PREDICTION OF ROAD TRAFFIC FROM MULTIPLE SOURCES USING GAUSSIAN APPROACH

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Abstract

Prediction of road traffic from multiple sources using Gaussian approach is most import in intelligent transport systems. Existing works are only focused on non-intrusive sensors that are very expensive. Sensors are detecting traffic conditions and image recognitionetc. The maintains of these sensors are very difficult. To address the issue, this paper aims to improve road traffic speed prediction by using tweet sensors and social media. This includes many challenges, including location uncertainty of low-resolution data, language ambiguity of traffic description in text etc. To response these challenges we provide a uniform modeling probabilistic framework called Topic Enhanced Gaussian Aggregation model (TEGPAM). It consists of three components location disaggregation model, traffic topic model, Traffic speed Gaussian model.

Index Terms: Gaussian process, multiple-sources.

I. INTRODUCTION

Transportation system is most important now-a-days system. Existing works are mainly focused on very expensive they are using cameras, image recognition tools. Existing techniques are not fit for the current road conditions. To address this issue in this paper we introduce,

Social media:

This is related to websites. ex: Face book, twitter. People are exchanging the information by using these social media. Messages are sent about the traffic conditions. Such as struck in traffic road no.22 are posted by the driver, passengers these can be viewed by the sensors. Meanwhile it is a traffic authority registered on public accounts and post messages to inform public about traffic status.

Car trajectory data:

Car trajectory data is getting the location in which the application is installed in the driver's cellphone. It is used to map the location. For ex: We can take uber, ola cabs and google maps which is used to navigate the location. This makes the travelling easier and comfort. If the origin destination (OD) is passed on a map, then the route will be mapped from source to the destination with the time (min, sec). According to origin destination, trajectory is a sequence of links in which the segments of a road is divided. The travelling time of a road link is so called trajectory travel time. If the road link is congested, then it may take longer trajectory travel time with longer traffic speed.

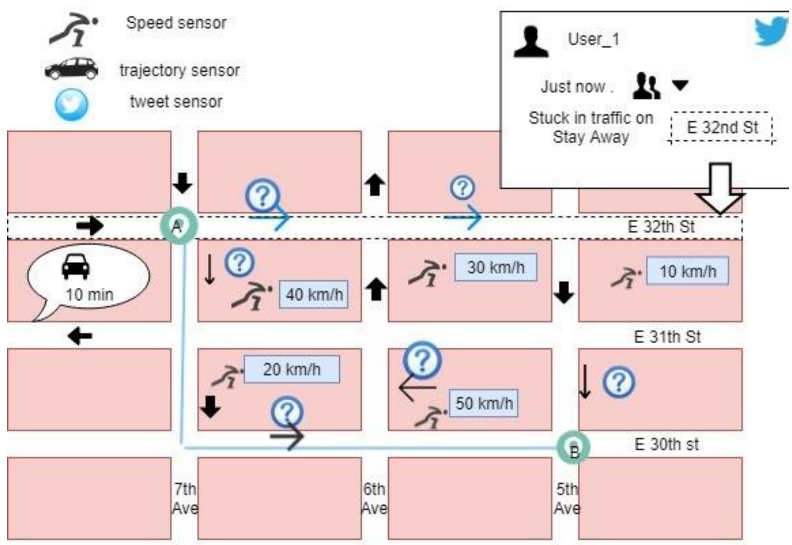

Fig1: System Architecture

From the above example in fig1, the question marks indicate that they are not covered by traditional speed sensors. But the traffic conditions are described in tweets.

1) Speed sensor collects the speed observations.
2) Trajectory sensor indicates the trajectory speed which is to predicted or observed.
3) Tweet sensor which covers multiple road links that is to be noted.

Challenges:

When you combine traditional traffic speed data (for example, sensor data) with data of a new type (for example, Twitter data and track data) to predict the speed of road traffic, technical challenges arise because of the characteristics of each data source:

Uncertainty location of low-precision data: Log and track data are called low-precision data because we cannot directly identify it in specific road links. Most tweets do not contain site tags, so the locale language is the main directory, but it's ambiguous. For example, the term "Stuck in traffic on E 32nd St. Stay away!" The entire street is without precise road sites. At the same time, the travel time of the route is a complex measure based on the speed of the multiple links, which may vary greatly. A strategy is therefore needed to separate the data into specific road links.

The linguistic ambiguity to describe traffic in Twitter: Expressions that illustrate traffic conditions are varied and may indicate different speed values. Figure 2 shows an example of frequency distribution of the word on the degree of congestion when people use busy words. At the same time, some words that are not directly related to traffic may have a strong impact on speeding, such as words that complain of bad weather. A language model is therefore required to capture patterns between separate descriptive words and continuous velocity values.

Multi source data heterogeneity: Data sources across domains include various characteristics and have latent relationships with the speed of traffic on the road. For example, tweets contain latent, speed-based themes, and there was a negative correlation between traffic time and traffic speed for links. Therefore, a uniform framework is needed for the model of these characteristics and for aggregating the inherent relationships between heterogeneous data for industrial speed prediction.

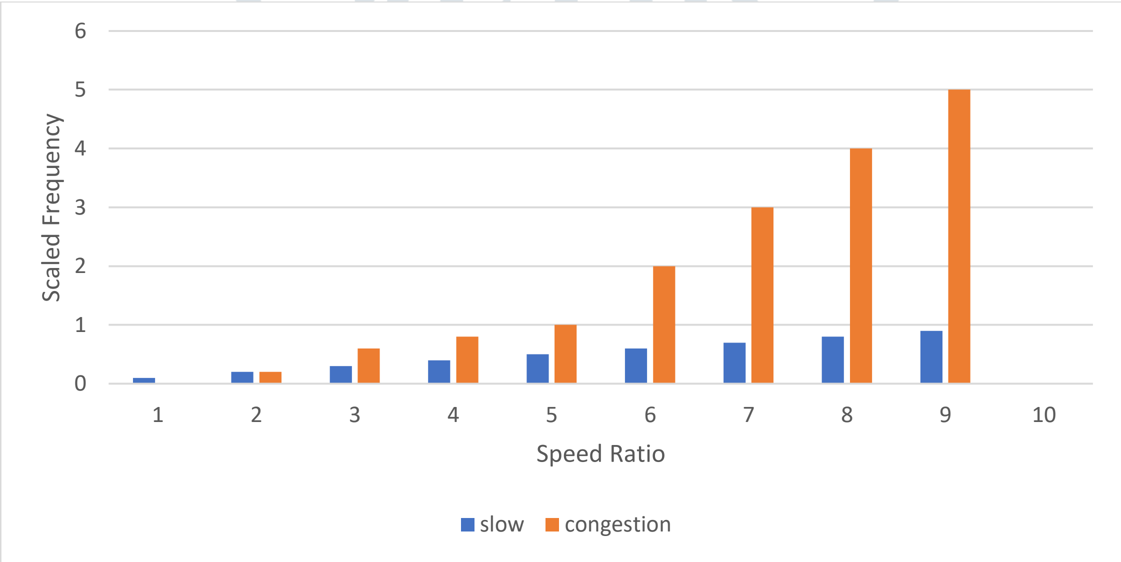

Fig2: Word Frequencies

II.RELATED WORK

In this non-intrusive sensor are used for detecting the traffic speed and volume based on road conditions. In these fixed andportable sensors are used for detecting the image recognition technologies were texted [1].The formation of reliable welding links in electronic assemblies is a critical problem in the manufacture of surfaces. Strict control is placed on the deposition of the welding paste to reduce welding defects and achieve high assembly yield. Modeling the time series process for quality properties of welding paste using neural networks (NN) is a promising approach that complements conventional control planning schemes deployed over the Internet. We are studying the construction of a multilayered neural network to monitor the deposition performance of the welding paste. Neural network modeling not only provides insights into process dynamics, but also predicts the future behavior of the process. The data measurements collected are used on ball network array (BGA) packages and Quadrilateral Flat Packet (QFP) packages to illustrate NN technology and the expected accuracy of the models is summarized [2].

Real time road traffic prediction is to address the smart transportation technologies. As the real-time route guidance describes from the point of view of network operators, travelers, which involves the first step i.e., short term traffic prediction [3]. As to overcome the existed technique which has only for some time in short term traffic prediction. Small transportations technologies can used which is fastest and scalable to the urban networks. Hence this provides the predictions of speed over minimal time interval [4]. Several models are proposed for short term traffic flow. They are univariate and multivariate. In this univariate historical average and ARIMA (Auto Regression Integrated Moving Average). In multivariate VARIMA (Vector Auto Regressive Moving Integrated Average) and STARIMA (Space-Time Auto Regressive Integrated Moving Average) [5]. Single point short-term traffic flow forecasting is a major key role need to the operational network models. Seasonal ARIMA (Auto Regressive Integrated Moving Average) is parametric approach to time series. Non-parametric approach is also well suited for the single point short-term traffic flow. Past researches have shown ARIMA (Auto Regressive Integrated

Moving Average) to deliver the results that are statistically [6]. It is application of STARIMA (Space-Time Auto Regressive Integrated Moving Average) for representing the traffic flow pattern. The traffic flow data are in the form of spatial time series and collected at the specific locations and different time intervals. Main characteristics of spatial-time is incorporated. The STARIMA (Space-Time Auto Regressive Integrated Moving Average) use of weighted matrices estimates basis of distances among the different locations [7].

It is a novel model. GSTARIMA (Generalized Space-Time Auto Regressive Integrated Moving Average) aim is short-term traffic flow of forecasting in urban networks. Compared to traditional methods, GSTARIMA is more flexible model where parameters are designed to different per location. Proposed model forecasting experiment based on actual traffic data in urban networks like china etc. [8]. Existing models that ate used in short-term forecasting are in univariate in nature. Extension of univariate time series model, a multivariate is involved and huge computational complexities. A different type time series model is the structural time series model that is in multivariate nature. In this it introduces a resources and computational simple and short-term algorithm is used [9]. The transportation literature is very rich for the prediction of travel time. It degrades the prediction performance of neural networks due to uncertainty in the operation of transportation systems. And also represent the uncertainty associated with predictions. For travelling, in the bus and freeway times, it applies the delta techniques for construction of prediction intervals. It depends on hyper parameter. For the selection and adjustment of hyper parameter, genetic algorithm-based method is developed [10]. In modern Intelligent Transportation Systems research, long range decisions of traffic parameters that is flow and occupancy are essential elements. Different methods are used to predict, literature is one of the best suggested neural networks for it. due to limited knowledge, networks optimal structure has a specific dataset, where researchers have to rely on time consuming [11]. This paper presents an illustrative introduction to the use of contrast methods for inference and learning in graphical models (Bayesian networks and random domains). We provide a number of examples of graphic schemes, including the QMR-DT database, the Sini Belief network, the Boltzmann device, and many Hidden Markov models that are not useful for running fine-grained algorithms. Then we introduce methods of variation, and we are half a general framework for making different transformations based on specific duality. Finally, we return to the examples and explain how the algorithms of variation can be formulated in each case [12].

III. TEGPAM MODEL DESIGN

In this paper we introduce three models are Location disaggregation model, Traffic topic model, System model, Traffic Related Tweets.

3.1 Location disaggregation model:

To address the challenge of uncertainty in locating new gender data, this section provides a classification strategy for assigning low-precision data, which are tweets and paths, to specific road links. Because only 1 percent of tweets have geographic coordinates, most location information is extracted from a tweet text by specifying road names or alias.

3.2 System Model:

In this module, we are developing a system with the disassembly model for site uncertainty in Twitter and track data, the traffic theme model to obscure Twitter language and GP model to capture the spatial correlation of speed sensor data. In this module, we first develop the system creation powers required for the proposed model. The system provides the new user with registration and permission to log on. Authorized users can post their Tweets. Users are also given the option to post comments. The module is designed with the features of a typical social web base, with functions that are related to the proposed model.

3.3Traffic topic data:

To meet the challenge of linguistic ambiguity and capture traffic description in tweets, it is proposed to model traffic theme. Through road logs that contain geographic coordinates, names, and aliases, we geotag to tweets via road links by matching their geographic content and text content with the front end of those links, which correspond to the direction of the outside and symbolize the header. Different driving directions are referred to as different road links.

3.4 Traffic Related Tweets:

Our goal is to quickly predict the traffic of certain links in a particular time stamp using previous and current observations from multiple sources of data, including traffic sensor data, tweets and paths. Tweets are aggregated in the same time period and cities via the Twitter REST search API. Traffic-related tweets are initially extracted by matching at least one of the predefined vocabularies developed by domain experts, which includes terms such as "traffic," "accident," "stuck," "crash," etc., and then classify and filter them.

3.5 ESTIMATION MAXIMIZATION ALGORITHM 1:

In this algorithm consists of both model parameters and variational parameters. In this algorithm consists of two steps.

1. E-step: we maximize the lower bound with respect to variational parameters
2. M-step: we maximize the bound with respect to the model parameters

INPUT: link speed observations, traffic-related corpus, travel times, link lengths

OUTPUT: Model parameters.

1. Estimate of GP priori.
2. Initialize the model parameters.
3. Initialize the variational parameters.
4. Calculate the initial lower bound.
5. Repeat.
6. Repeat.
7. E-step: Fix model parameters and update the variational parameters.
8. until convergence;
9. Repeat.
10. M-step: Fix variational parameters and update the model parameters.
11. until convergence;
12. until lower bound.
13. Return model parameters.

3.6 TEGPAM TEST ALGORITM 2:

INPUT: Learned model parameters, link length, link speed observations at time t*, traffic related time t*, travel time at t*.
OUTPUT: posterior Gaussian.

1. Repeat.
2. Update variational parameters.
3. until convergence:
4. Return variational parameters.

IV.CONCLUSION AND FUTURE SCOPE

This paper proposes a new potential framework for predicting road traffic speed with multiple cross-cutting data. The existing work is based mainly on speed sensor data, which suffer from data scarcity and low coverage. In our work, we have to deal with the challenges resulting from the explosive multi-source data, including location uncertainty, the ambiguity of language data homogeneity by using the site rating model traffic on a topic model for traffic speed Gaussian Process Model. Experience with real data shows the effectiveness and efficiency of our model. For future work we plan to implement the kernel-based distribution public, so the traffic prediction framework can be applied in real-time large of traffic on the network.

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