BLS

Bi-Level Selection via Meta Gradient for Graph-based Fraud Detection

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DASFAA-2022

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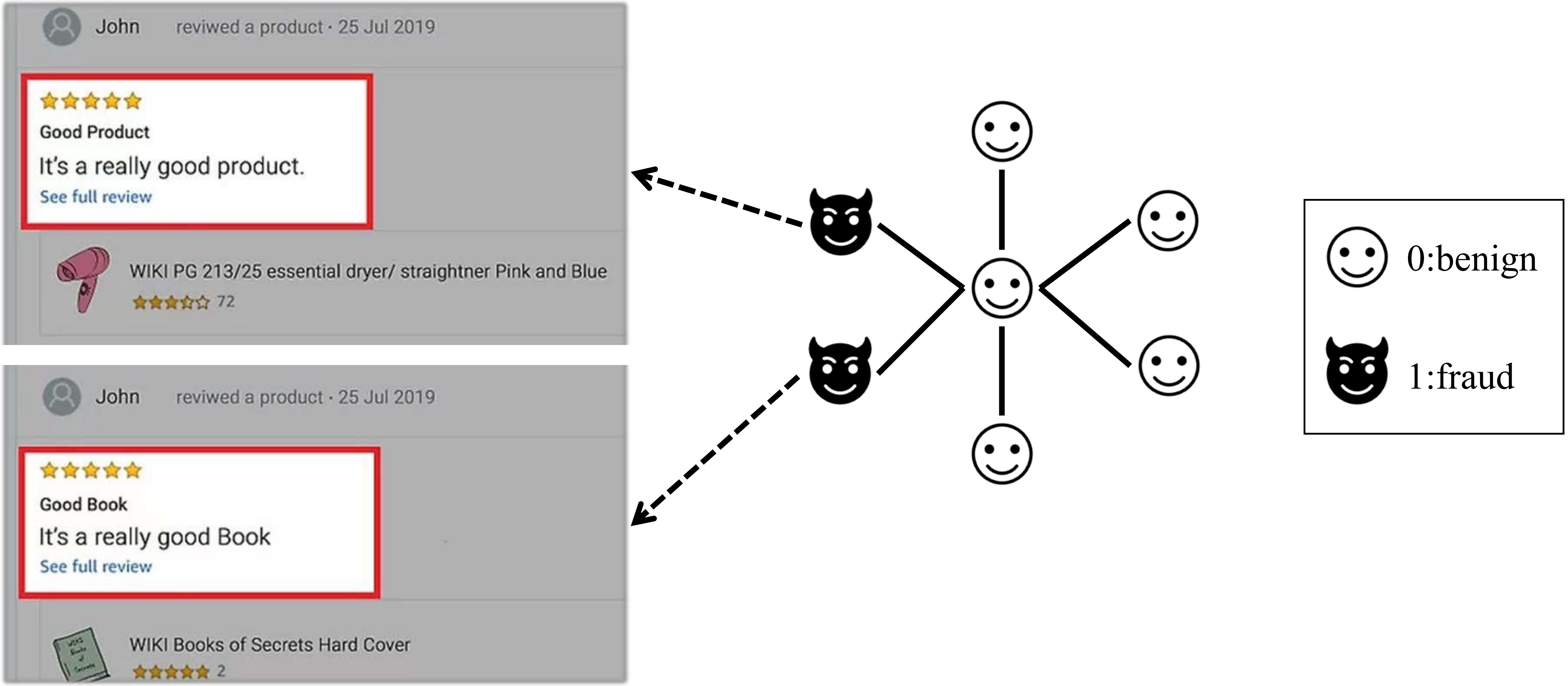
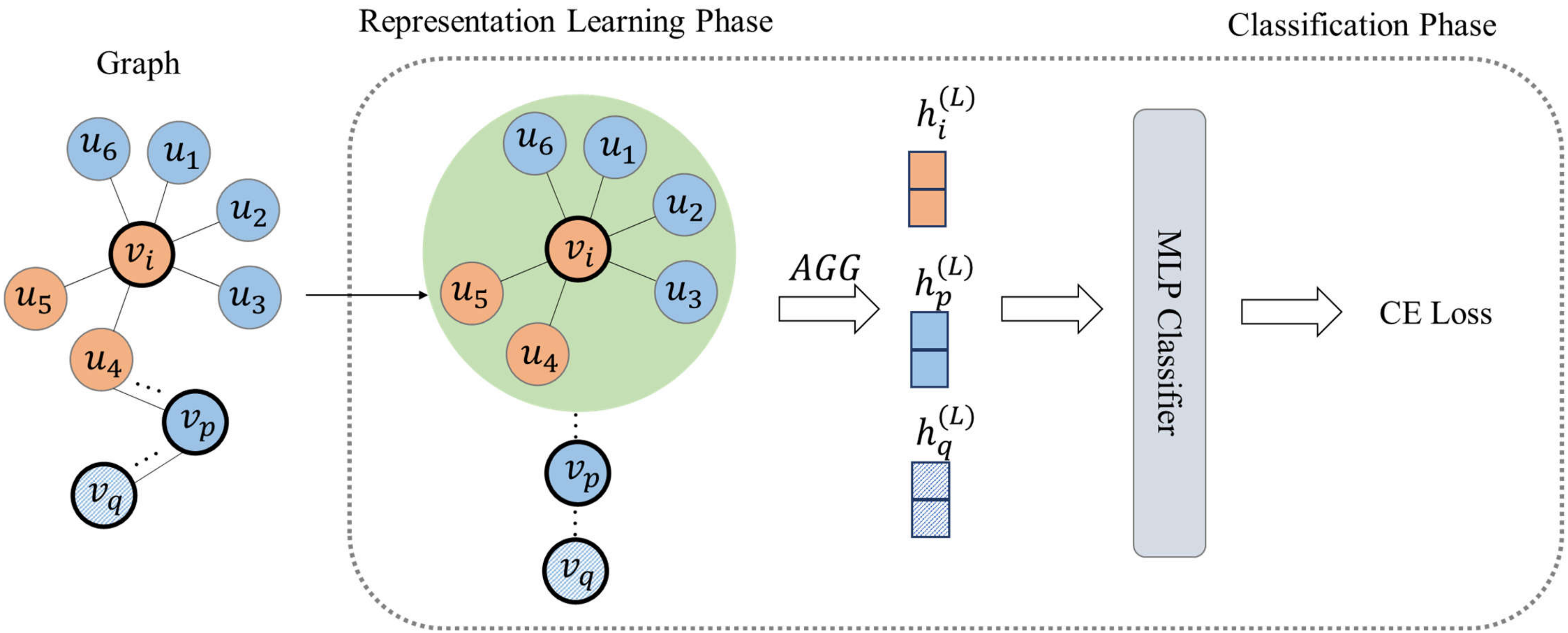


Introduction

General Workflow of GNN



Introduction

Key Challenges

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➢ **Neighborhood-level imbalance and noise**

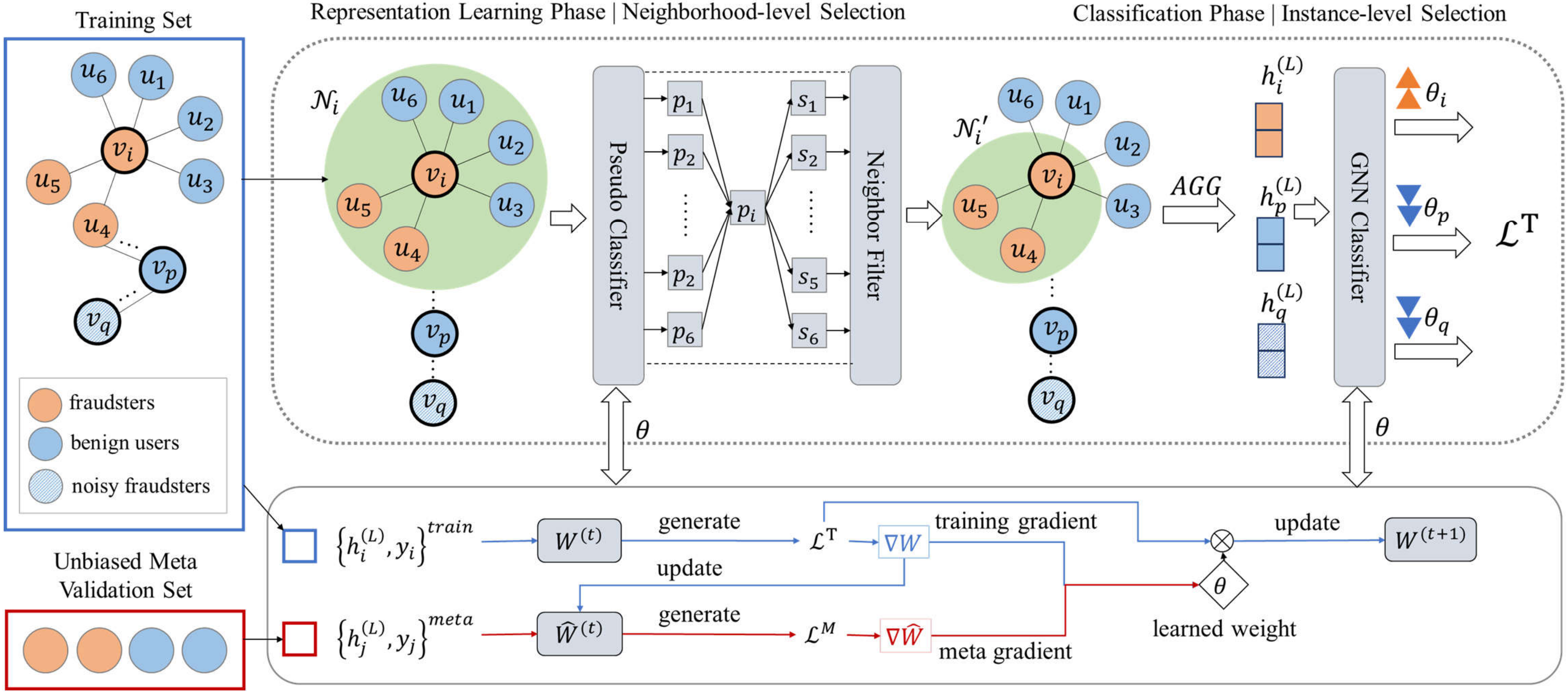
- In the representation learning phase, due to the propagation mechanism on topology, excess benign neighbors will dominate the network structure and dilute the feature of fraudsters, resulting in inaccurate embeddings of fraudulent nodes.

➢ **Instance-level imbalance and noise**

- In the classification phase, the majority class will dominate the training loss during the gradient descent step, leading to a biased decision boundary. Undiscovered fraudsters (noise) will contribute wrong gradient direction, thus polluting the learned classification boundary.

Method-BLS

Framework



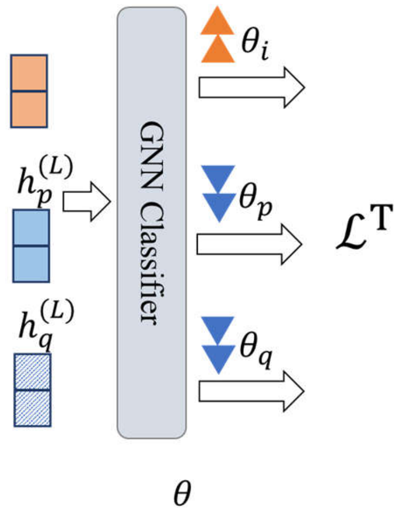
Method-BLS

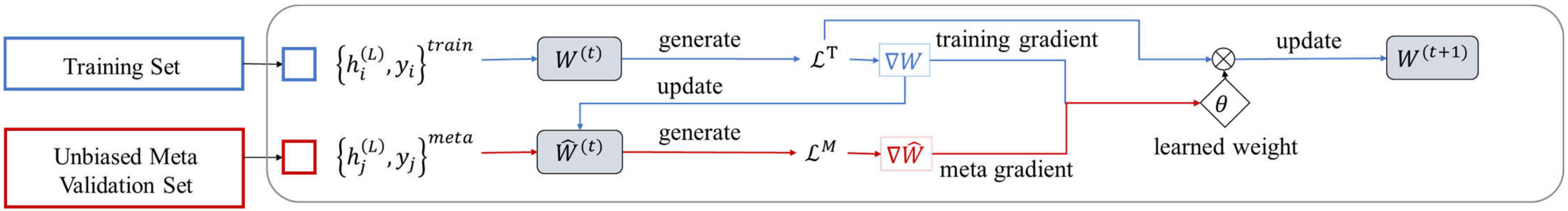
Insatance-level Selection

➢Learn a weight θ_i for each node v_i in the training set that minimizing the CE loss on an unbiased meta validation set.

$$\theta_i \propto -\beta \cdot \frac{1}{M} \sum_{j=1}^{M} \left(\frac{\partial l_j(\hat{W}_f)}{\partial \hat{W}_f} \Bigg|_{\hat{W}_f = \hat{W}_f^{(t)}} \right)^{\top} \left(\frac{\partial l_i(W_f)}{\partial W_f} \Bigg|_{W_f = W_f^{(t)}} \right)$$

$$\mathcal{L}_{GNN} = -\sum_{i=1}^{N} \theta_i \cdot (y_i \log p_i + (1 - y_i) \log(1 - p_i))$$



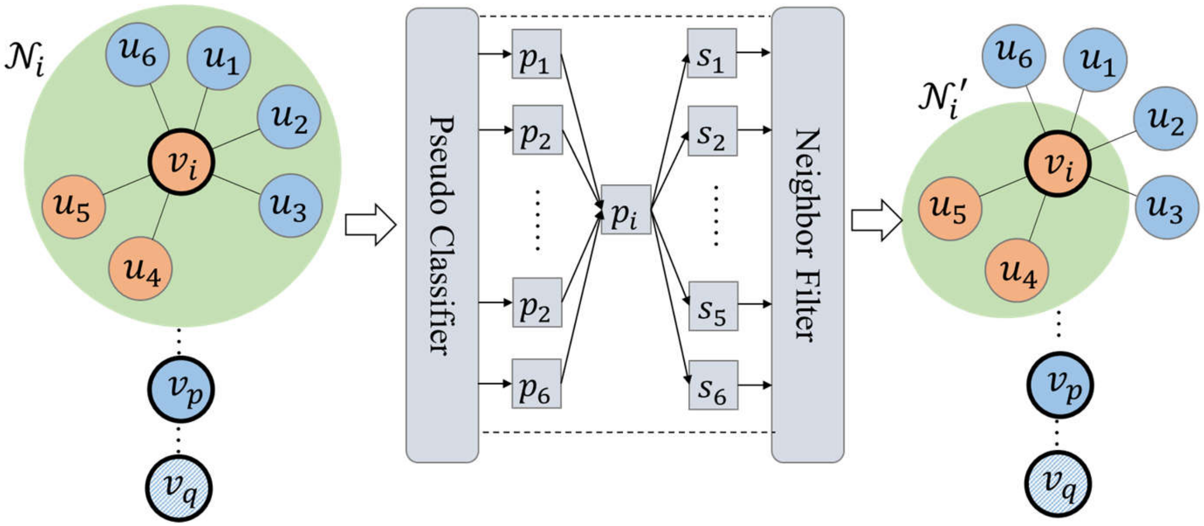


Model

Neighborhood-level Node Selection

➢Select neighborhood-level valuable nodes to form subset $\mathcal{N}'_{i,r} \subseteq \mathcal{N}_{i,r}$

1. Generate pseudo label
2. Compute pseudo label affinity scores between center node and its neighbors
3. Select top-k neighbors to participate in neighborhood aggregation



$$\hat{p}_i^{(\ell)} = G^{(\ell)}(h_i^{(\ell-1)}, W_g^{(\ell)})$$

$$S_{ij}^{(\ell)} = 1 - \|\hat{p}_i^{(\ell)} - \hat{p}_j^{(\ell)}\|_1$$

$$\mathcal{L} = \mathcal{L}_{GNN} + \sum_{\ell=1}^{L-1} \mathcal{L}_{PSE}^{(\ell)}$$

Experiments

Datasets

- YelpChi
  - hotels and restaurants reviews on Yelp.com, nodes are reviews associated with 100-dimension Word2Vec embeddings as features
- Amazon
  - product reviews under the Musical Instrument category, nodes are users associated with 100-dimension Word2Vec embeddings as features

Dataset	#Node	#Edge	IR	Relation	#Edge-R
YelpChi	45,954	3,846,979	5.9	R-U-R	49,315
				R-T-R	573,616
				R-S-R	3,402,743
Amazon	11,944	4,398,392	13.5	U-P-U	175,608
				U-S-U	3,566,479
				U-V-U	1,036,737

Experiments

Baselines and Evaluation Metrics

- Base models (extended for multi-relational graph + BLS)
  - **GCN / GAT / GraphSAGE**

- Comparison SOTA
  - **GraphConsis[1] / CARE-GNN[2] / PC-GNN[3]**

- Evaluation Metrics
  - **AUC / G-Mean**

[1] Liu, Z., Dou, Y., Yu, P.S., Deng, Y., Peng, H.: Alleviating the inconsistency problem of applying graph neural network to fraud detection. In: SIGIR. pp. 1569–1572 (2020)

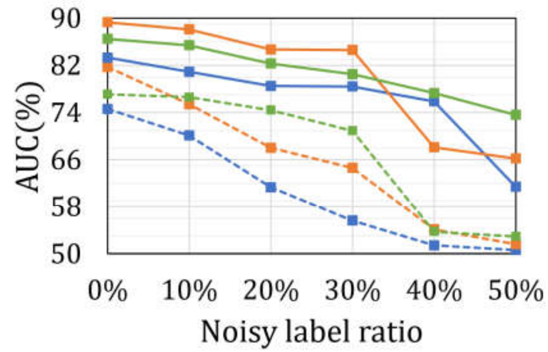
[2] Dou, Y., Liu, Z., Sun, L., Deng, Y., Peng, H., Yu, P.S.: Enhancing graph neural network-based fraud detectors against camouflaged fraudsters. In: CIKM. pp. 315–324 (2020)

[3] Liu, Y., Ao, X., Qin, Z., Chi, J., Feng, J., Yang, H., He, Q.: Pick and choose: A gnnbased imbalanced learning approach for fraud detection. In: WWW. pp. 3168–3177 (2021)

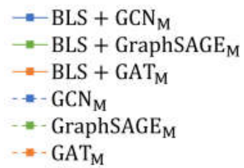
Experiments

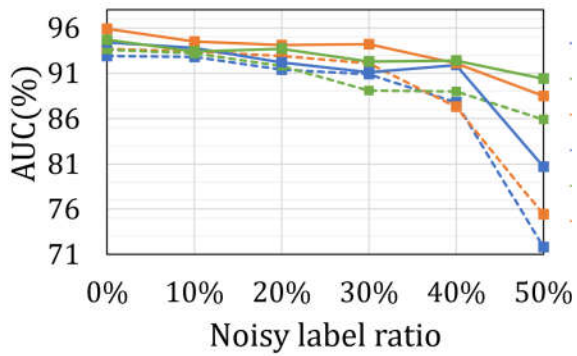
Main Result

Dataset	YelpChi		Amazon	
Methods	AUC	G-Mean	AUC	G-Mean
GCN	59.02±1.08	55.61±2.96	79.83±1.38	73.38±4.29
GraphSAGE	58.46±3.03	46.90±5.82	81.13±2.93	75.17±5.28
GAT	64.18±1.84	59.53±4.37	88.48±1.36	85.69±4.72
GraphConsis	69.83±3.42	58.57±3.85	87.41±3.34	76.77±4.86
CARE-GNN	78.44±0.69	70.13±2.17	93.14±0.74	85.63±0.71
PC-GNN	79.87±0.14	71.60±1.30	95.86±0.14	90.30±0.44
GCN_M	74.62±1.38	68.72±1.92	92.93±2.04	83.22±3.85
GraphSAGE_M	77.12±2.56	69.15±3.96	93.63±3.17	85.92±4.20
GAT_M	81.73±1.48	75.33±3.52	93.71±1.06	85.82±3.65
BLS+GCN_M	83.28±0.86	76.31±2.74	94.42±1.55	87.41±0.78
BLS+GraphSAGE_M	86.50±0.78	80.02±2.93	94.71±1.33	87.44±2.02
BLS+GAT_M	**89.26±1.04**	**81.82±3.02**	**95.93±0.73**	**90.72±1.64**



(a) YelpChi





(b) Amazon

Conclusion

- We propose BLS, a meta gradient based algorithm to address the imbalanced and noisy label problem in graph-based fraud detection. In both representation learning and classification phase, BLS adopts a unified meta-learning paradigm to select instance-level and neighborhood-level valuable nodes.

- Compared to existing methods, BLS is the first work that considers the impact of class imbalance and noisy label on the message-passing mechanism of GNNs.

- The proposed BLS algorithm has high portability that can be applied on any GNN framework. By applying BLS on widely-used GNNs, we achieved significant improvement compared to base models and state-of-the-art on two real-world datasets.

Acknowledgment

Thanks for listening!

If you have any question, feel free to contact us at

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