Effectiveness of Graph Neural Networks and Simpler Network Models in Various Traffic Scenarios

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1. INTRODUCTION

The **goal** of **traffic forecasting** is to predict future traffic states using historical data and road network structure [2]. This task is crucial for improving urban transport systems and reducing congestion and pollution.

Traditionally, simple statistical or neural network-based models have been used for traffic forecasting, but they often have difficulty capturing complex traffic patterns [1]. Recently, more advanced methods such as **Graph Neural Networks** (GNNs) have been introduced, achieving promising results.

The **key difference** between GNNs and other models is that GNNs take graphs as input. In these graphs, sensors installed on roads (such as loop detectors) act as nodes, and the roads themselves serve as edges.

Although they achieve very accurate predictions, GNNs are **complex and costly** to train raising questions about their necessity in all traffic forecasting scenarios, especially when simpler models can be effective in less demanding conditions.

2. RESEARCH QUESTION

Are there possible scenarios in which models based on simpler network structures are more effective than GNNs in traffic forecasting?

3. MODELS

DCRNN: Diffusion Convolutional Recurrent Neural Network, a GNN model that incorporates both spatial and temporal dependencies. DCRNN explicitly models traffic as a diffusion process over a road graph, reflecting the actual structure and dynamics of the road network [2].

LSTMs: Long Short-Term Memory Networks, a type of Recurrent Neural Network (RNN) capable of learning and remembering long sequences of data. One of the most popular models for traffic forecasting before GNNs era.

4. METHODOLOGY

The **experiments** focused on traffic forecasting tasks using popular benchmark datasets containing traffic speed data. They investigated **scenarios** in which simpler LSTM could perform comparably to more complex DCRNN.

Considered scenarios:
- Different **numbers** of sensors: (35, 20, 10, 5, 1 sensors)
- Different prediction **horizons***: (5, 10, 15 minutes)
- Different sensors **distribution**:
  - Sensors placed on the same road (red area on the maps)
  - Sensors placed on different roads with shared crossroads (blue area on the maps)

*The horizon is the number of future time steps that the model tries to predict.

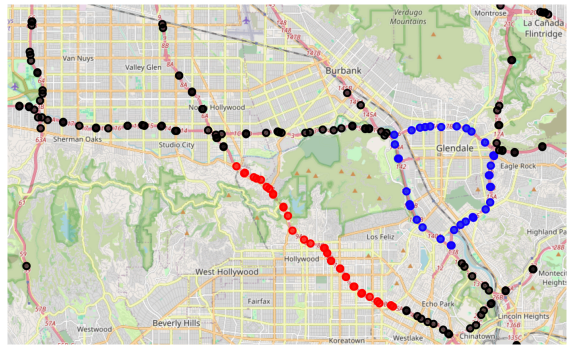

Figure 1: Sensors from **METR-LA** dataset

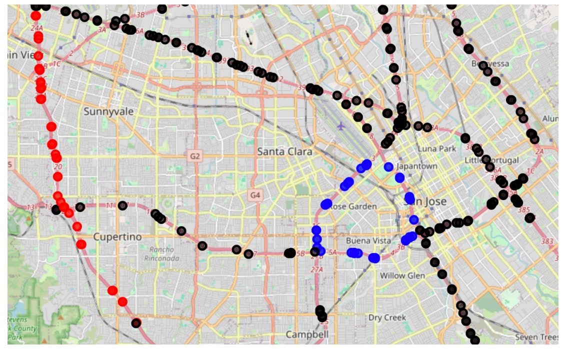

Figure 2: Sensors from **PeMS-BAY** dataset

5. RESULTS

Initial Hypothesis: LSTM models should achieve comparable performance to GNN models in traffic scenarios where spatial interconnections are minimal, such as highways with few intersections, and the number of available sensors is limited.

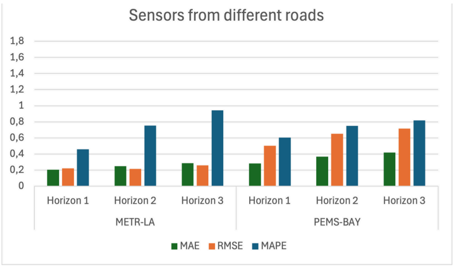

Figure 3: Average difference of models' performance in different prediction horizons on different roads. DCRNN systematically increases its lead in each metric over LSTM with an increasing horizon. However, this increase is smaller in METR-LA, where both models performed worst on average.

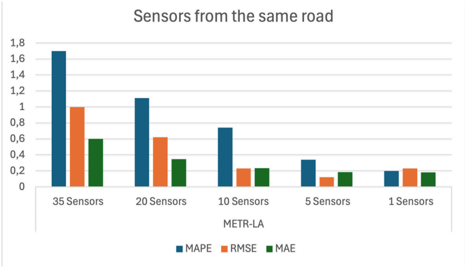

Figure 4: Difference in models' performance for varying numbers of sensors on the same road for horizon 1. The difference in performance decreases as the number of sensors decreases. This shows a relationship between these differences and the number of sensors used.

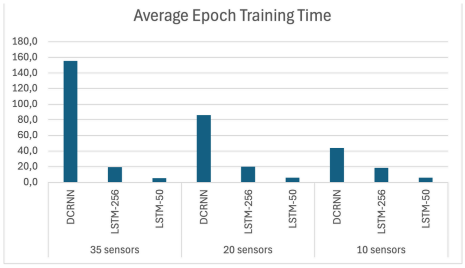

Figure 5: Average epoch training times (in seconds) for DCRNN and LSTM models (with 256 and 50 hidden state units) across three subsets of sensors.

6. CONCLUSIONS

DCRNN: Consistently outperformed LSTM under scenarios with a higher number of sensors and longer prediction horizons.

LSTM: Performed comparably to DCRNN in a scenario where the number of sensors was limited and for the closest prediction horizon.

Impact of Sensor Distribution: Interestingly, the LSTM performed closer to the DCRNN when the sensors were placed along different intersecting roads rather than on the same road. This was contrary to the initial hypothesis.

Training times: The analysis showed that DCRNN training time is very sensitive to the number of sensors, increasing rapidly as their number increases. On the other hand, the training time of the LSTM depends strongly on the number of LSTM hidden state units used in a model. Once the optimal configuration of hyperparameters is found, LSTM has a significant advantage over DCRNN in terms of training time.

7. FUTURE WORK

- **Hyperparameter Optimization**: Further development should include optimising the hyperparameters of LSTM models to improve their performance. Tuning parameters such as the number of layers or LSTM hidden state units and dropout rates could close the performance gap with DCRNN.
- **Comparison of Other Models**: Future research should also consider comparing other GNNs and simpler network models like Fully Connected Long-Short Term Memory networks [3].

8. REFERENCES

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[2] Yaguang Li, Rose Yu, Cyrus Shahabi, and Yan Liu. Diffusion convolutional recurrent neural network: Data-driven traffic forecasting, 2018.

[3] Ilya Sutskever, Oriol Vinyals, and Quoc V Le. Sequence to sequence learning with neural networks. In NIPS, pp. 3104–3112, 2014.