From Single Intersections to Network Traffic State: Machine Learning in Traffic State Estimation

Master‘s Thesis of MD ATIKUR RAHMAN

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Introduction

Traffic state estimation at intersections, particularly at the link level, is essential for optimizing transportation management and enabling dynamic route guidance. It also plays the most important role in improving traffic signal operations within the network. The goal of this master's thesis is to estimate the traffic state of an urban road network by focusing on individual links in each traffic signal intersection. This will be achieved through the implementation of various machine-learning algorithms. This study utilizes an open-source dataset of traffic signal volumes consisting of vehicle counts collected from inductive loop detectors installed at intersections across Melbourne, Australia. The thesis is dedicated to predicting short-term traffic flow within entire networks, specifically focusing on forecasting conditions 15,30,45 and 60 minutes ahead. The following research questions are raised for this study of traffic state estimation:

- How can spatial-temporal dependency be effectively characterized and modeled with traffic flow data?
- How does the multi-step prediction horizon influence the accuracy of spatial-temporal correlation-based traffic state estimation models?
- Which machine learning methods accurately capture spatial-temporal correlations for predicting traffic conditions on urban road networks?

Methodology

Traffic network is represented as a graph, with an adjacency matrix prepared accordingly. Combining graph convolutional neural network (GCN) with long short-term memory (LSTM) is considered the optimal approach for capturing spatial-temporal correlations within the traffic network for multi-horizon traffic flow prediction. GCN is utilized for spatial dependency modeling, while LSTM handles temporal dependencies. Furthermore, the performance of the proposed model is compared against two baseline models called convolutional neural network LSTM (CNN-LSTM) and encoder-decoder LSTM to measure its effectiveness.

Results of the case study

Prediction horizon	Evaluation Metrics	Model name		
		GCN-LSTM	LSTM	CNN-LSTM
15 min	RMSE	17.49	26.22	27.70
	R^2	0.97	0.93	0.92
30 min	RMSE	19.69	27.74	29.32
	R^2	0.96	0.92	0.91
45 min	RMSE	22.38	29.85	31.35
	R^2	0.95	0.91	0.90
60 min	RMSE	25.36	32.20	32.80
	R^2	0.93	0.90	0.89

Table 1 : Performance comparison of the models in different time horizons prediction.

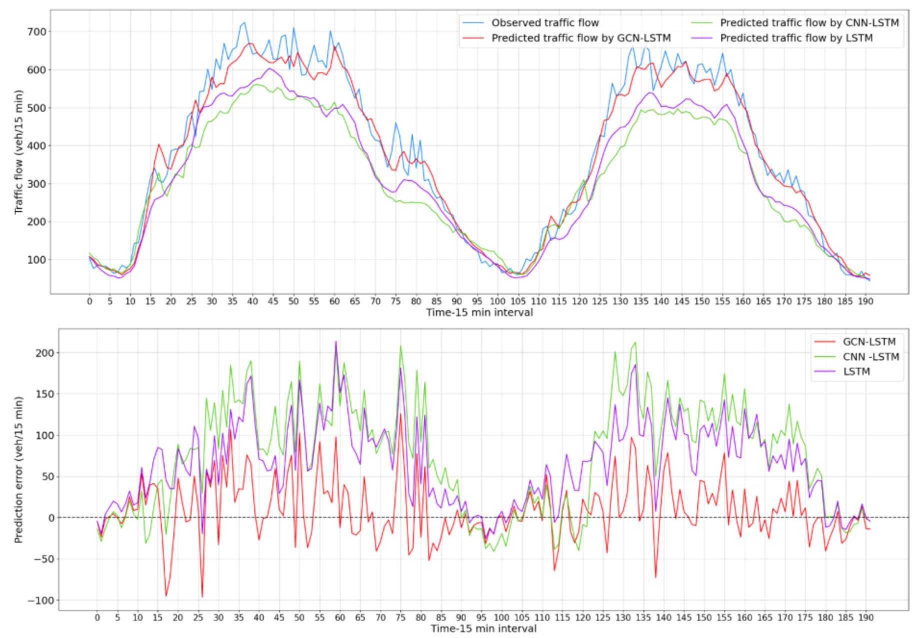

Figure 1 : Westbound traffic flow prediction at 15 minutes ahead on Princes highway east.

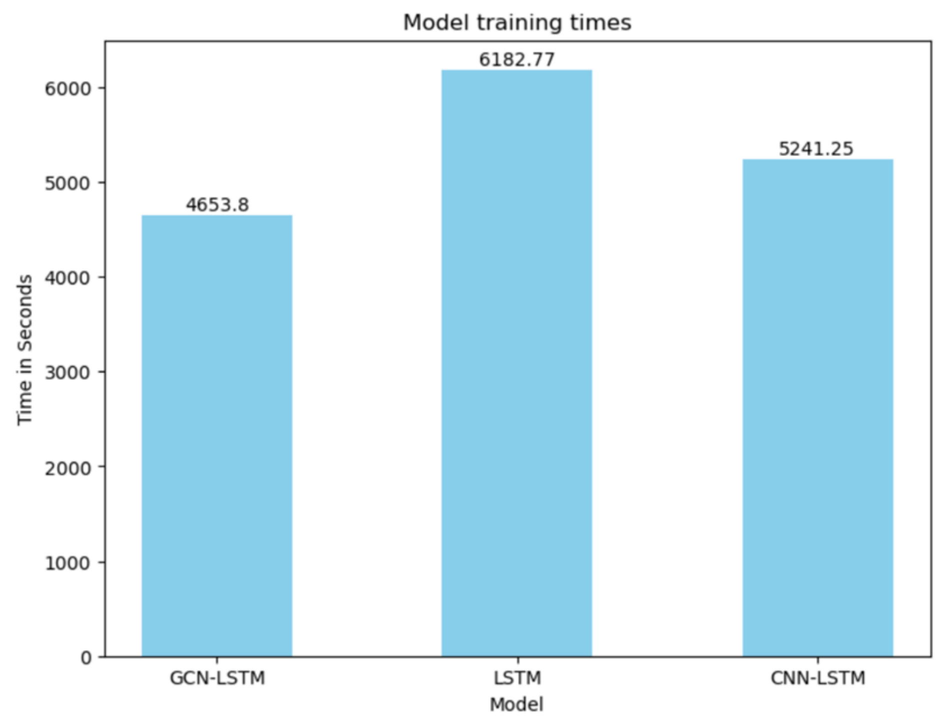

Figure 2 : Comparison of model efficiency in terms of training times.

Summary of the results

- GCN-LSTM performed better than baseline models in terms of RMSE and R-squared.
- Multi-Horizon Prediction: Accuracy decreases as prediction horizon increases.
- R-squared values of GCN-LSTM is 0.97 at 15 minutes horizon prediction, indicating strong capture of spatial-temporal correlations.
- GCN-LSTM models are more efficient in terms of training times (4653 seconds) compared to other deep learning models used as baseline.