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Learning to rank documents with support vector machines via active learning

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University of Iowa

LEARNING TO RANK DOCUMENTS WITH SUPPORT VECTOR MACHINES VIA ACTIVE LEARNING

by

Robert James Arens

An Abstract

Of a thesis submitted in partial fulfillment of the
requirements for the Doctor of Philosophy
degree in Computer Science in the
Graduate College of The
University of Iowa

December 2009

Thesis Supervisor: Professor Alberto Segre

ABSTRACT

Navigating through the debris of the information explosion requires powerful, flexible search tools. These tools must be both useful and useable; that is, they must do their jobs effectively without placing too many burdens on the user. While general interest search engines, such as Google, have addressed this latter challenge well, more topic-specific search engines, such as PubMed, have not. These search engines, though effective, often require training in their use, as well as in-depth knowledge of the domain over which they operate. Furthermore, search results are often returned in an order irrespective of users' preferences, forcing them to manually search through search results in order to find the documents they find most useful.

To solve these problems, we intend to learn ranking functions from user relevance preferences. Applying these ranking functions to search results allows us to improve search usability without having to reengineer existing, effective search engines. Using ranking SVMs and active learning techniques, we can effectively learn what is relevant to a user from relatively small amounts of preference data, and apply these learned models as ranking functions. This gives users the convenience of seeing relevance-ordered search results, which are tailored to their preferences as opposed to using a one-size-fits-all sorting method. As giving preference feedback does not require in-depth domain knowledge, this approach is suitable for use by domain experts as well as neophytes. Furthermore, giving preference feedback does not require a great deal of training, adding very little overhead to the search process.

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Iowa City, Iowa

CERTIFICATE OF APPROVAL

PH.D. THESIS

This is to certify that the Ph.D. thesis of

Robert James Arens

has been approved by the Examining Committee for the thesis requirement for the Doctor of Philosophy degree in Computer Science at the December 2009 graduation.

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Alberto Segre, Thesis Supervisor

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Nick Street

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Juan Pablo Hourcade

To my family

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INTRODUCTION

1.1 Overview

Navigating through the debris of the information explosion requires powerful, flexible search tools. These tools must be both useful and useable; that is, they must do their jobs effectively without placing too many burdens on the user. While general interest search engines, such as Google, have addressed this latter challenge well, more topic-specific search engines, such as PubMed, have not. These search engines, though effective, often require training in their use, as well as in-depth knowledge of the domain over which they operate. Furthermore, search results are often returned in an order irrespective of users' preferences, forcing them to manually search through search results in order to find the documents they find most useful.

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1.2 Motivation: Searching MEDLINE with PubMed

MEDLINE search via PubMed serves as an illustrative microcosm of the challenges we seek to address. While work presented in this thesis does not focus solely on this search domain, it is used in our simulation framework simulation and as a sample application for our user study. The importance of improving the search experience for this system is evidenced not only by its ubiquity, but also by the amount of academic work seeking to improve it.

1.2.1 MEDLINE and PubMed

MEDLINE is the National Library of Medicine's bibliographic database. It contains over 18 million citations from over 5,000 publications [39], and can be searched online using the PubMed search engine. The use of this resource is ubiquitous throughout the biomedical community and beyond, by researchers, clinicians, and amateurs interested in the field.

The PubMed search engine is quite robust, implementing a number of features to improve coverage and automatically improve user queries. Chief among these refinements is the use of Medical Subject Heading (MeSH) hierarchy metadata terms. Citations in MEDLINE are tagged with one or more MeSH terms, describing the content of the article as well as its structure (e.g., drug study, clinical trial, cohort study, etc.) and country of origin. These terms are arranged hierarchically, with specific topics organized under more general topics (e.g., "Head" is under "Body Regions", which is under "Anatomy"). Users can employ MeSH terms in their queries, terms in the query will be expanded with relevant MeSH terms (e.g., “flu” expanded to include “influenza, human”, etc.), and any matching acronyms will be expanded as well (e.g., “IL-1” expands to “interleukin-1”).

While PubMed search is quite powerful, sifting through the search results can be quite inconvenient. No relevance-based sorting of results is implemented; users can sort results alphabetically by first author, last author, citation title, journal, or by publication date. The sheer size of the MEDLINE database often makes manually searching through results unfeasible; a search for “liver cancer”, for example, returns over 130,000 results. This leads to a “search boomerang”, where users alter their search queries with more specific criteria (resulting in too few results), then relaxing their criteria (resulting in too many), repeating until a reasonably sized result set is obtained.

This behavior is far from hypothetical, or limited to domain novices. Bronander et al. [8] showed that the expertise of fourth-year medical students was not sufficient to identify optimal MEDLINE search queries, and furthermore, even practicing physicians “demonstrated deficiencies” in their search skills. The only source of improvement they found was practice; education and computer literacy appeared to have no influence on search performance.

Clearly, this is undesirable behavior. Suboptimal search queries which lead to “boomerang” searches waste time, resulting in frustration and lost productivity. However, the searcher is not to blame for this problem if neither domain knowledge nor instruction can improve the efficiency of search. Improvements must be made to the tool itself.

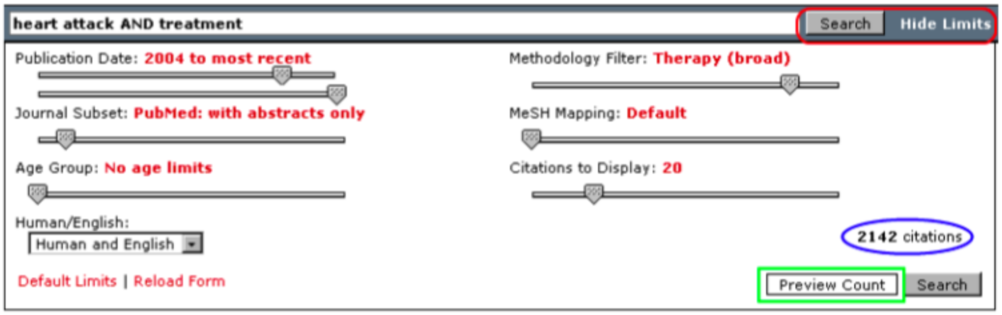
1.2.1.1 Improvements to PubMed/MEDLINE

Here we present a selection of work aimed at improving the search experience for users of MEDLINE and PubMed. This is by no means a comprehensive survey of the available literature, but a representative view of different approaches illustrating the breadth of the improvement problem. This section is split into two general areas of research; improvements to the search faculty itself, and improvements to the presentation of search results.

Improvements to Search

While PubMed offers users a powerful search system, learning that system can be an impediment to its use. Lewis et al. [33] sought to obviate this issue by implementing a "free-text" query system, which took as its input a paragraph of prose text regarding the subject to be searched, and returned documents similar to that input paragraph. A number of methods for computing similarity were tested, each producing a score based on comparing individual words from the input paragraph to words in the target documents. In a similar vein, Goetz and von der Lieth [22] used a pool of representative documents to generate search results by mining that pool for a set of words occurring significantly more often in the pool than MEDLINE documents in general. Other documents were scanned and scored for their relevance to the set of discriminating words.

These search methods provide a number of improvements over PubMed search. Both systems remove the need for a user to learn the complicated PubMed search system. Furthermore, search results can be presented in order of relevance to the user's query since a similarity score is computed. These improvements come at the cost of not taking advantage of PubMed's features, which is quite a high price to



heart attack AND treatment

Publication Date: 2004 to most recent

Methodology Filter: Therapy (broad)

Journal Subset: PubMed: with abstracts only

MeSH Mapping: Default

Age Group: No age limits

Citations to Display: 20

Human/English: Human and English

2142 citations

Figure 1
PubMed Interact search form with search terms and slider settings. Red rounded rectangle: Text link to hide slider limits beside the search button. Blue ellipse: Preview of the number of citations. Green box: Preview count button

Figure 1.1: Picture of slider interface from [36]

pay when taking into account such problems as synonym resolution. An input text referring to a signaling molecule named interleukin-1 using a common shorthand, “IL-1”, will not generate a higher similarity score when compared to a target text using the longer name. Such occurrences are common in biomedical literature [46]. These approaches also assume its users possess a fairly high level of domain knowledge, enough at least to produce a paragraph on their search subject or identify some group of exemplar documents. While one can assume that the average MEDLINE searcher is a professional in the biomedical field, it will be the case that some searchers are entering a new field of research, and will be unable to perform these tasks.

Muin and Fontelo [36] addressed the problem by introducing a user interface that would allow users to interact with PubMed on a more intuitive level. “Slider” bars, representing various search options and MeSH terms, are used to construct the query without requiring the user to manually enter them. The settings shown in figure 1.1, for example, correspond to the query in Figure 1.2. Again, this system presents a superior user experience to PubMed. Unlike previous systems [33, 22],

```
heart attack AND treatment AND ("2004"[PDAT]:"3000"[PDAT])
AND hasabstract AND (clinical trials[MeSH Terms] OR clinical
trial[Publication Type] OR random*[Title/Abstract] OR random
allocation[MeSH Terms] OR therapeutic use[MeSH Subheading]) AND
"humans"[MeSH Terms] AND English[Lang]
```

Figure 1.2: PubMed query produced by the settings in Figure 1.1, from the system described in [36]

the full power of PubMed's search features are leveraged. Users are not required to learn the MeSH terms that will allow them to search for differing age groups or methodology types, and restricting results by date is quite intuitive. However, users are presented with only a very narrow subset of the MeSH terms available for search. Terms dealing with specific diseases, parts of the body, etc. are not presented to the user. Furthermore, those terms that are presented are specifically targeted towards papers dealing with human subjects. While this is certainly an important avenue of research, the system is shutting out the not inconsequential number of biomedical professionals conducting other types of research. As such, its utility is limited.

Improvements to Results Presentation

Rather than attempting to improve PubMed at the retrieval stage, much work has focused on improving the presentation of PubMed search results. This allows researchers to leverage the power of PubMed's retrieval refinements, allows seasoned users to continue using search methods they're already familiar with, and helps mitigate the “boomerang” problem for both new and experienced users - since the most relevant results are (theoretically) easily accessible, large retrieval sets are not a problem.

Herskovic and Bernstam [27] used the PageRank algorithm [40] to rank results by the number of citations to each result document, as well as the importance of those citations, giving a ranking based on popularity and perceived authority of the documents. Expanding on this idea, Plikus et al. [41] produced a suite of analytic tools including a ranking scheme which used a statistical combination of the impact factor of the journal in which the document was published, and the number of forward citations to the document. This ranking scheme ensures that "important" documents, those cited heavily and published in highly-regarded journals, will be ranked above lesser-known works published in lower-impact journals. Lin et al. [34] departed from the traditional ranking framework by first clustering similar documents together, and then ranking documents in each cluster using citation data. These clusters give users a more intuitive overview of their results than a single ranked list can provide.

Each of these systems relies on citation-based ranking. While many searchers will appreciate such a scheme, others may not; if a user's information need can be best satisfied by a less popular citation, that user will find such a ranking scheme frustrating, and perhaps no better than no ranking at all.

Similar to the work done by Goetz and von der Lieth [22], Suomela and Andrade [47] used a set of documents representing a certain area of interest to generate a set of significant keywords, which were then used to score result documents for relevance. Ranking in this way rewards documents similar to those used to generate the keyword set and penalizes those which deviate. These methods share similar drawbacks, in that they both require enough familiarity with the subject matter to compile a set of exemplar documents. This potential failing may be addressed by automatically generating the exemplar set; in Suomela and Andrade [47], the authors generated an exemplar set of 81,416 documents by retrieving all PubMed documents tagged with the MeSH term “stem cells”. While expedient, a ranking generated in this manner will be too general to be of use when a more specific query is presented. Furthermore, the authors show no evidence that their method works well with a much smaller exemplar set, perhaps a few dozen or hundred documents.

1.2.1.2 Core Criticisms, and a Way Forward

The body of work presented in the previous section can be roughly divided into two categories: systems which make assumptions of the users’ information needs, and systems which require users to produce an exemplar before using the system. The core issue with the former systems is that although those systems state the assumptions they are making, and provide explanations for why those assumptions are made, those systems will be of little to no use to users for whom those assumptions do not stand. The core issue with the latter systems is the burden placed on the users, both in terms of requisite domain knowledge and creation of the exemplar. A reasonable middle ground must be struck in this tradeoff between assumption and burden, providing users as much flexibility and freedom from assumption as possible while requiring as little input as can be managed.

We here propose to achieve this middle ground by using machine learning techniques to learn ranking functions from user feedback. This will be achieved by using four existing technologies: information retrieval, feedback collection, support vector machine (SVM) learning, and active learning. Information retrieval, in the form of the PubMed search engine, will conduct the retrieval of documents based on a user query. Feedback collection will allow us to collect information from the user regarding the user’s preference on retrieved documents. SVM learning will extrapolate a ranking function based on feedback collected, which will be used to rank retrieved documents. Finally, active learning will provide a methodology to minimize the amount of feedback needed to produce an accurate ranking function.

In Chapter 2, we present the foundations and work related to this thesis. Chapter 3 presents the data sets used in simulation experiments on the system, which is described in Chapter 4. The simulation experiments themselves are described in Chapters 5 and 6. In Chapter 7, we describe a preliminary user study designed to assess the viability of the proposed system in an online, ad-hoc search environment. We offer concluding remarks in Chapter 8, along with future directions for the work presented in this thesis.

CHAPTER 2
FOUNDATIONS AND RELATED WORK

2.1 Information Retrieval

Document retrieval is a subfield of information retrieval dealing with the retrieval of text documents which contain information relevant to a user's information needs from a larger collection of documents. Use of a document retrieval system is often an ad-hoc retrieval task; that is, users express their information needs as a query to a search interface operating over the collection of documents they wish to search. Results from this search are then presented to the user. Current document retrieval systems often return these results to users sorted by their relevance to users information needs, allowing users to quickly find the documents most relevant to their searches.

2.1.1 Basic Retrieval and Sorting of Documents

Ad-hoc retrieval of documents in a collection based on a user query can be done quite simply by finding documents which contain the same words contained in the query, and returning them in a batch to the user. However, this method fails to provide any measure of relevance these documents may have to the query in question. Without this notion of relevance, users will be forced to sift through these potentially large, unordered batches of documents to find the information they require.

In order to conduct relevance-based retrieval, some method of comparison between documents and queries must be employed. For this reason, documents and queries in retrieval systems are expressed as vectors of the terms comprising the collection over which the retrieval system operates. A document d_j and query q_k can be expressed as vectors

$$d_j = (t_{1,j}, t_{2,j}, t_{3,j}, \ldots, t_{N,j})$$

$$q_k = (t_{1,k}, t_{2,k}, t_{3,k}, \ldots, t_{N,k})$$

of t features representing the N terms in the document collection [32]. The simplest values these features can take on are binary values of one or zero, indicating the presence or absence of a term. In this case, retrieval can be carried out by summing the number of terms the document and query have in common with the following similarity function [32].

$$sim(d_j, q_k) = \sum_{i=1}^{N} t_{i,j} \times t_{i,k} \tag{2.1}$$

This similarity method, beyond simply finding documents relevant to the query, also computes a score telling us how similar a document is to a query. This score can be used to rank the documents in order of relevance, allowing the user to focus on highly ranked documents instead of manually sorting through all retrieved documents to find the ones most relevant to the user's information needs.

Though simple, this binary retrieval scheme fails to acknowledge that certain terms in a document may be more important than others. Weighting terms based on some notion of the importance of the terms in the document and the collection in general can greatly improve the effectiveness of the document retrieval system. In this case, vectors are expressed as weights [32]

$$d_j = (w_{1,j}, w_{2,j}, w_{3,j}, \ldots, w_{n,j})$$

$$q_k = (w_{1,k}, w_{2,k}, w_{3,k}, \ldots, w_{n,k})$$

where a weight w_i, j is the weight of term i in document j. This notation allows us to represent the document collection as a term-by-document matrix, where the columns of the matrix hold the documents and the rows hold the terms. Retrieval can be conducted by finding the distance in vector space between a query and a document via a vector dot product, yielding the following similarity function [32].

$$sim(d_j, q_k) = d_j \cdot q_k = \sum_{i=1}^{n} w_{i,j} \times w_{i,k} \tag{2.2}$$

2.1.2 Term Weighting

Term weighting refers to the process of assigning numerical significance to words in a document in order to reflect the relative importance of those words in reference to the rest of the document collection. Documents to be retrieved using this similarity measure must have their terms weighted carefully in order to ensure that retrieval is done correctly and efficiently. For example, terms could be weighted by simply counting the number of occurrences of a term in a document (called term frequency, or tf). More specifically, the tf of a term t_i in a document d_j can be calculated as [2, 32]

$$tf_{i,j} = \frac{c_{i,j}}{\sum_{k \in d_j} c_{k,j}} \tag{2.3}$$

where $c_{i,j}$ indicates the count of occurrences of the term in the document. Similarities computed from documents using this weighting scheme will be dominated by longer documents, which will have large term weights, and thus produce higher scores. These vectors can be converted into unit length vectors, or normalized, by dividing each weight in a vector by the overall length of the vector, which is $\sum_{i=1}^{N} w_i^2$ for each document.

An additional factor in term weighting has to do with the number of documents in which a term appears. A term appearing many times in a document may seem to be important in describing the content of that document, but if many documents in the collection also contain that term, then it cannot be considered to be a term which discriminates the document from the rest of the collection. The tf of a term can be scaled by this document frequency; since it is seen in the denominator of this calculation, it is referred to as inverse document frequency (idf). It can be obtained for a term t_i in a collection D containing documents d_j as follows [2, 32].

$$idf_i = \log \frac{|D|}{|d_j : t_i \in d_j|} \tag{2.4}$$

$tf{*}idf$ is a standard term weighting score for text retrieval systems. It provides an accurate method to determine a term's importance in a document relative to its importance in a collection.

2.1.3 Stemming

Document representation for retrieval hinges on properly identifying the words which make up the document's content. Often, it is useful to reduce inflected forms of words to their root form; for example, when trying to discover documents relating how much money a business makes, we might like to lump the words *earned*, and *earnings* together with their root *earn*. This process, called stemming, can greatly increase retrieval performance by ensuring that terms are correctly weighted in a document.

2.1.4 Relevance Feedback and Query Expansion

Performance of a document retrieval system can be improved by improving user queries. Relevance feedback alters a query based on the distribution of terms in documents relevant to the user's information need. More specifically, given a query q_i returning a set of documents d with subsets r and s (where $r \cup s = d$) corresponding to the relevant and non-relevant documents respectively, the query can be reformulated as [2, 32]

$$q_{i+1} = q_i + \frac{\beta}{|r|} \sum_{j=1}^{|r|} r_j - \frac{\gamma}{|s|} \sum_{k=1}^{|s|} s_k \tag{2.5}$$

where β and γ are scaling values between 0 and 1 where $\beta + \gamma = 1$. This new query is then given to the document retrieval system. Relevance feedback can be repeated on the new set of retrieved documents, or the set can be returned to the user.

Deciding which documents are relevant is a key element of relevance feedback. In explicit relevance feedback, a set of documents is shown to the user, and the user indicates which of these seem relevant [2]. In implicit relevance feedback, the system records the user's interaction with the system in order to determine relevance, e.g., by clicking on a link to a document, the system marks the document as relevant [31]. In pseudo-relevance feedback, the user's input is never requested; the system simply assumes that some number of the top documents retrieved by the system are relevant [2].

Another method of improving user queries is to expand them by adding terms relevant to terms already in the query, before performing any retrieval. Resources for expanding queries can include thesauri, taxonomies, and other controlled vocabulary schemes. A thesaurus is a collection of lists of terms highly correlated to one another, and is generally pre-computed by the document retrieval system [32]. It can be based on a taxonomy or concept network, on the collection itself, or a combination of these. Taxonomies arrange concepts in parent-child or super-subtype relationships, as well as listing terms related to those concepts and synonyms for those terms. They are generally created for a specific domain or text genre, though more general taxonomies do exist, e.g., WordNet, a collection of 155,000 words from English. Subject heading classification schemes, such as MeSH (see 1.2.1), can utilize taxonomic arrangements while retaining thesaurus-like properties.

2.1.5 Evaluation of Information Retrieval Systems

When evaluating an information retrieval system, one must keep the primary function of that system in mind; namely, to satisfy a user's information need by finding and providing pieces of information that fit that need. This must be done both in an attempt to provide the best information possible, and to minimize the time spent finding that information. Evaluation of this time component is appropriate for offline systems, as they have the luxury of spending minutes, hours, or even days before returning a result. Online, ad-hoc systems, on the other hand, must return results within the time of a web page loading to be useful; measuring the exact amount of time taken beyond this is unnecessary. Therefore, we will focus on measures for the effectiveness of the search.

2.1.5.1 Precision, Recall, and F-Score

Documents in a collection over which an information retrieval system operates can be divided along two axes: documents which are relevant to a users need or not, and documents which are retrieved by the users query or not [45]. Relevant documents which are retrieved are called true positives (tp), and those not retrieved are called false negatives (fn). Non-relevant documents which are retrieved are called false positives (fp), and those not retrieved are called true negatives (tn). One measure of the system's performance, called precision, is the ratio of relevant documents to total documents returned to the user. Another measure, recall, is the ratio of relevant documents returned to total relevant documents in the set. These measures are calculated as follows [45],

$$\text{Precision} = \frac{tp}{tp + fp} \tag{2.6}$$

$$\text{Recall} = \frac{tp}{tp + fn} \tag{2.7}$$

A high precision score indicates that the results returned to the user include a low proportion of non-relevant documents, while a high recall score indicates that the results include a large proportion of the available relevant documents.

Precision and recall usually exist in opposition to each other. By retrieving more documents, a system is more likely to retrieve more relevant documents, increasing its recall score; however, the results are likely to be diluted by non-relevant documents, decreasing its precision. Similarly, by retrieving fewer documents, a system is less likely to return non-relevant documents, increasing its precision at the cost of recall. Individual system designers and users must decide whether their needs are best met by systems focusing on one measure or the other, and tune those systems accordingly. If both measures are equally important, a measure of their harmonic mean can provide a single effectiveness number, called an F-score. F-score is a standard measure used in information retrieval, and is calculated as follows [32].

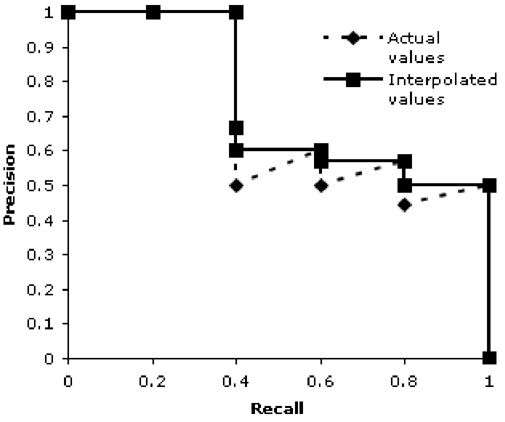
$$F = \frac{2 \times \text{precision} \times \text{recall}}{\text{precision} + \text{recall}} \tag{2.8}$$

2.1.5.2 Evaluating Ranked Lists

Precision and recall, as defined above, are calculated over the entire set of retrieved documents. However, most information recall systems return documents in sorted order. For a set of n retrieved documents, precision and recall numbers can be calculated at positions one through n, showing how each measure changes with respect to the other. The tradeoff between precision and recall can be shown

Doc. Position	Relevant?	Precision	Recall
1	Yes	1.000	0.200
2	Yes	1.000	0.400
3	No	0.667	0.400
4	No	0.500	0.400
5	Yes	0.600	0.600
6	No	0.500	0.600
7	Yes	0.571	0.800
8	No	0.500	0.800
9	No	0.444	0.800
10	Yes	0.500	1.000

(a)



(b)

Figure 2.1: Sample precision and recall curve

by plotting these values. Table 2.1a shows example precision and recall numbers for a system retrieving ten documents, five of which are relevant. Figure 2.1b shows the graph of precision vs. recall. In order to show the "best-case scenario" performance of the system, an interpolated graph is also shown, computed by interpolating a drop in precision as equal to the highest precision attained before the next drop [45].

If the position of all relevant documents in the list is known, a picture of the system's recall performance with respect to perfect recall can be constructed. Again, we use Table 2.1a as an example. In this case, the ideal retrieval scenario would be for the five relevant documents to be returned before all other documents. We can plot the difference between this ideal recall curve and the actual recall curve as in Figure 2.2. The difference between the ideal recall and actual recall is called normalized recall, and is calculated as [45]

$$\text{Recall}_{\text{norm}} = 1 - \frac{\sum_{i=1}^{j} r_i - \sum_{i=1}^{j} i}{j \times (n-j)} \tag{2.9}$$

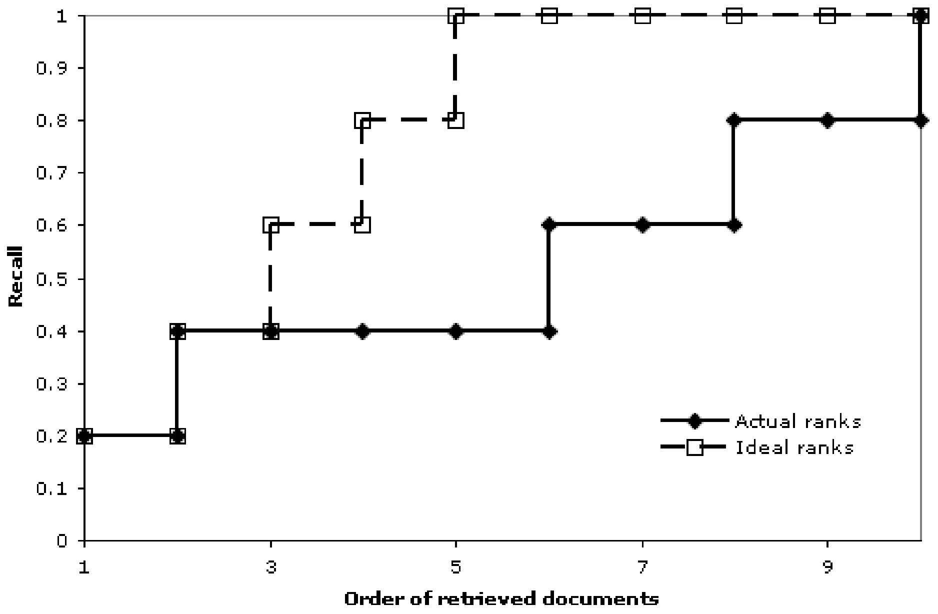


Figure 2.2: Normalized recall curve

for j relevant documents with document ranks r_i. The normalized recall for the example in Table 2.1a is 0.6.

2.1.5.3 Evaluation for Multiple Levels of Relevance

A core assumption of the above measures is that relevance is a binary judgement; a document is either relevant, or not relevant. These measures cannot incorporate notions of partial relevance, or relative preference between relevant documents. Furthermore, these measures require that the relevance of each document in the retrieved set be judged.

Normalized discounted cumulative gain (NDCG) [29] is an attractive alternative to precision and recall based measures. It is measure that can incorporate multiple levels of relevance, and can be calculated at any point in the order of retrieved documents. Discounted cumulative gain (DCG) at position i in a ranked list of documents is calculated as

$$\text{DCG@}i = \begin{cases} s_i & \text{if } i\text{=}1 \\ \text{DCG@}(i\text{-}1) + \frac{s_i}{\log_2 i} & \text{otherwise} \end{cases} \tag{2.10}$$

where s_i is the relevance score of the document at position i. For example, relevant documents could receive a score of 2, possibly relevant documents could receive a score of 1, and irrelevant documents could receive a score of 0. NDCG is calculated by dividing the DCG vector by an ideal DCG vector, DCG_I, calculated from an ideally ranked list (all documents scoring 2, followed by documents scoring 1, followed by documents scoring 0). Perfect ranking scores an NDCG of 1.0 at all positions.

2.2 Support Vector Machines

Support vector machines (SVMs) are a family of supervised machine learning methods. The main idea behind the SVM algorithm is to map input vectors into a feature space of higher dimension, construct a linear decision surface (hyperplane), and then optimize that hyperplane for generalization [6, 15]. SVMs are used for classification, regression, and ranking, and are used for related tasks such information retrieval and optical character recognition [31, 50]. In particular, the ranking SVM (Section 2.2.3) is a core component to the work presented in this thesis.

2.2.1 Linear SVMs

SVMs are also known as maximal margin classifiers, as they seek to optimize the bounds of generalization error by maximizing the margin of the hyperplane separating the data. For a linearly separable set of examples $S = ((\mathbf{x_1}, y_1), \ldots, (\mathbf{x_\ell}, y_\ell))$

consisting of data points $\{\mathbf{x_i} = (x_1, x_2, \ldots, x_\ell)' \mid \mathbf{x_i} \in X, X \subseteq \mathbb{R}^n\}$ and associated class labels $y_i = -1$ or 1, the optimal hyperplane separating the examples can be expressed as

$$f(\mathbf{x}, \boldsymbol{\alpha}^*, b^*) = \sum_{i=1}^{\ell} y_i \alpha_i^* \langle \mathbf{x_i} \cdot \mathbf{x} \rangle + b^* \tag{2.11}$$

where $\mathbf{x}$ is the point to be classified, $\boldsymbol{\alpha}^*$ is an optimized set of values α_i proportional to the number of times an example $\mathbf{x_i}$ was misclassified during training, and b^* is an optimized bias value [11]. When computing the weight vector defining this hyperplane, only the input points closest to the hyperplane are involved. These points are called *support vectors*, denoted SV. Hence, the hyperplane can be expressed as follows.

$$f(\mathbf{x}, \boldsymbol{\alpha}^*, b^*) = \sum_{i \in SV} y_i \alpha_i^* \langle \mathbf{x_i} \cdot \mathbf{x} \rangle + b^* \tag{2.12}$$

The parameter $\sum_{i \in SV} y_i \alpha_i^* \langle \mathbf{x_i} \rangle$ is often denoted simply as a weight vector $\mathbf{w}$, with the hyperplane denoted as $(\mathbf{w}, b^*)$ [11]. Optimization for the maximum margin can be realized by solving the problem

$$\begin{aligned} \text{minimize} \quad & \langle \mathbf{w} \cdot \mathbf{w} \rangle \\ \text{subject to} \quad & y_i(\langle \mathbf{w} \cdot \mathbf{x_i} \rangle + b) \geq 1, i = 1, \ldots, \ell \end{aligned} \tag{2.13}$$

which produces the following margin [11].

$$\gamma = \frac{1}{\|\mathbf{w}\|} = \left(\sum_{i \in SV} \alpha^* \right)^{-1/2} \tag{2.14}$$

If the set of examples provided for SVM training is not linearly separable, the optimization problem cannot be solved. By ‘softening’ the margin, allowing some examples to be misclassified, we can again solve the optimization [15]. Slack variables can be introduced which will allow for noisy and outlying examples to violate the margins. An example $(\mathbf{x_i}, y_i)$ is considered to have violated the margin when $y_i f(\mathbf{x_i}) > \gamma$. Hence, we define the slack variable for the example:

$$\xi((\mathbf{x_i}, y_i), f, \gamma) = \xi_i = \max(0, \gamma - y_i f(\mathbf{x_i})) \tag{2.15}$$

and the slack variable vector for the set S:

$$\boldsymbol{\xi} = \boldsymbol{\xi}(S, f, \gamma) = (\xi_1, \ldots, \xi_\ell) \tag{2.16}$$

We can now solve the optimization on data which is not linearly separable as

$$\begin{aligned} \text{minimize} \quad & \langle \mathbf{w} \cdot \mathbf{w} \rangle + C \sum_{i=1}^{\ell} \xi_i \\ \text{subject to} \quad & y_i(\langle \mathbf{w} \cdot \mathbf{x_i} \rangle + b) \geq 1 - \xi_i, i = 1, \ldots, \ell, \\ & \xi_i \geq 0, i = 1, \ldots, \ell \end{aligned} \tag{2.17}$$

where C is a parameter to be tuned during training [11].

2.2.2 Nonlinear SVMs

Real-world data sets are often not linearly separable, even when allowing for a soft margin. In this case, we can map the input data points into another space via a nonlinear mapping function $\boldsymbol{\phi} : X \rightarrow F$, where X is the original data, or input, space and F is known as the feature space [6, 11]. With this mapping in place, the separating hyperplane can be represented as follows.

$$f(\mathbf{x}, \boldsymbol{\alpha}^*, b^*) = \sum_{i \in SV} y_i \alpha_i^* \langle \boldsymbol{\phi}(\mathbf{x_i}) \cdot \boldsymbol{\phi}(\mathbf{x}) \rangle + b^* \tag{2.18}$$

The inner product $\langle \boldsymbol{\phi}(\mathbf{x_i}) \cdot \boldsymbol{\phi}(\mathbf{x}) \rangle$ is known as a kernel function, written $K(\mathbf{x_i}, \mathbf{x})$. Kernels must be positive semi-definite transforms to be valid for use as an SVM kernel [11]. As this work uses only linear SVMs, we will conclude our discussion of kernelized SVMs here.

2.2.3 Ranking SVMs

Joachims [31] presented a modification to the traditional SVM algorithm which allows it to rank instances instead of classifying them. Given a collection of data points ranked according to preference R^* with two points $d_i, d_j \in R^*$, and a linear learning function f, we can say

$$d_i \succ d_j \Rightarrow f(d_i) > f(d_j) \tag{2.19}$$

where $\succ$ indicates that d_i is preferred over d_j. We can define the function f as $f(d) = \mathbf{w} \cdot d$, where the following holds true.

$$f(d_i) > f(d_j) \Leftrightarrow \mathbf{w} \cdot d_i > \mathbf{w} \cdot d_j \tag{2.20}$$

The vector $\mathbf{w}$ can be learned via the standard SVM learning method using slack variables as in 2.2.1, expressed as follows.

$$\begin{aligned} \text{minimize} \quad & \langle \mathbf{w} \cdot \mathbf{w} \rangle + C \sum_{i,j \in |R|} \xi_{ij} \\ \text{subject to} \quad & \forall (d_i, d_j) \in R^* : \mathbf{w} \cdot d_i \geq \mathbf{w} \cdot d_j + 1 - \xi_{ij} \\ & \forall (i,j) : \xi_{ij} \geq 0 \end{aligned} \tag{2.21}$$

Discovery of the vectors defining the hyperplane, called *ranking vectors*, and the generalization of the ranking SVM is done differently [53]. For the sake of explanation, we assume that the data are linearly separable, and therefore the ξ_{ij} are all equal to 0. In this case, we can view the ranking function as projecting the data points onto the separating hyperplane. In this case, the ranking vectors are the points d_i and d_j nearest each other on the hyperplane. Generalization is achieved by calculating $\mathbf{w}$ to maximize the distance between these closest points. The distance between these points is calculated as $\frac{\mathbf{w}(d_i - d_j)}{\|\mathbf{w}\|}$. Taking this as our margin γ, we can, as with the classification SVM algorithm, maximize the margin by minimizing $\|\mathbf{w}\|$.

2.2.4 SVMs and Information Retrieval

SVMs have proven useful for information retrieval tasks similar to the one proposed here. Drucker et al. [17] compared the use of SVMs for relevance feedback to the Rocchio [44] and Ide [28] algorithms, and found that SVMs outperformed both. Cao et al. [10] looked specifically at the problem of using SVMs for retrieval and ranking of documents. One important finding of theirs relevant to this work is that while an information retrieval system ought to be optimized for ranking the most preferable documents, SVMs optimize generally for both high and low document rankings. Ranking SVMs have also been used to learn ranking functions from implicitly generated feedback [31, 42]. In [31], Joachims learned ranking functions from search engine log files, using the clickthrough data from users as a way to implicitly gather preference data. Results showed that models learned in this fashion were effective at improving retrieval.

2.3 Active Learning

Active learning describes a learning method wherein the learning algorithm itself has some control over which examples are added to its training set. Specifically, we need to ask a user to provide labels for some number of unlabeled examples. The learner chooses these examples based on some measure of learning utility; for example, choosing examples which will decrease the region of uncertainty in a learned function [14]. Repeated rounds of active learning improve both the learned function and the examples chosen for learning. Taking our previous measure as an example, the reduction in the region of uncertainty produces a function with better generalization power; however, reducing the region of uncertainty has an added benefit of leaving behind only examples which continue to contribute to uncertainty.

2.3.1 SVMs and Active Learning

Much of the literature on active learning for SVMs has focused on classification, as opposed to ranking [19, 49]. Brinker [7] applied active learning to learning ranking SVMs; however, this research focused on learning label ranking functions, which is a fundamentally different task from document ranking. While document ranking attempts to impose an ordering on a set of documents, label ranking attempts to determine the preferred ordering of a fixed set of alternatives (labels) for a given input instance. Tong and Chang [48] used pool-based active learning for image retrieval. Their method of selecting examples for labeling was based on the finding that by choosing examples which shrink the size of the version space in which the optimal weight vector $\vec{w}$ can lie, the SVM learned from those examples will approximate $\vec{w}$. Therefore, examples are chosen which will most nearly bisect the version space they occupy. This was achieved in practice by choosing examples based on their proximity to the SVM boundary; examples close to the boundary are likely to be more centrally located in the version space, and are thus more likely to bisect it.

2.4 Learning to Rank from Preferences

Yu [53] constructed a system similar to the one to be presented here, operating over real estate data, and noted that methods such those in [49] could not be extended to learning ranking SVMs. As the ranking problem is more complex than the classification problem, selective sampling for learning ranking SVMs was conducted by selecting the most ambiguously ranked examples for labeling. This was done by noting that ambiguity in ranking could be measured based on how similarly the examples were ranked, with the closest pairs of examples being the most ambiguous. This method for selection is directly analogous to that in [49], even though it does not address reduction in version space; just as the support vectors in a classifying SVM are those examples closest to the SVM boundary, the support vectors in a ranking SVM are those examples that are most closely ranked. You and Hwang [52] used a similar framework and data set to learn ranking in a context-sensitive manner. Both of these works focused on general data retrieval, however, as opposed to focusing on document retrieval.

Cohen, Schapire and Singer [13] modeled the ranking problem as a directed graph $G = (V, E)$ with instances as the graph's vertices and the weight on an edge between vertices $E_{u,v}$ representing the strength of the preference of u over v. The problem was split into two steps, i.e., learning the weights and then constructing a ranking from the graph, and two methods for addressing this latter step were introduced. Independent of ranking was the learning method, based on the Hedge algorithm [21], which learned by updating weights based on expert input. The first ranking algorithm was a greedy algorithm which computed the difference between the total weight leaving a vertex and the total weight entering it, with larger values indicating greater overall preference. The second ranking algorithm improved upon the first by separating strongly connected vertices into separate ranking problems, and combining the resulting rankings.

Burges et al. [9] used neural networks to rank using preferences by modeling a probabilistic cost function for pairs of ranked instances. *Cost* in this case was modeled as the cross-entropy cost between the known ranking of the pair and the probability that the model will produce that ranking. The authors then showed how these probabilities can be combined, allowing for computation of a cost function for preference pairs. A neural network training algorithm was then implemented, using the gradient of this function as an updating rule for the network's weights.

Har-Peled et al. [24] formulated the problem in terms of constraint classification using pairwise preferences. Specifically, given a set of instances and a set of labels, the task is to find a function which will produce an ordering of the labels for each instance. The authors achieve this by learning a binary classification model $\mathcal{M}_{i,j}$ for each pair of labels y_i, y_j, with $\mathcal{M}_{i,j}$ predicting $y_i \succ y_j$. The output from each classifier is tallied as a vote for the preferred label, and the labels are ranked according to these votes.

CHAPTER 3
DATA COLLECTIONS

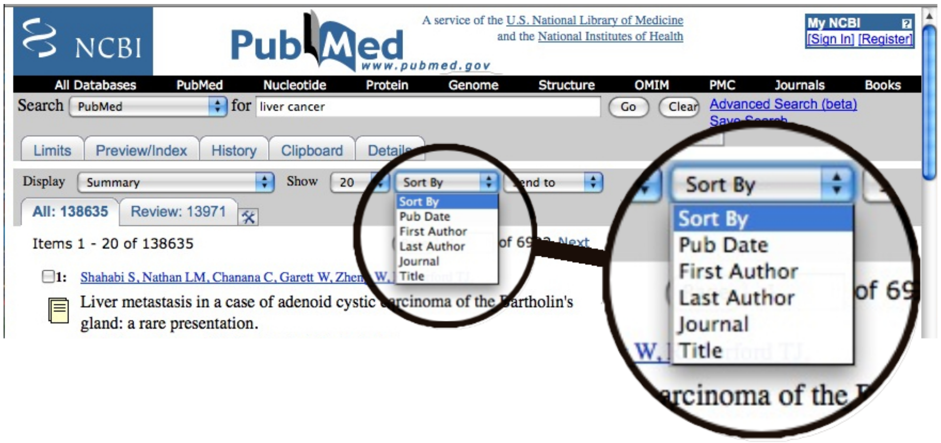
In this chapter, we give an overview of the data collections used in this thesis. The biomedical data is used in the simulations found in Chapter 5 as well as the user study in Chapter 7. The enterprise data set is used in the simulations found in Chapter 6.

3.1 Biomedical Data Collections

3.1.1 MEDLINE

As stated in Section 1.2, MEDLINE is a database of bibliographic references in biomedicine and health sciences, collected and curated by the NLM. Citations are taken from approximately 5,200 sources (mostly journals) in 37 languages, with the majority of journals selected for inclusion by a committee set up by the National Institutes of Health (NIH). Other sources are included based on NLM or NIH priorities (e.g., AIDS research). Dates covered range from 1949 to the present, with some older material. The database currently contains over 16 million references, with between two and four thousand added each week. 670,000 references were added in 2007.

MEDLINE's subject coverage is extensive. It covers areas ranging from public heath policy to clinical care to bioengineering research, from humans to plants to bacteria. The target audience for MEDLINE is the biomedical community at large, including researchers, clinicians, educators, and amateurs. Most references include full citation data, as well as the abstract for the reference. Many references also contain links to the full article.



Search PubMed for liver cancer

Display Summary Show 20 Sort By

Items 1 - 20 of 138635

1: Shahabi S, Nathan LM, Chanana C, Garett W, Zhen W,

Liver metastasis in a case of adenoid cystic carcinoma of the Bartholin's gland: a rare presentation.

Figure 3.1: Sample view of the results page from PubMed. Inset: document ranking options.

Searching MEDLINE is done most often via Entrez PubMed, the NLM's search engine operating over the database[1]. Figure 3.1 shows an example of a results page from the PubMed search interface. While it is a robust retrieval system, PubMed lacks relevance-based ranking of search results. Users are limited in their choice of results sorting to date of publication, author names, or journal of publication. This leads to information overload for users of the system. As mentioned before, this is partly due to the size of the MEDLINE database; for example, a search for "heart disease" returns over eight hundred thousand results. This can lead to a "search boomerang", where users alter their search queries with more specific criteria (resulting in too few results), then relaxing their criteria (resulting in too many), repeating until a reasonably sized result set is obtained.

[1] http://www.ncbi.nlm.nih.gov/sites/entrez

3.1.1.1 MeSH Terms

To assist users in navigating through MEDLINE's wealth of information, each reference in the database is tagged with a number of MeSH terms. The preface to [38] states that, "The Medical Subject Headings (MeSH) thesaurus is a controlled vocabulary produced by the National Library of Medicine and used for indexing, cataloging, and searching for biomedical and health-related information and documents." The terms themselves are heterogeneous, and are of three types. *Descriptors*, or *main headings*, cover the content of the reference, as well as metadata such as the publication type and components (e.g., clinical trial, editorial, historical article, etc.) and the country of the reference's origin. *Qualifiers*, or *subheadings*, are used with descriptors to group together references dealing with a particular aspect of the descriptor; for example, pairing the qualifier "abnormalities" with the descriptor "heart" would indicate that the reference in question is concerned with congenital defects in the heart, as opposed to the heart itself. Finally, *Supplementary Concept Records*, or SCRs, catalogue specific drugs and chemicals referenced in the article. Currently, there are 25,186 MeSH descriptors, with 83 qualifiers and over 180,000 SCRs. References are manually tagged by human annotators.

MeSH is arranged hierarchically in 16 trees, grouped by the most general category of the descriptor. There is a tree for descriptors relating to parts of the anatomy, another for organisms, another for techniques and equipment, etc. As one descends a tree, the descriptors become increasingly specific. Figure 3.2 shows a sample from subtree A01 - Body Regions, the first subtree in tree A - Anatomy. The position of the entry "Toes" indicates that is more general than "Hallux", but more specific than "Forefoot, Human", which is itself more specific than "Foot".

Searching MEDLINE with MeSH terms can be done by entering the MeSH

```
Body Regions [A01]
  ...
  Extremities [A01.378]
    ...
    Lower Extremity [A01.378.610]
      Buttocks [A01.378.610.100]
      Foot [A01.378.610.250]
        Ankle [A01.378.610.250.149]
        Forefoot, Human [A01.378.610.250.300]
          Metatarsus [A01.378.610.250.300.480]
          Toes [A01.378.610.250.300.792]
            Hallux [A01.378.610.250.300.792.380]
        Heel [A01.378.610.250.510]
      Hip [A01.378.610.400]
      Knee [A01.378.610.450]
      Leg [A01.378.610.500]
      Thigh [A01.378.610.750]
```

Figure 3.2: Sample MeSH hierarchy

```
‘‘diabetes mellitus’’[MeSH Terms] OR
(‘‘diabetes’’[All Fields] AND ‘‘mellitus’’[All
Fields]) OR ‘‘diabetes mellitus’’[All Fields]
OR ‘‘diabetes’’[All Fields] OR ‘‘diabetes
insipidus’’[MeSH Terms] OR (‘‘diabetes’’[All
Fields] AND ‘‘insipidus’’[All Fields]) OR
‘‘diabetes insipidus’’[All Fields]
```

Figure 3.3: Full translation of the query “diabetes”

term into a PubMed search, just as one would any other search term. A mapping of 160,000 common terms to their synonymous MeSH headings is used along with the PubMed query system to expand and refine the user’s query. Figure 3.3 shows the full PubMed translation of the query “diabetes”.

3.1.2 OHSUMED

OHSUMED is a collection of MEDLINE citations, created in order to carry out information retrieval experiments on MEDLINE [26]. It is composed of the results of 106 queries run against a five-year span of MEDLINE documents. Queries were generated from a questionnaire filled out by participants in the study, over a ten-month period, filtering out duplicate topics and author searches, as well as queries with inadequate information for replication by annotators. Eleven medical librarians and eleven physicians, all familiar with searching MEDLINE, replicated the searches and judged the retrieved references for relevance. Of 348,566 available references from 270 medical journals, 16,140 query-document pairs were retrieved, with the 12,565 unique pairs annotated for relevance. Pairs were classified as definitely, partially, or not relevant, with 69.3% annotated as not relevant, 16.3% partially relevant, and 14.3% relevant. Five queries returned no citations judged relevant by the annotators. Inter-annotator agreement, a measure of how closely any two annotators agreed in their annotations, was calculated by having 11% of the documents annotated by two people. A kappa statistic of 0.41 was calculated for agreement, which the authors claim is comparable with other similar experiments. Queries returned an average of 152.27 documents.

3.1.3 LETOR

LETOR is a benchmark dataset created for information retrieval rank learning applications [35]. It consists of two parts; the first is based on the .gov dataset from the 2003 and 2004 TREC Web Track [16], and the second is based on OHSUMED (see section 3.1.2). We will limit our discussion to the OHSUMED section of LETOR.

LETOR assigns a feature vector to each query-document pair in the OHSUMED collection. These feature vectors are composed of classical and more recently developed measures. Both high and low-level features are calculated, where "[l]ow-level features include term frequency (tf), inverse document frequency (*idf*), document length, (*dl*) and their combinations" [35], and high-level features include measures such as BM25 [43] and language models [54]. Vectors contain 25 features, 10 low-level features (L1-L10 in Table 3.1) calculated from the title, the same 10 calculated again from the abstract, and 5 (H1-H5 in Table 3.2) from combined title-abstract text for each of the documents.

Benchmarks for ranking learning with LETOR over the OHSUMED data set have been calculated using two learning methods, RankBoost and Ranking SVM, achieving NDCG@10 of 0.436 and 0.441 respectively [35]. Ranking quality for the individual LETOR features can also be calculated. Since each feature corresponds to a relevance score for a particular query-document pair, a ranking over all documents in that query can be constructed, and the quality of that ranking calculated using the interquartile mean NDCG@10 over the 101 queries used (see Section 5.2.1 for an explanation and motivation for using interquartile mean). Figure 5.5 shows the ranking quality for each of the 25 LETOR features, with the best performance being an NDCG@10 of 0.461 from feature 10.

3.2 Enterprise Data Collection

3.2.1 TREC Enterprise 2007

TREC, the Text Retrieval Conference, began in 1992. Co-sponsored by the National Institute of Standards and Technology and the Department of Defense, it purpose is "to support research within the information retrieval community by

Table 3.1: Calculation of low-level LETOR features

Feature	Source	**Calculated as...**
L1	tf [2]	$\sum_{q_i \in q \cap d} c(q_i, d)$
L2	[37]	$\sum_{q_i \in q \cap d} \log(c(q_i, d) + 1)$
L3	Normalized tf [2]	$\sum_{q_i \in q \cap d} \frac{c(q_i, d)}{\|d\|}$
L4	[37]	$\sum_{q_i \in q \cap d} \log(\frac{c(q_i, d)}{\|d\|} + 1)$
L5	idf [2]	$\sum_{q_i \in q \cap d} \log(\frac{\|C\|}{df(q_i)})$
L6	[37]	$\sum_{q_i \in q \cap d} \log(\log(\frac{\|C\|}{df(q_i)}))$
L7	[37]	$\sum_{q_i \in q \cap d} \log(\frac{\|C\|}{c(q_i, C)} + 1)$
L8	[37]	$\sum_{q_i \in q \cap d} \log(\frac{c(q_i, d)}{\|d\|} \log(\frac{\|C\|}{c(q_i, C)}) + 1)$
L9	$tf * idf$ [2]	$\sum_{q_i \in q \cap d} c(q_i, d) \log(\frac{\|C\|}{df(q_i)})$
L10	[37]	$\sum_{q_i \in q \cap d} \log(\frac{c(q_i, d)}{\|d\|} \frac{\|C\|}{c(q_i, C)} + 1)$

Table 3.2: Calculation of high-level LETOR features

Feature	**Source**
H1	BM25 score [43]
H2	log(BM25 score) [43]
H3	LMIR with DIR smoothing [54]
H4	LMIR with JM smoothing [54]
H5	LMIR with ABS smoothing [54]

providing the infrastructure necessary for large-scale evaluation of text retrieval methodologies."[2] Each year, the TREC program committee decides on a number of areas, or tracks, for research, and defines a number of tasks for each track as well as a collection of documents for each track. One of the tracks for 2007 was an enterprise search track. "Enterprise" in this case refers to any large business or similar organization, in this case the Australian Commonwealth Scientific and Industrial Research Organization (CSIRO) [4]. There were two tasks for this track, both based on the idea of providing resources to construct a "missing overview page", in which a user is tasked with creating an informative web page for an existing past or present CSIRO research project. The first was a document search task, requiring participants to find key documents explaining the given project. The second was a staff search task, requiring participants to identify key CSIRO staff members (specifically, their email addresses) for the given project. We will limit our discussion to the document search task.

The projects for which these hypothetical overview pages would be constructed were defined as a set of 50 topics, each consisting of a keyword-style query, a narrative describing the topic, some URLs pointing to example web pages informative on the topic, and the email addresses of some people involved in the topic. Participants were allowed to use the query and narrative for their submitted retrieval runs if their systems used no feedback; feedback-based systems were allowed to used queries and the example web pages. The data collection for the TREC Enterprise 2007 track was constructed from a crawl of the csiro.au website. This yielded a collection of 370,715 documents (4.2 gigabytes). Though largely composed of web pages, all public documents including PDF files, videos, and even some geo-positioning data

[2] http://trec.nist.gov/overview.html

were harvested. Each document collected included header information, such as the URL of the document, its date of collection, and the type of content represented (e.g., 'text/html', 'video/x-ms-asf').

21,532 documents potentially relevant to the 50 topics were retrieved to create a set of 33,813 topic-document pairs used to evaluate systems participating in the track. Annotation was done by TREC Enterprise participants, classifying pairs as definitely, partially, or not relevant, with 76.9% annotated as not relevant, 12% partially relevant, and 11% relevant. Each pair was annotated by at least two different annotators. A later study compared participant annotation with expert annotation, reporting kappa statistics of 0.39 and 0.42 for relevant and not relevant documents, respectively [3]. Partially relevant annotations achieved agreement of 0.19, indicating that these judgements may not be completely reliable. The queries returned an average of 676.28 documents.

3.2.2 Dublin Core Metadata

Just as our biomedical data included metadata describing the documents in the set, some of the CSIRO documents included metadata, adhering to the Dublin Core (DC) metadata framework. The Dublin Core Metadata Initiative is "an open organization engaged in the development of interoperable metadata standards that support a broad range of purposes and business models,"[3] and defined a set of fifteen DC metadata elements in 1995. These elements are used to tag documents with information such as the document's creator, the date it was created, the language in which it is written, etc. [18]. Certain non-core elements, such as keywords, are also used in the CSIRO set. 4,738 documents comprising 6,029 topic-document pairs

[3] http://dublincore.org/

have at least one element of DC metadata.

CHAPTER 4
DESCRIPTION OF SYSTEM AND SIMULATION FRAMEWORK

Here, we present a domain-independent overview of our framework for learning a function to produce such a relevance ranking from feedback provided by the user. As this is an online task, two factors beyond raw system performance must be addressed. First, the system must perform well enough to provide the user a reasonable search experience, both in terms of performance and in speed. Second, the amount of feedback required for learning must be a reasonably small fraction of the number of search results. If either of these factors are not well addressed, the system will provide no benefit to users over traditional search engines. We choose to employ ranking SVMs for rank function learning because of their performance in this area [10, 31, 53]. SVMs also provide reasonable speed for learning and ranking; empirical data supporting this claim is presented in Chapter 7. To ensure users will have to provide as little feedback as possible, we employ active learning to choose examples that will be most useful for learning [14].

The system works as follows (see Figure 4.1). A user with an information need formulates that need as a query to an existing information retrieval source, which may or may not return ranked results. A small number of results are shown to the user, who indicates preference for or against those results. Those preference scores are then used to create a small training set for a machine learning method which produces a ranking function. That function then ranks the retrieved documents. A quality measure is consulted to decide whether or not the process should finish. If so, the ranked results are returned to the user. If not, another set of documents is chosen and shown to the user for feedback, and the process repeats.

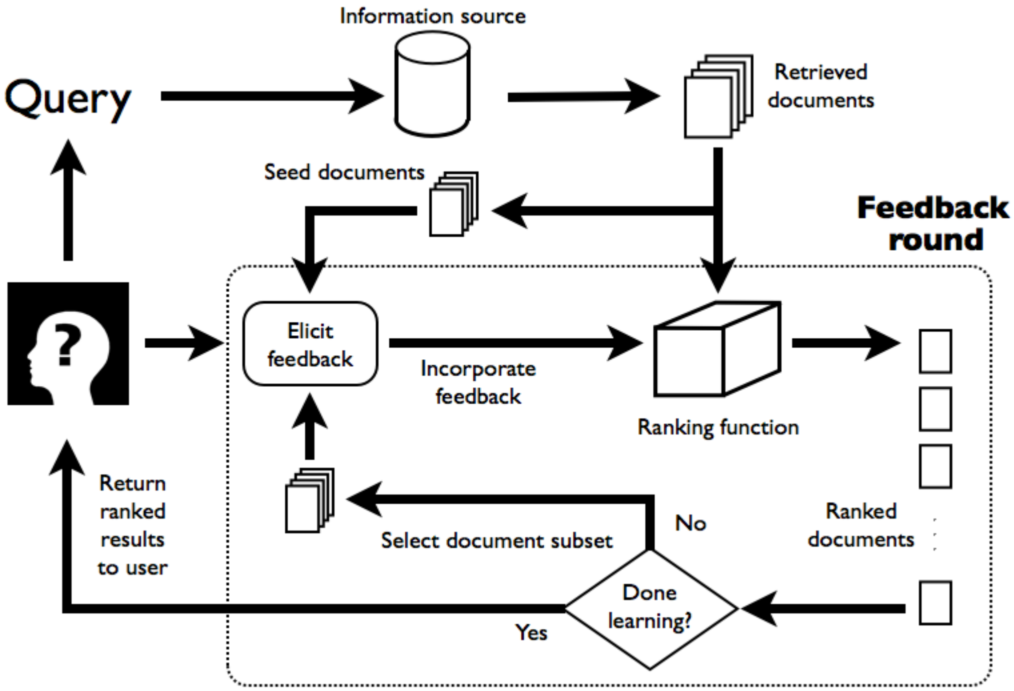


Figure 4.1: Illustration of learning ranking functions from user feedback

The framework consists of three variable components we wish to investigate for their effects on ranking performance: how examples are chosen (Section 4.4), the amount of feedback elicited (Section 4.5), and the criterion for stopping the feedback-learning process (Section 4.6). These components will be the subject of the experiments discussed in Chapters 5 and 6.

4.1 Initial Retrieval

We take initial retrieval as given. As our system is in essence a reranking system, we assume that the input to the system is a set of documents which has either been retrieved by an information retrieval system used as an industry standard (such as PubMed, described in Section 1.2), or prepared as a testbed for information retrieval systems (such as the TREC Enterprise 2007 data set, described in Section 3.2).

4.2 The Feedback Round

A *feedback round* is one iteration of choosing examples for feedback, requesting feedback from the user, learning from the feedback, and checking the stopping criterion. Future references will be made to this sequence of steps as a performance measure, with number of feedback rounds used as one measure of how much overhead the user has incurred using the system. The number of rounds multiplied by the number of examples seen per round gives the total number of examples seen, which is the other overhead measure used.

4.3 Ranking

We learn and rank using ranking SVMs with a linear kernel, as described in Section 2.2.3. Features used for learning will be depend on the document set over which retrieval is conducted, and are described in Sections 5.1 and 6.1. Data collection for ranking SVM learning is done cumulatively; the user's feedback on the examples presented is added to feedback from previous rounds, with learning done over the entire accumulated set of feedback. Default values for learning and ranking (margin size, error weighting, etc.) are used[1].

4.4 Choosing Examples

In order to learn a ranking function, we require a training set. This set will be provided to us by the user in the form of explicit preference feedback on a subset of the retrieved documents. To ensure that we are asking for user feedback on as few examples as possible, we choose this subset via active learning (Section 2.3). Active learning techniques employed will be the subject of experimentation, described in their respective sections.

4.5 Eliciting Feedback

Feedback is elicited by asking the user to rate a document's relevance to his/her information need. We allow users to express preference on a neutral point scale (“yes”, “maybe”, “no”), rather than using a forced-choice (“yes or no”) method, as the former shows higher measurement reliability [12]. The number of examples presented for feedback in each round may influence both how quickly the ranking function is learned, and the quality of the ranking function. The amounts of feedback elicited for individual experiments are described in their respective sections.

In Chapter 5, feedback is simulated using scores from the OHSUMED data

[1] See http://svmlight.joachims.org/

set (Sec. 3.1.2). In Chapter 6, feedback is simulated using scores from the TREC Enterprise 2007 data set (Sec. 3.2.1). In Chapter 7, feedback is given by live users.

4.6 Convergence Threshold

At some point, feedback rounds must terminate. Rather than arbitrarily choosing a number of rounds or amount of feedback required before termination, feedback ends when the lists produced by the ranking function appear to be converging towards a stable list. Our convergence criterion is based on the Kendall tau rank correlation coefficient, calculated between on the current and immediately previous orderings produced by the ranking function. Once the correlation between these rankings exceeds a certain threshold, feedback rounds terminate. Again, the ranges of thresholds investigated in different experiments are detailed in their respective sections.

4.6.1 The Kendall Tau Rank Correlation Coefficient

The Kendall tau rank correlation coefficient calculates the similarity between two different rankings of one set of objects [1]. The two rankings, $\mathcal{O}_1$ and $\mathcal{O}_2$ will each produce two sets of ordered pairs, $\mathcal{P}_1$ and $\mathcal{P}_2$. The Kendall's tau measure seeks to measure the difference between the rankings in terms of how many of these ordered pairs are different, called the symmetric difference distance $d_\Delta(\mathcal{P}_1, \mathcal{P}_2)$. We wish to normalize the concordance score between 1 for perfectly identical rankings, and -1 for perfectly reversed rankings. Each set of ordered pairs contains $\frac{1}{2}N(N-1)$ pairs (where N is the number of objects); hence, the maximum $d_\Delta(\mathcal{P}_1, \mathcal{P}_2)$ is $N(N-1)$, and the minimum is 0. Therefore, we can calculate the correlation as follows [1]:

$$\tau = 1 - \frac{2 * d_\Delta(\mathcal{P}_1, \mathcal{P}_2)}{N(N-1)} \tag{4.1}$$

For example, given a set of objects ranked as $\mathcal{O}_1 = [a, b, c, d]$ and a second ranking $\mathcal{O}_2 = [a, b, d, c]$, the pairs of ranked objects are

$\mathcal{P}_1 = \{\{a, b\}, \{a, c\}, \{a, d\}, \{b, c\}, \{b, d\}, \{c, d\}\}$

$\mathcal{P}_2 = \{\{a, b\}, \{a, d\}, \{a, c\}, \{b, d\}, \{b, c\}, \{d, c\}\}$

for $\mathcal{O}_1$ and $\mathcal{O}_2$ respectively. The set of objects in one set of pairs and not the other is $\{c, d\}, \{d, c\}$. The symmetric difference $d_\Delta(\mathcal{P}_1, \mathcal{P}_2) = 2$, $N = 4$, so $\tau = 1 - \frac{2*2}{4(3)=\frac{2}{3}}$, indicating a strong correlation.

CHAPTER 5
SIMULATIONS IN THE BIOMEDICAL DOMAIN

In this chapter, we test our framework experimentally via simulation, using the OHSUMED data set (described in Section 3.1.2). The five queries which returned no relevant citations have been excluded from the simulations. All experiments were run ten times per query, and the results averaged. We evaluate ranking performance using normalized discounted cumulative gain (NDCG) as described in Section 2.1.5.3. We compute NDCG@10 for our evaluation. NDCG is a commonly used metric for these applications [4, 9, 10, 35]. Furthermore, a retrieval size of 10 is considered the "first page" of results from a search results, and is therefore a reasonable position to measure ranking performance [20]. We evaluate user overhead by counting the number of feedback rounds to produce a given ranking, as well as the total number of documents used for feedback. The interquartile mean is calculated for both metrics over the 101 queries (motivated in Section 5.2.1).

5.1 Adapting the General Framework to the Biomedical Domain

Adapting our general framework to simulation in the biomedical domain begins with initial retrieval. PubMed, as described in Section 3.1.1 is an excellent retrieval system, employing many recall-boosting strategies such as term expansion and synonym matching, which we do not care to replicate. For our experiments, we use the existing OHSUMED data set (described in Section 3.1.2) and perform no retrieval on our own.

Two sets of features are used for learning. For the first set, we use the features from LETOR (Section 3.1.3). We leave these features intact, with no modification.

These textual features model the content of the query-document pair. The second set is built from the MeSH descriptors (Section 3.1.1.1) for the OHSUMED documents. Each vector is composed of 25,186 binary features, with each feature indicating inclusion of the MeSH descriptor. These features model the metadata assigned to the documents by the MeSH annotators. It should be noted that MeSH terms offer an improvement over the textual features, in that annotators assigning MeSH terms to citations in MEDLINE have access to the entire article, while LETOR features are limited to the title and abstract.

5.2 Simulations Using OHSUMED

Our initial simulation experiment is designed to explore the variable components of the user preference feedback framework described in Chapter 4 operating in the biomedical domain, as well as investigating the use of feature vectors built from textual vs. metadata features as described in Section 5.1.

We employ two active learning methods for these simulations. We use *random sampling*, simply choosing unseen examples at random, as a lower bound for determining active learning effectiveness. The first active learning method is *top sampling*. As discussed in [10], ranking functions should have their performance optimized towards top-ranked documents. Therefore, top sampling chooses unseen documents ranked highest by the current ranking function at each round for feedback. The other active learning method is *mid sampling*. Similar to Cohn et al. [14], we wish to reduce uncertainty in our ranking function. A learned ranking function will rank the best and worst documents with great confidence, but less so those in the middle. These middle-ranked documents are, conceptually, the ones ranked with the least confidence; therefore, learning from them should result in a stronger model.

We hypothesize that both top and mid sampling will outperform random sampling, both in ranking performance and overhead cost. We further hypothesize that top sampling will outperform mid sampling in ranking performance, as mid sampling is training to improve overall performance as opposed to focusing on the performance of highly-ranked documents.

The amount of feedback collected varies between one and five examples per round. We hypothesize that collecting more examples per round will result in better performance, as well as fewer total examples needed to achieve that performance; more examples should produce stronger models at each round, resulting in better examples selected for feedback in the next round, speeding up the entire process.

The convergence threshold varies between a Kendall's tau of 0.5 to 0.9, in increments of 0.1. We hypothesize that greater thresholds will result in better performance, with a commensurate increase in rounds to convergence; as the stopping criterion becomes more difficult to meet, more preference data will be collected, producing a stronger ranking function.

5.2.1 Motivation for Using the Interquartile Mean

When analyzing the results from the 101 queries for the various methods, convergence thresholds, and examples per round, it was found that the distribution of performance values did not follow a normal distribution. To the contrary, at higher levels of performance the results were strongly skewed away from the top performing queries. Figure 5.1 shows this effect for top sampling at the 0.9 convergence threshold. We quantify the magnitude of this deviation by calculating the skewness of the distribution,

$$\frac{1}{n}\sum_{x_i \in \boldsymbol{x}} \left(\frac{(x_i - \bar{x})}{s}\right)^3 \tag{5.1}$$

where n is the sample size, $\bar{x}$ is the sample mean, and s is the sample size [51]. Table 5.1 shows skewness calculated for top sampling with random seeding, across all thresholds and examples per round.

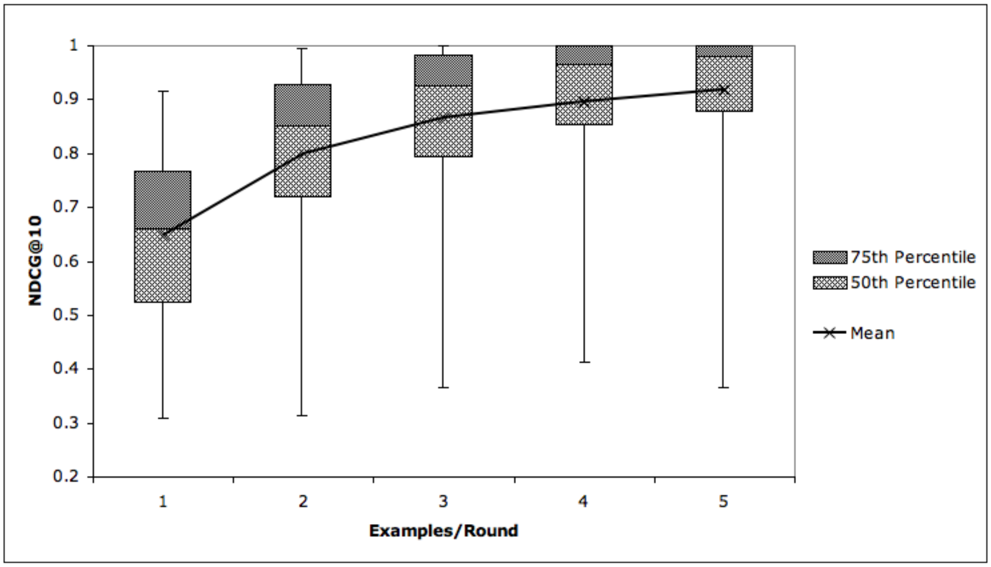


Figure 5.1: Box and whisker plot of the distribution of performance across the 101 queries for top sampling at a convergence threshold of 0.9, across all examples per round.

The modest skewness encountered at lower thresholds, correlating with lower performance (see section 5.2.2), increased greatly at higher thresholds, indicating a “long tail” of poorly performing queries away from the large number of queries performing well.

In order to more accurately reflect the performance of the ranking functions across the 101 queries, we choose to report the interquartile mean of the performance metrics as opposed to the mean. The interquartile mean can be calculated by discounting the top and bottom quarter of the ranked scores, calculating the mean of the inner quarters. Generally, this can be expressed as

$$\frac{2}{n} \sum_{i=(n/4)+1}^{3n/4} x_i \tag{5.2}$$

Table 5.1: Skewness calculated across all thresholds and examples per round for top sampling

Threshold	Examples per round				
	1	2	3	4	5
0.5	0.567	0.393	0.303	0.092	-0.036
0.6	0.473	0.237	0.115	-0.196	-0.234
0.7	0.417	0.153	-0.057	-0.674	-0.919
0.8	0.335	-0.194	-0.786	-0.980	-1.466
0.9	-0.106	-1.116	-1.506	-1.838	-2.182

5.2.2 Results and Discussion

Table 5.2: NDCG calculated across all queries at positions 1 through 10 for ranking SVMs trained on all data available for a query.

	@1	@2	@3	@4	@5	@6	@7	@8	@8	@10
MeSH	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
LETOR	0.748	0.679	0.640	0.620	0.600	0.600	0.585	0.586	0.591	0.589

Learning from MeSH features clearly outperformed learning from LETOR features in ranking performance. An upper bound for performance comparison was calculated by ranking documents for each OHSUMED query using a ranking SVM learned from all documents in the query, for both MeSH and LETOR feature vectors. Table 5.2 shows SVMs learned from MeSH terms yielded perfect interquartile mean ranking performance, vastly outperforming SVMs learned from LETOR features.

A performance gain is to be expected, as the MeSH terms are tailored to this data; however, we did not expect the gain to be this great. This trend continues in the active learning experiments. As shown in Tables 5.3-5.5, across all sampling methods, thresholds, and examples per round, ranking performance of SVMs learned from MeSH features outperform their LETOR counterparts. For thresholds above 0.5, though LETOR SVMs consistently reached convergence before MeSH SVMs (indicating a much lower overhead), the performance was consistently poor.

Overall, our results are encouraging. We have achieved an NDCG@10 ranking performance of 0.970 after an average of 13.55 feedback rounds and 67.74 examples seen, using top sampling with five examples per round and a convergence threshold of 0.9 (Table 5.5).

Top sampling produced better ranking functions than the other two methods. Curiously, mid sampling performed worse than random sampling. This may be due to the fact that mid sampling is more likely to encounter documents ranked as possibly relevant as opposed to definitely relevant or irrelevant than random sampling. Mid sampling did incur less overhead than the other active learning methods, but it appears as though it converged to a poor final ranking.

In all cases, a greater number of examples per round produced better ranking performance. This is to be expected, as more examples per round yields a larger set of training data (see Figure 5.3, Section 5.6). More examples per round also decreased rounds to convergence; however, the decrease in the number of rounds was never great enough to lead to a decrease in the total number of examples seen.

As expected, higher thresholds for convergence resulted in higher ranking performance, at the cost of more feedback rounds. While performance climbed steadily, there was a marked jump in overhead between thresholds of 0.8 and 0.9.

Table 5.3: Averaged performance for random sampling method, for all examples per round and thresholds. The top subtable reports NDCG@10, middle reports number of rounds until the convergence threshold is met, bottom reports number of examples seen until convergence.

Random Sampling

NDCG@10

Threshold	MeSH					LETOR				
	1	2	3	4	5	1	2	3	4	5
0.5	0.426	0.472	0.511	0.544	0.560	0.359	0.369	0.384	0.393	0.405
0.6	0.442	0.482	0.519	0.552	0.592	0.358	0.373	0.388	0.401	0.411
0.7	0.455	0.484	0.554	0.585	0.592	0.361	0.372	0.392	0.407	0.425
0.8	0.467	0.525	0.604	0.653	0.693	0.358	0.376	0.405	0.412	0.422
0.9	0.502	0.611	0.673	0.739	0.783	0.370	0.384	0.419	0.440	0.456

Rounds to Convergence

Threshold	MeSH					LETOR				
	1	2	3	4	5	1	2	3	4	5
0.5	5.607	3.781	3.145	2.951	2.840	7.329	4.823	3.804	3.386	3.088
0.6	5.634	4.007	3.547	3.359	3.318	7.461	4.533	3.858	3.540	3.190
0.7	6.245	4.719	4.363	4.147	4.075	7.672	4.788	4.223	3.736	3.601
0.8	7.169	5.871	5.816	5.889	5.931	7.760	5.284	4.612	4.326	4.144
0.9	10.29	9.494	10.02	10.97	11.20	9.205	7.073	6.681	6.640	6.618

Total Examples to Convergence

Threshold	MeSH					LETOR				
	1	2	3	4	5	1	2	3	4	5
0.5	5.607	7.562	9.435	11.80	14.20	7.329	9.646	11.41	13.54	15.44
0.6	5.634	8.015	10.64	13.44	16.59	7.461	9.065	11.58	14.16	15.95
0.7	6.245	9.439	13.09	16.59	20.37	7.672	9.576	12.67	14.94	18.00
0.8	7.169	11.74	17.45	23.55	29.66	7.760	10.57	13.84	17.30	20.72
0.9	10.29	18.99	30.07	43.86	56.01	9.205	14.15	20.04	26.56	33.09

Table 5.4: Averaged performance for mid sampling method, for all examples per round and thresholds. The top subtable reports NDCG@10, middle reports number of rounds until the convergence threshold is met, bottom reports total number of examples seen until convergence.

Mid Sampling										
NDCG@10										
Threshold	MeSH					LETOR				
	1	2	3	4	5	1	2	3	4	5
0.5	0.442	0.469	0.488	0.514	0.539	0.322	0.339	0.355	0.368	0.364
0.6	0.433	0.487	0.502	0.518	0.543	0.325	0.344	0.354	0.366	0.364
0.7	0.449	0.486	0.523	0.550	0.568	0.332	0.339	0.352	0.369	0.378
0.8	0.460	0.516	0.543	0.593	0.607	0.328	0.345	0.371	0.369	0.389
0.9	0.490	0.567	0.627	0.653	0.664	0.330	0.349	0.382	0.406	0.427
Rounds to Convergence										
Threshold	MeSH					LETOR				
	1	2	3	4	5	1	2	3	4	5
0.5	5.523	3.567	3.110	2.912	2.697	5.713	3.686	3.253	2.884	2.779
0.6	5.750	3.972	3.437	3.179	3.092	5.710	3.794	3.236	3.049	2.908
0.7	6.059	4.506	3.963	3.858	3.722	5.582	3.830	3.579	3.406	3.344
0.8	7.123	5.587	5.175	5.026	4.904	6.223	4.468	4.050	3.924	3.923
0.9	9.747	9.156	9.120	8.754	8.733	7.145	5.629	5.768	5.680	5.712
Total of Examples to Convergence										
Threshold	MeSH					LETOR				
	1	2	3	4	5	1	2	3	4	5
0.5	5.523	7.135	9.330	11.65	13.48	5.713	7.372	9.760	11.54	13.89
0.6	5.750	7.944	10.31	12.71	15.46	5.710	7.587	9.708	12.20	14.54
0.7	6.059	9.012	11.89	15.43	18.61	5.582	7.659	10.74	13.62	16.72
0.8	7.123	11.17	15.53	20.10	24.52	6.223	8.936	12.15	15.70	19.61
0.9	9.747	18.31	27.36	35.02	43.66	7.145	11.26	17.30	22.72	28.56

Table 5.5: Averaged performance for top sampling method, for all examples per round and thresholds. Top subtable reports NDCG@10, middle reports number of rounds until the convergence threshold is met, bottom reports total number of examples seen until convergence.

Top Sampling										
NDCG@10										
Threshold	MeSH					LETOR				
	1	2	3	4	5	1	2	3	4	5
0.5	0.439	0.497	0.559	0.617	0.667	0.347	0.368	0.387	0.423	0.436
0.6	0.459	0.527	0.601	0.678	0.725	0.346	0.369	0.401	0.432	0.451
0.7	0.471	0.573	0.665	0.762	0.833	0.355	0.389	0.426	0.446	0.458
0.8	0.523	0.663	0.794	0.865	0.910	0.359	0.396	0.437	0.468	0.491
0.9	0.652	0.840	0.913	0.948	0.970	0.381	0.446	0.484	0.538	0.534
Rounds to Convergence										
Threshold	MeSH					LETOR				
	1	2	3	4	5	1	2	3	4	5
0.5	5.639	3.800	3.460	3.288	3.234	6.001	3.888	3.292	3.051	2.986
0.6	5.677	4.329	4.160	4.305	4.079	5.645	3.960	3.590	3.377	3.144
0.7	6.459	5.539	5.546	5.564	5.584	6.062	4.315	3.792	3.565	3.455
0.8	8.228	7.970	8.354	8.214	8.030	6.514	4.793	4.452	4.308	4.322
0.9	14.79	15.32	15.20	14.66	13.55	7.958	6.602	6.678	6.732	6.173
Total Examples to Convergence										
Threshold	MeSH					LETOR				
	1	2	3	4	5	1	2	3	4	5
0.5	5.639	7.600	10.38	13.15	16.17	6.001	7.776	9.876	12.20	14.93
0.6	5.677	8.657	12.48	17.22	20.39	5.645	7.921	10.77	13.51	15.72
0.7	6.459	11.08	16.64	22.26	27.92	6.062	8.630	11.38	14.26	17.28
0.8	8.228	15.94	25.06	32.86	40.15	6.514	9.586	13.36	17.23	21.61
0.9	14.79	30.64	45.61	58.64	67.74	7.958	13.20	20.03	26.93	30.87

Experiments have shown that our hypotheses regarding ranking performance regarding sampling methods, examples per round, and convergence threshold are generally supported, with the exception of the performance of mid sampling. However, our assumptions regarding the overhead incurred to reach convergence as it relates to examples per round and ranking performance seem to have been incorrect. We had initially assumed that while seeing more examples per round would increase performance, the total amount of overhead required to reach that performance would decrease as seeing more examples per round would produce a more robust model at each ranking round, thus allowing the sampling methods to choose better examples and reducing the total number of rounds to convergence significantly. While rounds to convergence fell slightly as the number of examples per rounds increased, the decline was not enough to decrease the total number of examples seen until convergence as examples per round increased.

This led us to investigate whether the number of examples seen was the dominant predictor of performance. As shown in Figure 5.2, however, the sampling method used played a greater role in performance. Top sampling provided better ranking performance than random or mid sampling independent of number of examples seen, in many cases requiring fewer than half the number of examples to reach performance similar to the other active learning methods.

A note must be made regarding the convergence threshold. Since termination is determined as a function of learning, it effectively falls to the active learning technique to ensure that termination is not premature, as choosing uninformative examples will cause little to no shift in the ranking function. If this were the case, the learning process would not fulfill its potential, denied the chance to exhaust its stock of “good” examples to learn from. The effect of this would be that an

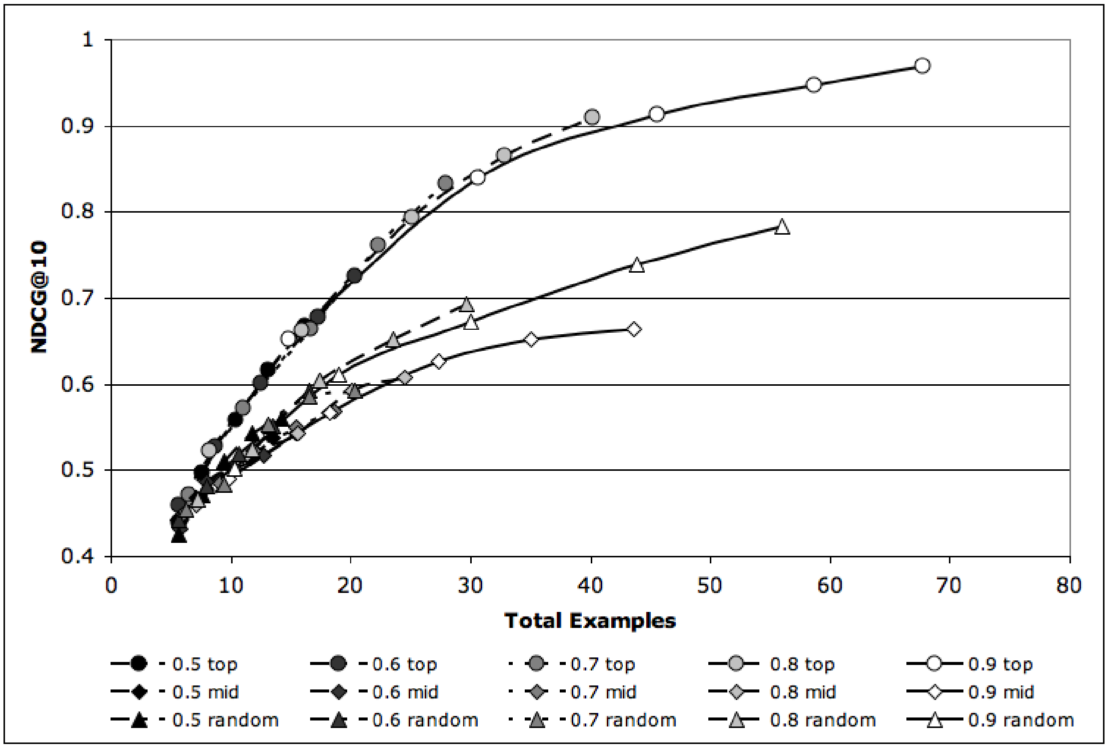


Figure 5.2: Comparison of the total number of examples seen to NDCG@10 for all sampling methods, at thresholds 0.7, 0.8 and 0.9. Markers indicate number of examples per round, from one to five.

active learning method which could potentially perform as well as another method would have worse performance and fewer total examples seen than a method which did not end prematurely. Examples of this happening may be present in this work, especially at high thresholds looking at 4 or 5 examples per round.

We argue that this effect is likely to be minimal. In Figure 5.2, it is clear that the strict dominance of one active learning method over another is consistent over all amounts of feedback greater than around 10 documents. If it is the case that one sampling method would outperform another if both were allowed to continue learning, it appears as though this would not occur until the amount of feedback seen by both methods was in the hundreds.

The remainder of our analysis focuses on factors affecting top sampling. Something to note in Figure 5.2 is that performance gains began leveling off after reaching an NDCG@10 of around 0.8, requiring increasingly more examples for smaller gains in performance. Considering the OHSUMED queries returned 152.27 documents on average, it may appear that decent performance requires feedback on an unreasonable percentage of the returned data. Recall, however, that queries to MEDLINE often result in thousands of results. Further investigation is required to see if queries which return such large results sets require feedback on a similar percentage of documents, a similar number of documents, or something in between.

We see in Figure 5.3 that increasing examples per round increased the total number of examples seen before the convergence threshold was reached. This ran counter to one of our hypotheses; we expected that seeing more examples in each feedback round would reduce the total number of examples required to meet the convergence threshold. Note also that higher convergence thresholds strictly dominate the total number of examples seen as compared to lower thresholds for all values of examples seen per round, showing that increasing the values of these parameters increases the total number of examples seen.

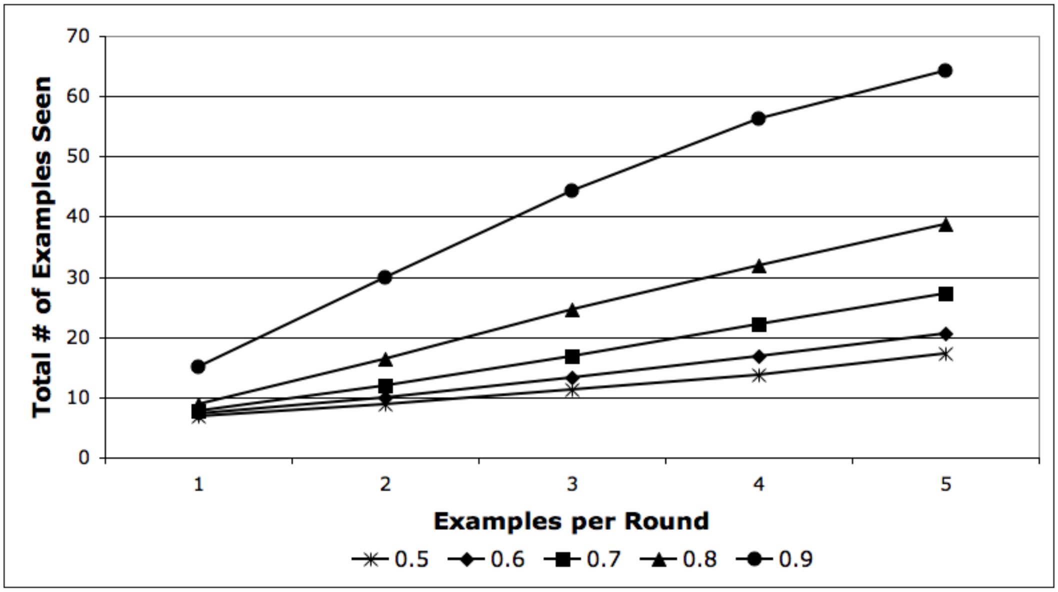


Figure 5.3: Total number of examples seen vs. examples per round, plotted for all convergence thresholds.

We must initially conclude, therefore, that examples per round and the convergence threshold may be largely immaterial to the learning process except as driving the total number of examples seen. A Kendall's tau rank correlation of 0.993 was calculated between system performance and number of examples seen, across all examples per round and stopping thresholds for top sampling. If ranking performance is tied only to the active learning method and number of examples seen, there may simply be a lower bound on the number of rounds required for effective active learning to take place, requiring a number of examples per round equal to the number of examples needed to reach the desired ranking performance divided by this number of rounds. Further investigation is required to determine this lower

Table 5.6: Standard deviations in performance for top sampling. *Italics* indicates standard deviations significantly higher than the mean standard deviation, while **boldface** indicates significantly smaller standard deviations.

Top Sampling					
	1	2	3	4	5
0.5	0.208	0.216	0.216	0.222	0.213
0.6	0.207	0.213	0.224	0.221	0.215
0.7	0.206	0.223	0.215	0.220	0.215
0.8	0.217	0.220	*0.224*	0.207	**0.191**
0.9	*0.237*	*0.225*	0.218	**0.176**	**0.160**

bound, if indeed it exists.

However, this initial conclusion requires further investigation. Recall that performance has been calculated as an average over all OHSUMED queries. Table 5.6 shows the standard deviations in the means of the NDCG scores calculated across all queries, for all thresholds and examples per round for the top sampling method. We find a mean standard deviation of around 0.212, with this mean having a standard deviation of around 0.016. At thresholds 0.8 and 0.9, we find standard deviations which deviate strongly from the mean. At four and five examples per round, the standard deviations are significantly lower than the mean, indicating that the performance is more stable across all queries.

5.3 Active Learning by Proximity Sampling

As explained in Section 2.2.3, the ranking SVM seeks to generalize its ranking hyperplane by finding the hyperplane which maximizes the minimum distance between any two projected points, calculated as $\frac{\mathbf{w}(d_i-d_j)}{\|\mathbf{w}\|}$. The proximity of these points to each other indicates that the ranking function, mathematically, has the least confidence regarding their pairwise preference order, and can therefore be considered the most ambiguous in terms of ranking [53]. Sampling points in this way is targeted at the the mechanism of SVM optimization, and should produce high-quality ranking functions with little feedback.

This method of *proximity sampling* was implemented, and compared with the best performing method from the first set of simulations, top sampling, and a baseline, random sampling. Simulations are carried out using MeSH features, with the convergence threshold and number of examples per round varying as in Section 5.2. We hypothesize that proximity sampling will outperform top sampling.

5.3.1 Results and Discussion

Top sampling strictly dominated the other two active sampling methods (fig. 5.4). Surprisingly, proximity sampling performed only marginally better than random sampling. We believe this may be due to the fact that proximity sampling seeks to optimize the ranking function over the entire ranking function, while top sampling optimizes for the top-end documents. As we report NDCG at the tenth position along the retrieved documents, a reasonable cutoff point for a retrieval task, the top-end optimization produces the better result. The proximity sampling method may prove more useful in future work (see Chapter 8).

5.4 Nonrandom Seeding of Feedback Rounds

Rather than seeding feedback rounds with random documents, we can seed with documents that support the feedback process. Specifically, we can support top sampling by seeding the first round with the highest ranked documents as

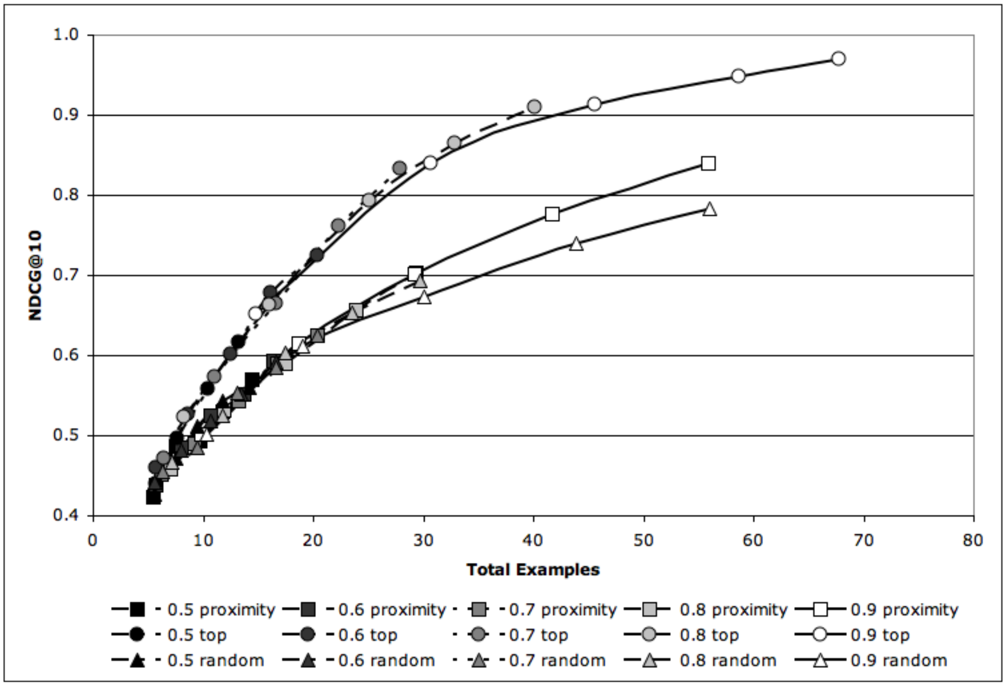


Figure 5.4: NDCG@10 vs. total examples seen until convergence for proximity sampling learning experiments. Values are for all sampling methods, thresholds, and examples per round.

Table 5.7: Averaged performance for proximity sampling method, for all examples per round and thresholds. Top subtable reports NDCG@10, middle reports number of rounds until the convergence threshold is met, bottom reports total number of examples seen until convergence.

Proximity Sampling					
NDCG@10					
Threshold	Examples per round				
	1	2	3	4	5
0.5	0.424	0.487	0.493	0.531	0.569
0.6	0.438	0.485	0.525	0.551	0.593
0.7	0.451	0.489	0.543	0.590	0.626
0.8	0.459	0.531	0.589	0.656	0.703
0.9	0.502	0.615	0.701	0.777	0.840
Rounds to Convergence					
Threshold	Examples per round				
	1	2	3	4	5
0.5	5.460	3.739	3.214	2.935	2.879
0.6	5.753	3.990	3.571	3.426	3.269
0.7	6.228	4.623	4.397	4.177	4.085
0.8	7.071	5.941	5.804	5.972	5.879
0.9	9.805	9.339	9.743	10.43	11.17
Total Examples to Convergence					
Threshold	Examples per round				
	1	2	3	4	5
0.5	5.460	7.477	9.642	11.74	14.39
0.6	5.753	7.979	10.71	13.70	16.35
0.7	6.228	9.247	13.19	16.71	20.42
0.8	7.071	11.881	17.41	23.89	29.39
0.9	9.805	18.68	29.23	41.70	55.86

ranked by some standard relevance-based ranking method. Many such methods are available; to choose which methods to test, we used features from the OHSUMED section of the LETOR learning to rank benchmark data set [35]. Performance for rankings produced by each LETOR feature is presented in Figure 5.5. The top four performing LETOR features are used for seeding, i.e., features L4, L8, and L10 calculated over the title, and feature H5. Tables 3.1 and 3.2 in Section 3.1.3 show how these features are calculated, as well as the portion of the document over which the measure is calculated.

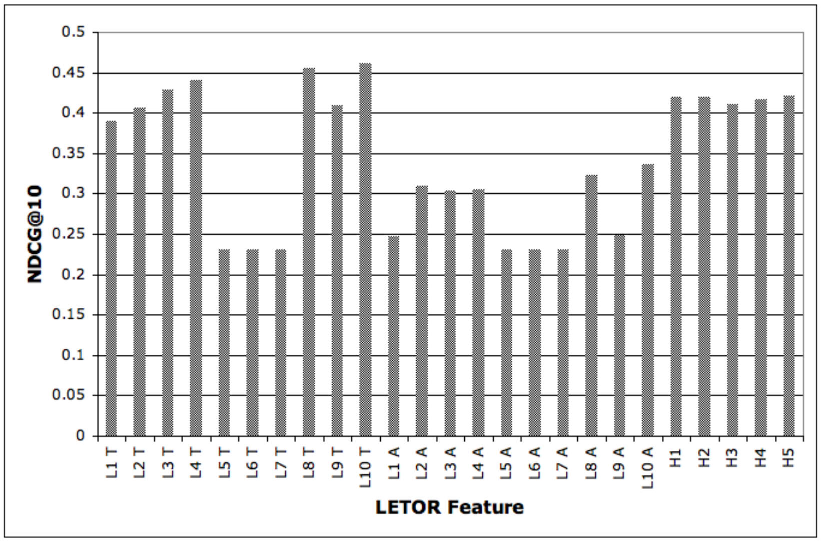


Figure 5.5: NDCG@10 calculated for rankings produced by the 25 LETOR features. L1 T through L10 T indicate features L1-L10 calculated over the title, and L1 A through L10 A indicate features L1-L10 calculated over the abstract.

Simulations are carried out using MeSH features, with the number of examples per round varying as in Section 5.2 and the convergence threshold set at 0.9. We hypothesize that nonrandom seeding will reduce the amount of feedback needed to produce ranking functions that perform similarly to ranking functions learned with random seeding. We do not expect to see an overall increase in performance. Top sampling with random seeding was used as a baseline.

5.4.1 Results and Discussion

As shown in Table 5.8 and Figure 5.6, nonrandom seeding did indeed produce functions that performed comparably to those produced by random seeding with fewer examples. While no initial ranking method clearly dominated the others, L25 produced the best top-end performance. There was also a modest increase in top-end performance over random seeding for all nonrandom seeding methods.

Simulating the effect of a round of sampling by asking for initial feedback on documents ranked by a relevance-based method was especially effective as performance begins leveling off; while proportionally similar amounts of feedback are required to increase performance for both random and nonrandom seeding methods, the absolute amount of feedback required to reach this point is much less for the nonrandom methods, reducing the overall burden for the user.

5.5 Simulation with a Gradient Oracle

OHSUMED judgments are used as an oracle, or perfect knowledge, source for the simulations, as the judgments were made by a panel of professionals in the biomedical field. While actual users of this system are likely to be biomedical professionals as well, it is possible that due to simple human error they will not provide feedback perfectly in line with their preferences. Furthermore, we would like non-professionals to be able to use the system as well; their feedback may include guesses as to the relevance of documents regarding subjects with which they are uninformed. In order to explore the effects of incorrect feedback on system

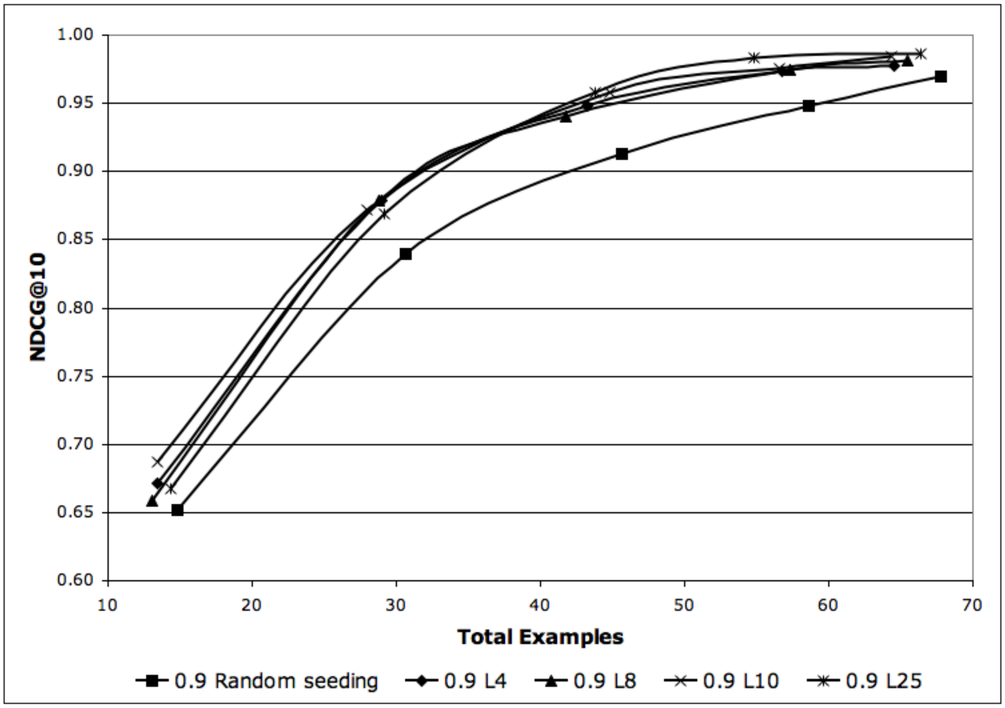


Figure 5.6: NDCG@10 vs. total examples seen until convergence for nonrandom seeding methods for all examples per round and at a convergence threshold of 0.9.

Table 5.8: Averaged performance for random vs. non-random seeding methods over all examples per round at a threshold of 0.9. Top subtable reports NDCG@10, middle reports number of rounds until the convergence threshold is met, bottom reports total number of examples seen until convergence.

NDCG@10					
Seeding method	Examples per round				
	1	2	3	4	5
Random	0.652	0.840	0.913	0.948	0.970
LETOR Feature 4	0.672	0.879	0.948	0.974	0.977
LETOR Feature 8	0.658	0.879	0.940	0.974	0.981
LETOR Feature 10	0.687	0.872	0.958	0.976	0.984
LETOR Feature 25	0.667	0.869	0.958	0.984	0.986
Rounds to Convergence					
Seeding method	Examples per round				
	1	2	3	4	5
Random	14.29	15.32	15.20	14.66	13.55
LETOR Feature 4	13.42	14.49	14.42	14.18	12.90
LETOR Feature 8	13.02	14.38	13.91	14.33	13.09
LETOR Feature 10	13.43	13.96	14.94	14.14	12.87
LETOR Feature 25	14.38	14.56	14.61	13.70	13.28
Examples to Convergence					
Seeding method	Examples per round				
	1	2	3	4	5
Random	14.29	30.64	45.61	58.64	67.74
LETOR Feature 4	13.42	28.98	43.25	56.73	64.51
LETOR Feature 8	13.02	28.76	41.73	57.31	65.47
LETOR Feature 10	13.43	27.93	44.82	56.55	64.33
LETOR Feature 25	14.38	29.13	43.82	54.81	66.41

Table 5.9: Averaged results for the gradient oracle experiments.

Gradient Oracle	1.0	0.95	0.90	0.85	0.8	0.75	0.70	0.65	0.60
NDCG@10	0.970	0.861	0.776	0.693	0.633	0.554	0.498	0.444	0.398

performance, we conducted a experiments using a *gradient oracle*. The gradient oracle provides correct answers with a certain probability, and incorrect answers for the remaining probability. For example, if the OHSUMED judges assigned a score of 1 ("possibly relevant") to a given query-document pair, a 90% oracle asked to judged the same query-document pair has a 90% chance of assigning the pair a 1, a 5% chance of assigning the pair a 2, and a 5% chance of assigning the pair a 0. We conducted these experiments with MeSH feature vectors, using top sampling at a convergence threshold of 0.9 with 5 examples per round, and using gradient oracle values from 1.0 to 0.6 at intervals of 0.05.

5.5.1 Results and Discussion

Table 5.9 shows NDCG@10 for the gradient oracle experiments, showing a clear degradation in performance as the oracle's quality decreases. A linear interpolation of the points results in a slope of 1.4113, indicating that a drop in feedback quality creates an even greater drop in performance (see Figure 5.7). A likely reason for this is that poor feedback will be used to generate poor examples in future rounds, which cripples the sampling process. The primary implication of this finding is that the system will have to implement some form of consistency check if it is to be used by non-experts, and would be a benefit as well to even the most knowledgeable and careful professionals.

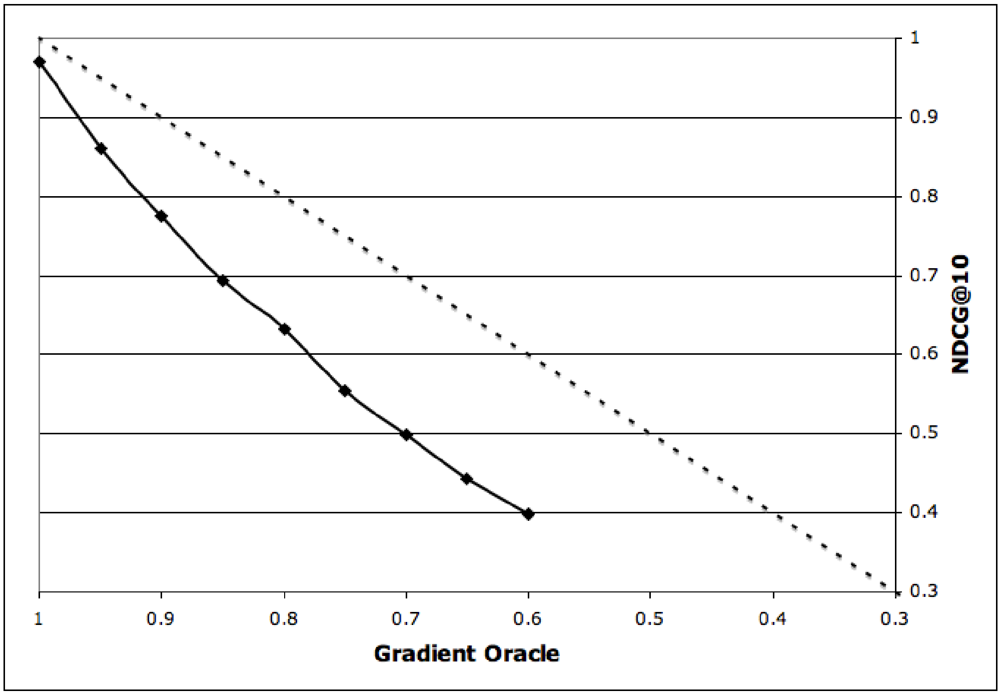


Figure 5.7: NDCG@10 calculated for Gradient Oracle values, dashed line indicates the line $x = y$. Note that values along the x-axis are in decreasing order, to better demonstrate declining performance as the oracle's accuracy declines.

5.6 Conclusion

The experiments presented here show the framework presented for learning to rank documents with SVMs via user feedback is effective in the biomedical domain. Simulations show that ranking functions learned in this way perform at levels approaching perfect ranking with less than half of the available data, indicating that the top sampling method of active learning is well suited to this task. Sampling method was clearly shown to be the driving force behind system performance. The other variable system components, number of examples per round and convergence threshold, were found not to be directly related to the system's performance, but rather indirectly related as they drive the more important factor of total number of examples seen.

Complex active learning methods for example selection may be unnecessary. The proximity sampling method, while targeted at the mechanism of ranking SVM optimization, failed to outperform top sampling, and in fact had performance closer to random sampling. This is a helpful finding as this framework is designed to be used in an online ad-hoc search environment, and simple sampling methods such as top sampling clearly require fewer computing resources than methods such as proximity sampling.

Seeding ranking rounds with examples ranked via some standard relevance-based ranking methods provided a modest improvement in system performance. Though no relevance measure was strictly dominant, all increased top-end performance. More importantly, fewer examples were required to reach high-end performance.

The findings of the gradient oracle simulations are quite important to the end goal of an online tool to be used by biomedical professionals, as the framework has been shown not to be robust to “wrong” or inconsistent feedback. Future work must be done to strengthen the method against such occurrences, especially if the system is to be used by domain neophytes. Section 8.1.4 expands upon this subject.

CHAPTER 6
SIMULATIONS IN THE ENTERPRISE DOMAIN

In order to show that the rank learning framework presented is generally applicable, as opposed to specifically designed for the biomedical domain, we present simulations using the CSIRO data set from the TREC Enterprise 2007 track (Section 3.2.1). This data set is larger than the MEDLINE data set, with many more documents associated with each query. In this chapter, we show that the framework can function successfully over this data set without modification. Furthermore, we show that increase in the size of the data set and number of documents retrieved per query do not pose an issue to system performance.

6.1 Adapting the General Framework to the Enterprise Domain

Again, we perform no live retrieval runs for our enterprise retrieval simulations, preferring instead to use the CSIRO data set. Feature vectors use available DC metadata (Section 3.2.2) as binary inclusion features, similar to MeSH terms in the biomedical simulations (Section 5.1). While many types of DC metadata exist, the only types in the set of judged documents were “keywords” and “format”. Only 88 documents had format metadata, so feature vectors were built with the keywords metadata alone. Since the majority of the documents are not annotated with metadata, feature vectors also include $tf * idf$ term weighting calculations for each term appearing in the document, as in [17]; i.e., terms are stemmed and stopwords are removed.

6.2 Simulations Using the TREC Enterprise 2007 Data Set

These simulations are run to explore the efficacy of the general ranking framework on a data set separate from the biomedical domain. Similar to the simulations run in Section 5.2, our simulations use top sampling, the amount of feedback collected varies between one and five examples per round, and the convergence threshold is set at 0.9. As we use the performance of systems submitted to TREC Enterprise 2007 for performance comparison [4], we choose not to investigate the poorly performing active learning measures and stopping thresholds; as TREC systems are in competition with each other, we are concerned only with achieving peak performance. As a threshold of 0.9 with five examples per round achieved nearly perfect ranking on the biomedical data set (see Section 5.2.2), we assume that we will see similar results here.

6.3 Results and Discussion

Table 6.1: Averaged performance for top sampling method, for all examples per round at a stopping threshold of 0.9.

	Examples per Round				
	1	2	3	4	5
NDCG@10	0.350	0.403	0.469	0.499	0.538
Rounds to Convergence	11.32	9.470	9.722	9.250	9.352
Examples to Convergence	11.32	18.94	29.17	37.00	46.76

Again, we evaluate NDCG@10, rounds to convergence, and total examples to convergence. We use NDCG@10 as a retrieval size of 10 is considered the “first page” of results from a search results, and is therefore a reasonable position to measure ranking performance [20]. Results indicate that our system does not outperform the top TREC Enterprise systems [4], performing nearer to the lower performing systems as shown in Figure 6.1. Our assumption regarding system performance was shown to be incorrect; the enterprise system's ranking performance was far below the that of the biomedical system's performance, achieving a maximum NDCG@10 of 0.538 as compared to the biomedical system's best score of 0.970. There are a number of potential explanations for this finding. First, TREC systems are highly tuned to the task and data set, whereas our system replicated the design and parameters of the biomedical simulations. However, TREC systems do not benefit from user feedback, offsetting this apparent advantage enjoyed by TREC systems. Second, and most importantly, the excellent performance on the biomedical data set was due in large part to the high quality of MeSH annotations; fewer than one-fifth of the enterprise query-document pairs had any metadata of any kind.

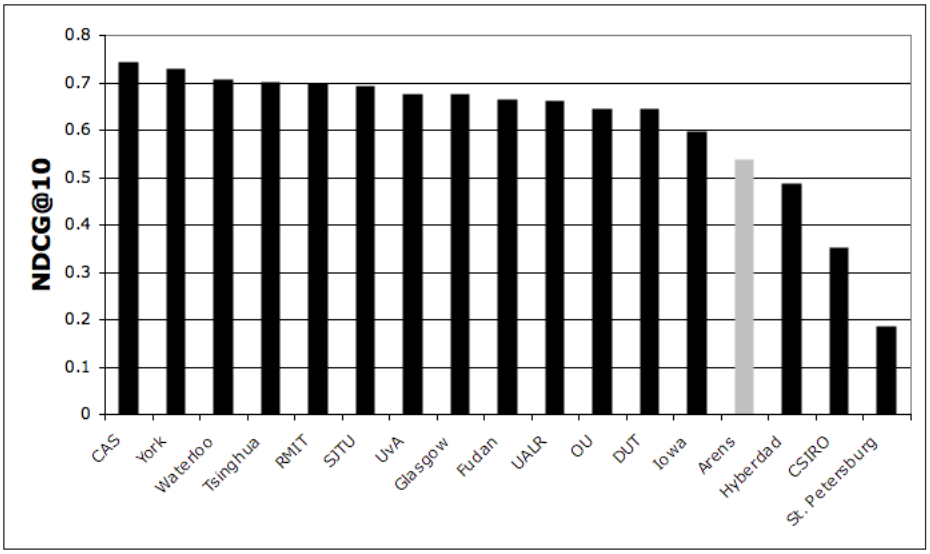


Figure 6.1: Performance comparison with TREC Enterprise 2007 systems, our performance in grey.

In fact, this system's performance is quite comparable to that of the biomedical simulation with LETOR features using top sampling (see Table 5.5 in Section 5.2.2). And while the average OHSUMED query returned 152.27 documents, the average TREC Enterprise query returned 676.28 documents. Table 6.2 compares system performance to the average percentage of data used to achieve that performance for simulations running over both OHSUMED and TREC Enterprise data sets. Note that the similar performance is achieved by the TREC Enterprise system despite utilizing proportionally far less data. This shows that the number of examples needed to reach a certain level of performance stayed generally consistent across the two data sets.

Table 6.2: NDCG@10 compared to average percentage of data utilized, for OHSUMED data vs. TREC Enterprise data. Calculation is done for all numbers of examples per round using top sampling and a stopping threshold of 0.9.

	NDCG@10					% Utilization				
	1	2	3	4	5	1	2	3	4	5
OHSUMED	0.381	0.446	0.484	0.538	0.534	0.052	0.087	0.132	0.177	0.203
TREC	0.350	0.403	0.469	0.499	0.538	0.017	0.028	0.043	0.055	0.069

6.3.1 Limitations

A major limitation of this experiment is that the system was not tuned for this data set in any way. The assumption that the parameters that made the biomedical simulations successful, specifically the top sampling method and convergence threshold of 0.9, would be the same for the enterprise simulations seem to be incorrect. Further testing of lower convergence thresholds and other sampling methods may show that another combination is more effective.

6.4 Conclusion

Our system has been shown to be somewhat effective in the enterprise domain. System performance was below that of the majority of the TREC Enterprise systems, and far below our best performance in the biomedical domain. In retrospect, we should have altered our hypothesis to reflect the fact that we had too little metadata to perform ranking on par with the MeSH data, and instead hypothesized that the system would perform comparatively to the LETOR data. While performance was disappointing, an important result of the simulation was the finding that proportionally more data was not required to achieve proportional performance for differently sized retrieval sets.

CHAPTER 7
USER STUDY IN THE BIOMEDICAL DOMAIN

As the framework presented in this thesis is designed to be used as an online, ad-hoc search system, its performance outside of simulation must be measured. In this chapter, we present a preliminary user study to assess whether or not a large-scale user study is warranted for this system. This study is conducted using PubPref, an online implementation of the rank learning framework presented in Chapter 4 operating over the MEDLINE dataset. We show that human users of the live system report satisfaction with the system, and that good ranking performance is achieved using relatively little feedback regardless of how many documents their queries returned.

7.1 User Study

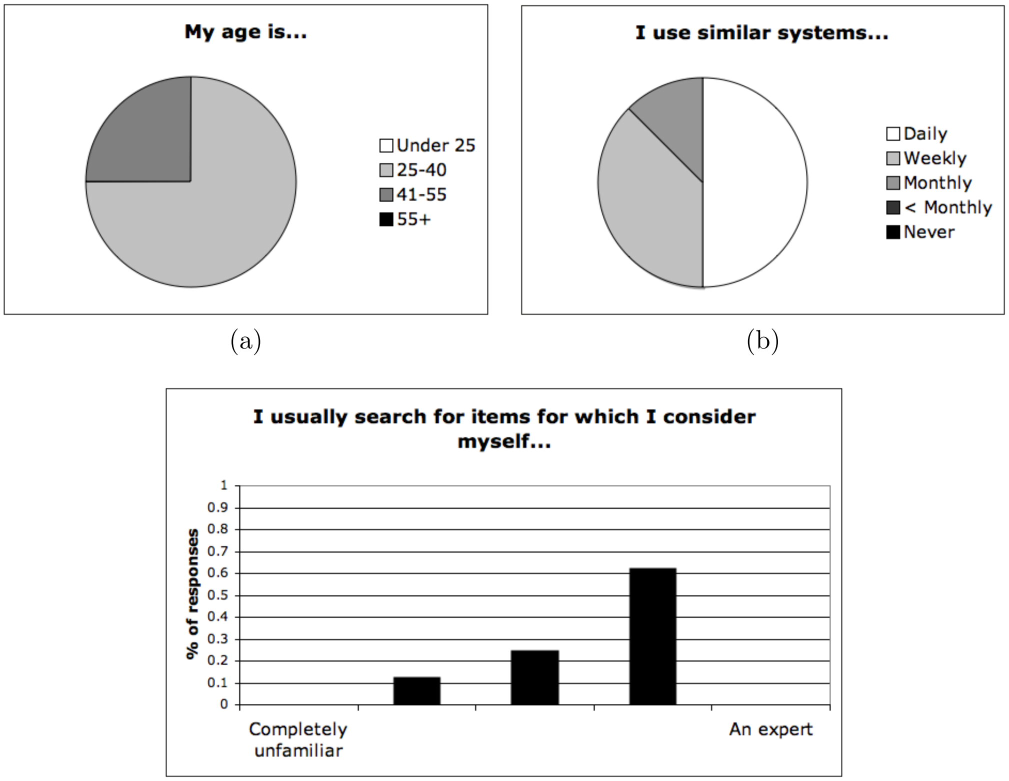
The objective of this study is to ascertain whether or not a full-scale user study of a live, online, ad-hoc system implementing the framework described in this thesis is reasonable. To show this, we intend to compare system performance in simulations to performance in a live system with real users. Specifically, we recreate the conditions of the simulation with MeSH feature vectors, using top sampling with three feedback examples collected per round, and a convergence threshold of 0.7. These parameters were chosen somewhat arbitrarily in order to reproduce the conditions under which our simulations provided a reasonable level of performance, given a reasonable amount of feedback. Furthermore, we wish to determine if the implementation is fast enough to be used in an online, ad-hoc environment. We will consider the framework worthy of further study if we are able to achieve an interquartile mean NDCG@10 of 0.665 with fewer than 17 feedback examples, and an average satisfaction rating above 3.0 regarding system speed (see Section 7.1.2).

7.1.1 Participants

Nine non-remunerated participants engaged in the study, recruited through colleagues of the author. Participants were asked to fill out a demographic survey, as presented in Appendix A.3. The majority of users were between the ages of 26 and 40, and used systems similar to PubPref weekly or daily. The majority of users also reported searching for items with which they had familiarity, but not complete expertise. Demographic data is summarized in Figure 7.2.

7.1.2 Materials and Procedure

The study was conducted online. Participants were given login information for the web-based implementation described in Section 7.1.2.1, along with a copy of the training document described in Appendix A.1 instructing them in basic use of the system. Participants used the system from their personal computers, at a time of their choosing. Upon logging in for the first time, participants were asked to digitally sign a consent form (see Appendix A.2). The study task was to perform a search using the PubPref system, just as one would if searching PubMed. The only guidance they received regarding how they should search was that "PubPref works best with several hundred search results". The intent of this instruction was to encourage participants to submit queries that would return more than ten documents, the minimum required for the PubPref system to function. The practical effect of this instruction is that participants were likely to enter very broad, non-specific queries. As we did not assign arbitrary search queries, participants were allowed to search for documents on subjects they were familiar with.



(a)

(b)

(c)

Figure 7.2: Results from the demographic survey. Each graph is labeled with the question answered, and the percentage of respondents choosing the indicated response.

After entering their query, users are brought to the feedback page, where feedback rounds begin. Rounds continue until the stopping criterion has been met, or the user abandons the search. Abandoned searches are discounted from analysis. Once feedback rounds terminate, results are displayed to the user. The user then has the option of ranking another ten documents, allowing us to be sure that we can calculate NDCG@10 for the final ranking. Finally, the users are asked to fill out a survey regarding their satisfaction with the system, presented in Appendix A.4. The most important facet of satisfaction for this experiment will be question 2, i.e., the user's perception of system speed.

7.1.2.1 Web-Based Implementation of the General Framework

The rank learning framework is implemented as a series of Python CGI scripts supported by a PostgreSQL database backend. User searches are processed using the Entrez eUtils[1] which process the search just as if the user had searched at the main PubMed site. Result identifiers are returned, as the abstracts and their associated MeSH feature vectors are stored locally. SVM ranking and learning is done with the SVMLight package [30]. Searches returning fewer than ten results are not put through ranking rounds, as there is too little data to perform adequate learning and ranking.

7.2 Results and Discussion

Nine participants made a total of twelve queries to the PubPref system. Here, we report the results of the demographic survey administered to the participants, of the use of the system itself, and of the satisfaction survey filled out by participants

[1] http://www.ncbi.nlm.nih.gov/entrez/query/static/eutils_help.html

following system use.

7.2.1 Ranking Performance

Table 7.1: Search query, number of results retrieved, and NDCG@10 for the eight queries analyzed for ranking performance.

Search query	# results	NDCG@10
hepatorenal syndrome	835	0.992
domestic violence in lesbian relationships	20	0.987
cardiac arrest	928	0.986
SETX	17	0.985
rhabdomyolysis alcohol	298	0.999
limb girdle muscular dystrophy	923	1.000
muscular dystrophy genome wide analysis	38	1.000
HPV vaccine male	318	0.974

Nine of the twelve queries returned enough documents for system the system to perform its learning task. The file holding the ranking data for one of these searches was found to have been corrupted in the file system, and had to be discarded, leaving a total of eight ranking sessions for analysis. Table 7.1 shows the searches, the number of document retrieved for the search, and the NDCG@10 calculated for the ranking produced. The results are excellent, far exceeding our expectations and outperforming simulation data for higher stopping thresholds and number of examples per round. One possible explanation for the nearly perfect performance is that the users' queries were simpler than queries used in OHSUMED; still, this performance is based upon actual system use, and is valid on its own merits.

Figure 7.3 shows the relationship between amount of feedback required to complete feedback rounds and the size of the retrieved set of documents. A Kendall's

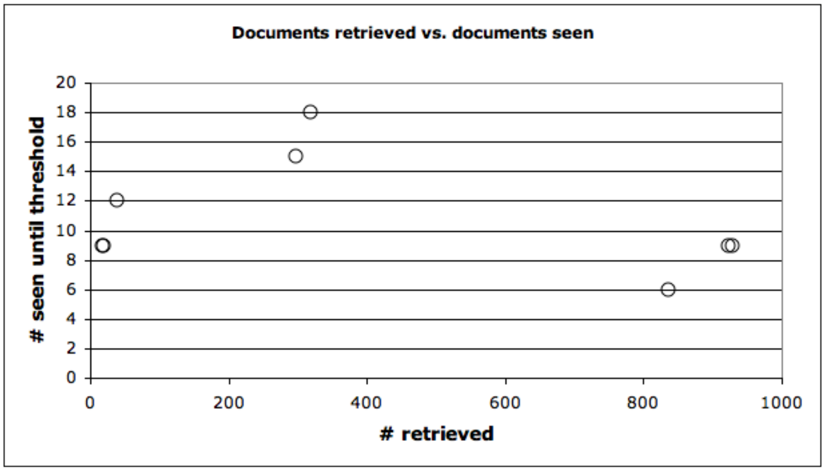


Figure 7.3: Documents retrieved vs. documents seen for all queries.

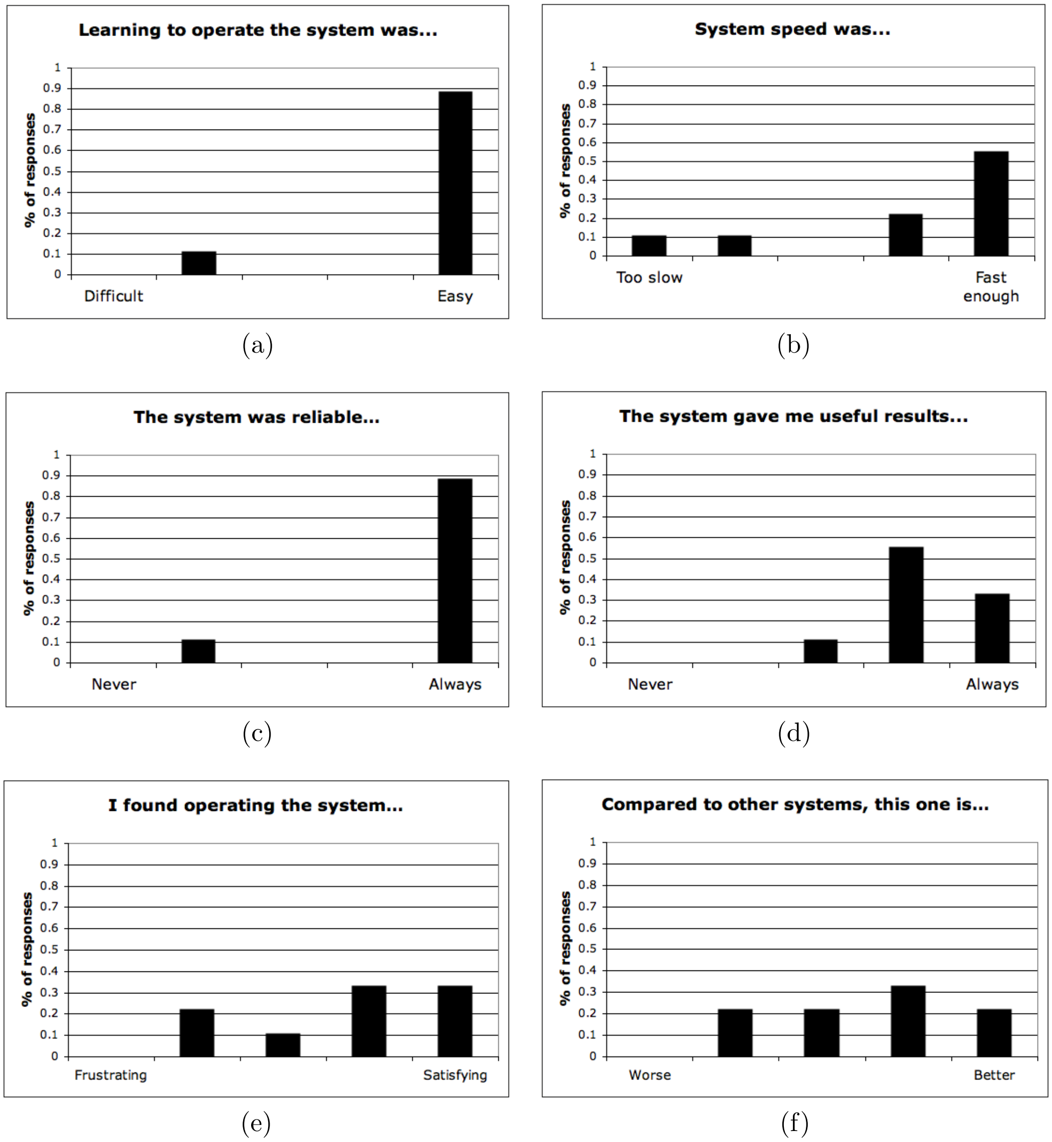
tau rank correlation of 0.00 was calculated for for this relationship, indicating that there is no correlation at all between the number of documents retrieved and the number of documents seen until ranking reaches the stopping threshold.

7.2.2 Satisfaction Survey

Overall, users seem to be well satisfied with the system as it exist. Survey results are summarized in Figure 7.5. Of particular note is Figure 7.5(b) regarding system speed. The vast majority of respondents indicated that they found system speed to be sufficient, with an average score of 4 out of 5.

7.2.3 Limitations

This study is greatly limited in that it has only eight data points from which to draw conclusions. As such, no definitive statements regarding this system's performance can be made. This is appropriate, as the objective of this study was to decide if the system merits further study, based on comparing its performance



(a) (b) (c) (d) (e) (f)

Figure 7.5: Results from the user satisfaction survey. Each graph is labeled with the question answered, and the percentage of respondents choosing the indicated response.

to simulation. Any results we obtained from this study must be verified in a much larger, full-scale study of the system. A second limitation is that we neglected to compare performance of this system to a simple PubMed search ranked by date (the default setting). Thus, we cannot at this point conclude whether or not this system is superior to the existing PubMed search.

7.3 Conclusion

The user study showed that the system works well in an ad-hoc online environment. Ranking data shows that excellent results were obtained with reasonable amounts of feedback, often far less than the number of retrieved documents. We are confident that these results indicate that a full-scale user study is warranted, and that the system will prove useful to members of the biomedical community at large.

CHAPTER 8
CONCLUSION AND FUTURE WORK

In this thesis, we have shown that ranking functions can be learned by support vector machines via user feedback. Ranking functions produced in this way perform well, and can be learned with a reasonable amount of user feedback when examples are chosen via active learning methods. In the biomedical domain, ranking functions produced with a fraction of the available data approached perfect ranking down to the tenth retrieved document, with examples for feedback chosen using the simple top sampling method (Sec. 5.2.2). Seeding the ranking process with ranked documents greatly reduced the amount of feedback required to produce high quality rankings (Sec. 5.4.1). A limitation was found, however, as poor quality feedback had a profound effect on ranking performance, limiting the system's usefulness to non-experts (Sec. 5.5.1). It was found that the general framework for rank learning with SVMs via feedback was also applicable to the enterprise domain, though the untuned system was not found to be superior to existing systems (Sec. 6.4). Finally, a user study to investigate the feasibility of implementing the framework in an online ad-hoc search environment showed that the system performance was comparable to our simulations, as well as showing that large sets of retrieved documents do not require proportionately large amounts of feedback to be ranked (Sec.

7.3).

8.1 Future Work

8.1.1 Full User Study

A natural extension of this work is to conduct a full user study of the online system. A much larger user base would be tapped, and variables such as the convergence threshold and number of feedback examples per round could be studied. Furthermore, general issues such as how much feedback a user is willing to give and user interface issues such as how feedback is provided by the user could be investigated.

8.1.2 Expansion into Legal Discovery

The domain of legal discovery is an interesting one, and worthy of research into whether or not the general rank learning framework is a reasonable solution to problems in the domain. Legal discovery is the process of searching business records for information pertinent to a legal case [5], and carries a number of interesting challenges to information retrieval in general, and more specifically, learning to rank. Search is done neither online, nor is it done in an ad-hoc manner; the most common context for search in legal discovery involves a query that has been constructed through negotiation between opposing legal teams. Furthermore, all documents retrieved by the search must be judged for relevance, due to the consequences involved in failing to produce relevant documents during the discovery process. Compounding these factors and adding to the usual challenges in document retrieval, the document sets over which discovery must be performed may be heterogeneous, composed of many media types and domains.

Document ranking enters the scenario largely as a matter of economy. While retrieval must be balanced towards recovery, precision can help limit time spent reviewing documents not relevant to discovery. Personnel reviewing documents retrieved for discovery are usually paralegals, and cannot be expected to be experts in the material contained in the documents being reviewed. While reviewers making the final determination regarding a document's relevance to discovery must obviously be well trained, less training is required to provide feedback to a system such as the one proposed in this work. A small team of paralegals could be trained quickly to provide feedback to a ranking system, focusing on documents highly likely not to be relevant, limiting the chances of false negative annotation. The resulting ranking function would allow reviewers to better target their efforts.

Another interesting facet of legal discovery is that, since each retrieved document must be reviewed, it is prudent to perform evaluation over the entire retrieval set. The success of the top sampling method in the work presented may not be duplicated in such a task. Experimentation regarding the suitability of other active learning methods, such as proximity sampling, should be repeated for this domain.

8.1.3 Active Learning Methods

This work does not present an exhaustive investigation of active learning methods which could be employed to learn ranking functions as part of the proposed framework. As top sampling produces high quality rankings, future investigations into alternate active learning methods should focus on reducing the amount of feedback required to achieve this level of performance. One potential method would be to measure the similarity between the feature vectors of documents already seen for ranking and those unseen. By choosing highly ranked but unseen examples with feature vectors that do not resemble those already seen, the document space can be more effectively searched.

Beyond investigating different active learning methods, techniques to increase the speed of learning should also be investigated. As performance gains begin to level off at an NDCG@10 of around 0.8, it may be possible to "jump start" learning gains by changing how we sample. Relevant documents dissimilar to those already seen and annotated for feedback may not be seen by top sampling, leading to performance stagnation as documents the system is already ranking with confidence reinforce the existing model without adding any new information. Sampling in a different manner once a reasonable ranking has been achieved will at worst reinforce the existing model, and at best add new information. A simple metric for determining when to change from top sampling could involve identifying when a user gives feedback indicating that all documents submitted for relevance information are relevant. Assuming the set of relevant documents has not been exhausted, this should occur at some point if the ranking is of high quality; if not, new information is presumably being learned.

8.1.4 Consistency Checking and Concept Drift

The gradient oracle experiment showed that poor quality feedback is a major issue for the framework as presented; incorrect or inconsistent relevance judgements result in a disproportionate degradation of system performance. For this reason, it is critical to investigate methods of ensuring that feedback provided by users is consistent with their information need.

A simple way to check for this consistency is to group, or "cluster", feedback. Clustering is an unsupervised machine learning method which seeks to group examples together based on some notion of similarity. If users' feedback is consistent with their information needs, their relevance judgements should eventually cluster together, highly relevant documents clustering with other highly relevant documents, etc. Feedback inconsistent with these clusters could be discarded, or presented to the user again for relevance judgement.

A related topic for future work involves concept drift; as a user searches for documents, the user's information need may change as more is learned about the topic. In this case, inconsistent feedback from early feedback rounds might be the norm. While a fundamentally different task than document retrieval, the framework presented could be adapted to data exploration, allowing the user to explore retrieved documents with no stopping criterion, reranking documents and perhaps retrieving new documents through a relevance feedback mechanism as the user's information need evolves.

8.1.5 Collaborative Filtering

The online tool described in Chapter 7 provides a platform for investigation into collaborative filtering for biomedical professionals. Collaborative filtering involves using data from a number of users in order to filter items in a large data set; it was originally described as a way to filter email and Usenet messages [23], and has been used more recently in recommender systems [25]. Preference data collected from the PubPref user base could be employed to help recommend articles to other users, as well as acting as an active learning method; if a new search is found to be similar to some others done in the past, documents rated highly relevant by other users on those similar searches could be shown to the new user for feedback.

APPENDIX A
USER STUDY MATERIALS

A.1 Training Document

The following text was sent to all study participants. A copy was also viewable online.

PubPref Instructions & FAQ

* What is PubPref? PubPref is a system designed to provide relevance-based ranking for PubMed queries, learned from user feedback. Its aim is to reduce the amount of time spent sifting through search results by sorting those results based on the user's preferences.

* How do I access PubPref? PubPref can currently be found at http://arens.cs.uiowa.edu/cgi-bin/ranking/login.py and is accessible with a username and password. Contact us at pubpref@gmail.com if you're interested in participating!

* How do I use PubPref? Use of PubPref begins at the search panel. Enter a search just as you would at the PubMed interface. Feel free to make your queries less specific than they might normally be; PubPref works best with several hundred search results. The system is currently limited to a maximum of 1000 results, and our pilot study document collection is current up to the year 2007. Search may take up to ten seconds, please be patient.

Once the search returns, you will be instructed to begin the feedback process. Three results from your search will be displayed, with title, abstract, and a link to the result on PubMed. Feel free to click on this link, as it should open in a new window. You are asked to rate each result based on how closely you feel it satisfies your information need. Simply put, is this result the sort of thing you're looking for? Click the "Submit feedback" button at the bottom of the page to continue.

The learning process begins once feedback has been submitted. You will repeat the feedback process a number of times, until a ranking for your search has been learned that meets or exceeds our quality standards. If at any time you wish to abandon the feedback process, click the "Abandon feedback" button at the bottom of the page, and your search results will be displayed using the best ranking data available. Please refrain from hitting the "back" button on your browser during the learning process, as this may cause unexpected behavior in the system.

We consider learning to have been successful when our quality measure has been satisfied. Once this happens, you will be invited to view your search results. Links to the results in PubMed will open in new windows. Once you have finished viewing your results, we ask that you complete our usage survey to let us know your thoughts on the search experience.

* Further questions or comments? Feel free to email us: pubpref@gmail.com

A.2 Consent Form

Following is the text of the consent document participants were required to agree to before using the system.

We invite you to participate in a research study being conducted by investigators from The University of Iowa. The purpose of the study is to assess the efficacy of a web-based search engine system using user feedback for the creation of relevance-based ranking functions for search over high volume document sets.

If you agree to participate, we would like you to use the search system and rate the relevance of search results shown to you over a number of feedback rounds.

After you provide this feedback, we ask that you fill out a short survey regarding your use of the system. You are free to skip any questions that you prefer not to answer. It will take approximately twenty minutes to a half hour to complete this task.

We will not collect your name or any identifying information about you. We will not record your computer's IP address. Each search task you undertake will be given a randomized ID, which will be unconnected to any other searches you have undertaken in the past. It will not be possible to link you to your responses on the survey.

Taking part in this research study is completely voluntary. If you do not wish to participate in this study, simply refrain from logging in to the search website.

If you have questions about the rights of research subjects, please contact the Human Subjects Office, 300 College of Medicine Administration Building, The University of Iowa, Iowa City, IA 52242, (319) 335-6564, or e-mail irb@uiowa.edu.

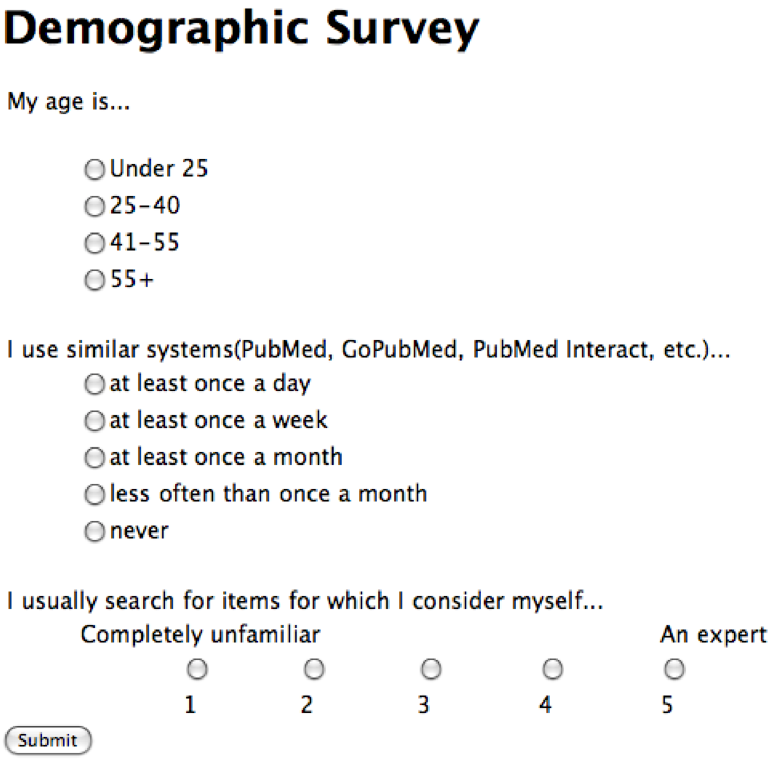
Thank you very much for your consideration of this research study.

A.3 Demographic Survey

Figure A.1 is a screenshot of the demographic survey participants were asked to fill out.

A.4 Satisfaction Survey

Figure A.2 is a screenshot of the satisfaction survey participants were asked to fill out.



Demographic Survey

My age is...

○ Under 25
○ 25-40
○ 41-55
○ 55+

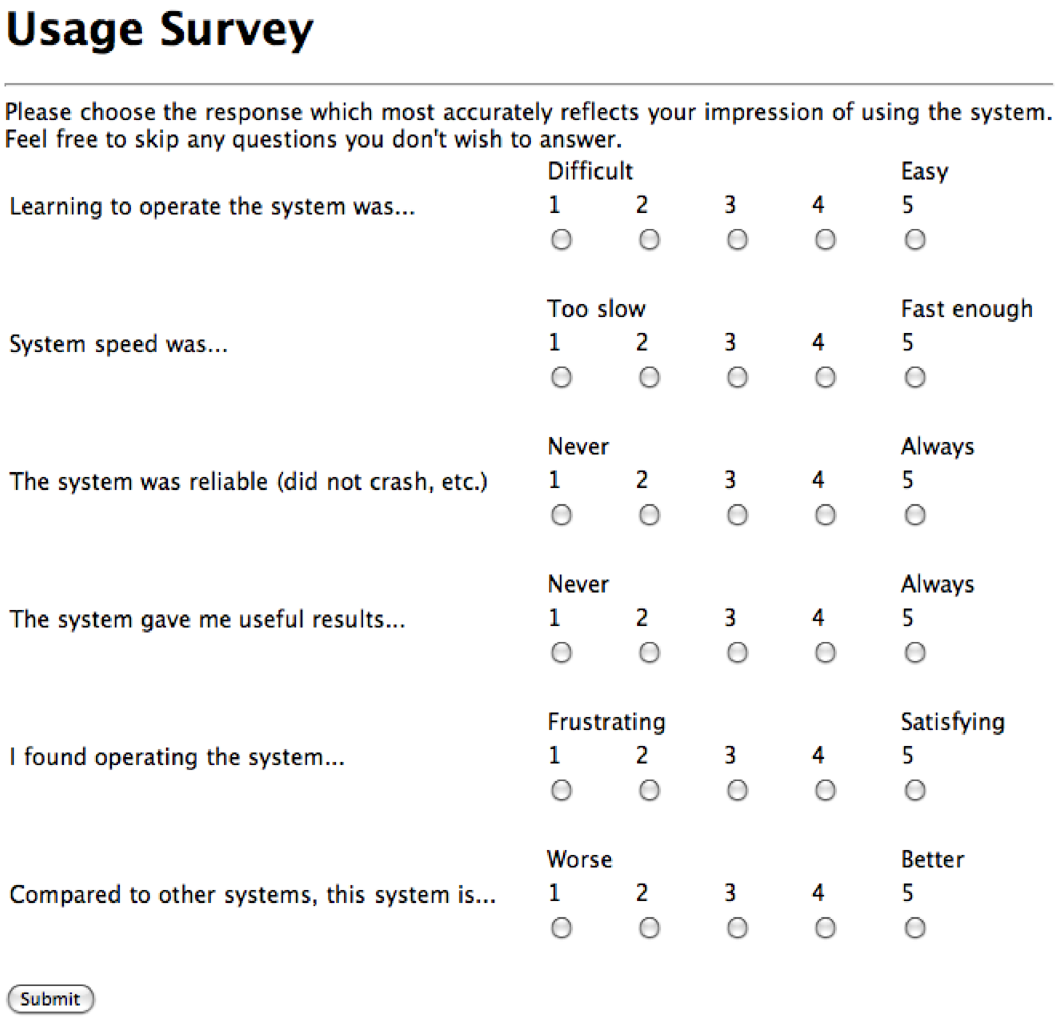
I use similar systems(PubMed, GoPubMed, PubMed Interact, etc.)...

○ at least once a day
○ at least once a week
○ at least once a month
○ less often than once a month
○ never

I usually search for items for which I consider myself...

Completely unfamiliar				An expert
○	○	○	○	○
1	2	3	4	5

Figure A.1: Screenshot of the demographic survey



Usage Survey

Please choose the response which most accurately reflects your impression of using the system. Feel free to skip any questions you don't wish to answer.

	Difficult				Easy
Learning to operate the system was...	1	2	3	4	5
	○	○	○	○	○
	Too slow				Fast enough
System speed was...	1	2	3	4	5
	○	○	○	○	○
	Never				Always
The system was reliable (did not crash, etc.)	1	2	3	4	5
	○	○	○	○	○
	Never				Always
The system gave me useful results...	1	2	3	4	5
	○	○	○	○	○
	Frustrating				Satisfying
I found operating the system...	1	2	3	4	5
	○	○	○	○	○
	Worse				Better
Compared to other systems, this system is...	1	2	3	4	5
	○	○	○	○	○

Figure A.2: Screenshot of the satisfaction survey

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