A Survey on Graph Neural Networks for Time Series: Forecasting, Classification, Imputation, and Anomaly Detection

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[3] Griffith University

October 12th, 2023

Outline

- Introduction
- Framework and Categorization

Part 1

- Graph Neural Networks for Time Series Forecasting
- Graph Neural Networks for Time Series Classification
- Graph Neural Networks for Time Series Anomaly Detection
- Graph Neural Networks for Time Series Imputation

Part 2

- Practical Applications
- Future Directions

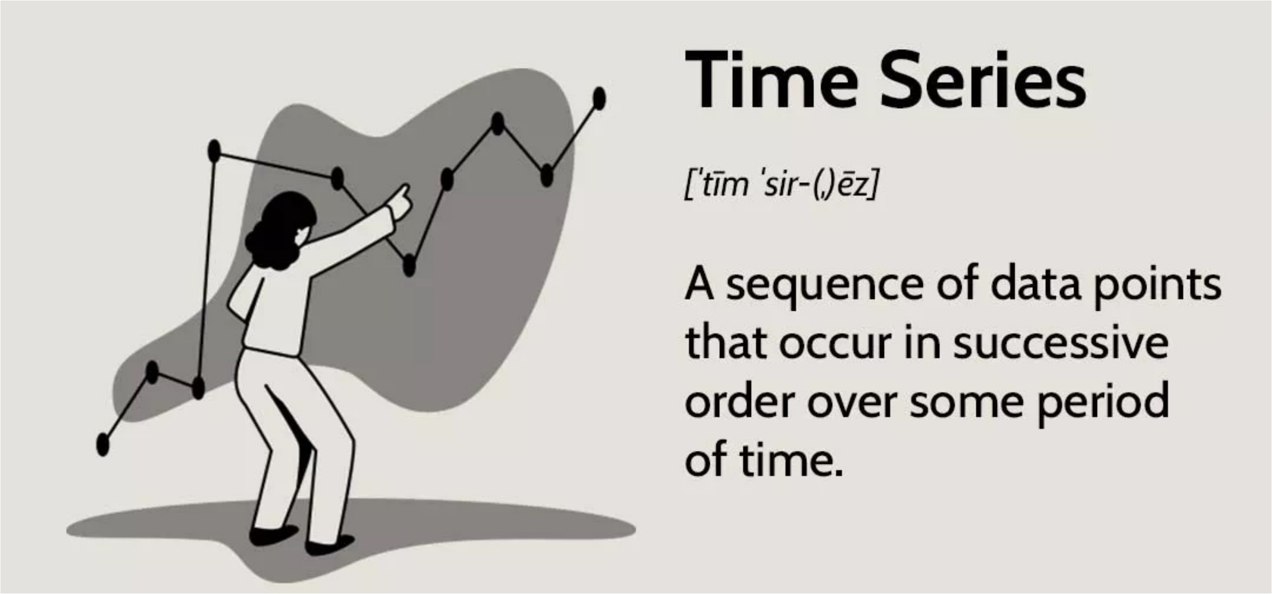
Part 3

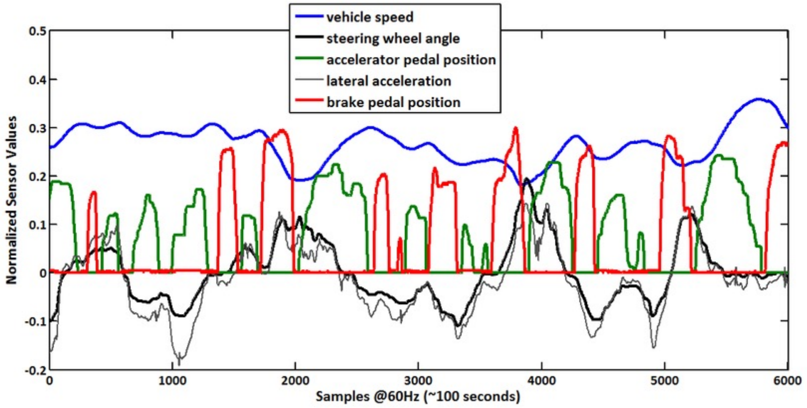
Part 1. Introduction & Taxonomy

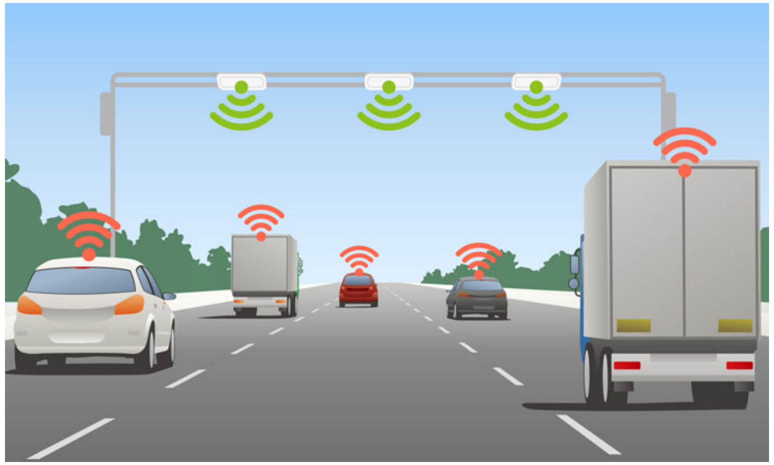
- Time series and graph neural networks: background
- Graph neural networks for time series analysis: an overview
- Framework and categorization

Introduction

- What are time series?





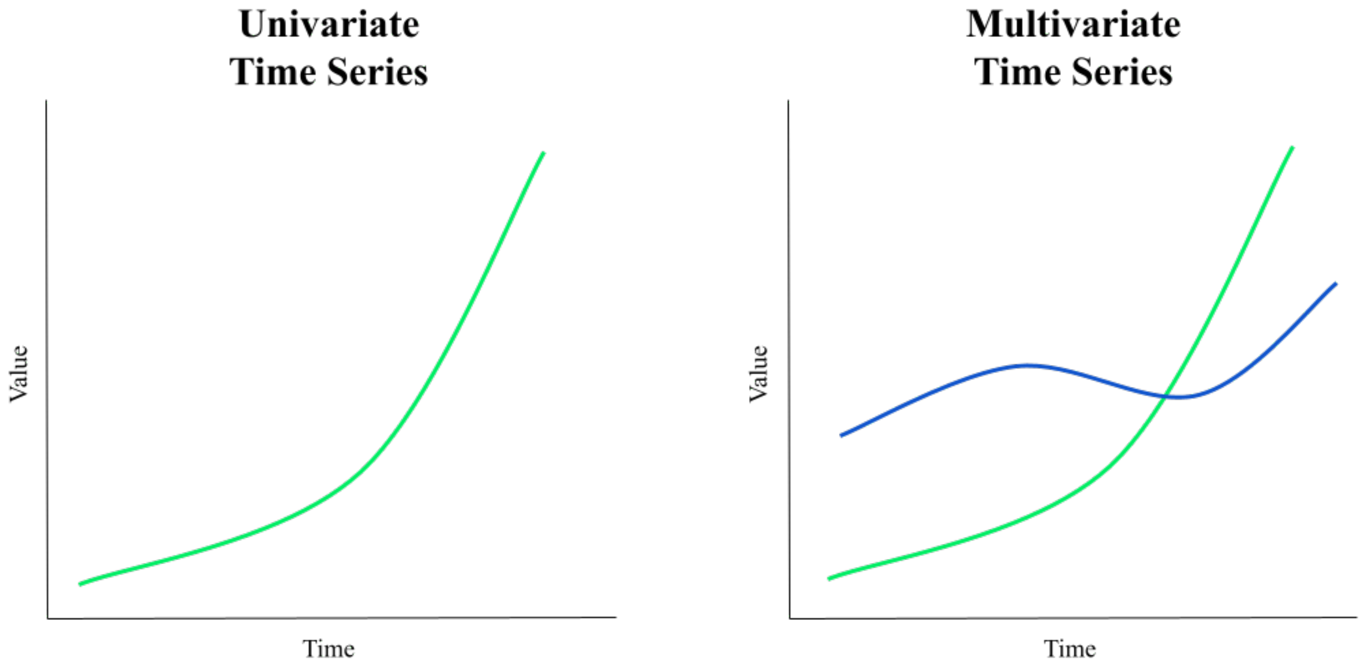


https://www.investopedia.com/terms/t/timeseries.asp

Enev, M., Takakuwa, A., Koscher, K., & Kohno, T. (2016). Automobile Driver Fingerprinting. Proc. Priv. Enhancing Technol., 2016(1), 34-50.

Introduction

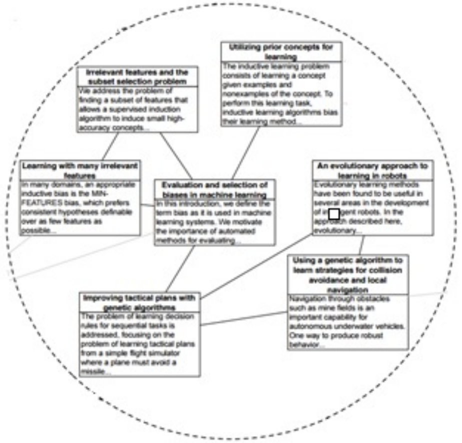
- What are time series?



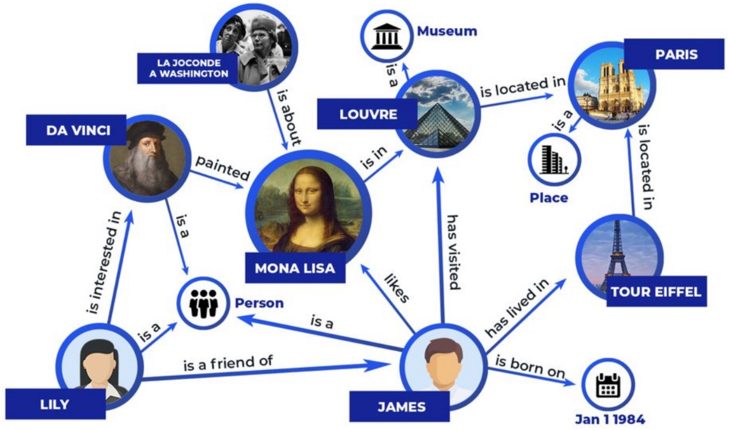
https://www.mongodb.com/basics/time-series-data-analysis

Introduction

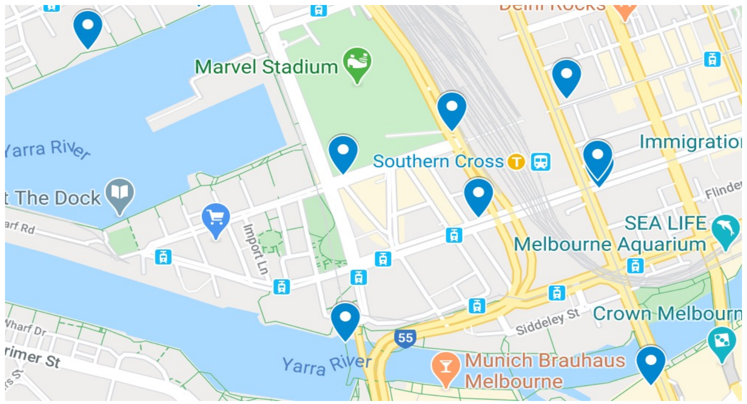
- What are graphs?



Bibliography Networks



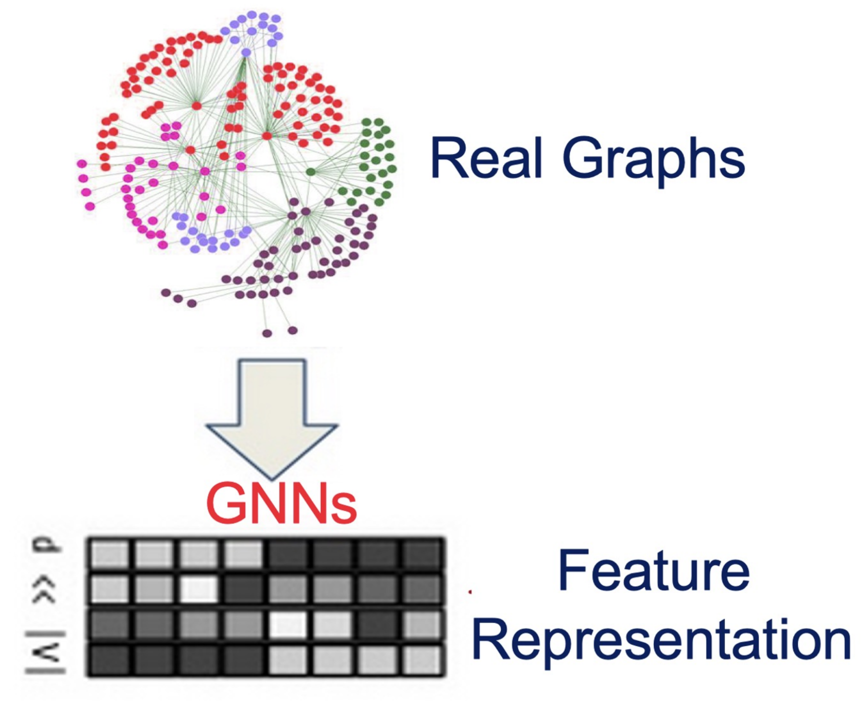
Knowledge Graphs

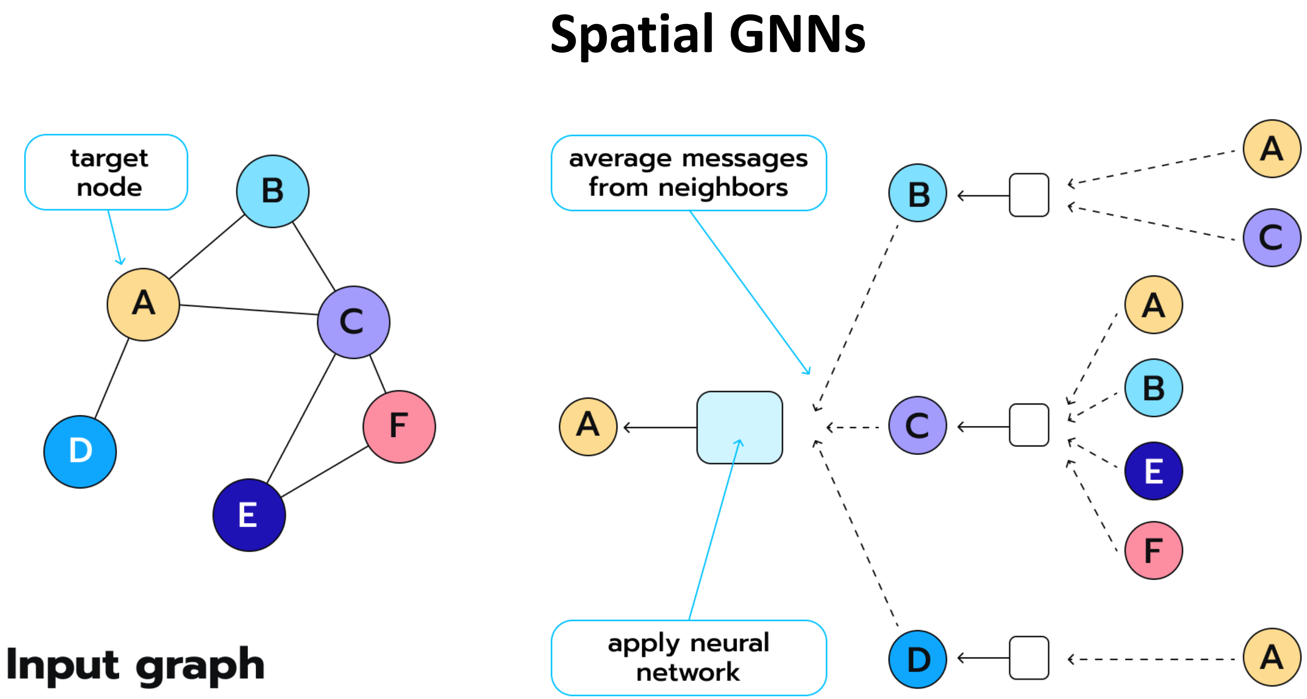


Traffic Networks

Introduction

- What are graph neural networks (GNNs)?

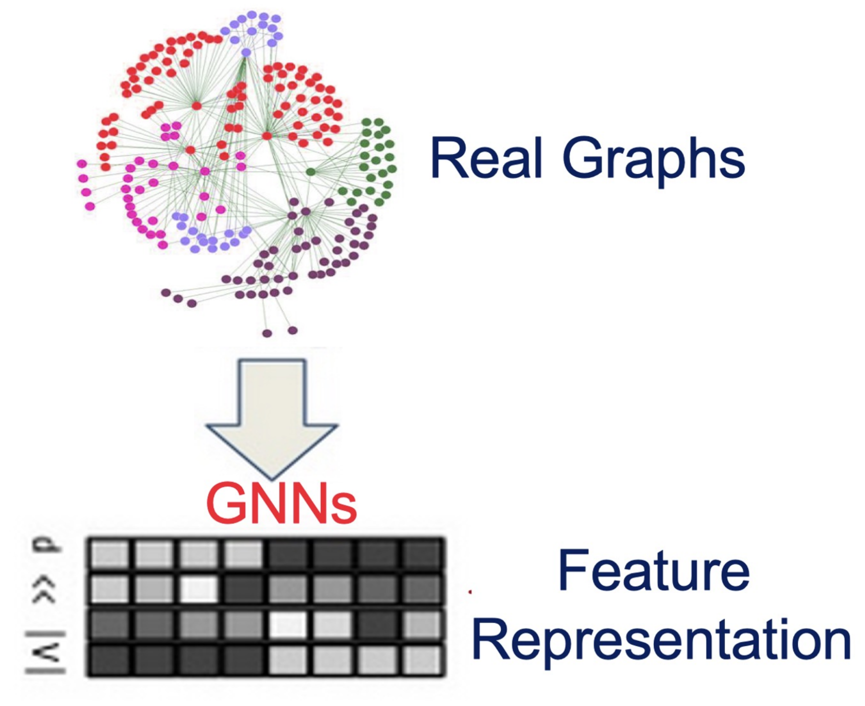


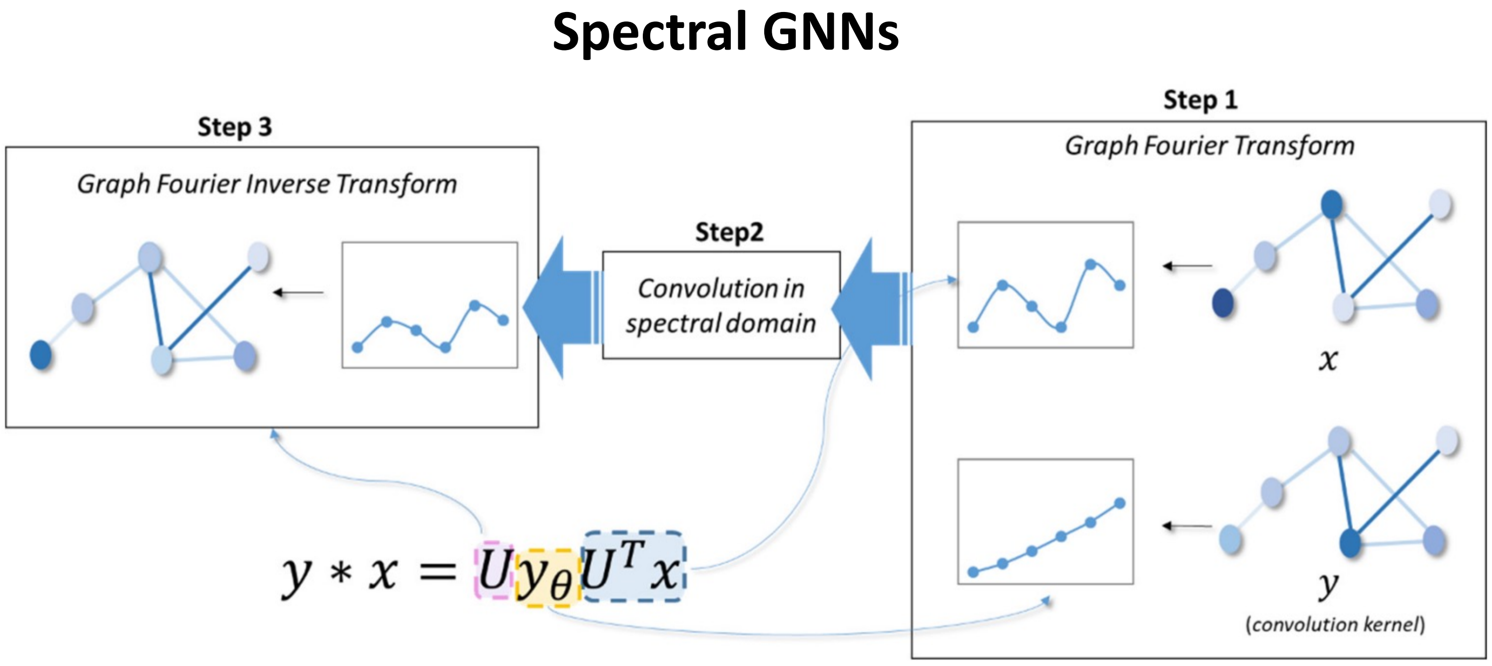


https://www.avenga.com/magazine/graph-neural-networks-and-graph-convolutional-networks/

Introduction

- What are graph neural networks (GNNs)?

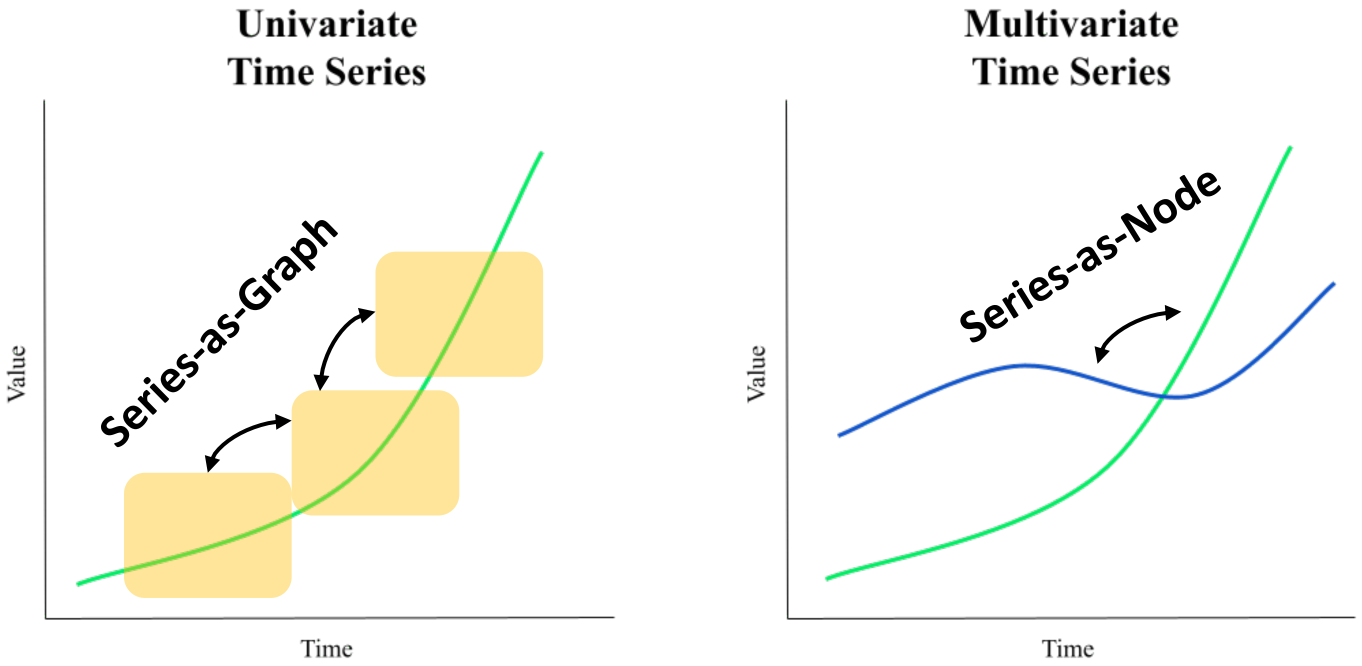




Li, J., Guo, W., Liu, H., Chen, X., Yu, A., & Li, J. (2021). Predicting User Activity Intensity Using Geographic Interactions Based on Social Media Check-In Data. ISPRS International Journal of Geo-Information, 10(8), 555.

Introduction

- Graph neural networks for time series analysis (GNN4TS)

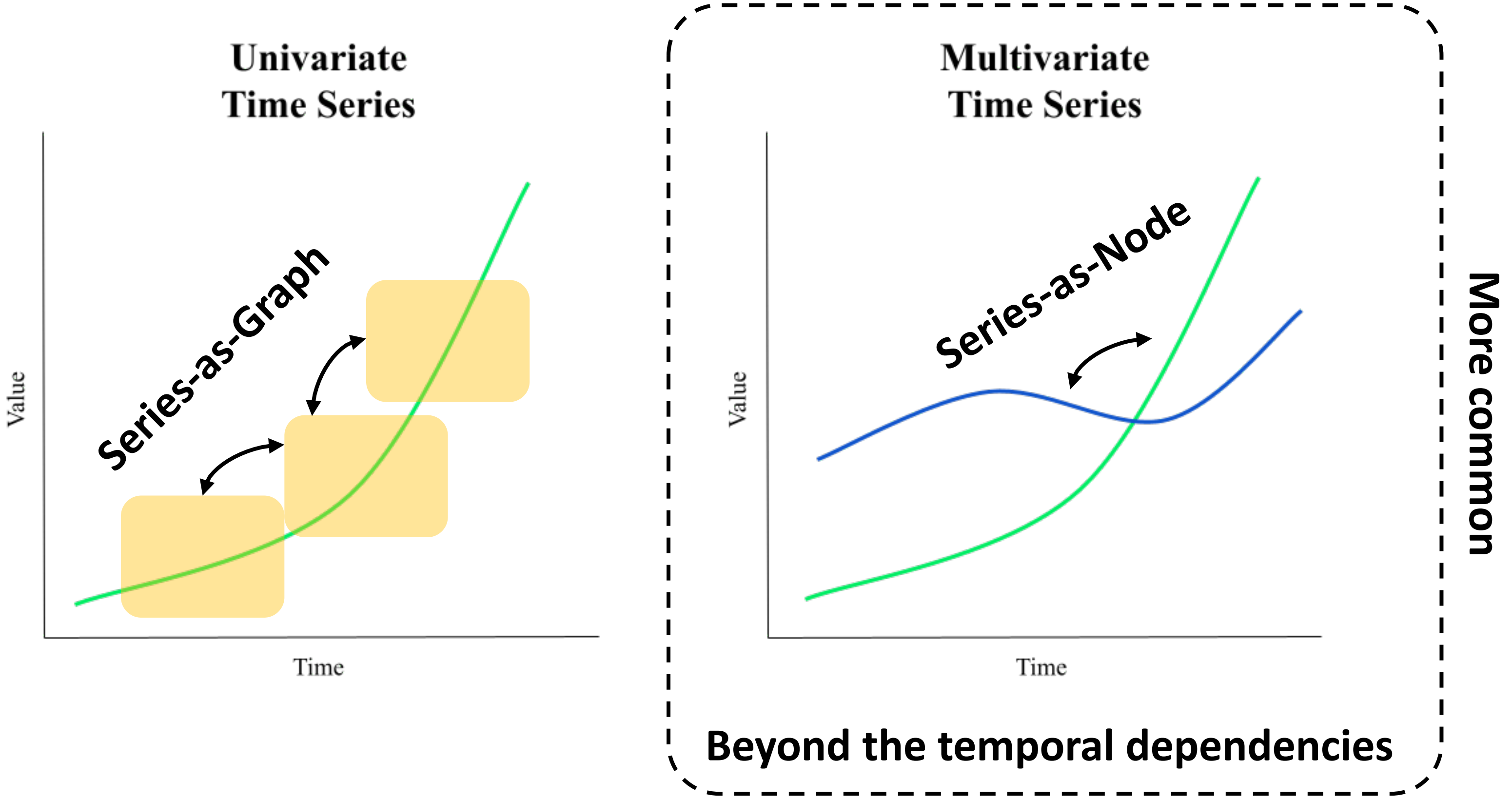


Beyond the temporal dependencies

https://www.mongodb.com/basics/time-series-data-analysis

Introduction

- Graph neural networks for time series analysis (GNN4TS)



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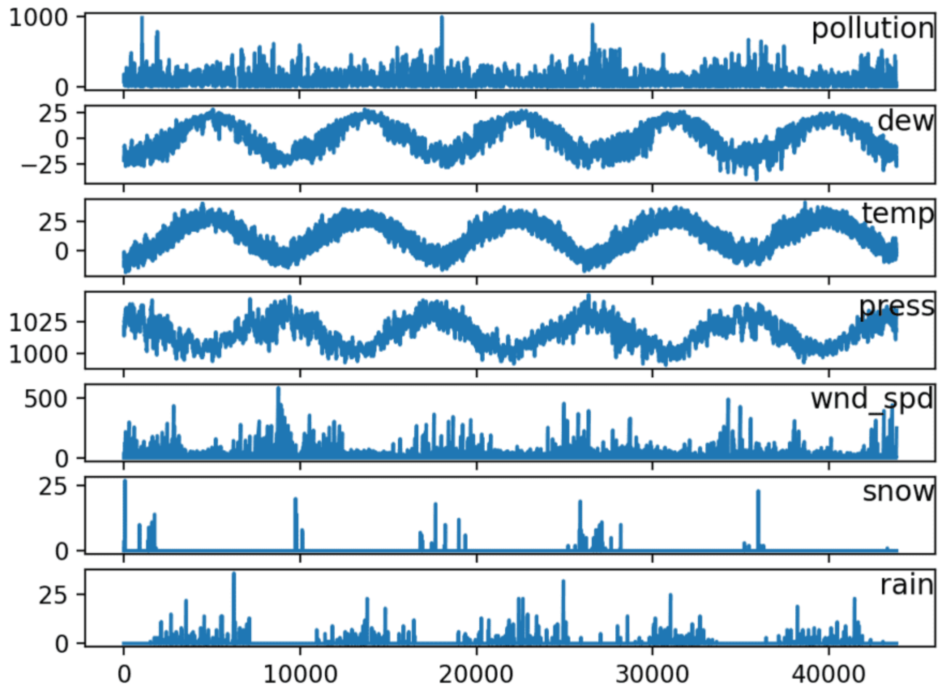
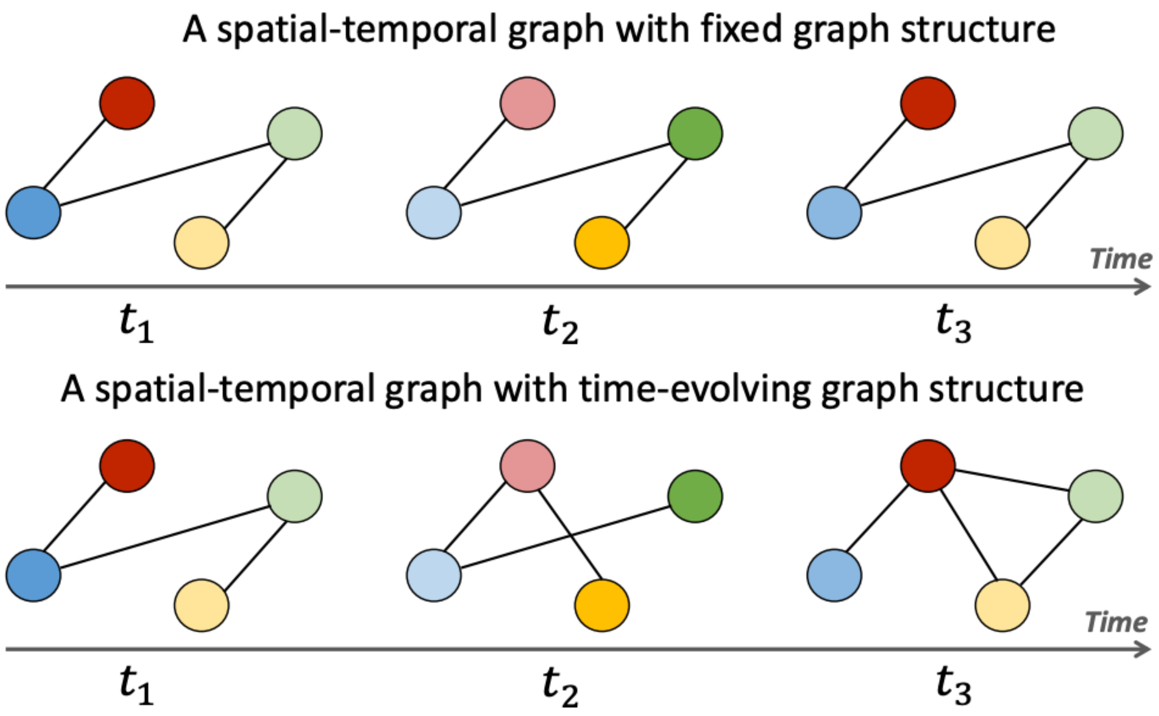
Introduction

- Graph neural networks for time series analysis (GNN4TS)

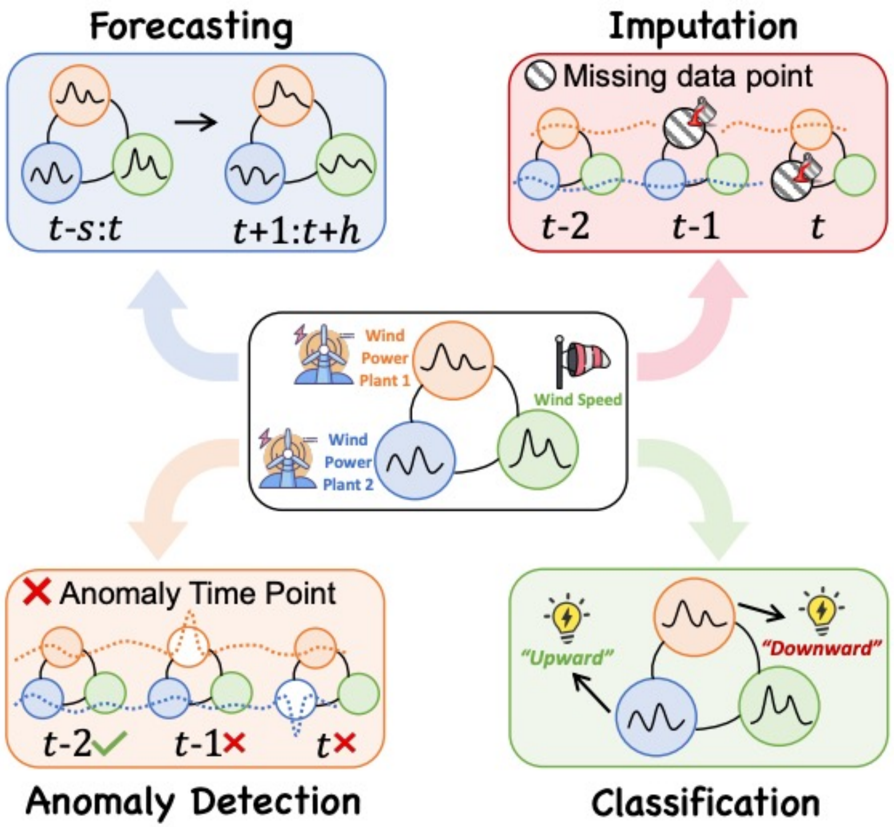




https://www.mongodb.com/basics/time-series-data-analysis

Introduction

- Graph neural networks for time series analysis (GNN4TS)



In this example of wind farm, different analytical tasks can be categorized into time series **forecasting**, **classification**, **anomaly detection**, and **imputation**

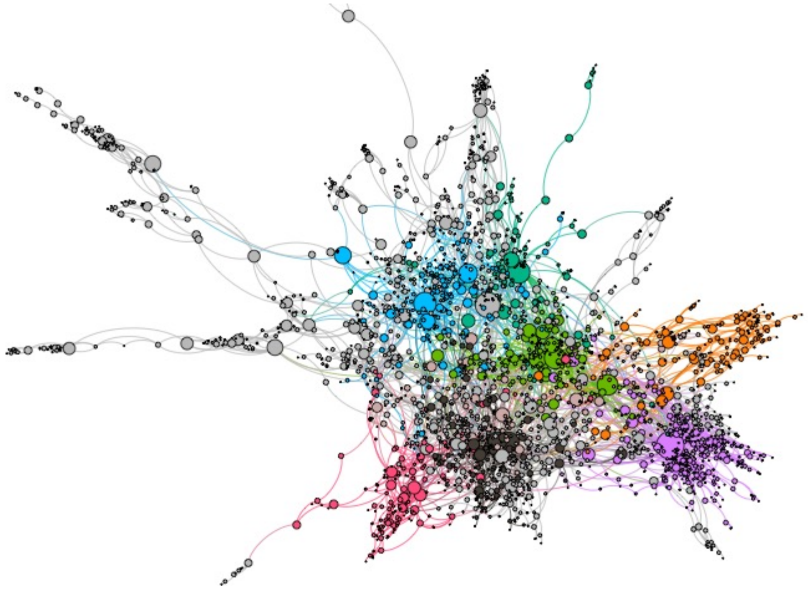
Introduction

- How to obtain the graph structures?

  - To employ GNNs for time series analysis, it is implied that a graph structure must be provided

  - However, not all time series data have readily available graph structures

Heuristic-based approaches



Learning-based approaches

https://www.linkedin.com/pulse/future-forensics-heuristic-approach-vidhura-sethu/
https://www.kdnuggets.com/2019/08/neighbours-machine-learning-graphs.html

Introduction

- **Heuristic-based graphs**
  - *Spatial proximity*: This approach defines the graph structure by considering the proximity between pairs of nodes based on, e.g., their geographical location.

$$\mathbf{A}_{i,j} = \begin{cases} \frac{1}{dij}, & \text{if } d_{ij} \neq 0, \\ 0, & \text{otherwise,} \end{cases}$$

d_{ij} denotes the shortest travel distance between node i and j

  - *Pairwise connectivity*: The graph structure is determined by the connectivity between pairs of nodes, like that determined by transportation networks.

$$\mathbf{A}_{i,j} = \begin{cases} 1, & \text{if } v_i \text{ and } v_j \text{ are directly linked,} \\ 0, & \text{otherwise.} \end{cases}$$

Introduction

- **Heuristic-based graphs**
  - *Pairwise similarity*: This method constructs the graph by connecting nodes with similar attributes.

$$\mathbf{A}_{i,j} = \frac{\mathbf{x}_i^\top \mathbf{x}_j}{\|\mathbf{x}_i\| \|\mathbf{x}_j\|}$$

x_i and x_j are two time series (variables), and $\|\,.\,\|$ denotes the Euclidean norm

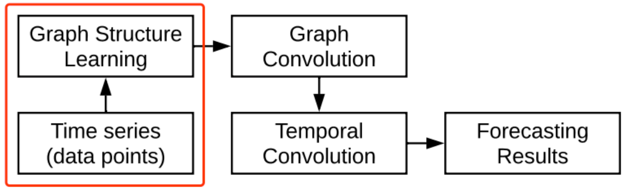
  - *Functional dependence*: This approach defines the graph structure based on the functional dependence between pairs of nodes.

$$\mathbf{A}_{i,j} = \begin{cases} 1, & \text{if node } j \text{ Granger-causes} \\ & \text{node } i \text{ at a significance level } \alpha, \\ 0, & \text{otherwise.} \end{cases}$$

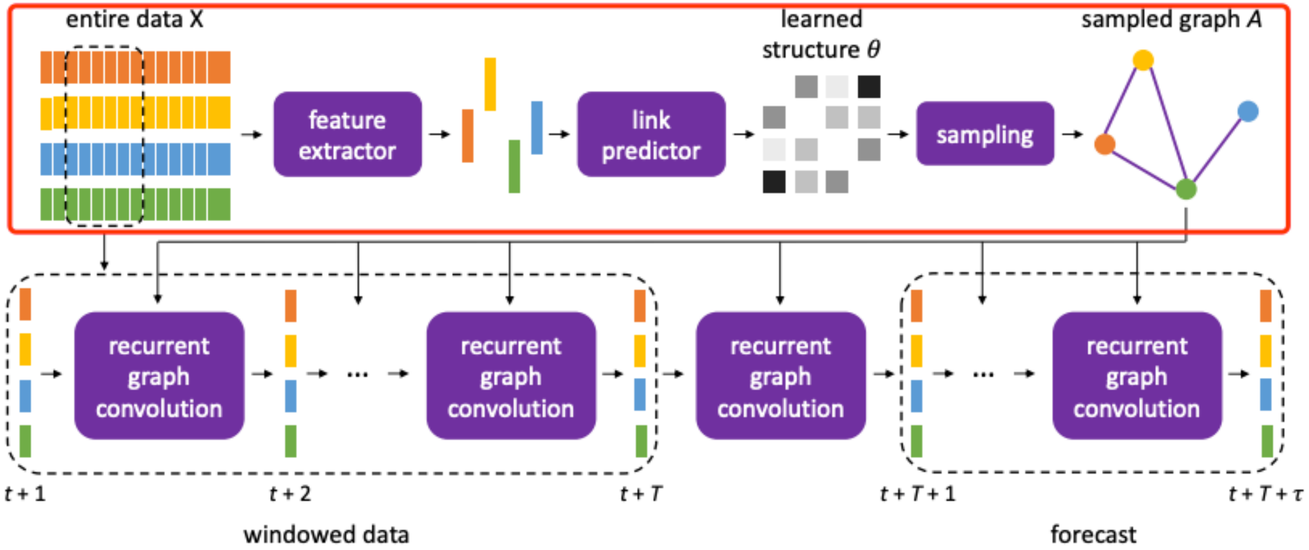
Other examples involve transfer entropy (TE) and discrete phase lag index (DPLI)

Introduction

- **Learning-based graphs**



$$\mathbf{M}_1 = tanh(\alpha \mathbf{E}_1 \mathbf{\Theta}_1)$$
$$\mathbf{M}_2 = tanh(\alpha \mathbf{E}_2 \mathbf{\Theta}_2)$$
$$\boxed{\mathbf{A} = ReLU(tanh(\alpha(\mathbf{M}_1 \mathbf{M}_2^T - \mathbf{M}_2 \mathbf{M}_1^T)))}$$
$$for\ i = 1, 2, \cdots, N$$
$$\mathbf{idx} = argtopk(\mathbf{A}[i,:])$$
$$\mathbf{A}[i, -\mathbf{idx}] = 0,$$



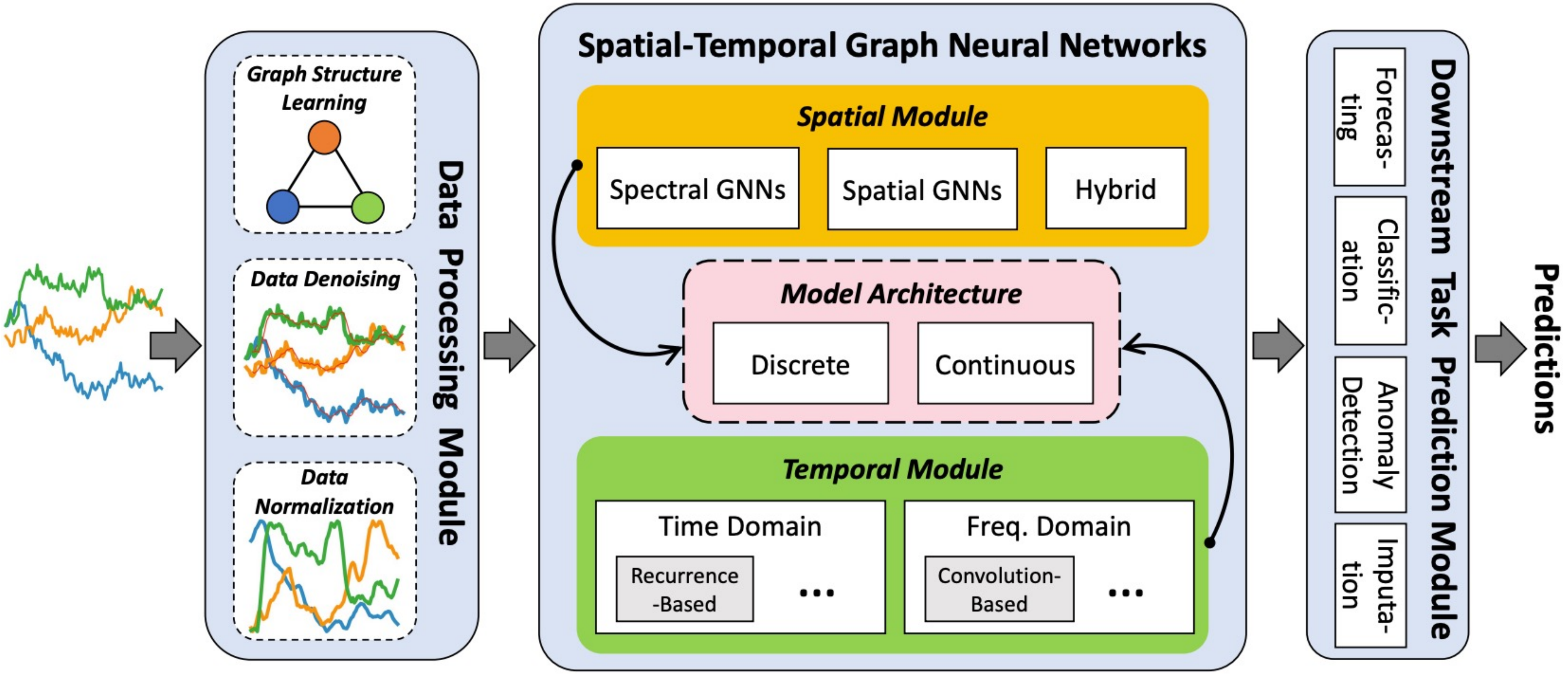
Embedding-based (e.g., MTGNN)

Sampling-based (e.g., GTS)

Shang, C., Chen, J., & Bi, J. (2021). Discrete graph structure learning for forecasting multiple time series. In ICLR

Wu, Z., Pan, S., Long, G., Jiang, J., Chang, X., & Zhang, C. (2020). Connecting the dots: Multivariate time series forecasting with graph neural networks. In KDD.

Outline of GNN4TS

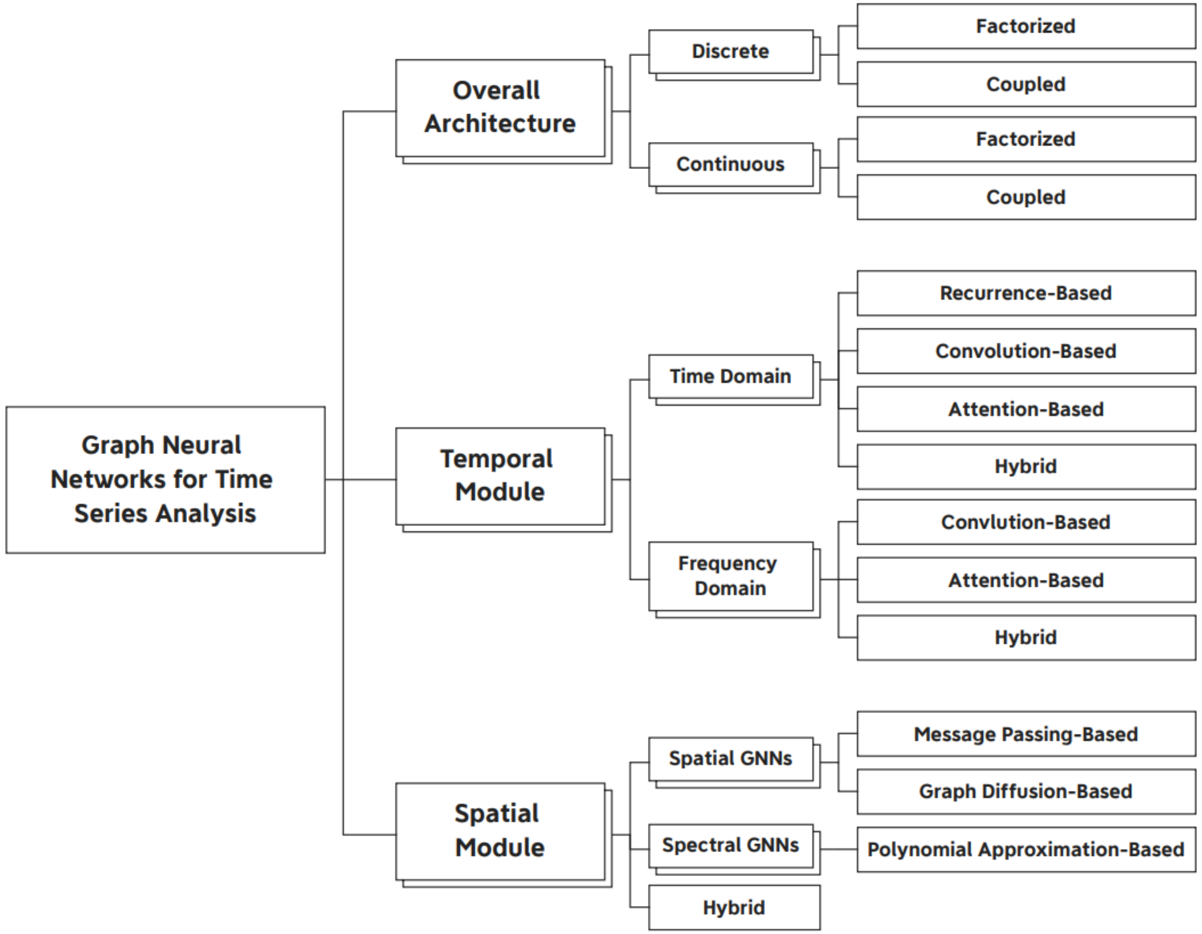


General pipeline for time series analysis using graph neural networks

Outline of GNN4TS

Task-oriented taxonomy of GNN4TS

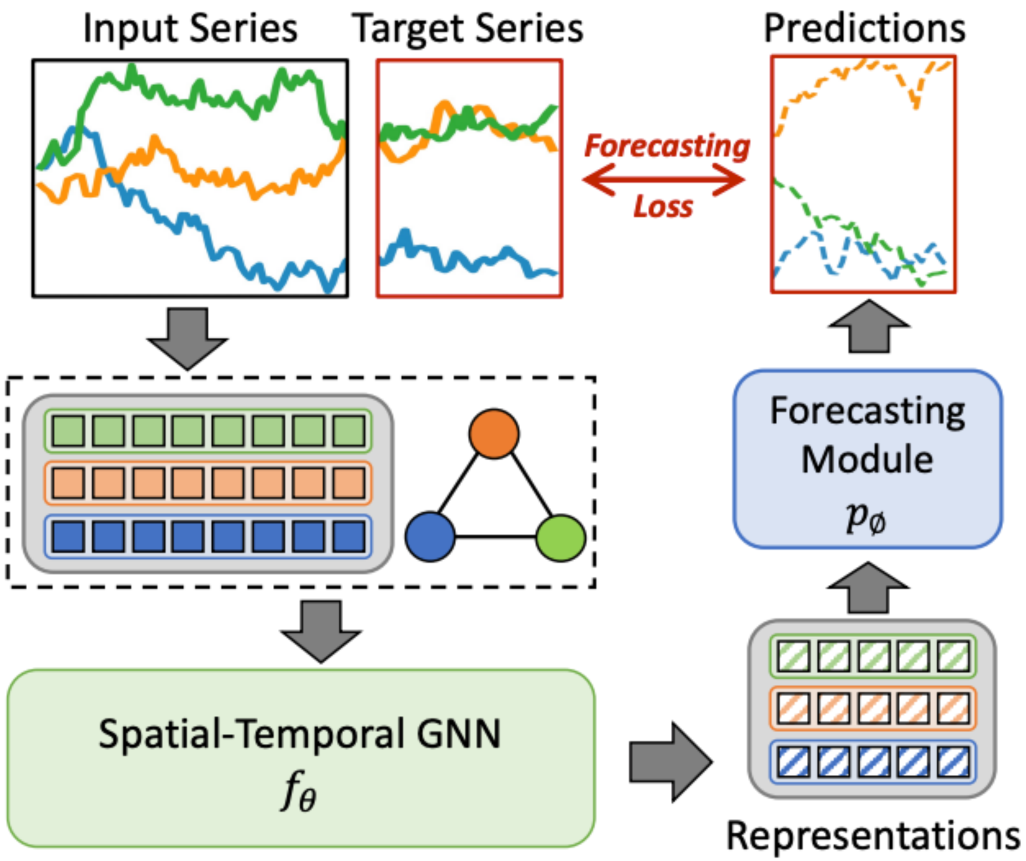
Methodology-oriented taxonomy of GNN4TS



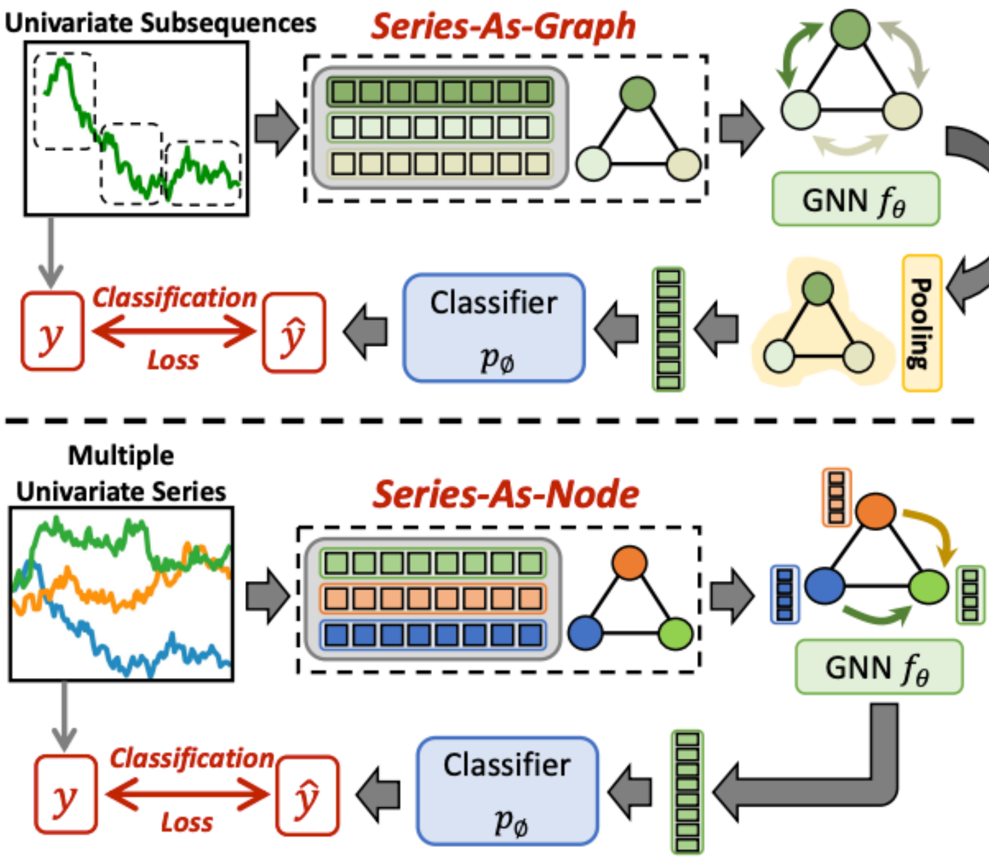
Part 2. GNNs for Time Series Analysis

- Time series analytical tasks: an overview
- Graph neural networks for time series analysis: 4 categories

Time Series Analysis

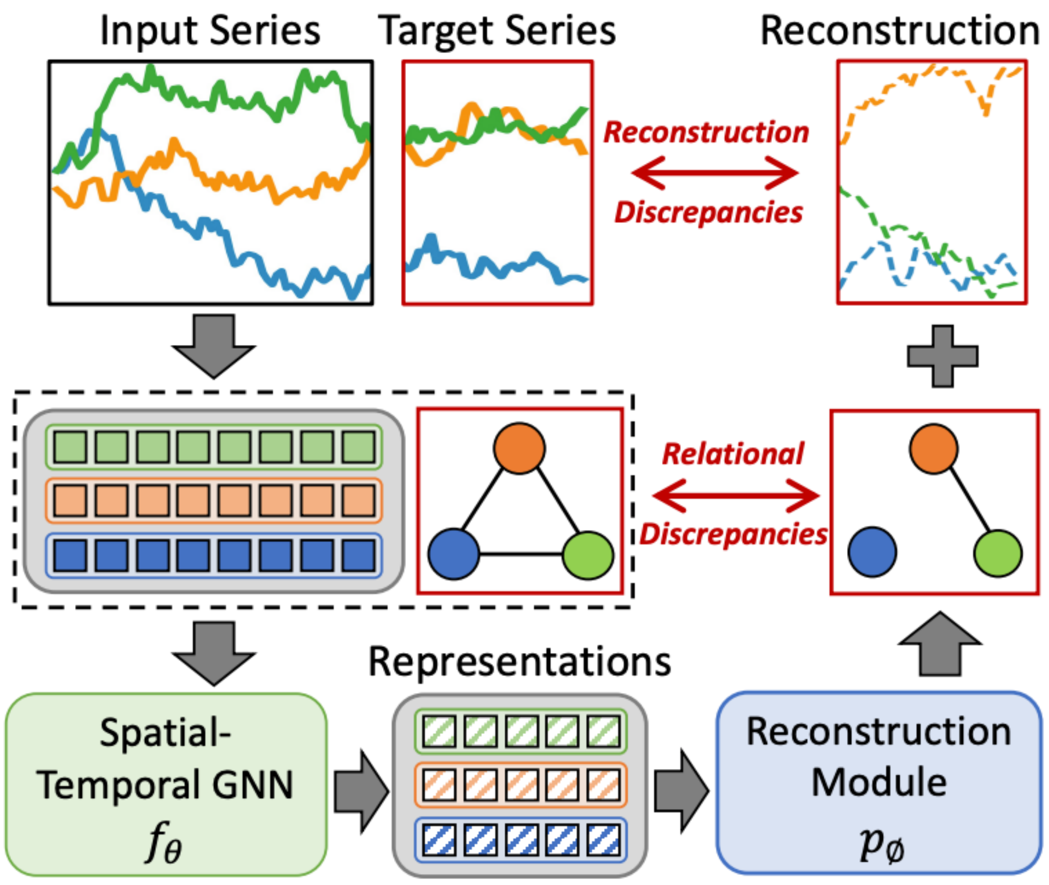


GNNs for time series forecasting

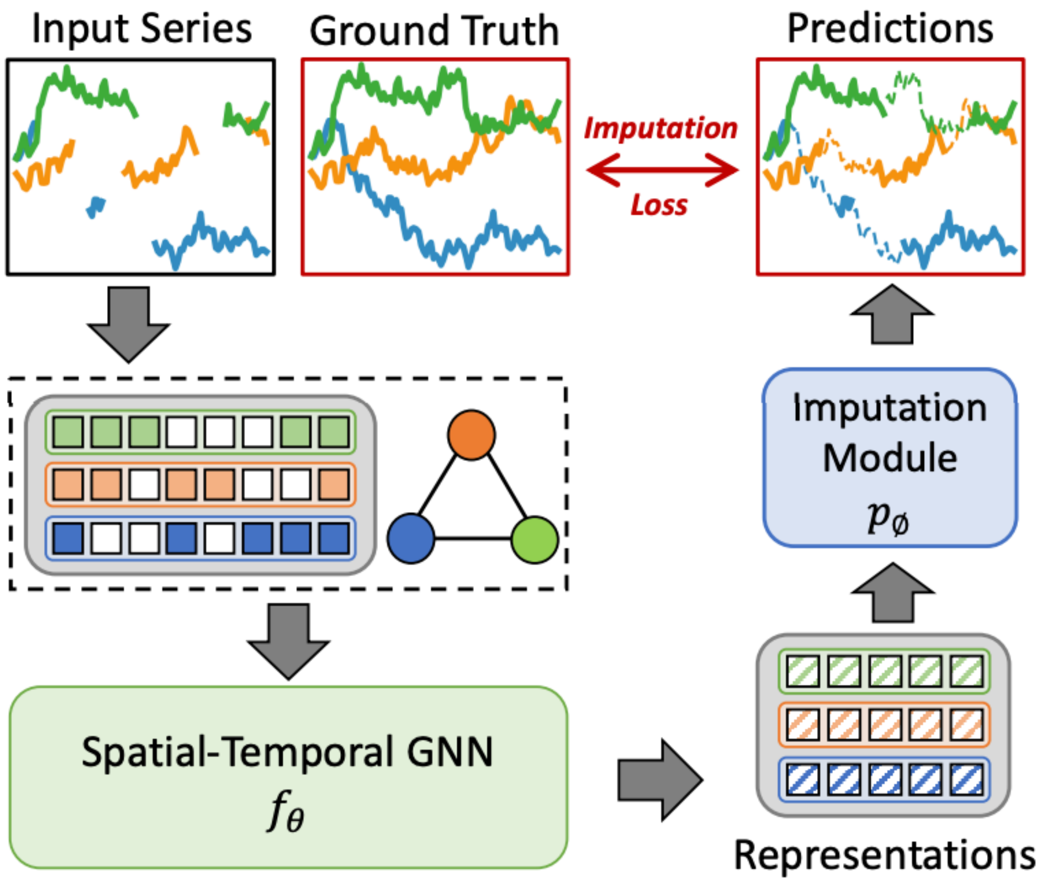


GNNs for time series classification

Time Series Analysis

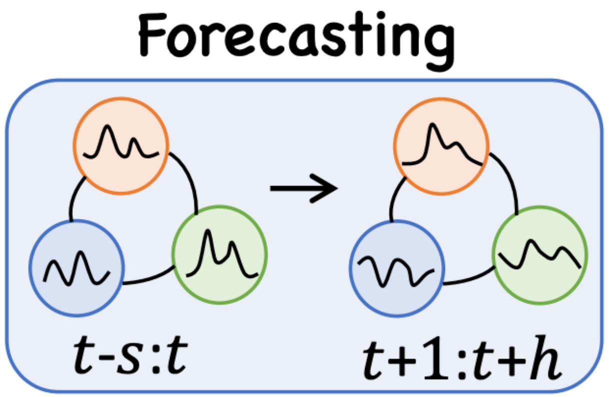


GNNs for time series anomaly detection



GNNs for time series imputation

GNNs for Time Series Forecasting



- **Modeling the inter-variable dependencies**
  - Spectral GNNs, spatial GNNs, or a hybrid of both
- **Modeling the inter-temporal dependencies**
  - In the time or/and frequency domains
  - Recurrent models, convolution models, attention models, or hybrid models
- **Forecasting architecture fusion**
  - Discrete and continuous neural architectures
  - Spatial and temporal modules can be factorized or coupled

GNNs for Time Series Forecasting

Approach	Year	Venue	Task	Architecture	Spatial Module	Temporal Module	Missing Values	Input Graph	Learned Relations	Graph Heuristics
DCRNN [71]	2018	ICLR	M-S	D-C	Spatial GNN	T-R	No	R	-	SP
STGCN [58]	2018	IJCAI	M-S	D-F	Spectral GNN	T-C	No	R	-	SP
ST-MetaNet [73]	2019	KDD	M-S	D-F	Spatial GNN	T-R	No	R	-	SP, PC
NGAR [74]	2019	IEEE IJCNN	S-S	D-F	Spatial GNN	T-R	No	R	-	-
ASTGCN [75]	2019	AAAI	M-S	D-F	Spectral GNN	T-H	No	R	-	SP, PC
ST-MGCN [46]	2019	AAAI	S-S	D-F	Spectral GNN	T-R	No	R	-	SP, PC, PS
Graph WaveNet [76]	2019	IJCAI	M-S	D-F	Spatial GNN	T-C	No	O	S	SP
MRA-BGCN [77]	2020	AAAI	M-S	D-C	Spatial GNN	T-R	No	R	-	SP
MTGNN [53]	2020	KDD	S-S, M-S	D-F	Spatial GNN	T-C	No	NR	S	-
STGNN* [78]	2020	WWW	M-S	D-C	Spatial GNN	T-H	No	R	-	SP
GMAN [79]	2020	AAAI	M-S	D-C	Spatial GNN	T-A	No	R	-	SP
SLCNN [80]	2020	AAAI	M-S	D-F	Hybrid	T-C	No	NR	S	-
STSGCN [81]	2020	AAAI	M-S	D-C	Spatial GNN	T	No	R	-	PC
StemGNN [54]	2020	NeurIPS	M-S	D-F	Spectral GNN	F-C	No	NR	S	-
AGCRN [82]	2020	NeurIPS	M-S	D-C	Spatial GNN	T-R	No	NR	S	-
LSGCN [83]	2020	IJCAI	M-S	D-F	Spectral GNN	T-C	No	R	-	SP
STAR [84]	2020	ECCV	M-S	D-F	Spatial GNN	T-A	No	R	-	PC
GTS [56]	2021	ICLR	M-S	D-C	Spatial GNN	T-R	No	NR	S	-
GEN [85]	2021	ICLR	S-S	D-F	Spatial GNN	T-R	No	R	-	-
Z-GCNETs [86]	2021	ICML	M-S	D-C	Spatial GNN	T-C	No	NR	S	-
STGODE [70]	2021	KDD	M-S	C-F	Spatial GNN	T-C	No	R	-	SP, PS
STFGNN [49]	2021	AAAI	M-S	D-F	Spatial GNN	T-C	No	R	-	SP, PS
DSTAGNN [87]	2022	ICML	M-S	D-F	Spectral GNN	T-H	No	R	-	PC, PS
TPGNN [88]	2022	NeurIPS	S-S, M-S	D-F	Spatial GNN	T-A	No	NR	D	-
MTGODE [23]	2022	IEEE TKDE	S-S, M-S	C-C	Spatial GNN	T-C	No	NR	S	-
STG-NCDE [89]	2022	AAAI	M-S	C-C	Spatial GNN	T-C	Yes	NR	S	-
STEP [90]	2022	KDD	M-S	D-F	Spatial GNN	T-A	No	NR	S	-
Chauhan et al. [91]	2022	KDD	M-S	-	-	-	Yes	O	S	SP
RGSL [92]	2022	IJCAI	M-S	D-C	Spectral GNN	T-R	No	R	S	SP, PC
FOGS [93]	2022	IJCAI	M-S	-	-	-	No	NR	S	-
METRO [94]	2022	VLDB	M-S	D-C	Spatial GNN	T	No	NR	D	-
SGP [95]	2023	AAAI	M-S	D-F	Spatial GNN	T-R	No	R	-	SP, PS
HiGP [96]	2023	arXiv	M-S	D-F	Spatial GNN	T-R	No	R	S	SP, PS
Jin et al. [29]	2023	arXiv	M-S, M-L	D-F	Spectral GNN	F-H	No	NR	S	-

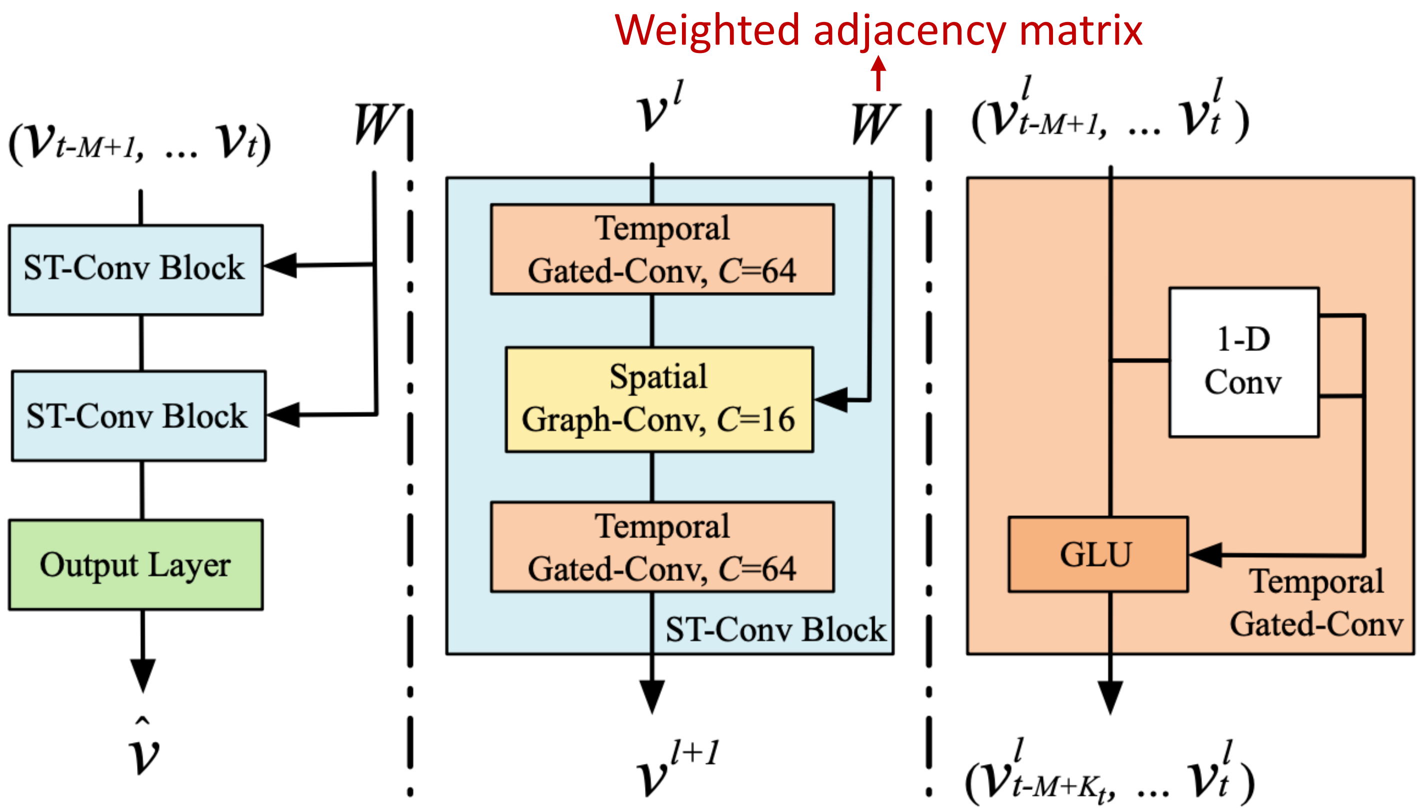
- **Task**: “S” and “L” denote short-term and long-term forecasting
- **Architecture**: “D” and “C” represent discrete and continuous; “C” and “F” stand for coupled and factorized
- **Temporal module**: “T” and “F” denote time and frequency domains; “R”, “C”, “A”, and “H” are recurrent, convolutional, attentional, and hybrid models
- **Input graph**: “R”, “O”, and “NR” stand for required, optional, and not required
- **Graph heuristics**: “SP”, “PC”, “PS”, and “FD” are spatial proximity, pairwise connectivity, pairwise similarity, and functional dependency

GNNs for Time Series Forecasting

- **Modeling the inter-variable dependencies**
  - Spectral GNNs (e.g., **StemGNN**) & Spatial GNNs (e.g., **DCRNN**)
- **Modeling the inter-temporal dependencies**
  - Time domain (e.g., DCRNN) & Frequency domain (e.g., StemGNN)
  - Recurrent models (e.g., DCRNN) & Convolution models (e.g., **STGCN**) & Attention models (e.g., **GMAN**)
- **Forecasting architecture fusion**
  - Discrete factorized (e.g., **MTGNN**) & Continuous coupled (e.g., **MTGODE**)

GNNs for Time Series Forecasting

- STGCN (Yu et al., 2018)

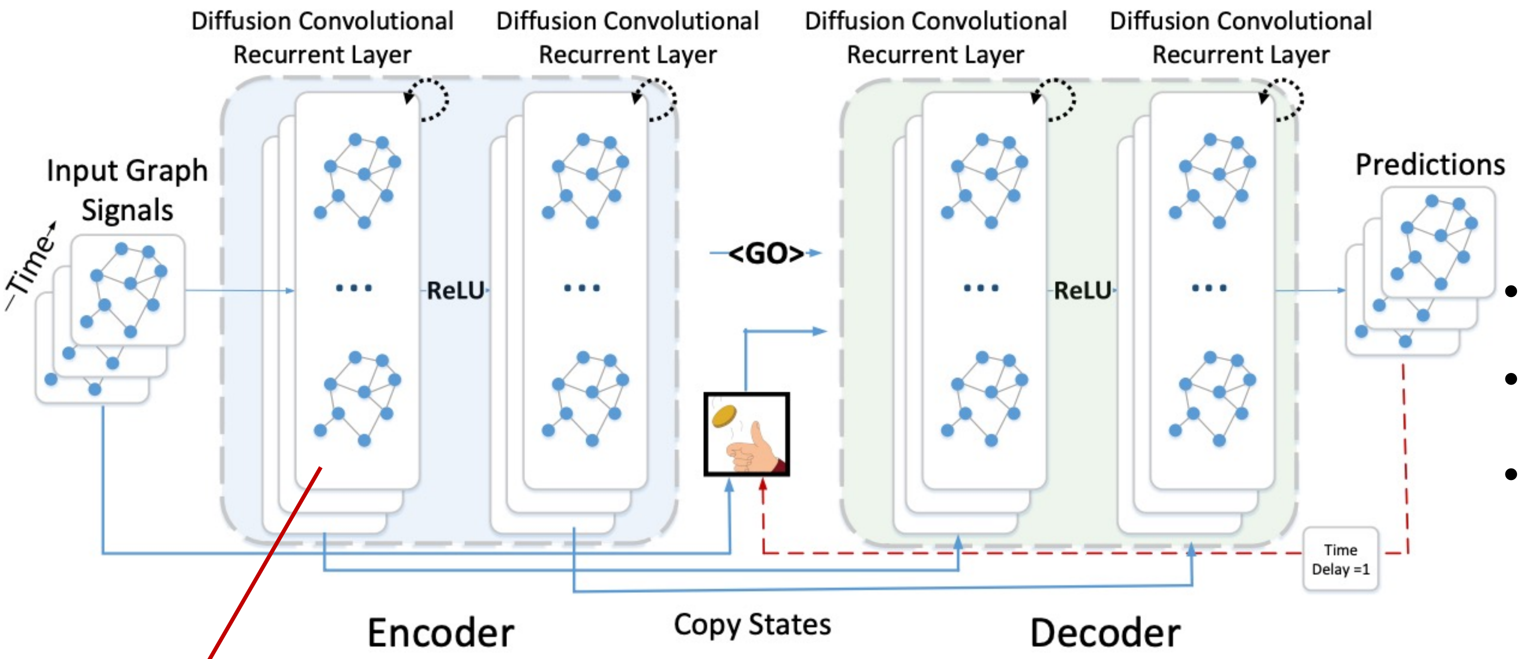


- **Model architecture:** discrete factorized
- **Spatial module:** ChebConv or GCN
- **Temporal module:** convolution-based

Yu, B., Yin, H., & Zhu, Z. (2018, July). Spatio-temporal graph convolutional networks: a deep learning framework for traffic forecasting. In Proceedings of the 27th International Joint Conference on Artificial Intelligence (pp. 3634-3640).

GNNs for Time Series Forecasting

- DCRNN (Li et al., 2018)



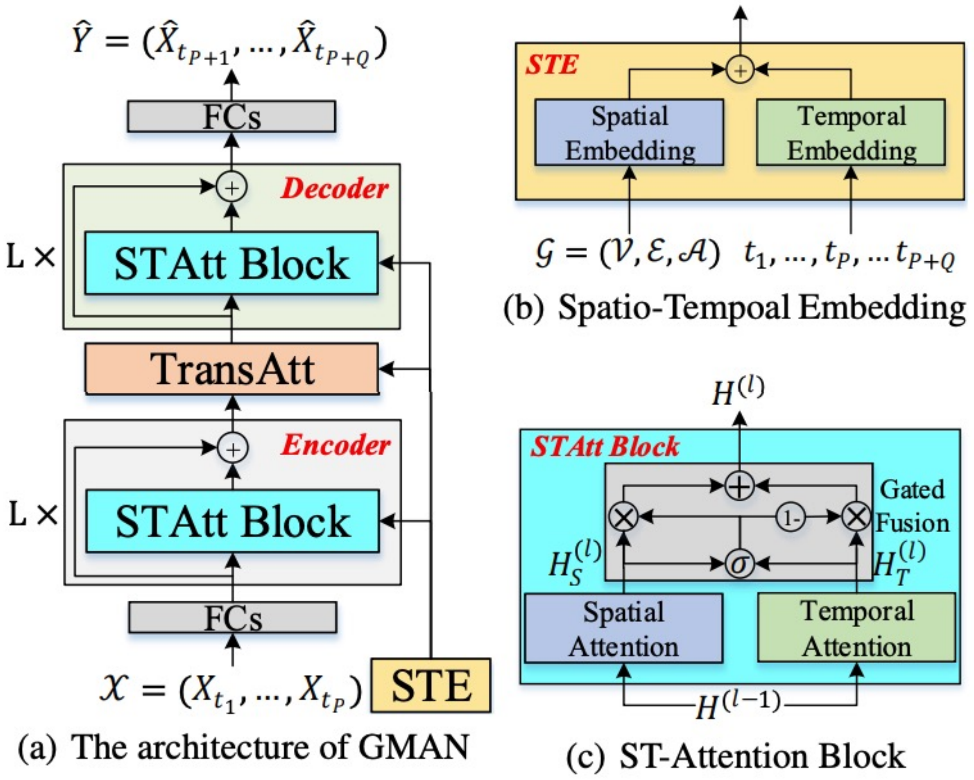
$$
\begin{aligned}
\boldsymbol{r}^{(t)} &= \sigma(\boldsymbol{\Theta}_r \boxed{\star_{\mathcal{G}}} [\boldsymbol{X}^{(t)},\ \boldsymbol{H}^{(t-1)}] + \boldsymbol{b}_r) & \boldsymbol{u}^{(t)} &= \sigma(\boldsymbol{\Theta}_u \boxed{\star_{\mathcal{G}}} [\boldsymbol{X}^{(t)},\ \boldsymbol{H}^{(t-1)}] + \boldsymbol{b}_u) \\
\boldsymbol{C}^{(t)} &= \tanh(\boldsymbol{\Theta}_C \boxed{\star_{\mathcal{G}}} [\boldsymbol{X}^{(t)},\ (\boldsymbol{r}^{(t)} \odot \boldsymbol{H}^{(t-1)})] + \boldsymbol{b}_c) & \boldsymbol{H}^{(t)} &= \boldsymbol{u}^{(t)} \odot \boldsymbol{H}^{(t-1)} + (1 - \boldsymbol{u}^{(t)}) \odot \boldsymbol{C}^{(t)}
\end{aligned}
$$

- **Model architecture:** discrete coupled
- **Spatial module:** graph diffusion
- **Temporal module:** recurrent-based

Li, Y., Yu, R., Shahabi, C., & Liu, Y. (2018, February). Diffusion Convolutional Recurrent Neural Network: Data-Driven Traffic Forecasting. In International Conference on Learning Representations.

GNNs for Time Series Forecasting

- GMAN (Zheng et al., 2020)



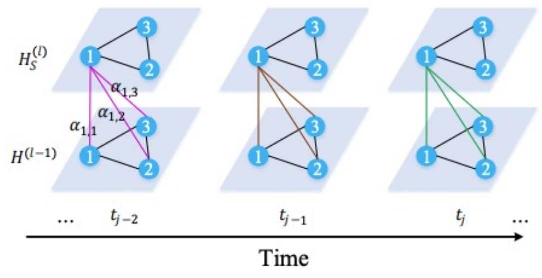


Figure 3: The spatial attention mechanism captures time-variant pair-wise correlations between vertices.

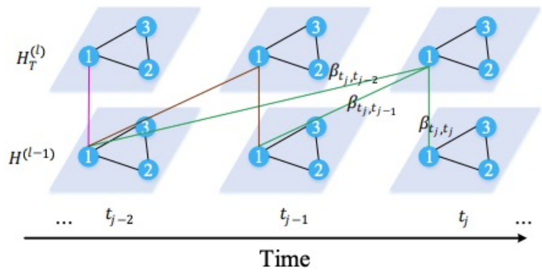


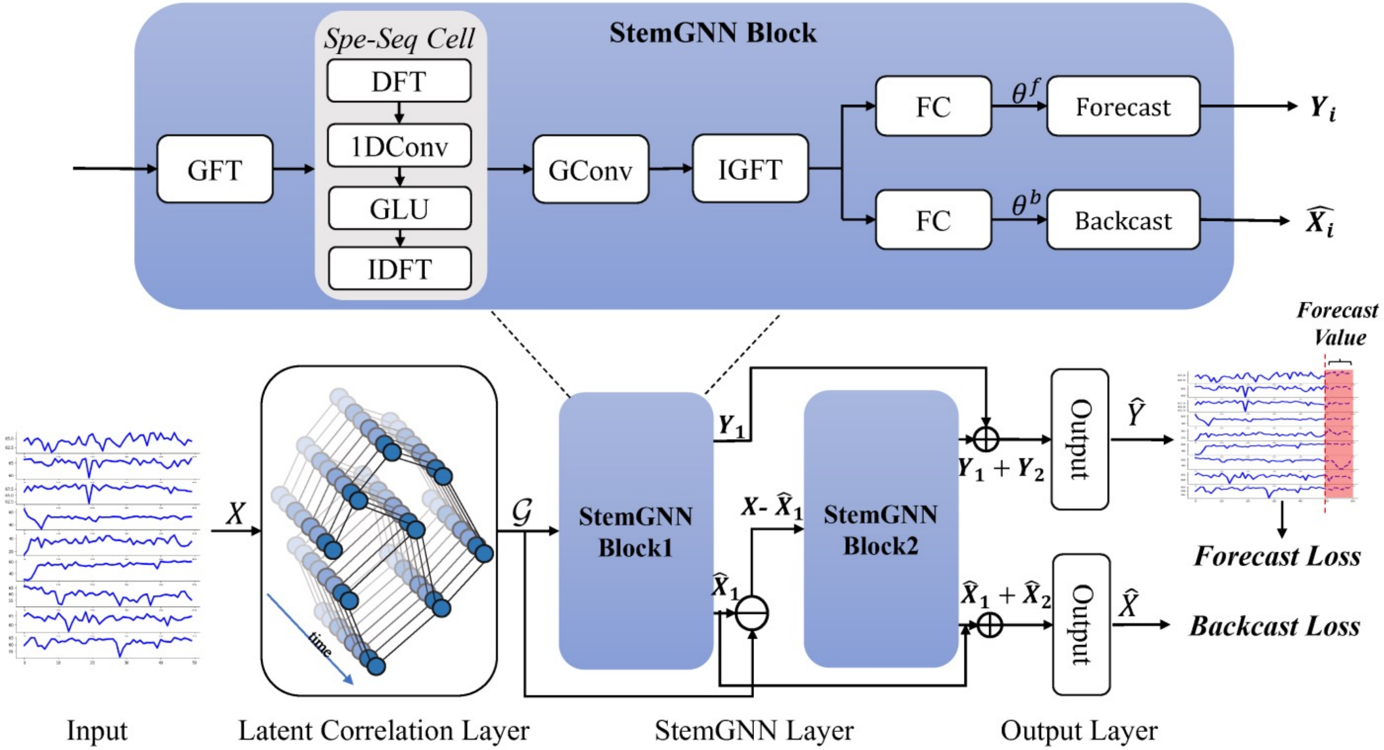
Figure 5: The temporal attention mechanism models the non-linear correlations between different time steps.

- **Model architecture:** discrete coupled
- **Spatial module:** GAT
- **Temporal module:** attention-based

Zheng, C., Fan, X., Wang, C., & Qi, J. (2020, April). Gman: A graph multi-attention network for traffic prediction. In Proceedings of the AAAI conference on artificial intelligence (Vol. 34, No. 01, pp. 1234-1241).

GNNs for Time Series Forecasting

- StemGNN (Cao et al., 2020)

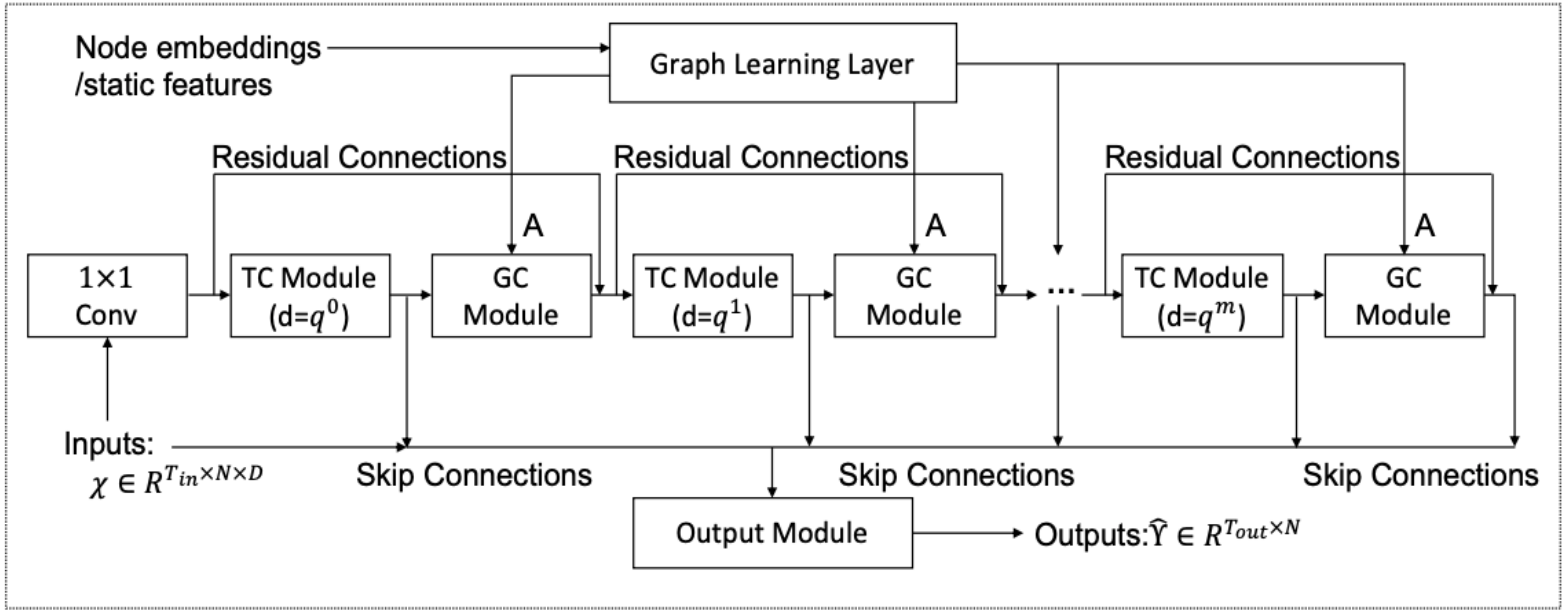


- **Model architecture:** discrete factorized
- **Spatial module:** ChebConv
- **Temporal module:** convolution-based but in the frequency domain

Cao, D., Wang, Y., Duan, J., Zhang, C., Zhu, X., Huang, C., ... & Zhang, Q. (2020). Spectral temporal graph neural network for multivariate time-series forecasting. Advances in neural information processing systems, 33, 17766-17778.

GNNs for Time Series Forecasting

- MTGNN (Wu et al., 2020)

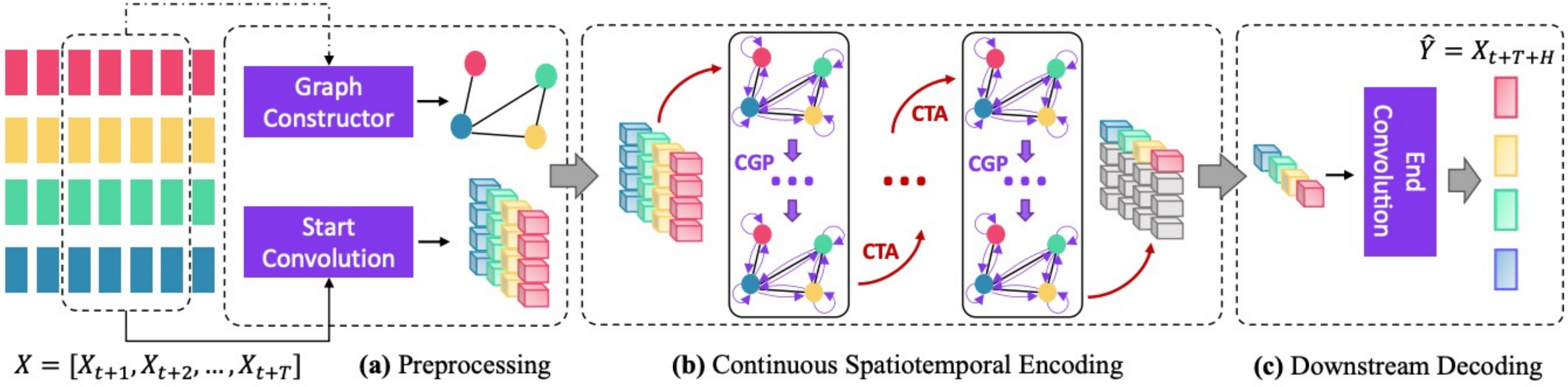


- **Model architecture:** discrete factorized
- **Spatial module:** mix-hop MPNN
- **Temporal module:** convolution-based

Wu, Z., Pan, S., Long, G., Jiang, J., Chang, X., & Zhang, C. (2020, August). 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 (pp. 753-763).

GNNs for Time Series Forecasting

- MTGODE (Jin et al., 2022)

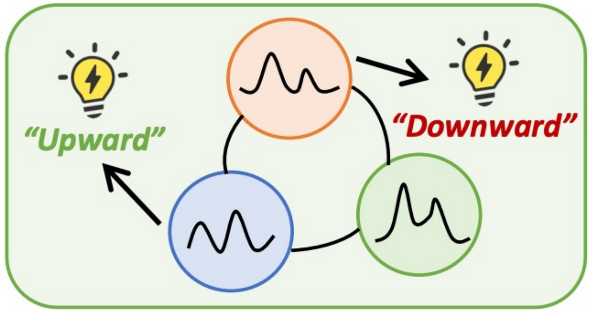


- **Model architecture:** continuous coupled
- **Spatial module:** GDEs
- **Temporal module:** TDEs

Jin, M., Zheng, Y., Li, Y. F., Chen, S., Yang, B., & Pan, S. (2022). Multivariate time series forecasting with dynamic graph neural odes. IEEE Transactions on Knowledge and Data Engineering.

GNNs for Time Series Classification

- **Univariate time series classification**
  - *Series-as-Graph*: the core idea is to transform a univariate time series into a graph to identify unique patterns
  - *Series-as-Node*: each time series sample in a given dataset can be viewed as a node to construct a data graph
- **Multivariate time series classification**
  - This branch of methods maintains fundamental similarities with its univariate counterpart
  - However, it introduces an additional layer of complexity: the necessity to capture the inter-variable dependencies



Classification

GNNs for Time Series Classification

Approach	Year	Venue	Task	Conversion	Spatial Module	Temporal Module	Missing Values	Input Graph	Learned Relations	Graph Heuristics
MTPool [171]	2021	NN	M	-	Spatial GNN	T-C	No	NR	S	-
Time2Graph+ [64]	2021	IEEE TKDE	U	Series-As-Graph	Spatial GNN	-	No	R	-	PS
RainDrop [37]	2022	ICLR	M	-	Spatial GNN	T-A	Yes	NR	S	-
SimTSC [65]	2022	SDM	U+M	Series-As-Node	Spatial GNN	T-C	No	R	-	PS
LB-SimTSC [66]	2023	arXiv	U+M	Series-As-Node	Spatial GNN	T-C	No	R	-	PS
TodyNet [172]	2023	arXiv	M	-	Spatial GNN	T-C	No	NR	D	-

- **Task**: “M” and “U” denote univariate and multivariate time series classification
- **Temporal module**: “T” and “F” denote time and frequency domains; “R”, “C”, “A”, and “H” are recurrent, convolutional, attentional, and hybrid models
- **Input graph**: “R”, “O”, and “NR” stand for required, optional, and not required
- **Learned relations**: “S” and “D” denote static and dynamic graph structures
- **Graph heuristics**: “SP”, “PC”, “PS”, and “FD” are spatial proximity, pairwise connectivity, pairwise similarity, and functional dependency

GNNs for Time Series Classification

- Time2Graph+ (Cheng et al., 2021)

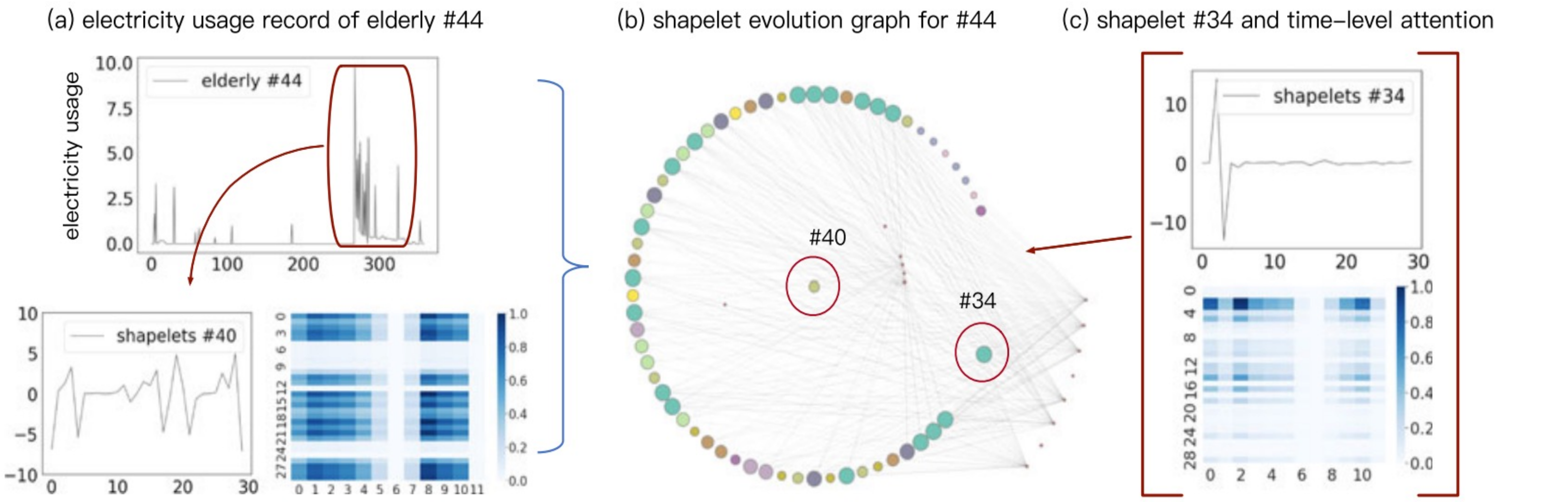


Fig. 1. Illustration of *Time2Graph+* framework in the scenario of user electricity consuming. (a) shows a one-year electricity consumption of an empty-nest elderly user, along with the assigned shapelet #40. After time-aware shapelets being extracted, it constructs the shapelet graph for each single sequence, and captures the evolutionary patterns of shapelets using graph attention networks (b), and (c) visualizes one typical shapelet #34 and its time-level attentions. Note that in (b), the node size is proportional to its in-degree, from which the node color is mapped; and the edge width is proportional to the attention score between two nodes.

- Each time series is transformed into a graph where shapelets form nodes and transition probabilities create edges
- GAT is then leveraged along with a graph pooling operation to derive the global representation of the time series

Cheng, Z., Yang, Y., Jiang, S., Hu, W., Ying, Z., Chai, Z., & Wang, C. (2021). Time2Graph+: Bridging time series and graph representation learning via multiple attentions. IEEE Transactions on Knowledge and Data Engineering.

GNNs for Time Series Classification

- SimTSC (Zha et al., 2022)

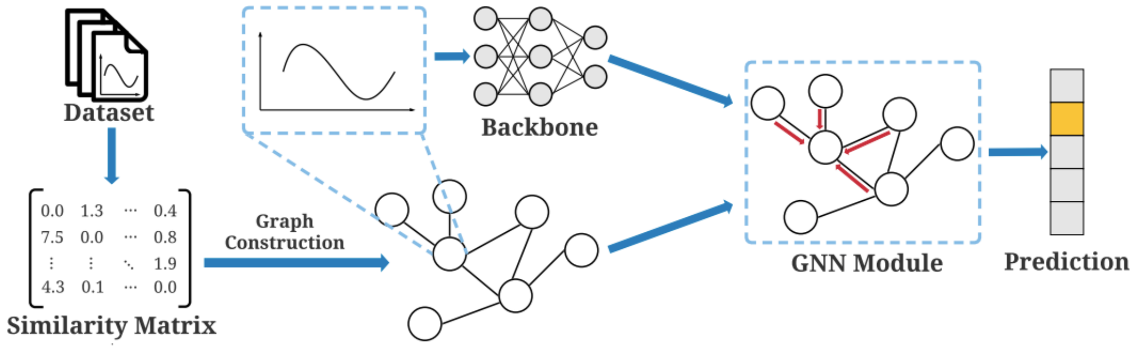


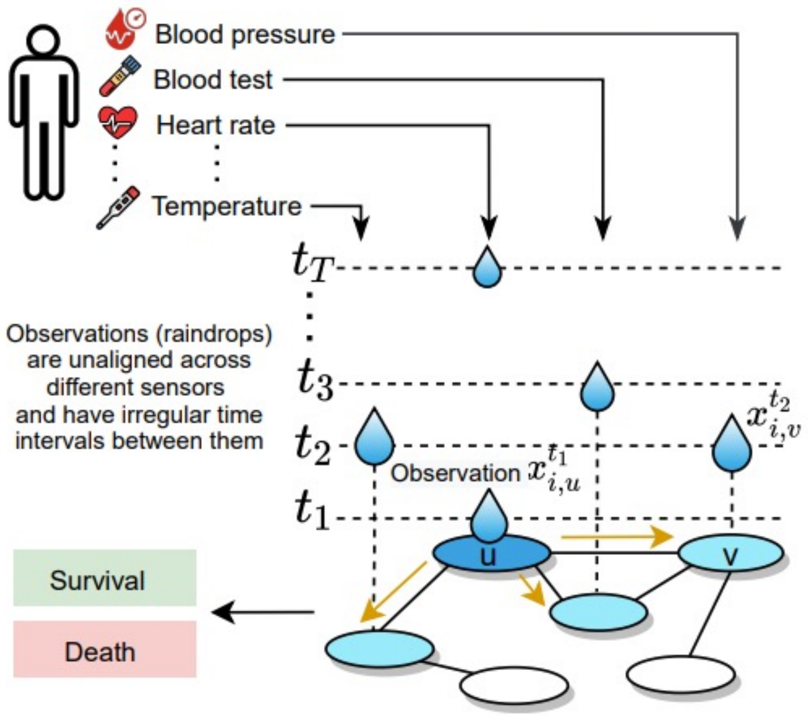
Figure 2: An overview of SimTSC framework. The graph is constructed based on the pair-wise similarities (e.g., DTW distances) of the time-series. Each time-series is processed by a backbone (e.g., ResNet) for feature extraction. The GNN module will aggregate the features and produce the final representations for classification.

- Time series nodes are connected using edges, which are defined by their pairwise DTW distance, to construct a graph
- A backbone network is initially employed to encode each time series into a feature vector
- Subsequently, a standard GNN operation is implemented to derive node (time series) representations, capturing the similarities between the series, for better classification

Zha, D., Lai, K. H., Zhou, K., & Hu, X. (2022). Towards similarity-aware time-series classification. In Proceedings of the 2022 SIAM International Conference on Data Mining (SDM) (pp. 199-207). Society for Industrial and Applied Mathematics.

GNNs for Time Series Classification

- RainDrop (Zhang et al., 2021)



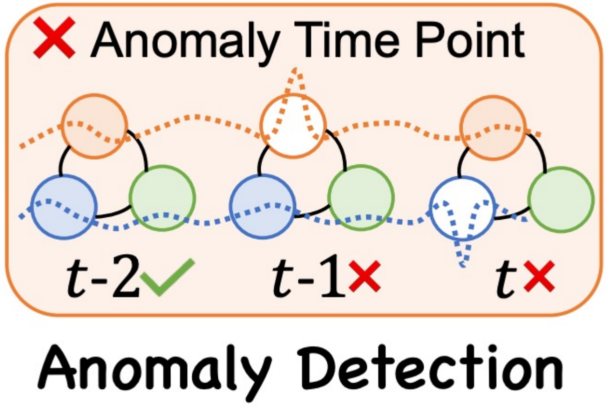
- To classify irregularly sampled multivariate time series where subsets of variables have missing values at certain timestamps, Raindrop adaptively learns a “sensor graph”

- It then dynamically interpolates missing observations within the embedding space, based on any available recorded data

Zhang, X., Zeman, M., Tsiligkaridis, T., & Zitnik, M. (2021, October). Graph-Guided Network for Irregularly Sampled Multivariate Time Series. In *International Conference on Learning Representations*.

GNNs for Time Series Anomaly Detection

- **Discrepancy framework for anomaly detection**
  - *Reconstrction discrepancy*: the reconstructed error should be low during normal periods, but high during anomalous periods
  - *Forecast discrepancy*: the forecast error should be low during normal periods, but high during anomalous periods. Here the backbone is substituted with a GNN forecaster that is trained to predict a one-step-ahead forecast
  - *Relational discrepancy*: the relationship between variables (e.g., each time series) should exhibit significant shifts from normal to anomalous periods
  - *Hybrid and other discrepancy*



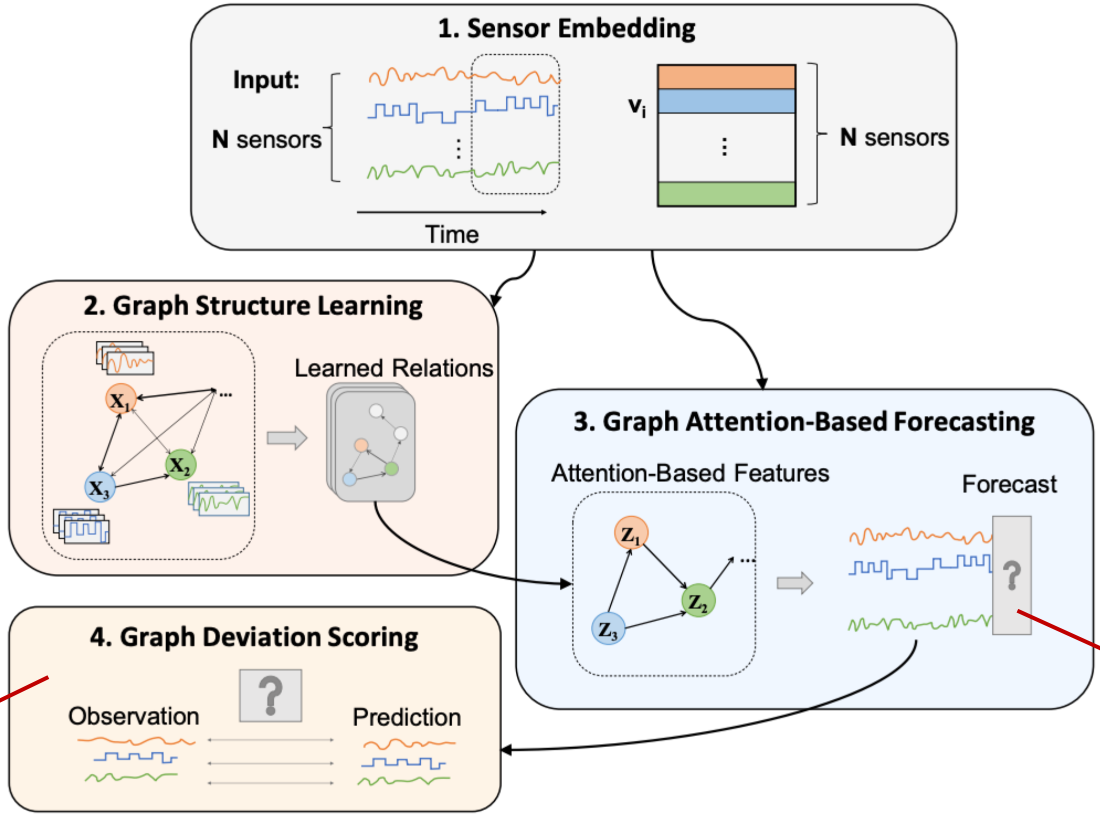
GNNs for Time Series Anomaly Detection

Approach	Year	Venue	Strategy	Spatial Module	Temporal Module	Missing Values	Input Graph	Learned Relations	Graph Heuristics
CCM-CDT [52]	2019	IEEE TNNLS	RC	Spatial GNN	T-R	No	R	-	PC, FD
MTAD-GAT [39]	2020	IEEE ICDM	FC+RC	Spatial GNN	T-A	No	NR	-	-
GDN [40]	2021	AAAI	FC	Spatial GNN	-	No	NR	S	-
GTA [147]	2021	IEEE IoT	FC	Spatial GNN	T-H	No	NR	S	-
EvoNet [148]	2021	WSDM	CL	Spatial GNN	T-R	No	R	-	PS
Event2Graph [149]	2021	arXiv	RL	Spatial GNN	T-A	No	R	-	PS
GANF [61]	2022	ICLR	RC+RL	Spatial GNN	T-R	No	NR	S	-
Grelen [150]	2022	IJCAI	RC+RL	Spatial GNN	T-H	No	NR	D	-
VGCRN [151]	2022	ICML	FC+RC	Spatial GNN	T-R	No	NR	S	-
FuSAGNet [60]	2022	KDD	FC+RC	Spatial GNN	T-R	No	NR	S	-
GTAD [152]	2022	Entropy	FC+RC	Spatial GNN	T-C	No	NR	-	-
HgAD [153]	2022	IEEE BigData	FC	Spatial GNN	-	No	NR	S	
HAD-MDGAT [154]	2022	IEEE Access	FC+RC	Spatial GNN	T-A	No	NR	-	-
STGAN [154]	2022	IEEE TNNLS	RC	Spatial GNN	T-R	No	R	-	SP
GIF [155]	2022	IEEE IJCNN	RC	Spatial GNN	-	No	R	-	SP, PC, FD
DyGraphAD [156]	2023	arXiv	FC+RL	Spatial GNN	T-C	No	R	-	PS
GraphSAD [157]	2023	arXiv	CL	Spatial GNN	T-C	No	R	-	PS, PC
CST-GL [158]	2023	arXiv	FC	Spatial GNN	T-C	No	NR	S	-

- **Strategy**: “RC”, “FC”, “RL”, and “CL” indicate the reconstruction, forecast, relational, and class discrepancies

GNNs for Time Series Anomaly Detection

- GDN (Deng & Hooi, 2021)



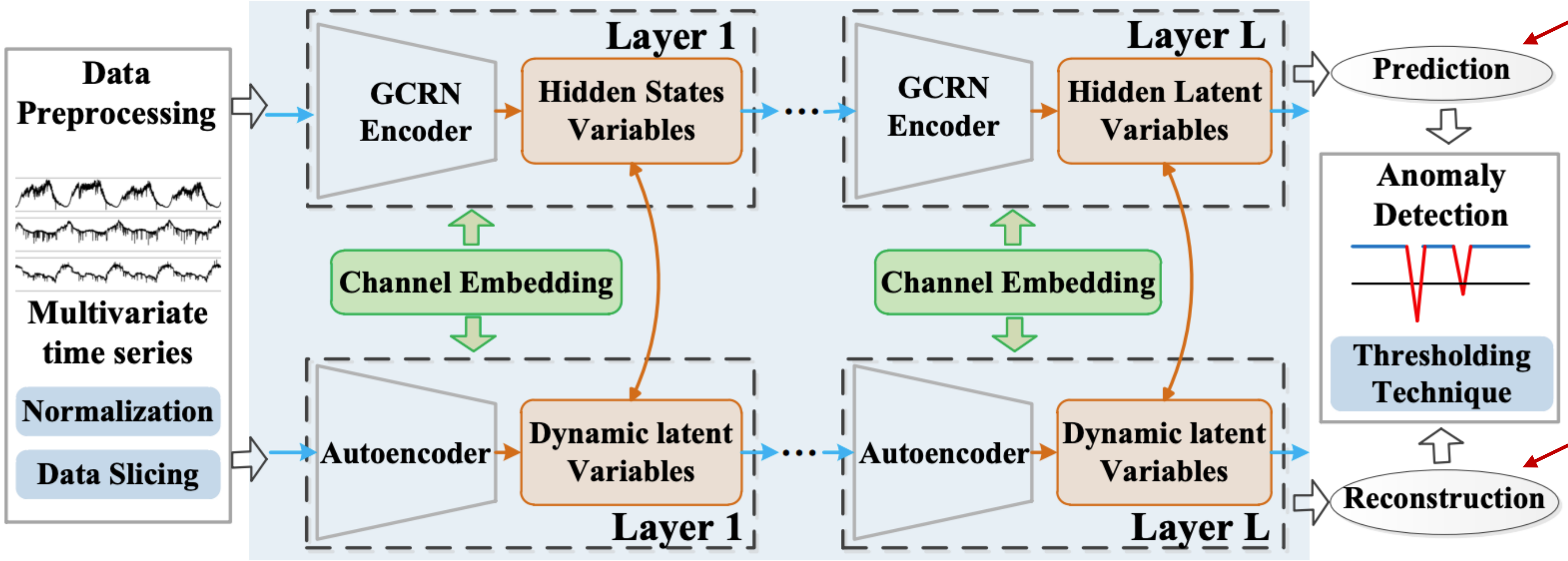
Forecast discrepancy

One-step-ahead forecasting

Deng, A., & Hooi, B. (2021, May). Graph neural network-based anomaly detection in multivariate time series. In Proceedings of the AAAI conference on artificial intelligence (Vol. 35, No. 5, pp. 4027-4035).

GNNs for Time Series Anomaly Detection

- VGCRN (Chen et al., 2022)



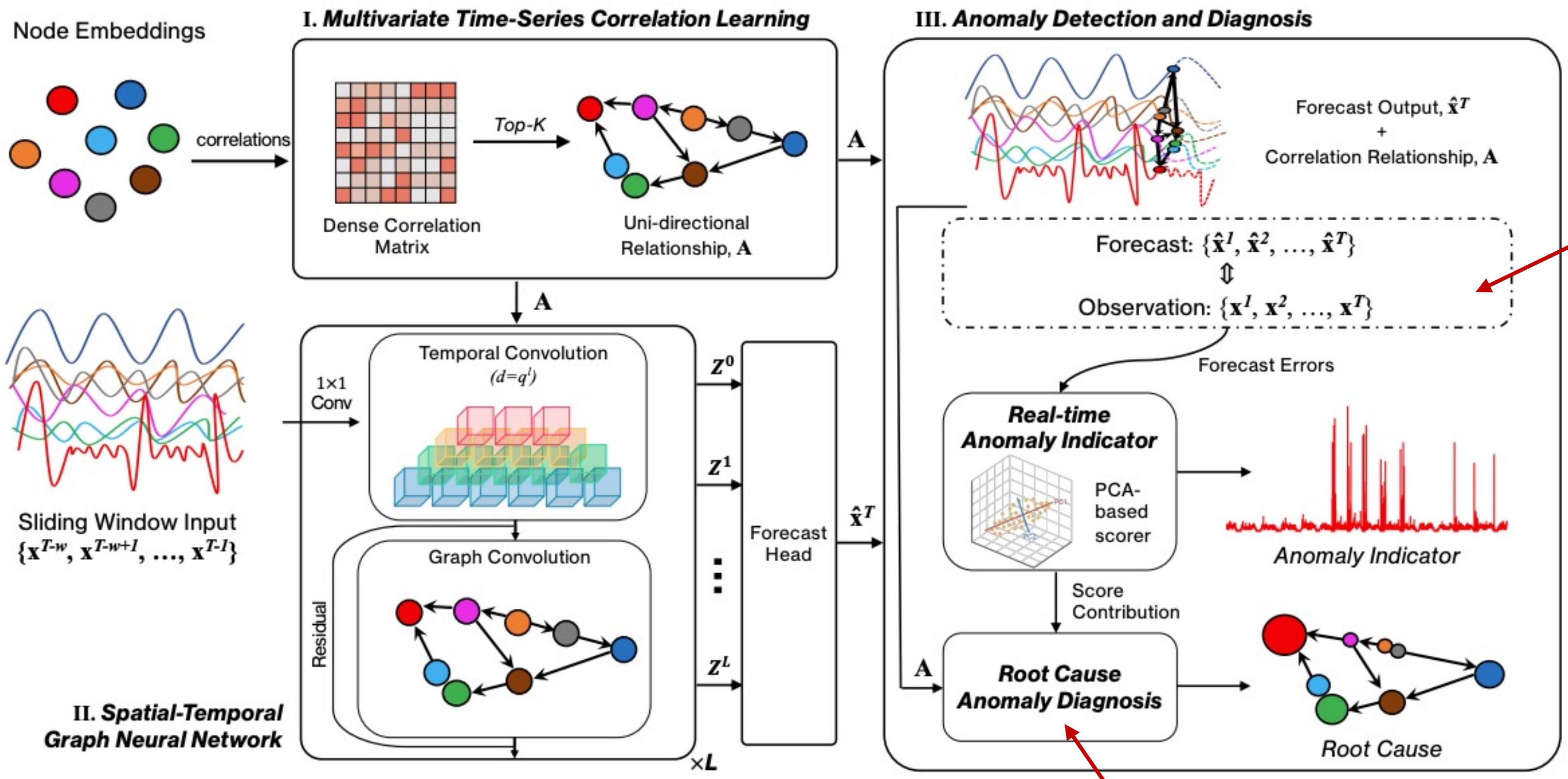
Forecast discrepancy

Reconstruct discrepancy

Chen, W., Tian, L., Chen, B., Dai, L., Duan, Z., & Zhou, M. (2022, June). Deep variational graph convolutional recurrent network for multivariate time series anomaly detection. In International Conference on Machine Learning (pp. 3621-3633). PMLR.

GNNs for Time Series Anomaly Detection

- CST-GL (Zheng et al., 2023)



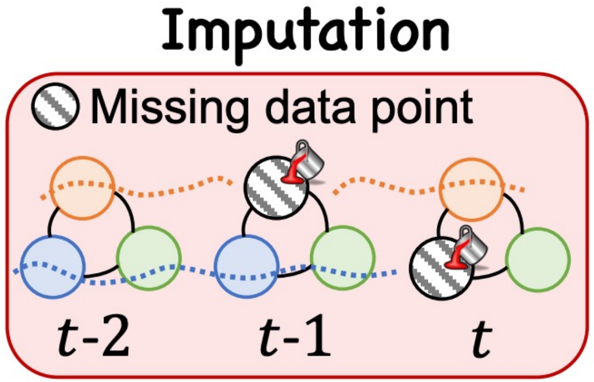
Forecast discrepancy

Detection interpretation

Zheng, Y., Koh, H. Y., Jin, M., Chi, L., Phan, K. T., Pan, S., ... & Xiang, W. (2023). Correlation-aware Spatial-Temporal Graph Learning for Multivariate Time-series Anomaly Detection. arXiv preprint arXiv:2307.08390.

GNNs for Time Series Imputation

- **Task categorization**
  - *In-sample imputation:* this involves filling in missing values within the given time series data
  - *Out-of-sample imputation:* this predicts missing values in disjoint sequences



- **Methodology categorization**
  - *Deterministic imputation*: this provides a single best estimate for the missing values
  - *Probabilistic imputation*: this accounts for the uncertainty in the imputation and provides a distribution of possible values

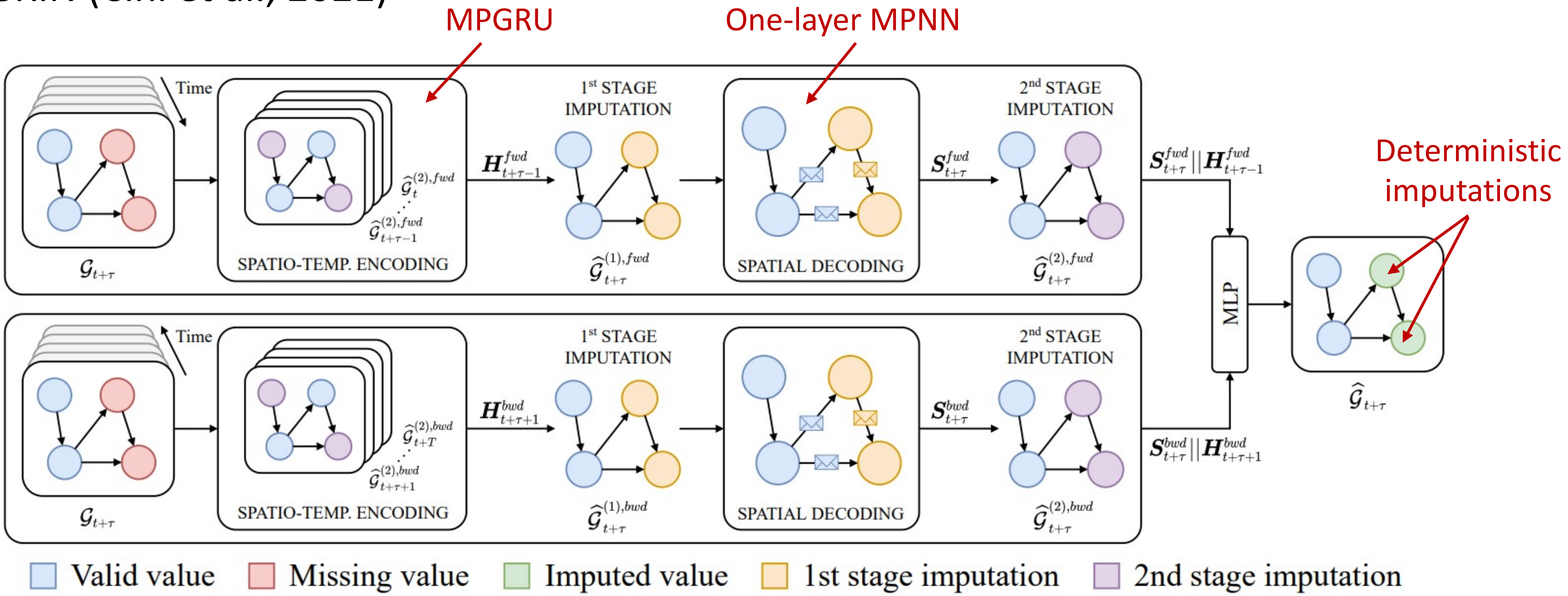
GNNs for Time Series Imputation

Approach	Year	Venue	Task	Type	Spatial Module	Temporal Module	Inductiveness	Input Graph	Learned Relations	Graph Heuristics
IGNNK [187]	2021	AAAI	Out-of-sample	Deterministic	Spectral GNN	-	Yes	R	-	SP, PC
GACN [188]	2021	ICANN	In-sample	Deterministic	Spatial GNN	T-C	No	R	-	PC
SATCN [189]	2021	arXiv	Out-of-sample	Deterministic	Spatial GNN	T-C	Yes	R	-	SP
GRIN [41]	2022	ICLR	Both	Deterministic	Spatial GNN	T-R	Yes	R	-	SP
SPIN [190]	2022	NIPS	In-sample	Deterministic	Spatial GNN	T-A	No	R	-	SP
FUNS [191]	2022	ICDMW	Out-of-sample	Deterministic	Spatial GNN	T-R	Yes	R	-	-
AGRN [192]	2022	ICONIP	In-sample	Deterministic	Spatial GNN	T-R	No	NR	S	-
MATCN [193]	2022	IEEE IoT-J	In-sample	Deterministic	Spatial GNN	T-A	No	R	-	-
PriSTI [42]	2023	arXiv	In-sample	Probabilistic	Spatial GNN	T-A	No	R	-	SP
DGCRIN [194]	2023	KBS	In-sample	Deterministic	Spatial GNN	T-R	No	NR	D	-
GARNN [195]	2023	Neurocomputing	In-sample	Deterministic	Spatial GNN	T-R	No	R	-	PC
MDGCN [196]	2023	Transp. Res. Part C	In-sample	Deterministic	Spatial GNN	T-R	No	R	-	SP, PS

- **Inductiveness**: this indicates whether a method can generalize to unseen nodes

GNNs for Time Series Anomaly Detection

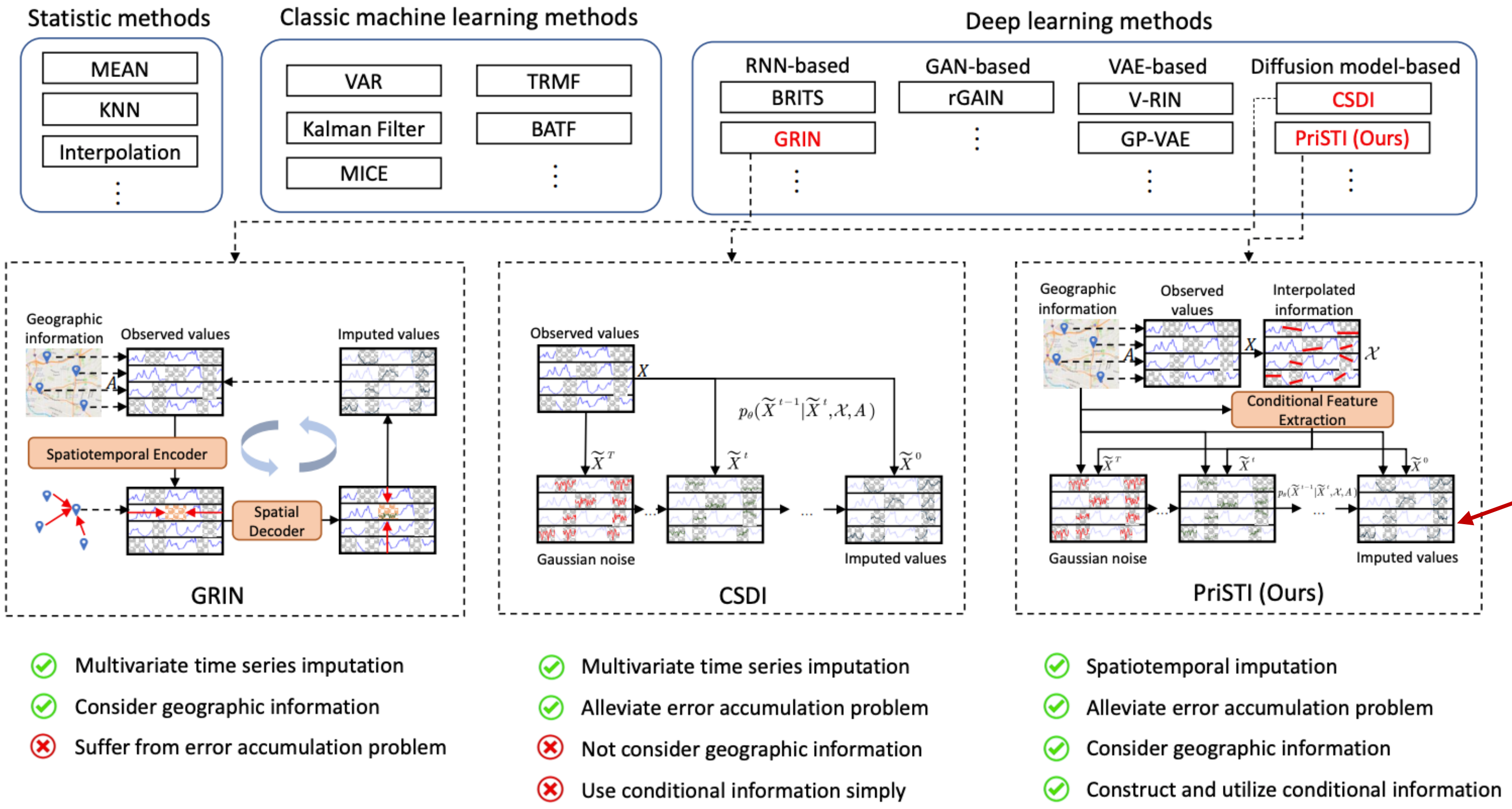
- GRIN (Cini et al., 2021)



Cini, A., Marisca, I., & Alippi, C. (2021). Filling the g_ap_s: Multivariate time series imputation by graph neural networks. arXiv preprint arXiv:2108.00298.

GNNs for Time Series Anomaly Detection

- PriSTI (Liu et al., 2023)



- PriSTI leverages the diffusion model for spatio-temporal imputation

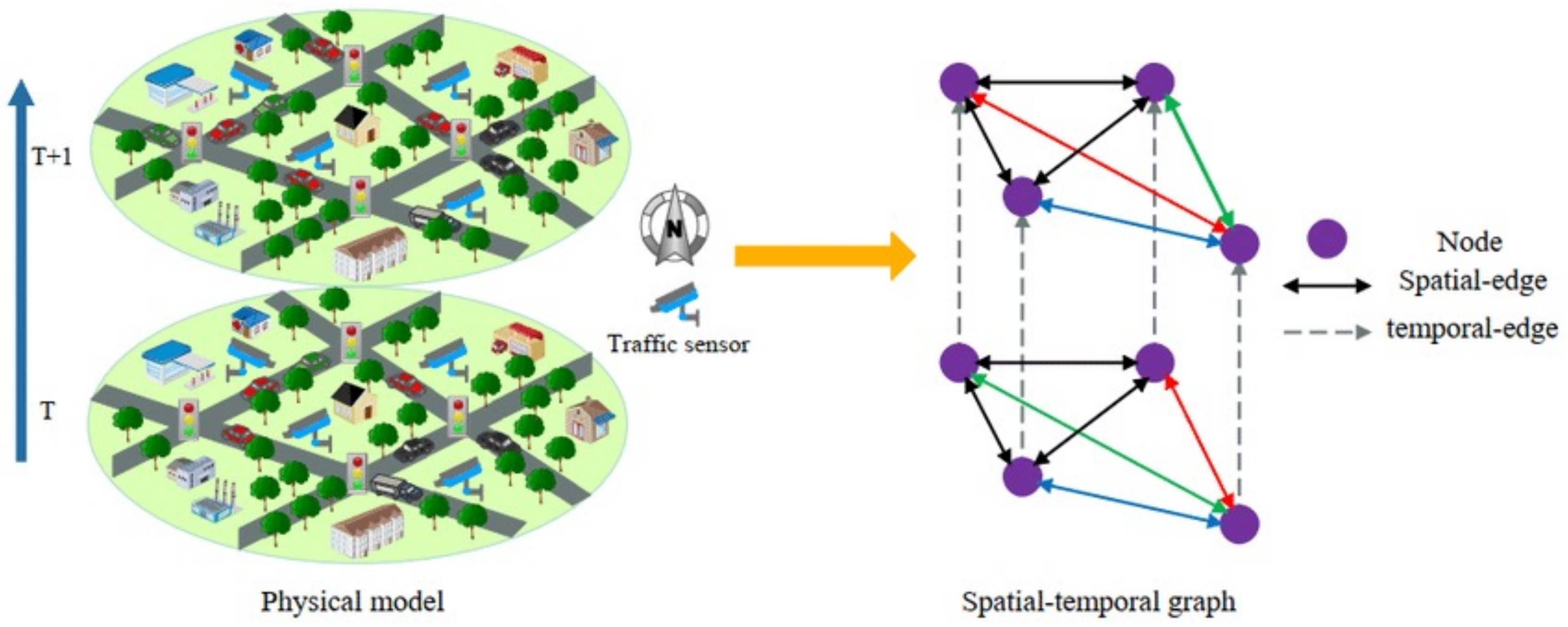
Probabilistic imputations

Liu, M., Huang, H., Feng, H., Sun, L., Du, B., & Fu, Y. (2023). PriSTI: A Conditional Diffusion Framework for Spatiotemporal Imputation. arXiv preprint arXiv:2302.09746.

Part 3. Applications & Future Directions

Applications

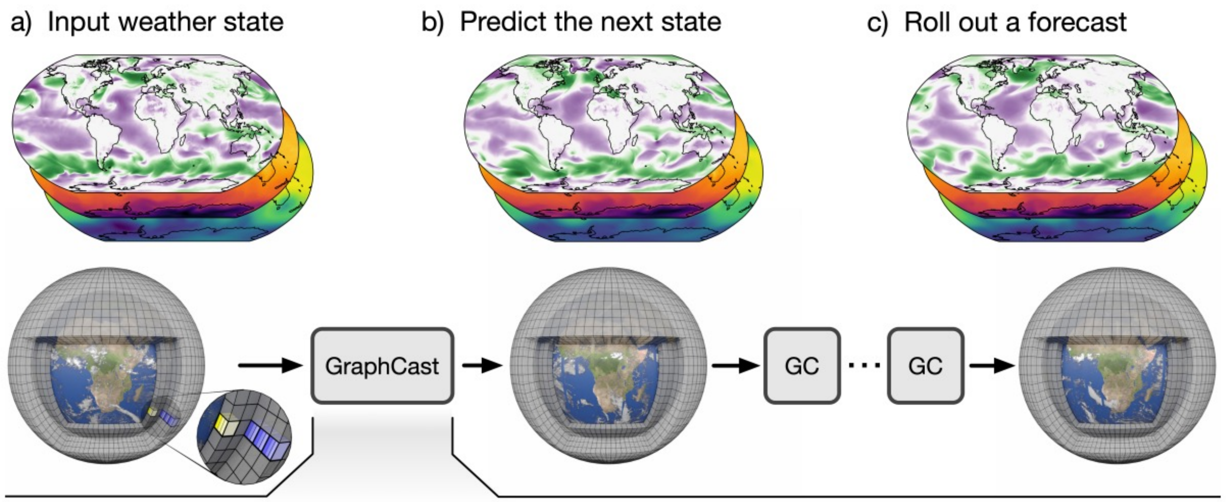
- Smart Transportation

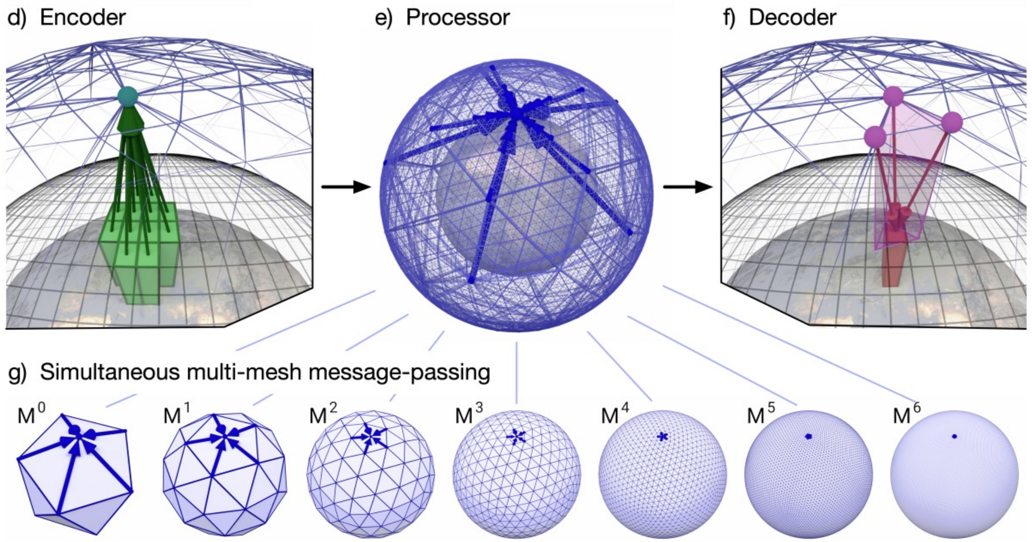


Sun, B., Zhao, D., Shi, X., & He, Y. (2021). Modeling global spatial–temporal graph attention network for traffic prediction. IEEE Access, 9, 8581-8594.

Applications

- Environment & Sustainable Energy

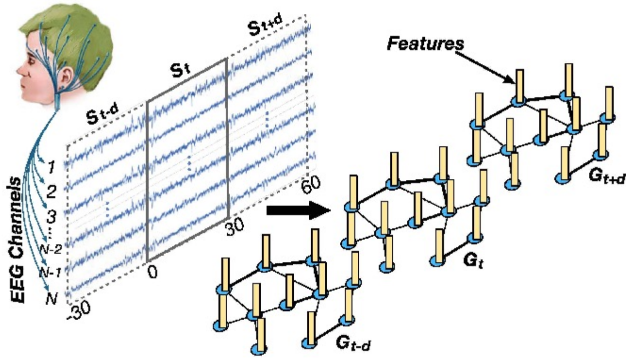


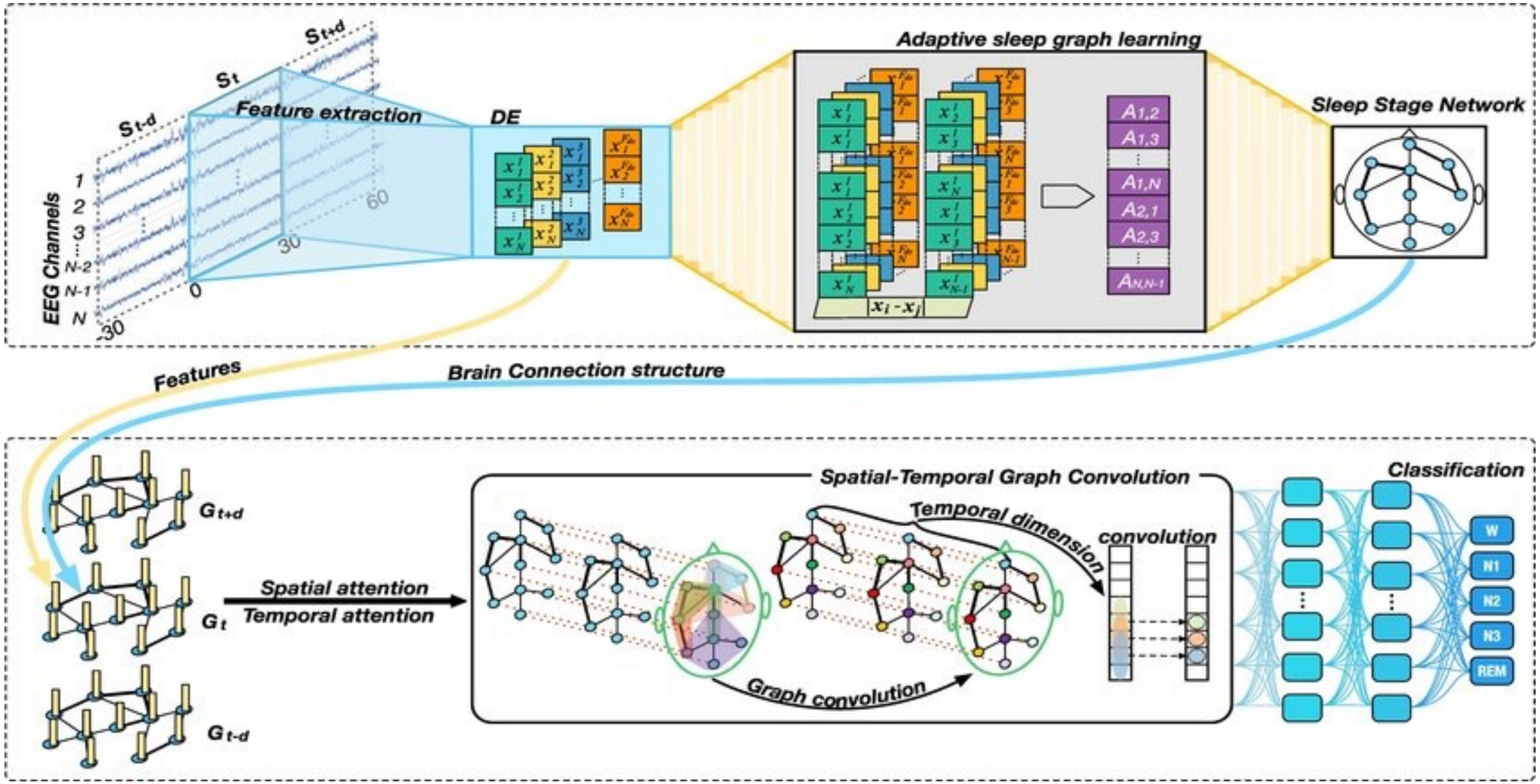


Lam, R., Sanchez-Gonzalez, A., Willson, M., Wirnsberger, P., Fortunato, M., Pritzel, A., ... & Battaglia, P. (2022). GraphCast: Learning skillful medium-range global weather forecasting. arXiv preprint arXiv:2212.12794.

Applications

- Healthcare

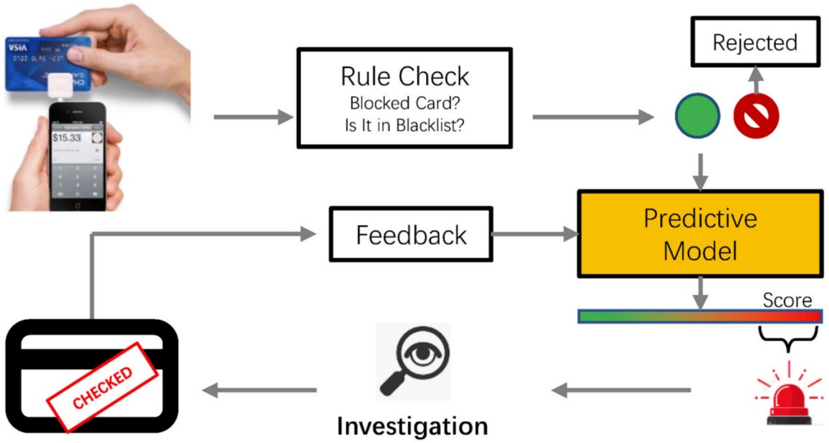


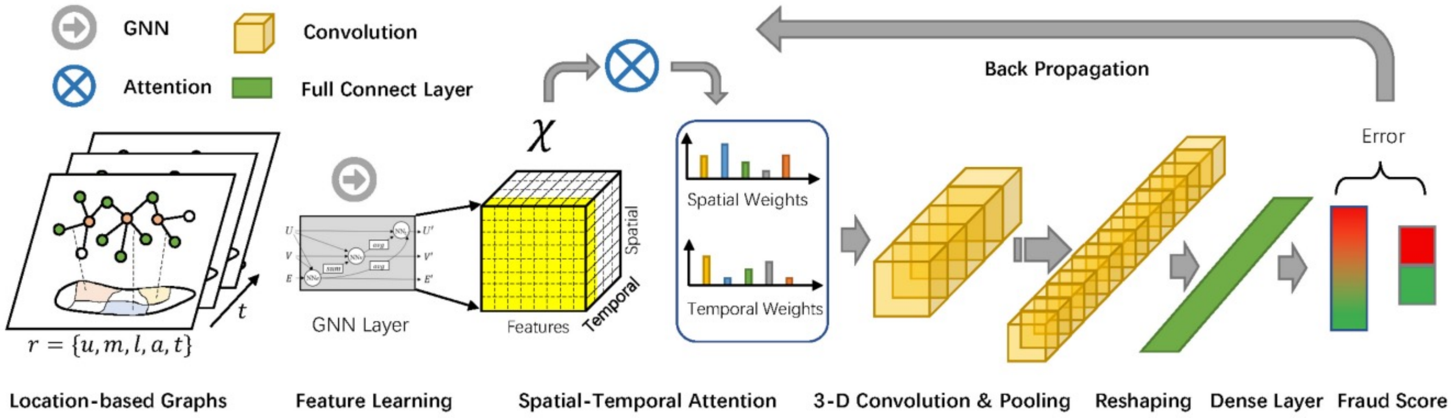


Jia, Z., Lin, Y., Wang, J., Zhou, R., Ning, X., He, Y., & Zhao, Y. (2020, July). GraphSleepNet: Adaptive Spatial-Temporal Graph Convolutional Networks for Sleep Stage Classification. In IJCAI (Vol. 2021, pp. 1324-1330).

Applications

- Fraud Detection



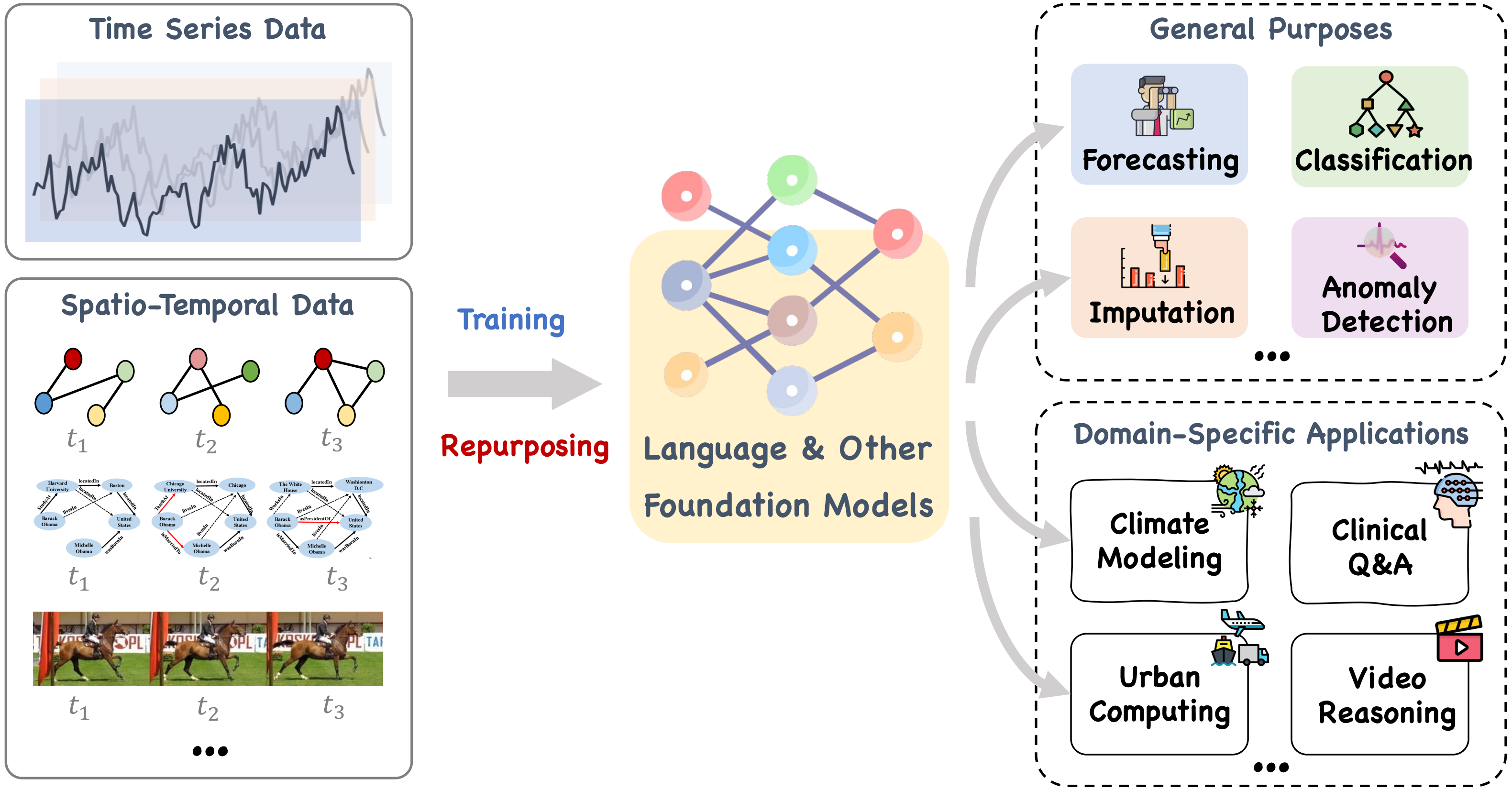


Transaction payments

Cheng, D., Wang, X., Zhang, Y., & Zhang, L. (2020). Graph neural network for fraud detection via spatial-temporal attention. IEEE Transactions on Knowledge and Data Engineering, 34(8), 3800-3813.

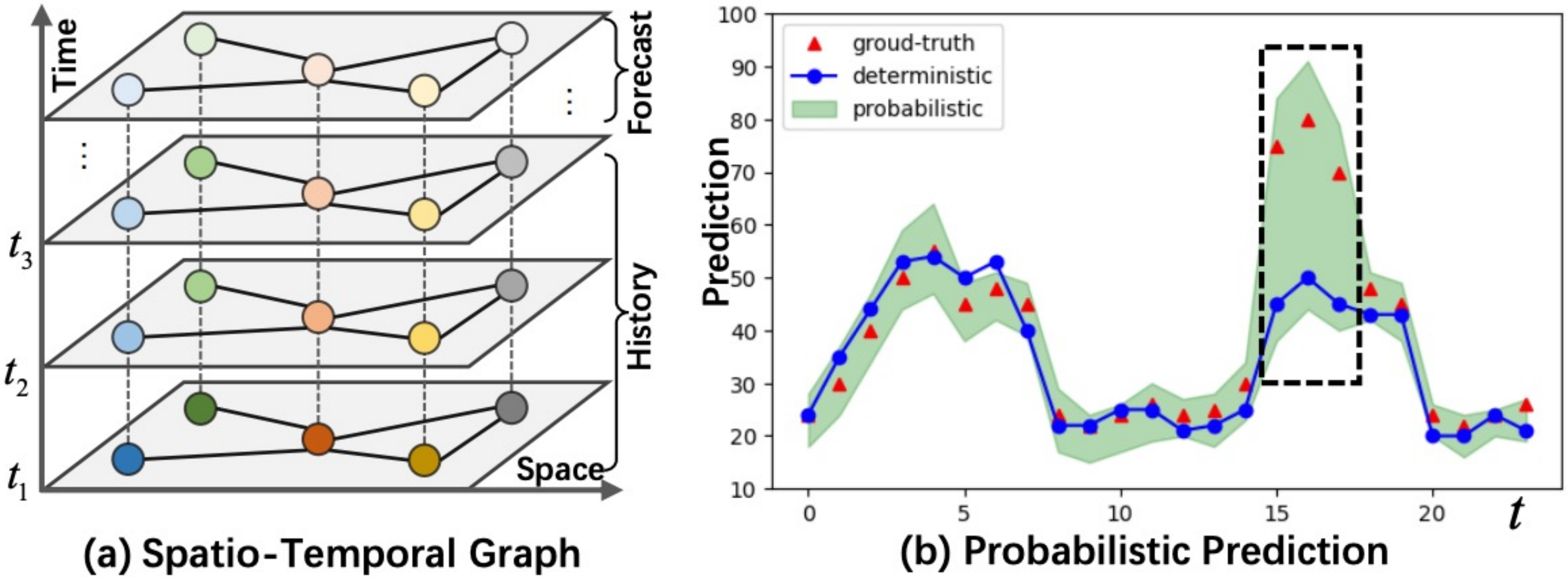
Future Directions

- Pre-training, transfer learning, and large models



Future Directions

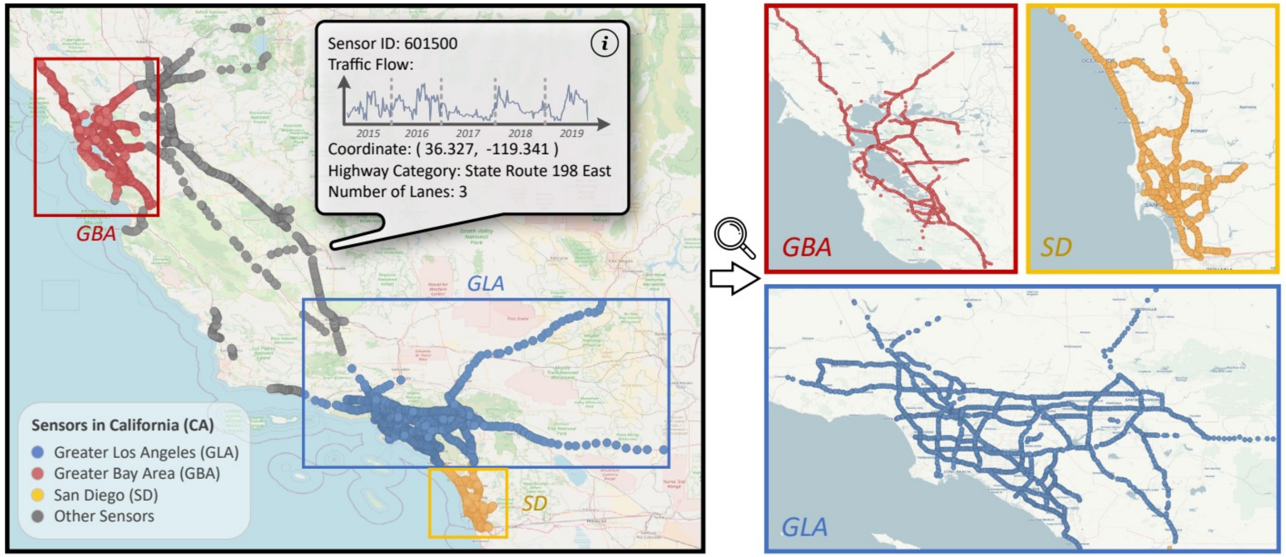
- Uncertainty quantification



Wen, H., Lin, Y., Xia, Y., Wan, H., Zimmermann, R., & Liang, Y. (2023). Diffstg: Probabilistic spatio-temporal graph forecasting with denoising diffusion models. *arXiv preprint arXiv:2301.13629*.

Future Directions

- Scalability



(a) Overview of the LargeST dataset (b) Fine-grained distribution of sensors

Figure 1: An illustration of the LargeST benchmark dataset.

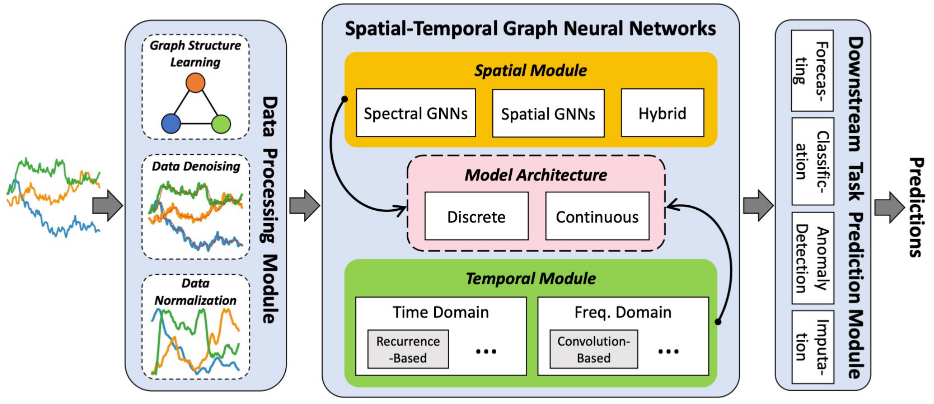
Released Source	Dataset	Nodes	Edges	Degree	Meta	Time Range	Frames	Data Points
Yu et al. [34]	PeMSD7(M)	228	1,664	7.3	6	05/01/2012 – 06/30/2012	12,672	2.89M
	PeMSD7(L)	1,026	14,534	14.2	0	05/01/2012 – 06/30/2012	12,672	13.00M
Li et al. [19]	METR-LA	207	1,515	7.3	3	03/01/2012 – 06/27/2012	34,272	7.09M
	PEMS-BAY	325	2,369	7.3	3	01/01/2017 – 06/30/2017	52,116	16.94M
Song et al. [30]	PEMS03	358	546	1.5	1	09/01/2018 – 11/30/2018	26,208	9.38M
	PEMS04	307	338	1.1	0	01/01/2018 – 02/28/2018	16,992	5.22M
	PEMS07	883	865	1.0	0	05/01/2017 – 08/06/2017	28,224	24.92M
	PEMS08	170	276	1.6	0	07/01/2016 – 08/31/2016	17,856	3.04M
LargeST (ours)	CA	8,600	201,363	23.4	9	01/01/2017 – 12/31/2021	525,888	4.52B
	GLA	3,834	98,703	25.7	9	01/01/2017 – 12/31/2021	525,888	2.02B
	GBA	2,352	61,246	26.0	9	01/01/2017 – 12/31/2021	525,888	1.24B
	SD	716	17,319	24.2	9	01/01/2017 – 12/31/2021	525,888	0.38B

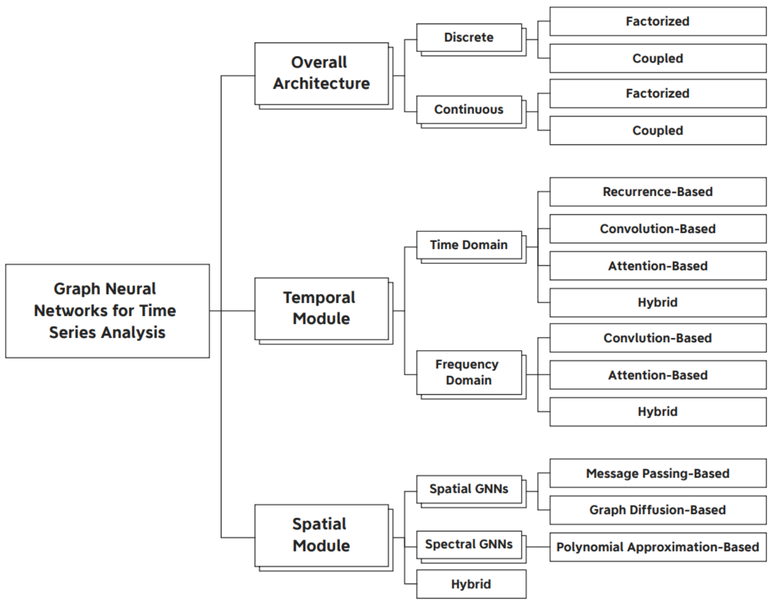
Liu, X., Xia, Y., Liang, Y., Hu, J., Wang, Y., Bai, L., ... & Zimmermann, R. (2023). LargeST: A Benchmark Dataset for Large-Scale Traffic Forecasting. arXiv preprint arXiv:2306.08259.

Part 4. Conclusion

Conclusion

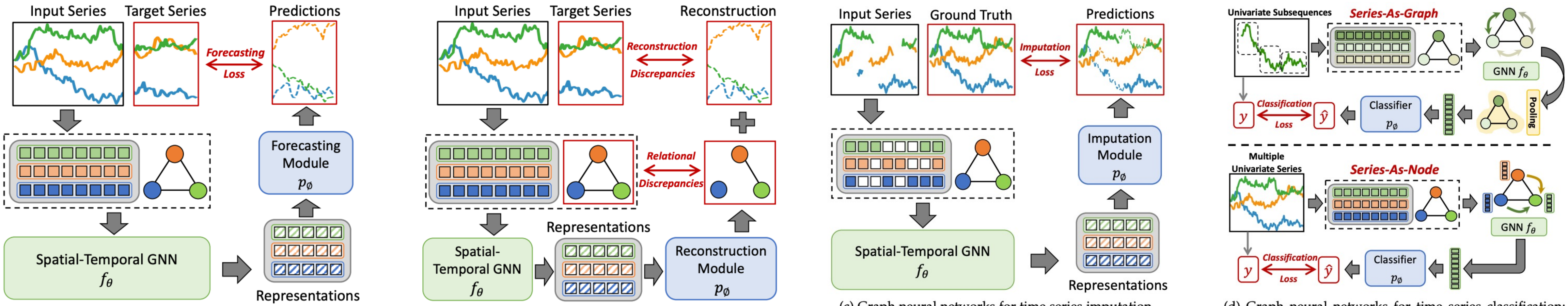
- **What we have covered?**
  - Taxonomies of graph neural networks for time series analysis (GNN4TS)





Conclusion

- **What we have covered?**
  - An overview of graph neural networks for time series analysis (GNN4TS)



(a) Graph neural networks for time series forecasting.

(b) Graph neural networks for time series anomaly detection.

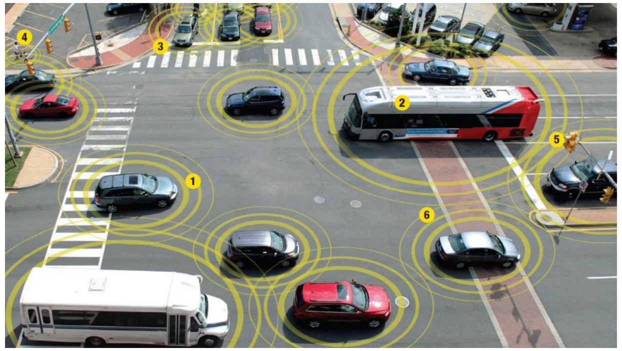
(c) Graph neural networks for time series imputation.

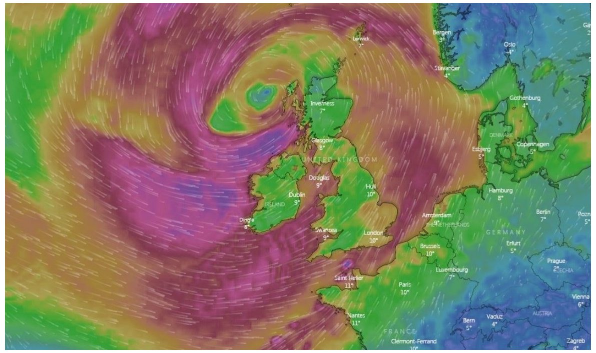
(d) Graph neural networks for time series classification: Formulates green series classification as a graph (top) or node (bottom) classification task.

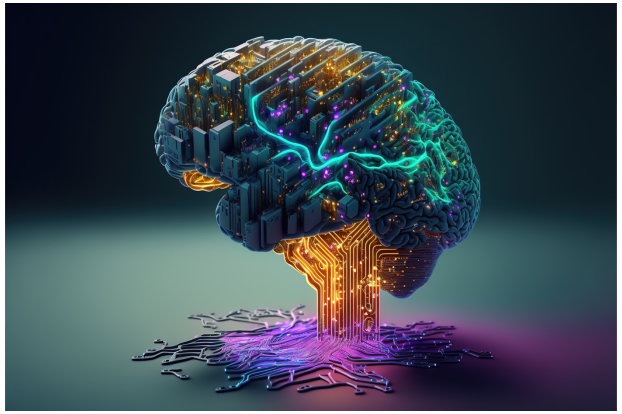
Fig. 4: Four categories of graph neural networks for time series analysis. For the sake of simplicity and illustrative purposes, we assume the graph structures are fixed in all subplots.

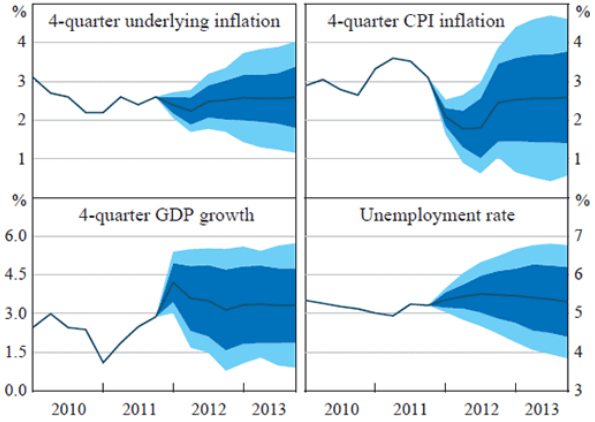
Conclusion

- **What we have covered?**
  - Applications & Future directions of GNN4TS









Thank you

Paper: https://arxiv.org/pdf/2307.03759.pdf

GitHub Page: https://github.com/KimMeen/Awesome-GNN4TS