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Deep Learning-Driven Rural Tourism Platform Visitor Behavior Analysis and Prediction Dual-Module Model

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Abstract With the improvement of material living standards, tourism has become an important part of people's spiritual lives, and the demand for tourism has also grown rapidly. Rural tourism platforms serve as vehicles for disseminating unique cultures and play a significant role in the integration of culture and tourism. This study first selects Qiandongnan Prefecture as its research subject, utilizing an intelligent rural tourism service platform to analyze tourists' behavioral patterns through their online travel diaries, thereby indirectly validating the effectiveness of the intelligent rural tourism service platform. In view of the shortcomings of LSTM that some tourism data will still be lost when the input sequence is too long, the attention mechanism is introduced on the basis of the SAE-LSTM model, and the Attention-SAE-LSTM prediction model is constructed, and the empirical research based on the tourist number dataset in Jiuzhaigou and Siguniang Mountain Scenic Area shows that the prediction effect of the Attention-SAE-LSTM model is better than that of AE-LSTM and SAE-LSTM models. Proving the prediction ability of the prediction model in the forecasting of tourism volume is conducive to the tourism sector to understand the distribution of tourist flow in advance.

Index Terms LSTM neural network, rural tourism, attention mechanism, tourist behavior

I. Introduction

Rural tourism is based on rural areas and integrates agriculture and tourism to provide visitors with sightseeing, recreation, and leisure services for short vacations. It can effectively promote local employment and income growth, strengthen the collective economy, improve the living environment, and preserve local culture. Through tourism assistance mechanisms such as “scenic areas leading villages” and measures such as staff training and brand building, various regions have established a broad platform for farmers' entrepreneurship and employment and the integration of rural industries [1], [2]. Additionally, rural tourism contributes to improved ecological environments, enhanced public service facilities, and elevated rural cultural standards, further laying a solid foundation for high-quality rural tourism development [3], [4]. However, rural tourism still faces numerous obstacles in empowering rural revitalization, including low levels of professionalization and refinement in public services, long-term lack of scientific planning and coordination, and urgent need to improve the quality of supporting services such as tourism information, transportation, safety, and sanitation [5]-[7]. The absence of tourism public services has severely constrained the high-quality development of rural tourism. Rural tourism urgently needs to address the shortcomings in public services, taking the needs of tourists and the aspirations of villagers as the guiding principles for the supply of public services, and enhancing service efficiency [8]-[10]. Against this backdrop, the rural tourism intelligent platform has emerged.

In the process of rural tourism development, to identify the hidden issues in current rural tourism and promote the healthy and orderly development of rural tourism activities, it is necessary to conduct in-depth analysis of rural tourism consumers [11]-[13]. Consumers are the core of rural tourism activities. By focusing on their travel motivations and behavioral characteristics, we can identify their actual needs for rural tourism activities [14], [15]. Only through analyzing tourist consumption behavior can we accurately position the development of the rural tourism market and product design, thereby improving and accelerating the development of the rural tourism market in this region [16], [17].

Analyzing the relationship between tourist consumer behavior and destination management using intelligent platforms is of great significance for improving the service quality of tourist attractions and visitor satisfaction. Literature [18] indicates that social media platforms are an important source of information for analyzing tourist behavior, proposing a predictive model based on Convolutional Long Short-Term Memory Deep Learning (CLSTDL) methods. By inputting tourist behavior sequence data, this model predicts future tourist destinations, providing valuable insights for tourism planning. Literature [19] introduces a tourist behavior analysis method based on digital lifestyle patterns, connecting tourists with the digital world to analyze their behavioral data sequences, thereby providing insights for improving smart tourism services and related commercial activities. Literature [20] utilizes a long short-term memory (LSTM) deep learning model to analyze tourists' travel preferences and search behaviors, thereby forming short-term travel demand predictions. Literature [21] designs and evaluates a “big data analysis” method to support strategic decision-making in tourism destination management, using tourist behavior data generated by social media websites as the analysis target, thereby enhancing the applicability and utility of tourism destination management for tourists. Literature [22] employs a convolutional neural network (CNN) technical model to provide technical support for analyzing tourist consumption psychology and behavior. Its analysis results can be combined with and improve smart tourism management measures to promote the comprehensive development of the tourism market. Since China's rural tourism market is still in its early stages of development and various aspects are not yet mature or complete, it is of great significance to explore high-quality development measures supported by smart tourism platforms in the face of a rural tourism model with severe deficiencies in tourism public services.

This paper constructs a comprehensive intelligent rural tourism service platform from five layers: the hardware network layer, the data information layer, the service system layer, the application layer, and the user layer. Taking Qiandongnan Prefecture as an example, we collect online travel diaries from Ctrip Travel Network from 2022 to 2024 as raw data and combine data analysis methods to explore tourist behavior. Then, LSTM-based autoencoders are deeply stacked, and an attention mechanism is introduced on the basis of SAE-LSTM to propose the Attention-SAE-LSTM prediction model. Through experiments on datasets of tourist numbers in the Jiuzhaigou and Siguniangshan tourist attractions, the experimental results of the proposed model and the benchmark model are obtained, demonstrating the superiority of the model in tourism prediction.

II. Intelligent platform for rural tourism based on data analysis

II. A. Technical Architecture of the Global Intelligent Rural Tourism Platform

The All-Region Intelligent Rural Tourism Platform is a comprehensive intelligent platform involving multiple parties and covering the entire region. It is based on technologies such as sensor devices, wireless local area networks, 5G communication, and GPS positioning to collect information, which is then integrated, consolidated, and interconnected by a network data information platform. This forms a data information repository centered on suppliers, demanders, and management supervisors, enabling seamless connectivity, collaborative development, and overall intelligence of the data information repository. Real-time updates of multi-party data and automatically processed visitor information are presented to visitors, managers, and other stakeholders through an intelligent service system, providing visitors with comprehensive, accurate, and timely services. The technical architecture of the All-Region Intelligent Rural Tourism Platform is shown in Figure 1, primarily divided into five layers: the hardware network layer, data information layer, service system layer, application layer, and user layer.

II. B. Modules of the Global Intelligent Rural Tourism Platform Service System

II. B. 1) Intelligent Tourism Service Module

The Smart Tourism Service Module is a service functionality module designed for tourists. This module integrates tourism services within scenic areas and aggregates comprehensive data. Tourists can use computers or mobile devices to access information about scenic areas, leisure services, and event activities, as shown in Figure 2. This module is specifically divided into five sub-modules: Information Inquiry, Cultural Promotion, Commerce, Smart Interaction, and Personalized Recommendations. Among these, the Smart Interaction module runs throughout the entire Smart Tourism Service Module, empowering other modules and fostering communication and collaboration between them, thereby highlighting the platform's intelligent attributes. The Information Inquiry, Cultural Promotion, and Commerce modules operate in parallel, providing users with comprehensive inquiry and experiential services. The Personalized Recommendations module, based on the other four modules, offers customized, precise recommendations to meet users' diverse needs.

II. B. 2) Intelligent Tourism Management Module

The management module is the foundation and core of the intelligent rural tourism platform's command, dispatch, and management. It is divided into platform management and scenic spot management, and connects the two modules to achieve integrated remote intelligent monitoring and management of scenic spot personnel, equipment, and tourists, as shown in Figure 3.

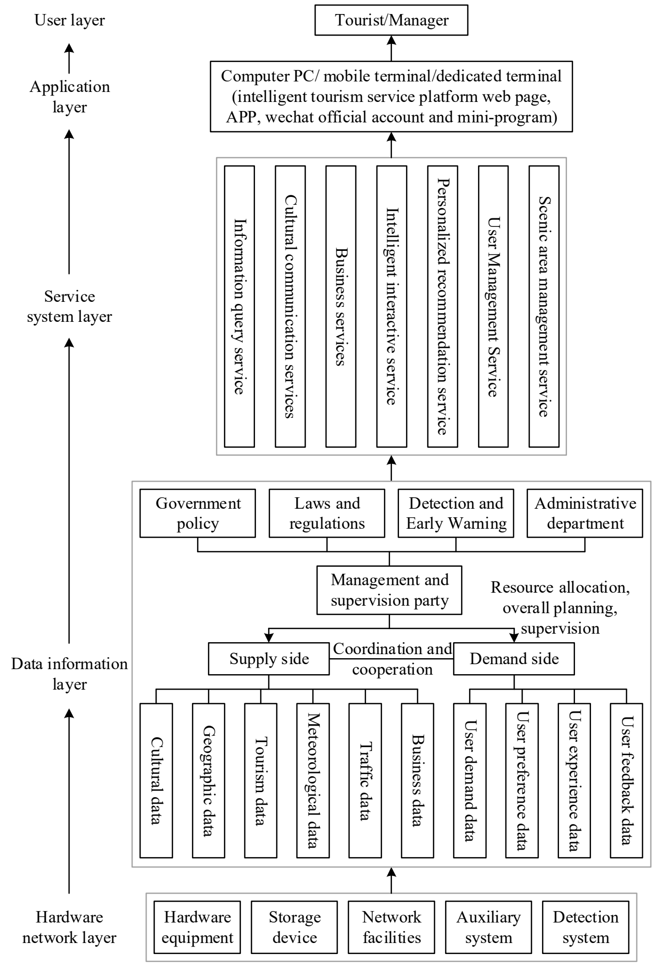

Figure 1: The technical architecture of the omnidirectional intelligent rural tourism platform

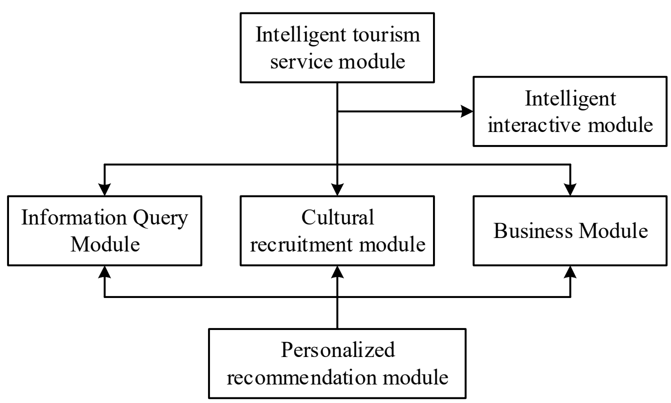

Figure 2: Smart travel service module

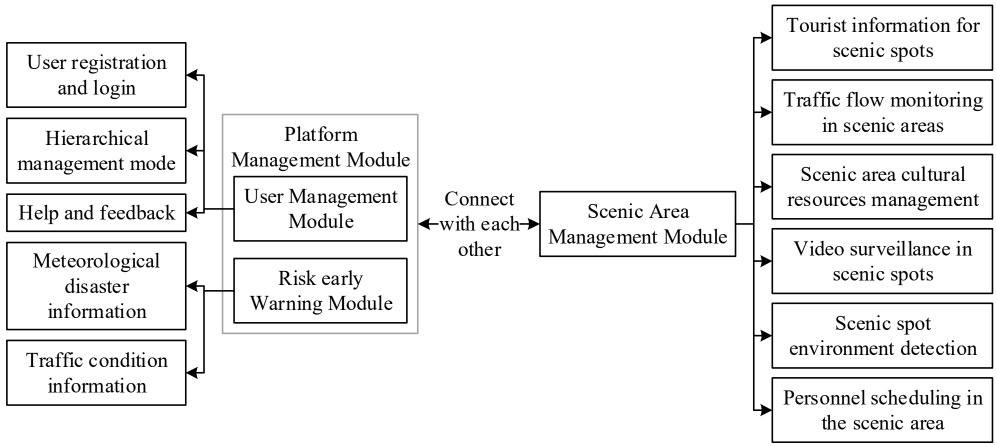

Figure 3: Intelligent travel management module

III. Analysis of rural tourism visitor behavior

III. A. Study Design

III. A. 1) Overview of the case study site

Qianxinan Miao and Dong Autonomous Prefecture, located in the southeastern part of Guizhou Province, is the region with the highest concentration of Miao and Dong ethnic groups in China. It is often referred to as the “Museum of Ethnic Cultural Ecology,” the “Forest State,” and the “State of Songs and Dances.” According to the latest statistical data from the People's Government of Qiandongnan Miao and Dong Autonomous Prefecture, as of December 11, 2024, the prefecture boasts 1 5A-rated scenic area, 20 4A-rated scenic areas, and 55 3A-rated scenic areas.

III. A. 2) Data collection and organization

This paper first collected a total of 903 online travel diaries posted by users on travel websites such as Ctrip, Tuniu, Qunar, Maofengwo, and Lvmama from 2022 to 2024 as raw data; Second, duplicate entries, invalid data, and online marketing advertisements were removed to clean the data. Typos and descriptions of tourist attractions were modified and standardized using Word's find and replace function. Effective information such as origin of visitors, number of travelers, travel companions, travel time, mode of transportation, tourist attractions visited, duration of stay, and per capita expenditure was extracted, categorized, and summarized using Excel, forming a database of tourist digital footprint information; Finally, statistical analysis methods were applied to organize and summarize data on tourist origin, mode of transportation, travel companions, tourism consumption, travel time, duration of stay, and preferences for tourist destinations, providing a data foundation for further exploration of tourist behavior characteristics.

III. B. Data Analysis Methods

III. B. 1) Text Mining Analysis

To extract and utilize useful information hidden within online text data, methods such as text mining and content analysis have been widely adopted in tourism research. Text mining primarily consists of three typical stages: data collection, data mining, and result output. The data mining stage includes two sub-steps: data preprocessing and pattern discovery.

The first step is data collection. UGC data collection primarily involves two methods: open API retrieval and web crawling. In studies based on tourism UGC data, researchers categorize data sources into two types: first, large social media platforms such as Weibo, Twitter, and Flickr, which provide open APIs for accessing UGC data; second, tourism websites like Ctrip and MaFengWo, which do not offer open APIs and thus require data retrieval via web crawling. Web crawlers are programs that automatically access web pages and can be divided into general-purpose crawlers (which simply iteratively access and download web pages) and focused crawlers (which target specific themes or objectives for data extraction).

The second step is data mining. Analyzing the collected online text data involves two sub-stages to extract useful information: data preprocessing and pattern discovery. In data preprocessing, different techniques are used for different research purposes, and common operations in existing tourism literature include data cleaning, word segmentation, and part-of-speech tagging.

Pattern discovery is another critical stage in text mining, aiming to explore interesting information within documents. Typical techniques in existing tourism research include LDA analysis, sentiment analysis, statistical analysis, clustering and classification, text summarization, and dependency modeling.

Step 3: Result output. The interesting information extracted through data mining is converted into useful knowledge to further serve tourism research. According to relevant studies, valuable knowledge encompasses aspects such as tourist satisfaction, consumption preferences, tourism destination image, tourism routes, and review characteristics, which are highly beneficial for improving tourism management and providing tourism recommendations.

III. B. 2) Co-occurrence analysis

Co-occurrence refers to the phenomenon of specific keywords appearing together in a text corpus. Co-occurrence analysis is a quantitative study of co-occurrence phenomena to reveal the content relationships and knowledge implied by feature items. Its basic principle is to reflect the strength of the relationship between these words by statistically analyzing the co-occurrence of high-frequency words in a text corpus.

The specific process of co-word analysis mainly consists of four stages: first, determine the analysis data set; Second, determine the analysis objects: extract high-frequency words related to the research object from the text corpus; Third, construct a binary co-occurrence matrix to obtain quantitative information such as co-occurrence frequency; Fourth, conduct co-occurrence analysis, typically combined with social network analysis for visualization.

This paper primarily uses NLPIR software to perform co-occurrence analysis, with the calculated quantitative information including co-occurrence frequency, binary probability, and binary word pair information entropy. Co-occurrence frequency refers to the number of times two words co-occur in sequential order, reflecting the strength of their association. Generally, the higher the co-occurrence frequency of a word pair, the closer the relationship between the two words. Binary probability refers to the probability of a co-occurring word pair appearing, while binary word pair information entropy indicates the information breadth of the word pair. The formula for calculating information entropy is:

$$H(p,q) = -\sum_{x \in X} p(x) \log q(x) \tag{1}$$

III. C. Spatio-temporal characteristics of tourists

III. C. 1) Number of travel days

Short-term tourists and long-term tourists are two distinct categories of visitors. In this study, tourists staying in Qiandongnan Prefecture for less than 20 days are classified as short-term tourists, while those staying longer are categorized as long-term tourists. The primary purpose of short-term tourists is typically leisure activities and sightseeing in Qiandongnan Prefecture, making them the focus of tourist behavior analysis. Among long-term tourists, a significant proportion are visiting relatives or settling permanently, with their behaviors more aligned with those of local residents. Therefore, researchers are more interested in the behavioral patterns of short-term tourists, with the primary objective being to distinguish between the two tourist groups.

Figure 4 shows the distribution of tourist stay durations. The horizontal axis represents the number of days tourists stay in Qiandongnan Prefecture, while the vertical axis indicates the number of tourists corresponding to each stay duration. The figure reveals that short-term tourists staying for 10 days or less constitute a significant proportion, with the highest number of tourists opting for a 5-day trip. This aligns with the phenomenon observed on travel websites, where 5-day tours in Qiandongnan Prefecture are the most popular. In addition to short-term tourists, there is also a peak in the number of long-term tourists who stay for 31 days, who are non-local residents settled in Qiandongnan Prefecture. Furthermore, since December is the peak tourist season in Qiandongnan Prefecture, the total number of tourists in November is significantly higher than that in August. Therefore, it is reasonable to select tourists in December for behavioral analysis in this study.

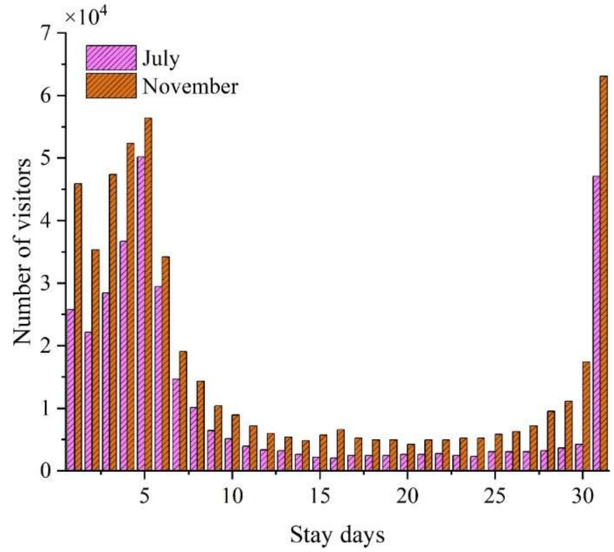

Figure 4: Contrast chart of tourist days in Scenic spot province in July and November

III. C. 2) Maximum transfer distance

The maximum transfer distance D is defined as:

$$D = \max_{i,j\in\{1,2,\ldots,n\}} d(sp_i, sp_j) \tag{2}$$

where sp_i and sp_j represent the stopping points in the tourist trajectory, and the value of D represents the distance between the two points with the greatest interval distance among all the stopping points in the tourist trajectory. The magnitude of this distance can indirectly reflect the scope of tourist activities. Tourists with a large maximum transfer distance usually appear in multiple different cities.

Figure 5 plots the cumulative distribution function (CDF) curves for the maximum transfer distances of one-day trips, five-day trips, eight-day trips, and long-term visitors. The horizontal axis represents the maximum transfer distance d in kilometers, while the vertical axis represents the cumulative probability corresponding to each distance. This figure effectively describes the cumulative distribution of maximum transfer distances.

As shown in the figure, each curve exhibits a distinct inflection point at approximately 220 km. According to available data, the straight-line distance from the departure location to Qiandongnan Prefecture is roughly 220 km. Therefore, the sudden change at this point reflects the number of tourists from the corresponding visitor group traveling from the departure location to Qiandongnan Prefecture. Among short-term tourist groups, as the number of travel days increases, the proportion of tourists visiting Qiandongnan Prefecture from the departure point also increases. Among 8-day tour groups, over 40% of tourists have visited cities surrounding Qiandongnan Prefecture. For long-term tourist groups, the CDF curve is relatively smooth, and the proportion of tourists at the inflection point is only 20%. This indicates that the activity range of long-term tourists is primarily confined to a single city, and their behavior is more akin to that of local residents rather than tourists.

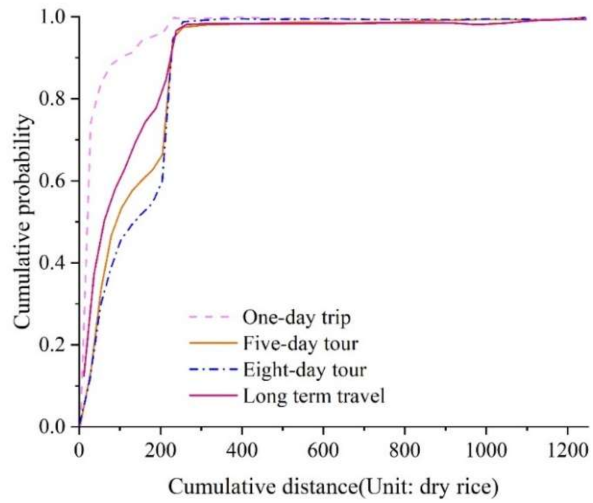

Figure 5: Comparison of CDF curves of maximum transfer distance for tourists with different travel days

III. C. 3) Turning radius

In this topic, the radius of rotation can reflect the degree of aggregation of tourists at the stopping point, which is defined as follows:

$$R = \sqrt{\frac{1}{\sum_{i=1}^{n} t_i} \sum_{i=1}^{n} t_i d(sp_i, sp_{cemer})} \tag{3}$$

Among these, Spcenter represents the centroid of visitor trajectories, which can be calculated as the average of all point coordinates along the trajectory. The turning radius R is the square root of the weighted average of the distances from each point to the centroid, where the weighting factor is the dwell time at each point. By weighting based on time, the turning radius effectively reflects the degree of aggregation at dwell points, with points having longer dwell times exerting a greater influence on the calculation results.

Figure 6 illustrates the differences in turning radius characteristics between short-term visitors (5-day trips) and long-term visitors. The horizontal axis represents the turning radius in kilometers, while the vertical axis shows the number of visitors corresponding to each turning radius value. The curve for short-term visitors shows two peaks, with the second peak occurring at an x-value of approximately 90 km. This group of visitors represents the turning radius for users traveling from their departure point to Qiandongnan Prefecture, which is approximately half the straight-line distance between the two locations. The other peak, corresponding to a smaller radius, represents tourists who only visit within a single city. The turning radius for long-term tourists forms a decreasing curve, with the number of long-term tourists decreasing as the turning radius increases, further highlighting the behavioral differences between long-term and short-term tourists.

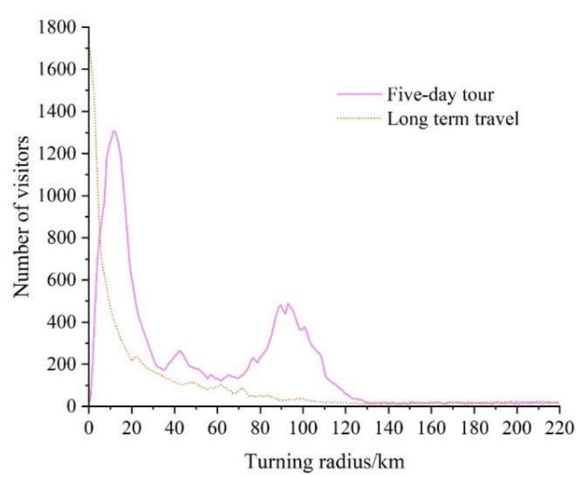

Figure 6: The distribution curve of short-term tourists and long-term tourist turning radius

III. C. 4) Proportion of time spent on leisure activities and accommodation

To distinguish between different types of tourists, researchers calculated the proportion of time tourists spent sightseeing and staying in hotels in Qiandongnan Prefecture based on their semantic trajectories. Figure 7 shows a scatter plot of visitors' sightseeing time and accommodation time. The points in the figure represent visitors divided into several categories. Visitors on the x-axis only appear at hotels during the day, with a time spent in Qiandongnan Prefecture of 0. This group of visitors may be on business trips or attending meetings, so they have no records of visiting Qiandongnan Prefecture. Tourists on the y-axis only appear in Qiandongnan Prefecture during the day and have no records of staying at hotels. This group can be confirmed as tourists visiting Sanya for leisure. The middle group of tourists, who have both Qiandongnan Prefecture and hotel records, can be roughly divided into two categories. The first category, in the lower right corner of the figure, consists of tourists who spend significantly more time at the hotel during the day. These tourists may not be purely recreational visitors; they may be attending meetings and visiting Qiandongnan Prefecture during breaks, or their primary purpose may be to visit relatives and friends. The second category, shown in the upper left corner of the figure, consists of tourists who spend most of their time in Qiandongnan Prefecture but also spend a small portion of their time at hotels. This behavior aligns with the characteristics of tourists visiting for leisure, with the time spent at hotels potentially being used for rest or planning subsequent travel arrangements.

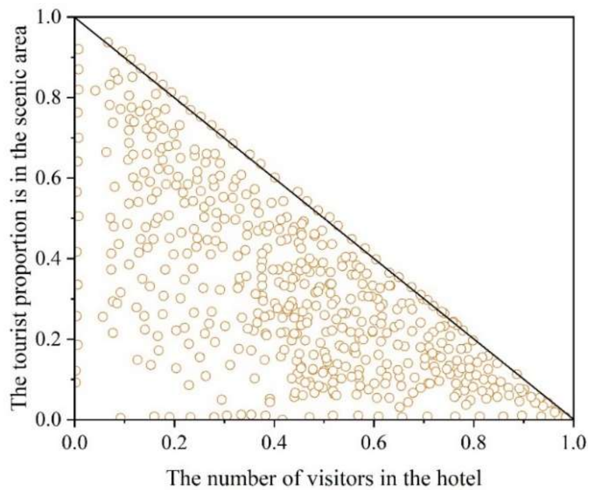

Figure 7: The difference of time and time percentage of visitors in the area

IV. SAE-LSTM-based attention mechanism for predicting rural tourism behavior

IV. A. Stacked Autoencoders

Deep learning is a machine learning method based on data learning, which extracts data features through multi-layer nonlinear processing units. Data is transformed from the bottom layer to the top layer, with each layer using the output of the previous layer as input [23]. Deep networks can learn more representations and better discover correlations between data by stacking layers one by one.

A stacked autoencoder (SAE) essentially uses the output of the hidden layer of the previous autoencoder as the input for the next autoencoder, consisting of multiple autoencoders.

A single autoencoder, through a three-layer network as shown in Equation (4), can learn a feature representation as shown in Equation (5):

$$x \to H_1 \to \hat{x} \tag{4}$$

$$H_1 = f_\theta(x) \tag{5}$$

The stacked autoencoder obtains H_1 through the training of the first autoencoder, then uses H_1 as input to train the next autoencoder, obtaining H_2, and continues to train this deep learning structure. In other words, first train equation (4) to obtain the transformation in equation (6), then train equation (7) to obtain the transformation in equation (8), and finally stack them layer by layer to form the SAE.

$$x \to H_1 \tag{6}$$

$$H_1 \to H_2 \to H_1 \tag{7}$$

$$H_1 \to H_2 \tag{8}$$

IV. B. Attention Mechanism

IV. B. 1) Seq2Seq Model

The Seq2Seq model [24] is a sequence-to-sequence model, a type of encoder-decoder architecture that generates an output sequence based on an input sequence. Its model structure is shown in Figure 8. In the Seq2Seq model, the sequence of Chinese-to-English translation input is first processed by the Encoder to obtain the language encoding c. The semantic encoding is then further processed in the Decoder. The output of Seq2Seq is not fixed in length; it can be 3 characters long or any arbitrary length. The application scope of Seq2Seq is extremely broad, not only being widely used in machine learning translation tasks but also in smart speakers and human-machine chat domains.

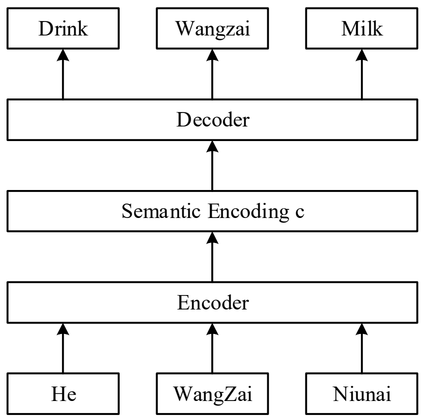

Figure 8: Seq2Seq model

IV. B. 2) Attention Mechanism

The attention mechanism is derived from humans. When viewing certain images, the human brain often focuses its attention only on the parts that interest it, rather than looking at every part once. Furthermore, when viewing similar images again, it will skip the other parts and go directly to the parts it is interested in.

In Figure 8, if the attention mechanism is not introduced, the input sequence obtains the language encoding c from the Encoder, and the semantic encoding c is passed in the Decoder, the content of which is independent of the Encoder. When people want to pay attention to the conversion of drink → drink when translating the drink from Wangzi milk, they want the Decoder to pay more attention to the features extracted by the Encoder from drinking, which is the attention mechanism, which allows the machine to pay attention to the places it needs to pay attention to when doing a specific task.

In neural networks, to make the model pay attention to certain content, you need to change the weights of different content. When people need the model to pay attention to drinking, you just need to increase the weight of the drinking feature. Given that function f can extract feature function g to achieve decoding, you need to make the neural network pay attention to drinking, which can be achieved by equation (9).

$$C_{drink} = g(0.8^* f(\text{drink}), 0.1^* f(\text{WangZai}), 0,1^* f(\text{milk})) \tag{9}$$

IV. B. 3) Attention Mechanism Structure

The attention mechanism is a crucial component in modeling time series data. When sequence data is output, the attention mechanism generates an attention scope to highlight the portions of the sequence data that should receive significant attention from the network [25]. In essence, the attention mechanism identifies specific parts of the input data that are more useful based on the features within the neural network.

The attention mechanism used in this paper primarily consists of two parts. The first part is implemented using a fully connected layer with a softmax activation function, which calculates the weight of each feature. The second part involves multiplying the output of the Dense layer by the input, thereby completing the allocation of attention weights.

IV. C. Attention-SAE-LSTM prediction model construction

IV. C. 1) Improvement ideas for the SAE-LSTM model

LSTM methods have been widely applied to tourism demand forecasting problems. Compared to RNN models, LSTM overcomes the issue of RNN's inability to retain long-term memory through its gate structure. However, LSTM methods still lose important sequence information when the input sequence is too long. The attention mechanism is a feature engineering method applicable to various deep learning architectures. By assigning different weights to different inputs, the model can understand the importance of inputs before model fitting. This paper combines the SAE-LSTM model with the attention mechanism, which can extract key information from input data, thereby addressing the issue of important information loss.

IV. C. 2) Attention-SAE-LSTM prediction model construction

The Attention-SAE-LSTM model consists of two stages: the pre-training stage based on a stacked autoencoder using LSTM and the supervised learning stage. This paper introduces an attention mechanism in the supervised learning stage, and the Attention-SAE-LSTM model is constructed using the Keras deep learning framework.

The supervised learning stage is constructed in four steps:

First, the attention structure is constructed. First, the input is dimension-flipped using a Permute layer, then a fully connected Dense layer and Softmax activation function are used to obtain the weights of each feature of the input. Next, a second Permute layer is used to perform dimension replacement on the data, and the output of the second Permute neural layer is multiplied by the input layer to obtain a weighted feature combination.

The second step is to add a packaged Attention structure before the LSTM. If Attention is used after the LSTM, the features learned by the LSTM layer will be more abstract, causing some of the attention to be dispersed by other features.

The third step is to use the three-layer LSTM model saved during the pre-training stage and its learned network parameters on the encapsulated Attention.

The fourth step is to add an output layer above the three hidden layers, where the output layer consists of only one node, which is used to handle the tourist volume prediction problem.

IV. C. 3) Obtaining Attention Scores

The Attention-SAE-LSTM model constructed in this paper can obtain attention layer weights through training, thereby obtaining attention weights. The specific implementation is shown in Figure 9.

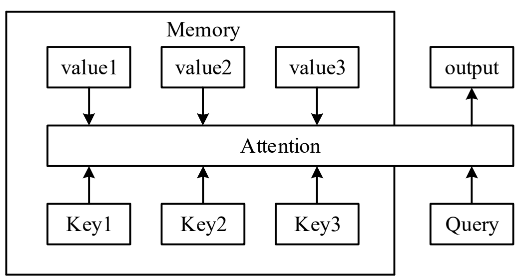

Figure 9: Attention score acquisition

The input consists of two parts: the first part is the query, and the second part is the key-value pairs, such as key1 corresponding to value1, key2 corresponding to value2, and key3 corresponding to value3. After the query passes through the Attention layer of the Attention-SAE-LSTM model, its output has the same dimension as the previous value. For any given query, the Attention layer of the Attention-SAE-LSTM model calculates the relationship between the query and each key to obtain the corresponding weights, and then performs a weighted sum to obtain the corresponding output for the query. The specific calculation steps are divided into three steps:

The first step is for the Attention layer to use the function α to calculate the relationship between the query and each key, as shown in Equation (10):

$$a_i = \alpha(Query, key_i) \tag{10}$$

The second step is to obtain the attention weights of the query through the Softmax activation function in the Attention layer, as shown in Equation (11):

$$b_1, b_2, ..., b_i = Soft\max(a_1, a_2, ..., a_i) \tag{11}$$

The third step is to perform a weighted sum of $b_1, b_2, ..., b_n$, as shown in Equation (12):

$$output = \sum_{i=1}^{n} b_i v_i \tag{12}$$

The $b_1, b_2, ..., b_n$ obtained in the second step is the attention score obtained by each input through Attention-SAE-LSTM.

IV. D. Experiments and Analysis

IV. D. 1) Data Description

On the one hand, considering the availability of visitor flow data, and on the other hand, taking into account the numerous external factors influencing visitor flow in scenic areas, this study selected daily visitor numbers (unit: number of visitors) from two major domestic 5A-rated scenic areas, Jiuzhaigou and Siguniangshan, as experimental data. The visitor numbers for Jiuzhaigou and Siguniang Mountain were obtained from the official websites of the scenic areas using Python web scraping technology. Additionally, the Baidu Index values corresponding to the keywords were also obtained using web scraping technology from their official websites. Considering the opening dates of the scenic areas and the onset of the pandemic, the selected data spans from April 1, 2021, to July 31, 2023. As shown in Figures 10 and 11, daily visitor numbers for Jiuzhaigou and Siguniang Mountain, along with daily Baidu Index data for keywords related to the same time period, were selected as the dataset to ensure data continuity and consistency. The training set and test set were then divided from the dataset in an 8:2 ratio.

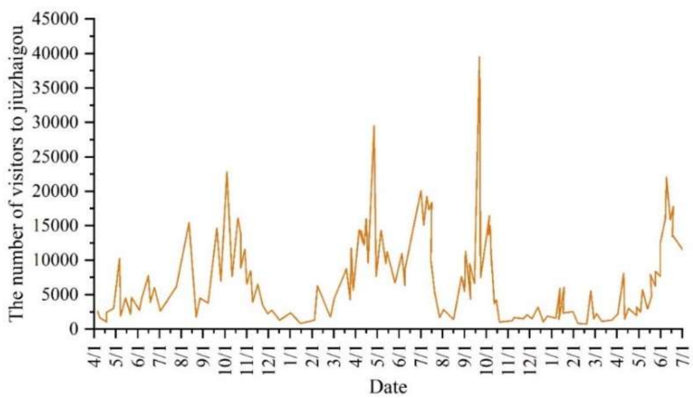

Figure 10: Daily data of tourist numbers in Jiuzhaigou

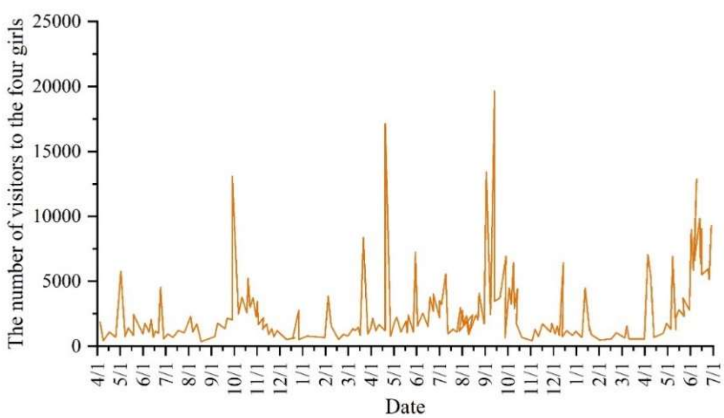

Figure 11: Tourist numbers in Four Girls Mountain

The statistical indicators for the sample of visitor numbers at Jiuzhaigou and Siguniangshan Scenic Areas are shown in Table 1. Among these, the standard deviation and absolute median difference for the Jiuzhaigou sample are 5,837.1729 and 3,825.1173, respectively, while the standard deviation and absolute median difference for the Siguniangshan sample are 2,532.0147 and 831.8154, respectively. This indicates that, during the same time period, the visitor data set for Jiuzhaigou Scenic Area is more volatile compared to that of Siguniangshan Scenic Area. On the other hand, considering that the data selected is from a period after the outbreak of the pandemic, it can be concluded that visitor flow in Jiuzhaigou Scenic Area was more significantly impacted by the pandemic compared to Siguniangshan Scenic Area. Additionally, the mean values for the Jiuzhaigou and Siguniang Mountain datasets are 5,249.4423 and 1,763.6728, respectively, indicating that during the selected post-pandemic time period, the Jiuzhaigou Scenic Area was more popular with visitors and had a higher visitor count; The kurtosis values are 2.1794 and 21.2761, respectively, indicating that the Siguniangshan Scenic Area dataset has more extreme values, which may be due to factors such as holidays, resulting in a steeper peak-like growth pattern for the Jiuzhaigou Scenic Area.

Table 1: The basic statistical description of the number of tourists in Jiuzhaigou and the four girls

Scenic spot	Number	Statistical standard					
		Standard deviation	Kurtosis	Mean	Absolute median difference	Skewness	Variance
Jiuzhaigou	873	5837.1729	2.1794	5249.4423	3825.1173	6.2714	33317259.1574
Four Girls Mountain	873	2532.0147	21.2761	1763.6728	831.8154	4.1863	6152241.0079

IV. D. 2) Prediction of the number of visitors to Jiuzhaigou Scenic Area

Forecasts for the number of visitors to the Jiuzhaigou Scenic Area were conducted using 1-, 3-, and 5-step forecasting methods. The prediction errors of the Attention-SAE-LSTM (M0) model and the benchmark models (M1-M6) were represented by RMSE, MAE, MAPE, and DS, as shown in Table 2. The table includes six benchmark models for comparison: LSTM (M1); AE-LSTM (M2); SAE-LSTM (M3); ARIMAX (M4); SVR (M5); and MLP (M6).

(1) Overall, compared with the benchmark models (M1-M6), except for the DS metric in the 5-step forecast, the proposed model (M0) achieved the best performance in terms of RMSE, MAE, MAPE, and DS metrics in the 1-step, 3-step, and 5-step forecasts.

(2) The Attention-SAE-LSTM model demonstrated the best prediction performance in 1-, 3-, and 5-step predictions, with the greatest improvement in MAPE for M5, at 92.3795%, 4.7555%, and 89.5244%, respectively.

Table 2: The prediction error of the number of tourists in Jiuzhaigou Scenic Spot

Model	One step prediction				Three-step prediction				Five-step prediction			
	RMSE	MAE	MAPE(%)	DS(%)	RMSE	MAE	MAPE(%)	DS(%)	RMSE	MAE	MAPE(%)	DS(%)
M0	0.0464	0.0395	0.8851	58.536	0.0633	0.0478	0.6236	65.676	0.0561	0.0407	0.9426	55.8905
M1	0.0553	0.0426	1.0685	50.2027	0.0814	0.0485	2.4355	57.2422	0.0833	0.0607	2.7213	51.6223
M2	0.0542	0.0461	1.5688	56.7503	0.0739	0.0499	1.5973	53.6283	0.1334	0.0883	3.0898	49.7943
M3	0.0556	0.0434	1.2977	56.9884	0.0778	0.0507	1.9268	56.6398	0.0728	0.0486	1.4394	57.7198
M4	0.1075	0.0729	1.8784	53.7741	0.2794	0.1203	2.9241	53.6278	0.4031	0.1616	4.1514	60.7686
M5	0.1047	0.1057	9.6658	56.7503	0.1082	0.0963	8.9809	59.0494	0.1063	0.0919	7.8492	61.3784
M6	0.0944	0.0809	3.3418	53.1789	0.1123	0.0863	4.4946	50.6157	0.1125	0.0857	4.7319	52.2321

To evaluate the effectiveness of the LSTM, AE-LSTM, SAE-LSTM methods, and their ensemble in the Attention-SAE-LSTM model (M0) for visitor number prediction, a comparison of the MAPE optimization rate was conducted across 1-, 3-, and 5-step forecasts, as shown in Table 3. Under 1-, 3-, and 5-step forecasts, the improvements in prediction results achieved by the LSTM, AE-LSTM, and SAE-LSTM methods were relatively modest, at 18.0117%, 35.8216%, and 27.0455%, respectively.

Table 3: Optimization rate of MAPE of each method in tourist number prediction model

	Measured method	Measured model	Reference model	One step prediction	Three-step prediction	Five-step prediction
Single method for predicting performance optimization	LSTM	M1	M4	44.8187	18.3519	35.948
			M5	90.4797	74.553	66.8298
			M6	69.6961	47.5099	43.998
Integrated method for predicting performance optimization	AE-LSTM	M2	M4	18.0117	47.1373	27.0455
			M5	85.2973	83.8988	62.1278
			M6	54.6707	66.2097	36.1904
	SAE-LSTM	M3	M4	32.5377	35.8216	66.917
			M5	88.1055	80.2249	83.1866

			M6	62.8126	58.8588	71.158
	Attention-SAE-LSTM	M0	M4	54.6457	80.5759	78.9166
			M5	92.3795	94.7555	89.5244
			M6	75.2041	87.9325	81.6818

To further evaluate the performance of the predictive model, DM tests and first- and second-order FE metric calculations were conducted, as shown in Tables 4–5. It can be concluded that in the 1-step and 5-step prediction experiments, the predicted results of the proposed model (M0) exhibit at least a 10% significant difference compared to the benchmark models (M1–M6), with DM values of 1, 3, 3, and 5-step prediction experiments, the proposed model (M0) showed at least a 10% significant difference in prediction results compared to the benchmark models (M1-M6). The DM values for the proposed model were at least less than -1.3925, -1.3763, and -2.3278 in the 1, 3, and 5-step predictions, respectively; The first-order and second-order FE indicator results of the proposed model (M0) are both greater than those of the other benchmark models, further validating the superior predictive performance of the proposed model.

Table 4: Jiuzhaigou DM test results

Measured model	One step prediction	Three-step prediction	Five-step prediction
M1	-2.1754(0.0211**)	-2.1365(0.0295**)	-3.8174(0.0002***)
M2	-2.5943(0.0074***)	-1.5732(0.0873*)	-4.5163(0.0001***)
M3	-1.3925(0.0439*)	-1.3763(0.0494*)	-2.4765(0.0112**)
M4	-5.0942(0.0001***)	-2.2571(0.0197**)	-2.3278(0.0143**)
M5	-10.3851(0.0001***)	-7.3529(0.0001***)	-7.2816(0.0001***)
M6	-5.4179(0.0001***)	-5.1078(0.0001***)	-4.6718(0.0001***)

Table 5: Fe results of Jiuzhaigou

Model	One step prediction		Three-step prediction		Five-step prediction	
	Level 1	Level 2	Level 1	Level 2	Level 1	Level 2
M0	0.6039	0.4241	0.5765	0.3591	0.5016	0.3391
M1	0.5339	0.3478	0.4238	0.2507	0.3496	0.2322
M2	0.4587	0.2949	0.4562	0.2848	0.2528	0.1789
M3	0.4942	0.3236	0.4446	0.2715	0.4321	0.2805
M4	0.3639	0.2263	0.2972	0.1822	0.2491	0.1701
M5	0.2313	0.152	0.2844	0.1725	0.2602	0.1733
M6	0.2618	0.1757	0.2443	0.1572	0.2403	0.1654

V. Conclusion

This paper first uses online travel diaries from Qiandongnan Prefecture as data to construct a comprehensive intelligent rural tourism service platform. It explores the tourism behavior of visitors to Qiandongnan Prefecture from aspects such as travel time and distance, thereby validating the reliability of the rural tourism service platform. Then, an attention mechanism is introduced into the SAE-LSTM model to propose the Attention-SAE-LSTM prediction model. Empirical research results from the two 5A-rated scenic areas of Jiuzhaigou and Siguniangshan demonstrate that the proposed model exhibits the best prediction performance in 1-, 3-, and 5-step predictions, with the greatest improvement in MAPE compared to SVR, at 92.7759%, 95.2256%, and 90.0978%, respectively.

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