Personalized Combination Recommendation of Short Video Online Learning Resources

https://doi.org/10.3991/ijet.v18i06.38719

Shujuan Ouyang(✉)
Guizhou Industry Polytechnic College, Guiyang, China
shujuan_ouyang@163.com

Abstract—Short video online learning resources are widely used in online learning classes because of their strong display ability, popularity and easiness to understand and concise content. The existing learning resource recommendation methods usually ignore the local time series dependence information and possible periodic changes of students' historic online learning rules, and are not suitable for the recommendation scenarios of short video online learning resources. Therefore, this article studies the personalized combination recommendation method of short video online learning resources. Preprocessing of short video online learning resources is carried out, including content feature analysis and candidate recommendation list generation. Then, based on the initial recommendation list, a combination recommendation model of short video online learning resources based on information enhancement and overlapping information of knowledge points is proposed, and the construction ideas of the model are described in detail. Experimental results verify the effectiveness of the model.

Keywords—short video, online learning resources, personalized combination recommendation

1 Introduction

With the development of multimedia and Internet technology, short video online learning resources are widely used in online learning classes because of their strong display ability, popularity and easiness to understand and concise content [1–4]. More short video online learning resources have become the most important auxiliary learning tools of online learning platforms [5, 6]. Developing and applying short video online learning resource recommendation algorithm has become an important way for online learning platforms to enhance students' interest in learning and enhance students' learning persistence.

The personalized recommendation algorithm of online learning resources is to infer the learning preferences of different college students based on their basic information and social information, and further recommend learning resources suitable for their learning [7–11]. The performance of the algorithm directly affects the precision and efficiency of learning resource recommendation, and further affects students' satisfaction with online learning [12–14]. Short videos involve few knowledge points, and it is of great significance to accurately and effectively recommend the combination of short video online learning resources for improving students' learning effect [15–21]. Therefore, how to mine students' online learning rules based on time series data to improve the performance of short video online learning resource combination is an urgent problem to be solved in existing recommendation algorithms.

Software development video tutorials are becoming a new resource for developers to support their information needs. Parra et al. [22] proposes the first set of methods for automatically generating tags describing the content of software development video tutorials. Among the seven tagging methods studied, some use information retrieval technology, and two are commercial video tagging methods. Nineteen different configurations of these tagging methods are evaluated. The results show that some methods based on information retrieval perform best and can recommend tags that developers think are relevant for describing programming videos.

The recommendation algorithm of combination recommendation algorithms in e-commerce system is faced with the problems of high sparsity of user rating data and interest transfer, which greatly affect the performance of recommendation. Therefore, Li et al. [23] proposes a combination recommendation algorithm based on improved similarity and forgetting curve. Firstly, Pearson similarity is improved by a wide range of weighting factors, so as to improve the Pearson similarity quality of highly sparse data. Secondly, Ebbinghaus forgetting curve is introduced to track the interest transfer of users. The user score is weighted according to the residual memory of the forgetting function. The precision of the recommendation algorithm and the satisfaction of users are improved by tracking the change of users' interest with time through scoring. Wang et al. [24] studies and proposes a recommendation model combining GRU and CNN with self-attention mechanism. The model uses GRU and Self Attention mechanism to extract user features, and combines CNN to capture local related features of projects. Then, through the full connection calculation of each feature, the prediction rating is obtained and the recommendation is generated. In this article, MovieLens 1M data set and Amazon digital music data set are used for experiments. The results show that compared with other recommendation models based on deep learning and traditional recommendation models, the proposed model has achieved better results in MSE and MAE indicators. Based on gradient lifting decision tree algorithm in machine learning and Zernike feature extraction in machine vision, a method of intelligent product recommendation system is proposed in Yang et al. [25]. The overall structure of product recommendation system consists of user shopping module, system management module, database module and visualization module. Zernike moments are used to extract the key features of products, and cluster analysis is carried out to obtain the association rules between products and users. Experimental results show that this method has short recommendation time and high user satisfaction.

Existing learning resource recommendation methods usually ignore the local time-dependent information and possible periodic changes of students' historic online learning rules, which limit the representational learning ability of recommendation models to a certain extent. Some learning resources involve overlapping knowledge points. If learning resources with overlapping relationship are used in combination recommendation, it will not only fail to assist students in learning, but also reduce students' interest in learning. The above defects limit the function of the traditional recommendation model in the personalized combination recommendation task of short video online learning resources, and then cannot recommend an accurate and appropriate combination of short video online learning resources for students. Therefore, aiming at the above challenges, this article studies the personalized combination recommendation method of short video online learning resources. In the second chapter, the short video online learning resources is preprocessed, including content feature analysis and candidate recommendation list generation. Then, in the third chapter, based on obtaining initial recommendation list, a short video online learning resource combination recommendation model based on information enhancement and overlapping information of knowledge points is proposed, and the construction ideas of the model are described in detail. The experimental results verify the effectiveness of the model for personalized combination recommendation of short video online learning resources.

2 Preprocessing method of short video online learning resources

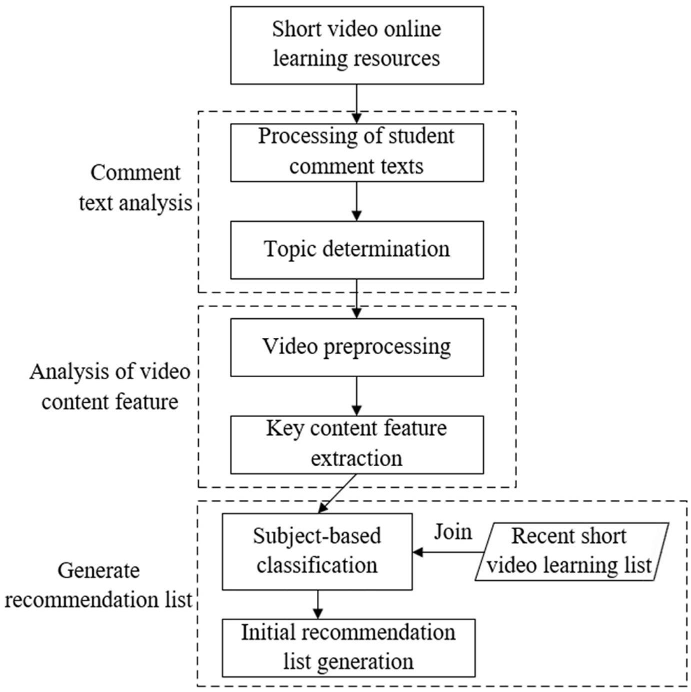

Fig. 1. Process of preprocessing method for short video online learning resources

At present, in the field of personalized recommendation of short video online learning resources, few scholars take student comment texts as the recommendation basis. In fact, with the development and wide application of video comment technology, it has become very common for students to express their opinions on short videos and understand knowledge points through comments, and student comment texts can increasingly reflect their learning preferences.

Figure 1 shows the process of preprocessing method for short video online learning resources. Firstly, this article analyzes the student comment texts based on LDA model. Assuming that the student comment text is represented by e, a topic in the student comment text is represented by c, and the number of topics in the student comment text is represented by C, then the conditional probability of a topic in the student comment text is represented by $FV(c_i|e)$, and a word in the text topic is represented by q, then the distribution probability of different words in the current comment text topic can be represented by $FV(q|c_i)$. The following formula gives the calculation formula of the probability that the word q occupies in the whole student comment text information:

$$FV(q \mid e) = \sum_{i=1}^{C} FV(q \mid c_i) FV(c_i \mid e) \tag{1}$$

Based on *Gibbs* sampling, the model of student comment text analysis is constructed, and the topic of students' comments is determined based on the probability of each word in the student comment texts. Each word q_i in the student comment text ${}_ie_i$ is cyclically sampled, assuming that the new topic is represented by $c_i = m$, the distribution matrix of "text-topic" and the distribution matrix of "topic-word" are represented by d^{E_c} and d^{qc}, respectively, while for d^{qc}, the number of times the word q is assigned to the topic $c_i = m$ is represented by $d^{E_c}_{e_i m}$. Similarly, in d^{E_c}, the number of times a word in a student comment text e_i is assigned the topic $c_i = m$ can be expressed by $d^{E_c}_{e_i m}$, with β and γ as adjustment parameters. The following formula gives the formula for calculating the probability $FV(c_i = m|q_i, e_i, c_{-i})$ of generating c_i from q_i:

$$FV(c_i = m \mid q_1, e_i, c_{-i}) \propto \frac{d^{q_c}_{q_i m} + \gamma}{\sum_q d^{qc}_{q\pi} + q\gamma} \cdot \frac{d^{E_c}_{e_i m} + \beta}{\sum_c e_1 c + c\beta} \tag{2}$$

For repeated sampling of student comment texts through Gibbs, when the sampling times are enough, the probability of implied topics in student comment texts will obey Dirichlet distribution and tend to be stable, and then adjust parameters β and γ to achieve convergence. The following formula gives the calculation formula of prior probability:

$$FV(q_1 \mid c_i = m) = \frac{d^{q_c}_{q_i m} + \gamma}{\sum_q d^{qc}_{q\pi} + q\gamma} \tag{3}$$

$$FV(c_i = m \mid e_i) = \frac{d^{E_c}_{e_i m} + \beta}{\sum_c e_1 c + c\beta} \tag{4}$$

Through the analysis of student comment texts, short video online learning resources can be classified based on the obtained topic distribution of student comment texts, and the topics of short video online learning resources in the same category contain several short videos.

According to students' historical learning behavior records, it's possible to obtain students' recent learning list of short video online learning resources. For the short video online learning resources that students have watched recently, the topic is determined based on their key content features. In this article, with the help of the idea of single hot coding, each status register is used to represent each information representing the topic category of short video online learning resources. It's essential to calculate the similarity and sort the similarity of short video online learning resources under different categories, and select the learning resources ranked lower in each category to form a candidate recommendation list. Assuming that the key contents of short video online learning resources watched by students recently are represented by E_1, the learning resource vector is represented by k_l, and the key contents of other learning resources under different categories are represented by E_2, the similarity calculation formula is given by the following formula:

$$sim(E_1, E_2) = \frac{\sum_{l=1}^{m} k_l(E_1) \times k_l(E_2)}{\sqrt{\left(\sum_{l=1}^{m} k_l^2 (E_1)\right) \times \left(\sum_{l=1}^{m} k_l^2 (E_2)\right)}} \tag{5}$$

Vector calculation is carried out for the key contents of short video online learning resources by single hot coding, so the numerator of the above formula is the point product of two learning resource vectors of different categories, and the denominator is the product of their modules. Through similarity calculation, the learning resources with knowledge points different from the watched short video online learning resources are further screened out.

3 Construction of personalized combination recommendation model based on feature fusion

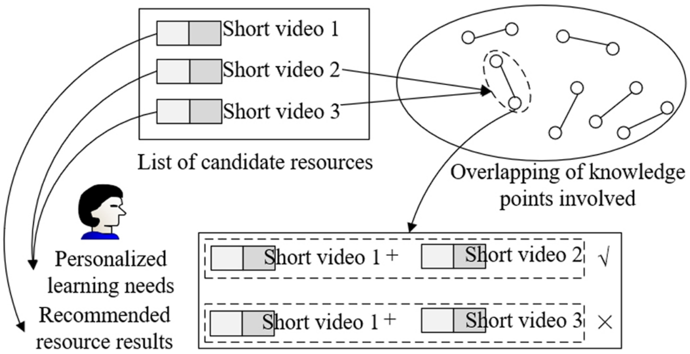

Fig. 2. Schematic diagram of overlapping relationship in short video online learning resource combination recommendation

Knowledge points overlap in some learning resources. If learning resources with overlapping relationship are used in combination recommendation, it will not only fail to assist students in learning, but also reduce students' interest in learning. Figure 2 shows the overlapping relationship diagram in the combination recommendation of short video online learning resources. Based on the initial recommendation list and inspired by information fusion, this article proposes a combination recommendation model of short video online learning resources based on information enhancement and overlapping information of knowledge points. On the one hand, the introduction of short video online learning resources in the model involves overlapping information of knowledge points, so as to avoid the existence of overlapping online learning resource pairs in the recommended online learning resource combination. In addition, in order to enhance the representational ability of the recommendation model, the model sets up a feature fusion module of student comment text perception, which is used to learn the unstructured student comment text information, and integrates the student comment text information by jumping connection to solve the problems such as gradient disappearance and gradient explosion caused by redundant calculation of the model. Figure 3 shows the structure of short video online learning resource combination recommendation model.

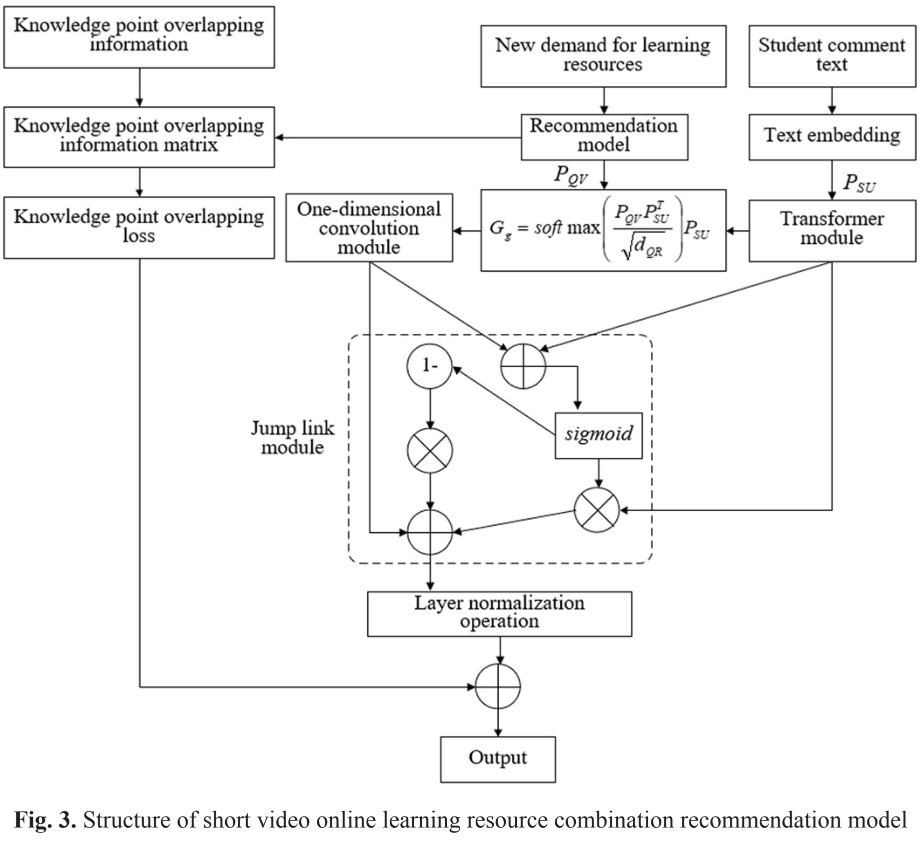

Fig. 3. Structure of short video online learning resource combination recommendation model

Feature fusion of student comment text is to combine the topic distribution features of student comment text obtained in the previous section with heterogeneous features based on different layers or branches of the model, and then fuse them into unified features for further calculation. In this article, a multi-scale channel attention module is set up for the recommendation model to fuse the topic distribution features of students' comments with different scales.

For students' historical comment texts of short video online learning resources, this article uses text embedding method to learn its embedding representation. Because of the large number of historical comment texts, this article treats the historical comment texts produced by different visits as different topic description sentences, and adds [*END*] keywords at the end of each topic description sentence to distinguish between different visits. Different students' historical comment texts are regarded as different topic description paragraphs, and the [*STA*] keywords are added before the first student comment text of different students to distinguish different students. Thus, the embedded $P_{DR}(SU_i)$ of each entry and the embedded $P_{TQ}(SU_i)$ of the topic description statement can be obtained, then $i \in \{1, 2, \ldots, M\}$, where M is the length of the topic description statement, and the topic description statement is divided with [*END*] as the interval.

Because the semantics of student comment texts is related to the order, and the Transformer model using attention mechanism can't learn the semantics contained in the order of student comment text entries, it is necessary to use position embedding to save the relative or absolute positions of students' comment entries in topic description sentences. Assuming that the position of an entry in the topic description statement is represented by WZ, the dimension where the entry is embedded in P_{FG} is represented by e, the even dimension is represented by $2i \leq e$, and the odd dimension is represented by $2i + 1 \leq e$, the following formula gives the calculation formula of position embedding:

$$P_{FG}(WZ, 2i) = \sin(WZ / 10000^{2i/e}) \tag{6}$$

$$P_{FG}(WZ, 2i+1) = \cos(WZ / 10000^{2i/d}) \tag{7}$$

The above position embedding method avoids the problem caused by the length limitation of topic description sentences, and at the same time, it is more convenient to calculate the relative position of entries by two trigonometric function calculation rules of $sin(X + Y) = sinXcosY + cosXsinY$ and $cos(X + Y) = cosXcosY - sinXsinY$.

By adding P_{TQ}, P_{DR} and P_{FG}, the embedding representation of each entry in the student comment text can be obtained:

$$P(SU_i) = P_{DR}(SU_i) + P_{TQ}(SU_i) + P_{FG}(SU_i) \tag{8}$$

The final embedding result of the student comment text is the concatenation of embedding representations of each entry of the student comment text, i.e., $[P(SU_1), P(SU_2), \ldots, P(SU_M)]$.

In this article, the dot product attention mechanism is used to effectively combine the information of student comment text with students' new demand P_{QV} of short video learning resources for model learning. P_{QV} is used as query vector, and the embedding vector P_{SU} of student comment text information is used as key vector and value vector. Assuming that the students' new learning need is represented by P_{QV}, the embedding result of student comment text information is represented by P_{SU}, and the hidden layer dimension of the model is represented by e_{QR}, then the information fusion result expression is as follows:

$$G_g = soft\max\left(\frac{P_{QV}P_{SU}^T}{\sqrt{d_{QR}}}\right)P_{SU} \tag{9}$$

After information fusion, Transformer module and one-dimensional convolution module based on the model learn their global and local dependencies. It is assumed that the global dependency hidden layer is represented by f_{YC} and the local dependency hidden layer is represented by f_{YU}. In the layer normalization $LN(\ )$ operation, the vector items are represented by a, the mean and variance of each layer are represented by τ and ε^2, the parameter vectors of scaling and translation are represented by β and γ respectively, and the corresponding position elements multiplied are represented by ⊗. The following calculation formulas are given:

$$f_{YC} = Transfoemer(P(SU_1), P(SU_2), ..., P(SU_M)) \tag{10}$$

$$f_{YU} = LN(CNN_{1e}(G_{g_1}, G_{g_2}, ..., G_{g_M})) = \beta \otimes \frac{a-\lambda}{\sqrt{\varepsilon^2+\tau}} + \gamma \tag{11}$$

In the personalized combination recommendation model of short video online learning resources constructed in this article, because the model adds short video online learning resources, which involve two parts: knowledge point overlapping loss calculation module and student comment text information feature fusion module, the complexity of the model increases several times, which can be hardly solved with conventional optimization model strategies such as batch normalization processing and adding activation function. Therefore, this article introduces a jumping connection module which can perceive student comment texts, and combines the global dependence representation and local dependence representation of the learned information of student comment text. Let the Sigmoid activation function be expressed by Γ, and the calculation formula is $g(a) = 1/1 + e^{-a}$. The following formula gives the calculation formula of this module:

$$f_{SC} = f_{YC} \times \Gamma(f_{YC} + f_{YU}) + f_{YU} \times (1 - \Gamma(f_{YC} + f_{YU})) \tag{12}$$

$$f_{SCO} = LN(f_{SC}) = \beta \otimes \frac{a-\lambda}{\sqrt{\varepsilon^2+\tau}} + \gamma \tag{13}$$

In this article, the representation output by the jumping connection module and the representation generated based on the information of student comment text are concatenated, and the final representation of the model can be obtained:

$$f_{Total} = Concat(f', f_{SCO}) \tag{14}$$

Assuming that the learnable parameters of the model are represented by $Q_z \in R^{|Dn|\times 6f-}$, $y_z \in R^{|Dn}$, a prediction layer based on multilayer perceptron is used to predict the learning resources that may be selected next time:

$$\hat{b}_o = \mathrm{Re}\,LU(Q_z f_{ZH} + y_z) \tag{15}$$

The loss function of the model is divided into two parts: the predicted loss and the cross entropy loss between the predicted label and the real label. The real label at time *e* is represented by $b_o \in \{0,1\}^{|Dn|}$. The optimization objective function of the model is as follows:

$$\phi_{PR} = -\frac{1}{O-1}\sum_{t=2}^{O}(\hat{b}_o^O \log b_o + (1-\hat{b}_o^O)\log(1-b_o)) \tag{16}$$

The other part is the loss φ_{KPO} of short video online learning resources involving overlapping knowledge points. Assuming that the super parameters used to balance the proportion of the two parts of losses are represented by λ and α, the following formula gives the final optimized loss function expression:

$$\phi_{Total} = \lambda\phi_{PR} + \alpha\phi_{kpo} \tag{17}$$

4 Experimental results and analysis

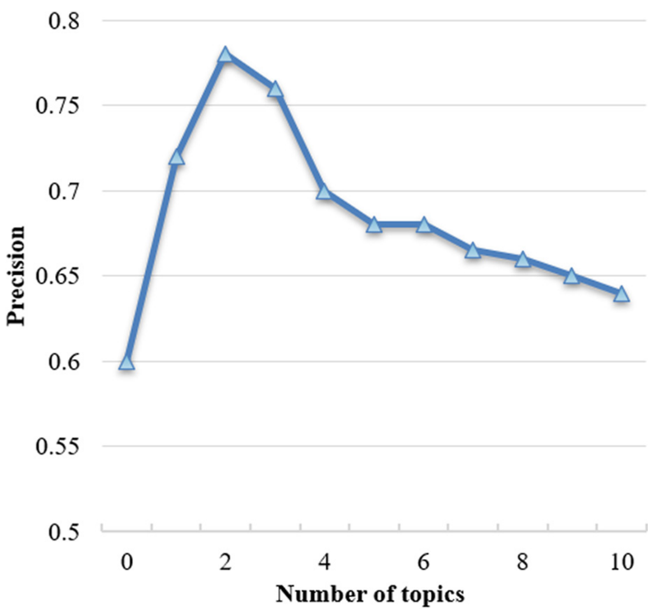

Fig. 4. Influence of the number of topics in student comment text on the precision of initial recommendation list

In order to ensure that student comment texts can highlight their topics, experiments are conducted on the precision of the initial recommendation list under different number of topics in student comment texts. Because there are hundreds of students' comments in short video online learning resources, there are at least ten to dozens of topic categories. In order to ensure the effectiveness of topic category classification, this article sets the value range of topic category number to [1, 10]. Figure 4 shows the influence of the number of topics in student comment texts on the precision of initial recommendation list. It can be seen from the figure that the precision of the initial recommendation list reaches the best when the number of topics is 2, and when the number of topics is greater than 4, the influence of the number of topics in student comment text on the precision of the initial recommendation list gradually decreases.

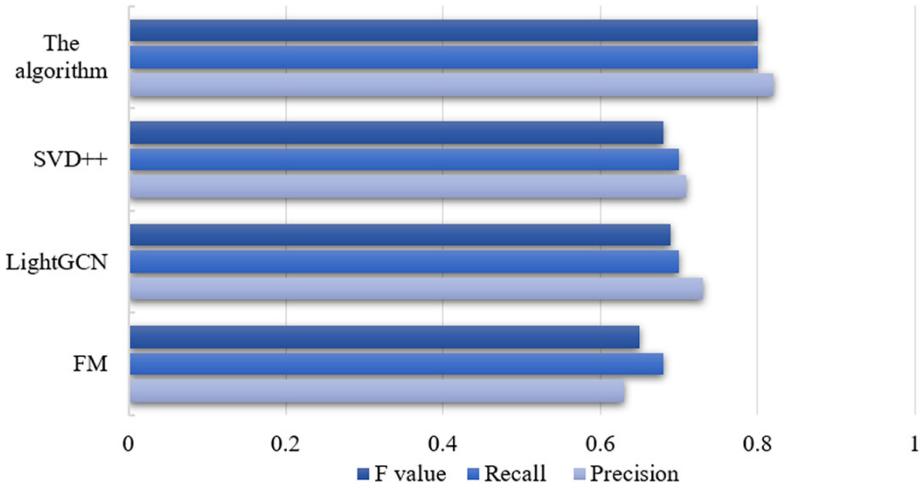

Fig. 5. Precision, recall, F1 value of candidate recommendation list

Figure 5 shows the precision, recall and F1 value of generating candidate recommendation list. It can be seen from the figure that the precision, recall and F1 value of the candidate recommendation list method proposed in this article are higher, which verifies that the proposed method has higher recommendation. Based on Gibbs sampling, this article constructs a student comment text analysis model, and introduces the probability of each word in the student comment text to determine the topic of the student comment text, which greatly improves the personalized recommendation service ability using student comment texts as the recommendation basis, and improves the recommendation performance index in three aspects of the model to a certain extent.

Then, this article analyzes the real-timeness of candidate recommendation list generation. When responding to students' new learning needs, the response time consumption of this algorithm is calculated under the conditions of updating and not updating the candidate recommendation list. Comparing the duration of video learning resources in the recommendation list with the duration of algorithm time consumption, this article analyzes the impact of updating the candidate recommendation list on students' learning from the perspective of students. The results are shown in Figure 6.

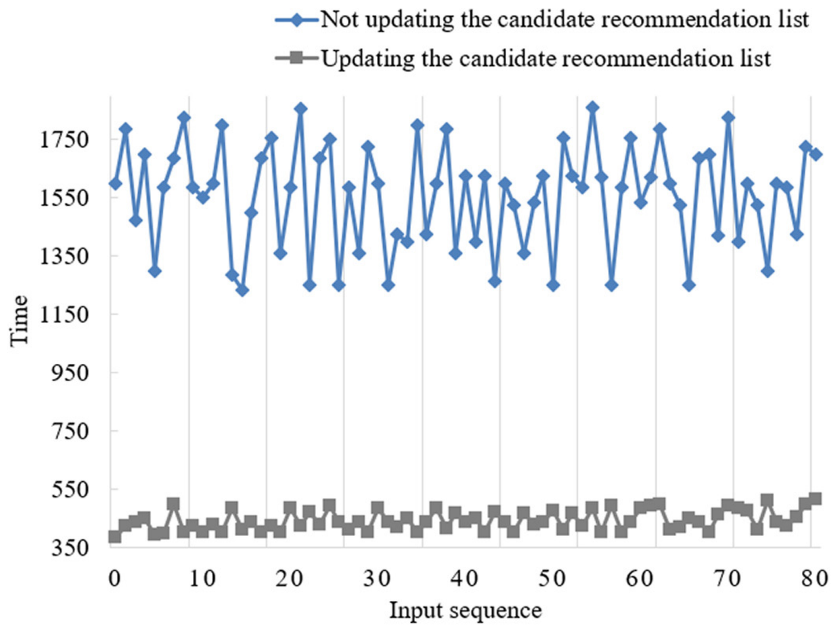

Fig. 6. Variation of real-time response ability of the algorithm with text sequence input

Table 1. Performance evaluation results of combination recommendation model

Sample No.	Jaccard	F1 Value	PR-AUC
1	0.4251 ± 0.0036	0.5269 ± 0.0014	0.6374 ± 0.0002
2	0.4625 ± 0.0047	0.5284 ± 0.0036	0.6295 ± 0.0014
3	0.3142 ± 0.0001	0.5147 ± 0.0095	0.5348 ± 0.0025
4	0.4692 ± 0.0009	0.6124 ± 0.0001	0.6741 ± 0.0036
5	0.4518 ± 0.0062	0.5328 ± 0.0047	0.6392 ± 0.0021
6	0.4958 ± 0.0007	0.6374 ± 0.0095	0.6471 ± 0.0035
7	0.4305 ± 0.0002	0.5347 ± 0.0048	0.6295 ± 0.0001
8	0.4628 ± 0.0024	0.5748 ± 0.0024	0.6284 ± 0.0024
9	0.4032 ± 0.0008	0.5362 ± 0.0011	0.6347 ± 0.0015
10	0.4958 ± 0.0037	0.6241 ± 0.0095	0.6392 ± 0.0001
11	0.4517 ± 0.0025	0.6374 ± 0.0013	0.6384 ± 0.0027
12	0.4195 ± 0.0032	0.6385 ± 0.0024	0.7513 ± 0.0051

When students' new learning needs do not trigger the update of candidate recommendation list, the response time of this algorithm is about 0.5s. When the new learning needs trigger the update of the candidate recommendation list, the response time of this algorithm is about 1.5s, which is longer than the update of the candidate recommendation list. It can be inferred that the longest response time of this algorithm is

1.5s when updating the candidate recommendation list, which verifies that this algorithm can update the new candidate recommendation list after students finish learning resources. This algorithm can make real-time personalized learning resource recommendation based on students' historical comment texts without affecting students' learning experience.

In this article, Jaccard similarity coefficient, average F1 value and area under precision-recall curve (PR-AUC) are selected to evaluate the performance of the personalized combination recommendation model based on feature fusion. Table 1 shows the performance evaluation results of the combination recommendation model. As can be seen from the table, the recommendation performance of the combination model has achieved ideal results in three indicators. Therefore, it is verified that the model building strategy of adding short video online learning resources, which involves knowledge point overlapping loss calculation module and student comment text information feature fusion module, is effective.

Table 2. Performance evaluation results of combination recommendation model and its variants

Model	Jaccard	F1	PR-AUC
The model	0.4952	0.6951	0.7362
Omitting position embedding	0.4362	0.6324	0.6195
Omitting text information feature fusion	0.4458	0.6028	0.6351
Omitting knowledge point overlapping	0.4251	0.6471	0.6846

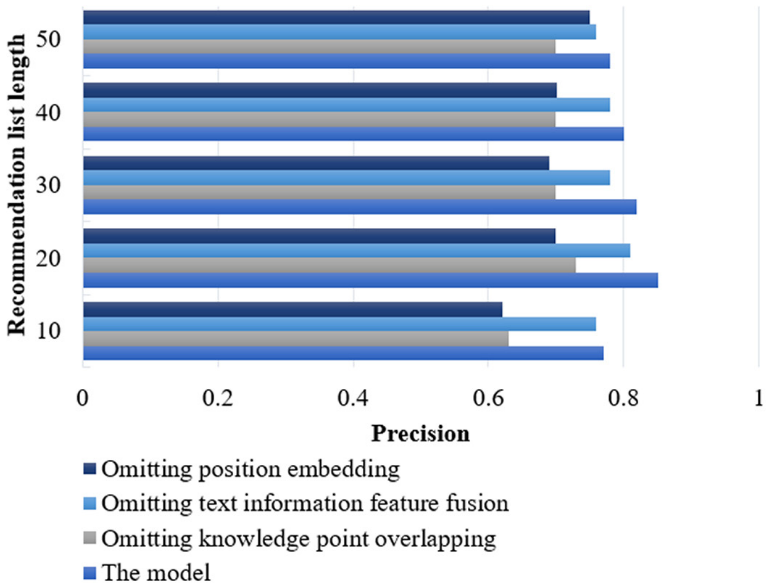

Fig. 7. Performance evaluation results of combination recommendation model and its variants

In order to further verify the validity of the constructed model, this article has carried out 50 experiments on three variants, namely, omitting position embedding, omitting text information feature fusion and omitting knowledge point overlapping, under the condition of the same sample set, and the best results are recorded in Table 2. It can be seen from the table that the performance of the three variants of omitting position embedding, omitting text information feature fusion and omitting knowledge point overlapping is lower than that of this model, which verifies that all the three model building strategies in this article can optimize the recommendation performance of the model. There are differences in the degradation of recommendation performance among the three variants, which shows that there are differences in the improvement of model recommendation performance among the three model building strategies, and the contribution of text information feature fusion to the improvement of model recommendation performance is greater than that of knowledge point overlapping. Figure 7 shows the performance evaluation results of the combination recommendation model and its variants in the form of a bar graph. Considering that the core reason of adding overlapping relationship module is to recommend a more suitable combination of learning resources for students, this module is also necessary.

5 Conclusion

This article studies the personalized combination recommendation method of short video online learning resources. Preprocessing of short video online learning resources is carried out, including content feature analysis and candidate recommendation list generation. Then, based on the initial recommendation list, a combination recommendation model of short video online learning resources based on information enhancement and overlapping information of knowledge points is proposed, and the construction ideas of the model are described in detail. Experimental results verify the effectiveness of the model. Experiments are conducted on the precision of initial recommendation list under different number of topics in student comment texts, and the appropriate number of topics is selected for the experiment. The precision, recall and F1 value of generating candidate recommendation list are demonstrated, which verifies that the proposed method has higher recommendation. The real-timeness of candidate recommendation list generation is analyzed, and the experimental results verify that the proposed algorithm can make real-time personalized learning resource recommendation based on students' historical comment text without affecting students' learning experience. The performance of the personalized combination recommendation model based on feature fusion is evaluated, and the performance evaluation results of the model and its variants are given to have verified that the three model construction strategies in this article can optimize the recommendation performance of the model.

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7 Author

Shujuan Ouyang, received her master degree in Engineering from Xiamen University, and work at Guizhou Industry Polytechnic College, her main research interests are accounting teaching, teaching management and transformation of education.

Article submitted 2022-11-25. Resubmitted 2023-01-27. Final acceptance 2023-01-28. Final version published as submitted by the authors.