Constructing Geographic and Long-term Temporal Graph for Traffic Forecasting

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Abstract—Traffic forecasting influences various intelligent transportation system (ITS) services and is of great significance for user experience as well as urban traffic control. It is challenging due to the fact that the road network contains complex and time-varying spatial-temporal dependencies. Recently, deep learning based methods have achieved promising results by adopting graph convolutional network (GCN) to extract the spatial correlations and recurrent neural network (RNN) to capture the temporal dependencies. However, the existing methods often construct the graph only based on road network connectivity, which limits the interaction between roads. In this work, we propose Geographic and Long-term Temporal Graph Convolutional Recurrent Neural Network (GLT-GCRNN), a novel framework for traffic forecasting that learns the rich interactions between roads sharing similar geographic or long-term temporal patterns. Extensive experiments on a real-world traffic state dataset validate the effectiveness of our method by showing that GLT-GCRNN outperforms the state-of-the-art methods in terms of different metrics.

I. INTRODUCTION

As one significant category of intelligent systems, ITS [1], [2] has developed rapidly due to artificial intelligence (AI) for transportation recently. Putting AI to analyze the dynamic traffic patterns under the massive spatial-temporal data has obtained the promising performance in many basic and essential tasks of ITS [3], [4], [5].

Traffic forecasting is considered as predicting future traffic states of links (road segments) given sequential historical traffic states and the road network [6]. It is one of the most crucial, indispensable and challenging tasks in ITS [6], [7], [5]. Traffic forecasting is of great importance not only for governments to monitor and control urban traffic congestion [3] but also for road users to plan the trip using electronic map and ride-hailing mobile apps, such as Google Map and DiDi. Furthermore, traffic forecasting provides significant road condition information for various other important tasks in ITS, such as estimated time of arrival (ETA) [4] and route planning [9]. Traffic forecasting, especially the speed prediction is a particularly challenging spatial-temporal prediction problem due to complicated and dynamic traffic patterns [6].

Traffic forecasting has attracted a lot of attention in the past. Existing methods can be divided into the following two categories. The first category is the classical statistical methods, such as autoregressive integrated moving average (ARIMA) [10] and its variants. The main disadvantage of this category of methods is that it can hardly handle high dimensional and nonlinear spatial-temporal data.

The second category is the data-driven method analysing the complex and non-linear traffic patterns. In this flexible category methods, traditional machine learning methods [11], [12], [13], [14], [15], [16], outperforms the first category. Nonetheless, traditional machine learning methods are not the first choice given massive and complex spatial-temporal data though having solid mathematical foundations.

Recently, deep learning [17] based methods [8], [7], [5], [6] are adept in capturing spatial-temporal dependences with large-scale datasets and become state-of-the-art. Compared with the relatively early dense networks for traffic forecasting [18], [19], [20], [21], the approach [22] combining convolutional neural network (CNN) and RNN to model spatial-temporal correlations concurrently achieves better prediction performance. Nevertheless, CNN are good at mining spatial-temporal correlations but they are not effective for the graph-structured data which is not in the Euclidean space. The middle part of Fig. 1 show a sketch map of road network topological structure.

Recent works introducing graph convolutional network (GCN) to learn the road network spatial relationships and...
adopter RNN or one-dimensional (1D) convolution along the time axis [6], [3] become state-of-the-art. The graph learned by GCN of most works is constructed entirely based on the geographic information – distance or connectivity of links. Note that distant links may also share the similar temporal patterns, for example, there is a high probability of similar congestion on two distant links near office buildings at rush hours [7]. We think that when the state of one link is updated using the spatial GCN [23], [24], [25], its similar links in both geographic and temporal aspects should be considered. If two links’ speed distribution are resemble for a long time, this relationship should not be neglected in the traffic graph. To construct what kind of graph for traffic forecasting is a fundamental problem.

Therefore, we propose a novel geographic and long-term temporal (GLT) graph construction method. As illustrated in Fig. 1 the more comprehensive traffic graph is constructed according to both geographic and long-term temporal similarity of links. On the traffic graph for GCN, the neighboring nodes of each link are selected considering the geographic and long-term temporal similarity. The geographic similarity focuses on the spatial distance and the road connectivity of any two links, while the long-term temporal similarity compares the links’ average speed distribution across the training dataset. In the light of the novel road network graph, we present the geographic and long-term graph convolution operation followed by modified RNN mining the temporal correlation. In such a manner, our GLT-GCRNN can adopt GCN to more effectively capture the spatial correlations of one link and its similar ones in geographical as well as long-term temporal aspects, leading to more precision traffic forecasting.

The main contributions in this paper are summarized as follows:

- To our best knowledge, GLT-GCRNN is the first deep learning framework which considers both the geographic and long-term temporal information when adopting GCN to mining the spatial dependency.
- We propose a novel road network graph construction method making use of the similarity among links in two aspects. On this graph, the neighboring nodes of each link contains the geographic as well as long-term temporal similar ones. Sufficient experiments indicate that the relationship between two distant links sharing quite similar patterns in long-term temporal is beneficial for GCN based spatial information mining.
- We evaluate our method on the real-world network-scale dataset which is publicly accessible [6] over the entirety of one year in the Greater Seattle Area. The abundant experiments demonstrate that our GLT-GCRNN’s prediction performance achieves clear improvements over other state-of-the-art methods.

We organize the rest of this paper as follows. Section II summarizes the related works. Section III introduces the detailed description of each component as well as the overall structure of our GLT-GCRNN. In Section IV experimental result comparisons on the real-world open dataset and traffic prediction result visualization are presented to show the superiority of GLT-GCRNN. Finally, we conclude this paper and discuss the future work in Section V.

II. RELATED WORK

Traffic forecasting. Traffic forecasting is one of the most essential and challenging tasks in ITS and has attracted a lot of attention in the literature. Existing methods can be summarized into the following two categories. The first category is the classical statistical methods, such as ARIMA [10], KARIMA [26], SARIMA [27] and vector autoregression (VAR) [28]. These approaches are not satisfactory because the real-world traffic data can hardly satisfy the assumptions of these methods.

The second category is the data-driven method. Among the methods that fall into this category, traditional machine learning methods, such as Support Vector Regression (SVR) [11], Bayesian approaches [13], [14] and k-nearest neighbor (KNN) [15], [16], outperforms the first category. Nonetheless, traditional machine learning methods rely heavily on handcraft feature engineering and are not skilled in mining massive and complex data.

Recently, due to the advance of deep learning in various domains [17], [29], [30], deep learning based methods [6], [7], [8], [9] are adept in capturing spatial-temporal dependences with large-scale datasets and become state-of-the-art. Among these methods, relatively early dense networks for traffic forecasting contains deep belief network (DBN) [18] and stacked autoencoder [20], [21], [19] adopt the DBN at the bottom and a multitask (MTL) [31] regression layer at the top to take use of the sharing weights. Compared with the traditional machine learning methods, these methods which only analyse a single region each time [32] improve the accuracy of prediction, but the improvement is limited due to the lack of effective mining for spatiotemporal information. Some works [33], [34], [35] adopt CNN to capture the adjacent spatial correlation inspired by the rapid development of computer vision (CV) research [17]. Some methods [36], [37], [38] mine the temporal dependencies mainly using RNN or its variants which are famous for sequential prediction tasks. The varieties of RNN includes long short-term memory (LSTM) [39] and gated recurrent unit (GRU) [40] networks. As traffic forecasting is a spatial-temporal data mining problem, the approach [22] combining CNN and RNN to model spatial-temporal correlations simultaneously get more accurate results for traffic forecasting. However, CNN are good at mining spatial relationships of data with the grid structure [6], [7] while the road network is the more complex graph-structured data.

Graph Convolutional Network. Graph convolution concentrates on generalizing convolution to work on structured graphs and analyze its local patterns. The graph convolution methods can be divided into two categories: the spectral methods and the spatial methods. The former methods [41], [42] are based on the spectral graph theory and [41] proposes the Graph Laplacian. [43] adopts Chebyshev polynomial approximation
for eigenvalue decomposition, resulting in reduced computational complexity. The latter spatial GCN [23, 24, 25] directly completes generalized convolution on a graph’s nodes with their neighboring nodes. These methods are also known as adjacency matrix based GCN and the spectral methods can be regarded as a special case of the spatial GCN. The spatial GCN incorporating the adjacency matrix is more flexible to be applied with other network structures, furthermore, it has more potential to dispose of relatively large graph structure. Therefore, we also choose the spatial GCN for GLT-GCRNN.

The traffic road network can be considered as a graph naturally, thus some researchers are inspired to introduce graph convolutional network (GCN) to learn the road network spatial relationships and adopt RNN or 1D convolution along the time axis [6, 8]. These methods become state-of-the-art recently. 5 introduces the attention mechanism on the graph for GCN based traffic forecasting. Nonetheless, the graph learned by GCN of most works is constructed entirely based on the geographic information, such as the distance and the connectivity of links. 7 uses a temporal only graph in terms of links’ time series similarity by dynamic time warping algorithm. Selecting the neighborhood of nodes is of great importance for the spatial method of GCN [5], it is essential to construct comprehensive and appropriate graph for traffic forecasting in the same light. GLT-GCRNN presenting a novel geographic and long-term temporal (GLT) graph construction method for road network is of great research significance and potential.

### III. METHODOLOGY

We first give the definition of traffic forecasting along with the road network:

**Definition 3.1: Traffic forecasting.** The road network can be represented by an undirected graph \( \mathcal{G} = (\mathcal{V}, \mathcal{E}) \), where \( \mathcal{V} \) is a set of nodes. \( |\mathcal{V}| = N \) represents \( N \) links or sensor stations. \( \mathcal{E} \) is a set of edges which means the intersections and relevances of these links. In our study, the time interval is 5-minute, therefore, there are 288 time steps during one day. On the time step \( t \), we denote the signal which represents the \( \mathcal{V} \)−th traffic state of all links as \( x_t \in \mathbb{R}^N \). The aim of traffic forecasting is adopting a function \( F(\cdot) \) which can be learned to predict next \( H \)-th traffic state of all links according to previous signals of \( M \) time steps and the road network \( \mathcal{G} \),

\[
[x_{t-M+1}, \ldots , x_t] \xrightarrow{F(\cdot)} \mathcal{G} x_{t+H}.
\]

(1)

In this study, we focus on forecasting the representative state – speed in the subsequent one time step, i.e. \( H = 1 \).

We present the GLT Graph construction method in Section III-A, expound the GLT graph convolution operation and relevant modified LSTM in Section III-B and introduce the overall framework of our method in Section III-C.

#### A. Constructing the GLT Graph

How to construct the graph for road network is crucial to mining the dependencies among links for predicting the traffic condition. Furthermore, it is of great importance for spatial GCN to select the neighborhood nodes. A comprehensive graph could make GCN play its full role. On the graph for GCN in this study, the neighborhood links of each link are selected considering the geographic and long-term temporal similarity.

In the geographic aspect, we adopt the adjacency matrix \( \mathbf{A} \in \mathbb{R}^{N \times N} \) to represent the connectedness of links, following the previous work [6]. The \( k \)-hop similar matrix in geographic aspect \( S_G \) can be computed:

\[
S_{G_{i,j}}^k = \min \left( (A + I)_{i,j}^k, 1 \right).
\]

(2)

In the long-term temporal aspect, we propose a novel method. The long-term temporal difference matrix \( \mathbf{Q} \) is constructed. Each element of \( \mathbf{Q} \) is defined by the Euclidean distance of any two links’ average speed distribution \( \hat{v}(i) \) and \( \hat{v}(j) \) across the training set after the combination every three time steps,

\[
Q_{i,j} = Q_{ji} = \| \hat{v}(i) - \hat{v}(j) \|_2.
\]

(3)

The combination which means averaging the speed of every three time steps lead to the result that the dimension of the link’s one day speed distribution vector is reduced from 288 to 96. The similar matrix in the long-term temporal aspect \( S_{LT} \) is constructed by preserving top \( \gamma \) the closest links for each link:

\[
S_{LT_{i,j}} = \begin{cases} 1, & Q_{i,j} \in Q_{i,:} \text{ top } \gamma \text{ small elements} \\ 0, & \text{otherwise} \end{cases}
\]

(4)

where \( \gamma \) is a hyper-parameter to adjust the number of preserved long-term temporal similar links.

The \( k \)-hop geographic and long-term temporal similar matrix \( S_{GLT} \) can be formulated as below:

\[
S_{GLT_{i,j}}^k = S_{G_{i,j}}^k + S_{LT}.
\]

(5)

In the light of \( S_{GLT} \), we could realize the effective interaction of geographic and long-term temporal similar links in the process of GCN updating features. We show two representative groups of long-term temporal similar links in Fig. II-A to demonstrate the importance of \( S_{LT} \) visually. The Open dataset adopted will be introduced in Section IV-A. As illustrated in Fig II-A, link 3 (ID) is the most Long-term Temporal (LT) similar link of link 17, nevertheless, they are not geographic similar which is ignored by \( S_G \).

With reference to the established traffic flow theory [14], we also adopt free-flow reachable matrix \( \mathbf{S}_F \) which is the same as [6]. For two elements links with ID=i and ID=j, \( V_{i,j} \) is the free-flow speed which is the traffic flow speed unaffected by upstream or downstream conditions [45] or the average speed without adverse conditions, such as congestion [6]. \( D_{i,j} \) is the real roadway distance from link \( i \) to \( j \). Free-Flow Reachable Matrix \( \mathbf{S}_F \) is defined:

\[
S_{F_{i,j}} = \begin{cases} 1, & V_{i,j}m\Delta t \geq D_{i,j} \\ 0, & \text{otherwise} \end{cases}
\]

(6)
where $\Delta t$ is the time quantum duration whose value is often chosen as a relatively big number, such as 20 minutes and $m$ is the considered time interval number when calculating the distance.

Then, the $k$-hop ultimate similar matrix for GCN $S_U^k$ can be calculated:

$$S_U^k = S_{GLT}^k \odot S_F,$$

(7)

where $\odot$ is the Hadamard product operator. The main role of $S_F$ is to filter out the links that are far away even though the traffic condition is free flow.

### B. GLT Graph Convolution Operation and Modified LSTM

We then modify the graph convolution operation and LSTM according to constructed GLT graph. The spatial GCN is adopted to extract localized features of the input $x_t$ which is similar to the previous work [6]. Specifically speaking, the product of a trainable weight matrix $W_g^k$ Hadamard produced by $S_U^k$ and $x_t$ to realize the GLT graph convolution operation.

$$g^k_t = \left( W_g^k \odot S_U^k \right) x_t,$$

(8)

where $g^k_t$ is the feature extracted by GLT graph convolution operation. To enrich the feature space for capturing spatial correlation effectively, $g^k_t$ extracted according to various hops $S_U^k$, i.e. 1 to $K$ are concatenated as:

$$G^K_t = [g^1_t, g^2_t, \ldots, g^K_t].$$

(9)

The $G^K_t$ considering various receptive field replaces the input of following LSTM for mining the dynamic temporal dependencies. Another improvement for the vanilla LSTM is as follows which is with reference to [6]. Because the LSTM cell state of each link in the graph should also be affected by its neighboring links’ cell states, we design a cell state gate as follows in the LSTM cell.

$$C^*_t = W_C \odot S_U^K \cdot C_{t-1},$$

(10)

where $W_C$ is the weight matrix which is constrained by $S_U^K$ to measure the influence degree of neighboring links’ cell states. $C^*_t$ replaces the $C_{t-1}$ when calculating the final cell state.

### C. Overall Framework of GLT-GCRNN

We present the GLT-GCRNN deep learning framework for traffic forecasting, as shown in Fig. 3. GLT-GCRNN consists of three components: (1) the GLT graph construction which is introduced in Section III-A. This novel graph construction method ensures that each link’s neighboring nodes contrain the long-term temporal similar links besides geographic similar ones. This road network graph of comprehensive information is beneficial for spatial GCN to aggregate neighboring information; (2) the GLT graph convolution operation is the main module to learn the spatial correlation of the center link and its neighboring links; (3) the modified LSTM is adopted to capture the temporal dependency of the link’s traffic state considering the neighboring nodes. The components: (2) and (3) are presented in detail in Section III-B.

The final time step $t$ hidden state $h_t$ of the modified LSTM is served as the predicted value for traffic forecasting. For the objective function, we choose the Mean Squared Error (MSE) function which is defined as

$$L_{MSE} = \frac{1}{n} \sum_{i=1}^{n} (y_i - \hat{y}_i)^2,$$

(11)

where $y_i$ is the ground-truth traffic state of one link of one sample and $\hat{y}_i$ is the predicted one. $n$ represents the product of the total number of samples and the number of links in the road network. The MSE function minimized by backpropagation (BP) in our study is popular for traffic prediction.

### IV. EXPERIMENT

The evaluation is on the open network-scale real-world dataset. The dataset, the competing methods, the implementation details and the experimental results will be introduced successively.

#### A. Dataset

The real-world dataset which is adopted to demonstrate the advantages of our framework is publicly accessible [6]. The traffic state data is collected from inductive loop detectors deployed on four connected freeways: I-5, I-405, I-90, and SR-520 [6]. The data statistics are summarized in Table I. For the dataset, we use 70% of the data as training set and 20% and 10% as validation set and test set, respectively. The speed limit (60mph) is adopted as the free-flow speed and
the distance adjacency matrices as well as free-flow reachable matrix and characteristics, which are the same as [6].

### C. Implementation Details

Evaluation metrics. Their computations are as followed:

$$\text{RMSE} = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (y_i - \hat{y}_i)^2},$$

$$\text{MAPE} = \frac{1}{n} \sum_{i=1}^{n} \frac{|y_i - \hat{y}_i|}{y_i},$$

$$\text{MAE} = \frac{1}{n} \sum_{i=1}^{n} |y_i - \hat{y}_i|.$$

### D. Experimental Results

We set the maximal epoch number to 200 with the early stopping mechanism. The dimensions of the hidden states of GLT-GCRNN are set as the amount of the nodes in the GLT graphs which is equal to the number of sensors. The size of hops $K$ in the GLT graph convolution is set as 3. The initial learning rate is set to $10^{-5}$ and the mini-batch size is 10. All the parameters are jointly trained using RMSProp optimizer, which could solve the gradient exploding and vanishing problems. The $\alpha$ and $\epsilon$ of RMSProp is set as 0.99 and $10^{-8}$. The settings of the above parameters are consistent with [6] for comparing fairly. For GLT-GCRNN, the hyper-parameter $\gamma$ of GLT graph selected by the results on validation set is 3.

### B. Competing Methods

We compare the proposed GLT-GCRNN with the following baselines including the state-of-the-art method.

1. **ARIMA**: Auto-Regressive Integrated Moving Average model [10] which is a representative method of the classical statistical methods.
2. **SVR**: Support Vector Regression.
3. **FNN**: Feed forward neural network which is also known as the multilayer perceptron (MLP) with two hidden layers.
4. **LSTM**: Long Short-Term Memory recurrent neural network [39].
5. **DiffGRU**: diffusion convolutional gated recurrent network whose gate units are defined based on diffusion convolution is first proposed by [45] for traffic forecasting. Since the graph is undirected in our study, the diffusion convolution is replaced with the spectral graph convolution in DiffGRU that is the consistent with [6].
6. **Conv+LSTM**: a 1D convolution layer (kernel size=5 and stride=2) with two channels followed by an LSTM layer which is also a baseline used by [6].
7. **SGC+LSTM**: a spectral graph convolution layer [42] stacked with an LSTM layer.
8. **LSGC+LSTM**: stacking a one-layer localized spectral graph convolution layer [43] which is stacked with an LSTM layer just like SGC+LSTM.
9. **TGC-LSTM**: The method using spatial GCN to learn the road network spatial relationships and adopting LSTM along the time axis [6] becomes state-of-the-art.

For the comparison of all these methods quantificationally, we take Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE) and Mean Absolute Error (MAE) which are used widely in traffic prediction tasks [7] as the evaluation metrics. Their computations are as followed:

$$\text{RMSE} = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (y_i - \hat{y}_i)^2},$$

$$\text{MAPE} = \frac{1}{n} \sum_{i=1}^{n} \frac{|y_i - \hat{y}_i|}{y_i},$$

$$\text{MAE} = \frac{1}{n} \sum_{i=1}^{n} |y_i - \hat{y}_i|.$$

### C. Implementation Details

GLT-GCRNN are implemented in PyTorch [47], and the training process is accelerated on a single NVIDIA P40 GPU.

### Table I

Statistics of the Real-world Traffic Forecasting Dataset

| Location          | Time Span | # Sensor | Interval |
|-------------------|-----------|----------|----------|
| Greater Seattle Area | 1 year (2015) | 323      | 5-minute |

### Table II

Traffic Forecasting Result Comparison on the Network-scale Dataset

| Model              | RMSE (mph) | MAPE (%) | MAE (mph) |
|--------------------|------------|----------|-----------|
| ARIMA              | 10.65      | 13.85    | 6.10      |
| SVR                | 11.12      | 14.39    | 6.85      |
| FNN                | 7.83       | 10.19    | 4.45      |
| LSTM               | 4.97       | 6.83     | 2.70      |
| DiffGRU            | 8.22       | 11.18    | 4.64      |
| Conv+LSTM          | 5.02       | 6.79     | 2.71      |
| SGC+LSTM           | 4.80       | 6.52     | 2.64      |
| LSGC+LSTM          | 6.18       | 7.51     | 3.16      |
| TGC-LSTM           | 4.63       | 6.01     | 2.57      |
| GLT-GCRNN (ours)   | 3.59       | 5.90     | 2.45      |

As illustrated in Table II the following results can be summarized: (1) the proposed GLT-GCRNN outperforms all the competitors regarding to all metrics. GLT-GCRNN improves the accuracy to predict the future traffic condition, even compared with state-of-the-art TGC-LSTM. GLT-GCRNN reduces 22.46% RMSE, reduces 1.83% MAPE and reduces 4.67% MAE respectively in contrast to TGC-LSTM. This could be explained that the key GLT graph of GLT-GCRNN is constructed considering both geographic and long-term temporal information, therefore the spatial graph convolution operation and LSTM which are modified based on GLT graph could capture the spatial-temporal correlations more effectively; (2) it can be observed that deep learning based methods are superior to the representative traditional statistical method and traditional machine learning method, i.e. ARIMA and SVR; (3) there is also a performance gap between the basic FNN and LSTM as well as Conv+LSTM which are good at mining the time series information. GCN do good to capture the spatial correlation for the road network with graph structure by comparing the predictive capability of GCN based methods, such as SGC+LSTM, TGC-LSTM, GLT-GCRNN, and LSTM.
E. Influence of Hyper-parameter

To study the influence of different hyper-parameter values of GLT-GCRNN, we further train 50 models with different values of the main hyper-parameter: \( \gamma \) (10 models for each \( \gamma \) value). We plot the prediction error boxplots regarding to three metrics in Fig. 4. \( \gamma \)'s main function is to balance the trade-off between the geographic and the long-term temporal information in the road network graph for GLT-GCN. Greater \( \gamma \) means more retention ratio of the temporal information. We find that the RMSE, MAPE and MAE varies slightly under different \( \gamma \). The moderate \( \gamma = 3 \) achieves the best performance considering the Fig. 4 (a), (b) and (c) comprehensively.

Furthermore, GLT-GCRNN is robust enough in terms of the multiple training random error through observing three box-plots. GLT-GCRNN achieves better performance than state-of-the-art TGC-LSTM from \( \gamma = 2 \) to 6, which demonstrates that the superiority of GLT-GCRNN is not sensitive to the \( \gamma \) hyper-parameter.

For visualizing the prediction performance of our GLT-GCRNN, we randomly select one link’s sequential predicted traffic speed and ground truth during one day. The Fig. 5 demonstrates that GLT-GCRNN could effectively capture the changing trend of the traffic condition at different time quantum of the day. The prediction of sequential traffic speeds and the real ones match very accurately which implies that GLT-GCRNN is useful in analyzing the complex traffic patterns.

V. Conclusion and Future Work

In this work, we propose a novel deep learning based traffic forecasting framework: GLT-GCRNN which better utilizes the GCN and LSTM for mining the spatial-temporal information simultaneously. This paper is firstly devoted to a more comprehensive geographic and long-term temporal (GLT) graph construction method. Furthermore, we complete the corresponding improvement of the spatial graph convolution operation and modified LSTM based on the GLT graph. Experimental results on the large real world dataset demonstrate that GLT-GCRNN outperforms other state-of-the art methods on the prediction performance. Future efforts will be made to explore whether we could improve GLT-GCRNN with the heterogeneous graph neural network and adopt our method for other tasks in spatial-temporal structured sequence prediction.

REFERENCES

[1] G. Dimitrakopoulos and P. Demestichas, “Intelligent transportation systems,” IEEE Vehicular Technology Magazine, vol. 5, no. 1, pp. 77–84, 2010.
[2] L. Figueiredo, I. Jesus, J. T. Machado, J. R. Ferreira, and J. M. De Carvalho, “Towards the development of intelligent transportation systems,” in ITSC 2001. 2001 IEEE Intelligent Transportation Systems. Proceedings (Cat. No. 01TH8585). IEEE, 2001, pp. 1206–1211.
[3] J. Zhang, F.-Y. Wang, K. Wang, W.-H. Lin, X. Xu, and C. Chen, “Data-driven intelligent transportation systems: A survey,” IEEE Transactions on Intelligent Transportation Systems, vol. 12, no. 4, pp. 1624–1639, 2011.
[4] Z. Wang, K. Fu, and J. Ye, “Learning to estimate the travel time,” in Proceedings of the 24th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining. ACM, 2018, pp. 858–866.
[5] S. Guo, Y. Lin, N. Feng, C. Song, and H. Wan, “Attention based spatial-temporal graph convolutional networks for traffic flow forecasting,” in Proceedings of the AAAI Conference on Artificial Intelligence, vol. 33, 2019, pp. 922–929.
[6] Z. Cui, K. Henriksson, R. Ke, and Y. Wang, “Traffic graph convolutional recurrent neural network: A deep learning framework for networkscale traffic learning and forecasting,” IEEE Transactions on Intelligent Transportation Systems, 2019.
[7] B. Yu, M. Li, J. Zhang, and Z. Zhu, “3d graph convolutional networks with temporal graphs: A spatial information free framework for traffic forecasting,” arXiv preprint arXiv:1903.00919, 2019.
[8] B. Yu, H. Yin, and Z. Zhu, “Spatio-temporal graph convolutional networks: A deep learning framework for traffic forecasting,” arXiv preprint arXiv:1709.04875, 2017.
[9] E. Kanoulas, Y. Du, T. Xia, and D. Zhang, “Finding fastest paths on a road network with speed patterns,” in 22nd International Conference on Data Engineering (ICDE’06). IEEE, 2006, pp. 10–10.
[10] M. M. Hamed, H. R. Al-Masaeid, and Z. M. B. Said, “Short-term prediction of traffic volume in urban arterials,” Journal of Transportation Engineering, vol. 121, no. 3, pp. 249–254, 1995.
[11] W.-C. Hong, “Traffic flow forecasting by seasonal svr with chaotic simulated annealing algorithm,” Neurocomputing, vol. 74, no. 12-13, pp. 2096–2107, 2011.
[12] T. Evgeniou, M. Pontil, and T. Poggio, “Regularization networks and support vector machines,” Advances in computational mathematics, vol. 13, no. 1, p. 1, 2000.
