Title:

Predict short-term traffic flow with prediction error from traffic sensor data using deep learning

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Introduction

The traffic flow prediction is considered as a fundamental requirement for the improvement of traffic management system in intelligent transportation system. Several approaches have been developed for traffic flow prediction such as integrated moving average (ARIMA) (*2*), subset Autoregressive Integrated Moving Average Model (*3*), Seasonal ARIMA (*4*), Holt Winters' exponential smoothing model and seasonal ARIMA model (*5*), Box-Jenkins (B-J) approach (*6*), support vector machine (SVM) (Su, Zhang, & Yu, 2007),online (*7*), adaptive multi-kernel SVM (Feng, Ling, Zheng, Chen, & Xu, 2019), Seasonal SVR(Hong, 2011), Locally Weighted Learning(LWL) (*8*). k nearest neighbor (k-nn)(*9*). However, due to non-linearity and randomness in traffic flow data and huge data size, those models are not suitable options to analyze traffic flow data. In machine learning technique, neural network (NN) has potential to overcome the limitations of large data size (*10*). However, a shallow artificial neural network (ANN) does not perform well when complex non linearity existed in data (*11*). Recently, the long short-term memory (LSTM), a deep learning approach, achieved good performance in traffic flow prediction. However, a framework for traffic flow prediction with prediction error does not exist. To address this need, we propose a deep learning approach based on long short-term memory (LSTM) and conventional neural network (CNN). We apply LSTM to forecast traffic flow and named as MLSTM and apply CNN to predict the error of the MLSTM and finally combine the results of both MLSTM and CNN to generate the final output.

Methodology

The proposed framework has been developed in three steps: (1) Data processing (2) MLSTM Model and CNN model development (3) Final model Development.

(1) Data processing: the traffic sensor data is prone to missing values and outliers because of malfunction of sensor, manual system closer and error in signal transmission. In this study, we used 7 data validity tests from (*12*) which are (1) missing data check,(2) univariate range checks,(3) zero consistency checks: (3.1) positive volume or occupancy with zero speed,(3.2) positive speed or occupancy with zero volume,(3.3) positive speed and volume with zero occupancy, (4) high free flow volume and (5) average effective vehicle length (AEVL). The observation which fails any of the 7 tests has been detected and considered as event. The event can be categorized into short period and long period event. The short period events happens due to the unsteady equipment or cluttered environment and the later events happen usually due to system closer (*1*). In this study, the short-term event period lasts for less than 6 time-steps (30 minutes) missing observation. In this case, a moving average on most recent observation with a window size 5 has been used for data imputation. The event period which lasts for more than 5 sequences has been considered as long period events. In this case, the average of previous 5 observations of the same day-and-time has been used for data imputation.

(2) MLSTM and CNN Model development

LSTM network is a special kind of RNN whose basic unit is cell state instead of traditional neuron node. The cell state is treated as memory block which is a set of input gate, forget gate and output gate. The LSTM model learns when to forget previous memories and when to update memories through these gets. In our proposed model, we used 2 hidden layers with 64 neurons each and one fully connected dense layer. The input and output of the MLSTM model is traffic count. The CNN model includes 2 Conv1D layers with filter size 100 and kernel size 2 and two MaxPooling1D layers with size 2. Finally, a flatten layer and two fully connected dense layers have been used. The input is the error of the MLTM. The error is difference between predicted and true observations for the whole dataset. As activation layer, we used Rectified linear unit (ReLU) for both MLSTM and CNN.

(3) Final model Development

The final model merges the output of the MLSTM and CNN results and displays the final output.

Experimental result

In this paper, the traffic sensor data from 16 sensors on interstate highway I-93 North of Milwaukee in Wisconsin (July 1 to September 30, 2019) has been selected for experiment. The observation time interval is 5 minutes and each detector generate 288 pieces of data every day. The root mean square error (RMSE) has been used to examine model performance. The RMSE of MLSTM is 8.66 and the RMSE of CNN is 8.219. The MLSTM model performs well when the traffic counts are usually larger than 20 or during peak hours. The performance of both MLSTM and CNN starts to deteriorate when traffic counts closer to zero value (figure 1).

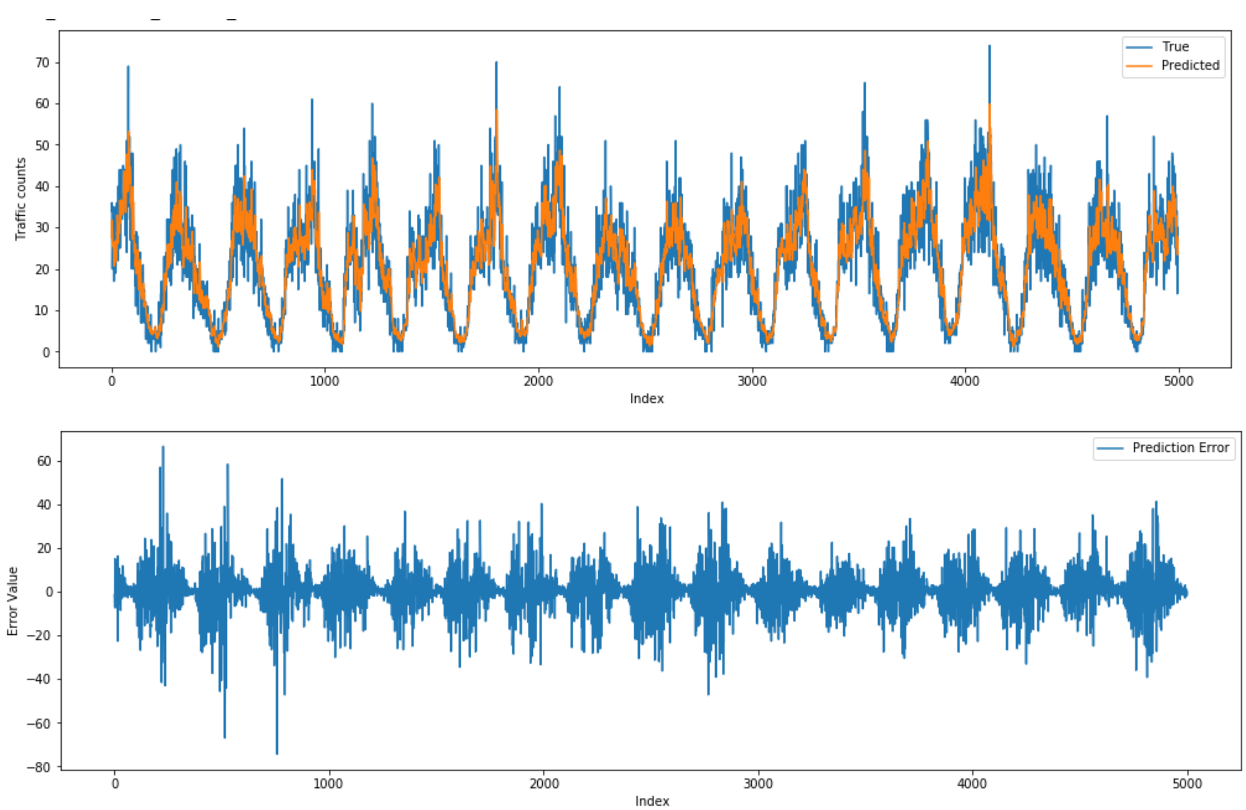

Figure 1: Traffic flow prediction for first 10000 observation from test set.

Conclusion:

In this study, we are trying to develop a deep learning-based framework to predict the traffic flow with prediction error. The initial result shows that LSTM can capture the temporal pattern of traffic flow. We found that CNN performs well compared to LSTM for error prediction. Continuation of this study will explore the prediction error more detail to improve the result and develop a robust traffic flow prediction model.

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