Traffic Data Analysis of Tourist Attractions Based on Time Domain Partition Model

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Abstract. The traffic data around the scenic spot and the daily average passenger flow trend data associated with the tourist attractions are closely related to the travel. Considering the multiple factors hindering travel, the traffic structure adjustment model around the scenic spot to meet the needs of tourists is put forward, which can also be used as a reference for the management and guidance of tourist attractions. As for solving the problem that the traditional linear regression statistical model has a large error in the parameters of a single function, this paper proposes a prediction model based on Fourier transform. Using the least squares method of time trajectory and the corresponding relationship of spatial trajectory fusion, it improves the matching mode of the convolutional network and establishes a time domain division model to ensure the smooth flow of tourism traffic. Through the integration of real-time data optimization calculation of the time trajectory and spatial adjacent nodes, it provides short-term traffic commuting trend prediction for tourism projects. The experimental results indicate that the prediction results of the proposed method have the best fitting degree with the actual data. The calculation accuracy is more than 8. 5% higher than that of the comparative method, which can more accurately predict the traffic trend around the scenic spot. It also provides a reference for intelligent traffic management as well as for other traffic management platforms.

Keywords: Tourist attractions, Traffic conditions, Time domain division, Multi-dimensional model, Convolutional neural network

1 INTRODUCTION

Tourism activities are considered to be the mainstream form of fitness and entertainment, and moderate travel is the core element to further enhance the effect of tourism and vacation. Tourists have different travel needs. The scope of tourism vacation and holiday activity prediction varies with different purposes [1]. At present, the traditional traffic commuting situation of scenic spots relies on the parameter prediction of a single function and the implementation of passenger flow management. However, the prediction accuracy is low, which directly affects the satisfaction of tourists [2]. With the development and application of intelligent technology such as machine learning, future prediction technology is developing towards multi-dimensional data, association rules,

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and other advanced technology fields, which plays an important role in solving the prediction accuracy of scenic spot data.

Literature [3] has improved how to solve the problem of daily average passenger flow congestion in tourist attractions. The corresponding solutions for normal and congestion as well as abnormal conditions are proposed. Among them, GA-SVR, AGA-SVR, and SVR-ARIMa are more accurate. Literature [4] also continues to use this prediction strategy, from the natural seasonal changes, weather, and other historical average daily passenger flow, tourism suitability index, and other aspects of research. Literature [5] takes the average daily passenger flow of tourist attractions as an example. It uses an in-depth learning model to study the factors of average daily passenger flow and smoothness of tourist attractions and studies different statistical models based on sparse factor and neural network models respectively to achieve accurate prediction. To better integrate the spatio-temporal multi-scale external characteristics, literature [6] proposed a multi-dimensional model to predict the flow of crowd activities around scenic spots. At present, the research on the predictability of tourism traffic maintenance and the combination of machine learning and artificial intelligence will become the main technical means of future traffic analysis and prediction.

To effectively extract the multi-dimensional external characteristics of traffic data, reduce the association conflict caused by different data, and accurately predict the short-term traffic commuting information of travel routes, the rule problem of the local optimal solution and global optimal solution of traffic index is proposed. In this paper, the travel suitability prediction model of tourist attractions based on the Fourier transform is proposed to determine the time-domain division scheme of traffic data around scenic spots. The real-time traffic data statistical model is adopted to deal with high-dimensional random correlation. Then, a deep learning model of time trajectory is established. To verify the execution efficiency of the time-domain partition model, the multi-dimensional data fusion is carried out in the time series data of the traffic data flow around the relevant scenic spots and the tourist flow of tourist attractions. Simulation results verify that the performance and prediction ability of the proposed method is better than those of the traditional prediction methods. It can deeply excavate and analyze the tourism data of scenic spots, and provide technical support for the future development of tourism and vacation in scenic spots.

2 CONVOLUTION MOEDEL FOR TIME DOMAIN DIVISION OF TRAFFIC DATA

In this paper, the historical data and real-time data divided into the time domain are chosen to jointly model and fuse the hidden state information in the subspace. The relevant information is collected to complete the machine-learning task. Each task is directly input into the model component as an independent index to perform the calculation. Then the weight value and data structure characteristics of each index are analyzed to determine the assignment of task weight to each task. The weight value is used as the processing rule of the model, which is associated with the time trajectory and prediction. The result of this task is output. Finally, the collected real-time data and historical data are input into the neural network for convolution calculation. The model of the neural network is displayed in Figure 1.

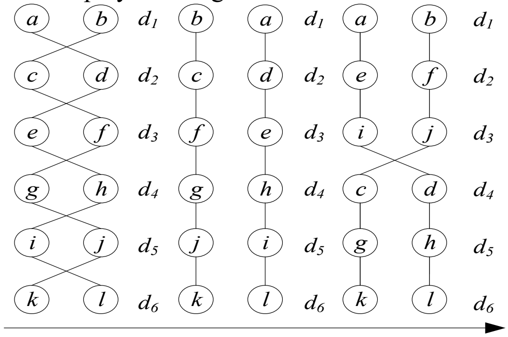

Fig. 1. Neural network model

In Figure 1, if each traffic index $(a,b,\cdots,l)$ needs to be able to distinguish the prediction fitting degree of real-time traffic data i and historical data j, the hidden index d_i parameter in the historical data needs to be corrected to the normal state and compared and analyzed in the next step.

The choice of the attentional control mechanism needs to be determined. In the historical data, the relevant information from different structural feature subspaces is chosen. The Fourier transform is adopted to map the input into different linear transformations of $Q(\text{query})$, $K(\text{key})$ and $V(\text{value})$. The process is as follows:

$$\begin{cases} Q_{i,j}^{t} = \sqrt{\lambda_{(w)} R_Q} \\ K_{i,j}^{t} = \sqrt{\lambda_{(w)} R_K} \\ V_{i,j}^{t} = \sqrt{\lambda_{(w)} R_V} \end{cases} \tag{1}$$

In Equation 1, λ is the convolution layer, w is the pooling layer, and R is the feature vector. Referring to the connection density of K and Q to measure the concentration of attention of V, the composite function is as follows:

$$\Delta f_{(t)}{}^{i} = \frac{\lambda_{(W)}^{\min}}{R_i} + \frac{\lambda_{(W)}'^{\max}}{R_j'} \tag{2}$$

The weight vector space of the focus of attention obtained from the product calculation is:

$$\theta_t^{i,j} = \sqrt[Q]{\frac{R_i}{\lambda^{\min} - \lambda^{\max}}} + \sqrt[K]{\frac{R_i}{\lambda^{\min} - \lambda^{\max}}} + \sqrt[V]{\frac{R_i}{\lambda^{\min} - \lambda^{\max}}} \tag{3}$$

The composite function of the time trace can be expressed as:

$$\phi_{i,j}^{t}=\frac{\lambda_{t}^{i}}{f_{i}^{\min-\max}}-1 \tag{4}$$

To achieve the effect of high similarity, the time dependence between the local optimal solution and the global optimal solution is considered first. When the output of the custom module is input according to the weight of the Fourier transform volume superimposed by the n-layer structure, the neural network model is used as the input item with a high hit rate in the historical information. The relevant historical information collected for a long time can be captured.

The time-domain custom algorithm flow is shown in Figure 2.

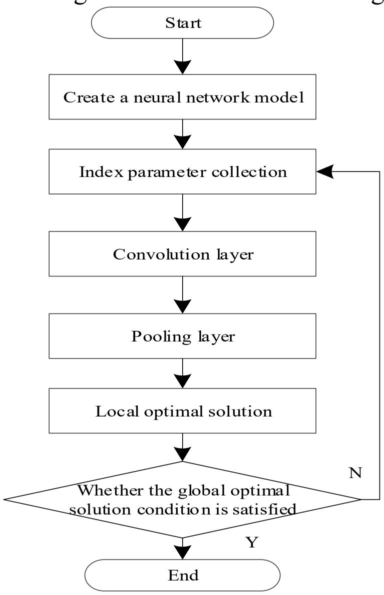

Fig. 2. Time-domain custom algorithm flow

3 CONVOLUTION REPRESENTAION OF THE SCENIC SPOT TRAFFIC DATA

GCN can update the external features of two nodes by aggregating the external features of all adjacent nodes and two nodes. The number of layers of a convolutional network improves over time, as does the number of neighbors immediately adjacent to two nodes. When the number of convolutional network layers reaches a certain number, the two neighboring nodes of two nodes are almost all distributed in the whole traffic network topology, which will lose the diversity of the external characteristics of the two nodes, resulting in the external characteristics of the two tourism project nodes in scenic spots are too similar to be identified. Therefore, GCN collects correlation information from the edge position in space and time trajectory tracking to determine the influencing factors, which is to avoid wrong dimension operation caused by wrong factors collected by machine learning. It also improves the analytical accuracy of the neural network model. Figure 3 shows the Fourier transform force custom module. The time outside the convolutional neural network is unknown.

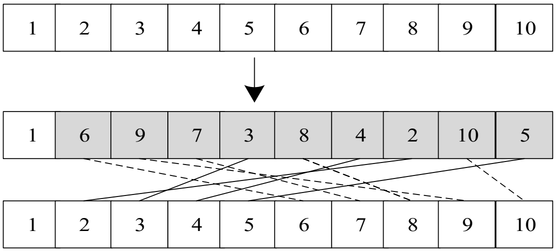

Fig. 3. Fourier transform force customization module

As shown in the attention customization module in Figure 3, the normal state of the traffic around the scenic spot and the internal traffic relationship are interdependent, which are affected by two adjacent tourism project nodes, such as potential factors and traffic accidents that result in obstacles to real-time traffic indicators. Therefore, the association of real-time indicators is the relationship of model dynamic information collection. In this paper, the global optimal solution graph convolutional network is taken to analyze different potential influencing factors. The different effects of traffic networks are compared and analyzed. Then, the internal and external characteristics of the traffic network are obtained.

4 THE EXPERIMENTAL ANALYSIS

4.1 The simulation test platform

In this paper, the real-time data of traffic flow around tourist attractions is substituted into the deep learning model to verify the convolutional network. The real-time monitoring data provided by literature [7] is adopted to compare the prediction results of different statistical models on the surrounding traffic. In this paper, two scenic spot road traffic data sets are selected to evaluate the overall quality and performance. The improvement level of innovative technology is compared.

In the analysis of HA and ARIMA evaluation indicators, the smaller the range of congestion threshold is, the smaller the measurement error of the model is, and the higher the prediction accuracy is required. The traditional linear regression method only models the historical adjacent traffic data nodes but ignores the spatial correlation between adjacent traffic data nodes. Spatio-temporal statistical models such as STGCN consider not only the conflict of temporal trajectories but also the correlation of spatial trajectories. It ignores the internal relationship between traffic networks around tourist attractions when extracting spatial external features. Although GCGRU considers the correlation of time and space, it only chooses the form of GRU to extract external features with unknown time, but it needs to collect external feature data for a long time to provide analysis.

4.2 Comparative analysis of model performance

The model proposed in this paper can more accurately fit the actual value in the short-term prediction of road traffic congestion using 10 minutes, 30 minutes, and 60 minutes of time trajectory. The fitting degree is significantly higher than the traditional model. Table 1 shows the performance comparison of the convolutional network road traffic congestion prediction model on different deep learning models.

Table 1. Comparison test results of data set

Index	10min		30min		60min	
	MAPE	MAE	MAPE	MAE	MAPE	MAE
HA	15.24	17.07	16.55	17.09	15.93	16.39
ARIMA	15.22	16.37	17.01	16.24	15.13	16.11
STGCN	14.28	13.93	11.47	12.83	12.87	12.91
GCGRU	10.63	10.87	9.39	10.87	10.42	10.38
Algorithm	3.88	4.25	4.21	3.97	3.69	3.68

This model establishes an evaluation model to solve the problem of road traffic congestion prediction. The test results are presented in Figure 4 and Figure 5.

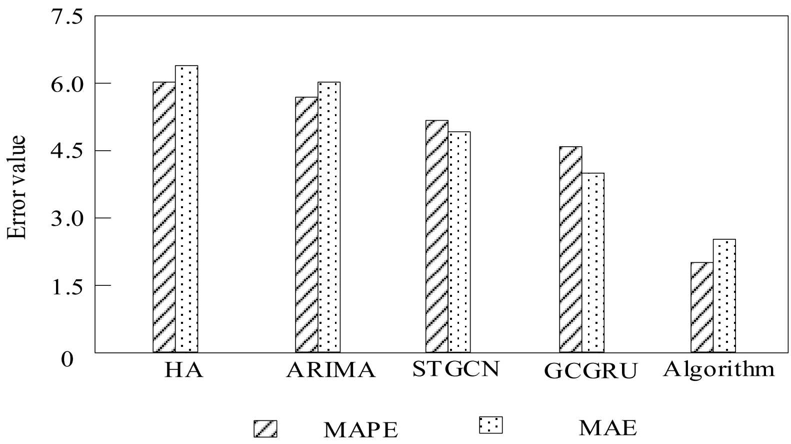

Fig. 4. Comparative analysis of the prediction results (1)

In Figure 4, the method in this paper can obtain the optimal solution for short and medium term prediction, which reflects the accuracy of the Fourier transform gated convolution network.

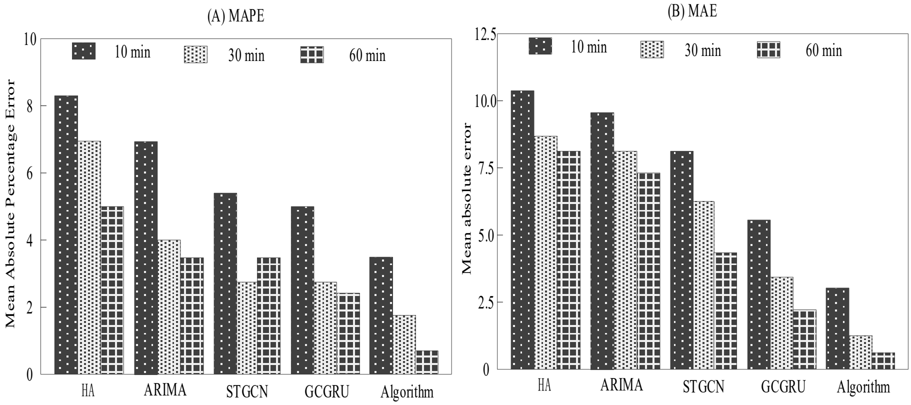

Fig. 5. Calculation results of each model on different time trajectories

In Figure 5, from the comparative analysis of different basic indicators in deep learning, the measurement error of this method in all basic indicators is better than that of other comparative methods. With the extension of the time trajectory in the short and medium term, this method can predict more accurately, which shows that this method has the best performance in the short and medium-term prediction.

5 CONCLUSION

In this paper, a neural network model is established to collect time trajectory data. A convolutional network custom module is adopted to model the surrounding short-term traffic flow data and determine the gate control mechanism. It can effectively screen unknown information in the future time, provide a judgment basis and analyze solutions, and solve the problems of emergency response and unpredictable data extraction. Experiments verify that the prediction results are almost consistent with the real-time data. The tourism traffic prediction model based on the Fourier transform is more accurate than the traditional method in the predictability of time series data and has higher feasibility. It verifies the technical advantages of the deep learning model and proves that the performance of this paper is feasible in practical application.

The research content is only based on the traffic prediction around the tourist attractions, lacking portability. The next step will focus on the expansion of user tourism planning and achieving intelligent navigation prediction and analysis capabilities.

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