminators of why the performance varied so much.

Earn is composed of earnings reports from various companies and industries, which are released whenever there is a change in a company's assets. The high frequency of these reports has led to the creation of a standard set of abbreviations for the specific terminology. Table 2 lists the top 15 terms from the feature lists of the respective representations. Nine of the top 15 words terms are earnings report lingo, such as "shr" for shares and "rev" for revenue. Of these nine terms, many are removed in the process of isolating nouns; some do not appear at all, such as the most important word feature "ct," and others are considered nouns only in certain contexts. Since these defining features are not represented in synchronic imprints, the performance is hindered. The hybrid representation regains some performance by placing emphasis on these word terms.

Table 4: Feature lists for the category of earnings reports (*earn*)

earn	χ^2	earn si	χ^2	earn hybrid	χ^2
0.964		0.769		0.961	
ct	5491	shr-year	1275	ct	5491
shr	4052	loss-year	1232	shr	4052
net	3931	rev-shr	1207	net	3931
qtr	3224	loss-profit	1188	qtr	3224
rev	2593	loss-rev	1181	rev	2593
loss	1791	loss-shr	999	loss	1791
4th	1574	rev-year	994	4th	1531
profit	1388	dlr-loss	893	profit	1388
div	1275	profit-year	815	shr-year	1275
dividend	1231	profit-rev	721	div	1275
prior	971	dlr-rev	719	loss-year	1232
record	961	dlr-shr	707	dividend	1231
qtly	961	loss-oper	637	rev-shr	1207
avg	951	dlr-profit	573	loss-profit	1188
note	852	profit-shr	573	loss-rev	1181

An analogous case can be found in *acq*, the category describing corporate acquisitions. Because the category represents a process (acquiring), many of the defining word terms are verbs: "acquire," "buy,"

and "complete," all have higher χ^2 values than the first-ranked synchronic imprint, and are discarded by the part-of-speech tagger. It is important to keep in mind that this is not a disadvantage of synchronic imprints, rather a difference in representation that determines strengths and certain weaknesses. In the case of classes that depend on a highly specialized set of abbreviations (*earn*) or are associated with a process (*acq*), it happens to be a weakness.

Table 5: Feature lists for the category of acquisitions (*acq*)

acq	χ^2	acq-si	χ^2	acq-h	χ^2
0.904		0.886		0.889	
acquir	1991	share-stake	520	acquir	1991
stake	1243	corp-share	509	stake	1243
acquisit	1195	offer-share	445	acquisi	1195
merger	952	group-share	418	merger	952
share	841	exchang-share	380	share	841
compani	762	commis-share	379	compani	762
sharehold	724	cash-share	372	sharehold	724
bui	628	approv-subject	356	bui	628
undisclos	550	compani-merger	341	undisclos	550
complet	549	exchang-file	336	takeov	532
takeov	532	secur-share	336	share-stake	520
common	509	acquisi-corp	332	common	509
group	499	commis-file	322	corp-share	509
ct	480	group-stake	321	group	494
corp	460	group-investor	317	ct	480

Coping with polysemy

One of the purported strengths of synchronic imprints is that it provides context to terms that are otherwise ambiguous. Two of the top performing categories for synchronic imprints are related to the ambiguous term "money." The first, *money-fx* covers the topic of foreign exchanges, while the second, *money-supply*, contains stories about shifts in the currency market. In both of these categories, the term "money" is in one of the distinguishing words, despite the fact that is ambiguous. This ambiguity is resolved by synchronic imprints, which represent the same frequency of "money" with two separate relationships: "money-market," and "money-supply." Other contexts of the term money appear as well, such as "london-money" and "england-money" in the case of *money-fx* and "growth-money" for *money-supply*. In both cases these terms are considered much more significant in terms of feature selection, and make up a large percentage of the hybrid terms.

Table 6: Feature lists for the category of foreign financial markets (*money-fx*)

money-fx	χ^2	money-fx si	χ^2	money-fx hybrid	χ^2
0.596		0.656		0.644	
currenc	1604	market-monei	1799	market-monei	1799
dollar	1585	london-monei	1716	london-monei	1716
england	1134	bank-market	1649	bank-market	1649
interven	1121	england-market	1403	currenc	1604
monei	1058	dollar-yen	1363	dollar	1585
central	907	bank-england	1326	england-market	1403
shortag	883	england-monei	1288	interven	1382
bank	865	bank-stg	1258	dollar-yen	1363
dealer	856	monei-stg	1255	bank-england	1326
yen	842	london-market	1174	england-monei	1288
intervent	826	shortag-stg	1152	bank-stg	1258
market	753	bank-shortag	1151	monei-stg	1255
band	746	england-stg	1151	london-market	1174
assist	641	exchang-rate	1148	shortag-stg	1152
stabil	584	market-stg	1104	bank-shortag	1151

Table 7: Feature lists for the category of the currency market (*money-supply*)

money-supply	χ^2	money-supply si	χ^2	money-supply hybrid	χ^2
0.429		0.613		0.619	
monei	850	monei-suppli	2175	monei-suppli	2175
fed	756	monei-rise	1681	monei-rise	1681
suppli	750	dlr-week	1447	dlr-week	1447
m3	731	monei-rose	1424	monei-rose	1424
m1	413	dlr-monei	1282	dlr-monei	1282
narrowli	356	growth-monei	1052	growth-monei	1052
m2	346	monei-week	1026	monei-week	1026
reserv	343	rose-suppli	1015	rose-suppli	1015
chequabl	338	reserv-week	954	reserv-week	954
defin	332	billion-suppli	954	billion-suppli	954
week	326	growth-suppli	834	busi-loan	947
m0	301	monei-reserv	802	billion-monei	901
window	297	borrow-week	772	monei	850
grew	293	bank-suppli	760	growth-suppli	834
deposit	291	borrow-discount	683	monei-reserv	802

Trading off

In each of the cases observed so far, there has been a direct correlation between the χ^2 value of a term and the value of that term in classifying documents in the given class. For *earn* and *acq*, the value of χ^2 for the words terms was significantly higher than those of synchronic imprints, predicting a better classification by words, and for *money-fx* and *money-supply*, the same was true for SIs. For the entire corpus, this is not

the case; in some instances, the χ^2 metric for feature selection is not as well correlated with the relative strengths of the approaches. The final two examples of varying performance fall into this category.

Table 8: Feature lists for the shipping industry (*ship*)

ship	χ^2	ship si	χ^2	ship hybrid	χ^2
0.777		0.922		0.810	
ship	3450	ship-vessel	957	ship	3450
vessel	2605	gulf-missil	861	vessel	2605
port	1633	port-strike	861	port	1633
tanker	1397	port-spokesman	819	tanker	1397
warship	957	port-ship	819	warship	957
seamen	874	port-union	771	ship-vessel	957
missil	761	ship-strike	766	seamen	874
escort	718	oil-tanker	766	port-strike	861
strike	709	iran-missil	765	gulf-missil	861
cargo	689	gulf-iran	733	port-ship	819
shipown	669	seamen-strike	686	port-spokesman	819
load	552	seamen-union	671	port-union	771
freight	529	cargo-port	640	oil-tanker	766
hormuz	526	gulf-ship	623	ship-strike	766
sea	520	seamen-ship	623	iran-missil	765

Ship is the category of the shipping industry, and presents and interesting case for feature selection. The features important to synchronic imprints include two types: combinations of important words features ("ship-vessel," "port-strike," "port-ship," etc.), and combinations of important words features with other features ("gulf-missil," "port-spokesman," and "iran-missil"). The most surprising characteristic of *ship* is the χ^2 values for the top SI terms, which are significantly less than the corresponding words terms. This discrepancy accounts for the marked drop in hybrid performance, placing the better SI terms down in the list.

The *grain* category represents a similar type of category (industry), for the commodity of grains. Terms in synchronic imprints are almost entirely constructed from combinations of the top words terms. The χ^2 values for synchronic imprints are analogous to *ship*, with top terms less than half of words terms. In this case though, the improved hybrid results suggest that this weighting is actually correct.

Table 9: Feature lists for the category of the grain commodity (*grain*)

grain	χ^2	grain si	χ^2	grain hybrid	χ^2
0.892		0.826		0.921	
wheat	4559	tonn-wheat	2054	wheat	4559
grain	3611	agricultur-depart	1623	grain	3611
corn	2426	export-wheat	1470	corn	2426
agricultur	2171	grain-tonn	1280	agricultur	2171
usda	1785	wheat-year	935	tonn-wheat	2054
tonn	1667	export-tonn	893	usda	1785
crop	1307	agricultur-wheat	872	tonn	1667
maiz	1065	corn-tonn	870	agricultur-depart	1623
barlei	1041	grain-wheat	829	export-wheat	1470
farmer	831	grain-year	809	crop	1307
rice	754	program-wheat	808	grain-tonn	1280
soviet	687	market-wheat	787	maiz	1065
bushel	665	crop-wheat	765	barlei	1041
soybean	653	enhanc-export	722	wheat-year	935
ussr	637	grain-trade	703	export-tonn	893

The clearest observation of these analyses of *grain* and *ship* is that the χ^2 metric is not perfect at predicting the importance of a term to classification. This score is normalized and should be comparable across models; in the case of *grain*, this discrepancy between models produced an increased performance in the hybrid model, whereas in the *ship* category, it resulted in a decline. This suggests that the different levels of detail provided by words and synchronic imprints are not equivocally analyzed by the given feature selection, and that for the optimal results in a hybrid scenario, a different model of recombination would be necessary.

Conclusion

The successes of synchronic imprints in the task of automatic classification far exceeded what was originally expected. SIs provide a level of description I thought might be useful in some circumstances, but at the expense of generality, which was assumed to be equally important. Furthermore, about one third of all word terms are discarded in the creation of synchronic imprints (this includes verbs, adjectives, and unrecognized parts of speech), which in some cases, for example *acq* and *earn* were crucial to understanding the class, but in most did not seem to adversely affect performance. In classes where non-nouns were important, a simple combination of both representations often performed better than either representation.

Synchronic imprints provide an intermediate representation, between the lowest-level atomic features of text and the high-level conceptual structures that define its semantics. Using the customary evaluation measures, it was shown that this new level of description could be a useful tool for computers performing

automatic classification. Furthermore, through an analysis of the best and worst cases, the strengths and weaknesses of the SI approach were revealed. In the words case, synchronic imprints are hindered by the inability to account for categories that are strongly influenced by process, dependent on verbs for definition. In the best case, words that were insignificant or ambiguous were combined in synchronic imprints to create new features that defined a particular category. Overall, synchronic imprints are an exploration into representations alternative to the standard bag-of-words approach that dominate information retrieval.

5.2 Visual design for relational information

The second part of this evaluation is an inquiry into how the new representation of synchronic imprints might be used by people. Obviously, information systems using SIs to perform various tasks are useful to people, but as outlined in chapter 3, representations themselves can be transformed into extensible tools with an appropriate interface. The interface in question here is the spring-model visualization *flux* developed to explore synchronic imprints.

Information visualization is a relatively new field and has yet to agree on a standard set of evaluation metrics. This is in large part because people working in the domain of visualizing information come from varied disciplines and work with substantially different models. To evaluate flux, I am choosing to look to the work of AI researchers from the 1970's, a time when the field was also a budding discipline without formal structure. Evaluations from that period are introspections into the development and refinement of the systems in question, and all of the lessons learned in the process.

An alternative would be to use the techniques of the human-computer interaction community, looking at how using flux for a particular task is enabling, by comparing some measure of a person's effectiveness at the task with and without the tool. However, this thesis is about a representation that is not tightly coupled with one specific task. Evaluating it on such a task would be at the expense of describing some of the lessons I have learned while building flux. The initial goals of flux were threefold:

1. To create a visual representation that accurately describes and distinguishes the underlying text.
2. To create a visual model that evokes the larger structural relationships in the concepts that exist above the micro-interactions of terms.
3. To create a system in which explicit relationships between words can be comparatively analyzed.

To evaluate flux, I will reflect upon the design rationale that went into its construction and the effectiveness of the final product.

For experimentation, Time Inc. was generous to donate a corpus of *Time* magazine in digital form. This substantial body of text constitutes the time range of 1985 until the present, with each issue accounted for. This corpus was visualized at the level of one issue of *Time*, with all of the stories represented in one visual form. This level of detail was chosen because of the focal nature of the magazine itself; generally each issue contains two or three major themes, with varying stories on each topic. This allows for an analysis along two dimensions, both at the micro-level, looking at the interrelationships between individual words, and at a macro-level, looking for the partitioning of the sets of words into these thematic groups. Most of the visualization variables (spring lengths, word sizes, and color intensity) were adjusted to bring out these two levels of investigation, which are highly related to the corpus chosen, knowing they would need to be altered in order to provide the same performance for another set of text.

Recognition

Text can be an impenetrable interface to knowledge at times, as most of the information occurs at the same level of visual description. Most of us have had the experience of remembering that a piece of text exists, but not being able to find it among the entire body. This attribute of recognition is a limiting factor to people's ability to categorize text. In the case of standard objects, the important features can be recognized immediately, e.g. organizing your wardrobe can be accomplished with little attention. This discrepancy between text and objects has to do with our ability to easily recognize the important features for classification; since synchronic imprints were being used to accomplish the same task for automatic classifiers, it seemed like a natural extension to use them visually for the same purpose. I hoped to give text a visual signature that enabled the rapid recognition of the underlying concepts.

In the initial design, I assumed two visual features would be important for conveying the structure of information: the size of words and their distance from each other. In other systems that use spring systems, such as Fry's *Valence* (Fry, 2000), Chalmer's *Bead* (Chalmers & Chitson, 1992) or the *Visual Thesaurus* (Plumb Design, 1998), the size of all nodes are equal. I assume that this model was chosen to focus attention on the relationships, instead of on any individual node. In the case of recognizing a certain text, the nodes of flux (namely the words) were assumed to be an important feature. For this reason, the size of the words was varied by the frequency of the word, a feature that directly related to a word's significance in that text.

In this sense, the visualization had two separate representational goals: to describe the relative weight of terms, and expose the overall structure of the text, size was varied to give visual prominence to frequency. Synchronic imprints were used to lay out the terms spatially by creating a model for their interaction. The result was the separation of the cognitive task associated with different parts of recognition. The first task

is to recognize the important concepts, i.e. the ones that are the focus of the text. The second task is to look at these concepts and determine the significant relationships, or lack thereof.

The initial implementation of flux was successful in this task, providing a good lens for the Time corpus. In most cases the particular foci of the issue were immediately recognizable by the largest terms in the system, and given that people were familiar with the topics, they could piece together the actual themes by exploring the relationships.

At one point it was suggested that the relational information extracted from the network be used to define the size of terms, instead of the frequency. Although many terms might appear frequently, this usage is not necessary correlated with co-usage. For instance, the terms "George" and "Bush" may appear very frequently, but "Bush" will probably occur more often with other words than "George." From this conceptualization, three new parameterizations of the word size were created: the connectedness of a term, the difference between connectedness and frequency, and the inverse of that difference.

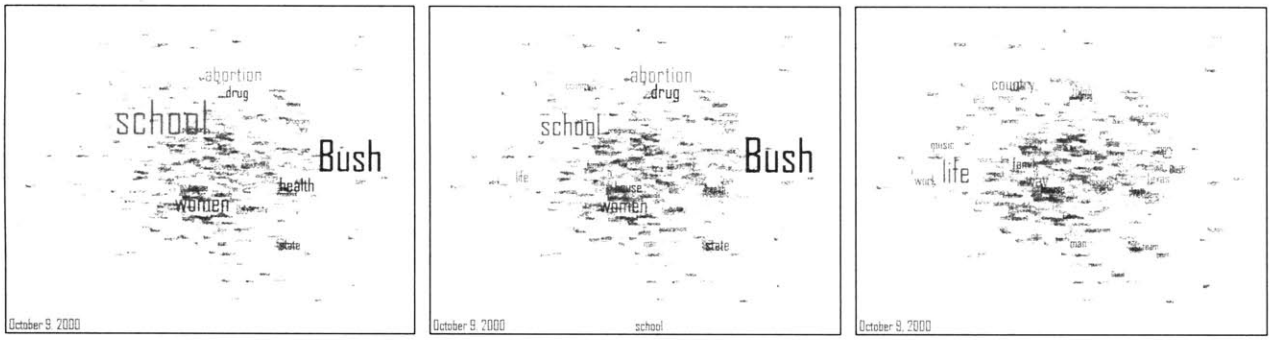


Figure 22: Three sizing models for flux: frequency, connectedness, and the difference between frequency and connectedness

For each of the three sizing models, depicted in Figure 22, the visualization has a distinctly different signature despite the fact that the data model remained unchanged. In the first case the terms "Bush" and "school" appear to be the most significant concepts, while in the second "abortion" has become more significant with the diminishing of "school," and in the third an entirely different term "life" has become prominent. If this variable was not constrained between usages of flux, it was difficult to recognize particular issues, despite the fact that the underlying data was always the same. This parameterization of size turned out to be a major distraction from our goal; by dividing the same data into three different visual models, it became extremely difficult to think of the data as a distinct object.

The model of interaction for visualizations outlined in Chapter 3 (see Figure 8) describes three levels of user control: data transformations, visual mappings, and view transformations. In the case of flux,

interaction made at the first two levels, either to the data itself, or to the mapping of this data to a visual representation have a negative correlation with the goal of recognition. Transformations made at the highest level do not adversely impact recognition. This is not a universal attribute of visualizations; in the case of a word processor, modifications to the visual mapping have little effect on our conception of the text itself. Once I realized this level at which manipulation (at or below the visual mappings) affected a person's recognition of the underlying data, the parameters of the final implementation were constrained to simple view transformations.

Higher structure

A feature used in recognition, as mentioned above, is the relational information extracted from the interaction between terms in the spring model. This recognition feature was used to establish the themes of concepts; the relationships between large (frequent) terms the smaller (less frequent) terms connected to them dictates how those large terms are interpreted. Contextual information depends on the correct portrayal of relational information, which is determined by the lengths of springs; if tuned appropriately, the correct semantic interaction would be evoked, otherwise any number of misunderstandings could occur.

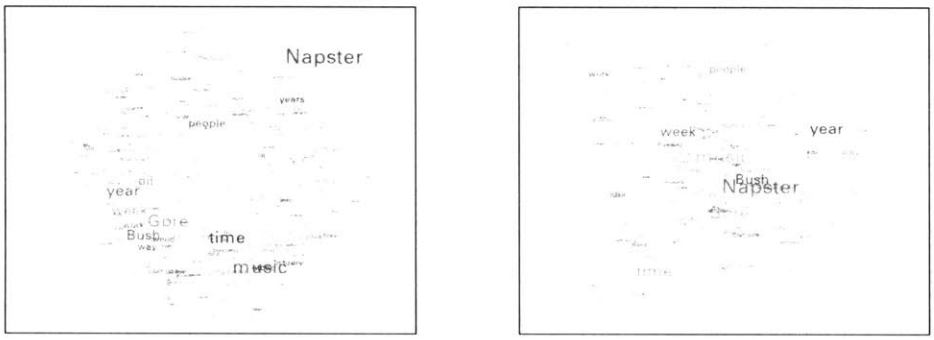


Figure 23: Springs scaled by co-occurrence (left) and normalized by frequency (right)

The initial implementation of flux assumed that the length of springs should be inversely related to the number of times that two words co-occur, i.e. the more frequently that they appear together, the closer they should want to be. This results in the following equation for spring length:

$$L_{a,b} = \frac{1}{cof_{a,b}},$$

where $cof_{a,b}$ is the co-frequency, or number of co-occurrences. This model led to a very instable spring system; while the model was updating at a very rapid rate (upwards of 10 times a second), after many

hours it had still not found stable equilibrium. The general state of this system is pictured on the left in Figure 23. The two major topics of this issue of *Time* were the campaign trails of George Bush and Al Gore, and the music property-rights issue introduced by Napster. Judging from the image, this is not entirely apparent, considering that connected terms "music" and "Napster" are at a significant distance, and many of the terms have a seemingly unconnected distribution.

The curious "doughnut" distribution of the terms was examined and attributed to the large number of infrequent terms. Co-occurrence of a term is highly correlated with frequency; the more often that it occurs, the more likely it is to co-occur often with other terms. About half of the terms in the system occur only *once* in the body of the text, meaning also that they co-occur only once. Given that co-occurrence is inversely proportional to the length of the spring, half of the terms are connected by only one spring at a maximum possible distance. This distance can be seen in the image above as the diameter of the doughnut, where terms on the perimeter are largely separated from their partner terms across the void in the middle. Terms that occur more frequently have shorter spring lengths, but because they co-occur with these infrequent terms, they too rest on the edge of the doughnut.

This creates a state where the relational information of the system is determined by the distribution of terms, not their relationships. To adjust for this undesirable interaction, insignificant terms need to be relationally defocused, analogous to giving the system mass. This is accomplished by adding a factor to the spring length related to the frequency of the terms connected. The exact equation for this distance was given in Chapter 4:

$$L_{a,b} = \frac{\min(f_a, f_b)}{cof_{a,b}}.$$

The factor in question is the numerator of this fraction, which is the minimum of the two frequencies of attached terms. This value normalizes the spring around the case where one term occurs only with the other, and maximizes the spring length when large terms occur infrequently with other large terms. This has the tendency to spatially separate the entire network, by moving the hubs of the system apart from each other, allowing them to interact more locally with the less frequent terms occurring only in their space. This model is seen in action on the right of Figure 23. Here a clumping effect can be seen, with related terms forming thematic sub-networks of the system; the concepts of "Bush" and "Gore" are surrounded by topics related to their campaign (e.g. "oil"), whereas "Napster" sits near related terms "music" and "Internet."

Relational analysis

In any visualization of interactions, unless the goal is to evoke an overwhelming feeling of complexity, focus is necessary. Interacting with flux provides a great deal of information; by dragging words around the visual field, one can see what sets of words are attached, and what the general independent networks of a body of text are. However, due to the complexity of the physical model, namely that there can be thousands of springs being updated many times, it can be difficult to parse what explicit interactions are causing the movement on the screen. A typical example is that one word attached to another only secondarily appears to be directly attached, due to some strong intermediate term. While this interaction is interesting, it impairs a person from properly analyzing the relations.

The relationships between concepts produce unexpected observations that create new understandings of the text. For instance, in an article on campaign politics, the closeness of certain words to a candidate implies information about the importance of that issue to their platform (in the opinion of the writer on that issue). To be able to understand relationships in more detail, some focus must be provided to the system.

In most of the initial testing and demonstration of flux, the lack of focus was a common complaint: it is too hard to understand the relationships with the size and complexity of the system. Based on method of creating focus introduced by work with the fisheye lens (Furnas, 1981) an initial highlighting of terms was created using the intensity of color.

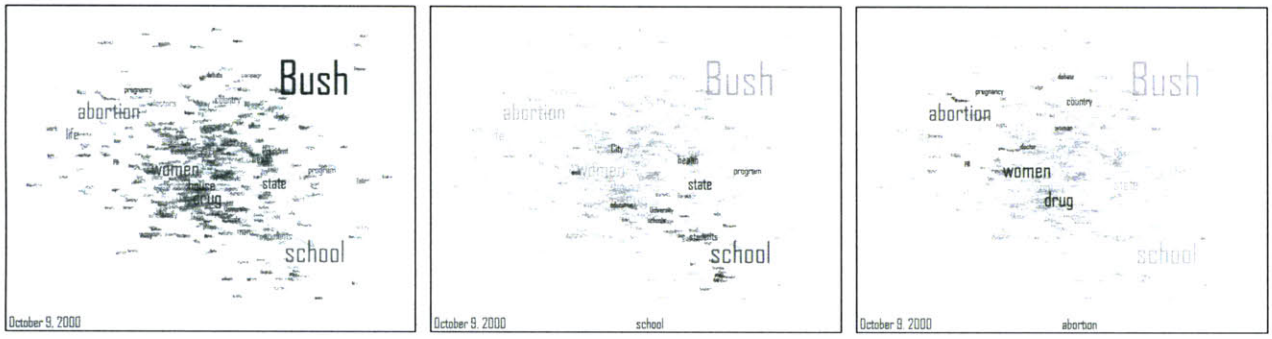


Figure 24: Using color to provide focus in a fluctuating visualization

Color was not being used for any parameter of the system, as words are initially colored randomly to provide distinction. Focus was established by varying the color of the words not immediately connected to a given term. Figure 24 shows three views of the exact same state of a synchronic imprint. The first image shows the standard coloring, the second sets the color to focus on the word "school" and the third on "abortion." All of the words not immediately connected to the term are brought to the same low-

intensity color, distinguishing the relationships of the given word. In the case of "abortion," the words "rights," "doctor" and "drug" can be used to contextualize the use, implying that the theme of these articles was on the potential use of the abortion drug RU-486.

Users typically use the focus feature when interested in the immediate relationships of a given word. This has two consequences on the design. First, in terms of the fisheye algorithm, the immediate context is initially shown in complete detail, with a very sharp drop off to the rest of the field of view. As a user lingers the word, the focus is iteratively broadened, providing the larger context for the word. Second, since the lengths of the words surrounding a given term reflect the relational value, in focus the springs are set to their desired length. This allows the user to visually compare and extract the differences between terms. These modifications provide focus on the task of exploring relational information in bringing visual attention to a subset of the model.

Conclusion

The initial goals of the flux visualization were satisfied through these design innovations. Through iteration on the visual model, and the addition of important features, it became applicable to various classificatory applications. First, it created a visual apparatus for quickly identifying a body of text. The concise visual form allowed for recognition on many levels, from the remembrance of the overall body of text, to the separation of general thematic structures contained within. Second, it became an apparatus for engaging people about particular relationships in the text. By exposing unforeseen connections and higher-level structures, it proved a new way of analyzing the message of a text; both style and opinion are features related to structure that can be extracted from the flux representation. Generally speaking, given a relatively small number of parameters (size, color, and location in two dimensions), all of the important characteristics of the synchronic imprint representation are available in a straightforward interface and a useful set of explorative features.

6 Conclusion

This thesis introduced two new tools for categorical analysis: the computational model of synchronic imprints and its visual representation in flux. Using the coherence provided by the lexical function of the sentence, a simple and extensible structural representation of language was described and evaluated with respect to the standard measure of the bag-of-words approach. Furthermore, employing the physical modeling of springs, this structural information was converted into spatial layout that conveyed recognition, higher-level structures, and focused relationships between words.

6.1 Contributions

Synchronic imprints present an alternative model to the historical hegemony of the bag-of-words approach in information retrieval. Built from purely second-order structural features, they achieved a performance exceeding the standard approach despite a deficit of any active or descriptive features (imparted by verbs and adjectives). Furthermore, imprints express a general necessity to think about representation when confronting an information related task; in the case of classification, the extension of words to second-level features allowed for a level of description necessary to deal with polysemy.

The initial hypothesis that structural information is an integral to the category discrimination was manifested in the results of the automatic-classification evaluation. It was further substantiated by the recognition of thematic arrangements falling naturally out of the physical model of springs. Despite the massive connectedness of the semantic network imparted by imprints, flux was able to find a surprisingly stable equilibrium in a matter of seconds, without any initial constraints.

The hybrid model used in evaluating synchronic imprints proved to be an effective recombination of multiple representations using the simplest algorithm possible, adjoining the two features spaces together. A considerable performance gain could be achieved from reevaluating the effectiveness of the χ^2 feature-

selection algorithm in ordering the importance of the two dissimilar distributions provided by the respective models. However, despite this setback, the hybrid model's accomplishments are evidence that the feature spaces of words and synchronic imprints are not coincident.

6.2 Extensions

While the evaluation of synchronic imprints in the tasks of automatic and computer-aided classification provides a substantial set of preliminary results for the importance of structural information, this research is not complete. In compiling these results, a number of possible extensions to the experiments became apparent. Some of these extensions have been collected in the following sections.

Feature selection

The performance of the χ^2 feature-selection algorithm for text classification is built on the assumption that events in language, namely the occurrences of words, are not normally distributed. This accounts for the sharp falloff of the χ^2 values for terms in a category. However, the combinatorial expansion of words into synchronic imprints changes the distribution of terms, a shift that could affect the performance of the χ^2 statistic in predicting the importance of terms. While Yang found a strong correlation between χ^2 and information gain for word features (Yang & Pedersen, 1997), this might not be true for a different distribution of terms. Judging from the large discrepancies in the χ^2 feature selection for the hybrid model, a comparative evaluation of different feature selection algorithms could provide a significant gain in performance for both the imprints and hybrid approaches.

Further evaluation

Although the evaluation of flux provided a good first step in understanding how synchronic imprints can be used for various classification-related tasks, the visualization could be the subject of a number of different formal evaluations along these lines. For the task of recognition, an experiment could be designed to compare how the different elements of flux (word size, spring lengths, and model controls) affect the ability of an individual to recognize a given text. Research along this line would substantiate the claim that flux-like interfaces would be useful in performing real classificatory work.

Support-vector machines were chosen to evaluate automatic classification based on their previous performance with words, and due to their ability to handle the high dimensionalities that could result from the combinatory nature of synchronic imprints. However, considering that the maximal f-measure for imprints often occurred at 25 features, the latter quality of SVMs was not necessarily exploited. On

further consideration, other learning techniques, such as rule-based or Bayesian methods would have provided representations more amiable to cross-representational analysis. In addition, testing other learning mechanisms might expose a system that favors the types of features presented by synchronic imprints.

The Reuters-21578 corpus is a convention in text classification research, and was chosen for this evaluation due to its use in other comparative analyses. However, it is a quirky set of categories and documents, which are not typical of the kind one might find in an average person's computer. To direct the evaluation towards the original goal, namely helping people make classificatory decisions more easily, a set of different corpora related to common tasks should be investigated. Given that much of this information, such as email or chat is too personal to be transformed into research corpora, informal tests could be run merely to extract the comparison between words and synchronic imprints.

6.3 Future work

The discovery of a new text representation compatible with standard information systems begs for future work in a number of different information-retrieval areas. The structural information revealed by synchronic imprints could be potentially useful to any task where polysemy is a problem. The following are a few of the topical areas in which synchronic imprints might be successfully applied.

Query expansion

Users are bad at communicating their informational desires to information systems. In a typical Internet searches, users assume very small numbers of words (e.g. 2-3 terms) are necessary to separate relevant documents from a corpus of over a billion. To focus a users interaction, the technique of *query expansion* is employed, taking the user's initial query and adding terms to specify the context. If the query expansion chooses the right terms, the results will be much more appropriate for the user's query. A standard technique is to use feedback from the user to find documents that satisfy the user's request, and then use terms in those documents to seed further queries.

Synchronic imprints could be used to provide the contextual terms necessary for query expansion. If a system can determine a piece of text related to a user's query, either through previous interaction or through feedback, then links in the synchronic imprint which contain query terms can be used to find good expansion words. This is explicitly the strength of synchronic imprints, and represents a large alternative to the standard methods, which typically use frequency information to find contextual features.

SI + LSI

Considering the strengths of latent semantic indexing in addressing synonymy, and the ability of synchronic imprints in tackling polysemy, an interesting experiment would result from the synergy of these two techniques. As noted in chapter 3, LSI intensifies the effect of polysemy by sometimes combining two dimensions, one of which has two meanings, the other of which is only related to one of those meanings. In this case, one of the senses of the first dimension is completely lost, and the overall meaning of the new dimension conflated.

In order to alleviate this problem in LSI, the text could first be represented as a synchronic imprint, thus expanding each of the polysems into its unique imprint terms. Many of the synchronic imprints features might be combined simply by the LSI technique, but in the case of polysems, the distinct meanings would remain intact after recombination.

Text summarization

Flux provides a solution for the visual recognition of concepts in large bodies of text. This representation could also be seen as a visual summary of the content, as most terms are subjugated into larger thematic structures. The problem of *text summarization* shares a similar goal of representing a large body of text in a succinct and quickly comprehensible format; the distinction lies in representation of this format, namely as another body of text (which is much smaller).

The visual structures that are resultant from the spring model could be used to aid in the process of text summarization. Using either a network topological analysis, or simply a spring simulation, the hubs of themes could be identified, along with the significant relationships around those themes. These terms of these relationships could be fed into conventional text summarizers to determine the important passages of text. Another approach might be to find all of the most crucial pairs around the distinct hubs of an imprint, and find sentences that satisfy these pairs (such as the ones they came from). Assuming the first sentence with each of these pairs would introduce the connection between the words, a simple summary might be made just from these introductory sentences.

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