A Hybrid Spatio-Temporal Graph Convolutional Network with Attention Mechanism for Dynamic Traffic Prediction and Intelligent Vehicle Routing

Siyuan Zhang[1,2,*]
[1]*School of Engineering, Royal Melbourne Institute of Technology, Melbourne, Victoria, 3000, Australia*
[2]*College of Civil Aviation NUAA, Nanjing University of Aeronautics and Astronautics, Nanjing, Jiangsu, China*
**Corresponding Author*

Abstract: The proliferation of urban traffic data from sensors, GPS, and connected vehicles presents a significant opportunity to alleviate traffic congestion through intelligent routing systems. The core challenge lies in accurately predicting network-wide traffic states, which are influenced by complex spatio-temporal dependencies. This paper proposes a new hybrid deep learning traffic prediction model and integrates it into a dynamic routing framework. Based on the Attention-based Spatio-temporal Graph Convolutional Network (ASTGCN), my model collaboratively combines the Graph Convolutional Network (GCNs) to capture the spatial correlations between road segments, gated recurrent units (GRUs) to simulate temporal dynamics, and temporal attention mechanisms to prioritize influential historical temporal steps. The predicted traffic speeds are then incorporated as dynamic edge lights in a graph-based routing algorithm, specifically an adapted algorithm, to calculate time-optimal paths. After the evaluation of the PeMSD4 dataset, all the indicators of the proposed ASTGCN model demonstrated superior performance. The integrated routing system subsequently reduces average travel time by 17.3% compared to traditional shortest-path routing under congested conditions. This study confirms the efficacy of deep learning-based model for predicting traffic as a foundational element for developing robust Intelligent Transportation Systems.

Keywords: Spatio-Temporal Data; Gated Recurrent Units; Intelligent Transportation Systems; Traffic Prediction; Graph Convolutional Networks; Attention Mechanism; Dynamic Routing

1. Introduction

Urban traffic congestion is a pervasive global challenge, resulting in substantial economic losses, increased fuel consumption, and elevated environmental pollution. The development of Intelligent Transportation Systems (ITS) aims to mitigate these issues by leveraging data and computational intelligence to optimize traffic flow. Two cornerstone functionalities of modern ITS are accurate short-term traffic prediction and intelligent, dynamic routing.

Short-term traffic forecasting is inherently complex because of the complex spatiotemporal dependencies within a road network. The traffic condition is not only influenced by its own historical state, but also by the conditions of the relevant sections and the environment (e.g., upstream feeders). Traditional statistical methods like Auto-Regressive Integrated Moving Average and Historical Average [1] often fail to capture these non-linearities. While machine learning models have shown improvements, they struggle with modeling the intricate spatial correlations at a network level.

The recent success of deep learning in sequence and structured data processing offers promising solutions. Specifically, models like Recurrent Neural Networks (RNNs) are adept at modeling temporal sequences. Conversely, Graph Convolutional Networks (GCNs) [2] provide a powerful framework for processing non-Euclidean data, making them ideal for representing road networks as graphs where nodes are sensors/intersections and edges are roads.

This paper makes a threefold contribution:

I propose a novel hybrid deep learning architecture (ASTGCN) that integrates GCNs, GRUs, and a temporal attention mechanism for robust spatio-temporal traffic forecasting.

I develop a practical intelligent routing system that utilizes the predictions from my model to compute time-optimal paths dynamically, moving beyond static shortest-path algorithms.

I rigorously evaluate my model on a public, real-world dataset, demonstrating its superiority over established benchmarks and quantifying the tangible benefits for vehicle routing.

2. Literature Review

Traffic Prediction Models Research in traffic prediction has evolved from statistical to deep learning models. Early approaches relied on time-series models like ARIMA. Subsequent works incorporated neural networks, with [3] using simple RNNs for prediction. The limitations of vanilla RNNs led to the adoption of LSTM [4] and GRU networks, which better handle long-term dependencies. A key limitation of these models is that they treat traffic sensors as independent time series and lack spatiality.

To address it, recent works have integrated convolutional neural networks (CNNs) to capture spatial features, often by transforming the network into a 2D grid [5], which is a suboptimal representation. The advent of GCNs has enabled more natural modeling of spatial relationships. Seminal work by [6] combined GCNs with GRUs to simultaneously capture spatial and temporal dependencies, forming the basis for many subsequent models. The attention mechanism is an improvement in natural language processing. Unlike the previous indiscriminate treatment of all programs, this model can focus on the most relevant steps. [7]

Intelligent Routing Systems Classic routing algorithms like Dijkstra and A* find the shortest path in a graph based on static lights (e.g., distance). For dynamic routing, these lights must reflect real-time or predicted travel times. Previous systems have integrated predictions from various models [8], but often with simplified spatial modeling or without the ability to focus on critical temporal events, which my attention mechanism provides.

3. Methodology

Problem Formulation The traffic network is represented as a graph $G = (V, E, A)$, where $A \in R^{(N\times N)}$, E is a set of edges, and V is a set of $|V| = N$ nodes (sensors) is the lighted adjacency matrix encoding the proximity between nodes (e.g., based on road connectivity or distance). The traffic observations of all nodes at a specific moment are defined as a graph signal $X^{(t)} \in R^{(N\times C)}$ (C=1 for speed). Then, historical T time steps of graph signals are given. So that, the next step is to learn a function h (·) that predicts the next T' steps: $[X^{((t+1))}, ..., X^{((t+T'))}] = h (G; X^{((t-T+1))}, ..., X^{((t))})$. [9]

Model Architecture: ASTGCN The ASTGCN model consists of three key components:

Spatial Modeling via GCN: The spectral-based GCN layer is used to summarize the features of adjacent nodes. The rule of it is: $H^{(l+1)} = \sigma(\tilde{D}^{(-1/2)} \tilde{A} \tilde{D}^{(-1/2)} H^{(l)} W^{(l)})$, where $\tilde{A} = A + I_N$ (with self-loops), $\tilde{D}$ is the degree matrix of $\tilde{A}$, $H^{(l)}$ is the activation matrix in layer l, and $W^{(l)}$ is a trainable Iight matrix.

Temporal Modeling via GRU: The output features from the GCN layers are fed into a GRU layer. The GRU's gating mechanism (update and reset gates) controls the flow of information, effectively learning patterns across time such as periodicity and trend.

Temporal Attention Mechanism: Before the GRU, an attention layer should be used to the input sequence. It computes attention scores $e_{(ij)} = a (h_i, h_j)$ for all time steps i, j in the input window, where a is a feed-forward network. The softmax-normalized scores $\alpha_{(ij)}$ are used to create a context vector, allowing the model to focus on historically influential moments (e.g., the beginning of a congestion event).

Intelligent Routing Integration The predicted average speeds for each road segment are converted into predicted travel times. These times serve as dynamic, time-dependent edge lights $w_e(t)$ in the road network graph. I employ an adapted A* algorithm where the heuristic function is the geometric distance divided by a maximum speed limit. For a departure time t, the algorithm finds the path P that minimizes the total predicted travel time: $\min \Sigma_{(e\in P)} w_e(t)$.

4. Results

The traffic flow data comes from the PeMSD4 dataset, which is derived from 307 sensors in the San Francisco Bay Area in the first six months of 2018. I use the corresponding speed data. The data is split chronologically: 10% for validation, 20% for testing, and 70% for training. The adjacency matrix A is constructed using a thresholded Gaussian kernel based on road network distance. Data is normalized to zero mean and unit variance.

Baseline Models and Evaluation Metrics I compare ASTGCN against:

· Historical Average (HA)

· ARIMA

· SVR (with radial basis function kernel)

· GCN-only (ignores temporal dynamics)

· GCN-GRU (without attention) Metrics: MAE, RMSE, and MAPE.

Table 1. Prediction Performance (15-minute Horizon) on PeMSD4 Test Set

Model	MAE	RMSE	MAPE (%)
HA	6.82	10.11	15.64
ARIMA	5.93	8.76	13.21
SVR	5.42	8.03	11.95
GCN-only	5.01	7.88	10.87
GCN-GRU	4.45	7.01	9.68
ASTGCN	4.21	6.83	9.32

As shown in Table 1, the superiority of the ASTGCN model can be clearly seen. The integration of spatial (GCN) and temporal (GRU) modeling in GCN-GRU already provides a significant boost over models that ignore either aspect. The introduction of the time-attention mechanism can enable ASTGCN to achieve better performance, as it allows the model to light critical past events more heavily.

Routing Simulation I simulate 1000 trips during the PM peak period (5:00 PM - 6:00 PM) on the network. For each trip, I compare the travel time of the path generated by:

· Shortest Distance Path (Static): Uses distance as a static light.

· my Dynamic Routing: Uses my predicted travel times as dynamic lights. The dynamic routing system achieved an average reduction of 17.3% in travel time compared to the static shortest-distance path, highlighting the practical benefit of accurate prediction for downstream routing tasks.

5. Discussion

The empirical results confirm that the ASTGCN framework effectively captures both spatial and temporal dependencies in urban traffic networks, with the attention mechanism providing a valuable interpretability layer by identifying which historical states contribute most to future traffic conditions. However, despite these strengths, several inherent limitations remain that must be addressed before such models can be robustly deployed in large-scale, real-world Intelligent Transportation Systems.

The main limitation lies in the reliance on fixed sensor networks and static adjacency matrices, which affects the model's ability to reflect the inherent dynamic spatial relationships in real traffic systems. The spread of congestion is not uniform; it depends on the severity of the accident, traffic control intervention, weather or time. Static graphics cannot capture these dynamic dependencies. This will lead to a decline in prediction accuracy in special circumstances, such as accidents or extreme weather. [10] Recent studies have emphasized that dynamic graph learning can enable models to automatically update spatial dependencies. [11] [12] Integrating these methods into ASTGCN can provide more resilient performance in the rapidly changing traffic environment.

Another limitation is the reliance on fixed-position sensors, which brings two challenges. Firstly, the spatial coverage is uneven. The lack of sensors on the streets leads to blind spots in predictions. Secondly, sensor failure will reduce data availability. Research shows that self-supervised graph learning methods can reconstruct a relatively complete traffic state from sparse sensor data. [13] Combining these methods will enable the framework based on astgcn to better adapt to the sensor limitations of the real world. In addition, external factors such as events and weather conditions are usually the main triggers for non-frequent congestion. Multi-mode integration can enhance the accuracy and robustness of predictions. [14] [15] Extending ASTGCN to a multimodal framework may significantly enhance its practical utility through cross-attention or graph-based fusion mechanisms. Finally, although the attention mechanism increases interpretability, it is still limited in providing causal insights. To ensure that the attention weights are consistent with the real propagation paths, future research should explore causal relationity-aware traffic prediction models. [16]

In conclusion, these restrictions highlight several directions for the future. Solving these problems will ensure that spatio-temporal deep learning models not only achieve high prediction accuracy in benchmark datasets, but also provide resilient, adaptive and interpretable performance in real-world intelligent transportation systems.

6. Conclusion

This paper proposes a new deep learning model for intelligent traffic prediction. The ASTGCN model integrates gated recurrent units, time-attention mechanisms, and graph convolutional networks. It efficiently analyzes and predicts urban traffic with complex spatiotemporal characteristics. In addition, its advanced predictive performance was verified by applying it to real error datasets. Furthermore, I demonstrated that integrating these accurate predictions into a dynamic routing algorithm yields significant reductions in simulated travel times. This work provides a robust and effective foundation for building next-generation intelligent transportation systems that can actively mitigate urban congestion.

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