Transferable Graph Backdoor Attack

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ABSTRACT

Graph Neural Networks (GNNs) have achieved tremendous success in many graph mining tasks benefitting from the message passing strategy that fuses the local structure and node features for better graph representation learning. Despite the success of GNNs, and similar to other types of deep neural networks, GNNs are found to be vulnerable to unnoticeable perturbations on both graph structure and node features. Many adversarial attacks have been proposed to disclose the fragility of GNNs under different perturbation strategies to create adversarial examples. However, vulnerability of GNNs to successful backdoor attacks was only shown recently.

In this paper, we disclose the TRAP attack, a Transferable GRAPh backdoor attack. The core attack principle is to poison the training dataset with perturbation-based triggers that can lead to an effective and transferable backdoor attack. The perturbation trigger for a graph is generated by performing the perturbation actions on the graph structure via a gradient based score matrix from a surrogate model. Compared with prior works, TRAP attack is different in several ways: i) it exploits a surrogate Graph Convolutional Network (GCN) model to generate perturbation triggers for a blackbox based backdoor attack; ii) it generates sample-specific perturbation triggers which do not have a fixed pattern; and iii) the attack transfers, for the first time in the context of GNNs, to different GNN models when trained with the forged poisoned training dataset. Through extensive evaluations on four real-world datasets, we demonstrate the effectiveness of the TRAP attack to build transferable backdoors in four different popular GNNs using four real-world datasets.

KEYWORDS

Graph Neural Networks, backdoor attack.

1 INTRODUCTION

Graphs represent an important data structure to model complex real-world relationships and are used in many domains from social networks to chemistry, leading to many important applications such as toxic molecule classification, community detection, link prediction and malware detection [47]. Recently, Graph Neural Networks (GNNs) have achieved great success in graph-structured data processing by learning effective graph representations via message passing strategies, which recursively aggregate features from neighboring nodes [16, 18, 38, 46]. GNNs have outperformed many traditional machine learning techniques for graph processing and become the dominant method for many graph mining tasks [47, 52].

On the one hand, GNNs can achieve superb performance compared with other traditional graph mining methods, as they combine node features and graph structure to learn better representations. For example, Graph Convolutional Networks (GCN) [18] exploit feature propagation via the adjacency matrix of graphs for node representation learning. On the other hand, the intrinsic attribute of the graph-structured data can be easily attacked as the attacker can easily manipulate the local structure of a victim node in a graph to infect others (e.g., a fake connection or user profile in a social network) and thus affect the performance of GNNs. What is more, the message passing strategy of many GNN models can also become an important vulnerability under adversarial attacks [49] via graph structure perturbation. Similar to other type of deep neural networks, GNNs have been shown to be vulnerable and can be easily attacked via unnoticeable perturbation on the graph structure or node features [17, 37].

In recent years, many works [7, 39, 43, 49, 53, 54] have investigated the vulnerability of GNNs to adversarial attacks, where the attackers either modify the graph structure or perturb the node features or both to degrade the performance of GNNs on tasks such as graph-level classification, node-level classification, link prediction, etc. Depending on different type of tasks (inductive or transductive), such adversarial attacks can happen at training or inference phase where the adversarial graphs are used to degrade the performance of GNN models [7, 40, 49, 53, 54]. For example, Dai et al. [7] proposed to use reinforcement learning to determine the perturbation actions (adding or deleting edges) for modifying a graph via querying the feedback from a target GNN classifier for both graph-level and node-level classification tasks. Zügner et al. [53] proposed Nettack, which exploits incremental computations to perturb an attributed network with respect to node features and structures and influence the prediction for a target node. Later, Zügner et al. [54] proposed to perturb a graph based on the meta-gradient of the graph w.r.t.
a surrogate model, and then use the poisoned graph to train new GNNs from scratch to degrade their performance on node classification task. Zang et al. [49] proposed Graph Universal Adversarial Attacks (GUA), whose core idea is to connect a victim node to a bad anchored node and thus misguide the prediction.

Despite the plethora of prior adversarial attacks proposed for GNNs, the threats of backdoor attacks to GNNs have been rarely explored. Backdoor attacks intend to inject a maliciously hidden functionality into the deep learning models. The backdoor model would behave normally on benign inputs, but the hidden backdoor will be activated to mislead the model when the attack-defined trigger is presented [15]. Fig. 1 illustrates the graph backdoor attack, where a trojan GNN manifests the attacker desired decision on a poisoned graph but performs normally on a clean graph. Backdoor attacks have been widely explored in computer vision and natural language processing domains. For example, using a small patch as a trigger could cause the trained image recognition model to malfunction [25]. But only several backdoor attacks against GNNs have been proposed in recent years [44, 50]. For example, Zhang et al. [50] proposed a subgraph based backdoor attack against GNN models which exploits subgraph as universal trigger to poison the training graphs and attacks the graph classification task (We refer this method as Subgraph Backdoor for simplicity). Xi et al. [44] proposed Graph Trojaning Attack (GTA) which also uses subgraphs as triggers for graph poisoning. But unlike Subgraph Backdoor [50], GTA learns to generate adaptive subgraph structure for a specific graph. Different from Subgraph Backdoor and GTA, TRAP learns to generate perturbation trigger, which is adaptive and flexible to different graphs. Fig. 2 illustrates the trigger-embedded graphs based on different backdoor attacks on GNNs. As we can see, subgraph backdoor attack uses the same subgraph as trigger to poison different graphs. GTA generates adaptive subgraphs as triggers for different graphs, where the triggers have the same number of nodes but different structures. We can observe the following characteristics in the current backdoor attacks on GNNs:

1. In Subgraph Backdoor [50], the attacker uses the same subgraph structure as a trigger for poisoning different graphs. Hence, the trigger might not be able to optimally poison different graphs in backdoor attack. The experimental study in [50] shows that the subgraph trigger needs to be very dense to be informative and effective for injecting a backdoor into a GNN.

2. The GTA [44] methods, instead, learns to generate adaptive triggers for graph poisoning. The attack, whilst being effective, is reliant on white-box access to the victim model (assumes having fully control of the targeted GNN model, i.e., model parameters and architecture) to inject the backdoor.

In contrast, we present TRAP attack, a method to generate adaptive perturbation triggers for a black-box and transferable backdoor attack against GNNs. Compared with Subgraph Backdoor, TRAP learns to generate adaptive perturbation based triggers for different graphs to attain better attack effectiveness than a universal subgraph trigger. Compared with GTA, TRAP does not require control over the attacked models. On the contrary, TRAP attack exploits a surrogate GNN model to generate trigger-embedded graphs for data poisoning and then relies on the transferability of the trigger to inject a backdoor into a victim’s GNN model. Fig. 3 shows our attack framework, where the attacker has control over the training dataset, but does not require access to the GNN models adopted by the victims.

The generated trigger is adaptive to different graphs without specific patterns. To determine the best trigger for a graph, we propose a gradient based score matrix to determine the positions of perturbing the graph structure that can lead to the best attack effectiveness. The adversarial trigger-embedded graphs generated by TRAP turn out to be transferable and effective in attacking different GNN models such as Graph Convolutional Networks (GCN) [18], Graph Attention Networks (GAT) [38] and Graph Isomorphism Networks (GIN) [46]. Our contributions are summarized as follows:

- We propose a new attack on GNNs; TRAP attack—a graph structure perturbation based backdoor attack on GNNs.
- The TRAP attack method exploits a surrogate model to learn to generate perturbation-based triggers that are sample-specific and pattern flexible to poison a small fraction of the training data. The poisoned data capable of injecting a backdoor into the surrogate model is shown to successfully transfer to an unseen victim model to enable injecting a backdoor into the model. Hence, TRAP attack can be mounted in a black-box setting, and is a first demonstration of a transferable backdoor attack in GNNs. This is significant because data-driven model building pipelines of GNNs are reliant on, often, publicly available training data, and now, that data may be poisoned to inject a backdoor into the learned model.
- We extensively evaluate our attack on four real-world graph datasets from various domains and test the transferability of the attack across to four different GNNs. Our empirical results show that the poisoned training dataset generated by the TRAP attack can achieve better attack effectiveness than relevant baselines in regards to transferable backdoor attacks.

2 RELATED WORK

Graph Neural Networks (GNNs) have received much attention in recent years and played a critical role in many domains. But similar to the other types of deep neural networks, GNNs are also vulnerable to malicious attacks. Based on the literature, there are two popular types of attacks against GNNs: adversarial attacks and backdoor attacks. Here, we briefly review the two different attacks in the following sections.

2.1 Adversarial Attacks

Adversarial attacks forge adversarial examples with unnoticeable perturbation on the raw data samples to degrade the performance of the trained models. To launch adversarial attacks, attackers require to have knowledge of the targeted model (i.e., white-box attack) [37] or have access to query feedback of the targeted model (i.e., black-box attack) to forge adversarial samples [23, 32]. For example, some adversarial attacks forges adversarial examples by exploiting the gradients of the trained deep learning models with respect to their inputs. These attacks include FGSM [13], JSMA [33], Deepfool [27] and PGD [26].

Most of the above adversarial attacks have been applied to domains such as computer vision and natural language processing [2]. With the
Figure 2: Illustration of trigger-embedded graphs generated by different attacks: (a) original clean graphs; (b) subgraph backdoor by Zhang et al. [50] adopts the same subgraph as a trigger for all graphs; (c) GTA [44] generates subgraphs with different structure for different graphs; (d) TRAP adopts a trigger generation method via structure perturbation akin to adversarial example generation.

Figure 3: TRAP attack framework. TRAP forges perturbation based triggers for graphs to poisons the training dataset. A hidden neural Trojan or backdoor will be embedded into a victim’s GNN once the victim adopts the poisoned dataset to train their GNN model.

development of Graph Neural Networks in recent years, the vulnerabilities of GNNs under adversarial attacks begin to attract researchers’ attention. Some adversarial attacks have been proposed to attack GNNs on different tasks such as link prediction, node-level classification, graph-level classification, graph representation learning, etc. The graph adversarial examples are forged by perturbing the original graph structure (i.e., adding or deleting an edge), or node features (i.e., flipping node feature), or both graph structure and node features [43, 45, 53]. Existing gradient-based adversarial attacks have been adapted to the graph domain. For example, Wu et al. [43] proposed integrated gradients based on FGSM and JSMA to overcome the challenges in perturbing the discrete graph structure or features for crafting adversarial examples. The integrated gradients are used as guidance to decide the positions for perturbing edges or features. In addition, other gradient-based attack methods such as Nettack [53] have been proposed to forge perturbations on graph structure and node features to create adversarial samples to perform attack on Graph Convolutional Networks (GCN) [18].

2.2 Backdoor Attacks

Backdoor attacks attempt to mislead the deep learning models via embedding a hidden malicious functionality (i.e., backdoor) into the affected model. Backdoor attacks appear in both the training phase and inference phase. During the training phase, a hidden malicious functionality is embedded into the targeted model by poisoning a small ratio of training samples with a special pattern called a trigger. The trigger can be either sample-agnostic (e.g., same patch or sticker for different images) or sample-specific (i.e., adaptive perturbation noise for different images). During the inference phase, the backdoor model behaves normally for benign inputs with the absence of a trigger. But as long as the inputs are embedded with a trigger, the backdoor would be activated and mislead the model’s prediction. Backdoor attacks have been mainly studied in the computer vision domain. For example, Gu et al. [14] first revealed the backdoor threat is realistic in deep neural networks and demonstrated backdoor attacks via using a small sticker as a trigger to mislead an
image classifier to label a stop sign as a speed limit sign. Liu et al. [25] also revealed the threats of neural trojans by using a simple patch into a digit number dataset as trigger to train a backdoor model. Liao et al. [21] proposed to use small static or adaptive perturbation as invisible triggers to attack a CNN model for image classification. Similarly, Li et al. [20] proposed to using auto-encoder to generate sample-specific invisible noise as trigger via encoding an attacker specified string to poison images. Zhao et al. [51] proposed to apply backdoor attacks into video recognition models with universal adversarial perturbations and hidden backdoor triggers into clean-label poisoned data samples. Muñoz-González et al. [29] and Bao et al. [9] exploited GANs to generate triggers, the latter focusing on spatially constrained naturalistic trigger generation while the former investigated generating adversarial training samples.

In addition to adversarial attacks on GNNs, backdoor attacks against GNNs have also been proposed in recent years. For example, Zhang et al. [50] proposed to use subgraph as universal trigger to poison the training dataset and train backdoor GNN models. Their backdoor attack is targeted, where the labels of the poisoned graphs are manipulated to be different with the targeted label. Similar to the backdoor attacks in the other domains, the special subgraph trigger pattern is embedded into GNNs as a hidden backdoor. The backdoor GNNs would predict a graph as the desired label as long as the same subgraph trigger is embedded. They tested their attack transferability on three GNN models (i.e., GIN, SAG-Pool and HGP-SL) and the results showed that the attack effectiveness heavily relies on the trigger size. Xi et al. [44] proposed Graph Trojaning Attack (GTA) for targeted backdoor attacks on GNNs. Compared with [50], GTA creates adaptive subgraphs as trigger for different graphs. Specifically, GTA iteratively train a trigger generator with a pre-trained GNN which used to forge backdoor. To make sure that GTA is effective on the trigger-embedded graphs and evasive on benign graphs. They have two constraint when training a trojan GNN: (1) the embeddings of benign graphs generated by the trojan GNN are forced to be similar to the embedding generated by the pre-trained clean GNN; (2) the embeddings of poisoned graphs generated by the trojan GNN are forced to be similar with the embedding of benign graphs in the targeted class. They formulated the two constraints as a bi-level optimisation problem, and adopted $L_2$ distance as the loss function to train a trojan GNN model.

3 PROBLEM FORMULATION

We consider the task of graph classification, which has been widely applied in security-critical domains such as toxic chemical classification and malware call graph classification. Given a set of graphs as training data with labels, the goal of graph classification is to train a graph classifier (using Graph Neural Networks) and infer the class of an unlabeled graph. Formally, let $\mathcal{D}$ be a graph dataset containing $n$ graph instances $\{(G_1, y_1), \ldots, (G_n, y_n)\}$, where $G_i$ is the $i^{th}$ graph and $y_i$ is one of the $K$ labels in the label space $\mathcal{Y} = \{c_1, c_2, \ldots, c_K\}$. The goal is to learn a function $F : G \rightarrow \mathcal{Y}$, which maps each unlabeled graph $G$ to one of the $K$ classes in $\mathcal{Y}$. A graph $G$ contains two parts: $A$ is the adjacency matrix and $X$ is the node feature matrix.

Note that the mapping function $F$ contains two modules in our setting: $f$ is normally the representation learning module (i.e., Graph Neural Networks) and $h$ is the classifier module (e.g., a fully connected neural network). The parameters of $f$ are learned by gradient-descent based optimization with a loss function $\mathcal{L}_{\text{train}}$ (e.g., cross-entropy) on the labeled dataset $\mathcal{D}$ as:

$$\theta^* = \arg \min_{\theta} \mathcal{L}_{\text{train}}((h \circ f)_{\theta}(\mathcal{D})).$$  \hspace{1cm} (1)

3.1 Threat Model

**Attacker’s goal.** Backdoor attacks inject malicious functions as hidden neural trojans into the target model, and the hidden trojan would be activated and mislead the model to make a desired output when the pre-defined patterns, called triggers, are present. In our work, the attacker’s goal is to exploit backdoor attacks to impact the GNN models trained by end users with two objectives [44]: (1) the backdoor GNN models should have normal accuracy on benign graphs; (2) the backdoor GNN models should make desired decisions on trigger-embedded graphs.

Suppose we have a backdoor GNN model $F = (h \circ f)_\theta$ and a clean GNN model $F_\theta = (h \circ f)_\theta$. The two objectives of the attack can be formally defined as follows:

$$\begin{align*}
F(G) &\approx F_\theta(G) \\
F(G_{y_t}) &\approx y_t,
\end{align*}$$  \hspace{1cm} (2)

where $y_t$ is the targeted attack class and $y_t$ denotes a trigger. $G$ and $G_{y_t}$ represents a clean graph and a trigger embedded graph, respectively. From Eq. 2 we can see that the first objective specifies the evasiveness of a trojan GNN model, i.e., that the trojan and clean models behave similarly on the clean graphs, while the second objective represents the attack effectiveness, i.e., that the trojan model will predict the trigger-embedded graph in the targeted attack class.

**Attacker’s knowledge.** To launch backdoor attacks, the attacker can have different levels of knowledge about the target, such as access to the training data $\mathcal{D}$, the parameters and structure of the target GNN models $F_\theta$ used by users, the classifier $h$, etc. Usually, if the attacker requires less knowledge to the target, then the attacks are also more realistic and dangerous. In our work, we focus on more realistic attacks and assume the attacker has limited knowledge as shown in the following:

- The architecture and parameters of the GNN models are agnostic to the attacker.
- The attacker could poison a small ratio of the training dataset with triggers.

Our attack aims at poisoning the training data with trigger-embedded graphs for backdoor attacks, and do not assume any knowledge on the targeted GNN models.

**Attacker’s capability.** As the attacker has no access to the targeted GNN models, we thus use a surrogate model as the object of our attack. We use the surrogate model to tune the trigger generation on the training dataset and train backdoor GNN models. We then publish the poisoned training dataset to transfer the backdoor attack on GNN models that will be adopted by the end users. In order to achieve the attack goals (i.e., effectiveness and evasiveness), our attacks have to meet the two requirements:

- The poisoned graphs should be transferable to different unseen GNN models.
- The triggers embedded in the poisoned graphs should be unnoticeable to users.

To meet the first requirement, our attack forges a trigger to poison a graph by perturbing the graph structure at the edge positions where the message passing of a surrogate GNN model would be maximally influenced. To meet the second requirement, different from [44] and [50] where a trigger is a subgraph, our attack generates an adaptive trigger for a graph which does not have specific pattern and has small perturbation size.

3.2 Surrogate GNN model

Graph Neural Networks (GNNs) have demonstrated great expressiveness in graph representation learning by fusing both graph structure
and node features with the message passing strategies over the graph edges. Moreover, GNNs can also implicitly aggregate features from k-hop neighbors with multi-layers. There are many variants of GNNs. We adopt a Graph Convolutional Networks (GCN) [18] as our surrogate model to launch the backdoor attack, considering the universality of its message passing strategy. Specifically, for a graph \( G = (A, X) \) where \( A \) is the adjacency matrix and \( X \) is the node attribute matrix, the graph representation learning of a multi-layer GCN is performed as follows:

\[
Z^{(l)} = \delta(D^{-\frac{1}{2}}A D^{-\frac{1}{2}}Z^{(l-1)}W^{(l)}),
\]

where \( \delta = A + I, D \) is the degree matrix based on \( \delta \), \( \delta \) is an activation function such as \( ReLU(\cdot) = \max(0, \cdot) \), and \( W^{(l)} \) is the trainable parameters for the \( l \)-th GCN layer. \( Z^{(l)} \) is the leaned representations for the graph nodes. As shown in Eq. 3, GCN aggregates the node features from the local neighborhood structure through the normalized adjacency matrix. Since GCN is original designed for node classification, it learns the representation of a graph at the node level. In order to classify a graph, we use a pooling layer (e.g., max pooling) to get the graph-level representation and then use a simple fully connected neural network layer with softmax for classification.

4 ATTACK METHOD

In this section, we detail our proposed TRAP attack. From a high-level aspect, the core idea of TRAP is to construct trigger-embedded graphs to poison the training dataset. Once the poisoned dataset is used to train a new GNN model from scratch, the trained model will be embedded with a backdoor.

4.1 Attack Design

Suppose we have a clean graph dataset \( D \) which can be partitioned into two parts: \( D[y_t] \) and \( D[\neg y_t] \). The candidate graphs for embedding trigger are randomly sampled from \( D[\neg y_t] \), whose true labels are not the targeted attack label \( y_t \). To forge trigger-embedded graphs, our attack goals can be formulated as the following optimization problem:

\[
\min_{G_{gt} \in \Phi(G)} L_{atk} \left( F_{\theta'}(G_{gt}) \right) \quad \text{s.t.} \quad \theta^* = \arg \min_{\theta} L_{train} \left( F_{\theta}(D) \right),
\]

where \( L_{atk} \) is the loss function used by the attacker for constructing poison graphs while \( L_{train} \) is the loss function for training a graph classifier (surrogate model in our attack). \( \Phi(G) \) denotes an admissible space for constructing a trigger-embedded graph with a given constraint. Recall that the attacker can manipulate the label of the poisoned graphs and replace them with the targeted attack class. Also, the ratio of poisoned graphs compared with the clean training graphs is low (e.g., 5%). Once we have a trained model, \( F_{\theta'} \), a candidate graph \( G \) for poisoning tend to be classified by \( F_{\theta'} \) as its true label. Hence, the attacker needs to generate a trigger that the graph can mislead the \( F_{\theta'} \) under a limited budget. Therefore, the loss function of \( L_{atk} \) can be the same as \( L_{train} \) as the training label of a poisoning \( G \) for attack is already manipulated as \( y_t \).

Unlike the previous graph backdoor attacks [44, 50] that regard the trigger as a subgraph, the trigger in our attack is more flexible and without a specific shape. We generate an adaptive trigger for a graph in adversarial style by perturbing the structure of the graph via adding or deleting edges that lead to the maximum decrease of the attacking loss \( L_{atk} \). Meanwhile, we limit the edge perturbation size so that the changes on poisoned graphs are unnoticeable. The benefit of perturbing the graph structure to forge trigger are two-fold: (1) Since GNNs rely on message passing on the graph structure for feature aggregation, perturbing the structure may lead to transferable triggers. (2) A perturbation based graph trigger at flexible edge positions shows randomness and does not have specific patterns, which could be stealthier.

To determine the best edge position to perturb, an intuitive way is to treat the graph adjacency matrix as hyper-parameter and compute its gradients with respect to the attack loss:

\[
\nabla_{G_{gt}} = \nabla_{G_{gt}} L_{atk} \left( F_{\theta'}(G_{gt}) \right) \quad \text{s.t.} \quad \theta^* = \arg \min_{\theta} L_{train} \left( F_{\theta}(D) \right)
\]

The best model parameter \( \theta^* \) is normally determined after training the surrogate model via stochastic gradient descent as:

\[
\theta_{t+1} = \theta_t - \alpha \nabla_{\theta} L_{train} \left( F_{\theta}(D) \right)
\]

We then update \( G_y \) based on \( \nabla_{G_{gt}} \). A straightforward way is to perturb \( G_y \) with gradient descent: \( G_{y_t} = G_y - \beta \nabla_{G_{gt}} \). However, unlike the continuous domains (e.g., images), graphs are unstructured and discrete, so directly applying the gradient-based update is not suitable for graphs. Moreover, due to the limited budget for perturbing a graph, we also can not perform a global update on the graph structure. Thus, we propose to partially perturb the graph structure based on the gradient with a simple strategy to maintain the graph discreteness and maximize the attack performance under a limited budget.

4.2 Perturb Graph Structure for Trigger Embedding

Recall that we treat the graph structure as a hyper-parameter and compute the gradient of the attack loss with respect to it. Thus, for a graph \( G \) with node size \( n \), the shape of the gradient matrix is \( \nabla_{G_{gt}} \in \mathbb{R}^{n \times n} \), where each entry denotes the gradient between two nodes. Considering the discreteness of the graph, the perturbation on a graph structure can only have two possible cases: Delete an existing edge or add a new edge between two nodes. Similar to the adversarial attack in [54], we define a score function to combine the gradient and the adjacency matrix, and assign the possible perturbation between each node pair a numerical value to indicate the change. Specifically, for a given node pair \((u, v)\) with \( e_{uv} \) as its existing edge status (i.e., 0 or 1) in the graph adjacency matrix. The score function is defined as

\[
S(u, v) = \nabla_{G_{gt}} \cdot (2e_{uv} - 1).
\]

The score function retains the sign of the node pair’s gradient if there is an existing edge such that its edge can be changed in the gradient direction or vice versa. Then, we greedily pick the \( M \) highest scores in \( S \) for perturbation, where \( M \) is our attack budget (i.e., number of edge perturbations). The updates meet the requirement of the discreteness of graph structure via adding or deleting an edge given the current status of \( e_{uv} \). Algorithm 1 sketches our attack flow.

5 ATTACK EVALUATION

In this section, we conduct empirical studies to answer the following research questions:

Q1: Is TRAP effective on graph classification task?
Q2: Is TRAP transferable to different GNNs?
Q3: Is the transferability of TRAP affected by the structure of the attacked GNN?
Q4: What is the impact of data poisoning rate on TRAP?
Q5: What is the impact of edge perturbation size to TRAP?
Algorithm 1: TRAP Attack

**Input:** Graph dataset \( D \), targeted attack class \( y_t \), attack budget \( M \), training epochs \( T \), learning rate \( \alpha \);

**Output:** Poisoned graph set \( \{ G_{yt} \} \);

1. \( G_{yt} \leftarrow \) randomly sample candidate graphs from \( D \) \( \setminus \{y_t\} \);
2. Change label of graphs in \( \{ G_{yt} \} \) to \( y_t \);
3. Initialize surrogate model \( F_{yt} \);
4. for \( t \leftarrow 0 \) to \( T - 1 \) do
   5. \( \theta_{t+1} \leftarrow \theta_t - \alpha \nabla \theta_t, L_{\text{train}}(D) \);
5. end
6. for \( G_{yt} \in \{ G_{yt} \} \) do
   7. // Eq. 5, calculate the gradient of graph structure
5. \( \nabla G_{yt} = \nabla G_{yt} L_{\text{atk}}(F_{yt}(G_{yt})) \);
8. // Gradient based score matrix for graph structure
9. \( S \leftarrow \nabla G_{yt} \cdot (2G_{yt} - 1) \);
10. // Find \( M \) number of entries for perturbation
11. \( \{(u, v)\}_i^M \leftarrow \) get \( M \) number of maximum node pairs based on score \( S \);
12. Add or delete edges \( \{(u, v)\}_i^M \) for \( G_{yt} \);
13. end
14. // The trigger-embedded graphs will be used to poison training dataset
15. return trigger-embedded graphs \( \{ G_{yt} \} \).

Experimental Settings

**Datasets.** We evaluate TRAP with four real world datasets. Table 1 shows the basic statistics for each dataset, including the graph numbers in the dataset, the average number of nodes per graph, the average number of edges per graph, the number of classes, the number of graphs in each class and the target class for attack. We choose the class which has least data samples as the target class for attack.

FRANKENSTEIN, Fingerprint and PROTEINS are collected from TU-DATASET [28], which is a collection of graph datasets for graph classification and regression. FRANKENSTEIN is created by the fusion of the BURLSI and MNIST datasets, where BURLSI corresponds to 4337 molecules, with 2401 mutagens and 1936 nonmutagens [30]. Fingerprint is a collection of fingerprints formatted as graph structures from the NIST-4 database [42]. PROTEINS is a set of macromolecules used to predict the existence of enzymes in a protein molecule [10]. WinMal is a collection of API call graphs extracted from 1,361 Windows PE (portable executable) files, including 815 malware and 546 goodware [34].

**Metrics.** We evaluate the compared methods with two metrics to evaluate the effectiveness and evasiveness of the attacks. The first metric is Attack Success Rate (ASR), which measures the success rate with which a backdoor GNN model predicts a trigger-embedded graph into the designated class:

\[
\text{Attack Success Rate (ASR)} = \frac{\# \text{successful attacks}}{\# \text{total trials}}.
\]

The second metric is Clean Accuracy Drop (CAD), which measures the accuracy difference between a clean GNN model and a trojan GNN model in prediction on clean data samples.

**Baselines.** We compare TRAP attack with two state-of-the-art baselines.

- Subgraph backdoor by Zhang et al. [50] embeds a predefined subgraph as a universal trigger into training graphs to backdoor GNN models. The subgraph trigger is controlled by the graph size, the density and synthesis method.

- Graph Trojaining Attack (GTA) by Xi et al. [44] trains a trigger generator to generate adaptive subgraphs as a trigger for a graph. The trigger generator is trained together with a pre-trained target GNN model by iteratively updating parameters. The training process will continue until the trigger generator generates triggers that can successfully backdoor the pre-trained GNN model.

**Attacked GNN models.** We investigate the transferability of TRAP to different GNN models and assume that the attacked GNN models are agnostic. We choose four popular GNN models: Graph Convolutional Networks (GCN) [18], Graph Isomorphism Network (GIN) [46], GraphSAGE (GSAE) [16] and Graph Attention networks (GAT) [38] as the attack models. Table 2 shows the clean model accuracy on different datasets and GNN models.

To launch attacks, we poison the training dataset with trigger-embedded graphs. Then, the poisoned training dataset will be used to train and backdoor the GNN models. Subgraph backdoor [50] generates a subgraph as a universal trigger to poison the training dataset. For the GTA [44] and TRAP, a surrogate GNN model is required to forge an adaptive trigger into a graph. We choose GCN as the surrogate model for both GTA and TRAP. By default, we apply the same structure settings (i.e., the number of layers and neurons) between surrogate model and victim GNN models to test the attack transferability.

**Dataset splits and construction.** The same data split rules are applied to all the methods. We randomly split the dataset into three parts: 70% is used for a clean training dataset, 20% is used as a clean testing dataset and the remaining 10% will be used to embed triggers (poisoned graphs).

The graphs used for trigger embedding are chosen from the non-targeted classes, and their label will be manipulated into the target class. Half of the poisoned graphs will be mixed with the clean training dataset to construct a poisoned training dataset, and the remaining poisoned graphs will be used for testing at inference time.

**Parameter settings.** All the adopted GNN models contain a two-layer (the neuron sizes are 16 and 8 in each layer) structure followed by a max pooling layer for node level feature aggregation, and a fully connected layer with softmax for graph classification. The subgraph trigger size for and GTA is set as 5 nodes. Subgraph Backdoor adopts the Erdős-Rényi (ER) [12] model to generate a subgraph as trigger with its trigger density set as 0.8. GTA adopts a three layer fully connected neural network as trigger generator. Adam optimizer with learning rate of 0.01 is used to train the GNN models. Table 3 shows the parameter settings for all the adopted GNNs and our experimental studies.

**Q1: Is TRAP Effective on Graph Classification Tasks?** Table 4 summarizes the performance of different attacks on the GCN model. Overall, TRAP achieves much better attack effectiveness and evasiveness than its counterpart methods.

Specifically, all the attacks achieve high attack effectiveness on the FRANKENSTEIN dataset. The best attack is from the proposed TRAP, with over 0.95 ASR achieved, while the ASR of Subgraph Backdoor and GTA are 0.8360 and 0.9429, respectively. On the other three datasets, TRAP still achieves the highest ASR compared with the other two baselines. For instance, on Fingerprint, the ASR of TRAP on GCN is 0.7241, while TRAP still shows much better ASR than the other attacks.
Table 1: Dataset statistics.

| Dataset    | # Graphs | # Nodes (Avg.) | # Edges (Avg.) | # Classes | # Graphs in Class | Target Class |
|------------|----------|----------------|----------------|-----------|-------------------|--------------|
| FRANKENSTEIN | 4,337    | 16.90          | 17.88          | 2         | 1936 [0], 2401 [1]| 0            |
| Fingerprint | 1,459    | 8.92           | 7.55           | 3         | 472 [0], 536 [1], 451 [2] | 2            |
| PROTEINS   | 1,113    | 39.06          | 72.82          | 2         | 663 [0], 450 [1]  | 1            |
| WinMal     | 1,361    | 781.87         | 1849.41        | 2         | 546 [0], 815 [1]  | 0            |

Table 2: Clean model accuracy.

| Dataset    | GNN models |
|------------|------------|
|            | GCN | GIN | GSAGE | GAT |
| FRANKENSTEIN | 0.6737 | 0.6194 | 0.5899 | 0.6275 |
| Fingerprint | 0.8255 | 0.8356 | 0.6947 | 0.8767 |
| PROTEINS   | 0.7195 | 0.7014 | 0.6995 | 0.7354 |
| WinMal     | 0.8322 | 0.8220 | 0.8066 | 0.8791 |

Table 3: Parameter settings.

| Type       | Parameter                  | Settings              |
|------------|----------------------------|-----------------------|
| GIN        | Architecture              | two layers (16, 8)    |
| GCN, GIN, GSAGE, GAT | Classifier         | FCN + Softmax         |
|            | Aggregator                | Max Pooling           |
| GAT        | Number of heads           | 3                     |
| Subgraph Backdoor | Trigger size   | 5                     |
|            | Trigger density           | 0.8                   |
|            | Trigger generation        | Error (12)            |
| GTA        | Trigger size              | 5                     |
|            | Trigger generator         | 3 layers FCN          |
| TRAP       | Edge perturbation size    | 5 (insertion or deletion) |
|            | Optimizer                 | Adam                  |
|            | Learning rate             | 0.02                  |
|            | Weight decay              | 5e^-4                 |
|            | Batch size                | 100                   |
|            | Epochs                    | 50                    |
|            | Poisoned data rate        | 5%                    |

CAD achieved by Subgraph Backdoor and GTA (0.0271 and 0.0274 respectively). The CAD of TRAP is less than 2.5%. Even though Subgraph Backdoor and GTA show lower CAD on the other three datasets, they can not achieve better ASR indicating that the attacks from Subgraph Backdoor and GTA are less effective. Overall, TRAP shows better balance between effectiveness (ASR) and evasiveness (CAD) than Subgraph Backdoor and GTA.

Q2: Is TRAP Transferable to Different GNNs?
In this set of experiments, we investigate the attack transferability of TRAP to different GNN models. The attacked models have the same structure setting as the surrogate model (i.e., two layers with each neuron sizes are set as 16 and 8).

Table 5 and Table 6 summarize the attack efficacy of transferability on GAT, GIN and GSAGE with regard to the attack effectiveness (ASR) and attack evasiveness (CAD). The results show that TRAP can achieve much better attack transferability to different GNN models. However, the backdoor attacks from the two baselines cannot be transferred effectively to different GNN models.

First, we can see from Table 5 that TRAP achieves better ASR than the other two baselines on most of the datasets. For example, on the FRANKENSTEIN dataset, the ASR achieved by TRAP is 0.8208, 0.9823 and 1.0 for GAT, GIN and GSAGE, respectively. GTA achieves the best ASR on GAT and second best on GSAGE, which are 0.9018 and 0.9523, but lowest ASR on GIN which is only 0.68. Subgraph Backdoor achieves the second best ASR on GIN, which is 0.9206, but lower ASR on GAT and GSAGE, which are 0.5079 and 0.8677, respectively.

On the other three datasets, TRAP still achieves the highest ASR compared with the other two baselines, except for GSAGE on Fingerprint. For instance, on Fingerprint, the ASR of TRAP method on GAT and GIN are 0.8621 and 0.7586, which are higher than GTA (0.6939 and 0.4318) and Subgraph Backdoor (0.3596 and 0.3864). Similar trends can be found on the PROTEINS and WinMal datasets. The ASR achieved by GTA and Subgraph Backdoor has dropped significantly. For example, on the WinMal dataset, the ASR of GTA on GAT, GIN and GSAGE can only achieve 0.4615, 0.3056 and 0.1613, respectively, while TRAP still shows much better ASR across the three GNN models (i.e., 0.7222, 0.6111 and 0.6111) on the Winmal dataset.

Table 6 shows the attack evasiveness in regard to clean accuracy drop. The TRAP method shows overall lower clean accuracy drop compared with Subgraph Backdoor and GTA, which indicates that the TRAP attack method has better evasiveness. On the FRANKENSTEIN dataset, the clean accuracy drop of the TRAP attack is less than 2% across different GNN models. The average CAD of Subgraph Backdoor on FRANKENSTEIN across the GNNs is over 3% and the highest CAD is over 6%. GTA shows slightly lower CAD than Subgraph Backdoor on FRANKENSTEIN. For example, the CAD on GIN is 1.5%, which is the lowest among the three attack methods, but higher CAD on GAT and GSAGE than TRAP. For some cases, the CAD of GTA and Subgraph Backdoor is over 3% and the highest CAD is over 6%. GTA shows slightly lower CAD than Subgraph Backdoor on FRANKENSTEIN.

Q3: Is the Transferability of TRAP Affected by the Structure of the Attacked GNNs?
In this set of experiments, we evaluate the transferability of the backdoor attack when the attacked GNNs have different structures compared to the surrogate model. The structure of the surrogate model is set as two layers with neuron sizes set as 16 and 8, and the structure of the attacked GNN models is set as two layers with neuron sizes set 32 and 16.

Tables 7 and 8 show the attack success rate and clean accuracy drop, respectively. For the attack effectiveness, we can see in Table 7 that our TRAP attack still outperforms the other two baselines in attack success rate in most of the cases. GTA has higher ASR than the TRAP attack, but only on the datasets FRANKENSTEIN and PROTEINS when attacking GCN and GAT. The Subgraph Backdoor performs the worst...
Table 4: Comparison of attack effectiveness on the GCN model (the model employed as the surrogate). Highest Attack Success Rate (ASR) and lowest Clean Accuracy Drop (CAD) scores are highlighted.

| Dataset    | Subgraph Backdoor | GTA | TRAP |
|------------|-------------------|-----|------|
|            | ASR       | CAD   | ASR    | CAD     | ASR       | CAD   |
| FRANKENSTEIN | 0.8360 | 0.0271 | 0.9429 | 0.0274 | 0.9595 | 0.0197 |
| Fingerprint | 0.2955 | 0.0147 | 0.6818 | 0.0014 | 0.7241 | 0.0171 |
| PROTEINS    | 0.3333 | 0.0004 | 0.4137 | 0.0084 | 0.7778 | 0.0224 |
| WinMal      | 0.4909 | 0.0150 | 0.1176 | 0.0215 | 0.7593 | 0.0183 |

Table 5: Attack Success Rate (effectiveness) comparison. Highest ASR are highlighted. The structure of surrogate GNN is same with the attacked GNNs.

| Dataset    | Subgraph Backdoor | GTA | TRAP |
|------------|-------------------|-----|------|
|            | ASR       | CAD   | ASR    | CAD     | ASR       | CAD   |
| FRANKENSTEIN | 0.5079 | 0.9206 | 0.8677 | 0.9018 | 0.9018 | 0.9823 | 1.0 |
| Fingerprint | 0.3596 | 0.3864 | 0.4205 | 0.6939 | 0.4318 | 0.6591 | 0.8621 | 0.7586 | 0.5862 |
| PROTEINS    | 0.2576 | 0.4697 | 0.3333 | 0.5294 | 0.6552 | 0.5517 | 0.5556 |
| WinMal      | 0.40   | 0.60  | 0.5818 | 0.4615 | 0.3056 | 0.1613 | 0.7222 | 0.6111 | 0.6111 |

Table 6: Clean Accuracy Drop (evasiveness) comparison. Lowest CAD are highlighted. The structure of surrogate GNN is same with the attacked GNNs.

| Dataset    | Subgraph Backdoor | GTA | TRAP |
|------------|-------------------|-----|------|
|            | ASR       | CAD   | ASR    | CAD     | ASR       | CAD   |
| FRANKENSTEIN | 0.0360 | 0.0660 | 0.0368 | 0.0192 | 0.0155 | 0.0264 | -0.0116 | 0.0185 | 0.0080 |
| Fingerprint | -0.0190 | 0.0314 | 0.0047 | 0.1327 | 0.0186 | 0.0413 | 0.024 | 0.0 | -0.0136 |
| PROTEINS    | 0.0194 | 0.049 | 0.0407 | 0.0401 | 0.1786 | 0.0862 | 0.0134 | 0.0224 | 0.009 |
| WinMal      | -0.0229 | 0.0884 | 0.0361 | 0.0116 | 0.0280 | 0.0932 | 0.0036 | 0.0183 | 0.0147 |

Table 7: Attack Success Rate (effectiveness) comparison. Highest ASR are highlighted. The structure of surrogate GNN is different with the attacked GNNs.

| Dataset    | Subgraph Backdoor | GTA | TRAP |
|------------|-------------------|-----|------|
|            | ASR       | CAD   | ASR    | CAD     | ASR       | CAD   |
| FRANKENSTEIN | 0.7302 | 0.4497 | 0.8783 | 0.9247 | 0.9247 | 0.9827 | 0.9769 |
| Fingerprint | 0.2247 | 0.4270 | 0.2022 | 0.6957 | 0.5909 | 0.3259 | 0.6379 | 0.8448 | 0.6034 | 0.5517 |
| PROTEINS    | 0.2879 | 0.2424 | 0.1818 | 0.3607 | 0.1936 | 0.1724 | 0.3125 | 0.7778 | 0.8889 | 0.5333 | 0.4444 |
| WinMal      | 0.3455 | 0.2545 | 0.4    | 0.2121 | 0.1026 | 0.1290 | 0.2941 | 0.1290 | 0.3125 | 0.8 | 0.6222 | 0.5333 | 0.4444 |

Table 8: Clean Accuracy Drop (evasiveness) comparison. Lowest CAD are highlighted. The structure of surrogate GNN is different with the attacked GNNs.

| Dataset    | Subgraph Backdoor | GTA | TRAP |
|------------|-------------------|-----|------|
|            | ASR       | CAD   | ASR    | CAD     | ASR       | CAD   |
| FRANKENSTEIN | 0.0270 | 0.0225 | 0.07   | 0.02    | 0.0296 | 0.0524 | -0.0035 | 0.0184 | 0.0011 | -0.0185 | 0.0150 | -0.0023 |
| Fingerprint | 0.0253 | 0.0063 | 0.0127 | 0.0 | -0.0099 | -0.0005 | 0.0406 | 0.0368 | 0.0170 | 0.0034 | 0.0442 | -0.0274 |
| PROTEINS    | 0.0129 | 0.0064 | 0.0194 | 0.0129 | 0.0411 | 0.0768 | 0.024 | 0.0420 | 0.0179 | 0.0044 | -0.0090 | 0.0090 |
| WinMal      | 0.0367 | 0.0184 | 0.0091 | 0.0459 | 0.0158 | 0.1013 | 0.0307 | 0.0317 | -0.0037 | -0.0183 | 0.0219 | 0.0073 |

among the three attacks. Specifically, on FRANKENSTEIN, TRAP shows good overall ASR across the four different GNNs. The ASR scores are 0.8786, 0.8844, 0.9827 and 0.9769 on GCN, GAT, GIN and GSAGE, respectively. Compared with the TRAP, GTA reaches better ASR scores on FRANKENSTEIN with GCN and GAT, which are 0.9247 and 0.9135, but lower ASR scores with GIN and GSAGE, which are 0.5534 and 0.7272. On Fingerprint, the ASR scores of TRAP are 0.6379, 0.8448, 0.6034 and 0.5517 with GCN, GAT, GIN and GSAGE. GTA shows higher ASR (0.6957) on Fingerprint with GCN but lower ASR with the other GNN models. Both Subgraph Backdoor and GTA show decreased ASR scores when the attacked GNNs have increased the complexity (bigger neuron sizes). Subgraph Backdoor use a universal trigger to poison the graphs and does not require a surrogate model to generate triggers. As the GNN model increases in complexity, the universal trigger based attack becomes weak. On the other hand, when the attacked GNNs have different structures to the surrogate model, the attack from GTA becomes less effective. This indicates that the backdoor attack from GTA is sensitive to the GNN structure.

As for the clean accuracy drop shown in Table 8, we can see that the TRAP has lower drop in most of the cases. Even though the GTA
and Subgraph Backdoor attacks show lower CAD scores in some cases, TRAP shows better balance between the two objectives: effectiveness and evasiveness.

Q4: What is the Impact of Data Poisoning Rate on TRAP?

This set of experiments evaluate the impacts of data poisoning rate on the effectiveness and evasiveness of TRAP. Intuitively, more trigger-embedded graphs contained in the training data would make the neural networks become better in recognizing the pattern of the trigger. Fig. 4 shows the attack success rate and clean accuracy drop based on different training data poisoning rates on the adopted datasets. The ASR of TRAP monotonically increases with the training data poisoning rate, and the trend is consistent on different datasets. Take FRANKENSTEIN as an example. When the poisoning rate is 1%, the ASR on GCN, GSAGE, GIN and GAT is around 0.60, 0.80, 0.95 and 0.70, respectively. When the data poisoning rate increases to 7%, we can see that the ASR on GCN, GSAGE, GIN and GAT increases to 0.96, 1.0, 1.0 and 0.89, respectively. The ASR shows a sharp increase when the poisoning rate increased from 1% to 5%. This trend can be found on other datasets such as FRANKENSTEIN and PROTEINS. But the ASR does not increase much when the poisoning rate is increased from 5% to 7%. This phenomenon indicates that TRAP does not rely on higher data poisoning rate to be successful. On the contrary, the generated adversarial style trigger pattern is quite poisonous for effectively training a backdoor GNN model.

As for the influence of poisoning rate on clean accuracy drop, we can see that the CAD does not show a consistent pattern with the increasing of poisoning rate. In most of the cases, the clean accuracy drop is less then 2%. A higher data poisoning rate does lead to a big CAD. On the contrary, the CAD keeps at a similar level on most datasets when the data poisoning rate changes from 3% to 7%.

Q5: What is the Impact of Edge Perturbation Size on TRAP?

This set of experiments evaluate the impacts of edge perturbation size on the effectiveness and evasiveness of TRAP. Fig. 5 shows the impact of edge perturbation size on the attack effectiveness and evasiveness. Normally, larger perturbations on the graph could lead to more informative triggers in a backdoor attack (e.g., the pattern of the trigger is significant enough to influence the neural networks). As we can see in most of the cases, when only one edge is perturbed, the attack success rate is quite low. As the perturbation size increases, the ASR can show a significant increase. For example, on the Fingerprint dataset, the ASR is around 0.3, 0.25, 0.4, 0.45 for GCN, GIN, GSAGE and GAT when only one edge is perturbed. As the perturbation size increases to 5, the ASR also increases to 0.7, 0.75, 0.56 and 0.85 for GCN, GIN, GSAGE and GAT. Similar results can also be found on PROTEINS and WinMal. Similar to the data poisoning rate, a larger edge perturbation number can not always guarantee higher attack effectiveness. When the perturbation size increases from 5 to 7, the attack success rate does not increase much as shown on Fingerprint and PROTEINS. WinMal shows slightly increased ASR when the perturbation size increases. This is because WinMal has large graphs with the average edge number reaching to over 700. Hence, a larger perturbation could make the trigger become more informative. As for the clean accuracy drop shown in Fig. 5, we can see that there is also no specific patterns and the overall CAD is less than 5% in most of the cases.

Table 9: Training with subsampling.

| Dataset        | Clean Accuracy | Backdoor Accuracy | Attack Success Rate |
|----------------|----------------|-------------------|---------------------|
| FRANKENSTEIN   | 0.5121         | 0.4971            | 0.2775              |
| Fingerprint    | 0.8116         | 0.8150            | 0.6379              |
| PROTEINS       | 0.4081         | 0.4036            | 0.6125              |
| WinMal         | 0.7766         | 0.7504            | 0.6557              |

6 RANDOMIZED SUBSAMPLING DEFENSE

As the backdoor attacks on GNNs like TRAP and GTA are quite new and their is no available mitigation specifically designed for graph domain. One possible way is to adopt the countermeasures from the other domains (e.g., images) for defending backdoor attacks against GNNs. The existing defenses either perform inspections on the suspicious models [4, 24, 41] or detect the possibly poisoned inputs at inference time [3, 5, 8, 11]. For example, STRIP [11] performs input inspection via classification entropy difference on inputs with strong perturbation. Februus [8] performs input purification where the trigger patterns in the images are detected and removed before sending them to the neural networks. Based on different principles, the countermeasures can some be classified as empirical and certified defenses [50]. Empirical defenses are designed for specific attacks and they can be bypassed when the attackers adopts adaptive attacks [35]. Certified defenses predict the inputs in a certain bound [19, 36].

As for defense against GNN backdoor attacks, Xi et al. [44] extended the model inspection method NeuralCleanse (NC) [41] to defense GTA and adopted a minimum perturbation cost (MPC) measure for detection. They found that the MPC distributions of backdoor model attacked by GTA and benign models are similar, which shows the difficulty to defense GTA with MPC measures. Zhang et al. [50] proposed to use randomized subsampling training as a certified defense [1, 6, 22], which shows effectiveness in some cases. Therefore, we adopts the same subsampling strategy to defense the attack of TRAP. We use randomized subsampling on the graph structure to defense the training datasets which may contain the perturbation trigger generated by TRAP.

Table 9 shows the results when training with subsampling for both clean and backdoor GNN model. Here, we choose GCN model for a concrete since TRAP achieves the best attack effectiveness on GCN. Following Subgraph Backdoor [50], the subsampling ratio and sub-sampled graphs are set as 10% and 10, respectively. When trained without defense strategy, the clean accuracy (shown in Table 2) is 0.6737, 0.8235, 0.7195 and 0.8322 on the four datasets, respectively. However, when training with randomized subsampling for defense, the accuracy of both clean model and backdoor model drops significantly. For example, on FRANKENSTEIN and PROTEINS, the clean accuracy drops about 16% and 31%. The attack success rate of backdoor GCN also drops which shows the impact of randomized subsampling. However, the drop of ASR is not significant on most datasets except FRANKENSTEIN. The reason is that our trigger generated by TRAP only cause quite small perturbation on the graph structure and therefore, the randomized subsampling can not complete destroy the trigger on the poisoned graphs. The results highlight that TRAP is still robust under the randomize subsampling defense strategy.

7 DISCUSSION

Here, we discuss the potential reasons that lead to the effective and transferable attack of TRAP. As disclosed by previous works that adversarial samples show transferable property that some adversarial samples produced by one model could mislead other models that are unseen and
even their architectures are totally different [31, 32]. TRAP generates perturbation trigger for graph poisoning. The trigger-embedded graphs can be regarded as adversarial examples except that the purpose of the perturbation trigger is for backdoor attack. Hence, one possible explanation for the transferable attack of TRAP is that the vulnerability on a surrogate GNN model caused by the trigger could transfer to other GNN models.

What is more, TRAP generates perturbation trigger which can impact the message passing of the surrogate GNN model and lead its feature aggregation to the opposite: the representation of a poisoned graph tend to be similar with the representation of a graph in the targeted attack class. And the different GNNs roughly have the similar type of message passing strategies in high-level aspect. As a result, the same perturbation trigger generated by a surrogate GCN model could also be transferred to the other GNNs for backdoor attack.

8 CONCLUSION
In this paper, we propose TRAP, a new backdoor attack against GNNs. Compared with the existing backdoor attacks on GNNs, our attack excels in several aspects. Our attack is more realistic, since we assume no control over the targeted GNN models. To be effective, our attacks are prepared on a surrogate model and can be transferable to different GNN
models through poisoning the training dataset. Moreover, our generated triggers are adaptive and without specific patterns for different graphs, and are dynamically generated via perturbing the graph structures. We evaluate our attacks on real-world datasets, and the empirical studies demonstrate the effectiveness and evasiveness in backdoor attack against different GNN models. Moreover, the transferability of our attacks is evaluated on four different GNNs, to which the attack is agnostic. TRAP is also tested on the randomized subsampling based certified defense strategy, the results show that the defense cannot effectively defense TRAP, which highlight the requirements for new defenses against backdoor attacks on GNNs.

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