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Social Navigation Support in E-Learning: What are the Real Footprints?

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Abstract

Social navigation support is a new approach for helping users to find their way through complex navigation-based environments of hypermedia by following the "footprints" of other users. A significant challenge to social navigation support encounters is to construct a trail of beneficial footprints. Traditional social navigation support considers the user clicks to be "footprints." However, in our work we have found that simple click-based footprints lack information about the true intention of the users. We evaluated the benefit of considering time spent reading each page when calculating "footprints" for social navigation support. In this paper, we present a discussion of the possible problems with simple click-based footprints and the advantages of adding the measurement of time spent on pages into the footprints. We have studied this in an educational application, which helps students find relevant information in online tutorials, in the domain of C-programming.

1 Introduction

Information overload is an unfavorable result of the prolific growth of the Internet. The complexity of finding just the right information makes it crucial to provide navigation support in the endless ocean of information. Social navigation support is a new approach to help users find their way in the complex, navigation-based environments of hypermedia, by using the "footprints" of other users. The idea of social navigation is driven by the natural tendency of people to follow other people's footprints when they feel lost (Dieberger et al., 2000). Social navigation support seems to be successful in many different domains by helping people to find the information they need easier and faster. Svensson et al. (2001) used social navigation support in a food recipe recommendation system. Their user study reveals the values of social navigation. Users fully appreciated the social feeling added to the search space through social navigation. Recommender systems such as Amazon.com and movielens.org are another well-known type of web-based system that uses social navigation to help users find information.

Social navigation support relies heavily on feedback provided by users of the system. Feedback from early users helps to guide subsequent users. The feedback can be provided in an implicit or explicit form. Explicit feedback is mainly through ratings provided directly by the users, through a voting process. Explicit feedback is more accurate and precise; however, users must be very motivated to provide explicit feedback and usually the process of providing explicit feedback can interfere with the natural actions they are performing. Providing feedback can make users tired and can increase their cognitive load (Claypool et al., 2001).

Implicit feedback, which is obtained indirectly from the users' interaction with the system, lacks the accuracy of explicit feedback; however, it has several advantages. Implicit feedback does not have any overload for the users and every interaction of the user with the system can potentially contribute to an understanding of what the user is trying to achieve. Traditionally, social navigation systems keep track of user clicks in order to generate a trail of user actions. Simple tracking of user clicks is known as *footprints* in the social navigation literature. Wexelblat (1998) introduced the use of interaction history to improve social navigation systems, in order to help users find useful information. Dieberger (1997) used footprints in a collaborative web-based system, in order to provide information about the users' history of interaction with the system.

We explored the original definition of footprints in a practical system, Knowledge Sea II. We found that footprint-based navigation, in its "pragmatic" click-counting interpretation, can achieve success in helping users find their way through hyperspace. At the same time, our experience and user feedback points out that click-based footprints can mislead users due to lack of accuracy. Knowing that a user has clicked on a page does not tell us much information about the quality of the page and does not express reliably the relevance of the visited page to the user's goals and needs. In our search for more reliable social navigation support we attempted to take into account total time spent reading (TSR) a page. Namely, we hypothesized that not just the presence of a "footprint", but its "depth" is critical when guiding future users. A visit to a page that was followed by some reading can certainly be counted as one real "footprint". However, a short visit should not count as much as a real visit, since it may indicate that the page had a lower relevance or was simply a navigation error.

We were motivated by recent research done in the field of recommender systems and information filtering which demonstrated that time spent reading a page is an important interest indicator. Recommender systems and social navigation research share a lot of similarities; therefore, we hoped to observe improvement in social navigation support while taking into account the time spent reading, in addition to the footprint. However, there are some differences between the two fields as well. The main idea behind the recommender system is to identify items of interest for their users, while the main idea behind social navigation in the educational context is to distinguish two similar items as more or less useful and relevant to the users' goals. As a result, instead of relying on findings in recommender systems research, we decided to re-evaluate them in the context of social navigation. For example, Kelly and Belkin (2001) show that total user time spent reading a document is not significantly related to the user's relevance judgment in an information retrieval task. They conclude that the complication of the task can affect the generalization of the relationship of TSR and interest. Keller et al (2004) also show that TSR does not contribute equally to an understanding of the users' interest in different tasks. They believe that TSR is a better indicator of interest in more complex tasks.

In this research, we are evaluating the gain achieved by adding TSR into footprints while providing social navigation support in an e-learning environment. In the remainder of this paper, we will first describe the previous research regarding the value of TSR. Then we will describe our social navigation system and our approach to providing footprint-based versus TSR-based social navigation support. We next provide a discussion comparing click-based and TSR-based social navigation support. The last section of the paper presents our conclusion and discusses the future direction of our work.

2 Implicit feedback

Understanding the users' interest and intent is an important issue in different research areas within human computer interaction. Adaptive hypermedia, personalized information retrieval, recommender systems, information filtering, and social navigation are examples of areas interested in retrieving the users' preferences, interest, and goals. The disadvantages of explicit rating have motivated researchers to explore the efficiency of implicit feedback. Implicit feedback can be collected passively by monitoring the users' interaction with the system. Depending on the domain, different behaviors of users such as reading, saving, bookmarking and printing can be considered to be implicit feedback. Reading behavior includes different actions that can contribute to the understanding of user interest and intention. The number of mouse clicks, time spent reading a page, time spent scrolling, and time spent moving the mouse are examples of actions associated with reading.

Specifically, time spent reading (TSR) a page is well appreciated as one of the most reliable implicit indicators of interest, by several researchers. Claypool et al. (2001) talk about the importance of using implicit feedback indicators in recommender systems. They examine different types of implicit feedback such as time spent reading, number of mouse click, time spent moving the mouse,and time spent scrolling. They conclude that time spent reading a page is one of the most important implicit indicator of interest. Miller et al (2002) show that there is a high correlation between the user's rating of news articles and time spent reading the article. Morita and Shinoda (1994) present similar results, showing a very high correlation between the user's interest (specified through explicit ratings) and time spent reading. Rafter and Smyth (2001) provide evidence in favor of TSR in the job search domain. They report a high correlation between the user's interest in a job and the time they spend reading the job description. Kim et al (2000) demonstrate that TSR can be used for predicting how a population of undergraduate students will judge the relevance of academic journal papers.

3 Social navigation in an educational digital library

We are interested in using social navigation to provide navigation support for online educational resources. Online resources have an important value in helping learners expand their knowledge. However, finding the right information is a big challenge and navigation support is essential to making the information-seeking experience satisfying.

The problem of student access to online educational resources is being explored by our system Knowledge Sea (Brusilovsky & Rizzo, 2002). The system was designed to provide access to open and closed-corpus resources on C-programming for students of programming-related courses. Closed-corpus resources are lecture notes specially prepared for the courses. Open-corpus materials are presented as a set of links to online resources for C-programming. Knowledge Sea helps users navigate from lecture notes to the relevant online tutorials, using a knowledge map. Every cell of the Knowledge Sea map includes links to online material that are related to keyword(s) presented in the cell. The adjacent cells present similar materials. To facilitate student navigation, more recent versions of the system offered traffic-based social navigation support.

We used a coloring schema to provide social navigation cues: The background color of a cell on the map represents the density of the group traffic. All the cells of the map are initially a very light shade of blue. As students visit the pages, the background color gets darker and darker. In this way, a student can easily follow the footprints of others by visiting cells with darker backgrounds. When students choose a specific cell, they get to see details about the documents inside each cell. All the links inside the cell content interface are annotated with visual cues showing group traffic. A small rectangle is added at the left side of each link and, similar to map, the background color of the small rectangle represents the density of the group traffic. Once the students click on a link inside the cell content window, the actual tutorial page is opened in a new window. All links inside pages are also annotated with the same traffic-based social navigation cues. Figure 1 presents a general view of the three interfaces of the Knowledge Sea system.

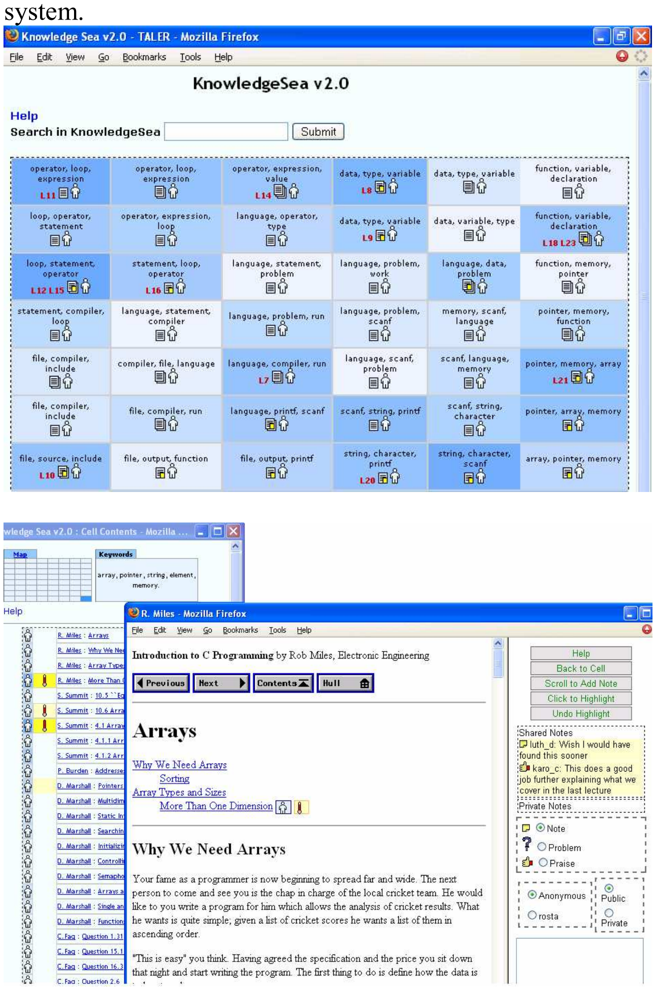

Figure 1 - General view of 3 interfaces of Knowledge Sea

We started the utilization of social navigation by implementing traffic-based social navigation: tracking the number of clicks made on each tutorial page. We evaluated the usefulness of traffic-based navigation support in three semesters of classroom studies and our results were promising. Our result showed that traffic-based navigation support positively affects students' navigation behavior and helps to lead students to pages that are useful to them (Brusilovsky et al. 2004). At the same time, several students pointed out that the number of visits to a page does not reflect its quality of usefulness for the course.

Upon finding of previous research regarding the usefulness of TSR in the prediction of interest, we decided to evaluate the efficiency of using TSR to calculate "better footprints" for social navigation support in e-learning context. The next section describes our approach for adding TSR into the footprint-based social navigation support that already existed in our Knowledge Sea system.

3.1 TSR-based footprints for social navigation support

To utilize TSR information, we developed a simple algorithm to increase the visited counter of each page in relation with time spent on that page. Based on TSR information, the algorithm decides what percentage of the page is read and increases the visited counter accordingly. Important feature of our algorithm is that it uses both TSR and page length to calculate the "real footprints:"

Previous research shows that there is very low correlation between the length of an article and the TSR of the article. In reality readers would ignore reading an article very quickly if it does not seem interesting no matter what the length of the article is (Claypool et al., 2001 - Miller et al., 2002). Rafter and Smyth (2001) suggest using the median TSR over articles and over all users to set the reading threshold. Using our data from the past two semesters, we tried Rafter and Smyth's idea for setting the threshold. However, after looking into the data we figured out this approach does not suit our need perfectly. Knowledge Sea system currently includes over 25000 online documents. However, the number of students who have been using the system is relatively small. The chance of a page being read by many users is very low; i.e. many pages have had very small if any visits. As a result the reading threshold in many cases will be biased with very few numbers of visits. For example a page could have only a single visit with a very short TSR which will set the threshold too low and another page could have only a long TSR which will set the threshold too high. Using the median approach would end up producing very high threshold variances for different pages with no meaningful reason.

Ng et al. (2002) suggest a more elaborate procedure for using TSR in prediction of user activity. They believe it is important to consider an effective individual reading time since individuals have different reading speed and different rate of comprehension even at the same reading speed. They propose that the optimal individual reading time depends on prior knowledge, reading speed, and comprehension rate. To assess each one of these factors, they suggest asking the learner to perform a test at the beginning of the usage of the system. They show that TSR becomes a precise indicator of interest while taking into account the three abovementioned elements. Although this approach seems very accurate, it is very expensive since students are required to perform a couple of tests before being able to use the system. This could become a real barrier in using the system, especially since the use of the Knowledge Sea system is not mandatory for the students. On the other hand, what they look at is associating time spent with comprehension rate which is a little bit different from our intention that is associating time spent with interest. A small period of time might not be sufficient to comprehend a page yet might be sufficient to determine whether or not the page will be useful. At this stage of our work, we decided not to apply this complex approach.

Contrary to previous, we hypothesized that the length of the page would be important to our task. We attempted to take the page length into account to go beyond merely eliminating pages with short TSRs. Especially in the domain of programming, some pages that describe a brief concept can have a very short length. Therefore it is possible to read these pages in a very short amount of time yet the pages are interesting to the students. For evaluation of our hypothesis we made use of the data collected previously in our classroom studies. We found out that on average, students spent significantly more time reading pages with more than 1000 words than pages with less than 1000 words. Therefore, we decided to take into account the length of the page while updating the visited counter.

The TSR is calculated based on the information logged on the server. Every time students access the new page the exact access time is recorded and TSR is computed by subtracting the next access time from the previous one. This approach has the well known problem of TSR for the last access page in a session. In our calculation the TSR for the last page will be very large since it will be calculated by subtracting the access time of the first access of the next session. In our algorithm, we treat very large and very small TSR as noise and we ignore them. Therefore, the last access of each session is basically ignored. This is one of the problems that we will try to fix in the future work. One approach can be considering an average TSR of the student for the last access or an average TSR for the last access page by all other students.

The next step we used our previously collected data to calculate the threshold of reading. For this purpose, we used the annotation ability of Knowledge Sea system. Knowledge Sea allows students to annotate tutorial pages while reading. We assume that a page gets annotated when it is read. Therefore, to compute the reading threshold, we calculated the average TSR for annotated pages by the annotator student for pages with less and more than 1000 words. Table 1 shows the result that was pretty consistent over both semesters of the classroom study.

Table 1 - Average TSR for pages with different length

	< 1000 words	**> 1000 words**
Mean TSR (in second)	65	100

Taking into account the abovementioned factors, we developed an empirical algorithm for updating the traffic counter (Figure 2). As shown in the flowchart, on the first step we discard noisy data by ignoring pages with TSR less than 5 seconds or greater than 10 minutes. The second step takes into account pages with several sections. When a page has more than one individually accessible section it is not clear which part of the page has been the focus of the student at each accessing time. Therefore, the effective length of the page is not clear. In these cases we treat the page as a short page (to be on the safe side) and handle it as described below. The pages with several sections are being determined by having hash sign (#) in the URL. The remaining part of the algorithm classifies pages into short (pages with less than 1000 words) and long (pages with more than 1000 words) and handles them differently. For each access to a short page the traffic counter is increased by 1 if TSR is greater than 65 seconds and is increased by TSR/65 if TSR is less than 65 seconds. Similarly, for long pages the traffic counter is increased by 1 if TSR is greater than 100 seconds and is increased by TSR/100 if TSR is less than 100 seconds. Figure 2 presents the algorithm.

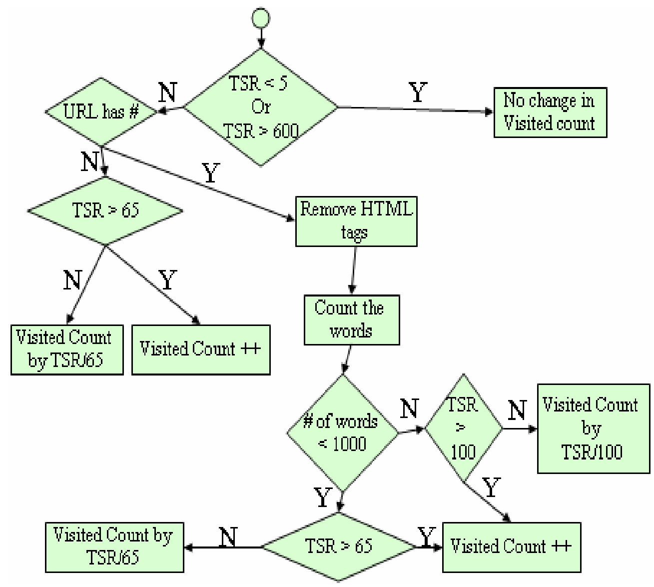

Figure 2 - Algorithm for updating visited counter, based on TSR

4 Evaluation

In order to evaluate our system over two past semesters, we logged every interaction the students had with the system. To evaluate the TSR-based social navigation support we considered the data collected during Spring 2004 and Fall 2004. We were interested in evaluating the difference between simple footprint-based social navigation support with a system supplemented with TSR-based social navigations support. We were expecting to observe an improvement in navigation support when TSR information was added in. We also expected to observe a more precise analysis of our data when TSR information was added in.

4.1 Evaluation of tutorial pages

When adding TSR information, we expected to find some tutorial pages, which had a high number of clicks but a short amount of time spent on each click. First, we were interested in checking to see what percentage of highly accessed pages fit into this category, and more importantly, what type of tutorial pages fit into this category. For evaluation purposes, we computed the number of clicks and the visited count for each accessed tutorial page, based on TSR. We refer to the number of clicks as “Simple click” or “Raw click” and the TSR-based visited count as “TSR click” in the remainder of this paper.

The TSR click score is computed by the abovementioned algorithm and is always less than or equal to the simple click score. If the TSR click is very close to the simple click score, it means that most visits to this page took a reasonable amount of time. To compare simple click and TSR click we defined the following quantity:

$$\alpha = \frac{SimpleClick - TSRClick}{SimpleClick}$$

We computed α for all tutorial pages with at least 2 clicks, over both semesters. A higher value means that there was a high difference between the simple click and TSR click scores. This means there were a lot of clicks with short amount of time associated with them, which is our main category of interest. Over Spring 2004, 158 pages overall had at least two clicks. 38% of these pages have the value α <=0.5; i.e. for these 38% of the pages TSR clicks are at most 20% more than simple clicks. The remaining 62% of the pages have $\alpha > 0.5$. Over Fall 2004, 148 pages have at least two clicks, 36% with α<=0.5 and 64% with α>0.5. We can observe that over both semesters, the majority of pages have a lot of short clicks. This shows the importance of considering TSR when providing traffic-based navigation support. Not considering the TSR will result in more and more students being attracted to low worth pages, which the students will quickly return from without finding useful information.

We were also interested in evaluating the quality of pages with a lot of short clicks in comparison to pages with usually long clicks. As mentioned before, the Knowledge Sea system allows students to annotate tutorial pages they are visiting, in order to express their thoughts while reading the page. We consider pages with annotation to be pages that the student finds noteworthy. Therefore, for evaluating the quality of pages, we make use of annotation information. For pages with small and large value of α we looked at the percentage of pages with annotation. As shown in Table 2, a larger percentage of pages with smaller α get annotated and the difference is statistically significant. The result confirms the importance of considering TSR. The pages with longer TSRs seems to attract more annotation from students while a many not so important pages accumulated a lot of short clicks, misleading the following students to those pages as well.

	Spring 2004		**Fall 2004**	
	α <= 0.5	**α<= 0.5**	**α > 0.5**	**α>0.5**
Document Num	61	97	54	94
Annotation Num	16	10	25	25
Percentage	26%	10%	46%	27%
p-value	0.0024		0.0203	

Table 2-Comparison of pages with long clicks vs. short clicks

4.2 Evaluation of the convergence of students’ activity over two different semesters

As mentioned before, we evaluated our system over two different semesters of classroom studies. Since the instructor of the class and the material covered in the class would stay similar over different semesters, we expected that the students would share similar learning goals in the class. Therefore, we expected to observe an overall similar pattern of usage for the Knowledge Sea system over both semesters. We expected the mappings of the two different semesters to converge into almost similar mappings, with a similar pattern of dark and light background colors by the end of each semester.

On the other hand, we hypothesized that considering TSR clicks instead of simple clicks would lead to a more precise convergence of the maps. We expected that adding TSR information would remove some of the noise and reveal a more accurate usage of the system.

For the evaluation, we computed the percentage of simple clicks and TSR clicks for each cell on the Knowledge Sea map. Figure 3 shows the percentage of simple clicks over each cell on the map, for the Spring and Fall semesters, and Figure 4 presents the percentage of TSR clicks for each cell of the map over both semesters.

As can be seen in Figure 3, the pattern of usage is quite similar over spring and fall semester and the peaks and dips happen at similar points over both semesters. Very similar pattern of peaks and dips can be observed in Figure 4 as well. The dashed circle shows the cases where the convergence happens more closely in the TSR case. However, the data does not seem more convergent when considering TSR clicks. For better evaluation of our hypothesis for each cell, we computed the difference between the percentage of simple clicks for fall and spring and the difference between the percentage of TSR clicks for fall and spring semester. We expect to observe higher differences for simple clicks compared to those with TSR clicks. However the result shows that although the median difference is lower for TSR click, we cannot observe an overall lower difference for the TSR click. Figure 5 shows the box plot of the simple click difference and the TSR click difference.

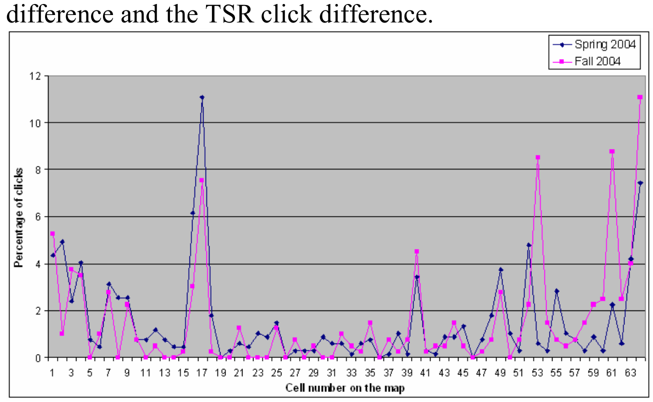

Figure 3 - Percentage of simple clicks for each cell on the map, over two semesters

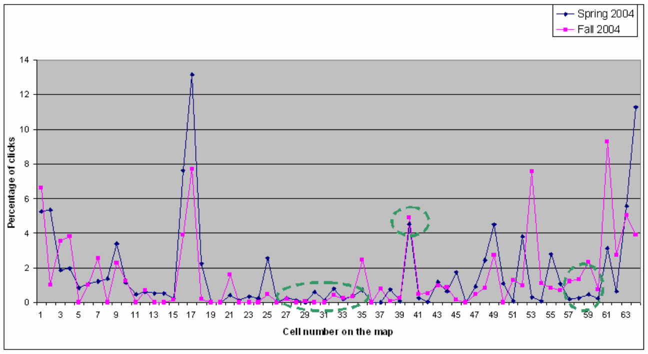

Figure 4 - Percentage of TSR clicks for each cell on the map over two semesters

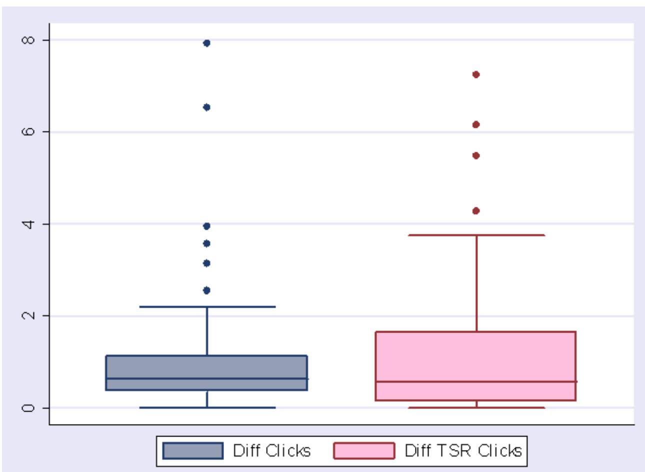

Figure 5 - Difference of simple click and TSR click in convergence of the Knowledge Sea map over two semesters

We believe the reason we did not observe better convergence while using TSR click is the fact that students were not guided by the TSR clicks over these two semesters. They were only able to make their navigation decision based on footprint-based social navigation cues. Footprints influence them to visit pages with high group traffic. Therefore, we could not see any difference when considering the TSR click. We are interested in evaluating our hypothesis once again when we test our new TSR-based guidance system. In that case, we expect to observe the effect of TSR.

3.3 Evaluation of search

Another feature of the Knowledge Sea system is it's search capability. Students are able to perform keyword searches among the same resources available through Knowledge Sea. The search result provides the usual relevance ranking information. In addition it also provides social navigation support for each link in the search result. Figure 6 shows the general view of the search interface. As can be seen in the figure, relevance rank and social navigation information can interfere with each other in some cases, i.e., links with a high rank can also have very low group traffic or links with a low rank can have also very high group traffic.

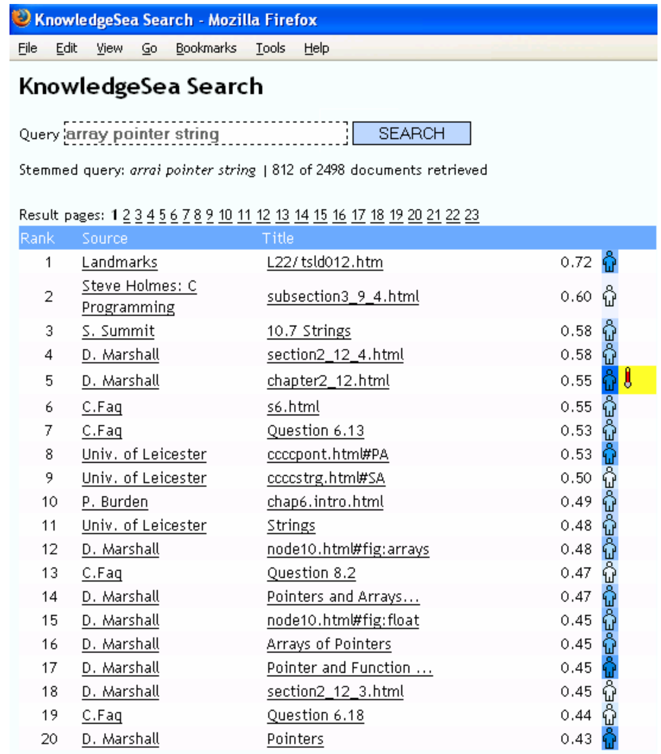

Figure 6 - Search Interface

Our analysis of the effect of social navigation support on search result points out that students do not select links with high group traffic as much as we expected. We think that since choosing a link from the search result is in effect choosing one out of 20 links, students base their decision mostly on the title of the link. However, we were interested in comparing time spent reading pages with high rank versus those with high group traffic. We hypothesized that students spend more time on pages that had high group traffic scores at the time of selection. To evaluate this, we categorized pages selected by the search result into four categories: low rank versus high rank, and low group traffic versus high group traffic. We considered rank 1 to 3 as high rank and more than 3 clicks as high group traffic. As shown in Table 3, the data confirms our hypothesis and shows that students are spending more time on pages selected from high group traffic categories versus pages selected from high rank category. Therefore, the results show the importance of considering TSR. We suspect that TSR-based social navigation support affects students' decisions in selecting a link from search result more strongly since it highlights more important pages than are highlighted by footprint-based social navigation support.

Table 3-Median TSR for pages selected from search result

	Low rank	High rank	Total
Low Group Traffic	50	8	25
High Group Traffic	21	56.5	31
Total	41.5	13	26.5

4.4 Evaluation of students' performance

We hypothesized that adding more information about the usage pattern of each student through the TSR would help us evaluate the correlation of usage of the system with the performance of the students. A typical use case of Knowledge Sea is when students are working on their C-programming homework and they need more information to solve a problem. Since KS provides access to thousands of pages related to C-programming, we hoped that usage of KS would improve students' homework performance. Students were required to complete six C-programming homework assignments over the Spring 2004 semester and five over the Fall 2004 semester.

We evaluated the general effect of using Knowledge Sea on homework performance by looking at the homework grades for different usage levels of Knowledge Sea. For evaluation purposes, we categorized usage of the system into four categories based on number of clicks on the tutorial pages. The following table shows the description of each category and the number of students in each category per semester. We performed the categorization based on both simple click and TSR click.

Table 4 -Categorization of students based on usage rate

		Spring 2004		**Fall 2004**	
		Simple Click	TSR Click	Simple Click	TSR Click
Rare	[0-5]	7	8	5	5
Medium	(5-30]	7	8	5	6
High	(30-70]	7	8	3	3
Very High	>70	6	3	2	1

For each category we computed the average weighted homework grade for students in that category. We weighted the homework grade based on the difficulty of the homework and thus the score (Y axis in) can be more than 100%. As can be seen in the figure (darker line), there is not a constant, positive relationship between the grades and increase in usage of the system in terms of simple click score. In some cases, the grade has decreased with increased usage of the system. However, when the graph is depicted in terms of TSR click (lighter line) we can observe a constant increase of grades over increase of usage. Therefore, the result shows that students who are using the system effectively by actually spending time reading the tutorial pages are more likely to utilize the information and improve their performance. Again, the result shows that TSR click scores are more reliable than simple click scores.

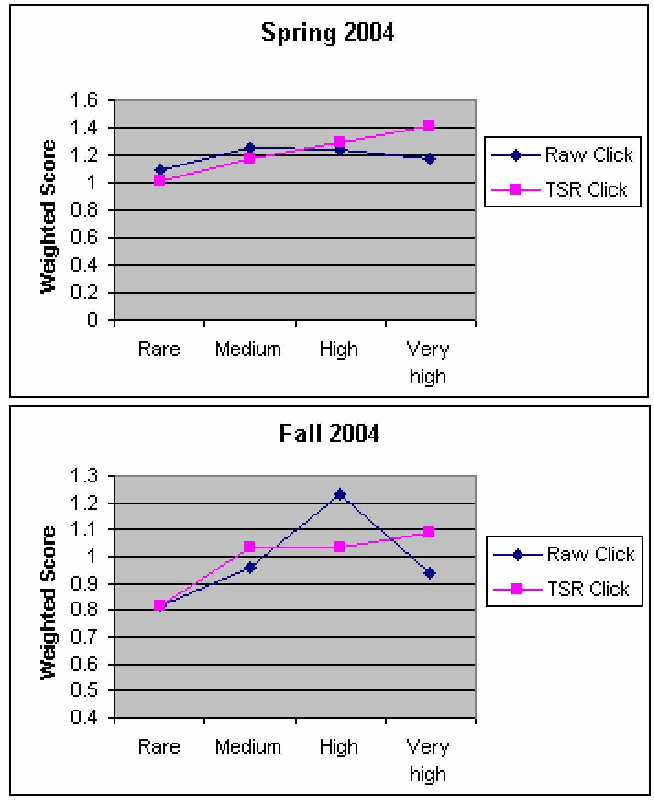

Figure 7 - Homework performance of students with different usage patterns of the system

5 Conclusion & Future work

In this paper, we presented our evaluation of the effect of adding TSR into traditional footprints when providing social navigation support. Our results show that taking TSR into consideration provides a more precise insight into the intention of the group of users. We observed that many pages accidentally accumulate a lot of clicks and therefore attract other members of the group, while the clicks are often very short and thus are not a true indicator of student interest. Adding TSR information into footprints allows us to make only the more important pages attractive. We also observed that adding TSR information provides more accurate information about pages selected from search results. Furthermore, considering TSR information helps to classify the usage patterns of students more precisely and helps to identify the relationship between usage of the system and student performance.

In future work, we would be interested in performing more evaluations on TSR-based social navigation support by trying our system with a new population of students. We hypothesize that TSR-based social navigation support helps students find the information they are looking for faster and easier since TSR provides more reliable information about the importance of the documents. Since short clicks will not accumulate as high traffic in our TSR-based system, pages with very short clicks will no longer attract students anymore and we expect to see less clicks on this type of pages, which used to get a lot of clicks in the footprint-based version of the system.

We are also interested in implementing other types of implicit feedback, such as scrolling time. We would like to evaluate the effect of different types of implicit feedback in the domain of social navigation. We expect to provide more reliable social navigation support by extracting more implicit feedback from the interaction of students with our system.

6 Acknowledgement

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