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Combined Traffic Flow Prediction Based on Graph Convolution

Wang Ke
College of Communication Engineering
Chengdu University of Information Technology
Chengdu China

Abstract: Traffic flow data has strong temporal and spatial correlation. The traffic flow in the previous moment will affect the traffic flow in the next moment, and the traffic flow in the upstream and downstream will affect each other in space. . In order to alleviate traffic congestion and improve the accuracy of traffic flow prediction, this paper proposes a combined traffic flow prediction model C GCN based on graph convolution. product to extract the temporal features of the traffic flow. The experimental results show that the prediction effect of the C- GCN combination prediction model is better.

Keywords: traffic flow prediction; temporal convolution; spatial convolution

1. INTRODUCTION

In recent years, with the improvement of residents' living standards, the per capita car ownership is also increasing, and the resulting traffic congestion problem has become more and more serious. Traffic congestion not only brings many problems to people's travel, but also increases. The work load of public transport managers increases the occurrence of traffic accidents, and the exhaust emissions caused by traffic congestion also lead to environmental pollution and waste of resources. Because of the seriousness and harmfulness of this problem, it has attracted the research of various scholars, and various countries have also established the ITS system[1]. The key of this system is the accuracy of traffic flow prediction.

At present, the existing methods and models in the field of traffic flow prediction can be mainly divided into three categories, namely, prediction models based on statistical theory, prediction models based on traditional machine learning, and prediction models based on deep learning. Prediction models based on statistical theory include historical average model, time series model, Kalman filter model[2]; traffic flow prediction models based on traditional machine learning include support vector regression model[3], K Nearest neighbor algorithm[4], BP neural network and other methods; Traffic flow prediction models based on deep learning mainly include Long-Short Term Memory (LSTM), Convolutional Neural Networks (Convolutional Neural Networks, CNN)[5] and Gated Recurrent Unit (GRU)[6] and other combined models, etc.

The statistical-based prediction model was popular in the early days due to its simple algorithm and the advantages of using less equipment, but its conditions are relatively limited, it is only suitable for a single road with stable traffic flow, and the prediction in complex road sections The effect is poor[7]; the prediction model based on traditional machine learning is generally a nonlinear model, which usually starts with traffic data to explore its hidden features and changing relationships, so as to achieve the purpose of improving the accuracy of the model[8]; the prediction model based on deep learning is a multi-layer perceptron with a hidden layer, which can extract high-level feature information and discover hidden features of data by aggregating low-level feature information[9]. Its core idea is to extract important information through continuous learning and parameter optimization in the modeling process. And obtain accurate prediction results, and its expression ability is better[10]. Therefore, in recent years, deep learning has become more and more popular in the field of traffic flow prediction. With the development of deep learning models in the field of traffic flow, it is found that combined models can better extract the characteristics of traffic flow. More and more scholars use different Combination methods extract different features to improve prediction accuracy.

2. THE SPATIOTEMPORAL CHARACTERISTICS OF TRAFFIC FLOW

Traffic flow refers to the actual number of traffic participants passing through a certain location or section of the road within a unit time. The number of vehicles, also known as traffic flow[11].

Because the traffic volume is affected by many factors, such as time, weather, environment, road conditions, driving status, etc., the traffic volume has strong complexity and uncertainty. Since the traffic flow is constantly changing, its dynamic characteristics are very strong, so it also shows strong randomness. And due to various subjective and objective factors, the traffic flow has nonlinear characteristics[12].

Temporal characteristics and spatial characteristics are the main factors affecting traffic flow prediction, and these two characteristics are random and nonlinear, and become the main problems in the study of traffic flow.

Time correlation means that in a given road section, the traffic flow at the current moment is not only affected by the current traffic conditions, but also by the historical traffic data of the previous time period, because traffic congestion has a dissipation period, and the dissipation period is determined by the congestion state. And the congestion state is generally longer, so the traffic flow at the previous moment also affects the traffic flow at the next moment. The traffic flow of urban roads is a complex and huge data set with strong similarity in daily, weekly and monthly traffic volumes. In the long run, the traffic volume has obvious periodic characteristics, and it exhibits strong static stability. Periodicity is the most important characteristic of temporal correlation of traffic flow. Traffic flow data usually shows strong regularity within a certain period of time, showing its trend information and characteristics. For example, in urban road traffic, on the whole, the data of each day in the week will show a certain similarity, but there is a big difference between the week and the weekend, and there is a strong similarity between the weekend and the weekend. All of these are caused by people's travel habits. Because of the laws of people's life and work, the peak of traffic flow is generally fixed. The correlation of traffic flow in time, so it can be regarded as a time series data processing.

Spatial correlation refers to the influence between the upstream and downstream of the traffic flow, because the traffic road network is also a huge connected system, and the traffic flow of each road segment will affect and be affected by other road segments, such as when a traffic segment is congested, the upstream section will also be congested due to fluctuations, and the traffic volume on the downstream section will increase. The traffic flow of the road at each time period is more dependent on the flow of the upstream and downstream sections. Therefore, each road cannot be simply considered as an independent study. It is these complex road network structures that make traffic flow also spatially correlated. Spatial correlation distinguishes traffic flow data from other time series data. The early prediction of short-term road traffic flow only extracts temporal features and ignores spatial features, so the prediction results are quite different from the actual results. The spatial feature extraction of traffic flow in this paper makes the prediction results more accurate.

Traffic network diagram is shown in Figure 1:

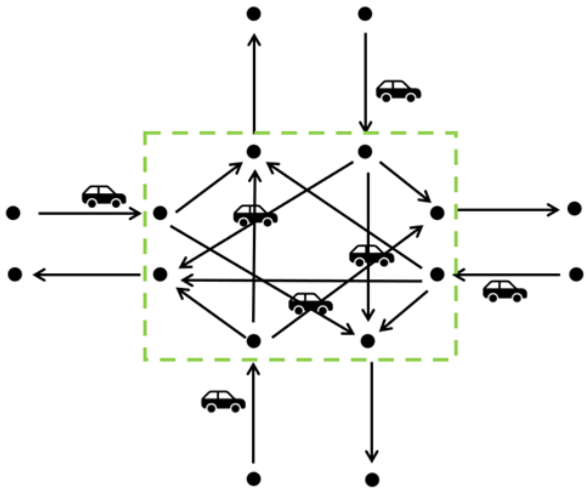

figure 1. Traffic road network map

3. GRAPH CONVOLUTIONAL NEURAL NETWORKS

3.1 Basic theory

In mathematics and signal systems, Fourier transform is used to describe a function that is expressed as a linear combination of several orthogonal functions. Through Fourier transform, the image domain and the frequency domain can be transformed into each other.

The traditional Fourier transform is defined as:

$$F(w)=F\left[f(t)\right]=\int f(t)e^{-iwt}d(t) \tag{1}$$

The inverse Fourier transform is:

$$F^{-1}\left[F(w)\right]=\frac{1}{2\Pi}\int F(w)e^{iwt}d(w) \tag{2}$$

For finding the Fourier transform of Graph is to find the eigenvector of the Laplacian matrix of Graph. The Fourier transform on Graph is discrete, while the traditional one is continuous. The latter can represent the Fourier of the eigenvalues of the former. Lie transform is:

$$F(\lambda_l)=\overline{f}(\lambda_l)=\sum_{i=1}^{N} f(i)u_l^*(i) \tag{3}$$

Among them, f it represents an N-dimensional vector, $f(i)$which is a mapping relationship with the point in Graph, and $u_l(\mathrm{i})$represents the i-th component of the l-th feature vector.

So the graph is represented by the Fourier transform on Graph as:

$$\overline{f}=U^T f \tag{4}$$

The traditional Fourier transform is to integrate the frequency, and when describing the transformation on the graph, it is called the sum of the eigenvalues λ_l:

$$f(i)=\sum_{i=1}^{N} f(i)u_l(i) \tag{5}$$

inverse Fourier transform on Graph is also expressed as:

$$f=U\overline{f} \tag{6}$$

Given two sets of graph signals x_1, $x_2$the graph convolution operation can be expressed as:

$$x_1 * Gx_2=(Udiag(\bar{x}_2)U^T)x_2 \tag{7}$$

* G represents graph convolution, which ⊙is the Hadamard product. The result of graph convolution of the available graph signal is:

$$x_1 * Gx_2=g_\theta(H)x=Ug_\theta(\Lambda)U^T x \tag{8}$$

It is a trainable filter, where:

$g_\theta(\Lambda)=diag(\theta),\theta\in R^N$ are the parameters to be learned.

For GCN, the convolution from graph to frequency domain is realized by Fourier transform, which can reduce a lot of computation. First perform Fourier transform on the graph and the convolution kernel, you can get their frequency domain representation, then multiply, and then inversely transform back to get the graph domain convolution, the formula is as follows:

$$g * x = U\left(U^T g \cdot U^T x\right) \quad (9)$$

g is the filter function, that is, the convolution kernel, x is expressed as $x = (f(1)\dots f(n))\in R^n$, that is, the signal set at the point of the graph, and U is the basis of the Fourier transform, that is, the feature vector of the Laplacian matrix.

Combining graph Fourier transform and discrete convolution, we can get:

$$(f * h)_G = Udiag[\theta_1,\dots,\theta_n]U^T f \quad (10)$$

3.2 Development of Spectral Convolution

Please The first generation of graph convolutional neural networks is also called spectral GNN, as in Eq. 2-13, in which its convolution operation is replaced by graph theory.

$$y = \sigma\left(Ug_\theta U^T\right) = \sigma\left(Udiag[\theta_1,\dots,\theta_n]\right)U^T x \quad (11)$$

The computational complexity of the first generation graph convolution is too high, and its convolution operation is based on the global rather than a single node, so the second generation GCN appears, such as Equation 2-14:

$$F_T(\lambda_k) = \hat{g}_k(i)u_k(i) \quad (12)$$

g_θ The eigenvalue function $g_\theta(\Lambda)$ used to represent the Laplacian matrix can be obtained:

$$y = \sigma\left(Ug_\theta U^T\right) = \sigma\left(Ug_\theta(\Lambda)U^T x\right) \quad (13)$$

The schematic diagram of the graph convolutional network is shown in Figure 2:

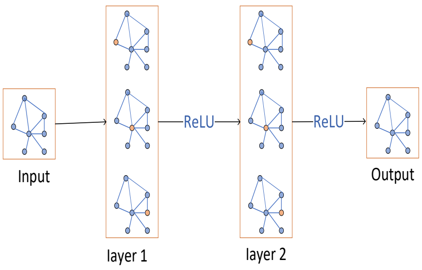

figure 2. Schematic diagram of graph convolutional network

4. EXPERIMENTAL SIMULATION AND RESULT ANALYSIS

4.1 Source of experimental data

Caltrans PeMS, a web-based software tool designed by the California Department of Transportation, which collects data sets from Caltrans traffic sensors from highways in California. Traffic speed data in the San Francisco Bay Area from January 1 to February 28, including 307 sensors on 29 roads, with a total of 16,992 data. In the experiment, the training set and the test set were divided in a ratio of 8:2. As shown in Table1:

Table 1. Data set division

data set	P EMS04	
sensor	3 07	
time	2 0180101~20180228	
sample interval	5min	
\	Proportion	quantity
Training set	80%	13593
test set	2 0%	3398

4.2 Evaluation indicators

In the experiments of this paper, the mean absolute error (MAE) and the root mean square error (RMSE) are used as evaluation indicators. The introduction of the two indicators is as follows:

(1) MAE

MAE is the average of the absolute error between the actual value and the predicted value, and its calculation formula is as follows:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|v_i - \overline{v_i}\right| \quad (14)$$

Another variant of MAE is MAPE. Because MAPE is more intuitive, it is easy to understand. You can know the result by looking at its value. If the MAPE is how much, it means how much the predicted result deviates from the real result. Its calculation formula is as follows:

$$MAPE = \frac{100\%}{n}\sum_{1^1=1}^{n}\left|\frac{v_i - \overline{v}_i}{v_i}\right| \quad (15)$$

(2) RMSE

The root mean square error is a representation of the degree of dispersion and an important evaluation index to describe the stability, not the absolute error. Its formula is as follows:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(v_i - \overline{v}_i\right)^2} \quad (16)$$

v represents the actual value, $\overline{v}$ represents the predicted value, and n represents the number of predicted values. The smaller the value of these three evaluation indicators, the better the prediction effect of the model.

4.3 Experimental environment and data settings

This experiment is based on the Python language and uses the Pytorch framework to implement the graph convolutional network (CGCN) model that introduces the spatiotemporal attention mechanism in this paper. The model training is mainly performed on the GPU. The relevant configuration of the experimental environment is shown in Table 4-1:

Table 2. Experimental environment settings

	category	version model
hardware	CPU	Main frequency 3.2GHz
	GPU	16G
software	language	Python 3.6
	Deep Learning Framework	C UDA 11.1
		Pytorch 1.8.0

4.4 Comparison of experimental results

In order to compare and analyze the prediction results of the CGCN model, this paper selects several models of HA[13], LSTM[14], GRU, and T-GCN[15] as the control group. First, the prediction results of CGCN and each model are compared to verify the prediction accuracy of CGCN. The performance of CGCN is analyzed by comparison, and the experimental comparison results are shown in Table 3:

Table 3. Comparison of experimental results

Model	PEMS04	
	RMSE	MAE
HA	67.60	54.03
LSTM	58.05	36.99
GRU	56.61	35.06
TGCN	48.28	34.51
CGCN	**42.01**	**30.17**

It can be seen from the experimental results that the traditional prediction method HA has a particularly poor effect. This is because the traditional time series prediction method cannot handle the multi-dimensional data of traffic flow, and the traffic flow data is multi-dimensional and complex data with many features. These are the traditional methods. traditional methods that only deal with simple one-dimensional time series data are less effective in predicting traffic flow. GRU and LSTM are slightly better than HA, but they are still worse than the combined model TGCN, because GRU and LSTM can only extract single-dimensional features, and the data extraction effect for multi-dimensional features such as traffic flow is still poor. For the combined model TGCN, it uses GCN to extract spatial features and GRU to extract temporal features, which shows that the more sufficient the feature extraction of traffic flow data, the more accurate the prediction results. Overall, the combined C-GCN model proposed in this paper can better predict traffic flow. The prediction results are shown in Figure 3:

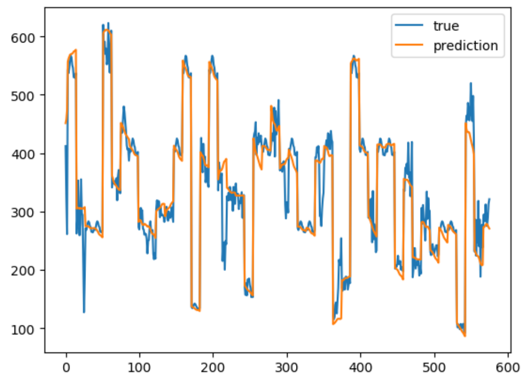

figure 3. Prediction result graph

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