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Machine Learning-Based Traffic Flow Prediction and Intelligent Traffic Management

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ABSTRACT

With the rapid development of information technology, multiple time series forecasting, which is typical of traffic flow forecasting, has become increasingly important in big data analysis. As the cornerstone of intelligent transportation system, traffic flow forecasting has important scientific research value and practical application value for urban traffic operation scheduling, quality and efficiency improvement of logistics transportation industry and public travel planning. Traffic flow prediction is always an important task of intelligent transportation system. Due to the complex temporal and spatial dependence of traffic flow sequence, it is very challenging to construct accurate traffic flow prediction in its ring neural network, graph network and Transformer model. Much of the existing work is based on very good models. Considering the advantages of convolutional networks, such as high computational efficiency and strong feature extraction ability, a traffic flow prediction model based on multi-view spatiotemporal convolution is proposed.

KEYWORDS

Traffic flow prediction; Deep learning; Machine learning; Graph neural network.

1. INTRODUCTION

With the rapid development of information technology, multiple time series forecasting, which is typical of traffic flow forecasting, has become increasingly important in big data analysis. As the cornerstone of intelligent transportation system, traffic flow forecasting has important scientific research value and practical application value for urban traffic operation scheduling, quality and efficiency improvement of logistics transportation industry and public travel planning. In the face of complex multi-dimensional traffic flow data, how to effectively extract spatio-temporal features and realize end-to-end integrated forecasting has become a research hotspot.

As a typical time series forecasting problem, the main challenge of traffic flow forecasting lies in the characterization of complex coupling correlation between multivariate data and the extraction of ever-changing spatio-temporal features. Traditional mathematical statistics methods and classical machine learning methods, such as local weighted regression, integrated moving average autoregression, Kalman filter, non-parametric regression and dynamic pattern decomposition, are mostly suitable for single sequence prediction.

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(CNN), recurrent neural networks (RNN) and autoencoders have achieved more accurate time series feature extraction. Graph convolutional network (CCN) extracts the unique spatial features of traffic flow data by convolutional operation of graphs. By extracting spatial and temporal features simultaneously, the multiple depth models constantly refresh the best results of traffic flow prediction

At present, the methods based on graph representation and graph convolution have made remarkable progress in multivariate time series prediction. Deep learning models such as CNN and RNN show good feature capture ability on Euclidean data, but these methods are difficult to directly deal with graph data, so CCN came into being. Graph convolution operations cover spatial graph convolution as well as spectral domain graph convolution. Spatial graph convolution acts directly on the vertices in the graph and its operation is similar to traditional CNNH. Spectral domain graph convolutional networks were proposed earlier by Zhang et al. The Fourier transform of graphs and the convolution operation of spectral domain graphs are studied. In order to reduce the computational complexity of the Laplacian matrix of the graph during feature decomposition,Niepent et al proposed the Chebyshev network (Chebyshev network, Chebyshev Network). ChebNet and the 1st-orderChebyshev network1stChebNet, and gradually became the common framework for GCN. This paper analyzes the development of artificial intelligence in traffic field through the practical application and case study of convolutional networks based on artificial intelligence in traffic flow prediction.

Through a meticulous synthesis of mechanical engineering principles and cutting-edge computer science techniques, this re- search not only addresses the immediate challenges of logistics automation but also lays the groundwork for the broader integration of these disciplines across various domains. The subsequent sections of this paper elucidate in detail the methodologies employed, the relevant literature in the field, and the experimental results, culminating in a conclusive assessment of the contri butions and potential avenues for future research.

2. RELATED WORK

2.1. Dynamic hypergraph representation of traffic flow data

Traffic forecasting has always been a challenging task due to its complex spatiotemporal dependence:

(1) Spatial dependence. The change of traffic volume is mainly affected by the topology of urban road network. The upstream road traffic conditions affect the downstream road traffic conditions through the transfer effect, and the downstream road traffic conditions affect the upstream road traffic conditions through the feedback effect [4]. As shown in Figure 1, due to the strong influence between adjacent roads, the short-term similarity changes from state 1(the upstream road is similar to the midstream road) to state 2(the upstream road is similar to the downstream road).

(2) Time dependence. The traffic volume changes dynamically with time, which mainly shows periodicity and trend. As shown in Figure 2(a), the volume of traffic on the road changes periodically during the week. As shown in Figure 2(b), the traffic volume of a day varies with time; For example, the current volume of traffic is affected by the traffic conditions of the previous moment or even longer.

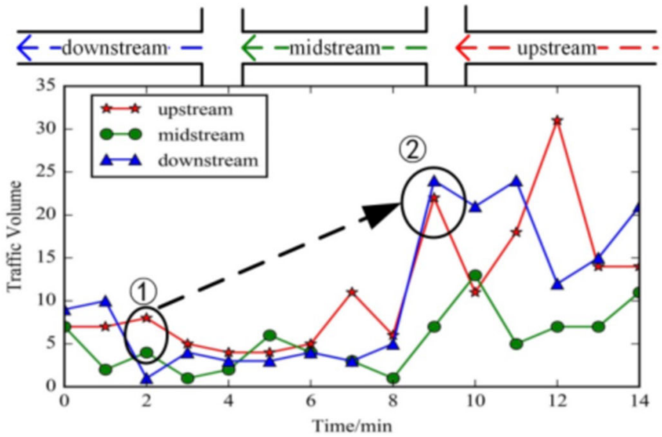

Figure 1: Spatial dependence is restricted by the topological structure of theroad network. Due to the strong influence between adiacent roads, the short-term traffic fow similarity is changed from state D to state (2).

Therefore, in order to solve the problems existing in the current situation of traffic flow

(1) In this paper, the graph neural convolutional network and gated cycle unit are used. The graph convolutional network is used to capture the topology of the road network and model the spatial correlation of the road network. The gated cycle unit is used to capture the dynamic change of traffic data on the road and model the time dependence. The CNN model can also be applied to other space-time prediction tasks.

(2) The prediction results of T-GCN model show steady state under different prediction horizons, indicating that T-GCN model can not only realize short-term prediction, but also be used for long-term traffic prediction tasks.

(3) We used two real-world traffic datasets to evaluate our approach. The results show that compared with all baseline methods, the prediction error of this method indicates that the model has an advantage in traffic prediction.

2.2. Convolutional network

Convolutional networks realize feature extraction of data based on convolutional kernel. For image data, two-dimensional convolutional networks are commonly used. For time series data, two typical 1D convolutional networks are introduced in this paper. The feature of two-dimensional convolutional networks is that the convolutional kernel moves in two dimensions. One dimensional convolutional networks are characterized by the fact that the convolution kernel only moves in one direction. In particular, the origin of the geo-dimensional convolutional network is that its movement direction is limited to one dimension, independent of the convolution kernel dimension.

The working principle of a conventional one-dimensional convolutional network is shown in Figure 2(a), where the time series dimension is 1, the number of input channels and outputs is 1, and the size of the convolutional kernel is 3. Convolution kernel from left to right and equal length input subsequence by dot product operation to obtain the corresponding output. If you want the input sequence to be the same length as the output sequence, you can padding the input sequence. When the output channels are greater than 1, you simply repeat the process for each output channel with a different kernel matrix, and then stack the output vectors on top of each other.

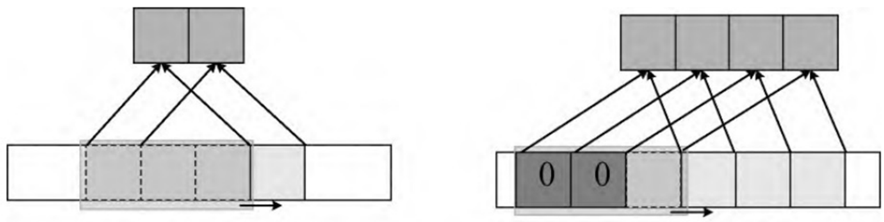

Figure 2: (a) one-dimensional convolution (b) a bunch of convolution

As shown in Figure 2 (b), causal convolution works in such a way that an element in the output sequence can only depend on the element that precedes it in the input sequence. To ensure that the output tensor has the same length as the input tensor, zero fill needs to be applied. When the output channel is greater than 1, the operation mode is the same as that of one-dimensional convolutional networks.

2.3. T-GCN model problem definition

The road network is G, we use the unweighted graph G = (V, E) to describe the topology of the road network, each road as a node, V is the set of road nodes, V = {v1, v2,···, V N}, N is the number of nodes, E represents the set of edges. The adjacency matrix A represents the connection between roads, A∈R (N×N). The adjacency matrix contains only elements of 0 and 1.

The eigenmatrix X∈R (N×P). The traffic information network on the road is the attribute feature of the nodes in the network, P represents the quantitative feature of the node attributes (the length of the historical time series), Xt∈R (N×i) I use to represent the speed of each road. Similarly, the node attribute property can be any traffic information, such as traffic speed, traffic flow, and traffic density

Therefore, the space-time traffic prediction problem can be considered as learning the mapping function f on the premise of road network topology G and feature matrix X, and then calculating the future traffic information at time T, as shown in Equation 1:

$$\left[X_{t+1}, \cdots, X_{t+T}\right] = f\left(G; \left(X_{t-n}, \cdots, X_{t-1}, X_t\right)\right) \tag{1}$$

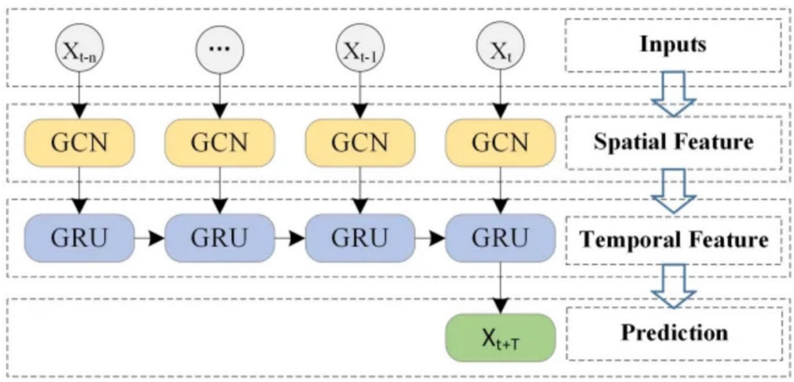

Figure 3: T-GCN model building

T-GCN model consists of graph convolutional network and gated recursive unit. As shown in Figure 3, we first use historical n time series data as input, and capture the topological structure of the urban road network by using the graph convolutional network to obtain spatial features. Secondly, the obtained time series with spatial characteristics are input into the gated recursive unit model, and the dynamic changes are obtained through the information transfer between units to capture the time characteristics. Finally, the results are obtained through the fully connected layer.

2.4. Model detailed introduction

The urban road network is not a two-dimensional grid, but a graph, which means that the CNN model cannot reflect the complex topology of the urban road network and therefore cannot accurately capture the spatial dependency. Given an adjacency matrix A and an eigenmatrix X, the GCN model constructs a filter in the Fourier domain. The filter acts on the nodes of the graph, captures the spatial features between the nodes through its first-order neighborhood, and then builds a GCN model by superimposing multiple convolutional layers, which can be expressed as:

$$H^{(l+1)} = \sigma\left(\widetilde{D}^{-\frac{1}{2}}\,\widehat{A}\,\widetilde{D}^{-\frac{1}{2}}\,H^{(l)}\,\theta^{(l)}\right) \tag{2}$$

The convolutional network used in this paper has two layers, and its GCN model captures spatial dependencies, which can be expressed as:

$$f\,(X, A) = \sigma\left(\widehat{A}\,ReLU\left(\widehat{A}\,X\,W_0\right)W_1\right) \tag{3}$$

As outlined in the above functional formula, this paper uses the GCN model to learn spatial features from traffic data. As shown in Figure 4, assuming node 1 as the central road, the GCN model can obtain the topological relationship between the central road and its surrounding roads, code the network topology structure and road attributes, and obtain the spatial dependency relationship.

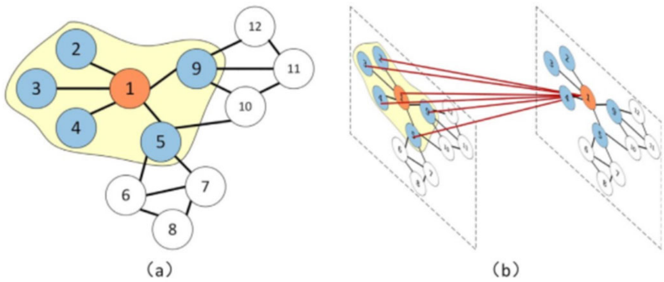

Figure 4: Assuming that node l is a central road.

Time-graph Convolutional networks: To obtain both spatial and temporal dependencies from traffic data, we propose a time-graph convolutional network model (T-GCN) based on graph convolutional networks and gated cycle units. As shown in Figure 6, the left side is the space-time flow prediction process, the right side is the specific structure of T-GCN unit, ht−1 is the output at time T-1, GC is the graph convolution process, ut and rt are the update gate and reset gate at time t, and ht is the output at time t.

3. METHODOLOGY

Data Description: In this section, we evaluate the predictive performance of the T-GCN model on two real datasets: the SZ-taxi dataset and the Los-loop dataset. Because both data sets are related to traffic speed. On the premise of not losing generality, we use traffic speed as traffic information in the experiment.

3.1. Data creation

The dataset consists of taxi tracks in Shenzhen City from January 1 to January 31, 2015. We selected 156 main roads in Luohu District as the research area. The experimental data mainly includes two parts. One is the adjacency matrix of 156*156, which describes the spatial relationship between roads. Each row represents a road, and the values in the matrix represent the connectivity between the roads. The other is the eigenmatrix, which describes how the speed on each road changes over time. Each line represents a road; Each column is the traffic speed on the road at different times of day. We calculate the speed of traffic on each road every 15 minutes.

And the data set was collected in real time by loop detectors from freeways in Los Angeles County. We selected 207 sensors and their traffic speeds from March 1 to March 7, 2012. We measure the traffic speed every five minutes. The data consists of adjacency matrix and eigenmatrix. The adjacency matrix is calculated by the distance between sensors in a traffic network. Since the Losloop dataset contains some missing data, we use a linear interpolation method to fill in the missing values.

In the experiment, the input data is normalized to the interval [0,1]. In addition, 80% of the data is used as the training set, and the remaining 20% is used as the test set.

3.2. Evaluation index

Three metrics are used to evaluate the predictive performance of the T-GCN model:

(1) Root Mean Squared Error (RMSE):

$$RMSE = \sqrt{\frac{1}{MN}\sum_{j=1}^{M}\sum_{i=1}^{N}(y_i^j - \widehat{y_i^j})^2} \tag{4}$$

(2) Mean Absolute Error(MAE):

$$MAE = \frac{1}{MN}\sum_{j=1}^{M}\sum_{i=1}^{N}\left|y_i^j - \widehat{y_i^j}\right| \tag{5}$$

(3) Accuracy:

$$Accuracy = 1 - \frac{\| Y - \widehat{Y} \|_F}{\| Y \|_F} \tag{6}$$

M is the number of time samples; N is the number of roads; The picture and picture represent the real traffic information, one of the JTH time samples to predict the i road, Y and picture represent the collection of pictures and pictures respectively, and the picture is the average of Y. Specifically, RMSE and MAE are used to measure the prediction error, and the smaller the value, the better the prediction effect. Accuracy is used to test the prediction accuracy. The larger the value, the better the prediction effect. R2 and var calculate the correlation coefficient, which measures the ability of the prediction results to reflect the actual data. The larger the value, the better the prediction effect.

3.3. Model parameter selection

The hyperparameters of T-GCN model include learning rate, batch size, training epoch and number of hidden units. In the experiment, we manually adjusted and set the learning rate to 0.001, the batch size to 32, and the training epoch to 5000. The number of hidden elements is a very important parameter in T-GCN model, and the different number of hidden elements will have a great impact on the prediction accuracy. To select the best value, we perform experiments on different hidden units and select the best value by comparing the predictions. In our experiment, for the SZ-taxi dataset, we select the number of hidden units from [8,16,32,64,100,128] and analyze the change in their prediction accuracy. As shown in Figure 7, the horizontal axis represents the number of hidden units and the vertical axis represents the changes in different metrics. Figure 7(a) shows the RMSE and MAE results for different hidden units in the training set. As can be seen, the error is minimal when the value is 100. Figure 7(b) shows the variation of precision, R2, a n d var for different hidden units. Figures 7(c) and 7(d) show the results of the test set. Again, when the number is 100, the result reaches the maximum. In summary, when the number is set to 100, the prediction results are better.

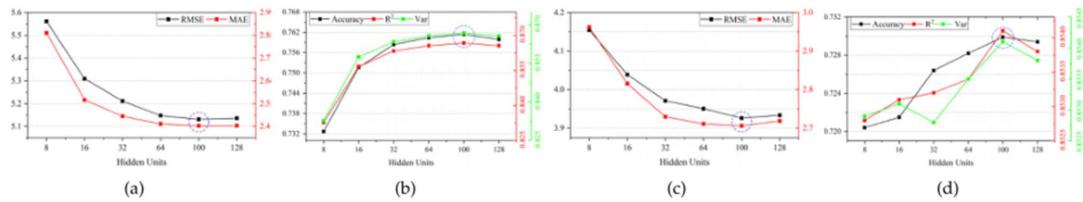

Figure 5: (a) Changes in RMSE and MAE in the training set. (b) Changes in Accuracy, R‘ and var in the training set.(c) Changes in RMsE and MAE in the test set. (d) Changes in Accuracy.R2 and var based in the test set.

With the increase of the number of hidden units, the prediction accuracy first increases and then decreases. This is mainly because when the hidden unit is greater than a certain degree, the model complexity and calculation difficulty are greatly increased, resulting in overfitting of training data. Therefore, we set the number of hidden cells to 100 in our experiment on the SZ-taxi dataset. Again, the results of Los-loop are shown in Figure 5(a), 5(b), 5(c), 5(d). It can be seen that when the number of hidden elements is 64, the prediction accuracy is the highest and the prediction error is the smallest. For the input layer, the training data set (80% of the total data) is used as input during the training process, and the remaining data is used as input during the test process. The T-GCN model is trained using the Adam optimizer.

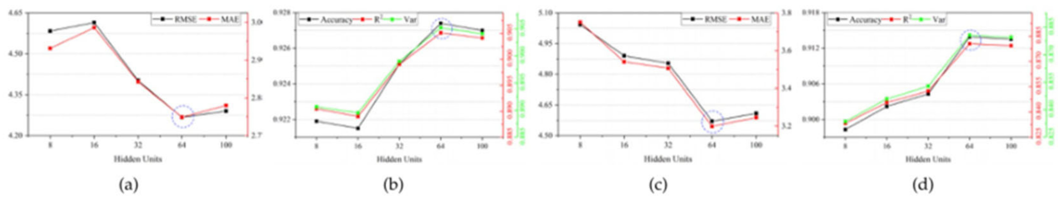

Figure 6: (a) Changes in RMsE andMAE in the training set. (b) Changes in Accuracy, R" and var in the training set.(e) Changes in RMsE and MAE in the test set. (d) Changes in Accuracy.R2 and par in the test set..

3.4. Experimental result

Table 1: Predictions of the T-GCN model and other baseline methods on the sz-taxi and los-loop datasets

T	Metric	SZ-taxi						Los-loop					
		HA	ARIMA	SVR	GCN	GRU	T-GCN	HA	ARIMA	SVR	GCN	GRU	T-GCN
15min	$RMSE$	4.2951	7.2406	4.1455	5.6596	3.9994	**3.9265**	7.4427	10.0439	6.0084	7.7922	5.2182	**5.1264**
	MAE	2.7815	4.9824	2.6233	4.2367	**2.5955**	2.7117	4.0145	7.6832	3.7285	5.3525	**3.0602**	3.1802
	$Accuracy$	0.7008	0.4463	0.7112	0.6107	0.7249	**0.7299**	0.8733	0.8275	0.8977	0.8673	0.9109	**0.9127**
	R^2	0.8307	*	0.8423	0.6654	0.8329	**0.8541**	0.7121	*	0.8123	0.6843	0.8576	**0.8634**
	var	0.8307	0.0035	0.8424	0.6655	0.8329	**0.8541**	0.7121	*	0.8146	0.6844	0.8577	**0.8634**
30min	$RMSE$	4.2951	6.7899	4.1628	5.6918	4.0942	**3.9663**	7.4427	9.3450	6.9588	8.3353	6.2802	**6.0598**
	MAE	2.7815	4.6765	**2.6875**	4.2647	2.6906	2.7410	4.0145	7.6891	3.7248	5.6118	**3.6505**	3.7466
	$Accuracy$	0.7008	0.3845	0.7100	0.6085	0.7184	**0.7272**	0.8733	0.8275	0.8815	0.8581	0.8931	**0.8968**
	R^2	0.8307	*	0.8410	0.6616	0.8249	**0.8456**	0.7121	*	0.7492	0.6402	0.7957	**0.8098**
	var	0.8307	0.0081	0.8413	0.6617	0.8250	**0.8457**	0.7121	*	0.7523	0.6404	0.7958	**0.8100**
45min	$RMSE$	4.2951	6.7852	4.1885	5.7142	4.1534	**3.9859**	7.4427	10.0508	7.7504	8.8036	7.0343	**6.7065**
	MAE	2.7815	4.6734	**2.7359**	4.2844	2.7743	2.7612	4.0145	7.6924	4.1288	5.9534	**4.0915**	4.1158
	$Accuracy$	0.7008	0.3847	0.7082	0.6069	0.7143	**0.7258**	0.8733	0.8273	0.8680	0.8500	0.8801	**0.8857**
	R^2	0.8307	*	0.8391	0.6589	0.8198	**0.8441**	0.7121	*	0.6899	0.5999	0.7446	**0.7679**
	var	0.8307	0.0087	0.8397	0.6590	0.8199	**0.8441**	0.7121	*	0.6947	0.6001	0.7451	**0.7684**
60min	$RMSE$	4.2951	6.7708	4.2156	5.7361	4.0747	**4.0048**	7.4427	10.0538	8.4388	9.2657	7.6621	**7.2677**
	MAE	2.7815	4.6655	2.7751	4.3034	**2.7712**	2.7889	4.0145	7.6952	**4.5036**	6.2892	4.5186	4.6021
	$Accuracy$	0.7008	0.3851	0.7063	0.6054	0.7197	**0.7243**	0.8733	0.8273	0.8562	0.8421	0.8694	**0.8762**
	R^2	0.8307	*	0.8370	0.6564	0.8266	**0.8422**	0.7121	*	0.6336	0.5583	0.6980	**0.7283**
	var	0.8307	0.0111	0.8379	0.6564	0.8267	**0.8423**	0.7121	*	0.5593	0.5593	0.6984	**0.7290**

Table 1 shows the performance of the T-GCN model and other baseline methods for 15 -, 30 -, 45 -, and 60-minute prediction tasks on the SZ-taxi and Los-loop datasets. * indicates that these values are small enough to be negligible, indicating that the model's predictions are poor. It can be seen that the T-GCN model obtains the best prediction performance under almost all evaluation indexes of all prediction horizons, which proves its effectiveness for spatio-temporal traffic prediction tasks.

(1) High prediction accuracy. We can find that neural network-based methods, including T-GCN models, GRU models, emphasize the importance of time feature modeling and generally have better predictive accuracy than other baselines such as HA models, ARIMA models, and SVR models.

(2) spatio-temporal prediction ability. To verify whether the T-GCN model has the ability to characterize spatiotemporal features from traffic data, we compared the T-GCN model with the GCN model and the GRU model. As shown in Figure 9, we can clearly see that the method based on temporal and spatial features (T-GCN) has better prediction accuracy than the method based on single factor (GCN, GRU), indicating that the T-GCN model can capture temporal and spatial features from traffic data.

Model interpretation: In order to better understand the T-GCN model, we selected a road in the SZ-taxi dataset and visualized the prediction results of the test set as the visualization results of the prediction horizons of 15 minutes, 30 minutes, 45 minutes, and 60 minutes, respectively.

These results show that:

(1) The T-GCN model has poor prediction at local minimum/maximum values. We speculate that the main reason is that the GCN model defines a smoothing filter in the Fourier domain and captures spatial features by constantly moving the filter. This process results in less variation in the overall forecast results, making the peaks smoother.

(2) "Zero taxi value" leads to a certain error between the real traffic information and the predicted results. Zero taxi value refers to the phenomenon that the traffic feature matrix whose true value is not zero will be set to zero because there is no taxi on the road.

(3) No matter what the prediction horizon is, the T-GCN model can always obtain better prediction results. T-GCN model can capture the temporal and spatial characteristics of road traffic information and obtain the changing trend of road traffic information.

In addition, the T-GCN model detects the beginning and end of rush hour, and the prediction results are similar to actual traffic speed patterns. These properties help predict traffic congestion and other traffic phenomena.

4. CONCLUSION

This paper based on machine learning convolutional model has significant advantages in traffic prediction. The T-GCN model (Time-Graph Convolutional Network) mentioned in this paper successfully captures the spatio-temporal characteristics of the traffic data by combining the Graph Convolutional Network and the gated cycle unit, and achieves a good prediction effect. Compared with traditional methods, T-GCN model performs better in prediction accuracy and spatio-temporal feature extraction.

T-GCN model has high prediction accuracy. The experimental results show that T-GCN model has the best prediction performance in almost all prediction tasks, and its prediction error is small, which proves its effectiveness in spatio-temporal traffic prediction tasks.

T-GCN model can capture temporal and spatial characteristics well. Compared with models based only on a single factor, such as GCN model and GRU model, T-GCN model based on temporal and spatial features can predict the changing trend of traffic data more accurately, which indicates that T-GCN model can effectively extract temporal and spatial features from traffic data.

In summary, traffic prediction methods based on machine learning convolutional model, especially T-GCN model, have high prediction accuracy and good ability to capture spatio-temporal characteristics, which is of great significance for solving complex spatio-temporal dependence problems in traffic prediction.

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