Explainable Graph-based Fraud Detection via Neural Meta-graph Search

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Peering In

What drives the model to make predictions?

How to develop a fraud detector giving high-quality predictions and explanations simultaneously?

Our contributions:

1. Propose NGS to search the optimized message passing graph structure.
2. The meta-graphs offer explanations.

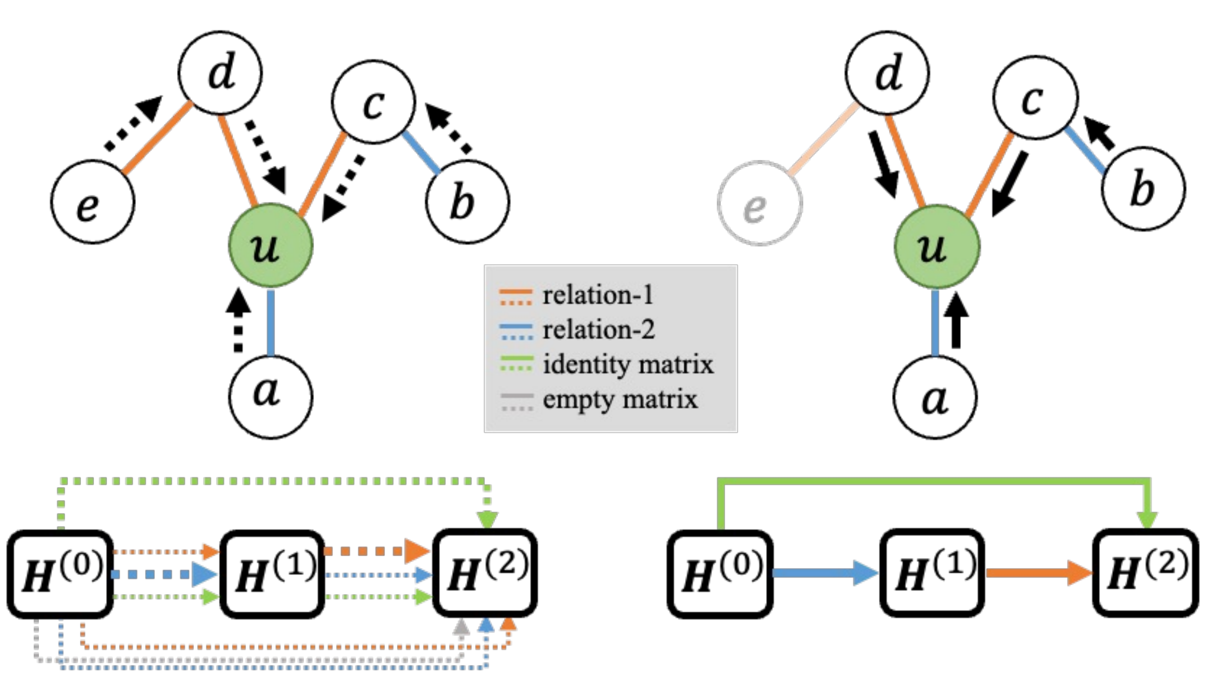
Methodology

The message passing scheme of GNN:

$$\boldsymbol{H}^{(0)} = \mathrm{MLP}\,(\boldsymbol{X}), \quad \boldsymbol{H}^{(l+1)} = \mathrm{Aggr}\left(\boldsymbol{H}^{(l)}; A\right)$$

Use meta-graph $M_{\mathcal{A}}$ to describe which relation the message is passed along, when dealing with multi-relation graph $\mathcal{A} = \{A_r\}|_{r=1}^{R}$

NGS



(a) (b)

We relax the discrete edge type selection to be continuous like DARTS.

$$f_{i,l}\left(\boldsymbol{H}^{(i)}; \mathcal{A}_{i,l}\right) = \sum_{A \in \mathcal{A}_{i,l}} \frac{\exp\left(\alpha_{i,l}^{A}\right)}{\sum_{A' \in \mathcal{A}_{i,l}} \exp\left(\alpha_{i,l}^{A'}\right)} \cdot \mathrm{Aggr}\left(\boldsymbol{H}^{(i)}; A\right)$$

Ref: Yuhui Ding, et al, KDD 2021. DiffMG: Differentiable Meta Graph Search for Heterogeneous Graph Neural Networks.
Hanxiao Liu, et al, ICLR 2019. DARTS: Differentiable Architecture Search.

Search space:

$$\mathcal{A}_{i,l} = \begin{cases} \mathcal{A} \cup \{I\} & l \le L \text{ and } i = l-1 \\ \mathcal{A} \cup \{I\} \cup \{O\} & l \le L \text{ and } i < l-1 \end{cases}$$

Optimization:

$$\min_{\alpha} \mathcal{L}_{\text{val}}\left(\omega^*(\alpha), \alpha\right), \ \text{s.t. } \omega^*(\alpha) = \arg\min_{\omega} \mathcal{L}_{\text{train}}(\omega, \alpha)$$

$$\mathcal{L} = -\sum_{v \in \mathcal{V}} \left[y_v \log p_v + (1 - y_v) \log (1 - p_v)\right]$$

Experiments

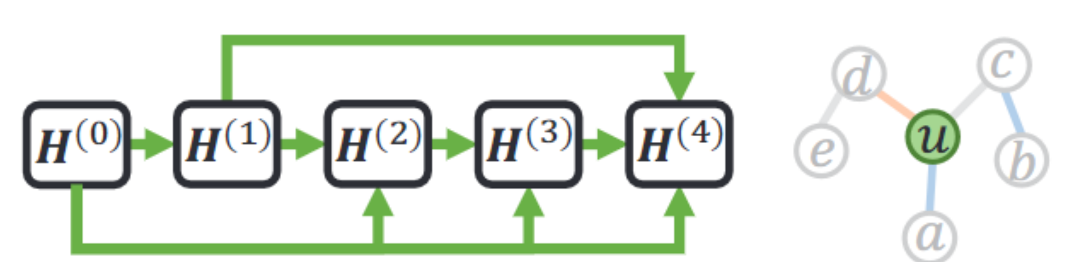
Dataset	#Nodes (Fraud%)	#Edges	Relation	#Relations
Amazon	11, 944 (9.5%)	4, 398, 392	U-P-U U-S-U U-V-U	175, 608 3, 566, 479 1, 036, 737
YelpChi	45, 954 (14.5%)	3, 846, 979	R-U-R R-T-R R-S-R	49, 315 573, 616 3, 402, 743

Two real-world graph-based fraud detection datasets Amazon and YelpChi are adopted to validate NGS's performance.

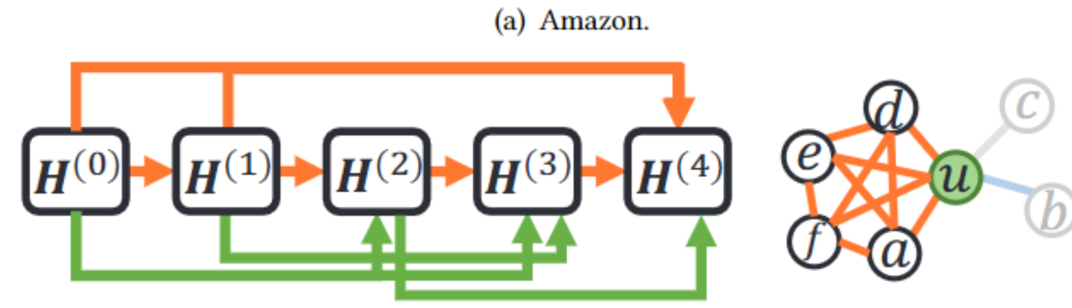
Method	Dataset	Amazon			YelpChi		
	Metric	F1-macro	AUC	GMean	F1-macro	AUC	GMean
Baselines	GCN	0.6571±0.0008	0.8189±0.0008	0.6629±0.0037	0.4963±0.0005	0.5504±0.0001	0.2143±0.0019
	GAT	0.5390±0.0021	0.7426±0.0020	0.3081±0.0173	0.5228±0.0070	0.5519±0.0012	0.2921±0.0193
	GraphSAGE	0.8383±0.0109	0.9149±0.0077	0.8518±0.0077	0.5781±0.0239	0.7409±0.0034	0.6815±0.0049
	CARE-GNN	0.8997±0.0064	0.9482±0.0044	0.8982±0.0015	0.6052±0.0170	0.7748±0.0008	0.7071±0.0035
	PC-GNN	0.8660±0.0164	0.9642±0.0035	0.8986±0.0203	0.6192±0.0479	0.8104±0.0057	0.7225±0.0166
	FRAUDRE	0.8519±0.1055	0.9408±0.0052	0.8847±0.0280	0.6057±0.0381	0.7582±0.0041	0.6862±0.0128
	AO-GNN*	0.8921±0.0045	0.9640±0.0020	0.9096±0.0105	0.7042±0.0051	0.8805±0.0008	0.8134±0.0232
	H^2-FDetector*	0.8392±0.0000	0.9689±0.0000	0.9203±0.0000	0.6944±0.0000	0.8877±0.0000	0.816±0.0000
	ProtGNN	0.7351±0.0112	0.8826±0.0106	0.7785±0.0126	0.5663 ±0.0024	0.6004 ±0.0056	0.4595 ±0.0196
	DiffMG	0.8826±0.0049	0.9290±0.0044	0.8855±0.0057	0.7316±0.0144	0.8799±0.0142	0.7873±0.0147
Ablation	$\mathrm{NGS}_{\backslash A}$	**0.9234±0.0078**	0.9692±0.0136	0.9191±0.0087	0.7604±0.0227	0.9009±0.0215	0.7981±0.0279
Ours	NGS	0.9228±0.0046	**0.9736±0.0035**	**0.9218±0.0042**	**0.7828±0.0055**	**0.9218±0.0032**	**0.8351±0.0056**

Compared with various baselines, NGS exceeding or matching performance across all of them.

Explainability



(a) Amazon.



(b) YelpChi.

Amazon

No relation is involved;
User attributes are the key to identifying fraudsters.

Yelpchi

R-U-R relation is highly relevant to fraud detection;
Suggesting a typical default phenomenon: click farming.

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