Does Learning From Examples Improve Tutored Problem Solving?

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Abstract

Although problem solving supported by Cognitive Tutors has been shown to be successful in fostering initial acquisition of cognitive skills, this approach does not seem to be optimal with respect to focusing the learner on the domain principles to be learned. In order to foster a deep understanding of domain principles and how they are applied in problem solving, we intend to combine the theoretical rationales of Cognitive Tutors and example-based learning. Our main hypothesis states that enriching a Cognitive Tutor unit with examples whose worked-out steps are gradually faded leads to better learning. This research question will be investigated in a preparatory lab experiment and a subsequent field experiment in a Geometry Cognitive Tutor.

Introduction

In the acquisition of cognitive skills, three phases are often distinguished. For example, VanLehn (1996) distinguishes among early, intermediate, and late phases of skill acquisition. During the early phase, learners attempt to gain a basic understanding of the domain without necessarily striving to apply the acquired knowledge. During the intermediate phase, learners turn their attention to learning how to solve problems. Ideally, learning is focused on how abstract principles are used to solve concrete problems. One potential outcome of this phase is that flaws in the knowledge base, such as lack of certain elements and relations as well as misunderstandings, are corrected. It is important to note, however, that the construction of a sound knowledge base is not an automatic by-product of studying examples or solving problems. Rather, learners have to actively self-explain the solutions, that is, they have to reason about the rationale of the solutions (Chi, Bassok, Lewis, Reimann & Glaser, 1989; Neuman & Schwarz, 1998; Renkl, 1997; VanLehn, 1996). Finally, the learners enter the late stage in which speed and accuracy are increased by practice. During this phase, actual problem solving as opposed to reflective considerations such as self-explanations is crucial (Renkl & Atkinson, 2003).

Our research focuses particularly on the intermediate stage of skill acquisition in which the primary instructional aim is to gain understanding – especially understanding of how domain principles are applied during problem solving – and to close knowledge gaps. There are several instructional approaches that try to optimize cognitive skill acquisition in this phase. One very successful approach is the use of Cognitive Tutors (Anderson, Corbett, Koedinger, & Pelletier, 1995; Koedinger, Anderson, Hadley, & Mark, 1997). These computer-based tutors provide individualized support for learning by doing (i.e., solving problems) by selecting appropriate problems to-be-solved, by providing feedback and problem-solving hints, and by on-line assessment of the student's learning progress. Cognitive Tutors individualize the instruction by selecting problems based on a model of the students' present knowledge state that is constantly updated, through a Bayesian process called "knowledge tracing" (Corbett & Anderson, 1995).

Although Cognitive Tutors have many advantages, they are not without limitations. As with most tutoring systems, their main focus is on correct answers during problem solving and not on gaining an understanding of how the domain principles apply in problem solving (cf. VanLehn et al., 2005). It is uncertain to what extent students working in Cognitive Tutors reflect deeply on the principles when trying to solve problems or whether they rely on shallow strategies (e.g., using key words as hints for specific algorithms) or general problem-solving strategies (e.g., means-ends analyses) that do not necessarily deepen their domain understanding. The problem of focusing more on correct answers than on understanding the domain principles in problem solving is aggravated by many students' performance orientation, meaning that their main subjective goal is to find the correct solution (e.g., Dweck & Leggett, 1988); yet a learning orientation that is connected with the main goal of understanding would be preferable. The conjecture that Cognitive Tutors could be improved by strengthening the "principle orientation" was tested by Aleven and Koedinger (2002). They found that adding self-explanation prompts and support focusing on domain principles to a Cognitive Tutor module substantially enhanced its effectiveness.

One instructional idea to further improve the focus on principles in Cognitive Tutors, and thereby their effectiveness, can be taken from cognitive load theory research (e.g., Sweller & Cooper, 1985; Sweller, van Merriënboer, & Paas, 1998) or more specifically from the instructional model of example-based learning by Renkl (2005) as well as Renkl and Atkinson (in press). The basic idea is to reduce problem-solving demands by providing worked-out solutions in the intermediate stage, when the primary instructional goal is to gain understanding (cf. Sweller et al., 1998). Thereby, more of the learners' limited processing capacity (i.e., working memory capacity) can be devoted to understanding the domain principles and their application in problem solving, especially when worked-out examples are combined with self-explanation prompts (cf. Renkl, 2005). In addition, by removing performance demands and by providing prompts that focus the learner on acquiring an understanding of domain principles, the learner's performance orientation is likely to give way to a (more favorable) learning orientation (cf. Renkl, 1999).

So far, the effectiveness of worked-out examples has mainly been shown relative to problem solving that was not supported except for some feedback (e.g., Sweller & Cooper, 1985; Sweller et al., 1998). When students solve problems using Cognitive Tutors, however, they receive extensive guidance that supports both the eventual successful solution of problems and, in some versions, the deep processing of the learning materials by self-explanation prompts. This kind of tutored problem solving thus represents a far tougher control condition than those that have been investigated in previous studies. Nevertheless, it is plausible that beginning cognitive skill acquisition is better supported by examples than by tutored problem solving, because examples prevent the potential pitfalls mentioned above: a performance orientation, combined with the use of shallow strategies or general heuristics instead of efforts to apply domain principles in problem solving (cf. also VanLehn et al., 2005). Worked-out examples combined with self-explanation prompts are an appropriate means to focus learning on the domain principles right from the beginning.

However, as learners progress through training worked-out examples might not be as effective in later stages of the training as postulated by the expertise reversal effect (Kalyuga, Ayres, Chandler, & Sweller, 2003). The empirical results actually indicate that actual problem solving is more favorable in later stages. This means that the effectiveness of learning methods reverses in the course of skill development. The notion of expertise reversal effect has, however, three drawbacks. First, the term "expertise" is misleading as the learners that are typically considered in research on learning and instruction (this hold also for the studies of Kalyuga, Sweller, and colleagues) do not really gain domain expertise. To become a domain expert it takes approximately 10 years of practice (e.g., Ericsson, Krampe, Tesch-Römer, 1993; Ericsson & Charness, 1994). Thus, the use of the term "expertise" is potentially confusing. Therefore, we prefer the notion knowledge-gain reversal effect. Second, as explanation of the reversal effect it is argued that studying examples becomes a redundant activity that induces unnecessary (extraneous) load. However, there are no detailed descriptions of the actual learning processes that lead to favorable learning outcomes in the respective stages of skill acquisition. Third, there is no precise assumption about when it is sensible to move from studying examples to problem solving. Against this background, we propose a more elaborated model of the empirically observable reversal effect.

The knowledge-gain reversal effect can be explained by the following assumptions. When the learners lack an understanding of how domain principles can be instantiated for solving a certain type of problem solving step, they typically employ shallow strategies to determine the numerical answer when confronted with problem solving demands. Due to their lack of principle understanding, they cannot rely on domain principles in their problem solving effort. Employing shallow strategies for problem solving does not deepen domain understanding. Thus, it is more favorable in the beginning of skill acquisition to provide worked-out steps that the learner can self-explain and thereby gain an understanding of how the domain principles can be instantiated. In order to overcome potentially passive learning behaviors and to assure self-explanation activities corresponding prompts can be used.

When the learners have already gained an understanding of the instantiation of the domain principles, self-explaining the instantiation does not lead to the acquisition of new knowledge. When the learner has already gained an understanding of the relation between a type of problem solving step - even when this understanding is not perfect, for example, because of two narrowly specified conditions of the principle application - it is sensible to solve a step. In the case of a temporary impasse the knowledge deficit can be repaired. In the case of successful problem solving a specific production rule can be formed.

The assumptions of our knowledge-growth reversal model lead to the following instructional implications. First, provide worked-out steps together with self-explanation prompts. When the learner indicates understanding (e.g., by successful self-explanations) fade the step and have the learner solve it. More specifically, a fading method should be employed in which the worked-out steps are gradually faded from worked-out examples to problems (Atkinson, Renkl, and Merrill, 2003; Renkl, Atkinson, and Große, 2004; Renkl, Atkinson, Maier, and Staley, 2002; for a detailed theoretical rationale see Renkl & Atkinson, 2003; Renkl & Atkinson, in press). In such a fading procedure first a complete example is presented. When the learner shows understanding, i.e. by successful self-explanations, one single step can be faded and the learner has to solve it in the next example. After trying to solve the faded step in this incomplete example, the learner receives feedback informing her or him of the correct solution. Then, in the following examples, the number of blanks is increased step by step until just the problem formulation is left, that is, a problem to-be-solved.

For instance, for an example/problem type with three solution steps, the following instructional procedure is proposed: (1) problem formulation (pf) - worked step - worked step - worked step; (2) pf - worked step - worked step - faded step; (3) pf - worked step - faded step - faded step; (4) pf - faded step - faded step - faded step. In this way, a smooth transition from example study, to working on incomplete examples, to problem solving is implemented.

Several experiments (Renkl et al., 2002, 2004) showed that the positive effects of fading on learning outcomes (transfer performance) is mediated by greater problem-solving success at the faded steps, in comparison to a condition with example/problem pairs that included the same amount of steps to-be-solved. This result is consistent with the cognitive load assumption that fading helps to avoid overtaxing the learners by problem solving demands. Furthermore, Atkinson, Renkl, and Merrill (2003) showed that combining fading with self-explanation prompts is especially effective. They provided prompts in the form of a menu of probability principles, from which learners had to select the principle that was applied in the worked-out step they were studying.

We expect that the effectiveness of a Cognitive Tutor unit, even one enriched with support for self-explanation, will be further enhanced when it presents faded worked-out examples to learners in the beginning of each curricular section. When studying worked-out examples, more of the learners' limited processing capacity can be devoted to an effort to understand solution steps in terms of the application of domain principles. Assuring that learners have a basic understanding before they start to solve problems should help them to deal with the problem-solving demands by referring to already-understood principles instead of shallow strategies. The use of principles during problem solving not only enables learners to deepen their knowledge, by successfully applying it to new problems, but will also cause them to notice gaps in their understanding of the principles when they reach an impasse (cf. VanLehn et al., 2005). Cognitive Tutors can then help to repair the knowledge gaps.

Research Questions

More specifically, in our 1st experiment we will test the following predictions with respect to the comparison of an "example-enriched" Cognitive Tutor and the standard version, where both versions support menu-based self-explanation by means of prompts and feedback:

(1) The "example-enriched" version leads to more effective self-explanation activity, as determined by the analysis of the learner's input to the prompts.

(2) The "example-enriched" version leads to a greater learning orientation, as assessed by questionnaires.

(3) The "example-enriched" version leads to better learning performance and better learning on problem-solving steps, better initial performance and faster reduction of errors.

(4) The "example-enriched" version leads to more favorable learning outcomes, as assessed by transfer problems and questions that address understanding of the domain principles.

Procedure for Experiment 1

These predictions will be tested in our first experiment which will involve two conditions: Problem-Solving Only and Fixed Fading. The students in both conditions will work through a single unit of the Geometry Cognitive Tutor curriculum and take a pre- and post-test before and after, respectively. The only difference between the conditions is the version of the Cognitive Tutor version used. Students in Problem Solving Only condition will use a version that presents problems only, whereas students in the Fixed Fading condition will have a version that is modified so that it initially presents examples, which are gradually faded according to a fading procedure. This fading procedure, described in more detail in the Implementation section, will present the same sequence of examples to all students (hence the term "Fixed"). A preparatory experiment will be done in Freiburg which will involve the same two conditions. A key purpose of this laboratory experiment is to test a new sequencing of learning tasks that is more amenable to the kind of fixed fading procedure that we have in mind than is the current task sequence in the Circles unit of the Geometry Cognitive Tutor. The field experiment, which will take place after the data of the Freiburg laboratory experiment have been analyzed, will cover about 3-4 weeks of class time, during which students in both conditions will work through the Circles unit of the Geometry Cognitive Tutor.

Students' learning will be assessed by means of pre/post tests that include near- and far-transfer items. The near-transfer items are of the same type as practiced with the Cognitive Tutor and involve problem-solving and explanation steps. The far-transfer items require application of the targeted geometry principles in a slightly new context. In the past we have used "Not Enough Info" items, in which students are asked to judge whether they have enough information to make certain inferences (e.g., find a particular unknown angle measure) as one possible way of exposing shallow learning is the use of “Not Enough Info” (e.g., Aleven & Koedinger, 2002). Finally, we developed some post-test items that test the conceptual understanding of the domain principles (e.g., requiring the learner to explain domain principles).

Preparatory Activities

In order to prepare for these experiments, we have developed a sequence for the learning tasks in the Geometry Cognitive Tutor that is suitable for use with the example-fading procedures. The former sequencing of learning tasks in the Circles unit of the Cognition Tutor unit is not ideal for implementing such a fading procedure. In the tried-and-tested fading procedures employed by Renkl and colleagues (e.g., Renkl, & Atkinson, 2003) the same problem-solving principle re-appears every third step. Hence, after a learner figures out the rationale behind a worked-out step, s/he is able to apply the newly-acquired knowledge within a very short time span, namely, in the next partially worked-out example or problem.

In the present Cognitive Tutor, however, such “proximity” is not always realized: in some instances, a certain type of step does not re-appear until several problems later. Due to interference effects, the application of the newly acquired principle-related knowledge is hindered (for evidence that immediate application is favorable see Trafton & Reiser, 1993). We have developed a rationale of re-sequencing the Cognitive Tutor lessons, by using instructional methods proven to be effective (Renkl, Atkinson, & Große, 2004; Renkl, Atkinson, Maier, & Staley, 2002; van Merriënboer, Kirschner, & Kester, 2003; van Merriënboer, Schuurman, De Croock, & Paas, 2002). Particular attention has been paid to ensure sufficient example/problem variability. By varying the sequence of principles in the problems that follow the initial examples (Paas & van Merriënboer, 1994) students will have a wider exposure to possible combinations between principles. This is more likely to enhance deep processing and lead to improved transfer performance.

Implementation

The sequencing of the Geometry principles will be as systematic as possible. Most ideally, the sequencing and the fading of worked-out steps would look like table 1, in which W stands for worked-out examples and S for problem solving. The table shows that first, the application of each principle (that is relevant as a sub-lesson) is introduced by a single-principle problem. After, for instance, three such single-principle problems, we present the students with a more complex worked-out example which combines all three principles. Following this, we implement a fading procedure using more complex three-principle problems - fading one principle at each newly presented partially worked-out example. Although the table indicates a fixed progression from principle 1 to principle 3 in all problems, this does not necessarily have to be the case. By presenting problems which have different orders in which the principles should be applied the variability is high which exposes students to how and when certain principles should be applied. The Freiburg lab experiment will adopt the ideal sequencing as depicted in Table 1 and focus on 1 section of the Circles unit in the Geometry Cognitive Tutor.

Table 1: The ideal sequencing of problems and fading of worked-out steps.

	Examples			Problem solving		
Problems	Principle 1	Principle 2	Principle 3	Principle 1	Principle 2	Principle 3
P1	W			S		
P2		W			S	
P3			W			S
P4	W	W	W	S	S	S
P5	W	W	S	S	S	S
P6	W	S	S	S	S	S
P7	S	S	S	S	S	S

The field experiment will focus on the entire Circles section and will use the ideal sequencing as a guideline to implement the fading procedure into the existing classroom material. Furthermore, we will determine in advance how many times each problem-solving principle should be explained before example steps involving that principle are faded. Different thresholds can be used for different principles. The tutor’s cognitive model will be employed to map steps to principles in much same way as it is used during model tracing. The mapping could be determined at the beginning of each problem (i.e., by having the cognitive model solve the full problem at the moment that it is presented to the student) or it could be done off-line, with the results stored in database or special file.

Purpose of the Freiburg Laboratory Experiment

The main purpose of the lab experiment conducted in Freiburg is to test the new task sequencing method described above and its suitability for use with the example-fading procedures studied in the proposed research. More specifically, the lab experiments test the new sequencing with respect to the following two main issues: (1) is the new sequencing conducive to learning? Are the faded steps recognized as new instances of previous steps so that principle-based problem-solving attempts can be made? (2) Are there enough instances of worked-out steps in order to assure that the last worked-out steps is self-explained correctly by most students and the first faded steps is solved correctly by referring to domain principles by most students.

This preparatory lab experiment is scheduled to be conducted in the second half of February 2006, followed by the field experiment which is scheduled to take place at a high school in Westmoreland in the second half of May 2006.

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