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Deep Learning for Trajectory-Based Transportation Mode Identification

by Christos Markos

Thesis submitted in fulfilment of the requirements for the degree of

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Certificate of Original Authorship

I, Christos Markos declare that this thesis, is submitted in fulfilment of the requirements for the award of Doctor of Philosophy in the School of Electrical and Data Engineering, Faculty of Engineering and Information Technology at the University of Technology Sydney.

This thesis is wholly my own work unless otherwise referenced or acknowledged. In addition, I certify that all information sources and literature used are indicated in the thesis. I certify that the work in this thesis has not previously been submitted for a degree nor has it been submitted as part of the requirements for a degree at any other academic institution except as fully acknowledged within the text. This thesis is the result of a Collaborative Doctoral Research Degree program with the Southern University of Science and Technology.

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ABSTRACT

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Understanding users' mobility patterns and associated transportation modes is essential for intelligent transportation management and infrastructure design. Through the ubiquity of Global Positioning System (GPS) sensors in modern smartphones and vehicles, rich spatiotemporal trajectories can be readily captured for use in intelligent transportation applications. Key among the latter is transportation mode identification, or how to infer travel modes within GPS trajectories. Although studied extensively, its real-world applicability remains limited due to several challenges.

GPS trajectories are often incomplete due to signal lapses, thereby complicating subsequent analysis. Since learning from raw GPS data restricts model generalization to the regions best covered in the training set, this thesis sets an alternative imputation target: approximate missing GPS points by learning to impute relative magnitude and angle of displacement features. The proposed Uncertainty-aware Imputation Generative Adversarial Network (UI-GAN) leverages a Bayesian generator to capture imputation uncertainty and a window-level discriminator for localized sequence structure penalization. UI-GAN produces high-fidelity GPS points and outperforms established imputation baselines.

A single GPS trajectory may encompass multiple transportation modes. Existing trajectory segmentation approaches often exhibit poor scalability and require extensive feature engineering or transportation domain knowledge. As such, this thesis reframes trajectory segmentation as timestep-level transportation mode identification. Concretely, it proposes a shuffling-based data augmentation

scheme and a *majority-vote* post-processing step to effectively train a convolutional neural network for timestep-level classification and refine the extracted segments. The proposed segmentation model is nearly twice as accurate as the best performing baseline in detecting transportation mode changes.

In reality, GPS trajectories are neither automatically annotated nor segmented by transportation mode. In addition, predictive uncertainty tied to model parameters or noise in GPS readings is typically unaccounted for. Therefore, this thesis proposes an unsupervised channel-calibrated Bayesian Temporal Convolutional Network (BTCN) trained to maximize the mutual information between neighboring feature map patches. By approximating variational inference, BTCN can both classify each input timestep and estimate its predictive uncertainty. BTCN significantly outperforms established trajectory segmentation baselines without using any labels.

Finally, this thesis proposes an unsupervised deep learning approach to transportation mode identification. First, a clustering layer maintaining cluster centroids as trainable weights is attached to the embedding layer of a convolutional autoencoder. The composite model is then trained by optimizing a weighted sum of reconstruction and clustering losses to encourage learning clustering-friendly representations. By further incorporating segment-level features, the proposed model outperforms traditional clustering and state-of-the-art semi-supervised methods without using any labels.

Dedication

I dedicate this thesis to my wonderful parents Costas and Sophia, whose constant support, love, and encouragement saw me through the difficult times of this journey. I also dedicate my thesis to my grandfather, Christos, whose unwavering pride in me boosted my self-confidence and gave me the motivation to someday be the man he saw me as. Finally, I dedicate this work to my partner Danae and her mother Lucy, who were always there to both listen to my frustrations and celebrate my accomplishments.

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List of Publications

Journal Papers

J-1. C. Zhang, Y. Zhu, **C. Markos**, S. Yu, and J. J. Q. Yu, "Towards Crowd-sourced Transportation Mode Identification: A Semi-supervised Federated Learning Approach," *IEEE Internet of Things Journal.* Under review.

J-2. S. Zhang, **C. Markos**, and J. J. Q. Yu, "Autonomous Vehicle Intelligent System: Joint Ride-Sharing and Parcel Delivery Strategy," *IEEE Transactions on Intelligent Transportation Systems.* Under review.

J-3. J. J. Q. Yu, **C. Markos**, and S. Zhang, "Long-Term Urban Traffic Speed Prediction with Deep Learning on Graphs," *IEEE Transactions on Intelligent Transportation Systems*, in press.

Conference Papers

C-1. Y. Zhu, **C. Markos**, and J. J. Q. Yu, "Improving Transportation Mode Identification with Limited GPS Trajectories," in *IEEE 24th International Conference on Intelligent Transportation Systems (ITSC)*, 2021. Under review.

C-2. Y. Zhu, **C. Markos**, R. Zhao, Y. Zheng, and J. J. Q. Yu, "FedOVA: One-vs-All Training Method for Federated Learning with Non-IID Data," in *2021 International Joint Conference on Neural Networks (IJCNN)*, 2021.

C-3. **C. Markos**, J. J. Q. Yu, and R. Y. D. Xu, "Capturing Uncertainty in Unsupervised GPS Trajectory Segmentation Using Bayesian Deep Learning," in *Proceedings of the AAAI Conference on Artificial Intelligence (AAAI)*, vol. 35, no. 1, 2021, pp. 390–398.

C-4. **C. Markos** and J. J. Q. Yu, "Unsupervised Deep Learning for GPS-Based Transportation Mode Identification," in *IEEE 23rd International Conference on Intelligent Transportation Systems (ITSC)*, 2020.

C-5. X. Song, **C. Markos**, and J. J. Q. Yu, "MultiMix: A Multi-Task Deep Learning Approach for Travel Mode Identification with Few GPS Data," in *IEEE 23rd International Conference on Intelligent Transportation Systems (ITSC)*, 2020.

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Nomenclature

Acronyms / Abbreviations

ACC	Accuracy
AUC	Area Under Curve
CAE	Convolutional AutoEncoder
CNN	Convolutional Neural Network
FCN	Fully Convolutional Network
GAN	Generative Adversarial Network
GIS	Geographic Information System
GMM	Gaussian Mixture Model
GPS	Global Positioning System
HAC	Hierarchical Agglomerative Clustering
ITS	Intelligent Transportation System
KL	Kullback-Leibler
KM	k-Means
k-NN	k-Nearest Neighbors
LSTM	Long Short-Term Memory
MAE	Mean Absolute Error
MC	Monte Carlo
MF	Matrix Factorization
MICE	Multiple Imputation using Chained Equations
mIoU	mean Intersection over Union
MLP	MultiLayer Perceptron

NMI	Normalized Mutual Information
PR	Prediction Ratio
ReLU	Rectified Linear Unit
RF	Random Forest
RNN	Recurrent Neural Network
SAE	Stacked AutoEncoder
SC	Spectral Clustering
SVM	Support Vector Machine
TCN	Temporal Convolutional Network
VAE	Variational AutoEncoder

Notation

Lowercase non-bold characters denote scalar quantities (e.g., x, λ); uppercase non-bold characters denote constant scalars (e.g., M, N, K); lowercase bold characters denote vectors (e.g., $\mathbf{x}$); uppercase bold characters denote matrices (e.g., $\mathbf{X}$); uppercase bold Euler characters denote tensors (e.g., $\boldsymbol{\mathcal{X}}$). We let $\mathbf{x}_i$ denote the i-th element of vector $\mathbf{x}$. Instead, $\mathbf{X}_{i,:}$ denotes the i-th row of matrix $\mathbf{X}$, while $\mathbf{X}_{i,j}$ denotes the element at row i, column j. We use $\mathbf{X} \odot \mathbf{Y}$ to denote the Hadamard or element-wise product between matrices $\mathbf{X}$ and $\mathbf{Y}$. We denote the transpose operation on matrix $\mathbf{X}$ as $\mathbf{X}^\mathsf{T}$. Finally, we use $\mathbb{R}$ and $\mathbb{Z}^+$ to denote the sets of real numbers and positive integers, respectively.