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A Generalizable Anomaly Detection Method in Dynamic Graphs

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Dynamic Graph Anomaly Detection

Target: Develop a generalizable framework for detecting anomalies in dynamic graphs.

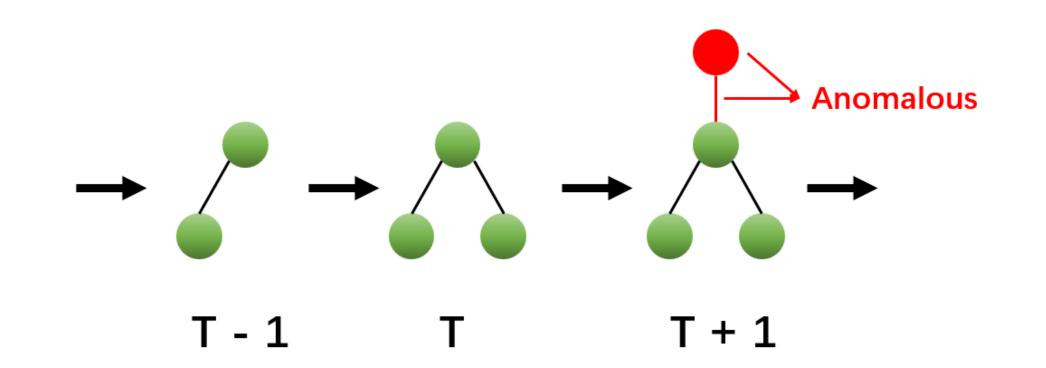
Unique Merits:

• Adaptability, Efficiency, Robustness, Generalization, etc.

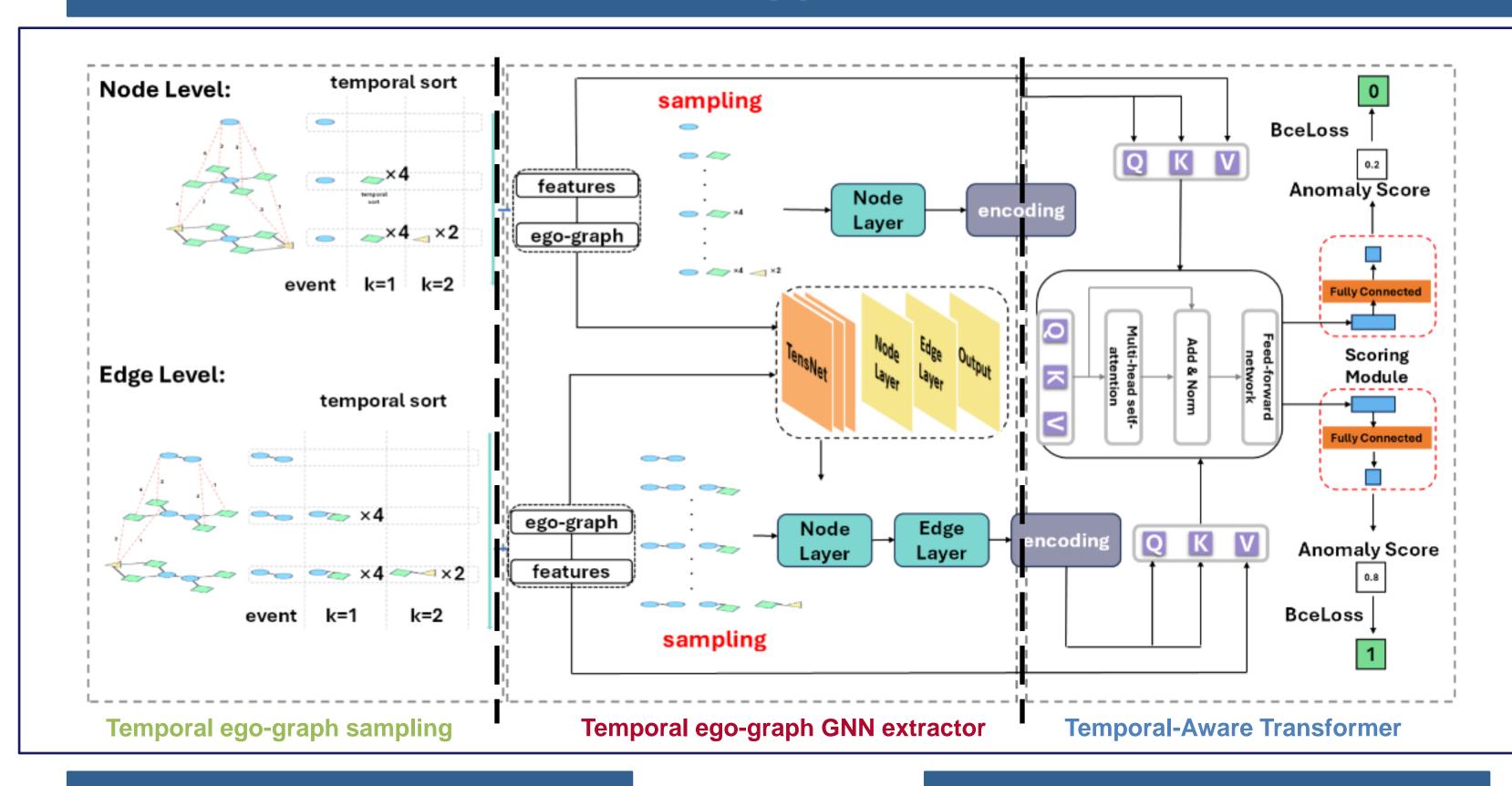
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- Input: A dynamic graph with temporally evolving nodes, edges, and attributes (e.g., timestamps, interaction features).
- Output: Anomaly scores for nodes and edges, identifying deviations from normal patterns.



Our Approach



1. Temporal ego-graph sampling:

- Contextual representation & hierarchical information
- ◆ Temporal k-hop ego-graph

2. Temporal ego-graph GNN extractor:

- Encodes events
- Alternately applying node and edge layers

3. Temporal-Aware Transformer :

- Query and Key: topological structure information
- Value : original event features

Solved Challenges

1. Data Diversity:

Mapping node, edge, and topological structure information into the feature space

2. Dynamic Feature Capture:

Incorporating hierarchical tokens

3. Computational Cost

Sampling temporal ego-graphs to efficiently capture dynamic features

Evaluations

> Outperform state-of-the-art methods on Node-Level and Edge-Level datasets

			Bitcoin	-Alpha					Bitcoir	n-OTC			Methods	SWaT	WADI		
Methods	19	%	59	%	10	%	19	%	59	%	10	%	PCA	23.16	9.35		
	AUC	AP	AUC	AP	AUC	AP	AUC	AP	AUC	AP	AUC	AP	KNN	7.83	7.75		
node2vec	69.10	9.17	68.02	7.31	67.85	9.95	69.51	8.31	68.83	6.45	67.45	4.77	GDN	80.82	56.92		
DeepWalk	69.85	8.56	68.74	9.68	67.93	10.78	74.23	10.58	73.56	9.41	72.87	8.22	BTAD	81.43	53.77		
TGAT	85.32	11.36	84.16	11.08	83.98	12.05	88.87	16.87	87.59	15.24	87.55	15.37	GRN-100	74.96	48.28		
TGN	86.92	13.00	86.78	16.85	86.21	17.00	84.33	11.33	83.49	11.25	83.47	10.79	DAGMM	39.37	36.09		
ADDGRAPH	83.41	13.21	84.70	13.01	83.69	14.28	86.00	16.04	84.98	15.21	84.77	14.21					
StrGNN	85.74	12.56	86.67	13.99	86.27	14.68	90.12	18.34	87.75	18.68	88.36	18.10	MST-GAT	83.55	60.31		
TADDY	94.51	16.51	<u>93.41</u>	18.32	<u>94.23</u>	19.67	94.55	16.10	<u>93.40</u>	18.47	<u>94.25</u>	18.92	FuSAGNet	83.69	60.70		
SAD	90.69	<u>19.99</u>	90.55	21.08	90.33	22.99	91.88	<u>26.32</u>	90.99	<u>27.33</u>	90.04	<u> 26.79 </u>	LSTM-VAE	73.85	24.82		
SLADE	90.32	18.78	89.99	<u>22.02</u>	88.71	<u>24.41</u>	91.53	20.32	91.24	22.11	91.01	20.04	MTAD-GAT	31.71	16.94		
GeneralDyG	<u>94.01</u>	24.00	95.41	24.02	96.28	26.73	94.66	27.89	94.86	29.97	95.59	27.13	GeneralDyG	85.19	<u>60.43</u>		

Node-Level

26.80

26.11

60.43

60.11

59.74

59.70

Discussions

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			'			 96	Method	Bitcoi
							Method	AUC
	4					 95	GeneralDyG	96.28
\mathcal{L}						0.4	no special	96.27
	2	_			-	 94	no sort	95.37
						 93	no sort & special	95.20
	0					00		
	υ,	1	9	4	C			

 $\mathcal{K} = 3$ $\mathcal{K} = 4$ $\mathcal{K} = 5$

23.38 22.84

21.62 21.11

25.63

24.21

22.95

21.88

26.73 (peak) 24.45

23.62

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	Genera	lizability	

lode-Level	Bitcoin	-Alpha	Edge-Level	WADI
Method	AUC	AP	Method	F1
eneralDyG	96.28	26.73	GeneralDyG	60.43
GDN	83.84	13.28	TADDY	40.05
MST-GAT	86.66	18.97	SimpleDyG	33.24
SuSAGNet	87.76	20.01	SAD	36.75

Ablation Study

Edge-Level

Method	Bitcoin	WADI	
Method	AUC	AP	F1
GeneralDyG	96.28	26.73	60.43
w/o ego-graph	96.01	19.33	59.45
w/o TensGNN	92.02	22.63	55.13
w/o Transformer	93.71	20.20	58.46

> Ablation Study (Bitcoin-Alpha)

Method	1%	5%
GeneralDyG (Full)	24.00	24.02
W/o ego-graph sampling	14.72	18.69
W/o TensGNN	17.99	19.90
W/o Transformer	21.78	17.24