

Adapting to the Stream: An Instance-Attention GNN Method for Irregular Multivariate Time Series Data

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Problems & Proposed Approach

Problems of irregular multivariate time series (IMTS):

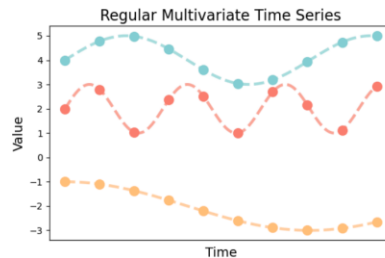
- Challenges such as sensor failures can result in **irregular, a misaligned data with missing values**, thereby complicating time series analysis.
- The **graph structure** is essential for GNN-based methods, either pre-existing or inferred from adequate data to properly capture node correlations.
- IMTS data are often streamed and waiting for future data to estimate a suitable graph structure becomes **impractical**.

Proposed approach

- A **dynamic GNN** model suited for streaming characteristics of IMTS data, incorporating an **instance-attention mechanism**, embedding learning and spatial-temporal learning that **dynamically** learns and updates graph edge weights for **real-time analysis**.

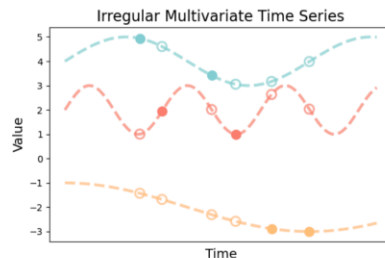
Regular

- regular sampling
- no missing observation

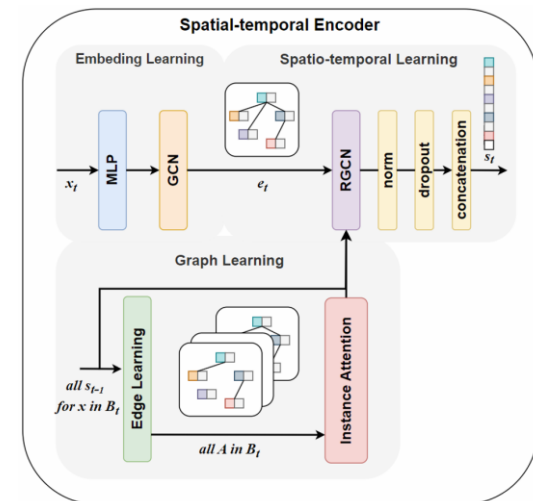


Irregular

- irregular sampling
- missing observation



Comparison of regular and irregular MTS. Different colors represent variables. Solid circles denote observed data points; hollow circles indicate missing data points.

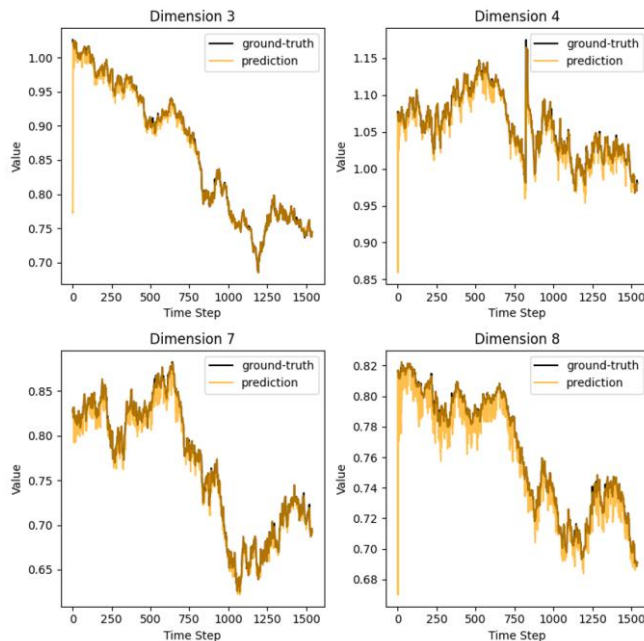


Framework of DynIMTS

Main Contributions

Contributions:

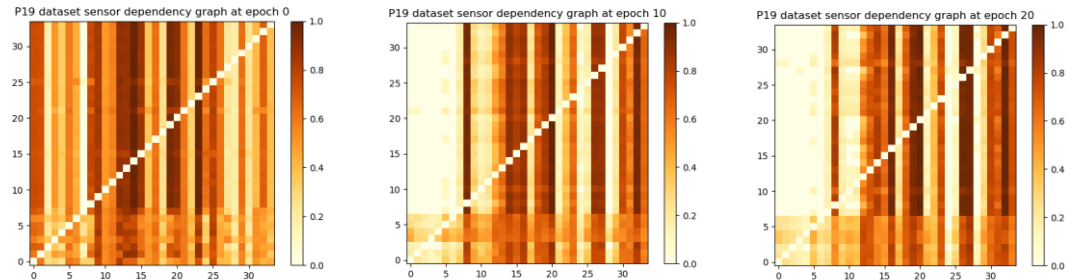
- We introduce a **novel instance-attention** strategy that learns and dynamically updates the graph structure in response to newly incoming data at each timestamp.
- Our model is versatile, **efficiently managing both imputation and non-imputation** tasks, with customized strategies for different sampling rates in IMTS.
- Experimental results show that our model's performance **surpasses current state-of-the-art** approaches.



Visualization of the imputation results produced by our model with a 20% missing data ratio on the Exchange-rate dataset across four dimensions.

Table 2 Evaluation on P12 and P19 datasets using AUROC% and AUPRC% (mean \pm std).

	P12		P19	
	AUROC	AUPRC	AUROC	AUPRC
RITS	71.2 \pm 2.0	16.4 \pm 2.7	86.7 \pm 0.7	47.2 \pm 3.1
Raindrop	60.9 \pm 5.3	14.7 \pm 2.0	74.1 \pm 0.8	33.6 \pm 1.7
GRIN (all-ones)	70.8 \pm 2.0	12.5 \pm 2.8	87.1 \pm 1.1	48.4 \pm 2.0
DynIMTS	75.1 \pm 1.6	25.2 \pm 3.0	87.1 \pm 1.1	48.4 \pm 1.9



Visualization of the adjacency matrices of epochs 0, 10 and 20 on the P19 dataset.