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Research Article

Design and Application of Multiattribute Tourist Information Recommendation Model Based on User Interest

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There exist various challenges introduced by a large number of multimedia photos and videos for personalized travel recommendation in the era of big data. In order to resolve such challenges, a context-aware personalized travel recommendation system based on data mining is proposed in this study. It is a framework that can locate and summarize travel locations based on a user-given collection of geotagged photos and build up each user's travel history to obtain their travel preferences, so as to perform contextual multiattribute personalized queries, thereby recommending travel locations that best suit their interests. The primary objective is to lay the foundation for developing personalized travel solutions and help the transformation and upgrading of the tourism industry. Thus, this paper proposes a design and application of a multiattribute travel information recommendation model based on user interests for the contradiction between the personalized travel demand of tourists and traditional travel methods. It analyzes the designed travel transportation network and builds a prototype system for travel recommendation by mining a large number of scenic spot information datasets. In association to this, an advanced recommendation algorithm is also designed. The experimental results reveal the fact that by integrating various attributes, the comprehensive evaluation mechanism of scenic spots is capable of providing enhanced reasonable and comprehensive evaluation of scenic spots, which lays the foundation for subsequent route recommendation. Secondly, in comparison to the existing path recommendation algorithms, the recommendation algorithm proposed in this paper has the potential to meet various constraints and goals of the users and recommend routes that have better reasonableness and diversity. Also, this algorithm has low complexity in terms of running time which acts as an added advantage.

1. Introduction

With the advent of the 5G Internet era and the emergence of tourism portals, the contribution of tourism to the national economy and social employment is increasing, and tourism-related data is growing exponentially, resulting in an increasingly serious problem of tourism information overload [1]. The new media, represented by the Internet, has also had a profound impact on the tourism industry, and it can already be seen that most of the tourism information on the Internet is not a direct result of government-led marketing but is provided by travel agency websites, professional websites, commercial media, or individuals, and the use of data mining technology, data analysis, and processing of tourism information on the Internet and the development of related applications has a very broad application situation, which is of great significance to promote the development of the tourism market. The research of tourist attraction recommendation methods can promote the cross-fertilization of machine learning and tourism management concepts. This can help the tourism industry to develop in the direction of intelligence and provide accurate services for tourism users in applications, which in turn can drive the economic growth of the tourism industry. Therefore, the proposed method of tourist attraction recommendation is of great significance. Although recommendation methods can largely alleviate the information overload problem, there are challenges in solving its own problems such as data sparsity and cold start.

With the booming development of tourism, the research on tourism recommendation has also attracted wide attention. In the modern world, tourism has become one of the most important recreational activities for people. The rapid development of mobile devices, especially the smartphone industry, and the increasing accuracy of GPS, enables people to post their current location and itinerary on various social networking sites at any time [2, 3]. People can also score and comment on the places they have visited on major travel websites, making the tourism information on the network more and more rich. Tourists can also get more and more travel information from the Internet, but the huge amount of information also allows users to spend more time planning their trips screening through information that is useful to them. An important source of information includes positive and negative comments of different historical tourist spots given by tourists. It also makes it difficult for users to judge whether a scenic spot is worth visiting. At the same time, as the number of tourists increases, many transnational tourists and inexperienced tourists still face many difficulties when planning their trips.

When people travel to a strange city, they habitually consult travel agencies to help arrange the itinerary or join the tour group directly. However, travel agencies do not take into account the actual needs of users and the scenic spots' actual situation, such as scenic spots' open room, ticket prices, and the journey and schedule of users to these attractions [4]. Participating in tour groups often makes tourists feel that a quick tour cannot well meet the personal needs of tourists. Therefore, it is of great significance to recommend the personalized tourist routes and provide tourists with tourist routes to meet their actual needs.

The unique contributions of the paper include the following:

(i) Development of a multiattribute travel information recommendation model based on user interests for the contradiction between the personalized travel demand of tourists and traditional travel methods

(ii) Analysis of the designed travel transportation network and development of a prototype system for travel recommendation by mining a large number of scenic spot information datasets

(iii) Design of an advanced recommendation algorithm

2. Related Work

The basis of travel route recommendation is data mining, while location-based service, GPS track mining, and point of interest recommendation are the most commonly used technical methods in the field of travel route recommendation, while the greedy algorithm in graph theory can be used for the generation of travel path.

2.1. Data Mining Technology. Data mining refers to the nontrivial process of automatically extracting the useful information hidden in the data from the data collection, in the form of rules, concepts, and patterns. It helps decision-makers analyze historical and current data and discover hidden relationships and patterns to predict possible future behavior. The process of data mining is also called the process of knowledge discovery [5]. It is a very wide interdisciplinary emerging discipline involving a wide range of disciplines, involving database, artificial intelligence, mathematical statistics, visualization, parallel computing, and other fields. It is a wide range of interdisciplinary emerging discipline, involving database, artificial intelligence, mathematical statistics, visualization, parallel computing, and other fields. Data mining is a new information processing technology; its main feature is to extract, transform, analyze, and model a large amount of data in the database and extract the key data to assist decision-making.

2.1.1. Data Mining Technology. The process of data mining involves many steps that require users to make decisions, as shown in Figure 1. Brachman and Anand (1996) give a very practical view to emphasize the interactive nature of the data mining process. Here, we can summarize the following basic steps [6]:

(1) First of all, we should have an in-depth understanding of the application field of data mining and related prior knowledge and also eliminate it from the point of view to determine the goal of the data mining process

(2) Establish a target dataset: the method is to choose a dataset or choose one with a variable sampling of subsets or data which allows the process of data mining to be performed towards this goal

(3) Data cleaning and preprocessing: the basic operation is to properly remove the noise and collect the necessary letters for the model to explain the impact of noise, determine the strategy to process missing data, and explain time series information and the known changes

(4) Data simplification and planning: find good features to represent the data required for the target task. Use dimension reduction to reduce scalars if you consider or find constants to represent the data

(5) Data processing: to meet the data mining goal in step (1), a special one needs to be selected to fix data mining methods, such as overview

(6) Select the algorithm of data mining: select a method and look for one that can fully meets the criteria in the data mining process

(7) Data mining: look for a pattern of interest in special manifestations, or look for these representations—a decision tree with classification rules, regression, clustering, etc. Users can go through the previous

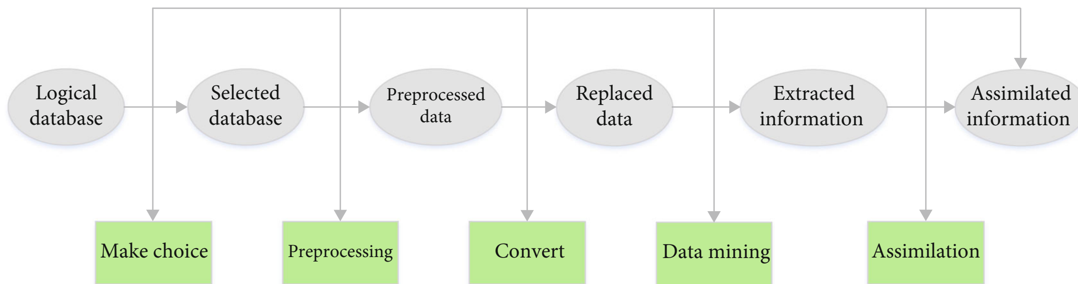

FIGURE 1: The basic process of data mining.

steps. Suddenly, I can intuitively find out the method of data mining

(8) Explain the mining mode: it is possible to return to step (7) for more iterations, which includes the visualization of the extraction mode and the visualization of the data

(9) Consolidate the mining knowledge: summarize this knowledge so that it can be used in other systems in the future, or the right parts of interest are simply copied and duplicated, which also includes an examination of the previously extracted knowledge to solve potential conflicts

2.1.2. Application of Data Mining in the Recommendation System. The recommendation system is an important application point of data mining. The recommendation system mines user behavior and relationship data, establishes user models and preferences, and predicts and recommends users' personalized needs. It can make users more tolerant to find the information that they are interested in, so the recommendation systems are more and more inclined to provide personalized services for users, and the historical data mining of users is the basis of providing personalized services. At the same time, in order to convey the information to suitable users more quickly and conveniently, and in order to meet the search needs of users in real time, high requirements are put forward for the real-time performance of the recommendation system [7, 8]. Therefore, the ability to quickly process and feedback massive data is the basic requirement to realize the real-time performance of the recommendation system.

With the rapid growth of network, data mining application in the recommendation system is becoming more and more deep. A recommendation system based on association rule mining was proposed by Literature [9]; Literature [10] proposed a user model by recording the historical data of user shopping. To recommend products to users through user models, a recommendation system based on Bayesian classification mining was proposed by Literature [11]; Literature [12] proposed the application of decision tree algorithm, association rules, web mining, and other technologies to the e-commerce recommendation system; Literature [13] proposed to provide corresponding recommendation services by mining the web log.

For the recommendation of tourist routes, the most important thing is to mine the information data of scenic spots and extract the scenic spots and related information that users are interested in and feedback to users. However, the tourism information on the Internet is characterized by massive, multidimensional, incompleteness, diversity, and complexity [14]. It is difficult to do with traditional recommendation technology to recommend travel information satisfying their personalized and interest preferences to users from such complex information. Therefore, it is an inevitable trend to apply data mining technology in this field.

2.2. GPS Track Mining Technology. With the rapid development of GPS positioning technology, people can record their current geographical location information and publish their mobile trajectories to the Internet. At the same time, more and more websites, including Twitter, Foursquare, and Facebook, have also developed platforms to support location or trajectory data sharing. Such a large amount of GPS trajectory data enables various new applications. One of the most emerging applications is the search and recommendation of trajectories, namely, by discovering a series of similar trajectories and recommending them to users as a reference.

2.2.1. Generation of GPS Trajectory Data. With the development of various positioning technologies, people obtain their own location information through portable mobile devices and record their own location information in a track way [15]. Users record these tracks for many purposes, such as the following:

(1) In order to ensure the safety of effective scheduling and vehicles, as well as the effective analysis of the current traffic conditions and flow, many taxis, buses, and even some private cars have built-in GPS equipment; the GPS equipment every once in a while at a certain frequency connect to a specific control center to send their own geographical coordinates, so that the control center can accept the GPS coordinates into the trajectory of the vehicle

(2) For those who often travel frequently or love mountaineering or cycling, you will record your trip with portable GPS devices. The lines formed through these GPS tracks will ensure that they will not get lost, at least to be able to return along the original road, at the same time. After the tour or ride, these

users can also extract information of interest from their own GPS tracks, such as the total mileage of the tour, the highest altitude of climb, the change of sports speed, and the difficulty of climbing. This trajectory information can help them to improve the level of outdoor sports; for a much longer time to come, these preserved tracks can be a historical testimony of how they have experienced or conquered certain challenges. It also provides more route references and choices for other mountaineering or travel enthusiasts

(3) If photos taken during travel are associated with the trajectory and uploaded to an electronic map, users can not only intuitively see their own action journey again intuitively. They can also easily communicate and share your travel experience with your friends. Apart from the relatively dry text elaboration, these routes associated with photos with track data can be intuitively and vividly displayed to others (such as important directions, ride places and transfer vehicles, tour time and order of each scenic spot, and evaluation of characteristic scenery). When someone wants to repeat and recreate the tour, these trajectories, in turn, can serve as the most effective navigation, save users the time for schedule planning, and, in some key points, provide the later users with real-time, effective tips

2.2.2. Application of GPS Trajectory Mining. The GPS data have closely linked people activities to their location and timestamp information, as shown in Figure 2.

Through the data mining technology and postprocessing of various GPS data, many applications can get useful information for a large number of users. For example, GPS tracks can be used to analyze and discover patterns and predict repeat patterns. Through the postprocessing of the data, the raw GPS data can be converted into more useful forms, for example, by routable path maps [16]. For travel and travel apps, GPS data can be used to discover the location of attractions, which can be integrated to form mobile guides, or used in combination with pictures with geographic coordinates.

The GPS trajectory data can also be used to classify different traffic patterns, such as driving, walking, taking a bus, and cycling. Different methods recommend geographical locations by mining relevant location information and using historical location data, such as stores and restaurants, which also inspires our users' similarity recommendation to consider the similarity of geospatial information through their historical trajectory and hierarchy.

2.3. GPS Interest Point Recommendation. With the rapid development of mobile devices, wireless networks, and Web2.0 technology, a large number of user-location-based social networking services (LBSN) continue to emerge. These services enable users to establish connections with friends or other users through the network and share their trip to colorful interest points (POI); for POI-recommended services, the purpose is to recommend new POI points and, at the same time, help them find new goals, have a better understanding of their city, and enjoy life better.

2.3.1. Overview of Interest Points. In fact, because people have been able to obtain the network connection between users and the connection between users and their geographical location, how to promote the development of POI recommendation is a question of great research value. However, this class of information has not been fully utilized in previous studies to recommend points of interest.

In location-based social network services, users and points of interest (POI) are two different forms of entities (see Figure 3). In the figure below, users are labeled u_1, u_2, u_3, and u_4, and the social connection between them forms a social network between users. Meanwhile, the point of interest (POI) is marked as I_1, I_2,…, I_6 and is connected through the user's "check-in" behavior, reflecting the user's taste for different points of interest. Finally, each point of interest (POI) has a geographical coordinate of latitude and longitude. To recommend points of interest to the user, apparently, the users' previous check-in records have an important role. Using such information, we can adopt the traditional collaborative filtering technology to perform the recommendation of POI points. That is, POI points are recommended as "items" in the algorithm based on collaborative filtering. Such user-based or project-based system-filtering techniques may be used to recommend points of interest.

2.3.2. Recommended Techniques for Points of Interest. Before recommending a travel route, we should know what attractions are interesting and also know when they are appropriate to visit. Generally, this task can be seen as a recommendation for attractions. At present, there are many research and related technologies. Literature [17] has proposed an enhanced collaborative filtering algorithm based on the current location of their attractions, providing users with a more reasonable and effective recommendation result. However, the information on which these technologies rely on all has expert definitions in the field, and in fact, this kind of information is rare in the real world. Additional information as defined by domain experts is easily outdated. Recent studies have proposed attraction recommendations based on user-generated data from LBSNs and geographically tagged photos. Literature [18] proposed personalized recommendations by assessing similarity between attractions through geotagged photographs. However, the above techniques do not take into account the time factor, and the time characteristic is also a very important factor in the practical application.

2.4. Tourism Route Optimization

2.4.1. Constrained-Based Travel Recommendation System. This kind of system is interactive to effectively integrate tourism resources, inspire user needs online by session, help group users overcome information overload, give support in the decision-making process of users, and then recommend appropriate tourism service information for users, as shown in Figure 4. Compared with the tourism recommendation system based on traditional recommendation technology or

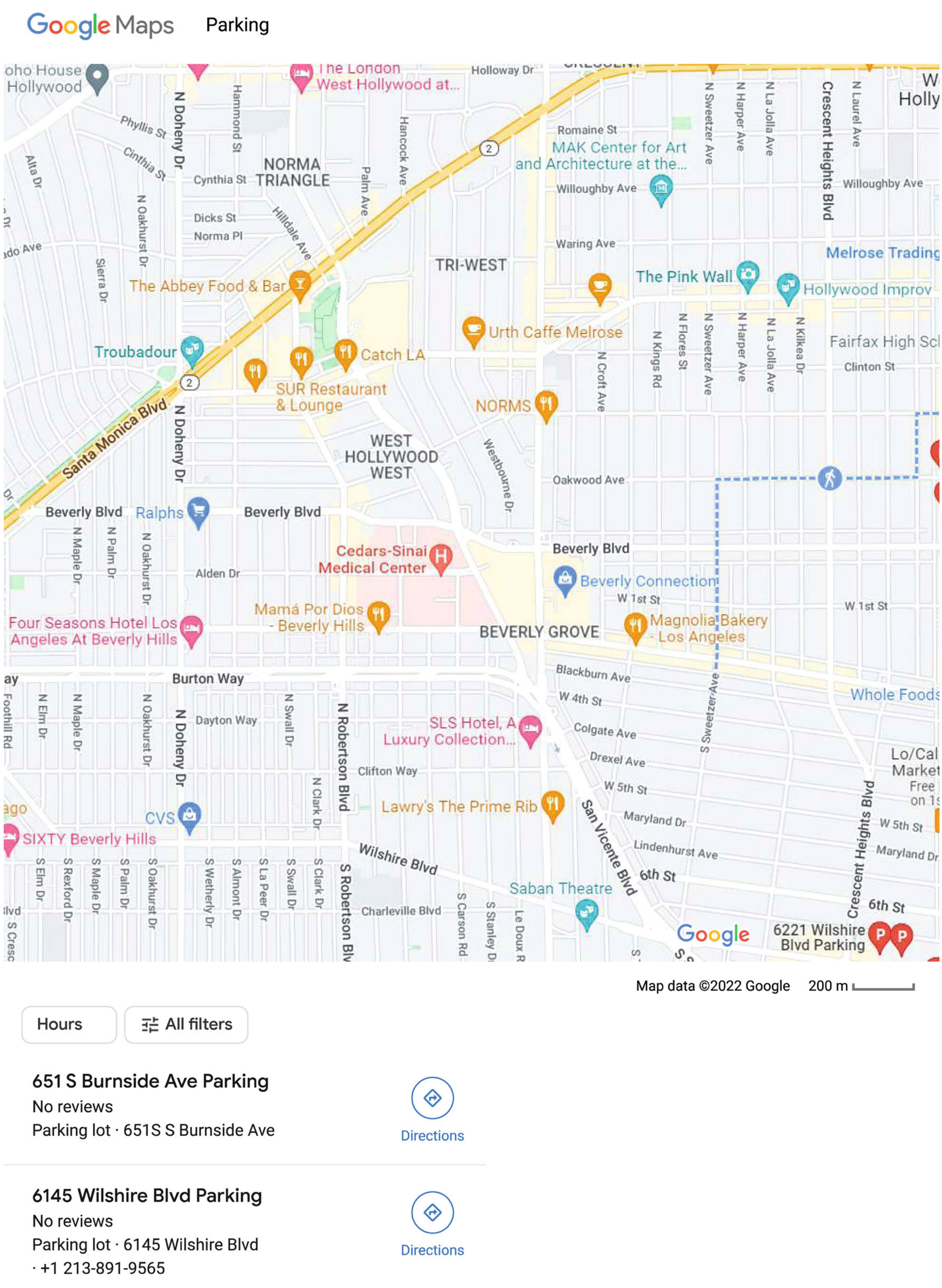

Figure 2: Map matching sample of GPS.

data mining technology, the system fully considers the unique characteristics and constraints of the tourism field and obtains user preferences and needs through more humanized and flexible conversational interactive access, not historical travel information data of mobile phone users. Therefore, there is no cold start problem.

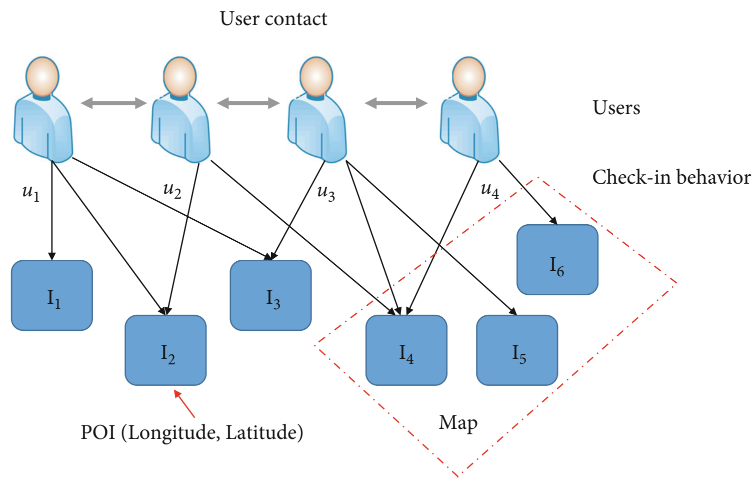

Figure 3: Relationship between user friends and user check-in behavior and user location.

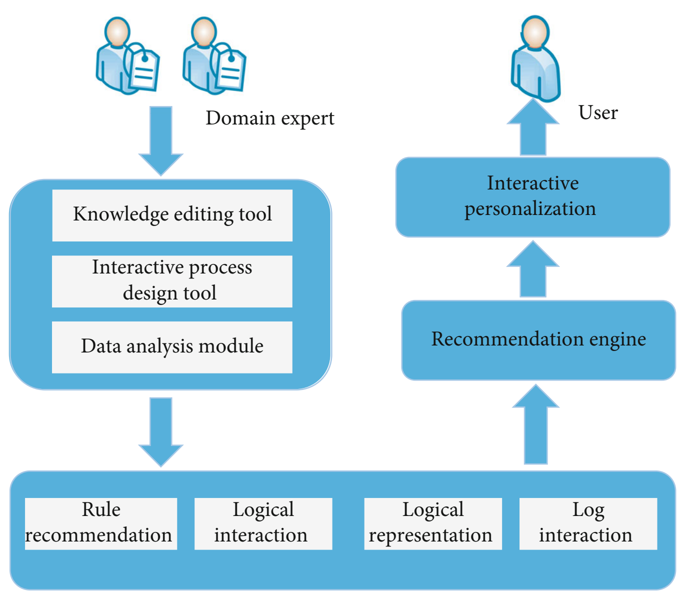

Figure 4: A constraint-based travel recommendation system framework.

2.4.2. Travel Recommendation System Based on User-Generated Data. This kind of system puts forward the tourism route planning algorithm; through the interaction with the user, the user can add or delete attractions, change input, set time, etc.; by putting forward the scenic internal route fusion algorithm, we can dig out high-quality attraction internal route and overcome the user upload photo sparsity, as shown in Figure 5.This kind of system realizes the purpose of real-time direction and road guide. The system can help users to automatically plan their travel routes, saving people's time and energy.

2.4.3. Travel Recommendation System Based on "Check-In" Behavior. This system proposes a new framework called personalized travel recommendation (PTR), which performs personalized travel recommendation by mining user "check-in" behavior and multiple constraints proposed by user personalized travel recommendation [19]. In this system, models developed by considering user preferences and temporal property-based data mining are proposed for the first time to evaluate point-of-interest rankings and scores, as shown in Figure 6. A new trip recommendation algorithm is also proposed to meet the needs of multiple special constraints [20]. The system showed excellent performance by testing on the Gopala dataset.

The tourism sector acts as a huge source of economic growth in many countries due to their potential in tourism. Although the tourism trip design problem is traditionally considered as an operation research-based problem, various information technology-based solutions are also proposed and implemented in this sector for achieving enhanced prediction results [21, 22]. Various studies have been

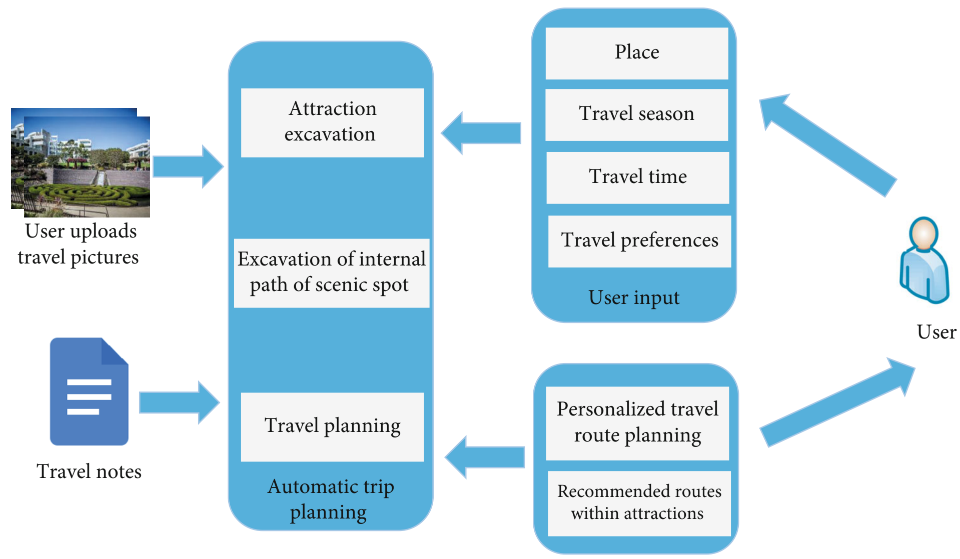

Figure 5: Travel recommendation system based on user-generated data.

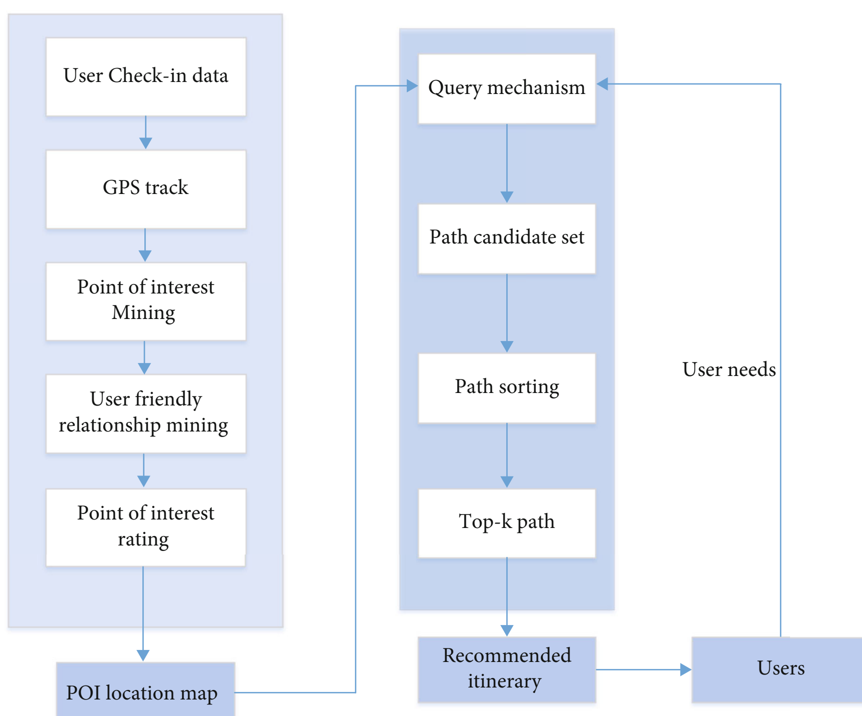

Figure 6: Personalized travel recommendation system based on "check-in" behavior.

conducted implementing the greedy heuristic algorithm to predict the next destination for tourists. The study in [23, 24] implemented a two-step greedy algorithm which considered the challenges associated with space-time conflicts and also eliminated issues pertinent to sparse data. The study in [25] implemented a multiconstrained K-greedy algorithm considering opening hours of scenic spots, GIS coordinates of the tickets, and scenic spot evaluation information.

3. Multiattribute Scenic Attraction Scoring Mechanism Established

Spot score is the basis of recommendation, and the recommended path is the main body; a scenic score determines the appeal to the user or users who may be interested in the attractions, thus establishing a scenic scoring mechanism which can meet the needs of users, for scenic spots and route recommendation has an important role, which is the important premise of path recommendation. In order to meet the multiconstraints of users and achieve the multigoal recommendation, we need to integrate multiple scoring methods to form an effective scenic spot scoring mechanism.

3.1. Source and Analysis of Scenic Attraction Information Data. The data used in this paper are obtained from the travel website, the data obtained are 702 northern attractions with user ratings and reviews, and the cutoff for obtaining the data is April 2022.

The attractions we found have a 5-point user rating; the worst is 1 point and the best 5 points, with a total of 702 attractions, as well as important features of the attractions (opening hours, ticket prices, etc.), as shown in Table 1. Among them, scenic spot A represents the Forbidden City, scenic spot B refers to the Summer Palace, scenic spot C refers to Mutiny Great Wall, scenic spot D refers to Beijing Happy Valley, scenic spot E refers to Tiananmen Gate Tower, scenic spot F refers to Sarmatia Great Wall, scenic spot G refers to Temple of Heaven, scenic spot H refers to Tiananmen Square, scenic spot I means Houhai, and scenic spot J means CCTV Tower. In the following text, we only use symbols to denote these attractions.

The user satisfaction score, attraction type, opening time, ticket price, and other information are extracted as the basis for the attraction score.

The GPS coordinate information of scenic spots is extracted, and the travel time relationship between scenic spots is calculated through the transformation of latitude and longitude coordinates and the actual geographical distance, so as to generate the path relationship map between scenic spots.

3.2. Establishment of a Multiconstraint-Oriented Scoring Mechanism. For each scenic spot, the algorithm must first know the degree of the attraction to the users in the current location, which is also known as the attraction score of the attraction to the users. It consists of three aspects:

(1) Based on the user rating data, this is a measure of the popularity of the site and the historical user evaluation of the site. Due to the need of scoring mode fusion, we had to normalize the score, defined as ECI

(2) Based on the score of the time between users and scenic spots, generally speaking, being farther away from the user's current location is relatively less attractive to users. Users are more willing to choose close scenic spots. For the score of distance, we define DC, which also needs to be normalized, defined as DCI

(3) Based on the opening time of the score, this is a measure of a certain time when it is appropriate for users to visit the attractions; different attractions have different appropriate access times, and more than the opening time is not considered to visit the attractions, so according to different opening time, we only set this aspect as a parameter. We combine EC and DC to form a scenic spot score SS (s, u_L, t); the score indicates the attraction score to the user u at time t. The subscript L represents the current geographic coordinate location of the user

3.2.1. Ratings Based on the Attraction User Ratings. Each scenic spot s has user rating data over the years. According to the data we get, the rating of the scenic spot is 5, from 1 to 5, of which 1 is very poor and 5 is very satisfied. We believe that the rating data of historical users is strongly related to whether current users choose to visit the attraction, and the more the number of people rating a certain attraction, the higher the popularity of the attraction. For example, for the museum, 313 people participated in the rating, and 277 people were rated above 4 points, indicating that historical users generally have a high evaluation of the attraction, so it is highly likely that the scenic spot will be recommended to current users. The main idea based on user rating is to count the rating of historical users and find the score expectation value of each scenic spot. We then normalized the expected value scores for all attractions to take values between 0 and 1, which we defined as ECI as shown in the following formula.

$$\mathrm{ECI}(s_i) = \frac{|\mathrm{EC}(s_i)|}{\arg_{s_i \in S} \max (|\mathrm{EC}(s_i)|)}. \tag{1}$$

For current users, we mark its rating score for each attraction at the current position L and the current time t as a feature vector $\mathrm{UV}(u)$, defined as follows:

$$\mathrm{UV}(u) = <\mathrm{ECI}(s_1), \mathrm{ECI}(s_2), \cdots, \mathrm{ECI}\left(s_{|s|}\right)>. \tag{2}$$

Then, for all the attractions in the attraction collection, we can calculate their user-based rating scores, and we list the top 10 attraction rating values; using 1~5 indicates the rating level, with 5 being the highest and 1 being the lowest.

3.2.2. Ratings Based on User Time to the Attraction. We can dig out the GPS coordinate point information of each scenic spot and calculate the distance between them through the standard geographical coordinates from the conversion formula to the actual distance. Then, taking the average speed of the vehicle inside and outside the city, you can approximate the arrival time between the various attractions. The two attractions can pass in two directions, and the back and forth time is the same; that is, an undirected graph path network is established, plus the user's starting position to each scenic spot time, forming a $|s+1| \cdot |s+1|$ adjacency matrix. The main idea based on the score of the time to the attractions is that the closer to the user, that is, the less the time to arrive, the more attractive to the user and the higher the score. Similarly, we also normalized this score, and the score result was defined as DCI, making it take values between 0 and 1, defined as follows:

$$\mathrm{DCI}(u_L, s_i) = \frac{\mathrm{avg}(T(u_L, S))}{\mathrm{avg}(T(u_L, S)) + T(u_L, s_i)}. \tag{3}$$

Table 1: Ratings and related information of the attractions.

Rank	Total	1	2	3	4	5	Types	Attractions	Opening	Fare
1	313	3	6	27	105	172	1	A	8:30~16:00	60
2	170	1	8	22	86	86	1	B	6:30~18:00	30
3	39	0	0	0	24	24	1	C	8:00~16:00	35
4	41	0	0	3	24	24	2	D	8:30~16:00	120
5	320	0	4	7	14	14	1	E	9:00~22:00	30
6	36	0	0	1	24	35	1	F	8:00~16:30	40
7	93	1	2	13	35	23	1	G	6:00~17:00	35
8	66	0	0	9	23	27	1	H	0:00~24:00	0
9	62	0	2	12	27	21	2	I	0:00~24:00	0
10	21	0	0	3	10	10	3	J	8:30~21:00	50

The average value of the time that the user points to all the attractions is used as a reference, and the time $T(u)$ of the user's current point to a certain scenic spot can be obtained from the above formula. If$T(u_L, s_i)$is larger, the smaller the score, that is, the less attractive the attraction. The average value is obtained as defined as follows:

$$\operatorname{avg}(T(u_L, S)) = \frac{\sum_{i=1}^{|s|} T(u_L, u_L)}{|s|}, \tag{4}$$

where s represents the total number of all attractions in the attraction collection. Again, for all the attractions in the scenic spot collection, we can calculate their score based on the user to the attraction.

3.2.3. Ratings Based on Attraction Opening Hours. In the actual tourism process, different scenic spots have different time periods suitable to visit. Most tourist attractions have scheduled opening hours every day. For example, the opening time of the Summer Palace is 6:30~18:00; only within this time range can tourists visit, and beyond the time range is not suitable to visit. So for each attraction s, we define a 24-hour score (s, t), and t indicates at some point in the day. You can consider it from the following two aspects:

(1) Which time period is suitable to visit the scenic spot; for each scenic spot, we can know its daily opening hours; during the opening hours of the attractions, visits are allowed, but not beyond the opening hours

(2) In the suitable access period, which time to attract users more, for this, we think that in the middle of the open time, users whether early or late can have a lot of visit time, so the score should be the highest, and the closer to the user interest is less, which we also normalized, making its value between 0 and 1. Therefore, we define it as follows

$$\beta(s, t) = \begin{cases} \dfrac{2t - 2t_{\min}}{t_{\max} - t_{\min}}, t_{\min} \le t < \dfrac{t_{\max} + t_{\min}}{2}, \\ \dfrac{2t_{\max} - 2t}{t_{\max} - t_{\min}}, \dfrac{t_{\max} + t_{\min}}{2} < t < t_{\max}, \\ 0, t < t_{\min} \text{ or } \mathrm{t} > \mathrm{t}_{\max}. \end{cases} \tag{5}$$

Among them, $t_{\min}$ and $t_{\max}$ indicate the opening and closing times of the attractions, respectively.

$\beta(s, t)$ indicates the score value of all the attractions in the attraction collection at the current moment according to the opening time. For all attractions in the collection, each attraction got the same score at different points of the day.

The attractions have different attractions to users at different times. If you go too early, the scenic spot is too cold and has no atmosphere, and if there is enough time to meet the users' play time, the score is low. Therefore, the midpoint of the open time is the most attractive point to the user. Also, moments outside open time naturally have no reference value for the current user, namely, a score of 0.

3.2.4. Establishment of a Scoring Mechanism for Multiple Constraints. After obtaining user-based rating and user-to-site time for each attraction, our path planning algorithm should not only meet the interest needs of users but also meet the requirements of attraction opening time. Therefore, we use formula (5) to the first two scoring methods after the preliminary score $\mathrm{SS}'(s, u_L)$, the third scoring method, to get the final score of $\mathrm{SS}(s, u_L, t)$; it represents the user in the position u_L (lat, lon), scenic spot s at time t appeals to the user. Parameters were used to control ratings based on user ratings and weights based on user-to-attraction time ratings.

$$\mathrm{SS}'(s, u_L) = \alpha \cdot \mathrm{ECI}(s) + (1 - \alpha) \cdot \mathrm{DCI}(u_L, s). \tag{6}$$

Among them, ECI and DCI are the normalized scoring results of the first two scoring methods, respectively, and then, the third score is fused:

$$\mathrm{SS}(s, u_L, t) = \beta(s, t) \cdot \mathrm{SS}'(s, u_L). \tag{7}$$

For formula (6), the key to score fusion lies in the value of the weights in the first two scoring methods. If the value is large, it indicates that the rating data of historical users has a great impact on the current users' choice of scenic spots; otherwise, it indicates that users pay more attention to the distance of the scenic spots.

The larger the value, the larger the user rating data in the scenic spot score, but if the fixed value is taken, there will be some problems. For example, some scenic spots have only one or a few user rating data, so that if there is a large value, it will produce bias problems; that is, the score of scenic spots is mainly determined by the evaluation of several people, which is obviously unreasonable. For those scenic spots with more user rating data, more user evaluation should be able to give the scenic spots an objective score, but if the value is small, it cannot well reflect the role of historical user rating data. Therefore, the median value in the algorithm is as shown in the following formula.

$$\alpha(s) = \frac{\sum_{i=1}^{5} c_i}{\arg_{s\in S} \max \left(\sum_{i=1}^{5} c_i \right)}. \quad (8)$$

According to formula (8), the size of the value determines the proportion of the scenic attraction score based on the user rating data. The more historical user rating data, the greater the value and the more its rating data affects the score value of the current attraction.

4. Multiconstrained Multiobjective k-Greedy Algorithm Designs

According to the definition in Section 3 and the establishment of the scoring mechanism in this section, a specific system framework is proposed that focuses on solving the following problems: given a user's current location and departure time and a variety of user constraints, such as time constraints and budget constraints and attractions type constraints. Our goal is to establish an effective multiobjective recommendation framework for travel routes to provide users with recommended route options that meet their constraints.

Suppose there is a tourist, starting from s_u at 9:00 am and planning to end at 14:00. His planned travel time is 300 minutes, assuming his budget is 100 yuan. From s_1 to s_4 are 4 different attractions, each with a stay time calculated by the scoring formula and a fixed ticket price. A starts from the starting point u_L, assuming that for the starting point, his ECI and DCI are shown in Table 2.

The time of a man to reach s_1 is 30, so the time of arriving at s_1 is 9:30, with $\beta = 0.35$. Similarly, the value of the other 3 attractions is obtained, as shown in Table 3.

While we assume $\alpha = 0.35$, Table 4 shows the final score for each attraction, calculated separately based on Tables 2 and 3.

Because we also consider the praise and distance factors of the scenic spot, the man will choose the highest score point after comprehensively considering the above factors, and judging from Table 4, according to the greedy algorithm, the first scenic spot selected by the man is s_4. Thus, when the man reaches s_4, the value of the DCI and the next attraction to calculate the next spot has the highest score. Finally, the greedy algorithm concluded that the route is $\{s_4, s_2, s_1\}$, as shown in Table 5.

For the path derived from the greedy algorithm, TPS $= 0.35 + 0.45 + 0.60 = 1.3$, and then, we need to check whether the stroke derived by the algorithm meets the constraint; then, the final calculated TPT $\{s_u < s_4, s_2, s_1 > \} = 275$ is less than 300, which is the user time constraint; TPC $\{s_4, s_2, s_1\} = 75 < 100$ also meets the constraint, so $\{s_4, s_2, s_1\}$ is an effective trip for the man.

Table 2: ECI and DCI scores.

Attractions/scoring	ECI	DCI
$\{s_1\}$	0.8	0.8
$\{s_2\}$	0.7	0.6
$\{s_3\}$	0.6	0.7
$\{s_4\}$	0.8	0.6

Table 3: Scoring of attractions at different times.

Attraction/time	…	9:00	10:00	11:00	12:00	…
$\{s_1\}$	…	0.3	0.4	0.5	0.6	…
$\{s_2\}$	…	0.2	0.4	0.6	0.8	…
$\{s_3\}$	…	0.35	0.5	0.65	0.5	…
$\{s_4\}$	…	0.4	0.5	0.6	0.7	…

Table 4: Final score of the attraction.

Attractions/ ratings	$\alpha \cdot \text{ECI} + (1-\alpha) \cdot \text{DCI}$	$\beta \cdot \text{SS}'$
$\{s_1\}$	$0.5 * 0.8 + (1 - 0.5) * 0.8 = 0.8$	$0.35 * 0.8 = 0.28$
$\{s_2\}$	$0.5 * 0.7 + (1 - 0.5) * 0.6 = 0.65$	$0.4 * 0.65 = 0.26$
$\{s_3\}$	$0.5 * 0.6 + (1 - 0.5) * 0.7 = 0.65$	$0.5 * 0.65 = 0.325$
$\{s_4\}$	$0.5 * 0.8 + (1 - 0.5) * 0.6 = 0.7$	$0.7 * 0.5 = 0.35$

Table 5: Simple path derivation.

Attractions	Period	$\beta \cdot \text{SS}'$
$\{s_u\}$	9:00	—
$\{s_4\}$	9:50-10:35	0.35
$\{s_2\}$	11L05~11:35	0.45
$\{s_1\}$	12:15~12:55	0.60
$\{s_u\}$	13:25	—

5. Experimental Results and Analysis

We use data mining technology to obtain real Beijing attraction information for the experiment. Experimental data ended on April 2022. Across the entire dataset, all attractions and attraction ratings were 702 and 69670, respectively, with

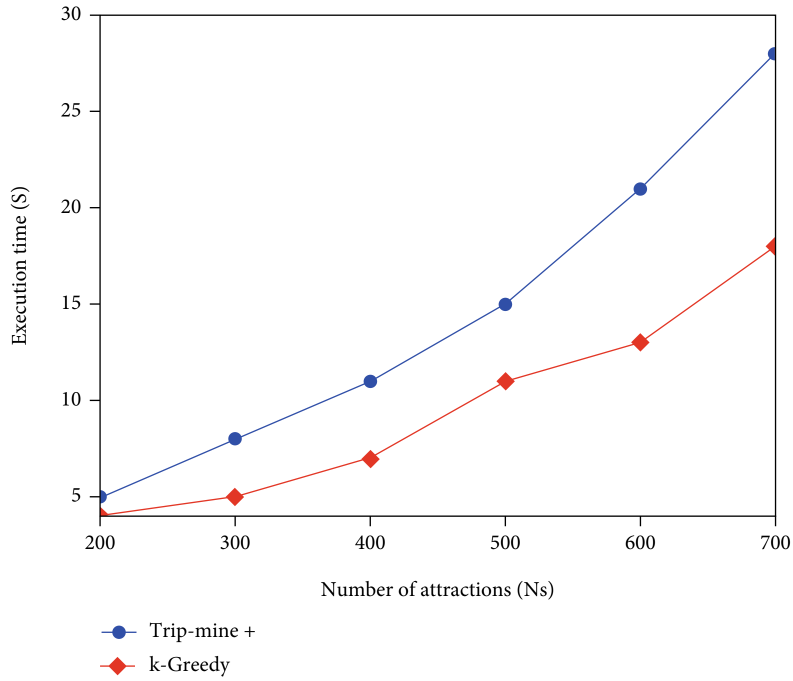

Figure 7: Effect of change of attraction numbers on execution time.

an average rating data of 33.66 times per attraction. For each attraction, their stay time is determined by the historical user's rating score, and the higher the score, the longer the stay; ticket prices and opening hours for each attraction are directly available. The arrival time between attractions is determined based on their GPS coordinates. The GPS coordinate information for each attraction were obtained via Google Maps.

We input the user's travel time and budget constraints, as well as the location where the user starts, to query the optimal path. The user's departure position is a randomly selected point in Beijing; travel time, budget, and starting point are, respectively, by CTT, CB, and $\mathrm{LOC}_{\mathrm{UL}}$ to decide.

5.1. The Effect of Different Constraint Values on the Results. We analyze the experiments to compare the efficiency between our proposed multiconstrained multiobjective-based *k*-Greedy algorithm and Trip-Mine+, which is also recommended as multiobjective. The main idea of the Trip-Mine+ algorithm is to delete the number of scenic spots that do not meet the constraints by continuously expanding the number of scenic spots that do not meet the constraints. Finally, we rank all the paths obtained by the algorithm and select the *k* paths with the highest score value.

5.1.1. Effect of the Number of Attractions on the Experimental Results. In this experiment, we use the dataset information of more than 700 scenic spots in Beijing. When the number of scenic spots increases from 200 to 700, the execution time of the *k*-greedy algorithm and the traditional greedy algorithm is analyzed. Figure 7 reflects that the *k*-greedy algorithm always has a short execution time compared with the Trip-Mine+ algorithm. But both algorithms increase the execution time as the number of scenic spots increases. The reason is that when the number of attractions increases, the alternative path increases, so the overall execution time increases. Since our *k*-greedy algorithm is based on the extension of the greedy algorithm, it only scores the next extension attraction that meets the constraint, giving it a shorter execution time compared to Trip-Mine+, which is also the advantage of the greedy algorithm.

5.1.2. Effect of Travel Time Constraint (CTT) on Experimental Results. In this experiment, we mined a dataset of more than 700 scenic spots in Beijing to analyze the execution time of the *k*-greedy algorithm and Trip-Mine+ when the travel time constraint (CTT) is changed from 200 to 500, as shown in Figure 8.

Figure 8 reflects that the *k*-greedy algorithm still has a shorter execution time than the Trip-Mine+ algorithm with different time constraints. We observed that as the constraint time increases, the execution time of the program increases accordingly. On the one hand, because of the increased constraint time, the number of user-accessible attractions on each path has also increased. On the other hand, the number of paths that generating users can choose from will also increase.

5.1.3. Effect of Budget Constraints (CB) on the Experimental Results. This experiment uses a dataset of more than 700 attractions in Beijing to analyze the execution time of the *k* -greedy algorithm and Trip-Mine+ algorithm when the travel budget constraint (CB) is changed from 50 to 300, as shown in Figure 9.

Figure 9 reflects that the *k*-greedy algorithm still has a shorter execution time than the Trip-Mine+ algorithm with different time constraints. We observed a corresponding increase in program execution time as the travel budget

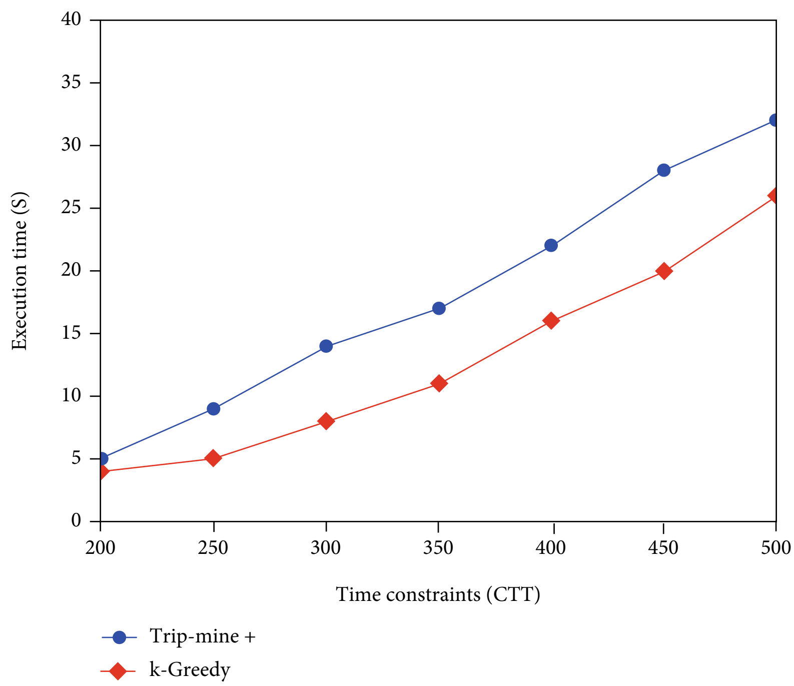

FIGURE 8: Effect of travel time constraints on program execution time.

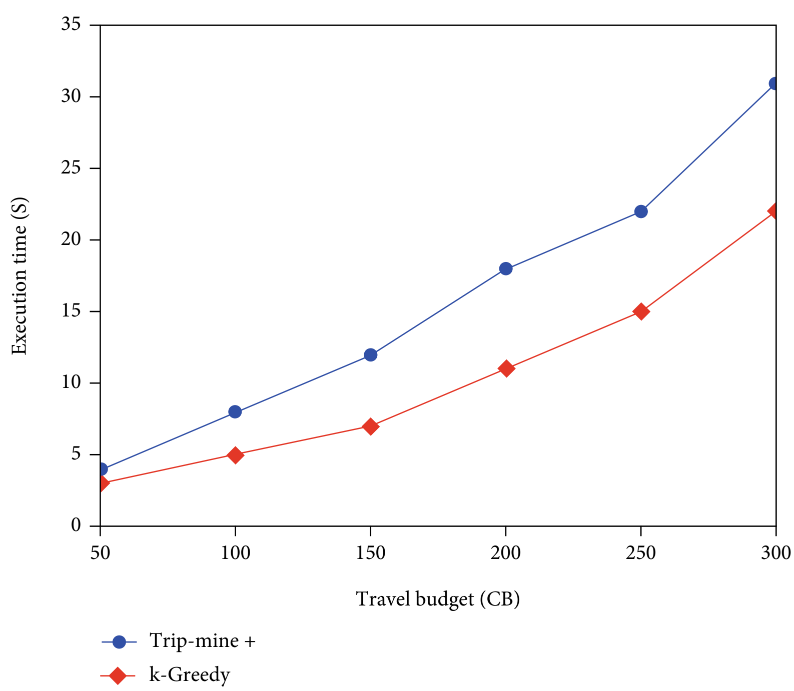

FIGURE 9: Effect of travel budget constraints on the time of program execution.

increased. Similar to the travel time constraints, the number of attractions available to users on each path increased because the budget increased. On the other hand, the number of paths that generating users can choose from will also increase.

5.1.4. Effect of Travel Time and Budget Constraints on the TPS Score. In practical recommendations, we consider more of the time and budget constraints given by the user, and this experiment observes the effect of another constraint on the final path score TPS by qualifying one constraint. Figure 10 reflects the effect of the *k*-greedy algorithm and the Trip-Mine+ algorithm on the highest scoring path in the recommended results when the constrained time varies from 200 to 500, when we have a budget for a given user of 100.The less time, the recommended attractions in the

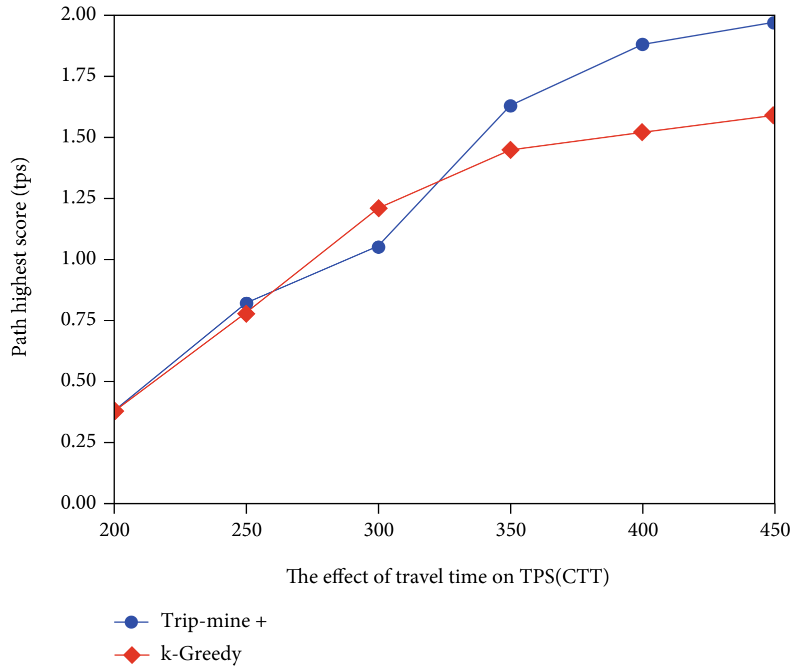

Figure 10: Effect of travel time constraints on the TPS.

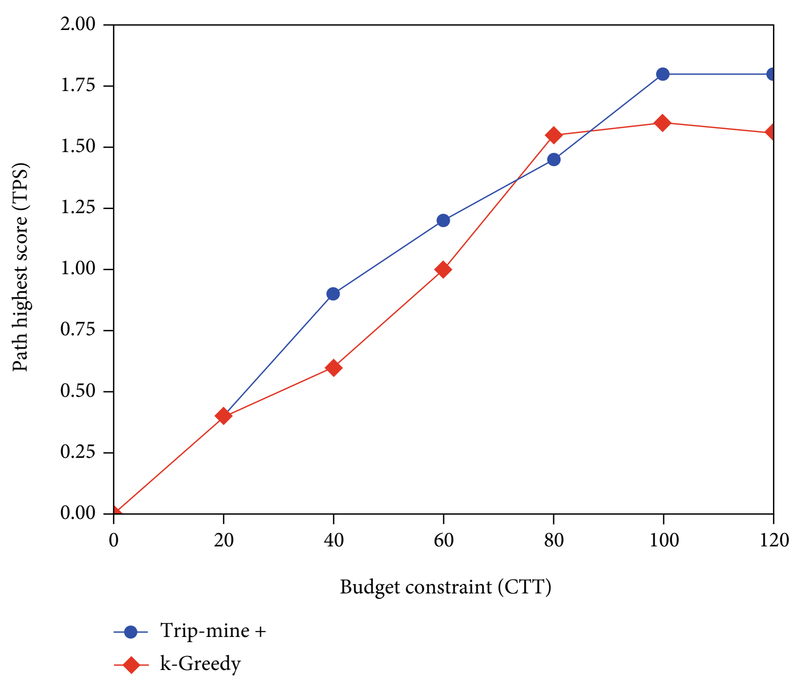

Figure 11: The impact of travel budget constraints on the TPS.

path is less, so the TPS is lower; with the increase of time, the more recommended spots, and the greater the TPS value, and when the value of the TPS reached to a critical point, the algorithm no longer increases; the reason is that the user's budget constraints prevent the user from continuing to visit more attractions. Because the *k*-greedy algorithm considers the local optimal situation, sometimes, it cannot recommend the best score result, but sometimes, you can find the best score.

Figure 11 reflects the effect of the *k*-greedy algorithm and the Trip-Mine+ algorithm on the highest scoring path in the recommended results at 500 when we give users a budget constraint change from 0 to 120. The less is the budget, the recommended attractions in the path is less, so the TPS is

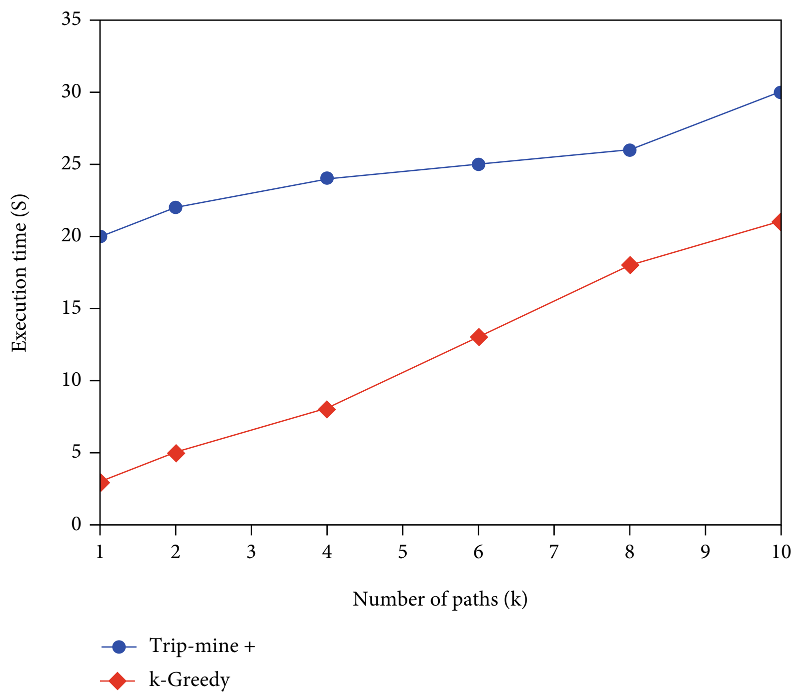

FIGURE 12: Shows the effect of the parameter k on the experimental results.

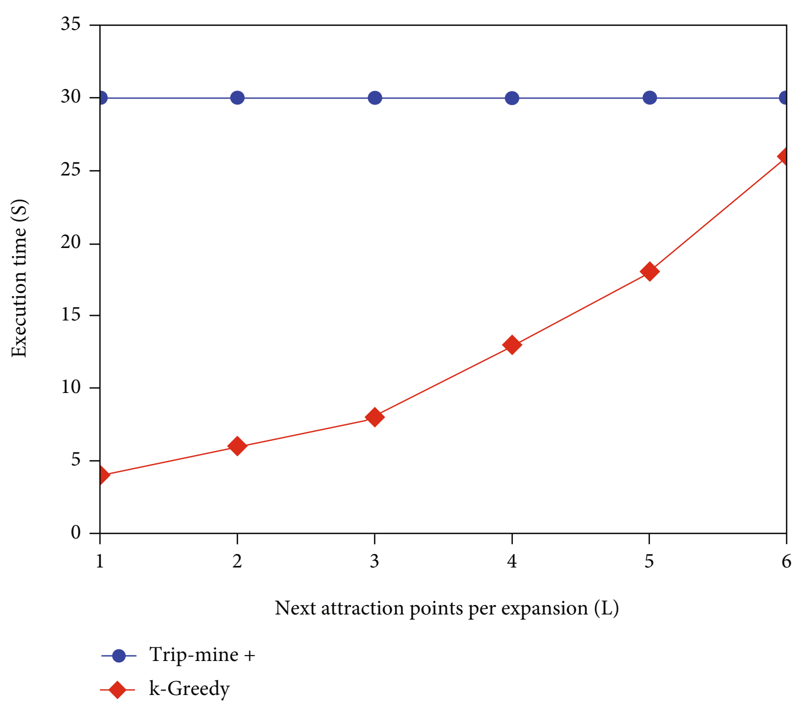

FIGURE 13: Effect of parameter l on the experimental results.

lower; with the increase of the budget, the more recommended spots, and the larger the TPS value, and when the value of the TPS reached to a critical point, the algorithm is no longer increased; the reason is that the user time constraints prevent users from continuing to visit more attractions.

5.2. The Effect of Different Parameter Values (k, l) *on the Experimental Results.* This experiment observed the effect of another parameter change on the execution time of the experiment by limiting one parameter. First, we qualify the l value to 4 and k varies from 1 to 10. Then, the execution time of the two algorithms is shown in Figure 12. Because the Trip-Mine+ algorithm first selects all eligible paths and gives the first k paths with high scores, so the execution time only increases with the value of k in the last ranking. However, in the k-greedy algorithm, the value of k determines the number of paths to be retained in the candidate set, and the more paths are retained, the faster the time of the algorithm grows.

When we qualify the value of k to 4, l changes from 1 to 6; then, the execution time of both algorithms is shown in Figure 13, because the l value has no effect in any way on the Trip-Mine+ algorithm, because it always selects all the paths that meet the constraints anyway. For the k-greedy method, the value of l determines the number of nodes that each point should expand in the next step, so the larger the l, the greater the time growth.

6. Conclusion

The utility function of tourist experience is constructed. Based on the utility maximization of tourism experience, the travel route optimization model is established and the k-greedy algorithm for solving the model. The model and algorithm can assist tourists in planning reasonable tourist routes.

Through the example analysis, it is found that the crowding of scenic spots has a great impact on the effectiveness of tourist experience and the time of tourism activities. In the process of travel, tourists can change the order of scenic spots or the departure time to avoid crowding, which requires the scenic spot management department to release the tourist crowding information in advance, so that tourists can plan their tour itinerary.

The experimental results highlight the fact that integration of the various attributes involved enables reasonable and comprehensive evaluation of scenic spots, which lays the foundation for subsequent route recommendation. Also, the proposed recommendation algorithm performs with enhanced reasonability and diversity.

The actual tourism route optimization problem often involves other complex factors, and more influencing factors should be included in the future to further expand the model established.

Data Availability

The datasets used during the current study are available from the corresponding author on reasonable request.

Conflicts of Interest

The authors declare that they have no conflict of interest.

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