

SARLR: Self-adaptive Recommendation of Learning Resources

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Abstract. Personalized recommendation is important for online students to select rich learning resources and make their own learning schedules. We propose SARLR, a new self-adaptive recommendation algorithm of online learning resources. The SARLR algorithm integrates an IRT-based learning cognitive model named T-BMIRT into the recommendation framework and is able to adaptively adjust learning path recommendations based on dynamic of individual learning process. The experimental results show that the SARLR algorithm outperforms the existing recommendation algorithms.

Keywords: Online Education, Learning Recommendation, ITS

1 Introduction

With the growing prevalence of online education, students have access to all kinds of electronic learning resources, including electronic books, exercises and learning videos. Given the diversity of students' background, learning styles and knowledge levels, it is essential to have personalized recommendation tools to facilitate students in choosing their own learning paths to satisfy their individual needs [1]. Previous studies have introduced personalized learning recommendation algorithms following the two major approaches including rule-based recommendation and data-driven recommendation.

Most Intelligent Tutor Systems (ITS) such as [2], primarily adopt the rule-based approach to design their recommendation algorithms, which requires domain experts to evaluate learning scenarios for different kinds of students and define extensive recommendation rules accordingly. Apparently, such a labor-intensive approach can only be applied in specific learning domains. For modern online educational systems, designers often take the data-driven approach by utilizing collaborative filtering methods to implement learning recommendation algorithms. These data-driven recommendation algorithms [3] attempt to identify suitable learning resources for students by comparing similarity among students and learning objects.

Although the data-driven recommendation approach is more scalable and general than the rule-based approach, current proposed solutions have common problems in achieving highly adaptive recommendation towards students' latent learning state. They often focus on either searching for similar learning resources based on content or

identifying similar student groups based on their learning behaviors. The recommended learning objects or paths fail to consider the impact of difficulty of learning objects and dynamic change in students' learning states.

In this paper, we propose a novel learning recommendation algorithm named SARLR, which attempts to integrate an IRT-based learning cognitive model into the recommendation framework and to adaptively adjust learning path recommendations based on dynamics of individual learning process. Specifically, we introduce a temporal, multidimensional IRT-based model named as T-BMIRT, which can accurately infer student proficiency of multiple latent skills and difficulties of exercise assessments. In addition, the T-BMIRT model incorporates the parameter of video learning, which can describe the improvement in student skills after their interactions with video lectures. Based on the T-BMIRT model, the SARLR algorithm can comprehensively analyze every student's skill progress at each learning step and recommend to them a personalized learning path with the matching online video lectures and homework problems.

The contributions of this paper are the two-fold. First, we introduce the T-BMIRT model, to estimate students' latent skill levels and difficulties of learning resources for recommendation. Second, we propose the SARLR algorithm by integrating the T-BMIRT model in the adaptive recommendation process of learning resources. The experimental results confirm that the SARLR outperforms regular recommendation algorithms. Lastly, we present an evaluation strategy for recommendation algorithms in terms of rationality and effectiveness.

2 Related Work

Data-driven learning recommendation algorithms often utilize common recommendation methods widely adopted in the e-Commerce area, including Collaborative Filtering (CF) and Latent Factor Model (LFM). CF can be further divided into UCF (User-based Collaborative Filtering) and ICF (Item-based Collaborative Filtering). The core idea of LFM is to connect users and items through latent features [4].

EduRank [5] is a collaborative filtering based method for personalization in e-learning. It can generate a difficulty ranking of questions for a target student by aggregating the ranking of similar students. Although this method is able to rank the available exercise questions based on their difficulties for similar students, it doesn't integrate cognitive learning models in its framework for estimating the ability of individual students. Thus, it can't generate the matching learning paths for students based on their state of latent skills.

The most related work to our research in previous studies is the Latent Skill Embedding (LSE) model [6], which also presents a probabilistic model of students and lessons. Although the LSE model provides a good foundation for designing a recommendation framework for personalized learning, the paper [6] doesn't propose a detailed recommendation algorithm. Our T-BMIRT model is more fine-grained than the LSE model because it defines a video learning parameter to capture student progress through their

interaction with video lectures. Moreover, we present the SARLR algorithm that utilizes the T-BMIRT model to identify similar students for a target student and recommend their learning paths according to the dynamic state of the target student's latent skills. We also extend the recommendation evaluation criteria expected gain by incorporating two more metrics including relevance accuracy and difficulty accuracy. These new metrics can support more comprehensive performance evaluation for learning recommendation algorithms.

Recently, reinforcement learning has been explored in personalized study planning in ITS [7-9]. Most of them have not evaluated their approaches in real online learning scenarios and compared their performance to existing problem selection strategies used in current systems. Moreover, calculating an optimal personalized learning path in a POMPD is often time-consuming and even becomes intractable as the dimensions of the knowledge state and strategy spaces increase. Therefore, our SARLR algorithm adopts the collaborative filter based approach and we plan to investigate the possibility of utilizing reinforcement learning in our framework in future work.

3 SELF-ADAPTIVE RECOMMENDATION

Fig.1 illustrates the major components in the SARLR algorithm. First, it uses the T-BMIRT model to estimate every student's skill levels and difficulties of learning resources. Second, it searches for similar students based on their skill vectors from the outputs of the T-BMIRT model. Third, it extracts the learning path of the best student, whose skill level is the highest among the similar students after learning related knowledge. Lastly, it recommends the learning path to the target student and sets up two pre-warning conditions to adaptively adjust his recommended contents. The target student's latest behavior data are collected instantly and used as a feedback to update the T-BMIRT model. Thus, all of the modules form a closed loop, which constantly optimizes our model.

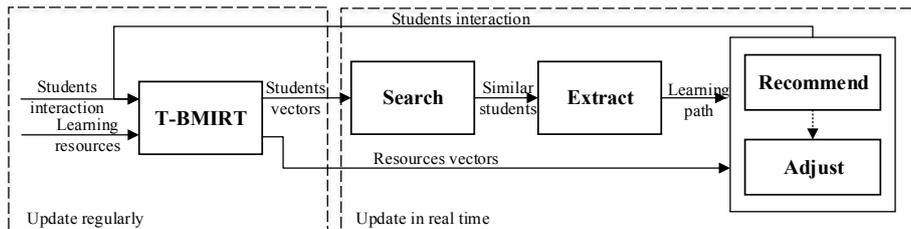


Fig. 1. The Overall architecture of the SARLR algorithm

3.1 The T-BMIRT model

The T-BMIRT model aims to model students and learning resources to infer students' latent skills and learning resources' attributes on multiple knowledge components. We

define the model based on IRT, T-IRT and MIRT model [10]. In a two-parameter IRT model, the probability of the student s correctly answering the question q is given by:

$$p_{sq} = \frac{1}{1+\exp[-(\alpha_q(\theta_s-\beta_q))]}, \quad P(\theta_{t+\tau}|\theta_t) = \phi_{\theta_t, v_2\tau}(\theta_{t+\tau}) \quad (1)$$

Where α_q is the question discrimination, β_q is the question difficulty, θ_s is the student's ability value. The Temporal IRT (T-IRT) model [11] extends the original IRT and MIRT model by modeling a student's latent skills over time as a Wiener process, where $\theta_{t+\tau} - \theta_t \sim N(\theta_t, v_2\tau)$. The model indicates the ability value of the student at the next moment is only relevant to his current ability value.

The T-IRT model only considers interactions between students and assessments, ignoring their interactions with learning videos. However, we believe that the students' ability can be significantly improved after completing a learning video. Therefore, in [12], we introduce a new model T-BMIRT by incorporating learning video parameters to describe the impact of students' interaction with learning videos. The major equations are defined in Eq (2):

$$P(\vec{\theta}_{s,t+\tau}|\vec{\theta}_{s,t}, \vec{l}_{s,t}) = \phi_{\vec{\theta}_{s,t} + \vec{l}_{s,t}, v_2\tau}(\vec{\theta}_{s,t+\tau}), \quad \vec{l}_{s,t} = \frac{d_{s,t}}{d_t} \cdot \vec{g}_t \cdot \frac{1}{1+\exp\left(-\left(\frac{\vec{\theta}_{s,t} \cdot \vec{h}_t}{\|\vec{h}_t\|} - \|\vec{h}_t\|\right)\right)} \quad (2)$$

Where $\vec{l}_{s,t}$ represents knowledge that student s gains from the video t , \vec{g}_t represents knowledge of the video t , \vec{h}_t is the prerequisites of video t , $d_{s,t}$ is the duration in which student s watches video t and d_t is the total length of the video t . In Eq (2), both student ability and learning video requirements have been expanded from one-dimensional to multidimensional. We utilize the vector projection method to determine whether the relevant abilities of the student exceed the relevant skill requirements of the video lectures.

The T-BMIRT model enables us to infer every student's current ability θ , video knowledge g and video skill requirements h through the student's responses of assessment questions. The detailed model fitting process of the T-BMIRT can be found in [12]. An approximation technique makes it possible to train the T-BMIRT in an online way. As a result, the T-BMIRT can be effectively used in the framework of the SARLR algorithm to estimate the parameters of learning resources and students' ability levels.

3.2 Similar Students Search and Learning Path Extraction

SARLR Phase 1 describes the process of searching similar students and extracting a suitable learning path for a target student. At Step 1, the algorithm identifies the students MS with the similar skill levels to the target student s_x through k-nearest neighbor search method over the k-dimension tree (kd-tree) structure and k-nearest neighbor search method. At Step 2-4, the algorithm selects the best student $s_b \in MS$ with the highest ability level at the moment when they complete learning specific knowledge units. At Step 5, the algorithm extracts the learning path p of s_b to the target student s_x .

SARLR Phase 1: Search and Extraction

INPUT:

Set of students $S = \{s_1, s_2, \dots, s_n\}$, target student $s_x \in S$
Matrix of abilities $A = [\theta_{s,t}]$, where $\theta_{s,t}$ is the ability value of student s at time t
Set of learning resources $E = \{e_1, e_2, \dots, e_m\}$
The time in this paper is the index of learning resources with the student just completed learning.

OUTPUT: learning path p

- 1: **search for** similar students MS , where $s_k \in MS$ and θ_{s_k, t_0} is similar to θ_{s_x, t_0}
 - 2: **for each** $s_i \in MS$ **do**
 - 3: find $s_b = \text{argmax}(\text{distance}(\theta_{s_i, T_{s_i}} - \theta_{s_i, t_0}))$, where T_{s_i} is the time of s_i completing learning
 - 4: **end for**
 - 5: **extract** the learning path $p = (e_{i_1}, e_{i_2}, \dots, e_{i_T})$ of s_b
 - 6: **return** p
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3.3 Adaptive Adjustment

Because each individual student has his/her inherent learning style, even when he follows the recommended learning path generated in SARLR phase 1, the learning outcome may not be as good as expected by the recommendation algorithm. In order to deal with this problem, we set up the two conditions in Eq (3) to initiate the Adaptive Re-planning phase, which is defined in *SARLR Phase 2*.

$$p_{sq} = \frac{1}{1 + \exp(-(\bar{\theta}_{s,i} \bar{a}_q - b_q))}, p_{se} = \frac{1}{1 + \exp\left(-\left(\frac{\bar{\theta}_{s,i} \bar{r}_e}{\|\bar{r}_e\|} - \|\bar{r}_e\|\right)\right)} \quad (3)$$

Eq (3) specifies p_{sq} and p_{sl} to evaluate the progress of the target student in the learning path. p_{sq} indicates the probability of student s correctly answering exercise q , where $\bar{\theta}_{s,i}$, \bar{a}_q and b_q represent the same symbols as the T-BMIRT model in Eq (1-2). p_{se} indicates the degree of knowledge that student s can acquire from the video e , where \bar{r}_e represents the level of knowledge required for the learning video.

When p_{sq} becomes less than the threshold C_{sq} , it means that the difficulty of the exercise q in the recommended learning path has significantly exceeded the student's ability. When p_{se} becomes less than the threshold C_{se} , it means that the skill level of the target student is lower than the requirement of the recommend video e , thus he can only acquire little knowledge from the video. When either condition is met, the SARLR determines that the original recommended path has to be re-planned to match the student's knowledge state.

SARLR Phase 2: Adaptive Re-planning

INPUT:

Target student s_x , recommended learning path $p = (e_{i_1}, e_{i_2}, \dots, e_{i_T})$
Result of s_x interacted with learning resources in p

OUTPUT: new learning path

- 1: **for each** $e \in p$ **do**
 - 2: **if** e is a video **and** $p_{se} < C_{se}$ **do**
 - 3: **return** *SARLR Phase 1* to re-plan path p
 - 4: **else if** e is an exercise **and** s_x failed it **and** $p_{sq} < C_{sq}$ **do**
 - 5: **return** *SARLR Phase 1* to re-plan path p
 - 6: **end if**
 - 7: **end for**
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4 EXPERIMENTS

We selected two datasets to perform our experiments, the public ‘‘Assistments’’, including 224,076 interactions, 860 students, 1,427 assessments and 106 skills, and a blended learning data from our learning analysis platform including 14,037,146 learning behavior data from 140 schools and 9 online educational companies.

4.1 Experiments for T-BMIRT

We divided each data set into two parts, one part only contains single skill assessments, and the other part contains multiple skills assessments. The IRT, T-IRT are single skill models, and the MIRT and T-BMIRT are multiple skills models. The dimensions for models are related to the numbers of knowledge components. The values in Table 1 are average results of the cross-validation. It shows that T-BMIRT outperforms the other models on each dataset, especially on the multidimensional dataset.

Table 1. Prediction Results of each model

Models	Assistments				Blended learning data			
	One-dimensional		Multidimensional		One-dimensional		Multidimensional	
	ACC	AUC	ACC	AUC	ACC	AUC	ACC	AUC
Frequency method	0.694	N/A	0.683	N/A	0.702	N/A	0.688	N/A
IRT	0.716	0.779	0.701	0.758	0.721	0.784	0.706	0.752
MIRT	0.714	0.771	0.721	0.786	0.718	0.775	0.722	0.783
T-IRT	0.738	0.805	0.712	0.769	0.744	0.801	0.717	0.764
T-BMIRT	0.743	0.815	0.738	0.803	0.757	0.820	0.748	0.816

4.2 Rationality Evaluation

The rationality evaluation verifies whether the algorithm can recommend the suitable learning resources that meet the student’s needs and ability levels. We set the following two indicators for it.

$$RC_{s_x} = \frac{\sum_{e_i \in p} similarity(h_{e_i}, KC_{s_x})}{m}, DC_{s_x} = \frac{\sum_{e_i \in p} similarity(h_{e_i}, \theta_{s_x, i})}{m} \quad (4)$$

Where $e_i \in p$ is the learning resources in a recommended path, m is the length of the path, KC_{s_x} is the knowledge components which s_x is learning in the current chapter, function $similarity()$ calculates the adjusted cosine similarity of the two vectors in the parentheses. The relevance accuracy RC_{s_x} is used to evaluate whether the difficulties of the recommended learning resources for the target student s_x are matched with his ability. The difficulty accuracy DC_{s_x} is set to evaluate whether the difficulties of the recommended learning resources for the target student can match his current ability levels.

We selected the blending data to do this experiments. Table 2 shows the average of the 10-fold cross-validation results. It can be seen that the UCF and ICF have a similar effect, but the UCF works better on the relevance accuracy, while the ICF is better at

the difficulty accuracy. The LFM performs better than the first two algorithms in terms of both indicators. The SARLR algorithm performs best among all these algorithms.

Table 2. Results of Rationality Experiment.

Model	Relevance accuracy	Difficulty accuracy
UCF	0.86	0.77
ICF	0.71	0.83
LFM	0.87	0.84
SARLR	0.97	0.92

4.3 Effectiveness Evaluation

The effectiveness evaluation verifies whether the students' abilities can be improved by the recommendation algorithm. We clustered the students into six groups according their ability levels. We calculated "expected gain" $G = \frac{E(R_{S'}) - E(R_S)}{E(R_S)}$ by using PCA and K-means method to further split the students of the same group into two parts based on their learning paths [6]. One part is the students whose learning paths are strictly recommended, denoted as S' , and the other part is the students whose learning path are randomly selected, denoted as S . $E(R_{S'})$ and $E(R_S)$ and indicate that the students' average score in the last online assessment. We sorted the six groups of the students ascendingly based on their ability levels: group 1 has the lowest skill level, group 2 has a higher skill level than group 1, and group 6 has the highest.

Table 3. Results of Effectiveness Experiment

Model	Expected gain					
	1	2	3	4	5	6
UCF	-0.04	-0.06	0.07	-0.03	0.08	0.01
ICF	0.05	0.04	-0.03	0.07	-0.02	0.05
LFM	0.04	0.12	0.09	0.10	0.03	-0.05
SARLR	0.11	0.27	0.24	0.23	0.17	0.06

We selected the public data "Assistments" to do this experiments. Table 3 shows that the SARLR algorithm performs much better than the other three algorithms. Especially for the students in group 2 to group 5, the SARLR algorithm helps them to achieve noticeable progress from the recommendation learning paths. It indicates that SARLR is more effective on improving learning gain of students with average ability levels.

5 CONCLUSIONS

We developed a self-adaptive recommendation algorithm of learning resources (SARLR) to personalize students' learning path. It contains the T-BMIRT, a temporal blended multidimensional IRT model, which performs well on the prediction task of

multi-dimensional skills assessments, especially when the study process contains learning video interactions. Based on the T-BMIRT model, the SARLR algorithm adopts a reasonable recommendation strategy and establishes conditions to adaptively adjust recommendations towards the dynamic needs of the students. In addition, we extend the evaluation criteria for personalized learning recommendation in term of rationality and effectiveness. Experimental results prove that the SARLR algorithm outperforms the other recommendation algorithms based on CF and LFM.

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