Personalized Ranking of Search Results with Learned User Interest Hierarchies from Bookmarks

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ABSTRACT
Web search engines are usually designed to serve all users, without considering the interests of individual users. Personalized web search incorporates an individual user's interests when deciding relevant results to return. We propose to learn a user profile, called a user interest hierarchy (UIH), from web pages that are of interest to the user. The user's interest in web pages will be determined implicitly, without directly asking the user. Using the implicitly learned UIH, we study methods that (re)rank the results from a search engine. Experimental results indicate that our personalized ranking methods, when used with a popular search engine, can yield more relevant web pages for individual users.

Categories and Subject Descriptors
H.3.3 [**Information Storage and Retrieval**]: Information Search and Retrieval – *retrieval models, selection process, information filtering, data mining.*

General Terms
algorithms, experimentation.

Keywords
personalized web search results, implicit user interest hierarchy, scoring function, user profile, contents based method.

1. INTRODUCTION
Web personalization adapts the information or services provided by a web site to the needs of a user. Web personalization is used mainly in four categories: predicting web navigation, assisting personalization information, personalizing content, and personalizing search results. Predicting web navigation anticipates future requests or provides guidance to client. If a web browser or web server can correctly anticipate the next page that will be visited, the latency of the next request will be greatly reduced [11,20,32,5,2,13,37,38]. Assisting personalization information helps a user organize his or her own information and increases the usability of the Web [26,24]. Personalizing content focuses on personalizing individual pages, site-sessions (e.g., adding shortcut), or entire browsing sessions [1]. Personalized web search results provide customized results depending on each user's interests [19,18,25,2,17,29,4]. In this work, we focus on personalizing web search by ordering search engine results based on the interests of each individual user, which can greatly aid the search through massive amounts of data on the internet.

There are two main techniques for performing web personalization: collaborative filtering [2,5] and user profiles [28,33]. Collaborative filtering uses information from many different users to make recommendations. Collaborative filtering assumes that people have common interests, and would suggest web pages that are the most popular. Disadvantages of this method are that it cannot predict whether a user will like a new page, and it requires a large amount of data from many users to determine what pages are the most popular. Obtaining data on the web pages visited by many different users is often difficult (or illegal) to collect in many application domains. In contrast, user profiles require the web page history of only a single user. There are two techniques for building a user profile: explicit and implicit. The explicit approach has major disadvantages. It takes time and effort for a user to specify his or her own interests, and the user's interests could change significantly over time. Alternatively, an implicit approach can identify a user's interests by inference, and can automatically adapt to changing or short-term interests.

In this paper, we propose a method to personalize web search by ranking the pages returned from a search engine. Each page's ranking is determined by using the individual's implicitly-learned user profile. Pages are ranked based on their "score," where higher scores are considered to be more interesting to the user after comparing the text of the page to the user's profile. For example, if a user searches for "Australia" and is interested in "travel," then links related to "travel" will be scored higher; but if a user is interested in "universities," then pages related to "universities" will be scored higher. We wish to devise a scoring function that is able reorder the results from Google [14], based on a user's implicitly learned interests, such that web pages that the user is most interested in appear at the top of the page. A User Interest Hierarchy (UIH) is built from a set of interesting web pages using a divisive hierarchical clustering algorithm. A UIH organizes a user's interests from general to specific. The UIH can

WebKDD'05, August 21, Chicago, Illinois, USA.

be used to build a scoring function for personalizing web search engines or e-commerce sites [6]. The web pages in a user's bookmarks are used as the set of interesting web pages for this work [24,26] in order to identify user interests.

While using a search engine, people find what they want. Often times they also find web pages they want to visit next time again. We define *interesting* web pages and *potentially interesting* web pages. The definition of *interest* is whether a user found what they want; the definition of *potential interest* is whether a web page will be interesting to a user in the future.

Our contributions are:

- We introduce personalized ranking methods – Weighted Scoring function (WS) and Uniform Scoring function (US) – that utilize an implicitly learned user profile (UIH);
- We identify four characteristics for terms that match the user profile and provide a probabilistic measure for each characteristic;
- Our experimental results indicate that WS method can achieve higher precision than Google for Top 10, 15 and 20 web pages that are relevant to the user search query;
- The WS method can also yield higher precision than Google for Top 1, 5, 10, 15 and 20 web pages that are *potentially interesting* to the user;
- When incorporating the (*public*) ranking from the search engine, we found that equal weights for the public and personalized ranking can result in higher precision.

The rest of this paper is organized as follows: Section 2 presents related work regarding personalized search results and the use of bookmarks; Section 3 details our approach to reorder search results; Section 4 provides a detailed description of our user-interest scoring methods; Section 5 discusses our evaluation; Section 6 analyzes our results; and Section 7 summarizes our work.

2. RELATED WORK

Page et al. [29] first proposed personalized web search by modifying the global PageRank algorithm with the input of bookmarks or homepages of a user. their work mainly focuses on global "importance" by taking advantage of the link structure of the web. Haveliwala [17] determined that PageRank could be computed for very large subgraphs of the web on machines with limited main memory. Brin et al. [4] suggested the idea of biasing the PageRank computation for the purpose of personalization, but it was never fully explored. Bharat and Mihaila [2] suggested an approach called *Hilltop*, that generates a query-specific authority score by detecting and indexing pages that appear to be good experts for certain keywords, based on their links. Hilltop is designed to improve results for *popular* queries; however, query terms for which experts were not found will not be handled by the Hilltop algorithm. Haveliwala [18] used personalized PageRank scores to enable "topic sensitive" web search. They concluded that the use of personalized PageRank scores can improve web search, but the number of hub vectors (e.g., number of interesting web pages used in a bookmark) used was limited to 16 due to the computational requirements. Jeh and Widom [19] scaled the number of hub pages beyond 16 for finer-grained personalization. Our method does not use the structure of hyperlinks.

Liu et al. [25] also tried mapping user queries to sets of categories. This set of categories served as a context to disambiguate the words in the user's query, which is similar to Vivisimo [35]. They studied how to supply, for each user, a small set of categories as a context for each query submitted by the user, based on his or her search history. Our approach does not personalize the set of categories, but personalizes results returned from a search engine.

Another approach to web personalization is to predict forward references based on partial knowledge about the history of the session. Zukerman et al. [39] and Cadez et al. [5] use a Markov model to learn and represent significant dependencies among page references. Shahabi and Banaei-Kashani [32] proposed a web-usage-mining framework using navigation pattern information. They introduced a feature-matrices (FM) model to discover and interpret users' access patterns. This approach is different from ours since we use the contents of web pages, and not navigation patterns.

PowerBookmarks [24] is a web information organization, sharing, and management tool, that monitors and utilizes users' access patterns to provide useful personalized services. PowerBookmarks provides automated URL bookmarking, document refreshing, bookmark expiration, and subscription services for new or updated documents. BookmarkOrganizer [26] is an automated system that maintains a hierarchical organization of a user's bookmarks using the classical HAC algorithm [36], but by applying "slicing" technique (slice the tree at regular intervals and collapse into one single level all levels between two slices). Both BookmarkOrganizer and PowerBookmarks reduce the effort required to maintain the bookmark, but they are insensitive to the context browsed by users and do not have reordering functions.

3. PERSONALIZED RESULTS

Personalization of web search involves adjusting search results for each user based on his or her unique interests. Our approach orders the pages returned by a search engine depending on a user's interests. Instead of creating our own web search engine, we retrieved results from Google [14]. Since the purpose of this paper is to achieve a personalized ordering of search engine results, we can score a page based on the user profile and the results returned by a search engine as shown in the dashed box in Figure 1. This paper focuses on the scoring function.

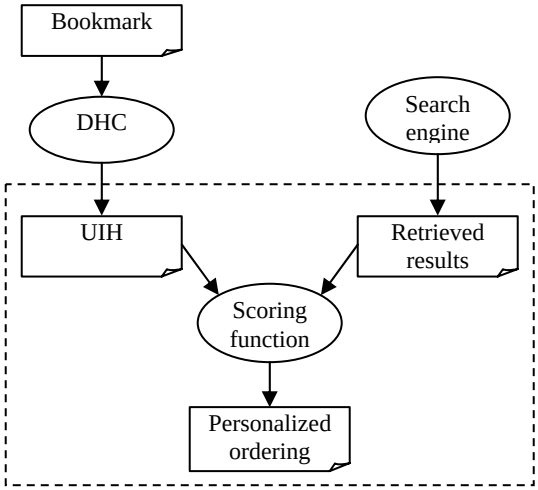
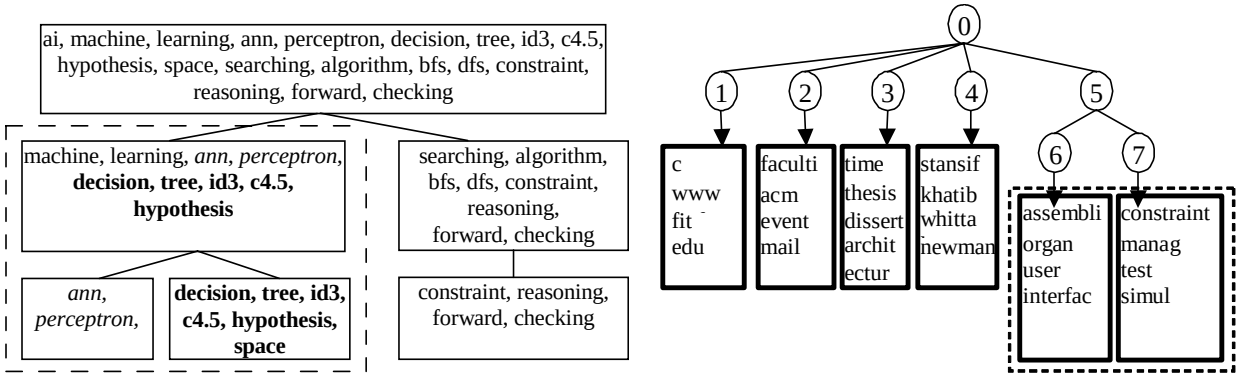


Figure 1. Diagram of Scoring



(a) With sample data set (b) With real data set

Figure 2. Sample user interest hierarchy

To build the user profile, called UIH, we use the web pages in his/her bookmarks [24,26] and the Divisive Hierarchy Clustering (DHC) algorithm [23]. A UIH organizes a user's interests from general to specific. Near the root of a UIH, general interests are represented by larger clusters of terms while towards the leaves, more specific interests are represented by smaller clusters of terms. In this paper, "term" refers a phrase that has one or more word. The root node contains all distinct terms in the bookmarked web page. The leaf nodes contain more specifically interesting terms. The relations between terms are calculated based on the co-occurrence in the same web page.

The DHC algorithm [23] calculates the strength of the relationship between a pair of words and removes all weak correlation values based on the calculated cutoff value for determining strong and weak correlation values. Since related words are more likely to appear in the same document than unrelated terms, it measures co-occurrence of words in a document. It then builds a weighted undirected graph with each vertex representing a word and each weight denoting the correlation between two words. Given the graph, the algorithm recursively partitions the graph into subgraphs, called clusters, each of which represents a sibling node in the resulting. At each partitioning step, edges with "weak" weights are removed and the resulting connected components constitute sibling clusters.

Two examples of a UIH are shown in Figure 2 – UIH (a) is generated from a sample dataset and UIH (b) is generated from a user's real dataset. Each node (cluster) contains a set of words. The root node contains all words that exist in a set of web pages. Each node can represent a conceptual relationship if those terms occur together at the same web page frequently, for example in Figure 2 (a), 'perceptron' and 'ann' (in italics) can be categorized as belonging to neural network algorithms, whereas 'id3' and 'c4.5' (in bold) in another node cannot. Words in these two nodes are mutually related to some other words such as 'machine' and 'learning'. This set of mutual words, 'machine' and 'learning', performs the role of connecting italicized and bold words in sibling nodes and forms the parent node. We illustrate this notion in the dashed box. In Figure 2 (b), Cluster 1 represents the homepage of Computer Science department. Cluster 3 illustrates academic degree programs. Cluster 4 contains names of faculty

members. The tree has a node with two child clusters, Cluster 6 and 7, which contains words from course titles and hence represents the concepts of different courses (in the dashed box).

This paper focuses on devising a scoring method that receives two inputs (UIH and retrieved results) and one output (personalized ranking).

4. APPROACH

In order to provide personalized, reordered search results to a user, we need to score each page depending on personal interests. Therefore, the goal is to assign higher scores to web pages that a user finds more interesting. This section explains how to score a retrieved web page using a user's UIH. First, we explain the basic characteristics for each matching term. Second, based on the characteristics, we propose functions to score a term. These functions determine how interesting a term is to a user. Third, based on the score and the number of the matching terms, we calculate an overall score for the page. Last, since the search engine provides a score/ranking for a web page, we incorporate this ranking into our final score of the web page.

4.1 Four Characteristics of a Term

Given a web page and a UIH, we identify matching terms (words/phrases) that reside both in the web page and in the UIH. The number of matching terms is defined *m*, which is less than the number of total distinct terms in the web page, *n*, and the number of total distinct terms in the UIH, *l*.

Each matching term, t_i, is analyzed according to four characteristics: the deepest level of a node where a term belongs to (Dt_i), the length of a term such as how many words are in the term (Lt_i), the frequency of a term (Ft_i), and the emphasis of a term (Et_i). *D* and *L* can be calculated while building a UIH from the web pages in a user's bookmarks. Different web page has different values for *F* and *E* characteristics. We estimate the probability of these four characteristics and based on these probabilities, we approximate the significance of each matching term. Suppose a web page A has most of the terms bold formatted and the other web page B has only a few terms bold formatted. The bold formatted terms in B may be more significant than the bold formatted terms in A. The probability (0~1) of the bold formatted term can be used to represent the significance/emphasis of the term.

4.1.1 Level/depth of a UIH Node

A UIH represents general interests in large clusters of terms near the root of the UIH, while more specific interests are represented by smaller clusters of terms near the leaves. The root node contains all distinct terms and the leaf nodes contain small groups of terms that represent more specific interests. Therefore, terms in more specific interests are harder to match, and the deepest level (depth) where the term matches indicates significance. For example, a document that contains terms in leaf nodes will be more related to the user's interests than a document that contains the terms in a root node only. If a term in a node also appears in several of its ancestors, we use the level (depth) closest to the leaves.

There is research that indicates user-defined query scores can be used effectively [31,16,8]. From the acquisition point of view, it is not clear how many levels of importance users can specify if we ask a user directly. In I^{3}R [9], they used only two levels: important or default. Harper [16] used 5 levels of importance, and Croft and Das [8] used 4 levels. We calculate the scores of terms using the deepest level (depth) of a node in the UIH instead of explicitly asking the user.

The significance of a term match can be measured by estimating the probability, $P(Dt_i)$, of matching term t_i at depth (level) Dt_i in the UIH. For example, Dt_i=0 includes 100 terms (all terms), Dt_i=1 has 20 terms, and Dt_i=2 contains 10 terms. Then, $P(Dt_i=1)$ will be 0.2 and $P(Dt_i=2)$ becomes 0.1. A term that matches more specific interests (deeper in the UIH) has a lower $P(Dt_i)$ of occurring. Lower probability indicates the matching term, t_i, is more significant. The probability is estimated by:

$$P(D_{t_i}) = \frac{\text{number of distinct terms at depth } Dt_i \text{ in the UIH}}{l}$$

4.1.2 Length of a Term

Longer terms (phrases) are more specific than shorter ones. If a web page contains a long search term typed in by a user, the web page is more likely what the user was looking for.

In general, there are fewer long terms than short terms. To measure the significance of a term match, the probability, $P(Lt_i)$, of matching term t_i of length Lt_i in the UIH is calculated. Lt_i is defined as *MIN* (10, the length of a term) (e.g., t_i = "apple computer", then Lt_i = 2). We group the longer (greater than 10) phrases into one bin because they are rare. Longer terms has a smaller probability, $P(Lt_i)$, of occurring, which indicates a more significant match. The probability is estimated by:

$$P(L_{t_i}) = \frac{\text{number of distinct terms of length } Lt_i \text{ in the UIH}}{l}$$

4.1.3 Frequency of a Term

More frequent terms are more significant/important than less frequent terms. Frequent terms are often used for document clustering or information retrieval [34]. A document that contains a search term many times will be more related to a user's interest than a document that has the term only once.

We estimate the probability, $P(Ft_i)$, of a matching term t_i at frequency Ft_i in a web page to measure the significance of the term. However, in general, frequent terms have a lower probability of occurring. For example, in a web page most of the terms (without the terms in a stop list [12]) will occur once, some terms happen twice, and fewer terms repeat three times or more. Lower probabilities, $P(Ft_i)$, of a term t_i indicates the significance of a term. The probability is estimated by:

$$P(F_{t_i}) = \frac{\text{number of distinct terms with frequency } Ft_i \text{ in a web page}}{n}$$

4.1.4 Emphasis of a Term

Some terms have different formatting (HTML tags) such as title, bold, or italic. These specially-formatted terms have more emphasis in the page than those that are formatted normally. A document that emphasizes a search term as a bold format will be more related to the search term than a document that has the term in a normal format without emphasis. If a term is emphasized by

the use of two or more types of special formatting we assign a priority in the order of title, bold, and italic.

The significance for each type of format is estimated based on the probability, $P(Et_i)$, of matching term t_i with the format type Et_i in a web page. Those format types are more significant/important if the format type has lower probability of occurring in a web page. Lower probability $P(Et_i)$ of a matching term, t_i, indicates the term is more significant. The probability is estimated by:

$$P(E_{t_i}) = \frac{\text{number of distinct terms with emphasis } Et_i \text{ in a web page}}{n}$$

4.2 Scoring a Term

4.2.1 Uniform Scoring

$P(Dt_i, Lt_i, Ft_i, Et_i)$ is the joint probability of all four characteristics occurring in term t_i -- Dt_i is the depth of a node where a term belongs to, Lt_i is the length of a term, Ft_i is the frequency of a term, and Et_i is the emphasis of a term. We can easily observe that there is no significant correlation among the four characteristics. Assuming independence among the four characteristics, we estimate:

$$P(D_{t_i}, L_{t_i}, F_{t_i}, E_{t_i}) = P(D_{t_i}) \times P(L_{t_i}) \times P(F_{t_i}) \times P(E_{t_i})$$

The corresponding log likelihood is:

$$\log P(D_{t_i}, L_{t_i}, F_{t_i}, E_{t_i}) = \log P(D_{t_i}) + \log P(L_{t_i}) + \log P(F_{t_i}) + \log P(E_{t_i}) \quad \text{Eq. 1}$$

Smaller log likelihood means the term match is more significant. In information theory [27], $-\log_2 P(e)$ is the number of bits needed to encode event e, hence using $-\log_2$, instead of log, in Eq. 1 yields the total number of bits needed to encode the four characteristics. The uniform term scoring (US) function for a personalized term score is formulated as:

$$S_{t_i} = -\log_2 P(D_{t_i}) - \log_2 P(L_{t_i}) - \log_2 P(F_{t_i}) - \log_2 P(E_{t_i}) \quad \text{Eq. 2}$$

which we use as a score for term t_i. Larger St_i means the term match is more significant.

4.2.2 Weighted Scoring

The uniform term scoring function uses uniform weights for each characteristic. It is possible that some characteristics are more important than the others. For instance, the depth of a node (D) may be more significant than frequency (F). Therefore, we attempted to differentiate the weights for each characteristic. F and E characteristics represent the relevance of a web page. Longer terms (greater L) represent a user's interest more specifically; however, longer terms do not mean that a user is more interested in that term. Therefore, those L, F, and E characteristics do not fully reflect a user's interests. It is more reasonable to emphasize D characteristic more than other characteristics, because D (depth) represents the strength of a user's interests.

A simple heuristic is used in this paper that assumes the depth of a node is at least two times more important than other characteristics. Based on this heuristic, the weights w_1=0.4, w_2=0.2, w_3=0.2, and w_4=0.2 are assigned. The weighted term scoring (WS) function for a personalized term score is formulated as:

$$S_{t_i} = -w_1 \log_2 P(D_{t_i}) - w_2 \log_2 P(L_{t_i}) - w_3 \log_2 P(F_{t_i}) - w_4 \log_2 P(E_{t_i}) \quad \text{Eq. 3}$$

The performance of WS may depend on how the weights for each characteristic are assigned. We will examine this further in the future.

4.3 Scoring a Page

The *personal* page score is based on the number of interesting terms and how interesting the terms are in a web page. If there are many terms in a web page that are interesting to a user, it will be more interesting to the user than a web page that has fewer interesting terms. If there are terms in a page that are more interesting to a user, the web page will be more interesting to the user than a web page that has less interesting terms.

The personalized page scoring function for a web page Sp_j adds all the scores of the terms in the web page and can be formulated as:

$$S_{p_j} = \sum_{i=1}^{m} S_{t_i} \quad \text{Eq. 4}$$

where m is the total number of matching terms in a web page and St_i is the score for each distinct term. The time complexity of scoring a page is $O(n)$, where n is the number of "distinct" terms in a web page. D and L characteristics can be calculated during the preprocessing stage of building a UIH. F and L characteristics can be calculated while extracting distinct terms from a web page.

4.4 Incorporating Public Page Score

Personal page scoring is not sufficient for some search engines. The success of using *public* scoring in popular search engines, such as Google's PageRank, indicates the importance of using a public page-popularity measure to determine what page a user is interested in. Many existing methods determine the public popularity of a page by determining the number pages that link to it [18,19]. Many collaborative filtering approaches also use the popularity of a web page for recommendation [11,20]. Section 4.3 described our personal web page scoring function. We wish to incorporate the *public* scoring into our page scoring function so both the popularity of a page and individual interests are taken into account. We use the rank order returned by Google as our *public* score. $GOOGLEp_j$ is the score of a web page p_j based on the page rank returned by Google for a search term. Users tend to find the answers they are looking for with Google [10], so we decide to use the Google's rank as the *public* page score. The use of Google's page rank makes our experimental comparison with Google clearer, because any improvement in the ordering is due to the contribution of our *personal* page score. For a given web page, p_j, the *personal* and *public* page score (*PPS*) equation can be written as:

$$PPSp_j = c \times R(Sp_j) + (1-c) \times R(GOOGLEp_j) \quad \text{Eq. 5}$$

where function $R(GOOGLEp_j)$ return the rank of a web page, p_j, with the *public* page score of $GOOGLEp_j$, and $R(Sp_j)$ is the rank of a web page, p_j, with the *personal* page score, Sp_j. If the function R returns the rank in an ascending order, more interesting web pages will have lower *PPS* values. Therefore, the function R reverses the rank. The *personal* page score and the *public* page score are weighted by the value of the constant c. In this paper, both functions are weighed equally: $c = 0.5$.

The performance of US or WS may depend on how much we weigh the *personal* page score over the *public* page score. The experiment with various c will be our future work.

5. EXPERIMENTS

In our experiments data were collected from 11 different users. Of the 11 human subjects, 4 were undergraduate students and 7 were graduate students. In terms of major, 7 were Computer Sciences, 2 were Aeronautical Sciences, 1 was Chemical Engineering, and 1 was Marine Biology. We asked each volunteer to submit 2 search terms that can contain any Boolean operators. Some examples of the search terms used are

{review forum +"scratch remover", cpu benchmark, aeronautical, Free cross-stitch scenic patterns, neural networks tutorial, DMC(digital media center), artificial intelligence , etc.}

Then, we used Google to retrieve 100 related web pages for each search term. Those collected web pages (about 2,200 in total) were classified/labeled by user based on two categories: *interest* and *potential interest*. The data set for *interest* has more authority because it indicates direct relevance to the current search query. The data set for *potential interest* reflects the user's general personal interests, which might not be directly relevant at the time of query. The areas of a user's *potential* interests often go beyond the boundary of a search term's specific meaning. Sometimes users find interesting web pages while searching for different subjects. These unexpected results help the user as well. Therefore, it is also a contribution if a method shows higher precision in finding *potentially* interesting web pages.

In order to build UIHs, we also requested each volunteer to submit the web pages in their bookmarks. If there were fewer than 50 web pages in their bookmarks, we asked them to collect more pages up to around 50. The minimum number of web pages was 38 and the maximum number was 72. Web pages from both bookmarks and Google were parsed to retrieve only texts. The terms (words and phrases) in the web pages are stemmed and filtered through the stop list [12]. A phrase-finding algorithm [22] was used to collect variable-length phrases. Words in selection boxes/menus were also removed because they did not appear on the screen until a user clicks on them. Unimportant contexts such as comments and style were also removed. Web pages that contain non-text (e.g., ".pdf" files, image files, etc.) were excluded because we are handling only text. To remove any negative bias to Google, broken links that were still ranked high erroneously by Google were excluded from the test, since those web pages will be scored "Poor" by the user for sure. The data used in this study is accessible at http://cs.fit.edu/~hkim/dissertation/dissertation.htm.

Microsoft .NET language was used, and the program ran on an Intel Pentium 4 CPU.

Users categorized the *interest* as "Good", "Fair", and "Poor"; the *potential interest* is categorized as "Yes" and "No". A web page was scored as "Good", "Fair", and "Poor" depending on each individual's subjective opinion based on the definition of *interest*. We are interested in the small number of "Good" web pages, since users tend to open only the top several web pages. That is why we use the three scales instead of two scales such as "related" and "not related". It was also marked as "Yes" or "No" based on the user's *potential interest*. We evaluated a ranking method based on how many interesting (categorized as "Good") or *potentially* interesting web pages (categorized as "Yes") the method collected within a certain number of top links [2] (called "Top link analysis"). It is realistic in a sense many information retrieval systems are interested in the top 10 or 20 groups. Precision/recall graph [34] is used for evaluation as well (called "precision/recall analysis"). It is one of the most common evaluation methods in information retrieval. However, traditional precision/recall graphs are very sensitive to the initial rank positions and evaluate entire rankings [8]. The formula for precision and recall were:

```
Precision = Number of "Good" or "Yes" pages
retrieved in the set / Size of the set

Recall = Number of "Good" or "Yes" pages
retrieved in the set / Number of "Good" or
"Yes" pages in the set
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where the "set" is the group of top ranked web pages. In this paper we study five groups: Top 1, 5, 10, 15, and 20.

6. ANALYSIS

We compare four ranking methods: Google, Random, US, and WS. Google is the ranking provided by Google. Random arbitrarily ranks the web pages. US and WS are the two proposed methods based on a personal UIH learned from a user's bookmarks. For Random, US, and WS, the top 100 pages retrieved by Google are re-ranked based on the method. Each method is analyzed with two data sets: a set of web pages chosen as interesting and another chosen as potentially interesting by the users. Top link analysis, precision/recall analysis, the sensitivity of personal score weight c (Section 4.4) are discussed.

6.1 Interesting Web Page

6.1.1 Top Link Analysis

Web search engine users are usually interested in the links ranked within top 20 [7]. We compare each method only with Top 1, 5, 10, 15, and 20 links on the *interesting* web page data set and present the results in Table 1. The first column is the methods; the next five columns present the precision values of each method with respect to the five Top links. The values in each cell are the average of 22 search terms' precision values. High precision value indicates high accuracy/performance. Precision values higher than Google's are formatted as bold and the percentage of improvement is within parentheses. The highest precision value in each column is underscored.

Table 1. Precision in Top 1, 5, 10, 15 and 20 for interesting web pages

	Top 1	Top 5	Top 10	Top 15	Top 20
Google	.36	.34	.277	.285	.270
Random	.14	.25	.205	.206	.209
US	.32	.31	**.323(17%)**	**.315(11%)**	**.305(13%)**
WS	.36	.34	**.314(13%)**	**.327(15%)**	**.309(14%)**

Table 2. Precision in Top 1, 5, 10, 15 and 20 for potentially interesting web pages

	Top 1	Top 5	Top 10	Top 15	Top 20
Google	.59	.53	.514	.509	.475
Random	.36	.39	.350	.358	.364
US	.59	**.58 (9%)**	**.536 (4%)**	**.521 (2%)**	**.493 (4%)**
WS	**.64 (8%)**	**.62 (17%)**	**.541 (5%)**	**.524 (3%)**	**.498 (5%)**

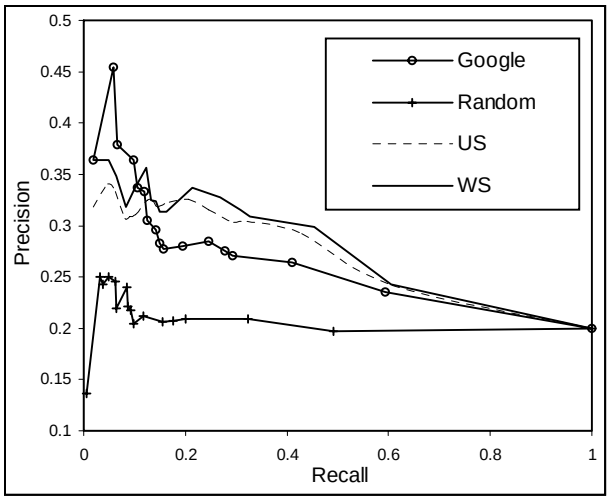

Figure 3. Precision/recall graph for interesting web pages

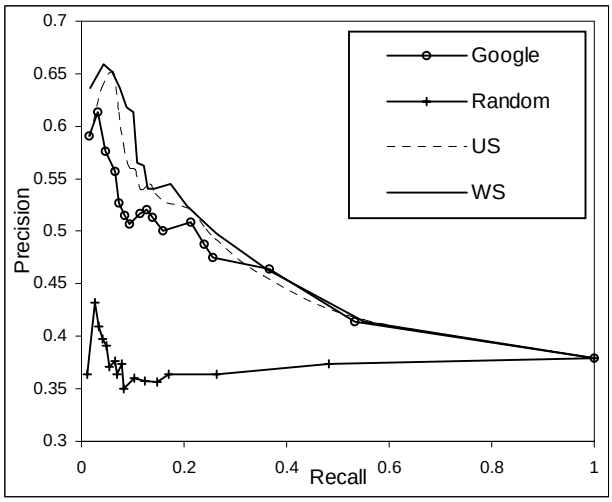

Figure 4. Precision/recall graph for potentially interesting web pages

The results show that our WS method was more accurate than Google in three Top links (Top 10, 15, and 20) and the percentages of improvements are at least 13%, while WS ties with Google for Top 1 and Top 5. In terms of the highest precision, WS showed highest performance in four columns; Google showed in only two columns and the values are equal to WS. Compared to US, WS showed higher precision in four (Top 1, 5, 15 and 20) of the five columns. Random was the lowest as we expected, showing the lowest precisions in all five columns. These results indicate that WS achieves the highest overall precision.

We also wanted to know which search terms yielded higher precision with WS than with Google and analyzed the precision with respect to each individual search term. Out of 22 search terms (11 users × 2 search terms), WS achieved higher precision for 12 search terms (55%), Google did for 8 search terms (36%), and they were even for 2 search terms (9%). The terms that WS win are {Caribbean History, complex variables, DMC(digital media center), XML Repository, beos operating system, artificial intelligence, military weapons, windows xp +theme +skin, extreme programming principles, java design patterns, Australia adventure tours, Australia ecology}. The terms that Google win are {aerospace, aeronautical, boston pics, cpu benchmark, sniper rifle, review forum +"scratch remover", woodworking tutorial, neural networks tutorial}. Since the UIH is built from a user's bookmarks, we analyse the bookmarks to understand the search terms that did not perform well using WS. When we compare the bookmarks with the "good" retrieved web pages, we found that they are unrelated. For example, a volunteer used "woodworking tutorial" as a search term, but he never bookmarked web pages related to that term. This implies bookmarks are useful for building user profiles, but they are not sufficient. We will discuss enhancements in the conclusion.

6.1.2 Precision/Recall Analysis

Precision/recall analysis visualizes the performance of each method in graphs as shown in Figure 3. The *x*-axis is recall and *y*-axis is precision. The line closer to the upper-right corner has higher performance. WS and US are closer to the upper-right corner than Google except with recall values lower than .15 (after Top 5). The consistent higher performance after Top 5 tells us that WS yields higher performance than Google. In general, WS outperforms US and Random.

6.2 Potentially Interesting Web Page

6.2.1 Top Link Analysis

We compare our four methods with Top 1, 5, 10, 15, and 20 links on the *potentially* interesting web page data set and present the results in Table 2. The values in each cell are the average of 22 search terms' precision values. The ways of reading this table and the table for *interesting* web pages are similar.

WS showed higher performances than Google in all five Top links. All five precisions achieved by WS are the highest values as well. The percentages of improvements are between 3% and 17%. Random showed the lowest in all five Top links. The reason for the improvement of WS is, we predict, because the UIH that was

derived from a user's bookmarks supported the user's *potential* interest. It might be difficult for Google that used the *global*/*public* interest to predict individual user's broad *potential* interests.

We also counted what search terms yielded higher precision with WS than with Google. WS achieved higher performance for 12 search terms (55%), Google made for 8 search terms (36%), and they were even for 2 search terms (9%) out of 22 search terms. The reason for the low performance of some search terms might be because there is no relation between his/her bookmarks and the search terms.

6.2.2 Precision/Recall Analysis

The results from precision/recall graph for *potentially* interesting web pages in Figure 4 and the Top link analysis in Table 2 are similar. WS was closer to the upper-right corner than Google, US, and Random over all. WS outperformed other methods on *potentially* interesting web pages data set.

7. Conclusion

The purpose of this research is to devise a new method of ranking web search results to serve each individual user's interests. A user profile called UIH is learned from his/her bookmarks. For scoring a term in a web page that matches a term in the UIH, we identified four characteristics: the depth of tree node in the UIH that contains the term, the length of the term, the frequency of the term in the web page, and the html formatting used for emphasis. Our approach uses the terms filtered though stop list in web pages [12]. This approach removes the process of selecting important/significant terms unlike other information retrieval techniques [30]. Therefore, we can handle smaller data set and reduce the danger of eliminating new important terms. We evaluated methods based on how many interesting web pages or potentially interesting web pages each algorithm found within certain number of top links [2]. Traditional precision/recall graphs [34] were also used for evaluation. We counted which search term showed higher performances with WS than with Google as well.

We compared four ranking methods: Google, Random, US, and WS. Google is the most popular search engine and posts the best ordering results currently. Random method was chosen to see the improved performance of Google and our new methods. We used two data sets: interesting web pages that are relevant to the user search term and potentially interesting web pages that could be relevant in the future. On interesting web pages, the Top link analysis indicated WS achieved at least 13% higher precision than Google for Top 10, 15 and 20 links on average. WS outperformed US and Random in general also. The precision/recall analysis showed that WS outperformed Google except with recall values lower than .15. Out of 22 search terms, WS achieved higher precision than Google for 12 search terms (55%). On potentially interesting web pages, WS achieved the highest performance in all five Top links with improvement over Google between 3% and 17%. It also outperformed the other methods in the precision/recall graph. The analysis of individual search terms yielded the same results as on interesting web pages. Therefore, these results conclude that WS can provide more accurate ranking than Google on average.

The improvement of WS was not statistically significant because the precision values of Google had large variance. The reason for the low performance of some search terms might be because there is no relation between his/her bookmarks and the search terms. We may be able to relieve this problem by incorporating interesting web pages based on implicit interest indicators such as mouse movements [21] in addition to bookmarking. There is a downside to using bookmarks because it relies on users deleting old bookmarks that they no longer consider relevant, so the data may become polluted with uninteresting documents with time. Therefore, we may have to adjust the time as the fifth characteristic. In this work, we used two characteristics of a term for personalization. The effect of these qualitatively different features should be evaluated in the future as well.

During the experiment, we observed that users do not tend to measure index pages as "Good". It is because index pages usually contain long lists of hyperlinks with little description for a user to find interesting. To identify index pages automatically, we count the number of "outside words" (the text outside anchor tags), which usually provide the subject content. However, our approach of penalizing the index pages did not make much improvement in our initial experiments. We will examine this approach further in the future.

Measuring the precision with clustered search results like the results from Vivisimo [35] may show different performance from Google's. In a clustered search engine, a link that does not belong to the top 10 in whole can belong to the top 10 in some sub clusters. The clustered search results provide users easier access to the *interesting* links after Top 10 or 20. Since WS showed higher performance for those links than Google as shown in Section 6.1.3, we assume that our method may get higher performance with clustered search engines.

8. Acknowledgments

We appreciate all volunteers who participated in our experiment: Akiki, Michel, Timmy, Matthew Scripter, Ayanna, Da-hee Jung, Jae-gon Park, Ji-hoon Choi, Jun-on, Chris Tanner, and Grant Beems.

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