# Semantics-preserving Reinforcement Learning Attack Against Graph Neural Networks for Malware Detection

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Abstract—As an increasing number of deep-learning-based malware scanners have been proposed, the existing evasion techniques, including code obfuscation and polymorphic malware, are found to be less effective. In this work, we propose a reinforcement learning based semantics-preserving (i.e. functionality-preserving) attack against black-box GNNs (Graph Neural Networks) for malware detection. The key factor of adversarial malware generation via semantic Nops insertion is to select the appropriate semantic Nops and their corresponding basic blocks. The proposed attack uses reinforcement learning to automatically make these "how to select" decisions. To evaluate the attack, we have trained two kinds of GNNs with five types (i.e., Backdoor, Trojan-Downloader, Trojan-Ransom, Adware, and Worm) of Windows malware samples and various benign Windows programs. The evaluation results have shown that the proposed attack can achieve a significantly higher evasion rate than three baseline attacks, namely the semantics-preserving random instruction insertion attack, the semantics-preserving accumulative instruction insertion attack, and the semanticspreserving gradient-based instruction insertion attack.

Index Terms—Adversarial samples generation, Malware detection, Graph Neural Networks, Reinforcement Learning.

## I. INTRODUCTION

The detect-evade "game" between malware scanners (e.g., antivirus software) and malware writers is a long-lasting theme in cybersecurity. With the emergence of public online malware scanning platforms such as VirusTotal, it has been reported in recent years that some in-development malware were found on VirusTotal before their major outbreaks. For example, the very first known LeakerLocker sample could data back to November 2016 when it was submitted to VirusTotal [1], but not until July 2017 did security analysts find it widespread. The study conducted in [2] shows that many malware writers have been anonymously submitting indevelopment malware samples to online malware scanning platforms. Since such platforms are hosting a comprehensive collection of state-of-the-art malware scanners, the scan reports would provide malware writers with a best possible assessment. In addition, through a continuous submit-and-revise process, an in-development malware sample can evolve in such a way that when it was released into the wild and known to public, no signature was available and all the malware scanners running on VirusTotal mistakenly reported benign. Since it usually takes more than six months to generate wellcrafted signatures [3], the above-mentioned evasion strategy renders a very serious security threat to the society.

In order to help solve this serious problem, new kinds of malware scanners (e.g., [4], [5], [6]) have been proposed

in recent years to complement the existing scanners, and a key characteristic of these new malware scanners is that they all leverage machine learning, especially deep-learning (DL) models, to detect malware. The main merits of DL-based malware scanners are reflected in the following comparison: (a) while signature-based malware scanners often require substantial manual effort to extract signatures, DL-based malware detection models are automatically trained. (b) While signature-based malware scanners usually require a significant amount of domain knowledge, DL-based malware detection models could be well trained with minimum domain knowledge. (c) Due to the **generalization** ability of DL-based malware detection models, a malware sample revised (by its malware writer) to avoid having any known signatures could still be detected.

Since the DL-based malware scanners could make the above-mentioned evasion strategy ineffective, the malware writers must answer three key questions. **Question 1:** Are the current malware revising techniques (e.g. code obfuscation) still effective? If not, why? **Question 2:** If the current malware revising techniques are no longer very effective, how to revise a malware sample in a new way? **Question 3:** How to ensure that the new way of malware revising will not introduce too much extra burden?

Although how to evade DL-based malware detection models has been attracting an increasing interest in the research community, the existing works are still very limited in answering the three questions. Almost all the existing works (e.g., [7], [8], [9], [10], [11]) focus on investigating how CNN (convolutional neural network) or RNN (recurrent neural network) detection models could be evaded by adversarial examples. Although these works have made substantial progress on answering Question 2, most of them could not answer Question 1 or Question 3 due to the following reasons. First, to avoid changing the malware semantics (i.e. functionality of the malicious code), most existing works restrict the adversarial examples by only modifying certain metadata, such as PE header metadata and Section metadata[7], or injecting some bytes [12], [13], [8] Second, although code obfuscation techniques such as polymorphic malware have been playing a very dominant role in real-world to evade malware scanners, very few existing works study the relationships between code obfuscation and adversarial examples. Since byte-level data (i.e., a malware sample is largely viewed as a stream of bytes) is used, the trained CNN and RNN models are largely a black box and very hard to be explained. Accordingly, the semantics of the

generated adversarial examples are very hard to be linked with code obfuscation (unless the models are assumed to be white-box). Hence, it is very difficult to answer Question 3 and reduce the extra burden by piggybacking the generation of adversarial examples on code obfuscation.

In this work, we seek to answer these three questions in a systematic manner. Our new insight is as follows: instead of using CNN or RNN models, Graph Neural Network (GNN) malware detection models (e.g., [14], [5]), which are as effective as CNN and RNN models, can be leveraged to discover and understand the inherent relationships between code **obfuscation**, the dominant technology in malware revising, and adversarial examples, the dominant concept in evading a deep neural network. These inherent relationships then enable us to answer the three key questions. To the best of our knowledge, this is the **first** work investigating how GNN detection models could be automatically evaded by revising the basic blocks of a malware sample in a semantics-preserving way. (Unfortunately, the attack proposed in [15], though intending to evade a GNN detection model, cannot preserve the malware semantics/functionality, and thus it cannot be used in real

Our new insight is gained based on two observations. First, since Control Flow Graphs (CFG) play an essential role in both code obfuscation and training of GNN detection models [5], CFGs are a natural connection between code obfuscation and adversarial examples. Second, since CFG and basic block data are used to train a GNN detection model, some adversarial examples are inherently related to basic-block-level code obfuscation.

To systematically answer the aforementioned key questions, we face the following challenges:

- Given a malware sample, the features in its graph structure involve discrete data, so we cannot directly leverage gradient-based attacks to generate infinitesimal small perturbation to its original CFG.
- The generated adversarial examples should not change the
  original malware semantics. In each adversarial example,
  which is also a malware sample, the attacker must preserve exactly the same functionality as the original malware sample. Thus, the manipulation should not remove
  original features including edges and nodes.

To address these challenges, we proposed a novel method to automatically generate adversarial examples for GNN malware detection models while preserving the original malware functionality and semantics. We designed a reinforcement learning approach, namely the Semantics-preserving Reinforcement Learning (SRL) attack, to generate adversarial examples. The key factor of adversarial malware generation via semantic nops injection is to select the appropriate semantic nops and their corresponding basic blocks. However, since the decision making process involves discrete values, we cannot directly apply gradient based attack to make such decisions. The proposed SRL attack uses reinforcement learning to automatically make the above-mentioned decisions. These decisions result in sequentially injecting semantic nops into the CFGs. Since semantic nops will never change malware functionality, the SRL attack achieves semantics-preserving.

To evaluate the proposed SRL attack, we let it be compared with three baseline attacks: the Semantics-preserving Random Insertion (SRI) attack inspired by classical code obfuscation methods [16], [17], the Semantics-preserving Accumulated Insertion (SAI) attack inspired by hill-climbing methods [9], and the Semantics-preserving Gradient based Insertion (SGI) attack inspired by FGSM attacks[18]. For this purpose, we extracted CFGs from 8,000 benign and malicious real-world Windows programs and constructed abstract directed graphs to represent the CFGs. We then trained two kinds of GNN models, the basic GCN model [19] and the DGCNN model[14], respectively, to classify the graphs.

We found that the three baseline attacks are limited in evading GNN malware detection models. The experimental results have shown that SRI attacks achieved an evasion rate of 45% on the basic GCN models and 72% on the DGCNN models. The SGI attack fooled the basic GCN model with an evasion rate near 41% and deceived the DGCNN models with evasion rate 83%. The SAI attack achieved over 90% evasion rate on both models. In contrast, the proposed SRL attack achieved 100% evasion rate on both the basic GCN models and the DGCNN models. We added the adversarial samples and retrain the detection models to defend against those attacks. The retrained models can achieve similar detection accuracy, but the evasion rates of the SRI attack, the SGI attack, and the SAI attack significantly dropped to 2%, 0.7%, and 16%, respectively. In contrast, the evasion rate of the proposed SRL attack dropped to 85%, which is still a fairly high evasion rate.

In summary, we have made the following contributions:

- We proposed a reinforcement learning based semanticspreserving attack against black-box GNNs for malware detection.
- To the best of our knowledge, this is the first work on semantics-preserving black-box attacks against GNN malware detection models.
- Using both the basic GCN malware detection models and the DGCNN models, we evaluated and demonstrated the effectiveness of the proposed reinforcement learning attack via extensive experiments with different settings.
   We built a baseline with three attacks, and we thoroughly compared the proposed SRI attack with the baseline attacks. The results show that the proposed attack is significantly more effective than the baseline attacks.

The remaining of the paper is organized as follows. In Section II, we review some background of malware detection and graph neural networks. The threat model and problem statement are presented in Section III. The proposed SRI attack is described in Section IV. The proposed attack is compared with three baseline attacks in Section V. In Section VI, we discuss the related works. Finally, we conclude the paper in Section VII.

## II. BACKGROUND

In this section, we provide a backgroud of malware detection methods, graph neural networks and code obfuscation methods.

## A. Malware Detection

Malware detection models primarily make use of analysis techniques to understand the intention of malware. Features leveraged in malware detection can be grouped into three categories: static features, dynamic features, and hybrid features. Static features are extracted without running the executable files. Dynamic features are extracted by analyzing the behaviors of a program while it is being executed in a simulated and monitored environment. Hybrid features combine both static and dynamic features.

Various approaches are deployed to extract static features. Some of them make use of the binary file itself as indicators to detect the malware[20], [21]. The characteristics of the binary files, such as PE import features, metadata, and strings, are also ubiquitously applied in malware detection[4]. Others leverage reverse engineering to understand the programs' architecture and extract related features. Reverse engineering is employed to disassemble the program to extract high-level representation, including instruction-flow- graph, control flow graphs, call-graph, and opcode sequences[4], [22], [6].

Dynamic analysis executes the programs in a virtual environment to monitor their behaviors and observe their functionality. Features obtained by dynamic analysis are API calls, system calls, registry changes, memory writes, network patterns, etc[23], [24], [25]. Dynamic analysis can address some obfuscated malware and hence provide more accurate programs' behaviors. In line with the static analysis, attackers adopt approaches to prevent malware from dynamic analysis[26]. The malware starts an early check and immediately exits if it runs on virtual machines. Even worse, some of malware execute benign behaviors so humans draw incorrect conclusions about the intent of the malware.

Because the signature-based detection method is not resilient to slight variations, researchers have applied conventional machine learning algorithms (e.g., Random Forest) and deep learning method to detect malware. Convolutional neural networks and fully connected dense layers are leveraged to learn the high level features out of the selected features[20], [21], [6]. For sequential data such as API calls and instruction sequence, recurrent neural networks (RNNs) are applied to classify the malware [25], [27], [24]. Recently some researchers use graph neural networks to classify malware programs represented as control flow graphs[5]. The structure information contained by CFGs can be used to find unreachable code, find syntactic structure (like loops), and predict programs' defect[28], [29].

#### B. Graph Neural networks

In this work, we study attacks targeting malware detection models built from CFG-represented data.

To embed structural information inherent in graph like data, we use two graph neural network: the basic GCN model[19] and the DGCNN model[14]. In alignment with the DGCNN model[14], our graph convolution layer takes the following propagation rule:

$$H_{l+1} = \sigma(\widetilde{D}^{-1}\widetilde{A}H_lW) \tag{1}$$

Here,  $\widetilde{A}=A+I$  is the adjacency matrix A of the directed graph G with added self-connections I.  $\widetilde{D}_{ii}=\sum_{j}\widetilde{A}_{i}j$  is its diagonal degree matrix. W is a layer-specific trainable weight matrix.  $\sigma(\cdot)$  is a nonlinear activation function.  $H_{l}$  is the matrix of activations in the l-th layer;  $H_{0}=X$ , where X denotes the node information matrix of graph G.

The graph convolutional layer propagates node features to neighboring nodes as well as the node itself to extract local substructure information. We stack multiple graph convolution layers to get high-level substructure features. For the basic GCN model, we add a classification layer after node embedding to extract graph features. The classification layer simply flattens the high-level substructure features and adds a fully-connected layer followed by a nonlinear activation function. For another model, we follow the same architectures as the DGCNN model [14]. First, we concatenate the output of multiple GCN layers. Then, we use the SortPooling layer to sort the features followed by 1-D convolutional layers and dense layer to learn the graph-level features.

## C. Code Obfuscation

Code obfuscation tools serve two main purposes: (1) to protect intellectual properties; (b) to evade malware detection systems. There are a variety of code obfuscation schemes. A basic requirement is that the program semantics must be preserved after the code is transformed by such tools. Traditionally, attackers use obfuscation methods, including dead-code insertion, register reassignment, subroutine reordering, instruction substitution and so on, to morph their malware to evade malware detection[16], [17]. Here we list the definition of some obfuscation methods:

- Semantic nops insertion: inserting certain ineffective instructions to the original binary without changing its behavior, such as nop;
- Register reassignment: switching registers while keeping the program code and its behavior same, such as changing registers EAX in the binary are reassigned to EBX;
- Instruction substitution: replacing some instructions with other equivalent ones, such as in some cases, xor can be replaced with sub;
- Code transposition: reordering the sequence of the instructions of a binary;

The recent research findings on the existence and effectiveness of adversarial examples indicate that the evasion ability of code obfuscation tools should be examined in the context of the existing adversarial attacks. Attacks on deep learning models can be grouped into three scenarios: 1) In the white-box scenarios, the adversaries have full knowledge of the target DL model;2) In the gray-box scenarios, they have access to the structure of the DL models;3) In the black-box scenarios, they can only query the DL models to get the confidence value or the prediction label. Attacks on the white-box attack are generally based on the gradient of the neural network. Meanwhile, in the black-box/gray-box scenarios, the adversary morphs adversarial examples by following white-box attack strategies on a local model or a surrogate model[30]. However,

the infinitesimal small perturbation generated by gradientbased attacks can not be directly applied to our target model because the graph structured data involves in discrete value.

Code obfuscation is effective to evade the signature-based detection system because it could significantly change the syntactic of original malware. Although code obfuscation tools have enabled attackers to successfully evade various real-world malware detection systems, the unique capabilities of deep learning models, especially graph neural networks, indicate that the evasion ability of code obfuscation tools can no longer be taken for granted. The experiments in our paper demonstrate that randomly inserting dead instruction can not achieve a good result compared to other attacks with the help of prediction confidence or gradients.

#### III. PROBLEM STATEMENT

To answer the overarching research question, "How effectively can we exploit the potential shortcomings of the deep learning malware detection models?", we studied the resilience of GNN malware detection models over CFG-represented malware. After showing how to represent malware using CFG, we formulate the evasion problem based on the code obfuscation methods.

## A. CFG-Represented Malware Model

A CFG is a directed graph representation that illustrates all reachable paths of the program during execution. Nodes of the CFG represents the basic blocks of the program. Each basic block is a consecutive, single-entry code without any branching except at end of the sequence. Edges in the CFG represent possible control flow in the program. Control enters only at the beginning of the basic block and leaves only at the end of the basic block. Each basic block can have multiple incoming/outgoing edges. Each edge corresponds to a potential program execution.

By using only opcodes such as MOV, ADD or JMP as features of the instruction after ignoring all operands, we abstract a basic block. For example, sub %eax, %ebx and sub [%ecx], %edx would be both represented by sub in a basic block. This is because some instructions, such as JMP and INC, share the same bytes, but they have different semantic meanings. Also, operands or instruction values result in large syntactic differences, e.g. different registers being used, but the semantic meaning of the instructions can be similar.

From the executable files, we generate a CFG G=< V, E>, where  $v_i \in V$  and  $e_{ij} \in E$ . Each node  $v_i$  represents a basic block in a CFG, while a directed edge  $e_{ij}$  points from the first basic block  $v_i$  to the second basic block  $v_j$ . We also adopted the concepts of Bag-of-words (BoW) in NLP to vectorize the basic blocks. First, we map n opcodes of the x86 instruction set to a list  $S=\{s_1,s_2,...,s_n\}$ , where  $s_i$  is a particular opcode. After counting the occurrence of opcodes in the basic block  $v_i$ , a basic block  $v_i$  in a CFG G=< V, E> is transformed as an array of integer counts with size same as S. Let  $v_i=\{x_1...x_n\}$ , a vector of counts over each opcode.  $x_k$  is set as the occurrence if the k-th opcode exists in the basic block, otherwise, it is set as 0.

In the context of the adversarial malware functionality, we can not directly change edges in the CFG to modify the adversarial malware. To preserve the functionality of the malware, we limit manipulation on the malware into semantic *nops* insertion. That is, when defining a list of semantic *nops* that will not affect the program functionally, we do not change the structure of the original CFG.

#### B. Problem Formula

In this paper, we consider the black-box setting where the attacker can only receive the final estimation(probability) results from the malware detection model  $\mathbb C$ . Even though a malicious CFG G=< V, E> can be correctly labeled as a malware by the pretrained and fixed malware detection model, the attacker aims to safely manipulate the basic blocks and generate an adversarial graph  $\widetilde{G}=<\widetilde{V}, E>$  to deceive the malware detection model  $\mathbb C$ .

Let  $G = \langle V, E \rangle$  be a given graph, where  $V \in \mathbb{R}^{m \times n}$ and  $E \in \mathbb{R}^{m \times m}$ , m is the number of nodes and n is the number of opcodes in the instruction set. The semantic nops are encoded using the aforementioned method in Section III-A. The manipulation on malware is a small and imperceptible perturbations that should not change the program's original functionality. We define a list of dead instructions  $\zeta \in \mathbb{R}^{I \times D}$ . where I is the number of dead instructions. By selecting and inserting the dead instructions into the original sample G, we generate an adversarial sample  $G = \langle V + \delta, E \rangle$ . The adversarial sample has the same graph structure as the original sample. The proposed semantics-preserving attacks aim to maximize the probability of the target label under the constraints that at most  $\Delta$  instructions can be injected. Thus, an adversarial example is generated by solving the following constrained optimization problem:

$$\underset{\widetilde{G}}{\operatorname{argmin}}_{\widetilde{G}} \quad \mathbb{C}(\widetilde{G}, \widetilde{y}; \theta)$$
s.t.  $d(G, \widetilde{G}) \leq \Delta$ , (2)

where  $\widetilde{y}$  is the target label,  $\mathbb{C}(\cdot)$  is the malware detection model with parameters  $\theta$ , and  $d(\cdot)$  is the distance function to calculate the number of injected instructions.

## 

To solve the optimization problem in Eq. 2, we designed four semantics-preserving attacks against GNN for malware detection. While one is a semantics-preserving reinforcement learning attack which is designed by sequentially injecting semantic *nops* into the CFG, the other three attacks are semantics-preserving attacks designed using the ideas such as random insertion, hill-climbing, gradient-based insertion methods respectively.

## A. Semantics-preserving Reinforcement Learning(SRL) Attack

The key factor of adversarial malware generation via semantic nops injection is to select the appropriate semantic nops and their corresponding basic blocks. However, since the decision making process involves discrete values, we can

not directly apply gradient based attack to inject semantic nops. Reinforcement learning can be a valid approach to attack GNNs for malware detection when modifying the graph structure and node features [31], [32]. Thus, we design a semantics-preserving reinforcement learning attack which results in sequentially injecting semantic nops into the CFGs.

As illustrated in Figure 1, the the proposed semanticspreserving reinforcement learning(SRL) attack is trained using a deep reinforcement learning agent. The deep reinforcement learning agent iteratively chooses basic blocks and dead instructions while modifying the malicious input until it successfully misleads the malware detection model. The deep reinforcement learning model is considered as a finite horizon markov decision process(MDP)  $\mathbb{M}(\mathbb{C}, G, S, A, V, R)$ , which contains a malware detection model  $\mathbb{C}$ , a malicious input G, the state space S, the action set A, and the reward R. First, a CFG is represented as a state  $s_0$ . Second, for each turn t, the reinforcement learning agent chooses an action  $a_t \in \mathcal{A}$ based on a policy  $\pi(a|s_t)$  to decide which dead instruction should be inserted into the observable environmental state vector  $s_t$ . Third, to determine topk basic blocks  $v_t$  that will be manipulated at each iteration, the reinforcement learning agent sorts the basic blocks in the graph according to their importance. Also, we will get a new state which will be sent to the malware detection model  $\mathbb C$  to get the rewards  $r_t \in \mathbb{R}$  for the actions. This process repeats at most niter iterations. With the action  $a_t$  and the sorted list of the basic blocks  $v_t$ s, the trajectory of the proposed MDP is set into  $(s_0, a_0, v_0, r_0, s_1, ..., s_{t-1}, a_{t-1}, v_{t-1}, r_{t-1}, s_t)$ . Also, the rewards are used when updating the reinforcement learning agent.

To solve the optimization problem in Eq. 2, we design reinforcement learning environment and reward as follows:

#### State

The state  $s_t$  at time t represents a partially modified CFG  $G_t = \langle V_t, E \rangle$  with some of the manipulated basic blocks.

## • Action:

Each action includes two folds: 1) the importance of the basic blocks  $v_t$ ; 2) a dead instruction  $a_t$ . The action space of picking up a dead instruction is O(I), where I is the numbers of semantic nops. Similar to [9], below is the rule we followed when generating the semantic nops:

- Some atomic instructions that do not change the memory or register value, e.g. NOP.
- An invertible instruction, such as arithmetic operation and logical operation, followed by the inverse instruction, e.g. *PUSH*, *POP*, *ADD* and *SUB*.

#### Reward:

The ultimate goal of the reinforcement learning model is to generate new samples that can misclassify the detection model. In practice, the decision process will take long to find the right action during training process. Thus, we calculate the rewards of each state as an intermediate feedback. If one CFG can successfully avoid detection, the reward  $r_t$  is associated with the action sequence length. We design the guiding reward  $r_t$  to be one if

it increases the probability  $p_{s_t,a_t,v_t} = \mathbb{C}(s_t,a_t,v_t,\widetilde{y})$  of successfully evading the prediction model after being recognized as the target label  $\widetilde{y}$ , and to be zero otherwise.

$$r_t(s_t, a_t, v_t) = \begin{cases} 1; & if \quad p_{s_t, a_t, v_t} > p_{s_{t-1}, a_{t-1}, v_{t-1}} \\ 0; & otherwise. \end{cases}$$
(3)

## Terminal:

Once the injected instructions reach the budget  $\Delta$ , or current state can be misclassifed, the process stops. The generated set of samples contain at most niter new instructions.

## Algorithm 1 SRL attack against malware detection

```
Input: \mathbb{C}(\cdot), \widetilde{y}, NopsList, topk, niters, \Delta, T
 1: Initialize Q(s, a, v) with random parameters \theta
 2: Set target function \hat{Q} with parameters \theta^- = \theta
 3: Initialize replay memory buffer \mathcal{M}
 4: queries \leftarrow 0
 5: for each G = \langle V, E \rangle do
        t \leftarrow 0
 6:
        s_t \leftarrow G
 7:
        while \operatorname{argmax}(\mathbb{C}(s_t)) \neq \widetilde{y} and t < niters do
 8:
           Choose a_t and v_t based on Eq.6 and Eq. 7
 9:
           Insert the action a_t from NopsList into topk basic
10:
           block sorted by v_t to get new graph G' as s_{t+1}
           Compute r_t based on Eq. 3
11:
12:
           if Diff(s_{t+1}, s_t) > \Delta then
              t = niter
13:
              r_t = 0
14:
           end if
15:
           Store \{s_t, a_t, v_t, r_t, s_{t+1}\} in memory \mathcal{M}
16:
           if queries\%T = 0 then
17:
              Sample minibatch transitions from \mathcal{M} based on
18:
              Eq. 8 and Eq.9
19:
              Update parameters according to Eq.10
20:
           end if
           s_t \leftarrow s_{t+1}
21:
           t \leftarrow t + 1
22:
           queries \leftarrow q + 1
23:
        end while
25: end for
```

As other work on adversarial graph generation[31], the policy network used to learn the MDP  $\mathbb{M}(\mathbb{C},G,S,A,V,R)$  is Q-learning. Q-learning is an off-policy control algorithm and fits Bellman optimality equation as follows:

$$Q(s_t, a_t) = r(s_t, a_t) + \gamma \max_{a'} Q(s_{t+1}, a')$$
 (4)

In our case, Q-learning is adopted as follows:

$$Q(s_t, a_t, v_t) = r(s_t, a_t, v_t) + \gamma \max_{t} Q(s_{t+1}, a', v')$$
 (5)

The goal of the reinforcement learning agent is to learn a policy model  $\pi(s_t, a_t, v_t)$  and an action-value function  $Q(s_t, a_t, v_t)$ . To score the nodes in the graph and insert the dead instruction in the sorted basic blocks, we first use the same structure as the DGCNN model to embed the graph. After the result of the SortPooling layer is obtained from

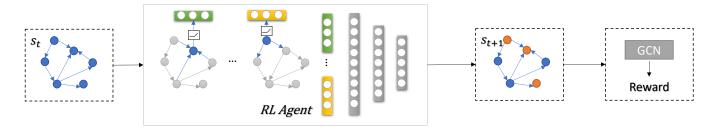


Fig. 1. Architecture of the SRL Attack

topk basic blocks, the agent calculates the Q value from the following Q function:

$$Q(s_t, a_t, v_t; \theta) = W_1 \sigma(W_2[\mu(e(s_t))]),$$
 (6)

where  $\theta$  represents the trainable weights of the deep Q learning(DQN),  $e(s_t)$  is the embedding of graph  $s_t$ . We use greedy policy to select the action  $a_t$  estimated by the Q function:

$$\pi(a_t, v_t | s_t; Q) = \operatorname{argmax}_{a \in \zeta} Q(s_t, a, v; \theta)$$
 (7)

We use the prioritized experience replay technique with memory buffer  $\mathcal{M}$  to train the DQN. The buffer records past experience denoted as  $(s_t, a_t, r_t, s_{(t+1)}, |\delta_t|)$  with states, actions taken at those states, the rewards and the next state and its absolute temporal difference(TD) error. When training the DQN, we draw past experiences for a given minibatch from the memory buffer  $\mathcal{M}$  with probability P(i):

$$P(i) = \frac{p_i^{\alpha}}{\sum_k p_k^{\alpha}}. (8)$$

Here, the priority  $p_i$  of an experience i was set as:

$$p_i = |\delta_i| + \epsilon, \tag{9}$$

where  $\epsilon$  is a small constant to ensure that samples with a low  $\delta_i$  have some non-zero probabilities of being drawn. The Q-learning loss function is as follow:

$$\mathbb{E}_{(s_t, a_t, v_t, r_t, s_{t+1}) \sim D} [(r_t + \gamma \max_{a \in \zeta} \hat{Q}_{\theta^-}(s_{t+1}, a, v) - Q_{\theta}(s_t, a_t, v_t)^2]$$
(10)

In Algorithm 1, we show the operational procedure of the Q-learning algorithm for generating the proposed SRL attack. For each malicious CFG, attacker chooses topk basic blocks and one semantic nop in the list of semantic nops. The transformation is applied to the original graph G. We obtain the reward from the generated graph G' and store the current state, actions, rewards and next state to the memory buffer  $\mathcal{M}$ . For every T queries, a minibatch set of samples from the memory buffer are selected when training the Q function. The algorithm runs until niters iterations, the inserted features is more than the defined budget  $\Delta$ , or the generated samples are misclassified as the target label  $\widetilde{y}$ . Each attack iteratively modifies a malicious CFG until the malicious CFG is misclassified as a benign program or the maximum number of iterations reaches.

## Algorithm 2 SRI Attack against Malware Detection

```
Input: \mathbb{C}(\cdot), G = \langle V, E \rangle, \widetilde{y}, NopsList, topk, niters, \Delta
Output: \widetilde{G} = <\widetilde{V}, E>
 1: i \leftarrow 0
 2: \widetilde{G} \leftarrow G
 3: while \operatorname{argmax}(\mathbb{C}(\widetilde{G})) \neq \widetilde{y} and i < niters do
         node\_mask \leftarrow RandomBasicBlock(V, topk)
 5:
         X \leftarrow RandomInstruction(NopsList)
         \widetilde{V} \leftarrow V * node\_mask + (V + X) * node\_mask
         G' \leftarrow < \widetilde{V}, E >
 7:
         if Diff(G',G) \le \Delta then
 8:
             \widetilde{G} \leftarrow G'
 9:
         end if
10:
         i \leftarrow i + 1
11:
12: end while
```

## B. Other Semantics-preserving Attacks

In this section, we introduce the proposed other three attacks: (1) Semantics-preserving Random Insertion(SRI) attack using the idea of random insertion; (2) Semantics-preserving Accumulated Insertion(SAI) Attack using the idea of hill-climbing; and (3) Semantics-preserving Gradient based Insertion(SGI) Attack using the idea of gradient-based insertion.

1) Semantics-preserving Random Insertion(SRI) Attack: In Algorithm 2, we show the pseudocode of the SRI attack. In each iteration, after randomly choosing topk basic blocks in the CFG  $G = \langle V, E \rangle$ , the algorithm picks up one dead instruction in the list of semantic nops. Next, the algorithm inserts the dead instruction into the chosen basic blocks. Here, to limit the numbers of manipulation on the original CFG, difference between the generated CFG and the original CFG should be less than the predefined value of  $\Delta$ . The algorithm repeats until niters iterations. The manipulated graph is an adversarial sample if it is misclassified as the target label  $\tilde{y}$ . To perform the SRI attack, the attackers do not require the additional information about the architectures, the weights, and the predicted probabilities of malware detection models. Also, we assume that attackers constrain the number of probing the detection models into niters times and the number of the effected basic blocks into topk. This is because the SRI attack may be identified due to the large number of queries on the malware detection model.

2) Semantics-preserving Accumulated Insertion(SAI) Attack: Instead of directly transforming the original binary with

## Algorithm 3 SGI attack against malware detection

```
Input: \mathbb{C}(\cdot), G = \langle V, E \rangle, y, \widetilde{y}, NopsList, niters, \Delta, N,
Output: \widetilde{G} = <\widetilde{V}, E>
  1: i \leftarrow 0
  2: \widetilde{G} \leftarrow G
 4: while argmax(\mathbb{C}(\widetilde{G})) \neq \widetilde{y} and i < niters do
5: g_i \leftarrow sgn(\frac{\partial J_{\mathbb{C}}(G,y)}{\partial V})
6: for i \leftarrow 1 to N do
                for j \leftarrow 1 to K do
  7:
                    d_j \leftarrow \|g_i - NopsList_j\|_p
  8:
  9:
                X_i \leftarrow NopsList_{argmin(d_i)}
 10:
           end for
 11:
           V \leftarrow V + X
 12:
           G' \leftarrow < \widetilde{V}, E >
 13:
           if Diff(G',G) \le \Delta then
 14:
                G \leftarrow G'
 15:
           end if
 16:
 17:
           i \leftarrow i + 1
18: end while
```

the random decision as in Algorithm 2, the SAI algorithm follows a hill-climbing approach[9]. The SAI algorithm declines some decisions if the probability of the target class identification decreases.

For each CFG, attacker probes the detection model  $\mathbb{C}(\cdot)$  to retrieve the probability p of the target class. Next, in each iteration, attacker randomly chooses topk basic blocks and one dead instruction in a list of semantic  $nops\ NopsList$ . Attackers query the detection model using the transformed CFG  $G'=<\widetilde{V},E>$  to obtain the changed probability of the target class, p'. The transformation is accepted only if the probability increases. Similar to the SRI attack, the SAI attack can also limit the number of effected basic blocks in each iteration and the total number of inquiries. Manipulation on the original CFG should also be less than  $\Delta$ . However, attackers require the predicted probability of the targeted model to apply the SAI attack.

3) Semantics-preserving Gradient based Insertion(SGI) Attack: The SGI attack solves the constrained optimization problem in Eq. 2 with a gradient-descent algorithm. To fit the black box setting, we train a substitute model  $\mathbb{C}'$  which approximates decision boundaries of the malware detection model  $\mathbb{C}$  [33]. We assume that the attackers have some fundamental knowledge of the malware detection model including the input and the expected output. The substitute model  $\mathbb{C}'$  is trained iteratively with the graphs and the predicted labels.

The substitute model  $\mathbb{C}'$  is used when generating adversarial samples. In Algorithm 3, we show the pseudocode for generating the adversarial samples. Here, N is the number of basic blocks in the CFG, and K is the number of semantic nops. As shown in Algorithm 3 when generating adversarial samples, the adversary computes the perturbation, i.e., the

TABLE I
NUMBER OF BENIGN AND MALICIOUS BINARIES

Class	Train	Val	Test
Benign	2822	348	830
Malware	2778	372	850
All	5600	720	1680

TABLE II EXAMPLES OF SEMANTIC Nops

NOP	
PUSH %rbx	POP %rbx
NOT %rbx	NOT %rbx
XCHG %rax,%rax	XCHG %rax,%rax
ADD \$5,%r10	SUB \$5,%r10

signed gradient from the  $i_{th}$  iteration, as follows:

$$g_i = sgn(\frac{\partial J_{\mathbb{C}}(G, y)}{\partial V}),$$
 (11)

where V is the feature matrix, each row of which describes instructions in a basic block  $v_i$  of the graph G, and y is the label of the CFG. Attacker heuristically inserts a semantic Nop that is closest to the gradient  $g_i$  into the corresponding basic block of the CFG. In each iteration, attacker injects the closet semantic nops to the sign gradient descent. Attacker repeats this procedure until a maximum number of iterations T.

## V. Assessing the resilience of GNN for malware detection

We conducted experiments to answer the overarching research question, "What kind of manipulations can be applied on original CFGs to avoid the malware detection models without changing the programs' behaviors?". We evaluated the performance of the proposed four semantics-preserving attacks under various parameters such as the impacts of graph size and the semantic nops. From the experiments, we observed that:

1) the proposed four semantics-preserving attacks achieve the high evasion rate; 2) they generate small-scale manipulations on original features to succeed attacks; 3) they do not change malicious behaviors while avoiding malware detection model.

## A. Experimental Environment

To evaluate the performance of the proposed semantics-preserving attacks, we conducted experiments using the VXHeavens-Dataset [34]. It includes 5 types of Windows Malware families: Backdoor, Trojan-Downloader, Trojan-Ransom, AdWare, Worm. For benign programs, we installed standard packages on a x86 Windows 10 virtual machine using Ninite and Chocolatey2 package managers and collected the benign binaries generated by those packages. The categories of the installed packages vary including popular applications(such as Chrome, Firefox, and Zoom), security applications(such as Spybot2, SUPERAntiSpyware, and Malwarebytes), developer tools(such as Python, Github, and PuTTY), and so on. We use a Python framework for analyzing binaries, called Angr, to extract CFG in those datasets. After extracting CFGs, we transform the basic blocks in CFGs to a directed graph.

 ${\bf TABLE~III}\\ {\bf CLASSIFICATION~PERFORMANCE~OF~THE~MALWARE~DETECTION~MODEL}$ 

Model	Train	ACC Val	Test	FPR	FNR
DGCNN	98.37%	93.61%	95.77%	4.70%	3.73%
Basic GCN	97.35%	93.61%	93.92%	5.52%	6.62%

TABLE IV
PERFORMANCE OF THE PROPOSED ATTACKS AGAINST TWO GNN MODELS
FOR MALWARE DETECTION

Attack	I	Basic GCN			DGCNN	
Attack	ER(%)	FG(%)	GT(s)	ER(%)	FG(%)	GT(s)
SRI	45.58	0.96	0.98	72.25	1.28	0.65
SAI	97.27	0.54	0.38	96.74	0.62	0.33
SGI	41.22	1.99	3.31	83.08	1.22	3.43
SRL	100.0	0.17	0.37	100.0	0.23	0.08

- \*ER=Evasion Rate
- \*FG=Average Number of Features Inserted
- \*GT=Generating Time in Seconds per Sample

Because some graphs have millions of basic blocks, it is impossible to train on the entire graph at once due to GPU memory and training time constraints. In our experiments, the CFGs with less than 3,000 basic blocks are used for malware classification. Next, we mix benign programs and malware together, and randomly select 70% samples of the whole dataset as train dataset, 10% samples as validation dataset, 20% samples as test dataset. In Table I, we describes the data distribution in the datasets. We generated 28 semantic Nops based on rules mentioned in section III-B. In Table II, we show some examples of semantic *Nops*.

All experiments are conducted on Ubuntu 16.04, using Python 3.7 and Tensorflow 2.1 with NVIDIA GTX980 Ti Graphics Processing Unit(GPU). We trained two GNNs as malware detection models over CFG-based features: the basic GCN model; and the DGCNN model. The basic GCN model stacks four graph convolution layers with 128, 64, 32, 16 output channels followed by a fully-connected layer. The DGCNN model[14] leverages four graph convolution layers with 32, 32, 32, 1 output channels, followed by a SortPooling layer to keep top 1000 nodes. Two 1-D convolutional layers with 16 and 32 output channels followed by one dense layer with 128 hidden units are applied to learn the graph features. We trained two models for 200 epochs with the batch size 100. In Table III, we show the classification performance of the malware detection models.

## B. Evaluation Results

To fool the malware detection model, we generated the proposed four semantics-preserving attacks by inserting semantic Nops as follows. By default, the parameter values for the four attacks are configured as follows. Each attack probes the detection model less than 30 iterations. We set 5% as the maximum injection budget. In the SRI, SAI, and SRL attacks, the maximum effected basic blocks in each iteration is set as 1250. If the number of the nodes in a CFG is less than 1250, one semantic nop is inserted into all basic blocks each step.

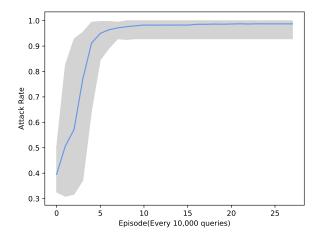


Fig. 2. Impact of the SRL attack on the basic GCN model

The norm value of the distance function in the SGI attack is set as 2 to calculate the semantic *nops* that is close to the direction of the gradient.

For the SGI attack, we trained two substitute models using the validation dataset to approximate the malware detection models[33]. The substitute models have the same structure as the basic GCN model. Both of them are trained for 10 epochs from scratch with CFGs and their corresponding predicted labels. After 10 epochs, while the accuracy of the substitute model for the basic GCN model reached by 85.83% on the test dataset, the substitute model for the DGCNN model showed an accuracy by 81.42%.

For the SRL attack, we used the RMSProp algorithm with minibatches of size 512. We trained the model with malicious samples in the training dataset. Each graph can query the detection model for at most 30 steps. We used a replay memory of 3000 most recent queries. The policy during training continuously decayed with  $\epsilon$  decaying linearly from 1 to 0.1 over the first 3000 queries, and fixed at 0.1 thereafter. The agent drops actions that returned negative actions with probability 50% instead of keeping every queries.

We independently measured the performance of each attack 10 times to obtain the average attack (success) rates and the percentage of injected instructions. In Table IV, we show the performance of four attacks against two GNNs for malware detection. The SRI attack showed the evasion rate by 48.87% on the basic GCN model when inserting instruction by 0.96% on average, and by 72.25% on the DGCNN model when 1.06% of features changed on average. The SGI attack showed the evasion rate by 41.22% on the basic GCN model and by 83.08% on the DGCNN model. Overall, we observed that SAI and SRL attacks have shown a good performance in general. The SAI attack showed the evasion rate by more than 96% with fewer features changed.

In Figure 2 and Figure 3, we show the performance of the SRL attack against the basic GCN model and the DGCNN model. We run the attacks against two models 10 times and periodically compute the evasion rate on the validation dataset

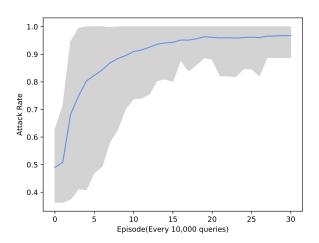


Fig. 3. Impact of the SRL attack on the DGCNN model

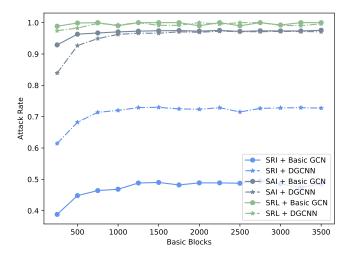


Fig. 4. Impact of the effected basic blocks

every 10,000 queries during training. Here, while the bold lines shows average values over 10 independent learning trials, the shaded area show the maximum and minimum values from 10 independent learning trials. We observed that evasion rate against the basic GCN model converged smoother and faster than evasion rate against the DGCNN model. This result implies that the SRL attack can train a deep Q network in a stable manner. As a result, the SRL attack against both models showed the evasion rate by 100%.

In practice, SRI attacks took more time when generating an sample compared with SAI attack on average. This is because the SAI attack drops some transformation and causes the misclassification from the detection model within fewer iterations. Also, the SGI attack costs longer time because of the gradient calculation.

1) Impact of Various Attack Parameters: In this section, we discuss the impact of various attack parameters including the number of effected basic blocks, maximum iterations, and insertion budget.

In Figure 4, we shows evasion rates of SRI, SAI and SRL

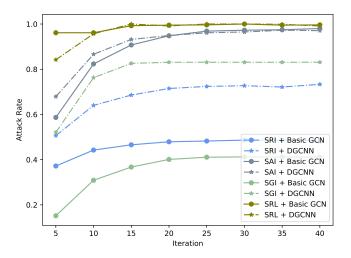


Fig. 5. Impact of iteration

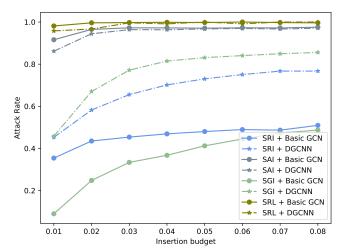


Fig. 6. Impact of insertion budget

attacks under different numbers of effected basic blocks in each iteration. Here, the number of iterations and the insertion budget are set as 30 and 5% respectively. We immediately observed that more effected basic blocks do not significantly improve the evasion rate after the number of effected basic blocks reaches 1250. On the other hand, the evasion rate even reduces slightly. That is because when the number of the effected basic blocks is more than the node size of the CFG, one dead instruction is inserted to all basic blocks. With more effected basic blocks, we observed that the evasion rate tends to depend on other factors such as the number of iterations and the insertion budget as shown in Figure 5 and Figure 6.

In Figure 5 and Figure 6, we show how the evasion rates on two detection models vary under different maximum iterations and insertion budget. Generally, we observed that attacks with more iterations and higher budget are more successful. Four attacks showed a good performance at about 30 iterations. Also, most attacks showed a good performance when insertion budges reached 5%. As one would expect, more iterations and insertion budget change more features when generating

an adversarial sample. For example, for SGI attack against the DGCNN model, the number of changed features increased from 0.57% to 1.22% with the increase of the insertion budget on average.

Even though the insertion budget is small, e.g. 1%, we observed that the SRL attack showed the high evasion rate close to 100%. However, let us note that the evasion rate is highly dependent on the initial value of the action-value function. If the evasion rate before training the Q function is less than 40%, most queries in the earlier training process will get negative rewards, and consequentially need more time when training the Q function for a good result. Moreover, smaller iterations and insertion budget restrict the length of action sequences, which may reduce the number of queries with positive rewards. We also observed that although a smaller number of iterations and insertion budget obtained a good performance, it might take longer time to train the Q function because most queries in the beginning of the training process return negative rewards.

- 2) Impact of Graph Size: We measured the evasion rates of four attacks under various size of graph using the test dataset, which is separated into four groups according to the the number of the nodes in a graph. As shown in Table V, we consider the first quartile, the median, and the third quartile of the graph size to group the test dataset. For the SGI attack, larger graphs significantly showed higher evasion rates. However, from the other attacks, we did not observe any meaningful relationship between the graph size and the evasion rate. This observation indicates that the evasion rate is not highly dependent on the graph size.
- 3) Impact of Dead Instructions: To evaluate the impact of dead instructions, we investigated the performance of a single dead instruction while using different dead instructions. In Table VI, we show impact of some dead instructions with different semantic Nops. With some semantic Nops on the DGCNN model, we observed that the SAI attacks can not show the same performance as the SRI attacks because the SAI attacks reject some insertions and consequentially reduce the action sequences. With some dead instructions, such as "NOT, NOT", three attacks on different models also showed divergent evasion rates. We also observed that even though some dead instructions may not cause the misclassification on the GCN model, the SAI, SGI and SRL attacks can reject those instructions or locate a better combination to deceive the detection model.

#### C. Potential Mitigation

In this section, we briefly discuss a potential mitigation method to make malware detection robust against the proposed semantic-preserving attacks. To defend against the proposed semantic-preserving attacks, we retrained the detection model using the original training dataset together with the adversarial samples generated by the attacks. For each attack, we randomly selected 500 adversarial samples and added them into the training dataset. As shown in Table VII, detection models showed the same accuracy as the original one after 200 epochs. For SRI, SAI and SGI attacks, the evasion rate of the retrained

model significantly decreased as shown in Table VIII. Let us note that even though such a defense method is effective, the cost of retraining the detection model is large if the training set is large. Also, to decrease the susceptibility against those attacks, we recommend to design a malware detection system which combines multiple detection algorithms.

#### VI. RELATED WORK

In this section, we introduce research on attacking neural networks and malware detection models.

#### A. Attacks on Neural networks

Adversarial samples are generated by adding imperceptible perturbations to original samples to deceive deep learning algorithms. Attacks can be grouped into three scenarios based on their knowledge: white-box attack, black-box attack, and semi-white (gray) box attack.

In the white-box scenario, attacks have access to the architecture and parameters of the neural networks. The FGSM attack[18] is a fast method to generate adversarial samples x' using the following equation:

$$x' = x + \epsilon sgn(\nabla_x J(\theta, x, l)) \tag{12}$$

where x is the original input of the neural network, and l is its corresponding label,  $\epsilon$  is the perturbation threshold,  $sign(\cdot)$  denotes the sign function, J is the loss function

Carlini and Wagner [35] proposed gradient-based attacks to generate adversarial samples by calculating one back-propagation step. The perturbations are generated by minimizing the following function:

$$loss(f(x+r), l) + \epsilon \cdot ||r||_2 \tag{13}$$

where x is the original input, r is the perturbation, l is the target label, and the parameter  $\epsilon$  is for tuning the  $L_2$ -norm.  $loss(\cdot)$  is a function to measure the distance between the target label and the output of the neural network with the perturbed input.

In a black-box attack setting, the architecture parameters of the neural network is unavailable to attackers. Attackers only have the query access to generate adversarial samples. Papernot et al. [33] design a substitute neural network to fit the black-box neural network and then generated adversarial examples according to the substitute neural network. This method assumes the attackers can only obtain the label information from the target neural network. Zeroth order optimization based black box attack has a different assumption that the attackers have access to the prediction confidence (score) from the target neural networks[36].

In the grey-box setting, attackers have access to the the structure of the target model. Generative Adversarial Network(GAN) is introduced to generate adversarial examples directly from the generative network[37], [38].

TABLE V
IMPACT OF GRAPH SIZE(%)

A 441-		Basic GCN			DGCNN			
Attack	25%	50%	75%	100%	25%	50%	75%	100%
SRI	44.44	51.44	47.44	53.64	70.81	71.29	77.94	79.47
SAI	98.06	98.55	98.97	94.79	94.73	95.83	97.43	95.78
SGI	10.14	17.30	54.59	86.97	54.02	82.87	84.10	88.94
SRL	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0

TABLE VI IMPACT OF DEAD INSTRUCTIONS(%)

ID	ID Comotio None		Basic GCN			DGCNN		
ID	Sematic Nops	SRI	SAI	SGI	SRI	SAI	SGI	
0	NOP	39.97	39.22	41.34	96.04	81.23	95.67	
1	PUSH,POP	2.24	2.36	2.24	62.09	32.59	60.86	
2	NOT,NOT	0.12	0.12	0	54.19	45.18	50	
3	XCHG,XCHG	0	0	0	9.01	3.08	9.38	
4	SUB,ADD	0	0	0	1.23	0.24	1.11	

TABLE VII
CLASSIFICATION PERFORMANCE AFTER RETRAINING THE MODEL

Model	Train	ACC Val	Test	FPR	FNR
DGCNN	98.71%	93.61%	95.23%	3.41%	6.14%
Basic GCN	98.96%	93.33%	94.70%	4.94%	5.66%

TABLE VIII
IMPACT OF A POTENTIAL MITIGATION METHOD BASED ON RETRAINING

Attack	Basic	GCN	DGCNN		
Attack	ER(%)	FG(%)	ER(%)	FG(%)	
SRI	1.05	0.91	2.02	1.01	
SAI	13.24	0.94	16.96	0.94	
SGI	0.24	2.94	0.73	1.03	
SRL	27.22	1.20	85.74	0.83	

## B. Attacks on Malware Detection

Adversarial malware generation contrasts with previous applications of adversarial sample generation in computer vision because most features in malware detection involve in discrete data, which means the gradients to train the generator are zero almost everywhere. There are two constraints for adversarial malware generation: 1) large-scale manipulations on original features may change the program's functionality; 2) generated samples should not remove original features[39].

Multiple attacks are introduced to evade deep learning models. Some of them modify original malware, for example, add benign code to malware, to mimic benign program[40], [12], [13], [8], [9]. Anderson et al.[7] modify PE header metadata, Section metadata, Import and Export Table metadata, etc. by reinforcement learning to evade static PE machine learning malware models. Park et al.[11] generate the executable adversarial malware examples by inserting semantic *nops* to evade CNN based detection models. Other attacks focus on the gradient of the detection model or the substitute model to tweak some features of the target model, e.g. adding new API calls

[41], [27], [10], [42]. The evolutionary computation techniques are used to develop new variants of mobile malware[43].

Although researchers have been developing graph based neural network models for malware detection, no systematic study on whether such models can be attacked. Unlike to image data, it is harder to generate adversarial samples on graph-based data for two reasons: 1) the graph structure is discrete so we cannot use infinitesimal small perturbation, and 2) large graphs can not easily be verified visually.

The attacks on graph based model can be grouped into two categories: gradient-based attack and non-gradient-based attack[44]. Gradient-based attacks retrieve or estimate the gradient information of the detection model to modify the original samples. Chen et al.[45] introduced a network embedding attack that uses the gradient information of the adjacency matrix to iteratively add or delete some key links. Zügner et al.[46] first proposed a method Nettack to perturb the graph data to perform poisoning attack on GCN model. Nongradient-based attacks solve the graph based optimization problem without using the gradient of the detection model. Dai et al.[31] proposed a reinforcement learning based attack method RL-S2V that learns to modify the graph structure by sequentially adding or dropping edges from the graph. Wang et al.[47] developed two algorithms, Greedy and Greedy-GAN, to attack GCN models by adding fake nodes into the original graph. Wang et al.[48] formulated a graph-based optimization problem to manipulate edges and solved the problem using projected gradient descent method. Sun et al.[32] extend the idea of RL-S2V to sequentially add fake nodes, introduce fake links, and modify the labels of fake nodes.

Differently from some of the prior works, e.g. [9], [41], our target models are graph based deep learning models from CFGs. The generated samples should not change the program's functionality. So we can not arbitrarily add or remove the edges and nodes features of the CFGs. In our paper, we focus on generate adversarial CFGs by iteratively insert semantic Nops into original graphs. Perhaps most closely related to

our work on evading CFG based deep learning model[15]. First, instead of using graph neural networks, they extracted some indicators such as closeness centrality, density, and betweenness centrality, to represent the CFG and constructed a detection model. Because those features are continuous value, they can directly apply methods of white box attack to generate adversarial samples. However, those generated adversarial samples can not be reverted to CFG and might change the structure, features, and consequently, the programs' behaviors. The graph embedding and augmentation method they proposed reply on expert experience on modify the CFG and doesn't consider the guidance of the malware detection.

## VII. CONCLUSION

In this work, we propose a reinforcement learning based semantics-preserving attack against black-box GNNs The key factor of adversarial malware generation via semantic Nops insertion is to select the appropriate semantic Nops their corresponding basic blocks. The proposed attack uses reinforcement learning to automatically make these "how to select" decisions. To evaluate the attack, we have trained two kinds of GNNs with five types of Windows malware samples and various benign Windows programs. The evaluation results shown that the proposed attack can achieve a significantly higher evasion rate than three baseline attacks, namely the semantics-preserving random instruction insertion attack, the semantics-preserving accumulative instruction insertion attack, and the semantics-preserving gradient-based instruction insertion attack.

Our work focuses on attacks targeting GNNs for malware detection using CFGs as input. We believe the method can be applied to other ML models based on sequential data. For example, prior work studied the effectiveness of instruction sequences and API Call sequences as features for malware detection [42]. By inserting semantic *nops* into the instruction sequences, one can potentially mislead RNN-based detection models. Another potential extension for the SRL attack is to leverage other code obfuscation techniques such as instruction substitution and code transposition.

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