Informed Along the Road: Roadway Capacity Driven Graph Convolution Network For Network-wide Traffic Prediction

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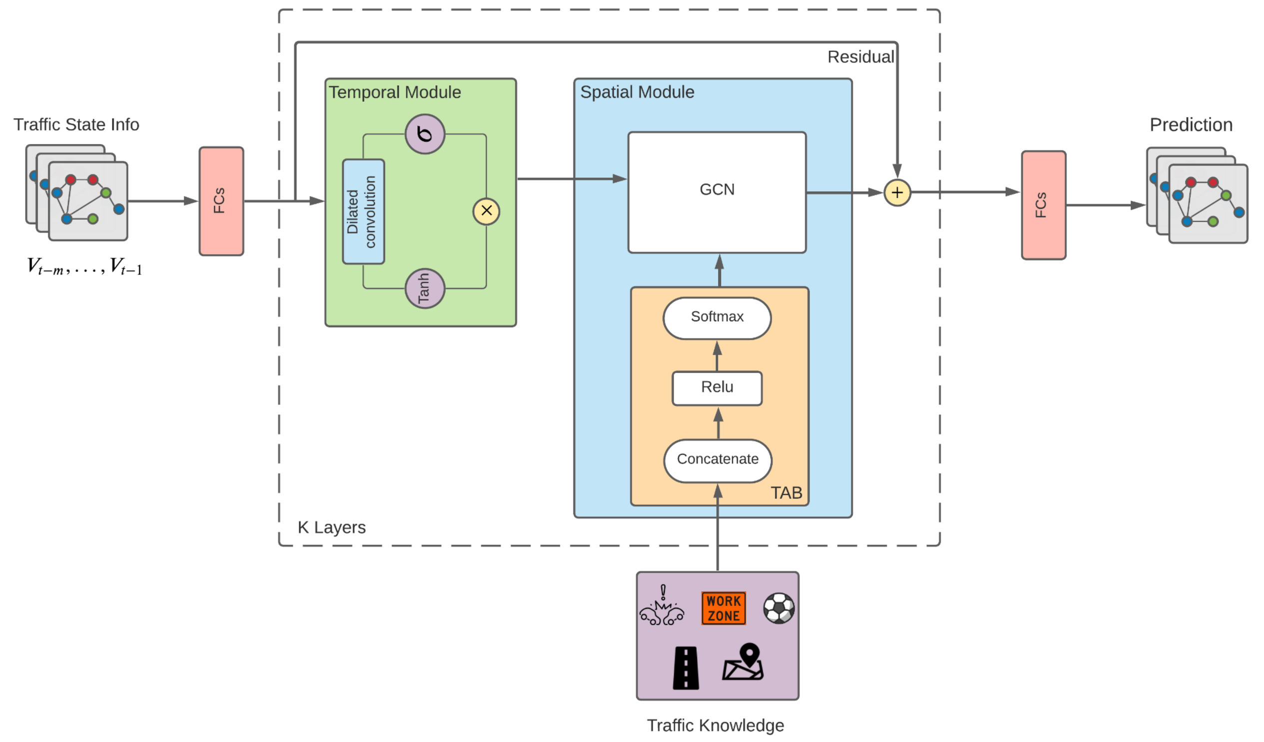
Abstract

Although the deep learning methods have met a big success in predicting traffic states of transportation networks, most of them simply treat the problem as one of the general prediction tasks without including its transportation aspects. Recently, spatio-temporal models with the graph neural network structure showed their power in predicting traffic states for the transportation network. However, few of them considered of the external factors which could significantly affect the roadway capacity of road segments and interrupt the traffic propagation process. Therefore, this study introduced a roadway capacity driven graph convolution network (RCDGCN) model that incorporated static and dynamic attributes of roadway capacity in the spatio-temporal settings to predict the network-wide traffic states. Two real-world datasets with different transportation factors are used in this study to evaluate the proposed model, including a highway network called ICM-495 and an urban dense network in Manhattan, New York City. Experimental results show that the proposed model outperformed other baseline methods in the forecasting accuracy. Analyses including ablation experiment, weight analysis and case studies were conducted to investigate the effect of capacity-related factors. Finally, this study showed implications in the potentials of using the proposed model to help the management of transportation system.

Framework

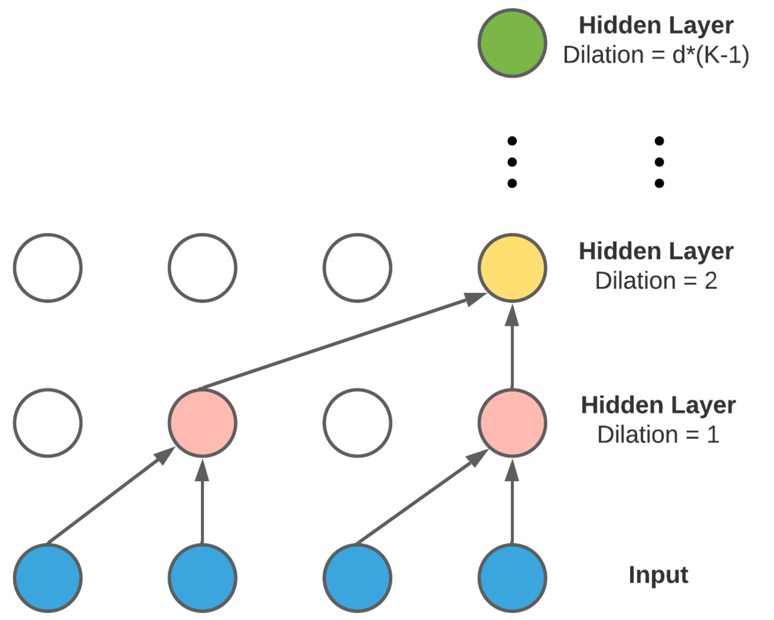


Methodology and Contribution

1. Analogy between Model Choice and Traffic Propagation

Similar with the traveling mode choice (e.g., walk, car, transit) faced by the travelers, the traffic propagation process along a road segment also faces the similar mode choice problem, but at a macro level. The utility of mode choice of a traveler is affected by the attributes/ characteristics of the available alternatives. Similarly, the traffic propagation of a road segment to its neighboring segments is also affected by the attributes/ characteristics along the road segments.

2. TCN and Traffic Attention blocks



$$P_i = \frac{exp(V_i)}{\sum_{i=1}^{j} exp(V_i)}$$

$$\alpha_{ij} = softmax(e_{ij}) = \frac{exp(e_{ij})}{\sum_{k \in N_i} exp(e_{ik})}$$

$$V_{ij} = \beta_{ij}^0 \times TT_{ij} + \sum_{1}^{L} (\beta_{ij}^L \times Z_{ij}^L)$$

$$e_{ij} = W_i^0 \times X_i + \sum_{1}^{L} (W_i^L \times Z_i^L) + W_j^0 \times X_j + \sum_{1}^{L} (W_j^L \times Z_j^L)$$

$$\tilde{A}_{ij} = Relu(\alpha_{ij})$$

$$H^{(l+1)} = \sigma(\tilde{D}^{-\frac{1}{2}} \tilde{A} \tilde{D}^{-\frac{1}{2}} H^{(l)} W^{(l)})$$

$$\mathbf{S} = \mathrm{softmax}\left(\frac{H^{(l)} H^{(l)\top}}{\sqrt{d_{\mathrm{model}}}}\right) \in \mathbb{R}^{N \times N}$$

$$\mathrm{GCN}(H^{(l)}, \tilde{A}) = \sigma\left(\left((\tilde{D}^{-\frac{1}{2}} \tilde{A} \tilde{D}^{-\frac{1}{2}}) \odot \mathbf{S}\right) H^{(l)} W^{(l)}\right)$$

Contribution 1: Inspired by Multinomial logit model (MNL), we designed a traffic attention block (TAB) in the RCDGCN to learn the spatial dependencies from the roadway capacity-related factors by assigning different intensities of traffic propagation.

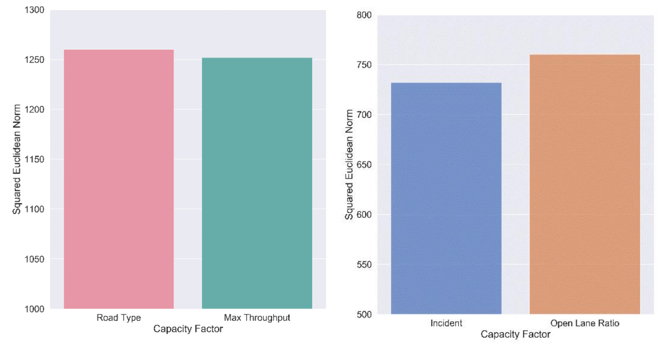
Contribution 2: The predicted performance of RCDGCN before and after removing the external capacity factors were compared in TAB. The incorporating external capacity factors to TAB can improve the prediction performances.

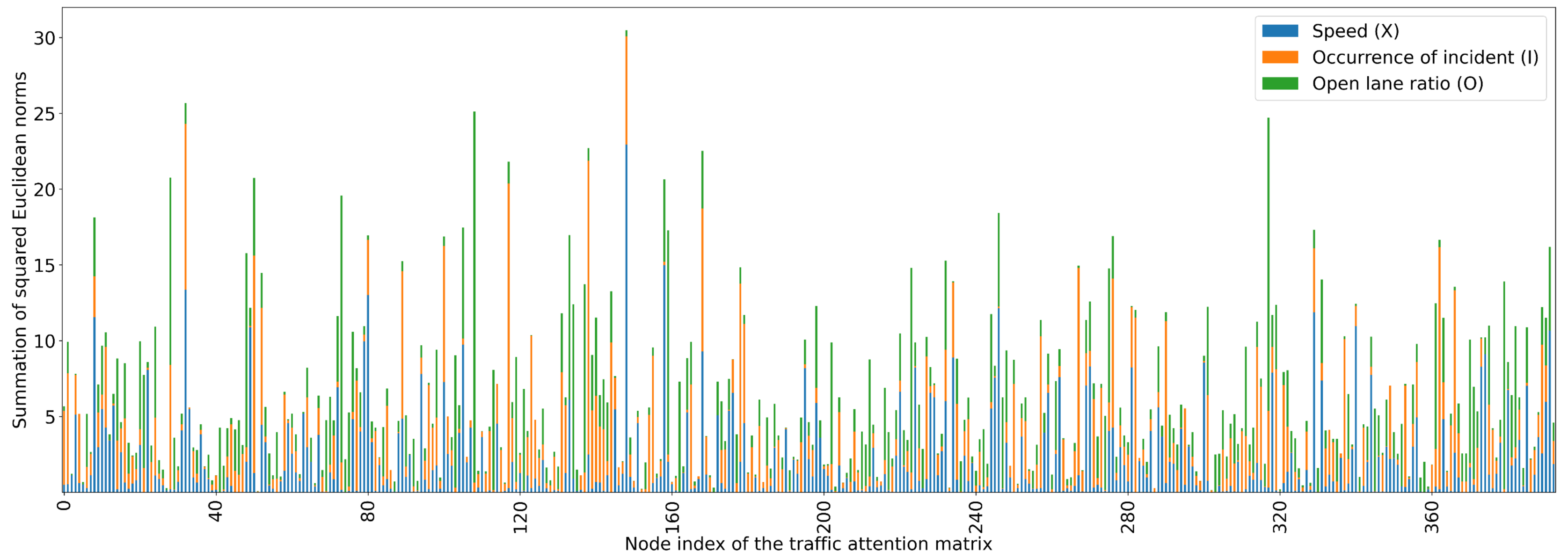
Contribution 3: By extracting the learned weight parameters from TAB, the learned weights of external factors can enhance the interpretability of the model and help to identify the roadway links that are most significantly influential.

Experiments, Results and Takeaways

1. Graph Weight Analysis of Road Capacity Factors

The visualization of the squared Euclidean norms for the capacity factors helps to understand their contributions to the intensity of the traffic propagation process, which further improves the interpretability of the TAB in the RCDGCN.





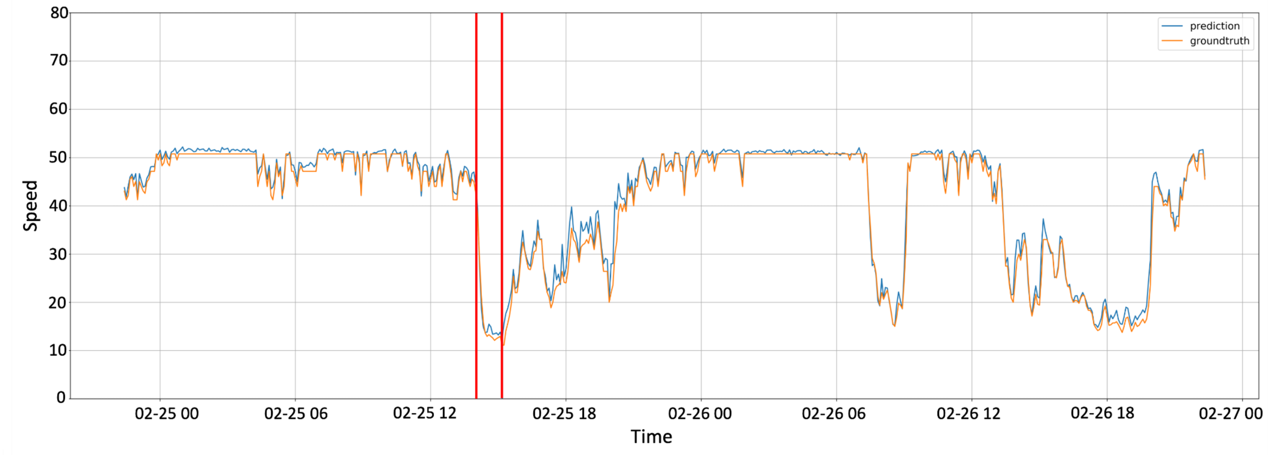
2. Significant Road Segments Identification

The learned traffic attention matrix helps interpret the model results for transportation networks that contain the inter-borough and intra-borough traffic by identifying the significant traffic hot spot areas.

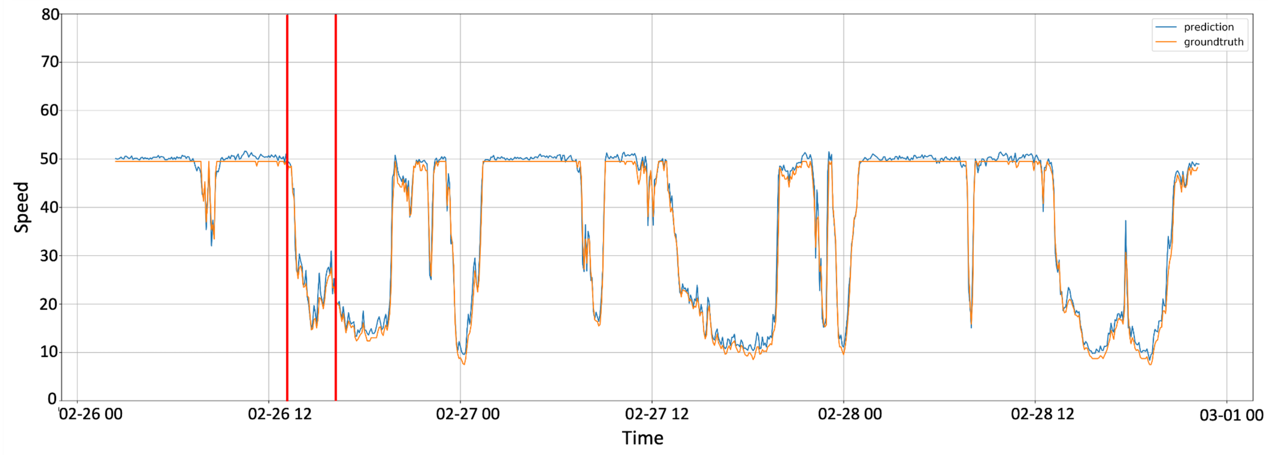
3. Case Studies

We raised up several cases to compare the predicted traffic speeds with the ground truth speed values of road segments selected from the ICM-495 dataset. Furthermore, we picked special cases with the occurrence of traffic incidents and validated if the proposed RCDGCN can capture the traffic interruptions caused by the incidents. In particular, we picked three types of traffic incidents including accident, emergency construction and pre-planned construction events.

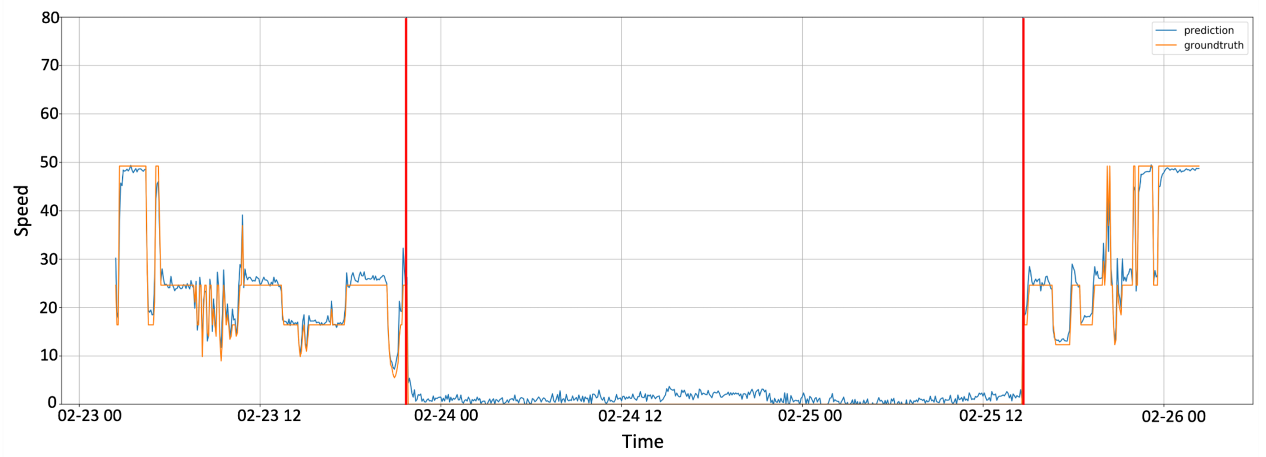
Case 1: Right-lane closure accident, 2PM-3PM, Sunday



Case 2: Left-lane closure construction, 12PM-3PM, Monday



Case 3: All-lane closure construction, 11PM (Day1)-3AM (Day3), Three-day



5. Conclusion for Road Capacity Driven Traffic Forecasting

- The study introduced a Roadway Capacity Driven Graph Convolution Network (RCDGCN) for predicting traffic states, which incorporates roadway capacity factors and outperforms other deep learning methods.
- A Traffic Attention Block (TAB) within the RCDGCN assigns intensity scores to road links based on capacity factors, with experiments showing improved prediction accuracy and the model's ability to identify significant road links.
- The RCDGCN effectively captures traffic disruptions, as demonstrated through case studies involving various types of traffic incidents.

- $H = \sigma(AGG(\psi_{s_1}\Gamma_{s_1}\psi_{s_1}^{-1}, \psi_{s_2}\Gamma_{s_2}\psi_{s_2}^{-1}, \ldots, \psi_{s_e}\Gamma_{s_e}\psi_{s_e}^{-1}))$

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