Traffic Volume Estimation Using Trajectory Data

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***Abstract*—Traffic volume estimation at the city scale is an important problem useful to many transportation operations and urban applications. This paper proposes a hybrid framework that integrates both state-of-art machine learning techniques and well-established traffic flow theory to estimate citywide traffic volume. In addition to typical urban context features extracted from multiple sources, we extract a special set of features from GPS trajectories based on the implications of traffic flow theory, which provide extra information on the speed-flow relationship. Using the network-wide speed information estimated from a travel speed estimation model, a volume related high level feature is first learned using an unsupervised graphical model. A volume re-interpretation model is then introduced to map the volume related high level feature to the predicted volume using a small amount of ground truth data for training. The framework is evaluated using a GPS trajectory dataset from 33,000 Beijing taxis and volume ground truth data obtained from 4,980 video clips. The results demonstrate effectiveness and potential of the proposed framework in citywide traffic volume estimation.**

***IndexTerms*—Hybrid framework, Trajectory Data.**

I.INTRODUCTION

Traffic volume is a central traffic state measure that has a wide range of applications.Local transportation agencies also need real-time volume information to perform interventions on traffic.Traffic volume serves as the input data for computing vehicle emission, which is required in many pollution monitoring systems.Estimating citywide traffic volume is a difficult task involving many challenges. First, due to the high cost of installing and maintaining road-based sensors, we typically do not have direct information about traffic volume at a city scale.To address the aforementioned challenges, we proposes a scalable traffic volume estimation procedure, referred as Traffic Volume Estimation(TVE).TVE achieves citywide traffic volume estimation using data from GPS trajectories, road networks, POI information as well as weather conditions, rather than relying on traffic data from road-based sensors.

II.EXISTING SYSTEM

Traditional approaches for traffic volume estimation and prediction heavily rely on data from various road-based sensors, i.e. loop detectors or surveillance cameras, thus mainly applicable to major road sections or limited-scale road networks. In many of these studies, traffic volume measures are directly monitored by sensors, and the volume estimation or prediction is achieved using filtering based algorithms.

III.PROPOSED SYSTEM

Estimating citywide traffic volume is a difficult task involving many challenges. First, due to the high cost of installing and maintaining road-based sensors, we typically do not have direct information about traffic volume at a city scale. Although it is possible to observe the real time traces from some sample vehicles (e.g. GPS equipped taxis) or mobile phone users (e.g. social media check-ins or cellular record data), it is generally insufficient to infer the detailed traffic volume on each road segment. As sample vehicles such as taxis only account for a small fraction of the total traffic and lacks representativeness of the overall traffic.

IV.MODULES DESCREPTION

1) Urban Context Extraction

This subcomponent extracts two classes of urban context features from multiple data sources: 1) physical features of the road and network; and 2) historical traffic patterns to facilitate travel speed estimation. The physical features of a road segment r consists of three parts: 1) road features fr, including attribute information of length, class, direction, speed limit, number of lanes, and number of connections, etc. All the roads are further classified into three groups based on speed limit: highway (70-120km/h), major road (50-60km/h) and small roads (30-40km/h). 2) POI features fp within 50 meter radius from r's end points (see Figure 4A)). We only considered the top 10 categories that are located near road segments most frequently, namely: Schools, Companies & Offices, Banks & ATMs, Malls & Shopping, Restaurants, Gas stations & Vehicle services, Parking, Hotels, Residences, Transportation, and Entertainment & Living Services.

2) Travel Speed Estimation

The GPS trajectories from sample vehicles are mapped to the road network. The urban context features related with road network, Point of Interest (POI) as well as course-grained traffic pattern is then extracted from multiple data sources. Based on the extracted urban context features, a speed inference model is used to estimates the mean and standard deviation of road speeds for the entire network, which serves as the direct input of road traffic states.

3) Traffic Volume Estimation

The TVE component is the main focus of this paper, which operates in three steps. First, a set of traffic flow related features are extracted from GPS trajectories, which help to establish the speed-flow relationship. Second, the volume related high level feature is learned from a partially observed Bayesian network using all the extracted features. Finally, we introduce a volume reinterpretation model to map the volume related high level feature into the predicted volume using a small amount of ground truth volume data.

V.ARCHITECTURE DIAGRAM

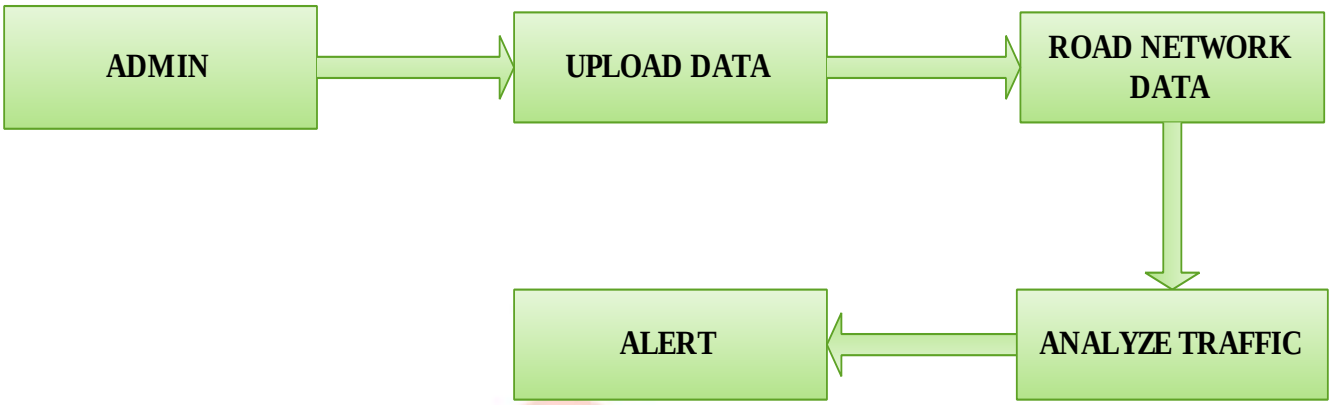

Fig1:Proposed architecture

VI.CONCLUSION

We develop a new framework that integrates both highly scalable machine learning techniques and well-established traffic flow theories to estimate the citywide traffic volume using data from GPS trajectories and several other sources. We extract a set of traffic flow features from GPS trajectories based on the traffic flow theory, which lead to improved estimation quality. The relevant features that involved in the dependency structure in determining traffic volume are also investigated using partially observed Bayesian networks.

VII.REFERENCES:

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