Black-box Gradient Attack on Graph Neural Networks: Deeper Insights in Graph-based Attack and Defense

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ABSTRACT
Graph Neural Networks (GNNs) have received significant attention due to their state-of-the-art performance on various graph representation learning tasks. However, recent studies reveal that GNNs are vulnerable to adversarial attacks, i.e., an attacker is able to fool the GNNs by perturbing the graph structure or node features deliberately. While being able to successfully decrease the performance of GNNs, most existing attacking algorithms require access to either the model parameters or the training data, which is not practical in the real world.

In this paper, we develop deeper insights into the Mettack algorithm, which is a representative grey-box attacking method, and then we propose a gradient-based black-box attacking algorithm. Firstly, we show that the Mettack algorithm will perturb the edges unevenly, thus the attack will be highly dependent on a specific training set. As a result, a simple yet useful strategy to defense against Mettack is to train the GNN with the validation set. Secondly, to overcome the drawbacks, we propose the Black-Box Gradient Attack (BBGA) algorithm. Extensive experiments demonstrate that our proposed method is applicable when attacking against various defense methods.

1 INTRODUCTION
Graph structured data is widely used in a variety of domains, such as social networks[20], academic publishing[5], recommender systems[24] and financial transactions[16]. How to learn effective graph representations has long been an important research direction. Recently, Graph Neural Networks (GNNs) has become the mainstream method for graph representation learning[26]. Firstly introduced by [17], the Graph Convolutional Network (GCN)[11] achieved state-of-the-art performance in the node-classification task and is considered as the most representative GNN model. Then, numerous GNN models, such as GAT[19], GraphSAGE[8] and JK-Net[22], have been proposed.

It has been revealed that deep learning models are often in lack of robustness[7]. It is possible to fool the model by generating perturbations deliberately. Adversarial attacks on GNNs could be classified using various criteria. According to the attackers’ knowledge, we could divide existing GNN attacks into white-box attacks, grey-box attacks and black-box attacks[3]. In the white-box scenario, the adversary has access to both the model parameters and the training data, which even include the ground-truth labels. Grey-box attacks only need partial information and they are more practical than the white-box ones. Representative grey-box attacking methods include Nettack[28], which aims to misclassify a set of targeted nodes, and Mettack[29], which aims to reduce the overall classification accuracy rates. Since model parameters are not accessible in grey-box scenarios, a surrogate model is usually trained on the training set to approximate the gradients of potential perturbations. Black-box attacks allow the most limited knowledge such that only black-box queries are possible[18]. Since the access to the training set is also prohibited, reinforcement learning is introduced to perform black-box attacks[9]. However, the queries are still considered to be impractical and RWCS, a black-box attack based on the theory of random walk, has been proposed[13].

Various defense methods have also been proposed. For instance, GCN-Jaccard [21] increases the robustness of GCNs by eliminating edges with low similarity before the training process. R-GCN [27] utilizes the attention mechanism which regards node features as Gaussian distributions and assigns attention scores according to the variances. By introducing structure learning, Pro-GNN[10] achieves promising results when defending against structure perturbations.

Although defense algorithms have emerged to enhance the security of GNNs, studies on deep learning models show that it
is possible to improve the adversarial attacks to degrade the defense performance [1, 2]. Meanwhile, in-depth studies on adversarial attacks is an efficient tool to develop insights in deep learning models [6]. Comparing with Deep Neural Networks (DNNs), adversarial attacks on GNNs remain poorly understood.

One perspective to improve adversarial attacks is to understand how existing attacks work at first. In this paper, we target on investigating Mettack, which is the most representative non-targeted grey-box attack, to develop a deeper understanding of graph attack and defense. Our case studies show that the perturbations chosen by Mettack are highly correlated with the training set and they are distributed unevenly on the graph. As a result, we reveal that a simple defense strategy is to train the GNN with the validation set. Based on the findings, we propose the Black-Box Gradient Attack (BBGA) algorithm to evenly perturb the graphs without accessing any ground-truth labels. Extensive experiments on three real-world benchmark datasets demonstrate that our proposed method can effectively attack the graph structure without accessing any training labels.

In summary, our contributions of this paper are as follows:

- **How Mettack works:** We studies the patterns of Mettack perturbations and we show that the perturbations are denser near the training set. We show that such unevenness helps in grey-box attacks but it could also be utilized by defenders.
- **Black-box Gradient Attack (BBGA):** While it is believed that training surrogate model without ground-truth labels are impossible, we propose the first gradient-based black-box attacking method to our best knowledge. It is also the first non-targeted graph structure attack without permission to do black-box queries. Exploiting the spectral clustering, we train the surrogate model with pseudo-labels and then evenly distribute the perturbations via a novel k-fold training strategy.
- **Extensive experiments:** We conduct numerous experiments to show the effectiveness of our proposed method. Further studies are provided for the explanability of the method.

The rest of our paper is organized as follows. In Section 2, we define the mathematical notations used in this paper and then we introduce the preliminaries. In Section 3, we analyse Mettack perturbations via a series of case studies. In Section 4, we introduce our propose BBGA method and explain it in details. Experimental results, ablation studies and parameter analysis are reported in Section 5. Finally, we conclude the paper in Section 6.

## 2 PRELIMINARIES

In this section, we introduce the notations used in this paper as well as fundamental concepts.

### 2.1 Mathematical Notations

In this paper, we denote a graph with $N$ nodes as $G = (V,E)$ where $V = \{v_1,\ldots,v_N\}$ is the node set and $E = \{e_1,\ldots,e_E\} \subseteq V \times V$ is the edge set. The set of vertices $V$ is usually divided into the training set $V_{\text{train}}$, the validation set $V_{\text{val}}$ and the testing set $V_{\text{test}}$. We denote the structure of the $G$ via the adjacency matrix $A \in \{0,1\}^{N \times N}$ whose element $A_{ij} = 1$ if and only if there exists an edge $e_i \in E$ connects $v_i$ and $v_j$. Node features are stored in a matrix $X \in \mathbb{R}^{N \times F}$ where $F$ is the number of dimensions of node features. The labels of a dataset is denoted by $C$ while pseudo-labels used during training are denoted as $C_p$.

### 2.2 Graph Convolutional Networks (GCNs)

Despite a number of GCN models have been proposed, in this paper we mainly consider the most representative one introduced by [11]. Each layer of a GCN aggregate messages according to the graph structure and then perform linear transformation on the node features. Such a graph convolutional layer could be denoted as the following equation:

$$ H^{(l+1)} = \sigma(\hat{A}H^{(l)}W^{(l)}), $$

where $\hat{A} = \hat{D}^{-\frac{1}{2}}\hat{A}\hat{D}^{-\frac{1}{2}}$ is the normalized adjacency matrix such that $\hat{A} = A + I_N$, $\hat{D}_{ii} = \sum_j A_{ij}$, $\sigma$ is a non-linear activation function. A typical GCN network consists of two layers, the whole network is usually described as:

$$ Z = f(X, A) = \text{softmax}(\hat{A}\sigma(\hat{A}XW^{(0)})W^{(1)}). $$

The GCN network is usually trained with a cross entropy loss. Noticing that two-layer GCNs aggregate information within 2-hop neighborhoods for each node, a simplified and linearized version is usually used in adversarial attacks:

$$ Z = f(A, X) = \text{softmax}(\hat{A}XW). $$

To utilize GCN in inductive settings, [8] introduced a variant of GCN with a different normalization method:

$$ h_u^{(l)} = \sigma\left(W_l \cdot \frac{1}{D(\{u\})} \sum_{v \in N(u)} h_v^{(l-1)}\right), $$

where $h_u^{(l)}$ is the hidden representation of node $u$ in the $l^{th}$ layer and $N(u)$ is the neighborhood of node $u$ in the self-looped graph with $A$ as the adjacency matrix.

### 2.3 Mettack

Mettack [29] is a gradient-based grey-box graph attacking algorithm. Being directly connected to the training loss, gradients are widely used in deep learning adversarial attacks [25]. Being denied to access model parameters, Mettack trains the surrogate model described in Eq. 3 to approximate the gradients of the GCN model. In order to find the best edge to perturb, the adjacency matrix is regarded as a hyperparameter and the meta-derivatives are computed after the training of the surrogate model:

$$ \nabla_{\Theta}^\text{meta} := \nabla_{\Theta} L_{\text{atk}}(f_\Theta(G)) \text{ s.t. } \Theta^* = \text{opt}_{\Theta} (L_{\text{train}}(f_\Theta(G))), $$

where $L_{\text{atk}}$ is the target function that the attacker aims to optimize, opt is a training procedure and $L_{\text{train}}$ is the training loss. It is revealed that when $L_{\text{atk}} = -L_{\text{self}}$, where $L_{\text{self}}$ is the cross-entropy loss on the unlabelled nodes with predicted pseudo-labels, the algorithm reaches its best performance.

A greedy algorithm, which chooses exactly one edge at a step, is employed to perform perturbations. The score of a node pair $(u, v)$ is defined as:

$$ S(u, v) = \nabla_{A_{uv}} \cdot (-2 \cdot A_{uv} + 1), $$

$\nabla_{\Theta}^\text{meta}$ is the variable for to be updated in the gradient-based attack.

In this paper, we denote a graph with $N$ nodes as $G = (V,E)$ where $V = \{v_1,\ldots,v_N\}$ is the node set and $E = \{e_1,\ldots,e_E\} \subseteq V \times V$ is the edge set. The set of vertices $V$ is usually divided into the training set $V_{\text{train}}$, the validation set $V_{\text{val}}$ and the testing set $V_{\text{test}}$. We denote the structure of the $G$ via the adjacency matrix $A \in \{0,1\}^{N \times N}$ whose element $A_{ij} = 1$ if and only if there exists an edge $e_i \in E$ connects $v_i$ and $v_j$. Node features are stored in a matrix $X \in \mathbb{R}^{N \times F}$ where $F$ is the number of dimensions of node features. The labels of a dataset is denoted by $C$ while pseudo-labels used during training are denoted as $C_p$.
$A$ is the adjacency matrix. The signs of meta-gradients are flipped for connected node pairs to yield the gradients for removing the edge. In each iteration, the algorithm picks the potential perturbation with the highest score. The total number of perturbations is controlled by a budget constraint $\Delta$, which is usually defined via a perturbation rate $\delta = \frac{\Delta}{|E|}$.

3 CASE STUDIES ON METTACK
Adversarial attacks generate deliberate perturbations on graph data. Hence, to investigate why adversarial attacks work, it is necessary to analyze the perturbations made by attacking algorithms. Previous studies find that dissimilar nodes tend to be connected by attackers\cite{21}. In this paper, we focus on the distributions of such carefully-crafted perturbations.

3.1 Unevenness of perturbations
Consisting of 2 graph convolutional layers, a typical GCN network is only able to aggregate information with the 2-hop neighborhood of each node. Xu et al. proved the following theorem:

**Theorem 3.1 (\cite{22}).** If all paths in the computation graph of the model are activated with the same probability. Given a $L$-layer GCN with Eq. 4 as the normalization method, then $\forall i, j \in V, \mathbb{E}\left[\frac{\partial H_j}{\partial X_i}\right]$ is equivalent to the probability of reaching node $j$ via a $k$-step random walk starting at node $i$.

Inspired by Theorem 3.1, it is nature to raise the question that whether grey-box gradient attacks mainly perturb edges that are adjacent to the training set or not.

We conducted a case study on the Cora dataset with Mettack. Figure 1 demonstrates the local perturbation rates both inside and adjacent to the training set. As illustrated in the figure, the local perturbation rate exceeds 100% when the global perturbation rate reaches 25%. Thus, instead of perturbing the edges evenly, Mettack essentially flips a much higher proportion of edges near the training set than the assigned perturbation rate.

3.2 Ablation Study on The Unevenness
In order to show the effects of such unevenness, an ablation study on the Cora dataset is conducted. We create two variants of the DICE (Disconnect Internally, Connect Externally) algorithm, which disconnects nodes with the same label and connects nodes with different labels randomly. DICE-Free randomly flips edges on the whole graph. DICE-Control ensures that 10% of the perturbations are within the training set and 90% of the flips are adjacent to the training set. Following \cite{29}, we suppose that the attacker knows all the ground-truth labels in this study.

As reported in Figure 2, the enforced unevenness does not boost the attacking performance too much when perturbation rates are low. However, with the increasing of perturbation rates, DICE-Control outperforms DICE-Free significantly. When the perturbation rates are 50%, DICE-Control leads to a 56.05% higher misclassification rate than DICE-Free. The result demonstrates that when the training set is accessible, the unevenness of perturbations helps a lot in grey-box adversarial attacks.

3.3 Defend Mettack via Validation Set
Although the unevenness helps in attacking, it could also be utilized by the defender. We develop Flip-GCN, which is a training strategy that trains the GCN with the validation set, to defend against Mettack. Following the experimental settings of \cite{10}, we randomly select 10% of nodes as the training set, 10% for validation and the remaining 80% as the testing set. The graph is perturbed by...

**Table 1: The experimental results of the flip strategy (Accuracy±Std).**

| Ptb Rate | GCN | Flip-GCN |
|----------|-----|----------|
| 10%      | 71.59±1.79 | 81.19±0.89 |
| 20%      | 55.88±5.03  | 80.50±0.69  |

**Figure 1: The local perturbations rates of mettack perturbed graphs.**

**Figure 2: The testing accuracies of GCN on DICE-attacked graphs.**
Mettack without the log-likelihood restraint. As reported in Table 1, when $V_{\text{train}}$ and $V_{\text{val}}$ are flipped, the testing accuracy increased dramatically.

4 BLACK-BOX GRADIENT ATTACK

As demonstrated in the above studies, Mettack has the tendency to perturb the edges unevenly. While such unevenness contributes to the performance, it is in lack of robustness since even training the GCN with the validation set will degrade its performance severely. Meanwhile, the tendency to connect dissimilar nodes are also easily utilized by defense algorithms [10, 21].

To increase the robustness of adversarial attacks, the perturbations should be unbiased to any data splits. Thus, indeed the attack is supposed to be black-box to prevent such biases.

While most black-box attacks are based on reinforcement learning [4, 14], random walk-based attacks such as RWCS are also promoted recently to avoid model inquires [13]. However, RWCS focuses on perturbing features instead of graph structures. To our best knowledge, no existing structure-oriented black-box attack works without black-box inquires. Meanwhile, gradients are not exploited in black-box attacks since a surrogate model is needed. However, gradients are powerful tools to pick edges for perturbations. In this paper, by disengaging gradients from any specific training set, we propose the novel Black-Box Gradient Attack (BBGA) algorithm.

4.1 Attack Condition

In this subsection, we introduce the attacking condition of our model systematically.

Goal: As an untargeted attack, the attacker’s goal is to decrease the classification accuracies of GNNs.

Knowledge: As a black-box attack, the access to model parameters, training data and ground-truth labels are denied. The graph $G = (V, E)$ and the node features are considered to be accessible.

Constraints: The number of changes is restricted by a budget $\Lambda$ such that $||A' - A||_0 \leq 2\Lambda$. Here $A'$ is the modified adjacency matrix and we have $2\Lambda$ due to the symmetry of adjacency matrices. In addition, various defense algorithms have taken advantage of the connections between dissimilar nodes [10, 21]. We believe that such easily-detected modifications are supposed to be restricted since they could be easily eliminated by a pre-processing algorithm. Noticing that node features in common graph tasks are encoded in such easily-detected modifications are supposed to be restricted.

Constraints w.r.t. hyperparameters:

\[
\theta^* = \text{opt}_{\theta}(L_i(f_0(G))),
\]

where $L_i$ is the cross-entropy loss on partition $V_i$. Similar to Mettack, the partition score function $S^i : V \times V \rightarrow \mathbb{R}$ on the $i$th partition is defined as:

\[
S^i(u, v) = \nabla_u f_0^i \cdot (2 \cdot A_{uv} + 1).
\]

For each pair of node $(u, v)$, we compute $\sigma_{uv}$, which is the standard deviation of its $k$ partition scores. The greedy score for $(u, v)$ is defined as:

\[
S(u, v) = \begin{cases} 
\sum_{i=1}^{k} S^i(u, v), & \sigma_{uv} < \bar{\sigma} \\
0, & (\sigma_{uv} > \bar{\sigma}) \lor (u = v)
\end{cases}
\]

where $\bar{\sigma}$ is the median of all $\sigma_{uv}s$. The definition eliminates all self-loops and ensures that the gradients of the chosen perturbation on the $k$ partitions are not too diverse.

In each step, we greedily pick exactly one perturbation $e' = (u', v')$ with the highest score:

\[
e' = \arg \max_{e=(u,v) \in \phi(G)} S(u, v),
\]

where $e \in \phi(G)$ ensures that the modification does not conflict with the attack constraints. Then the algorithm updates $G$ according to $e' = (u', v')$ by flipping the value of $A_{u'v'}$.

4.4 Algorithm

Following the detailed description, we now present the pseudo-code of the BBGA algorithm in Algorithm 1.

The meta-gradients of all the nodes $2^2$ pairs of nodes will be computed in the algorithm, the computing of meta-gradients have $T$ steps due to the chain rule and the meta-gradients are calculated for each of the $k$ partitions. Thus, the computational complexity for the attacking procedure itself is bounded by $O(k \cdot T \cdot N^2)$. Considering
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Algorithm 1 Black-Box Gradient Attack (BBGA)

Input: $G = (V, E)$, node features $X$, attack budget $\Delta$, constraint $\phi(G)$, training iteration $T$, partition $\{V_1, \cdots, V_k\}$.

Output: Modified graph $G' = (V, E')$.
1. $C_p \leftarrow$ SpectralClustering($G, X$).
2. $C_s \leftarrow$ training surrogate model with $C_p$ and a random training set.
3. $A' \leftarrow A$
4. while $\|A' - A\|_0 < 2\Delta$ do
5. for $i \in [1, k]$ do
6. randomly initialize $\theta_0$;
7. $\theta_T \leftarrow$ update parameters for $T$ iterations;
8. $V_{G}^{\prime} \leftarrow \nabla_G L_{atk}^{\prime}(f_{\theta_T}(G))$;
9. $S_i \leftarrow V_{G}^{\prime} \odot (-2A' + 1)$;
10. end for
11. $S \leftarrow$ according to Eq. 12;
12. $e' \leftarrow$ the index of the maximum element in $S$ that are in $\phi(G)$;
13. $A' \leftarrow$ flip edge $e'$.
14. end while
15. $G' \leftarrow$ use $A'$ as the new adjacency matrix;
return: $G'$.

5 EXPERIMENTS

In this section, we evaluate our proposed BBGA algorithm against both vanilla GCN and several defense methods. We introduce our experimental settings at first and then we aim to answer the following research questions:

- **RQ1**: How does BBGA works without accessing the training set of the model?
- **RQ2**: Are the attacked graph as expected such that the perturbations are not distributed mainly around the training set?
- **RQ3**: How do different components and hyperparameters affect the performance of BBGA?

5.1 Experimental Settings

5.1.1 Datasets. Cora, Citessor and Cora-ML, which are three commonly-used real-world benchmark datasets, are employed in our experiments. Following [29], we only consider the largest connected components of the graphs. The statistics of the datasets are summarized in Table 2. Following [10], we randomly pick 10% of nodes for training, 10% of nodes for validation and the remaining 80% of nodes for testing.

5.1.2 Defense Methods. To demonstrate the effectiveness of our proposed BBGA method, both vanilla GCN and several defense algorithms are employed in our experiments. For GCN and RGCN we use the official implementation along with its hyperparameters. For other models we use the implementation and hyperparameters in [12].

- **GCN**: In this work, we focus on attacking the representative Graph Convolutional Network (GCN).
- **GCN-Jaccard**: Noticing that existing graph adversarial attacks tend to connect dissimilar nodes, GCN-Jaccard remove the edges that connect nodes with Jaccard similarity scores lower than a threshold $\eta$ before training the GCN.
- **R-GCN**: R-GCN utilizes the attention mechanism to defend against perturbations. Modelling node features as normal distributions, the R-GCN assigns attention scores according to the variances of the nodes.
- **Pro-GNN**: Exploring the low rank and sparsity properties of adjacency matrices, Pro-GNN combines structure learning with the GNN in an end-to-end manner.

5.1.3 Baselines. Since we propose a novel attack condition which is not explored in previous literature, we utilizes baselines from [29] under our proposed constraints. All baselines are restricted by the $\phi(G)$ constraint.

- **DICE-BB**: This baseline is the black-box version of the DICE (Disconnect Internally, Connect Externally) algorithm. No ground-truth labels are accessible and spectral clustering is utilized to generate pseudo-labels.
- **Random**: We also use random attack as a baseline. This baseline randomly adds $\Delta$ edges in the graph.
- **Mettack**: We created a black-box version of Mettack. For fair comparison it also utilizes pseudolabels and the first partition of the nodes is used for training.

5.1.4 Parameters and Experimental Settings. We utilize scikit-learn [15] for spectral clustering with parameter $\gamma = 0.001$. Following [12] we set $\eta = 0.01$. For other hyperparameters, we set $k = 5$ and $T = 100$.

We conducted our experiments on an Ubuntu 16.04 LTS server with two E5-2650 CPUs and 4 GTX 1080Ti GPUs. Python packages we used include Pytorch 1.5.0, Scikit-Learn 0.23.1, NumPy 1.18.5 and SciPy 1.3.1. Tensorflow 1.15.0 is used in R-GCN defenses.

For each perturbation rate we ran the experiments for 10 times. To verify that our proposed BBGA algorithm is not engaged to any specific training set, we randomly altered the dataset splits with scikit-learn[15] each time before the training of the defense algorithms. Following previous works [10, 29] we choose accuracy rate as the primary evaluation metric.

5.2 Attack Performance

In this subsection, we answer the research question **RQ1**. Selected results when attacking against the original GCN is reported in Table 3.

We observe from the table that our proposed method outperforms the baselines in all situations when attacking against the original GCN model. Especially, BBGA outperforms the baselines by 20% in several experimental settings.

| Dataset       | $|V|$ | $|E|$ | Classes | Features |
|---------------|------|------|---------|----------|
| Cora          | 2485 | 5069 | 7       | 1433     |
| Citessor      | 2110 | 3668 | 6       | 3703     |
| Cora-ML       | 2810 | 7981 | 7       | 2879     |

Table 2: Statistics of datasets. Notice that only the largest connected components of the graphs are considered.

the computational efforts needed to find the pseudo-labels [23], the overall computational complexity of BBGA is $O(k \cdot T \cdot N^2) + O(n^3)$.
### Table 3: Misclassification rates when attacking against the GCN (Classification accuracy ± Std).

| Dataset      | Attack | 20%           | 40%           | 60%           | 80%           |
|--------------|--------|---------------|---------------|---------------|---------------|
| Cora         | BBGA   | 23.90±1.28    | 28.98±1.69    | 33.48±2.01    | 37.12±2.09    |
|              | DICE-BB| 21.42±1.16 (-10.37%) | 25.69±1.19 (-10.71%) | 29.43±1.31 (-12.10%) | 33.14±1.52 (-10.72%) |
|              | Random | 21.34±1.74 (-10.71%) | 25.77±1.19 (-11.08%) | 28.43±1.71 (-15.08%) | 32.73±1.76 (-11.83%) |
|              | Mettack| 22.58±1.19 (-5.23%) | 26.82±1.57 (-7.45%) | 28.88±1.26 (-13.74%) | 32.71±1.51 (-11.88%) |
| Citeseer     | BBGA   | 29.44±1.22    | 32.17±1.15    | 35.69±1.24    | 39.46±2.01    |
|              | DICE-BB| 27.92±0.85 (-5.16%) | 30.85±1.41 (-4.10%) | 33.91±1.53 (-4.99%) | 37.22±2.21 (-5.68%) |
|              | Random | 27.25±1.10 (-7.44%) | 29.96±1.48 (-6.87%) | 32.12±0.85 (-10.00%) | 33.68±1.52 (-14.65%) |
|              | Mettack| 27.19±0.76 (-7.64%) | 30.55±1.29 (-5.04%) | 32.59±1.69 (-8.69%) | 36.70±1.67 (-6.99%) |
| Cora-ML      | BBGA   | 30.29±3.03    | 45.10±3.58    | 52.69±5.26    | 60.36±4.96    |
|              | DICE-BB| 25.81±2.47 (-14.79%) | 34.10±4.35 (-24.39%) | 42.27±7.37 (-19.78%) | 55.77±5.60 (-7.60%) |
|              | Random | 24.79±1.64 (-18.16%) | 30.78±2.40 (-31.75%) | 40.74±3.79 (-22.68%) | 47.74±3.90 (-20.91%) |
|              | Mettack| 28.07±1.79 (-7.33%) | 36.81±3.11 (-18.38%) | 42.96±2.93 (-18.47%) | 46.92±2.93 (-22.27%) |

Figure 3: Misclassification rates when attacking against GCN-Jaccard, (a) Cora, (b) Citeseer, (c) Cora-ML.

Figure 4: Misclassification rates when attacking against R-GCN, (a) Cora, (b) Citeseer, (c) Cora-ML.
The performance when attacking against various defend methods are reported in Figures 3, 4 and 5. As shown in the figures, our proposed BBGA algorithms achieves the best misclassification rates in most of the situations. The experiments show that our proposed method is able to achieve a higher misclassification rates when the training set is not accessible.

5.3 Case Study on Perturbations
In this subsection, we answer the research question RQ2 via analysing the perturbations. For a random split of the Cora dataset, we reveal the local perturbation rates in Figure 6. As illustrated in the figure, the perturbations are not biased toward the training set. This demonstrate the evenness of the modifications of our proposed method. It explains the reason why our BBGA algorithm works without accessing the training set.

5.4 Ablation Study and Parameter Analysis
To answer the research question RQ3, we conducted ablation studies and parameter analysis. For ablation study, we created two variant of our method. BBGA-α removes the filter of low-variance node-pairs in Eq. 12. BBGA-β removes the \( k \)-fold greedy choice procedure and in each step, exactly one partition is chosen randomly to compute the meta-gradient. We took Cora and the GCN model as an example. As revealed in Figure 7, BBGA has the best performance while BBGA-β performs the worst. This indicates that both considering multiple partitions and filtering low-variance node-pairs help in increasing the attack performance.

For parameter analysis, we varied the number of partitions \( k \). Taking 80% perturbation rates on Cora as an example, it is revealed that the attack performance grow as \( k \) increases in general. However, since a larger \( k \) implies a longer training time, we suggest to use the hyperparameter \( k = 5 \). The results of the parameter analysis is reported in Figure 8.

6 CONCLUSION
Previous studies demonstrated that GCNs can be easily fooled by adversarial attacks. However, most existing adversarial attacks requires conditions that are not practical in real-world situations. In this paper, we demonstrate that utilizing training set in adversarial...
attacks, which is considered to be unrealistic, leads to the lack of robustness. By utilizing pseudo-labels and the \( k \)-fold greedy strategy, we propose the novel Black-Box Gradient Attack (BBGA) algorithm. Experimental results demonstrate that our proposed algorithm achieves promising performance as a black-box structure-oriented attack. To the best of our knowledge, this is the first gradient-based black-box graph attack and the first non-targeted structure attack that doesn’t require any inquiry. Future directions include further utilization of gradients in black-box scenarios and further investigations in black-box structural attacks.

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