Short Term Traffic Flow Forecasting Model Based on Convolutional Neural Network

Smitha Shetty (190980018)

Usha Rani A V (190980012)

LITERATURE REVIEW

Guowen Dai et al. have proposed a short-term traffic flow prediction model that combined the spatio-temporal analysis with a Gated Recurrent Unit (GRU). In the model, firstly, time correlation analysis and spatial correlation analysis were performed on the collected traffic flow data, and then the spatiotemporal feature selection algorithm was employed to get the optimal input time interval and spatial data volume. At the same time, the selected traffic flow data were extracted from the actual traffic flow data and converted into a two-dimensional matrix with spatio-temporal traffic flow information. The results showed that the proposed model is superior to CNN model and GRU model in accuracy and stability. There exists some weakness about this paper, other factors (e.g. weather conditions,) of traffic flow are not considered, and only the traffic flow of a single road segment is predicted [1].

Zibin Zheng et al. have proposed a deep and embedding learning approach (DELA) that can help to explicitly learn from fine-grained traffic information, route structure, and weather conditions. In particular, our DELA consists of an embedding component, a convolutional neural network (CNN) component and a long short-term memory (LSTM) component. The integration of the three models together can improve the prediction accuracy of traffic flow. The experimental results show that the proposed DELA outperforms the existing methods in terms of prediction accuracy. The embedding component can capture the categorical feature information, such as the structure of routes and weather information. The experiment results show that our proposed DELA outperforms existing methods in terms of prediction accuracy [2].

Wentian Zhao et al. have proposed the temporal convolutional network (TCN) and a deep learning framework based on TCN model for short-term city-wide traffic forecast to accurately capture the temporal and spatial evolution of traffic flow. The real-world traffic flow data was compared with four deep learning-based models including LSTM models, GRU models, SAE models, Deep Trend and CNN-LSTM models in terms of the mean absolute error (MAE) and mean relative error (MRE) regarding the actual flow data. The experimental results demonstrate that our framework achieves the state-of-art performance with superior accuracy in short-term traffic flow forecasting.

The optimized structure of the TCN found by the Taguchi method is demonstrated to have much more improved performance over other methods. The accuracy rate can reach as high as 95% [3].

Aniekan E. Essien et al. have proposed a model that adopts an integrated assess-forecast-simulate approach in which traffic flow characteristics are applied on deep Convolutional Neural Network Long Short-Term Memory (CNN-LSTM) stacked auto encoders to forecast traffic flow and speed, which are subsequently passed on to a traffic micro simulation tool – Simulation of Urban Mobility (SUMO) – where the predicted parameters are used to generate a traffic future state simulation. This paper presented Deep-PRESSIM, a proactive traffic management model comprising two distinct stages – prediction and simulation respectively. The proposed model can be further trained on more complex transport networks to accommodate real time traffic input. A proactive traffic management model, such as Deep-PRESIMM, can be a step in the direction of providing holistic control and proactive management of traffic with potential for facilitating the coordination of driverless cars by traffic authorities [4].

Shengjian Zhao et al. have proposed a novel hybrid network called TreNet to predict the time series value. TreNet is target data drive and does not require any prior knowledge in practice. It uses convolutional neural networks (CNN) to extract local salience features from adjacent raw data and uses long short-term memory networks (LSTM) to capture long-range memory. Experiments demonstrate that this method can capture useful information to enhance the prediction performance. In seven traffic datasets, TreNet achieves the best performance in six datasets compared with other methods. The experimental results show that this kind of hybrid neural networks architecture is suitable for many different types of traffic time series prediction problems [5].

Zifeng Kang et al. have proposed that the Traffic flow forecasting (TFF) problem is essential to modern intelligent transport systems (ITS). Massive flow data from contemporary transport systems have put forward the challenge of effectively capturing both the latent spatial patterns and the temporal dynamics of traffic flow data, when an ITS is doing forecasting. To cope with this challenge, we introduce a novel spatial-temporal graph self-attentive model (STGSA) for short-term traffic flow forecasting. Our model learns graph-level spatial embedding using graph selfattention layers with Gumbel-Softmax technique, and the temporal embedding leveraging RNN cells integrated with Gated Recurrent Units [6].

Muhammad Arif at al. have proposed a traffic flow prediction approach with deep learning and parametric regression model. In our paper we consider the three parameters, MAE, MRE,MRSE,MAPE and APE, and compared our results with three other approaches, OL-SVR, SAE and BP NNet, the results presents that our approach better than the other methods. It shows that our approach is more suitable for the real world traffic application. The strength of our approach is the data pre-processing and correct data analysis that makes our approach for the best suitable traffic operations. For next we will consider the multivariate time series for traffic prediction. For the future perspective it would be better to explore the other regression model with new deep learning approaches for the better flow prediction and for improvement of the performance [7].

Changhee Song et al. have proposed a CNN-based speed prediction model since the CNN-base model has advantages that it can capture local dependencies and is less sensitive to noise in data. And has designed two MLP prediction models for the comparison with CNN-based prediction model. One MLP prediction model has only one input layer which takes temporal data and speed data on the four links all together. The other MLP model, on the other hand, has multiple input layers and consists of the multiple sub-MLP models. For comparison of the three models, MAE of the three models on the test data is estimated 5 times. The comparison results show that CNN-based model outperforms the other two MLP models for all prediction time internals. Also, it is shown that the models composed of multiple sub-models outperform the model without multiple sub-models [8].

Lu Wenqi et al. have proposed an accident prediction model based on convolution neural network is designed by the author to predict the traffic accident in the highways. The influence of learning rates and different iterations on the prediction accuracy of TAP-CNN model is analyzed. Compared with traditional back propagation network neural network model, the TAP-CNN model exhibits its advantages in accuracy and efficiency, and the prediction accuracy comes to 78.5%, which is 7.7% higher than the traditional model (TAP-BP) [9].

Hao-Fan Yang et al. have proposed that a predictor SAE-LM, an optimized structure is used to forecast the traffic flow. Due to the fact that the trial-and-error method is very time consuming with too many design factors involved, the Taguchi method is adopted to improve the effectiveness of the design of traffic flow forecasting model. The evaluation results indicate that the SAE-LM model with an optimized structure is an accurate and efficient approach to traffic flow forecasting. In addition, it has superior performance (about 90% accuracy rate) in traffic flow forecasting and is the most suitable approach to deal with the lumpy data in this research. Some significant findings include the following.

The SAE-LM is able to generate forecasting results with approximately 90% accuracy rate, which is 5% more than the other predictors. In addition, the prediction performance of the SAE-LM is relatively stationary (only 1.6% difference), which is 0.93% better than the EXP-LM, 2.11% better than the PSONN, and 0.82% better than the RBFNN. The disadvantage of the SAE-LM model is that it may not be able to perform well if the observed traffic data has a highly smooth distribution. However, when lumpy traffic data are collected, the SAE-LM has superior performance in traffic flow forecasting. Since the observed traffic flow data are always lumpy in nature, the SAE-LM model is demonstrated to be more effective and promising for traffic flow prediction in practice than the other models [10].

Research gap:

In the proposed framework, traffic flow forecasting is done using univariate regression model of deep neural networks that collectively predicts network-scale traffic flow with Recurrent Neural Network (RNN). RNN is used as the data series is time series. It was found that RNN model has better performance in traffic network prediction for its strong learning ability in spatial-temporal features. This paper aims to address the daily traffic flow forecasting problem given historical data. We would like to show that the proposed method can in general outperform alternative prediction methods in daily traffic flow forecasting in terms of prediction accuracy.

Finalized objectives:

- To develop a framework aiming to improve traffic forecasting accuracy.
- To investigate the stability and efficiency of neural network for short term prediction of traffic volume based on day to day traffic conditions.

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