Mining Topic Signals from Text

by

Reem Khalil Al-Halimi

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Abstract

This work aims at studying the effect of word position in text on understanding and tracking the content of written text. In this thesis we present two uses of word position in text: topic word selectors and topic flow signals. The topic word selectors identify important words, called *topic words*, by their spread through a text. The underlying assumption here is that words that repeat across the text are likely to be more relevant to the main topic of the text than ones that are concentrated in small segments. Our experiments show that manually selected keywords correspond more closely to topic words extracted using these selectors than to words chosen using more traditional indexing techniques. This correspondence indicates that topic words identify the topical content of the documents more than words selected using the traditional indexing measures that do not utilize word position in text.

The second approach to applying word position is through *topic flow signals*. In this representation, words are replaced by the topics to which they refer. The flow of any one topic can then be traced throughout the document and viewed as a signal that rises when a word relevant to the topic is used and falls when an irrelevant word occurs. To reflect the flow of the topic in larger segments of text we use a simple smoothing technique. The resulting smoothed signals are shown to be correlated to the ideal topic flow signals for the same document.

Finally, we characterize documents using the importance of their topic words and the spread of these words in the document. When incorporated into a Support Vector Machine classifier, this representation is shown to drastically reduce the vocabulary size and improve the classifier's performance compared to the traditional word-based, vector space representation.

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To my beloved parents

Your unconditional love and encouragement were my guiding star. Nothing would ever suffice to repay your endless sacrifices.

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Your patience and support sailed me through it all.

And to my kids Mostafa and Shereen

All you need to fulfill your dreams is within your souls. Do what is right and never give up!

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Chapter 1

Introduction

Text is an intensely rich medium where words, structure, and situational context interact to weave the text's meaning. Varying aspects of this fabric of meaning have been used by researchers in text retrieval, text classification, text summarization, and various natural language understanding tasks.

At the very basic level, the individual words in the document can provide a crude picture of the text's content. Many retrieval systems adopt this approach in measuring the similarity of a document to other documents or to the users' requests. SMART [Sal71] is one of the earliest examples of such systems. We are interested in examining how to augment such a "bag-of-words" approach to obtain characterization of text that is better suited for text retrieval, text classification, and related text manipulation tasks.

Some systems improve on the basic model by utilizing the semantic interaction between the words and recognizing those words that tend to co-occur in similar contexts. *Latent Semantic Indexing* [DDL$^+$90] and *Linear Least Squares Fit* [YC93] achieve this through numerical analysis methods that measure the possibility of co-occurrence between any two words in the same context, while Morris and Hirst [MH91] and Green [Gre97] [Gre98] utilize an online-thesaurus to create semantic links between words in a process called *lexical chaining*.

Syntactic structure has also been used in understanding text. Clarke *et al.* [CCKL00], for instance, parse users' questions to identify the specific information requested in the question.

Another useful aspect is the document's logical structure. This structure helps indicate the importance of words and sentences to the content, and it can thus be useful in identifying and extracting important sentences for tasks such as summarization (see for example [KPC95])

Other systems go even further by attempting to capture information about the situation in which the text is produced. For example, in the Jabber project we indexed video conferences by several aspects including the content of discussion, the meeting agenda, and the forms of interaction between participants such as arguments, discussions, brainstorming, and question-and-answer [KAHHM96].

Although these methods are useful in creating some idea about the text content, they generally tend to group document words together regardless of their position in the text, thus losing information about order. Therefore, such methods are difficult to use for tracking the change in topic and the degree of this change within a document. Some researchers attempt to address this problem by dividing the document into fixed segment sizes and studying the content in each of these segments (e.g. [Hea94a] [SSBM96]), but this approach restricts our understanding of the text content to these segment sizes. In some cases the approach also requires knowledge of the whole text before its content can be analyzed (e.g [SSBM96] [MSB97]) making it unsuitable for tracking content of incoming streams of text. Bookstein *et al.* [BKR98] exploit the influence of content on word usage in extracting index words that are likely to be useful in satisfying user requests. They predict that such words will tend to occur in close proximity to each other, or will have a pattern of occurrence in the text that is quite different from the expected random pattern of occurrence.

We extend Bookstein's predictions in this work to extract words that signal certain topics in text. We find it intuitive that as topics change, so do the words we use. By tracking these words, we should also be able to track the change in topic as new text is produced. The hope is that such information is readily available and can be quite useful in providing an insight into the text's content in real-time at varying levels of detail.

We begin by describing our view of text and comparing it to other popular views. We then present two uses of word position in text: topic word selectors and topic flow signals. The topic word selectors identify important words, called *topic words*, by their spread through a text. For example, a word that occurs many times in a single paragraph of the document is considered less important than one that occurs as often but its occurrence is spread throughout the document. The underlying assumption here is that words that spread out in the text are likely to be more relevant to the main topic of the text than ones that are concentrated in small segments. We also show that manually selected keywords correspond more closely to topic words than to words selected using more traditional indexing techniques. This correspondence indicates that topic words identify the subject matter of the documents more than words selected using traditional indexing measures that do not utilize word position in text.

Armed with better topic identifiers, we then move on to tracking the flow of topics in text through what we call *topic flow signals*. In this representation, topic words are replaced by their relative relevance to the topic. The flow of any one topic can then be traced throughout the document and viewed as a signal that remains strong when words relevant to the topic are used and weakens when an irrelevant word occurs. To reflect the flow of the topic in larger segments of text we use a simple smoothing technique. The resulting smoothed signals are shown to correlate to the ideal topic flow signals for the same document.

Finally, we represent documents by the relative importance of their topic words and by the spread of these words in the document. This representation is then incorporated into a Support Vector Machine for text classification and shown to drastically reduce vocabulary size without loss in the classifier's performance when compared with the traditional TF*IDF representation.

Chapter 2

Text as a Signal

A solid comprehension of a retrieval approach is rooted in a clear vision of the approach's view of text and the criteria it attempts to preserve in a model. In this chapter we discuss our view of text in addition to several text views that have been used in the past. We then focus on how to represent text according to the view we adopt in our work.

2.1 Logical Views of Text

Natural language text encodes large amounts of information at many levels, including the syntactic, semantic, and structural levels. As far as we know, only some of the information in text is needed for a retrieval task. The logical view of a text defines criteria that capture the essential contents of a document for the task at hand.

There are two dimensions for our view of text: the first is at the word level, whereas the second is at the document level. The word level view defines the semantics of a word and the objects to which it refers, while the document level view determines how the words in the text weave the meaning of the whole text. At its simplest, a text is just an unordered collection of words. This is the *bag of words* approach. More involved views take into account other information about the text such as information regarding its structural content, the context in which a word is used, or the position of the word in the text. The remainder of this section focuses on several of these document level views along with some examples.

2.1.1 Text as a Bag of Words

The *bag of words* view assumes that the words used in a document are sufficient to capture the main contents of the document. It also assumes that the probability of using a word is independent of the other words in that document and of the position of the word in the text. Under this view, a text is a flat entity with no structural information.

This is one of the earliest text views and is very common in current information retrieval research. Its main attraction is its simplicity. It may also be effective for some simple retrieval tasks requiring exact word matching. In general, however, many systems with this view attempt to enhance the system's performance by boosting their word semantics views through removing grammatical inflections, by ignoring empty words through stopword removal, or other preprocessing tasks. An early example of systems with the bag of words view is the earlier versions of SMART [Sal71, SM83].

More recent systems augment the bag of words view with knowledge of word co-occurrence in an attempt to boost their word semantics view, as is done in the Least Linear Squares Fit approach [YC93], and the Latent Semantic Indexing

(LSI) system [DDL$^+$90]. In LSI, for example, a document is viewed as a bag of words and is represented by the words it contains. The system then uses algebraic methods to distinguish words that tend to co-occur in the database documents. The assumption here is that words occurring in the same context are most likely to share a common reference. If the system realizes that the words *stocks* and *shares*, for instance, co-occur frequently in the database, a query containing the word *shares* may retrieve a document on *stocks* even though the word *shares* is not used in that document. A pure bag-of-words method retrieves only documents containing the word *shares*.

The simplicity and effectiveness of this view are the main reasons behind its popularity. But sometimes the bag of words view is too simple for the user's task. If a text is viewed as an unordered collection of words, then we lose all information about the text's structure. Systems using this view cannot retrieve relevant segments of a document, nor can they identify key content indicators or analyze the flow of discussion in the text. These capabilities are important for text segmentation systems, document visualization systems, and paragraph retrieval systems among others.

2.1.2 Documents as Structured Units

The bag of words method views documents as flat, unordered, sequences of words. In reality, however, documents are sophisticated physical entities. Baeza-Yates and Ribeoro-Neto [BYRN99] divide the physical structure of documents into three types: flat fixed structures, hypertext, and hierarchical structures.

Flat structures separate the document into a list of independent units, each of which is a bag of words. Emails, for example, consist of fields for the sender's name, the recipient's name, the date, the subject, and the message. Newspaper articles and technical reports may be viewed as titles followed by lists of paragraphs. Flat structures have the advantage that they retain the simplicity of the bag-of-words view and yet are also capable of searching and retrieving relevant units only, rather than retrieving the whole document. They may also provide additional information about the contents of the text that can boost the effectiveness of a retrieval system.

More recent versions of SMART [SAB93] combined the bag of words view with the view of a document as a list of paragraphs. Salton, Allan, and Buckley measured an input query against both the full document in its flat bag of words form, and against single paragraphs. If one or more paragraphs were found more relevant to the query than the full text, then these paragraphs were returned, otherwise the system returned the whole text if it were found relevant. This combined view proved more effective than the simple bag of words view [SAB93].

Unlike flat structures, where a document is a linear list of structural units, hypertext graph structures view a document as a set of interconnected units. HTML web pages are one example of these structures. This view is usually extended to the whole database, in which case each document acts as a node in a web of interconnected documents.

The hypertext view is adopted by some of the World Wide Web search engines. Only a few of these search engines, however, utilize the document-document connections in evaluating their retrieval results. Google's PageRank [PBMW98] measures the importance of a web page, and thus its expected usefulness to the user, by the number of "good" web pages pointing to the page in question. Google is a good example of how links between documents can provide a rich resource for the system to understand the document contents, and the author's view of how other documents relate to it. However, graph structures are usually expensive to process, and the quality of the links is dependent on the context in which they appear, as well as on the authors' good judgment. Also, not all documents are prepared as hypertext documents.

Hierarchical structures are a compromise between the richness of hypertext and the simplicity of flat structured text. Examples of tree structured documents are books containing chapters, which contain sections, which in turn may contain subsections etc. Markup languages are usually used to reflect the relation between units in the structure and allow search engines to exploit this structure [Tom89, Tom97]. PAT [ST94], MultiText [CCB94], and many web search engines such as Google [PBMW98], for example, allow users to specify the particular substructure, called *region*, they are interested in searching.

Imposing structure on text usually conveys the author's view of which consecutive portions of the text share a common attribute. It helps users search and understand the document and the database as a whole. However, structure does little to amend the drawbacks of the bag of words view if the latter is adopted for segments within a structure. Although with structured text we can now search and retrieve smaller segments of text, the contents of each of these segments is still represented as an unordered set of words, and we are still missing information regarding the local context within a segment and the topic flow in the text.

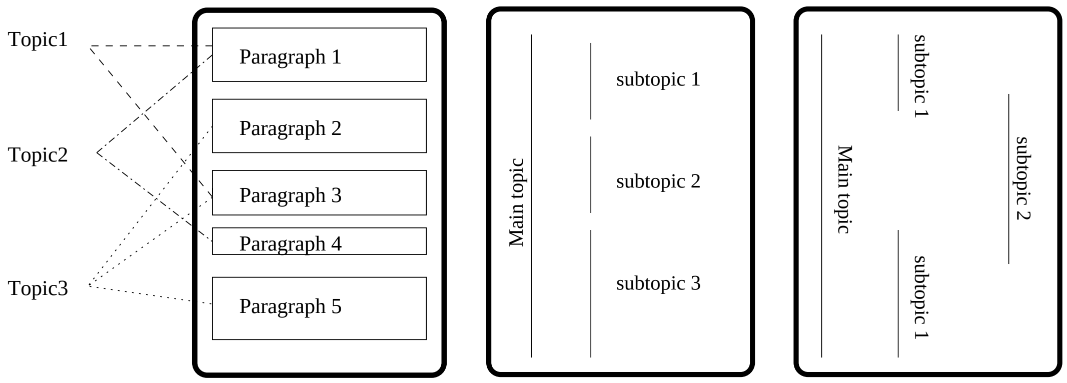
2.1.3 Words in Context

Rather than attempting to impose some structure on the whole text, some research tasks require a more detailed view of the local context of the text. The local context of a word is the words surrounding it in the document. This immediate context usually assists the reader in restricting the possible meanings of the word, as well as the topics under discussion. For example, the word *bank* can carry many different meanings, including a commercial bank and a river bank. But the phrase *river* immediately adjacent to *bank* in the phrase *river bank* disambiguates it and clarifies the local content of the text.

The idea of using surrounding words to disambiguate text has been investigated for many different applications such as word sense disambiguation [CL85, Les86, GCY93], query expansion [BYRN99], and character recognition [GCY93] with varying degrees of success. The definition of "local context" or *window* also varies: many systems define a local context as the words immediately preceding a word as is done in the n-gram language model [MS99]. In this model a word is assumed to be independent from all other words in the text except for the $n-1$ words immediately preceding it.

Other researchers have defined a word's context as the n words immediately preceding and succeeding it. Gale *et al.* [GCY93], for instance, used local context for sense disambiguation. They also studied a more relaxed definition of the local context where the context of a word w begins some l words away from w. Interestingly, they found that words as far away from w as $10,000$ words may be useful in the disambiguation task. Recognizing the importance of local context, PAT [ST94] and many web search engines such as AltaVista [SHMM98] and Google [PBMW98] allow users to search for words within some proximity to each other. In MultiText the relevance of a paragraph to a given set of terms is influenced by the proximity of the matched terms in the paragraph [CCKL00].

This view of text retains partial information about the relative order of the text words, and it is sufficient for applications where those local contexts are of interest. However local context cannot provide a global view of the text and is thus insufficient for representing the flow of topics in a document, nor is it appropriate



(a) Text as a connected set of topics

(b) Text as main topics that enclose a sequence of subtopics

(c) Text as a collection of main topics that enclose parallel subtopics

Figure 2.1: Views of a document as a collection of topics

for other tasks requiring a more unified view of the whole text.

2.1.4 Documents as Collections of Topics

Text words weave together the topics conveyed by the document. The words-in-context view fragments the text and lacks an insight of the text as one unit within which run many, possibly overlapping, topics. Figure 2.1 shows four text views that focus on the document as a collection of topics.

The first view 2.1(a) is of the text as a connected set of topics. This view makes no assumptions regarding the organization of the topics in the text. A topic may be discussed in any set of text segments, and it may be discussed along with any other. The main topic is defined as the one that is discussed in the greatest number of segments. This view was adopted by Salton *et al.*in [SSBM96], where they represented a topic as a set of mutually similar segments. In this work a document is segmented into paragraphs. The similarity of each paragraph is measured against every other paragraph, and those paragraphs whose similarity is higher than a preset threshold are assumed to discuss a common topic.

The attractiveness of this view is its flexibility allowing for topics to be interrupted and re-introduced several times during the course of the text. However, the view's flexibility also entails the loss of the hierarchical relations between a main topic and its subtopics.

The next text view, shown in 2.1(b), accounts for this relation between main topics and their subtopics. In this view, a text is a set of one or more main topics that run through the text in parallel with their subtopics. The subtopics are expected to be linearly consecutive and mutually exclusive. Hearst adopted this view in the automatic segmentation system TextTiles [Hea94c, Hea97]. Her goal was to discover points of topic shift (thematic change) in any given document, and use these boundaries as guides towards automatically segmenting text.

The first version of Hearst's algorithm divides the document into several equal-sized segments. It then measures the similarity between adjacent segments and places topic boundaries where there is a sudden decrease in similarity relative to adjacent segments. In this version of the algorithm a topic is a set of consecutive segments of text bounded by two topic boundaries.

The second version of her algorithm is based on the *lexical chains* of Morris and Hirst [MH91], who showed that coherent texts usually contain groups of semantically related words. Each of these groups is called a *lexical chain.* This version of TextTiles represents a topic as a set of parallel lexical chains and places a topic boundary when a set of chains ends and a new set begins.

The view adopted in both versions of the algorithm assumes that subtopics are consecutive and mutually exclusive. Although the linearity and mutual exclusion expectations are justified in the automatic segmentation context, they are not generally accurate assumptions. Digressions, interruptions, and topic re-introduction are to be expected in most types of text. At the same time, the ability to recognize the main topics' subtopics provides a deeper insight into the flow of topics in the text. Therefore, our view of text is a combination of the two previous views. We adopt Hearst's view of the text as a set of main topics running throughout the text, in parallel with their subtopics, as well as the view of Salton *et al.*that topics can be modeled as independent entities which may be temporarily interrupted and then revisited any number of times, and any paragraph may discuss any number of topics simultaneously [SSBM96]. Figure 2.1(c) reflects this view. In this figure the main topic is discussed across the text, and within the context of the main topic the first subtopic $subtopic_1$ is discussed in several segments of the document, and the second subtopic $subtopic_2$ is discussed only in the middle of the text where it temporarily intersects with $subtopic_1$. This model is less general than the model adopted by Salton *et al.* [SSBM96] since it assumes at least one common theme throughout a document. But when this assumption is true, as in news stories and technical reports, it allows for a simpler representation. The model of Figure 2.1(c) is also more flexible than the one adopted by Hearst [Hea94c, Hea97]. But the flexibility and simplicity of a model is largely dependent on how we choose to represent it.

2.2 Representing the Flow of Topics in Text

An ideal representation of our topic flow model should preserve as much of the model's flexibility as possible and permit many simultaneous topics at any point in the text. This can best be achieved by representing each topic in the text independently of all other topics. The text will then consist of parallel topic flow representations, and the problem reduces to representing the flow of each individual topic in a document.

Topic flow reflects the degree of relevance of the topic to various points in the document. Assume we can measure the relevance level of a word w at point p in the document to a topic t using a measure $M_D(p,t)$. To view the relevance of the topic to every point containing a content word in the document, we can plot the relevance levels given by this measure for each position in document D one after the other. The resulting plot will reflect the flow of topic t in document D. Take for example the following sentence:

Example 2.2.1 *Belief revision focuses on how an agent should change her beliefs when she adopts a particular new belief. [FH99]*

and assume that our relevance measure $M_D(p,t)$ produces the relevance levels shown in Table 2.2 for each word position p containing a content word in the sentence for the topic *Artificial Intelligence* where the most important relevance level is 1. Then Figure 2.3 plots the relevance of *Artificial Intelligence* versus word positions in the sentence. Note the variation in height as the relevance level, as defined by our measure, of the word position to *Artificial Intelligence* changes. This stream of importance levels represents the flow of the topic *Artificial Intelligence* in the sentence. A stream that conveys information about the source is called a *signal* [SIG]. The flow of any topic can be represented for thesame text resulting in a multiband signal of topic flow information.

Signals are powerful and versatile representation forms that have been used to represent audio, speech, and image. Brewster *et al.* [BM00] also represent docu-

Word POSITION	WORD	RELEVANCE
0	belief	1
1	revision	1
2	agent	33
3	change	78
4	beliefs	1
5	belief	1

Figure 2.2: Relevance of content word positions in sentence 2.2.1 to the topic *Artificial Intelligence*. Positions containing non-content words such as *how*, *at*, and *her* have been ignored.

ments in terms of signals. They begin by identifying content-bearing words using the method proposed by Bookstein *et al.* [BKR98]. The highest weighted content words whose weights are higher than a preset threshold are called *topics*. Those with weights below that threshold but higher than another, lower, threshold are called *cross-terms* while all remaining content words with lower weights are discarded. In their work each signal, or *channel*, reflects the association of each document term to a topic. The collection of topic signals is used to build a single *composite energy* signal that is meant to represent the document content and is the basis for their document visualization and segmentation prototype [MWBF98]. No experimental results have been reported on the accuracy of the channels and the collective energy signal in representing text content nor on their usefulness for the purposes of visualization. Instead of forming a single compound signal, we represent documents by multiple signals, each of which reflects a topic characterized by a user-defined collection of documents.

Representing topics as signals allows us to preserve the flow of information and

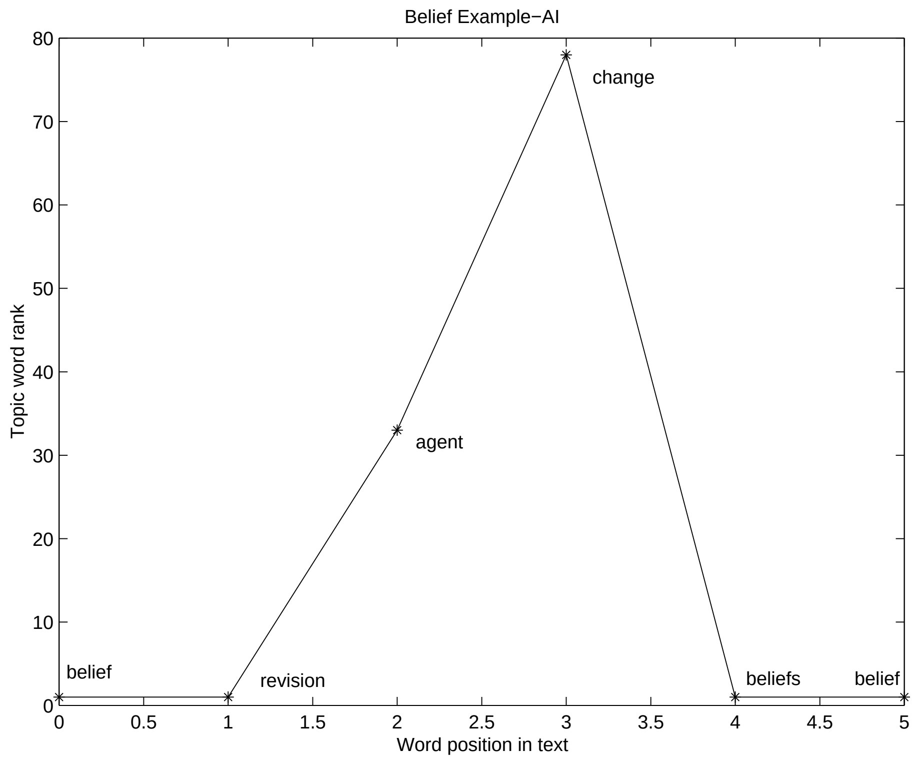


Figure 2.3: Relevance signal for the topic *Artificial Intelligence* based on the relevance values in Table 2.2. Each vertex in the signal is labeled by the word that generated the vertex.

retain the flexibility of our original flow model. It also provides multiple views of the text simultaneously and efficiently. Even text streams produced in real-time can be easily represented in terms of moving topic signals. These features can prove useful in many areas of information retrieval including text segmentation, text summarization, paragraph retrieval, and text filtering. It also opens up for text processing a wide range of efficient and effective signal processing tools that cannot be applied in conjunction with other representations of text.

Of course the quality of our signal is sensitive to the relevance measure $M_D(p,t)$ used in constructing the signal. In the next chapter we discuss and compare several candidate measures. Then, in the following chapter, we adopt these measures to build topic flow signals. Finally, we study the effect of these relevance measures and word position on text classification.

Chapter 3

Topic Relevance Measures

In the previous chapter we argued for representing topic flow in text in the form of signals. We also showed some signal representation examples based on hypothetical topic relevance values at each point in a sample text. In this chapter we define topic relevance, then define and compare four different topic relevance measures $M(w,t)$ for a given word w and topic t. First let us attend to the basic question of topic relevance.

3.1 Topic Relevance

A word w is strongly relevant to topic t if w reflects a concept that can be discussed as a subtopic of t. For example, *belief networks* and *agents* are strongly relevant to the topic *Artificial Intelligence*, and *corpora* and *discourse analysis* are strongly relevant to the topic *Computational Linguistics*, but *the* and *conductor* are less relevant to either topic. Figure 3.1 shows a list of concepts that are strongly relevant to *Artificial Intelligence*, taken from the index of the Encyclopedia of Artificial

- `Bayes' theorem`
- `Bayesian belief networks`
- `Bayesian decision theory`
- `Belief networks`
- `Belief revision`
- `Constraint logic programming`
- `Constraint networks`
- `Constraint propagation`
- `Constraint satisfaction`
- `Feature Detection`

Figure 3.1: Concepts that are topically relevant to *Artificial Intelligence*

Intelligence [Sha92].

Document keywords may also be viewed as topic words. Keywords indicate the main topics of the document so the set of keywords used to describe a topic's documents acts as a partial set of topic words for the topic discussed in the document. These keywords can either be found in a preset keyword field in the document, or they can be recognized through some visual features throughout the document. InfoFinder [KB97], for example, extracts keywords (called topic phrases) from documents using a set of heuristics based on 'visually significant features' such as italics and document structure. The keywords of a topic's documents are used to build decision trees that reflect the topic's content.

Topically relevant words are Damerau's *domain-oriented vocabulary* [Dam90]. Damerau defines such vocabulary as

> a list of content words (not necessarily complete) that would characteristically be used in talking about a particular subject, say *education*, as opposed to the list of words used to talk about, say *aviation*. [Dam90]

Damerau tests two different approaches which extract domain-oriented vocabulary from the body of plain text documents. In the first he sorts the list of all words in the domain documents by their frequency, eliminates words bearing little content such as *the* and *it* (called stopwords) from the list, and finally trims the list size to a predetermined constant by removing the lowest frequency words. In the second approach he creates two domain lists: for the first list he extracts from a dictionary all words whose label is that of the domain, and for the second list he indexes the words used in the domain documents. He then creates the final domain list from words in common between these two lists. Given a previously unseen set of documents for a domain, Damerau found that more of the domain's list appeared in the domain's documents than words from most other domains' lists. However, this acceptance test does not guarantee that the words are *domain-oriented*. It only shows that the selected words are used more often in the domain's documents. Therefore, words like *she* and *her* can easily be accepted as topic words by this test if they happened to be used more often in one domain than in the other domains tested. In this case *she* and *her* may be good discriminators of that domain, but they are not topically relevant words.

This difference between topically relevant words and good discriminators also applies to traditional information retrieval index terms. Unlike topically relevant words (topic words), the importance of an index term in information retrieval is measured by how well it can discriminate a topic or document from all other topics or documents, as well as how relevant it is to the content of the topic or document [van79] [Sal75] [Dam90]. For example, the *Earnings and Earnings Forecasts* category in the Reuter's database [REU] contains the term &*lt* in place of the left bracket at the end of company names. Therefore, &*lt* is a good discriminator of that category against other categories in the database [MS99]. However, even if &*lt* may be a good discriminator for the *Earnings and Earnings Forecasts* category, it is not relevant to the meaning of the category. Therefore, although such discriminators are appropriate as category markers, they lack essential content relevance information and are not acceptable topic words.

With this definition of relevance, topic flow representation becomes a representation of the distribution (in a non-statistical sense) of topic concepts in the document. Furthermore, the variation in relevance values reflects the variation in the strength of topic relevance to the various concepts across the text.

The ability to measure the relevance of a topic to a word implies some knowledge of the word and the topic. In information retrieval this knowledge is usually acquired by analyzing some sample documents and the topics to which they belong. Assume we have access to a representative sample of plain text documents for each topic t in the set of all possible topics T, and that each document is represented by the words it contains in the order they occur in the document. In this chapter we will call this set of sample documents the database of training documents, or simply the database. Our task is to recognize strongly relevant words for each topic from the representative sample. In the remainder of the chapter we will discuss and compare several different measures of relevance.

3.2 Measuring Topic Relevance

Topic words are clearly associated with their topics. Otherwise, it would be hard to argue that they are "characteristically" used in discussing the topic. To measure this association we use *Pointwise Mutual Information* (PMI). PMI is an extension of the information theoretic measure *Mutual Information* [MS99]. It has been used for many different retrieval tasks including feature extraction [YP97] and word concordance discovery [CH90]. PMI measures the likelihood of observing two events simultaneously as opposed to observing either event separately. This measure is defined as follows:

$$I(x, y) = log\frac{p(x, y)}{p(x)p(y)} \tag{3.1}$$

where:

- $p(x, y)$ is the probability of observing x and y together in the database.
- $p(x)$ $(p(y))$ is the probability of observing x (y) separately.

Within the context of topic relevance, x is the topic, y is the word whose relevance to x is of interest, and $I(x, y)$ reflects the relative likelihood of using a word y when discussing topic x as compared to using either independently, or, since $I(x, y) = I(y, x)$, the relative likelihood that an observed instance of word y refers to topic x as compared to using either independently.

In order to measure the PMI between a word and a topic, their probability of co-occurrence $p(w, t)$ should be estimated, as well as their probabilities of occurring separately $p(w)$ and $p(t)$. The probability of occurrence of a word is usually estimated using some observable statistic of that word such as the number of documents in which it occurs (document frequency), or the word's total number of instances in the database (term frequency).

In what follows we will discuss how document frequency and term frequency can be used to measure the relevance of a topic to a word, and we compare the effectiveness of these two statistics to two other word statistics.

3.2.1 Measuring Topic Relevance using Document Frequency

Document frequency (DF) is the number of documents in which a word occurs. Using DF our PMI measure of the relevance of word w to topic t becomes

$$\begin{aligned} M^{DF}(w,t) &= log\frac{p(w,t)}{p(w)p(t)} \\ &= log\left(\frac{\frac{DF(w,t)}{|db|}}{\frac{DF(w,db)}{|db|} * \frac{|t|}{|db|}}\right) \\ &= log\frac{DF(w,t) * |db|}{DF(w,db) * |t|} \\ &= log\frac{DF(w,t)}{DF(w,db)} + log\frac{|db|}{|t|} \end{aligned} \tag{3.2}$$

where:

- $DF(w,t)$ is the number of topic t documents containing the word w.
- $DF(w,db)$ is the number of database db documents containing the word w.
- $|t|$ is the number of documents in the database whose main topic is t.
- $|db|$ is the number of documents in the database.

Since the term $log\frac{|db|}{|t|}$ is independent of words for a fixed topic t and database db, $M^{DF}(w,t)$ in Equation 3.2 compares words under t based on the ratio $\frac{DF(w,t)}{DF(w,db)}$. Words that occur in significantly more documents of t than in the rest of the database will be weighed more heavily than those occurring in relatively fewer documents of t than the rest of the database.

Measuring topic relevance of a word by the number of documents in which it occurs assumes that words that are not frequently used in a variety of documents usually occur in a document if they are strongly relevant to a main topic of that document, and that a word that is strongly relevant to a topic t will have a higher proportion of the documents in which it appears falling under t. For example, a word that only occurs in documents of t will have a higher weight than another word where only some of its documents belong to t.

We find the basic assumption in this measure troublesome. In particular, the measure will assign a high weight to singletons (words occurring only once in the document) such as misspellings and other infrequent and irrelevant words. For instance, mentioning the word *treaty* in this thesis does not mean the word is strongly relevant to the topic of the thesis. Yet the above measure will count this thesis as evidence of the relevance of the word to the main topic of the text.

One way to filter out some of these irrelevant words is to discard documents where the word is a singleton, as we shall see next.

3.2.2 Measuring Topic Relevance using Modified Document Frequency

As we mentioned in the previous section, the problem with using pure DF in measuring topic relevance is that it exaggerates the importance of single occurrences in a document. To overcome this drawback we suggest discarding from the DF count those documents where the word occurs only once. In this case our topic relevance measure becomes:

$$\begin{aligned} M^{\widetilde{DF}}(w,t) &= log\frac{\widetilde{DF}(w,t) * |db|}{\widetilde{DF}(w,db) * |t|} \\ &= log\frac{\widetilde{DF}(w,t)}{\widetilde{DF}(w,db)} + log\frac{|db|}{|t|} \end{aligned} \tag{3.3}$$

where

- $\widetilde{DF}(w,t)$ is the number of topic t documents containing more than one occurrence of the word w.
- $\widetilde{DF}(w,db)$ is the number of database db documents containing more than one occurrence of the word w.
- $|t|$ and $|db|$ are the number of documents in t and db respectively.

The new measure assumes that the probability of two occurrences of an irrelevant word is quite low, and that those words occurring at least twice anywhere in the document may be strongly relevant to the main topic of the document. These assumptions were made by Katz [Kat96], who argued that when a word is relevant to the topic of the document it occurs in a *burst* of repetitions. Church also used $\widetilde{DF}(w,db)$ in one of his adaptation measures [Chu00], where he shows that content words[1] tend to occur at least twice in documents to which they are strongly relevant.

[1]Manning and Schütze define *non-content* words informally as "words that taken in isolation .. do not give much information about the contents of the document" [MS99]. Note that although a content word is usually relevant to the topic being discussed in the document, it does not need to be.

Based on the above assumptions, if the proportion of topic t documents containing more than one occurrence of a word is high, then the measure assumes the word is strongly relevant to t.

Replacing document frequency with $\widetilde{DF}$ alleviates the singleton-word problem. But $\widetilde{DF}$, as well as DF, assumes an independence of the number of times a word is used within the document from the degree of relevance of the word to the document's topic. For both statistics a word repetition of 10 times in one document is as good as repeating the same word twice only in that same document. Yet some researchers assert that this is not valid. Katz for example states that

> the total number of observed occurrences of the content word or phrase in the document ought to be a function only of the degree of relatedness of the concept named by the word to the document or, in other words, of the intensity with which the concept is treated. [Kat96]

Luhn also hypothesized that the frequency of a word in a document is a strong indicator of the word's significance in the text [van79].

3.2.3 Measuring Topic Relevance using Term Frequency

Many researchers in the information retrieval community use term frequency TF as an indicator of the importance of a word to a document. We can carry this concept of frequency as an indicator of importance towards measuring topic relevance by plugging TF into Equation 3.1 above:

$$\begin{aligned} M^{TF}(w,t) &= log\frac{TF(w,t) * ||db||}{TF(w,db) * ||t||} \\ &= log\frac{TF(w,t)}{TF(w,db)} + log\frac{||db||}{||t||} \end{aligned} \tag{3.4}$$

where

- $TF(w, t)$ is the number of occurrences of w in topic t documents.
- $TF(w, db)$ is the number of occurrences of w in the database db.
- $||t||$ and $||db||$ are the number of terms in t and db respectively.

Equation 3.4 assumes that strongly relevant words are those that occur more frequently in topic t than in the whole database. Damerau used essentially this measure in determining domain-oriented vocabulary [Dam90] as discussed above, and he uses a function similar to Equation 3.4 to extract 2-word domain phrases for a set of pre-specified domains, based on the ratio of the frequency of the phrase within the domain to its frequency in the whole database [Dam93]. The assumption here is that good domain phrases will tend to occur more often on average in the domain's documents than in the whole database.

3.2.4 Incorporating Relative Word Positions in Measuring Topic Relevance

Whether using term frequency or document frequency, the measures proposed so far assume a bag of words document view, where the total number of occurrences in the topic documents and in the database is sufficient to describe the contents of the topic regardless of where the words occur. The bag of words view is incomplete for our notion of text as an interweaved collection of topics. As we argued in Chapter 2, the position of words in a document can be useful in understanding the document's content.

In Chapter 2 we presented text as a collection of topics, with the main topic(s) spanning the length of the text. Since words are the atomic units describing document content, we expect topic words to span across the text as well. Some of these topic words will occur in small segments of the text, while others will repeat throughout the text. Bookstein *et al.* [BKR98] use this behavior of content-bearing words to extract good index words that are likely to be useful in satisfying users' requests. The authors apply goodness measures of such words that compare the word's occurrence behavior in the text to the expected random occurrence. They define two occurrence behaviors: the word's tendency to clump by repeating in close proximity in a single textual unit such as a paragraph, and the word's tendency to occur at least once in several consecutive textual units in a document. Their experiments show that such information on word occurrence improves the quality of words selected for indexing when compared to pure inverse document frequency. The experiments also indicate a link between content-bearing words and these words' tendency to clump.

Although their method identifies content words, the authors do not show how to use the method to characterize the topic of a whole document or which words are indicative of that topic.

Katz [Kat96] notes that although content words are likely to repeat in close proximity to each other, those that are treated heavily and continuously in the text will occur across the length of the text. We speculate that these intensely treated content words are strongly related to the main topic of the document and are thus good topic words. The challenge here is to identify words that repeat across the text, and evaluate them based on their tendency to span the length of text in a topic's documents.

To identify words that repeat across the text we turn to a second measure introduced by Church [Chu00]. Church uses the notion of word spread to show that content words *adapt*, i.e. their probability of occurrence changes based on the lexical content of the document. Church divides each document into two halves: the first half is called the *history*, and the second is called the *test*. He shows that when a content word appears in the history, its probability of occurring in the test segment rises significantly.

If a word spans the length of the text, then it will occur in both halves of the document. Adopting Church's idea of segmenting a document into two halves, our topic relevance measure becomes

$$\begin{aligned} M^{DF_2}(w,t) &= log\frac{p(w,t)}{p(w)p(t)} \\ &= log\left(\frac{\frac{DF_2(w,t)}{|db|}}{\frac{DF_2(w,db)}{|db|} * \frac{|t|}{|db|}}\right) \\ &= log\frac{DF_2(w,t) * |db|}{DF_2(w,db) * |t|} \\ &= log\frac{DF_2(w,t)}{DF_2(w,db)} + log\frac{|db|}{|t|} \end{aligned} \tag{3.5}$$

where:

- $DF_2(w,t)$ is the number of topic t documents containing the word w *in both halves of the document.*
- $DF_2(w,db)$ is the number of database db documents containing the word w *in both halves of the document.*
- $|t|$ is the number of documents in the database whose main topic is t.
- $|db|$ is the number of documents in the database.

Under this measure, topically relevant words are those that occur in both halves of the document in topic t significantly more often than in both halves of the database documents.

The idea of segmenting a document into two halves can be easily generalized into any number n of segments. In this case words are said to spread across the document if they occur in all n segments. Our measure of topic relevance becomes

$$M^{DF_n}(w,t) = log\frac{DF_n(w,t)}{DF_n(w,db)} + log\frac{|db|}{|t|} \tag{3.6}$$

where:

- $DF_n(w,t)$ is the number of topic t documents containing the word w *in all n segments of the document.*
- $DF_n(w,db)$ is the number of database db documents containing the word w *in all n segments of the document.*
- $|t|$ is the number of documents in the database whose main topic is t.
- $|db|$ is the number of documents in the database.

DF_n restricts the frequency count to the number of documents where the word occurs in all n segments. Words that never occur in all n segments of any document in the database have a frequency $DF_n(w,db)$ of 0. Such words are assumed to be not topically relevant to any topic t in the database and are therefore excluded from the $M^{DF_n}(w,t)$ vocabulary for all topics t. The immediate effect of using the DF_n frequency count is a vocabulary size smaller than that used by M^{DF}, M^{TF}, and $M^{\tilde{DF}}$. The higher the value of n, the more words are excluded, and the larger the reduction in the size of the vocabulary. But this reduction is acceptable only if it does not harm the effectiveness of the M^{DF_n} measure in recognizing topic words. In what follows we will look at the effectiveness of M^{DF_n} in extracting topic words for several different values of n and compare that to the other three topic relevance measures.

3.3 Evaluation

In Section 3.2 we proposed four different functions to measure the relevance of a word to a topic. All measures use the PMI formula from Equation 3.1, with different definitions of $p(w,t)$, $p(w)$, and $p(t)$ for a given word w and topic t. Up until now we have been deliberately ignoring the question of what constitutes a topic. This is because the discussion has been general enough to apply to any topic one may think of, be it *politics* or *"today's lunch."* However in order to compare the topic relevance measures experimentally, we must simplify the concept of *topic* so that it can be easily captured and quantified. For evaluation purposes we define a topic as a predefined subject or category, such as the classes in Yahoo!'s classification hierarchy [Yah], the subject classes of the ACM Computing Classification System [ACM], or the classification used in the Reuter's database [REU].

For this evaluation we use the CoRR database [CORa] and the classification system used by that database. For our purposes, CoRR has the advantage of longer documents (all having several pages) which are not found in other, more widely used databases such the Reuter's database (most having one or two paragraphs only). Documents longer than a few paragraphs are essential for testing the effectiveness of the M^{DF_n} measure which is based on segmenting each document into many small sections.

Given a predetermined set of categories, and a database of manually classified documents, we can now generate topic words and evaluate the four measures.

3.3.1 The CoRR Database

The CoRR database [CORa] is an online repository for research in computer science. The database consists of theses, technical reports, conference papers, and journal papers from the last decade. Documents range in length between 5 pages and around 250 pages, but are on average about 13 pages long. They are mainly in LaTeX format, with a few pdf, and some ps and html files.

Each document in the CoRR database has been classified by the paper's authors under one or more of the pre-determined 34 categories listed in the Appendix.

Our version of the database consists of documents submitted between January 1998 and June 2001 for a total of 1151 documents, mostly in LaTeX format. The LaTeX documents were converted to text using a version of detex [DeT] that was modified to ignore text preceding the *begin*{*document*} command, as well as ignoring abstracts and footnotes. A few of the pdf files were converted using Adobe's pdf2txt. In total, 824 text files were converted successfully. Many of the 34 categories contain very few documents. Documents that belong exclusively to one or more of these small categories were removed from the database leaving 736 documents. The remaining categories and their sizes in number of documents are shown in Table 3.1. Some of these categories are still quite small, but they are useful in understanding the effect of category size on the quality of the extracted vocabulary.

Category	**Description**	**size**
CL	Computation and Language	194 documents
LO	Logic in Computer Science	130 documents
AI	Artificial Intelligence	160 documents
CC	Computational Complexity	100 documents
CG	Computational Geometry	62 documents
DS	Data Structures and Algorithms	90 documents
PL	Programming Languages	76 documents
SE	Software Engineering	38 documents
LG	Learning	61 documents
DC	Distributed, Parallel, and Cluster Computing	41 documents
CE	Computational Science, Engineering, and Finance	23 documents
NI	Networking and Internet Architecture	25 documents

Table 3.1: The CoRR database categories used in this evaluation

3.3.2 Preprocessing

The details of preprocessing vary from one system to another but certain steps are considered by all system designers. First we have to define the building blocks, called *tokens*, of text. The input text is merely a sequence of characters prior to preprocessing. It is the responsibility of the preprocessor to break the sequence into semantic units in the *tokenization step*. These units can either be simple words such as the words *program* and *creation*, or multi-word phrases such as *The United States* (as opposed to *United* and *States*).

We define tokens as case-insensitive sequences of alphanumeric characters consisting of at least one letter. Abbreviations containing a dot interleaved with the alphanumerics are accepted, as well as words containing an underscore, as in the sequence *w_t*. The total vocabulary in our version of the CoRR database is $53,877$ unique words.

Two other pre-processing steps are widely used when indexing databases: stopword removal and word stemming. Stopword removal ignores words that are generally accepted as being content-free such as *the* and *it*, and stemming removes morphological inflections from words.

Many researchers opt to remove stopwords using a preset stopword list for efficiency and effectiveness [SM83] [YL99] [Joa98b]. Removing these words drastically reduces the system's vocabulary size thus improving its efficiency, and allows the system to focus only on important content words thus improving its effectiveness. The difficulty in this step is to remove stopwords only. If we remove too many non-stopwords or leave in too many stopwords, we will increase the noise in the database and reduce the system's effectiveness. But this balance is hard to strike because different databases have different stopwords, and what constitutes a stopword in one database may be an important content word in another. Consider, for example, the word *computer*: whereas *computer* may be a stopword in a computer science database, it is most likely a content word in a general science database. Alternatively, some systems resort to more general *feature selection* methods which aim to weigh the uniqueness of each word and its value for the categorization task, and keep only words deemed important for the task [YP97] [Lew92].

Stopword removal raises a concern when using the DF_n frequency counts: removing words from the body of a document will disrupt the position of the remaining words in the document thus disrupting the DF_n frequency counts. The approach we choose to deal with this change in DF_n frequencies depends on our view of the role of word position: if the importance of a word position is affected by the word's content then stopword positions are of little importance and can be safely ignored. If, on the other hand, word position in a document is a rough reflection of the word's sentence position then all word positions are important, including those of stopwords, and words that occur in some segment of the document before stopword removal should still occur in this same segment after stopword removal. In this case, before removing stopwords their positions should be held by some null word that can safely be discarded after all DF_n frequencies are counted.

Stemming is another common preprocessing step. It reduces words with varying morphological inflections to one common representation. Thus, *runs* and *running* will both be represented by the stem *run*. This process has been reported to help compress an index by up to 50% [Fra92]. Stemming has also been used to increase the number of documents found by search systems although there is no strong evidence of its effectiveness in discovering documents that satisfy the users' request [Fra92].

There are many different approaches to stemming from simple table look-up and predefined stemming rules to methods that attempt to discover stems statistically with no prior knowledge of any stemming rules. None of these approaches has been shown to outperform the others in terms of precision or retrieval effectiveness, but they differ in their compactness and simplicity. One of the most compact is the Porter stemmer [Fra92] [BYRN99], which gradually reduces a word to its simplest form by iteratively looking for the longest suffix it can remove based on a set of predefined rules [Por80].

Thus we have four possibilities for representing documents' words: with or without stopwords and with or without stemming. To explore the effects of stopword removal and stemming on the precision of our topic relevance measures, we created four independent indices for the CoRR database. The first index (SIMPLE) is the simplest one with no stopwords removed and no stemming performed. The second index (STEM) does not remove stopwords, but replaces words by their stems using the Porter stemmer prior to frequency count. The third index (STOP) removes stopwords found on the SMART stopword list [STO], but does not stem the remaining words. While the fourth version of the CoRR index (S&S) removes stopwords as was done for the STOP index and stems the remaining words as was done in the STEM index. We have opted to replace stopwords in the STOP and S&S indices by a null word in order to preserve the words' original positions in the database.

Because the resulting topic word lists for two indices consist of stemmed words while the STOP and SIMPLE indices may include several different morphological variants of the same stem, we subsequently convert the unstemmed topic word lists of STOP and SIMPLE into stemmed lists of topic words as follows: Each word in the list is stemmed using the Porter stemmer and assigned the unstemmed word's weight. When several variants of the same stem occur in the list, only the first

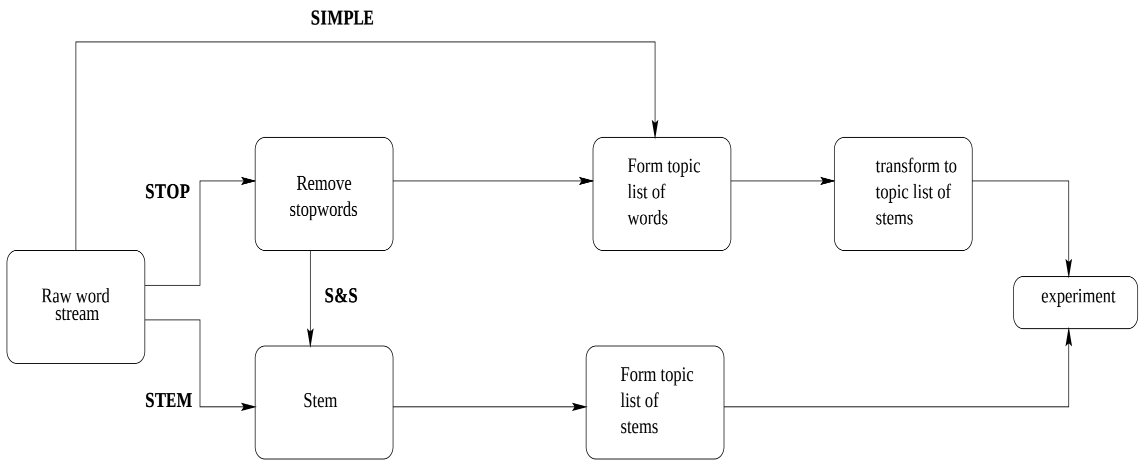


Figure 3.2: The steps involved in creating each of the indices used in the evaluation experiments

occurrence of the stem is preserved thus giving it the highest relevance weight of all its variants. This removes from the unstemmed lists variations of the same word and produces homogeneous topic word lists that can be cross-compared easily. The creation process of the different indices is shown in Figure 3.2.

It is important to note that stemming after topic word list generation is different from stemming prior to index creation. When words are stemmed before they are indexed, their frequency counts will include the occurrence of all morphological variants of the word in the database. But when stemming is done after the initial topic word lists are created a stem will be assigned the highest topic relevance weight of its variants *each treated separately.*

Now that we have our final topic word lists, we turn to the method used to evaluate the relevance measures.

3.3.3 Creating the Baseline

At the beginning of this chapter we define topic words for a category. The definition highlights the criterion by which to judge our topic relevance measures: a word that is identified by a relevance measure is acceptable as a topic word if the word is used by humans in discussing that topic. According to this criterion we must evaluate each topic relevance measure by comparing it against a manually selected list of topic words for each category. The most obvious source for these words are the keyword fields in the CoRR papers. These fields are usually assigned by the authors to briefly describe the main contents of the paper. Thus, for a paper that is classified under *Artificial Intelligence* for instance, its keywords will describe issues discussed under *Artificial Intelligence*. The collection of all keywords used in all the *Artificial Intelligence* papers could then form the list of manually selected topic words for the *Artificial Intelligence* category. Unfortunately, very few papers in the CoRR database contain the keyword field.

Luckily, since our goal is to compare the effectiveness of the topic relevance measures in capturing what humans consider topic words, any database discussing the category is a potential source for the manual topic word list. Furthermore, seeking the target topic word list from a source other than our CoRR database has the advantage that the words are more likely to be database independent. Thus the success of a topic relevance measure in finding words from this ideal list is an indication of the measure's success in recognizing vital topic words independently of the database. Also, since the ideal list is extracted from an external source, the success of our topic relevance measures in finding some of these words shows that topic words are universal for a topic and that given a sufficient amount of data about a topic, the topic words found by these measures are in fact good representations of the topic.

One source of an ideal list is the index of the Encyclopedia of Artificial Intelligence [Sha92] which provides a comprehensive list of artificial intelligence concepts. Some online journal indices also provide topic words for many different categories. These indices are easily searchable, and such large databases reduce the chances of missing good topic words for any category in the index. The most accessible index we found for the range of topics in the CoRR database was the Computer and Information Systems Abstracts index from the Cambridge Scientific Abstracts (*CSA database*) [CSA]. The online index is a database of 329,660 records from 850 serials. Each record contains several fields describing a serial's article. The fields include, among others, the *title* of the article, the *author*, the *classification* field which contains the list of general classes under which the article falls, the *descriptors* field which contains a list of closed vocabulary items describing the category of the article, and the list of *identifiers* which are open vocabulary terms found by human indexers to be strongly relevant to the contents of the article. Figure 3.3 shows a sample CSA record.

We assume that identifiers that are believed to be relevant to an article are also relevant to the categories to which the article belongs. The identifiers are used in discussing those categories and are therefore the equivalent to what we have been calling topic words. Thus, given a large enough list of identifiers for each category, we expect good topic words to appear on this list. To create such a list for a category C we collect a large number of CSA records that are classified under category C and extract the identifiers used to describe the papers indexed in these records. We will call this *the identifier list* for C. The more of these identifiers a topic relevance measure can discover, the better the measure.

But identifier lists contain phrases as well as individual words. Since we deal

TI: Title On the hardness of approximate reasoning

AU: Author Roth, Dan

AF: Author Affiliation Harvard Univ, Cambridge, MA, USA

SO: Source Artificial Intelligence [ARTIF INTELL], vol. 82, no. 1-2, pp. 273-302, 1996

IS: ISSN 0004-3702

PB: Publisher ELSEVIER SCIENCE B.V., AMSTERDAM, (NETHERLANDS)

AB: Abstract Many Al problems, when formalized, reduce to evaluating the probability that a propositional expression is true. In this paper we show that this problem is computationally intractable even in surprisingly restricted cases and even if we settle for an approximation to this probability. We consider various methods used in approximate reasoning such as computing degree of belief and Bayesian belief networks, as well as reasoning techniques such as constraint satisfaction and knowledge compilation, that use approximation to avoid computational difficulties, and reduce them to model-counting problems over a propositional domain. We prove that counting satisfying assignments of propositional languages is intractable even for Horn and monotone formulae, and even when the size of clauses and number of occurrences of the variables are extremely limited. This should be contrasted with the case of deductive reasoning, where Horn theories and theories with binary clauses are distinguished by the existence of linear time satisfiability algorithms. What is even more surprising is that, as we show, even approximating the number of satisfying assignments (i.e., 'approximating' approximate reasoning), is intractable for most of these restricted theories. We also identify some restricted classes of propositional formulae for which efficient algorithms for counting satisfying assignments can be given.

LA: Language English

PY: Publication Year 1996

PT: Publication Type Journal Article

DE: Descriptors Approximation theory; Probability; Computational methods; Constraint theory; Algorithms; Problem solving

ID: Identifiers Approximate reasoning; Bayesian belief networks; Model counting problems; Propositional languages; Horn theory

CL: Classification C 723.4 Artificial Intelligence; C 921.6 Numerical Methods; C 922.1 Probability Theory; C 721.1 Computer Theory (Includes Formal Logic, Automata Theory, Switching Theory, Programming Theory)

SF: Subfile Computer and Information Systems Abstracts

AN: Accession Number 0225588

Figure 3.3: A Sample Record From the CSA's Computer and Information Systems Abstracts database

with single words only, each identifier phrase is broken into its constituent words. Stopwords are then removed from the resulting identifier list and the remaining words are stemmed (using the Porter stemmer) and sorted by the total number of CSA records in which the stem occurs.

In order to use the CSA database for evaluating our topic relevance measures, we still have to attend to one more issue: the classification hierarchy defined by the CSA database is quite different from the categories defined by the CoRR database, but most of the twelve categories in the CoRR database can be mapped to ones in the CSA database. One CoRR category cannot be mapped to an acceptable equivalent, while two had too few documents for a reliable evaluation. The mappings for the remaining nine out of the twelve CoRR category areas are shown in Table 3.2. Some of the CoRR categories are equivalent to CSA classes used in the classification field, such as *Artificial Intelligence* which maps the *C 723.4 Artificial Intelligence* class, and *Programming Languages* which maps the *C 723.1.1 Computer Programming Languages* class; while other more specific classes can only be mapped to descriptors: *Computational Linguistics* for example is mapped to the descriptor *Natural Language Processing.* Two categories cover more than one class or descriptor in the CSA database. For example *Networking and Internet Architecture* covers many different descriptors in the CSA database each pertaining to some aspect of the category such as *Wide Area Networks*, *Network Protocols*, and *Computer Networks.*

In summary, to create the ideal topic list for each of the nine CoRR categories shown in Figure 3.2 we collected a total of $18,700$ CSA records, each satisfying the CSA equivalent of at least one CoRR category. Table 3.3 shows the exact number of records collected for each of the nine CoRR categories. We then extracted the identifiers used in the identifier fields of all CSA records in each category. Identi-

CoRR Category	**CSA Equivalent**	**CSA Field**	**#CSA Records**
AI	Artificial Intelligence	classifiers	21,910
PL	Programming Languages	classifiers	8,940
LO	formal languages and grammars; mathematical logic;	classifiers	7,124
	formal logic; formal languages; theorem proving; computational logic; lambda calculus; set theory; temporal logic; verification; correctness proofs; logic programming;	descriptors	
CC	Computational Complexity	descriptors	9,016
CG	Computational Geometry	descriptors	2,257
SE	Software Engineering	descriptors	4,428
CL	Natural Language Processing	descriptors	810
DS	Data Structures; Algorithms	descriptors	45,053
NI	Computer Networks; Communication Networks; Network Protocols; Wide Area Networks; Packet Networks	descriptors	12,218

Table 3.2: CoRR Category to CSA category mapping and the number of CSA records under each mapped CoRR category

CoRR Category	**# CSA Records**	**Target List Size**
AI	$2,357$	$2,400$
PL	$2,159$	$2,081$
LO	$2,000$	$2,574$
CC	$2,159$	$2,463$
CG	$2,210$	$2,576$
SE	$2,381$	$2,301$
CL	783	$1,153$
DS	$2,500$	$2,583$
NI	$2,151$	$2,106$

Table 3.3: The number of CSA records collected to create the target list for each of the nine CoRR categories, and the number of words in the resulting target list.

fier phrases were broken into single words, words found on the SMART stopword list [STO] were removed, and the remaining words were stemmed using the Porter stemmer [Por80]. The number of words in each category's identifier list is shown in Table 3.3.

Once the identifier lists were created, each list was sorted by the number of occurrences of the identifier stem. This sorting de-emphasizes words that are rarely used to discuss the category or which may have been used to discuss additional categories to which the indexed paper belongs. Table 3.4 shows the ten most frequent stems in AI's identifier list. The final identifier list is pruned down to the top n words to form the target topic word list. We experimented with target lists of size $n =$ 100, 200, 300, 400, 500, 1000, and 2000 words.

Identifier Word Stem	**Example Identifier Phrase**
neural	Neural Networks
network	Neural Networks
learn	Cooperative Learning Method
system	Multi-agent Systems
model	Recurrent Fuzzy Neural Model
algorithm	Learning Algorithms
function	Horn Function
base	Knowledge Based Systems
method	Cooperative Learning Method
fuzzi	Fuzzy Rules

Table 3.4: Ten most frequent word stems in the *AI* identifier list along with example phrases containing these identifier words

3.3.4 Evaluation Method

The target lists provide us with the basis for comparing the effectiveness of each of our topic relevance measures. Each of these lists contains a sample set from the space of words used to discuss the list's corresponding category. The measure that consistently finds more of these stems, especially when more of the stems are found near the start of the topic word list, is deemed to be more effective in extracting topic words than the other measures. In the remainder of this section *target list* refers to the list of identifiers (i.e. stems) presumed to represent a topic and *topic word list* and *word list* refers to the list of words that has been extracted by a topic relevance measure for a category. Each word list is sorted in decreasing order by topic relevance value.

The aim in these experiments is to evaluate the relative effectiveness of our topic relevance measures in extracting words humans view as topic words. We would also like to see the effect of stemming and stopword removal on a measure's word list.

To compare the effectiveness of the topic relevance measures we follow standard procedure in information retrieval experimentation and use the average interpolated 11-point precision-recall curves [Har01]. Precision at any point in the sorted word list is defined as the ratio of target words found until that point in the list to the number of words seen so far, while recall at any word in the sorted list is the ratio of the number of target words found up to this point in the sorted word list to the total number of identifiers in the target list. The 11-point precision-recall curves show the precision at 11 recall points from 0 to 1 with increments of 0.1. Specifying the recall values allows us to compare the results for different topic word list sizes. Since some of these recall points may not exist in our sorted list, we use interpolated 11-point precision-recall curves (p-r curves). In the interpolated curves the precision at each one of the recall points is the highest precision found at recall greater than or equal to the current recall point. The average interpolated 11-point precision-recall curves (average p-r curves) are calculated over all 9 CoRR categories for each topic relevance measure to compare the average effectiveness of each measure.

3.3.5 Results

In this section we study the effectiveness of the topic relevance measures M^{tf}, M^{DF}, $M^{\tilde{DF}}$, and M^{DF_n} for $n =$ 2,4,6,8,10,12,14,16 using the four indices SIMPLE, STEM, STOP, and S&S. The p-r curves for each of these measures were produced using target lists comprising a maximum of 100, 200, 300, 400, 500, 1000, and 2000 word stems. Recall that these lists are a sample set of topic words taken from a different database that covers topics similar to those in the CoRR database. Therefore, we do not expect any of the measures to reach high precision or recall values. However, if a measure consistently succeeds in discovering more target words than the other measures, then by comparison this measure is a better topic relevance measure.

The average p-r curves for each of the seven list sizes using the SIMPLE index are shown in Figures 3.4– 3.10. Each curve in these figures is labeled by the type of frequency used in the topic relevance measure associated with the curve. For example the curve for M^{TF} is labeled as TF. All seven lists produce a similar pattern: the more traditional measures M^{TF}, M^{DF}, and $M^{\tilde{DF}}$ have a lower precision than those of M^{DF_n}. This pattern becomes more apparent as we increase the target list size. Measures that are based on a pure count of occurrences, M^{TF} and M^{DF}, have the lowest precision values. Accounting for the minimum frequency of the term in calculating its document frequency in $\tilde{DF}$ improves precision but even $M^{\tilde{DF}}$ falls behind M^{DF_n} at all recall levels. M^{DF_2} is a further improvement over $M^{\tilde{DF}}$, which indicates that *how* the term occurs in a document influences the term's relevance to the contents of the document. This is corroborated further by the improvement in precision when using M^{DF_n} for $n > 2$. The figures also show that the precision may start to degrade at very high values of n (e.g. $n = 12$, 14, and 16) while the maximum recall will still decrease.

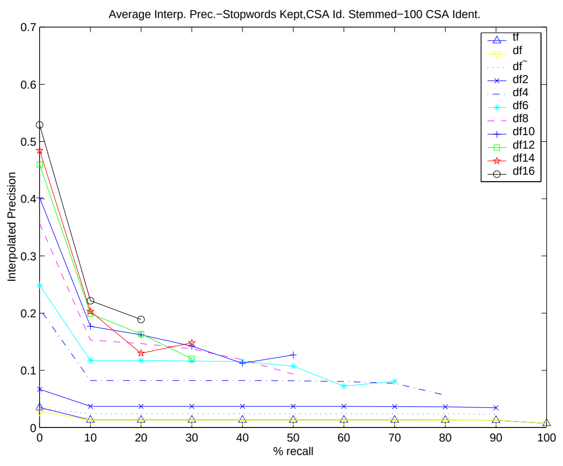
Interestingly, the increased precision for M^{DF_n} over the more traditional measures is coupled with a large decrease in vocabulary size. While M^{TF} and M^{DF} produce a total vocabulary of $54,381$ words in the SIMPLE index, M^{DF_4} extracts a vocabulary of $5,576$ words only. This is 10.25% of the vocabulary size of M^{TF} and M^{DF}. The vocabulary sizes of all measures tested are shown in Table 3.5 for the SIMPLE and STOP indices. As we have mentioned in Section 3.2.4, this reduction is to be expected since there are more words with non-zero DF and TF values than those with non-zero DF_n values in the database.

The smaller vocabulary size does have its drawback: fewer words mean a smaller chance of finding all the target words on our word list. This translates into a recall that is less than 100%. But by using reasonable values for n such as 4, 6, or 8 we improve precision by at least 30% over TF and DF without significant loss in recall.

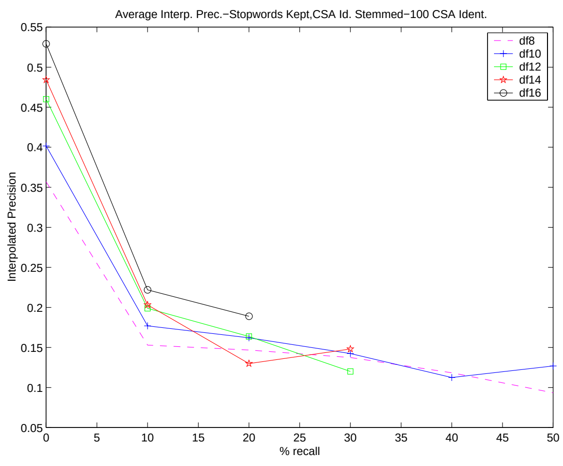
Word lists from the other three indices produced very similar p-r graphs, which shows that the relative effectiveness of the topic relevance measures is not influenced by whether stemming or stopword removal is performed, as long as the same pre-processing functions are done for all measures uniformly. This is not to say that stemming and stopword removal have no effect on the precision of topic relevance measures. In fact we found that stopword removal improves precision while stemming degrades it. Figures 3.11 and 3.12 show the p-r graphs for each M^{DF_n}

Measure	**SIMPLE Voc.**	**STOP Voc.**
M^{tf}	$54,381$	$53,877$
M^{DF}	$54,381$	$53,877$
$M^{\widetilde{DF}}$	$26,964$	$26,478$
M^{DF_2}	$15,921$	$15,447$
M^{DF_4}	$5,576$	$5,194$
M^{DF_6}	$3,022$	$2,715$
M^{DF_8}	$1,842$	$1,600$
$M^{DF_{10}}$	$1,192$	$1,002$
$M^{DF_{12}}$	849	687
$M^{DF_{14}}$	616	471
$M^{DF_{16}}$	441	315

Table 3.5: Size of the CoRR database index used by each topic relevance measure in the SIMPLE and STOP indices.

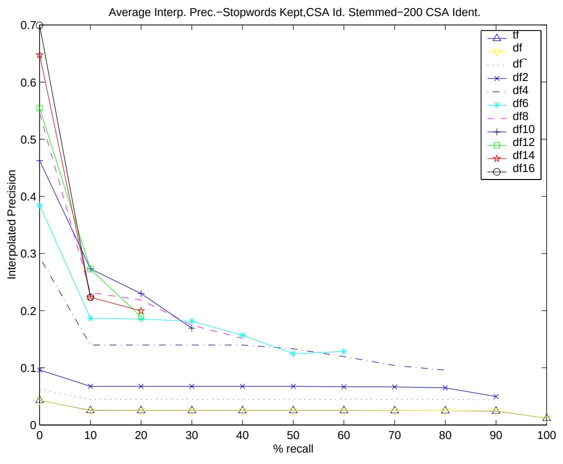


(a) The full p-r curve

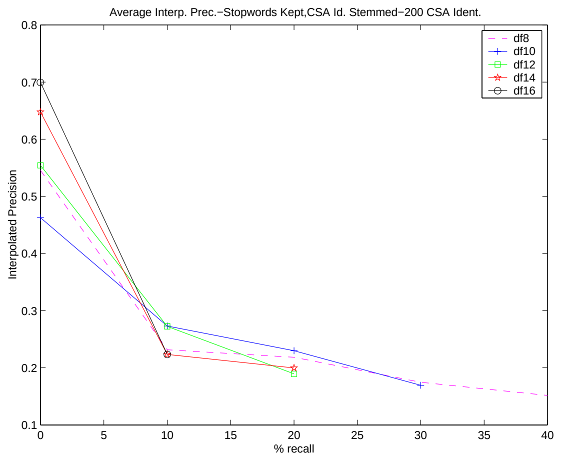


(b) The curves for $M^{DF_8} - M^{DF_{16}}$

Figure 3.4: The average interpolated 11-point average precision-recall using a 100-word target list

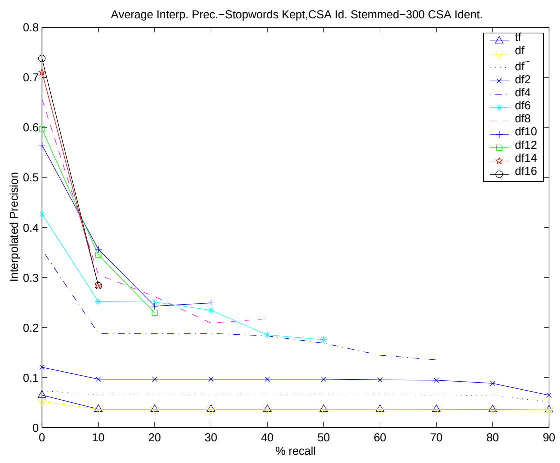


(a) The full p-r curve

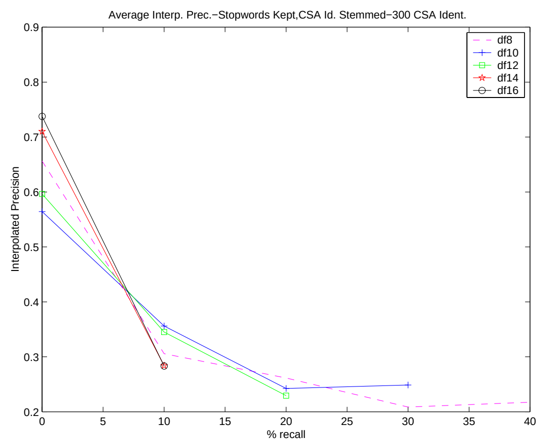


(b) The curves for $M^{DF_8} - M^{DF_{16}}$

Figure 3.5: The average interpolated 11-point average precision-recall using a 200-word target list

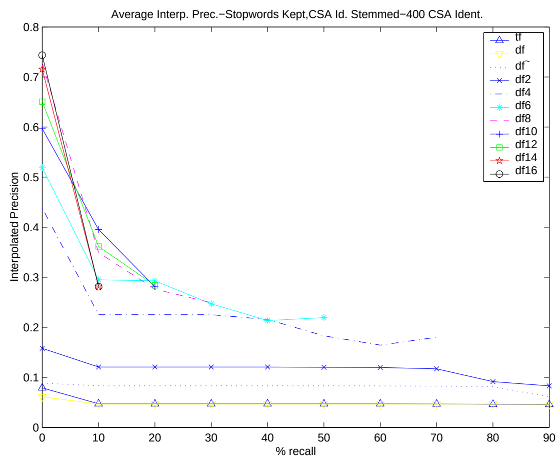


(a) The full p-r curve

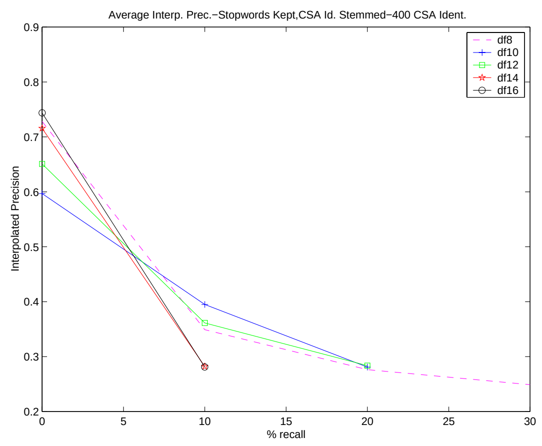


(b) The curves for $M^{DF_8} - M^{DF_{16}}$

Figure 3.6: The average interpolated 11-point average precision-recall using a 300-word target list

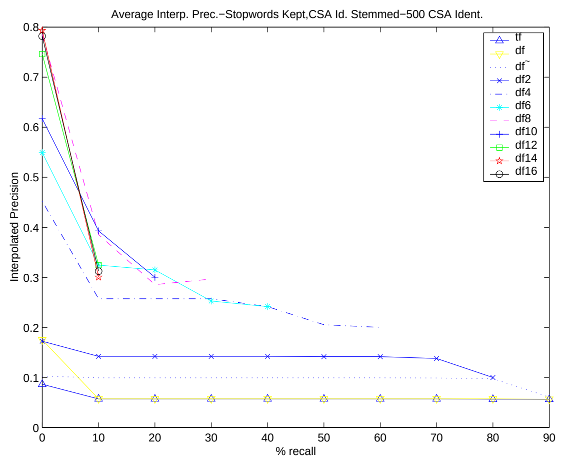


(a) The full p-r curve

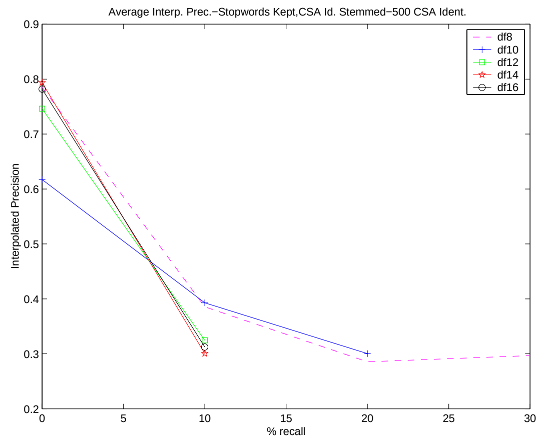


(b) The curves for $M^{DF_8} - M^{DF_{16}}$

Figure 3.7: The average interpolated 11-point average precision-recall using a 400-word target list

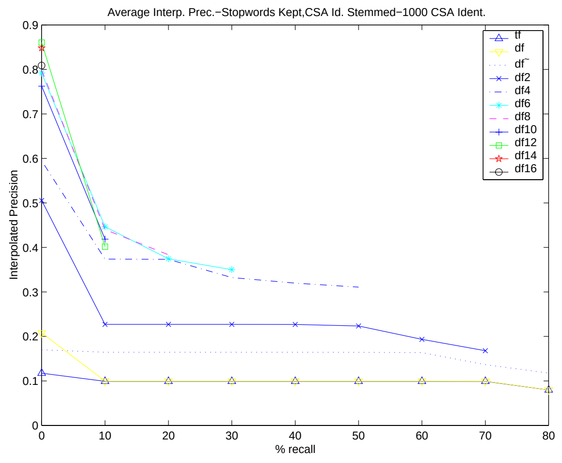


(a) The full p-r curve

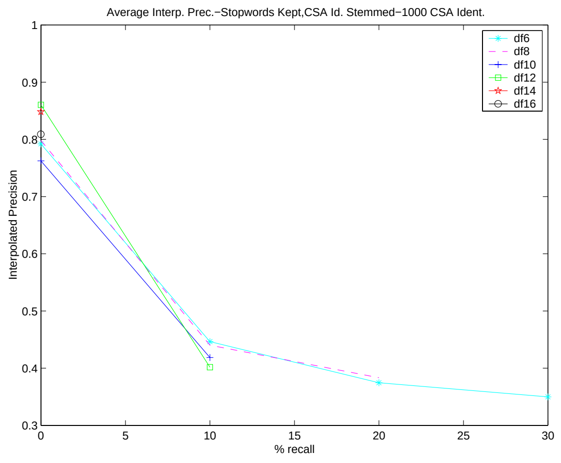


(b) The curves for $M^{DF_8} - M^{DF_{16}}$

Figure 3.8: The average interpolated 11-point average precision-recall using a 500-word target list

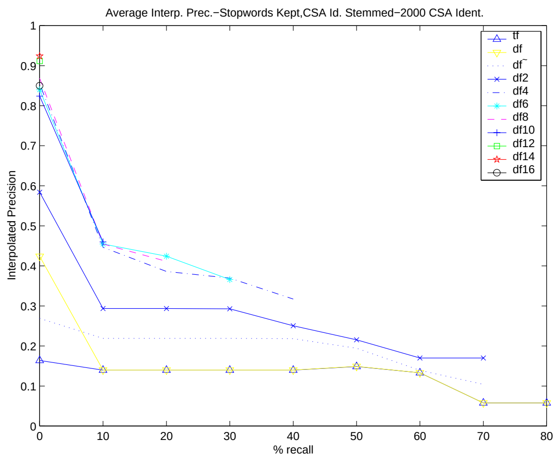


(a) The full p-r curve

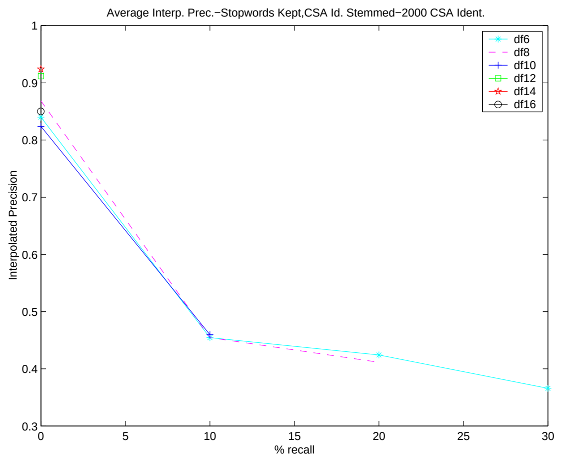


(b) The curves for $M^{DF_6} - M^{DF_{16}}$

Figure 3.9: The average interpolated 11-point average precision-recall using a 1000-word target list



(a) The full p-r curve



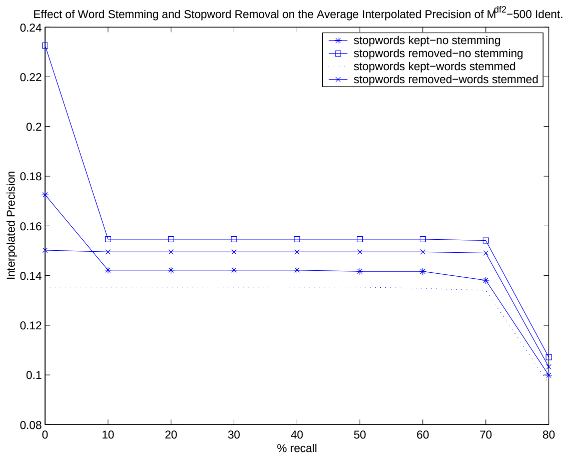
(b) The curves for $M^{DF_6} - M^{DF_{16}}$

Figure 3.10: The average interpolated 11-point average precision-recall using a 2000-word target list

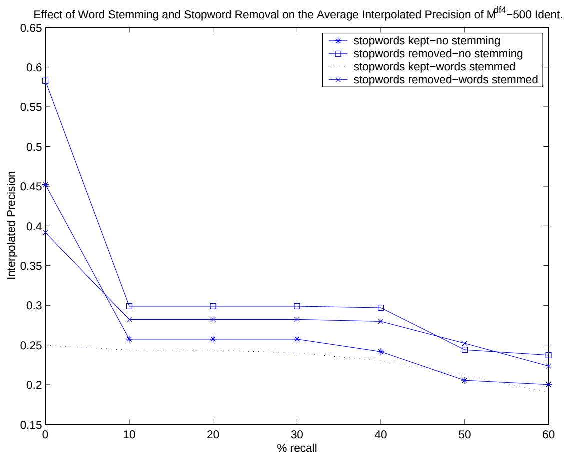
for $n = 2, 4, 6, 8, 10, 12, 14, 16$ against the top 500 target words for topic words from the SIMPLE, STOP, STEM, and S&S indices. These figures clearly show that for $n \geq 2$ stopword removal produces the highest precision while stemming always generates the least precise word lists.

The negative effect of stemming might be due to several factors: first, it could be that the genre of technical writing tends to repeat words in the same form. Also, the stemmer used might be too aggressive. The Porter stemmer reduces words to the smallest stem possible. This clusters together words that do not have a common meaning (e.g. *factory* and *factorial*) thus over-emphasizing incorrect words. A weaker stemmer that does limited stemming might have a more positive effect on precision.

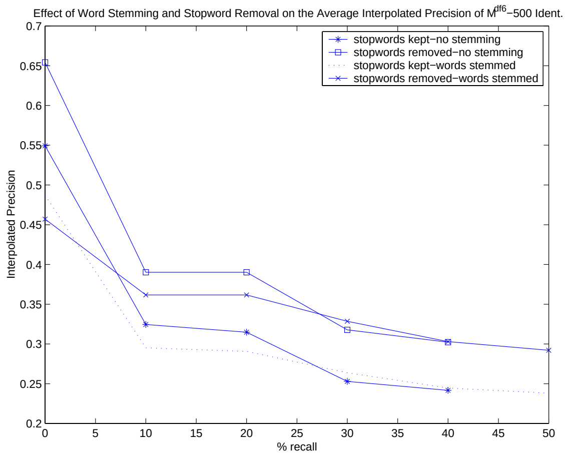
The effect of stopword removal on precision is rather surprising. Stopwords are expected to behave in a similar manner across topics, thus getting a low topic



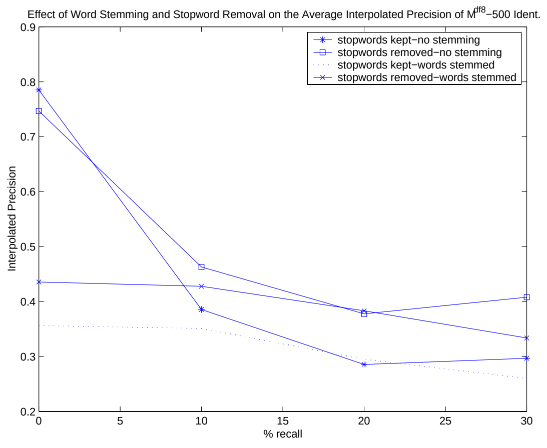
(a) M^{DF_2}



(b) M^{DF_4}

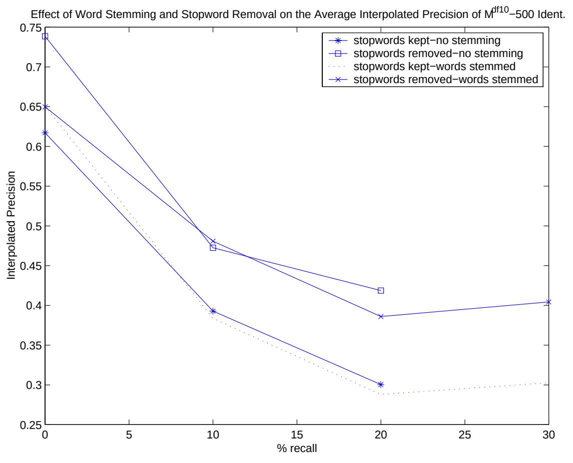


(c) M^{DF_6}

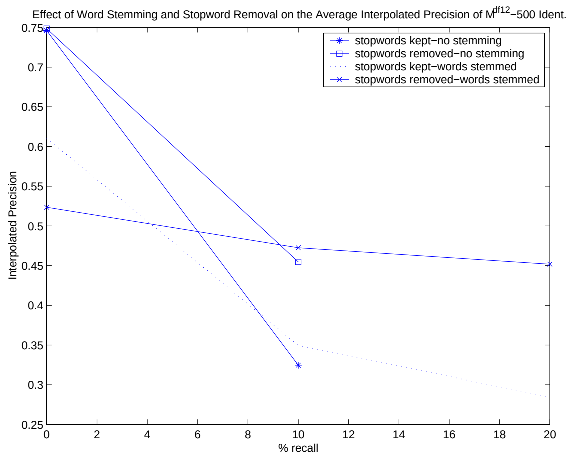


(d) M^{DF_8}

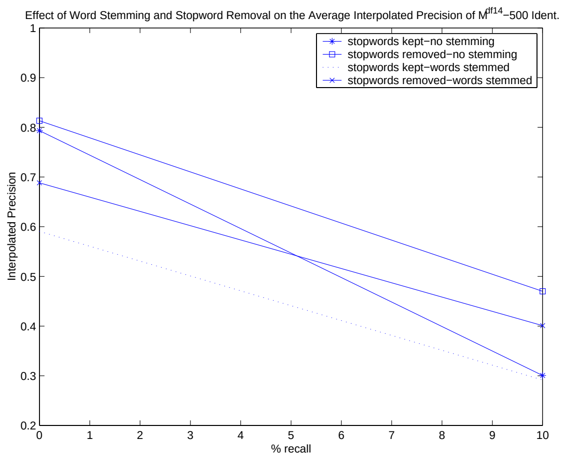
Figure 3.11: The average precision of the word lists generated by the M^{DF_2}, M^{DF_4}, M^{DF_6}, and M^{DF_8} measures using the SIMPLE, STOP, STEM, and S&S indices.



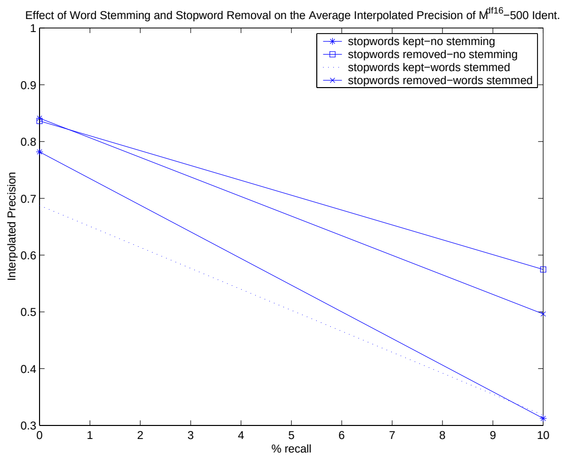
(a) $M^{DF_{10}}$



(b) $M^{DF_{12}}$



(c) $M^{DF_{14}}$



(d) $M^{DF_{16}}$

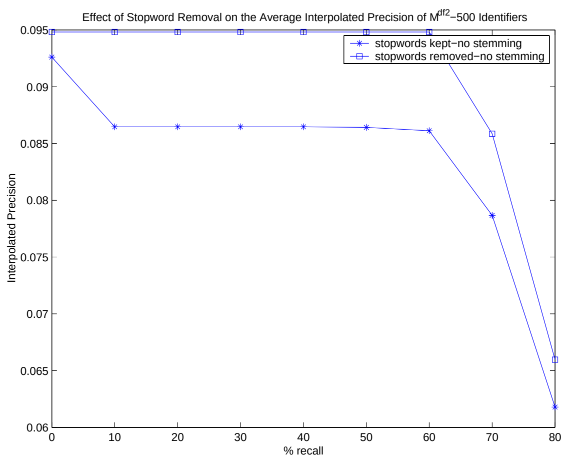
Figure 3.12: The average precision of the word lists generated by the $M^{DF_{10}}$, $M^{DF_{12}}$, $M^{DF_{14}}$, and $M^{DF_{16}}$ measure using the SIMPLE, STOP, STEM, and S&S indices.

relevance weight. This seems to be the case for the most frequent stopwords, such as *the* and *in*, which are usually at the bottom of the sorted topic word list. But there are also stopwords that are more common within some topics than others. An example is *behind* which is near the top of M^{DF_4}'s word list for categories AI and CL, but is not considered a topic word for any other category.

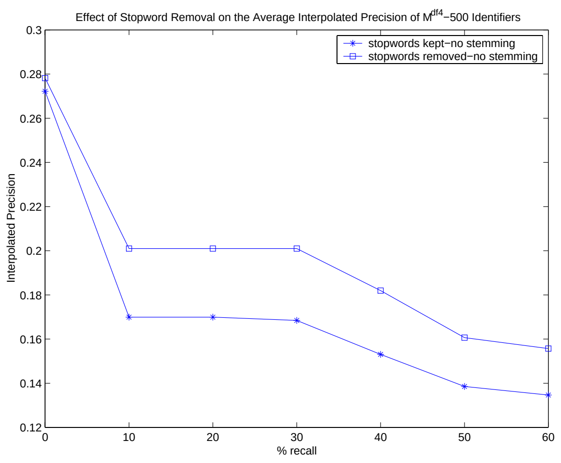
The positive effect of stopword removal is also evident in Figures 3.13 and 3.14. In these figures we compare the unstemmed word lists obtained from the STOP and STEM indices against the *unstemmed* target list which is created in the same manner as the target list we have been using so far, except that we skip the stemming step and sort CSA identifier words by their total frequency in their unstemmed form.

3.4 Conclusion

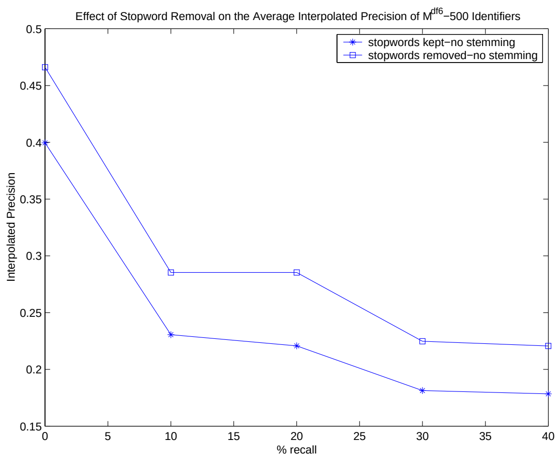
In this chapter we define topic relevance and distinguish topically relevant words from traditional information retrieval index terms. We then present four different measures of topic relevance, each using a different word frequency statistic. The first three of these measures are based on the document as a bag of words. These measures use frequency statistics that are independent of word position in the text to assess the word's topic relevance. The other measure M^{DF_n} is based on our view of text as a sequence of topic indicators. Under such a view the position of the word in the document can be useful in understanding the document's content. This measure evaluates the topic relevance of a word by how it spreads out in the document. We show that M^{DF_n} is more effective in selecting good topically relevant words than the other three measures, and that medium values of n, namely $n = 4, 6$, and 8, produce the best topic word lists. Moreover, these three measures generate



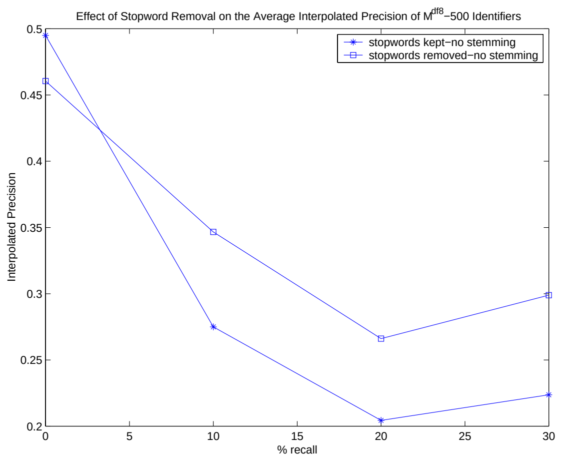
(a) M^{DF_2}



(b) M^{DF_4}

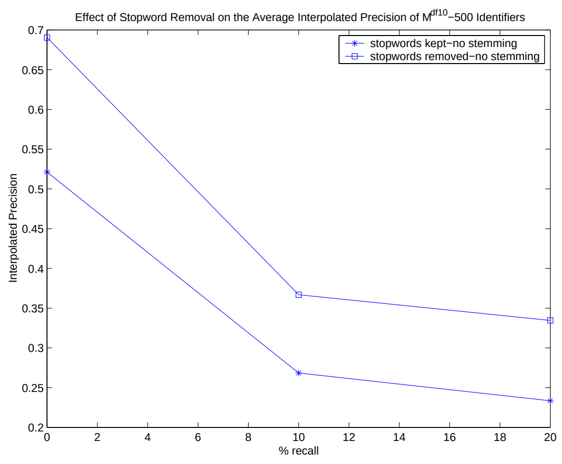


(c) M^{DF_6}

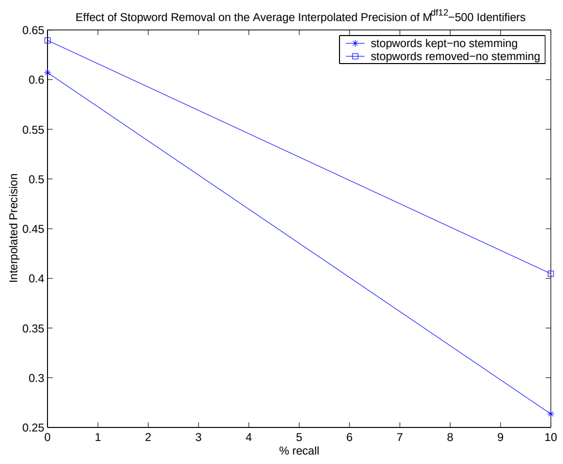


(d) M^{DF_8}

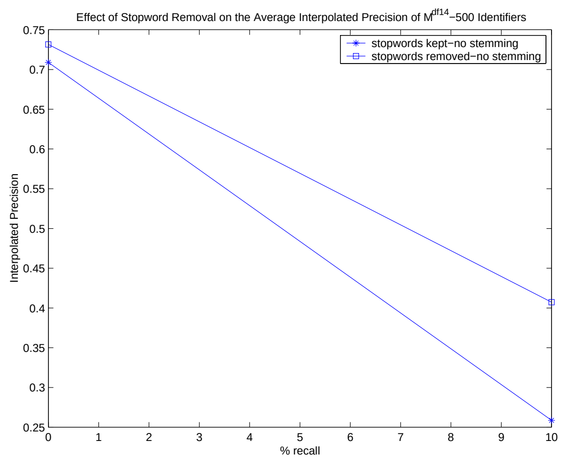
Figure 3.13: The average precision of the word lists generated by the M^{DF_2}, M^{DF_4}, M^{DF_6}, M^{DF_8} measures using the SIMPLE and STOP indices versus the *unstemmed* ideal list.



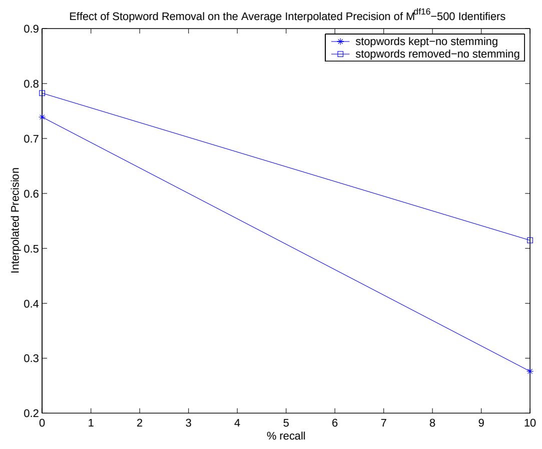
(a) $M^{DF_{10}}$



(b) $M^{DF_{12}}$



(c) $M^{DF_{14}}$



(d) $M^{DF_{16}}$

Figure 3.14: The average precision of the word lists generated by the $M^{DF_{10}}$, $M^{DF_{12}}$, $M^{DF_{14}}$, and $M^{DF_{16}}$ measures using the SIMPLE and STOP indices versus the *unstemmed* ideal list.

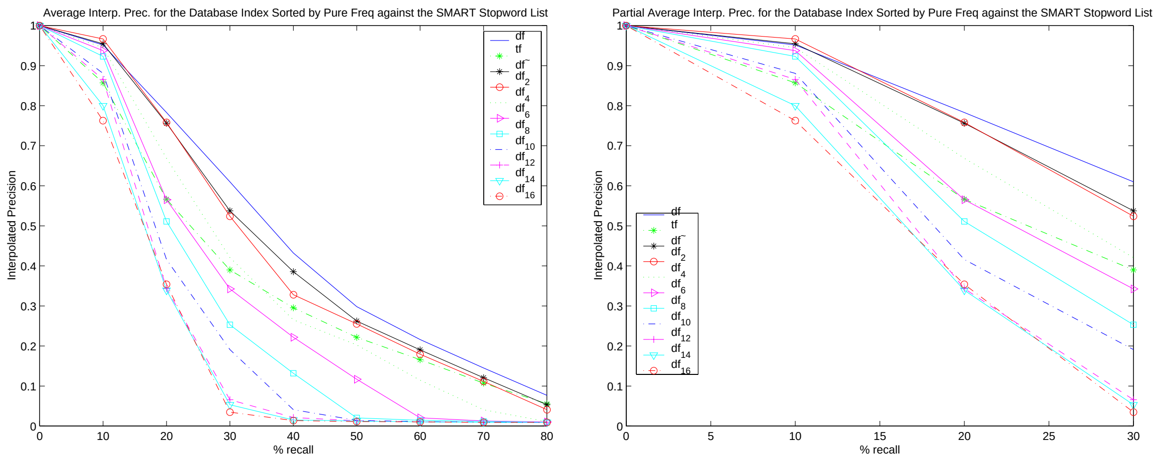


Figure 3.15: The precision of the SIMPLE index words sorted by their frequencies against the SMART stopword list.

vocabulary sizes that are between 3% and 10% of the size used by the other more traditional measures. The evaluations also indicate that stopword removal improves the precision of the topic words extracted whereas stemming degrades it.

Although we use a preset stopword list for stopword removal in the evaluation, it is preferable to be able to remove stopwords automatically with no reference to a preset list. One possible approach is to sort index words by their pure DF_n database frequency and remove the top words from this sorted list. For example, if we plan to use M^{DF_4} to weigh topic words, we can start by sorting the SIMPLE index words by $DF_4(w, db)$ and removing the top 10% of the words from the index. Figure 3.15 compares the sorted pure frequency lists to SMART's stopword list. The plots in this figure are the traditional 11-point precision-recall plot *with SMART's stopword list as the target vocabulary.* These plots show that a high proportion of the top words in any of the sorted lists are stopwords found on the SMART stopword list. Therefore, removing these words will likely improve the precision of our M^{DF_4} measure without losing too many non-stopwords from the list. This approach is similar to the adhoc feature selection method mentioned by Yang and Pedersen [YP97], where they report that removing words with the highest DF values is one of the most effective feature selection methods for text categorization. We leave further studies along these lines for future work.

In our evaluations we replaced stopwords by some null term to preserve their positions in the text. For completeness, it would be interesting to further study the effect of simply removing stopwords without preserving their position.

Another aspect we would like to investigate is the effect of a stemmer that is less aggressive than the Porter stemmer used in our evaluations. A weaker stemmer might reduce the number of words incorrectly represented by the same stem when an aggressive stemmer is utilized, but at the same time recognize words with slightly varying morphological formats, such as plurals, which would otherwise be treated as different words when no stemming is performed.

It is also interesting to explore the effect of relaxing our spread measure to allow for documents in which a word appears in m out of n segments for DF_n, for some preset value of $m < n$. This would recognize that the major topic of a paper could be interrupted in one or two places for a tangential discourse.

Chapter 4

Putting it Together: Building the Topic Flow Signal

Topic flow signals reflect the variation in the intensity of discussion related to the topic across the text. Heavily discussed topics in a text tend to recur throughout and remain relevant to most of the document. Therefore, such topics have a continuous stream of strongly relevant topic words throughout the text. Topics that are discussed less intensely, however, are either relevant to limited portions of the text, or are interrupted often thus shifting the focus of discussion away from that topic. Such topics have a more sparse distribution of relevant topic words indicating a weaker presence in the text. So generating a topic flow signal for a given text is simply a matter of representing the relevance of the topic to each segment of the text.

We start by describing the signal construction algorithm, which generates the most basic topic flow signals. The constructed signals are then used to view the flow of the topic at varying levels of detail within the text. Finally, we show that topic flow signals reflect the actual change in the intensity of discussion within the document.

4.1 Constructing the Initial Signal

The most basic topic flow signal relies on our earlier observation that given a sufficient list of topic words for a category we will find strongly relevant topic words in text segments which discuss the category. By tracking the topic relevance of the words across the text we can construct a word-based representation of the topic flow within the text. The algorithm for representing the flow of a topic t in a given document D is presented in Algorithm 1. The algorithm iterates through the document, and at each word w's position in the text the corresponding position in the signal is assigned a value reflecting the word's relevance to the topic. Our measure of topic relevance is based on the sorted topic word lists of $M^{DF_4}(w,t)$ which, as we have seen in the previous chapter, produces one of the most accurate topic word lists with little loss in vocabulary.

Given the topic word lists sorted by their M^{DF_4} weights, at each word position w in the text the algorithm assigns the corresponding signal position a value equal to the rank of w in the sorted topic word list for topic t as described in the Rank subroutine in Algorithm 1. If w is not on t's topic word list but on some other topic's list, it is assigned one plus the maximum rank in topic t's list, otherwise it is discarded.

The resulting topic flow signal should remain low at points of strong relevance to the topic and peak at points where there are shifts away from the topic. Therefore, the signal should provide a good representation of the progression of the topic in the document. We have already seen a sample signal in Chapter 2 for the text in Example 4.1.1:

Example 4.1.1 *Belief revision focuses on how an agent should change her beliefs when she adopts a particular new belief. [FH99]*

The signal in Figure 2.3 was constructed using M^{DF_4}'s topic word list for *Artificial Intelligence*. The same signal is reproduced in Figure 4.1 with each vertex labelled by the word that generated the vertex's topic relevance value.

To take another example, Figure 4.2(a) shows the *Computation and Language* signal for a segment from the paper entitled "Applying Natural Language Generation to Indicative Summarization" [KMK01]:

Example 4.1.2 *We have presented a model for indicative multi-document summarization based on natural language generation. In our model, summary content is based on document features describing topic and structure instead of extracted text. [KMK01]*

As expected, the signal in Figure 4.2(a) has relatively low ranks for many terms relevant to *Computation and Language*, such as *model*, *language*, *content*, and *text*.

The flow of any other topic in the text can be represented in a similar manner through another signal. The assumption here is that any number of topics can be discussed simultaneously in a document, and each of these topics can be represented by a separate topic flow signal. The topic flow of *Artificial Intelligence* for Example 4.1.2 is shown in Figure 4.2(b). The variation among the vertex values and the word ranks in this signal are higher than those in the *Computation and Language* signal, indicating a relatively weaker presence of *Artificial Intelligence*'s topic words in the segment, and thus a relatively weaker discussion of the topic.

Algorithm 1 Construct topic flow signal S_t for topic t in input document D

```
**INPUT:** Document $D$;
        $||D||$ = The number of word positions in $D$;
        Topic $t$;
        $T$= Topic word list for $t$ sorted by $M^{DF_4}(w,t)$;
        $Voc$= $\bigcup_{\forall \text{topics } t_i}$ topic word list for $t_i$
**OUTPUT:** Topic flow signal $S_t$ for topic $t$ in document $D$;

$sig\_position = 0$;
**for** ($text\_position = 0$; $text\_position < ||D||$; $text\_position{+}{+}$) **do**
  $w$ = word at $text\_position$ in $D$;
  **if** ($w \in T$) **then**
    $S_t[sig\_position] = rank(w, T)$;
    $sig\_position{+}{+}$;
  **else if** ($w \in Voc$) **then**
    $S_t[sig\_position] = 1 + maximum\_rank(T)$;
    $sig\_position{+}{+}$;
  **else**
    ignore $w$;
  **end if**
**end for**
```

(continued)

SUB Rank

```
{Find the number of weights lower than word $w$'s in topic word list $T$}
**INPUT:** word $w$; Sorted topic list $T$;
**OUTPUT:** rank of weight of $w$ in $T$;

$tmp\_rank = 0;$
$i = 0;$
$prev\_wt = T[i]\{WEIGHT\};$
**while** (NOT($Done$) AND ($i \leq ||T||$)) **do**
  **if** ($T[i]\{WEIGHT\} \neq prev\_wt$) **then**
    $prev\_wt = T[i]\{WEIGHTT\};$
    $tmp\_rank++;$
  **end if**
  **if** ($T[i]\{WORD\} == w$) **then**
    $Done = TRUE;$
  **end if**
  $i++;$
**end while**
return($tmp\_rank$);
```

Algorithm 1 (continued)

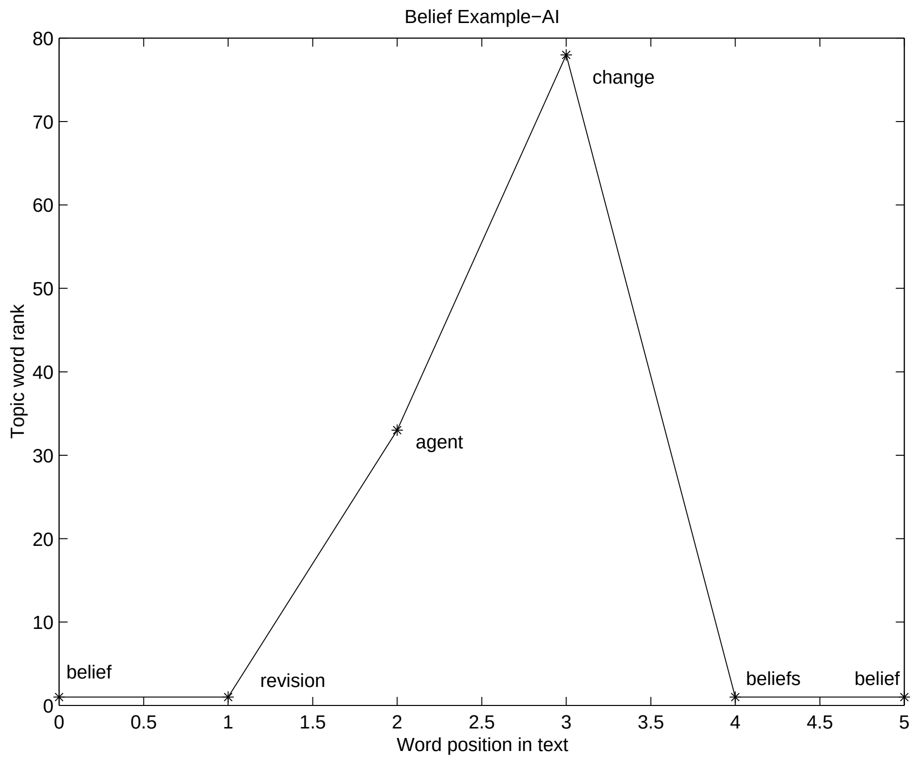
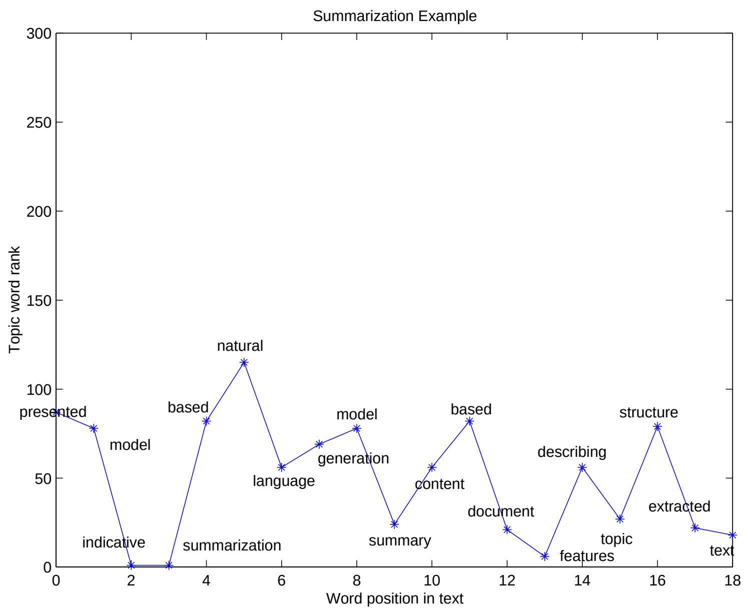
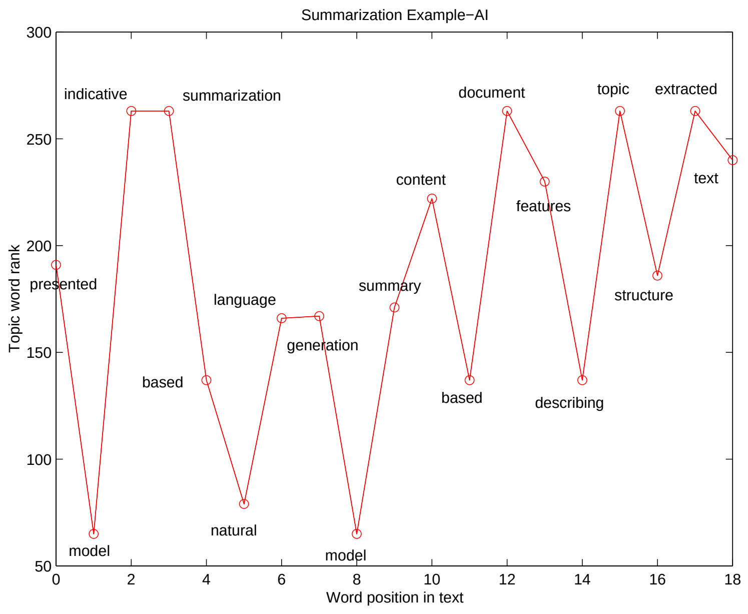


Figure 4.1: Topic flow signal for the topic *Artificial Intelligence* based on the relevance values in Table 2.2. Each vertex in the signal is labelled by the word that generated the vertex.



(a) The *Computation and Language* topic flow signal



(b) The *Artificial Intelligence* topic flow signal

Figure 4.2: Topic Flow signals for the topics *Computation and Language* and *Artificial Intelligence* in Example 4.1.2. Each vertex in the signal is labelled by the word that generated the vertex. Note the higher ranks and the wider variation in these ranks within the *Artificial Intelligence* signal.

4.2 Zooming out: Representing the topic flow of larger segments

The topic flow signals constructed in the previous section represent the change in topic relevance at individual word positions. Although words are the basic units for expressing a topic, the overall topic of a sequence of words is a complex function of many variables including the constituent words, the structure governing these words, the order of the words, and the situational context within which the text was produced. For simplicity we focus here on identifying the general topic of a sequence of words from its constituent words and the context of each word. This word sequence can be as long as the document itself. It can also be a segment of the text in which case the topic relevance of the whole word sequence represents the topic relevance of the document at that particular segment.

By dividing the whole text into consecutive word sequences we can represent the topic flow within the text through these text segments rather than representing it at individual word positions. The resulting segment-based topic flow signal should provide a more general view of the text, and by varying the segment size we can monitor the change in topic flow at different levels of detail.

We assume that the relevance of a single segment to a topic is a function of the importance of the constituent words to that topic. Given the ranks of these individual words in the sorted topic word list, the segment's topic relevance is represented by the average rank of the words in the segment:

$$M(SEG,t) = \frac{\sum_{\forall w:((w \in SEG) \wedge (\text{w a topic word for some topic } \tau \in T))} RANK(w,t)}{||SEG||} \tag{4.1}$$

where:

- $M(SEG, t)$ is the importance of topic t in segment SEG.
- $RANK(w, t)$ is the rank of the topic relevance value for word w in the sorted topic word list for t as defined in the RANK subroutine in Algorithm 1.
- $||SEG||$ the number of words in segment SEG.
- T is the set of all possible topics.

This approach allows us to include all words within the segment when estimating its topic relevance. Averaging the words' ranks also smoothes out the effect of the occasional noise word.

To view the topic flow in document D at the n-word segment size, we start by dividing the document into equal segments, each consisting of approximately n words. Next we calculate $M(SEG, t)$ the importance of topic t for each of these segments as described in Equation 4.1 above. Algorithm 2, which is a slightly modified version of the word-based signal construction algorithm described in Algorithm 1, can then be used to construct the topic flow signal for this segment size.

With a few more operations we can also generate the topic flow at increasingly larger segment sizes: Starting with the word-based signals, we can get the topic flow at 2-word segment sizes by averaging every pair of consecutive words in the signal. The signal for the 2-word segment size can then be used to generate the 4-word segment signals. Similarly, for any segment size 2^i we use the signal for segment size 2^{i-1}. This algorithm, shown in Algorithm 3, is extremely efficient requiring only $O(||D||)$ operations to construct the topic flow signals for all 2^i segment sizes from $i = 1..log(||D||)$, where $||D||$ is the number of words in the document D.

Algorithm 2 Construct topic flow signal S_t for topic t in input document D at segment size n

```
INPUT: Document $D$ divided into segments of size $n$ each;
        $||S||$ = The number of segments in $D$;
        Topic $t$;
        Topic relevance value $M(SEG, t)$ for each segment $SEG$;
OUTPUT: Topic flow signal $S_t$ for topic $t$ in document $D$;

for ($seg\_num = 0$; $seg\_num < ||S||$; $seg\_num$++) do
  $SEG$ = segment $seg\_num$ in $D$;
  $S_t[seg\_num] = M(SEG, t)$;
end for
```

Algorithm 3 The averaging algorithm for the Haar Wavelet Transform

```
  {Construct topic flow signals $R_t$ for larger segment sizes using the word-based topic flow signal $S_t$}
  INPUT: Word-based topic flow signal $S_t$ for topic $t$ in document $D$;

          $||S_t||$ = the number of points in signal $S_t$

  OUTPUT: Set of topic flow signals $R_t[0..(log(||S_t||))]$ where $R_t[i]$ is the topic flow signal representing text segments of size $2^{((log||S_t||)-i)}$;

  $max_l = log||S_t||$;
  for ($i = 0$; $i < ||S_t||$ ; $i{+}{+}$) do
    $R_t[max_l][i] = S_t[i]$;
  end for
  for ($l = max_l - 1$; $l >= 0$ ; $l{-}{-}$) do
    $i = 0$;
    for ($position = 0$; $position < ||R_t[l+1]|| - 1$; $position = position + 2$) do
      $R_t[l][i] = \frac{R_t[l+1][position]+R_t[l+1][position+1]}{2}$;
      $i{+}{+}$;
    end for
  end for
```

Just as averaging pairs of consecutive points in a signal smoothes the signal, taking the difference between these pairs emphasises the local changes in topic relevance, usually due to noise. Adding the averaged signal and the difference signal reproduces the original unsmoothed signal. Similarly, if we keep the signal representing topic flow for segments of size n, for some value of n, as well as the difference between consecutive pairs at all the levels preceding that signal, we can reconstruct our initial word-based signal. In this case, we will have transformed the initial word-based signal into another equivalent representation that provides us with a different view of the same text. This transformation is called the *Haar Wavelet Transform*, the simplest type of wavelet transforms, which are used in many applications including noise reduction, image processing, and signal compression [SN96] [JlCH01].

Since we are not interested in the noise within the signal, nor are we interested in reconstructing the signal, we will not keep these differences. Instead, we are interested in the various views of the text at different segment sizes, each of which reflects the flow at a different level of detail. We will call these levels of detail *levels of resolution*. Wavelet transformation is an efficient method to obtain these multi-resolution signals. However they require a signal length that is a power of 2. When this is not the case the signal is extended to the nearest power of 2 size by padding it with some constant, by repeating a portion of the signal, or by some other signal extension method [SN96] [JlCH01]. In the context of topic flow, concatenating the signal with any artificial value disrupts the real topic flow representation. This problem has posed serious concerns for us regarding the accuracy of the extended signals in reflecting topic flow. The solution, however, turns out to be quite simple. The power of 2 length requirement stems from the averaging approach where we average every two consecutive words starting from the word-based topic flow signal. Instead, we can start by recursively dividing the text into segments of equal sizes. At each level of resolution, we are now certain that all segments are of roughly the same size, thus representing equal portions of the text with no artificial values added. The detailed algorithm is presented in Algorithm 4. For instance, a document consisting of 9 words can be divided into 4 and 5 word segments, each of these two segments can then be divided into 2 and 2, and 2 and 3 word segments respectively for topic flow at the lower, more detailed, segment size. At the very bottom we will find seven consecutive segments of size 1 word, and one segment of size 2. The segment sizes for each level of resolution in this 9-word text is shown in Figure 4.3. Now that we have segments of roughly equal size at each level of resolution, we can proceed as before in finding the topic relevance for each segment at a certain resolution level and constructing the topic flow signal for that resolution starting from the most detailed level up to the more general levels with larger segments. The main difference from the original averaging step in the wavelet transform is that our segment sizes do not necessarily have power of 2 length, nor does our text. We do, however, need to know apriori the total size of the text which may not be available in some situations such as when streams of text are being received and their signals constructed in real-time. Figure 4.4 shows the topic flow signals for the topics *Computation and Language* and *Artificial Intelligence* at resolution levels 0–5 for the sample text in Figure 4.1.2.

4.3 Evaluation

So far we have been concerned with building topic flow signals and viewing the flow of topics at different levels of resolution. The assumption has been that words are the “atomic units” used to describe the topics under discussion [Kat96], that by following the relevance of these words to the topic we will manage to create a signal

Algorithm 4 The Gradual Averaging algorithm

```
{Construct topic flow signals $R_t$ for larger segment sizes using the word-based topic flow signal $S_t$}
**INPUT:** Word-based topic flow signal $S_t$ for topic $t$ in document $D$;
        $||S_t||$ = the number of points in signal $S_t$
**OUTPUT:** Set of topic flow signals $R_t$ where:
        $R_t[i]$ is the topic flow signal at resolution level $i$, with the the most general level at $i = 0$ which consists of one point representing the overall average of relevance in the text.

{Get number of words in each segment at each level in the transform}
get_segment_sizes( $segment\_sizes$, $max_l$ );
for ($i = 0$; $i < ||S_t||$ ; $i{+}{+}$) do
  $R_t[max_l + 1][i] = S_t[i]$;
end for
{Create the first level of the transform after $R_t[max_l + 1]$}
get_first_sums( $R_t$, $segment\_sizes$, $max_l$ );
for ($l = max\_l - 1$; $l >= 0$ ; $l - -$) do
  $i = 0$;
  for ($position = 0$; $position < ||R_t[l + 1]|| - 1$; $position = position + 2$) do
    $R_t[l][i] = R_t[l + 1][position] + R_t[l + 1][position + 1]$;
    $R_t[l + 1][position] = R_t[l + 1][position]/segment\_sizes[l + 1][position]$;
    $R_t[l+1][position+1] = R_t[l+1][position+1]/segment\_sizes[l+1][position+1]$;
    $i{+}{+}$;
  end for
end for
$R_t[0][0] = R_t[0][0]/segment\_sizes[0][0]$;
```

(continued)

```
**SUB** get_segment_sizes

  **INPUT:** $||S_t||$;
  **OUTPUT:** $segment\_sizes$ : an array containing number of words to include in
  each segment at each level in the transform;
          $max_l$ the maximum level in $segment\_sizes$;

  $i = 0$;
  $segment\_sizes[0][0] = ||S_t||$;
  **for** ( $l = 1$; $2^l \leq ||S_t||$; $l$++) **do**
    $p = 0$;
    $max_l = l$;
    **for** ( $i = 0$; $i <$ number of elements in $segment\_sizes[l-1]$; $i$++) **do**
      $segment\_sizes[l][p] = \lfloor \frac{segment\_sizes[l-1][i]}{2} \rfloor$;
      $segment\_sizes[l][p+1] = segment\_sizes[l-1][i] - segment\_sizes[l][p]$;
      $p = p + 2$;
    **end for**
  **end for**
```

Algorithm 4 (continued)

SUB get_first_sums

```
INPUT: $segment\_sizes$ : an array containing number of words to include in
each segment at each level in the transform;
        Topic flow signals array $R_t$;
        Current resolution level $l$;
OUTPUT: Topic flow signal $R_t[l]$ at resolution level $l$;

$position = 0$;
for ( $p = 0$; $p <$ number of elements in $segment\_sizes[l]$; $p{+}{+}$) do
  $R_t[l][p] = 0$;
  for ( $i = 0$; $i < segment\_sizes[l][p]$; $i{+}{+}$) do
    $R_t[l][p] = R_t[l][p] + R_t[l+1][i + position]$;
  end for
  $position = position + segment\_sizes[l][p]$;
end for
```

Algorithm 4 (continued)

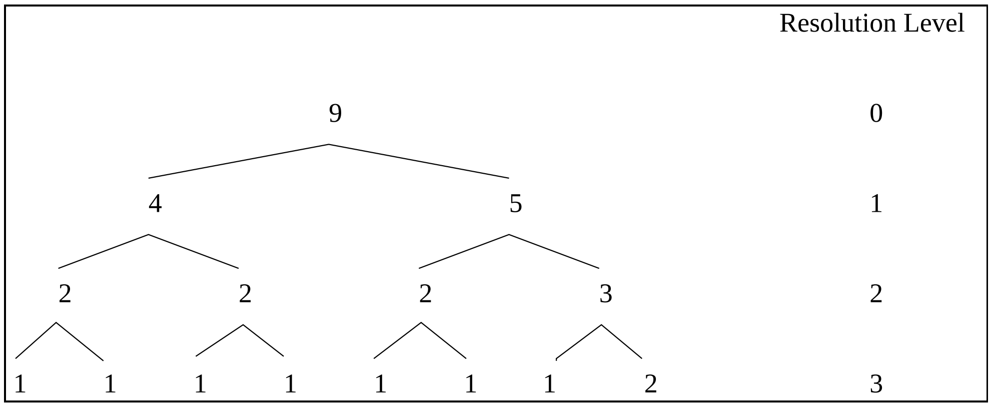


Figure 4.3: Segment sizes at different resolution levels for a 9-word text

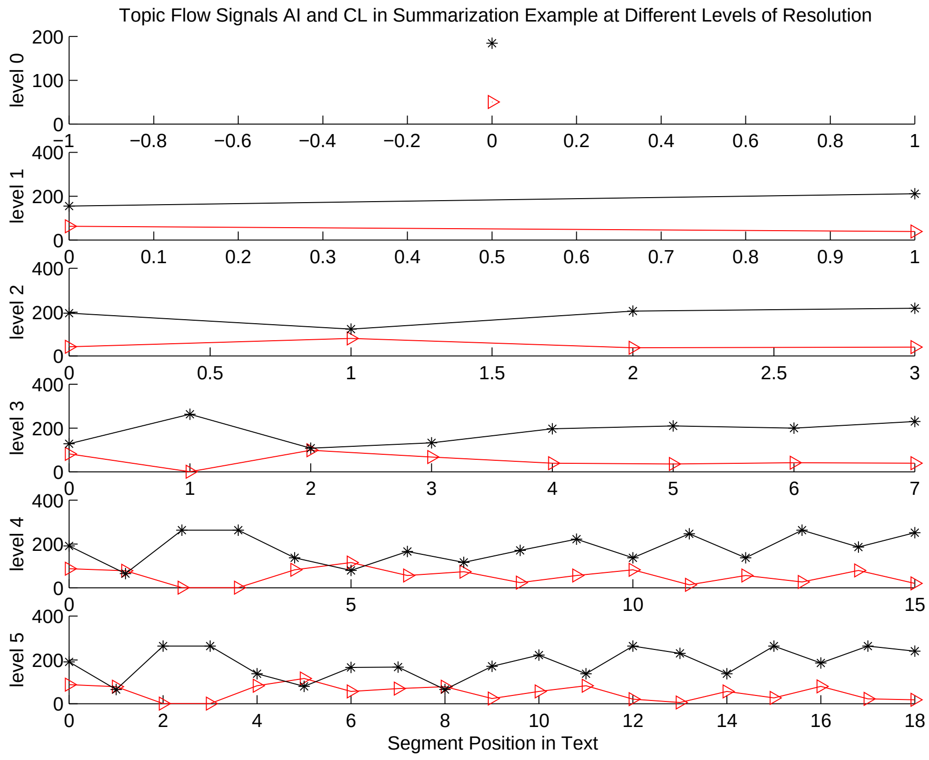


Figure 4.4: The transform of the *Computation and Language* (triangles) and *Artificial Intelligence* (asterisks) signals for the paper segment 4.1.2

that can reflect topic flow in the text. By gradually smoothing this word-based signal we get a more robust topic flow representation at larger text segments. This section aims at evaluating the signals' ability to represent topic flow.

4.3.1 The Ideal Topic Flow Signal

Evaluating the quality of our topic flow signals requires comparing these signals to the ideal topic flow representation in the text. An *ideal* topic flow signal should remain low when the corresponding text intensifies its discussion on the topic indicating strong topic relevance, and peak when the corresponding text significantly reduces its discussion of the topic indicating. But the knowledge of when the topic discussion intensifies and when it abates necessitates usage of documents whose different segments have been manually categorized for any segment size. This manual categorization would reflect the flow of topics at different segment sizes including temporary digressions that take up small segments, as well as subtopics that may span larger segments.

An alternative to manually categorizing document segments is to construct our evaluation documents from smaller pre-categorized texts. Ideally, we would also like these smaller texts to discuss the topics under which they have been categorized throughout the text with no digressions to any other topic. These criteria are best met in the abstracts of technical papers: abstracts are concise so the possibility of digressions is minimal, and they aim to describe only the main topics of the paper so they are more likely to discuss these topics throughout the abstract.

Given a sequence of abstracts each of which belongs to at least one category, the ideal topic flow signal for a category t within this sequence is a reflection of the distribution of the category's abstracts. Such a signal would indicate the strongest

This paper compares the tasks of part-of-speech (POS) tagging and word-sense-tagging or disambiguation (WSD), and argues that the tasks are not related by fineness of grain or anything like that, but are quite different kinds of task, particularly becuase there is nothing in POS corresponding to sense novelty. The paper also argues for the reintegration of sub-tasks that are being separated for evaluation.

This paper describes the design of a control and management network (orderwire) for a mobile wireless Asynchronous Transfer Mode (ATM) network. This mobile wireless ATM network is part of the Rapidly Deployable Radio Network (RDRN). The orderwire system consists of a packet radio network which overlays the mobile wireless ATM network, each network element in this network uses Global Positioning System (GPS) information to control a beamforming antenna subsystem which provides for spatial reuse. This paper also proposes a novel Virtual Network Configuration (VNC) algorithm for predictive network configuration. A mobile ATM Private Network-Network Interface (PNNI) based on VNC is also discussed. Finally, as a prelude to the system implementation, results of a Maisie simulation of the orderwire system are discussed.

We present a memory-based learning (MBL) approach to shallow parsing in which POS tagging, chunking, and identification of syntactic relations are formulated as memory-based modules. The experiments reported in this paper show competitive results, the F-value for the Wall Street Journal (WSJ) treebank is: 93.8% for NP chunking, 94.7% for VP chunking, 77.1% for subject detection and 79.0% for object detection.

Figure 4.5: A sample sequence of abstracts. The first and last abstracts belong to *Computation and Language*, while the second abstract is on *Networks and the Internet*.

topic relevance at points where the abstract belongs to category t, and peak to its highest rank values indicating no topic relevance otherwise. Figure 4.5 shows a sample sequence of abstracts.

The topic flow signals we have constructed in the previous sections are all word-based. Our ideal signals should similarly be word-based. We will make the unrealistic assumption that if an abstract is categorized under a topic, then every vocabulary word in the abstract will be relevant to that topic. This is a restrictive assumption that hypothesizes there is absolutely no noise in our abstracts, even though it is possible to have vocabulary words within the abstract that are not relevant to the abstract topic. Nevertheless, we believe that due to the concise nature of abstracts, and the noise reduction effect of averaging, this assumption will not have a huge impact on our evaluation.

Given a sequence of abstracts, we now proceed to build the ideal word-based topic flow signals as follows: we start by removing from the abstracts all non-vocabulary words. A vocabulary word is one that is known to be a topic word for any of our 12 categories using the M^{DF_4} topic word lists. We then create the ideal topic flow signal for each of the 12 CoRR categories where for every topic t we trace each word in the abstracts and mark its corresponding position in the signal with a 1 if the abstract belongs to the topic t, or with a $(max\_rank(t) + 1)$ if the abstract does not belong to t, where $max\_rank(t)$ is the maximum possible rank in the topic word list for t. To get the ideal topic flow at larger segments, we simply use the gradual averaging algorithm described earlier 4. Figure 4.6 shows the ideal word-based topic flow signals as well as the topic flow at resolution levels $0 - 7$ for the simple document in Figure 4.5 whose first and third abstracts are *Computation and Language* abstracts, while its second abstract is a *Networks and the Internet* abstract.

4.3.2 Evaluation Abstract Sequences

We created our evaluation abstract sequences using the abstracts of the technical papers submitted to the CoRR website [CORa] between January 1998 and Dec 2001. There are two evaluation sequences: The first, called the T sequence, consists of 736 abstracts summarizing the CoRR papers used by our system in creating its list of topic words. The corresponding set of full papers is called the *CoRR training set*. It is important to note, however, that before the training set was used to

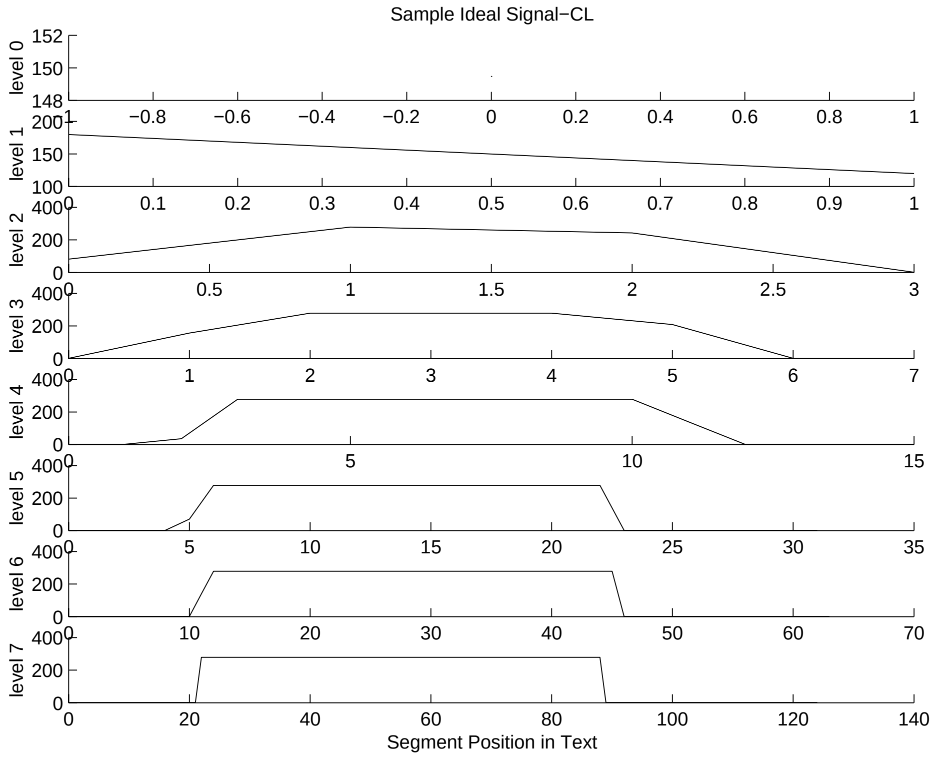


Figure 4.6: The *Computation and Language* ideal topic flow signal at the word level (level 7), and at increasingly larger segment sizes (levels 6 up to 0) for a sample document consisting of 3 abstracts the first and last of which are *Computation and Language* abstracts and the second is on *Networks and the Internet*

extract topic words, the abstracts were stripped from the set's papers. So although the papers from which these abstracts come were in the training set, the abstracts themselves were not. Nevertheless, the system will have been trained on most of the topic words appearing in these abstracts. Therefore, the T abstract sequence will assist us in evaluating our topic flow signals given that the system recognizes all the important topic words, and that there is no inconsistency in the categorization of the segments in the T abstract sequence versus the training set papers.

The second evaluation abstract sequence, called the N sequence, consists of 447 abstracts of papers that were submitted to the CoRR website between January 1998 and December 2001, but whose papers were not part of the training set. Since the papers to which these abstracts belong were not used in training, the chances of missing good topic words are much higher than in the T sequence. Therefore, this document is useful in evaluating the robustness of our topic flow signals in the presence of noise due to missing topic words, or due to inconsistencies in categorizing the abstracts compared to the training set. Table 4.1 shows the number of abstracts that fall under each of the 12 categories tested, as well as the number of abstracts that belong solely to that category ("one-topic abstracts") in the T and N abstract sequences.

To ensure that there is no bias for the order in which abstracts are concatenated, we created three different versions of each abstract sequence T and N where each version contains a random ordering of the abstracts used in the sequence. We will call the T sequence versions T_1, T_2, and T_3, and those using the N sequence N_1, N_2 and N_3.

TOPIC	# abs in T (TA)	# one-topic abs in T (OTA)	$\|\|T\|\|$	# abs in N (NA)	# one-topic abs in N (ONA)	$\|\|N\|\|$
CL	179	149	736	94	47	447
CC	100	49	736	41	15	447
SE	38	17	736	33	11	447
CG	62	26	736	10	1	447
NI	25	8	736	90	71	447
DC	41	13	736	44	17	447
AI	160	40	736	90	24	447
PL	76	19	736	53	16	447
LO	130	22	736	44	14	447
DS	90	15	736	22	4	447
LG	60	9	736	20	1	447
CE	23	3	736	24	4	447

Table 4.1: The number TA and NA of abstracts belonging to each of our 12 CoRR topics in the T and N evaluation sequences, and the number OTA and ONA of documents among the TA and NA documents that have the topic as the only correct topic

4.3.3 Evaluation Method

For each of our evaluation sequences T_1–T_3 and N_1–N_3 we first generate 12 ideal topic flow signals each representing the flow of one of the 12 CoRR database topics. These signals are then smoothed at resolution levels 0 through the maximum size (the log of the size of the evaluation sequence).

Next, for each of the six sequences, we generate a topic flow signal as described in Sections 4.1 and 4.2 above for each of the 12 CoRR categories. We will call these the *test* signals.

For a given sequence, each one of the ideal signals is compared to each one of the 12 test signals. Two signals match perfectly when they rise and fall at exactly the same point. This match indicates that both signals reflect the same flow. The most appropriate statistical measure for our purposes is the correlation coefficient [Ost88]:

$$CORRCOEF(X,Y) = \frac{(\sum_{\forall x \in X \text{ and } y \in Y}(x-\bar{x})(y-\bar{y}))}{(\sum_{\forall x \in X}(x-\bar{x})^2)(\sum_{\forall y \in Y}(y-\bar{y})^2)} \qquad (4.2)$$

where X and Y are the two signals to be matched composed of a sequence of ranks, and $\bar{x}$ and $\bar{y}$ are the average ranks across X and Y respectively. The highest correlation coefficient is $+1$ indicating a perfect match. A correlation coefficient of 0.65 or higher indicates strong correlation, a correlation coefficient between 0.3 and 0 indicates weak to no correlation between the shapes of the two signals, while a -1 indicates a reverse correlation between X and Y which means that when X is high, Y is low, and vice versa. Figure 4.7 shows an example of highly correlated test and ideal signals in the T_1 evaluation sequence for the topic *Computation and Language* at resolution level 6 (i.e. 2^7 segments). The correlation coefficient between the two signals at this level is 0.9. Note how the two signals rise and decline at about the same pace indicating similar changes in topic flow. Two non-correlated signals, with correlation coefficient -0.05, are shown in Figure 4.8 for the *Computational Engineering, Finance, and Science* ideal and test signals in the N_1 sequence at resolution level 7. In this case the test signal's fluctuations are independent of those of the ideal signal thus painting different pictures of topic flow in the document. In between highly correlated signals and weakly correlated ones, some signals are said to be *moderately* correlated. An example of moderately correlated signals is shown in Figure 4.9. In this figure, the test and ideal signals represent the topic flow for *Software Engineering* at resolution level 6 in the N_1 evaluation sequence. The two signals have a correlation coefficient value of 0.56. When the ideal signal indicates a strong topic relevance through a low rank value, so does the test signal, but the test signal also fluctuates at points where the ideal signal is constant.

The correlation between the test and ideal signals can be measured at any level of resolution. At the most detailed levels we expect the effect of noise to be high in the signals and, consequently, the correlation to be low. But as we proceed to lower resolution levels, the noise should gradually diminish and correlation should increase if the flow in both signals is similar. Ideally, we would like the noise to have diminished completely at the resolution level where each point in the signal corresponds to an average abstract size. At this segment size each abstract will be represented by one low ranked point to reflect the fact that it discusses its topic(s) throughout the abstract with minimal digressions. Thus, any noise will have been mostly smoothed out at previous levels of resolution. In the T and N sequences this segment size corresponds to the resolution levels $\lceil log_2(736) \rceil = 10$ and $\lceil log_2(447) \rceil = 9$, respectively. From this resolution level up to the most general level 0, noise should be minimal, and correlation between the ideal and test signals should be high. In order to evaluate the correlation between any test and ideal

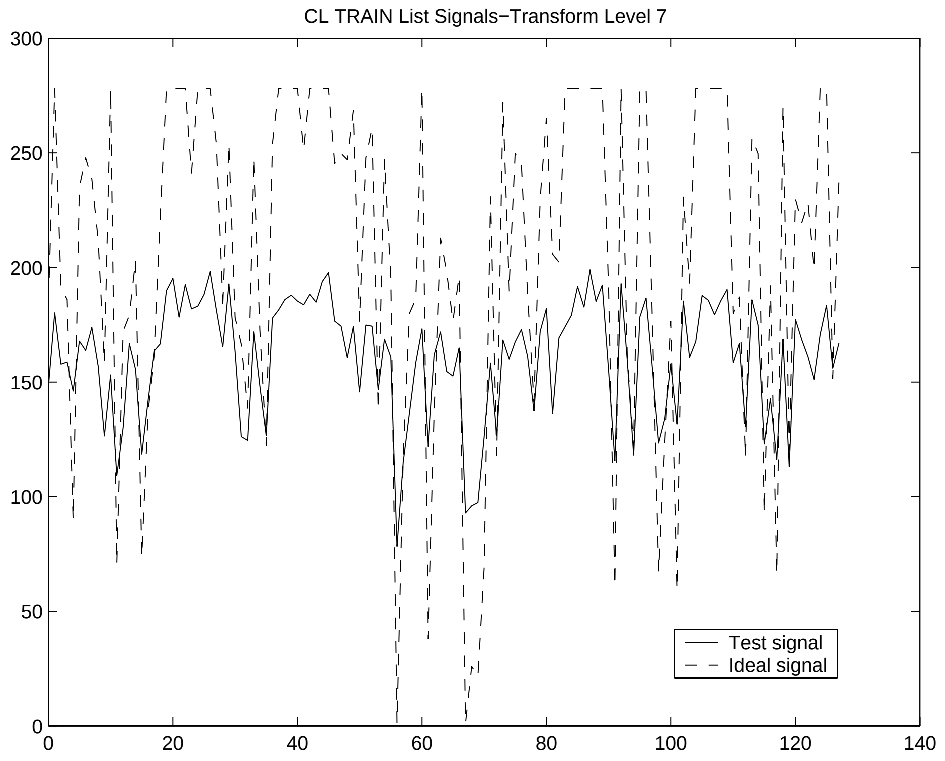


Figure 4.7: An example of highly correlated ideal and test topic flow signals. The signals represent the flow of *Computation and Language* in the T_1 abstract sequence at resolution level 7

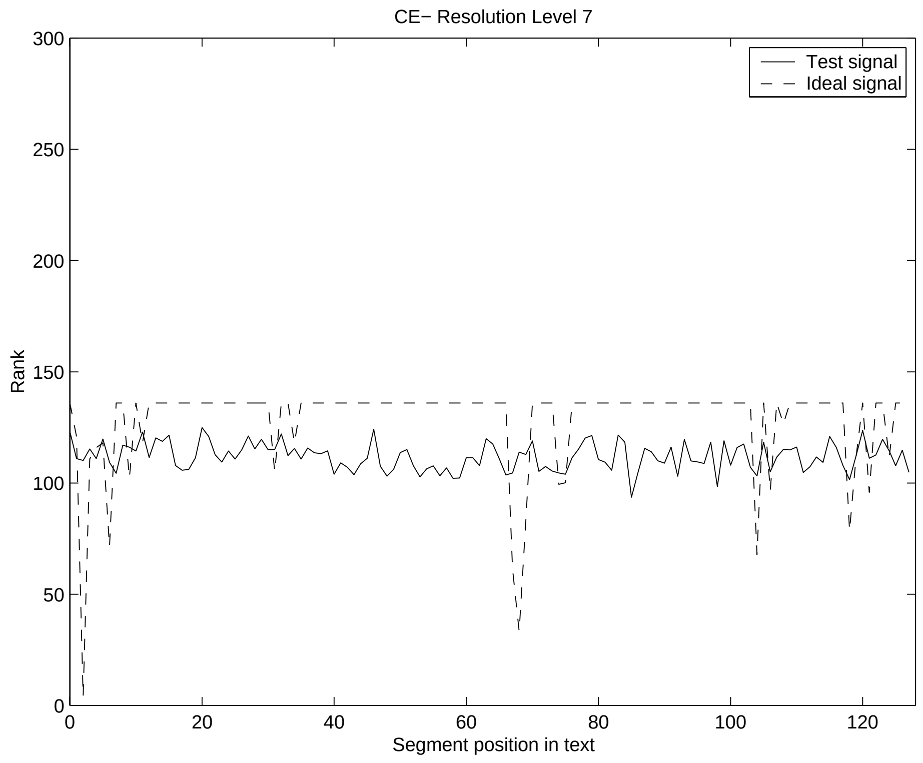


Figure 4.8: An example of weakly correlated ideal and test topic flow signals. The signals represent the flow of *Computational Engineering, Finance, and Science* in the N_1 abstract sequence at resolution level 7

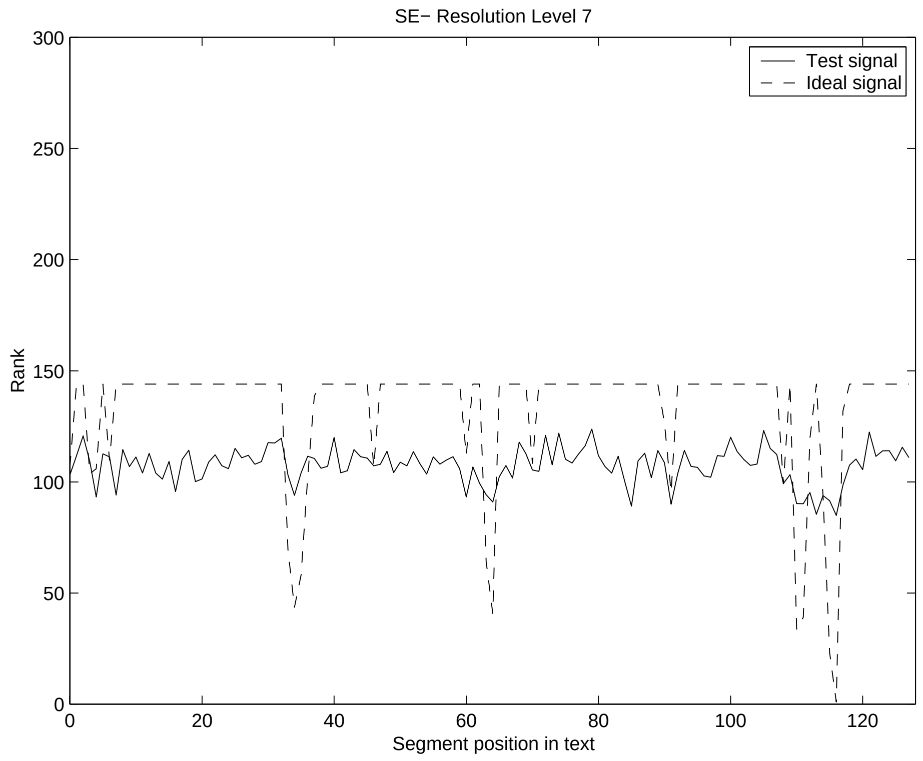


Figure 4.9: An example of moderately correlated ideal and test topic flow signals. The signals represent the flow of *Software Engineering* in the N_1 abstract sequence at resolution level 7

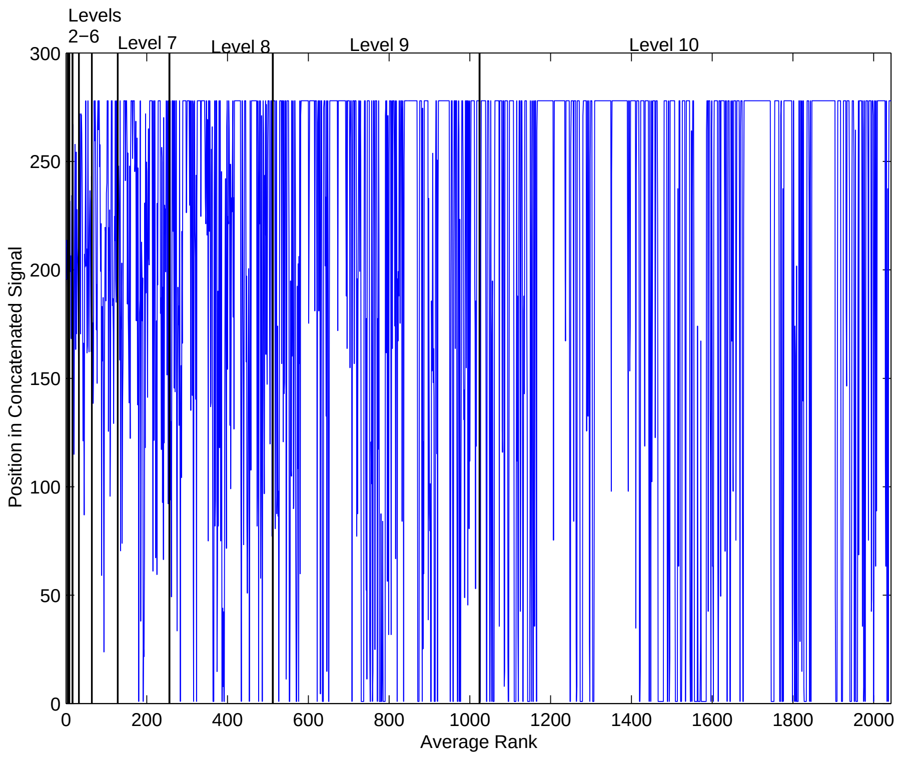


Figure 4.10: The *Computation and Language* ideal signal resulting from concatenating the signals at resolution levels 2–10 in the T_1 abstract sequence

signal pairs at several levels of resolution we start by concatenating each topic's test signals at resolution levels 2–10 for each of the T abstract sequences, and levels 2–9 for each of the N abstract sequences. The same concatenation process is done for the ideal signals. Levels 1 and 0 are excluded because they contain too few points for meaningful correlation coefficient values. Figures 4.10 and 4.11 show the concatenated signals for the *Computation and Language* category. By concatenating the signals we can get a single pair of vectors for determining the correlation between the test and ideal signals at multiple levels of resolution.

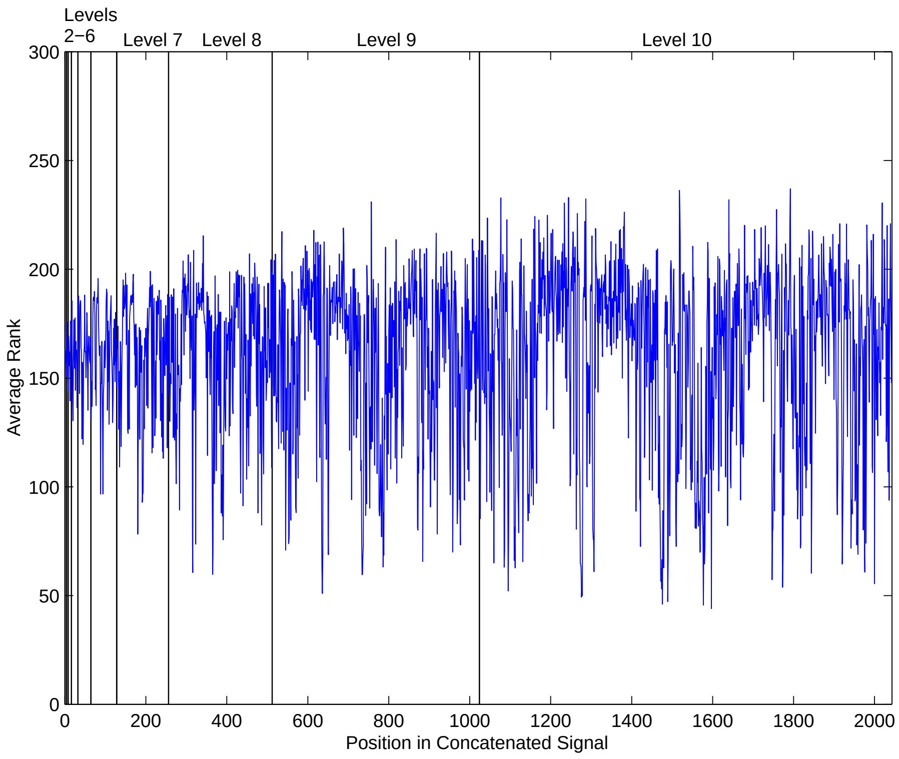


Figure 4.11: The *Computation and Language* test signal resulting from concatenating the signals at resolution levels 2–10 in the T_1 abstract sequence

4.3.4 Results

We measured the correlation between every concatenated ideal signal and each one of the 12 concatenated test signals for each one of the abstract sequences. Tables 4.2 and 4.3 show the top four correlation coefficients for these signal pairs for each of the T and N abstract sequences.

The table shows a consistently high correlation between the ideal signal and its corresponding test signal for the same topic in the T abstract sequences all of which are statistically significant within a 95% confidence interval. All of the ideal signals in these sequences best resemble the corresponding test signal for the same category. This shows that when sufficient topic words are provided, and when categorization consistency can be guaranteed, then the topic flow representation algorithms succeed in creating signals that accurately reflect the flow of the topic.

The table also shows the effect of extracting the topic word list from a training set of multi-category documents. Since the CoRR training documents may belong to more than one category, several resulting topic word lists may be influenced by a single document. For example, the topic word *chunker* is a *Computation and Language* word. However, because it occurs in a *Computation and Language* and *Learning* training document, the word also occurs in the *Learning* topic word list as well. Therefore, topic flow signals will tend to share more topic words than might be expected. The higher the proportion of training documents a group of categories share, the stronger the similarity between their signals. Table 4.4 shows the number of training documents belonging to each category in the CoRR database and the top three categories with which it shares documents. Looking back at Table 4.2 we note that the second most similar test signals to a topic's ideal signal in the T sequences are those of the top co-occurring categories.

Table 4.2: Correlation between the concatenated ideal and test signals for the T abstract sequences (continued on next page)

Ideal	T_1				T_2				T_3			
	Test	Corr	Signif	t	Test	Corr	Signif	t	Test	Corr	Signif	t
AI	AI	0.73	1	48.45	AI	0.74	1	49.56	AI	0.73	1	48.20
	LO	0.42	1	20.75	LO	0.43	1	21.60	LO	0.42	1	20.65
	PL	0.17	1	7.87	PL	0.18	1	8.28	PL	0.18	1	8.19
	SE	0.04	1	1.89	SE	0.04	1	1.7	SE	0.05	1	2.19
CL	CL	0.87	1	79.47	CL	0.86	1	74.76	CL	0.86	1	76.68
	LG	0.20	1	9.35	LG	0.20	1	9.15	LG	0.19	1	8.59
	SE	-0.19	1	-8.93	SE	-0.21	1	-9.70	SE	-0.21	1	-9.59
	NI	-0.20	1	-9.40	NI	-0.20	1	-9.21	NI	-0.19	1	-8.52
CC	CC	0.76	1	52.18	CC	0.74	1	50.26	CC	0.75	1	51.33
	DS	0.28	1	12.96	DS	0.28	1	13.39	DS	0.28	1	13.25
	CE	0.15	1	6.96	CE	0.16	1	7.11	CE	0.16	1	7.38
	CG	0.10	1	4.40	CG	0.13	1	6.01	CG	0.12	1	5.63

Table 4.2: (continued)

Ideal	T_1				T_2				T_3			
	Test	Corr	Signif	t	Test	Corr	Signif	t	Test	Corr	Signif	t
CE	CE	0.60	1	34.30	CE	0.58	1	32.27	CE	0.60	1	33.49
	DS	0.23	1	10.48	DS	0.19	1	8.61	DS	0.22	1	10.10
	NI	0.09	1	3.91	NI	0.09	1	4.28	NI	0.09	1	4.27
	CG	0.07	1	3.38	CG	0.05	1	2.18	CG	0.07	1	3.14
CG	CG	0.72	1	47.12	CG	0.73	1	47.73	CG	0.72	1	46.73
	DS	0.17	1	7.62	DS	0.17	1	7.77	DS	0.17	1	7.75
	CE	0.045	1	2.05	CE	0.05	1	2.25	CE	0.07	1	3.04
	CC	0.04	1	1.75	CC	0.09	1	3.91	CC	0.08	1	3.41
DS	DS	0.69	1	42.88	DS	0.68	1	41.80	DS	0.68	1	42.22
	CE	0.42	1	21.16	CE	0.42	1	20.66	CE	0.42	1	20.74
	CG	0.29	1	13.78	CG	0.29	1	13.68	CG	0.30	1	14.15
	CC	0.26	1	12.26	CC	0.25	1	11.87	CC	0.26	1	11.99
DC	DC	0.71	1	45.35	DC	0.69	1	43.51	DC	0.68	1	41.47
	NI	0.39	1	19.05	NI	0.34	1	16.60	NI	0.36	1	17.70
	CE	0.12	1	5.58	CE	0.08	1	3.78	CE	0.11	1	4.98

Table 4.2: (continued)

Ideal	T_1				T_2				T_3			
	Test	Corr	Signif	t	Test	Corr	Signif	t	Test	Corr	Signif	t
	LG	0.12	1	5.54	LG	0.07	1	3.29	LG	0.10	1	4.48
LG	LG	0.63	1	37.02	LG	0.63	1	36.46	LG	0.62	1	36.05
	CL	0.15	1	6.84	CL	0.16	1	7.22	CL	0.17	1	8.01
	DC	0.09	1	4.31	DC	0.07	1	3.29	DC	0.07	1	3.26
	NI	0.07	1	3.29	NI	0.05	1	2.21	NI	0.07	1	3.21
LO	LO	0.69	1	43.52	LO	0.68	1	41.56	LO	0.70	1	43.75
	AI	0.44	1	22.30	AI	0.44	1	21.92	AI	0.43	1	21.76
	PL	0.42	1	21.13	PL	0.41	1	20.61	PL	0.42	1	20.70
	SE	0.10	1	4.40	SE	0.12	1	5.42	SE	0.095	1	4.30
NI	NI	0.67	1	41.26	NI	0.67	1	40.49	NI	0.66	1	39.89
	DC	0.40	1	19.82	DC	0.35	1	17.01	DC	0.39	1	19.23
	CE	0.09	1	4.19	CE	0.08	1	3.63	CE	0.09	1	4.06
	LG	0.09	1	4.15	LG	0.07	1	3.36	LG	0.11	1	4.95
PL	PL	0.67	1	40.74	PL	0.67	1	41.10	PL	0.68	1	42.08
	SE	0.42	1	21.09	SE	0.43	1	21.32	SE	0.42	1	20.91

Table 4.2: (continued)

Ideal	T_1				T_2				T_3			
	Test	Corr	Signif	t	Test	Corr	Signif	t	Test	Corr	Signif	t
	LO	0.30	1	14.33	LO	0.30	1	14.26	LO	0.31	1	14.52
	AI	0.09	1	4.16	AI	0.10	1	4.61	AI	0.09	1	4.22
SE	SE	0.63	1	36.59	SE	0.61	1	35.09	SE	0.62	1	35.53
	PL	0.26	1	12.10	PL	0.25	1	11.84	PL	0.24	1	11.05
	NI	0.0	0	0.22	NI	0.03	0	1.45	NI	0.00	0	0.02
	LO	-0.02	0	-0.74	LO	-0.02	0	-0.90	LO	-0.03	0	-1.59

Table 4.2: The correlation coefficient of the concatented resolution levels 10–2 For the T abstract sequences. Each topic in the *Topic* column is the name of an ideal topic flow signal. At each row, the *Most Similar* column identifies the four topics whose test signals have the highest correlation with the ideal signal, their correlation coefficient, t value for the student's ttest, and the statistical significance witha 95% confidence interval

Table 4.3: Correlation between the concatenated ideal and test signals for the N abstract sequences (continued on next page)

Ideal	N_1				N_2				N_3			
	Test	Corr	Signif	t	Test	Corr	Signif	t	Test	Corr	Signif	t
AI	AI	0.49	1	17.76	AI	0.44	1	15.44	AI	0.47	1	17.06
	LO	0.38	1	13.23	LO	0.34	1	11.69	LO	0.38	1	12.95
	PL	0.15	1	4.95	PL	0.12	1	3.99	PL	0.15	1	5.02
	LG	0.056	1	1.78	CL	0.097	1	3.10	CL	0.08	1	2.51
CL	CL	0.75	1	36.45	CL	0.73	1	33.88	CL	0.73	1	34.17
	LG	0.16	1	5.12	LG	0.15	1	4.78	LG	0.15	1	4.77
	AI	-0.06	1	-2.04	AI	-0.015	0	-0.47	AI	-0.02	0	-0.65
	LO	-0.13	1	-4.12	LO	-0.096	1	-3.09	LO	-0.11	1	-3.47
CC	CC	0.60	1	23.81	CC	0.61	1	24.83	CC	0.62	1	25.17
	DS	0.34	1	11.45	DS	0.35	1	11.94	DS	0.34	1	11.60
	CG	0.29	1	9.62	CG	0.30	1	9.92	CG	0.30	1	9.85
	LO	0.12	1	3.94	LO	0.1	1	3.5	LO	0.13	1	4.23

Table 4.3: (continued)

Ideal	N_1				N_2				N_3			
	Test	Corr	Signif	t	Test	Corr	Signif	t	Test	Corr	Signif	t
CE	CG	0.25	1	8.15	CG	0.19	1	6.03	CG	0.17	1	5.52
	DS	0.20	1	6.63	DS	0.16	1	5.18	CE	0.13	1	4.33
	CE	0.17	1	5.45	CE	0.15	1	4.91	DS	0.12	1	4.03
	CC	0.14	1	4.50	CC	0.11	1	3.62	CC	0.10	1	3.11
CG	CG	0.36	1	12.43	CG	0.37	1	12.57	CG	0.40	1	13.80
	DS	0.14	1	4.50	DS	0.15	1	4.85	DS	0.18	1	6.01
	CE	0.03	0	0.82	CE	0.07	1	2.38	CE	0.09	1	2.85
	CC	0.01	0	0.30	CC	0.02	0	0.67	CC	0.08	1	2.65
DS	CG	0.36	1	12.34	CG	0.37	1	12.62	CG	0.34	1	11.63
	DS	0.32	1	10.63	DS	0.30	1	10.11	DS	0.27	1	8.87
	CE	0.29	1	9.52	CE	0.28	1	9.26	CE	0.24	1	7.80
	CC	0.24	1	7.94	CC	0.23	1	7.50	CC	0.20	1	6.52
DC	DC	0.43	1	15.18	DC	0.42	1	14.92	DC	0.42	1	14.62
	SE	0.26	1	8.52	SE	0.25	1	8.37	SE	0.24	1	7.90
	CE	0.25	1	8.10	CE	0.19	1	6.25	CE	0.18	1	5.96

Table 4.3: (continued)

Ideal	N_1				N_2				N_3			
	Test	Corr	Signif	t	Test	Corr	Signif	t	Test	Corr	Signif	t
	PL	0.095	1	3.06	PL	0.10	1	3.24	PL	0.08	1	2.47
LG	LG	0.25	1	8.22	LG	0.28	1	9.18	LG	0.26	1	8.57
	CL	0.16	1	5.33	CL	0.21	1	6.90	CL	0.19	1	6.27
	AI	0.05	1	1.72	AI	0.07	1	2.26	AI	0.05	0	1.60
	DS	0.01	0	0.32	DS	-0.01	0	-0.31	DS	0.00	0	0.06
LO	LO	0.61	1	24.55	LO	0.59	1	23.08	LO	0.60	1	23.83
	AI	0.37	1	12.76	AI	0.33	1	11.15	AI	0.35	1	11.79
	PL	0.28	1	9.42	PL	0.32	1	10.90	PL	0.33	1	11.15
	CC	0.17	1	5.45	CC	0.15	1	4.86	CC	0.13	1	4.36
NI	NI	0.79	1	40.58	NI	0.78	1	40.28	NI	0.79	1	40.52
	DC	0.40	1	13.74	DC	0.38	1	13.06	DC	0.39	1	13.48
	CE	0.18	1	5.94	CE	0.17	1	5.68	CE	0.19	1	6.35
	DS	-0.015	0	-0.47	DS	-0.01	0	-0.18	DS	0.01	0	0.28
PL	PL	0.47	1	17.01	PL	0.48	1	17.29	PL	0.47	1	17.19
	SE	0.30	1	10.15	SE	0.31	1	10.50	SE	0.33	1	11.11

Table 4.3: (continued)

Ideal	N_1				N_2				N_3			
	Test	Corr	Signif	t	Test	Corr	Signif	t	Test	Corr	Signif	t
	LO	0.17	1	5.62	LO	0.25	1	8.15	LO	0.19	1	6.10
	AI	0.14	1	4.48	AI	0.17	1	5.65	AI	0.11	1	3.66
SE	SE	0.49	1	17.88	SE	0.47	1	17.12	SE	0.49	1	18.14
	PL	0.38	1	13.018	PL	0.37	1	12.77	PL	0.38	1	13.05
	CL	0.02	0	0.70	LO	0.02	0	0.58	LO	0.00	0	-0.04
	NI	-0.01	0	-0.29	NI	-0.01	0	-0.35	NI	0.00	0	0.06

Table 4.3: The correlation coefficient of the concatented resolution levels 10–2 For the N abstract sequences. Each topic in the *Topic* column is the name of an ideal topic flow signal . At each row, the *Most Similar* column identifies the four topics whose test signals have the highest correlation with the ideal signal and their correlation coefficient, t value for the student's ttest, and statistical significance within a 95% confidence interval.

The effect of sharing training documents is also evident in the N sequence results in Table 4.3 where the categories sharing the highest proportion of documents with a category C are always among the top four signals most similar to C's ideal signal.

The N sequence results also reveal the effect of topic word lists with insufficiently many words and categorization that is inconsistent with that of the training set. The sequence has a generally lower correlation than the T sequences: only 10 out of the 12 categories have a high or medium correlation with their corresponding test signal, and 2 ideal signals (for CE and DS) were most similar to the test signal of a different topic. We suspect this is due to a combination of factors, including training set size, multi-topic training documents, and important keywords being discarded from the N abstract sequences because they were not present in any training documents.

One way to reduce the noise in the topic word lists and, consequently, in the topic flow signals, is to extract the lists from a training set with a high proportion of single-category documents. The number of single-category training documents in the CoRR training set is shown in Table 4.5. The table also shows the proportion of single-category documents to the total number of training documents for each CoRR category. Nine of the ten categories containing the highest proportion of single-category documents succeed in generating test topic flow signals that are highly to moderately correlated with the corresponding ideal signal. The three categories containing the lowest proportion of single-category documents all generate test signals that are at best weakly correlated with the corresponding ideal signal.

The correlation values we have seen so far show that our approach for generating topic flow signals succeeds in creating signals that reflect the flow of the topic in the text. However, these correlations between the concatenated signals incorporate noise from all resolution levels. Such noise causes the overall correlation to be lower

Main Topic		1^{st} co-topic		2^{nd} co-topic		3^{rd} co-topic	
TOPIC	training	topic	docs	topic	docs	topic	docs
CL	194	AI	18	LG	17	SE,PL,LO,CC,&DS	1
CC	100	DS	19	AI	9	LO&LG	7
SE	38	PL	13	AI	3	LO&DS	2
CG	62	DS	5	AI	2	SE&NI	1
NI	25	DC	6	CC	3	DS	2
DC	41	PL&DS	6	LG	5	AI	4
AI	160	LO	54	LG	21	CL	18
PL	76	LO	29	SE	13	AI	10
LO	130	AI	54	PL	29	CC	7
DS	90	CC	19	CE	8	AI&LG	6
LG	61	AI	21	CL	17	CC	7
CE	23	DS	8	CC	5	AI	3

Table 4.4: The number of training documents belonging to each of our 12 topics, and the most frequently co-occuring categories in the training documents for each category.

TOPIC	# training docs (TD)	# one-topic training docs (OTD)	ratio TD:OTD
CL	194	149	0.79
CC	100	49	0.49
SE	38	17	0.45
CG	62	26	0.42
NI	25	8	0.32
DC	41	13	0.32
AI	160	40	0.25
PL	76	19	0.25
LO	130	22	0.17
DS	90	15	0.17
LG	61	9	0.15
CE	23	3	0.13

Table 4.5: The number TD of training documents belonging to each of our 12 CoRR topics, and the number OTD of documents among the TD documents that identify no co-topic

than the correlation between the test and ideal signals at individual resolution levels. For example, the correlation between the test and ideal concatenated *Learning* signals is 0.63 in the T_1 text, yet the correlation between the individual levels 2–10 in this text are 0.76, 0.82, 0.75, 0.71, 0.69, 0.65, 0.61, 0.55, and 0.47, respectively. This higher correlation can be observed for all topics in all 6 sequences. Table 4.6 for example shows the four most correlated test signals for each ideal signal at resolution level 5.

Table 4.6: Top Four Correlated Test Topics for each Ideal Signal at Resolution Level 5 in the T_1 Text

Ideal	Test	Corr	Signif	t
AI	AI	0.86	1	18.75
	LO	0.60	1	8.51
	PL	0.31	1	3.72
	SE	0.08	0	0.91
CL	CL	0.92	1	26.68
	LG	0.28	1	3.25
	CG	-0.23	1	-2.71
	NI	-0.25	1	-2.86
CC	CC	0.80	1	15.23
	DS	0.31	1	3.67
	CG	0.20	1	2.31
	CE	0.13	0	1.52
SE	SE	0.73	1	12.07
	PL	0.24	1	2.81
	NI	0.11	0	1.20

Table 4.6: (continued)

Ideal	Test	Corr	Signif	t
	CE	0.03	0	0.35
CE	CE	0.68	1	10.44
	DS	0.42	1	5.14
	CG	0.21	1	2.47
	CC	0.16	1	1.79
CG	CG	0.78	1	13.82
	DS	0.25	1	2.95
	CC	0.18	1	2.01
	CE	0.10	0	1.15
DS	DS	0.75	1	12.64
	CE	0.62	1	8.83
	CG	0.35	1	4.17
	NI	0.28	1	3.23
DC	DC	0.81	1	15.34
	NI	0.49	1	6.30
	CE	0.17	1	1.92
	LG	0.16	1	1.86
LG	LG	0.71	1	11.47
	CL	0.24	1	2.80
	NI	0.10	0	1.18
	DC	0.06	0	0.64
LO	LO	0.76	1	13.06
	AI	0.56	1	7.53

Table 4.6: (continued)

Ideal	Test	Corr	Signif	t
	PL	0.54	1	7.28
	SE	0.19	1	2.17
NI	NI	0.77	1	13.46
	DC	0.49	1	6.38
	LG	0.23	1	2.61
	CE	0.12	0	1.42
PL	PL	0.70	1	11.081
	SE	0.48	1	6.11
	LO	0.33	1	3.92
	AI	0.14	0	1.59

Table 4.6: The four most correlated test categories for each ideal signal in the T_1 abstract sequence at resolution level 5 and the statistical significance of these correlation coefficients at the 95% confidence interval.

Interestingly, the *noise* that affects the correlation is not all rooted in the test signals. Some of this noise, especially at the lower levels, comes from the ideal signals themselves. Remember that in building the ideal signals we assumed that all words of an on-topic abstract are on topic, and all words of an off-topic abstract are also off topic. Throughout this discussion we have assumed that by the time we reach a resolution level in which the segment size is approximately equal to the size of an abstract, the noise resulting from our assumption will have disappeared. However, the scatter plots for the ideal signal values versus the test signal values reveal that this noise takes one or two more levels before it dissipates (see Figure 4.12. These scatter plots show for each value in the ideal signal at a specific resolution level all the values in the corresponding positions in the test signal at the same level of resolution. For example, the ideal signal of *Computation and Language* at resolution level 10 has the value 77.175 at two points in the signal: point number 3 and number 213. At these points the test signal has the values 127.0625 and 122.6375, respectively.

Figure 4.12 shows the scatter plot of the *Computation and Language* ideal signal versus the test signal at resolution levels 2–10. The plot shows the linear relationship between the ideal and test signals for this category. In general, when the ideal signal is low, so is the test signal. The range of the test signal values that correspond to a specific ideal signal value is also generally narrow except at the extremes 1 and 278. These extremes correspond to the lowest possible and the highest possible ranks for the *Computation and Language* category. A segment at resolution level as high as 10 can only have such extreme values if all its words have the same extreme values, and the only case where this occurs is in the ideal signal when the segment is all on-topic or all off-topic. The test signal, on the other hand, cannot have such a value in most cases since some of the words in an on-topic abstract will undoubtedly be off-topic, and some of the words in an off-topic abstract may appear to be on-topic. The ratio of on-topic words in the abstract affect its overall average rank therefore creating a wide range of possible values, which plays a role in lowering the correlation between the test and ideal signals at this resolution level.

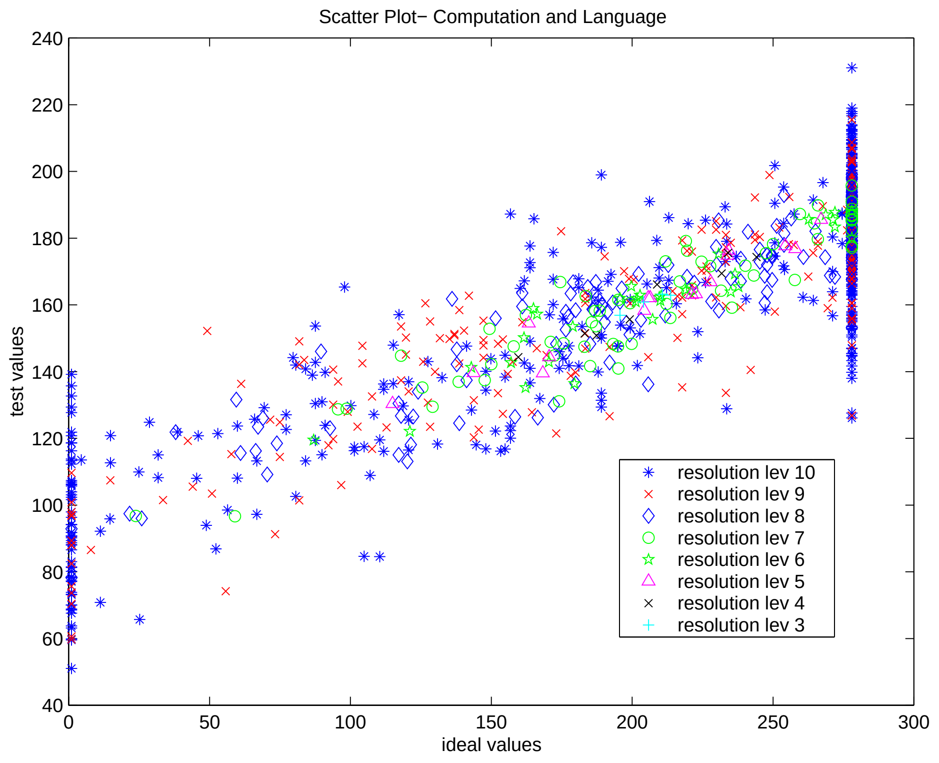


Figure 4.12: The Computation and Language scatter plot of resolution levels 10–2 for the ideal and test signals in the T_1 abstract sequence.

4.4 Conclusions

In this chapter we have shown how to construct signals that represent the flow of topics in text. We started with a basic algorithm to construct word-based topic flow signals. Next, we presented an averaging algorithm that allows us to use the word-based topic flow signals in viewing the flow of topics in various sized segments of text. Finally, we tested the quality of the topic flow signals and showed that given a good topic word list, our algorithm is able to represent the flow of the topic accurately. Our experiments also revealed that the quality of the topic flow signal is dependent upon the quality of the topic word list, which in turn is dependent upon the training set used to create the list. In the future we propose to study the effect of varying the proportion of single-category documents in the training set on the quality of the topic word lists and on the generated topic flow signals. We also propose to experiment with the effect of different smoothing methods on the topic flow signal. In particular, we would like to reduce the oscillation found in off-topic segments thus reducing noise in these segments and clarifying the topic flow.

Topic flow signals provide a versatile representation of text content. An important distinction between our topic flow signals and other work in fields such as text segmentation is that each individual point in the topic flow signal represents the relevance of an individual segment in the text independent of the rest of the text. This relevance is measured using our unique topic relevance measure M^{DF_n} described in the previous chapter. This is quite different from the plots used in segmentation by TextTiling [Hea97], for example, where each point in the plot represents the similarity between two consecutive segments. Our signals are meant to represent the content of the text in such a way that they can be used for a variety of applications including text segmentation, topic detection, topic tracking, and document visualization.

In the next chapter we present one possible application for topic flow signals in text categorization.

Chapter 5

An Application to Text Categorization

The view of text as a sequence of topics can be beneficial for retrieval tasks that rely on text content and on similar tasks such as text summarization, text segmentation, document clustering, and text categorization. This chapter examines the benefits of topic spread for text categorization. We first define text categorization and present a general categorization model. Next, we describe Support Vector Machines, a state-of-the-art categorization method, and show how we can improve its performance through the use of topic words and topic distribution in text.

5.1 Text Categorization

5.1.1 Definition and Applications

Text categorization systems group text data under a pre-specified set of labels or categories. Applications of automatic text categorization are numerous [DPHS98], the most obvious of which is automating manually categorized databases such as Yahoo!'s and Infoseek's. Automation provides a more consistent, less expensive, and more efficient categorization. Another useful application is text filtering where the system learns the user's interests, then filters incoming documents or emails that fall under categories deemed interesting to the user. In addition, automatic text categorization can make large amounts of data more manageable, it may be used to browse the data by topic, to search only data that belongs to certain categories, or to view search results by category rather than viewing them as long lists of documents (e.g. [CD00] [Hea94b]). But the applicability of text categorization is dependent on its effectiveness and robustness against noisy real-life data. To this end, many approaches have been proposed, each with its own advantages and disadvantages. These systems share a common general model that we describe next.

5.1.2 Preprocessing

The input to a text categorization system is a set of categories and the document to be categorized, and the output is the subset of categories most relevant to the input text. But since text comes in many different formats and contains significantly more information than the categorizer requires, the input document is usually preprocessed before being passed through the classifier. The tokenization, stopword removal, and stemming steps discussed in detail in Section 3.3.2 apply here.

5.1.3 Document Representation

Once the input text is tokenized and stemmed and stopwords are removed, the text must be converted to a representation that is acceptable to the categorizer. In the most common representation, each document is represented by a vector in which every dimension is associated with a unique feature and the value of the feature represents its *weight* in the text. The method used to calculate the feature's weight varies, but in general the weight is meant to reflect the dominance of that feature in the document. Many researchers (see for example [van79, BYRN99, SM83, MN98]) experimented with words as document features where each word is weighted by pure term frequency, by the binary value of occurrence in the document, or by the tf*idf function:

$$W_{tf*idf}(w_i) = TF(w_i) * log(\frac{|D|}{DF(w_i)}) \tag{5.1}$$

where:

- w_i is a word in the document.
- $TF(w_i)$ is the term frequency of w_i in the document.
- $|D|$ is the number of documents in the training set.
- $DF(w_i)$ is the document frequency of the word w_i.

Using term frequency has generally been found to perform better than binary feature weights, but the extent of this improvement is influenced by the classification method and the database used [MN98] [MS99] [Joa02].

To take a simple example, let us assume that our categorizer has the vocabulary: *bank*, *commerce*, and *money*, and that our input text after tokenization and

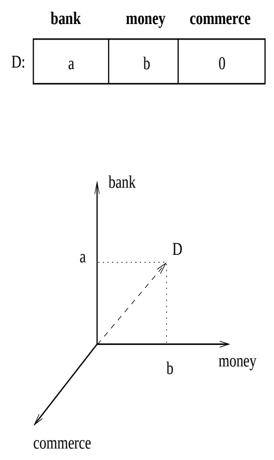


Figure 5.1: A vector representing a sample document D which consists of the terms *bank* and *money* with term weights a and b respectively.

stemming consists of the words *bank* and *money.* Then the vector representation of the document is shown in Figure 5.1 where a and b are the weights of *bank* and *money* in the input text.

5.1.4 Document Classification

Now the input is ready to be forwarded to the categorizer. Before the system can categorize documents, however, it needs to model each category in the category set. One method to achieve this is *supervised learning.*

Supervised learning involves training the system using pre-labeled data. The labels of the data reflect each document's categories and are usually prepared by a human and assumed to be correct. From this data, the system identifies criteria that distinguish documents belonging to a category from those under other categories.

Once the training phase is done, the categorizer is ready to accept and categorize unlabeled input documents.

In binary text classification, supervised learning approaches are presented with a set of training documents each labeled by humans as either positive or negative examples of the category. The system creates from the given training data an approximation function that represents the criteria distinguishing between positive and negative training examples for that category. The learned model becomes the classifier for the category and is used to label previously unseen documents as either belonging to the category or not. For more than one category, several binary classifiers are built, one for each category. If the documents can be multi-labeled then each classifier makes its own independent decision of whether the document belongs to its category. In some cases, however, each document is allowed only a single label. One possible approach in this case is to attach a confidence level with each category label for the document and allow only the label with the highest confidence [Joa02]. Examples of these supervised learning systems are the Rocchio algorithm [LSCP96], the Naive Bayes algorithm [Lew98], and Support Vector Machines [Joa98b].

This general approach is shown in Figure 5.2. There are other variations of this architecture. For instance, some categorizers skip the learning stage and represent a category directly by its training documents. This is called *lazy learning*. In this type of learning the system does minimal work, or none at all, during the training stage. Instead, it compares incoming (unlabeled) input documents directly to the training data. The most prominent example in this class is K-Nearest Neighbor [Mit97].

Of these categorization methods, Support Vector Machines (SVMs) have been found to perform as well as or better than most other categorization systems (e.g. [Joa02, YL99, Coo99]). In what follows we will discuss the basics of SVMs fol-

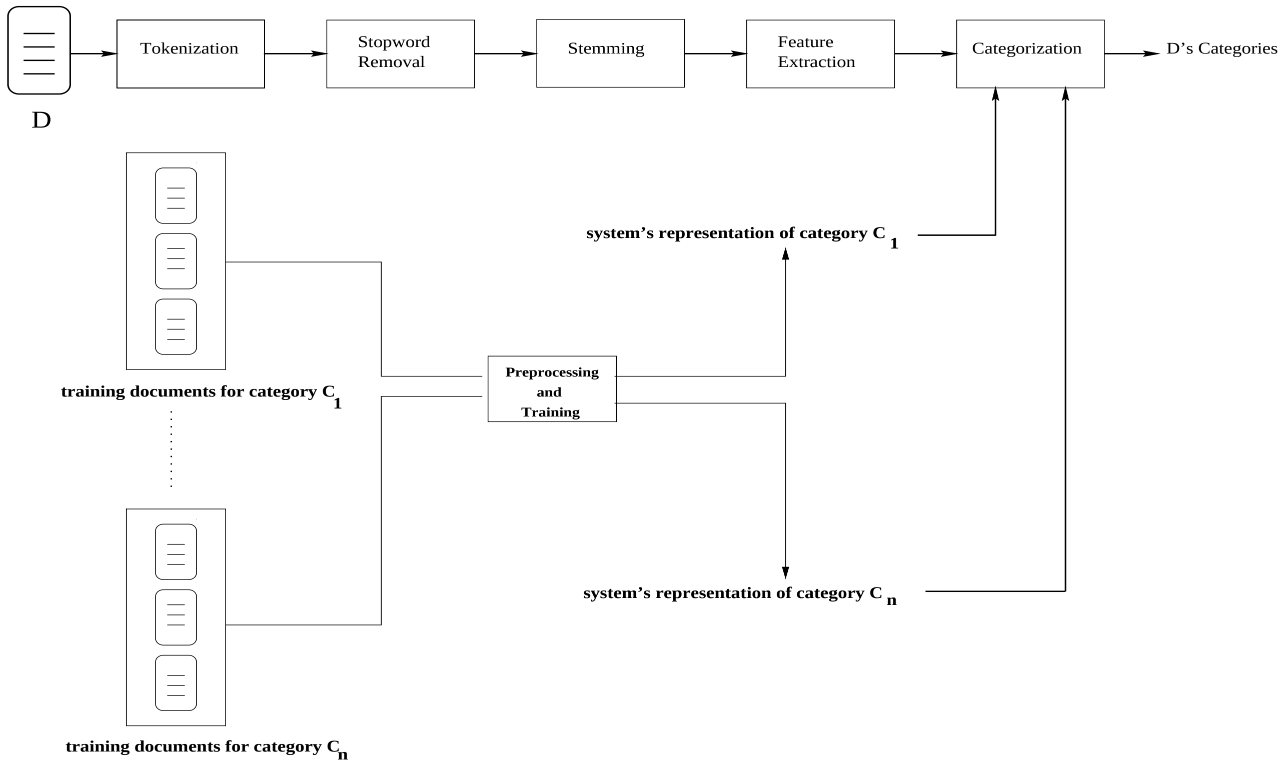

Tokenization
Stopword Removal
Stemming
Feature Extraction
Categorization
D's Categories
D
system's representation of category C 1
training documents for category C1
Preprocessing and Training
system's representation of category C n
training documents for category Cn

Figure 5.2: A general architecture for a text categorization system. The system is categorizing document D under one or more of the categories $C_1..C_n$. The system is trained to recognize those categories using training documents for each of the categories.

lowing the description of Joachims [Joa02], then explore the effect of replacing the traditional documents-as-bags-of-words vectors with representations which reflect the distribution of topics in the document.

5.2 Text Categorization with Support Vector Machines

The simplest type of SVMs are Linear Support Vector Machines. Linear SVMs create a hyperplane separating positive examples from negative ones. In placing these hyperplanes, SVMs attempt to maximize the distance between the negative and positive examples closest to the hyperplances which in turn minimizes the error. The distance between the negative and positive examples closest to the hyperplane is called the *margin*, while the closest training examples themselves are called *support vectors*. The separating hyperplane that maximizes the margin δ is described by a weight vector $\vec{w}$ and the maximum margin δ. Given this plane, the resulting classification function requires that a document $\vec{x}$ is relevant to the category if $(\vec{w}\vec{x} + b) > 0$. Figure 5.3(a) shows an example of a set of training examples that can be separated by a hyperplane with margin δ.

An indication of the expressiveness of an SVM is its *VC-dimension* (VCdim). When a VCdim of a model is too small the model is likely to overfit the data creating too many false negatives, but a VCdim that is too large may indicate that the model is too simple and the classifier may tend to over-generalize which means the classifier tends to generate too many false positives. Joachims reports that Vapnik [Joa02] showed that the hyperplane with the optimum VCdim is the one with the largest distance from the closest training examples.

SVMs that separate all positive examples from all negative ones are called *Hard-margin SVMs*. In some cases it is not possible to find such a hyperplane. In this case, it is possible to soften the condition of separation and allow some training examples to be on the wrong side of the hyperplane for some cost C. These SVMs are called *Soft-margin SVMs*. Sometimes there are many more positive examples than negative ones or vice versa, in which case it may be desirable to assign two different costs C and C' for each type of example to avoid putting more emphasis on avoiding errors in assigning the more frequent type of examples.

Yet in other cases the training data may not be linearly separable. Figure 5.3(b) shows one such example. SVMs solve this problem by using seed functions, called *Kernel functions*, which succeed in mapping the data from the non-linear space into a much simpler linear space for training. More specifically, the kernel functions map the data from the original space into a high-dimensional space via implicit basis expansion. Once the classifier is created, the same kernel function is used to map test documents into the linear space before they can be classified. Examples of popular kernels used in SVMs are polynomials (POLY) and radial basis functions (RBF). For example, a document with two features x_1 and x_2 in the non-linear space can be mapped onto a linear space using the polynomial kernel with degree d: $K_{poly}(\vec{x_1}, \vec{x_2}) = (s.\vec{x_1}.\vec{x_2} + r)^d$, or the RBF kernel $K_{rbf}(\vec{x_1}, \vec{x_2}) = \exp -\gamma(\vec{x_1} - \vec{x_2})^2$, where the values r,s, d, and γ can be set by the user of the SVM learner. A more detailed description of SVMs and their parameters can be found in Joachims' dissertation [Joa02].

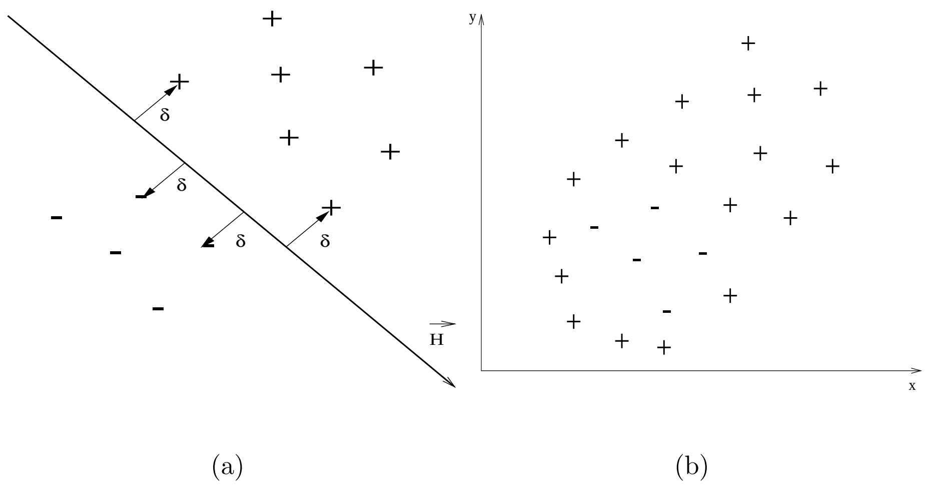


Figure 5.3: (a) An example of a linear data set with a linear hyperplane $\vec{H}$ separating the positive and negative examples with a margin δ. (b) A nonlinear data set which cannot be separated by a linear hyperplane.

5.2.1 Model Selection

Given a SVM and a training set, our mission is to generate a good classifier based on this training data. It is possible that several different kernels and many variations of parameter values can generate a classifier. Unfortunately, there is no automatic way to select the one that will generate the best performance on unseen documents. Rather, to choose between these classifiers we follow the algorithm described by Joachims [Joa02], in which we first select the set of parameters and variables we would like to consider. For each combination of these values, we calculate an estimate of the expected performance using the training data and choose the model with the best estimate.

Joachims [Joa02] tested the effectiveness of two different estimates in predicting classifier performance, and determined that the *Leave-One-Out Precision Recall*

Break Even Point(BEP_{loo}) is most effective. In leave-one-out cross-validation estimation, the system trains on $n-1$ training examples and then tests its performance on the remaining document and records whether it succeeded in predicting the class of the document. The same process is repeated n times until all the training documents have been used to test the classifier's performance. Finally, the results are used to calculate the classifier's leave-one-out estimation of the precision and recall, whose arithmatic mean is the BEP_{loo} for this model.

5.3 Using Topic Distribution in Documents with Support Vector Machines

5.3.1 Previous Work

SVM expects training documents to be represented as weighted vectors of features. Many researchers experimented with SVMs using words as document features where each word is weighted by pure term frequency, by the binary value of occurrence in the document, or by the tf*idf function [Joa02, YL99]. But the definition of a feature does not have to be a word; it can be any datum that helps distinguish documents belonging to a category from all other documents. Among the other interesting features studied are those suggested by Bekkerman *et al.* [BEYTW03], where documents are represented by vectors of semantically similar word clusters generated automatically using the *Information Bottleneck* approach (IB) [TPB99]. Initially, each word is labeled by the classes in which it occurs. The main idea behind IB is to cluster words with minimal loss of the mutual information between the words and the class labels, thus maximizing:

$$I(C_W, L) - \beta I(C_W, W) \tag{5.2}$$

where:

- W is the set of labeled words.
- C_W are the clusters created from W.
- L is the set of all labels.
- $I(C_W, L)$ ($I(C_W, W)$) is the mutual information of C_W and L (C_W and W).
- β is the factor controlling the allowed amount of reduction in mutual information caused by clustering W into C_W.

Bekkerman *et al.* compare this cluster-based SVM to the TF*IDF SVM which uses tf*idf weights with and without feature selection. Their tests show a $0 - 3\%$ improvement in the microaveraged *BEP* over the tf*idf SVM using the ten most frequent categories in the Reuters21578 database [REU].

Word clustering has also been used by Cristiani *et al.* to group words by their co-occurrence statistics through what is called the *Latent Semantic Kernels*. The features in this approach are still the document words, but the Latent Semantic Kernels create a map between individual words and a cluster of semantically related words. Unfortunately, tests using the Reuters21578 database did not result in an improved performance over the linear TF*IDF SVM classifier.

5.3.2 Incorporating Topic Distribution into Document Features

Throughout this thesis we show the benefits of word spread in identifying important topic words and in representing the relevance of topics within a document. Thus, rather than using words as document features, one can represent documents by the number of occurrences of the *relevance rankings* within the document, as defined in Chapter 3. A document vector will thus contain a list of ranking levels each weighted by the number of occurrences in the document. The more dominant the category's top ranking words are, the stronger the evidence of the document's relevance to the category.

To represent a document by the relevance ranking of its words to a category we begin by replacing each word in the document by its relevance ranking. The importance of each rank r in the document is then weighted by the number of times the rank r occurs in that document. For example, in the previous chapter we saw the signal for the Example 4.1.1:

Example 5.3.1 *Belief revision focuses on how an agent should change her beliefs when she adopts a particular new belief. [FH99]*

In this example, four words *belief*, *revision*, *beliefs*, and *belief* have top rank 1 for category AI, while the remaining two vocabulary words *agent* and *change* have lower ranks 33 and 78, respectively. Assuming that the maximum rank in the topic word list for the category AI is 300, the vector representing this example with respect to AI will have the features 1..300, with feature 1 having weight 4, features 33 and 78 having weight 1 each, and features 2..32, 34..77, and 79..300 having weight 0 as shown in Figure 5.4. The same procedure is followed to represent the

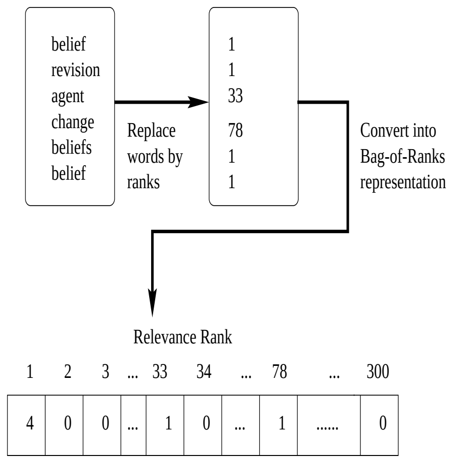


Figure 5.4: Converting the Example 5.3.1 into the Bag-of-Ranks representation.

document with respect to another category using that category's topic word ranks.

In this representation, relevance rankings replace words but, as with the bag-of-words method, no position information is retained. Thus, we call this the *Bag-of-Ranks* representation.

Our experiments in Chapter 3 show that word position information may be useful in identifying better topic words. The idea behind the M^{DF_n} measure is that when we discuss a topic, the topic's words will spread across the length of the text and occur in many segments of the document. The more important these topic words and the more segments they occur in, the stronger the evidence that the document is about the topic. Thus we can measure the spread of a rank by the number of segments in which it occurs. Under this approach the vector representing a document in a category T becomes a two dimensional matrix with n rows reflecting the maximum number of segments, and R features in each row where R is the maximum rank for category T. A feature weight for feature (i, r) is the number of times relevance rank r occurs in at least i segments. For example if

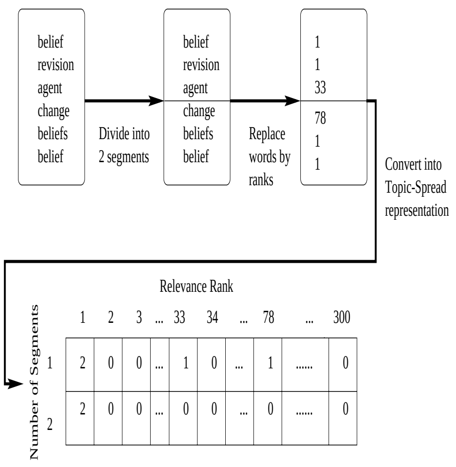


Figure 5.5: Converting the Example 5.3.1 into the Topic-Spread representation.

we divide Example 5.3.1 above into 2 segments the first segment will consist of the vocabulary words *belief*, *revision*, and *agent* which correspond to the ranks 1, 1, and 33 respectively. The second segment will consist of *change*, *beliefs*, and *belief* which correspond to the ranks 78, 1 and 1 respectively. The vector representation for the text will be a $2X300$ matrix with feature $(2, 1)$ having weight 2 since relevance rank 1 occurs twice in at least 2 segments, feature $(1, 1)$ having weight 2 since rank 1 occurs twice in at least one segment, features $(1, 33)$ and $(1, 78)$ having weight 1 since relevance ranks 33 and 78 occur once each in at least one segment each, and all other features having weight 0 as shown in Figure 5.5. We will call this representation the *Topic-Spread* representation.

5.4 Experiments

In the experiments to follow we will compare the performance of the SVM classifier using the TF*IDF document representation (TF*IDF SVM), the Bag-of-Ranks document representation (Bag-of-ranks SVM), and the Topic-Spread representation

(Topic-Spread SVM). We use Joachim's SVM implementation SVM^{light} [Joa98a] for all three methods.

5.4.1 Database

We use the same training database and 12 categories as described in Section 3.3.1. Our test documents consist of those submitted to the CoRR website between July 2001 and December 2001. These test documents were converted to text using the same version of detex [DeT] that was used to convert the training documents. After removing empty test documents and ones that do not belong to any of the categories used in the training database, we are left with 142 test documents each categorized under at least one category. Of these test documents 125 have one correct category belonging to the 12 CoRR categories considered in our tests, 38 have two, only 2 test files have three correct categories each, and 20 do not to any of the 12 CoRR categories considered. Table 5.1 shows the number of test files for each of the 12 categories.

5.4.2 Experimental Setup

There are 12 training sets, one for each category. For every category we begin by preprocessing each training document as was done in Section 3.3.1. Each document is then represented as a vector of features: For the TF*IDF SVM we use the tf*idf function to weigh document words; while the Bag-of-Ranks SVM uses the category's topic word list sorted by M^{DF_4} to replace document words by their relevance ranking. Each ranking is then weighed by its frequency of occurrence in the document. For the Topic-Spread method we linearize the two-dimensional matrix into the one dimensional vector representation expected by SVM^{light} using

CATEGORY	#test files
NI	2
LG	5
CE	5
SE	6
CG	7
DS	10
DC	12
LO	19
PL	21
AI	22
CC	24
CL	27

Table 5.1: The number of test files for each category

row-major order, that is, by mapping each feature (n, r) in the two-dimensional matrix to $((n * 1000) + r)$ where: r is the rank, n is the number of segments, and the maximum value for r is always less than 1000. Each document is then divided into 4 segments, and rank occurrences within the document are counted using the ranking in the sorted M^{DF_4} topic word list for the category. Thereafter the weight for feature $(4, r)$ is the minimum number of occurrences of rank r in all 4 segments, the weight for feature $(3, r)$ is the minimum number of occurrences of rank r in at least 3 segments, and so forth.

Once the document vectors are created for each of these methods, each vector is normalized by its Eucledian length, and labeled in the training set as a positive example if it belongs to the category, or as a negative example otherwise.

After the training set for each category is constructed, we move onto selecting the best model for that category. We experimented with several different values for the cost factor C, the factor J which adjusts the misclassification cost of positive examples to $(J*C)$ while keeping the cost of negative examples to C, the polynomial degree d, and the γ factor for the RBF kernel. For each combination of these values, SVM^{light} produces the leave-one-out estimate of the precision and recall. The model that produces the highest $PRAVG_{loo}$ for a category is the one we choose to classify the test documents with respect to that category. Table 5.4.2 shows the values used to search for the best classifier for each category. We will discuss our observations regarding the resulting models in the results section below.

5.4.3 Evaluation Measures

Categorization systems are usually evaluated by comparing their category assignments to those of humans. Two popular evaluation measures are *Precision* and

General Parameters	C	0, 0.05, 0.1, 0.5, 1, 5, 10, 1000
	J	0.5, 1, 2, $\frac{-ve}{+ve}$
Polynomial kernel	b	1, 2, 3, 4, 5, 10
	s	1
	r	0
RBF kernel	γ	0.01, 0.03, 0.1, 0.3, 1, 3

Table 5.2: The values used to search for the best category model for each CoRR category. $\frac{-ve}{+ve}$ is the ratio of the number of negative category examples to the number of positive examples in the training database

category	Ratio
AI	3.6
CC	6.4
CE	31
CG	10.8
CL	3.1
DC	17
DS	7.2
LG	11.3
LO	4.7
NI	28.4
PL	8.7
SE	18.4

Table 5.3: The ratio of negative to positive examples used for the J parameter.

Recall. Precision is the proportion of correct categories assigned by the system for test documents to the total number of categories the system assigns. Recall is the proportion of correct categories assigned by the system to the total number of categories assigned by humans.

When we are presented with several test documents we can calculate precision by counting the number of correct categories assigned across all the test documents, then dividing that by the total number of categories assigned by the system:

$$P = \frac{\sum_{\forall d \in Test} Corr\_S(d)}{\sum_{\forall d} Num(d)} \tag{5.3}$$

where:

- $Test$ is the set of all test documents.
- $Corr\_S(d)$ is the number of correct categories assigned by the system to test document d.
- $Num(d)$ is the number of categories, both correct and incorrect, assigned by the system to test document d.

Recall can be calculated in a similar manner by dividing the number of correct categories assigned by the system to the total number of correct categories assigned by humans:

$$R = \frac{\sum_{\forall d \in Test} Corr\_S(d)}{\sum_{\forall d} Corr\_H(d)} \tag{5.4}$$

where:

- $Test$ and $Corr\_S(d)$ are as before.

- $Corr\_H(d)$ is the number of categories assigned by human judges to test document d.

The two measures can be combined in one measure called the F_1-measure which reflects the effectiveness of the system assuming precision and recall are equally important [Lew95] [YL99] [MS99] . F_1 is defined as:

$$F_1 = \frac{2PR}{(P+R)} \tag{5.5}$$

where P is precision and R is recall.

Precision and Recall are also used in calculating the *Breakeven Point* (BEP) which is the point at which precision is expected to equal recall. The higher the BEP the better the performance of the system. In the case of binary classifiers it is defined as the mean of the precision and recall values:

$$BEP = \frac{P+R}{2} \tag{5.6}$$

where P and R are as before.

Since all of the above measures pool together all the classifiers' decisions, they are called the *microaveraged* P, R, F_1, and BEP. The microaveraged performance measures give each categorization decision equal weight across all categories. Thus, these measures are influenced more heavily by categories with a higher number of test documents.

Alternatively, we can group the test documents by their human-assigned categories, then calculate the precision, recall, F_1, and BEP values for each group. The overall average of these values is the *macroaveraged* P, R, F_1, and BEP, respectively. Unlike the microaveraged version it weighs all categories equally.

In the experiments below we will be reporting both the microaveraged and the macroaveraged BEP, F_1, recall, and precision.

5.4.4 Results and Analysis

Model Selection

Starting with the parameter values shown in Table 5.4.2, we use SVM^{light} [Joa98a] to evaluate the leave-one-out BEP for each combination for each of the TF*IDF, the Bag-of-Ranks, and the Topic-Spread methods. When two models have equal BEP the model with the lower VC-dim is selected. The resulting models are ranked by their BEP and the top model for every category for each method is selected. The 12 selected models and their parameters are shown in Tables 5.4, 5.5, and 5.6. The tables also show the kernel used in the model, the parameters that apply for that kernel, the VC-dimension of each model as well as the leave-one-out estimate of the precision, recall, and the BEP.

Although these models have the highest BEP values, there are several models whose BEP is close to the top. This agrees with Joachims' observation that there is usually a range of classifiers that can produce similar performance [Joa02]. It is interesting to note, however, that the TF*IDF method tends to select the linear polynomial and the RBF kernels, whereas the Bag-of-Ranks and the Topic-Spread methods tend to select the polynomial kernel but with varying degrees. Note also the wide difference in the BEP_{loo} values for the TF*IDF models which are mostly around 70%, and those of the Bag-of-Ranks and Topic-Spread SVM's which are mostly around 90%. These estimates either indicate a tendency for overfitting the data, or that the Topic-Spread and Bag-of-Ranks document representations succeed in capturing useful information about the document content. Thus, in the presence

cat	C	J	kernel	γ	d	VCdim	recall	prec	BEP
AI	5	0.5	POLY		1	341.62336	0.5897	0.8598	0.7248
CC	0.1	6.4	RBF	0.1		7.5105	0.7071	0.7778	0.7425
CE	0.5	31	RBF	0.03		27.86897	0.3043	0.7778	0.5411
CG	0.1	10.8	POLY		1	61.39553	0.8167	0.9608	0.8888
CL	10	3.1	RBF	0.01		98.0634	0.9167	0.9888	0.9528
DC	1	2	POLY		1	101.3259	0.4878	0.9524	0.7201
DS	10	1	RBF	0.1		200.02401	0.5056	0.9574	0.7315
LG	5	2	RBF	0.1		138.80971	0.5085	0.9677	0.7381
LO	5	4.7	RBF	0.03		143.39289	0.7752	0.7246	0.7499
NI	0.05	28.4	POLY		1	41.34812	0.6800	0.8947	0.7874
PL	5	8.7	RBF	0.03		118.3939	0.7600	0.7215	0.7408
SE	5	1	RBF	0.3		120.90823	0.3784	1.00	0.6892

Table 5.4: The cost factor C, the optimization parameter J, the γ factor for the RBF kernel, and the degree d for the polynomial kernel for the top ranking models for each CoRR cat for the TF*IDF approach. The table also shows the VC-dimensions of the selected classifier and the leave-one-out estimate of the precision, recall, and breakeven point.

cat	C	J	kernel	γ	d	VCdim	recall	prec	BEP
AI	1	3.6	POLY		5	119.80557	0.9038	0.9156	0.9097
CC	1	6.4	POLY		4	100.22017	0.9394	0.9029	0.9212
CE	0.1	31	RBF	1		57.65913	0.8261	1.00	0.9131
CG	1	2	POLY		10	25.80709	0.9000	1.00	0.9500
CL	5	1	POLY		2	74.60417	0.9896	0.9845	0.9871
DC	0.1	17	POLY		3	28.61864	0.9512	0.9070	0.9291
DS	5	2	POLY		1	240.319	0.8427	0.9615	0.9021
LG	0.5	2	POLY		3	40.23411	0.8475	0.9615	0.9045
LO	5	4.7	RBF	3		488.06805	0.8760	0.9040	0.8900
NI	1	2	RBF	3		39.90703	0.9600	1.00	0.9800
PL	5	8.7	POLY		1	379.84627	0.9733	0.7935	0.8834
SE	5	2	POLY		10	103.79613	0.9189	1.00	0.9595

Table 5.5: The cost factor C, the optimization parameter J, the γ factor for the RBF kernel, and the degree d for the polynomial kernel for the top ranking models for each CoRR cat for the Bag-of-Ranks approach. The table also shows the VC-dimensions of the selected classifier and the leave-one-out estimate of the precision, recall, and breakeven point.

cat	C	J	kernel	γ	d	VCdim	recall	prec	BEP
AI	1.0	2	POLY		4	101.05862	0.8974	0.9272	0.9123
CC	5	6.4	POLY		1	444.08250	0.9293	0.92	0.9246
CE	10	31	POLY		5	104.08289	0.9130	0.8750	0.894
CG	5	10.8	POLY		5	165.31334	0.9167	1.00	0.9583
CL	5	1	POLY		2	77.88067	0.9896	0.9845	0.9870
DC	5	2	POLY		5	84.34398	0.8780	1.00	0.939
DS	10	7.2	RBF	0.3		532.55819	0.8876	0.9186	0.9031
LG	0.5	2	POLY		4	39.91318	0.8475	0.9615	0.9045
LO	10	4.7	POLY		5	223.74791	0.8682	0.9032	0.8857
NI	0.5	2	POLY		5	17.32727	0.92	1.00	0.96
SE	1000	1	RBF	0.3		1094.67241	0.9189	0.9714	0.9451
PL	5	8.7	RBF	0.1		141.38082	1.00	0.75	0.875

Table 5.6: The cost factor C, the optimization parameter J, the γ factor for the RBF kernel, and the degree d for the polynomial kernel for the top ranking models for each CoRR cat for the Topic-Spread approach. The table also shows the VC-dimensions of the selected classifier and the leave-one-out estimate of the precision, recall, and breakeven point.

of complete topic word lists, the two representations should produce more accurate models than those found using the TF*IDF SVM. If, however, there is an overfitting problem, then we expect the test results to show the recall falling behind that of the TF*IDF method.

Table 5.7 shows the number of cpu seconds used by each method to create the selected classification models on a shared Sun machine with 8 cpu's and 16G RAM running SunOS-5.8. The average time for the Topic-Spread method is 0.912 cpu-seconds which is 11% that of the TF*IDF method, while the average time for the Bags-of-Ranks approach is 0.549 which is only 6.9% the average time for the TF*IDF approach. Once the models are selected, they are used to classify each one of the test documents.

Categorization Performance

The average classification time for each of the three approaches is shown in Table 5.7. Again, the average time for the Topic-Spread and the Bag-of-Ranks approaches is much less than that for the TF*IDF method. The Topic-Spread method has an average classification time of 1.66 cpu-seconds which is 7.4% the classification time for the TF*IDF approach, while the Bag-of-Ranks approach has an average classification time of 0.076 cpu-seconds which is only 3.4% the time for the TF*IDF approach.

Table 5.8 shows the performance results on the test data. The micro and macro averaged BEP and F_1 for the Topic-Spread method are the highest among the three methods indicating a positive effect of the DF_4 frequency and the topic spread information on classification performance. Note that this is coupled with the fact that the Topic-Spread method and the Bag-of-Ranks method use a vocabulary

cat	**Classification**			**Building Classification Model**		
	Topic-Spread	**Bags-of-ranks**	**TF*IDF**	**Topic-Spread**	**Bags-of-Ranks**	**TF*IDF**
AI	0.32	0.14	2.45	1.66	0.85	8.72
CC	0.19	0.07	3.37	1.02	0.5	9.04
CE	0.08	0.12	3.18	0.57	1.55	8.98
CG	0	0.01	1.99	0.39	0.21	7.73
CL	0.08	0.01	2.28	0.62	0.27	8.1
DC	0.08	0.15	1.39	0.47	0.76	6.38
DS	0.27	0.06	1.96	1.37	0.45	7.69
LG	0.18	0.09	1.72	1	0.44	7.17
LO	0.36	0.14	2.41	1.72	0.76	8.41
NI	0.05	0.02	2.24	0.36	0.13	8.16
PL	0.28	0.06	1.96	1.36	0.46	7.68
SE	0.1	0.04	1.94	0.41	0.21	7.69
AVERAGE	**0.166**	**0.076**	**2.241**	**0.912**	**0.549**	**7.979**

Table 5.7: The cpu time (in cpu seconds) taken by each of the three methods to build the selected classification model and to classify each of the 12 CoRR categories. All experiments were run on an 8-cpu shared Sun Sparc machine runing SunOS-5.8.

cat	TF*IDF				Bags of Ranks				Topic Spread			
	P	R	BEP	F_1	P	R	BEP	F_1	P	R	BEP	F_1
AI	**0.687**	0.50	**0.594**	**0.579**	0.522	**0.545**	0.534	0.533	0.571	**0.545**	0.559	0.558
CC	**0.850**	**0.708**	0.779	**0.773**	0.809	**0.708**	**0.759**	0.755	0.842	0.667	0.754	0.744
CE	**1.0**	0.20	**0.60**	0.333	**1.0**	0.20	**0.60**	0.333	0.667	**0.40**	0.533	**0.50**
CG	**0.875**	**1.0**	**0.938**	**0.933**	0.778	**1.0**	0.889	0.875	0.70	**1.0**	0.85	0.823
CL	0.923	0.889	0.906	0.906	0.893	**0.926**	0.909	0.909	**0.926**	**0.926**	**0.926**	**0.926**
DC	**0.750**	0.250	**0.50**	0.375	0.50	**0.50**	**0.50**	**0.50**	0.60	0.250	0.425	0.353
DS	0.0	0.0	0.0	0.0	0.250	0.30	0.275	0.273	**0.333**	**0.40**	**0.367**	**0.364**
LG	**0.40**	0.40	0.40	0.40	**0.429**	**0.60**	**0.514**	**0.50**	0.375	**0.60**	0.487	0.461
LO	0.667	**0.842**	**0.754**	**0.744**	**0.722**	0.684	0.703	0.703	0.706	0.632	0.669	0.667
NI	0.333	**1.0**	0.667	0.50	**0.50**	**1.0**	**0.750**	**0.667**	**0.50**	**1.0**	**0.750**	**0.667**
PL	**0.750**	0.429	0.589	0.545	0.684	**0.619**	**0.652**	**0.650**	0.650	**0.619**	0.634	0.634
SE	**1.0**	0.167	0.583	0.286	0.333	0.167	0.250	0.222	**1.0**	0.333	**0.667**	**0.50**
macro	**0.686**	0.532	0.609	0.531	0.618	0.604	0.611	0.577	0.656	0.614	**0.635**	**0.60**
micro	**0.721**	0.581	0.651	0.644	0.656	**0.644**	0.65	0.65	0.682	0.631	**0.657**	**0.656**

Table 5.8: The micro and macroaveraged precision, recall, and breakeven points for the approaches TF*IDF, Bag-of-Ranks, and Topic-Spread. The maximum values among all three methods are bold faced.

that is 10% the size of the vocabulary used by the TF*IDF method. The average recall for both the Bag-of-Ranks and the Topic-Spread methods is higher than that of TF*IDF which reflects the effect of the relevance ranking in identifying relevant documents unrecognized by the tf*idf function. The method's effect on recall also makes it less likely that the high BEP_{loo} values seen during training are due to overfitting. Rather, it is more likely that the use of topic spread information produces a more accurate category model than that produced using the TF*IDF approach.

This improvement in recall is statistically significant at a 90% confidence interval with 11 degrees of freedom. The improvement however comes at the cost of a slightly lower precision which goes down from a macroaverage of 68.6% for TF*IDF to 61.6% for Bag-of-Ranks. Adding the topic word spread information in the Topic-Spread method manages to compensate for most of that lost precision bringing the macroaverage up to 65.6%. The effect on the microaveraged precision and recall is similar. The overall BEP and F_1 values are statistically insignificant at the 90% confidence interval.

The TF*IDF method's macroaveraged BEP of 0.609 is close to the estimated BEP_{loo} of 0.689 in Table 5.4. Unlike the TF*IDF method, however, the overall BEP for the Topic-Spread and the Bag-of-Ranks methods are quite different from those predicted from the training set falling from an estimated macroaveraged BEP_{loo} of 0.924 and 0.919 seen in Tables 5.5 and 5.6, respectively, to a BEP macroaverage of 0.63 and 0.611. This difference is probably due to the coverage of the M^{DF_4} topic word list which was created from multi-labeled training documents thus introducing noise within the lists and adversely affecting the quality of the vector representations for the two methods. Nevertheless, the resulting classifiers still perform at least as well as the TF*IDF method, while using only 10% the vocabulary size used by

TF*IDF SVM.

5.5 Conclusions

This chapter presents text categorization as one possible application for the topic spread and topic relevance methods discussed in the previous chapters. It proposes document representations based on topic relevance rankings (Bag-of-Ranks) and the distribution of these rankings within the document (Topic-Spread). Our tests show that the two representations produce small improvements in performance over the SVM which uses the traditional tf*idf vector representation even though they use a vocabulary size that is only 10% the size of the vocabulary used by the tf*idf vector representation. The proposed methods also reduce the model creation time to as little as 6.9% the average time for the TF*IDF approach, and the classification time to 3.4% the average classification time for the TF*IDF approach.

The experiments in this chapter explore the effect of using the M^{DF_4} topic word lists for the Bag-of-Ranks and the Topic-Spread representations. It would be interesting to investigate the effect of using topic word lists produced by M^{DF_n} for $n > 4$. Similarly, we would like to study the effect of increasing the maximum number of segments n used in the Topic-Spread approach.

We suspect that the use of multi-labeled documents for creating the topic-word lists has affected the quality of the results by introducing into the lists topic words that are relevant to frequently co-occurring categories. It would be interesting to look at the change in performance resulting from restricting training documents to those with single labels only.

Chapter 6

Conclusions and Future Work

This work originated from our experience with the Jabber project [KAHHM96]. The project was aimed at indexing videoconferences by several aspects including content of discussion, meeting agenda, and the forms of interaction between participants. Our work in the project highlighted the importance of the temporal positioning of words in tracking content. Word position information can be useful for tasks requiring local content analysis such as topic flow identification, as well as for passage retrieval, text summarization and segmentation.

In this thesis we presented two methods to utilize word position in text: topic word selectors and topic flow signals. The topic word selectors identify important words, called *topic words*, by their spread through a text. For example, a word that occurs many times in a single paragraph of the document is considered less important than one that occurs as often but its occurrence is spread throughout the document. The underlying assumption here is that words that spread out in the text are likely to be more relevant to the main topic of the text than ones that are concentrated in small segments. In our experiments we divide each document into

n equal-length segments, for a preset value of n. The spread of a topic word is then defined by the number of documents in which the word occurs in all n segments of the document DF_n. Our experiments showed that manually selected keywords correspond more closely to topic words selected using these selectors than to words selected using more traditional indexing measures. This correspondence indicates that topic words identify the topical content of documents more than words selected using the traditional indexing measures which do not utilize word position in text. The experiments also indicated that the topic word quality improves as the number of segments n increases up to a certain value for n after which the quality of the words starts to decrease. Word stemming using the Porter Stemmer [Por80] degrades the quality of the selected words but it remains to be seen if a less aggressive stemmer has a different effect on topic word quality.

We would like to further study the effect of relaxing the condition on word spread by allowing a topic word to occur in a subset of the document's segments. It is also interesting to explore the effect of document length on the quality of the generated topic words. Another issue worth investigating is that of stopword removal. We have used a predefined stopword list in this thesis for stopword removal but our preliminary experiments indicate that using DF_n for feature selection might be an acceptable alternative.

Topic words can be useful in many applications. For instance, the short context of topic words can form a helpful starting point for users trying to create a lexicon for a particular topic by selecting from a set of short topic word contexts those that reflect the topic. The idea of evaluating the quality of a word through its spread within a document may also prove useful for feature selection which can help improve the performance of the categorization and text retrieval systems.

The second approach to representing word position is through *topic flow signals*.

In this representation, words are replaced by a measure of their relevance to the topic. The flow of any one topic can then be traced throughout the document and viewed as a signal that remains low when a word relevant to the topic is used, and rises to indicate an irrelevant word occurrence. The intended flow of topics can be represented by a multi-band signal. To reflect the flow of the topic in larger segments of text we use a simple smoothing technique. The resulting smoothed signals were shown to be correlated to the ideal topic flow signals for the same text sequence. We would like to explore the effect of other smoothing techniques on the quality of the signals. Incorporating the immediate short context of words may also be useful in refining the signals although our preliminary experiments on using a moving window for smoothing the signal did not show substantial improvements. Our results have shown that the topic flow signals succeed in representing the flow of a topic in the document when a sufficient list of topic words is used. However, we suspect that the quality of the topic word lists, and, therefore, the quality of the resulting topic flow signals, is influenced by the proportion of multi-labeled training documents used. The relationship between the use of multi-labeled training documents to extract topic-word lists and the quality of the topic flow signals using these lists is left for further study.

Topic flow signals are versatile text representations emphasizing the relevance to the topic at each individual point in the text. Thus, there are many applications for topic flow signals. For example, topic flow signals may be used for topic tracking in spoken discussions. Kazman *et al.* [KAHHM96] introduced an interesting interface in the Jabber prototype JabPro. In that system users could view the progress of a meeting in terms of parallel streams, each representing the speech content of a meeting participant. Topic flow signals can be used to implement a similar interface where users can track the change in intensity of discussion for any particular topic at any moment for each meeting participant. Our smoothing technique would also allow users to view such change at different levels of detail in real time. A similar application is possible through the visualization tool proposed by Miller *et al.* [MWBF98]. They present a text visualization prototype that allows users to view changes in the text content through a content signal and to navigate through the text and its keywords using that signal at several levels of resolution. Our topic flow signals would allow a richer view of the text since each signal reflects an individual topic.

Topic flow signals can be useful for text segmentation by recognizing points in the text where there is a sudden change in the topics being discussed, as was done using different representations by Green [Gre97] and Hearst [Hea94c]. We may also segment text by topic using individual topic flow signals. In this case different text segments would reflect different degrees of relevance to the topic. These relevant segments can then assist us in summarizing the document with respect to the topic. It is important to note, however, that the topic flow signals discussed in this work are quite different from those used in Hearst's TextTiling [Hea94c]. While both representations look like signals, the graphs generated by TextTiling reflect the inter-similarity between consecutive text segments. There is no such inter-segment similarity represented within our topic flow signals. Rather, each point in the signal reflects the relevance of the corresponding point in the text to a specific topic. Once a signal is smoothed, we get the *average* topic relevance of the text segment within the smoothed portion not the cross similarity between the points in that segment. Moreover, each text can be represented through any number of simultaneously running topic flow signals. Methods which can be used to compare those bands of signals effectively need further study.

Throughout this work we have defined topics as stationary entities represented by a fixed set of topic words. One may be able, however, to allow for dynamic topic representations by continuously introducing new training documents discussing relevant issues not seen before by the system. Such a dynamic representation is essential in tasks where topic content changes continuously such as in the Topic Tracking task of the Topic Detection and Tracking Conference (TDT) [TDT]. In the TDT context, topics are defined as *events* through a set of newspaper stories [ACD+98] [Way98]. Any progress in that *event* is still viewed as part of the same topic. For example, if the topic is *The cow found in the U.S. infected with the Mad Cow disease*, all updates on this story which have yet to take place are part of the topic. Given a dynamic topic representation, topic flow signals may then be used in tracking the progress of a topic in an incoming stream of text.

Finally, Support Vector Machines were used to show the benefits of topic spread for text categorization. In these experiments we showed that the way topic words spread in a document is a good indication of the document's main topics. To reflect topic spread, we proposed two document representations, Topic-Spread and Bags-of-Ranks, which define document features by the relevance of the document's words to each topic based on the M^{DF_4} topic relevance selector, and by the spread of these relevance values across the document. We then compared the categorization effectiveness of these two representations to the SVM which used the traditional words-as-features representation weighted by the tf*idf function (TF*IDF SVM). Our document representations improved the recall levels over the TF*IDF SVM classifier while reducing the average document vector length to $20\% - 50\%$ of the length of the traditional tf*idf vector representation, and the vocabulary size to 10% of the vocabulary size used by the TF*IDF representation. Our proposed methods also reduced the SVM model creation time to as little as 6.9% of the average time of the TF*IDF SVM, and the classification time to as little as 3.4% of the average classification time for the TF*IDF SVM. The effect of using other topic relevance selectors M^{DF_n} on categorization performance is left for further study.

Written text has been the focus of this thesis. But we expect word position to be even more beneficial in spoken discussions where important issues are discussed for longer periods of time, and are more likely to be reintroduced repeatedly during a meeting.

This work is a first step towards studying the effect of word position in text on understanding and tracking the content of text. The results we have seen so far are promising. We expect that with further refinement we can achieve an even more accurate picture of written and spoken text content.

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Appendix A

Subject Areas of the CoRR Database

(from [CORb])

AR - Architecture Covers systems organization and architecture. Roughly includes material in ACM Subject Classes C.0, C.1, and C.5.

AI - Artificial Intelligence Covers all areas of AI except Vision, Robotics, Machine Learning, Multiagent Systems, and Computation and Language (Natural Language Processing), which have separate subject areas. In particular, includes Expert Systems, Theorem Proving (although this may overlap with Logic in Computer Science), Knowledge Representation, Planning, and Uncertainty in AI. Roughly includes material in ACM Subject Classes I.2.0, I.2.1, I.2.3, I.2.4, I.2.8, and I.2.11.

CC - Computational Complexity Covers models of computation, complexity classes, structural complexity, complexity tradeoffs, upper and lower bounds.

Roughly includes material in ACM Subject Classes F.1, F.2.3, and F.4.3. Some material in F.2.1 and F.2.2 may also be appropriate here, but is more likely to have Data Structures and Algorithms as the primary subject area. Some material in F.4.3 may have Logic in Computer Science as the primary subject area.

CG - Computational Geometry Roughly includes material in ACM Subject Classes I.3.5 and F.2.2.

CE - Computational Science, Engineering, and Finance Covers the use of computational methods in all areas of Science (including Computational Biology and Computational Chemistry), Engineering, and Finance. Roughly includes material in ACM Subject Classes J.2, J.3, and J.4.

CL - Computation and Language (subsumes cmp-lg) Covers natural language processing. Roughly includes material in ACM Subject Class I.2.7.

CV - Computer Vision and Pattern Recognition Covers image processing, computer vision, pattern recognition, and scene understanding. Roughly includes material in ACM Subject Classes I.2.10, I.4, and I.5.

CY - Computers and Society Covers impact of computers on society, computer ethics, information technology and public policy, legal aspects of computing, computers and education. Roughly includes material in ACM Subject Classes K.0, K.2, K.3, K.4, K.5, and K.7.

CR - Cryptography and Security Covers all areas of cryptography and security including authentication, public key cryptosytems, proof-carrying code, etc. Roughly includes material in ACM Subject Classes D.4.6 and E.3.

DB - Databases Covers database management, datamining, and data processing. Roughly includes material in ACM Subject Classes E.2, E.5, H.0, H.2, and J.1.

DS - Data Structures and Algorithms Covers data structures and analysis of algorithms Roughly includes material in ACM Subject Classes E.1, E.2, F.2.1, and F.2.2.

DL - Digital Libraries Covers all aspects of the digital library design and document and text creation. Note that there will be some overlap with Information Retrieval (which is a separate subject area). Roughly includes material in ACM Subject Classes H.3.5, H.3.6, H.3.7, I.7.

DM - Discrete Mathematics Covers combinatorics, graph theory, applications of probability. Roughly includes material in ACM Subject Classes G.2 and G.3.

DC - Distributed, Parallel, and Cluster Computing Covers fault-tolerance, distributed algorithms, stabilility, parallel computation, and cluster computing. Roughly includes material in ACM Subject Classes C.1.2, C.1.4, C.2.4, D.1.3, D.4.5, D.4.7, E.1.

GL - General Literature Covers introductory material, survey material, predictions of future trends, biographies, and miscellaneous computer-science related material. Roughly includes all of ACM Subject Class A, except it does not include conference proceedings (which will be listed in the appropriate subject area).

GR - Graphics Covers all aspects of computer graphics. Roughly includes material in all of ACM Subject Class I.3, except that I.3.5 is is likely to have

Computational Geometry as the primary subject area.

HC - Human-Computer Interaction Covers human factors, user interfaces, and collaborative computing. Roughly includes material in ACM Subject Classes H.1.2 and all of H.5, except for H.5.1, which is more likely to have Multimedia as the primary subject area.

IR - Information Retrieval Covers indexing, dictionaries, retrieval, content and analysis. Roughly includes material in ACM Subject Classes H.3.0, H.3.1, H.3.2, H.3.3, and H.3.4.

LG - Learning Covers machine learning and computational (PAC) learning. Roughly includes material in ACM Subject Class I.2.6.

LO - Logic in Computer Science Covers all aspects of logic in computer science, including finite model theory, logics of programs, modal logic, and program verification. Programming language semantics should have Programming Languages as the primary subject area. Roughly includes material in ACM Subject Classes D.2.4, F.3.1, F.4.0, F.4.1, and F.4.2.

MS - Mathematical Software Roughly includes material in ACM Subject Class G.4.

MA - Multiagent Systems Covers multiagent systems, distributed artificial intelligence, intelligent agents, coordinated interactions. and practical applications. Roughly covers ACM Subject Class I.2.11.

MM - Multimedia Roughly includes material in ACM Subject Class H.5.1.

NI - Networking and Internet Architecture Covers all aspects of computer communication networks, including network architecture and design, network protocols, and internetwork standards (like TCP/IP). Also includes topics, such as web caching, that are directly relevant to Internet architecture and performance. Roughly includes all of ACM Subject Class C.2 except C.2.4, which is more likely to have Distributed, Parallel, and Cluster Computing as the primary subject area.

NE - Neural and Evolutionary Computation Covers neural networks, connectionism, genetic algorithms, artificial life, adaptive behavior. Roughly includes some material in ACM Subject Class C.1.3, I.2.6, I.5.

NA - Numerical Analysis Roughly includes material in ACM Subject Class G.1.

OS - Operating Systems Roughly includes material in ACM Subject Classes D.4.1, D.4.2., D.4.3, D.4.4, D.4.5, D.4.7, and D.4.9.

OH - Other This is the classification to use for documents that do not fit anywhere else.

PF - Performance Covers performance measurement and evaluation, queueing, and simulation. Roughly includes material in ACM Subject Classes D.4.8 and K.6.2.

PL - Programming Languages Covers programming language semantics, language features, programming approaches (such as object-oriented programming, functional programming, logic programming). Roughly includes material in ACM Subject Classes D.1 and D.3.

RO - Robotics Roughly includes material in ACM Subject Class I.2.9.

SE - Software Engineering Covers design tools, software metrics, testing and debugging, programming environments, etc. Roughly includes material in all of ACM Subject Classes D.2, except that D.2.4 (program verification) should probably have Logics in Computer Science as the primary subject area.

SD - Sound Covers all aspects of computing with sound, and sound as an information channel. Includes models of sound, analysis and synthesis, audio user interfaces, sonification of data, computer music, and sound signal processing. Includes ACM Subject Class H.5.5, and intersects with H.1.2, H.5.1, H.5.2, I.2.7, I.5.4, I.6.3, J.5, K.4.2.

SC - Symbolic Computation Roughly includes material in ACM Subject Class I.1.