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Empirical Investigation of Assistance Dilemma with a Tutoring System that Can Control Levels of Support

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Abstract: We experimentally investigated the assistance dilemma with a learning system that can control levels of support (LOS). Our system supports learning of natural deduction (ND) and was established based on the client-server framework. An experiment was performed. In the first, half of the participants learned ND in the high LOS condition, and the other half learned in the low LOS. In the learning phase, the solution time was shorter and the trial and error steps until solution were greater in the high LOS group than in the low LOS group. However, in the posttest, more participants successfully reached the solution in the low LOS group.

Keywords: Levels of Scaffolding, Assistance Dilemma, Natural Deduction.

1 Introduction

Recent tutoring systems have highly interactive features. Learning is not only a solo activity but also collaboration with computers. Control and management of learning support has become a crucial issue in the studies of artificial intelligence in education. Koedinger and Aleven proposed the assistance dilemma issue in such a context (Koedinger & Aleven, 2007). They pointed out a crucial question: How should learning environments balance assistance giving and withholding to achieve optimal student learning? High assistance sometimes provides successful scaffolding and leads to better learning, but other times elicits superficial responses without consideration from students; on the other hand, low assistance sometimes encourages students to make great effort in learning, but other times results in enormous errors and interferes with effective learning.

Cognitive load theory, first proposed by Sweller (Sweller, 1988), may play an important role in understanding and solving this problem. The theory predicts that cognitive load largely influences both participants' learning process and learning effects; and can be controlled by a learning environment. He and his colleagues have empirically demonstrated that learning by examples promotes participants' learning by reducing their cognitive load compared to learning through problem solving (Sweller, Merrienboer, & Paas, 1998). They have tried to control participants' cognitive load and maximize learning effects by manipulating ways of using learning examples.

The studies above hypothesize an optimum point of learning effects as a function of cognitive load. Koedinger et al. (2008) indicated two dimensions of assistance: the practice spacing dimension and the example-problem dimension, and actually demonstrated a reverse U-shape learning curve on the two dimensions (Koedinger, et al., 2008). In the current study, we focus on the scaffolding dimension. On the scaffolding dimension, high assistance means much information such as hints and indications for problem solving, and low assistance means little information and participants' autonomous problem solving.

Our focus in the current study is to understand the relationship among three factors: levels of scaffolding (LOS), learning process, and learning effects. The dilemma was originally defined as an issue between levels of assistance and learning effects. However, the learning process intermediates LOS and learning effects. It is important to understand the relationship among LOS, process, and learning effects for establishing a baseline in the investigation of the assistance dilemma issue. Our research question is: Does LOS affect the participants' learning process? If so, how do participants' learning outcomes actually reflect the learning process?

Hypothesis 1: The first hypothesis is that high LOS helps the participants solve problems in the learning phase; therefore, learning time in the learning phase decreases in the high LOS condition.

Hypothesis 2: If the participants are given candidates about what they do in the next step in high LOS, the participants' trial and error behavior increases because they select one of the candidate actions without deep consideration. As a result, the number of steps until the solution increases even though learning time decreases in the high LOS condition.

Hypothesis 3: Confirmation of hypotheses 1 and 2 means that the participants may be led to superficial learning in the high LOS condition. Much information for problem solving may prevent the participants from deeper consideration of the solution. This means that high LOS shortens learning time in the learning phase, however, high LOS does not have larger learning effects; rather it has negative effects.

2 Learning System and Task

2.1 Task

We address the assistance dilemma issue by using a relatively complex learning task. The task that the participants learn is natural deduction (ND), which is a kind of proof calculus in which logical reasoning is expressed by inference rules closely related to the natural way of reasoning.

The participants learn this reasoning for about five hours with a tutoring system we developed. Problem solvers need to learn inference rules and strategies for applying the rules. The participants in the current experiment learned nine basic rules and five strategies. These are fundamental knowledge in ND, and almost all problems can be solved using this knowledge.

2.2 System

Our tutoring system was developed for teaching ND to university undergraduates. Our system was constructed based on the server-client framework. We developed a web-based production system architecture called DoCoPro that enables this system design (Miwa, et al. 2009). The complex inferences in ND were performed by the problem solver constructed on a server. Client computers connected with the server only undertake easy processing for the interface. Using this server-client framework, our system can work in any educational environment where computers of varying performance and configuration are used.

The system provides the participants with lists of the inference rules and strategies. Users select one of the rules or strategies from the lists, and the system automatically runs the rules or presents a template of the inference process. The system scaffolds the students by giving help information about the selection of the rules and strategies, and presents candidates of the rules that should be applied in a given situation. From two viewpoints, rule selection and application, levels of scaffolding can be controlled.

LOS for rule selection

Level 3: System presents both candidates (applicable rules) and propositions to which the rules should be applied.

Level 2: System presents applicable rules from a set of inference rules.

Level 1: System presents only a set of inference rules (no scaffolding).

LOS for rule application

Level 2: System generates a proposition inferred automatically.

Level 1: System presents partial information about a proposition inferred. Participants should compensate for terms to infer a complete proposition.

3 Experiment

We conducted Experiment to investigate Research Question.

3.1 Participants and Procedure

Twenty-nine participants joined our experiment. The experiment was performed over three weeks in an introductory cognitive science class. In the initial week, the participants learned the basics of formal inference systems and ND as an example of the systems.

2nd day: After a week, they learned four basic inference rules. These rules are fundamental because they are applied without sub-derivation with hypothesized assumptions. No strategies for setting sub-goals are needed for derivation. The participants solved a total of eight problems using the tutoring system. When solving four of the eight problems, the instructor first demonstrated the solution process, then the participants followed the solution with the tutoring system. Next, the participants solved other four problems, Problems 1 to 4 by themselves. In the second class, LOS in the rule selection and application was set at Level 3 and Level 1.

3rd day: A week later, the third class was performed. The participants solved relatively complex problems for which the sub-derivation process with sub-goal setting is needed for solution. The instructor demonstrated the solution of two problems, then the participants solved Problems 5 to 8 with the tutoring system. In the third class, the participants were divided into two groups: high LOS and low LOS. The participants in the high LOS group solved Problems 5 to 8 with Level 3 in the rule selection scaffolding, whereas the participants in the low LOS group solved them with Level 1. LOS in the rule application was fixed at Level 1 in both groups. After the learning phase, two posttests were performed. Posttest 3 was identical to Problem 6, which they solved in the learning phase, and Posttest 4 as a transfer problem was a new challenge for the participants.

3.2 Result

Table 1 shows (1) the ratio of correct solutions, (2) solution time, and (3) steps until solution when the participants solved each problem in the learning phase. The result shows that there are no differences in all indexes between the two groups in the second class where both groups learn in identical conditions. In the third class, half of the participants learned with low LOS (low LOS group) and the other half learned with high LOS (high LOS group). The solution time was shorter in the high LOS group than in the low LOS group when solving Problems 7 and 8, and more steps were repeated until solution in the high LOS group than in the low LOS group when solving Problems 5 and 6. This result supported Hypotheses 1 and 2.

Table 1. Results of performance of solving problems in learning phase.

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Table 2 shows the result of the posttests. There are no differences between the two groups in the second class. In the third class, when solving the transfer problem, more participants who learned in the low LOS group reached the solution than in the high LOS group. This result supports Hypothesis 3.

Table 2. Results of posttests.

QuickTimeý Ç²
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Overall results imply that high LOS leads the participants to superficial learning in which they used trial and error without deep consideration, even though the solution time was shortened. This learning manner reduced the learning effects especially in solving the transfer problem.

4 Discussion and Conclusions

We developed an intelligent tutoring system for ND learning that can control levels of scaffolding, and successfully implemented it in a university class. ND is being taught in many universities to have undergraduates and graduates understand human normative thinking principles. There is another software for teaching ND called Fitch, which provides students with templates for reasoning, and runs reasoning automatically (Barwise & Etchemendy, 2003). However, the system does not provide information for scaffolding about which rule should be applied in each reasoning phase. This scaffolding is the most important support for introductory naïve participants who are unfamiliar with formal reasoning such as ND. To achieve this scaffolding, a system needs to have the ability to run ND. To establish this function, an adaptive AI-based reasoning system, such as a production system, is needed. In our system, the complex reasoning is processed at the server; and the clients perform only light processing such as management of the interface. This server-client framework constructs an educational environment where any type of computer, such as those with different operating systems and even poorly performing old ones, can be used as terminal computers.

The experimental results supported Hypotheses 1, 2, and 3. This means that the participants may be led to superficial learning in the high LOS condition. This finding was supported by the experimental result that the posttest scores in the high LOS condition were lower than the scores in the low LOS condition. Note that this difference was observed only in the solution of the transfer problem (Posttest 4) (Singley & Anderson, 1989). We should note that this result only supported half of the assistance dilemma (the right half of the reverse U-shape curve). The other side (left side) predicts the following: the learning effects are lower (the participants can learn nothing) in the much lower LOS or no scaffolding conditions. In such a situation, the participants might not decide what to do next, and may make enormous errors. Currently, we have no empirical data about this side. This side of the effects of LOS is expected to appear when the students face very difficult problems in which they need much assistance. Actually, in another class, when we let the students solve a very difficult problem that involves a method of indirect proof such as reductio ad absurdum, they had much difficulty learning without assistance. More experiments are needed for detailed analysis, and this remains as important future work.

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