A New Learning Resource Recommendation Method for Improving the Efficiency of Students' Online Independent Learning

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Abstract—If the learning resource recommendation method fully considers the efficiency improvement of college students' online independent learning, it can save college students' learning energy and improve their learning quality, but also can promote students to develop such learning attitudes as active participation, willingness to explore and frequent practices. Therefore, this article studies the learning resource recommendation method for improving the efficiency of college students' online independent learning. This article quantitatively evaluates the learning efficiency of college students in the process of online independent learning, and takes the evaluation results as a reference for learning resource recommendation methods. The capsule network combined with self-attention routing algorithm is used to represent the various demands of college students' online independent learning with multiple vectors, and the sequence information layer based on Transformer model is set up to construct the learning resource recommendation model. Experimental results verify the effectiveness of the model.

Keywords—college students' online learning, independent learning efficiency, learning resource recommendation

1 Introduction

At present, online learning is becoming a hot spot in the field of higher education, and is widely used in various sections and disciplines of college students' training for higher education. Under the online learning environment, college students have undergone great changes in learning methods and habits [1–8]. Based on the laws and characteristics of online learning, in order to obtain better learning efficiency, it is necessary to guide college students to study consciously and actively, and further realize student-centered high-quality education [9–15]. The development of data mining, learning analysis and other technologies makes it possible to realize the auxiliary service of college students' online independent learning [16–22]. The learning resource recommendation method considering the efficiency improvement of college students' online independent learning not only saves college students' learning energy and improves their learning quality, but also promotes such learning attitudes as active participation, willingness to explore and frequent practices.

Aiming at the lack of hierarchy and systematicness of resource recommendation caused by abundant online learning resources and numerous learning platforms, Hao and Yang [23] proposed an attention-based ADCF online learning resource recommendation model by introducing attention mechanism into deep collaboration DCF model. Experimental results show that compared with the DCF model before improvement, the proposed ADCF model achieves accurate recommendation of online learning resources. In order to overcome the low feasibility of traditional resource recommendation methods, Liu [24] proposed a personalized resource recommendation method based on machine learning. Firstly, the user-based collaborative filtering algorithm is used to calculate the personalized similarity of users, and then the content-based collaborative filtering algorithm is used to calculate the similarity of resource content through cosine similarity. The results show that this method can effectively improve the accuracy and feasibility of personalized recommendation results. Dien et al. [25] proposes a deep matrix decomposition model extended from standard matrix decomposition to recommend learning resources based on learners' abilities and needs. Compared with some baselines, the experiment shows promising results. This work is expected to be a good choice for large-scale data sets. Existing teaching resource recommendation algorithms cannot distinguish student users and push the same teaching resources through students' personality, or think that student user personality is not enough to meet students' personalized learning needs. Therefore, in view of the above problems, combined with TDINA model, users establish a cognitive diagnosis model for students. Zhou et al. [26] proposed a method of probabilistic matrix factorization decomposing teaching resources based on convolution (CUPMF), which combines students' answer history, cognitive ability, mastery of situation knowledge and forgetting influencing factors. Combining with the student knowledge mastery matrix obtained by TDINA model, it's possible to recommend corresponding teaching resources to students, so as to improve learning efficiency and help students improve their grades. Jia [27] designed an online learning resource recommendation method based on difficulty matching. Aiming at the difficulty matching problem, an online learning resource recommendation method based on automatic encoder is proposed. The flow chart of learning resource recommendation is given, and the proposed algorithm is described in detail. The effectiveness of the model is verified by experiments.

Existing learning resource recommendation methods have achieved a lot of valuable research results, but there are still many difficult problems. On the one hand, when there is little or no sample data, the conventional recommendation algorithms cannot play their role. On the other hand, the model with complex structure has huge parameters and is unstable in training, easy to over-fit and unsatisfactory in robustness. In addition, the existing recommendation model does not consider the improvement of college students' independent learning efficiency, which greatly limits the recommendation direction of the recommendation model, and cannot meet the needs of college students' learning efficiency improvement in combination with the rules and characteristics of online learning. Therefore, taking musicology majors as an example, this article studies the recommendation methods of learning resources for improving the efficiency of college students' online independent learning. Firstly, in the second chapter, the article quantitatively evaluates the learning efficiency of college students in the process of online independent learning, and takes the evaluation results as a reference for learning resource recommendation methods. In the third chapter, the capsule network combined with self-attention routing algorithm is used to represent the various needs of college students' online independent learning with multiple vectors, and the sequence information layer based on Transformer model is set up to build a learning resource recommendation model. Experimental results verify the effectiveness of the model.

2 Quantitative evaluation of college students' online independent learning efficiency

This article first quantitatively evaluates the college students' learning efficiency in the process of online independent learning, and takes the evaluation results as a reference for learning resource recommendation methods.

The vector matrix of college students' online independent learning courses is represented by D, and the independent learning courses are divided into m categories. Assuming that each independent learning course category is represented by $d_i(i = 1, …, m)$, d_i contains several specific independent learning resources in the i-th independent learning course, namely $d_i = [d_i^{(1)}, d_i^{(2)}, …]$. The following formula gives the expression of D:

$$D=[d_1, d_2, \ldots, d_m]=\begin{pmatrix} d_1^{(1)} & d_2^{(1)} & \cdots & d_m^{(1)} \\ d_1^{(2)} & d_1^{(2)} & \cdots & d_m^{(2)} \\ \vdots & \vdots & \vdots & \vdots \end{pmatrix} \tag{1}$$

Because d_i contains different number of learning resources for college students' online independent learning. Let the number of learning resources contained in the independent learning course with the largest number of learning resources be represented by D_{max}, then D is the matrix of column m of row D_{max}. For columns in the matrix where the number of learning resources is less than D_{max}, the vacancies without values are supplemented with 0.

Let the duration vector of college students' online independent learning in this article be represented by B, and the student set represented by r, then $r = [R_1, R_2, …, R_{mm}]$, where sets of all the college students under a certain major are represented by $R_j(j = 1, …, n)$. For the specific learning efficiency of college students' online independent learning, it is expressed by X_{xyz}, where $x \in R$, $y \in D$ and $z \in B$. X_{xyz} represents the specific learning efficiency of z courses in y learning cycles of online independent learning for college student x. Let $b_0 = minB$, $b_1 = maxB$ and $b_{1/2}$ be the time points of mid-term assessment. B can be split into the following two parts:

$$B=\begin{cases} B_1, B_1=\left[b_0, b_{\frac{1}{2}}\right] \\ B_2, B_2=\left[b_{\frac{1}{2}}, b_1\right] \end{cases} \tag{2}$$

The main goal of this article is to compare and analyze the learning resource data of college students' online independent learning in B_1 and B_2 so as to analyze the implementation effect of learning resource recommendation method.

According to the needs, firstly, select a subset $\dot{D}^*$ from the targeted college students' online independent learning course D^*, and make a basic analysis of the learning resources in D^*, including calculating all the duration in B_l, the average learning efficiency XBO_{djl}, the excellent rate OAD_{djl}, the passing rate WVX_{djl} of R_j majors in course d. Assuming that the total number of students corresponding to the learning efficiency score interval is represented by M, XBO_{djl} can be calculated by the following formula:

$$XBO_{djl} = \frac{\sum_{x,z} X_{xyz}}{M}, x \in R_j, z \in B_l \tag{3}$$

The excellent rate OAD_{djl} (score greater than or equal to 90) and the passing rate WVX_{djl} (score greater than or equal to 60) can be calculated by the following formula:

$$OAD_{djl} = \frac{M\left(X_{xyz} \geq 90\right)}{M} \tag{4}$$

$$WVX_{djl} = \frac{M\left(X_{xyz} \geq 60\right)}{M} \tag{5}$$

Based on the calculation results of the above evaluation indexes such as excellent rate and passing rate of learning efficiency, it's possible to compare the average duration of the learning efficiency of college students' online independent learning of the target courses before and after the implementation of the learning resource recommendation method in each major to obtain a more intuitive implementation effect of learning resource recommendation method.

Based on the above analysis, it's possible to further classify the efficiency of college students' online independent learning according to the interval. According to the statistics of the proportion of college students in each interval, the learning efficiency interval is represented by $HE = [H_1, H_2, \ldots, H_m]$, the number of college students in the corresponding interval is represented by M, and college students' online independent learning efficiency in the corresponding interval is represented by X_{xyz}. Then the proportion h_{djl} of students whose learning efficiency is in the H interval when R_j majors learn course d online in B_l can be calculated by the following formula:

$$h_{djl} = \frac{M\left(X_{xyz} \in H_h\right)}{M}, H \in HE \tag{6}$$

Based on the calculation results of the above formula, it's possible to more intuitively understand the proportion of college students in each learning efficiency score interval and the overall distribution of college students' online independent learning efficiency, and also to compare the changes of college students' learning efficiency distribution before and after the implementation of learning resource recommendation methods, which is helpful to further adjust and update the recommendation strategies of learning resource recommendation methods.

3 Construction of learning resource recommendation model

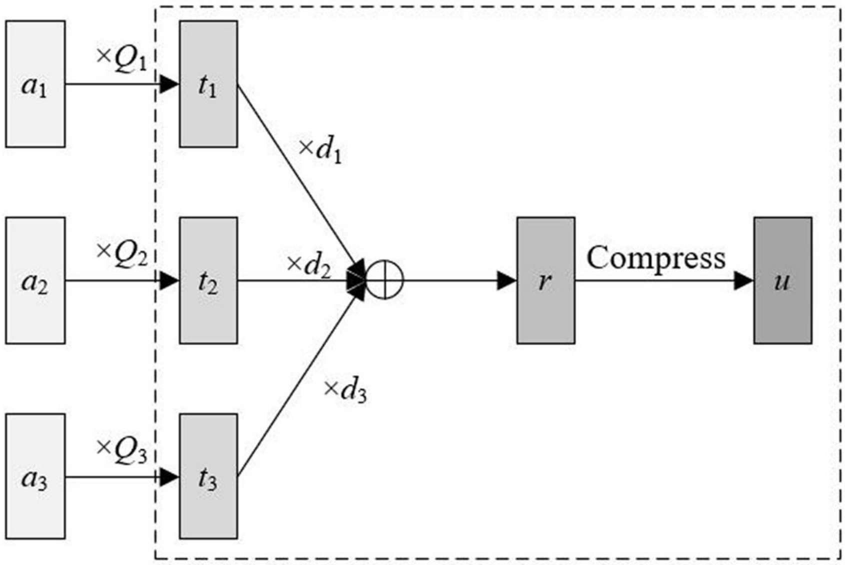


Fig. 1. Capsule network workflow

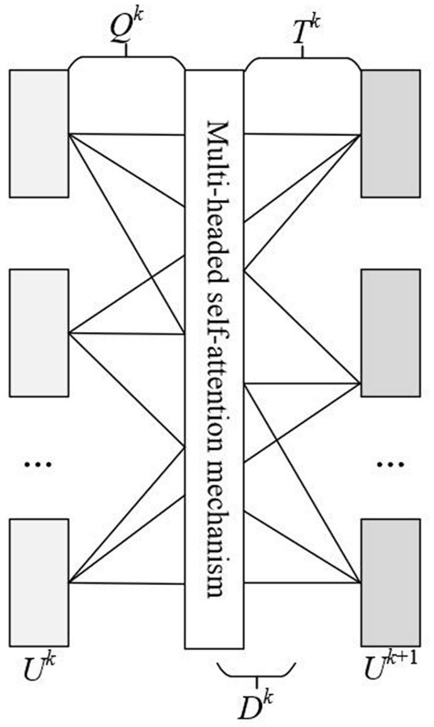


Fig. 2. Workflow of self-attention routing algorithm

The learning resource recommendation method considering the efficiency improvement of college students' online independent learning is aimed to require college students to actively adapt to online independent learning, rather than passively adapt to it. It allows and encourages college students to give full play to their advantages according to their cognitive level, learning interests and learning habits; allows college students to have the right to choose their own learning contents, learning ways and learning methods. According to the demands of all-round development and specialty development, it can scientifically guide college students interested in partial subjects.

Representing a variety of demand information for improving the efficiency of college students' online independent learning through a vector may lead to the loss of some important information, and finally lead to inaccurate and single recommended learning resources. In order to solve the above problems, this article uses capsule network combined with self-attention routing algorithm to express the various needs of college students' online independent learning with multiple vectors. The following is a detailed description of the capsule network and self-attention routing algorithm which is suitable for the research scenario in this article. Figures 1 and 2 show the workflow of capsule network and self-attention routing algorithm.

The input vectors of self-attention routing algorithm and dynamic routing algorithm are both primary capsules. In order to complete the affine transformation between two adjacent capsule layers, the self-attention routing algorithm multiplies the primary capsule with the weight matrix to obtain the prediction vector. Assuming that the prediction matrix composed of all the prediction vectors is represented by $\tilde{U}^k$, the input matrix composed of a plurality of primary capsules is represented by U^k, and the weight matrix of the k-th layer with dimensions (m^k, m^{k+1}, c^k, c^{k+1}) is represented by Q^k, where the number of capsules in the k-th layer is m^k and the vector dimension of capsules in the k-th layer is c^k, then:

$$\tilde{U}^k = U^k \times Q^k \tag{7}$$

Assuming that the output matrix is represented by U_{k+1}, the logarithmic prior matrix with dimensions (m^k, m^{k+1}) is represented by T^k, and the coupling coefficient matrix with dimensions (m^k, m^{k+1}) obtained by self-attention algorithm is represented by Λ^k, the output vector of capsule network is weighted summation of all $\tilde{U}^k$:

$$U^{k+1} = \tilde{U}^k \times (\Lambda^k + T^k) \tag{8}$$

It's assumed that the attention matrix is represented by X^k, the number of capsules in the c-th layer is represented by m^k, and the calculation formula of D^k is as follows.

$$\Lambda^k = \frac{\exp\left(\sum_{m^k} X^k\right)}{\sum_{m^{k+1}} \exp\left(\sum_{m^k} X^k\right)} \tag{9}$$

It's assumed that the dimension of the k-th prediction vector is represented by c^k, the attention matrix is calculated as follows based on the scaled dot-product attention:

$$X^k = \frac{\tilde{U}^k \times (\tilde{U}^k)^T}{\sqrt{c^k}} \tag{10}$$

In order to ensure that the output vector of the algorithm can fully represent the probability of the existence of the object represented by the capsule, a compression function is introduced to control the modulus of the output vector of the algorithm. Assuming that the output matrix is represented by U^{k+1}, the following formula gives the specific calculation formula:

$$SQ(U^{k+1}) = \frac{\left\|U^{k+1}\right\|^2}{1+\left\|U^{k+1}\right\|^2} \frac{U^{k+1}}{\left\|U^{k+1}\right\|} \tag{11}$$

The compression function can only compress the length of the vector, so that the length of the short vector is close to 0 and the length of the long vector is close to 1, without changing the direction of the vector, thus the compressed output vectors can express the interest of users.

Learning records of students' historical resources, which are helpful to improve the efficiency of college students' online independent learning, are very important for recommendation algorithms. Before recommending resources, this article sets up a sequence information layer based on Transformer model to extract sequence information, and then takes the output of this layer as the input capsule of capsule network in the multi-demand extraction layer of college students' online independent learning, so as to realize the accurate expression of various demands of college students' online independent learning. Sequence information is mainly extracted by multi-headed self-attention mechanism in Transformer model, that's, using multi-headed self-attention mechanism, students' learning behavior of historical resources is embedded in multiple subspaces for scaling dot-product Attention, and all the processing results are merged and linearly transformed to output the final recommendation results. It is assumed that the self-attention head is represented by M, the number of multi-headed self-attention heads is represented by f, the weight matrix is represented by QF, and the weight matrix corresponding to each self-attention heads is represented by Q^W, Q^L and Q^U. The matrix composed of behavior and position embedding of all students' learning behaviors of historical resources is represented by O. The specific calculation formula of multi-headed self-attention is as follows:

$$MA = Concat\,(M_1, M_2, ..., M_f)Q^F \tag{12}$$

$$M_i = attention\,(OQ^W, OQ^L, OQ^U) \tag{13}$$

Assuming that *Query*, *Key* and *Value* matrices are represented by W, L and U respectively, the scaling factor is represented by $(c)^{1/2}$, and the dimension of Key vector is represented by c, the calculation process of scaling dot-product Attention is as follows:

$$attention(W, L, U) = soft\max\left(\frac{WL^T}{\sqrt{c}}\right)U \tag{14}$$

Figure 3 shows the learning resource recommendation model architecture. After obtaining a variety of demand vector, the *argmax* operation is performed for the current learning resource recommendation target. From all the demand vectors of college students' online independent learning, it's possible to find out the most relevant demand vector with the learning resource recommendation target. Assuming that the learning resource recommendation target embedding calculated by the sequence information layer is represented by o_i, and the demand matrix composed of all the demand vectors of college students' online independent learning is represented by U_v, the calculation formula is as follows:

$$u_v = U_v\left[:, \arg\max\,(U_v^T o_i)\right] \tag{15}$$

In the training phase of learning resource recommendation model, for the college students' learning demand vector u_v and learning resource recommendation target o_i, the interaction probability between college students and o_i should be maximized, and can be calculated by *sample softmax* function. It is assumed that the recommended target set of learning resources is represented by *ST* and the set of college students is represented by *CS*. The loss function expression of the model is given by the following formula:

$$Loss = \sum_{v \in CS} -\log \frac{\exp(u_v^T o_i)}{\sum_{e \in SA(ST)} \exp(u_v^T o_e)} \tag{16}$$

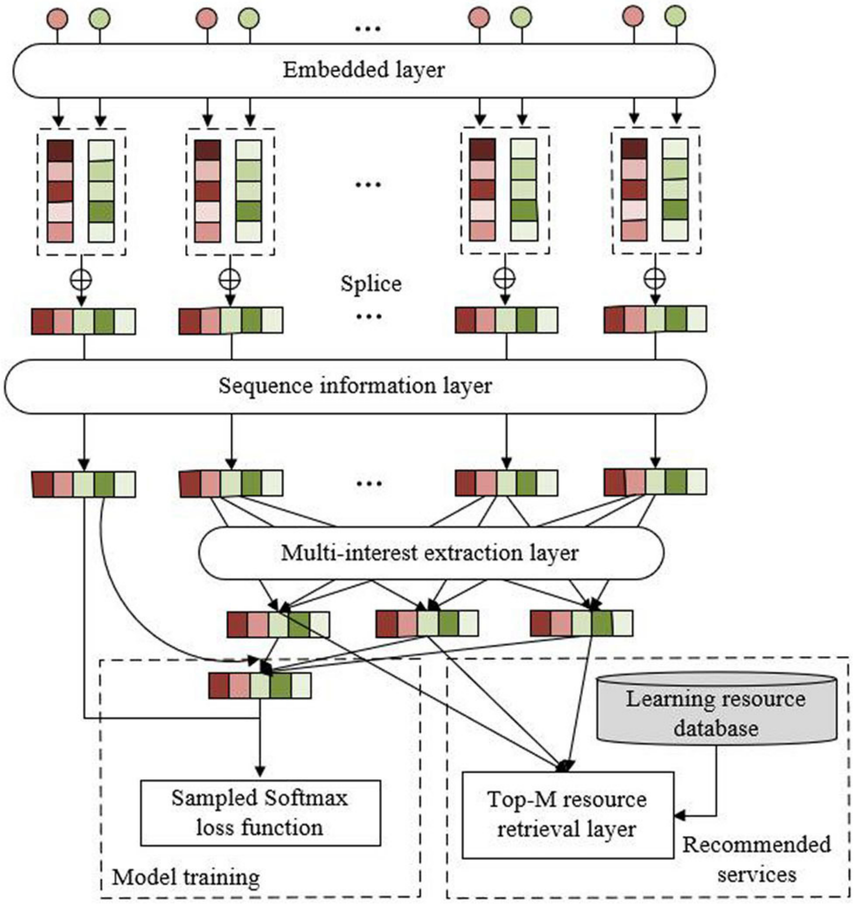


Fig. 3. Learning resource recommendation model architecture

When recommending learning resources, K learning resources matching with the demands are retrieved from the candidate learning resources database based on the nearest neighbor method for all the demand vector extracted by the multi-demands extraction layer. If N demands are extracted, $N \times K$ candidate learning resources can be retrieved. The learning resource recommendation goal of this algorithm is to recommend *Top-M* learning resources for college students, that's, M learning resources that can best promote the efficiency improvement of college students' online independent learning are selected from the candidate learning resource library for recommendation, and M learning resources that have the highest similarity with the efficiency improvement needs of college students' online independent learning are found from $N \times K$ projects to construct the final recommendation list.

4 Experimental results and analysis

In order to verify the effectiveness of the proposed learning resource recommendation method for improving the efficiency of college students' online independent learning, taking musicology majors as an example, this article compares the experimental results of learning resource recommendation under different models, and selects three evaluation indexes: Hit Rate, Recall and Normalized Discounted Cumulative Gain (NDCG). The learning resource recommendation method proposed in this article achieves better recommendation results than DNN, CNN, RNN, GNN, DeepFM, Wide & Deep and other models. The main reason is that the model of this article combines capsule network with self-attention routing algorithm, and realizes multi-demand extraction for improving the efficiency of college students' online independent learning. Other models do not fully mine the sequence information of students' learning behavior of historical resources, which affects the recommendation effect.

In order to further verify the effectiveness of the self-attention routing algorithm optimization and setting the sequence information layer, this article conducts ablation experiments on the recommended model. Table 2 shows the ablation experimental results of the learning resource recommendation model. Based on the experimental results in Tables 1 and 2, it's possible to see that the resource recommendation model with sequence information layer after self-attention routing algorithm optimization has achieved better performance in three indicators. Self-attention routing algorithm aggregates students' historical learning behavior into the function of multiple demand vectors for improving the efficiency of their online independent learning and the function of sequence information extraction in sequence information layer, which is extremely necessary for resource recommendation model.

In addition to the accuracy of recommendation, the diversity of recommendation results is also an important index to measure the learning resource recommendation model, and represents the experience of college students' online learning. Rich and diverse learning resources can bring better learning efficiency to college students. Therefore, this article compares the *Diversity*@60 index values of different recommended models on sample sets from different sources, and the experimental results are given in Table 3. As can be seen from Table 3, the model in this article is obviously higher than other recommended models in *Diversity*@60 value, which verifies that this article uses capsule network as the basic structure of multi-demand extraction module, and obtains better diversity performance than other models. It shows that using multiple vectors to express the various demands for improving the efficiency of college students' online independent learning has obvious positive effects on improving the diversity of students' learning resources recommendation results.

Table 1. Experimental results of learning resource recommendation for different models

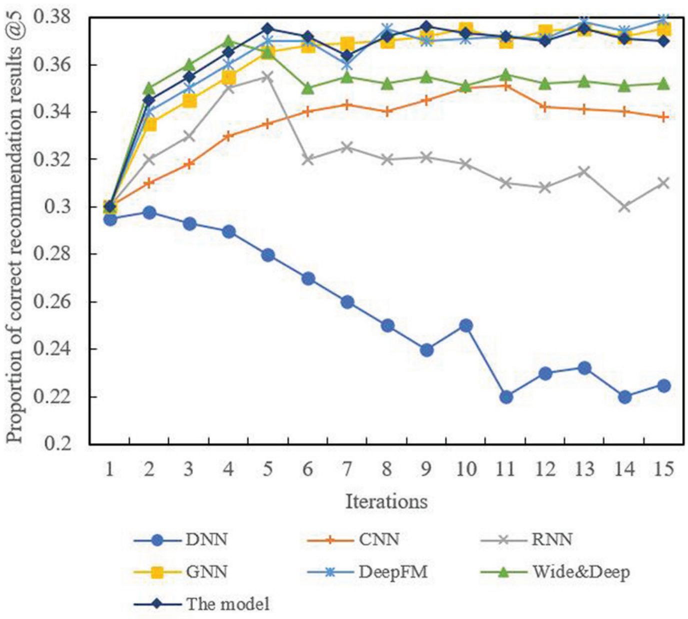
Model	Top-5			Top-10		
	Hit Rate	Recall	NDCG	Hit Rate	Recall	NDCG
DNN	8.142	4.152	6.341	12.362	6.352	12.527
CNN	11.362	4.639	7.253	16.295	7.142	14.281
RNN	16.528	4.385	7.241	14.274	7.269	13.629
GNN	24.274	4.217	7.152	23.625	7.285	17.258
DeepFM	25.825	5.251	7.629	21.208	7.361	13.562
Wide&Deep	33.629	4.629	7.352	37.249	7.528	19.251
The Model	41.205	5.382	8.524	41.647	7.639	14.274

Table 2. Ablation experiment results of learning resource recommendation model

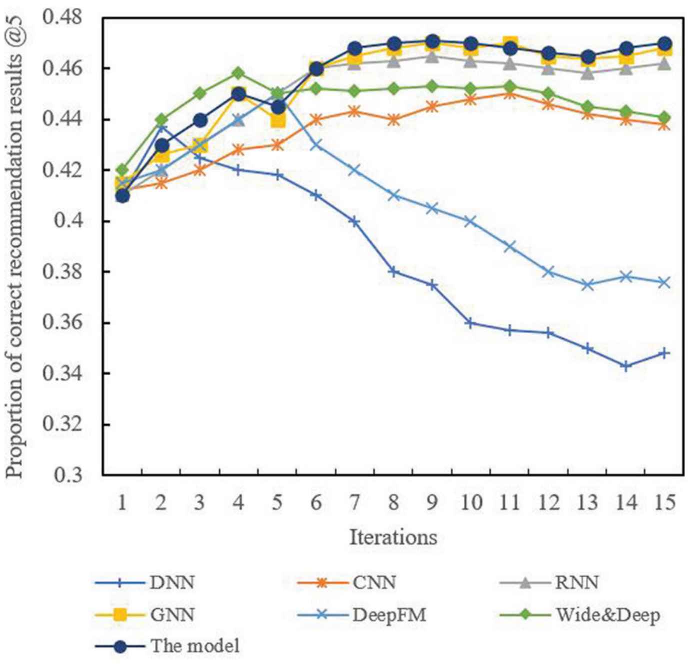
Model	Top-5			Top-10		
	Hit Rate	Recall	NDCG	Hit Rate	Recall	NDCG
Before optimization of self-attention routing algorithm	25.142	6.417	12.625	22.581	9.428	12.625
Before setting sequence information layer	28.526	6.285	15.619	23.629	8.517	15.917

Table 3. Experimental results of recommendation diversity of learning resource recommendation model

Model	Sample Set 1	Sample Set 2
	Diversity@60	Diversity@60
DNN	22.141	15.629
CNN	26.352	24.518
RNN	31.295	23.625
GNN	34.162	26.581
DeepFM	37.519	33.251
Wide&Deep	32.528	37.249
The Model	52.417	42.501



(a)



(b)

Fig. 4. Convergence result of learning resource recommendation model

Figure 4 shows the convergence results of learning resource recommendation model under different sample sets. It can be seen from the figure that compared with other learning resource recommendation models, which are prone to over-fitting after training to the 5th-6th round, this model has achieved better anti-over-fitting performance and robustness, without a sharp decline in the proportion of correct recommendation results, and the index value basically tends to be stable after convergence.

In order to test the practical application effect of the learning resource recommendation model constructed herein, this article makes a statistical analysis of the changes in the distribution of college students' learning efficiency before and after the implementation of the learning resource recommendation method. See Table 4 for the influence of learning resource recommendation on learning efficiency. It can be seen from the table that after the implementation of the learning resource recommendation method, the corresponding college students' investment in online learning time and overall cognitive load are significantly higher than the corresponding values before the implementation. As far as academic performance is concerned, whether in test scores or final grades, college students who use recommended learning resources for assisted learning have higher academic performance, better knowledge retention effect and better learning satisfaction.

Table 4. Effect of learning resource recommendation on learning efficiency

Learning Efficiency		Significance	Analysis Results
Learning time investment		Significant	After implementation> before implementation
Knowledge retention effect	Test results	Significant	After implementation> before implementation
	Final exam	Significant	After implementation> before implementation
Overall cognitive load		Significant	After implementation> before implementation
Learning satisfaction		Significant	After implementation> before implementation

5 Conclusion

Taking musicology majors as an example, this article studies the learning resource recommendation methods for improving the efficiency of college students' online independent learning. This article quantitatively evaluates the learning efficiency of college students in the process of college students' online independent learning, and takes the evaluation results as a reference for learning resource recommendation methods. The capsule network combined with self-attention routing algorithm is used to represent the various demands of college students' online independent learning with multiple vectors, and the sequence information layer based on Transformer model is set up to construct the learning resource recommendation model. Combined with experiments, the results of learning resource recommendation experiments under different models are compared, and ablation experiments are carried out on the recommended models to verify the effectiveness of the proposed learning resource recommendation method for improving the efficiency of college students' online independent learning. The *Diversity@*60 values of different recommended models are compared on different sample sets to verify that the capsule network is used as the basic structure of multi-demands extraction module in this article with better diversity performance than other models. The convergence results of learning resource recommendation model under different sample sets are given to verify that the proposed model has better anti-over-fitting performance and robustness. This article makes a statistical analysis of the change in the distribution of college student learning efficiency before and after the implementation of the learning resource recommendation method, and tests the practical application effect of the learning resource recommendation model constructed in this article.

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