Intelligent Recommendation Method of Sports Tourism Route Based on Cyclic Neural Network

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Abstract. Due to the low matching degree between scenic spot characteristics and tourists' interests, the accuracy of route recommendation is low. Therefore, an intelligent recommendation method of sports tourism route based on cyclic neural network is designed. On the premise of determining the recommendation target of sports tourism route, the characteristics of sports tourism attractions and routes and tourists' interest are extracted. After clustering, the recommendation list is collaborative filtered from the perspective of tourists. Finally, the circular neural network is used to optimize the recommended route. The test results show that the MAE of the design method opinion results is basically within 0.1, which has high accuracy.

Keywords: Recurrent neural network · Sports tourism route · Intelligent recommendation · Clustering processing · Collaborative filtering

1 Introduction

The World Tourism Organization and the United Nations Statistical Commission have made a scientific explanation of "tourism": people leave the environment of daily life for leisure, business or other purposes, go to certain places and stay there, but do not continue activities for more than one year. Most people think that travel is just for entertainment, vacation, and relaxation of their lives. In fact, it has other purposes, including: leisure, visiting relatives and friends, business, professional visits, health care, religion/pilgrimage, etc. [1–3]. Tourism has become an indispensable part of people's lives. It brings the baptism of both body and mind to busy people. At the same time, it allows us to feel the beauty of nature, feel the customs of exotic folk customs, and feel the joy of traveling together with relatives and friends. In recent years, my country's travel industry has developed rapidly [4, 5]. According to the "Communiqué on the Statistical Survey of National Travel Agencies in the Fourth Quarter of 2013" published by the National Tourism Administration on February 21, 2014, my country's tourism industry revenue reached 223.3 billion during the November long holiday last year, a year-on-year comparison of 2012. The Mid-Autumn Festival and National Day holidays increased by 6.1%. In the fourth quarter of 2013, national travel agencies and domestic tourism organizations had 35,737,500 person-times, 114,798,100 person-days, received 40,040,400

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person-times, and 92,446,900 person-days. Numerous data show that the tourism industry has become one of the industries with the strongest development momentum and the largest scale. On the contrary, the problems that people encounter during the tourism process are also endless. The most important ones are the planning of tourist routes and the navigation of tourist attractions. And the real-time conditions in the scenic area, etc. [6, 7]. In the past, the solution to these problems was to use paper maps and scenic spots announcements, etc., which had strong limitations and could not meet the needs of tourists. With the development of science and technology, electronic technology positioning and navigation has brought fresh blood to the tourism industry, and they influence each other and develop in coordination. The navigation equipment we use now generally has a GPS antenna placed inside it. In addition, there are 24 global satellites in the sky above our earth. Generally, at least 3 of them can be received at any time. The GPS antenna receives the data information transmitted by the satellites and combines the stored electronic map to determine the position coordinates for positioning., And then display a route for tourists' reference. The positioning accuracy deviation of the positioning equipment on the market today does not exceed 3 to 5 m. There are many types of positioning systems. Among them, the most commonly used one is similar to car GPS, and its terminals can be smart phones, Pads, and so on.

In the traditional tourism industry, the tour guide tools used by tourists are basically paper maps, which can be used to tour the scenic spot by manually drawing the route from the starting point to the destination. The main disadvantages of manually drawn tourism route map are: first, it has unreasonable use and low efficiency in terms of time and money. Because tourists must first determine a path from the starting point to the target point, and then piece together the maps containing these scenic spots into a set of paper maps covering scenic spots for navigation and play; Second, it can not give tourists real-time scenic spot change information, which will bring a lot of inconvenience to tourists' playing process.

With the continuous development of computer technology, electronic navigation technology has become more and more mature. More and more tourists are used to querying their travel routes through positioning and navigation in the process of playing. However, most mobile terminal navigation software on the market only provides a route based on a single tourist preference, for example, a shortest time route, a shortest distance route and so on. These methods often can not provide tourists with a route that is really suitable for their current actual situation, and usually do not provide alternative routes [8, 9]. In order to solve these problems, a circuitous route system is proposed, which provides another route when tourists deviate from the predetermined route. However, this type of system requires the tourist guidance system to recalculate and generate routes, rather than automatically generate alternative routes. Another disadvantage of the currently available navigation system is that when tourists choose a route to play, the situation in the scenic spot may change. For example, the performance of a scenic spot is about to begin. It is wise to change the route at this time.

Based on this, this paper designs an intelligent recommendation method of sports tourism route based on cyclic neural network. Based on the route of sports scenic spots and the preference characteristics of tourists, the optimization is realized, the most qualified tourism route is obtained, and it is used as the recommended route. Finally, the effectiveness of the design method is verified by experimental tests. Through this study, in order to provide a valuable reference for the development of tourism industry.

2 Recommended Goals for Sports Tourism Routes

The recommendation of tourist route information is highly subjective and plays a decisive role in the overall evaluation. The recommended information cannot be absolute. It can only provide tourists with a tourist route that is more satisfactory than the current situation and other helpful tourist routes. Information [10]. Therefore, most of the recommended content of this article is subjective. Let us study the subjective and objective evaluation criteria used in similar topics below:

(1) Subjective evaluation criteria

The subjective evaluation standard is that tourists compare the given route information and then give feedback. Obtain the value of the information from the feedback information, and then make corresponding changes, forming an iterative and continuous improvement of the recommended information. The value of information is a subjective evaluation standard, and the positive feedback given by most tourists is the basis.

(2) Objective evaluation criteria

The objective evaluation criterion is to study the best path method, take the factors in the current scenic spot into consideration, and combine the path generated by the best path method. This path is the best path. After that, we reasonably compare our recommendation information with the path information, and finally get an evaluation. However, the difficulty of this standard is how to study the best path method. There are different opinions on this method, and there is no standard answer. Therefore, objective evaluation is difficult to achieve in similar subjects.

3 Feature Extraction

3.1 Extraction of Sports Tourist Attractions and Route Features

This paper does not consider the self characteristics of tourists, but focuses on the domain characteristics of scenic spots and routes in the field of sports tourism, and then extracts the feature points of tourists' interest from the domain characteristics. Therefore, before the extraction of tourists' interest features, we must extract the interest feature points of scenic spots and routes in the field of sports tourism. The characteristics of sports tourist attractions are extracted from the existing data of sports tourist attractions. When analyzing the content of the crawled original web page, keyword matching and information extraction are carried out according to the attribute description of sports tourist attractions on the web page. Finally, it is concluded that the interest characteristics of sports tourist attractions are divided into provinces, districts and counties, categories, stars Development time and ticket price. According to the classification of China's sports tourism resources, sports tourism attractions are divided into eight categories: geographical landscape, water scenery, biological landscape, ruins, astronomical and climatic landscape, buildings and facilities, sports tourism commodities and cultural activities.

Based on this, for the feature extraction of sports tourism routes, this paper selects sports tourism route data as the basis, combined with the principles of sports tourism route design: sports tourism purpose, physical conditions of the sports tourism subject, tourists' economic conditions and travel time, tourists In terms of hobbies, special sports tourism subjects, etc., with the introduction of sports tourism classification as a reference, the characteristics of sports tourism routes are summarized into six categories: travel days, reference costs, route types, departure cities, and destination cities.

The interest characteristics of sports tourism routes are mainly summarized for tourists, because for the characteristics of sports tourism routes, this article only cares about the correlation between sports tourism routes and tourist interest characteristics. The types of routes are divided into: self-view.

Light sports tourism, humanities sports tourism, leisure and vacation sports tourism, shopping sports tourism, and experience sports tourism.

3.2 Extraction of Tourist Interest Features

In this paper, the understanding of tourists' interest characteristics has two aspects: on the one hand, based on the integration of sports tourist attractions and route characteristics, tourists extract the types of interest points of recommended content; on the other hand, it analyzes the historical records of tourists who have selected sports tourist routes as an input factor of recommendation methods. On the other hand, it is a static and attribute standard, The latter aspect is dynamic and attribute content. According to the previous analysis of the attribute characteristics of sports tourist attractions and sports tourism routes, in the field of sports tourism, the interest characteristics of tourists include the above two characteristics. Because the sports tourism industry is originally oriented to tourists, the feature extraction of the first two is based on tourists' hobbies.

Therefore, this paper concludes that the common interest characteristic attributes of tourists and scenic spots are: Province, district and county, category, star, opening time and ticket price. Thus, the measurement of tourist attraction correlation can be quantified as the feature vector of tourist attraction common interest: (province, district and county, category, star level, opening time and ticket price). Similarly, the common interest feature vector of tourist sports tourism route: (travel days, reference cost, route category, departure time, departure city, destination city).

Based on this, the feature vector is quantized. The feature vector quantization types designed in this paper are divided into three categories: 0–1 relationship, single threshold range relationship, and double threshold range relationship. The specific quantification method is as follows:

(1) 0–1 relationship

Some characteristic relationships between tourists and sports tourism routes are 0–1 relationships, such as provinces and departure cities. The interest characteristics of tourists are either completely consistent with the characteristic attributes of the sports tourism route, and the corresponding characteristic relationship value in the tourist-tourism route characteristic vector is recorded as 1; or completely different, the corresponding characteristic relationship value is recorded as 0 at this time.

(2) Single threshold range relationship

There is a single threshold range relationship between tourists and some characteristic relationships of sports tourism routes, such as the number of days spent playing, star ratings, and so on. Suppose the tourist wants to play *m* day, then the tourist's play days feature value is *m*, and the sport tourism route's play days is *n*, then the sport tourism route's play days value *n*. At this time, the relationship between the number of play days in the feature vector of the tourist and the sports tourism route The value λ is written as:

$$\lambda = \frac{\min(m, n)}{\max(m, n)} \tag{1}$$

(3) The relationship between the dual threshold range

There is a dual-threshold range relationship between tourists and some characteristic relationships of sports tourism routes, such as ticket prices and opening hours. Assuming that the fare range that the tourist wants to pay is $m_i - m_a$, and the fare of the sports tourism route is n, then the fare relationship value δ in the feature vector of the tourist and the sports tourism route is recorded as:

$$\delta = \begin{cases} 0, n > m_a \| n < m_i \\ \frac{|avg(m_i, m_a) - n|}{avg(m_i, m_a)}, m_i < n < m_a \end{cases} \tag{2}$$

In this way, visitors' interest characteristics are obtained. The specific tourist interest feature extraction process is shown in Fig. 1.

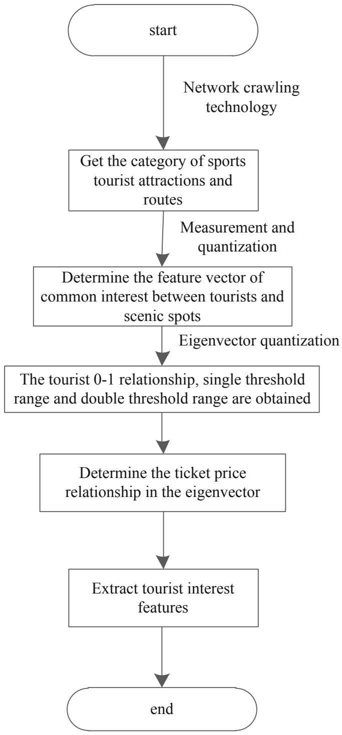

Fig. 1. Tourist interest feature extraction process

According to the analysis of Fig. 1, this paper obtains the categories of sports tourist attractions and routes through network crawling technology. Through measurement and quantification, according to the common interest feature vector of tourists and scenic spots, the interest feature types of tourists are divided into three categories through feature vector quantization, 0–1 relationship, single threshold range and double threshold range, and the relationship between double threshold range determines the ticket price relationship value in the feature vector of sports tourist routes, Finally, tourists' interest feature extraction is realized.

4 Route Recommendation Method Design Based on Recurrent Neural Network

4.1 Sports Tourist Attractions and Routes and Feature Clustering of Tourists

Based on the features extracted from sports tourist attractions, routes and tourists' interests, the above section clusters the features of tourist attractions, routes and tourists respectively. The clustered sports tourist attractions, routes and tourists are quickly indexed to speed up the query based on the similar set of interest features, so as to improve the recommendation efficiency.

The above extracted features cluster sports tourist attractions, sports tourism routes and tourists respectively, which greatly improves the data reading speed. The feature clustering of sports tourist attractions is divided into two parts. One part is to cluster the existing scenic spot database, and the other part is to analyze the features of new sports tourist attractions and add them to the corresponding feature cluster set. Here, a scenic spot may have multiple features, so a scenic spot may be clustered into multiple feature sets. The similarity of features is defined as:

$$p = \sum_{i} D_i Y_i \tag{3}$$

Among them, i respectively represent the existence strength of different features, D_i represents the fixed factor of the feature, and Y_i represents the non-fixed factor of the feature. This method is used to analyze the extracted data results.

And through formula (3), the clustering criterion between the features of scenic spots is judged, which can be expressed as:

$$C = \frac{p}{E} \tag{4}$$

where, E represents the sum of the intensity of the factors that occur in the scenic spot. When the similarity of features determined by fixed and non fixed features is greater, the degree of clustering is higher.

The clustering of sports tourism routes and tourist information is similar to that of scenic spots.

4.2 Build a Recommendation List

After clustering the features of scenic spots, routes and tourists, the corresponding feature clustering table is established in the database to reduce the time occupied by the recommendation method in data search and improve the recommendation efficiency. It can be seen from the discussion in the previous section that in real life, tourists think more about what is the most suitable next scenic spot at the current location, and don't care too much about others. Although the neural network method can also be used to solve the problem of route selection, the neural network method can not be directly used in the problem solving of this paper, because our scenic spot scoring is a dynamic process. Every time a tourist arrives at a scenic spot, he will re score the other scenic spots based on the scenic spot, so as to make a choice. In addition, the most important thing is that the direct use of greedy method can only get one path, which can not meet the requirements of multi-objective, that is, it can not provide tourists with multiple paths for tourists to choose. However, in our problem, if the order of sports tourist attractions is different, the scores of sports tourism paths are also different. At the same time, we hope to provide tourists with multiple alternative paths based on the use of cyclic neural network. Therefore, we propose a cyclic neural network to solve the problem of generating multiple paths. The method is described as follows:

Each time a tourist arrives at a scenic spot, based on their location, they select the next top N scenic spot with the highest score to form N paths. When $N > K$, by calculating the TPS of each path, keep the first K TPS values larger Paths, after cutting out $N - K$ paths, and following this, keep the first K paths with the largest TPS each time. The final method obtains K paths, and then through the diversity evaluation of the K paths, the best path is obtained. Youlu recommended to tourists. The specific execution process is as follows:

Input: the current latitude and longitude position of the tourist $u_L(l_{at}, l_{on})$, departure time st, end time et, budget b. The number of scenic spots expected to be visited M.

Output: k paths with higher scores and each path score $TPS[]$.

1) Initialization: $VT[] = \emptyset$, mark the scenic spots $SS[] = 0$ visited by each path.
2) Calculate SS of each scenic spot at time t according to tourist $u_L(l_{at}, l_{on})$.
3) For the current scenic spot, select the first l points with higher scores as the scenic spots to be expanded in the next step, that is, extend l paths.
4) Choose the first N path with the highest score and add them to $VT[0]$ to $VT[k]$ respectively. If $N > k$, then cut the $N - k$ paths with lower TPS. Reserve the first k paths with higher TPS. l represents the length of the path, and N represents the number of scenic spots that can be selected in the next step each time the method is executed based on the current point.
5) Determine whether each path meets the time constraint $et - st$ and budget constraint b. If not, delete the path.
6) For the reserved path, repeat steps 2 ~ 4 based on each current point.
7) When $M = 1$, or $t > st$ or TPC $> b$. End the method, and finally get k paths and TPS scores for each path.

According to actual needs, the multiple routes before the score are taken as the basic recommendation list.

4.3 Collaborative Filtering Based on the Recommendation List of Tourists

Collaborative filtering recommendations based on the recommendation list of tourists. First, use the correlation between tourists to obtain a group of "neighbors" similar to the target tourists, and then calculate the target tourists' predicted scores for unrated items based on the historical preferences of this group of tourists. And recommend to the target tourists based on the predicted score.

The basic principle of collaborative filtering based on tourists: Assume that tourist A likes scenic spots 1 and 3, tourist B likes scenic spots 2, and tourist C likes scenic spots 1, scenic spots 3 and 4. From the historical information, we can see that tourist A and tourist B do not Commonly liked scenic spots, but both tourist A and tourist C like scenic spot 1 and scenic spot 3. That is to say, tourist A and tourist C have greater similarity, and tourist C likes scenic spot 4 in addition to scenic spot 1 and scenic spot 3, so it is speculated Tourist A may also like scenic spot 4, so we recommend scenic spot 4 to tourist A. User CF, a collaborative filtering recommendation method based on tourists. Based on this, the main steps involved in the process of using this method to achieve collaborative filtering of recommendation lists are as follows:

(1) Tourist data preprocessing

Using the methods of data mining and preprocessing, the original data of tourists, including tourist attribute data, behavior data and scoring data, are preprocessed and modeled to form a tourist item scoring matrix, so that it can be processed and calculated by using the recommendation method, and the recommendation results can be quickly obtained in combination with the characteristics of sports tourist attractions and routes obtained above.

(2) Calculate the nearest neighbor set

The calculation of the nearest neighbor set is a particularly important step in the recommended method, and it is also a key point that affects the performance of the method. It is generally believed that similar tourists are also more similar in preference. First, calculate the tourist set $R = (r_1, r_2, ...r_i)$ that is most similar to the target tourist A, then calculate the score of the target tourist A for the unrated items through the scores of the items in the similar tourist set R, and finally recommend the target tourist from high to low according to the predicted score.

There are three existing methods for calculating similarity: cosine similarity, modified cosine similarity and Pearson correlation coefficient. This article adopts the method of cosine similarity to realize this process. The tourist item rating matrix is regarded as a vector in an n-dimensional space, where the value of the unrated item is initialized to 0, and the similarity between tourists is calculated by calculating the cosine of the angle between the vectors. Let vector $\vec{u}$ represent the score of tourist u in the space, and vector $\vec{v}$ represent the score of tourist v in the space, then the similarity formula between tourist u and tourist v is shown in formula (5):

$$sim(u, v) = \frac{\vec{u} \bullet \vec{v}}{\|\vec{u}\| * \|\vec{v}\|} \tag{5}$$

(3) Calculate forecast score

On the basis of the nearest neighbor set, the non scored items of the target tourists are calculated according to the similarity between the nearest neighbor set and the target tourists. User CF selects formula (2.46) to predict the score of non scored items:

$$p(u, i) = \sum\nolimits_{v \in M(u,k)} S_{uv} R_{vi} \tag{6}$$

Among them, $p(u, i)$ represents the predicted score of tourist u on item i, S_{uv} represents the tourist similarity between tourist u and tourist v, R_{vi} represents the real score of tourist v on item i, and $M(u, k)$ represents the k nearest neighbors of tourist u.

Thus, the collaborative filtering of recommendation list based on tourists is realized.

4.4 Intelligent Selection of Recommended Routes

When using the recurrent neural network to search the initial population, this paper adopts the coding method of real number matrix, and carries out a separate real number coding for each filtered route. A single route map is regarded as a matrix chromosome, route map is used as a vector, route type, route location, route opening time, route number attribute map is used as a gene location, a represents the number of recommended routes, b represents a route attribute, and the chromosome matrix is expressed as (a + 1)(b + 1). Then the route coding matrix model is

$$\begin{pmatrix} X_{11} & \dots & X_{1b} \\ \vdots & \ddots & \vdots \\ X_{a1} & \cdots & X_{ab} \end{pmatrix} \tag{7}$$

In the above route coding matrix model, the fitness function is set to screen the recommendation results and obtain the optimization of the optimal solution. The larger the fitness function value, the stronger the individual's ability to adapt to the environment and the greater the opportunity to reproduce. On the contrary, the smaller the individual function value, the smaller the individual's ability to adapt to the environment and is likely to be eliminated.

This article uses a piecewise function to design the fitness objective function, B represents the attribute of the target, and ε represents the maximum allowable error. Then the calculation method of the objective function value is:

$$f_a = \begin{cases} \left|\frac{b-B}{B}\right|, & \frac{b-B}{B} \le \varepsilon \\ 1, & \frac{b-B}{B} > \varepsilon \end{cases} \tag{8}$$

Suppose the corresponding value of the route attribute is λ_a, and the number of routes included in the initial population is A, then the fitness objective function of the entire route can be expressed as:

$$f = f_{\max} = \sum_{a=1}^{A} \lambda_a f_a \tag{9}$$

In this way, the continuous optimization of the recommendation results is realized, and the degree of fit between the route and the recommendation requirements is improved.The recommendation process of specific tourist routes is shown in Fig. 2:

According to the analysis of Fig. 2, the characteristics of sports tourist attractions, routes and tourists are obtained through data clustering, and the tourist data is preprocessed; Calculate the nearest neighbor set and calculate the route recommendation prediction score; The recommendation list of tourists is determined based on collaborative filtering, and the circular neural network model is constructed to realize the intelligent screening of recommended routes; The fitting degree of fitness objective function is calculated by piecewise function, and the recommendation effect of tourism route is obtained.

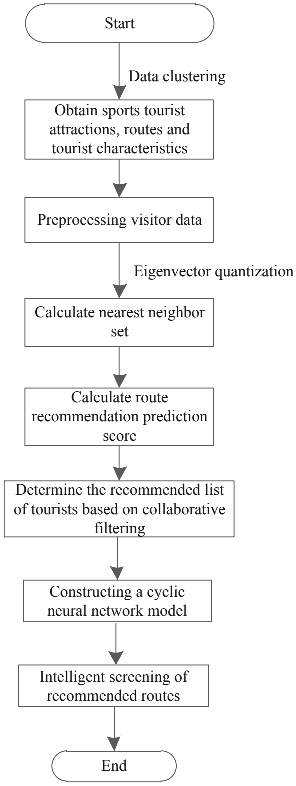

Fig. 2. Recommendation process of tourist routes

5 Experimental Results and Analysis

5.1 Experimental Design

The paper chooses to test the recommendation effect of the scenic spot recommendation method from the aspect of accuracy. In order to ensure that the experiment is true and effective, the design crawler grabbed the real score data and basic information of 2389 scenic spots through the network as experimental data. Since the paper sets a loop

Fig. 3. Experimental scene

parameter when building the tourist preference model, the loop parameter value 0 is analyzed experimentally.The specific experiment is shown in Fig. 3.

5.2 Experimental Index

Assuming that the true value of a group of time series is $y = \{y_1, y_2, ..., y_n\}$ and the predicted value is $y' = \{y'_1, y'_2, ..., y'_n\}$, the mean absolute value deviation (MAE) is taken as the experimental index,

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|y'_i - y_i\right| \tag{10}$$

The value of MAE is between $[0, +\infty]$, and the greater the error, the greater the value of MAE.

5.3 Result Analysis

(1) When conducting experiments, under different values of N in the recommended list Top N, set the cycle coefficient 8 to 0, 0.3, 0.5, 0.7, and judge the influence of different cycle coefficients on the accuracy of the method, as shown in Fig. 4.

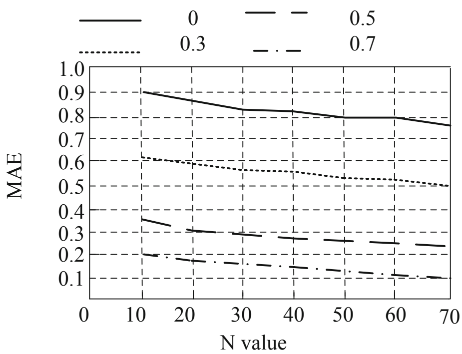

Fig. 4. Different cycle coefficients for the accuracy of the method

It can be seen from Fig. 4 that the accuracy of the method changes greatly under the influence of different cycle coefficients. When the circulation coefficient is, that is, tourists' preference is not affected by time, the high Mae value means that the accuracy of the method is not high. The greater the circulation coefficient, the greater the influence of time on tourists' preference. It can be seen from the experimental results that no matter what value n is, the greater the cyclic coefficient, the higher the accuracy of the method. When the cycle parameters are 0, 0.3 and 0.5, the MAE value decreases greatly. When the cycle parameter changes from 0.5 to 0.7, the MAE value decreases, but the range is small. That is, when the cycle parameter is 0.7, the recommendation accuracy of the recommended method is high.

When the loop parameter is constant, and the value of N is 10, the MAE value is too high, that is, the accuracy of the method is not high. As the value of N increases, the value of MAE gradually decreases, and the accuracy of the method gradually increases. When the value of N changes from 60 to 70, the change of the MAE value tends to be stable, that is, the accuracy of the method does not change much.

(2) In order to verify the performance of the improved method, when the cycle parameter is 0.7, the paper method is compared with the method proposed in literature [8] and the method proposed in literature [9], and the performance of the paper method is verified from the aspect of MAE value. For the three methods, the MAE values are compared when the values of N in the top n of the recommendation list are 10, 20, 30, 40, 50, 60 and 70 respectively. The experimental results are shown in Table 1.

Table 1. Mae comparison of recommended results of different methods

N value	Reference [8] method	Reference [9] method	Paper method
10	0.75	0.66	0.12
20	0.69	0.58	0.08
30	0.62	0.56	0.07
40	0.60	0.52	0.05
50	0.58	0.49	0.05
60	0.76	0.63	0.05
70	0.69	0.70	0.05

It can be seen from Table 1 that the MAE value of the general collaborative cycle method is significantly higher than that of the other three methods, and the MAE value decreases with the increase of N, that is, the accuracy of the method continues to improve. There is little difference in Mae value between the method in literature [8] and the method in literature [9].The MAE value of the method in document [8] is not affected by N, that is, the accuracy of the method does not change significantly when n is taken, while the MAE value of the method in document [9] decreases with the increase of n. The MAE value of the scenic spot recommendation method in this paper is much smaller than that of the other three methods, and the MAE value of this method decreases with the increase of n value. When the n value changes from 40 to 50, the MAE value tends to be stable.That is, the accuracy of the scenic spot recommendation method in the paper is higher than the other three comparison methods, and with the increase of N, the accuracy of the scenic spot recommendation method will gradually stabilize.

6 Conclusion

This paper designs an intelligent recommendation method of sports tourism route based on cyclic neural network. Determine the recommendation target of sports tourism route, extract the characteristics of sports tourism attractions and routes and tourists' interest, collaborative filter the tourism recommendation list through data clustering, and finally optimize the recommended route by using cyclic neural network. The experimental results show that the MAE value of the recommended route of this method decreases continuously, and the MAE value tends to be stable when the n value changes from 40 to 50. It shows that the route recommendation effect of this method is good.

However, there are still some deficiencies in this method. The unified time calculation method between scenic spots is adopted in this paper, but in practice, there may be traffic jams and other problems between scenic spots, which will lead to the scenic spots of one day can not be visited in the original time period. Therefore, according to the preferences of tourists when playing in different types of scenic spots, the fluctuation of playing time and the consideration of traffic conditions between scenic spots when designing sports tourism routes will be the next research content of the paper.

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