# Improving traffic speed prediction by embedding road dependence in the learning matrix of CNN

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## ABSTRACT

Due to the lack of sufficient exploration of global spatial-temporal characteristics of traffic dynamics, large-scale and long-term vehicle speed prediction problems have not been well solved. To this end, this study presents a 3-dimensional road matrix based deep learning model (3DM-DLM) to embed global similarities of road segments in constructing learning matrix. The global similarity is measured by sampling the correlation of vehicle speed, and the correlation aggregation of adjacent road segments in the matrix is realized by clustering and Z-order curve. The learning matrix is then used to train a deep neural network composed by convolution layers and residual units. We collected traffic speed data in Beijing to validate the 3DM-DLM. The results showed that compared with the baseline model, the prediction accuracy of the proposed model is improved by 8.05 % in the acceptable time, and it also proved the generalization ability of 3DM-DLM in specific cases.

**Keywords:** Vehicle speed prediction, 3-dimensional road matrix, clustering, Z-order

## 1. INTRODUCTION

Measuring traffic parameters such as traffic volume, speed and density is necessary for traffic management. Among these parameters, traffic speed is the basic index to evaluate the level of traffic management[1]. Since the speed on a given road segment is affected by the current and past speed of the nearby road segment, an effective prediction model must reflect the relevant traffic conditions of the entire road network at relevant moments. Based on this potential principle, researchers have tried a variety of methods from traditional time series analysis to the recent deep learning technology to predict traffic speed[2-5].

Machine learning model is also used for vehicle speed prediction and has achieved good results[6-8] but the single hidden architecture of machine learning model cannot better identify the complex nonlinear structure in data. Deep learning model overcomes the above drawbacks by using long time series and large-scale data training to achieve highly nonlinear fitting[9-11]. Recently, researchers have found that the vehicle speed prediction accuracy can be improved by designing a reasonable input matrix of deep learning[12-15]. Some methods of transforming a directed graph into a two-dimensional matrix[13,16-20]. This method has high precision, but the matrix generation algorithm is complex and it is difficult to obtain the required data; To address this problem, numerous methods[16,21], which encode according to the direction and time sequence of traffic flow, have been proposed, but the mining of the relationship between road segments is not sufficient[13]; In addition, in the input matrix design, the similar feature of vehicle speed change is also an implicit feature that needs to be mined[12]. Yu et al.[22] measured the similarity of vehicle speed change through the Dynamic Time Warping algorithm based on Euclidean distance, but it is very subjective to set the degree threshold as 5%. Shen et al.[23] and Modi, Bhattacharya, and Basak[24] proposed algorithms for generating multiple similarity matrices by hierarchical clustering based on Pearson correlation, but this method is not suitable for long-time traffic speed like next-day traffic speed prediction.

In order to overcome the above shortcomings, this paper proposes a design algorithm of 3-Dimensional Road input Matrix(3DM), which does not need to consider the geometric (spatial) information of the road network and directly executes the raw input data. The main innovation of the algorithm is to fully excavate the spatial and temporal correlation characteristics of vehicle speed change in the global road network through the reasonable layout of the matrix. In the experimental part, in addition to the comparison of time efficiency and accuracy with typical algorithms, this paper also

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makes a comparative verification of traffic conditions under special cases.

# 2. MODELING FRAMEWORK

The overall framework of 3DM-DLM (3-Dimensional Road Matrix based Deep Learning Model) consists of two major parts. The first part transforms raw traffic data into a series of well-structured learning matrices that embed road dependence, which is the key to the improvement of traffic prediction. The second part addresses data training and prediction by feeding the learning matrices to a classic deep neural network architecture that integrates convolution layers and residual layers.

## 2.1 Constructing 3D matrix

(1) Road segments encoding

The speed data of a road segment is represented by $S_i=[x_1, x_2, \ldots, x_n]$, where $i$ denotes the $i^{th}$ road, and $x_1, x_2, \ldots, x_n$ denote the sequence of the speed for each time interval. In this study, the intervals are of equal length.

In the first step, road segments are sorted by a similarity-based clustering method. In this study, the similarity is measured by the Pearson's correlation of the speed data[21], as shown in equation (1).

$$Corr(S_i, S_j) = \left| \frac{\sum_{t=1}^{n}(x_t-\bar{x})(y_t-\bar{y})}{\sqrt{\sum_{t=1}^{n}(x_t-\bar{x})^2}\sqrt{\sum_{t=1}^{n}(y_t-\bar{y})^2}} \right| \tag{1}$$

where $x_t$ and $y_t$ represent the speeds of two road segments for the $t^{th}$ timespan, $\overline{x}$ and $\overline{y}$ denote the mean values.

In the second step, this study employs agglomerative hierarchical clustering to group similar road segments[25], as shown in equation (2).

$$f(x,y) = \sum_{i=1}^{num_C}\left(\frac{1}{2|C_i|}\sum_{x\in C_i}\sum_{y\in C_i} Corr(x,y)^2\right) \tag{2}$$

where, $num_c$ represents the number of classes, $C_i$ represents the $i^{th}$ class, and $Corr(x,y)$ represents the correlation coefficient of road segment x and road segment y, and $|C_i|$ represents the number of road segments in the class.

In the last step, the road segments are uniquely numbered based on the tree structure generated by hierarchical clustering. As shown in Figure 1, firstly, in order to prevent the sorting confusion caused by too many road segments, 0.15 (the shortest distance method of hierarchical clustering) is used as the threshold to roughly stratify the tree. Secondly, the coding sequence is identified by a 6-bit decimal number (the coding length can be dynamically increased). Among them, the first two bits of the code identify the rough layers of the tree, the middle two bits identify the number of layers corresponding to the road segments in the same rough layer, and the last two bits identify the location of the road segments starting from the left in the same layer.

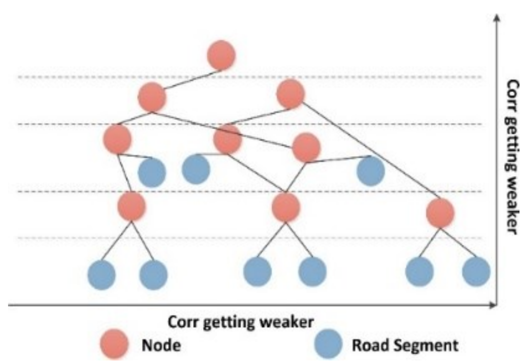


Figure 1. Schematic diagram of the hierarchical clustering result.

(2) 3D Matrix filling

The calculation formula of matrix size is as follows:

$$n = \lfloor log_2^S \rfloor \tag{3}$$

$$col = 2^\wedge\lfloor n/2 \rfloor \tag{4}$$

$$row = col + \left\lceil \frac{s-col^2}{col} \right\rceil \tag{5}$$

where $s$ is the total number of road segments, *col* denotes the number of columns, and *row* denotes the number of rows.

In this section, Z-order curve is used to realize matrix filling, mainly because it conforms to the convolution process and is simple and feasible.

The interactions between road segments are complex, and thus a 2D matrix may not be sufficient to characterize their spatial-temporal relationships. For example, a traffic state $x^t$ on road segment is not only related to the road segment with high similarity of speed change, but also related to the previous moment of the road segment ($x^{t-\triangle t}$), the time of the previous cycle ($x^{L*t}$) and the previous moment of the previous cycle ($x^{L*t-\triangle t}$). Therefore, the third dimensional order of 3D matrix is represented by $Z$=[$x^{t-\triangle t}$, $x^{t-2\triangle t}$, $x^{l*t}$, $x^{l*t-\triangle t}$, $x^{l*t+\triangle t}$, $x^{l*t-2\triangle t}$, $x^{2*l*t}$, $x^{2*l*t-\triangle t}$, $x^{2*l*t+\triangle t}$], where $l$ denotes the day cycle and week cycle.

### 2.2 Deep neural network training and forecasting

The deep neural network dedicated to road speed training and prediction is composed by an input layer, multiple learning layers, and an output layer. The input layer is a series of 3D matrices that characterize road dependence at different timestamps and the output layer shares the same size with the input layer. The learning layer is based on the 3D convolution process proposed by Ji et al.[25], and the ST-ResNet (Deep Spatio-Temporal Residual Networks) model proposed by Yan et al.[26].

The definition of the convolution function in this paper is as follows: The value of unit at position ($x$,$y$) in the $j^{th}$ 2D matrix in the $i^{th}$ 3D matrix, denoted as $X_{ij}^{xy}$, is given by

$$X_{ij}^{xy} = ReLU\left(\sum_m \sum_{p=0}^{P_i-1} \sum_{q=0}^{Q_i-1} w_{ijm}^{pq}\, x_{(i-1)m}^{(x+p)(y+q)} + b_{ij}\right) \tag{6}$$

where $ReLU(\cdot)$ is the rectified linear unit, $m$ index over the set of 2D matrix in the ($i$-1)$^{th}$ 2D matrix connected to the current 2D matrix, $w_{ijm}^{pq}$ is the value at position ($p$,$q$) of the kernel connected to the $k$th 2D matrix, $P_i$ and $Q_i$ are the height and width of the kernel, and $b_{ij}$ is the bias for this 2D matrix, respectively.

The convolution layer can identify features at multiple scales, and residual units improve network performance to prevent network training from disappearing gradient problems. All neurons in the network are globally connected, and in order to prevent the loss of corner information of the matrix, we use a border-mode which allows a filter to go outside the border of an input, padding each area outside the border with a zero. In addition, the loss function ($L(\theta)$) is defined as follows:

$$\mathrm{L}(\theta) = ||X_t - X_t'||_2^2 \tag{7}$$

where $X_t$ denotes the real value of speed and $X_t'$ denotes the predicted value of speed.

## 3. EXPERIMENTS AND RESULTS

### 3.1 Datasets

This study evaluates the performance of 3DM-DLM using the traffic speed dataset of Beijing. Having more than 13 million residents, the capital city presents a representative sample to study complex urban traffic dynamics. Accurate traffic forecast is beneficial to solving the traffic congestion problem in such a super city. The traffic dataset is composed of 12494 road segments with average speed data recorded at a 15-minute interval from April 16th to August 22nd, 2018 (https://lbs.amap.com). As shown in Table 1, these road segments are classified as highways, ring roads, main roads, and other roads, which are used to examine the performance in difference types of road segments. This study also divides the dataset into five subsets of randomly selected road segments with the number of records increased from 20% to 100% of the total size, which are used to examine the performance in different size of datasets (Table 2).

Table 1. Categories of road segments.

| Road category | D11 (highway) | D12 (ring road) | D13 (main road) | D14 (other road) |
|---|---|---|---|---|
| Road segments | 965 | 2331 | 6797 | 2401 |

Table 2. Number of road segments in the five sub-datasets.

| Dataset | D21 | D22 | D23 | D24 | D25 |
|---|---|---|---|---|---|
| Road segments | 2499 | 4998 | 7496 | 9995 | 12494 |

During training, this study uses Max-min function to normalize the data to [0, 1]. In the evaluation, the predicted value is rescaled back to the standard value and compared with the ground truth value. In addition, 80% of the data is used as the training set and the remaining 20% is used as the test set.

### 3.2 Baseline methods and evaluation metrics

The baseline methods in the comparison include: TCA-DCNN (Temporal Clustering Analysis and Convolutional Neural Network with Deformable kernels)[23], DSF-LAM (Dynamic Spatiotemporal Framework-combining LSTM and Attention Mechanism)[27] and EN-GRN (Graph Recurrent Network)[20]. TCA-DCNN expresses the upstream and downstream relationship between road segments by designing spatial-temporal correlation matrix, and improves speed prediction accuracy by time clustering and designing variable convolution kernel. DSF-LAM gridizes the road network, uses bidirectional LSTM and CNN to dynamically obtain the time correlation of vehicle speed, and then uses a more refined attention mechanism to learn short-term and long-term cycle characteristics. Lei et al. (EN-GRN) constructed a parameter matrix that can represent the specific spatio-temporal characteristics of each node to enhance the representation of road-specific traffic patterns, and used node embedding to reduce the size of the parameter matrix. In the comparative experiments, the above three algorithms are typical and have good accuracy in speed prediction. In addition, these three algorithms use the speed data which are easy to obtain, and the experimental processes are easy to implement.

The evaluation benchmarks for speed prediction performance of the proposed methods are root-mean-square error (RMSE), mean absolute error (MAE) and sample standard deviation (STD.S). These can be calculated by the following equations:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{m}(y_i-\widehat{y_i})^2}{m}} \tag{8}$$

$$MAE = \frac{\sum_{i=1}^{m}|y_i-\widehat{y_i}|}{m} \tag{9}$$

$$\mathrm{STD.S}_i = \sqrt{\frac{\sum_{j=1}^{n}\left(x_j-\widehat{y_i}\right)^2}{n-1}} \tag{10}$$

where $y_i$ denotes the $i^{th}$ predicted speed value, $\widehat{y_i}$ denotes the $i^{th}$ actual speed value, $m$ is the total number of road segments, $STD.S_i$ denotes the $i^{th}$ time point's deviation between the predicted speed and the actual speed, $\widehat{x_j}$ denotes the $i^{th}$ time point's predicted speed value, and $n$ is number of experiments at time point $i$.

### 3.3 Comparison of different prediction algorithms

In this section, we compare the training efficiency of the 3DM-DLM and other algorithms. Table 3 shows the RMSE variation curves versus the training epoch. The loss of the 3DM-DLM decreases fastest among the compared algorithms.

Table 3. Parameter comparisons of four algorithms when the deep learning enters a stable state.

| Algorithm | D11 | | D12 | | D13 | | D14 | |
|---|---|---|---|---|---|---|---|---|
| | Step | RMSE | Step | RMSE | Step | RMSE | Step | RMSE |
| 3DM-DLM | 67 | 2.08 | 78 | 2.17 | 91 | 2.5 | 99 | 2.61 |
| EN-GRN | 73 | 2.15 | 84 | 2.21 | 99 | 2.49 | 101 | 2.84 |
| DSF-LAM | 68 | 2.18 | 76 | 2.14 | 89 | 2.49 | 98 | 2.99 |
| TCA-DCNN | 69 | 3.05 | 73 | 3.37 | 96 | 4.32 | 118 | 5.16 |

| Algorithm | D21 | | D22 | | D23 | | D24 | |
|---|---|---|---|---|---|---|---|---|
| | Step | RMSE | Step | RMSE | Step | RMSE | Step | RMSE |
| 3DM-DLM | 118 | 3.4 | 121 | 3.36 | 115 | 3.15 | 109 | 3.01 |
| EN-GRN | 114 | 3.35 | 124 | 3.43 | 112 | 3.56 | 110 | 3.25 |
| DSF-LAM | 133 | 3.76 | 198 | 4.11 | 121 | 4.01 | 116 | 3.77 |
| TCA-DCNN | 135 | 6.12 | 130 | 5.8 | 124 | 5.66 | 117 | 5.57 |

Figure 2 shows the training and prediction time of different algorithms on different datasets. It can be seen from the figure that the trend line (jujube red) shows an upward trend, indicating that compared with the speed prediction of heterogeneous roads (D21-D25), the speed prediction experiment after road classification (D11-D14) has better time efficiency in the training and prediction stage. In addition, in the training and prediction stage, the time ratios consumed by the four algorithms are all greater than 1, indicating that due to the design of the correlation matrix, 3DM-DLM can quickly complete the learning and prediction process, and the time advantage becomes more and more obvious with the increase of data volume and road type complexity.

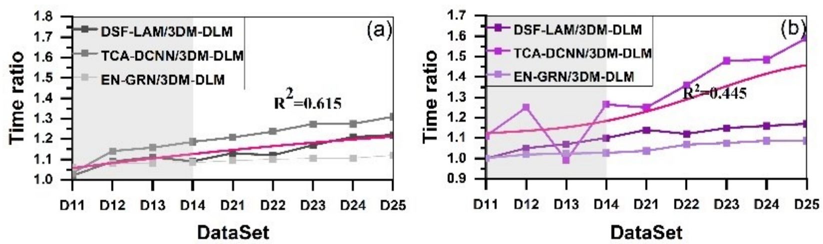


Figure 2. Time ratio of different algorithms. (a) training time; (b) predicting time.

Figure 3 shows the overall rating prediction error of 3DM-DLM and other three algorithms under different ratios of training set for the nine datasets. As shown in Figures 3a-3d, from D11 to D14, although the road type is relatively single, the factors affecting vehicle speed (more intersections, narrower road width, etc.) are becoming more and more complex. The average MAE of the four algorithms is increased from 1.56 to 2.43, but the prediction accuracy of 3DM-DLM is improved from 4.68 % to 28.97 %. It can be seen from Figures 3e-3i that with the increase of data volume, the prediction accuracy of 3DM-DLM increases from 11.69 % to 33.08 %. We also found that the prediction accuracy of 3DM-DLM increased from 19.75 % to 21.70 % with the increase of prediction horizon. In addition, we tested the experimental results and found that the difference in the prediction accuracy of the four algorithms was statistically significant (P<0.01, double tail) by paired *t*-test. The results show that 3DM-DLM has strong robustness to extend to new data samples.

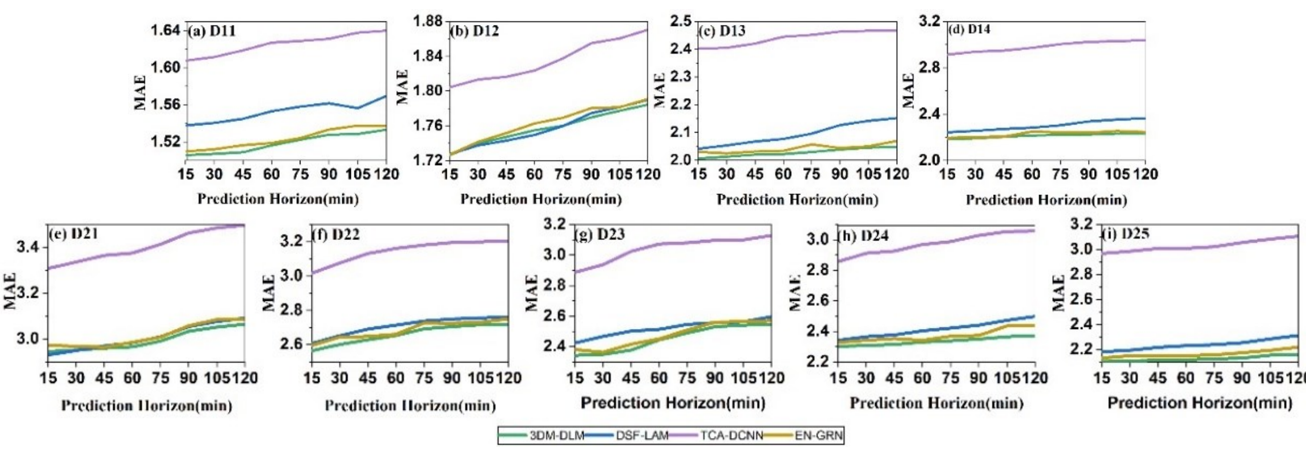


Figure 3. MAE Results of different algorithms.

### 3.4 Performance for specific cases

Rainfall is an important factor affecting the efficiency of urban road traffic. This part takes the rainstorm event on July 16, 2018 in Beijing as an example to carry out empirical research on Zhongguancun South Road, which is greatly affected by rainfall. As shown in Figure 4a, the rainfall period in this road segment is 8:00-9:00 and 18:00-19:00, at which the speed is 5.01 km/h lower than the weekly average, and the prediction error (STD. s) of each algorithm is as high as 2.39 (Figure 4b). However, compared with the other three algorithms, the speed prediction accuracy of 3DM-DLM is improved by 19.67 % (especially during rainfall, its accuracy is increased by 60.38 %), which provides data support for emergency response and management of urban rainfall events.

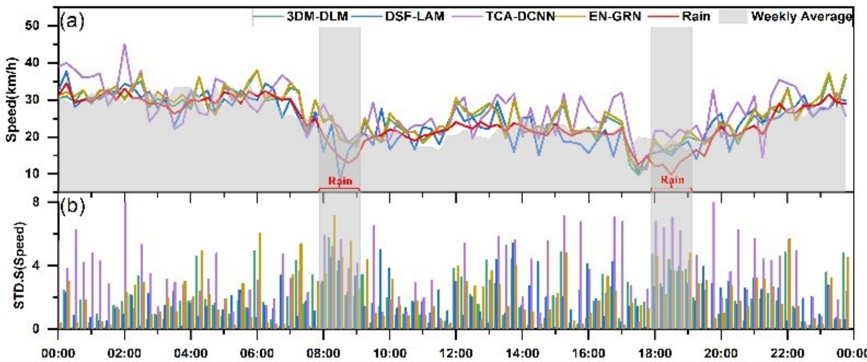


Figure 4. Performance comparison of four algorithms under rainfall events. (a): Comparison of vehicle speed prediction; (b): Comparison of sample standard deviation of vehicle speed.

Congestion is an important cause of waste of traffic resources[8]. This section introduces the accuracy of each algorithm in the prediction of the congestion index of Zhongguancun South Road, which is the main road in Haidian District. Among them, the congestion index is obtained based on the fitting of the existing congestion index data and vehicle speed data. As shown in Figure 5a, the prediction accuracy of 3DM-DLM increased by 63.54% in the peak period of work and 34.78% in the whole day (as shown in Figure 5b). The main reason for the better performance of 3DM-DLM is that in addition to the higher prediction accuracy of vehicle speed, as shown in the zoom diagram of Figure 5a, the smaller gap of vehicle speed data may correspond to the larger gap of congestion index and congestion level.

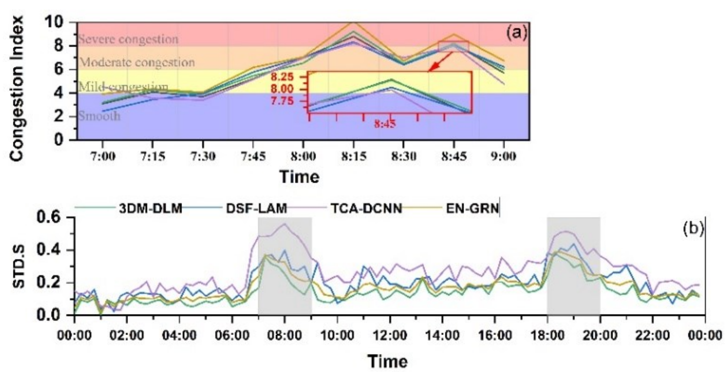


Figure 5. Performance comparison of four algorithms for Zhongguancun South Road on 16 July 2018 (prediction horizon: 15 min). (a): Traffic congestion index and traffic congestion level prediction during peak hours of work; (b): Traffic index prediction for 24 hours.

# 4. CONCLUSIONS

Future smart traffic needs to process large-scale, long-term series of speed data to predict, analyze and understand complex traffic conditions. Aiming at the problem of inaccurate and untimely vehicle speed prediction, this paper proposes a novel and effective model (3DM-DLM). This model transforms the original traffic data into a series of well-structured embedded road correlation learning matrices by mining the spatio-temporal correlation characteristics of vehicle speed changes, and uses the deep learning model to realize the speed prediction. In this study, a group of empirical experiments are performed using the traffic speed collected at 15 min intervals from a Beijing transportation network with 12494 road segments.

Compared with the existing algorithms, 3DM-DLM has high accuracy and computational efficiency in large-scale and long-time interval vehicle speed prediction. Furthermore, the prediction accuracy under specific cases were tested, and the results shows that our 3DM-DLM can acquire the optimal result.

This study only focuses on the use of speed data from a single data source to predict speed. However, changes in speed will be related to holidays, rainfall, snow and other external conditions, which may be more accurate and meaningful for travelers, commuters and administrative departments. In future work, we will try to fuse multiple types of data from different sources to establish traffic prediction models for predicting traffic condition-related properties.


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