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Improving knowledge tracing model by integrating problem difficulty

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Improving Knowledge Tracing Model by integrating problem difficulty

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***Abstract*—Intelligent Tutoring Systems (ITS) are designed for providing personalized instructions to students with the needs of their skills. Assessment of student knowledge acquisition dynamically is nontrivial during her learning process with ITS. Knowledge tracing, a popular student modeling technique for student knowledge assessment in adaptive tutoring, which is used for tracing student's knowledge state and detecting student's knowledge acquisition by using decomposed individual skill or problems with a single skill per problem. Unfortunately, recent KT models fail to deal with practices of complex skill composition and variety of concepts included in a problem simultaneously. Our goal is to investigate a student model that compatible for problems with multiple skills and various concept.**

***Index Terms*—Student model, knowledge tracing, complex skill composition, problem difficulty, robust learning, deep learning**

I. Introduction

The task of student modelling is known as an interdisciplinary research topic across education, psychology, neuroscience and cognitive science. One of the main challenges for ITS designers is tracing student's knowledge and learning behaviour for providing more supportive pedagogical instruction adaptively. As human learning is grounded with complexity in various dimensions such as human brain, knowledge, experiences and practices, it is inherently difficult to trace student's knowledge.

With Cognitive Diagnosis algorithm used in Intelligent Tutoring Systems, the student need to be instructed to practice similar problems with particular skill, when the system does not recognize that the student has sufficient knowledge about that skill. Personalized decisions about skipping or delaying problems should also be automatically updated for each individual student. One can even argue that most of the main techniques found in Artificial Intelligence and Data Mining have found their way into the field of ITS, and in particular for the problem of knowledge tracing, which aims to model the student's mastery of conceptual or procedural knowledge from observed performance on problems [1], [2], [3], [4].

II. Previous Works

Most of ITS still need human instructions to provide appropriate problem that fit for student's current knowledge state. Popular educational platforms such as Coursera, EdX require student models for better understanding student learning styles by using large scale student interaction data to model students and improve their online educational experiences. We review here four of the best known state-of-the-art student modelling methods for estimating student's performance (see [5] for a review). They are chosen either because of their predominance in psychometrics (IRT) or Educational Data Mining (BKT), or because they are best performers (PFA, DKT, DKT-DSC).

- Item Response Theory (IRT) is arguably the best known technique for student modelling and it dates back to the 1950s [6]. Numerous improvements have been proposed since [7], [8], [9].
- Bayesian Knowledge Tracing (BKT) was introduced in late 1990s [4]. There have been various extensions of BKT for prediction of student performance in last decades. Baker [10] proposed BKT model with contextual guess and slip.
- Performance Factor Analysis (PFA) was proposed by Pavlik [11] as an alternative way to Bayesian Knowledge Tracing (see below) with better prediction performance.
- Deep Knowledge Tracing (DKT) was proposed by Piech [12] and uses a Recurrent Neural Network (RNN) to model student's skill learning.
- Deep Knowledge Tracing - Dynamic student classification (DKT-DSC) was proposed by Minn [3] that takes on-the-fly student's learning ability into account and best performance among algorithms.

III. Preliminary Work

As initial discovery, I found that problem difficulty have huge influences in practices of student learning process. All previous methods described in above, just only take the skill level sequence that student practiced and outcomes from those practices. Not all problem are composed with exactly same concept with same combination of skills or quite similar concept with combination of similar skills in ITS. Various concepts with different combination of skills of problem in each practice of student may end up with different level of problem difficulty for students and have huge impact in their learning outcomes. Measuring how much difficult for thousands of different type of complexity of problem is impractical when our available data is sparse (only few problems have been answered by most students). It is not an easy process if we consider complex combination of concepts and skills into account. Based on those assumptions, I defined problem category based on difficulty (ranging from 1 to 10) as following:

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$$Category(x_j) = \begin{cases} \delta(x_j, c), & \text{if } |N_j| \geq 10 \\ c, & \text{else} \end{cases} \quad (1)$$

where:

$$\delta(x_j, c) = \left\lfloor \sum_i^{|N_j|} \frac{|\{x_{ij} == 0\}|}{|N_j|} \right\rfloor \cdot (c - 1) \quad (2)$$

and where N_j is the set of students who attempted problem x_j, and x_{ij} is the outcome of the first attempt from student i, to problem x_j. An outcome of 0 is a failure. Constant c is the number of categories (levels) that we wish to retain. It is substracted by 1 in function $\delta(x_{ij}, c)$ because, as shown in Eq. (1), the last category is kept for the cases where fewer than 10 students answered problem x_j.

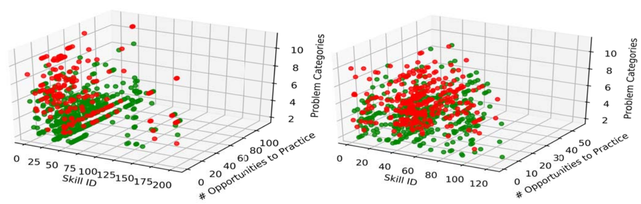

Fig. 1. Visualization on students' problem attempt outcomes in KDD and Assistment09 datasets.

According to visualization two random students in KDD [1] and Assistement09 [2] datasests, we can see that if the student answers problems with higher difficulty in their first few practices, she is most likely to get fail for those practices. In later practices, even the student had practiced particular specific skill for several times before, It still have higher possibility for getting wrong when she answers difficult problems. Most of the students in the datasets share similar characteristic as outcomes of two students illustrated in above Figure 1.

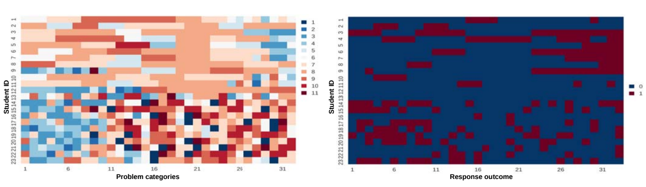

Fig. 2. Orders of (a) problem categories Vs (b) response outcome over first 33 problems attempted by 23 students.

Figure 2 (a) illustrates the order of problems (based on their category) each student answered, whereas figure 2 (b) shows responses of each student made on those problems in their first 33 problems by 23 students. Figure 2 (a) shows that students do not systematically start with easy problems to progress towards more difficult ones. One may see the that if the students are taking harder problems (a), they are more likely to get incorrect answer, while it also depends on the ability of each student. In Figure 2 (a), even though student 12 took the problems with lower problem difficulty in his first 15 practices, we see in Figure 2 (b) that the student was still not able to answer a single problem correctly. Besides, some students (12–23) start their practice with the easier problems, yet some others (1–11) start with harder problems.

[1]https://pslcdatashop.web.cmu.edu/KDDCup/downloads.jsp

[2]https://sites.google.com/site/assistmentsdata/home/assistment-2009-2010-data

IV. Work In Progress

Our ongoing work consists of three potential directions.

- Predictive Optimization: probability of getting answer correctly should be estimated by taking the fact of how much difficulty for that problem, rather than only using skills practised.
- Assessment of Student's Knowledge: provide an assessment of student knowledge by reasoning why that problem is being correctly answered by student based on the mastery of skills and capability of handling various concepts in problem. Including investigating what kind of model has more potential for assessment according to cognitive theory.
- Recommendation: provide recommendation for students automatically and dynamically to practise their skills based on their knowledge state.

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