Graph modelling approaches for motorway traffic flow prediction

by A.S. Mihaita, Zac Papachatgis, Marian-Andrei Rizoiu

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Summary

1. **Introduction**

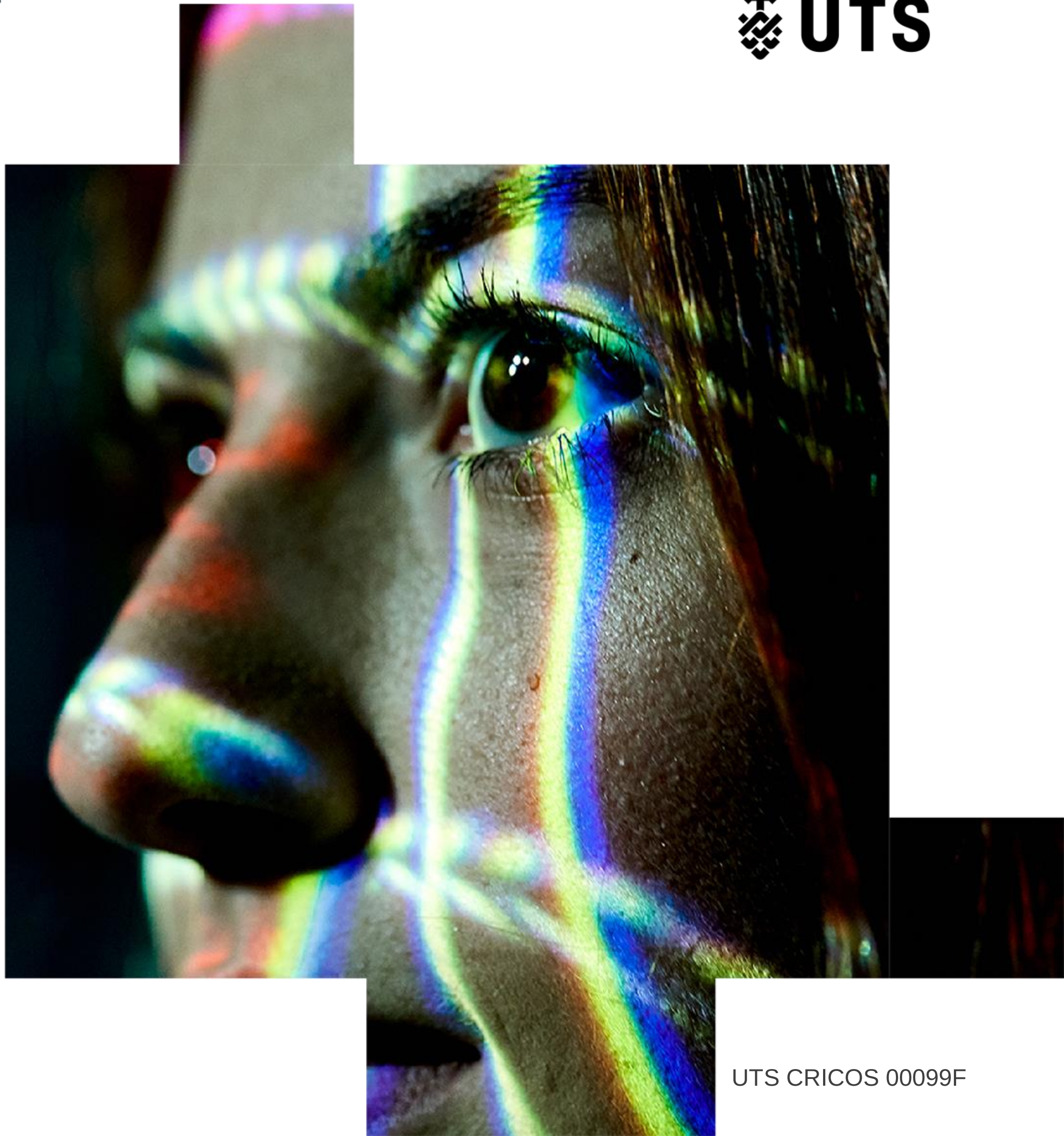
2. **Methodology**
    1. Spatial and Graph Structure
    2. Backtracking Prediction Method (BKTR-P)
    3. Interpolation Prediction Method (INTR-P)

3. **Case Study**
    1. Sydney M7 motorway
    2. Daily Profile and traffic flow map

4. **Experimental setup**
    1. Prediction setup
    2. Past and future prediction horizon selection
    3. Other baseline models

5. **Results**
    1. BKTR-P and INTR-P results
    2. Past vs future time horizon analysis
    3. Comparison with other Deep Learning models

6. **Conclusions**

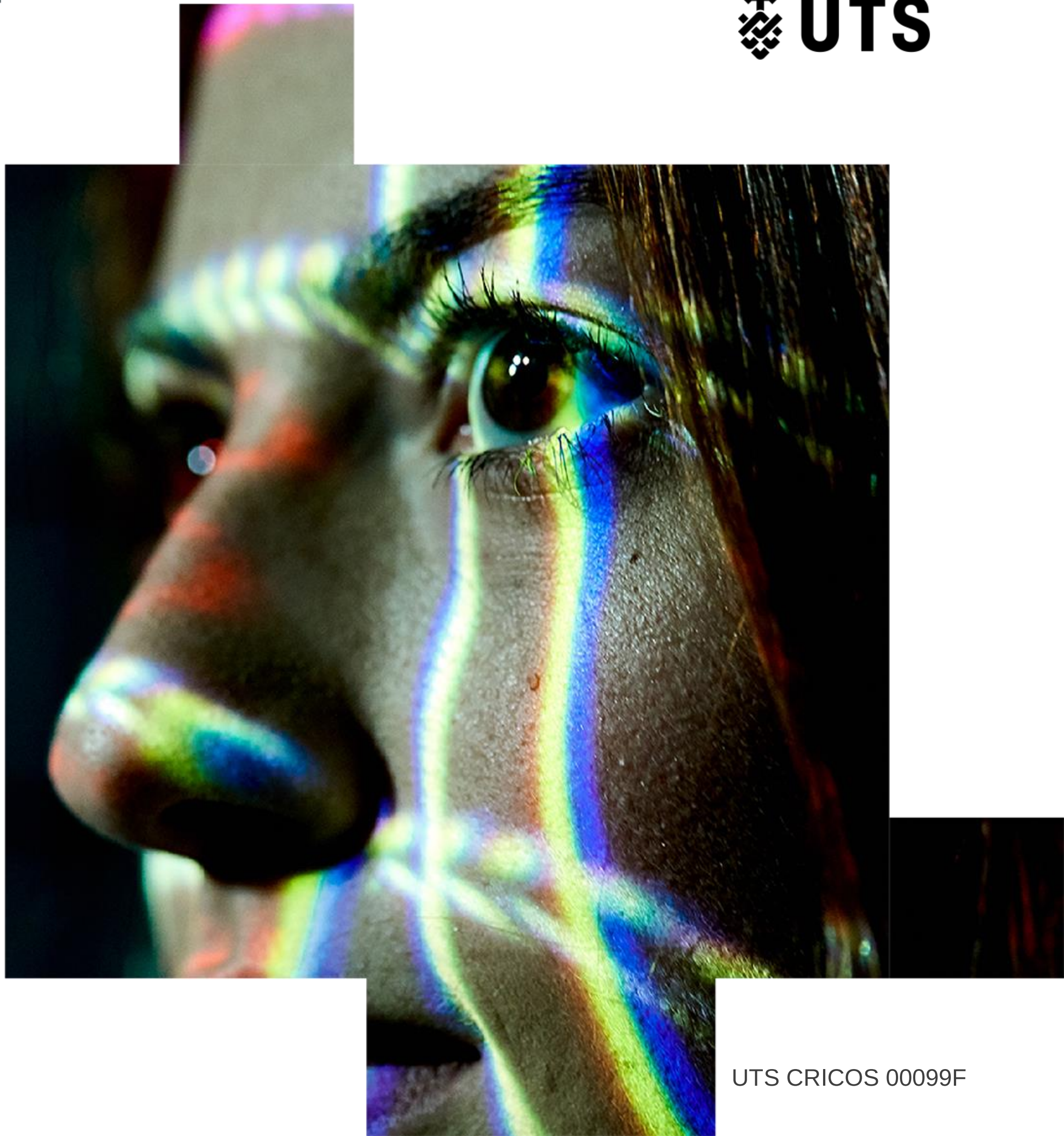


Introduction

Challenges for accurate flow prediction:

a) large amounts of data sets generated every minute across large areas,
b) the spatial structure and layout of the network can induce high complexity in the localisation of traffic count stations and their utilisation,
c) stochastic events which can severely disturb regular traffic conditions,
d) the spatial and temporal distribution of traffic flow can induce direct and indirect congestion propagation patterns and
e) missing or erroneous data due to varying equipment functioning state, or inconsistent human reporting.

Summary

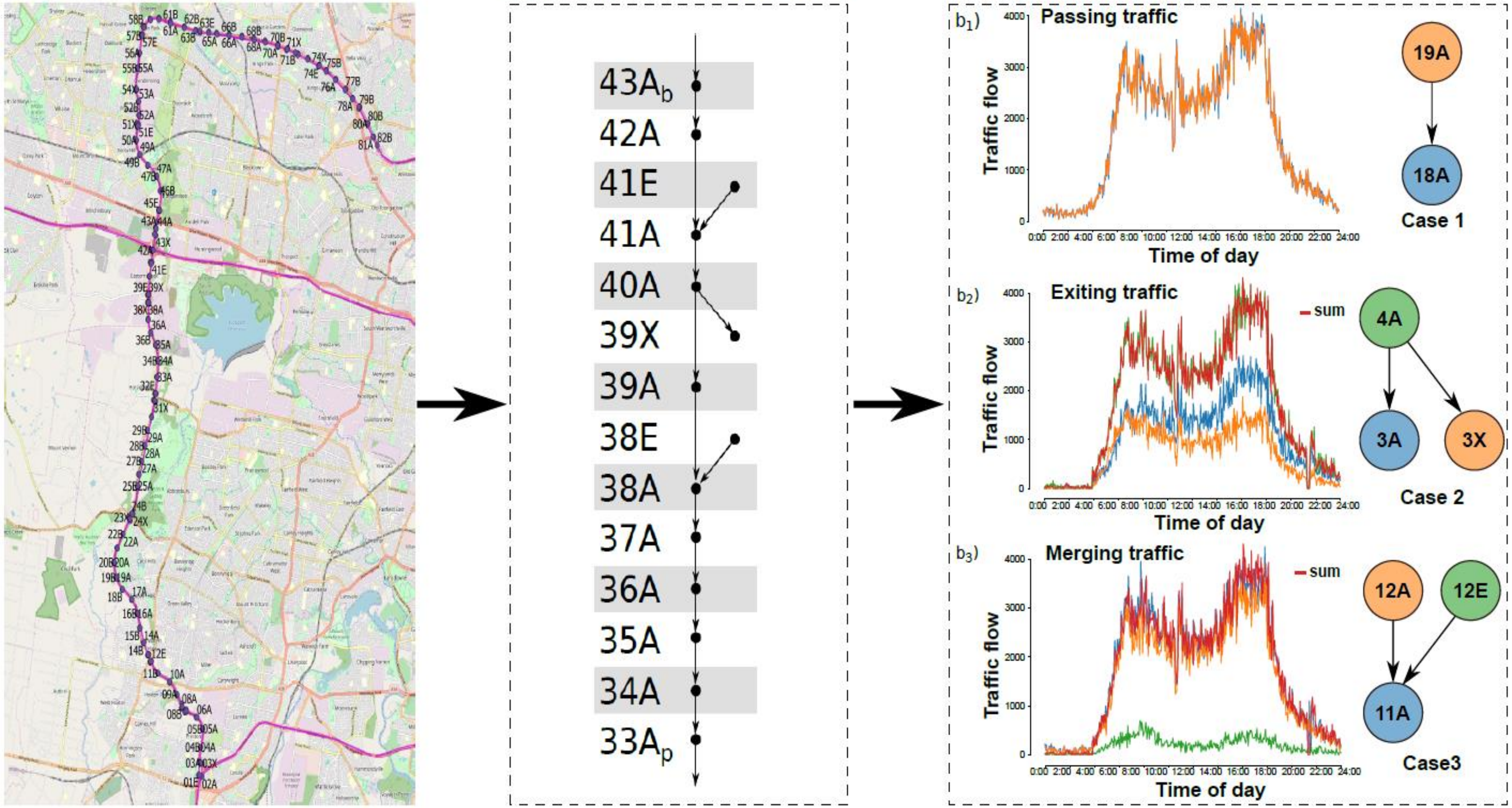


Methodology

a) Mapping stations to geography

b) Build the graph structure of traffic flow

c) Three spatial spatial configurations



Spatial station configurations:

Passing traffic:

$$F(19A;i) = F(18A;i) \pm \varepsilon.$$

Exiting traffic:

$$F(4A;i) = F(3A;i) + F(3X;i) \pm \varepsilon.$$

Merging traffic:

$$F(11A;i) = F(12A;i) + F(12E;i) \pm \varepsilon.$$

Methodology

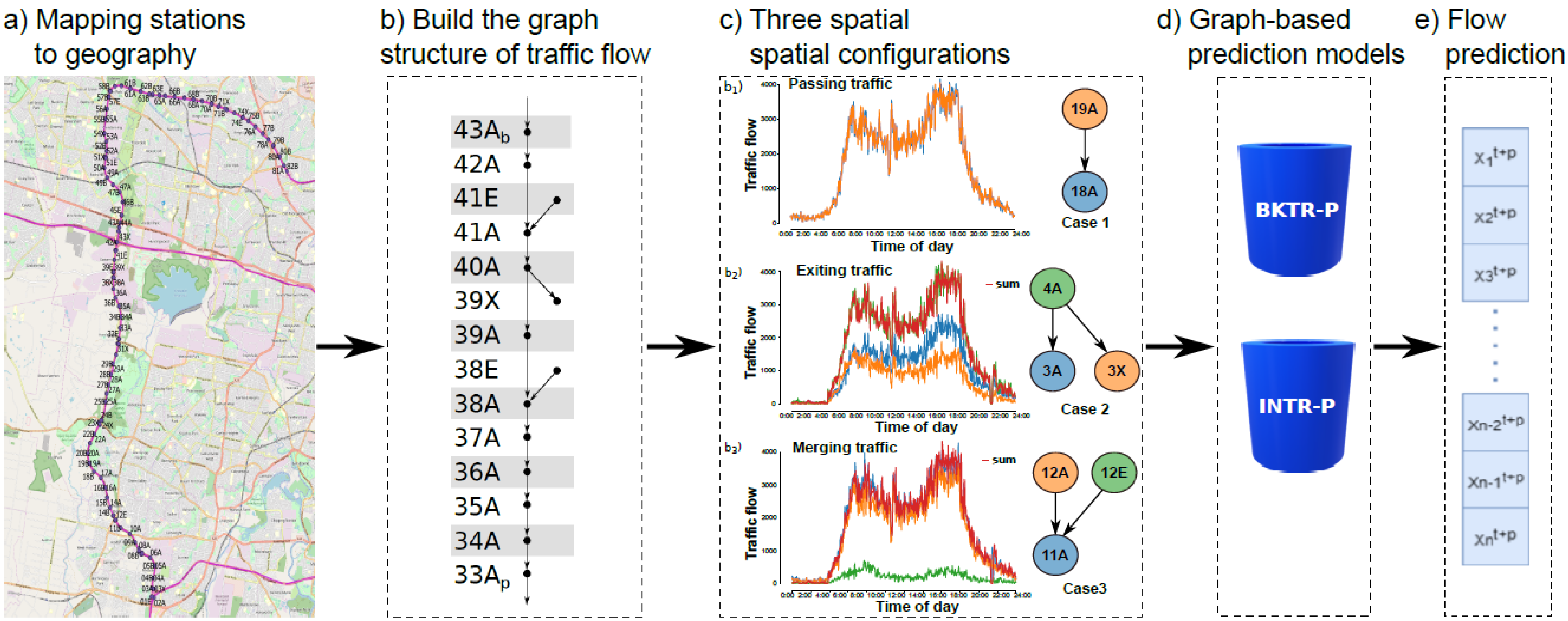


Fig. 1: Methodology for the proposed graph-flow prediction along the M7 motorway, as a succession of five steps.

Methodology

Some notations:

- F(s; i) the vehicle flow recorded by a station s, during the i_{th} time interval
- Three types of station profiles: E.g. 39A (straight station), 12E (exit station), 15X(exit stations)
- s_1 -> s_2: a car that is recorded by s_1 could be recorded next by s_2.

Graph structure:

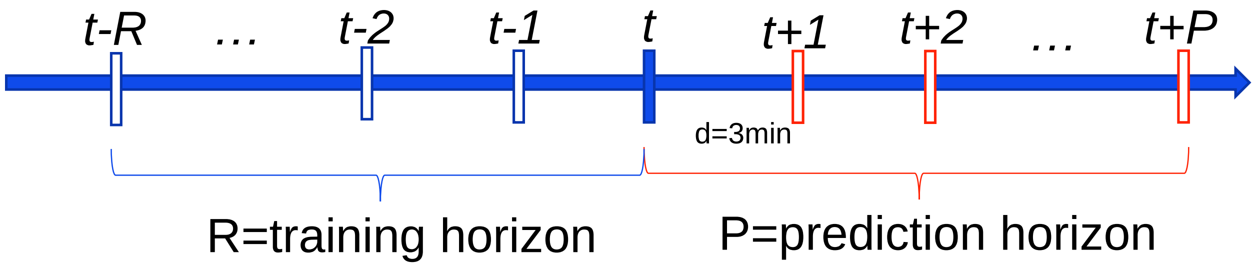
- G(V;E): V is the set of vertexes (or nodes) here the stations. E is the set of edges (or arcs)
- s_1 -> s_2 : a car that is recorded by s_1 could be recorded next by s_2; s_1, s_2 are from G.
- Unidirectional edges with attributes (distance, travel time)
- separate ways for upstream and downstream traffic

Methodology

1. Backtracking Prediction Method (BKTR-P)

Aim: $\underbrace{\text{predict flow of a station } \mathbf{v} \text{ at } \mathbf{p} \text{ intervals in the future from current time}}_{\widehat{F}(v,t+p)}$ $\underbrace{\text{using the flow from } \mathbf{r} \text{ intervals in the past.}}_{F(\cdot,t-r)}$

Past and future horizons:



Solution:

- look upstream for a station **u** of type **a** which lies **r+p** time intervals upstream of station at expected distance **(r+p)*d*avg(speed(u,v))**

How?

- By building the distance matrix between **u** and **v** during **r+p** time intervals
- We transverse the graph between **u** and **v** and detect all entries/exits

One step prediction $\widehat{F}(v;t+1) = F(u;t-1) + \sum_{e \in \mathscr{E}} F(e;t-1) - \sum_{x \in \mathscr{X}} F(x;t-1)$

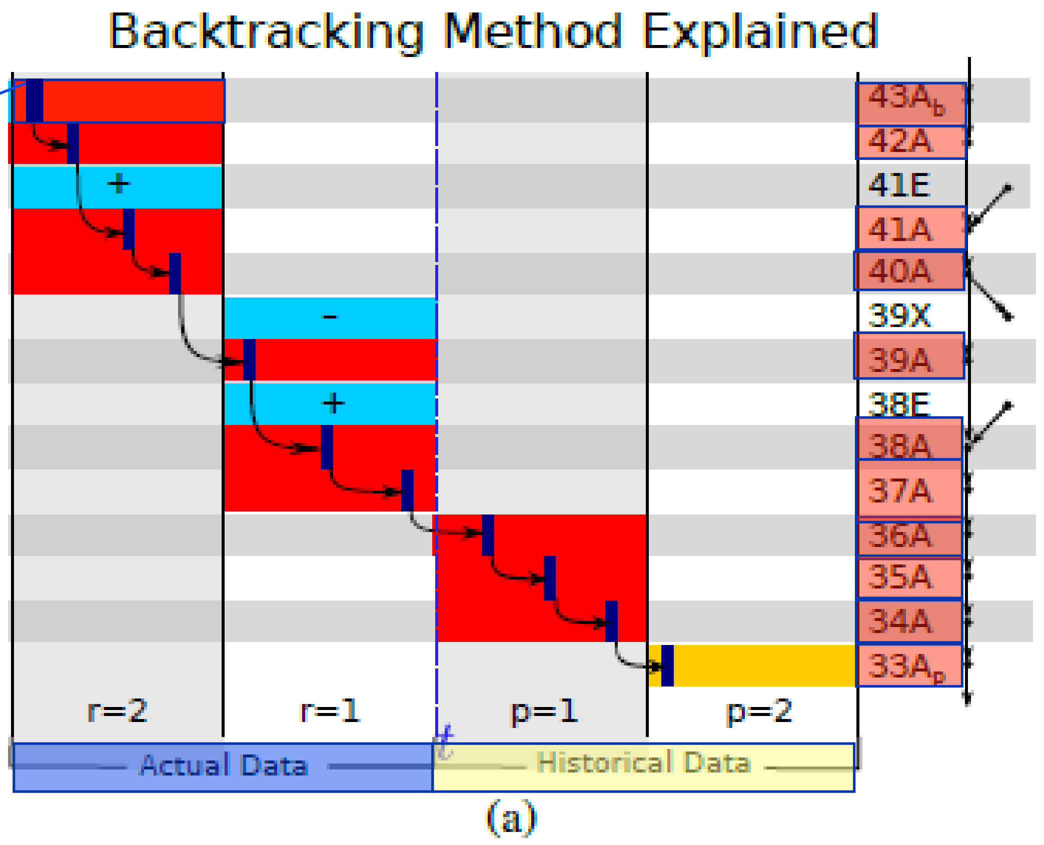
p=1, r=1: predict the flow at station v using flow at station u and add/extract flow of entries/exits

Methodology

1. Backtracking Prediction Method (BKTR-P)

Multiple step prediction

Position of vehicles passing through stations

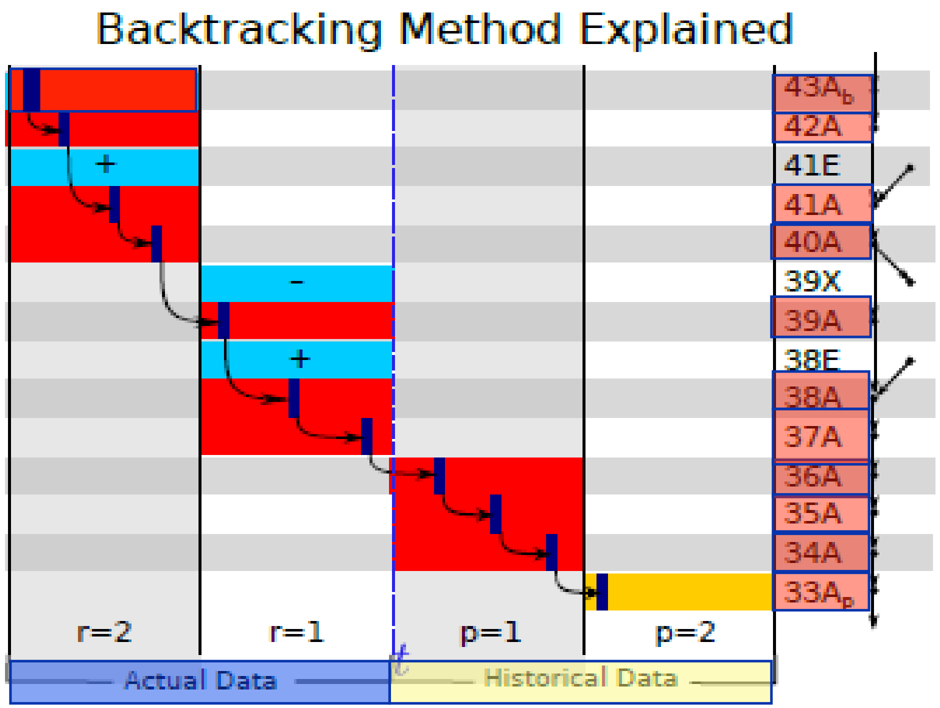


a) BKTR-P exemplification

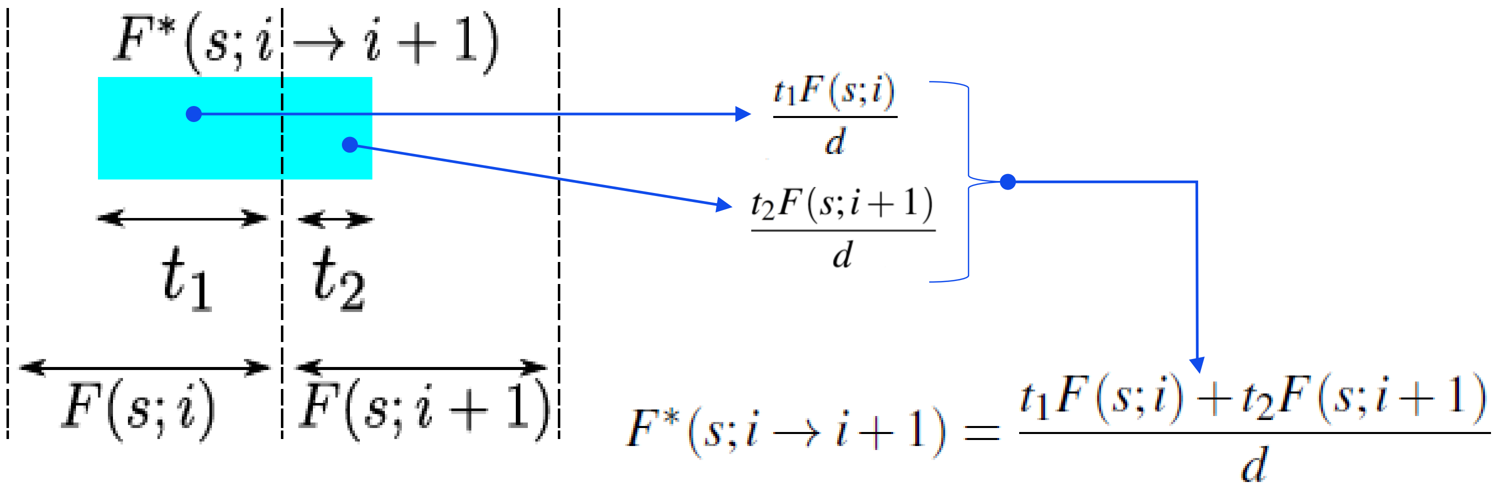
Methodology

1. Interpolation Prediction Method (INTR-P)

Similar to BKTR-P but interpolating the recorded flow values in two consecutive time intervals t_1, t_2: $F^*(s; i \to i+1)$
Where $t_1 + t_2 = d$



(a)



(b)

a) BKTR-P exemplification

b) flow representation between two time intervals

Methodology

1. Interpolation Prediction Method (INTR-P)

Similar to BKTR-P but interpolating the recorded flow values in two consecutive time intervals t_1, t_2: $F^*(s; i \rightarrow i+1)$
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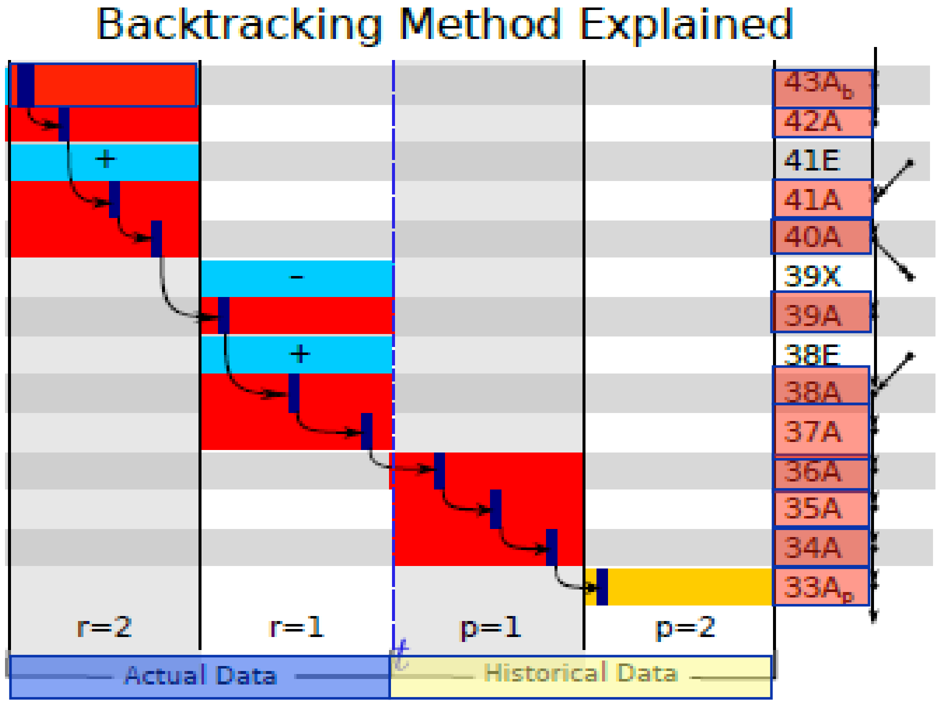

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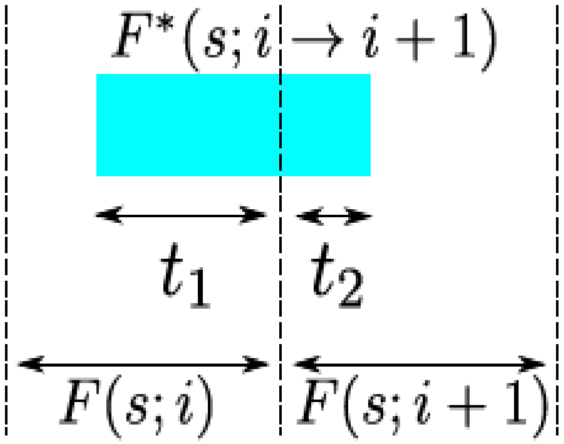
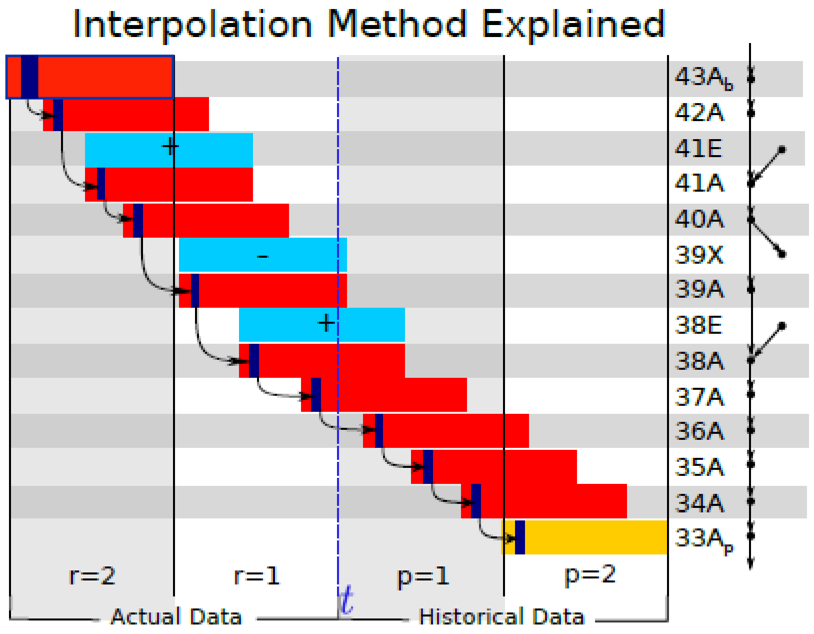


(b)



(c)

a) BKTR-P exemplification b) flow representation between two time intervals c) INTR-P exemplification.

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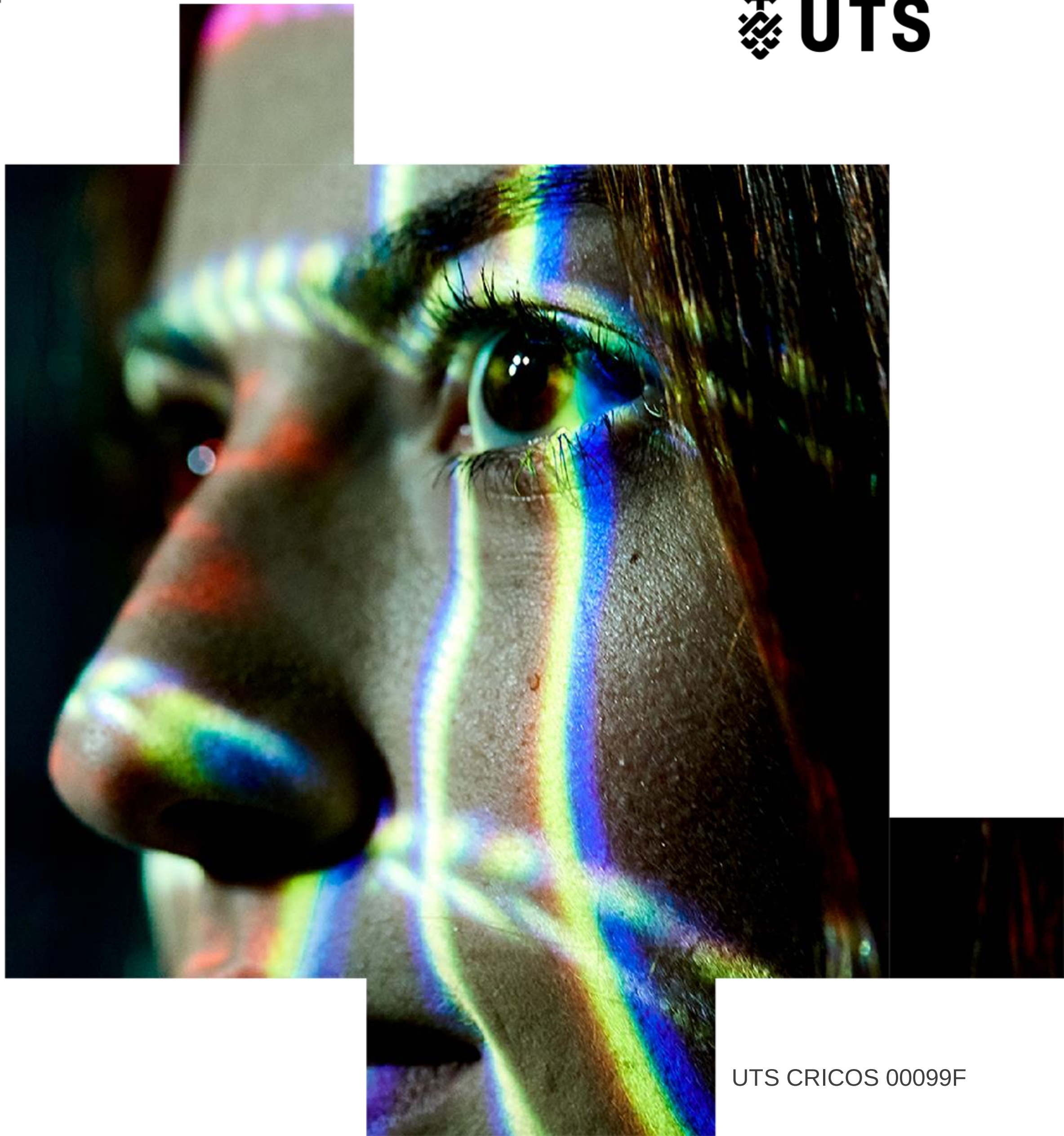


Daily profiling and outlier identification

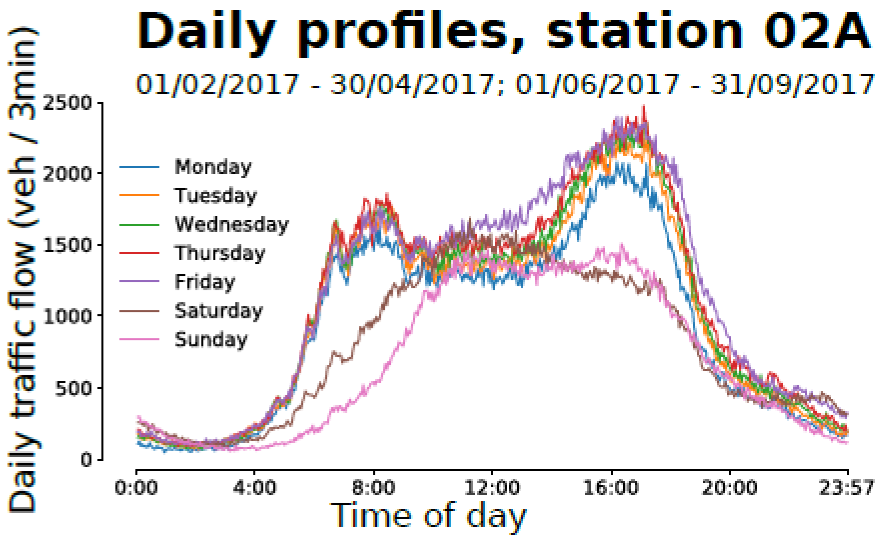
M7 motorway details:

- 2017 data set
- 208 bi-directional “flow counting stations”
- 36.34 million data points
- d = 3min
- d_i the i_{th} interval of a day, i = 1:480.

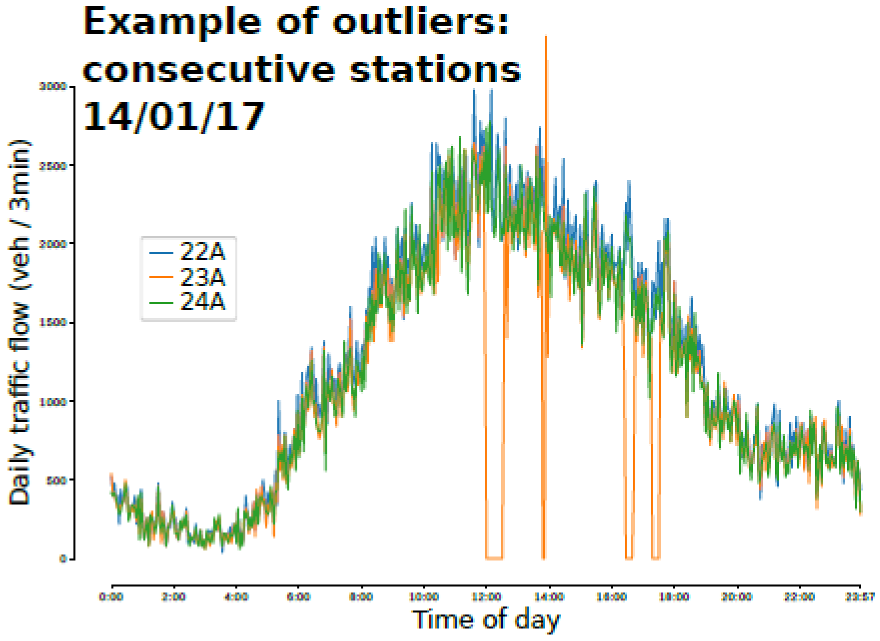
Outlier and anomaly detection

- Missing records
- All-zero records
- Abnormal long data records

Current work on anomaly detection using Deep Learning Submitted (Mihaita, A.S., Li, H., Rizoiu, M.A., Traffic congestion anomaly detection and prediction using deep learning, Transport Part C, August 2020).



(a)



(b)

Fig. 3: a) Daily Profile - Historical data by day of the week, b) Example of traffic outliers and anomaly detection across consecutive traffic flow stations without any entries/exits in between.

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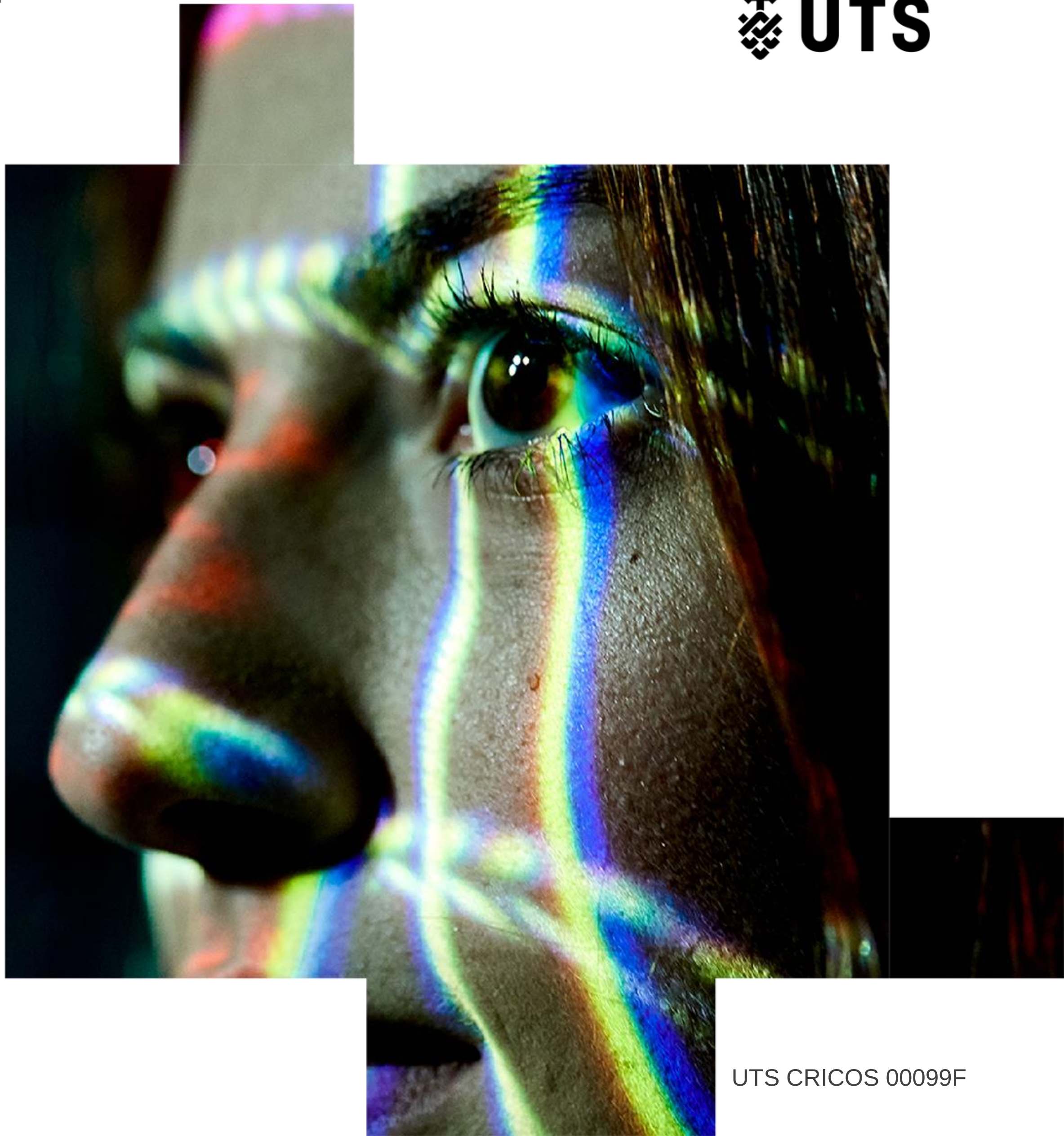

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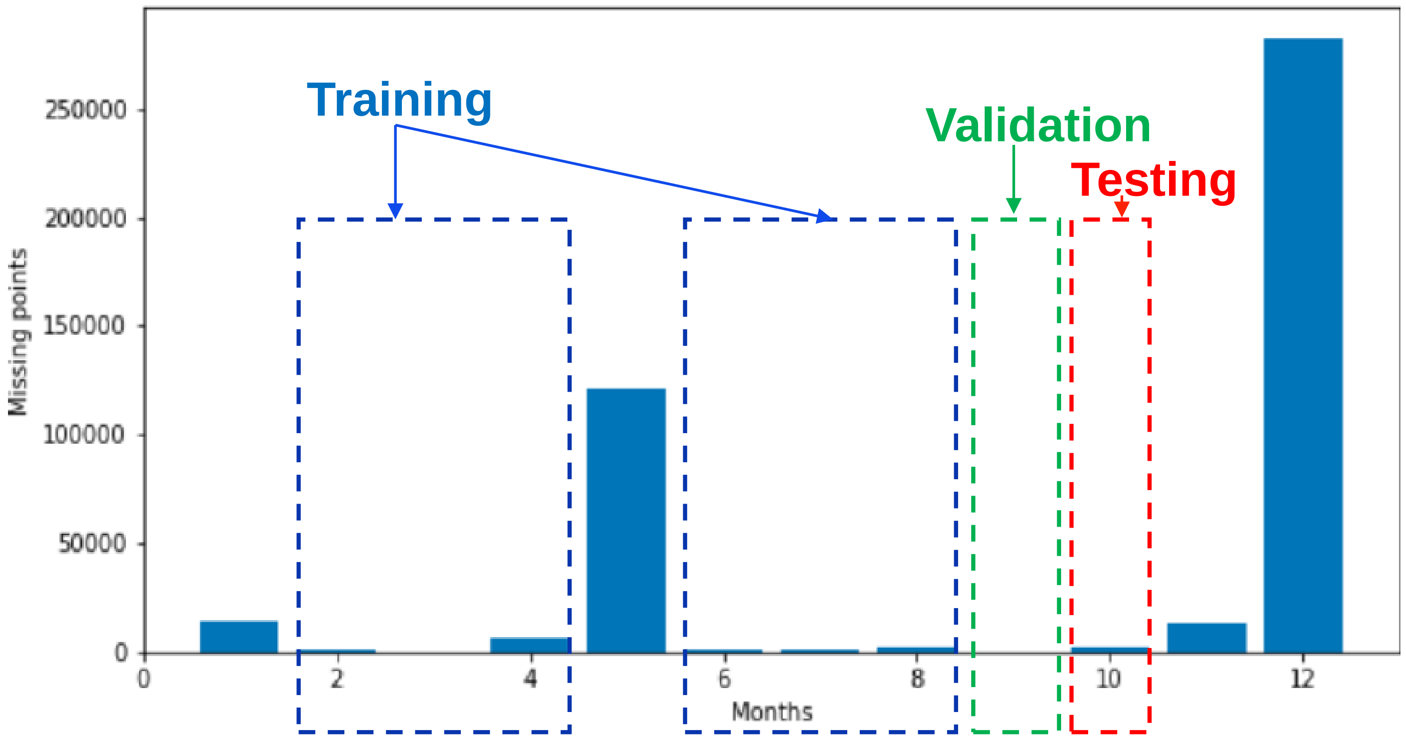
Experimental Set-up

1) Prediction setup - 36.34 million data points



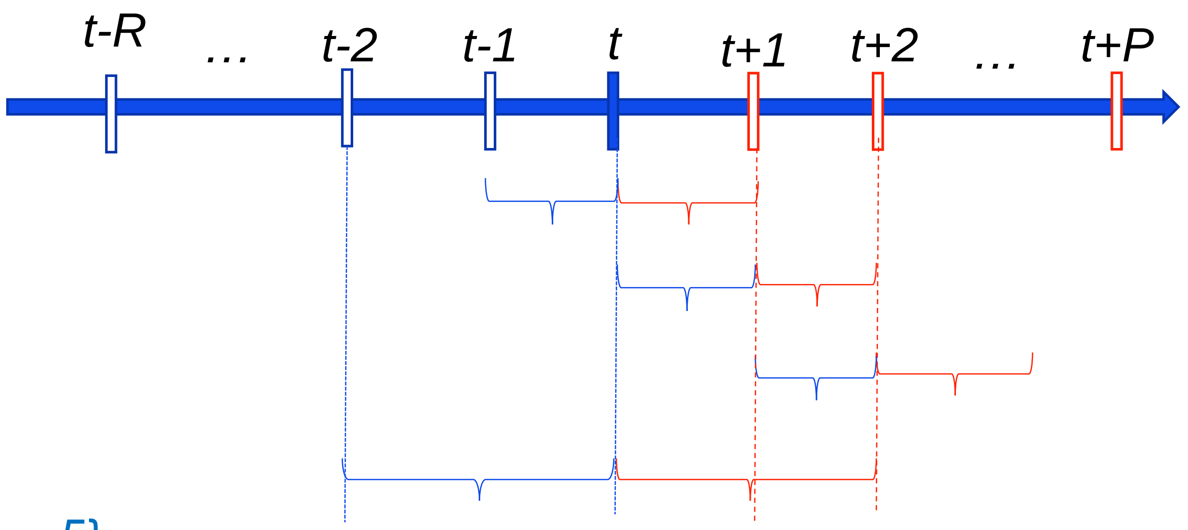
Choosing the training/testing and validation periods based on the total number of missing data points.

Experimental Set-up

2) Past and future prediction horizon

By varying *t* on a dataset with n time points, we obtain n-R-P+1 pairs of inputs and outputs.

Ex1. R=2, P=1



Our experimental range : R = {1…5}, P = {1,…5}

Constraints: given by the length of the motorway in km in each direction:

R=1, p=1 – BKTR-P and INTR-P have been applied on ALL stations from 72A->03A
R=5,p=5 - – BKTR-P and INTR-P have been applied on limited stations from 26A->03A

Experimental Set-up

3) Other models used for comparison

1. **Daily Profile Predictor (DPP)** – using historical average traffic flow from daily patterns

2. **BPNN** – Back –propagation neuronal networks;

3. **CNN** – convolutional neuronal networks

4. **LSTM** – long short term memory models

5. **CNN-LSTM** – the hybrid combination model of CNN and LSTM

implemented in previous work published in :

Mihaita, A.S., Li Haowen, He Zongyang, Rizoiu Marian-Andrei, Motorway Traffic Flow Prediction using Advanced Deep Learning, IEEE Intelligent Transport Systems Conference, Auckland, New Zealand, 27-30 October 2019.

Experimental Set-up

4) Performance evaluation:

i) the Root Mean Square Error:

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(\widehat{F}(v;t) - F(v;t)\right)^2}$$

ii) the R-squared value:

$$R^2 = 1 - \frac{\sum_{i=1}^{N}\left(\widehat{F}(v;t) - F(v;t)\right)^2}{\sum_{i=1}^{N}\left(F(v;t) - \overline{F}(v;t)\right)^2}$$

iii) Symmetric Mean Absolute Percentage Error:

$$SMAPE = \frac{100\%}{n}\sum_{i=1}^{N}\frac{|\widehat{F}(v;t) - F(v;t)|}{|\widehat{F}(v;t)| + |F(v;t)|}.$$

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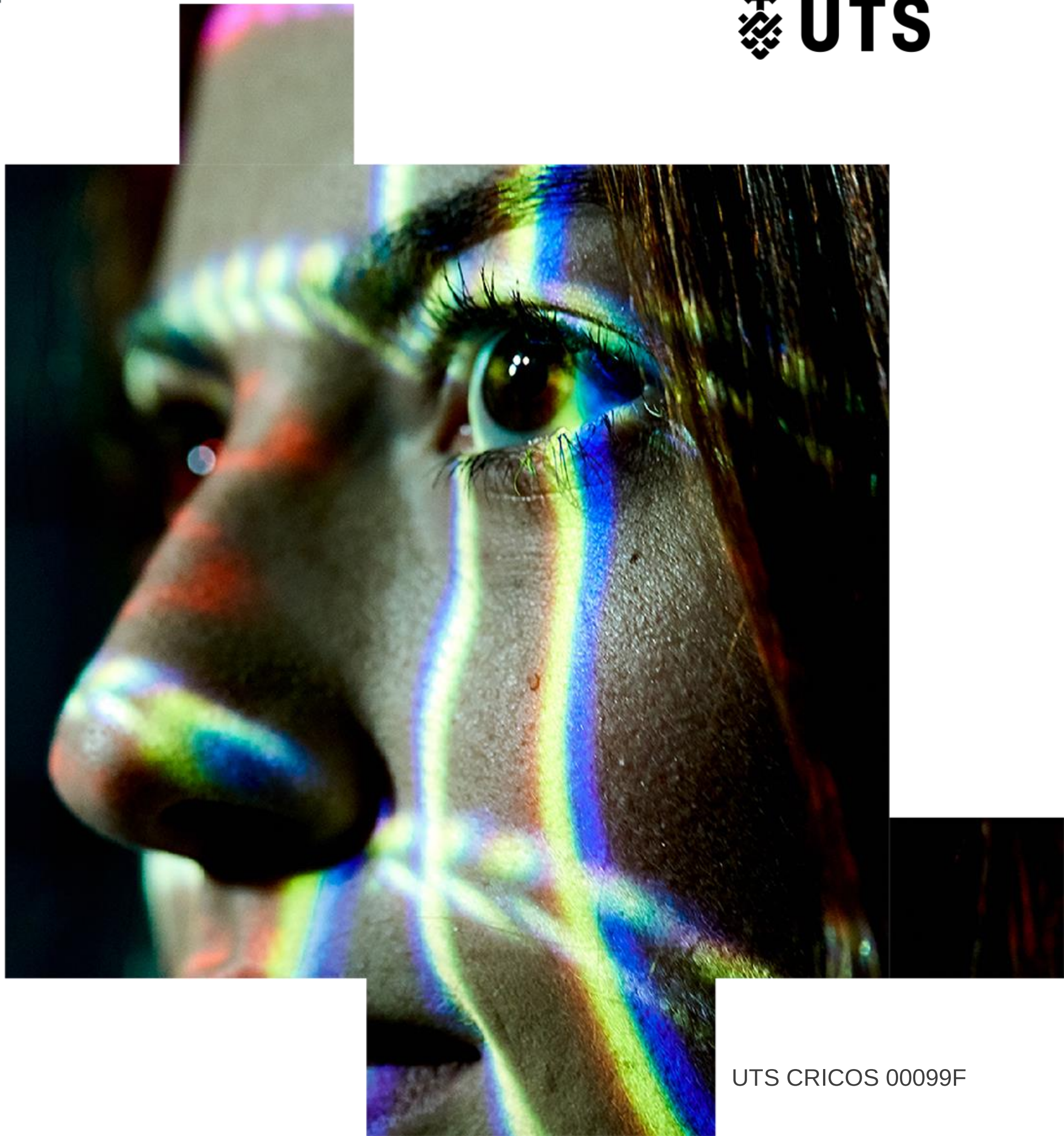


Results – anomaly and outlier treatment

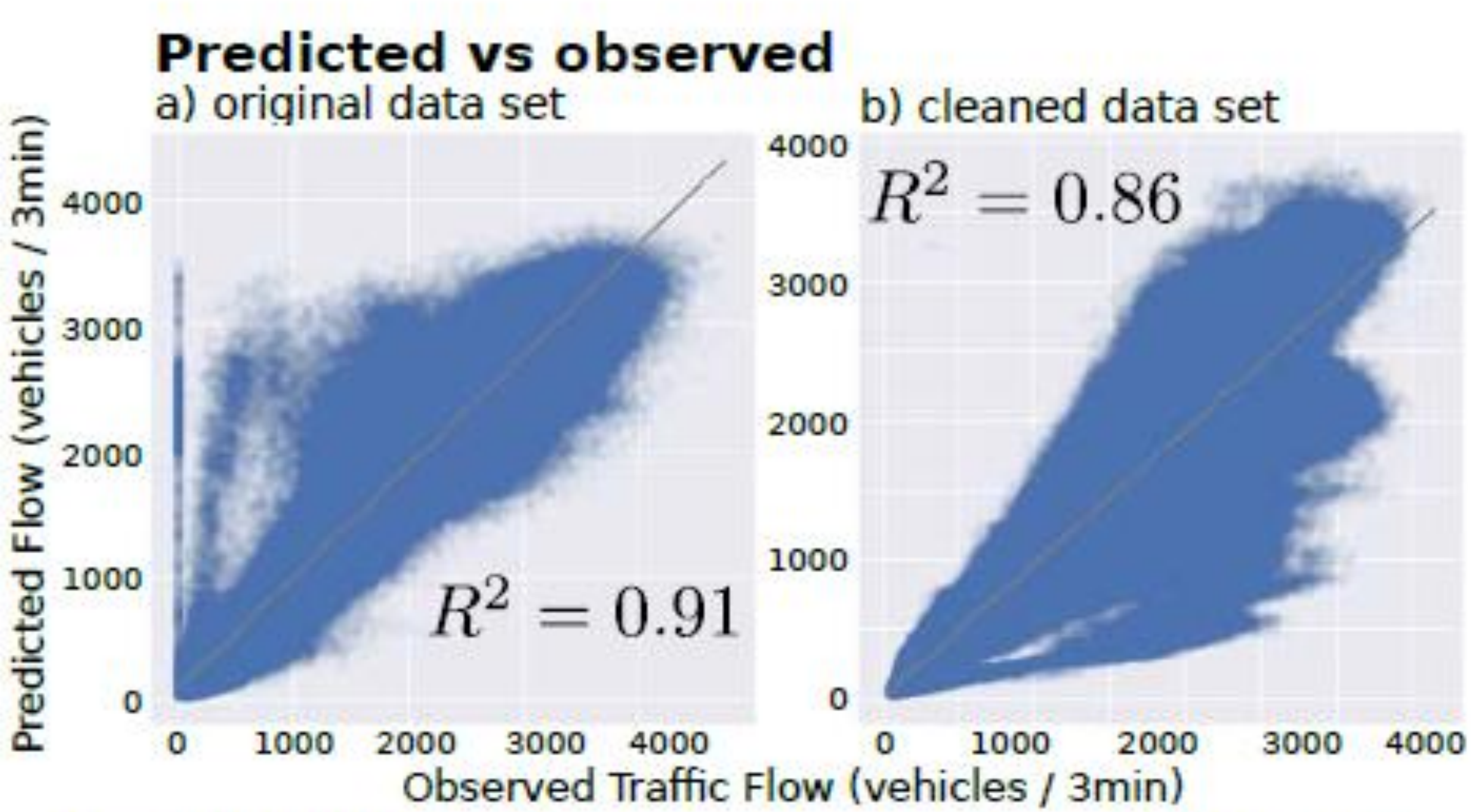
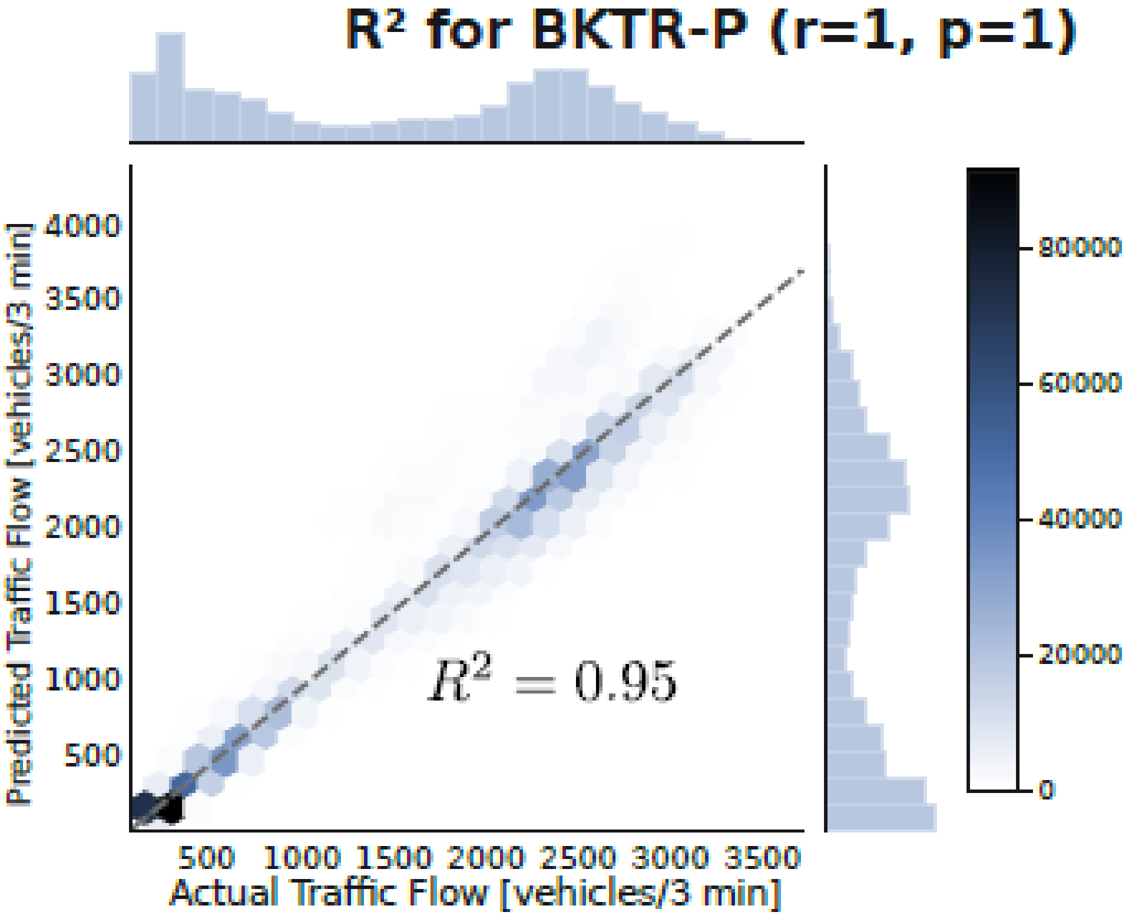
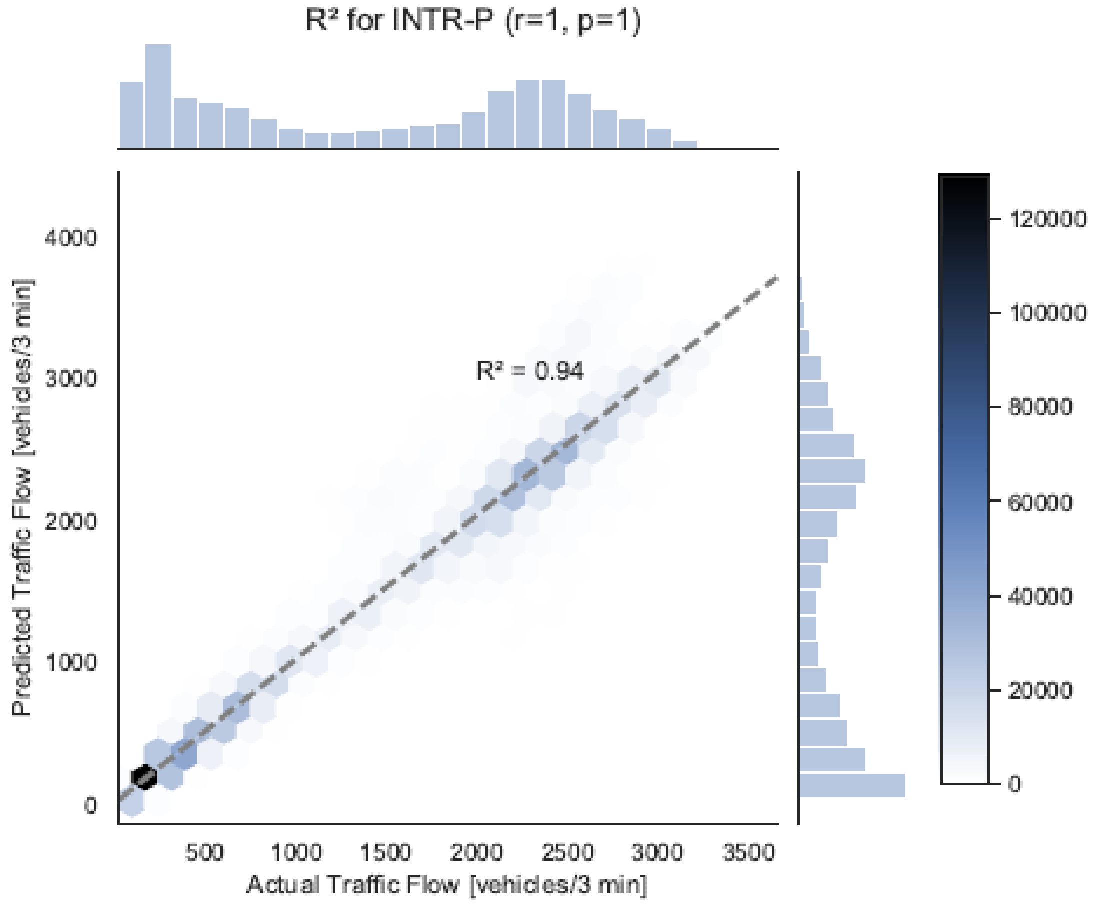


Fig. 4: Daily Profile Predictor before and after data cleaning.

Results – BKTR-P and INTR-P





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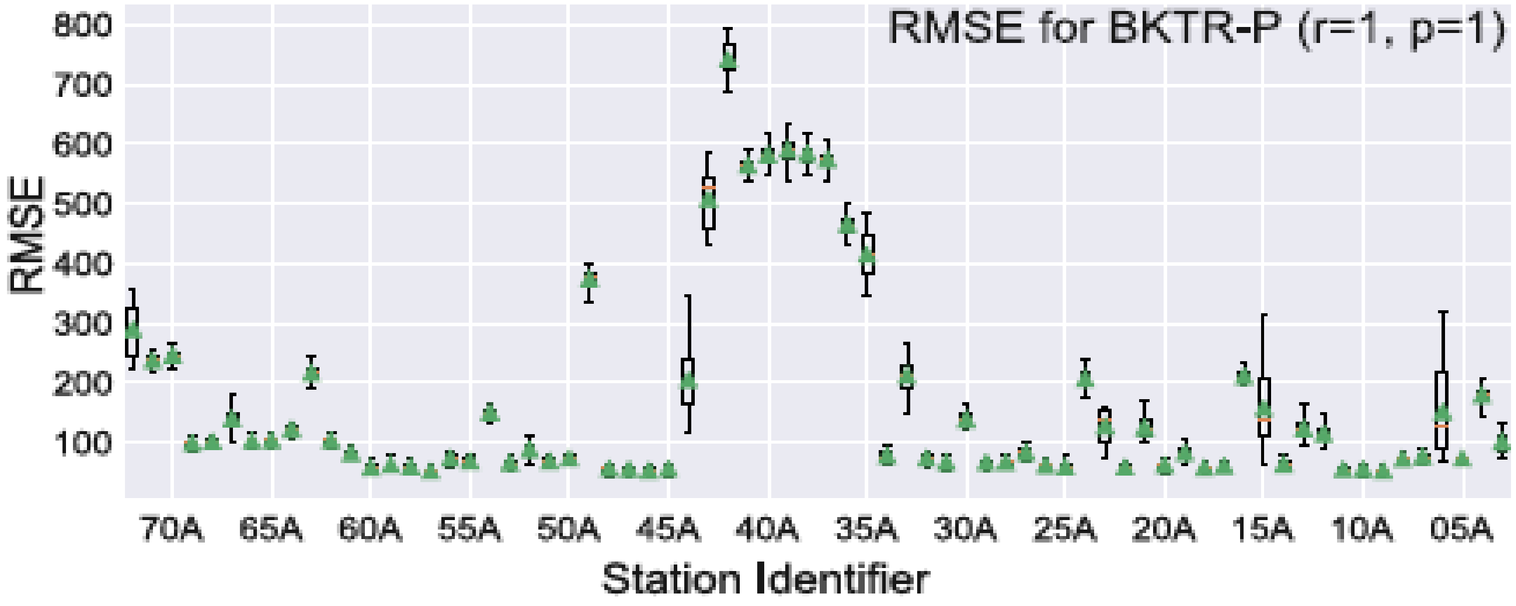

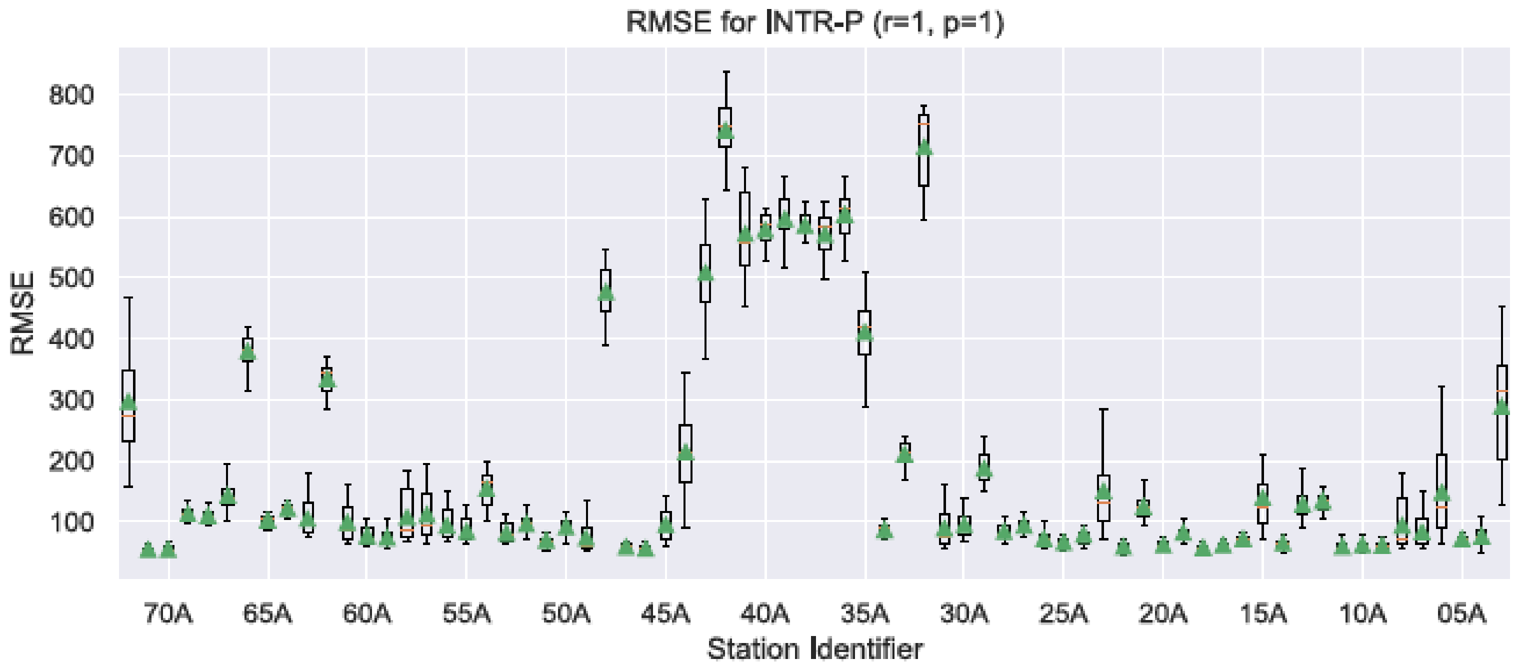

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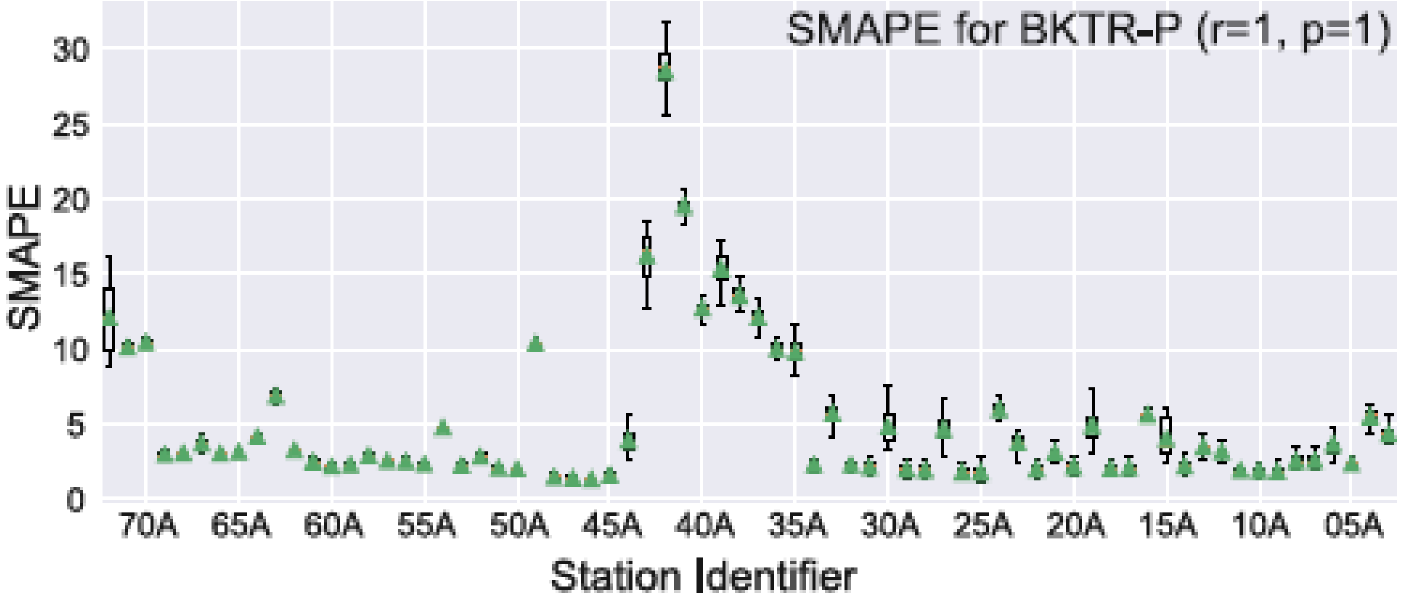
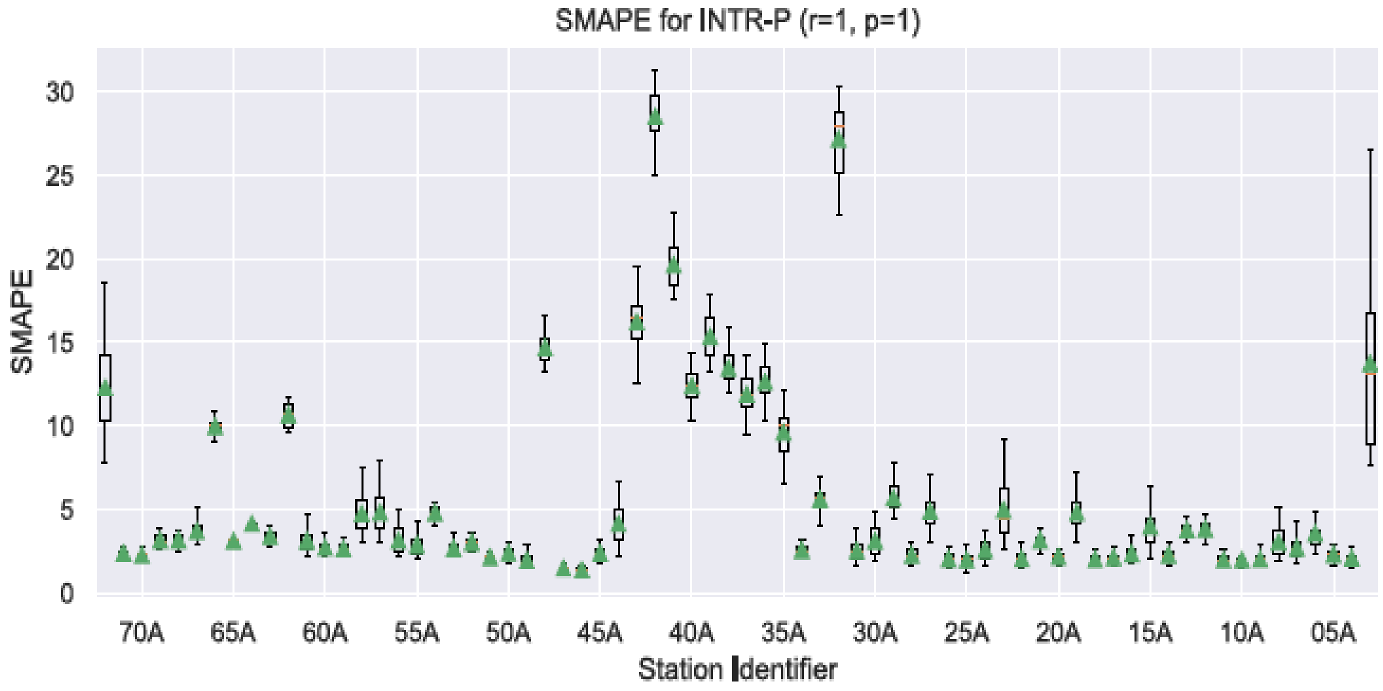
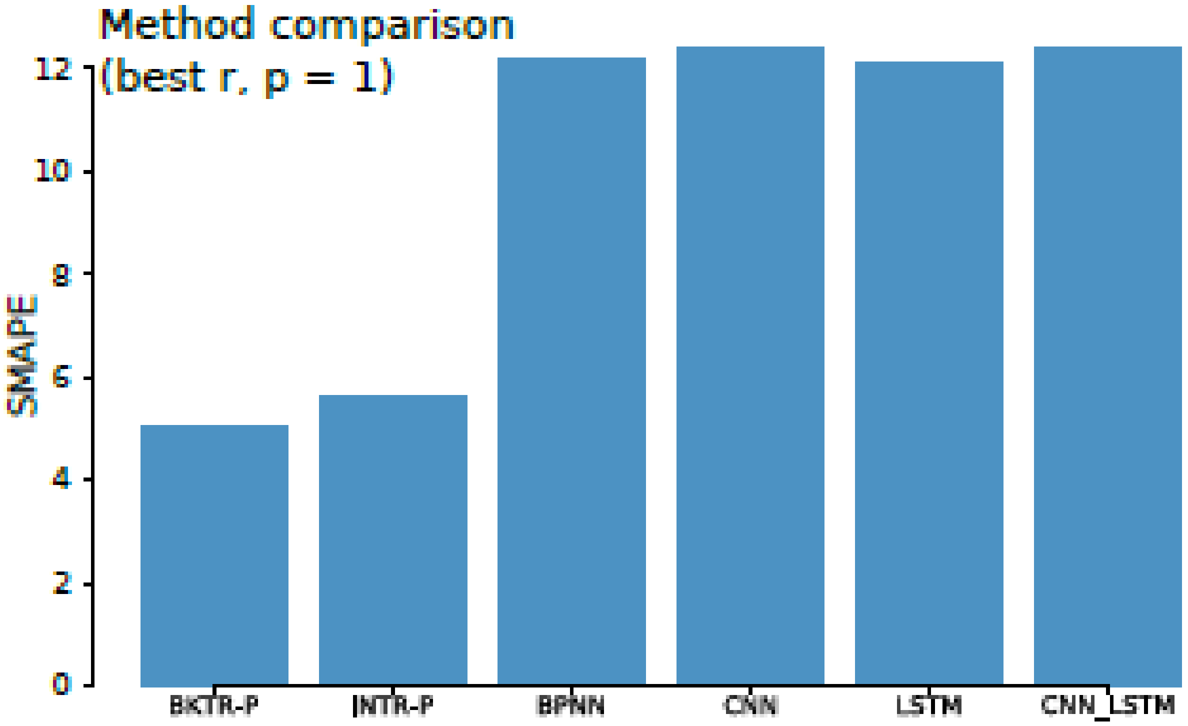




Results – comparison with other DL models



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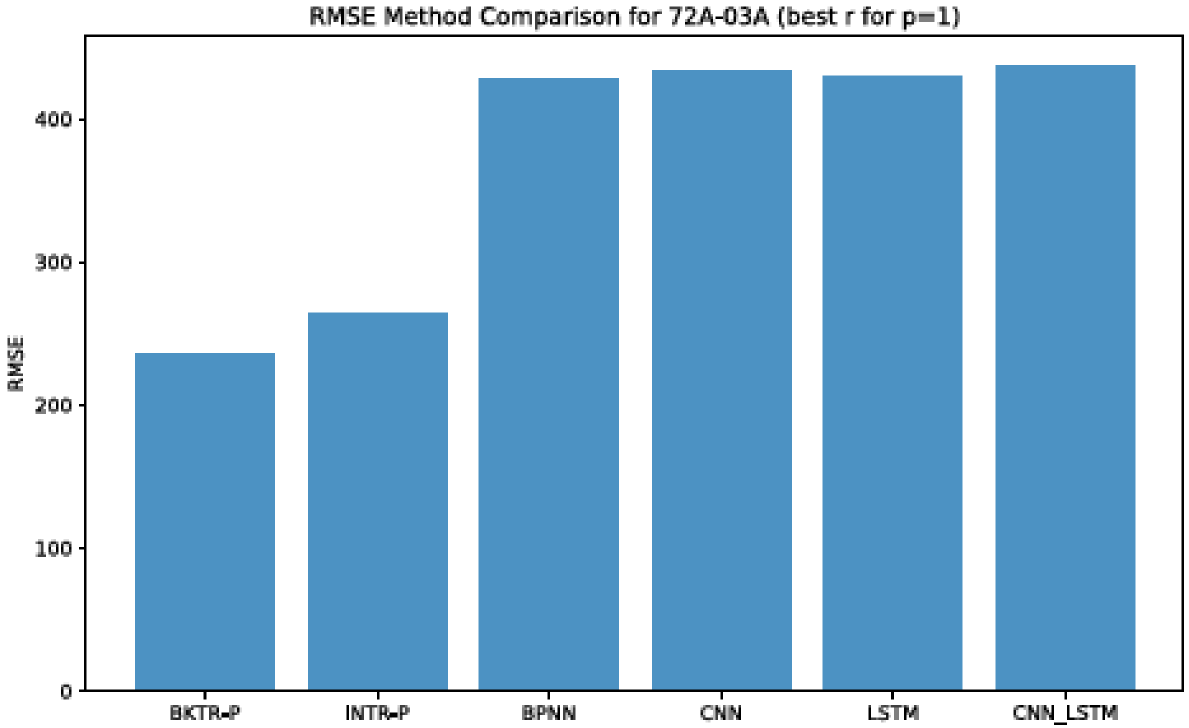

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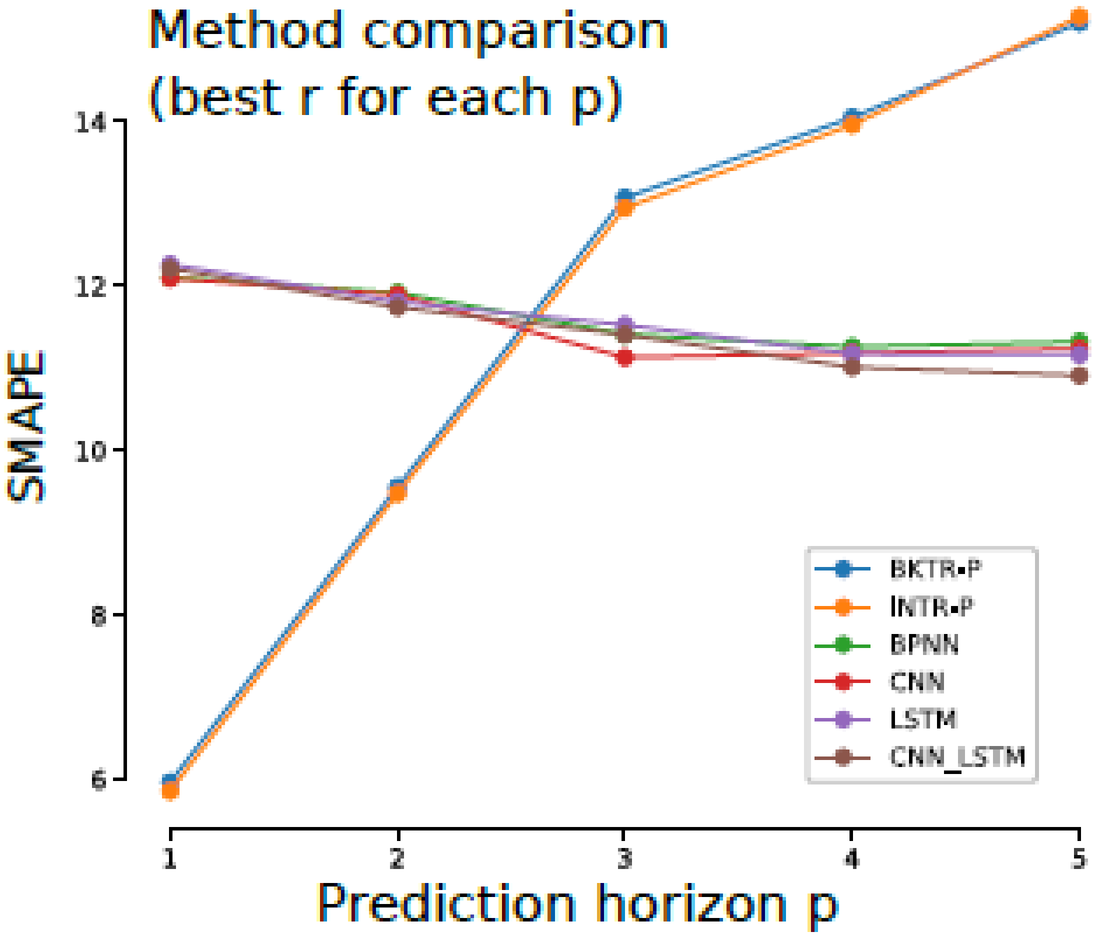

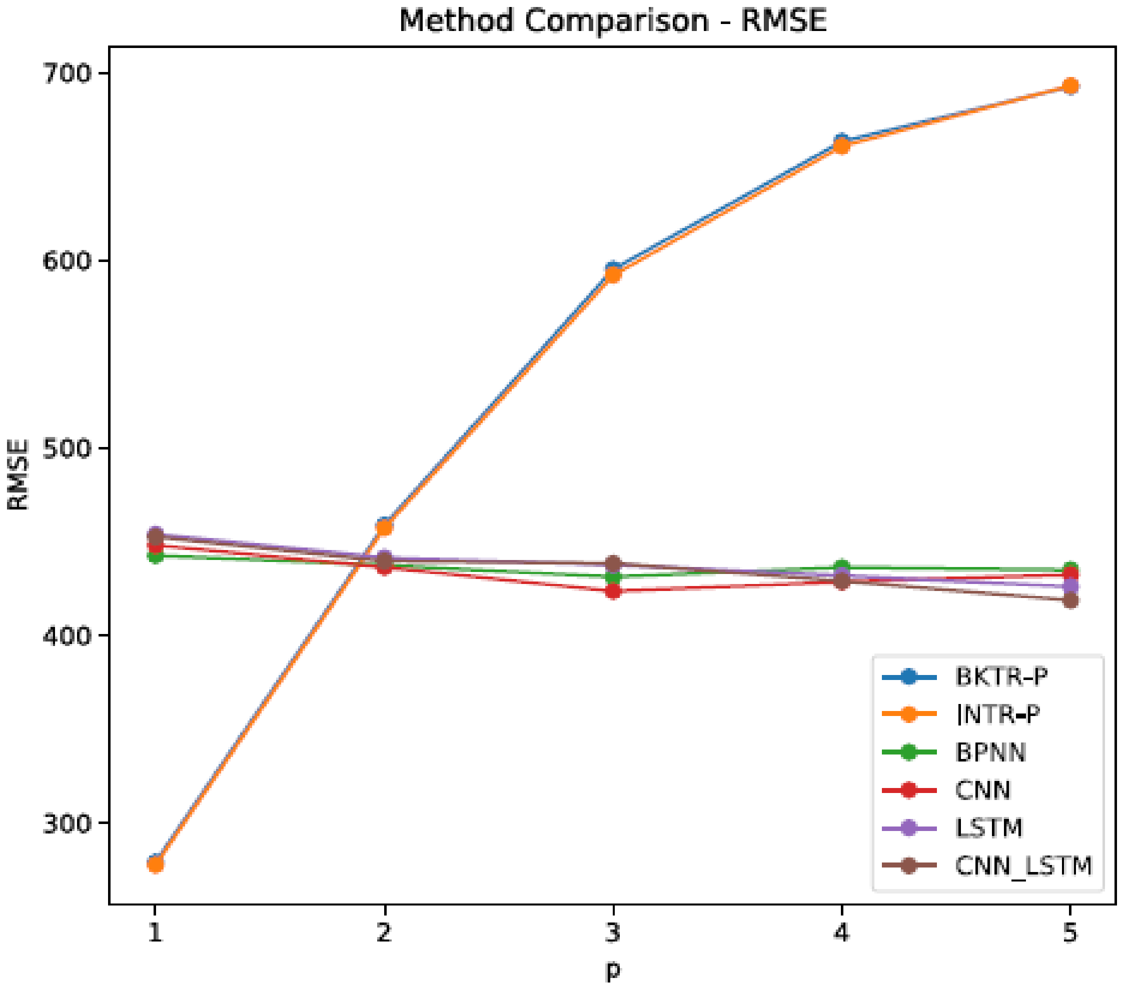

Conclusions

1. Backtracking algorithm outperforms for short term predictions (less than 10 minutes) all other models, including daily profile prediction, interpolation model and deep learning models (LSTM, CNN, and hybrid CNN-LSTM).

2. The more complex deep learning models do not improve the prediction accuracy for our motorway flow prediction study.

Limitations

(1) The algorithms assume no branching structure of the motorway, i.e. we only have one main flow, plus entries and exits. If we had two or more motorways, the traffic at a given station, at a given time point could have originated from multiple points in the past, from all motorways;

(2) the methods need to be tested against more complex network structures such as regular urban traffic networks, when the complexity of the graph increases;

(3) testing the performance of the current models against GCNNs, a popular version of CNN which embeds the graph structure of the network as well

QUESTIONS?

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2 PhD Opportunities:

- A.I. for traffic management
- Traffic control for connected and autonomous vehicles

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