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1. Introduction

With the great development of modern cities, the rapid growth of population and the acceleration of urbanization has made transportation systems to an essential infrastructure. In the meantime, transportation systems are becoming more and more complex, which causes great pressure on urban traffic management. As a result, it is important to develop the Intelligent Transportation System (ITS)[1] for efficient traffic management.

Modern transportation systems contain road vehicles, railway transportation and a variety of newly emerged shared travel modes, including online ride-hailing, bike-sharing, etc.. In order to alleviate transportation related problems and manage the expanding transportation systems efficiently, traffic prediction or traffic forecasting is brought up for ITS by researchers in recent years. Traffic prediction is the process of analyzing urban road traffic conditions, including flow, speed and density, mining traffic patterns, and predicting road traffic trends. Traffic prediction can not only provide a scientific basis for traffic managers to perceive traffic congestion and limit vehicles in advance, but also provide a guarantee for travelers to choose proper travel routes and improve travel efficiency.

Traffic prediction is typically based on consideration of historical traffic state data. In the development of intelligent transportation systems, traffic states are detected by traffic sensors, bus and metro transactions logs, traffic surveillance cameras and GPS devices. However, traffic state data is hard to manage because it involves large data volumes with high dimensionality. Its typical characteristic is that it contains both spatial and temporal domains. Therefore, traffic prediction becomes a challenging topic because of spatial and temporal dependencies

1. **Spatial dependency.** Urban road network has a topological structure that seriously affects the change of traffic state of each road. To be specific, the upstream traffic state influences the downstream roads for the reason like vehicle transfer.

2. **Temporal dependency.** Traffic state varies over time with periodicity. For example, in general, the traffic state over weekdays are similar to each other but has a huge difference with holidays, and vice versa. In detail, the traffic state at a specific moment is impacted by the previous moments or even hours.

Traditional time series prediction models (e.g., Moving Average (MA), Auto-regressive (AR), Auto-regressive Integrated Moving Average (ARIMA)) cannot handle such spatiotemporal prediction scenarios well. Therefore, to address the complex dependencies, deep learning methods have been introduced to this area.

Graph convolution networks (GCN)[2] becomes popular in recent years due to its ability to capture spatiotemporal dependencies efficiently. Many GCN-based models reached state-of-the-art performance, such as STGCN[3], DCRNN[4], Graph WaveNet[5] and AGCRN[6]. To represent road network, a graph is constructed where each node in the graph stands for a road segment or a traffic sensor. And edges means connectivity between road segments or sensors. As a result, spatial dependency can be extracted directly from the graph. Concerning temporal dependency, every node is linked with a feature vector that consists of traffic states at each moment. Several different methods were applied such as recurrent neural networks (RNN) and 1D convolutions. As mentioned above, in GCN-based models, spatial dependency is expressed only by the relationship among nodes in the graph. However, the traffic condition in real world is much more complicated. For example, the main roads in a city are often congested during peak hours. Although it is usually the shortest path to travel through main roads, commuters will probably prefer a father but clearer path. That is, the graph only shows the road connectivity which cannot represent the transfer preference by real drivers. Despite that it is impractical to collect all the traffic patterns, the trajectories reflect them well and thoroughly. In addition, when counting road flow or calculating road traffic speed, a trajectory is treated as discrete points, while the road transfer information naturally lies in the sequential order of the trajectory. Fortunately, such trajectories can be tracked by GPS devices and mobile apps with GPS service, and we have a completely raw GPS dataset which is copied directly from the logs of GPS devices in Shenzhen's taxis.

Based on these facts, we believe that the trajectories will give us the actual road transfer information. By analyzing road transfer, we propose a concept named **trajectory-based road correlation** that stands for the relevance or similarity among roads. With this, a better spatial dependency can be captured. Therefore, the focus of this paper is to design a general method to extract road correlation through trajectories and utilize it for state-of-the-art neural networks to predict traffic state.

To summarize, in this paper, we propose a procedure to learn trajectory-based road correlation via GPS data and use it to improve traffic state prediction.

The contribution of our paper is:

- We build a road-network-based trajectory dataset upon completely raw GPS data.
- We proposed a procedure to learn road correlation through trajectories.
- We refine traffic state prediction by utilizing the trajectory-based road correlation.

2. Related Work

Public Traffic Datasets. There are several public traffic datasets which are frequently used for traffic prediction. They can be briefly categorized into three classes by spatial domain, which are **grid-based**, **sensor-based** and **road-network-based**.

For grid-based datasets, there are *TaxiBJ*[7] that consists of the taxi in and out flow data in Beijing, and *TaxiNYC* for taxis in New York City published by the New York City Taxi and Limousine Commission (TLC). For sensor-based datasets, *METR-LA*[4] and *PEMS-BAY* are the most widely used datasets in urban traffic prediction area. In detail, *PEMS-BAY* is collected from 325 sensors all over the San Jose bay area every 5 minutes. The traffic sensors can directly record the traffic flow of each road, which makes the dataset easy to handle and process. And for road-network-based datasets, *Didi GAIA*'s open data has a good quality but they are seldom applied to build a model. It is GPS data containing taxi locations with timestamp that collected by *Didi* company's mobile app, which is similar to ours. In conclusion, as suggested by Jiang and Luo[8], most traffic prediction models are built upon traffic sensor datasets, while road-network-based datasets are mainly used for test. Therefore, we need to make better use of it.

Road Network Modeling. Road network is the basic component of urban traffic system. To make use of the spatial information inside it, many approaches have been proposed. Statistical models are used to represent road network. For recent traffic prediction articles, Li et al.[9] model road transition as a Markov Process over road network and use a first order Markov matrix to represent it. The growth of deep learning models makes it possible to model more complex road network and learn road characteristics efficiently. In basic GCN[2], the authors use adjacency matrix to calculate Graph Laplacian Matrix in order to represent the whole graph. Lately, Wu et al.[10] proposed a hierarchical graph neural networks to capture both structural and functional characteristics of road network through several pre-defined attributes of each road. Wu et al.[5] use graph convolution to learn a new adjacency matrix of sensor graph, which is quite related to our work. To conclude, the two methods mentioned above need prior knowledge or history traffic state of roads. In contrast, our work is to learn a representation of each road to model its spatial characteristics only by trajectories.

Traffic Prediction Models. Early attempts use traditional time series forecasting model including ARIMA[11] and VAR[12], as well as machine learning techniques like k-NN[13] and SVM[14]. As mentioned in section 1, these models cannot capture the spatiotemporal dependency well. Many state-of-the-art deep neural networks have been proposed in the last several years. Yu et al.[3] proposed two different convolution blocks to capture spatial and temporal dependencies separately. Li et al.[4] take advantage of seq2seq[15] architecture and perform diffusion convolution on the graph. From our observation, few existing work leverage trajectories in traffic prediction. Hui et al.[16] extract the temporal features of roads by convolution with recent, daily-periodic and weekly-periodic traffic state data. Then they perform feature smoothing by propagating features through trajectories. On the contrary, our work attempts to combine the spatial representation that learned from trajectories into traffic state prediction models.

3. Preliminaries

In this section, we will introduce the notations used in this paper and problem definitions in our task.

3.1 Notations

Table 1 Notations

Notation	**Definition**
n_r	#roads
$\mathcal{R}$	road set
r	a single road in $\mathcal{R}$
$\mathcal{E}$	edge set
A	adjacency matrix
$\mathcal{G}$	road network graph
$\mathcal{T}$	trajectory set
T	a trajectory in $\mathcal{T}$
ts	timestamp
s	speed
E	road embedding matrix
$\mathbf{e}_i$	embedding vector for road r_i
d_r	dimension of embedding vectors
C	road correlation matrix
t	time interval
n_t	#time intervals
X	traffic state matrix
$\mathbf{x}_t$	traffic state vector at time interval t

The above table 1 gives the notations and their definitions.

3.2 Problem Definition

This section gives the definitions[9] of the concepts and tasks occurred in this paper.

Definition 1 (Road Network Graph) *The road network can be represented by a directed graph $\mathcal{G} = (\mathcal{R}, \mathcal{E}, A)$, where $\mathcal{R} = \{r_1, r_2, \ldots, r_{n_r}\}$ is a finite set of roads that each r_i stands for a real road in the road network. $\mathcal{E}$ is the set of directed edges where $(r_i, r_j) \in \mathcal{E}$ indicates that there is a directed edge from r_i to r_j, i.e. r_j is the downstream road in the road network. $A \in [0,1]^{n_r \times n_r}$ is the adjacency matrix whose entry A_{ij} is a binary value that indicates whether there exists an edge $(r_i, r_j) \in \mathcal{E}$.*

Definition 2 (Trajectory) *Given a road network graph $\mathcal{G} = (\mathcal{R}, \mathcal{E}, A)$, a trajectory $T = [(r_1, s_1, ts_1), (r_2, s_2, ts_2), \ldots, (r_l, s_l, ts_l)]$ is a sequence of (road, speed, timestamp) tuples. Each tuple (r_i, s_i, ts_i) specifies that the vehicle is driving on r_i with speed s_i at timestamp ts_i. Besides, $\forall i = 1, 2, \ldots, l-1$, $r_i \neq r_{i+1}$ and $(r_i, r_{i+1}) \in \mathcal{E}$.*

Definition 3 (Traffic State) *Traffic state stands for the traffic flow or speed of a road during a particular time interval. Traffic flow is defined as the number of vehicles passing* *by the road, and traffic speed is the average speed of these vehicles. For a road graph $\mathcal{G} = (\mathcal{R}, \mathcal{E}, A)$, we use $X \in \mathbb{R}^{n_r \times n_t}$ to record the traffic state of each time interval. For time interval t, $\mathbf{x}_t = X_{:,t} \in \mathbb{R}^{n_r}$ represents the traffic state of all roads during t.*

Problem 1 (Road Correlation) *Given a road network graph $\mathcal{G} = (\mathcal{R}, \mathcal{E}, A)$, find a road correlation function Cor which takes two roads as input and returns a real number $0 \leqslant Cor(r_i, r_j) \leqslant 1$ to quantify the spatial dependency between two roads r_i and r_j. The value is bigger if the two roads have a stronger dependency, e.g. r_i is the only way to r_j. The road correlation matrix C stores all the correlation values s.t. $C_{ij} = Cor(r_i, r_j)$.*

Problem 2 (Traffic State Prediction) *Given a road network graph $\mathcal{G} = (\mathcal{R}, \mathcal{E}, A)$, find a function f and its parameter set Θ s.t. given historical traffic states $\{\mathbf{x}_{t-\tau_{in}+1}, \mathbf{x}_{t-\tau_{in}}, \ldots, \mathbf{x}_t\}$ for an input window τ_{in}, f estimates the most likely traffic states $\{\mathbf{x}_{t+1}, \mathbf{x}_{t+2}, \ldots, \mathbf{x}_{t+\tau_{out}}\}$ for an output window τ_{out}.*

$$\hat{X}_{:,t+1:t+\tau_{out}} = f_{\Theta}(X_{:,t-\tau_{in}+1:t-1}) = \underset{X_{:,t+1:t+\tau_{out}}}{\arg\max}\; p(X_{:,t+1:t+\tau_{out}} | X_{:,t-\tau_{in}+1:t-1}) \tag{1}$$

4. Dataset

This is dataset.

5. Methodology

This is methodology.

6. Experiments

This is experiments.

7. Conclusion and Future Work

This is conclusion.

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致谢

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