

Research Article

Multisource Information Fusion Algorithm for Personalized Tourism Destination Recommendation

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Received 27 July 2022; Revised 8 September 2022; Accepted 12 September 2022; Published 28 September 2022

Academic Editor: Zaoli Yang

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In this paper, the existing scenic spot recommendation algorithms ignore the implicit trust and trust transmission of users when dealing with user relationships, and the lack of historical browsing behavior data of users in new city scenes leads to an inaccurate recommendation. In this paper, a personalized scenic spot recommendation method combining user trust relationship and tag preference is proposed. Firstly, the trust degree is introduced when the recommendation quality is poor only considering the similarity of users. By mining the implicit trust relationship of users, the problem that the existing research cannot make recommendations when the direct trust is difficult to obtain is solved, and the data sparsity and cold start problems are effectively alleviated. Secondly, in the process of user interest analysis, the relationship between scenic spots and tags is extended to the relationship among users, scenic spots and tags, and users' interest preferences are decomposed into long-term preferences for different scenic spots tags, which effectively alleviates the problem of poor recommendation quality when users' historical tour records are lacking. The personalized tourism recommendation method proposed in this paper effectively integrates many features of social networks and effectively alleviates the problems of data sparseness and feature learning in tourism recommendation based on social networks by using vectorization and deep learning technology. Its research has very important usage scenarios and commercial value in the tourism industry. This model can efficiently mine the association rules between scenic spots in multisource information data. The experimental results show that mining the correlation between the scenic spots selected by tourists can provide effective information for tourism decision-making.

1. Introduction

In the era of Web2.0, people's daily life has been inseparable from the Internet. The change of users from passively receiving information to actively acquiring information increases the amount of data and makes the data types complex and diverse. Because users cannot quickly and accurately locate the information they need from the mass of information, the phenomenon of "information overload" arises. The problem of "information overload" exists in the recommendation system. The two main manifestations are data sparsity and data scalability. As an information filtering technology, collaborative filtering can be used to solve the problem of poor recommendation performance. At present, the multisource information available for recommendation

systems on the Internet is becoming more and more abundant and easy to obtain. Multisource information is a variety of auxiliary information from different sources, such as user information, item information, and interactive information between user items, which brings new opportunities for the optimization of collaborative filtering algorithm. Multisource information can be used to supplement the single historical scoring information in traditional collaborative filtering algorithm, and this idea can be used to solve the existing challenges of collaborative filtering algorithm [1, 2]. Information push refers to the Internet application that draws people's portraits based on the user's online browsing trajectory and actively pushes the travel information that the user may be interested in. Currently, most of the recommendations of tourist attractions apply the

information push theory [2]. Although this tourism information recommendation method solves the problem that users are difficult to choose to some extent, its recommendation accuracy is usually very low, and it cannot provide users with reference tourism goals. Looking at the tourism recommendation research, it is not difficult to find that the existing methods have some problems, such as sparse data, cold start, and low recommendation accuracy, and the accurate recommendation of tourist attractions still faces great challenges.

Theoretically speaking, scenic spot recommendation is an important research direction of the recommendation system, which is a further extension of the development direction of the recommendation system and helps to enrich and improve the existing recommendation algorithms and models. From the application point of view, the application of a recommendation system to tourism websites will help to improve the recommendation function of tourism websites, thus saving users' time, greatly enhancing users' travel experience, and finally enhancing the core competitiveness of tourism websites [3]. Personalized travel route recommendation refers to the generation of travel routes for each user that meet their own travel restrictions on the basis of considering users' personalized factors. In the process of traveling, users' interest preferences drift between geographical regions, that is, users often have different interests when traveling in different regions. Social media is not only a platform where users can freely share their opinions and opinions but also the problem of information overload [4]. In order to enable users to quickly and accurately find what they want in the vast amount of information, a personalized recommendation system is a very effective solution.

With the popularity of social networks such as multi-source information, the rich user behavior data in the network brings new opportunities and challenges for the accurate application of tourism information recommendation. Multi-source information, as a new generation network application form, has the characteristics of a large user base, frequent status updates, and rapid information dissemination. It is not only more suitable for the fast pace of life in modern society but also more convenient for tourists to share their travel experiences and feelings through mobile terminals. Because of its strong real-time, rich semantics, and large amount of data, it has been widely used in different fields [5]. Multi-source information data contains abundant information related to tourism, such as personal information of users, information of scenic spots, location of users, and visiting time. Therefore, it can make up for the data sparseness defect to some extent, and provide a new way for obtaining tourism information. Tourism data itself has no consciousness and cannot present valuable information on its own, but machine learning can dig out useful information and then solve the problem of accurate recommendation of tourist attractions.

2. Related Work

With the new opportunities brought by Internet technology, the development trend of tourism is also undergoing unprecedented changes. The output value of global tourism is

increasing steadily almost every year, and the huge tourism demand and huge tourism resources cannot be reasonably matched. The asymmetry of mutual information is an important problem that the tourism industry needs to overcome today. How to integrate these demands and provide personalized travel plans for users is a hot research topic in the current tourism industry [6].

Renjith et al. use a clustering algorithm to solve the scalability problem in collaborative filtering. However, due to the lack of enough information to learn users' hidden preferences, only using users' activity record information cannot fundamentally solve the inherent problems in the recommendation system. In recent years, various types of multi-source information have become more and more abundant, such as item attribute information, social network information, geographical location information, and user comment information. The available multisource information is a useful supplement to the user's historical activity record, which brings an opportunity to solve the problem of information shortage in the recommendation system [7]. Zhang et al. proposed the DTMF model to fuse rating and comment texts, and LDA algorithm fused the potential themes of commodity and user comment texts with the potential factors of the matrix decomposition algorithm to recommend them [8]. Yong and Huang proposed to integrate time, location, and comment text and mine the topic probability distribution of users and points of interest through the LDA topic model and spatial coordinates for POI recommendation [9]. Han-Da et al. based on the heterogeneous information in social media, put forward the PAS model to mine the internal connection of heterogeneous information, calculate the similarity between scenic spots through multimodal fusion, and recommend scenic spots by combining contextual information [10]. Shen et al. proposed to use of natural language processing and ontology technology in the tourism field to analyze the sentiment of comment texts and obtain tourists' preferences, so as to provide tourists with scenic spot recommendations [11]. Zheng et al. put forward a hybrid recommendation algorithm that combines a collaborative filtering algorithm, content-based recommendation, and demographic-based recommendation by switching and weighting [12]. Pan proposed the DTMF model to fuse rating and comment texts and fused the potential themes of commodity and user comment texts with the potential factors of the matrix decomposition algorithm through the LDA algorithm to recommend them [13]. Zheng et al. think that a user-based collaborative filtering algorithm assumes that users have a common preference in historical activity records, so they may share similar preferences in the future. In contrast, the collaborative filtering algorithm based on items assumes that users tend to like similar items, and predicts the preference of active users to target items by their preferences on similar items [14]. Pei and Zhang adopt the Agent technology with a semantic Web environment to help customers choose the appropriate travel company according to their needs and preferences, take users' preferences as the sole basis, coordinate services among multiple transportation networks, and make end-to-end route planning by using a variety of

transportation tools [15]. Pavez et al. combine social network information, introduce a mixed topology structure centered on social networks, and make use of the circulation nature of information among social networks to transfer information from auxiliary data sources to target areas, helping to complete the recommendation [16].

Relevant scholars focus on mining data sets in the multidata source domain and strengthen their study in the target data source domain by constructing auxiliary data sources. The feasible condition of multidata source cross-domain recommendation is that users' interest characteristics in different data sources have a certain correlation. At the same time, it is pointed out that the purpose of multidata source cross-domain is more inclined to improve users' experience and enhance the correlation among various data source domains. In this paper, the data source to be recommended is called the target data source domain, and the data source recommended by the auxiliary target domain is called the auxiliary data source domain. By studying the auxiliary data source domain, the problem of data sparsity and cold start in the target data source can be effectively alleviated.

3. Design of Recommendation System with Multisource Information Fusion

3.1. Simulation of Tourist Attraction Recommendation System.

In all aspects of society, all walks of life are considering using the Internet as a medium to promote their information more timely and effectively. The best way is to establish a network management system and manage its information. Due to the development of the network, tourism information management through the network has set off an upsurge. Therefore, a set of tourist attraction recommendation system is developed according to the user needs of tourist attraction recommendation. A perfect recommendation system can help most active users to actively obtain relevant information they are interested in when browsing relevant information on the Internet, solve the problem of information lost caused by the massive increase of data and enable users to obtain valuable information for themselves from massive Internet data [17]. After the recommendation system determines the similar users of the target users, it selects the corresponding similar users to build the target neighbors. At this time, the recommendation system has discovered some users with similar interests and preferences to the target users. Then, according to these users, it can realize the most critical step of collaborative filtering, namely, score prediction. Combine the scoring data of the target users on the projects, predict the projects that the target users have not scored, present the scored recommendation results to the users in the way of a scoring flashback, and finally complete the recommendation process. The calculation method of target user rating prediction is shown in the following equation:

$$P(i, j) = \frac{\sum \text{sim}(i, v)(\bar{j}_{i,j} - \bar{j}_v)}{\sum |\text{sim}(i, v)|} + \bar{r}. \quad (1)$$

According to the user's rating on the project, the user's interest degree is calculated, and the recommendation results are presented to the user in the corresponding order. Labels can be used to organize articles according to a certain level more conveniently so as to recommend them. The basic execution process of the tag-based recommendation algorithm is to first count the tag frequency of each user or commodity in the current recommendation field, then build a statistical set of tags corresponding to entities in the system, and finally sort the user tags according to the number of tags involved by users in the statistical set of tags. The tag-based interest formula is shown in the following equation:

$$P(i, j) = \sum \frac{n_{u,j}}{\log(1 + n_j^i)} \cdot \frac{n_{b,j}}{\log(1 + n_j^u)}. \quad (2)$$

In view of the scarcity of tags, which makes it impossible to obtain a complete match, this problem can be solved by constructing the correlation between related tags and expanding the tags by calculating the similarity among the tags in the system. The recommendation system does not require users to provide clear demand information. It has become an important means of information filtering and is the mainstream method to solve the problem of information overload at present. Its workflow is shown in Figure 1.

Firstly, the system obtains the similarity between the target user and the neighboring users according to their historical data; secondly, according to the interest preference of the most similar neighbors of the target users, the preference degree of the target users to the recommended objects is predicted, and the system recommends the target users according to the different preference degrees. Fusion is based on one recommendation model, mixed with another recommendation model, based on a content-based recommendation model, mixed with a collaborative filtering model. Before fusion, various recommendation models are mixed into one model, and then features are extracted from all kinds of data as the input of the model, and the recommendation results are generated by the mixed model. For an object to be recommended, there are four final recommendation results, as shown in Table 1.

Experience-based collaborative filtering makes predictions by analyzing the scores given by users before. The unknown rating of a user's item is usually obtained by weighting the item by other users, and the set of different users who have given the rating is shown in the following equations:

$$r_{s,c} = \frac{1}{W} \sum_{c \in C} r_{s,c'}, \quad (3)$$

$$r_{s,c} = U \sum_{c \in C} r_{s,c} \text{sim}(c, s') \times (r_{r,c} - r_c). \quad (4)$$

Different recommendation systems can adopt different similarity metrics according to the specific needs of applications. Different measurement methods can be adopted according to different data characteristics. In machine

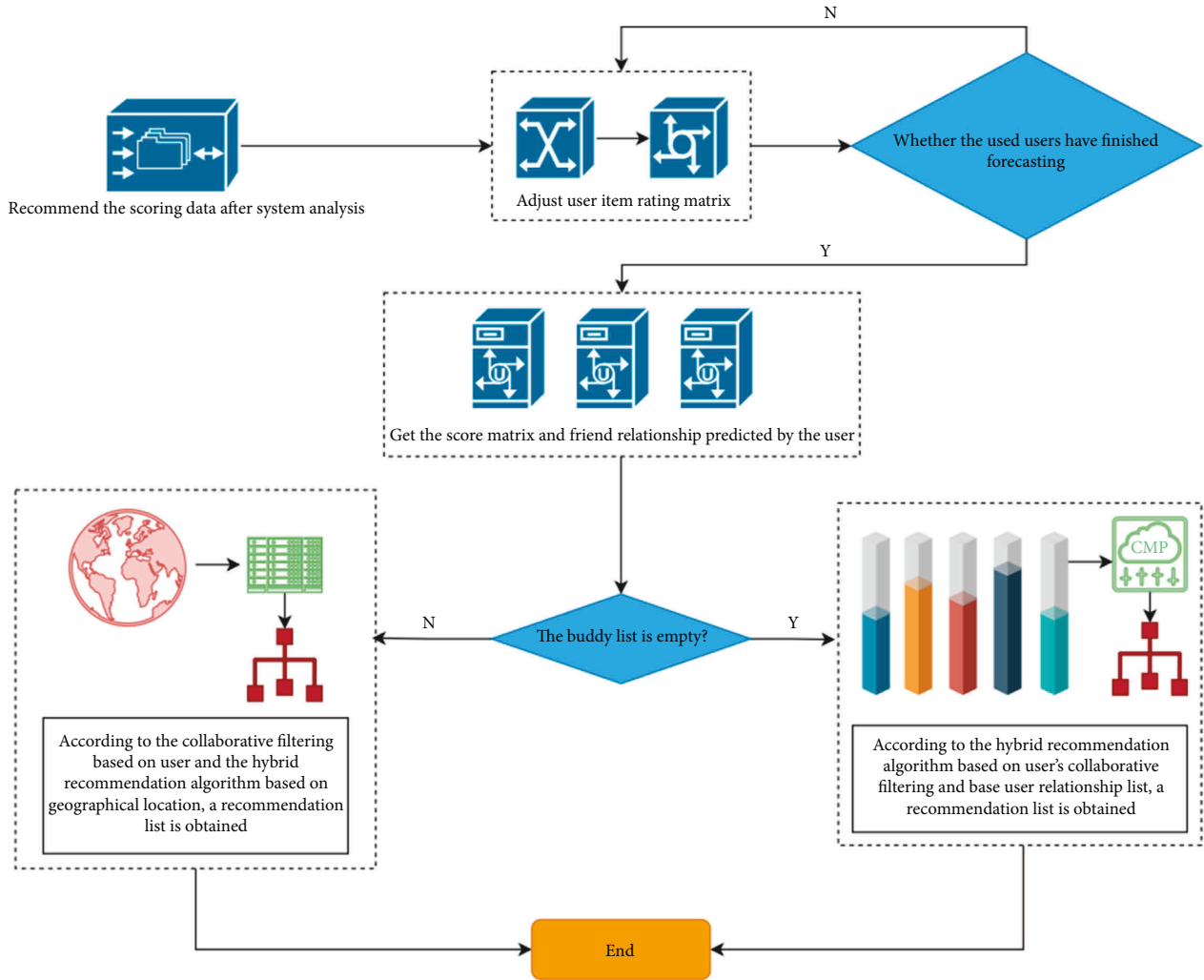


FIGURE 1: Workflow of recommendation system.

TABLE 1: Four categories of objects to be predicted.

User preference	Recommender system	System not recommended
Be satisfied	True-positive N_p	False-positive N_{rp}
Dissatisfied	False-negative N_{rm}	True-negative N_n

learning and data mining, we often need to know the difference between individuals and then evaluate the similarity and category of individuals. The most common are correlation analysis in data analysis, classification, and clustering algorithms in data mining, such as k-nearest neighbor (KNN) and k-means (K-means), and so on. Generally, the similarity between users is calculated based on the ratings of two users on the same item. It is not obtained from the predicted recommendation system, so it can be assumed that the unused items in the data will not be used, even if they have been recommended to users, and users are not interested in these items. This assumption may not be valid. For example, unused items may also contain items that users are interested in but have not yet chosen. If users of each item choose, its index is shown in the following equation:

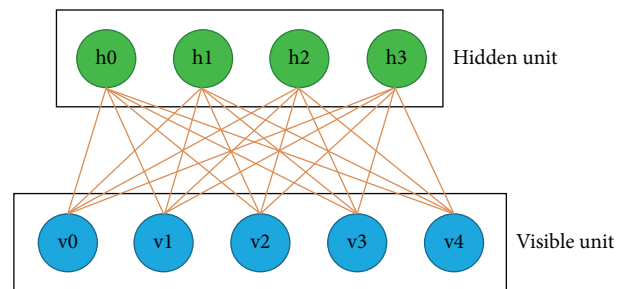


FIGURE 2: Test set data prediction system.

$$G = \frac{\sum_{i=1}^{4.3j-n-1} p(i_j)}{n+1} \quad (5)$$

In some systems, some users may not get any recommendation results, because when the system predicts these users, its accuracy confidence is very low. However, from the perspective of user experience, this paper hopes that the recommendation system can provide recommendation information for the vast majority of users. This should take into account the tradeoff between user coverage and

recommendation accuracy. The process of restoring neuron values from hidden cells to visible cells is decoding. The goal is to minimize the difference between the expected values of optimization, iteratively calculate and update the model, and at the same time predict the test set data through the decoding process. Its structural process is shown in Figure 2.

The existing recommendation algorithms do not fully consider the problem that users' interests will change dynamically according to the attributes of destinations when they visit different destinations. This paper proposes a personalized travel route recommendation model based on users' dynamic interests. Firstly, according to the user's historical travel records, the user's interest vector is composed of the user's preference of topic categories and popularity of interest points, and then integrated into the collaborative filtering model, so as to effectively mine the user's access preferences. In the aspect of vectorization processing of social network data features, a new probabilistic topic model is defined to model the user's topic information and get the user's topic vector representation. The historical access matrix of users on POI is constructed, and the feature embedding method of matrix decomposition is introduced to model the relationship between users and POI. Using the user's access relationship to POI, it is converted into the vector of users and POI by the MF algorithm, so as to extract the user's access feature vector. By vectorizing the data features, the problem of data sparsity is alleviated.

3.2. Scenic Spot Recommendation Based on Self-Coding. In social networks, different users often have different social status. Users with low social status usually ask for advice from users with high social status. On the contrary, users with social status quotient will not consider the suggestions of users with low social status [18, 19]. In other words, users with high social status are often less influenced by other users; Users with low social status are greatly influenced by other users because of their lack of knowledge in related fields. In this paper, a personalized recommendation algorithm based on a trust relationship is proposed, which uses a trust propagation mechanism and user similarity method to establish a direct and indirect trust relationship between users. In this paper, the above methods are used to simulate users' social relations and analyze the characteristics of trust spreading and aggregation. The calculation formula of trust value between users is shown in the following equation:

$$T = \frac{\sum_{v \in V} t_{f,i} \cdot t_{f,v}}{\sum_{v \in V} t_{f,i}}. \quad (6)$$

Recommend neighbors with high similarity and high trust value to users. And, the calculation formula of the new trust value between the user and the user is shown in the following equation:

$$T_{i,f} = \frac{2\text{sim}(f, i) \cdot t_{f,i}}{\text{sim}(f, i) + t_{f,i}}. \quad (7)$$

The minimization of the recommended objective function of location points of interest based on social relations is shown in the following equation:

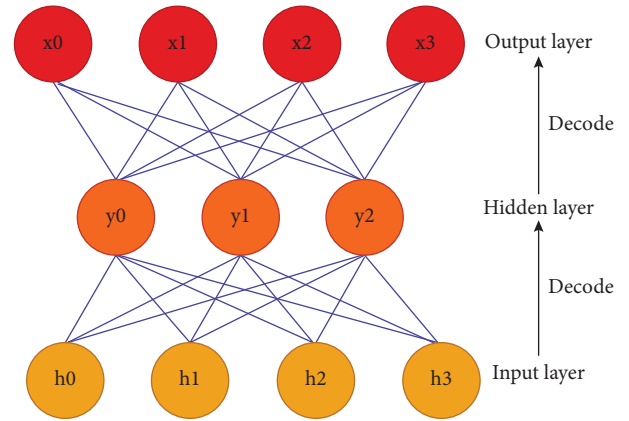


FIGURE 3: Schematic diagram of self-coding structure.

$$\min = \frac{1}{2} \sum_{i=1}^k \sum_{f \in u} T_{f,i} (u^2 - u_f). \quad (8)$$

Sometimes, the reconstruction strategy in the self-encoder cannot extract useful information, so the obtained model may not be the best solution. In order to avoid the above problems, this paper proposes to use a denoising factor in the original data and defines it as a denoised self-encoder [20]. Among many anomaly detection methods, spectral anomaly detection techniques try to find low dimensional embedding of original data, where abnormal and normal data are expected to be separated from each other. After finding the embeddings of lower dimensions, they are brought back to the original data space, which is called the reconstruction of the original data. By reconstructing the data using a low dimensional representation, we expect to obtain the true nature of the data without uninteresting features and noise. The reconstruction error of the data point (the error between the original data point and its low dimensional reconstruction) is used as an abnormality score for detecting an abnormality. The method based on principal component analysis (PCA) belongs to this method for detecting abnormalities. A denoising self-encoder is a variant of a self-encoder, which can be trained to reconstruct the original input data from the damaged data. Since the denoising factor can handle the damaged data, it makes the self-encoder more stable. The self-encoding structure is shown in Figure 3.

Denoising self-encoder is a special kind of self-encoder, which is characterized by destroying the input data. Stack denoising self-encoder is the superposition of many self-encoders. Using a denoising self-encoder in the recommended system can predict the missing value of damaged data. Stack denoising is used to extract text features from an encoder, and scoring and comment text information are combined to improve the accuracy of recommendation. The encoder realizes the prediction by minimizing the root mean square error, which is the most commonly used accuracy index in the recommendation system. Compared with the self-encoder without a stack, the stack self-encoder can learn hidden features more deeply, so it can produce a more accurate prediction [21]. Neural networks with multiple

TABLE 2: Data statistics.

Event	LA	NYC
Users	m56115	56115
POIs	248332	248332
Reviews	439190	439190
Social links	643252	643252
User-POIs matrix density	0.0627	0.0365

hidden layers can be used to solve the classification problem of complex data such as images. Each layer can learn features at different levels of abstraction. However, training a neural network with multiple hidden layers may be difficult in practice. An effective method to train multilayer neural networks is to train one layer at a time. This can be achieved by training a special network called self encoder for each hidden layer. In the process of data preprocessing, each data set is divided into two data subsets: training set and test set, and the training data is used to predict the test set results, as shown in Table 2.

This algorithm uses the document topic generation model to infer the user's interest preference and local area preference, expresses the local preference and user's personalized interest preference as a mixed topic model, and learns the topic distribution of interest points from the check-in data and classification information of location interest points. Because LCARS ignores the user's geographical location information and social characteristics. Inaccurate filling may seriously distort the expression of the original data, so this paper proposes to use only the directly observed scoring data for modeling, and at the same time, add regularization term to avoid overfitting, and minimize the error square sum of the objective function with regularization term in the known scoring data set as shown in the following subitems:

$$\text{RPQ} = \min \sum_{(i,u) \in K} \left(\sum_{k=1}^k q_{ik} p_{ku}^T \right)^2 + \lambda \|p_2\|, \quad (9)$$

$$\frac{\partial p}{\partial E_{uk}} = -2 \left(\sum_{k=1}^K p_{uk} q_{ik} \right) + \lambda_{ki} 2p, \quad (10)$$

$$\frac{\partial q}{\partial E_{ik}} = -2 \left(\sum_{k=1}^K q_{uk} p_{ik} \right) + \lambda_{ki} 2p. \quad (11)$$

The core problem of location interest point recommendation proposed in this paper is how to analyze the location interest point check-in record of a given user and other available context information, and recommend the location interest point to the user. The user's check-in frequency reflects the user's preference for location points of interest, and the user and location points of interest data are mapped to the potential low-dimensional hidden space. The matrix decomposition model of interest point recommendation can approximate the user's potential interest in nonvisited places by optimizing the solution, as shown in the following equation:

$$X = \min \frac{1}{2} \left(I_o(R - NU^2)^T \right). \quad (12)$$

Loss optimization of functions is easy to cause overfitting, so regularization term is added to prevent overfitting, as shown in the following equation:

$$E = \sum_{i=1}^M (r_{ij} - P_i \times Q_j)^2 + \lambda (\|P_i\| + \|Q_i\|^2). \quad (13)$$

In order to get a suitable matrix, optimize its loss function, as shown in the following equation:

$$E = \sum_{i=1}^M \sum_{j=1}^N (r_{ij} - \log(P_i \times Q_j))^2. \quad (14)$$

The normalized cumulative loss gain is evaluated according to the position of the correct item, and the definition formula of normalized cumulative loss gain is shown in the following equation:

$$E = \sum_{i=1}^M \sum_{j=1}^N (r_{ij} - \log(P_i \times Q_j))^2. \quad (15)$$

The input sentence is regarded as an ordered model, and the sequence information is extracted by using the bidirectional gated loop unit. In addition, the attention mechanism can directly access the hidden feature representation of the previous time step, thus reducing the long-term memory burden of the bidirectional gated loop unit. The experimental results show that extracting important words and sentences is extremely important in the research based on comment text recommendation.

4. Performance Experiment of Multisource Information Fusion Recommendation System

4.1. Stratified Sampling Statistical Model. According to the stratified sampling statistics, it can be seen that the tourism preferences corresponding to different user attributes will be quite different. Based on this, the subjective weighting evaluation method is used to set the weight of stratified sampling statistical results and calculate the Precision value of the system, as shown in Figure 4.

It can be seen from the figure that the FCM model in the recommendation system plays a major role in a mixed recommendation; that is, most recommendation results are decided by the BPR model. The user's travel preference information obtained based on stratified sampling statistics plays an auxiliary role, which makes the recommendation result smoother, that is, the user's preference information is used to make up the recommendation bias of the FCM model. There are some negative information in the results after HC decomposition, which is of little significance to the recommendation and will interfere with the recommendation. The Recall value of the recommended system is shown in Figure 5.

From the perspective of recall rate, the tourist attraction recommendation system based on stratified sampling

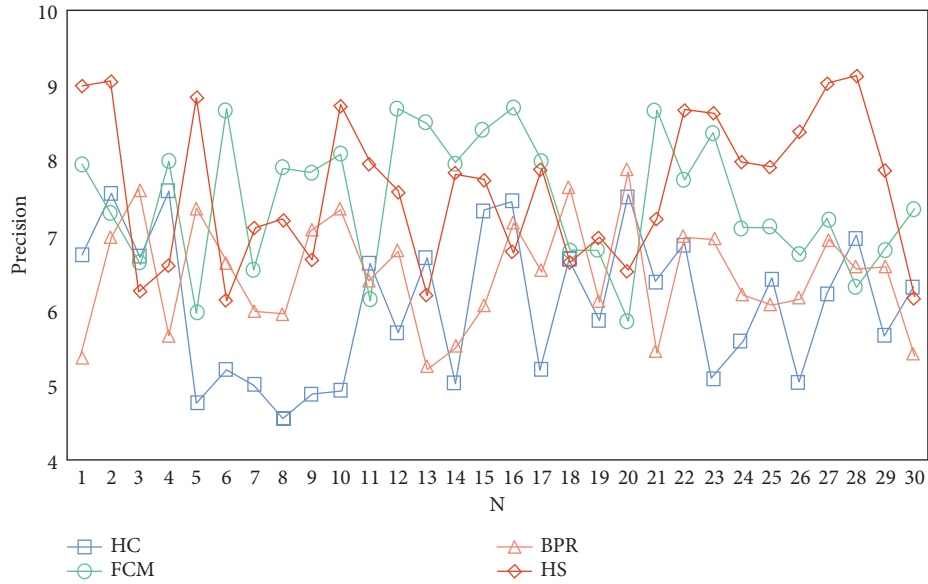


FIGURE 4: Comparison of Precision values of recommended systems.

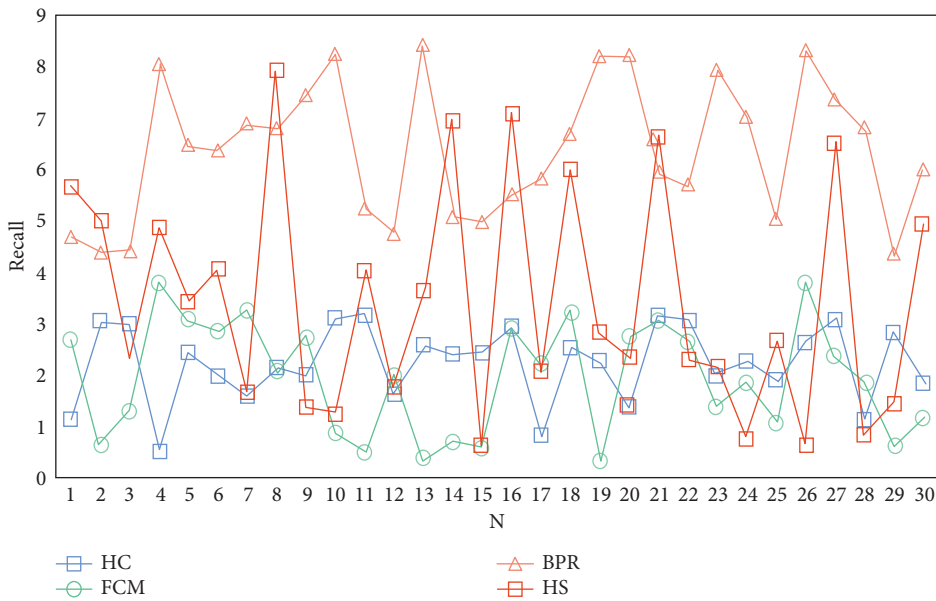


FIGURE 5: Comparison of Recall values of recommended systems.

statistics and improved BPR model has certain practical value. In this paper, singular value matrix decomposition technology is used to vectorize the user’s check-in data. After matrix decomposition, the user’s check-in record matrix is transformed from high-dimensional sparse data to a low-dimensional user potential vector. Users with similar sign-in records, the potential vectors of users obtained by matrix decomposition, are closer in vector space. That is, the closer the distance between user vectors is, the higher the similarity of access is.

In this experiment, the experimental data set is divided into a training set and a test set according to the ratio of 1 : 1. The data in the training set are evaluated and the results are verified by the data in the test set. The score similarity and

attribute similarity of scenic spots are combined to construct the global similarity of scenic spots, and the result is shown in Figure 6.

At first, the knowable value of the graph decreases with the increase of the weight parameter, and when it exceeds 0.6, it begins to rise. This is mainly because when the weight parameter exceeds 0.6, the algorithm gradually ignores the evaluation of the scenic spot attributes. However, when the scenic spot data is relatively sparse, it makes it difficult to accurately calculate the nearest neighbor of the target scenic spot. In this paper, the algorithm adopts the comprehensive similarity calculation method of scenic spot score and project attribute. When the project score is missing, the inherent attribute of the project is combined to assist the

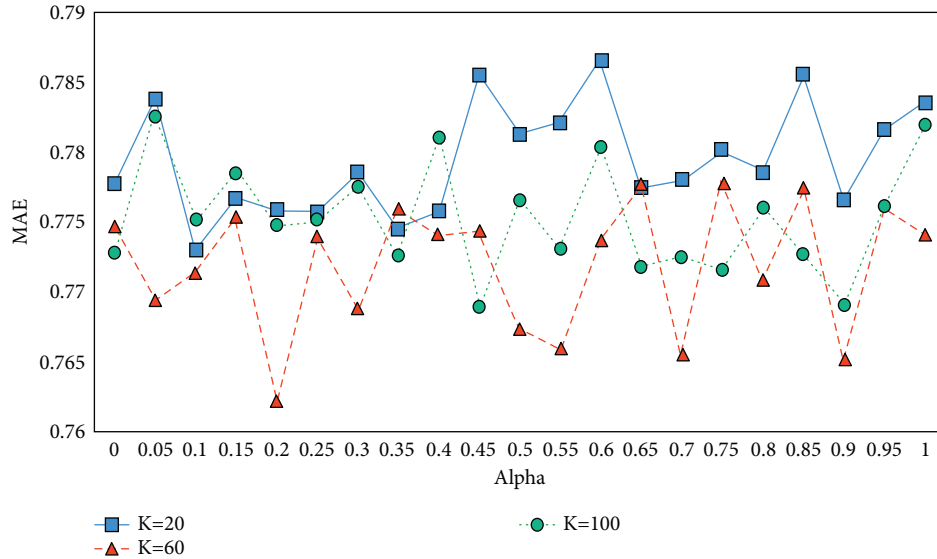


FIGURE 6: Influence of weight parameters.

TABLE 3: Dataset partitioning and proportional partitioning.

Data source	Project	Average number of times a single item is graded	Evaluate the rating times of each user.	Sparsity
Book	6874	65	73	0.02483
Movie	8748	84	56	0.01967
Travel	37730	28	88	0.01657

global similarity calculation, which alleviates the problem of data sparseness to some extent.

4.2. Tensor-Based Multidata Source Fusion Tourism Recommendation Algorithm Model. This experiment involves three data sources: movie data source, book data source, and tourism data source. Movies and books are used as auxiliary data sources to predict the tourism field of the target data source. In the experiment, the data set partition was uniformly constructed in the form of a proportional partition, and the scores in auxiliary data sources were statistically analyzed to verify the correlation between data sources. The experimental results are shown in Table 3.

On the basis of personalized POI recommendation, users prefer to recommend a tourist route composed of many interesting points of users. In this paper, a personalized tourism route recommendation model based on users' dynamic interest is proposed. The dynamic interest preference in the model is obtained by weighting the characteristics of users' past personalized interest and the characteristics of target tourist areas. In this paper, the optimal segmentation ratio of the model is determined according to the prediction accuracy of the model in different sampling percentages, and the prediction results of the RFPAP model are shown in Figure 7.

There are many factors that affect the prediction of scenic spots, but not every feature variable will have a significant effect on the classification accuracy, and there is often a strong correlation among feature factors. If all features are

used for modeling without screening, it will not only increase the computational load but also reduce the classification accuracy of the model. In order to achieve higher prediction accuracy of scenic spots, it is necessary to eliminate the characteristic factors that have accumulated errors in the prediction.

Among the recommendation algorithms proposed in this chapter, the parameter WH is an important parameter that affects the recommendation performance. A larger WH value means that we rely more on social network relationships in the matrix decomposition model. The recommendation algorithm proposed in this chapter will completely rely on the social network relationship to learn the hidden feature vectors of users and items while ignoring the rating information of users. On the contrary, a smaller WH value means that we give more weight to the rating information of users. In this section, we set WH as the independent variable to test the influence of WH on the recommended algorithm proposed in this chapter. The dimension k of the hidden feature vector is set to 10, and the experimental results are shown in Figure 8.

As can be seen from Figure 8, the WH parameter does affect the performance of the recommendation algorithm proposed in this chapter. Secondly, on the three data sets, RMSE values show a similar trend: with the increase of input, RMSE decreases first, and the accuracy of recommendation improves. After reaching the optimal value, RMSE increases with the increase of input WH, and the accuracy of recommendation decreases. To realize the case similarity algorithm with trust, it is necessary to calculate the

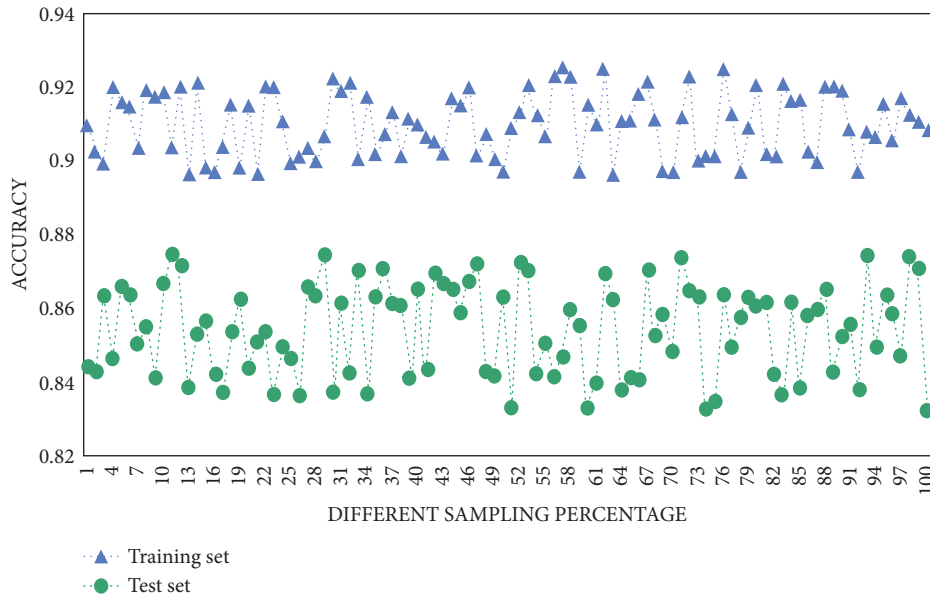


FIGURE 7: Prediction accuracy of RFPAP model with different sampling percentages.

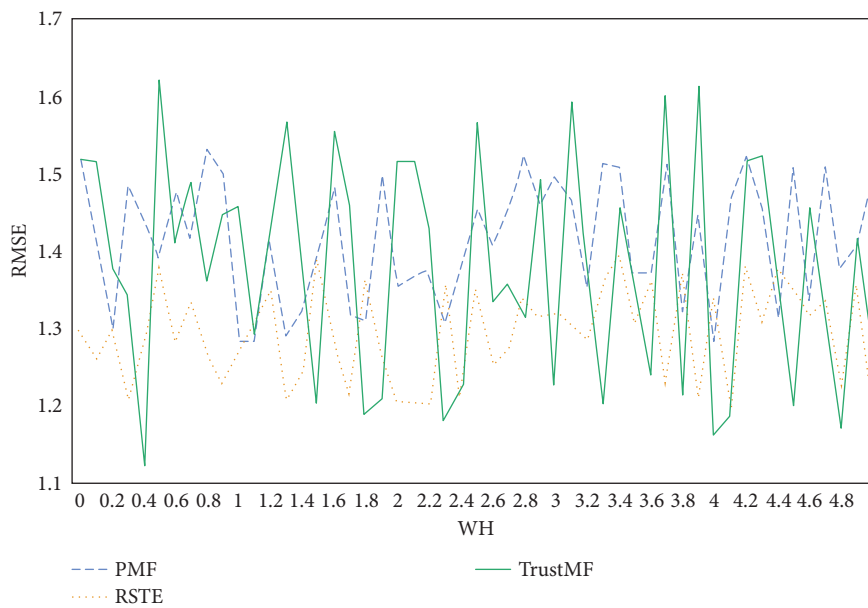


FIGURE 8: Influence of parameter WH.

case similarity first. Before calculating the case similarity, it is necessary to calculate the local similarity of each attribute in the case. So as to better represent the needs of users. However, when processing the data and calculating, the obtained user's travel demand is a range value, and the corresponding attribute in the case is a specific value, which is not conducive to calculation. In order to simplify the calculation, this paper takes the average value of these two interval values to obtain a specific value. This paper compares the memory consumption under different minimum utility thresholds. During the running of the algorithm, several test points are inserted. In each test point, the garbage nodes generated during the running of the algorithm are

forcibly deleted, and then the current memory consumption value is extracted, and the maximum of these values is used as the memory consumption value of the current algorithm. The result is shown in Figure 9.

As can be seen from the figure, with the decrease of the minimum utility threshold, the memory consumption of the algorithm Growth is increasing. This is because with the decrease of the minimum utility threshold, the number of nodes in the utility pattern tree increases, but the memory consumption of the CPCU algorithm and Growth algorithm basically does not change much. This is because these two algorithms adopt parallel strategies. PUCP algorithm uses the clustering method to build similar transactions into a

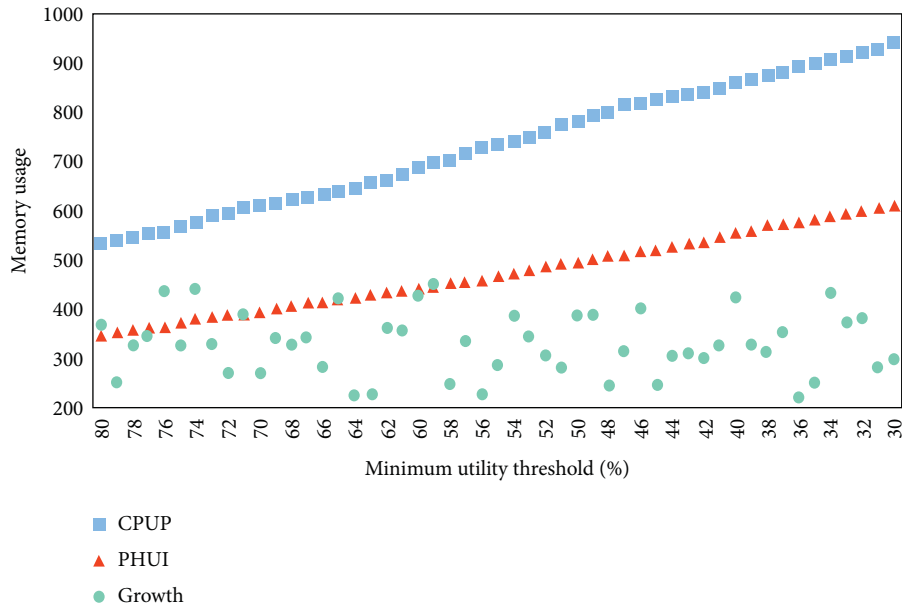


FIGURE 9: Memory consumption ratio.

utility pattern tree, which has fewer branches and uses pattern Growth to mine, which reduces the number of candidate itemsets. It uses a tree structure and does not store noncandidate itemsets, so it takes up less memory than the Growth algorithm.

The user's interest in the process of tourism should be a dynamic vector that conforms to the characteristics of the tourism area. In this method, users' historical travel interests and regional characteristics of tourist destinations are weighted, and their dynamic interest preferences in the process of travel are mined, so as to recommend tourist routes to users. Through the experimental verification on real experimental data sets, the measurement index of the recommendation algorithm of this method is obviously higher than that of other comparative personalized tourist route recommendation methods, and it is closer to the real tourist route. The personalized tourism recommendation method proposed in this paper effectively integrates many features of social networks and effectively alleviates the problems of data sparseness and feature learning in tourism recommendation based on social networks by using vectorization and deep learning technology. Its research has very important usage scenarios and commercial value in the tourism industry.

5. Conclusions

In this paper, rich tourism characteristic factors are extracted, the problem of data sparseness in the research of tourist attractions recommendation is solved, and the importance of tourism characteristic factors is analyzed. In order to capture the deep and valuable preference information of users, a convolution neural network is used as the basis of the recommendation framework of location interest points, and three types of content information are introduced, namely, attribute information of location interest

points, user preference and user emotion classification information. The experimental results show that the proposed algorithm can capture semantic and emotional information from the content of comments and prove that the related text information in comments can improve the performance of recommendation of interest points in location-based social networks.

This paper only considers the use of project attribute information to alleviate the cold start problem of the project side and does not consider the cold start problem of the user side at the same time. Under the condition that social network information and project attribute information can be obtained, it is a problem that needs to be studied in the future to use social network information and project attribute information simultaneously to alleviate the cold start problem of the client and the project. The attribute information of centralized items is classified data. When the item feature information contains both category data and numerical data, how to calculate the similarity between items more accurately and integrate it into the recommendation system is also a problem to be considered in the future.

Data Availability

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

Conflicts of Interest

The authors declare that there are no conflicts of interest.

Acknowledgments

This work was supported by 2022 Planning Project Achievements of Philosophy and Social Sciences of Hainan Province: from the standpoint of experience economy,

research on the development path of public service facilities at the Hainan Tourism Highway Station (Grant no. HNSK(ZC) 22-169).

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