Title: Analysis and Prediction of Spatiotemporal Impact of Traffic Incidents for Better Mobility and Safety in Transportation System

PIs: Cyrus Shahabi and Ugur Demiryurek
Department of Computer Science
University of Southern California
Los Angeles, CA 90089-0626
Email: shahabi@usc.edu; demiryur@usc.edu

Project Objective

The goal of this research is to develop a machine learning framework to predict the spatiotemporal impact of traffic accidents on the upstream traffic and surrounding region. We propose a Latent Space Model for Road Networks (LSM-RN), which enables more accurate and scalable traffic prediction by utilizing both topology similarity and temporal correlations. Our framework further enables real-time traffic prediction by 1) exploiting real-time sensor readings to adjust/update the latent spaces, and 2) training as data arrives and predicting on-the-fly.

Problem Statement

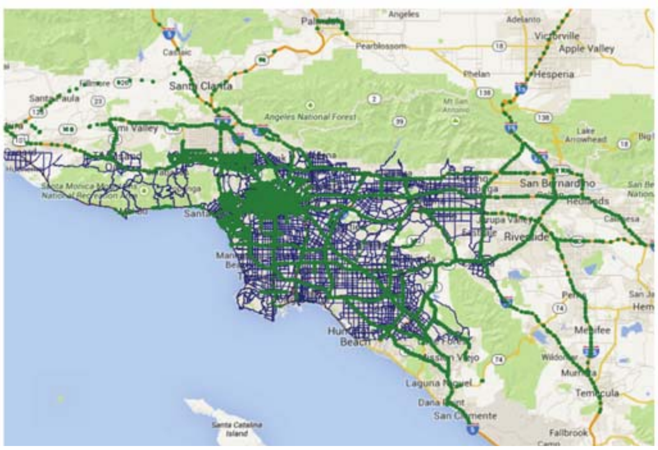

Figure 1. Los Angeles Road Network and Sensors

Recent advances in traffic sensing technology have enabled the acquisition of high-fidelity spatiotemporal traffic datasets. For example, for the past five years, we have been collecting data from 15000 loop detectors installed on the highways and arterial streets of Los Angeles County, covering 3420 miles cumulatively. The collected data include several main traffic parameters such as occupancy, volume, and speed at the rate of 1 reading/sensor/min. These data streams enable traffic prediction, which in turn improves route navigation, traffic regulation, and variety of urban planning applications.

In this research, we aim to predict the spatiotemporal impact of traffic accidents on the upstream traffic and the surrounding regions. Specifically, given the historical speed readings sensed from the sensors on the road network, we want to predict the future travel speed of each and every edges of a road network. However, this is a challenging problem due to the following reasons. First, the spatial relationship among sensors' readings is dictated by the network topology and not a less complex space such as Euclidean. Second, the temporal relationship among sensors' readings is highly time-dependent, e.g., tow sensors may be correlated during morning rush hour but not the afternoon rush hours. Third, the sensor data is streaming and hence any prediction model should be able to change/adjust as new data becomes available. Finally, the network is large and hence any prediction model must be able to get trained and updated at scale.

Research Methodology

Motivated by these challenges, we propose Latent Space Modeling for Road Networks (LSM-RN), which enables more accurate and scalable traffic prediction by utilizing both topology similarity and temporal correlations. Specifically, with LSM-RN, vertices of dynamic road network are embedded into a latent space, where two vertices that are similar in terms of both time-series traffic behavior and the road network topology are close to each other in the latent space. Therefore, the attribute distribution of vertices and how the attributes interact with each other jointly determine the underlying traffic pattern. We further enforce the topology of road network and incorporate the temporal properties into our LSM-RN model so that we can better understand how traffic patterns form and evolve.

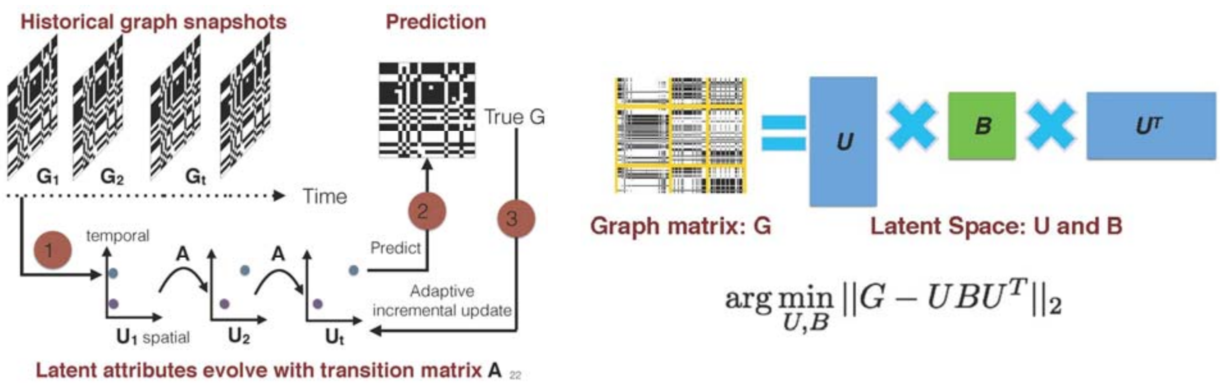

Figure 2. Latent Space Modeling For Traffic Prediction

To infer the time-dependent latent attributes of LSM-RN model, we propose both global learning and incremental learning approaches. In global learning, we jointly infer the whole latent attributes via iterative updates until they become stable. However, global learning is not only slow but also not practical for real-time traffic prediction. We thus propose an incremental online learning approach with which we sequentially and adaptively learn the latent attributes from the temporal graph changes. Leveraging global and incremental learning algorithms, our LSM-RN model can strike a balance between accuracy and efficiency for real-time forecasting. In particular, our framework enables real-time traffic prediction by 1) exploiting real-time sensor readings to adjust/update the existing latent spaces, and 2) training as data arrives and making predictions on-the-fly.

Results

We conducted extensive experiments using our large volume traffic sensor dataset. We demonstrated that the LSM-RN framework achieves better accuracy than that of both existing time series methods (e.g., ARIMA and SVR). Moreover, we show that our algorithm scales to large network. For example, it only takes 4 seconds to make a prediction for a network with 19,986 edges. Finally, we show that our batch time window setting works for streaming data, alternating the executions of our global and incremental algorithms