Hindawi
Mobile Information Systems
Volume 2022, Article ID 5905490, 10 pages
https://doi.org/10.1155/2022/5905490

Research Article

Tourism Destination Recommendation and Marketing Model Analysis Based on Collaborative Filtering Algorithm

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Received 10 May 2022; Accepted 15 June 2022; Published 29 September 2022

Academic Editor: Yajuan Tang

The Internet has penetrated into all fields. As the most dynamic "sunrise industry," tourism has also been swept into such a wave of Internet. In such an era of "information overload," how to find one's favorite attractions among the massive tourist attractions has become a difficult problem. In order to solve this problem, personalized recommendation technology is applied, among which collaborative filtering recommendation technology is one of the core technologies while the collaborative filtering algorithm still has problems. The research and analysis of the algorithm, this paper improves the technology for the problems of low recommendation accuracy that considers user interest changes. It for attribute scoring. It uses the multiattribute score of the item to calculate the user's overall evaluation score of each attribute of the item; for the change of user interest, a time function based on the Ebbinghaus forgetting law is introduced to calculate the user similarity. It is given a certain weight, that is, a time function, to ultimately ensure the accuracy of the recommendation. Exploring the tourism destination recommendation and marketing model based on the collaborative filtering algorithm can enrich the relevant theories of it on the one hand, and on the other hand, it can lay the foundation for building a real tourism recommendation website.

1. Introduction

The Internet has penetrated into every aspect of our life. You can watch movies and TV series on video websites like IQiyi and Mango TV, watch news on portal websites like Sina Weibo and Sohu News and keep up with current events, select all kinds of products on websites like Taobao and JINGdong Mall, and enjoy music websites like QQ. Massive information swarmed into us, so that we are dazzled, do not know what to do. Users have to effectively present the information in front of users [1].

Although this method is extensive, the algorithm only relies on the user's score, and the number and authenticity of score will directly affect the recommendation result. Therefore, this paper will characteristics of users and projects to combine static with traditional dynamic recommendation methods, so as to improve some defects of the algorithm and reduce the error between prediction results and actual results [2].

With the emergence of recommendation system, users' access to information has changed. It is no longer just searching simple and clear targets as before but is transformed into information discovery that is higher and closer to users' usage habits.

Recommendation system was first applied in the field of e-commerce. By analyzing consumers' purchase and browsing behavior [3], websites predict and recommend products that may be of interest to consumers. By using recommendation system, the sales volume of websites has increased a lot compared with that before. Nowadays, recommendation systems being used in the more and more widely [4], for example: social network recommended, advertising, news, movies, music, etc, its commercial value is becoming more and more big, also got more and more academic attention and discussion, not only in theory has a lot to improve, more have a qualitative leap in practice, gradually formed an independent discipline.

The main content is to help users to extricate themselves from the massive information of tourist attractions and automatically recommend the tourist attractions that they may be interested in. Based on the research and analysis it, this paper improves the technology to solve the problems of low accuracy and user interest change and proposes a score considering user interest change. First, the total score, which lacks a comprehensive understanding of users' interests and preferences, leads to inaccurate recommendations. Therefore, the project multiattribute score and w-TOP project attribute evaluation score are introduced to calculate the overall score of users for the project. Second, a time function based on Ebbinghaus forgetting rule is introduced to change. In the calculation of user similarity, the item is given a certain weight, namely, the time function, to ensure it.

The purpose of this is to explore the tourism destination recommendation and marketing model. On the one hand, the research of this paper can enrich the relevant theories of collaborative filtering algorithm, and on the other hand, it can lay a foundation for the construction of real travel recommendation websites.

2. State of the Art

The first discovery of recommendation system can be traced back to the 1980s. David K. Gifford and other scholars published an article entitled "architecture of a large-scale information system" [5]. In 1988, Stephen Pollock described the screen system for filtering text messages, including the high-level interface component for defining rules, the component for displaying text messages on the screen, and the conflict detection component for checking inconsistencies. This component definition and conflict detection provided ideas for later recommendation systems. In 1990, Ernst Lutz and other researchers [6] proposed a system called "black hand." Under the conditions at that time, the network filter program could not process strictly structured messages, but the "black hand" system could automatically identify and process internal files, indirectly weakening the relevant concepts of file systematization and indirectly providing the automation concept in the recommendation system. In the early 1990s, paved Goldberg and other researchers [7] proposed a system called "tapestry," which was later called the first CF system. Its original purpose was to solve the continuous disordered and unclassified spam in email. In order to overcome this problem, researchers have found two solutions through continuous attempts and improvements. One is to set up a vertical demand form in the page so that users can only check the content they are interested in. The other is to set up a screening mechanism in the system to traverse all emails. The design concept of tapestry is to extract the keywords in the title for users to make targeted choices. At the time point when the recommendation system was discovered by the public and paid special attention to, it began with the "prism" system developed by the GroupLens group of the University of Minnesota in the early 1990s [8]. The system has two important contributions: first, it defines what is the CF recommendation idea at that time and the second is to establish a complete set of structured models for CF problem. In 1998, researchers such as John S. Breese evaluated the CF system based on the user. The first method is to evaluate a small range of paired data, that is, MAE. The second method is to evaluate the overall effect of the whole recommendation ranking. In 1998, mf-svd algorithm was created by people, which is a method with the help of singular value decomposition. Specifically, CF is regarded as a classification task, and the algorithm itself is further optimized [9]. In 1999, Thomas Hoffman [10] proposed the p-lsa algorithm and described the difference between p-lsa and hidden context evaluation in his relevant research notes, that is, hidden context evaluation is mainly based on singular value decomposition and p-lsa is more focused on hybrid processing. In 2001, Badrul, George, Joseph, and John [11] made in-depth analysis and comparison of various algorithms based on things and took the k-nearest neighbor method as the research topic. Through continuous demonstration and research, they found that the algorithm based on things has better recommendation effect than the algorithm based on people. In 2003, Amazon used the item to item-CF algorithm on its recommendation system to make users experience an unprecedented online commodity browsing experience; that is, when searching for commodities, the website will recommend some commodities that meet the user's expected purchase direction. This algorithm was well known in the Internet field and also made CF algorithm become the mainstream recommendation model at that time. Netflix is the company that has achieved great success in using CF technology. The company has achieved good results by using personalized recommendation technology [12].

The research on tourism marketing in western developed countries started earlier and has formed a relatively mature theoretical system. Some experts and scholars believe that the tourism resources of different countries are different, and this difference will lead to obvious differences in the level and characteristics of tourism and development in different countries. Through statistical analysis, it is found that countries with roughly the same level of economic development also show many similarities in the development of tourism market. However, it should be noted that the closer the economic development level of the two countries is, the higher the overlap degree of residents' tourism needs will be, thus providing a good opportunity for tourism cooperation between the two countries. Thus, the level of national economic development is closely related to the development of the whole tourism industry.

It originated from foreign countries; the results are relatively perfect, relatively mature technology. However, China started late. The earliest recommendation system proposed and successfully applied in various fields is collaborative filtering recommendation system [13]. The earliest recommendation algorithm [14] lays a foundation for other algorithms. It was proposed by David Goldberg et al. in the seventh reference [15] of this paper in 1992. In this paper, Typestry is applied to filter and select e-mail, which proposes personalized recommendation, recommendation systems and exerting a great influence on subsequent researchers. Its ideas and research methods are constantly adopted and optimized. Then there are all kinds of new ideas and new technologies [16].

Recommendation system is then applied in various fields, including news recommendation, book recommendation, music recommendation, electrical recommendation, film recommendation, web recommendation, and so on [17]. Amazon uses the item-based recommendation algorithm [18] to widely apply personalized recommendation service to its products, which greatly improves the turnover of the website. According to statistics, only 16% of the users who consume on the website clearly know what they want to buy [11]. By analyzing users' ratings and other records of news they read [19], the system can infer what news users like and then recommend the selected news in line with users' reading habits. Hulu, a foreign online video website, has improved CTR by more than 10% since it adopted the recommendation system [20]. MovieLens for movies, Pandora for music, You Tube for video, etc. [21].

The research level of relevant recommendation algorithm is low, and there is a big gap compared with international research level [22].

Recommendation service level, Baidu organized the National Recommendation System Innovation Competition to improve the recommendation quality and promote the rapid improvement of the recommendation system, which not only got the active participation of teachers and students in colleges and universities [23]. Which each team was required to test their recommendation system based on the data set of real behaviors of Tmall users, which further promoted the development of the recommendation system [24].

Through the review of the above research status, it can be found that the current recommendation system has been optimized to a certain extent, but there are few studies on the tourism recommendation system, which is further studied in this paper.

3. Methodology

3.1. Introduction to Recommendation System. The main frame structure of the algorithm is shown in Figure 1.

The behavior data of users when using the website will be recorded, and the recommendation system will obtain the interests of each user by analyzing these data, so as to find the information they need for each user [25]. For users and products, from one point of view, it can help users find useful products, and from another point of view, it can also make products recommended to users who are interested in it, so that consumers and the website. Figure 2 is the recommendation system, which depicts the relationship between each layer in detail.

In the era of more and more complicated information, recommendation system is more and more important; many fields should be used, convenient for users at the same time but also for businesses to add benefits [26]; and then the resources that the user might like or potentially need are recommended. Recommendation system has three parts: data collection module, data analysis model construction, and recommendation algorithm design [27].

(1) Data collection: record users' scores and comments on products, access, consultation, purchasing ability, and other information. Then, collect some dominance of readily available information, such as user information such as the grade and evaluation of commodities, but most users do not like or do not have time to do it, so you need to gather more implicit feedback information to analyze, such as the user's browsing history, sharing situation, recommend, goods than the situation, the collection, page retention time, buying behavior, and so on [28].

(2) Data analysis model: this part uses the collected data to build corresponding models for analyzing user behaviors and mining user interests and potential preferences [29].

(3) The results of the data analysis model, the algorithm selects the appropriate algorithm from the recommendation algorithm and selects the products that users may like from the jumbled goods for recommendation. Algorithm is a very important part [30].

3.2. Overview of Collaborative Filtering. The algorithm for recommending products to users. This algorithm was proposed in 1989, but its advantages were discovered and its industrial application began in the twenty-first century. Collaborative filtering algorithm in both in domestic and foreign well-known commercial websites play a role, as in the domestic online shopping website, there will be a "guess you like" function, is the collaborative filtering technology is used by some of the customer purchase records to suspected customers favorite products, and recommendations.

It is mainly follow the idea is that if two users for several items is close to the be fond of, is the two users are close to the be fond of of other items, in order to infer the user may favorite project, if there is no clear user ratings, can according to the user to log on the website instead of scoring. Keeping track of particularly uninteresting information is also important.

The user algorithm mainly has the following two steps:

(1) There are user u and user v, $N(u)$ is the item in the history, $N(v)$ is the item in the history, and formula (1) can be used to represent similarity between u and v.

$$W_{uv} = \frac{\sum_{i\in N(u)\cup N(v)} 1/\log(1+|N(i)|)}{\sqrt{|N(u) \parallel N(v)|}}. \quad (1)$$

(2) After the neighbor user is established, the item set that the neighbor user likes is obtained, and the item in the item set that the target user does not produce historical behavior is recommended to the target user. Formula (2) shows the preference of the target user u to the item i under the user collaborative filtering technology:

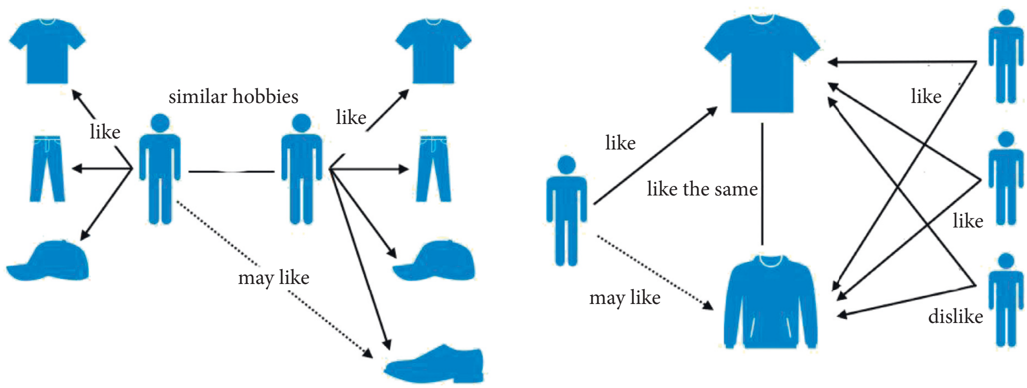

Figure 1: The main frame structure of collaborative filtering algorithm.

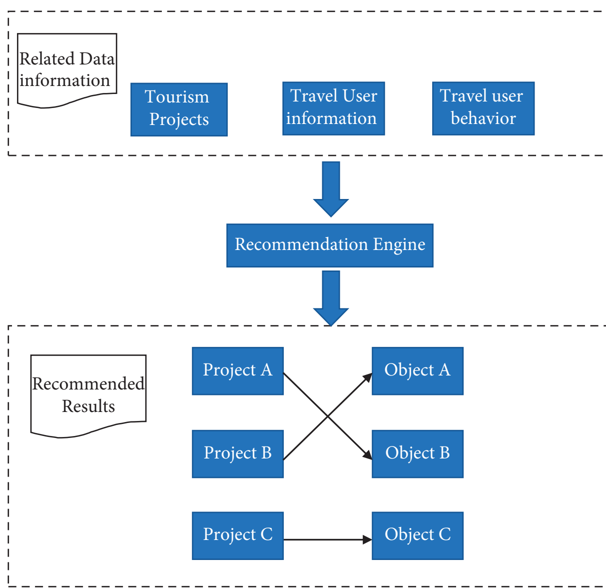

Figure 2: How the recommendation system works.

$$p(u,i) = \sum_{v \in S(u,K) \cap N(i)} w_{uv} r_{vt}. \tag{2}$$

(1) Calculate the similarity as shown in the following formula:

$$w_{ij} = \frac{|N(i) \cap N(j)|}{\sqrt{|N(i) \| N(j)|}}. \tag{3}$$

(2) Select the recommended items from them. Formula (4) expresses the target user u's interest in the item j:

$$p_{uj} = \sum_{i \in S(j,k) \cap N(u)} w_{ji} r_{uj}. \tag{4}$$

3.3. Introduction to Collaborative Filtering Algorithm. The user as his neighbor according to the similarity of the user's liking for the project (score), and then analyze the items that the user may like according to the neighbor's liking for the project, and finally recommend them.

Assume that the user's liking for the project is shown in Figure 3.

In order to facilitate observation and explanation, users' preferences are sorted according to the items they like in Figure 3, the characteristics of the user-item rating matrix, and the scenic spot-evaluation index matrix. The specific selection of influencing factors is shown in Figure 3.

Figure 4 represents that there are two users, and two users like item B, A, C, and so on. The figure clearly shows the number of common favorite items owned by any two users. If user C is set as the target user, since user C, user A, and user D all share A favorite project, it can be considered that user A and user D are the nearest neighbors of user C, and since user A and user D both like project D, it can be assumed that user C also likes project D.

The specific steps are as follows:

Input: user-project scoring matrix.

Output: recommended collection.

Steps:

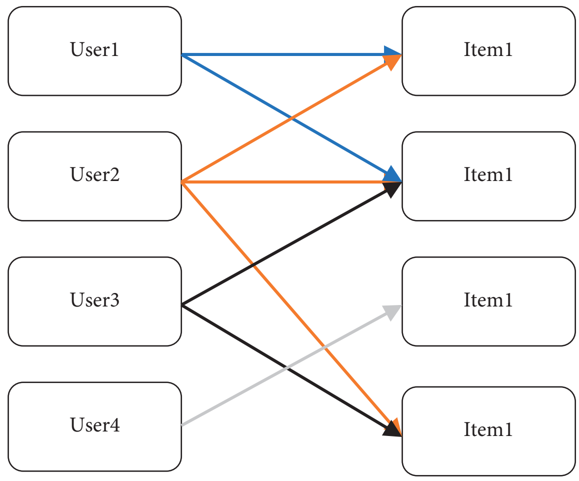

Figure 3: Schematic diagram of sample user favorite items.

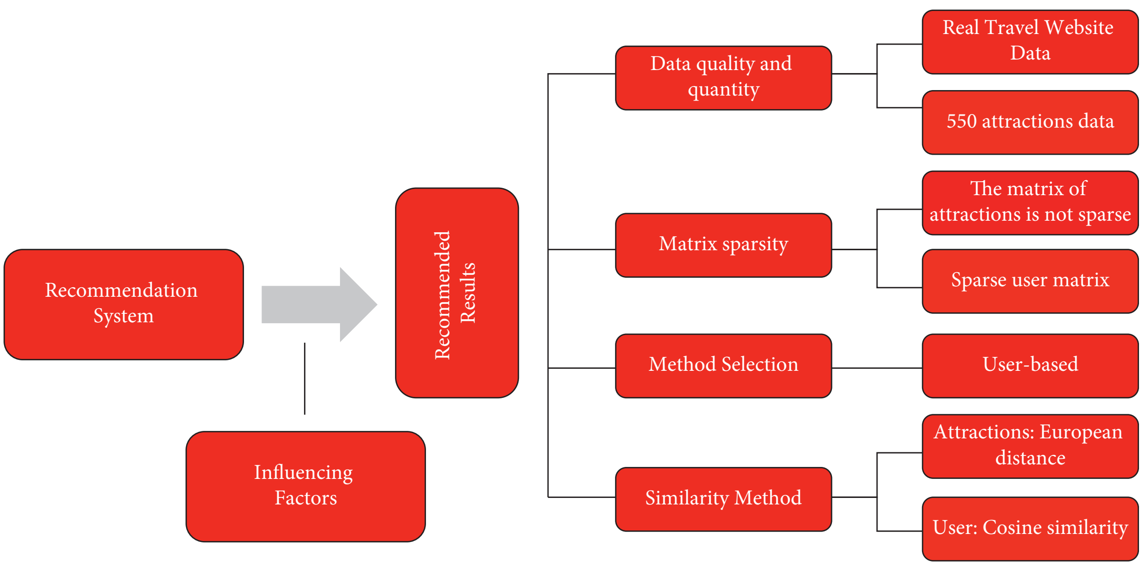

Figure 4: Selection diagram of influencing factors of recommendation results.

(1) Calculate the similarity of each two users A and B, sim A, B, and form the similarity matrix of users, where A and $B \in \mathrm{U}$

(2) For the target user U, take the first k users after sorting and put them into the neighbor set of U

(3) For item I that has no score from each user U, the formula is used to calculate the predicted score of user U for item I

(4) After ranking, recommend the first n items to the target user U

First, input a user-project scoring matrix, with columns U_1, U_2, U_3, ..., representing all user numbers and rows A, B, C, ... representing all item numbers, where the matrix element represents the JTH item.

Then, the user similarity can be obtained by using relevant formulas. The following three methods of computing user similarity will be introduced, respectively.

3.3.1. Pearson Correlation Coefficient. It is a very commonly used method to measure the similarity. It is mainly calculated based on the linear relationship between two vectors, so as to define the similarity between the two vectors. The calculation method is the ratio of the covariance of the two variables. Pearson correlation coefficient calculation formula between two users A and B is shown in the following formula:

$$\operatorname{sim}(a,b)=\frac{\mathring{a}_{\hat{\lambda}/(A)Q/(B)}\left(r_{a,i}-\mu_a\right)\left(r_{bi}-\mu_b\right)}{\sqrt{\mathring{a}_{\hat{\lambda}/(A)Q/(B)}\left(r_{a,i}-\mu_a\right)^2}\sqrt{\mathring{a}_{\hat{\lambda}/(A)Q/(B)}\left(r_{bi}-\mu_b\right)^2}}, \tag{5}$$

where I represents the similarity and $I(a)$ and $I(b)$, respectively, represent the list of items.

3.3.2. Cosine Formula. The idea of cosine formula to calculate user on the project is regarded as the value of the item without score represented by 0. The cosine similarity calculation formula between two users A and B is shown in the following formula:

$$\operatorname{sim}(a, b) = \cos\left(\overset{r}{a}, \overset{r}{b}\right) \frac{\overset{r}{a} \times \overset{r}{b}}{|a| \times |b|} = \frac{\mathring{a}_{i=1}^{n} r_{a,i} \times r_{bi}}{\sqrt{\mathring{a}_{i=1}^{n} r_{a,i}^{2}} \sqrt{\mathring{a}_{i=1}^{n} r_{b,i}^{2}}}. \tag{6}$$

Represents the ratings given by user B; Represents the modulus of the vector; Represents the modulus of the vector; and, respectively, represent the project I by user A and user B.

3.3.3. Modified Cosine Formula. Because different user's score benchmark is not the same, which some users are often used to give low scores, and some users often give a project go well, this does not mean that the two kinds of user preference difference is big, therefore, modified cosine formula on the basis of the cosine formula, each user to adjust the difference. The calculation formula of modified cosine similarity between two users A and B is shown in the following formula:

$$\operatorname{sim}(a, b) = \frac{\mathring{a}_{\widehat{\lambda}/(A)Q/(B)} \left(r_{a,i} - \mu_a\right)\left(r_{bi} - \mu_b\right)}{\sqrt{\mathring{a}_{\widehat{\lambda}/(A)Q/(B)} \left(r_{a,i} - \mu_a\right)^2} \sqrt{\mathring{a}_{\widehat{\lambda}/(A)Q/(B)} \left(r_{bi} - \mu_b\right)^2}}. \tag{7}$$

After the similarity between users is calculated, a user similarity matrix is obtained:

After obtaining the similarity matrix of users, the first K and U on the ungraded item are as follows:

$$P_{u,i} = \frac{\mathring{a}_{\partial \hat{I} N(u,k)} \operatorname{sim}(u, a) \times \left(r_{a,i} - r_a\right)}{\mathring{a}_{\partial \hat{I} N(u,k)} |\operatorname{sim}(u, a)|}, \tag{8}$$

where and, respectively, represent the average values of all the scores given by user A and user B. Respectively, represent the average values of all the scores given by users A and U.

Rating prediction refers to predicting how many points a user, mainly by analyzing the user's rated data. There are two main methods for predicting scores. The definition formula expressions are shown in the following formulas:

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{i,i \in T} \left(r_{ui} - \widehat{r}_{ui}\right)^2}{|T|}}, \tag{9}$$

$$\mathrm{MAE} = \frac{\sum_{i \in T} \left|r_{ui} - \widehat{r}_{ui}\right|}{|T|}. \tag{10}$$

Since the recommendation results of many recommendation systems are similar, the user's interest will be lost in the long run. The TOP-N recommendation algorithm can provide users with personalized recommendation list services, and accuracy rate can be used to judge the recommendation accuracy of the recommendation. The definition formulas are shown in the following formulas:

$$\mathrm{recall} = \frac{\sum_{u \in U} |R(u) \cap T(u)|}{\sum_{u \in U} |T(u)|}, \tag{11}$$

$$\mathrm{precision} = \frac{\sum_{u \in U} |R(u) \cap T(u)|}{\sum_{u \in U} |R(u)|}. \tag{12}$$

Coverage is the ratio of the recommended result set to the total item set. Information entropy and Gini coefficient are two well-known measures of coverage. The formula of information entropy is as follows:

$$H = -\sum_{i=1}^{n} p(i) \log\, p(i). \tag{13}$$

If an item is recommended to the user multiple times, the H value is 0; and if n entropy is log n. The formula for the Gini coefficient is shown as follows:

$$G = \frac{1}{n-1} \sum_{j=1}^{n} (2j - n - 1) p\left(i_j\right), \tag{14}$$

$$\operatorname{diversity}(L) = \frac{\sum_{i,j \in R_u} (1 - \operatorname{sim}(i, j))}{L(L-1)}. \tag{15}$$

For the travel recommendation system, it can be measured with reference to the popularity of the item, as shown in the following formula:

$$\operatorname{novelty}(L) = \frac{\sum_{u \in U} \sum_{i \in R_u} k_i}{|U| L}. \tag{16}$$

4. Result Analysis and Discussion

Because the improved algorithm is for tourism guides, the tourism websites, and collect users' historical behavior records and high-quality tourism guides.

Tour evaluation of the tourism strategy can be in various forms, such as direct scoring and written comments. These data adopt the method of user's rating of travel strategy.

Therefore, input data should be processed as model input data in the stage of it.

Ensuring the authenticity and scientificity of data, this paper collects real data based on tourism websites as a data set.

4.1. Measured Data and Scheme. In the tourism strategy recommendation system, there are three evaluation indexes, which are accuracy, novelty, and coverage. Coverage is a more comprehensive test of algorithm performance. Coverage was used as an index to evaluate the experiment. The experiment was using off-line experiment method

The methods for determining the weight of data in this paper are expert scoring method and AHP analytic hierarchy process. The construction method of the judgment matrix. After the judgment matrix is obtained, the CR value needs to

Table 1: Consistency test result table.

Summary of consistency test results				
Largest characteristic root	CI	RI	CR	Consistency test results
9.000	0.000	1.460	0.000	Pass

Table 2: Coverage table of item-based collaborative filtering recommendation algorithm before and after improvement.

	User-city coverage (%)	City-book coverage (%)	User-book coverage (%)
Item-CF	47.93	59.69	21.9
Item-CF-1	68.6	59.69	26.59

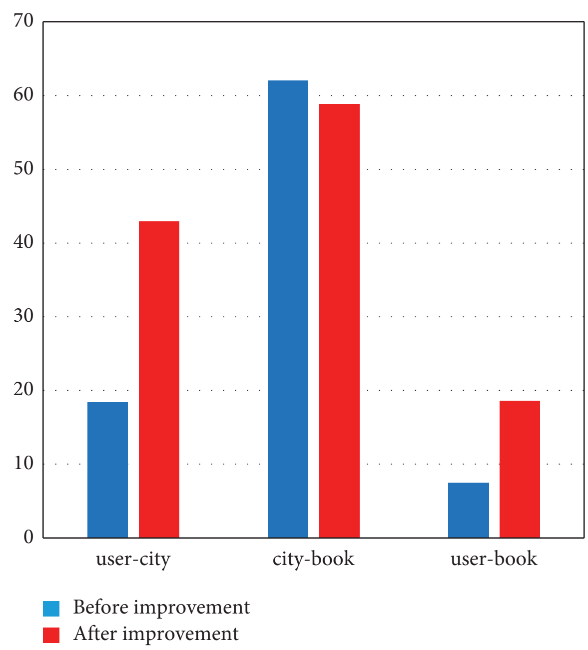

Figure 5: Coverage comparison diagram of user-based collaborative filtering recommendation algorithm before and after improvement.

be calculated, and the specific is shown in the following formula:

$$\mathrm{CR} = \frac{\mathrm{CI}}{\mathrm{RI}}, \tag{17}$$

$$\mathrm{CR} = \frac{\text{largest characteristic root-1}}{n-1}. \tag{18}$$

The criterion for judging whether the matrix is consistent is the CR value. The smaller the CR value, the higher the consistency of the matrix. The threshold for judging whether the matrix is consistent with the CR value is 0.1. According to the constructed scenic spot-evaluation index system, it can be known that there are 13 index values for tourist attractions, of which there are 9 available indicators for determining the weight. Therefore, the judgment matrix is a 9-order matrix and the CI value is 0.000. For the RI value, the table is 1.460., the calculated CR value is $0.000 < 0.1$, and it can be seen that this evaluation index judgment matrix meets the relevant requirements in the consistency result test, so the obtained weight results are consistent. The results are shown in Table 1.

Different from the problem of different sample benchmarks in traditional cosine similarity, the Pearson coefficient has scale invariance and uses a value between −1 and 1 to measure the degree of correlation between commodities. The correlation coefficient slopes toward −1 for positive correlation and shifts toward −1 for negative correlation, and the specific calculation formula is shown as follows:

$$\rho_{x,y} = \frac{\operatorname{cov}(X,Y)}{\sigma_X \sigma_Y} = \frac{E\left[\left(X-\mu_X\right)\left(Y-\mu_Y\right)\right]}{\sigma_X \sigma_Y}, \tag{19}$$

$$E\left[\left(X-\mu_X\right)\left(Y-\mu_Y\right)\right] = E[XY] - E[X]E[Y]. \tag{20}$$

4.2. Experimental Results and Analysis. The table of coverage and its comparison are shown in Table 2 and Figure 5.

The number of strategies recommended to users is 2762, and the coverage is 26.59%. The table of coverage and its comparison are shown in Table 3 and Figure 6.

Table 3: Coverage table of user-based collaborative filtering algorithm before and after improvement.

	User-city coverage (%)	City-book coverage (%)	User-book coverage (%)
User-CF	18.25	62.04	7.45
User-CF-1	42.91	58.8	18.6

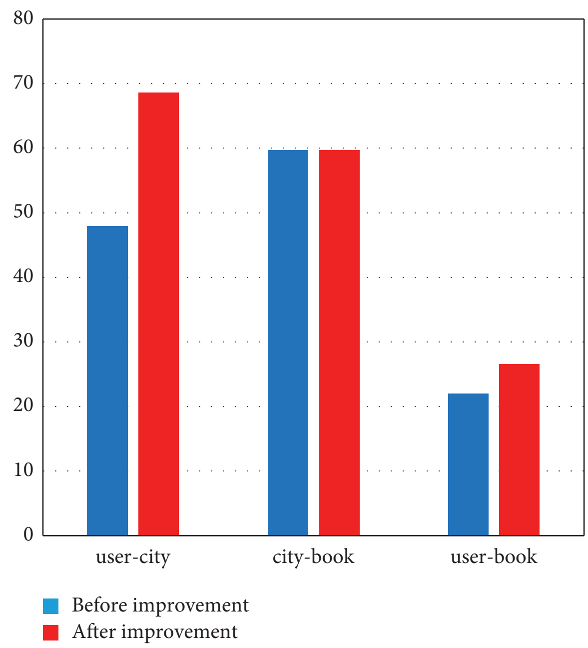

Figure 6: Comparison of coverage before and after the improvement of object-based collaborative filtering recommendation algorithm.

Table 4: Table of coverage of each algorithm.

	User-cf (%)	User-cf-1 (%)	Item-cf (%)	Item-cf-1 (%)	Final (%)
Coverage	7.45	18.6	21.9	26.59	41.3

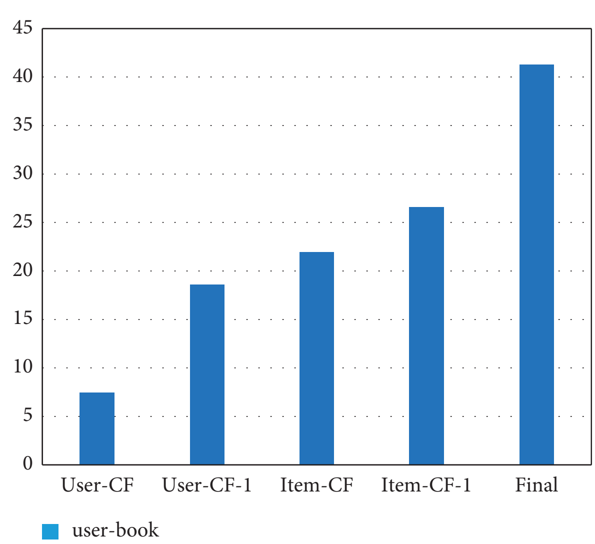

Figure 7: Comparison of coverage of five algorithms.

The situation of experiment C is as follows.

The recommendation effect of the algorithm is excellent. Table of coverage and comparison of each algorithm are shown in Table 4 and Figure 7.

It can be seen that the improvement of each algorithm has improved coverage to a certain extent on the original basis, with relatively good effect.

It can be seen that the first behavior algorithm recommends the strategy id and heat with high popularity in the strategy to the user. The second behavior recommends the id and heat of the strategy with low heat to the user, which indicates that the algorithm can recommend the unpopular strategy with low heat to the user. It can be seen from this example that the algorithm is relatively comprehensive, including recommendations with high popularity and recommendations with low popularity, which can provide users with all-round recommendations.

5. Conclusion

The features of users and items are introduced, and the dynamic rating recommendation is combined with the static feature recommendation, which makes up for some shortcomings of the traditional algorithm. This is the focus and innovation point of this paper. Among them, the algorithm is improved, respectively, in the cosine similarity, and then use public data will be two kinds of improved algorithm corresponding classical algorithm on the basis of the comparison, in this paper, the data in the travel sites of real users and real behavior, real data. There are 42,523 historical behavior records of users, 1452 cities, and 10,389 high-quality strategies. The algorithm is finally applied to the data in the field of tourism, and the recommendation results are obtained. The algorithm has a relatively comprehensive coverage, including well-known recommendations and low-visibility recommendations, and can provide users with a full range of recommendations.

Data Availability

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

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Acknowledgments

This work was supported by the Langfang Normal University, Jeonju University, Qinhuangdao Vocational and Technical College.

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