Short Paper: Creating Adversarial Malware Examples using Code Insertion

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Abstract

There has been an increased interest in the application of convolutional neural networks for image based malware classification, but the susceptibility of neural networks to adversarial examples allows malicious actors to evade classifiers. We shed light on the definition of an adversarial example in the malware domain. Then, we propose a method to obfuscate malware using patterns found in adversarial examples such that the newly obfuscated malware evades classification while maintaining executability and the original program logic.

1. Introduction

With the growth of the internet, the number of malware found on the internet has been rapidly increasing. As malware classification is the first step in analysis, and crucial in detecting new malware, researchers are developing new machine learning methods to stay ahead. Machine learning has significantly improved existing solutions in malware detection, classification, and network intrusion. Nataraj et al. (2011) proposed image representation of malware as input, allowing use of image processing and classification techniques for malware classification. The method proposed by Zhou et al. (2017) only used malware image features and achieved high classification accuracy. Deep learning has been proposed as a method to improve classification accuracy and has proved to be successful in other domains, such as image classification and speech recognition.

However, Szegedy et al. (2013) found that neural networks are vulnerable to adversarial examples. Adversarial examples are crafted by perturbing valid inputs such that they are indistinguishable from the valid inputs when viewed by humans but are confidently misclassified by a machine learning classifier. As the concept of adversarial examples has mostly been explored in the domain of natural images, interest has shifted to further research and understanding of adversarial examples in the malware domain.

In this paper, we are interested in the application of machine learning to malware classification and the effect that adversarial examples have in this regard. Our work focuses on creating executable adversarial examples by minimally modifying malicious raw binaries using a novel obfuscation algorithm.

2. Background

In this section, we describe the relevant background and malware classification setup. We also discuss the nature of adversarial examples in malware image domain.

2.1. Data representation

In this work, we represent malware binaries as grayscale images generated from the bytecode.

A malware binary, usually a sequence of assembly instructions, is read into 2-dimensional array as 8-bit unsigned integers. Because each of these 8-bit unsigned integers are between 0 and 255, they can be visualized as a grey-scale image where 0 is black and 255 is white, as seen in Figure 1.
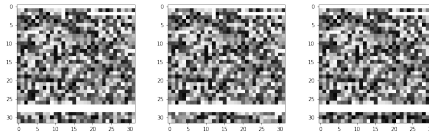

Figure 1. The three images above are unique malware images of class 11 included in the Malimg dataset. As can be seen, there are repeated patterns that can be seen shared among the three images, namely the sequence of white pixels near the bottom of the images.

Previous work has shown that this image representation of malware can be used to see shared repeated patterns and distinct characteristics between binaries in the same class (Nataraj et al., 2011).

It is important to note that these images can be transformed back into executable code so that they can be fed as input into classifiers that extract features or take in raw bytes. This is done by reading in each pixel value between 0 and 255, converting that value into either a binary or hex string, and then replacing that string with the corresponding assembly instructions. In this way, we can test the transferability of our adversarial examples.
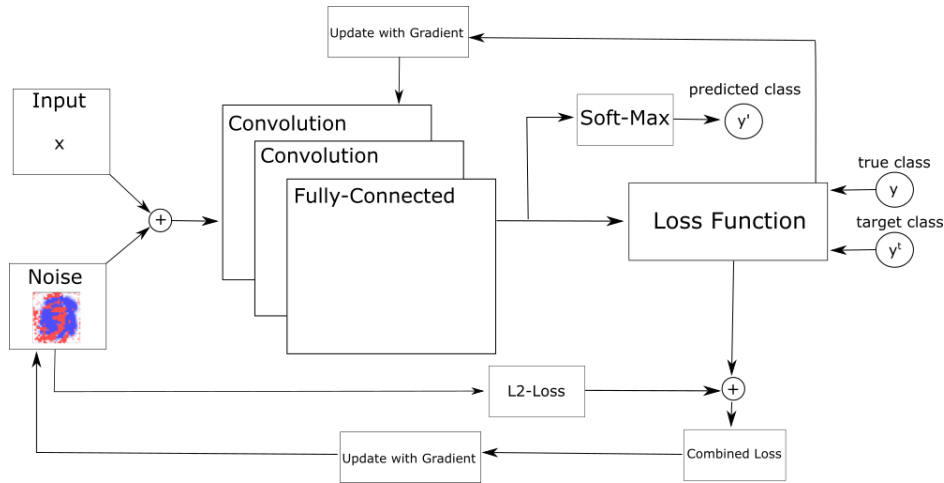
Figure 2. This is the architecture of the fully trained convolutional neural network that is used to generate our adversarial noise. During the noise optimization process, we begin with Gaussian noise added to valid inputs before adjusting that noise such that the now perturbed input is misclassified (as a target class y' if it was provided). The optimizer for the adversarial noise minimizes both the normal loss-measure and the l_2-loss measure to cause misclassification but to also bound the perturbation.

2.2. Adversarial examples & malware

The popularity of the image representation of malware has led to increased usage of deep learning techniques for classifying malware. Yue (2017) and EK. Kabanga (2018) used convolutional neural networks to classify malware images and reported classification accuracies of 96.7% and 98% accuracy respectively.

Adversarial examples of malware images, generated using Fast Gradient Signed Method (FGSM) or the Carlini and Wagner (C&W) method can be used to evade classification. However, real adversarial examples for malware must also be executable and have the same effective program logic when converted back into binary form. A perturbation on a malware image does not necessarily ensure these properties. For example, let $x = [137, 200]$, two pixels representing a binary. When converted to hexadecimal and then to x86 instructions, we get $89c8$ and *mov eax, ecx*, respectively. The intent of x is to move the value in register *ecx* to register *eax*. Consider a small perturbation on the image which results in $x' = [137, 201]$. When x' is converted into assembly instructions, we get *mov ecx, ecx*, which does not produce the same results as x. In fact, the perturbed pixels may not even translate to real instructions.

Another point of consideration is the purpose of limiting the magnitude of adversarial perturbation to the input image. For natural images, the perturbations are limited in magnitude such that they are undetectable to the human eye. Limiting the magnitude of adversarial perturbation for malware images is used for different reasons. Firstly, using large perturbations would allow easy detection of adversarial examples by measuring a simple distance metric, such as the L_2 norm. Secondly, specifically for our proposed method, unlimited perturbation can require an increase in obfuscation needed to modify malware to fool a classifier. This increase in size is undesirable as the input size of an image classifier is usually fixed. Bounding the perturbation, as we would with natural images allows our obfuscation method to be size preservering.

3. Methodology

Two popular methods, the Fast Gradient Sign Method and the Carlini & Wagner method, are commonly used to generate adversarial examples. We describe how these methods can be applied to generate **non-executable** adversarial examples from malware images. We introduce a dynamic programming based algorithm, Adversarial Malware Alignment Obfuscation (AMAO), that uses established obfuscation techniques and non-executable adversarial examples to generate **executable** adversarial examples.

3.1. Generating adversarial examples

Adversarial examples are images where a perturbation of the original image causes it to be misclassified even though it appears to be a copy of the original. In this work, we generate executable adversarial malware examples using l_2-bounded noise to control the level of perturbation on the original image. We define adversarial examples and the methods used to generate them below before introducing the proposed method for generating executable adversarial examples.

Given an input binary file x, an adversarial example gener-

ated using x is a perturbed version of x, x', such that

$$x' = x + \delta \tag{1}$$

where δ is some additive perturbation, which causes a classifier to incorrectly label the binary file while preserving the functionality of the original file.

In a non-targeted attack, the goal is to cause misclassification. The task for the adversary is to generate an l_2-bounded perturbation of a binary x with true class y such that

$$||x' - x||_2 < \epsilon \tag{2}$$

where x' is the modified binary, $|| \cdot ||$ is the l_2-norm, and x' is executable and preserves the functionality of x.

In a targeted attack, equation 2 still applies. The only additional requirement is that the adversarial example is misclassified as target class y'.

3.2. Obfuscation

Obfuscation is applied to make programs harder to understand. It was first created to protect source code and intellectual property from competitors but is now often used maliciously to make malware undetectable (Schiffman, a;b). In this section, we will briefly go over obfuscation before explaining its application in creating adversarial examples.

The main goal of obfuscation is to make a program difficult to understand while preserving the logic of the original program. Dummy code insertion is a type of obfuscation that introduces new code sequences that do not affect the logic of the program. These sequences are also called garbage code, junk code, or *nops*. There are multiple ways to insert dummy code into a source program, in addition to the simply inserting the *nop* instruction as seen in Figure 3. These are called semantic *nops* and are instructions or sequences of instructions that do not affect program behavior.

```
1 xor eax, eax
2 mov eax, 0x45
3 mov ecx, 0x20
4 ret
```

```
1 xor eax, eax
2 nop
3 mov eax, 0x45
4 mov ecx, 0x20
5 ret
```

Figure 3. On the left, we have a simple assembly program that zeros out the eax register before moving the hex numbers 45 and 20 into registers eax and ecx, respectively. On the right, we have another program that has the same functionality, but has a *nop* or no-operation code inserted.

We compiled a list of 26 semantic *nops* that are used in a dynamic programming algorithm below to create our executable adversarial examples.

3.3. Adversarial Malware Alignment Obfuscation

At this point, we have an adversarial example which will fool the convolutional neural network used to generate it. But, this adversarial example is not executable. In this section, we introduce a dynamic programming algorithm which will find the optimal way, with respect to some distance function D, to insert semantic *nops* into the original malware sample to make it resemble the adversarial example. This results in an adversarial example that is executable also preserves the original functionality.

Adversarial Malware Alignment Obfuscation (AMAO) begins with completing our base cases. Consider an $n \times m$ table where n is the length of the binary representation of our adversarial example and m is the length of the binary representation of the original malware sample. Each cell represents an additional index of the adversarial example and/or malware sample that are being considered. Naturally, the base case is when we compare only one index of the original malware sample against segments of the adversarial example, increasing in length. The base case also covers the comparison of one index of the adversarial example against increasing segments of the malware sample. This comparison is done with distance function D. In our experiments, our distance metric was the sum over all bit differences, or

$$D(x_1, x_2) = \sum_{i=0}^{n} \begin{cases} 0 & x_1[i] = x_2[i] \\ 1 & x_1[i] \neq x_2[i] \end{cases} \tag{3}$$

where x_1 and x_2 are the adversarial example and malware sample, respectively, read in as a binary string. They are assumed to have the same length. In the case that x_1 and x_2 have different lengths, we pad the front of the shorter binary string with 0's.

After the base cases are completed, we complete the rest of the table with the solutions of the subproblems denoted in Algorithm 1.

At the completion of the algorithm, the optimal solution's distance from the adversarial example is located in $O[i][j]$. From this, we can traceback to the binary string that the optimal solution represents.

3.4. Closed loop model

Because our method obfuscates a malware sample to match a real adversarial example as much as possible, the output executable may not fool the classifier. Thus, we propose a closed loop model, in which we continue to train the adversarial noise until a 0% classification accuracy is achieved.

Our initial adversarial examples are generated using the architecture shown previously in Figure 2 with FGSM. In subsequent loops, we begin to apply more computationally expensive adversarial example generation algorithms

Algorithm 1 Adversarial Malware Alignment Obfuscation

Input: adversarial example $B1$, original malware $B2$, insertion points list L_{ins}, *nops*, list L_{nop}, distance function D

for $i \in \text{range}(1, len(B1))$ **do**
  for $j \in \text{range}(1, len(B2))$ **do**
    minCode = None
    code = None
    for $c \in L_{nop}$ **do**
      $m = len(c)$
      if $i \in L_{ins}$ && $j - m - 1 \geq 0$ **then**
        cost = O[i][j-m-1]+D(B1[j-m:j], c)
        if minCode is None || cost $\leq$ minCode **then**
          minCode = cost
          code = c
        end if
      end if
      noCode = O[i][j-1] = D(B1[j], B2[i])
    end for
  end for
end for

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by generating adversarial noise specific to each malware sample and creating adversarial examples using the C&W attack.

4. Experimental results

In this section, we will outline and discuss the experimental results of our method on different classifiers. We also separate our results into a white-box and black-box setting.

4.1. Dataset

We evaluated the effectiveness of our method using the Malimg dataset (Nataraj et al., 2011) and the MMBIG dataset (Ronen et al., 2018). The Malimg dataset is already in the necessary black and white image representation, as discussed in Section 1, and contains 25 unique classes. We transformed the MMBIG dataset into the correct format by using and parsing the given hex dumps. The MMBIG dataset consists of 9 unique classes.

For each sample in the dataset, we created three executable adversarial examples as follows.

- Output of AMAO after one loop

- Final output of AMAO

- Randomly inserted semantic *nops*

We used random insertion as there is no algorithmic approach to dummy code insertion, to the best of our knowledge.

4.2. White-box setting

In this section, we consider the results of our method with access to the classifier's computational graph and weights.

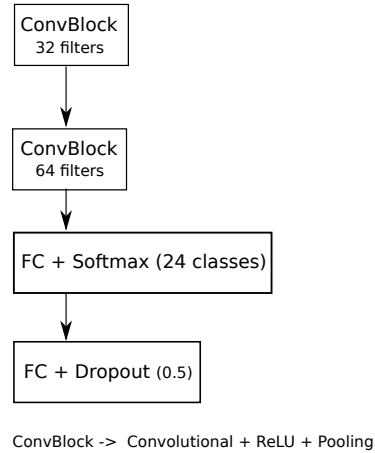ConvBlock -> Convolutional + ReLU + Pooling

Figure 4. This is the simple CNN architecture used in the white-box experiments. The convolutional layers use a kernel size of 5, pool size and stride of 2. The fully connected layer has 128 units and the dropout layer use a rate of 0.5. The adversarial examples generated using this CNN are also used to fool classifiers in a black box setting to demonstrate transferability.

We trained a very simple convolutional neural network, depicted in Figure 4 to classify the Malimg dataset until it had a classification accuracy of 90% on the training set. This translated to an 85% accuracy rate on the test set. We, then, optimized adversarial noise for each of the 25 classes using the gradients of the trained model in a closed loop, which consists of FGSM and C&W. Our method was designed to terminate at a 0% accuracy rate, or some number k iterations. As expected, our generated adversarial examples were all misclassified by the previously trained classifier.

4.3. Black-box setting

There will always be cases when adversarial examples must be crafted without uninhibited access to the model and its weights. To evaluate or method in these circumstances, we first trained two models on the Malimg dataset. **1.)** The first is InceptionV3, which is Google's convolutional neural network architecture for image recognition introduced in (Szegedy et al., 2016). InceptionV3 was trained using transfer learning to classify the Malimg dataset. **2.)** The second is a gradient boosted tree classifier, using XGBoost, based on top MMBIG Kaggle competition submissions, using popular op-codes, the top 500 4-grams, and features extracted from image representation of the malware (Chen & Guestrin, 2016). We then fed the same adversarial examples generated during our white-box setting attack, to

these two classifiers without any further optimization or alteration.

Table 1. Classification accuracies during the white-box and black-box setting experiments when using different obfuscation methods before input. We report accuracies using no obfuscation, one loop (AMAO$_1$) of the proposed method, the full proposed method (AMAO$_f$), and randomly inserted semantic *nops*. For the randomized insertions, we record the range over 10 experiments.

Model	None	AMAO$_1$	AMAO$_f$	Random
Simple CNN	85.1%	44.4%	0.0%	20-30%
Boosted Trees	99.0%	1.98%	0.0%	80-85%
InceptionV3	86.1%	50.0%	31.0%	40-50%

4.4. Analysis

The results of both black-box and white-box experiments are given in Table 1. It is interesting to note the differences between running only 1 loop of AMAO versus the full algorithm. One loop of AMAO resulted in malware samples of which only 55.6% were able to successfully fool the classifier. However, the same output malware samples were much more effective against our boosted trees classifier, achieving 98% misclassification rate. Our method also consistently outperformed randomized dummy code obfuscation.

It is also interesting to note that the initial highest performing classifier is not necessarily the most robust. InceptionV3 was marginally better than our simple CNN with respect to classification accuracy, but proved to be much more robust against our executable adversarial examples, maintaining a 50% and 31% classification accuracy against single-loop and full AMAO, respectively. This gives us confidence that with deep learning will prove to be an effective tool in cybersecurity, especially with further research in building robust classifiers.

5. Future work

In future work, we plan to incorporate additional, and more complex, obfuscation techniques to allow for greater flexibility in perturbing malware samples. We also plan to research generative methods for applying obfuscation to generate adversarial examples.

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