Investigating Users' Needs and Behavior for Social Search

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Abstract. Traditional Web search systems have limitations due to its unrealistic assumption on users' query formulation and lack of context-sensitivity. To overcome these limitations, we designed and implemented a social search system which is based on a social adaptive navigation system Knowledge Sea and exploits the past usage history of users. By conducting a survey and transaction log analysis, we could observe users' strong attitudes to the need for the social search capability. We could also observe their active use of the new feature and change of behavior while they were using the search system. At the initial stage of our experiment, users did not show big difference in their usage of the system compared to the conventional search services but as time passes and the usage history accumulates, meaningful changes in their behavior toward the use of social navigation support features of the system were discovered.

1 Introduction

The explosive growth of the Web and its information contents addresses the need for the design of effective tools which can help people to find out proper information they need in an efficient way. Various Web search services have been developed and used so far but their quality of services in terms of user needs has been far from perfection and the problems of these services have been continuously pointed out.

Most of these Web search services are based on the traditional approach of information retrieval, which assumes that the query space and the document space are identical. However, in a real situation, especially in the new Web environment, it is not quite true. Web search service users are formulating very ambiguous and short queries unlike the experimental setting where a lot of queries were formulated and refined by domain experts and the length of them was long enough to express users' information needs. Most users are not familiar with expressing their needs in exact query terms which appears in the document space and the number of terms used for their queries are just two or three in average [8]. This situation brings the mismatch between the query space and the document space [6].

Also, most of the Web search engines adopt a "one size fits all" approach. Different users get the same set of search results if they use the same query with other users when they use search engines based on this approach. They are not personalized and are context-independent, so they can't serve different users' different needs.

Various new ideas have been developed to overcome the limitations of the traditional approach. For example, Google is exploiting link-connectivity information in addition to the traditional term based retrieval model. It applies higher weights to the documents which has more in-link counts and let them appear closer to the beginning of the retrieved result list [1]. *Social search* is another attempt to improve the traditional approach. Like link-connectivity based approach, it makes use of new features to promote the effectiveness of search results. A group of different users who share the same interest can use similar query terms for the same task and their search experiments can be shared. Based on this observation, social search approach exploits past search histories. When a user enters a query, the social search system looks up the search history of the group where the user belongs to and can provide better search results by re-ranking with the clues extracted from the search history or by providing the user with more evidences in addition to the baseline term matching retrieval systems. We have designed and implemented a social search engine for a social navigation system Knowledge Sea. In order to test users' need for this system and to find out if their behavior is different with that of conventional search systems, we conducted user surveys and transaction log analysis.

2 Background

2.1 Social navigation

Social navigation [4] research tries to explore methods for organizing users' explicit and implicit feedback in order to support information navigation in a meaningful way [2]. This approach includes two features. The first feature is to support a known social phenomenon, which means that people tend to follow the "footprints" of other people. The second important feature is self-organization, which allows social navigation systems to function with little or without manual endeavors of human administrators or experts. The well known exemplar systems based on this approach are Web auctions or Weblogs.

Jon Dron and others [5] also introduced CoFind (Collaborative Filter in N Dimensions), which structures and selects learning resources for teachers. This system was inspired by the concept of *stigmergy*. Stigmergy is a word coined by Grasse and it refers to systems employed by termites when building mounds [7]. When termites build mounds or ants form trails, they can produce mounds and trails by following their colleagues' traces in a collaborative way. These outputs can become stronger as time passes and more group members participate. They also can dissipate if a specific cause runs out and the members' participation decreases, in such a way that when food runs out, the trail to the location of the food dissipates as time passes and ants follow less after they found out no more food from there.

2.2 Knowledge Sea

Knowledge Sea is a Web-based social navigation support system. It organizes Web-based open and closed corpus C language teaching materials including online tutorials and lecture slides. In order to implement this mixed corpus based social navigation, Knowledge Sea uses a knowledge map of the domain [3] – a two-dimensional table consisting of 64 cells. It is built by self-organized map (SOM) algorithm. Semantically related keywords and documents were assigned for each cell. Contents of neighboring cells are semantically related.

Background colors of the cells indicate the popularity of the cells. As more users click and visit a cell, the background color of the cell gets darker. When they click a cell, they can see a list of documents and can choose a document from the list.

The same logic to represent popularities by color lightness is applied to the representation of documents inside each cell. Each item of the list provides two types of information, traffic and annotations. “Human-figure” icons and colors provide users with popularity information and “thumbs-up” or “thermometer” icon and colors provide users with annotation information. If a document is popular among the group where a user belongs to, the background color of the icon gets darker. The foreground color of the icon gets lighter if the user clicked the document fewer times than other group members. Just like popularity, darker background color of an annotation icon indicates there are a lot of annotations for the document. “Sticky-note,” “thumbs-up,” and “question-mark” icons indicate “General,” “Praise,” and “Question” annotations respectively. A red “thermometer” icon indicates the overall annotations are positive, and a blue icon indicates the overall annotations are negative. Therefore, users can navigate socially by referring to other users’ behavior and opinions by looking up these icons and colors provided by Knowledge Sea [2].

2.3 Social search

Social search or collaborative search is an approach to promote the effectiveness of web search by relying on past search histories [6]. Smyth and others [6] implemented and tested I-SPY which is based on the concept of social search. This system is based on the observation that for specialized topic searches, the number repetition of query terms is higher than that of general topic searches. Therefore, they stored query-document frequency matrix from past search histories of the community users and re-ranked search results by looking up these query-document frequencies. They reported improvement of search results by this approach.

This study tried to implement social search capability to the existing Knowledge Sea social navigation system. Along with the browsing mode provided by Knowledge Sea, we added a search interface and let users directly search for documents they needed. Because it is based on Knowledge Sea and share the corpus and database with Knowledge Sea, the users could retrieve search results with social navigation information and make use of it.

3 System Design and Implementation

As described above, the search functionality was added to the social navigation system Knowledge Sea. In the original Knowledge Sea, users access documents through navigation using knowledge map and links between documents. Social navigation support assists the users in their navigation. With the additional search functionality, users are able access documents by entering query terms and continue their social navigation (Figure 1).

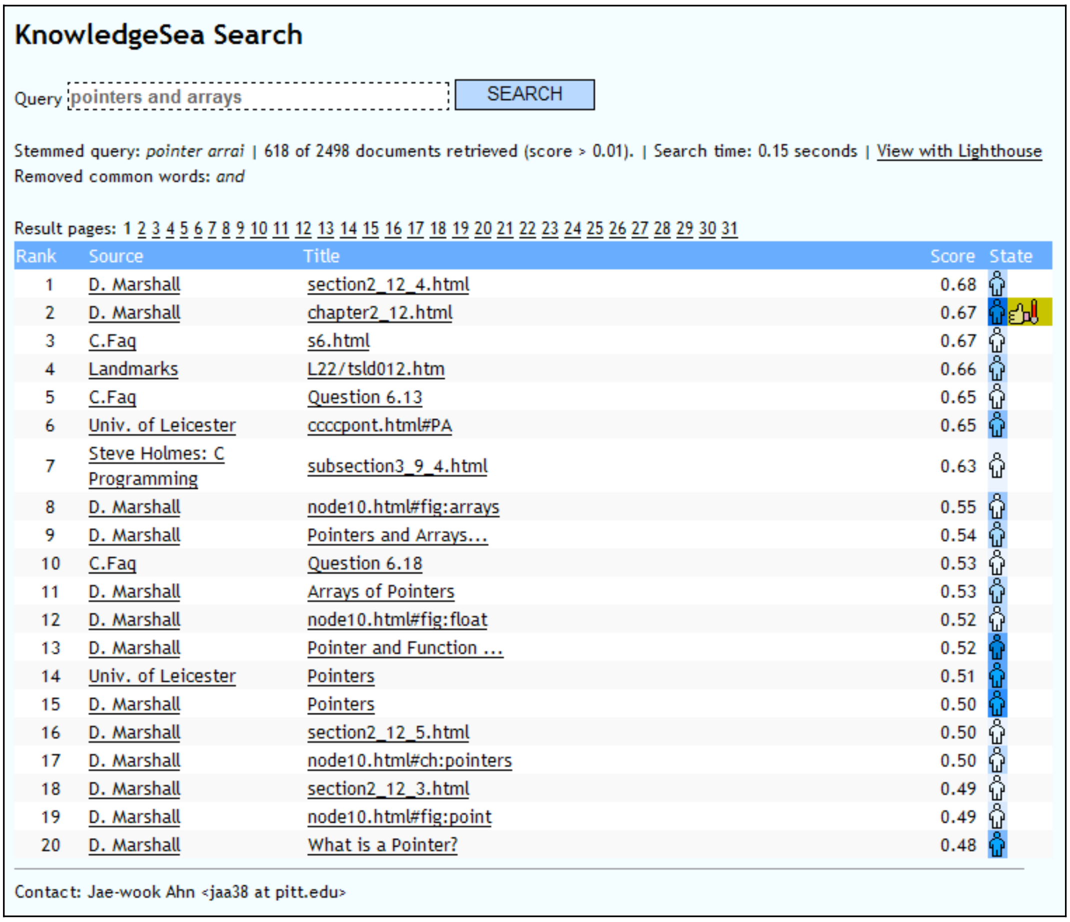

Fig. 1. Knowledge Sea search interface

3.1 Document Processing

The document collection indexed by the search system is the Knowledge Sea collection of C language educational materials. Knowledge Sea stores URL's of all documents to generate social navigation cues in runtime. The search system fetches these URL's, downloads and indexes them to make them searchable.

Terms collected from the documents are stemmed according to Porter's stemming algorithm [9]. Very common or rare terms which are stored in a stopword list were excluded. However, due to the characteristics of the document collection, which is a C language tutorial pages, some stopwords such as "if", "for", and "while" should be stored in the index because users can use them as query terms and retrieve documents containing them. Therefore, a C keyword list was constructed and they were also included in the index. The identical process is applied to query terms when users enter queries.

The terms stored in the index of the search system were weighted by their importance for each document. The weighting scheme used is TF-IDF, which means TF (Term Frequency, frequencies of terms for each document) multiplied by IDF (Inverse Document Frequency, inverse of the number of documents where a term appears). TF means how many times a given term appeared in a document and indicates the importance of the term in the document. IDF means the degree of concentration of a given term in the document corpus. Therefore, if a term appears in a small number of documents with high frequencies within them, it is more highly weighted than other terms. For queries, the same weights 1 were used for every term.

3.2 Retrieval Model

The vector space model [10] was used for representing documents and queries. Documents in the corpus and users' queries were represented as vectors. Each element in document vectors represents a term and it has TF-IDF weight. If a term appears in a document, it has the weight of term frequency in the document multiplied by inverse document frequency in the corpus. Elements in query vectors also represent terms and they were represented as binary, that is, the weight of the term is 1 if it appears in the query or zero otherwise.

By comparing a query and document vectors, we can produce a list of documents, which are similar to the user query. They are ranked and ordered by their similarity to the query. We use traditional *cosine similarity* between query and document vectors. Cosine similarity coefficient was calculated with equation 1, where x and y represents query and document vectors. Documents with similarity values above 0.01 were displayed (20 per page).

$$Sim(x,y) = \frac{\sum_i x_i y_i}{\sqrt{\sum_i x_i^2}\sqrt{\sum_i y_i^2}} \tag{1}$$

3.3 Implementation of Social Search

In addition to the conventional features of this search engine, social navigational features are supported. In response to users' queries, a set of documents sorted by their similarity with the query are retrieved and ranks, document titles, sources of the documents, and similarity scores are displayed for one record. Along with this conventional information, social navigation information is also displayed with proper icons and different foreground/background colors at the end of each record.

The search service shares traffic and annotation database with Knowledge Sea. It retrieves social navigation information from the database and shows it along with search results. When a user clicks any record and views its contents, a document display window of Knowledge Sea is opened. Page visit information in database is automatically updated and users can make annotations just like when they annotate using Knowledge Sea.

This system supports two types of social navigation information: *navigation traffic* (how many times users selected a document) and *annotation* (annotations made by users to a document). Traffic includes user traffic and group traffic. User traffic means the traffic of the current user who is using the system and group traffic means the traffic of other users of the group the current user belongs to. Annotations include "Praise," "General," and "Question" types and it also represents whether they are positive or negative. Traffic part of social navigation makes use of human-shaped icons. The blue background colors of the icon represent the group traffic. As group members select and view the corresponding document, the group traffic increases and the blue background gets darker. The foreground colors of the icon means user traffic. If the user has viewed the document more than the average user of the group, the icon is darker than the background. If the user has viewed the document less than the average, the icon is lighter than the background. Figure 2 shows two different records with same similarity scores. Even though their similarity with a given query is identical, the traffic information is different. We can easily see that group users have visited the second record more times than the first record by its darker background color. We can also see that the current user visited these records as frequently as other group users because the foreground and background colors of these records are identical.

Fig. 2. Traffic information

The number of annotations is represented as the darkness of background colors. As users annotate a document more, the yellow background color of the annotation part gets darker. For three different types of "General," "Praise," and "Question" annotations, "sticky-note" "thumbs-up," and "question-mark" icons were used respectively. In order to represent whether the overall annotations for a document are positive or negative, "thermometer" icons were used. For positive annotations, red colored "thermometer" icons were used and for negative annotations, blue colored "thermometer" icons were used. From the example record in Figure 3, we can find out that it has a lot of annotations (darker background), "Praise" annotations ("thumbs-up" icon), and the annotations are positive (red "thermometer icon").

Fig. 3. Annotation information

4 Research Design

4.1 Research questions and hypotheses

This study attempts to answer the following questions.

1. Do users agree with the need for the search functionality of social navigation?
2. Do they consider the social navigation information more important than document ranks when they select a document in the list of search results?

The first question is about whether the real users will need the new search capability with social navigation support along with the baseline Knowledge Sea system. The other one is related to the situation when the users retrieved documents using the social search. The search result provides users with two types of different information at the same time, conventional similarity ranks and social navigation information. Therefore, users should select documents on the basis of these information and we are interested in the type of information users depend on more. Based on these questions, we have established two hypotheses.

1. Users will need the social search capability and will use it meaningful times.
2. Users will actively select documents with higher social navigation scores. Especially, they will select lower ranked documents (appeared lower part of the retrieved results) if the documents have high group traffic and/or positive annotations.

4.2 Data collection

To answer these questions, user survey and usage log analysis of the system were conducted. For the survey, following questions were asked to the students of INFSCI 0012 Introduction to Programming class at the School of Information Sciences, University of Pittsburgh.

1. "The availability of search interface in Knowledge Sea was important".
2. "Unlike traditional search engines that return the list of results ordered by relevance, Knowledge Sea search also shows you using standard color metaphors how many visits you and your group made to the pages found. This feature was useful in deciding which pages in the list of search results to visit."

We have kept the transaction records of how users behave when they browse, search, and select documents using this system. The transaction logger keeps track of users' navigational behavior. Therefore, we can find out whether users used browsing or searching mode to select an educational document from this data. Also, we can extract the similarity rank and the social navigation score of the documents when users selected and viewed them.

5 Analysis of Results

5.1 User Survey

Nine students answered the survey questions. The results are shown in Figure 4. For the first question asking about the need for the search interface, about 88.9% of the students agreed the need for the search capability for social navigation system. 11.1% of them were neutral, and no student expressed disagreement with this need. For the question asking the need for the social navigational functionality of retrieved results, 77.8% of the students agreed, 11.1% of them were neutral, and 11.1% disagreed.

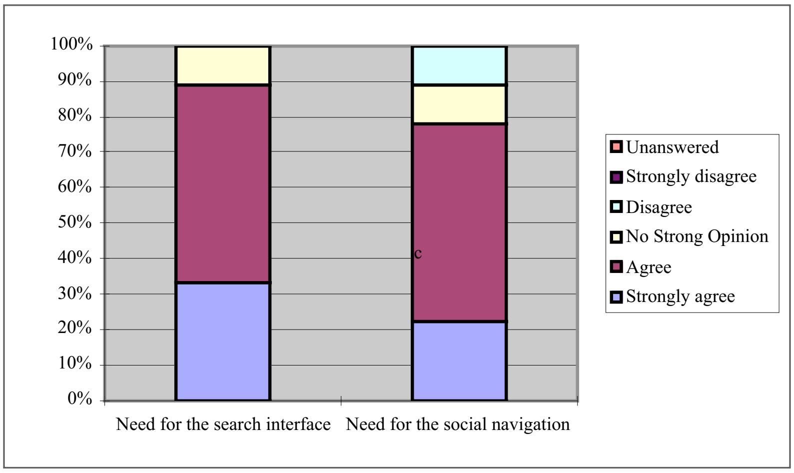

Fig. 4. Students' attitude to the need for the search interface and the social navigation

5.2 Transaction log analysis

First, the transaction log for two months (from 10/19/2004 to 12/18/2004) was analyzed. This data contains the frequencies of each mode users had used before they finally located and opened a document. Users can choose a cell and browse using Knowledge Sea's baseline system, or directly search for relevant documents by entering queries to locate relevant materials they need. With this data, we can find out users' preference on each mode before they reached educational document. The result is summarized in Table 1. The most frequently used mode was browsing. Map mode and searching mode were used about 1.5 and 4 times less than the browsing mode respectively.

Map	Browsing	Searching	Total
299 (36.2%)	423 (51.1%)	105 (12.7%)	827

Table 1. Number of times used for each navigation mode

Part of the transaction log data contains more information about users' behavior. For one month (from 11/16/2004 to 12/18/04), we have recorded data which can be used to analyze social search activities. The additional information includes document rank calculated by similarity, document ID, query string, number of accesses for the corresponding document made by the user himself and other users, the number of annotations, and annotation types. By analyzing this data, we can see if users preferred conventional rank information provided by the search engine or the popularity and annotations of other group users.

53 document selections were recorded within this time period. Each selection was made on the basis of information available to the users before they opened a specific document. That includes rank, social navigation cues (if present), and title. Table 2 shows the average rank and count of selected documents for two groups. One group is documents with social navigation cues and the other is without such information. This

result is corresponding to our expectation in a part and not in part. As we have expected, the users selected documents with social cues slightly more frequently than documents without social information (29 to 24) even though most of the documents in the result list were not annotated. Together with the user survey, this data provides some support for our first hypothesis that users will need the social search capability and will use it meaningful times.

We also have expected that the users would select documents with lower ranks if they were popular and/or annotated. However, the overall average rank in Table 2 shows that users still preferred higher ranked documents even though the documents were emphasized by social navigation information.

	With social navigation	Without social navigation
Average rank	6.48	8.54
Selection count	29	24

Table 2. Average rank of documents with and without social navigation information. Note that the higher rank corresponds to lower numbers.

Table 3 shows the number of documents viewed per query by popularity and a n-notations. Users can distinguish popular documents among group users with higher group traffic by looking at the background colors of the "human-figure" icons and they can also distinguish positively annotated documents by looking at the colors of the "thermometer" icons. They selected and viewed about 1.3 times more documents when they retrieved results which include documents other group members had viewed before them. For positive social annotation, they selected and viewed 2.4 times more documents among the retrieved results than they retrieved results without positive annotations. To summarize, users tried more items among their retrieved set when they saw higher traffic items or positively annotated item

	Average	Total	# of queries
With group traffic cues	2.69	35	13
Without group traffic cues	2	18	9
With positive annotations	4.5	18	18
Without positive annotations	1.94	35	4

Table 3. Number of documents viewed per each query split by presence of traffic and annotation social cues

The data above shows that the retrieved documents with social navigational information were popular among the users. However, in terms of the average rank of the selected documents, the average rank score of the documents with social navigation information was higher (numerically smaller) than the others. This does not correspond to our expectations that the users will choose lower rank documents if they have higher traffic or positive annotations.

For more careful evaluation of social navigation support in the list of search results, we considered two factors: which pages were selected and how much time the student spent reading each page after it was selected in the list. Since students do not see the content of the page while looking at search results, the fact of page selection reflects the perceived relevance of page for the students that is formed on the basis of page title, rank in the list, and possible social cues. In contrast, time spent reading (TSR) the page reflects the "true relevance" of the page – it's usefulness for the student. The more clicks were made on links of a specific category, the higher is the perceived value of this category. The larger is TSR pages behind the links of a category, the higher is the "true relevance" of this category.

To evaluate the "true relevance" of pages with low and high group traffic we compared time spent reading a page for pages with high group traffic and low group traffic. Similarly, we assessed TSR for pages with high rank versus pages with low rank. To evaluate the perceived relevance for these categories, we compared the number of accessed documents in each category. We hypothesize that pages with social cues will have higher perceived relevance (because the cues attract students attention) and higher true relevance (because they are "approved" by the group as a whole). In contrast, we expected high-ranked pages to have higher perceived relevance and lower true relevance. For evaluation we looked at median TSR over all selected pages from search result. We used median to discard too long or too short TSR. The group traffic represents the number of clicks before the page is being chosen from the search result. We consider pages with 3 or more clicks as pages with high group traffic since 3 clicks make the background clearly dark. Also we consider the first three search results as "high rank".

Our result is consistent with our hypotheses. As shown in the table 4, high-ranked links attract students – almost 1/2 of all clicks are done one the top three links. Yet, as table 5 shows, this attraction is often misleading: students realize quickly that the page is not relevant and spent little time reading it. Overall, as we expected, high rank is a very poor predictor of how interesting and relevant the page really is – as measured by very low average TSR (13 sec). At the same time, high traffic annotation, while not attracting student attention as much as high rank (17 vs. 20) is a much better predictor of relevance with average TSR 31 sec. Interesting is that the best predictor of relevance is a combination of high rank and high traffic – with TSR 56.5 second. While high rank/high traffic pages turned out to be the best for students, they are less frequently visited. So, while the students like traffic-based annotation and it does help to get to relevant pages, they still do not trust it as much as it deserves according to its performance.

Number of accessed documents			
	Low rank	High Rank	Total
Low group traffic	19	12	31
High group traffic	9	8	17
Total	28	20	48

Table 4. Document distribution by rank and group traffic

Median TSR			
	Low rank	High Rank	Total
Low group traffic	50	8	25
High group traffic	21	56.5	31
Total	41.5	13	26.5

Table 5. Effect of social navigation on accessing from search result by TSR (Time Spent Reading)

6 Conclusions

In this study, we added a social search capability to a social adaptive navigation system Knowledge Sea and tested its usability. We implemented a service, which shares traffic and annotation information with Knowledge Sea and let users make use of social navigation features within our social search system. We expect this new feature will improve the effectiveness of our system and the social search capability will overcome the limitations of the traditional Web search services.

By implementing this system, we tried to find out if users really needed the social search capability and if they would show behavior, which is different from when they use traditional search services. Users tend to select documents displayed in the upper part of the retrieved result set. However, with additional clues like group user traffic and positive annotations implemented in our system, we could expect a change in users' document selection behavior.

Therefore, we established two hypotheses. First, users will need the social search capability and will use it meaningful times. Second, users will actively select documents with higher social navigation scores. To test these hypotheses, we conducted a survey and analyzed the transaction log. According to the survey, very high number of users agreed with the importance of search interface and the usefulness of the social navigation support for the search interface. We were also able to find out from the transaction log that the search interface was used in a significant number of times even though the existing map and browsing system of Knowledge Sea were used more often.

To analyze users' document selection behavior in terms of social navigation information, we observed selection counts and the ranks of the selections and tried to find out if users were willing to select and view documents with higher group user traffic and positive annotations. Our assumption was that users would actively select and view popular and positively annotated documents and they would select such documents even though the documents had lower rank score and appeared at the lower part of the retrieved result set. However, overall average rank of documents with social navigation information was higher than those with such information unlike our expectation. Therefore, we tried to see how users' behavior change as time passes and found out users tended to select lower rank documents as their usage history accumulates.

We also analyzed TSR (Times Spent Reading), which means how much time users spent for reading pages according to their characteristics like ranks and group traffics.

Results show that users spent much more time reading documents with lower ranks and higher group traffics. It also supports the relationship between ranks and group traffic of documents and users' choices of those documents. From these results, we can conclude that users tend to select documents with lower ranks if they are provided with additional social navigation information like group traffic.

We have also found out that users' inactive selection behavior in the earlier stage of the experiment was caused from the Cold-Start-Problem, which happens at the earlier stage of social navigation systems when enough user history information is not collected. Therefore, we can expect users to exploit popular and positively rated items more and more actively with a system that supports social search and social navigation features as the accumulation of social navigation information increases.

Conventional rank information for information retrieval system is not enough for support users to select relevant documents. With the help of group users' tacit or explicit evaluation on that information, user can more effectively complete their task to find out documents they really need.

7 Acknowledgement

This material is based upon work supported by the National Science Foundation under Grant No. 0447083.

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