Improving Long-Term Retention Level in an Environment of Personalized Expanding Intervals

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ABSTRACT

The ability to retain a skill long-term is one of the three indicators of robust learning. Researchers in Intelligent Tutoring Systems (ITS) and Educational Data Mining (EDM) have focused increasing attention on predicting students' long-term retention performance as well as attempting to find effective methods to help improve student knowledge retention. But traditional practices of spacing and expanding retrieval practices have typically fixed their spacing intervals to one or few predefined schedules. In this work, we introduce the Personalized Adaptive Scheduling System (PASS) in ASSISTments' retention and relearning workflow and we have evidence to show that the PASS is helping to improve students' long-term retention performance.

Keywords

Robust learning, spacing effect, knowledge retention, educational data mining

1. INTRODUCTION

1.1 Robust learning and long-term retention

Robust learning is a desirable instructional outcome that goes beyond typical answering a problem correctly immediately following instruction or tutoring. The level of robust learning is assessed by at least one of the three criteria: whether students will be able to transfer their knowledge, whether they will be prepared for future learning, and whether they will retain their knowledge over the long-term [1]. Expanding retrieval practice is often regarded as a superior technique for promoting long-term retention relative to equally spaced retrieval practice [2]. This is specifically crucial to subjects such as mathematics where we are more concerned with students' capability to recall the knowledge they acquired over a long period of time.

1.2 Automatic Reassessment and Relearning System

Inspired by the importance of long-term retention and the design of the enhanced ITS mastery cycle proposed by Wang and Beck [3], we developed and deployed a system called the Automatic Reassessment and Relearning System (ARRS) [4] to make decisions on when to review skills students have mastered in ASSISTments, a non-profit, web-based tutoring system. ARRS is an implementation of expanding retrieval in the ITS environment. ARRS assumes that if a student mastered a skill with three correct responses in a row, such mastery is not necessarily an indication of long-term retention. Therefore, ARRS will present the student with retention tests on the same skill at expanding intervals spread across a schedule of at least three months: the first level of retention tests takes place seven days after the initial mastery, the second level of retention tests 14 days after successfully passing the first retention test, then 28 days, and 56 days. If a student answers incorrectly in one of these retention tests, ASSISTments will give him an opportunity to relearn this skill before redoing the same level of test.

1.3 Personalized Adaptive Scheduling System

Although ARRS helps students review knowledge after a time period, it neither knows a student's knowledge level nor does it have the mechanism to change the retention schedule based on a particular student's performance. Here we formed a hypothesis that we can improve students' long-term retention levels by adaptively assigning students with gradually expanding and spacing intervals over time and we proposed to design and develop such a system, called Personalized Adaptive Scheduling System (PASS), as shown in Figure 1. In the spring of 2014, we enhanced the traditional ARRS with the PASS and deployed it in ASSISTments.

The current workflow of PASS aims to improve students' long-term retention performance by setting up personalized retention test schedules based on their knowledge levels. Here we rely on the *mastery speed* of a skill [4] (number of problems required achieving three consecutive correct responses) as an estimate of the student's knowledge. We retained the ARRS design of 4 expanding intervals of retention tests for each skill; however, PASS alters how tests behave within each interval, especially for the first interval. When a student finishes initially learning a skill, PASS uses his mastery speed to decide when to assign his first level 1 retention test. The longest delay is seven days as students' mastery speed can be as good as three and shortest delay is one day for students who spend seven or more opportunities to achieve initial mastery.

When a student passes the first test, PASS will schedule another test with a longer delay. Once the student passes the seven-day test, he will be promoted to Level 2 with a delay of 14 days. From that point on the intervals are the same as in ARRS system. Note that mastery speed can be extracted from both students' initial learning and relearning processes. Therefore, when a student fails a retention test, a relearning assignment will be assigned to the student immediately and how quickly the student relearns this assignment will be used to set the interval for his next test. The mechanism of Level 2 to Level 4 tests is simpler. When a student fails a retention test, the retention delay will be reduced to the previous level (e.g., from 56 days to 28 days). It will be increased to the next level if the student passes the delayed retention test.

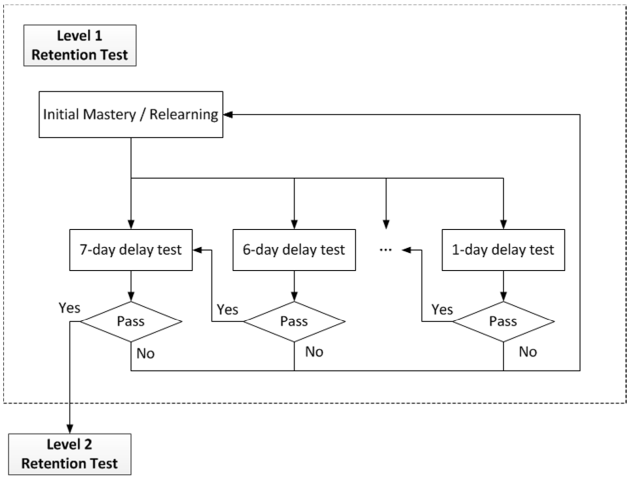

Figure 1. Design of Personalized Adaptive Scheduling System (PASS)

2. IMPACT OF PERSONALIZED EXPANDING RETENTION INTERVALS

A previous study [5] on Level 2 retention tests revealed that students in the PASS condition outperformed those in the ARRS condition and PASS helped to close the performance gap between two groups of students. In fact, in the PASS condition, the long-term performance of medium-knowledge students even slightly outperformed the high-knowledge students.

In this work, we extended our investigation to how students performed on much longer delay after the initial mastery. We collected data that recorded between May 2014 and Feb 2015, which consisted of 4,352 students who have worked on PASS retention tests. We calculated the percentage of correctness on retention tests that within 10 weeks after the completion of a homework assignment, as shown in Figure 2. The data was grouped by the three identified mastery speed bins to represent high-, medium- and low-knowledge students on their initial mastery levels.

It is important to notice that since PASS strictly requires students to achieve a certain level of retention of skills before promoting to the next level of practice, a longer delay doesn't mean a student was working at a higher level of retention test. As we have observed in the previous study [5], some students had to spend four weeks to reach Level 2 retention test while high knowledge level students only need 18 days on average.

The relationship between retention performance and delays in Figure 2 contradicts the general assumption that with strong prior knowledge, performance should decrease as delays get longer. What is seen here is the performance trends got slightly better compared to how students performed at the beginning of PASS workflow. We fitted the performance lines with linear regression trend lines and received positive slopes (0.0057 on average) for all three groups of retention performance. This is can be explained by PASS aggressively assigning short-delay retention tests to weaker students during the first retention level. Another observation is that we again see the persistence of performance differential across three group of students; however, we also noticed the gap between different levels of students was reduced from 12.04% to 7.98% at the end of Week 10. This is further evidence that PASS helps to improve students' retention performance in a classroom context.

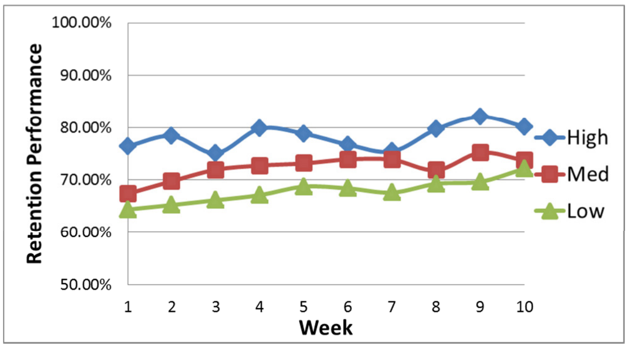

Figure 2. Scatter plot of long-term retention performance in PASS

3. CONCLUSIONS AND FUTURE WORK

This experiment improved the enhanced ITS mastery-cycle model with a personalized expanding interval-scheduling system and explored a simple but effective approach for using ITS to help students achieve better long-term mastery learning. Next, we will work on modeling students' long-term retention performance with data gathered from PASS.

4. ACKNOWLEDGMENTS

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