Improving Retention Performance Prediction with Prerequisite Skill Features

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ABSTRACT

This paper describes our experiment and analysis of utilizing prerequisite skill features to improve the predicting of student retention performance. There are two aspects that make this paper interesting. First, instead of focusing on short-team performance, we investigated the student retention performance after a delay of 7 days. We explored several prerequisite skill features that can be captured in an intelligent tutoring system; in our particular case, these prerequisite skill features were acquired from Common Core standard skills and student data while working on these skills. We showed that some of these features have encouraging predictive power. Our analysis confirmed the value of prerequisite skill features in predicting retention performance, the prediction results showed an improvement from an R^2 of 0.182 with a baseline feature set to an R^2 value of 0.192.

Keywords

Educational data mining, feature selection, knowledge retention, intelligent tutoring system

1. INTRODUCTION

Inspired by the notion of robust learning [1] and the design of the enhanced ITS mastery cycle proposed by Wang and Beck [3], we developed a system called the Automatic Reassessment and Relearning System (ARRS) to make decisions about when to review skills that the student have mastered in the ASSISTments system (www.assistments.org). One of the important compounds of ASSISTments is the mastery learning problem set, which simplifies the notion of skill mastery to three consecutive correct responses with the number of attempted problems before students achieve mastery. The current workflow of ARRS is relatively simple: after classroom teaching of a certain skill, teachers use ASSISTments to assign a mastery learning problem set of that skill to students, and students are required to first master the skill by completing the Mastery learning problem set; ARRS will then automatically reassess students on the same skill 7 days later with a retention test (also called the reassessment test in ASSISTments) built from the same sets of problems the student already mastered. If students answer the problem correctly, we treat them as if they are still retaining this skill, and ARRS will test them 14 days later, 28 days later, and then finally 56 days after that. If a student fails the retention test, ARRS will give him an opportunity to relearn the skill.

Cognitive domains usually have a model that represents the relationship between knowledge components. Each of these knowledge components is a major skill in the domain that students are expected to have. The relationship between these knowledge components or skills is either prerequisite or post-requisite. A prerequisite skill of a skill A is a skill that students are expected to have to be able to succeed in assessments of requiring skill A. Without knowledge of the prerequisite skill(s) of a given skill, a student is not expected to respond correctly to questions from that given skill. The map in Figure 1 is representation of a subset of the prerequisite skill model used by a number of features in ASSISTments. The ovals represent the skills and the arrows linking the ovals show the prerequisite and post-requisite relationships between the skills. The codes are the Massachusetts Common Core State standards for the Math skills [2]. ASSISTments started adopting the Common Core standards since fall 2013.

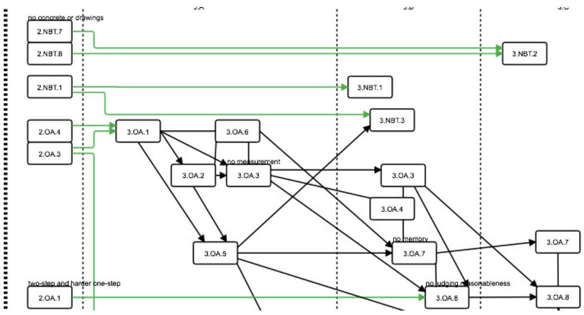

Figure 1. A subset of the Common Core skills

Cognitive models, together with their skills maps, have been used to determine students' cognitive levels in a given domain. For example, when a student answers a problem from a given skill incorrectly, problems are presented from the prerequisite skill to determine how well they know the prerequisite skills.

2. MODELING PREREQUISITE SKILL EFFECTS

Consider a situation where a student has very high performance in general but performed poorly in prerequisite skills to a particular skill. When this student encounters the postrequisite skill, we would not expect him to have robust mastery; therefore, his performance on retention tests to that postrequisite skill could be poor. However, most models have only focused student's general performance on their most recent performance. Hence we formed a hypothesis that the prerequisite skill performance can be independent from student local performance and can be used to enhance our models of predicting retention performance. We initially noticed [4] that the number of problems required to achieve mastery has great influence on the delayed performance. We refer to this number as the Mastery Speed. We first employed the mastery speed, as well as two other basic features to establish a baseline for our modeling work. These features relate to item and skill information, including: (1) *problem easiness* and (2) *skill ID*. Note that because we are not using the identifier of students in the modelling work, thus our models can test our ability of generalizing to new students. To test our hypothesis, the next step was to gather a set of prerequisite skill features and identify which features can be used as predictors. Towards this end, we selected the following three features to capture different prerequisite skill information:

(1) *prerequisite skill ID*: the unique identifier of each prerequisite skill. By modeling skill ID as a factor, we are estimating an overall effect of these skills;

(2) *student prerequisite skill performance*: this is a measure of a student's performance on a direct prerequisite skill of the retention test skill. This number is presented by the percentage of correctness of all the problems that are answered by the students for this prerequisite skill;

(3) *prerequisite skill easiness*: the percentage of correctness for this prerequisite skill across all answers and all students.

We experimented with using *prerequisite skill ID* as a factor, as well as *student prerequisite skill performance* and *prerequisite skill easiness* as covariates; hence there are three models to be calculated besides the baseline model. Table 1 provides the results for each of these models, the prediction performance were measured in terms of R^2 on the testing set.

Table 1. Prerequisite skill model performance

Model	R^2
base model + *student prerequisite skill performance*	0.189
base model + *prerequisite skill ID*	0.185
base model + *prerequisite skill easiness*	0.182
base model	0.182

From the results in Table 1, we can see that improved models were obtained both on *prerequisite skill ID* and *student prerequisite skill performance*. The results from using student prerequisite skill performance clearly indicate that a student's performance on prerequisite skills is helpful for improving predictions. The predictive power of *prerequisite skill ID* may suggest that there seems to be an overall skill effect, which is different from the average performance of prerequisite skills, which is modeled by prerequisite skill easiness. Furthermore, a model using both *prerequisite skill ID* and *student prerequisite skill performance* achieved an R^2 value of 0.192 and the result is statistically reliable ($p \approx 4.5 \times 10^{-4}$). This led us to believe that these two features are largely independent predictors and whatever *prerequisite skill ID* represents, it is relatively distinct from *student prerequisite skill performance* as the R^2 increases noticeably when both are modeled. The Beta coefficient values and p-values for each covariate are shown in Table 2.

Table 2. Parameter table of covariates

Covariate	Beta	p-value
problem easiness	6.306	.00
prerequisite skill performance	2.24	.00

The positive Beta values indicate that the larger the covariate is, the more likely the student responded to this problem correctly. So we see that the easiness of retention test problem is still more likely to affect students' performance compared to their *prerequisite skill performance*.

3. CONCLUSIONS AND FUTURE WORK

In this work we attempted to model prerequisite skill features to better predict student retention performance in an intelligent tutoring system on a small dataset. We need to further investigate our model with larger datasets and other data sources.

In this paper we only investigated the direct prerequisite skill of test skills. We have not yet looked into the skill system as a hierarchy of complete knowledge components. For future work we will consider the notion of the student's performance in all prerequisite skills prior to the skills we are investigating. For example, we could measure how well a student did on the retention tests of prerequisite skills. Also, it is possible that skill interference is also affecting the retention performance. Exploring these avenues to discover prerequisite skill impacts on performance is an interesting future direction.

4. ACKNOWLEDGMENTS

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