An intelligent recommendation method of personalised tour route based on association rules

Yumei Jing

Henan Vocational College of Economics and Trade,
Zhengzhou, 450018, China
Email: yumeij@mls.sinanet.com

Abstract: In this paper, an intelligent recommendation method of personalised tourism routes based on association rules was proposed. Firstly, the membership matrix is constructed to mine tourist attractions, and the scope of tourist attractions is determined by attribute clustering. Secondly, the association rule algorithm is used to extract the features of scenic spots, tourists and tourist interest points to complete the personalised classification of tourist routes. Finally, the similarity of tourist routes is calculated by dynamic and static attributes, and the maximum probability scenic spots are output intelligently. The personalised recommendation method of tourist routes is optimised to realise personalised intelligent recommendation of tourist routes. The simulation results show that the proposed method has 98.5% accuracy, 97% recall rate and only 6s recommendation time. Therefore, the proposed method improves the performance of the intelligent recommendation method and has practicability.

Keywords: association rules; personalised recommendation; artificial intelligence; travel route selection.

Reference to this paper should be made as follows: Jing, Y. (2023) 'An intelligent recommendation method of personalised tour route based on association rules', *Int. J. Reasoning-based Intelligent Systems*, Vol. 15, No. 1, pp.22–28.

Biographical notes: Yumei Jing graduated from Shanxi University of Finance and Economics with a Master degree in Finance in 1993. Currently, she is an Associate Professor of Henan Institute of Economics and Trade. Her research interests are mainly on accounting and tourism economics.

1 Introduction

Due to the rapid development of the internet and multimedia technology, the amount of information in tourism is increasing (Bao, 2020; Liao and Nong, 2021; Huyan and Li, 2021). Due to the lack of effective information retrieval means, tourists spend a lot of time and energy looking for tourist routes before traveling. Therefore, personalised travel route recommendation is particularly important for tourists, it can effectively reduce the time and effort for tourists to find information in a large amount of data, and provide convenience for tourists to travel it. Personalised tourism route recommendation refers to recommending personalised tourism routes that are more suitable for tourists to improve their retrieval efficiency when searching tourism information based on tourists' information. In recent years, personalised tourism route recommendation has gradually become a hot topic, but most algorithms are based on tourists' evaluation of scenic spots and routes to screen 'similar users', to achieve the purpose of recommending tourist routes.

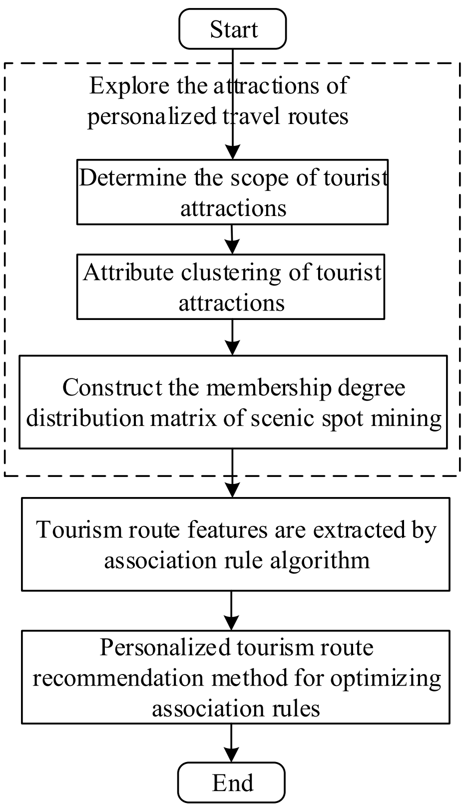
Ye et al. (2021) proposes a model based on implicit dirichlet distribution and short – and long-term user preferences of personalised travel recommendations, the method using LDA subject model for scenic spot features information, mining sites, the correlation between reuse attention mechanism and short – and long-term memory network respectively study the user's preferences and short-term preference for a long time, Finally, the dynamic changes of user preferences are captured by combining long-term and short-term preferences to realise personalised tourism route recommendation. However, the method does not divide the scenic spots' popularity on the time latitude, which leads to the lack of time information constraint of some tourist routes, which reduces the recommendation accuracy and is difficult to meet the personalised needs of users. Liao (2020) puts forward a personalised route recommendation method based on the graphic information of travel notes. Through the analysis of tourists' historical travel footprints, according to the frequency and co-occurrence of scenic spots in the footprints, and the number of photos taken by each scenic spot, the popularity of scenic spots and the interest preference of various types of tourists are analysed, and combined with the given starting and ending points or passing points, the generation method of optimal travel routes is designed, and the optimal personalised travel routes are recommended. However, when building interest model, this method lacks the integration of time correlation factors of users' visits to scenic spots, and the recommendation results are mostly random combinations of popular scenic spots, which cannot provide personalised route recommendation to the maximum extent.

Combined with the above research results on personalised tourism route recommendation methods, aiming at the shortcomings of personalised recommendation methods, this paper proposes an intelligent recommendation method for personalised tourism routes based on association rules. In this method, the range of tourist attractions is determined by attribute clustering. On this basis, the association rule algorithm is adopted to extract the features of tourist attractions, tourists and tourist points of interest, and the similarity of tourist routes is calculated by combining the similarity calculation method of dynamic and static attributes to realise personalised tourism route recommendation. In order to improve the efficiency and accuracy of personalised tourism route recommendation, and contribute to the development of tourism.

2 Design personalised travel route intelligent recommendation method

In view of the limitations of the intelligent recommendation method for personalised tourism routes and to improve the recommendation accuracy, this paper applies the association rule algorithm to optimise the recommendation method based on this and in combination with other algorithms. The flow chart of personalised intelligent recommendation method of tourism routes based on association rules designed in this paper is shown in Figure 1.

Figure 1 Flow chart of personalised intelligent recommendation method for tourism routes based on association rules



According to Figure 1, the personalised recommendation method of association rules designed in this paper mainly involves three steps, namely, mining scenic spots in personalised tourism routes, extracting characteristics of tourism routes through association rules algorithm, and optimising the recommendation method of personalised tourism routes based on association rules. Mining the scenic spots in personalised tourist routes includes determining the scope of scenic spots, clustering the attributes of scenic spots, and constructing the membership distribution matrix of scenic spots mining.

2.1 Explore the attractions of personalised travel routes

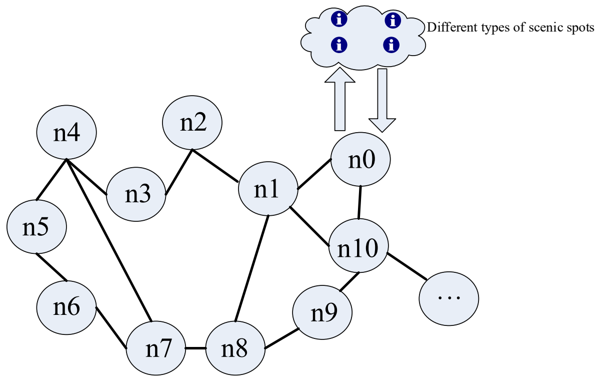
Accurate and effective recommendation of tourist attractions is one of the key points of algorithm research, which can provide effective key feature points for route recommendation. The membership matrix can directly reflect the distribution, number and types of tourist attractions. Therefore, this paper realises the effective mining of tourist attractions by constructing the membership matrix. Firstly, the scope of tourist attractions is determined, and the specific contents are as follows.

For a tourist who has already decided on a destination, it is necessary to first identify the surrounding tourist attractions and understand the scope of the attractions in order to accurately plan the route. Suppose the tourist attractions are classified into J types, including natural scenic spots, green space parks, theme parks, ethnic monuments and famous museums, etc. and a specific tourist attraction is set as J_k, and there are altogether m tourist attractions, the scope of tourist attractions is as follows:

$$J = \{j_{11}, j_{12}, \cdots j_{1k}, j_{m2}, j_{m3}, \cdots j_{mk}\} \tag{1}$$

Among them, j_{mk} refers to the krd specific tourist attraction among m tourist attractions. Figure 2 shows the construction of a tourist attractions chain distribution map.

Figure 2 Map of chain distribution of tourist attractions (see online version for colours)



By analysing the distribution range set of tourist attractions, the transformation relation of target characteristic data of tourist attractions is obtained as follows:

$$A = \frac{1}{J}\sum_{k=1}^{m}(u_k \times J_k) \quad (2)$$

Among them, u_k shows the heat coefficient of scenic spot. Therefore, the quantitative characteristics of the target scenic spots in the intelligent recommendation of personalised tourism routes are as follows:

$$B = A\frac{m}{C}(l, x) + \frac{1}{J} \times \frac{m}{b(J, x)} \quad (3)$$

Among them, $C(l, x)$ refers to a set of normalised orthogonal bases of all tourist attractions; $b(J, x)$ represents the linear threshold model, then, the entropy feature quantity of tourist attractions is obtained as:

$$S = B / C(l, x) + w \quad (4)$$

Among them, w represents the threshold value, its role is to configure tourist attractions. Quantification of the tourist attractions of the entropy (Chen and Wang, 2021), the quantitative characteristics of the solution:

$$Z = J_k S + \Delta x_k \quad (5)$$

Δx_k is the iterative step in scenic spot mining.

Select the tourism quantitative data with the highest fitness as the mining training set, which is:

$$H = Z\sum_{k=1}^{m} J_k \quad (6)$$

Suppose any two tourist attractions are represented by J_k and J_{k+1}, and V_E represents E cluster areas, then the distance between any two tourist attractions is obtained as:

$$d(J_k, J_{k+1}) = \sqrt{\sum_{k=1}^{m} V_E (J_{k+1} - J_k)^2} \quad (7)$$

Among them, $d(J_k, J_{k+1})$ represents the distance between two scenic spots of J_k and J_{k+1}, and determines the centroid of the cluster as follows:

$$R_k = d(J_k, J_{k+1})\exp\left(\frac{V_E}{\varepsilon}\right) \Big/ \varphi(k) \quad (8)$$

Among them, ε represents equilibrium configuration coefficient; φ(k) represents variable transfer coefficient. By analysing the differences among different tourist attractions, the clustering results of tourist attractions are as follows:

$$F = \ln \varphi(k)\sum_{k=1}^{m} R_k \quad (9)$$

Based on the cluster of tourist attractions, if the best tourist route is searched, it can be determined that the membership degree of the cluster centre Y and the affiliated tourist attractions of the same type is 1, and the membership degree of the affiliated tourist attractions of different types is 0. At this point, the membership distribution function is constructed based on the result that the membership degree of all tourist attractions is worth achieving (Anand et al., 2020).

Assuming that σ_k represents the distribution state of the affiliated tourist attractions, the subordination distribution matrix is constructed as shown in equation (8). In the matrix, row elements represent the number and type of different tourist attractions, and column elements represent the subordinate value of the tourist attractions, and the tourist attractions can be classified and counted according to the subordinate value (Mariotte et al., 2021). The maximum number of columns in the matrix is k. If the number of tourist attractions under a certain type of tourist attractions is 0, the matrix element is also 0.

$$\sigma_k = Y\begin{pmatrix} \sigma_{11} & \cdots & \sigma_{1k} \\ \vdots & \ddots & \vdots \\ \sigma_{m1} & \cdots & \sigma_{mk} \end{pmatrix} \quad (10)$$

So far, the construction of the membership distribution matrix of tourist attractions has been realised, the type and quantity of tourist attractions can be mined, which provides the basis for personalised recommendation of tourist attractions and increases the intelligence of recommendation results.

2.2 Feature extraction of scenic spots and tourists by association rule algorithm

In association rule algorithm (Liu et al., 2020), there are mainly two important indicators, namely, support and confidence, which are specifically defined as:

1 Degree of support: The degree of support refers to the Number of items contained in a given set of items in a specific target database, while the ratio of the number of items in a given set of items to the number of items in the target database is called conditional probability, and the degree of support count can reflect the frequency of a given set of items to a certain extent. Assuming that the support degree of a given itemset x is $\gamma(x) = [\rho_1, \rho_k]$ under the condition of rule $x_1 \rightarrow y_1$, the support degree can express the probability of x_1 appearing in the whole target database as a subsequent occurrence of y_1.

2 Confidence: confidence refers to the conditional probability that a y_1 occurs to a certain target in the process of carrying out a certain task in the target database, including the x_1 of a certain project. That is, the probability of the occurrence of x_1, y_1 in a target database can be tested by using the index of trust, that is, also indicates the frequency of x_1, y_1 occurrences. The concrete association rules are as follows: Suppose under the condition of $x_1 \rightarrow y_1$ rule, $x_1 \in I$, $y_1 \in I$, $x_1 \cap y_1 = \varphi$, the trust means the number of occurrences of x_1 as first occurrence followed by y_1 divided by the number of occurrences of x_1.

In association rules, frequent set is also a special term of association rule algorithm. It refers to the itemset at this time when the support of association rules is not less than the set support threshold, the itemset at this time is called frequent set. If the support is less than the support threshold, the itemset at this time is not frequent set (Balakrishna et al., 2021). Apriori algorithm (Wang and Gao, 2021) is the most classical method to study association rules, and this paper is based on the improved Apriori algorithm to achieve the association rule algorithm. Based on the clustering and mining of the attributes of tourist attractions in Chapter 2.1, the specific characteristics of tourist routes are extracted. This paper divides the characteristics of tourist routes into tourist attractions and tourists. According to this feature, the interest points of passengers are calculated. Specific methods are as follows:

2.2.1 Extracting features of scenic spots

When matching tourists and tourist routes, it is necessary to master the characteristics of both. Therefore, features of scenic spots should be extracted. Build a collection of information on tourist attractions (Babkov et al., 2020), including the evaluation of existing tourists on different attractions, software and hardware of attractions, popularity, scope of attractions, etc. and all the information on attractions constitutes a collection of information D, which may be represented as:

$$D=\{d_1,d_2,\cdots,d_i,\cdots,d_n\} \tag{11}$$

Among them, d_i represents the ith information value in information set D. Thus, the characteristics of a tourist attraction can be expressed as the distribution probability of the information of the tourist attraction:

$$P_L=\left(P_{L1},P_{L2},\cdots,P_{Li}\right) \tag{12}$$

$$P_{Li}=\begin{cases}\varphi d_i,\, if\;\; d_i\in k\\ 0,\;\; if\;\; d_i\notin k\end{cases} \tag{13}$$

Among them, P_L represents the features of attractions; P_{Li} represents the features of attractions of the i value; φ_{di} represents the information of attractions variable transfer value. Therefore, the features of the scenic spots are extracted effectively.

2.2.2 Extracting tourist characteristics

After the completion of feature extraction of scenic spots, tourist features are extracted, collect the historical scenic spot records of tourists and make statistics. If the user has visited a certain scenic spot, the default user is interested in the scenic spot, that is, there is a certain preference (Adigraha and Juanda, 2019). At the same time, the number of trips made by users to scenic spots of the same type is counted, and the user's historical scenic spot records are obtained by clustering according to the passenger information. During this process, passenger information is kept confidential. After obtaining the passenger information, the characteristics of each historical scenic spot visited by the passenger are summed and processed, which are used as the characteristics of the passenger to obtain the extraction results. The specific expression is as follows:

$$P_y=\sum\nolimits_{L=1}^{n}P_L \tag{14}$$

Among them, P_y represents passenger characteristic.

Based on the feature extraction of tourist attractions and tourists, feature extraction of tourist interest points is beneficial to understand the tourist interest points, so as to realise personalised recommendation of tourist routes. Based on the historical records of tourists' sightseeing in scenic spots in Section 3.2.2, the interest points of tourists are modelled, and the similarity between tourist features and tourist features can be used as the result of preference calculation. The following may be derived:

$$P\left(L|\; U_k\right)=sim\left(P_L,P_y\right) \tag{15}$$

Among them, U_k represents the history of visitors to visit the attractions recorded.

Feature extraction based on this, to complete the research object, but the association rules recommendation methods only consider the tourists point of interest can not accurate recommendation tourist routes, there might be recommended to the problem of low accuracy, therefore, in order to realise precise intelligent recommendation tourist route, need to travel through the calculation of dynamic and static properties of similarity, thus acquiring probability of scenic spots, to optimise the recommended method, Implement intelligent recommendation.

2.3 Optimisation of recommended methods

In order to improve the accuracy of the recommended method and intelligent degree, calculating the similarity between the tourists and attractions, scenic spots and tourist will depth matching, namely the tourist route similarity, grounding probability of similarity for scenic spots, according to the probability of high to low order tourist attractions, and output in order to arrange the front of the scenic spots. Firstly, the similarity calculation method based on static attributes is used to calculate the similarity of tourist routes. However, because of the dynamic change of tourists' preferences under static attributes (Zhou et al., 2020), the similarity results obtained based on static attributes need to be dynamically adjusted. Therefore, this paper uses static attributes to preliminarily calculate the similarity of tourist routes, and uses dynamic attributes to optimise the similarity calculation. Finally, the method of outputting scenic spots with high probability is adopted to realise intelligent recommendation of tourist routes.

2.3.1 Similarity calculation for dynamic and static attributes

2.3.1.1 Similarity of static attributes is preliminarily calculated

When a travel route is provided in the database for selection, because it belongs to a new travel recommendation route and lacks access records, the specific recommendation of the relevant association rules cannot be completed. Therefore, when a traveller or a user in need browses the travel route, through the method of recommending similar travel routes, the intelligent recommendation of travel routes is realised. In this case, the new itinerary is required to have the same label as the similar itinerary (Ls and Em, 2020), which can be used as a similarity or similarity between the two itineraries if the type of attraction to which the itinerary belongs, the size of the scenic spot, the city where the itinerary is located, etc. At this time, the calculation based on the static attribute is the ratio of the two routes containing the same label to occupy all the labels contained in the two routes, and the preliminary calculation result of the static-based similarity is:

$$sim(d_m, d_n) = \frac{Tags(d_m) \cap Tags(d_n)}{Tags(d_m) \cup Tags(d_n)} \tag{16}$$

Among them, d_m, d_n represents two travel routes to be recommended.

2.3.1.2 Dynamic attribute calculation of similarity

Due to the dynamic nature of the preferences of tourists, and the small applicability of similarity calculation under static attributes, it is generally only suitable for a small number of tourists to select travel routes. Therefore, this paper optimises the similarity calculation method through dynamic attributes, mainly by means of cosine similarity. The specific expression is shown as follows:

$$sim(d_m, d_n))' = sim(d_m, d_n) \\ \frac{\sum_{k=1}^{m} R_k \left(M_{i,k} - w_{k,m}\right)\left(M_{j,k} - w_{k,n}\right)}{\sqrt{\sum_{k=1}^{m} R_k \left(M_{i,k} - w_{k,m}\right)^2 \left(M_{j,k} - w_{k,n}\right)^2}} \tag{17}$$

Among them, $sim(d_m, d_n)'$ represents the result of similarity optimisation based on dynamic attributes; $M_{i,k}$ and $M_{j,k}$ represent the interest of i and j respectively, and $w_{k,\mathrm{m}}$ and $w_{k,n}$ represent the average interest of the travellers respectively.

2.3.2 Intelligent recommendation

In association rules, the main task of implementing personalised intelligent recommendation of travel route is to find out all the travel routes whose support is greater than or equal to the minimum support threshold from the information set D of all the tourist attractions, and the trust of the travel route must be greater than or equal to the minimum trust threshold. Therefore, when intelligently recommending travel routes through association rules, the support and trust degrees of each travel route are calculated one by one and judged. Because of the high complexity and high cost of this method, under the support of the improved Apriori algorithm in association rules, after the similarity results of the tourist routes are obtained, comprehensively consider the similarity between tourist routes, and consider the interest points of tourists or target users in tourist attractions, determine the probability of tourists or target users visiting a certain scenic spot, and personalised intelligent recommendation of tourist routes can be realised by selecting tourist attractions with the maximum probability and output display, namely, intelligent recommendation of scenic spots with the maximum probability. The specific expression is as follows:

$$P(L_t L_{t-1}, h_k) = sim(d_m, d_n)' \times \frac{P(L_t | h_k)}{P(L_t)} \tag{18}$$

Among them, L_t and L_{t-1} represent a tourist attraction visited under t and t–1 time condition respectively; h_k indicates the preference degree of a tourist or target user to a certain scenic spot.

3 Simulation experiment verification

3.1 Experimental protocol and data

Taking Kunming, Yunnan Province as an example, 30 typical tourist attractions were selected as the experimental tourist attractions. All selected tourist attractions must meet the following conditions: First, all tourist attractions are located in Kunming City, that is, visitors can take buses, subways, taxis and other urban transportation to any tourist attractions, excluding the urban transport inaccessible tourist attractions in suburban counties. Second, the thermal index of tourist attractions can be checked, with a certain tourism value and visit value. Third, the locations of scenic spots are independent of each other, even if they belong to the same category of tourist attractions, the tourist experience obtained by tourists in one scenic spot does not affect the tourist experience in another scenic spot. Under the condition of comprehensive consideration of all conditions, the algorithm constructed in this paper is used to extract tourism big data and mine interest information. Obtain basic data for experiments from services such as AutoNavi Map Service, Baidu Map Service, Mafengwo travel network, and tourist attraction information service. The experiment scheme is randomly selected from five to five people on the basis of the historical browsing history, combined with the set of tourist attractions, recommended method is applied to intelligent recommendation tourist routes, and according to the review of the limitations of the recommendations, set up the experimental performance indicators, the indicators are the recommendation accuracy and recall rate, time consuming, expectations set respectively for 93%, 95%, and 6s, experiments were conducted in the form of comparative real analysis to verify the performance of the recommended methods in this paper. The comparative methods were the recommended methods in Ye et al. (2021) and Liao (2020) respectively.

3.2 Experimental performance indicators

In order to verify the feasibility and effectiveness of the method recommended in this paper, choose the accuracy and recall rate of personalised lines recommended as experiment performance indicators, time-consuming, recommendation accuracy refers to the number of hot spot location by the user orientation of recommended circuit and the percentage of the number of hot spot location in recommended circuit, the recall rate refers to the tourist information retrieval in the prescriptive time data, time consuming refers to the time to recommend the best personalised travel route, the selected performance indexes can effectively reflect the recommendation accuracy of the recommendation method, etc. and its calculation formula is shown as follows.

The recommended accuracy is the ratio of the number of hot spot locations accessed by users in the recommended line to the number of hot spot locations in the recommended line. The formula is as follows:

$$precision = \frac{|V_{rgt}|}{|V_r|} \tag{19}$$

Among them, $|V_{rgt}|$ represents the number of hot spots accessed by users in the line recommended in this paper; $|V_r|$ represents the number of hotspot locations in the line recommended in this document.

The recommended recall rate is the ratio of the number of hot spots visited by users in the recommended route to the number of scenic spots actually visited by users. The formula is as follows:

$$recall = \frac{|V_{rgt}|}{|V_{gt}|} \tag{20}$$

Among them, 1 represents the number of scenic spots actually visited by the user.

Recommended time Use the software delivered with the PC to calculate the time.

The higher the accuracy and recall rate of the experimental performance index, the better the recommendation effect of the method, and the shorter the time, the better the recommendation effect of the method.

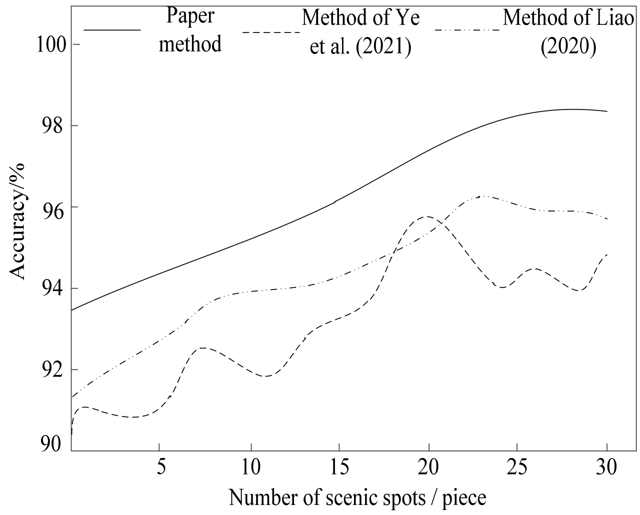
3.3 *Analysis of performance indicators*

3.3.1 *Accuracy analysis*

The efficiency and accuracy of recommendation are especially important for route recommendation, and accuracy is taken as the standard to measure recommendation effect in this paper. The accuracy analysis results of three different methods are shown in Figure 3.

According to Figure 2, with the increase of the number of attractions, the accuracy of this method is stable, and tends to be stable in 25 attractions, the accuracy rate is 98.5%, and the fluctuation range is small, which is obviously higher than the Ye et al. (2021) method and the Liao (2020) method. This is because this method uses the improved Apriori algorithm of association rules to optimise the similarity of dynamic attributes and improve the accuracy of personalised route recommendation.

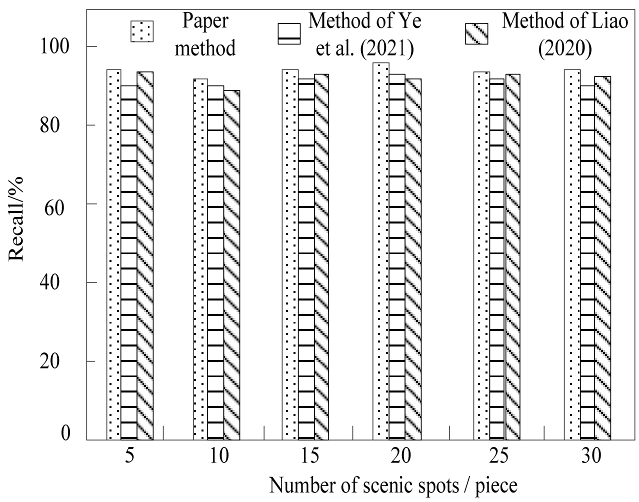
Figure 3 Results of accuracy of personalised itinerary recommendation



3.3.2 *Recall rate analysis*

In order to better verify the recommendation effect of the recommendation algorithm in this paper, recall rate was calculated. The superiority of this method was verified by comparing the recall rate of the method in this paper with the method in Ye et al. (2021) and the method in Liao (2020). The results are shown in Figure 4.

Figure 4 Results of personalised route recommendation recall rate



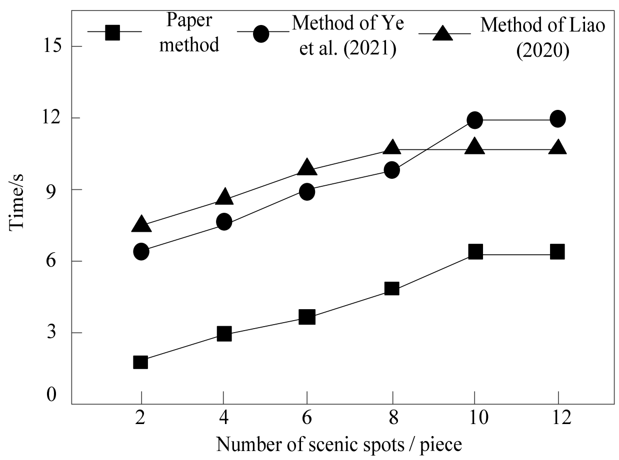
According to Figure 4, the paper travel recommendations recall rate reached 97%, and the method of Ye et al. (2021) the recall rate is only 91%, the method of Liao (2020) the recall rate is only 94%, so the method effectively improves the recall rate, the reason is due to the method, this paper builds distribution of membership degree matrix, mining the type of tourist attractions and the number of parameters, And take this as the follow-up personalised tourism route recommendation basis.

3.3.3 Time-consuming analysis

Randomly select 12 attractions in Kunming, Yunnan Province, personalised tourist route recommendation information data as time-consuming analysis data, the results as shown in Figure 5.

According to the Figure 5 shows that the method recommended 12 scenic spots of personalised travel only takes 6s, the method of Ye et al. (2021) and the method of Liao (2020) take 10s and 12s respectively, compared with the literature method, this method reduces the 4 s and 6 s respectively, as a result, the efficiency of the method are significantly higher than the other two methods, has strong applicability, The reason for reducing the time consumption is that the method in this paper extracts the features of scenic spots, tourists and tourists' points of interest, so as to reduce the time consumption of personalised recommendation of tourist routes.

Figure 5 Results of time taken for personalised tour recommendation



4 Conclusions

Personalised travel route recommendation can facilitate the travel of tourists and reduce the preparation time and energy of travel. After mining the tourist attractions, this paper introduces the association rule algorithm to extract the characteristics of tourist routes and optimise the algorithm with dynamic and static attributes to make it more intelligent and realise personalised intelligent recommendation of tourist routes. The experiment result shows that the method of personalised travel recommendations of accuracy reached 98.5%, the recall rate reached 97%, and recommend to take only 6 s, its performance has improved, therefore, show that the method has strong application value, can be recommended for the future of personalised travel intelligence system design to provide theoretical support.

References

Adigraha, E.M. and Juanda (2019) 'Influence of information technology in attracting tourist interest', *IOP Conference Series: Materials Science and Engineering*, Vol. 662, No. 2, p.22074.

Anand, A., George, V., Kanthi, R., Tagore, M. and Padmashree, M.S. (2020) 'Basics on categorizing travel-time-based degrees of satisfaction using triangular fuzzy-membership functions', *Transportation Research Procedia*, Vol. 48, No. 3, pp.1555–1574.

Babkov, D., Kuznetsova, D. and Surkova, N. (2020) 'Individual tourism information support in the regions of Russia', *E3S Web of Conferences*, Vol. 208, p.5010.

Balakrishna, E., Rama, B. and Satyavathi, N. (2021) 'Mining of negative association rules using correlate frequent pattern tree', *Materials Today: Proceedings*, Vol. 13, No. 6, p.597.

Bao, C. (2020) 'FPGA processor and visual keyword matching to optimize feature recognition of tourism resources', *Microprocessors and Microsystems*, Vol. 80, No. 4, p.103624.

Chen, T. and Wang, Y.C. (2021) 'A calibrated piecewise-linear FGM approach for travel destination recommendation during the COVID-19 pandemic', *Applied Soft Computing*, Vol. 109, No. 3, p.107535.

Huyan, W. and Li, J. (2021) 'Research on rural tourism service intellectualization based on neural network algorithm and optimal classification decision function', *Journal of Ambient Intelligence and Humanized Computing*, Vol. 23, No. 99, pp.1–21.

Liao, C. and Nong, L. (2021) 'Smart city sports tourism integration based on 5G network and internet of things', *Microprocessors and Microsystems*, Vol. 8, No. 6, p.103971.

Liao, W.S. (2020) Application of personalized trip recommendation based on travelogues' text and pictures', *Computer Applications and Software*, Vol. 37, No. 6, pp.108–113.

Liu, Y., Hu, X., Luo, X., Zhou, Y., Wang, D. and Farah, S. (2020) 'Identifying the most significant input parameters for predicting district heating load using an association rule algorithm', *Journal of Cleaner Production*, Vol. 275, No. 12, p.122984.

Ls, A. and Em, A. (2020) 'Extensions of the tourist travel design problem for different travel styles', *Procedia Computer Science*, Vol. 176, No. 41, pp.339–348.

Mariotte, G., Leclercq, L., Gonzalez, R.H., Krug, J. and Bécarie, C. (2021) 'Assessing traveler compliance with the social optimum: a stated preference study', *Travel Behaviour and Society*, Vol. 23, No. 1, pp.177–191.

Wang, H.B. and Gao, Y.J. (2021) 'Research on parallelization of Apriori algorithm in association rule mining – ScienceDirect', *Procedia Computer Science*, Vol. 183, No. 29, pp.641–647.

Ye, F., Sun, Y., Chen, C.C. and Yu, D.Y. (2021) 'A personalized attraction recommendation method based on geotagged photos', *Journal of Geo-Information Science*, Vol. 23, No. 8, pp.1391–1400.

Zhou, X., Sun, B., Li, S. and Liu, S. (2020) 'Tour route planning algorithm based on precise interested tourist sight data mining', *IEEE Access*, Vol. 52, No. 99, p.1.