Spatial-Temporal Bipartite Graph Attention Network for Traffic Forecasting (STBGAT)

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Introduction

Traffic congestion

- Transportation systems become more crowded and complex
- Social cost of **30Bn by 2030** in 8 Australian capital cities [1].
- **Intelligent Transportation Systems** were introduced.
- Traffic condition forecasting systems.
    - A core component of ITSs
    - **Predict future traffic condition given historical observations**

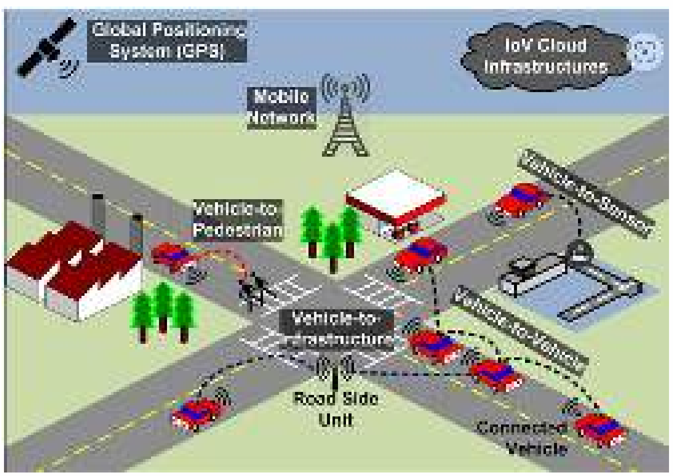


Fig 1: Intelligent transportation system

Fig 2: Traffic congestion

Traffic Flow Forecasting

- Traffic flow forecasting problem is a **spatial-temporal graph modeling problem**
    - Historical observations
    - Spatial structure of the sensor network
- Various types of **Spatial-Temporal Graph Neural Networks (STGNN)**

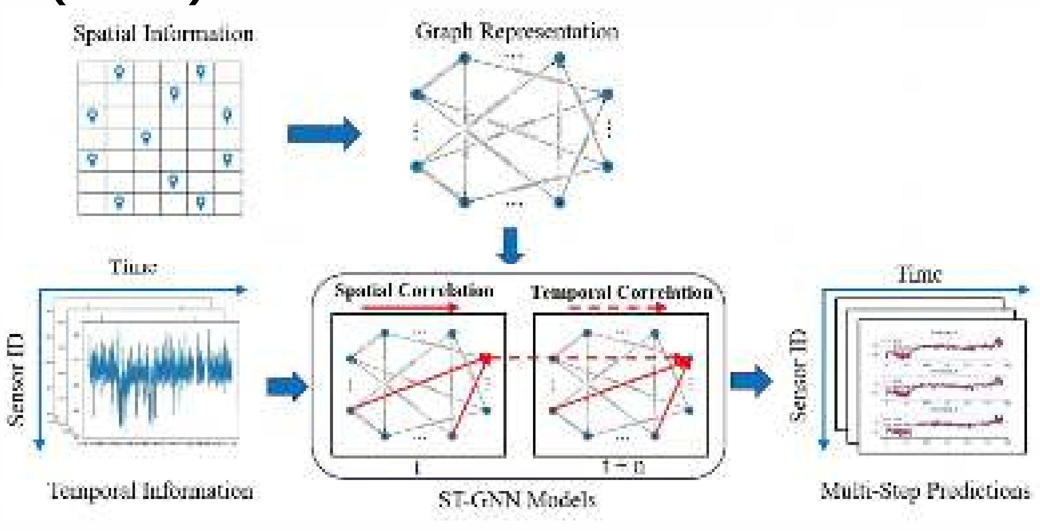


Fig 3: A general pipeline of ST-GNN models for traffic prediction [2]

Fig 4: A traffic flow sequence

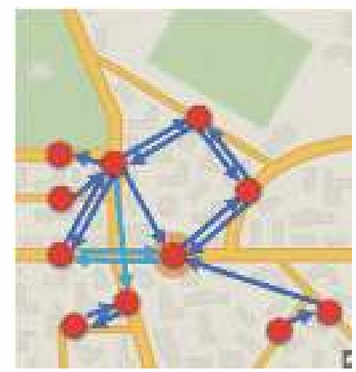


Fig 5: Spatial structure of sensor network

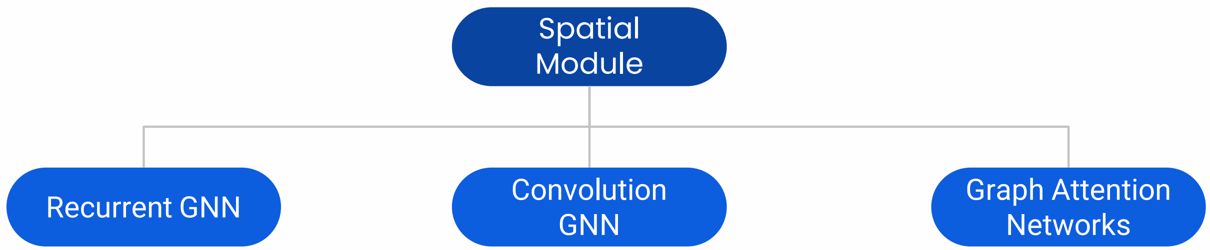
Spatial-Temporal Graph Neural Networks for Traffic Flow Forecasting

- Before STGNNs, Statistical Time Series Algorithms and ML models.
- GNNs models spatial dependencies in complex road networks.
- **STGNN => A model architecture with Graph Neural Network paired with a temporal ML model.**
- **STGCN** [3] is one of the earliest STGNN followed by number of complex STGNNs [4-6]

- ***Fails to model past information propagation from neighbouring nodes.***
- ***Most of them fails to incorporate features beyond raw traffic flow sequences.***

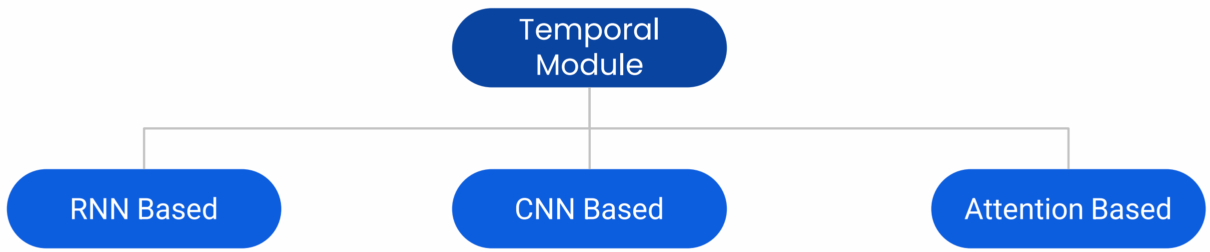
Spatial Module of Spatial-Temporal Graph Neural Networks

- Various Graph Neural Network Architectures [7-9].



- Wide adoption of STGNNs after the introduction of **Graph Convolution Network (GCN)** [10].
- **GAT assigns different weights to neighbours** according to their importance [11].
- **Bipartite GAT aggregate neighbourhood information spanning multiple time steps.**

Temporal Module of Spatial-Temporal Graph Neural Network



- RNNs suffer from **vanishing gradient problem**.
- CNNs **unable to capture long-distance dependencies** [12].
- Attention based approaches are superior compared to RNNs and CNNs
- Transformer model is an **encoder-decoder architecture built on an attention mechanism** [13].

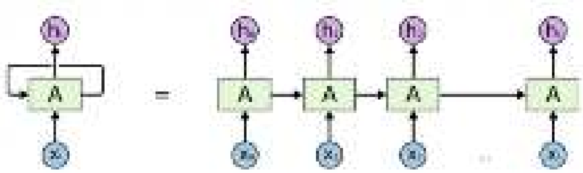


Fig 6: RNN

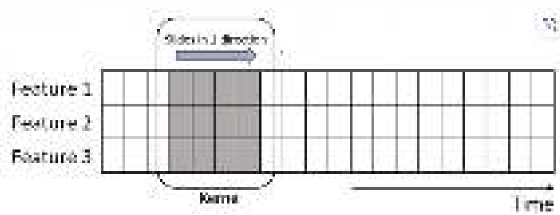


Fig 7: 1D CNN

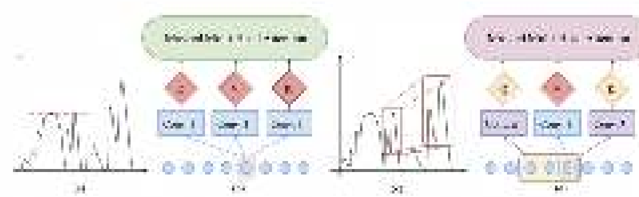


Fig 8: 1D CNN + Attention

Motivation

- **Two major issues** in current STGNNs.
  - Fail to ascertain how the traffic flow on a specific road at a given time is **impacted by previous traffic conditions on adjacent roads**.
  - Fails incorporate **multiple types of input sequences for predictions** which could reveal more temporal and spatial dependencies.

Contribution

- A new STGNN architecture; **Spatial-Temporal Bipartite Graph Neural Network (STBGAT)**.
- Main contributions:
  - **A novel bipartite Graph Attention Network** facilitating explicit past information propagation from neighbourhood.
  - **A heterogeneous cross-attention mechanism** for transformers which enables feature-wise attention distribution, and allows integration of multiple feature sequences..

Contribution

Bipartite Graph Attention Network

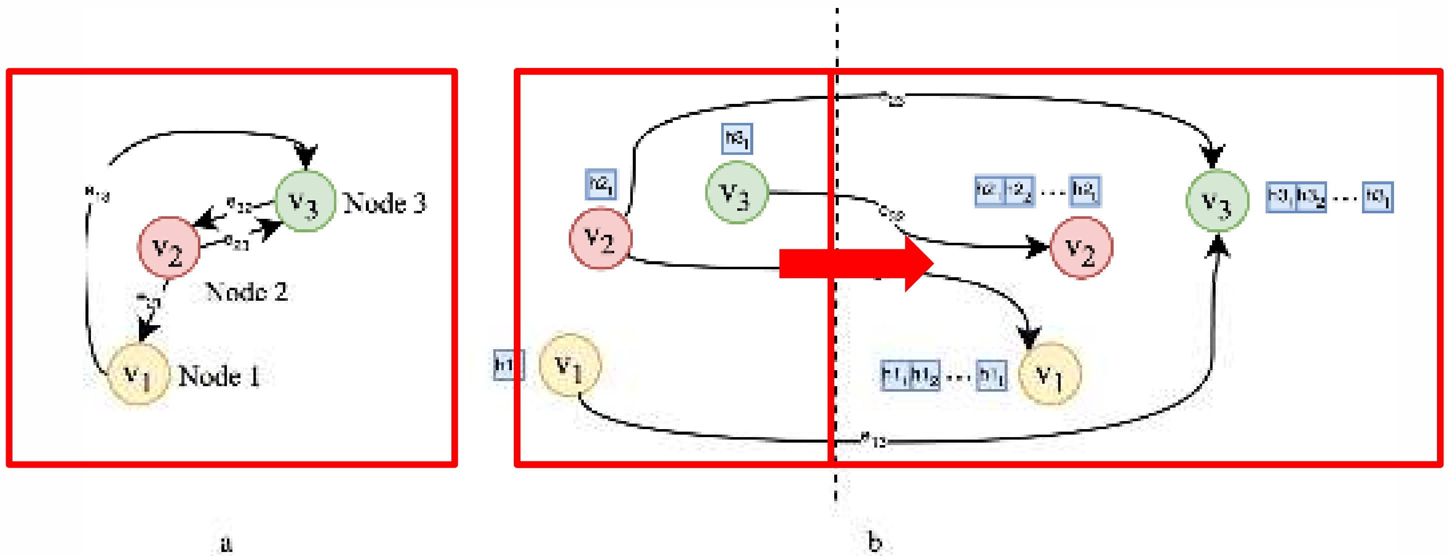


Fig 11: Formation of Bipartite Graph

- Traffic flow recorded on a sensor at a specific time step is influenced by;
  - **Traffic flow on adjacent roads in previous time steps due to propagation delay** [6].
  - What will happen if a road accident occurs in a road section?

Heterogeneous Cross Attention Layers

- Cross attention component assigns attention values for encoder input sequence.
- Naive implementation does not support feature-wise attention distribution.
- **Allows more precise and finer-grained modeling of temporal relationships.**
- Two feature sequences
    - **Historical observation sequence**
    - **Representative sequence**

Problem Statement

Given the historical observations spanning across a specific time window and **sensor network information**,

Problem is to **establish a mapping function to output a sequence of future traffic flow values**

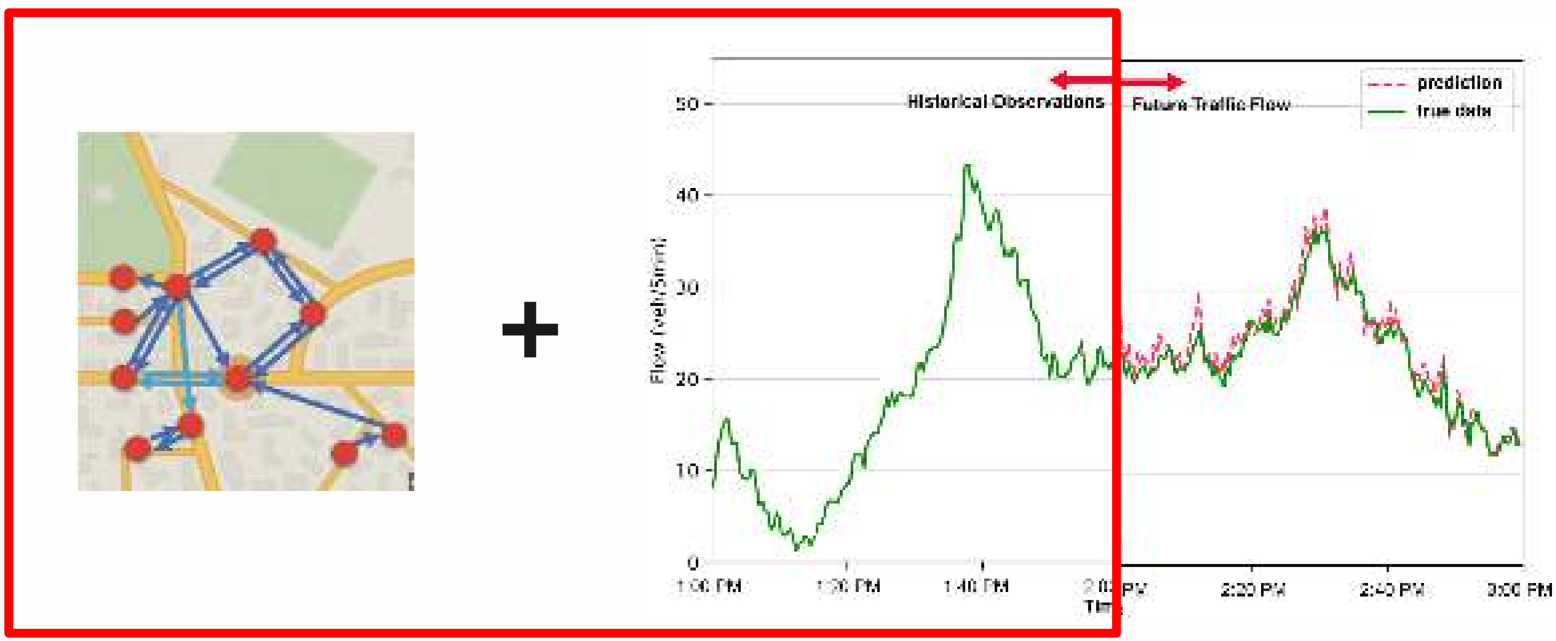


Fig 9: Problem Statement

Data Inputs

- First Input sequence generated by **traffic flow values in;**
    - **Last hour.**
    - **Same one hour duration in the previous day.**
    - **Same one hour duration in the last week.**
- Advantages of using observations in previous day and last week.
    - Identify long-term and short-term trends.
    - Mitigate the impact of missing values in shorter sequences.
- Second Traffic input sequence is a **representative traffic flow sequence.**
    - Averaging traffic flow values in training dataset.

Data Preprocessing

- Representative traffic flow sequences using the average behavior within training dataset.
- Redefined connectivity of road network.

Graphs

- Distance based graph
- Semantics based graph

Methodology

Encoder Decoder Architecture

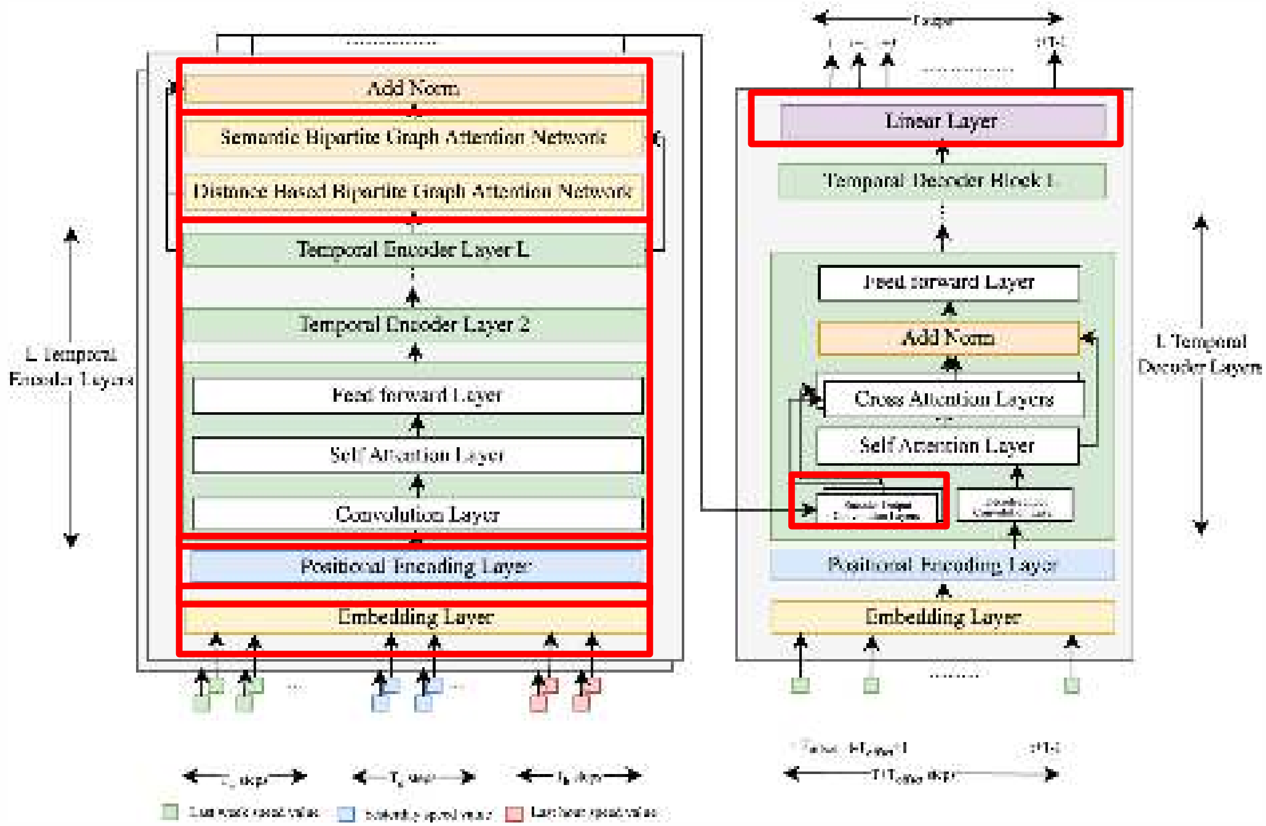


Fig 10: Overall Architecture

Datasets

- Comprehensive evaluation on two widely used dataset groups.
    - **PEMS dataset**
    - **PEMS-BAY, METR-LA datasets.**

Dataset	Sensors	Time Range
PEMS04	307	01/01/2018 - 28/02/2018
PEMS07	883	01/05/2017 - 31/08/2017
PEMS08	170	01/07/2016 - 31/08/2016
PEMS-BAY	325	01/01/2017 - 30/06/2017
METR-LA	207	01/03/2012 - 30/06/2012

Table 1: Details of Datasets

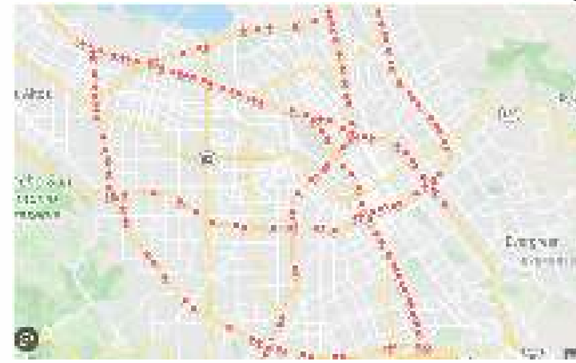


Fig 12: PEMS sensor network

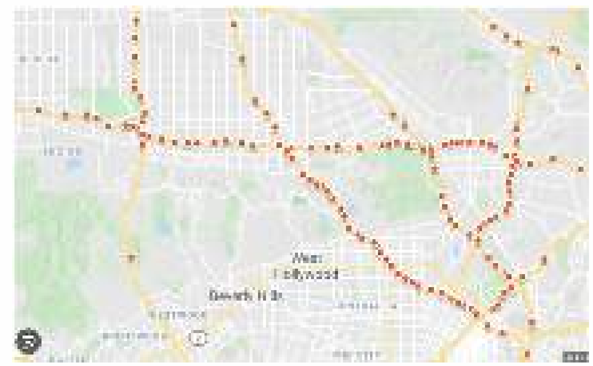


Fig 13: METR-LA sensor network

Experiment

Baselines

- Analyzed performance against current state-of-the-art models.
- Baselines:

PEMS dataset	PEMS-BAY, METR-LA
○ VAR ○ SVR ○ LSTM ○ DCRNN ○ STGCN ○ GMAN ○ **ASTGNN** ○ **PDFormer**	○ VAR ○ SVR ○ LSTM ○ DCRNN ○ STGCN ○ GMAN ○ **STEP** ○ **STGM**

Table 2: Baselines

Comparison of Performance

Table 3: Prediction Accuracy Results (PEMS04-08)

		VAR	SVR	LSTM	DC-RNN	ST-GCN	GMAN	AST-GNN	PDF-ormer	PDF-ormer(L)	ST-BGAT
PEMS04	MAE	23.75	28.66	26.81	23.65	22.27	19.14	18.60	18.39	18.40	**18.17**
	RMSE	36.66	44.59	40.74	37.12	35.02	31.60	31.03	30.01	30.25	**28.23**
	MAPE	18.10	19.15	22.33	14.75	13.87	13.19	12.63	12.13	12.23	**12.02**
PEMS07	MAE	101.20	32.97	29.71	23.63	22.90	20.97	20.62	19.83	N/A	**18.34**
	RMSE	155.14	50.15	45.32	36.51	35.44	34.10	34.02	32.87	N/A	**30.86**
	MAPE	39.69	15.43	14.14	12.28	11.98	9.05	8.86	8.53	N/A	**7.63**
PEMS08	MAE	22.32	23.25	22.19	18.19	17.84	15.31	13.29	13.58	12.51	**12.39**
	RMSE	33.83	36.15	33.59	28.18	27.12	24.92	23.33	23.51	22.10	**21.02**
	MAPE	14.47	14.71	18.74	11.24	11.21	10.13	9.03	9.05	8.55	**8.43**

Table 4: Prediction Accuracy Results (PEMS-Bay, METR-LA)

		VAR	SVR	LSTM	DCRNN	STGCN	GMAN	STGM	STEP	STBGAT
PEMS -BAY	MAE	2.93	3.28	2.37	2.07	2.49	1.86	1.86	1.79	**1.75**
	RMSE	5.44	7.08	4.96	4.74	5.69	4.32	4.37	4.20	**3.60**
	MAPE	6.50	8.00	5.70	4.90	5.79	4.37	4.34	4.18	**4.01**
METR -LA	MAE	6.52	6.72	4.37	3.60	4.59	3.44	**3.23**	3.37	4.56
	RMSE	10.11	13.76	8.69	7.60	9.40	7.35	7.10	**6.99**	8.12
	MAPE	15.80	16.70	14.00	10.50	12.70	10.07	**9.39**	9.61	10.96

Conclusion

- Introduced a novel spatial-temporal for traffic flow forecasting.
- STBGAT outperforms latest state-of-the-art baselines in four real-world datasets.
- Ablation study demonstrated the effectiveness of two new concepts;
    - **Bipartite Graph Attention Network**
    - **Heterogeneous Cross Attention Mechanism**

Thank you

Source Code: https://github.com/DimuthuLakmal/STBGAT

References

[1] Traffic and congestion cost trends for Australian capital cities. (n.d.). Traffic and congestion cost trends for Australian capital cities. Retrieved May 24, 4 C.E., from https://www.bitre.gov.au/sites/default/files/is_074.pdf

[2] Bui, K. H. N., Cho, J., & Yi, H. (2022). Spatial-temporal graph neural network for traffic forecasting: An overview and open research issues. *Applied Intelligence*, *52*(3), 2763-2774.

[1] Yan Tian, Kaili Zhang, Jianyuan Li, Xianxuan Lin, and Bailin Yang. 2018. Lstm-based traffic flow prediction with missing data. Neurocomputing, 318:297–305.

[2] Qing Wang, Jianying Zheng, Hao Xu, Bin Xu, and Rong Chen. 2017. Roadside magnetic sensor system for vehicle detection in urban environments. IEEE Transactions on Intelligent Transportation Systems, 19(5):1365–1374.

[3] Bing Yu, Haoteng Yin, and Zhanxing Zhu. 2017. Spatio-temporal graph convolutional networks: A deep learning framework for traffic forecasting. arXiv preprint arXiv:1709.04875.

[4] heonbok Park, Chunggi Lee, Hyojin Bahng, Yunwon Tae, Seungmin Jin, Kihwan Kim, Sungahn Ko, and Jaegul Choo. 2020. St-grat: A novel spatio-temporal graph attention networks for accurately forecasting dynamically changing road speed. In Proceedings of the 29th ACM international conference on information & knowledge management, pages 1215–1224.

[5] Chuanpan Zheng, Xiaoliang Fan, Cheng Wang, and Jianzhong Qi. 2020. Gman: A graph multi-attention network for traffic prediction. In Proceedings of the AAAI conference on artificial intelligence, volume 34, pages 1234–1241.

[6] Jiawei Jiang, Chengkai Han, Wayne Xin Zhao, and Jingyuan Wang. 2023. Pdformer: Propagation delay-aware dynamic long-range transformer for traffic flow prediction. arXiv preprint arXiv:2301.07945.

[7] Rongzhou Huang, Chuyin Huang, Yubao Liu, Genan Dai, and Weiyang Kong. 2020. Lsgcn: Long short-term traffic prediction with graph convolutional networks. In IJCAI, volume 7, pages 2355–2361.

[8] Xiangyuan Kong, Weiwei Xing, Xiang Wei, Peng Bao, Jian Zhang, and Wei Lu. 2020. Stgat: Spatial-temporal graph attention networks for traffic flow forecasting. IEEE Access, 8:134363–134372.

[9] Zhilong Lu, Weifeng Lv, Yabin Cao, Zhipu Xie, Hao Peng, and Bowen Du. 2020. Lstm variants meet graph neural networks for road speed prediction. Neurocomputing, 400:34–45.

[10] Thomas N Kipf and Max Welling. 2016. Semi-supervised classification with graph convolutional networks. arXiv preprint arXiv:1609.02907.

[12] Shengnan Guo, Youfang Lin, Huaiyu Wan, Xiucheng Li, and Gao Cong. 2021. Learning dynamics and heterogeneity of spatial-temporal graph data for traffic forecasting. IEEE Transactions on Knowledge and Data Engineering, 34(11):5415–5428.

[13] Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N Gomez, Łukasz Kaiser, and Illia Polosukhin. 2017. Attention is all you need. Advances in neural information processing systems, 30.

[14] Teng Zhou, Guoqiang Han, Xuemiao Xu, Chu Han, Yuchang Huang, and Jing Qin. 2019. A learning-based multimodel integrated framework for dynamic traffic flow forecasting. Neural Processing Letters, 49:407–430

[15] Yatao Zhang, Tianhong Zhao, Song Gao, and Martin Raubal. 2023. Incorporating multimodal context information into traffic speed forecasting through graph deep learning. International Journal of Geographical Information Science, 37(9):1909–1935

[16] Xiaoan Qin. 2023. Traffic flow prediction based on two-channel multi-modal fusion of mcb and attention. IEEE Access, 11:58745–58753.

[17] Qi Chen, Wei Wang, Kaizhu Huang, Suparna De, and Frans Coenen. 2021. Multi-modal generative adversarial networks for traffic event detection in smart cities. Expert Systems with Applications, 177:114939

[18] R. S. D. Sousa, A. Boukerche, and A. A. Loureiro, "Vehicle trajectory similarity: models, methods, and applications," ACM Computing Surveys (CSUR), vol. 53, no. 5, pp. 1–32, 2020

[19] P. Tong, M. Li, M. Li, J. Huang, and X. Hua, "Large-scale vehicle trajectory reconstruction with camera sensing network," in Proceedings of the 27th Annual International Conference on Mobile Computing and Networking, 2021, pp. 188–200

[20] X. Zeng, C. Lancelle, C. Thurber, D. Fratta, H. Wang, N. Lord, A. Chalari, and A. Clarke, "Properties of noise cross-correlation functions obtained from a distributed acoustic sensing array at garner valley, california," Bulletin of the Seismological Society of America, vol. 107, no. 2, pp. 603–610, 2017.

[21] "Distributed acoustic sensing," https://www.bandweaver.com/fiber_optic_sensing_technology/distributed-acoustic-sensing/, May 2017, accessed: 2023-9-30.

[22] I. Corera, E. Piñeiro, J. Navallas, M. Sagues, and A. Loayssa, "Long-range and high-resolution traffic monitoring based on pulse-compression das and advanced vehicle tracking algorithm," in Optical Fiber Sensors. Optica Publishing Group, 2022, pp. Th2–3.

Appendix

Ablation Study