GNNGuard: Defending Graph Neural Networks against Adversarial Attacks

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Abstract

Deep learning methods for graphs achieve remarkable performance on many tasks. However, despite the proliferation of such methods and their success, recent findings indicate that small, unnoticeable perturbations of graph structure can catastrophically reduce performance of even the strongest and most popular Graph Neural Networks (GNNs). Here, we develop GNNGuard, a general defense approach against a variety of training-time attacks that perturb the discrete graph structure. GNNGuard can be straightforwardly incorporated into any GNN. Its core principle is to detect and quantify the relationship between the graph structure and node features, if one exists, and then exploit that relationship to mitigate negative effects of the attack. GNNGuard uses network theory of homophily to learn how best assign higher weights to edges connecting similar nodes while pruning edges between unrelated nodes. The revised edges then allow the underlying GNN to robustly propagate neural messages in the graph. GNNGuard introduces two novel components, the neighbor importance estimation, and the layer-wise graph memory, and we show empirically that both components are necessary for a successful defense. Across five GNNs, three defense methods, and four datasets, including a challenging human disease graph, experiments show that GNNGuard outperforms existing defense approaches by 15.3% on average. Remarkably, GNNGuard can effectively restore the state-of-the-art performance of GNNs in the face of various adversarial attacks, including targeted and non-targeted attacks.

1 Introduction

Deep learning on graphs and Graph Neural Networks (GNNs), in particular, have achieved remarkable success in a variety of application areas [1, 2, 3, 4]. The key to the success of GNNs is the neural message passing scheme [5] in which neural messages are propagated along edges of the graph and typically optimized for performance on a downstream task. In doing so, the GNN is trained to aggregate information from neighbors for every node in each layer, which allows the model to eventually generate representations that capture useful node feature as well as topological structure information [6, 7]. While the aggregation of neighbor nodes’ information is a powerful principle of representation learning, the way that GNNs exchange that information between nodes makes them vulnerable to adversarial attacks [8].

Adversarial attacks on graphs, which carefully rewire the graph topology by selecting a small number of edges or inject carefully designed perturbations to node features, can contaminate local node neighborhoods, degrade learned representations, confuse the GNN to misclassify nodes in the graph, and can catastrophically reduce the performance of even the strongest and most popular GNNs [9, 10]. This lack of GNN robustness is a critical issue in many application areas where adversarial perturbations can not only undermine public trust and slow down science and development of technology but can also substantially interfere with human decision making [11]. For this reason, it
is vital to develop GNNs that are robust against adversarial attacks. While the vulnerability of machine learning methods to adversarial attacks has raised many concerns and has led to theoretical insights into robustness [12] and the development of effective defense techniques [9, 11, 13], adversarial attacks and defense on graphs remain poorly understood.

**Present work.** Here, we introduce GNNGuard\(^1\), an approach that can defend any GNN model against a variety of training-time attacks that perturb graph structure (Figure 1). GNNGuard takes as input an existing GNN model. It mitigates adverse effects by modifying the GNN’s neural message passing operators. In particular, it revises the message passing architecture such that the revised model is robust to adversarial perturbations while at the same time the model keeps it representation learning capacity. To this end, GNNGuard develops two key components that estimate neighbor importance for every node and coarsen the graph through an efficient memory layer. The former component dynamically adjusts the relevance of nodes’ local network neighborhoods, prunes likely fake edges, and assigns less weight to suspicious edges based on network theory of homophily [14]. The latter components stabilizes the evolution of graph structure by preserving, in part the memory from a previous layer in the GNN.

We compare GNNGuard to three state-of-the-art GNN defenders across four datasets and under a variety of attack types, including direct targeted, influence targeted, and non-targeted attacks. Experiments show that GNNGuard improves state-of-the-art methods by up to 15.3% in defense performance. Importantly, unlike existing GNN defenders [15, 16, 17, 18], GNNGuard is a general approach and can be effortlessly combined with any GNN architecture. To that end, we integrate GNNGuard into five GNN models. Remarkably, results show that GNNGuard can effectively restore state-of-the-art performance of even the strongest and most popular GNNs [3, 19, 7, 20, 21], thereby demonstrating broad applicability and relevance of GNNGuard for graph machine-learning.

### 2 Related Work

**Adversarial attacks in continuous and discrete space.** Adversarial attacks on machine learning have received increasing attention in recent years [12, 22]. The attackers add small perturbations on the samples to completely alter the output of the machine learning model. The deliberately manipulated perturbations are often designed to be unnoticeable. Modern studies have shown that machine leaning models, especially deep neural networks, are highly fragile to adversarial attacks [23, 24, 25]. The majority of existing works focus on grid data or independent samples [26] whilst a few work investigate adversarial attack on graphs.

**Adversarial attacks on graphs.** Based on the goal of the attacker, adversarial attacks on graphs [27, 28] can be divided into poisoning attacks (e.g., Nettack [8]) that perturb the graph in training-time and evasion attacks (e.g., RL-S2V [28]) that perturb the graph in testing-time. GNNGuard is designed to improve robustness of GNNs against poisoning attacks. There are two types of poisoning attacks: a targeted attack and a non-targeted attack [29]. The former deceives the model to misclassify a specific node (i.e., target node) [8] while the latter degrades the overall performance of the trained model [26].

The targeted attack can be categorized into direct targeted attack where the attacker manipulates the target node’s neighbors. Nettack [8] generates perturbations by modifying graph structure (i.e., structure attack) and node attributes (i.e., feature attack) such that perturbations maximally destroy downstream GNN’s predictions. Bojcheshki et al. [30] derive adversarial perturbations that poison the graph structure. Similarly, Zügner et al. [26] propose a non-targeted poisoning attacker by using

\(^1\)We will share the GNNGuard implementation, baseline defense algorithms, and all datasets upon publication.
While GNN-Jaccard can defend targeted adversarial attacks on known and already existing GNNs, we briefly overview the state-of-the-art defense methods on graphs. GNN-Jaccard [15] is a defense where graph neural networks learns compact, low-dimensional and PGN’s loss. The attacker finds optimal perturbation them through perturbation and rewiring. In doing so, the attacker aims to fool the GNN into making incorrect predictions [18]. The attacker tries to fool a GNN by corrupting the graph topology. While deep learning on graphs has shown exciting results in a variety of applications [5, 21, 31, 32, 33], little attention has been paid to the robustness of such models, in contrast to an abundance of research for image (e.g., [34]) and text (e.g., [35]) adversarial defense.

We briefly overview the state-of-the-art defense methods on graphs. GNN-Jaccard [15] is a defense approach that pre-processes the adjacency matrix of the graph to identify the manipulated edges. While GNN-Jaccard can defend targeted adversarial attacks on known and already existing GNNs, there has also been work on novel, robust GNN models. For example, RobustGCN [17] is a novel GNN that adopts Gaussian distributions as the hidden representations of nodes in each convolutional layer to absorb the effect of an attack. Similarly, GNN-SVD [16] uses a low-rank approximation of adjacency matrix that drops noisy information through an SVD decomposition. Tang et al. [18] improve the robustness of GNNs against poisoning attack through transfer learning but has a limitation that requires several unperturbed graphs from the similar domain during training. However, all these approaches have drawbacks (see Section 4.3) that prevent them from realizing their potential for defense to the fullest extent. GNNGUARD eliminates these drawbacks, successfully defending targeted and non-targeted poisoning attacks on any GNN without decreasing its accuracy.

3 Background and Problem Formulation

Let $G = (V, E, X)$ denotes a graph where $V$ is the set of nodes, $E$ is the set of edges and $X = \{x_1, ..., x_n\}, x_u \in \mathbb{R}^M$ is the $M$-dimensional node feature for node $u \in V$. Let $N = |V|$ and $E = |E|$ denote the number of nodes and edges, respectively. Let $A \in \mathbb{R}^{N \times N}$ denote an adjacency matrix whose element $A_{uv} \in \{0, 1\}$ indicates existence of edge $e_{uv}$ that connects node $u$ and $v$. We use $N_u$ to denote immediate neighbors of node $u$, including the node itself ($u \in N_u$). We use $N_u^*$ to indicate $u$’s neighborhood, excluding the node itself ($u \notin N_u^*$). Without loss of generality, we consider node classification task, wherein a GNN $f$ classifies nodes into $C$ labels. Let $y_u = f_u(G)$ denote prediction for node $u$, and let $y_u \in \{1, ..., C\}$ denote the associated ground-truth label for node $u$. To degrade the performance of $f$, an adversarial attacker perturbs edges in $G$, resulting in the perturbed version of $G$, which we call $G' = (V, E', X)$ ($A'$ is adjacency matrix of $G'$).

**Background on graph neural networks.** Graph neural networks learn compact, low-dimensional representations, i.e., embeddings, for nodes such that representation capture nodes’ local network neighborhoods as well as nodes’ features [5, 3, 36]. The learned embeddings can be used for a variety of downstream tasks [3]. Let $h_u^k \in \mathbb{R}^{D_k}$ denote the embedding of node $u$ in the $k$-th layer of GNN, $k = \{1, ..., K\}$. The $D_k$ stands for the dimension of $h_u^k$. Note that $h_u^0 = x_u$. The computations in the $k$-th layer consist of a message-passing function $MSG$, an aggregation function $AGG$, and an update function $UPD$. This means that a GNN $f$ can be specified as $f = (MSG, AGG, UPD)$ [5, 32]. Given a node $u$ and its neighbor $v \in N_u$, the messaging-passing function $MSG$ specifies what neural message $m_{uv}^k$ needs to be propagated from $v$ to $u$. The message is calculated by $m_{uv}^k = MSG(h_u^k, h_v^k, A_{uv})$, where $MSG$ receives node embeddings of $u$ and $v$ along with their connectivity information $e_{uv}$. This is followed by the aggregation function $AGG$ that aggregates all messages received by $u$. The aggregated message $m_u^k$ is computed by $m_u^k = AGG(\{m_{uv}^k ; v \in N_u^*\})$. Lastly, the update function $UPD$ combines $u$’s embedding $h_u^k$ and the aggregated message $m_u^k$ to generate the embedding for next layer as $h_u^{k+1} = UPD(h_u^k, m_u^k)$. The final node representation for $u$ is $h_u^K$, i.e., the output of the $K$-th layer.

**Background on poisoning attacks.** Attackers try to fool a GNN by corrupting the graph topology during training [37, 38]. The attacker carefully selects a small number of edges and manipulates them through perturbation and rewiring. In doing so, the attacker aims to fool the GNN into making incorrect predictions [18]. The attacker finds optimal perturbation $A'$ through optimization [26, 8]:

$$\arg\min_{A' \in P_G} L_{\text{attack}}(f(A', X; \Theta^*), y) \quad \text{s.t.} \quad \Theta^* = \arg\min_{\Theta} L_{\text{predict}}(f(A', X; \Theta), y)$$

where $y$ denotes ground-truth labels, $L_{\text{attack}}$ denotes the attacker’s loss function, and $L_{\text{predict}}$ denotes GNN’s loss. The $\Theta^*$ refers to optimal parameters and $f(A', X; \Theta^*)$ is prediction of $f$ with parameters $\Theta^*$ on the perturbed graph $A'$ and node features $X$. To ensure that attacker perturbs only a small number of edges, a budget $\Delta$ is defined to constrain the number of perturbed edges: $||A' - A||_0 \leq \Delta$ and $P_G^\Delta$ are perturbations that fit into budget $\Delta$. Let $T$ be target nodes that are intended to be
mis-classified, and let $A$ be attacker nodes that are allowed to be perturbed. We consider three types of attacks. (1) Direct targeted attacks. The attacker aims to destroy prediction for target node $u$ by manipulating the incident edges of $u$ [8, 15]. Here, $T = A = \{u\}$. (2) Influence targeted attacks. The attacker aims to destroy prediction for target node $u$ by perturbing the edges of $u$'s neighbors. Here, $T = \{u\}$ and $A = N_u$. (3) Non-targeted attacks. The attacker aims to degrade overall GNN classification performance [26, 39]. Here, $T = A = \mathcal{V}_{\text{test}}$ where $\mathcal{V}_{\text{test}}$ denotes the test set.

## 3.1 GNNGuard: Problem Formulation

GNNGuard is a defense mechanism that is easy to integrate into any GNN $f$, resulting in a new GNN $f'$ that is robust to poisoning attacks. This means that $f'$ can make correct predictions even when trained on poisoned graph $G'$. Given a GNN $f = (\text{MSG}, \text{AGG}, \text{UPD})$, GNNGuard will return a new GNN $f' = (\text{MSG}', \text{AGG}', \text{UPD}')$, where MSG is the message-passing function, AGG' is the aggregation function, and UPD' is the update function. The $f'$ solves the following defense problem.

**Problem (Defense Against Poisoning Attacks on Graphs).** In a poisoning attack, the attacker injects adversarial edges in $G$, meaning that the attack changes training data, which can decrease the performance of GNN considerably. Let $G'$ denote the perturbed version of $G$ that is poisoned by the attack. We seek GNN $f'$ such that for any node $u \in G'$:

$$
\min f'_u(G') - f_u(G),
$$

(2)

where $f'_u(G') = \hat{y}_u$ is the prediction when GNN $f'$ is trained on $G'$. Here, $f_u(G) = \hat{y}_u$ denotes a hypothetical prediction that the GNN would make if it had access to clean graph $G$.

It is worth noting that, in this paper, we learn a defense mechanism for semi-supervised node classification. GNNGuard is a general framework for defending any GNN on various graph mining tasks such as link prediction. Since there exists a variety of GNNs that achieve competitive performance on $G$, an intuitive idea is to force $f'_u(G')$ to approximate $f_u(G)$ and, in doing so, ensure that $f'$ will make correct predictions on $G'$. For this reason, we design $f'$ to learn neural messages on $G'$ that, in turn, are similar to the messages that a hypothetical $f$ would learn on $G$. However, since it is impossible to access clean graph $G$, Eq. (2) can not be directly optimized. The key to restore the structure of $G$ is to design a message-passing scheme that can detect fake edges, block them and then attend to true, unperturbed edges. To this end, the impact of perturbed edges in $G'$ can be mitigated by manipulating the flow of neural messages and thus, the structure of $G$ can be restored.

## 4 GNNGuard

Next, we describe GNNGuard, our GNN defender against poisoning attacks. Recent studies found [27, 15] that most damaging attacks add fake edges between nodes that have different, i.e., dissimilar, features and labels. Because of that, the core defense principle of GNNGuard is to detect such fake edges and alleviate their negative impact on prediction by them or assigning them lower weights in neural message passing. GNNGuard has two key components: (1) neighbor importance estimation, and (2) layer-wise graph memory, the first component being an essential part of a robust GNN architecture while the latter is designed to smooth the defense.

### 4.1 Neighbor Importance Estimation

GNNGuard estimates an importance weight for every edge $e_{uv}$ to quantify how relevant node $u$ is to another node $v$ in the sense that it allows for successful routing of GNN’s messages. In contrast to attention mechanisms (e.g., GAT [19, 40]), GNNGuard determines importance weights using theory of network homophily [14], positing that similar nodes (i.e., nodes with similar features) are more likely to interact than dissimilar nodes. To this end, we quantify similarity $s^k_{uv}$ between $u$ and its neighbor $v$ in the $k$-th layer of GNN as follows: $s^k_{uv} = d(h^k_u, h^k_v) = (h^k_u \odot h^k_v)/(|h^k_u||h^k_v|)$, where $d$ is a similarity function and $\odot$ denotes dot product. In this work, we use cosine similarity for $d$ [41]. Larger similarity $s^k_{uv}$ indicates that edge $e_{uv}$ is strongly supported by node features of the edge’s endpoints.

We normalize $s^k_{uv}$ at the node-level within $u$’s neighborhood $N_u$. The problem here is to specify what is the similarity of the node to itself. We normalize node similarities as:

$$
\alpha^k_{uv} = \begin{cases} 
\frac{s^k_{uv}}{\sum_{v \in N_u} s^k_{uv} \times \hat{N}^k_u/(\hat{N}^k_u + 1)} & \text{if } u \neq v \\
1/(\hat{N}^k_u + 1) & \text{if } u = v,
\end{cases}
$$

(3)
where \( \alpha_{uv}^k \) represents defense coefficient for edge \( e_{uv} \) in the \( k \)-th layer and \( \beta \) is a memory coefficient specifying memory, i.e., the amount of information from the previous layer that should be kept in the current layer. Memory coefficient \( \beta \in [0, 1] \) is a learnable parameter and is set to \( \beta = 0 \) in the first GNN layer, meaning that \( \omega_{uv}^0 = \alpha_{uv}^0 \). Using defense coefficients, GNNGUARD controls information flow across all neural message passing layers. It strengthens messages from \( u \)'s neighbors with higher defense coefficients and weakens messages from \( u \)'s neighbors with lower defense coefficients.

### 4.3 Overview of GNNGUARD

GNNGUARD is shown in Algorithm 1. The method is easy to plug into an existing GNN to defend the GNN against poisoning attacks. Given a GNN \( f = (\text{MSG}, \text{AGG}, \text{UPD}) \), GNNGUARD formulates a revised version of it, called \( f' = (\text{MSG}', \text{AGG}', \text{UPD}') \). In each layer, \( f' \) takes current...
node representations and (possibly attacked) graph $G'$. It estimates importance weights $\hat{\alpha}_{uv}$ and generates defense coefficients $\omega_{uv}$ by combining importance weights from the current layer and defense coefficients from the previous layer. In summary, aggregation function $AGG'$ in layer $k$ is: $AGG' = AGG(\{\omega_{uv}^k \odot m_{uv}^k; v \in N_u^k\})$. The update function $UPD'$ is: $UPD' = UPD(\omega_{uv}^k \odot h_u^k, AGG'(\{\omega_{uv}^k \odot m_{uv}^k; v \in N_u^k\}))$. The message function $MSG'$ remains unchanged $MSG' = MSG$ as neural messages are specified by the original GNN $f$. Taken together, the guarded $f'$ attends differently to different node neighborhoods and propagates neural information only along most relevant edges. Our derivations here are for undirected graphs with node features but can be extended to directed graphs and edge features (e.g., include them into calculation of characteristic vectors).

**Algorithm 1: GNNGUARD.**

**Input:** GNN model of interest $f = (MSG, AGG, UPD)$; Poisoned graph $G' = (V, E', X)$, $(A')$ is adjacency matrix of $E'$; Trainable parameters $\Theta, W$, and $\beta$ Initialize parameters $\Theta, W$, and $\beta$; initialize node representations $h_u^0 = x_u \forall u \in V$

for layer $k \leftarrow 1$ to $K$

- for $u \in V$ do
  - Calculate $c_{uv}^k$ using Eq. (3) for all $v \in N_u$ // Neighbor Importance Estimation
  - $c_{uv}^k = [\alpha_{uv}^k, \hat{\alpha}_{uv}^k]$
  - $\hat{\alpha}_{uv}^k = \alpha_{uv}^k \cdot 1_{P_0(\sigma(c_{uv}^k, W))}$ using Eq. (5)
  - $\omega_{uv}^k = \beta \alpha_{uv}^k \cdot (1 - \beta)\hat{\alpha}_{uv}^k$ using Eq. (6) // Layer-Wise Graph Memory
  - $m_{uv}^k = MSG'(h_u^k, h_v^k, A_{uv})$ using Section 4.3 // Neural Message Passing
  - $\bar{m}_v^k = AGG'(\{\omega_{uv}^k \odot m_{uv}^k; v \in N_u^k\})$ using Section 4.3
  - $h_{u}^{k+1} = UPD'(\omega_{uv}^k \odot h_u^k, \bar{m}_v^k)$ using Section 4.3

end

**Any GNN model.** State-of-the-art GNNs use neural message passing comprising of MSG, AGG, and UPD functions. As we demonstrate in experiments, GNNGUARD can defend such GNN architectures against adversarial attacks. GNNGUARD works with many GNNs, including Graph Convolutional Network (GCN) [3], Graph Attention Network (GAT) [19], Graph Isomorphism Network (GIN) [7], Jumping Knowledge (JK-Net) [20], GraphSAINT [21], GraphSAGE [36], and SignedGCN [42].

**Computational complexity.** GNNGUARD is practically efficient because it exploits the sparse structure of real-world graphs. The time complexity of neighbor importance estimation is $O(D_k E)$ in layer $k$, where $D_k$ is the embedding dimensionality and $E$ is the graph size, and the complexity of layer-wise graph memory is $O(E)$. This means that time complexity of GNNGUARD grows linearly with the size of the graph as node embeddings are low-dimensional, $D_k \ll E$. Finally, the time complexity of a GNN endowed with GNNGUARD is on the same order as that of the GNN itself.

**Further related work on adversarial defense for graphs.** We briefly contrast GNNGUARD with existing GNN defenders. Compared to GNN-Jaccard [15], which examines fake edges as a GNN preprocessing step, GNNGUARD dynamically updates defense coefficients at every GNN layer for defense. In contrast to RobustGCN [17], which is limited to GCN, a particular GNN variant, and is challenging to use with other GNNs, GNNGUARD provides a generic mechanism that is easy to use with many GNN architectures. Further, in contrast to GNN-SVD [16], which uses only graph structure for defense, GNNGUARD takes advantage of information encoded in both node features and graph structure. Also, [16] is designed specifically for the Nettack attacker [8] and so is less versatile. Another technique [18] uses transfer learning to detect fake edges. While that is an interesting idea, it requires a large number of clean graphs from the same domain to successfully train the transfer model. On the contrary, GNNGUARD takes advantage of correlation between node features and graph structure and does not need any external data. Further, recent studies (e.g., [43, 44]) focus on theoretical certificates for GNN robustness instead of defense mechanisms. That is an important but orthogonal direction to this paper, where the focus is on a practical adversarial defense framework.

## 5 Experiments

**Datasets.** We test GNNGUARD on four graphs. We use two citation networks with undirected edges and binary features: Cora [45] and Citeseer [46]. We also consider a directed graph with numeric node features, ogbn-arxiv [47], representing a citation network of CS papers published between 1971 and 2014. We use a Disease Pathway (DP) [48] graph with continuous features describing a system
of interacting proteins whose malfunction collectively leads to diseases. The task is to predict for every protein node what diseases the protein might cause. Details are in Appendix D.

Setup. (1) Generating adversarial attacks. We compare our model to baselines under three kinds of adversarial attacks: direct targeted attack (Nettack-Di [8]), influence targeted attack (Nettack-In [8]), and non-targeted attack (Mettack [26]). In Mettack, we set the perturbation rate as 20% (i.e., $\Delta = 0.2E$) with ‘Meta-Self’ training strategy. In Nettack-Di, $\Delta = \hat{N}_u^0$. In Nettack-In, we perturb 5 neighbors of the target node and set $\Delta = \hat{N}_v^0$ for all neighbors. In the targeted attack, we select 40 correctly classified target nodes (following [8]): 10 nodes with the largest classification margin, 20 random nodes, and 10 nodes with the smallest margin. We run the whole attack and defense procedure for each target node and report average classification accuracy. (2) GNNs. We integrate GNNGUARD with five GNNs (GCN [3], GAT [19], GIN [7], JK-Net [20], and GraphSAINT [21]) and present the defense performance against adversarial attacks. (3) Baseline defense algorithms. We compare GNNGUARD to three state-of-the-art graph defenders: GNN-Jaccard [15], RobustGCN [17], and GNN-SVD [16]. Hyperparameters and model architectures are in Appendix E.

5.1 Results: Defense Against Targeted and Non-Targeted Attacks

(1) Results for direct targeted attacks. We observe in Table 1 that Nettack-Di is a strong attacker and dramatically cuts down the performance of all GNNs (cf. “Attack” vs. “No Attack” columns). However, the proposed GNNGUARD outperforms state-of-art defense methods by 15.3% in the accuracy on average. Further, it successfully restores the performance of GNNs to the level comparable to when there is no attack. We also observe that RobustGCN fails to defend against Nettack-Di, possibly because the Gaussian layer in RobustGCN cannot absorb big effects when all fake edges are in the vicinity of a target node. In contrast, GNN-SVD works well here because it is sensitive to high-rank noise caused by the perturbation of many edges that are incident to a single node. (2) Results for influence targeted attacks. As shown in Table 2, GNNGUARD achieves the best classification accuracy comparing to other baseline defense algorithms. Taking a closer look at the results, we can find that Nettack-In is relatively less threat than Nettack-Di indicating part of the perturbed information was scattered during neural message passing. (3) Results for non-targeted attacks. Table 2 shows that Mettack has a considerable negative impact on GNN performance, decreasing the accuracy of even the strongest GNN by 18.7% on average. Moreover, we see that GNNGUARD achieves a competitive performance and outperforms baselines in 19 out of 20 settings. In summary, experiments show the GNNGUARD consistently outperforms all baseline defense techniques. Further, GNNGUARD can defend a variety of GNNs against different types of attacks, indicating that GNNGUARD is a powerful GNN defender against adversarial poisoning.

5.2 Results: Ablation Study and Inspection of Defense Mechanism

(1) Ablation study. We conduct an ablation study to evaluate the necessity of every component of GNNGUARD. For that, we took the largest dataset (ogbn-arxiv) and the most threatening attack (Nettack-Di) as an example. Results are in Table 3 (Left). We observe that full GNNGUARD behaves
We introduce GNNGUARD, an algorithm for defending any graph neural network (GNN) against poisoning attacks, including direct targeted, influence targeted, and non-targeted attacks. GNNGUARD mitigates adverse effects by modifying neural message passing of the underlying GNN. This is achieved through the estimation of neighbor relevance and the use of graph memory, which are two critical components that are vital for a successful defense. In doing so, GNNGUARD can prune likely fake edges and assign less weight to suspicious edges, a principle grounded in network theory of homophily. Experiments on four datasets and across five GNNs show that GNNGUARD outperforms state-of-the-art defense algorithms by a large margin. Lastly, it would be interesting to extend GNNGUARD to fight adversaries that exploit structural equivalence (a principle orthogonal to homophily). While such adversarial attackers do not exist yet, this is a fruitful future direction.

6 Conclusion

We introduce GNNGUARD, an algorithm for defending any graph neural network (GNN) against poisoning attacks, including direct targeted, influence targeted, and non-targeted attacks. GNNGUARD mitigates adverse effects by modifying neural message passing of the underlying GNN. This is achieved through the estimation of neighbor relevance and the use of graph memory, which are two critical components that are vital for a successful defense. In doing so, GNNGUARD can prune likely fake edges and assign less weight to suspicious edges, a principle grounded in network theory of homophily. Experiments on four datasets and across five GNNs show that GNNGUARD outperforms state-of-the-art defense algorithms by a large margin. Lastly, it would be interesting to extend GNNGUARD to fight adversaries that exploit structural equivalence (a principle orthogonal to homophily). While such adversarial attackers do not exist yet, this is a fruitful future direction.
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Appendices to “GNNGUARD: Defending Graph Neural Networks against Adversarial Attacks”

Appendix A  Defense Performance Against Influence Targeted Attacks

Results are shown in Table 4. We find that the proposed GNNGUARD achieves the best defensive performance against influence targeted attack across five GNN models and four datasets. In particular, GNNGUARD outperforms state-of-the-art defense models by 8.77% on average. Furthermore, compared to the case where the GNN is attacked without any defense, GNNGUARD brings a significant accuracy improvement of 22.6% on average. Remarkably, results show that even most recently published GNNs (e.g., GraphSAINT [21]) are sensitive to adversarial perturbations of the graph structure (cf. “Attack” vs. “No Attack” columns in Table 4), yet GNNGUARD can successfully defend GNNs against influence targeted attacks and can restore their performance to levels comparable to learning on clean, non-attacked graphs.

Table 4: Defense performance (multi-class classification accuracy) against influence targeted attacks.

| Model      | Dataset | No Attack | Attack | GNN-Jaccard | RobustGCN | GNN-SVD | GNNGUARD |
|------------|---------|-----------|--------|-------------|-----------|---------|----------|
| GCN        | Cora    | 0.826     | 0.410  | 0.520       | 0.605     | 0.425   | **0.665**|
|            | Citeseer| 0.721     | 0.435  | 0.675       | 0.575     | 0.615   | **0.745**|
|            | ogbn-arxiv | 0.667   | 0.545  | 0.615       | 0.620     | 0.445   | **0.725**|
|            | DP      | 0.682     | 0.475  | 0.550       | 0.565     | 0.460   | **0.655**|
| GAT        | Cora    | 0.827     | 0.425  | 0.550       | 0.605     | 0.450   | **0.635**|
|            | Citeseer| 0.718     | 0.510  | 0.675       | 0.575     | 0.615   | **0.815**|
|            | ogbn-arxiv | 0.669   | 0.635  | 0.525       | 0.620     | 0.505   | **0.675**|
|            | DP      | 0.714     | 0.470  | 0.540       | 0.565     | 0.570   | **0.645**|
| GIN        | Cora    | 0.831     | 0.525  | 0.635       | 0.605     | 0.615   | **0.775**|
|            | Citeseer| 0.725     | 0.480  | 0.675       | 0.575     | 0.630   | **0.845**|
|            | ogbn-arxiv | 0.661   | 0.570  | 0.605       | 0.620     | 0.525   | **0.710**|
|            | DP      | 0.719     | 0.505  | 0.585       | 0.565     | 0.605   | **0.695**|
| JK-Net     | Cora    | 0.834     | 0.525  | 0.665       | 0.605     | 0.625   | **0.755**|
|            | Citeseer| 0.724     | 0.485  | 0.675       | 0.575     | 0.610   | **0.865**|
|            | ogbn-arxiv | 0.678   | 0.545  | 0.580       | 0.620     | 0.475   | **0.720**|
|            | DP      | 0.726     | 0.495  | 0.635       | 0.565     | 0.590   | **0.685**|
| GraphSAINT | Cora    | 0.821     | 0.405  | 0.495       | 0.610     | 0.395   | **0.645**|
|            | Citeseer| 0.716     | 0.460  | 0.665       | 0.590     | 0.605   | **0.735**|
|            | ogbn-arxiv | 0.683   | 0.525  | 0.595       | 0.615     | 0.570   | **0.705**|
|            | DP      | 0.739     | 0.435  | 0.615       | 0.645     | 0.575   | **0.675**|
Appendix B  Defense Performance Against Non-Targeted Attacks

Results are shown in Table 5. To evaluate how harmful non-targeted attacks can be for GNNs, we first give results without attack and under attack (without defense), i.e., “Attack” vs. “No Attack” columns in Table 5. We also show defense performance of GNNGuard relative to state-of-the-art GNN defense techniques. First, we find that non-targeted attacks can have a considerable negative impact on the performance of the GNNs. The accuracy of even the strongest GNN is reduced by 18.7% on average. In addition, results show that our GNNGuard outperforms baselines in most experiments and improves upon baselines considerably. Experiments indicate the proposed GNN defender can successfully mitigate negative impacts brought forward by non-targeted attacks on graphs.

Table 5: Defense performance (multi-class classification accuracy) against non-targeted attacks.

| Model    | Dataset     | No Attack | Attack | GNN-Jaccard | RobustGCN | GNN-SVD | GNNGuard |
|----------|-------------|-----------|--------|-------------|-----------|---------|----------|
| GCN      | Cora        | 0.826     | 0.578  | 0.684       | 0.571     | 0.678   | 0.714    |
|          | Citeseer    | 0.721     | 0.601  | 0.646       | 0.583     | 0.668   | 0.681    |
|          | ogbn-arxiv  | 0.667     | 0.410  | 0.409       | 0.436     | 0.413   | 0.444    |
|          | DP          | 0.682     | 0.487  | 0.513       | 0.528     | 0.493   | 0.539    |
| GAT      | Cora        | 0.827     | 0.566  | 0.691       | 0.571     | 0.681   | 0.718    |
|          | Citeseer    | 0.718     | 0.676  | 0.667       | 0.583     | 0.680   | 0.699    |
|          | ogbn-arxiv  | 0.669     | 0.420  | 0.428       | 0.436     | 0.433   | 0.432    |
|          | DP          | 0.714     | 0.519  | 0.548       | 0.528     | 0.534   | 0.566    |
| GIN      | Cora        | 0.831     | 0.588  | 0.702       | 0.571     | 0.692   | 0.722    |
|          | Citeseer    | 0.725     | 0.565  | 0.638       | 0.583     | 0.615   | 0.711    |
|          | ogbn-arxiv  | 0.661     | 0.424  | 0.459       | 0.436     | 0.459   | 0.486    |
|          | DP          | 0.719     | 0.537  | 0.559       | 0.528     | 0.513   | 0.571    |
| JK-Net   | Cora        | 0.834     | 0.615  | 0.726       | 0.571     | 0.683   | 0.713    |
|          | Citeseer    | 0.724     | 0.574  | 0.647       | 0.583     | 0.679   | 0.698    |
|          | ogbn-arxiv  | 0.678     | 0.433  | 0.419       | 0.436     | 0.443   | 0.457    |
|          | DP          | 0.726     | 0.486  | 0.537       | 0.528     | 0.541   | 0.587    |
| Graph    | Cora        | 0.821     | 0.657  | 0.617       | 0.659     | 0.647   | 0.705    |
|          | Citeseer    | 0.716     | 0.628  | 0.596       | 0.637     | 0.652   | 0.659    |
|          | ogbn-arxiv  | 0.683     | 0.394  | 0.428       | 0.563     | 0.533   | 0.583    |
|          | DP          | 0.739     | 0.473  | 0.572       | 0.499     | 0.524   | 0.537    |

Appendix C  Classification Accuracy on Clean (i.e., Non-attacked) Datasets with and without GNNGuard

Next, we want to investigate whether the GNN defender can harm the performance of the underlying GNN if the defender is used on clean, non-attacked graphs. Note that this is a practically important question, as in practice, users might not know a priori whether malicious agents have altered their graph datasets. Because of that, it is essential that a successful GNN defender does not decrease the predictive performance of the GNN in cases when GNNGuard is turned on, but there is no attack. From results in the main paper and Appendix A-B, we already know that GNNGuard can defend GNNs when they are attacked. Here, we show that GNNGuard does not hinder GNNs even when they are not attacked.

Results are shown in Table 6. We observe that GNNs, trained on clean datasets, yield approximately the same performance irrespective of whether a GNN integrates GNNGuard defense or not. These results suggest that the use of GNNGuard does not reduce GNN’s expressive power or its representation capacity when there are no adversarial attacks.

Appendix D  Further Details on Datasets

Upon publication, we will share GNNGuard implementation as well as all datasets and baseline algorithms with the community through a public project website, which will be accompanied by a Github repository with relevant data loaders.
Table 6: Classification accuracy on clean (i.e., non-attacked) datasets with and without GNNGUARD.

|                | Cora-CLEAN | Citeseer-CLEAN | ogbn-arxiv-CLEAN | DP-CLEAN |
|----------------|------------|----------------|------------------|----------|
|                | w/o        | w              | w/o              | w        |
| GCN            | 0.826      | 0.817          | 0.716            | 0.667    |
| GAT            | 0.827      | 0.829          | 0.719            | 0.669    |
| GIN            | 0.831      | 0.832          | 0.726            | 0.661    |
| JK-Net         | 0.834      | 0.829          | 0.727            | 0.678    |
| GraphSAINT     | 0.821      | 0.819          | 0.721            | 0.683    |

Table 7: Dataset statistics. $N$, $E$, $M$, and $C$ denote the number of nodes, edges, node feature dimensionality, and the number of labels/classes, respectively.

| Dataset        | N   | E   | M   | C   | Node features |
|----------------|-----|-----|-----|-----|---------------|
| Cora           | 2,485 | 5,069 | 1,433 | 7   | Binary        |
| Citeseer       | 2,110 | 3,668 | 3,703 | 6   | Binary        |
| ogbn-arxiv     | 31,971 | 71,669 | 128  | 40  | Continuous    |
| DP             | 22,552 | 342,353 | 73   | 519 | Continuous    |

We provide further dataset statistics in Table 7.

The new, Disease Pathway (DP) [48] dataset describes a system of interacting human proteins whose malfunction collectively leads to a variety of diseases. Nodes in the network represent human proteins and edges indicate protein-protein interactions. The task is to predict for every protein node what diseases (i.e., labels/classes) that protein might cause. The dataset has 73-dimensional continuous node features representing graphlet-orbit counts (i.e., the number of occurrences of higher-order network motifs), which we normalize via z-scores. This is a multi label node classification dataset. We select 10 most-common labels (diseases), reformulate the task as 10 independent balanced binary classification problems and report average performance across multiple independent runs. We randomly split the dataset into training (10%), validation (10%), and test set (80%) following the experimental setup in [8].

Appendix E  Further Details on Hyperparameter Setting

To select hyperparameters and GNN model architectures, we closely follow original authors’ guidelines and relevant papers on GNNs (GCN [3], GAT [19], GIN [7], JK-Net [20], and GraphSAINT [21]), baseline defense algorithms (GNN-Jaccard [15], RobustGCN [17], and GNN-SVD [16]), and models for generating adversarial attacks (Nettack-Di [8], Nettack-In [8], and Mettack [26]).

We use PyTorch DeepRobust package (https://github.com/DSE-MSU/DeepRobust) to implement adversarial attack models and baseline defense algorithms, and PyTorch Geometric package (https://github.com/rusty1s/pytorch_geometric) to implement and train GNN models. In all experiments, we set the number of epochs to 200 and use early stopping (we stop training if validation accuracy does not increase for 10 consecutive epochs). We repeat every experiment 5 times and report average performance across independent runs. We set $P_b = 0.5$, $K = 2$, $D_2 = 16$, and dropout rate as 0.5, optimize cross-entropy loss using Adam optimizer and learning rate of 0.01. For other parameters, we follow the setup in [8].