Demand Forecasting in Bike-sharing Systems Based on A Multiple Spatiotemporal Fusion Network

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ABSTRACT

Bike-sharing systems (BSSs) have become increasingly popular around the globe and have attracted a wide range of research interests. In this paper, the demand forecasting problem in BSSs is studied. Spatial and temporal features are critical for demand forecasting in BSSs, but it is challenging to extract spatiotemporal dynamics. Another challenge is to capture the relations between spatiotemporal dynamics and external factors, such as weather, day-of-week, and time-of-day. To address these challenges, we propose a multiple spatiotemporal fusion network named MSTF-Net. MSTF-Net consists of multiple spatiotemporal blocks: 3D convolutional network (3D-CNN) blocks, eidetic 3D convolutional long short-term memory networks (E3D-LSTM) blocks, and fully-connected (FC) blocks. Specifically, 3D-CNN blocks highlight extracting short-term spatiotemporal dependence in each fragment (i.e., closeness, period, and trend); E3D-LSTM blocks further extract long-term spatiotemporal dependence over all fragments; FC blocks extract nonlinear correlations of external factors. Finally, the latent representations of E3D-LSTM and FC blocks are fused to obtain the final prediction. For two real-world datasets, it is shown that MSTF-Net outperforms seven state-of-the-art models.

1. Introduction

The earliest bike-sharing system (BSS), i.e., the White Bike Sharing Manifesto (Floret, 2014), dates to the 1960s. Examples of similar systems include Citybike in New York City, Divvy in Chicago, Capital Bikeshare in Washington D.C., Ecobici in the Mexico City, and Vélib in France. These systems are called station-based since a user has to rent or return a bike to some fixed bike station and may have to end the trip early or waste time returning the bike. Owing to GPS technology, station-free bike-sharing systems (SF-BSSs) have become prevalent. They alleviate the inconvenience of renting and returning bikes at station-based BSSs. With a GPS-enabled smartphone, a user can locate a bike nearby and park it at her/his convenience. Recently, SF-BSSs have become increasingly popular in many cities around the World, and have introduced a way of living lighter, consuming less, and protecting the environment. As an example, station-free BSSs dominate the market in China, and millions of bikes from such systems have flooded most large cities. The dataset used in this paper is from a global bike-sharing company named Mobike (acquired by a company named Meitun in 2018), which provides riding services to more than 200 million users in more than 200 cities in 19 countries around the world as of 2018. A crucial problem for BSSs is the imbalance of bikes owing to one-way trips between regions and customer-demand uncertainties. This problem has attracted researchers and practitioners (Rudloff and Lackner, 2014; Dell’Amico et al., 2014; Alvarez-Valdes et al., 2016; Schuijbroek et al., 2017; Caggiani et al., 2018; Li et al., 2018). An adequate solution to the problem relies on the forecasting of customer demand. It is this issue of demand forecasting that is the focus of the present paper.

A few papers (e.g., Singhvi et al., 2015; El-Assi et al., 2017) have been devoted to forecasting problems in BSSs, which are reviewed in more detail in Section 2. Recently, deep-learning approaches have been used in forecasting problems in large-scale bike-sharing networks. A common method is to generate traffic flow videos for each region of a city from transactions, each of which consists of the start time, end time, start location, and end location. The videos are then fed into deep-learning models. Chen et al. (2018) employ a 3D convolutional neural network (3D-CNN) to effectively capture the spatiotemporal dependence jointly from low- to high-level layers for traffic flow data. Since the 3D-CNN architecture captures long-term relations by sampling and assembling, it does not perform well in discovering the spatiotemporal dependence between cause and effect. Ai et al. (2019) uses a convolutional long short-term memory network (ConvLSTM) to extract the spatial dependence by the encapsulated 2D convolutions and the long-term relations by LSTM, and shows better performance in traffic flow prediction. However, the ConvLSTM network only establishes temporal connections on the high-level features at the top layer, while leaving the spatial and temporal correlations on the low-level features not fully exploited. Motivated by this research, an objective of the present study is to combine the advantages of both 3D-CNN and ConvLSTM in spatiotemporal predictive learning. A newly developed deep-learning model (Wang et al., 2019) is used, which is named the eidetic 3D convolutional long short-term memory network (E3D-LSTM), to process the short-term frame dependence and long-term high-level relations. The encapsulated 3D-CNN makes local perceptors of LSTM motion-aware and enables the memory cell to store better short-term features. In addition, the present memory state can interact with its historical records via a gate-controlled...
self-attention module for long-term spatiotemporal relations. Demand for bikes in a BSS can be directly affected by external factors such as weather, day-of-week, and time-of-day. For example, fewer people tend to ride bikes on a rainy day. As another example, bike demands around central business districts are usually high on weekdays, but low on weekends. Fusing the external factors and the spatiotemporal data is the second objective of this study.

Letting inflow (outflow) of the region be the number of bikes that enter (leave) the region during a time interval, inflow and outflow videos are first generated from transaction data by partitioning a city into a grid map based on the longitude and latitude, where a grid denotes a region. We propose a multiple spatiotemporal fusion network named MSTF-Net. The videos are processed by 3D-CNN Encoder layers to extract short-term dependence and obtain high-dimensional feature maps. Then, the feature maps are fed into E3D-LSTM layers to extract long-term spatiotemporal interaction as hidden states. Next, the hidden states are decoded by 3D-CNN Decoder layers to obtain a latent representation, and a 1 × 1 2D-CNN layer is implemented to map the latent representation to inflow-outflow channel. Meanwhile, fully-connected layers are implemented to extract non-linear correlations for external factors. Finally, we add the outputs of the 2D-CNN layer and the fully-connected layers to obtain the final prediction.

The contributions of this paper are summarized as the following.

- We propose a multiple spatiotemporal fusion network named MSTF-Net that can enhance the prediction capacity in bike-sharing demand forecasting problem.
- In MSTF-Net, 3D-CNN blocks highlight extracting short-term spatiotemporal dependence in each fragment (i.e., closeness, period, and trend); E3D-LSTM blocks extract long-term spatiotemporal dependence over all fragments; FC blocks extract nonlinear correlations of external factors.
- We conduct ablation studies for the multiple blocks design. It is shown that MSTF-Net significantly performs better than the pure 3D-CNN or E3D-LSTM models.
- The spatial and temporal correlations are visualized and the significances of spatial and temporal dependence in demand forecasting are validated.

2. Literature review

A transaction record consists of spatial features and temporal features. Forecasting models, such as the Linear Regressor, SVR, and Adaboost Regressor, take these records in vector form as model inputs directly. Papers that use these models are briefly reviewed first. Instead of using these records directly, some researchers first generate flow videos from transaction data, and then use deep-learning models such as 2D-CNN, 3D-CNN, and ConvLSTM models. These papers are closer to our research and are the focus of this review.

Hong (2011) presents a model that combines the seasonal support vector regression model with chaotic simulated annealing algorithm (SSVRCSA), to forecast inter-urban traffic flow. Giot and Cherrier (2014) use the Adaboost Regressor, Ridge Regression, SVR, Random Forest Regressor, and Gradient Boosting Regressor to forecast demand in bike-sharing systems; it is found that most regressors are sensitive to overfitting by multiple experiments. Ashqar et al. (2017) first proposed a bipartite clustering algorithm to cluster bike stations into groups, and then use a Gradient Boosting Regression Tree (GBRT) to predict the inflow and outflow of each station in the groups. Xu et al. (2018) investigated the mobility pattern of SFBSSs, and employed long short-term memory (LSTMs) neural networks to forecast the demand. Negahban (2019) proposed a methodology combining simulation, bootstrapping, and subset selection that uses the useful partial information in every bike pickup/drop-off observation to estimate the true demand in bike-sharing systems.

The following papers describe the transformation of transaction data to flow videos and use deep-learning models for forecasting. Zhang et al. (2016) proposed a deep-learning model based on a 2D convolutional neural network (2D-CNN) to simultaneously extract spatial dependence, temporal closeness, periods, and trends in bike-sharing systems. Li and Shuai (2018) employed 2D-CNN and LSTM models to capture spatial and temporal dependence, respectively, for forecasting distributions of origin and destination. Chen et al. (2018) employed a 3D convolutional neural network (3D-CNN), which redesigns the inner mechanism by considering the temporal dimension based on a 2D-CNN, to forecast outflow and inflow in bike-sharing systems, and showed that a 3D-CNN model has better performance than a 2D-CNN model. A 3D-CNN model can extract features from both the spatial and temporal dimensions by performing 3D convolutions, thereby capturing the motion information encoded in multiple adjacent frames. Ai et al. (2019) employed a convolutional long short-term memory network (ConvLSTM), a deep combination of 2D-CNN and LSTM, to forecast bike distribution, and showed that the ConvLSTM model has better performance than 2D-CNN and LSTM models. ConvLSTM extends LSTM to have 2D convolutional structures in both the input-to-state and state-to-state transitions, which can process the spatial and temporal dependence in one approach.

Demand prediction problems in bike-sharing systems were studied in all the aforementioned papers. In online ride-hailing systems, the problem of demand prediction is also important, and has attracted numerous researchers. Herein, only two closely related papers are reviewed. Ke et al. (2017) proposed a new fusion deep-learning architecture based on ConvLSTM to fuse exogenous variables such as weather, day-of-week, and time-of-day to predict the demand of each region. Zhang et al. (2019) proposed a fully convolutional neural network architecture based on 3D-CNN, and employed locally connected 2D convolutional layers to predict the de-
mand of each region. Recently, in active traffic management systems, Zhang et al. (2020) proposed a hybrid forecasting approach by integrating 3D-CNN with ensemble empirical mode decomposition to forecast traffic speed.

3. Preliminaries

We first define the problem of demand forecasting in bike-sharing systems.

**Definition 1. (Region and time partition (Zhang et al., 2016))**

The city area is partitioned into $I \times J$ grids uniformly according to coordinates, as shown in Figure 1.

![Figure 1: Regions in Shanghai](image)

**Definition 2. (Inflow/outflow (Zhang et al., 2016))** Let $R$ be a collection of trajectories at the $i$th time interval. For a grid $(i, j)$ that lies at the $i$th row and the $j$th column, the inflows and outflows at time interval $t$ are defined respectively as:

$$d_{t}^{i,n,j} = \sum_{\text{Tr} \in R} | \{ k \geq 1 \mid g_{k}^{\text{end}} \in (i, j) \} |$$

$$d_{t}^{i,o,j} = \sum_{\text{Tr} \in R} | \{ k \geq 1 \mid g_{k}^{\text{start}} \in (i, j) \} |$$

where $\text{Tr} : g_{1} \rightarrow g_{2} \rightarrow \cdots \rightarrow g_{k} \rightarrow g_{t} \rightarrow g_{t+1}$ is a trajectory in $R$, and $g_{k}^{\text{start}}$, $g_{k}^{\text{end}}$ are the geospatial coordinate; $g_{k}^{\text{start}} \in (i, j)$, $g_{k}^{\text{end}} \in (i, j)$ mean the trajectory start or end in the grid $(i, j)$, note that the trajectory can start and end in the same region, $\cdot | \cdot$ denotes the cardinality of a set.

At time interval $t$, inflows and outflows in all $I \times J$ regions can be denoted by a tensor $D_{t} \in \mathbb{R}^{2 \times I \times J}$, where $D_{t}^{i,j}$, $(D_{t})_{i,j} = d_{t}^{i,n,j}$, $(D_{t})_{i,j} = d_{t}^{i,o,j}$. The outflow matrix is shown in Figure 1(a).

**Problem 1.** Predict $D_{n}$ given historical observations $[D_{t}|t = 0, \cdots, n-1]$ and external factors such as weather conditions, wind speed, temperature, and day-of-week.

4. Method

This section presents our new model named MSTF-Net. We introduce the architecture of MSTF-Net, which is illustrated in Figure 2. First, 3D-CNN Encoder layers are implemented to process historical observations to extract short-term dependence and obtain high-dimension feature maps. Then the feature maps are directly fed into E3D-LSTM layers to further extract the long-term spatiotemporal interaction as hidden states. Next, the E3D-LSTM hidden states are decoded by 3D-CNN Decoder layers and one $1 \times 1$ 2D-CNN layer to get a latent representation $\mathcal{Z}$. Meanwhile, FC blocks are implemented to extract non-linear correlations $\mathcal{Y}$ for external factors. Finally, we fuse $\mathcal{Z}$ and $\mathcal{Y}$ to obtain our final prediction $D_{n}$.

4.1. Input

We sample historical flow videos from recent time to near history and distant history according to three corresponding temporal views: closeness, period, and trend. We select hours, daily, and weekly as the key timesteps to construct the three views. For each of temporal views, we fetch a list of key timesteps’ flow matrices and concatenated them, to construct the input as:

$$D_{\text{closeness}} = [D_{t-1}, D_{t-2}, \ldots, D_{t-l_{c}}] \in \mathbb{R}^{N \times C \times l_{c}}$$

$$D_{\text{period}} = [D_{t-p_{d}}, D_{t-2p_{d}}, \ldots, D_{t-l_{d}p_{d}}] \in \mathbb{R}^{N \times C \times l_{d}}$$

$$D_{\text{trend}} = [D_{t-p_{w}}, D_{t-2p_{w}}, \ldots, D_{t-l_{w}p_{w}}] \in \mathbb{R}^{N \times C \times l_{w}}$$

$$\{ D_{t}|t = 0, \cdots, n-1 \} = [D_{\text{closeness}}, D_{\text{period}}, D_{\text{trend}}],$$

where $l_{c}$, $l_{d}$, $l_{w}$ are input lengths of hours, daily, and weekly, $p_{d}$, $p_{w}$ are daily and weekly periods.

4.2. Structures for spatiotemporal variables

For flow videos, each fragment is encoded by a shared 3D-CNN Encoder to extract short-term dependence obtain high-dimensional feature maps. The motivation for the implementation of 3D-CNN in encoding representation is that 3D-CNN is suitable to extract short-term appearance and local motions in a consecutive short-term period:

$$\langle Y_{0}, Y_{1}, \ldots, Y_{n-1} \rangle = \text{RELU}(P_{l}^{\text{Encoder}} \cdots P_{l}^{\text{Encoder}}(D_{0}, D_{1}, \ldots, D_{n-1})),$$

where $D_{n-1} = D_{0,j}$ is the $n-1$th fragment that consists of $i$ frames, as shown in Figure 3, $\text{RELU}$ is activation function, $l$ is the number of layers, $n$ is the number of fragments, and $P_{l}^{\text{Encoder}}$ is the 3D-CNN Encoder.

Next, the outputs $\langle Y_{0}, Y_{1}, \ldots, Y_{n-1} \rangle$ are fed into the E3D-LSTM blocks that integrate 3D convolutions into LSTM to capture long short-term dependence. The purpose for implementation of the E3D-LSTM is to learn better representations for both short-term frame dependence and long-term high-level relations. Specifically, the encapsulated 3D convolution makes local perceptsions of units motion-aware and enables the memory cell to store better short-term features. For long-term relations, the present memory state interacts with its historical records via a gate-controlled self-attention LSTM module:

$$\langle U_{0}, U_{1}, \ldots, U_{n-1} \rangle = \text{RELU}(P_{l}^{\text{E3D-LSTM}} \cdots$$
Figure 2: Architecture of MSTF-Net

![Figure 2](image)

Figure 3: A fragment of flow videos on MoBike dataset. \( i \) is the number of frames in a fragment.

\[
F_{E3D-LSTM}(Y_0, Y_1, \ldots, Y_{n-1}),
\]

where \( F_{E3D-LSTM} \) is the E3D-LSTM block.

The inner architecture of the E3D-LSTM is illustrated in Figure 4, where the red arrows indicate short-term information flow and the blue arrows denote long-term information flow in hour dimension. The architecture can be divided into the temporal part and the spatiotemporal part.

In the temporal part, recurrent 3D convolution as motion-aware perceptrons to extract 10-minute appearance and local motions in continuous space-time fields and store them in a small spatiotemporal volume. A memory RECALL mechanism is designed for the recurrent transition function of the memory states to capture hourly interactions:

\[
\begin{align*}
R_n &= \sigma (W_{xr} \ast X_n + W_{hr} \ast H_{n-1}^k + b_r) \\
I_n &= \sigma (W_{xi} \ast X_n + W_{hi} \ast H_{n-1}^k + b_i) \\
G_n &= \tanh \left( W_{xg} \ast X_n + W_{hg} \ast H_{n-1}^k + b_g \right) \\
\text{RECALL} (R_n, C_{n-\tau:n-1}^k) &= \text{softmax}(R_n \\
&\cdot (C_{n-\tau:n-1}^k)^{\top} \cdot C_{n-\tau:n-1}^k) \\
C^k_n &= I_n \odot G_n + \text{LayerNorm} \left( C_{n-1}^k + \text{RECALL}(R_n, C_{n-\tau:n-1}^k) \right)
\end{align*}
\]

where \( n \) is the hour, \( \sigma \) is the sigmoid function, \( \ast \) is 3D convolution operation, \( \odot \) is Hadamard product, \( \text{LayerNorm} \) is layer normalization, \( \cdot \) is matrix product after reshaping the recall gate \( R_n \) and long-term memory states \( C_{n-\tau:n-1}^k \) into matrixes, \( b_r, b_i, b_g \) are intercept parameters. \( G_n \) is an interaction of the current input \( X_n \) and the previous short-term memory state \( H_{n-1}^k \), and \( I_n \) is an input gate controls which parts of \( G_n \) should be added to the long-term state like standard LSTM. \( R_n \) is a recall gate, acting as memory access instructions, controls where and what to attend in historical memory records. The RECALL function is implemented as an attentive module to compute the relationship between the encoded local patterns and the whole long-term memory space to get the current long-term memory state \( C_n^k \). The hyper-parameter \( \tau \) means how many historical memory states are attended by the recall gate \( R_n \). On the other hand, the RECALL function is a self-attention mechanism that is used to evoke past memories from distant timestamps for memorizing and distilling useful information from what has been perceived (i.e., \( \tau = n - 1 \) in our study).

With the updated memory state \( C_n^k \), the hidden states are:

\[
\begin{align*}
I'_n &= \sigma \left( W'_{xi} \ast X_n + W_{mi} \ast M_{n-1}^k + b'_i \right) \\
G'_n &= \tanh \left( W'_{xg} \ast X_n + W_{mg} \ast M_{n-1}^k + b'_g \right) \\
F'_n &= \sigma \left( W'_{xf} \ast X_n + W_{mf} \ast M_{n-1}^k + b'_f \right) \\
M_n &= I'_n \odot G'_n + F'_n \odot M_{n-1}^k
\end{align*}
\]
\[ O_n = \sigma(W_{so} \ast \mathcal{X}_n + W_{ho} \ast \mathcal{H}^k_{n-1} + W_{co} \ast \mathcal{C}^k_n + W_{mo} \ast M^k_n + b_o) \]
\[ \mathcal{H}^k_n = O_n \odot \tanh(W_{1 \times 1} \ast \mathcal{M}^{k} + \mathcal{M}^{k} + \mathcal{H}^k_n) \]

where \( W_{1 \times 1} \) is the 1 \times 1 \times 1 convolution for the transformation of the channel number. In the spatiotemporal part (see Appendix for details), \( I_n, G_n \) are the gate structures similar to \( I_n, G_n \) mentioned before, the forget gate \( \mathcal{F}^k_n \) controls which parts of the long-term state should be erased, \( M^k_n \) is the previous spatiotemporal memory states. Finally, the output gate \( O_n \) controls which parts of the long-term state should be read and output short-term memory state \( \mathcal{H}^k_n \) at the current timestamp. For simplicity, the number of layers \( k \) is omitted in the current layer. Note that there are two E3D-LSTM layers in MSTF-Net, so \( \mathcal{H}^k_n = \mathcal{H}^k_n \) and \( \mathcal{H}^k_n = \mathcal{H}^k_n \) when \( k = 2 \):

\[ (U_0, U_1 \ldots U_{n-1}) = (\mathcal{H}^k_0, \mathcal{H}^k_1 \ldots \mathcal{H}^k_{n-1}) \]

Then, 3D-CNN Decoder layers are employed to get the latent representation \( \mathcal{Z} \):

\[ \mathcal{Z} = P^{Decoder}_D \ldots P^{Decoder}_1 (U_0, U_1, \ldots, U_{n-1}) \]

where \( P^{Decoder} \) is the 3D-CNN layer. The Decoder extracts higher-level feature maps.

4.3. Structures for temporal variables

Temporal variables include current external factors \( \mathcal{E}x_{t_n-1} \) such as weather condition, day-of-week, temperature, wind speed, and time-of-day. We use fully-connected layers to extract the non-linear correlations \( \mathcal{V} \) between them. This is represented by

\[ \mathcal{V} = P^{FC}_D \ldots P^{FC}_1 (\mathcal{E}x_{t_n-1}) \]

where \( P^{FC} \) is the fully-connected layers.

4.4. Fusion

We process \( \mathcal{Z} \) and \( \mathcal{V} \) to obtain final prediction \( \mathcal{D}_n \):

\[ \mathcal{D}_n = F^{2D-CNN}(\mathcal{Z}) + \text{Reshape}^\text{vector\rightarrow\tensor}(\mathcal{V}) \]

where \( F^{2D-CNN} \) is a 1 \times 1 2D-CNN layer that maps \( \mathcal{Z} \) back to inflow-outflow channel. \text{Reshape} is a function that transforms vectors back to videos, denoted by \( \text{Reshape}^\text{vector\rightarrow\tensor} : R^M \rightarrow R^{T \times C \times I \times J}, M = T \ast C \ast I \ast J \).

4.5. Training algorithm

During the training process of MSTF-Net, the object is to minimize the Mean Squared Error (MSE) between the real flow \( D_n \) and the estimated flow \( \mathcal{D}_{n+1} \). The objective function is formulated by

\[ \min_{w, b} \| D_n - \mathcal{D}_{n+1} \|^2 \]

The training steps are illustrated in Algorithm 1.

5. Experiment

In Section 5.1, we present the datasets. In Section 5.2, we set up experiments. In Section 5.3, we show the results and analysis. In Section 5.4, we show the parameter sensitivity. In Section 5.5, we show the ablation study. In Section 5.6, we visualize the results.

5.1. Datasets

We use two datasets, including the trajectory data of station-free sharing bike in Shanghai and station-based sharing bike in New York City (NYC).

**MoBike:** The trajectory data is station-free sharing bike GPS data of MoBike for Shanghai from 1st Aug. 2018 to 31st Aug. 2018 about 100 thousand trajectories. We partition Shanghai into 16 \times 16 regions. For MoBike, we just sample historical flow videos from recent time and select 10-minutes as the key timestamp, because the time span is just one
employing the Pearson correlation, given by

\[
\text{Corr}(Y, X) = \frac{E[(Y - E(Y))(X - E(X))]}{\sqrt{E[(Y - E(Y))^2]E[(X - E(X))^2]}}.
\]

where \(Y\) and \(Z\) are two random variables with the same number of observations.

Take outflow in central grid (7, 7) as an example, as shown in Figure 5. The grid distance of grid (i, j) and (7, 7) equals \(i - 7\) or \(j - 7\). Figure 6 shows correlations between grid (7, 7) and grid (i, j) from 6 hours ago. Overall, correlations drop gradually with the increase of grid distance, which indicates that there exit strong spatial correlations between grid (7, 7) and its neighbor regions. On the other hand, it is not surprising that variables with shorter look-back windows have higher correlations. This correlation analysis of MoBike provides evidence that spatial and temporal dependence exist among spatiotemporal variables.

Exploring the feature importance. Take MoBike as an example, to measure the feature importance of the spatiotemporal and temporal variables, we model the flow (outflow or inflow) in a given region and its neighbor regions with XGBoost (Chen and Guestrin, 2016), which is a gradient boosting tree model.

Take outflow in central grid (7, 7) as an example, as shown in Figure 5 (b), we show the top 20 critical features measured by weight (i.e., the number of times a feature appears) and information gain (i.e., the average information gain a feature appears), which are generally used to evaluate the features in general. As shown in Figure 7 and Figure 8, the neighbor flow \((t - n)\) means the average outflow of the neighbor grids at the \(t - n\) time interval and the flow \((t - n)\) means the self-outflow in the grid (7,7) at the \(t - n\) time interval, \(n \in \{1, 2, ..., 36\}\) and time interval is 10 minutes.

Figure 7 shows the variable importance partitioned by category. It can be observed that the neighbor flow, self-flow, and time-of-day are the dominating factors. Other variables, such as weather and day-of-week have less contribution (less than 5%) to the prediction. Figure 8 shows the top 20 important features. It can be found that the importance of neighbor flow \((t - 6)\) significantly surpasses the other features for prediction, measured by information gain. The top features of neighbor flow and self flow are located in shorter time intervals. The other variables such as weather, time-of-day, and day-of-week are not as important as expected. One reason is that variables are not independent, and there exists multicollinearity between the other variables and the flow. The other variables have influenced the flow before measuring the importance. For example, the small historical flows on a rainy day generally also predict a little flow even though we don’t know today is a rainy day.

5.2. Experimental setups and Baselines

Our experiments are conducted with an Nvidia V100 16GB GPU. MSTF-Net consists of 2-layer 3D-CNN encoder blocks, 2-layer E3D-LSTM blocks, 2-layer 3D-CNN decoder blocks, and 2-layer FC blocks. During the training process of deep learning models, we stop training when the validation error does not improve for consecutive maximum (i.e., 50 epochs in our study) iterations. For comparison, we have selected seven baseline models: MST3D-ResNet, E3D-LSTM, ST-ResNet, 3D-CNN-ResNet, ConvLSTM, 2D-CNN-ResNet, and HA. For the deep learning models, the number of filters is set to 32, and the size of filter is set to 3.

(1) **HA**: The traditional time-series model that averages the historical flow to forecast the future flow. For example, the future flow during 7-8 AM in the grid (i, j) is predicted by averaging the historical flow during 7-8 AM in (i, j).

(2) **2D-CNN-ResNet**: 6-layer residual 2D convolutional neural network. Input dimensions of flow videos are shown in Figure 9 (c).

(3) **ConvLSTM**: 4-layer convolutional long short-term memory network (Xingjian et al., 2015), which utilizes 2D convolution to extract spatial dependence and LSTM to extract temporal dependence for spatiotemporal data. Input dimensions of flow videos are in Figure 9 (b).

(4) **3D-CNN-ResNet**: 6-layer residual 3D convolutional neural network (Tran et al., 2015). Input dimensions of flow videos are in Figure 9 (b).
videos are shown in Figure 9 (b).

(5) **ST-ResNet**: 12-layer residual 2D convolutional neural network (Zhang et al., 2017), which consists of three branches for the closeness, period, and trend properties. Input dimensions of flow videos are shown in Figure 9 (c). Note that the inputs of 2D-CNN require images without temporal dimension, so the temporal dimensions $N$ and $T$ are squeezed to the channel dimension $C$.

(6) **E3D-LSTM**: 2-layer or 4-layer eидик 3D convolutional long short-term memory network (Wang et al., 2019). It consists of same FC blocks with MSTF-Net for processing external factors. Input dimensions of flow videos are shown in Figure 9 (a).

(7) **MST3D-ResNet**: 12-layer residual 3D convolutional neural network (Chen et al., 2021), which consists of three branches for the closeness, period, and trend properties. It can be regarded as an improving version of ST-ResNet. Input dimensions of flow videos are shown in Figure 9 (b).

### 5.3. Results and Analysis

For each baseline model, we choose the best performing parameters on the validation set for comparison. The performance of each model is evaluated on Root Mean Squared Error (RMSE), given by

$$
RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (y_i - \hat{y}_i)^2},
$$

where $y_i$ is the $i$th real hourly flow, $\hat{y}_i$ is the $i$th estimated hourly flow, $n$ is the size of test set.

The following experiments results (see details in Table 1) can be observed:

(1) The proposed MSTF-Net performs best by RMSE.

(2) Increasing layers from 2 to 4 little improves the performance for pure E3D-LSTM models.

(3) MSTF-Net significantly performs better than the pure 3D-CNN or E3D-LSTM models such as E3D-LSTM-2, E3D-LSTM-4, MST3D-ResNet, and 3D-CNN-ResNet.

(4) 3D-CNN-ResNet performs the same or better than 2D-CNN-ResNet, and MST3D-ResNet performs better than...
Figure 9: Inputs for different models. \( N \) is the fragment, \( T \) is the frame in the fragment, \( C \) is channel, \( I \) is width, and \( J \) is height.

### Table 1
The prediction results. The total frames are 36 on MoBike and 18 on NYCBike. E3D-LSTM-2 and E3D-LSTM-4 contain 2 layers and 4 layers, respectively.

| Datasets          | MoBike | NYCBike |
|-------------------|--------|---------|
| MSTF-Net          | 1.16   | 5.59    |
| MST3D-ResNet      | 1.28   | 5.85    |
| E3D-LSTM-2        | 1.21   | 6.03    |
| E3D-LSTM-4        | 1.28   | 6.00    |
| ST-ResNet         | 1.39   | 6.02    |
| 3D-CNN-ResNet     | 1.18   | 5.90    |
| ConvLSTM          | 1.18   | 6.53    |
| 2D-CNN-ResNet     | 1.22   | 5.90    |
| HA                | 1.74   | 16.18   |

### Table 2
Parameter sensitivity for input length of frames on NYCBike.

| Total frames | 18 | 36 | 72 |
|--------------|----|----|----|
| Datasets     |    |    |    |
| MSTF-Net     | 5.59 | 5.56 | 5.79 |
| MST3D-ResNet | 5.85 | 5.94 | 5.89 |
| E3D-LSTM-2   | 6.03 | 6.14 | 6.20 |
| ST-ResNet    | 6.02 | 6.00 | 6.25 |
| 3D-CNN-ResNet| 5.90 | 5.72 | 5.95 |
| ConvLSTM     | 6.53 | 6.10 | 6.20 |
| 2D-CNN-ResNet| 5.90 | 5.89 | 6.43 |

### Table 3
Ablation study of external factors. MST-Net excludes the external factors and FC blocks of MSTF-Net.

| Datasets | MoBike | NYCBike |
|----------|--------|---------|
| Num of frames | 36 | 18 | 36 | 72 |
| Datasets |    |    |    |    |
| MSTF-Net | 1.16 | 5.59 | 5.56 | 5.79 |
| MST-Net  | 1.18 | 5.55 | 5.56 | 5.57 |

ST-ResNet. In other words, keeping temporal dimension independent, and performing 3D convolution simultaneously on spatial and temporal dimensions significantly improve the performance.

(5) MST3D-ResNet and ST-ResNet perform worse than 3D-CNN-ResNet and 2D-CNN-ResNet on MoBike. We conclude that the design of three branches for the closeness, period, and trend properties is improper for MoBike that only has closeness property.

### 5.4. Parameter Sensitivity
We perform the sensitivity analysis for input length on NYCBike. In Table 2, we can observe that:

(1) MSTF-Net still performs best when the input length increases from 18 to 36 and 72.

(2) When the input length dramatically increases from 18 to 72, RMSE rapidly increases for 2D CNN based models: 2D-CNN-ResNet and ST-ResNet. For 3D-CNN based models: 3D-CNN-ResNet and MST3D-ResNet, RMSE slightly increases possibly because 3D convolution is more suitable than 2D convolution for capturing long-term spatiotemporal dependence.

(3) When the input length increase, almost all models’ RMSE increases. Although longer input contains more information, it also introduces more noises and dramatically increases training time. ConvLSTM’ RMSE decreases because it behaves poorly on short sequences (i.e., 18), and has more potential to reduce on long sequences.

### 5.5. Ablation study
We explore the influence of multiple blocks design in MSTF-Net and observe that:

(1) In Table 1 and Table 2, MSTF-Net that consists of mul-
multiple blocks significantly performs better than pure 3D-CNN and E3D-LSTM models on MoBike and NYCBIke. We conclude that 3D-CNN blocks highlight extracting short-term spatiotemporal dependence in each fragment. The preprocessing of 3D-CNN blocks helps following E3D-LSTM blocks to further extract long-term spatiotemporal dependence over all fragments.

(2) In Table 3, we show that the fusion of flow videos and external factors has different influences. Specifically, on a total of four datasets, MSTF-Net performs better on one dataset, MST-Net performs better on two datasets, and they perform the same on one dataset.

5.6. Visualization

Take MoBike as an example, we present some samples of heat maps of the ground truth outflow and predicted results by MSTF-Net, as shown in Figure 10, where the brighter color means a larger outflow. It is obvious that the outflows in morning rush hours and evening rush hours (e.g., 7 am and 5 pm) are much higher than that in day time and night time (e.g., 3 pm and 11 pm). The outflow is unbalanced across space: the central grids are much higher than the marginal grids. The trend of the outflow over time is even different in different grids, which makes it hard to predict. From the samples of visualization, we can find that MSTF-Net primarily captures the spatiotemporal characteristics of the outflow. The combination of demand forecasting and visualization helps operators to rebalance bikes efficiently.

6. Conclusions

In this study, a deep learning architecture called MSTF-Net is proposed to forecast bike demands in bike-sharing systems. In MSTF-Net, 3D-CNN blocks highlight extracting short-term spatiotemporal dependence in each fragment (i.e., closeness, period, and trend); E3D-LSTM blocks extract long-term spatiotemporal dependence over all fragments; FC blocks extract nonlinear correlations of external factors. We show that MSTF-Net significantly performs better than the pure 3D-CNN or E3D-LSTM models.

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A. Appendix

The spatiotemporal part of LSTM unit at time stamp $t$ and layer $k$ is described as follows:

$$
i_t = \sigma \left( W_{xi} \odot \mathbf{x}_t + W_{hi} \odot H_{i-1}^k + b_i \right)$$  \hspace{1cm} (2)

$$g_t = \tanh \left( W_{xg} \odot \mathbf{x}_t + W_{hg} \odot H_{i-1}^k + b_g \right)$$  \hspace{1cm} (3)

$$f_t = \sigma \left( W_{xf} \odot \mathbf{x}_t + W_{hf} \odot H_{i-1}^k + b_f \right)$$  \hspace{1cm} (4)

$$i_t' = \sigma \left( W_{x'i} \odot \mathbf{x}_t + W_{mi} \odot \mathbf{M}_{i-1}^k + b_i' \right)$$  \hspace{1cm} (5)

$$g_t' = \tanh \left( W_{x'g} \odot \mathbf{x}_t + W_{mg} \odot \mathbf{M}_{i-1}^k + b_g' \right)$$  \hspace{1cm} (6)

$$f_t' = \sigma \left( W_{x'f} \odot \mathbf{x}_t + W_{mf} \odot \mathbf{M}_{i-1}^k + b_f' \right)$$  \hspace{1cm} (7)

$$C_t^k = i_t \odot g_t + f_t \odot C_{t-1}^k$$  \hspace{1cm} (8)

$$\mathbf{M}_t^k = i_t' \odot g_t' + f_t' \odot \mathbf{M}_{t-1}^k$$  \hspace{1cm} (9)

$$o_t = \sigma \left( W_{xo} \odot \mathbf{x}_t + W_{ho} \odot H_{i-1}^k + W_{co} \odot C_t^k + W_{mo} \odot \mathbf{M}_t^k + b_o \right)$$  \hspace{1cm} (10)

$$H_t^k = o_t \odot \tanh \left( W_{1x1} \odot \left[ C_t^k, \mathbf{M}_t^k \right] \right)$$  \hspace{1cm} (12)

where $\sigma$ is the sigmoid function, $\odot$ is the convolution operator, and $\odot$ denotes the Hadamard product. There are four inputs: $\mathbf{x}_t$, the raw frame or hidden states from the previous layer; $\mathbf{M}_t^k$, the previous spatiotemporal memory; $H_{i-1}^k$, the previous hidden states and memory states. Two sets of gate structures, including input gate $i_t$ and $i_t'$, forget gate $f_t$ and $f_t'$, as well as the output gate $o_t$, control the information flow in space-time domain. All of them can be presented by $R^{H \times W \times C}$ dimensional tensors, where the first two dimensions are the width and height of feature maps, and the last one is the number of feature map channels.