Application of Human-Computer Interaction in Religious Music Resources System Based on Artificial Intelligent Powered CAD

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Abstract. The integration of religious music resources is of great significance to the inheritance of national culture and historical exploration. Collaborative filtering recommendation is a kind of artificial intelligent recommendation based on a group of users or projects with the same interests. It generates a recommendation list for target users according to the preferences of neighboring users. This paper summarizes the most representative methods available and points out their advantages and disadvantages. Then, based on CF, a model of integration and recommendation of religious music resources is proposed and constructed. Finally, the software prototype of the whole music resource integration and recommendation system is realized by using a B/S software structure. In addition, this paper introduces the control factor to comprehensively weigh the two scores of users and projects so as to get more accurate predictions and finally improve the quality of system recommendations. The results show that this algorithm has certain accuracy and superiority. To some extent, this algorithm makes up for the shortcomings of traditional recommendation methods and can provide some technical support for the integration and recommendation of religious music resources, thus promoting the development of religious music.

Keywords: Artificial intelligence; Collaborative filtering; Religious Music; Resource integration; Human-Computer Interaction
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1 INTRODUCTION

Music rejects entertainment, does not aim at competition, and is positioned as a tool to save people's spirits. Because religious music is related to human thinking on the other shore, religious music is often mysterious, dignified, and solemn. With the development and progress of society, people's aesthetic concepts and audio-visual pursuit of music are constantly developing and changing [1]. People's choice of music is increasing, which makes the music resources with religious characteristics neglected by the mainstream music culture of the society, losing the chance of survival and development. Even a few religious music resources have been dissolved in the society and disappeared into the long river of history and culture. How to protect and develop religious music resources is a very practical subject [2]. Music is an important part of ethnic music. With the development of modern society, ethnic-religious music is gradually becoming secular. One of the fundamental characteristics of music is to sing with religious beliefs as the theme. Historically, all ethnic groups in this area have kept close contact, and their rituals and sound traditions have their own characteristics and cross-flows, which contain rich cultural information [3]. Under the modern rational vision, trees, mountains, and grains, which were originally regarded as gods by ethnic minority people, are only simple material beings, so the sacredness of primitive worship formed by related materials has gradually disappeared, and various religious music formed around related worship has changed from religious music to pure music existence because of the disappearance of sacred colors of worshippers. Generally speaking, the most direct and effective way to protect religious music resources is to carry out cultural inheritance through educational means [4]. However, with the change in social demand, the educational level of religious music resources is generally not high. At present, music education in cultural education is mainly based on Western music theories, lacking attention to religious music resources. In the study of religious music, the complexity of folk beliefs is analyzed through different ways of presentation and inheritance systems of sound and sound, and the connotation and significance of its sound and sound attributes, belief in cosmology, and cultural and social values are revealed.

Strengthening the awareness of inheriting religious music culture and enriching national traditional culture are the issues that must be considered by current music teaching and music culture inheritors [5]. Therefore, the integration of religious music resources is of great significance to the inheritance of national culture and historical exploration [6]. The collaborative filtering system is the first recommendation system that has been put forward and widely used, and it is also the most widely used and successful technology among various recommendation systems at present [7]. Analyze users' hobbies, find users with the same hobbies in the user group, analyze the evaluation of related specific information by these same users, and predict the degree of interest of this specified user in this information [8]. The core idea of the collaborative filtering recommendation algorithm can be described as two steps: firstly, the similarity between users is calculated by using the feature information of users to find the nearest neighbors; Then, the evaluation of the target products by the nearest neighbors is used to predict whether the target users like the target products [9]. Based on the in-depth discussion and research of relevant literature, this paper puts forward a CF (Collaborative filtering)--based model for the integration and recommendation of religious music resources.

The innovations of this paper are as follows:

① Aiming at the sparsity and cold start of traditional CF, this paper proposes a hybrid CF based on users and projects. Based on a series of recommendations made by users or projects with the same interest, a recommendation list for target users is generated by referring to the preference information of adjacent users. It can effectively improve the quality of the system recommendation.

② Based on the music emotion classification of lyrics and audio, this paper proposes to combine lyrics classification with audio classification. At the same time, the control factor is introduced to comprehensively weigh the two scores of users and projects so as to get more accurate predictions and finally improve the quality of system recommendations.

2 RELATED WORK

In the modern environment, the secularization of ethnic and religious music is an inevitable trend in the development of modern society. The integration and development of religious music resources need to be considered from many aspects. At present, there are many scholars who study the integration and recommendation of music resources, but there are few studies on the integration of religious music resources.

Based on user ontology modeling, Kim T Y et al. calculated user preference by analyzing users' social dynamics and music-on-demand records with emotional words and established a quadruple of "user, emotion, music type, preference" [10]. This method can provide higher-quality music service items for more users with large differences in contextualized music preferences. Li G et al. classified context instances through an ontology inference engine and further inferred to obtain the user's current mood and corresponding music preference [11]. In terms of audio classification, Roy A et al. first carried out feature selection and then used the BP neural network to complete the emotional classification of music. In terms of music emotion classification that integrates lyrics and audio, the improved LFSM is used to fuse the two classification methods [12]. The experimental results show that the improved LFSM algorithm has higher accuracy than the classification algorithm based on lyrics or audio alone and the unimproved LFSM algorithm. Cai D et al. designed and implemented a multi-layer collaborative filtering music recommendation algorithm based on ontology modeling and tensor decomposition [13]. Lee K et al. proposed an automatic stress-relieving music recommendation system for music listeners [14]. The system uses a portable, wireless photoelectric recording module and a finger sensor, as well as a procedure to convert the heartbeat signal from the sensor to a stress index. Using ontology and linked data technology, Li W et al. tried to study the relationship between network open data and cataloging data in libraries by investigating the existing music resources and users' acquisition requirements for music resources. Integration strategy [15]. Shi Y et al. proposed a method that can handle sparse data efficiently. This method uses probabilistic shallow semantics to analyze the information that users are interested in on the basis of content and CF and then expresses the information as some topics; finally, it uses the full probability formula to predict the topics that users may be interested in [16]. Yao L et al., based on the user knowledge model, make full use of the user's listening behavior implicit feedback to calculate the user's preference information and obtain the user's candidate neighbor set through the improved multi-layer CF [17]. Kashani S et al. proposed a music recommendation method that integrates music sub-personality and social media behavior analysis. But, the musical sub-personality is a product of culture and art, not individualized and representative [18].

3 METHODOLOGY

3.1 Introduction of Related Theories and Technologies

Traditional recommendation systems based on music titles or singers have some defects. For example, based on the recommendation system of music titles, although music titles can often reflect the theme of music, this kind of information is incomplete and cannot fully reflect the content of music. Music titles are not a complete summary of music content. It is not enough to judge whether the user is interested or not based only on the information in the title [19]. Collaborative filtering technology makes use of the similarity between users' interests and preferences to generate recommendations, and the process of recommendation is completely automatic. That is, the recommendation results are generated by the system from users' purchasing behaviors or browsing records, and users' interest information does not need to be obtained by filling out survey forms online. It can make use of some potential information and make recommendations based on complex and difficult-to-express concepts. Collaborative filtering can be applied to complex projects, such as feelings, evaluations, art, and so on, which are difficult for computers to handle. The reason is that collaborative filtering does not calculate the attributes of an item but the user's preference for the item. The main procedures of user-based collaborative filtering and project-based collaborative filtering are as follows: firstly, the similarity between customers is calculated according to the user's history, the user's interests, and other data feedback. Then, the target customers with similarities are sorted, and the items of known users are recommended to similar users.

Using computers to manage resources requires the support of knowledge and requires the transformation from information to knowledge. However, music exists as an art that exists by sound waves shows in time, and causes various emotional reactions and emotional experiences through human auditory organs. Therefore, using a computer to express complex knowledge of music is a great challenge and has practical significance [20]. In our content-based recommendation, the recommended results are often items familiar to users. However, the recommendation based on collaborative filtering uses users' scores to calculate the similarity between users and items, so the recommendation results may be completely irrelevant information in content, thus mining users' potential interests. Association rule-based recommendation is based on association rules, which take the scored items as the rule header and the recommended objects as the rule body. Association rule mining can find the relevance of different items, and it has been widely used in e-commerce websites in the retail industry and has achieved good results. K-nearest neighbor algorithm is widely used and popular in collaborative filtering based on memory. The related technical architecture diagram is shown in Figure 1.

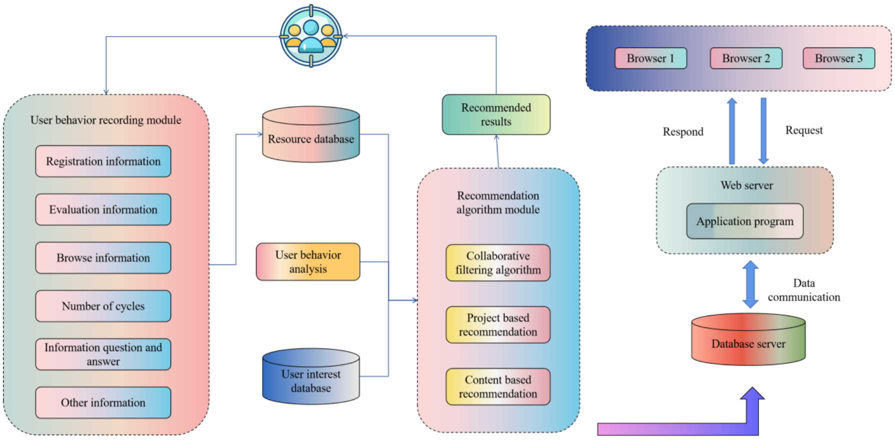

Figure 1: Recommended system and B/S architecture diagram.

The attribute information of music refers to the singer, author, and style of music. Using this information, we can cluster music, calculate the similarity of music, and then generate a recommendation list. A collaborative filtering recommendation system has no special requirements for recommended items and can handle items such as music and movies that are difficult to express in structured text [21]. At the same time, the novelty of collaborative filtering can help users predict music that they have never heard before and may be interested in. Constructing an excellent user preference prediction model is an important part of the recommendation algorithm application process. At present, many excellent models, such as the matrix decomposition model, clustering model, and Bayesian network model, are used in model-based collaborative filtering recommendation algorithms [22]. The collaborative filtering recommendation algorithm is good at mining users' new points of interest and can handle complex unstructured objects. However, there are still some problems that need to be solved in personalized recommendation systems. As a typical recommendation technology, although collaborative filtering has been widely used, it still has many problems and challenges. This paper improves the traditional CF to solve its shortcomings and then constructs the integration and recommendation model of religious music resources.

3.2 Construction of Recommendation Model for Religious Music Resources Integration

The recommendation system of this paper consists of three parts: recommendation candidate, user, and recommendation algorithm. This chapter introduces the goal, data collection method, and process of the religious music integration recommendation system, as well as the detailed architecture of the whole system. In this paper, the user project scoring matrix is established first, and the similarity between users is calculated. Then, the k nearest neighbors of active users are selected according to their similarity. Finally, the active users' ratings of projects are calculated according to the nearest neighbors' ratings of unrated projects. Before data collection, the data model needs to be determined. This paper develops a music recommendation system with the combined model. On the one hand, it needs the user's rating data as the object of CF processing, and on the other hand, it needs the feature information of music as part of content-based processing. The algorithm flow is shown in Figure 2.

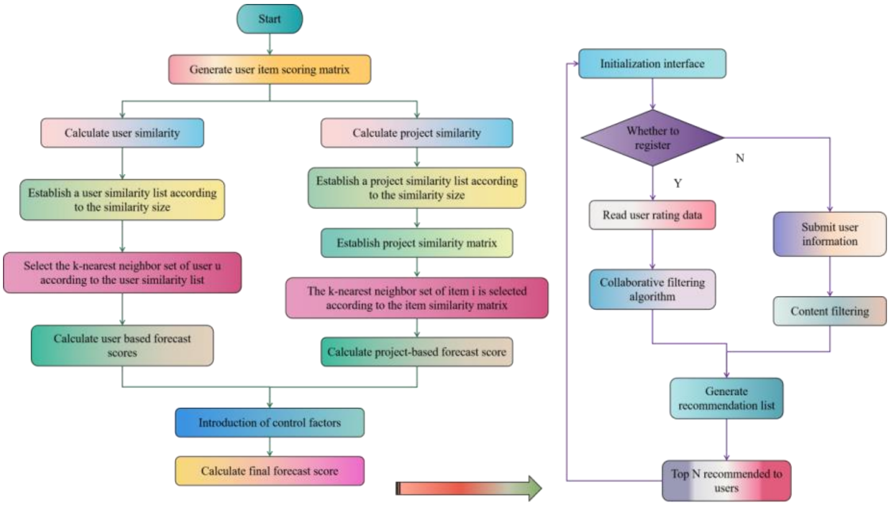

Figure 2: Flow chart of the algorithm.

There is a very close relationship between personalized search and recommendation systems. Essentially, a recommendation can be regarded as a zero-query search, and conversely, the personalized search engine can be regarded as a query-based recommendation system. If the target user adds a new score, the recommendation system should be able to select the recommended music tracks from the database in real-time. The system should be able to process the newly added scoring information with a small calculation cost. For projects, the similarity between them is much more stable. A great deal of similarity calculation can be done offline, thus reducing the online calculation and improving the recommendation efficiency.

Let C denote the set of all users and S denote all possible recommended candidates. Let u be a utility function to measure the benefit of item s to user c, namely:

$$u : C \times S \to R \tag{1}$$

Among them, R a totally ordered non-negative real number within a certain range is represented. The task of the recommender system is to find those s with the greatest benefit, as shown in the formula:

$$\forall c \in C, s'_c = \arg\max_{s \in S} u\ c, s \tag{2}$$

For any user u, denoting the predicted score of the item c by $\tilde{r}_{u,c}$, then:

$$\tilde{r}_{u,c} = \bar{r}_u + k \sum_{u' | u' \neq u, u' \in U} w_{u,u'} \times r_{u',c} - \bar{r}_{u'} \tag{3}$$

Among them, $w_{u,u'}$ represents the similarity between user u and u'; $\bar{r}_u$ represents the average rating value of user u; k represents the normalization factor. From the perspective of probability theory, find the expected value of the target user's unrated items:

$$\tilde{r}_{u,c} = E\left(r \middle| u,c\right) = \sum_r r \times p\left(r \middle| u,c\right) \tag{4}$$

Among them, r is the value of all possible scores; $p\left(r \middle| u,c\right)$ is the conditional probability of the value of r when user u and item c appear at the same time.

The similarity calculation method is used to calculate the similarity between users. For the user-item rating matrix, the similarity calculation is performed between rows. That is, the correlation between two-row vectors is calculated. Function means that the function value of the same parameter is uniquely determined, while the inverse function is the opposite. If an attribute is transitive, then its inverse attribute is transitive. Transitivity and functionality are incompatible. If an object property is transitive, it can't be functional. After getting the user's favorite list, it needs to be converted into scoring data. Considering that the user's interest decays with time, this paper defines the scores of different songs according to the time when the favorite songs are marked. In the standard cosine similarity calculation method, the biggest defect is that the user's rating scale is not considered. Each user's evaluation scale is different. Some users are very strict and tend to give low scores, while others are relatively loose and tend to give high scores. Therefore, we revised the standard cosine similarity.

Suppose that the set jointly scored by user u and user v is denoted by I_c, and I_u and I_v denote the set of items scored by user u and user v, respectively; then the similarity $Sim(u,v)$ between user u and user v is:

$$Sim(u,v) = \frac{\sum_{i \in I_c} \left(R_{u,i} - \bar{R}_u\right)\left(R_{v,i} - \bar{R}_v\right)}{\sqrt{\sum_{j \in I_u} \left(R_{u,j} - \bar{R}_u\right)^2} \sqrt{\sum_{j \in I_v} \left(R_{v,j} - \bar{R}_v\right)^2}} \tag{5}$$

Among them, $R_{u,i}$ represents the rating of the item i by the user u, $\bar{R}_u$ and $\bar{R}_v$ represent the average rating of the item by the user u and user v, respectively; I_c represents the set of items jointly scored by the user u and user v, and I_u represents the set of items scored by the user u, I_v represents the set of items that user v has rated. Pearson similarity is a similarity measure based on correlation coefficients. Pearson similarity is expressed as:

$$Sim(u,v) = \frac{\sum_{k=1}^{K} \left(R_{u,k} - \bar{R}_u\right)\left(R_{v,k} - \bar{R}_j\right)}{\sqrt{\sum_{k=1}^{K} \left(R_{u,k} - \bar{R}_u\right)^2} \sqrt{\sum_{k=1}^{K} \left(R_{v,k} - \bar{R}_j\right)^2}} \tag{6}$$

Among them, $R_{u,k}$ and $R_{v,k}$ represent the ratings of user u and user v on item k, respectively, $\bar{R}_u$ and $\bar{R}_v$ represent the average rating of user u and user v on the jointly rated items, respectively; K is the number of repeated reviews by user u and user v.

In the same type of music, the user u's preference for the unmarked music n is calculated using the music m that has been marked with preference. First calculate the similarity between music m and music n, as shown in the following formula:

$$Sim\ m,n\ = \frac{\vec{m} * \vec{n}}{\left\|\vec{m}\right\|\left\|\vec{n}\right\|} \tag{7}$$

Set the similarity threshold s, and take the music whose similarity value is greater than the threshold s as the nearest neighbor of music n; s_n represents the nearest neighbor music set of music n. Use the following formula to predict the preference P of music j:

$$P_{u,j} = \frac{\sum_{m \in s_n} Sim\ m,n\ * P_{u,n}}{\sum_{m \in s_n} Sim\ m,n} \tag{8}$$

Finally, among this kind of music, the music with the top ten preference degrees is arranged in the recommendation list from front to back according to the preference degree.

In this paper, we use MSE (Mean squared error), RMSE (Root mean square error) and MAE (Mean absolute error) as measurement standards. MAE, as one of the statistical accuracy measurement methods, can directly measure the quality of recommendation results. It is the most commonly used measure of recommended quality, and RMSE and MSE can be used as numerical indicators to measure the accuracy of the measurement. Assuming that the predicted user score set is $p_1, p_2, p_3, \ldots, p_n$ and the corresponding actual score set is $q_1, q_2, q_3, \ldots, q_n$, the calculation formulas of each indicator are as follows:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}\ p_i - q_i\ ^2 \tag{9}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left|p_i - q_i\right|^2} \tag{10}$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|p_i - q_i\right| \tag{11}$$

Using user-based CF can make accurate recommendations when the data set is complete, the similarity algorithm is reliable, and it can avoid the differences in project content for an accurate recommendation. Be able to explore project relationships and user preferences implicitly and transparently. Most of the data are captured from music websites, and the data to be captured include user data, song data, and user rating data on songs. By entering the user interface, you can get the user's basic information, user ID, user name, etc., and get the user's favorite songs. This paper gives different scores to different songs according to the time sequence of users' favorite songs.

4 RESULT ANALYSIS AND DISCUSSION

The experimental data set of this paper comes from the Million Song Dataset. The number of times that 2000 users played 1000 pieces of music was randomly selected as the experimental data set. Each user played at least 50 pieces of music more than once. Because the number of times a user plays music is the implicit score of the user, in order to apply the data set in CF, this paper converts it into the user's display score of the music in a certain way. In order to show the sparsity of the experimental data set, I introduce the concept of sparsity level in this chapter, which is used to show the percentage of unrated items in the data set, and the sparsity is 0.921. In this paper, Python language is used to write related programs, and the software operating environment is Windows. Figure 3 shows the system's stability test results.

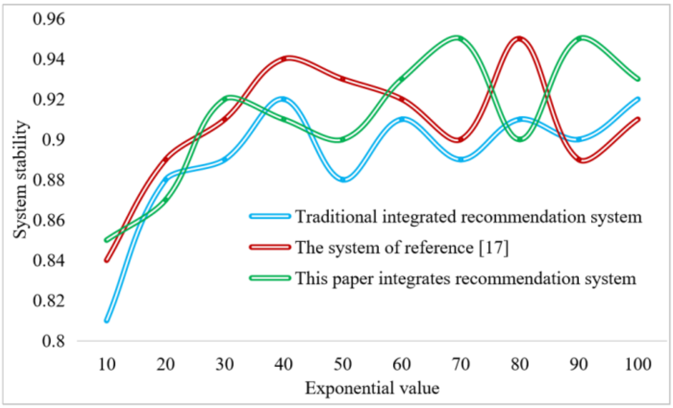

Figure 3: System stability test results.

Generally speaking, the stability of this system is good. After preprocessing the original data set, we get the user-music score data set and further divide the data set into training set and testing set, with a ratio of 8:2. Table 1 shows the results of user rating.

System	*Satisfaction with system use (%)*	*Music recommendation satisfaction (%)*
Traditional music integration recommendation system	*82.5*	*79.8*
The system of reference [15]	*89.3*	*88.7*
The system of reference [17]	*91.2*	*90.3*
The music integration recommendation system in this paper	*94.3*	*96.1*

Table 1: User rating results.

An important part of the algorithm recommendation experiment is to choose and set reasonable experimental standards. If we want to detect the performance of the algorithm well, we must have a reliable evaluation standard. With a reliable evaluation standard, we can also detect the areas to be corrected in the recommended algorithm. The MSE, RMSE, and MAE indexes selected above were tested. The experimental results of MSE are shown in Figure 4. The experimental results of RMSE are shown in Figure 5. The results of the MAE experiment are shown in Figure 6.

In order to make the experimental results more reliable, this chapter tests the RMSE of different algorithms 10 times, and the test results are shown in Table 2. From the experimental data, it can be found that the traditional CF and SVD-based CF are not as effective as the improved CF in this paper. The reason may be that the data of known scores are too few, which leads to the sparseness of the whole score matrix. The SVD decomposition method can't effectively reflect the internal structural characteristics of the matrix. The recommendation accuracy results of different algorithms are shown in Figure 7.

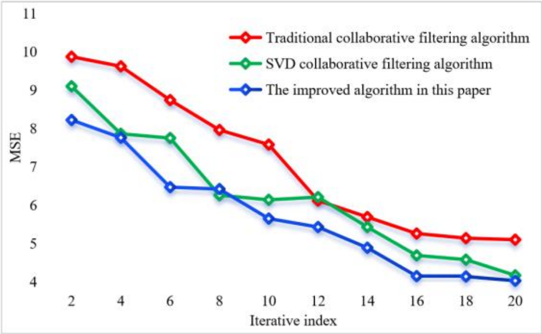

Figure 4: MSE experimental results.

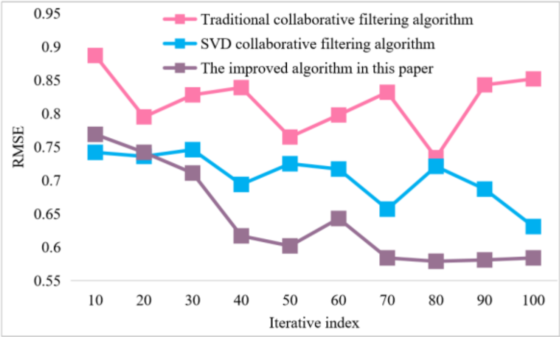

Figure 5: RMSE experimental results.

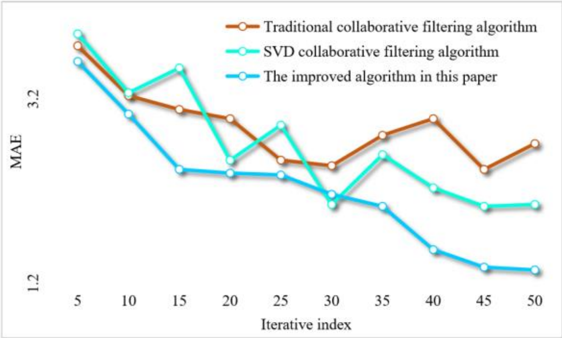

Figure 6: MAE experimental results.

Number of experiments	*Recommendation algorithm based on traditional collaborative filtering*	*Recommendation algorithm based on SVD collaborative filtering*	*An improved collaborative filtering recommendation algorithm in this paper*

1	*0.864*	*0.751*	*0.613*
2	*0.874*	*0.716*	*0.641*
3	*0.881*	*0.742*	*0.605*
4	*0.879*	*0.721*	*0.613*
5	*0.864*	*0.711*	*0.601*
6	*0.871*	*0.702*	*0.587*
7	*0.852*	*0.698*	*0.596*
8	*0.856*	*0.703*	*0.584*
9	*0.861*	*0.715*	*0.603*
10	*0.857*	*0.687*	*0.591*

Table 2: RMSE results of different algorithms.

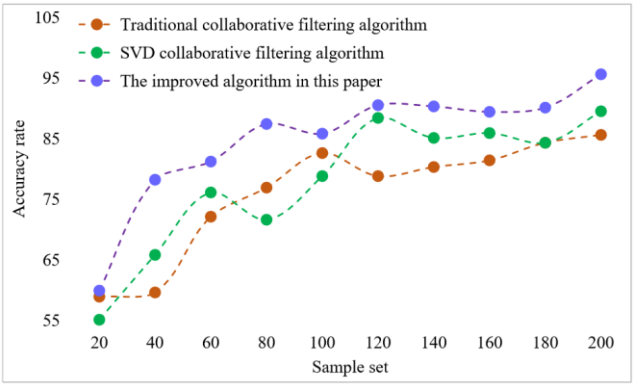

Figure 7 Recommendation accuracy results of the algorithm.

It can be seen that the algorithm in this paper has the highest recommendation accuracy compared to recommendation accuracy.

The experimental results show that the accuracy of religious music recommendations can reach 95.64%. The accuracy is 6.12% higher than that based on SVD CF and 9.97% higher than that of traditional CF. To some extent, this algorithm makes up for the shortcomings of traditional recommendation methods, and it can still achieve a good recommendation implementation even when the data is extremely sparse.

5 CONCLUSIONS

Only when we truly understand the inherent meaning of the religious music inheritance can these cultural treasures be truly respected and valued, and the excellent traditional culture can be carried forward So as to promote the religious identity among all ethnic groups and promote the great cultural development. Therefore, integrating religious music resources is of great significance to the inheritance of national culture and historical exploration. This paper proposes a CF-based model for integrating and recommending religious music resources. Based on the music emotion classification of lyrics and audio, this paper proposes to combine lyrics classification with audio classification. At the same time, the control factor is introduced to comprehensively weigh the two scores of users and projects so as to get more accurate predictions and finally improve the quality of system recommendations. Through experiments, it is found that the accuracy of this algorithm in recommending religious music can reach 95.64%. The accuracy is 6.12% higher than that based on SVD CF and 9.97% higher than that of traditional CF. The research in this paper has obviously achieved some good results, but there are still some problems that need to be improved.

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