DMGCRN: Dynamic Multi-Graph Convolution Recurrent Network for Traffic Forecasting

Yanjun Qin, Yuchen Fang, Haiyong Luo, Fang Zhao, and Chenxing Wang

Abstract—Traffic forecasting is a problem of intelligent transportation systems (ITS) and crucial for individuals and public agencies. Therefore, researches pay great attention to deal with the complex spatio-temporal dependencies of traffic system for accurate forecasting. However, there are two challenges: 1) Most traffic forecasting studies mainly focus on modeling correlations of neighboring sensors and ignore correlations of remote sensors, e.g., business districts with similar spatio-temporal patterns; 2) Prior methods which use static adjacency matrix in graph convolutional networks (GCNs) are not enough to reflect the dynamic spatial dependence in traffic system. Moreover, fine-grained methods which use self-attention to model dynamic correlations of all sensors ignore hierarchical information in road networks and have quadratic computational complexity. In this paper, we propose a novel dynamic multi-graph convolution recurrent network (DMGCRN) to tackle above issues, which can model the spatial correlations of distance, the spatial correlations of structure, and the temporal correlations simultaneously. We not only use the distance-based graph to capture spatial information from nodes are close in distance but also construct a novel latent graph which encoded the structure correlations among roads to capture spatial information from nodes are similar in structure. Furthermore, we divide the neighbors of each sensor into coarse-grained regions, and dynamically assign different weights to each region at different times. Meanwhile, we integrate the dynamic multi-graph convolution network into the gated recurrent unit (GRU) to capture temporal dependence. Extensive experiments on three real-world traffic datasets demonstrate that our proposed algorithm outperforms state-of-the-art baselines.

Index Terms—traffic forecasting, spatial-temporal data, graph convolution network, latent graph.

I. INTRODUCTION

Traffic forecasting is crucial for transportation management, public safety, and route planning in ITS [1]. If accurate traffic forecasting in advance, it will provide some useful assistance to the transportation agencies who implement measures of controlling traffic flow, regulate route planning [2], and give early warnings to prevent the spread of COVID-19 [3]. However, traffic forecasting is very challenging, because of the complex spatio-temporal dependencies.

In the past decades, existing methods have devoted enormous efforts to capture complex spatio-temporal dependencies and forecast time-varying traffic conditions. Traditional statistical methods, such as ARIMA [4] and VAR [5], are failing to capture non-linear dependencies of traffic system. The shallow machine learning methods [6], [7] are weak to generalize because most of them rely on hand-craft features. With the successful of deep learning in various fields intensified, early researches consider the traffic forecasting as a univariate time-series forecasting task and pay more attention to temporal dependence. The recurrent neural network (RNN) methods [8], [9], variants of RNN methods [10], [11], [12], and temporal convolution networks (TCNs) [13] are mainly used for traffic forecasting. Gradually, researchers found it was not enough only to capture temporal dependence. The spatial dependence of traffic system is also crucial. Therefore, some methods [14], [15] utilize convolution neural networks (CNNs) to obtain spatial dependence from 2-D grid structure data (e.g., pictures and videos) for traffic forecasting. However, CNNs are difficult to handle the commonly used traffic data with non-Euclidean structure. Recently, graph neural networks (GNNs) [16], [17] are widely used to model non-Euclidean spatial correlations. [18], [19] combine GNNs with RNNs and TCNs to capture spatio-temporal dependencies of traffic system simultaneously. Subsequently, more GNN-based methods are proposed and they are still faced with two fundamental following challenges.

The first weakness is lacking the ability to capture the spatial dependence of remote sensors. It is not enough to only explore the spatial dependence of proximal sensors. Because of two distant sensors may be in two regions with similar functions and similar temporal patterns, i.e., they can bring useful information to each other [20]. Temporal graph based methods [21], [22] use the dynamic time warping (DTW) [23] algorithm to calculate the similarity of time series of all sensors and construct a static temporal graph to get correlation information of each sensor from its temporal neighbours with a similar temporal pattern. Self-attention based methods [24] dynamically calculate correlations of all sensors through the training phase. However, temporal graph based methods consume a lot of time, and the self-attention based methods...
Our major contributions can be summarized as follows: and dynamically assign weights to regions, respectively. The graph convolution network and the attention mechanism to capture the diverse spatial dependencies in different regions. Within a day is like each other. We use the latent graph to search based distance graph to collaboratively discover spatial correlations. As shown in Figure 1, three sensors that are far apart in the road network are in similar structures, and the trend of their speed within a day is like each other. We use the latent graph to replace the temporal graph in prior models to obtain remote information because it is more resource-efficient. Besides, the change of speed of sensors in the road network can not only be modeled as a fine-grained sensor relationship but also as a message passing from different regions to the sensors. Therefore, we split neighbors of each sensor into different regions according to the relationship between the sensor and neighbors in the coordinate, then we utilize the graph convolution network and the attention mechanism to capture the diverse spatial dependencies in different regions and dynamically assign weights to regions, respectively. The major contributions of our work can be summarized as follows:

- A dynamic graph convolution network is proposed. Different from existing fine-grained methods, our method dynamically captures coarse-grained region correlations.
- A latent graph is constructed by the similarity of latent representation of sensors in road networks, which can discover similar temporal patterns of remote sensors.
- We conduct extensive experiments on three real-world traffic datasets, METR-LA, PEMS03, and PEMS05. Our model consistently outperforms all the baseline methods.

II. RELATED WORKS

A. Traffic Forecasting

Traffic forecasting has been studied for decades. Researchers use traditional time series methods (e.g., autoregressive integrated moving average (ARIMA) and machine learning models (e.g., support vector regression (SVR)) and Kalman filtering in the early year. However, traditional time series models usually rely on the stationary assumption and machine learning models need to extract hand-craft features, which require a lot of prior knowledge. As the development of deep learning, (30), (31) utilize deep learning models for traffic forecasting, they only consider the temporal dependence. (13), (14) use convolution neural networks (CNNs) to capture spatial correlations of images. STGCN and DCRNN further leverage the GCN to capture spatial dependence in non-Euclidean structure but limited by the local receptive field of pre-defined graph. Subsequent methods, such as STFGNN, use DTW algorithm to get global spatial information by calculating the historical traffic pattern correlation. They are limited by the slow calculation speed of DTW in long sequences. Although (31), (32), (33) learn a more complete graph through back-propagation and (24) learn the self-attention mechanism instead of GCN to extract the global spatial dependence. They are negatively affected by irrelevant sensors.

B. Graph Convolution Network

Recently, Graph convolution networks (GCNs) have been a widely applied graph structure data analysis method. Graph convolution networks are categorized as spatial convolution and spectral convolution approaches. Spectral convolution approaches define graph convolution operation in the spectral domain. For example, (34) proposes a spectral graph convolution operation, which is defined in the Fourier domain by computing eigen-decomposition of the graph Laplacian. ChebNet suggests that the convolution operation can be further approximated by the K-th order polynomial of graph Laplacian. Kipf et al. (17), (16) propose a simpler GCN which limits the layer-wise convolution operation to \( K = 1 \) and introduces a re-normalization trick. Spatial convolution methods usually define graph convolution operations directly on the graph. For instance, DCNN proposes the diffusion convolution neural network represents the diffusion process on the graph. GraphSAGE generates embeddings by sampling and aggregating features from the neighborhood of nodes. Graph attention networks incorporates the attention mechanism to assign different weights to a neighborhood.

C. Attention mechanism

The additive attention proposed to improve the word alignment in the translation task. Then, (40) proposes the widely used general and dot-product attention. The popular dot-product based self-attention has been proposed in Transformer and has achieved brilliant success in the NLP and CV. In this paper, we use the attention mechanism to distinguish the importance of regions for each sensor.
III. PRELIMINARIES

A. Problem Definition

The goal of the traffic forecasting task is to predict future traffic data (e.g., traffic volume, traffic speed, etc.) based on the historical data recorded by sensors in the road network. The topology of the real road network is expressed as a weighted directed graph $G = (V, E, A)$, where $|V| = N$ is a set of nodes and each node represents a sensor in the road network. $E$ is a set of edges and $A \in \mathbb{R}^{N \times N}$ is the adjacency matrix of $E$. The traffic data in the road network at time slice $t$ is represented as a graph signal $X_t \in \mathbb{R}^{N \times F}$, where $F$ is the feature dimension of the traffic data. Given historical traffic data of the whole traffic network over past $T^h$ time slices, denoted as $X = [X_1, X_2, ..., X_{T^h}] \in \mathbb{R}^{T^h \times N \times F}$, the aim of traffic forecasting problem is learn a function $f(\cdot)$, which is used to predict the next $T^p$ time slices traffic data, denoted as:

$$ [X_1, X_2, ..., X_{T^h}; G] \rightarrow \hat{Y}_{T} = [\hat{Y}_1, \hat{Y}_2, ..., \hat{Y}_{T^p}] \in \mathbb{R}^{T^p \times N \times F}. \quad (1) $$

IV. METHODOLOGY

A. Dynamic Multi-Graph Convolution Network

To discover hidden spatial correlations among sensors, as shown in Figure 3, DMGCN uses a graph learning module to construct the distance graph adjacency matrix based on the shortest path distance and the latent graph adjacency matrix based on the latent representation of sensors, which are later used as inputs to two individual dynamic graph convolution modules. Moreover, the dynamic graph convolution module uses the graph region division layer, graph convolution layer, and attention layer in turn to dynamically capture spatial dependence. At the end of DMGCN, we utilize a fusion module to fuse the results of the two graphs.

1) Graph Learning Module:

a) Distance Graph Generation Layer: We get a directed weighted graph according to the actual road network follow the previous study [26], and we use the Dijkstra algorithm [44] to calculate the shortest path distance $D^{spd}$ between all pairs of nodes to obtain an augmented fully graph. Finally, we use threshold Gaussian kernel to build the shortest path distance based graph adjacency matrix $A^{d} \in \mathbb{R}^{N \times N}$:

$$ A_{i,j}^{d} = \begin{cases} 1, & i \neq j \text{ and } \exp(-\frac{D^{spd}_{i,j}}{\delta}) \geq \epsilon \\ 0, & \text{otherwise} \end{cases}, \quad (2) $$

where $\delta$ denotes the standard deviation and $\epsilon$ is the thresholds to control the distribution sparsity of $A^{d}$.

b) Latent Graph Generation Layer: Existing frameworks typically only utilize the graph of the actual road network to model spatial correlations, which ignores the spatial dependence of remote sensors for traffic forecasting. The way of increasing the number of layers of GCN can expand recen-
tive field and receive traffic information from distant nodes, which also leads to the over-smoothing phenomenon [45] and increases the resource consumption during training. Inspired by methods of constructing a temporal graph by calculating the similarity of time series of sensors using the DTW to capture remote spatial correlations, we construct a novel latent graph to replace temporal graph to capture remote spatial correlations by calculating the similarity of the local structure of sensors using the struc2vec [46]. The struc2vec is a graph representation learning algorithm. Specifically, we first use struc2vec on the road network based graph adjacency matrix to learn the latent representation $E \in \mathbb{R}^{N \times d}$ of all nodes with local spatial structure information. Because struc2vec can create particular hyperbolic spaces that preserve hierarchies and local structures in a graph [47], we use the distance metric in the hyperbolic space to calculate the similarity of the latent representation between all sensors. For instance, the calculation of the similarity $D_{i,j}^{lr}$ between sensor $i$ and $j$ is:

$$D_{i,j}^{lr} = \text{arccosh}(1 + 2 \frac{\|E_i - E_j\|^2}{(1 - \|E_i\|^2)(1 - \|E_j\|^2)}) , \quad (3)$$

where $E_i, E_j \in \mathbb{R}^d$ are the latent representations of sensor $i$ and $j$, and $d$ denotes the embedding dimension of struc2vec. Besides, the $\text{arccosh}(x) = \ln(x + \sqrt{x^2 - 1})$ is an inverse hyperbolic cosine function.

Similar to the build of shortest path distance based adjacency matrix $A^d$, we use threshold Gaussian kernel to build the latent representation based adjacency matrix $\bar{A}^l \in \mathbb{R}^{N \times N}$:

$$\bar{A}^l_{i,j} = \begin{cases} 1 & i \neq j \quad \text{and} \quad \exp(-\frac{D_{i,j}^{lr}}{\delta}) \geq \epsilon \\ 0 & \text{otherwise} \end{cases} . \quad (4)$$

2) Dynamic Graph Convolution Module: In this section, we use two completely consistent dynamic graph convolution modules to capture the spatial dependence in the road network, except that graphs are different. For brevity, we only introduce the process of the latent graph.

a) Mask Mechanism: In order to distinguish the importance of different neighbor nodes in the latent graph, we design a mask mechanism to adjust the edge weights of the graph. Specifically, we use a learnable parameter matrix $M \in \mathbb{R}^{N \times N}$ to multiply the latent graph adjacency matrix $A^l \in \mathbb{R}^{N \times N}$, and then change the value of the parameter matrix through back-propagation to change the value of the adjacency matrix:

$$\hat{A}^l = M \odot A^l , \quad (5)$$

where $\hat{A}^l$ denotes the learnable latent graph adjacency matrix.

b) Graph Region Division Layer: The previous methods use a static adjacency matrix to model the spatial correlations and can not reflect the dynamically evolving road network. However, using attention mechanism to fine-grained model the spatial correlations between nodes in each time slice requires a lot of computing resources. The transportation system contains hierarchical spatial correlations, i.e., in addition to fine-grained node-level correlations, there are also coarse-grained region-level correlations. The dynamic modeling of the region can greatly reduce the complexity of the model and increase the running speed. Different from the existing method, which absolutely divides nodes into different regions [28], we divide neighbors of each node into different regions according to the relative relationship between nodes. For the distance graph, we use the relative position of the sensor’s location (i.e., latitude and longitude) in the 2-D Euclidean space to divide the neighbors of each sensor into four different regions. Therefore, we use an embedding space of dimension 2 in struc2vec to divide the neighbors of each sensor in latent graph into four different regions according to their relative position of the sensor’s latent representation in the hyperbolic space. Concretely, we select edges from different regions of each sensor and save all sensors edge of each region into an adjacency matrix. The adjacency matrix of the latent graph which saves all regions’ edge is $\hat{A}^l \in \mathbb{R}^{4 \times N \times N}$.

c) Graph Convolution Layer: To capture spatial dependence of the non-Euclidean structure efficiently and accurately, we use the graph convolution network as proposed in [16], where node representations are computed by aggregating messages from direct neighbors. For the hidden input $\hat{h} \in \mathbb{R}^{N \times d_h}$ of each time slice, the formulate of information propagates on the latent region graph $\hat{A}^l$ is:

$$\hat{h}^l = \sigma \left( \sum_{i=1}^{4} \left( \frac{D_{i,j}^{l-2}}{D_{i,i}^{l-2}} (\hat{A}^l + I) D_{i,j}^{l-2} \right) hW \right) , \quad (6)$$

where $d_h$ is the feature dimension of input, $d_h = d + F$ and $d_h = 2d$ in DMGCNs where in the first layer of GRU and other layers. Besides, $d$ is the feature dimension of GRU units. $\hat{h}^l \in \mathbb{R}^{4 \times N \times d}$ is the output updated by edges of four regions in the latent graph. $\| \|$ denotes the concatenate operation. $W \in \mathbb{R}^{d \times d}$ is a shared parameter in graph convolution, which reduces the number of parameters and enhances the generalization ability of the model. In Equation 6, the identity matrix $I \in \mathbb{R}^{N \times N}$ is added to the adjacency matrix $\hat{A}^l$ to obtain self-loops for each node, and the resultant matrix is normalized using the diagonal degree matrix $D^{-\frac{1}{2}} \in \mathbb{R}^{4 \times N \times N}$ to obtain the output of different regions. Then we utilize the attention mechanism to aggregate spatial information from different regions dynamically. For sensor $i$, we first adopt linear transformation to reduce the feature dimension of all regions hidden representation $\hat{h}^l_i \in \mathbb{R}^{4 \times 1}$ to 1, and then apply the softmax activation function on it to derive the attention coefficient $\alpha_i \in \mathbb{R}^{4 \times 1}$, which denotes the correlations between the final output and regions. Finally, the output $O^l_i \in \mathbb{R}^d$ can be obtained by the dot-product between with attention coefficients and the corresponding region outputs. The operation can be represented as:

$$e^l_i = W^l_2(ReLU(W^l_1\hat{h}^l_i + b^l_1)) + b^l_2 , \quad \alpha^l_i = \text{softmax}(e^l_i) , \quad O^l_i = \alpha^l_i \hat{h}^l_i , \quad (7)$$

where $ReLU$ is the activation function. $W^l_1 \in \mathbb{R}^{d \times d}$, $W^l_2 \in \mathbb{R}^{d \times 1}$ are learnable parameters. $b^l_1 \in \mathbb{R}^d$, $b^l_2 \in \mathbb{R}$ are bias terms. $O^l \in \mathbb{R}^{N \times d}$ is the output of dynamic graph convolution with the latent graph. Similarity, we derive the output $O^d \in \mathbb{R}^{N \times d}$ of dynamic graph convolution with the distance graph.

3) Fusion Module: In this part, we make the dimension of hidden input consistent with the outputs of the attention layer
by linear transformation and then fuse the outputs of three components. The fusion of DMGCN is formulated as:

$$O = W^h_1(W^h_2 h) + W^d L + W^d O^d,$$  \tag{8}

where $W^h_1 \in \mathbb{R}^{h \times d}$ and $W^h_2, W^d, W^d \in \mathbb{R}^{d \times d}$ are learnable parameters, reflecting the impact of each components on the DMGCN. $O \in \mathbb{R}^{N \times d}$ is the output of DMGCN.

B. Temporal Dependence Modeling

RNN, LSTM and GRU are the common methods to model the temporal dependence. We choose GRU to learn temporal correlations because it is a simple and powerful variant of RNN. We replace the linear operator in GRU with the ral correlations because it is a simple and powerful variant

$$R_{GRU} \text{ at timestep } t$$

the previous hidden state and output hidden state of DMGC-⊙ activation vector at timestep $H_t = U_t \odot H_{t-1} + (1 - U_t) \odot C_t,$ \tag{9}

where $G(\cdot)$ denotes the DMGCN. $X_t \in \mathbb{R}^{N \times F}$ and $H_t \in \mathbb{R}^{N \times d}$ are the previous hidden state and output hidden state of DMGC-GRU at timestep $t$, respectively. $U_t$ denotes the update gate, $R_t$ denotes the reset gate, and $C_t$ denotes the candidate activation vector at timestep $t$. $\sigma$ is the sigmoid activation function and $\odot$ is the hadamard product. $\Theta_U, \Theta_R, \Theta_C$ are parameters for the corresponding filters, respectively. Besides, the scheduled sampling \cite{48} is applied in our DMGC-GRU for better generalization.

C. Loss Function

DMGCGRN can be trained end-to-end via back-propagation by minimizing the L1 Loss between the predicted values and ground truths:

$$L(\Theta) = \frac{1}{N \times T_p} \sum_{t=1}^{T_p} \sum_{i=1}^{N} |X_{t,i} - \hat{Y}_{t,i}|,$$ \tag{10}

where $\hat{Y}$ is the prediction value, $X$ denotes the ground truth, and $\Theta$ represents all trainable parameters. The detailed training procedure of DMGCGRN is summarized in Algorithm 1.

V. EXPERIMENTS

A. Datasets Description

We evaluate the performance of DMGCGRN on three real-world traffic network datasets. METR-LA released by \cite{18}, PEMS03 released by \cite{26}, and PEMS05 constructed by us. The statistical information is shown in Table I.

| Datasets     | #Nodes | #Edges | #TimeSteps | TimeSpan  |
|--------------|--------|--------|------------|-----------|
| METR-LA      | 207    | 1515   | 34272      | 2012/5-2012/6 |
| PEMS03       | 358    | 547    | 26208      | 2018/9-2018/11 |
| PEMS05       | 205    | 269    | 18144      | 2020/6-2020/8  |

b) PEMS03: This traffic dataset is collected by California Transportation Agencies (CalTrans) Performance Measurement System (PeMS) in 3 districts, with 358 sensors and for 2 months of data ranging from Jan 1st 2018 to May 31th 2018.

c) PEMS05: This traffic dataset is collected by PeMS in 5 districts, with 205 sensors and collects 2 months of data ranging from Mar 1st 2012 to Jun 30th 2012.

We aggregate these traffic datasets into 5-minute windows. Besides, inputs are normalized by z-score normalization.

B. Metrics

We adopt three commonly used metrics, including Mean Absolute Errors (MAE), Mean Absolute Percentage Errors (MAPE), and Root Mean Squared Errors (RMSE) to measure

Algorithm 1: Training algorithm of DMGCGRN.

Data: Road network graph $\mathcal{G} = (\mathcal{V}, \mathcal{E}, \mathcal{A})$, traffic tensor $X \in \mathbb{R}^{T \times N \times F}$ of train set, initialized DMGC-GRU unit $f_{\theta}(\cdot)$, pre-defined function for scheduled sampling $f_{ss}(\cdot)$, learning rate $\gamma$, learnable parameters $\Theta$.

1.Employ dijkstra and struc2vec algorithm to get the distance graph $A_d$ and the latent graph $A_l$.
2. Initialize all learnable parameters $\Theta$ in DMGCGRN.
3. set $\text{iter} = 1$.
4. repeat
5. initialize hidden state $H_0$ and $\text{iter} = \text{iter} + 1$.
6. randomly select a batch of input sample $X \in \mathbb{R}^{B \times T_h \times N \times F}$ from X.
7. randomly select a batch of label sample $Y \in \mathbb{R}^{B \times T_p \times N \times F}$ from X.
8. for $t \leftarrow 1 \text{ to } T_p$ do
9. compute $H_t = f_{\theta}(X_t, H_{t-1}, A_d, A_l, \Theta)$.
end
11. initialize traffic signal $\hat{Y}_0 \in \mathbb{R}^{B \times N \times F}$ as a zero vector for decoder.
12. for $t \leftarrow 1 \text{ to } T_p$ do
13. randomly select a number $c \sim \mathcal{U}(0,1)$.
14. if $c < f_{ss}(\text{iter})$ then
15. $\hat{Y}_t = X_t$.
16. else
17. $\hat{Y}_t = \hat{Y}_{t-1}$
end
19. compute $\hat{Y}_t, H_{T_p+t} = f_{\theta} (\hat{Y}_t, H_{T_p+t-1}, A_d, A_l, \Theta)$.
end
21. compute the loss of the Equation 10.
22. compute stochastic gradient of $\Theta$ according to loss.
23. update $\Theta$ according to gradient and learning rate $\gamma$.
24. until met model stop criteria;

Result: Learned DMGCGRN model.
the performance of different methods. As follows:

\[
MAE = \frac{1}{N \times T^p} \sum_{t=1}^{T^p} \sum_{i=1}^{N} |X_{t,i} - \hat{Y}_{t,i}|,
\]

\[
RMSE = \sqrt{\frac{1}{N \times T^p} \sum_{t=1}^{T^p} \sum_{i=1}^{N} (X_{t,i} - \hat{Y}_{t,i})^2},
\]

\[
MAPE = \frac{1}{N \times T^p} \sum_{t=1}^{T^p} \sum_{i=1}^{N} \left| \frac{X_{t,i} - \hat{Y}_{t,i}}{X_{t,i}} \right|.
\]

C. Baselines

The description of baselines is as follows:

- **HA** [4]: Historical average, which uses the average of the historical series to predict the future traffic value.
- **SVR** [6]: Linear support vector regression uses a support vector machine to do regression on the traffic sequence. This framework ignores the spatial dependence on traffic forecasting. We use the rbf kernel in SVR for iterative multi-step prediction.
- **FC-LSTM** [49]: The Encoder-decoder framework implemented by using three LSTM layers with 64 hidden units.
- **DCRNN** [18]: Diffusion convolution recurrent neural network, which combines graph convolution networks with recurrent neural networks in an encoder-decoder architecture. The most limit of this model is that it only relies on the road network. We use the parameters in the original paper for experiments.
- **STGCN** [19]: Spatial-temporal graph convolution network, which combines graph convolution with 1D CNN. The spatio-temporal convolution comprises graph convolution layers and 1-D causal convolutions to model spatial and temporal dependencies. The 1D convolution is lack of capacity for modeling long-term dependence. We keep settings in experiments consistent with original paper.
- **Graph WaveNet** [31]: It uses a self-adaptive graph in graph convolution networks to capture spatial dependence and uses 1D dilated convolution to capture temporal dependence. All settings follow the original paper.
- **AGCRN** [32]: It uses a self-adaptive graph in graph convolution networks to capture the hidden spatial dependence and uses GRU to capture the temporal dependence. We fine-tuned node embedding based on each dataset.
- **STFGNN** [21]: It proposes a spatio-temporal fusion graph to capture spatio-temporal dependencies synchronously. Besides, it designs a learnable matrix to adjust weights of adjacency matrix through back-propagation.
- **GMAN** [24]: Graph multi-attention network is a Transformer-like model that applies the self-attention mechanism to spatio-temporal dimensions to capture global spatio-temporal dependencies dynamically. However, it is limited by the quadratic problem of the self-attention, which consumes a lot of time and memory.

D. Experiment Settings

We split the METR-LA dataset with a ratio 7 : 1 : 2 into training sets, validation sets and test sets, as well as we split the PEMS03 and PEMS05 datasets with a ratio 6 : 2 : 2 into training sets, validation sets and test sets in chronological order. All experiments are run on a CentOS Linux server (CPU: Intel(R) Xeon(R) Gold 6132 CPU @ 2.60GHz, GPU: Tesla-V100). We use the historical one hour data (i.e., 12 timesteps) to forecast traffic conditions in the next hour.

\[
\text{MAPE} = \frac{1}{N \times T^p} \sum_{t=1}^{T^p} \sum_{i=1}^{N} \left| \frac{X_{t,i} - \hat{Y}_{t,i}}{X_{t,i}} \right|
\]

\[
\text{RMSE} = \sqrt{\frac{1}{N \times T^p} \sum_{t=1}^{T^p} \sum_{i=1}^{N} (X_{t,i} - \hat{Y}_{t,i})^2}
\]

\[
\text{MAE} = \frac{1}{N \times T^p} \sum_{t=1}^{T^p} \sum_{i=1}^{N} |X_{t,i} - \hat{Y}_{t,i}|
\]

\[
\text{MAPE} = \frac{1}{N \times T^p} \sum_{t=1}^{T^p} \sum_{i=1}^{N} \left| \frac{X_{t,i} - \hat{Y}_{t,i}}{X_{t,i}} \right|
\]

\[
\text{MAE} = \frac{1}{N \times T^p} \sum_{t=1}^{T^p} \sum_{i=1}^{N} |X_{t,i} - \hat{Y}_{t,i}|,
\]

\[
\text{RMSE} = \sqrt{\frac{1}{N \times T^p} \sum_{t=1}^{T^p} \sum_{i=1}^{N} (X_{t,i} - \hat{Y}_{t,i})^2},
\]

\[
\text{MAPE} = \frac{1}{N \times T^p} \sum_{t=1}^{T^p} \sum_{i=1}^{N} \left| \frac{X_{t,i} - \hat{Y}_{t,i}}{X_{t,i}} \right|.
\]

E. Experiment Results

Table II and Table IV show the comparison of different models on traffic speed and flow forecasting. METR-LA and PEMS03 are widely used for traffic forecasting performance evaluation. We observe DMGCRN achieves state-of-the-art results on all the tasks. In the following, we discuss experimental results of traffic forecasting.

SVR merely captures periodic patterns of traffic data but ignores recent temporal correlations, while HA is just the opposite. We can easily observe that several deep learning-based models (FC-LSTM, DCRNN, Graph WaveNet, and so on) usually out-performance traditional statistical methods (HA) and shallow machine learning methods (SVR). Recently, other researchers provide some deep learning models, such as LSTM, to capture non-linear temporal dependence. They achieve insignificant improvement compared with the traditional methods because of the limitation of employing temporal correlations only. STGCN combines GCN and 1D-CNN to capture spatio-temporal correlations in traffic data, respectively. We think that performing STGCN on the METR-LA dataset is not satisfactory because 1D-CNN is difficult to capture the long-term temporal correlations. DCRNN uses DCN and RNN to capture spatial dependence and long short-term temporal dependencies and achieves a significant improvement in the three datasets compared with the previous methods. However, DCRNN and STGCN lack of consideration for the complex and dynamic conditions of the actual road network because they adopt the fixed road network structure as the prior graph adjacency matrix. Graph WaveNet and AGCRN propose to learn an adaptive adjacency matrix through back-propagation and make improvements to STGCN and DCRNN. Although the adaptive adjacency matrix is more complete and accurate than the road network based adjacency matrix, they are limited by over-fitting, just like performing AGCRN.

| Hyperparameter description | Value |
|----------------------------|-------|
| Batchsize                  | 32    |
| Number of training epochs  | 80    |
| Learning rate              | 0.001 |
| Learning decay rate        | 0.2   |
| Learning decay epoch       | [30,40,50] |
| Optimizer                  | Adam  |
| GRU layers                 | 2     |
| Dimensions                 | 64    |
| Embedding dimensions       | 2     |

**TABLE II: Experiment hyperparameter settings**
on the METR-LA dataset. STFGNN proposes a novel temporal graph mechanism because they believe that sensors with the similar temporal pattern are highly close. We consider that when the multivariate time series data are relatively similar, the temporal graph will not be effective, just as they cannot achieve better results in traffic speed prediction. Besides, they use 1D-CNN to extract temporal correlations, thus ignore long-term correlations result in worse performance of one hour forecasting. GMAN uses the self-attention mechanism to capture spatio-temporal dependencies and make significant improvements in long-term prediction tasks. We noticed that the self-attention mechanism is not sensitive to local information. Therefore, GMAN is not effective in short-term prediction tasks. Moreover, the self-attention mechanism is limited by the quadratic problem, which requires abundant computing resources and cannot train efficiently.

DMGCRN proposes not only a novel latent graph to mine spatio-temporal correlations of sensors with similar structure but also a novel dynamic GCN mechanism to coarsely-grained dynamic modeling spatial region correlations. Therefore, DMGCRN has achieved better results on more complex datasets of the road network, i.e., the results of DMGCRN on METR-LA and PEMS03 are better than PEMS05. Besides, DMGCRN integrates the DMGCN into GRU to capture long short-term temporal dependencies, thus DMGCRN has the best performance in long short-term traffic forecasts on all tasks.

### F. Evaluation on Hyperparameter Settings

We tune hyperparameters on the validation set of all datasets and show the results of DMGCRN on the test set of METR-LA dataset under different parameters in Figure 4. As shown in Figure 4a and 4c, we observe that increasing layers and dimensions of DMGCRN initially lowers the performance but then encounters over-fitting problem when the model becomes too complex. From Figure 4b we find that our model performance is better as the batch size decreases.

### G. Ablation Study

1) **Evaluation on the Number of Regions:** The distance graph can naturally use the latitude and longitude to divide the neighbors of each sensor into four different regions, but the number of regions of the latent graph determined according to the dimension of latent representation of sensors, i.e., if...
the dimension of latent representation of sensors is \( r \), there are \( 2^r \) regions. We conduct experiments of region division. According to the experimental results on METR-LA dataset shown in Figure 5a, the effect of dividing four regions is the best and the most practical choice.

2) Evaluation on Attention: In order to investigate the effect of the attention operation in our model, we conduct experiments on METR-LA dataset. As shown is Figure 5b, the attention method is outperforms other methods. We consider that the attention operation can consider all regions, unlike max method to lose some regions information. The spatial dependence change dynamically over time, so we use attention method to calculate the weight of each region at different time steps instead of directly summing or averaging.

3) Ablation Experiments: To verify the different parts in DMGCRN, we propose three variants and compare them with DMGCRN for ablation experiments on METR-LA dataset. These variants follow the setup of DMGCRN. The predicted value of the next hour is shown in Figure 5c. The detailed description of three variants is described as below:

- Basic: This model replaces the linear unit in the GRU with graph convolution, and the adjacency matrix does not equip with mask matrix. Meanwhile, we use an encoder-decoder architecture for traffic forecasting.
- +Latent: This method uses dual-channel graph convolution to capture neighboring spatial correlations and structural spatial correlations through the distance graph and the latent graph. Besides, we also utilize the fusion module in this method as in DMGCRN.
- +Dynamic: Based on the +Latent model, we divide neighbors of each sensor into four regions and perform dynamic graph convolution according to the method in Section IV-A2 except using the mask matrix.
- DMGCRN: This model adds mask matrix based on the +Dynamic model.

As Figure 5c illustrates, +Latent is significantly better than the Basic model. Because the graph convolution based on the latent graph adjacency matrix can capture the remote spatial dependence efficiently. Different regions at different times should have different effects for sensors in the road network. However, the +Latent model ignores to dynamically capture spatial dependence. +Dynamic aggregates information from different regions dynamically and outperforms the +Latent by a large margin in MAE, RMSE, and MAPE metric. Besides, the mask matrix is a learnable matrix, which tunes the weights adaptively between each sensor and its neighbors through back-propagation and improves the forecasting performance.

H. Visualization

Figure 6 visualizes neighbors of sensor 182 in the latent graph and the distance graph on the PEMS03 dataset. The location of neighbors of sensor 128 in the latent graph are like itself at intersections, and their locations in the city have similar functions. Therefore, we use sensors with similar spatio-temporal patterns through the latent graph to assist in more accurate traffic predictions. Besides, we find the weights of neighbors in different regions are different during the weekday and the weekend, which proves the correctness of dynamically modeling of the hierarchical spatial dependence.

VI. Conclusion

In this paper, we propose a novel dynamic multi-graph convolution recurrent network for traffic forecasting. The
dynamic multi-graph convolution recurrent network integrates the DMGCN into GRU to capture spatio-temporal dependencies simultaneously. In the DMGCN, we construct the latent graph and the distance graph to capture the neighboring and remote spatial correlations individually. Then neighbors of each sensor in the latent graph and the distance graph are divided into four regions corresponding to the relative relationships, respectively. Finally, we use GCN and attention to dynamically capture the hierarchical spatial dependence of sensors and regions. The experiment results on the METR-LA, PEMS03, and PEMS05 datasets show DMGCRN achieves the state-of-the-art performance. In the future, we will extension the and PEMS05 datasets show DMGCRN achieves the state-of-the-art performance. In the future, we will extension the proposed model for more general spatio-temporal forecasting tasks such as the stock price prediction.

ACKNOWLEDGMENT

Many thanks to the Beijing Key Laboratory of Mobile Computing and Pervasive Device, Institute of Computing Technology Chinese Academy of Sciences.

REFERENCES

[1] G. Dimitrakopoulos and P. Demestichas, “Intelligent transportation systems,” IEEE Vehicular Technology Magazine, vol. 5, no. 1, pp. 77–84, 2010.

[2] Y. Wu and H. Tan, “Short-term traffic flow forecasting with spatial-temporal correlation in a hybrid deep learning framework,” arXiv preprint arXiv:1612.01022, 2016.

[3] D. Cao, Y. Wang, J. Duan, C. Zhang, X. Zhu, C. Huang, Y. Tong, B. Xu, J. Bai, J. Tong, and Q. Zhang, “Spectral temporal graph neural network for multivariate time-series forecasting,” in Advances in Neural Information Processing Systems 33: Annual Conference on Neural Information Processing Systems, NeurIPS, December 6-12, virtual, 2020.

[4] B. M. Williams and L. A. Hoel, “Modeling and forecasting vehicular traffic flow as a seasonal arma process: Theoretical basis and empirical results,” Journal of transportation engineering, vol. 129, no. 6, pp. 664–672, 2003.

[5] Z. Lu, C. Zhou, J. Wu, H. Jiang, and S. Cui, “Integrating granger causality and vector auto-regression for traffic prediction of large-scale wans,” KSII Transactions on Internet and Information Systems (TIIS), vol. 10, no. 1, pp. 136–151, 2016.

[6] C.-H. Wu, J.-M. Ho, and D.-T. Lee, “Travel-time prediction with support vector regression,” IEEE transactions on intelligent transportation systems, vol. 5, no. 4, pp. 270–281, 2004.

[7] J. Van Lint and C. Van Hinsbergen, “Short-term traffic and travel time prediction models,” Artificial Intelligence Applications to Critical Transportation Issues, vol. 22, no. 1, pp. 22–41, 2012.

[8] J. Chung, C. Gulcehre, K. Cho, and Y. Bengio, “Empirical evaluation of gated recurrent neural networks on sequence modeling,” arXiv preprint arXiv:1412.5555, 2014.

[9] Z. Lv, J. Xu, K. Zheng, H. Yin, P. Zhao, and X. Zhou, “Le-rnn: A deep learning model for traffic speed prediction,” in IJCAI, 2018, pp. 3470–3476.

[10] K. Cho, B. van Merriënboer, D. Bahdanau, and Y. Bengio, “On the properties of neural machine translation: Encoder-decoder approaches,” in Proceedings of SSST@EMNLP 2014, Eighth Workshop on Syntax, Semantics and Structure in Statistical Translation, Doha, Qatar, 25 October, 2014, pp. 103–111.

[11] H. Yao, F. Wu, J. Ke, X. Tang, Y. Jia, S. Lu, P. Gong, J. Ye, and Z. Li, “Deep multi-view spatial-temporal network for taxi demand prediction,” in Proceedings of the AAAI Conference on Artificial Intelligence, vol. 32, no. 1, 2018.

[12] Z. Cui, R. Ke, Z. Pu, and Y. Wang, “Deep bidirectional and unidirectional lstm recurrent neural network for network-wide traffic speed prediction,” arXiv preprint arXiv:1801.02143, 2018.

[13] R. Wu, S. Mei, J. Wang, M. Liu, and F. Yang, “Multivariate temporal convolutional network: A deep neural networks approach for multivariate time series forecasting,” Electronics, vol. 8, no. 8, p. 876, 2019.

[14] J. Zhang, Y. Zheng, D. Qi, R. Li, and X. Yi, “Drn-based prediction model for spatio-temporal data,” in Proceedings of the 24th ACM SIGSPATIAL International Conference on Advances in Geographic Information Systems, 2016, pp. 1–4.

[15] J. Zhang, Y. Zheng, and D. Qi, “Deep spatio-temporal residual networks for citywide crowd flows prediction,” in Proceedings of the AAAI Conference on Artificial Intelligence, vol. 31, no. 1, 2017.

[16] T. N. Kipf and M. Welling, “Semi-supervised classification with graph convolutional networks,” in 3th International Conference on Learning Representations, ICLR 2017, Toulon, France, April 24-26, 2017, Conference Track Proceedings, 2017.

[17] M. Defferrard, X. Bresson, and P. Vandergheynst, “Convolutional neural networks on graphs with fast localized spectral filtering,” in Advances in Neural Information Processing Systems 29: Annual Conference on Neural Information Processing Systems 2016, December 5-10, 2016, Barcelona, Spain, 2016, pp. 3837–3845.

[18] Y. Li, R. Yu, C. Shahabi, and Y. Liu, “Diffusion convolutional recurrent neural network: Data-driven traffic forecasting,” in 6th International Conference on Learning Representations, ICLR, Vancouver, BC, Canada, April 30 - May 3, Conference Track Proceedings, 2018.

[19] B. Yu, H. Yin, and Z. Zhu, “Spatio-temporal graph convolutional networks: A deep learning framework for traffic forecasting,” in Proceedings of the Twenty-Seventh International Joint Conference on Artificial Intelligence, IJCAI , July 13-19, Stockholm, Sweden, 2018, pp. 3634–3640.

[20] M. Lv, Z. Hong, L. Chen, T. Chen, T. Zhu, and S. Ji, “Temporal multi-graph convolutional network for traffic flow prediction,” IEEE Transactions on Intelligent Transportation Systems, 2020.

[21] M. Li and Z. Zhu, “Spatial-temporal fusion graph neural networks for traffic flow forecasting,” in Thirty-Fifth AAAI Conference on Artificial Intelligence, AAAI , Virtual Event, February 2-9, 2021, pp. 4189–4196.

[22] Z. Fang, Q. Long, G. Song, and K. Xie, “Spatio-temporal graph ode networks for traffic flow forecasting,” in Proceedings of the 27th ACM SIGKDD Conference on Knowledge Discovery & Data Mining, 2021, pp. 364–373.

[23] D. I. Berndt and J. Clifford. “Using dynamic time warping to find patterns in time series.” in KDD workshop, vol. 10, no. 16. Seattle, WA, USA., 1994, pp. 359–370.

[24] C. Zheng, X. Fan, C. Wang, and J. Qi, “Gman: A graph multi-attention network for traffic prediction,” in Proceedings of the AAAI Conference on Artificial Intelligence, vol. 34, no. 01, 2020, pp. 1234–1241.

[25] J. Chen, Y. Chen, Y. Xie, W. Cao, Y. Gao, and X. Feng, “Multi-range attentive bicomponent graph convolutional network for traffic forecasting,” in Proceedings of the AAAI Conference on Artificial Intelligence, vol. 34, no. 04, 2020, pp. 3529–3536.
