Research Article

Tourism Destination Recommendation Based on Association Rule Algorithm

Na Lou

Zhengzhou College of Finance and Economics, Zhengzhou 450000, China

Correspondence should be addressed to Na Lou; louna@zzife.edu.cn

Received 8 April 2022; Revised 13 May 2022; Accepted 16 May 2022; Published 30 June 2022

Academic Editor: Adarsh Kumar

Copyright © 2022 Na Lou. This is an open access article distributed under the Creative Commons Attribution License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

With the development of information technology and the arrival of intelligent era, the tourism industry has also changed from traditional information service to intelligence. In this study, the recommendation system is studied. By comparing the advantages and disadvantages of various recommendation methods, the association rule algorithm is selected as the recommendation method in this study. Then, the user’s operation behavior is obtained and the personalized tourism destination recommendation model is established. This model is based on the user’s access operation behavior data, and it introduces the user’s interest degree as a parameter to measure the operation behavior data, forming the basic data of data mining. The popularity of tourist routes and the change weight of longitudinal interest characteristics among users are introduced into the algorithm. The change weight of user’s lateral interest characteristics is added to the prediction of target users’ future interest. Compared with the classified recommendation method, users can easily locate the information of scenic spots they are interested in under the guidance of scenic spot recommendation. The results further verify that the research of this model has certain practical significance and practical value.

1. Introduction

With the improvement of material conditions, people’s demand for tourism is increasing while meeting their basic living needs. People not only pursue general group sightseeing but also the demand for personalized tourism has increased greatly. Due to the diversity of tourist groups, under the restriction of funds and time, how to choose the scenic spots that tourists are interested in is often a problem that tourists or tourism marketing departments both pay attention to and need to solve urgently [1]. Usually, before traveling, tourists will search the tourist information through the Internet to get the detailed information of the scenic spots, but the traditional tourist information service has been unable to meet the needs of the public [2]. Although the traditional tourist information service can help tourists to screen out the information of scenic spots they need, the popular and well-known scenic spots are often searched and recommended, while the unpopular scenic spots that are interested in some users are rarely discovered and recommended. At present, the relevant information channels for tourists to obtain tourist destinations are diversified, and the tourism consumption concept and experience demand are more personalized. Popular sightseeing tourism products and industries are gradually unable to meet the needs of tourists, but are more in pursuit of customized, experienced, and soulful tourism experiences. With the upgrading of tourism informatization, the operation mode and management of traditional tourism industry are gradually transforming into informatization, intelligence, and personalization. This fully reflects the core position of computer information technology in the development of smart tourism. Smart tourism is a huge tourism service system, which brings great convenience to users and creates greater value for enterprises. Whether it is the independent experience of users or the marketing promotion of enterprises, it will be promoted.

In such an era full of information and data, how to use personalized recommendation system [3] to provide personalized tourism information for users and solve the
problem of users’ difficulty in choosing when faced with huge tourism information is the focus of personalized recommendation research in the tourism field. Nowadays, big data are also a hot issue. Tourism data conform to the characteristics of big data, and a large amount of tourism data is chaotic and huge. Using data mining technology [4, 5] to mine tourism data can provide reference for tourists to recommend tourism destinations. Data mining refers to the process of obtaining potentially useful and temporarily undiscovered information and value through the analysis of random, huge, hidden, and irregular historical data. The basic data mining algorithms are divided into the following categories: mining algorithm based on association rules, clustering analysis [6], classification [7] and regression, etc. Among them, the association rule algorithm is one of the algorithms widely used in data mining. The key point of this algorithm is how to find frequent itemsets and generate rules. The association rule algorithm is to discover the implicit relationship between items from a large number of data sets, and its typical case is shopping basket analysis. The problem of shopping basket is described as follows: after giving the purchase records of users, it is necessary to find out the possibility of users buying other goods after purchasing a certain kind of goods. Obviously, this is to find out the purchase patterns of users and explore the potential relationship between different goods. Its purpose is to find out the relationship between various commodities in the transaction database, to understand the buying habits of users. This study studies the recommendation of tourist destinations based on the association rule algorithm. Its innovations are as follows:

1. This study constructs a case user preference model, which mainly expresses tourists’ interest in different types of tourist destinations. In the process of scenic spot recommendation, the recommendation algorithm learns the scenic spots that users are interested in according to the update of users’ browsing behavior data. On the basis of these scenic spots, rules are applied to form a recommended scenic spot sequence as the scenic spot information that users expect to obtain. According to the change in each user’s interest characteristics, the parameters and thresholds of the recommendation algorithm are dynamically and individually adjusted, which increases the self-learning ability of the recommendation system and makes the recommendation results more personalized.

2. In this study, weighted values are used to distinguish the difference in users’ interest in each scenic spot, which makes the recommendation more accurate. Using the collected data of scenic spots, the algorithm is applied for simulation test and mining analysis. Experiments show that this system can improve the accuracy of recommendation and the satisfaction of users and provide users with better personalized recommendation of tourist destinations. This research broadens the research field of tourism recommendation algorithm to some extent.

According to the research needs, this study is divided into five sections, each of which is arranged as follows.

The first section is the introduction. This part summarizes the background and research significance of this study and gives the organizational structure and innovation of this study. The second section is related work. This section briefly describes the research status and shortcomings of tourism recommendation at home and abroad and leads to the research contents and methods of this study. The third section focuses on the construction of tourism destination recommendation system based on the association rule algorithm. Section 3.1 is the theoretical basis, which introduces the related contents of personalized tourism recommendation system. Section 3.2 proposes and constructs a tourism destination recommendation system based on the association rule algorithm. In the fourth section, the tourism destination recommendation system based on the association rule algorithm proposed in this study is simulated many times, and the results are analyzed. The fifth section is the conclusion. This part summarizes the research contents of this study and looks forward to the future.

2. Related Work

Every technological innovation in the development of tourism has brought great changes to our lives, and technological innovation can provide more possibilities for tourism industry services. At present, the Internet has become the main way for users to search and query travel information. Most tourists usually use the scores and evaluation information of other tourists on the Internet as a reference to plan their own trips before they travel. The research and market application of personalized recommendation of tourist routes at home and abroad have taken shape, and there are many related recommendation algorithms and corresponding recommendation systems. A personalized recommendation system can conform to the trend of modern social development and analyze and filter useless junk information for people in the era of information explosion, to provide accurate and effective information for people and make people’s life more convenient.

A Xiao et al. designed a knowledge-based travel recommendation system. The system provides users with the tourist information they are interested in through the user’s operation behavior [8]. This method needs to continuously and timely update the knowledge base to match the user’s interest and simulate human tour guides for recommendation. Iliopoulos et al. studied quantitative association rules in big data environment based on the MapReduce framework [9]. Li et al. studied the intelligent tourism information push system based on the cloud platform, improved the collaborative filtering algorithm using MapReduce model under the Hadoop platform, and finally recommended the analysis results to users [10]. The system consists of user interface, inference engine, knowledge base, dynamic database, and other parts, which is a typical expert system structure. In the aspect of constrained association rules, Arif A et al. studied association rules considering
itemset constraints and explored the mining of category association rules based on lattice structure [11]. Zhang et al. proposed a constraint-based travel recommendation system, which gradually gained users’ interest through interaction [12]. The algorithm improves the rationality and efficiency of the recommendation results. However, most of these recommendation technologies rely on the evaluation of experts in the corresponding field, and the user’s interest prediction is prone to become outdated and cannot fully reflect the real interest orientation of the recommended user. Younes and Boukerche et al. studied efficient association rule mining considering itemset constraints and improved the efficiency of algorithm mining by pruning uninteresting itemsets and rules that users are not interested in the process of generating frequent itemsets of each order [13]. Wei et al. put forward the recommendation method of online travel service [14]. Sarkar and Majumder studied the mining of spatiotemporal association rules without time constraints and performed a demonstration application in the mining of global terrorism events [15]. Nitu studied the influence of online recommendation on consumers’ consumption decisions. Research on the evaluation information of other users on the Internet can influence the consumption intention of potential users and will maximize the consumption desire of potential users for the products recommended by the Internet [16]. Arbulu et al. designed a constraint-based travel recommendation system. It interacts with users in a conversational way and gradually locates the places of interest to users in this progressive way [17]. This constraint-based recommendation technology can better locate the interests of users, but it lacks the function of autonomous learning. Ahmad S et al. proposed a travel itinerary planning algorithm based on time frame [18] for the tourism itinerary planning problem with multiple constraints (as shown in 1).

The combination of online tourism and traditional industries has begun to enter a period of steady development. However, at present, most tourism e-commerce websites mainly focus on the functional development and operation mode of websites. Faced with the problem of information overload, how to provide users with more satisfactory services and better user experience requires new methods to solve this problem. On the basis of consulting and sorting out relevant literature studies at home and abroad, this study deeply understands and analyzes the present situation of tourism recommendation and puts forward a tourism destination recommendation model based on the association rule algorithm. The database of users’ dynamic interest characteristics is established, and the parameters and thresholds of the recommendation algorithm are dynamically adjusted according to the changes in each user’s interest characteristics, which increases the self-learning ability of the recommendation system and makes the recommendation results more personalized.

3. Methodology

3.1. Personalized Tourism Recommendation Algorithm. In the era of big data with information expansion, personalized recommendation technology is gradually integrated into various e-commerce systems and so is tourism e-commerce. With the application of recommendation system in different fields, tourism recommendation has become an important field of research on the recommendation system [19]. At present, most of the tourism industry is oriented to group tourism, but with the rapid development of modern information, the pace of people’s life is accelerating, and the development of tourism will tend to individual travel, and it will be personalized to meet the individual needs of tourists with different interests and at the same time improve the quality of tourism services and management efficiency. The quality of recommendation algorithm directly determines the efficiency of the whole recommendation system, so the research of recommendation system focuses on two aspects: algorithm design and algorithm implementation. According to different recommendation methods, recommendation algorithms are generally divided into recommendation based on collaborative filtering, recommendation based on content, recommendation based on user characteristics, recommendation based on knowledge, and recommendation based on association rules and hybrid recommendation. User-based collaborative filtering is to find similar users through their basic information and generate recommendations according to the activities of similar users. A content-based recommendation is put forward by scholars after the research and improvement of collaborative filtering. The recommendation based on user characteristics only considers the similarity between different users and will not lead to differences in recommendation due to different types of items. Knowledge-based recommendation algorithms mainly need experts to propose relevant domain knowledge from users’ implicit information or attributes of commodities. It is recommended to combine various algorithms together. Combining the advantages of different algorithms, making up for the disadvantages of each other, makes the recommendation more accurate. The association rule algorithm is a commonly used and classic technology in data mining, and it has been applied in many aspects, especially in the big data environment, which requires data processing and analysis, and the algorithm has been taken out and studied again.

The association rule algorithm is one of the algorithms widely used in data mining. The focus of this algorithm is how to find frequent itemsets and generate rules. In the development of association rule algorithm, the Apriori algorithm and FP_growth algorithm are regarded as the two most classic representative algorithms [20]. The basic Apriori algorithm is relatively simple to implement, but the time complexity increases. The basic idea of the Apriori algorithm is very simple. If we want to find frequent itemsets, we must first find all candidate itemsets that may be frequent itemsets and then the first thing we can think of is the exhaustive method. The disadvantages of exhaustive method are obvious, and the system cost will be very high. The Apriori algorithm finds out all frequent itemsets usually by connecting and pruning. The process of generating candidate itemsets is called connection, while pruning is the process of removing itemsets that cannot be frequent.
Joining and pruning are two steps of the Apriori algorithm. Joining produces candidate itemsets, and pruning cannot be the candidate itemsets of frequent itemsets.

The main idea of FP_growth algorithm is as follows: first the frequent itemsets are found, then the frequent pattern tree is constructed with the found frequent itemsets, then the frequent pattern tree is divided into several conditional databases, and finally the association information is mined among itemsets in the conditional databases, respectively [21]. FP tree algorithm is a data structure based on frequent pattern tree, which directly extracts association rules from such a tree structure. Here, FP tree actually plays the role of data compression, mapping each transaction to a path on FP tree. Because transactions have the same items, there are overlapping parts; if there are many overlapping parts, the storage space of transactions can be greatly reduced. Compared with the Apriori algorithm, the FP_growth algorithm only needs to scan the database twice, thus reducing the number of visits to the database and improving the execution efficiency by an order of magnitude. Figure 1 shows the process of obtaining and recommending tourist users’ interest characteristics.

Association rules are a kind of very important knowledge in database. Mining association rules is to find the association and frequent pattern relationship among items in data set in a large amount of data information or Web information. Although the Apriori algorithm obviously reduces the size of candidate itemsets when dealing with data sets, and its running effect is good, and its space complexity is relatively small, it increases the time complexity and fails to remove some combination elements that should not appear in the process of generating candidate itemsets. The association rule discovery algorithm based on the aggregation tree has indeed achieved an improvement in efficiency. The interest characteristics of tourist routes are mainly summarized for tourists, because this study only cares about the correlation between tourist routes and users’ interest characteristics [22]. Whether it is using aggregation tree to organize transactions, or improving the basic Apriori algorithm according to the characteristics of data to be mined and the characteristics of rule formation, it is successful. Because of the randomness, diversity, and variability of the recommendation of tourist routes, it is the mainstream method to introduce other technical means and methods into the research of tourist route recommendation. To make the recommendation system recommend tourist routes that are more in line with the actual needs of users, it is necessary to comprehensively consider many factors of tourists before and during the tour.

### 3.2. Tourism Destination Recommendation System Based on the Association Rule Algorithm

Tourism is a complex system, which not only covers a wide range but also involves a lot of fields. How to better combine the multifaceted nature of tourism with the recommendation system requires more in-depth research on the recommendation methods. The
recommendation system is to mine the information of users’ needs, then use the corresponding recommendation algorithm to find the objects that meet users’ needs, and finally provide useful information to users to complete the recommendation. The recommendation system has the following advantages: it turns users into buyers; provides personalized service for users; and improves the loyalty of users to the website. At present, most recommendation systems recommend users based on a single score. However, due to the diversity of project attributes, users may have different preferences for each attribute of the project, so a single score cannot accurately calculate the user’s preferences for the project, but only know the user’s preferences in general. The interest features submitted by users during interaction are “explicit features,” which can clearly guide the recommendation system to lock in where users like to visit, when to visit, and what kind of scenic spots to visit [23]. This study solves the problems of traditional recommendation algorithms, such as cold start, sparse data, low real-time performance, and low recommendation accuracy, and constructs a new tourism destination recommendation model. Generally speaking, the recommendation system consists of three important modules: ① user module, ② recommended object module, and ③ recommendation algorithm module. The structure diagram of the tourist destination recommendation system is shown in Figure 2.

According to the abstract hierarchy, association rules can be divided into single layer and multilayer. The former means that it is easy to find out the correlation between the items in the original data set and does not involve abstract items; the latter means that it is not easy to find the relationship between items or attributes at the bottom level, and data sets need to be mined at multiple abstract levels. The first thing to do in association rule algorithm is to find association rules, which is also the most time-consuming and crucial in the whole algorithm. To reduce the difficulty of the algorithm, we can also use offline analysis to extract rules. In the association rule generation algorithm, the generation of rules has a great relationship with the order of nodes in the user access sequence. According to this feature, the number of combination items is reduced. The algorithm of association rules aims to improve the efficiency of mining rules. Aiming at the traditional method, the method of item merging and pruning is proposed, which can effectively improve the efficiency of mining process and then quickly generate the required rules.

In the recommendation system, an effective recommendation usually consists of three parts: user modeling, item matching, and recommendation output. User modeling is the process of summarizing the user model from the user’s historical behavior data and interest records. User modeling is the foundation of recommendation system, and the quality of its model directly affects the efficiency of recommendation results. There are two ways of weighting: direct weighting and normalized weighting. The direct weighting is the direct addition of the weights of items in the itemset, but there is no normalization. The normalized weighting is normalized on the basis of the former, and normalization adds one step of calculation, but the setting of the minimum support will be more convenient. In the process of generating rules, due to the huge amount of data at present, the number of generated rules is also huge, and there is great redundancy among rules. The model not only pays attention to the historical score data but also pays attention to the generation time of the score. Because it reflects the user’s interest preferences in real time, it fully considers the nearest neighbors similar to the user’s interest preferences in the latest time and seldom considers the nearest neighbors similar to the user’s interest preferences in the previous time, so that the calculated nearest neighbors take into account the actual interest changes, thus improving the recommendation quality.
To extract tourists’ interest $R$ in scenic spots, suppose that when browsing pictures and texts for any scenic spot $a_i$ in the scenic spot set $A$, $q_i$ and $T_i$ are used to denote the visiting time of the pictures and texts, respectively. Since the same attraction may be visited multiple times by tourists, and the time of each visit is $T_{pi}$ and $T_{ti}$, then

$$
T_p = \sum_{i=1}^{n} T_{pi},
$$

$$
T_t = \sum_{i=1}^{n} T_{ti},
$$

$$
R = f(T_p, T_t). \tag{1}
$$

If, within a certain period of time, the amount of information that tourists get from browsing pictures is twice as much as that obtained by browsing texts, then the weighted values of pictures and texts can be set to be $2/3$ and $1/3$, respectively, and then,

$$
R = \frac{2}{3} T_p + \frac{1}{3} T_t. \tag{2}
$$

The user’s evaluation is calculated using the following algorithm:

$$
q_{ia} = \frac{\sum_{a=1}^{n} k_{ia} n_{ia}}{\sum_{a=1}^{n} n_{a}},
$$

$$
q_{ib} = \frac{\sum_{b=1}^{n} k_{ib} n_{ib}}{\sum_{b=1}^{n} n_{b}}. \tag{3}
$$

Among them, $q_{ia}$ and $q_{ib}$ represent the lower critical value and the upper critical value of the comprehensive evaluation interval value of the $i$th case attribute, respectively. $k_{ia}$ represents the lower critical value of the interval value given by the article in the $a$th article of the $i$th case attribute; $k_{ib}$ represents the upper critical value of the interval value assigned by the article in the $b$th article of the $i$th case attribute. $n_{ia}$ and $n_{ib}$ represent the number of user evaluations of the $a$ or $b$ assigned interval value. In this study, the following algorithm is used to calculate the weight of case attributes:

$$
\omega_i = \frac{q_{ia} + q_{ib}/2}{\sum_{i=1}^{n} q_{ia} + q_{ib}/2}. \tag{4}
$$

Among them, $\omega_i$ represents the weight of the $i$th case attribute and $q_{ia}$ and $q_{ib}$ represent the lower critical value and the upper critical value of the comprehensive evaluation interval value of the $i$th case attribute, respectively.

In this study, the personal preference information provided by tourists is combined with the preference information mined by the system. With the increasing tourists’ behavior, the system will get more feedback. Then, the system builds a model according to the information of tourists’ preferred scenic spots and the interactive information between tourists and scenic spots. After the modeling is completed, recommendations are given according to relevant algorithms. Multi-minimum support allows items with low probability to participate in the rules, and users’ browsing probabilities for all scenic spots cannot be equal. If the same minimum support is set, scenic spots with low browsing probability cannot participate in the rules. When users who are interested in this kind of scenic spots log on to the website, we can only recommend scenic spots with high support. Multi-support mining algorithm not only meets the needs of the public but also takes into account the special needs of small groups. When calculating similarity to find the nearest neighbor, the system should fully consider the change and transformation of users’ interests. The recommendation method of the system will change with the change in users’ interests, and the recommended content will also change accordingly. After determining that the user’s tourism destination preference matches the type in the tourism destination model, the cases in the sub-case base of the tourism destination type in the basic case base are extracted. The similarity between the users to be recommended and the extracted cases is calculated using the similarity algorithm of case attributes, the weight addition of case attributes, and the trust degree of case users. In this recommendation model, the recommendation process is
judged; if the matching is successful, it means that the user content matches the cases in the preprocessed case base is contained between nonadjacent frequent itemsets can be found that as long as the rules contained between adjacent frequent closed itemsets are found, the rules contained between nonadjacent frequent closed itemsets can be deduced. After recommending users, it is necessary to track them. Every once in a while, whether the user has new travel notes is checked. If so, whether the new travel note content matches the cases in the preprocessed case base is judged; if the matching is successful, it means that the user has adopted the recommended content, and the cases adopted by the users in the preprocessed case base are stored in the basic case base to complete the update of the case base.

4. Result Analysis and Discussion

The historical interaction information of users can reflect the characteristics of users’ interests to a certain extent, and the rich historical interaction information of users contains the implicit information that users’ interests change with time [25]. To better reflect the recommendation effect of the algorithm proposed in this study in smart tourism destinations, several simulation experiments are carried out in this section. The representation of the case in this study is composed of tourism demand elements, the destination of the case user’s travel notes, and the user level. The valuable information in travel websites is mined by experiments. By compiling the URL information of websites, setting the rules of collecting URLs, and inputting the URL where the content to be collected is located, before and after interception, the location of the required content is determined, and the information of users, people, travel days, travel modes, per capita spending, etc., needed in the experiment is collected from the specified Web page by setting regular expressions and label information, and the collected information will be stored in the database. In the test process, based on the number of scenic spots, we continuously increase the number of scenic spots to form a comparison of recommendation effects under different scenic spots. At the same time, under the recommendation of the same number of scenic spots, the system updates the rule base at certain transaction intervals, and through this kind of autonomous learning, a comparison of recommendation effects in time dimension is formed. The data come from the travel notes of tourists in travel websites, from which we can get the scenic spots that tourists have been to. After obtaining the user and the user’s travel information, firstly, the users are classified and analyzed, respectively. B—here result shown in Figure 3.

In this section, the minimum support is selected as 4% and 8%, respectively, and the experimental efficiency of the improved algorithm and the traditional algorithm is compared and analyzed, respectively. The result shown in Figure 4 is obtained.

For comparison in time dimension, the rules are updated every 1000 access records; every update is based on all transactions in the transaction database under the current number of scenic spots, and the weighted association rule mining algorithm is run once to replace all the rules generated in the previous time. To verify the effectiveness of the destination recommendation algorithm and recommendation system in this study, the minimum support
weighted association rule algorithm and the traditional association rule recommendation algorithm are compared with the improved recommendation algorithm proposed in this study. By analyzing the accuracy and recall rate of recommended scenic spots, a conclusion is drawn. The accuracy results of different recommendation algorithms are shown in Figure 5. The recall results of different recommendation algorithms are shown in Figure 6.

From the data analysis in the above two figures, it can be concluded that the accuracy rate of this recommendation algorithm is higher than that of the other two recommendation algorithms, and the recall rate of this recommendation algorithm is the highest. The acquisition of frequent itemsets is actually an iterative process, and the conditional tree is constructed recursively based on the conditional pattern base. Among them, the weighted support degree of recursive term is taken as the support degree of candidate frequent itemsets. When giving feedback to users, eight cases in the sub-case base of the user’s preferred tourist destination type are also selected to form a case table, and the recommendation algorithm is calculated to form a recommendation for users. Then, the specific recommendation cases are sent to users in the way of top N. The coverage rates of different algorithms are shown in Figure 7.

The analysis of Figure 6 shows that the coverage rate of this algorithm is at a high level. In the process of recommending scenic spots, similar scenic spots with similar attributes can be included in the rules according to tourists’ previous travel records and preferences, to make more accurate recommendations for scenic spots. The performance of the weighted association rule algorithm with minimum support, the traditional association rule recommendation algorithm, and the improved recommendation algorithm proposed in this study are tested using F1 value and average absolute error, and the results are shown in Table 3.

This study adopts a priori method for processing; that is, the similarity is calculated in the case table of the sub-case database of the tourist destination type expected by the user, and then, the total similarity results of the cases in the case table are sorted and recommended to the user. In this way, the user to be recommended can choose according to his own situation in the recommended case of the type of tourist destination he expects, to provide the user with a more comprehensive recommendation. To verify the performance of the algorithm proposed in this study, the representative mean square error is selected to experiment with this algorithm, and the experimental results are compared with other different algorithms, and the results are shown in Figure 8.

It can be seen from the data in Figure 8 that the mean square error of this algorithm is at a low level, which verifies the effectiveness and accuracy of this algorithm. The subjective satisfaction of tourists is obtained by averaging the scores of tourists on the scenic spots recommended by the system, and the objective satisfaction is the average of tourists’ browsing time to the scenic spots. Using different systems to recommend travel destinations, the comparison of user satisfaction is shown in Figure 9.

The analysis shows that the recommendation accuracy of the model in this study is up to 95.6%, and the user satisfaction is up to 94.8%. The method in this study improves and improves the accuracy and recommendation quality of traditional recommendation methods, thereby improving
the experience of tourism consumers. With the advancement of time, the type recommendation does not change much, but the accuracy of the recommendation is improving, which shows that the recommendation system can find more valuable browsing patterns of users from the growing transactions. As the number of attractions increases, the effect of the recommendation in this article will be better, and it will show more advantages compared with the type recommendation. There must be some relationship between the overall rating of the project and the rating of the project attributes. If a person is not very satisfied with all aspects of the scenic spot, then his overall rating for the scenic spot will not be high. Only in high cases the overall score can be very high.
The improved recommendation algorithm proposed in this paper.

**Table 3: Performance test results.**

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>F1</th>
<th>Average absolute error</th>
</tr>
</thead>
<tbody>
<tr>
<td>Traditional association rule recommendation algorithm</td>
<td>0.847</td>
<td>0.543</td>
</tr>
<tr>
<td>Minimum support weighted association rule algorithm</td>
<td>0.926</td>
<td>0.287</td>
</tr>
<tr>
<td>The improved recommendation algorithm proposed in this study</td>
<td>0.948</td>
<td>0.265</td>
</tr>
</tbody>
</table>
5. Conclusions

The traditional recommendation technology does not take into account the problems caused by a single score and interest migration, so the recommendation performance is low, and the recommended products may not be the products that users like. Based on the in-depth understanding and analysis of various algorithms for travel recommendation, this study proposes a travel destination recommendation system based on the association rule algorithm. The algorithm in this study can take into account the needs of different groups of people and provide personalized services for different users. At the same time, the rules of this article can be updated in time, and with the passage of time, the user’s interest in scenic spots will also change; the rules are updated from time to time, so that the entire system is consistent with the current general interest of users. The algorithm in this study can correctly obtain the association rules under the given constraints, which improves the efficiency of the algorithm to a certain extent. Through the proposed concept of constrained subset, the frequent itemset search
required for association rule mining can be limited to a smaller constrained subset. Through simulation experiments, it is found that the recommendation accuracy of the model in this study is up to 95.6%, and the user satisfaction rate is up to 94.8%. The method in this study improves the experience of tourism consumers, thereby enhancing and improving the accuracy and recommendation quality of traditional recommendation methods. It has certain theoretical and practical significance. This study has achieved some research results and value, but this method needs to update the knowledge base in time and accurately, to match the user's interest, and to simulate human guides to make recommendations. There are still some difficulties in the implementation process, and the function and security of the system need to be further strengthened and improved. The next step will be to study and discuss these issues in more detail.

Data Availability

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

Conflicts of Interest

The author does not have any possible conflicts of interest.

Acknowledgments

This study was supported by the Research Project of Henan Federation of Social Sciences "Research on the Integrated Development Path of Culture and Tourism in Dabie Mountain Area of Henan Province under the Rural Revitalization Strategy" (SKL—2021-1008).

References

