A Physics-informed Spatiotemporal Network for Traffic Prediction

Haoyang Chen

Supervisors:
Dr. Joyce Zhang, Dr. Jianzhong Qi,
Dr. Tingjin Chu, Dr. Mingming Gong

Background
Traffic Prediction

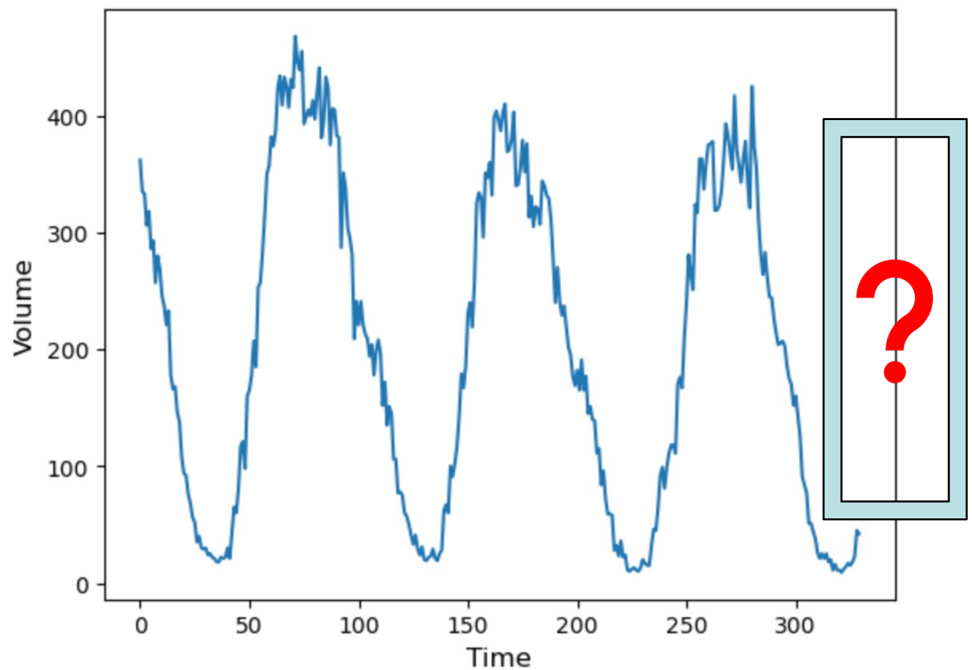
What is traffic prediction?

Predicting future traffic conditions (e.g. speed, volume etc.) given historical traffic data in a specific region.

Time-series prediction

Past ✓

Future ?



Background
Traffic Prediction

Why do we need it?

- Reducing traffic congestion
- Optimising transportation systems
- Helping with event planning

How to predict?

Model-driven or data-driven approaches

Early solutions | Increasing popularity

Background
Traffic Prediction

Model-driven:

- Statistical models [1-4]
- Describing relationships among traffic variables.

Data-driven:

- Machine learning models: KNN, Bayesian [5-8]
- Deep learning models: CNN, GNN, RNN, LSTM, Transformer [9-13]

State-of-the-arts: spatiotemporal neural networks [14-16]

Aims and Objectives
Our Key Insight

Most approaches are ***one-sided***:

1. Deep-learning-based models

   → ignore the underlying physics of traffic

2. Physical models

   → not taking advantage of data

A few combined approaches:

- None of them considers the spatiotemporal correlations

Embedding physical laws into ML/DL models.

Aims and Objectives

Why? Taking advantages of both model-driven and data-driven approaches

How?

- transforming or augmenting the data
- modifying model architecture
- Incorporate constraints into loss functions (learning bias)

We aim to integrate physics into spatiotemporal networks through learning bias.

Preliminaries
Traffic Flow Theory

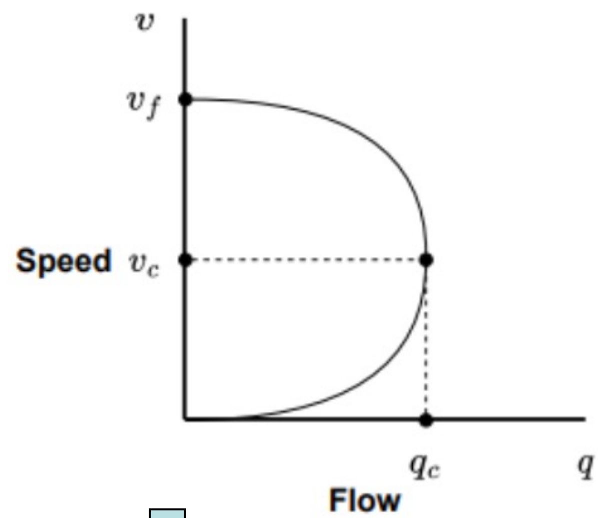
Macroscopic Variables:

- $Density\ k\ (vehicles\ /\ km)$
- $Flow\ q\ \ (vehicles\ /\ h)$
- $Speed\ v\ (km\ /\ h)$

Fundamental Relationship:

$$q = k * v$$

Fundamental Diagram:



Exists in link, region, and network level

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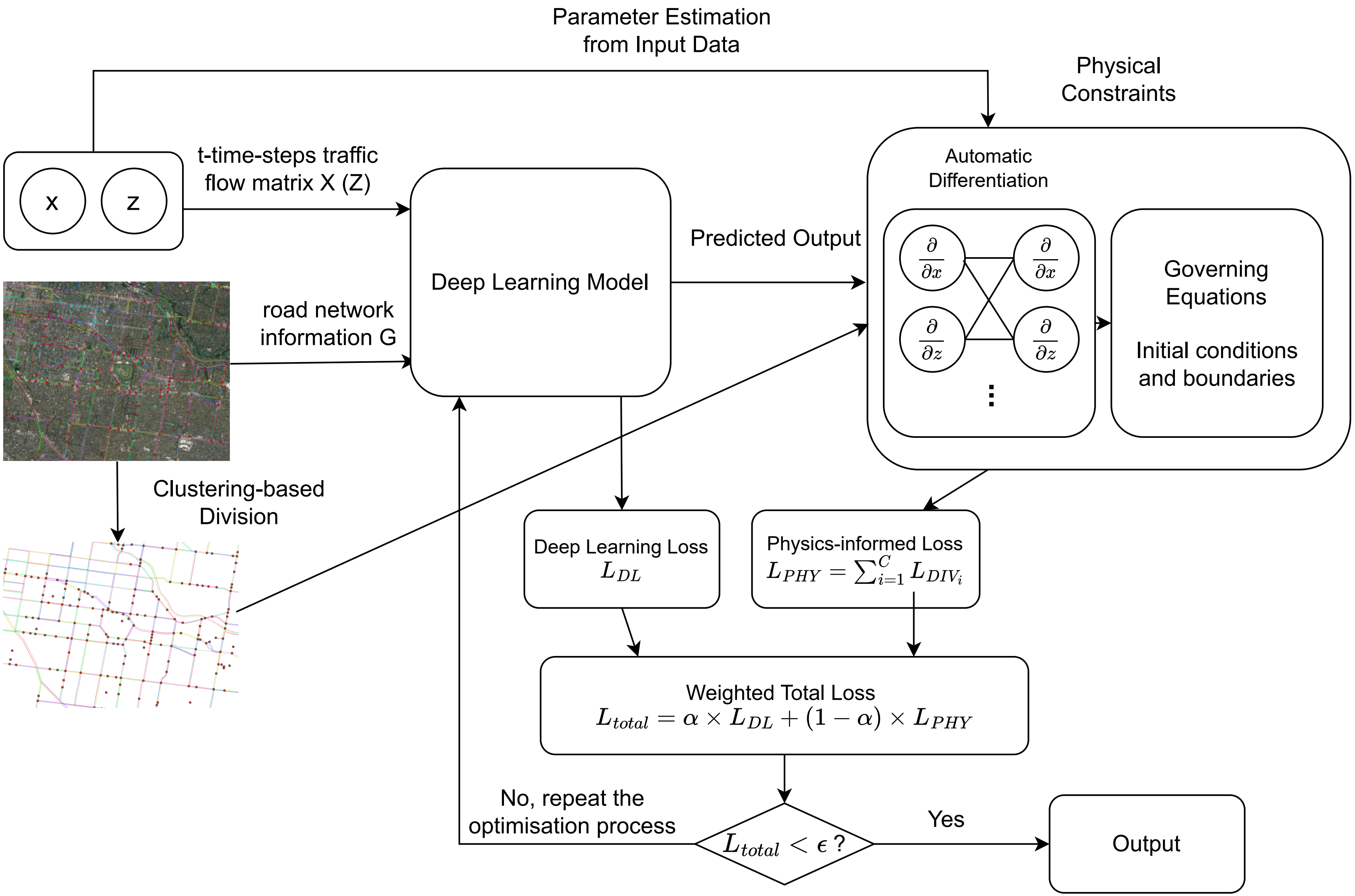
Preliminaries
Problem Formulation

- The road network can be represented as a ***weighted directed graph G = (V, E, A)***
- Denote the traffic feature matrix at timestamp t as $X_t \in R^{N*D}$, N for number of nodes and D for number of features.
- We aim to find a functional mapping f:

$$f(\underbrace{[X_{t-\beta}, \dots, X_{t-1}], G)}_{\text{Historical data}} \rightarrow \underbrace{[X_t, \dots, X_{t+\alpha}]}_{\text{Future trends}}$$

Methodologies and Findings
Overall Framework



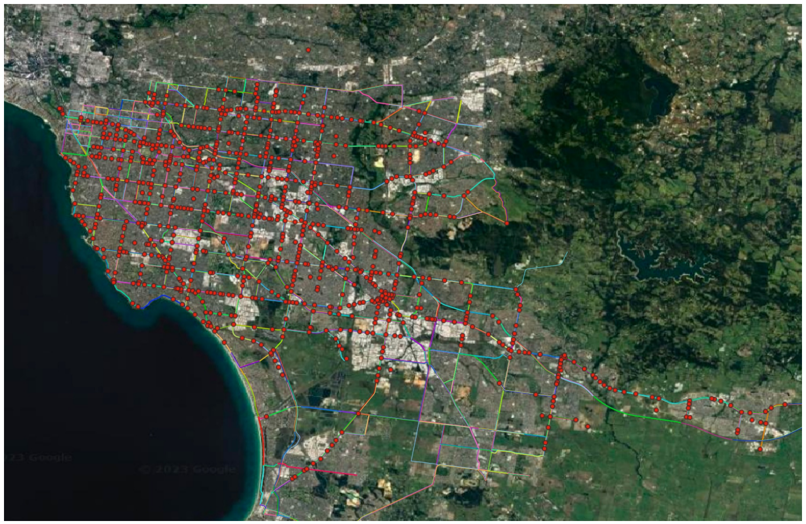
Data are sourced from VicRoads and PeMS:

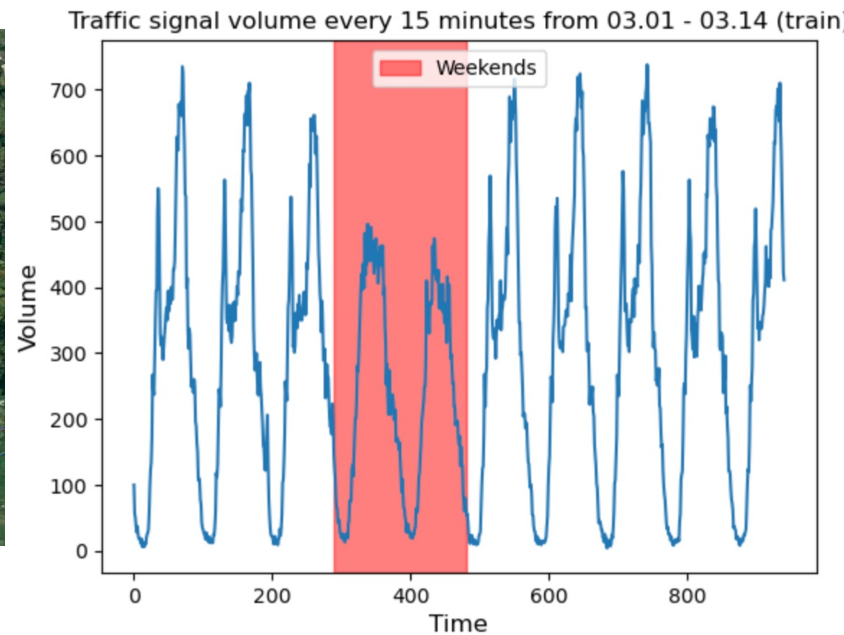
	Sensors	Time range	Time interval
VicRoads	313	Jan 1st 2023 to March 15th 2023	15 min
PeMS-BAY	325	Jan 1st, 2017 to May 31st 2017	5 min

Preprocessing:

- Z-score normalisation
- 7:2:1 train-test-split

Regional Map shows our study area in Melbourne.





Simple 2 weeks' data visualisation demonstrates clear patterns of traffic volume.

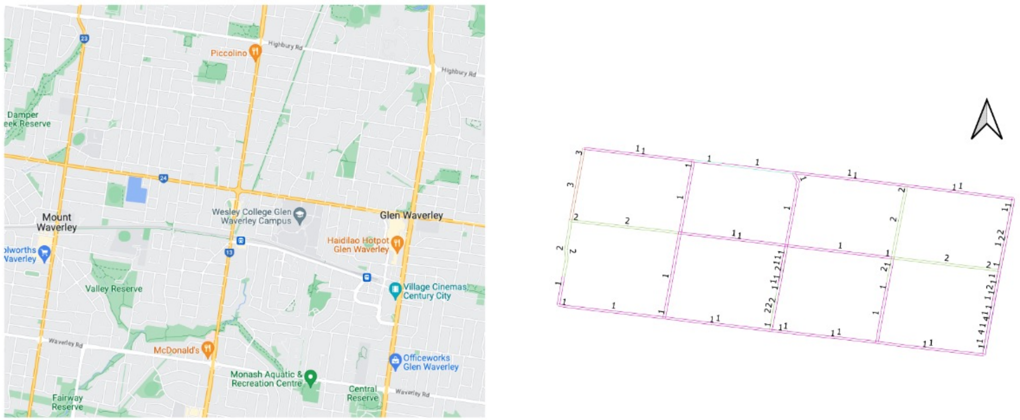
Existing models:

- Ignoring the possible variation of ***regional traffic properties***.

We plan to:

- Clustering on road network
- Aggregating regional losses to obtain the total loss

Sample clustering



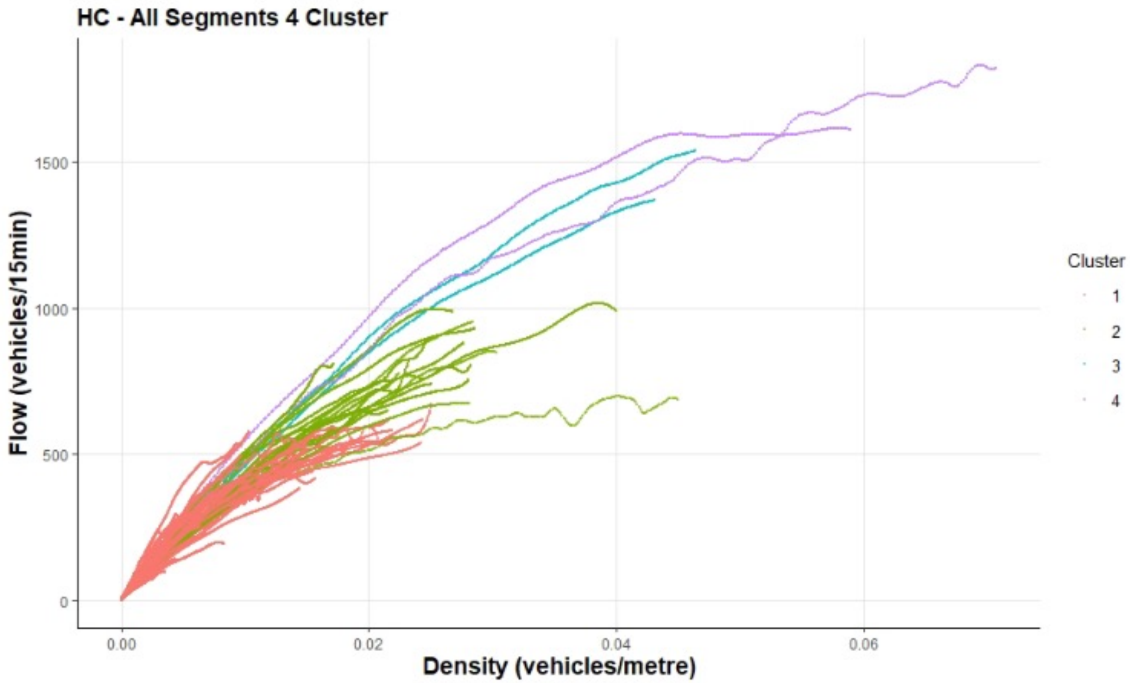
(a) Melbourne Eastern Suburbs

(b) Cluster Groups Map

Methodologies and Findings
Evaluation

Planned metrics: Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), Root Mean Squared Error (RMSE)

Visualisation based on clusters:



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Timeline and Progress

Semester 1	Date	Feb-23	6-Mar	13-Mar	20-Mar	27-Mar	3-Apr		17-Apr	24-Apr	1-May	8-May	15-May	22-May	SWOT	Progress (until 18-May)
Milestones	Week	1	2	3	4	5	6	Break	7	8	9	10	11	12	13	
Identifying the research problem (broad)		3														100%
Conducting relevant literature review		6														100%
Establishing the research question				4												100%
Exploring VicRoads Dataset & Running simple models on the data				3												100%
Examining the geological dataset									4							90%
Research proposal writing						5										100%
Running existing models & Analysing results									6							10%
Processing spatial and temporal data & Preparing for ready-to-use data embedding												4				50%
Preparing for oral presentation													2			100%
	Date	24-Jul	31-Jul	7-Aug	14-Aug	21-Aug	28-Aug	4-Sep	11-Sep	18-Sep		2-Oct	9-Oct	16-Oct	23-Oct	
Semester 2	Week	1	2	3	4	5	6	7	8	9	Break	10	11	12	13	
Thesis writing		All Semester														Not yet started
Designing loss function with fundamental relationship involved		4														
Clustering-based division of cities				3												
Overall model architecture design						3										
Experiments on effectiveness of model							5									
Evaluation & Comparison									4							
Final write up of thesis													3			

Finished tasks: literature review, method identification, dataset exploration, simple model experiments

Current stage: about to finish examining the geological dataset

Next steps: creating data embeddings (2 weeks), physical loss design (4 weeks), clustering of road network (3 weeks)

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Thank you
Any Questions?