

# Traffic Flow Prediction using Spatial-Temporal Graph Neural Networks

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# Overview

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Traffic congestion is a world-wide problem

Waste of Time -> Waste of Money [1]

	City	Hours wasted per vehicle	Cost of congestion per driver
1	Boston, Massachusetts	149 hours	\$2,205
2	Chicago, Illinois	145 hours	\$2,146
3	Philadelphia, Pennsylvania	142 hours	\$2,102
4	New York City, New York	140 hours	\$2,072
5	Washington, D.C.	124 hours	\$1,835
6	Los Angeles, California	103 hours	\$1,524
7	San Francisco, California	97 hours	\$1,436
8	Portland, Oregon	89 hours	\$1,317
9	Baltimore, Maryland	84 hours	\$1,243
10	Atlanta, Georgia	82 hours	\$1,214

Economic Loss [2]

Area	Loss in billions	Note
US	\$305 [22]	[23]
UK	\$52.01	[24]
NYC	\$33.7	
LA	\$19.2	[25]
Manila	\$18.615	[26]
Bangladesh	\$11.4	[27]
SF	\$10.6	
Atlanta	\$7.1	
Jakarta	\$5	[28]
Dhaka	\$4.463	[29]
GTHA	\$3.3	[30]

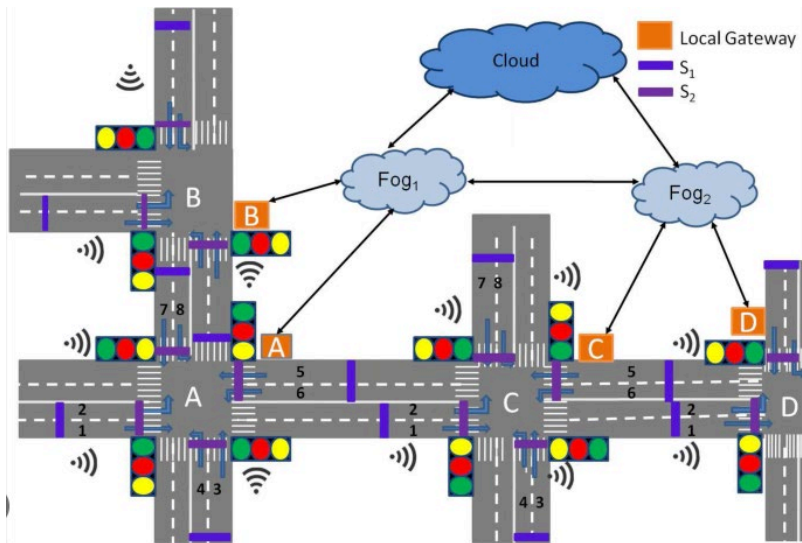
[1] Levin, Tim. ["The 31 US cities that had the worst traffic in 2019 according to a study"](#). *Business Insider*. Retrieved November 25, 2021.

[2] [https://en.wikipedia.org/wiki/Traffic\\_congestion](https://en.wikipedia.org/wiki/Traffic_congestion)

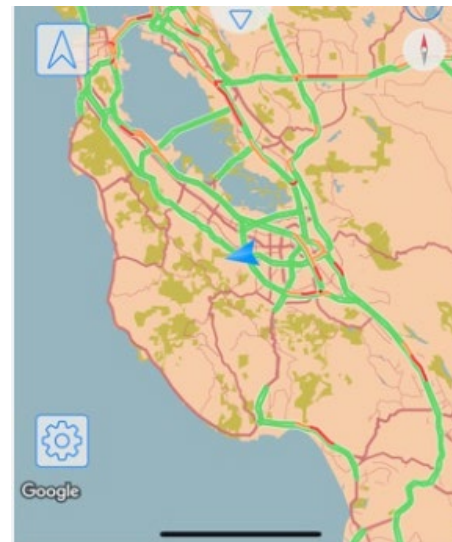
# Overview

Traffic Prediction plays a crucial role in mitigating traffic problem

Dynamic Signal Timing [3]



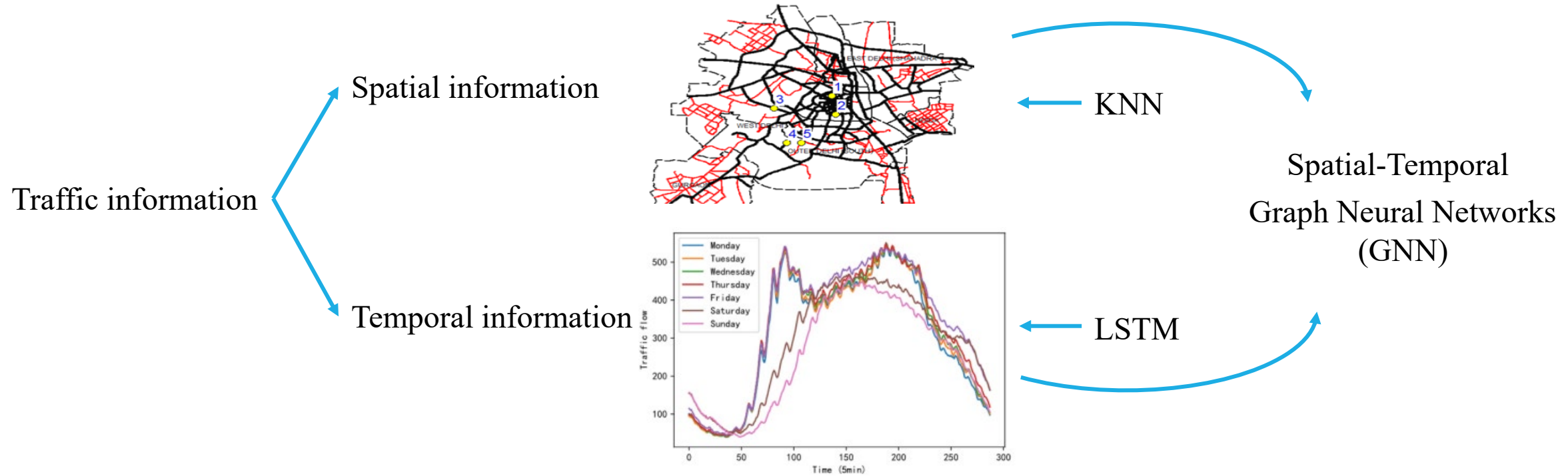
Navigation App



[3] <https://link.springer.com/article/10.1007/s12469-020-00235-z>

# Methods

Previous KNN[4] and LSTM[5] are not best choices



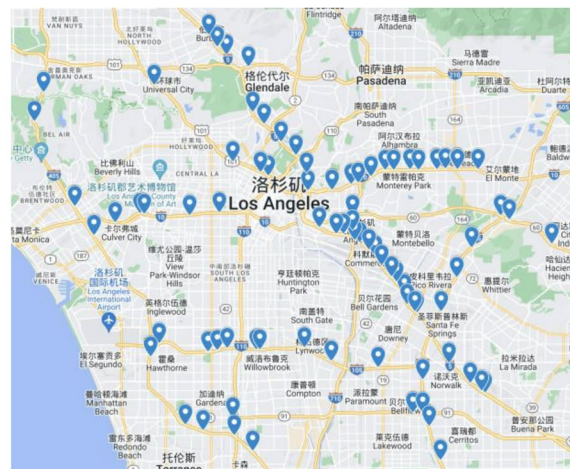
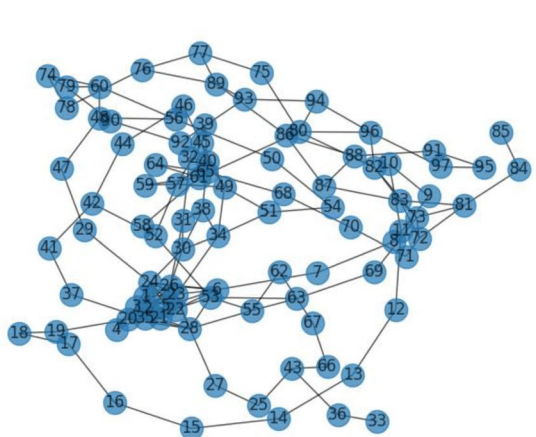
[4] Aslan, Y., & Baracli, H. (2019). Short-Term Traffic Flow Prediction with K-Nearest Neighbor (KNN) Regression. *International Journal of Intelligent Systems and Applications in Engineering*, 7(3), 188-194. DOI: 10.18201/ijisae.2019356192

[5] Zhang, Z., Wang, W., & Feng, G. (2019). Traffic Flow Prediction With Big Data: A Deep Learning Approach. *IEEE Transactions on Intelligent Transportation Systems*, 21(2), 488-497. DOI: 10.1109/TITS.2019.2892405.

# Methods

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Reason 1: Traffic is originally a graph structure



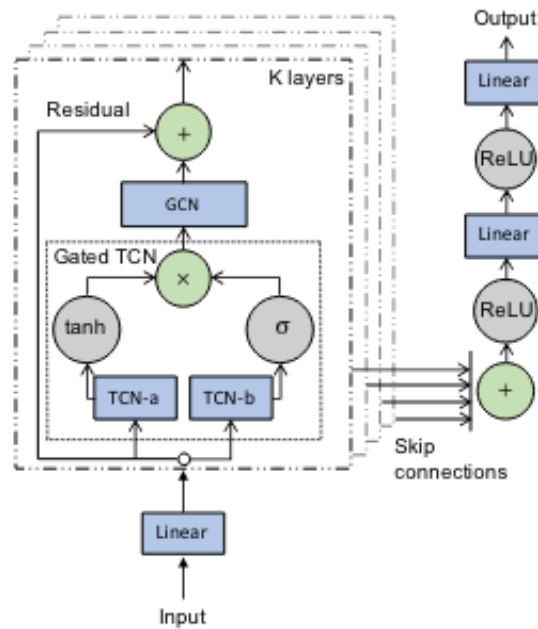
Crossroad  $\longrightarrow$  node  
+  
Road  $\longrightarrow$  edge

Reason 2: Combining the Spatial-Temporal information

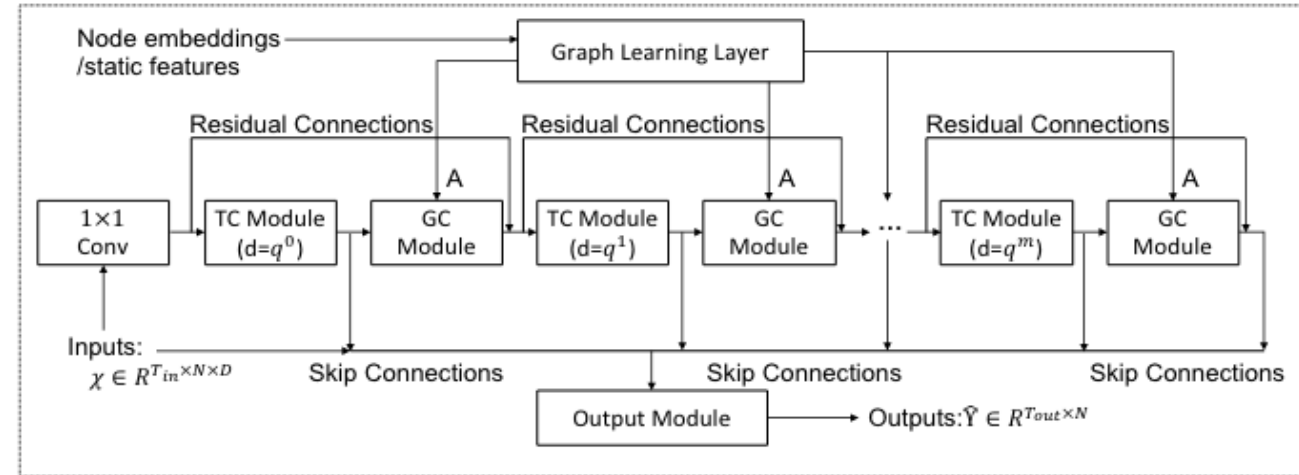
$\longrightarrow$  Higher Accuracy

# Methods

## Two STGNN based methods



GWN[6]



MTGNN[7]

[6] Zonghan Wu, Shirui Pan, Guodong Long, Jing Jiang, and Chengqi Zhang, "Graph wavenet for deep spatial-temporal graph modeling," in Proceedings of the 28<sup>th</sup> International Joint Conference on Artificial Intelligence. 2019, IJCAI'19, p. 1907–1913, AAAI Press

[7] Zonghan Wu, Shirui Pan, Guodong Long, Jing Jiang, Xiaojun Chang, and Chengqi Zhang, "Connecting the dots: Multivariate time series forecasting with graph neural networks," in Proceedings of the 26th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining

# Dataset

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- **PEMS04 records two months of traffic flow on 307 sensors on the California freeway, with time interval is 5 min.**
- **PEMS08 contains two months of traffic flow on 170 sensors on the California freeway, with time interval is 5 min.**

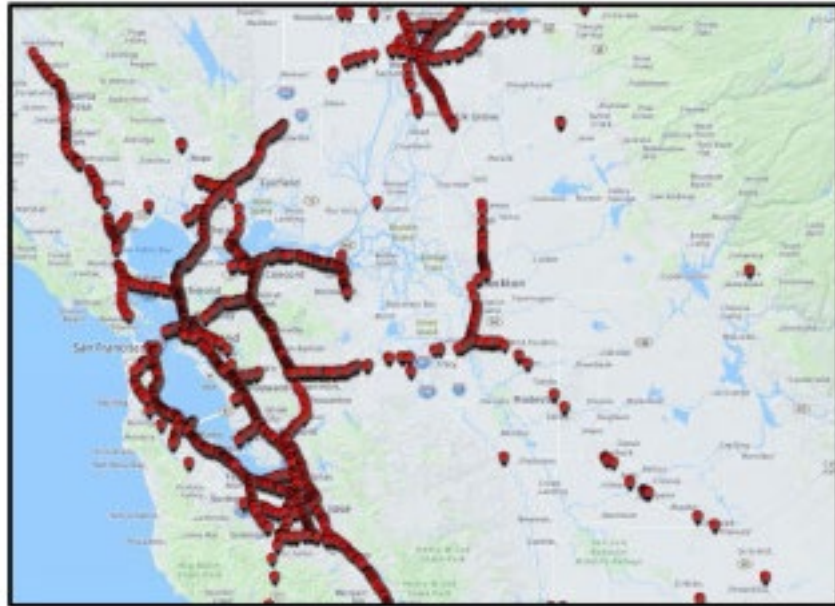
Data	#Nodes	#Time Steps	Data Range
PEMS04	307	16992	0-919
PEMS08	170	17856	0-1147



# Dataset

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PEMS04[8]: 307 sensors



Sensor Distribution

[8]<https://github.com/Davidham3/ASTGCN/tree/master/data/PEMS04>

PEMS08[9]: 170 sensors



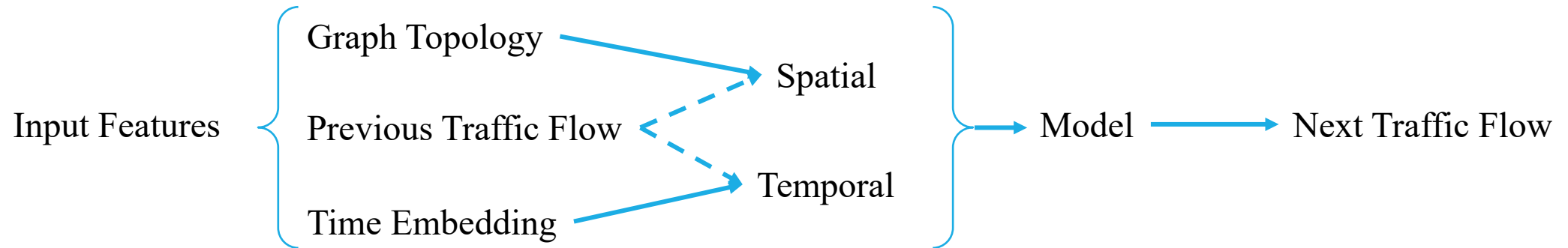
Sensor Distribution

[9]<https://github.com/Davidham3/ASTGCN/tree/master/data/PEMS08>

# Training and Evaluation

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## Training

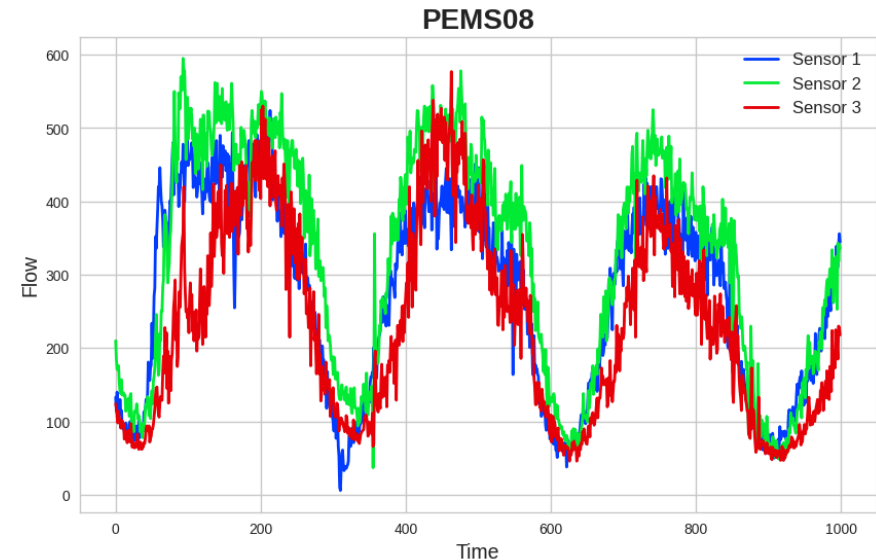
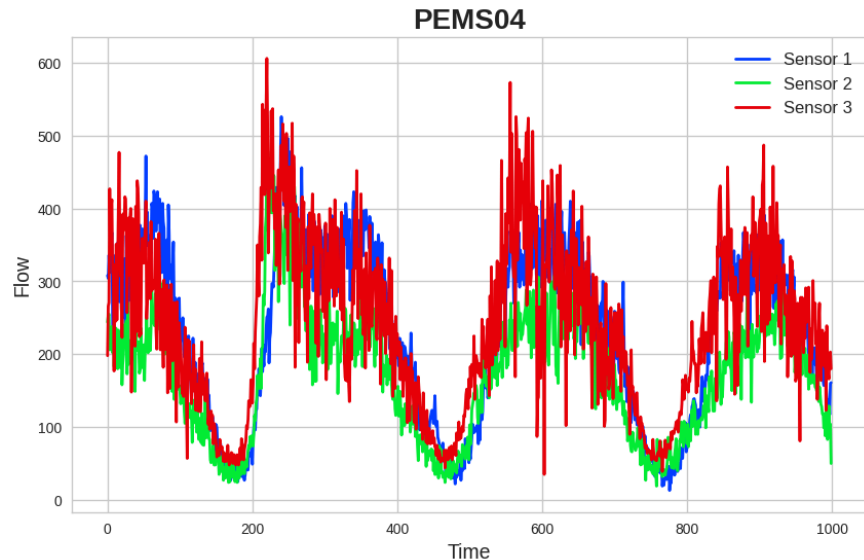


## Evaluation

$$\text{MAE} = \frac{1}{n} \sum_{i=1}^n |y_i - \hat{y}_i|$$

$$\text{RMSE} = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2}$$

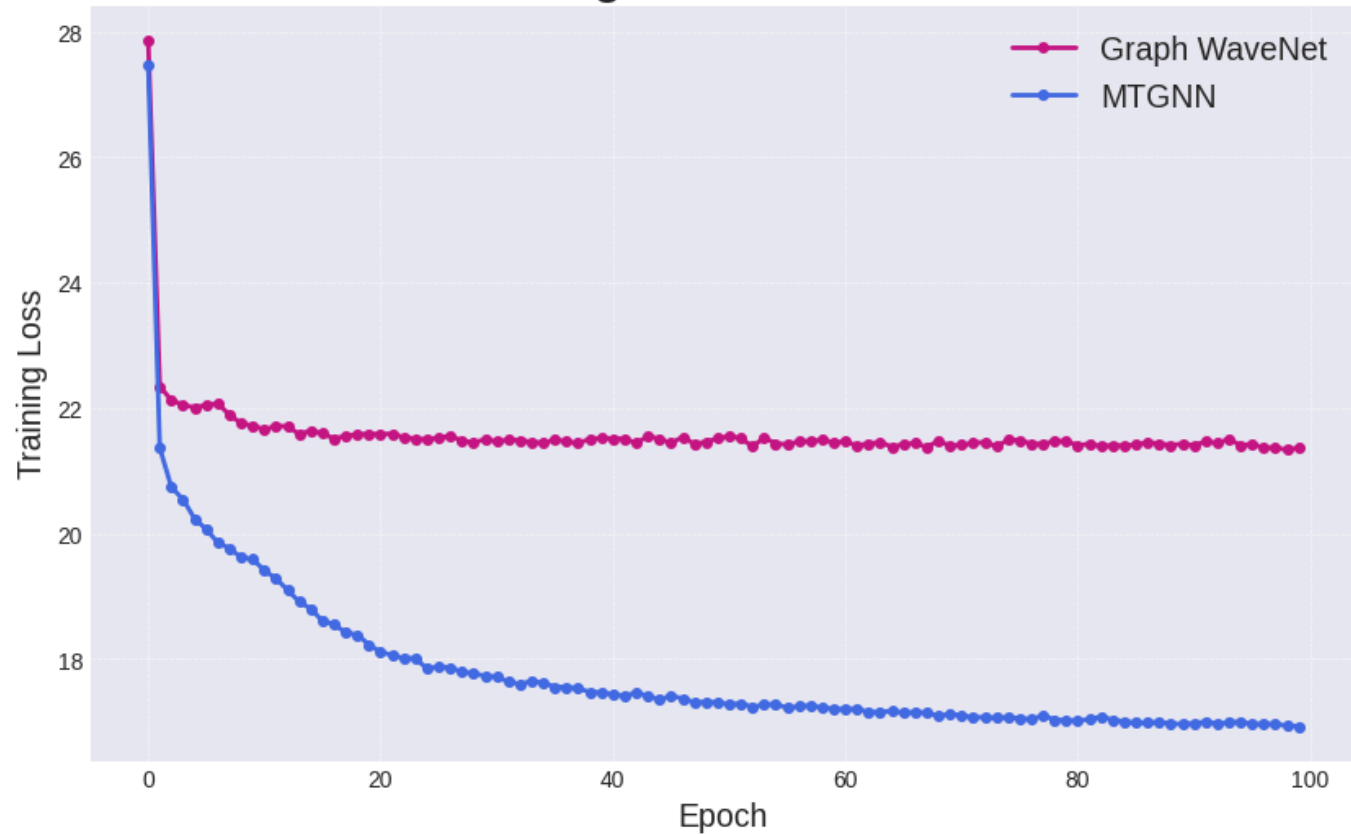
# Data Visualization & Preprocessing



- **Normalization:**  $(\text{data} - \text{mean}) / \text{std}$
- Datasets are split in chronological order with **70% for training**, **10% for validation**, and **20% for testing**.
- Add **two time embeddings**: `time_in_day` (1D), `day_in_week` (7D)

# Results on PEMS04

Training Loss on PEMS04

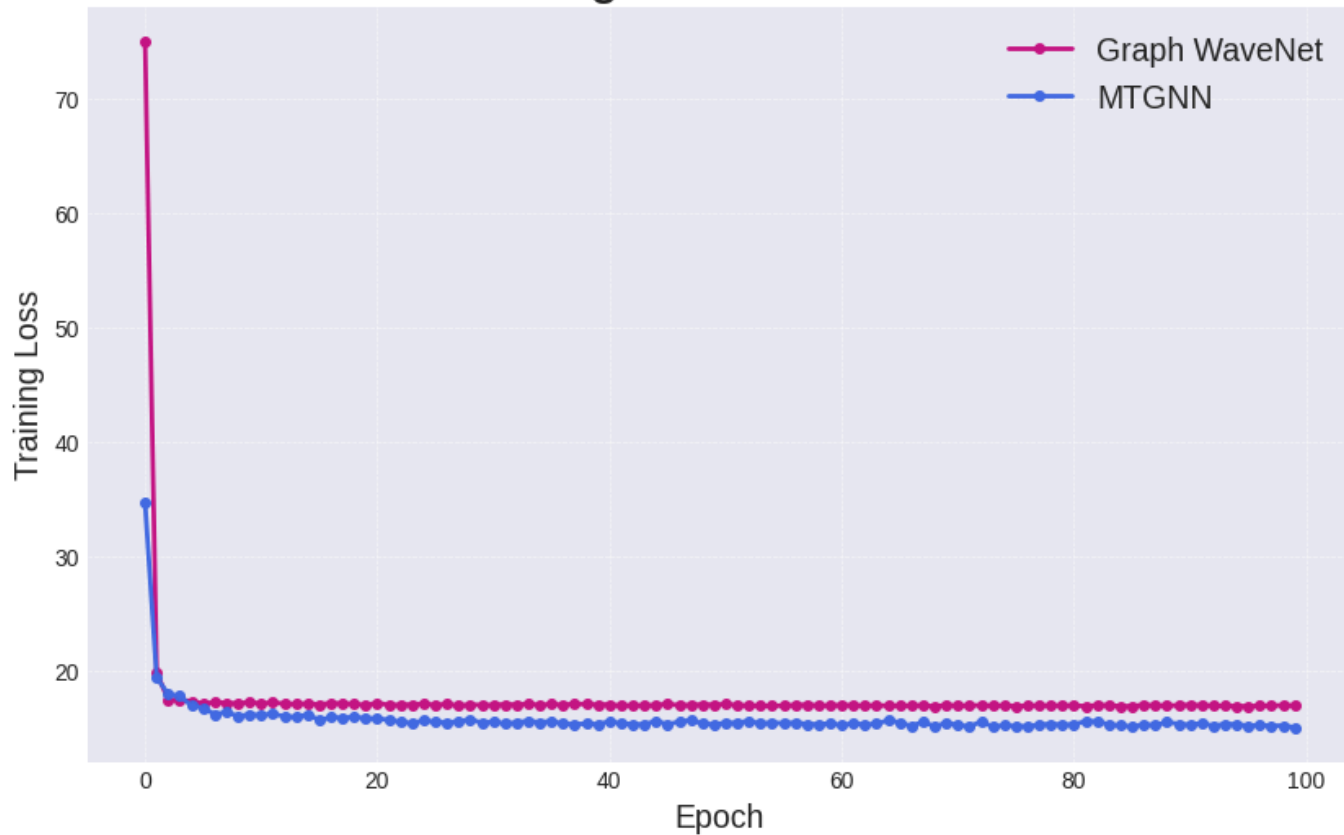


MAE & RMSE on Test Set

Method	MAE	RMSE
Graph Wave Net	21.3659	33.9601
MTGNN	16.9265	27.1356

# Results on PEMS08

Training Loss on PEMS08



MAE & RMSE on Test Set

Method	MAE	RMSE
Graph Wave Net	16.9493	26.1909
MTGNN	15.0600	23.2096

# Thanks for Listening

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## Q & A