A FRAMEWORK FOR TRAFFIC PREDICTION INTEGRATED WITH DEEP LEARNING

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ABSTRACT

City-scale traffic prediction is an important task for public safety, traffic management, and deployment of intelligent transportation systems. Many approaches have been proposed to address traffic prediction task using machine learning techniques. In this paper, we present a framework to help on addressing the task at hand (density-, traffic flow- and origin-destination flow predictions) considering data type, features, deep learning techniques such as Convolutional Neural Networks (CNNs), e.g., Autoencoder, Recurrent Neural Networks (RNNs), e.g., Long Short Term Memory (LSTM), and Graph Convolutional Networks (GCNs). An autoencoder model is designed in this paper to predict traffic density based on historical data. Experiments on real-world taxi order data demonstrate the effectiveness of the model.

1 Introduction

Traffic prediction, mainly at the city-scale is a very important task for public safety and traffic management [1] and deployment of intelligent transportation systems (ITS) [2]. Traffic prediction models require traffic data as input. However, traditional data collection approaches such as on-road sensors (inductive loop, magnetometer, visual camera) are not sufficient due to their limited coverage and the high cost of implementation and maintenance [3]. Therefore, taxi and bus companies have been collecting GPS data and make it available for research purposes [4, 5]. Similarly, mobile network operators (MNOs) collect their subscribers' mobile phone activities known as Call Detail Records (CDRs) for billing and business purposes. Using anonymized CDR is possible to derive for instance population density [6, 7, 8], origin-destination (OD) matrix flows [9, 10, 11], traffic volume [3, 12], travel time and speed [13] which are very important information for the road and traffic management sector.

Many methods have been developed and proposed to support long-, medium- and short-term traffic predictions. Autoregressive model [14], autoregressive integrated moving average (ARIMA) model and its variants [15, 16] have been used to address long-term traffic prediction task. Recursive least-square model [17] and probability tree based on dynamic Variable-order Markov Model [18] have been proposed to deal with medium-term traffic prediction. In recent years, many researchers have been focusing on the development of short-term traffic prediction models to support ITS applications [19]. These models use statistical techniques to minimize or capture stochasticity in the observed data [20]. The statistical techniques used for the problem of traffic flow prediction can be classified as non-parametric (include non-parametric regression and artificial neural network) or parametric (include linear and nonlinear regression, historical average algorithms, smoothing techniques, and autoregressive linear processes) [21].

Recently, the problem of short-term traffic prediction has been addressed using deep learning [22]. Deep learning is a form of machine learning which provides a good short-term prediction of traffic flows by exploiting the dependency in the high dimensional set of explanatory variables. Deep Learning uses Artificial Neural Networks (ANNs) models to create intelligent machines that work and react like humans. The most common types of ANNs are Feedforward Neural Network, Convolutional Neural Network (CNN) and Recurrent Neural Network (RNN) [23]. In Feedforward Neural Network the data moves in one direction from the input layer to the hidden layer to the output layer. CNN and RNN are usually referred to as Deep Learning Techniques due to the multiple hidden layers structured in their architectures

[23]. RNN and its variant LSTM can learn temporal dependence well and achieve better prediction results. However, they ignore the spatial dependence, so that the change of traffic data is not constrained by the urban road network and thus they cannot accurately predict the traffic state on the road. CNN has been used to model spatial dependence and made great progress in traffic prediction tasks. However, CNN is suitable for Euclidean space, such as images, regular grids, etc., and has limitations on traffic networks with a complex topological structure, and thus cannot essentially characterize the spatial dependence. To overcome such limitation Graph al Network (GCN) model has been used to capture structural feature of graph network.

While many researchers are focusing on using a specific model to address long-, medium-, or short-term traffic prediction, in this paper, we gather different deep learning techniques such as CNN, RNN, and GCN to propose a framework for short-term traffic prediction. The proposed framework is a road map for researchers that helps to identify different possible research paths. To demonstrate its usability, we use one path to perform traffic density prediction using autoencoder and taxi trips data covering part of Chengdu from DiDiChuXing, China.

The rest of this paper is organized as follows. Section 2 presents the traffic prediction related work. Section 3 describes the proposed traffic prediction framework and density prediction process using autoencoder. Section 4 presents and discusses the preliminary results and finally, Section 5 concludes and presents the future direction of this research.

2 Related work

Traditionally, the traffic prediction problem has been addressed as long-term prediction using time series analysis applying autoregressive model [14] and the ARIMA model and its variants [15, 16]. For the medium-term traffic prediction, Cremer and Keller [17] applied recursive least-square estimation for the online prediction and recently, Yuan et al. [18] proposed medium-term prediction model using probability tree which is based on dynamic Variable-order Markov Model and Genetic Algorithm. However, for short-term, Deep Learning techniques have been proposed as alternatives approach for traffic prediction due to the stochastic nature and nonlinear characteristics of this phenomena [24]. Lv et al. [2] proposed the first stacked autoencoder (SAE) model to learn generic traffic flow features for prediction, which is trained considering the spatial and temporal correlations. Moreover, Goves et al. [25] used data from Highways England's Motorway Incident Detection and Automatic Signalling (MIDAS) system to build a short-term prediction model using artificial neural networks which forecasts traffic conditions in next 15 minutes given current / historic traffic information and autoencoder to reduce the complexity which comes from the number of input dimensions. Zhang et al. [26] proposed a deep-learning based Spatio-Temporal Residual Networks approach, called ST-ResNet to predict in-flow and outflow of crowds in each and every region of study areas. The experimental results in Beijing and New York City demonstrate that the proposed ST-ResNet outperforms six well-known methods namely ARIMA, Sazonal ARIMA (SARIMA), Highways Agency Models (HA), Vector Auto-Regressive (VAR), Spatio-Temporal Artificial Neural Network (ST-ANN), and deep neural network (DNN)-based prediction model for spatio-temporal data called DeepST. Wang et al. [27] used online car-hailing order data of Didi Chuxing to predict the gap between the car-hailing supply and demand. They designed an architecture to concatenate blocks built from multiple data sources such as car-hailing orders, weather and traffic data. Recently, Yao et al. [28] proposed a spatio-temporal Deep Learning framework called DMVST-Net (Deep Multi-View Spatial-Temporal Network) to model spatial and temporal relations using both al Neural Network (CNN)- and Long-Short Term Memory (LSTM) Models. The experimental study was conducted using real taxi demand big data from Didi Chuxing (in China) and the results showed the effectiveness of their approach over state-of-the-art.

3 Methodology

3.1 Traffic prediction framework

The proposed prediction framework is composed of four layers namely data, features, methods and tasks. Three common data sources in the data layer are floating car (trajectory), taxi order (e.g. origin-destination) and CDRs which have different spatial-temporal characteristics and refer to the movement of objects of different types that are in different spatial context. These data sources are transformed into four mobility feature types such as density map, sequence, OD matrix and graph which in turn encode density and flow information and have different characteristics. The mobility features representations are used as input data for different deep learning techniques namely RNN and CNN which defer on the type of hidden layers each consists of. In addition, RNN is suitable to capture temporal dependence and CNN for spatial dependence. To capture the structural feature of graph mobility features GCN is used. With these models, different tasks of short-term traffic prediction such as density, traffic flow, and OD flow predictions can be carried out. The prediction framework is shown in Figure 1. In Figure 1, the elements in gray show an example of path selection from the framework. In this path, an autoencoder is trained to predict the density map based on historical data.



Figure 1: Framework of traffic prediction

Component	Layer	Configuration	Output Shape (H,W,C)	Parameters
Input	Input Layer	-	(28, 28, 5)	-
Encoder		32 x 3 x 3	(28, 28, 32)	1472
	Max Pooling	2 x 2	(14, 14, 32)	-
		16 x 3 x 3	(14, 14, 16)	4624
	Max Pooling	2 x 2	(7, 7, 16)	-
Decoder		16 x 3 x 3	(7, 7, 16)	2320
	Up-Sampling	2 x 2	(14, 14, 16)	-
		32 x 3 x 3	(14, 14, 32)	4640
	Up-Sampling	2 x 2	(28, 28, 32)	-
		1x 5 x 5	(28, 28, 1)	801
Output		-	(28, 28, 1)	-
Sum				13,857

Table 1: The architecture of autoencoder for density prediction.

3.2 Traffic density prediction with autoencoder

The architecture of autoencoder is presented in Table 1. It takes 5 images as input representing the previously observed 5 density maps and exports a single image as the predicted density map for the current time. The encoder contains 2 layers while the decoder consists of 2 de layers to extrapolate the features. The final layer contains a single filter, which maps the features to an image with a single channel. The autoencoder also ensures that both the input and output images have the same width and height of (28,28).

As for training of the autoencoder, the mean-squared-error (MSE) is adopted as the loss function. Let $D_{i,j}^k$ denote the true density at the grid or pixel (i, j) of the k-th density map in the training data with size of K. Let $\hat{D}_{i,j}^k$ denote the predicted density of that grid. The MSE loss is calculated from the training data as:

$$L = \frac{1}{K} \sum_{k}^{K} \sum_{i}^{W} \sum_{j}^{H} (D_{i,j}^{k} - \hat{D}_{i,j}^{k})^{2}$$
(1)

where W and H denote the width and height of the density map respectively. The loss is minimized in the training process using the *Adam* optimization algorithm [29].

4 Preliminary results

In this section, a case study is presented where the autoencoder is evaluated with a publicly available taxi order dataset collected by DiDiChuXing,China¹. It contains taxi trips observed in part of Chengdu, China covering one-month

¹The data can be downloaded at https://outreach.didichuxing.com/research/opendata/en/



Figure 2: Hourly density map of taxi trip origins in one day. Each map is in shape of 28×28 .



Figure 3: Loss of linear regression (LR) and autoencoder (AE) during the training process

period in November, 2016. On each day, there are about 235,000 trip observations. Each observation records the vehicle ID, timestamp and location of the origin and destination of a taxi trip.

The training and test data are created using four weeks' taxi order data as follows. The taxi trip origins are firstly aggregated temporally by hour. In each hour, a density map is generated by aggregating these points to a fixed grid space with width and height of (28,28), as shown in Figure 2. From the four weeks' data, 672 (28×24) images are obtained, which are split into two sets: training and test. Since the prediction takes input from previously observed 5 density maps, it is important to avoid overlapping of samples in the training and test set. To achieve that goal, training samples are only drawn from these images observed in the first 22 days while test samples are only drawn from the remaining 6 days. During the sampling, an image is randomly drawn first, which is treated as the label. At the same time, its previous 5 images are retrieved as input. The input and the label collectively form a single sample in the training and test data. Consequently, the training data contains 523 samples and the test data contains 139 samples, which are shuffled before training. It ensures that the model can learn different patterns from a batch set of samples.

The training process is designed with 500 epochs where in each epoch the model is trained with a batch set of 64 randomly selected samples. The autoencoder is compared with a linear regression (LR) model, which performs a global pixel-wise regression over the same training data. Therefore, the size of training data for LR model is 410,032 $(523 \times 28 \times 28)$ and that of test data is 108,976 $(139 \times 28 \times 28)$. The losses of these two models are shown in Figure 3.



Figure 4: Prediction error for each sample in the test data containing 139 samples



Figure 5: Comparison of autoencoder and linear regression. The samples t1-t4 are labeled in Figure 4

As can be observed, the loss of autoencoder converges consistently during the training and finally stays around 60% of the LR model.

To get more detailed comparison of the two models, MSE is computed from the true and the predicted image for each sample in the test data. That prediction error and the total count of taxi trip origins in the ground truth image are shown in Figure 4. It can be observed that the errors for both models follow a daily pattern, which is also highly correlated with the total number of observations in each hour. The errors in the time period from 8:00 to 22:00 are higher than the rest of the day. Four representative samples labeled from t1 - t4 are further selected with their prediction result displayed in Figure 5. It shows that autoencoder tends to predict more accurate density map than conventional LR model and its superiority is more apparent in specific hours, e.g. 8:00 and 24:00.

5 Conclusion and future work

In this paper, a traffic prediction framework was described and an autoencoder was designed for predicting traffic density map using historical data. Experiments on real-world taxi trip data demonstrated the advantage of autoencoder over conventional linear regression model. Future work is planned in integrating additional information (e.g., time of prediction) to further improve the accuracy. In addition to that, a spatial error metric mechanism will be incorporated into the model during training to better assess the predictions.

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