Providing accurate traffic speed prediction is essential for the success of Intelligent Transportation Systems (ITS) deployments. Accurate traffic speed prediction allows traffic managers to take proper countermeasures when emergent changes happen in the transportation network. In this thesis, we present a computationally less expensive machine learning approach XGBoost to predict the future travel speed of a selected sub-network in Beijing's transportation network. We perform different experiments for predicting speed in the network from future 1 min to 20 min. We compare the XGBoost approach against other well-known machine learning and statistical models such as linear regression and decision tree, gradient boosting tree, and random forest regression models. Three metrics MAE, MAPE, and RMSE are used to evaluate the performance of the selected models. Our results show that XGBoost outperforms other models across different experiment conditions. Based on the prediction accuracy of different links, we find that the number of vehicles operating in a network also affects prediction performance.

In addition, understanding individual mobility behavior is critical for modeling urban dynamics. It provides deeper insights on the generative mechanisms of human movements. Recently, different types of emerging data sources such as mobile phone call detail records, social media posts, GPS observations, and smart card transactions have been used to analyze individual mobility behavior. In this thesis, we report the spatio-temporal mobility behaviors using large-scale data collected from a ride-hailing service platform. Based on passenger-level travel data, we develop an algorithm to identify users' visited places and the functions of those places. To characterize temporal movement patterns, we reveal the differences in trip generation characteristics between commuting and non-commuting trips and the distribution of gap time between consecutive trips.