Exploring and Describing Search Expertise

Catherine L. Smith
Kent State University, School of Library and Information Science
PO Box 5190, Kent, OH, 44242, USA
330-672-2116
csmit141@kent.edu

ABSTRACT
We present work in progress on an exploratory longitudinal study of the search behavior of students as they worked on assignments for a semester-long course on expert search. Our goals were to observe students as they acquired search skills, and to describe behavior associated with the skills learned. Nine MLIS graduate students completed the remote study, providing detailed logs of searches conducted during coursework. In this poster, we focus on assignments completed using Dialog Classic. We briefly review motivations for the study, related work, and our method. We then discuss our analysis approach, and conclude with an example from our data.

Keywords
search expertise, search behavior, search interaction, Dialog.

MOTIVATION AND RELATED WORK
In describing web search, the foraging paradigm [10] conceptualizes search as movement from patch to patch in information space. The analogy of an information space is often used in descriptions of web search behavior, with terms such as parachuting in, orienteering, trails, routes and path following [e.g. 9, 12]. These descriptions assume an information space that searchers traverse after finding a starting point using a search engine. Of course, foraging isn’t the only strategy for maximizing sustenance; food is gathered, cultivated, and stored in order to make it available in the future. In effect, food sources can be arranged to form concentrated superpatches. This reorganizing behavior is analogous to two strategies for collecting information sources in specialized spaces. Sources may be cultivated in patches such as indexes or full-text databases. Searchers can also gather sources into sets using tools such as advanced queries and faceted interfaces. A searcher can forage for superpatches, but there are obvious advantages in knowing how to create concentrated patches, and where to find them. A searcher might also find superpatches by following someone who knows where they are located, or someone who often gathers new patches [3], but this strategy is imperfect. Sometimes there is an advantage in collecting information others are unlikely to have, and this requires the ability to find information independently. Expert searchers know how to do this.

Web search expertise has been identified by the use of query operators [13]. Of course, to be of any value, searchers must use operators correctly [8]. Web search expertise has also been associated with the ability to select effective query terms. Lucas & Topi [8] found that this skill has a greater effect on the value of web retrieval than does the use of operators. In studies of searchers using structured information sources such as the Dialog system, expert searchers have been found adept at using the information environment to acquire useful query vocabulary [6, 11]. In summary, search expertise involves the ability to find effective query terms and predict how combining terms with operators will affect the value of a retrieved information space. These are learned skills.

The problem of helping people learn to search more effectively is an active area of research. Bateman, Teevan, and White [2] developed and tested a dashboard system that provides feedback to web searchers, informing them about the potential value of changes in their behavior. Our research focuses on the skills of expert searchers. We have two goals: to observe people gaining expertise, and to develop a descriptive model of behavior associated with expertise. Clearly, extensive experience in the practice of searching is fundamental to gaining true expertise, however, expert search is also taught formally as part of professional training in library and information science. This affords us the opportunity to make close observations of learning. This poster presents work in progress on a study of expert search.

METHOD
Because our goals are to observe learning and describe behavior, we used a longitudinal design to collect detailed logs of search interaction from students enrolled in a semester-long, online graduate course in expert search. The course was conducted completely online, and the students were geographically disbursed, therefore, we ran the study

ASIST 2012, October 26-31, 2012, Baltimore, MD, USA.
on a remote basis. The course instructor very generously gave us access to his class and materials, including detailed answers for each assignment. The course ran according to its normal schedule.

As is customary for the course, students used the Dialog Classic command-line interface to the Dialog service [4]. In its normal operating environment, Dialog stores a detailed log of each user’s interactions. As was the instructor’s usual practice, all students in the course collected their logs when completing assignments, and study participants periodically uploaded their unedited logs to our server. Study participants also used logging software to record browser activity as they completed their coursework. In this paper, we focus on the analysis of the Dialog logs.

In online questionnaires and interviews, volunteers were also asked for demographics and other information that is not pertinent here.

Nine students consented to participate and completed the study (the initial participation rate was 50%; two students dropped out due to personal circumstances and their data are excluded from analysis). Those who completed the study were paid $375 and were allowed to keep a laptop computer we supplied. Six of the participants were 25 years old or older, with the others being between 18 and 25. Six were female. The study ran between January and May of 2012.

EXPLORATORY ANALYSIS

Currently, we are in the process of conducting an exploratory analysis of the logs collected from the first five assignments completed on Dialog. Because each student collected and aggregated their logs by hand, we have carefully organized the logs by volunteer, exercise, and problem within exercise. Because students often worked on a problem several times, we also captured the order of multiple tries at a problem (similar to a search session).

Dialog involves a large and complex set of commands and operations. In order to make our analysis tractable, we have developed a classification scheme for commands and queries. We plan to continue developing and refining the classification.

The command classification presented here has six major categories, plus a code for errors. Table 1 lists the codes, and serves as a key for Figure 1. In Dialog, a set of commands is used to set up and manage an information space, including commands for controlling connection-time charges. We classify these as environment commands. Another set of commands allows searchers to display the information space, apply operations to the entire space, or organize the contents of a retrieved set. We term these meta commands. Browse commands are used to display the contents of retrieved sets. Vocabulary commands display information about index terms. We use two classifications for query commands that create sets, Set Create Basic and Set Create Complex, however, we are working to improve our classification of queries, so we will not discuss the details of this classification here.

We have also developed a visual analysis tool, tailored specifically for the Dialog log data (see Figure 1). Similar to other such systems [1, 7], the display allows us to select search sessions for detailed comparison. Each try at a problem is displayed as a separate line of color-coded boxes, with one box for each command issued during the try. A volunteer’s multiple tries are displayed in time order down the page, allowing us to observe changes in behavior as learning evolves. We also display the instructor’s expert search answers for comparison. Using checkboxes, we can change the display to show different classification schemes. Within a sequence of commands, queries may be displayed in detail. The system also uses Graphviz [5] to draw a directed graph of each try (see Figure 2). The graphs are displayed with a mouse click on a search sequence.

In the remainder of the paper, we discuss some observations and questions that have emerged during our initial explorations of the data.

OBSERVATIONS AND CONTINUING QUESTIONS

The graphs in Figure 2 depict the space of results sets created during a student’s try at solving an assigned problem. Each node represents a set of documents produced by a query command. As sets are created, Dialog assigns a unique identifier to each set, as S1, S2, etc. The nodes are labeled with these numbers, which represent the command sequence. Dependencies between sets are represented by the directed edges, which are unlabeled.

The graphs in Figure 2 depict every set created during a try, even when a set is a duplicate of a prior set. For example, if the query “cats” was submitted four times, four nodes would be drawn, although logically only one set has been used. Also, Dialog allows a searcher to make an implicit reference to an existing set by restating the definition of the set in a subsequent query, as in “cats AND dogs.” The graphs in Figure 2 depict set dependencies only when a set has been referenced explicitly, as in the query “S1 AND dogs”. In this way, the graphs in Figure 2 represent a
searcher’s explicit behavior during the construction of the information space. Every set created, and only explicit references between sets, are represented in a behavior graph.

There is another way to represent the information space. An alternative graph depicts what we term the logical structure of the space. In this type of graph, we don’t draw duplicate sets, so the nodes represent only unique logical sets. Also, we draw all dependencies between logical sets, whether a set was referenced explicitly by its identifier, or implicitly in a subsequent query. We are interested in the similarity of the two representations. We postulate that the two graphs of the same search will be more similar for searchers with greater skill. Also, we are interested in how a more supportive system and user-friendly interface will affect this measure.

We conclude here by reviewing behavior graphs (Figure 2) and a logical graph (Figure 3) of work on problem 6. For this assigned problem, students were given a database to use, and they were asked to find articles about a food-safety issue in the UK. They were prompted to find as many index terms as possible, but no other direction was given.
As depicted in Figure 2-B, Vol-8 started by successfully creating two sets of resources indexed in the two primary subject areas, sets S1 and S2. Two attempts to create a subset of S2 simply duplicated the set (S3, S4). Finally, the desired subset was created in S5, and it was then duplicated in S6. Two unsuccessful attempts to join S6 with S1 using implicit references created two empty sets (S7, S8). Finally, by explicit reference, S1 and S6 were joined to create S9. A set indexed on the third primary subject area was then created (S10) and joined with S9 to create the answer set (S11), which was then duplicated. Figure 2-A depicts the behavior graph of the instructor’s expert search on the problem, and Figure 2-C shows Vol-8’s second try. Except for the order of the commands, the two graphs are identical. Clearly, during the first try Vol-8 learned about the needed information space and how to create it.

The logical graph of Vol-8’s first try (Figure 3) is quite different from its behavior graph. The logical structure has only seven sets. If we drew the logical structure of the second try (2.C), we would see that it looks just like the graph of the behavior that produced it because no empty, incorrect, or duplicate sets were made.

In our ongoing analysis, we are interested in developing measures of information spaces produced by expert searchers in structured information environments. Our goal is to describe how structure is created and used by skilled searchers. Ideally, our descriptions will be useful for understanding how expert and novice searchers use structured resources such as facets, ontologies, and the interfaces that provide access to these types of resources.

ACKNOWLEDGMENTS

Thanks go to extra-capable research assistants Cheri Radke and Martha Roseberry, with extra thanks to Xiaoke Huang, who developed the analysis systems. Thanks also to our hardworking participants, and to the course instructor. This work is funded by a Google Research Award.

REFERENCES


