Exploiting Spatio-Temporal Correlations with Multiple 3D Convolutional Neural Networks for Citywide Vehicle Flow Prediction

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***Abstract*—Predicting vehicle flows is of great importance to traffic management and public safety in smart cities, and very challenging as it is affected by many complex factors, such as spatio-temporal dependencies with external factors (e.g., holidays, events and weather). Recently, deep learning has shown remarkable performance on traditional challenging tasks, such as image classification, due to its powerful feature learning capabilities. Some works have utilized LSTMs to connect the high-level layers of 2D convolutional neural networks (CNNs) to learn the spatio-temporal features, and have shown better performance as compared to many classical methods in traffic prediction. However, these works only build temporal connections on the high-level features at the top layer while leaving the spatio-temporal correlations in the low-level layers not fully exploited. In this paper, we propose to apply 3D CNNs to learn the spatio-temporal correlation features jointly from low-level to high-level layers for traffic data. We also design an end-to-end structure, named as MST3D, especially for vehicle flow prediction. MST3D can learn spatial and multiple temporal dependencies jointly by multiple 3D CNNs, combine the learned features with external factors and assign different weights to different branches dynamically. To the best of our knowledge, it is the first framework that utilizes 3D CNNs for traffic prediction. Experiments on two vehicle flow datasets Beijing and New York City have demonstrated that the proposed framework, MST3D, outperforms the state-of-the-art methods.**

***Index Terms*—3D CNNs, spatio-temporal dependencies, traffic prediction, vehicle flow prediction.**

I. Introduction

Traffic prediction is of great importance to the traffic management, public safety, and environmental pollution [1]. Vehicle flow prediction is one of vital activities in traffic prediction [2]. The latest report from the United Nations [3] states that more than 55% of the world's population now lives in city areas in 2017. Many researchers attempt to use machine learning techniques to predict traffic flows so as to avoid traffic congestion situations in cities. A city first can be divided into many small regions. The inflow and outflow of a region are the number of vehicles that have entered the region and the number of vehicles that have left the region, respectively. Predicting the traffic condition in every region of a city can be basically affected by three categories of important factors as follows.

Factor 1: Spatial dependencies. The inflow of one region (i.e., r_i) of a city can be affected by outflows of its nearby and distant regions. The nearby regions are the neighbors which are either adjacent or near to the border of the region r_i and the distant regions otherwise. In a similar way, the outflow of that region r_i can affect other regions of the city. Besides, it is affected by its own inflow of the region r_i.

Factor 2: Multiple temporal dependencies. The inflow and outflow of the region r_i of the city are affected by short, middle, and long term intervals. For example, the traffic congestion of the region r_i occurring at 6 pm will affect the region's traffic condition at the following hour, i.e., 7 pm. For example, rush hour pattern repeats every 24 hours on the workdays.

Factor 3: External factors. The inflow and outflow of the region r_i can be directly affected by external factors such as vehicle accidents, road maintenance, weather conditions, and other special events.

Many existing machine learning techniques have been used in traffic prediction, e.g., k-nearest neighbours (KNN) [4], and support vector machines (SVM) [5]. The fast development of neural networks in recent years, especially in deep learning techniques, provides flexibility and generalizability to perform prediction on large multi-dimensional data (e.g, image and video recognition, and bioinformatics). CNN is

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one of the most commonly-used neural networks for traffic prediction problems. Many studies use two dimensional CNN (2D CNN) and LSTM [6]–[9] to capture spatio-temporal feature of traffic data. The models of the methods only connect temporal features at the high level of spatial features, while not connecting temporal features at low-level of spatial features. In this regards, the temporal correlations of the low-level spatial features cannot be fully exploited. Therefore, some discriminative features cannot be extracted so as to improve the traffic prediction accuracy.

To overcome the limitations, we propose a novel spatio-temporal correlation based multiple 3D CNNs architecture (MST3D) in this work. The proposed MST3D builds a traffic prediction model considering all the three categories of factors as discussed above. To the best of our knowledge, our proposed MST3D is the first time that 3D CNNs are applied in the traffic prediction problem and our proposed MST3D can capture both low-level and high-level layers of spatio-temporal features jointly. In this paper, our contributions are summarized in the following.

- We propose to utilize novel spatio-temporal correlation based 3D convolutional neural networks (3D CNNs) to learn the spatio-temporal features jointly for traffic prediction. The spatio-temporal correlation features can be extracted and learned simultaneously for traffic data from low-level to high-level layers.
- We design a neural network framework, named as MST3D, based on multiple 3D CNNs for vehicle flow prediction, considering spatial and multiple temporal dependencies with external factors. The MST3D can combine the output features of the multiple 3D CNNs with external factors, assigning different weights to different branches dynamically. The inflow and outflow of vehicles can be jointly predicted in our framework
- We evaluate our approach using Beijing taxi and NYC bike datasets. The results demonstrate the advantages of our proposed MST3D over other state-of-the-art methods in the literature.

II. Related Work

In recent years, many researchers have used different traffic prediction approaches to solve traffic prediction problems occurred in many cities. Classical statistical methods can construct different linear or non-linear models to predict the traffic flow, such as Markov chain [10], Bayesian networks [11], and Auto-regressive Integrated Moving Average (ARIMA) [12]–[14], are constructed to solve time-series traffic prediction problems. These models can give better correlations on the successive time sequences of traffic variables. However, they still cannot capture most of important spatial and temporal features in the traffic network. However, it is hard for the classical statistical methods to discover the non-linear spatial and temporal relations of traffic networks..

Unlike the classical statistical methods, ANNs can easily capture the non-linear spatial and temporal relations among the spatiotemporal data. Hence, ANNs are widely applied in different fields such as speech recognition [15], computer vision [16], and many more. Another neural network, CNN, can extract the spatial dependencies of the traffic networks by converting the dynamic traffic data into images [17]. But, these neural networks can only capture spatial or temporal information or correlation of the traffic flow data respectively. To overcome the limitation, some combinations of both RNN and CNN networks [6], [9], [18]–[20] have been proposed to learn spatial and temporal dependencies. Yu et al. [8] proposed a deep LSTM model and mixture deep LSTM model using the normal traffic hours and the incident traffic period, respectively. Yao et al. [9] proposed a multi-view spatio-temporal network that combines local CNN, LSTM and semantic network to predict short-time traffic condition.

III. Problem Definition and Analysis

A. Citywide Traffic Prediction Problem

In this section, we shall first define the citywide traffic prediction problem and the corresponding notations as follows.

Definition 1 (Citywide Region): Following the previous studies [6], [17], [20], [21], we divide a city into an $I \times J$ grid map based on the longitude and latitude where a grid denotes a region. The regions in the grid map could be defined as non-overlapping pairs (i, j) where i and j mean the region is in the i^{th} row and the j^{th} column of the grid map.

Definition 2 (Citywide Vehicle Flow): Following the previous studies [6], [20], let P be a collection of trajectories at t time interval. For a grid (i, j) that lies at the i row and the j column, the inflow and outflow of the vehicles at the time interval t are defined as Equ. 1 and Equ. 2, respectively.

$$x_t^{in,i,j} = \sum_{Tr \in \mathrm{P}} |\{\lambda > 1 | g_{\lambda-1} \notin (i,j) \wedge g_\lambda \in (i,j)\}| \quad (1)$$

$$x_t^{out,i,j} = \sum_{Tr \in \mathrm{P}} |\{\lambda \geq 1 | g_\lambda \in (i,j) \wedge g_{\lambda+1} \notin (i,j)\}| \quad (2)$$

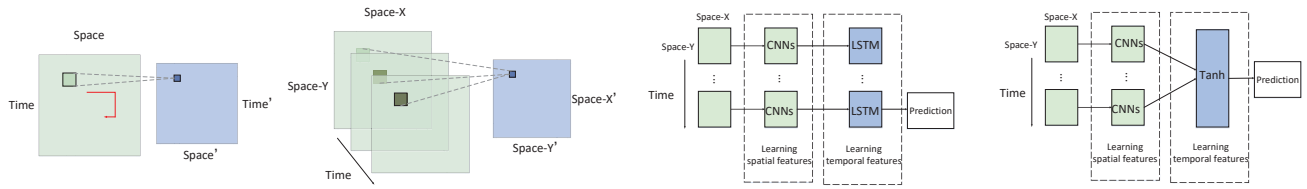
where $Tr : g_1 \rightarrow g_2 \rightarrow, ..., \rightarrow g_{|Tr|}$ is a trajectory in P, and g_λ is the geospatial coordination; $g_\lambda \in (i, j)$ means the point g_λ lies within grid (i, j), and vice versa.

Problem 1 (Citywide Vehicle Flow Prediction): Given a set of observed historical citywide vehicle flow data with time span $T = 1, 2, ..., t-1$. The problem of vehicle flow prediction aims to predict the inflow and outflow at the next time interval t of the whole grid map of the city.

B. Limitations of 2D CNN based Methods for Traffic Prediction

As discussed in Section I, we need to consider the spatial and temporal dependencies jointly in traffic prediction. We demonstrate that 3D CNN is well suited for spatio-temporal correlation feature learning compared with the 2D CNN and other 2D CNN based methods (e.g., 2D CNN plus LSTM).

In 2D CNN, two dimensions of features can be learned owing to 2D convolution and 2D pooling operations. Many researchers have made efforts to utilize 2D CNN to learn the



(a) (b) (c) (d)

Fig. 1: Limitations of 2D CNN based methods; (a) Model spatio-temporal dependencies in a 2D image; (b) Utilize RGB channels to construct the time dimension; (c) Combine 2D CNN with LSTM or RNN; (d) Utilize 2D CNN for a slice of image along the time dimension and then aggregate them together by a Tanh function.

spatio-temporal correlation features. Generally, these works can be divided into four catalogs. (1) Treat a dimension of a 2D image as space and another dimension as time [17] as shown in Figure 1(a). However, the two-dimension of spatial dependency are flattened into one dimension and some actual information in the spatial dimension is lost. (2) Another way to adapt 2D CNN to support spatio-temporal feature learning is to replace the RGB channels with slices of the time. However, 2D convolution applied on multiple images (treating them as different channels) also results in an image. Hence, it also loses temporal information of the input signal right after every convolution operation. (3) Some works utilize 2D CNN with LSTM or RNN [9], [19] as shown in Figure 1(c). 2D CNN captures the near- and far-side spatial dependencies and subsequently the long-term temporal feature is learned by LSTMs. Therefore, the integrated networks inherit the advantages of 2D CNNs and LSTMs neural networks. This category of approaches, however, only build temporal connections on the high-level features at the top layer while the correlations in the low-level spatial features cannot be fully exploited. (4) Some works utilize 2D CNN to learn the spatial feature for a slice of image in time dimension and then aggregate them together by a Tanh function [6]. However, similar to the third method, the temporal dependency of the low-level spatial features cannot be learned.

C. Learning Spatio-temporal Features with 3D CNN

Compared to 2D CNN, 3D CNN has the ability to model 3-dimension information owing to 3D convolution and 3D pooling operations. If we model the traffic data into 3D volumes with spatial and temporal dimensions, 3D CNN could preserve the temporal dependencies of the volumetric data resulting in an output volume [22]. Moreover, adopting the same kernel sharing across space and time dimensions, the model could take full advantage of spatial and temporal dependencies.

In view of the definite advantage of 3D CNN to learn spatial and temporal features, an architecture of 3D CNNs is proposed by stacking the convolution layers, pooling layers and fully connection layers. 3D feature volumes are learned from low-level to high-level by stacking the convolution layers, and it employs different spatio-temporal kernels followed by the non-linear activation functions. In the layer of pooling, the produced feature volumes can be subsampled with max-pooling operation in order to reduce variance and computation complexity and extract low level features from the cubic neighborhood [22].

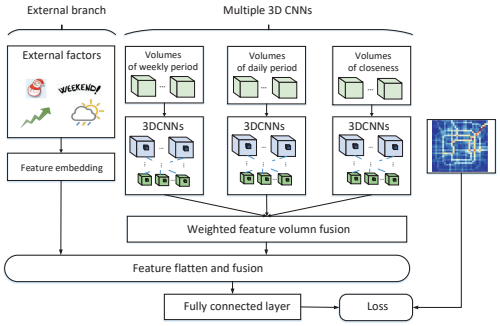


Fig. 2: Architecture of MST3D.

IV. Proposed MST3D Framework

This section describes the details of our proposed MST3D framework to predict citywide vehicle flow as depicted in Figure 2. Utilizing MST3D consists of 3 steps: modeling, training and testing.

The spatial and multiple temporal correlation features of traffic data can be learned in MST3D using 3D convolution layers and pooling layers. Multiple temporal dependencies contain the *closeness* dependency and different *periodic* (e.g., *daily*, *weekly* and *monthly*) dependencies. A single 3D CNN branch is normally to learn the spatial information and a single type of temporal dependency together. In the external branch, we need to manually extract some features from external datasets that provide weather conditions, event information and other external information. Then, we feed the extracted features into a two-layer fully-connected neural network. As a result, spatio-temporal features and external features are fused together. Lastly, we apply a fully-connected neural network that calculates the cross-entropy loss.

A. Modeling

We first describe how to model citywide inflow/outflow traffic situation with spatio-temporal correlation based 3D volumes. Then we analyse the influence of multiple temporal dependencies in traffic prediction and present the process of modeling multiple temporal dependencies in our methodology.

1) Modeling Spatio-temporal Correlation with 3D Volumes: Given a city that is partitioned into $I \times J$ grid map, at the t time interval, the traffic status can be represented by a tensor $X_t \in R^{i \times j \times k}$, where k denotes the number of traffic variables. The generated tensor can be regarded as a special multi-channel image with i pixels height, j pixels width and k channels of each pixel. This multi-channel image captures the spatial information of citywide traffic conditions. Specifically, the multi-channel image can capture the spatio-temporal correlation information of citywide vehicle inflow and outflow by setting $k = 2$. In the next contents, we set $k = 2$ for convenient.

In case of given h time segments, the inflow/outflow of these time segments can be denotes as a tensor $V \in R^{h \times i \times j \times 2}$ This tensor can be regarded as a 3D volume with as a size of $h \times i \times j \times 2$, where h is the number of frames (images). This 3D volume captures the spatio-temporal information of citywide traffic conditions for a slice of time segments.

Formally, the multi-channel image for citywide vehicle flow and the 3D volume for a certain time of citywide vehicle flow are defined in Definition 4 and 5 separately:

Definition 4 (Multi-channel Images for Citywide Vehicle Flow): At the time segment t, inflow and outflow in all $I \times J$ regions can be denoted as a multi-channel image $X_t \in R^{i \times j \times 2}$ where $(X_t)_0$ and $(X_t)_1$ denotes the inflow matrix and outflow matrix, respectively.

Definition 5 (3D Volumes for a Certain Time of Citywide Vehicle Flow): Given h time segments, all the multi-channel images in these time segments can be denoted as a 3D volume $V \in R^{h \times i \times j \times 2}$.

2) Modeling Multiple Temporal Dependencies: From the above cases, it is clearly shown that the temporal dependencies and correlation have significant impacts on the traffic state, such as close time, daily periodicity and weekly periodicity regardless of the degrees of influences which are not completely the same. We consider the temporal dependency of *closeness* and *periods*.

For the *closeness* 3D volumes, a few 2 channel images of intervals in the recent time are used to model temporal *closeness* dependency. Let a recent fragment be $[X_{t-l_c}, X_{t-(l_c-1)}, ..., X_{t-1}]$. This *closeness* is dependent sequence that can be constructed as a 3D volume, $V_c \in R^{l_c \times i \times j \times 2}$.

In a similar way, we also can construct the *periods* volumes. We take the *daily* period as an example. Suppose that l_d is time intervals from the period fragment, and d is the period span. Therefore, the *daily* period of a dependent sequence is $[X_{t-l_d \times d}, X_{t-(l_d-1) \times d}, ..., X_{t-1}]$. This sequence can be constructed as a 3D volume $V_d \in R^{l_d \times i \times j \times 2}$. Generally, our proposed framework can support other user-defined periods (e.g., monthly, seasonally).

B. Multiple 3D CNNs

The spatio-temporal correlation based 3D volumes constructed in the modeling phase is then fed into our proposed MST3D. Each branch of 3D CNNs targets for a type of temporal dependency. For example, the *closeness* 3D volumes are fed into the *closeness* branch, and the *daily* branch takes the *daily* 3D volumes as inputs.

We take the *closeness* branch to describe how to learn the spatio-temporal features simultaneously. The equation of 3D convolutional operation is as follows:

$$u_{ij}^{\beta}(x, y, z) = \sum_{m,n,l} V_i^{\beta-1}(x - m, y - n, z - l) W_{ij}^{\beta}(m, n, l), \tag{3}$$

where W_{ij}^{β} is the 3D kernel in the β^{th} layer convolving over the 3D feature volume $h_i^{\beta-1}$, $W_{ij}^{\beta}(m, n, l)$ is the element-wise weight in the 3D convolution kernel.

Thus, the equation of the 3D feature volume for the *closeness* branch in β^{th} layer is:

$$V_j^{\beta} = f(\sum_i u_{ij}^{\beta} + b_j^{\beta}), \tag{4}$$

where f is an activation function, b is a bias term connecting the feature maps of adjacent layers.

As discussed in Section IV-A, all the regions are affected by multiple temporal dependencies. The degrees of influence on the regions may be different. Inspired by the observations, we propose a novel parametric-tensor-based fusion method that can fuse *closeness*, *daily* and *weekly* branches, similar to the method in [6]. The equation of fusion method is as follows,

$$V_{fusion} = W_c \otimes V_c + W_d \otimes V_d + W_w \otimes V_w \tag{5}$$

where V_{fusion} denotes the fused features; $\otimes$ is Hadamard product (i.e., element-wise multiplication for tensors); V_c, V_d, V_w are the feature volumes extracted by *closeness*, *daily* and *weekly* branches respectively; W_c, W_d, W_w are the learnable parameters that adjust the degrees affected by different branches.

Then, the fused features V_{fusion} is flattened into a vector named as V_{mc}. V_{mc} is the output of the multiple 3D CNNs.

C. External Branch

Many complex external factors, such as weather conditions and special events, have great influence on the citywide traffic situation. In this paper, we mainly focus on the weather condition, holiday event, and metadata (i.e., day of the week, weekday and weekend). We stack two fully-connected layers upon E_t, i.e., the first layer can be viewed as an embedding layer for each sub-factor followed by an activation, and the second layer is to map low to high dimensions as V_{ext} that have the same shape with V_{mc} which is generated by multiple CNNs.

We then directly merge the output of the multiple CNNs with that of the external components. The fused output $\widehat{V}$ of the multiple CNNs and the external components is defined in Equ. 6:

$$\widehat{V} = V_{mc} + V_{ext} \tag{6}$$

.

Finally, the fused output $\widehat{V}$ is connected with a fully-connected layer using Tanh function.

V. EXPERIMENT

A. Experiment Settings

We configure a Linux server with configurations as follows: 8 Intel(R) Xeon(R) CPU E5-2680 v4 @ 2.40GHZ; 256GB RAM; 4 NVIDIA P100 GPUs. Two large real-world datasets, i.e., New York City (NYC) and BeiJing (BJ) datasets, are used in the experiment. **NYCBike:** The bike trip data is collected from NYC Bike system in 2014 from Apr. 1st to Sept. 30th. We choose the data in the last 10 days as the testing data, while others as the training data. For the external information, holidays are provided in the dataset. **BJTaxi:** This is the taxi trajectoriy data in Beijing that has 4 time periods: 1st Jul. 2013 - 30th Otc. 2013, 1st Mar. 2014 - 30th Jun. 2014, 1st Mar. 2015 - 30th Jun. 2015, 1st Nov. 2015 - 10th Apr. 2016. The last four weeks are selected as the testing data, and others as the training data. External information includes holidays, weather conditions and temperature.

B. Implementation Details

Data Preprocessing. For the NYCBike dataset, we split the whole city into 8×16 regions. The length of each time segment is set to 1 hour. For the BJTaxi dataset, we split the whole city into 32×32 regions. The length of each time segment is set to 30 minutes. We apply Min-Max normalization to convert traffic values by $[0, 1]$ scale. After the prediction step, we de-normalize the prediction values.

Parameters. The python libraries, the Tensorflow (version 1.2.1) and the Keras (version 2.1.6) are used to build our models. The inflow and outflow are fixed as 2 channels in the generated volumes. The lengths of *closeness*, *daily* and *weekly* on NYCBike are set to 4, 4, and 4, respectively. As the time segment in BJTaxi is set to half an hour, the lengths of *closeness*, *daily* and *weekly* are set to 6, 4, and 4.

For the NYCBike dataset, we apply two 3D convolutional layers as the sizes of our 3D volumes are small (i.e., $4\times8\times16$ in all the branches). The kernel sizes in all the branches are set to $(2, 3, 3)$. The number of 3D convolutional filters of the first layer is 32, and of that the second layer is 64. For the BJTaxi dataset, three 3D convolutional layers are applied on all the multiple CNNs. One of the main reasons is that the spatial dimensions are 32×32 which is bigger than that of the NYCBike dataset. The number of 3D convolutional filters on three 3D convolutional layers are set to 32, 64 and 64, respectively.

In our experiment, we choose Rooted Mean Square Error (RMSE) and Mean Average Percentage Error (MAPE) as the evaluation metrics, which are the same metrics used in [9], [20], [21]. In the calculation of MAPE value, the samples with flow values that are less than 10 are ignored, which is a common practice used in the traffic prediction [9], [20].

C. Methods in Traffic Prediction

We compare our model with the following three categories of spatio-temporal prediction methods. (1) HA: Historical average predicts traffic (HA) for a given region basing on the average values of the previous relative time interval in the same region. (2) ARIMA: Auto-regressive integrated moving average (ARIMA) is a well-known model for understanding and predicting future values in a time series. (3) LinUOTD: a a linear regression model with a spatio-temporal regularization. (4) XGBoost: a widely used boosting tree method. (5) ConvLSTM [19]: ConvLSTM adds convolutional layers to LSTM. (6) ST-ResNet [18]: a CNN-based deep learning framework for traffic prediction. The model uses CNNs to capture trend, period, and closeness information. (7) STDN [20]: STDN uses local CNNs, LSTM and attention mechanism to model the spatial, temporal and dynamics dependencies.

TABLE I: Inflow and outflow results on NYCBike

Methods	Inflow		Outflow	
	RMSE	MAPE	RMSE	MAPE
HA	14.02	38.75%	14.91	39.68%
ARIMA	9.97	28.97%	10.49	29.49%
LinUOTD	9.56	27.59%	10.11	28.74%
XGBoost	6.89	22.93%	7.06	23.43%
ConvLSTM	7.74	25.57%	8.32	25.72%
ST-ResNet	6.08	21.23%	6.63	22.17%
STDN	5.98	21.01%	6.51	21.96%
MST3D	**5.66**	**20.21%**	**5.96**	**21.14%**

TABLE II: Inflow and outflow results on BJTaxi

Methods	Inflow		Outflow	
	RMSE	MAPE	RMSE	MAPE
HA	57.57	37.76%	57.89	39.68%
ARIMA	22.58	22.12%	22.96	22.19%
LinUOTD	21.19	20.02%	21.44	20.33%
XGBoost	17.61	17.42%	18.23	17.69%
ConvLSTM	19.29	18.55%	19.98	18.72%
ST-ResNet	16.74	15.01%	17.01	15.78%
STDN	16.43	15.12%	16.78	15.44%
MST3D	**15.98**	**14.71%**	**16.11**	**14.85%**

D. Performance Evaluation

From Table I and II, we can clearly see that our proposed MST3D framework can give the best accuracy of both the inflow and outflow predictions. HA and ARIMA cannot get good prediction results as they rely on historical records to predict the future values and overlook spatial and external features. Even the regression-based methods (e.g., LinUOTD, XGBoost) take spatial correlations as their features. However, they still failed to capture the complex non-linear temporal dependencies and the dynamic spatial relationships. Therefore, MST3D outperforms above all the existing methods.

Our proposed model also achieves better performance than ST-ResNet. One of main reasons is that ST-ResNet only uses CNN to capture spatial information without considering the temporal sequential dependency.

MST3D also outperforms the methods (e.g., ConvLSTM and STDN) which use 2D CNNs and LSTM together for traffic prediction. This category of methods only captures the temporal dependencies for the high-level spatial features, but not considers the temporal correlations with low-level spatial features.

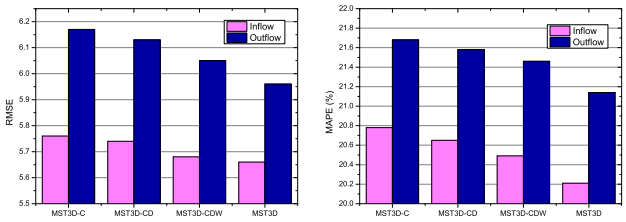


Fig. 3: Results of MST3D and its variants on NYCBike. (a) RMSE results. (b) MAPE results.

TABLE III: Running time of different methods

Methods	NYCBike		BJTaxi	
	Training time (s)	Testing time (s)	Training time (s)	Testing time (s)
ST-ResNet	150	0.75	4994	1.92
STDN	18980	89.8	379600	207.4
MST3D	126	0.23	5902	2.74

E. Performance of Multiple 3D CNNs Architecture and External Factors

We also studied the performance of multiple 3D CNNs and external factors by applying different variants of MST3D: **MST3D:** Our proposed framework, which combines *closeness*, *daily*, *weekly* and *external* branches. **MST3D-C:** This method only captures spatial and temporal dependency of *closeness*. **MST3D-CD:** This method uses *closeness* and *daily* branches only. **MST3D-CDW:** This method uses *closeness*, *daily* and *weekly* branches.

Figure 3 shows that the results of our proposed MST3D and its variants on the NYCBike. We can see that MST3D-C which uses the *closeness* branch only performs better than the other baselines. It demonstrates the effectiveness of applying 3D CNNs to learn spatio-temporal features in traffic prediction. The performance is further improved by adding the *daily* and *weekly* branches. Again, it proves that considering the multiple temporal dependencies can help to increase the accuracy of vehicle flow prediction. The RMSE and MAPE values further decrease by adding the *external* branch.

F. Time Complexity of Different Methods

Table III lists the running time of different existing methods in the training and testing. We utilized a single P100 GPU in all the methods. The running time of STDN are the longest for both of training and testing. The scheme of STDN uses a sliding window over the whole city to train and then predict every region.

In NYCTaxi, our proposed MST3D performs slightly better than ST-ResNet. In BJTaxi, the training time of the MST3D is similar to that of the ST-ResNet. However, the testing time of MST3D that uses three 3D layers is slightly longer than that of the 2D ST-ResNet.

VI. Conclusions

In this paper, we propose to utilized 3D CNNs to learn the spatio-temporal features jointly for traffic prediction. A framework, named as MST3D, that based on multiple 3D CNNs is proposed especially for citywide flow prediction considering the correlation of spatial and multiple temporal dependencies, as well as external influences. Experiments on two different real-world datasets have been implemented and the results demonstrated that the proposed MST3D outperforms the state-of-the-art baselines.

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