Recommendation of Micro Teaching Video Resources Based on Topic Mining and Sentiment Analysis

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Jie Liu, Haiping Lv(✉)
Foreign Languages Department, Cangzhou Normal University, Cangzhou, China
lhp2021xx@caztc.edu.cn

Abstract—Video learning resources are preferred by many students, owing to their intuitiveness and attractiveness. It is of practical significance to study the recommendation methods of video learning resources. Most of the existing research methods treat the scoring matrix as the main element, failing to consider video contents and learner interests. As a result, few of them can realize precise recommendation of videos. To solve the problem, this paper explores the recommendation of micro teaching video resources based on topic mining and sentiment analysis. Firstly, the dialog text features of English dialog videos and learner interest features were mined based on the deep word vector, and a topic mining model was established to achieve similarity-based resource recommendation. Next, the micro teaching videos with text information were subjected to sentiment analysis, improving the pushing accuracy of micro teaching videos. Finally, the scientific nature of our algorithm was demonstrated through experiments.

Keywords—topic mining, sentiment analysis, micro teaching videos, resource recommendation

1 Introduction

In recent years, online learning platforms have sprung up, effectively promoting the development of online learning [1-7]. Online learning is an indispensable form of learning for today's college students, thanks to its unique advantages of openness, resource sharing, and time-space flexibility [8-14]. To improve the online learning effect and individualize teaching and education, online educators must effectively obtain online learning resources, and increase the utilization rate of online learning resources [15-18]. Compared with boring text learning resources, video learning resources are preferred by many students, owing to their intuitiveness and attractiveness. Therefore, it is of practical significance to study the recommendation methods of video learning resources.

To grasp the search habits of online learners and establish a more reasonable multi-level recommendation scheme, Dibie et al. [19] designed a multi-level recommendation system for college online learning resources based on multi-intelligence algorithms, and analyzed the multi-level recommendation behavior in the system under a given topology. The hardware execution environment of the system was developed, combined with various application units of resource recommendation. On this basis, a multi-intelligence neural network was established to generate a more reasonable implementation scheme of multi-level recommendation.

The traditional technology of learning resource recommendation mainly aims to improve the recommendation accuracy. The recommendation results are not necessarily novel or diverse. Wu and Guo [20] modeled the learning resource recommendation task as a multi-objective optimization problem, and proposed an online learning resource recommendation model based on a multi-objective evolutionary algorithm. The model covers the following four steps: learning clustering, objective configuration, individual representation, and genetic operations. Experimental results show that the algorithm can improve the recommendation performance of online learning resources.

With the proliferation of the Internet and mobile devices, informal online English learning has become more and more popular. Hu [21] provided a set of concise and effective evaluation criteria for online English learning resources, and tested its reliability and validity. This set of criteria will help teachers and students to select high-quality resources in line with their English teaching purposes. Based on big data analysis and recommendation, Li et al. [22] carried out personalized recommendation of short videos for different scenarios. Tseng et al. [23] researched and applied latent factor models in short video recommendation algorithms, trying to recommend video contents that truly meets learners' needs and interests.

To sum up, the domestic and foreign research into video resource recommendation faces two problems: (1) With the scoring matrix as the main element, the existing algorithms are not very accuracy, and unable to avoid the cold start problem; (2) Most of the existing methods recommend vides according to the historical management records, without considering video contents and learner interests. As a result, few of them can realize precise recommendation of videos.

To solve the problems, this paper explores the recommendation of micro teaching video resources based on topic mining and sentiment analysis. Section 2 mines the dialog text features of English dialog videos and learner interest features based on the deep word vector, and establishes a topic mining model to achieve similarity-based resource recommendation. Section 3 carries out a sentiment analysis on the micro teaching videos with text information, improving the pushing accuracy of micro teaching videos. Finally, the scientific nature of our algorithm was demonstrated through experiments.

2 Topic mining-based recommendation

2.1 Topic mining model

Topic mining and sentiment analysis can effectively solve problems related to the processing of text information. The development of deep learning network in natural language processing has further promoted the technical advancement of text topic mining and sentiment analysis. The recommendation of English dialog video resources is an important component of online applied learning services. To improve the recommendation effect, this paper firstly mines dialog text features of English dialog videos and learner interest features based on deep word vector.

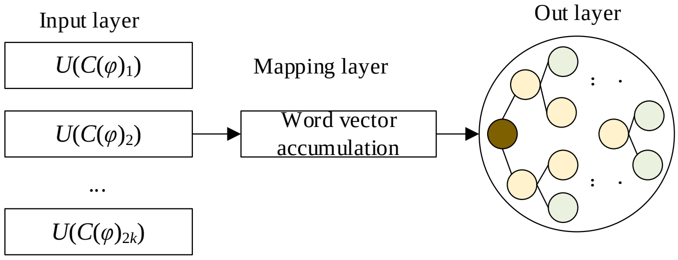

Fig. 1. Continuous bag-of-words model based on hierarchical softmax

Based on deep learning model, the proposed word vector acquisition tool is a continuous bag-of-words model, using hierarchical softmax. As shown in Figure 1, the network mainly consists of an input layer, a mapping layer, and an output layer. The continuous bag-of-words model judges the occurrence probability of a word in the video dialog text based on its context:

$$WP\left(\phi_o \mid l\left(\phi_{o-l}, \phi_{o-l-1}, \ldots, \phi_{o+l-1}, \phi_{o+l}\right)\right) \tag{1}$$

where, φ_o is used to judge the probability of words appearing in the environment of $\varphi_{o-l},\varphi_{o-l-1},\ldots,\varphi_{o+l-1},\varphi_{o+l}$; l is the adjustable window parameter, which determines the scope of the context environment. The summation result of the words in the context of the input φ_o is denoted as $k(\varphi_{o-l},\varphi_{o-l-1},\ldots,\varphi_{o+l-1},\varphi_{o+l})$.

In the continuous bag-of-words model based on hierarchal softmax, the Huffman tree of the input layer uses p_i to represent the i-th element containing the root node and leaf node. Let A_φ be the input of the root node. Then, the probability of the leaf node being allocated to the positive class can be calculated by:

$$\varepsilon\left(A_\phi^T \omega\right) = \frac{1}{1+f^{-A_\phi^T \omega}} \tag{2}$$

The probability of the leaf node being allocated to the negative class can be calculated by $1\text{-}\varepsilon(A^T_{\varphi\omega})=1\text{-}1/1+f^{AT\varphi\omega}$. The probability of moving from the root node to the leaf node corresponding to φ can be calculated by:

$$\begin{aligned} WP\left(\phi \mid A_\phi, \omega\right) &= \prod_{i=2}^{k^\phi} WP\left(p_i^\phi \mid A_\phi, \omega_{i-1}^\phi\right) \\ &= \left(1-\varepsilon\left(A_\phi^T \omega_1\right)\right) \cdot \varepsilon\left(A_\phi^T \omega_2\right) \cdot \varepsilon\left(A_\phi^T \omega_3\right) \end{aligned} \tag{3}$$

where,

$$WP\left(p_i^{\phi} \mid A_{\phi}, \omega_{i-1}^{\phi}\right) = \begin{cases} \varepsilon\left(A_{\phi}^{T} \omega_{i-1}^{\phi}\right), p_i^{\phi} = 0 \\ 1-\varepsilon\left(A_{\phi}^{T} \omega_{i-1}^{\phi}\right), p_i^{\phi} = 1 \end{cases} \tag{4}$$

Let k^{φ}=2l-1 be the size of the text composed of the kl words before and after the center word φ. The element of the i-th node in the Huffman tree corresponds to $p^{\varphi}{}_{i}$. The goal of the entire continuous bag-of-words model is to maximize the probability of moving from the root node to the leaf node corresponding to φ. Under the general condition, the objective function can be expanded as:

$$K = \sum_{\phi \in C} \prod_{i=2}^{EQ^{\phi}} \left\{ \left[\varepsilon\left(A_{\phi}^{T} \omega_{i-1}^{\phi}\right)^{1-p_i^{\phi}} \right] \left[1-\varepsilon\left(A_{\phi}^{T} \omega_{i-1}^{\phi}\right)^{1-p_i^{\phi}} \right] \right\} \tag{5}$$

Taking the logarithm on both sides of formula (5):

$$\sum_{\phi \in C} \sum_{i=2}^{k^{\phi}} \left\{ \left(1-p_i^{\phi}\right) \cdot log\left[\varepsilon\left(A_{\phi}^{T} \omega_{i-1}^{\phi}\right) \right] + p_i^{\phi} \cdot log\left[1-\varepsilon\left(A_{\phi}^{T} \omega_{i-1}^{\phi}\right) \right] \right\} \tag{6}$$

This paper solves the maximum of the above objective function through stochastic gradient descent. The key is to solve the gradients of $\omega^{\varphi}{}_{i-1}$ and $\omega^{O}{}_{\varphi}$:

$$\begin{aligned} \frac{\partial k(\phi, i)}{\partial \omega_{i-1}^{\phi}} &= \frac{\partial}{\partial \omega_{i-1}^{\phi}} \left\{ \left(1-p_i^{\phi}\right) \cdot log\left[\varepsilon\left(A_{\phi}^{T} \omega_{i-1}^{\phi}\right) \right] + p_i^{\phi} \cdot log\left[1-\varepsilon\left(A_{\phi}^{T} \omega_{i-1}^{\phi}\right) \right] \right\} \\ &= \left(1-p_i^{\phi}\right)\left[1-\varepsilon\left(A_{\phi}^{T} \omega_{i-1}^{\phi}\right)\right] A_{\phi} - p_i^{\phi} \varepsilon\left(A_{\phi}^{T} \omega_{i-1}^{\phi}\right) A_{\phi} \\ &= \left[1-p_i^{\phi} - \varepsilon\left(A_{\phi}^{T} \omega_{i-1}^{\phi}\right) A_{\phi}\right] \end{aligned} \tag{7}$$

After computing the gradients, $\omega^{\varphi}{}_{i-1}$ can be updated by:

$$\omega_{i-1}^{\phi} = \omega_{i-1}^{\phi} + \gamma\left[1-p_i^{\phi} - \varepsilon\left(A_{\phi}^{T} \omega_{i-1}^{\phi}\right)\right] A_{\phi} \tag{8}$$

Similarly, the gradient of A_{φ} can be calculated by:

$$\frac{\partial k(\phi, i)}{\partial \omega_{i-1}^{\phi}} = \left[1-p_i^{\phi} - \varepsilon\left(A_{\phi}^{T} \omega_{i-1}^{\phi}\right) A_{\phi}\right] \omega_{i-1}^{\phi} \tag{9}$$

The words can be updated by:

$$U\left(C(\phi)_i\right) = U\left(C(\phi)_i\right) + \gamma \sum_{j=2}^{k^{\phi}} \frac{\partial k(\phi, j)}{\partial A_{\phi}}, i \in \left(0, 2l\right], k^{\phi} = 2l \tag{10}$$

The above is the principle of continuous bag-of-words model based on hierarchical softmax. The representation effect of word vectors can be adjusted by changing the dimensionality of word vector, and the window length of video dialog text.

2.2 Similarity-based resource recommendation

Even if different people understand English dialog all the same, they may express the dialog differently after translation. To a certain extent, this will cause differences to the data of video dialog text. Figure 2 shows the current commonly used model of video recommendation systems. It can be seen that a video recommendation system centers on leaner interest model and resource recommendation model. To realize practical content-based recommendation of micro teaching video resources, this paper designs a deep learning model, and trains it on the word vectors of video dialog text. Combined with learner interest features, a recommendation strategy was defined for the recommendation of micro teaching video resources. The following is a description of the theoretical research of deep word vector in the recommendation of micro teaching video resources, which mainly includes the word vector-based vectorization of the feature distribution for micro teaching video resources, the word vector-based vectorization of the feature distribution for learner interests, and the similarity computation between the two types of vectors.

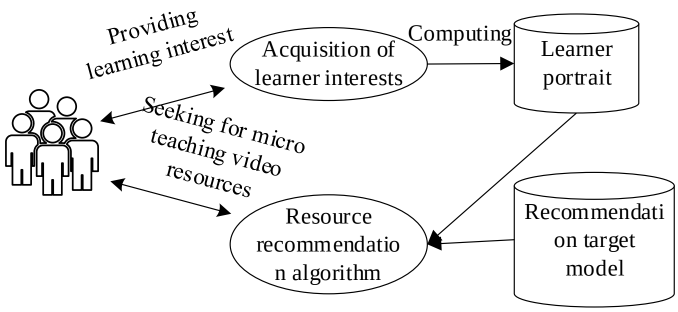

Fig. 2. Common model of video recommendation systems

This paper constructs the distribution vector of micro teaching video texts, in the light of the additive operation property of word vectors in the vector space, and the word frequency-inverse document frequency (WF-IDF) method. Let $U(TMV)$ be a vector of micro teaching video texts. To prevent differences from the varied number of keywords extracted from different micro teaching video texts, this paper sets a normalization coefficient $1/S$, which satisfies $S=\Sigma^{m}_{i=1}\phi_i$. Let m be the number of keywords extracted from one micro teaching video; $u(\varphi_i)$ be the vector of the i-th keyword; ϕ_i be the WF-IDF weight of the i-th keyword. Then, the distribution vector of micro teaching videos can be calculated by:

$$U(TMV)=\frac{1}{S}\sum_{i=1}^{m}\varphi_i\cdot u(\phi_i) \tag{11}$$

Let $\eta_{\varphi(i)}$ be the number of the i-th word appearing in a micro teaching video text; η_O be the total number of words in the micro teaching video text; p_O be the total number of texts in the corpus of micro teaching video texts; $p_{\varphi(i)}$ be the number of texts containing the *i*-th word. Then, ϕ_i can be calculated by:

$$\varphi_i = \frac{\eta_{\phi(i)}}{\eta_O} \cdot log\left(\frac{p_O}{1+p_{\phi(i)}}\right) \tag{12}$$

Formula (12) shows that the mean word vector can be simply derived from the weighted mean of the WF-IDFs of keywords, thereby differentiating between the influence of different keywords.

In the proposed recommendation scheme of micro teaching video resources, the learner's clicking on the pushed micro teaching video is considered as a positive behavior, and the learner's failure to click on that video is considered as a negative behavior. Then, a vector model was established for the positive and negative behaviors, respectively. For convenience, this paper defines the targets of a micro teaching video as the selected learners to be pushed. The set of the optional pushing targets is called the set of candidate learners.

Let $U(v^+)$ be the vector of the positive behaviors of learner v; n^+ be the number of micro teaching videos clicked by learner v; m^+ be the number of keywords in micro teaching video u^+_j; ϕ^+_i be the WF-IDF weight of the *i*-th word in micro teaching video u^+_j; φ^+_i be the *i*-th keyword clicked by the learner in micro teaching video u^+_j; $\tau_j=1/(1+log(1+M))$ be a coefficient, with M being the view counts of the video on Tencent Classroom. To prevent differences from the varied number of micro teaching videos clicked by different learners, and from the varied number of keywords extracted from different micro teaching videos, this paper sets up normalization coefficients $1/n^+$ and $1/S^+$, which satisfy $S^+=\Sigma^m{}_{i=1}\phi^+_i$. Based on the WF-IDF method, the positive behaviors of a learner can be vectorized by:

$$U\left(v^+\right) = \frac{1}{n^+}\sum\nolimits_{j=1}^{n+}\tau_j\left(\frac{1}{S^+}\sum\nolimits_{i=1}^{m+}\varphi_i^+ \cdot u_j^+\left(\phi_i^+\right)\right) \tag{13}$$

Let $U(v^-)$ be the vector of the negative behaviors of learner v; n^- be the number of micro teaching videos not clicked by learner v; m^- be the number of keywords in micro teaching video u^-_j; ϕ^-_i be the WF-IDF weight of the *i*-th word in micro teaching video u^-_j; φ^-_i be the *i*-th keyword not clicked by the learner in micro teaching video u^-_j. To prevent differences from the varied number of micro teaching videos clicked by different learners, and from the varied number of keywords extracted from different micro teaching videos, this paper sets up normalization coefficients $1/n^-$ and $1/S^-$, which satisfy $S^-=\Sigma^m{}_{i=1}\phi^-_i$. Based on the WF-IDF method, the negative behaviors of a learner can be vectorized by:

$$U\left(v^-\right) = \frac{1}{n^-}\sum\nolimits_{j=1}^{n-}\tau_j\left(\frac{1}{S^-}\sum\nolimits_{i=1}^{m-}\varphi_i^- \cdot u_j^-\left(\phi_i^-\right)\right) \tag{14}$$

After vectorizing the positive and negative behaviors of learners, the next is to compute the cosine distance between each micro teaching video vector and the positive and negative behavior vectors of every learner. The cosine ratio between the positive/negative behavior vector and the micro teaching video vector:

$$\chi = \frac{cos < U(TMV) \cdot U(v^+) >}{cos < U(TMV) \cdot U(v^-) >} = \frac{\dfrac{U(TMV) \cdot U(v^+)}{\|U(TMV)\| \cdot \|U(v^+)\|}}{\dfrac{U(TMV) \cdot U(v^-)}{\|U(TMV)\| \cdot \|U(v^-)\|}} \tag{15}$$

where,

$$\begin{aligned} a &= \frac{U(TMV) \cdot U(v^+)}{\|U(TMV)\| \cdot \|U(v^+)\|}, -1 \le a \le 1 \\ b &= \frac{U(TMV) \cdot U(v^-)}{\|U(TMV)\| \cdot \|U(v^-)\|}, -1 \le b \le 1 \end{aligned} \tag{16}$$

The closer *a* is to 1, the positive behavior vector is more correlated with the micro teaching video vector, i.e., the learner is more interested in the pushed video; the closer *a* is to -1, the positive behavior vector is less correlated with the micro teaching video vector, i.e., the learner is less interested in the pushed video.

The closer *b* is to 1, the negative behavior vector is more correlated with the micro teaching video vector, i.e., the learner is less interested in the pushed video; the closer *b* is to -1, the negative behavior vector is less correlated with the micro teaching video vector, i.e., the learner is more interested in the pushed video.

Based on the above meanings of a and b, the ideal values are *a*=1 and *b*=-1, when micro teaching videos are being pushed to learners. However, the a and b values of learners generally fall in [-1, 1]. Figure 3 shows the distribution of a and b values of learners in the coordinate plane.

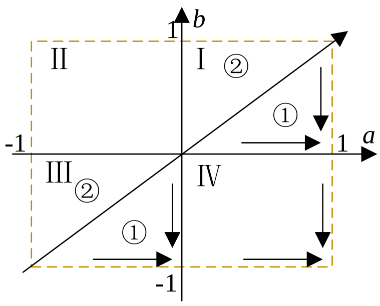

Fig. 3. Distribution of a and b values of learners in the coordinate plane

3 Sentiment analysis-based recommendation

It is very important for English learners to understand the context, which includes the time, space, situation, object, discourse premise, and many other factors related to the use of words. In order to improve the pushing accuracy of micro teaching videos, this paper conducts a sentiment analysis on micro teaching videos with text information. Figure 4 shows the flow of text sentiment classification of micro teaching videos.

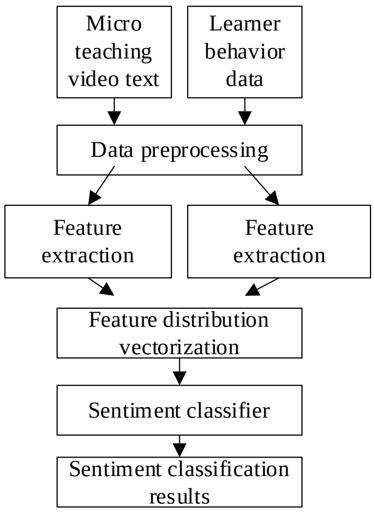

Fig. 4. Flow of text sentiment classification of micro teaching videos

Firstly, Ψ classes are randomly extracted from the multi-class micro teaching videos, which are waiting for sentiment classification, to serve as the support set. Let $e(a_j)$ be the feature extracted from each video sample $h_j(j\in[1,\Psi\times\Omega])$ in the support set. In each classification training, Ω micro teaching video samples are selected from each class to serve as the support set D. The remaining N video samples are organized into the query set.

Then, the features $e(h_i)$ and $e(h_j)$ extracted from $h_i(i\in[1,N])$ are spliced into $\rho(e(h_i),e(h_j))$. After splicing, the covariance matrix between feature row vectors can be expressed as $Z\in R^{p\times p}$, which is a symmetric matrix composed of $F_{\xi,\delta}(\xi\in[1,p],\delta\in[1,p])$. Note that $F_{\xi,\delta}=(\rho_\xi-\lambda_\xi)(\rho_\delta-\lambda_\delta)^T$, where ρ_ξ and ρ_δ are the feature representations of rows ξ and δ after splicing, respectively; λ_ξ and λ_δ are the means of rows ξ and δ after splicing, respectively. The metric module can be expressed as:

$$s_{j,i}=\left(e\left(a_j\right)-e\left(a_i\right)\right)^T Z\left(e\left(a_j\right)-e\left(a_i\right)\right) \tag{17}$$

Based on the similarity between micro teaching videos in the query set and the support set, this paper employs the softmax classifier to predict the sentiment class of the samples in the query set. Let $s_{j,I}$ be the similarity between a support set sample h_j and a query set sample h_i. Then, the sentiment classification probability χ_{ji} for h_i to belong to h_j can be calculated by:

$$\chi_{ji} = \frac{exp\left(s_{j,i}\right)}{\sum_{j=1}^{\Psi\times\Omega}\sum_{i=1}^{N} exp\left(s_{j,i}\right)} \tag{18}$$

Batch stochastic gradient descent was adopted to optimize the adopted cross entropy loss function. Let b^i be the predicted class of h_i; b^j be the true label of support set sample h_j; QU be the indicator function reflecting whether the expression is true. Then, the loss function can be expressed as:

$$loss = -\sum_{j=1}^{\Psi\times\Omega}\sum_{i=1}^{N} QU\left[b^i = b^j\right] log\left[\chi_{ji}\right] \tag{19}$$

Figure 5 shows the structure of the min loss model obtained through learning.

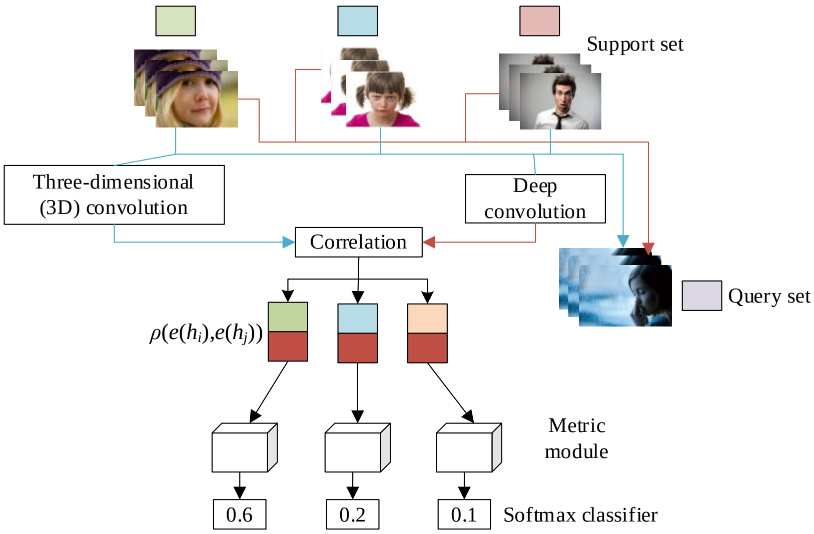

Fig. 5. Structure of sentiment classification model of micro teaching videos

4 Experiments and results analysis

The online learning participation of the learners were observed based on the cumulative probability distribution curves of view counts for videos in 2, 4, 6, and 8 days, respectively. The results in Figure 6 show that the learners differed significantly in online learning participation. The previous analysis indicates that our recommendation algorithm is usually correlated with the online learning participation of learners. Hence, this paper divides the learners into high participation ones and low participation ones. The participation level was measured by the number of pushed micro teaching videos being accepted by the learners. The cumulative probability distribution of view counts for videos of high participation learners was compared with that of low participation learners. The results (Figure 7) show that the high participation learners were only slightly different from the low participation learners in terms of the activity of watching micro teaching videos. Hence, our algorithm achieves an ideal recommendation effect, despite a slight deviation.

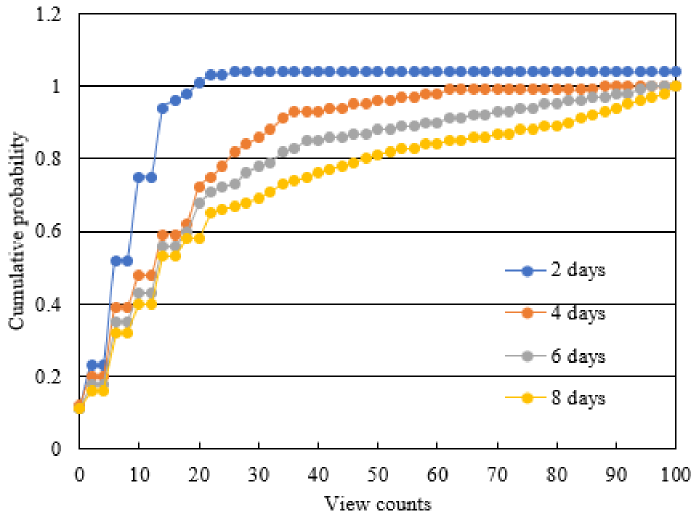

Fig. 6. Cumulative probability distribution of view counts for videos at different learning durations

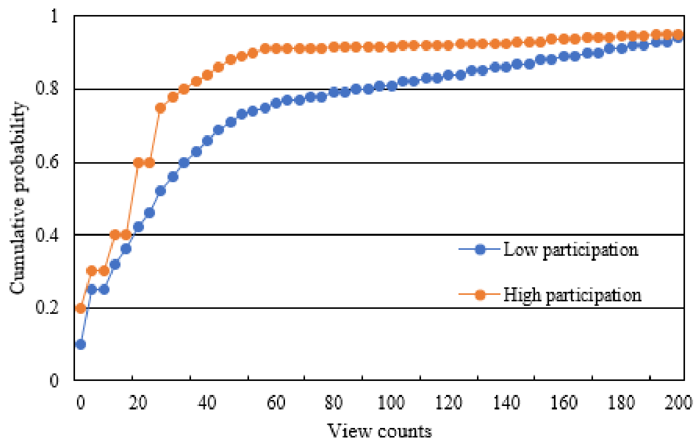

Fig. 7. Cumulative probability distribution of view counts for videos at different learning participation levels

This paper further compares the resource push accuracy between our model and traditional convolutional neural network. Figure 8 presents the cumulative distribution curves of the accuracy for the two models pushing micro teaching videos to learners. It can be observed that our model achieved better accuracy of resource recommendation than traditional CNN. According to the actual test results, our model effectively improves the view count of the micro teaching videos pushed to learners.

Table 1 compares the sentiment classification effects of different models, including our model, random forest, decision tree, logistic regression, and k-nearest neighbors. The latter four are common classification tools. The results in Table 1 shows that our model achieved the best performance in terms of precision, recall, and F1-score.

To measure the recommendation effect of our optimization algorithm for micro teaching videos, the traditional CNN, our model with sentiment analysis, and our model without sentiment analysis were subjected to offline experiments. The results in Figure 9 show that the resource recommendation effect was significantly improved through learner interest expansion and feature extraction of learner behavior vectors. Therefore, our algorithm is highly effectively.

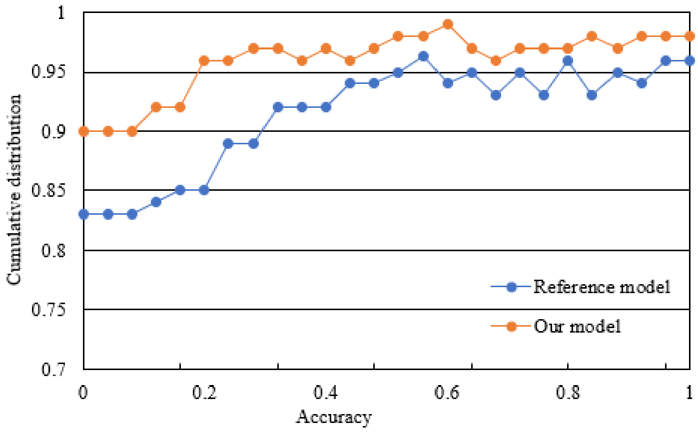

Fig. 8. Resource push accuracy of different models

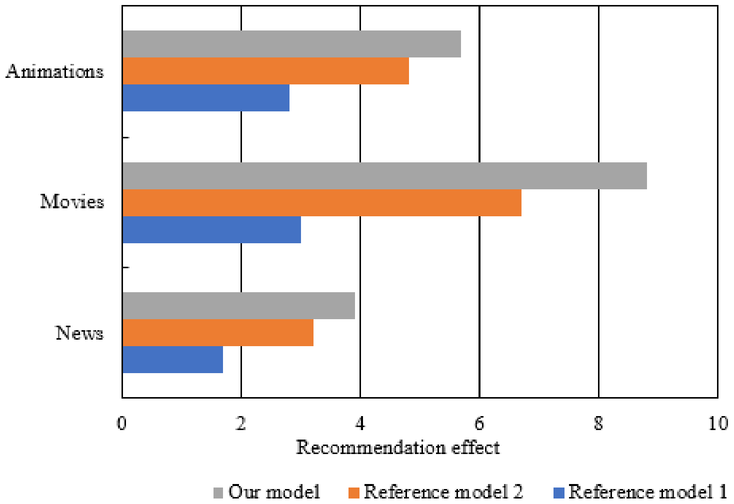

Fig. 9. Recommendation effects of micro teaching videos after learner vector classification

Table 1. Comparison of sentiment classification effects of different models

Algorithm	Random forest	Decision tree	Logistic regression	K-nearest neighbors	Our model
Precision	0.85	0.82	0.95	0.93	0.98
Recall	0.91	0.86	0.92	0.96	0.97
F1-score	0.93	0.97	0.86	0.92	0.95

5 Conclusions

This paper explores the recommendation of micro teaching video resources based on topic mining and sentiment analysis. Firstly, the dialog text features of English dialog videos and learner interest features were mined based on deep word vector, and a topic mining model was established to realize similarity-based resource recommendation. Next, a sentiment analysis was performed on micro teaching videos with text information, which improves the pushing accuracy of micro teaching videos. Finally, relevant experiments were carried out to summarize the cumulative probability distribution of the view count of videos at different learning durations and participation levels. Besides, the resource push accuracy was discussed with different models, and the video sentiment classification effects of different models were compared carefully. Finally, the authors obtained the recommendation effects of micro teaching videos after learner vector classification. The experimental results confirm that our algorithm can be effectively applied to the recommendation of micro teaching video resources.

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7 Authors

Jie Liu was born on 13th, February, 1986 in Huanghua City, Hebei Province, China. She received B.A. Degree of English Education from Huaibei Normal University in 2008 and M.A. degree of English Literature from Tianjin Foreign Studies University in 2011. She started her teaching career in 2016 in Cangzhou Normal University. Her research interests include English Teaching and English Literature (email: liuziqi 20212021@126.com).

Haiping Lv was born on 4th, June, 1975 in Cangzhou City, Hebei Province, China. She received B.A. Degree of English Education from Hebei Normal University in 1998 and M.A. degree of English Literature from Hebei Normal University in 2009. She started her teaching career in 1998 in Cangzhou Normal University. Her research interests include English Teaching and English Literature (email: lhp2021xx@ caztc.edu.cn).

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