MIT Fall 2019 V20191024

Deep Learning for Urban Mobility

Logistics

- Course Number: Old: 11.s938J/11.S196J → New: 11.S955 and 11.S198
- Instructors
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- Tuesday 11:00-12:30; MIT 9-450A
- Credit: 2-0-4 P/D/F
- Graduate and Undergraduate (Years 3 and 4):
- Prerequisite: 6.001 Python and 6.036 Introduction to Machine Learning or equivalent
- Course listing: http://dusp.mit.edu/subject/fall-2019-11s938
- Stellar:

Introduction

Explores deep learning (DL) methods for urban mobility applications. Covers concepts of algorithmic prediction, interpretability, causality, and fairness in the context of urban mobility system design and policy making. Topics include demand prediction at both individual and aggregate levels, decision making with and without uncertainty, vehicle and ride sharing, built environment and travel behavior, traffic prediction and control, maps and information provision, and multimodal system design. Students learn intuitions and methods in DNN, CNN, RNN and reinforcement learning, build hands-on models using real-world datasets, and design and implement group projects. At the intersection of machine learning methods and urban mobility applications, the course seeks to reconcile the tension between generic-purpose models and domain-specific knowledge. Furthermore, the course envisions and critically reflects on how machine learning methods shape transportation research and mobility industry, and examines the potentials and pitfalls of their applications in urban mobility business and policies.

Schedule (13 Tuesdays)

Part I: Introduction and DNN Basics		Term Project
Sep 10	Introduction: Deep Learning Meets Transportation	
Part II: Passenger and Traffic Flow Prediction		
Sep 17	Introducing the toolbox: Deep Learning Basics, CNN, RNN, LSTM	
Sep 24	Advanced models: ConvLSTM, encoder-decoder, Attention	
Oct 1	Guest Lecture Prof. Justin Dauwels	
Oct 8	Advanced models: graph embeddings and Generative models (VAE)	Idea
Part III: DNN and Demand Analysis		
Oct 22	DNN and Discrete Choice 1	
Oct 29	DNN and Discrete Choice 2 Guest Lecture Prof Hai Wang	
Nov 5	DNN and Prospect Theory	Proposal
Part IV: Reinforcement Learning and Control in Transportation		
Nov 12	RL and Control Part 1	
Nov 19	RL and Control Part 2	
Nov 26	Guest Lecture Prof. Cathy Wu	Full Report
Part V: FAT and Summary		
Dec 3	Fairness, Accountability and Transparency	
Dec 10	Student Presentation	Revised Report

Modules

Part I: Course Introduction: Deep Learning Meets Urban

1. Urban Mobility Overview
2. Data in Urban Transportation
3. Machine Learning Applications in Transportation
    a. ML for Public Transit: Demand, Supply and Control
    b. ML for ride hailing services
    c. Representation

    d. ML and Travel Behavior Modeling
    e. Population synthesis
    f. Transportation Planning
4. Tensions in DNN and Transportation
    a. Role of Models
    b. Role of Theory
    c. Knowledge production
5. Reading
    a. Karlaftis, M. G., & Vlahogianni, E. I. (2011). Statistical methods versus neural networks in transportation research: Differences, similarities and some insights. Transportation research part C: emerging technologies, 19(3), 387-399.
    b. LeCun, Y., Bengio, Y., & Hinton, G. (2015). Deep learning. Nature, 521(7553), 436-444.
    c. Poggio, T., Banburski, A., & Liao, Q. (2019). Theoretical Issues in Deep Networks: Approximation, Optimization and Generalization. *arXiv preprint arXiv:1908.09375*.

Part II Passenger and Traffic Flow Prediction [Peyman]
Introducing the toolbox: Deep Learning Basics

1. Predictive methods; statistical vs Machine learning
2. Deep Neural Network 101: Theory and Practice:
    a. DNN Basics
    b. Regularization techniques
    c. Demand Prediction
    d. CNN, RNN, LSTM
3. Core Reading
    a. Wang, Y., Zhang, D., Liu, Y., Dai, B., & Lee, L. H. (2018). Enhancing transportation systems via deep learning: a survey. Transportation research part C: emerging technologies. [Paper]
    b. Yao, H., Wu, F., Ke, J., Tang, X., Jia, Y., Lu, S., ... & Li, Z. (2018, April). Deep multi-view spatial-temporal network for taxi demand prediction. In Thirty-Second AAAI Conference on Artificial Intelligence. [Paper]
4. Recommended Reading
    a. Vlahogianni, E. I., Karlaftis, M. G., & Golias, J. C. (2014). Short-term traffic forecasting: Where we are and where we're going. *Transportation Research Part C: Emerging Technologies*, *43*, 3-19. [Paper]
    b. Ke, J., Zheng, H., Yang, H., & Chen, X. M. (2017). Short-term forecasting of passenger demand under on-demand ride services: A spatio-temporal deep learning approach. Transportation Research Part C: Emerging Technologies, 85, 591-608.
    c. Traffic speed prediction for urban transportation network: A path based deep learning approach [Papers]

d. Polson, N. G., & Sokolov, V. O. (2017). Deep learning for short-term traffic flow prediction. *Transportation Research Part C: Emerging Technologies*, *79*, 1-17. [Paper]
e. Lv, Y., Duan, Y., Kang, W., Li, Z., & Wang, F. Y. (2014). Traffic flow prediction with big data: a deep learning approach. *IEEE Transactions on Intelligent Transportation Systems*, *16*(2), 865-873. [Paper]

5. Practicals: * Tensorflow/Keras/PyTorch

Advanced models: ConvLSTM, encoder-decoder, Attention

1. Application: Aggregate and individualized prediction models
2. Core Reading
   a. Zhang, J., Zheng, Y., Qi, D., Li, R., Yi, X., & Li, T. (2018). Predicting citywide crowd flows using deep spatio-temporal residual networks. Artificial Intelligence, 259, 147-166. [Paper]
   b. Yao, Huaxiu, Fei Wu, Jintao Ke, Xianfeng Tang, Yitian Jia, Siyu Lu, Pinghua Gong, Jieping Ye, and Zhenhui Li. "Deep multi-view spatial-temporal network for taxi demand prediction." In Thirty-Second AAAI Conference on Artificial Intelligence. 2018.
3. Recommended Reading
   a. Liu, Yang, Zhiyuan Liu, and Ruo Jia. "DeepPF: A deep learning based architecture for metro passenger flow prediction." Transportation Research Part C: Emerging Technologies 101 (2019): 18-34.
   b. Yu, Haiyang, Zhihai Wu, Shuqin Wang, Yunpeng Wang, and Xiaolei Ma. "Spatiotemporal recurrent convolutional networks for traffic prediction in transportation networks." Sensors 17, no. 7 (2017): 1501.

Prof. Justin Dauwels: Perception for autonomous vehicles.

1. Prediction of the intention of pedestrians by means of variational RNNs
2. Affine disentangled GANs for robust perception.
3. Readings:
   a. Liu, L., Saerbeck, M., & Dauwels, J. (2019). Affine Disentangled GAN for Interpretable and Robust AV Perception. arXiv preprint arXiv:1907.05274.
   b. Hoy, M., Tu, Z., Dang, K., & Dauwels, J. (2018, November). Learning to Predict Pedestrian Intention via Variational Tracking Networks. In 2018 21st International Conference on Intelligent Transportation Systems (ITSC) (pp. 3132-3137). IEEE.

Advanced models: graph embeddings and generative models

1. Applications: Missing data imputation, traffic speed prediction, passenger demand prediction, traffic flow prediction
2. Core Readings

    a. Borysov, Stanislav S., Jeppe Rich, and Francisco C. Pereira. "How to generate micro-agents? A deep generative modeling approach to population synthesis." Transportation Research Part C: Emerging Technologies 106 (2019): 73-97.
    b. Lin, Lei, Zhengbing He, and Srinivas Peeta. "Predicting station-level hourly demand in a large-scale bike-sharing network: A graph convolutional neural network approach." Transportation Research Part C: Emerging Technologies 97 (2018): 258-276.
3. Recommended Reading
    a. Short-term forecasting of passenger demand under on-demand ride services: A spatio-temporal deep learning approach [Paper]
    b. A hybrid deep learning based traffic flow prediction method and its understanding [Paper]
    c. Wu, Yuankai, Huachun Tan, Lingqiao Qin, Bin Ran, and Zhuxi Jiang. "A hybrid deep learning based traffic flow prediction method and its understanding." Transportation Research Part C: Emerging Technologies 90 (2018): 166-180.
    d. Yao, Huaxiu, Xianfeng Tang, Hua Wei, Guanjie Zheng, Yanwei Yu, and Zhenhui Li. "Modeling spatial-temporal dynamics for traffic prediction." arXiv preprint arXiv:1803.01254 (2018).
    e. DeepTransport: Learning Spatial-Temporal Dependency for Traffic Condition Forecasting [Paper]

Part III DNN and Demand Analysis [Shenhao]
Demand Analysis without Uncertainty: DNN + Discrete Choice Model

1. Travel Demand Analysis: Theory, Method and Data
    a. Choice Models and Other Classifiers
    b. Connect Discrete Choice Model to Deep Neural Network
    c. DNN & DCM: Interpretability & Robustness
2. Core Readings
    a. Train, K. E. (2009). Discrete choice methods with simulation: Cambridge university press. Chapter 1 & 3. [Paper]
    b. Lipton, Z. C. (2016). The mythos of model interpretability. arXiv preprint arXiv:1606.03490. [Paper]
    c. Wang, S., Wang, Q., and Zhao, J. (2019). Deep Neural Networks for Choice Analysis: Extracting Complete Economic Information for Interpretation. [Paper]
    d. Wang, S. and Zhao, J. (2019). Deep Neural Networks for Choice Analysis: Architectural Design with Alternative-Specific Utility Functions. [Paper].
3. Recommended Readings
    a. Ben-Akiva, M., Bierlaire, M., McFadden, D., & Walker, J. (2014). Discrete Choice Analysis. Chapter 1 & 4.
    b. Wang, S., Wang, Q., Bailey, N., and Zhao, J. (2019) Deep Neural Networks for Choice Analysis: A Statistical Learning Theory Perspective. [Paper].

c. Wang, S., Wang, Q., and Zhao, J. (2019). Multitask Learning Deep Neural Networks to Combine Revealed and Stated Preference Data. [Paper].
d. McFadden, D. (1974). Conditional logit analysis of qualitative choice behavior. [Paper]

Demand Analysis with Uncertainty: DNN + Prospect Theory

1. Uncertainties in Transportation
2. Prospect Theory
3. Core Reading
    a. Kahneman, D., & Tversky, A. (1979). Prospect theory: An analysis of decision under risk. Econometrica: Journal of the Econometric Society, 263-291. [Paper]
    b. Li, Z., Hensher, D. A., & Rose, J. M. (2010). Willingness to pay for travel time reliability in passenger transport: A review and some new empirical evidence. Transportation Research Part E: Logistics and Transportation Review, 46(3), 384-403. [Paper]
4. Recommended Readings
    a. Tomomi, T., Camerer, C., and Nguyen, Q. (2010). Risk and time preferences: linking experimental and household survey data from Vietnam. American Economic Review, 100(1) [Paper]
    b. Wang, S. and Zhao, J. (2019). Theory-Based Deep Residual Neural Networks for Analyzing Individual Decision-Making.

Part IV: RL and Control in Transportation [Peyman]
Control Part I: Transit and Traffic: Classical Reinforcement learning with discrete actions space

1. Control in Transportation
2. Q-learning and Sarsa
3. DQN and its variants
4. Practicals: implementing DQN
5. Core readings
    a. Flow: Architecture and Benchmarking for Reinforcement Learning in Traffic Control [Paper]
    b. Emergent behavior in mixed-autonomy traffic [Paper]
6. Recommended Readings
    a. Real-Time Bus Holding Control on a Transit Corridor Based on Multi-Agent Reinforcement Learning [Paper]
    b. Individual Versus Difference Rewards on Reinforcement Learning for Route Choice [Paper]
    c. Dissipating stop-and-go waves in closed and open networks via deep reinforcement learning [Paper]

Control Part II: Advanced deep reinforcement learning with applications in Shared Mobility

1. Shared Mobility: Concept, System and Method
2. Reinforcement learning with continuous action space
3. Readings
    a. Rebalancing Shared Mobility-on-Demand Systems: a Reinforcement Learning [Paper]
    b. A Traffic Prediction Enabled Double Rewarded Value Iteration Network for Route Planning [Paper]
    c. DeepPool: Distributed Model-free Algorithm for Ride-sharing using Deep Reinforcement Learning [Paper]

Control Part III: Prof. Cathy Wu

Part V: FAT and Summary

Dec 3 Fairness, Accountability and Transparency

Dec 10 Student Presentation

Student Expectations

Class participation 20%

Term Project (two students per team)

1. Idea 5% due Oct 8
2. Proposal 15% due Nov 5
3. Full report 30% due Nov 26
4. Revise report 30% due Dec 10

Guidelines on Research Projects

Research Idea

1. 1~2 pages
2. Research questions and significance: why is it important to examine the question from the TRANSPORTATION perspective?
3. Data sets: describe the content of and access to the dataset
4. Machine learning methods (including any methods that are not covered in the class yet)

5. Team: 2~3 persons/team. If you do not have a partner yet, please describe your strengths and weakness, and the complimentary quality of your ideal partners. We'll facilitate to form the team.
6. Risk: any uncertainties and risks in terms of the question, data access, method challenge, or any other things that we can help you with.

Example datasets

1. Smart Card Data: a sample of two weeks' data of a major subway system
2. New York City TLC Trip Record [Link]
3. NHTS 2017
4. Blue Bikes Comprehensive Trip Histories [Link]
5. Open transit data toolkit [Link]
    a. MTA Bus Time® Historical Data [Link]
        i. Bus speeds
        ii. headways
    b. Subway Turnstile Data
        i. Turnstile data tracks the number of entries and exits of passengers in the subway system
6. Didi Opendata [Link]
7. New York City MTA GTFS data [Link]
8. NYC open data including many transportation datasets [Link]
9. Flow provides a way of creating a simulation based on OpenStreetMap data [Link]
10. Google Street View [Link]
11. IOT data [link]