Constructing Geographic and Long-term Temporal Graph for Traffic Forecasting

Yiwen Sun[1], Yulu Wang[1], Kun Fu[2], Zheng Wang[2], Changshui Zhang[1], Jieping Ye[2]

[1]Institute for Artificial Intelligence, Tsinghua University (THUAI), State Key Lab of Intelligent Technologies and Systems, Beijing National Research Center for Information Science and Technology (BNRist), Department of Automation, Tsinghua University, Beijing, P.R.China

[2]DiDi AI Labs, Beijing, P.R.China

E-mail: syw17@mails.tsinghua.edu.cn

I Background of Traffic Forecasting & GLT

Traffic forecasting: predicting future traffic states of road segments given sequential historical traffic states and the road network. It is one of the most crucial and challenging tasks in intelligent transportation system. 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 the geographic information – distance or connectivity of links. This may ignore the relationship between two distant road segments sharing similar long-term temporal patterns. Therefore, we propose a novel Geographic and Long-term Temporal (GLT) graph construction method, as shown in Figure 1.

- The neighboring nodes of each node are selected considering the geographic as well as long-term temporal similarity.
- 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 learn the interactions between links.

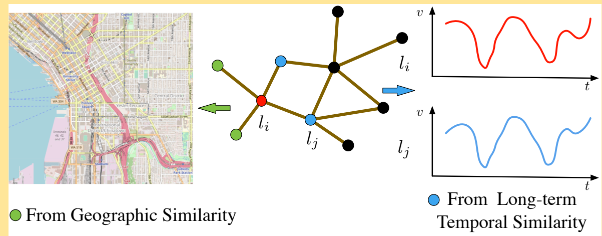

Figure 1 : The conceptual demonstration of the construction process of GLT Graph.

II Methodology

(1) Constructing the GLT Graph.

- In the geographic aspect, the k-hop similar matrix based on the adjacency matrix: $S^k_{G_{i,j}} = \min((A+I)^k_{i,j}, 1)$.
- In the long-term temporal aspect, the difference matrix based on the Euclidean distance of any two links' average speed distribution after the combination every three time steps: $Q_{ij} = Q_{ji} = \|\hat{v}(i) - \hat{v}(j)\|_2$. The similar matrix is constructed by preserving top γ the closest links for each link:

$$S_{LT\,i,j} = \begin{cases} 1, & Q_{i,j} \in Q_{i,:}\ top\ \gamma\ small\ elements \\ 0, & otherwise \end{cases}$$

- The k-hop geographic and long-term temporal similar matrix: $S^k_{GLT} = S^k_G + S_{LT}$
- The k-hop ultimate similar matrix considering free-flow reachable matrix: $S^k_U = S^k_{GLT} \odot S_F$

(2) GLT Graph Convolution and Modified LSTM.

- Spatial GCN: $g^k_t = (W^k_g \odot S^k_U) x_t$
- Modified cell state gate of LSTM :

$$C^*_{t-1} = W_C \odot S^k_U \cdot C_{t-1}$$

(3) Overall Framework of GLT-GCRNN.

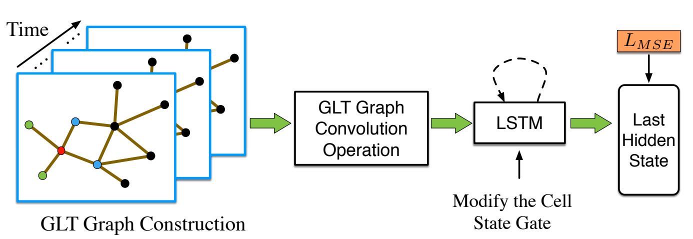

Figure 2 : The overall framework of GLT-GCRNN.

III Experimental results

- Our GLT-GCRNN outperforms all the competitors, including the state-of-the-art TGC-LSTM regarding to all metrics.

Table I. Traffic forecasting results on the network-scale dataset

	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**

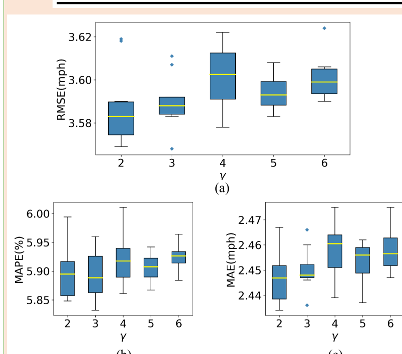

Figure 3 : The influence of hyper-parameter γ: (a) Regarding to RMSE. (b) Regarding to MAPE. (c) Regarding to MAE.

- The result demonstrates the robustness of our framework.

IV Traffic Forecasting Visualization

- GLT-GCRNN could effectively capture the changing trend of the traffic condition at different time quanta of the day.

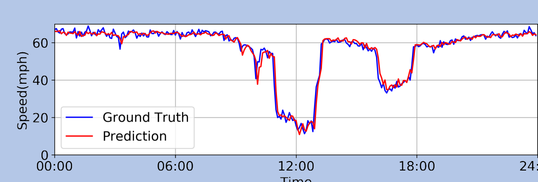

Figure 4 : The traffic forecasting visualization of GLT-GCRNN. The link's ID is 190 and the date is 2015-12-27.