MAF-GNN: Multi-adaptive Spatiotemporal-flow Graph Neural Network for Traffic Speed Forecasting

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Abstract

Traffic forecasting is a core element of intelligent traffic monitoring system. Approaches based on graph neural networks have been widely used in this task to effectively capture spatial and temporal dependencies of road networks. However, these approaches can not effectively define the complicated network topology. Besides, their cascade network structures have limitations in transmitting distinct features in the time and space dimensions. In this paper, we propose a Multi-adaptive Spatiotemporal-flow Graph Neural Network (MAF-GNN) for traffic speed forecasting. MAF-GNN introduces an effective Multi-adaptive Adjacency Matrices Mechanism to capture multiple latent spatial dependencies between traffic nodes. Additionally, we propose Spatiotemporal-flow Modules aiming to further enhance feature propagation in both time and space dimensions. MAF-GNN achieves better performance than other models on two real-world datasets of public traffic network, METR-LA and PeMS-Bay, demonstrating the effectiveness of the proposed approach.

Keywords: Traffic speed forecasting, graph neural network, spatiotemporal data analysis

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1. Introduction

Traffic forecasting is the foundation of other traffic services, such as bike flow prediction[1], traffic light control[2], and ride-hailing demand analysis[3]. The task is to forecast an indicator reflecting the traffic situation in the future, such as traffic speed, according to a given traffic network and historical traffic data.

However, traffic forecasting is a challenging task due to the complex spatiotemporal dependencies. First, traffic data has obvious periodicity and cycle fluctuation. A prediction method is required to summarize the long-period trends as well as to handle the rapid changes caused by sudden burstiness. Second, as traffic data is defined on an interconnected traffic network, the traffic nodes will interfere with each other. For example, traffic congestions caused by incidents will have an impact on the traffic node’s neighbors soon. Thus, the topological structure of the traffic network should be fully utilized. But it’s difficult to describe the non-Euclidean topological structure and model the spatial correlations between traffic nodes.

Spatiotemporal graph neural network is a mainstream approach for handling problems with strong spatiotemporal correlations. The main idea is to combine deep learning-based time series models with Graph Neural Networks(GNNs). GNNs are generalizations of classical Convolutional Neural Networks(CNNs) to handle graph data. It has been widely utilized in traffic forecasting[4], weather forecasting, skeleton-based action recognition[5], air quality prediction[6], etc. Previous works applying spatiotemporal graph neural networks have achieved remarkable performance in traffic forecasting, such as STGCN[7], ASTGCN[8], MRA-BGCN[9], etc. They have illustrated the effectiveness of capturing both spatial and temporal dependencies jointly. However, they often utilized traffic properties (eg. distance) to pre-define fixed adjacency matrices of traffic graphs, which requires prior domain knowledge. Besides, a pre-defined adjacency matrix may not completely reflect the topological structures of road networks and was not related to the prediction task.

In this paper, we propose a Multi-adaptive Spatiotemporal-flow Graph Neural Network (MAF-GNN) for traffic speed forecasting. Considering the various correlations between nodes, we introduces a Multi-adaptive Adjacency Matrices Mechanism to model the multiple latent spatial correlations in which the adjacency matrices are tunable during the training phase. In addition, we improve the spatiotemporal modules by adding skip-connections between spatial and temporal layers to enhance information propagation and forbid information loss.

The main contributions of this paper are as follows:
• We propose a Multi-adaptive Adjacency Matrices Mechanism for GNNs by designing parameterized adjacency matrices. It is able to learn the task-specific adjacency matrices representing the multiple latent correlations between traffic nodes.

• We propose an improved network architecture. By transmitting features as spatiotemporal flow through the same-type layers, the model is able to retain maximum information in the time and space dimensions.

• We evaluate our model on two real-world public traffic datasets, METR-LA and PeMS-Bay. The experiment results of the traffic speed forecasting task demonstrate the effectiveness of the proposed approach.

The rest of this paper is organized as follows. Section 2 reviews existing work on traffic forecasting. Section 3 defines the traffic speed forecasting problem and introduces our proposed MAF-GNN, including the multi-adaptive adjacency matrices mechanism and the spatiotemporal-flow architecture. Section 4 presents the experiment results and performance discussions. Conclusion remarks are described in Section 4.4.

2. Related Works

Traffic forecasting is a challenging task due to the complex dependencies in spatial and temporal dimensions. It heavily depends on historical and real-time traffic data. Over the past few decades, a large number of methods have been proposed for traffic forecasting, aiming at improving prediction accuracy and robustness.

In the early years, traffic forecasting approaches mainly employed statistical-based methods and machine learning methods. Hamed et al.[10] applied the Autoregressive Integrated Moving Average (ARIMA) model of order (0, 1, 1) for forecasting traffic volume in urban arterials. Asif et al.[11] utilized unsupervised learning methods (e.g. K-means clustering, Principal Component Analysis and Self Organizing Maps) to mine spatial and temporal performance trends and performed prediction with Support Vector Regression (SVR). Shen et al.[12] employed a novel learning method involving the relevance vector machine to capture the inner correlation between sequential traffic flow data. Cai et al.[13] proposed an improved K-Nearest Neighbors (KNN) model based on spatiotemporal correlation to enhance forecasting accuracy. Besides, non-parametric approaches are
also widely used in traffic prediction problems such as the Kalman filter and its variants [14].

With the rapid development in computational power and growth in traffic data volume in recent years, models capable of modeling highly non-linear temporal dependencies are required for traffic forecasting. Hua et al. [15] first applied a feed-forward neural network for vehicle travel time estimation. After that, many other deep learning-based models were proposed to forecast traffic situation. Recurrent neural network (RNN) and its variants (e.g. LSTM [16] and GRU [17]) formulate the state-space representation with a chain-like topology. For example, Lint et al. [18] used RNN for freeway travel time prediction and Zhao et al. [19] adopted LSTM for short-term traffic forecasting. Compared to RNNs, CNNs have the advantage in calculating efficiency. Ma et al. [20] proposed a CNN-based method that learns traffic as images and describes the time and space relations of traffic flow via a two-dimensional time-space matrix. In addition, there are some other deep learning-based methods for traffic forecasting, like Deep Belief Networks (DBN) [21] and Auto-Encoders (AE) [22, 23].

However, the methods aforementioned are not capable of fully utilizing the implicit spatial correlations. To capture spatial and temporal dependencies, ST-ResNet [24] first partitions traffic zone into grids based on the longitude and latitude and then employs the residual convolutional units and LSTM to model spatial and temporal dependencies respectively. But the non-Euclidean topology between nodes are ignored because CNNs are limited to process regular grid structures. More recently, Graph Neural Network (GNN) is developed to overcome the limitation.

GNN utilizes an adjacency matrix to describe arbitrary graphs so that it can process non-Euclidean data. A large number of studies combine graph neural networks with deep learning-based time series models to mine the spatial and temporal dependencies simultaneously. T-GCN [25] uses graph convolution to capture spatial dependence and employs GRU to capture temporal dependence. STGCN [7] includes several spatiotemporal convolutional blocks which consists of ChebNet [26] and gated CNNs. ASTGCN [8] further introduced a spatial-temporal attention mechanism to dynamically learn the spatial-temporal correlations. Similarly, Guo et al. [27] proposed GATCN which deals with the spatial feature by graph attention network and the temporal feature by temporal convolutional network. Xu et al. [28] proposed a spatial-temporal transformer network (STTN) composed of graph neural networks and transformer layers [29] to dynamically model various scales of spatial dependencies and capture long-range temporal dependencies. Lu et al. [30] presented a temporal directed attributed graph to model
complex traffic flow and then employed a message-passing mechanism and several variants of LSTMs to model spatial-temporal dependencies.

The key component of a graph neural network is the adjacency matrix, which represents the correlations between nodes. For traffic forecasting task, most works (e.g. such as STGCN and ASTGCN) usually construct the adjacency matrices based on Euclidean distance between sensors. But Chen et al. argued that the graph constructed in this way neglects the complexity and interaction of edges. Thus, they defined extra adjacency matrices corresponding to an edge-wise graph to model the correlations between edges. Although the above methods achieved good performance, pre-defined adjacency matrices can not completely represent the topological structure of a traffic network. To address this problem, AGCN learns a task-driven adaptive graph for each task while training, so that the spectral convolution kernel is truly feasible with the diverse graph topology of data. Graph WaveNet sets learn-able source node embedding and target node embedding to construct a self-adaptive adjacency matrix. But it assumes that there is a hidden dependency between any two nodes, which introduces redundant spatial correlations.

3. Methodology

3.1. Problem Definition

Given a graph as \( G = (V, E, A) \), where \( V \) is the set of traffic sensor nodes (\( |V| = N \)), \( E \) is the set of edges in the graph, \( A \in \mathbb{R}^{N \times N} \) is the adjacency matrix reflecting the relationships between nodes (eg. distance between sensors nodes, time-series similarities). Traffic series that contains multiple graph signals is represented as \{\( X_1, \cdots, X_t, \cdots \)\}. At time-step \( t \), the graph signal is defined as \( X_t \in \mathbb{R}^{N \times d} \), where \( d \) is the input feature size. The goal is to learn a model \( f(\cdot) \) that takes graph signals of length \( T \) as input and predicts the graph signals in the next \( T' \) time steps.

\[
\{X_{t+1}, \cdots, X_{t+T'}\} = f(X_{t-T+1}, \cdots, X_t; G) \tag{1}
\]

3.2. Multi-adaptive Adjacency Matrices Mechanism

In this section, we show how to construct an adaptive adjacency matrix. Denote \( E = [e_1, \cdots, e_N] \) as the embedding of traffic nodes, where \( e_i \in \mathbb{R}^{d_e \times 1} \) and \( d_e \) is the size of embedding vectors. To compute the adaptive adjacency matrix \( \hat{A} \in \mathbb{R}^{N \times N} \), we first transform the embeddings as
Figure 1: Overall perspective of the network architecture. The network consists of 1) a Multi-adaptive Adjacency Matrices Mechanism; 2) Spatiotemporal-flow Modules; 3) a Global Temporal Attention Layer; 4) a LSTM layer.
\[ U = W_1^T E \; \; V = W_2^T E \]  

(2)

where \( W_1, W_2 \in \mathbb{R}^{d_e \times d_e} \) are linear projections. \( U = [u_1, \ldots, u_N], V = [v_1, \ldots, v_N] \). The pair-wise similarity between node \( i \) and \( j \) is computed using cosine distance as

\[ S_{ij} = \frac{u_i^T v_j}{|u_i||v_j|} \]  

(3)

where \( S_{i,j} \) represents the relation between nodes and is adaptive along with the embeddings during training.

Then, the adaptive adjacency matrix is restricted by the original graph topological structure, which is a directed adjacency matrix \( A \in \mathbb{R}^{N \times N}, A_{ij} \in \{0, 1\} \), where \( A_{ij} = 1 \) denotes an road between two sensor nodes in the traffic graph, and \( A_{ij} = 0 \) means none.

\[ \hat{A}_{ij} = \text{masked}(S, A) = \begin{cases} S_{ij} & A_{ij} = 1 \\ 0 & A_{ij} = 0 \end{cases} \]  

(4)

Nonetheless, it is found that directly optimizing the adaptive adjacency matrix results in network divergence. Inspired by residual connection[33], the adaptive adjacency matrix is computed as

\[ \hat{A} = \text{masked}(S, A) + A \]  

(5)

To extract multiple relations, as shown in Figure 1, the MAF-GNN uses multiple adaptive adjacency matrices \( \{\hat{A}_1, \ldots, \hat{A}_M\} \). During the interfering phase, the multiple adjacency matrices are initialized once and kept fixed, so there is no additional time consumption.

3.3. Spatiotemporal-flow Module

As shown in Figure 1, the MAF-GNN contains \( L \) Spatiotemporal-flow Modules to simultaneously capture spatial and temporal dependencies. A Spatiotemporal-flow Module consists of a Temporal Convolutional Layer and a Spatial Graph Convolutional Layer. To ensure maximum information flow in the time and space dimensions, skip-connections between same-type layers are added to transmit spatial and temporal features. The computation is as follows:
\[ H_t^l = f_t(H_t^{l-1} + \varphi_t(H_t^{l-1})) \]  
\[ H_s^l = f_s(H_t^l + \varphi_s(H_s^{l-1}), G) \]

where \( H_t^l, H_s^l \in \mathbb{R}^{N \times T \times D} \) are output temporal and spatial features of layer \( l, l \in \{1, \cdots, L\} \). \( \varphi_t(\cdot) \) and \( \varphi_s(\cdot) \) are linear transformations. \( f_t(\cdot) \) and \( f_s(\cdot) \) denote the temporal convolution and spatial graph convolution separately.

### 3.3.1 Temporal Convolutional Layer

Since CNN takes full advantage of parallel computation and produces stable gradient, we choose CNN to model the temporal dependency. To address the network degradation problem in deep neural networks, residual connections are applied. Besides, we apply a gating mechanism to control information through layers.

\[ G_{t-1} = \sigma(\Gamma_{\Theta_1}(H_t^{l-1})) \]  
\[ \tilde{H}_{t-1} = \Gamma_{\Theta_2}(H_t^{l-1}) \]  
\[ H_t^l = G_{t-1} \otimes \tilde{H}_{t-1} + (1 - G_{t-1}) \otimes H_{t-1} \]

where \( \sigma(\cdot) \) is the sigmoid function that controls the information passed to the next layer. \( \Gamma_{\Theta}(\cdot) \) is an one-dimensional convolution with parameter \( \Theta \). \( \otimes \) denotes the Hadamard product.

### 3.3.2 Spatial Graph Convolutional Layer

We adopt a diffusion graph convolutional method\cite{34} to model spatial dependencies, which regards the graph convolution as a diffusion process and assumes that the information of each node is transferred to its neighbors with a probability. Therefore, the graph signals will reach a balanced status after several iterations. We extend the above diffusion graph convolution to utilize multiple adjacency matrices as follows:

\[ H_s^l = \sigma \left( \sum_{m=1}^{M} \sum_{k=0}^{K} (D_{O_m}^{-1} \hat{A}_m)^k H_s^{l-1} W_{O_m}^{(k)} \right) \]

\[ + (D_{I_m}^{-1} \hat{A}_m)^k H_s^{l-1} W_{I_m}^{(k)} \]
where $\sigma(\cdot)$ is the activation function, $K$ is the number of diffusion iterations. $W^{(k)}_O, W^{(k)}_I \in \mathbb{R}^{D \times D}$ are learnable parameters for graph convolution. $(D^{-1}_O \hat{A}_m)^k$ and $(D^{-1}_I \hat{A}_m^T)^k$ indicate the forward and backward diffusion processes of order $k$ with the adaptive adjacency matrix $\hat{A}_m$, where $D_I$ and $D_O$ are the degree matrices of $\hat{A}_m$ and $\hat{A}_m^T$.

3.4. Multi-step Output

The MAF-GNN model uses the output features of all the Spatiotemporal-flow Modules to compute the final multi-timestep output. It enforces direct and early supervision for all the Spatiotemporal-flow Modules, leading to faster convergence and better performance[35].

$$H = \sum_{l=1}^{L} H^l_s$$

Then, $H$ is used to compute the final multi-timestep output. To get the temporal feature in a global perspective, a Global Temporal Attention Layer using the multi-head scaled dot-product attention[29] is applied in the time dimension. The output in the $h$th head is a weighted sum of the values as

$$\tilde{H}_h = \text{Softmax} \left( \frac{(HW^Q_h)(HW^K_h)^T}{\sqrt{d_k}} \right) (HW^V_h)$$

where $W^K_h \in \mathbb{R}^{D \times d_k}$, $W^Q_h \in \mathbb{R}^{D \times d_k}$ are the linear transformations of the query vector and the key vector of size $d_k$. $W^V_h \in \mathbb{R}^{D \times d_v}$ is the linear transformation of the value vector of size $d_v$. The output features of attention heads are concatenated and projected as

$$H_g = \text{Concat}(\tilde{H}_1, \cdots, \tilde{H}_h) W^O$$

where $W^O \in \mathbb{R}^{(h \times d_v) \times D}$ is the linear projection. Followed by a LSTM layer[16], the network finally produces a $T'$-step prediction $\hat{Y} \in \mathbb{R}^{N \times T' \times 1}$, as shown in Figure[1].

4. Experiments

4.1. Datasets and Pre-processing

We evaluate our model on two real-world public traffic datasets, METR-LA and PeMS-Bay, which are two standard datasets for traffic speed forecasting. 1)
### Dataset Statistics

| Dataset   | #Nodes | #Edges | #Timesteps |
|-----------|--------|--------|------------|
| METR-LA   | 207    | 1515   | 34272      |
| PeMS-Bay  | 325    | 2369   | 52116      |

Table 1: Summary statistics of datasets.

METR-LA was collected on the highway of Los Angeles County. It recorded four months of traffic speed data from Mar. 1, 2012 to Jun. 30, 2012 on 207 sensors.

2) PeMS-Bay was collected by California Transportation Agencies (CalTrans) Performance Measurement System (PeMS) in the Bay Area of California, which recorded six months of traffic speed data from Jan. 1, 2017 to May 31, 2017 on 325 sensors. The summary statistics are shown in Table 1. The sensors of each area are marked in the maps as shown in Figure 2.

![Figure 2: Sensor networks of METR-LA and PeMS-Bay.](image)

The pre-processing procedure follows DCRNN[36]. The original topological structure is not accessible, so we binarize the given adjacency matrix built by a thresholded Gaussian kernel[37] to get a binary one for Equation (5). The datasets are split into training, validation, and testing sets with a proportion of $0.7 : 0.1 : 0.2$.

### 4.2. Implementation Details

MAF-GNN predicts the speed of next 12 timesteps, given the previous 12 input timesteps, i.e., $T = T' = 12$. The size of the hidden units of the input layer is 256. The model consists of 4 Spatiotemporal-flow Modules with hidden units size of 64. In each Spatiotemporal-flow Module, the number of iterations of the
diffusion graph convolution is 2 and the one-dimensional temporal convolution’s kernel size is 3. We apply 4 parallel attention heads in the Global Temporal Attention Layer and the hidden units size of each head is 256. As for the Multi-adaptive Adjacency Matrices Mechanism, the model randomly initializes 4 embedding vectors of size 8 for each node with a uniform distribution. We train our model using Adam optimizer with initial learning rate of 0.001 and weight decay of $1e^{-4}$. The number of epochs is 100 both for METR-LA and PeMS-Bay, and the batch size is 64.

| Data       | Models            | MAE (t=3) | RMSE (t=3) | MAPE (t=3) | MAE (t=6) | RMSE (t=6) | MAPE (t=6) | MAE (t=12) | RMSE (t=12) | MAPE (t=12) |
|------------|-------------------|-----------|------------|------------|-----------|------------|------------|-----------|------------|------------|
| METR-LA    | FNN               | 3.99      | 7.94       | 9.90%      | 4.23      | 8.17       | 12.90%     | 4.49      | 8.69       | 14.00%     |
|            | FC-LSTM           | 3.44      | 6.30       | 9.60%      | 3.77      | 7.23       | 10.90%     | 4.37      | 8.96       | 13.20%     |
|            | STGCN             | 2.88      | 5.74       | 7.62%      | 3.47      | 7.24       | 9.57%      | 4.59      | 9.40       | 12.70%     |
|            | DCRNN             | 2.77      | 5.38       | 7.30%      | 3.15      | 6.45       | 8.80%      | 3.60      | 7.59       | 10.50%     |
|            | GWaveNet          | 2.69      | 5.15       | 6.90%      | 3.07      | 6.22       | 8.37%      | 3.53      | 7.37       | 10.01%     |
|            | FC-GAGA           | 2.75      | 5.34       | 7.25%      | 3.10      | 6.30       | 8.57%      | 3.51      | 7.31       | 10.14%     |
|            | MRA-BGCN          | 2.67      | 5.12       | 6.80%      | 3.06      | **6.17**   | 8.30%      | 3.49      | **7.30**   | 10.00%     |
|            | MAF-GNN           | 2.65      | 5.11       | 6.75%      | 3.03      | 6.18       | 8.22%      | 3.46      | 7.30       | 9.88%      |

Table 2: Performance comparison with approaches for traffic speed forecasting.

4.3. Performance Analysis

To show the effectiveness of our model, we compare the performance of our model with following approaches.
1) **FNN**: Feed-forward Neural Network; 2) **FC-LSTM**: Fully-Connected LSTM; 3) **STGCN**[7]: Spatial-Temporal Graph Convolution Network; 4) **DCRNN**[36]: Diffusion Convolutional Recurrent Neural Network; 5) **GWaveNet**[32]; 6) **FC-GAGA**[38]: Fully Connected Gated Graph Architecture; 7) **MRA-BGCN**[9]: Multi-Range Attentive Bicomponent Graph Convolutional Network; 8) **STGNN**[39]: spatial Temporal Graph Neural Network; 9) **ST-TrafficNet**[40]; 10) **STFGNN**[41]: Spatial Temporal Fusion Graph Neural Network.
Table 3: Performance comparison. The results are the average values on multiple timesteps in these works.

| Data       | Models        | $\leq 15\text{min}(t=1-3)$ | $\leq 30\text{min}(t=1-6)$ | $\leq 60\text{min}(t=1-12)$ |
|------------|---------------|-----------------------------|-----------------------------|-------------------------------|
|            |               | MAE | RMSE | MAPE | MAE | RMSE | MAPE | MAE | RMSE | MAPE |
| METR-LA    | ST-GNN        | 2.62 | 4.99 | 6.55% | 2.98 | 5.88 | 7.77% | 3.49 | 6.94 | 9.69% |
|            | ST-TrafficNet | 2.56 | 5.06 | 6.82% | 2.89 | 6.17 | 8.35% | 3.46 | 7.29 | 9.89% |
|            | STFGNN        | 2.57 | 6.51 | 4.73% | 2.83 | 7.46 | 5.46% | 3.18 | 8.81 | 6.40% |
|            | MAF-GNN       | **2.46** | **4.58** | **6.13%** | **2.70** | **5.25** | **7.03%** | **2.99** | **6.05** | **8.11%** |
| PeMS-Bay   | ST-GNN        | 1.17 | 2.43 | 2.34% | 1.46 | 3.27 | 3.09% | 1.83 | 4.20 | 4.15% |
|            | ST-TrafficNet | 1.26 | 2.72 | 2.68% | 1.58 | 3.57 | 3.59% | 1.93 | 4.61 | 4.88% |
|            | STFGNN        | 1.16 | 2.41 | 2.33% | 1.39 | 3.02 | 3.02% | 1.66 | 3.77 | 3.74% |
|            | MAF-GNN       | **1.09** | **2.17** | **2.22%** | **1.30** | **2.81** | **2.81%** | **1.54** | **3.50** | **3.49%** |

Table 4: Ablation study. ST-GNN: a general spatiotemporal graph neural network; SF: using spatiotemporal flow; SA: using only one adaptive adjacency matrix; MA: using four adaptive adjacency matrices.
Following previous works, we adopt Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE) as the metrics. The missing values are excluded from datasets during metric computing. On timestep $t$, the computation of these metrics is:

- $\text{MAE}(\hat{Y}, Y) = \frac{1}{N} \sum_{i=1}^{N} |\hat{Y}_t(i) - Y_t(i)|$,
- $\text{RMSE}(\hat{Y}, Y) = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (\hat{Y}_t(i) - Y_t(i))^2}$,
- $\text{MAPE}(\hat{Y}, Y) = \frac{1}{N} \sum_{i=1}^{N} \left| \frac{\hat{Y}_t(i) - Y_t(i)}{Y_t(i)} \right|$,

where $N$ denotes the number of samples, $\hat{Y}_t(i)$ and $Y_t(i)$ denote the ground truth and the predictions on timestep $t$.

Table 2 shows the performance comparison of our MAF-GNN with other models for 15 minutes, 30 minutes, and 60 minutes ahead prediction on datasets of METR-LA and PeMS-Bay. In other works, like STGNN\cite{39}, ST-TrafficNet\cite{40} and STFGNN\cite{41}, the computation of metrics is different, as the average value on multiple timesteps is taken as the result. For instance, the result of timestep 15min is the average value on timesteps 5min, 10min, and 15min. Thus, the results of these methods are incomparable with results in Table 2 and are shown in Table 3.

From the tables we observe that: 1) Our proposed MAF-GNN performs better than FNN and FC-LSTM with lower test error, because FNN and FC-LSTM ignore the spatial dependencies so that much information is lost. 2) Compared to the spatiotemporal graph convolutional networks in previous works, like STGCN, DCRNN, and Graph WaveNet, our approach achieves competitive results. It indicates the effectiveness of the Multi-adaptive Adjacency Matrices Mechanism and transmitting distinct features in the time and space dimensions. 3) MRA-BGCN performs better in RMSE on the timestep $t = 30$ min. It shows that the edge-wise graph is also important while our model only takes node-wise graph for modeling spatial dependencies.

We plot the real and predicted values of the test data of METR-LA and PeMS-Bay in Figure 3. In general, our model can fit the data well and is not sensitive to noise. Take METR-LA as an example, in the first sub-figure (row 1, column 1), the traffic speed fluctuates significantly. Our model can handle this well and the predicted curve almost coincides with the real one. In the row 2, column 1 of Figure 3, the traffic speed fluctuates within a small range. Our model also performs well in this case which requires the ability to capture the details of the
Figure 3: Visualization of real values and predicted values of test data of METR-LA and PeMS-Bay.
sequence. In the third sub-figure (row 3, column 1), there are some missing values which are padded with 0. Our model produces stable predictions here, which indicates that our model is robust to abnormal values.

4.4. Ablation Study

We conduct experiments to validate the effects of the key components that contribute to the improvement. We remove the spatiotemporal flow and adaptive adjacency matrix of MAF-GNN. So, it degenerates into a general spatiotemporal graph neural network named ST-GNN. Then, we add spatiotemporal flow and adaptive adjacency matrices to ST-GNN to compare the performances. The experiments are conducted under the same training settings and the results are listed in Table 4.

MAF-GNN (row 4 in Table 4) achieves the best performance. The effectiveness of the spatiotemporal-flow network architecture is evaluated from the results of row 1 and 2 in Table 4. It shows that removing spatiotemporal flow has a negative impact on the performance. This is because spatiotemporal flow enhances feature propagation in the time and space dimensions and it ensures maximum information flow. Compare the row 2, 3, 4 in Table 4, it is found that the performance is improved when multi-adaptive adjacency matrices are adopted and as the number of adjacency matrices increases, better performance is achieved, because a single adjacency matrix is not sufficient for representing the complicated spatial dependencies and it allows the model to extract multiple latent correlations. To better understand the multi-adaptive adjacency mechanism, we visualize the adjacency matrices of the first 20 nodes of METR-LA in Figure 4.

Conclusion

In this paper, we present a multi-adaptive spatiotemporal-flow graph neural network named MAF-GNN for traffic speed forecasting. The model captures multiple latent spatial correlations in an end-to-end manner by a Multi-adaptive Adjacency Matrices Mechanism. We further design an improved network architecture, which can enhance information propagation in time and space dimensions. The model achieves significant improvements on two public traffic network dataset, METR-LA and PeMS-Bay. In the future, we plan to solving other spatiotemporal-relevant problems using MAF-GNN. It is also considerable to extend the advantages of the adaptive adjacency matrix to other graph-based tasks.
Figure 4: Visualization of the multiple adaptive adjacency matrices of the first 20 nodes of METR-LA, each of which indicates a correlations between sensor nodes.
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