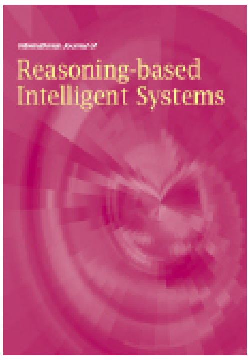

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Personalised leisure tourism route recommendation method based on knowledge map

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Abstract: In order to improve the efficiency of tourism route recommendation, this paper introduces knowledge map and designs a personalised leisure tourism route recommendation method based on knowledge map. Firstly, we build a leisure tourism route knowledge map, generate a tourism route database through tourism notes, and then we search the candidate tourism route sequence in the database. Finally, based on the comprehensive analysis of the attributes of tourists, such as travel time and user category, we determine the score of candidate tourism routes according to the value of tourist attractions, user category, and user preference, and take the three routes with the highest score as the recommendation result. The experimental results show that this method can complete the recommendation of tourist routes in about 10 s, and can significantly increase the number of tourists in the scenic spot, with an average increase of nearly 10%, which has certain application value.

Keywords: knowledge map; personalisation; leisure tourism; route recommendation; data mining; user preference.

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1 Introduction

As the demand for national tourism has been greatly increased, the information related to tourism has also increased in a massive way (Li et al., 2021), which leads to tourists wasting a lot of time and energy when making tourism routes (Liao, 2020). Designing unreasonable tourism routes will make tourists has an unfavourable travel experience, and will also affect the development of tourism. In addition, the number of tourist attractions increases greatly nowadays, so studying an effective recommendation method to recommend tourism routes to users that meet their actual needs has become a research hotspot of relevant enterprises and departments in the tourism industry (Lai et al., 2019). At the current stage, some scholars have carried out research on this. For example, Zhou et al. (2020) used the mining algorithm to mine tourist attractions that are close to tourists' interests to the maximum extent. On this basis, they combined geographic information elements and traffic information elements as model inputs in the nerve cell model of multiple traffic modes, and finally got route recommendation results. This method does not consider the user's preference, so the recommendation results lack pertinence. Li et al. (2019) used the stratified sampling statistical model to obtain users' preferences for different group attributes, and generated a new recommendation list named LA in turn by fitting users' preferences. The user preference simulation performance of this method is poor, so the final recommendation result is not accurate. Chen et al. (2021b) used the collaborative filtering algorithm to predict users' preferences, on which they built positive and negative user profiles, thus achieving the purpose of recommendation. This method has poor performance in processing tourism data.

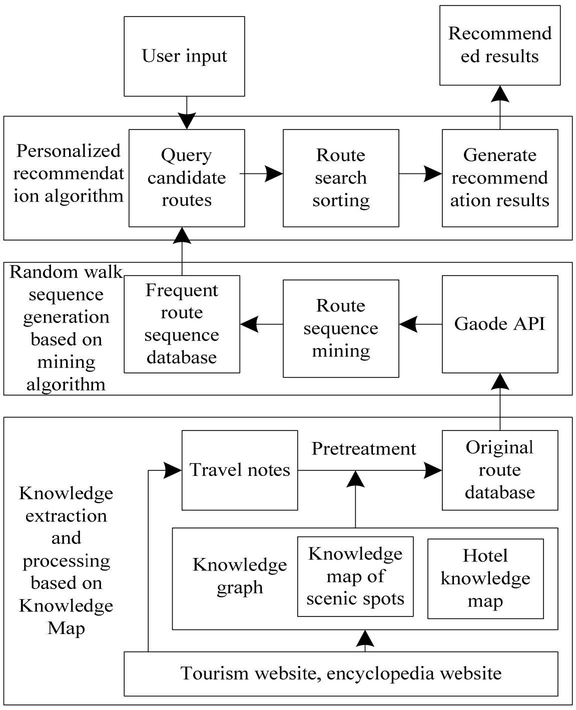
Although the above research can achieve tourism route recommendation with high accuracy, the processing speed of relevant data is low; resulting in the recommendation process needs a lot of time. In order to provide personalised leisure tourism route recommendation to tourists in time, it is necessary to design a new tourism route recommendation method. Knowledge map is a series of different graphs that reflect the relationship between knowledge development process and knowledge structure. Visualisation technology is used to describe knowledge resources and their carriers, mine, analyse, construct, draw, display knowledge and their relationships, and has strong analysis ability. In order to improve the efficiency of travel path recommendation, this paper introduces knowledge map into this field, and proposes a personalised leisure travel path recommendation method based on knowledge map. Firstly, the knowledge map of leisure tourism routes is constructed, and on this basis, the tourism route database is generated through tourism notes; then searches the candidate tourist route sequence in the database. Finally, based on the comprehensive analysis of the attributes of tourists such as travel time and user category, the scores of candidate tourist routes are determined according to the value of tourist attractions and user category preferences, and the three routes with the highest scores are taken as the recommendation results, in order to help improve the efficiency of tourist route recommendation.

2 Personalised leisure tourism route recommendation method

2.1 Structure design of the personalised leisure tourism route recommendation method

On the whole, the recommendation method is divided into three main parts, namely, tourism knowledge extraction and processing based on knowledge map, arbitrary tour sequence generation based on mining algorithm and personalised recommendation. Figure 1 shows the overall structure of the method.

Figure 1 Overall structure of personalised leisure tourism route recommendation method based on knowledge map



In order to improve the efficiency for users to obtain tourism information in the process of formulating leisure tourism planning, tourism websites and related structured knowledge bases are used to collect tourism related knowledge and build leisure tourism route knowledge map. On this basis, the leisure tourism route database is generated based on the tourism data, and the frequent path sequence patterns are obtained through the mining algorithm. According to the user input preferences and conditions, personalised recommendation algorithm is used to quickly get personalised leisure travel route recommendation results.

2.2 Tourism knowledge extraction and processing based on knowledge map

The extraction and processing of tourism knowledge based on knowledge map is to collect the relevant knowledge in the tourism field from the tourism website and related structured knowledge base, construct the knowledge map of leisure tourism routes, extract travel notes from the tourism website and related structured knowledge base, and construct the original tourism route database.

The construction level of knowledge map in the field of leisure tourism routes directly affects the quality of personalised leisure tourism route recommendation results (Malik and Kim, 2019). Therefore, it is necessary to collect relevant data in tourism websites, and analyse the collected data through big data technology to determine that it meets the standard of knowledge map construction. On this basis, the collected tourism related data is analysed with the current existing data (Qu et al., 2019), and the data that meets the threshold standard is defined as valid data and stored in the original route database.

Figure 2 shows the construction process of knowledge map in the field of leisure tourism routes. The construction process of knowledge map in the field of leisure routes can be roughly divided into four links:

1 Data acquisition

The main function of this link is to collect relevant data of scenic spots from various websites, and realise noise elimination through the pre-processing process in the data crawling process (Kim et al., 2021). On this basis, based on the differences of data types (structured, semi-structured and unstructured), the collected data are stored and processed.

2 Data extraction

The main function of this link is to use the data extraction model to extract different data needed to construct the knowledge map of leisure tourism routes from all kinds of collected data (Guo et al., 2020a).

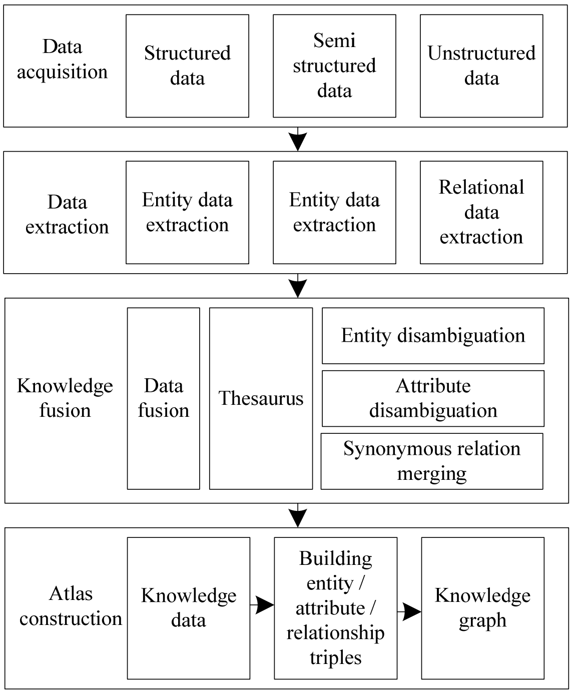
3 Knowledge integration

The main function of this link is to use thesaurus to fuse the extracted data and in this process, to eliminate the ambiguity of entities/attributes and merge the synonymous relations (Shi, 2021).

4 Map construction

The main function of this link is to use the fused data to generate entity/attribute/relationship triples, thus finally completing the construction of knowledge map in the field of leisure tourism routes.

Figure 2 Construction process of knowledge map in leisure tourism route field



2.3 *Frequent route sequence of leisure tourism routes based on the mining algorithm*

The frequent route sequence of leisure tourism routes based on the mining algorithm is the process of acquiring frequent route sequence patterns by the mining algorithm in leisure tourism route database (Cheng, 2021). It is specifically described as follows:

e and $S = \{e_1, e_2, \cdots, e_m\}$ are adopted to represent a given source tourist attraction and an arbitrary tour with a sequence of length of L (e_i is the i^{th} tourist attraction in any tour) respectively. $e_0 = e$ represents the initial tourist attraction of the tour process, which can be determined by formula (1):

$$P\left(e_i = x \middle| e_{i-1}\right) = \begin{cases} \dfrac{\pi_{ex}}{H}, & (e, x) \in W \\ 0, & \text{Others} \end{cases} \tag{1}$$

where π_{ex} and H respectively represent the transfer probability and regularisation parameter between tourist attraction e and tourist attraction x, and W represents the set of the inner edges of the knowledge map in the field of leisure tourism routes. The formula (2) can be used to determine π_{ex}:

$$\pi_{ex} = \left(\lambda_{pq}(t, x) \times \beta\right) \times w_{vx} \tag{2}$$

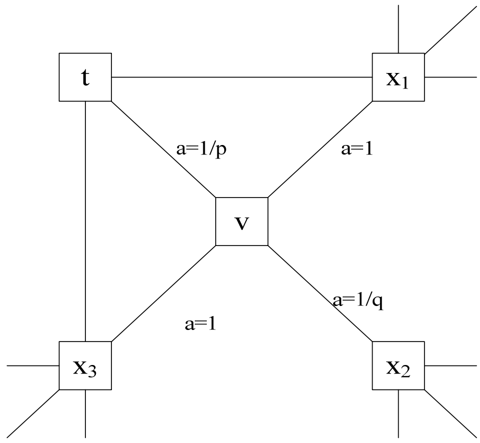
where $\lambda_{pq}(t, x)$ and β represent deviation and deviation correction coefficients on the inside of the knowledge map, wherein, p and q are both parameters for controlling sightseeing; w_{ex} indicates the weight of the edge between tourist attractions. Formula (3) can be used to describe $\lambda_{pq}(t, x)$:

$$\lambda_{pq}(t, x) = \begin{cases} \dfrac{1}{p}, & z_{tx} = 0 \\ 1, & z_{tx} = 1 \\ \dfrac{1}{pq}, & z_{tx} = 2 \end{cases} \tag{3}$$

where $z_{tx} = \{0, 1, 2\}$ represents the shortest path between tourist attractions t and x.

Figure 3 shows an example of arbitrary tour.

Figure 3 Example diagram of arbitrary motion



The parameter p can realise the probability control of returning to the visited tourist attractions immediately during the tour (Chen et al., 2021a). Under the condition of $p < \max(q, 1)$, the position of the subsequently sampled tourist attractions will remain near the last visited tourist attraction t.

Through the parameter q, we can realise the control of the tour mode of tourist attractions. When q is greater than 1 and less than 1, the arbitrary tour process tends to breadth-first search and breadth-first search respectively, and achieves structural consistency and similarity among tourist attractions respectively.

2.4 *Implementation of personalised tourism route recommendation algorithm*

In the process of recommending leisure tourism routes, it is necessary to analyse the attributes of tourists including travel time, user categories and personal preferences as a whole (Guo et al., 2020b). Therefore, before searching for leisure tourism routes, users are required to input information such as travel time, user categories and personal preferences in the personalised recommendation process. At the same time, in order to obtain better route recommendation results, the leisure tourism route personalised recommendation algorithm not only considers the rating of tourist attractions, but also determines the overall rating of tourist attractions by integrating the value of tourist attractions and users category preference (Ahmad et al., 2020).

With g_i and $s_c(g_i)$ as scenic spot and scenic spot score, respectively, the calculation formula of $s_c(g_i)$ is as follows:

$$s_c(g_i) = p_r(g_i) + p_v(g_i) + Int(a, yg_i) \tag{4}$$

where $p_r(g_i)$ represents the score of g_i; $p_v(g_i)$ and $Int(u, cp_i)$ represent the value of g_i and the interest of user a to the type of g_i, y, respectively. If there are tourist preference types in tourist attractions, then the value is 1; otherwise, the value is 0.

Formula (5) can be used to obtain $p_v(g_i)$:

$$p_v(g_i) = \frac{T_v(g_i)}{T_v(g_i, g_{i-1}) + T_v(g_i, g_{i+1})} \tag{5}$$

where $T_v(g_i)$ indicates the visiting time of g_i, and g_{i-1} and g_{i+1} represent the previous scenic spot and the next scenic spot in the tourism route g_i, respectively.

Therefore, l_i is adopted to represent the tourism route. The final score of r_i that can be obtained by formula (6) is:

$$s_c(l_i) = \frac{\sum_{j=1}^{n} s_c(g_j)}{n} \tag{6}$$

where n represents the number of tourist attractions in l_i.

In the process of personalised leisure tourism route recommendation, the three routes with the highest scores are taken as the final recommendation results.

3 Experimental results

In order to verify the tourism route recommendation efficiency of the method designed in this paper, this paper takes a popular tourism website as the application object for experiments, and the experimental results are as follows.

3.1 Knowledge map construction

A total of 23,296 pieces of tourism information of tourist attractions in Dalian were extracted from popular tourism websites, including entity/attribute/relationship ternary information. This information is used to build a knowledge map in the field of urban leisure tourism, as shown in Figure 4.

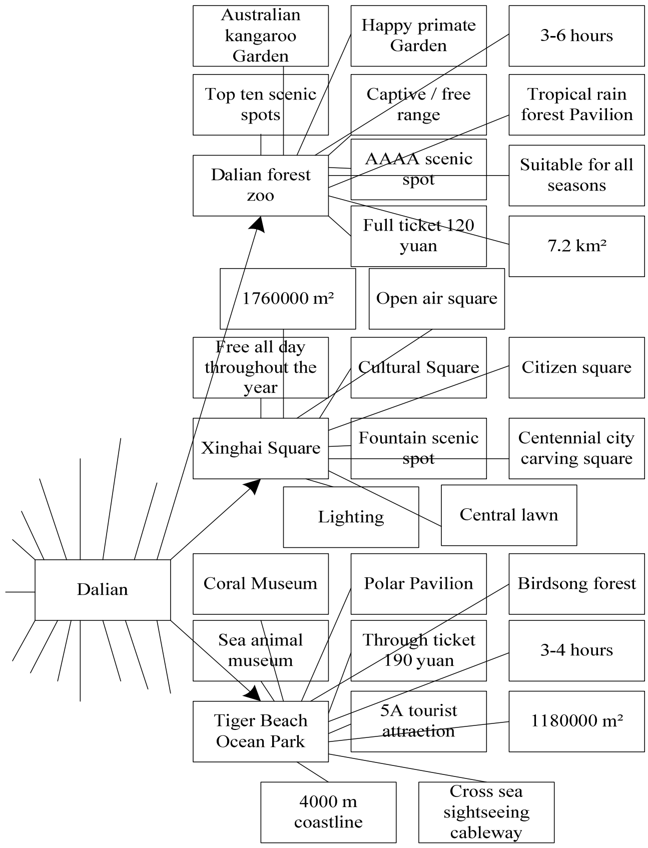
In Figure 4, the knowledge map in the field of leisure tourism constructed by this method contains information such as tourists' ticket prices, places of interest, recommended travel time and the floor area of each scenic spot. The information is comprehensive, which is conducive to improving the recommendation effect of tourism routes.

3.2 Recommended results

3.2.1 Implementation process of this method

According to the leisure tourism domain knowledge map shown in Figure 4, set the user category input by the user as parents and newlyweds; the preference is sightseeing and entertainment, and the travel time is set to two days. The personalised leisure travel route recommendation method based on knowledge map designed above is used to recommend travel routes, and the recommended results are shown in Table 1.

Figure 4 Construction results of knowledge map in leisure tourism field



According to the analysis of Table 1, among the six different tourism routes, Dalian Forest Zoo, Laohutan Ocean Park, Xinghai Square, Discovery Kingdom Theme Park, and Fisherman's Wharf are the representative popular attractions in Dalian, so they appear frequently and are suitable for all kinds of people to visit. For parents, Dalian Forest Zoo, Dalian Lushun Huaying Peony Garden, Xinghai Square, and Hengshan Beiputuo theme park are more popular. The common feature of these scenic spots is beautiful scenery, which is suitable for older users. The highest score of route 2 is 8.7. For young users, Laohutan Ocean Park, Xinghai Square, Discovery Kingdom Theme Park, and Fisherman's Wharf appear frequently, because these scenic spots contain more entertainment facilities and romantic atmosphere, which are suitable for young users to play. Among them, route 2 has the highest score reaching 9.0.

The above is the whole process of tourism route recommendation using the method proposed in this paper.

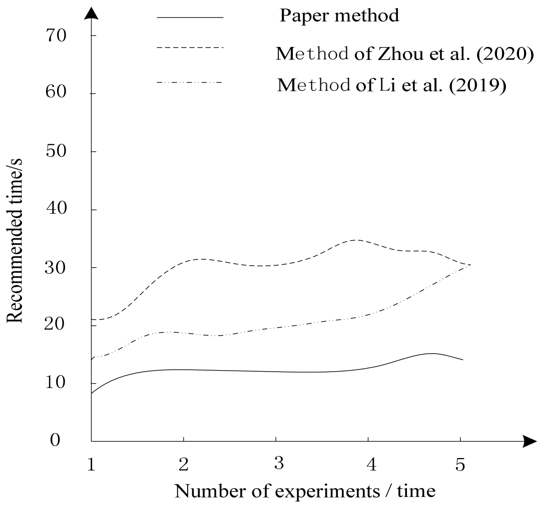
Table 1 Recommended tourism routes

	Route 1	*Route 2*	*Route 3*
User category: parents; preference: sightseeing; travel time: two days	Dalian Station – Dalian Botanical Garden – Bangchui Island – Dalian Forest Zoo – Xinghai Square – West Lake mountain scenic spot – Dalian lvshunhua brewing Peony Garden – Hengshan Beiputuo theme park	Dalian railway station – Zhongshan Square – Dalian Forest Zoo – Nature Museum – Xinghai Square – Yingge stone Botanical Garden – Dalian lion tiger Garden – Hengshan Beiputuo theme park	Dalian Station – Dalian Forest Zoo – Nature Museum – Xinghai Square – Dalian Lushun Huaying Peony Garden – Qianshou Guanyin scenic spot – Hengshan Beiputuo theme park
Score	8.5	8.7	8.1
	Route 1	*Route 2*	*Route 3*
User category: newlyweds; preferences: entertainment; travel time: two days	Dalian railway station – Laohutan Ocean Park – longwangtang cherry garden – Xinghai Square – Dalian TangliLeyou Valley – Discovery Kingdom Theme Park – Fisherman's Wharf	Dalian Station – Bangchui Island – Laohutan Ocean Park – Xinghai Square – Dalian TangliLeyou Valley – Discovery Kingdom Theme Park – Fisherman's Wharf	Dalian railway station – Laohutan Ocean Park – Dalian Forest Zoo – Xinghai Square – Dalian TangliLeyou Valley – Discovery Kingdom Theme Park – Fisherman's Wharf
Score	8.7	9.0	8.6

3.2.2 Comparison of recommended efficiency

To verify the recommendation efficiency of the design method, the Zhou et al. (2020) and Li et al. (2019) are used as comparison methods to compare the recommended time of different methods. The experimental results are shown in Figure 5.

Figure 5 Comparison of recommended time

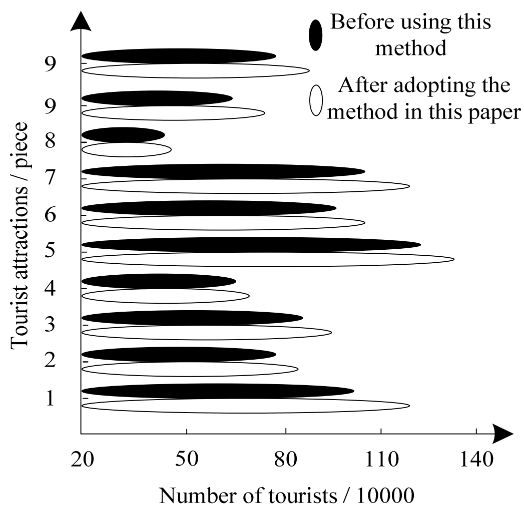


It can be seen from Figure 5 that compared with the other two methods, the method proposed in this paper can complete the recommendation of tourist routes in the shortest time, which is 10 s, while the other two methods have the shortest time, which is 14 s and 20 s respectively, It is proved that the proposed method has high recommendation efficiency.

3.2.3 Comparison of tourist numbers before and after recommendation

Then, ten scenic spots were randomly selected, and the number of tourists/year in different scenic spots before and after under this method was compared. The results are shown in Figure 6.

Figure 6 Number of visitors



From the analysis in Figure 6, it can be seen that after applying the tourism route recommendation method proposed in this paper, the number of tourists in each scenic spot has increased significantly, with an average increase of nearly 10%. Therefore, using the method proposed in this paper to recommend tourist routes can increase the number of tourists in the scenic spot. It is proved that the design method is helpful to improve the recommendation satisfaction and enhance the attraction of the scenic spot to tourists. The reason for this result is that the design method uses the knowledge map to analyse the needs of tourists in an all-round way, and can make recommendations for tourist routes on the basis of knowing their real needs, so as to improve the satisfaction of tourists.

4 Conclusions

1 In this paper, a personalised leisure tourism route recommendation method based on knowledge map is studied. The concept of knowledge map is introduced into the route recommendation, so as to obtain more abundant and comprehensive information of tourist attractions. On this basis, according to the travel time, user categories and personal preferences, the purpose of personalised leisure tourism route recommendation is achieved based on the value of tourist attractions and user category preferences.

2 The experimental results show that this method can complete the recommendation of tourism routes in about 10 s, and can also significantly increase the number of tourists in scenic spots, with an average increase of nearly 10%. It has a certain application value. The knowledge map information in the field of leisure tourism is relatively comprehensive, and there is no cross-trip phenomenon in tourism routes.

3 In the follow-up research process, the knowledge map of leisure tourism routes will be further optimised to better improve the application performance of the method proposed in this paper.

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