Research Article

A Personalized Recommendation Method for Ethnic Music Teaching Resources Based on Video Tags

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In order to improve the effect of ethnic music teaching and improve the recommendation accuracy of teaching resources, this paper proposes a personalized recommendation method for ethnic music teaching resources based on video tags. A national music teaching resource library is constructed as the resource source, and the K-nearest neighbor (KNN) algorithm is used to classify the teaching resources in the resource library. According to the results of resource classification, describe the characteristics of teaching resources, so as to recommend suitable teaching resources to corresponding students to meet individual needs. According to the main characteristics of tags, a tagging system is established, and at the same time, the decay of user interest over time is considered, and weights are assigned to user video interest tags in descending order of time, and the total user interest tag vector is calculated. In this paper, the obtained user total interest label vector is normalized. The vector space model is used to represent teaching resources and user interests, so as to realize personalized recommendation of teaching resources. The experimental results show that the accuracy rate of the proposed method is higher than 90%, the recall rate is more than 97%, and the F1 value is larger, and the convergence is better, reflecting the better recommendation effect of the method.

1. Introduction

At present, a large number of online learning resources are distributed in a scattered state in the learning platform, and learners cannot quickly find the resources they need and are interested in, resulting in the problem of "information loss and overload" [1, 2]. For this reason, a large number of scholars have begun to study the combination of personalized learning and information recommendation technology. However, in the field of education, most of the traditional online learning platforms directly apply mature information recommendation technology, which lacks the analysis of learners' own personalized characteristics and provides personalized services. To a lesser extent [3, 4], how to save the time of learners retrieving resources in the learning platform, so as to improve the learning efficiency and the utilization rate of resources, has become a hot issue of current research [5].

Literature [6] proposed a personalized learning resource recommendation method based on three-dimensional

feature collaborative domination. Firstly, by improving the matching relationship between learners and online learning resource features, the personalized learning resource recommendation model based on three-dimensional feature collaborative domination is established and described by parameters. Secondly, a binary particle swarm optimization algorithm (FCBPSO) based on Gaussian membership function fuzzy control is designed to solve the objective function of the recommended model. Finally, under multiple evaluation indexes, the recommendation performance of the recommendation method is verified by five groups of comparative experiments. Experimental results show that this method has high resource recommendation efficiency, but the accuracy of recommendation results is not high. Literature [7] proposed a collaborative filtering and recommendation method of online learning resources based on learner model. According to education and teaching theory and learners' relevant data in online education platform, a learner model suitable for personalized recommendation of online learning resources was studied and constructed.

Taking the collaborative filtering recommendation method as the starting point, the collaborative filtering method is improved by integrating the static and dynamic features in the learner model, and a collaborative filtering recommendation method of online learning resources integrated into the learner model is established. Based on the real learning data and behavior data set, this method is verified. Finally, it is proved that the recommendation performance of this method is good, but there is a problem of low recall rate. Literature [8] proposes a learning resource recommendation method based on multidimensional relational ontology. First, a multidimensional relational ontology model (MCOM) for learning resource recommendation is constructed, and the learning resource ontology, learner ontology, and context ontology are associated through semantic relations; secondly, there is the design dynamic self-balancing binary particle swarm optimization algorithm (DSEBPSO); finally, the MCOM ontology model and DSEBPSO algorithm are integrated and applied, and a learning resource recommendation method based on multidimensional relational ontology (MCOM-LROM) is proposed to provide learners with the optimal learning resources or learning paths. . The experimental results show that the MCOM-LROM method has better performance in response speed and content quality, but there is a problem of low F1 value.

In view of the above problems, in order to meet the individual needs of learners for learning resources, this paper takes ethnic music teaching resources as the research object and conducts research on the personalized recommendation method of ethnic music teaching resources. In this paper, the KNN algorithm is used to classify the teaching resources in the resource library. According to the resource classification results, describe the characteristics of teaching resources, so as to recommend suitable teaching resources to corresponding students. According to the main characteristics of tags, a tagging system is established, the decay of user interest over time is considered, and the user's total interest tag vector is calculated. In this paper, after normalizing the interest label vector, the vector space model is used to represent the teaching resources and user interests, and the personalized recommendation of teaching resources is realized.

2. Materials and Methods

2.1. Construction of National Music Teaching Resource Database.
Before recommending teaching resources, first build the corresponding ethnic music teaching resource library. The database is developed in C# language on the .Net platform, using B/S mode based on IE browser, the client is IE browser, and the server is IIS (Internet Information Server). The resource library adopts a three-layer structure, namely, the data layer, the transaction layer, and the presentation layer. The data layer mainly deals with all data operations in the resource library; the transaction layer encapsulates most of the actual operations; the presentation layer is the web pages that users can browse with the IE

browser. Figure 1 is a schematic diagram of the architecture of the folk music teaching resource library.

According to Figure 1, in the folk music teaching resource library, in addition to the general resource library function, the design of the resource sharing function is focused on. In the entire resource library, around the resource sharing mechanism based on the learning object concept, it mainly provides some direct learning object-oriented functions such as Learning Object Metadata (LOM) generation. By describing it in terms of consistent characteristics of learning objects, searching becomes more precise, management can be more consistent, and sharing can be more efficient and deeper. With the LOM import and export, LOM-based content list file is generated, while opening the corresponding Web Service for external program calls.

2.2. Classification of Ethnic Music Teaching Resources.
A variety of teaching resource data can be obtained in the folk music teaching resource database. In order to make these data have a certain standard, the KNN algorithm is used to classify them. KNN algorithm [9, 10] (also known as K-nearest neighbor algorithm) is currently the most commonly used and one of the classification algorithms with the best classification effect, which is very suitable for solving multiclass problems. The core idea is that, in the feature space, if most of the K samples closest to the sample to be classified belong to a certain category, the sample to be classified also belongs to this category.

For example, as shown in Figure 2: the training space includes two categories: blue squares and red triangles, and green texts are samples to be classified. When $K = 3$, there are 2 red and 1 blue among the 3 samples closest to the green sample, and the green sample should be classified into the red triangle class. When $K = 5$, among the 5 samples closest to the green sample to be classified, there are 3 blue and 2 red, and the green samples will be divided into the blue square class. From this, it can be seen that the selection of the value directly affects the final result of KNN classification.

At present, similarity is often used to measure the distance between different resources in resource classification. The commonly used similarity calculation methods are Euclidean distance method and included angle cosine method. This paper uses the included angle cosine method for calculation, and the expression is

$$
\begin{aligned}
\mathrm{Sim} &= \left(w_i, w_j\right) \\
&= \frac{\sum_{i,j=1}^{n} w_i \times w_j}{\sqrt{\sum_{l=1}^{n} w_{il} + \sum_{l=1}^{n} w_{jl}}}.
\end{aligned}
\tag{1}
$$

Among them, w_i and w_j represent any two texts i and j in the training set; n represents the total number of feature vectors; w_{il} and w_{jl} represent the corresponding feature item weights in the text vectors of texts w_i and w_j.

The larger the cosine value $\mathrm{Sim} = (w_i, w_j)$ of the included angle, that is, the smaller the included angle between the vectors of the two texts, the higher the similarity between the two vectors. Conversely, the smaller the cosine value
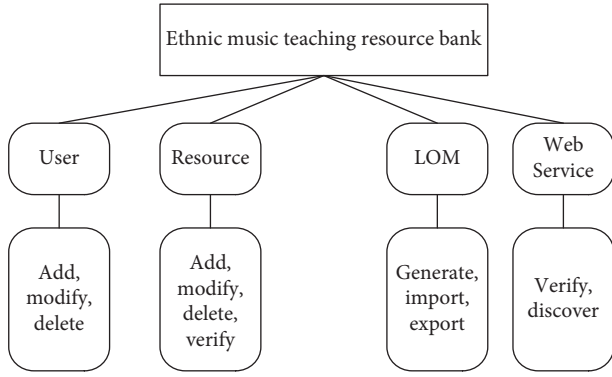
Figure 1: Schematic diagram of the structure of the ethnic music teaching resource library.
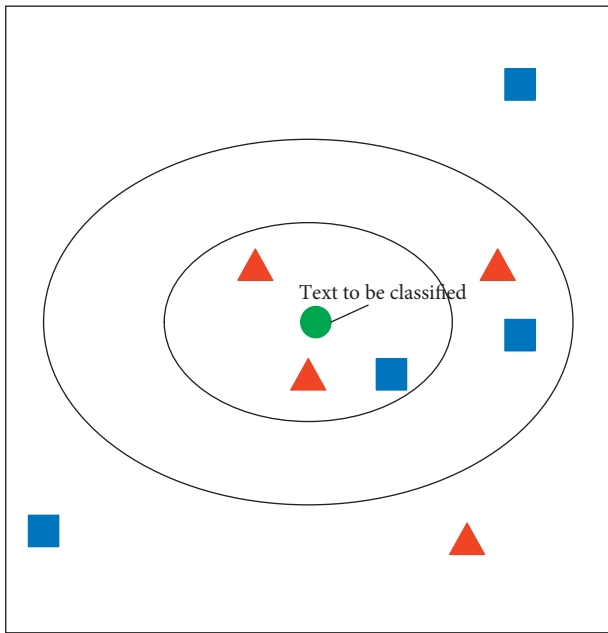

Figure 2: Schematic diagram of the principle of KNN algorithm.

$\mathrm{Sim} = (w_i, w_j)$ of the included angle, that is, the larger the included angle between the vectors of the two texts, the lower the similarity. In addition, the value range of the cosine value of the included angle should be [0, 1]. If it is not within this range, the calculation result is incorrect. When Sim = 0, the text is completely irrelevant; when Sim = 1, the text is exactly the same.

The specific steps of the KNN algorithm are given below:

(1) The text of the training set is represented by a vector space model, and the weight of each dimension of the feature item is calculated.

(2) The test set text is also represented by the vector space model, and the feature weight of each dimension is also calculated.

(3) Calculate the spatial distance between the text to be classified in the test set and each text in the training set, that is, the text similarity.

(4) Arrange the calculated $\mathrm{Sim} = (w_i, w_j)$ values in descending order, and select the K training set texts with the highest similarity to the text X to be classified. The K value needs to be determined according to the actual situation. At present, there is no good method to directly determine the optimal K value. The K value can only be adjusted continuously through experiments, and the appropriate value can be determined according to the test classification effect.

(5) Finally, count the distribution of the selected K texts in each category, and classify the texts to be classified into the categories that most of the texts belong to. However, due to the large number of classifications of ethnic music teaching resources, it is easy to show that several categories contain the number of texts. Among them, ethnic music teaching resources can be divided into media materials, test papers, courseware, teaching cases, literature materials, frequently asked questions, and so on. In the same situation, therefore, it is necessary to calculate the weight of each category of the text to be classified according to the category to which the K most recent texts belong, as shown in formula

$$P(X,Y) = \sum_{i,j=1}^{n} \mathrm{Sim}(w_i, w_j) \times W(X_i, Y_j). \qquad (2)$$

Among them, $P(X,Y)$ represents the similarity between the text to be classified and the text in the training set; $W(X_i, Y_j)$ represents the category attribute function, when the text X belongs to the class Y, $P(X,Y) = 1$; otherwise $P(X,Y) = 0$; finally, the text X to be classified is classified into the $P(X,Y)$ category with the largest value.

2.3. Characteristic Description of Ethnic Music Teaching Resources. Based on the classification of ethnic music teaching resources, the characteristics of the teaching resources are described, so that suitable teaching resources can be recommended to the corresponding students to achieve personalized recommendation.

Describe the characteristics of ethnic music teaching resources as

$$\begin{cases} D = \{D_1, D_2, \ldots, D_N\}, \\ GH = \{GH_1, GH_2, \ldots, GH_M\}, \\ S = \{S_1, S_2, \ldots, S_M\}, \\ Q = \{Q_1, Q_2, \ldots, Q_N\}, \\ T = \{T_1, T_2, \ldots, T_M\}. \end{cases} \qquad (3)$$

Among them, represents the D concepts that the learner expects to learn from the learning resources; GH represents the M candidate learning resources matching the learning concept; S represents the difficulty level of the M candidate learning resources; S_M represents the difficulty level of the learning resource GH_M level; T represents the time required to complete the learning resource; T_M represents the time

required to complete the learning resource GH_M; Q represents the candidate resource that matches all learning concepts, each Q_N has M binary values, and the matrix expression is

$$Q_{n \times m} = \begin{bmatrix} Q_{11} & Q_{21} & Q_{N1} \\ Q_{12} & Q_{22} & Q_{N2} \\ Q_{1M} & Q_{2M} & Q_{NM} \end{bmatrix}, \tag{4}$$

$Q_{n \times m}$ is used to judge whether the learning resource GH_M matches the learning concept D_n, where $1 \le n \le N$, namely:

$$Q_{km} = \begin{cases} 1, & \text{match}, \\ 0, & \text{unmatch}. \end{cases} \tag{5}$$

As a reinforcement feature, the individual learner's personalization feature plays a decisive role in the accuracy of learning resource recommendation, which can be described as

$$\begin{cases} FP = \{FP_1, FP_2, \ldots, FP_m\}, \\ HP = \{HP_1, HP_2, \ldots, HP_m\}, \\ UB = \{UB_1, UB_2, \ldots, UB_m\}, \\ UA = \{UA_1, UA_2, \ldots, UA_m\}. \end{cases} \tag{6}$$

Among them, FP represents the learner's preference for the knowledge point medium, and each FP_m contains Z one-dimensional vectors, namely:

$$FP_{m \times z} = \begin{bmatrix} FP_{11} & FP_{21} & FP_{M1} \\ FP_{12} & FP_{22} & FP_{M2} \\ FP_{1z} & FP_{2z} & FP_{MZ} \end{bmatrix}. \tag{7}$$

Among them, the value of z represents the number of media types contained in the learning resource, $1 \le z \le Z$. The value of FP_m is a real number, representing the learner's preference value for the $z-$ th media type of the m -th concept.

HP represents the learner's content preference for knowledge points, and each HP_m contains Z one-dimensional vectors, namely:

$$HP_{m \times z} = \begin{bmatrix} HP_{11} & HP_{21} & HP_{M1} \\ HP_{12} & HP_{22} & HP_{M2} \\ HP_{1z} & HP_{2z} & HP_{MZ} \end{bmatrix}. \tag{8}$$

Among them, the number of z is the number of content types included in the learning resource. The value of HP_m is a real number, indicating the learner's preference value for the $z-$ th content type of the $m-$ th knowledge point.

UB stands for the type of learning resource medium that matches the concept, i.e., pictures, slides, documents, audio and video, etc. Each UB_m contains N one-dimensional vectors, namely:

$$UB_{m \times n} = \begin{bmatrix} UB_{11} & UB_{21} & UB_{M1} \\ UB_{12} & UB_{22} & UB_{M2} \\ UB_{1n} & UB_{2n} & UB_{MN} \end{bmatrix}. \tag{9}$$

Among them, the value of $UB_{m \times n}$ is an integer, which represents the media type of the $n-$ th learning resource corresponding to the m -th knowledge point.

UA is the content type of the learning resource corresponding to the knowledge point, that is, introduction, detailed concept explanation, theoretical knowledge, and cases. Each UA_m contains N one-dimensional vectors, namely:

$$UA_{m \times n} = \begin{bmatrix} UA_{11} & UA_{21} & UA_{M1} \\ UA_{12} & UA_{22} & UA_{M2} \\ UA_{1n} & UA_{2n} & UA_{MN} \end{bmatrix}. \tag{10}$$

Among them, the value of $UA_{m \times n}$ is an integer, indicating the content type of the $n-$ th learning resource corresponding to the $m-$ th knowledge point.

3. Personalized Recommendation of Ethnic Music Teaching Resources

3.1. The Main Features of the Label. As an important element in the entire labeling system, video tags mainly have the following characteristics:

(1) Ease of use. Adding video tags does not require a lot of effort and time from the user. From the perspective of organizing information, adding multiple video tags establishes multiple paths to find the resource, and video tags can be applied to most situations, any purpose, and any kind of information. For example, video tags can describe sentiment, memo, status, or even the topic of an article. [11].

(2) Freedom and personalization. Users can mark any resource on the Internet according to their own wishes and habits, regardless of whether other people have already marked the resource. There are no restrictions on tagging, and it is also possible not to tag but only to see the tagging of the resource by others, etc.

(3) Collaboration and sharing. Video tags can help individuals manage information efficiently, while also providing a simple and powerful method for social information management. The tags in the tag system belong to the shared resources in the whole system, and the tags created by each user can be used by other users.

Compared with the traditional information retrieval system, video tags can be more convenient for users to organize information. Users can use any text to tag an item to create a tag. Adding multiple tags to an item is equivalent to establishing multiple paths to find the item. It greatly speeds up the user's speed of retrieving information and reduces the time for retrieving information. The labeling system is a flat classification structure generated by the user, which is relatively more flexible and real-time. The labeling system usually consists of three basic elements: user, label, and resource, as shown in Figure 3.
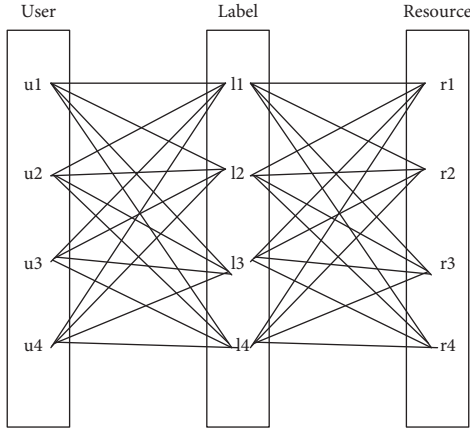
FIGURE 3: Schematic diagram of labeling system.

The behavior of users labeling with tags can be simply represented by a triple (u, r, l), which means that user u has tagged resource r with l. Similarly, the labeling system can also be expressed as $LS = (U, R, L)$, where U represents the set of all users in the system, $U = \{u_i, \quad i = 1, 2, \ldots, n\}$, and R represents all the users in the system The set of resources $R = \{r_i, \quad i = 1, 2, \ldots, n\}$, and L represents the set of tags used by all users in the system, $L = \{l_i, \quad i = 1, 2, \ldots, n\}$.

From the whole label system, the set of labels that a user has used can represent the user's interests and preferences. The more frequently a tag is used, the more interested the user is in the resource corresponding to the tag, and a tag can be used by different users. Two different users use the same tag to label resources, which can indicate that the two users have the same or similar interests in one aspect. If a label is used by many different users, it can represent a classification recognized by the public or a popular trend. A label can be marked on different resources, or it can indicate that these resources are the same or similar in some way. Similarly, a resource can also be labeled with different labels, which can completely describe the resource from various angles [12, 13].

3.2. Video Interest Tags.

Considering the decay of user interest over time, an exponential decay constant is introduced to construct a time-exponential decay video interest label similar to the cooling law proposed by Newton in physics. In order to control the exponential decay process, that is, the control index starts to decay from the value of η_0, and then decreases to η_t after the decay of time t, and establish functional relationship between "temperature of interest" and "time," which is used to describe the exponential decay of temperature of interest with time change, see

$$I(\eta) = \sum_{k=1}^{n} \Delta I_{ij}^k (\eta_t - \eta_0).$$ (11)

Among them, $I(\eta)$ represents the time function of the temperature of interest; the constant k represents the proportional relationship between the temperature of interest and the cooling rate, which can prevent the value from decaying from I_0. Assuming that the decay needs to start from I_a and decay to I_b after d days, the constructed differential equation expression is shown in formula

$$\begin{cases} I_a = u_i - C_v^{\sigma 2}, \\ I_b = u_j - C_v^{\sigma 2}. \end{cases}$$ (12)

The expressions of the constant σ and the offset v are obtained after the initial decay value I_a, decay duration d, and decay final value I_b are known; see (13) and (14):

$$\sigma = \sum_{i=1}^{n} |G(i) - H(i)|^2,$$ (13)

$$v = \sum_{k=1}^{n} (e_{ik} - f_{ik})^2.$$ (14)

Among them, $G(i)$ and $H(i)$ represent the recommendation candidate set; e_{ik} represents the feature vector of the content label; f_{ik} represents the user interest feature vector.

The expression for calculating the exponential decay constant from a given time d is shown in

$$I(d) = \ln\left(\frac{1}{W(d)}\right).$$ (15)

Among them, $W(d)$ represents the content type preference of the learner for the knowledge point.

3.2.1. Time-Exponential Decay User Video Interest Tags.

Due to the change of user interest over time, a time-exponential decaying user video interest label is formed. Using the obtained time-exponential decay constant, the user video interest label is weighted in descending time order, and the total user interest label vector is calculated. The obtained user's total interest label vector is normalized. The purpose of normalization may be to make noncomparable data comparable, but also to maintain the relative relationship between the two compared data, such as the size relationship; the big one is still big, the small one is still small. Specifically, a video interest matrix is first formed. The video tag vector of the β-th video watched by user α containing n feature tags is $L_{\alpha,\beta} = (l_{\beta,1}, l_{\beta,2}, \ldots, l_{\beta,n})$. Among them, the value of $l_{\beta,n}$ is 0 or 1. The feature label corresponding to the β-th video watched: if it contains the n-th feature vector, the value is 1, and if it is not included, the value is 0. Finally, a user interest matrix with j rows and n columns is formed, as shown in formula

$$L_{\alpha,\beta} = \begin{bmatrix} l_{1,1} & l_{1,2} & l_{1,n} \\ l_{2,1} & l_{2,2} & l_{2,n} \\ l_{j,1} & l_{j,2} & l_{j,n} \end{bmatrix}.$$ (16)

Secondly, the videos viewed by the user are sorted in reverse chronological order, and the user's video tag vector $L_{\alpha,\beta} = (l_{\beta,1}, l_{\beta,2}, \ldots, l_{\beta,n})$, respectively, multiplied by ϕ exponential decrement delay over time delay (ϕ), namely:

$$L_{\alpha,\beta} = \begin{bmatrix} l_{1,1} \times \text{delay}(1) & l_{1,2} \times \text{delay}(1) & l_{1,n} \times \text{delay}(1) \\ l_{2,1} \times \text{delay}(2) & l_{2,2} \times \text{delay}(2) & l_{2,n} \times \text{delay}(2) \\ l_{j,1} \times \text{delay}(\phi) & l_{j,2} \times \text{delay}(\phi) & l_{j,n} \times \text{delay}(\phi) \end{bmatrix}. \tag{17}$$

Then add the λ feature vectors to form the exponential decay vector of the user's total video interest tags. The formed exponential decay vector is normalized, the sum of the weights of each vector is 1, and it is distributed according to the proportion to form the normalized user video feature vector $L'_{\alpha,\beta} = (L'_{\beta,1}, L'_{\beta,2}, \dots, L'_{\beta,n})$.

3.3. Implementation of Personalized Recommendation of Ethnic Music Teaching Resources.

In the past content-based filtering recommendation, the vector space model is used to represent the teaching resources and user interests; that is, the extracted teaching resource feature words and their weights are used to represent the teaching resource features, and the user interest features are mainly extracted from the interest information. Feature words and their weights are used to represent them. Finally, the similarity between teaching resource features and user interest features is calculated, and teaching resources with high similarity are recommended to target users [14, 15]. In this paper, when building a personalized recommendation model, the extracted feature words and their weights and the trained feature word vectors will be directly used to calculate the matching degree between user interests and teaching resources. First, formula (18) is used to calculate the cosine value μ:

$$\mu = \frac{|\tau_i \cdot \tau_j|}{\sqrt{|\tau_i| \cdot |\tau_j|}}. \tag{18}$$

Among them, τ_i represents the i-th feature word vector with a large weight selected according to the teaching resources; τ_j represents the j-th feature word vector with a large weight screened according to the user's interests; among them, $1 \le i \le K$, $1 \le j \le P$, and K and P represent the number of feature words with larger weights screened by teaching resources and user interests, respectively.

Then use formula (19) to calculate the matching degree value:

$$\text{Sim}_{KP} = \int_{i=1}^{K} \int_{j=1}^{P} (K_i, P_j) \times \mu. \tag{19}$$

Among them, K_i and P_j, respectively, represent the weights of feature words with larger weights selected from teaching resources and user interests, $1 \le i \le K$, $1 \le j \le P$.

According to the above analysis, the personalized recommendation of ethnic music teaching resources is divided into three parts: teaching resource processing, user interest processing, and teaching resource recommendation basis calculation. Among them, teaching resource processing is mainly used for teaching resource extraction; user interest processing is mainly used for user interest feature extraction; teaching resource recommendation basis calculation is mainly used to calculate the matching degree value between teaching resources and user interests, and this link is the core part.

Based on the above analysis, the main process of personalized recommendation of ethnic music teaching resources is given:

(1) Data preprocessing. Data cleaning, text type conversion, etc. are performed on the collected user reading record information and teaching resources to make them meet the data requirements of the model, so as to facilitate word segmentation, feature extraction, and word vector training.

(2) Feature extraction is performed on user interest information and teaching resources, and the weights of feature words are calculated.

(3) Calculate the cosine value and the matching degree value, normalize the matching degree value, and recommend the top N documents with larger matching degree value to the target user.

4. Results and Discussion

In order to verify the effectiveness of the personalized recommendation method for ethnic music teaching resources based on video tags, an experimental study was conducted. In the experiment, the personalized learning resource recommendation method based on the collaborative domination of 3D features and the online learning resource collaborative filtering recommendation method based on the learner model are compared with the proposed method to verify the effectiveness of the proposed method.

4.1. Data Sources.

Taking the literature teaching resources used by students in their learning as an example, the experiment selects literature read by 8 users with different research themes as experimental data and follows two principles when selecting research themes: (1) The research theme is completely relevant; (2) The research theme is completely irrelevant. Similarity. According to manual classification, the documents are divided into user reading records and related documents. Among them, there are 185 reading records and 235 related documents used to extract user interest features. The details are shown in Table 1.

4.2. Experiment Evaluation Criteria.

Precision and recall are the most commonly used evaluation methods at present. In this experiment, these two indicators are used to evaluate the performance of the recommended algorithm in this paper. The accuracy rate in the experiment represents the proportion of all the items in the test set that the learner is really interested in, in the recommended item list. The more the resources actually operated by the user overlap with the recommended items, that is, the more the correctly recommended items are, the greater the accuracy is. The formula for calculating the accuracy is as follows:

Table 1: Experimental data information.

User	Reading records/articles	Related literature/articles
1	20	23
2	31	25
3	19	26
4	18	29
5	20	39
6	31	32
7	19	28
8	23	37

$$\text{Precision} = \frac{\sum_{c \in C}^{n} |S(c) \cap G(c)|}{\sum_{c \in C}^{n} |S(c)|}. \tag{20}$$

The recall rate is used to measure the proportion of the learners' actual interest in the recommended resource list in the test set to all the learners' interested resources. The formula for calculating the recall rate is as follows:

$$\text{Recall} = \frac{\sum_{c \in C}^{n} |S(c) \cup G(c)|}{\sum_{c \in C}^{n} |S(c)|}. \tag{21}$$

Among them, $S(c)$ represents the list of resources recommended by the system to the learner; $G(c)$ represents the list of all resources that the learner is interested in on the test set.

In addition, in order to balance these two classification indicators, the F1 indicator metric is introduced to evaluate the quality of the recommendation method. The larger the obtained F1 value, the better the recommendation effect obtained by the recommendation method proposed in this paper. The formula for calculating the F1 value is as follows:

$$F_1 = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}. \tag{22}$$

4.3. Analysis of Experimental Results

4.3.1. Accuracy. Five experiments were carried out in the same experimental environment to compare the accuracy of personalized recommendation of ethnic music teaching resources by different methods. The results are shown in Figure 4.

From the curve trend in Figure 4, it can be seen that the three methods have good recommendation accuracy, and the accuracy is higher than 90%, but the proposed method has significant advantages. It can be seen that, in the same experimental environment, through the comparison of different recommendation methods, the proposed method can improve the ability of mining users' potential interests to a certain extent, which verifies the correctness and credibility of the proposed method, because this paper uses single learner personalization features as reinforcement features, which improves the accuracy of recommendation.

4.3.2. Recall Rate. In the same experimental environment, the recall rate of personalized recommendation of ethnic
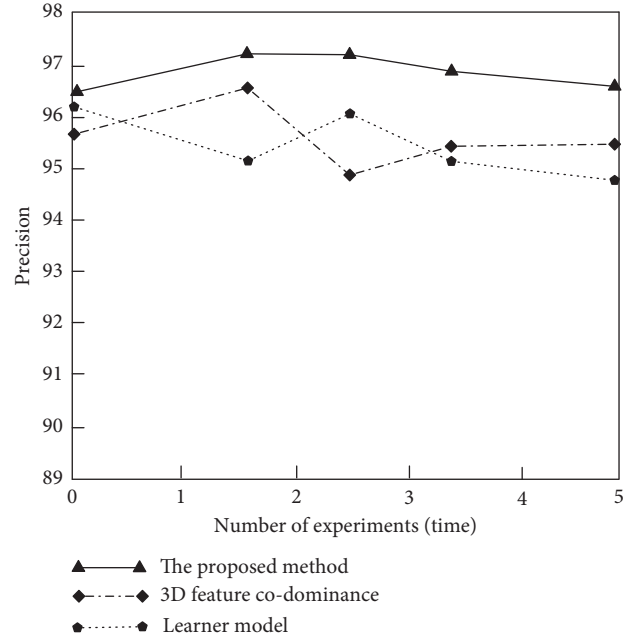

Figure 4: Comparison of recommendation accuracy of different methods.

music teaching resources of different methods is compared, and the results are shown in Figure 5.

It can be seen from Figure 5 that the recommended recall rates of the three methods during testing will not show a regular trend of changes with the increase of the number of experiments. By comparison, the recall rates of the proposed methods are higher than those of the other two methods. The highest value reached more than 97%, so it can be judged that the proposed method has the best teaching resource recommendation effect, because the method in this paper builds a tagging system based on the main characteristics of tags. At the same time, considering the decay change of user interest over time, weights are given to user video interest tags in descending order of time. And calculate the user's total interest tag vector. It makes the recommended recall rate of the method higher.

4.3.3. F1 Value. In the same experimental environment, the F1 value of personalized recommendation of ethnic music teaching resources of different methods is compared, and the results are shown in Figure 6.

From the perspective of verifying the effectiveness of the proposed method, the F1 values of different methods are compared and analyzed. After many experiments, the recommended results are the most accurate. The F1 value of the method in this paper is higher than 0.75, which is higher than the comparison of the two methods. The experimental results show that the proposed method is superior to the personalized learning resource recommendation method based on three-dimensional feature collaborative domination and the online learning resource collaborative filtering recommendation method based on learner model in accuracy, recall, and F1 value.
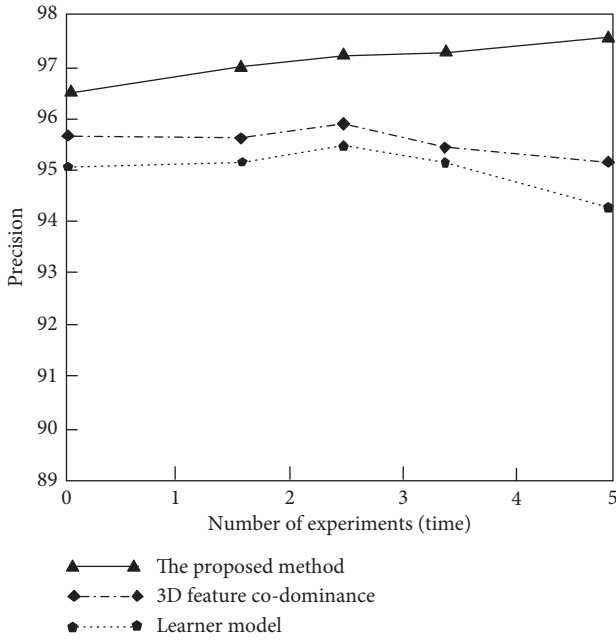
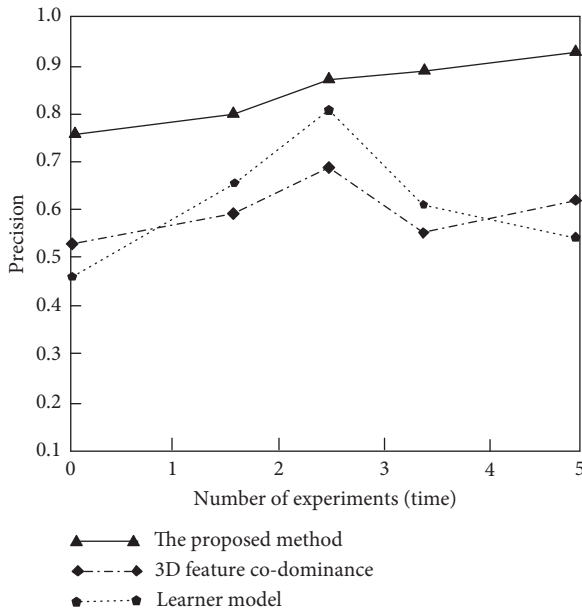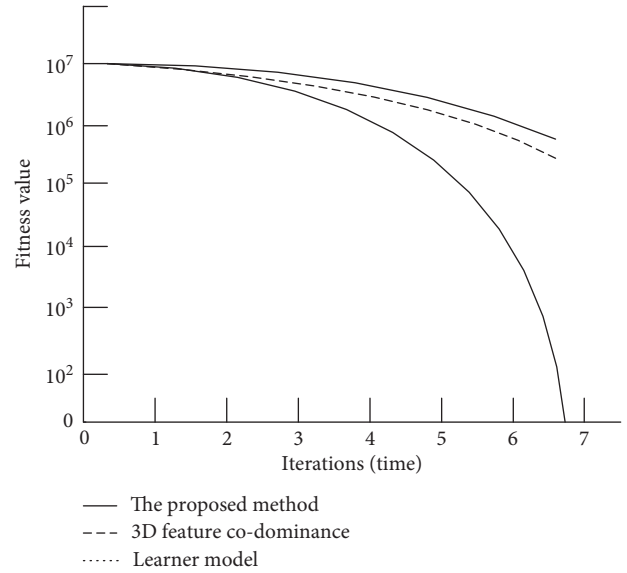Figure 5: Comparison of recommended recall rates for different methods.

Figure 7: Convergence comparison of different methods.

resources in the resource base before recommending teaching resources, the convergence of the algorithm in this paper is improved. It shows that the proposed method can accurately and quickly recommend the sequence of learning resources that meet the needs of learners when the number of learning resources and learners increases, so as to achieve the purpose of personalized learning resource recommendation.

5. Conclusion

Aiming at the problems of low accuracy, recall, and F1 value and poor convergence of traditional methods, a personalized recommendation method of ethnic music teaching resources based on video tag is proposed.

Figure 6: Comparison of F1 values of different methods.

4.3.4. Convergence Comparative Analysis. Figure 7 shows the comparison results of the convergence of different methods. It can be seen from the convergence curve that different methods have a tendency to converge.

By observing the convergence curves of different methods in Figure 7, it can be seen that the proposed method shows the best convergence speed, which shows that, with the increase of the number of iterations, the proposed method has the best adaptability. Because the method in this paper uses the KNN algorithm to classify the teaching

(1) Construct the national music teaching resource database, classify the teaching resources in the resource database by using KNN algorithm, describe the characteristics of teaching resources, and match appropriate resources for students through the above operations to meet personalized needs.

(2) The tag system is established according to the main characteristics of the tag. At the same time, the exponential attenuation constant is introduced to give the weight to the user's video interest tags in descending order of time and calculate the user's total interest tag vector. Vector space model is used to represent teaching resources and user interests, so as realize the personalized recommendation of teaching resources.

(3) The experimental results show that the accuracy of the recommended results of the proposed method is higher than 90%, the highest recall rate is more than 97%, the F1 value is larger and higher than the traditional method, and the convergence is good, which verifies the feasibility and effectiveness of this method.

(4) In the future research, this paper will continuously analyze the teacher feedback records on mobile phones to automatically optimize the content recommendation features of this method, making the recommendation results more and more accurate.

Data Availability

The author confirms that the data supporting the findings of this study are available within the article.

Conflicts of Interest

The author declares that there are no conflicts of interest.

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