FORECASTING OF TRAFFIC FLOW

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Introduction

Forecasting traffic flow using data provided by Google through PyTorch neural network implementation.

Data Configuration

The data consists of the **average speed** on road segments around the Nørrebro Campus in Copenhagen for **2013** and **2015**. These average speeds were taken at five minute intervals.

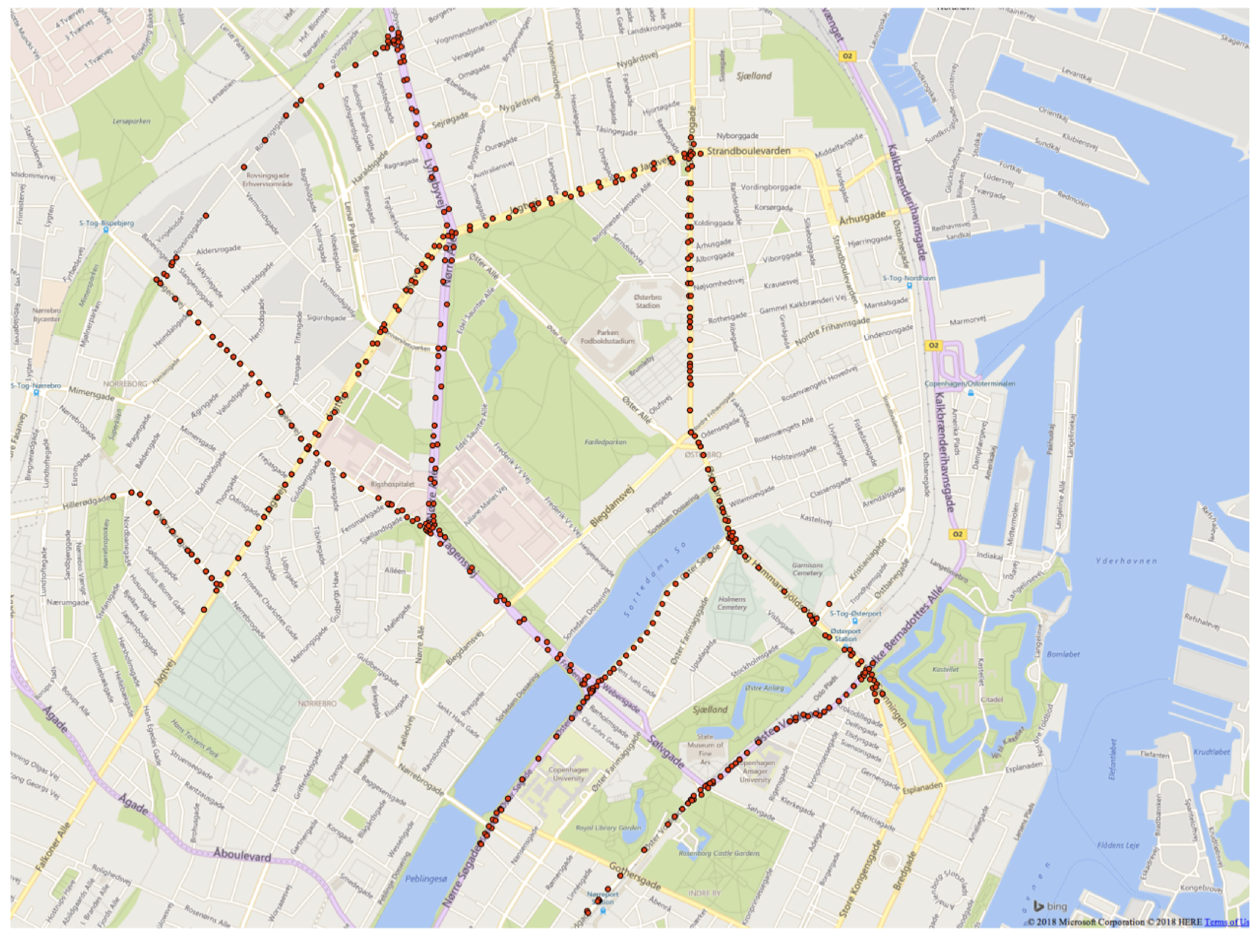

Figure 2: The location of the measurement points on a map of Copenhagen.

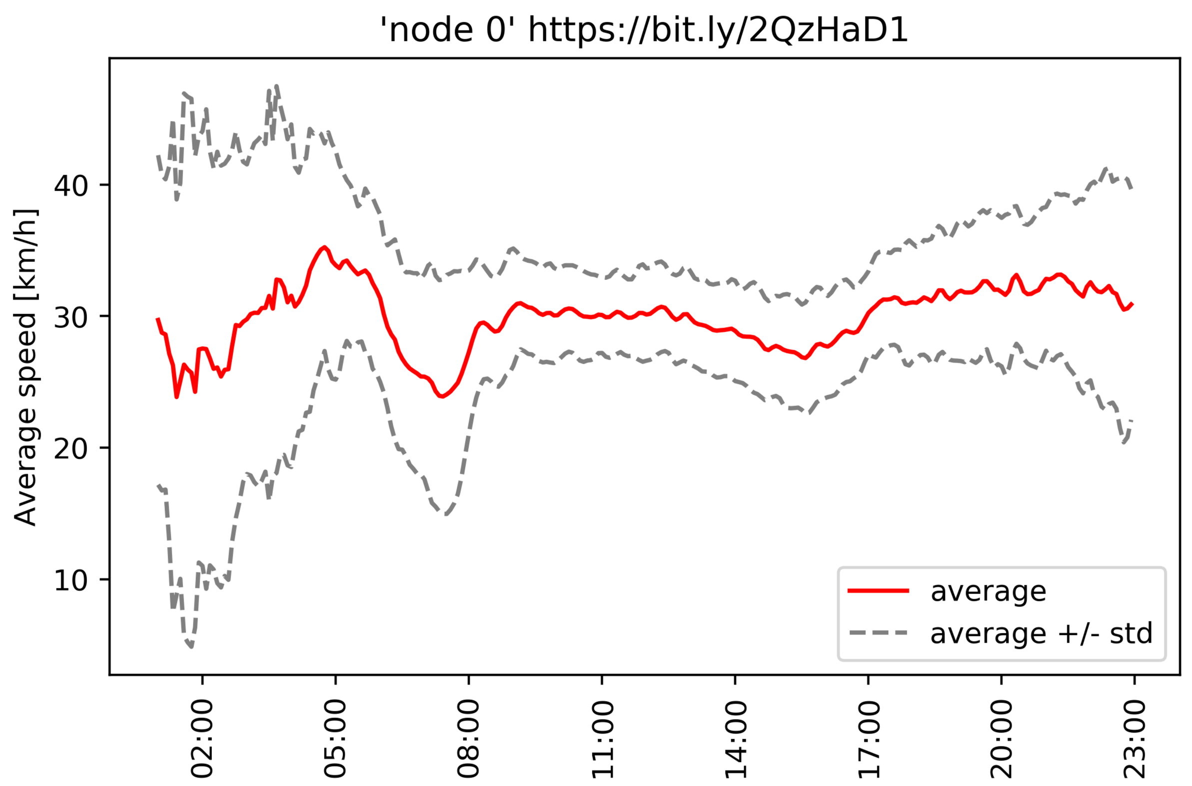

Figure 3: The location of the measurement points on a map of Copenhagen.

Data Cleaning

The initial visualization of the data aided in the selection of the 'time of day' for analysis. Evidently, the standard error and deviation of the average speed was reduced during daylight hours (**9:15-19:15**), in which case the data used in the neural network was reduced.
The data was cleaned through various other adjustments, these adjustments included the following:

- Removal of days, where datapoints are missing
- Included only data from 2015 (since the data for this year is more reliable)

Network Development

Several approaches were adopted in order to forecast the traffic in Copenhagen. For simplicity, each network utilized identical data preparation and graphing functions ensuring comparisons concerned only the networks.
The data was prepared using the data preparation script used for the DCRNN [1]. Following, the data was normalized, batched, and organized for each network implementation. Unless stated, all networks were trained using data from four nodes. Predictions were made based on the previous 12 time intervals (1 hour) for the next 3 time intervals (5, 10 and 15 minutes). The networks implemented are listed below:

- LSTM network
- GRU network
- Simple fully connected network considering multiple nodes
- LSTM Network considering larger and alternative parameters
- Fully connected network considering one node

Network Comparison

Network	MSE
Naive Copying	$13.850 \cdot 10^{-8}$
LSTM Network	$8.388 \cdot 10^{-8}$
Fully connected-multiple nodes	$8.436 \cdot 10^{-8}$
LSTM Network- alternative approach	$6.140 \cdot 10^{-8}$
Fully connected-one node	$5.219 \cdot 10^{-8}$
GRU Network	$5.042 \cdot 10^{-8}$
DCRNN	$4.263 \cdot 10^{-8}$

DCRNN - Diffusion Convolutional Recurrent Neural Network[1]

All of these approaches do not consider the relational position of the nodes within the road network. For example, if the distance between two points is small in the road network, it is expected, these points will have a higher correlation in regards to traffic. The **DCRNN** model accounts for these relative distances.

A DCRNN network was compared with the best performing networks of those listed in the above table against the ground truth for three days as seen in the figures aside.

Conclusion & Outlook

Larger and more complex networks were attempted but due to the complexity of the data and the computation power of the processors used, the networks implemented were limited. Effective and competitive results were implemented which challenged the DCRNN network. [1]
We hope to implement a DCRNN network to further the investigate the forcasting of traffic flow in Copenhagen.

References

[1] Yaguang Li, Rose Yu, Cyrus Shahabi, and Yan Liu. Graph convolutional recurrent neural network: Data-driven traffic forecasting. *CoRR*, abs/1707.01926, 2017. URL `http://arxiv.org/abs/1707.01926`.

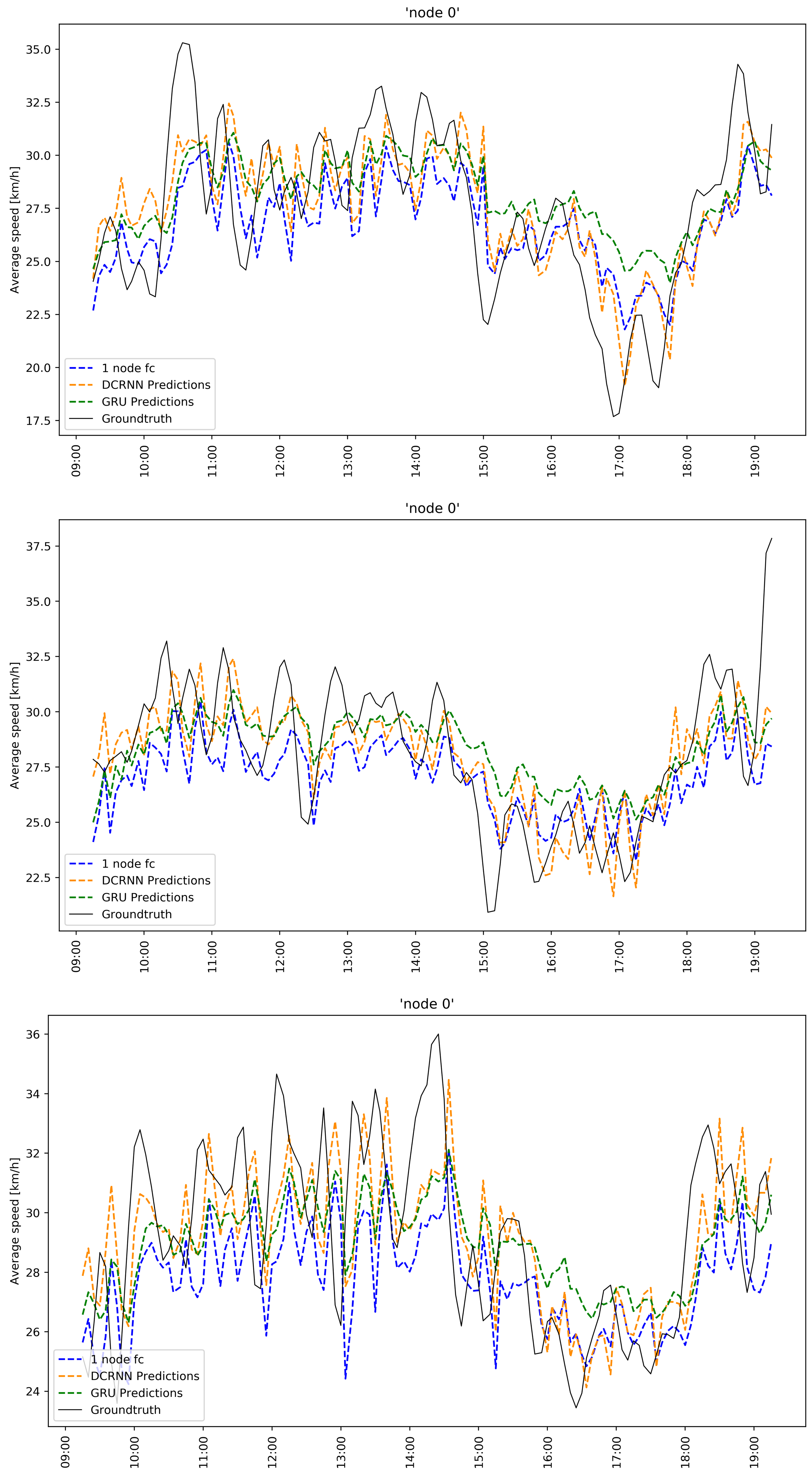

Figure 4: Various data sequences visualizing network predictions for traffic flow 15 minutes ahead.