LEX-GNN: Label-Exploring Graph Neural Network for Accurate Fraud Detection

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Introduction

Background

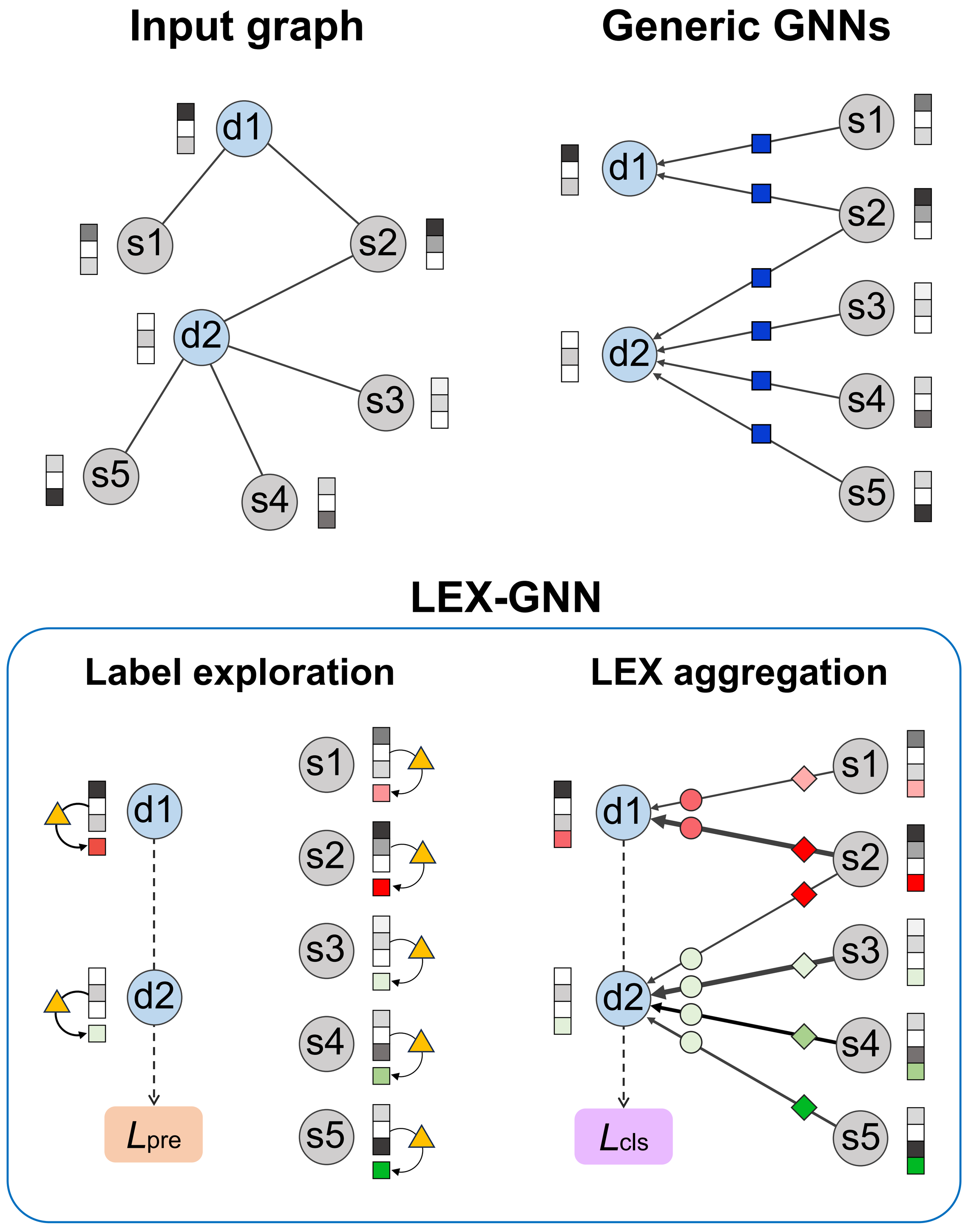
- GNNs are promising for fraud detection due to their ability to capture relational data. However, they face challenges such as class imbalance and heterophilic connections.

Existing Approaches

- **Node-based:** Focuses on similar nodes but struggles when fraudsters resemble legitimate ones.
- **Edge-based:** Discerns homophilic from heterophilic edges but can be computationally expensive as #edge $\gg$ #node.
- **Label-based:** Incorporates label information but has limitations in properly handling unlabeled nodes, as it treats them equally.

Proposed Framework

- **LEX-GNN:** Label-Exploring Graph Neural Network
- Predicts the soft labels of nodes in advance utilizing a semi-supervised learning approach.
- Adjusts message passing and aggregation pipeline dynamically based on the predicted labels.



In generic GNNs, source nodes pass their representations as messages toward destination nodes, applying a learnable weight (■) uniformly.

LEX-GNN explores the probability of a node being fraudulent through a neural classifier (▲).

Based on the prediction, source nodes transform (◆) and send messages, while destination nodes adjust their reception adaptively (●).

Figure 1: A conceptual diagram of LEX-GNN.

Method

Label Exploration

- We predict the soft (probable) label of nodes using a double-layer MLP at the beginning of each layer.

$$p_v^{(l)} = \Phi_{\text{pre}}^{(l)}(h_v^{(l-1)})$$

LEX Aggregation

- **Differentiated message passing:** We incorporate the label embedding into the node representation and interpolate the outgoing message according to the fraudulent probability.

$$\tilde{m}_v^{(l)} = h_v^{(l-1)} + \Psi^{(l)}(p_v^{(l)}), \quad \Psi^{(l)}(p_v^{(l)}) = p_v^{(l)}\Psi_1^{(l)} + (1 - p_v^{(l)})\Psi_0^{(l)}$$

$$m_v^{(l)} = \mathcal{W}_{\text{s},v}^{(l)}(\tilde{m}_v^{(l)}), \quad \mathcal{W}_{\text{s},v}^{(l)} = p_v^{(l)}\mathcal{W}_{\text{s},1}^{(l)} + (1 - p_v^{(l)})\mathcal{W}_{\text{s},0}^{(l)}$$

- **Attention-based aggregation:** The messages are aggregated through multi-head dynamic attention.

$$\tilde{h}_u^{(l)} = \sigma\left(\frac{1}{H}\sum_{h=1}^{H}\sum_{v\in\mathcal{N}_u}\alpha_{uv}^{(l,h)}\mathcal{W}_a^{(l,h)}m_v^{(l)}\right), \quad \alpha_{uv}^{(l,h)} = \frac{\exp\left(a^{(l,h)}\cdot\sigma\left(\mathcal{W}_a^{(l,h)}\left(m_u^{(l)} + m_v^{(l)}\right)\right)\right)}{\sum_{v'\in\mathcal{N}_u}\exp\left(a^{(l,h)}\cdot\sigma\left(\mathcal{W}_a^{(l,h)}\left(m_u^{(l)} + m_{v'}^{(l)}\right)\right)\right)}$$

- **Differentiated message reception:** Destination nodes also incorporate the aggregated messages based on their own predicted labels to make final representations.

$$h_u^{(l)} = \mathcal{W}_{\text{self}}^{(l)}(h_u^{(l-1)}) + \mathcal{W}_{\text{d},u}^{(l)}(\tilde{h}_u^{(l)}), \quad \mathcal{W}_{\text{d},u}^{(l)} = p_u^{(l)}\mathcal{W}_{\text{d},1}^{(l)} + (1 - p_u^{(l)})\mathcal{W}_{\text{d},0}^{(l)}$$

Optimization

- The overall loss is formulated reflecting the accuracy of label exploration.

$$\mathcal{L}_{\text{cls}} = -\sum_{u\in\mathcal{V}_{\text{t}}}[y_u\log(q_u) + (1 - y_u)\log(1 - q_u)], \quad q_u = \Phi_{\text{cls}}(h_u^{(L)})$$

$$\mathcal{L} = \mathcal{L}_{\text{cls}} + \beta\mathcal{L}_{\text{pre}}^{(L)}, \quad \mathcal{L}_{\text{pre}}^{(l)} = -\sum_{v\in\mathcal{V}_{\text{t}}}[y_v\log(p_v^{(l)}) + (1 - y_v)\log(1 - p_v^{(l)})]$$

Conclusion

- LEX-GNN effectively detects fraud by integrating label predictions into the message passing process, even when dealing with unlabeled data.
- The dual transformation on both the source and destination ends with attention effectively captures the relational characteristics of the graph.
- The superior accuracy and robustness of the proposed framework have been validated through experiments on real-world datasets.

Results

Dataset

- Yelp: 6,677 fraud reviews / 45,954 (14.53%)
- Amazon: 821 fraudsters / 11,944 (6.87%)

Performance Comparison

- LEX-GNN outperforms state-of-the-art baselines in all metrics, except for F1-macro on Amazon with 1% training condition.
- The performances on Yelp with 40% training are significant, showing improvements of over 3.05% in AUC and 5.29% in F1-macro.

Table 1: Performance comparison on *Yelp* and *Amazon* under 40% and 1% training conditions.

Method	Dataset	*Yelp* (40%)		*Amazon* (40%)		*Yelp* (1%)		*Amazon* (1%)	
	Metric	AUC	F1-macro	AUC	F1-macro	AUC	F1-macro	AUC	F1-macro
Baselines	CARE-GNN	80.15±1.13	67.41±1.61	94.18±0.85	89.35±0.72	72.91±0.86	59.51±1.27	89.35±2.37	65.34±1.68
	PC-GNN	81.64±1.08	65.72±1.52	94.42±0.75	89.82±1.64	74.12±1.51	57.63±1.54	90.70±2.16	72.18±2.47
	H^2-FDetector*	89.48±1.26	74.38±2.42	96.03±0.69	86.91±1.01	74.19±0.52	57.42±0.45	83.26±0.17	67.60±0.31
	GHRN*	90.57±0.36	77.54±1.02	97.07±0.73	92.36±0.97	76.76±0.37	64.30±0.61	90.27±0.30	**89.16±0.89**
	GTAN	92.86±0.60	80.12±0.26	96.65±0.41	92.53±0.48	81.05±1.02	66.10±0.77	91.70±1.54	85.67±1.34
	PMP	93.54±0.25	82.01±0.70	97.37±0.18	92.29±0.27	81.58±0.57	67.15±0.56	91.55±0.80	82.49±1.26
Ours	**LEX-GNN**	**96.40±0.28**	**86.35±0.39**	**97.91±0.15**	**93.48±0.25**	**83.14±0.53**	**69.73±0.68**	**93.02±0.21**†	87.33±1.76†

* Results of H^2-FDetector and GHRN are obtained from [28]. † Results on *Amazon* of 1% learning are derived from a single-layer LEX-GNN with $\beta = 1$.

Ablation Study

- All components are beneficial, the exclusion of attention on Yelp and the source-side transformation on Amazon has the most detrimental impact.

Effect of Label Exploration

- When $\beta > 0$, label exploration is activated, and the accurate p is fed into the LEX aggregation, which enhances the overall performance.
- In addition to conventional pseudo-labeling which primarily aims at data augmentation, our approach adjusts the message passing based on predicted labels, thus enabling more precise relational representation.

Table 2: Ablation study. All components are beneficial.

Method	*Yelp* (40%)		*Amazon* (40%)	
	AUC	F1-macro	AUC	F1-macro
LEX-GNN	**96.40±0.28**	**86.35±0.39**	**97.91±0.15**	**93.48±0.25**
– label emb.	96.08±0.26	85.89±0.27	97.75±0.24	93.24±0.19
– src. trans.	96.30±0.15	86.16±0.14	97.16±0.15	92.74±0.67
– dst. trans.	95.87±0.39	85.17±0.08	97.78±0.10	93.22±0.23
– attention	94.61±0.25	82.85±0.53	97.54±0.01	93.10±0.27

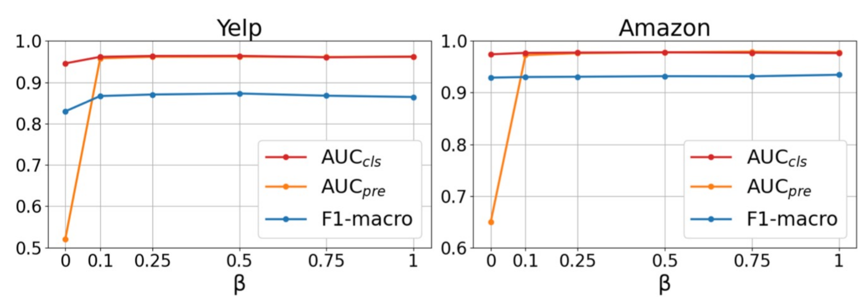


Figure 2: Performance w.r.t β. When $\beta > 0$, label exploration is activated, which enhances overall model accuracy.

Our code is available at https://github.com/wdhyun/LEX-GNN