What goals do students have when choosing the actions they perform?

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Introduction

Several models were built recently in the metacognitive level of the students' interaction with Cognitive Tutors, an intelligent tutoring system based on ACT-R theory. After finding suboptimal help-seeking behavior, we built a metacognitive model of desired help-seeking behavior (Aleven et al. in press). In a different Cognitive Tutor, Baker et al. (2004) built a model that identifies misuse of the tutor.

Here we take another step and describe a model of students' goals and strategies, which rely in the basis of their metacognitive actions. By comparing the model's predictions to students' log-files we find the correlation between having the goals and learning gains.

Goals and actions

According to the model, each student has tendencies towards four different local-goals. Each goal is related to a certain strategy, which leads to specific action/s with the tutor (table 1). The unique personal pattern of tendencies categorizes the individual learning process with the tutor.

Table 1: goals, strategies and actions.

Goal	Strategy	Action/s
Learning Orientation (I want to learn as much as possible)	First I try. If I cannot, I ask for help.	Slow attempts, slow help requests.
Performance Orientation (I want to work quickly)	I ask for hints until I get the answer	Fast repeated help requests
Least Effort (I want to get done with minimal mental effort)	I guess repeatedly without thinking much about it. Eventually I get it right	Fast solution attempts, most of them are wrong.
Solve by myself (I am determined to be independent)	First I try. If I cannot, I do as much as I can and guess something, since I don't want to use help.	Slow solution attempts. Some of which are correct and some are educated guesses.

At each point, student can perform one of the following actions: Solve the question, guess an answer, or ask for a hint. Students can perform these actions quickly or slowly. Each attempt to answer the question (whether by solving it or by guessing) has a certain probability of being correct. The correct-rate of solution-attempts is much higher then that of guesses.

The model

In the model, at each action, the student chooses (whether consciously or not) one local goal and acts according to it. The model assumes that the student's likelihood to choose a certain local goal is determined by the following considerations:

1. Individual differences in the tendencies to choose the different goals.
2. Skill level: The student's estimated ability to solve the problem. (We predict this ability using the skill-level that the tutor assigns to the student for each individual problem.)
3. Context: the student's earlier actions and the system's feedback to them (e.g., error messages).

To evaluate the model, we first applied an ACT-R version that identifies local-goals of students' actions within the same context and estimated level (Roll et al. in press).
The model describes the following process (figure 1):

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

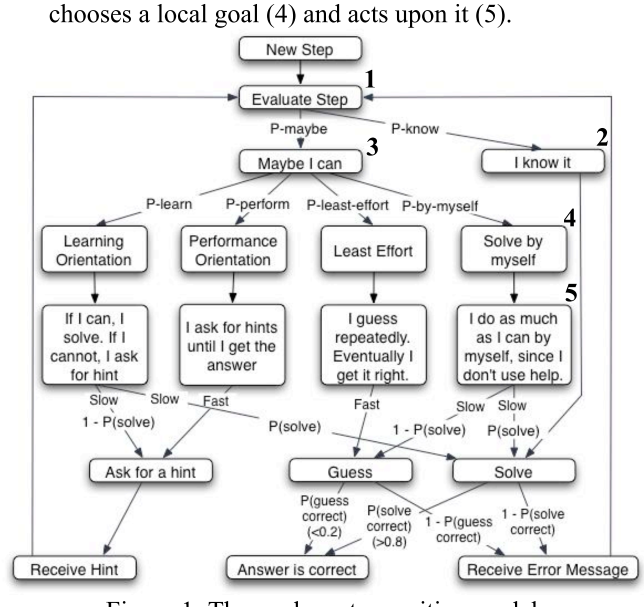

Figure 1: The goals metacognitive model.

Based on the ACT-R model we build an equivalent mathematical model. Though the ACT-R framework was appropriate in modeling the process, switching to a mathematical model enabled us to fit the data and conduct statistical analysis relatively easily.

By comparing the actual performed actions to the model's predictions, we could find the individual students' tendencies towards the different goals.
A total of 57,000 actions, performed by 21 students, were fitted by the model (Aleven et al., in press). The average square deviation between the model results and the original data was 0.003.
We correlated between the tendencies to act upon each goal and between an independent measure of learning outcomes (as defined by the improvement from pre- to post-test divided by maximum possible improvement for the same student), in order to identify the relation between the goals and learning. We found a significant negative correlation between learning outcomes and the tendency to be Performance Oriented ($F(1,19)=6.35$, $p=0.02$, $r=-0.50$). We also found some significant positive correlation between Learning Orientation and learning outcomes in several contexts – for example, across all skills, being Learning Oriented after a hint was significantly correlated with learning gains ($F(1,19)=6.00$, $p<0.03$, $r=0.49$). Having the goal of Solve-by-Myself had a positive correlation with learning outcomes across most of the skills and contexts, but wasn't always significant.
One main flaw is that the model is too local and has 54 parameters per student (for 72 data points per student across all skills and contexts), a number that should be reduced dramatically. The many parameters make it harder to generalize regarding students' general tendencies.

Currently we build a new version of the model with fewer parameters. In this version, besides the set of tendencies, each student is assigned parameters that represent the adaptation to different skills and adaptation to different contexts.
Just like we defined several strategies to choose what action to perform, we now define several strategies to adapt the single set of tendencies to the various skills and contexts.
We relate to the basic set of tendencies of each student as the *basic vector*. At each point, the sum of all tendencies is 1.00. When a certain tendency is getting strengthened by the adaptation vector, it has higher chances of being selected by the model while others maintain the ratio between them.
For example, let us take the following set of tendencies:

Basic vector = (0.26, 0.41, 0.13, 0.20).

This vector describes the tendencies to choose (learning orientation, performance orientation, least effort, solve by myself). When acting after an error, let us suppose that the student increases the tendency to have a least-effort goal while decreases the tendency to solve-by-myself. This student has two adaptation vectors:

Increase least-effort vector = (1, 1, x, 1)   x>1

Decrease solve-by-myself vector = (1, 1, 1, y)   y<1

In this case, the chances of having any goal (for example, least-effort) will be calculated in the following way:

$$\frac{(basic-value)_j \times (adaptation-value)_j}{\sum_{i=1}^{number-of-goals}(basic-value)_i \times (adaptation-value)_i} =$$

$$= \frac{0.13 \times X}{0.26\times 1 + 0.41 \times 1 + 0.13 \times X + 0.20 \times Y}$$

We find x and y by fitting the prediction to the data.
Since there are only few strategies that make sense at each context or skill, we expect to find very limited number of adaptation vectors. This will enable us to generalize conclusions as to the efficiency of each vector.

Conclusions and future work

The current model gives a good description of students' specific goals when working with cognitive tutors. In addition, we found a link between the tendency to have various goals and learning outcomes. However, due to its many parameters, it is too difficult to generalize from it about students' overall goals and strategies.
Through identifying *adaptation strategies*, we categorize the interaction of each student using three types of vectors: (i) the basic vector – the student's overall tendencies towards the different goals, (ii) skill adaptation-vectors, and (iii) context adaptation-vectors (first action, after a hint or after an error).
Once completed, these strategies will be correlated with learning outcomes in order to identify which patterns lead to better learning. In addition, the model should be fitted to data from different tutors and its predictions should be compared to other metacognitive models.
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