How should SE be supported – during problem solving or separately?

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Abstract. Self-explanation (SE) has proven to be an effective meta-cognitive strategy. However, some performance-oriented students tend to not take advantage of the SE opportunities provided as they are seen as extra work that does not directly contribute to problem solving. We focus on approaches that can be used to motivate such students to take advantage of SE support. As a first step, we analysed SE support provided in some systems and discuss their limitations. We also outline a study that compares the two approaches: separating SE support from problem solving versus interleaving the two.

1 Introduction

Self-explanation (SE) has proven to be an effective meta-cognitive strategy. Bransford et al. [1] suggest focusing on metacognition as one of three principles that should be applied to educational research and design, as stated in the influential volume "How People Learn". According to previous research studies, only a few students self-explain spontaneously, and therefore SE prompts have been used to encourage students to explain instructional material to themselves [2]. SE prompts can be of different types, according to the knowledge they focus on. For instance, Hausmann et al. [3] compared *justification-based prompts* (e.g. "what principle is being applied in this step?") and *meta-cognitive prompts* (e.g. "what new information does each step provide for you?") with a new type called *step-focused prompts* (e.g. what does this step mean to you?"). They found that students in the step-focused and justification conditions learnt more from studying examples than students in the meta-cognitive prompts condition. In another study, Chi and VanLehn [4] categorised SE as either procedural explanation (e.g. answer to "Why was this step done"), or derivation SE (e.g. answer to "where did this step come from?"). In [5], SE prompts are categorized into *procedural-focused self-explanation* (P-SE) prompts and *conceptual-focused self-explanation* (C-SE) prompts. P-SE prompts were given after examples to assist students to focus on procedural knowledge as the examples have shown to increase conceptual knowledge. On the other hand, after solving problems, students were given C-SE prompts in order to help the students to gain the corresponding conceptual knowledge covered in the problems they just completed.

SE has generally been supported in the context of a problem-solving environment. Even though many systems use the problem-solving context, they include additional steps to support SE. For instance, an enhanced version of Geometry Explanation Tutor expects students to explain every problem-solving step [6]. Asking students to explain each step is an additional task in the typical problem-solving process. How a student interacts with the learning environment depend on his/her attitude and learning goals [7]. If a student has a performance-oriented focus (i.e. attempting to demonstrate their ability by completing as many problems as they can without paying much attention to acquiring knowledge), it is possible that they may view this as extra work. In such situations, do we keep including such opportunities anyway to support SE as it is beneficial for students' leaning? This decision may have a negative impact as the student may be demotivated and likely to be disengaged from the learning. The other alternative is to provide only problem-solving support and support SE when they become more proficient; are students less likely to take advantage of SE opportunities when they are novices?

As a first step towards exploring these questions, we analysed the SE support provided by different systems. The way these systems support SE can be categorized as separating SE from problem solving vs interleaving the two. The systems in the first category provide SE opportunities immediately after a problem/step is completed. This may also result in disengagement from taking advantage of a learning opportunity as they have completed the problem/step and want to move to the next problem/step. Interleaving SE support with problem solving expect students to self-explain during problem solving. Will the students be more motivated if these opportunities to self-explain are integrated with problem-solving? What is the effect of each approach on student's mental model of process of problem-solving i.e. if the integrated approach is used, will the students feel that SE is a vital ingredient of learning by solving problems and vice versa. Exploring these issues will provide us with initial insights about students' behaviour towards SE support. This will enable us to design ITSs that dynamically adapt their pedagogical decisions such as SE support not only on the individual student's competency of the instructional task, but also on their learning goals.

In this paper we discuss some studies that use one of the two strategies (integrated approach vs. separation approach) and our plans to conduct an evaluation study that compares these two approaches.

2 Interleaving SE support with problem solving

We now discuss two systems that interleave SE support with problem solving. Both these systems expect students to provide self-explain during problem-solving.

2.1 Geometry Explanation Tutor

A new version of the Geometry Explanation Tutor was created to provide support for SE while students learn about the properties of angles in various kinds of diagrams [6]. In addition to solving problems, students were expected to explain all the steps for each problem. For example, a student could explain a step in which the triangle sum theorem was applied by typing “Triangle Sum”. A Glossary of geometry knowledge was provided as a way of helping students to provide self-explanations. The Glossary lists relevant theorems and definitions, illustrated with short examples. It is meant to be a reference source which students can use freely to help them solve problems. Students could enter explanations by selecting a reference from the Glossary or could type their explanations. The tutor provided feedback on the students’ solutions as well as their explanations. Further, it provided on-demand hints, with multiple levels of hints for each step. SE is supported via the additional task of explaining each problem-solving step: the students were expected to solve each step in a problem and provide explanations at the same time. Hence this system supports SE during problem solving, but support is provided using an additional task. As the SE is not adaptive, students may have to specify a theorem multiple times for a problem, if it has been used in several steps within the problem.

A study was conducted to compare the performances of students when they explain their problem-solving steps in their own words with their peers who did not. The students who explained the problem-solving steps learnt with greater understanding compared to their peers who did not. The explainers were also more successful on transfer problems.

2.2 NORMIT-SE

NORMIT, an ITS that teaches data normalization, was enhanced to support SE [8]. The enhanced system, NORMIT-SE, expects an explanation for each action type performed for the first time. For the subsequent actions of the same type, explanation is required only if the action is performed incorrectly. This approach would reduce the burden on more able students (by not asking them to provide the same explanation every time an action is performed correctly), and also that the system would provide enough situations for students to develop and improve their explanation skills.

Students provide explanations by selecting one of the offered options. The order in which the options are given is random, to minimize guessing. For example, if the specified candidate key is incorrect, NORTMIT-SE asks the following question “This set of attributes is a candidate key because……:”

If the student’s explanation is incorrect, he/she will be given another question, asking to define the underlying domain concept (i.e. candidate keys). An example of such a question is “A candidate key is………… ”. In contrast to the first question, which was problem-specific, the second question focuses on domain concepts. If the student selects the correct option for a question, he/she can resume problem solving. If the student’s answer is incorrect, NORMIT will provide the correct definition of the concept.

An evaluation study was conducted to investigate the effect of explaining problem-solving steps on both procedural and conceptual knowledge [8]. The students in the experimental group were expected to explain their problem-solving steps while their peers in the control group just solved problems. The experimental group acquired knowledge (represented as constraints) significantly faster than the control group. There was no significant difference between the two conditions on the post-test performance, and it might be due to the short duration of their sessions interacting with the system. Furthermore, the analysis of the self-explanation behavior shows that students find problem-specific question (i.e. explaining their action in the context of the current problem state) more difficult than defining the underlying domain concepts.

3 Separating SE support from problem solving

SQL-Tutor is an ITS that teaches database querying and was enhanced to provide SE support after each problem was completed [5]. The students were expected to solve the given problems as in the original version of SQL-Tutor which provided multiple levels of feedback. Upon completion of a problem, students were given an opportunity to self-explain. The student received a C-SE prompt with multiple options from which the correct one has to be selected. "What does DISTINCT in general do??" is an example of a C-SE prompt. There was only one SE prompt per problem. The prompts were non-adaptive and depended only on the problem. As the SE support focused only on conceptual knowledge, the problem-solving context does not have to be used to support SE.

A study was conducted to investigate the effects of such SE support on student learning. This was a part of a larger study and we report only the relevant results. Problems were provided in pairs. i.e. students solved two isomorphic problems in each pair. The participants were 12 students enrolled in an introductory database course at the University of Canterbury. Participants were informed that they would see ten pairs of problems, and that the tasks in each pair were similar. Providing this information to students may have motivated them to use problem pairs more efficiently. Analysis revealed that students performance on the post-test was significantly higher in comparison to the pre-test performance ($p<.01$).

4 Discussion and Future Work

The three research attempts discussed can be categorized using different criteria such as the type of approach used, the type of SE supported and the target instructional task. Both the enhanced Geometry Explanation Tutor and NORMIT-SE provide SE support during problem-solving. In contrast, SQL-Tutor provides SE support after problem solving. Furthermore, NORMIT-SE provides both conceptual and procedural SE. In contrast, the other two systems use only conceptual prompts.

The only system that provides adaptive SE support is NORMIT-SE. However, NORMIT-SE does not consider the learning goals of each student to customise SE support. However we believe that SE support could be more effective when it is customized based on both a learner's knowledge and learning goals. Such customising has the potential to motivate students to take advantage of SE support instead of burdening them.

In order to explore how students utilise the different ways of SE support, we plan to conduct a study within the context of NORMIT-SE with four groups. All the groups will be asked to solve several problems while receiving typical feedback with multiple levels of help from NORMIT-SE. Groups 1 and 2 will be given conceptual SE-prompts and the other two (groups 3 and 4), procedural prompts. Groups 1 and 3 will be asked to self-explain after a problem is completed. The remaining two groups (groups 2 and 4) will self-explain when they submit their first attempt for a problem. We hypothesise that providing conceptual prompts at the end of each problem or procedural prompts after the first attempt are more beneficial than the other two scenarios. We also plan to identify measures related to a student's problem-solving behavior to infer learning goals for each student. Such measures can include the number of times a student access the full solution, number of times each help level is accessed and the number of times help is sought for a problem. Based on this analysis, we plan to classify students as having a performance-oriented or a learning-oriented focus. This classification will enable us to design ITSs that dynamically adapt SE support not only on the individual student's competency of the instructional task, but also on their learning goals

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