

UNIVERSITY OF TECHNOLOGY SYDNEY

School of Electrical and Data Engineering

**Modeling, Analysis and Application of Big Traffic
Data for Intelligent Transportation Systems**

by

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Certificate of Authorship/Originality

I, Peibo Duan declare that this thesis, is submitted in fulfillment of the requirements for the award of doctorate, in the School of Electrical and Data Engineering at the University of Technology Sydney.

This thesis is wholly my own work unless otherwise reference or acknowledged. In addition, I certify that all information sources and literature used are indicated in the thesis.

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ABSTRACT

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Intelligent Transportation System (ITS), an integrated system of people, roads, and vehicles by utilizing information and communications technology, has emerged as an efficient way of improving the performance of transportation systems, enhancing travel security, and providing more choice to travelers. Recently, it has been seen that the big data era for ITS is coming due to the wide use of traffic detectors like traffic cameras and GPSs. These traffic detectors can collect various types of traffic data that significantly contribute to the development of ITS, which has the benefit of the public with convenient and safe travel.

With big traffic data, data-driven methods provide powerful and theoretical support for data modeling, analysis, and applications. However, existing methods still suffer from some shortcomings. First, traffic predictors usually use black-box methods to capture the spatiotemporal correlation between traffic. As a result, it reduces the flexibility of predictors due to the time-varying spatial-temporal correlation caused by frequent variation of road conditions. Second, it is impossible to cover all urban areas with traffic detectors. Thus, data absence and data sparsity have an essential impact on the reliability of travel state monitoring in a large road network. Lastly, most big data applications are based on the centralized method for processing and analyzing data, which consume more time and computational resources, optimal decision making. These make research on big traffic data in ITS become both exciting and essential.

In this thesis, a physically intuitive approach is developed for short-term traffic

flow prediction that captures the time-varying spatiotemporal correlation between traffic, mainly attributed to the road network topology, travel speed, and trip distribution. Experimental results demonstrate its superior accuracy and lower computational complexity compared with its counterparts. After that, a novel methodology is presented to estimate link travel time distributions (TTDs) using end-to-end (E2E) measurements detected by the limited traffic detectors. The experimental results show that the estimated results are in excellent agreement with the empirical distributions. Lastly, a distributed scheme is proposed for taxi cruising route recommendations based on taxi demands predicted by the proposed Graph Convolutional Network (GCN) based method. Experiment and simulation are both implemented. Experimental results validate the accuracy of the proposed taxi demand predictor. Simulation results indicate that our proposed taxi recommendation scheme is better than its counterparts in the aspects of minimizing the number of vacant taxis and maximizing the global revenue of taxi drivers.

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List of Publications

The following is a list of publications in refereed journals and conference proceedings produced during my Ph.D. candidature. In some cases, the journal papers contain material overlapping with the conference publications.

Journal Papers

- J-1. **Peibo Duan**, Changsheng Zhang, Guoqiang Mao, and Bin Zhang, "Applying distributed constraint optimization approach to the user association problem in heterogeneous networks," *IEEE Transactions on Cybernetics*, vol. 48, no. 6, pp. 1696-1707, 2018.
- J-2. **Peibo Duan**, Guoqiang Mao, Weifa Liang, Degan Zhang, "A Unified Spatio-temporal Model for Short-term Traffic Flow Prediction," **Accepted** by *IEEE Transactions on Intelligent Transportation System*, NOV. 2018.
- J-3. **Peibo Duan**, Guoqiang Mao, Baoqi Huang, Jun Kang, "Estimation of Link Travel Times Distribution with Limited Traffic Detectors," **Accepted** by *IEEE Transactions on Intelligent Transportation System*, 2019.

Conference Papers

- C-1. **Peibo Duan**, Guoqiang Mao, Shangbo Wang, Changsheng Zhang and Bin Zhang, "STARIMA-based Traffic Prediction with Time-varying Lags," *IEEE 19th Int. Conf. on Intelligent Transportation Systems*, pp. 1610-1615, 2016.
- C-2. **Peibo Duan**, Guoqiang Mao, Wenwei Yue, and Shangbo Wang, "A Trade-off between Accuracy and Complexity: Short-term Traffic Flow Prediction with Spatio-temporal Correlations," *IEEE 21th Int. Conf. on Intelligent Transportation Systems*, pp. 1658-1663, 2018.

- C-3. **Peibo Duan**, Guoqiang Mao, Changsheng Zhang, and Jun Kang, "A Unified STARIMA based Model for Short-term Traffic Flow Prediction," *IEEE 21th Int. Conf. on Intelligent Transportation Systems*, pp. 1652-1657, 2018.
- C-4. **Peibo Duan**, Guoqiang Mao, Baoqi Huang, and Jun Kang, "Estimating Link Travel Time Distribution Using Network Tomography Technique," **Accepted** by *IEEE 22th Int. Conf. on Intelligent Transportation Systems*, Jun. 2019.

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Abbreviation

ARIMA - AutoRegressive Integrated Moving Average

ANN - Artificial Neural Network

ARIMAX - ARIMA with EXogenous variables

BPNN - Back Propagation Neural Network

BN - Bayesian Network

BTMS - Bluetooth Traffic Monitoring System

BFS - Breadth First Search

CNN - Convolutional Neural Network

CDF - Cumulative Density Function

DTMC - Discrete Time Markov Chains

DCRNN - Diffusion Convolutional Recurrent Neural Network

EM - Expectation Maximization

E2E - End-to-End

FCL-Net - Fusion Convolutional Long short-term memory Network

GNN - Graph Neural Network

GMM - Gaussian Mixture Model

GCN - Graph Convolutional Network

GN - GirvanNewman

HPP - Homogeneous Poisson Process

HW - Holt Winters

ITS - Intelligent Transportation System

KARIMA - Kohonen ARIMA

KNN - K Nearest Neighbor

KDE - Kernel Density Estimator
LSTM - Long Short Term Memory
MAC - Media Access Control
MDP - Markov Decision Process
MIP - Mixed Integer Programming
POI - Position of Interest
PDF - Probability Density Function
RNN - Recursive Neural Network
STARIMA - Space-Time ARIMA
SVR - Support Vector Regression
SARIMA - Seasonal ARIMA
STW-KNN - Spatio-Temporal Weighted KNN
SVD - Singular Value Decomposition
STL - Seasonal and Trend decomposition using Loess
STGCNN - Spatial-Temporal Graph Convolutional Neural Network
STM-GCN - Spatio-Temporal multi-GCN
SACF - Spatial AutoCorrelation Function
SPACF - Spatial Partial AutoCorrelation Function
SMS - Space Mean Speed
TTP - Traffic Transition Probability
TMS - Time Mean Speed
TTD - Travel Time Distribution