Spatial-Temporal Graph Convolutional Gated Recurrent Network for Traffic Forecasting

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Abstract
As an important part of intelligent transportation systems, traffic forecasting has attracted tremendous attention from academia and industry. Despite a lot of methods being proposed for traffic forecasting, it is still difficult to model complex spatial-temporal dependency. Temporal dependency includes short-term dependency and long-term dependency, and the latter is often overlooked. Spatial dependency can be divided into two parts: distance-based spatial dependency and hidden spatial dependency. To model complex spatial-temporal dependency, we propose a novel framework for traffic forecasting, named Spatial-Temporal Graph Convolutional Gated Recurrent Network (STGCGRN). We design an attention module to capture long-term dependency by mining periodic information in traffic data. We propose a Double Graph Convolution Gated Recurrent Unit (DGCCGRU) to capture spatial dependency, which integrates graph convolutional network and GRU. The graph convolution part models distance-based spatial dependency with the distance-based predefined adjacency matrix and hidden spatial dependency with the self-adaptive adjacency matrix, respectively. Specially, we employ the multi-head mechanism to capture multiple hidden dependencies. In addition, the periodic pattern of each prediction node may be different, which is often ignored, resulting in mutual interference of periodic information among nodes when modeling spatial dependency. For this, we explore the architecture of model and improve the performance. Experiments on four datasets demonstrate the superior performance of our model.

Introduction
Recently, many cities have been committed to developing intelligent transportation systems (ITS). As an important part of ITS, traffic forecasting has attracted tremendous attention from academia and industry. From the perspective of traffic managers, traffic forecasting can help reduce congestion and provide early warning for safety accidents. From the traveler’s perspective, traffic forecasting can help plan travel routes and improve travel efficiency.

Traffic forecasting is a time series forecasting problem, using the past traffic data to predict the data in the future. Early works simply deployed the classic time series analysis models, e.g., history average (HA), vector auto regression (VAR), and auto regressive integrated moving average (ARIMA)(Ahmed and Cook 1979). These models can only model the linear dependency in the data, while the traffic data has complex nonlinear relationship, so the performance of these linear models is poor in the real scenario. Therefore, researchers shift to traditional machine learning methods, such as support vector regression (SVR)(Wu, Ho, and Lee 2004) and k-nearest neighbors (KNN)(Davis and Nian 1991). However, their performance relies heavily on the handcrafted features, which need to be designed by domain experts. Recently, deep learning models have become the mainstream choice for traffic forecasting due to their automatic feature extraction ability and better empirical performance.

In deep learning, the temporal dependency of traffic data can be modeled with recurrent neural networks (RNNs)(Fu, Zhang, and Li 2016) or temporal convolution modules(Zhang, Zheng, and Qi 2017) or graph convolution networks (GCN)(Wu et al. 2019). However, such approaches only mines short-term dependency but ignores long-term dependency. Traffic data has strong daily and weekly periodicity, which is crucial for traffic forecasting. We can mine the periodicity in traffic data to model long-term dependency in traffic data.

The spatial dependency can be captured by convolutional neural network (CNN)(Fang et al. 2019) or graph convolutional networks (GCN)(Wu et al. 2019) or graph convolutional networks (GCN)(Wu et al. 2019) or graph convolutional networks (GCN)(Wu et al. 2019). CNN can be applied to grid-based maps to capture spatial dependency. In this case, the data needs to be divided into $H \times W$ equal size grids, where $H$ and $W$ represent the height and width of the grid-based map respectively. However, CNN cannot handle non-Euclidean data, which is a more common form when describing road topology in real scenarios, with the predicted positions as nodes and the roads as edges. GCN can process non-Euclidean data, calculating the weight of the edge by the distance between the nodes, obtaining a distance-based predefined adjacency matrix, and then feeding it into GCN to capture distance-based spatial dependency(Li et al. 2018). Besides, the self-adaptive adjacency matrices can be used to model hidden spatial dependency(Wu et al. 2019). Wang et al. 2020 and Bai et al. 2020. However, there may be multiple hidden spatial dependencies, which have not been considered in existing works. In addition, the periodic patterns of each prediction node may be different, which need to be taken into account when modeling the spatial...
dependency to prevent the periodic information of different nodes from interfering with each other.

To solve the above problems, we propose Spatial-Temporal Graph Convolutional Gated Recurrent Network (STGCGRN) to improve the accuracy of traffic forecasting. Our contributions are as follows:

- We propose a new framework to better exploit temporal and spatial dependency: We capture long-term temporal dependency by explicitly introducing daily and weekly periodic data, which are fed into the attention module with a sliding window. The DGCGRU layer is designed to extract the distance-based spatial dependency and multiple hidden spatial dependencies, which are captured by the predefined distance-based adjacency matrix and the multi-head self-adaptive adjacency matrix, respectively.

- We explore the model structure and find that mining the periodic information of a single node, and then performing spatial dependency modeling can reduce the interference of periodic information among different nodes.

- We conduct experiments on four datasets. The results show that our model outperforms the baseline methods. We also conduct ablation experiments to evaluate the impact of each component of our model on the performance.

### Related Work

#### Graph Convolutional Neural Network

Graph convolutional neural network is a special form of CNN generalized to non-Euclidean data, which can be applied to different tasks and domains, such as node classification (Kipf and Welling 2017), graph classification (Ying et al. 2018), link prediction (Zhang and Chen 2018), node clustering (Wang et al. 2017), spatial-temporal graph forecasting, etc. Bruna et al. (Bruna et al. 2014) is the first work to generalize the convolution operation to non-Euclidean data, and proposes a spatial method and a spectral method.

Spatial-based approaches aggregate neighborhood feature information in the spatial domain to extract a node’s high-level representation. DCNs (Atwood and Towsley 2016) extend convolutional neural networks (CNNs) to general graph-structured data by introducing a ‘diffusion-convolution’ operation. Message Passing Neural Network (MPNN) (Gilmer et al. 2017) describes a general framework for supervised learning on graphs, applying graph convolution to supervised learning of molecules. GraphSage (Hamilton, Ying, and Leskovec 2017) proposes a general inductive framework to efficiently generate node embeddings for previously unseen data, sampling and aggregating features from the node’s local neighborhood.

Spectral-based approaches implement the convolution operation in the spectral domain with graph Fourier transforms. ChebyNet (Defferrard, Bresson, and Vandergheynst 2016) achieves fast localized spectral filtering by introducing C order Chebyshev polynomials parameterization. GCN (Kipf and Welling 2017) further reduces computational complexity of ChebNet by limiting C=2.

### Traffic Forecasting

As an important component of ITS, traffic forecasting has received wide attention for decades. Most of the early traffic forecasting works are based on some classic time series analysis models. ARIMA (Ahmed and Cook 1979) is used to predict the short-term freeway traffic data. Subsequently, many variants of ARIMA are applied to this task, such as KARIMA (Van Der Voort, Dougherty, and Watson 1996), subset ARIMA (Lee and b. Pambro 1999), ARIMAX (Williams 2001), etc. Traffic data contains complex spatial-temporal dependency. However, the aforementioned works only consider the linear relationship in the temporal dimension, which is obviously insufficient. Researchers apply traditional machine learning algorithms to traffic forecasting, including SVR (Wu, Ho, and Lee 2004), KNN (Davis and Nihan 1991), and so on. These methods need handcrafted features, which require expert experience in related fields.

Due to the advantages of deep learning in solving nonlinear problems and automatically extracting features, scholars pay more attention to deep learning. RNN (Fu, Zhang, and Li 2016; Yu et al. 2017) and CNN (Zhang, Zheng, and Qi 2017; Yu, Yin, and Zhu 2018; Wu et al. 2019) are adopted to capture temporal dependency. For example, Graph Wavenet (Wu et al. 2019) uses dilated casual convolutions to model the temporal dependency to increase the receptive field. To model the spatial dependency, some works (Fang et al. 2019; Lin et al. 2019; Yao et al. 2019a) divide the traffic data into grid-based map, and extract spatial information by CNN. However, due to natural limitations, CNN cannot handle non-Euclidean data. For this reason, researchers apply GCN to the field of traffic forecasting. DCRNN (Li et al. 2018) captures the spatial dependency using bidirectional random walks on the graph. STGCN (Yu, Yin, and Zhu 2018) employs a generalization of Chebnet to capture the spatial dependency of traffic data. These methods only utilize the predefined graph structures, which is not sufficient. Some works (Wu et al. 2019; Wang et al. 2020; Bai et al. 2020) calculate similarities among learnable node embeddings to capture the hidden spatial dependency in the data. DGCGRN (Li et al. 2021a) filters the node embeddings and then uses them to generate dynamic graph at each time step. However, these works do not adequately model spatial dependency and ignore periodic information.

### Preliminaries

- **Definition 1: Traffic Network.** The traffic network is an undirected graph $G = (V, E, A)$, where $V$ is a set consists of $N$ nodes, $E$ is a set of edges and $A \in \mathbb{R}^{N \times N}$ is the adjacency matrix representing the nodes distance-based proximity.

- **Definition 2: Traffic Signal Matrix.** Traffic signal matrix can be denoted as a tensor $X \in \mathbb{R}^{N \times C}$, where $C$ is the number of traffic features of each node (e.g., the speed, volume), $t$ denotes the time step. The problem of traffic forecasting can be described as: given the traffic network $G = (V, E, A)$ and $P$ steps traffic signal matrix $X_{(t-P):t} = (X_{t-P}, X_{t-P+1}, \ldots, X_{t-1}) \in \mathbb{R}^{P \times N \times C}$, learning a function $f$ which maps $X_{(t-P):t}$.
The purpose of placing the DGCGRU layer behind the attention module is to next Q steps traffic signal matrix $X_{t:t+Q} = (X_t, X_{t+1}, ..., X_{t+Q-1}) \in \mathbb{R}^{P \times N \times C}$, represented as follows:

$$X_{t:t+Q} = f(X_{t-P:t}; G)$$  \hspace{1cm} (1)

**Spatial-Temporal Graph Convolutional Gated Recurrent Network**

We design the STGCGRN based on the sequence-to-sequence architecture to capture spatial-temporal dependency. The architecture of our model is shown in Figure 1.

**Periodic Data Construct**

Before introducing the model, we first explain the input data structure.

In order to model periodicity, we replace the traffic signal matrix $X_{t-P:t}$ in Equation (1) with three time granularity inputs: recent data, daily periodicity, and weekly periodicity, denoted by $R, D, W$ respectively. Details about the three parts are as follows:

1. The recent traffic data:
   
   The recent traffic data is a segment of traffic data before the forecast period. Intuitively, the recent traffic data have a great impact on the traffic data in the future.
   
   $$R = (R_{t-P}, R_{t-P+1}, ..., R_{t-1}) \in \mathbb{R}^{P \times N \times C}$$  \hspace{1cm} (2)

   where $R_{t-i}$ means the traffic data of node $i$ at time step $t$.

2. The daily periodic traffic data:

   The daily periodic part is the data of the same period of the previous $l_d$ days. Since traffic data is determined by people’s daily routine, there are often obvious fixed patterns, such as morning and evening peaks. The daily periodic traffic data is introduced for the pattern.

   $$D = (D_1, D_2, ..., D_1) \in \mathbb{R}^{d \times (P+L) \times N \times C}$$

   where $l_d$ means the number of samples per day, $|d|$ represents the number of days used, $L$ will be introduced later.

3. The weekly periodic traffic data:

   The weekly periodic part is the data of the same period of the previous $l_w$ weeks, which is to model the weekly periodicity.

   $$W = (W_1, W_2, ..., W_1) \in \mathbb{R}^{w \times (P+L) \times N \times C}$$

   where $l_w$ means the number of samples per week, $|w|$ represents the number of weeks used.

   After introducing the period information, we can update the Equation (1) to the following form:

   $$X_{t:t+Q} = f(R, D, W; G)$$  \hspace{1cm} (5)

**Attention Module**

Weekly periodicity can be obtained through $W$. For example, the traffic data from last Saturday is helpful for the traffic forecast of this Saturday. However, due to the temporal shifting of periodicity [Yao et al., 2019], daily periodicity cannot depend only on the same moment of the previous days. For example, yesterday’s traffic peak occurred at 5:00 pm, but today’s traffic peak may occur at 5:10 pm. So it is incorrect to use the traffic data of 5:10 pm yesterday as daily periodic data. The traffic data at 5:00 pm yesterday is a better choice. That is to say, the daily periodicity is not strictly periodic, and there will be a certain time deviation. But in general, this deviation is not very large. To cope with the deviation, we consider several time steps adjacent to the predicted time step. We open a time window around the prediction moment, and only focus on the moment within the window. The size of the window is set according to the maximum time deviation.
window is $2 + S + 1$. We introduce the variable $L$ when we construct $D$ and $W$. According to the above analysis, we let $L = Q + S$.

The attention module is shown in Figure 2. We apply attention mechanism to the data within the window to capture daily periodicity. The decoder generates a hidden state vector $h_{i,t}$ for node $i$ at time step $t$. Meanwhile, we generate a time window centered on $t$ for the hidden state vectors of the daily periodic and weekly periodic data, and then concatenate the hidden state vectors in the window to get $h_{i,t}^{period}$:

$$
\begin{align*}
    h_{i,t}^{period} &= (h_{i,t+S,1}^{d,1}, ..., h_{i,t+S,1}^{d,S}, ..., h_{i,t+S,1}^{w,1}) \\
    &\in \mathbb{R}^((|w|+|d|)\times(2S+1)) \times d_h \\
    h_{i,t}^{d,j} &= (h_{i,t-S-j*l_d,1}, ..., h_{i,t+S-j*l_d,1}) \in \mathbb{R}^{(2S+1)\times d_h} \\
    h_{i,t}^{w,j} &= (h_{i,t-S-j*l_w,1}, ..., h_{i,t+S-j*l_w,1}) \in \mathbb{R}^{(2S+1)\times d_h}
\end{align*}
$$

(6)

where $d_h$ is the dimension of the hidden vector.

In order to simplify the representation, we use $h_p$ to represent the hidden state vector in $h_{i,t}^{period}$. We use the attention mechanism to assign a weight $w_p$ to each $h_p$. Then the content vector $c_{i,t}$ is obtained by weighted sum of $h_p$, which is defined as:

$$
c_{i,t} = \sum_s w_p h_p
$$

(7)

where $w_p$ measures the importance of $h_p$, which is calculated as follows:

$$
w_p = \frac{\exp(score(h_{i,t}, h_p))}{\sum_s \exp(score(h_{i,t}, h_p))}
$$

(8)

where $h_{i,t}$ means the hidden state of node $i$ at time step $t$ generated by the GRU layer.

The implementation of the score function refers to (Luong, Pham, and Manning 2015):

$$
score(h_{i,t}, h_p) = v^T \tanh(W_1 h_{i,t} + W_2 h_p + b)
$$

(9)

where $v^T$, $W_1$, $W_2$, $b$ are learnable parameters.

The output of the attention module is shown in the following equation:

$$
a_{i,t} = c_{i,t} + h_{i,t}
$$

(10)

To sum up, the weekly periodicity is introduced through the weekly periodic traffic data $W$. Then the attention mechanism is applied to the daily periodic data $D$ and weekly periodic data $W$ to capture the daily periodicity. By processing $R$ with GRU, we can capture short-term dependency in traffic data. By mining periodicity in traffic data, we can model long-term dependency.

**DGCGRU**

The attention module generates tensor $A_t = (a_{1,t}, a_{2,t}, ..., a_{N,t}) \in \mathbb{R}^{N \times d_h}$. Next, we send $A_t$ to the DGCGRU layer to model the spatial dependency from two aspects: the distance-based spatial dependency and the hidden spatial dependency, as shown in Figure 3.

**Distance-based Spatial Dependency** Graph Convolution Networks (GCNs) generalize convolution operation to non-Euclidean data. The idea of GCNs is to learn the representation of nodes by exchanging information between them. Specifically, given a node, GCNs first generate an intermediate representation of the node by aggregating the representations of its neighbor nodes, and then perform a transformation
on the intermediate representation to obtain the node’s representation.

Traffic network is usually a graph structure. The vector \( a_{i,t} \) generated at each time step can be regarded as the signal of the graph. In general, the closer two predicted points are, the higher the correlation between them. To take full advantage of the topology of the traffic network, we perform a graph convolution operation on \( A_i \) based on distance information of the graph at each time step. The k-hop graph convolution operation is as follows:

\[
\begin{align*}
\sigma^{pre} &= \sum_{i=0}^{K} S^k W^k \\
S^k &= S^{k-1} \tilde{A}^{pre} \\
S^0 &= i_{dgc} \\
\tilde{A}^{pre} &= (\tilde{D}^{pre})^{-1} A^{pre} \\
\tilde{D}^{pre}_{i,j} &= \sum_{j} A^{pre}_{i,j}
\end{align*}
\]

where \( A^{pre} \in \mathbb{R}^{N \times N} \) is predefined adjacency matrix that contains the distance information among nodes. \( i_{dgc} \) is the input of the double graph convolution operation. \( W^k \in \mathbb{R}^{d_x \times d_y} \) are learnable parameters. \( K \) is the number of hops for graph convolution. \( \sigma^{pre} \) is the output of this submodule.

Hidden Spatial Dependency

The distance-based predefined adjacency matrix lacks hidden spatial dependency that are usually directly related to prediction tasks.

To solve this problem, some works (Bai et al. 2020; Wu et al. 2019) adopt a self-adaptive adjacency matrix to automatically infer the spatial dependency between nodes, which is learned through stochastic gradient descent. However, these works ignore that there may be multiple hidden spatial dependencies among nodes.

In our work, we combine the self-adaptive adjacency matrix with multi-head mechanism to model multiple hidden dependencies. We randomly initialize two sets of node embeddings \( E_1, E_2 \in \mathbb{R}^{N \times n_{head} \times d_e} \), where \( n_{head} \) is the number of heads, and \( d_e \) represents the dimension of the embedding of each head. Next, we calculate the hidden dependencies among nodes according to the following formula:

\[
\tilde{A}_{i,j}^{adp} = softmax\left(\frac{ReLU\left(\begin{array}{c}E_1_{i,j} \times E_2^T_{i,j} \end{array}\right)}{d_e}\right)
\]

where \( i \) indicates the \( i \)th head, and the ReLU function is used to eliminate some weak connections. Through the multi-head mechanism, we divide the embedding into multiple subspaces, and learn the corresponding self-adaptive graph in each subspace. It is worth noting that instead of generating the adjacency matrix \( A^{adp} \) and then calculating the Laplacian matrix, we directly obtain the normalized self-adaptive adjacency matrix \( \tilde{A}_{i,j}^{adp} \) through the softmax function, avoiding unnecessary calculations.

We replace \( A^{pre} \) in Equation[11] with \( \tilde{A}_{i,j}^{adp} \), and then perform a graph convolution operation to obtain \( o_{i}^{adp} \). The output \( o^{adp} \) models multiple hidden spatial dependency by averaging the \( o_{i}^{adp} \) of each head.

Multi-Component Fusion

The final output of the spatial dependency module is as follows:

\[
o_{dgc} = w^{pre} \sigma^{pre} + w^{adp} o^{adp}
\]

where \( w^{pre}, w^{adp} \) are hyper parameters.

Experiments

Datasets

To evaluate the performance of our model, we conduct experiments on four datasets.

Dataset Description

We use the following four datasets: PEMS03, PEMS04, PEMS07, and PEMS08, which are constructed from four districts, respectively in California. All data is collected from the Caltrans Performance Measurement System(PEMS)(Chen et al. 2001). The traffic data is aggregated into every 5-minute interval, which means every sensor contains 12 traffic data points per hour. The detailed information of the dataset is shown in Table[1].

Data Preprocessing

We split all datasets into training set, validation set and test set with the ratio of 6:2:2.

We compute the distance-based predefined adjacency matrix \( A^{pre} \) using thresholded Gaussian kernel (Shuman et al. 2013):

\[
w_{i,j} = \begin{cases} 
\exp\left(-\frac{\text{dist}(i,j)^2}{\sigma^2}\right) & \text{if } \text{dist}(i,j)^2 \leq \kappa \\
0 & \text{otherwise}
\end{cases}
\]

where \( n_{i,j} \) is the weight of the edge between node \( i \) and node \( j \), \( \text{dist}(i,j) \) is distance between node \( i \) and node \( j \), \( \sigma \) is the standard deviation of distances and \( \kappa \) is the threshold.

Baseline Methods

- **MLP:** Multilayer Perceptron uses two fully connected layers for traffic forecasting.
- **CNN:** Convolutional Neural Network performs convolution operations in the temporal dimension to capture temporal correlations.
- **GRU:** Gate Recurrent Unit with fully connected layer is powerful in modeling time series.
- **DRCRNN:** Diffusion Convolutional Recurrent Neural Network captures the spatial dependency using bidirectional random walks on the graph, and the temporal dependency using the encoder-decoder architecture.
- **STGCN:** Spatio-Temporal Graph Convolutional Networks combines graph convolutional layers and convolutional sequence learning layers, to model spatial and temporal dependency.

| Datasets | #Nodes | #Edges | Time range         |
|----------|--------|--------|--------------------|
| PEMS03   | 358    | 547    | 9/1/2018-11/30/2018|
| PEMS04   | 307    | 340    | 1/1/2018-2/28/2018 |
| PEMS07   | 883    | 866    | 5/1/2017-8/31/2017 |
| PEMS08   | 170    | 295    | 7/1/2016-8/31/2016 |

Table 1: Dataset description.
We compare our model with the baseline methods on four different perspectives, performing better than MLP, CNN, and GRU. DCRNN, STGCN, ASTGCN capture distance-based spatial dependency through the predefined adjacency matrix, and achieve a good performance. AGCRN benefits a lot from the self-adaptive adjacency matrix, mining hidden spatial dependency. Graph Wavenet simultaneously model distance-based spatial dependency and hidden spatial dependency. By modeling dynamic spatial dependencies, DGCRN further improves model performance. By introducing periodic information, ASTGNN outperforms other baselines. Our model avoids the interference of periodic information among nodes while modeling spatial-temporal dependence, further enhancing the performance.

### Ablation Study
To further verify the effectiveness of different components of STGCGRN, we conduct ablation experiments on the PEMS08 dataset. We design five variants of the STGCGRN model as follows:

- w/o pre: We remove the distance-based predefined adjacency matrix from the DGCGRU layer.
- w/o adp: We remove the self-adaptive adjacency matrix from the DGCGRU layer.
- w/o pre&adp: We remove the distance-based predefined adjacency matrix and self-adaptive adjacency matrix from the DGCGRU layer, replacing them with identity matrix.
- w/o window: We remove the sliding window in the attention module.
- w/o period: We remove the period information from STGCGRN.

We visualized the MAE, MAPE, RMSE of STGCGRN and its variants in the next 15min, 30min, 45min, 60min, as shown in the Figure 4. The introduction of periodic information has the most obvious improvement in model performance, which shows that long-term temporal dependency are critical to traffic forecasting. In addition, with the growth of time, the effect of periodic information becomes more and more obvious. This is because the error of the decoder gradually accumulate, and the period information can provide the decoder with historical data as a reference to help the decoder correct the error. The effect of the hidden spatial dependency is second only to the period information. This is because the self-adaptive adjacency matrix is trained with the model, and the learned hidden dependency are directly related to the downstream task. The predefined adjacency matrix can help to improve the performance of the model without the self-adaptive adjacency matrix, otherwise it has almost no effect, which indicates that the self-adaptive adjacency matrix has learned the part of the distance information that is helpful for prediction during the training process. In addition, the sliding window also helps to improve the performance of the model, indicating that the time near the prediction time is of great help to the prediction task, which helps the attention mechanism to converge to a better position.

### Multi-Head Mechanism Study
Since there may be multiple hidden spatial dependencies between nodes, our work introduces the multi-head mechanism,
we explore how to better combine single-node periodic information and multi-node spatial dependencies to prevent periodic information of nodes from interfering with each other. The result is shown in Table 4. STGCGRN_rev is a variant of STGCGRN where the order of the DGCGRU layer and the attention module is reversed.

We can see that the performance of STGCGRN_rev declines, indicating that modeling spatial dependencies first will cause the periodic information of each node to interfere with each other when mining periodic information later. The architecture of STGCGRN is better.

**Conclusion**

In this paper, we proposed Spatial-Temporal Graph Convolutional Gated Recurrent Network (STGCGRN) for traffic forecasting. For temporal dependency, we model short-term dependency by processing recent traffic data with GRU, and capture long-term dependency by mining daily and weekly periodicity. For spatial dependency, we model distance-based spatial dependency and multiple hidden spatial dependencies with predefined adjacency matrix and multi-head self-adaptive adjacency matrix, respectively. In addition, we also explored the model structure to avoid the mutual interference of periodic information among nodes during spatial dependency modeling. Experiments and analysis on four datasets show that our model achieves
state-of-the-art results. The code have been released at: https://github.com/ZLBryant/STGCGRN.

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