TRAFFIC FLOW PREDICTION BASED ON CASCADED ARTIFICIAL NEURAL NETWORK

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ABSTRACT

The prediction of traffic flow is of great significance for the prevention of accidents, the avoidance of congestion and the dispatch of command center. Considering the complexity of traffic data in reality, it is an extraordinarily challenging task to forecast accurately from historical patterns. In this paper, we propose a method based on the cascaded artificial neural network (CANN) to predict traffic flow at positions. In order to express the spatial correlation of traffic data, the actual road network distance is introduced in our model. The real-world data derived from video surveillance cameras in Xiamen is used in the experiment which is compared with five baselines. To the best of our knowledge, this is the first time that CANN is applied to forecast traffic flow. The experimental results demonstrate that the CANN method has superior performance. In addition, We also discuss the impact of some external factors such as temperature, weather and holidays on the prediction results.

Index Terms— Traffic flow forecasting, artificial neural network, cascaded, feature analysis

1. INTRODUCTION

The excessive increase of the number of motor vehicles may cause the congestion of urban roads. However, scientific prediction of traffic trends in urban road network can guide the public to travel and reduce the occurrence of accidents. To achieve this goal, some related works on traffic flow prediction are done recently. Huang et al. [1] presented a deep framework consisting of a underlying deep belief network (DBN) and a multitask regression layer at the top level to forecast road flow. Shortly afterwards, Moretti et al. [2] developed a combination of artificial neural networks and a simple statistical approach to predict an hour's urban traffic flow. Lv et al. [3] proposed the use of stacked autoencoder to learn the characteristics of traffic flow. Similarly, Yang et al. [4] built a stacked autoencoder Levenberg-Marquardt model to develop an optimal structure and then forecast traffic flow. Polson et al. [5] used an architecture together with a linear model on traffic flow prediction during special events. Influenced by the success of LSTM in speech recognition [6], machine translation [7] and image annotation [8], Yu et al. [9] proposed a mixture deep LSTM model to forecast peak-hour traffic. There are also some methods that apply CNN, Wu et al. [10] fuse the spatio-temporal features captured by CNN and LSTM to predict short-term traffic flow. In addition, Yu et al. [11] proposed a convolution-based spatiotemporal recurrent network.

In this paper, the traffic flow of multiple locations are predicted simultaneously, which means the number of vehicles passing through those positions within 60 minutes. There is one available record produced, when a vehicle identified by pattern recognition technology passes. Traffic flow data combined by available records can be accurate statistical, since license plate recognition technology has been relatively mature currently. In practical applications, the amount of devices may be increased by urban development or reduced by damage. For the experiment, however, the selected equipment need steadily work. Our contributions are four-fold as follows: (1) Instead of straight-line distance, the actual network distance is introduced to express the spatial characteristic. (2) CANN is first applied to forecast traffic flow, and its loss function is put forward according to the structure feature of the model. (3) The proposed method has superior performance and its result is beyond 5 baseline methods. (4) The external factors such as weather, temperature and holidays are introduced, and their effect on the experimental results is analyzed.

2. DEEP MODEL FOR INFERENCE

Figure 1 shows the depth architecture model of CANN, which is mainly composed of three parts that are inputs, preprocess-

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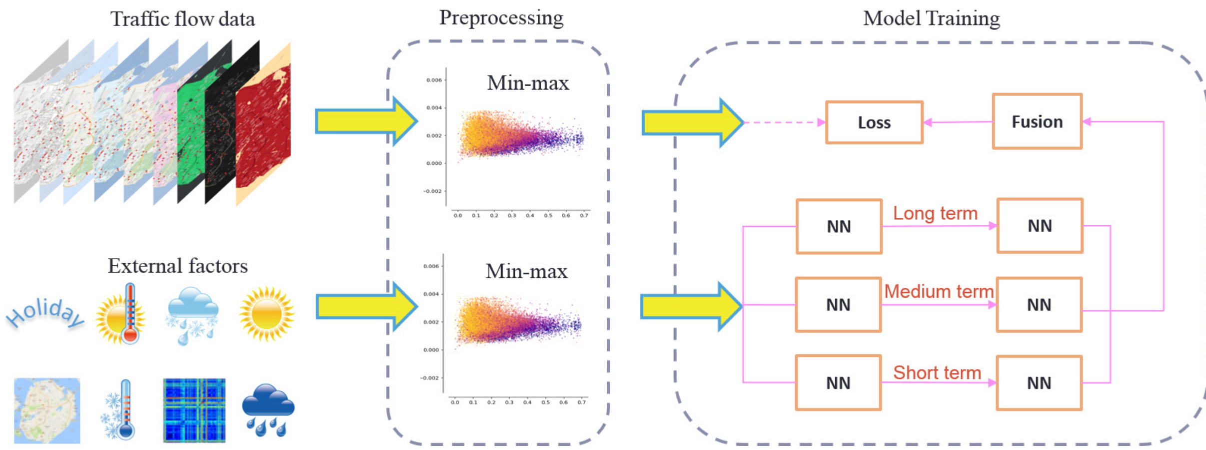


Fig. 1. Deep models for traffic flow prediction.

ing and model training. At the bottom left of Figure 1, a large quantity of external factors are introduced in our model, such as road network distance, weather, temperature and holidays. We use Baidu's Route Matrix API service provided with latitude and longitude to get the actual road network distance. Weather conditions and temperatures can be accessed from the Meteoro-logical Bureau, which are the most concerns before traveling, and as for the element of holiday, we can turn to the General Office of the State Council. In the part of preprocessing, these different types of data are preprocessed using the Min-Max scaler module in the Scikit-learn API and are concatenated and stretched into a long vector. The predicted value can be rescaled to normal values with Min-Max scaler. The effect of external factors on the prediction is negligible compared to the larger flow value. The scaler makes different features have comparability in numerical value, which can improve the accuracy of prediction. In the last part, according to the requirements, the preprocessed data is combined into inputs of the model which consists of three ANNs: long, medium and short term. Traffic flow have obvious periodicity on a weekly basis, which is captured by long-term ANN. The medium-term ANN reveals the daily periodicity of the driver's travel habits while the short-term one catches numeric variation trends of traffic flow. The flow of different parts is forecasted by different types of ANN, and then weighted fusion is carried out to form the predicted traffic flow of the next moment.

The model is trained using back propagation algorithm with the following cost function:

$$L = \left\| x_t - \sum_i \alpha_i \cdot \widehat{x}_{i,t} \right\|^2 + \sum_j \lambda_j R\left(W_j\right) \tag{1}$$

Where $\cdot$ denotes scalar multiplication. x_t is the observed value at the moment t. α_i is the weighted factor. Denote the output of the i-th ANN as $\widehat{x}_{i,t}$. W_j is the j-th weight in the forecasting model and λ_j is a regular term coefficient for W_j.

3. EXPERIMENTS

3.1. Settings

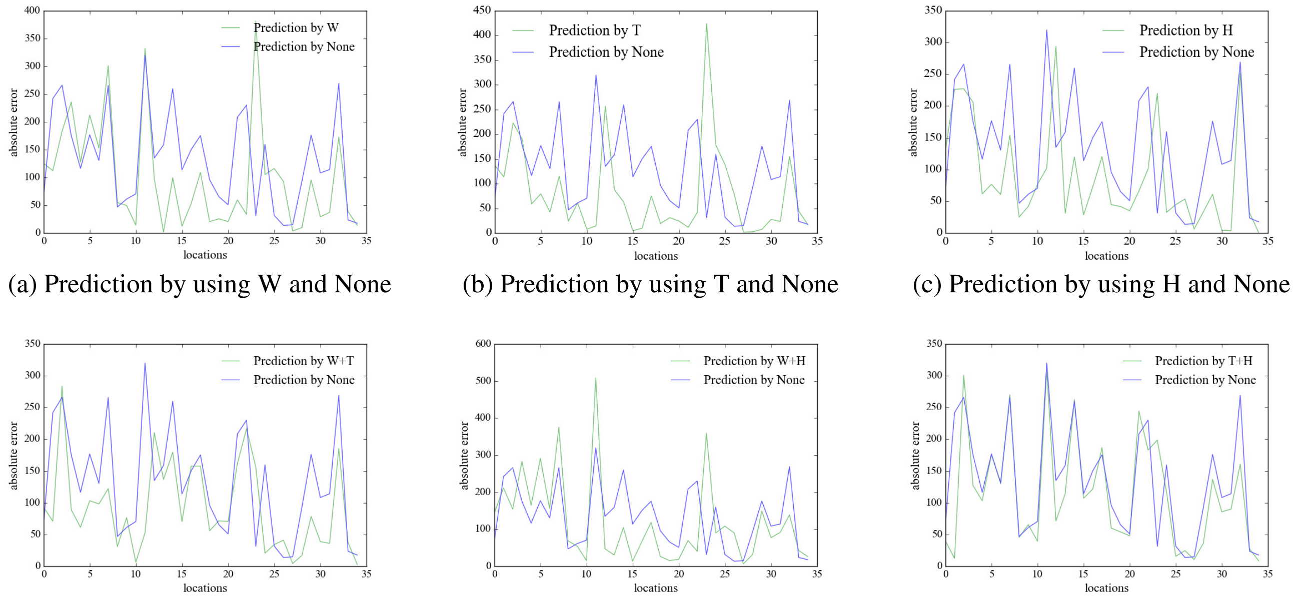
Datasets. The traffic records in Xiamen are collected from road video surveillance camera, including license plate number, vehicle passing time, equipment ID, etc. The time interval of data in this paper is from 1st April, 2016 to 31st August, 2016, and the last month is used as test set. External factors are obtained by accessing the corresponding network interface, which is mentioned in the deep model for inference module. Table 1 shows the data sets we use.

Table 1. Datasets.

Data item	Description
Traffic flow	169
Location	Xiamen
Date type	vacations, weekend, weekday
Time Span	1/4/2016-31/8/2016
Road network distance	(169,169)
Time interval	60 minutes
Weather conditions	36 types (*e.g.*, Cloudy, Rainy)
Max temperature / °C	[22,35]
Min temperature / °C	[15,27]

Baselines. Our proposed model is compared with the following baselines:

- **SVR**: Considering that the variation of traffic flow is nonlinear, we use Support Vector Regression with radial basis function (RBF) kernel to predict traffic flow.
- **GBRT**: Gradient Boost Regression Tree (GBRT) is suitable for processing heterogeneous data with strong predictive capability.



(a) Prediction by using W and None (b) Prediction by using T and None (c) Prediction by using H and None

(d) Prediction by using W+T and None (e) Prediction by using W+H and None (f) Prediction by using T+H and None

Fig. 2. Forecasting results of models with different external factors.

- **DTR**: Decision Tree Regression establishes a regression model in the form of a tree structure, which has value even with little hard data.
- **LSTM**: As the most common method of traffic forecasting, LSTM predicts the flow at the next moment, with the flow of the first k moments as input.
- **SAE**: Stacked Autoencoder can improve feature expression as well as capability of noise resistance.

Setup. For all models in the experiment, historical traffic data are utilized to forecast the next 60 minutes of traffic flow. All experiments were performed under PC (Ubuntu 16.06, GPU: 2 * Titan X 12G, CPU: Intel i5, Memory: 64G), which installed $TensorFlow^{TM}$ (Version 1.2.0 GPU) and Python (Version 2.7). The parameter settings are as follows:

$$
\begin{aligned}
&Optimizer = Adam,\\
&L2\_norm = 0.002,\\
&Learning\ rate = 0.0001,\\
&Keep\_prob = 0.4,\\
&The\ number\ of\ iteration = 100000,\\
&Batch\ size = 64.
\end{aligned}
$$

Comparison results. The performance of the model is evaluated by the prediction errors. Here are two widely used methods to evaluate traffic prediction performance: mean absolute error (MAE) and root mean square error (RMSE). The MAE from Eq. 2 is used to measure the error between the predicted value and the true. The RMSE from Eq. 3 is a measure of the accuracy of the model.

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|t_i - p_i| \tag{2}$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(t_i - p_i)^2} \tag{3}$$

Where p_i = predicted traffic flow; t_i = actual traffic flow; N = the number of predictions.

Table 2 shows the prediction errors for different models. It can be seen that the results of the proposed model are significantly more than 5 baseline methods. However, not all neural networks are always superior to traditional methods, such as LSTM and SVR. With strong feature representation-SAE achieved relatively acceptable results in this experiment. Though it is much better than other methods, the result of SAE is not as good as that of CANN, probably due to the utilization of cascaded structures and the consideration of external factors.

Table 2. The result of models.

models	MAE	RMSE
SVR	186.643	276.696
GBRT	183.592	253.459
DTR	195.968	277.969
LSTM	204.434	348.634
SAE	179.849	324.692
CANN (ours)	**136.861**	**252.176**

Analysis of Features. In order to understand the model's fitting ability and the influence of external factors on this experiment more intuitively, we give the absolute error curve under different conditions in Figure 2. In the experiment, W, T, and H represent weather conditions, temperatures and holidays respectively, while None represents no external factors. The detailed experimental results are given in Table 3. For a better visualization, only 35 locations are displayed in Figure 2. It can be seen from its subfigure that the absolute error of experiments with external factors is a little lower than that without external factors, and there are just slightly differences between the absolute errors predicted with different external factors. Coupled with the results in Table 3, we can conclude that the impact of external factors on flow prediction in our experiments is small.

Table 3. The result with different external factors.

models	MAE	RMSE
None	163.095	285.337
W	153.106	272.696
T	157.551	282.349
H	141.879	260.474
W+T	148.476	269.105
W+H	147.914	265.969
T+H	144.146	260.425

As for reasons, three points are summed up: (1) Due to the undersized number of holidays in the historical data, our model has rarely seen it in the course of training, leading to its minute impact. (2) From April to August, the fluctuation of the temperature in Xiamen is relatively minimal. (3) Weather conditions like rain may have a greater impact on cycling, but have almost no effect on driving, unless severe weather conditions such as typhoon and heavy rainfall are encountered. However, these bad weather are also hard to see. So, what we mainly capture is the variation tendency of flow, but it also can be seen that the accuracy of the prediction can be improved under the consideration of all the three external factors. The impact of external factors on traffic forecasts is not the same for different cities. For example, the traffic flow of tourism-oriented cities may be much more affected by holidays.

4. CONCLUSION AND FUTURE WORK

We propose a novel depth model that considers external factors and simultaneously predicts traffic flow of multiple positions, the experimental results are exciting, which are beyond five baseline methods. Furthermore, we confirm that the fusion of the cascaded structure in our model is more effective for the flow prediction, and the influence of external factors on the forecast results is analyzed at the end of the paper.

In the future, we will try other network architectures and consider other external factors, such as point of interest (POI), to expand.

5. REFERENCES

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