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Short-Term Traffic Flow Prediction Based on Graph Convolutional Network Embedded LSTM

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ABSTRACT

Short-term traffic flow prediction, which is useful to improve traffic congestion and road efficiency, has been a hot issue in the field of transportation. However, only considering Euclidean space, conventional methods are always unable to make good use of the spatial-temporal correlation of traffic flow data which is usually a topological structure. In this paper, a deep learning model, GCN-LSTM (graph convolutional network-LSTM), was proposed with encoder and decoder structure. GCN-LSTM will simultaneously capture the spatial and temporal characteristic of traffic flow by embedding GCN into the structure of LSTM. Training with the traffic flow data of previous T moments and adjacent section, GCN-LSTM effectively perform short-term traffic flow prediction. Experiments on real data demonstrate that our method, considering both of spatial and temporal features, has a more powerful representation ability and higher prediction accuracy compared with LSTM.

INTRODUCTION

Accurate prediction of short-term traffic flow is an important part of the intelligent transportation system (Vlahogianni et al. 2014)(Zhang et al. 2011), which is helpful to solve the traffic congestion, improve the efficiency of the road network, and reduce the traffic accidents. However, due to its characteristics of non-linearity, complexity, and unpredictability, short-term traffic flow prediction has been a hot issue at home and abroad.

The current research can be divided into three categories.

The first one is the prediction model based on statistical analysis, which mainly includes historical average analysis prediction method, time series analysis prediction method, Kalman filter analysis prediction method, etc. The premise of these methods is to assume that the data predicted in the future has the same characteristics as the one in the past. In 1976, ARIMA (Auto-Regressive Integrated Moving Average) was proposed, which was the most commonly used method for time sequence including traffic flow prediction. In 2003, (Williams and Hoel 2003) found seasonal ARIMA, considering the impact of the different season on the traffic flow, makes ARIMA more suitable to the prediction task. Moreover, Kalman filter analysis-based method (Xie et al. 2007) can extract the informative signal by using recursive algorithm to estimate the best state variables of the filter. In general, most of the statistics analysis-based models, with the simple structure, is suitable for the section with stable traffic conditions but can hardly deal with the suddenly-happened traffic condition.

The second one is the prediction model based on artificial intelligent, such as SVM, neural network, deep learning etc. In 2013, (Fu et al. 2013), introducing a kernel function, proposed a support vector machine based model which transformed the short-term traffic flow prediction problem into the linear regression problem in high dimension space. (Huang et al. 2014) and (Lv et al. 2015) respectively proposed the deep belief networks and the stacked auto-encode to complete this task. (Chen et al. 2018) proposed a deep autoencoder-based model with symmetrical layers to learn the temporal correlations of traffic network and predicting traffic congestion. And nowadays, graph convolution is a generalization of convolution operation for learning non-grid data. STGCN (Yu et al. 2018) considering the spatial and temporal dependency, was proposed. Recent years, deep learning-based method, such as LSTM, performs better than the traditional one. Compared with the traditional one, these kinds of method have a higher accuracy and more robust, but with a huge computing cost which means that it will spend lots of time to train and has high hardware requirements.

The third kind of method is hybrid model. Obviously, it is difficult for signal model to balance the seasonal, climatic and man-made factors. Therefore, the hybrid model, combining two or more models together, is the most commonly used solution for traffic flow prediction task. (Dou et al. 2008) mixed the wavelet analysis and ARIMA together. (Wang et al. 2015) combined the KNN and SVM to improve the reliability of the prediction significantly. And Traffic Graph Convolutional Long Short-Term Memory Neural Network (TGC-LSTM) (Cui et al. 2018) Was proposed to learn the interactions between the roadways and forecast the network-wide traffic state. These kinds of methods can gather the strengths of each models and complement each other. But it will increase the computation cost, complexity or even cause other concerns.

Nowadays, most of the methods are only utilize the historical traffic flow data, which means that they ignore the spatial relationship of the detectors. In this work, we proposed a novel hybrid method, termed as GCN-LSTM, based on graph convolutional neural network and Long Short-Term Memory. It can simultaneously extract the topological structure feature and capture the historical trend of the traffic network.

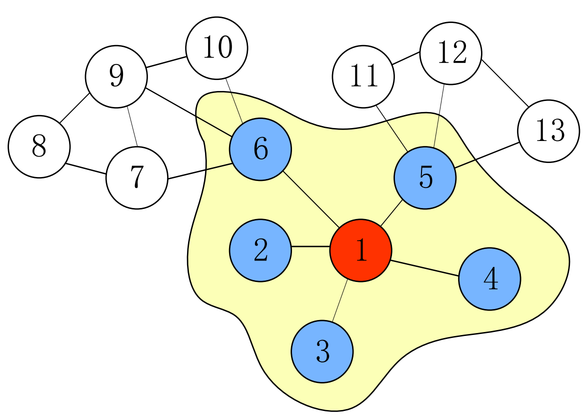


Figure 1. A small part of the traffic network. Nodes 1~13 represent 13 roads and the blue nodes indicate the roads connected to the central road (the red one).

METHOD

In traffic flow prediction work, traffic network can be regard as a graph structure in non-euclidean space. In this space, each road can be seen as a node of the graph as shown in Figure 1, and the traffic flow information is the signal. Extracting topological properties effectively plays a key role to traffic flow prediction. But the connections of the nodes in non-euclidean space is various, traditional convolutional operation can hardly find a suitable kernel to handle non-grid-based data. Therefore, it is important to introduce the graph convolution based on the spectral graph theory.

Spectral graph convolution

In spectral graph analysis, the convolution operation was defined as the multiplication of a signal x with a filter g parameterized by θ in the Fourier domain like Eq. 1.

$$g_\theta * x = U g_\theta U^T x \qquad \text{Eq. 1}$$

Where U is the matrix of eigenvectors of the normalized graph Laplacian $L = I_N - D^{-\frac{1}{2}} A D^{-\frac{1}{2}} = U \Lambda U^T$, with a diagonal matrix of its eigenvalues Λ and $U^T x$ being the graph Fourier transform of x. We can understand g as a function of the eigenvalues of L, i.e. $g_\theta(\Lambda)$.

However, when the graph becomes bigger, such as the intricate traffic network, the eigendecomposition of L might cause a massive of computing cost. Suggested by (Hammond et al), the g can be well-approximated by a truncated expansion in terms of Chebyshev polynomials $T_k(x)$ up to K^{th} order. And we finally got the definition of graph convolution operation in Eq. 2.

$$g_{\theta'} * x \approx \sum_{k=0}^{K} \theta'_k T_k(\tilde{L}) x \qquad \text{Eq. 2}$$

where $\tilde{L} = \frac{2}{\lambda_{\max}} L - I_N$, $\lambda_{\max}$ is equal to the largest eigenvalue of L. θ denotes a vector of Chebyshev coefficients. The Chebyshev polynomials are recursively defined as $T_k(\tilde{\mathrm{L}}) = 2\tilde{L} T_{k-1}(\tilde{\mathrm{L}}) - T_{k-2}(\tilde{\mathrm{L}})$, with $T_0(\tilde{\mathrm{L}}) = 1$ and $T_1(\tilde{L}) = \tilde{L}$ especially.

LSTM

Not only the spatial character, but also the temporal one is playing a crucial role. The data at previous amounts inextricably links with the next. And the RNN is one of the most commonly used structures to handle the time series data. Nevertheless, the original RNN presents several limitations on the data with large time span, because of the gradient vanishing and exploding. Fortunately, there are various kinds of variety to circumvent this problem. With the gate mechanism skillfully added, LSTM, one of the varieties, has the ability to reserve the useful information from previous moment. The Basic structure of LSTM was shown on Figure 2.

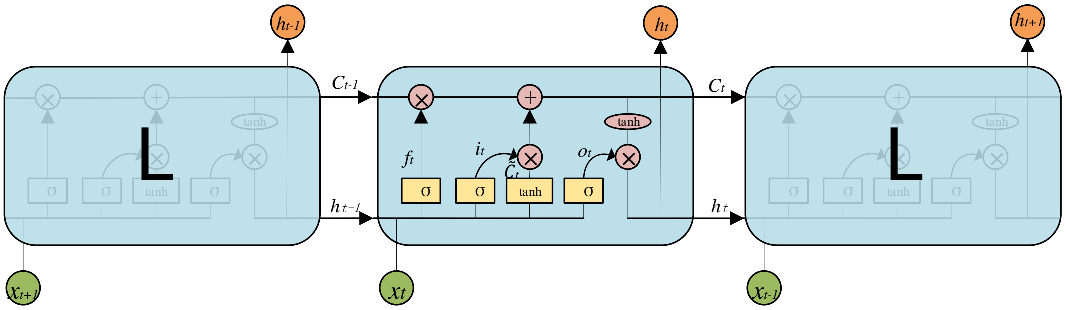


Figure 2. Basic structure of LSTM.

GCN-LSTM

In order to fully exploit the spatial and temporal characters of the traffic flow data simultaneously, GCN-LSTM was proposed, based on Graph convolution network and Long Short-Term Memory network. As shown in Figure 3, h_{t-1} denotes the hidden state at time t-1; x_t denotes the traffic flow at time t; $f(x_t, A)$ represents the graph convolutional operation to x_t and output $x_{t'}$, like figure 4 shown.

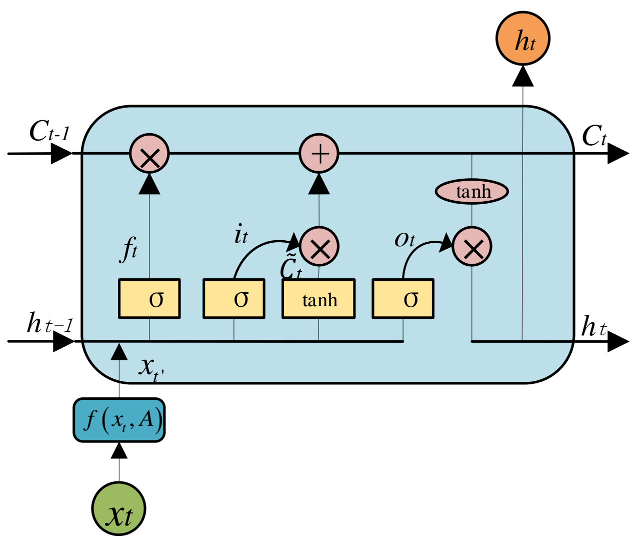


Figure 3. Basic structure of GCN-LSTM.

Relative equations of GCN-LSTM are shown on Eq. 3 ~ Eq. 8. f_t, the forget gate, decides what information will be discarded from cell status. And i_t is the input gate, which is used to update the cell status C_t with f_t, C_{t-1} *and* $\tilde{C}_t$, as Eq. 6 does. o_t is the output gate, which controls the output value with the C_t, as Eq. 8 does.

$$f_t = \sigma\left(W_f \cdot \left[h_{t-1}, f\left(x_t, A\right)\right] + b_f\right) \quad \text{Eq. 3}$$

$$i_t = \sigma\left(W_i \cdot \left[h_{t-1}, f\left(x_t, A\right)\right] + b_i\right) \quad \text{Eq. 4}$$

$$\tilde{C}_t = \tanh\left(W_C \cdot \left[h_{t-1}, f\left(x_t, A\right)\right] + b_C\right) \quad \text{Eq. 5}$$

$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t \quad \text{Eq. 6}$$

$$o_t = \sigma\left(W_o\left[h_{t-1}, f\left(x_t, A\right)\right] + b_o\right) \quad \text{Eq. 7}$$

$$h_t = o_t * \tanh\left(C_t\right) \quad \text{Eq. 8}$$

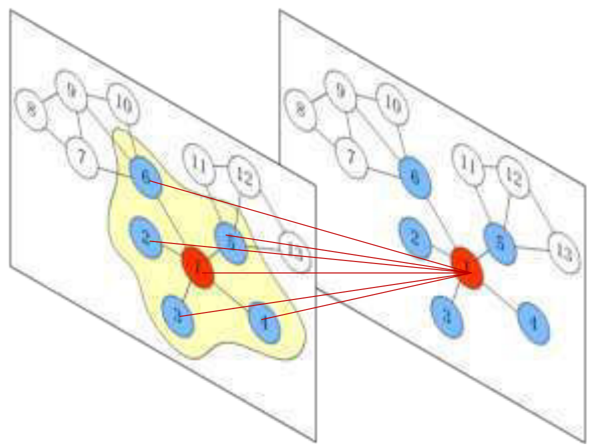


Figure 4. Graph convolution operation, obtaining the topological relationship between the central road and adjacent sections. In this picture, only the one neighbor was considered.

Our GCN-LSTM obtains the traffic status at t moment by taking the hidden state, cell state at t-1 moment and the current traffic flow data as inputs. Figure 5 shows the whole flow chart of our model. $\{x_1, x_2, \cdots, x_{12}\}$ denotes the time sequence data of traffic flow, $\{S_0, S_1, \cdots, S_{11}, S_{1'}, S_{2'}\}$ is the hidden states of the LSTM model and $\{y_1, y_2, y_3\}$ represents the predictions of our network. While capturing the topological properties after graph convolution operation at current time, the model still learns the temporal feature from the historical traffic flow.

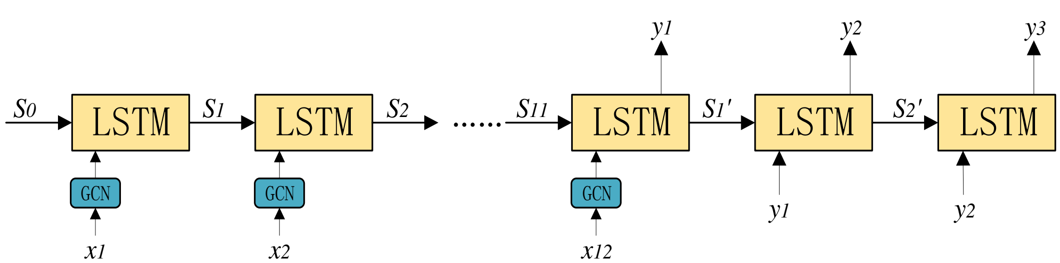


Figure 5. The flow chart of GCN-LSTM network.

EXPERIMENT

Dataset

Our model was validated on the California highway traffic datasets PeMSD4, which is collected by the Caltrans Performance Measurement System (PeMS) (Chen et al. 2001). Collected from January to February in 2018, the PeMSD4 reflects the traffic data in San Francisco Bay Area where there are 3848 sensors on 29 roads. Furthermore, Geographic information of each detector are recorded in the dataset, which is helpful to extract the spatial characters of the road structure. In our experiment, the traffic flow data was normalized between 0 to 1. And the dataset was split into training set and test set, with the ratio of 90% and 10% respectively.

Setting

With the help of GTX1070 GPU, we implemented the GCN-LSTM model based on the tensorflow framework from scratch. Xavier uniform (Glorot and Bengio 2010) and zeros were used to initialize weights and biases respectively. Mini batch size was set to 64, and Adam Optimizers was employed, as well as L2 loss function. The learning rate was set to 0.001, and the total training epoch was 2000. In Chebyshev polynomials, K was set to be 3. In LSTM, 128 hidden units were set to have a good representation ability for temporal character.

Evaluation metrics

To evaluate the prediction performance of GCN-LSTM, four metrics, shown in Eq. 9, Eq. 10, Eq. 11 and Eq. 12, were used to validate the difference between the traffic flow data in real time and the predicted result.

Root Mean Squared Error (RMSE)

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(Y_t - \hat{Y}_t\right)^2} \qquad \text{Eq. 9}$$

Mean Absolute Error (MAE)

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|Y_t - \hat{Y}_t\right| \qquad \text{Eq. 10}$$

Coefficient of Determination (R2):

$$R^2 = 1 - \frac{\sum_{i=1}\left(Y_t - \hat{Y}_t\right)^2}{\sum_{i=1}\left(Y_t - \overline{Y}\right)^2} \qquad \text{Eq. 11}$$

Explained Variance Score (Var):

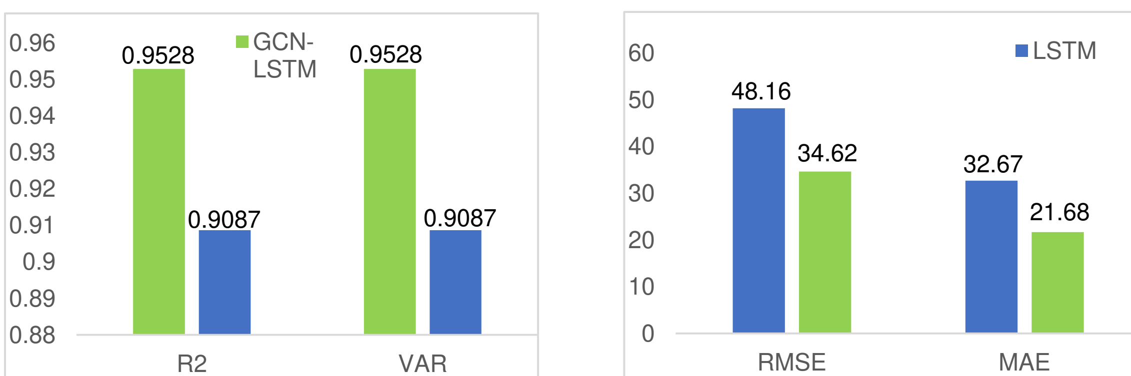
$$var = 1 - \frac{\mathrm{Var}\{Y - \hat{Y}\}}{\mathrm{Var}\{Y\}} \quad \text{Eq. 12}$$

Experimental Result

Table 1 shows the comparison between LSTM and GCN-LSTM model on PeMSD4 datasets. Compared with LSTM which only considers only temporal features, the RMSE of the GCN-LSTM model is decreased by 28%, and 33.6% for MAE. The histogram comparison is depicted on Figure 6(a). Furthermore, the R2 and VAR of GCN-LSTM, shown on Figure 6(b), are both increased by 4.86%. All of these evaluation indexes indicate that the GCN-LSTM can capture spatial dependence well. Figure 7. Shows the contrast between the true traffic flow value and the predictive value of each road.

Table 1. Evaluation metrics for LSTM and GCN-LSTM.

Model	RMSE	MAE	R2	VAR
LSTM	48.16	32.67	0.9087	0.9086
GCN-LSTM	34.62	21.68	0.9528	0.9528



(a) (b)

Figure 6. The histogram comparison of RMSE, MAE, R2, VAR between LSTM and GCN-LSTM.

Influence of K in Spectral graph convolution

The impact of K on the performance of GCN-LSTM was found, which is show on Figure 8. We choose the value of K from [1,2,3,4] and analyze the difference of each evaluation metric. Figure 8(a) shows the performance of RMSE and MAE for different K. When K is equal to 3, both of RMSE and MAE reach the minimum. And Figure 8(b) represent the relationship of R2, VAR and K. It can be seen that R2, VAR is the largest when K=3. Therefore, K=3 was found to be the better hyperparameters in our model.

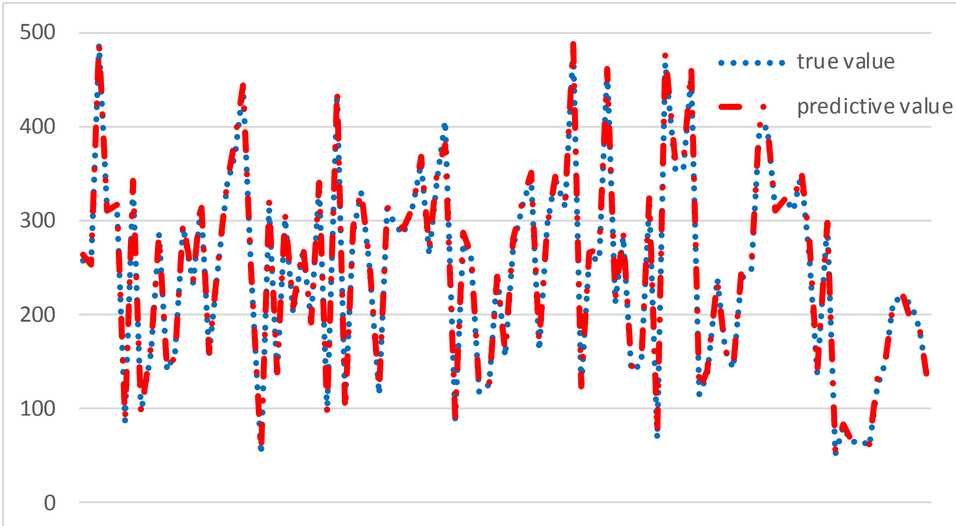
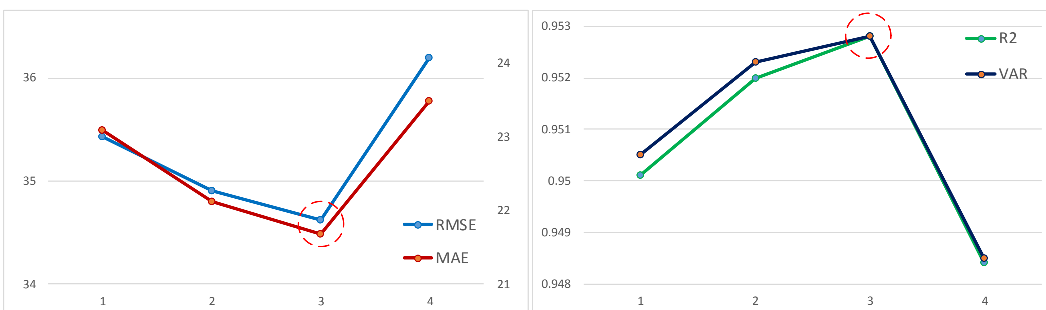


Figure 7. The contrast between the true traffic flow value and the predictive value of each road.



(a) Changes in RMSE and MAE (b) Changes in R2 and VAR

Figure 8. Comparison of prediction performance under different K.

The precise prediction of GCN-LSTM on PeMSD4 can be expanded to other traffic managements, such as real time traffic condition forecasting with the help of the mobile-GPS data gathered by mobile-GPS mapping companies. Such data contains the latitude and longitude information of the driver at that time. After deleting the abnormal data, we made up the deficiency by using the least square method. And then, data smoothing technology was used to denoise the mobile-GPS data. Utilizing transfer learning, the GCN-LSTM, pretrained on PeMSD4, is fine-tuned by the mobile-GPS data to identify the real time condition of the traffic network. The flow-process diagram is shown on Figure 9.