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A study on the recommendation method of intelligent media learning resources in the foreign communication and teaching of international communication of Chinese central plains culture

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Abstract—Today, with the development of intelligent media, the foreign communication and teaching activities of the Chinese central plains culture should actively seek experiences that can be learned from, establish a multi-channel foreign communication mode, and then promote the Chinese central plains culture to go out of the country and into the world better. The study improves the collaborative filtering recommendation algorithm and the joint matrix decomposition algorithm based on the theory of migration learning, aiming to improve the learning to optimize the resource recommendation system by calculating the user similarity and establishing the user preference-resource feature matrix. The experimental results show that the average absolute error and root mean square error of the improved algorithms are lower than those of other algorithms, proving that the optimized algorithms improve the accuracy and efficiency of resource recommendation in the foreign communication and teaching activities of the Chinese central plains culture while operating stably and with wide applicability on the recommendation system.

Keywords—Chinese central plains culture, Collaborative filtering algorithm, Foreign communication, Migration learning, TOP-N, Web resources

I. INTRODUCTION

THE Chinese central plains culture is the source of traditional Chinese culture. With the development of global information digitization, the traditional means of cultural communication have gradually moved towards a fast, efficient, and diverse way of integrated communication, and the international exchange of culture has become more and more frequent. In this context, with the unique cultural advantages of Henan, it is the main task to build the brand of Chinese central plains culture, tell the story of Chinese central plains culture, and enhance the cultural soft power of Henan and even China, [1]. At present, the dissemination of the Chinese central plains culture to the outside world has achieved some success, but it still faces many external and internal challenges. The dissemination of cultural resources at this stage cannot be achieved without the interaction of the Internet, and the dissemination of Chinese central plains culture on intelligent media requires scientific theoretical, and technical support. Using the characteristics of smart media that are subject to many, widespread, and mobile, it is necessary to create multi-angle and multi-window cultural communication channels, so that smart media can truly become a gas pedal of cultural communication. Domestic and international research on ubiquitous learning has yielded considerable results, prompting educational theories and teaching evaluations to push forward while requiring further optimization of internet platform design and information resource pushing, [2]. The disadvantage of these recommendation methods is that with the explosive growth of learning users and online resources, the quality and applicability of the recommended resources to learners are getting lower and lower, and the stagnation and backwardness of teaching theory and learning resource recommendation methods will become a hindrance to cultural foreign exchange and economic development models, [3]. Therefore, the study explores the direction of resource recommendation and optimizes the migration learning recommendation algorithm with Cross-Collectiont Matrix Factorization (C-CMF) to improve the data processing performance of the recommendation system while recommending resources according to users' interests and improving the recommendation accuracy. The purpose of this study is to strengthen the communication between countries along the " Belt and Road" in the fields of language, culture, and education, and open a convenient channel for China's long history and culture to go abroad.

II. The Personalized Recommendation of Chinese Central Plains Cultural Resources in Communication and Teaching Activities

A. Theory of the Value of Intelligent Communication of the Teaching and Cultural Resources of the Chinese Central Plains Culture to the Outside World

Chinese central plains culture has gradually become the backbone of Chinese culture due to its strong inclusiveness, long history, and diverse content. It is an important link in the construction of "One Belt, One Road", and cultural exchange has become an important communication base in China's economic exchange activities, [4]. At the present stage, the dissemination of Chinese central plains culture to the outside world mainly relies on two main actors, namely the academy and the enterprise, [5]. However, both of them, as the backbone of the communication of Chinese central plains culture, still face difficulties and challenges in foreign communication. The difficulties and ways of teaching and disseminating the culture of the Central Plains to the outside world are shown in Fig. 1.

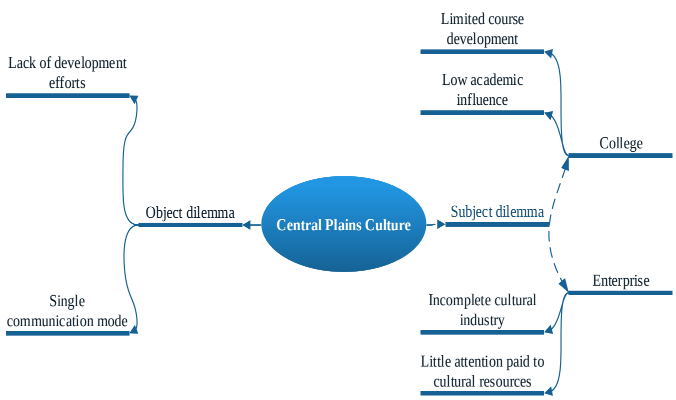

Figure 1. Difficulties and ways of teaching and spreading central plains cultural resources to foreign countries

As shown in Fig. 1, the primary reason for the difficulties in the external communication and external teaching activities of the Chinese language and culture is the lack of development and excavation of the Chinese central plains culture in the country, and the rich historical and cultural resources are difficult to show their vitality and value influence role in the external communication. Secondly, it is due to the single mode of communication and the homogeneity of the content of the Chinese central plains culture. The multimodal mode of communication of the Central Plains culture not only has a deeper demand for content but also has higher requirements for the influence of social media application channels in social consumption, [6]. Finally, the failure to develop the backbone of academies and enterprises is one of the major difficulties in the external communication of Chinese central plains culture. To address the challenges facing the external communication of Chinese central plains culture, the study explores the use of online resources in the external communication of Chinese central plains culture from the perspective of smart media applications and in the external teaching activities of Chinese central plains culture from the perspective of the academy, [7]. A variety of cultural resources exist in modern smart media and social software, and an intelligent cultural resource recommendation method constructed through machine learning is shown in Fig. 2.

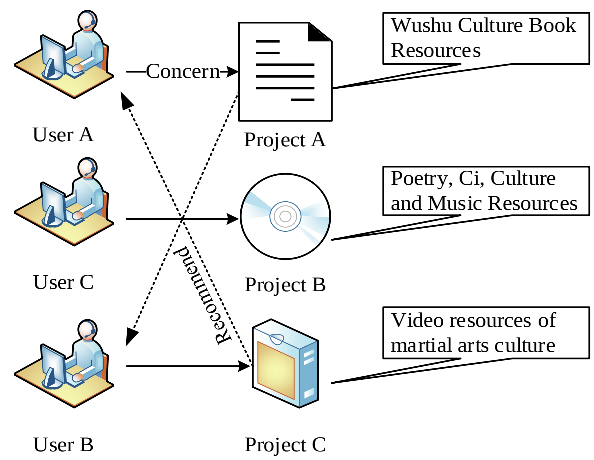

Figure 2. Recommendation method of intelligent cultural resources constructed by machine learning

As shown in Fig. 2, the main idea of the personalised recommendation approach based on machine learning is to use attributes to analyse the connection between users and items, to build a personalised recommendation model, to predict the user's rating of a new item by the model, and to personalise the recommendation to the user based on the model's predictions. These attributes represent potential characteristics of users and items in the system such as the type of item the user prefers. Personalised recommendation methods based on machine learning have outstanding advantages in characterising the underlying factors of user preferences. Finally, the evaluation metrics for recommender systems rely on the rating prediction problem and the Top-N recommendation problem, [8]. In the former, Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) are the main calculations, and their formulas are expressed as Equation (1).

$$\begin{cases} MAE = \dfrac{\sum_{u,i\in N}\left|r_{ui}-p_{ui}\right|}{|N|} \\ RMSE = \sqrt{\dfrac{\sum_{u,i\in N}\left|r_{ui}-p_{ui}\right|^2}{|N|}} \end{cases} \tag{1}$$

In Equation (1), is the user, is the resource item, u i N is the number of items in the resource set, r_{ui} is the user's actual rating of the resource item, and p_{ui} is the user's predicted rating of the resource item. Meanwhile, the evaluation of the recommendation method through the Top-N recommendation problem is mainly done by the accuracy, recall, and F1 values, which are calculated as shown in Equation (2).

$$\begin{cases} ACC = \dfrac{\sum_{u\in U} |R(u) \cap T(u)|}{\sum_{u\in U} |R(u)|} \\ \mathrm{Re} = \dfrac{\sum_{u\in U} |R(u) \cap T(u)|}{\sum_{u\in U} |T(u)|} \\ f1 = \dfrac{2 \times ACC \times \mathrm{Re}}{ACC + \mathrm{Re}} \end{cases} \tag{2}$$

Equation (2), U represents the set of users, $R(u)$ represents the list of recommendations provided to users based on the model predictions, and $T(u)$ represents the real list of recommendations from users.

B. User-Based Collaborative Filtering for Optimal Recommendation of Chinese Central Plains Culture

The promotion of Chinese central plains culture in countries along the Belt and Road through foreign teaching and intelligent media resource dissemination is not only of cultural strategic importance but also an effective contribution to the economic development of both countries. The research applies collaborative filtering recommendation algorithms based on users and migration learning algorithms based on resource items to recommend resources for the culture of the Middle Kingdom. User interests and preferences are mined from historical user information data, and the information mined is used to classify resources more effectively to meet learners' personalised resource requirements. The basic principle of transfer learning is to apply the experience gained from machine learning and training in the data domain of supplementary learning to the target domain of user data, [9]. Transfer learning algorithms that make use of the learning experience in the secondary domain can not only solve the problem of lack of data in the target domain but also improve the performance of the learning model. The user-based collaborative filtering recommendation algorithm uses user similarity information to integrate multiple users and predicts individual users' ratings of resource items based on the average ratings of the user set, and then recommends several items with the highest predicted ratings for individual users, with the similarity formula shown in Equation (3).

$$sim(a,b) = \frac{\sum_{X\in I_{ab}} \left(R_{b,X} - \bar{R}_b\right)\left(R_{b,X} - \bar{R}_a\right)}{\sqrt{\sum_{X\in I_{ab}} \left(R_{b,X} - \bar{R}_b\right)^2 \cdot \sqrt{\sum_{k\in I_{ab}} \left(R_{b,X} - \bar{R}_a\right)^2}}} \tag{3}$$

Equation (3), $sim(a,b)$ is the similarity between user a and user, b I_a and I_b represent the set of items rated by user a and user b , $I_{ab} = I_a \cap I_b$, indicates that $R_{a,X}$ and $R_{b,X}$ are the ratings of resource items by user X a and user, b $\bar{R}_a$ and $\bar{R}_b$ represent the average ratings of resources by user a and user b . The formula is then calculated using the cosine similarity algorithm as shown in Equation (4).

$$sim(a,b) = \frac{\vec{a} \cdot \vec{b}}{\|\vec{a}\| \cdot \|\vec{b}\|} = \cos(\vec{a}, \vec{b}) \tag{4}$$

Equation (4), $\vec{a}, \vec{b}$ is the rating vector of the user a and the user b . Since the collaborative filtering recommendation algorithm computing process utilizes a large amount of historical data and relies too much on the similarity between users and users, it is difficult to incorporate new resources with few ratings into the recommendation system, so the accuracy of the collaborative filtering algorithm recommendation decreases while new users good new resources keep increasing, and there is the problem of cold start and data sparsity [10]. Therefore, the study introduces Radial Basis Function (RBF) neural network to optimize the collaborative filtering algorithm, where the similarity algorithm optimization formula is shown in Equation (5).

$$sim'(I_a, I_b) = sim(I_a, I_b) \times \frac{|U_a \cap U_b|}{|U_a \cup U_b|} \tag{5}$$

In Equation (5), I_a and I_b are the sets of items rated by user a and user b , and U_a are the sets of users with similar ratings to user a and user b respectively. The optimization formula introduces the a proportion of commonly rated users to the total number of the two sets based on the original similarity calculation formula, which improves the applicability and accuracy of the similarity calculation.

After defining the target user a , calculate the set of its neighboring users, randomly select the user b in the set, build an RBF neural network evaluation model based on its evaluation set, bring the evaluation data of the user into the training model, and finally recommend the predicted scores of the items through the neighboring set, with the formula shown in Equation (6), [11].

$$P_{a,i} = \frac{\sum_{b\in U} \left(R_{b,i} - \bar{R}_b\right) \cdot Sim(a,b)}{\sum_{b\in U} Sim(a,b)} + \bar{R}_a \tag{6}$$

Equation (6), $P_{a,i}$ represents the predicted rating of the item i by the user a , $R_{b,i}$ represents the rating of the item i by the user b , $Sim(a,b)$ represents the similarity between the user a and the user, and b $\bar{R}_a$ $\bar{R}_b$ the average ratings of all rating actions of the user a and the user b .

C. Intelligent Media Resource Recommendation Design Based on Improved CMF Algorithm

The existing resource recommendation algorithms include recommendation methods for clustering rules and association rules, as well as content-based recommendation methods and mixed-use recommendation methods. Because of the fuzzy clustering problem, the accuracy of the recommendation of clustering rules is not high. The recommended method of association rules requires manual topping of recommendation rules, which is difficult to ensure progress and also increases the workload of management platform personnel. The problem with content recommendation is that it is difficult to distinguish the style and quality of the resource content, so personalized and interesting recommendations cannot be carried out, and the mixed recommendation method needs a lot of work to get the correct balance. The core of the collaborative filtering algorithm is the collection of information based on user similarity, but there is a lack of information about the characteristics of resource items for classification. The study introduces the Collection Matrix Factorization (CMF) algorithm based on the Transfer Collections Factorization (TCF). Due to the similarity of evaluation behaviour of the same user for the same resource item at different numerical ratings, the study introduces the resource features of shared auxiliary data and updates the parameter rules of the CMF algorithm, so that the new recommendation system has the advantages of both the collaborative filtering algorithm for shared user features and the CMF for shared resource item features, [12]. The study uses numerical scores as the target domain and binary scores as the auxiliary training domain, and the expressions of both feature matrices are shown in Equation (7).

$$\begin{cases} R \sim UV^T, \tilde{R} \sim WV^T \\ E = \tilde{E} \end{cases} \tag{7}$$

In Equation (5) $R \sim UV^T$ and $\tilde{R} \sim WV^T$ correspond to the resource rating matrix of the target domain and the resource rating matrix of the auxiliary domain, respectively, U and W represent the corresponding user feature matrices, V^T is the resource item feature matrix, and E $\tilde{E}$ represent the error of both data because of the similarity of users' evaluation behaviour when rating the same resource item at different values as a basis for predicting user preferences. Based on the nature of the shared characteristics of the target and auxiliary resources, the stochastic gradient descent method was used to optimise the formula, as shown in Equation (8).

$$\nabla V_i = -e_{ui}\left[\rho U_{u.} + (1-\rho) W_{u.}\right] + aV_{i.} \tag{8}$$

In Equation (8), V_i is the feature matrix of the resource item i, e_{ui} is the error of missing scores in the target field and auxiliary data of the item i, $U_{u.}$ and $W_{u.}$ are the user matrix features of the target and auxiliary resources respectively, ρ is the parameter of linear integration of the two gradients, $0 < \rho < 1$. Finally, the following Equation (9) is obtained using the auxiliary binary scores and the target resource scores.

$$y_{ui} = 1 \begin{cases} \nabla b_u = -e_{ui} + \beta b_u \\ \nabla b_i = -e_{ui} + \beta b_i \\ \nabla U_u = -e_{ui} V_i + a_u U_u \\ \nabla V_i = -e_{ui} Z_u + a_v V_i \end{cases} \tag{9}$$

$$\tilde{y}_{ui} = 1 \begin{cases} \nabla V_i = -\lambda \tilde{e}_{ui} \tilde{Z}_u + \lambda a_v V_i \\ \nabla W_u = -\lambda \tilde{e}_{ui} V_i + \lambda a_w W_u \end{cases}$$

In Equation (9), y_{ui} $\tilde{y}_{ui}$ represent the target learning resource rating and the auxiliary binary rating respectively, b_u and b_i represent the bias of the user u and the item i, V_i is the feature matrix of the resource item, and i U_u W_u represent the user matrix features of the target resource and the auxiliary resource respectively, where $Z_u = \rho U_u + (1-\rho) W_u$, $\tilde{Z}_u = \rho W_u + (1-\rho) U_u$. Through the proposed migration learning and collaborative filtering methods constructed above, the study also designed a Zhongyuan cultural resource recommendation system for Chinese language and culture teaching, using mobile phone APP software to introduce the representative cultural resources of Zhongyuan, such as the history of China's Yellow River basin, Chinese character culture, Shaolin martial arts culture and poetry artworks, to foreign learners and foreign media users through resource recommendation. The specific framework is shown in Fig. 3.

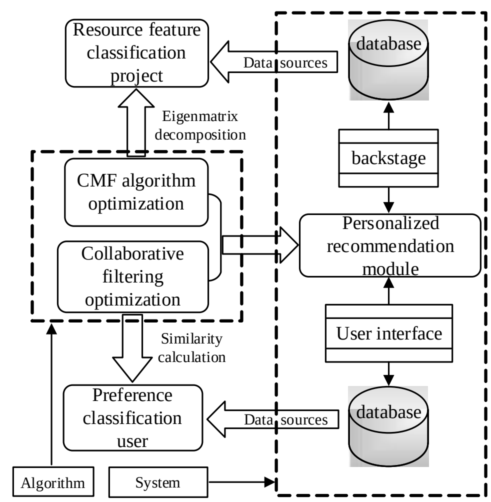

Figure 3. Module design of recommendation system based on the optimization algorithm

As can be seen in Fig. 3, the learning resource recommendation system is optimised for collaborative filtering recommendations and migration learning algorithms by using RBF neural networks to improve the construction of user feature sets and user similarity calculation methods, while the C-CMF algorithm is used to build a resource item feature matrix that combines and shares user interest features and resource features. In this model, the database is the core part to store data such as user data, resource data, and user communication

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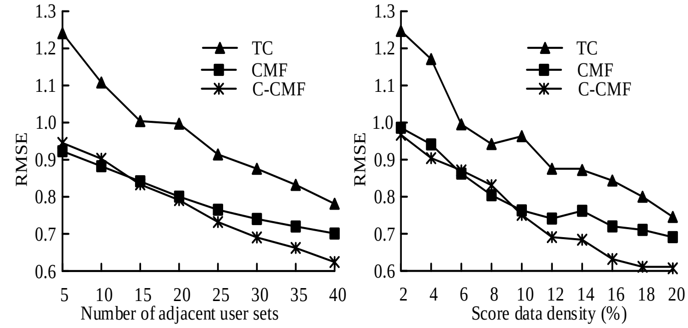
information. The personalised recommendation module is the core component of the system service, which records users' learning behavior and analyses their evaluation behavior. It not only accelerates the efficiency of user learning but also improves the overall utilization of learning resources within the system. The user interface is the user-oriented functional interface of the ubiquitous learning recommendation system, including user personal information management, user communication channels, resource classification interface, etc. The background management module is an important component of system configuration and maintenance and user account management. The administrator can supplement and classify learning resources according to user needs, and also regulate and manage user communication information. Through the four modules, users can rate the resources in the system. The system uses the CMF algorithm to construct a matrix model of user ratings and resource types based on the ratings, after which the system performs similarity calculations on users who need resource recommendations, finds a collection of users with highly overlapping interests and preferences with the target users and finally recommends several resource items with the highest ratings from the user collection to the target users. By giving full play to the subjective initiative of foreign Chinese language teaching workers, the beauty of the Chinese central plains culture can be fully explored, and while spreading the beautiful image of China, it can also be actively integrated into local cultural exchanges and economic construction activities.

III. Recommended System Performance Analysis Experiments

A. Simulation Experiments for the Recommendation System Scoring Prediction Problem

To verify the performance of the resource recommendation algorithm, the study is used here to evaluate the performance of the recommendation model using both mean absolute error (MAE) and root mean square error (RMSE) data. The data used for the experiments is an experimental analysis using the publicly available resource recommendation dataset Wikipedia to obtain the difference in the accuracy of the recommendation system under different influencing factors. The data set Wikipedia is a collaborative encyclopedia written by Wikipedia users. It provides each user with a data dump of each article and each edit. The data set has been widely used in social network analysis, graphics and database implementation testing, and Wikipedia user behavior research. A control factor of 0.2 was used to compare the MAE of the traditional collaborative filtering, the traditional CMF algorithm, and the C-CMF algorithm, and the results are shown in Fig. 4.

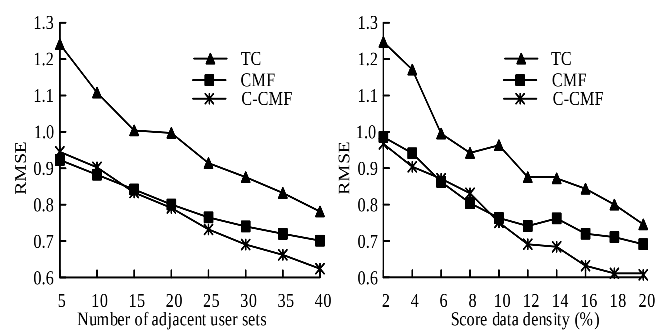


(a)The influence of the number of neighboring user sets on the recommendation algorithm MSE

(b)Influence of score density on recommendation algorithm MSE

Figure 4. Line graph of the mean absolute error for different algorithms

From Fig. 4(a), it can be learned that when the number of set influence factors neighboring the set of users is increased from 5 to 40, the MAE of the traditional collaborative filtering decreases from 0.85 to 0.64, the MAE of the unoptimized CMF algorithm decreases from 0.89 to 0.54, and the MAE of the optimized C-CMF recommendation algorithm decreases from 0.64 to 0.41, and at the set number of 10, the maximum average The absolute error was 0.67. All three algorithms showed an overall decreasing trend in the mean absolute error as the set of users increased, but the optimized C-CMF algorithm had significantly smaller errors, indicating that the optimized algorithm was more accurate and had better performance. As can be seen from Fig. 4(b), when the density of the set influence factor scoring data increases from 2% to 20%, the MAE fold of the traditional collaborative filtering shows an overall decreasing trend, from a maximum error of 0.88 at 2% density to 0.55 at 20% density, while the error of the traditional migration learning CMF algorithm decreases from 0.76 to 0.52, and the error of the optimized C-CMF algorithm decreases from a maximum The root mean square error calculation experiments of the three algorithms were conducted simultaneously with a crossover factor of 0.2 and 100 iterations of gradient descent, and the experimental results are shown in Fig. 5.



(a)The influence of the number of neighboring user sets on the recommendation algorithm RMSE

(b)Influence of score density on recommendation algorithm RMSE

Figure 5. Root mean square error line graph for different algorithms

In Fig. 5(a), the number of user sets in the vicinity of the influencing factor is set to increase from 5 to 40, and all three algorithms have the highest RMSE for 5 user sets and the lowest RMSE for 40 user sets. The overall RMSE of the traditional collaborative filtering algorithm was greater than that of the CMF and C-CMF recommendation algorithms, ranging from a maximum error of 1.241 to a minimum error of 0.781. The difference between the RMSEs of the CMF and C-CMF algorithms is small when the set of users is within 20, with a maximum difference of 0.022 between the two. As can be seen in Fig. 5(b), the RMSEs of the three recommendation algorithms show an overall decreasing trend when the density of the set influence factor scores is increased from 2% to 20%, with the maximum error of 1.247 at 2% density decreasing to 0.745 at 20% density for the traditional collaborative filtering and from 0.986 to 0.691 for the traditional migration learning CMF algorithm. The experimental results show that the accuracy performance of the C-CMF recommendation algorithm is optimal for both the number of user sets and the rating density.

B. Simulation experimental analysis for the recommendation system scoring TOP-N problem

Meanwhile, to verify the performance of the TOP-N problem of the recommendation method proposed in the study, resource recommendations were performed on the same Wikipedia dataset to test the best recommendation accuracy and recommendation recall of different algorithms for the different maximum number of items, and the specific experimental results are shown in Fig. 6.

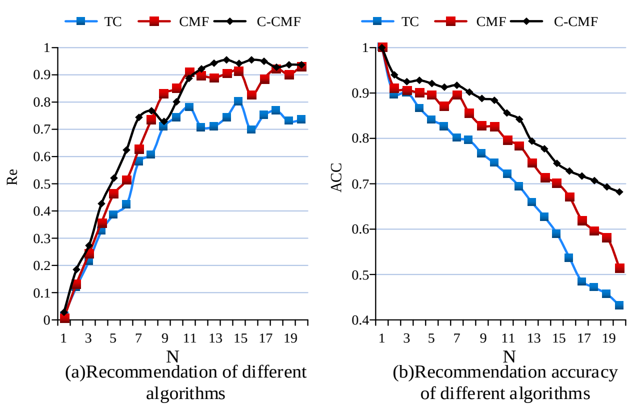


Figure 6. Comparison of precision value and recall rate of different recommendation algorithms

As a whole, from Fig. 6, when the recommendation algorithm performs Top-N personalized recommendation, N takes different values, resulting in different accuracy recall rates and different trends. Among them, the recommendation accuracy rate will decrease with the increase of the N value, but the recall rate will increase with the increase of the N value. It can be seen from Fig. 6 (a) that the average recommended recall rate of the traditional collaborative filtering algorithm is 0.578 under the number of 1-20 items. At the same time, the recall rate of the algorithm can only rise and fall between 0.7-0.8 after the number of recommended items is more than 9. The CMF algorithm has an average recall rate of 0.687 under the same conditions. When the recommended items are more than 11, the RE value tends to be stable, but it is generally lower than the algorithm built in the study. The average recall rate of the algorithm built in this study is the highest, with a value of 0.7228. At the same time, when the number of recommended items is more than 13, the RE value is still stable above 0.9. From Fig. 6 (b), we can compare the recommendation accuracy of the three algorithms under different project quantities. The average accuracy of the traditional collaborative filtering algorithm, CMF, and the optimized C-CMF algorithm are 0.705, 0.781, and 0.838, respectively. With the increase in the number of recommended items, the recommendation accuracy of the traditional algorithm decreases the fastest, while the CMF algorithm is the second. When the number of recommended items is 20, the accuracy of the algorithm proposed in this study is still higher than 0.65. The accuracy rate of personalized recommendation reflects how many items of the Central Plains cultural resources recommended to users are in the user's real recommendation list, while the recommendation recall rate reflects how many items of the cultural resources that users like are retrieved. This often leads to the contradiction between the accuracy rate and the recall rate, that is, the high accuracy rate of the recommendation and the low recall rate. Therefore, in order to balance the impact of the accuracy rate and the recall rate, this experiment further calculates the F1 value of personalized recommendation. The higher the value, the better the personalized recommendation result. The specific experimental results are shown in Table I.

Table I. F1 comparison of different recommended algorithms

Top-n	1	2	3	4	5	6	7	8	9	10
C-CMF	0.054	0.309	0.422	0.585	0.666	0.741	0.821	0.830	0.801	0.840
CMF	0.014	0.232	0.383	0.512	0.610	0.646	0.738	0.791	0.829	0.837
TC	0.033	0.213	0.348	0.474	0.530	0.559	0.674	0.689	0.738	0.745
Top-n	11	12	13	14	15	16	17	18	19	20
C-CMF	0.871	0.880	0.862	0.857	0.832	0.826	0.817	0.803	0.797	0.789
CMF	0.850	0.837	0.812	0.798	0.795	0.740	0.730	0.725	0.707	0.663
TC	0.750	0.701	0.684	0.681	0.679	0.606	0.589	0.584	0.562	0.544

From Table I, it can be seen that the single CMF algorithm and the traditional collaborative filtering algorithm reach the maximum F1 value at the value of 11 for N, which is 0.85 and 0.75 respectively, while the C-CMF optimized recommendation algorithm constructed by the study reaches the maximum F1 value at the value of 12 for N, which is 0.88. From the data in the table, it can be seen that the C-CMF algorithm proposed by the study has a higher overall F1 value than the single CMF algorithm and the traditional collaborative filtering algorithm. Moreover, the best value for the number of items recommended by the traditional algorithm is smaller than that of the algorithm proposed in this study, indicating that the C-CMF algorithm increases the number of recommended resources while maintaining high recommendation accuracy, improving the efficiency of resource recommendation in the teaching and dissemination teaching activities of Chinese central plains culture to the outside world.

To verify the actual application effect of the optimized recommendation system, the recommendation system is applied to the electronic service system of the university library. The number of recommended items is set to 15 at a time, and user satisfaction is shown in Fig. 7.

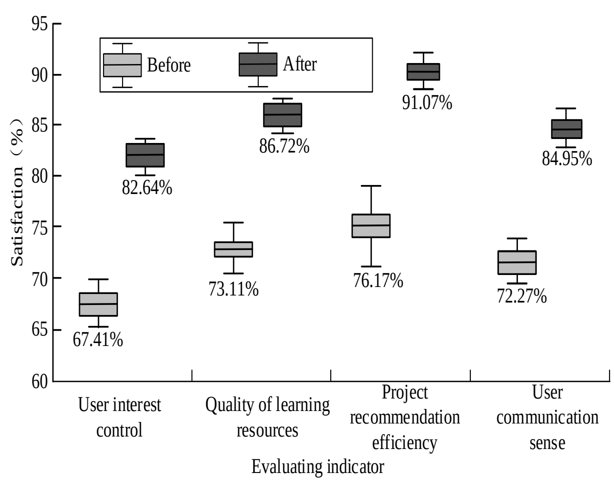


Figure 7. Diagram of average user satisfaction of recommendation system

As can be seen from Fig. 7, the average user satisfaction with the new system is 82.64% ± 1.76%, higher than 15.23% of the old system, in terms of feedback on user interest based on user rating behavior, indicating that users generally agree with the performance of the optimized system in user type classification.

In terms of the quality of recommendation resources, user satisfaction with the new system is in the range of 86.72% ± 1.86%, and that of the old system is 73.11% ± 0.79%, indicating that the recommendation system has solved the problem of cold start of recommendation and improved the utilization rate of learning resources. In terms of recommendation efficiency, the average satisfaction increased by 14.9%, proving that users spend less time searching for resources after the optimization of the recommendation system; The user satisfaction with the comment interface of the recommendation system has increased by 12.68%, indicating that the new system provides users with a platform for sharing experience and evaluation on user-resource feature information.

IV. Conclusion

The study improved the collaborative filtering algorithm based on user similarity, and also optimized the CMF migration learning method based on the user-resource feature matrix. To verify the application value of the optimized algorithm in recommendation systems, the study used the publicly available dataset Wikipedia to calculate the mean absolute error and root mean square error for the C-CMF algorithm, and the results showed that under different numbers of neighboring user sets, the C The results show that the C-CMF algorithm has the smallest error with MAE value of 0.41 and RMSE value of 0.624 under the influence of different rating data densities; the C-CMF algorithm also has the highest accuracy with the smallest MAE of 0.47 and RMSE value of 0.607 under the influence of different rating data densities. The experiments prove that the C-CMF algorithm has superior performance and is efficient and accurate in the calculation of the user-resource feature matrix when applied to learning resource recommendation systems. And in the simulation experiments of the TOP-N recommendation problem, the average precision and recall distributions of the C-CMF recommendation model constructed in the study were 0.838 and 0.7228 for 1-20 resource recommendation items, with F1 being maximum at

N=12. The experiments show that the recommendation accuracy performance and recommendation coverage performance of the C-CMF algorithm is both higher than those of the traditional recommendation algorithm, which increases the number of recommended resources while maintaining high recommendation accuracy and improves the efficiency of resource recommendation in the teaching and dissemination teaching activities of Chinese central plains culture to the outside world.

Data Availability Statement

The data used to support the findings of this study are available from the corresponding author upon request.

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Conflict of Interest
The author has no conflict of interest to declare.