Personalized Learning Resources Recommendation for Interest-Oriented Teaching

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Abstract—An interest-oriented teaching method can stimulate students' interest in learning, thus generating great internal drive. The personalized learning resource recommendation method for interest-oriented teaching meets students' personalized learning preference needs, reduces students' learning resource selection cost, and provides students with more diversified and rational learning resource supply. Different from traditional recommendation algorithms, the recommendation algorithm constructed in this article essentially adjusts the recommendation results in real time based on college students' adoption behavior of historical recommendation information. This article describes the problem of personalized learning resource recommendation for interest-oriented teaching, and constructs a personalized learning resource recommendation model based on the communication power of high-scoring learning resources. Experimental results verify the effectiveness of the model.

Keywords—interest-oriented teaching, personalized online learning, learning resource recommendation

1 Introduction

Interest-oriented teaching method is a method that takes intuitive teaching as the starting point and interest as the means and motive force of teaching, cultivates students' interest in learning and gives full play to their subjective initiative, so as to enable them to study actively [1, 2]. In English teaching, interest-oriented teaching method refers to how to make students have a strong need for English, stimulate their interest, and thus generate great internal drive [3–7]. Stimulating students' interest in learning is to make students have the enthusiasm to learn English, which usually comes from both needs and interests [8–14]. Personalized recommendation technology, which is widely used in Internet platform, can also be applied to the field of higher education, so as to achieve accurate matching between learning resources and college students, meet students' personalized learning preference needs, reduce students' learning resource selection cost, and provide students with more diversified and rational learning resource supply [15–20].

A challenging task of online learning system is to find suitable learning resources for college students when online learning is carried out in an open and dynamic environment.

A good personalized online learning environment should recommend suitable learning content for learners. In order to find learning materials suitable for learners with different preferences, Ding [21] proposes a fuzzy set theory method for online learning system, in which a similarity measurement algorithm based on various fuzzy set theories is introduced to find the online learning content that meets the requirements of learners. Compared with the proposed method, the proposed method improves the accuracy without losing recall. Li et al. [22] proposes an online learning resource recommendation method based on learning environment. By constructing learners' learning context map and context-related model of "knowledge resources", combined with personalized recommendation technology, it can provide learners with learning resources that meet their learning objectives, knowledge abilities and personal preferences. This strategy can help learners master the knowledge system and learning direction, and improve learning efficiency. Li et al. [23] puts forward two aspects of recommendation strategy. The first is the basic recommendation strategy, including teaching process, error record and learning resource label record, to recommend learning resources. The second is student-based collaborative filtering algorithm, which uses genetic algorithm to optimize the interest function. It will accurately recommend learning resources to students and meet their learning needs. Xu and Dong [24] proposes an online learning resource recommendation system to recommend feasible learning courseware for students. It first introduces the architecture of the system and the functions of each component, then discusses the course structure and how to design object-oriented (OO) learning courseware based on the Sharable Content Object Reference Model (SCORM). In addition, a fuzzy algorithm is proposed to estimate students' cognitive ability.

Different from the traditional recommendation algorithm, the recommendation algorithm constructed in this article essentially adjusts the recommendation results in real time based on college students' adoption behavior of historical recommendation information. When the online learning platform recommends a learning resource to students, if the students accept the recommended results and give positive feedback, the online learning platform will give the algorithm a positive score, which will help the algorithm gain students' interest in learning. The second chapter describes the recommendation of personalized learning resources for interest-oriented teaching. In the third chapter, a personalized learning resource recommendation model based on the communication power of high-scoring learning resources is constructed. The effectiveness of the model is verified by experiments.

2 Description of personalized learning resource recommendation for interest-oriented teaching

Traditional personalized recommendation models determine the sequence of college students' behaviors through timestamps, and the default time interval of college students' behavior is consistent. The modeling of college students' behavior sequence based on this has the problem of over-dependence on time interval, and they cannot be applied to the application scenario of personalized learning resource recommendation for interest-oriented teaching studied in this article. For example, in a certain learning period (week) of English interest-oriented teaching, the behavior sequence of college students' online learning is "vocabulary concept, vocabulary association and vocabulary application"; then vocabulary learning resources will occupy a large proportion in the recommendation to college students in this period, while the recommendation weight of vocabulary learning resources will be reduced in the recommendation to college students in the next learning period. If the behavior sequence of college students in a certain learning period (month) is also "vocabulary concept, vocabulary association and vocabulary application", vocabulary learning resources will occupy a greater weight in the recommendation to college students in that learning period. Therefore, it is very necessary to emphasize the time interval information of college students' learning behavior when recommending personalized learning resources in the process of interest-oriented teaching.

In addition, in the practical interest-oriented teaching process with learning resources recommendation, college students' score feedback information is also very important, and can also reflect the features of college students' learning interest in real time. The higher the feedback score of college students for the recommended learning resources is, the higher the students' interest in learning the learning resources is. However, the traditional personalized recommendation model directly input the feedback score of college students into the recommendation model, and does not affect the learning experience of other students when college students score the feedback of learning resources. For example, in a learning resource recommendation scenario of English interest-oriented teaching, a learning resource with high scores given by most students will have a better search response among college students, and college students who have never been exposed to this learning resource are more likely to learn it and abandon other learning resources. Because of being influenced by other people's scores and not accessing other learning resources, the college student is very likely to score the learning resources lack of objectivity, which makes the evaluation of the learning resources inaccurately.

In order to accurately capture the learning interest preference of college students in the process of interest-oriented teaching, this article will modify and optimize the feedback scores of college students on the recommended learning resources based on the information dissemination model, and then input the scores into the recommendation model to ensure that the recommendation strategies of the model are more suitable for the actual needs of college students.

Assuming that the timestamp of the l-th behavior of college student i is represented by P_i^l, the following formula gives the timestamp sequence expression corresponding to the online learning behavior sequence of college students:

$$P_i = \left[P_i^1, \dots, P_i^l, \dots, P_i^{|P_i|} \right] \tag{1}$$

Assuming that the l-th timestamp in a timestamp sequence is represented by p_l, the following formula gives a fixed-length timestamp sequence expression:

$$p = \left[p_1, \dots, p_l, \dots, p_{|l|} \right] \tag{2}$$

Assuming that the learning resource feedback information of college student *i* at *l* is expressed by ξ_i^l, the following formula gives the feedback score sequence expression of college students to the recommended learning resources:

$$\xi_i = \left[\xi_i^1, \dots, \xi_i^l, \dots, \xi_i^{|\xi_i|}\right] \tag{3}$$

Finally, the time interval matrix corresponding to college student v's learning behavior in the process of interest-oriented teaching is expressed by Φ^v, and the personalized scoring matrix of college students to recommended learning resources is expressed by H^v. Figure 1 shows a schematic diagram of generating personalized scoring matrix.

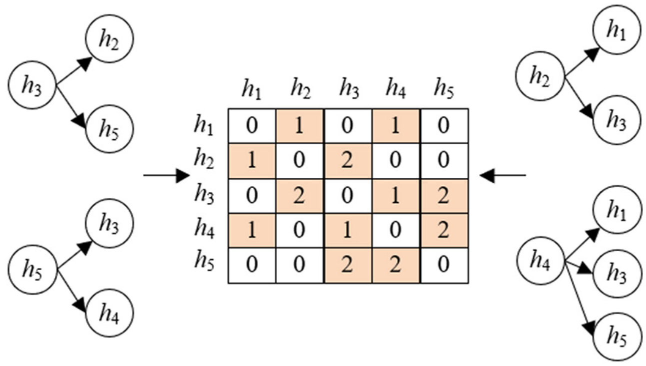

Fig. 1. Schematic diagram of generating personalized scoring matrix

3 Construction of personalized learning resource recommendation model

In the process of interest-oriented teaching, the behavior patterns in the sequence of college students' learning behaviors are complex and changeable. In order to fully capture the features of students' individualized learning behavior, this article fully considers the time interval of college students' learning behavior, and constructs a personalized learning resource recommendation model based on the communication power of high-scoring learning resources. Figure 2 shows the recommendation model structure. This model extracts the features of college students' learning interest preference by constructing the feedback scoring matrix of learning resources, and excavates the correlation between college students' learning behavior sequences by constructing the time interval matrix. The learning interest preference extraction module of the model is composed of Transformer encoder module and deep convolution module, which can extract both long-term interest preference and short-term interest preference of college students' online learning in the process of interest-oriented teaching.

The model can be divided into four layers: relation matrix calculation layer, embedding layer, interest preference extraction layer and prediction layer. Firstly, the model constructs the time interval matrix and feedback scoring matrix based on the timestamp information in the online learning behavior sequence of college students and the feedback score information of learning resources. In order to make college students' scores more objectively, firstly, it's essential to calculate the probability that college students are affected by high-rated learning resources in the process of interest-oriented teaching and modify the feedback scoring matrix based on the calculated results. Then, the original learning behavior sequence, the time interval matrix and the modified feedback scoring matrix are transformed into vector forms, and all the data in the vectors are mapped in other dimensional spaces. Finally, the source is fused with all the data information of the three matrices. The fused results can be processed by the model interest preference extraction module to generate the required feature information of college students' learning behavior. The feature information can be processed by the model prediction layer to output the final learning resource recommendation result. The following is a detailed introduction to the specific details of the four layers of the built model.

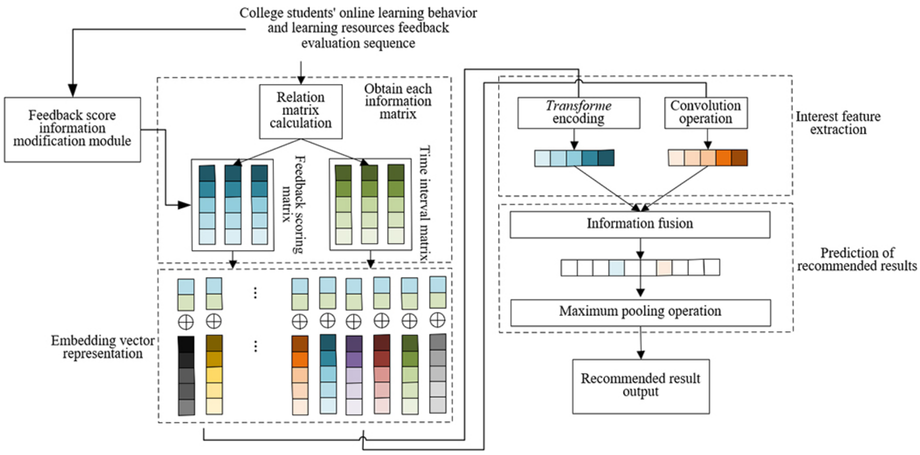

Fig. 2. Structure of personalized learning resource recommendation model

In the relation matrix calculation layer, the length of college students' learning behavior sequence with limited input is fixed as m. The following formula gives the timestamp sequence score sequence and behavior sequence expression corresponding to college students' online learning behavior:

$$p = [p_1, \ldots, p_l, \ldots, p_m] \tag{4}$$

$$v = [v^1, \ldots, v^l, \ldots, v^m] \tag{5}$$

$$X = [x_1, \ldots, x_l, \ldots, x_m] \tag{6}$$

According to the above sequence, the difference between the timestamp of the learning resource and the timestamp of other learning resources in the behavior sequence is firstly compared to obtain a time interval. To avoid excessive time interval, set the threshold HZ. Assuming that the time interval matrix corresponding to college student v is represented by $\Phi^n \in R^{m\times m}$, and the time interval information between learning resource i and learning resource j in v learning behavior sequence is represented by Φ^m_{ij}, then the calculation formula is as follows:

$$\Phi^v_{ij} = \frac{\min\left(HZ, \Phi^v_{ij}\right)}{\left\|\Phi^v\right\|_2} \tag{7}$$

The final online learning time interval matrix of college students is given by the following formula:

$$\Phi^n = \begin{bmatrix} \Phi^v_{11} & \Phi^v_{12} & \cdots & \Phi^v_{1m} \\ \Phi^v_{21} & \Phi^v_{22} & \cdots & \Phi^v_{2m} \\ \cdots & \cdots & \cdots & \cdots \\ \Phi^v_{m1} & \Phi^v_{m2} & \cdots & \Phi^v_{mm} \end{bmatrix} \tag{8}$$

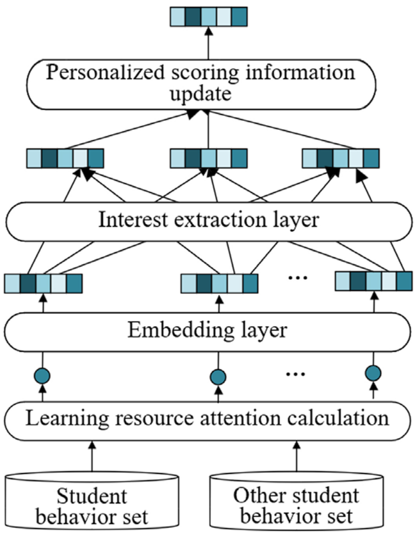

Fig. 3. Modification process of feedback score information

Then, the feedback score information is extracted. By multiplying the feedback score and the influence probability, the modified feedback score information shown in the following formula can be obtained. Figure 3 shows the feedback score information modification process. Assuming that the probability of v being affected by learning resource i at time p is represented by $\varphi^u_{it}\psi^v_{ip}$, the probability of college students being initially affected by learning resource i is represented by i_0, the probability of individual college students being affected is represented by α, the initial time is represented by p_0, and the score of college students after being affected by learning resource *i* at time p is represented by PF^v_{ip}, then:

$$\psi^v_{it} = \frac{1}{1+\left(\frac{1}{i_0}-1\right)o^{-\alpha|p-p_0|}} \tag{9}$$

$$PF^v_{ip} = \xi^v_{ip} \times \psi^v_{ip} \tag{10}$$

Assuming that the attention of the learning resource *i* is expressed by HD^v_i, the number of accessing with learning resource *i* is represented by $JH(DJ_i)$, the sum of all accesses is represented by $JH(DJ)$, the modified score of the learning resource by college students v is represented by *H*, and the *L*2 norm of the score sequence of the college student is represented by $||\xi^v||_2$. The following formula gives the quantitative calculation formula of students' attention to learning resources and the calculation formula of modified learning resources scores:

$$HD^v_i = \frac{JH(DJ_i)}{JH(DJ)} \tag{11}$$

$$H^v_{ip} = \frac{PF^v_{ip} + HD^v_i \times \xi^v_{ip}}{\left\|\xi^v\right\|_2} \tag{12}$$

Assuming that the scoring information matrix corresponding to college student v is represented by $H^v \in R^{m\times m}$, the final expression of personalized scoring information matrix for college students to learning resources is given by the following formula:

$$H^m = \begin{bmatrix} H^v_{11} & H^v_{12} & \cdots & H^v_{1n} \\ H^v_{21} & H^v_{22} & \cdots & H^v_{2m} \\ \cdots & \cdots & \cdots & \cdots \\ H^v_{m1} & H^v_{m2} & \cdots & H^v_{mm} \end{bmatrix} \tag{13}$$

In the embedding layer, firstly, the embedding matrix $Y\in R^{m\times c}$ with dimension *c* is defined, and the row vector of *Y* is the embedding vector $y_i \in R^c$ of each learning behavior in the sequence of college students' learning behaviors. In order to ensure that the self-attention mechanism in the interest preference extraction layer can fully learn the position information of the learning behavior sequence, this article introduces two matrices Y^T_L and Y^T_U, which respectively learn the key information and the value information in the self-attention mechanism. The following formula gives their embedding vector expressions:

$$Y^T_L = \left[t^l_1,\ldots,t^l_l,\ldots,t^l_m\right]^T \tag{14}$$

$$Y_U^T = \left[t_1^u, \ldots, t_l^u, \ldots, t_m^u\right]^T \tag{15}$$

The detailed calculation process of interest preference extraction layer includes convolution calculation process and Transformer encoder calculation process. Firstly, the embedding matrix Y and its transposed matrix Y^T are convolved respectively. If the two convolution calculations are represented by $M_1 M_2$ respectively, the maximum pooling operation is represented by $XP(\cdot)$, the transposition of the embedding matrix Y is represented by Y^T, the splicing function is represented by $PJ(\cdot)$, and the online short-term interest preference features of college students obtained after convolution layer operation are represented by $\varepsilon \in R^{c\times c}$, then:

$$\theta_1 = XP(M_1(Y)) \tag{16}$$

$$\theta_2 = M_2(Y^P) \tag{17}$$

$$\varepsilon = PJ(\theta_1, \theta_2) \tag{18}$$

Q^W, Q^L and Q^U are spatial projection matrices corresponding to *Query*, *Key* and *Value* patterns of Transformer encoder. In order to add the information of students' learning behavior sequence, time interval matrix and modified feedback scoring matrix to the recommendation model, it is necessary to project the three aspects of information to the three directions corresponding to *Query*, *Key* and *Value* patterns respectively. The specific process is as follows:

$$Query_i = y_i Q^W \tag{19}$$

$$Key_{ij} = y_i Q^L + \Phi_{ij}^l + H_{ij}^l + t_j^l \tag{20}$$

$$Value_{ij} = y_j Q^U + \Phi_{ij}^u + H_{ij}^v + t_j^v \tag{21}$$

By inputting the three feature vectors obtained from the above formula into the self-attention mechanism formula of Transformer encoder, the feature representation of college students' learning behavior after weight allocation can be obtained. The attention mechanism here can sense the time interval and feedback the scoring information. Assuming that the feature representation of the embedding vector after self-attention mechanism is represented by $c_i \in R^c$, the calculation formula is as follows:

$$o_{ij} = \frac{Query_i (Key_{ij})^T}{\sqrt{c}} \tag{22}$$

$$h_{ij} = \frac{\exp(o_{ij})}{\sum_{l=1}^{m} o_{il}} \tag{23}$$

$$c_i = \sum_{j=1}^{m} h_{ij} Value_{ij} \tag{24}$$

The embedding matrix $c = [c_1, \ldots, c_l, \ldots, c_m]$ can be obtained by linearly combining students' learning behavior information, time interval information and modified feedback score information. Furthermore, the feature representation c_i is processed by nonlinear activation function to realize the nonlinearization of the model. Assuming that the nonlinear activation function *ReLU* is denoted by Γ and the learnable parameters are denoted by $B_1, B_2 \in R^{c\times c}$ and $d_1, d_2 \in R^c$, the following formula is obtained:

$$GGM(c_i) = \Gamma(c_i B_1 + d_1) B_2 + d_2 \tag{25}$$

A random inactivation operation module, a layer regularization operation module and a residual connection module are introduced into the constructed model to improve the ability of suppressing over-fitting and the stability of the model, so that the feature representation processed by the above three modules is represented by $c_i^* \in R^c$, and the final sequence can be represented as:

$$c^* = \left[c_1^*, \ldots, c_l^*, \ldots, c_m^*\right]^T \tag{26}$$

The convolution calculation results and Transformer encoder calculation results are weighted and combined, assuming that the weight parameters of the calculation results of the two results are represented by ω_1 and ω_2, respectively, and the final expression of college students' online learning interest preference feature $C \in R^{m\times c}$ is given by the following formula:

$$\begin{cases} C = \omega_1 \times \tilde{c} + \omega_2 \times \varepsilon \\ \omega_1 + \omega_2 = 1 \end{cases} \tag{27}$$

In the prediction layer of the model, matrix decomposition is used to calculate the interest preference score of college students for the *i*-th learning resource. Assuming that the score of learning resource *i* at time *p* is represented by $s_{i,j}^*$, the embedding vector of learning resource *i* is represented by $y_i \in R^c$, and the feature representation vector of college students integrating students' learning behavior information, time interval information and modified feedback score information in the first p periods is represented by $C_i \in R^c$, then the calculation formula is as follows:

$$s_{i,s}^* = C_p (y_i)^P \tag{28}$$

4 Experimental results and analysis

Figure 4 intuitively shows the influence of the number of college students' online learning behaviors on the recommendation effect of the constructed model under different sample sets. As can be seen from the figure, regardless of whether the sources of samples are consistent or not, with the increase of college students' recent online learning behaviors, the interest preference extraction layer of the model can accurately extract students' online learning behavior features, and the hit rate of learning resource recommendation is also gradually increasing. When the number of college students' recent online learning behaviors reaches 3–4 times, the hit rate of model learning resource recommendation has reached high values of 11.124 and 40.671 on two sample sets. If the number of learning behaviors is greater than 4 times, the hit rate of learning resource recommendation of the model will no longer change significantly.

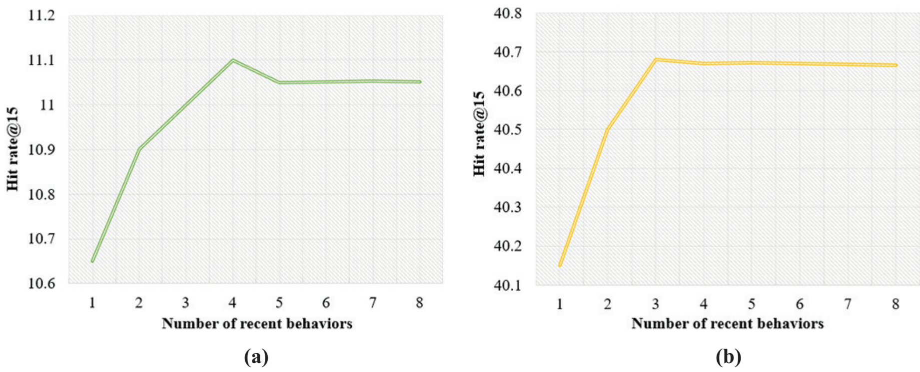

Fig. 4. Influence of the number of college students' online learning behaviors on the recommendation effect

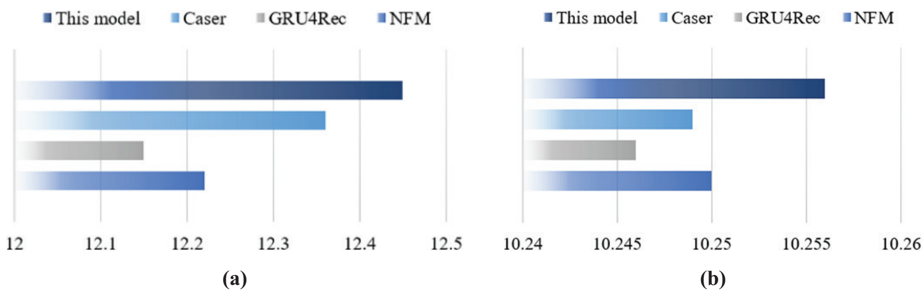

Fig. 5. Influence of modification of feedback score information on model recommendation effect

Figure 5 shows the influence of the modification of feedback score information on the model recommendation effect. Comparing the performance of this model, Caser, GRU4Rec and lNFM in different sample sets, it's possible to see that this model with the modification of feedback score information has achieved better learning resource recommendation effect, which verifies that the modification of feedback score information is very effective. The modification of feedback score information avoids the non-objective scoring of the learning resources by college students due to the influence of other students' learning experiences, realizes the accurate capture of college students' learning interest preferences in the process of interest-oriented teaching, and ensures that the recommendation strategies of the model are more suitable for the actual needs of college students.

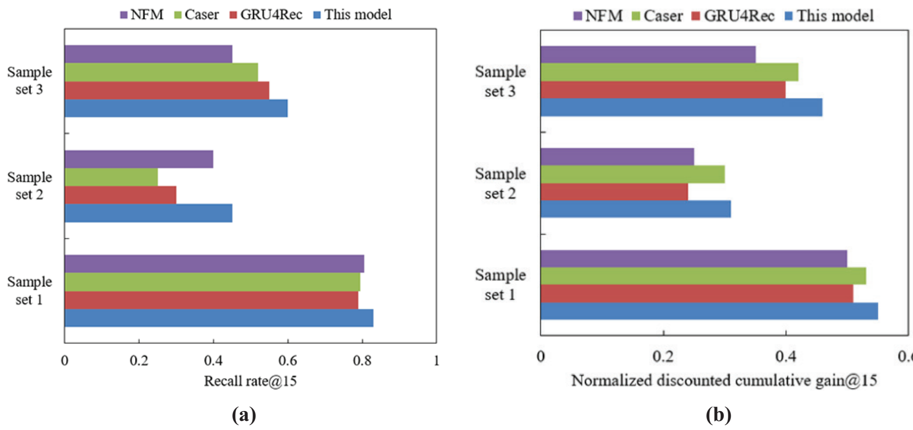

Fig. 6. Comparison results of recommendation effect of the model under different time interval thresholds

Figure 6 shows the comparison results of recommendation effect of the model under different time interval thresholds. Recall rate *Recall@*15 and normalized discounted cumulative gain *NDCG@*15 of recommended learning resources under 15 recommended targets are selected as the indicators to measure the recommendation effect of the model. It can be seen from the figure that only reasonable threshold setting can ensure that the model has good recommendation performance. Excessive pursuit of a larger threshold will reduce the recommendation performance of the model.

Table 1. Comparison results of recommended performance of different models under the condition of timestamp length change

Model	**Length 50**	
	***Recall*@15**	***NDCG*@15**
lNFM	0.6142	0.3417
GRU4Rec	0.7418	0.4261
Caser	0.7362	0.5932
The model	0.7753	0.6141
Model	**Length 30**	
	***Recall*@15**	***NDCG*@15**
lNFM	0.3269	0.1369
GRU4Rec	0.3251	0.1425
Caser	0.3857	0.2417
The model	0.4218	0.4216
Model	**Length 10**	
	***Recall*@15**	***NDCG*@15**
lNFM	0.4369	0.2417
GRU4Rec	0.4158	0.2639
Caser	0.5237	0.3152
The model	0.6625	0.4271

Table 1 shows the recommended performance comparison results of different models under the change of timestamp length. From Table 1, it's possible to get the following conclusions. The learning resource recommendation performance of Caser, GRU4Rec and lNFM models on three sample sets with timestamp lengths of 50, 30 and 10, respectively, is not as high as that of the model constructed in this article. In the model herein, students' learning behavior information, time interval information and modified feedback score information are linearly combined, and an interest preference extraction layer to extract the rich association of college students' online learning behavior sequence, with the best learning resource recommendation effect on three sample sets obtained, which verifies the excellent recommendation performance of the constructed model.

Table 2. Ablation experimental results of the model

Model	**Length 50**	
	***Recall*@10**	***NDCG*@10**
Before students' learning behaviors are integrated	0.7142	0.5263
Before the time interval information is integrated	0.7362	0.5174
Before integrating the modified scoring information	0.7485	0.5912
The model	0.7617	0.6126
Model	**Length 30**	
	***Recall*@10**	***NDCG*@10**
Before students' learning behaviors are integrated	0.3412	0.2362
Before the time interval information is integrated	0.3629	0.2578
Before integrating the modified scoring information	0.4857	0.2514
The model	0.5172	0.2639
Model	**Length 10**	
	***Recall*@10**	***NDCG*@10**
Before students' learning behaviors are integrated	0.5241	0.3147
Before the time interval information is integrated	0.5817	0.3692
Before integrating the modified scoring information	0.6235	0.3518
The model	0.6847	0.4251

Finally, the model ablation experiment is conducted before and after the linear combination of students' learning behavior information, time interval information and modified feedback score information. Table 2 shows the ablation experimental results of the model. It can be seen from the table that the capture ability of the model before the time interval information is integrated into to the online learning behavior law of college students is greatly reduced. The model before integrating the sequence of students' learning behavior and the modified score information cannot obtain the explicit learning interest preference information of college students. Only by making full use of the model of three kinds of information can we get the most ideal recommendation effect of learning resources.

5 Conclusion

This article studies the recommendation method of personalized learning resources for interest-oriented teaching. This article describes the personalized learning resource recommendation for interest-oriented teaching, and constructs a personalized learning resource recommendation model based on the communication power of high-scoring learning resources. Combined with experiments, this article analyzes the influence of the number of college students' online learning behaviors on the recommendation effect of the model under different sample sets, and verifies that the hit rate of model learning resources recommendation is the best when the number of college students' recent online learning behaviors reaches 3–4 times. The influence of feedback score information modification on model recommendation effect is analyzed to verify that the model is very effective in modifying feedback score information. The model recommendation effects are compared under different time interval thresholds and timestamp length changes, and the excellent recommendation performance of the constructed model is verified. A model ablation experiment is conducted before and after the linear combination of students' learning behavior information, time interval information and modified feedback score information, which verifies that only the model with full use of the three types of information can obtain the most ideal learning resource recommendation effect.

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