Hindawi
Mobile Information Systems
Volume 2022, Article ID 3974382, 10 pages
https://doi.org/10.1155/2022/3974382

Research Article

A Personalized Recommendation Technique for Travel Route Based on Fuzzy Consistent Matrix

Yang Huiling and Jiang Jing

Tourism Management Department, Sichuan Engineering Technical College, Sichuan 618000, China

Correspondence should be addressed to Yang Huiling; yanghuiling@scetc.edu.cn

Received 17 June 2022; Revised 16 July 2022; Accepted 20 July 2022; Published 12 August 2022

Academic Editor: Santosh Tirunagari

Recommending travel routes for tourists has become a research hotspot in the present tourism industry. Various machine learning methods have been well studied for recommendation systems. However, the accuracy of these systems is not up to the expected levels. In order to increase the ranking accuracy, as well as, the recall rate of the recommended routes by the personalized travel recommendation algorithm, in this paper, a fuzzy consistent matrix technique is introduced for personalized travel recommendation systems. First of all, the user's travel interest data are obtained through the fuzzy consistency matrix. Next, the user's travel interest data are de-noised to determine the user's preferred interest points and the coverage of the user's interest points. Besides this, the constraints of the route recommendation systems have also become a research topic. Therefore, the proposed method also uses the fuzzy consistent matrix technology to determine the users' similarity and classifies the personalized recommendation algorithm. Finally, a personalized travel recommendation model is constructed to comprehend the personalized travel route recommendation. The investigational outcomes, using real datasets, illustrate that when the number of routes is 5000, then the accuracy rate of the proposed method is approximately 97.21%, and the accuracy rate of the recommendation ranking is 97.54%. We also observed that when using 60 GB of data, the recall rate of the proposed method, for personalized travel recommendation routes, can reach as high as 97.59%.

1. Introduction

In the modern ages, with the continuous advancement and popularization of information technology, especially big data and machine learning technologies, the Internet has gradually integrated into all facets of folks' life, providing many conveniences for people's study and life. However, with the rapid proliferation of network and information resources, the popular service mode of traditional websites or platforms has been difficult to keep up with the personalized pursuit of users in different scenes. Based on this, in what way to scientifically acquire the information that users are really interested in from massive resources has been urgently analyzed and solved by professionals and researchers internationally [1]. The personalized information recommendation system is used to resolve the issue that users do not know how to obtain the content they are categorically fascinated in when facing an enormous volume of information. The principle of the recommendation system is to first obtain the user's browsing record data, build its corresponding interest model, and then analyze the user's current interest preference and predict the possibility of future interest preference change through the model. Finally, the system recommends the content of interest to different users. The information of personalized recommendation system comes from and mostly depends on user interest modeling.

The research on user interest preference in the modeling stage is very important, which is unswervingly associated with the worth and importance of a recommendation system [2]. Therefore, the system can really push satisfactory projects for each user only after obtaining and fully understanding the user's interest and preference information. However, so far, user interest modeling still faces many challenges, which can be divided into three parts: (i) the first part, users' interest preferences are often diverse, and each user may have different needs and preferences, with obvious diversity characteristics; (ii) in the second part, the user's curiosity and attention frequently fluctuate with the change (passage) of time and situation. In fact, even the same user may lead to different interest preferences in different situation environments, which has obvious changeable characteristics; and (iii) in the third part, the data information of user interest resources that can be obtained is extremely scarce [3]. Such problems have not been effectively solved, which also leads to the fact that few of the existing recommendation algorithms can really solve the two problems of user cold start and interest overfitting. In fact, this makes the efficiency and performance of the existing recommendation systems significantly low and, also, the user's experience of the system is not high.

The introduction of personalized recommendation service into the tourism industry is the trend of the development of smart tourism. Tourism is a mobile, real-time, and changeable activity. Real-time and personalized push of tourism information services of interest to users is an important way to improve user satisfaction. Tourism is an activity with a more situational interactive experience. Its personalized service should be properly combined with the user's current situation and provide users with real-time personalized and efficient recommendation service according to the user's situational conditions, which is a hot issue in the research of tourism service at home and abroad [4]. Experiments of state-of-the-art literature demonstrate that this personalized recommendation algorithm and method can resolve the issue of scarce tag data, and the recommendation performance of the trained recommendation system is significantly good as compared to other techniques. However, unfortunately, the accuracy of the personalized tourism recommendation procedure is poor [5–7].

As a result, the fuzzy consistent matrix method is introduced for the purpose of recommending personalized travel. To begin, the user's travel interest data are obtained via the fuzzy consistency matrix, and the user's travel interest data are de-noised in order to determine a particular user's preferred points of attention, i.e., POI (point of interest) and the coverage of the user's interest points. Then, the optimal route is automatically planned, and the user similarity is calculated using fuzzy consistent matrix technology. In addition, the personalized recommendation algorithm is classified. Finally, the personalized travel recommendation model is constructed to comprehend the personalized travel recommendation for routes. The major contributions of the research conducted in this study can be shortened as follows:

(1) The fuzzy consistent matrix method is introduced for personalized travel recommendation algorithm;
(2) The user's travel interest data is obtained through the fuzzy consistency matrix;
(3) The data are de-noised to determine the user's preferred interest points. We use the fuzzy consistent matrix technology to compute the users' resemblance and similarity, and classifies the personalized recommendation algorithm; and
(4) A personalized travel recommendation model is then constructed to comprehend the recommendations for the personalized travel route.

The rest of the manuscript is arranged along these lines. In Section 2, we deliberate state-of-the-art related works. In Section 3, interest analysis of tourism users based on fuzzy consistent matrix is explained in details. Along with the geographical feature, in this section, we also discuss the similarity calculation between users based on fuzzy consistent matrix. The personalized tourism recommendation algorithm based on the fuzzy consistent matrix is proposed in Section 4. Experiments using real datasets are analyzed in Section 5. At the end, Section 6 completes this paper and offers guidelines for additional work.

2. Related Work

The introduction of personalized recommendation service into the tourism industry is the trend of the development of smart tourism. Tourism is a mobile, real-time, and changeable activity. Real-time and personalized push of tourism information services of interest to users is an important way to improve user satisfaction. Tourism is an activity with more situational interactive experience. Its personalized service should be properly combined with the user's current situation and provide users with real-time personalized and efficient recommendation service according to the user's situational conditions, which is a sizzling subject in the research of tourism service at home and abroad [4]. Because user demand changes dynamically with time and scene, tourists' requirements for tourism services are generally closely related to their current scene conditions. In order to provide users with efficient recommendation applications, it is indispensable to investigate and judge the user's situation state, identify effective situation feature elements, and then provide users with a personalized recommendation list in line with their current situation features. Relevant scholars have studied this and made some progress.

Heng et al. suggested a personalized tourism recommendation procedure grounded on attribute features [8]. The algorithm considers the similarity of each attribute feature of the project and improves the calculation method of the traditional method of similarity. Moreover, it has the capability to measure the similarity from multiple dimensions. Their attained investigational outcomes indicate that the suggested algorithm can increase the superiority of recommendation, but the accuracy of personalized travel recommendation route ranking is extremely poor. Chunsheng et al. proposed the research on tourist attraction recommendation algorithm based on user online comments [9]. The authors used crawler software and Jieba word segmentation to obtain and preprocess the user's online comment information on tourist attractions. Furthermore, they also used the emotion intensity analysis method to determine the evaluation scale of each comment relative to each attribute of scenic spots. Through this process, they calculated the user's weight on each attribute of scenic spots according to the processed online comment information. In fact, the well-known TOPSIS ranking technique is usually used to endorse users' tourist attractions. Experiments demonstrate that this algorithm can effectively determine the user's preference for scenic spots and successfully increase the correctness of scenic spot recommendation, but the recall rate of personalized tourism recommendation is low and the recommendation efficiency is low.

Zheng et al. offered the state-of-the-art research on personalized recommendation systems for traveler attractions grounded on the concept of domain adaptation [10]. By using the domain adaptation technology, an enormous amount of labeled data in other fields related to the target task are used as auxiliary data. In the next step, the recommendation model is trained to obtain a recommendation system with good performance and efficiency. The authors conducted several experiments and the acquired outcomes indicate that the offered personalized recommendation system can effectively solve the problem of scarce tag data, and the recommendation performance of the trained recommendation system is significantly good. However, the accuracy of the personalized tourism recommendation algorithm is poor [5–7]. Thus, improving the efficiency, as well as, accuracy of such recommendation systems is the focus of this research.

3. Interest Analysis of Tourism Users Based on Fuzzy Consistent Matrix

3.1. Data Denoising and Filtering. The Foursquare and Flickr social networking sites cover the check-in records of major cities in the world, and at least 10000 people in each city sign-in on the social network. In this paper, several cities are selected as the experimental data set in the two social networks. On the Foursquare data set, the data of L City are selected as the city where the check-in record belongs. In the Flickr dataset, the data of X city, Y City, Z City, and r city are selected. The POI is an abbreviation for "Point of Interest". From the perspective of the GIS (i.e., geographic information system), a POI can be a mailbox, a shop, a house, a bus station, or any other location. The location information (in terms of longitude and latitude) in the data set is an important feature to determine the user's specific location and calculate the distance between different POIs [11]. To begin, all data items in the data set that lack location information are removed. Due to the loss of location data, it is impossible to determine the location of the user's punch in record, and thus the POI accessed by the user.

In the field of personalized recommendation, location data can effectively mine users' access preferences and then better recommend POIs that meet those preferences when recommending to users [12]. Second, this paper determines the location of the user's stopover rendering to the location information of the check-in record. When the user visits a particular location, multiple check-in records will be generated. For example, when the user is in a point of interest or shopping mall, multiple record data will be generated, but multiple check-in records belong to the same location. The process of computing whether a user belongs to a particular POI or not is given as follows. We match the POI accessed by the user according to the location information of the check-in record, as shown in Figure 1 [13]. Using the position information of the POI, we set the position of the POI as the center with a radius of 200 m. In the next stage, we determine the coverage of the POI and judge whether the user's check-in location belongs to the POI by calculating the European distance between the longitude and latitude. If the check-in record is within the coverage of the POI, it is determined that the user's check-in location belongs to the POI, otherwise the user's check-in location does not belong to the POI.

If a particular user's check-in information, unfortunately, does not match the appropriate POI, that is, the distance between the location information of the check-in record and all POIs is greater than 200 m, then the check-in record is regarded as a noise point and the check-in information is removed from the user's historical check-in record set. In addition, in order to better mine user preferences, this paper removes the basically inaccessible POI from the POI set. This also ensures that redundant data are removed which basically is a preprocessing technique. This ensures that only essential and most important data are processed.

3.2. Geographical Factor Feature Analysis. Geographical location has a certain impact on users' check-in behavior. Users generally like to visit POI close to themselves. First, the user's historical TOP-K punch-in record POI is counted in the check-in records of social networks based on all of their historical check-in records. The user's access frequency to POI may serve as a proxy for their own preferences. As shown in Figure 2, the ArcGIS tool [14] visually analyses all historical information and the user's TOP-K points of interest. This time the historical access record with user ID 6715 is adopted, and the POI with user historical access frequency of TOP-10 is counted for analysis. Among them, the black triangle points represent the interest points with the user access frequency of top-10, that is, the user activity center point. The green dot indicates the user_ All history points of User_ID6715 [15].

The depiction in Figure 2 makes it clear that every interest point in the user's top 10 is scattered throughout the user's activity center, meaning that the user's actions primarily take place in and around these centers. It may be deduced that users' past actions have been concentrated in their frequent locations, and users are accustomed to accessing POI there, meaning they prefer to do so constantly [16]. The user's inclination for POI in various topographical regions can therefore be utilized as one of the benchmarks to quantify the user's inclination for the POI. Therefore, as a result, the geographical factor features and characteristics can be incorporated into the personalized recommendation model.

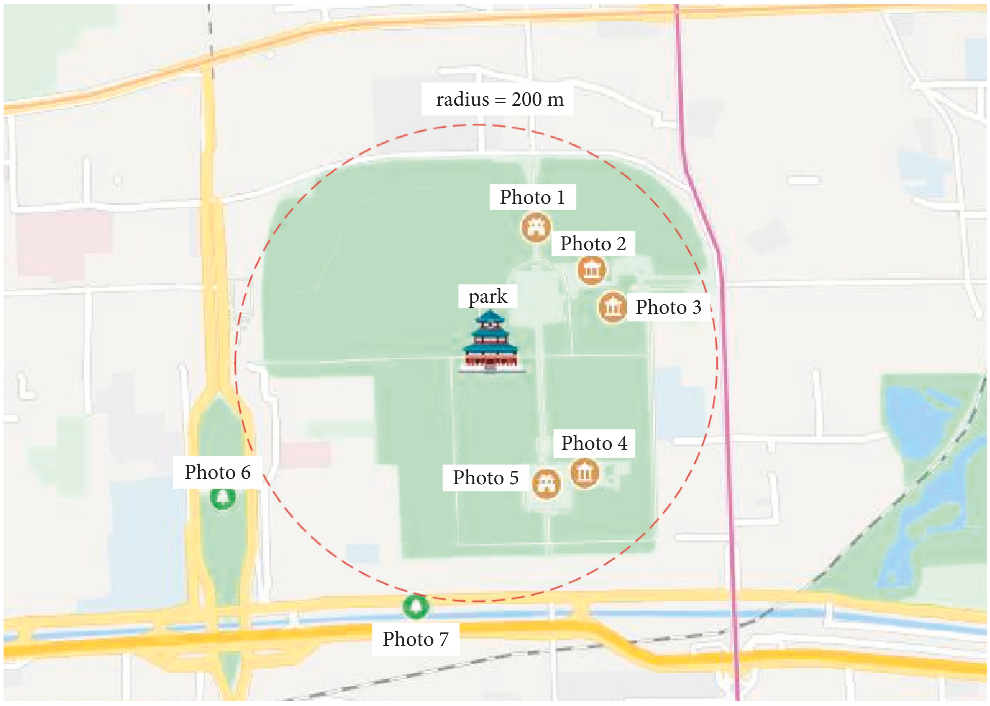

Figure 1: The POI matching diagram.

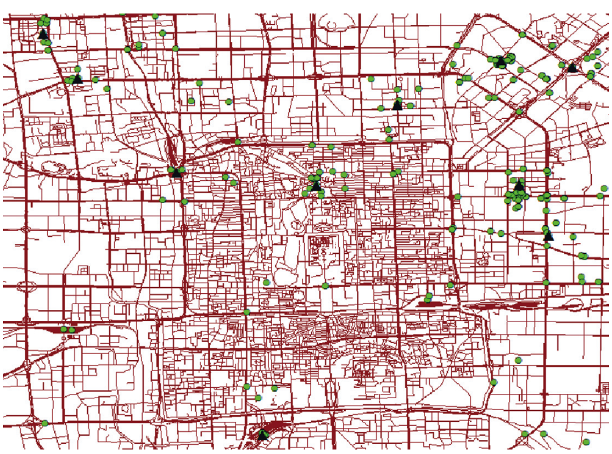

Figure 2: The distribution of interest points of users on TOP-10.

3.3. Similarity Calculation between Users Based on Fuzzy Consistent Matrix. In the process of fuzzy decision-making, when the elements are compared, the established judgment matrix is the fuzzy complementary matrix. It can be regarded as a complementary relationship that the values of the elements compared with each other satisfy and when experts compare elements, it is necessary to judge the rationality of expert judgment. If experts believe that it is more important than others, there should be more important, that is, the expert's judgment should meet the consistency [17]. In order to resolve the above difficulties, the concept of fuzzy uniform matrix is introduced.

Definition 1. If a particular fuzzy matrix that is denoted by $R = (r_{ij})_{n\times n}$ and essentially satisfy $r_{ij} = r_{ik} - r_{jk} + 0.5\,(\forall i, j, k \in I)$, then the matrix R is known as a fuzzy uniform matrix. According to the definition of fuzzy uniform matrix, it can be obtained that it has the following two properties:

(1) Fuzzy consistent matrix must be fuzzy complementary matrix [18].

It is proved that taking the fuzzy uniform matrix $T = (t_{ij})_{b\times b}$, when $k = j$, then there is $r_{jj} = 0.5, \forall j \in I$, and when $k = i$, then there is $t_{ij} = t_{ii} - t_{ji} + 0.5$, that is, there is $t_{ij} + t_{ji} = 1, \forall i, j \in I$.

(2) The difference between the corresponding elements of any two rows of fuzzy uniform matrix $T = (t_{ij})_{b\times b}$ is a constant.

It is proved that if rows i and j are arbitrarily specified, then the fixed i, i, j, $\forall k \in I$, and $r_{ij} = r_{ik} - r_{jk} + 0.5$ can be obtained from the definition of fuzzy consistent matrix. In fact, the following formula (1) is used to carry out this task.

$$\forall k \in I, r_{ik} - r_{jk} = r_{ij} - 0.5. \tag{1}$$

In the above formula (1), i, j are a fixed value, only it is taken arbitrarily, so the conclusion is tenable. At the same time, the following Lemmas 1 and 2 hold.

Lemma 1. *The lemma says that a particular matrix is a fuzzy consistent matrix if the dissimilarity amongst the analogous elements of any two rows is a fixed value [19].*

It is proved that if $T = (t_{ij})_{b\times b}$ is a fuzzy complementary matrix, there is $r_{jj} = 0.5, \forall j \in I,$. Furthermore, when $\forall i, j, k \in I$, there is $r_{ik} - r_{jk} = g$, where g is a fixed value. From the arbitrariness of k, the above formula also holds when $k = j$, so there is $r_{ij} - r_{jj} = g$, that is, $r_{ij} - 0.5 = g$, so there is $r_{ik} - r_{jk} = r_{ij} - 0.5$, which holds for $\forall i, j, k \in I$.

For the traditional reciprocal judgment matrix denoted by $T = (t_{ij})_{b\times b}$, if its weight vector is given by $W = (w_1, w_2, \ldots, w_n)^T$, then the relationship satisfied between its element characterized by r_{ij} and weight can be approximately regarded as $r_{ij} = w_i/w_j$. In other words, the relationship illustrates the weight ratio of the corresponding two elements. This should be noted that the complementary judgment matrix describes the relationship between them from another angle, that is, the difference between the weights of two elements. For any fuzzy judgment matrix, there is the following lemma w that must hold [20]:

Lemma 2. *Let $T = (t_{ij})_{b\times b}$ be a fuzzy complementary matrix and $W = (w_1, w_2, \ldots, w_n)^T$ be a nonnegative normalized vector. For a given positive number g, $\forall i, j \in I$ the following relationship holds.*

$$t_{ij} = \left(w_i - gw_j\right) + 0.5. \tag{2}$$

Then, T is a fuzzy uniform matrix.

$$\forall i, j \in I, t_{ij} = \left(w_i - gw_j\right) + 0.5, \tag{3}$$

$$\begin{aligned} &\Rightarrow \forall i, k \in I, t_{ik} = \left(w_i - gw_k\right) + 0.5,\\ &\Rightarrow t_{ik} - t_{ij} = \left(w_j - gw_k\right) = t_{jk} - 0.5,\\ &\Rightarrow t_{ij} = t_{ik} - t_{jk} + 0.5. \end{aligned} \tag{4}$$

The above equation $\forall i, j, k \in I$ is true, so T is a fuzzy uniform matrix. Calculate the similarity between users according to the above matrix to realize the personalized recommendation of user travel routes.

4. Personalized Tourism Recommendation Algorithm Based on Fuzzy Consistent Matrix

4.1. Personalized Recommendation Algorithm Classification. At present, there are several categories of personalized recommendation systems. This section briefly introduces the recommendation algorithms that need to be used in this paper. This section first introduces the two common technologies of: (i) content-based recommendation; and (ii) demographic-based recommendation. Due to the fact that the later model is used in the process of construction of model proposed in this paper and draws on its ideas, therefore it is necessary to elaborate it further [21].

4.1.1. Content-Based Recommendation. The fundamental concept behind the content-based recommendation algorithm must be to use the attributes of the recommended items. For example, when recommending a tourism item, the characteristics of the tourism item may include the style, geographical location, and other attributes of the tourism item. These attributes are used to calculate the similarity of the tourism item and list the similar tourism items of the user's favorite tourism items in history and recommend tourism projects that users have not experienced to target users [22]. In fact, the notion of content-based recommendation procedure is to mine the attribute eigenvalues of recommended items and calculate the similarity between contents according to the attribute eigenvalues. The key point of this technology is to model the attributes of items and analyze users' interests and preferences. The process of generating recommendation results in content-based recommendation algorithm is shown in Figure 3, which generally includes three steps [23]:

(1) Extract the item attribute values.
(2) Calculate the similarity between items according to the item attributes.
(3) Obtain the user's historical interest preference from the user's historical behavior data in the system,
(4) Establish the user's interest model, compare the attribute value of the item with the user's interest model.
(5) Generate a list of recommendation results.
(6) Feedback to users.

The flow chart of a typical recommendation system, i.e., content-based is shown in Figure 3.

Although the content-based recommendation procedure can quickly establish and complete the recommendation process, it only considers the attributes of the item itself, has a certain one sidedness, and the recommendation result will be rough [5, 24].

4.1.2. Recommendation Algorithm Based on Demographics. These algorithms are based on users' particular characteristics and the information which is available. The recommendation algorithm will collect the user's characteristic information, and explore the user's background and other information. In the next step, the system computes the resemblance and similarity amongst usersand recommends the items loved by the target user's neighbors to the target user [25]. The process of generating recommendation results by this technology is shown in Figure 4, which mainly comprises of three different steps:

(1) Model the user's eigenvalues, such as user's occupation, occupation, interest, and other information;
(2) Using the model, the similarity between system users is calculated and the nearest neighbor of the target user is found; and
(3) Recommend the favorite items of the nearest neighbor users to the target users.

Figure 4 shows a flow chart of recommendation based on demographics when using user characteristics for recommendation, historical behavior data, and project attributes are not required. The project can be recommended directly. However, the algorithm is relatively rough and can only make simple recommendations, which is difficult to meet the requirements of personalized tourism recommendation.

4.2. Personalized Travel Route Recommendation Algorithm

4.2.1. User Model Initialization. In this paper, the user's vector space model uses vector u' to characterize the feature vector of user u. First, the demographic attribute information

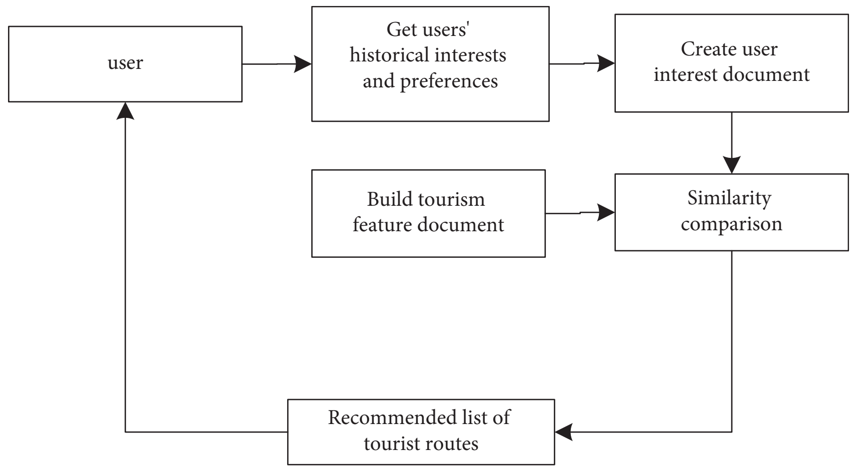

Figure 3: The flow chart of content-based recommendation system.

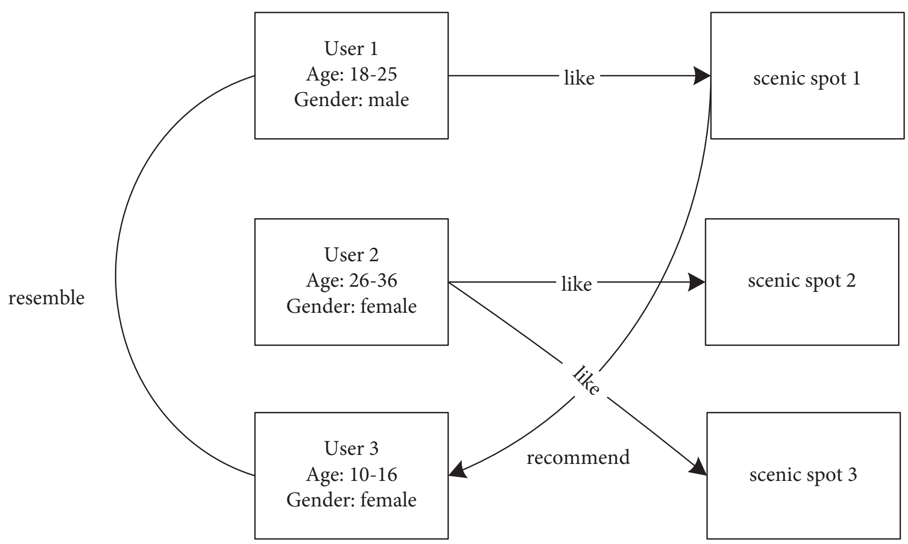

Figure 4: Flow chart for the demographic-based recommendation system.

of user u is introduced into user feature vector u'. After initialization, the user space vector is expressed as $u' = \{(b_u^1, b_u^2, \ldots, b_u^k)\}$. In the formula, each element is a basic information, out of a total of k basic information [26]. In order to solve the system cold start problem, after a particular user enters the system, let the user select the category in which the user is interested. Suppose that the interest category of a user is expressed as $Fav_u' = (m_u^1, m_u^2, \ldots, m_u^n)$, and after introducing the interest category attribute, the user's feature vector is expressed as $Fav_u' = (m_u^1, m_u^2, \ldots, m_u^n)$.

4.2.2. Modeling Users with Content Information. Content analysis enriches the user interest model by studying the user's scoring, booking, or browsing records to obtain the user's preference information. The common analysis method is TF-IDF method, which is separated into two different steps. The primary step is to segment the item, remove the stop word, merge synonyms, and get r phrases. The second step is to obtain the information value of F_{ij} according to the calculation formula (1).

$$F_{ij} = \frac{g f_{ij}}{\max_z f_{zj}} + \frac{N}{n_i}, \tag{5}$$

where N is the overall quantity of items, f_{ij} is the amount of times phrase i looks in item j, and phrase i appears in n_i items. Item j is calculated with this formula for the p phrases of each document and expressed as a p-dimensional feature vector $\{(k_1, v_1), (k_2, v_2), \ldots, (k_p, v_p)\}$. Furthermore, combined with the attribute information of the item user u likes, the attribute information $k_u' = \{(k_u^1, v_u^1), (k_u^2, v_u^2), \ldots, (k_u^p, v_u^p)\}$ of user u represented by p phrases can be obtained. When the p size is large, users have more attributes, and different attributes have different selection weights for users. If the noise attributes are considered, in addition to increasing the cost of information acquisition and the amount of calculation, it will also reduce the prediction accuracy.

Therefore, when selecting attributes, some attribute information that can better describe users' preferences should be selected [25, 27].

This should be noted that attribute selection is a heuristic learning process. According to domain knowledge or statistical knowledge, the attribute selection in this paper uses the χ^2-test method in statistics to set the classification set as D and the attribute to be detected as I_t. The relationship between attribute and category is given in Table 1.

The χ^2-test is based on the assumption that D and I_t are independent, and the following test formula (4) is given as follows:

$$\chi^2 = \sum_{I,m} \frac{\left(k_{lm} - \Pr(D = l) + n\Pr(I_t = m)\right)^2}{Pr(D = l)\Pr(I_t = m)}. \quad (6)$$

In the above formula, when χ^2 is larger, the correlation between category D and attribute I_t is higher. The calculation strategy of χ^2 is to calculate the χ^2 value of each attribute, sort it from large to small, select the top N most important attributes to model the user, and the value of N is obtained by maximizing the prediction accuracy. Through the above selection, s attributes are obtained to get the best effect, and $u_u' = \{\alpha(e_u^1, e_u^2, \ldots, e_u^k), \beta(m_u^1, m_u^2, \ldots, m_u^n), \delta(v_u^1, v_u^2, \ldots, v_u^s)\}$ are its user model.

4.2.3. User Personalized Travel Route Recommendation. There are two types of user project interaction information: explicit and implicit. Explicit behavior generally includes scoring and buying, while implicit behavior includes browsing, collecting, and sharing. This paper studies the explicit behavior of users and uses the user-item scoring matrix to model. The user project scoring matrix is given in Table 2. Note that U characterizes a particular user.

In Table 2, $S_{i,j}$ is the user's score for the project, and the scoring matrix is a $m \times n$ two-dimensional matrix. In this paper, we use the common singular value decomposition technique in order to decompose the scoring matrix into: (i) a user characteristic matrix P; and (ii) an item characteristic matrix Q, that is, $R = P^T Q$. In subsequent steps, then the scoring of the user u on item i becomes $r_{ui} = (p_u q_i)'$. The process continues to learn and obtain matrices P and Q through the random gradient descent method, and then predict score r_{ui}. The user model not only considers the basic attributes of users, but also comprehensively considers the user project interaction information, and adds the factor of collective intelligence to the user model [7]. The user u is expressed in the characteristic matrix P as: $p_u' = \{p_u^1, p_u^2, \ldots, p_u^k\}$.

In this way, we can realize the accurate recommendation of personalized tourism routes. It can be seen that our method is general and can be used in recommendation in other fields.

5. Experiments and Results

5.1. Experimental Data Description. The Flickr dataset is used in our experiments and evaluation of the proposed recommendation system. Each picture in the dataset includes a photo ID, a user ID, shooting time, geographic coordinate information, and the accuracy of geographic coordinates. This paper extracts images taken in Toronto from Flickr dataset, Budapest, Vienna, and Osaka are the four different cities marked with geographic information. The data set description is shown in Table 3.

Table 1: The attributes category and relationships.

D	I_t 0	I_t 1
0	K_{00}	K_{01}
1	K_{10}	K_{02}
2	K_{20}	K_{03}

Table 2: The user project scoring matrix.

	I_1	I_2	...	I_m
U_1	S_{11}	S_{12}	...	S_{1n}
U_2	S_{21}	S_{22}	...	S_{2n}
...	...	...	...	...
U_n	S_{n1}	S_{n2}	...	S_{mn}

We use the process of matching to ensure that the obtained data are preprocessed and have no duplicate entries. The preprocessed is then used to verify the proposed personalized tourism recommendation algorithm. Various valuations metrics are then used to measure the overall performance of the system in terms of prediction accuracy, sorting or ranking accuracy, and the recall ratio. In the next subsections, we briefly explain these metrics and discuss their calculation mechanism through mathematical equations.

5.2. Index Calculation

5.2.1. Accuracy. Obviously, accuracy is the most important evaluation index for recommendation system. In fact, it measures the accuracy of recommendation algorithm in predicting users' preference for recommended products. From different angles, accuracy can be divided into prediction score accuracy, prediction score relevance, classification accuracy, and sorting accuracy. The accuracy evaluation of the prediction score is the similarity between the score predicted by the algorithm and the user's actual score [6]. There are many methods to evaluate the prediction accuracy, and the most commonly used are the mean square error (MSE) metric, mean absolute error (MAE) metric, root mean square error (RMSE), and standard mean absolute error (NMAE) metric. The most commonly used is the former one and it is given by formula (5):

$$MAE = \frac{\sum_{u,i\in T} \left| r_{ui} - r_{u,i}' \right|}{|T|}, \quad (7)$$

where r_{ui} is the actual score of the user u on item i, $r_{u,i}'$ is the prediction score obtained by the algorithm, and T is the test set. The prediction accuracy of mean absolute error calculation has obvious advantages, e.g., simple calculation and uniqueness of the obtained mean absolute error. The

Table 3: Description of the flickr dataset.

City	Number of photos	Number of users	Number of POI	Number of tourism sequences
Toronto	157505	1395	39419	6057
Budapest	36000	935	18513	2361
Vienna	85149	1155	34515	3193
Osaka	39240	450	7747	1115

disadvantage is also obvious, that is, when the difference between the average absolute error of the two scenic spots is small, then the difference is not significant. In such scenarios, the MAE cannot be a good evaluation metric.

5.2.2. Sorting Accuracy. The ranking accuracy is defined as the accuracy of the ranking of the recommendation list relative to the user's real ranking of the tourist route. This index is suitable for the recommendation system that provides users with a ranking list. For example, if the top 10 scenic spots in the list are liked by users, and the user's sorting is completely different from the order given by the algorithm, then in that case the sorting accuracy will also be very low [28]. The average ranking index is used to calculate the ranking accuracy of the tourism route recommendation algorithm, which is defined as given by formula (6):

$$r_i = \frac{P_i}{M}. \tag{8}$$

In the above formula, M is the number of items not selected by the user in the training set, and P_i is the position of the item i to be predicted in the recommendation list in the test set.

5.2.3. Recall Rate. Recall rate, also known as "recall ratio", refers to the ratio of the number of recommended tourist attractions to the number of all relevant tourist attractions. In fact, it measures the recall rate of the tourist route recommendation algorithm [29]. Assuming that the set of tourist attractions recommended by the recommendation system to users is known and the set of tourist attractions actually liked by users is $T(u)$, then the recall rate of the recommendation results is defined as given by formula (7):

$$\text{Recall} = \frac{\sum_{u\in U}|R(u)\cap T(u)|}{\sum_{u\in U}T(u)}. \tag{9}$$

In this paper, the experimental verification of the proposed and other state-of-the-art recommendation systems is carried out according to the above experimental indexes and evaluation metrics.

5.3. Effect of Personalized Travel Recommendation Route

5.3.1. Accuracy of Personalized Travel Recommendation Route. In order to verify the accuracy of the personalized tourism recommended routes under different methods, the approaches proposed in [8–10] and this paper are used to verify the accuracy of the personalized tourism recommended routes. The results are shown in Table 4.

According to the analysis of Table 4, when the number of recommended routes is 2000, the accuracy of [8] is 87.52%, the accuracy of [9] is 79.52%, the accuracy of [10] is 76.52%, and the accuracy of our proposed method is 96.66%. Moreover, when the number of recommended routes is 5000, the accuracy of [8] is 72.28%, the accuracy of [9] is 73.38%, the accuracy of [10] is 88.46%, and the accuracy of the proposed method is 97.21%. These outcomes show that the accuracy of the personalized tourism recommendation route using the proposed method is significantly higher than that of other state-of-the-art methods, which shows that the personalized tourism recommendation route of this method has a better effect.

5.3.2. Ranking Accuracy of Personalized Travel Recommended Routes. In order to verify the ranking accuracy of personalized tourism recommended routes under different methods, the approaches proposed in [8–10] and this paper are adopted. The results are shown in Table 5.

According to Table 5, the ranking accuracy of personalized tourism recommended routes is different under different methods. When the number of recommended routes is 1000, then the sorting accuracy of [8] is approximately 64.65% while the sorting accuracy of [9] is 70.21%. Similarly, the sorting accuracy of personalized tourism recommended routes of the method suggested in [10] is 75.32%, while the sorting accuracy of our proposed method is 99.65%. In our empirical evaluation, we observed that when the number of recommended routes is 3000, then the sorting accuracy of the method suggested in [8] is 62.53%. Furthermore, the sorting accuracy of [9] was noted at approximately 78.52%, while the sorting accuracy of [10] was observed as high as 76.75%. This should be noted that the sorting accuracy of personalized tourism recommended routes of our proposed method is as high as 98.26%.

Furthermore, our experimental outcomes revealed that when the number of recommended routes is 6000, then the sorting accuracy of personalized tourism recommended routes of [8] is 78.54%. Similarly, we noted the sorting accuracy for [9] approximately 68.54%, while the sorting accuracy of [10] was recorded at 80.32%. The results shown in Table 5 demonstrate that the sorting accuracy of personalized tourism recommended routes of our suggested method is as high as 95.76%. To summarize our findings and results, the accuracy of personalized travel recommendation route ranking of our proposed method is significantly higher than that of other methods [8, 9], and [10], which shows that the personalized travel recommendation route ranking effect of our method is better than these closest rivals and techniques.

TABLE 4: Accuracy of the personalized travel recommended routes.

Number of recommended routes	Accuracy (%)			
	[8]	[9]	[10]	Proposed method
1000	88.56	78.38	72.59	93.32
2000	87.52	79.52	76.52	96.66
3000	86.43	80.31	78.23	98.27
4000	78.56	82.27	80.32	93.54
5000	72.28	73.38	88.46	97.21
6000	75.76	75.42	81.59	99.81

TABLE 5: The ranking accuracy of personalized tourism recommended routes.

Number of recommended routes	Ranking accuracy (%)			
	[8]	[9]	[10]	Proposed method
1000	64.65	70.21	75.32	99.65
2000	66.69	79.32	78.13	98.65
3000	62.53	78.52	76.75	98.26
4000	76.32	77.54	79.45	97.87
5000	77.54	76.54	81.67	97.54
6000	78.54	68.54	80.32	95.76

5.3.3. Recall Rate of Personalized Travel Recommended Routes. In order to verify the recall rate of personalized tourism recommendation under different methods, the approaches proposed in [8–10] and this paper are used to obtain the recall rate of the personalized tourism recommendation system. The obtained results and outcomes are shown in Table 6.

According to Table 6, the recall rate of personalized travel recommended routes is different under different methods. When the amount of data is 10 GB, the recall rate of the method proposed in [8] is 67.86%. Similarly, the recall rate of [9] was noted 66.32% and the recall rate of [10] was observed at approximately 64.32%. This should be noted that the recall rate of the personalized travel recommendation route is 98.32%. Generally speaking, with the increase of data amount the accuracy of the recommendation system increases and vice versa. For example, when the amount of data are increased from 10 GB to 30 GB, then the recall rate of the method suggested in [8] is approximately 68.62% and the recall rate of the method in [9] is 70.32%. Furthermore, the recall rate of the method proposed in [10] is approximately 66.87% while the recall rate of our proposed approach is 98.21%.

When the amount of data is 60 GB, the recall rate for the method in [8] is 71.05% and the recall rate of the proposed method in [9] is as high as 70.31%. Similarly, align with previous outcomes, the recall rate of the method in [10] is 72.61%. This should be noted that the recall rate of our proposed method is as high as 97.59%. Using these experimental outcomes, we can easily observe that our proposed method always has a higher recall rate for personalized travel recommendation routes as compared to other methods as proposed in [8, 9], and [10].

TABLE 6: The recall rate of personalized travel recommendation system.

Data volume/GB	Recall rate (%)			
	[8]	[9]	[10]	Proposed method
10	67.86	66.32	64.32	98.32
20	79.46	67.98	62.38	97.54
30	68.62	70.32	66.87	98.21
40	69.36	72.58	69.95	99.32
50	70.21	75.32	70.32	96.32
60	71.05	70.31	72.61	97.59

6. Conclusion and Future Work

In this paper, we proposed a personalized tourism recommendation algorithm based on the introduction of fuzzy consistent matrix. In the process, we obtained the user's travel interest data through the fuzzy consistency matrix and obtained the coverage of the user's POI. Next, we determined the user's preferred POI and conducted a visual analysis through ArcGIS tool. Third, we obtained the user's historical access frequency in order to realize the user's geographical factor feature analysis and calculate the similarity between users using the fuzzy consistency matrix technology. Finally, we build a personalized tourism recommendation model in order to realize personalized travel route recommendation. The following conclusions were drawn through experiments: (i) when the number of recommended routes is 5000, then the accuracy of our method is approximately 97.21%, which shows that the recommended routes are effective; (ii) when the number of recommended routes is 6000, then the ranking accuracy of our method is approximately 95.76%, which shows that the route ranking effect of our method is better; and (iii) when the data volume is 60 GB, the recall rate of our proposed method is 97.59%. Across several experiments, we observed that the proposed method always has a high recall rate for personalized tourism recommended routes.

In the future, we will introduce deep learning technology to further improve the recommendation quality, recall rate, and system accuracy. Furthermore, larger datasets will be used to generalize the findings of this study. This should be noted that along with the increase in data the complexity of the proposed algorithm will definitely increase. Therefore, big data technologies such as cloud computing and edge intelligence can be used to improve the response time of the recommendation system. Edge intelligence uses the state-of-the-art machine learning methods to improve decision-making power that could be of interest of the modern recommendation systems. Finally, we will continue working toward the real implementation of the proposed systems in a particular traveling and routing system [30].

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 no conflicts of interest.

References

[1] C. Li and S. Zhang, "Research on scenic spot recommendation model based on user specific characteristics and content," *Computer and digital engineering*, vol. 47, no. 10, pp. 5–18, 2019.

[2] Q. Zhang and xingting Zhang, "Multi-objective tourism route recommendation based on check-in data and transportation," *Journal of Xi'an University of Engineering Science and Technology: Social Science Edition*, vol. 29, no. 3, pp. 11–22, 2019.

[3] Y. Gong and H. Ai, "Folk culture tourism resources recommendation system based on Hadoop platform," *Science and Technology Bulletin*, no. 2, pp. 5–18, 2021.

[4] R. Liu, S. Yuan, J. Zhao, and W. Yang, "Scenic spot recommendation algorithm based on user attribute clustering and matrix filling," *Computer technology and development*, vol. 30, no. 11, pp. 5–12, 2020.

[5] H. Xiao, "Scenic tourist route planning algorithm based on mobile computing and grey entropy decision model," *Wireless Communications and Mobile Computing*, vol. 2022, Article ID 4030565, 10 pages, 2022.

[6] F. Ying, "Intelligent rural tourism environmental suitability evaluation system based on a wireless sensor network," *Journal of Sensors*, vol. 2021, Article ID 8924970, 12 pages, 2021.

[7] G. Chen, S. Zhang, B. Yan, and S. Miao, "Environmental safety evaluation of geopark based on CPTED concept and fuzzy comprehensive analysis," *PLoS One*, vol. 16, no. 11, Article ID e0260316, 2021.

[8] H. Ding and Q. Huang, "Research on personalized tourism recommendation algorithm based on attribute features [J]," *Intelligent Computer and Applications*, vol. 10, no. 1, pp. 193–196, 2020.

[9] C. U. I. Chunsheng, X. Wang, and LI. Wenlong, "Research on the algorithm of tourist attraction recommendation based on user's online comments," *Journal of Systems Science and Mathematical Sciences*, vol. 40, no. 6, pp. 1103–1116, 2020.

[10] enrang Zheng, G. Han, and L. Chen, "Research on personalized recommendation algorithm of tourist attractions based on domain adaptation," *Journal of Shaanxi University of Science & Technology*, vol. 37, no. 1, pp. 135–139, 2019.

[11] P. Yang, "Yunnan ethnic cultural tourism information recommendation system based on Cloud Server," *Microcomputer application*, vol. 36, no. 11, pp. 3–18, 2020.

[12] G. Li, T. Zhu, H. Jin, J. Ziliang, and Z. Hongbin, "Research on tourist attraction recommendation model based on mixed stratified sampling statistics and Bayesian personalized ranking," *Journal of central China Normal University: Natural Science Edition*, vol. 18, no. 2, Article ID 2072375, pp. 8–20, 2019.

[13] B. Guo, Z. Li, and J. Zhang, "Context related travel route recommendation based on swarm intelligence data," *Journal of Zhengzhou University: Science Edition*, vol. 52, no. 2, pp. 7–19, 2020.

[14] Si Chen and J. Tian, "Research on tourist attraction recommendation model based on collaborative filtering algorithm," *Modern electronic technology*, vol. 43, no. 11, pp. 4–16, 2020.

[15] C. Cui, X. Wang, and W. Li, "Research on tourism product recommendation algorithm based on user portrait in situational environment," *Practice and understanding of Mathematics*, vol. 49, no. 20, pp. 10–18, 2019.

[16] R. Shi, "Design and implementation of tourism recommendation system based on collaborative filtering algorithm," *Computer knowledge and technology: Academic Edition*, vol. 16, no. 35, pp. 3–12, 2020.

[17] Z. song, R. Yin, G. Tan, and Z. Shi, "Research on tourist attraction recommendation model based on segmented user group and time context," *Data analysis and knowledge discovery*, vol. 4, no. 5, pp. 13–21, 2020.

[18] W. Liao, "Application of personalized travel route recommendation based on travel notes and graphic information," *Computer applications and software*, vol. 37, no. 6, pp. 6–12, 2020.

[19] enrang Zheng, G. Han, and L. Chen, "Research on personalized recommendation algorithm of tourist attractions based on domain adaptation," *Journal of Shaanxi University of Science & Technology*, vol. 37, no. 1, pp. 135–139, 2019.

[20] Y. Liu and X. Lin, "Development of tourism location recommendation system," *Information technology and informatization*, vol. 18, no. 11, pp. 3–15, 2020.

[21] L. Pan, "Research on personalized Gansu tourism route recommendation method based on Knowledge Map," *Electronic Production*, vol. 16, no. 17, pp. 4–22, 2021.

[22] J. Zhou and M. Li, "Design of recommendation system based on Tourism user data and comments," *Software*, vol. 40, no. 11, pp. 4–18, 2019.

[23] C. Liang, R. Fan, W. Lu, and S. Zhao, "Personalized recommendation based on cnn-lfm model," *Computer Simulation*, vol. 37, no. 03, pp. 399–404, 2020.

[24] K. R. Sekar, M. Sarika, M. Mitchelle Flavia Jerome, V. Venkataraman, and C. Thaventhiran, *An Enhanced Fuzzy TOPSIS in Soft Computing for the Best Selection of Health Insurance Cybernetics Cognition and Machine Learning Applications*, pp. 361–369, Springer, Singapore, 2021.

[25] T. L. Saaty, "Transport planning with multiple criteria: the analytic hierarchy process applications and progress review," *Journal of Advanced Transportation*, vol. 29, no. 1, pp. 81–126, 1995.

[26] X. Wang, X. R. Li, F. Zhen, and J. Zhang, "How smart is your tourist attraction?: measuring tourist preferences of smart tourism attractions via a FCEM-AHP and IPA approach," *Tourism Management*, vol. 54, pp. 309–320, 2016.

[27] G. Bakioglu and A. O. Atahan, "AHP integrated TOPSIS and VIKOR methods with Pythagorean fuzzy sets to prioritize risks in self-driving vehicles," *Applied Soft Computing*, vol. 99, Article ID 106948, 2021.

[28] M.-C. Chiu, J. H. Huang, S. Gupta, and G. Akman, "Developing a personalized recommendation system in a smart product service system based on unsupervised learning model," *Computers in Industry*, vol. 128, Article ID 103421, 2021.

[29] Xu Yang, Z. Huan, Y. Zhai, and T. Lin, "Research of personalized recommendation technology based on knowledge graphs," *Applied Sciences*, vol. 11, p. 7104, 2021.

[30] G. Liu, "Research on personalized minority tourist route recommendation algorithm based on deep learning," *Scientific Programming*, vol. 2022, Article ID 8063652, 9 pages, 2022.