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Predicting Traffic Breakdown in Expressways using Linear Combination of Vehicle Detector Data

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Abstract—Traffic congestion brings about various social issues to be solved urgently. With the recent advancement of machine learning technologies, various methods for predicting traffic congestion have been developed. Specifically, traffic prediction using deep learning can provide highly accurate performances. However, there are several problems due to the complexity of the deep learning models, namely, they require a large amount of data and computational power. In this study, we examine a precision of traffic prediction with a simple linear model. Instead of improving the complex models, we appropriately select training data with a linear model and verify the feasibility of prediction by exploring "data complexity". We use actual data collected by detectors on expressways.

1. Introduction

The automobile is one of the major means of transportation recently and plays an important role in the social system. However, it is also true that they have problems such as traffic congestion and accidents. In Japan, traffic congestion in urban areas causes an annual time loss of about 3.81 billion hours [1]. As a solution against these problems, Intelligent Transport Systems (ITS) are promoted all over the world, so that the development of information infrastructure for road traffic using AI and IoT technologies is rapidly progressing [2, 3]. According to these backgrounds, predicting traffic congestion using machine learning techniques have attracted much attention [3, 4, 5, 6]. A technology that predicts future traffic congestion is based on various current and past information in a road network. If the prediction technology is developed to a practical level, it is expected to contribute to the development of ITS in a way of facilitating traffic flow and selecting optimal routes that avoid traffic congestion. Currently, the major technology for prediction of traffic congestion is based on deep learning models with big data. However, these models have some disadvantages, namely, they require a large amount of data and tuning algorithms according to the complexity of the models. In this paper, we discuss the usefulness and significance of a prediction model with a linear combination of detected data.

Traffic congestion is in general classified into two types based on its characteristics: recurring and non-recurring congestion, and studies have attempted to predict each type of congestion by machine learning using traffic data. This paper deals with recurring congestion, which is caused by the bottleneck's inability to cope with excessive traffic during peak hours such as commuting [7]. In predicting recurring traffic congestion, it is a challenge to accurately predict the time and scale of periodic traffic congestion. For this purpose, it is important to capture the characteristics of spatio-temporal variations in traffic data. Recently, as seen in the DEEPLSTM method in [8] and the DCRNN method in [9], the mainstream approach is to model nonlinear dynamics and improve prediction accuracy by creating more complex deep learning models based on CNN and RNN techniques. In contrast to this research line, this paper considers predicting traffic congestion using a linear model. To this aim, we demonstrate that it is possible to make predictions by exploiting physical phenomena in the real world as a part of computational processes.

In this study, we perform a prediction of traffic congestion on expressways using a linear model based on previous studies [10]. We examine whether the accuracy can be improved by modifying the training data compared with the previous studies. The purpose of this study is twofold. The first is to show that the complexity of the data can be successfully extracted by selecting the data, thereby increasing the accuracy of the prediction. This allows us to propose a methodology for prediction that does not rely on the complexity of the model, but rather allows the computational process to depend on the complexity inherent in the data. Secondly, we show the usefulness and significance of linear models in predicting traffic congestion. Specifically, we demonstrate the high explanatory ability of the linear model in the prediction by investigating the causes of changes in accuracy through parameter analysis. The subject of this study is the No. 11 inbound line of the Hanshin Expressway.

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2. Model

As described in the previous section, this study uses a linear combination of the data to predict the occurrence of traffic congestion. Additionally, we divide the occurrence of traffic congestion at a particular location into two categories based on spatial characteristics, namely, traffic breakdown (i.e., bottleneck activation at this location) and spillback from the downstream active bottleneck.

2.1. Data Summary

In this study, a prediction model was constructed using vehicle detector data installed on the Hanshin Expressway. First, as explanatory variables, per-detector traffic data recorded every 5 min at the installation points are used. Four types of traffic data are recorded for each detector: average speed, traffic volume, high-vehicle traffic volume, and detector occupancy. Additionally, the daily traffic congestion report data, which records the presence or absence of traffic congestion at that location every 30 seconds, is used as the explained variable.

2.2. Linear model

The prediction model used in this study is a linear model. Ridge regression (Eq. (1)) is used for training, and Y is calculated using the estimated weights (Eq. (2)), and label identification is performed according to a threshold value (Eq. (3)).

$$W^{out} = \left(X^T X + \lambda I\right)^{-1} X^T, \tag{1}$$

$$Y(t+\tau) = X(t) W^{out}, \tag{2}$$

$$u_k(t) = \begin{cases} 1, & y_k(t) >= 0.5, \\ 0, & y_k(t) < 0.5, \end{cases} \tag{3}$$

where τ is prediction horizon. As can be seen from these equations and the data summary, only spatial data at one point in time are used for the prediction. Also, when estimating parameters, we do not train backward in the time-series direction as RNNs do.

2.3. Prediction targets and their correctness criteria

The objective of this traffic congestion forecasting is to predict whether traffic congestion will occur at a target location 10 min later. Therefore, the label identification is performed for congested and non-congested traffic, and the accuracy is measured by the percentage of correct answers to the occurrence of traffic congestion. A congestion occurrence is defined as a congestion label that satisfies the following conditions: (1) the first time traffic congestion is predicted, and (2) no traffic congestion has been predicted in the previous 30 minutes. The correctness criterion is defined as the actual occurrence of traffic congestion between 5 min before and 30 min after the predicted time of the traffic congestion. The performance of the prediction is evaluated by the recall, precision, F1 value.

3. Data sampling

A total of three methods of sampling with respect to one type of traffic congestion occurrence, namely, traffic breakdown, were tested for accuracy improvement and compared with previous studies. In this paper, the definition of the training data is different for each verification because we fix the model and aim to improve the accuracy only by appropriately selecting the training data. Therefore, this section details how to select the training data used in each verification. Unless otherwise noted, the traffic data used are divided into two parts: the period from April 2015 to November 2017 as training data and the period from April 2018 to March 2019 as test data. For the training data, we devised each verification within that period. This is to facilitate comparisons by aligning the period with that of a previous study [10, 11, 12].

3.1. Sampling from just before and after the traffic congestion

In this verification, the training data is devised in the time-series direction to predict the occurrence of traffic congestion. Specifically, the training data is defined as a set of three steps in the time-series direction around the timing when a traffic congestion occurs. Therefore, the training data consist of data right before and after the occurrence of traffic congestion. The purpose of this sampling data is to eliminate extreme traffic congestion and non-congested data from the training data, and to increase the ratio of data around the occurrence of traffic congestion in the training data. To examine the change in accuracy resulting from this sampling, parameter estimation was performed on three types of training data, and prediction accuracy was compared with test data. Each training data used is shown in Table 1.

Table 1: Definition of training data used in 3.1

Training data	A	B	C
Definition	Vehicle detector data for No. 11 line		
Explained variable	Daily traffic congestion report data for forecasted locations		
Period	April 1, 2015 ~ November 30, 2017		
Constraints	None	6am-21pm only	3 time points before and after traffic congestion

The training data C is newly proposed training data, which consist of a set of 7 points in time: 10 minutes before the occurrence of the traffic congestion and 3 points before and after the occurrence of the traffic congestion. There are two reasons for using this as the training data. The first is to balance traffic congestion labels and non-traffic congestion labels. The training data used in the previous study [10, 11] (similar to A) was imbalanced data with a very large proportion of non-traffic congestion labels, and we thought that the accuracy could be improved by balancing the data. The second is to improve the quality of each label. In this prediction task, it is important to correctly predict the occurrence of traffic congestion. Therefore, we estimated that increasing the proportion of data near the occurrence of traffic congestion in the training data and making each label closer to the occurrence of traffic congestion would lead to an improvement in the classification performance of the boundary. As comparison targets for data C, we prepared data A, which is the same as in the previous study [10, 11], and data B, which is intermediate between A and C and consist of training data only during periods of heavy traffic flow. The obtained results were also compared with those of the previous study [11].

3.2. Refine the detector data

In this velification, we investigate the training data in both the time and spatial directions to predict the occurrence of traffic congestion at 0.0 kp. First, for the time-series direction, the same division of training data as in Section 3.1 is used. In the spatial direction, two additional modifications are made: the explanatory variables are composed of only vehicle detectors in the vicinity of the prediction target point, and the detector data are treated by lane rather than by the set of lanes. The purpose of these modifications is to more accurately observe intersections of traffic flow caused by the merging of routes and traffic conditions that vary from lane to lane.

The spatial arrangement of the vehicle detectors used in this verification is shown in Figure 1. The triangles in Figure 1 indicate the location of the vehicle detectors used in this verification, and their color indicates the route to which they belong.

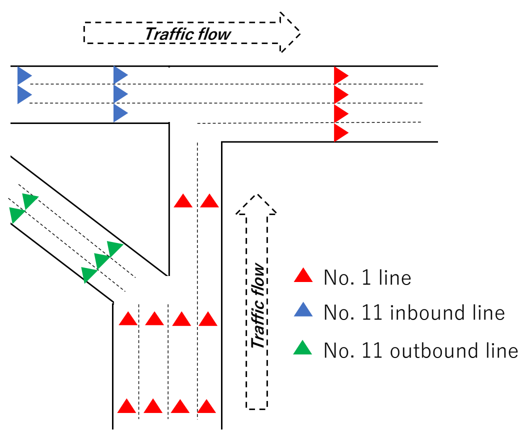

Figure 1: Detectors used in Section 3.2

In order to examine the change in accuracy due to this refinement, parameter estimation was performed on two types of training data and the prediction accuracy were compared. The definition of each training data used is as in Table 2.

Table 2: Definition of training data used in Section 3.2

	Explanatory variable		Devices for time sequence direction	number of points in time
	Definition	Total		
A	Consolidate data by location	32	3 steps before and after a traffic congestion	6519
B	Per detector	96		

In Table 2, the pattern B is the method proposed here. Pattern A, on the other hand, uses detector data from the same locations, but aggregates the detectors at each location into one detector data set per location used as an explanatory variable. The obtained results were also compared with those of the previous study [12].

4. Results

This section describes the results obtained from each of the two verification described in the Data sampling section.

4.1. Results of Verification 3.1

The prediction accuracy obtained for each pattern are shown in the following table. However, in this paper, only the bottleneck point of 4.0 kp, where the results are characteristic, is shown. From this table, it can be seen that at 4.0 kp, data C gives the most accurate prediction. In addition, the prediction results when training data C are compared with previous studies [11] as shown in Table 4. It can be seen that the congestion prediction using the training data C is more accurate than the previous study at 4.0 kp [11], even though the number of data in the time-series direction is considerably reduced.

Table 3: Prediction accuracy of each training data

training data	precision	recall	F1 value
A	0.685	0.662	0.673
B	0.72	0.718	0.719
C	0.75	0.878	0.809

4.2. Results of Verification 3.2

The results of the accuracy are shown in Table 5. The F1 value in the training data for B is more than 0.1 points higher than that for A. The F1 value in the training data for B is almost the same that by Graph convolutional neural networks (GCN) in the previous study, even though there are fewer explanatory variables.

5. Conclusion

We have shown that the accuracy of predicting traffic congestion in the expressways can be improved by selecting the training data in an appropriate way. In this paper,

Table 4: Comparison of the results of Section 3.1 with the accuracy of previous studies (Convolutional neural networks(CNN) models)

Model	F1 value	Length of time series
linear model(C)	0.809	13886
CNN	0.794	280497

Table 5: Comparison of the results of Section 3.2 with the accuracy of a previous study (GCN)

Model	F1 value	Number of parameters
linear model(A)	0.2089	32
linear model(B)	0.384	96
GCN	0.385	2163

we have also made an effort to reduce the volume of the training data in the time-series and spatial directions. Since these modifications drastically reduce the amount of data to be trained, they are not expected to work in deep learning models that require big data for training. In future works, it will be necessary to show the effectiveness of the linear model in predicting the occurrence of traffic congestion by the following two steps. The first is to extract the set of data characterized by the important parameters for prediction. The second is to identify what characteristics data are captured from those parameters and used to predict traffic congestion. Furthermore, by analyzing the parameters, we are able to explain which quantity causes the improvement in accuracy, i.e. explainability, thanks to the linear properties of the prediction method.

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