Personalized Recommendation Service of Educational Media Resources Based on Multi-Dimensional Feature Fusion

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Abstract—Video is an important carrier of all kinds of information on the Internet. More and more students choose to watch online learning videos from online learning platforms with various forms of intelligent terminals. To allow students to get the videos which they really need and are interested in from the mass videos, it is necessary to improve the existing personalized recommendation algorithm. Content-based recommendation method, collaborative filtering-based recommendation method and hybrid recommendation method often have the problems of loss of feature information or cocoon. To this end, this paper studies the personalized recommendation service of media educational resources based on multi-dimensional user features. This paper constructs a multi-feature candidate set based on student-video interaction, extracts and splices category feature, label feature and semantic feature of Internet media educational videos, and generates the representation of students' learning preference feature. Based on the improved forward and backward recurrent neural network, this study constructs a recommendation model of Internet media educational videos oriented to students' preference points. The experimental result verifies the validity of the model.

Keywords—multi-dimensional feature fusion, internet media, educational resources, personalized recommendation

1 Introduction

The media mode and information carrier of Internet media are different from traditional media such as telephone, record, film, radio, television and mobile phone communication [1, 2]. The flexibility and maneuverability of Internet media, which is the main development platform of future media, are beyond the reach of traditional media [3–7]. Video is an important carrier of various forms of information on the Internet. Video has been welcomed by students as an important type of learning resources for its simple operation and abundant information. More and more students are choosing to watch online learning videos from online learning platforms in various forms of intelligent terminals [8–12]. However, as the number of online videos on video websites grows rapidly, the problem of information overload becomes more serious. It becomes difficult for students to get the videos which they really need and are interested in from the mass videos [13–21]. Online learning platforms that cannot solve this problem well will gradually lose student user group they already have.

Pardi et al. [22] introduces a new methodology for capturing and analyzing the processing and use of texts, images, and video contents in web search-based learning. To calculate the degree of overlap, the words in the articles searched by the participants are traced back to the words encountered in the recording of fixed texts or viewing videos. The result shows that the participants focus on the texts for significantly longer than the videos or image resources. Learning a foreign language via YouTube videos is a very popular learning method for many people. Kao et al. [23] selects 30 most concerned videos and analyzes their contents according to cultural framework. The conclusion is that YouTube videos may be suitable for foreign language learners, especially for Japanese students' cross-cultural knowledge. The emergence of a large number of online learning platforms has changed the needs and learning styles of learners, and the society has put forward higher requirements for the personalization, intelligentization and adaptability of learning resource platforms. Aiming at large-scale, multi-source and fragmented micro-video learning resources and personalized education, Lin et al. [24], based on micro-video online learning resource data, studies accurate, comprehensive and available portrait method of micro-video teaching resources. Through the application of depth learning technology, the theory and method of micro-video learning resource data analysis and personalized learning resource recommendation are studied. It explores and forms the basic theory and method of data-driven micro-video learning resource analysis to support the research of personalized educational theory and method. Schulten et al. [25] explores a way to provide such intelligent learning resource recommendation based on a specific learning environment, aiming to automatically analyze learning videos to extract key words, which can then be used to discover and recommend new learning materials related to videos. The result shows that the extracted key words are consistent with those generated by users and well summarize the contents of videos. Han [26] proposes an improved collaborative filtering algorithm (TRCP) to increase the accuracy of learning resource recommendation. TRCP algorithm generates the learner evaluation matrix of the recommended items by classifying the learning resources. It considers the influence of learners' online learning behavior, learning time and the popularity of learning resources on learners' interests, and optimizes the sample data in the evaluation matrix. The experimental result on the school online teaching platform shows that the method achieves effective results in the accuracy and satisfaction of learning resource recommendation.

In order to achieve accurate Internet media educational video recommendation, scholars at home and abroad have carried out relevant researches and achieved certain results. There are three types of common personalized video recommendation methods: content-based recommendation method, collaborative filtering-based recommendation method and hybrid recommendation method. However, these methods do not combine the features of different granularities well, nor fully consider the high-order relationship among students, thus resulting in the loss of feature information or cocoon problems. In the recommendation system, the students who participate in learning and the items they learn all have different granularities and different types of features. In order to make full use of the multi-dimensional features of the students participating in the learning and the items they learn to significantly improve the performance of the personalized recommendation system, this paper studies the personalized recommendation service of media educational resources based on multi-dimensional user features. In Chapter 2, this paper constructs a multi-feature candidate set based on student-video interaction, extracts and splices category feature, label feature and semantic feature of Internet media educational videos, and generates the representation of students' learning preference feature. In Chapter 3, based on the improved forward and backward recurrent neural network, this study constructs a recommendation model of Internet media educational videos oriented to students' preference points. The experimental result verifies the validity of the constructed model.

2 Construction of multi-feature candidate set based on interactive relationship

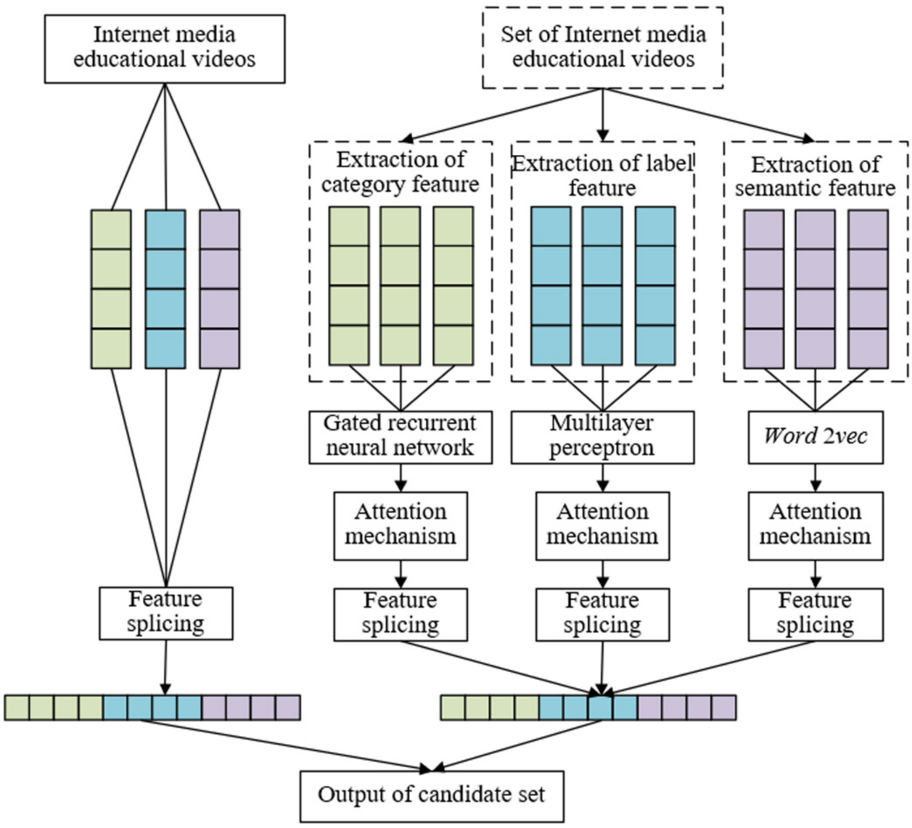

Fig. 1. Method and flow of constructing multiple feature candidate set based on interactive relationship

In the personalized recommendation of media educational resources, the multiple interactive relationships between students and Internet media educational videos can reflect students' preferences. How to make full use of the hidden information in the interactive relationship is the key to improve the accuracy of personalized recommendation of media educational resources. The existing research methods often only pay attention to the coarse-grained information such as the video category and the label that students put on the video in Internet media educational videos, but pay less attention to the fine-grained information obtained by semantic mining. In order to solve the problem of effective information loss caused by the different focus points, it is necessary to combine the multi-dimensional feature information in the interaction between the students and Internet media educational videos. Therefore, this paper firstly constructs the multi-feature candidate set based on the student-video interaction before conducting personalized recommendation of media educational resources. The input of the model is student information, educational video information and student-video interactive information. The model constructs the students' preference feature on the category and label of the students' interactive video items, extracts the semantic feature and processes the attention mechanism. After the different features are spliced, the corresponding student preference feature representation can be obtained. The output of the model is the video candidate set obtained by recalling the student preference feature vector and the target video feature vector. Figure 1 shows the method and flow of constructing multiple feature candidate set based on interactive relationship.

2.1 Extraction of category feature

The preference of students in Internet media educational videos is often to one type of video, rather than a single video. Therefore, in order to ensure the accuracy of personalized recommendation, too fine-grained or too specific recommendation results should not be used because accidental interactive behavior between students and educational videos have a very low contribution degree to recommendation and too much attention will lead to recommendation error. This is also precisely for this reason that this paper focuses on the category of Internet media educational videos instead of specific video contents.

For each educational video of students' history interaction, this paper constructs the corresponding video category feature vector according to the category of videos, represented by $\{u_{i1}^{VC}, u_{i2}^{VC}, \ldots, u_{iU}^{VC}\}$. At the same time, the influence of interaction period on students' preference in the history of students' interaction with videos is fully considered. In this paper, a two-way gated recurrent neural network is used to process the video feature vector of different interactive periods in the history, so as to excavate the internal relationship of Internet media education.

$$f_{gj} = GRU_g(u_{ij}^{VC}), j \in [1, U] \tag{1}$$

$$f_{yj} = GRU_y(u_{ij}^{VC}), j \in [U_i, 1] \tag{2}$$

The hidden state corresponding to u_{ij}^{VC} can be obtained by splicing f_{gj} and f_{yj}:

$$f_j = f_{gj} \oplus f_{yj} \tag{3}$$

The expression of the hidden state of the entire two-way gated recurrent neural network is given by:

$$F_o = (f_1, f_2, ..., f_U) \tag{4}$$

The contribution degree of accidental and frequent interactive videos to the generation of students' preference feature is quite different, so the attention mechanism is adopted to deal with the network hidden state F_o. The following formula is to calculate the attention weight of each video in the video set:

$$\beta_j = \frac{\exp\,(g(f_U, f_j))}{\sum_{j=1}^{U}(g(f_U, f_j))} \tag{5}$$

where,

$$g(f_U, f_j) = Q_o \tanh\,(Q_1 f_U + Q_2 f_j) \tag{6}$$

The video category feature vector weight obtained by Formula 5 represents the contribution degree of different categories of educational videos to the construction of students' preference feature. The following formula gives the student-side video category feature vector expression after weighting:

$$v_i^{VC} = \sum_{j=1}^{U} \beta_j f_j \tag{7}$$

2.2 Extraction of label feature

In the personalized recommendation of media educational resources, online learning platforms are often equipped with a labeling system that allows students to actively label videos. The student *V*, educational video *U*, label *E*, and the relationship *X* among the three can be represented by a tuple *G* = (*V*, *U*, *E*, *X*). In this paper, the number of times an educational video *j* is marked *w* is defined by u_i^{VT} as a video-label feature, expressed by $u_i^{VT} = (m_1^{uj}, m_2^{uj}, \dots, m_o^{uj})$. The labels obtained by the label system are all the labels that have been marked by the students, their feature vectors are high dimensional and sparse. In this paper, multi-layer perceptron is adopted to compress the features of educational video labels. Formula 8 gives the expressions for the input and output of the first layer of the multilayer perceptron:

$$a_u^{(1)} = \mathrm{Re}\,LU(Q^{(1)} u_i^{VT} + y^{(1)}) \tag{8}$$

Formula 9 is the expression for the input and output of the second layer of the multilayer perceptron:

$$a_u^{(2)} = \mathrm{Re}\,LU(Q^{(2)} a_u^{(2)}(j) + y^{(2)}) \tag{9}$$

The obtained video label feature is represented by a_j^u. A set of educational video label feature vectors can be further generated for the video set of student *i* history interaction, which is represented by $\{a_{i1}^u, a_{i2}^u, \ldots, a_{iU}^u\}$. To differentiate the contribution degree of different types of videos to generate students' preference feature, this paper still adopts the attention mechanism to process the network output.

The following formula calculates the attention weight of each video in the video set:

$$\beta_j = \frac{\exp(g(a_{iU}^u, a_{ij}^u))}{\sum_{j=1}^{U}(g(a_{iU}^u, a_{ij}^u))} \tag{10}$$

where,

$$g(a_{iU}^u, a_{ij}^u) = Q_0 \tanh(Q_1 a_{iV}^u + Q_2 a_{ij}^u) \tag{11}$$

The expression of the student-side video label feature vector after the weighting is given by:

$$v_i^{tag} = \sum_{j=1}^{U} \beta_j a_{ij}^u \tag{12}$$

2.3 Extraction of semantic feature

The semantic feature vector representation of video can be obtained by extracting and processing the semantic information from the label and category information of Internet media educational videos at word level. The titles of most educational videos can not accurately represent the properties of video contents and are not suitable for semantic extraction, so this paper chooses the expression words of label and classification information of videos to extract Word2Vec semantic, in order to obtain semantic relevance of video expression key words. For a given educational video *j*, it is assumed that the label word vector obtained by the pre-trained semantic feature extraction model is represented by t_j^{VT}, and the obtained category word vector is represented by t_j^{VC}. The video label semantic feature vector expression is given by:

$$t_{ej} = \frac{1}{T^{VT}} \sum_{T}^{VT} t_j^{VT} \tag{13}$$

The following expression shows the video category semantic feature vector:

$$t_{tj} = \frac{1}{T^{VC}} \sum_{T}^{VC} t_j^{VC} \tag{14}$$

After t_{ej} and t_{tj} are spliced, the video semantic feature vector can be expressed as $t_j = concat(t_{ej}; t_{tj})$. The set of educational video semantic feature vectors can be further generated for the video set of student *i* history interaction, which is represented by $\{t_{i1}, t_{i2}, \ldots, t_{iU}\}$. To differentiate the contribution degree of different types of videos to generate students' preference feature, this paper still adopts the attention mechanism to process the network output.

The following formula calculates the attention weight of each video in the video set:

$$\beta_j = \frac{\exp\left(g(t_{i_U}, t_{i_j})\right)}{\sum_{j=1}^{U}\left(g(t_{i_U}, t_{i_j})\right)} \tag{15}$$

where,

$$g(t_{iU}, t_{ij}) = Q_o \tanh\left(Q_1 t_{iU} + Q_2 t_{ij}\right) \tag{16}$$

The following is the expression of the student-side video label feature vector after weighting:

$$t_i^{VW} = \sum_{j=1}^{U} \beta_j t_{i_j} \tag{17}$$

2.4 Generation of students' learning preference feature

The learning preference feature of student i can be represented by $c_i^v = (v_i^{VC}, v_i^{VT}, t_i^{VW})$ by splicing various feature representations of Internet media educational videos obtained in the first three sections. In order to recall the video candidate set through the student preference feature vector and the target video feature vector, this study adopts the attention mechanism to process the obtained learning preference feature representation. Assuming that the similarity calculation function is represented by *sim* and the activation function is *softmax*, then:

$$\beta(i, j) = soft\max\left(sim(c_i^v, c_i^v)\right) \tag{18}$$

The feature representation of the target video j is $c_i^u = (v_j^{VC}, v_j^{VT}, t_j^{VW})$, and the preference representation vector of student i for the video j is obtained by:

$$b^v = \sum_{l=1}^{U} \beta(i, j) c_i^v \tag{19}$$

The probability of the interaction between student i and video j can be obtained by the following formula:

$$o(i, j) = \frac{\exp\left(c_i^v c_i^u\right)}{\sum \exp\left(c_i^v c_i^u\right)} \tag{20}$$

Assuming that the training sample set is represented by ER, the following formula gives the target loss function expression of the training model:

$$LOSS = -\sum_{ER} \log\left(o(i, j)\right) \tag{21}$$

3 Recommendation of media educational videos based on students' preference points

Based on the video candidate set obtained in the previous section, the ranking and recommendation of Internet media educational videos are carried out. This paper constructs a recommendation model of Internet media educational videos oriented to students' preference points, which is based on the improved forward and backward recurrent neural network infrastructure and used to model students' continuous viewing behavior. The model structure is shown in Figure 2.

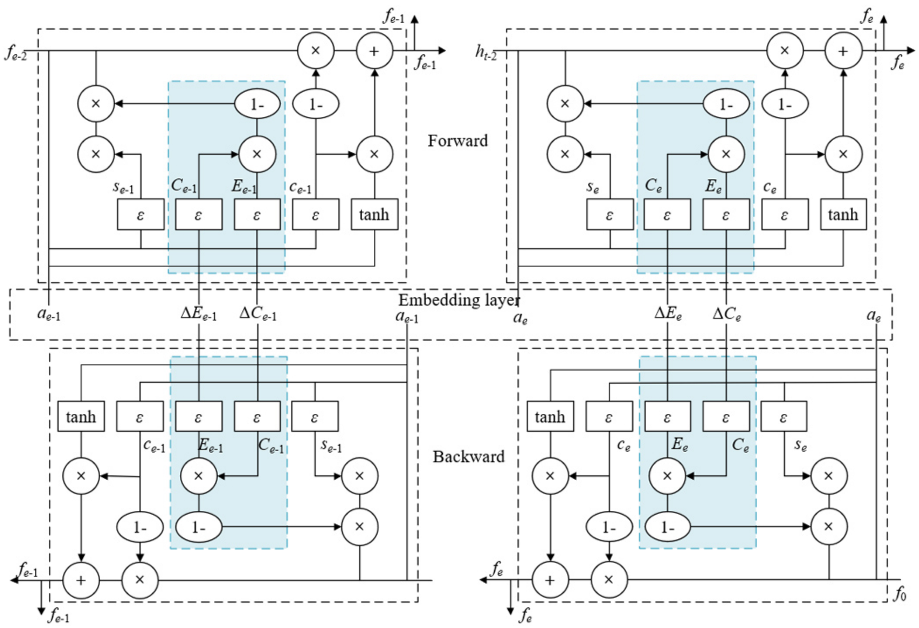

Fig. 2. Recommendation model structure of Internet media educational videos

The structure of forward recurrent neural network is used to fully excavate the above feature information of students' continuous viewing behavior, that is, to realize forward memory of the sequence feature of students' continuous viewing behavior. Assuming that the activation function in the neural network element is represented by ε and *tanh*, the parameters in the network element node are represented by Q_c, Q_e, Q_s, Q_c, Q_f, and the offset parameters are represented by φ_c, φ_e, φ_s, φ_c, φ, the parameter of the output layer is represented by Q_p, and the predicted probability that student v may access the preference point k at e + 1 is represented by $U_{m,ke+1}$. The calculation formula of the network structure is given below:

$$E_e = \varepsilon(Q_e \Delta E_e + \phi_e) \tag{22}$$

$$C_e = \varepsilon(Q_c \Delta C_c + \phi_c) \tag{23}$$

$$s_e = \varepsilon(Q_s[\vec{f}_{e-1}, a_e] + \phi_s) \tag{24}$$

$$c_e = \varepsilon(Q_c[\vec{f}_{e-1}, a_e] + \phi_c) \tag{25}$$

$$c_e = \varepsilon(Q_r[s_e \otimes \vec{f}_{e-1} \otimes (1 - C_e \otimes E_e), a_e] + \phi_f) \tag{26}$$

$$\vec{f}_e = (1 - c_e) * \vec{f}_{e-1} + c_e * \tilde{f}_e \tag{27}$$

The backward recurrent neural network structure is used to fully mine the following feature information of students' continuous viewing behavior, that is, to realize backward memory of the sequence feature of students' continuous viewing behavior. The calculation formula of the network structure is given below:

$$E_{e-1} = \varepsilon(Q_e \Delta E_{e-1} + \phi_e) \tag{28}$$

$$C_{e-1} = \varepsilon(Q_c \Delta C_{e-1} + \phi_c) \tag{29}$$

$$s_{e-1} = \varepsilon(Q_s[\overleftarrow{f}_e, a_{e-1}] + \phi_s) \tag{30}$$

$$c_{e-1} = \varepsilon(Q_c[\vec{f}_e, a_{e-1}] + \phi_c) \tag{31}$$

$$\tilde{f}_{e-1} = \tanh(Q_f[s_{e-1} \otimes \vec{f}_{e-1} \otimes (1 - C_{e-1} \otimes E_{e-1}), a_{e-1}] + \phi_f) \tag{32}$$

$$\overleftarrow{f}_{e-1} = (1 - c_{e-1}) * \overleftarrow{f}_e + c_{e-1} * \tilde{f}_{e-1} \tag{33}$$

A possible next video viewing preference point of students may be predicted based on the obtained contextual information of students' continuous viewing behavior, and then a personalized recommendation preference point list of Internet media educational videos for the target students can be generated. The corresponding calculation formula is given by:

$$U_{v,k_{e+1}} = Q_p(\vec{f}_e \oplus \overleftarrow{f}_1) \cdot a_{e+1} \tag{34}$$

4 Experimental result and analysis

Ablation experiment is conducted on the multi-feature candidate set model based on the interactive relationship proposed in this paper and analysis is performed based on the experimental result of the sample set. It can be seen from Table 1, the proposed method makes full use of various kinds of information in educational videos by integrating the category feature, label feature and semantic feature of Internet media educational videos. Thus, its whole performance is better than that of the single feature to express students' learning preferences, which verifies the effectiveness of this method.

Table 1. Performance comparison under different feature extraction conditions

Model	*Precision@15*	*Precision@25*	*Recall@15*	*Recall@25*
Extracting only semantic feature	0.1623	0.1883	0.1783	0.1934
No category feature	0.1872	0.2064	0.2001	0.2289
No label feature	0.2912	0.2934	0.3175	0.3276
Category feature + label feature	0.2553	0.2809	0.3706	0.3653
Model in this paper	0.3634	0.3953	0.4855	0.5181

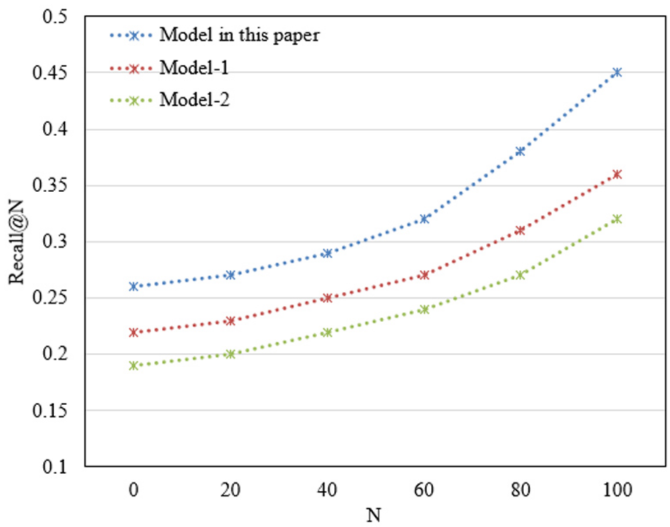

Fig. 3. Comparison of feature extraction recall rates of different models

Figures 3 and 4 show a comparison of recall rate and accuracy of different models. Model-1 is a model that merges category feature and label feature, and Model-2 is a model that extracts only semantic feature. As can be seen from Figures 3 and 4, Model-1 and Model-2 without fusion of category feature, label feature, and semantic feature cause performance degradation. The main reason is that the two-way gated recurrent neural network, which can well explore the internal relationship between videos, is used to extract category feature of videos, and the multi-layer perceptron is adopted to compress the label feature of educational videos. *Word2Vec* semantic extraction is carried out on the label and classification information expression words of videos, which makes full use of video resource information. The main reason why this paper only considers a greater impact of semantic feature on the model performance is that category and label features can better reflect the content features of Internet media educational videos. The experimental result verifies the necessity and rationality of the fusion of category feature, label feature and semantic feature.

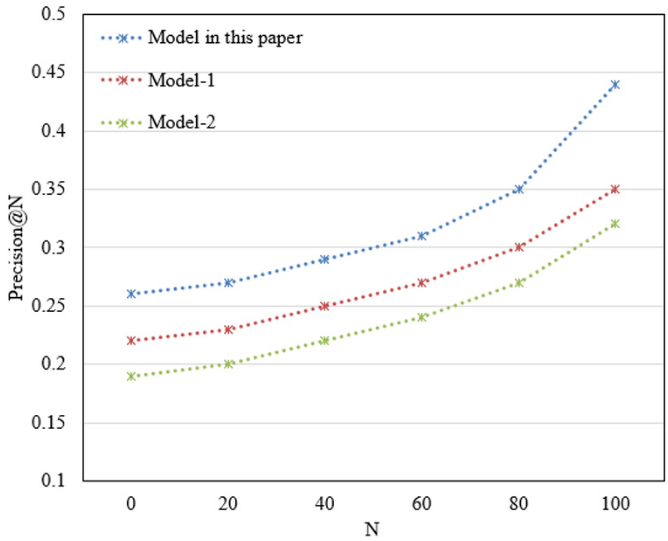

Fig. 4. Comparison of feature extraction accuracy of different models

Finally, this study analyzes the influence of window size and embedding size on the recommendation model in the case of *Top* values of different recommendation lists. This paper sets the number of recommended targets in the list as {15, 25, 35, 45}, the window size as {5, 10, 15, 20}, and the embedding size as {16, 32, 64, 128}, respectively. Table 2 shows the experimental result.

Table 2. Result of model performance evaluation indicators under different dimensions

Window Size Embedding Size	*Precision@20*				*Recall@25*			
	5	**10**	**15**	**20**	**5**	**10**	**15**	**20**
32	0.15	0.1259	0.1357	0.1362	0.0243	0.0205	0.0221	0.0453
64	0.1357	0.0934	0.0529	0.0534	0.0457	0.013	0.008	0.0072
128	0.0583	0.1153	0.2084	0.2092	0.0082	0.0362	0.008	0.0775
256	0.0912	0.0583	0.0641	0.0647	0.0167	0.0081	0.0193	0.0089
Window size Embedding size	*F1@30*				*MAP@35*			
	5	**10**	**15**	**20**	**5**	**10**	**15**	**20**
32	0.057	0.0443	0.0635	0.0812	0.2253	0.2045	0.2552	0.1975
64	0.0703	0.0281	0.0234	0.0236	0.2543	0.1366	0.1052	0.0931
128	0.0231	0.0623	0.0225	0.1285	0.0972	0.19	0.984	0.2841
256	0.0354	0.0189	0.045	0.0213	0.1481	0.0965	0.1523	0.1072

As can be seen from Table 2, there is a difference in the model recommendation performance under four evaluation indicators *Precision*@20, *Recall*@25, *F*1@30 and *MAP*@35 under different window sizes and embedding sizes. When the window size is set to 20 and the embedding size is set to 64, the evaluation indicator value reaches the maximum and the model recommendation performance reaches the optimum.

Table 3 presents the comparison result of recommendation performance of different models. As can be seen from the table, in the open source Internet media educational video sample set, the recommendation model of Internet media educational videos based on students' preference points has achieved the best effect on the four evaluation indicators, namely, *Loss*@15*, Precision*@15*, Recall*@15 and *F*1@15. It is verified that the constructed recommendation model has good generalization ability, and has achieved ideal performance in the Internet media educational video recommendation task.

Table 3. Comparison of recommendation performance of different models

Model	*Loss*@15	*Precision*@15	*Recall*@15	*F*1@15
Text-CNN	0.0073	87.57%	68.12%	74.12%
TextR-CNN	0.0050	84.65%	87.63%	85.58%
SVD++	0.0028	90.72%	94.87%	92.41%
NMF	0.0022	93.12%	95.31%	93.86%
DMF	0.0021	93.34%	95.52%	94.02%
Model in this paper	0.0017	94.79%	94.63%	94.50%

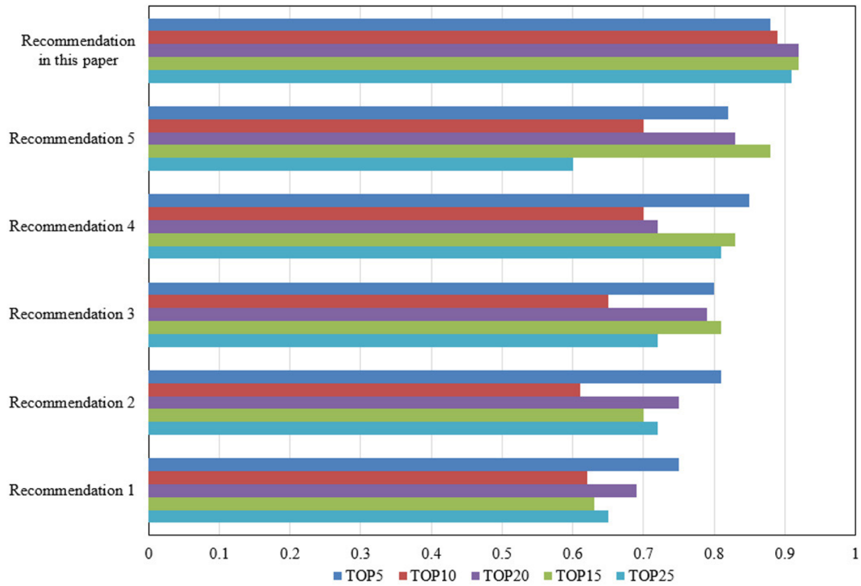

Fig. 5. Comparison of accuracy of model recommendation results under different *Top* values

Furthermore, the recommendation performance of each model under the condition of the number of recommendation targets in different lists is compared. The recommendation accuracy comparison result is given in Figure 5. The recommendation MRR comparison result is shown in Figure 6.

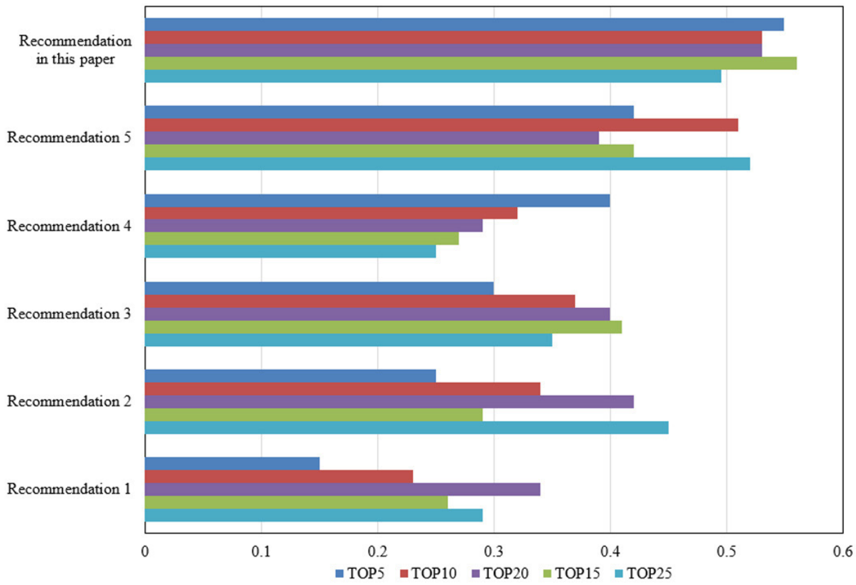

Fig. 6. MRR comparison of model recommendation result under different *Top* values

As can be seen from Figures 5 and 6, by comparing the data, the recommendation model constructed in this paper has higher accuracy than other methods in the case of lower or higher number of recommendation targets in the list. In the experimental result based on MRR indicator, the maximum value of the recommendation model is 0.56. In addition, compared with other methods, the experimental data of the constructed recommendation model is larger in the case of the number of recommendation targets in different lists. In general, the recommendation model constructed in this paper has high recommendation accuracy in Internet media educational video recommendation task, verifying its validity and reliability.

5 Conclusion

This paper studies the personalized recommendation service of media educational resources based on multidimensional user features. This paper constructs a multi-feature candidate set based on student-video interaction, extracts and splices category feature, label feature and semantic feature of Internet media educational videos, and generates the representation of students' learning preference feature. Based on the improved forward and backward recurrent neural network, this study constructs a recommendation model of Internet media educational videos oriented to students' preference points. Ablation experiment is conducted on the multi-feature candidate set model based on the interactive relationship proposed in this paper, and recall rate and accuracy of different models are compared. In addition, this study verifies the necessity and rationality of the fusion of category feature, label feature and semantic feature. This study also analyzes the influence of window size and embedding size on the constructed recommendation model in the case of *Top* values of different recommendation lists. The comparison result of recommendation performance of different models is given. The result shows that the recommendation model constructed in this paper has higher recommendation accuracy in Internet media educational video recommendation task, verifying the validity and reliability of the model.

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