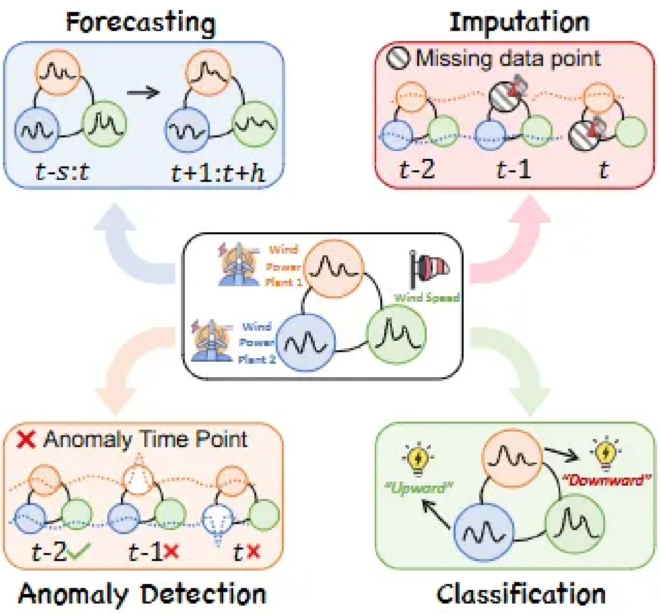
A Survey on Graph Neural Networks for Time Series: Forecasting, Classification, Imputation, and Anomaly Detection

https://arxiv.org/abs/2307.03759

0. Introduction

- 시계열 데이터는 시간적 변화뿐 아니라 요소 간 관계를 고려해야 함
- Graph Neural Network(GNN)는 시계열 데이터의 관계성을 효과적으로 반영 가능
- 이 논문은 시계열 데이터에서 GNN 적용 사례와 연구 동향을 종합적으로 정리함

1. Overview

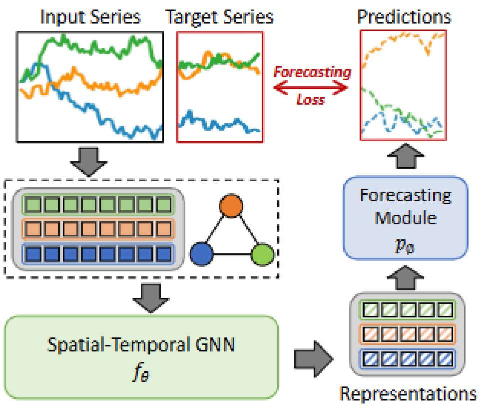


- 시계열 GNN 연구는 주로 Forecasting, Classification, Imputation, Anomaly Detection 네 가지 태스크로 구분됨
- 각 태스크마다 GNN의 설계와 적용 방식이 다름
- 관계 그래프 설계와 시간 정보 통합이 핵심적인 설계 요소임

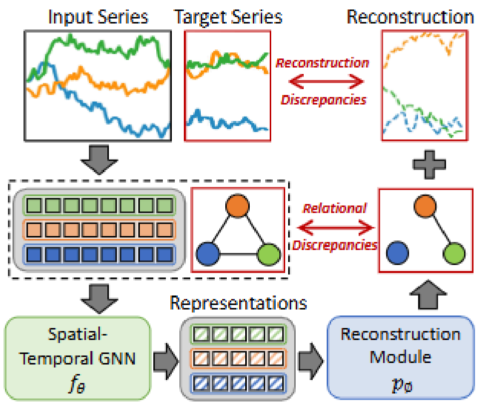
2. Challenges

- 시계열 데이터의 복잡한 관계성 반영의 어려움
- 노이즈와 결측치 문제
- 대규모 그래프 계산의 효율성 문제
- 일반화 성능 확보의 어려움

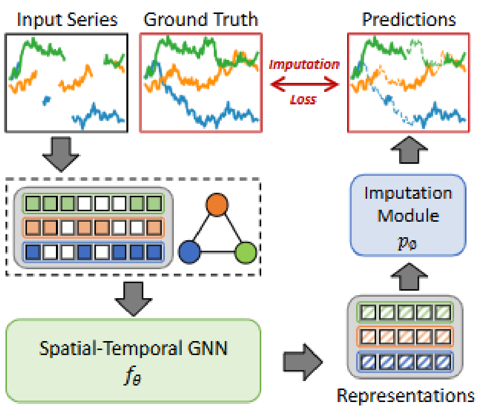
3. Method



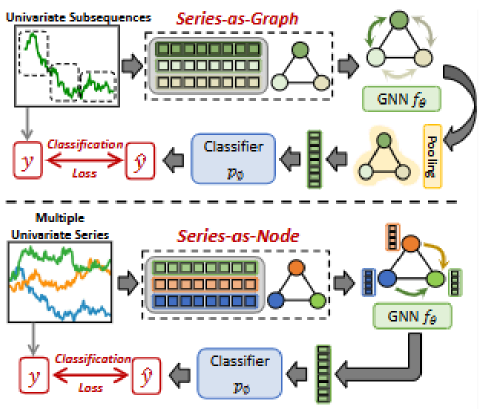
(a) Graph neural networks for time series forecasting.



(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.

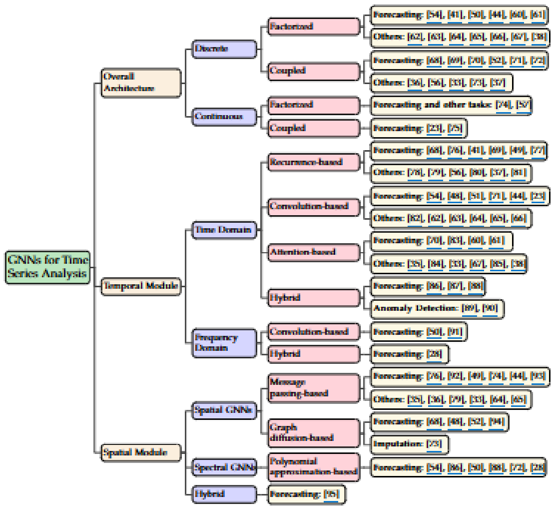


Fig. 5: Methodology-oriented taxonomy of graph neural networks for time series analysis.

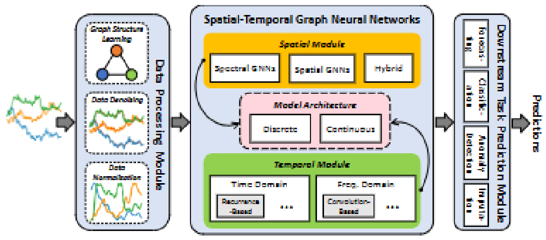


Fig. 6: General pipeline for time series analysis using graph neural networks.

- Forecasting : GNN을 통해 관계 정보를 학습하고 시간 축 변화를 모델링
- Classification : 시계열 그래프 구조를 기반으로 시계열 데이터의 카테고리를 분류
- Imputation : 그래프 구조를 활용해 결측값을 보완
- Anomaly Detection : 관계 기반 시계열 분석으로 이상 패턴 탐지
- 시간-관계 통합 방법 : Temporal Graph Neural Networks, Spatio-Temporal Graph Networks 등이 활용됨

4. Experiments

Survey	Year	Domain		Scope			
		Specific	General	Forecasting	Classification	Anomaly Detection	Imputation
Wang et al. [11]	2019		✔	●	●	●	○
Ye et al. [12]	2020	✔		●	◐	○	○
Jiang and Luo [13]	2021	✔		●	○	○	○
Bui et al. [14]	2021	✔		●	○	○	○
Jin et al. [15]	2023	✔		●	○	○	○
Al Sahili and Awad [16]	2023		✔	◐	○	○	○
Rahmani et al. [17]	2023		✔	●	○	○	◐
Our Survey	2024		✔	●	●	●	●

* Specifically, ○ represents "Not Covered", ◐ signifies "Partially Covered", and ● corresponds to "Fully Covered".

- 데이터셋 : 금융 시계열, 교통량 데이터, 기상 관측 데이터 등 다양하게 사용됨
- 비교 모델 : 전통적 시계열 모델(RNN, LSTM), GNN 기반 모델

- 평가 지표 : RMSE, MAE, F1-score, Precision, Recall 등
- 실험 항목 : 관계 그래프 설계 방식, 시간 통합 방법, 모델 성능 비교
- 추가 실험 : 결측치 보완 성능 비교, 이상치 탐지 정확도 분석

5. Results

TABLE 2: Summary of representative graph neural networks for time series forecasting. *Task notation*: The first letter, "M" or "S", indicates multi-step or single-step forecasting, and the second letter, "S" or "L", denotes short-term or long-term forecasting. *Architecture notation*: "D" and "C" represent "Discrete" and "Continuous"; "C" and "F" stand for "Coupled" and "Factorized". *Temporal module notation*: "T" and "F" signify "Time" and "Frequency" domains; "R", "C", "A", and "H" correspond to "Recurrence", "Convolution", "Attention", and "Hybrid". *Input graph notation*: "R" indicates that a pre-calculated graph structure (with a certain graph heuristic) is a required input of the model, "NR" that such graph is not required (not a model's input), while "O" signifies that the model can optionally exploit given input graphs. *Notation of learned graph relations*: "S" and "D" indicate "Static" and "Dynamic". *Notation of adopted graph heuristics*: "SP", "PC", "PS", and "FD" denote "Spatial Proximity", "Pairwise Connectivity", "Pairwise Similarity", and "Functional Dependency". The "Missing Values" column indicates whether corresponding methods can handle missing values in input time series.

Approach	Year	Venue	Task	Architecture	Spatial Module	Temporal Module	Missing Values	Input Graph	Learned Relations	Graph Heuristics
DCRNN [68]	2018	ICLR	M-S	D-C	Spatial GNN	T-R	No	R	-	SP
STGCN [54]	2018	IJCAI	M-S	D-F	Spectral GNN	T-C	No	R	-	SP
ST-MetaNet [76]	2019	KDD	M-S	D-F	Spatial GNN	T-R	No	R	-	SP, PC
NGAR [104]	2019	IEEE IJCNN	S-S	D-F	Spatial GNN	T-R	No	R	-	-
ASTGCN [86]	2019	AAAI	M-S	D-F	Spectral GNN	T-H	No	R	-	SP, PC
ST-MGCN [41]	2019	AAAI	S-S	D-F	Spectral GNN	T-R	No	R	-	SP, PC, PS
Graph WaveNet [48]	2019	IJCAI	M-S	D-F	Spatial GNN	T-C	No	O	S	SP
MRA-BGCN [69]	2020	AAAI	M-S	D-C	Spatial GNN	T-R	No	R	-	SP
MTGNN [51]	2020	KDD	S-S, M-S	D-F	Spatial GNN	T-C	No	NR	S	-
STGNN* [87]	2020	WWW	M-S	D-C	Spatial GNN	T-H	No	R	-	SP
GMAN [70]	2020	AAAI	M-S	D-C	Spatial GNN	T-A	No	R	-	SP
SLCNN [95]	2020	AAAI	M-S	D-F	Hybrid	T-C	No	NR	S	-
STSGCN [92]	2020	AAAI	M-S	D-C	Spatial GNN	T	No	R	-	PC
StemGNN [50]	2020	NeurIPS	M-S	D-F	Spectral GNN	F-C	No	NR	S	-
AGCRN [49]	2020	NeurIPS	M-S	D-C	Spatial GNN	T-R	No	NR	S	-
LSGCN [105]	2020	IJCAI	M-S	D-F	Spectral GNN	T-C	No	R	-	SP
STAR [83]	2020	ECCV	M-S	D-F	Spatial GNN	T-A	No	R	-	PC
GTS [52]	2021	ICLR	M-S	D-C	Spatial GNN	T-R	No	NR	S	-
GEN [106]	2021	ICLR	S-S	D-F	Spatial GNN	T-R	No	R	-	-
Z-GCNETs [71]	2021	ICML	M-S	D-C	Spatial GNN	T-C	No	NR	S	-
STGODE [74]	2021	KDD	M-S	C-F	Spatial GNN	T-C	No	R	-	SP, PS
STFGNN [44]	2021	AAAI	M-S	D-F	Spatial GNN	T-C	No	R	-	SP, PS
DSTAGNN [88]	2022	ICML	M-S	D-F	Spectral GNN	T-H	No	R	-	PC, PS
TPGNN [60]	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 [75]	2022	AAAI	M-S	C-C	Spatial GNN	T-C	Yes	NR	S	-
STEP [61]	2022	KDD	M-S	D-F	Spatial GNN	T-A	No	NR	S	-
Chauhan et al. [107]	2022	KDD	M-S	-	-	-	Yes	O	S	SP
RGSL [72]	2022	IJCAI	M-S	D-C	Spectral GNN	T-R	No	R	S	SP, PC
FOGS [108]	2022	IJCAI	M-S	-	-	-	No	NR	S	-
METRO [93]	2022	VLDB	M-S	D-C	Spatial GNN	T	No	NR	D	-
SGP [77]	2023	AAAI	M-S	D-F	Spatial GNN	T-R	No	R	-	SP, PS
HiGP [109]	2023	arXiv	M-S	D-F	Spatial GNN	T-R	No	R	S	SP, PS
Jin et al. [28]	2023	arXiv	M-S, M-L	D-F	Spectral GNN	F-H	No	NR	S	-
CaST [91]	2023	NeurIPS	M-S	D-F	Spectral GNN	T&F-C	No	O	S	PC
GPT-ST [110]	2023	NeurIPS	M-S	D-F	Spatial GNN	T-C	No	NR	S	-

TABLE 3: Summary of representative graph neural networks for time series anomaly detection. *Strategy notation*: "CL", "FC", "RC", and "RL" indicate "Class", "Forecast", "Reconstruction", and "Relational Discrepancies", respectively. The remaining notations are shared with Table 2.

Approach	Year	Venue	Strategy	Spatial Module	Temporal Module	Missing Values	Input Graph	Learned Relations	Graph Heuristics
CCM-CDT [47]	2019	IEEE TNNLS	RC	Spatial GNN	T-R	No	R	-	PC, FD
MTAD-GAT [35]	2020	IEEE ICDM	FC+RC	Spatial GNN	T-A	No	NR	-	-
GDN [36]	2021	AAAI	FC	Spatial GNN	-	No	NR	S	-
GTA [89]	2021	IEEE IoT	FC	Spatial GNN	T-H	No	NR	S	-
EvoNet [78]	2021	WSDM	CL	Spatial GNN	T-R	No	R	-	PS
Event2Graph [84]	2021	arXiv	RL	Spatial GNN	T-A	No	R	-	PS
GANF [57]	2022	ICLR	RC+RL	Spatial GNN	T-R	No	NR	S	-
Grelen [90]	2022	IJCAI	RC+RL	Spatial GNN	T-H	No	NR	D	-
VGCRN [79]	2022	ICML	FC+RC	Spatial GNN	T-R	No	NR	S	-
FuSAGNet [56]	2022	KDD	FC+RC	Spatial GNN	T-R	No	NR	S	-
GTAD [130]	2022	Entropy	FC+RC	Spatial GNN	T-C	No	NR	-	-
HgAD [131]	2022	IEEE BigData	FC	Spatial GNN	-	No	NR	S	
HAD-MDGAT [80]	2022	IEEE Access	FC+RC	Spatial GNN	T-A	No	NR	-	-
STGAN [80]	2022	IEEE TNNLS	RC	Spatial GNN	T-R	No	R	-	SP
GIF [132]	2022	IEEE IJCNN	RC	Spatial GNN	-	No	R	-	SP, PC, FD
DyGraphAD [82]	2023	arXiv	FC+RL	Spatial GNN	T-C	No	R	-	PS
GraphSAD [133]	2023	arXiv	CL	Spatial GNN	T-C	No	R	-	PS, PC
CST-GL [62]	2023	IEEE TNNLS	FC	Spatial GNN	T-C	No	NR	S	-

TABLE 4: Summary of graph neural networks for time series classification. *Task notation*: "U" and "M" refer to univariate and multivariate time series classification tasks. *Conversion* represents the transformation of a time series classification task into a graph-level task as either graph or node classification task, represented as "Series-as-Graph" and "Series-as-Node", respectively. The remaining notations are shared with Table 2.

Approach	Year	Venue	Task	Conversion	Spatial Module	Temporal Module	Missing Values	Input Graph	Learned Relations	Graph Heuristics
MTPool [151]	2021	NN	M	-	Spatial GNN	T-C	No	NR	S	-
Time2Graph+ [96]	2021	IEEE TKDE	U	Series-as-Graph	Spatial GNN	-	No	R	-	PS
RainDrop [33]	2022	ICLR	M	-	Spatial GNN	T-A	Yes	NR	S	-
SimTSC [63]	2022	SDM	U+M	Series-as-Node	Spatial GNN	T-C	No	R	-	PS
LB-SimTSC [97]	2023	arXiv	U+M	Series-as-Node	Spatial GNN	T-C	No	R	-	PS
TodyNet [64]	2023	arXiv	M	-	Spatial GNN	T-C	No	NR	D	-
EC-GCN [152]	2023	Comput. Netw.	U	Series-as-Graph	Spatial GNN	T-C	No	R	D	PS
MTS2Graph [153]	2024	Pattern Recognit.	M	Series-as-Graph	Spatial GNN	T-C	No	NR	-	-

TABLE 5: Summary of graph neural networks for time series imputation. *Task notation*: "Out-of-sample", "In-sample", and "Both" refer to the types of imputation problems addressed by the approach. *Type* represents the imputation method as either deterministic or probabilistic. *Inductiveness* indicates if the method can generalize to unseen nodes. The remaining notations are shared with Table 2.

Approach	Year	Venue	Task	Type	Spatial Module	Temporal Module	Inductiveness	Input Graph	Learned Relations	Graph Heuristics
IGNNK [73]	2021	AAAI	Out-of-sample	Deterministic	Spatial GNN	-	Yes	R	-	SP, PC
GACN [65]	2021	ICANN	In-sample	Deterministic	Spatial GNN	T-C	No	R	-	PC
SATCN [66]	2021	arXiv	Out-of-sample	Deterministic	Spatial GNN	T-C	Yes	R	-	SP
GRIN [37]	2022	ICLR	Both	Deterministic	Spatial GNN	T-R	Yes	R	-	SP
SPIN [67]	2022	NIPS	In-sample	Deterministic	Spatial GNN	T-A	No	R	-	SP
FUNS [165]	2022	ICDMW	Out-of-sample	Deterministic	Spatial GNN	T-R	Yes	R	-	-
AGRN [166]	2022	ICONIP	In-sample	Deterministic	Spatial GNN	T-R	No	NR	S	-
MATCN [85]	2022	IEEE IoT-J	In-sample	Deterministic	Spatial GNN	T-A	No	R	-	-
PriSTI [38]	2023	arXiv	In-sample	Probabilistic	Spatial GNN	T-A	No	R	-	SP
DGCRIN [167]	2023	KBS	In-sample	Deterministic	Spatial GNN	T-R	No	NR	D	-
GARNN [168]	2023	Neurocomputing	In-sample	Deterministic	Spatial GNN	T-R	No	R	-	PC
MDGCN [81]	2023	Transp. Res. Part C	In-sample	Deterministic	Spatial GNN	T-R	No	R	-	SP, PS
INCREASE [169]	2023	WWW	Out-of-sample	Deterministic	Spatial GNN	T-R	Yes	R	-	SP, PC, FD
Yun et al. [170]	2023	OpenReview	In-sample	Probabilistic	Spatial GNN	-	No	R	-	-

- GNN 기반 시계열 모델이 기존 순차 모델 대비 높은 성능을 보임
- 관계 그래프 설계가 예측 정확도와 이상치 탐지 성능에 큰 영향
- Temporal Graph 설계 방식이 성능 개선에 기여
- 다양한 데이터셋에서 일관된 성능 향상 확인

- 결측치 보완 태스크에서 그래프 기반 방법의 강점 확인

6. Insight

- 시계열 GNN 연구는 관계 정보 활용이 핵심임
- 그래프 구조 설계와 시간 정보 통합 전략이 성능을 결정
- 계산 효율성과 일반화 성능을 함께 고려해야 함
- 향후 연구에서는 스케일 확장성, 실시간 처리, 동적 그래프 모델링이 중요할 것으로 예상됨