Attention based Stack ResNet for Citywide Traffic Accident Prediction

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***Abstract*—The fine-grained citywide traffic accident prediction is of great significance for urban traffic management. Existing approaches mainly apply classic machine learning methods based on historical accident records. Thus they failed to involve the cross-domain data, which contains spatial and temporal dependency. Recently, with more cross-domain urban data available, leveraging the cross-domain data by deep learning algorithms to predict fine-grained accidents becomes possible, we propose an attention based ResNet framework to model the sophisticated correlation between urban data.**

***Keywords*-traffic accident prediction; ResNet; spatio-temporal patterns; urban computing;**

I. Introduction

Traffic accidents are annoying and time-consuming, mostly lead to loss of property and even people's lives. Therefore, there is an urgent demand for fine-grained city-wide traffic accident prediction. The task of citywide traffic accident prediction is challenging due to various types of cross-domain data should be aggregated appropriately. Besides, not all types of data are available all the time and more human factors are involved in this problem.

Previous studies tend to be classified into traditional mathematical model and deep learning methods. NMF based method was first proposed to handle the accident prediction problem [1]. To achieve high accuracy, researchers started to focus on deep learning methods, LSTM [2], ConvLSTM [3, 4] were proposed in recent literatures. Unfortunately, majority of the methods without considering the inter-correlation between temporal dimension failed to capture the periodical and trend patterns. Moreover, they didn't take road sign distribution and population density into account, then failed to analyze difference between rural and urban areas. Hence, traffic accident prediction is still challenging.

To tackle the limitations above, we propose a novel framework, Attention based Stack ResNet for traffic Accident Prediction (ASRAP). From the aspect of data, we first introduce road sign distribution, weather forecast and density of population into our framework, providing contextual information both spatially and temporally. From the aspect of the model, our framework involves traffic speed inference module to fill the missing speed values, and three ResNet model the dynamic of spatio-temporal variant variables. We also introduce attention mechanism to accident prediction task, aggregating different properties in temporal dimension. As a consequence, citywide traffic accidents can be fine-grained predicted by our framework.

II. Traffic-related Data

We collect traffic-related cross-domain data in New York City (except Staten Island) in 2017. More details are explained as follows:
Road Network Structure: We collect (1) Number of road lanes, (2) Road types, (3) Truck proportion, (4) Overhead electronic sign distribution. **Meteorological Data**: Extreme weather always makes road condition worse. We collect (1) Precipitation, (2) Wind speed, (3) Snowfall, (4) Temperature, (5) Pressure for our prediction task. **Social Data**: (1) demographic data, (2) Point of Interest (POI) with several auxiliary attributes. **Human Mobility Data**: Taxi trip records imply people's arrivals and departures, which helps the model capture the mobility pattern of urban citizens. **Calendar Data**: Accident count varies periodically like crowd flows, and holidays make a difference to flows as well as accident risk.

III. Framework Overview

A. Analysis on Accident's Spatio-temporal Pattern

Firstly, we categorize variables into three types. Type I: variables spatially varied but temporally static: POI, road network and demographic data. Type II: variables both spatially and temporally varied: accident counts, average speed and taxi trip records. They are converted into grid feature maps. Type III: variables only temporally varied but spatially static like weather and calendar data, they are encoded as vectors. For accident occurrence of a specific region, it follows properties of closeness, period and trend like traffic flow [5]. Additionally, counts of accident can be influenced by its neighborhood and even distant regions. For example, accidents usually cause congestion and vehicles accumulation, leading to frequent overtaking and high variance of vehicles' speed. Besides, the congestion push drivers to change the route, leading to propagation of traffic flow and accident risk. Furthermore, average speed of road segment, taxi trips and meteorological data are indicators of human mobility and real-time urban condition. Therefore, all data above contributes to the dynamic accident risk distribution.

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B. Model Description

Figure 1(a) shows the framework of our spatio-temporal accident prediction model, which is comprised of three components: (i) CNN feature extractor, (ii) Feature fusion module, (iii) Accident prediction based on feature sequence.

Step 1: Feature Extraction. The study area is divided into grids. We first split 2017 NYC accident datasets into one-hour interval datasets, and each feature is assigned to its corresponding region. All of them are transferred into matrices or encoded as vectors.

Step 2: The Citywide Speed Inference Model. To handle the missing values of average speed, we make the assumption that road average speed depend on the following region-wise causalities: (1) geographically adjacent road segments tend to share similar traffic speed patterns and (2) those road segments which are geographically distant but have the same road type and functionality share similar average speed. Thus we can formulate our inference model as a weigted-regression problem. We produce region description vectors by concatenating the POI vector with the road type vector. Hence, we fill the entry of the missing speed values with the similarity of each region, which is defined as the euclidean distances between region description vectors.

Step 3: The proposed model ASRAP. Based on feature matrices and vectors, we propose an Attention based Stack ResNet for Accident Prediction (ASRAP) framework to predict citywide accident distribution. According to the classification of variables, each group of Type I data becomes a multi-channel frame. Type II data becomes feature maps. We also introduce the weather forecast of next time into V_0 to improve the accuracy of prediction. Then our task degenerates into predicting the next frame based on a series of sequences appearing before. Road network features are extracted in the form of grid by CNN structures. Temporal dynamic in the road network can be decomposed into trend, period and closeness. Inspired by it, features of type I are extracted by three ResNet structures respectively. Three CNNs share the same structure and model the three properties respectively. This structure not only extracts features from neighborhood spatially including congestion propagation and danger of intersections, also makes the best of fitting residual information, which facilitates the training process. Type III data is encoded by two fully-connected layers. With the attention mechanism, our model reweights different temporal dependency, thus it can aggregate the outputs of the three residual neural networks autonomously. Finally, our model outperforms other baselines in terms of MSE and accuracy rate, and reach 0.16 and 88.89%. Figure 1(b) reveals one of the results of predicted risk distribution.

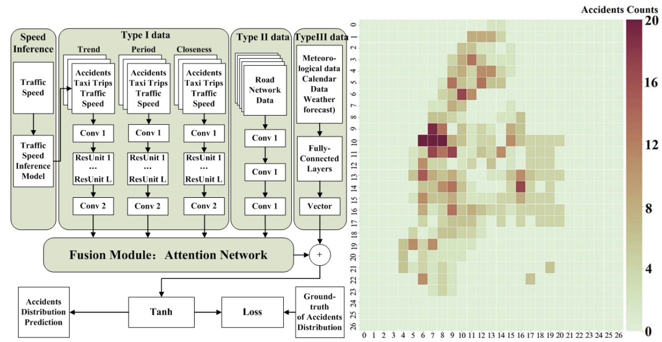

Figure 1. (a)Framework of ASRAP (b)Result of traffic accident distribution

IV. Conclusion

In this paper, we propose a novel Attention based ResNet framework to predict the citywide fine-grained traffic accidents. Speed inference model considering both adjacent and distant region is applied to fill missing values. In addition, ResNet and attention mechanism are introduced to accident prediction task, making our model outperforms other deep learning methods. For future work, our model can be extended to other metropolitan areas, and establish an online real-time accident risk warning system, making a difference to traffic police force arrangements and intelligent driving system.

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