Research Article

The Application of Personalized Recommendation System in the Cross-Regional Promotion of Provincial Intangible Cultural Heritage

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With the accelerated trend of globalization and modernization, many provincial intangible cultural heritages (PICH) are in danger of being lost. In the context of Internet technology, the use of digital multimedia for personalized recommendation is an effective way to promote the transmission of intangible cultural heritage. However, traditional recommendation systems tend to treat different members as homogeneous objects, ignoring the relationship between members' professional backgrounds and the inherent properties of items, and cannot truly solve the problem of conflicting preferences in the integration process. In view of this, this paper proposes a group recommendation system based on nonnegative matrix decomposition. First, the group rating information is decomposed into a user matrix and item matrix by nonnegative matrix decomposition. Then, the item affiliation matrix and member expertise matrix are calculated by using the affiliation and expertise weights for the two matrices, respectively, and the contribution degree of each member to different item ratings is obtained from them. Finally, the group preference model is constructed by weighted fusion of members' preferences based on their contribution degrees, and different recommendation lists are generated for different user preferences. The experimental results prove that this system has high recommendation accuracy in cross-regional promotion of PICH.

1. Introduction

Intangible cultural heritage is a precious treasure developed in the long process of human civilization, known as the DNA of regional culture, with historical geography and cultural inheritance [1].

The contents of China's intangible cultural heritage can be divided into six categories: (1) oral tradition, including language as a cultural carrier; (2) traditional performing arts; (3) folk activities, rituals, and festivals; (4) traditional folk knowledge and practices related to nature and the universe; (5) traditional handicraft skills; and (6) cultural space related to the above forms of expression.

Communication media for promoting intangible cultural heritage contents can be divided into oral media, printing media, electronic media, and media infiltration and integration. Early across areas of nonmaterial cultural heritage rely mainly on oral media and print media, such as the nonma-terial cultural heritage offline activities and nonmaterial cultural heritage related books published. In recent years, electronic media has also been widely used. Contents recorded by electronic media include text, pictures, video, and audio, which are more timely and vivid and spread in a wider range. Media penetration and integration are the fusion and complementary of the first three modes, which are suitable for emerging we-media platforms. For example, an online broadcast of PICH is carried out on Tiktok and Weibo platforms, and audio recordings of oral intangible cultural heritage are recorded and released on listening software.

The protection and promotion of PICH is a requirement for carrying forward national culture and enhancing cultural confidence, as well as for carrying out international cultural exchanges [2]. The existing provincial intangible cultural heritage recommendation system mainly adopts a stand-alone platform. However, as the amount of intangible cultural

heritage information increases every day, the processing speed of the single-machine platform has reached its limit, making the provincial intangible cultural heritage recommendation efficiency extremely low.

How to promote provincial intangible cultural heritage diversity protection, scientific development, utilization, and promotion has become an urgent matter. Therefore, the use of digital multimedia for personalized recommendation, that is, mining users' preferences and then recommending different digital multimedia of intangible cultural heritage for different users, provides a new path for the promotion of PICH.

Personalized services have begun to be applied in daily life, such as online shopping and movie recommendation, showing vigorous vitality. However, due to the data "overload" caused by the explosive growth of data volume, users cannot obtain a better personalized service experience. At the same time, the data can often bring huge economic benefits. Recommendation systems emerge as the times require. It can not only alleviate the problem of data "overload" but also provide better personalized recommendation and bring considerable economic benefits to merchants. With the increase of data, the sparsity of data will become larger and larger, which makes it difficult to obtain user preference information. The core idea of matrix decomposition is to map users and items to the same space according to a certain relationship that can be established between users and items and then use algorithms to learn the low-dimensional representation of users and items. Finally, the dot product is used as the matching function to calculate the matching score. On this basis, He et al. [3] proposed the eALS algorithm, which takes the interaction data that has not been observed as negative sampling and assigns values to them by using item popularity. The disadvantage of this kind of algorithm is that it does not fully excavate the user's preference information for the item and cannot obtain a good recommendation effect. Dahdouh et al. [4] adopted the Hadoop platform to manage and recommend resources and completed massive resource management and push with the help of Hadoop. El Handri and Idrissi [5] used the Spark platform to recommend a large number of resources to improve the efficiency of resource recommendation. Both are recommendation studies based on massive resources, focusing more on the construction of a cloud computing data push platform, without in-depth development of microresource details and methods. Wu [6] adopted the collaborative filtering algorithm and multiclassification support vector machine algorithm to construct an intelligent recommendation system and carried out specific empirical analysis. Recommendation accuracy was improved, but microresource details still could not be effectively reflected.

Recently, deep learning technology has been prominent. Due to the representation of deep learning having a strong ability to learn, many experts and scholars put forward various recommendation algorithms based on the depth of the neural network [7]. For example, Huang et al. [8] proposed the Wide & Deep algorithm and successfully applied it to APP recommendation. Its core idea is to use the Wide model to learn memory information in data. They analysed the data and found "memory information" in the data; that is, if a user likes to shop on Taobao, he is also likely to shop in Jingdong mall. Batmaz et al. [9] believed that the Wide & Deep algorithm could not share input and parameter optimization. However, these algorithms simply make use of the deep neural network without obtaining the weight values of each user and item; that is, they do not fully use the relational information obtained from interactive data.

On this basis, this paper proposes a group recommendation algorithm based on nonnegative matrix factorization (GRBNMF). The group was found by K-means clustering; user matrix and project matrix were obtained by nonnegative matrix decomposition for the user score matrix in the group. The membership degree of each item in the project matrix under different implicit categories and the professional degree of each member in the user matrix under different implicit categories are calculated, and the contribution degree of each member to different projects is obtained by combining the membership degree and professional degree. The group preference is weighted and fused according to the member's contribution degree to generate the group recommendation list. Compared with the traditional provincial interregional recommendation system for intangible cultural heritage, this system can recommend different digital multimedia information on intangible cultural heritage for different users according to their preferences.

The main contributions of this paper are as follows:

(1) A group preference modelling method is proposed. The method starts from the expertise of group members on the implied item categories, and obtains the contribution degree of group members on each item through nonnegative matrix decomposition, and constructs a group preference model based on it

(2) A group recommendation algorithm based on nonnegative matrix decomposition is proposed. It can avoid the interference of nonexpert members on the fusion results and solve the general group recommendation problem

(3) Excavate and analyse the relationship between members' professional backgrounds and the inherent attributes of the project and solve the problem of preference conflict in the process of integration

This paper consists of five main parts: the first part is the introduction, the second part is state of the art, the third part is the methodology, the fourth part is result analysis and discussion, and the fifth part is the conclusion.

2. State of the Art

Many scholars have carried out in-depth research on group recommendation systems, which basically focus on the preference fusion of group members.

Preference fusion can be divided into two fusions (model fusion and recommendation fusion) according to the different times of group modelling, as shown in Figures 1 and 2.
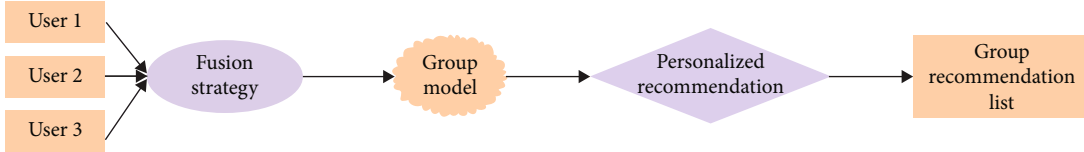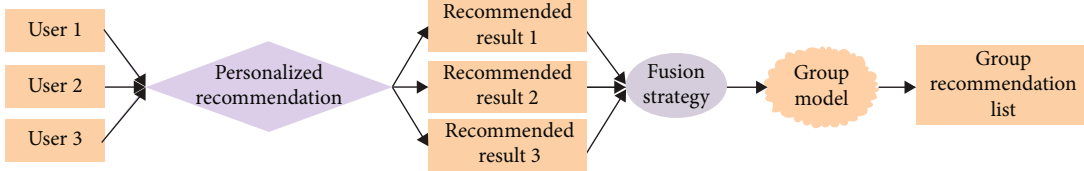
Figure 1: Model fusion.

Figure 2: Recommendation fusion.

In model fusion, firstly, member preferences are fused to build a group preference model, and a recommendation list can be generated according to the group model. Recommendation fusion is to make a personalized recommendation to group members first and then fuse the recommendation results of individual members to get group recommendation results. The advantages and disadvantages of the two fusion methods cannot be generalized, but their shortcomings are obvious, and the model fusion is susceptible to the impact of the sparsity of score. Recommendation fusion ignores the interaction between groups because individual behaviour is susceptible to group influence.

The following are specific studies on recommendation systems by different scholars (see Table 1).

Based on the above research inspiration, this paper considers starting from the implied item category and analysing the members' professionalism by nonnegative matrix decomposition, in an attempt to mitigate the influence of nonprofessional members on the fusion results, in order to establish a group preference model with higher accuracy and achieve efficient group recommendation.

3. Methodology

3.1. Proposed Algorithm. Matrix decomposition decomposed the high-dimensional user project score matrix $R^{w \times t}$ into two low-dimensional user matrices $P^{w \times z}$ and project matrix $Q^{z \times t}$. The user matrix represents the user's preference degree for z implicit item categories. The item matrix represents the degree of membership of the item in z implied item categories. Two characteristic matrix multiplication fitting of the original score matrix and the process of fitting the characteristic matrix are constantly updated. Matrix decomposition can be expressed as

$$R^{w \times t} \approx P^{w \times z} Q^{z \times t}, \tag{1}$$

where $R^{w \times t}$ represents the original user project scoring matrix. $P^{w \times z}$ represents the user characteristic matrix. $Q^{z \times t}$ represents the item eigenmatrix. w and t represent the number of users and projects, respectively. z is the implied item category.

NMF (nonnegative matrix factorization) adds nonnegative constraint conditions to the eigenmatrix on the basis of matrix factorization; that is, the elements in P and Q are not less than 0.

This nonnegative constraint will lead to the sparsity of corresponding descriptions to a certain extent. But the sparse sexual expression has proven to be between the fully distributed and a description of a single active component of an effective form of data description, and this description of the sparse sex can make the interpretation of the data become convenient and reasonable.

In order to maximize the approximation of Formula (1) to the original scoring matrix, the established objective function is shown in

$$\min_{\text{the elements in } P \text{ and } Q \text{ are not less than } 0} J(P, Q) = \frac{1}{2} \sum_{x,y} \left[r_{x,y} - (PQ)_{x,y} \right]^2 + \beta(\|P\|)_2^2 + (\|Q\|)_2^2, \tag{2}$$

where $r_{x,y}$ represent the element values in the original scoring matrix. β is the coefficient of the regular term.

The objective function was solved according to the multiplicative iteration rule proposed by a scholar, and the finally obtained iteration formula is shown in

$$P_{x,z} \longleftarrow P_{x,z} \cdot \frac{(RQ^N)_{x,z}}{(PQQ^N)_{x,z}},$$

$$Q_{z,y} \longleftarrow Q_{z,y} \cdot \frac{(P^N R)_{z,y}}{(P^N PQ)_{z,y}}. \tag{3}$$

At present, there is no unified formal definition of a group recommendation system, so this paper simply explains it from the general steps of group recommendation.

Definition 1. Group G is a collection of users with preferences. $A = \{p_x | 0 < x \leq w\}$, p_x indicates the group members, and w indicates the group size.

TABLE 1: Literature review details on recommendation system.

Literature	Author	Year	Methodological characteristics
[10]	Dara et al.	2020	A satisfaction balance strategy for tourism group recommendation. This strategy combined mean value strategy and minimum pain strategy in the process of fusion to improve the recommendation satisfaction of group members.
[11]	Schedl et al.	2018	A hybrid integration strategy, differences in both sides of the threshold, respectively, adopt the strategy of the most respected person and mean complete preference fusion strategy. However, the selection of threshold value often depends on the situation.
[12]	Jiang et al.	2019	A preference prediction algorithm based on the theory of unknown preferences of users in the same group would be affected by other members in the group. However, the algorithm had a high time complexity.
[13]	Camacho et al.	2018	A method for combining trust in social networks to modify group members' preferences, but it is usually difficult to obtain trust, so this method is not easy to implement.
[14]	Khelloufi et al.	2020	The method added the relationship between group members to the joint probability matrix decomposition; it improves the accuracy of cluster recommendation.
[15]	Deldjoo et al.	2020	The method added weight to candidate projects by calculating the number and consistency of project scores of group members and then made group recommendation by integrating project weights.
[16]	Yi et al.	2019	A matrix decomposition model. It is combined with the timing function to improve the search completeness and accuracy of the group recommendation system.
[17]	Luo et al.	2019	A nonnegative matrix decomposition model. It is widely used in computer vision and data mining due to its simplicity of implementation, interpretability of decomposition form, and decomposition result.
[18]	Jiang et al.	2018	A group preference model by weighted fusion of member scores based on the contribution degree of members. However, it lacks consideration of the relationship between the user's knowledge background and the inherent properties of the item in the preference fusion process.

Definition 2. Group preference $profile_{A,x} = \sum_{p_p \in A} \omega_{p,x} profile\ e_{p,x}$, where $profile_{A,x}$ profile represents group A's preference for item x_x, usually expressed as a score. $profile\ e_{p,x}$ profile represents member P's preference for item x_x. $\omega_{p,x}$ is the weight of member p_p on item x_x in group A. Different weights can represent different preference fusion strategies. If $\omega_{p,x} \equiv 1/|A|$, the above equation can represent the mean value strategy. When the weight of the member with the lowest score is 1 and the weight of other members is 0, the formula above can represent the strategy of least pain.

Definition 3 (top T group recommendation). The group recommendation system generally recommends the top T items with the highest preference score to the group. A candidate item set is typically a collection of items not consumed by all members. For a given group A, it can be obtained from the candidate item sets X a X_A group recommended list, as shown in

$$|X_A| = T, \quad \forall x_x, x_y \in X,$$
$$s.n.profile_{A,x} \geq profile_{A,y}, x_x \in X_A, x_y \notin X_A. \quad (4)$$

And the items in X_A are arranged in descending order according to group preference.

In group recommendation systems, the recommendation results not only depend on the design of preference fusion strategy but also are greatly affected by intragroup similarity. In general, the higher the intragroup similarity, the smaller the preference conflict of the group and the higher the over-

all satisfaction of the recommendation results, on the other hand, the lower the intragroup similarity, the different interests of the members of the group. In this case, the group's satisfaction with the recommendation results is often low. Therefore, the discovery of internally more similar groups is crucial to improve the satisfaction of recommendation results.

The K-means clustering algorithm has become one of the most commonly used clustering algorithms because of its advantages of simple implementation and fast convergence. In this paper, the Pearson correlation coefficient between the user rating vectors is used as the measurement, and k-means is used to perform multiple clustering of users in the rating data set to generate multiple groups of different sizes.

Generally, the number of users in the scoring data set is much smaller than the number of items, so the average scoring data set tends to be very sparse. At the same time, the calculation of the Pearson correlation coefficient depends very much on common scoring items. To alleviate the impact of the sparse score on user clustering results, items are clustered before users, so that similar items are located in the same cluster. After that, the average score of each project cluster was calculated as the scoring vector of users, which reduced the blank score of users and made the calculation of the Pearson correlation coefficient more accurate. Finally, cluster users to generate groups (see Table 2). Among them, $X_1, X_2, \cdots, X_{10}$ represents the project and $P_1, P_2, \cdots, P_8$ represents the user. The score ranges from 0 to 5, with the lowest being 0 and the highest being 5.

Firstly, cluster the items in Table 2. Then, the mean of the score of each project cluster can achieve dimensionality

TABLE 2: Scoring table.

	X_1	X_2	X_3	X_4	X_5	X_6	X_7	X_8	X_9	X_{10}
P_1	4	5	5	1	2	1	0	3	2	2
P_2	0	4	5	5	4	3	1	1	3	0
P_3	3	1	4	5	3	3	2	4	1	1
P_4	4	5	1	5	1	1	2	3	3	2
P_5	1	2	1	1	1	5	4	1	5	2
P_6	2	1	3	2	2	1	3	5	4	4
P_7	0	3	1	4	1	5	1	5	5	2
P_8	0	4	1	3	0	4	3	4	1	3

reduction of the user's score vector, for example, the score vector of user P_1 after dimensionality reduction is $[3.2, 1.4]$. On this basis, user clustering is performed, assuming that Table 2 produces two groups.

In real life, a project usually has multiple attributes, such as a movie, which can belong to a certain era or several genres. In the process of group decision-making, according to different project attributes, members often have different discourse rights. In general, members with more professional background knowledge about the attributes involved in the project have a higher right of speech and contribute more to the decision-making process, and the decision-making results tend to be this way. In general, the user's degree of expertise is directly proportional to his degree of interest, which is often expressed by the preference value in the user's feature matrix.

By analysing the group members' expertise in the implied item category, the algorithm makes the result of preference fusion tend to the more professional members. The filling score matrix is obtained by filling the null value of the original score matrix with the prediction score matrix. According to the influence of members' professional background knowledge on group preference, the membership degree of items under each implied item category is calculated by the item matrix. Combined with the professional degree of each member in the implicit category calculated by the user matrix, the contribution degree of each member's preference fusion is formed, and the group preference is weighted by the preference fusion according to the contribution degree of each member.

The group $A_1 = \{p_1, p_2, p_3, p_4\}$ obtained in Table 2 is used as an example for demonstration. The steps of establishing the group preference model by using NMF are shown as follows.

For a given group A, its scoring matrix is set as $R^A \in R^{|A| \times t}$, as shown in

$$P_A = \begin{bmatrix} r_{1,1} & r_{1,2} & \cdots & r_{1,t} \\ r_{2,1} & r_{2,1} & \cdots & r_{2,t} \\ \vdots & \vdots & & \vdots \\ r_{|A|,1} & r_{|A|,2} & \cdots & r_{|A|,t} \end{bmatrix}. \quad (5)$$

Among them, $|A|$ indicates the group size and t indicates the number of projects. $r_{x,y}$ represents member p_x's rating of item x_y.

User matrix $PA \in R^{|A| \times Z}$ and project matrix $QA \in R^{Z \times T}$ are obtained by nonnegative matrix decomposition of R^A, as shown in Formulas (6) and (7), respectively,

$$P_A = \begin{bmatrix} p_{1,1} & p_{1,2} & \cdots & p_{1,z} \\ p_{2,1} & p_{2,1} & \cdots & p_{2,z} \\ \vdots & \vdots & & \vdots \\ p_{|A|,1} & p_{|A|,2} & \cdots & p_{|A|,z} \end{bmatrix}, \quad (6)$$

$$Q_A = \begin{bmatrix} x_{1,1} & x_{1,2} & \cdots & x_{1,t} \\ x_{2,1} & x_{2,1} & \cdots & x_{2,t} \\ \vdots & \vdots & & \vdots \\ x_{z,1} & x_{z,2} & \cdots & x_{z,t} \end{bmatrix}, \quad (7)$$

where z is the number of implied project categories and $Z \leq |A| \leq t$. px_i represents the preference value of the member p_x for the implied item category i. $x_{i,y}$ represents the attribute value of item x_y on the implied category i.

Then, for group G_1,

$$R_{A_1} = \begin{bmatrix} 5 & 4 & 4 & 0 & 3 & 0 & 1 & 2 & 1 & 3 \\ 0 & 3 & 5 & 4 & 5 & 2 & 0 & 0 & 2 & 1 \\ 4 & 0 & 3 & 5 & 4 & 2 & 3 & 3 & 0 & 0 \\ 5 & 4 & 0 & 4 & 0 & 0 & 3 & 2 & 2 & 3 \end{bmatrix}. \quad (8)$$

Let $z = 2$, the factorization of R_{A_1} can be obtained (round to keep 2 decimal places):

$$P_{A_1} = \begin{bmatrix} 1.84 & 0.95 \\ 0.17 & 2.66 \\ 1.24 & 1.79 \\ 2.55 & 0 \end{bmatrix}, \quad (9)$$

$$Q_{A_1}^N = \begin{bmatrix} 2.28 & 0.16 \\ 1.38 & 0.51 \\ 0.31 & 1.89 \\ 0.96 & 1.37 \\ 0.22 & 2.00 \\ 0 & 0.80 \\ 1.10 & 0.13 \\ 0.99 & 0.26 \\ 0.49 & 0.37 \\ 1.15 & 0.04 \end{bmatrix}.$$

The dot product of the characteristic matrix can be predicted rating matrix $\widehat{R}_A \in R^{|A| \times T}$, as shown in

$$\widehat{R}_A = \begin{bmatrix} \widehat{r}_{1,1} & \widehat{r}_{1,2} & \cdots & \widehat{r}_{1,t} \\ \widehat{r}_{2,1} & \widehat{r}_{2,2} & \cdots & \widehat{r}_{2,t} \\ \vdots & \vdots & & \vdots \\ \widehat{r}_{|A|,1} & \widehat{r}_{|A|,2} & \cdots & \widehat{r}_{|A|,t} \end{bmatrix}, \qquad (10)$$

where $\widehat{r}_{x,y}$ represents the predicted score of project x_y by member p_x.

When obtaining the preferences of members in the group, the prediction scoring matrix $\widehat{R}_A$ is used to fill the null values in the original scoring matrix R_A, and the filling scoring matrix $RF_A \in R^{|A| \times T}, rf_{x,y} \in RF_A$ can be obtained:

$$rf_{x,y} = \begin{cases} r_{x,y}, & r_{x,y} \neq 0, \\ \widehat{r}_{x,y}, & r_{x,y} = 0. \end{cases} \qquad (11)$$

After the above steps, the filling score matrix RF_{A_1} of A_1 can be obtained, as shown in

$$RF_{A_1}^N = \begin{bmatrix} 5 & 0.82 & 4 & 5 \\ 4 & 3 & 2.62 & 4 \\ 4 & & 5 & 3 \\ 3.07 & 4 & 5 & 4 \\ 3 & 5 & 4 & 0.55 \\ 0.76 & 2 & 2 & 0 \\ 1 & 0.53 & 3 & 3 \\ 2 & 0.86 & 3 & 2 \\ 1 & 2 & 1.26 & 2 \\ 3 & 1 & 1.49 & 3 \end{bmatrix}. \qquad (12)$$

The membership degree $x\text{weight}(y, i)$ of project x_y under the implied project category i can be calculated by item matrix, as shown in

$$x\text{weight}(y, i) = \frac{x_{i,y}}{\sum_{c=1}^{z} x_{c,y}}. \qquad (13)$$

In the above matrix Q_{A_1}, the value of x_1 under the two implied item categories is 2.28 and 0.16, respectively, and the calculated total attribute value is 2.44. After that, $x\text{weight}(1, 1) = 2.28/2.44 = 0.93$, $x\text{weight}(1, 2) = 0.07$ are obtained.

Different from the attribute weight of the item oriented to the implicit item category, the weight calculation of member professionalism is oriented to the group. Therefore, the specialization $p\text{weight}(x, i)$ of member p_x for implied item category i in group A can be obtained through the user

matrix, as shown in

$$p\text{weight}(x, i) = \frac{p_{x,i}}{\sum_{a=1}^{|A|} p_{a,i}}. \qquad (14)$$

For example, in matrix P_{A_1}, the total preference value of the four members on implied item category 1 is $1.84 + 0.17 + 1.24 + 2.55 = 5.8$, which can be calculated as $p\text{weight}(1, 1) = 1.84/5.8 = 0.32$.

After the group modelling is completed through the above method, the top N items with the highest scores can be selected from the group preferences for recommendation. The frame of the proposed algorithm is shown in Figure 3.

In the first stage, the k-means algorithm is used to find potential groups by clustering users. In the second stage, the NMF model is used to decompose the group scoring matrix. Based on the relationship between members' knowledge background and project inherent attributes, the contribution degree of group members to different projects is obtained, and the group preference model is constructed according to the contribution degree of group members. In the third stage, a top N recommendation list is generated through the group model.

3.2. System Design. The design of the PICH recommendation system using the Hadoop platform can improve the scalability of the recommendation system on the basis of solving the problems of massive intangible cultural heritage information analysis and processing. Figure 4 shows the structural framework of the PICH recommendation system based on the Hadoop platform. In Figure 4, the system as a whole is divided into three components. They are the PICH information collection module, information pretreatment module, and Hadoop platform. The main function of the PICH information collection module is to use professional information collection software: locomotive collector to obtain PICH information on the Internet, including intangible cultural heritage information and visitors to the intangible cultural heritage information query and evaluation information. This module obtains intangible cultural heritage information through formal and legal network resources, guarantees the authenticity of PICH information to the maximum extent, and improves the accuracy of PICH information recommendation. After the intangible cultural heritage information is collected successfully, it is transmitted to the information pretreatment module. This module implements coding and format conversion processing on the initial intangible cultural heritage information to improve the convenience of information identification in the process of PICH recommendation. The preprocessed PICH information is transferred to the Hadoop platform and stored in the HDFS distributed file system. Based on the preprocessed information, the parallel Map Reduce programming model describes the optimized collaborative filtering recommendation algorithm, and the background program builds the recommendation model to obtain the recommendation list and complete PICH recommendation.
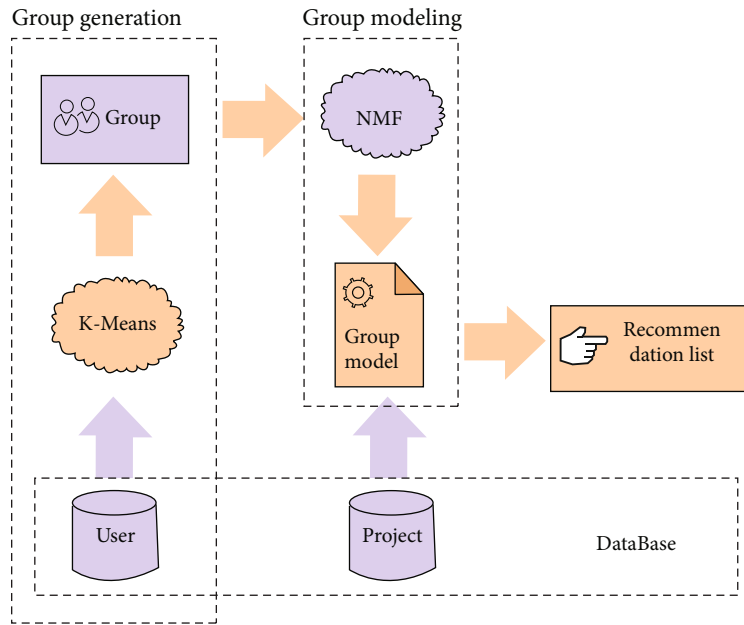
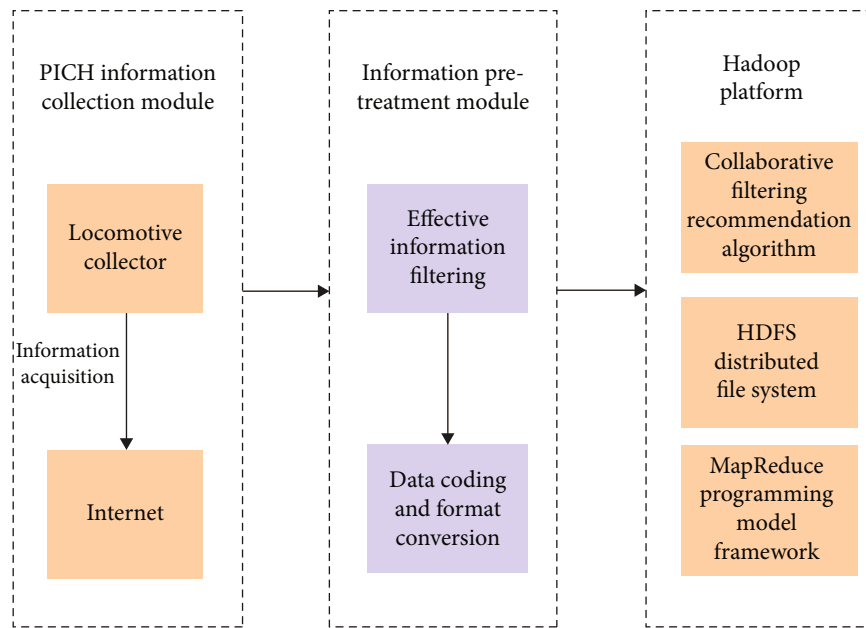FIGURE 3: GRBNMF algorithm framework.

FIGURE 4: PICH recommendation system structure.

In the Hadoop platform, the Map Reduce programming model is used to present the above recommendation algorithm. The intangible cultural heritage information in the HDFS distributed file system is divided into several Map tasks, and these tasks are mapped to Data nodes in the cluster for parallel computing. An intermediate key/value pair ($<$key, value$>$) is constructed through the Map function, and a list ($<$k2, v2$>$) is generated based on the key value. Job Tracker is scheduled and input into a single Reduce function for operation, and the recommendation result is output. $<$/k2, v2$>$ $<$/key, value$>$ The specific process is shown in Figure 5. The recommendation algorithm is divided into four processing processes in the Hadoop platform: Map Reduce processing of attention matrix, Map Reduce processing of consistency calculation, Map Reduce processing generated by neighbor set, and Map Reduce processing generated by recommendation set. Each processing process is divided into the Map processing stage and Reduce processing stage. Through the parallelization of the processing process and processing stage of different information
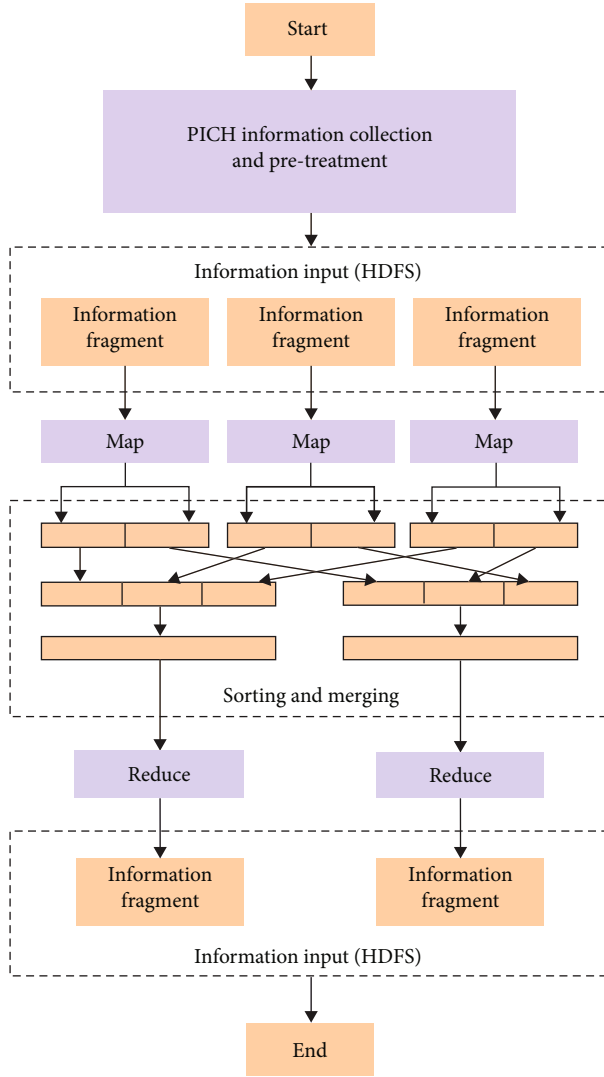
Figure 5: Map Reduce execution process.

fragments, the recommended set of PICH can be obtained efficiently.

4. Result Analysis and Discussion

To verify the effectiveness of the proposed algorithm, it is compared with other collaborative filtering algorithms, and the selected comparison algorithm is as follows.

(1) Literature [19] made predictions based on users' scores of known projects by calculating the correlation between projects, so as to recommend unrated projects

(2) Literature [20] solved the local optimal problem by using the bee colony algorithm, calculated the similarity by using the improved cosine similarity, and made recommendations

(3) Literature [21] calculates the UICPR matrix by calculating the priority ratio of user item categories to reduce the dimension of data. Meanwhile, users are

clustered, and the closest users are found so as to obtain the predicted rating and make recommendations

(4) Literature [22] determined the cluster number by clustering validity function and Xie-Beni method and performed FCMC clustering according to attribute characteristics

The tourism data set is a record of how users rate the PICH recommendation system; the user's score determines the user's liking degree for the recommendation. And the tourism data set is obtained by collecting visitors' query and evaluation of intangible cultural heritage information on the Internet.

In order to measure the accuracy of the recommendation, mean absolute error (MAE) and root mean square error (RMSE) were adopted as the evaluation criteria for the accuracy of the prediction:

$$
\begin{aligned}
\mathrm{MAE} &= \frac{\sum_{r\in I}|r-\hat{r}|}{|I|}, \\
\mathrm{RMSE} &= \sqrt{\frac{\sum_{r\in I}(r-\hat{r})^2}{|I|}},
\end{aligned}
\tag{15}
$$

where i is the number of samples in the test set. R is the user's actual rating. $\hat{r}$ is the predicted value of the score.

This paper analyses the fluctuation of prediction accuracy by continuously expanding the number of neighbor users and comparing and observing the changes in MAE and RMSE values in the two data sets, where smaller MAE and RMSE values indicate higher scoring accuracy. The specific experimental comparison is shown in Figure 6.

Figure 6 shows the MAE value changes of each algorithm. On the whole, MAE values of the five algorithms show a decreasing trend with the increase of neighbor numbers recently. In addition, the MAE value of each algorithm is lower than that of literature [19]. It shows that the proposed algorithm has a good improvement effect.

The changes in RMSE values of each algorithm are shown in Table 3. On the whole, with the recent increase in the number of neighbors, although RMSE values of the five algorithms fluctuated, they all showed an obvious downward trend. Compared with the algorithm in this paper, literature [20] is more stable than other algorithms. When the number of neighbor users is 50, the RMSE value of the algorithm proposed in this paper is 0.81. The comparison shows that the algorithm proposed in this paper has the best effect among the five algorithms. Compared with traditional algorithms, the accuracy of the proposed algorithm is improved.

MAE and RMSE values of the proposed algorithm are compared with those of the other four algorithms (see Table 4).

5. Conclusion

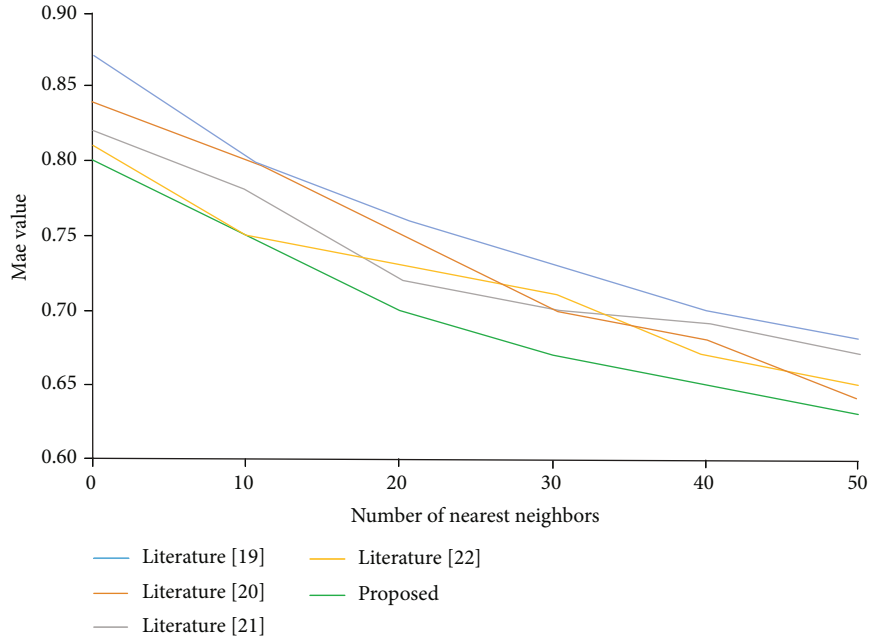How to reveal the characteristics and audience psychology of intangible cultural heritage through data collection and

FIGURE 6: MAE values of each algorithm.

TABLE 3: RMSE values of each algorithm.

Number of nearest neighbors	Literature [19]	Literature [20]	Literature [21]	Literature [22]	Proposed
0	0.95064	0.93401	0.91792	0.91792	0.9088
10	0.91577	0.90504	0.89431	0.88948	0.88734
20	0.87661	0.85944	0.85354	0.85676	0.84442
30	0.85247	0.84818	0.84281	0.84442	0.82189
40	0.83745	0.84067	0.82564	0.82725	0.81867
50	0.83476	0.82296	0.82457	0.81974	0.81009

TABLE 4: Comparison of MAE value and RMSE value of five algorithms.

Algorithm	MAE	RMSE
Literature [19]	0.799	0.796
Literature [20]	0.781	0.739
Literature [21]	0.712	0.704
Literature [22]	0.704	0.728
Proposed	0.681	0.624

analysis is of great significance for digital inheritance of PICH. Therefore, this paper proposes a group recommendation algorithm based on nonnegative matrix factorization. Based on the relationship between the members' knowledge background and the inherent attributes of the project, the algorithm uses nonnegative matrix decomposition to analyse the contribution degree of each member in the group during the preference fusion, and builds a more accurate group preference model, and generates the recommendation list. This algorithm can avoid the interference of nonexpert members to the fusion result and solve the general group recommendation problem. The validity of the algorithm is verified on the tourism data set. Compared with MAE and RMSE values of other algorithms, it is proved that the proposed algorithm has high recommendation accuracy. In future work, we will continue to explore the factors affecting the recommendation performance to further improve the recommendation efficiency of the model.

Data Availability

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

Conflicts of Interest

The author declares no competing interests.

Acknowledgments

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