Adversarial Attacks and Defenses on Graphs: A Review and Empirical Study

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Deep neural networks (DNNs) have achieved significant performance in various tasks. However, recent studies have shown that DNNs can be easily fooled by small perturbation on the input, called adversarial attacks. As the extensions of DNNs to graphs, Graph Neural Networks (GNNs) have been demonstrated to inherit this vulnerability. Adversary can mislead GNNs to give wrong predictions by modifying the graph structure such as manipulating a few edges. This vulnerability has arisen tremendous concerns for adapting GNNs in safety-critical applications and has attracted increasing research attention in recent years. Thus, it is necessary and timely to provide a comprehensive overview of existing graph adversarial attacks and the countermeasures. In this survey, we categorize existing attacks and defenses, and review the corresponding state-of-the-art methods. Furthermore, we have developed a repository with representative algorithms. The repository enables us to conduct empirical studies to deepen our understandings on attacks and defenses on graphs.

CCS Concepts: • Computing methodologies → Neural networks; Semi-supervised learning settings.

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1 INTRODUCTION

Graphs can be used as the denotation of a large number of systems across various areas such as social science (social networks), natural science (physical systems, and protein-protein interaction networks) and knowledge graphs. Graph Neural Networks (GNNs), which generalize traditional deep neural networks (DNNs) to graphs, pave a new way to effectively learn representations for graphs [46]. Due to their strong representation learning capability, GNNs have gained practical significance in various applications ranging from data mining [21], natural language processing [29], and computer vision [22] to healthcare and biology [26].

As new generalizations of traditional DNNs to graphs, GNNs inherit both advantages and disadvantages of traditional DNNs. Similar to traditional DNNs, GNNs are also powerful in learning representations of graphs and have permeated numerous areas of science and technology. Traditional DNNs are easily fooled by adversarial attacks [16, 47]. In other words, the adversary can...
insert slight perturbation during either the training or test phases, and the DNN models will totally fail. It is evident [55] that GNNs also inherit this drawback. The attacker can generate graph adversarial perturbations by manipulating the graph structure or node features to fool the GNN models. As illustrated in Figure 1, originally node 7 was classified by the GNN model as a green node; after node 7 creates a new connection with node 3 and modifies its own features, the GNN model misclassifies it as a blue node. Such vulnerability of GNNs has arisen tremendous concerns on applying them in safety-critical applications such as financial system and risk management. For example, in a credit scoring system, fraudsters can fake connections with several high-credit customers to evade the fraudster detection models; and spammers can easily create fake followers to increase the chance of fake news being recommended and spread. Therefore, there is an urgent need to investigate graph adversarial attacks and their countermeasures.

Pushing this research has a great potential to facilitate the successful adoption of GNNs in a broader range of fields, which encourages increasing attention on graph adversarial attacks and defenses in recent years. Thus, it is necessary and timely to provide a comprehensive and systematic overview on existing algorithms. Meanwhile, it is of great importance to deepen our understandings on graph adversarial attacks via empirical study. These understandings can not only provide knowledge about the behaviors of attacks but also offer insights for us to design defense strategies. These motivate this survey with the following key purposes:

- We categorize existing attack methods from various perspectives in Section 3 and review representative algorithms in Section 4.
- We classify existing countermeasures according to their defense strategies and give a review on representative algorithms for each category in Section 5.
- We perform empirical studies based on the repository we developed that provide comprehensive understandings on graph attacks and defenses in Section 6.
- We discuss some promising future directions in Section 7.

2 PRELIMINARIES AND DEFINITIONS

Before presenting the review and empirical studies, we first introduce concepts, notations and definitions in this section.

2.1 Learning on Graph Data

In this survey, we use $G = (V, E)$ to denote the structure of a graph where $V = \{v_1, \ldots, v_N\}$ is the set of $N$ nodes and $E = \{e_1, \ldots, e_K\}$ is the edge set. We use matrix $A \in \{0, 1\}^{N \times N}$ to denote
the adjacency matrix of $G$, where each entry $A_{ij} = 1$ means nodes $v_i$ and $v_j$ are connected in $G$. Furthermore, we use $X \in \mathbb{R}^{N \times D}$ to denote the node attribute matrix where $D$ is the dimension of the node feature vectors. Thus, graph data can be denoted as $G = (A, X)$. There are a lot of learning tasks on graphs and in this work, we focus on the classification problems on graphs. Furthermore, we use $f_\theta$ with parameters $\theta$ to denote the learning models in this survey.

**Node-Level Classification** For node-level classification, each node in the graph $G$ belongs to a class in the label set $Y$. The graph model aims to learn a neural network, based on labeled nodes (training nodes), denoted as $V_L$, to predict the class of unlabeled nodes (test nodes). The training objective function can be formulated as:

$$\min_\theta \mathcal{L}_{train}(f_\theta(G)) = \sum_{v_i \in V_L} \ell(f_\theta(X, A)_i, y_i),$$

where $f_\theta(X, A)_i$ and $y_i$ are the predicted and the true label of node $v_i$ and $\ell(\cdot, \cdot)$ is a loss function such as cross entropy.

**Graph-Level Classification** For graph-level classification, each individual graph has a class in the label set $Y$. We use $\mathcal{G}$ to denote a set of graphs, and $\mathcal{G}_L$ is the labeled set (training set) of $\mathcal{G}$. The goal of graph-level classification is to learn a mapping function $f_\theta : \mathcal{G} \to Y$ to predict the labels of unlabeled graphs. Similar to node-level classification, the objective function can be formulated as

$$\min_\theta \mathcal{L}_{train}(\mathcal{G}) = \sum_{G_i \in \mathcal{G}_L} \ell(f_\theta(G_i), y_i),$$

where $G_i$ is the labeled graph with ground truth $y_i$ and $f_\theta(G_i)$ is the prediction of the graph $G_i$.

### 2.2 A General Form of Graph Adversarial Attack

Based on the objectives in Section 2.1, we can define a general form of the objective for adversarial attacks, which aims to maximize the loss value of the model in order to get wrong predictions. Thus, the problem of node-level graph adversarial attacks can be stated as:

**Problem 1.** Given $G = (A, X)$ and victim nodes subset $V_t \subseteq V$. Let $y_u$ denote the class for node $u$ (predicted or using ground truth). The goal of the attacker is to find a perturbed graph $\hat{G} = (\hat{A}, \hat{X})$ that maximizes the loss value of the victim nodes,

$$\max \mathcal{L}_{atk}(f_\theta(\hat{G})) = \sum_{u \in V_t} \ell_{atk}(f_\theta(\hat{G})_u, y_u)$$

$$\text{s.t., } \theta^* = \arg \min_\theta \mathcal{L}_{train}(f_\theta(G')),$$

where $G'$ can either be $G$ or $\hat{G}$. Note that $\hat{G}$ is chosen from a constrained domain $\Phi(G)$. Given a fixed perturbation budget $\Delta$, a typical $\Phi(G)$ can be implemented as,

$$\|\hat{A} - A\|_0 + \|\hat{X} - X\|_0 \leq \Delta.$$
Table 1. Commonly used notations

| Notations | Description | Notations | Description |
|-----------|-------------|-----------|-------------|
| $G$       | Graph       | $u$       | Target node |
| $\hat{G}$| Perturbed graph | $y_u$ | Label of node $u$ |
| $V$       | The set of nodes | $f_\theta$ | Neural network model |
| $V_L$     | The set of labeled nodes | $\mathcal{L}$ | Loss function |
| $E$       | The set of edges | $l(\cdot, \cdot)$ | Pair-wise loss function |
| $A$       | Adjacency matrix | $\| \cdot \|_0$ | $\ell_0$ norm |
| $\hat{A}$| Perturbed adjacency matrix | $\Delta$ | Perturbation budget |
| $X$       | Node attribute matrix | $Z$ | Predicted probability |
| $\hat{X}$| Perturbed node attribute matrix | $h_u$ | Hidden representation of node $u$ |
| $D$       | Dimension of node features | $e_{ij}$ | Edge between node $v_i$ and $v_j$ |

2.3 Notations
With the aforementioned definitions, we list all the notations which will be used in the following sections in Table 1.

3 TAXONOMY OF GRAPH ADVERSARIAL ATTACKS
In this section, we briefly introduce the main taxonomy of adversarial attacks on graph structured data. Attack algorithms can be categorized into different types based on different goals, resources, knowledge and capacity of attackers. We try to give a clear overview on the main components of graph adversarial attacks.

3.1 Attacker’s Capacity
The adversarial attacks can happen at two phases, i.e., the model training and model testing. It depends on the attacker’s capacity to insert adversarial perturbation:

- **Evasion Attack**: Attacking happens after the GNN model is trained or in the test phase. The model is fixed, and the attacker cannot change the model parameter or structure. The attacker performs evasion attack when $G' = G$ in Eq. (3).

- **Poisoning Attack**: Attacking happens before the GNN model is trained. The attacker can add “poisons” into the model training data, letting trained model have malfunctions. It is the case when $G' = \hat{G}$ in Eq. (3).

3.2 Perturbation Type
The attacker can insert adversarial perturbations from different aspects. The perturbations can be categorized as modifying node features, adding/deleting edges, and adding fake nodes. Attackers should also keep the perturbation unnoticeable, otherwise it would be easily detected.

- **Modifying Feature**: Attackers can slightly change the node features while maintaining the graph structure.

- **Adding or Deleting Edges**: Attackers can add or delete edges under certain budget of total actions.

- **Injecting Nodes**: Attackers can insert fake nodes to the graph, and link it with some benign nodes in the graph.

3.3 Attacker’s Goal
According to the goals of attacks, we can divide the attacks into the following two categories
• **Targeted Attack:** There is a small set of test nodes. The attacker aims to let the trained model misclassify these test samples. It is the case when $V_T \subset V$ in Eq. (3). We can further divide targeted attacks into (1) direct attack where the attacker directly modifies the features or edges of the target nodes and (2) influencer attack where the attacker can only manipulate other nodes to influence the targets.

• **Untargeted Attack:** The attacker aims to insert poisons to let the trained model have bad overall performance on all test data. It is the case when $V_T = V$ in Eq. (3).

### 3.4 Attacker’s Knowledge

Attacker’s knowledge means how much information an attacker knows about the model that he aims to attack. Usually, there are three settings:

• **White-box Attack:** All information about the model parameters, training input (e.g., adjacency matrix and attribute matrix) and the labels are given to the attacker.

• **Gray-box Attack:** The attacker only has limited knowledge about the victim model. For example, the attacker cannot access the model parameters but can access the training labels. Then it can utilize the training data to train surrogate models to estimate the information from victim model.

• **Black-box Attack:** The attacker does not have access to the model’s parameters or training labels. It can access the adjacency matrix and attribute matrix, and do black-box query for output scores or labels.

### 3.5 Victim Models

In this part we are going to summarize the victim models that have been proven to be susceptible to adversarial examples.

**Graph Neural Networks** Graph neural networks are powerful tools in learning representation of graphs [35]. One of the most successful GNN variants is Graph Convolutional Networks (GCN) [21]. GCN learns the representation for each node by keeping aggregating and transforming the information from its neighbor nodes. Though GNNs can achieve high performance in various tasks, studies have demonstrated that GNNs including GCN are vulnerable to adversarial attacks [35, 55].

**Other Graph Learning Algorithms** In addition to graph neural networks, adversary may attack some other important algorithms for graphs such as network embeddings including LINE [38] and Deepwalk [31], graph-based semi-supervised learning (G-SSL) [54], and knowledge graph embedding [4, 24].

### 4 GRAPH ADVERSARIAL ATTACKS

In this section, we review representative algorithms for graph adversarial attacks. Following the categorizations in the previous section, we first divide these algorithms into white-box, gray-box and black-box and then for algorithms in each category, we further group them into targeted and untargeted attacks. An overall categorization of representative attack methods is shown in Table 2. In addition, some open source implementations of representative algorithms are listed in Table 5.

#### 4.1 White-box Attacks

In white-box attack setting, the adversary has access to any information about the victim model such as model parameters, training data, labels, and predictions. Although in most of the real world cases we do not have the access to such information, we can still assess the vulnerability of the victim models under the worst situation. Typically, white-box attacks use the gradient information from the victim model to guide the generation of attacks [6, 9, 45, 48].
### Table 2. Categorization of representative attack methods

| Attack Methods | Attack Knowledge | Targeted or Non-targeted | Evasion or Poisoning | Perturbation Type | Application | Victim Model |
|----------------|------------------|--------------------------|----------------------|------------------|-------------|--------------|
| PGD, Min-max [48] | White-box | Untargeted | Both | Add/Delete edges | Node Classification | GNN |
| IG-FGSM [45] | White-box | Both | Evasion | Add/Delete edges | Node Classification | GNN |
| [41] | White-box | Targeted | Poisoning | Add/Delete edges | Node Classification | GNN |
| Nettack [55] | Gray-box | Targeted | Both | Add/Delete edges | Node Classification | GNN |
| Metattack [56] | Gray-box | Untargeted | Poisoning | Add/Delete edges | Node Classification | GNN |
| NIPA [36] | Gray-box | Untargeted | Poisoning | Inject nodes | Node Classification | GNN |
| RL-S2V [11] | Black-box | Targeted | Evasion | Add/Delete edges | Graph Classification Node Classification | GNN |
| ReWatt [27] | Black-box | Untargeted | Evasion | Add/Delete edges | Graph Classification | GNN |
| [25] | White-box | Untargeted | Poisoning | Flip label | Classification Regression | G-SSL |
| GF-Attack [5] | Black-box | Targeted | Evasion | Add/Delete edges | Node Classification | Network Embedding |
| [2] | Black-box | Both | Poisoning | Add/Delete edges | Node Classification Community Detection | Network Embedding |
| [51] | White-box | Targeted | Poisoning | Add/Delete facts | Plausibility Prediction | Knowledge Graph Embedding |
| CD-Attack [23] | Black-box | Targeted | Poisoning | Add/Delete edges | Community Detection | Community Detection Algorithm |

#### 4.1.1 Targeted Attack.**

Targeted attack aims to mislead the victim model to make wrong predictions on some target samples. A lot of studies follow the white-box targeted attack setting with a wide range of real-world applications. FGA [9] extracts the link gradient information from GCN, and then greedily selects the pair of nodes with maximum absolute gradient to modify the graph iteratively. Genetic algorithm based Q-Attack is proposed to attack a number of community detection algorithms [6]. Iterative gradient attack (IGA) based on the gradient information in the trained graph auto-encoder, which is introduced to attack link prediction [7]. Furthermore, the vulnerability of knowledge graph embedding is investigated in [51] and the plausibility of arbitrary facts in knowledge graph can be effectively manipulated by the attacker. Recommender systems based on GNNs are also vulnerable to adversarial attacks, which is shown in [52]. In addition, there are great efforts on attacking node classification. Traditional attacks in the image domain always use models’ gradients to find adversarial examples. However, due to the discrete property of graph data, directly calculating gradients of models could fail. To solve this issue, the work [45] suggests to use integrated gradient [37] to better search for adversarial edges and feature perturbations. During the attacking process, the attacker iteratively chooses the edge or feature which has the strongest effect to the adversarial objective. By this way, it can cause the victim model to misclassify target nodes with a higher successful rate. The work [50] assumes there is a set of “bad actor” nodes in a graph. When they flip the edges with any target nodes in a graph, it will cause the GNN model to have a wrong prediction on the target node. These “bad actor” nodes are critical to the safety of
GNN models. For example, Wikipedia has hoax articles which have few and random connections to real articles. Manipulating the connections of these hoax articles will cause the system to make wrong prediction of the categories of real articles.

4.1.2 Untargeted Attack. Currently there are not many studies on untargeted white-box attack, and topology attack [48] is one representative algorithm. It first constructs a binary symmetric perturbation matrix $S \in \{0, 1\}^n$ where $S_{ij} = 1$ indicates to flip the edge between $i$ and $j$ and $S_{ij} = 0$ means no modification on $A_{ij}$. Thus, the goal of the attacker is to find $S$ that minimizes the predefined attack loss given a finite budget of edge perturbations $\Delta$, i.e., $\|S\|_0 \leq \Delta$. It considers two different attack scenarios: attacking pre-trained GNN with fixed parameters $\theta$ and attacking a re-trainable GNN $f_\theta$. For attacking a fixed $f_\theta$, the problem can be formulated as,

$$\min_{S \in \{0, 1\}^n} L_{\text{atk}}(f_\theta(S, A, X)) \quad \text{s.t.} \quad \|S\|_0 \leq \Delta.$$  

(5)

It utilizes the Projected Gradient Descent (PGD) algorithm in [28] to search the optimal $S$. Note that the work [28] is also one popular attack algorithm in the image domain. For the re-trainable GNNs, parameter $\theta$ will be retrained after adversarial manipulation, thus the attack problem is formulated as a min-max form where the inner maximization can be solved by gradient ascent and the outer minimization can be solved by PGD.

4.2 Gray-box Attacks

White-box attacks assume that attackers can calculate gradient through model parameters, which is not always practical in real-world scenarios. Gray-box attacks are proposed to generate attacks with limited knowledge on the victim model [36, 55, 56]. Usually they first train a surrogate model with the labeled training data to approximate the information of the victim model and then generate perturbations to attack the surrogate model. It is noted that these models need the access to the labels of training data, thus they are not black-box attacks that will be introduced in the following subsection.

4.2.1 Targeted Attack. The early work on targeted gray-box attacks is for graph clustering [10]. It demonstrates that injecting noise to a DNS query graph can degrade the performance of graph embedding models. Different from [10], the work [55] proposes an attack method called Nettack to generate structure and feature attacks, aiming at solving Eq. (3). Besides, they argue that only limiting the perturbation budgets cannot always make the perturbation “unnoticeable”. They suggest the perturbed graphs should also maintain important graph properties, including degree distribution and feature co-occurrence. Therefore, Nettack first selects possible perturbation candidates not violating degree distribution and feature co-occurrence of the original graph. Then it greedily chooses the perturbation that has the largest score to modify the graph, where the score is defined as,

$$\max_{i \neq y} \ln (Z_{u,y}(G')) - \ln (Z_{u,i}(G'))$$  

(6)

where $Z_{u,i}$ is the probability of node $u$ to be the class $i$ predicted by the surrogate model. Thus, the goal of the attacker is to maximize the difference in the log-probabilities of the target node $u$. By doing this repeatedly until reaching the perturbation budget $\Delta$, it can get the final modified graph. Furthermore, it suggests that such graph attack can also transfer from model to model, just as the attacks in the image domain [16]. The authors also conduct influence attacks where they can only manipulate the nodes except the target. It turns out that influencer attacks lead to a lower decrease in performance compared with directly modifying target node given the same perturbation budget.
4.2.2 Untargeted Attack. Although following the same way of training a surrogate model as Nettack, Metattack \cite{metattack} is a kind of untargeted poisoning attack. It tackles the bi-level problem in Eq. (3) by using meta-gradient. Basically, it treats the graph structure matrix as a hyper-parameter and the gradient of the attacker loss with respect to it can be obtained by:

$$\nabla^\text{meta}_G = \nabla_G \mathcal{L}_{\text{atk}} (f_{\theta^*}(G)) \quad (7)$$

Note that $\nabla_G \mathcal{L}_{\text{atk}} (f_{\theta^*}(G))$ is actually a function with respect to both $G$ and $\theta$. If $\theta^*$ is obtained by some differential operations, we can compute $\nabla^\text{meta}_G$ as follows,

$$\nabla^\text{meta}_G = \nabla_f \mathcal{L}_{\text{atk}} (f_{\theta^*}(G)) \cdot [\nabla_G f_{\theta^*}(G) + \nabla_{\theta^*} f_{\theta^*}(G) \cdot \nabla_G \theta^*] \quad (8)$$

where $\theta^*$ is often obtained by gradient descent in fixed iterations $T$. At iteration $t + 1$, the gradient of $\theta_{t+1}$ with respect to $G$ can be formulated as,

$$\nabla_G \theta_{t+1} = \nabla_G \theta_t - \alpha \nabla_{\theta^*} \mathcal{L}_{\text{train}} (f_{\theta_t}(G)) \quad , (9)$$

where $\alpha$ denotes learning rate of the gradient descent operation. By unrolling the training procedure from $\theta_T$ back to $\theta_0$, we can get $\nabla_G \theta_T$ and then $\nabla^\text{meta}_G$. A greedy approach is applied to select the perturbation based on the meta gradient.

Instead of modifying the connectivity of existing nodes, a novel reinforcement learning method for node injection poisoning attacks (NIPA) \cite{nipa} is proposed to inject fake nodes into graph data. Specifically, NIPA first injects singleton nodes into the original graph. Then in each action $a_t$, the attacker first chooses an injected node to connect with another node in the graph and then assigns a label to the injected node. By doing this sequentially, the final graph is statistically similar to the original graph but can degrade the overall model performance.

4.3 Black-box Attacks

Different from gray-box attacks, black-box attacks \cite{rls2v, nipa, mae2vec, pggan, pgat} are more challenging since the attacker can only access the input and output of the victim model. The access of parameters, labels and predicted probability is prohibited.

4.3.1 Targeted Attack. As mentioned earlier, training a surrogate model requires access to the labels of training data, which is not always practical. We hope to find a way that we only need to do black-box query on the victim model \cite{rls2v} or attack the victim in an unsupervised fashion \cite{rls2v, pgat}.

To do black-box query on the victim model, reinforcement learning is introduced. RL-S2V \cite{rls2v} is the first work to employ reinforcement learning technique to generate adversarial attacks on graph data under the black-box setting. They model the attack procedure as a Markov Decision Process (MDP) and the attacker is allowed to modify $m$ edges to change the predicted label of the target node $u$. They study both node-level (targeted) and graph-level (untargeted) attacks. For node-level attack, they define the MDP as follows,

- **State** The state $s_t$ is represented by the tuple $(G^{(t)}, u)$ where $G^{(t)}$ is the modified graph at time step $t$.
- **Action** A single action at time step $t$ is denoted as $a_t$. For each action $a_t$, the attacker can choose to add or remove an edge from the graph. Furthermore, a hierarchical structure is applied to decompose the action space.
- **Reward** Since the goal of the attacker is to change the classification result of the target node $u$, RL-S2V gives non-zero reward $r$ to the attacker at the end of the MDP:

$$r(s_m, a_m) = \begin{cases} 
1 & \text{if } f_{\theta} (G^{(m)}, u) \neq y \\
-1 & \text{if } f_{\theta} (G^{(m)}, u) = y 
\end{cases}$$
In the intermediate steps, the attacker receives no reward, i.e., $\forall t = 1, 2, \ldots, m - 1, r(s_t, a_t) = 0$.

- **Termination** The process terminates when the attacker finishes modifying $m$ edges.

Since they define the MDP of graph-level attack in the similar way, we omit the details. Further, the Q-learning algorithm [30] is adopted to solve the MDP and guide the attacker to modify the graph.

Instead of attacking node classification, the work [2] shows a way to attack the family of node embedding models in the black-box setting. Inspired by the observation that DeepWalk can be formulated in matrix factorization form [32], they maximize the unsupervised DeepWalk loss with matrix perturbation theory by performing $\Delta$ edge flips. It is further demonstrated that the perturbed structure is transferable to other models like GCN and Label Propagation. However, this method only considers the structure information. GF-Attack [5] is proposed to incorporate the feature information into the attack model. Specifically, they formulate the connection between the graph embedding method and general graph signal process with graph filter and construct the attacker based on the graph filter and attribute matrix. GF-Attack can also be transferred to other network embedding models and achieves better performance than the method in [2].

### 4.3.2 Untargeted Attack

It is argued that the perturbation constraining only the number of modified edges may not be unnoticeable enough. A novel framework ReWatt [27] is proposed to solve this problem and perform untargeted graph-level attack. Still employing a reinforcement learning framework, ReWatt adopts the rewiring operation instead of simply adding/deleting an edge in one single modification to make perturbation more unnoticeable. One rewiring operation involves three nodes $v_1, v_2$, and $v_3$, where ReWatt removes the existing edge between $v_1$ and $v_2$ and connects $v_1$ and $v_3$. ReWatt also constrains $v_3$ to be the 2-hop neighbor of $v_1$ to make perturbation smaller. Such rewiring operation does not change the number of nodes and edges in the graph and it is further proved that such rewiring operation affects algebraic connectivity and effective graph resistance, both of which are important graph properties based on graph Laplacian, in a smaller way than adding/deleting edges.

### 5 COUNTERMEASURES AGAINST GRAPH ADVERSARIAL ATTACKS

In previous sections, we have shown that graph neural networks can be easily fooled by unnoticeable perturbation on graph data. The vulnerability of graph neural networks poses great challenges to apply them in safety-critical applications. In order to defend the graph neural networks against these attacks, different countermeasure strategies have been proposed. The existing methods can be categorized into the following types: (1) adversarial training, (2) adversarial perturbation detection, (3) certifiable robustness, (4) graph purification, and (5) attention mechanism.

#### 5.1 Adversarial Training

Adversarial training is a widely used countermeasure for adversarial attacks in image data [16]. The main idea of adversarial training is to inject adversarial examples into the training set such that the trained model can correctly classify the future adversarial examples. Similarly, we can also adopt this strategy to defend graph adversarial attacks as follows,

$$\min_{\theta} \max_{\delta_A \in \mathcal{P}_A \delta_X \in \mathcal{P}_X} L_{\text{train}}(f_\theta(A + \delta_A, X + \delta_X)),$$

where $\delta_A, \delta_X$ denote the perturbation on $A, X$, respectively; $\mathcal{P}_A$ and $\mathcal{P}_X$ stand for the domains of imperceptible perturbation. The min-max optimization problem in Eq (10) indicates that adversarial training involves two process: (1) generating perturbations that maximize the prediction loss and (2) updating model parameters that minimize the prediction loss. By alternating the above two process
iteratively, we can train a robust model against adversarial attacks. Since there are two inputs, i.e., adjacency matrix $A$ and attribute matrix $X$, adversarial training can be done on them separately. To generate perturbations on the adjacency matrix, it is proposed to randomly drop edges during adversarial training [11]. Though such simple strategy cannot lead to very significant improvement in classification accuracy (1% increase), it shows some effectiveness with such cheap adversarial training. Furthermore, projected gradient descent is used to generate perturbations on the discrete input structure, instead of randomly dropping edges [48]. On the other hand, an adversarial training strategy with dynamic regularization is proposed to perturb the input features [15]. Specifically, it includes the divergence between the prediction of the target example and its connected examples into the objective of adversarial training, aiming to attack and reconstruct graph smoothness. Furthermore, batch virtual adversarial training [13] is proposed to promote the smoothness of GNNs and make GNNs more robust against adversarial perturbations. Several other variants of adversarial training on the input layer are introduced in [8, 12, 42].

The aforementioned adversarial training strategies face two main shortcomings: (1) they generate perturbations on $A$ and $X$ separately; and (2) it is not easy to perturb the graph structure due to its discreteness. To overcome the shortcomings, instead of generating perturbation on the input, a latent adversarial training method injects perturbations on the first hidden layer [20]:

$$\min_{\theta} \max_{\delta \in \mathcal{P}} \mathcal{L}_{\text{train}} \left( f_{\theta}(G; \mathbf{H}^{(1)} + \delta) \right),$$

where $\mathbf{H}^{(1)}$ denotes the representation matrix of the first hidden layer and $\delta \in \mathcal{P}$ is some perturbation on $\mathbf{H}$. It is noted that the hidden representation is continuous and it incorporates the information from both graph structure and node attributes.

5.2 Detecting Adversarial Perturbations

To resist graph adversarial attacks during the test phase, there is one main strategy called adversary detection. These detection models protect the GNN models by exploring the intrinsic difference between adversarial edges/nodes and the clean edges/nodes [17, 49]. The work [49] is the first work to propose detection approaches to find adversarial examples on graph data. It introduces four methods to distinguish adversarial edges or nodes from the clean ones including (1) link prediction (2) sub-graph link prediction (3) graph generation models and (4) outlier detection. These methods have shown some help to correctly detect adversarial perturbations. The work [17] introduces a method to randomly draw subsets of nodes, and relies on graph-aware criteria to judiciously filter out contaminated nodes and edges before employing a semi-supervised learning (SSL) module. The proposed model can be used to detect different anomaly generation models, as well as adversarial attacks.

5.3 Certifiable Robustness

Previous introduced adversarial training strategies are heuristic and only show experimental benefits. However, we still do not know whether there exist adversarial examples even when current attacks fail. Therefore, there are works [3, 19, 57] considering to seriously reason the safety of graph neural networks which try to certify the GNN’s robustness. As we know, GNN’s prediction on one node $v$ always depends on its neighbor nodes. In [57], they ask the question: which nodes in a graph are safe under the risk of any admissible perturbations of its neighboring nodes’ attributes. To answer this question, for each node $v$ and its corresponding label $y_v$, they try to find an upper bound $U(v)$ of the maximized margin loss:

$$U \geq \max_{\hat{X} \in \mathcal{X}} \left( f_{\theta}(\hat{X}, A)[y_v] - f_{\theta}(\hat{X}, A)[y] \right),$$

(12)
where $X$ denotes the set of all allowed attributes perturbations. This upper bound $U$ is called the certificate of node $v$, and it is tractable to calculate. Therefore, for $v$, if $U \leq 0$, any attribute perturbation in $X$ cannot change the model’s prediction, because its maximized margin loss is below 0. During the test phase, they calculate the certificate for all test nodes, thus they can know how many nodes in a graph is absolutely safe under attributes perturbation. Moreover, this certificate is trainable, directly minimizing the certificates will help more nodes become safe. However, the work [57] only considers the perturbations on node attributes. Analyzing certifiable robustness from a different perspective, the work [3] deals with the case when the attacker only manipulates the graph structure. It derives the robustness certificates (similar to Eq. (12)) as a linear function of personalized PageRank [18], which makes the optimization tractable. Besides the works concentrate on GNN node classification tasks, there are also other works studying certifiable robustness on GNN’s other applications such as community detection [19].

5.4 Graph Purification

Both adversarial training or certifiable defense methods only target on resisting evasion attacks, which means that the attack happens during the test time. While, graph purification defense methods mainly focus on defending poisoning attacks. Since the poisoning attacks insert poisons into the training graph, purification methods first purify the perturbed graph data and then train the GNN model on the purified graph. By this way, the GNN model is trained on a clean graph. The work [45] proposes a purification method based on two empirical observations of the attack methods: (1) Attackers usually prefer adding edges over removing edges or modifying features and (2) Attackers tend to connect dissimilar nodes. As a result, they propose a defense method by eliminating the edges whose two end nodes have small Jaccard Similarity [33]. Because these two nodes are different and it is not likely they are connected in reality, the edge between them may be adversarial. The experimental results demonstrate the effectiveness and efficiency of the proposed defense method. However, this method can only work when the node features are available. In [14], it is observed that Nettack [55] generates the perturbations which mainly changes the small singular values of the graph adjacency matrix. Thus it proposes to purify the perturbed adjacency matrix by using truncated SVD to get its low-rank approximation. It further shows that only keeping the top 10 singular values of the adjacency matrix is able to defend Nettack and improve the performance of GNNs.

5.5 Attention Mechanism

Different from the purification methods which try to exclude adversarial perturbations, attention-based defense methods aim to train a robust GNN model by penalizing model’s weights on adversarial edges or nodes. Basically, these methods learn an attention mechanism to distinguish adversarial edges and nodes from the clean ones, and then make the adversarial perturbations contribute less to the aggregation process of the GNN training. The work [53] first assumes that adversarial nodes may have high prediction uncertainty, since adversary tends to connect the node with nodes from other communities. In order to penalize the influence from these uncertain nodes, they propose to model the $l$-th layer hidden representation $h_i^{(l)}$ of nodes as Gaussian distribution with mean value $\mu_i^{(l)}$ and variance $\sigma_i^{(l)}$,

$$h_i^{(l)} \sim N(\mu_i^{(l)}, \text{diag}(\sigma_i^{(l)})), \quad (13)$$
where the uncertainty can be reflected in the variance $\sigma_i^{(l)}$. When aggregating the information from neighbor nodes, it applies an attention mechanism to penalize the nodes with high variance,

$$\alpha_i^{(l)} = \exp \left( -\gamma \sigma_i^{(l)} \right),$$

(14)

where $\alpha_i^{(l)}$ is the attention score assigned to node $i$ and $\gamma$ is a hyper-parameter. Furthermore, it is verified that the attacked nodes do have higher variances than normal nodes and the proposed attention mechanism does help mitigate the impact brought by adversarial attacks.

The work in [39] suggests that to improve the robustness of one target GNN model, it is beneficial to include the information from other clean graphs, which share the similar topological distributions and node attributes with the target graph. For example, Facebook and Twitter have social network graph data that share similar domains; Yelp and Foursquare have similar co-review graph data. Thus, it first generates adversarial edges $E_P$ on the clean graphs, which serve as the supervision of known perturbation. With this supervision knowledge, it further designs the following loss function to reduce the attention score of adversarial edges:

$$L_{dist} = -\min \left( \eta, \mathbb{E}_{e_{ij} \in E \setminus E_P} \alpha_{ij}^{(l)} - \mathbb{E}_{e_{ij} \in E_P} \alpha_{ij}^{(l)} \right),$$

(15)

where $\mathbb{E}$ denotes the expectation, $E \setminus E_P$ represents normal edges in the graph, $\alpha_{ij}^{(l)}$ is the attention score assigned to edge $e_{ij}$ and $\eta$ is a hyper parameter controlling the margin between the expectation of two distributions. It then adopts meta-optimization to train a model initialization and fine-tunes it on the target poisoned graph to get a robust GNN model.

6 EMPIRICAL STUDY

We have developed a repository that includes the majority of the representative attack and defense algorithms on graphs. The repository enables us to deepen our understandings on graph attacks and defends via empirical study. Next we first introduce the experimental settings and then present the empirical results and findings.

6.1 Experimental Setup

Different attack and defense methods have been designed under different settings. Due to the page limitation, we perform the experiments with one of the most popular settings – the untargeted poisoning setting. Correspondingly we choose representative attack and defense methods that have been designed for this setting. Three representative attack methods are adopted to generate perturbations including DICE [43], Metattack [56] and Topology attack [48]. It is noted that DICE is a white-box attack which randomly connects nodes with different labels or drops edges between nodes sharing the same label. To evaluate the performance of different defense methods under adversarial attacks, we compare the robustness of the natural trained GCN [21] and four defense methods on those attacked graphs, i.e., GCN-Jaccard [45], GCN-SVD [14], RGCN [53] and GAT [40]. Following [56], we use three datasets: Cora, Citeseer [34] and Polblogs [1]. For each dataset, we randomly choose 10% of nodes for training, 10% of nodes for validation and the remaining 80% for test. We repeat each experiment for 5 times and report the average performance. On Cora and Citeseer datasets, the most destructive variant CE-min-max [48] is adopted to implement Topology attack. But CE-min-max cannot converge on Polblogs dataset, we adopt another variant called CE-PGD [48] on this dataset.

2https://github.com/DSE-MSU/DeepRobust/tree/master/deeprobust/graph
6.2 Analysis on Attacked Graph

One way to understand the behaviors of attacking methods is to compare the properties of the clean graph and the attacked graph. In this subsection, we perform this analysis from both global and local perspectives.

Global Measure We have collected five global properties from both clean graphs and perturbed graphs generated by the three attacks on the three datasets. These properties include the number of added edges, the number of deleted edges, the number of edges, the rank of the adjacent matrix, and clustering coefficient. We only show the results of Metattack in Table 3. Results for DICE and Topology attacks can be found in Appendix A. Note that we vary the perturbations from 0 to 25% with a step of 5% and 0% perturbation denotes the original clean graph. It can be observed from the table:

- Attackers favor adding edges over deleting edges.
- Attacks are likely to increase the rank of the adjacency matrix.
- Attacks are likely to reduce the connectivity of a graph. The clustering coefficients of a perturbed graph decrease with the increase of the perturbation rate.

| Dataset   | r (%) | edge+ | edge- | edges | ranks | clustering coefficients |
|-----------|-------|-------|-------|-------|-------|------------------------|
| Cora      | 0     | 0     | 0     | 5069  | 2192  | 0.2376                 |
|           | 5     | 226   | 27    | 5268  | 2263  | 0.2228                 |
|           | 10    | 408   | 98    | 5380  | 2278  | 0.2132                 |
|           | 15    | 604   | 156   | 5518  | 2300  | 0.2071                 |
|           | 20    | 788   | 245   | 5633  | 2305  | 0.1983                 |
|           | 25    | 981   | 287   | 5763  | 2321  | 0.1943                 |
| Citeseer  | 0     | 0     | 0     | 3668  | 1778  | 0.1711                 |
|           | 5     | 181   | 2     | 3847  | 1850  | 0.1616                 |
|           | 1     | 341   | 25    | 3985  | 1874  | 0.1565                 |
|           | 15    | 485   | 65    | 4089  | 1890  | 0.1523                 |
|           | 20    | 614   | 119   | 4164  | 1902  | 0.1483                 |
|           | 25    | 743   | 174   | 4236  | 1888  | 0.1467                 |
| Polblogs  | 0     | 0     | 0     | 16714 | 1060  | 0.3203                 |
|           | 5     | 732   | 103   | 17343 | 1133  | 0.2719                 |
|           | 10    | 1347  | 324   | 17737 | 1170  | 0.2825                 |
|           | 15    | 1915  | 592   | 18038 | 1193  | 0.2851                 |
|           | 20    | 2304  | 1038  | 17980 | 1193  | 0.2877                 |
|           | 25    | 2500  | 1678  | 17536 | 1197  | 0.2723                 |

Local Measure We have also studied two local properties including the feature similarity and label equality between two nodes connected by three kinds of edges: the newly added edges, the deleted edges and the normal edges which have not been changed by the attack methods. Since features are binary in our datasets, we use jaccard similarity as the measure for feature similarity. For label equality, we report the ratio if two nodes share the same label or have different labels. The feature similarity and label equality results are demonstrated in Figures 2 and 3, respectively. We show the
results for Metattack with 5\% perturbations. Results for DICE and Topology attacks can be found in Appendix B. Note that we do not have feature similarity results on Polblogs since this dataset does not have node features. We can make the following observations from the figures.

- Attackers tend to connect nodes with different labels and dissimilar features.
- Attackers tend to remove edges from nodes which share similar features and same label.

![Graphs showing feature similarity for Cora and Citeseer](image1)

**Fig. 2. Node feature similarity for Metattack**

![Graphs showing label equality for Cora, Citeseer, and Polblogs](image2)

**Fig. 3. Label equality for Metattack**

### 6.3 Attack and Defense Performance

In this subsection, we study how the attack methods perform and whether the defense methods can help resist to attacks. Similarly, we vary the perturbations from 0 to 25\% with a step of 5\%. The results are demonstrated in Table 4. We show the performance for Metattack. Results for DICE and Topology attacks are shown in Appendix C. Note that we do not have the performance for Jaccard defense model in Polblogs since this mode requires node features and Polblogs does not provide node features. According to the results, we have the following observations:

- With the increase of the perturbations, the performance of GCN dramatically deceases. This result suggests that Metattack can lead to a significant reduce of accuracy on the GCN model.
- When the perturbations are small, we observe small performance reduction for defense methods which suggests their effectiveness. However, when the graphs are heavily poisoned, their performance also reduces significantly which indicates that efforts are needed to defend heavily poisoning attacks.
Table 4. Performance (Accuracy) under Metattack

| Dataset   | r (%) 0 | 5 | 10 | 15 | 20 | 25 |
|-----------|---------|---|----|----|----|----|
|           | GCN     | Jaccard\(^1\) | SVD\(^2\) | RGCN | GAT |    |
| Cora      | 83.10   | 82.39 | 77.97 | 84.81 | 81.69 | 74.53 |
|           | 76.69   | 81.02 | 75.67 | 81.32 | 74.75 | 72.59 |
|           | 65.58   | 77.28 | 70.51 | 72.12 | 61.69 | 63.96 |
|           | 54.88   | 72.74 | 64.34 | 72.68 | 52.56 | 61.66 |
|           | 48.66   | 69.16 | 55.89 | 69.38 | 45.30 | 61.06 |
|           | 38.44   | 64.56 | 45.92 | 67.12 | 43.22 | 50.58 |
|           |         |       |       |      |     |    |
| Citeseer  | GCN     | Jaccard\(^1\) | SVD\(^2\) | RGCN | GAT |    |
|           | 74.53   | 74.82 | 70.32 | 74.41 | 74.23 | 95.80 |
|           | 72.59   | 73.60 | 71.30 | 72.68 | 72.01 | 73.93 |
|           | 63.96   | 73.50 | 67.58 | 72.15 | 72.01 | 72.07 |
|           | 61.66   | 72.80 | 67.86 | 69.38 | 67.12 | 67.69 |
|           | 50.58   | 72.97 | 56.91 | 69.73 | 57.70 | 62.29 |
|           | 44.32   | 72.53 | 45.28 | 67.24 | 47.97 | 52.97 |
|           |         |       |       |      |     |    |
| Polblogs  | GCN     | SVD\(^2\) | RGCN | GAT |    |    |
|           | 95.80   | 94.99 | 95.60 | 95.40 | 94.83 | 95.97 |
|           | 73.93   | 82.64 | 72.01 | 84.83 | 77.03 | 73.07 |
|           | 72.07   | 71.27 | 67.12 | 77.03 | 69.94 | 62.29 |
|           | 67.69   | 66.09 | 57.70 | 69.94 | 53.62 | 52.97 |
|           | 62.29   | 61.37 | 47.97 | 53.62 | 53.62 | 53.76 |

\(^1\) Jaccard: GCN-Jaccard defense model.
\(^2\) SVD: GCN-SVD defense model.

7 CONCLUSION AND FUTURE DIRECTIONS

In this survey, we give a comprehensive overview of an emerging research field, adversarial attacks and defenses on graph data. We investigate the taxonomy of graph adversarial attacks, and review representative adversarial attacks and the corresponding countermeasures. Furthermore, we conduct empirical study to show how different defense methods behave under different attacks, as well as the changes in important graph properties by the attacks. Via this comprehensive study, we have gained deep understandings on this area that enables us to discuss some promising research directions.

- **Imperceptible perturbation measure.** Different from image data, humans cannot easily tell whether a perturbation on graph is imperceptible or not. The \(\ell_0\) norm constraint on perturbation is definitely not enough. Currently only very few existing work study this problem, thus finding concise perturbation evaluation measure is of great urgency.

- **Different graph data.** Existing works mainly focus on static graphs with node attributes. Complex graphs such as graphs with edge attributes and dynamic graphs are not well-studied yet.

- **Existence and transferability of graph adversarial examples.** There are only a few works discussing about the existence and transferability of graph adversarial examples. Studying this topic is important for us to understand our graph learning algorithm, thus helping us build robust models.

- **Graph structure learning.** By analyzing the attacked graph, we find that attacks are likely to change certain properties of graphs. Therefore, we can learn a graph from the poisoned graphs by exploring these properties to build robust GNNs.
REFERENCES

[1] Lada A Adamic and Natalie Glance. 2005. The political blogosphere and the 2004 US election: divided they blog. In Proceedings of the 3rd international workshop on Link discovery. 36–43.

[2] Aleksandar Bojchevski and Stephan Günnemann. 2018. Adversarial attacks on node embeddings via graph poisoning. arXiv preprint arXiv:1809.01093 (2018).

[3] Aleksandar Bojchevski and Stephan Günnemann. 2019. Certifiable Robustness to Graph Perturbations. In Advances in Neural Information Processing Systems. 8317–8328.

[4] Antoine Bordes, Nicolas Usunier, Alberto Garcia-Duran, Jason Weston, and Oksana Yakhnenko. 2013. Translating embeddings for modeling multi-relational data. In Advances in neural information processing systems. 2787–2795.

[5] Heng Chang, Yu Rong, Tingyang Xu, Wenbing Huang, Honglei Zhang, Peng Cui, Wenwu Zhu, and Junzhu Huang. 2019. The General Black-box Attack Method for Graph Neural Networks. arXiv preprint arXiv:1908.01297 (2019).

[6] Jinyin Chen, Lihong Chen, Xiyian Chen, Minghao Zhao, Shanqing Yu, Qi Xuan, and Xiaoniu Yang. 2019. Ga-based q-attack on community detection. IEEE Transactions on Computational Social Systems 6, 3 (2019), 491–503.

[7] Jinyin Chen, Ziqiang Shi, Yangyang Wu, Xuanheng Xu, and Haibin Zheng. 2018. Link prediction adversarial attack. arXiv preprint arXiv:1810.01110 (2018).

[8] Jinyin Chen, Yangyang Wu, Xiang Lin, and Qi Xuan. 2019. Can Adversarial Network Attack be Defended? arXiv preprint arXiv:1903.05994 (2019).

[9] Jinyin Chen, Yangyang Wu, Xuanheng Xu, Xiyian Chen, Haibin Zheng, and Qi Xuan. 2018. Fast gradient attack on network embedding. arXiv preprint arXiv:1809.02797 (2018).

[10] Yizheng Chen, Yacin Nadji, Athanasios Kountouras, Fabian Monrose, Roberto Perdisci, Manos Antonakakis, and Nikolaos Vasiloglou. 2017. Practical attacks against graph-based clustering. In Proceedings of the 2017 ACM SIGSAC Conference on Computer and Communications Security. 1125–1142.

[11] Hanjun Dai, Hui Li, Tian Tian, Xin Huang, Lin Wang, Jun Zhu, and Le Song. 2018. Adversarial attack on graph structured data. arXiv preprint arXiv:1806.02371 (2018).

[12] Quanyu Dai, Xiao Shen, Liang Zhang, Qiang Li, and Dan Wang. 2019. Adversarial training methods for network embedding. In The World Wide Web Conference. 329–339.

[13] Zhijie Deng, Yinpeng Dong, and Jun Zhu. 2019. Batch virtual adversarial training for graph convolutional networks. arXiv preprint arXiv:1902.09192 (2019).

[14] Negin Entezari, Saba A Al-Sayouri, Amirali Darvishzadeh, and Evangelos E Papalexakis. 2020. All You Need Is Low (Rank) Defending Against Adversarial Attacks on Graphs. In Proceedings of the 13th International Conference on Web Search and Data Mining. 169–177.

[15] Fuli Feng, Xiangnan He, Jie Tang, and Tat-Seng Chua. 2019. Graph adversarial training: Dynamically regularizing based on graph structure. IEEE Transactions on Knowledge and Data Engineering (2019).

[16] Ian J Goodfellow, Jonathon Shlens, and Christian Szegedy. 2014. Explaining and harnessing adversarial examples. arXiv preprint arXiv:1412.6572 (2014).

[17] Vassilis N Ioannidis, Dimitris Berberidis, and Georgios B Giannakis. 2019. GraphSAC: Detecting anomalies in large-scale graphs. arXiv preprint arXiv:1910.09589 (2019).

[18] Glen Jeh and Jennifer Widom. 2003. Scaling personalized web search. In Proceedings of the 12th international conference on World Wide Web. 271–279.

[19] Jinyuan Jia, Binghui Wang, Xiaoyu Cao, and Neil Zhenqiang Gong. 2020. Certified Robustness of Community Detection by Hiding Individuals. arXiv:2001.07933 [cs.SI]

[20] Thomas N Kipf and Max Welling. 2016. Semi-supervised classification with graph convolutional networks. arXiv preprint arXiv:1609.02907 (2016).

[21] Loic Landrieu and Martin Simonovsky. 2018. Large-scale point cloud semantic segmentation with superpoint graphs. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition. 4558–4567.

[22] Jia Li, Honglei Zhang, Zhichao Han, Yu Rong, Hong Cheng, and Junzhu Huang. 2020. Adversarial Attack on Community Detection by Hiding Individuals. arXiv:2001.07933 [cs.SI]

[23] Yankai Lin, Zhiyuan Liu, Maosong Sun, Yang Liu, and Xuan Zhu. 2015. Learning entity and relation embeddings for modeling knowledge graph completion. In Twenty-ninth AAAI conference on artificial intelligence.

[24] Xuanqing Liu, Si Si, Xiaojin Zhu, Yang Li, and Cho-Jui Hsieh. 2019. A unified framework for data poisoning attack on graph-based semi-supervised learning. arXiv preprint arXiv:1910.14147 (2019).

[25] Yizheng Chen, Yacin Nadji, Athanasios Kountouras, Fabian Monrose, Roberto Perdisci, Manos Antonakakis, and Nikolaos Vasiloglou. 2017. Practical attacks against graph-based clustering. In Proceedings of the 2017 ACM SIGSAC Conference on Computer and Communications Security. 1125–1142.
Adversarial Attacks and Defenses on Graphs:
A Review and Empirical Study

[28] Aleksander Madry, Aleksandar Makelov, Ludwig Schmidt, Dimitris Tsipras, and Adrian Vladu. 2017. Towards deep learning models resistant to adversarial attacks. arXiv preprint arXiv:1706.06083 (2017).

[29] Diego Marcheggiani and Ivan Titov. 2017. Encoding sentences with graph convolutional networks for semantic role labeling. arXiv preprint arXiv:1703.04826 (2017).

[30] Volodymyr Mnih, Koray Kavukcuoglu, David Silver, Alex Graves, Ioannis Antonoglou, Daan Wierstra, and Martin Riedmiller. 2013. Playing atari with deep reinforcement learning. arXiv preprint arXiv:1312.5602 (2013).

[31] Bryan Perozzi, Rami Al-Rfou, and Steven Skiena. 2014. Deepwalk: Online learning of social representations. In Proceedings of the 20th ACM SIGKDD international conference on Knowledge discovery and data mining, 701–710.

[32] Jiezhong Qiu, Yuxiao Dong, Hao Ma, Jian Li, Kuansan Wang, and Jie Tang. 2018. Network embedding as matrix factorization: Unifying deepwalk, line, pte, and node2vec. In Proceedings of the Eleventh ACM International Conference on Web Search and Data Mining. 459–467.

[33] Alan Said, Ernesto W De Luca, and Sahin Albayrak. [n.d.]. How social relationships affect user similarities.

[34] Prithviraj Sen, Galileo Namata, Mustafa Bilgic, Lise Getoor, Brian Galligher, and Tina Eliassi-Rad. 2008. Collective classification in network data. AI magazine 29, 3 (2008), 93–93.

[35] Lichao Sun, Ji Wang, Philip S Yu, and Bo Li. 2018. Adversarial attack and defense on graph data: A survey. arXiv preprint arXiv:1812.10528 (2018).

[36] Yiwei Sun, Suhang Wang, Xianfeng Tang, Tsung-Yu Hsieh, and Vasant Honavar. 2019. Node injection attacks on graphs via reinforcement learning. arXiv preprint arXiv:1909.06543 (2019).

[37] Mukund Sundararajan, Ankur Taly, and Qi Ji Yan. 2017. Axiomatic attribution for deep networks. In Proceedings of the 34th International Conference on Machine Learning-Volume 70. JMLR. org, 3319–3328.

[38] Jian Tang, Meng Qu, Mingzhe Wang, Ming Zhang, Jun Yan, and Qiaozhu Mei. 2015. Line: Large-scale information networks embedding. In Proceedings of the 24th international conference on world wide web. 1067–1077.

[39] Xianfeng Tang, Yudong Li, Yiwei Sun, Huaxiu Yao, Prasenjit Mitra, and Suhang Wang. 2020. Transferring Robustness for Graph Neural Network Against Poisoning Attacks. In Proceedings of the 13th International Conference on Web Search and Data Mining. 600–608.

[40] Petar Veličković, Guillem Cucurull, Arantxa Casanova, Adriana Romero, Pietro Lio, and Yoshua Bengio. 2017. Graph attention networks. arXiv preprint arXiv:1710.10903 (2017).

[41] Binghui Wang and Neil Zhenqiang Gong. 2019. Attacking graph-based classification via manipulating the graph structure. In Proceedings of the 2019 ACM SIGSAC Conference on Computer and Communications Security. 2023–2040.

[42] Xiaoyuan Wang, Xuangqing Liu, and Cho-Jui Hsieh. 2019. GraphDefense: Towards Robust Graph Convolutional Networks. arXiv:1911.04429 [cs.LG]

[43] Marcin Waniek, Tomasz P. Michalak, Michael J. Wooldridge, and Talal Rahwan. 2018. Hiding individuals and communities in a social network. Nature Human Behaviour 2, 2 (Jan 2018), 139–147. https://doi.org/10.1038/s41562-017-0290-3

[44] Marcin Waniek, Tomasz P Michalak, Michael J Wooldridge, and Talal Rahwan. 2018. Hiding individuals and communities in a social network. Nature Human Behaviour 2, 2 (2018), 139–147.

[45] Huijun Wu, Chen Wang, Yuriy Tsyshetskiy, Andrew Docherty, Kai Lu, and Liming Zhu. 2019. Adversarial examples for graph data: deep insights into attack and defense. In Proceedings of the 28th International Joint Conference on Artificial Intelligence. AAAI Press, 4816–4823.

[46] Zonghan Wu, Shirui Pan, Fengwen Chen, Guodong Long, Chengqi Zhang, and Philip S Yu. 2019. A comprehensive survey on graph neural networks. arXiv preprint arXiv:1901.00596 (2019).

[47] Han Xu, Yao Ma, Haochen Liu, Debayan Deb, Hui Liu, Jiliang Tang, and Anil Jain. 2019. Adversarial attacks and defenses in images, graphs and text: A review. arXiv preprint arXiv:1909.08072 (2019).

[48] Kaidi Xu, Hongge Chen, Sijia Liu, Pin-Yu Chen, Tsui-Wei Wei, Mingyi Hong, and Xue Lin. 2019. Topology attack and defense for graph neural networks: An optimization perspective. arXiv preprint arXiv:1906.04214 (2019).

[49] Xiaojun Xu, Yue Yu, Bo Li, Le Song, Chengfeng Liu, and Carl Gunter. 2018. Characterizing Malicious Edges targeting on Graph Neural Networks. (2018).

[50] Xiao Zang, Yi Xie, Jie Chen, and Bo Yuan. 2020. Graph Universal Adversarial Attacks: A Few Bad Actors Ruin Graph Learning Models. arXiv:2002.04784 [cs.LG]

[51] Hengtong Zhang, Tianhang Zheng, Jing Gao, Chenglin Miao, Lu Su, Yaliang Li, and Kui Ren. 2019. Towards Data Poisoning Attack against Knowledge Graph Embedding. ArXiv abs/1904.12052 (2019).

[52] Qi Zhou, Yizhi Ren, Tianyu Xia, Lifeng Yuan, and Linqiang Chen. 2020. Data Poisoning Attacks on Graph Convolutional Matrix Completion. In Algorithms and Architectures for Parallel Processing.

[53] Dingyuan Zhu, Ziwei Zhang, Peng Cui, and Wenwu Zhu. 2019. Robust graph convolutional networks against adversarial attacks. In Proceedings of the 25th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining. 1399–1407.

[54] Xiaojin Zhu and Zoubin Ghahramani. 2002. Learning from labeled and unlabeled data with label propagation. (2002).
A APPENDIX

A.1 Open Source Code

| Methods       | Framework | Github Link                                                                 |
|---------------|-----------|-----------------------------------------------------------------------------|
| Attack        |           |                                                                             |
| PGD, Min-max  | tensorflow | https://github.com/KaidiXu/GCN_ADV_Train                                   |
|               | pytorch   | https://github.com/DSE-MSU/DeepRobust                                      |
| DICE [44]     | python    | https://github.com/DSE-MSU/DeepRobust                                      |
| Nettack [55]  | tensorflow | https://github.com/danielzuegner/nettack                                   |
| Metattack [56]| tensorflow | https://github.com/danielzuegner/gnn-meta-attack                           |
|               | pytorch   | https://github.com/ChandlerBang/pytorch-gnn-meta-attack                     |
| RL-S2V [11]   | pytorch   | https://github.com/Hanjun-Dai/graph_adversarial_attack                      |
| [2]           | tensorflow | https://github.com/abojchevski/node_embedding_attack                       |
| GF-Attack [5] | tensorflow | https://github.com/abojchevski/node_embedding_attack                       |
| Defense       |           |                                                                             |
| RGCN [53]     | tensorflow | https://github.com/thumanlab/nrlweb/blob/master/static/assets/download/RGCN.zip |
|               | pytorch   | https://github.com/DSE-MSU/DeepRobust                                      |
| GCN-Jaccard [45]| pytorch  | https://github.com/DSE-MSU/DeepRobust                                      |
| GCN-SVD [14]  | pytorch   | https://github.com/DSE-MSU/DeepRobust                                      |
| Adversarial Training [48]| tensorflow | https://github.com/KaidiXu/GCN_ADV_Train                                   |
|               | pytorch   | https://github.com/DSE-MSU/DeepRobust                                      |
| PA-GNN [39]   | tensorflow | https://github.com/tangxianfeng/PA-GNN                                      |
| Graph-Cert [3]| python    | https://github.com/abojchevski/graph_cert                                   |
### A.2 Global Measures for Dice and Topology Attacks

#### Table 6. Properties of attacked graphs under Topology Attack

| Dataset | r(%) | edges+ | edges- | edges | ranks | clustering coefficients |
|---------|------|--------|--------|-------|-------|-------------------------|
| Cora    | 0    | 0      | 0      | 5069  | 2192  | 0.2376                  |
|         | 5    | 255    | 0      | 5324  | 2292  | 0.2308                  |
|         | 10   | 508    | 0      | 5577  | 2369  | 0.2185                  |
|         | 15   | 762    | 0      | 5831  | 2417  | 0.2029                  |
|         | 20   | 1015   | 0      | 6084  | 2442  | 0.1875                  |
|         | 25   | 1269   | 0      | 6338  | 2456  | 0.1736                  |
| Citeseer| 0    | 0      | 0      | 3668  | 1778  | 0.1711                  |
|         | 5    | 185    | 0      | 3853  | 1914  | 0.1666                  |
|         | 10   | 368    | 0      | 4036  | 2003  | 0.1568                  |
|         | 15   | 552    | 0      | 4220  | 2058  | 0.1429                  |
|         | 20   | 735    | 0      | 4403  | 2077  | 0.1306                  |
|         | 25   | 918    | 0      | 4586  | 2087  | 0.1188                  |
| Polblogs| 0    | 0      | 0      | 16714 | 1060  | 0.3203                  |
|         | 5    | 716    | 96     | 17334 | 1213  | 0.2659                  |
|         | 10   | 1532   | 128    | 18118 | 1220  | 0.2513                  |
|         | 15   | 2320   | 146    | 18887 | 1221  | 0.2408                  |
|         | 20   | 3149   | 155    | 19708 | 1221  | 0.2317                  |
|         | 25   | 3958   | 163    | 20509 | 1221  | 0.2238                  |

#### Table 7. Properties of attacked graphs under DICE Attack

| Dataset | r(%) | edge+  | edge-  | edges  | ranks | clustering coefficients |
|---------|------|--------|--------|--------|-------|-------------------------|
| Cora    | 0    | 0      | 0      | 5069   | 2192  | 0.2376                  |
|         | 5    | 125    | 128    | 5066   | 2210  | 0.2163                  |
|         | 10   | 251    | 255    | 5065   | 2238  | 0.1966                  |
|         | 15   | 377    | 383    | 5063   | 2246  | 0.1786                  |
|         | 20   | 504    | 509    | 5063   | 2261  | 0.1583                  |
|         | 25   | 625    | 642    | 5053   | 2270  | 0.1448                  |
| Citeseer| 0    | 0      | 0      | 3668   | 1778  | 0.1711                  |
|         | 5    | 91     | 92     | 3667   | 1803  | 0.1576                  |
|         | 10   | 183    | 183    | 3668   | 1828  | 0.1408                  |
|         | 15   | 276    | 274    | 3670   | 1840  | 0.1288                  |
|         | 20   | 368    | 365    | 3672   | 1860  | 0.1187                  |
|         | 25   | 462    | 455    | 36755  | 1871  | 0.1084                  |
| Polblogs| 0    | 0      | 0      | 16714  | 1060  | 0.3203                  |
|         | 5    | 420    | 415    | 16719  | 1155  | 0.2822                  |
|         | 10   | 846    | 825    | 16736  | 1192  | 0.2487                  |
|         | 15   | 1273   | 1234   | 16752  | 1208  | 0.2224                  |
|         | 20   | 1690   | 1652   | 16752  | 1214  | 0.2009                  |
|         | 25   | 2114   | 2064   | 16765  | 1217  | 0.1821                  |
A.3 Local Measures for Dice and Topology Attacks

Fig. 4. Node feature similarity for Topology Attack

Fig. 5. Node feature similarity for DICE Attack

Fig. 6. Label equality for Topology Attack
A.4 Attack and Defense Performance for Dice and Topology Attacks

Table 8. Performance(Accuracy) under DICE Attack

| Dataset     | r (%)  | 0   | 5   | 10  | 15  | 20  | 25  |
|-------------|--------|-----|-----|-----|-----|-----|-----|
| Cora        |        |     |     |     |     |     |     |
| GCN         | 83.10  | 82.20| 81.15| 80.54| 79.40| 77.78|
| Jaccard\(^1\) | 82.39  | 81.66| 80.94| 80.24| 79.41| 78.31|
| SVD\(^2\)   | 77.97  | 76.55| 74.35| 72.71| 59.77| 70.41|
| RGCN        | 84.81  | 83.87| 82.72| 81.64| 80.77| 79.53|
| GAT         | 81.69  | 79.33| 77.36| 75.23| 73.78| 72.05|
| Citeseer    |        |     |     |     |     |     |     |
| GCN         | 74.53  | 74.21| 73.90| 72.36| 72.27| 71.50|
| Jaccard\(^1\) | 74.82  | 74.56| 74.14| 73.51| 73.22| 72.22|
| SVD\(^2\)   | 70.32  | 70.91| 70.27| 69.19| 67.63| 66.82|
| RGCN        | 74.41  | 74.72| 74.22| 73.42| 72.71| 72.16|
| GAT         | 74.23  | 73.78| 72.86| 71.48| 70.25| 69.68|
| Polblogs    |        |     |     |     |     |     |     |
| GCN         | 95.80  | 92.78| 90.78| 90.12| 88.28| 87.79|
| SVD\(^2\)   | 94.99  | 93.09| 92.39| 91.31| 90.72| 90.61|
| RGCN        | 95.60  | 92.72| 90.70| 89.80| 88.34| 87.28|
| GAT         | 95.40  | 93.56| 91.82| 91.27| 89.65| 89.30|

\(^1\) Jaccard: GCN-Jaccard defense model.  
\(^2\) SVD: GCN-SVD defense model.
| Dataset |  \( r \) (%) | 0     | 5     | 10    | 15    | 20    | 25    |
|----------|---------------|-------|-------|-------|-------|-------|-------|
| Cora     | GCN           | 83.10 | 71.82 | 68.96 | 66.77 | 64.21 | 62.52 |
|          | Jaccard\(^1\) | 82.39 | 73.05 | 72.62 | 71.84 | 71.41 | 70.85 |
|          | SVD\(^2\)     | 77.97 | 78.17 | 75.92 | 73.69 | 72.03 | 70.11 |
|          | RGCN          | 84.81 | 72.68 | 71.15 | 69.38 | 67.92 | 67.23 |
|          | GAT           | 81.69 | 71.03 | 68.80 | 65.66 | 64.29 | 62.58 |
| Citeseer | GCN           | 74.53 | 79.29 | 75.47 | 72.89 | 70.12 | 68.49 |
|          | Jaccard\(^1\) | 74.82 | 79.07 | 76.76 | 74.29 | 71.87 | 69.55 |
|          | SVD\(^2\)     | 70.32 | 78.17 | 75.92 | 73.69 | 72.03 | 70.11 |
|          | RGCN          | 74.41 | 78.13 | 75.93 | 73.93 | 72.32 | 70.60 |
|          | GAT           | 74.23 | 77.52 | 74.09 | 71.90 | 69.62 | 66.99 |
| Polblogs | GCN           | 95.80 | 72.04 | 65.87 | 63.35 | 61.06 | 58.49 |
|          | SVD\(^2\)     | 94.99 | 71.90 | 65.42 | 63.01 | 60.74 | 58.26 |
|          | RGCN          | 95.60 | 71.27 | 65.30 | 62.76 | 60.25 | 57.89 |
|          | GAT           | 95.40 | 72.56 | 65.97 | 63.35 | 60.94 | 58.77 |

\(^1\) Jaccard: GCN-Jaccard defense model.
\(^2\) SVD: GCN-SVD defense model.