Adversarial Camouflage for Node Injection Attack on Graphs

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ABSTRACT

Node injection attacks on Graph Neural Networks (GNNs) have received increasing attention recently, due to their ability to degrade GNN performance with high attack success rates. However, our study indicates that these attacks often fail in practical scenarios, since defense/detection methods can easily identify and remove the injected nodes. To address this, we devote to camouflage node injection attack, making injected nodes appear normal and imperceptible to defense/detection methods. Unfortunately, the non-Euclidean structure of graph data and the lack of intuitive prior present great challenges to the formalization, implementation, and evaluation of camouflage. In this paper, we first propose and define camouflage as distribution similarity between ego networks of injected nodes and normal nodes. Then for implementation, we propose an adversarial camouflage framework for node injection attack, namely CANA, to improve attack performance under defense/detection methods in practical scenarios. A novel camouflage metric is further designed under the guide of distribution similarity. Extensive experiments demonstrate that CANA can significantly improve the attack performance under defense/detection methods with higher camouflage or imperceptibility. This work urges us to raise awareness of the security vulnerabilities of GNNs in practical applications.

1. Introduction

Graph Neural Networks (GNNs) have achieved great success in various graph mining tasks, such as node classification \cite{18, 42}, graph classification \cite{42}, cascade prediction \cite{2}, and recommender systems \cite{35, 23}. Despite their success, GNNs have been proved to be vulnerable to graph adversarial attacks \cite{6, 49}, i.e., small perturbations on graph data \cite{50, 49} can easily fool GNNs. These attacks can be categorized as graph modification attacks and node injection attacks \cite{48}. Specifically, graph modification attacks modify existing edges \cite{50, 49} or node attributes \cite{49}. Node injection attacks focus on a more executable scenario, where attackers inject malicious nodes \cite{30, 36, 31, 48} rather than modifying existing node features or edges like graph modification attacks. Node injection attacks have shown excellent attack performance \cite{31, 48}, e.g., more than 90\% nodes can be successfully attacked even when only injecting one malicious node with one edge \cite{31}.

Despite the success of node injection attacks in a simplified scenario without defense or detection, our study suggests that they can be prone to failure in practical situations. This is due to that defense and detection methods can easily distinguish and remove the injected malicious nodes from the original normal nodes. Taking the ogbn-products dataset \cite{14} as an example, Figure 1 shows the attribute distribution of both injected nodes and original normal nodes for state-of-the-art node injection attack methods, i.e., G-NIA \cite{31} and TDGIA \cite{48}, and heuristic imperceptible constraint HAO \cite{5}. Even with a simple t-SNE visualization method, we observe that the node attributes of injected nodes (red) look different from the normal ones (blue). We also report the average detection accuracy of the state-of-the-art unsupervised anomaly detection methods \cite{22, 48, 28, 1, 24, 8} for the injected nodes in Figure 1. Specifically, the nodes injected by G-NIA are almost all detected (detection accuracy=98\%), which means almost all injected nodes can be removed, making the attacks fail\textsuperscript{1}. Equipped with the imperceptible constraint HAO, the injected nodes of G-NIA+HAO become more imperceptible, but the detection accuracy is still 91\%. The defects weaken the effectiveness

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\textsuperscript{1}Further introduction on detection methods and detail analysis are shown in Section 3.2.}

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Figure 1: T-SNE visualizations of attributes of injected nodes (red) and original normal nodes (blue). The detection accuracy of the detection methods on the nodes injected by each attack method is reported. Smaller means better imperceptibility.

of such attacks in practical scenarios where defense/detection methods are commonly used. Addressing this issue is critically important. However, up to now, little attention has been paid to these defects of node injection attacks.

In this paper, we devote to camouflage node injection attack, which makes injected nodes as the normal ones considering both structures and attributions to be imperceptible to defense or detection methods. Unfortunately, the non-Euclidean nature of graph data and the lack of intuitive prior present significant challenges to camouflage node injection attack from three aspects: i) Definition of camouflage. Since graph data are difficult to visualize and understand, it lacks intuitive priors to define the camouflage of injected nodes, which is the first important problem to be solved [29]. ii) Camouflage attack. The challenge stems from how to achieve a camouflage node injection attack while maintaining the performance of existing node injection attack methods. iii) Evaluation for camouflage. The semantic complexity of graph data presents challenges for evaluation, similar to those encountered in defining it.

To address the Challenge i, we first propose and define the camouflage of injected nodes as the distribution similarity between the ego networks centered around the injected nodes and those centered around the normal nodes. This definition, which utilizes the original normal nodes to guide the imperceptibility of injected nodes, is intuitive and easy to understand. Our camouflage is more comprehensive and general compared to existing methods. Specifically, we integrate both network structure and node attributes into our camouflage definition, which is more comprehensive than the existing method [48] that only considers node attributes. Also, our proposed camouflage does not make any assumptions about the graph type. Thus, our camouflage is more general compared with HAO [5] which is only applicable to homogeneous graphs, but not to other types of graphs such as heterophily graphs. To address the Challenge ii, we design an adversarial CAMouflage framework for Node Injection Attack, namely CANA, to improve the camouflage while ensuring the attack performance. Specifically, CANA is under a generative adversarial framework [9, 27], dedicated to generating malicious nodes that are difficult to differentiate from normal nodes by an adversarial camouflage discriminator. Note that CANA is a general framework that can be attached to existing node injection attacks. Figure 1(c) and Figure 1(f) demonstrate that the incorporation of our proposed CANA leads to a significant reduction in the distinction between injected nodes and the original normal nodes. When tackling Challenge iii, measuring the similarity between distributions can be difficult due to the unknown probability densities of the
distributions. Inspired by Fréchet Inception Distance (FID) [13], we propose the Graph Fréchet Distance (GraphFD) as a metric to compute the distance using the respective means and covariances of the ego network distributions of normal and injected nodes. The proposed metric is further shown to be consistent with detection accuracy.

Extensive experiments are conducted on three kinds of network datasets across four node injection attack methods. When equipping existing node injection attack methods with our proposed CANA framework, the attack performance under defense and detection methods as well as node camouflage is significantly improved.

In a nutshell, our main contributions are as follows:

- Our study reveals that existing node injection attacks are prone to failure in practical scenarios because defense or detection methods can easily distinguish and remove the injected malicious nodes from the original normal nodes.

- We propose and formulate the camouflage of injected nodes, and design a general framework CANA for node injection attacks, which can be attached to existing methods to improve the camouflage and the attack performance in practical scenarios with defense/detection methods.

- We further propose a novel metric to evaluate camouflage under the guide of distribution similarity. Extensive experiments demonstrate that the integration of our CANA framework improves the attack performance under defense/detection methods and camouflage level of node injection attacks.

2. Related Work

This section briefly reviews existing adversarial attack and defense methods for GNNs, as well as existing studies on the imperceptibility of adversarial attacks.

2.1. Adversarial Attacks for GNNs

GNNs have achieved immense success in various graph mining tasks [47, 23, 20, 15, 40]. However, they are proven to be sensitive to adversarial attacks. Attackers can perturb both graph structure and node attributes to dramatically degrade the performance of GNNs [17, 49, 29, 41]. Unfortunately, modifying existing edges [50] or node features of the original graph [49] requires high authority and makes the attack difficult to perform in practice [30]. Node injection attack [30, 36] focuses on a more practical scenario, which only injects some malicious nodes without modifying original node features or edges. Specifically, AFGSM [36] provides an approximate closed-form attack solution for attacking a specific GNN, i.e., SGC [37]. NIPA [30] uses hierarchical reinforcement learning to sequentially generate the labels and edges of the malicious nodes. Unfortunately, NIPA suffers from high computational costs and is not scalable for large-scale datasets [48]. To offer a more flexible framework, TDGIA [48] heuristically selects the defective edges for injecting nodes and adopts smooth optimization to generate features for injected nodes. Recently, G-NIA [31] studies an extremely limited scenario of single node injection attack, showing excellent attack performance when only injecting one malicious node. These attacks attract increasing research attention [32, 31, 48, 29] due to their high success rate.

While existing node injection attacks demonstrate high success rates, our study reveals these attacks to be prone to failure under defense/detection methods, which can easily identify the injected malicious nodes. In real-world scenarios where defense and detection methods are commonly employed, these easy-to-detect attacks will be ineffective.

2.2. Imperceptibility of Adversarial Attacks

Adversarial attacks should be imperceptible to defense/detection methods [25]. In computer vision, the perturbations on digital adversarial examples are generally regularized by $\ell_1$ norm, $\ell_2$ norm, or $\ell_\infty$ norm, while the perturbations in physical-world adversarial examples require a more practical constraint, e.g., appear to be legitimate to human observers. To accomplish this imperceptibility goal, multiple techniques have been explored, including the use of natural styles to disguise physical-world adversarial samples [25, 4, 45], rendering them more convincing to human observers.

As for the imperceptibility of adversarial attacks on graphs, existing researchers simply perform imperceptible attacks by adopting heuristic constraints on specific aspects. For example, researchers either limit the budget of modified edges/nodes [30, 36, 31, 48], or heuristically constrains the feature co-occurrence [49], or injected feature range [48]. For the recent node injection attacks, HAO [5] tries to improve the unnoticeability of node injection attacks.
Figure 2: The accuracy and defense performance of five detection methods. (a,c) Accuracy of detecting injected nodes. Smaller means better imperceptibility. (b,d) Misclassification rate of node classification task after detection filtering the injected nodes. Larger means better attack performance.

by introducing smoothness or so-called homophily constraint. However, this approach remains a one-sided heuristic and requires the graph to have a high degree of smoothness.

2.3. Defense/detection methods for GNNs

In order to deal with attacks, lots of methods have been proposed [29, 17, 34, 32, 39, 33] to detect or defense under graph adversarial attacks.

Anomaly Detections. Anomaly detection methods have achieved great success in many real-world applications such as fraud detection and cyber intrusion detection [8, 28, 1]. They aim to find instances that are deviated from normal ones [24, 22], which are appropriate for detecting the injected nodes. They are also used to detect adversarial attacks [11]. Anomaly detection methods can be categorized into five types [12], namely probabilistic, linear model, proximity-based, outlier ensemble, and neural network methods. We select state-of-the-art methods for each, specifically COPOD [22] for probabilistic methods, PCA [28] for linear model methods, HBOS [8] for proximity-based methods, IForest [24] for outlier ensemble methods, and AE [1] for neural network methods. These methods are used to detect the injected nodes in this paper.

Defense methods. The defense methods can be mainly categorized into [17]: adversarial training and attention mechanism. Specifically, adversarial training [19, 21] adopts a min-max optimization style, iteratively generating perturbations that maximize the loss and updating GNNs parameters that minimize the loss. The attention mechanism aims to train a robust GNN model by penalizing the model’s weights on adversarial edges or nodes [17, 44, 16].

With the development of adversarial learning, more and more powerful defense methods are continuously proposed, just like an arms race between attackers and defenders. As a result, how to design attack methods that are imperceptible to detection/defense methods is one of the key points of adversarial attacks.

To sum up, there is still a lack of general definitions, effective methods, as well as evaluation metrics for the imperceptibility or camouflage of node injection attacks. Hence, it urges us to study the camouflage on graphs.

3. Preliminaries

In this section, we first introduce node injection attacks. Then we analyze the limitations of existing attacks.

3.1. Node Injection Attack

Node classification. We use the widely adopted node classification task as the downstream task. Let $G = (V, E, X)$ be an attributed graph, where $V = \{1, 2, \ldots, n\}$ is the set of $n$ nodes, $E \subseteq V \times V$ is the set of edges, and $X \in \mathbb{R}^{n \times d}$ is the attribute matrix of nodes with $d$-dimensional attributes. Given a class set $K$ of node labels, the task aims to predict the label of each node by learning a classifier $f_\theta$, i.e., $Z = f_\theta(G)$, where $Z \in \mathbb{R}^{n \times k}$ and $k = |K|$ is the number of classes. For example, GNN is a commonly used classifier $f_\theta(\cdot)$ containing feature transformation and aggregation operations, which benefits many graph mining tasks.

Node injection attack. The goal of node injection attacks is to degrade the performance of GNN by injecting malicious nodes rather than modifying original node features or edges. Specifically, the attacker $\mathcal{G}$ aims to mislead the prediction of a GNN model $f_\theta$ on the target nodes $V_{tar}$ by injecting malicious nodes to obtain a perturbed graph.
Formally, the objective function of node injection attack is as follows [31]:

\[
\max_{\mathcal{G}} \sum_{t \in V_{\text{tar}}} 1 \left( \arg \max_{\theta} f_{\theta^*}(\mathcal{G}(G)) \neq y_t \right) \\
\mathcal{G}(G) = (V \cup \tilde{V}, E \cup \tilde{E}, X \| \tilde{X}) \\
s.t. \quad \theta^* = \arg \min_{\theta} \mathcal{L}_{\text{train}} \left( f_{\theta}(\tilde{G}), y \right),
\]

where \(y_t\) is the ground truth label of the target node \(t\), \(\mathcal{G}(G)\) represents the perturbed graph obtained after applying the node injection attack method \(\mathcal{G}\) to the original graph \(G\), \(1(\cdot)\) is a binary metric that indicates whether the attack is successful in misleading the model prediction, and \(\arg \max_{\theta} f_{\theta^*}(\mathcal{G}(G))\) represents the predicted class of the target node \(t\) in the perturbed graph \(\mathcal{G}(G)\) using the model \(f_{\theta^*}\). Based on the original graph \(G = (V, E, X)\), the perturbed graph \(\mathcal{G}(G)\) additionally includes the injected nodes \(\tilde{V}\), injected edges \(\tilde{E}\), and the corresponding node attributes \(\tilde{X}\). \(f_{\theta^*}(\tilde{G})\) is the victim GNN model trained on original graph \(\tilde{G} = G\) or the perturbed graph \(\tilde{G} = \mathcal{G}(G)\).

3.2. Limitation of Existing Methods

Based on the objective described above, the injected nodes can be quite different from the surrounding normal nodes and easy to be perceived, which is demonstrated in our empirical study. As illustrated in Figure 1, we find that the nodes injected by existing methods are perceptible, as they are different from the original normal nodes with a simple t-SNE visualization. Anomaly detection methods can identify the outliers effectively, and show great success in real-world applications. We adopt the state-of-the-art unsupervised anomaly detection methods (COPOD [22], PCA [28], HBOS [8], IForest [24], and AE [11]) to detect injected nodes. Figure 2 (a) depicts the accuracy of detecting nodes injected by the state-of-the-art attack G-NIA, and imperceptible constraint HAO. Almost all of the nodes injected by G-NIA can be detected by detection methods. G-NIA+HAO slightly improves the imperceptibility but still results in 91% of the injected nodes being detected. After removing the detected nodes, we input the obtained new graph into GNN and evaluate the misclassification rate. Figure 2 (b) illustrates the poor attack performance of G-NIA, i.e., 20% of misclassification rate, under detection methods, which is a significant drop from the previous misclassification rates of around 99% when detection methods were not applied. We also show that our method (CANA) evades detection methods and achieves a high attack success rate. The implementations are elaborated in Section 4.2. Additionally, we conduct experiments for another state-of-the-art node injection attack TDGIA and observe similar problems, as shown in Figure 2 (c) and (d). The results demonstrate that existing node injection attacks are easy-to-detect and will fail in a practical scenario since detection models are commonly deployed in the real world.

4. Camouflage Node Injection attack

In this section, we propose and formulate the camouflage of injected nodes from the distribution similarity of ego networks. We also propose an adversarial camouflage framework for node injection attacks (CANA) to improve camouflage while ensuring attack performance for existing attacks.

4.1. Definition of Camouflage

We are dedicated to camouflage node injection attack. However, camouflage node injection attack is quite difficult, since the non-Euclidean nature of graph data makes it difficult to visualize and understand. To solve this issue, our intuition is that camouflaged injected nodes should be similar to the original nodes. Thus, an ideal state of camouflaged injected nodes is to follow the distribution of the original normal nodes. To capture both node attributes and network structure, we utilize the distribution of ego network [7] which consists of a focal node (ego) and its 1-hop neighbors. In this paper, we adopt the two-hop ego network \(G_{v} = (V_{v}, E_{v}, X_{v})\). Examples of ego networks can be found in Figure 3.

We propose to define the camouflage of injected nodes as the distribution similarity between the ego networks centering around the injected nodes and the ego networks centering around the normal nodes. In other words, the ego network distribution of the camouflaged injected nodes is similar to that of the original normal nodes, considering both the surrounding network structure and node attributes. Mathematically, we express the camouflage as:

\[
P_{v \sim V} (G_{v}) \sim P_{\tilde{v} \sim \tilde{V}} (\mathcal{G}(G)_{\tilde{v}}).
\]
Figure 3: The overall architecture of CANA. CANA adopts an adversarial paradigm, where the attack method (generator) aims to improve the camouflage while maintaining the attack performance. Discriminator aims to distinguish the distributions of ego networks between the injected nodes and the normal ones, providing informative guidance for the attacker.

Here, $G_v$ denotes the ego network of the normal node $v$ in the original graph $G$. $G(G)_v$ refers to the ego network of the injected node $v$ in the perturbed graph $G$. $P_v (G(e))$ represents the distribution of ego networks centering around the original nodes, $P_v (G(G)_v)$ indicates the distribution of ego networks centering around the injected nodes in the perturbed graph. To represent the distribution of ego networks, we encode each ego network as a vector and assemble these vectors as columns in a matrix. This matrix encapsulates the distribution of ego networks in the dataset. A detailed explanation of ego network representation can be found in Section 4.2. Note that the ~ denotes the distribution similarity. Ideally, camouflaged injected nodes satisfy $P_v (G(e)) = P_v (G(G)_v)$. We formally establish the objective of camouflage using the Jensen–Shannon divergence as follows:

$$\min_{\hat{G}(G)} D_{JS}(P_v (G(e)) \parallel P_v (G(G)_v)).$$

(3)

So far, we establish the definition and objective of camouflage and utilize the original normal nodes to guide the imperceptibility of injected nodes, providing a good guideline for solving the limitations of existing methods in Section 3.2. Our camouflage surpasses existing constraints because it is not restricted to specific aspects, such as attribute similarity [48] or smoothness [5]. For instance, in contrast to the smoothness constraint that necessitates a high degree of local smoothness, our camouflage is predicated on distribution similarity and guided by the original normal nodes. This allows for the learning of an appropriate degree of smoothness without requiring any a priori assumptions about the graph. Consequently, our camouflage is more versatile in nature. Moreover, it is reasonable to surmise that, in accordance with our camouflage definition, injected nodes can elude detection by prevailing methods. Detection mechanisms generally target nodes [22, 28, 1, 12] that display atypical behavior or possess uncommon attributes or structures. Our camouflage aims to ensure that the distribution of injected nodes resembles that of the original normal nodes, thereby making the behavior of injected nodes more akin to normal nodes and facilitating evasion from existing detection methods.

4.2. Adversarial Camouflage Framework for Node Injection Attack

In order to incorporate the camouflage into node injection attacks, we design and propose adversarial CAMouflage framework for Node Injection Attack, namely CANA. CANA is under a generative adversarial framework [9, 27], aiming to preserve the distribution similarity of ego networks. Note that CANA is a general framework that can be equipped on existing node injection attacks, making them more camouflage or imperceptible.

Figure 3 illustrates the overall architecture of our proposed CANA. CANA consists of two key components: node injection attack method $G$ and adversarial discriminator $D$. The discriminator $D$ learns the distinction between the distribution of the ego networks of injected nodes (fake) and normal nodes (real), providing camouflage guidance for attack method $G$. Meanwhile, the attacker $G$ injects nodes and edges into the original graph to generate perturbed graphs, as well as computes two kinds of losses involving attack performance and camouflage for optimization. For attack performance, the attacker learns to attack successfully under the guidance of the surrogate model. For camouflage, the attacker optimizes the injected nodes with the guidance of $D$ to make their distribution resemble that of the original nodes. Next, we introduce the fine details of each component of our CANA.
4.2.1. Camouflage Discrimination

Camouflage is defined by the distribution of ego networks, thus we employ a discriminator to identify whether the ego network is real or fake and provide the camouflage information to guide the attacker. The loss of camouflage discriminator is:

\[
\mathcal{L}^{GAN}_D = -\mathbb{E}_{v \sim \mathcal{V}} \log D(G_v) - \mathbb{E}_{\hat{v} \sim \hat{\mathcal{V}}} \log (1 - D(G(\hat{v}))).
\] (4)

Note that the discriminator needs to distinguish the real/fake label of ego networks, which is essentially a graph classification task. We adopt Graph Isomorphism Networks (GIN) [42] as the discriminator, due to its provably powerful discriminative ability on the graph classification task. By minimizing \(\mathcal{L}^{GAN}_D\), the discriminator learns the distribution similarity of ego networks of injected nodes and original normal nodes, to better assist the attacker.

4.2.2. Attack Generation

The goal of the attack method \(\mathcal{G}\) is to attack successfully while preserving camouflage. To ensure camouflage, we encourage the attacker to generate malicious nodes that are difficult to be distinguished by discriminator \(D\). Formally, the adversarial camouflage loss is:

\[
\mathcal{L}^{GAN}_G = -\mathbb{E}_{\hat{v} \sim \hat{\mathcal{V}}} \log D(G(\hat{v})).
\] (5)

According to the guide of \(D\), the attacker \(\mathcal{G}\) learns to generate injected nodes distributed similarly to normal ones. The main advantage of this loss is that it helps capture the underlying distribution of the original nodes, making it suitable for our definition of camouflage.

To avoid mode collapse (injected nodes are too similar to each other to ensure camouflage well), we adopt diversity sensitive loss to maximize the distance between each pair of injected nodes [10, 27]. The diversity sensitive loss is defined as:

\[
\mathcal{L}^{div}_G = -\mathbb{E}_{\hat{u}, \hat{v} \sim \hat{\mathcal{V}}} \sum_l d(G(\hat{u})_l, G(\hat{v})_l),
\] (6)

where \(d(\cdot)\) is the euclidean distance. Note that the diversity sensitive loss is defined on the deep features, which is the output of representation model \(R\). \(R^l(\cdot)\) is the representation on \(l^{th}\) layer of the ego network of an injected node. To better encode local graph patterns, we employ a pre-trained GIN as the representation model \(R\). This loss encourages the attacker to generate diverse injected nodes for better camouflage.

For attack performance, we apply the attack loss following [31]:

\[
\mathcal{L}^{atk}_G = \mathbb{E}_{r \sim \mathcal{V}_{tar}} [F(G(G))_{r,y_r} - \max_{j \neq y_r} F(G(G))_{r,j}],
\] (7)

where \(t\) is sample from target nodes, \(V_{tar}\), \(F(\cdot)\) is the surrogate model, \(F(G(G))_{r,y_r}\) is the output probability of \(t\) on its ground truth label \(y_r\) from \(F\), \(j\) is the class that is most likely to be misclassified among other classes. This attack loss has been demonstrated to provide the best attack performance compared with other kinds of losses [3]. Note that our CANA is a general framework, and \(\mathcal{L}^{atk}_G\) can be replaced by any node injection attack loss.

4.2.3. Overall Objective

The full objective function of our proposed CANA can be summarized as follows:

\[
\min_D \mathcal{L}^*_D = \mathcal{L}^{GAN}_D,
\]

\[
\min_G \mathcal{L}^{atk}_G = \mathcal{L}^{atk}_G + \alpha \mathcal{L}^{GAN}_G + \beta \mathcal{L}^{div}_G,
\] (8)

where \(\alpha\) and \(\beta\) are the weights to control the importance of camouflage and diversity, respectively. The discriminator \(D\) and generator \(G\) are updated alternatively until convergence.

4.3. Algorithm

We describe the training procedure of CANA in Algorithm 1. For each iteration, we first train the discriminator for several steps, and then train the attack generator once, following [9]. The complexity of CANA depends on the underlying basic attacks. Let the computational complexity of a basic attack be denoted by \(\mathcal{O}(T)\), the complexity after incorporating the CANA framework becomes \(\mathcal{O}(h + 1) \cdot T\). Here, \(h\) represents the number of discriminator training steps, which is usually a small constant.
Algorithm 1 Training Process for CANA Framework

Require: original graph $G = (V, E, X)$, pre-trained representation model $R$, pre-trained surrogate model $f$
Ensure: camouflage attack method $G$

1: for number of training iterations do
2:   for number of discriminator training steps do
3:     Sample minibatch of targets $V_{tar}$ from original normal nodes $V$
4:     Generate $G(G) = (V \cup \hat{V}, E \cup \hat{E}, X \parallel \hat{X})$ by $G$ attacking $V_{tar}$
5:     Sample minibatch of clean nodes $v$ from $V$, and take the ego networks $G_v$
6:     Sample minibatch of injected nodes $\hat{v}$ from $\hat{V}$, and take the ego networks $G(\hat{G})_\hat{v}$
7:     Compute discriminator loss $L_D^{GAN}$ by Eq. 4
8:     Compute gradient of $D$ and update $D$
9:   end for
10:  Sample minibatch of targets $V_{tar}$ from original normal nodes $V$
11:  Generate $G(G) = (V \cup \hat{V}, E \cup \hat{E}, X \parallel \hat{X})$ by $G$ attacking $V_{tar}$
12:  Sample minibatch of injected nodes $\hat{v}$ from $\hat{V}$, and take the ego networks $G(\hat{G})_\hat{v}$
13:  Compute adversarial camouflage loss $L_G^{GAN}$ by Eq. 5
14:  Sample $(u, v)$ in $\hat{V}$, compute diversity sensitive loss $L_G^{div}$ by Eq. 6
15:  Compute attack loss $L_G^{atk}$ by Eq. 7
16:  Compute overall loss $L_G$ by Eq. 8
17:  Compute gradient of $G$ and update $G$
18: end for

Table 1

| Dataset          | $N_{LCC}$ | $E_{LCC}$ | Classes | Degree | Feature dimension | Feature range       | Injected feature range | Injected node budget | Injected edge budget |
|------------------|-----------|-----------|---------|--------|------------------|-----------------------|-----------------------|---------------------|---------------------|
| ogbn-products    | 10,494    | 38,872    | 35      | 3.70   | 100              | [-74.70,152.71]       | [-20, 20]             | 2,099               | 3                   |
| reddit           | 10,004    | 73,512    | 41      | 7.35   | 602              | [-22.89, 80.85]       | [-20, 20]             | 2,001               | 7                   |
| ogbn-arxiv       | 169,343   | 2,484,941 | 39      | 14.67  | 128              | [-1.39, 1.64]         | [-1, 1]               | 33,869              | 14                  |

5. Experiments

In this section, we equip state-of-the-art node injection attacks with our CANA framework on three benchmark datasets and compare the attack performance under representative detection and defense methods. Further analysis of camouflage, case study, visualization, ablation study, and hyper-parameter analysis are also provided.

5.1. Experimental Settings

5.1.1. Datasets

We take the commonly-used node classification as the target task, following [49, 50, 31]. To illustrate the wide adaptability of CANA, we conduct experiments on three kinds of real-world datasets: a social network reddit [31] gathered from the Reddit website, an Amazon product co-purchasing network ogbn-products [14], and a citation network ogbn-arxiv [14] containing Computer Science (CS) arXiv papers.

- **reddit.** Each node represents a post, with word vectors as attributes and community as the label, while each edge represents the post-to-post relationship.
- **ogbn-products.** A node represents a product sold on Amazon with the word vectors of descriptions as attributes and the product category as the label, and edges between two products indicate that they are purchased together.
- **ogbn-arxiv.** A node denotes a CS arXiv paper with attributes indicating the average word embeddings of its title and abstract. An edge means the citation relationship and the node label is the primary category of each paper.

Experiments are conducted on the largest connected components (LCC) for all three network datasets, following [49, 50, 31]. The statistics of each dataset are summarized in Table 1.
5.1.2. Attack Methods

Since CANA serves as a general camouflage framework for node injection attacks, we instantiate CANA with several state-of-the-art node injection attack methods to verify the generality and effectiveness of CANA. We employ the PGD [26], TDGIA [48] and G-NIA [31] as the basic attack methods due to their high attack success rate and excellent scalability. We also adopt heuristic imperceptible constraint HAO [5] as our strong baseline. Note that all attacks are evasion attacks following [48, 31]. As for the attack scenario, we utilize the commonly-used black-box attack, which is considered as the most practical scenario in real-world applications 3.

- **Basic attack methods.**
  - PGD [26] is a widely adopted attack, using projected gradient descent to generate malicious nodes.
  - TDGIA [48] adopts topologically defective edge selection and smooth feature optimization to inject malicious nodes.
  - G-NIA [31] models the injection attacking process via a parametric model to ensure the attack efficiency and attack performance.

- **Imperceptible constraint.**
  - HAO [5] is our most related work, which tries to promote the unnoticeability of node injection attacks using homophily constraint.

5.1.3. Detection and Defense Methods

To better demonstrate the attack performance of node injection methods and the improvement of CANA, we evaluate attacks on SOTA anomaly detection and defense methods, which form a practical adversarial environment.

- **Detection methods** identify outlier items that deviate from the majority of data distribution [12] and are used in many applications such as fraud detection. Anomaly detections can be divided into five types [12], including probabilistic, linear model, proximity-based, and neural network methods. For each category, we select the SOTA method, i.e., COPOD [22], PCA [28], HBOS [8], IForest [24], and AE [1].

- **Defense methods** defend adversarial attacks via adversarial training, or attention mechanism [29, 17]. For each category, we adopt the most representative methods. For adversarial training, we leverage FLAG [19] which is efficient and effective. For the attention mechanism, we adopt the powerful model GNNGuard [44].

5.1.4. Hyperparameters Settings

We implement all the attack methods with our CANA framework. For all attack methods, we limit the range of injected node features, as well as the budget of injected nodes and edges to ensure that the perturbation is subtle, as shown in Table 1. In each dataset, we randomly choose 20% nodes as the target nodes and inject the same number of malicious nodes to perform the attack. For parametric G-NIA, we first train it on a part of non-target nodes and then infer the injected nodes for the target nodes based on the trained model. Other methods are directly optimized and obtain the injected nodes for the target nodes. The attack method $G$ and discriminator $D$ are trained alternatively following GAN [9], i.e., we update the discriminator $h$ steps and then optimize the generator $1$ step to ensure the convergence. The surrogate model and representation model are pre-trained on original normal node labels. We tune the hyper-parameters based on the validation performance within the following range: $\alpha$ over $\{0.1, 0.5, 1.0, 5.0\}$, $\beta$ over $\{10^{-2}, 10^{-2}, 10^{-1}, 1\}$, and $h$ over $\{1, 4, 10\}$, and learning rate over $\{10^{-3}, 10^{-2}, 10^{-1}\}$.

5.2. Metrics for Camouflage Evaluation

Existing works [48, 31, 5] mainly focus on adding constraints to introduce imperceptible attack methods, rather than proposing a metric to evaluate imperceptibility or camouflage. Based on these constraints, we develop several metrics to evaluate the camouflage of injected nodes. Specifically, TDGIA [48] limits the range of attributes based on attribute similarity. Inspired by this, we pose the Closest Attribute Distance (CAD), which measures the average Euclidean distance between the attribute and its most similar attribute of original normal nodes. Formally, $CAD_i = \min_{j \in V} d(X_i, X_j)$. HAO [5] constrains the homophily of injected nodes, i.e., the similarity between two connected

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3The black-box attack scenario assumes that the attacker has no access to the model structure, training parameters, or defense methods (if defense methods are added) of the victim model and can only interact with the model through input and output.
nodes, also known as smoothness. Building on this, we introduce Smoothness (Smooth) metric, which is the average distance between a node’s attribute and those of its neighbors. Formally, $\text{Smooth}_i = \frac{1}{|N_i|} \sum_{j \in N_i} d(X_i, X_j)$. However, these metrics only focus on specific heuristic aspects. There is still a lack of a general metric to evaluate camouflage from the perspective of distribution similarity.

Evaluating the similarity between distributions can indeed be a complex endeavor. Directly computing the JS divergence (Eq. 3) presents a challenge, as the probability densities of the ego network distributions for injected and original nodes are unknown. The loss of the optimal discriminator closely approximates JS divergence, but obtaining the optimal discriminator is challenging. Fortunately, we find the representations of ego networks of original normal nodes follow multidimensional Gaussians, and we assume that the imperceptible injected nodes follow multidimensional Gaussians. Inspired by Fréchet Inception Distance (FID) [13], we call Fréchet Distance to compute the distance between two Gaussian distributions by mean and covariance. We propose Graph Fréchet Distance (GraphFD) to measure the distance between distributions of ego networks of injected and normal nodes, evaluating the camouflage of attack methods. GraphFD is formalized as:

$$\text{GraphFD} = \left\| \mu_r - \mu_m \right\|^2_2 + \text{Tr} \left( \Sigma_r + \Sigma_m - 2 \left( \Sigma_r \Sigma_m \right)^{1/2} \right),$$

where $\mu_r$ and $\Sigma_r$ are the mean vector and variance matrix of the original normal nodes, $\mu_m$ and $\Sigma_m$ are those of the injected nodes.

**Rationality of GraphFD.** Our GraphFD measures the camouflage of injected nodes under the guide of distribution similarity. Such an evaluation metric is general, characterizing the network structure and node attributes at the same time. We demonstrate the validity of this metric through two aspects: the consistency between GraphFD and intuitive perceptibility, and the consistency between GraphFD and the accuracy of the detection method, as depicted in Figure 4. Figure 4(a) illustrates a monotonic increase in GraphFD as the perceptibility of injected nodes increases. Specifically, as the injected nodes become more noticeable, the GraphFD also becomes larger. This finding suggests that GraphFD is a reliable metric of the perceptible level of injected nodes on a graph. Figure 4(b) illustrates a positive correlation between GraphFD and the accuracy of a detection method for injected nodes. The larger the GraphFD, indicating a greater dissimilarity between the distributions, the easier it is to detect the injected nodes. These findings further support the rationality of using GraphFD as a measure of similarity/dissimilarity between distributions on graphs.

### 5.3. Attack Performance

To evaluate the effectiveness and applicability of CANA, we equip three representative attack methods (G-NIA, TDGIA, PGD) with CANA, as well as compare CANA with the above basic attacks and a SOTA imperceptible attack method HAO. Experiments are conducted on three benchmark datasets. To better demonstrate the attack

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4In previous work, deep representations are proved to capture high-level information of images [43]. In our case on the graph, the deep representations of ego networks can model and associate the attributes and structures of nodes.
Table 2: Misclassification rate (%) of node injection attack across detection and defense methods on ogbn-products, reddit, and ogbn-arxiv. The relative increases in Average and Median misclassification rates compared with basic attacks are written in parentheses.

|                | Detection methods | Defense methods | Average | Median |
|----------------|-------------------|-----------------|---------|--------|
|                | COPOD | PCA | HBOS | IForest | AE | FLAG | GNNGuard |         |        |
| ogbn-products  |       |     |      |         |    |      |          |         |        |
| Clean          | 25.20 | 25.54 | 24.87 | 25.30 | 25.49 | 21.11 | 19.29 | 23.83 | 25.20 |
| PGD            | 36.68 | 37.73 | 36.11 | 34.97 | 34.97 | 29.87 | 33.21 | 35.51 | 36.68 |
| +HAO           | 31.25 | 32.16 | 32.11 | 33.35 | 31.92 | 27.06 | 33.49 | 31.62 | 32.11 |
| +CANA          | 40.78 | 42.73 | 43.59 | 44.97 | 42.78 | 31.92 | 35.11 | 40.27 | 42.73 |
| TDGIA          | 37.26 | 46.21 | 42.21 | 44.07 | 46.02 | 33.35 | 39.21 | 41.19 | 42.21 |
| +HAO           | 24.92 | 31.30 | 25.01 | 25.96 | 31.30 | 25.58 | 33.68 | 27.31 | 25.51 |
| +CANA          | 45.97 | 49.36 | 45.55 | 48.79 | 49.21 | 27.49 | 30.63 | 42.43 | 45.97 |
| G-NIA          | 21.30 | 24.68 | 21.44 | 21.68 | 24.34 | 25.58 | 32.92 | 32.25 | 24.34 |
| +HAO           | 23.63 | 31.73 | 23.87 | 25.82 | 31.59 | 21.06 | 21.92 | 25.03 | 25.54 |
| +CANA          | 55.45 | 57.27 | 56.12 | 56.07 | 57.22 | 40.11 | 34.78 | 50.92 | 56.07 |

|                | Detection methods | Defense methods | Average | Median |
|----------------|-------------------|-----------------|---------|--------|
|                | COPOD | PCA | HBOS | IForest | AE | FLAG | GNNGuard |         |        |
| ogbn-arxiv     |       |     |      |         |    |      |          |         |        |
| Clean          | 9.25  | 9.25 | 9.25 | 9.15   | 9.25 | 8.05  | 17.59  | 10.25  | 9.25  |
| PGD            | 9.70  | 14.94 | 10.29 | 11.44 | 14.59 | 17.99 | 24.79 | 14.82 | 14.59 |
| +HAO           | 13.54 | 13.19 | 11.89 | 12.54 | 13.49 | 15.54 | 50.47 | 15.66 | 13.49 |
| +CANA          | 45.33 | 45.88 | 37.73 | 43.28 | 46.03 | 24.34 | 34.78 | 43.28 | 45.97 |
| TDGIA          | 10.94 | 20.24 | 20.04 | 15.49 | 20.24 | 20.09 | 26.34 | 19.06 | 20.09 |
| +HAO           | 8.15  | 9.45  | 8.15  | 9.45  | 8.15  | 15.79 | 50.47 | 15.66 | 9.45  |
| +CANA          | 31.73 | 33.48 | 24.29 | 33.73 | 26.34 | 18.92 | 25.84 | 27.82 | 28.79 |
| G-NIA          | 8.15  | 8.15  | 8.15  | 8.15  | 8.15  | 11.19 | 14.79 | 9.67  | 8.60  |
| +HAO           | 8.15  | 8.60  | 8.15  | 8.20  | 8.60  | 15.79 | 50.47 | 15.66 | 8.60  |
| +CANA          | 45.83 | 50.57 | 45.18 | 49.03 | 50.42 | 36.38 | 24.04 | 43.06 | 45.83 |
| G-NIA          | 28.49 | 30.38 | 28.43 | 28.43 | 30.38 | 28.43 | 32.51 | 32.51 | 28.50 |
| +HAO           | 32.31 | 34.60 | 33.32 | 34.00 | 34.46 | 38.25 | 31.45 | 34.06 | 34.00 |
| +CANA          | 32.92 | 34.93 | 33.74 | 35.04 | 34.74 | 44.16 | 32.51 | 35.43 | 34.74 |

ability in practice, we evaluate attacks under representative detection methods (COPOD, PCA, HBOS, IForest, and AutoEncoder), and defense methods (Adversarial training and GNNGuard). Specifically, the input of detection methods is the representation of ego networks capturing both network structure and node attributes.

Table 2 illustrates the misclassification rate on target nodes after filtering by detection methods or defending by defense methods. The misclassification on clean graphs (Clean) is also included here as a lower bound. We list the average and median of the misclassification rate across all the detection and defense methods (Average and Median) to show the overall attack performance. And we report in parentheses the relative increases of attack performance on Average and Median compared with basic attacks for clear comparison.

The basic attacks, namely PGD, TDGIA, and G-NIA, demonstrate poor performance under detection/defense methods across all datasets. As for the heuristic constraint, although the incorporation of HAO has resulted in performance improvements for certain attacks on certain datasets, such as the Average performance of PGD+HAO on reddit, HAO cannot guarantee consistent improvements for all attacks. For example, the Average performance of TDGIA+HAO and G-NIA+HAO even drops slightly on reddit. The results show that previous attacks are too perceptible to detection/defense methods, making the attacks ineffective in the real world.

The integration of our CANA framework brings significant improvement for all node injection attacks and shows superiority on Average and Median on all datasets. Our CANA achieves the best attack performance under all detection methods on all datasets. When defense methods are applied, CANA either outperforms or achieves comparable results to basic attacks and HAO, as some defense methods are not strong enough to distinguish and defend against injected attacks.
Table 3
Camouflage on various metrics on three datasets. Smaller is better, and the smallest is bolded.

|               | ogbn-products |               | ogbn-products |               | ogbn-arxiv |               | ogbn-arxiv |
|---------------|---------------|---------------|---------------|---------------|------------|---------------|------------|
|               | CAD ↓ | Smooth ↓ | GraphFD ↓ | CAD ↓ | Smooth ↓ | GraphFD ↓ | CAD ↓ | Smooth ↓ | GraphFD ↓ |
| Clean         | 0.727 | 0.964 | -       | 0.849 | 1.083 | -       | 0.350 | 0.570 | -       |
| PGD           | 3.206 | 3.698 | $3.158 \times 10^2$ | 2.823 | 3.081 | $3.839 \times 10^3$ | 1.731 | 1.947 | $2.179 \times 10^3$ |
| +HAO          | 2.517 | 2.835 | $1.712 \times 10^3$ | 1.615 | 1.875 | $1.556 \times 10^3$ | 0.422 | 0.736 | $2.043 \times 10^3$ |
| +CANA         | 2.295 | 2.810 | $1.244 \times 10^3$ | 1.154 | 1.568 | $1.414 \times 10^3$ | 0.538 | 0.735 | $2.031 \times 10^3$ |
| TDGIA         | 3.524 | 4.316 | $7.911 \times 10^2$ | 4.581 | 4.875 | $2.387 \times 10^3$ | 3.344 | 3.578 | $2.582 \times 10^3$ |
| +HAO          | 10.874 | 12.105 | $7.391 \times 10^3$ | 10.538 | 11.181 | $5.957 \times 10^3$ | 3.059 | 3.280 | $2.447 \times 10^3$ |
| +CANA         | 1.495 | 2.489 | $61.540$ | 1.322 | 1.698 | $1.491 \times 10^3$ | 0.745 | 1.097 | $2.086 \times 10^3$ |
| G-NIA         | 23.442 | 24.357 | $2.675 \times 10^4$ | 17.052 | 17.364 | $1.406 \times 10^3$ | 3.889 | 4.157 | $2.218 \times 10^3$ |
| +HAO          | 9.630 | 10.508 | $5.067 \times 10^3$ | 8.794 | 9.408 | $4.413 \times 10^3$ | 3.406 | 3.813 | $1.982 \times 10^3$ |
| +CANA         | 1.455 | 2.062 | $99.688$ | 1.094 | 1.573 | $898.593$ | 0.547 | 0.769 | $1.524 \times 10^3$ |

Figure 5: Visualization of a local network in clean graph and perturbed graphs. The heatmap represents the node attribute.

nodes. Specifically, on Median, CANA achieves a boosting improvement of 196% for PGD, 43% for TDGIA, and 462% for G-NIA on reddit. The results demonstrate the effectiveness of our CANA framework.

5.4. Effect of Camouflage

To evaluate the camouflage of CANA, we adopt three metrics, i.e., Closest Attribute Distance (CAD) [48], Smoothness (Smooth) [5], and our proposed GraphFD. We report the results of three basic attack methods and imperceptible attack HAO and our proposed CANA on three benchmark datasets. The imperceptibility of clean graphs, i.e., Clean, is reported as the upper bound. CAD and Smooth of clean graphs are computed across original nodes, while GraphFD of clean graphs is `-`, since there is no injected node in Clean.

As illustrated in Table 3, the camouflage of all the basic attacks on all datasets is quite poor. Although HAO improves the imperceptibility of the specific attack(G-NIA+HAO on ogbn-products), it even decreases the imperceptibility for other attacks(TDGIA+HAO on ogbn-products and reddit). This is due to its heuristic nature, which prioritizes smoothness. Additionally, it does not consider the distribution between injected and normal nodes, making it challenging to narrow the distribution distance like GraphFD. The incorporation of CANA significantly improves the imperceptibility of all basic attacks across all datasets, as evidenced by all metrics. CAD and Smooth of graphs perturbed by G-NIA+CANA, TDGIA+CANA, and PGD+CANA are very close to the original clean graphs on reddit and ogbn-arxiv. Since the GraphFD metric cannot be computed on a clean graph, any analysis that takes it into account should compare CANA with HAO and basic attacks GraphFD of the graphs attacked by CANA shows a significant narrowing when compared to the basic attacks and HAO, indicating that the representation distributions of injected nodes are closer to those of normal nodes. Specifically, for G-NIA+CANA, GraphFD decreases by 99.79% on ogbn-products, 19.02% on ogbn-arxiv, and 64.74% on reddit. The results prove the imperceptibility and camouflage ability of our proposed CANA.
Diversity sensitive loss weight

G-NIA+CANA w/o

1.0

0.5

1.0

0.5

camouflage of injected nodes by using the discriminator as a guide. Overall, each loss of our CANA plays a crucial role, and these results demonstrate its significance in attack performance under detection/defense methods.

5.7. Hyper-parameter Analysis

We conduct an ablation study to analyze the effectiveness of each part of CANA. We implement two variants of CANA including CANA without adversarial camouflage loss $L^G_{GAN}$ (CANA w/o $L^G_{GAN}$), and CANA without diversity sensitive loss $L^G_{div}$ (CANA w/o $L^G_{div}$), where we set $\alpha = 0$ and $\beta = 0$, respectively. We take the results on ogbn-products with G-NIA as an example, as the results on other datasets with other injection attack methods are similar.

Figure 6 presents the average attack performance across all detection and defense methods. The misclassification rates of CANA without $L^G_{GAN}$ and CANA without $L^G_{div}$ are significantly lower than those of the complete CANA, emphasizing the importance of our losses. Both variants can unilaterally increase the rate of misclassification under the defense/detection methods compared to the basic attack G-NIA. Specifically, CANA without $L^G_{GAN}$ causes a misclassification rate of 48.87%, and CANA without $L^G_{div}$ yields a misclassification rate of 33.70%. The results also indicate that adversarial camouflage loss is more important than diversity sensitive loss, because the former helps improve the camouflage of injected nodes by using the discriminator as a guide. Overall, each loss of our CANA plays a crucial role, and these results demonstrate its significance in attack performance under detection/defense methods.

5.5. Case Study

To intuitively understand CANA, we take ogbn-products as a case to study the changes before and after node injection attacks. Figure 5 visualizes a local network of the clean graph and that of graphs perturbed by G-NIA, G-NIA+HAO, and G-NIA+CANA. The large red node denotes the injected node. Node color refers to the prediction of a vanilla GCN trained on the clean graph. Compared with the results on the clean graph, all attack methods successfully cause GNN to classify most nodes incorrectly. The basic attack G-NIA injects one node and makes all original nodes misclassified, but the injected node attributes differ significantly from the original attributes, as depicted in the heat map in Figure 7(b). G-NIA+HAO results in the misclassification of four nodes and reduces perceptibility to some extent. Nevertheless, the injected node attributes remain easily detectable. G-NIA+CANA also makes four nodes misclassified, but the injected node attributes closely resemble those of the normal nodes, demonstrating CANA’s exceptional camouflage capabilities.

5.6. Ablation Study

We conduct an ablation study to analyze the effectiveness of each part of CANA. We implement two variants of CANA including CANA without adversarial camouflage loss $L^G_{GAN}$ (CANA w/o $L^G_{GAN}$), and CANA without diversity sensitive loss $L^G_{div}$ (CANA w/o $L^G_{div}$), where we set $\alpha = 0$ and $\beta = 0$, respectively. We take the results on ogbn-products with G-NIA as an example, as the results on other datasets with other injection attack methods are similar.

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5.7. Hyper-parameter Analysis

We analyzed the sensitivity of our CANA to the hyper-parameters α and β, from two perspectives: attack performance and node camouflage. The attack performance refers to the average misclassification rate across all detection and defense methods, and the camouflage refers to GraphFD. We vary the α in \{0.1, 0.5, 1.0, 5.0\}, β in \{10^{-3}, 10^{-2}, 10^{-1}, 1\}. As shown in Figure 7 (a), GraphFD (node camouflage) can be consistently improved with the increases of α, which validates the effectiveness of \( \mathcal{L}^{\text{GAN}}_{\mathcal{G}} \) on improving the camouflage of injected nodes. The attack performance initially improves with smaller values of α but degrades as α increases. Specifically, when α is large (α = 5.0), the dominance of camouflage in the attack task inevitably leads to a reduced attack success rate. The optimal trade-off between attack strength and node camouflage is achieved at α = 0.5, resulting in the best attack performance. As depicted in Figure 6 (b), the misclassification rate and GraphFD are observed to be insensitive to changes in β, as \( \mathcal{L}^{\text{div}}_{\mathcal{G}} \) is primarily used to prevent mode collapse, rather than to directly enhance the camouflage.

**Further Discussions.** We find that there is a trade-off between the attack performance and node camouflage under certain defense/detection mechanisms. This is because camouflage attacks can effectively evade detection/defense through appropriate node camouflage, an excessively camouflaged attack may compromise performance due to its high similarity to clean data. In the absence of any detection/defense mechanism, non-camouflage attacks exhibit better attack performance, as exemplified by G-NIA achieving a misclassification rate of up to 99%. However, in practical scenarios, the presence or absence of a detection/defense mechanism is often unclear, leading us to contemplate whether to employ a camouflaged attack. One possible way is first injecting a small number of nodes, and then evaluating the attack success rate of these injected nodes to determine whether a camouflaged attack is necessary. We believe this to be an intriguing research direction and intend to further investigate it in the future.

5.8. Time analysis

To clarify CANA’s computation time, we compare the complete training time of CANA, HAO, and basic attacks (PGD, TDGIA, and G-NIA), using a single NVIDIA V100 32 GB GPU. Taking ogbn-products as an example, we report the results in Table 4. The time of CANA is associated with the corresponding basic attacks. Specifically, the training time of PGD+CANA is approximately 8.1 times that of PGD training, TDGIA+CANA is nearly 5.4 times that of TDGIA, and G-NIA+CANA is about 3.3 times that of G-NIA. These results demonstrate that CANA necessitates only minimal additional computation, which will not hinder its practical application on large-scale datasets.

6. Conclusion and Future Work

In this paper, we find that the malicious nodes generated by existing node injection attack methods are easy to be identified by defense methods. To solve the issue, we first formulate the camouflage on graphs as the distribution similarity between the ego networks centering around the injected nodes and those centering around the normal nodes, characterizing both network structures and node attributes. Then we propose an adversarial camouflage framework for node injection attacks, namely CANA, to improve the camouflage of injected nodes through an adversarial paradigm. CANA is a general framework, which could be attached to any existing node injection attack methods, improving node camouflage while inheriting the performance of existing node injection attacks. A novel metric, i.e., GraphFD, is further proposed for evaluating the imperceptibility of injected nodes. Extensive experimental results demonstrate that equipped with our CANA framework, existing node injection attack methods significantly improve the attack performances under various detection and defense methods with better imperceptibility/camouflage.

**Practical implementation.** First, we train a surrogate model like other attacks. Next, we use an attack method to inject nodes. Since the presence or absence of a detection/defense mechanism is often unclear, we start by applying the basic attack method to inject 1% of the node budget. If the attack fails, it indicates the presence of a defense/detection method in the system. In this case, we integrate CANA to inject the remaining nodes for a camouflaged attack. Otherwise, if the attack is successful, it implies no defense or detection method is present, allowing us to rely solely on the basic attack.
Practical implications. Node injection attacks can significantly degrade the GNN performance, and the practical implications of these attacks largely depend on GNN applications, such as fraud detection, recommender system, bioinformatics, and so on. In security-critical scenarios, detection/defense methods are often used to distinguish and remove injected nodes. However, our CANA approach renders injected nodes indistinguishable from normal ones, making them imperceptible to defense or detection methods, thereby increasing their threat in practical scenarios. This study highlights the potential risks of node injection attacks when deploying GNNs in real-world settings and emphasizes the need to address the security vulnerabilities of GNNs in practical applications.

Future work. We view the camouflage of graph adversarial attacks as a fascinating and promising research direction. There are several valuable research questions, such as studying the trade-off between attack performance and camouflage under certain defense/detection mechanisms from both empirical and theoretical perspectives, exploring the more tractable loss functions for addressing camouflage, and experiments on more downstream tasks. We are enthusiastic about exploring directions further and plan to conduct additional investigations in the future.

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