Recognition and Application of Learner's Cognitive Ability for Adaptive E-learning

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***Abstract*— In adaptive learning system, the key to promote personalized learning is the learner model. The Elo model has great potential in online learning environment, so based on it, we propose the EELO which is an improved extension of Elo rating system, in view of polychotomously scored items and different granularity evaluations that the Elo rating system do not cover. The performance of the EELO estimating learners' abilities and predicting their future performances are evaluated on two large data set, which demonstrates that the EELO is better-performing. Then, we apply it in a real online learning environment to provide an analysis report for different user roles, which also can be used as the reference for the development of adaptive learning applications in the future.**

Keywords: adaptive learning system, learner modeling, ELO rating system, polychotomously scored item, cognitive ability.

I. INTRODUCTION

The adaptive learning environment [1] provides real-time responses to learning activities by continuously obtaining learner history responses and makes personalized guidance to learners to the next series of activities. In order to provide individualized guidance, it is necessary to understand the potential learning state of each learner. And how to estimate learners' abilities based on their history responses is the key challenge to the adaptive learning environment.

The overview of Elo rating system is shown in [2], and it shows a great potential to be trained to predict the learner's future performance [2-4]. However, since the Elo rating system has just been newly used in the field of the adaptive environment, several existing extensions of the Elo rating system do not cover educational applications, such as the polychotomously scored items and the assessments of different granularities. To solve the problems above, we propose an enhanced Elo rating system, EELO, to improve the accuracy of the prediction in consideration of the application scenarios of the polychotomously scored items and the different granularity evaluations.

II. RELATED WORK

In the online educational environments, IRT[5] is based on the assumption of the constant skill, which is not consistent with the reality of the learners, and BKT [6-8] can predict the learner's future performance according to the current state, but shows a poor performance when the knowledge system is complex. Besides, the costs of their extensions, TIRT [9], BKT+FSA [10], are relatively high. Compared to these models, the Elo rating system only requires less parameters and lower cost in online environment [2,3], and it has great performances on modeling the learner's cognitive ability.

The Elo rating system was first used to rate chess performances [11,12] and recently was applied to the adaptive learning environment by viewing a learner as a player, and an item as an opponent [13]. One extension of it is to use an "uncertainty function" instead of a constant K [14,15] to be more in line with the actual situation. Its another extension is called the multivariate extension which can make simultaneous measurement of several related skills [3].

In consideration of the factors above, we decided to build a new learner model based on the Elo model, aiming at improving its application scenarios in educational fields, and breaking through the defects of the existing learner model.

III. MODEL AND ALGORITHM OF EELO

In this section, we describe the EELO, an improved extension of Elo rating system that constructs the relationship between the learner and the polychotomously scored item. Furthermore, the EELO realizes the assessment of different granularities by extending the granularities of the learner and the question. The Figure 1 shows the structure of the EELO.

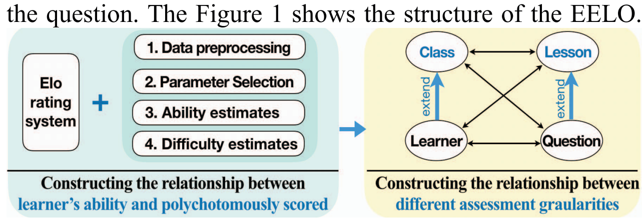

Figure 1. The structure of EELO.

A. Polychotomously Scored Item

1) The Basic Assumption: In Figure 2, the idea of the EELO and the explanations of the abbreviations DF, DIF, SR, SL are presented. Two assumptions are concluded as follows.

a) For any question, the score is firstly processed through normalization. Then it is divided into 10 difficulty levels (DLs) and each level has its corresponding difficulty(DIF).

b) For any response, the learner's actual score M is between 1 and 10, which means although a learner only answered a question once, this response will be expanded into 10 responses corresponding to 10 DLs in order to describe the learner's ability in more details. For any SR corresponding to the DL below the M DLs (In Figure2, the value of M is 7), it is assumed that the answer is correct and other SRs are wrong.

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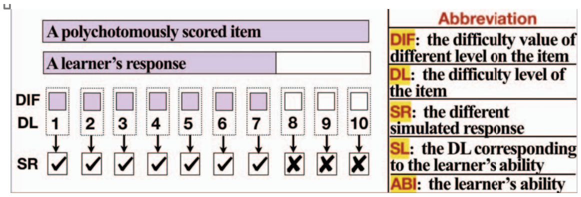


Figure 2. The idea of EELO of polychotomously scored item.

2) The algorithm process: The algorithm process of EELO includes data preprocessing, parameter selection, ability estimates and difficulty estimates, which is shown in Figure3.

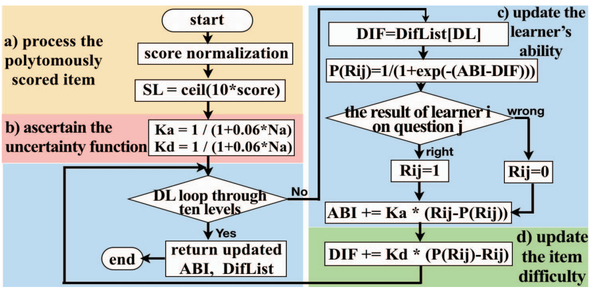


Figure 3. The algorithm flow chart of EELO.

a) Data preprocessing: $R_{i,j}$ is set as the score of the learner i answering question j. After the score normalization, we round up it and use SL to represent the result. Actually, SL means the DL corresponding to the learner's ability.

b) Parameter selection: The meta-parameters a and b in $K_a = a/(1 + b * N_a)$, $K_d = a/(1 + b * N_d)$ of the uncertainty function need to be selected,where K_a and K_d is the convergence speed control parameter of the ability and the difficulty respectively. After the grid search on Assigment2, the value of a = 1 and b = 0.06 shows the optimal performance.

c) Estimate of the learner's ability: For a learner who has used the system, we represent $R_{i,j\to x} \in \{0,1\}$ as the result of a match between the learner i and the DL x on question j. The expected probability that the learner i get x points on question j can be expressed by the Logistic function:

$$P(R_{i,j\to x}) = \frac{1}{1 + e^{-(\theta_i - d_{j\to x})}} \tag{1}$$

where $d_{j\to x}$ is the DIF of the DL x on question j (0<x<=full mark). θ_i is the ability of learner i. According to the learner's response, the ability is updated by:

$$\theta_i = \theta_i + K_a\left(R_{i,j\to x} - P(R_{i,j\to x})\right) \tag{2}$$

and in the process of updating, if the DL is higher than the SL, the result of the corresponding SR will be wrong, and the $R_{i,j\to x}$ will be set to 0. For a new learner, the initial ability value will be directly set to 0 and then be updated by the Equation 2.

d) Estimate of the question's difficulty: The process of estimating the question's difficulty is similar to estimating the learner's ability. For a trained question, according to the response of the learner, the difficulty is updated by:

$$d_{j\to x} = d_{j\to x} + K_d\left(P(R_{i,j\to x}) - R_{i,j\to x}\right) \tag{3}$$

For a new question, we set up an array(DifList) for the DIFs, and the initial state of the array is NAN. When we get the first response about the new question, the corresponding DIF will be updated by the basic Elo rating system, e.g. if a learner get 5 points and the DIFs higher than DL 5 are NAN, the question will be directly treated as a binary type question and then the DIF of DL 5 will be updated; when we get the second response about this question to be trained and the learner get 3 points, it can be found that the closest not-NAN DIF above DL 3 is the DIF of DL 5. The learner's expectation of 3 points is given by:

$$P(R_{i,j\to x}) = \frac{1}{1 + e^{-(\theta_i - d_{j\to x})}} - \frac{1}{1 + e^{-(\theta_i - d_{j\to x}')}} \tag{4}$$

where $d_{j\to x}'$ is the DIF of the closest DL higher than the current DL x.

B. Assessment Granularity

Different assessment granularities can mine more valuable information in the real adaptive learning environment. Specifically, we extend the granularity of a learner's cognitive ability to a class's ability, and the granularity of a question's difficulty to a lesson's difficulty. Table 1 describes the difference between the different assessment granularities.

TABLE 1. THE INFORMATION OF DIFFERENT ASSESSMENT GRANULARITIES

Object	Item	Information Obtained	Audience
Learner	Question	The status of mastering knowledge points	Learner
Learner	Lesson	The learner's ability of a lesson, and providing the teaching strategy for teachers	Teacher
Class	Question	The teacher's teaching quality	Teacher
Class	Lesson	The whole difficulty of a lesson, and adjusting the lesson's difficulty	Teaching administrator

The match between a class and a lesson is taken as an example, using the average score of the whole class to indicate the class's understanding for a lesson. Let θ_i'' be the ability of the class i, $d_{j\to x}''$ be the difficulty of the average score X on the lesson j, and $R_{i,j\to x}'' \in \{0,1\}$ be the result of a match between the class i and the lesson j. The expected probability that the average score of class i on lesson j can be expressed by:

$$P(R_{i,j\to x}'') = \frac{1}{1 + e^{-(\theta_i'' - d_{j\to x}'')}} \tag{5}$$

and the estimates of class i and lesson j are updated as follows:

$$\theta_i'' = \theta_i'' + C_l\left(R_{i,j\to x}'' - P(R_{i,j\to x}'')\right) \tag{6}$$

$$d_{j\to x}'' = d_{j\to x}'' + C_l'\left(P(R_{i,j\to x}'') - R_{i,j\to x}''\right) \tag{7}$$

where C_l, C_l' are the weight given to the new observation.

Similarly, the granularity can be changed to evaluate a learner's mastery of a lesson and a class's mastery of a question.

IV. EVALUATION

To measure the validity of the EELO, it is evaluated on one public data set(Assigment2) and one proprietary data set(HSK) by using the AUC which is the area under the ROC curve. The closer it is to "1", the more accurate the result is., the EELO is also evaluated with some settings to simulate the real situation on online teaching platform, e.g. the difficulties of the question will be updated rather constant in the process of estimating.

The learners' future performance on unknown questions is predicted based on their current ability. When the value of Equation1 equals to 0.5, the learner's ability and the difficulty of the level are equivalent. In this way, how to determine the score a learner can get is simplified to which DL of the question the learner is probably on.

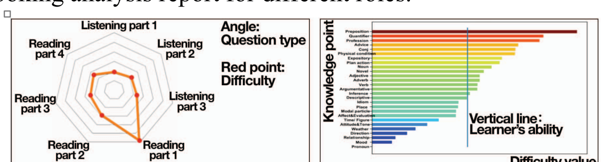
1) Assigment2: The American educational data mining general data set Assigment2 which comes from the online platform ASSISTments containins 3600 learners on 210,000 responses of Math subject. As shown in Figure 4(a), the AUC of the EELO tends to be 0.92 with the increase of the training set. By comparsion, the TIRT and the BKT+FSA respectively achieve an AUC of 0.76 [9] and 0.81 [10] on Assigment2, which shows the EELO has great performance.

2) HSK: To further verify the validity of the EELO, the real responses of Korean learners in the mock examination of HSK are used as our data sets which contains 40,000 learners' responses on 7843 questions including polychotomously scored questions after filtering. As can be seen from the Figure 4(b), the AUC on HSK tends to be stable at 0.84.

Figure 4. The change of AUC on HSK.

V. Case study: Adaptive practice of Chinese language learning

As noted above, the validity of the EELO has been proved, and in order to further illustrate the application of the EELO, we apply the EELO in an online adaptive system of Chinese language learning for Korean learners. After the continuous update on learners' current knowledge, not only can it predicts the learners' future performance, but also provides a forward-looking analysis report for different roles.



(a) The difficulty of different question types at a certain HSK level (b) The comparison of learner's ability and the knowledge point difficulty

Figure 5. the report for different users

For teachers, the analysis of the difficulty of different question types is presented in Figure 5(a) of a radar chart. The closer the red point is to the outer circle, the more difficult it is for the question type, which indicates it is necessary for them to practice the reading part 1 to improve their overall ability.

For learners, the comparison of the learner's ability and the concept's difficulty is represented by a histogram graph. The longer the length of the cylinder is, the more difficult the knowledge point will be. As shown in Figure 5(b), the learner has only mastered nearly half of the knowledge points of HSK6, which can provide the future learning guidance for them.

VI. Conclusion

We propose the EELO learner model in view of the basic Elo rating system not being able to evaluate polychotomously scored items, and we have made appropriate changes to the EELO to estimate different granularities to mine more valuable information from educational data.

The AUC metrics are used to measure the ability of the EELO to predict the learner's performance, and the EELO obtain best performance compared to the extensions of the benchmark model. Finally, the EELO is applied to the Korean learners' Chinese language learning system. The EELO can provide relevant and effective information for different users, which fully demonstrates a good prospect for the application of the EELO in adaptive learning system.

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