Graph Anomaly Detection via Prototype-Aware Label Propagation (Student Abstract)

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Abstract

Detecting anomalies on attributed graphs is a challenging task since labelled anomalies are highly labour-intensive by taking specialized domain knowledge to make anomalous samples not as available as normal ones. Moreover, graphs contain complex structure information as well as attribute information, leading to anomalies that can be typically hidden in the structure space, attribute space, and the mix of both. In this paper, we propose a novel model for graph anomaly detection named LP-GAD. Specifically, LP-GAD takes advance of label propagation to infer high-quality pseudo labels by considering the structure and attribute inconsistencies between normal and abnormal samples. Meanwhile, LP-GAD introduces the prior knowledge of class distribution to correct and refine pseudo labels with a prototype-aware strategy. Experiments demonstrate that LP-GAD achieves strong performance compared with the current state-of-the-art methods.

Introduction

Graph anomaly detection (GAD) has a profound impact on a variety of applications. Driven by the success of self-supervised learning (SSL) and sem-supervised learning (SemSL) on graphs, various attempts have been made to solve the graph anomaly detection problem. SSL-based GAD approaches aim to learn discriminative representations without relying on labels (Duan et al. 2023). Despite getting rid of the dependence on labels, these SSL methods haven't produced first-best performance since they lack prior knowledge of abnormal samples. In contrast, SemSL-based GAD methods leverage a few labeled anomalies to overcome SSL's drawback of having inadequate prior information (Chen et al. 2022). However, owing to the number of abnormal samples being extremely small, SemSL-based methods are infeasible to detect anomalies, leading to overfitting and oversmoothing (Tang and Liang 2023). Additionally, the majority of GAD models are predicated on the assumption that two linked nodes frequently share the same labels.

In this paper, we propose a novel model LP-GAD, which consists of one label generator and one target network. The label generator module utilizes the graph propagation strategy to generate pseudo labels on unlabeled nodes based on a few ground-truth labels and the target network acts as a prediction model to generate discriminative node representations. To increase the reliability and accuracy of the pseudo labels, we take into account the structure and attribute discrepancies between normal and abnormal nodes. For the structure inconsistency, we propose to exploit different operators to diffuse labels over the graph to generate the structure pseudo label. For the attribute inconsistency, we reweight all attributes based on their influence scores to increase the probability of anomalies during label propagation to generate attribute pseudo labels. Due to a lack of semantic information about class priors, explicitly training the label generator may result in out-of-domain results. To eliminate the negative impact, a prototype-aware strategy is introduced in the target network to correct and refine pseudo labels.

Main Structural of Our Model

We consider the inconsistency of structure and attribute between anomalies and normal nodes to generate pseudo labels in the propagation process. Similar to the feature propagation, we conduct the label propagation to transfer the prior structure knowledge of the labelled nodes into unlabeled nodes. However, this label propagation favours the homophily graphs, and it's hard to assign accurate pseudo labels with limited abnormal nodes. Hence, we model the structure label propagation as a Markov Diffusion Process, which is defined as:

$$\tilde{Y}_s = \mathrm{ReLU}(\frac{1}{K}\sum_{k=0}^{K}\vartheta_k \tilde{A}^k Y^{(0)}) \tag{1}$$

where $\tilde{Y}_s$ is the generated structure pseudo label. ϑ_k is the learnable coefficients to balance the contributions of different operators. To learn ϑ effectively, we propose a shared self-gating mechanism to compute the coefficient weight ϑ,

$$\vartheta_k = \frac{q^T tanh(g(\tilde{Y}_s^{(k)})^T + b)}{\sum_{j=0}^{K} q^T tanh(g(\tilde{Y}_s^{(j)})^T + b)} \tag{2}$$

where q is the attention vector, g is a class matrix, and b is the bias vector. By leveraging the attention mechanism, we can learn automatically different diffusing orders' importance to capture the global and local context of the graph structure.

Additionally, the attribute label information should also be propagated. We propose a method of measuring the

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nodes' influence to increase the weight of abnormal nodes by jointly considering node degree deg and local density den. Node degree reflects the relation with first-order neighborhoods. In general, nodes with large degrees are informative. The local density measures the proximity of a node to its neighborhoods. Finally the nodes' influence is defined as:

$$\begin{aligned} deg(i) &= \sum_{j=0}^{N-1} \tilde{A}_{ij} \\ den(i) &= \frac{1}{\mathcal{N}(i)} \sum_{j\in\mathcal{N}(i)} \exp(||x_i - x_j||_2^2) \\ \mathcal{NI}(i) &= deg(i) \times den(i) \end{aligned} \tag{3}$$

Then, we encode the prior knowledge of the node influence into the input space that transforms raw attributes to pseudo labels. The process can be formulated as:

$$\tilde{Y}_a = MLP(X), \quad X = \mathcal{NI} \cdot X \tag{4}$$

Finally, SPL and APL are element-wise additions to generate pseudo labels for unlabeled nodes:

$$\tilde{Y} = \alpha\tilde{Y}_s + (1-\alpha)\tilde{Y}_a \quad s.t. \quad \tilde{Y}_L = Y_L \tag{5}$$

where α is a hyperparameter to balance two types of pseudo labels. $\tilde{Y}_L$ denoets the nodes with ground-truth labels.

Directly training the target network with the pseudo labels may produce out-of-domain results, we propose a novel prototype-based label updation strategy, which introduces the class information to model the semantic relation between anomalies and normal nodes. Formally, the prototype embedding of the class m is

$$\mathcal{U}_m = \frac{1}{|V_m|} \sum_{i\in V_m} Z_i, \quad m = 1, 2, ..., C \tag{6}$$

$\mathcal{U}$ is the prototype representations. V_m indicates the set of labelled samples belonging to class m. Z_i is the represention of node i generated by the target network $\mathcal{Q}$.

We combine the coarse pseudo labels from the label generator with the prototype embeddings of classes to update the refined pseudo labels. Specifically, we iteratively update it with the following moving-average mechanism:

$$\begin{aligned} \tilde{Y} &= \gamma\tilde{Y} + (1-\gamma)\mathcal{J} \\ \gamma &= J(\tilde{Y}, \hat{Y}) = \frac{|\tilde{Y} \cap \hat{Y}|}{|\tilde{Y} \cup \hat{Y}|} \end{aligned} \tag{7}$$

where $\mathcal{J} = \arg\max_C Z\mathcal{U}^T/\kappa$, Z is the output of target network, κ is the temperature parameter, γ is denoted as Jaccard coefficient to measure the similarity between the pseudo labels $\tilde{Y}$ and the predictive labels $\hat{Y}$ of the target network. If the value of the Jaccard coefficient γ is larger, it means that the pseudo labels stay close to $\hat{Y}$ and the contribution of prototype knowledge will be decreased.

Experiment and Discussion

Experiments are conducted on six datasets and eight leading GAD methods. All detailes are referenced in (Han et al. 2022). We summarise the following observations from Table 1. The proposed LP-GAD outperforms other baseline methods and achieves the best anomaly detection performance except for the Cora dataset. In particular, compared with SSL baselines, LP-GAD obtains a significant improvement of 2.97% on Flickr at the AUC metric and 2.84% on Pubmed at the F1-macro metric. The main reason is that LP-GAD can provide some prior knowledge of samples to surprise models to effectively train. Moreover, compared with these SemSL methods, PC-GNN and Meta-GDN, their performance is limited by ignoring the relationship between labelled data and unlabeled data. LP-GAD utilizes label propagation to generate pseudo labels for unlabeled nodes and overcome the shortage of labelled abnormal samples.

Models	BlogCatalog	Flickr	ACM	Cora	Citeseer	PubMed
GAE	53.21	60.84	57.67	63.41	52.24	69.30
DOMINANT	74.68	74.42	76.01	81.55	82.51	80.81
ANEMONE	80.43	78.67	83.39	90.57	91.66	68.85
CoLA	78.54	75.13	82.37	87.79	89.98	95.12
GCCAD	78.70	76.24	82.64	86.38	91.24	94.34
Meta-GDN	80.33	75.39	81.47	84.22	89.37	92.89
SL-GAD	81.84	79.66	85.38	91.30	91.36	96.72
PC-GNN	81.41	79.75	84.25	**91.32**	93.03	97.09
LP-GAD	**82.95**	**82.62**	**86.89**	90.76	**93.80**	**98.14**

Table 1: AUC Results (%) of six anomaly datasets.

Conclusion

This paper aims to infer pseudo labels by considering the inconsistencies of graph structure and attributes on anomalies and normal nodes. We propose a prototype-aware label propagation strategy, which can eliminate the negative impact and correct pseudo labels in the propagation process. Meanwhile, the research of label propagation for graph anomaly detection in its infancy, and its application in detecting anomalies is worthy of further exploration.

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