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Traffic Flow Prediction based on Dynamic Spatio-temporal Convolution Network Model of Reachability Matrix

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Abstract

The application of intelligent transportation system in urban transportation is more and more deeply. To achieve accurate traffic volume prediction has important practical significance for traffic service, traffic engineering planning and traffic risk prevention. Although the traffic volume in the road network has periodicity and correlation, traffic accidents and bad weather will cause the change of the road network structure, and the adjacent nodes show time correlation. In this paper, a graph convolution neural network model of dynamic spatio-temporal based on reachability matrix is proposed from the point of view of dynamic reachability between nodes in traffic network. Based on the convolution network of spatiotemporal graph, the dynamic reachability matrix module of parameter learning is added to express the dynamic and spatio-temporal correlation of road network. The experimental results on the open data set PEMs show that the model can effectively capture the dynamics of the road network, improve the accuracy of traffic volume prediction, and is superior to the existing baseline model.

Keywords

Traffic Flow Prediction; Dynamic Reachability Matrix; Graph Convolution Neural Network; Spatio-temporal Correlation; Topological Structure.

1. Introduction

With the continuous construction and development of urban road networks in various countries, while transportation brings convenience to the public, it is also facing a series of conditions such as increasingly severe urban traffic congestion and traffic accidents. Traffic management departments have brought great troubles. Therefore, countries have increased their research on Intelligent Transportation System (ITS). ITS is a comprehensive computer, communication and sensor technology applied to the entire traffic management system. Thus, a larger-scale comprehensive transportation management system has been established. Its essence is to predict the traffic volume in the next time period by collecting historical traffic volume information, but at the same time it faces equipment collection data errors, low prediction accuracy, equipment life, equipment Regular maintenance and other issues. If ITS can accurately predict the traffic volume in real time, it can improve the experience of traffic participants and provide decision-making support to relevant management departments. This is still an important problem that needs to be solved urgently.

Traffic volume is essentially a type of spatio-temporal data. This type of data has the characteristics of volatility, spatio-temporal correlation and nonlinearity, which brings great challenges to the study of its forecasting problems. Generally, ITS ignores the way out to a certain extent The locality of the spatial structure of the network topology and the relevance of traffic volume in time and space. However, in most urban traffic scenarios, traffic volume will be affected by both time and space. The specific manifestations are as follows: First, a certain road section will be affected Simultaneously

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engrave the influence of other road sections; the second is that a certain road section will affect its own state at the next moment; the third is that a certain road section will affect the adjacent road sections at the next moment. Therefore, the core of the traffic volume prediction problem is how to effectively express the characteristics of time dimension and space dimension And its temporal and spatial correlation[1].

2. Related Works

Over the years, scholars have carried out a lot of fruitful research and practice on the traffic volume forecasting problem. Various new traffic volume forecasting algorithms have emerged one after another, which is one of the hotspots in the field of intelligent transportation. Traffic volume is a type of typical spatio-temporal data. It is relevant and heterogeneous in time and space dimensions. From the perspective of the development of its forecasting methods, it can be roughly divided into three categories: statistical methods, machine learning methods and deep learning methods.

Statistics-based methods mainly include history average (HA, History Average), autoregressive integrated moving average (ARIMA, Autoregressive Integrated Moving Average Model), and Kalman filtering (KF, Kalman Filtering), etc. HA is to count a certain historical time The average value of the segment data is used as the predicted value at the next moment; ARIMA regards the data sequence formed by the prediction object over time as a random sequence, and uses a certain mathematical model to approximate this sequence, which is only suitable for time series with stationarity; Kalman filter uses observations and state equations to compose a state space model to estimate the stationary and non-stationary random processes to describe the traffic volume. Such methods require high data and cannot handle nonlinearities. Traffic data cannot effectively deal with the randomness and complexity of short-term traffic forecasts.

Machine learning methods mainly include K nearest neighbors, Support Vector Machines (SVM, Support Vector Machines) and Random Forest (RF, Random Forest), etc. Traditional machine learning methods can model more complex data. K nearest neighbors method is to identify similar Traffic conditions are also used for prediction; support vector machines map. low-dimensional nonlinear data to high-dimensional space through a kernel function and then perform linear classification; random forest combines the Bagging ensemble learning theory and the idea of random subspace, in the sample subspace Establish a decision tree, and then integrate all decision trees to achieve the goal of processing limited samples, nonlinearity and high-dimensional traffic. Such methods still cannot effectively consider the temporal and spatial correlation of traffic data at the same time, and require a lot of feature engineering.

The deep learning method mainly solves the problem of time and space correlation of traffic volume through two types of models of recurrent neural network RNN and graph convolutional network GCN. Long short-term memory network[2] (LSTM, Long Short-Term Memory) is a special RNN , Through clever design, it can solve the problem of gradient disappearance and gradient explosion in the process of long sequence training, and it has become a popular time series prediction model. Scholar Ma Xiaolei[3] was the first to apply LSTM to the traffic volume prediction problem. The traffic data obtained by the sensor equipment is used to predict the future traffic volume. After that, he proposed to use the convolutional neural network CNN to predict the traffic volume. Scholar Feng Xinxin[4] takes into account the time characteristics, spatial characteristics and periodic characteristics of traffic data , Fusing these three features together to achieve the purpose of predicting traffic volume.

Scholar Yu Bing[5] proposed the Spatio-Temporal Graph Convolution Network (STGCN, Spatio-Temporal Graph Convolution Network), which uses a graph structure to express the spatial relationship of the road network, and effectively captures the spatio-temporal correlation by modeling the multi-scale transportation network. , But the adjacency matrix of the model is a fixed 0-1 structure, which limits the expressive ability of the model. The Wan Huaiyu team of Beijing Jiaotong University considered that from the spatial dimension, the traffic conditions of the nodes will affect each other; from the time dimension From a point of view, the traffic at different times in the history of a node

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will affect the traffic at different times in the future of the node, and the traffic at different times in the history of the node will also affect its neighbor nodes. Considering the periodicity of time, there is a certain periodic pattern to follow. Therefore based on STGCN, a multi-component spatio-temporal graph convolutional network MCSTGCN[6] is proposed. This model combines the characteristics of the near cycle, daily cycle, and weekly cycle of the traffic volume model to predict traffic volume. Also proposed ASTGCN[7], STSGCN[8] Other variant models, ASTGCN introduces the attention mechanism, which is divided into time attention and space attention, and pays more attention to the key parts; STSGCN introduces the concept of synchronization, and the adjacency matrix is no longer a pure time slice spatial structure, but It is an adjacency matrix composed of local space-time (multiple continuous time slices). In addition, it is also considered that connecting nodes at different time steps into a graph will blur the time attributes of each node. Position embedding is proposed to record the node's Time and space attributes, including time embedding matrix and space embedding matrix, so as to consider the space and time information of the node at the same time.

Scholar Xie Kun et al.[9] considered that traffic accidents may occur every day, which will affect the relationship between road segments in the road network, so that the adjacency matrix is dynamic, that is, the spatial dependence relationship will dynamically change with time. For this reason, DGCNN (Dynamic Spatial-Temporal Graph Convolutional Neural Network), by constructing a time-varying graph Laplacian matrix to capture the dynamic dependence of traffic volume, more accurately predict traffic volume, speed and other traffic volume. The specific process is to extract the overall picture from the traffic volume sample Component (global component determined by the road network structure) and local component (local component determined by a specific time or traffic event), use a special loss function to pre-train the tensor decomposition layer; in order to determine the global and local components in a day The Laplacian matrix is dynamically learned at a specific time, and the Laplacian matrix estimator based on deep learning is designed. The real-time estimated Laplacian matrix will be sent to the graph convolutional layer for prediction.

Scholar Rui Dai[10] considered that in previous studies, traffic state characteristics such as transit time were mainly used as model input, and it was difficult to predict the overall traffic situation. Therefore, he changed his mind and introduced planned traffic from the AutoNavi navigation system. In a sense, the traffic volume in the plan actually reflects the future traffic volume of the user’s trip, so that the future travel time can also be predicted. Secondly, the adjacency matrix itself that appeared in previous studies is considered. Characteristic, the weight of the general adjacency matrix is only attenuated according to the distance, without considering the inherent traffic proximity between the road segments, so a composite adjacency matrix is designed, which further introduces the covariance of the road segment transit time based on the distance attenuation, as This proposes the Hybrid Spatio-Temporal Graph Convolutional Network HSTGCN (Hybrid Spatio-Temporal Graph Convolutional Network).

In summary, with the application of various machine learning algorithms in the field of intelligent transportation, the problem of traffic volume prediction has been better solved, and it has begun to serve various fields of intelligent transportation. However, in the actual transportation network, the road network structure It will be affected by many factors. For example, traffic accidents or severe rain and snow will cause partial interruption of the road section. In addition, considering the correlation between various local road sections in the road network, when traffic jams occur at the intersection, the vehicle will choose the vicinity of the road section The passage of road sections. Due to the influence of these factors, the difficulty of predicting the traffic volume in the road network is greatly increased, which is still a challenging research topic.

This paper refers to the advantages of existing models and proposes a dynamic spatio-temporal graph convolutional network model based on reachability matrix. This model addresses the shortcomings of traditional traffic volume prediction models in expressing road network dynamics. On the one hand, it uses graph convolutional network extraction The spatial characteristics of the traffic network; on the other hand, the dynamic reachability matrix is used to effectively express the dynamics of the

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traffic network structure and the temporal and spatial correlation between neighboring nodes. The main contributions of this paper are summarized as follows:

1) In order to determine the proximity between the road network nodes and the degree of influence between different road sections, a dynamic reachable matrix is embedded in the graph convolution module, and the parameter learning in the matrix is used to express the dynamics of the road network structure and local spatio-temporal correlation To improve the training efficiency of the model by controlling the sparsity of the matrix;

2) On the real traffic data set PEMS, it is verified through experiments that the model proposed in this paper is better than the existing baseline model.

3. Preliminaries

3.1 Problem definition

Traffic volume is a type of typical spatio-temporal data. The essence of traffic volume forecasting is to predict the traffic volume values of the next y equal time intervals given historical x traffic volume observations at equal time intervals, as shown in Formula 1.

$$\Lambda_{\text{pred}} = \underset{\Lambda_{\text{pred}}}{argmax}\left[log\, P\left(\Lambda_{\text{pred}} \middle| \Lambda_{\text{his}}\right)\right] \tag{1}$$

Where $\Lambda_{\text{his}} = [\lambda_{t-x+1}, \lambda_{t-x+2}, \dots, \lambda_t] \in R^{N\times M\times x}$ represents historical traffic value of x equal time intervals, $\Lambda_{\text{pred}} = [\lambda_{t+1}, \lambda_{t+2}, \dots, \lambda_{t+y}] \in R^{N\times M\times y}$ represents future traffic value of y equal time intervals, $\lambda_t \in R^{N\times M}$ represents the feature vector composed of M traffic volume values for N road sections at time t, the feature matrix λ at different time is dynamically changing, and P is the probability function.

Usually, the traffic road network exists in the form of a graph structure. In order to facilitate subsequent research, the road network is defined as a graph G=(V, E, F), as shown in Figure 1. Where V is the set of all nodes in the graph, which is regarded as the detection device deployed in each section of the traffic road network, |V|=N is the total number of nodes; E is the set of edges in the graph G, which means the distance between road sections Connectivity; $R \in R^{N\times N}$ is the reachable matrix of graph G, which is a matrix that effectively expresses the temporal and spatial correlation of road networks. Assume that each node in the road network space will collect M feature values at a certain time t. After a period of time T, each node will collect M time series of length T. In this paper, M = 1, that is, each The node has only one traffic characteristic.

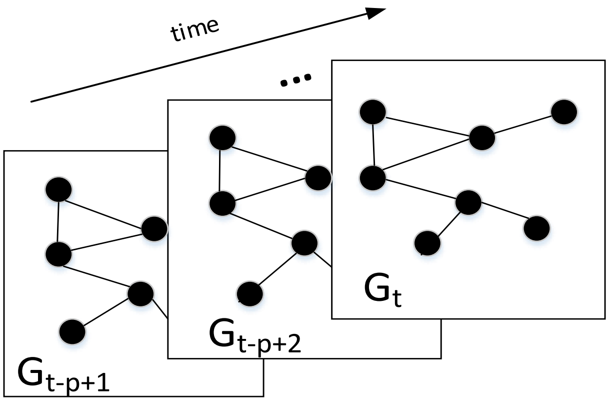

Figure 1. Traffic road network diagram structure

3.2 Graph Convolutional Network Based on Reachability Matrix

3.2.1 Graph convolutional neural network

Graph structure data like traffic road network belongs to non-European data. In graph structure data, the number of adjacent nodes corresponding to each node is not fixed, that is, the degree of each node

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is different, and the same size convolution kernel cannot be used for convolution. Therefore, the use of convolutional GCN (Graph Convolutional Neural Networks) suitable for graphs.

At present, there are two main ways of convolution for graphs: one is graph convolution based on spatial domain (time domain), that is, convolution directly on the graph, which is similar to the general convolutional neural network CNN, but at this time, the convolution The convolution kernel is not a fixed size. The number of nodes with the same degree will use the same size convolution kernel. The size of the convolution kernel changes with the degree of the node. At the same time, the spatial convolution will make different types of nodes after multiple smoothing. The features tend to be homogenized, which will lose important information of different categories, resulting in limited expression capabilities of the model; the other is based on Spectral Graph Convolution, which draws on the idea of Fourier transform in mathematics, namely Use the Fourier transform on the graph to transform the graph signal from the time domain to the frequency domain, and then perform the convolution operation, and finally the convolution result is through the graph inverse Fourier transform to the time domain, so that the correctness can be achieved. For the purpose of image signal convolution, this article chooses the latter to extract spatial structure features.

3.2.2 Dynamic reachability matrix

In the spatial structure of the traffic road network, in order to better describe the proximity between nodes, define the adjacency matrix $A \in R^{N\times N}$ on the road network graph. If node i and node j are directly adjacent, then $A_{ij} = 1$, otherwise $A_{ij} = 0$, at this time the adjacency matrix A is called the first-order adjacency matrix. In order to further enhance the expression ability of the model, based on the above-mentioned adjacency matrix, a dynamic matrix $\Phi \in R^{N\times N}$ is defined by The learnable parameter Φ_{ij} expresses the degree of influence of the adjacent road section i on the current road section j, not just a fixed 0-1 matrix structure, which enhances the generalization ability of the model to a certain extent.

In real traffic conditions, the influence between non-adjacent road sections is indirectly spread through intermediate road sections. At this time, the reachability between road sections can be considered. However, when the scale of the map is relatively large, the adjacent road sections of the current road section The number of is increased accordingly. This paper reduces the influence of noise information on the current node by controlling the sparsity of the dynamic reachability matrix. Here, the reachability matrix $R \in R^{N\times N}$ is defined, as shown in Equation 2.

$$R_{w_{ij}}^{\alpha} = \begin{cases} 1, & s_{ij}^{R}\alpha\Delta t - D_{ij} \geq 0 \\ 0, & else \end{cases} \tag{2}$$

Among them, s_{ij}^{R} is the average free flow speed of vehicles from node i to node j, Δt is the unit time interval, α is the number of unit time intervals set, and D_{ij} is the shortest distance from node i to node j. If the vehicle is the speed of s_{ij}^{R} reaches j from i within α unit time interval Δt, then $R_{w_{ij}}^{\alpha}$ is 1. The sparsity of the reachable matrix R can be controlled by α. When α is larger, the number of adjacent links will be more and the adjacency matrix will be denser. In addition, the distance space between the two nodes is related to the arrival time between the two nodes of the vehicle through the average speed. This matrix can model the time-space correlation between the nodes in the road network. The matrix proposed above is fused into a new matrix through the Hadamard product (that is, the matrix corresponding elements are multiplied), called the dynamic reachable matrix DR, and the matrix is embedded in the graph convolution module, as shown in formula 3.

$$DR = \phi \odot A \odot R \tag{3}$$

4. Model introduction

4.1 Model framework

The DRGCN framework structure of the dynamic spatiotemporal graph convolutional network model based on the reachable matrix proposed in this paper is shown in Figure 2. DRGCN consists of two

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convolution blocks (DRST-Block blocks) and a fully connected output layer, each DRST-Block The block contains two time-gated convolutional layers and a spatial graph convolutional layer, using residual connection and bottleneck strategies to apply to each block.

The network input is the feature vector $X_{his} = (X_{t-x+1}, X_{t-x+2}, \dots, X_t)^T \in R^{N \times M \times x}$ of the road network diagram for X time periods and the corresponding dynamic reachable matrix $DR \in R^{N \times N}$. Through the DRST-Block block to capture the time-dimensional features, space-dimensional features, and spatio-temporal dependence, and finally through the fully connected layer output X_{t+i}(i=1,2,…,y) to predict the traffic volume of each node after the i-th time step.

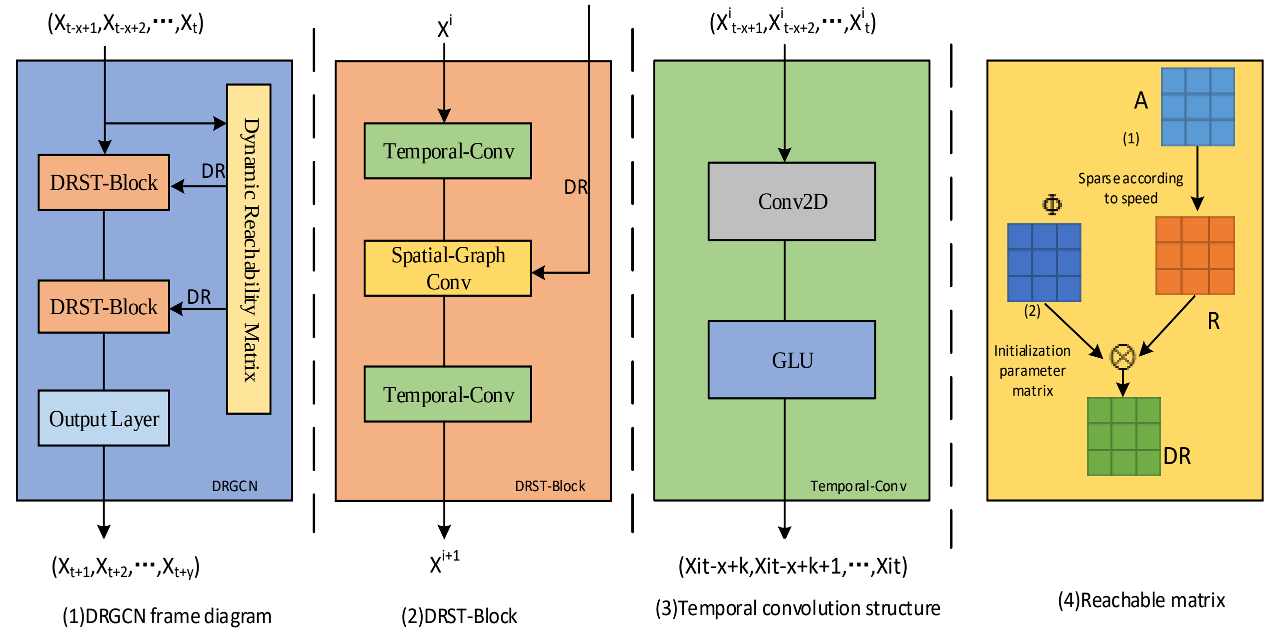

Figure 2. DRGCN model frame diagram

In the specific model structure, the input sequence is first convolved over time to reduce the sequence length. When passing through the graph convolution module, the embedded dynamic reachable matrix structure is calculated under a given time interval, average flow speed and other parameters The degree of reachability from a certain node to other adjacent nodes, the dynamic reachability matrix can effectively express the reachability relationship between nodes, and further describe the characteristics of the road network more accurately.

4.2 Spatial graph convolution module

In this paper, spectrogram convolution[11] is used to implement graph convolution operation. Spectrogram convolution essentially involves multiplying the spatial convolution operation through the Fourier transform to the frequency domain, and then the final result is subjected to the inverse Fourier transform In the time domain, the final convolution result is obtained. Each node on the traffic road network graph structure can be regarded as a kind of graph signal, and the graph signal can be used to capture the meaningful patterns and features in the topological space. The general research graph structure will be Converted to Laplacian matrix L to express, analyze the properties of the graph structure itself by studying the eigenvalues and eigenvectors of L.

Usually the Laplacian matrix of graph G is defined as $L = D - A$, and the symmetrical normalized form is $L = I_N - D^{-\frac{1}{2}} A D^{-\frac{1}{2}}$, where A is the adjacency matrix, I_N is the identity matrix, and D is the degree matrix. As the scale of the graph increases, the eigenvalue decomposition of L will produce greater time complexity, which will reduce the overall performance of the network. References in this article [12] Chebyshev Polynomials approximately replace the convolution kernel Θ, as shown in Equation 4.

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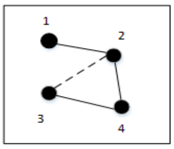
$$\Theta_{*g}x = \Theta(L)x \approx \sum_{k=0}^{K-1} \theta_k T_k(\tilde{L})x \tag{4}$$

Where Θ is the convolution kernel parameter, $*_g$ is the convolution operation, $x \in R^{N\times M}$ is the characteristic matrix, the Chebyshev polynomial is defined as $T_k(\tilde{L}) \in R^{n\times n}$, k is The order of the Chebyshev polynomial can be regarded as the size of the receptive field of the convolution kernel in the specific graph structure. The domain $x \in [-1,1]$ is defined in the $T_k(x)$ function, so it needs to pass $\tilde{L} = \frac{2L}{\lambda_{max}}$-$I_N$ scales the Laplacian matrix L to between [-1,1], $\theta_i \in R^K$ is the Chebyshev polynomial coefficient, λ_{max} is the maximum eigenvalue of L, in this paper λ_{max}=2. By using the Chebyshev polynomial approximate expansion to solve, extract the information of each node's $0{\sim}K-1$ order neighbor node, that is, update the space state information of the node itself.

After the dynamic reachability matrix structure is embedded in the graph convolution module, the dynamic reachability matrix structure mainly considers whether the vehicle is reachable from node i to j under given parameters to determine whether to take node j into consideration, as shown in Figure 3. If the reachable matrix R is calculated by formula (2) under given parameters, and R is applied to the adjacency matrix, a new adjacency matrix will be generated. In addition, the learning parameter matrix ϕ is added to make the influence of other adjacent nodes in $D^{-\frac{1}{2}}AD^{-\frac{1}{2}}$ on the current node adjustable, which can effectively express the characteristics of the road network to a certain extent. Thereby predicting traffic volume more accurately.



(a)

$$A = \begin{bmatrix} 1 & 1 & 0 & 0 \\ 1 & 1 & 1 & 1 \\ 0 & 1 & 1 & 1 \\ 0 & 1 & 1 & 1 \end{bmatrix} \quad R = \begin{bmatrix} 1 & 1 & 0 & 0 \\ 1 & 1 & 0 & 1 \\ 0 & 0 & 1 & 1 \\ 0 & 1 & 1 & 1 \end{bmatrix} \quad \Lambda_T = \begin{bmatrix} \lambda_1^1 & \lambda_2^1 & \dots & \lambda_T^1 \\ \lambda_1^2 & \lambda_2^2 & \dots & \lambda_T^2 \\ \lambda_1^3 & \lambda_2^3 & \dots & \lambda_T^3 \\ \lambda_1^4 & \lambda_2^4 & \dots & \lambda_T^4 \end{bmatrix}$$

(b)

$$R' = R \odot A = \begin{bmatrix} 1 & 1 & 0 & 0 \\ 1 & 1 & 0 & 1 \\ 0 & 0 & 1 & 1 \\ 0 & 1 & 1 & 1 \end{bmatrix} \quad D = \begin{bmatrix} 2 & 0 & 0 & 0 \\ 0 & 3 & 0 & 0 \\ 0 & 0 & 2 & 0 \\ 0 & 0 & 0 & 3 \end{bmatrix} \quad \Phi = \begin{bmatrix} w_{11} & w_{12} & w_{13} & w_{14} \\ w_{21} & w_{22} & w_{23} & w_{24} \\ w_{31} & w_{32} & w_{33} & w_{34} \\ w_{41} & w_{42} & w_{43} & w_{44} \end{bmatrix}$$

(c)

$$\Theta' *_G \Lambda_T = D^{-\frac{1}{2}}(R' \odot \Phi)D^{-\frac{1}{2}}\Lambda_T\Theta'$$

$$= \begin{bmatrix} \Theta'(0.5w_{11}\lambda_1^1 + 0.41w_{12}\lambda_1^2) & \dots & \Theta'(0.5w_{11}\lambda_T^1 + 0.41w_{12}\lambda_T^2) \\ \dots & \dots & \dots \\ \Theta'(0.33w_{42}\lambda_1^2 + 0.41w_{43}\lambda_1^3 + 0.33w_{44}\lambda_1^4) & \dots & \Theta'(0.33w_{42}\lambda_T^2 + 0.41w_{43}\lambda_T^3 + 0.33w_{44}\lambda_T^4) \end{bmatrix}$$

(d)

Figure 3. Graph convolution process and matrix representation

4.3 Time convolution module

For the time dimension feature extraction, this paper uses a one-dimensional convolutional neural network to capture the dynamic characteristics of the time dimension. The time convolution layer contains a one-dimensional convolution, and the width of the convolution kernel is K_t. The input of the time convolution of each vertex in the graph G can be regarded as a sequence of length T, with C_i input channels, denoted as $X \in R^{T\times n\times C_i}$, the time convolution on the input elements K_t neighbors of, the default step size of the time convolution kernel is 1, so that each time the sequence length is shortened by $K_t - 1$. Therefore, the output of each vertex is a time sequence of length $T - K_t + 1$, and the output channel is C_o, denoted as $Y \in R^{(T-K_t+1)\times n\times C_o}$. The convolution kernel $\Psi \in \mathrm{R}^{\mathrm{K_t}\times C_i\times 2C_o}$ is used to map the input Y to a single output element $[PQ] \in R^{(T-K_t+1)\times 2C_o}$ (P, Q are half of the number of channels), as shown in Equation 5.

$$\Psi *_\tau X = P \odot \sigma(Q) \in R^{(T-K_t+1)\times C_o} \tag{5}$$

Among them, P and Q are the gate inputs of GLU respectively, and $\odot$ represents Hadamard product. By using the same convolution kernel Ψ for each node $x_i \in R^{T\times C_i}$, time convolution can

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also be extended to three-dimensional variable $X \in R^{T \times n \times C_i}$, denoted as $\Psi *_\tau X$. The specific time dimension convolution method is shown in Figure 4:

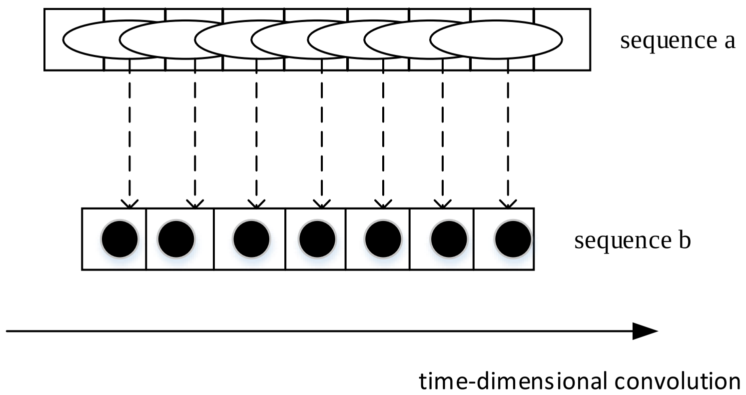

Figure 4. Convolution diagram of time series

Assuming that the sequence a in Figure 4 is the traffic flow time sequence of a node with a length of 9. After a one-dimensional time convolution with a convolution kernel size of 3, the output sequence *b* has a length of 7, which means that the adjacent nodes are gathered time slice information, after the previous layer of graph convolution, the node gathers the information of adjacent nodes at the same time, so that after a spatio-temporal convolution, the spatio-temporal correlation can be extracted, by stacking multiple spatio-temporal convolution blocks to extract Farther node information.

4.4 Output layer module

According to the one-dimensional convolution of the time-domain convolution block, the length of the data in the time dimension is reduced by $2(K_t - 1)$ after passing through a spatio-temporal convolution block. So after two spatio-temporal convolution blocks, the output $Y \in R^{(T-4(K_t-1)) \times n \times C_o}$. The output layer includes a time domain convolution layer and a fully connected layer. The number of convolution kernels in the time domain convolution layer is $T - 4(K_t - 1)$, and the output is mapped to $Z \in R^{n \times C_o}$, the fully connected layer $\hat{\lambda} = Z\omega + b$, where$\omega \in R^{C_o}$, then output $\hat{\lambda} \in R^n$. The model uses the L_2 regularized loss function, as shown in formula 6.

$$L(\hat{\lambda}; W_\theta) = \sum \| \hat{\lambda}(\lambda_{t-T+1,\dots,}\lambda_{t,}W_\theta) - \lambda_{t+1} \|^2 \tag{6}$$

Among them, W_θ is all trainable parameters, $\hat{\lambda}$ is the predicted value, and λ_{t+1} is the true value.

5. Experiment and analysis

5.1 Dataset description

In this experiment, the public data set PEMS is selected. This data set is the California highway traffic data collected by the Caltrans performance measurement system in real time. The measurement system contains about 39,000 sensor sites, which are deployed in major road sections for real-time collection Traffic data situation. The PEMS data set is actually collected every 30s, and then collected at a time interval of 5 minutes to form the final data. The specific conditions of the PEMS data set used in the experiment are shown in Table 1.

Table 1. Introduction of PEMS Dataset

DataSet	Acquisition Time	Number of sensors	Number of data	Forecast index
PEMSD4	2018.1.1-2018.2.28	307	16992	flow
PEMSD8	2016.7.1-2016.8.31	170	17856	flow

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5.2 Data preprocessing

First, filter out sites that are too close according to the actual situation. This article uses 4 miles as the shortest distance, and samples data at a time interval of 5 minutes, so that each site will generate 288 data per day. There will be some missing data in the collected data set. The existence of abnormal values and outliers will have a greater impact on subsequent experimental results. Therefore, data preprocessing is required. For missing values, linear interpolation can be used to fill in, and outliers can be filled with mean.

Then, because the attribute values will be different, and these different values will have a greater impact on the target predicted value, in order to eliminate the difference between the feature values, the attribute value needs to be controlled within a certain interval, which is beneficial to the model Training and optimization. Commonly used data standardization methods include maximum and minimum standardization, z-score standardization, normalization, etc. This article uses maximum and minimum standardization, that is, discrete standardization, which maps the original data to [0,1], such as the formula 7 shown.

$$X' = \frac{X - min(X)}{max(X) - min(X)} \tag{7}$$

Among them, X is the original data, and X' is the normalized new data.

5.3 Experimental setting

5.3.1 Evaluation index

In the experiments of this article, the root mean square error (RMSE), average absolute error (MAE) and average absolute percentage error (MAPE) are used as the evaluation indicators of the model. Their calculation formulas are as follows:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_{true} - y_{pred})^2} \tag{8}$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|y_{true} - y_{pred}\right| \tag{9}$$

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_{true} - y_{pred}}{y_{true}}\right| \tag{10}$$

Among them, y_{true} is the true value of traffic volume, y_{pred} is the predicted value of traffic volume in the future, and n is the number of traffic volume samples.

5.3.2 Baseline model

In order to better verify the prediction effect of the model proposed in this article, the baseline model selected in the experiment is as follows:

1) HA:The HA model calculates the average value of features such as traffic volume in the historical time period as the predicted value of the next moment;

2) ARIMA:The ARIMA model is mainly aimed at the time series with stationarity, and achieves the purpose of forecasting by constructing a mathematical model;

3) FC-LSTM:The FC-LSTM model can solve the problem of gradient explosion and gradient disappearance caused by long sequences. It is a special RNN model;

4) STGCN:The STGCN model effectively captures the spatio-temporal correlation by modeling the multi-scale transportation network. It uses the spatial method to divide the node set into different subsets, which can achieve the purpose of convolution kernel parameter sharing.

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5.3.3 Parameter selection

First, the data set is divided into training set, validation set and test set in a ratio of 6:2:2. After many experiments and adjustment of parameters, the final selected experimental parameters are obtained: the number of output channels of temporal convolution, spatial convolution and temporal convolution in the first layer of spatiotemporal convolution block are 64, 32 and 64 respectively; in the second layer of temporal convolution block, temporal convolution, spatial convolution and temporal convolution are The number of output channels are 32, 32 and 128 respectively. The number of output channels in each layer is the number of convolution kernels used in this layer. The time convolution layer uses GLU(Gated linear units)as the activation function, and the spatial convolution layer uses the RELU(Rectified Linear Units)function, where the time interval Δt in the reachable matrix is 5min, and the number of time intervals α is 1. In order to optimize the learning parameters, *adam* is selected as the optimizer, and the *batch_size* is 300. The rate *lr* is 0.001, and the training period *epochs* is 30 rounds.

5.4 Experimental comparison and result analysis

The model proposed in this paper is used to predict traffic flow on the PEMSD4 and PEMSD8 datasets, and compared with the four models proposed above. Table 2 shows the prediction results of various models for traffic flow in the next 15 minutes.

Table 2. Comparison of Traffic Flow Prediction Results Based on PEMSD4 / PEMSD8 Datasets

Model	PEMSD4			PEMSD8		
	RMSE	MAE	MAPE	RMSE	MAE	MAPE
HA	30.59	19.79	22.64	44.46	29.88	20.36
ARIMA	32.33	19.26	18.59	40.85	26.64	21.59
FC-LSTM	27.52	15.91	15.37	37.26	24.70	19.26
STGCN	24.69	15.00	17.62	34.41	23.57	15.95
DRGCN	22.56	15.45	14.25	32.19	22.66	15.18

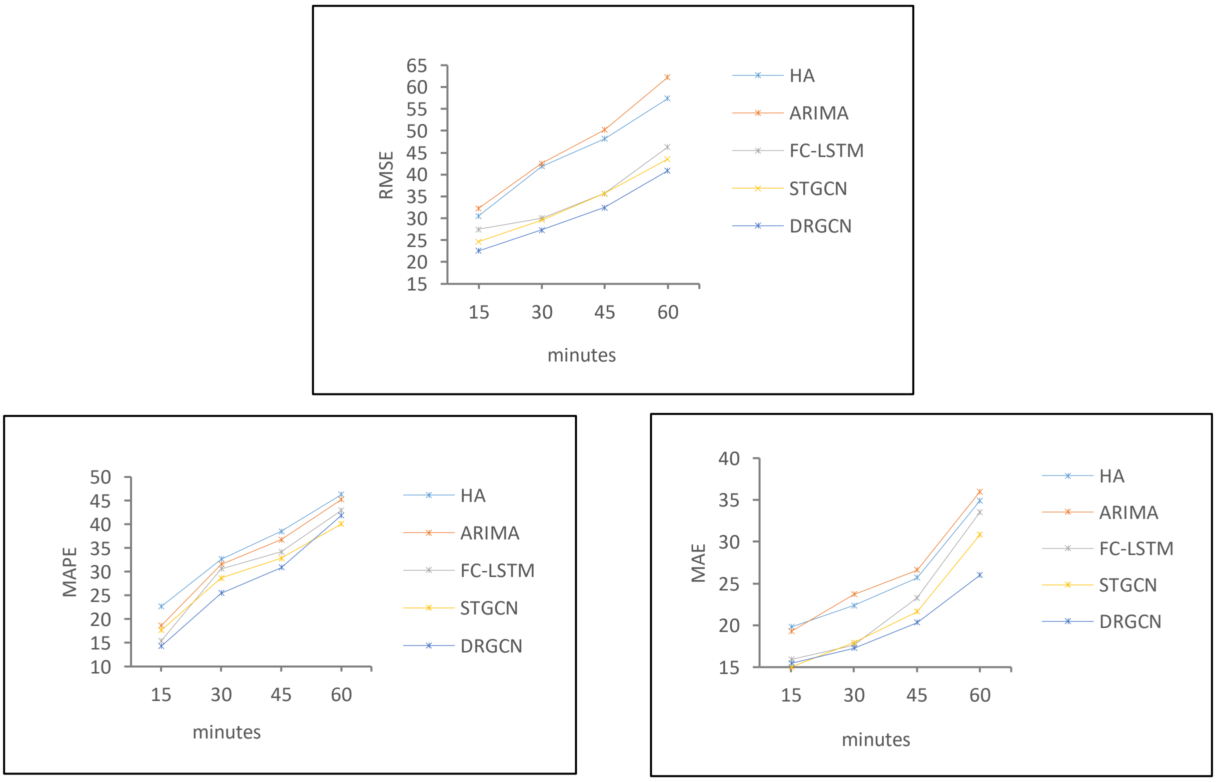

Figure 5. Schematic diagram of prediction duration change on PEMSD4

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It can be seen from Table 2 that the DRGCN model proposed in this paper has better prediction performance than other models. It can be seen from the table that the prediction accuracy of HA and ARIMA based on statistical models is lower than the prediction accuracy of deep learning methods. Characteristics such as linearity, instability, and spatio-temporal correlation, and this type of model assumes that the data is linear and stable, which is very different from the actual situation, so it cannot handle nonlinear data better. The deep learning method FC-LSTM ignores The spatial and temporal correlation cannot effectively describe the characteristics of the road network. Compared with the STGCN model, the RMSE of DRGCN is increased by 8.6% and 6.5% respectively. This is because the addition of the graph convolution module can better extract the spatial characteristics of the road network, and the DRGCN model introduces the dynamic reachability matrix to consider the reachability between adjacent road sections. In actual traffic, the influence between non-adjacent road sections must be indirectly propagated through intermediate nodes. If the non-adjacent nodes are unreachable under the given time interval and other parameters, the influence of other nodes can be considered. Fully consider the dynamic characteristics of the actual traffic network, so it can more accurately describe the characteristics of the road network and explore the temporal and spatial correlation.

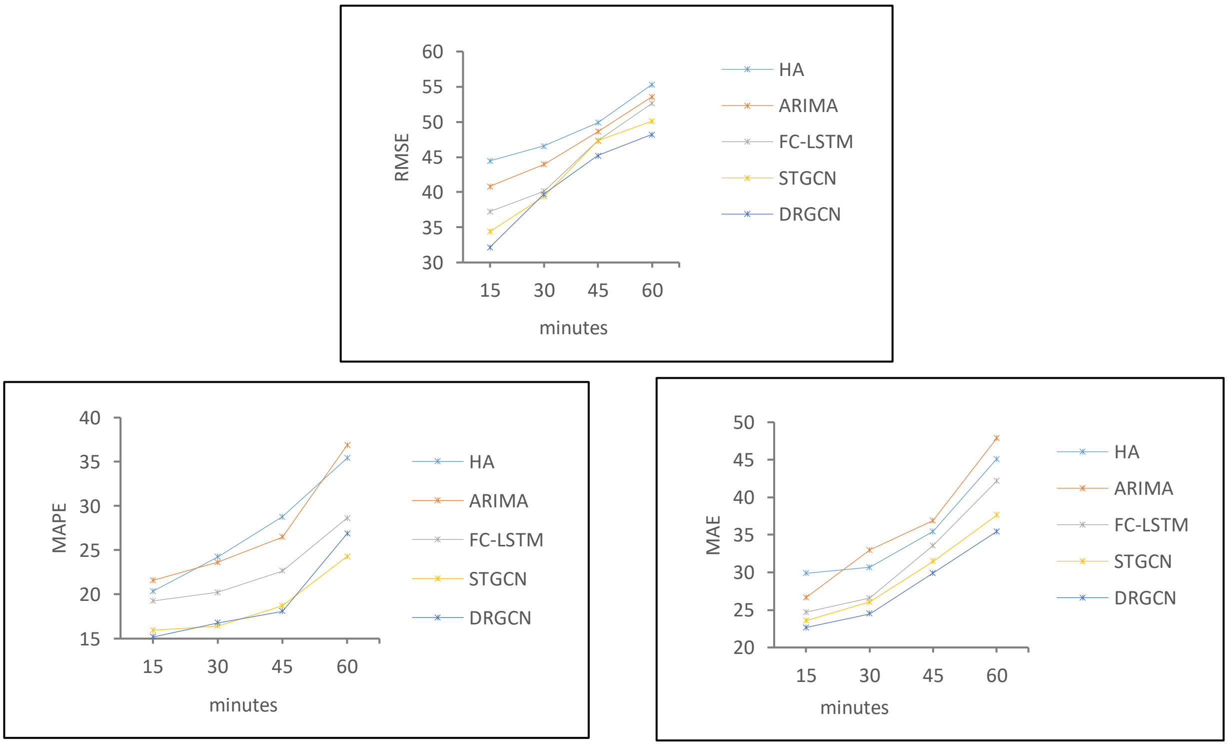

Figure 6. Schematic diagram of prediction duration change on PEMSD8

In addition, as the prediction time increases, the overall error is also increasing. As shown in Figures 5 and 6, it shows that it is more difficult to predict the future for a longer time, and the overall prediction performance of each model is reduced. Compared with other models, the error of this model is lower and it has a good prediction effect.

Next, in order to better analyze the DRGCN model, in the data set PEMSD4, select the site number 73 and the day of February 28th. Similarly, select the site number 9 and the date as August 31 in the data set PEMSD8. It can be seen that the model proposed in this paper is relatively closer to the true value, and the horizontal axis represents the time of the day, and the vertical axis represents the traffic flow. In addition, the peaks were reached at 9 am and 6 pm, respectively, which means that the morning peak and evening peak are coming, which is consistent with the reality, and further shows that the traffic volume prediction model proposed in this paper can effectively capture the temporal and spatial correlation and enhance Model expression ability and relatively better prediction effect.

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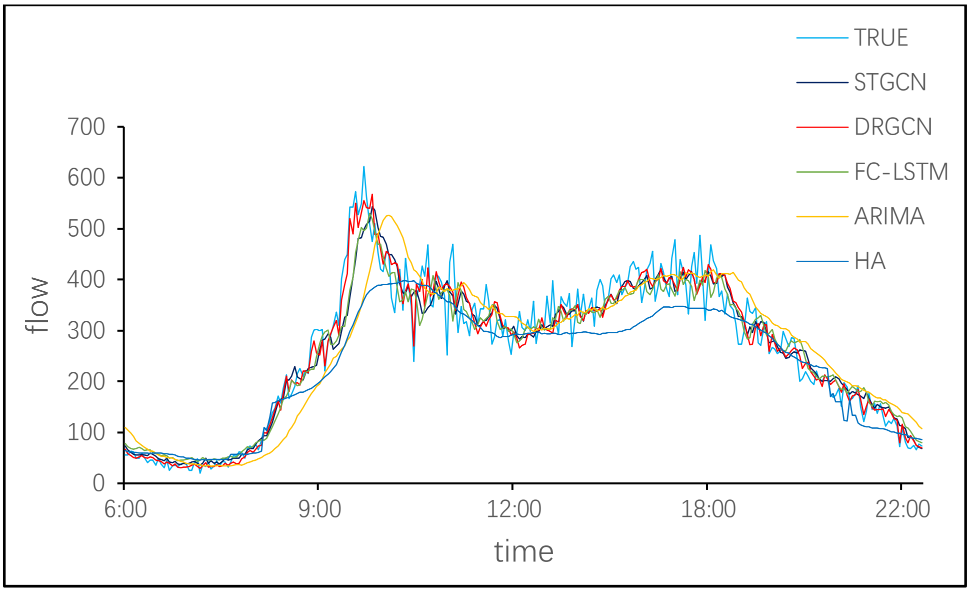

Figure 7. Prediction effect on PEMSD4

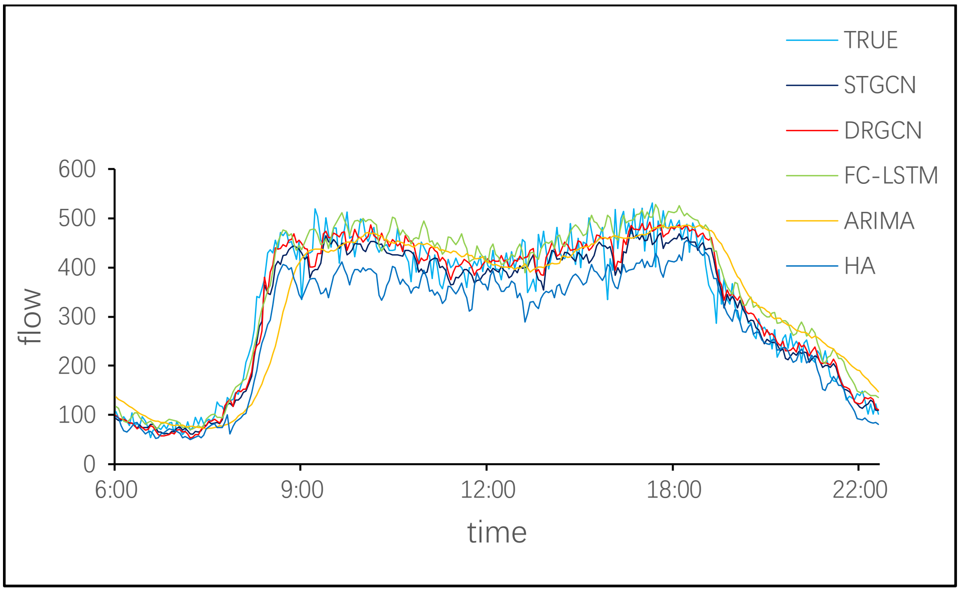

Figure 8. Prediction effect on PEMSD8

6. Conclusion and Future Work

In this paper, an improved graph convolutional neural network model is proposed in combination with the dynamic changes of the actual traffic road network. This model adds a dynamic reachability matrix to the original spatio-temporal graph convolution framework to effectively express the unique physical characteristics of the traffic road network. Expressing the dynamics of the road network structure by the reachability between nodes of the road network, and learning the reachability matrix with the speed of the traffic flow of the node, can more effectively express the relationship of the traffic volume of adjacent nodes in the time dimension. The model has been experimentally verified on the real PEMS data set. The experimental results show that the algorithm is superior to the existing baseline model algorithm STGCN, and has certain advantages in prediction accuracy. This paper proposes a graph convolutional network based on dynamic reachability matrix to explore how to effectively mine temporal and spatial dependence, future research work will look for better parameters and introduce attention mechanisms to further improve model prediction performance.

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