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Distributed Search over the Hidden Web: Hierarchical Database Sampling and Selection

Panagiotis G. Ipeirotis
pirot@cs.columbia.edu
Columbia University

Luis Gravano
gravano@cs.columbia.edu
Columbia University

Abstract

Many valuable text databases on the web have non-crawlable contents that are "hidden" behind search interfaces. Metasearchers are helpful tools for searching over many such databases at once through a unified query interface. A critical task for a metasearcher to process a query efficiently and effectively is the selection of the most promising databases for the query, a task that typically relies on statistical summaries of the database contents. Unfortunately, web-accessible text databases do not generally export content summaries. In this paper, we present an algorithm to derive content summaries from "uncooperative" databases by using "focused query probes," which adaptively zoom in on and extract documents that are representative of the topic coverage of the databases. Our content summaries are the first to include absolute document frequency estimates for the database words. We also present a novel database selection algorithm that exploits both the extracted content summaries and a hierarchical classification of the databases, automatically derived during probing, to compensate for potentially incomplete content summaries. Finally, we evaluate our techniques thoroughly using a variety of databases, including 50 real web-accessible text databases. Our experiments indicate that our new content-summary construction technique is efficient and produces more accurate summaries than those from previously proposed strategies. Also, our hierarchical database selection algorithm exhibits significantly higher precision than its flat counterparts.

1 Introduction

The World-Wide Web continues to grow rapidly, which makes exploiting all useful information that is available a standing challenge. Although general search engines like Google crawl and index a large amount of information, typically they ignore valuable data in text databases that are "hidden" behind search interfaces and whose contents are not directly available for crawling through hyperlinks.

Example 1: *Consider the medical bibliographic database* CANCERLIT[1]*. When we issue the query* [lung AND cancer]*,* CANCERLIT *returns 68,430 matches. These matches correspond to high-quality citations to medical articles, stored locally at the* CANCERLIT *site. In contrast, a query*[2] *on Google for the pages in the* CANCERLIT *site with the keywords "lung" and "cancer" matches only 23 other pages under the same domain, none of which corresponds to the database documents. This shows that the valuable* CANCERLIT *content is not indexed by this search engine.* □

One way to provide one-stop access to the information in text databases is through *metasearchers*, which can be used to query multiple databases simultaneously. A metasearcher performs three main tasks. After receiving a query, it finds the best databases to evaluate the query (*database selection*), it translates the query in a suitable form for each database (*query translation*), and finally it retrieves and merges the results from the different databases (*result merging*) and returns them to the user. The *database selection* component of a metasearcher is of crucial importance in terms of both query processing efficiency and effectiveness, and it is the focus of this paper.

Database selection algorithms are traditionally based on statistics that characterize each database's contents [GGMT99, MLY^{+}98, XC98, YL97]. These statistics, which we will refer to as *content summaries*, usually include the *document frequencies* of the words that appear in the database, plus perhaps other simple statistics. These summaries provide sufficient information to the database selection component of a metasearcher to decide which databases are the most promising to evaluate a given query.

To obtain the content summary of a database, a metasearcher could rely on the database to supply the summary (e.g., by following a protocol like STARTS [GCGMP97], or possibly using Semantic Web [BLHL01] tags in the future). Unfortunately many web-accessible text databases are completely autonomous and do not report any detailed metadata about their contents to facilitate metasearching. To handle such databases, a metasearcher could rely on manually generated descriptions of the database contents. Such an approach would not scale to the thousands of text databases available on the web [Bri00], and would likely not produce the good-quality, fine-grained content summaries required by database selection algorithms.

In this paper, we present a technique to automate the extraction of content summaries from searchable text databases. Our technique constructs these summaries from a *biased sample* of the documents in a database, extracted by adaptively *probing* the database with topically focused queries. These queries are derived *automatically* from a document classifier over a Yahoo!-like hierarchy of topics. Our algorithm selects what queries to issue based in part on the results of the earlier queries, thus focusing on the topics that are most representative of the database in question. Our technique resembles biased sampling over *numeric* databases, which focuses the sampling effort on the "densest" areas. We show that this principle is also beneficial for the text-database world. We also show how we can

[1] The query interface is available at `http://www.cancer.gov/search/cancer_literature/`.

[2] The query is *lung cancer site:www.cancer.gov.*

exploit the statistical properties of text to derive *absolute* frequency estimations for the words in the content summaries. As we will see, our technique efficiently produces high-quality content summaries of the databases that are more accurate than those generated from a related uniform probing technique proposed in the literature. Furthermore, our technique categorizes the databases automatically in a hierarchical classification scheme during probing.

In this paper, we also present a novel hierarchical database selection algorithm that exploits the database categorization and adapts particularly well to the presence of incomplete content summaries. The algorithm is based on the assumption that the (incomplete) content summary of one database can help to augment the (incomplete) content summary of a topically similar database, as determined by the database categories.

In brief, the main contributions of this paper are:

- A *document sampling technique* for text databases that results in higher quality database content summaries than those by the best known algorithm.
- A technique to estimate the *absolute* document frequencies of the words in the content summaries.
- A *database selection algorithm* that proceeds hierarchically over a topical classification scheme.
- A thorough, extensive experimental evaluation of the new algorithms using both "controlled" databases and 50 real web-accessible databases.

The rest of the paper is organized as follows. Section 2 gives the necessary background. Section 3 outlines our new technique for producing content summaries of text databases, including accurate word-frequency information for the databases. Section 4 presents a novel database selection algorithm that *exploits both frequency and classification information.* Section 5 describes the setting for the experiments in Section 6, where we show that our method extracts better content summaries than the existing methods. We also show that our hierarchical database selection algorithm of Section 4 outperforms its flat counterparts, especially in the presence of incomplete content summaries, such as those generated through query probing. Finally, Section 8 concludes the paper.

2 Background

In this section we give the required background and report related efforts. Section 2.1 briefly summarizes how existing database selection algorithms work. Then, Section 2.2 describes the use of uniform query probing for extraction of content summaries from text databases and identifies the limitations of this technique. Finally, Section 2.3 discusses how focused query probing has been used in the past for the classification of text databases.

CANCERLIT	
NumDocs: 148,944	
Word	*df*
breast	121,134
cancer	91,688
...	...

CNN.fn	
NumDocs: 44,730	
Word	*df*
breast	124
cancer	44
...	...

Table 1: A fragment of the content summaries of two databases.

2.1 Database Selection Algorithms

Database selection is a crucial task in the metasearching process, since it has a critical impact on the efficiency and effectiveness of query processing over multiple text databases. We now briefly outline how typical database selection algorithms work and how they depend on database content summaries to make decisions.

A database selection algorithm attempts to find the best databases to evaluate a given query, based on information about the database contents. Usually this information includes the number of different documents that contain each word, to which we refer as the *document frequency* of the word, plus perhaps some other simple related statistics [GCGMP97, MLY^{+}98, XC98], like the number of documents *NumDocs* stored in the database. Table 1 depicts a small fraction of what the content summaries for two real text databases might look like. For example, the content summary for the *CNN.fn* database, a database with articles about finance, indicates that 44 documents in this database of 44,730 documents contain the word "cancer." Given these summaries, a database selection algorithm estimates how relevant each database is for a given query (e.g., in terms of the number of matches that each database is expected to produce for the query):

Example 2: *bGlOSS [GGMT99] is a simple database selection algorithm that assumes that query words are independently distributed over database documents to estimate the number of documents that match a given query. So, bGlOSS estimates that query* [breast AND cancer] *will match* $|C| \cdot \frac{df(breast)}{|C|} \cdot \frac{df(cancer)}{|C|} \cong 74,569$ *documents in database* CANCERLIT*, where* $|C|$ *is the number of documents in the* CANCERLIT *database, and* $df(\cdot)$ *is the number of documents that contain a given word. Similarly, bGlOSS estimates that a negligible number of documents will match the given query in the other database of Table 1.* □

bGlOSS is a simple example of a large family of database selection algorithms that rely on content summaries like those in Table 1. Furthermore, database selection algorithms expect such content summaries to be accurate and up to date. The most desirable scenario is when each database exports these content summaries directly (e.g., via a protocol such as STARTS [GCGMP97]). Unfortunately, no protocol is widely adopted for web-accessible databases, and there is little hope that such a protocol will be adopted soon. Hence, other solutions are needed to automate the construction of content summaries from databases that cannot or are not willing to export such information. We review one such approach next.

2.2 Uniform Probing for Content Summary Construction

Callan et al. [CCD99, CC01] presented pioneer work on automatic extraction of document frequency statistics from "uncooperative" text databases that do not export such metadata. Their algorithm extracts a document sample from a given database D and computes the frequency of each observed word w in the sample, $\mathit{SampleDF}(w)$:

1. Start with an empty content summary where $\mathit{SampleDF}(w) = 0$ for each word w, and a general (i.e., not specific to D), comprehensive word dictionary.
2. Pick a word (see below) and send it as a query to database D.
3. Retrieve the top-k documents returned.
4. If the number of retrieved documents exceeds a prespecified threshold, stop. Otherwise continue the sampling process by returning to Step 2.

Callan et al. suggested using $k = 4$ for Step 3 and that 300 documents are sufficient (Step 4) to create a representative content summary of the database. Also they describe two main versions of this algorithm that differ in how Step 2 is executed. The algorithm *RandomSampling-OtherResource* (*RS-Ord* for short) picks a random word from the dictionary for Step 2. In contrast, the algorithm *RandomSampling-LearnedResource* (*RS-Lrd* for short) selects the next query from among the words that have been already discovered during sampling. *RS-Ord* constructs better profiles, but is more expensive than *RS-Lrd* [CC01]. Other variations of this algorithm perform worse than *RS-Ord* and *RS-Lrd*, or have only marginal improvements in effectiveness at the expense of probing cost.

These algorithms compute the sample document frequencies $\mathit{SampleDF}(w)$ for each word w that appeared in a retrieved document. These frequencies range between 1 and the number of retrieved documents in the sample. In other words, the actual document frequency $\mathit{ActualDF}(w)$ for each word w in the database is not revealed by this process and the calculated document frequencies only contain information about the *relative ordering* of the words in the database, not their *absolute* frequencies. Hence, two databases with the same focus (e.g., two medical databases) but differing significantly in size might be assigned similar content summaries. Also, *RS-Ord* tends to produce inefficient executions in which it repeatedly issues queries to databases that produce no matches. According to Zipf's law [Zip49], most of the words in a collection occur very few times. Hence, a word that is randomly picked from a dictionary (which hopefully contains a superset of the words in the database), is likely not to occur in any document of an arbitrary database.

The *RS-Ord* and *RS-Lrd* techniques extract content summaries from uncooperative text databases that otherwise could not be evaluated during a metasearcher's database selection step. In Section 3 we introduce a novel technique for constructing content summaries *with* *absolute frequencies* that are highly accurate and efficient to build. Our new technique exploits earlier work on text-database classification [IGS01a], which we review next.

2.3 Focused Probing for Database Classification

Another way to characterize the contents of a text database is to classify it in a Yahoo!-like hierarchy of topics according to the type of the documents that it contains. For example, *CANCERLIT* can be classified under the category *"Health,"* since it contains mainly health-related documents. Ipeirotis et al. [IGS01a] presented a method to automate the classification of web-accessible databases, based on the principle of *"focused probing."*

The rationale behind this method is that queries closely associated with topical categories retrieve mainly documents about that category. For example, a query *[breast AND cancer]* is likely to retrieve mainly documents that are related to the *"Health"* category. By observing the number of matches generated for each such query at a database, we can then place the database in a classification scheme. For example, if one database generates a large number of matches for the queries associated with the *"Health"* category, and only a few matches for all other categories, we might conclude that it should be under category *"Health."*

To automate this classification, these queries are derived *automatically* from a *rule-based document classifier.* A rule-based classifier is a set of logical rules defining classification decisions: the antecedents of the rules are a conjunction of words and the consequents are the category assignments for each document. For example, the following rules are part of a classifier for the two categories *"Sports"* and *"Health"*:

jordan AND bulls → Sports
hepatitis → Health

Starting with a set of preclassified *training documents*, a document classifier, such as RIPPER [Coh96] from AT&T Research Labs, learns these rules *automatically.* For example, the second rule would classify previously unseen documents (i.e., documents not in the training set) containing the word "hepatitis" into the category *"Health."* Each classification rule $p \rightarrow C$ can be easily transformed into a simple boolean query q that is the conjunction of all words in p. Thus, a query probe q sent to the search interface of a database D will match documents that would match rule $p \rightarrow C$ and hence are likely in category C.

Categories can be further divided into subcategories, hence resulting in multiple levels of classifiers, one for each internal node of a classification hierarchy. We can then have one classifier for coarse categories like *"Health"* or *"Sports,"* and then use a different classifier that will assign the *"Health"* documents into subcategories like *"Cancer," "AIDS,"* and so on. By applying this principle recursively for each internal node of the classification scheme, it is possible to create a hierarchical classifier that will recursively divide the space into successively smaller topics. The algorithm in [IGS01a] uses such a hierarchical scheme, and automatically maps rule-based document classifiers into queries, which are then used to probe and classify text databases.

To classify a database, the algorithm in [IGS01a] starts by first sending the query probes associated with the subcategories of the top node C of the topic hierarchy, and extracting the number of matches for each probe, without retrieving any documents. Based on the number of matches for the probes for each subcategory C_i, it then calculates two metrics, the *Coverage(C_i)* and *Specificity(C_i)* for the subcategory. *Coverage(C_i)* is the *absolute* number of documents in the database that are estimated to belong to C_i, while *Specificity(C_i)* is the *fraction* of documents in the database that are estimated to belong to C_i. The algorithm decides to classify a database into a category C_i if the values of *Coverage(C_i)* and *Specificity(C_i)* exceed two prespecified thresholds τ_c and τ_s, respectively. Higher levels of the specificity threshold τ_s result in assignments of databases mostly to higher levels of the hierarchy, while lower values tend to assign the databases to nodes closer to the leaves. When the algorithm detects that a database satisfies the specificity and coverage requirement for a subcategory C_i, it proceeds recursively in the subtree rooted at C_i. By not exploring other subtrees that did not satisfy the coverage and specificity conditions, we avoid exploring portions of the topic space that are not relevant to the database. This results in accurate database classification using a small number of query probes.

Interestingly, this database classification algorithm provides a way to zoom in on the topics that are most representative of a given database's contents and we can then exploit it for accurate and efficient content summary construction.

3 Focused Probing for Content Summary Construction

We now describe a novel algorithm to construct content summaries for a text database. Our algorithm exploits a topic hierarchy to adaptively send focused probes to the database. These queries tend to efficiently produce a document sample that is topically representative of the database contents, which leads to highly accurate content summaries. Furthermore, our algorithm classifies the databases along the way. In Section 4 we will exploit this categorization and the database content summaries to introduce a hierarchical database selection technique that can handle incomplete content summaries well. Our content-summary construction algorithm consists of two main steps:

1. Query the database using focused probing (Section 3.1) in order to:
   (a) Retrieve a document sample.
   (b) Generate a preliminary content summary.
   (c) Categorize the database.
2. Estimate the *absolute* frequencies of the words retrieved from the database (Section 3.2).

3.1 Building Content Summaries from Extracted Documents

The first step of our content summary construction algorithm is to adaptively query a given text database using focused probes to retrieve a document sample. The algorithm is shown

```
GetContentSummary(Category $C$, Database $D$)
  α: $\langle SampleDF, ActualDF, Classif \rangle = \langle \emptyset, \emptyset, \emptyset \rangle$
  if $C$ is a leaf node then return $\langle SampleDF, ActualDF, \{C\} \rangle$
  Probe database $D$ with the query probes derived from the classifier for the subcategories of $C$
  β: $newdocs = \emptyset$
     foreach query probe $q$
        $newdocs = newdocs \cup \{top\text{-}k\ documents\ returned\ for\ q\}$
        if $q$ consists of a single word $w$ then $ActualDF(w)$ = #matches returned for $q$
     foreach word $w$ in $newdocs$
        $SampleDF(w)$ = #documents in $newdocs$ that contain $w$
  Calculate Coverage and Specificity from the number of matches for the probes
  foreach subcategory $C_i$ of $C$
     if ($Specificity(C_i) > \tau_s$ AND $Coverage(C_i) > \tau_c$) then
        γ: $\langle SampleDF', ActualDF', Classif' \rangle$ = GetContentSummary($C_i$, $D$)
           Merge $\langle SampleDF', ActualDF' \rangle$ into $\langle SampleDF, ActualDF \rangle$
        $Classif = Classif \cup Classif'$
  return $\langle SampleDF, ActualDF, Classif \rangle$
```

Figure 1: Generating a content summary for a database using focused query probing.

in Figure 1. We have enclosed in boxes the portions directly relevant to content-summary extraction. Specifically, for each query probe we retrieve k documents from the database in addition to the number of matches that the probe generates (box β in Figure 1). Also, we record two sets of word frequencies based on the probe results and extracted documents (boxes β and γ):

1. $ActualDF(w)$: the actual number of documents in the database that contain word w. The algorithm knows this number only if $[w]$ is a single-word query probe that was issued to the database[3].

2. $SampleDF(w)$: the number of documents in the extracted sample that contain word w.

The basic structure of the probing algorithm is as follows: We explore (and send query probes for) only those categories with sufficient specificity and coverage, as determined by the τ_s and τ_c thresholds. As a result, this algorithm categorizes the databases into the classification scheme during probing. We will exploit this categorization in our database selection algorithm of Section 4.

Figure 2 illustrates how our algorithm works for the *CNN Sports Illustrated* database, a database with articles about sports, and for a hierarchical scheme with four categories

[3] The number of matches reported by a database for a single-word query $[w]$ might differ slightly from $ActualDF(w)$, for example, if the database applies stemming [SM83] to query words so that a query [computers] also matches documents with word *"computer."*

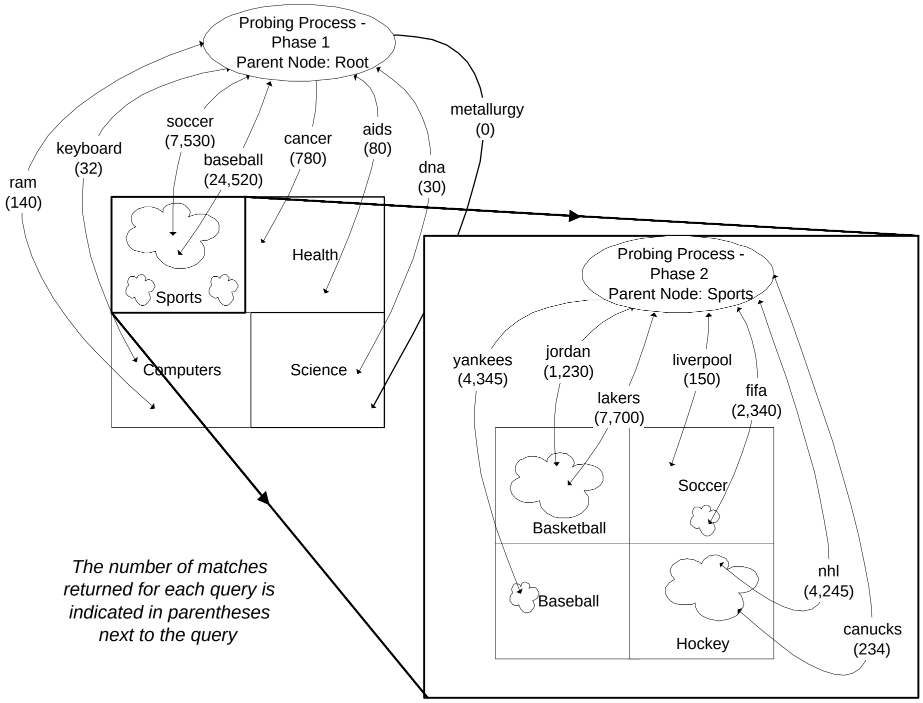


Figure 2: Querying the *CNN Sports Illustrated* database with focused probes.

under the root node: *"Sports," "Health," "Computers,"* and *"Science."* We pick specificity and coverage thresholds $\tau_s = 0.5$ and $\tau_c = 100$, respectively. The algorithm starts by issuing the query probes associated with each of the four categories. The *"Sports"* probes generate many matches (e.g., query *[baseball]* matches 24,520 documents). In contrast, the probes for the other sibling categories (e.g., *[metallurgy]* for category *"Science"*) generate just a few or no matches. The *Coverage* of category *"Sports"* is the sum of the number of matches for its probes, or 32,050. The *Specificity* of category *"Sports"* is the fraction of matches that correspond to *"Sports"* probes, or 0.967. Hence, *"Sports"* satisfies the *Specificity* and *Coverage* criteria (recall that $\tau_s = 0.5$ and $\tau_c = 100$) and is further explored to the next level of the hierarchy. In contrast, *"Health," "Computers,"* and *"Science"* are not considered further. The benefit of this *pruning* of the probe space is two-fold: First, we improve the efficiency of the probing process by giving attention to the topical focus (or foci) of the database. (Out-of-focus probes would tend to return few or no matches.) Second, we avoid retrieving spurious matches and focus on documents that are better representatives of the database.

During probing, our algorithm retrieves the top-k documents returned by each query (box β in Figure 1). For each word w in a retrieved document, the algorithm computes $SampleDF(w)$ by measuring the number of documents in the sample, extracted in a probing round, that contain w. If a word w appears in document samples retrieved during later phases of the algorithm for deeper levels of the hierarchy, then all *SampleDF*(w) values are added together ("merge" step in box γ). Similarly, during probing the algorithm keeps track of the number of matches produced by each single-word query $[w]$. As discussed, the number of matches for such a query is (a close approximation to) the *ActualDF*(w) frequency (i.e., the number of documents in the database with word w). These *ActualDF*$(\cdot)$ frequencies are crucial to estimate the absolute document frequencies of all words that appear in the document sample extracted, as discussed next.

3.2 Estimating Absolute Document Frequencies

No probing technique so far has been able to estimate the *absolute* document frequency of words. The *RS-Ord* and *RS-Lrd* techniques only return the *SampleDF*$(\cdot)$ of words with no absolute frequency information. We now show how we can exploit the *ActualDF*$(\cdot)$ and *SampleDF*$(\cdot)$ document frequencies that we extract from a database (Section 3.1) to build a content summary for the database with accurate absolute document frequencies. For this, we follow two steps:

1. Exploit the *SampleDF*$(\cdot)$ frequencies derived from the document sample to rank all observed words from most frequent to least frequent.

2. Exploit the *ActualDF*$(\cdot)$ frequencies derived from one-word query probes to potentially boost the document frequencies of "nearby" words w for which we only know *SampleDF*(w) but not *ActualDF*(w).

Figure 3 illustrates our technique for *CANCERLIT*. After probing *CANCERLIT* using the algorithm in Figure 1, we rank all words in the extracted documents according to their *SampleDF*$(\cdot)$ frequency. In this figure, *"cancer"* has the highest *SampleDF* value and *"hepatitis"* the lowest such value. The *SampleDF* value of each word is noted by the corresponding vertical bar. Also, the figure shows the *ActualDF*$(\cdot)$ frequency of those words that formed single-word queries. For example, *ActualDF*(*hepatitis*) $= 20,000$, because query probe *[hepatitis]* returned 20,000 matches. Note that the *ActualDF* value of some words (e.g., *"stomach"*) is unknown. These words appeared in documents that we retrieved during probing, but not as single-word probes. From the figure, we can see that *SampleDF(hepatitis)* $\approx$ *SampleDF(stomach)*. Then, intuitively, we will estimate *ActualDF*(*stomach*) to be close to the (known) value of *ActualDF*(*hepatitis*).

To specify how to "propagate" the known *ActualDF* frequencies to "nearby" words with similar *SampleDF* frequencies, we exploit well-known laws on the distribution of words over text documents. Zipf [Zip49] was the first to observe that word-frequency distributions follow a power law, which was later refined by Mandelbrot [Man88]. Mandelbrot observed a relationship between the rank r and the frequency f of a word in a text database: $f = P(r+p)^{-B}$, where P, B, and p are parameters of the specific document collection. This formula indicates that the most frequent word in a collection (i.e., the word with rank $r = 1$) will tend to appear in $P(1+p)^{-B}$ documents, while, say, the tenth most frequent word will appear in just $P(10+p)^{-B}$ documents.

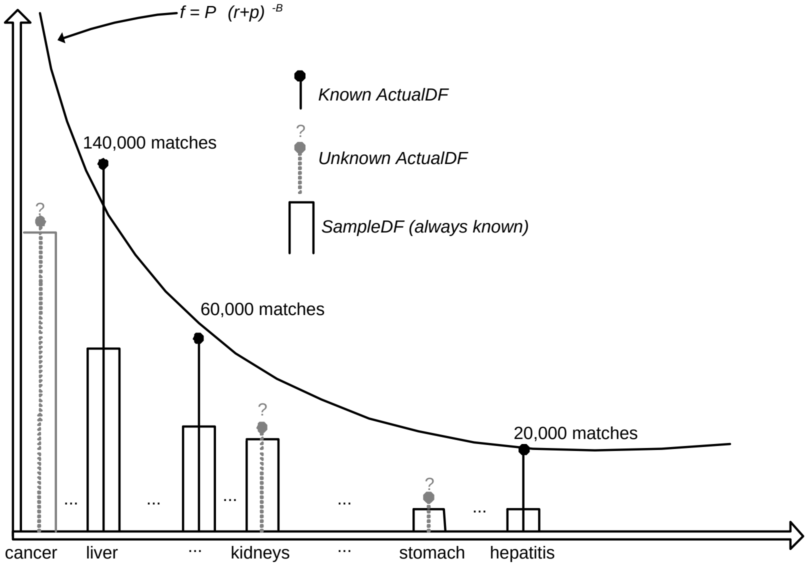


Figure 3: Estimating unknown *ActualDF* values.

Just as in Figure 3, after probing we know the rank of all observed words in the sample documents retrieved, as well as the actual frequencies of some of those words in the entire database. These statistics, together with Mandelbrot's equation, lead to the following procedure for estimating unknown $ActualDF(\cdot)$ frequencies:

1. Sort words in descending order of their $SampleDF(\cdot)$ frequencies to determine the *rank* r_i of each word w_i.

2. Focus on words with known $ActualDF(\cdot)$ frequencies. Use the *SampleDF*-based rank and *ActualDF* frequencies to find the P, B, and p parameter values that best fit the data.

3. Estimate $ActualDF(w_i)$ for all words w_i with unknown $ActualDF(w_i)$ as $P(r_i+p)^{-B}$, where r_i is the rank of word w_i as computed in Step 1.

For Step 2, we use an off-the-shelf curve fitting algorithm available as part of the *R-Project*[4], an open-source environment for statistical computing.

Example 3: *Consider the medical database* CANCERLIT *and Figure 3. We know that ActualDF(hepatitis)* = 20,000 *and ActualDF(liver)* = 140,000*, since the respective one-word query probes reported so many matches in each case. Additionally, using the SampleDF frequencies, we know that* "liver" *is the fifth most popular word among the extracted*

[4] `http://www.r-project.org/`

documents, while "hepatitis" *ranked number 25. Similarly,* "kidneys" *is the 10th most popular word. Unfortunately, we do not know the value of ActualDF*(*kidneys*) *since* [kidneys] *was not a query probe. However, using the ActualDF frequency information from the other words and their SampleDF-based rank, we estimate the distribution parameters to be* $P = 8 \cdot 10^5$, $p = 0.25$, *and* $B = 1.15$. *Using the rank information with Mandelbrot's equation, we compute* $ActualDF_{est}(kidneys) = 8 \cdot 10^5 (10 + 0.25)^{-1.15} \cong 55,000$. *In reality, ActualDF(kidneys)* $= 65,000$, *which is close to our estimate.* □

During sampling, we also send to the database query probes that consist of more than one word. (Recall that our query probes are derived from an underlying, automatically learned document classifier.) We do not exploit multi-word queries for determining *ActualDF* frequencies of their words, since the number of matches returned by a boolean-AND multi-word query is only a lower bound on the *ActualDF* frequency of each intervening word. However, the average length of the query probes that we generate is small (less than 1.5 in our experiments), and their median length is one. Hence, the majority of the query probes provide us with *ActualDF* frequencies that we can exploit. Another interesting observation is that we can derive a gross estimate of the number of documents in a database as the largest (perhaps estimated) *ActualDF* frequency, since the most frequent words tend to appear in a large fraction of the documents in a database.

In summary, we presented a new focused probing technique for content summary construction that (a) estimates the absolute document frequency of the words in a database, and (b) automatically classifies the database in a hierarchical classification scheme along the way. We show next how we can define a database selection algorithm that uses the content summary and categorization information of each available database.

4 Exploiting Topic Hierarchies for Database Selection

Any efficient algorithm for constructing content summaries through query probes is likely to produce incomplete content summaries, which can affect the effectiveness of the database selection process. Specifically, database selection would suffer the most for queries with one or more words not present in content summaries. We now introduce a database selection algorithm that exploits the database categorization and content summaries produced as in Section 3 to alleviate the negative effect of incomplete content summaries. This algorithm consists of two basic steps:

1. "Propagate" the database content summaries to the categories of the hierarchical classification scheme (Section 4.1).

2. Use the content summaries of categories and databases to perform database selection hierarchically by zooming in on the most relevant portions of the topic hierarchy (Section 4.2).

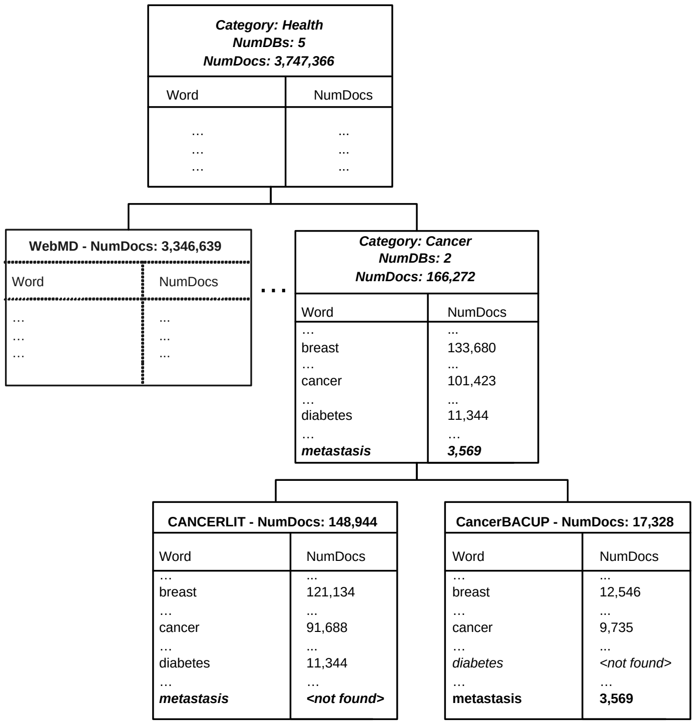


Figure 4: Associating content summaries with categories.

4.1 Creating Content Summaries for Topic Categories

Sections 2.2 and 3 showed algorithms for extracting database content summaries. These content summaries could be used to guide existing database selection algorithms, such as bGlOSS [GGMT99] or CORI [CLC95]. However, these algorithms might produce inaccurate conclusions for queries with one or more words missing from relevant content summaries. This is particularly problematic for the short queries that are prevalent over the web. A first step to alleviate this problem is to associate content summaries with the *categories* of the topic hierarchy used by the probing algorithm of Section 3. In the next section, we use these category content summaries to select databases hierarchically.

The intuition behind our approach is that databases classified under similar topics tend to have similar vocabularies. (We present supporting experimental evidence for this statement in Section 6.3.) Hence, we can view the (potentially incomplete) content summaries of all databases in a category as complementary, and exploit this view for better database selection. For example, consider the *CANCERLIT* database and its associated content summary in Figure 4. As we can see, *CANCERLIT* was correctly classified under *"Cancer"* by the algorithm in Section 3. Unfortunately, the word *"metastasis"* did not appear in any of the documents extracted from *CANCERLIT* during probing, so this word is missing from the content summary. However, we see that *CancerBACUP*[5], another database classified under *"Cancer"*, has a high $\mathit{ActualDF}_{est}(\mathit{metastasis}) = 3,569$. Hence, we might conclude that the word *"metastasis"* did not appear in *CANCERLIT* because it was not discovered during sampling, and not because it does not occur in the *CANCERLIT* database. We convey this information by associating a content summary with category *"Cancer"* that is obtained by merging the summaries of all databases under this category. In the merged content summary, $\mathit{ActualDF}_{est}(w)$ is the sum of the document frequency of w for databases under this category.

In general, the content summary of a category C with databases $db_1, \ldots, db_n$ classified (not necessary immediately) under C includes:

- *NumDBs(C)*: The number of databases under C (n in this case).
- *NumDocs(C)*: The number of documents stored in any db_i under C; *NumDocs(C)*$= \sum_{i=1}^{n} \mathit{NumDocs}(db_i)$.
- $\mathit{ActualDF}_{est}(w)$: The number of documents in any db_i under C that contain the word w; $\mathit{ActualDF}_{est}(w) = \sum_{i=1}^{n}(\mathit{ActualDF}_{est}(w) \mathit{for}\ db_i)$.

By having content summaries associated with categories, we can treat each category as a large "database" and perform database selection hierarchically; we present a new algorithm for this task next.

4.2 Selecting Databases Hierarchically

Now that we have associated content summaries with the categories in the topic hierarchy, we can select databases for a query hierarchically, starting from the top category. Earlier research indicated that distributed information retrieval systems tend to produce better results when documents are organized in topically-cohesive clusters [XC99, LCC00]. At each level, we use existing flat database algorithms such as CORI [CLC95] or bGlOSS [GGMT99]. These algorithms assign a *score* to each database (or category in our case) for a query, which specifies how promising the database (or category) is for the query, based on its content summary (see Example 2). We assume in our discussion that scores are greater than or equal to zero, with a zero score indicating that a database or category should be ignored for the query. Given the scores for the categories at one level of the hierarchy, the selection process will continue recursively onto the most promising subcategories. There are several alternative strategies that we could follow to decide what subcategories to exploit. In this paper, we present one such strategy, which privileges topic-specific over broader databases.

Figure 5 summarizes our hierarchical database selection algorithm. The algorithm takes as input a query Q and the target number of databases K that we are willing to search for the query. Also, the algorithm receives the top category C as input, and starts by invoking a flat database selection algorithm to score all subcategories of C for the query (Step 1),

[5] `http://www.cancerbacup.org.uk`

```
HierSelect(Query $Q$, Category $C$, int $K$)
1: Use a database selection algorithm to assign a score for $Q$ to each subcategory of $C$
2: if there is a subcategory $C$ with a non-zero score
3:         Pick the subcategory $C_j$ with the highest score
4:         if NumDBs($C_j$) $\geq K$ //$C_j$ has enough databases
5:             return HierSelect($Q$,$C_j$,$K$)
6:         else // $C_j$ does not have enough databases
7:             return DBs($C_j$) $\cup$ FlatSelect($Q$,$C - C_j$,$K$-NumDBs($C_j$))
8: else // no subcategory $C$ has non-zero score
9:     return FlatSelect($Q$,$C$,$K$)
```

Figure 5: Selecting the K most specific databases for a query hierarchically.

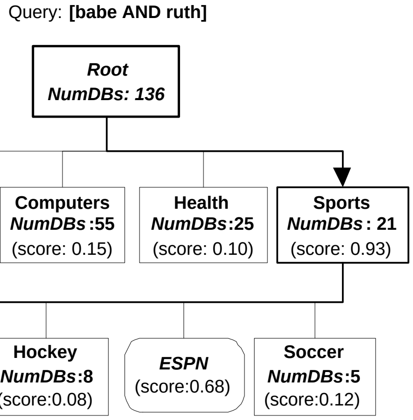


Figure 6: Exploiting a topic hierarchy for database selection.

using the content summaries associated with the subcategories (Section 4.1). If at least one "promising" subcategory has a non-zero score (Step 2), then the algorithm picks the best such subcategory C_j (Step 3). If C_j has K or more databases under it (Step 4) the algorithm proceeds recursively under that branch only (Step 5). As discussed above, this strategy privileges "topic-specific" databases over databases with broader scope. On the other hand, if C_j does not have sufficiently many (i.e., K or more) databases (Step 6), then intuitively the algorithm has gone as deep in the hierarchy as possible (exploring only category C_j would result in fewer than K databases being returned). Then, the algorithm returns all *NumDBs(*C_j*)* databases under C_j, plus the best $K -$ *NumDBs(*C_j*)* databases under C but not in C_j, according to the "flat" database selection algorithm of choice (Step 7). If no subcategory of C has a non-zero score (Step 8), again this indicates that the execution has gone as deep in the hierarchy as possible. Therefore, we return the best K databases under C, according to the flat database selection algorithm (Step 9).

Figure 6 shows an example of an execution of this algorithm for query *[babe AND ruth]* and for a target of $K = 3$ databases. The top-level categories are evaluated by a flat database selection algorithm for the query, and the *"Sports"* category is deemed best, with a score of 0.93. Since the *"Sports"* category has more than three databases, the query is "pushed" into this category. The algorithm proceeds recursively by pushing the query into the *"Baseball"* category. If we had initially picked $K = 10$ instead, the algorithm would have still picked *"Sports"* as the first category to explore. However, *"Baseball"* has only 7 databases, so the algorithm picks them all, and chooses the best 3 databases under *"Sports"* to reach the target of 10 databases for the query.

In summary, our hierarchical database selection algorithm chooses the best, most-specific databases for a query. By exploiting the database categorization, this hierarchical algorithm manages to compensate for the necessarily incomplete database content summaries produced by query probing. In the next sections we evaluate the performance of this algorithm against that of "flat" selection techniques.

5 Data and Metrics

In this section we describe the data (Section 5.1) and techniques (Section 5.2) that we use for the experiments reported in Section 6.

5.1 Experimental Setting

To evaluate the algorithms described in this paper, we use two data sets: one set of *"Controlled"* databases that we assembled locally with newsgroup articles, and another set of *"Web"* databases, which we could only access through their web search interface. We also report experiments involving the three databases used in [CC01], to validate our comparison further. We use a 3-level subset of the Yahoo! topic hierarchy consisting of 72 categories, with 54 "leaf" and 18 "internal" topics.

Controlled Database Set: We gathered 500,000 newsgroup articles from 54 newsgroups during April-May 2000. Out of these, we used 81,000 articles to train document classifiers over the 72-node topic hierarchy. For training we manually assigned newsgroups to categories, and treated all documents from a newsgroup as belonging to the corresponding category. We used the remaining 419,000 articles to build the set of *Controlled Databases*. This set contained 500 databases ranging in size from 25 to 25,000 documents. 350 of them were "homogeneous," with documents from a single category, while the remaining 150 are "heterogeneous," with a variety of category mixes (see [IGS01a] for details). These databases were indexed and queried by a SMART-based program [SM97] using the cosine similarity function with *tf.idf* weighting [SB88].

Web Database Set: We used a set of 50 real web-accessible databases over which we do not have any control. These databases were picked randomly from two directories of hidden-web databases, namely InvisibleWeb[6] and CompletePlanet[7]. These databases have

[6] `http://www.invisibleweb.com/`

[7] `http://www.completeplanet.com/`

Web Database	*URL*
U. of Michican Cancer Center	`http://www.cancer.med.umich.edu/search.htm`
Java @ Sun.com	`http://search.java.sun.com`
John Hopkins AIDS Service	`http://hopkins-aids.edu/index_search.html`

Table 2: Some of the real web databases in the *Web* set.

articles that range from research papers to film reviews. Table 2 shows a sample of three databases from the *Web* set.

5.2 Alternative Techniques

Our experiments evaluate two main sets of techniques: content-summary construction techniques (Sections 2 and 3) and database selection techniques (Section 4):

Content Summary Construction: We test variations of our *Focused Probing* technique against the two main variations of uniform probing, described in Section 2.2, namely *RS-Ord* and *RS-Lrd*. As the initial dictionary D for these two methods we used the set of all the words that appear in the databases of the *Controlled* set. For *Focused Probing*, we evaluate configurations with different underlying document classifiers for query-probe creation, and different values for the *thresholds* τ_s *and* τ_c that define the granularity of sampling performed by the algorithm in Figure 1. Specifically, we consider the following variations of the *Focused Probing* technique:

FP-RIPPER: *Focused Probing* using RIPPER [Coh96] as the base document classifier (Section 3.1).

FP-C4.5: *Focused Probing* using C4.5RULES, which extracts classification rules from decision tree classifiers generated by C4.5 [Qui92].

FP-Bayes: *Focused Probing* using Naive-Bayes classifiers [DH73] in conjunction with a technique to extract rules from numerically-based Naive-Bayes classifiers [IGS01b].

FP-SVM: *Focused Probing* using Support Vector Machines with linear kernels [Joa98] in conjunction with the same rule-extraction technique used for *FP-Bayes*.

We vary the specificity threshold τ_s to get document samples of different granularity. All variations were tested with threshold τ_s ranging between 0 and 1. Low values of τ_s result in databases being "pushed" to more categories, which in turn results in larger document samples. To keep the number of experiments manageable, we fix the coverage threshold to $\tau_c = 10$, varying only the specificity threshold τ_s.

Database Selection Effectiveness: We test variations of our database selection algorithm of Section 4 along several dimensions:

Underlying Database Selection Algorithm: The hierarchical algorithm of Section 4.2 relies on a "flat" database selection algorithm. We consider two such algorithms: CORI [CLC95] and bGlOSS [GGMT99]. Our purpose is not to evaluate the relative merits of these two algorithms (for this, see [FPC$^+$99, PFC$^+$00]) but rather to ensure that our techniques behave similarly for different flat database selection algorithms. We adapted both algorithms to work with the category content summaries described in Section 4.1.

Content Summary Construction Algorithm: We evaluated how our hierarchical database selection algorithm behaves over content summaries generated by different techniques. In addition to the content-summary construction techniques listed above, we also test *QPilot*, a recent strategy that exploits HTML links to characterize text databases [SE00]. Specifically, *QPilot* builds a content summary for a web-accessible database D as follows:

1. Query a general search engine to retrieve pages that link to the web page for D[8].

2. Retrieve the top-m pages that point to D.

3. Extract the words in the same line as a link to D.

4. Include only words with high document frequency in the content summary for D.

Hierarchical vs. Flat Database Selection: We compare the effectiveness of the hierarchical algorithm of Section 4.2, against that of the underlying "flat" database selection strategies.

6 Experimental Results

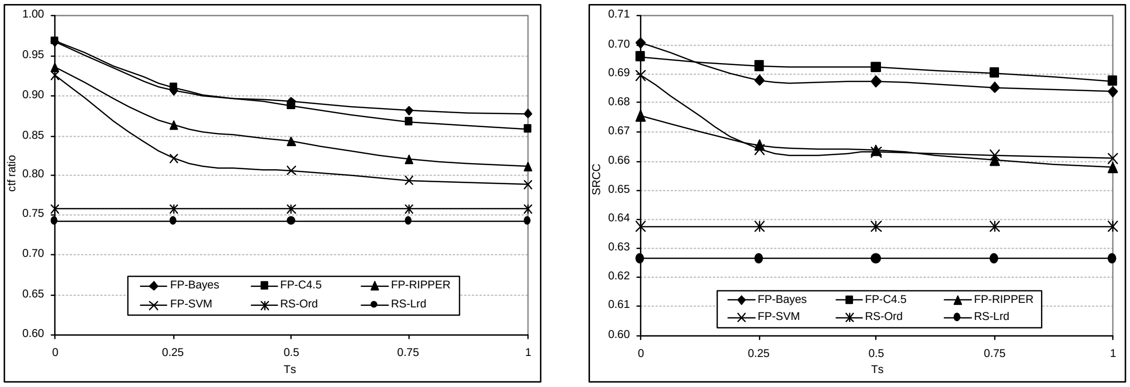
We use the *Controlled* database set for experiments on content summary quality (Section 6.1), while we use the *Web* database set for experiments on database selection effectiveness (Section 6.2). We report the results next.

6.1 Content Summary Quality

Coverage of the retrieved vocabulary: An important property of content summaries is their coverage of the actual database vocabulary. To measure coverage, we use the *ctf ratio* metric introduced in [CC01]: $ctf = \frac{\sum_{w \in T_r} ActualDF(w)}{\sum_{w \in T_d} ActualDF(w)}$, where T_r is the set of terms in a content summary and T_d is the complete set of words in the corresponding database. This metric gives higher weight to more frequent words, but is calculated *after* stopwords (e.g., "a", "the") are removed, so this ratio is not artificially inflated by the discovery of common words.

We report the *ctf ratio* for the different content summary construction algorithms in Figure 7(a). The variants of the *Focused Probing* technique achieve much higher *ctf* ratios than *RS-Ord* and *RS-Lrd* do. Early during probing, *Focused Probing* retrieves documents covering different topics, and then sends queries of increasing specificity, retrieving documents with more specialized words. As expected, the coverage of the *Focused Probing* summaries increases for lower thresholds of τ_s, since the number of documents retrieved for lower thresholds is larger (e.g., 493 documents for *FP-SVM* for $\tau_s = 0.25$ vs. 300 documents for *RS-Lrd*): a sample of larger size, everything else being the same, is better for content summary construction. In general, the difference between *RS-Lrd* and *RS-Ord* is small.

[8] *QPilot* finds backlinks by querying AltaVista using queries of the form "link:URL-of-the-database." [SE00]



(a) **(b)**

Figure 7: The *ctf ratio* **(a)** and the *Spearman Rank Correlation Coefficient* **(b)** for different methods and for different values of the specificity threshold τ_s.

Database	*Category*	*RS-Lrd*	*RS-Ord*	*FP-SVM*	*FP-RIPPER*	*FP-C4.5*	*FP-Bayes*
CACM	Computers	0.79	0.82	0.89	0.82	0.83	0.9
WSJ88	Root	0.79	0.82	0.85	0.83	0.85	0.83
TREC123	Root	0.68	0.69	0.67	0.67	0.69	0.69

Table 3: The *SRCC* metric for the three databases in [CC01], for different content summary extraction algorithms ($\tau_s = 0.25$ for the FP-* algorithms).

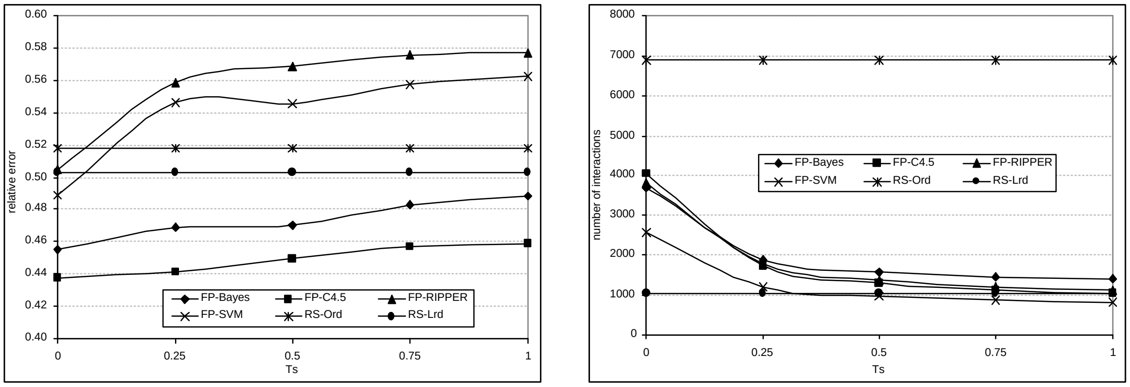
RS-Lrd has slightly lower *ctf* values, due to the bias induced from querying only using previously discovered words.

Correlation of word rankings: The *ctf ratio* can be helpful to compare the quality of different content summaries. However, this metric alone is not enough, since it does not capture the relative "rank" of words in the content summary by their observed frequency. To measure how well a content summary orders words by frequencies with respect to the actual word frequency order in the database, we use the *Spearman Rank Correlation Coefficient* (*SRCC* for short), which is also used in [CC01] to evaluate the quality of the content summaries. When two rankings are identical then *SRCC*=1; when they are uncorrelated, *SRCC*=0; and when they are in reverse order, *SRCC*=-1. The results for the different algorithms are listed in Figure 7(b). Again, the content summaries produced by the *Focused Probing* techniques have much higher *SRCC* values than for *RS-Lrd* and *RS-Ord*, hinting that *Focused Probing* retrieves a more representative sample of documents.

Coverage and correlation for additional data sets: In addition to the *Controlled* data set of Section 5, we evaluated content summary generation over the same three databases used by Callan et al. in [CC01]. Specifically, we computed the *SRCC* and *ctf* metrics for the CACM, WSJ88, and TREC123 databases [CC01]. CACM is a collection of titles and abstracts of 3,204 articles published in the *Communications of ACM*. WSJ88

Database	*Category*	*RS-Lrd*	*RS-Ord*	*FP-SVM*	*FP-RIPPER*	*FP-C4.5*	*FP-Bayes*
CACM	Computers	0.79	0.80	0.85	0.87	0.85	0.89
WSJ88	Root	0.85	0.88	0.88	0.89	0.89	0.90
TREC123	Root	0.80	0.80	0.79	0.82	0.82	0.83

Table 4: The *ctf* metric for the three databases in [CC01], for different content summary extraction algorithms ($\tau_s = 0.25$ for the FP-* algorithms).



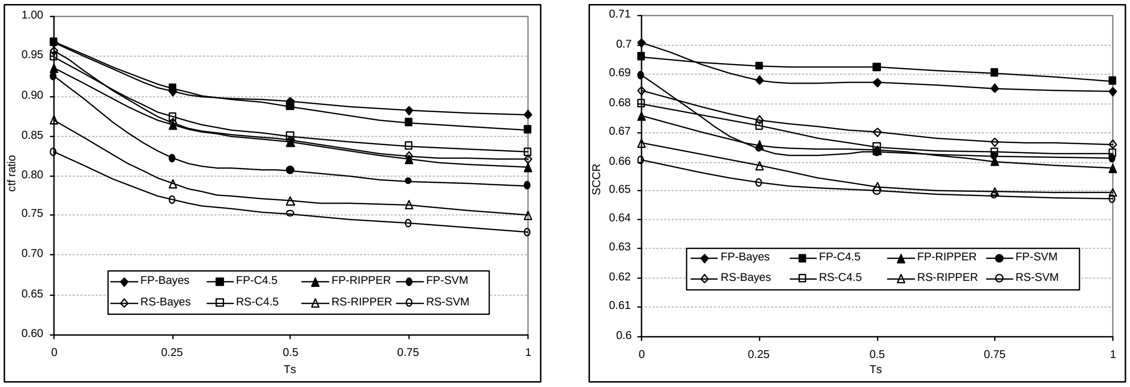
(a) The average relative error for the *ActualDF* estimations for words with *ActualDF*> 3.

(b) The average number of interactions per database.

Figure 8: Comparison of different methods for different values of the specificity threshold τ_s.

is a collection of 39,904 newspaper articles published in 1988 by the *Wall Street Journal*. TREC123 is a collection of 1,078,166 articles from the TREC CDs 1, 2, and 3. CACM is a topically focused collection while WSJ88 and TREC are not. The results are summarized in Tables 3 and 4. As expected, the focused probing algorithms work best for the CACM database, which is a topically focused collection, classified under *Computers* by our algorithm. For the other two databases, WSJ88 and TREC123, the uniform and focused probing techniques perform similarly. Our technique correctly classifies these two topically heterogeneous databases under the top *Root* category of the classification scheme, hence the relative benefit of focused probing is not realized.

Accuracy of frequency estimations: In Section 3.2 we introduced a technique to estimate the actual absolute frequencies of the words in a database. To evaluate the accuracy of our predictions, we report the average relative error for words with actual frequencies greater than three. (Including the large tail of less-frequent words would highly distort the relative-error computation.) Figure 8(a) reports the average relative error estimates for our algorithms. We also applied our absolute frequency estimation algorithm of Section 3.2 to *RS-Ord* and *RS-Lrd*, even though this estimation is not part of the original algorithms



(a) **(b)**

Figure 9: The *ctf ratio* **(a)**, the *Spearman Rank Correlation Coefficient* **(b)**, and the average number of interactions per database for *FP* and *RS* methods when they retrieve the same number of documents.

in [CC01]. As a general conclusion, our technique provides a good ballpark estimate of the absolute frequency of the words.

Efficiency: To measure the efficiency of the probing methods, we report the sum of the number of queries sent to a database and the number of documents retrieved ("number of interactions") in Figure 8(b). The *Focused Probing* techniques on average retrieve one document per query sent, while *RS-Lrd* retrieves about one document per two queries. *RS-Ord* unnecessarily issues many queries that produce no document matches. The efficiency of the other techniques is correlated with their effectiveness. The more expensive techniques tend to give better results. The exception is *FP-SVM*, which for $\tau_s > 0$ has the lowest cost (or cost close to the lowest one) and gives results of comparable quality with respect to the more expensive methods. The *Focused Probing* probes were generally short, with a maximum of four words and a median of one word per query.

Coverage, correlation and efficiency for identical sample size: We have seen that the *Focused Probing* algorithms achieve better *ctf* ratio and *SRCC* values than the *RS-Lrd* and *RS-Ord* algorithms. However, the *Focused Probing* algorithms generally retrieve a (moderately) larger number of documents than *RS-Ord* and *RS-Lrd* do. To test whether the improved performance of *Focused Probing* is just a result of the larger sample size, we increased the sample size for *RS-Lrd* to retrieve the same number of documents as each *Focused Probing* variant (We pick *RS-Lrd* over *RS-Ord* because *RS-Ord* requires a much larger number of queries to extract its document sample: most of its queries return no results (see Figure 8(b)), making it the most expensive method.) Then, we measured the *ctf* ratio and *SRCC* for the alternative versions of *RS-Lrd* (i.e., one per *Focused Probing* variant); we refer to the versions of *RS-Lrd* that retrieve the same number of documents as *FP-Bayes*, *FP-C4.5*, *FP-RIPPER*, and *FP-SVM* as *RS-Bayes*, *RS-C4.5*, *RS-RIPPER*,

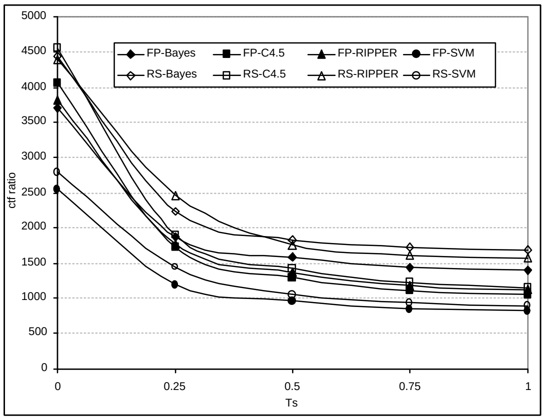


Figure 10: The average number of interactions per database for *FP* and *RS* methods when they retrieve the same number of documents.

and *RS-SVM*, respectively. The *ctf* ratio and the *SRCC* values for the alternative versions of *RS-Lrd* are listed in Figure 9(a) and (b), respectively. We observe that the achieved *ctf* ratio and *SRCC* values of the *RS* methods improve with the larger document sample, but are still lower than the values for the corresponding *Focused Probing* methods. Also, the average number of queries sent to each database is larger for the *RS* methods compared to the respective *Focused Probing* variant. The sum of the number of queries sent to a database and the number of documents retrieved ("number of interactions") is shown Figure 10.

Overall, the *Focused Probing* techniques produce significantly better-quality summaries than *RS-Ord* and *RS-Lrd* do, both in terms of vocabulary coverage and word-ranking preservation. The cost of *Focused Probing* in terms of number of interactions with the databases is comparable to or less than that for *RS-Lrd*, and significantly less than that for *RS-Ord*. Finally, the absolute frequency estimation technique of Section 3.2 gives good ballpark approximations of the actual frequencies.

6.2 Database Selection Effectiveness

The *Controlled* set allowed us to carefully evaluate the quality of the content summaries that we extract. We now turn to the *Web* set of real web-accessible databases to evaluate how the quality of the content summaries affects the database selection task. Additionally, we evaluate how the hierarchical database selection algorithm of Section 4.2 improves the selection task.

Evaluation metrics: We used the queries 451-500 from the Web Track of TREC-9 [Haw01]. TREC is a conference for the large-scale evaluation of text retrieval methodologies. In particular, the Web Track evaluates methods for retrieval of web content. TREC provides both web pages and queries as part of its Web Track. We use the queries for our database selection experiments over the Web database set described in Section 5.1. (We

Content Summary	*CORI*		*bGlOSS*	
Generation Technique	*Hier.*	*Flat*	*Hier.*	*Flat*
FP-SVM-Docs	0.27	0.17	0.163	0.085
FP-SVM-Snippets	0.2	0.183	0.093	0.090
RS-Ord	-	0.177	-	0.085
QPilot	-	0.052	-	0.008

Table 5: The average precision of different database selection algorithms for topics 451-500 of TREC.

ignored the "flat" set of TREC web pages since we are interested in evaluating algorithms for choosing *databases*, not individual pages or documents.)

Our evaluation proceeded as follows for each of the 50 TREC queries. Each database selection algorithm (Section 5.2) picked three databases for the query. We then retrieved the top-5 documents for the query from each selected database. This procedure resulted in (at most) 15 documents for the query for each algorithm. The *relevance* [SM83] of these 15 documents is what ultimately reveals the quality of each algorithm. We asked human evaluators to judge the relevance of each retrieved document for the query following the guidelines given by TREC for each query. Then, the precision of a technique for each query q is:

$$P_q = \frac{|relevant\ documents\ in\ the\ answer|}{|total\ number\ of\ documents\ in\ the\ answer|}$$

We report the average precision achieved by each database selection algorithm over the 50 TREC WebTrack queries in Table 5, ignoring queries with no results. In particular, we ignored 15 queries for which *all* database selection algorithms either selected only databases that return zero documents or failed to select any database giving to all databases a zero score.

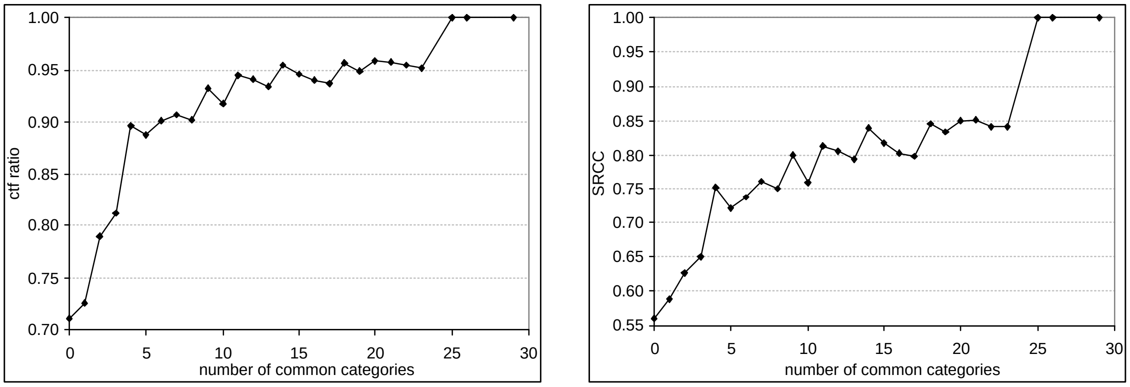
Our database selection algorithm of Section 4.2 chooses databases hierarchically. We evaluate the performance of the algorithm using content summaries extracted from *FP-SVM* probing (Section 5.2) with specificity threshold $\tau_s = 0.25$: *FP-SVM* exhibits the best accuracy-efficiency tradeoff (Section 6.1) while $\tau_s = 0.25$ leads to good database classification decisions for web databases [IGS01a]. We compare two versions of the algorithm, one using CORI [CLC95] as the underlying flat database selection strategy, and another using bGlOSS [GGMT99]. Note that *QPilot*, *RS-Ord*, and *RS-Lrd* do not classify databases while building content summaries, hence we did not evaluate our hierarchical database selection algorithm over their content summaries. Table 5 shows the average precision of the hierarchical algorithms against that of flat database selection algorithms over the same content summaries[9]. We discuss these results next:

[9] Although the reported precision numbers for the *distributed* search algorithms seem low, we note that the best precision score achieved in the TREC-9 WebTrack was 0.358 [Haw01], with the use of *centralized* search algorithms. A *distributed* search algorithm has lower performance given the lack of immediate access to the documents.

Effect of different content summaries: To analyze the effect of content summary construction algorithms on database selection, we tested how the quality of content summaries generated by *RS-Ord*, *Focused Probing*, and *QPilot* affects the database selection process. We picked *RS-Ord* over *RS-Lrd* because of its superior performance in the evaluation of Section 6.1. Also, rather than using the *SampleDF*$(\cdot)$ frequencies returned by *RS-Ord*, we applied our technique of Section 3.2 for *ActualDF* estimation to the *RS-Ord* summaries hence addressing a potential limitation of the original *RS-Ord* algorithm. In Table 5 we can see that, surprisingly, the performance of the flat selection algorithms that use *FP-SVM-Docs* and *RS-Ord* summaries did not reflect the gap in quality of the corresponding content summaries (Section 6.1). All the flat selection techniques suffer from the incomplete coverage of the underlying probing-generated summaries. A clear conclusion is that *QPilot* summaries do not work well for database selection because they generally contain only a few words and are hence highly incomplete.

Hierarchical vs. flat database selection: For both types of evaluation the hierarchical versions of the database selection algorithms gave better results than their flat counterparts. The *hierarchical* algorithm using CORI as flat database selection has 50% better precision than CORI for flat selection with the same content summaries. For bGlOSS, the improvement in precision is even more dramatic at 92%. The reason for the improvement is that the topic hierarchy helps compensate for incomplete content summaries. For example, in Figure 4 a query on *[metastasis]* would not be routed to the *CANCERLIT* database by a database selection algorithm like bGlOSS because “metastasis” is not in the *CANCERLIT* content summary. In contrast, our hierarchical algorithm exploits the fact that “metastasis” appears in the summary for *CancerBACUP*, which is in the same category as *CANCERLIT*, to allow *CANCERLIT* to be selected when the *“Cancer”* category is selected (the $ActualDF_{est}(metastasis)$ frequency from *CancerBACUP* propagates to the content summary of the *“Cancer”* category). To quantify how frequent this phenomenon is, we measured the fraction of times that our hierarchical database selection algorithm picked a database for a query that both produced matches for the query and was given a zero score by the flat database selection algorithm of choice. Interestingly, this was the case for 34% of the databases picked by the hierarchical algorithm with bGlOSS and for 23% of the databases picked by the hierarchical algorithm with CORI. These numbers support our hypothesis that hierarchical database selection compensates for content-summary incompleteness.

Snippet vs. Full Document Retrieval: The algorithms that we have described assume retrieval of full documents during probing to build content summaries. An interesting alternative is to exploit the *anchor text* and *snippets* that often accompany each link to a document in a query result. These snippets are short summaries of the documents that are often query-specific. Using snippets, rather than full documents, yields more efficient content summary construction, at the expense of less complete content summaries. We measured the impact of using just the snippets rather than full documents during content summary construction. We tested database selection over *FP-SVM* content summaries generated from full documents (*FP-SVM-Docs*), and from just snippets (*FP-SVM-Snippets*)



(a) **(b)**

Figure 11: The *ctf ratio* **(a)** and the *Spearman Rank Correlation Coefficient* **(b)** for pairs of database content summaries, as a function of the number of common categories in the corresponding database pairs.

for the *Web* set. Interestingly, the performance of *flat* database selection algorithms for *FP-SVM-Docs* and *FP-SVM-Snippets* was very similar (less than 0.01 difference in precision). An explanation for this is that snippets tend to contain highly-descriptive document portions (e.g., title and sentences that are relevant to the query). Hence, by retrieving only these parts it might be possible to create content summaries that are at least as good as their flat counterparts. In contrast, the performance of hierarchical database selection algorithms did suffer when we use the (less complete) summaries that result from only inspecting snippets. In the hierarchical case the precision of the *FP-SVM-Snippets* was 0.18 with the flat database selection algorithm and it improved only to 0.20 in the hierarchical version of the algorithm. On the other hand, for the *FP-SVM-Doc* algorithm we saw in Table 5 that the improvement in precision was much larger for the hierarchical database selection algorithm, with an increase from 0.18 to 0.27.

6.3 Content Summaries and Categories

A key conjecture behind our hierarchical database selection algorithm of Section 4.2 is that databases under the same category tend to have closely related content summaries. Thus, we can use the content summary of a database to complement the (incomplete) content summary of another database in the same category (Section 4.1). We now analyze this conjecture experimentally over the *Controlled* data set. For each pair of databases in the *Controlled* set, classified using $\tau_s = 0.25$, we measured:

- The number of common categories *numCategories*.
- The *ctf* and *SRCC* metrics of their *correct* content summaries.

Figure 11 reports the average *ctf* and *SRCC* metrics over all pair of databases in the *Controlled* set, discriminated by *numCategories*. The figure shows that the larger the number of common categories between a pair of databases, the more similar their corresponding content summaries tend to be according to *ctf* and *SRCC*. This conclusion supports the conjecture behind our hierarchical database selection of Section 4.2.

7 Related Work

A large body of work has been devoted to the task of database selection. Many database selection algorithms [GGMT99, MLY$^+$98, XC98, YL97, CLC95, Fuh99] rely on content summaries of the databases for this task. Some algorithms rely on hierarchical schemes [DAA99, She95, GGMT99] to direct the queries to the appropriate nodes of the hierarchy. Some approaches rely either on access to all documents or on metadata directly exported by the databases. Unfortunately, web-accessible databases rarely export such metadata. Recently, Etzioni and Sugiura [SE00] proposed the *QPilot* technique, which uses query expansion to route queries to the appropriate search engines (Section 5.2). Callan et al. [CC01, CCD99] suggested using query probes to extract document samples from databases for content summary construction. Craswell et al. [CBH00] compared the performance of flat database selection algorithms in the presence of such content summaries.

Hawking and Thistlewaite [HT99] used query probing at query time to perform database selection by ranking databases by similarity to a given query. Their algorithm relies on non-standard query interfaces that can handle normal queries and query probes differently, with smaller cost for query probes than for normal queries.

In [IGS01a] Ipeirotis et al. used focused query probing to automatically classify a database in a hierarchical taxonomy (see [IGS01a] for more references on database classification). We have built on the results in [IGS01a] to create an effective algorithm for content summary extraction that classifies databases while extracting document samples. This classification is used in the hierarchical database selection algorithm that we proposed in Section 4.

8 Conclusions and Future Work

In this paper we presented a novel and efficient method for the construction of content summaries of web-accessible text databases. Our algorithm creates content summaries of higher quality than current approaches and, additionally, categorizes databases in a classification scheme. We also presented a hierarchical database selection algorithm that exploits the database content summaries and the generated classification to produce accurate results even for imperfect content summaries. Experimental results showed that our techniques improve the state of the art in content-summary construction and database selection. Finally, we have implemented the content-summary construction algorithm described in this paper as part of the SDARTS toolkit for metasearching [GIG01]. The code with our implementation, plus some real content summaries extracted from real web databases are available from http://sdarts.cs.columbia.edu.

In Section 4 we used a "specificity-based" approach to locate the most topically-specific databases for a query. As future work, we will study alternative hierarchy traversing techniques. For example, an algorithm could treat databases and categories symmetrically and perhaps "route" queries to multiple categories if appropriate. In contrast, the algorithm in Figure 5 performs a depth-first search to find the most appropriate category for a query and then picks appropriate databases. We also plan to examine the effect of absolute frequency estimation (Section 3) on database selection. As discussed, absolute frequencies are helpful to distinguish, for example, between small and large databases on related topics (e.g., the word "cancer" appears in 1,416,852 documents in PubMed and in 1,291 documents in U. of Michigan Cancer Center). In the future, we will experimentally quantify the actual benefit of using absolute document frequency estimates for both flat and hierarchical database selection. Finally, we plan to examine alternative methods for creating content summaries. In particular, we will explore *smoothing* [Jel99] techniques to combine the content summaries of all databases under a category into the summary for the category itself.

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References

[BLHL01] Tim Berners-Lee, James Hendler, and Ora Lassila. The semantic web. *Scientific American*, 284(5):34–43, May 2001.

[Bri00] BrightPlanet.com LLC. The Deep Web: Surfacing hidden value. Available at http://www.completeplanet.com/Tutorials/DeepWeb/index.asp, July 2000.

[CBH00] Nick Craswell, Peter Bailey, and David Hawking. Server selection on the World Wide Web. In *Proceedings of the Fifth ACM Conference on Digital Libraries (DL 2000)*, pages 37–46, 2000.

[CC01] Jamie Callan and Margaret Connell. Query-based sampling of text databases. *ACM Transactions on Information Systems*, 19(2):97–130, 2001.

[CCD99] James P. Callan, Margaret Connell, and Aiqun Du. Automatic discovery of language models for text databases. In *Proceedings of the 1999 ACM SIGMOD International Conference on Management of Data (SIGMOD'99)*, pages 479–490, 1999.

[CLC95] James P. Callan, Zhihong Lu, and W.Bruce Croft. Searching distributed collections with inference networks. In *Proceedings of the 18th Annual International ACM SIGIR Conference on Research and Development in Information Retrieval, SIGIR'95*, pages 21–28, 1995.

[Coh96] William W. Cohen. Learning trees and rules with set-valued features. In *Proceedings of the 13th National Conference on Artificial Intelligence (AAAI-96) Eighth Conference on Innovative Applications of Artificial Intelligence (IAAI-96)*, pages 709–716, 1996.

[DAA99] Ron Dolin, Divyakant Agrawal, and Amr El Abbadi. Scalable collection summarization and selection. In *Proceedings of the Fourth ACM International Conference on Digital Libraries (DL'99)*, pages 49–58, 1999.

[DH73] Richard O. Duda and Peter E. Hart. *Pattern Classification and Scene Analysis*. Wiley, 1973.

[FPC$^+$99] James C. French, Allison L. Powell, James P. Callan, Charles L. Viles, Travis Emmitt, Kevin J. Prey, and Yun Mou. Comparing the performance of database selection algorithms. In *Proceedings of the 22nd Annual International ACM SIGIR Conference on Research and Development in Information Retrieval, SIGIR'99*, pages 238–245, 1999.

[Fuh99] Norbert Fuhr. A decision-theoretic approach to database selection in networked IR. *ACM Transactions on Information Systems*, 17(3):229–249, May 1999.

[GCGMP97] Luis Gravano, Chen-Chuan K. Chang, Héctor García-Molina, and Andreas Paepcke. *STARTS*: Stanford proposal for Internet meta-searching. In *Proceedings of the 1997 ACM SIGMOD International Conference on Management of Data (SIGMOD'97)*, pages 207–218, 1997.

[GGMT99] Luis Gravano, Héctor García-Molina, and Anthony Tomasic. *GlOSS*: Text-source discovery over the Internet. *ACM Transactions on Database Systems*, 24(2):229–264, June 1999.

[GIG01] Noah Green, Panagiotis G. Ipeirotis, and Luis Gravano. SDLIP + STARTS = SDARTS: A protocol and toolkit for metasearching. In *Proceedings of the First ACM+IEEE Joint Conference on Digital Libraries (JCDL 2001)*, pages 207–214, 2001.

[Haw01] David Hawking. Overview of the TREC-9 Web track. In *NIST Special Publication 500-249: The Ninth Text REtrieval Conference (TREC 9)*, page 87, 2001.

[HT99] David Hawking and Paul B. Thistlewaite. Methods for information server selection. *ACM Transactions on Information Systems*, 17(1):40–76, January 1999.

[IGS01a] Panagiotis G. Ipeirotis, Luis Gravano, and Mehran Sahami. Probe, count, and classify: Categorizing hidden-web databases. In *Proceedings of the 2001 ACM SIGMOD International Conference on Management of Data (SIGMOD 2001)*, pages 67–78, 2001.

[IGS01b] Panagiotis G. Ipeirotis, Luis Gravano, and Mehran Sahami. Qprober: A system for automatic classification of hidden-web resources. Technical Report CUCS-010-01, Columbia University, Computer Science Department, 2001.

[Jel99] Frederick Jelinek. *Statistical Methods for Speech Recognition.* The MIT Press, 1999.

[Joa98] Thorsten Joachims. Text categorization with support vector machines: Learning with many relevant features. In *ECML-98, 10th European Conference on Machine Learning*, pages 137–142, 1998.

[LCC00] Leah S. Larkey, Margaret E. Connell, and Jamie Callan. Collection selection and results merging with topically organized U.S. patents and TREC data. In *Proceedings of the 2000 ACM CIKM International Conference on Information and Knowledge Management*, pages 282–289, 2000.

[Man88] Benoit B. Mandelbrot. *Fractal Geometry of Nature.* W. H. Freeman & Co., 1988.

[MLY$^+$98] Weiyi Meng, King-Lup Liu, Clement T. Yu, Xiaodong Wang, Yuhsi Chang, and Naphtali Rishe. Determining text databases to search in the Internet. In *Proceedings of the 24th International Conference on Very Large Databases (VLDB'98)*, pages 14–25, 1998.

[PFC$^+$00] Allison L. Powell, James C. French, James P. Callan, Margaret Connell, and Charles L. Viles. The impact of database selection on distributed searching. In *Proceedings of the 23rd Annual International ACM SIGIR Conference on Research and Development in Information Retrieval, SIGIR 2000*, pages 232–239, 2000.

[Qui92] J.Ross Quinlan. *C4.5: Programs for Machine Learning.* Morgan Kaufmann Publishers, Inc., 1992.

[SB88] Gerard Salton and Christopher Buckley. Term-weighting approaches in automatic text retrieval. *Information Processing and Management*, 24:513–523, 1988.

[SE00] Atsushi Sugiura and Oren Etzioni. Query routing for web search engines: Architecture and experiments. In *Proceedings of the Ninth International World Wide Web Conference (WWW9)*, 2000.

[She95] Mark A. Sheldon. *Content Routing: A Scalable Architecture for Network-Based Information Discovery.* PhD thesis, M.I.T., 1995.

[SM83] Gerard Salton and Michael J. McGill. *Introduction to modern information retrieval.* McGraw-Hill, 1983.

[SM97] Gerard Salton and Michael J. McGill. The SMART and SIRE experimental retrieval systems. In *Readings in Information Retrieval*, pages 381–399. Morgan Kaufmann, 1997.

[XC98] Jinxi Xu and James P. Callan. Effective retrieval with distributed collections. In *Proceedings of the 21st Annual International ACM SIGIR Conference on Research and Development in Information Retrieval, SIGIR'98*, pages 112–120, 1998.

[XC99] Jinxi Xu and W.Bruce Croft. Cluster-based language models for distributed retrieval. In *Proceedings of the 22nd Annual International ACM SIGIR Conference on Research and Development in Information Retrieval, SIGIR'99*, pages 254–261, 1999.

[YL97] Budi Yuwono and Dik Lun Lee. Server ranking for distributed text retrieval systems on the internet. In *Fifth International Conference on Database Systems for Advanced Applications (DASFAA'97)*, pages 41–50, 1997.

[Zip49] George K. Zipf. *Human Behavior and the Principle of Least Effort.* Addison-Wesley, 1949.