Tailored Recommendations Through Data Mining for Enriching Historical and Digital Cultural Tourism

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Abstract. At present, the historical and cultural tourism industry has been impacted by many factors, resulting in unsatisfactory development.In order to improve the personalized recommendation effect for historical and cultural tourism, based on data mining technology, this paper uses the existing user click sequence to construct a conversation graph, and then designs a timing gated graph neural network unit to model time interval information in the sequence recommendation process.Moreover, this paper generates sequence vectors according to different weights of each node vector in the sequence, and completes the recommendation according to the fitting of the sequence vector and the one-hot vector of the item.In addition, this paper combines actual needs and data mining technology to build a personalized recommendation system for historical and cultural tourism, and sets the technical settings of functional modules.Finally, this paper designs an experiment to verify the performance of the system constructed in this paper.Through statistical test data, it can be known that the system constructed in this paper has certain effects and can be applied in practice.

Keywords: Data mining; history and culture; tourism; personalized recommendation; Tailored Digital Cultural
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1 INTRODUCTION

With the rapid development of the global tourism industry, how to provide users with convenient and high-quality services has become particularly important. According to the data report of the Data Center of the Ministry of Culture and Tourism, my country's tourism satisfaction is not high, and the national tourism satisfaction is at an "average" level.

Information overload is one of the reasons that affect the quality of tourism. In daily travel, the most common problem is that after arriving in a new city, how to choose a place of interest and how to plan your own itinerary is a very complex and arduous task. A high-quality itinerary can maximize the satisfaction of tourists under the premise of satisfying user constraints.Although current domestic travel websites (QYER, Ctrip, Backpack Rabbit, etc.) can provide information on scenic spots or travel notes of other tourists, for tourists, these unprocessed data are still massive. When tourists face these data, they still feel irritable. Therefore, how to automate and personalize the recommendation of scenic spots and itineraries has attracted more scholars' attention [9].

Personalized recommendation systems have been widely used in location-based services. Combining it with smart tourism can not only help tourists recommend tourist destinations, but also make personalized recommendations for accommodation and food near scenic spots, thereby reducing the preparatory work for tourists. At the same time, it can help tourists understand unfamiliar cities in a short time and help users enjoy a higher-quality travel experience [20].

With the unprecedented abundance of information, tourism has become popular, standardized, and following trends.Internet celebrity tourism and check-in tourism have become the mainstream. This type of tourism is often shallow-level tourism, and it is difficult for tourists to truly experience the cultural connotation, historical heritage, and customs of tourist destinations.Moreover, online celebrity tourism and check-in travel can easily cause undesirable phenomena such as overcrowding, traffic jams, and rising prices around scenic spots. At the same time, it is often difficult to meet the individual needs of tourists with online celebrity, standardization, and follow-up tourism methods.In addition, Internet celebrity tourism and check-in travel are all one-time tourism consumption. It is difficult for tourists to become repeat visitors after visiting. The impact of online celebrity attractions is short-lived and unsustainable. Once it retreats, the traffic of scenic spots will drop sharply.In the peak tourist season, there are crowds of hot spots and it is difficult to walk around, while on the other side, some small-influence and small-scale attractions are sparsely visited and difficult to survive, and even closures occur from time to time [13].

In the above context, historical and cultural tourism has suffered a certain impact. In order to improve the effect for historical inheritance and carry forward the traditional culture of the Chinese nation, based on data mining technology, this paper constructs a personalized recommendation system for historical and cultural tourism based on data mining.

2 RELATED WORK

The academic circle has no consensus on the concept of digitization of cultural heritage. However, the interpretation of digitization of cultural heritage in foreign countries is mostly analyzed from the perspective of experience. The literature [4] believed that the digitization of cultural heritage is to integrate heritage into popular culture through 3D models and other methods, innovate the form of cultural heritage participation, display cultural heritage to people, and trigger people's thinking about memory and identity.The literature [17] believed that the digitization of cultural heritage is the interpretation of cultural heritage through digital methods, and on the basis of preserving the cultural value of cultural heritage itself, it provides tourists with more immersive and in-depth experiences, including visual, auditory, tactile, etc.The literature [16] pointed out that the digitization of cultural heritage integrates multiple disciplines such as anthropology, art, technology, and design. Moreover, it pointed out that cultural heritage is presented to visitors with aesthetic and entertainment experiences through digital technology, attracting viewers intuitively or subconsciously, thus showing the content and spatial characteristics of digital cultural heritage. At the same time, the creativity and development of cultural heritage digitization are inseparable from public participation, so the needs of relevant stakeholders must be fully considered [3].Literature [18] defines "digitalization of cultural heritage" as "using digital collection, storage, processing, display, and dissemination technologies to transform, reproduce, and restore cultural heritage into a shareable and reproducible digital form, and interpret it from a new perspective, preserve it in a new way, and use it for new needs."The literature [22] believes that digital technology can alleviate the contradiction between cultural heritage inheritance and tourism development, so that the inherent value of cultural heritage can be further extended and developed. The literature [12] believes that the digitization of cultural heritage is beneficial to the protection of social memory. However, digitization is only one way, and the true inheritance and development of cultural heritage must be realized through innovation.The literature [15] further pointed out that digitization makes the display of cultural heritage more flexible, free from time and space constraints, and serves as a historical translator to spread cultural heritage to the public.The literature [23] designed an efficient and low power consumption indoor and outdoor detection and seamless location service framework. It utilizes a variety of location-aware technologies such as iBeacon protocol, WiFi signal and satellite positioning, and uses smart phones to efficiently detect the environmental status of the user to achieve seamless indoor and outdoor location services.The literature [7] designed an integrated location perception and service method for tourists that integrates GPS satellites and ultra-wideband UWB positioning technology. This method uses GPS satellites and ultra-wideband UWB positioning technology to seamlessly perceive the location information of tourists outdoors and indoors, and finally uses smart phones to realize intelligent navigation services based on real-time location.In terms of specific tour route recommendation, the literature [10] used low-power Bluetooth BLE location-aware technology and cloud service architecture, and designed dedicated wearable devices to sense the location information of museum visitors in real timeand provide visitors with intelligent guide and route planning services.The literature [21] used RFID bracelets to obtain theme park visitors' play behaviors, and used K-Medoids clustering algorithm to mine behavior sequences to classify a large number of visitors. Moreover, it used behavior sequences to construct a transfer preference matrix between amusement items, so as to recommend travel routes to other visitors in the park.The literature [14] used RFID technology to obtain the historical visit trajectory and duration of museum visitors, and designed the time interval sequence mining algorithm I-PrefixSpan to mine the follow-up route from the historical visit behavior sequence, and finally designed a route search algorithm to recommend specific visit routes for subsequent visitors.The literature [8] proposed a sequential pattern mining algorithm, LIT-PrefixSpan, which contains three kinds of information: tourist location, play item and play time, to solve the problem of theme park play route mining and recommendation.The personalized recommendation system can accurately recommend or predict potential interactive items for users. The most important step is to represent users and recommended items as numerical feature representations that can be directly calculated and reasoned by a computer.From the perspective of feature representation construction, traditional recommendation methods can be divided into three types: collaborative filtering [1] method, content-based recommendation method [11] and hybrid recommendation method [19].

3 UNIT DESIGN OF TIMING GATED GRAPH NEURAL NETWORK

In tourism and daily travel, point-of-interest recommendation is another important type of personalized location service.Atpresent, tourists can easily find a nearby point of interest with the help of mobile location-aware technology and mobile communication technology. However, when searching for information related to points of interest on the mobile terminal, due to the restriction of the point of interest retrieval or recommendation technology, the massive amount of irrelevant point of interest information the massive amount of irrelevant point of interest information has caused serious information overload problems for tourists, and at the same time caused travel inconvenience to tourists, and also restricted the further development of smart tourism and smart cities.

Therefore, research and realization of personalized point-of-interest recommendation has important practical significance and economic value. In this paper, the algorithm construction of the historical and cultural tourism personalized recommendation system is based on the neural network unit of the time sequence gated graph.

After clarifying the definition of the sequence recommendation problem and the data definition, this article first uses the existing user click sequence to construct the conversation graph, and then designs the timing gated graph neural network unit to model the time interval information in the sequence recommendation process.

The sequence of all user clicks in the data s is constructed into a directed graph by algorithm and denoted as $G_s=(v_s,\varepsilon_s)$. The node in the user sequence graph that the user clicks on the item is still denoted as $v_{s,i}\in V$, and the edge of the item $v_{s,i}$ in the sequence graph pointing to the item $v_{s,i-1}$ is denoted as $(v_{s,i-1},v_{s,i})\in\varepsilon_s$.Since there is a duplicate item m in the user click sequence s, in the structure graph G_s, the out-degree and in-degree of the weight identification node of the edge are shown in Figure 1[6].

Unit design

After constructing the sequence graph, we represent all items $v_{s,i}\in V$ in a unified vector space, and learn the vector representation $V\in R^d$ of each node through the graph neural network.The update process of the gated graph neural network for node $v_{s,i}$ and nodes in graph G_s is shown in formula (1) and formula (5).

$$a_{s,i}^t=A_{s,i:}\left[v_1^{(t-1)T}\cdots v_n^{(t-1)}\right]^T H+b \tag{1}$$

$$z_{s,i}^t=\sigma\left(W^z a_{s,i}^t+U^z v_i^{t-1}\right) \tag{2}$$

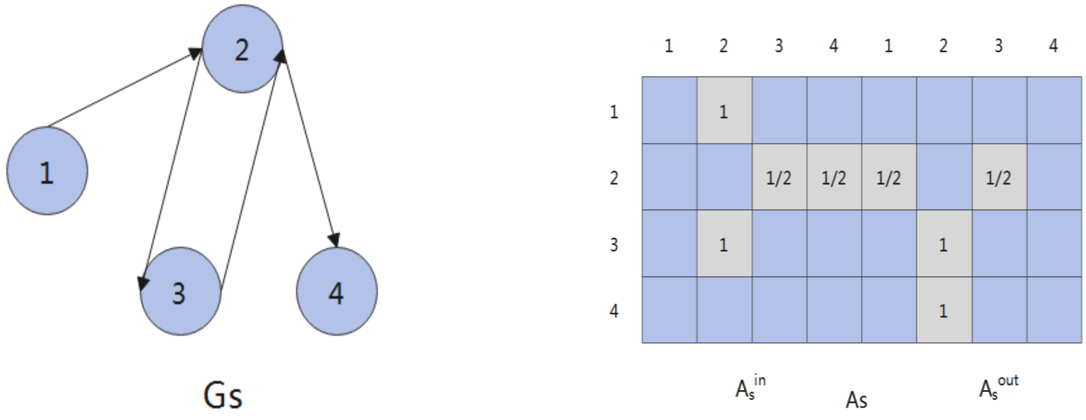
$$r_{s,i}^t=\sigma\left(W^r a_{s,i}^t+U^r v_i^{t-1}\right) \tag{3}$$

$$\tilde{v}_l^t=\tanh\left(Wa_{s,i}^{(t)}+U\left(r_{s,i}^t\odot v_i^{t-1}\right)\right) \tag{4}$$

$$v_i^t=\left(1-z_{s,i}^t\right)\odot v_i^{(t-1)}+z_{s,i}^t\odot\tilde{v}_l^t \tag{5}$$

Among them, in formula (1), $H\in R^{d\times 2d}$ is the weight coefficient for calculating the initial state $a_{s,i}^t$ of the node, $A_{s,i:}\in R^{n\times 2n}$ represents the adjacency matrix of the sequence graph G_s, and $\left[v_1^{(t-1)T}\cdots v_n^{(t-1)}\right]$ represents the initial state of the node list corresponding to the adjacency matrix A_s .In formula (2) and formula (3), $z_{s,i}^t$ and $r_{s,i}^t$ represent the forgetting gate and update gate, W^z and U^z are the weight coefficients of the forgetting gate, W^r and U^r are the weight coefficients of the update gate, and $\sigma(\cdot)$ represents the sigmoid function.In formula (3) and formula (5), $\odot$ represents the element-wise multiplication operation[5].

As shown in Figure 1, session $s=\{v_1,v_2,v_3,v_2,v_4\}$ can be constructed as a sequence graph G_s in the left diagram of Figure 1.The right figure of Figure 1 is the adjacency matrix A_s composed of the out-degree adjacency matrix A_s^{out} and the in-degree adjacency matrix A_s^{in} .The adjacency matrix A_s represents the connection between the nodes v_s in graph, the out-degree adjacency matrix A_s^{in} represents the out-degree of the sequence graph, and the in-degree adjacency matrix A_s^{in} represents the in-degree of the sequence graph.



(a) (b)

Figure 1: Schematic diagram of sequence graph and adjacency matrix.

The node v_s in the sequence graph G_s represents the item that the user clicks on, and the edges between the nodes represent the time interval between the user clicks on the item.In formula (6), the time interval information Δ_s is modeled into the model through the design time gate g_s.In formula (7) and formula (9), the node vector is updated by the way that the time gate, the forget gate and the update gate jointly control the forgetting ratio of the node at the previous moment[2].

$$g_s=\sigma\left(W_z a_{s,i}^t+U_z v_i^{t-1}+\lambda\Delta_s\right) \tag{6}$$

$$\tilde{v}_l^t=\tanh\left(W_o a_{s,i}^t+U_o\left(\underline{g_s\odot r_{s,i}^t}\odot v_i^{t-1}\right)\right) \tag{7}$$

$$v_i^t=\left(1-\underline{g_s\odot z_{s,i}^t}\right)\odot v_i^{t-1}+\underline{g_s\odot z_{s,i}^t}\odot\breve{v}_l^t \tag{8}$$

The neural network propagation of the timing gated graph is shown in formula (9) and formula (14).

$$a_{s,i}^t=A_{s,i:}\left[v_1^{(t-1)T}\cdots v_n^{(t-1)}\right]^T H+b \tag{9}$$

$$z_{s,i}^{t} = \sigma\left(W^{z} a_{s,i}^{t} + U^{z} v_{i}^{t-1}\right) \tag{10}$$

$$r_{s,i}^{t} = \sigma\left(W^{r} a_{s,i}^{t} + U^{r} v_{i}^{t-1}\right) \tag{11}$$

$$g_{s} = \sigma\left(W_{z} a_{s,i}^{t} + U_{z} v_{i}^{t-1} + W_{s} \Delta_{s}\right) \tag{12}$$

$$\breve{v}_{l}^{t} = \tanh\left(W_{o} a_{s,i}^{t} + U_{o}\left(\underline{g_{s} \odot r_{s,i}^{t}} \odot v_{i}^{t-1}\right)\right) \tag{13}$$

$$v_{i}^{t} = \left(1 - \underline{g_{s} \odot z_{s,i}^{t}}\right) \odot v_{i}^{t-1} + \underline{g_{s} \odot z_{s,i}^{t}} \odot \breve{v}_{l}^{t} \tag{14}$$

Through the timing gated graph neural network, the entire sequence graph node can be propagated every time. Through formula (9), it propagates the connected node vector in the graph according to the weight distribution method defined by the adjacency matrix to obtain the node input state $a_{s,i}^{t}$ .Then, the forgetting weight $z_{s,i}^{t}$, update weight $r_{s,i}^{t}$, and time interval weight g_s are calculated by formula (10), formula (11) and formula (12).Finally, formula (13) and formula (14) control the forgetting and updating ratio between the input state $a_{s,i}^{t}$ of the node and the state v_i^{t-1} of the node at the last moment through the forgetting weight $z_{s,i}^{t}$, update weight $r_{s,i}^{t}$ and time interval weight g_s to obtain the final node output state v_i^t.

It is difficult to model and express heterogeneous tourism data in a unified and efficient manner. The attribute data of interest points is a kind of unstructured discrete data. The use of traditional data representation methods will lead to high dimensionality and sparseness of the data, which in turn will cause the dimensional disaster of the recommendation model. The visitor trajectory is structured sequence data, and it is difficult to model the two types of structured data using traditional data mining methods such as generative probability model, matrix decomposition or tensor decomposition.Therefore, researching and designing a unified and efficient modeling method for heterogeneous data and then achieving a comprehensive characterization of the characteristics of tourists and points of interest is the key to improving the personalization and accuracy of recommendation of points of interest.

After completing the sequence control graph neural network, it is necessary to rely on the gate control graph neural network to establish the sequence recommendation algorithm. The basic idea is to first calculate each node vector in the sequence diagram through the timing gated graph neural network, then generate the sequence vector with different weights from each node vector in the sequence, and finally complete the recommendation based on the sequence vector and the item one-hot vector fitting.

The main idea of node vector calculation is to obtain each node vector v_i^t through sequence propagation through the timing gated graph neural network proposed earlier, as shown in Figure 2.

After getting each node vector v_i^t in the sequence, we start to calculate the sequence vector $s \in R^d$ .Early sequence recommendation algorithms are accustomed to using the output vector of the last node vector in the sequence as the vector representation of the entire sequence. This method makes the information of the distant nodes in the sequence unable to be used well.

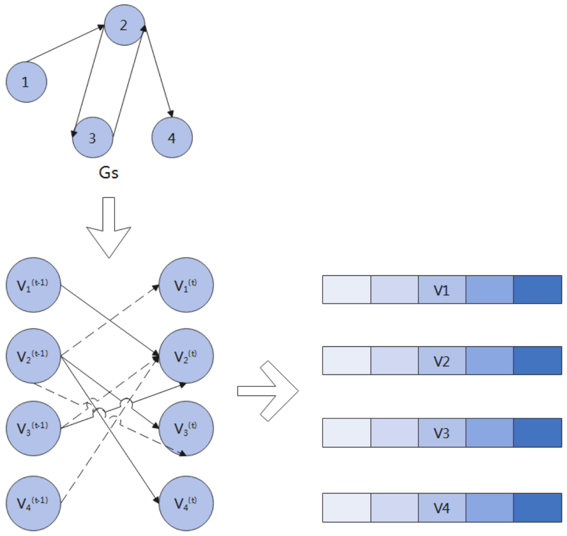


Figure 2: Schematic diagram of node vector calculation.

Although the timing gated graph neural network can model complex transitions between nodes, using the information of the last node as the vector representation of the entire sequence still has the problem of long sequence dependence.In order to better calculate the sequence vector to accurately predict the next clicked item, the attention network is used to calculate the entire sequence vector by combining the output states of all nodes in the sequence and the final output state of the entire sequence, as shown in Figure 3.

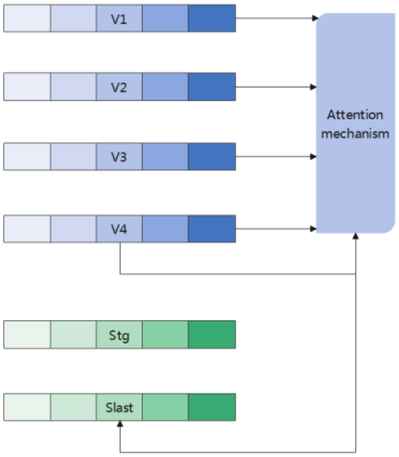


Figure 3: Schematic diagram of sequence vector calculation.

The node vector on the left of Figure 3 is the final vector v_i^t of the node outputted by the sequence $s=\{v_1,v_2,v_3,v_2,v_4\}$ through the neural network of the timing gated graph.After this, the final vector

$S_h \in R^d$ of the sequence graph begins.Since the next item click is predicted, the last node output vector S_{last} of the sequence is taken as a part of $S_h \in R^d$, and the weight of each node vector in the sequence graph G_s is calculated by the attention network and integrated into the sequence graph global vector S_{tg} , as shown in the following two equations.

$$\alpha_i^{'} = q^T \sigma(W_1 v_n + W_2 v_i + c) \tag{15}$$

$$s_{tg} = \sum_{i=1}^{n} a_i v_i \tag{16}$$

Among them, the parameters $q \in R^d$ and $W_1, W_2 \in R^{d \times 2d}$ control the weight of each node vector.

After obtaining the final node output vector S_{last} and the sequence diagram global vector S_{tg} , they are combined to obtain the final sequence diagram vector S_h by formula (17).Among them, $W_3 \in R^{d \times 2d}$ represents two integrated vectors in the vector space R^d . The sequence vector integration process is shown in Figure 4.

$$s_h = W_3 \left[s_{last}; s_{tg} \right] \tag{17}$$

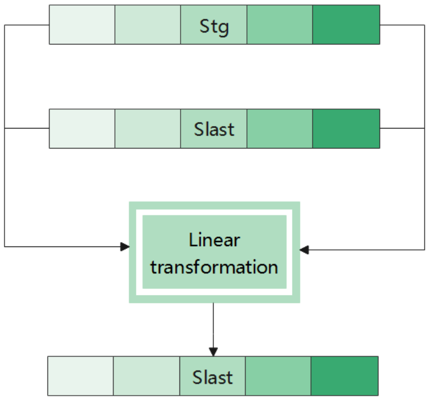


Figure 4: Schematic diagram of sequence vector integration.

After obtaining the final sequence vector S_h of each sequence diagram, it is necessary to calculate the candidate score of each item through the node vector V_i and the final sequence vector S_h of each sequence diagram, as shown in the following formula.

$$\hat{z}_i = s_h^T v_i \tag{18}$$

Then, the predicted probability $\hat{y}$ of each node is calculated by the softmax function, as shown in the following formula:

$$\hat{y}=soft\max(\hat{z}) \tag{19}$$

Among them, $\hat{z} \in R^m$ represents the recommendation scores of all candidate items, and $\hat{y} \in R^m$ represents the probability that the next click is each node. This process is shown in Figure 5.

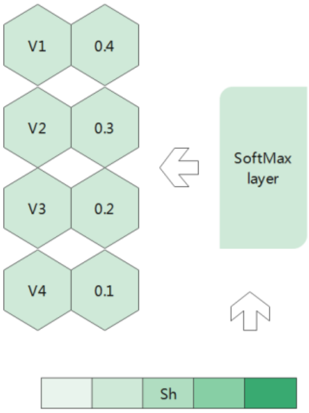


Figure 5: Schematic diagram of sequence vector integration.

Finally, the cross-entropy loss function is used to calculate the loss of each session graph, as shown in the following formula.

$$L(\hat{y})=-\sum_{i=1}^{m} y_i \log(\hat{y}_i)+(1-y_i^2)\log(1-\hat{y}_i) \tag{20}$$

Among them, y_i represents the one-hot vector of the product i.Same as GRU4Rec, this model is trained through the BPTT algorithm. Since most sequences are short sequences, a small number of training steps is usually set during model training to prevent overfitting. The overall structure of the model is shown in Figure 6, and this paper is named TGGNN4REC.

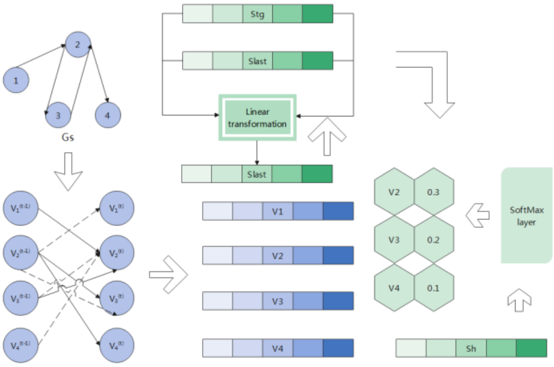


Figure 6: Overall sructure of TGGNN4REC.

4 PERSONALIZED RECOMMENDATION SYSTEM FOR HISTORICAL AND CULTURAL TOURISM BASED ON DATA MINING

Tourists participate in tourism activities for the purpose of obtaining tourism experience. As a new tourism product, digital tourism of cultural heritage is the purpose of its development and utilization for tourists to obtain tourism experience.The digitization of cultural heritage displays cultural heritage in a virtual way, which not only shows visitors the knowledge of cultural heritage, but also brings visitors a sensory experience.

Figure 7 shows the workflow of designing a personalized recommendation system for historical and cultural tourism, which is mainly composed of three stages. The first stage is the heterogeneous tourism data integration stage. Through organic integration of multi-source heterogeneous tourism data, a structured attraction visit sequence and attraction tourism knowledge base are generated.The second stage is the generation of scenic spot tour routes. The POI-Visit (PV) Prefix Span algorithm is proposed to mine the candidate place of interest sequential routes (PV Sequential routes) from the place of interest pattern sequential (PV Pattern Sequences), that is, POI routes. The last is the stage of personalized route recommendation. The goal is to recommend Top-k tourist routes for tourists based on their travel context information.

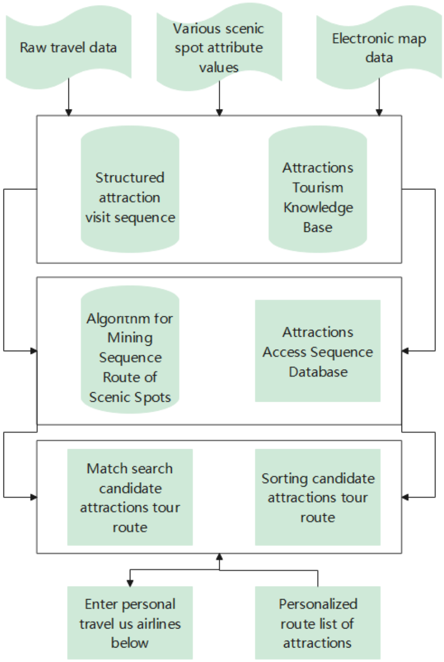


Figure 7: The workflow of a personalized recommendation system for historical and cultural tourism based on data mining.

The theme for historical and cultural tourism opportunities is multi-dimensional, and each theme of tourism opportunities contains multiple subdivided thematic latitudes. For example, flower viewing tours actually include photography, self-driving, and rural areas. Ancient town tours include photography tours, shopping tours, and other latitudes. Rural tours include shopping tours, photography tours, self-driving tours, and flower viewing tours. The subdivision latitudes of multiple travel opportunity themes have overlapping parts,Figure 8 is a multi-dimensional map of the theme of tourism opportunities. Self-driving tours are included in the subdivision dimensions of flower viewing tourism and rural tourism.

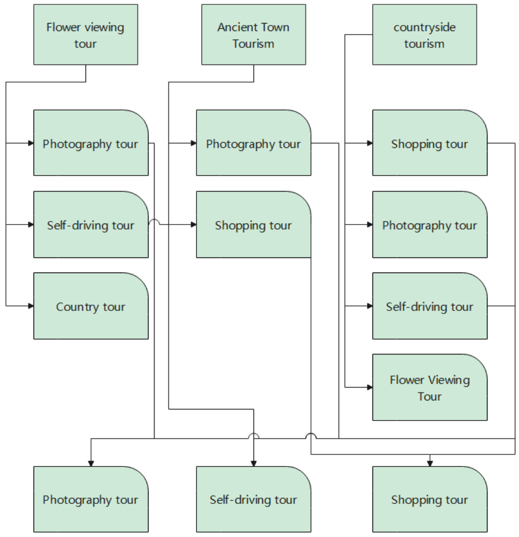


Figure 8: Multi-dimensional map of tourism opportunity theme.

Cultural heritage tourism experience is a kind of self-experience, which aims to obtain experiences such as knowledge, aesthetics, and enjoyment.Compared with traditional cultural heritage tourism, digitalization has transformed cultural heritage from physical display to vivid, visual or active display, combining static and dynamic. The digitization of cultural heritage breaks through space constraints and reproduces the historical and cultural landscape of cultural heritage. The diversified display and experience design gives full play to the advantages of combining technology and heritage, which not only guarantees the complete presentation of the original state of cultural heritage, but also expands the context of cultural heritage and spreads cultural connotations in educational experience, entertainment experience, and aesthetic experience, thereby effectively enhancing the travel experience .

Spatial attributes of tourism opportunities. Tourism opportunities cannot happen out of thin air. It always takes place as a carrier. The places and scopes involved in the occurrence of tourism opportunities are called the spatial attributes of tourism opportunities.There are different types of spatial relationships between travel opportunities in a certain theme in a certain space and travel opportunities in other themes in the space. Each theme of tourism opportunity has its own characteristics, and these characteristics also affect the suitable population of this theme of tourism opportunity. According to the differences of various factors of tourism opportunities, the range of suitable people for some themed tourism opportunities is very wide, but there are also some suitable people for thematic tourism opportunities are relatively narrow.

As a combination of cultural heritage and information technology, the digitization of cultural heritage is a new tourism product. Digital tourism of cultural heritage will affect the tourism experience, and cultural heritage, as a carrier of culture, bears the spiritual connotation of culture, which contains people's identity and sense of belonging to their own nation or region, that is, cultural identity. At the same time, the innovation of tourists will affect their perception of new products.

Based on this, on the basis of SOR theory, this paper combines innovation diffusion theory and social existence theory to construct the theoretical model of this research, as shown in Figure 9.

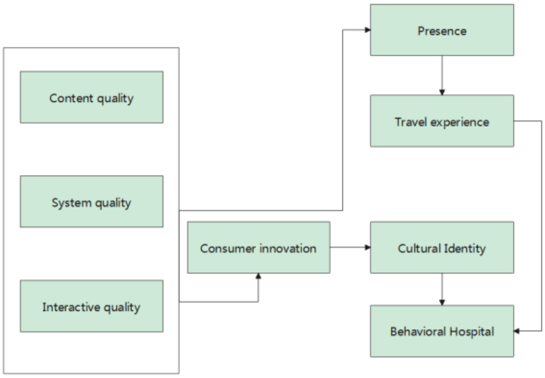


Figure 9: Model diagram of research theory.

5 PERFORMANCE VERIFICATION OF THE PERSONALIZED RECOMMENDATION SYSTEM FOR HISTORICAL AND CULTURAL TOURISM BASED ON DATA MINING

After constructing a personalized recommendation system for historical and cultural tourism based on data mining, this paper verifies the performance of the system. The purpose of this system is to provide tourists with personalized recommendations for historical and cultural recommendations, and to continuously improve the results of recommendations combined with data mining. Therefore, this paper mainly conducts system personalized recommendation effect evaluation and user satisfaction evaluation when performing department performance verification. First of all, this paper conducts the evaluation of the personalized cultural tourism recommendation effect of the system constructed in this paper and collects multiple sets of data through the Internet. The results are shown in Table 1 and Figure 10.

Number	*Personalized recommendation score*	*Number*	*Personalized recommendation score*	*Number*	*Personalized recommendation score*
1	*91.50*	*31*	*85.77*	*61*	*85.72*
2	*89.40*	*32*	*89.70*	*62*	*89.52*
3	*90.68*	*33*	*92.98*	*63*	*92.65*
4	*91.48*	*34*	*86.82*	*64*	*88.45*
5	*86.70*	*35*	*88.28*	*65*	*87.57*
6	*90.72*	*36*	*92.92*	*66*	*87.18*
7	*92.22*	*37*	*88.86*	*67*	*89.26*

8	*89.13*	*38*	*86.09*	*68*	*90.43*
9	*85.09*	*39*	*90.69*	*69*	*90.18*
10	*92.94*	*40*	*89.89*	*70*	*86.85*
11	*90.11*	*41*	*88.29*	*71*	*88.58*
12	*85.17*	*42*	*92.61*	*72*	*89.72*
13	*88.13*	*43*	*90.62*	*73*	*89.08*
14	*86.27*	*44*	*91.00*	*74*	*90.06*
15	*86.35*	*45*	*86.78*	*75*	*91.55*
16	*89.26*	*46*	*92.98*	*76*	*86.18*
17	*89.41*	*47*	*88.16*	*77*	*90.63*
18	*86.85*	*48*	*86.88*	*78*	*90.60*
19	*90.31*	*49*	*89.51*	*79*	*87.68*
20	*91.17*	*50*	*85.33*	*80*	*88.18*
21	*86.57*	*51*	*85.69*	*81*	*88.74*
22	*87.34*	*52*	*85.32*	*82*	*85.12*
23	*85.42*	*53*	*86.46*	*83*	*92.50*
24	*88.36*	*54*	*85.30*	*84*	*86.35*
25	*87.97*	*55*	*86.90*	*85*	*88.91*
26	*85.91*	*56*	*90.41*	*86*	*87.93*
27	*85.65*	*57*	*87.34*	*87*	*91.61*
28	*90.39*	*58*	*90.30*	*88*	*90.02*
29	*86.49*	*59*	*86.77*	*89*	*91.98*
30	*85.40*	*60*	*90.67*	*90*	*86.47*

Table 1: Statisticaltable of the recommendation effect of the personalized recommendation system for historical and cultural tourism based on data mining.

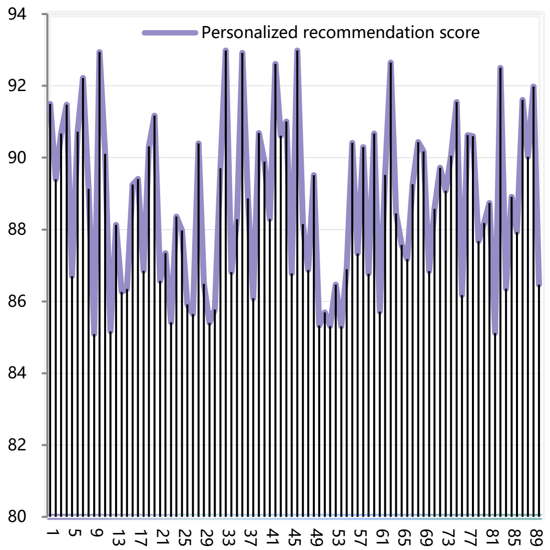


Figure 10: Statistical diagram of the recommendation effect of the personalized recommendation system for historical and cultural tourism based on data mining.

From the above analysis results, the personalized recommendation system for historical and cultural tourism based on data mining constructed in this paper has a high accuracy rate in personalized recommendation, so it can meet the actual needs of the development for historical and cultural tourism. On the basis of the above analysis, this paper conducts a user satisfaction survey of a personalized recommendation system for historical and cultural tourism based on data mining.

Number	*User satisfaction score*	*Number*	*User satisfaction score*	*Number*	*User satisfaction score*
1	*72*	*31*	*95*	*61*	*74*
2	*70*	*32*	*96*	*62*	*97*
3	*78*	*33*	*86*	*63*	*81*
4	*74*	*34*	*70*	*64*	*87*
5	*71*	*35*	*89*	*65*	*73*
6	*88*	*36*	*87*	*66*	*73*
7	*80*	*37*	*79*	*67*	*95*
8	*83*	*38*	*81*	*68*	*72*

9	*85*	*39*	*73*	*69*	*74*
10	*94*	*40*	*87*	*70*	*95*
11	*92*	*41*	*78*	*71*	*74*
12	*95*	*42*	*75*	*72*	*93*
13	*74*	*43*	*97*	*73*	*98*
14	*97*	*44*	*75*	*74*	*86*
15	*78*	*45*	*76*	*75*	*89*
16	*74*	*46*	*91*	*76*	*72*
17	*80*	*47*	*71*	*77*	*97*
18	*90*	*48*	*79*	*78*	*82*
19	*77*	*49*	*77*	*79*	*75*
20	*79*	*50*	*95*	*80*	*94*
21	*78*	*51*	*86*	*81*	*81*
22	*90*	*52*	*87*	*82*	*83*
23	*75*	*53*	*91*	*83*	*86*
24	*74*	*54*	*90*	*84*	*81*
25	*92*	*55*	*82*	*85*	*73*
26	*77*	*56*	*93*	*86*	*72*
27	*83*	*57*	*85*	*87*	*71*
28	*91*	*58*	*71*	*88*	*94*
29	*79*	*59*	*74*	*89*	*88*
30	*76*	*60*	*97*	*90*	*83*

Table 2: Statisticaltable of user satisfaction of the personalized recommendation system for historical and cultural tourism based on data mining.

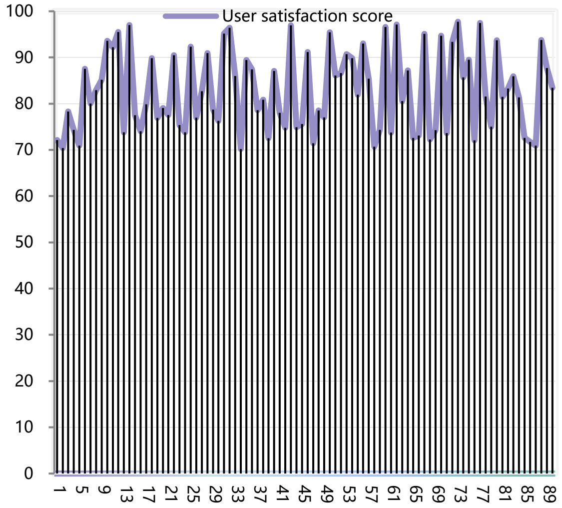


Figure 11: Statistical diagram of user satisfaction of the personalized recommendation system for historical and cultural tourism based on data mining.

From the above chart, the user response of the personalized recommendation system for historical and cultural tourism based on data mining constructed t in this paper is good, so the system can be applied to practice in the future.

6 CONCLUSION

With the further integration of culture and tourism, the influence of digital technology on tourists is increasing, which has changed the traditional tourism needs. In this context, this research combines the development status of the combination of cultural heritage and digital technology in my country to explore the impact of cultural heritage digitization on tourists' travel experience and their willingness to travel, which has certain research value and significance.This article combines data mining technology to construct a personalized tourism system, which lays the foundation for the development for historical and cultural tourism industry. Moreover, this paper proposes a brand-new Time-GGNN unit, and on this basis, proposes a sequence recommendation algorithm based on the Time-GGNN unit.Through experiments, it is found that the time interval information has a significant impact on the recommendation results. The TGGN4REC model that uses Time-GGNN unit for sequence recommendation proposed in this paper is obviously ahead of the SRGNN model that does not use time interval information and other sequence recommendation models in various indicators. The results of experimental research show that the system constructed in this paper has a certain effect.

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