Predicting the Distribution of Car Demand

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Background

Autonomous Mobility-on-demand (AMoD) is a new paradigm for future urban transportation systems. The main challenge of AMoD is that systems are out of balance by asysmmetric demand. To coordinate the system with the time-varying car request efficiently, **predicting the number of demanded cars** is needed. Thus, I build a **car demand forecast model** using **Long Short-Term Memory**.

Dataset and Features

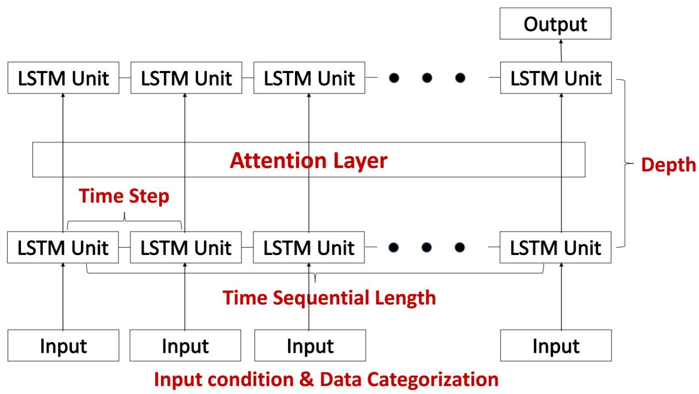
I used Yellow and Green Taxi Pickup Data in New York City from 2014 to 2017 for training and evaluation. Input features of car demands are **weather, date, time and previous car demand.**

	Weather									Date/Time			Previous Car Demand
pick up time	*Temp*	*Windspeed*	*Precipitation*	*Clear*	*Clouds*	*Fog*	*Rain*	*Snow*	*Thunderstorm*	*Holiday*	*Hour*	*Day*	*pick up num*
2014 – 01 – 01 01 : 00	268.90	2.0	1	0	0	0	0	0	0.0	1	2	1	33482
2014 – 01 – 01 02 : 00	268.48	3.0	1	0	0	0	0	0	0.0	2	2	1	36280
2014 – 01 – 01 03 : 00	268.33	3.0	1	0	0	0	0	0	0.0	3	2	1	33154

Model → **Future Car Demand**

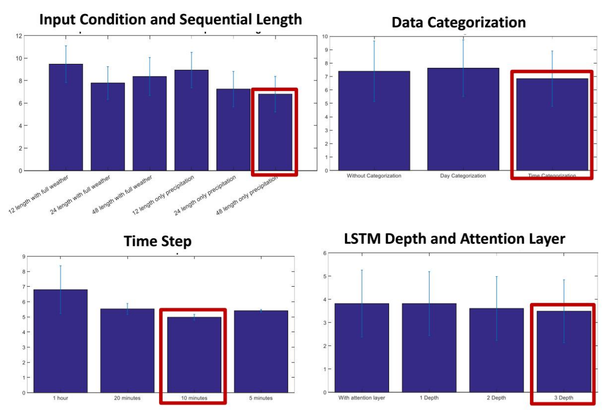
Models

To catch long-term time-series characteristics, I used LSTM models with different parameters. I experimented with respect to **time sequential length**, **time step**, **input condition**, **data categorization**, **depth of LSTM** and **an attention layer.** From these experiments, my goal is finding maximum accuracy of prediction. Except those parameters, I used 100 epochs and 100 batch size for all experiments.



Results and Discussion

From my experiments, I figured out that the optimal parameters are **48** time sequential length, using **only precipitation** input, **10 minutes** time step, **time categorization** and **3 Depth LSTM.** The result is predicting car demand with **3.49%** error.



Future Work

1. Predicting car demand with **other influential information** (e.g. events, news data).
2. Predicting more specific information - not only car demand number but also **area information** (departure and destination).

Reference

[1] Ramon Iglesias, Federico Rossi, Kevin Wang, David Hallac, Jure Leskovec, and Marco Pavone. Data-driven model predictive control of autonomous mobility-on-demand systems. arXiv preprint arXiv:1709.07032, 2017.
[2] Nikolay Laptev, Jason Yosinski, Li Erran Li, and Slawek Smyl. Time-series extreme event forecasting with neural networks at uber. In International Conference on Machine Learning, 2017.
[3] Xuan Song, Hiroshi Kanasugi, and Ryosuke Shibasaki. Deeptransport: Prediction and simulation of human mobility and transportation mode at a citywide level. In IJCAI, pages 2618–2624, 2016.