A Metacognitive ACT-R Model of Students' Learning Strategies in Intelligent Tutoring Systems

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Abstract. Research has shown that students' problem-solving actions vary in type and duration. Among other causes, this behavior is a result of strategies that are driven by different goals. We describe a first version of a computational cognitive model that explains the origin of these strategies and identifies the tendencies of students towards different learning goals. Our model takes into account (i) interpersonal differences, (ii) an estimation of the student's knowledge level, and (iii) current feedback from the tutor, in order to predict the next action of the student – a solution, a guess or a help request. Our long-term goal is to use identification of the students' strategies and their efficiency in order to better understand the learning process and to improve the metacognitive learning skills of the students.

1. Introduction

Studies have found some evidence to the connection between students' metacognitive decisions while working with ITS and their learning gains (Aleven et al. in press, Baker et al. 2004, Wood and Wood 1999). We describe here a computational model that explains such relations, by identifying various learning goals and strategies, assigning them to students, and relate them to learning outcomes.
We based our model on log-files of students working with the Geometry Cognitive Tutor, an ITS based on ACT-R theory (Anderson et al, 1995), which is now in extensive use in American public high schools.

2. The model

The model identifies various goals and associates each goal with a different local-strategy that attempts to accomplish it. It assumes that students' actions, which are determined by the strategies, are driven by (i) their estimated ability to solve the step, (ii) their earlier actions and the system's feedback (e.g., error messages), and (iii) their tendency towards the different goals. The model assumes that every student has some tendency towards all goals. The exact combination of tendencies uniquely identifies the pattern of the individual student.

Currently, the model includes the following goals and strategies:

Table 1: the goals and strategies in the model

Goal	Strategy
Learning Oriented (Learn as much as possible)	After thinking about the question, I will solve it if I can or ask for a hint.
Performance Oriented (Solve quickly, pretend to be working hard...)	Repeatedly ask for hints until the answer is revealed to me.
Least Effort Oriented (Make progress with minimal thinking effort)	Guess repeatedly until I get it right.
Help Avoider (I want to do it myself)	After thinking about the question, I will solve it if I can. Otherwise I will guess.

As seen in figure 1, the model has the following stages:

- The student evaluates her ability to solve the question correct immediately (1). If she thinks she can, she does so (2).
- If the student decides that she needs to spend more time thinking 3), she chooses a local strategy (4) and acts upon it (5).

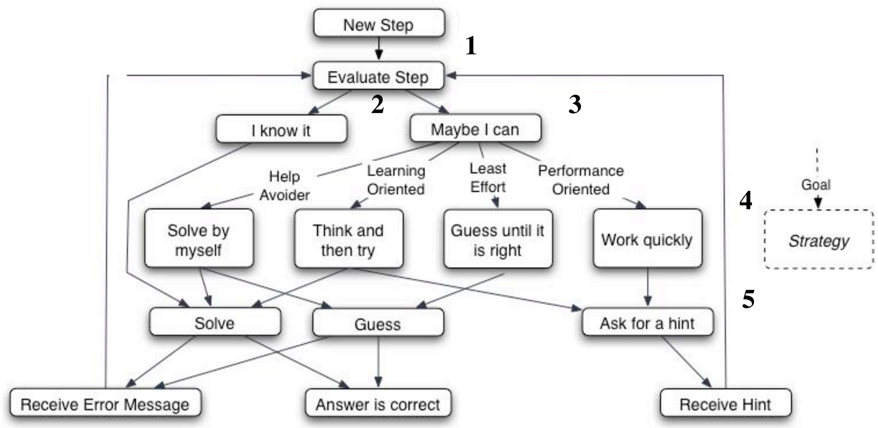

Figure 1: student's local goals determine their strategies and actions.

The model is implemented in ACT-R, a theory of mind and a framework for cognitive modeling (Anderson et al., 1998)

2.1 Fitting data

We used data from Aleven et al. (in press), to identify the students' tendencies according to the model. We included only "new questions" data (and not "after a hint" or "after an error") at this point, for tractability. In addition, only questions to which the Cognitive Tutor evaluates the skill-level of the student as intermediate were included since these actions had the most between-student variance. In total 1400 actions, performed by 11 students, were analyzed.

The correlation between the data to the model's prediction is 1.00 for all students, and the average SD across all students is 0.09 (SD = 0.02). The high correlation is probably an over-fit as a result of too many parameters.
We see a high tendency towards Learning-Orientated and Help-Avoider (0.29 and 0.28 respectively), whereas tendencies towards I-know-it, Performance-Oriented and Least-Effort are 0.15, 0.15 and 0.12 respectively. These values make sense, given that students take their time and rarely use hints on their first actions on a new step.

We calculated the correlation between these tendencies and an independent measure of learning outcomes (as measured by the progress students made from pre- to post-test, divided by their maximum possible improvement). The only significant result is that Help-Avoider is highly correlated with learning gain, $F(1,9)=5.14$, $p<0.05$, $r=0.58$, suggesting that students with higher tendency to avoid help on their first actions did better in the overall learning experience.

3. Conclusions and Future work

We observe high correlation with the actions of students, but poorer than expected correlation to learning gains. We hypothesize that due to too many parameters, the students' behavior can be explained in more than one manner, affecting the single representation of each student and the correlation to learning outcomes. We currently reduce the number of parameters and update the characteristics of the strategies.

The model should be fitted to all collected data, across all skill levels and including after errors and hints. In addition, we plan to run the model on data from other tutors and correlate the findings to other means of analysis.

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