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Learning by "Search & Log"

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Abstract: Although previous research has demonstrated the benefits of the "learning by searching" strategy, there is a new problem which is how to measure and analyze the effectiveness of "Learning by Searching" behaviors. In this paper, by using the record of the students' learning history, we have proposed a SNSearch system to analyze student web-searching behaviors of "Learning by Searching".

Keywords: Learning logs, Learning by Searching, Data Mining

1. Introduction

There are many issues with Web-based learning, including the processing of Web information, and the roles of teachers in the online learning environment, and analyzing the Web based learning behaviors of students (Bilal, 2000, Hwang et al., 2008). With the development of Internet and search engine technologies, online searching is becoming an important part of learning. Searching is a natural learning behavior like listening, speaking, reading or writing. The way of learning by online searching is called "Learning by Searching"(Yin et al., 2013).

We have developed a Milkyway system, which is based on the "Learning by Searching" theory (Yin et al., 2013). Through experiments, the Milkyway system has demonstrated the benefits of "learning by searching". Also at the same time new research topics have been identified, of which one of them is "analyzing student web-searching behaviors of using search engines for problem solving".

In this paper, we have proposed a SNSearch system to help students to share their 'learning by searching' experiences. Users can share their search queries and browsing history anytime, anywhere. We refer to the search queries and browsing history as "learning logs". By using these community learning logs, we built a system to analyze student web-searching behaviors of using search engines.

2. Measuring The Potential and Actual Effectiveness of Collaborative Learning

The collaborative potential of a system is how much the system supports sharing of information, experience, and activities. This can be thought of as the number of collaborative opportunities provided by the system, which can be constructed through the analysis logs. For example: Learners A, B, and C have been to the same results and left 2, 3, and 1 experiences or activities respectively in the log. When learner D goes to the same results the collaborative potential could be calculated as the sum of experiences/activities that are displayed from the log: 2 + 3 + 1 = 6.

The actual collaborative use of a system is how much collaborative potential of a system is used. This can be thought of as how many learners used collaborative opportunities offered by the system. The actual collaborative use of the system could be calculated using different degrees of use. To enable this analysis, collaborative actions need to be logged to the required level of granularity, such as: did the learner click on the title of the paper or on collaborative feedback *like* button? An example of the calculation of the actual collaborative use of the system can be seen in the following example: Learner D goes to the same results in the example about and clicks on two previously recorded activities of learner B and A. This equals a score of 2 for actual collaborative use of the system.

By using these measures, comparisons between the potential and actual collaborative could be used as a metric of system performance. It could also offer an evaluation method that can be used to compare the collaborative performance and effectiveness of improvements and different systems.

A naive score for collaborative system effectiveness could be seen as: E = A / P, where E is the effectiveness, A is the actual collaborative use, and P is the potential collaborative use of the system. However this could possibly skew the effectiveness towards results that have a small potential, as it might not be possible for a learner to actually use all the collaborative potential of a result.

3. Search & Log

3.1 Listing View, Item View and Log Map View

In this paper, we developed a demo system, which is an extension of the Community Search system (Flanagan et al., 2013) by introducing knowledge share mechanism into the search engine. Figure 1 shows a mockup image of the interface which has three areas (A) Listing View, (B) Item View and (C) Log Map View as well as the query input frame at the top of the screen.

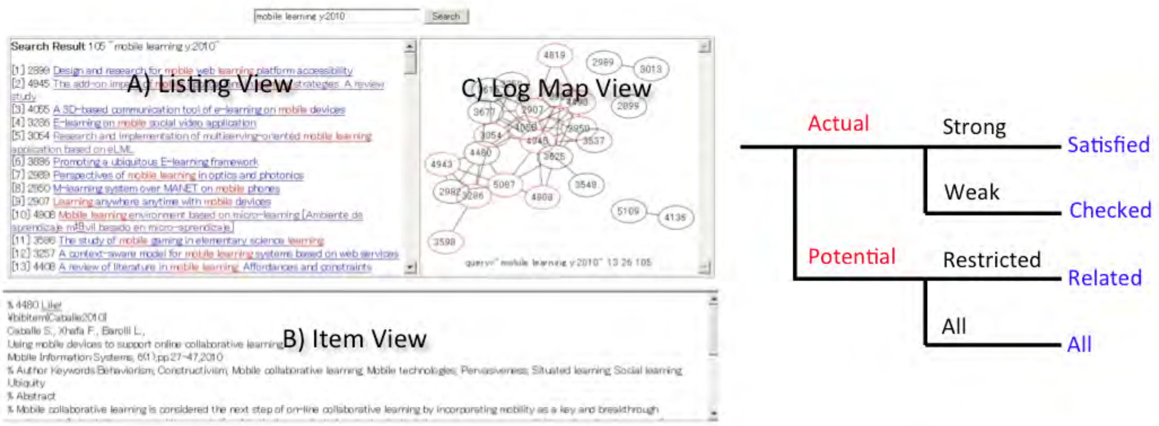

Figure 1. Search & Log triple view.

The list of search results is shown in the area (A). At the top of (A), the number of the search results and the query are shown followed by the ranked list of search results with their title. The IDs of articles are displayed at the beginning of the articles. The IDs are shown as the nodes in the area (C) to represent the articles. The most important article with the highest relation with the query is the article 2899 and is ranked at the top of the list. The detailed information of the article, e.g., the authors, the source and the abstract, is displayed at the area (B) if a user clicks the title or the ID of the article.

So far, the proposed system is the same as that of the usual search engine. The feature of the community search proposed in this paper is in the "*like*" button of the area B, and the diagram in the area C. User's response or evaluation of an article will be sent when the user clicks the *like* button. If he convinces himself that the article is appropriate with respect to his query, he can click the *like* button. The system keeps the triple of the query, user ID and the article ID, so that the user's judgments are stored and can be shared with other users.

Each node of the diagram in the area (C) represents an article in the search result. However, only the articles that have been viewed by at least one user are shown in the diagram. The nodes with the red circles represent the articles which received the *like* button at the area (B). The articles are not shown scattered, but shown with links. A link between two articles implies that the same user has checked the two articles. Thus the area (C) displays the responses of the all users with respect to the query.

3.2 Potential Knowledge and Actual Knowledge in Triple View

When a user sends a query to the system, log data from the system can be classified into four types, all, related, checked and satisfied log data, according to his intention, experience and knowledge. All log data represents all of the actions by users that have been recorded in the log. They do not have to be related to his query. Related data on the other hand is a subset of all log data that has a relation to his query. When some users paid attention to an article, this is recorded as checked log data. If a user particularly has interest in an article and clicks on the *like* button, then it is recorded as satisfied log data.

Each article displayed in the Listing View represents potential knowledge (related log). When a user clicks one of the articles, then the article becomes his pseudo actual knowledge (checked log). When he clicks the *like* button of the article in the Item View, then the article changes to his actual knowledge (satisfied log). The article shown in the Log Map View represents the common knowledge of other users with similar interests. They once asked the similar query to the system, viewed similar results and made some action that was recorded in the log.

4. Conclusion and Future Works

We considered that search learning behaviors can be examined through the analysis of the learner's action in this process. In this paper, we proposed a method to measure and analyze the effectiveness of "Learning by Searching" behaviors by using learning logs. Based on this method, a SNS-based system has been developed to help to analyze students learning behaviors of using search engines for problem solving. For future work, we will evaluate the environment.

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