Error-bounded Graph Anomaly Loss for GNNs

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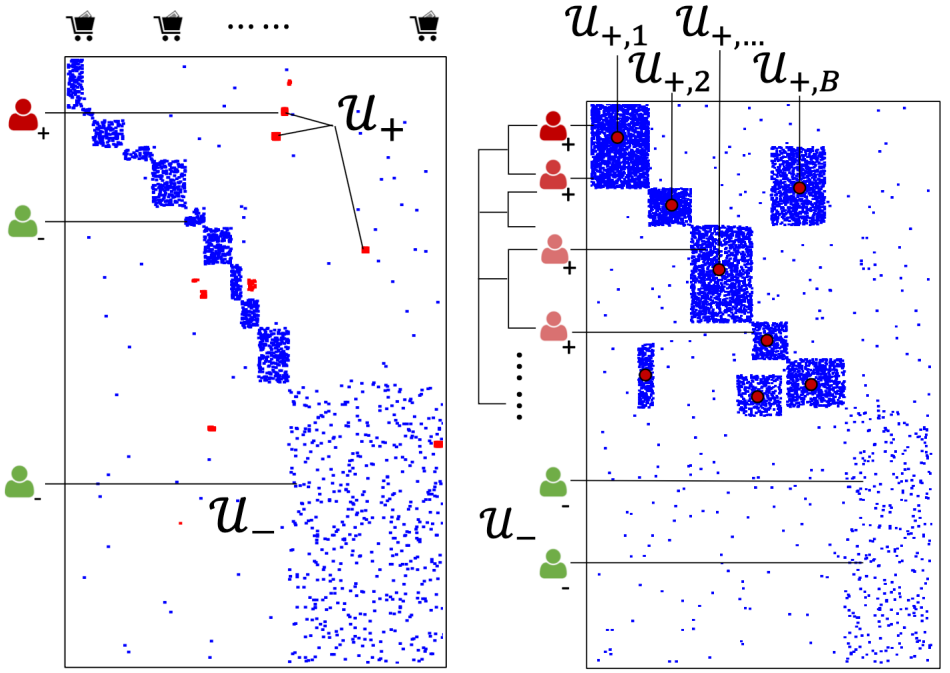
Graph Anomaly Detection

- Graph Outliers.
  - Fake/unfair reviewers on reviewing networks, etc.
- Dense Blocks.
  - Spammers/bot nets on social networks, etc.



(a) Anomalous node groups forming graph outliers

(b) Anomalous node groups forming dense blocks

How things were done

- Unsupervised graph mining methods:
  - Graph outlier detection:
    - Feature-based
    - Structure-based
    - Model-based
  - Dense block detection:
    - Average degree
    - Singular value
- Graph neural networks (GNNs) with unsupervised loss function for representation learning.

Random walk-based loss function

- Basic assumption:
  - Nodes that are closer to each other in the graph should have similar representations.
- With positive/negative sampling, can be formulated as:

$$\mathcal{L}_{\mathrm{RW}}(u) = \mathbb{E}_{u_+ \sim \mathcal{U}_{u+}, u_- \sim \mathcal{U}_{u-}} \max\{0, \mathbf{z}_u^T \mathbf{z}_{u_-} - \mathbf{z}_u^T \mathbf{z}_{u_+} + \Delta\}$$

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- Problem:
  - The assumption doesn't always hold true when the representations are used for anomaly detection.

Graph Anomaly Loss (GAL)

- Goal: design an unsupervised loss function that can learn node representations that are optimized for anomaly detection.
- Desired abilities:
  - Give anomalous nodes similar representations.
  - Utilize the global information given by graph mining methods.
  - Capable of dealing with severely imbalanced data.

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$$\mathcal{L}(u) = \mathbb{E}_{u_+ \sim \mathcal{U}_{u+}, u_- \sim \mathcal{U}_{u-}} \max\{0, g(u, u_-) - g(u, u_+) + \Delta_{y_u}\},$$

$$\text{where } \Delta_{y_u} = \frac{C}{n_{y_u}^{1/4}}. \tag{14}$$

Here $\mathcal{U}_{u+}$ denotes the set of user nodes that has the same label as u, $\mathcal{U}_{u-}$ denotes $\mathcal{U} \setminus \mathcal{U}_{u+}$, and $n_{y_u} = |\mathcal{U}_{u+}|$.

GAL with graph outlier loss

- Existing outlier detection methods can give us:
  - $\mathcal{U}_u$: set of normal nodes; $\mathcal{U}_o$: set of outlier nodes:
- Goals:
  - Encourage pairs of outlier nodes to have similar representations.
  - Encourage pairs of normal nodes to have similar representations.
  - Enforce the representations of pairs of outlier and normal nodes are distinct.

$$\mathcal{U}_{u+} = \begin{cases} \mathcal{U}_n & , \text{if } u \in \mathcal{U}_n \\ \mathcal{U}_o & , \text{if } u \in \mathcal{U}_o \end{cases}, \mathcal{U}_{u-} = \begin{cases} \mathcal{U}_o & , \text{if } u \in \mathcal{U}_n \\ \mathcal{U}_n & , \text{if } u \in \mathcal{U}_o \end{cases}.$$

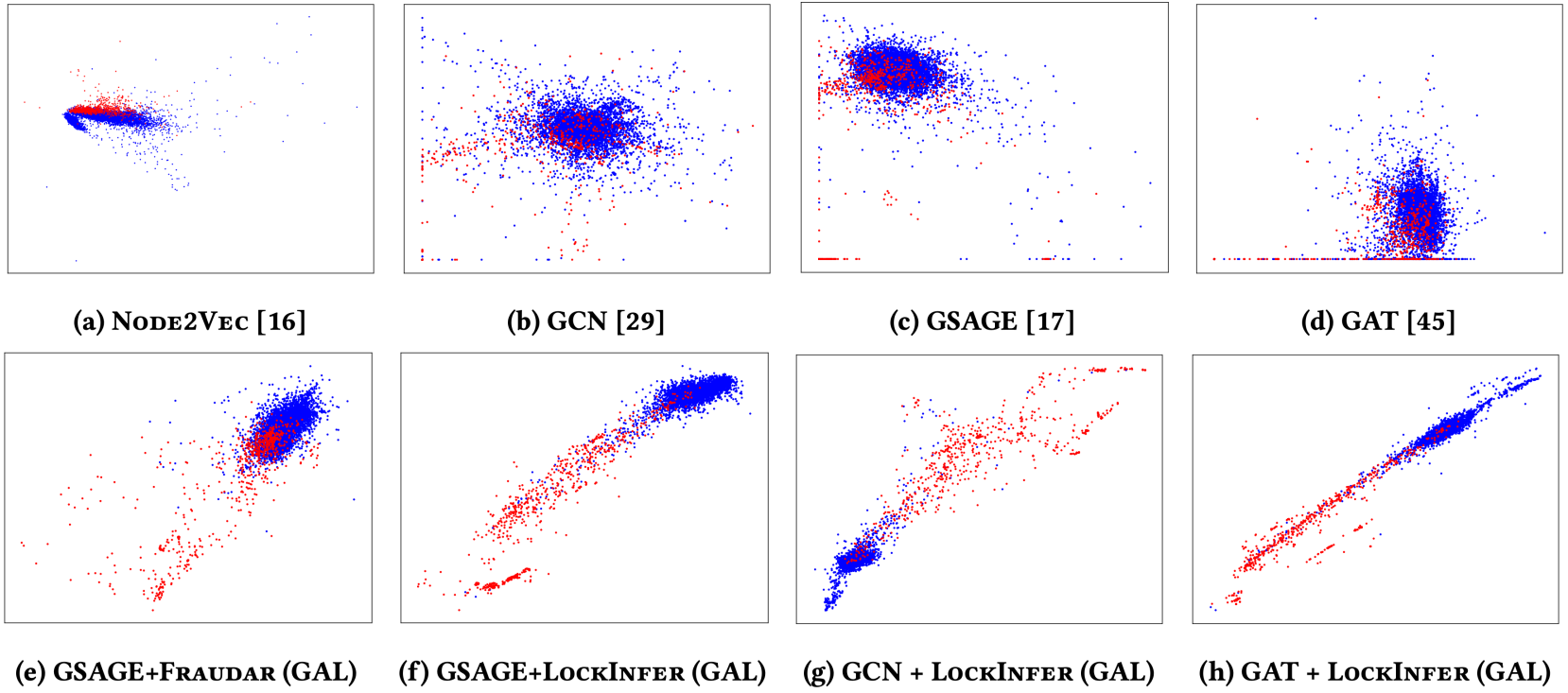
GAL with dense block loss

- Existing dense block detection methods can give us:
  - $\mathcal{U}_n$: set of normal nodes;
  - Sets of nodes in different dense blocks: $\mathcal{U}_{b,1}$, $\mathcal{U}_{b,2}$, …
- Goals:
  - Encourage node pairs in the same block to have similar representations.
  - Enforce nodes in different blocks to have distinct representations.

$$\mathcal{U}_{u+} = \begin{cases} \mathcal{U}_n & , \text{if } u \in \mathcal{U}_n \\ \bigcup_{i=1, u \in \mathcal{U}_{b,i}}^{B} \mathcal{U}_{b,i} & , \text{if } u \notin \mathcal{U}_n \end{cases},$$

$$\mathcal{U}_{u-} = \begin{cases} \bigcup_{i=1}^{B} \mathcal{U}_{b,i} & , \text{if } u \in \mathcal{U}_n \\ \mathcal{U} \setminus \bigcup_{i=1, u \in \mathcal{U}_{b,i}}^{B} \mathcal{U}_{b,i} & , \text{if } u \notin \mathcal{U}_n \end{cases}.$$

Visualization of learned representations



(a) NODE2VEC [16] (b) GCN [29] (c) GSAGE [17] (d) GAT [45]

(e) GSAGE+FRAUDAR (GAL) (f) GSAGE+LOCKINFER (GAL) (g) GCN + LOCKINFER (GAL) (h) GAT + LOCKINFER (GAL)

Figure 2: Visualizing user embeddings in Tencent-Weibo data. Blue dots represent benign users, and red dots represent anomalous users. Graph anomaly losses (e–h) are better than random-walk loss (b–d).

Thanks for listening!

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