The Impact of Instructional Intervention and Practice on Help-Seeking Strategies within an ITS

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ABSTRACT

Within intelligent tutoring systems, instructional events are often embedded in the problem-solving process. As students encounter unfamiliar problems there are several actions they may take to solve it: they may explore the space by trying different actions in order to 'discover' the correct path or they can request a hint to get 'direct instruction' about how to proceed. In this paper we analyze experimental data from a tutoring system that provides two different kinds of hints: (1) interface specific hints that guide students attention to relevant portions of a worked example, supporting student discovery of next steps, and (2) procedural hints that directly tell students how to proceed. We adapted a method of sequence clustering to identify distinct hinting strategies across the two conditions. Using this method, we discovered three help-seeking strategies that change due to experimental condition and practice. We find that differences in strategy use between conditions are greatest for students that struggle to achieve mastery.

1. INTRODUCTION

As an instructional practice, tutoring supports students as they learn by doing. The tutor passively observes while the student is successful, but intervenes when the student struggles. In this paper, we explore data from two intelligent tutoring system (ITS) experimental conditions that take different approaches to assisting students. The conditions utilized adaptations of two common instructional perspectives, direct instruction and independent student discovery. These methods are often discussed in contrast to one another. Direct Instruction (DI) involves explicitly identifying and teaching the key principles, skills, and procedures for performing a specific task. The Discovery Method (DM), on the other hand, fosters a student's discovery of these principles, skills, and procedures by referring to content in the learning environment and providing indirect feedback and guidance.

To explore how DI and DM impact student learning we analyzed data from two algebra equation solving tutors [1]. In both tutors students were provided with a worked example. However, in the DI condition, students were provided with explicit procedural hints whereas in the DM condition, hints provided general information about the interface. In their initial analysis, Lee et al. looked at average actions per problems across several units and found that on some early units students in the DM tutor showed a higher proportion of mastered skills than students in the DI tutor. This effect did not persist in later units of the tutor. They concluded that, in the early units, students in the DM condition were able to learn faster with the non-verbal worked examples scaffolding than with the informative hints of the DI condition. In the current paper we aim to take a more nuanced look at how the two experimental conditions impacted help-seeking strategies and how these strategies change over the course of problem solving.

2. METHODS

The experiment was conducted within the Carnegie Learning Algebra tutor. Twenty-two high school classes were randomly assigned to the DI condition and sixteen classes were randomly assigned to the DM condition. We restricted this sample to students who had completed all experimental problems in the 'Two-step linear equation solving' unit (DI=136, DM=138). Tutors in both conditions featured a worked example that faded as students achieved mastery. In the DI condition students were provided with hints that instructed them on what procedure to do and why to do it (e.g. "To eliminate -1, add 1 to both sides of the equation because -1 +1=0"). In the DM condition students were provided with hints about how to use the interface (e.g. "Select an item from the transform menu and enter a number"). Unlike the traditional Cognitive Tutor, the initial hint was a bottom out hint. Finally, in both tutors students could make two types of mistakes, which received different feedback. If they selected off-task actions (e.g. choosing to multiply when they should have divided), they received a 'bug' telling them to undo their action and ask for a hint. If they selected an on-task action, but incorrectly applied it (e.g. dividing by an incorrect amount), they would receive 'error' feedback that their action was incorrect.

To identify distinct strategic behaviors within these tutors we first generated a matrix of all problem-solving sequences for each participant. We had a total of 5541 sequences for the DI condition and 5430 sequences for the DM condition. Correct actions were coded as 'Success', off-path actions as 'Bug', on-path actions as 'Error', and hints as 'Hint'. Next, we used a clustering method previously used to detect strategy use within an ITS [2]. This method consists of fitting a Markov Chain (MC) to each sequence, evaluating the fit of each sequence's MC to every other sequence's MC to derive a dissimilarity matrix, and using k-mediods to cluster the sequences. We found that fitting 3 clusters produced the

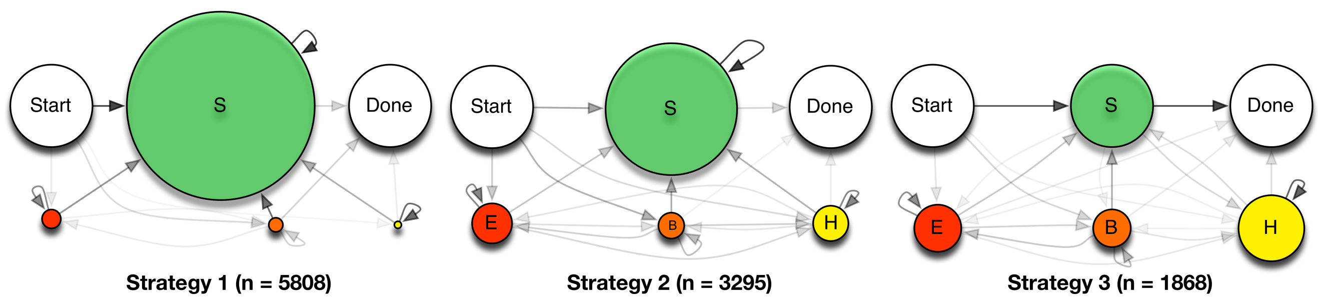

Figure 1: The student behavior for each cluster. Arrow gradients denote transition probability. Green nodes represent success, red error, orange bugs, and yellow hints.

highest average silhouette coefficient. Then, for each cluster we re-fit a single MC using all sequences assigned to that cluster to generate transition probabilities between states used to make Figure 1. After clustering the sequences we fit a binomial mixed-effects model to each cluster to better understand how students moved through the strategic clusters. Our models included fixed effects for experimental condition, the number of problems students solved (we refer to this as Practice Opportunity), and an interaction between experimental condition and practice opportunity. The models also included a random intercept for student to account for individual differences, and a random intercept for each specific problem to account for differences between the specific problems.

3. RESULTS

Figure 1 illustrates the occupancy and transitions between the different actions of the three clusters. A Chi-Squared test found that the cluster assignment of sequences from the two conditions are significantly different ($\chi^2(2) = 131.7$, $p < .001$). More sequences in the DM condition were observed in Strategy 1 (DI=2886, DI=2922) and Strategy 3 (DI=765, DM=1103) than students in the DI condition, whereas the reverse was true for Strategy 2 (DI=1890, DM=1405). Modeling Strategy 1 use, we found that the level of variability between conditions was not sufficient to include a random effect of problem. We found a marginally significant effect of intercept ($z = 1.94, p = 0.053$) along with a marginally significant interaction between the DM condition and practice opportunity ($z = 1.89, p = 0.059$). In modeling the use of Strategy 2, we found that there was a significant fixed effect of intercept ($z = -7.8, p < .001$) and of practice opportunity ($z = 3.4, p < .001$). Finally, in modeling the use of Strategy 3, we found that the random effect of practice opportunity was invariant across the different problems and model fit was improved by removing it. After removal, we found a significant fixed effect of intercept ($z = -11.2, p < .001$) as well as a significant effect of the DM condition ($z = 3.0, p < .005$). Figure 2, while not capturing the full nuanced relationship between the different factors and strategy assignments, offers some reference for understanding the model results.

Figure 2: The average usage of strategies across practice opportunity for the two conditions. The solid vertical and dashed lines indicate the average point of mastery for DM (M=39,SD=11.5) and DI (M=41, SD 14).

In conclusion, our approach enabled us to build a picture of the strategies students use and how they change over time. Our results suggest that strategy use in the DM and DI conditions is similar, with differences appearing after higher performing students begin to reach mastery. This suggests that students who do not need help and are not exposed to the experimental manipulations have similar strategies across the two conditions. In contrast, students who achieve mastery more slowly ask for more hints, receive the manipulation, and consequently vary in their use of strategy. Future work might benefit from focusing on students that take longer to reach mastery and from coding problem type.

4. ACKNOWLEDGMENTS

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