Intelligent recommendation method of intelligent tourism scenic spot route based on collaborative filtering

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Abstract

This paper tackles the prevalent challenges faced by existing tourism route recommendation methods, including data sparsity, cold start, and low accuracy. To address these issues, a novel intelligent tourism route recommendation method based on collaborative filtering is introduced. The proposed method incorporates a series of key steps. Firstly, it calculates the interest level of users by analyzing the item attribute rating values. By leveraging this information, the method can effectively capture the preferences and interests of users. Additionally, a user attribute rating matrix is constructed by extracting implicit user behavior preferences, providing a comprehensive understanding of user preferences. Recognizing that user interests can evolve over time, a weight function is introduced to account for the possibility of interest shifting during product use. This weight function enhances the accuracy of recommendations by adapting to the changing preferences of users, improving the overall quality of the suggested tourism routes. The results demonstrate the significant advantages of the approach. Specifically, the proposed method successfully alleviates the problem of data sparsity, enhances neighbor selection, and generates tourism route recommendations that exhibit higher accuracy compared to existing methods.

Keywords: Recommendation, Tourism scenic spot route, Collaborative filtering, Intelligent tourism

1. Introduction

As a result of the rapid economic expansion in many countries, tourism has become a top priority for leisure, vacation, research, practice, and education. However, planning a scenic route can be challenging when faced with unfamiliar tourist attractions. To address this challenge, researchers are increasingly focusing on the development of intelligent and effective travel route recommendations [1, 2].

Compared to recommendations for other types of products, travel recommendations are particularly challenging to formulate. Not only do travel recommendations need to consider user preferences, but they also need to take into account trip duration, location of scenic spots, transportation costs, and seasonal factors. Additionally, obtaining and quantifying travel preferences can be difficult, especially when there is limited browsing information available. These challenges result in serious problems with data sparsity and a cold start when recommending travel routes [3-4].

The proliferation of travel-related data on the internet has made it possible to analyze the travel patterns of internet users and, in turn, influence the travel patterns of others. While individual travel reviews or notes may contain personal biases, analyzing data from a large number of user reviews can provide a comprehensive view of a scenic location. In recent years, researchers have increasingly turned to data from the collective wisdom of internet users to make route recommendations [5]. For example, some academics have used the number of photos uploaded to the internet to determine the popularity of scenic areas and used this information to recommend popular tourist routes based on the different types of scenic areas along those routes. To ensure the reliability of their findings, researchers typically compile information from a variety of sources, including user feedback, photographs, and itineraries from past travels. Some researchers have proposed developing computer programs that consider factors such as admission cost, customer feedback, and geographic location to create an attractiveness index model for planning and recommending tourist routes [6]. Others have successfully developed algorithms for mining frequent route sequence patterns based on character types by incorporating data from the internet into a tourist route database, catering to the travel needs of various groups. However, when only limited data is available, these approaches may not fully meet the individual requirements of each user [7].

The field of recommender systems aims to mitigate the problem of information overload by providing personalized recommendations to users based on their historical rating data. Although collaborative filtering algorithms are widely used in recommendation systems, there is still a significant need for improvement. As the number of users and items continues to increase, the user-item rating matrix becomes increasingly sparse, leading to accuracy issues in similarity calculations [8]. Moreover, traditional collaborative filtering methods do not take into account the user's past interests and preferences, making it impossible to determine the similarity between newly added items or users. To address these limitations, researchers and industry professionals have dedicated their efforts to developing new algorithms that can improve the accuracy and efficiency of recommendation systems [9].

Several researchers have addressed the challenge of sparse data in collaborative filtering by proposing nonlinear similarity models that consider both user asymmetry and item similarity. Meanwhile, an enhanced method that incorporates trust relationships and user characteristics aims to tackle the issue of erroneously selecting nearest neighbors, with the goal of increasing recommendation precision [10-13]. To achieve this, some researchers advocate the use of a single rating scale for all users, adding a balance factor to refine cosine similarity calculation and improve user similarity accuracy. Furthermore, a new similarity measurement formula that factors in user attributes, interests, and ratings has been proposed to construct a user similarity model, which can accurately select neighboring users and enhance recommendation accuracy. To better reflect user preferences, some researchers suggest using a weighted method to calculate temporal similarity. To address the "cold start" issue, we developed an optimization framework that combines historical ratings and item attributes [14]. Additionally, a correction factor that accounts for disparities in user co-evaluation and scores has been proposed to enhance similarity calculation accuracy and reduce errors in recommendations. Finally, a few academics have suggested a collaborative filtering algorithm that combines discrete content with varying degrees of interest to provide useful recommendation results, even with limited data [15].

This article presents item classification attributes that take into account user interests, based on the findings of the aforementioned researchers. A final method for calculating similarity, designed specifically for tourism, considers the user's preference for attribute characteristics and how their interests change over time. This is achieved by combining user-item ratings with a time-weighted function. The recommendation is well-intentioned and supported by sound reasoning. Compared to traditional collaborative filtering algorithms, improved collaborative filtering algorithms result in more efficient travel route recommendations, better recommendation effects, and improved accuracy of similarity measurement.

2. Related Work

The challenge of the traveling salesman has inspired the problem of tourist route planning, which aims to follow predetermined guidelines and enhance urban environments for prospective candidates. This topic has gained significant interest domestically and internationally [1, 3]. In order to improve machine learning algorithms, researchers have developed additional methods such as the simulated annealing algorithm and the ant colony algorithm [5]. Minimizing expenses and maximizing benefits are primary considerations for route planners, as found by several studies. Researchers have proposed a mathematical model for urban domestic waste recycling path planning, utilizing an improved hybrid leapfrog algorithm to optimize garbage collection routes [4]. An enhanced version of the ant colony algorithm has been proposed as a solution for multi-scenic spot path planning, which converges more quickly and avoids slipping into local optima [6]. The Yellow River Golden Triangle tourism route has been successfully planned through parameter adjustments and improvements. The evolution speed and accuracy of the algorithm have been improved by utilizing an improved hybrid frog leaping algorithm in the process of optimizing artificial intelligence [7]. Potential field parameters can also be used to improve route planning [8]. To understand the effects of traveler density on link time and network distribution, researchers have proposed a mixed integer nonlinear programming model and an algorithm to solve it [8-10]. The challenging task of designing a sidewalk network that accommodates different types of foot traffic and traffic patterns is also a significant consideration.

Some researchers have proposed integrating biased randomization methods into a variable neighborhood-based search framework as a meta-heuristic approach for solving complex problems with economic, environmental, and social dimensions [11]. This approach exemplifies the application of the neighborhood-based search framework in the transportation of vehicles across multiple locations. To address the open vehicle routing problem, some researchers have suggested utilizing a general variable neighborhood search algorithm that minimizes the total number of routes, travel costs, and longest route. Moreover, an enhanced hybrid frog leaping algorithm has been proposed for personalized tourism route recommendations, incorporating a penalty factor to minimize the chances of missing a better solution and to remove abnormal solutions from the subgroup update, thus speeding up the algorithm and facilitating abnormal solution handling [12-14].

The shift from a quantity-oriented to a quality-oriented travel mindset has been accelerated by mobile devices and information technology. As players seek to create a unique travel experience, intelligent tourism development aims to generate individualized tourist itineraries, provide reliable tourism information, and boost tourism's economic value for industry players [15]. Some academics have developed landmark recommendation models based on historical travel trajectories to assist travelers in making travel arrangements. Additionally, some researchers have proposed travel route recommendation algorithms based on temporal geography, which accounts for the time it takes tourists to complete their trips, enhancing overall travel experiences [16-17]. Some researchers have used a recommendation model built on Word2vec and LDA to solve the problem of recommending travel routes, incorporating users' reviews and scenic spot ratings into the model. By analyzing tourists' activities, such as consumption and social interactions, researchers have discovered that tourists' activities vary depending on their location scenery [18-22].

Using geotagged photos to create travel footprints and generate personalized travel recommendations is a promising approach that combines Markov and topic models. By analyzing users' travel patterns over time, a probabilistic behavior model can be established, and relevant tourist information can be obtained. However, the current method has limitations in considering users' starting and ending points when recommending travel destinations and routes [23]. To address this issue, some researchers suggest providing users with tailored recommendations based on their constraints, preferences, and points of interest along the way [24]. To achieve this, algorithms such as recursive-based dynamic programming have been proposed and tested on real-world datasets such as Foursquare [25]. One recent breakthrough is the development of a new algorithm called PTIR (Personalized Travel Itinerary Recommendation) that takes into account individual preferences and achieves better performance than traditional methods in terms of precision and recall rates. PTIR also considers group dynamics and fairness, which can be challenging in group travel planning. Decentralized access routes have been proposed as a more effective solution to this issue than group routes.

Privacy protection in recommendations is also intuitively important, and Wu et al. have made certain contributions in the area of privacy protection, such as proposing a client-based system framework for protecting user privacy and defining relevant models that can improve the security of users' topic privacy on untrusted servers [26-31].

Many researchers argue that personalized recommendations should be a top priority when designing travel recommendation models. For example, some researchers propose creating personalized itineraries for visitors based on information they provide about themselves and their interests on the Minube website, as well as popular attractions in the region [32]. To make more accurate and tailored recommendations, some researchers analyze users' Flickr photos to determine their historical itineraries and preferences. This is done by examining the amount of time users spent at particular locations and the popularity of those locations at the time. Other researchers use a combination of the nearest neighbor algorithm classifier and Bayesian classifier to predict a user's preferred route based on their own geo-tagged photos [33]. Some researchers have developed an algorithm based on tags, which is combined with an ant colony algorithm and a list of scenic locations to create a route recommendation model that considers individual preferences and travel time. However, it is important to note that placing too much emphasis on individual preferences may not be effective in the real world [16, 19].

In summary, most travel route recommendation methods still suffer from cold start, sparse data and low recommendation accuracy, and do not adequately consider the possibility of user interest shifting during the course of using the product.

3. Method

The traditional collaborative filtering algorithm is based on historical scoring data in order to provide users with item recommendations that are relevant to their interests. **Fig. 1** presents the primary flowchart.

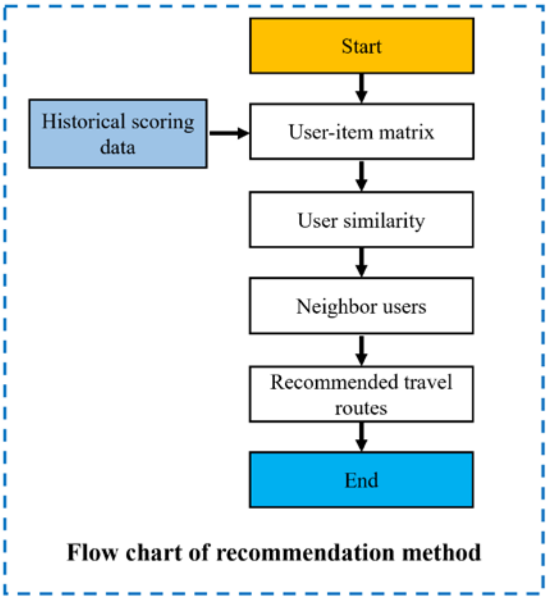

Fig. 1. Flowchart of traditional collaborative filtering-based travel route recommendation

Users and items are defined as $U=\{u_1,u_2,\cdots,u_m\}$ and $I=\{i_1,i_2,\cdots,i_m\}$, and the rating matrix is

$$\begin{matrix} s_{11} & s_{12} & \cdots & s_{1n} \\ s_{21} & s_{22} & \cdots & s_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ s_{m1} & s_{m2} & \cdots & s_{mn} \end{matrix} \tag{1}$$

The nearest neighbor of the target user is defined as $K=\{u_1,u_2,\cdots,u_k\}$, and the formulas for calculating the similarity between two users are

$$Dis1(u,v)=\frac{|I_u \cap I_v|}{|I_u \cup I_v|} \tag{2}$$

$$Dis2\left(u,v\right)=\frac{\sum\left(s_{u,i}-s_{u}\right)\left(s_{v,i}-s_{v}\right)}{\sqrt{\sum\left(s_{u,i}-s_{u}\right)^{2}}\sqrt{\sum\left(s_{v,i}-s_{v}\right)^{2}}} \tag{3}$$

Top N is calculated as follows

$$P_{u,i}=s_{u}+\frac{\sum Dis2\left(u,v\right)\left(s_{v,i}-\frac{s_{v}}{n}\right)}{\sum Dis2\left(u,v\right)} \tag{4}$$

If we use a conventional collaborative filtering algorithm, the recommendation will be generated based solely on predicted scores, disregarding any factors associated with the attributes of the item. However, the user's rating is influenced by the item's category attributes, which indirectly reflect the distribution of interests. By considering the item attribute scoring data, we can accurately capture the user's interests and hobbies, thus recording their background information. Therefore, we define the user's interest level by calculating their item attribute rating value and establish a user-attribute rating matrix by mining implicit data of user behavior preferences. These processes aim to determine the user's preferences. The first step in developing user-item attribute preference similarity is to calculate the degree of similarity between users.

The attribute matrix of the item is

$$\begin{matrix} A_{11} & A_{12} & \cdots & A_{1k} \\ s_{21} & s_{22} & \cdots & s_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ s_{n1} & s_{n2} & \cdots & s_{nk} \end{matrix} \tag{5}$$

Constructing a user-item attribute rating matrix involves combining item attribute feature data and user rating data with k related attribute description items. This results in the matrix having the user-item attribute rating. The attributes of the item have been given the same number of stars as the item itself, which means that they have been given the same rating as the item. If the user rates item j as a, and item I possesses attribute b, then the value of the rating in the rating matrix is equal to *a*+*b*. If the user's rating for item *j* is *c* and item *j* also possesses attribute a, then the rating matrix S(u, a) has a value for the rating that is equal to *t*+*c*. If the user does not rate the item or if the item does not have any attributes, the score on the matrix is equal to zero.

For instance, a user's interest in a product may shift over the course of their use of it. Users who visit the website on a regular basis are more likely to have an interest in a particular subject, whereas users who haven't visited the website in a considerable amount of time are more likely to have developed new passions in their lives. The change in the weight function that is of interest in this particular instance is

$$T=\exp\left(\frac{t_{i}-t_{0}}{L}\right) \tag{6}$$

where t_0 is start time, t_i is the current rating time, and *K* is the length of the current rating time and start time, then we have

$$Dis3(u,v)=\frac{\sum\left(Ts_{u,i}-s_u\right)\left(Ts_{v,i}-s_v\right)}{\sqrt{\sum\left(Ts_{u,i}-s_u\right)^2}\sqrt{\sum\left(Ts_{v,i}-s_v\right)^2}} \tag{7}$$

$$P_{u,i}=s_u+\frac{\sum Dis3(u,v)\left(s_{v,i}-\frac{s_v}{n}\right)}{\sum Dis2(u,v)} \tag{8}$$

The flow chart of the improvement method is shown in **Fig. 2**.

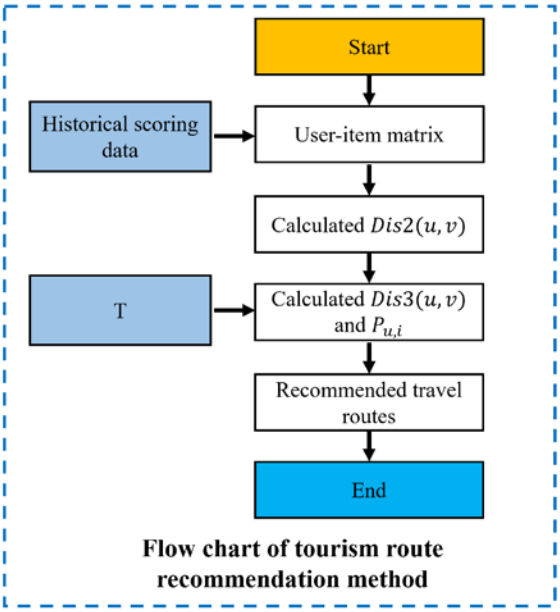

Fig. 2. Flow chart of our collaborative filtering algorithm

4. Experiment Results

4.1 Basic Setting

The experiment uses the MovieLens 100K open source data set, which is made up of 943 users' rating data for 1682 movies, in order to demonstrate that the improved collaborative filtering algorithm is effective. The rating scale goes from one to five, and eighty percent are chosen at random to serve as training. 20 percent will be used as the sample size.

The calculation method of the evaluation index is

$$MAE=\frac{1}{N}\sum\left|p_{u,i}-\hat{p}_{u,i}\right| \tag{9}$$

$$C=\frac{1}{N}\sum\hat{N} \tag{10}$$

where $\hat{p}_{u,i}$ is the predict rate, $\hat{N}$ is the number of items recommended by our method.

4.2 Recommended Accuracy Comparison

For the purpose of comparison, the improved similarity calculation method proposed in this paper is referred to as the traditional similarity calculation method developed by Jaccard and Pearson. The range of their nearest neighbors is [10, 50]. The outcomes of the experiments are depicted in **Fig. 3 and Fig. 4**, respectively.

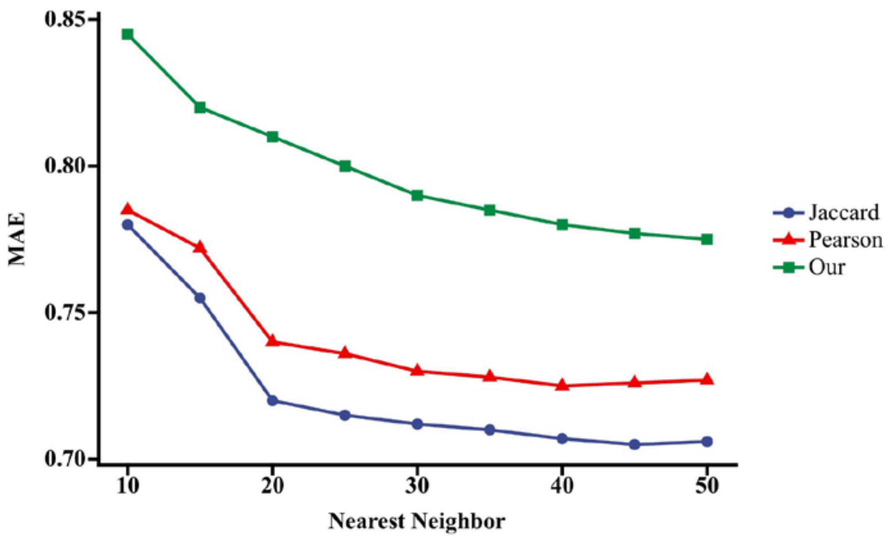

Fig. 3. Comparison of the MAE of different methods in different nearest neighbor

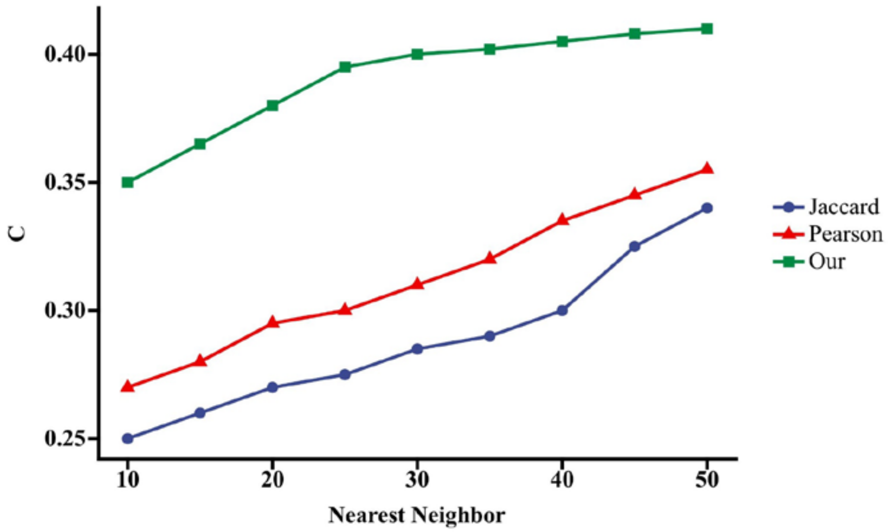

Fig. 4. Comparison of the C of different methods in different nearest neighbor

The Mean Absolute Error (MAE) is a useful measure that displays both the predicted and actual scores of users, along with the average difference between them. **Fig. 3** reveals that increasing the total number of nearest neighbors reduces the average absolute error caused by all three algorithms. Notably, our proposed algorithm achieves significantly lower MAE values than the other two algorithms, as it emphasizes the user's interest and preference for recently accessed items and avoids ignoring early relevant data information.

Fig. 4 compares the coverage rates of the three algorithms on the Movielens dataset, and our proposed algorithm demonstrates a relatively higher coverage rate than the other two methods due to the introduction of item attributes and the construction of an item-attribute matrix. However, selecting neighbor users can be inaccurate when the item rating matrix has a limited number of rows and columns. To address this issue, we proposed a theoretical approach that takes into account the user's preference for item attributes and the search ranges of identified "neighbor" users to increase recommendation coverage and diversity.

4.3 Algorithm Time Consumption Comparison

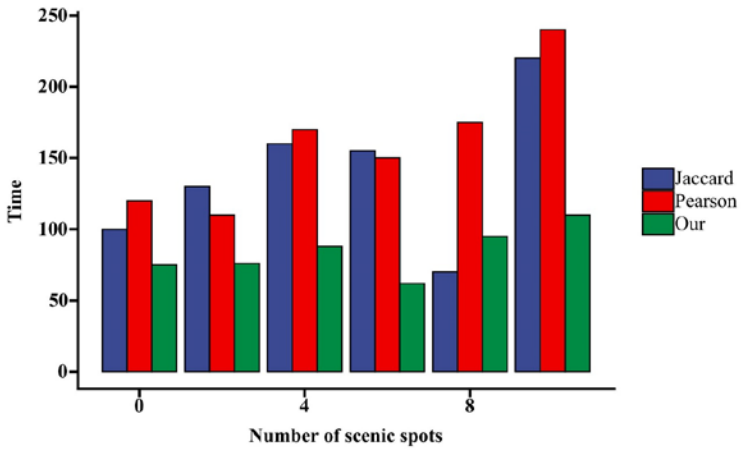

Fig. 5. Comparison of operating efficiency of different models

Furthermore, we evaluated the operational efficacy of the models by measuring their runtime in **Fig. 5**. The results indicate that the runtime increases proportionally with the number of picturesque locations. By summing the two computations and dividing the result by two, we can accurately measure the runtime for various models under different circumstances

In summary, the proposed algorithm achieves significantly lower MAE values than the other two algorithms by emphasizing the user's interest and preference for recently accessed items and avoiding ignoring early relevant data information. Moreover, the algorithm demonstrates a relatively higher coverage rate due to the introduction of item attributes and the construction of an item-attribute matrix. However, selecting neighbor users can be inaccurate when the item rating matrix has a limited number of rows and columns, which can be addressed by a theoretical approach that takes into account the user's preference for item attributes and the search ranges of identified "neighbor" users to increase recommendation coverage and diversity. Finally, the runtime increases proportionally with the number of picturesque locations, which can be accurately measured for various models under different circumstances.

4.4 Real-life Case Validation

Finally, in the Scottish Road Trip Scenic Spot, run the intelligent tourist scenic route recommendation algorithm in this paper, and the recommended route is shown in **Fig. 6**.

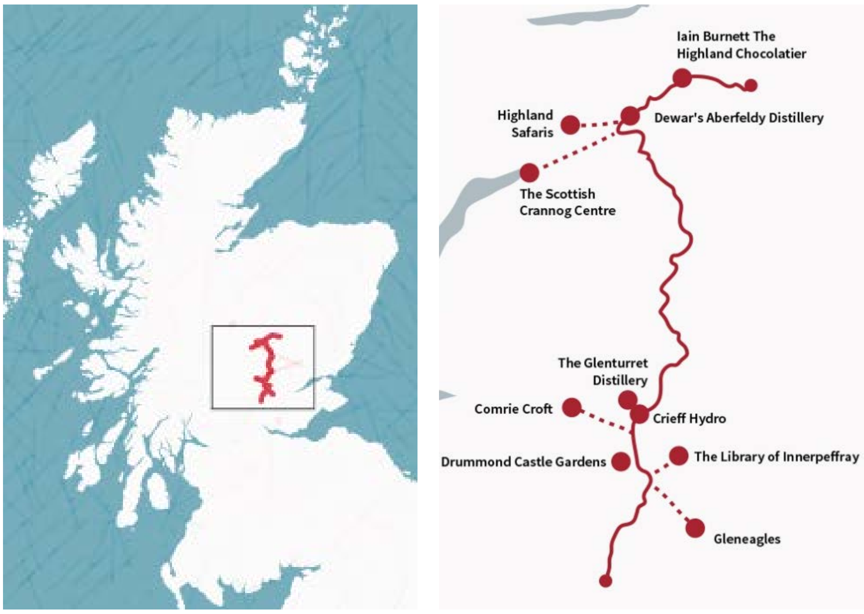

Fig. 6. Comparison of recommended routes in real scenic spots

5. Conclusion and Discussion

In this paper, we propose a collaborative filtering-based intelligent tourism scenic route recommendation method as a potential solution to address the issues of data sparsity, cold start, and low-precision similarities in user ratings. The findings of this study suggest that this method could be applied in the tourism industry. The construction of a new model for measuring user similarity using user interest classification attributes is a key aspect of this strategy. This model takes into account the shifting interests of users over their lifetimes. By utilizing this method, users can optimize their time spent at popular scenic spots while minimizing travel time, as opposed to traditional travel route recommendation methods. Research indicates that considering these variables can enhance user satisfaction with route planning, resulting in more appealing routes for tourists and reduced overall travel time. The proposed method offers additional benefits, including reducing data sparsity, improving nearest neighbor selection, and generating more accurate recommendations.

However, this paper has some limitations. It does not address how to effectively improve recommendation efficiency and reduce user waiting time. In future research, more advanced recommendation methods based on collaborative filtering should be explored. This could involve considering the correlation between users, optimizing path planning and recommendations for scenic spots, reducing the complexity of recommendation methods, and applying the proposed method to travel route recommendation.

Overall, this paper provides valuable insights into intelligent tourism route recommendation, but there is room for further improvement and exploration of more advanced techniques to enhance recommendation efficiency and user experience.

Data Availability

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

Conflicts of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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