SE-STGAE: A Shapelet-Enhanced Spatiotemporal Graph Autoencoder for Early Anomaly Detection

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Outline

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I. **Background and Motivation**

II. Problem and Framework

III. Method

IV. Performance Evaluation

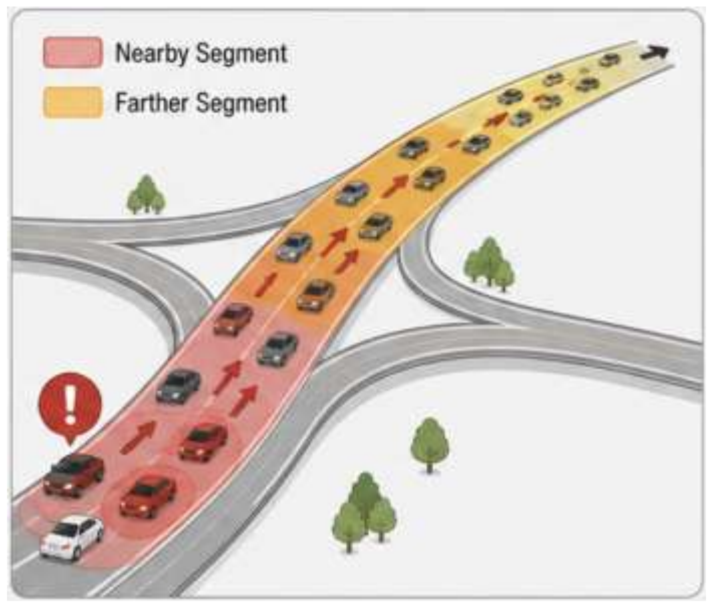
V. Conclusion

Freeway Early Anomaly Detection

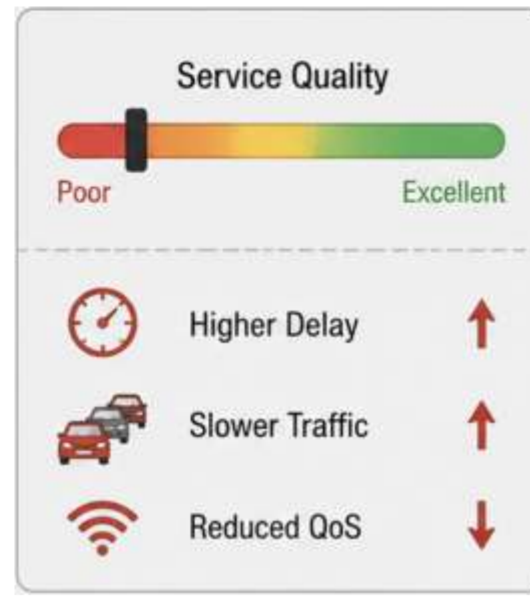
- Detect freeway anomalies early to protect QoS

Incident

Congestion Propagation

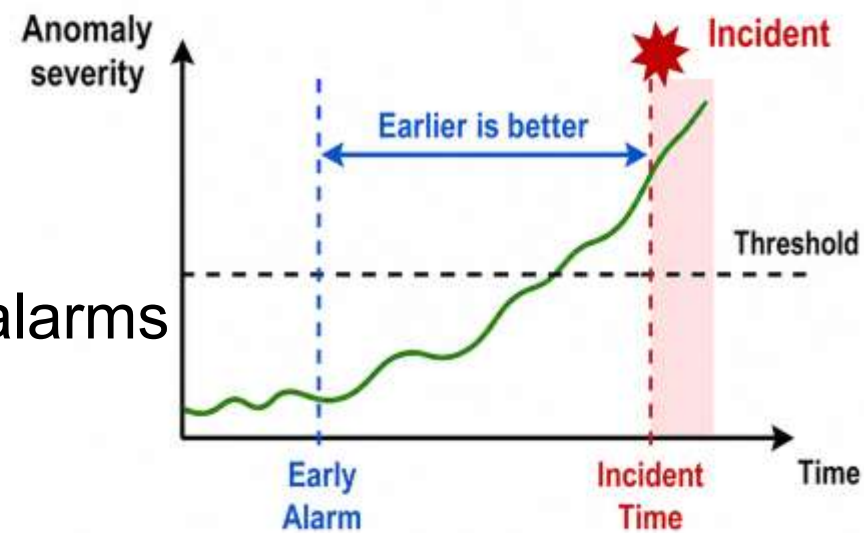


QoS Impact



QoS-aware Early Warning

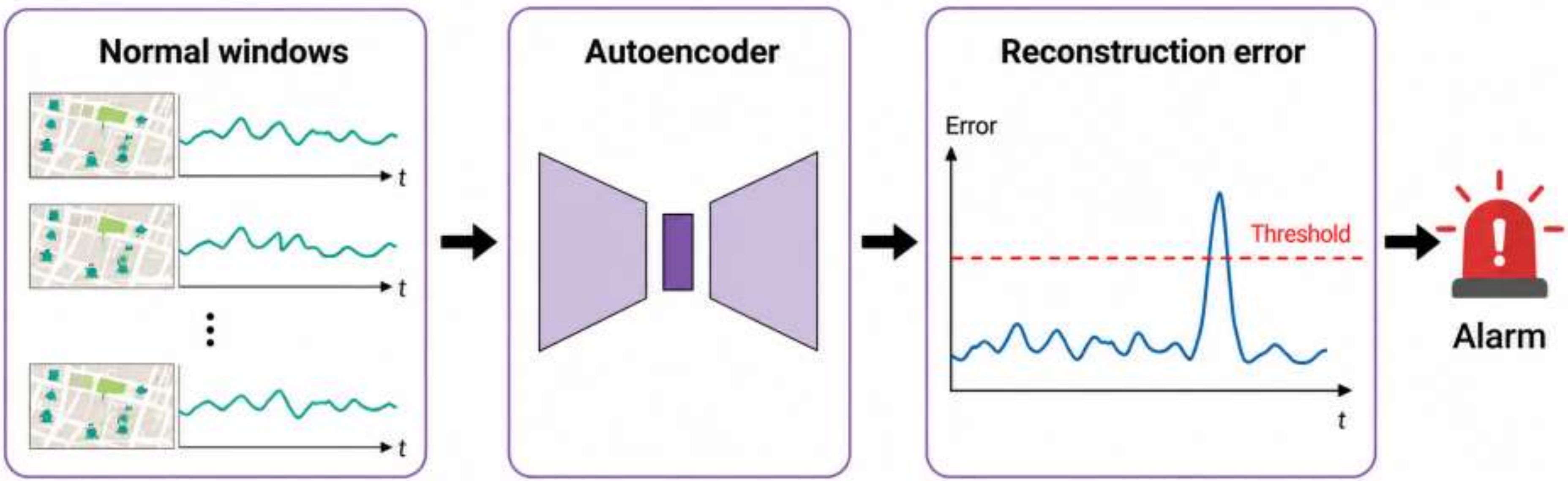
- Early warning under strict False Positive Rate(FPR) budgets
  - Alarm as early as possible
  - But keep false alarms low
- QoS needs early and reliable alarms



➢ **Need low-FPR early warning**

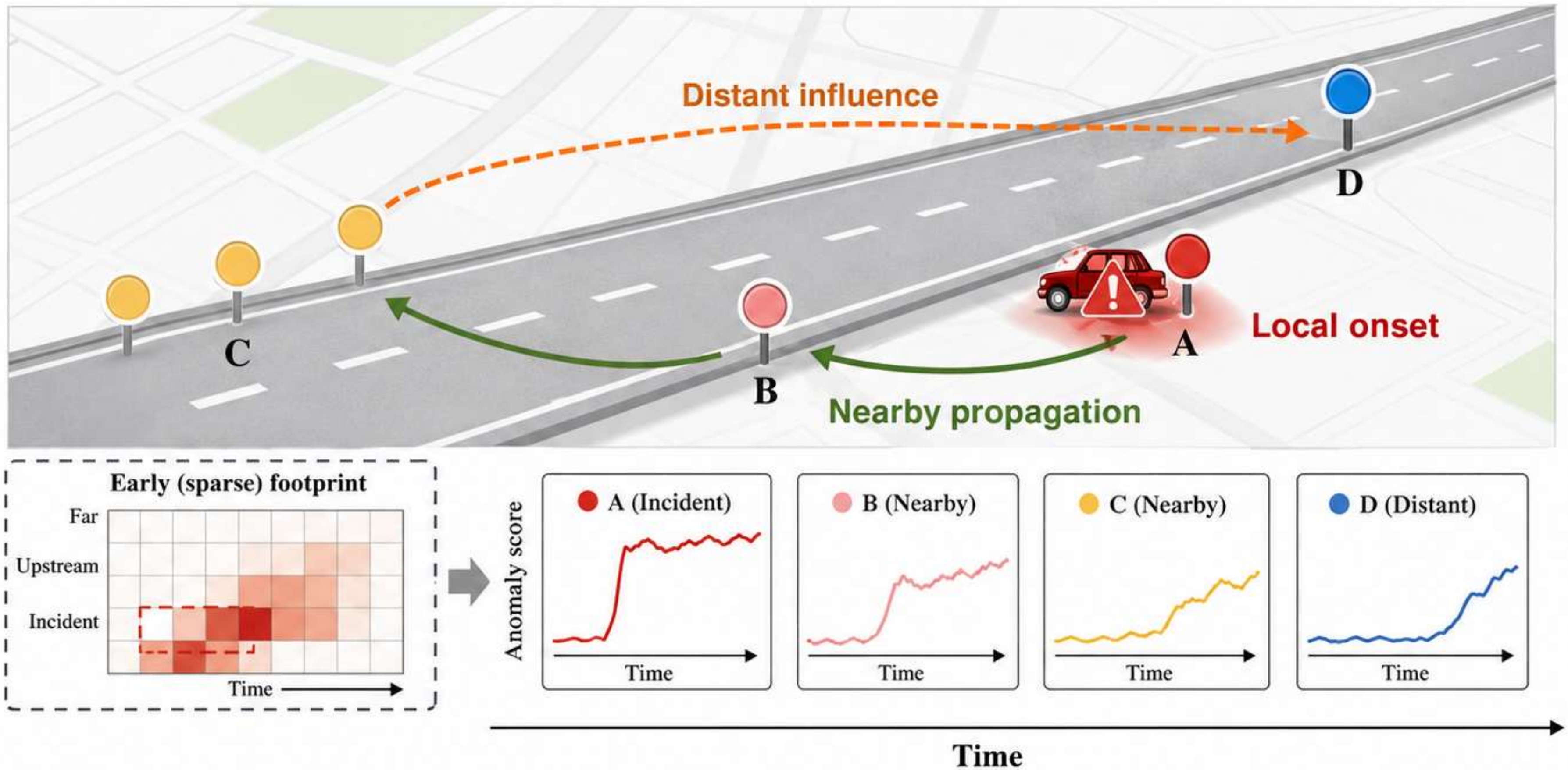
Existing Paradigm

- Train on normal data and alarm by reconstruction deviations



Why It Is Hard?

- Anomalies emerge locally, then propagate across time and space



Challenge

- How to capture complex anomaly propagation under sparse early precursors?
- How to distinguish real incidents from diverse normal fluctuations in traffic networks?
- How to identify and prioritize the most informative precursors from all signals?

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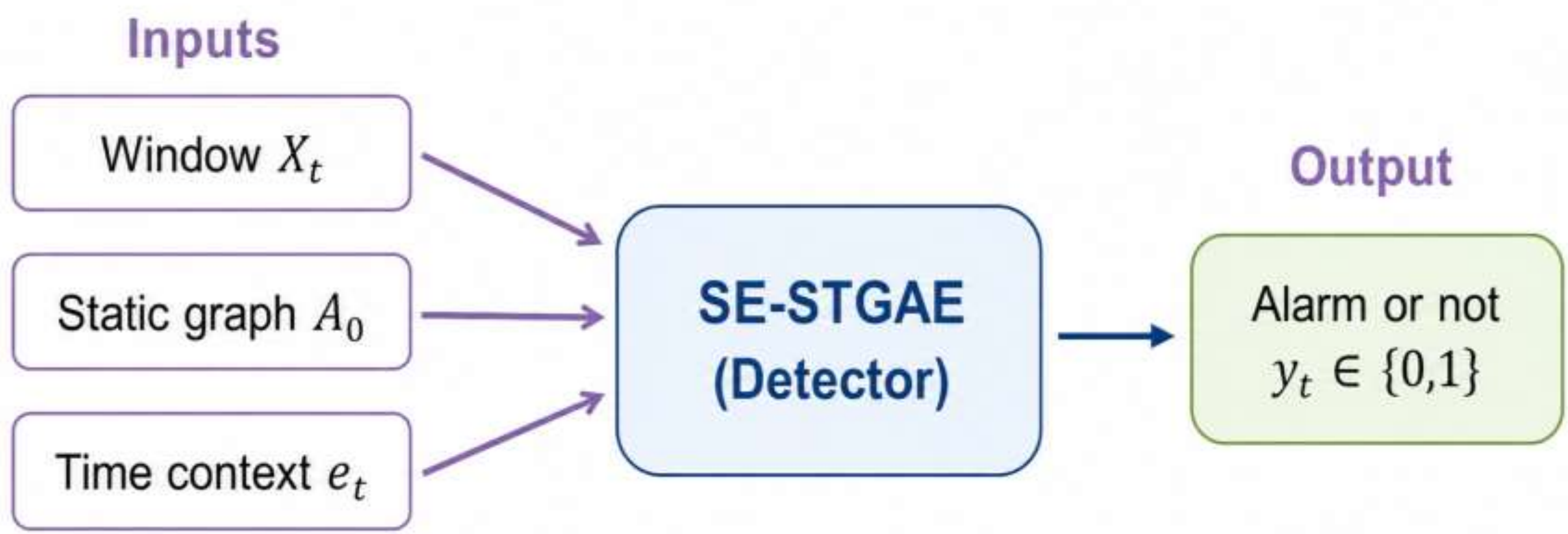
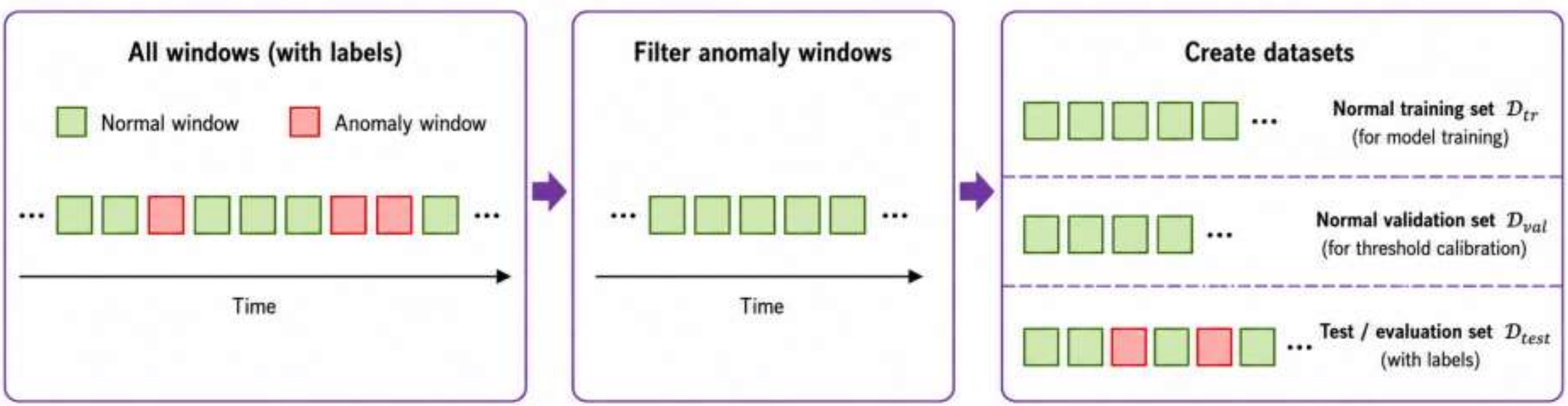
Problem Formulation

- Given current spatiotemporal observations, decide whether to alarm at time t

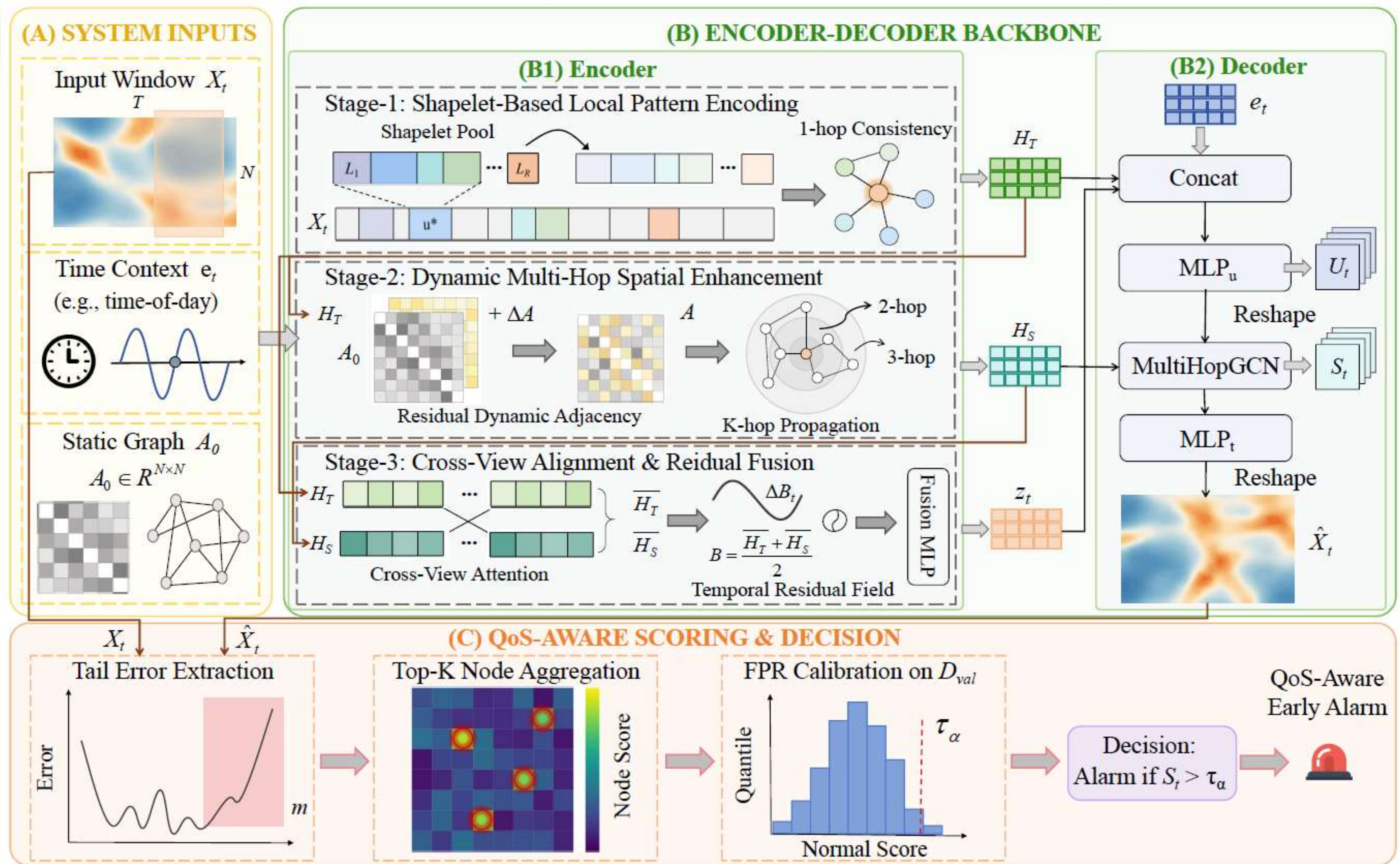


One-class Setting

- Train only on normal windows
- Anomaly labels are NOT used for supervised training, only for filtering training data and for evaluation

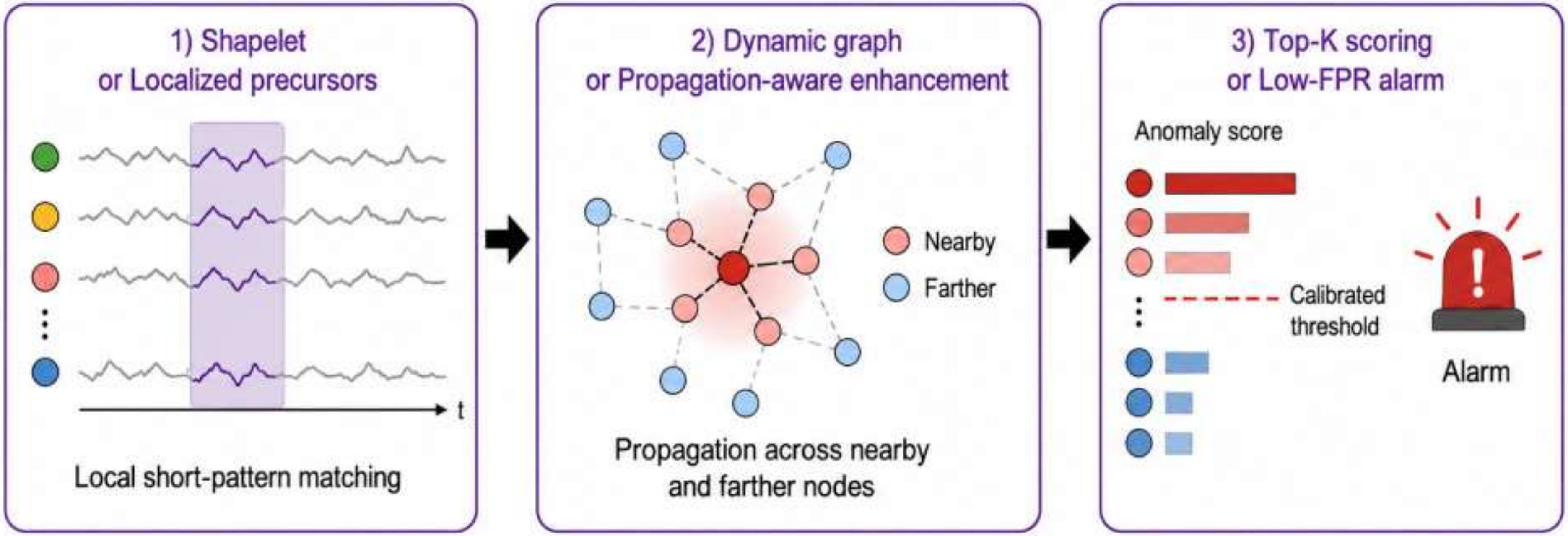


Framework Overview



Key Idea

- The detector combines localized precursor extraction, propagation modeling, and QoS-aware scoring



Localized evidence + dynamic propagation + low-FPR alarming

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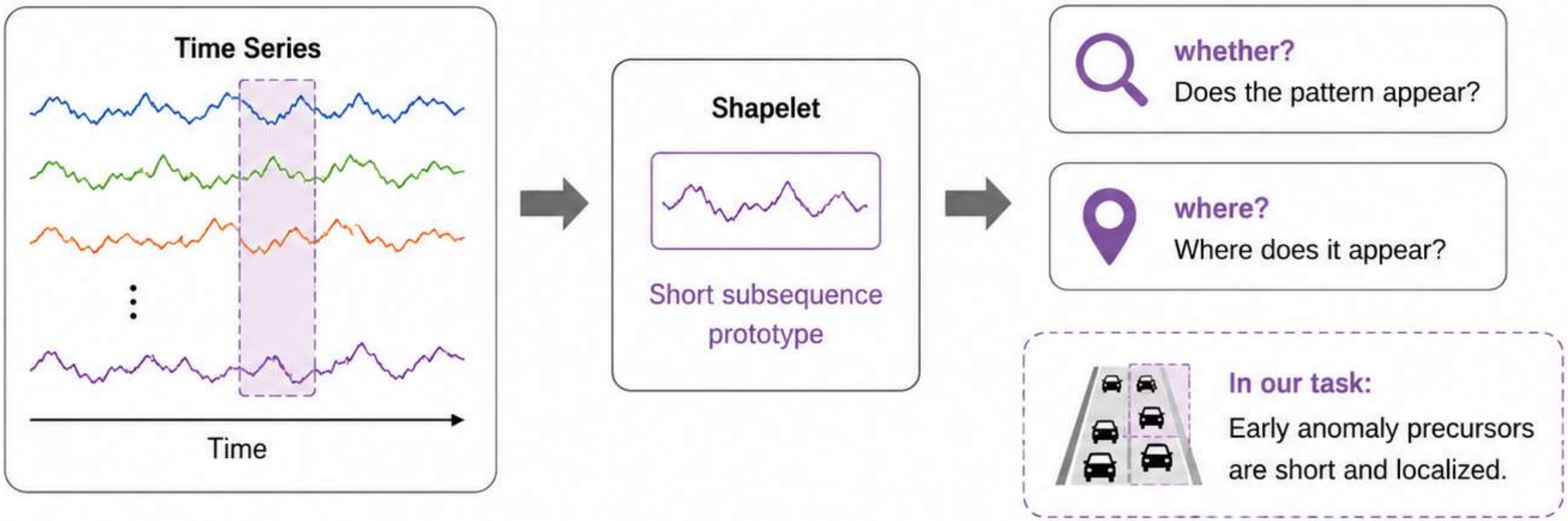
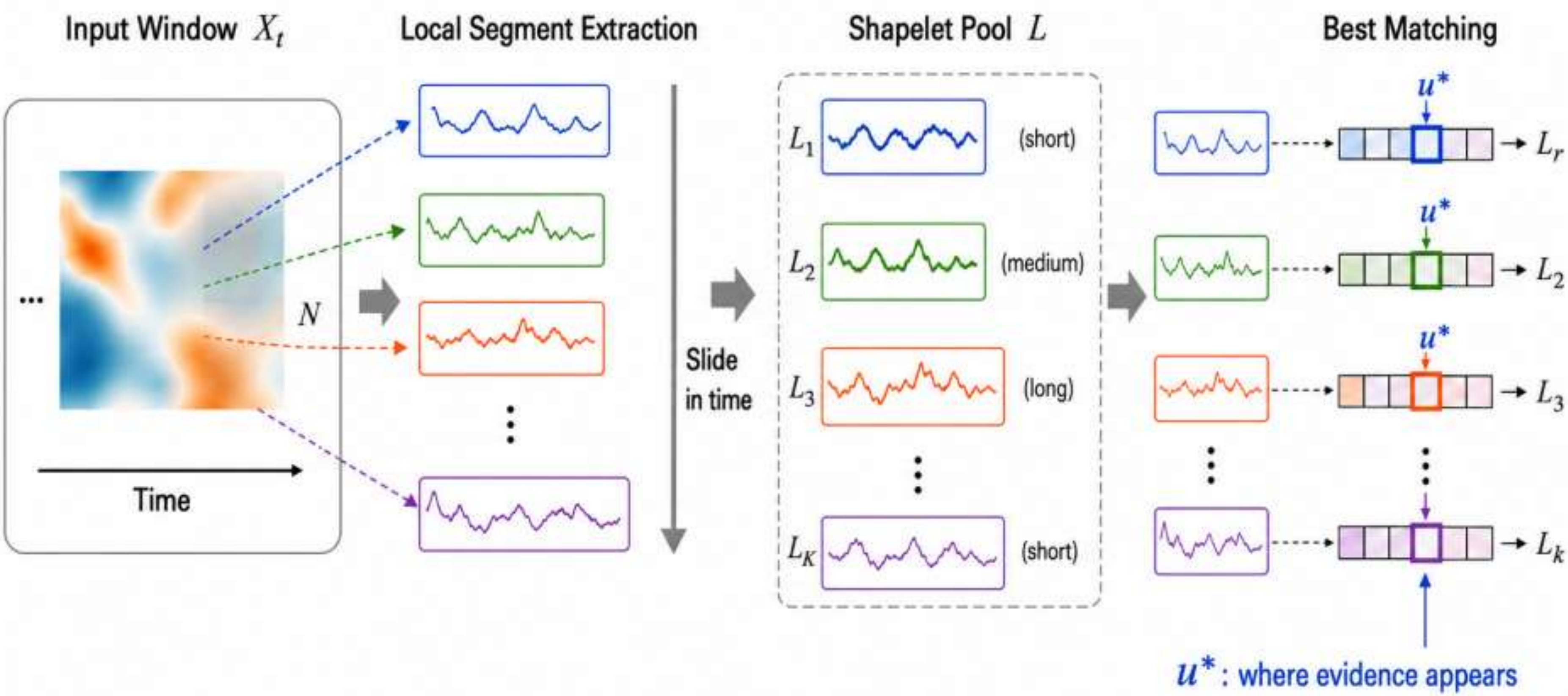
What is Shapelet?

- A short subsequence prototype in time series
- Captures localized temporal patterns
- Helps answer: whether a pattern appears and where it appears
- In our task: early anomaly precursors are short and localized



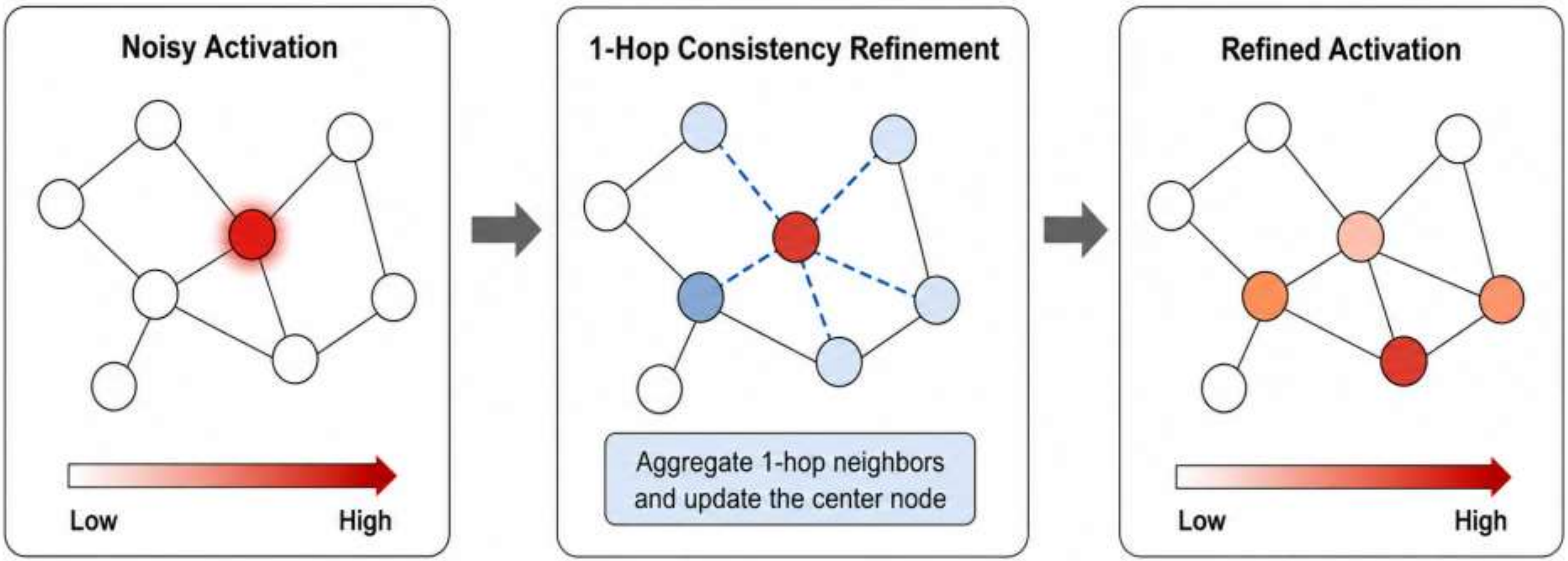
Shapelet-based Pattern Encoding



- Capture localized short precursors
- Preserve where evidence appears

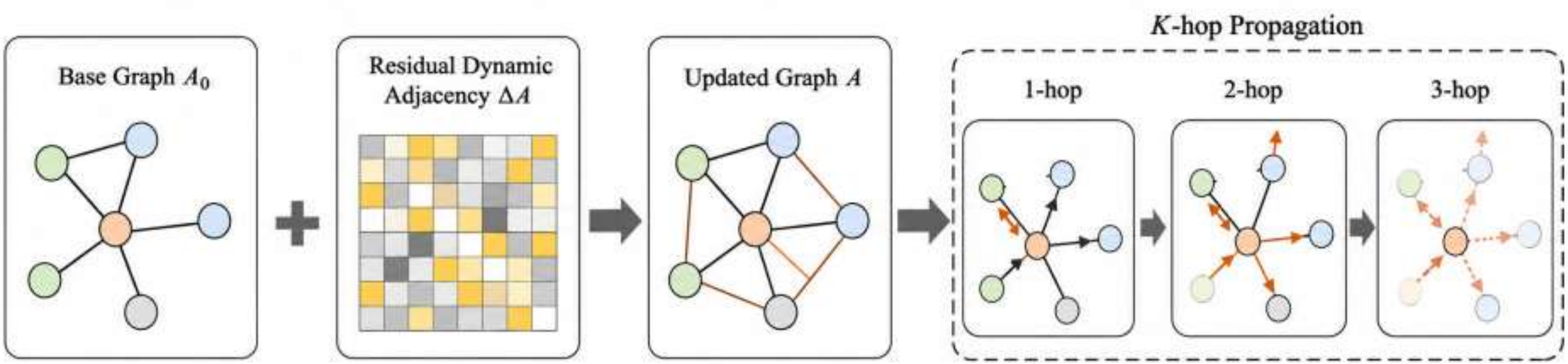
Spatial Consistency Refinement

- 1-hop consistency reduces isolated triggers
- Preserve locally supported evidence

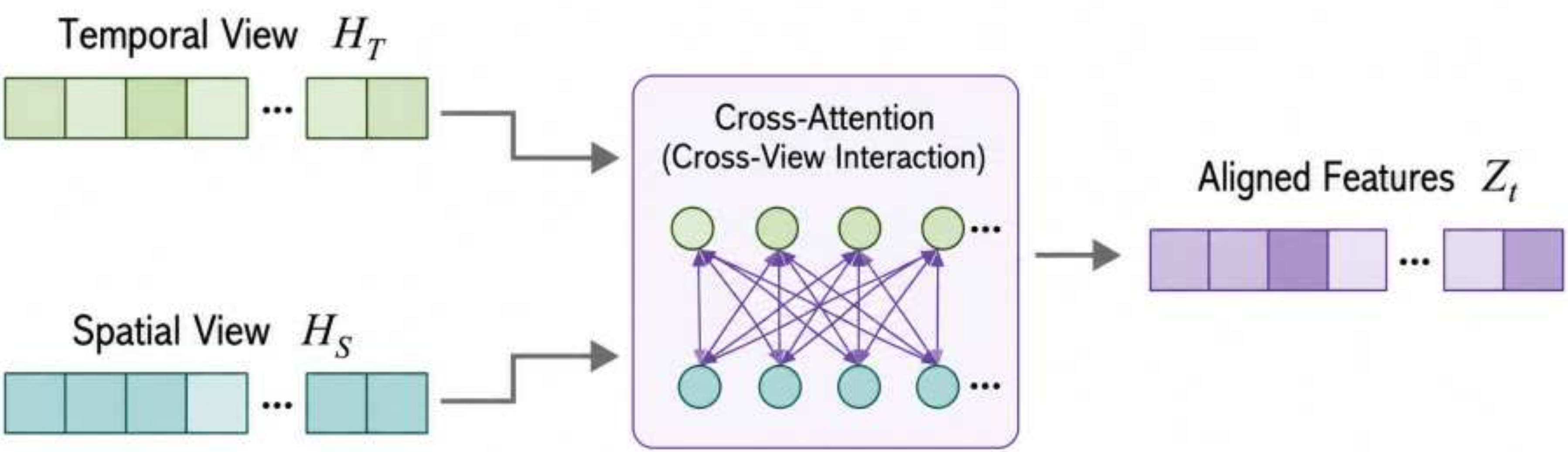


Dynamic Multi-Hop Spatial Enhancement

- Learn context-dependent adjacency
- Capture beyond-neighbor propagation



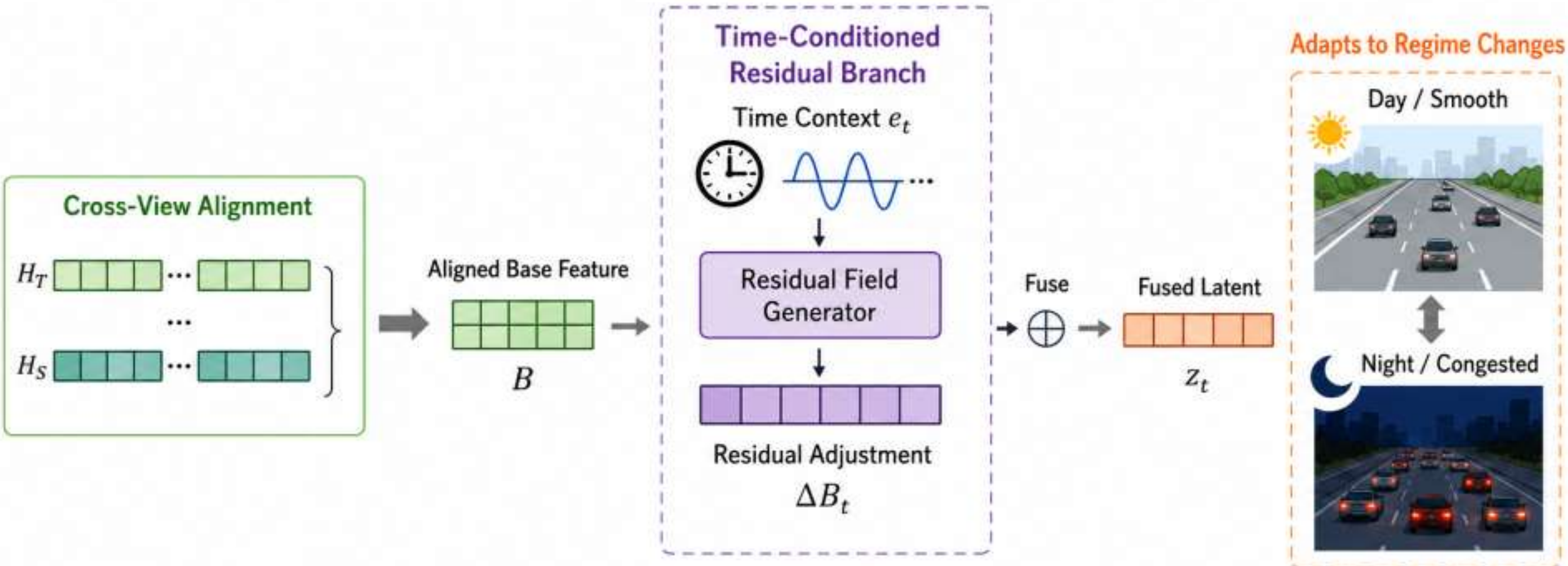
Cross-View Alignment



- Align temporal and spatial cues
- Improve a unified spatiotemporal representation

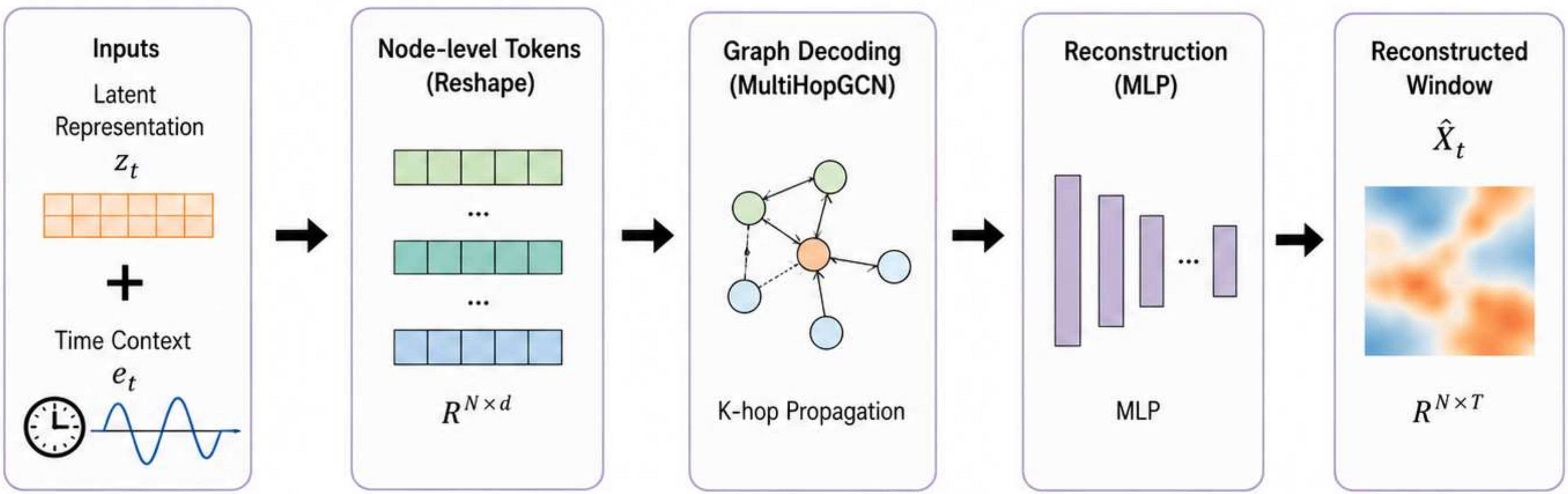
Residual Field Fusion

- Time-conditioned residual adapts to regime changes
- Refine the fused representation



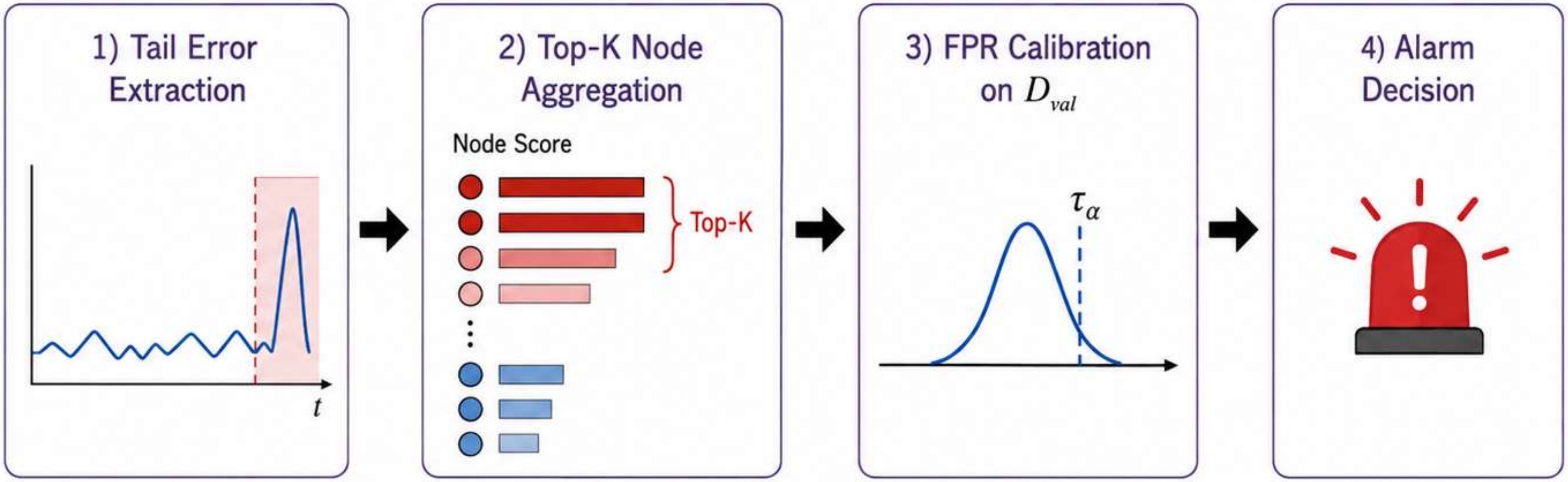
Reconstruction Decoder

- Decode latent features to node-level signals
- Reconstruct the current spatiotemporal window



Tail-Emphasized Top-K Scoring

- Focus on the tail part of each window
- Aggregate only the Top-K suspicious nodes



tail-sensitive scoring + Top-K aggregation + low-FPR thresholding

Outline

Dataset

- Three real-world freeway datasets
  - FT-AED [1] is collected on the Interstate 24 near Nashville, Tennessee.
  - PeMS [2] is collected from the California highway system.
  - XTraffic [3] is built from the California highway system.

[1] A. Coursey, J. Ji, M. Quinones-Grueiro, W. Barbour, Y. Zhang, T. Derr,G. Biswas, and D. B. Work, "Ft-aed: Benchmark dataset for early free-way traffic anomalous event detection," Advances in Neural InformationProcessing Svstems. vol. 37, pp. 15 526-15 549. 2024

[2] S. Guo, Y. Lin, H. Wan, X. Li, and G. Cong, "Learning dynamicsand heterogeneity of spatial-temporal graph data for traffic forecasting,"IEEE Transactions on Knowledge and Data Engineering, vol. 34, no. 11,pp. 5415-5428, 2021.

[3] X. Gou, Z. Li, T. Lan, J. Lin, Z. Li, B. Zhao, C. Zhang, D. Wang.and X. Zhang, "Xtraffic: A dataset where traffic meets incidents withexplainability and more," arXiv preprint arXiv:2407.11477, 2024.

Main results

TABLE I: Overall discrimination (AUC) and reconstruction quality (MSE) on three datasets.

Dataset	Metric	STG-RGCN	STG-GAT	GCN-LSTM	GCN	Transformer	MLP	CCB-GraphGAN	Our
FT-AED	MSE	0.0102	0.0089	0.0119	0.0095	0.0312	0.0122	**0.0061**	0.0082
	AUC	0.67	0.68	0.65	0.70	0.60	0.62	0.73	**0.75**
PeMS	MSE	0.0093	0.0098	0.0107	0.0112	0.0203	0.0126	0.0821	**0.0021**
	AUC	0.54	0.56	0.52	0.52	0.55	0.58	0.54	**0.85**
XTraffic	MSE	0.0487	0.0495	0.0541	0.0528	0.0632	0.0516	**0.0467**	0.0944
	AUC	0.59	0.58	0.57	0.54	0.56	0.53	0.62	**0.79**

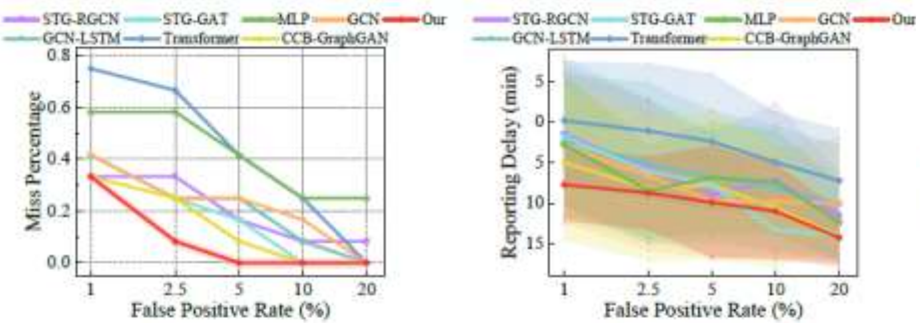
TABLE II: QoS-aware early detection on FT-AED under multiple FPR budgets.

Model	Miss Percentage					Reporting Delay				
	20%	10%	5%	2.5%	1%	20%	10%	5%	2.5%	1%
STG-RGCN	8.33%	8.33%	16.67%	33.33%	**33.33%**	-11.55 ± 5.28	-7.18 ± 9.62	-8.95 ± 7.59	-5.81 ± 8.62	-1.56 ± 8.83
STG-GAT	**0%**	**0%**	16.67%	25%	41.67%	-14.04 ± 2.14	**-13.33 ± 2.56**	-7.75 ± 6.58	-6.11 ± 8.81	-1.85 ± 10.01
GCN-LSTM	**0%**	8.33%	25%	25%	41.67%	-10.08 ± 7.2	-8.18 ± 7.73	-6.83 ± 8.19	-5.11 ± 9.94	-2.29 ± 8.11
GCN	**0%**	16.67%	25%	25%	41.67%	-10 ± 8.05	-9.85 ± 6.50	-9.78 ± 6.89	-6.67 ± 9.17	-3 ± 9.56
Transformer	**0%**	25%	41.67%	66.67%	75.00%	-7.25 ± 6.36	-5 ± 6.25	-2.43 ± 8.35	-1.13 ± 8.34	+0.16 ± 7.31
MLP	25%	25%	41.67%	58.33%	58.33%	-12.33 ± 4.99	-7.44 ± 6.38	-6.86 ± 6.87	-8.5 ± 5.71	-2.8 ± 8.68
CCB-GraphGAN	**0%**	**0%**	8.33%	25%	**33.33%**	-14.08 ± 1.24	-10.58 ± 7.31	-7.77 ± 9.18	-8.22 ± 8.83	-5.06 ± 9.61
Our	**0%**	**0%**	**0%**	**8.33%**	**33.33%**	**-14.28 ± 3.35**	-11.02 ± 5.98	**-9.92 ± 6.90**	**-8.75 ± 4.51**	**-7.75 ± 4.51**

Cross-dataset and early detection

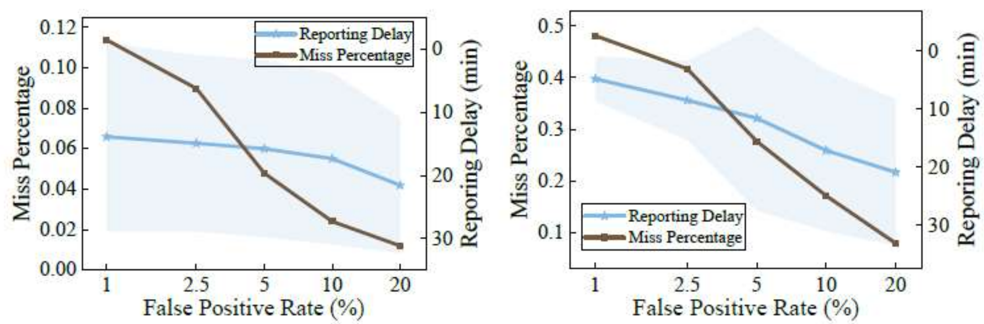
TABLE III: QoS-aware cross-dataset performance of our method under FPR budgets.

Dataset	Miss Percentage					Reporting Delay				
	20%	10%	5%	2.5%	1%	20%	10%	5%	2.5%	1%
PeMS	1.20%	2.40%	4.79%	8.98%	11.38%	-21.58 ± 10.74	-17.36 ± 13.52	-15.79 ± 13.98	-14.93 ± 13.94	-13.92 ± 14.89
XTraffic	7.96%	17.13%	27.68%	41.70%	48.10%	-20.86 ± 12.57	-17.11 ± 13.86	-11.56 ± 15.84	-8.46 ± 6.75	-4.78 ± 3.86



(a) Miss Percentage (b) Reporting Delay

Fig. 3: QoS-aware early detection under FPR budgets.



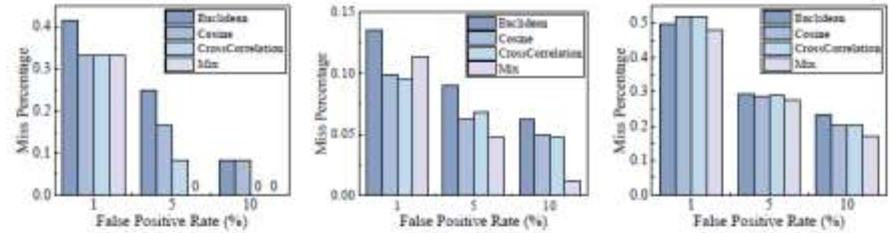
(a) PeMS (b) XTraffic

Fig. 4: Cross-dataset early detection.

Ablation and Running example

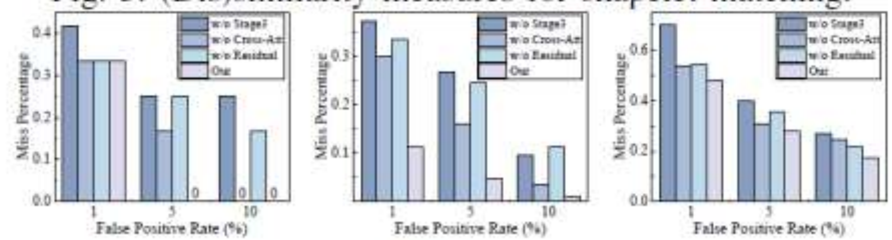
TABLE IV: Ablation study under the 5% FPR budget.

Method	Metric	FT-AED	PeMS	XTraffic
w/o Dynamic Adj	AUC	0.61	0.79	0.76
	Miss	25%	25.15%	29.37%
	Delay	-8.83 ± 4.56	-12.48 ± 15.45	-9.65 ± 16.45
w/o MultiHop	AUC	0.63	0.83	0.78
	Miss	33.33%	10.18%	32.07%
	Delay	-9.17 ± 4.84	-15.17 ± 13.74	-10.17 ± 15.93
w/o Tail	AUC	0.71	0.81	0.76
	Miss	25%	24.55%	30.72%
	Delay	-8.28 ± 6.49	-13.96 ± 13.81	-10.96 ± 16.90
w/o Top-K	AUC	0.71	0.78	0.75
	Miss	33.33%	12.57%	29.85%
	Delay	-9.25 ± 4.39	-14.64 ± 13.4	-9.22 ± 15.279
Our	AUC	**0.75**	**0.85**	**0.79**
	Miss	**0%**	**4.79%**	**27.68%**
	Delay	**-9.92 ± 6.90**	**-15.79 ± 13.98**	**-11.56 ± 15.84**



(a) FT-AED (b) PeMS (c) XTraffic

Fig. 5: (Dis)similarity measures for shapelet matching.



(a) FT-AED (b) PeMS (c) XTraffic

Fig. 6: Ablation study on cross-view attention and fusion.

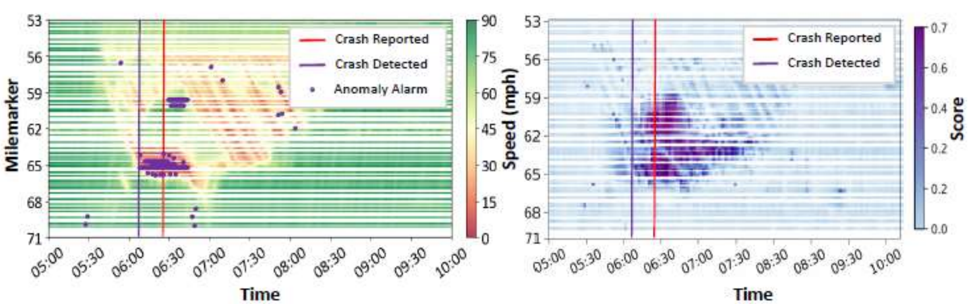


Fig. 8: Early-warning footprint of the crash event.

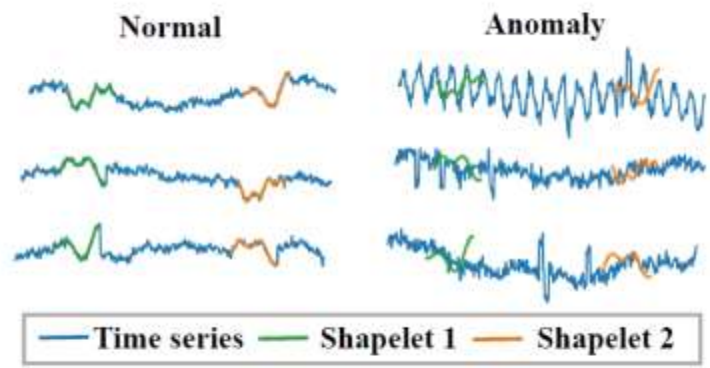


Fig. 9: Shapelet-matching evidence for the detection decision.

Outline

Conclusion

- Low-FPR freeway early anomaly detection
- Shapelet-based localized precursor modeling
- Dynamic propagation-aware spatiotemporal learning
- QoS-aware alarm decision