

Short-term Traffic Volume Prediction at a Signalised Intersection Using LSTM

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Abstract

Control by traffic signals is an important factor for short-term traffic state prediction at an intersection. Deep learning, which has the capability to capture nonlinear relationships, is achieving superior performance for an extensive range of prediction problems. Consequently, its application to traffic state prediction is expected. This study proposes a deep learning model that predicts traffic volume of the target road link downstream of an intersection, using the time-series traffic volume observation of the target link and multiple upstream links, and traffic signal control information at the intersection. The proposed model was validated with traffic volume data obtained from a traffic flow simulator. The validation results showed that the traffic volume data from upstream links and traffic signal control information contributed to improvements in prediction accuracy. However, when the signal control patterns of validation data were different from those of training data, the traffic signal control information made prediction accuracy worse.

Keywords: Deep Learning, Traffic Volume Prediction, Time Series, Traffic Signal Control.

1 Introduction

Traffic congestion causes many losses, including increased travel time. Therefore, taking measures against traffic congestion is socially significant.

Traffic state prediction is considered to play a crucial role in alleviating traffic congestion. Specifically, short-term traffic state prediction provides real-time information for road administrators and users to make their decisions. The demand for short-term prediction is high in urban areas, where traffic congestion occurs frequently.

Along with an increase of available traffic data in recent years, the development of traffic state prediction methods that utilise traffic data has advanced significantly. Deep learning, one of these data-driven methods, is distinguished from others in its capability to capture interrelationships of data automatically. Large amounts of traffic data have been obtained over long periods of observation, and deep learning is expected to leverage the accumulated data. Some studies employ deep learning as a method of traffic prediction. They focus on the spatial (Ma et al., 2017) or temporal nature (Tian et al., 2015; Ma et al., 2015) of traffic flow. However, because the existing deep learning models were only applied to access-controlled highways, the effect of traffic controls was not modelled.

Traffic flow at a signalised intersection behaves differently to access-controlled highways. To make

traffic volume prediction at a signalised intersection more precise, a model needs to incorporate traffic signal information. In addition, because the traffic flow at an intersection comes from multiple directions, it is also important to use traffic volume data from these directions.

This study proposes a deep learning model that predicts the traffic volume of the target road link downstream of an intersection. The proposed model is designed based on long short-term memory (LSTM), which is suitable for time-series data, and outputs predictions using time-series traffic volume observation of the target link and multiple road links upstream of the intersection, and traffic signal control information at the intersection. The feasibility of the model is examined through the validation of prediction accuracy.

2 Methodology

2.1 Long short-term memory (LSTM)

Long short-term memory (LSTM) is a type of neural network suitable for handling sequential data that has been proposed by Hochreiter et al. (1997). The architecture of LSTM is shown in Figure 1.

LSTM has a set of multiple numerical operations called LSTM blocks.

Let $x_{i,j}^{(t)}$ denote the (i, j) element of the input from the input layer at t -th step, and $h_{i,j}^{(t)}$ denote the (i, j) element of the output from the LSTM block at t -th step.

An LSTM block has four input gates, namely block input, input gate, forget gate, and output gate. Calculations at each gate are shown in Equation (1)–(4),

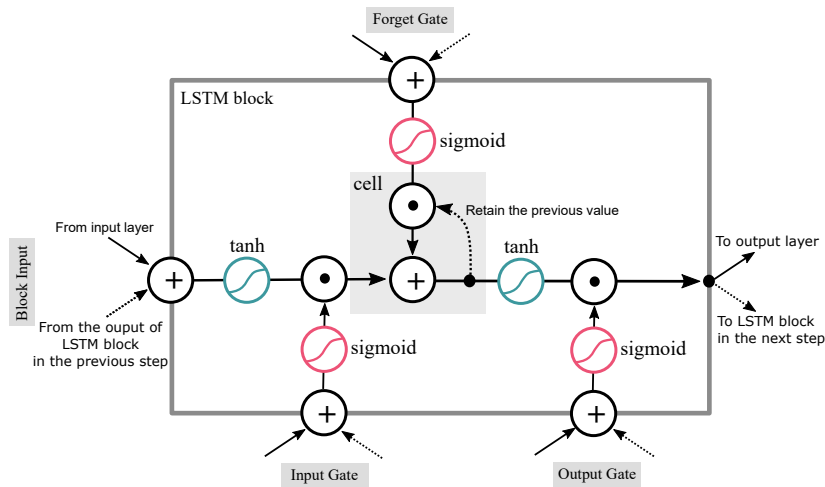


Figure 1: Structure of LSTM

$$z_{i,j}^{(t)} = \tanh \left(\sum_{k=1}^K w_{i,k}^{(Z)} x_{k,j}^{(t)} + \sum_{k=1}^K r_{i,k}^{(Z)} h_{k,j}^{(t-1)} + b_i^{(Z)} \right) \quad (1)$$

$$i_{i,j}^{(t)} = \sigma \left(\sum_{k=1}^K w_{i,k}^{(I)} x_{k,j}^{(t)} + \sum_{k=1}^K r_{i,k}^{(I)} h_{k,j}^{(t-1)} + b_i^{(I)} \right) \quad (2)$$

$$o_{i,j}^{(t)} = \sigma \left(\sum_{k=1}^K w_{i,k}^{(O)} x_{k,j}^{(t)} + \sum_{k=1}^K r_{i,k}^{(O)} h_{k,j}^{(t-1)} + b_i^{(O)} \right) \quad (3)$$

$$f_{i,j}^{(t)} = \sigma \left(\sum_{k=1}^K w_{i,k}^{(F)} x_{k,j}^{(t)} + \sum_{k=1}^K r_{i,k}^{(F)} h_{k,j}^{(t-1)} + b_i^{(F)} \right) \quad (4)$$

where $w_{i,k}, r_{i,k}$ are elements of the weight matrix for the input layer and the returned value, respectively, and b_i is a bias term. $\sigma(-)$ denotes the sigmoid function.

Cell does a calculation shown in Equation (5).

$$c_{i,j}^{(t)} = z_{i,j}^{(t)} i_{i,j}^{(t)} + c_{i,j}^{(t-1)} f_{i,j}^{(t)} \quad (5)$$

Cell holds $c_{i,j}^{(t-1)}$, the previous calculation result, and Equation (5) updates the value in Cell.

Finally, Equation (6) defines the output of an LSTM block.

$$h_{i,j}^{(t)} = o_{i,j}^{(t)} \tanh \left(c_{i,j}^{(t)} \right) \quad (6)$$

2.2 Proposed Model

Figure 2 shows the structure of the model, which consists of two components. The model uses LSTM to extract a feature from time-series data and fully connected layers to reflect the effect of traffic signal controls.

1. Extracting a feature from multiple time-series data

This component aims to extract the periodicity and the dependence among multiple time-series data by LSTM.

2. Extracting relationships between time-series data and traffic signal control information

This component combines the output from the first component and signal split distribution information, which is the proportion of time allocated to each phase in a signalised intersection, of the prediction target time and reflects the effect from traffic signal controls.

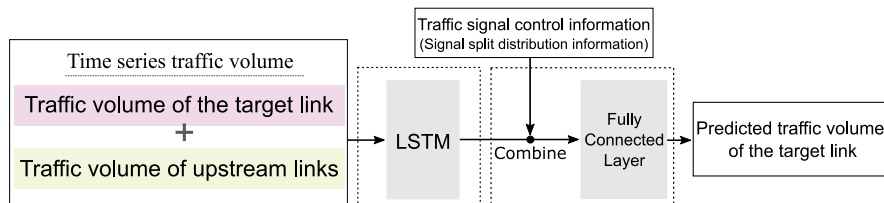


Figure 2: Structure of the proposed model

3 Validation of the Proposed Model

3.1 Validation Procedure

This study examines the improvement of prediction accuracy by using time-series traffic volume of the upstream links and traffic signal control information.

In the validation process, two possible hypotheses are considered. The first hypothesis is that the proposed model learns the physical relationship—that traffic signal controls affect the traffic volume downstream of an intersection. The second is that the proposed model learns the relationship—that traffic signal controls are decided in response to the traffic volume. If the first hypothesis is correct, the model outputs different predictions for the same upstream traffic volumes if the traffic signal controls are different. On the contrary, if the second hypothesis is correct, the model might fail to reflect the effect of signal controls.

However, the validation with actual traffic data cannot distinguish these hypotheses because it is impossible to observe the outflow of the intersection with the same inflow and a different signal control.

Therefore, this study validates the proposed model with the output of a traffic flow simulator, which can generate downstream traffic volume from the same traffic inflow and a different signal control at the intersection.

3.2 Generation of Traffic Volume Data

The time-series traffic volume data for ninety days used in validation are generated by traffic flow simulator “AVENUE”. The coverage of the simulation (Figure 3) includes two national roads (Route 6 and 16) in Kashiwa City, Chiba Prefecture, Japan. The two roads cross each other at a signalised intersection named “Yobatsuka intersection”.

The traffic inflow into the simulation field and signal controls of Yobatsuka intersection are set based on the actual traffic data collected from July 2, 2018 to November 16, 2018 by Japan Road Traffic Information Center at intervals of five minutes.

3.3 Training and Evaluation

The simulated traffic volume data are split into two periods: the first sixty days for training, and the remaining thirty days for evaluation.

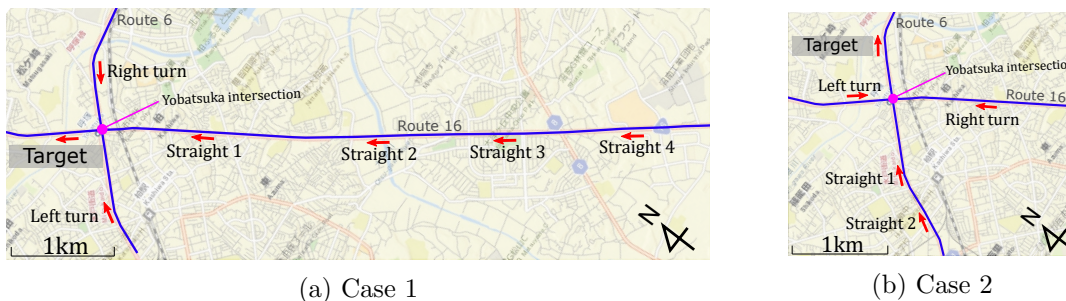


Figure 3: Prediction targets and upstream links (Source of map: Esri Japan and INCREMENT P)

The model is trained in supervised learning. The objective function is MSE (Mean Squared Error) and ReLU function is used as an activation function. The model is repeatedly trained until the improvement of MSE in the latest fifty epochs decreases to 10^{-4} or less. The models with 4, 8, 16, 32, 64, and 128 LSTM units, 0, 1, and 2 fully connected layers, and 64 and 128 units in a fully connected layer are tested and the one that minimises RMSE is adopted. Prediction accuracy is evaluated by MSE of evaluation data.

3.4 Validation 1: The effect of using upstream links

Validation 1 examines the effect of using upstream links compared to the case that uses only the target link. Validation 1 is performed with no fully connected layers.

The results are shown in Table 1 and Figure 4. In both cases, prediction accuracy was improved by using upstream links.

3.5 Validation 2: The effect of using traffic signal control information

Validation 2 utilises the signal split distribution information at an intersection in addition to upstream links.

To examine the effect of using traffic signal control information, traffic flow was simulated when traffic signal control was fixed to one of three patterns (Figure 2), which were switched to each other frequently based on traffic conditions in the real situation, and used for the validation.

Case	Upstream links used in prediction	Prediction Accuracy (RMSE, Vehicles/5 min.)
1	Not used	10.880
	Straight 1	8.110
	Straight 1, 2	6.692
	Straight 1-4	6.452
	Straight 1-4 + Right turn + Left turn	6.180
2	Not used	11.749
	Straight 1	10.541
	Straight 1, 2	10.413
	Straight 1, 2 + Right turn + Left turn	9.777

Table 1: The effect of using upstream links

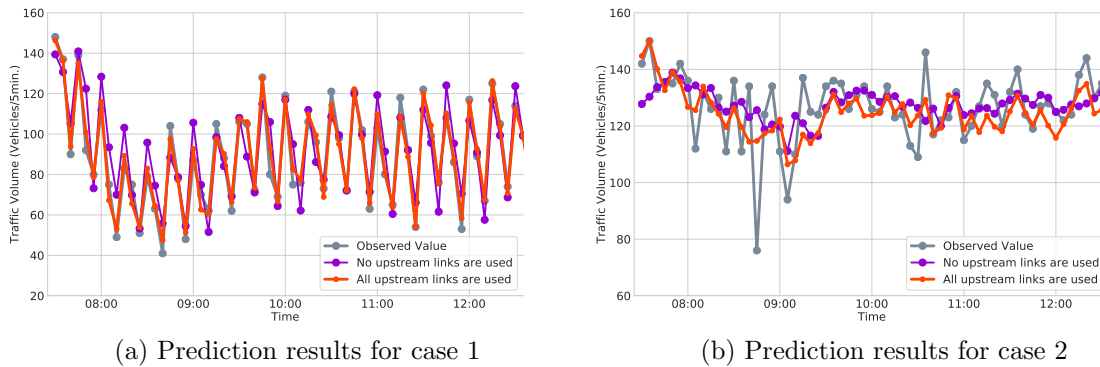


Figure 4: Prediction results on the 5th day of evaluation periods (Validation 1)

Pattern	Green time allocated to Route 16 (sec.)	Ratio of executed time (%)
A	126	50.0
B	114	34.4
C	108	15.3

Table 2: Signal control patterns at Yobatsuka intersection

Case	Evaluation data control pattern	Prediction Accuracy(RMSE, Vehicles/5 min.)	
		Without control information	With control information
1	Actual control	5.852	5.578
	Only A	5.322	5.364
	Only B	7.186	7.458
	Only C	10.963	10.388
2	Actual control	9.449	9.185
	Only A	11.561	11.497
	Only B	9.724	9.755
	Only C	9.828	9.863

Table 3: The effect of using traffic signal control information

The results are shown in Table 3 and Figure 5. The evaluation by the data with actual control pattern in each case suggests that traffic signal control information contributed to the improvement of prediction accuracy for evaluation data under actual traffic control. However, when the signal control patterns of validation data were different from those of training data, traffic signal control information worsened prediction accuracy. The results suggest that the proposed model learned the relationship that traffic signal controls were decided in response to the traffic volume.

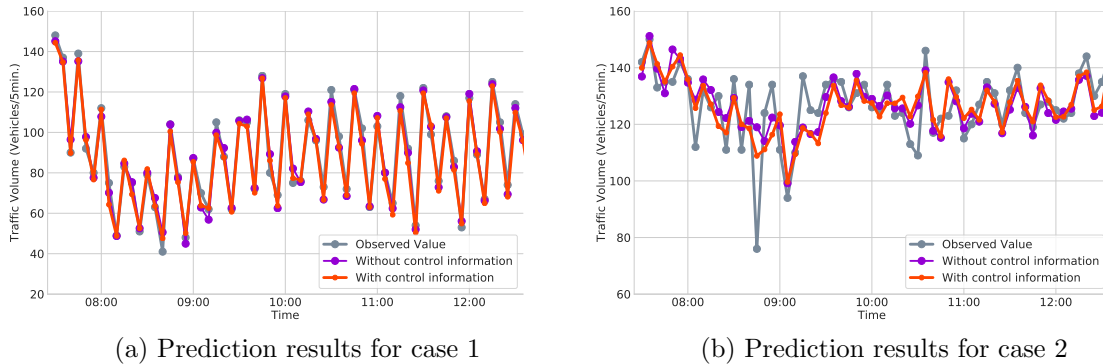


Figure 5: Prediction results on the 5th day of evaluation periods (Validation 2, Evaluation data: Actual control)

4 Conclusion

This study proposed a deep learning model that predicts the traffic volume of a road link downstream of an intersection.

It is confirmed that time-series traffic volume data from upstream links and traffic signal control information contributed to improvements in prediction accuracy. However, traffic signal control information worsened prediction accuracy when the signal control patterns of validation data were different from those of training data. The results suggest that the proposed model learned the

relationship that traffic signal controls were decided in response to the traffic volume. The application of the proposed model might therefore be limited to prediction under the situation included in training data.

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6 References

Hochreiter, S. and Schmidhuber, J. 1997. Long short-term memory, *Neural Computation*, **9**(8), 1735–1780.

Ma, X., Tao, Z., Wang, Y., Yu, H., and Wang, Y. 2015. Long short-term memory neural network for traffic speed prediction using remote microwave sensor data, *Transportation Research Part C: Emerging Technologies*, **54**, pp. 187–197.

Ma, X., Dai, Z., He, Z., Ma, J., Wang, Y., and Wang, Y. 2017. Learning traffic as images: A deep convolutional neural network for large-scale transportation network speed prediction. *Sensors*. **17**(4), article no: 818 [no pagination].

Tian, Y. and Pan, L. 2015. Predicting short-term traffic flow by long short-term memory recurrent neural network. In: *2015 IEEE International Conference on Smart City/SocialCom/SustainCom (SmartCity), 19–21 December 2015, Chengdu, China*. pp.153–158.