Augmented Multi-component Recurrent Graph Convolutional Network for Traffic Flow Forecasting

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Website Online**: https://www.mdpi.com/2220-9964/11/2/88/htm**

GitHub**: https://github.com/ILoveStudying/AM-RGCN**

Outline

1 Introduction

Research Significance

- Intelligent Transportation System (ITS) is an indispensable part of smart city, and traffic prediction is an important component of ITS.
- Precise traffic prediction assists in better vehicle dispatching, travel time estimating, and urban planning, which is of great significance to urban management, environmental protection, and residents' travel.

Vehicle dispatching

Traffic time estimating

Urban planning

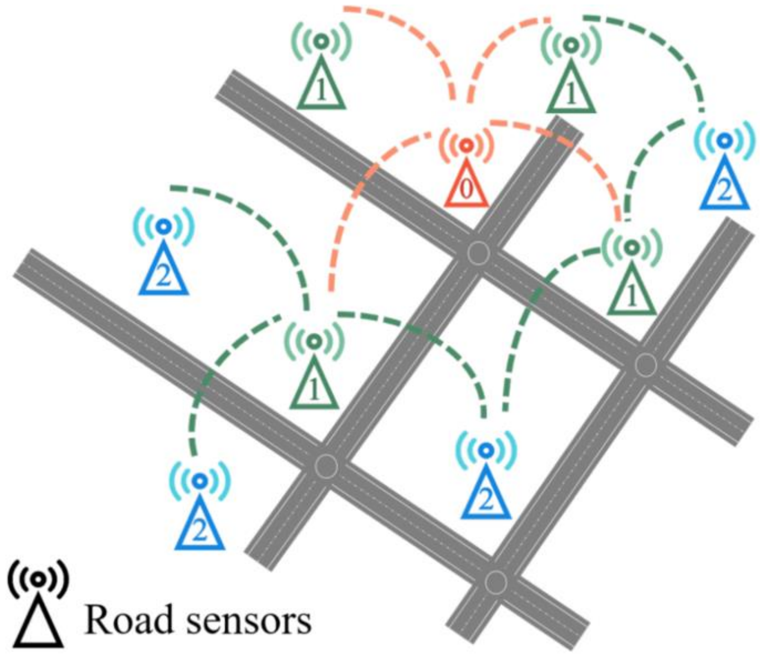
1 Introduction

Preliminaries of Traffic Flow Forecasting

- **Traffic flow**: the number of vehicles passing through a given point on the roadway in a certain period of time.
- We define the traffic road network as a graph $G = (V, E, A)$.

The traffic flow observed on G at time t is denoted as a graph signal $X^t \in \mathbb{R}^{N*F}$, where F is the feature dimension of each node (e.g., traffic flow, traffic speed, etc.).

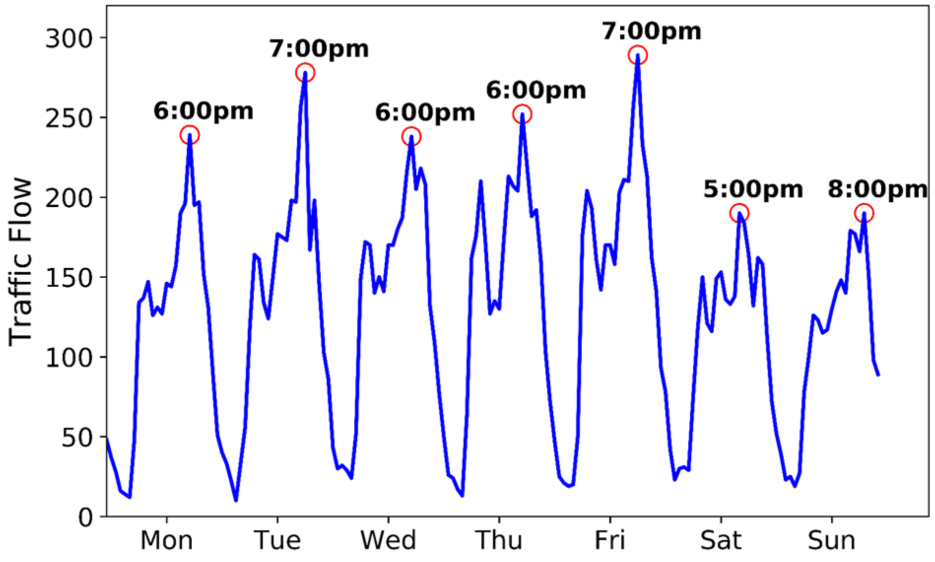
Problem Studied: Given the observations at N vertices of historical H time steps $\mathrm{X} = (X^{t-H+1}, X^{t-H+2}, \ldots, X^t) \in \mathbb{R}^{H*N*F}$, we aim to predict the traffic flow of the next P time steps for all vertices, denoted as $\hat{Y} = (\hat{X}^{t+1}, \hat{X}^{t+2}, \ldots, \hat{X}^{t+P}) \in \mathbb{R}^{P*N*F}$.

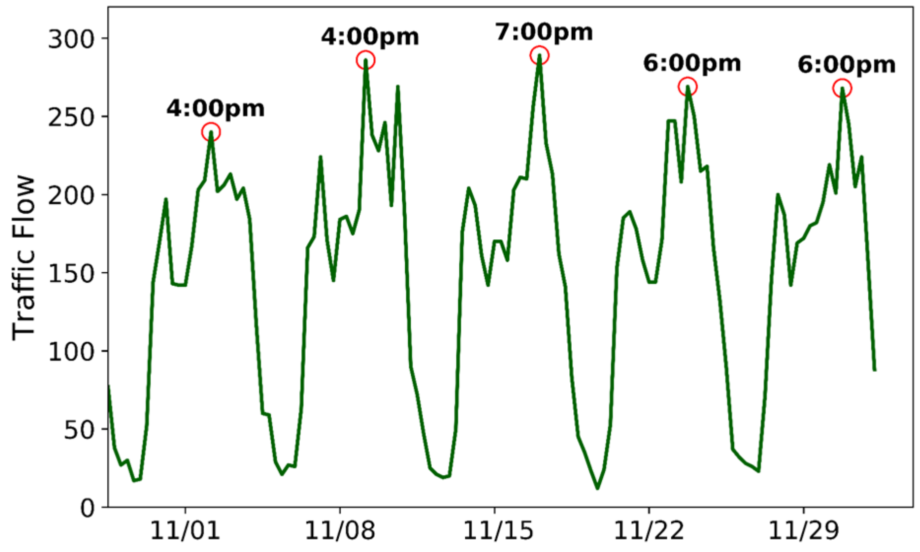


1 Introduction

Main Problem 1: Periodic Temporal Shift

- The characteristics of **periodic temporal shifts** in traffic flow are not taken into consideration.



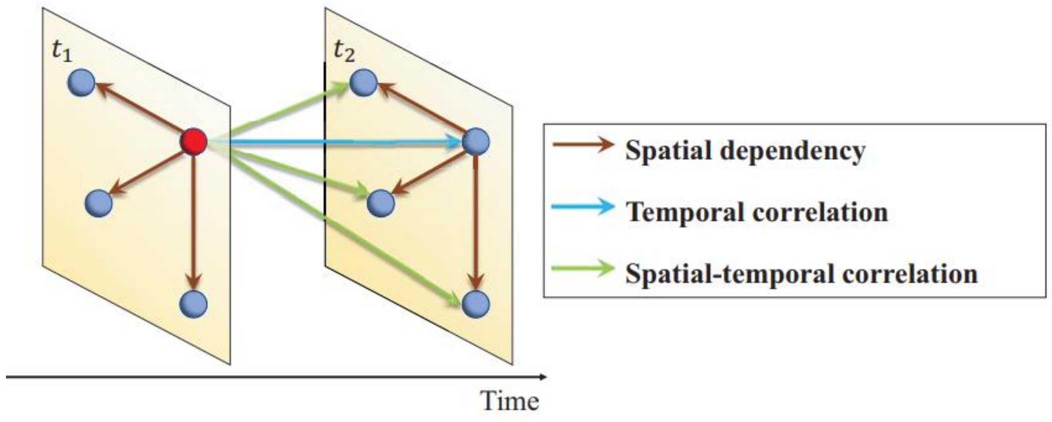


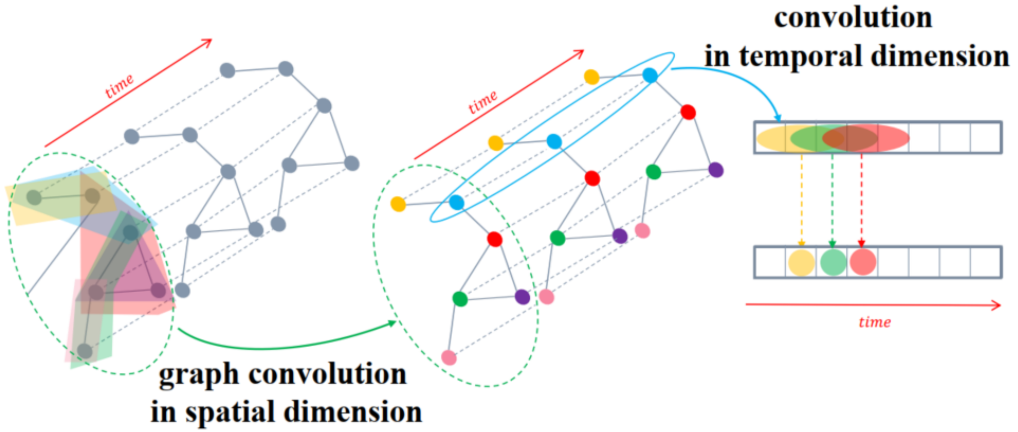
- Daily peak hours are usually between 6:00 p.m. and 7:00 p.m., but could vary from 5:00 p.m. to 9:00 p.m., depending on whether it is a workday and other factors such as abnormal weather and traffic congestion. Similarly, the fluctuation can be observed in weekly numbers.

1 Introduction

Main Problem 2: Spatial-temporal Correlations

- The **<u>spatial–temporal correlations</u>** in traffic networks are not captured effectively.





- There exists close correlations between spatial and temporal features, while most approaches model the spatial and temporal features separately without considering the mutual dependence between them.

1 Introduction

Contributions

- To address the two above-mentioned challenges, we propose a deep learning-based framework named AM-RGCN for traffic flow forecasting:

  - We propose an **augmented multi-component module** to capture the characteristics of the periodic temporal shift in traffic.

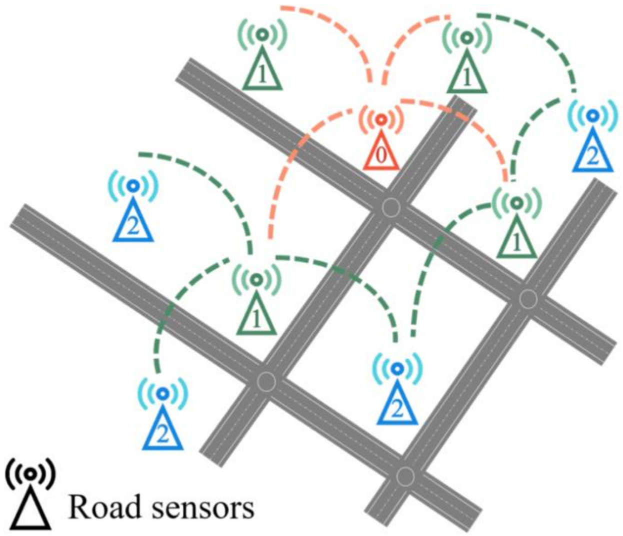
  - We propose the **Temporal Correlation Learner (TCL)** to handle the spatial–temporal correlations in the road network.

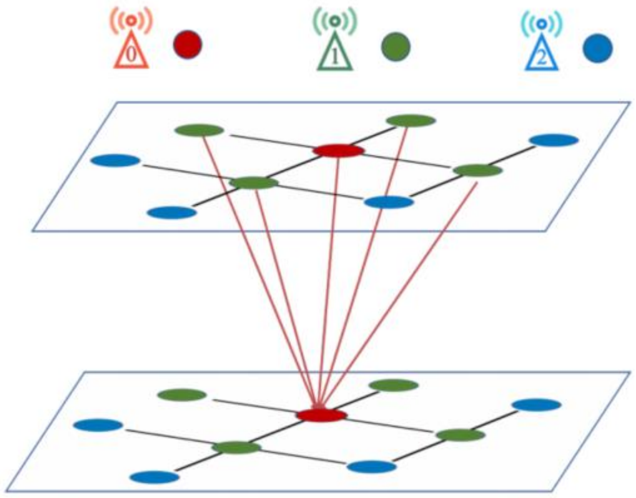
  - Extensive experiments on two real-world traffic datasets**, PEMSD4 and PEMSD8**, verify that our AM-RGCN achieves state-of-the-art results compared with the existing approaches.

2 Related Works

Graph Convolution Networks

- Graph convolutions networks fall into two categories, **spectral-based** and **spatial-based**:
  - Spatial-based approaches directly conduct convolution operations on the nodes of the graph.
  - Spectral-based approaches employ a Laplacian matrix to perform convolution operations on graphs in the Fourier domain.

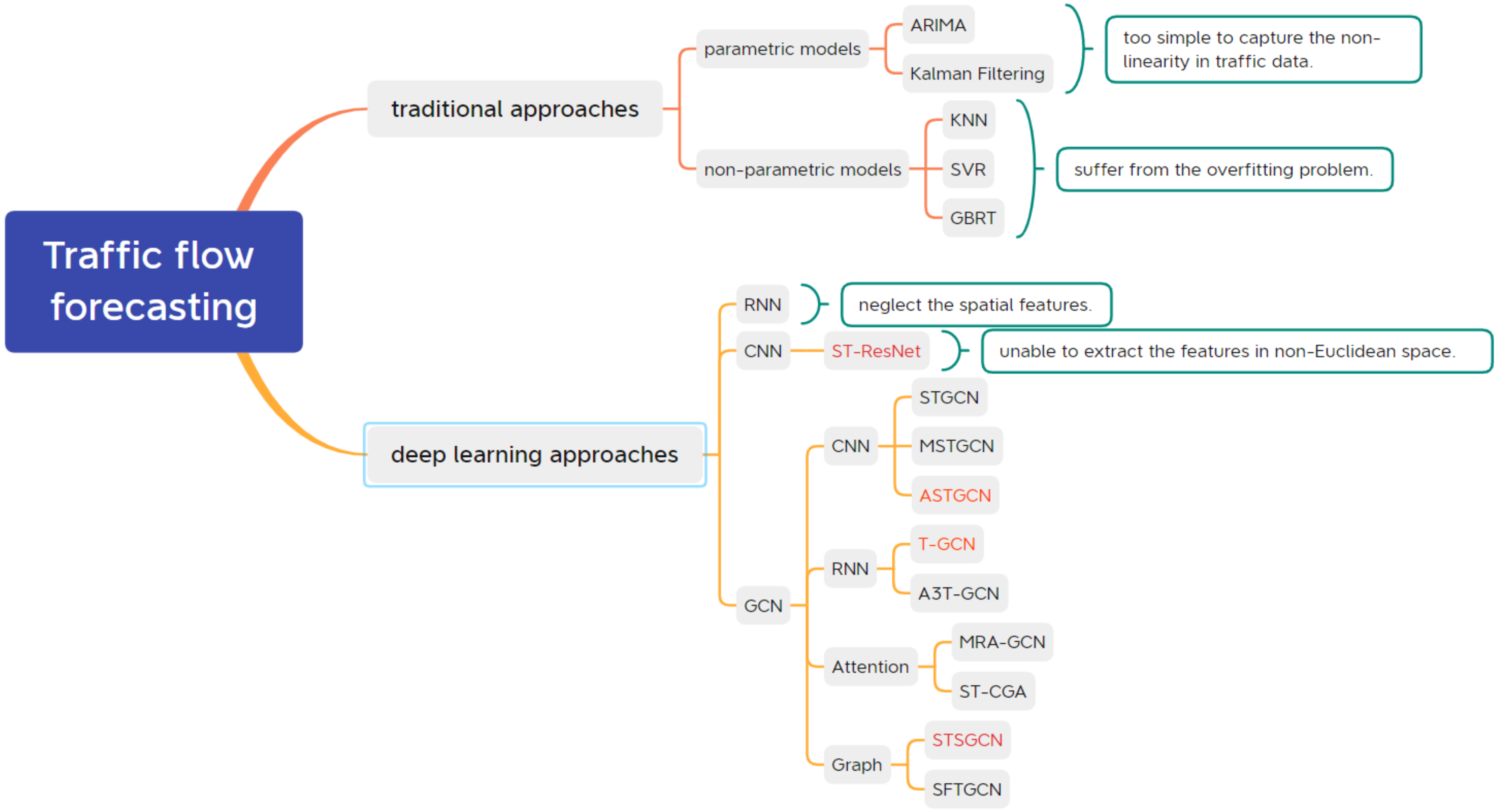




https://blog.csdn.net/yyl424525/article/details/100058264#GCN_848

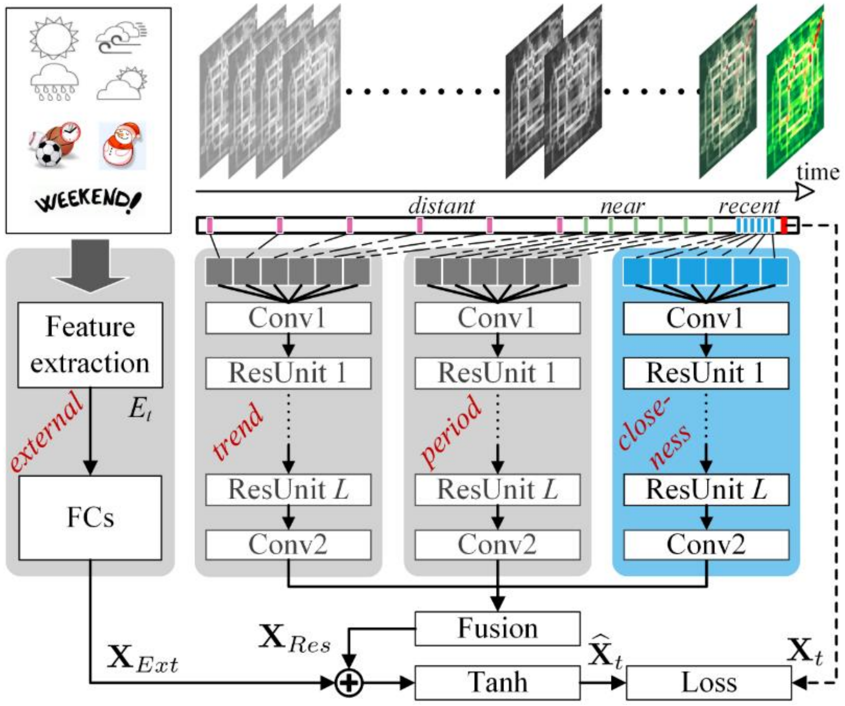
2 Related Works

Traffic flow forecasting

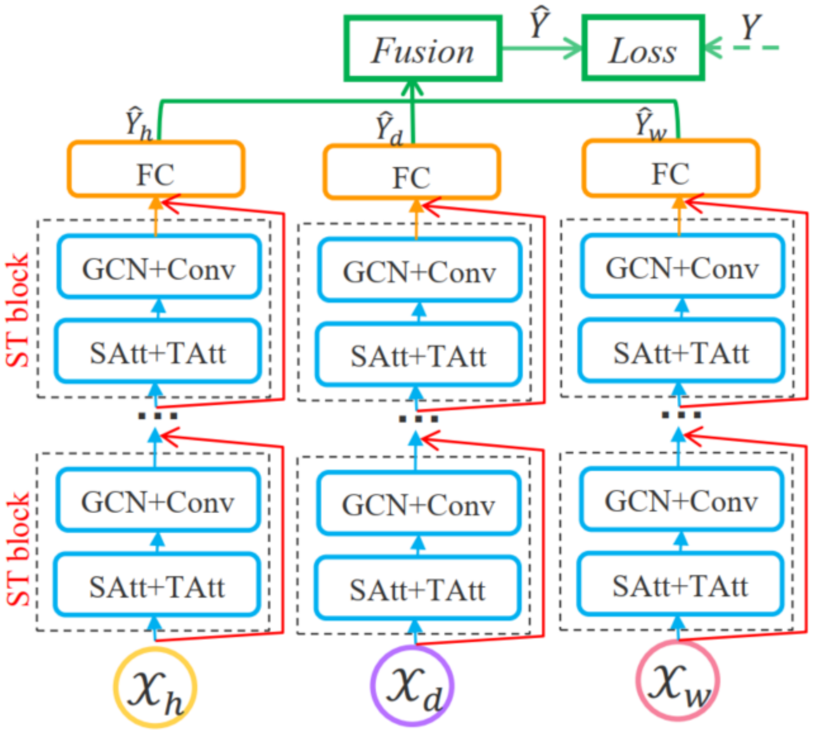


2 Related Works

Methods for Periodicity



ST-ResNet (CNN)



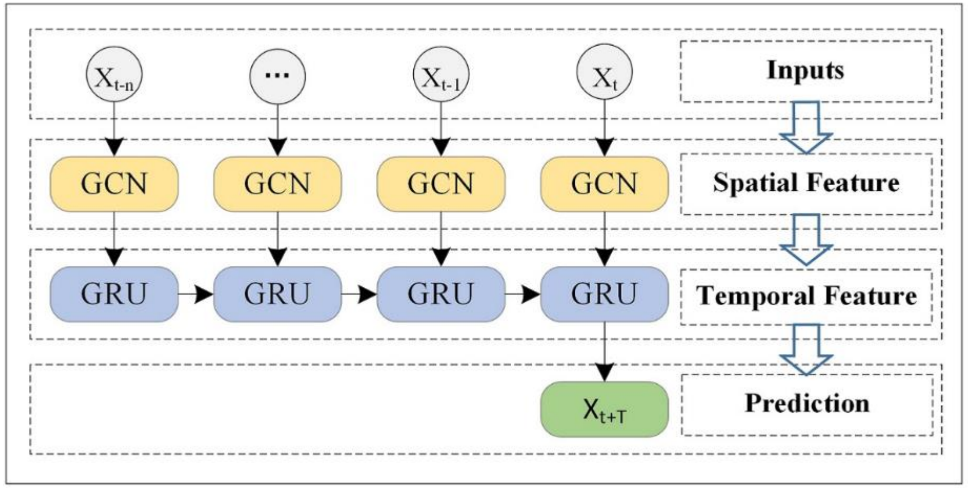
ASTGCN (GCN+CNN)

Zhang, J., Zheng, Y., & Qi, D. (2017). *Deep spatio-temporal residual networks for citywide crowd flows prediction.* Paper presented at the Thirty-First AAAI Conference on Artificial Intelligence.

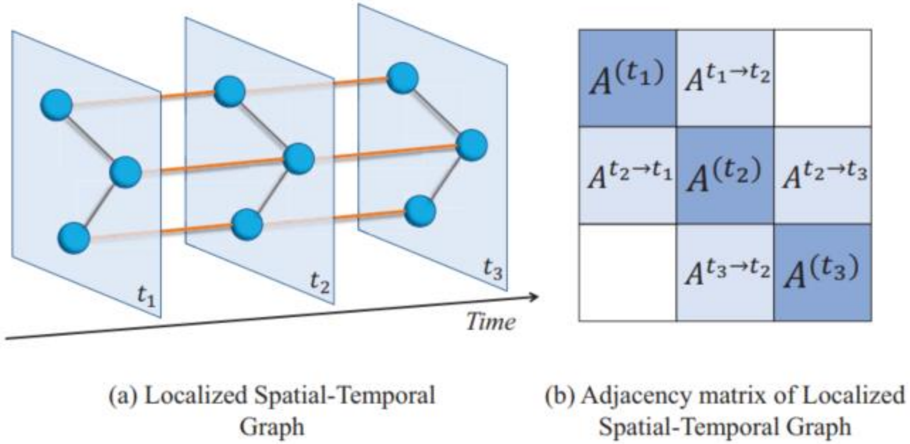
Guo S, Lin Y, Feng N, et al. Attention based spatial-temporal graph convolutional networks for traffic flow forecasting[C]//Proceedings of the AAAI conference on artificial intelligence. 2019, 33(01): 922-929.

2 Related Works

Methods for Spatial-temporal Correlations



T-GCN (GCN+RNN)



STSGCN (GCN+Graph)

Zhao, L., Song, Y., Zhang, C., Liu, Y., Wang, P., Lin, T., . . . Li, H. (2019). T-gcn: A temporal graph convolutional network for traffic prediction. *IEEE Transactions on Intelligent Transportation Systems*.

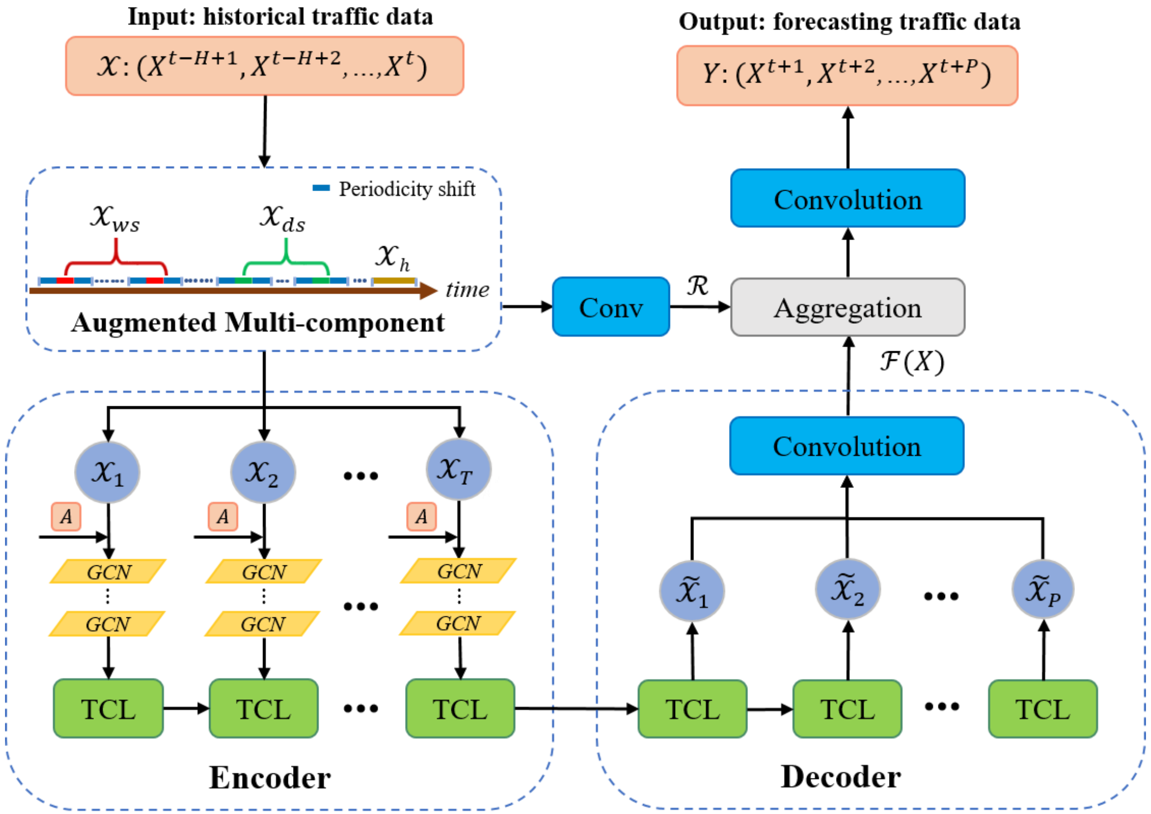
Song C, Lin Y, Guo S, et al. Spatial-temporal synchronous graph convolutional networks: A new framework for spatial-temporal network data forecasting[C]//Proceedings of the AAAI Conference on Artificial Intelligence. 2020, 34(01): 914-921.

3 Methodology

Overall Architecture

The AM-RGCN mainly consists of three modules:

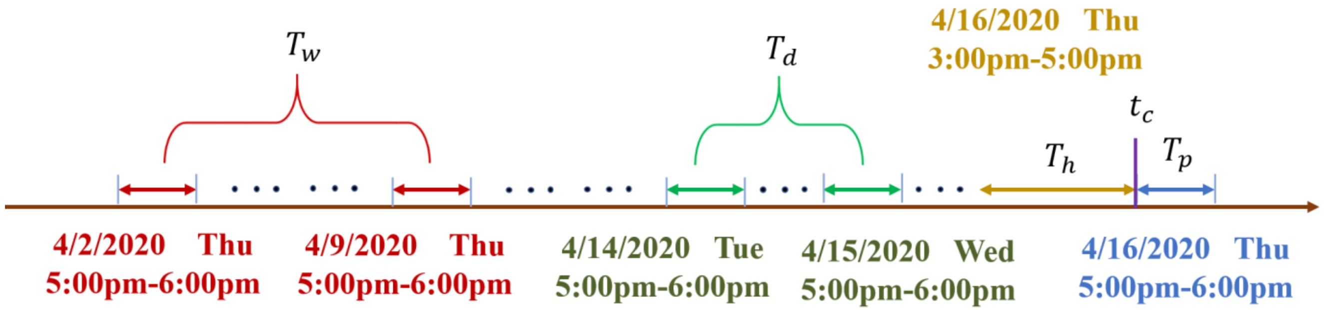
- The **augmented multi-component module** for periodicity and periodic temporal shift;
- The **encoder module** which aims to characterize the spatial–temporal correlations;
- The **decoder module** which performs multi-step predictions from spatial–temporal sequences.



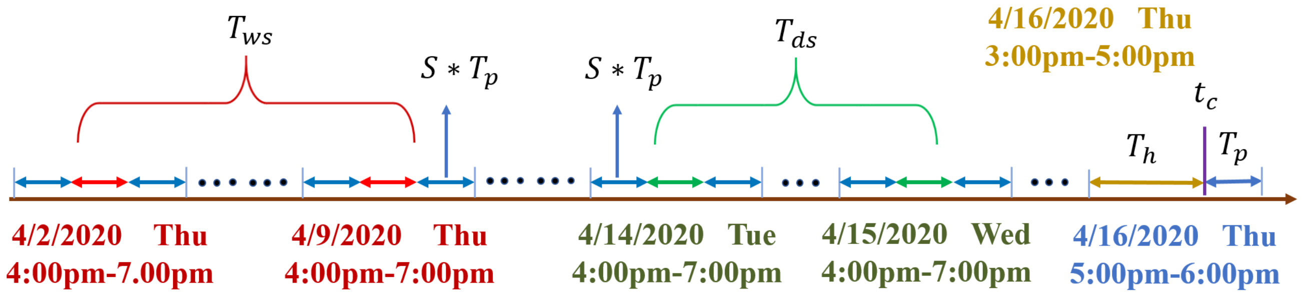
3 Methodology

Augmented Multi-component Module

- Tackle the problem of periodic temporal shift.
- It consists of the recent component T_h, daily augmented component T_{ds} and weekly augmented component T_{ws}.



$$T_h = N_h * T_p$$
$$T_d = N_d * T_p$$
$$T_w = N_w * T_p$$



The relationship between the augmented multi-component and multi-component:

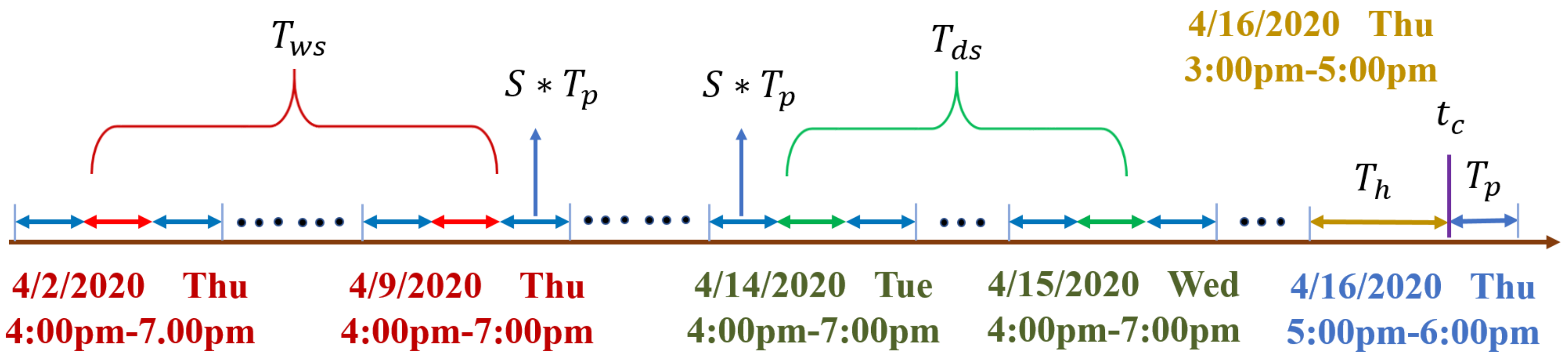
$$T_{ds} = T_d * (2 * S + 1) = N_d * T_p * (2 * S + 1),$$
$$T_{ws} = T_w * (2 * S + 1) = N_w * T_p * (2 * S + 1).$$

3

Methodology

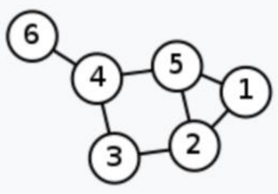
Example for Augmented Multi-component

- Suppose we wish to predict the traffic flow of next hour from 5:00 p.m. to 6:00 p.m. on Thursday. If we set the periodic offset as 1 hour, the daily augmented component means we use the traffic flow from 4:00 p.m. to 7:00 p.m. on the most recent Tuesday and Wednesday.



3 Methodology

Encoder——GCN

Labeled graph	Degree matrix	Adjacency matrix	Laplacian matrix
	$\begin{pmatrix} 2&0&0&0&0&0\\ 0&3&0&0&0&0\\ 0&0&2&0&0&0\\ 0&0&0&3&0&0\\ 0&0&0&0&3&0\\ 0&0&0&0&0&1 \end{pmatrix}$	$\begin{pmatrix} 0&1&0&0&1&0\\ 1&0&1&0&1&0\\ 0&1&0&1&0&0\\ 0&0&1&0&1&1\\ 1&1&0&1&0&0\\ 0&0&0&1&0&0 \end{pmatrix}$	$\begin{pmatrix} 2&-1&0&0&-1&0\\ -1&3&-1&0&-1&0\\ 0&-1&2&-1&0&0\\ 0&0&-1&3&-1&-1\\ -1&-1&0&-1&3&0\\ 0&0&0&-1&0&1 \end{pmatrix}$

- Spectral-based GCN for spatial characteristic.
- We exploit a two-layer shared weight GCN to capture the spatial features of the traffic network.

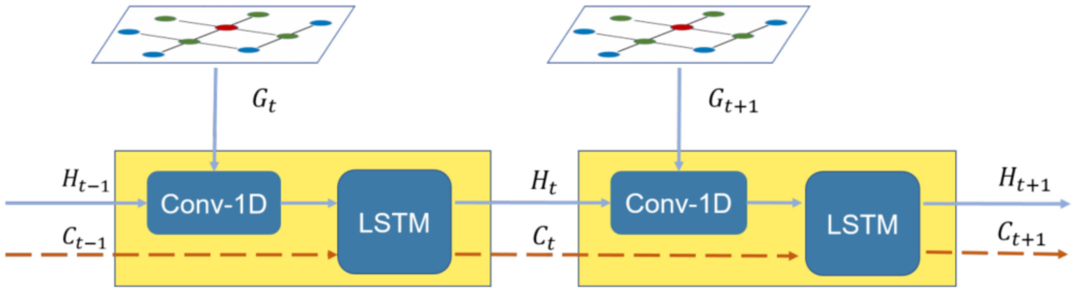
$$f(X_t, A) = \mathrm{ReLU}(\hat{A}(\hat{A}X_tW_0)W_1), \tag{5}$$

where $X_t \in \mathbb{R}^{N*F}$ denotes the characteristics of the road network at each time slice $t \in \{1, ..., T\}$; $\hat{A} = \tilde{D}^{-\frac{1}{2}}\tilde{A}\tilde{D}^{-\frac{1}{2}} \in \mathbb{R}^{N*N}$ indicates the renormalization trick; $\tilde{A} = A + I \in \mathbb{R}^{N*N}$ means to add self-loop to the adjacency matrix; $\tilde{D} = \sum_j \tilde{A}_{ij} \in \mathbb{R}^{N*N}$, $W_0 \in \mathbb{R}^{F*H}$ and $W_1 \in \mathbb{R}^{H*C}$ represent the parameters matrix from the input feature dimension F to the output feature dimension H and C respectively. ReLU is the activation function.

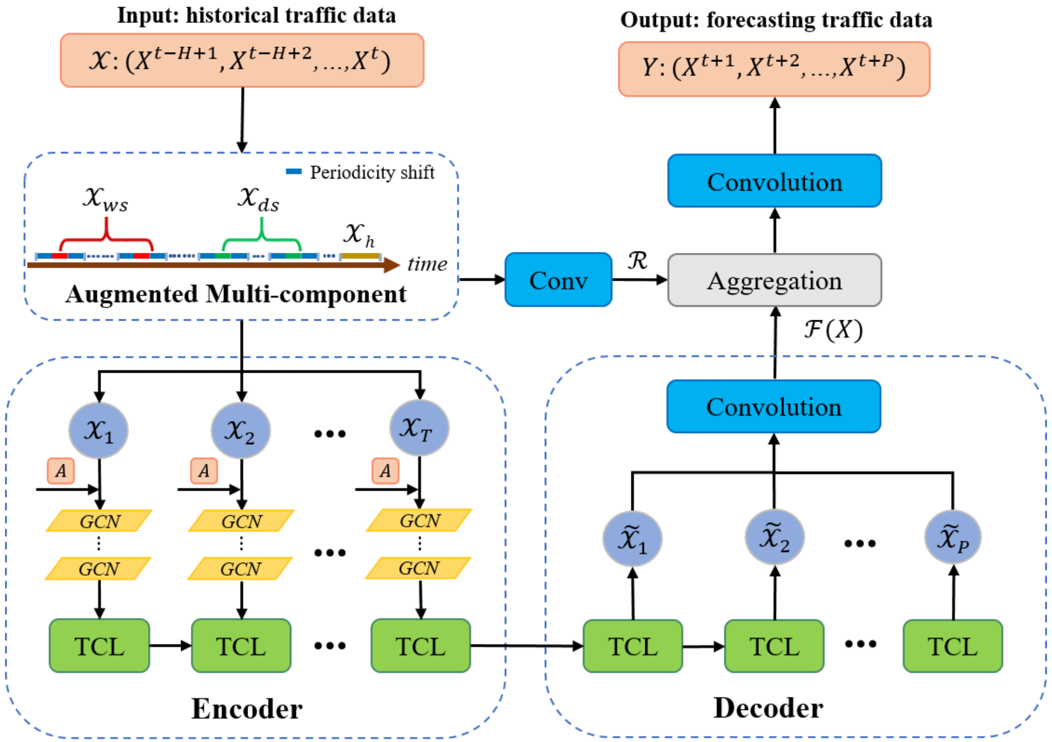
3 Methodology

Encoder——TCL

- TCL (Temporal Correlation Learner) for temporal features, which incorporates one-dimensional convolution into LSTM.
- The encoder combines the GCN and TCL at each time slice to address the spatial-temporal correlations.



$$I_t = \sigma(W_{gi} * G_t + W_{hi} * H_{t-1} + W_{ci} \odot C_{t-1}),$$
$$F_t = \sigma(W_{gf} * G_t + W_{hf} * H_{t-1} + W_{cf} \odot C_{t-1}),$$
$$C_t = F_t \odot C_{t-1} + I_t \odot \tanh(W_{gc} * G_t + W_{hc} * H_{t-1}),$$
$$O_t = \sigma(W_{go} * G_t + W_{ho} * H_{t-1} + W_{co} \odot C_t),$$
$$H_t = O_t \odot \tanh(C_t),$$



3 Methodology

Decoder

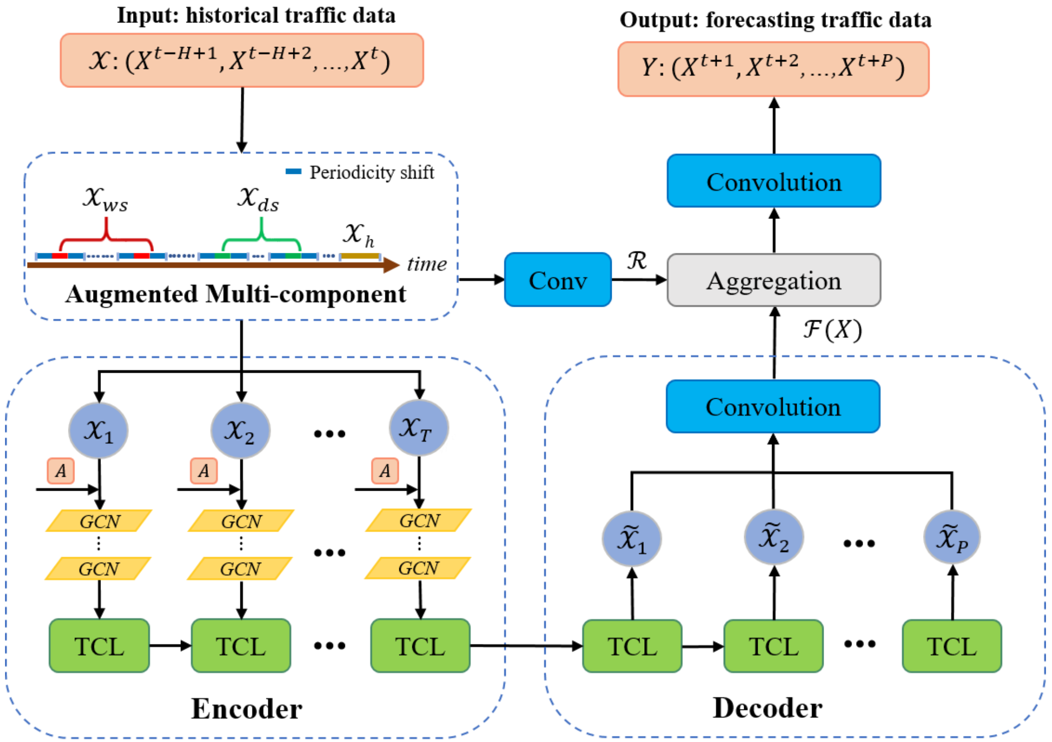
- Apply TCL for multi-step predictions.
- Employ CNN to convert the multi-step predictions into high dimensional representations.

$$\mathcal{X}_{t+1} = \mathrm{TCL}(\vec{0}; H_t; C_t)$$

where $t \in \{T, \ldots, T+P-1\}$ and $\vec{0}$ denote the all-zero arrays.

Fusion Module

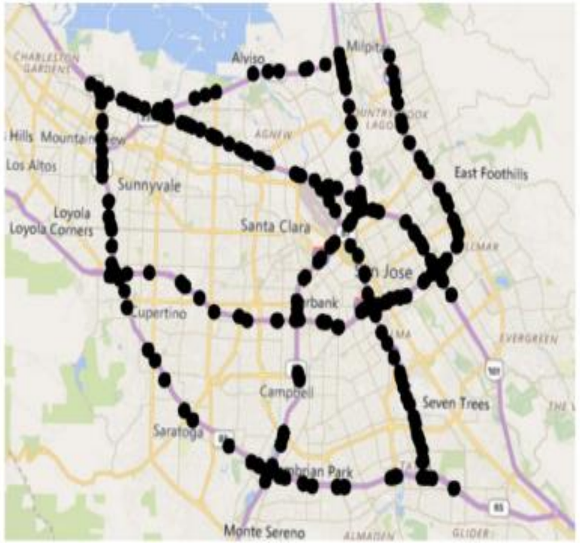
- *Conv* means convolution with 1 * 1 kernel size. R indicates residual information of augmented multi-component module and $F(X)$ represents the output of decoder. *Aggregation* denotes the addition operation of $F(X) + R$.



4 Experiments

Datasets

- The public traffic datasets PEMSD4 and PEMSD8 are the real highway traffic datasets collected by the California Transportation Agency Performance Measurement System (PeMS). The system is displayed on a map and has more than 39,000 independent sensors deployed on the highway system across all major metropolitan areas of the state of California.



PeMS-BAY

Datasets	Nodes	Edges	Interval	Time Range	Time Steps
PEMSD4	307	340	5 min	1 January 2018–28 February 2018	16,992
PEMSD8	170	295	5 min	1 July 2016–31 August 2016	17,856

- remove redundant sensors whose distance is less than 3.5 miles and adopt linear interpolation for missing values.

4 Experiments

Baseline Comparison

Data	Method	15 min RMSE	15 min MAE	30 min RMSE	30 min MAE	1 h RMSE	1 h MAE
PEMSD8	HA	40.14	23.15	41.49	24.64	46.37	29.20
	ARIMA [2]	28.96	27.77	30.38	29.59	48.33	44.25
	LSTM [22]	26.02	17.95	28.35	19.68	32.56	22.61
	GRU [23]	25.92	17.97	28.35	19.71	31.80	22.18
	STGCN [9]	24.58	16.33	27.31	17.91	31.24	20.85
	MSTGCN [13]	22.38	15.15	23.90	16.09	25.46	17.11
	ASTGCN [18]	21.81	14.76	23.33	15.71	24.40	16.33
	STSGCN [28]	21.93	14.20	23.71	15.28	26.05	16.67
	AM-RGCN	**20.43**	**13.54**	**21.77**	**14.58**	**22.87**	**15.03**
PEMSD4	HA	45.40	28.88	46.96	30.40	53.20	35.59
	ARIMA [2]	36.91	33.71	46.65	41.36	52.32	47.74
	LSTM [22]	34.00	22.02	35.81	23.34	38.81	25.58
	GRU [23]	34.17	22.05	35.88	23.45	38.84	25.83
	STGCN [9]	32.77	21.34	34.07	21.78	37.42	24.32
	MSTGCN [13]	28.97	19.40	30.61	20.49	32.71	22.01
	ASTGCN [18]	29.19	19.59	30.26	20.32	32.37	21.83
	STSGCN [28]	29.74	18.52	31.52	19.73	33.63	21.06
	AM-RGCN	**27.22**	**18.00**	**28.25**	**18.65**	**29.79**	**19.82**

(1) HA, ARIMA: traditional time series approaches;

(2) LSTM, GRU: traditional deep learning models;

(3) STGCN: typical graph-based method;

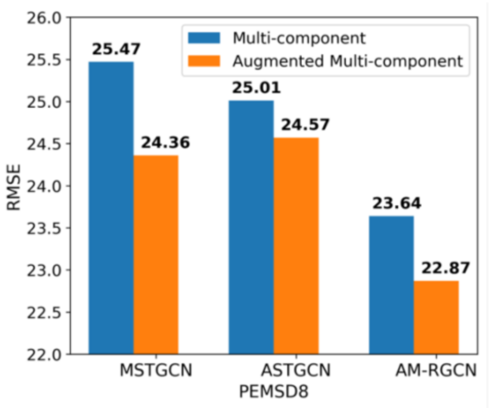
(4) MSTGCN, ASTGCN: considering periodicity;

(5) STSGCN: including spatial-temporal correlations;

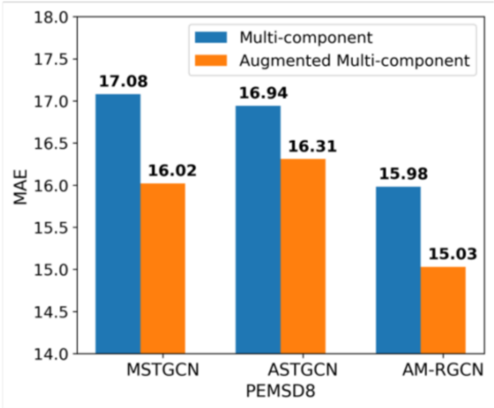
(6) AM-RGCN: periodic temporal shift besides (4), (5).

4 Experiments

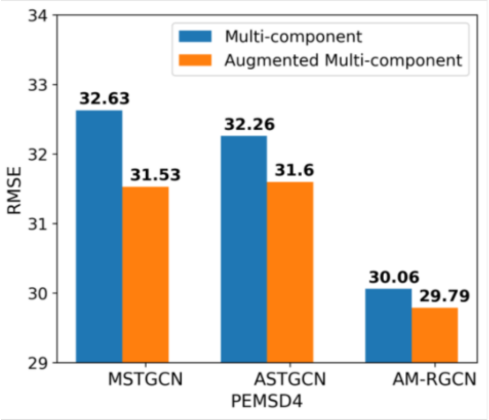
Effects of Augmented Multi-Component Module



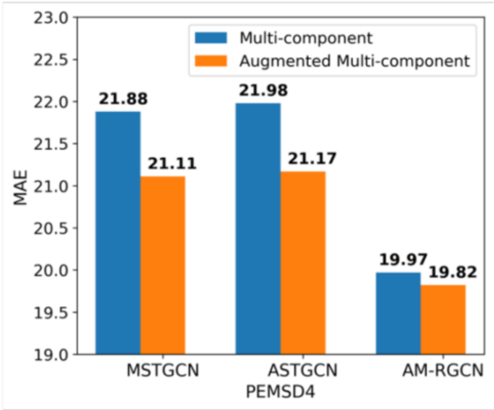
(a) RMSE on PEMSD8



(b) MAE on PEMSD8



(c) RMSE on PEMSD4



(d) MAE on PEMSD4

Method	Multi-Component			1 h	
	$\mathcal{X}_h$	$\mathcal{X}_{ds}$	$\mathcal{X}_{ws}$	RMSE	MAE
AM-RGCN		✓		36.61	25.08
			✓	34.80	22.34
	✓			25.03	17.00
		✓	✓	32.91	22.13
	✓	✓		24.56	16.85
	✓		✓	24.53	16.71
	✓	✓	✓	**22.87**	**15.03**

(1) Each approach using the augmented multi-component performs better than that with the multi-component;
(2) Time series forecasting depends primarily on the recent time slices when considering only one component;
(3) Compared with single X_h, the performance can be improved by combining the X_h with X_{ds} or X_{ws}. Moreover, the best performance can be achieved when the model is equipped with all components.

4 Experiments

Effects of Temporal Correlation Learner

- To further verify the advantages of the TCL, we compare AM-RGCN with its variants which replace the TCL with a CNN or LSTM

Method	Augmented Multi-Component		
	RMSE	MAE	Dataset
AM-CNN-GCN	24.31	16.00	
AM-LSTM-GCN	26.85	18.19	PEMSD8
AM-RGCN	**22.87**	**15.03**	

(1) AM-LSTM-GCN does not perform as well as AM-CNN-GCN. We suggest the underlying reason is that errors are accumulated via a step-by-step approach;
(2) AM-RGCN is superior to AM-CNN-GCN, owing to its combination of a GCN and TCL in the encoder network to capture the spatial–temporal correlations;
(3) AM-RGCN outperforms AM-LSTM-GCN. Our TCL works effectively when handling spatial topological features from the GCN, while AM-LSTM-GCN flattens it due to the ability restriction.

5 Conclusion

AM-RGCN

- We propose the Augmented Multi-component Recurrent Graph Convolutional Network (AM-RGCN) to perform traffic flow forecasting.
  - The augmented multi-component module proves to be effective to capture the periodic temporal shift emerging in traffic series.
  - The TCL block is conducive to representing the spatial-temporal correlations.

Improvement

- Directed graph;
- Transformer for long-term memory;
- Self-adaptive and learnable S.

THANKS FOR YOUR LISTENING