Relation between Proximity of Streets in Urban Network and Parameters of Neural Network for Traffic Volume Prediction

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Abstract

Deep learning has become very popular as a method to predict short-term traffic volumes on road networks, especially highway networks, based on real-time observation. Various studies have confirmed that the performance of deep learning in predicting traffic volumes is better than that of previous machine learning models and statistical models. Although it is natural to consider that the traffic conditions on road networks are highly dependent on network structures such as the connection relationship between roads, to date it is not clear whether the estimated parameters of neural networks are related to the proximities of roads in networks. This study was conducted with the objective of predicting traffic volumes in urban street networks, which are more complex than highway networks, and investigated the relation between proximity of streets and estimated weight parameters of a neural network. The results obtained confirm that the proximity of streets is significant in traffic volume prediction, although some streets have a strong relation with distant streets.

Keywords: Deep Learning, Neural Network, Traffic Volume Prediction, Urban Street Network.

1. Introduction

Traffic congestion is a serious social issue, as it increases travel time and causes deterioration in the roadside environment. Consequently, various technologies, such as roadside devices and probe vehicles, have been utilised to observe real-time traffic conditions. With the development and diffusion of information and communications technology in recent years, short-term traffic condition prediction based on real-time observation has been gaining increased attention.

One approach to traffic condition prediction is deep learning—a form of machine learning in which estimates are made via a multi-layer neural network model. Deep learning has been applied for the prediction of traffic volumes on highway networks in various studies. Yishen et al. (2015) and Yongxue et al. (2015) analysed the traffic volumes on a highway network using a neural network with a fully connected layer, and confirmed that the predictions by deep learning outperformed previous machine learning and statistical models.

However, to date it is not clear whether the estimated parameters of neural networks represent the proximities of roads in road networks. Further, the traffic on urban street networks is more complex than that on highway networks. Many travel origins and destinations are located in urban areas, with traffic controlled by signals. The traffic condition on urban street networks may have strong locality; thus, it is crucial to consider the network structure when predicting traffic volumes on urban streets.

This study focused on prediction of the traffic volumes on urban area streets using deep learning, and investigated the relation between the proximity of streets in urban street networks and the estimated parameters of neural networks. In general, interpreting the meanings represented by the estimated parameters of neural networks is difficult, although Zeiler and Fergus (2014) has attempted interpretation of the estimated parameters of convolutional neural networks in image recognition. In this research, our aim is to extract the spatial structure of street networks, which is useful for traffic volume prediction, with the ultimate objective of improving the efficiency of learning processes and traffic volume prediction accuracy.

This paper focuses on the estimated weight parameters of links between the input layer and the first hidden layer of a neural network and investigates the relationship between the estimated parameter values and the proximities of streets.

2. Methodology

We consider a simple traffic volume prediction problem. The input is the latest traffic volume data observed for each street in the target network in the given time interval, and the output is the predicted traffic volume of each street in the next time interval.

We use a multi-layer neural network with two hidden layers, in which all neurons are connected to all neurons of former and latter layers (Figure 1). Table 1 shows the activation function of each layer; the loss function is the mean squared error (MSE).

We analysed the relationship between the structure of the transformation weight matrix from the input layer to the first hidden layer ($\mathbf{W}_1$) and the proximities of streets in the target street network. To evaluate the degree of influence of traffic volume on street *i* at the latest observation to the prediction of traffic volume on street *j* at the first hidden layer, we focused on element (*j*, *i*) of $\mathbf{W}_1' \, \mathbf{W}_1$, where $\mathbf{W}_1'$ denotes the transpose of matrix $\mathbf{W}_1$.

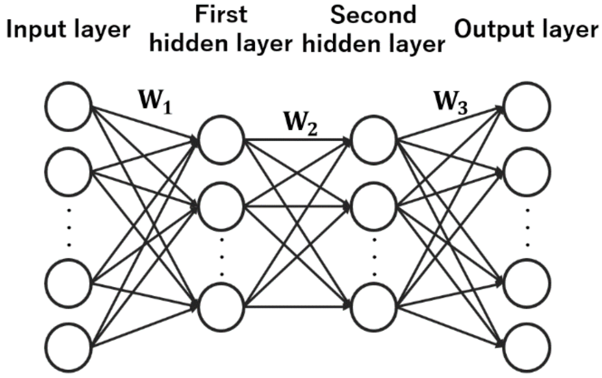


Figure 1: Neural network model used in this analysis

Layer	Activation function
First hidden layer	Sigmoid function
Second hidden layer	Sigmoid function
Output layer	Identity function

Table 1: Activation functions for the neural network

3. Analysis

3.1. Data description

The traffic volume data observed by the Okinawa Prefectural Police on streets in the urban area of the main island of Okinawa, Japan were used in this study. The data comprise traffic volumes recorded at five-minute intervals on 455 street links defined by the Vehicle Information and Communication System (VICS) Center in Japan.

The traffic volume data of each street were normalised with mean zero and variance one to analyse the scale of the weight on each street. Where data were missing for time intervals on any street, the missing data were linearly interpolated using the last and next observation associated with that street.

The observation data from June 2011 to August 2011 were used to estimate the neural network model, and the observation data for September 2011were used to evaluate its prediction accuracy.

3.2. Results

We first examined the prediction accuracy of traffic volume under the different settings of number of neurons in each hidden layer and the different length of data for learning processes. Table 2 shows details of settings and their prediction accuracy in MSE.

It is confirmed that models with smaller number of neurons and estimations by longer data period output better accuracy. It suggests that the prediction by neural network with large number of neurons utilizing small dataset might cause over-fitting problems and provide low-accuracy prediction.

Hereafter, we utilise the prediction results obtained by model A_3, which had the lowest MSE. Figure 2 shows that the prediction correlates well with the daily variation of observed traffic volume data, although some noisy fluctuations in observed data are neglected.

Table 3 shows the aggregation of $\mathbf{W}_1' \, \mathbf{W}_1$ by proximity of streets. It can be seen that the traffic volume prediction of the next intervals of each street is strongly affected by the latest traffic volume observation of that street and the streets with high proximity.

Model	[Number of neurons in first hidden layer, Number of neurons in second hidden layer]	Data period used for estimation	MSE
A_1	[100, 100]	1 month (Sep. 1 –Sep. 30)	0.201
A_2		2 months (Sep. 1 –Oct. 31)	0.190
A_3		3 months (Sep. 1 – Nov. 30)	0.160
B_1	[150, 150]	1 month (Sep. 1 –Sep. 30)	0.202
B_2		2 months (Sep. 1 –Oct. 31)	0.223
B_3		3 months (Sep. 1 – Nov. 30)	0.168
C_1	[200, 200]	1 month (Sep. 1 –Sep. 30)	0.321
C_2		2 months (Sep. 1 –Oct. 31)	0.249
C_3		3 months (Sep. 1 – Nov. 30)	0.177

Table 2: Hidden layer settings, data period used for estimation and prediction errors

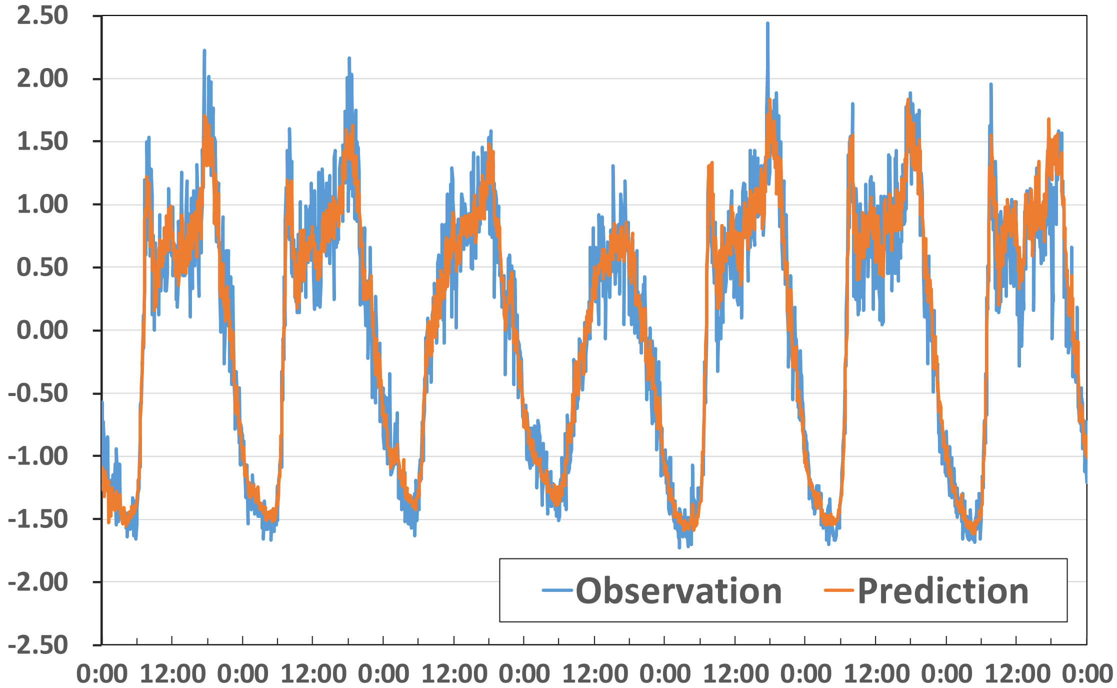


Figure 2: Traffic volume observations and predictions by Model A_3 for street VICS ID #17 from September 1 to September 7.

Connection of streets	Average	Variance	Maximum	Minimum
Target street	7.35	7.91	70.9	0.40
1st order	-0.126	1.80	2.45	-7.60
2nd order	0.135	1.16	8.87	-3.18
Others	0.016	1.11	14.4	-15.5

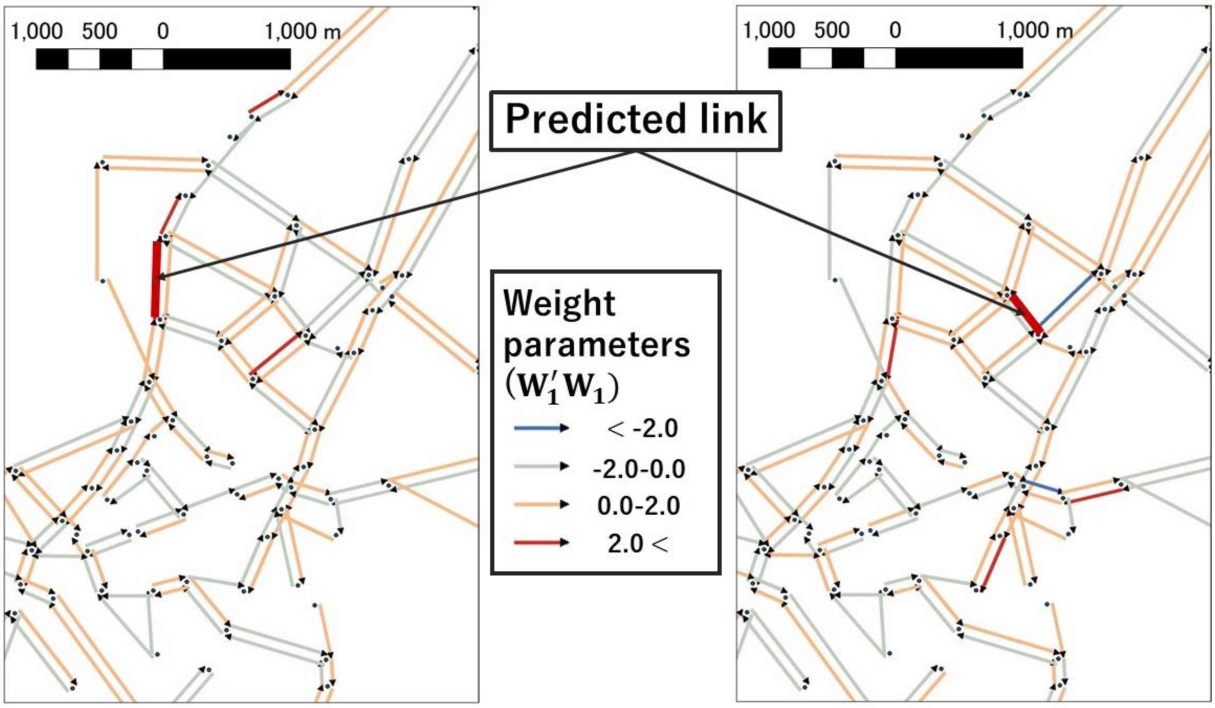
Table 3: Relation of proximity of streets to estimated weights

Figure 3(a) shows a street in which the prediction is highly affected by the observation of itself and a downstream neighbour street. Because a major traffic bottleneck exists downstream of the neighbour street, the traffic volume of this street is influenced by the downstream.

Conversely, Figure 3(b) and Table 4 show a street for which the traffic volume prediction has a strong relationship with distant streets. We assume that the similarity in daily variation of traffic volume makes the weight of distant streets higher. This study focused on the relationship between the similarity of traffic volume data and the spatial proximity in the network; however, Figure 3(b) and Table 4 indicate that consideration of the similarity of temporal changes in traffic volume data between streets is important for traffic volume prediction.

4. Conclusion

This study estimated the parameters of a neural network model for short-term traffic volume prediction in urban street networks using deep learning. Further, the relationship between the size of elements of the transformation weight matrix from the input layer to the first hidden layer and the proximities of



(a) (b)

Figure 3: Spatial distribution of estimated weight parameters. (a) Street #573 with strong relation to neighbours. (b) Street #592 with strong relation to distant streets.

Connection of streets	**Average**	**Variance**	**Maximum**	**Minimum**
Target street	0.118	-	-	-
1st order	-2.22	1.63	-0.67	-5.52
2nd order	-0.348	1.59	2.29	-2.93
Others	0.251	2.16	10.2	-5.15

Table 4: Relation of proximity of Street #592 to estimated weights

streets in the target street network were also analysed. The results obtained indicate that the predicted traffic volume of each street is strongly affected by the observed traffic volumes of that street and streets with lower order connections. This suggests that a neural network model that filters the traffic volume data of distant streets and considers that of adjacent streets may have a high prediction performance with only a small load in the machine learning process.

In this study, focus was only on the spatial aspects of the traffic volume dataset. However, as shown in Figure 3(b), the temporal variation in the traffic volume on each street is also useful for the prediction. It is necessary to determine how to efficiently utilise both the spatial and temporal distribution of traffic volume data for traffic volume prediction. It is also necessary to design neural network models that deal with the spatio-temporal information hidden in traffic data, not only traffic volume data but also traffic density and velocity data. These tasks will be dealt with in future work.

5. Acknowledgements

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6. References

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