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Paper:

Traffic Flow Prediction Model Based on Drivers' Cognition of Road Network

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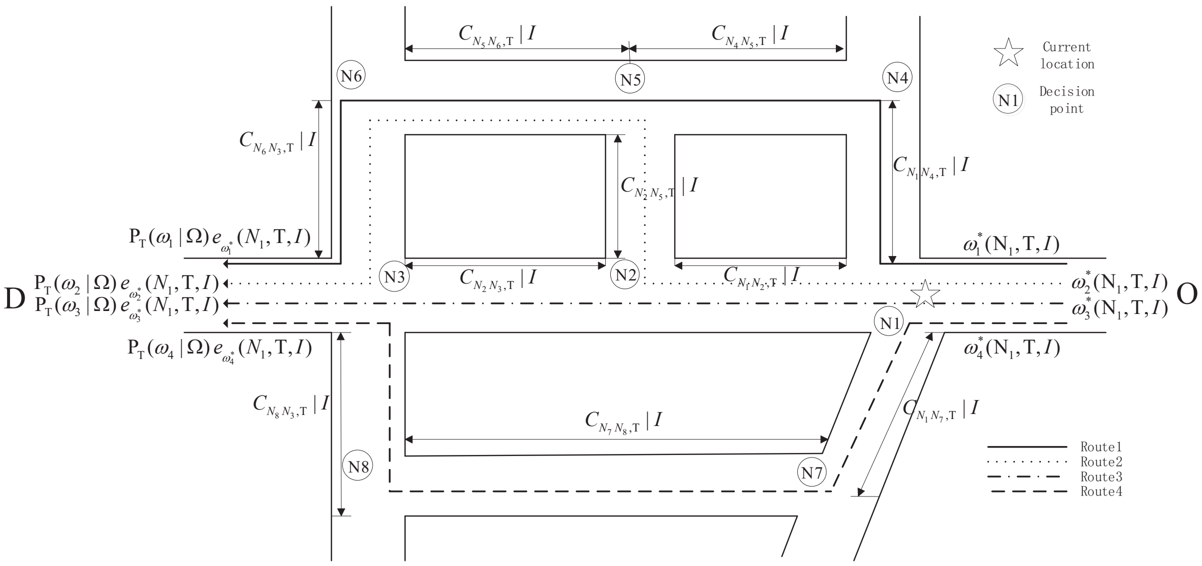
The traditional traffic flow prediction method is based on data modeling, when emergencies occur, it is impossible to accurately analyze the changes in traffic characteristics. This paper proposes a traffic flow prediction model (BAT-GCN) which is based on drivers' cognition of the road network. Firstly, drivers can judge the capacity of different paths by analyzing the travel time in the road network, which bases on the drivers' cognition of road network space. Secondly, under the condition that the known road information is obtained, people through game decision-making for different road sections to establish the probability model of path selection; Finally, drivers obtain the probability distribution of different paths in the regional road network and build the prediction model by combining the spatiotemporal directed graph convolution neural network. The experimental results show that the BAT-GCN model reduces the prediction error compared with other baseline models in the peak period.

Keywords: game decision-making, probability distribution, traffic flow prediction, spatiotemporal directed graph convolution

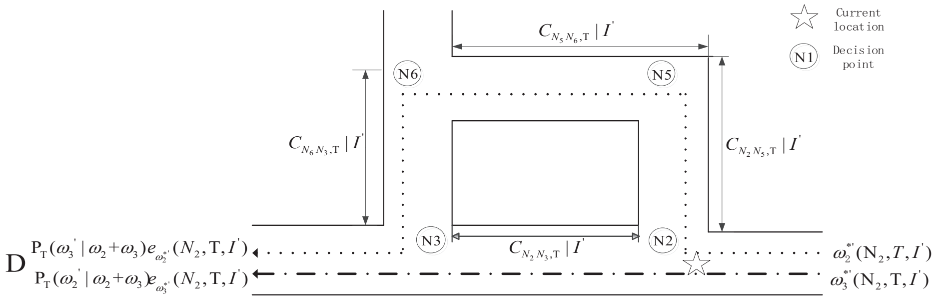
1. Introduction

Due to the complex, nonlinear and dynamic characteristics of the urban large-scale road network, it is difficult to predict traffic flow data. With the breakthrough of deep learning in many fields, more and more researchers apply deep learning to spatiotemporal data prediction. Cheng et al. [1] proposed a deep traffic prediction model, which explicitly collected the upstream and downstream neighborhood roads of each road and convolved these neighborhoods respectively, thus modeling the spatial dependence. Ke et al. [2] proposed a new deep learning method called fusion convolution long and short time memory network (FCL-NET), which takes into account spatial dependence, time dependence and external factor dependence to predict short-term passenger demand. Yu et al. [3] used the deep convolutional neural network (DCNN) to capture spatial dependence and Long Short-Term Memory (LSTM) to capture temporal dynamics, proved the superiority of the SRCN model through experiments on Beijing traffic network data. Yang et al. [4] built a predict model based on traffic flow information from the Caltrans Performance Measurement System (PeMS) and local datasets, predicted future traffic flow by an improved LSTM method. Zhu et al. [5] established predict model based on the historical vehicle Global Positioning System (GPS) information data. The CLustering in QUEst (CLIQUE)-based clustering algorithm V-CLIQUE is proposed to analyze the historical vehicle GPS data. Although the spatial correlation of CNN model introduced by the above method has made great progress in traffic prediction task, conventional convolutional neural network is applicable to Euclidean space, such as image, conventional power grid, etc., and limits the topological structure of complex traffic network, so it cannot describe spatial correlation in essence. In recent years, with the development of the graph convolution network model [6], it can be used to capture the structural characteristics of the non-Euclidean topological road network, providing a good solution for the above problems. Yu et al. [7] proposed a gated graph-based convolutional network for traffic prediction, but the model did not consider the uncertainty of traffic flow in case of emergencies.

Traditional traffic flow prediction only considers the spatial and temporal characteristics of traffic flow. The input datasets of prediction are convenient to get, and the path planning results are accurate and efficient in the majority traffic situation. In case of abnormal emergencies, such as traffic accidents, road congestion, traffic flow will present uncertainty and different complexity. The prediction existed will lose its correctness terribly. To solve the above problems, this paper simulates Variable Message Sign (VMS) road condition information, establishes the behavior model of drivers' path selection. We obtain the probability distribution of different paths and forecasts the traffic flow at a future time by combining the spatiotemporal directed graph convolutional neural network. When abnormal events occur, the parameter of drivers' cognition of road network is proposed to correct these deviations, thus avoiding the problem of inaccurate traffic flow prediction.



(a) Description of road condition information I when Reaching node N1 at time t information



(b) Description of road condition information I′ when Reaching node N2 at time t information

Fig. 1. Road network information description.

2. Driver Behavior Modeling

By stimulating the release of dynamic VMS information, this paper studies the changing rules of traffic flow characteristics under the influence of driver's behavior choice of route. To simplify the study of the model, the following assumptions are provided:

(1) When receiving the traffic information of the road network, drivers decide to choose the route according to the current traffic conditions and driving experiences;

(2) Drivers in different sections may have similar preferences. Under the influence of road condition information, drivers' behavior of the path selection leads to the potential traffic flow characteristics is correlated with the utility functions of drivers' preferences in different sections.

As it is shown in the **Fig. 1**, $G = (N, A, T, P)$ is established based on real road network information to be a random time-dependent network, $N = \{N_1, N_2, \ldots, N_n\}$ is the set of nodes; $A = \{A_1, A_2, \ldots, A_m\}$ is the set of road sections. The number of nodes is $|N| = n$ and the number of road sections is $|A| = m$; $T = \{t_1, t_2, \ldots, t_T\}$ is the set of period time; P is a set of the conditional probability distribution.

Let $e_{\omega}(x)$ denote the expected travel time when the state of the road network is x and the driver's route selection strategy is ω; $Node_{down}(j)$ as the set of downstream nodes of node j, $C_{jk,T}|I$ as the travel time variable for link (j, k) at time t conditional on current information I, as shown in **Fig. 1(a)**. When the driver at the decision point N1, the travel time of each road section in the current road network is $C_{N_1N_2,T}|I$, $C_{N_2N_3,T}|I$, $C_{N_1N_4,T}|I$, $C_{N_1N_7,T}|I$, $C_{N_2N_5,T}|I$, $C_{N_3N_6,T}|I$, $C_{N_3N_8,T}|I$, $C_{N_4N_5,T}|I$, $C_{N_5N_6,T}|I$, and $C_{N_7N_8,T}|I$, respectively. Ω is policy set for drivers choose a different path $\{\omega_1^*(N_1, T, I), \omega_2^*(N_1, T, I), \omega_3^*(N_1, T, I), \omega_4^*(N_1, T, I)\}$. When the driver deals with emergencies, the travel time of different paths can be obtained as $e_{\omega_1^*}(N_1, T, I)$, $e_{\omega_2^*}(N_1, T, I)$, $e_{\omega_3^*}(N_1, T, I)$, and $e_{\omega_4^*}(N_1, T, I)$, respectively, using the game behavior of drivers calculate the probability of different path selection $P_T(\omega_1|\Omega)$, $P_T(\omega_2|\Omega)$, $P_T(\omega_3|\Omega)$, and $P_T(\omega_4|\Omega)$, it can improve the ability of traffic flow prediction in case of emergency. In the same network, at time $T + C_{jk,T}|I$, the road condition information I' at the next decision point N2 is shown in **Fig. 1(b)**, the travel time of different sections is $C_{N_2,N_3}|I'$, $C_{N_2,N_5}|I'$, $C_{N_3,N_6}|I'$, and $C_{N_5,N_6}|I'$, respectively. When the driver in N1 decision points to choose conditions of $\omega_2^*(N_1,T,I)$ or $\omega_3^*(N_1,T,I)$, at the decision point N2, two strategies, $\omega_2^{*\prime}(N_2,T,I')$ or $\omega_3^{*\prime}(N_2,T,I')$ can be chosen. The travel time is $e_{\omega_2^{*\prime}}(N_1,T,I')$, $e_{\omega_3^{*\prime}}(N_1,T,I')$, and the path selection probability is $P_T(\omega_2{}'|\omega_2+\omega_3)$, $P_T(\omega_3{}'|\omega_2+\omega_3)$. Denote $Z(j,T)$ as the set of all the information available at node j and at time T. Then, for $\forall j \in U-\{d\}$, $\forall T$, $\forall I \in Z(j,T)$, e_{ω^*} and ω^* are optimal if and only if they are solutions of the following system of equations [8, 9]:

$$e_{\omega^*}(j,T,I) = \min_{k \in Node_{down}(j)} \left\{ E_{C_{jk,T}} \left[C_{jk,T} + E_{I'} \left[e_{\omega^*}\left(k, T + C_{jk,T}, I'\right) | C_{jk,T} \right] \middle| I \right] \right\}, \quad (1)$$

$$\omega^*(j,T,I) = \arg\min_{k \in Node_{down}(j)} \left\{ E_{C_{jk,T}} \left[C_{jk,T} + E_{I'} \left[e_{\omega^*}\left(k, T + C_{jk,T}, I'\right) | C_{jk,T} \right] \middle| I \right] \right\}, \quad (2)$$

with boundary conditions $e_{\omega^*}(d,T,I)=0$, $\omega^*(d,T,I)=d$, $\forall T, \forall I \in Z(d,T)$. The above equations are extended to take into account current time and information, so the solution of these equations is similar to the shortest path problem. We calculate the drivers' behavior model based on the logit random utility. The travel time distribution C is the input of the optimal strategy generation model, $\Omega = \Upsilon(C)$ denotes as the set of policies for OD path selection. Let $P_T(\omega|\Omega)$ the probability of choosing policy ω by a traveler if he or she departs the node j at time t. Then,

$$P_T(\omega|\Omega) = \frac{\exp\lambda\left(Y_{\omega,T}\right)}{\sum_{\omega\in\Omega}\exp\lambda\left(Y_{\omega,T}\right)}. \quad (3)$$

The model introduces the driver's game judgment, when he chooses the route to determine whether to choose the route or not, $\lambda = 1$ means the driver chooses this road; $\lambda = 0$ means the driver doesn't choose this road. $\exp(\cdot)$ is the natural exponential function and $Y_{\omega,T}$ is the utility of policy ω at time T. We compute $Y_{\omega,T}$ in terms of the expected travel time a traveler takes to reach node k if he or she follows policy ω and departs at time T from the node j:

$$Y_{\omega,T} = e_\omega(j,T,I), \quad (4)$$

where $e_\omega(j,T,I)$ is the expected travel time for travelers to follow the strategy ω departs from the node j to point D at time T. The algorithm of section selection probability is presented as **Table 1** and **Fig. 2** [10].

This algorithm takes the distribution of road travel time as input to obtain the road condition information at the current moment. We find the path with the shortest travel time through the optimal strategy model. The logit random utility model to calculate the probability matrix of drivers at decision points of different sections $P(N_n,T)$, as shown in Eq. (5), N_n nodes and T time step determine the selection probability of different sections in the road network.

$$P(N_n,T) = \begin{bmatrix} p_{1,1} & p_{1,2} & \cdots & p_{1,T} \\ p_{2,1} & p_{2,2} & \cdots & p_{2,T} \\ \vdots & \vdots & \ddots & \vdots \\ p_{m,1} & p_{m,2} & \cdots & p_{m,T} \end{bmatrix}. \quad (5)$$

Table 1. The optimal strategy.

Algorithm: Computing the optimal strategy
Input: distribution of segment travel time $\{C_{jk,T}, j, k\}$ are the starting and ending points of the segment, $T\{T_1,\dots,T_n\}$
Output: the selection probability of each road section P_T
Step 1 (Initialization step):
1.1 Compute $e_{\omega^*}(j,T,I)$ and $\omega^*(j,T,I)$, $\forall j \in U$, $\forall I \in (d,t)$
1.2 $e_{\omega^*}(j,T,I)=\infty$, $\forall j \in U-\{d\}$,
$e_{\omega^*}(d,T,I)=0$, $\forall t < T_n$, $\forall I \in (d,T)$;
Step 2 (Main Step):
For $t = T$ down to 1
For each $I \in (d,T)$
For each $link(j,k) \in M$
$temp = C_{jk,T} + \sum_{I' \in I(T+C_{jk,T})} e_{\omega^*}(k, T + C_{jk,T}, I') P\left(\frac{I'}{I(T+C_{jk,T})}\right)$;
If $temp < e_{\omega^*}(j,T,I)$
$e_{\omega^*}(j,T,I) = temp$;
$\omega^*(j,T,I) = k$;
$P_T = \frac{\exp\lambda(temp)}{\sum_{\omega\in\Omega}\exp\lambda(temp)'}$

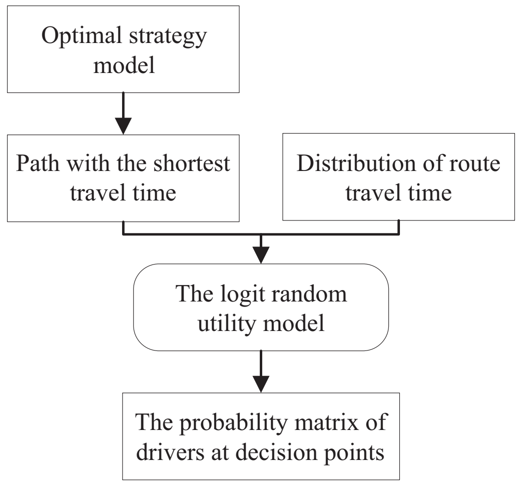


Fig. 2. Structure of the optimal strategy algorithm.

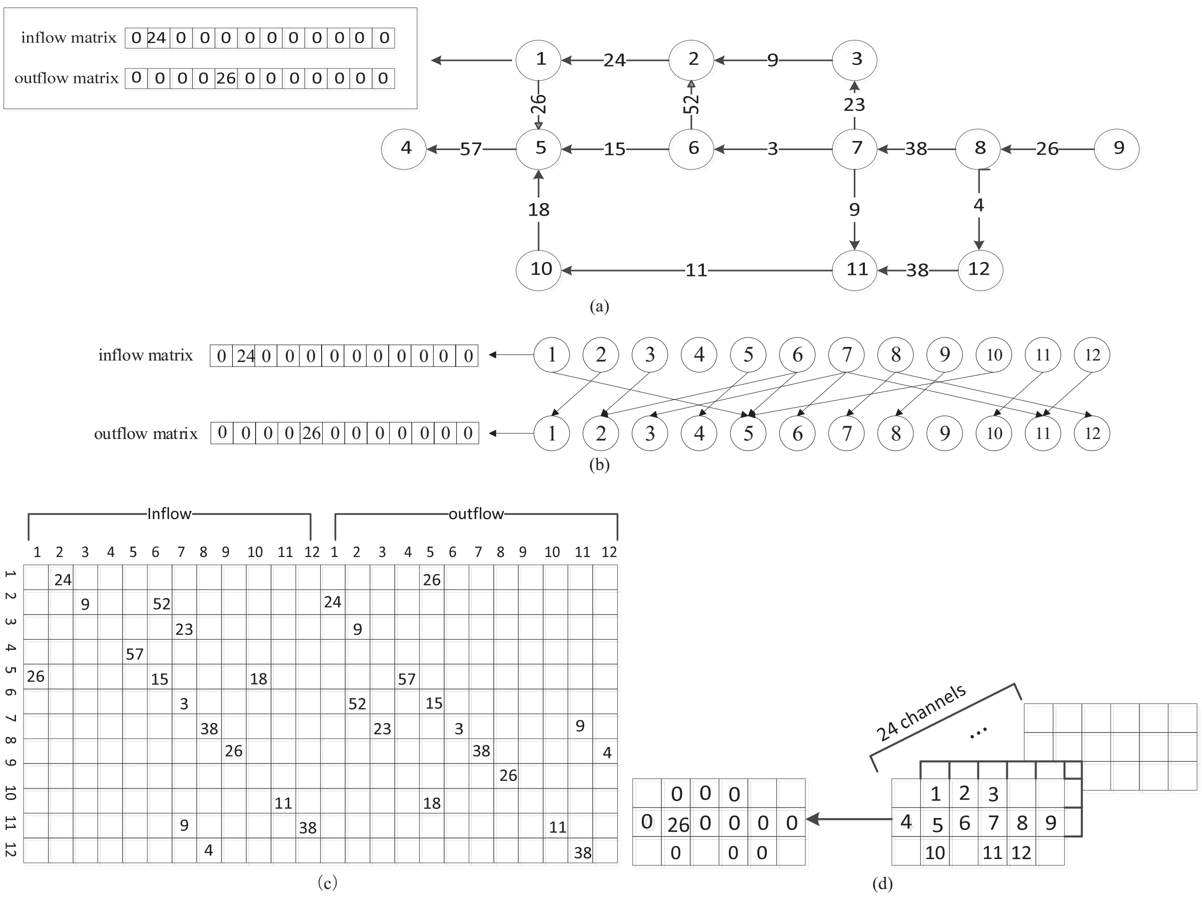


Fig. 3. Converting a space-time graph into a tensor.

3. Traffic Flow Prediction Model Based on Drivers' Cognition of Road Network (BAT-GCN)

In this paper, the driver's selection probability matrix of different sections as probability graph for convolution operation, and combined with the temporal and spatial diagram convolutional neural network of road network traffic flow, to predict the future traffic flow. Due to the interconnection, correlation and mutual influence of each road segment, its complexity poses a great challenge to the traditional graph structure model, which transforms the above space-time diagram and probability diagram into a tensor. For example, we propose transforming the space-time graph into a tensor [1, 11] $M_t \in \mathbb{R}^{2N\times I\times J}$, N is the number of nodes, and the transformation tensor of the probability graph is the same as the method. As it is shown in **Fig. 3(a)**, the road network is composed of 12 nodes and 15 edges at time t. We first unroll it that a directed graph (**Fig. 3(b)**). For each node, there are inflow and outflow transitions, represented by a vector (dimension = 24) (**Fig. 3(c)**). For example Node 1, its inflow matrix is [0 24 0 0 0 0 0 0 0 0 0 0], the outflow matrix is [0 0 0 0 26 0 0 0 0 0 0 0], which are further concatenated into one matrix [0 24 0 0 0 0 0 0 0 0 0 0 0 0 0 0 26 0 0 0 0 0 0 0], containing both outgoing and incoming information. Finally, we can reshape the matrix into a tensor, and each tensor consists of an inflow matrix and an outflow matrix (**Fig. 3(d)**). The first N channels are the inflow matrix, and the last N channels are the outflow matrix. Each node has a fixed spatial location according to the real road network, protecting the spatial correlation.

Suppose the t time-series recorded on each node in the traffic network G is the traffic flow sequence. We use ${x_t}^{c,N_n} \in \mathbb{R}$ to denote the value of the c-th feature of node N_n at time t, and ${x_t}^{N_n} \in \mathbb{R}^T$ denotes the values of all the features of node N_n at time t. $X_t = ({x_t}^{N_1}, {x_t}^{N_2}, \ldots, {x_t}^{N_n})^T \in \mathbb{R}^{n\times T}$ denotes the values of all the features of all the nodes at time t. Besides, we set $y_t^{N_n} = x_t^{T,N_n} \in \mathbb{R}$ to represent the traffic flow of node N_n at time t in the future.

Figure 4 shows the description of the traffic flow prediction model based on drivers' cognition of the road network. The model is composed of two parts, namely, the time-space diagram modeling of traffic flow and path selection probability. Taking the space-time diagram model of traffic flow as an example, the traffic flow data is input, and it is a time-ordered sequence of graphs $\{S_t \mid t = t_1, t_2, \ldots, t_T\}$, which is further converted into a sequence of tensors $M_t \in \mathbb{R}^{2N\times I\times J}$, $\{M_t \mid t = t_1, t_2, \ldots, t_T\}$, according to the above transformation method.

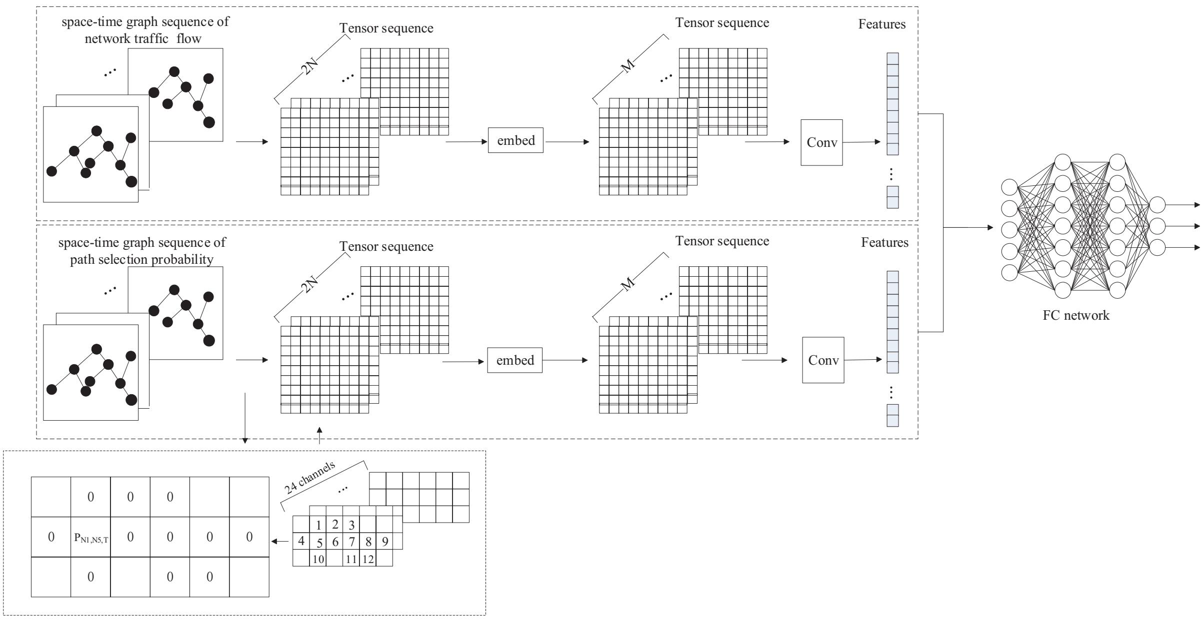


Fig. 4. Traffic flow prediction model based on drivers' cognition of road network.

For each node N_n, it has up to 2N transition possibility, including N incomings and outgoings. However, for a certain time interval, the transition between nodes may be very sparse. We propose employing a spatial embedding method, to tackle such sparse and high-dimensional problems. In detail, the spatial embedding tends to learn a function that maps a 2N-dimension vector of node $N_{i,j}$ into a M-dimension space as follows:

$$\begin{aligned} Z_t(:,i,j) &= W_m \mathcal{M}_t(:,i,j) + b_m, \\ & \qquad 1 \le i \le I, \quad i \le j \le J, \end{aligned} \quad . \qquad (6)$$

where $W_m \in \mathbb{R}^{M\times 2N}$ and $b_m \in \mathbb{R}^M$ are the learnable parameter matrix and vector, respectively. All $I \times J$ nodes share these parameters. $\mathcal{M}_t(:,i,j) \in \mathbb{R}^M$ means the vector located at (i,j).

We employ an embedding layer to deal with the problem of sparse matrix transition and carry out convolution operation. The space-time path selection probability graph model converts the tensor model is the same as the above method, the obtained probability tensor model is shown in the figure below. Firstly, the processed space-time graph sequence of road traffic flow and path selection probability is used as the input of convolution operation. Secondly, we obtain the relevant features in different spatial and temporal dimensions and compressed into one-dimensional vectors through the flattening layer in the convolution. Finally, the eigenvectors of the two models are taken as the input of the full connection, and the inner product is output to predict future traffic flow.

4. Experimental Analysis

4.1. Data Description

We used TensorFlow to predict the performance of the BAT-GCN model on the actual data set. The data set is the GPS trajectory data of floating cars in a demonstration area of Hefei from September 1 to September 30, 2016. We measure traffic volume, average speed, and travel time between sections every 10 minutes, 80% of data was used as training data sets, and the remaining 20% was used as test sets to predict future traffic volume. The hyperparameters set in the model mainly including learning speed, batch size, training cycle and the number of hidden layers. In the experiment, we set the learning rate to 0.001 and the batch size to 32. Since the iteration is about 1000 times, the training error is in an equilibrium state, the training period is 1500. After many experiments, the number of hidden layer units is set to be 64, which is the optimal prediction model.

4.2. Evaluation Metrics

To evaluate the prediction performance of the BAT-GCN model, we use five metrics to evaluate the difference between the real traffic flow Y_t and the prediction $\hat{Y}_t$ including:

(1) Root mean squared error (RMSE):

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(Y_t - \widehat{Y}_t\right)^2}. \quad \ldots\ldots\ldots \quad (7)$$

(2) Mean absolute error (MAE):

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n}\left|Y_t - \widehat{Y}_t\right|. \quad \ldots\ldots\ldots\ldots \quad (8)$$

Table 2. The prediction results of the BAT-GCN model and other baseline methods on datasets.

Metrics	Model						
	HA	SVR	ARIMA	GCN	LSTM	T-GCN	BAT-GCN
RMSE	24.145	25.475	26.587	27.875	22.899	23.001	21.208
MAE	15.094	18.277	17.640	18.075	15.032	14.053	12.825
R^2	0.565	0.422	$*$	0.420	0.610	0.605	0.666
Var	0.565	0.422	$*$	0.422	0.610	0.627	0.673

(3) Coefficient of determination (R2):

$$R^2 = 1 - \frac{\sum\limits_{i=1} \left(Y_t - \widehat{Y}_t\right)^2}{\sum\limits_{i=1} \left(Y_t - \widehat{Y}\right)^2}. \qquad (9)$$

(4) Explained variance score (Var):

$$\mathrm{Var} = 1 - \frac{\mathrm{Var}\left\{Y - \widehat{Y}\right\}}{\mathrm{Var}\left\{Y\right\}}. \qquad (10)$$

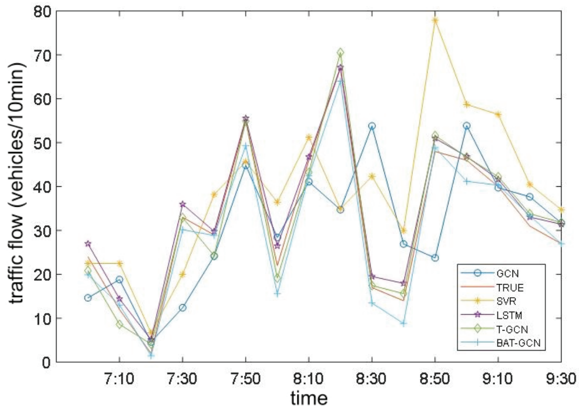
Specifically, RMSE and MAE are used to measure the prediction error: the smaller the value, the better the prediction effect. R2 and Var calculate correlation coefficients to measure the ability of prediction results to represent actual data: the larger the value, the better the prediction effect.

4.3. Experimental Results

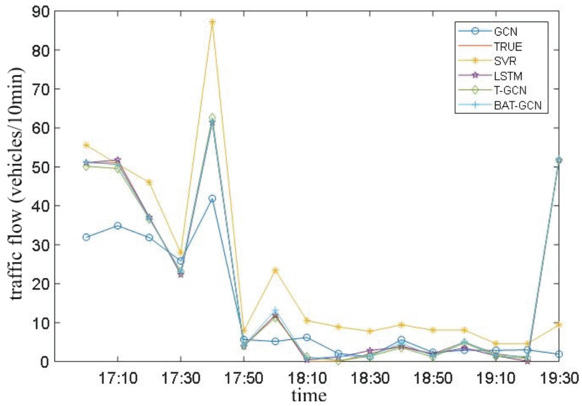
The performance of the BAT-GCN model is compared with the following baseline approach, as shown in **Table 2**.

Table 2 shows the evaluation indexes of the BAT-GCN model and other baseline methods. $*$ indicates that the value is too small to be ignored, indicating that the prediction effect of the model is poor. T-GCN and BAT-GCN models emphasize the importance of time feature modeling. Compared with other baselines, such as the HA model, the ARIMA model, and the SVR model, they have better prediction accuracy. The RMSE errors of T-GCN and BAT-GCN models are 9.71% and 16.7% lower than those of SVR models respectively, which is because it is difficult for HA, SVR, and ARIMA methods to process complex non-stationary time series data. Compared with the GCN model that only considers spatial features, RMSE decreases by 17.5% and 23.9% respectively. Compared with the LSTM model that only considers time characteristics, RMSE of BAT-GCN decreases by about 7.4%, while RMSE of the T-GCN model increases. It can be seen that the evaluation indexes of the BAT-GCN model in all prediction models are the best prediction performance, proving the effectiveness of the model in traffic flow prediction.

To more clearly see the effective value of evaluation, we selected the morning peak (7:00–9:30) as shown in **Fig. 5(a)**, and late peak (17:00–7:30) as shown in **Fig. 5(b)** of the traffic flow forecasting. By comparing our model with SVR, GCN, LSTM, and T-GCN models, we can see from these figures that in most cases, the performance of our BAT-GCN model is superior to other models.



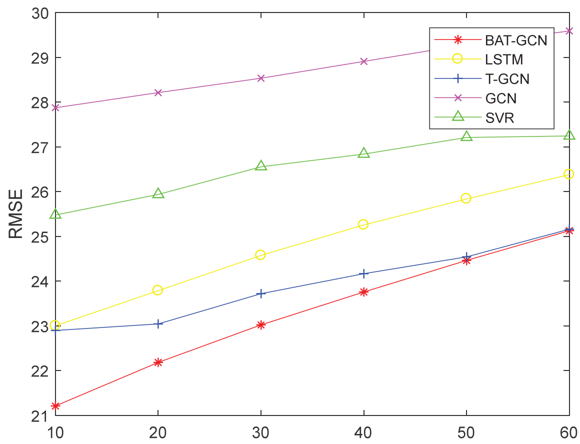
(a) Morning peak (7:00–9:30)



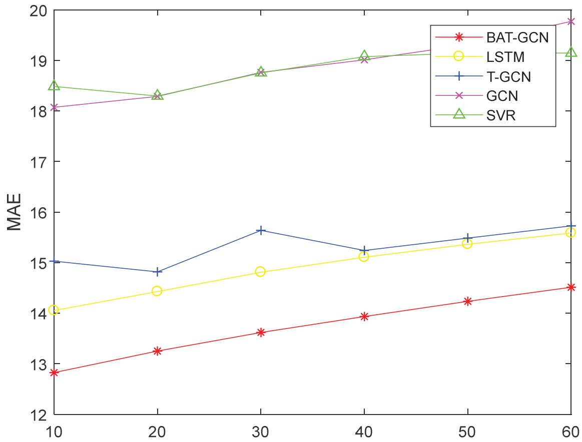
(b) Evening peak (17:00–7:30)

Fig. 5. Prediction of morning and evening peak traffic flow on September 25, 2016.

From the above results, we can draw the following conclusions: It is very important to predict the traffic flow accurately by the model of driver's behavior choice path strategy base on the condition of the known traffic network. Especially, when congestion occurs in morning and evening peak hours, drivers consider the shortest path to avoid congestion. Therefore, this paper proposes a traffic flow prediction model based on driver behavior selection. The distribution of route selection probability is obtained through the driver's judgment of road network information, and combined with the spatiotemporal di-



(a) RMSE



(b) MAE

Fig. 6. Error comparison.

rected graph convolution neural network model, predicted the traffic flow of the regional road network. The model can capture the spatiotemporal characteristics of the non-Euclidean space. Compared with the traditional prediction model, the prediction accuracy of our model is maintained at about 88%. The predicted curve law is basically consistent with the actual. The position with large deviation is mainly reflected in the traffic volume is small and the fluctuation is large, but the error is within the acceptable range.

With the increase of prediction interval, various prediction performance also changes, as shown in the figure. In general, as the prediction range increases, the prediction error also increases. As can be seen from **Fig. 6**, only consider the time correlation method can predict better results in a short time, such as LSTM, but with the increase of the prediction time range the prediction error increases sharply. The predicted effect of the GCN model is low, the main reason is that GCN only considers the spatial characteristics, ignoring the traffic flow data is typical of the time-series data. T-GCN and BAT-GCN models take into account both temporal and spatial features, they can almost always obtain the best prediction performance compared with other models. In particular, we proposed the BAT-GCN model has a more obvious difference from other baselines in the short-term prediction, which indicates that the optimal route selection strategy of drivers can be better used in the traffic flow prediction of urban complex road networks.

5. Conclusion

In this paper, we propose a novel approach for traffic forecasting called BAT-GCN, which analyzes the driver's path selection behavior of road network traffic information to obtain the selection probability distribution of different road sections in the road network. And then, combining with spatiotemporal directed graph convolution neural network. Because of the complexity of the urban road network, people often choose the best strategy to reach their destination based on selfish behaviors. This model can be better applied in the case of sudden accidents or serious congestion in the road network, drivers choose the path with the shortest travel time through game thinking to avoid traffic congestion. Our method reflects that drivers use GPS navigation, VMS, and other road information to judge the reality of the real road network, to select the shortest path. By the analysis of the driver's behavior, the accuracy of actual traffic flow prediction can be improved. In this paper, the proposed model is verified by the measured traffic flow data and compared with some other baseline models. The results show that the prediction results of the BAT-GCN model are closer to the real data.

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