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Transfer Learning for Traffic Speed Prediction

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DATA DESCRIPTION

The data source in this study is the Caltrans Performance Measurement System (PeMS), which stores multiple traffic variables over 39,000 individual traffic detectors in San Diego, California, US.

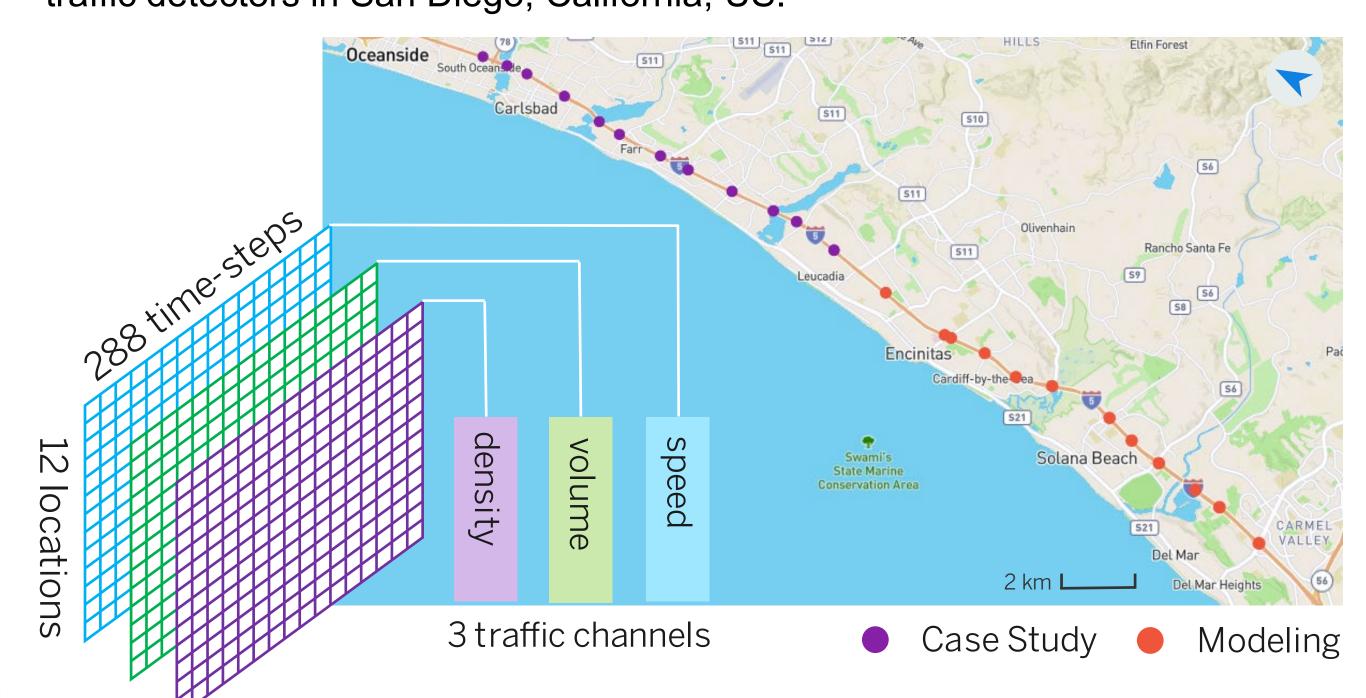


FIGURE 2 Detector Locations of two datasets and their input data shape

Two subsets are created, and multiple traffic data of speed, density, and flow are used for forecasting the traffic speed in the next {5,10,15,20} continues mins. Table 1 shows the comprehensive information on these two datasets.

TABLE 1 Dataset Information

Dataset	Modeling	Case Study			
Detectors	12	12			
Traffic direction	Northbound	Northbound			
Postmile	[34.033, 41.922]	[43.191, 51.327]			
Time Interval	5 mins	5 mins			
Start	1/03/2018 0:00	1/03/2018 0:00			
End	31/05/2018 23:55	7/03/2018 23:55			
Length	27,648	2,016			
Test Set	Last 300 time-steps	Last 300 time-steps			
Training Set	Random 90%	Random 90%			
Validation Set	Random 10%	Random 10%			

WORKFLOW OF EXPERIMENTS

All models appear in the figure share the same structure, but they use different methods to initialize the hidden weights and biases before training. The "Random" method generates trainable parameters from a uniform distribution, while the "Fine-tuning" method (B) initializes them from a trained model (A). For the second method, the learned traffic features (A) are expected to be transferred to a new case (B).

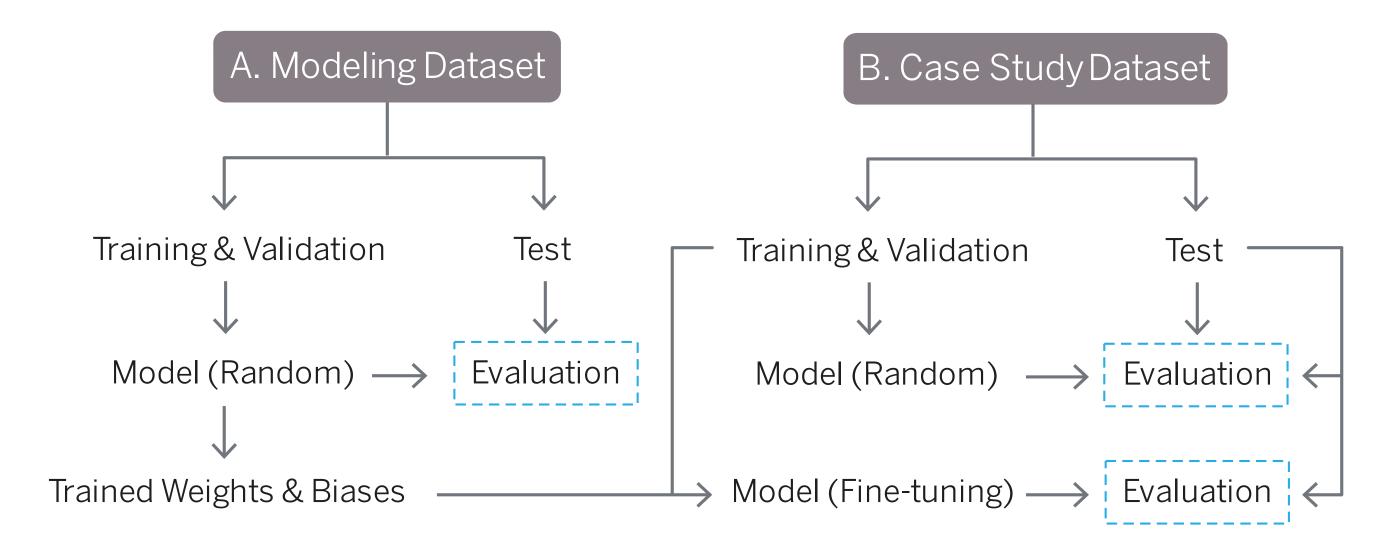


FIGURE 3 The workflow of transfer learning experiments

RESULTS

Table 2 shows the detailed results of the experiments. Each group performs model 3 training and evaluation using two different datasets. The data duration of the Modeling and Case 4 Study models are three months and one week, respectively.

TABLE 2 Forecasting Performance

Control Group						Experimental Group (Two Parallel CNN)					
(CNN+LSTM)											
Output	Params	MSE	RMSE	MAE	MAPE	Param s	MSE	RMSE	MAE	MAPE	
Random						Random					
5 mins	238792	57.118	4.489	1194	0.122	18020	2.862	1.518	367	0.021	
10 mins	463060	57.814	4.562	2450	0.123	32432	4.332	1.849	893	0.026	
15 mins	687328	58.717	4.666	3817	0.125	32432	5.657	2.056	1516	0.03	
20 mins	911596	59.198	4.699	5149	0.126	46844	6.977	2.235	2206	0.032	
Random 7.4% improved						Random 39.6% improved					
5 mins	238792	44.926	4,432	1144	0.091	18020	8.078	2.614	723	0.038	
10 mins	463060	46.879	4.657	2376	0.094	32432	9.625	2.803	1505	0.041	
15 mins	687328	47.351	4.688	3608	0.094	32432	11.452	2.988	2403	0.044	
20 mins	911596	48.637	4,734	4897	0.095	46844	12.13	3.087	3240	0.044	
Fine-tuning 🗸					Fine-tuning 🗸						
5 mins	238792	42.183	4.12	1044	0.086	18020	3.721	1.65	434	0.024	
10 mins	463060	42.733	4.179	2148	0.087	32432	5.818	2.132	1124	0.031	
15 mins	687328	44.549	4.381	3433	0.091	32432	7.55	2.243	1722	0.033	
20 mins	911596	44.485	4.336	4487	0.09	46844	8.399	2.355	2452	0.035	
	5 mins 10 mins 20 mins 10 mins 10 mins 10 mins 15 mins 20 mins 15 mins 10 mins 10 mins	Ra 5 mins 238792 10 mins 463060 15 mins 911596 Ra 5 mins 238792 10 mins 463060 15 mins 687328 20 mins 911596 Fine 5 mins 238792 10 mins 463060 15 mins 687328	Output Params MSE Random 5 mins 238792 57.118 10 mins 463060 57.814 15 mins 687328 58.717 20 mins 911596 59.198 Random 5 mins 238792 44.926 10 mins 463060 46.879 15 mins 687328 47.351 20 mins 911596 48.637 Fine-tuning 5 mins 238792 42.183 10 mins 463060 42.733 15 mins 687328 44.549	COUTPUT Params MSE RMSE Random 5 mins 238792 57.118 4.489 10 mins 463060 57.814 4.562 15 mins 687328 58.717 4.666 20 mins 911596 59.198 4.699 Random 7.4% imp 5 mins 238792 44.926 4.432 10 mins 463060 46.879 4.657 15 mins 687328 47.351 4.688 20 mins 911596 48.637 4/734 Fine-tuning 5 mins 238792 42.183 4.12 10 mins 463060 42.733 4.179 15 mins 687328 44.549 4.381	(CNN+LSTM) Output Params MSE RMSE MAE Random 5 mins 238792 57.118 4.489 1194 10 mins 463060 57.814 4.562 2450 15 mins 687328 58.717 4.666 3817 20 mins 911596 59.198 4.699 5149 Random 7.4% improved 5 mins 238792 44.926 4.432 1144 10 mins 463060 46.879 4.657 2376 15 mins 687328 47.351 4.688 3608 20 mins 911596 48.637 4/734 4897 Fine-tuning 5 mins 238792 42.183 4.12 1044 10 mins 463060 42.733 4.179 2148 15 mins 687328 44.549 4.381 3433	(CNN+LSTM) Output Params MSE RMSE MAE MAPE Random 5 mins 238792 57.118 4.489 1194 0.122 10 mins 463060 57.814 4.562 2450 0.123 15 mins 687328 58.717 4.666 3817 0.125 20 mins 911596 59.198 4.699 5149 0.126 Random 7.4% improved 5 mins 238792 44.926 4.432 1144 0.091 10 mins 463060 46.879 4.657 2376 0.094 15 mins 687328 47.351 4.688 3608 0.094 20 mins 911596 48.637 4/734 4897 0.095 Fine-tuning 5 mins 238792 42.183 4.12 1044 0.086 10 mins 463060 42.733 4.179 2148 0.087 15 mins	(CNN+LSTM) Output Params MSE RMSE MAE MAPE Params s Ramdom 5 mins 238792 57.118 4.489 1194 0.122 18020 10 mins 463060 57.814 4.562 2450 0.123 32432 15 mins 687328 58.717 4.666 3817 0.125 32432 20 mins 911596 59.198 4.699 5149 0.126 46844 Ramdom 7.4% improved 5 mins 238792 44.926 4.432 1144 0.091 18020 10 mins 463060 46.879 4.657 2376 0.094 32432 15 mins 687328 47.351 4.688 3608 0.094 32432 20 mins 911596 48.637 4/734 4897 0.095 46844 Fine-tuning 5 mins 238792 42.183 4.12 1044 0.086<	(CNN+LSTM) (Two MSE RMSE MAE MAPE Params MSE CNUTOUR Ramcom IMAE MAPE Params MSE S mins 238792 57.814 4.662 2450 0.123 32432 5.657 20 mins 911596 59.198 4.699 5149 0.125 32432 5.657 20 mins 238792 44.926 4.432 1144 0.091 18020 8.078 10 mins 463060 46.879 4.657 2376 0.094 32432 9.625 15 mins 687328 47.351 4.688 3608 0.094 32432 11.452 20 mins 911596 48.637 4.734 4897 0.095 46844 12.13 5 mins 238792 42.183 4.12	Output Params MSE RMSE MAE MAPE Params s MSE RMSE MAPE Param s MSE RMSE Random 5 mins 238792 57.118 4.489 1194 0.122 18020 2.862 1.518 10 mins 463060 57.814 4.562 2450 0.123 32432 4.332 1.849 15 mins 687328 58.717 4.666 3817 0.125 32432 5.657 2.056 20 mins 911596 59.198 4.699 5149 0.125 32432 5.657 2.056 5 mins 238792 44.926 4.432 1144 0.091 18020 8.078 2.614 10 mins 463060 46.879 4.657 2376 0.094 32432 11.452 2.988 20 mins 911596 48.637 4.734 4897 0.095 46844 12.13 3.087 Fine-tuning	(CNN+LSTM) (Two Parallel CNN) Output Params MSE RMSE MAE MAPE Params s MSE RMSE MAE 5 mins 238792 57.118 4.489 1194 0.122 18020 2.862 1.518 367 10 mins 463060 57.814 4.562 2450 0.123 32432 4.332 1.849 893 15 mins 687328 58.717 4.666 3817 0.125 32432 5.657 2.056 1516 20 mins 911596 59.198 4.699 5149 0.126 46844 6.977 2.235 2206 Ramom 7.4% inverted 1.44 0.091 18020 8.078 2.614 723 10 mins 463060 46.879 4.657 2376 0.094 32432 9.625 2.803 1505 15 mins 687328 47.351 4.688 3608 0.094 32432	

These results indicate that:

- 1. Fewer training data lead to worse performance in both control and experimental groups.
- 2. The results in the experimental group used fewer parameters and produced better results than the control group, which indicates that the proposed two parallel CNNs outperformed the CNN-LSTM structure
- 3. The learned experience can be transferred for other locations (from A to B), and the fine-tuning results of the Case Study are improved with limited training data.







INTRODUCTION

Neural Networks have achieved great performance in traffic prediction, but they need abundant data for supervised learning. In practice, the systematic replacement or expansion in traffic-related systems usually needs new sensors, which lack historical data for the model training. In this case, learned knowledge from the longer used sensors may help the forecasting accuracy for newly installed sensors by the application of the fine-tuning technique. This research uses the fine-tuning method for traffic speed prediction, and the average improvement of the control group and experimental group is 7.4% and 39.6%, respectively (based on the MSE).

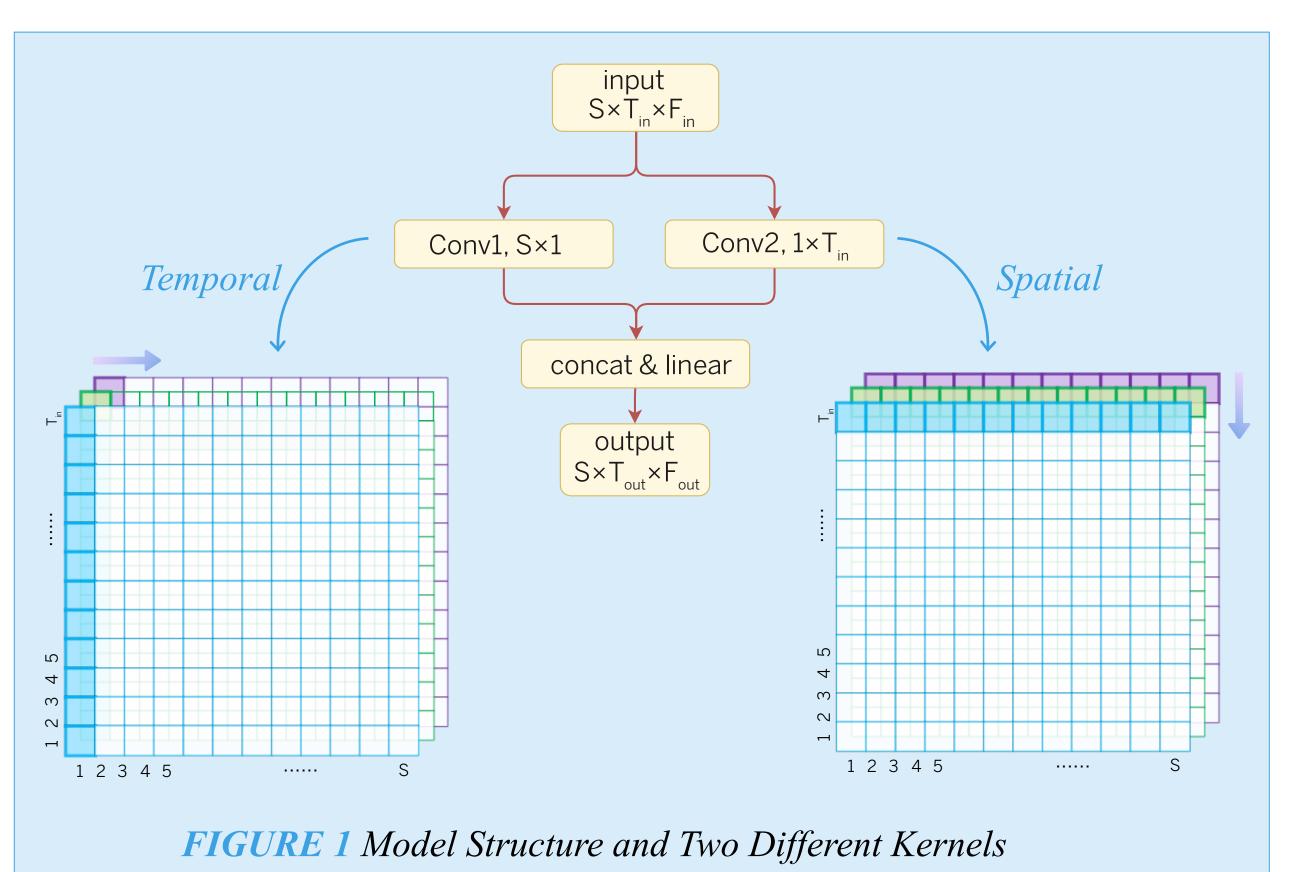
MODEL STRUCTURE

The proposed model uses multiple traffic variables for modeling. The data shape of the model inputs and outputs are different, which can be denoted

Input Data Shape = [N, S,
$$T_{in}$$
, F_{in}]

Output Data Shape = [N, S, T_{out} , F_{out}]

where N is batch size, S is the number of detectors, T_{in} and T_{out} are input and output time-steps, and F_{in} and F_{out} are the numbers of input and output traffic attributes.



Two kernels move through different time-steps and locations, respectively. After each CNN layer, the ReLU function would be performed. Finally, the linear layer concatenates all outputs from the previous two layers, then performs linear regression for correct output size.

DISCUSSION

There are four subplots in Figure 4 for four different output durations: {5,10,15,20} mins. In each subplot, the x-axis represents the training epoch, and the y-axis represents the MSE of the corresponding validation set. The fine-tuning weights are adaptive for all output durations, and they help the model converge much faster than when random starting values (see all subplots) are used.

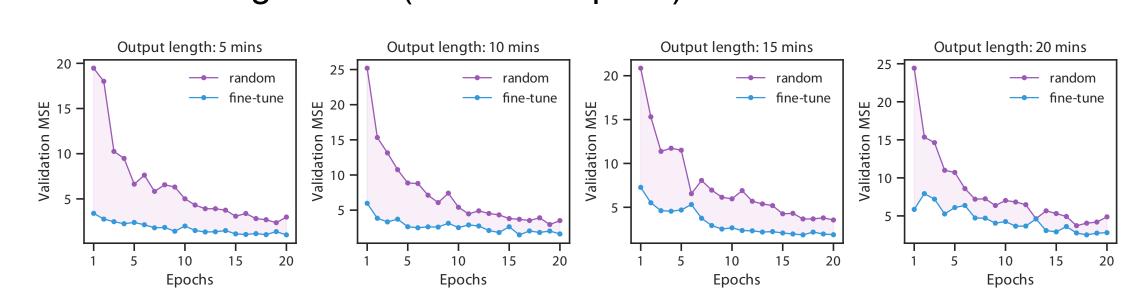


FIGURE 4 Comparison of Model Initialization Methods

Figures 5 (a) and (b) demonstrate the RMSE and real traffic speed distribution of the test set in the Modeling model. The error distribution varies significantly with different hours. We note two issues of RMSE preventing the model from further improvement: 1. The location 39.793 around 10:30 AM; 2. The general fluctuation between 14:00 and 19:00 PM. At the same time, the corresponding speed in subplot (b) also changes largely.

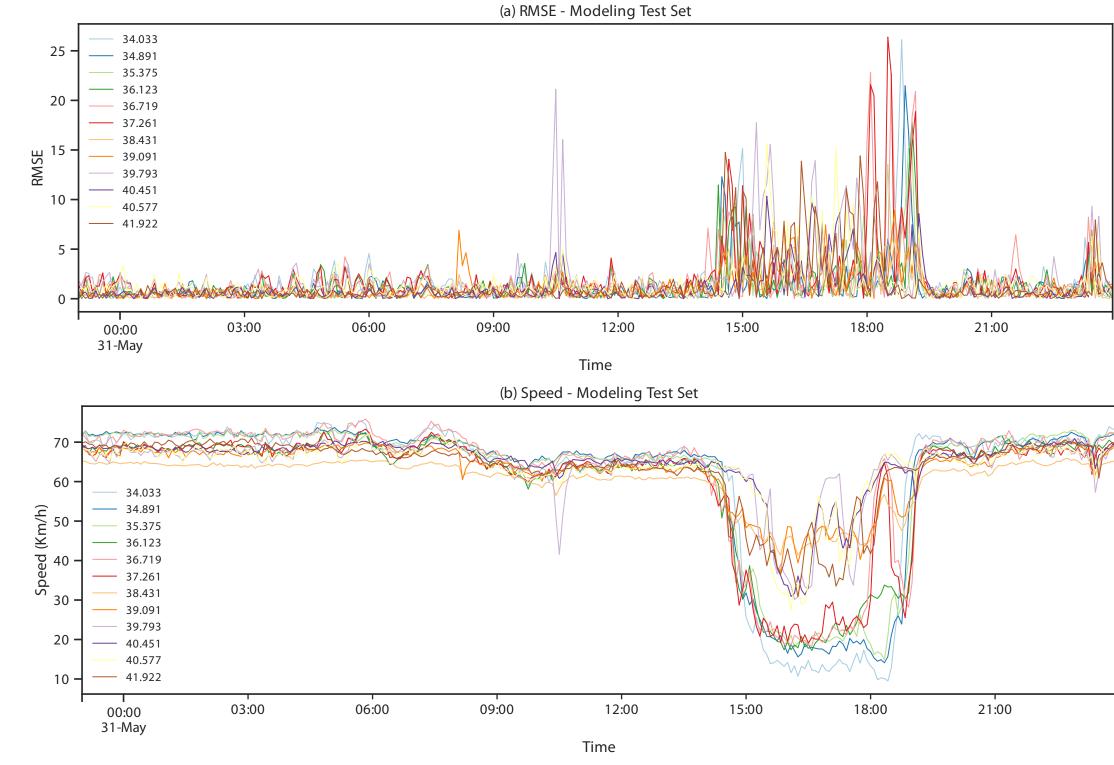


FIGURE 5 The RMSE and speed distribution in the test set

ACKNOWLEDGMENTS

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