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AnomalyGFM: Graph Foundation Model for Zero/Few-shot Anomaly Detection

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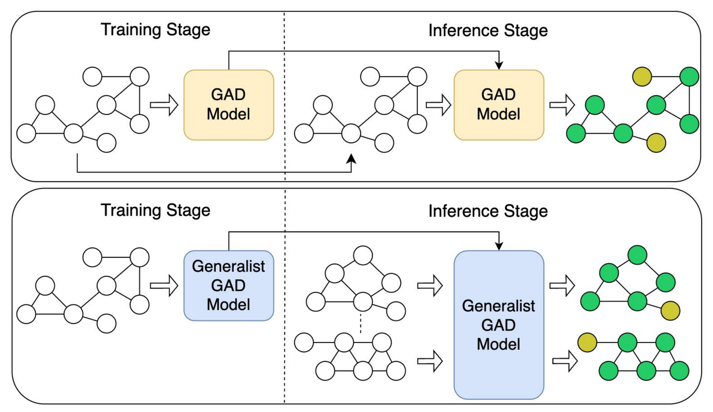
Motivation and Challenges

❖Foundation Model for GAD

- Pre-train a graph neural network designed to generalize across diverse graph domains and anomaly types.

Conventional GAD

Generalist GAD



❖ General Node Classification | **❖ Generalist GAD**

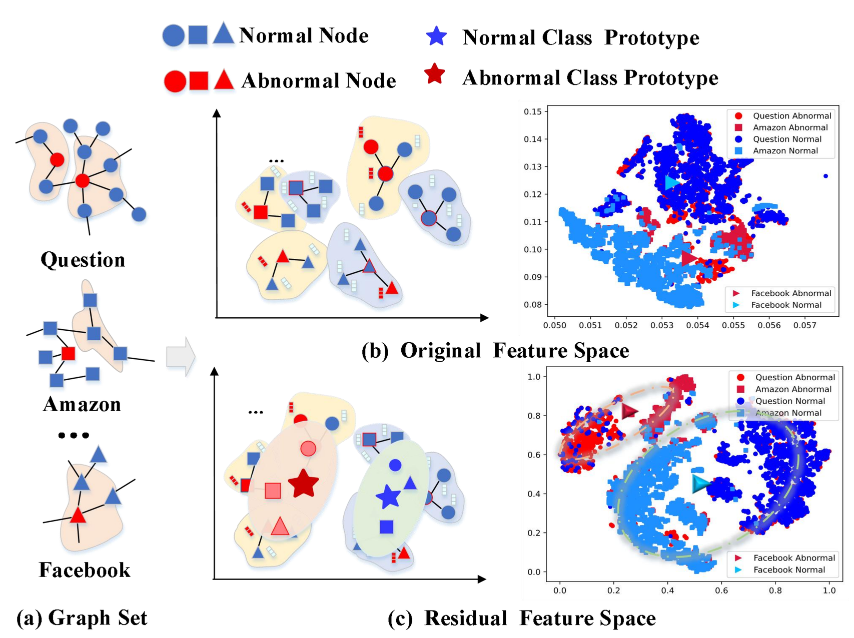
- ➢ Feature Heterogeneity
- ➢ Domain Difference
- ➢ Fine Tuning Mechanism

- ➢ Abnormality/Normality Difference
- ➢ Generalized Scoring Measurement

❖The residual features essentially project the node information into a unified feature space where we can effectively measure the abnormality of nodes from different graphs in a consistent way.

- **Residual Feature**

$$\mathbf{r}_i = \mathbf{h}_i - \frac{1}{|\mathcal{N}(v_i)|}\sum_{v_j \in \mathcal{N}(v_i)} \mathbf{h}$$



Feature Unification

Due to the feature dimension difference across the graphs, we need to align the node features/attributes into a shared feature space to ease the feature heterogeneity among the graphs

$$\mathbf{X}^{(i)} \in \mathbb{R}^{\mathbb{N}^{(i)} \times d^{(i)}} \xrightarrow[\text{Projection}]{\text{Fasture}} \widetilde{\mathbf{X}}^{(i)} \in \mathbb{R}^{\mathbb{N}^{(i)} \times d}$$

Dataset	Domain	#Nodes	#Edges	#Feat.	Ano.	Sim.
Facebook	Social Networks	1,081	55,104	576	27(2.49%)	0.690
Reddit	Social Networks	10,984	168,016	64	366(3.33%)	0.997
Amazon	Co-review	10,244	175,608	25	693(6.66%)	0.645
Disney	Co-purchase	124	335	28	6(4.8%)	0.804
Amazon-all	Co-review	11,944	4,398,392	25	821(6.87%)	0.645
YelpChi-all	Co-review	45,941	3,846,979	32	6,674(14.52%)	0.905
Tolokers	Work Collaboration	11,758	519,000	10	2,566(21.8%)	0.814
Question	Social Networks	48,921	153,540	301	1,460(2.98%)	0.679
Elliptic	Bitcoin Transaction	46,564	73,248	93	4,545 (9.8%)	0.356
T-Finance	Transaction Record	39,357	21,222,543	10	1,803(4.6%)	0.107
T-Social	Social Friendship	5,781,065	73,105,508	10	174,280(3.0%)	0.307

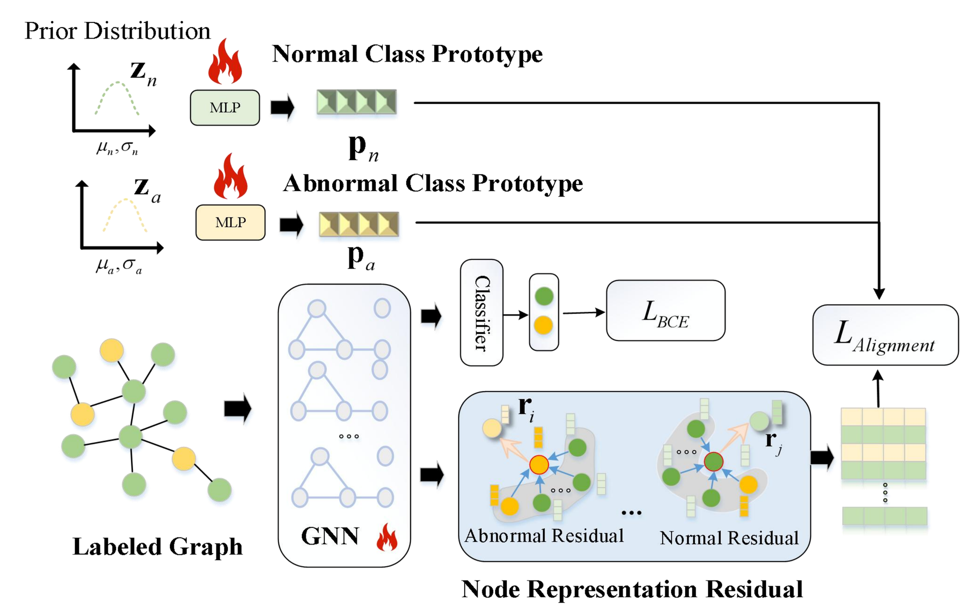
GNN for Representation Learning

Due to its simplicity and effectiveness, GNN is employed to learn the representation of each graph which can be formulated as follows

$$\mathbf{H}^{(l)} = \mathrm{GNN}\left(\mathbf{A}, \mathbf{H}^{(l-1)}; \mathbf{W}^{(l)}\right)$$

Pre-training via Prototype Alignment

❖Learn the graph-agnostic, discriminative prototypes for the normal and abnormal classes using alignment



(a) Pre-training

- **Standard binary classification loss**

$$L_{BCE} = \sum_{i=1}^{|\mathcal{V}|} y_i \log(p_i) + (1 - y_i)\log(1 - p_i)$$

- **Class-agnostic Prototype Alignment**

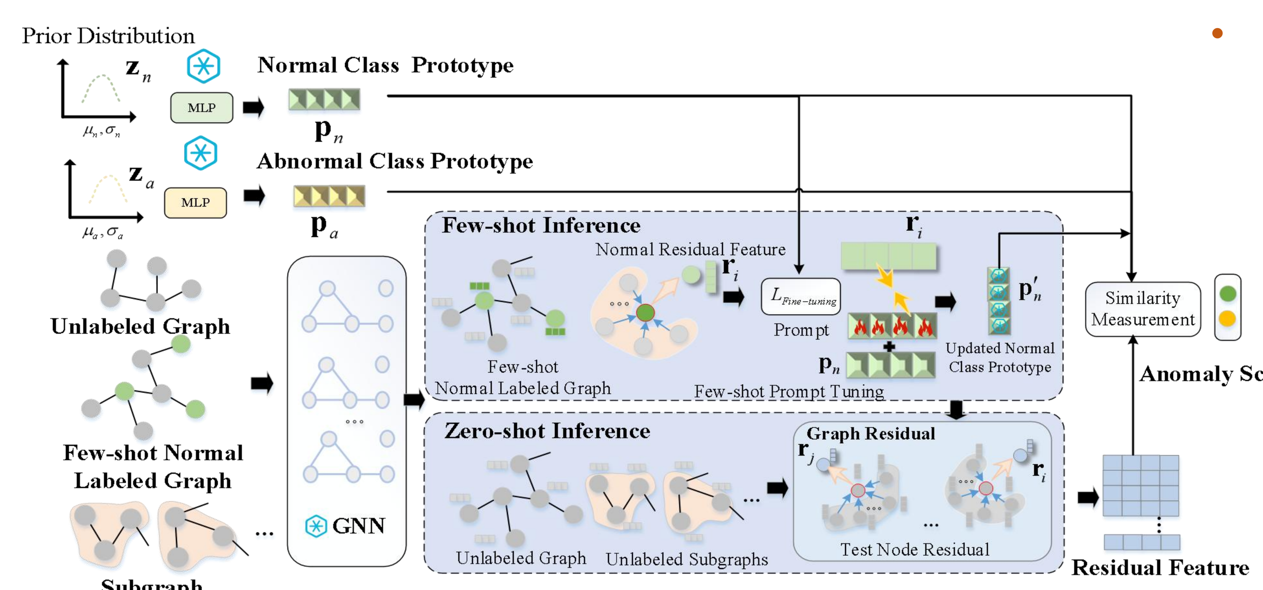
$$L_{\text{Alignment}} = \sum_{i=1}^{|\mathcal{V}|} I_{y_i=0}\|\mathbf{r}_i - \mathbf{p}_n\|_2^2 + I_{y_i=1}\|\mathbf{r}_i - \mathbf{p}_a\|_2^2$$

- **Main Optimization**

$$L_{\text{total}} = L_{BCE} + \alpha L_{\text{Alignment}}$$

Zero/Few-shot Inference

❖ A small learnable prompt and adaptation layer were involved into the normal class prototype to better align it with the normal node representation residuals on the test graph



(b) Zero-/Few-shot Inference

- **Normal Prototype-based Fine-tuning**

$$\mathbf{p}_n' = \mathbf{p}_n + g(\mathbf{p}_n; \phi) + \Psi_{\mathbf{p}_n}$$

$$L_{pt} = \sum_{i=1}^{|\mathcal{V}_l^{\text{Test}}|} \|\mathbf{r}_i - \mathbf{p}_n'\|_2^2$$

- **Zero-shot Inference**

$$s_i = \exp\left(\mathbf{r}_i^{\mathrm{T}}\mathbf{p}_a\right) + \beta \exp\left(-\mathbf{r}_i^{\mathrm{T}}\mathbf{p}_n\right)$$

- **Few-shot Inference**

$$s_i = \exp\left(\mathbf{r}_i^{\mathrm{T}}\mathbf{p}_a\right) + \beta \exp\left(-\mathbf{r}_i^{\mathrm{T}}\mathbf{p}_n'\right)$$

Experimental Results

- ❑ **Unsupervised methods**: AnomalyDAE, CoLA , TAM , and GADAM;
- ❑ **Supervised methods:** GCN , GAT , BWGNN, GHRN, and XGBGraph;
- ❑ **General GFM methods:** GraphPrompt for general graph tasks, and the one for zero-shot GAD UNPrompt.

AUROC and AUPRC results for zero-shot GAD on nine real-world datasets

Metric	Method	Reddit	Amazon	Disney	Aamzon-all	YelpChi-all	Tolokers	Question	Elliptic	T-Finance	Avg.	p-value
AUROC	Unsupervised Methods											
	AnomalyDAE (ICASSP'20)	0.5016	0.5818	0.4853	0.7228	0.5002	0.5948	0.4311	0.4197	0.2324	0.4966	0.007
	CoLA (TNNLS'21)	0.4623	0.4580	0.4696	0.4091	0.4879	0.4501	0.4945	0.5572	0.4889	0.4752	0.003
	TAM (NeurIPS'23)	0.5725	0.4720	0.4773	0.7543	0.4216	0.5351	0.5119	0.3282	0.2990	0.4857	0.003
	GADAM (ICLR'24)	0.4532	0.6646	0.4288	0.5959	0.4829	0.4832	**0.5594**	0.3922	0.1382	0.4664	0.007
	Supervised Methods											
	GCN (ICLR'17)	0.5645	0.5988	0.5000	0.7195	0.5486	0.5319	0.5161	**0.7640**	0.2345	0.5531	0.039
	GAT (ICLR'18)	0.5000	0.4981	0.5175	0.5005	0.4802	0.5030	0.4577	0.6588	0.5072	0.5136	0.007
	BWGNN (ICML'22)	0.5208	0.4769	0.6073	0.3648	0.5282	0.4877	0.4404	0.5843	0.5457	0.5062	0.003
	GHRN (WebConf'23)	0.5253	0.4560	0.5336	0.3382	0.5125	0.4860	0.4535	0.5400	0.5324	0.4863	0.003
	XGBGraph (NeurIPS'23)	0.4601	0.4179	0.6692	0.7950	0.4945	0.5462	0.5095	0.4274	0.3402	0.5177	0.003
	Generalist Methods											
	GraphPrompt (WebConf'23)	0.4677	0.4904	0.5192	0.3215	0.4976	0.4779	0.4204	0.3221	0.5405	0.4508	0.003
	UNPrompt (Arxiv'24)	0.5337	0.7525	0.6412	0.7962	0.5558	**0.6853**	0.4757	0.5901	0.2318	0.5847	0.074
	AnomalyGFM	**0.5974**	**0.8417**	**0.6751**	**0.9032**	**0.5791**	0.5843	0.5280	0.6195	**0.5614**	**0.6544**	/
AUPRC	Unsupervised Methods											
	AnomalyDAE (ICASSP'20)	0.0327	0.0833	0.0566	0.1921	0.1484	0.1876	0.0241	0.0798	0.0274	0.0924	0.003
	CoLA (TNNLS'21)	0.0391	0.0669	0.0701	0.0861	0.1466	0.0848	0.0292	0.0998	0.0430	0.0739	0.007
	TAM (NeurIPS'23)	0.0413	0.0666	0.0628	0.1736	0.1240	0.0970	0.0307	0.0697	0.0332	0.0776	0.007
	GADAM (ICLR'24)	0.0293	0.1562	0.0651	0.1595	0.1371	0.1001	0.0395	0.0733	0.0261	0.0873	0.003
	Supervised Methods											
	GCN (ICLR'17)	**0.0439**	0.0891	0.0484	0.1536	0.1735	0.1060	0.0387	**0.1963**	0.0274	0.0974	0.074
	GAT (ICLR'18)	0.0329	0.0688	0.0530	0.0696	0.1400	0.0822	0.0259	0.1366	0.0463	0.0728	0.003
	BWGNN (ICML'22)	0.0389	0.0652	0.0624	0.0586	0.1605	0.1030	0.0257	0.1158	0.0479	0.0753	0.007
	GHRN (WebConf'23)	0.0407	0.0633	0.0519	0.0569	0.1505	0.0957	0.0259	0.1148	0.0457	0.0717	0.007
	XGBGraph (NeurIPS'23)	0.0330	0.0536	0.1215	0.2307	0.1449	0.1256	0.0306	0.0816	**0.0754**	0.0996	0.027
	Generalist Methods											
	GraphPrompt (WebConf'23)	0.0334	0.0661	0.0610	0.0666	0.1542	0.2070	0.0266	0.0664	0.0492	0.0811	0.003
	UNPrompt (Arxiv'24)	0.0351	0.1602	0.1236	0.2430	0.1810	0.2219	0.0348	0.1278	0.0279	0.1283	0.003
	AnomalyGFM	0.0387	**0.5790**	**0.1242**	**0.6820**	**0.1819**	**0.2749**	**0.0397**	0.1371	0.0593	**0.2352**	/

Few-shot Fine-tuning Inference

- ❑ **General GFM methods:** GPPT and GraphPrompt
- ❑ **Few-shot GAD methods:** ARC

Results on the nine real-world GAD datasets under 1/5/10-shot with models tuned on the few-shot data

Metric	Setting	Method	Reddit	Amazon	Disney	Aamzon-all	YelpChi-all	Tolokers	Question	Elliptic	T-Finance	Avg.	p-value
AUROC	1-shot	GPPT (KDD'22)	0.5000	0.5303	0.4997	0.5010	0.5000	0.5061	0.4921	0.6162	0.3647	0.5011	0.003
		GraphPrompt (WebConf'23)	0.4216	0.4882	0.4223	0.2631	0.4811	0.5328	0.4086	0.6001	0.4000	0.4464	0.004
		ARC (NeurIPS'24)	0.4899	0.4571	0.3578	0.4570	0.4910	0.4667	**0.5865**	0.2904	0.2484	0.4272	0.008
		AnomalyGFM	**0.5922**	**0.8531**	**0.6649**	**0.8972**	**0.5872**	**0.5898**	0.5303	**0.6199**	**0.5916**	**0.6584**	/
	5-shot	GPPT (KDD'22)	0.5000	0.5098	0.5000	0.5051	0.5000	0.5181	0.4959	0.5736	0.2609	0.4848	0.003
		GraphPrompt (WebConf'23)	0.4406	0.4900	0.6497	0.4726	0.5359	0.5381	0.4069	0.6012	0.4069	0.5046	0.003
		ARC (NeurIPS'24)	0.4720	0.4458	0.4435	0.4473	0.5112	0.4746	**0.5906**	0.2714	0.2168	0.4303	0.007
		AnomalyGFM	**0.6023**	**0.8600**	**0.6613**	**0.9011**	**0.5951**	**0.6095**	0.5426	**0.6119**	**0.6248**	**0.6676**	/
	10-shot	GPPT (KDD'22)	0.5000	0.5087	0.4769	0.5023	0.5000	0.4971	0.5047	0.4212	0.5539	0.4961	0.003
		GraphPrompt (WebConf'23)	0.4321	0.4906	0.6314	0.7167	0.5367	0.5329	0.3826	0.6221	0.4260	0.5301	0.007
		ARC (NeurIPS'24)	0.4867	0.4323	0.4769	0.4467	0.5145	0.4786	**0.5901**	0.2644	0.2298	0.4355	0.003
		AnomalyGFM	**0.6252**	**0.8649**	**0.6649**	**0.9215**	**0.6064**	**0.6140**	0.5611	**0.6303**	**0.6283**	**0.6796**	/
AUPRC	1-shot	GPPT (KDD'22)	0.0333	0.0766	0.0488	0.0687	0.1453	0.2204	0.0294	0.1239	0.0432	0.0877	0.003
		GraphPrompt (WebConf'23)	0.0283	0.0680	0.0486	0.0426	0.1113	0.2321	**0.0448**	0.1108	0.0302	0.0796	0.012
		ARC (NeurIPS'24)	0.0332	0.0581	0.0453	0.0590	0.1402	0.2122	0.0468	0.0701	0.0277	0.0769	0.011
		AnomalyGFM	**0.0398**	**0.5801**	**0.1223**	**0.6921**	**0.1852**	**0.2786**	0.0332	**0.1401**	**0.0601**	**0.2368**	/
	5-shot	GPPT (KDD'22)	0.0333	0.0692	0.0504	0.0716	0.1453	0.2265	0.0297	0.1127	0.0365	0.0861	0.004
		GraphPrompt (WebConf'23)	0.0285	0.0681	0.0892	0.0600	0.1661	**0.2957**	0.0327	0.1416	0.0360	0.1019	0.009
		ARC (NeurIPS'24)	0.0312	0.0571	0.0546	0.0572	0.1464	0.2150	**0.0471**	0.0726	0.0267	0.0786	0.011
		AnomalyGFM	**0.0401**	**0.5831**	**0.1257**	**0.6985**	**0.1918**	0.2866	0.0336	**0.1437**	**0.0622**	**0.2405**	/
	10-shot	GPPT (KDD'22)	0.0334	0.0691	0.0526	0.0698	0.1453	0.2178	0.0301	0.0905	0.0511	0.0844	0.004
		GraphPrompt (WebConf'23)	0.0278	0.0681	0.0848	0.1427	0.1649	**0.2922**	0.0263	0.1421	0.0382	0.1096	0.007
		ARC (NeurIPS'24)	0.0327	0.0557	0.0743	0.0583	0.1491	0.2168	**0.0463**	0.0677	0.0272	0.0809	0.011
		AnomalyGFM	**0.0444**	**0.5895**	**0.1399**	**0.7124**	**0.1990**	0.2897	0.0346	**0.1570**	**0.0644**	**0.2478**	/

Ablation Study

(i) **BCE** which replaces the similarity measurement with the predicted probability from the BCE loss function for anomaly scoring

(ii) **BCE Residual (BCE-R)** which firstly removes the alignment loss and applies the BCE loss on the residual features to differentiate normal and abnormal nodes

(iii) **Feature Alignment (FA)** which replaces the alignment on the residual feature with the alignment on the original feature

Metric	Method	Reddit	Amazon	Disney	Amazon-all	YelpChi-all	Tolokers	Question	Elliptic	T-Finance	Avg.
AUROC	FA	0.5697	0.5680	0.6073	0.5097	0.5211	0.5594	0.5326	**0.7765**	**0.6674**	0.5901
	BCE	0.5445	0.4308	**0.7542**	0.5545	0.5232	0.5187	0.4593	0.2581	0.6581	0.5223
	BCE-R	0.5108	0.5314	0.4887	0.5777	0.4590	0.4788	0.4601	0.5414	0.5380	0.5095
	AnomalyGFM	**0.5974**	**0.8417**	0.6751	**0.9032**	**0.5791**	**0.5843**	**0.5380**	0.6195	0.5614	**0.6555**
AUPRC	FA	**0.0400**	0.0776	0.0960	0.0684	0.1555	0.2478	0.0356	0.1199	**0.1495**	0.1100
	BCE	0.0394	0.0544	**0.2254**	0.0718	0.1594	0.2264	0.0272	0.0287	0.1389	0.1079
	BCE-R	0.0314	0.0677	0.0685	0.0787	0.1294	0.2122	0.0305	0.0658	0.0971	0.0868
	AnomalyGFM	0.0387	**0.5790**	0.1242	**0.6820**	**0.1819**	**0.2749**	**0.0397**	**0.1371**	0.0593	**0.2352**

Inference on Very Large-scale Graphs

❖Most existing GAD methods typically require loading all nodes of the graph, which often leads to poor scalability on large graphs during inference.

❖ Privacy-sensitive settings where we do not want to reveal the entire graph structure

❑ AnonalyGFM can effectively infer the anomaly score without considering the entire graph structure, eliminating the bottleneck of loading the full graph for GAD inference.

$$\mathbf{r}_i = \mathbf{h}_i - \frac{1}{|\mathcal{S}(v_i)|}\sum_{v_j \in \mathcal{S}(v_i)} \mathbf{h}_j$$

Metric	Method	T-Finance	T-Social
AUROC	Unsupervised Methods		
	TAM (NeurIPS'23)	0.2990	/
	GADAM (ICLR'24)	0.1382	0.5155
	Supervised Methods		
	BWGNN (ICML'22)	0.5457	0.4964
	GHRN (WebConf'23)	0.5324	0.4934
	XGBGraph (NeurIPS'23)	0.3402	0.4602
	AnomalyGFM	**0.7852**	**0.5991**
AUPRC	Unsupervised Methods		
	TAM (NeurIPS'23)	0.0332	/
	GADAM (ICLR'24)	0.0261	0.0285
	Supervised Methods		
	BWGNN (ICML'22)	0.0479	0.0301
	GHRN (WebConf'23)	0.0457	0.0303
	XGBGraph (NeurIPS'23)	0.0754	0.0305
	AnomalyGFM	**0.1059**	**0.0398**

Hyperparameter Sensitivity Analysis

- AnomalyGFM outperforms all the competing methods under different dimensions. The main reason is that the deviation between connected nodes is still preserved with different d' which can be efficiently measured by the graph-agnostic prototypes

AUROC and AUPRC of AnomalyGFM w.r.t d'