Toward understanding novices' search process in programming problem solving

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***Abstract*—The usage of online search engine is growing rapidly not only in daily life, but also in education. We are interested in understanding what strategies students apply during search, especially the tactics they use to decompose a programming task. In this paper, we report a lab study to investigate students' programming information seeking behavior via Google search engine. Students were given a programming task with limited time, and they were also required to report their online search process including search query and web pages browsed. We analyze the web pages they browsed, model student's behavior, and cluster them into groups with different search tactics. The results show that the web pages they browsed during the task consisted of either conceptual knowledge or coding technical content. The students who performed better would browsed more about conceptual knowledge. Students who set more and smaller unit of subgoals outperformed the students with fewer and larger subgoals.**

I. Introduction

Web search engines have served information seekers a convenient channel to locate relevant information online. Consequently, the convenience may have empowered problem-solvers a possible avenue to search for solutions to their problems. Learners are becoming more comfortable of searching online to attempt to their problem-solving (Lee, S. W. Y., & Tsai, C. C. 2011). Both information seeking behavior and the effect of learning from searching have been studied for years. Prior research has shown that search tasks, search skills, search length, familiarity with topic, and search system design are among several factors that affect searchers' tactics(Miller, V. D., & Jablin, F. M. 1991). Specifically, information seeking literature has found that users have vary relevance judgments in different stages of the tasks(i.e. at the beginning of the tasks, use a fraction of query terms, and tended to use more synonyms and parallel terms in later stages)(Ellis, D., & Haugan, M. 1997). In addition, causal or explanatory links among solution steps have been found to help learners form a subgoal(Sweller, 1988). The observation of the connection between subgoals in practical situation would help improve learning materials, which could stimulate learners to solve problems independently. Besides, forming a solution procedure that is structured by subgoals improves knowledge transfer(Goh, S. C. 2002). Encouraging learners to form structured subgoals is an efficient way to improve learning effect. Our research aims to investigate the strategies students use to form subgoals, and identify factors in subgoal strategies affecting the learning outcome.

However, there is a gap in research between the information seeking behavior and the student's problem-solving planning. The subgoal strategies that learners use during problem-solving is especially valuable to study, which helps to understand the cognitive process of problem-solving, and further improves education quality. Our research focuses on the problem-solving strategies in programming learning and how programming related information seeking affects learning.

In order to investigate novice programmers' subgoals formation strategies during problem-solving, we conducted a lab study to collect and process data from programming learners. The data collected including the student's solution of the problems, and their information seeking behavior. By analyzing the student's behavior sequences and the quality of their solution, we attempted to uncover a set of subgoal strategies and the factors affecting the quality of their work. The result showed that there are two clusters of web pages browsed during the task, one provided base knowledge and the other taught coding skills. The students who browsed more about base knowledge turned out to perform better. The students who frequently set up subgoals and divide subgoals into smaller units outperformed the ones without.

The rest of the paper is structured as following: Section 1 introduces the background and motivation of the research; Section 2 lists related research in student modeling and information seeking behavior analysis; Section 3 illustrates the methodology of the study including the experiment setup and the techniques used in data processing; Section 4 analyzed the statistical results of data collection in the experiment; Section 5 discussed the behavior patterns identified from the result of behavior sequence clustering; Section 6 concludes the whole study and look forward to the future work.

II. Literature Review

A. Search behavior modeling

Search engine user behavior modeling has been studied for years to understand the preference of web search users. In these studies, "a user model is a set of rules that allow

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us to simulate user behavior on a search engine result page in the form of a random process"(M. J. Cole, et al. 2011). These studies also discuss different bias affecting the models, for example position bias means the first link listed in search result has a higher probability to be clicked(Guan & Cutrell, 2007, Joachims et al., 2005, Lorigo et al., 2008), while Kiseleva, J. etc reported that user with expertise "manage to detect better answers as they dig them from the bottom of search result"(Kiseleva, J. et al. 2013). User models, especially click model during web search, helps to detect general preference of users'. However, it takes little account of the text content in search results, and the actual need of users is difficult to collect when they use search engine. Ageev, M. et al. proposed a method analyzing searcher success in relation to the searcher behavior with realistic search tasks(Ageev, M. et al. 2011). Additionally, when users use search engine just for learning, it is interesting to study and model the difference, and data mining techniques can be involved to study the user behavior patterns (Beal, C., Mitra, S., & Cohen, P. 2007, Ellis, D., & Haugan, M. 1997, Guerra, J., Sahebi, S., Lin, Y. R., & Brusilovsky, P. 2014).

For specific programming learning behavior, sequential pattern mining techniques has been applied in several studies, such as programming problem solving(Guerra et al. 2014), programming assignments progression(Piech et al. 2012), learning programming with dialogic tutor(Boyer et al. 2011). Beal, Mitra, and Cohen(2007) studied about modeling engagement level of students by analyzing their action traces on a tutoring system with HMM. Jeong, et al.(2008) study a computer agent was taught by students, and the student's behavior in learning was captured with HMM. Another study established by Lu and Hsiao(2016) investigated the programming learners information seeking behavior on discussion forum, and modeled the students as novices and experts with HMM(Hidden Markov Model) to compare the pattern difference.

These studies proved that students do have different behavior patterns in learning. However, it is still not answered that what is the connection between learning behavior and learning affect behavior, considering the students' knowledge background. Katharina R. et al.(2013) studied how users judge a design of a website by colorfulness and visual complexity, and modeled their evaluation with quadtree and R-tree. In another study, a visualization system was designed to help learners understand their learning progress and helps to provide optional service. Additionally, interactive visualization is found to improves students' learning by engaging them to interact with their learners' models(Hsiao et al. 2013; Bull et al. 2016).

B. Student modeling and learning theory

From theoretical perspective, looking for information means to complement current knowledge and cognitive skill acquisition action(Aleven 2006). Empirical study results showed that learners often use help systems ineffectively or ignore them altogether or abuse the system hints, but when they do use help, learning processes and outcomes may be substantially improved. Another series of studies revealed that help-seeking errors are associated with poor learning(Baker et al. 2004; Aleven et al. 2006; Roll et al. 2014). These findings suggest that looking for right level of help in the right time will result in supporting learning. However, there are also various reasons that learners may not ask for help(such as fear that they will receive less credit for a successful outcome or being viewed as incompetent etc.)

Open Student Modeling(OSM) approach is another relevant research topic about student modeling, it offers a group of techniques that makes traditionally hidden student models available to the learner for exploration and possible editing. Representations of the student models vary, from displaying high-level summaries(such as skill meters) to charting out complex concept maps or networks. A spectrum of OSM benefits have been reported, such as increasing the learner's awareness of their own developing knowledge and difficulties in the learning process; as well as student engagement, motivation, and knowledge reflection.(Bull 2004; Hsiao et al. 2013; Mitrovic & Martin 2007; Zapata-Rivera & Greer 2000).

Another set of studies focus on the connection between the coding quality and behavior pattern. Buffardi and Edwards analyzed a 5 year dataset collected from programming novices to discover the testing behavior patterns and their connection to assignment submission quality (Buffardi, K., & Edwards, S. H. 2013). Carter and his team monitored the students error fixing behavior and social activeness, and provided a model to predict the students performance in computer science course, which is proved to outperform the baseline. Some studies provide other perspectives to look into coder behavior patterns. Hundhausen et al. did a case study on the record of coders' including the video and audio with semantic components, a set of patterns were detected including "Complete Solution with Few Missteps", "Succeed Through Persistence", "Cannot Get On Track, Despite Honest Effort", and "Gives Up Quickly. These studies proved that students have different behavior patterns in learning and searching. However, it is still not clear that what is the connection between learning effect and information seeking strategy. The novelty of this work is to use hierarchical clustering on the student's behavior sequence to find common patterns and strategies in subgoal, and connect it to the solution quality to identify positive and negative factors.

III. METHODOLOGY

In order to study students' search process in problem solving, an in-class lab study was conducted in a graduate student course about programming to collect the learners behavior of subgoal setting and problem solving. Students were asked to complete a programming task in writing R scripts to calculate linear regression, during which they were allowed to use Google search engine to locate any relevant resources. Students were also asked to report the entire searching process, including the search queries they had issued, the links to the web page they had read, the relevancy of the content they had identified to help them solve the tasks, and the final solution to the problem. We compiled the self-reported data and collected all the reading content that facilitated students' searches.

A. Study design

In lab class, the students were given 20 minutes to finish the task about R programming. The purpose of short time limit was to push the students to select the most helpful material to read. In this way it became possible to find the resources that students believe to be helpful, and strategies students believe to be effective.

The questions to answer in the task is as follows:

- *Question 1: What is the function used to do linear regression in R? What are the meaning of its parameters?(In your own words).*
- *Question 2: Given the data set, plot the linear regression result between two columns you think that are most correlated.*

After the task, the students were not only required to submit their task, but also to submit the record of their information seeking behavior. The task submission includes R code and an image of their plot result, while the information seeking record includes all the Google query they issued and the web pages they read.

In this study, the quality of student's task submission was evaluated manually and taken as the indicator of learning effect. For each of the question, the quality of an answer was categorized into different levels, the criteria is as follows from lower level to higher:

- Question 1:
  - *Level 0: Did not find the function lm;*
  - *Level 1: Found the function lm, and correctly describes it;*
  - *Level 2: Found the function lm, and correctly describes it with the student's own words;*
- Question 2:
  - *Level 0: Did not code anything in R;*
  - *Level 1: Successfully imported data in R;*
  - *Level 2: Successfully imported data in R, and correctly used lm function on it;*
  - *Level 3: Successfully imported data in R, correctly used lm function on it, and clearly plotted the result of linear regression;*

According to the criteria, each student will be separately evaluated with the two questions in his submission. In order to evaluate the submissions according to the criteria above, two computer science major graduate students were recruited, both of them have at least 2 years teaching assistant experiences relevant to programming. Their agreement of question 1 evaluation(kappa 0.378) indicates a fair agreement, even though it was subjective to judge whether the students used their own words to describe the function. The agreement of question 2(kappa 0.698) indicates substantial agreement, which was high enough to support the evaluation to be true.

B. Subgoal modeling

The information seeking behavior record for each student was modeled as a sequence of subgoals. Each subgoal was represented by a query and the following pages browsed. In order to further study the subgoal strategies, the text content of the web pages that the students browsed were analyzed.

First of all, the text content for each web page was crawled according to the url reported by students as their resource. Then a serial of text mining operations were applied on the content to clean up the text. The operations included changing to lowercase, punctuation removal, stop word removal, and stemming. Next, a term-document matrix was built according to the content generated, and tf-idf algorithm was applied to calculate the weight of each term in each document. After that, k-means clustering algorithm was applied on the term-document matrix as vector space of the web pages, so that main clusters can be classified according to the result. The text processing work-flow is shown in Fig 1.

After categorize all the pages read, a student's behavior during the task can be represented as a sequence of signs, where "q" represents a query was searched, and either "1" or "2" represents the category of pages he/she read after the query.

C. Sequence comparison

In order to find common patterns among students, and map them to learning effect, behavior sequences were compared and the distance between each pair of sequences was calculated. In this study, the edit distance was taken as the tool to quantify the difference between two sequences. When the edit distance between two behavior sequences was low, it indicates these two students have similar behavior pattern, and they use similar strategy to split a task into subgoals and follow similar steps to solve problems.

In order to identify group of students with similar behavior patterns, hierarchical clustering was applied since it only considers the distance between pairs.

IV. Data collection

Among all the 130 students in the class, 106 students successfully submitted the tasks, 91 of them reported their search queries and page browsed. Based on their submission logs, 176 queries were applied online, 349 pages were assessed and recorded during the task, and 105 unique pages were browsed.

Two experts coded the submissions according to the script discussed in section 3.1, and the quality distribution of question 2 is shown in Fig 2. The majority of students(76 out of 106 students) correctly answered the question, and submitted their behavior record. Most students(N = 102) successfully imported the data, and correctly applied the lm function on the data, while some students(N = 26) among them have problem in plotting the result correctly.

On the other hand, according to the clustering result, the pages

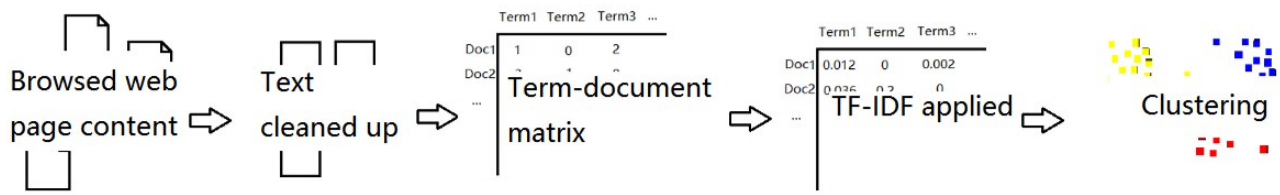

Fig. 1. Text processing work-flow

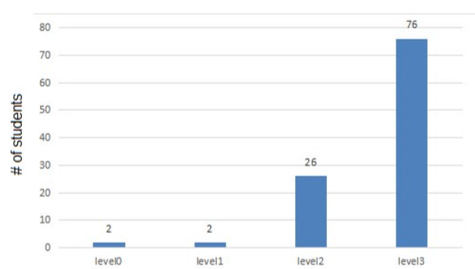

Fig. 2. Submission quality distribution

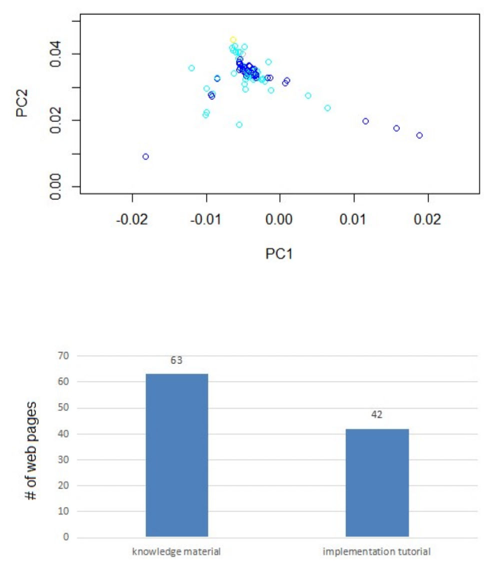

Fig. 3. Clustering result of browsed web page content

were clustered into two groups after removing outliers. The clustering result is shown in Fig 3 by using the first two PCs in each document.In this figure each dot represents a document, and the color labels the cluster it belongs to. The documents were clustered into two main groups named according to the top weighted terms According to the clustering result, there were two main groups classified. In the first main group, which was named "knowledge material", the web pages has representative terms including "linear", "regression", "model", and "data". These terms indicate that these pages were teaching knowledge closely related to the task; In the other main group, which was named "implementation tutorial", the top terms were "abline", "plot", "column", "question", and "answer". These terms indicates these pages were about detailed implementations in code, and mostly in Q&A sites.

V. Analysis Result

Hierarchical clustering algorithm was applied on the student's behavior sequences. In this clustering, each individual student was represented by a sequence of behavior. Character "q" represents a query behavior, while either "1" or "2" represents a page browse behavior. The value of number indicates the category of browsed page content. An example of a sequence is *"q1q22"*. In this example, the student started the process by querying on Google, and then browsed a page categorized as knowledge material. Then he/she queried again, and browsed two pages categorized as implementation tutorial. The data was modeled to represent the whole process of information seeking when students were given a task in limited time.

As discussed in Section 3.2, a session was defined as one query followed by a serial of page browsing behavior, and each session represents a single subgoal in the whole process of information seeking. A complete process of a student's was formed by a serial of query sessions("q1" and "q22" in the example). Each session was started by a query, and followed by a serial of page browse behavior. In this way, each session could be analyzed as a subgoal in the task, identified by the category and number of pages further browsed. To compare two students, we use edit distance to represent the difference between a pair of students' behavior sequence.

Since question 1 in the task was relatively easy, and the agreement of submission evaluation between two experts was not substantial(kappa 0.378), the evaluation of the question 2 answer(kappa 0.698) was used to represent the quality of the whole submission.

By comparing the student's behavior sequence with edit distance, the student behavior clustering result is shown in Fig 4. Colors are used to label different quality of submission. In the figure, students labeled in blue have the highest submission quality(level 3); green labels the students who made mistake in plotting(level 2); red labels the students who did not correctly

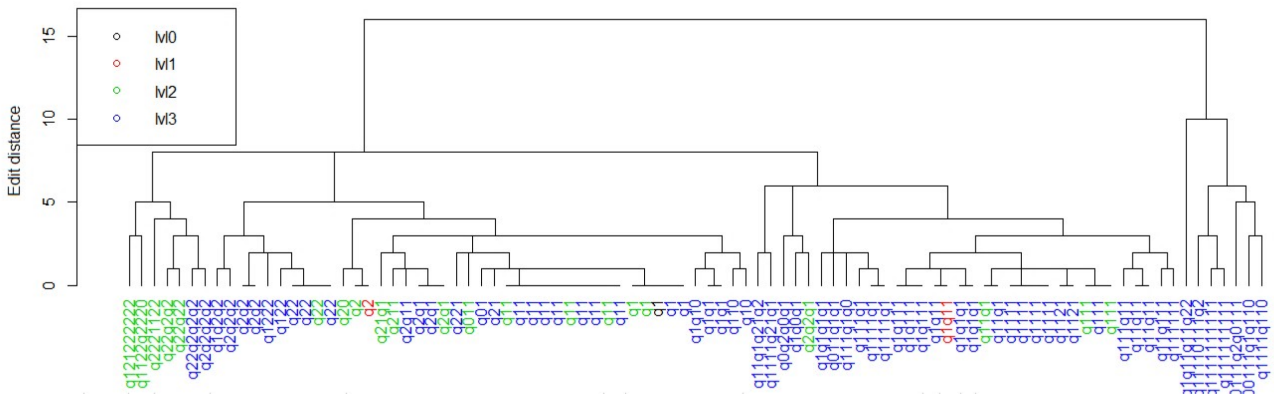

Fig. 4. Student behavior sequence hierarchical clustering

apply the function on data(level 1); black indicates the students who did not code anything(level 0).

The result indicates that students with more operations performed better insignificantly. Among the students with 5 or more operations(N=37), 7 of them did not correctly plot the result, and 1 of them did not correctly applied the function on data. So in this set of students, there were 21.5% students did not successfully finished the task. While among the students with operations less than 5(N = 54), 33% students did not finished the task correctly. Among the students did not do well in the task, one observation is that they have a lack of reading about base knowledge(fewer "1" in their sequence), especially for the long sequences. This fact indicates if the student did not understand the concepts in the task, even though he/she browsed a lot about coding skills, the quality would still be low.

Another observation in the clustering is in the left bottom part of the graph, there were 5 students with similar behavior pattern(placed closely in clustering) fail to plot the result correctly. In this small cluster, the students have several common behavior pattern including:

- The average length of their behavior sequence(Mean 8.2) was longer than average(Mean 5.5).
- They browsed more implementation tutorial than knowledge material.
- Their browse session was longer(Mean 4.6) than average session length(Mean 2.1).

These common patterns show a clue that students with more and shorter sessions would outperform the students with fewer but longer sessions. In order to investigate the relation between solution quality and session patterns, another clustering was applied on the behavior sequence of sessions. The session behavior sequence clustering was applied to discover the connection between submission quality and behavior sequence in single sessions. By comparing the behavior sequence with edit distance, the hierarchical clustering result is shown in Fig 5. In this figure, sessions are color labeled by the quality of the student's submission that the session belong to. In the clustering result, the left part was clustered as the sessions related to knowledge material(N = 106), and the right part was the sessions relevant to implementation tutorial(N = 57). According to the statistical analysis in the left sessions cluster, there were 16.0% sessions applied by the students with lower quality submission(level 2 or lower), while in the right cluster, the ratio was 29.8%. Moreover, among the 10% longest sessions(length longer than 3), 36.4% sessions were belong to lower quality submission(level 2 or lower). According to this result, it can be informed that longer sessions and implementation related sessions were associated to lower quality submission.

VI. Conclusion and Future Work

In this research, we analyzed the programming learner's problem-solving strategies by conducting in-class lab in a graduate student course about programming. In this lab class, the students were required to finish a task about programming in limited time. During the lab, students were free to use Google search, and they were required to report all queries and pages they browsed during the task. The student's submissions were graded into levels by two experts, and the agreement kappa was high enough to support the evaluations. On the other hand, the web-pages reported by the students were analyzed with text mining techniques, and finally clustered into two groups. The first group of web pages was about the base knowledge of the task, while the second group of pages was about the coding and implementation techniques. After the submission evaluation and web page content clustering, the behavior of each student were modeled as a sequence of querying and web page browsing operations. A subgoal was defined as a session in the behavior sequence, which was a query followed by a serial of web pages. After the data process and modeling, the connection between behavior pattern and submission quality was revealed. According to the hierarchical clustering result, students with shorter but more sessions would outperform the other students.

There are still limitations in the study. First of all, the query and browsing information were collected from the report of the students, which may not guarantee to be comprehensive data logs. It is possible to lose information when a student did not report all the queries and web pages, including those did not

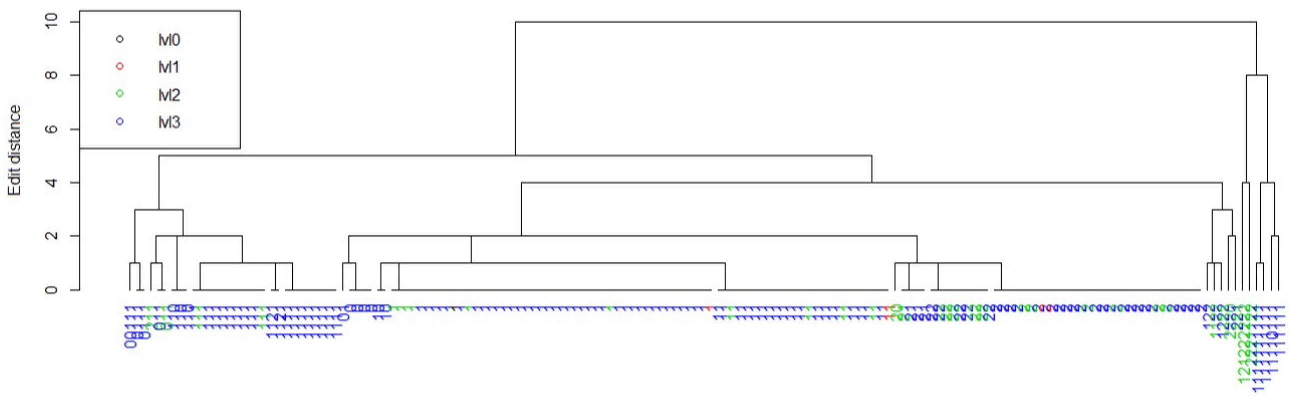

Fig. 5. Session behavior sequence hierarchical clustering

help a lot. The completeness process of information seeking can be critical even though there are irrelevant pages, because it could help to avoid detours. To overcome this shortage, a monitoring program (such as a browser plugin) can be installed in the computers that the students use to finish the task. In this way, all operations the students perform on the browser can be logged, including click, mouse movement, keyboard press, and wheel scroll operations, etc.

Another part to be improved is the text processing. Text collected from html can be further processed with LDA so that the topics can be identified from each document. With a better understanding of the text content, the web pages can be classified into more specific categories, so that the intention of the students when they browse the pages can be further revealed.

The most important part in the study is the behavior sequence clustering, in which students are clustered into groups. The purpose of the clustering is to find common patterns of behavior sequence, and identify the factors affecting the submission quality, and the result indeed shows some connection. However, the result should be further evaluated by regression or testing methods. It would be even more persuasive if the result can be proved valid in other experiments with similar setup.

Another work to do in the future is to research the connection between queries. It has been proved that students frequently refine their query when the search result is not satisfiable(Lu, Y. & Hsiao, I-H. 2016). Considering the connection between adjacent queries could improve the session and subgoal modeling, which could detect behavior patterns in a larger scale.

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