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Design of Tourism Information Recommendation System Based on Machine Learning under the Background of Digital Economy

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Abstract With the continuous improvement of people's living standards, tourism has also become one of the important activities for people to improve their quality of life. Especially in the context of the digital economy, the development of the tourism industry has been promoted very rapidly. However, most of the current tourism information recommendation systems are information recommendation in a fixed mode, and will not make corresponding changes according to changes in the actual situation. In order to solve this problem, this paper analyzes the development theory of tourism information system, and proposes the design and implementation scheme of tourism information recommendation system based on machine learning. The tourism information recommendation system mainly provides services for tourists and tourism industry players. Its main functions include map navigation, traffic query data and intelligent guidance. Aiming to further study the function of the tourism information recommendation system designed in this paper in real life, it conducts a test research on the recommendation system. The test results show that the tourism information recommendation system designed in this paper based on machine learning has certain practical significance. It can increase tourist attraction revenue by 4.7% and reduce traffic congestion by 3.3%. This prevents tourists from entering the peak tourist period, resulting in a lower feedback rate.

Index Terms Digital Economy, Machine Learning, Tourism Information Promotion, Data Flow Diagram, Component Diagram, Collaboration Diagram

I. Introduction

With the continuous improvement of people's quality of life, people's desire to travel is also stronger and stronger, and their demand for travel information is also relatively large. However, in the context of today's digital economy, the promotion of tourism information is relatively simple and cannot meet people's diverse needs. In order to solve this problem, many people have designed and researched the tourism information recommendation system, which has resulted in the current tourism information recommendation system being largely mature. But few people have introduced machine learning into the research of tourism information recommendation system. How to apply machine learning technology to the research of tourism information recommendation system and play an active role is an urgent problem to be solved. Therefore, it is very necessary to design a tourism information recommendation system based on machine learning research.

The promotion and management of tourism information is the key to the sustainable development of the tourism industry. In order to ensure the long-term development of the tourism industry, many teams have conducted research on this. Utama A employed a qualitative exploratory approach. He designed a QR code-based sales system on a goat farm tour to facilitate the payment and distribution of income to each tenant and tour manager [1]. Li M based on GIS technology to optimize the design of forest wetland tourism development strategy [2]. Kashevnik A M proposed a comprehensive multi-model approach to develop context-aware recommender systems in the field of travel information support to facilitate personalized and non-personalized recommendation methods [3]. In order for the tourists of destination customers to also use text ads on social media and websites to share their experiences, Sajjadian F identified the factors that influence tourists' decision to visit the most popular destinations [4]. To solve the problem that existing multi-criteria recommender systems do not utilize spatial and temporal information, Hong M proposed a multi-criteria tensor model that combines spatial and temporal information to reduce the response time of the learned model [5]. Since one of the things that tourists need to plan their travel activities is a recommender system, Arif Y M developed a travel destination recommender system with three nodes of user, server and sensor [6]. Due to the lack of visitor centers in Bali and the lack of access to data and information, Bagus R believed that the visitor center could serve as a network office for various nearby social and social activities [7]. Although many people have conducted research on the tourism information recommendation system, few people have introduced machine learning technology into the research of the tourism information recommendation system. Aiming to solve this problem, this paper studies and designs a tourism information recommendation system based on machine learning.

Machine learning technology is the key to unlocking the value of traveler data and making decisions that keep the travel industry ahead of the curve. Machine learning is widely used in various industries. In order to further dig out the important role of machine learning, many teams have conducted research on this. Buczak A described a focused literature survey of machine learning methods for network analysis in support of intrusion detection [8]. Mullainathan S proposed a way of thinking about machine learning that has given it a place in the econometric toolbox [9]. Chen J H identified how varying longitudinal historical training data affects predictions for future clinical decisions [10]. Liu S provided a comprehensive analysis and explanation of the rapidly developing field of machine learning, and he also explored and discussed possible future research opportunities [11]. Zhang J introduced a machine learning classifier. The calculations are performed in a standard 6T SRAM array. This array stores machine learning models [12]. Kolouri S provided a practical overview of the mathematical underpinnings of methods related to deep learning. He included numerical implementations, as well as reviews and demonstrations of several applications [13]. Zhang L summarized the history of machine learning and provides insights into recently developed deep learning methods and their applications in rational drug discovery [14]. Although many people have conducted research on machine learning technology in order to discover the important role of deep learning, few people have combined machine learning technology with tourism information recommendation system for research. Aiming to solve this problem, this paper designs and studies the machine learning technology combined with the tourism information recommendation system.

The tourism industry is a particularly enthusiastic industry in the current economic development. Its scale is also relatively large, and it involves a lot of resource information. In order to help tourists quickly sort out the tourism resource information they want and improve the efficiency of information acquisition, this paper studies and designs a tourism information system based on machine learning technology. The design of the system can improve user satisfaction and bus utilization, and reduce the feedback rate of tourist attractions. It has certain practical significance.

II. Tourism Information Promotion System

(1) Overall functional structure diagram of the system

The contents that can be inquired by the tourism information recommendation system include tourism resources and tourism service resources. It involves the five aspects of “tourism, housing, food, shopping and entertainment” in the tourism system and related social service institutions [15]. "Residence" includes hotels, guest houses, etc. "Food" mainly includes large hotels, special food and local famous food. "Purchase" refers to the main shopping places, including shopping malls, supermarkets, etc. "Entertainment" includes theaters, entertainment cities, gyms, bars, coffee shops and other leisure and entertainment venues. In order to make it easier for tourists to travel, "social service agencies" include information about travel agencies, travel service companies, local tourism management departments, etc., as well as gas stations, financial institutions, medical institutions, foreign-related agencies and other related information that may be involved in travel, which is shown in Figure 1.

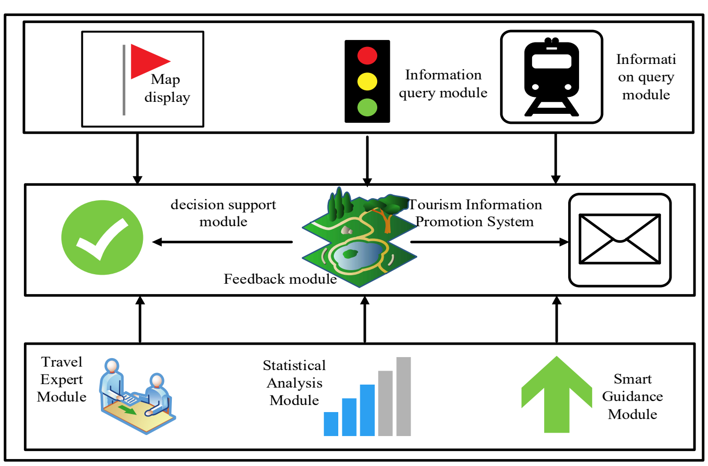

Figure 1: Overall functional structure diagram of the tourism information recommendation system

From Figure 1, the overall function of the system mainly includes eight modules: Map query module, tourism information query module, traffic query module, tourism expert query module, statistical analysis module, intelligent guidance module, decision support module and feedback module. When tourists use the tourism promotion system, they can inquire about tourist locations, tourist routes and other information. They can also inquire about the tourist attractions they want to visit by information such as name, area or attribute value. After finding the tourist attraction they want to go, tourists can go to the traffic inquiry module to inquire about the bus or self-driving route, so as to plan the tourist route.

If tourists are uneasy about the tourism information recommended by the system, they can go to the tourism expert query module to see the tourist attractions recommended by the experts. In addition, the tourism information recommendation system can also guide tourists in terms of accommodation, food, shopping and entertainment. This more quickly helps tourists decide where to travel and route planning. If tourists are not satisfied with the information recommended by the system, they can also give feedback in the feedback module. The tourism information recommendation system plays an important role for tourists to choose tourism locations from various aspects.

(2) Data flow diagram of tourism information promotion system

The data flow graph can reflect the data flow direction of tourism information to a large extent, and is an important criterion to measure the quality of the design of the tourism promotion system [16]. The data flow diagram of the tourism information recommendation system is shown in Figure 2.

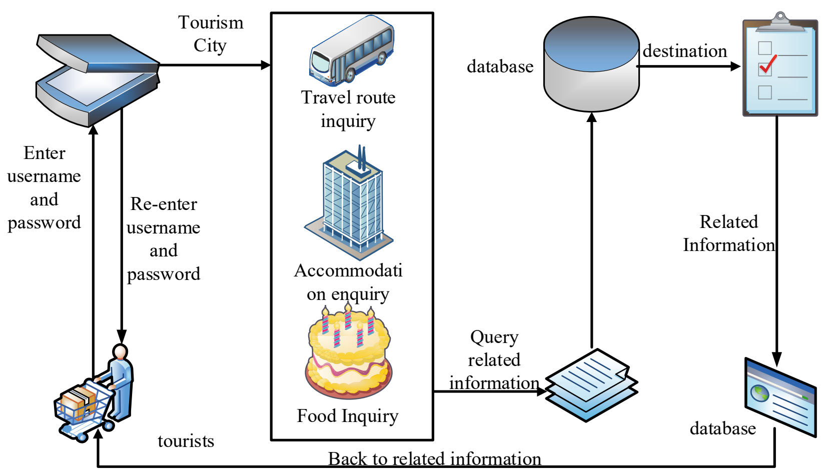

Figure 2: Data flow diagram of tourism information recommendation system

(3) Component diagram of tourism information promotion system

Component diagrams describe components and their relationships. It can be used to describe and clarify the functional responsibilities and software structure of each part in the tourism promotion system [17]. Component diagrams show dependencies between components at compile, link, or execution time. This helps to understand and analyze the relationship of components to each other. The component diagram of the tourism information recommendation system is shown in Figure 3.

As can be seen from Figure 3, there is an interface package in the tourist information system. It is used to connect visitor and system data. The tourist information recommendation system retrieves the tourist information required by tourists through the database. The database provides relevant information for the system through the search and storage of data such as bus transfer plans, travel route planning, location relationship between departure and destination, tourist attraction recommendations, and self-driving optimal routes. After that, the system will display the information fed back from the database to the tourists for the tourists to choose.

(4) Collaboration diagram for tourist tourism information query

Collaboration graphs model objects and chains between objects that have interactive significance in a travel information recommendation system [18]. Objects and relationships only make sense in interactions. Classifier roles describe an object, and association roles describe a chain in a collaborative relationship. Collaboration diagrams use geometric arrangements to represent roles in interactions. The arrows attached to the classifier roles represent messages. The order in which the messages occur is indicated by the numbers at the message arrows. A collaboration diagram consists of actor object connections and messages. Figure 4 is a collaboration diagram when a tourist conducts an information inquiry.

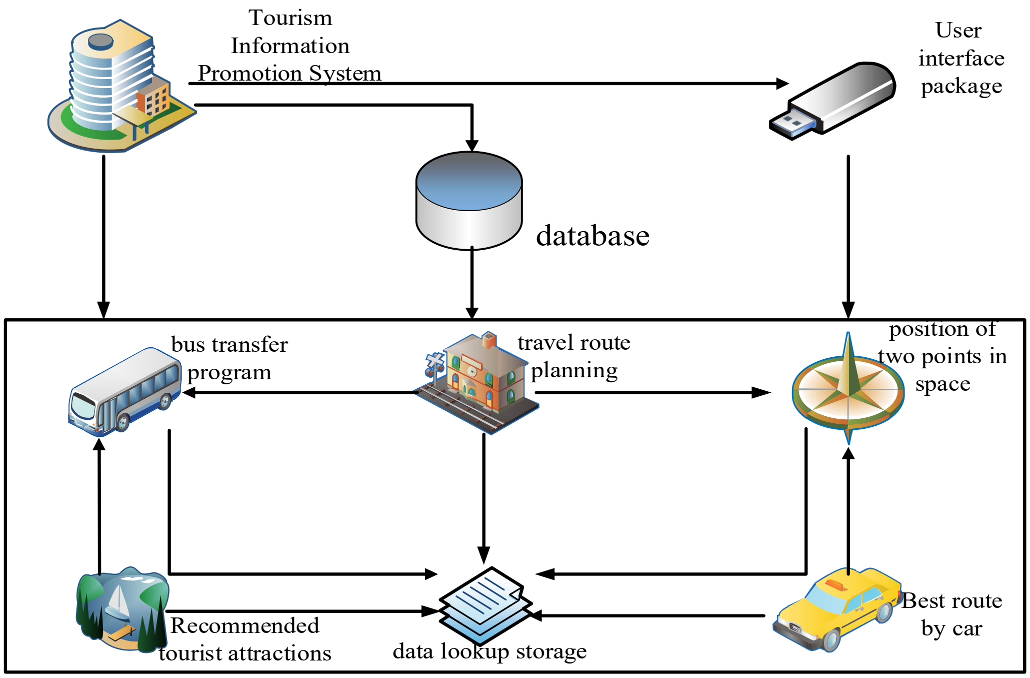

Figure 3: Component diagram of tourism information recommendation system

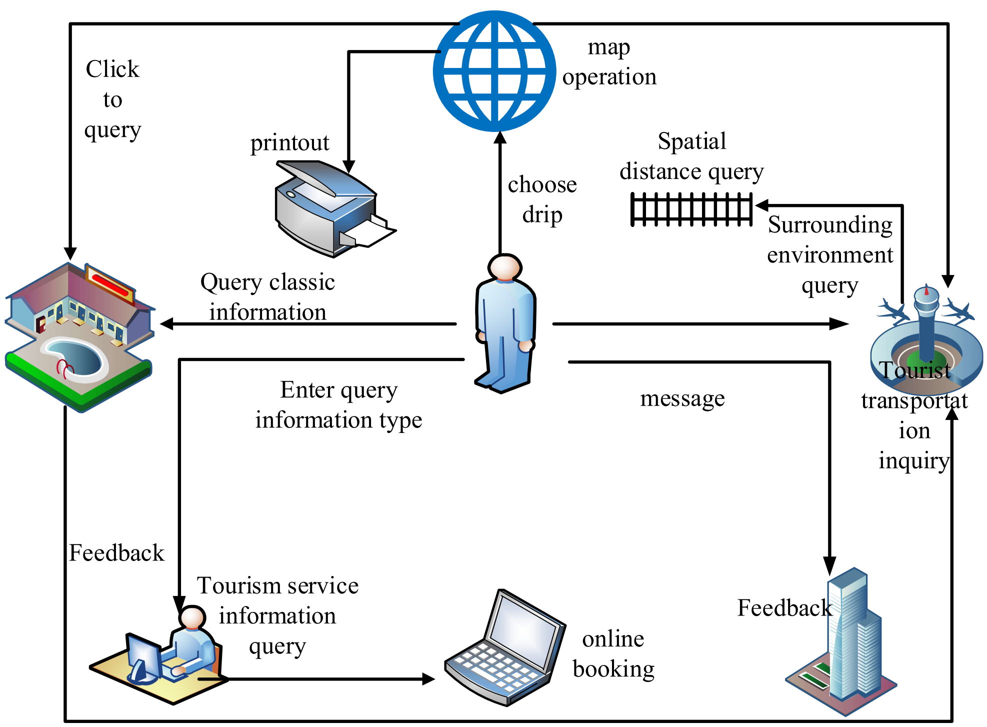

Figure 4: Information query collaboration diagram for tourists

As can be seen from Figure 4, in the tourist information recommendation system, tourists can select a map to view the tourist attractions information and surrounding tourist attractions information, and print them out. After tourists select tourist attractions, they can enter the service type in the system for query. They also book hotels, tickets and other travel essentials online under the condition that they are satisfied with the service information of the attractions. If tourists are afraid of traffic jams in tourist attractions, they can also enter the starting point and end point in the system to conduct real-time inquiries on the traffic of tourist attractions and surrounding areas. This prevents tourists from entering the peak traffic congestion period and affects the play experience.

(5) Vehicle information query sequence diagram

Vehicles are an important means of transportation for tourists to travel. Whether they are traveling by car or using public transportation, they need to check vehicle information, traffic conditions, and traffic flow information at each time point. The sequence diagram of vehicle volume information query is shown in Figure 5.

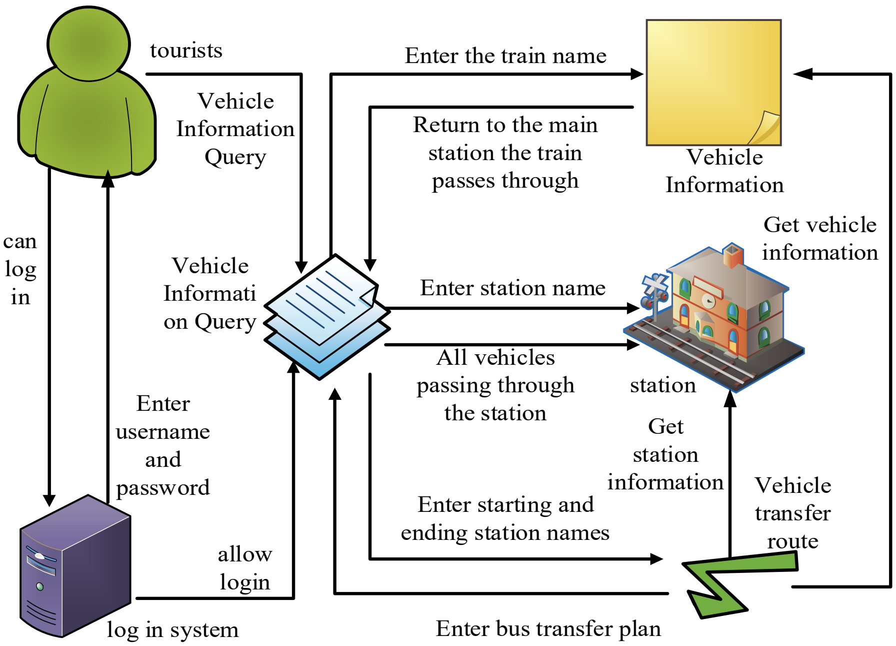

Figure 5: Query sequence diagram of vehicle volume information

As can be seen from Figure 5, the vehicle information search sequence: the tourist first inputs the user name and password on the Tourist Information System. They have been authenticated by the system and successfully logged into the tourist information inquiry system. Tourists input the name information of the vehicle to be inquired into the system. The system then returns the main stations that the trains pass through and the information of all attacking vehicles passing through the stations to tourists. If a tourist needs to transfer a vehicle during the tour, the tourist information system will return the obtained transfer quantity information to the tourist. This ensures the correctness of tourists' play route planning and improves the play experience.

III. Tourism Information Recommendation Algorithm

(1) One-dimensional input linear function

$$f_{\theta}(x)=\sum_{j=1}^{b}\theta_{j}\Phi(x) \tag{1}$$

When $\Phi_{j}(x)$ is nonlinear, $f_{\theta}(x)$ can represent complex models.

(2) Multi-dimensional input linear function

$$f_{\theta}(\vec{x})=\sum_{j=1}^{b}\theta_{j}\Phi_{j}(\vec{x}) \tag{2}$$

$\Phi_{j}(x)$ is the jth factor of basis function vector $\Phi(x)=(\Phi_{1}(x),\ldots,\Phi_{b}(x))^{\mathrm{T}}$ and θ_{j} is the jth factor of parameter vector $\theta=(\theta_{1},\ldots,\theta_{\mathrm{b}})^{T}$.

(3) Multiplication model

$$f_\theta(\vec{x}) = \sum_{jd=1}^{b'} \theta_{jd} \Phi_{jd}(x^{(d)}) \tag{3}$$

b' represents the number of parameters in each dimension. If the sum of the parameters is too large, $(b')^d$ will easily lead to dimensional disaster.

(4) Additive model

$$\theta(x) = \sum_{k=1}^{d} \sum_{j=1}^{b'} \theta_{k,j} \Phi j(x^{(x)}) \tag{4}$$

The smaller the parameter sum $b'd$, the smaller the complexity and the worse the expressiveness.

(5) Kernel model

Kernel models are models that are linearly combined with binary functions [19].

$$f_\theta(x) = \sum_{j=1}^{n} \theta_j K(x, x_j) \tag{5}$$

(6) Gaussian

$$K(x,c) = \exp\left(-\frac{\| x-c \|^2}{2h^2}\right) \tag{6}$$

h and c are the bandwidth and mean of the Gaussian function.

(7) S-type basis function

$$\Phi(x,y) = \frac{1}{1+\exp(-x^T w - \lambda)} \tag{7}$$

(8) Mean square error

$$J(\theta) = \frac{1}{2} \sum_{i=1}^{n} (f_\theta(xi) - y_i)^2 \tag{8}$$

(9) Assumption function

The hypothesis function is multivariate linear regression, which is a type of linear regression [20].

$$h(x) = \theta^T x \tag{9}$$

In the formula, T represents transpose, that is, the column vector θ becomes a row vector. It is multiplied (vector inner product) with another column vector x and the result is the norm.

(10) Cost function

$$J(\theta) = \frac{1}{2m} \sum_{i=1}^{m} (h_\theta(x^{(i)}) - y^{(i)})^2 \tag{10}$$

(11) Parameter iteration

$$\lambda_x = \lambda_x - \alpha \frac{\partial}{\partial \lambda_x} J(\theta) \tag{11}$$

(12) Statistical probability

Statistical probability is the high-precision probability obtained by the motion maximum likelihood function when the sample is known [20]. Its calculation formula is:

$$\theta = \max_{\theta} \prod_{i=1}^{y} q(x_i, y_i, \theta) \tag{12}$$

(13) Norm

The norm is a vector that measures the size of the matrix and is calculated as:

$$\|x\|_p = \left(\sum_i |x_i|^p\right)^{\frac{1}{p}} \tag{13}$$

The L1 norm ||x|| is the sum of the absolute values of the elements of the x vector. The L2 norm ||x||2 is the square root of the sum of the squares of each element of the x vector.

(14) Manhattan distance

Manhattan distance is also called city block distance [21], and its expression formula is:

$$\mathrm{d} = \sum_{k=1}^{n} |x_{1k} - x_{2k}| \tag{14}$$

(15) Euclidean distance

The Euclidean distance is actually the L2 norm, and its mathematical expression is:

$$\mathrm{d} = \sqrt{\sum_{k=1}^{n} (x_{1k} - x_{2x})}^{2} \tag{15}$$

(16) Minkowski distance

Minkowski distance is not a distance, but a set of distances. Its mathematical formula is:

$$\mathrm{d} = p\sqrt{\sum_{k=1}^{n} (x_{1x} - x_{2x})}^{p} \tag{16}$$

In fact, when p=1, it is the Manhattan distance; when p=0, it is the Euclidean distance.

(17) Chebyshev distance

The Chebyshev distance is the infinity norm, and the mathematical expression is:

$$\mathrm{d} = \max(|x_{1x} - x_{2x}|) \tag{17}$$

(18) Cosine of included angle

The value range of the cosine of the included angle is [-1, 1], which can be used to measure the difference between the directions of the two vectors, and its mathematical expression is:

$$\cos\beta = \frac{\sum_{k=1}^{n} x_{1k} x_{2k}}{\sqrt{\sum_{k=1}^{n} x_{1k}^2}\sqrt{\sum_{k=1}^{n} x_{2k}^2}} \tag{18}$$

(19) Jaccard similarity coefficient

The ratio of the 2 intersection elements of 2 sets A and B in the union of A and B is known as the Jaccard similarity coefficient of the 2 sets and is denoted by the symbol J(A, B). The mathematical expression is:

$$J(A,B) = \frac{|A \cap B|}{|A \cup B|} \tag{19}$$

The Jaccard similarity coefficient is a measure of the similarity between two sets. It can generally be used to measure the similarity of samples.

(20) Jaccard distance

The opposite concept to the Jaccard similarity coefficient is the Jaccard distance, which is defined as:

$$J_{\partial} = \frac{|A \cup B| - |A \cap B|}{|A \cup B|} \tag{20}$$

(21) Bayesian formula

$$P(B_i | A) = \frac{P(A | B_i) * P(B_i)}{\sum_{i=1}^{N} P(A | B_i) * P(B_i)} \tag{21}$$

IV. The Experimental Process of Tourism Information Recommendation System

Data analysis collects and studies the data of tourism cost, scenic spot, local living conditions, diet and local tourism conditions by scoring the same tourist attractions in several other tourism resource recommendation systems. It is then compared with the tourism information recommendation designed system presented in this paper based on machine learning in the context of the digital economy. After that, it combines different systems with the designed system presented in this paper to comprehensively score different tourist attractions. It then uses this score to compare and analyze the recommendation functions of different systems.

For the convenience of research, it names the tourist attractions as tourist attractions 1, tourist attractions 2, tourist attractions 3, tourist attractions 4, tourist attractions 5, tourist attractions 6, and tourist attractions 7. It names the systems as System 1, System 2, System 3, System 4, and System 5. Among them, tourist attractions 1-5 are 5A-level scenic spots, and other scenic spots are relatively low-level scenic spots. System 5 is the designed system presented in this paper. The quality of a tourism resource is divided into 5 points, with more than 5 points being good, and less than 5 points being bad.

V. Experiment Results of Tourism Information Recommendation System

(1) Tourism resource information recommended by the system

The tourist information that people pay attention to is nothing more than four aspects of food, clothing, housing and transportation. However, the general tourism information recommendation system lacks comprehensiveness of tourism resource information. For solving this problem, this paper designs a comprehensive tourism information recommendation system. The tourism resource information recommended by the system is shown in Figure 6.

Figure 6: Tourism resource information recommended by the system

From Figure 6, the tourism resource information mainly recommended by the tourism information recommendation system designed based on machine learning in this paper includes tourism cost, scenery, living conditions, food and tourism conditions. The recommended information is comprehensive and can meet the needs of all kinds of people. If tourists want to visit a little less, they can go to tourist attractions 1. When they want better living conditions, the system will recommend information about tourist attractions 3 for them. The tourism information recommendation system designed in this paper can meet people's individual needs to a great extent.

(2) Evaluation of the same scenic spot by different systems

Different tourist information promotions have different scenic spot evaluation systems. In order to facilitate the research of other tourism information recommendation systems and the recommendation designed by this paper based on machine learning, this paper selects the same evaluation object. The specific evaluation data is shown in Figure 7.

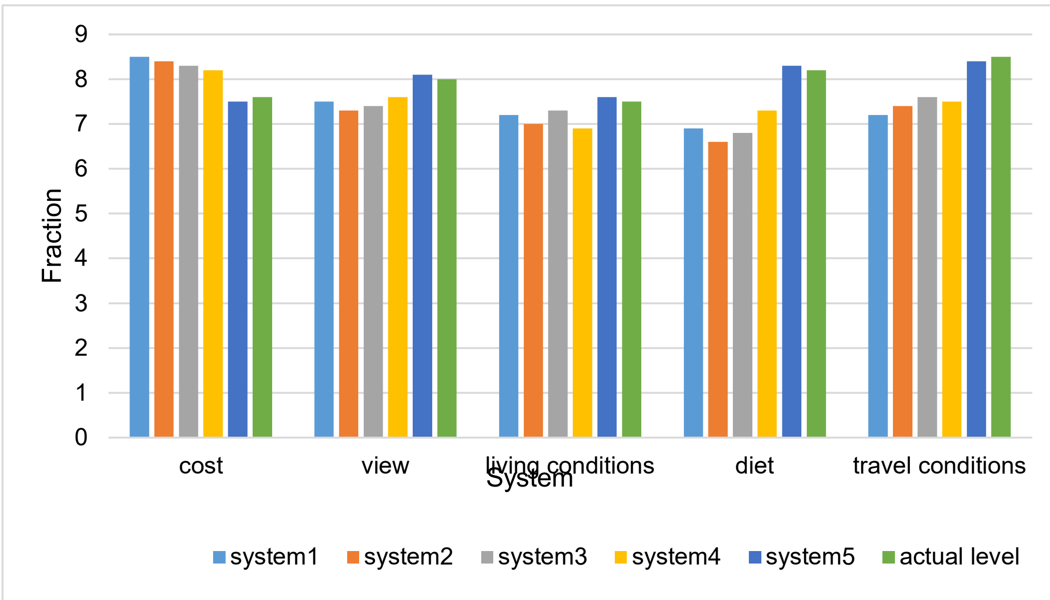

Figure 7: Evaluation of the same scenic spot by different systems

It can be concluded from Figure 7 that the tourism resource recommendation information of other systems is mostly higher or lower than the actual level of tourist attractions, which has a great deviation from the actual tourism resource information. If people inquire about the tourist attractions information they want to visit based on other tourism resource recommendation systems, it will be prone to deviations, causing psychological shadows and affecting tourists' play experience. It can be seen from the data that the information recommended by the tourism information recommendation system designed based on machine learning in this paper is more in line with the actual level of tourist attractions than other recommendation systems. It can meet people's play needs to a large extent and avoid tourists' realistic gap.

(3) Comprehensive ratings of different tourist attractions by different systems

It is impossible to compare and analyze the tourism information recommendation system designed based on machine learning in this paper from various aspects only by looking at the evaluations of different tourism information promotion platforms for the same tourist attraction. To better test the function of the tourism information recommendation system designed in this paper, this paper selects the scoring data of different scenic spots. The specific data is shown in Figure 8.

From Figure 8 can kow that the comprehensive score of the tourism information recommendation system designed based on machine learning for different scenic spots is the closest to the actual level of different scenic spots. Moreover, its comprehensive score for tourist attractions with low actual playability is also relatively low. The comprehensive scores of system 1 and system 2 for different scenic spots are relatively close to the actual level, but these two systems also have high comprehensive scores for tourist attractions with relatively low tourism degrees. It deviates greatly from the actual situation, and it is easy to cause the situation that the recommended information does not match the actual situation. The comprehensive scores of system 3 and system 4 for different scenic spots are far lower than the actual level, which is easy to make tourists lose interest in playing. Compared with other systems, the tourism information recommendation system designed in this paper based on machine learning has great advantages and is easier to meet the needs of tourists.

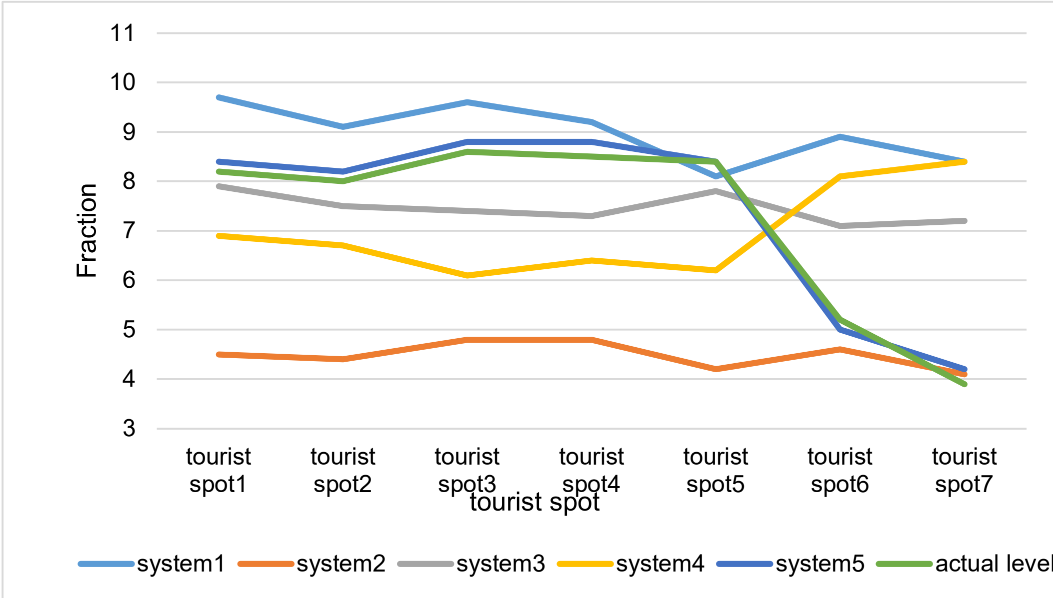

Figure 8: Comprehensive ratings of different tourist attractions by different systems

(4) Position stability of guidance information

In order to understand how tourists set the recommended information of the tourism information recommendation system designed in this paper, it studies the change of orientation information within 65 minutes after tourists leave the station and the information certainty. The specific data is shown in Figure 9.

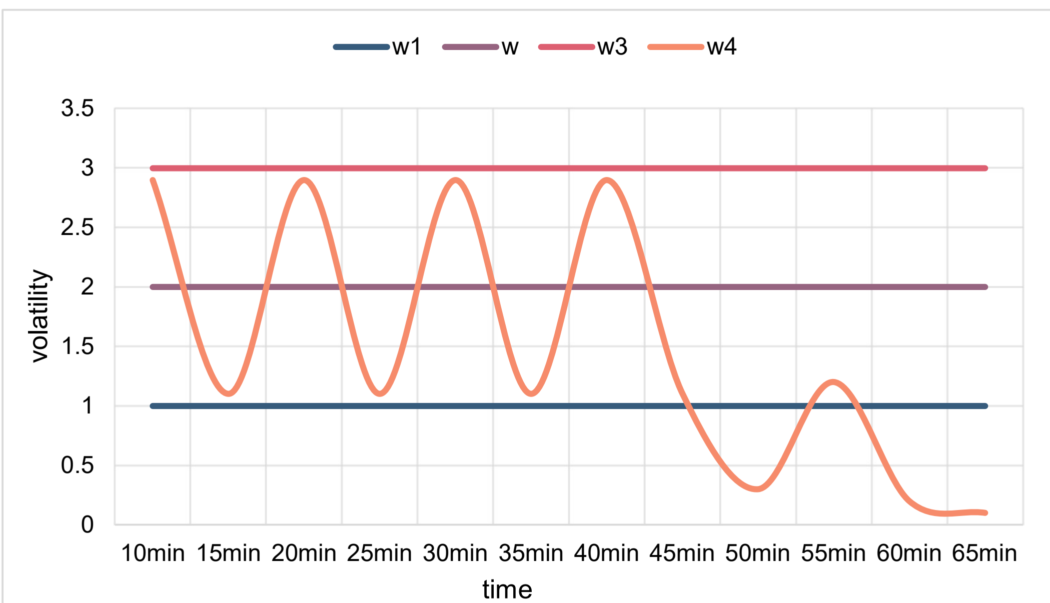

Figure 9: Guidance information position stability

Among them, w represents the amount of information stabilization. w1 represents the lower limit of information. If it is lower than the lower limit, it means that tourists have information blind spots in the process of leaving the station. w3 represents the upper limit of information. Exceeding the upper limit description information is useless to the traveler.

As shown in Figure 9, each point that the tourist passes through has guidance information, and the tourist can know his position and the direction of the walking at any time. In this case, the information certainty of tourists always maintains a value between the upper and lower limits with the growth of time, and remains unchanged. Between 10 and 45 minutes, the certainty of passenger information fluctuates with the increase of departure time. It always fluctuates within the upper and lower bounds of information certainty over time, but never exceeds the upper and lower bounds. 45-65 minutes are set for unreasonable guidance information location, lack of certain continuity. w4 represents the amount of change in the orientation information of tourists within 65 minutes after leaving the station. After the tourists receive the orientation information, the certainty of the information is strengthened. In the following period of time, if there is no guide information, the certainty of tourists' information will continue to weaken, and the rate of growth and decline over time will become faster and faster. The tourism information recommendation designed system presented in this paper based on machine learning sets reasonable guidance information, which can provide continuous guidance information after the battle. This ensures that the information certainty of tourists continues to increase, laying the foundation for tourists to play.

(5) Comparative analysis of the forecast data before and after using the tourism information recommendation system

The tourism information recommendation system designed in this paper based on machine learning will eventually be applied to real life. In order to understand the importance and significance of the tourism information recommendation system designed in this paper to the actual tourism, this paper makes a comparative analysis of the forecast data before and after using the tourism information recommendation system. The specific data is shown in Figure 10.

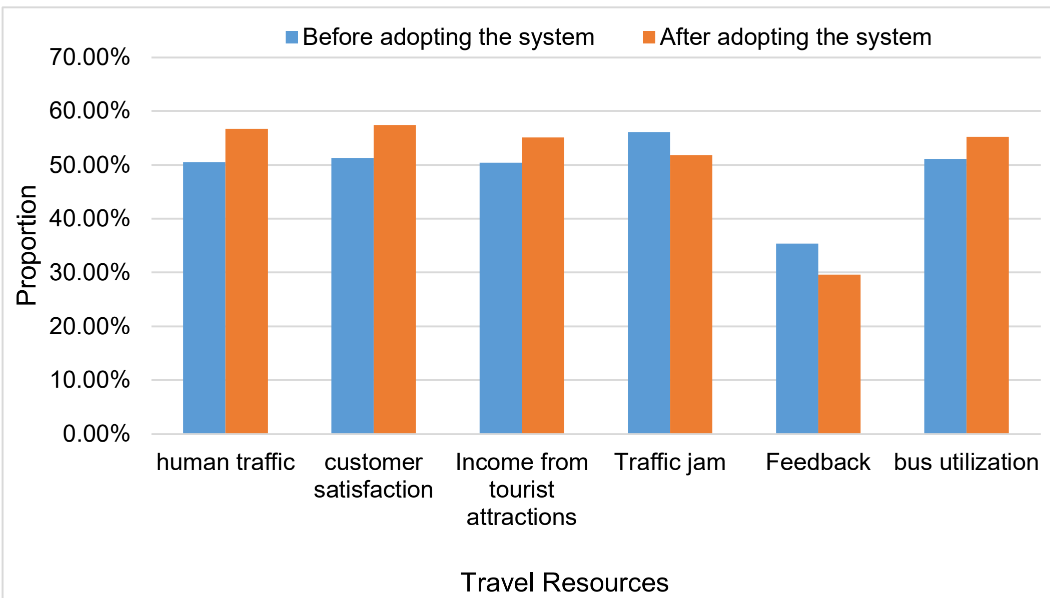

Figure 10: Comparative analysis of forecast data before and after using the recommendation system

As can be seen from Figure 10, after using the tourism information management system involved in this paper, the predicted traffic of tourist attractions has increased by about 6.2% compared with the previous one. The predicted user satisfaction increased by about 6.1% compared to before the adoption of the system, and the predicted revenue of tourist attractions also increased by about 4.7% compared with the previous period. The system has the function of route query, which can help users avoid the peak traffic period. The traffic prediction congestion rate after using the system can be reduced by 3.3%, and the feedback rate will also be reduced by 5.8%. Moreover, the fact that tourists use the system to avoid traffic jams, which will result in a 4.1% increase in bus utilization. Through data analysis, it can be seen that the design of the tourism information recommendation system based on machine learning in this paper is of practical significance.

With the vigorous promotion and development of the tourism industry under the background of the digital economy, it is difficult to meet the personalized needs of tourists when they only rely on a small amount of tourism resource information to formulate tourism plans. It can meet the individual needs of tourists to a large extent and help users formulate reasonable travel and play plans. The main work of this paper is as follows:

The function and framework of the whole tourism information recommendation system are expounded in detail. The overall function of the system designed based on machine learning in this paper mainly includes eight query modules, which play an important role in the selection of tourist locations for tourists from various aspects. In addition, this paper also uses the data flow diagram and the component diagram to describe the components and the relationship between the components in the tourism information recommendation system, which is helpful to understand and analyze the relationship between the components.

It conducts research on algorithms for machine learning. Because machine learning involves many fields and a wide range, there are many algorithms generated. But not all machine learning algorithms are suitable for the tourism information recommendation system designed in this paper. Therefore, this article lists the machine learning algorithms that are applicable to this article. These listed algorithms have certain practicality and innovation.

The tourism resource information recommended by the general tourism information recommendation system lacks comprehensiveness. The tourism resources recommended by the system mainly include tourism cost, scenery, living conditions, diet, etc., which can meet the various needs of various tourists.

Different tourist information recommendation systems have different scenic spot evaluation systems. For the same scenic spot, the tourism resource recommendation information of other systems is quite different from the actual tourist attraction level. Compared with other recommendation systems, the information recommended by the tourism information recommendation system designed in this paper based on machine learning is more in line with the actual level of tourist attractions. For different tourist attractions, the comprehensive rating of the tourist information recommendation system based on machine learning in this paper is the closest to the actual level of different tourist attractions. Its application in real life has great advantages.

Because the tourism information recommendation system has set reasonable guidance information. It can provide continuous guidance information after the battle to ensure that the information certainty of tourists is continuously enhanced. This provides strong guidance information support for tourists' play and ensures the smoothness of tourists' play.

When applied to real life, the tourism information recommendation system designed in this paper can increase the predicted traffic flow and predicted user satisfaction of tourist attractions by about 6.2% and 6.1% respectively. This, in turn, results in a much higher forecasted revenue for tourist attractions than before. Since the system designed in this paper has the function of route query, it can help users avoid peak traffic hours and improve the utilization rate of public transportation, which in turn reduces the feedback rate. The experimental data shows that the design of the tourism information recommendation system based on machine learning in this paper can achieve good social and economic benefits.

VI. Conclusion

Machine learning is an important area of artificial intelligence development. It is a valuable attempt to apply it to the tourism information management system. This is also the premise for the sustainable development of the tourism industry in the future. In order to ensure the sustainable development of the tourism industry and the experience of tourists, this paper introduces the overall framework of the tourism information system based on machine learning in the context of the digital economy, and describes several learning methods in the machine learning algorithm. Then it compares and analyzes the system designed in this paper with other tourism information recommendation systems. It concludes that compared with other systems, the tourism information recommendation system designed in this paper has great practical significance and can meet the needs of tourists to a large extent. In addition, this paper also combines the characteristics of other tourist information. It has carried on the scientific design and analysis to the tourist information system, adopted and carried out the component type development. The system not only includes the basic functions that a tourist information system should have, such as map display, information inquiry, traffic inquiry and intelligent guidance, but also includes personalized functions that tourists need beyond the basic functions, such as tourism expert functions. It provides professional services for tourists, so that tourists can make comprehensive travel plans. In addition to the design of the tourism information recommendation system at this stage, the follow-up work of this paper mainly includes the gradual improvement of the system's functions, and the gradual planning of the classification management module and functional module to meet the requirements of various aspects.

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References

[1] Utama A. Design of Agro-Education Tourism Accounting Information System[J]. South Asian Journal of Engineering and Technology, 2020, 2(6):54-61.

[2] Li M. An optimal design of forest wetland tourism development strategy based on gis technology[J]. Boletin Tecnico/Technical Bulletin, 2017, 55(11):679-685.

[3] Kashevnik A M, Ponomarev A, Smirnov A V. A multimodel context-aware tourism recommendation service: Approach and architecture[J]. Journal of Computer & Systems Sciences International, 2017, 56(2):245-258.

[4] Sajjadian F, Sheikh R, Souri M E. Application of rough set and netnography in tourism marketing analysis[J]. Journal of Modelling in Management, 2018, 13(4):1025-1036.

[5] Hong M, Jung J J. Multi-criteria tensor model consolidating spatial and temporal information for tourism recommendation[J]. Journal of Ambient Intelligence and Smart Environments, 2020, 13(3):1-15.

[6] Arif Y M, Nurhayati H, Kurniawan F. Blockchain-Based Data Sharing for Decentralized Tourism Destinations Recommendation System[J]. International Journal of Intelligent Engineering and Systems, 2020, 13(6):472-486.

[7] Bagus R. Tourism Visitor Center Flowchart As Recommendation for Bali Tourism Destination[J]. Test Engineering and Management, 2020, 83(4):18306-18319.

[8] Buczak A, Guven E. A Survey of Data Mining and Machine Learning Methods for Cyber Security Intrusion Detection[J]. IEEE Communications Surveys & Tutorials, 2017, 18(2):1153-1176.

[9] Mullainathan S, Spiess J. Machine Learning: An Applied Econometric Approach[J]. Journal of Economic Perspectives, 2017, 31(2):87-106.

[10] Chen J H, Asch S M. Machine Learning and Prediction in Medicine — Beyond the Peak of Inflated Expectations[J]. New England Journal of Medicine, 2017, 376(26):2507-2509.

[11] Liu S, Wang X, Liu M. Towards Better Analysis of Machine Learning Models: A Visual Analytics Perspective[J]. Visual Informatics, 2017, 1(1):48-56.

[12] Zhang J, Zhuo W, Verma N. In-Memory Computation of a Machine-Learning Classifier in a Standard 6T SRAM Array[J]. IEEE Journal of Solid-State Circuits, 2017, 52(4):1-10.

[13] Kolouri S, Park S R, Thorpe M. Optimal Mass Transport: Signal processing and machine-learning applications[J]. IEEE Signal Processing Magazine, 2017, 34(4):43-59.

[14] Zhang L, Tan J, Han D. From machine learning to deep learning: progress in machine intelligence for rational drug discovery[J]. Drug Discovery Today, 2017, 22(11):1680-1685.

[15] Parassa Y, Pairunan T T, Pongtuluran A K. Tourism Information System as a Promotion Container of Tourism Business in North Sulawesi Province[J]. International Journal of Computer Applications, 2020, 175(23):45-47.

[16] Martasubrata M F, Priyadi Y. Analisis Kesiapan UMKM Dalam Mengadopsi E-SCM Melalui Kolaborasi Technology Acceptance Model dan Data Flow Diagram di UMKM Clothing Line Lokal Bandung[J]. SOSIOHUMANITAS, 2020, 21(2):108-115.

[17] Drozin A D, Kurkina E Y. Application of Equilibrium State Diagrams for Calculating Segregation Kinetics during Cooling of a Two-Component Melt[J]. Steel in Translation, 2020, 50(2):90-94.

[18] Kaur A, Vig V. Automatic test case generation through collaboration diagram: a case study[J]. International Journal of System Assurance Engineering & Management, 2018, 9(2):1-15.

[19] Tertychny-Dauri V Y. Nuclear Electromagnetic Generator: Mathematical Model on Toroidal Vacuum Scheme[J]. Open Access Library Journal, 2018, 05(4):1-8.

[20] Khan K, Uddin R. Integrated bioinformatics based subtractive genomics approach to decipher the therapeutic function of hypothetical proteins fromSalmonella typhiXDR H-58 strain[J]. Biotechnology Letters, 2022, 44(2):279-298.

[21] Y Kenchappa, Karibasappa K. Dual Phase CBIR Model using Hybrid Feature Extraction and Manhattan Distance Measure[J]. International Journal of Intelligent Engineering and Systems, 2021, 14(3):72-81.