41st IEEE International Conference on Data Engineering
HONG KONG SAR, CHINA | MAY 19 – 23, 2025

MulTiSA 2025

北京郵電大學
Beijing University of Posts and Telecommunications

Variable Spatiotemporal Framework for Multivariate Time Series Prediction

Chen Xu, Qiang Wang, Yiyang Wu, and Lianxing Li

2025-05-19

Outline

Beijing University of Posts and Telecommunications

- Introduction & Motivation
- VSTGN Framework
- Experimental Evaluation
- Conclusion

Introduction & Motivation

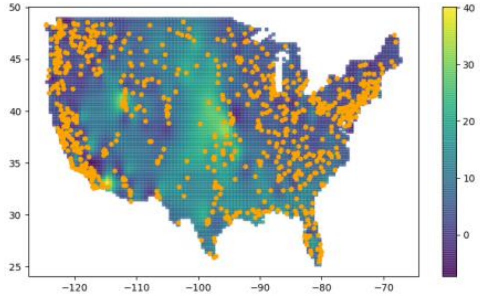
Multivariate Time Series Forecasting:

- Predicting future values of multiple interdependent variables by jointly modeling their temporal dependencies and cross-variable interactions.
- Ubiquitous applications: Transportation, Energy, Climate.

NYC movement

Spatiotemporal Graph Neural Network Framework (STGNN):

- Spatial Dependency Modeling: GCN-based $\mathcal{S}_{\theta_s}$
- Temporal Dependency Modeling: RNN-based $\mathcal{T}_{\theta_t}$
- Joint Spatiotemporal Learning: $\boldsymbol{X}_{t+1} = \mathcal{T}_{\theta_t}(\mathcal{S}_{\theta_s}(\boldsymbol{\mathcal{R}}\boldsymbol{X}_t))$



Beijing University of Posts and Telecommunications

Modeling Spatial Dependency in Spatiotemporal Data:

- the general form of a GCN-based model:

$$\mathbf{H}^{(l+1)} = \text{AGGREGATE}\left(\mathbf{H}^{(l)}, \mathbf{A}; \Theta^{(l)}\right)$$

  - ✓ H: Input or updated feature vectors.
  - ✓ A: a correlation matrix.
  - ✓ θ: a learnable mapping function that projects input features into latent spaces suitable for downstream tasks.

“Static-dynamic” misalignment limitations:

- Static correlation matrix.(Static adjacency matrix or spatially adaptive correlation matrix)
- Static projection function. (Shared parameters across time)

Introduction & Motivation

Proposed Solution and Key Contributions:

- We propose VSTGN, a novel spatiotemporal GNN framework that adaptively constructs **real-time correlation matrices** from observational data, capturing dynamic relational changes.
- VSTGN introduces a **spatiotemporally varying projection function** that jointly accounts for temporal periodicity and spatial heterogeneity.
- Experiments on real-world datasets demonstrate that our model outperforms state-of-the-art baselines.

Achieveing “dynamic-dynamic” alignment with real-world scenarios.

VSTGN Framework

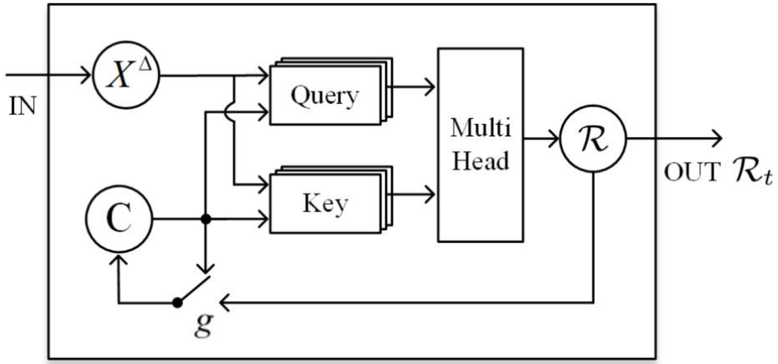
Adaptive Dynamic Correlation Modeling--Gated Attention Unit (GAU)

- Node correlation construction based on local data and self-attention mechanism.

$$\boldsymbol{Q}_t = [[\boldsymbol{X}_t^{\Delta}|\boldsymbol{C}_{t-1}]]^T \boldsymbol{W}_q, \quad \boldsymbol{K}_t = [[\boldsymbol{X}_t^{\Delta}|\boldsymbol{C}_{t-1}]]^T \boldsymbol{W}_k,$$

$$\text{head}_{t,i} = \text{softmax}(\frac{\boldsymbol{Q}_t \boldsymbol{K}_t^T}{\sqrt{d_{model}}}),$$

$$\boldsymbol{\mathcal{R}}_t = \text{sigmoid}([\![\text{head}_{t,0}, ..., \text{head}_{t,i}]\!] \boldsymbol{W}_r),$$



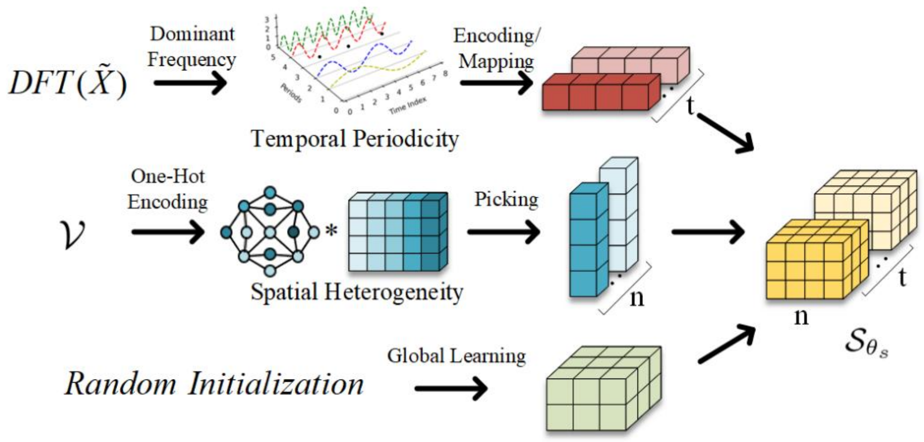
- Real-time correlation update based on Gated mechanism

$$\boldsymbol{g}_t = \text{sigmoid}([[\boldsymbol{X}_t^{\Delta}|\boldsymbol{C}_{t-1}]]^T \boldsymbol{W}_u),$$

$$\boldsymbol{C}_t = (\boldsymbol{1} - \boldsymbol{g}_t) \otimes \boldsymbol{C}_{t-1} + \boldsymbol{g}_t \otimes \boldsymbol{\mathcal{R}}_t,$$

VSTGN Framework

Spatiotemporal varying Projection Function Learning--Spatiotemporal Embedding Layer (SEL)



- Spatial variability

$$\boldsymbol{S}_i = \sigma(\text{One\_Hot}(v_i)\boldsymbol{W}_s) \in \mathbb{R}^{1\times d_s},$$

- Temporal variability

✓ Dominant frequency identification

$$\boldsymbol{w} = \text{Top\_p}(\text{DFT}(\tilde{\boldsymbol{X}})) \in \mathbb{R}^{1\times p},$$

✓ Periodic encoding

$$\boldsymbol{\Gamma}_t = [\Psi(\frac{2\pi}{w_1}I_t + \varphi_1), ..., \Psi(\frac{2\pi}{w_p}I_t + \varphi_p)],$$

✓ Temporal feature learning

$$\boldsymbol{T}_t = \text{MLP}(\boldsymbol{W}_c\boldsymbol{\Gamma}_t) \in \mathbb{R}^{d_s\times d_t}$$

✓ Spatiotemporal varying mapping function：

$$\boldsymbol{P}_{i,t} = \boldsymbol{S}_i\boldsymbol{T}_t\boldsymbol{W}_g \in \mathbb{R}^{1\times f}$$

VSTGN Framework

Variable Spatiotemporal Dependence Capture

- Variable graph convolution constructed based on GAU and SEL

$$\mathrm{VGNN}(\boldsymbol{X}_t) = \sigma(\boldsymbol{\mathcal{R}}_t \boldsymbol{X}_t^T \boldsymbol{P}_t) \in \mathbb{R}^{n \times f},$$

- Combined with a Gated Recurrent Unit to form a complete Variable Spatiotemporal Graph Neural Network (VSTGN):

$$\begin{aligned}
\boldsymbol{r} &= \mathrm{sigmiod}(\boldsymbol{\mathcal{R}}_t \left[\left[\boldsymbol{X}_t | \boldsymbol{h}_{t-1}^T\right]\right]^T \mathbb{S}\boldsymbol{T}_t \boldsymbol{W}_r^*), \\
\boldsymbol{z} &= \mathrm{sigmiod}(\boldsymbol{\mathcal{R}}_t \left[\left[\boldsymbol{X}_t | \boldsymbol{h}_{t-1}^T\right]\right]^T \mathbb{S}\boldsymbol{T}_t \boldsymbol{W}_z^*), \\
\boldsymbol{s} &= \tanh(\boldsymbol{\mathcal{R}}_t \left[\left[\boldsymbol{X}_t | (\boldsymbol{h}_{t-1}^T \otimes \boldsymbol{r})\right]\right]^T \mathbb{S}\boldsymbol{T}_t \boldsymbol{W}_s^*), \\
\boldsymbol{h}_t &= (\mathbf{1} - \boldsymbol{z}) \otimes \boldsymbol{s} + \boldsymbol{z} \otimes \boldsymbol{h}_{t-1},
\end{aligned}$$

- The final predictions are generated by feeding the hidden states into a fully connected neural network.

Experimental Evaluation

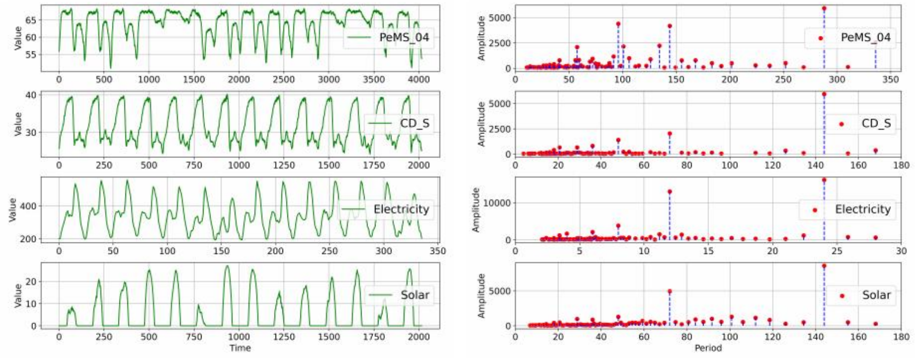
EXPERIMENTAL RESULTS OF MODELS FOR SINGLE-STEP PREDICTION (RMSE/MAE/MAPE).

Model	PeMS_04	CD_S	Electricity	Solar
TGCN [6]	28.95/18.61/13.82	4.35/2.79/11.04	0.150/0.083/29.71	0.241/0.172/176.75
ASTGCN [8]	31.81/19.57/13.03	4.03/2.65/10.66	0.126/0.077/30.81	0.235/0.161/274.19
STGCN [27]	27.76/17.59/11.72	3.76/2.31/9.37	0.156/0.091/36.11	0.201/0.169/211.68
DCRNN [28]	28.26/17.97/11.95	3.99/2.43/9.72	0.131/0.086/31.08	0.291/0.196/402.03
AGCRN [10]	28.15/17.91/11.93	3.81/2.37/9.57	0.116/0.074/26.08	0.264/0.123/353.60
DGCN [13]	28.11/18.02/12.03	3.33/2.19/9.12	0.121/0.079/28.11	0.226/0.143/179.96
DGCRN [19]	27.85/17.68/11.79	3.11/2.10/8.77	0.129/0.082/29.21	**0.209/0.155/152.32**
VSTGN†	27.01/17.11/11.35	3.01/2.02/8.51	0.118/0.073/26.05	0.219/0.169/167.12
VSTGN	**26.40/16.86/11.23**	**2.93/1.96/8.22**	**0.111/0.070/25.28**	0.221/0.163/166.01

Datasets: Traffic, Electricity, and Solar

Our model outperformed baseline methods by an average of 5.36%.

The data demonstrates prominent periodic patterns, mainly at daily, half-daily, and one-third-daily intervals.



(a) Visualization of the four datasets. (b) DFT of the four datasets.

Fig. 2. Data visualization and spectral analysis.

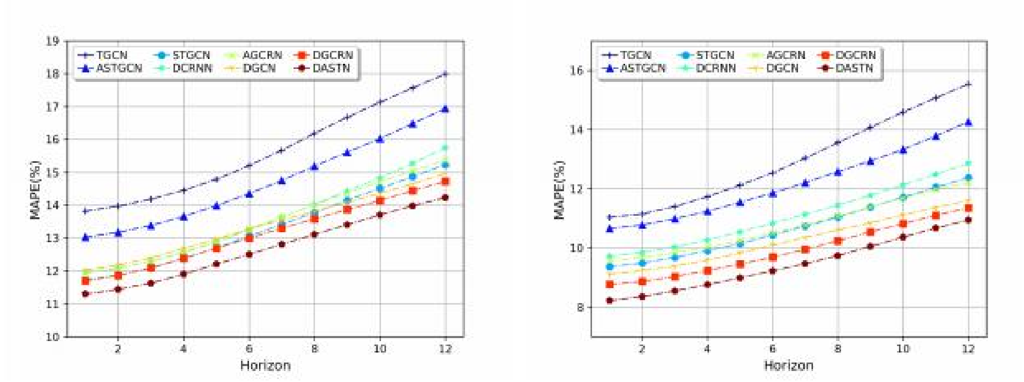
Experimental Evaluation

TABLE II
MAPE OF THE ABLATION EXPERIMENT.

Model	VSTGN_DC	VSTGN_SE	VSTGN_TE	**VSTGN**
PeMS_04	11.49	11.67	11.95	**11.23**
CD_S	8.52	8.83	8.90	**8.22**
Electricity	26.07	28.92	28.29	**25.28**
Solar	173.81	174.12	174.01	**166.01**

TABLE III
TRAINING TIME(S) OF MODELS.

Model	DCRNN	AGCRN	DGCN	DGCRN	**VSTGN**
CD_S	462.81	177.31	870.34	386.92	**357.15**
PeMS_04	37.67	17.17	76.81	33.91	**27.01**



(a) Multistep prediction on PeMS_04. (b) Multistep prediction on CD_S.

Fig. 3. Multistep prediction performance of VSTGN.

The ablation experiments validate the effectiveness of the GAU and the temporal-spatial embedding component of the SEL module.

VSTGN retains its superiority in multi-step prediction while avoiding substantial computational overhead.

Conclusion

- This study addresses the misalignment between static modeling approaches and the inherently dynamic nature of multivariate time series systems.
- We propose a novel variable spatiotemporal graph neural network framework that integrates dynamic adaptive node correlations with a spatiotemporal varying projection function.
- Experimental results demonstrate its superior performance in both single-step and multi-step predictions, significantly outperforming state-of-the-art baselines.

Thank you

Variable Spatiotemporal Framework for Multivariate Time Series Prediction

Chen Xu, Qiang Wang, Yiyang Wu, and Lianxing Li

Email: xuchen@bupt.edu.cn