SCUT

Learning Recursive Multi-Scale Representations for Irregular Multivariate Time Series Forecasting

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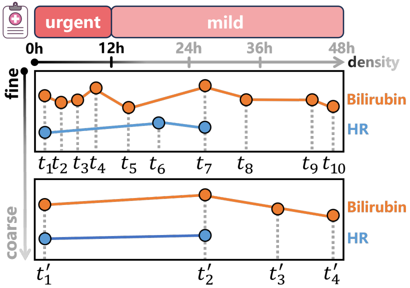
Background: Irregular Multivariate Time Series (IMTS)

- **Characteristics:** Uneven intervals between observations and unaligned variables.
- **Significance:** Common in healthcare (ICU data), climate, and biomechanics.
- **Sampling Patterns:** Irregular intervals are *informative*. They reflect clinical urgency or sensor-specific scheduling.
- **The Scale Challenge:** IMTS exhibit patterns across multiple resolutions (e.g., 6-hour clinical windows vs. 24-hour circadian cycles).

The Problem: Disrupted Sampling Patterns

Existing Multi-Scale Methods:

- Often use **resampling/downsampling** to create coarse scales.
- **Consequence:** Destroys the original timestamps and the information hidden in sampling frequency.
- Example: A patient monitored more frequently during a crisis loses that "urgency" signal in a downsampled view.

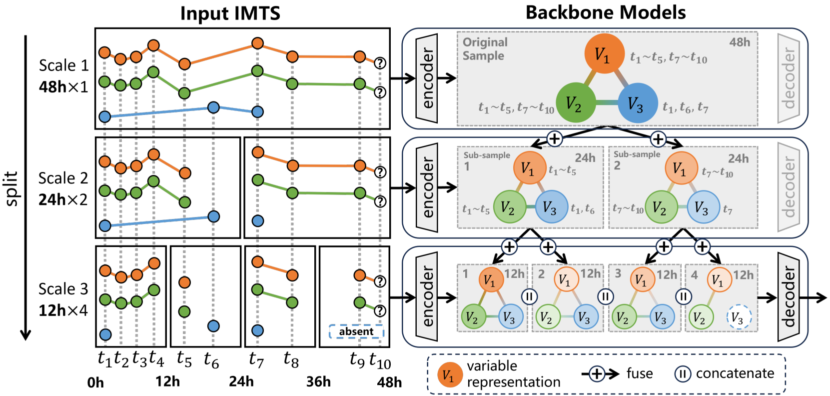


The Limitation

Resampling balances observation counts but alters the underlying temporal semantics of the "irregularity" itself.

Proposed Method: ReIMTS

Core Idea: Instead of resampling, **recursively split** the time period.



Proposed Method: ReIMTS

Top-down architecture transfers knowledge from Global → Local scales.

- **Recursive Splitting:** Keep all original timestamps. Divide the sample into subsamples based on time periods (top-down).
- **Global-to-Local:** Upper scales capture long-term context; lower scales capture high-resolution local details.
- **Plug-and-Play:** Compatible with most IMTS backbones (GNN, Transformer, ODE).

Irregularity-Aware Representation Fusion (IARF)

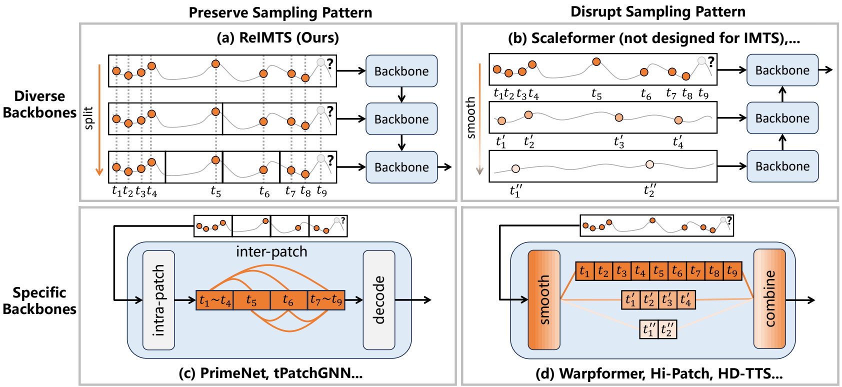
How do we combine representations from different scales?

$$\mathbf{G}^{n+1} = \mathbf{E}^{n+1} + \alpha(\mathbf{H}^{n} \cdot \mathbf{M}^{n+1}) \tag{1}$$

- $\mathbf{E}^{n+1}$: Local representation at current scale.
- $\mathbf{H}^{n}$: Global representation from upper scale.
- $\mathbf{M}^{n+1}$: Binary mask indicating presence of observations.
- α: Learned weight scoring the importance of global context relative to local irregularity.

Compared with Existing Methods

Preserve timestamps while maintain **extensibility**.



Experimental Results

- **Datasets:** MIMIC-III [1], MIMIC-IV [2], PhysioNet'12 [3], Human Activity, USHC [4].
- **Backbones tested:** PrimeNet [5], mTAN [6], TimeCHEAT [7], GRU-D [8], Raindrop [9], GraFITi [10].

	PrimeNet	mTAN	TimeCHEAT	GRU-D	Raindrop	GraFITi
+**ReIMTS**	↑**62.3%**	↑**24.3%**	↑**12.1%**	↑**25.8%**	↑**4.5%**	↑**6.3%**

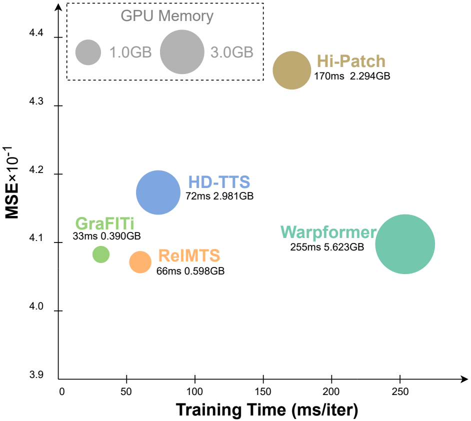
Table: Average Improvement over five datasets, evaluated using MSE.

Average Improvement

ReIMTS boosts performance across all models by an average of **27.1%**.

Efficiency & Scalability

- **Speed:** Faster than existing IMTS multi-scale methods like Warpformer [11] or Hi-Patch [12].
- **Flexibility:** Successfully integrated with 6 different architectures.



Conclusion

1. **ReIMTS** addresses the multi-scale dependency challenge in IMTS without destroying sampling patterns.
2. **Recursive Splitting** by time periods preserves the "when" and "how often" of data collection.
3. **IARF Mechanism** adaptively fuses global context with local irregularities.
4. **SOTA Results** achieved across five real-world datasets in healthcare and climate.

Code: `https://github.com/Ladbaby/PyOmniTS`

References I

[1] A. E. W. Johnson, T. J. Pollard, L. Shen, *et al.*, "MIMIC-III, a freely accessible critical care database," *Scientific Data*, vol. 3, no. 1, p. 160 035, 1 May 24, 2016, ISSN: 2052-4463.

[2] A. E. W. Johnson, L. Bulgarelli, L. Shen, *et al.*, "MIMIC-IV, a freely accessible electronic health record dataset," *Scientific Data*, vol. 10, no. 1, p. 1, 1 Jan. 3, 2023, ISSN: 2052-4463.

[3] I. Silva, G. Moody, D. J. Scott, L. A. Celi, and R. G. Mark, "Predicting In-Hospital Mortality of ICU Patients: The PhysioNet/Computing in Cardiology Challenge 2012," *Computing in cardiology*, vol. 39, pp. 245–248, 2012. pmid: 24678516.

References II

[4] M. Menne, C. Williams Jr., and R. Vose, "Long-term daily and monthly climate records from stations across the contiguous united states (u.s. historical climatology network),", Jan. 2016.

[5] R. R. Chowdhury, J. Li, X. Zhang, D. Hong, R. K. Gupta, and J. Shang, "PrimeNet: Pre-training for Irregular Multivariate Time Series," *Proceedings of the AAAI Conference on Artificial Intelligence*, vol. 37, no. 6, pp. 7184–7192, 6 Jun. 26, 2023, ISSN: 2374-3468.

[6] S. N. Shukla and B. Marlin, "Multi-Time Attention Networks for Irregularly Sampled Time Series," in *International Conference on Learning Representations*, Jan. 13, 2021.

References III

[7] J. Liu, M. Cao, and S. Chen, "TimeCHEAT: A Channel Harmony Strategy for Irregularly Sampled Multivariate Time Series Analysis," *Proceedings of the AAAI Conference on Artificial Intelligence*, vol. 39, no. 18, pp. 18 861–18 869, 18 Apr. 11, 2025, ISSN: 2374-3468.

[8] Z. Che, S. Purushotham, K. Cho, D. Sontag, and Y. Liu, "Recurrent Neural Networks for Multivariate Time Series with Missing Values," *Scientific Reports*, vol. 8, no. 1, p. 6085, 1 Apr. 17, 2018, ISSN: 2045-2322.

[9] X. Zhang, M. Zeman, T. Tsiligkaridis, and M. Zitnik, "Graph-Guided Network for Irregularly Sampled Multivariate Time Series," in *International Conference on Learning Representations*, Jan. 29, 2022.

References IV

[10] V. K. Yalavarthi, K. Madhusudhanan, R. Scholz, *et al.*, "GraFITi: Graphs for Forecasting Irregularly Sampled Time Series," *Proceedings of the AAAI Conference on Artificial Intelligence*, vol. 38, no. 15, pp. 16 255–16 263, 15 Mar. 24, 2024, ISSN: 2374-3468.

[11] J. Zhang, S. Zheng, W. Cao, J. Bian, and J. Li, "Warpformer: A Multi-scale Modeling Approach for Irregular Clinical Time Series," in *Proceedings of the 29th ACM SIGKDD Conference on Knowledge Discovery and Data Mining*, Aug. 6, 2023, pp. 3273–3285. arXiv: 2306.09368 [cs].

[12] Y. Luo, B. Zhang, Z. Liu, and Q. Ma, "Hi-Patch: Hierarchical Patch GNN for Irregular Multivariate Time Series," in *International Conference on Machine Learning*, Jun. 18, 2025.

Thank You

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