Hybrid Neural Network Model with Graph Convolutional Network and Long Short-Term Memory for Predicting Average Urban Traffic Speed

Introduction

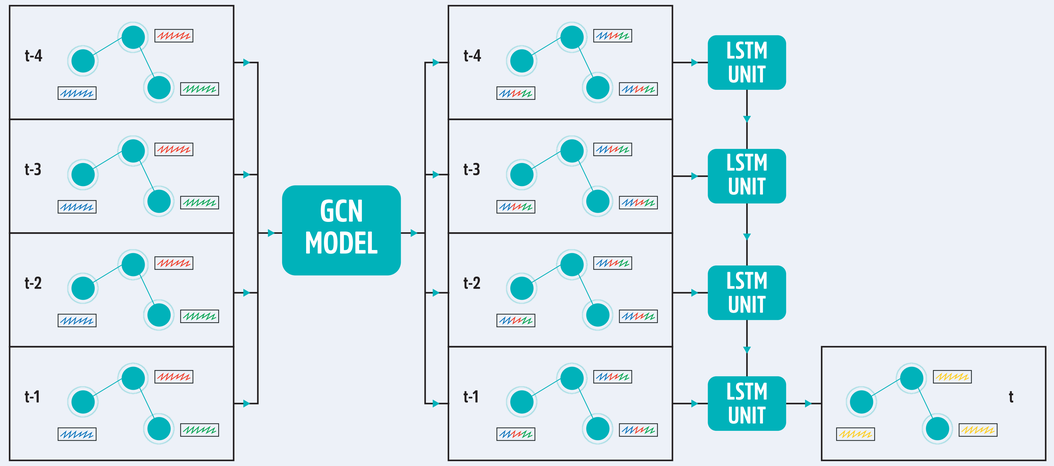
Hybrid GCN-LSTM Model: Combines Graph Convolutional Networks (GCN) to capture spatial relationships between nodes and LSTM to model temporal dependencies in the time series of average speed measurements per node.

Architecture:
Input: Traffic data (such as average speed) represented in a structural graph.
GCN Layer: Captures spatial information from neighboring nodes.
LSTM Layer: Processes the temporal sequence of data to identify patterns over time.
Output: Predicts the average speed at each node in the network.

Advantages:
Complex Pattern Capture: The GCN models complex spatial relationships, and the LSTM captures temporal patterns, providing a comprehensive view.
Scalability: Works well in large traffic networks and maintains good accuracy.

Methodology

- The dataset is processed to obtain a window of 4 measurements going back in time.
- This 4-measurement window is then processed for convolution in the GCN model.
- The measurements at **t-1, t-2, t-3, t-4** are the inputs for 4 LSTM units that enable the prediction of the value at t.
- The model weights are adjusted based on the labels from the measurements that are already available.



Conclusion

The GCN-LSTM hybrid model is capable of effectively **capturing the spatial and temporal dependencies** in the dataset with average speeds at each node due to its dual approach.

While the GCN-LSTM hybrid model has proven to be effective, it requires a **large amount of data for training.** This also results in **high computational costs for training.**

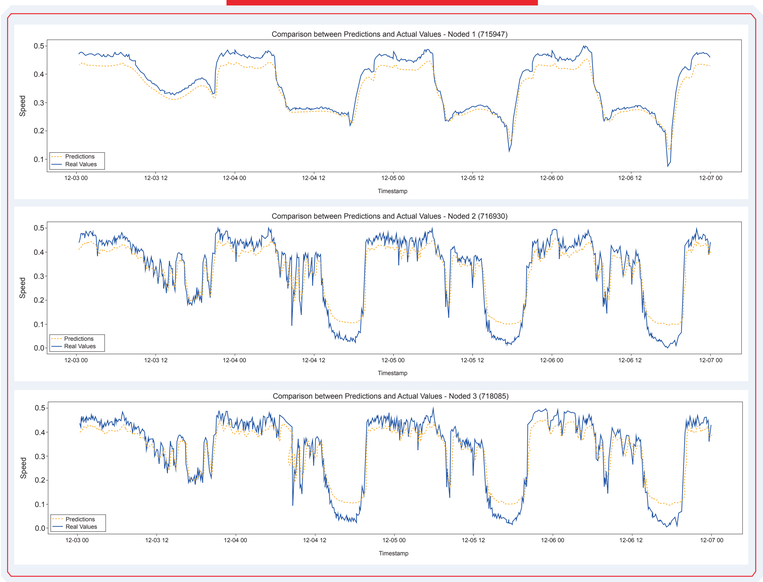
The GCN-LSTM hybrid model approach can be used to **improve traffic management,** optimize traffic light synchronization models, and make predictions in navigation systems for Smart Cities.

The GCN-LSTM hybrid model currently relies on a **single feature, which is the average speed**; however, for future research, additional features could be integrated, such as weather information, road capacity, unplanned events, etc.

Materials

We have a detailed dataset of **30 intersections** along **Interstate 5 in California**, with **measurements taken every 5 minutes recording the average speed** at each intersection. This dataset covers the **entire month of December 2023**, providing a robust and precise resource with 267,840 data points for analyzing traffic patterns and predicting road conditions in complex urban networks.

Results



References

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