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Research on Recommendation Framework for Personalized Push of Cultural and Creative Products in Tourist Cities Based on Multi-Level Computational User Profiling

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ABSTRACT
Currently, the development of cultural tourism has become a new trend of urban development, and how to use modern technology to realize the innovative development of urban cultural tourism has become a key issue to be considered in the process of urban construction. The research combines the Web domain ontology to construct a multi-level user portrait master model, which mainly includes four sub-models: retailer static attribute vector model, retailer domain dimension model, retailer marketing ability model and retailer social dimension model. The FCM algorithm based on the improved AP algorithm is utilized to cluster the user portraits, and the user portrait clusters obtained by the method studied in this paper perform well with an average number of iterations and an average time consumed of 21.3 and 60.35 compared with the traditional K-Means algorithm, the improved K-Means algorithm, and the traditional FCM algorithm, respectively. Then a personalized recommendation method for tourism products based on MAGFM is proposed, which achieves Top-N recommendation of tourism products by calculating the total interest value of users and the comprehensive similarity of tourism products. And test and analyze in the tourism e-commerce platform, the results show that the recommendation algorithm proposed in this paper has higher effectiveness compared with the traditional recommendation algorithm. Finally, the research content builds a personalized recommendation system for tourism cultural and creative products.

Keywords: user profiling; personalized recommendation; tourism cultural and creative products; FCM algorithm; recommendation system

1. Introduction

Cultural creative products are products based on cultural elements that are innovatively designed and developed for tourists in tourist cities. They often have unique creativity, cultural connotation and artistic value [1-2]. From exquisite handicrafts to creative digital works, from traditional folk culture

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derivatives to modern fashionable cultural peripherals, they cover an extremely wide range of fields [3-5]. However, it is not enough to have good products, how to successfully promote these cultural and creative products with city characteristics to the market, so that more tourists understand, love and buy them, is an important issue in front of many cultural and creative enterprises and practitioners in tourist cities [6-9]. The multi-level computing user profile recommendation framework with personalized recommendation can play an important role in the promotion and marketing of cultural and creative products [10].

User profile is a user model based on the user's basic information, interest characteristics, behavioral habits, consumption tendency and other factors. By collecting and analyzing multi-dimensional data of users, we can better understand their needs and preferences, and then provide personalized recommendation services for them [11-14]. Personalized recommendation algorithm is an important tool to help users filter out the interested content in the era of information explosion. The personalized recommendation framework based on user profiles can more accurately provide users with personalized recommended content by mining the information of user profiles, and with this framework, tourist cities can improve the sales of cultural and creative products through personalized recommendation, which is also an important way to reflect the charm of the city [15-18].

The research constructs a multi-level and multi-dimensional user portrait model, uses the improved FCM algorithm to cluster the user portrait model, and experimentally compares the improved FCM algorithm of this paper with the traditional FCM algorithm, the traditional K-Means algorithm and the improved K-Means on the experimental data set. Using MAGFM algorithm for personalized recommendation of tourism products, a personalized recommendation method for tourism products based on MAGFM is designed. Then the model is trained using the training set data, and the total user interest value as well as the comprehensive similarity of tourism products are calculated to obtain K similar tourism products and realize tourism product recommendation. Finally, the algorithm is applied to the product recommendation module of the tourism e-commerce platform, and the recommendation effect of the algorithm is tested and analyzed, which verifies the effectiveness of the algorithm in tourism product recommendation.

2. Modeling of user profiles for multi-level consumption of cultural and creative products

2.1. User Profile Management Based on Web Domain Ontology

2.1.1. User profile storage. There are three main ways of storing user profiles in relational databases: storing the ontology in MySQL databases using Jena, storing the ontology in databases using ORM mapping relationships, and directly connecting to databases with Protégé. Since the Protégé developers limited the storage function of the direct connection database to read-in/read-out use for the Protégé software, did not specify the representation of the fields in the database, and did not advocate direct user access to the contents of their relational database, it is not widely used.

Through the above analysis of the correspondence between the elements in the OWL language and the table elements, the above structural relationships can be expressed using the quintuple form of the relational schema, as in equation (1).

$$R(U, D, DOM, F) \tag{1}$$

where R is the name of the relationship, U is the set of attribute names composing the relationship, D is the domain from which the attribute group U comes, DOM is the set of images of the attributes to the domain, and F is the set of data dependencies between the attributes. In a real database management system (DBMS), the user does not need to consider D and DOM, and at the same time $R(U,F)$ is completely functionally dependent on $R(U)$, so the relational schema can be abbreviated as Eq. (2) or as Eq. (3), where $A_1, A_2, \cdots, A_n$ is the attribute name.

$$R(U) \tag{2}$$

$$R\left(A_1, A_2, \cdots, A_n\right) \tag{3}$$

After the above analysis and design, the following relational schema is finally obtained:

1) Class (class name, subclass).

2) Attributes (attribute name, definition field, value field, direct parent attribute name, inverse attribute name).

3) Instances (class name, instance name, attribute name, attribute value).

4) Constraints (class name, attribute name, constraint type, value).

2.1.2. User profile queries. User portrait query is the most commonly used, the most basic operation of the recommendation system, the efficiency of the query to a large extent determines the performance of the recommendation system, the query operation should be considered from the following two aspects:

1) The use of user profiles determines that the profile data is mainly query-based, so the query of user profile data is required to have a high degree of concurrency, and at the same time, the performance of the aggregation statistics is required to be high;

2) In the user portrait query, many queries are repeated, for this reason, the establishment of an effective caching mechanism to cache historical query information, when a new request for user queries arrives, the first to go to the cache area to look for, did not hit, then query the database, the frequent query data will be loaded into the cache area.

2.1.3. User profile update. Newton's cooling theorem [19] applied to the tourism product recommendation system, the “information attention” can be imagined as a “natural cooling” process, assuming that:

1) At any moment, all the information entries in the system, there is a “current temperature”, the higher the temperature the higher the ranking;

2) If the user browses a certain piece of information or evaluates the information, then the heat of the information rises by the corresponding number of degrees:

3) At any time information from the release time farther and farther away, all the temperature of the information are gradually “cool”.

Based on this assumption, Newton's Law of Cooling is utilized for user portrait updating, and according to the formula, the expression of user interest offset function can be obtained, where Cur_inst represents the current interest degree, His_inst represents the historical interest degree, $cool\_coeff$ represents the cooling coefficient, and $exit\_t$ represents the time of existence of the information, which is shown in Equation (4).

$$Cur\_inst = \left(His\_inst\right) \times \exp\left(-cool\_coeff \times exit\_t\right) \tag{4}$$

2.2. Group User Profile Modeling

2.2.1. User Portrait Model Clustering Based on FCM Algorithm. Clustering analysis of user profiles using fuzzy C-mean algorithm [20], fuzzy C-mean algorithm (FCM) belongs to the division-based clustering, the basic idea is to divide M N-dimensional vectors into k classes, and through the iterative constant update of the degree of affiliation, as well as the center of clustering, minimize the objective function of the data clustering, with the aim of dividing the objects in the same class to maximize the degree of similarity between them, and minimize the degree of similarity between the different classes. .

Suppose the set of user portraits is: $U = \{u_1, u_2, \cdots, u_m\}$, where each portrait u_i has n attributes, i.e., $u_i = \{u_{i1}, u_{i2}, \cdots, u_{im}\}$, and the corresponding attribute matrix is:

$$U^* = \begin{pmatrix} u_{11} & u_{12} & \cdots & u_{1n} \\ u_{21} & u_{22} & \cdots & u_{2n} \\ \vdots & \vdots & & \vdots \\ u_{m1} & u_{m2} & \cdots & u_{mn} \end{pmatrix} \tag{5}$$

According to the fuzzy set theory, it can be assumed that user portrait u_i is subordinated to class i with a certain degree of subordination, i.e., user portraits are subordinated to each class with different degrees of subordination respectively. Therefore, each class can be considered as a fuzzy subset on the set of objects U. If U is divided into k classes, so each such classification result corresponds to a fuzzy classification matrix, i.e.:

$$R_k = \begin{pmatrix} r_{11} & r_{12} & \cdots & r_{1m} \\ r_{21} & r_{22} & \cdots & r_{2m} \\ \vdots & \vdots & & \vdots \\ r_{k1} & r_{k2} & \cdots & r_{km} \end{pmatrix} \tag{6}$$

This matrix should satisfy the constraints:

1) $r_{ij} \in [0,1]$, denotes that the affiliation degree of u_j, which is subordinate to category i, takes a value between 0 and 1.

2) $\sum_{i=1}^{k} r_{ij} = 1$, denotes that u, the sum of the affiliation degrees belonging to each category is 1.

3) $\sum_{i=1}^{m} r_{ij} > 0$, denotes that each category is not empty.

If the set of user profiles is classified into k classes $(2 \le k \le n)$, it is necessary to iteratively update the degree of affiliation and the center of clustering, and under the above constraints, minimize the objective function to obtain the corresponding fuzzy classification matrix R^* and the center of clustering matrix V^*. The objective function is defined in the following form:

$$J_q\left(R^*, V^*\right) = \sum_{j=1}^{m} \sum_{i=1}^{k} \left(r_{ij}\right)^q \left\| u_j - v_i \right\|^2 \tag{7}$$

$$\left\| u_j - v_i \right\| = \sum_{p=1}^{n} \left| u_{jp} - v_{ip} \right| \tag{8}$$

2.2.2. Optimizing the Improved FCM Clustering Algorithm. Due to the existence of a large number of user profiles in the system, the number of cluster classes at the initial state is difficult to determine, and in practice people often do not know how many classes should be divided into for a sample space to be clustered. This section investigates the automated selection of the initial number of cluster classes. Near-neighbor propagation (AP) algorithm is a new clustering algorithm that does not need to specify the number of clusters and the initial cluster center in advance. The idea of AP algorithm is to cluster multiple objects based on the similarity between them. Initially, all the objects are treated as potential cluster centers called cluster centers, and each object is treated as a node in the network, and its iterative process is to pass and update the two types of classes in the constituted all-connectivity graph. Message.

2.3. Modeling User Profile of Cultural Creative Products

2.3.1. Indicator System of Product Consumption User Profiling. Based on the analysis of tourists' tourism product consumption data and the needs of the Internet + tourism industry, a preliminary design of the indicator system for user profiling was developed. The index system mainly includes comprehensiveness, timeliness, locality and diversity.

The index system of user portrait mainly includes four aspects: the basic attributes of product retailers, the domain dimension of product retailers, the commercial social dimension and the marketing ability of product retailers.

The basic attributes of cultural and creative product retailers mainly include multiple information such as retailer store name, retailer code, retailer address, legal person or person in charge, contact information, scale of operation, marketing capability, turnover inventory, purchase rate, purchase amount, and number of purchases.

2.3.2. Multi-level modeling of product consumer profiles. In the field of cultural and creative product retailers, in order to be able to accurately describe the tendency of cultural and creative product retailers in different fields, the user's field characteristics are more comprehensively portrayed. This requires that users cannot be described from a single dimension, but need to be portrayed from multiple levels and multiple dimensions for easy understanding.

The multilevel multidimensional user portrait model proposed in this paper is mainly composed of four parts: retailer basic attribute dimension, retailer domain dimension, retailer marketing ability dimension and business social dimension. In the personalized recommendation system of this paper, the social relationship between users and the similarity between users have a greater impact on the prediction score of the target user's product selection, which will affect the effect of the final personalized recommendation system.

According to the user portrait index system, a four-dimensional array User=<Basic attributes, Scopes, Marking ability, Relations> is defined to represent a user portrait information, as shown in Figure 1.

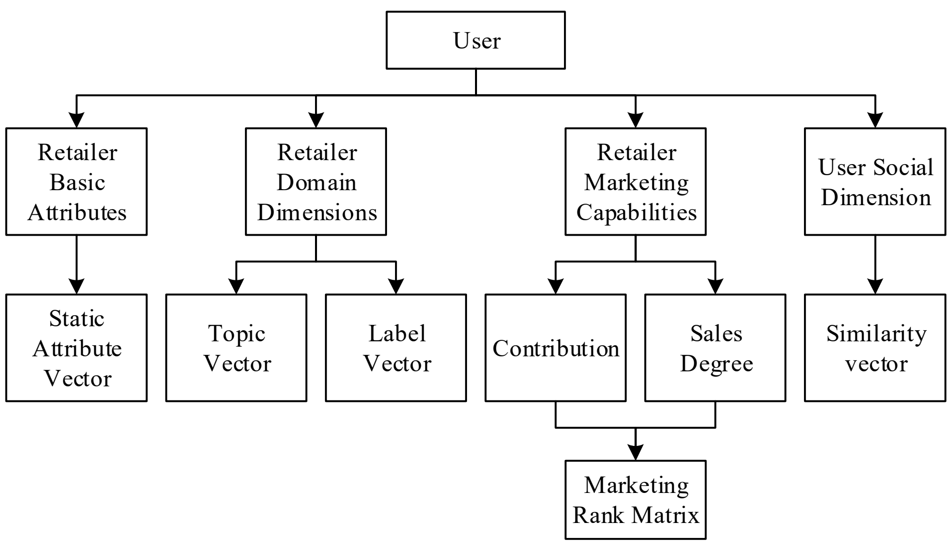

Fig. 1. Multi-level user portrait model

2.4. Experimental results and their analysis

2.4.1. Experimental standard data sets. The research object taken in this chapter is the 32721 tourists' consumption data of each travel platform of Ctrip.com and Tuniu. Based on the user portrait index system, this section starts from the four sub-models of retailer basic attribute dimension, retailer domain dimension, retailer marketing dimension and retailer social dimension in the four-dimensional array of the multi-level user portrait model, and filters, cleanses, processes and handles the raw data. A portion of the data is randomly extracted, and the new data can be obtained after normalization according to Equation (9) as shown in Table 1.

$$`\rho_{ij} = 1 - \frac{\rho_{j\max} - \rho_{ij}}{\rho_{j\max} - \rho_{j\min}} = \frac{\rho_{ij} - \rho_{j\min}}{\rho_{j\max} - \rho_{j\min}} \quad (9)$$

Where ρ_{ij} is the value of user x_i on attribute ρ_j, the maximum value on attribute ρ_j is $\rho_{j\max}$, the minimum value is $\rho_{j\min}$ and the normalized value is $`\rho_{ij}$.

Table 1. Normalized data (partial results are presented)

	ρ1	**ρ**2	**ρ**3	**ρ**5
X1	0.38366	0.15575	0.38363	0.19506
X2	0.70432	0.15078	0.7043	0.18879
X3	0.19341	0.50499	0.19439	0.64178
X4	0.39587	0.30721	0.39629	0.37217
X5	0.10423	0.04478	0.10418	0.05598
X6	0.17968	0.04112	0.05077	0.17964
X7	0.47779	0.05006	0.47777	0.06207
X8	0.3811	0.13831	0.38106	0.17373
X9	0.51024	0.12758	0.51021	0.15993
X10	0.02272	0.00759	0.02267	0.00937
...	...	...	...	...

2.4.2. Experimental environment. The hardware environment for the experiment is a PC with Microsoft Windows 8 operating system, 16 GB of RAM, and the processor used is Inter(R)Core(TM)4 i5-7500 @3.4GHz, and the simulation tool used is Matlab.The settings for the initial values of the improved FCM algorithm are shown in Table 2.

Table 2. Initial value setting of the modified FCM algorithm

Number of clustering m	Indicator **ρ**1 weight	Indicator **ρ**2 weight	Indicator **ρ**3 weight	Indicator **ρ**4 weight
4	0.3	0.1	0.3	0.3

2.4.3. Experimental results:

1) Clustering results of the algorithm. The improved FCM algorithm is used for clustering and dividing the multilevel user portrait, with a weighting factor of 2, and the clustered data has been set to 4. 10% of the standard dataset of the experiment is randomly selected for analysis, and taking into account that the weighting of indicator ρ_2 is only 0.1, the attribute eigenvalues of retailers are downgraded by three, which are the basic attribute dimensions, the marketing capability dimensions and the user's socialization dimensions, and are represented as ρ_1, ρ_3, and ρ_4, respectively. Are represented, and the clustering effect is shown in Fig. 2.

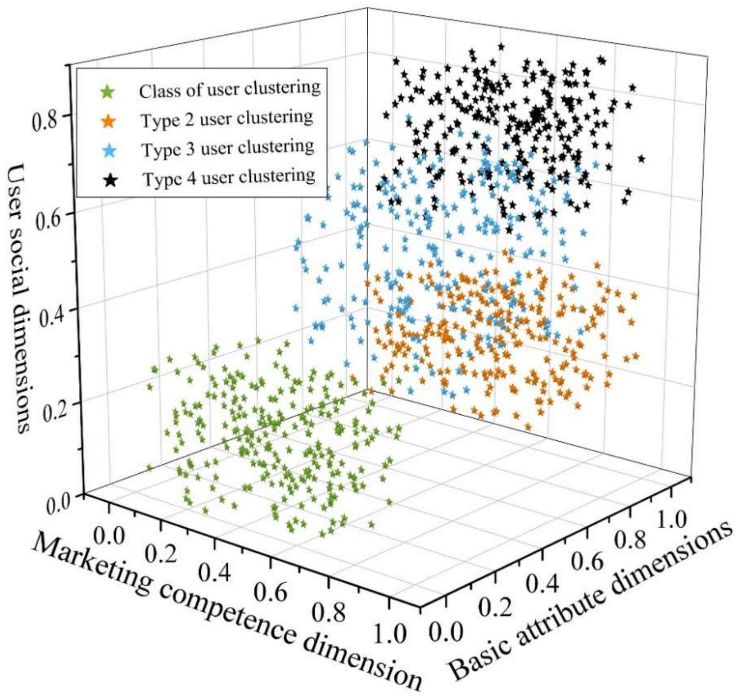

Fig. 2. Cluster rendering

As can be seen from the clustering effect diagram, the clustering is based on the basic attribute dimension, the marketing ability dimension and the user social dimension, and is finally divided into four types of user profile clusters. Due to the importance of the original data, this side is not listed and displayed. According to Figure 2, the improved FCM algorithm proposed in this paper is able to carry out better grouping spatially, one class to four classes of consumers were expressed as key consumers, consumers to be developed, ordinary consumers and worthless consumers of these four classes, the type of consumer attributes are mainly consumer loyalty, average profit share, profit growth rate discrimination, classification results are shown in Table 3.

According to the table clustering after all kinds of results can be concluded, and clustering center v2 affiliation degree of consumers accounted for 24.08% of the total consumers, the creation of the sum of the profit of 70.18%, this kind of retailers belong to the tourism enterprise important to maintain retailers. For this kind of retailers, tourism enterprises should not only satisfy their basic needs, but also provide personalized value-added services for different consumer needs, strengthen the daily maintenance between usual and retailers, and improve the loyalty of zero retailers. Although the profit occupation of the key development consumers in the table is not very high, it reaches 291.35% in terms of profit growth rate, with high loyalty and great potential for tourism consumption.

Table 3. The result of the clustering

Cluster center	Customer ratio	Profit ratio	Profit growth	Loyalty	Consumer type
V1	16.14%	15.19%	291.35%	0.611	Key development
V2	24.08%	70.18%	45.7%	0.278	Key maintenance
V3	40.14%	11.75%	99.17%	0.218	General customer
V4	19.64%	2.88%	-47.66%	0.034	Priceless value

2) Performance evaluation of improved FCM algorithm. The group user portrait obtained by improving FCM in this paper is compared with traditional FCM algorithm, traditional K-Means algorithm, and

improved K-Means algorithm, and the fuzzy division coefficient $F_c(\mu)$, the average fuzzy entropy $H_c(\mu)$, the average number of iterations, and the average running time indicators are compared to compare the performance of clustering algorithms, and the results are shown in Table 4.

$$F_c(\mu) = \frac{1}{n}\sum_{j=1}^{n}\sum_{i=1}^{c}\mu_{ij}^2 \tag{10}$$

$$H_c(\mu) = \frac{1}{n}\sum_{j=1}^{n}\sum_{i=1}^{c}\ln\mu_{ij} \tag{11}$$

From the table, it can be seen that the improved FCM algorithm is better than the traditional FCM algorithm in terms of fuzzy division coefficient, average fuzzy entropy, and in terms of average number of iterations and average time consumed are 21.3 and 60.35, respectively, which are better than the traditional K-means algorithm, improved K-means algorithm and traditional FCM algorithm.

Table 4. Comparison of algorithms

Algorithm	Fc(μ)	Hc(μ)	Mean iteration	Mean consumption time(s)
K-means	*	*	36.1	116.13
Improved k-means	*	*	31.7	91.37
FCM	0.784	-0.131	29.4	78.19
Improved FCM	0.912	-0.179	21.3	60.35

3. Design of product personalized recommendation based on MAGFM algorithm

3.1. Recommendation Algorithm Design

3.1.1. Problem Formulation. Let $U = \{u_1, u_2, \cdots, u_M\}$ be the set of M users and $I = \{i_1, i_2, \cdots, i_N\}$ be the set of N items. Let $Y = \{0,1\}^{M\times N}$ be the interaction matrix between users and items, where $y_{u,i} \in Y$ can be defined as:

$$y_{u,i} = \begin{cases} 1, if\ the\ uth\ user\ \text{int}eracted\ with\ the\ ith\ item \\ 0, otherwise \end{cases} \tag{12}$$

Here, user-item interactions can vary depending on the real-world problem, e.g., rating a movie, purchasing an item, listening to music, etc. User-item interactions in Top-N recommendation tasks create the problem of "implicit feedback," where unrated items are mixed with unobserved positive samples. Therefore, the goal of collaborative filtering in Top-N recommendation tasks is to determine which of the unrated items are unobserved positive samples.

Briefly, given a user-item pair (u,i), we first compute the predicted score $\hat{y}_{u,i}$, which represents the probability of their interaction, using function F as follows:

$$\hat{y}_{u,i} = F(u,i \mid \theta) \tag{13}$$

where θ denotes the Chi F related parameter for predicting the score of any given user-item pair. Therefore, the key issues in collaborative filtering are (1) finding a suitable function F to model the complex relationship between users and items, and (2) finding a suitable θ to achieve high generalization performance for user-item interaction F.

3.1.2. FM model. The factorization machine (FM) was first proposed by Rendle and can be viewed as a general-purpose predictor in both classification and regression tasks [21]. The FM model is equivalent to the introduction of a second-order combinatorial term based on logistic regression $x_i x_j$, with the following formula:

$$y(x) = w_0 + \sum_{i=1}^{n} w_i x_i + \sum_{i=1}^{n} \sum_{j=i+1}^{n} w_{ij} x_i x_j \tag{14}$$

where n represents the number of sample features, x_i is the value of the i rd feature, and w_0, w_i, and w_{ij} are the model parameters.

3.1.3. DeepFM model. DeepFM model includes two parts, FM and Deep, in which the FM model can extract to low-order features, while the Deep model is the deep neural network, which is mainly used to mine high-order features, these two parts share input features to serve the system, which is widely used in recommendation class algorithms. And the model can learn both low-order and high-order combination features from the most primitive features, no longer need manual feature engineering.

The prediction result of DeepFM can be expressed as:

$$\hat{y} = Sigmoid\left(y_{FM} + y_{DNN}\right) \tag{15}$$

where y_{FM} is the same as Eq. (15) for the output of the FM model and y_{DNN} is the output of the deep neural network.

3.1.4. The MAGFM model. The memory-aware gating factorization machine (MAGFM) is first introduced, followed by a detailed description of the individual components. The proposed MAGFM includes the following key components:

Input Layer and Embedding Layer. The MAGFM takes user id, item id, metadata of the user's most recently interacted items and the target user, the target item and the historical items as the input layer. Then, the sparse representation of the input is mapped to a low-dimensional representation using Embedding layer.

Gating Feature Extraction. Auxiliary information and historical items may not be completely relevant to the target user-item pairs, so we propose a gated filtering unit on top of the Embedding layer, aiming to filter out irrelevant information from auxiliary information and historical items. After filtering, we can obtain first-order features and generate corresponding second-order features. Then, the first-order and second-order features are connected to the prediction layer as part of the overall features.

Memory-aware feature extraction. After obtaining the filtered first-order features, we propose a memory-aware feature extraction network to extract the higher-order features. Then, the higher order features are used as part of the overall features for the prediction layer.

Prediction Layer. After obtaining the first-order, second-order, and higher-order features from the two separate components described above, we connect them as the final feature vector for prediction. The prediction layer uses a multilayer perceptron (MLP) to predict the final recommendation score.

3.1.5. Loss functions and optimization methods. The cross-entropy loss function is used to learn the parameters of MAGFM, and the cross-entropy loss has gained wide application in the top-N recommendation task, defined as follows:

$$Loss = -\sum_{(u,i)\in\Omega} y_{u,i} \log \hat{y}_{u,i} + \left(1 - y_{u,i}\right) \log\left(1 - \hat{y}_{u,i}\right) \tag{16}$$

where Ω is a set of training examples. We choose Adaptive Gradient Descent (AdaGrad) to optimize the loss function because it has fast convergence and good generalization performance in training deep neural networks.

3.2. Analysis of personalized recommendation of tourism cultural creative products

3.2.1. Calculation of total user interest value. Using the training set of data to train the tourism product recommendation algorithm based on the MAGFM algorithm, take the tourism product

“Xiamen + Gulangyu Island + Yunshui Rhyme Tour” as an example, Table 5 shows the results of the theme eigenvalues of the tourism product, the interest value of the user u in each theme, and the product of the theme eigenvalues and the user's interest value.

According to the calculation of the product of theme characteristic value and user interest value in the table, 1.28505 is obtained, so the interest value of user u in “Xiamen + Gulangyu Island + Yunshui Rhyme Double Fly 5-Day Group Tour” is 1.28505.

Table 5. User - travel product interest calculation

Subject number	Tourist product theme value	User-themed value	The topic feature value and the user interest on the product value
Meal	0.08033	1.55698	0.12507
Family travel	0.18179	0.4885	0.0888
Cost-effective travel	0.12759	0.75006	0.0957
Accommodation service	0.07635	0.42953	0.03279
Tour guide	0.04753	0.20191	0.0096
Play project	0.24299	2.93194	0.71243
Leisure series	0.0957	0.48687	0.04659
Environment	0.0776	1.46747	0.11388
Group mode	0.06228	0.96632	0.06018

3.2.2. Calculation of Similarity of Tourism Cultural and Creative Products. The similarity is calculated using the attribute features of tourism products, and with the increase in the number of tourism product reviews, the similarity is mainly calculated using the theme features of tourism products extracted from the review data, and the comprehensive similarity calculation alleviates the cold-start problem and improves the accuracy of the recommendation. Some of the calculation results are shown in Table 6.

The table lists some of the integrated similarity calculated according to the formula, the similarity between tourism product 1 and 4 is 0.74312, and the element on the diagonal line is 1, indicating that the similarity between itself and itself is 1.

Table 6. The comprehensive similarity matrix

Travel_pro	1	2	3	4	5
1	1	0.30062	0.69756	0.74312	0.37176
2	0.30062	1	0.43117	0.261	0.8045
3	0.69756	0.43117	1	0.69823	0.51125
4	0.74312	0.261	0.69823	1	0.33345
5	0.37176	0.8045	0.51125	0.33345	1
6	0.68672	0.21926	0.53587	0.60393	0.27879

For selecting similar tourism products, there are a total of two methods, one is to filter tourism products by setting a similarity threshold, those above the threshold are judged as similar tourism products, and those below the threshold are not judged as similar tourism products. The other method screens the top K tourism products after sorting them in descending order of similarity. In this paper, the second method is selected to screen the top K positions of tourism products according to the comprehensive similarity ordering and set N=10. The line graphs of K value versus accuracy and recall are obtained by training the model according to the training set data, as shown in Fig. 3 and Fig. 4.

With the increase of K value, the accuracy rate and recall rate are growing, and the most growth is observed at K=20, so it is optimal to choose K=20.

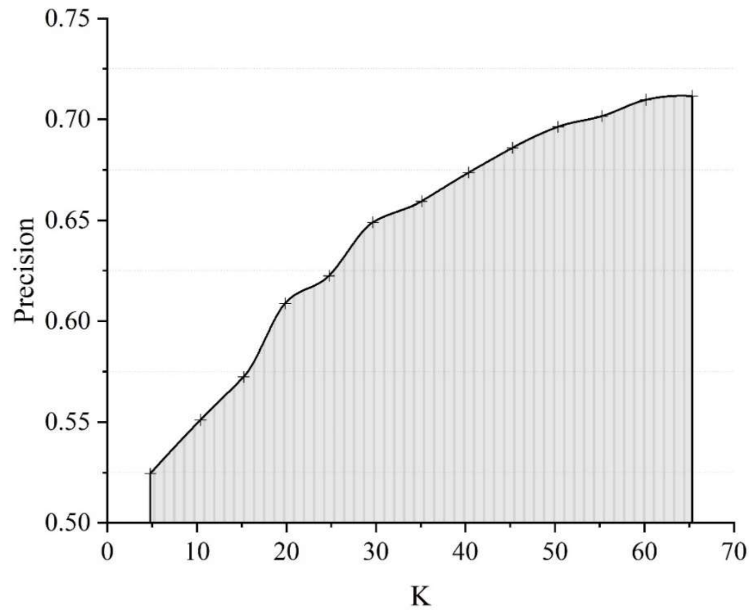

Fig. 3. MAGFM algorithm accuracy versus K

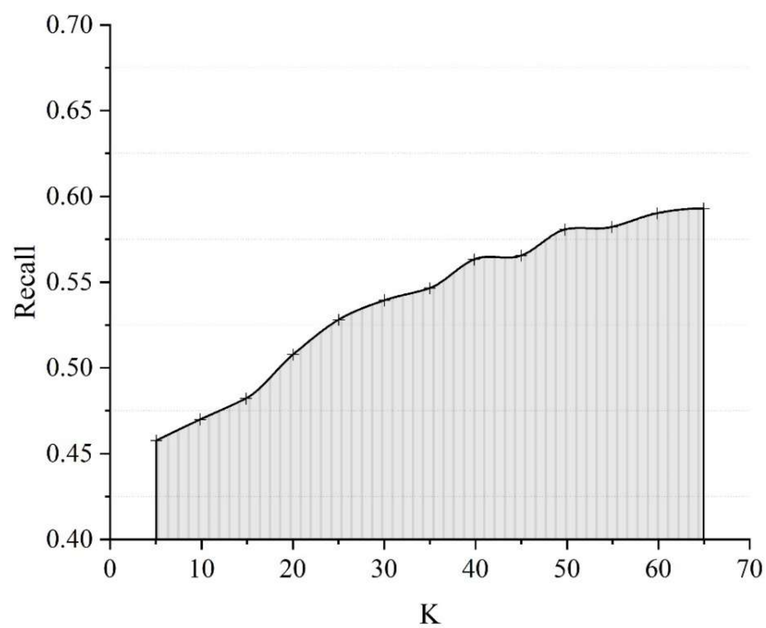

Fig. 4. Recall and K value for the MAGFM algorithm

3.2.3. Evaluation of improved tourism product recommendation methods. Based on the model training results to obtain the optimal K value, this section further evaluates the model based on the test set data.

Travel product recommendation methods can be broadly categorized into three types:

The first type utilizes the similarity of tourism product attributes to perform Top-N recommendation based on user history and user preferences.

The second one utilizes the theme distribution of tourism product topics and tourism product attribute feature data to calculate the comprehensive similarity of tourism products, and then makes Top-N recommendations based on user history and user preferences.

The third one is the MAGFM-based travel product recommendation algorithm proposed in this study.

Based on the test set data, the recommendation effect of the three methods is finally tested by combining the accuracy, recall and coverage respectively as shown in Fig. 5, Fig. 6 and Fig. 7. From the figures, it can be seen that the improved methods are better than the traditional method 1 and traditional method 2 in terms of accuracy, recall and coverage, so it can be inferred that the MAGFM-based tourism product recommendation method used in this paper is effective for tourism product recommendation. When recommending 10 tourism products to the user, the MAGFM-based tourism product recommendation method has the most obvious changes in accuracy and recall, and after considering the coverage rate, it is concluded that the recommendation method achieves the optimal effect when recommending 10 tourism products to the user.

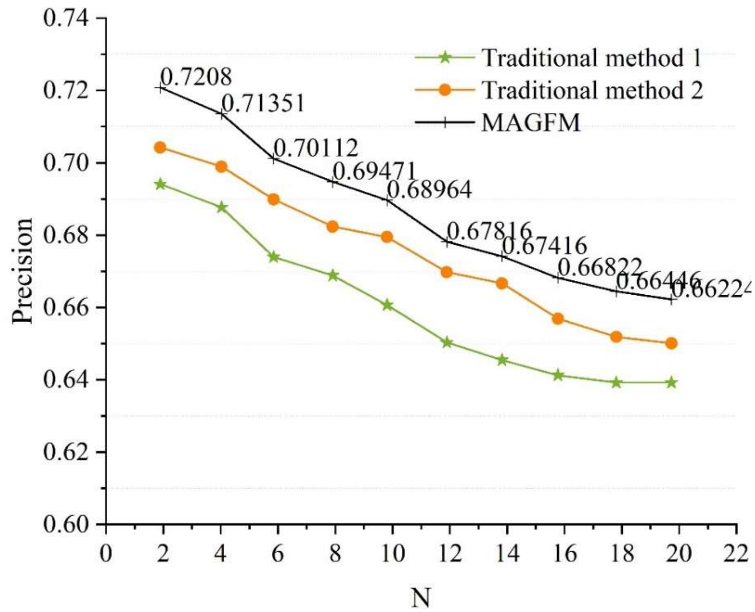

Fig. 5. recommends N values with accuracy

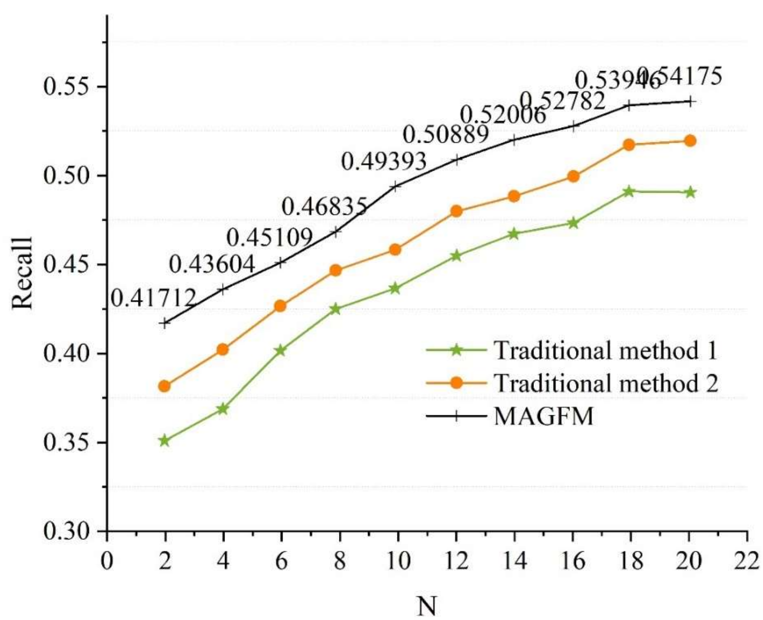

Fig. 6. recommends N values with recall

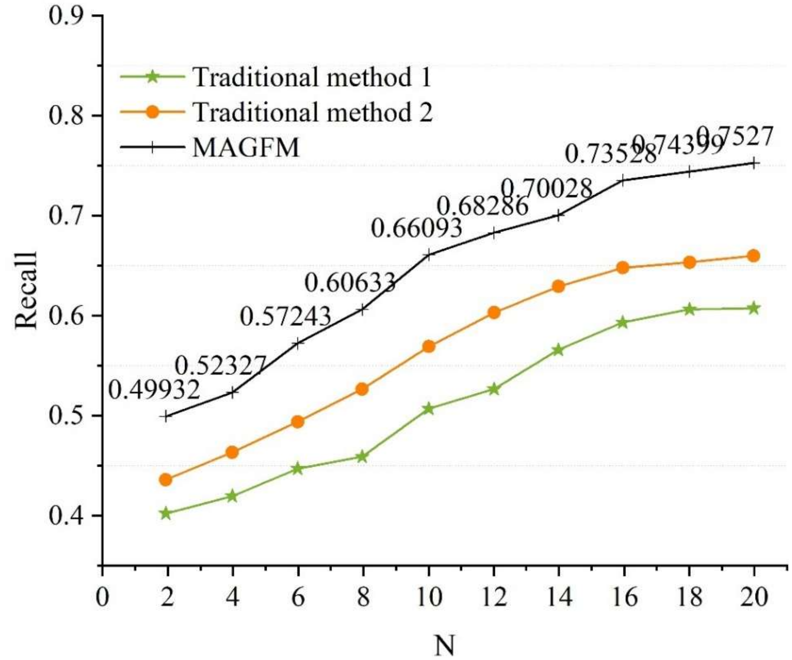

Fig. 7. recommends N values with coverage

3.3. Testing and analyzing the effectiveness of recommendations

Since the MAGFM-based travel product recommendation algorithm proposed in this paper, the user clicks on the recommended products, and the offline experimental approach is unable to obtain the commercially concerned metrics such as click-through rate and conversion rate, the online experimental approach is used to better test the recommendation effect of the algorithm. The travel e-commerce platform is a real online production environment, and a 3-week experiment is conducted on this website, in which User-based CF, Item-based CF, and MAGFM-based travel product recommendation algorithms are tested in the travel e-commerce platform during the 3 weeks, respectively. In order to ensure the fairness of the experiments, no historical behavioral data was used at the beginning of each weekly experiment. The data of the test experiments are shown in Table 7.

Table 7. Test the experimental data

	The first week	The second week	The third week
Product browsing times	10152	11783	11874
Recommended product views	1145	1485	1756
User purchase times	119	149	145
Number of purchases generated by the recommendation	26	35	35

Comparison of recommendation algorithms for travel products in terms of recommendation traffic conversion rate is shown in Figure 8. From the figure, it can be seen that the MAGFM-based recommendation algorithm for tourism products outperforms the traditional User-based CF or Item-based CF algorithms, indicating that the recommendation algorithm can better recommend tourism products for users that they have the intention to purchase, thus increasing the turnover of tourism products and bringing more benefits to the tourism enterprise.

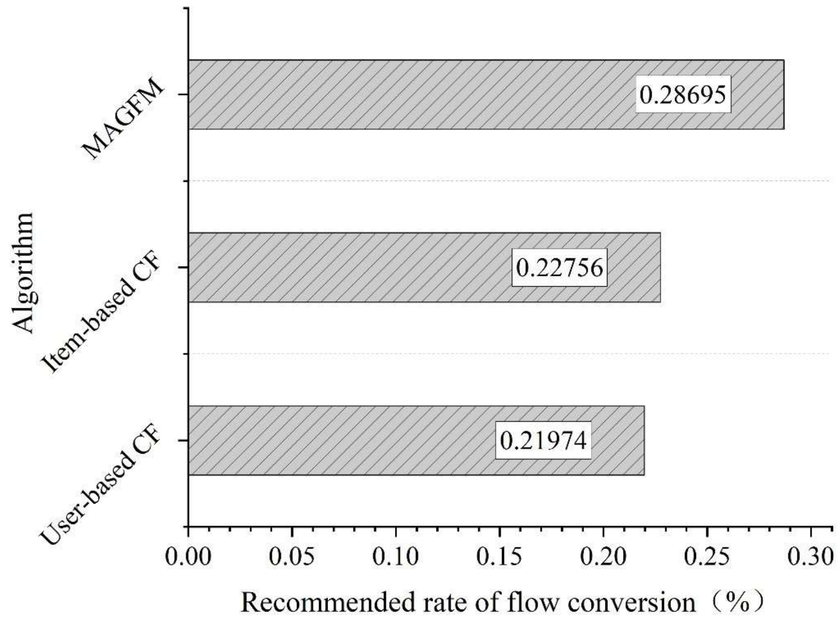

Fig. 8. Recommended traffic conversion rate

The proportion of users clicking on recommended products in browsing and purchasing behaviors of MAGFM recommendation algorithm for tourism products is shown in Fig. 9 and Fig. 10. It can be seen that the proportion of users who recommended products are higher than those using User-based CF or Item-based C algorithms, which can indicate that the algorithm recommends products of higher quality and can increase the proportion of users who purchase travel products through recommended products.

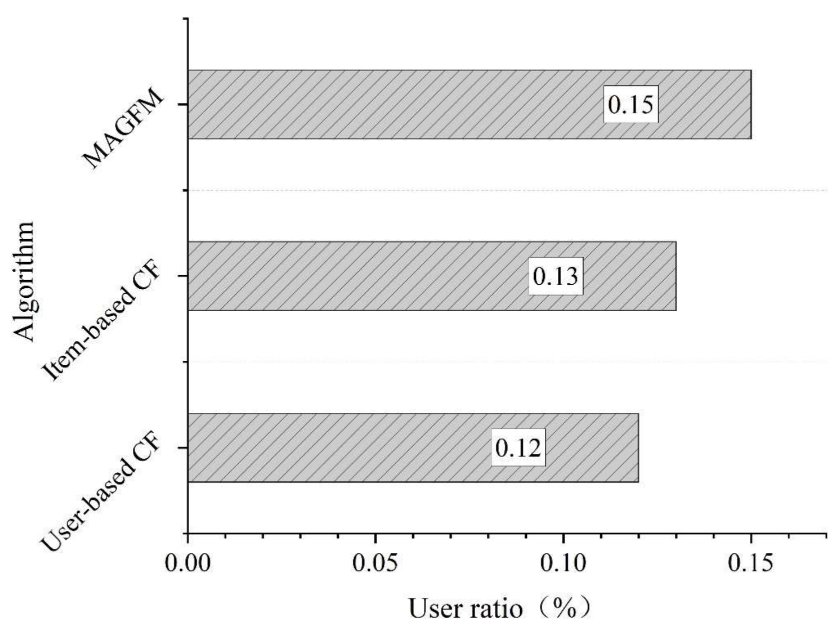

Fig. 9. The proportion of users who click recommended in the browsing behavior

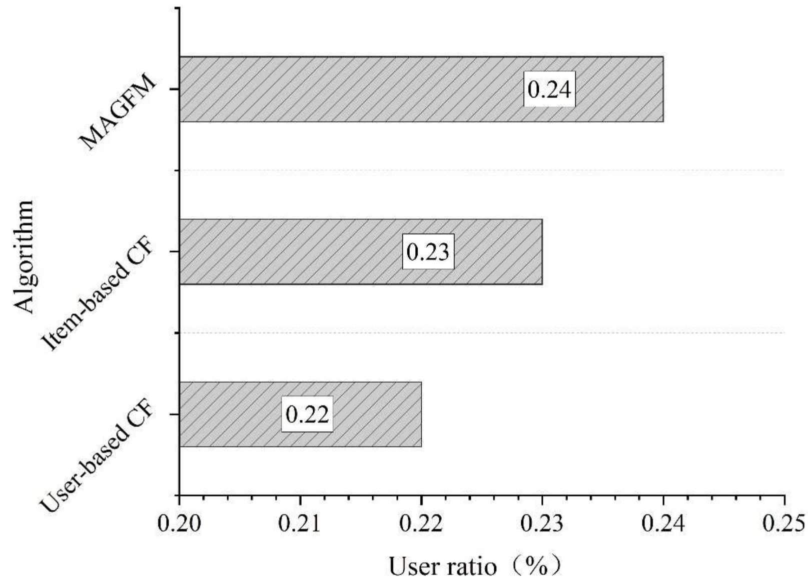

Fig. 10. The proportion of users clicking recommended in the purchase behavior

After the above test and analysis, it can be concluded that in the personalized recommendation of tourism products on this tourism e-commerce platform, the recommendation effect of using the MAGFM-based tourism product recommendation algorithm is better than that of using the User-based CF or Item-based CF algorithm, which suggests that the recommendation algorithm proposed in this paper has higher effectiveness than the traditional recommendation algorithm in the personalized recommendation of tourism products. This indicates that the recommendation algorithm proposed in this paper has higher effectiveness than the traditional recommendation algorithm in personalized recommendation of tourism products.

4. Recommendation framework for personalized push of cultural and creative products in tourist cities

4.1. Implementation of the overall system framework

4.1.1. Logical architecture. The travel e-commerce platform is logically designed according to the MVC three-layer architecture, and the overall system is divided into the representation layer, business layer and data layer. The logical architecture is shown in Figure 11.

In the whole architecture, the decoupling of representation logic, business logic and data storage logic is realized by using the design idea of MVC three-layer architecture, which makes the logic of the code clearer, greatly simplifies the difficulty of development and maintenance, and effectively reduces the workload of developers.

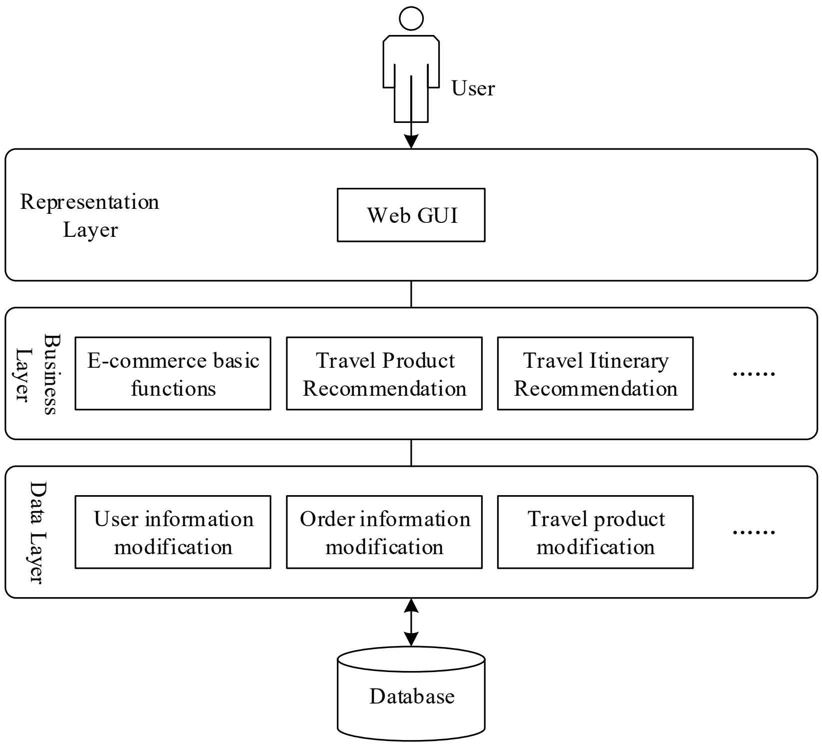

Fig. 11. Logic architecture diagram of tourism e-commerce platform

4.1.2. Functional modules. This system adopts the modular program design method to decompose each function in the system into independent modules. Modules have the characteristics of high cohesion and low coupling, which not only reduces the difficulty of adding and maintaining functions to the system, but also makes the reuse of functional modules more convenient.

According to the demand analysis of the system, the tourism e-commerce platform based on personalized recommendation is divided into three modules in terms of functionality, which are the basic function module, tourism product recommendation module and group activity itinerary recommendation module, among which the basic function module is divided into the foreground module and the background module, and the user oriented to the foreground module is the tourists, and the user oriented to the background module is the administrator. The overall functional structure of the system is shown in Figure 12.

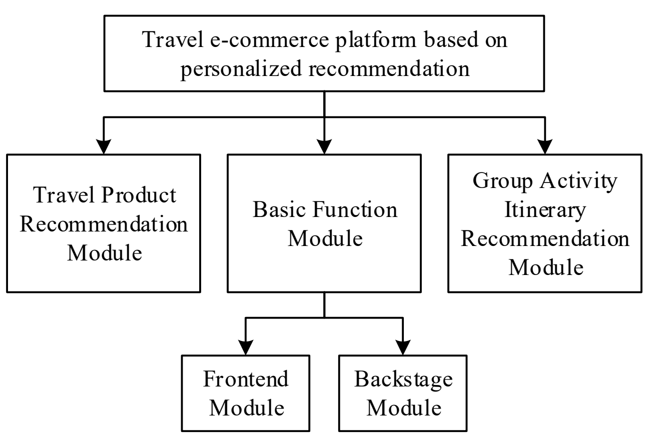

Fig. 12. The overall functional structure of the tourism e-commerce platform

4.2. Basic Function Module Design

The basic functional modules of the tourism e-commerce platform mainly include tourism product display and booking, tourism product management and user management modules.

1) Tourism product display and booking. Registered members can place an order to book tourism products after browsing the introduction of tourism products. Members need to log in before booking the product, after passing the system login verification, the system gets the personal information of the logged-in user from the session, and passes the user information to the backend, generates the order after checking the order data, and then returns the order data to the user's front-end, and after the order is generated, the system will prompt the user to pay the order. After the order is generated, the user can make online payment through Internet banking, Alipay, etc. After jumping to the third-party payment page and paying the corresponding amount successfully, the system prompts to complete the transaction.

The basic flow of tourism product display and booking is as follows:

(1) After member login, enter the tourism product display module.

(2) Select the tourism products that need to be booked.

(3) Fill in the booking quantity, package and other information.

(4) Submit the order after making sure it is correct.

(5) Jump to the third-party payment platform for online payment.

(6) Complete the product booking after successful payment.

(7) After the system confirms the successful payment, the product will be shipped according to the product type in the order.

2) Tourism product management. Tourism product management function mainly realizes the administrator to add, edit, delete and other functions of tourism products. Tourism product information mainly contains the product name, product details, departure date, package price, off-season and peak season prices, etc. Administrators can also add pictures, videos and detailed text descriptions for tourism products, so that tourists can more intuitively understand the details of the tourism product.

3) User Management. User management module is a very important functional module in tourism e-commerce platform, the main function is responsible for the management and maintenance of user accounts.

5. Conclusion

In this paper, from the perspective of data source, combined with the Web domain ontology to construct a multi-level user portrait master model, and compare the improved FCM algorithm of this paper for group user portrait clustering with the traditional FCM algorithm, traditional K-Means algorithm, and the improved K-Means algorithm, and the experimental results show that the improved FCM algorithm reduces the number of iterations of the algorithm and the average consumption time, and the MAE decreases significantly, and the Accuracy and recall are improved. Then the personalized recommendation method of tourism products based on MAGFM algorithm is proposed, and the total interest value of users in tourism products and the similarity of similar tourism products are weighted and sorted to achieve the Top-N recommendation of tourism products, and the results show that the recommendation method achieves the optimal effect when 10 tourism products are recommended to users.

Combining the above, the research constructs a recommendation system applicable to the personalization of cultural and creative products in tourist cities to promote the tourism development of tourist cities and drive the local economy.

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