A Student Model to Assess Self-Explanation while Learning from Examples

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Abstract. The SE-Coach is a tutoring system that supports students in applying the learning strategy known as self-explanation - the process of clarifying to oneself the solution of an example. In this paper, we describe the student model used by the SE-Coach to assess the students' self-explanations and to provide hints to improve them. The assessment is based on the student's prior physics knowledge and on the student's studying actions. We describe a version of the user model based on a Bayesian network, and a simplified version that is more efficient but handles only examples with no inferential gaps in the solution.

1 Introduction

The benefits of learning from examples strongly depend on how students study them. Many studies indicate that self-explanation - generating explanations to oneself while studying an example - can improve learning, and that guiding self-explanation can extend these benefits.

We have developed a tutoring module, the SE (Self-Explanation) Coach, that trains students in the application of this general learning skill. The SE Coach is part of the Andes tutoring system for university physics (Conati et al., 1997a). Within Andes, the SE Coach ensures that students generate appropriate self-explanations to understand each component of a physics example.

In this paper, we describe the student model that allows the SE Coach to decide when and how to elicit further self-explanations. We discuss the differences between the current student model, which efficiently handles examples without inferential gaps in the solution, and a more general model based on a Bayesian network (Conati et al., 1997), which provides principled assessment for a wider range of examples but that can have inadequate response times.

2 The SE-Coach's Bayesian student model

The SE-Coach provides the students with an interface, called the Workbench, to read and study examples (Conati and VanLehn, 1999). In the Workbench, the example text and graphics are covered with gray boxes, corresponding to single units of information. The boxes disappear when the student moves the mouse pointer over them. This allows the SE-Coach to track what the student is looking at and for how long, a crucial piece of information to assess

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whether a student is self-explaining or simply reading. The Workbench also provides tools to build self-explanations for each example item. These tools include 1) a Rule Browser and templates to explain which physics rules justify an example item, and 2) A Plan Browser to explain which goal a given item achieves in the solution plan underlying the example.

Every student action, including viewing times, is recorded in the SE-Coach's student model. The model is a Bayesian network that includes 1) a representation of the example solution (the *solution graph*), automatically generated from a set of physics rules (Conati et al., 1997a), and 2) nodes reflecting reading and self-explanation actions (see Figure 1).

Example 1

Jake is lowered from an helicopter, with an acceleration of $2m/s^2$.

Jake's mass is 80Kg.

Find the tension in the rope to which Jake is attached.

Solution

We apply Newton's 2^{nd} law to solve the problem.

We choose Jake as the body….

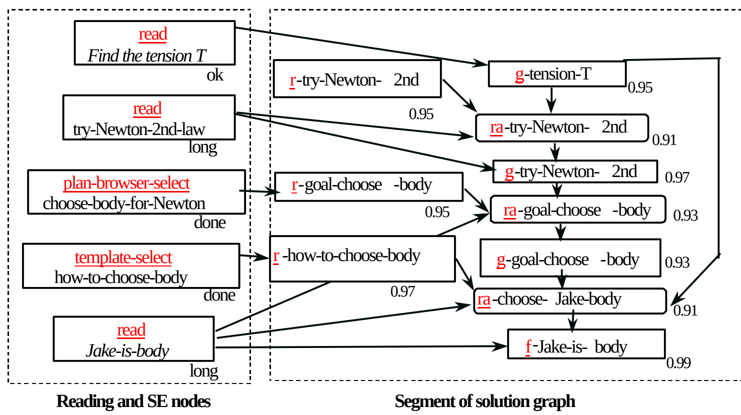

Figure 1. Segment of student model after the student reads and explains the solution lines on the left.

The solution graph consists of fact and goal nodes (f- and g- nodes in Figure 1) representing the solution items, linked through 1) rule (r-) nodes representing the rules that generated each item and 2) rule application (ra-) nodes representing the actual application of the rules.

Reading and self-explaining actions provide only indirect evidence that the student knows a solution item or a physics rule. The links and the probability tables in the Bayesian network encode the probabilistic relations between interface actions and knowledge of solution items and physics rules (Conati et. al, 1997b). The evidence provided by reading and self-explanation actions is propagated in the Bayesian network. Lack of self-explanation is identified with low probability of rule application nodes, and triggers the intervention of the SE-Coach to elicit additional explanations from the student (Conati et. al, 1997b).

3 Simplified student model

The student model needs to be updated every time the student uncovers a different example item. The available implementations of the Bayesian update algorithm proved to be too slow for this task. In order to be able to evaluate the SE-Coach with real students, we developed a simplified version of the student model, which works only for examples with no inferential gaps in the solution. Like the general model, the simplified model is based on the solution graph, and generates its predictions from the student's prior knowledge and student's studying actions. However, it does not use propagation of evidence in the Bayesian network to assess self-explanation. In the simplified model, an element in the solution graph is considered self-explained if and only if 1) the student has spent enough time reading one of the example items mentioning that element and 2) the student knows the rules necessary to self-explain the element.

When the student uncovers an example item, the corresponding node in the student model is marked as “not-read”, “read” and “read-for-SE”, depending on how much time the student has spent on the item. When the student fills in a rule template to self-explain an example item, the SE-Coach updates the probability of the corresponding rule node in the student model. The update formula takes into account the prior probability of the rule and how many attempts were made to fill in the template correctly.

When the student decides to close an example, the student model returns pointers to solution items that need more self-explanation. In particular it returns items that correspond to facts or goals derived from rules with probability below a certain threshold (0.75 in the current version). We do this because it is unlikely that correct self-explanation has occurred if the student is missing the relevant physics knowledge, no matter how much time the student spent on the solution item. The model also returns pointers to solution items related to physics rules with high probability, but with insufficient reading time for self-explanation.

It is important to notice that students do not have to use the Workbench tools to have their self-explanations acknowledged. If a rule has a high prior probability, and the student has spent enough time on a solution item derived from that rule, the student model assumes that the student self-explained the item correctly. Asking students to always use the Workbench to make their explanations explicit would allow more accurate assessment, but may also burden the students who are natural self-explainers with unnecessary work, compromising their motivation to use the system.

4 Future work

We are currently evaluating the accuracy of the simplified student model. The data for the evaluation come from a laboratory experiment that we conducted with 57 college students who were taking introductory physics (Conati and VanLehn, 1999). We plan to evaluate the accuracy of the student model by analyzing whether the probabilities assessing the knowledge of students in the experimental group are predictive of the students’ post-test results. We also plan to use log data files from the experiment to test the performance of the Bayesian network model with an improved update algorithm that may provide acceptable response times.

References

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