Towards Modeling Forgetting and Relearning in ITS: Preliminary Analysis of ARRS Data

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Researchers in the intelligent tutoring system field have been using the well known Knowledge Tracing model (Corbett and Anderson 1995) to modeling student learning for decades. A lot of variations of the standard Knowledge Tracing model have been developed to improve performance, such as works of Pardos and Heffernan (2010) and works of Baker, Corbett etc. (2010). These models all make the assumption that there is no forgetting during student learning. Yudelson and Medvedeva(2008) used the coupled HMM topology M3 to modeling forgetting aspects in their medical ITS, but didn't give a clear comparison of the model with forgetting and without it. In this paper, we applied the Knowledge Tracing model to analyze data from the Automatic Reassessment and Relearning System. We found that it statistical reliably over predicting student performance after a seven days duration. Corbett and Bhatnagar (1997) reported similar results in their experiments of predicting test performance. We then extended the knowledge tracing framework to model forgetting and relearning but failed to get better results in predicting student performance.

Key Words and Phrases: Intelligent Tutoring Systems, Knowledge Tracing, Bayesian Networks, Data Mining, Prediction

1. INTRODUCTION

The Automatic Reassessment and Relearning System (ARRS) is an extension of the "Mastery Learning" Problem sets in the ASSISTment system. ASSISTments system is a freely available web-based tutoring system for 4th through 10th grade mathematics. Mastery Learning is a strategy that requires students to continually work on a problem set until they have achieved a criterion (typically three consecutive correct answers). The idea of ARRS is if a student masters a problem set, the ARRS system will automatically reassess students a week later, a month later, and then finally two months after that. If students fail the re-assessment, they will be given an opportunity to relearn the topic.

We used the data from two ARRS experiment classes ran in September and November of 2010, with in total 136 students and 53449 data instances. To simplify the analysis, we focused on the first reassessment and relearning phase, that means only data from the original assignment and the one week later reassessment and relearning phase is considered.

2. METHODOLOGY AND RESULTS

First we analyzed the performance of the standard Knowledge Tracing model on the Automatic Reassessment and Relearning System data, which focus on enhance student

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long term learning instead of short term knowledge boost. The result shows that lacking of consideration of forgetting causes a significantly over predicting on students' first opportunity on a new phase of learning. This proves the necessity of modeling forgetting in student long term learning.

We tried simple extensions of the standard Knowledge Tracing trying to model forgetting and relearning on new reassessment and relearning phase. The design of the Knowledge Tracing with new phase forgetting model is shown in Figure 1.

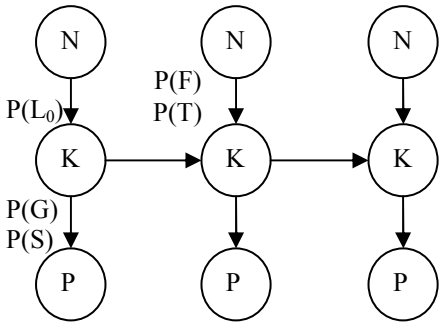

Fig. 1. The Knowledge Tracing with new phase forgetting model design. The node N indicates if it is a new reassessment and relearning phase, the node K indicates student current knowledge level, the node P indicates the student performance of current question. The parameter P(L0) is the probability of initial knowledge, P(G) is the probability of guess, P(S) is the probability of slip, P(T) is the probability of learning, and P(F) is the probability of forgetting when facing a new learning phase.

We did 10 fold cross validation and used the RMSE (Root Mean Squared Error) as a measurement of the predicting accuracy. The new models gave no better result than the standard Knowledge Tracing. Simulation experiment showed a difficulty of the "forgetting" parameter in these new models to converge into its real value.

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