PRNet: A Periodic Residual Learning Network for Crowd Flow Forecasting

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Abstract
Crowd flow forecasting, e.g., predicting the crowds entering or leaving certain regions, is of great importance to real-world urban applications. One of the key properties of crowd flow data is periodicity: a pattern that occurs at regular time intervals, such as a weekly pattern. To capture such periodicity, existing studies either explicitly model it based on the periodic hidden states or implicitly learn it by feeding all periodic segments into neural networks. In this paper, we devise a novel periodic residual learning network (PRNet) for better modeling the periodicity in crowd flow data. Differing from existing methods, PRNet frames the crowd flow forecasting as a periodic residual learning problem by modeling the deviation between the input (the previous time period) and the output (the future time period). As compared to predicting highly dynamic crowd flows directly, learning such stationary deviation is much easier, which thus facilitates the model training. Besides, the learned deviation enables the network to produce the residual between future conditions and its corresponding weekly observations at each time interval, and therefore contributes to substantially better predictions. We further propose a lightweight Spatial-Channel Enhanced Encoder to build more powerful region representations, by jointly capturing global spatial correlations and temporal dependencies. Experimental results on two real-world datasets demonstrate that PRNet outperforms the state-of-the-art methods in terms of both accuracy and robustness.

Introduction
Crowd flow forecasting aims to generate future crowd conditions for each region of a city, which is a crucial task in efforts toward achieving smart city. It can facilitate a wide range of applications in urban areas, such as assisting the transportation managers to estimate the congestion (Zhang et al. 2021), guiding transportation network companies to pre-allocate the vehicles (Geng et al. 2019), or helping the public traveler to improve travel plans in advance (Li et al. 2018), etc.

Spatio-temporal (ST) dependency is an important characteristic in crowd flow forecasting: one region’s future crowd flow volume is conditioned on its historical observations and other regions’ histories. Many works (Zhang et al. 2016; Lin et al. 2019) employ convolutional neural networks (CNNs) to capture spatial correlations and utilize different subbranches or channels to model temporal dependencies of different time scales. There are also some methods (Shi et al. 2015; Zonoozi et al. 2018) adopting recurrent neural networks (RNNs) to enhance temporal modeling via recurrent state transformations. Recently, Liang et al. (2020) suggest that CNNs can effectively model the spatial and channel-wise correlations in crowd flow data with the Squeeze-and-Excitation (SE) mechanism (Hu, Shen, and Sun 2018).

Another key characteristic in citywide crowd flow is periodicity (Zhang et al. 2016; Zhang, Zheng, and Qi 2017). As can be observed from Fig. 1, crowd flow data show periodic patterns, e.g., daily and weekly. For instance, on the daily scale, the volume in the grid follows a similar trend that increases during the morning and decreases during the night; on the weekly scale, the flow pattern repeats every week (see the red and yellow line). Existing works on presenting such periodic patterns can be grouped into two categories: 1) implicit methods feed the recent, daily, and weekly data into different branches (Zhang, Zheng, and Qi 2017; Guo et al. 2019) or concatenate these multi-scale time intervals as different channels for the network to process (Lin et al. 2019; Liang et al. 2020); 2) explicit approaches, such as Periodic-CRN (Zonoozi et al. 2018) and STDN (Yao et al. 2019), explicitly model the periodicity by looping back the recurrent hidden states or calculate the similarity of ST representations. However, they inevitably induce extra parameters and computational overheads.

In this paper, we propose to think from a new perspective - introducing the residual concept to represent the periodic behavior in a more efficient manner. As shown in Fig. 1,
through the daily crowd flow fluctuates almost all the time, the volume difference of a certain region at the same time in successive weeks (we term it as periodic residual) tends to be stable even in long-term trends (see the green line). Thus, we assume that the crowd flows of the current week can be trained more efficiently, even with fewer parameters.

Based on the aforementioned insight, we present a novel Periodic Residual Network (PRNet) for multi-step ahead crowd flow forecasting. Specifically, the model generates predictions based on the learned periodic residual at each time step, which makes the network more effective and robust in long-term forecasting. The key idea is that periodic residual features are consolidated representations extracted from raw data that can help to reduce the difficulties in modeling complex crowd flow patterns, even with a fewer number of model parameters. Furthermore, we notice that the existing works are inefficient to capture the global ST correlations, and therefore introduce a lightweight ST enhanced network, named Spatial-Channel Enhanced (SCE) Encoder to jointly encode the most salient global spatial correlations and channel dependencies, i.e., spatiotemporal relations, and therefore introduce a lightweight ST enhanced network, named Spatial-Channel Enhanced (SCE) Encoder for spatio-temporal representations. By learning the periodic residual, our network can be trained more efficiently, even with fewer parameters.

Our main contributions are summarized as follows:

- We devise a periodic residual learning framework that learns the periodic residual at each time interval to improve the accuracy in multi-step ahead prediction.
- We introduce a lightweight Spatial-Channel Enhanced (SCE) Encoder to better capture global spatio-temporal dependencies, which empirically proves to be more effective than standard convolutional layers.
- We evaluate PRNet on two real-world datasets. Experimental results demonstrate that PRNet achieves the best performance among state-of-the-art approaches, especially in long-term predictions.

Preliminaries

In crowd flow prediction tasks, the area of interest, e.g., a city, is evenly partitioned into a $H \times W$ regions based on their longitude and latitude (Zhang, Zheng, and Qi 2017). Given a grid cell $(h, w)$, there are two types of flows: inflow and outflow. Inflow refers to the total number of incoming traffic entering region $(h, w)$ from other regions during a given time interval, and outflow is the total number of outgoing traffic leaving from region $(h, w)$ to other regions.

Notation

We denote the multi-scale segments in crowd flows with four terms - closeness, periodic closeness, prediction, and periodic prediction. An example can be seen in Fig. 2.

In detail, given recent observations length $T_{obs}$, prediction length $T_{pred}$, the closeness $X_c = \{P_{\tau}\}_{\tau=1,...,T_{obs}} \in \mathbb{R}^{H \times W \times T_{obs}}$, the periodic closeness $X_p = \{P_{\tau}\}_{\tau=1,...,T_{obs}} \in \mathbb{R}^{H \times W \times T_{obs}}$, and periodic prediction $Y_p = \{Y_{\tau}\}_{\tau=1,...,T_{pred}} \in \mathbb{R}^{H \times W \times T_{pred}}$, which corresponds to the future crowd flows $\hat{Y}$.

Methodology

We define crowd flow forecasting as follows: given the closeness $X_c$, periodic closeness $X_p$, and periodic prediction $Y_p$, the target is to predict the residual periodic $\Delta \hat{Y} = \{P_{\tau}\}_{\tau=T_{obs}+1,...,T_{pred}} \in \mathbb{R}^{H \times W \times T_{pred}}$ that corresponds to the future crowd flows $\hat{Y}$.

Embedding Layer

Before feeding the raw inputs to the spatio-temporal learning module, we follow the previous studies (Zhang, Zheng, and Qi 2017; Lin et al. 2019) to employ an embedding layer for a feature transformation. In detail, this layer converts each observed segment $P \in \mathbb{R}^{H \times W \times 2 \times T}$ to feature maps $z \in \mathbb{R}^{H \times W \times C}$ through a convolutional operation with kernel size 1, where $T$ denotes the total time intervals of the segment, namely $T_{obs}$ for closeness and $T_{pred}$ for prediction. Differing from existing attempts that encode multi-scale time intervals into compacted features, we embed each segment separately with shared convolutional layers to save
parameter usage. These embedded features then work as inputs to the SCE Encoder for ST modelling.

Spatial Channel Enhanced Encoder

CNNs are widely used as the backbone to capture long-range spatial correlations (Zhang, Zheng, and Qi 2017; Lin et al. 2019), but they have underestimated the relationship between channels within feature maps. To this end, Liang et al. (2020) adopt squeeze-and-excitation networks (SENet) (Hu, Shen, and Sun 2018) to explicitly model the channel-wise relations to enhance spatio-temporal representation learning. However, it fails to capture complex global patterns as it squeezes global spatial features at each block.

To address the above issue, our SCE Encoder enhanced the SENet by introducing a lightweight global spatial enhanced module to emphasize the global salient spatial features. By stacking multiple SCE blocks, it can model long-term spatio-temporal dependencies effectively. In Fig. 4, we illustrate a single SCE block in SCE Encoder. It comprises three main modules: Standard CNN Module, Spatial Enhanced Module, and Channel Enhanced Module. Since the spatial and temporal information has been indexed to dimensions and channels, the Standard CNN Module can capture the local spatio-temporal correlation via convolution layers:

\[
\hat{h}^{(m)} = W_f^{(m)} \ast \left( \delta \left( W_f^{(m)} \ast h^{(m)} \right) + b_f^{(m)} \right) + b_f^{(m)}
\]

where \(W_f, b_f, b_f^{(m)}\) and \(b_f^{(m)}\) are learnable parameters, \(\ast\) refers to a convolution operator, \(\delta(\cdot)\) is ReLU activation function, and \(m\) denotes index number of SCE Blocks. Note that \(h^{(0)}\) is \(z\) and \(\hat{h}^{(m)} \in \mathbb{R}^{H \times W \times C}\). We will omit the index \(m\) for the same block in the following sections.

Spatial Enhanced Module

The crowd flow in the target grid is effected by other grids, which are not limited to its nearest neighbors, especially when vehicles move in a large time interval. Also, not all grids contribute equally. To better capture such behavior, one needs to consider the inherent spatial and temporal correlations in crowd flow data. Recent works (Zhang, Zheng, and Qi 2017; Liang et al. 2020) leverage 2D CNNs to extract spatio-temporal dependencies by mapping spatial features into two dimensions and indexing the spatio-temporal features to channels. However, the standard CNN layer cannot model these complex correlations because it only relies on the shared weight kernel with small receptive fields to process all regions.

Our Spatial Enhanced Module (SEM) enhances the standard CNN by selecting the salient features globally for better spatial representation. To achieve it, we adopt adaptive max pooling (AMP) to down-sample the hidden state \(h\) by selecting most important features \(S \in \mathbb{R}^{H \times W \times C}\) and translate it to \(S' \in \mathbb{R}^{H' \times W' \times C}\). Then the excitation operator (Hu, Shen, and Sun 2018) is adopted to adaptively recalibrate these global salient features for better spatial correlation modelling:

\[
\hat{h}_s = \sigma(g(S', W_s)) = \sigma(\delta(S'W_{s1})W_{s2})
\]

where \(\sigma\) refers to sigmoid function, \(\delta(\cdot)\) represents the ReLU function, \(g(\cdot)\) represents the gated function, \(W_{s1} \in \mathbb{R}^{H' \times W' \times H \times W}, W_{s2} \in \mathbb{R}^{H \times W'}, \hat{h}_s \in \mathbb{R}^{C \times H' \times W'},\) and \(r_s\) is the reduction ratio. By using learnable parameters \(W_{s1}\) and \(W_{s2}\) to reduce and increase the feature dimensions, the gated function can be regarded as a self-attention mechanism that enables the network to dynamically controls the bypass signals and ensures it only captures the most salient features. Then we reshape \(\hat{h}_s\), and obtain the final encoded global spatial feature \(\hat{h}_s \in \mathbb{R}^{C \times H' \times W'}\).

Channel Enhanced Module

Except for spatial correlations, dynamic spatio-temporal dependencies need to be considered in crowd flow tasks. We thus propose to use Channel

Figure 3: The overview of PRNet, where SCE Encoder captures the ST correlations of each observed segment simultaneously. Then the network employs a differencing function (DIFF) to provide the closeness residual, and a fusion function (FUSE) to generate representations for the prediction residual. The decoder generates predicted deviations for all periodical weeks.
Enhanced Module (CEM) to learn spatial correlations and temporal dependencies simultaneously for better ST understanding. CEM first summarizes the global spatial features into a channel descriptor, then the descriptor captures the spatio-temporal correlations based on the channel dimension. We adopt global average pooling (GAP) to squeeze the global spatial features and generate channel-wise statistics:

\[
c = \frac{1}{H' \times W'} \sum_{h=1}^{H'} \sum_{w=1}^{W'} h_x(h, w)
\]  

(3)

where \( c \in \mathbb{R}^C \). Then a similar strategy as Eq. 3 is used to enhance the spatio-temporal representation by producing the compacted channel-wise features:

\[
\tilde{h} = \sigma(g(c, W_c)) = \sigma(W_{c2} \delta(W_{c1} c))
\]  

(4)

where \( W_{c1} \in \mathbb{R}^{C \times C} \), \( W_{c2} \in \mathbb{R}^{C \times C} \), and \( r_c \) is the reduction ratio. Then the final output of one SCE Block can be obtained by scaling the compacted features \( \tilde{h}^{(m)} \in \mathbb{R}^{1 \times 1 \times C} \) and the feature map \( h^{(m)} \):

\[
h^{(m+1)} = \tilde{h}^{(m)} h^{(m)}
\]  

(5)

We stack a total number of \( M \) SCE blocks in the SCE Encoder. The receptive field of succeeding blocks in SCE Encoder is larger than the receptive field of former blocks. Therefore, our model constructs simple direct ST interactions between grids in former blocks and indirect global ST connections in the succeeding blocks. To this end, our model can efficiently describe correlations between grids over time.

**Residual Learning For Periodical Modelling**

Statistical methods have demonstrated robust prediction by removing trends and seasonality given time series data (Brockwell et al. 2016). We introduce a similar concept to the deep learning model by devising a residual learning architecture to eliminate the sequential seasonality (i.e., periodicity in this paper). This new architecture aims to learn the periodic residuals that are less complex but still maintain the periodic information. Specifically, it consists of two functions: differencing function and fusion function.

**Differencing function (DIFF)** removes the seasonality and provides the periodic closeness residual as a reference of temporal shifting to the network. Traditional statistical approaches use the subtraction function to eliminate the seasonality, and therefore we also choose it as our differencing operation given the embedded features are mapping from their corresponding raw observations. Then the periodic closeness residual can be calculated by subtracting the hidden state of closeness \( h_x^{(M)} \) from the hidden state of periodic closeness \( h_{px}^{(M)} \) generated by SCE Encoder:

\[
\nabla_d H = h_x^{(M)} - h_{px}^{(M)}
\]  

(6)

where \( \nabla_d \) denotes the differencing operator, and \( \nabla_d H \in \mathbb{R}^{P \times H \times W \times C} \). Note that dimension broadcast is used.

**Fusion function (FUSE)** works on generating the prediction residual, i.e., residual between future crowd flows \( Y \) and its corresponding periodic predictions \( Y_{p} \), based on the periodic closeness residual and periodic predictions. We use a concatenation function followed by a canonical linear layer as our fusion function:

\[
\tilde{H} = W_d(\nabla_d H \parallel h_{px}^{(M)})
\]  

(7)

where \( \parallel \) is the concatenation function, and \( W_d \) denotes learnable parameters. Therefore, the embedded vector \( \tilde{H} \in \mathbb{R}^{P \times H \times W \times C} \) can represent the prediction residual, which is conditioned on closeness residuals and periodic prediction. It enables the model to learn deviations between future conditions and its historical observations. It is worth noting that with the residual learning strategy, PRNet provides stationary features to the network so that it increases the model capacity with no extra costs in parameter space.

**Decoder for Prediction**

Our model adopts a fully-connected layer as the decoder to forecast future crowd flows. Instead of generating absolute values, our model focuses on fully uncovering the temporal shifting in periodicity by predicting the deviation \( \Delta \hat{Y} \in \mathbb{R}^{P \times H \times W \times 2 \times T_{pred}} \) between the future and its corresponding historical average flows based on \( \tilde{H} \). Besides, we consider all \( P \) historical segments to strengthen the robustness of our model. Therefore, we define the loss function as:

\[
L(\theta) = \sum_{\tau=1}^{T_{pred}} \left\| \Delta Y_\tau - \Delta Y_{p} \right\|_1
\]  

(8)

where \( \theta \) denotes learnable parameters in the model. The predicted average deviation \( \Delta \hat{Y} \) can be easy to convert to the absolute crowd flows \( \hat{Y} \in \mathbb{R}^{H \times W \times 2 \times T_{pred}} \):

\[
\hat{Y} = \sum_{i=1}^{P} \left( \Delta \hat{Y} + Y_{p} \right) / P
\]  

(9)
### Experiments

#### Experimental Settings

**Datasets**  We conduct experiments on two real-world datasets (Zhang et al. 2016), i.e., TaxiBJ and BikeNYC. TaxiBJ dataset is the crowd flow dataset that comprises four sub-datasets - P1, P2, P3 and P4, while BikeNYC is obtained from the NYC bike system. The detailed statistical information of the datasets is described in Table 2. In the experiments, we employ the last 10% data as test set, and randomly select the remaining 80% data as training set and 10% as validation set, respectively.

| Dataset | TaxiBJ | BikeNYC |
|---------|--------|---------|
| Map Size | (32, 32) | (16, 8) |
| Time Interval | 30 mins | 1 hour |

| Time Span (mm/dd/yyyy) | P1: 07/01/2013 - 10/31/2013 | P2: 03/01/2014 - 06/30/2014 | P3: 03/01/2015 - 06/30/2015 | P4: 11/01/2015 - 04/10/2016 |
|------------------------|-----------------------------|-----------------------------|-----------------------------|-----------------------------|
| Time Span (mm/dd/yyyy) | 04/01/2014 - 09/30/2014 |

| Method | MAE | RMSE | SMAPE(%) | MAE | RMSE | SMAPE(%) |
|--------|-----|------|----------|-----|------|----------|
| HA     | 14.13 | 25.38 | 0.30     | 13.37 | 24.00 | 0.28     |
| DeepST | 15.47 | 15.01 | 0.28     | 13.21 | 14.56 | 0.25     |
| STResNet | 10.08 | 24.38 | 0.17     | 10.77 | 24.84 | 0.15     |
| ConvLSTM | 13.02 | 23.03 | 0.15     | 12.31 | 23.52 | 0.13     |
| DeepSTN+ | 13.17 | 23.90 | 0.14     | 12.98 | 23.57 | 0.13     |
| DeepLGR | 11.62 | 19.98 | 0.13     | 10.34 | 18.01 | 0.11     |
| Ours   | 12.23 | 22.10 | 0.12     | 10.33 | 17.00 | 0.14     |

Table 2: The statistic of TaxiBJ and BikeNYC dataset.

**Evaluation Metrics**  Following the previous studies (Liang et al. 2020, 2021), we evaluate the model performance from different aspects with three metrics: Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and Symmetric mean absolute percentage error (SMAPE).

**Implementation Details**  Our model is trained on a single GTX 2080 Ti using Adam optimizer with a learning rate of 0.0005. We set $T_{obs}$ to 12, $T_{pred}$ to 12, $C$ to 64, and $M$ to 9. The convolution kernel size in $W_1$, $W_2$ is 3 × 3 with 64 filters. $H'$ and $W'$ are both set to 8. $r_s$ and $r_v$ are set to 8 and 4, respectively. We apply a scalar with 50 on taxi volume. The early-stop strategy is applied in all the experiments.

**Baselines**  We compare our model with six forecasting baselines: HA is a traditional time series method that averages the historical flow of the same time of the same day given the past three weeks. DeepST (Zhang et al. 2016) is the first deep learning-based approach for grid-based crowd flow prediction, which utilizes convolution operators to extract local spatial correlations and different CNN branches to capture temporal dependencies. STResNet (Zhang, Zheng, and Qi 2017) further introduces residual structure to DeepST to improve the prediction accuracy. ConvLSTM (Shi et al. 2015) integrates the convolution operation to RNN structure for better long-term spatiotemporal relationship modeling. DeepSTN+ (Lin et al. 2019) is one of the SOTA methods that can capture long-term correlations. DeepLGR (Liang et al. 2020) adopts SE mechanisms to capture spatial correlation and temporal dynamics concurrently.

| Method | # Params | MAE | RMSE |
|--------|---------|-----|------|
| HA     | 5.72    | 3.72 | 7.55 |
| DeepST | 21.0K   | 4.43 | 7.18 |
| STResNet | 2807K | 4.84 | 7.61 |
| ConvLSTM | 1839K | 3.94 | 8.18 |
| DeepSTN+ | 1588K | 4.53 | 7.78 |
| DeepLGR | 876K    | 3.50 | 6.81 |
| Ours   | 710K    | 3.19 | 5.99 |

Table 3: Prediction results and number of parameters comparison of our model with different baselines on BikeNYC dataset, where K denotes thousand.
important characteristic for crowd flow prediction. For example, HA surpasses all previous deep learning methods in P2. The reason is that P2 has a 16.3% missing ratio which causes the size of training samples to be relatively small so that the model becomes overfitted. Our model takes advantage of traditional methods by integrating explicit periodic knowledge to guide the network, and therefore achieves the best performance among all methods across all datasets. (2) ConvLSTM, DeepSTN+, and DeepLGR show better results compared to DeepST and STResNet, which demonstrate better spatiotemporal correlation understanding can lead to better performance. (3) Our method achieves superior performance over DeeSTN+. Deeplgr, ConvLSTM in terms of accuracy and robustness. Specifically, it reduces MAE error by 13.26%, 12.77%, 8.35%, and promotes the robustness by 78.36%, 83.41%, 77.44% on average on the TaxiBJ dataset and reduces the MAE error by 29.58%, 8.56%, and 19.04, and promotes the robustness by 87.50%, 84.62%, and 78.95 on the BikeNYC dataset with 2,34, 1,23, and 2.59 times fewer parameters. We notice that ConvLSTM produces favorable results because its gate mechanisms help it to capture better temporal dependencies in multi-step ahead prediction. However, it also requires high memory usage. Instead, our model utilizes a periodic learning strategy to provide stationary features to increase network capacity with fewer parameters. Additionally, this strategy is applied to each time interval and therefore helps the model to increase the robustness in long-term prediction. Overall, our work beats all the methods, which proves that with a well-designed periodic learning strategy, the network can produce good predictions in crowd flow forecasting.

**Ablation Study**

Table 4 illustrates the effectiveness of each component in PRNet. **w/o PRPC** only adopts a single SCE Encoder to encode the closeness and periodic predictions. **w/o PR** is the model without the periodic residual learning mechanism that adopts a single SCE Encoder to encode the closeness, periodic closeness, and periodic predictions. **w/o R** is PRNet without the residual learning mechanism, which utilizes seven shared parameters SCE Encoders to encode seven observed segments. **w/o S** is PRNet without Spatial Enhance Module (SEM).

| Method  | # Params | MAE   | RMSE  |
|---------|---------|-------|-------|
| w/o PRPC| 707K    | 12.58 ± 0.28 | 21.75 ± 0.58 |
| w/o PR  | 711K    | 12.36 ± 0.31 | 21.32 ± 0.59 |
| w/o R   | 702K    | 36.14 ± 1.29 | 61.45 ± 2.42 |
| w/o S   | 701K    | 10.92 ± 0.15 | 18.40 ± 0.40 |
| PRNet   | 710K    | 10.33 ± 0.06 | 17.00 ± 0.11 |

Table 4: Ablation studies of PRNet on TaxiBJ-P4.

According to the results shown in Table 4, we can observe that: (1) Periodic closeness is important in prediction tasks. The reason is that they can provide the reference on time-series shifting between periodic predictions and future conditions. (2) Residual learning is necessary for our model. Without it, the model cannot capture the correlations between the multi-scale time intervals because it only encodes the historical observations with seven shared parameters SCE Encoders separately. Different from **w/o PRPC** and **w/o PR** that model the periodic pattern implicitly via encoding all observations with one SCE Encoder, PRNet directly calculates dependencies of multi-scale time intervals, which provides an elegant solution for explicit periodicity representation without introducing redundant parameters. (3) Enhancing spatial information boosts model performance. Our SEM provides the most salient features based on city-scale grids, which further promotes model performance. In summary, the experimental results and parameter comparison show that PRNet successfully captures the periodicity information as well as complex spatio-temporal correlations without increasing the model complexity.

**Multi-Step Ahead Prediction**

In Fig. 5, we illustrate the effectiveness of our model in multi-step ahead prediction. The results show that our model performs the best in different step ahead settings (from 1 to 12 steps ahead). With the increase of the prediction steps, it outperforms other baselines significantly. The reason is that existing CNN-based approaches only rely on learned ST features to make predictions, while our model generates the future condition based on the periodic residual that captures the direct relationship between the future condition and its corresponding observation. Therefore, it provides the temporal shifting reference for each future time interval and results in better multi-step ahead prediction. We also notice that the LSTM-based method can perform well in short-term prediction thanks to its gate mechanisms, however, it becomes worse in long-term forecasting due to the error accumulation issue. By studying the multi-step ahead prediction, we exhibit that our model has good performance on both short-term and long-term predictions.

**Figure 5: Multi-step ahead prediction results on TaxiBJ-P4.**

**Robustness to Training Data Budget**

In real-world applications, the available data budget for network training can be varied. Therefore, we investigate the performance of our model under different sizes of training data budgets. The results on TaxiBJ-P4 are shown in Fig. 6. From the results, we can observe that: (1) The deep learning approach outperforms the traditional time-series model along with the increase of the training data budget. For example, HA can outperform its deep learning counterpart, i.e.
DeepLGR, given a small size of training data (10% ratio data budget), while it produces the highest error in terms of MAE and RMSE with a larger training budget. The reason is that the deep model fails to optimize a large number of parameters with limited training samples. (2) Our model surpasses both HA and DeepLGR given various sizes of training data budgets. Because our model explicitly captures the periodic residual which works as a strong periodic prior that provides the statistical knowledge to the deep learning network. With the deep model capturing the complex ST correlation, this periodicity prior knowledge can make our model bridge the gap between the traditional method and deep method, and thus help the model to generate good results with both small and large training data budgets.

![Figure 6: Prediction results of PRNet that trained on various data budgets, which is subsampled from the original training data with different ratios, i.e., 10%, 30%, 50%, and 100%.](image)

**Related Work**

**Grid-based Crowd Flow Forecasting** Crowd flow forecasting has been investigated for more than five decades. Early attempts employ statistical models (Brockwell et al. 2016) to make future condition predictions. In particular, some works (Williams and Hoel 2003; Tran et al. 2015) investigate the periodicity in crowd flows and apply the seasonal ARIMA to model it. However, these classical approaches rely on assumptions of linearity and stationarity and thereby cannot model the complex nonlinear ST dependency. Recently, deep learning models (Zhang, Zheng, and Qi 2017) [Geng et al. 2019; Liang et al. 2020] have been used to capture the complex ST correlations. For example, DeepST (Zhang et al. 2016) and ST-ResNet (Zhang, Zheng, and Qi 2017) adopt CNN-based architecture to learn ST correlations and achieve higher prediction accuracy. Specifically, they integrate the periodicity into the network by feeding multi-scale segments to different sub-branches. For better periodic representations, other works consider modeling the periodic pattern explicitly through looping back the periodic representation dictionary (Zonoozi et al. 2018) or learning the temporal similarity (Yao et al. 2019). However, they require massive computation costs to loop back the recurrent hidden states or compute attention scores. Recent efforts focus on improving ST modeling for more accurate forecasts. Although graph neural networks (GNNs) (Kipf and Welling 2017; Velivckovic et al. 2018) have drawn increasing attention in ST traffic prediction (Zheng et al. 2020; Han et al. 2021), they are hard to show the advantage in region-based forecasting due to the unexplicit graph structure of regions. Meanwhile, Liang et al. demonstrates CNNs can effectively capture the ST correlations by jointly modeling spatial correlations and temporal dynamics. However, it employs CNNs with different kernel sizes to learn global spatial representations, which requires high computational efforts. Instead of taking huge efforts in designing complex modules for ST representations, our work is inspired by statistical models and utilizes periodic differences to reduce hypothesis space and ease the network training. It shows that with a powerful periodicity learning mechanism, one can generate favorable predictions even with a lightweight ST module.

**CNNs and Attention Mechanisms** CNNs have been successfully applied to many domains, such as computer vision (He et al. 2016), audio generation (van den Oord et al. 2016), crowd flow prediction (Zhang, Zheng, and Qi 2017), etc. Recent works (Hu, Shen, and Sun 2018; Hou, Zhou, and Feng 2021) utilize gating and attention mechanisms to further enhance the feature interdependencies in CNNs. Specifically, SENet (Hu, Shen, and Sun 2018) introduces squeeze and excitation operations as the gating mechanism to recalibrate the channel-wise attention through sigmoid function. However, it adopts global average pooling to suppress spatial information, which makes the network unable to capture spatial correlations effectively. Although some works further introduce attention to enhance the spatial representation via operating additional convolutions layers on average- and max-pooled features (Woo et al. 2018) or employ dilated convolutions to enlarge the receptive field (Park et al. 2018), they fail to fully uncover the global correlations. DANet (Fu et al. 2019) can capture global ST dependencies by extending the self-attention to position attention and channel attention. However, it is computationally expensive since it takes all spatial information into account. In this paper, we model the global ST representation in a computationally efficient manner by only considering the most salient features.

**Conclusion and Future Work**

In this paper, we studied the periodic behavior in crowd flow and proposed PRNet, a deep learning architecture that integrates the statistical strategy for multi-step ahead forecasting. We further introduced a lightweight SCE Encoder to enhance the spatio-temporal dependency representations by suppressing and refining the intermediate features. The experiments on real-world data showed the effectiveness of PRNet, which reduces the error of MAE by 8.4%~29.6% and promotes the robustness by 77.4%~87.5% with 1.2~2.6 times fewer parameters compared with SOTA methods. It demonstrated the potential of bridging the gap between the traditional time-series approaches and deep neural networks. This work highlighted the inadequacy of previous works on periodicity modeling and shed some light on exploiting traditional statistics to boost the deep learning model performance. Additionally, PRNet is not limited to crowd flow forecasting. In the future, we will evaluate it on other tasks that contain strong periodicity.
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