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Question Asking During Procedural Learning: Strategies for Acquiring Knowledge in Several Domains

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Abstract

Questions asked during acquisition of a complex skill reflect the types of knowledge that learners require at different stages. Questions that learners ask themselves may serve to generate incomplete conceptual frames that can be used to guide explanation of future events. Question-asking data collected from students learning to use a spreadsheet program suggest that learners initially require knowledge about plans and the structure of the skill domain. Next they require knowledge about the structure of tasks that they will be performing. Finally they concentrate on plan refinement. Models of skill acquisition and explanation-based learning should incorporate mechanisms for monitoring levels of knowledge in several distinct domains and dynamically altering strategies for knowledge acquisition within these domains.

Introduction

The acquisition of new skills is difficult for both humans and machines. Traditional psychological learning theories stress the role of practice and reinforcement in learning. Current models of learning and skill acquisition stress cognitive components. Change in the structure of goal hierarchies and the clustering of actions with practice has been studied extensively by researchers in cognitive science (Anderson, 1982, 1983a, 1983b, 1986; Neves & Anderson, 1981; Newell & Rosenbloom, 1981; Robertson & Black, 1986; Rosenbloom & Newell, 1986; Rumelhart & Norman, 1978). Recently, researchers have begun to concentrate on the ability to generalize and reason from single instances or examples. Researchers in this area have emphasized analogy (Burstein, 1986; Carbonell, 1983; Forbus & Gentner,

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1986; Gentner, 1983), schema-based reasoning (DeJong, 1986; Schank, 1982), and more formal rules of induction and generalization (Hayes-Roth, 1983; Mitchell, Utgoff, & Banerji, 1983; Sammut & Banerji, 1986; Stepp & Michalski, 1986).

Reasoning from examples, especially during learning of complex interactive behaviors, requires utilization of knowledge from many different domains. What types of knowledge are typically required during acquisition of a new skill? How is domain search constrained during learning? Here these issues are addressed by examining the questions that people ask during complex skill acquisition.

Question Asking

In contrast to question answering, question asking is not a widely studied phenomenon. In one of the few AI implementations of a question asking system (Sammut & Banerji, 1986), questions to a teacher are used to test hypotheses about a problem. Miyake and Norman (1979) conducted one of the few studies of question asking in the psychological literature. They found that the number of questions asked depended on a combination of the learner's level of knowledge and the difficulty of the task. Novices asked more questions while doing easy tasks, but experts asked more questions while doing hard tasks. Miyake and Norman made the point that more questions are asked when the task difficulty is appropriate for the level of knowledge because question askers must have enough knowledge to formulate questions. While this study suggests how level of knowledge might affect question asking, it does not address how questions might be used to shape the learning process.

A question presents a concept or proposition to a listener along with information about unknown information related to the proposition. The question "How do I get to Newark from here?", for example, presents the fact that the question asker has a goal but no plan for achieving that goal. A cooperative answerer will provide a plan for achieving the goal as an answer to the question. The steps of the plan will become associated with the goal if they succeed so that the question asker can achieve the goal in the future without asking a question. We argue that self-directed questions are posed in order to generate incomplete knowledge structures (like a plan-less goal) that can be embellished by information gained from the learning situation. Thus self-directed question generation can be viewed as a strategy for acquiring knowledge by generating incomplete concepts and using them to guide exploration and constrain interpretation and explanation of new information.

As an example, consider a learner trying to learn about a spreadsheet program (this example is used because the upcoming data was collected from learners in this situation). At some point the question "How do I get rid of data in this cell?" might arise. A conceptual representation of the question shows a set of relationships among known and unknown aspects of the concept:

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(CAUSE
    (?ACT           (ACTOR learner)
                    (OBJECT ?system-obj))

    (STATE-CHANGE   (ACTOR system)
                    (INITIAL-STATE (CONTAIN cell-x data-obj))
                    (FINAL-STATE (CONTAIN cell-x nil))))
```

In question answering systems, the specified parts of the representation would serve as templates for simple memory search. When learners ask questions like this, however, they know that the answer is not in their memory and so the representation serves another purpose. If other types of reasoning processes (e.g. induction, analogy) can not solve the problem, the question representation can serve as an explanation daemon which will match any subsequent occurence of the desired outcome of the unknown action (i.e. the STATE-CHANGE). When the desired system action occurs, by design or by accident, the daemon will recognize a previously unknown relationship between learner and system actions and be able to fill in the unknown action (?ACT) and system object (?system-obj) slots. This constrains the process of explanation required when an unexpected system action is encountered and allows earlier lapses in understanding to be turned into opportunities for learning.

Some Data on Question Asking During Skill Acquisition

The previous diccussion suggests that questions can be used stategically to instantiate incomplete knowledge structures which will be useful for learning. If this is so then the questions that people ask during learning should fall into categories that reflect distinct and useful knowledge domains. As knowledge is acquired in certain domains, questions in that domain should decrease and questions in other domains should increase proportionately. In this section such data is discussed.

Six students were asked to learn the use of a subset of commands for a popular spreadsheet program and enter four sets of data. The students were given brief instructions about relevant keys, the nature of a spreadsheet and the spreadsheet display. The students were instructed to talk

Table 1. Examples of plan, system operation, task, and act questions asked during the learning trails.

Plan questions:

"How do I erase it?"
"Can I go back and erase and move it out?"
"Do I hit 'escape' to get out of this thing?"

System operation questions:

"Where did that go?"
"Is there a certain amount of spaces it will leave?"
"Why did it do that?"

Task questions:

"Would I do those lines underneath there?"
"Now I use the adding form?"

Act questions:

"What did I do wrong?"
"What was I doing before?"
"I don't even know what I did."

aloud as they completed the four data-entry tasks. We stressed that questions were of greatest interest, although the students were told they would not be answered.

The students asked a total of 166 questions, an average of 27.7 questions per subject. Students asked fewer questions as time went on, however this overall trend was not evident for all types of questions.

Questions were categorized by the feature of the learning situation that they referenced. Relevant features were the system being learned, human plans, human actions, and the spreadsheet tasks. The surface forms of questions were not used for categorization purposes. For example, the questions "How do I erase a cell?" and "Can I erase a cell with the DEL-key?" are procedural and verification questions respectively in terms of structure (Lehnert, 1978). Both questions refer to human plans for performing a system operation, however, so they would both be categorized as "plan questions."

Questions about plans, actions, system operation, and spreadsheet tasks accounted for 79% of all observed questions. Table 1 shows examples of each type of question. Figure 1 shows changes in the proportions of questions in each of these categories as the learning trials progressed.

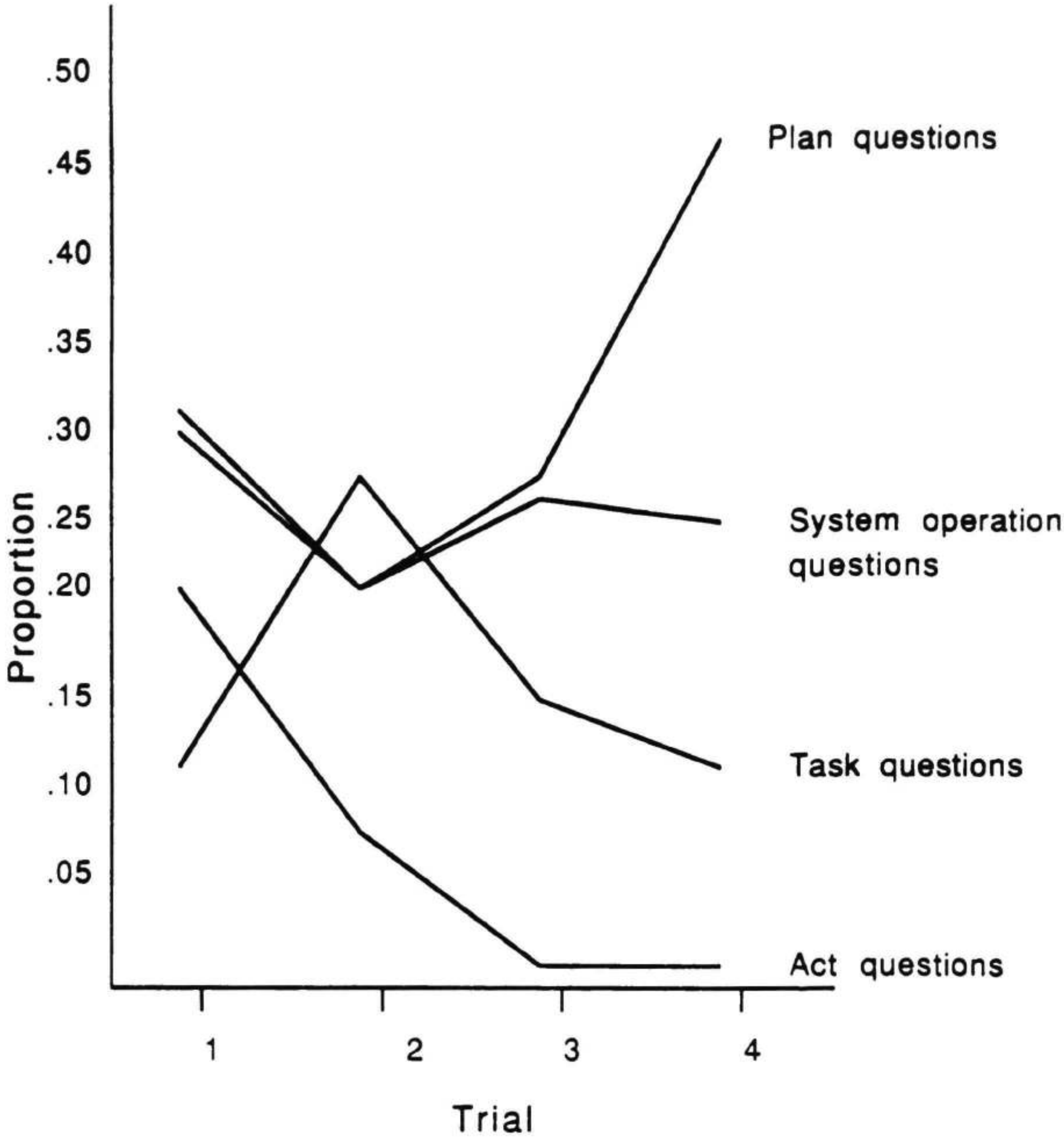

Figure 1. Changes in the proportions of different question types over trials.

Plan questions reflected lack of knowledge about a procedure, a step in a plan, or a goal. Plan questions often specified a goal or included a proposed procedure. As Figure 1 shows, plan questions were among the most consistent and important of all question types. They accounted for for 30% of all questions on the first trial and their frequency increased to 45% by the last trial.

System operation questions were the second most frequent type of question overall. These questions were about states of the system, reasons for system behavior, and causal links between system actions. System operation questions were as frequent as plan questions initially, but their frequency dropped to 24% of all questions by the last trial (Figure 1). Even so, in the last trial plan and system operation questions combined accounted for 56% of all questions asked.

Task questions were about the nature of the task itself or what was required of the learner. Specific procedures or characteristics of the system were not mentioned in these questions. Rather, they sought to clarify intentions of the experimenter or demands of the task. Figure 1 shows that the proportion of task questions increased in the second trials but remained constant and moderate otherwise.

Finally, act questions were about the learners' own actions. They indicated a lack of understanding of the consequences of an action or even a failure to remember what action was just performed. They generally arose in response to an unexpected system behavior. Even though act questions were rare overall, they were very frequent initially, accounting for 20% of all questions in the first trial (Figure 1). By the last two trials, act questions had disappeared completely.

Questions in each of the four conceptual categories either referred to something that had just happened (e.g. "What did I press?", "Did I fill in the right cell?") or to something that might happen (e.g. "What should I press?", "Could I press the delete key to remove that entry?"). The former are "reactive" questions and the latter are "predictive" questions. Novice subjects have no prior knowledge on which to base predictions or generate explanations, so few predictive questions and many reactive questions would be expected initially. As expertise develops, however, reactive questions should decrease and predictive questions should become more common. Figure 2 shows that both types of questions decreased over trials, but reactive ones decreased more rapidly. Also, reactive questions were much more frequent in the first trial than predictive ones, but this trend had reversed by the last trial.

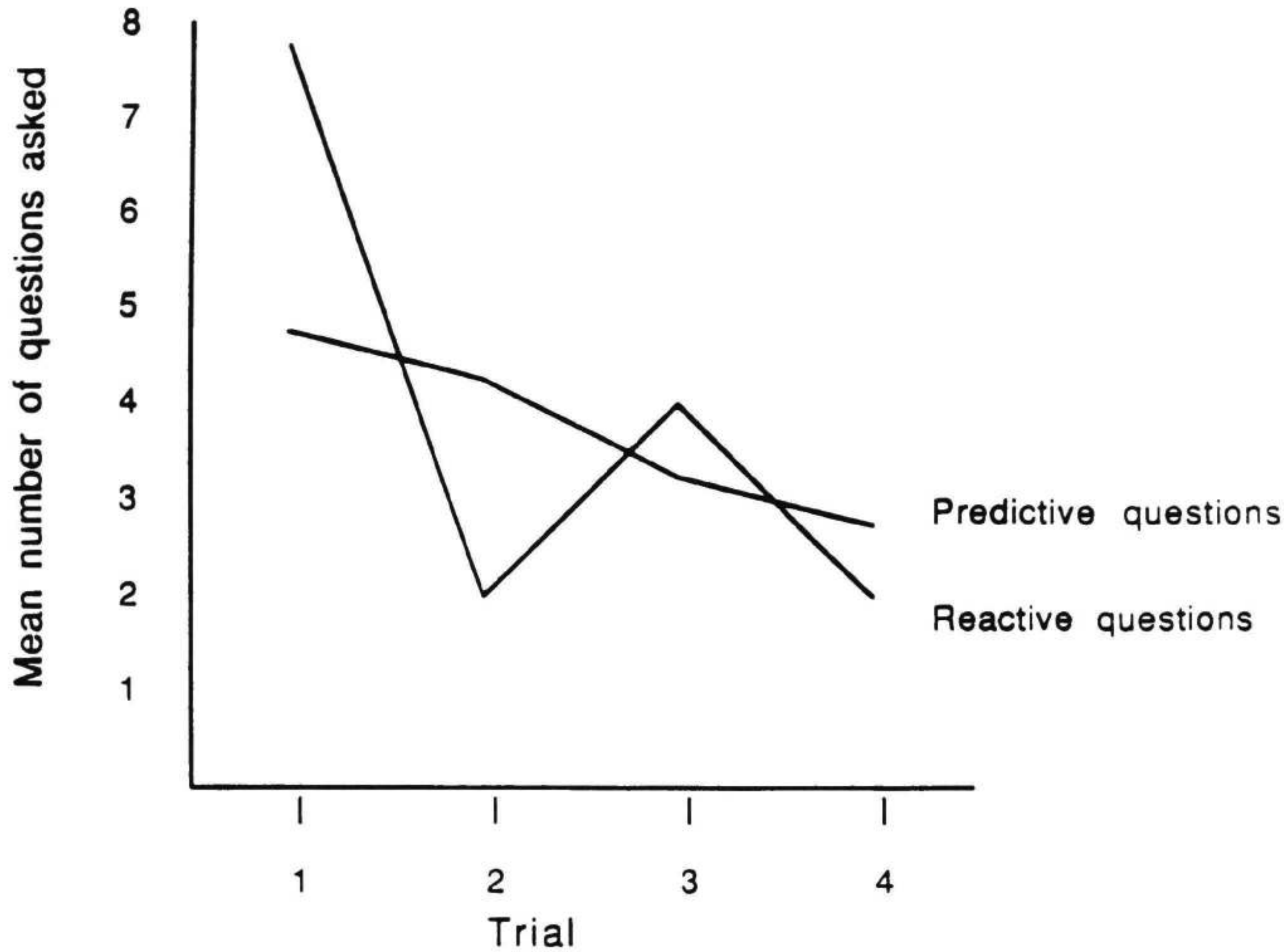

Figure 2. Mean number of predictive and reactive questions over trials.

Summary and Interpretation of the Question Asking Data

Several different types of questions that are relevant to distinct knowledge domains arose during learning. The distribution of question types changed dramatically as learning progressed. The most frequent questions were about plans and the operation of the system being learned. This suggests that priority is given initially to building a "user model" (Norman, 1986) of the system and its operation and to acquiring rules for its use. When basic concepts and rules have been acquired, the efficient achievement of specific tasks becomes more important and an increase in the number of task questions was observed. Unlike other question types, the proportion of plan questions increased in later trials suggesting that plan refinement begins after basic skills and an understanding of the tasks have been acquired.

The initial tendency for reactive questions to dominate predictive questions suggests that learners were trying to explain observed phenomena in the absence of well understood goals, plans, or system knowledge. Later, as knowledge develops it can be used to generate hypotheses about plans and their effects. Thus, predictive questions become more prevalent.

Implications for Models of Knowledge Acquisition

The questions that people ask during learning demonstrate that different learning strategies arise at different stages of skill acquisition. Novice learners must reason from very general plans, often from other skill domains, and without much understanding of the system they are using. A novice's strategy, therefore, is to test alternative plans, fill in procedures for achieving goals, and notice any behavior of the system that will contribute to problem solving. In order to do this, novices construct "question frames" that represent the relationships between human actions and system operations. These questions arise in reaction to unexpected system actions and serve to guide problem solving and constrain explanation during early, failure-driven learning.

Novice learners restrict themselves to elementary operations. Only when they understand basic concepts about the system and acquire procedures for performing elementary actions do they begin to worry about plans for achieving complex tasks. At this stage, learners begin to predict system actions based on a developing model of the system. Questions become more abstract and relate more to tasks and refined plans. This shift in strategy is an important consideration for models of skill acquisition.

General mechanisms for learning, whether they are automatic like plan compilation and chunking, or more strategic, like structure mapping and analogy, may only apply at one stage of learning. An exploratory learner will use different strategies that are determined by the learner's level of knowledge in several distinct domains. It is important in future work to understand how learners determine what they need to know and how they select exploration strategies based on their level of knowledge. Viewing self-generated questions as strategic components of knowledge construction during exploratory learning provides a productive perspective for this effort.

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