Evading the Machine Learning Detector: A Virus Perspective

Group 10
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Abstract

In this project, we intend to explore the classification-based virus scanners from the perspective of virus. We developed effective anti-antivirus schemes against a known classification model as the scanner. By adding or removing key attributes from the malicious executable instances, we are able to fool the scanner into classifying a malicious instance as a non-malicious one. We did exploration about how to choose the attributes to be modified and designed our self-defined Relative-Ratio-based feature selection. We also compared our method with the feature selection methods from Weka and LibSVM.

1 Introduction

1.1 Problem Description

There are a bunch of anti-virus software on market nowadays, such as Norton and McAfee. They can detect malicious apps/binaries and prevent them from jeopardizing the user's data. However, in our project, we are not aiming at improving the detection rate of anti-virus software; instead, we want to study from a virus' perspective: how should a virus disguise itself to evade the detection? To answer this question, we designed a novel evasion scheme and conducted experiments the test its efficiency on a dataset from UCI Machine Learning Repository. We will introduce them in more detail in Section 4.

1.2 Classification Algorithms

In this project, we use LibSVM [1] as our machine learning algorithm, which implements Support Vector Machine (SVM). To compare with our feature selection scheme, we use Weka's `weka.attributeSelection.CfsSubsetE` module as the feature selection method. It implements correlation-based feature selection. We will present the detail of algorithms in Section 3.

1.3 Assumptions

We make reasonable assumptions in this project. The classifier should be already known to the attacker and will not change after it is trained. Also, in experiments we assume that the training set and classification algorithm are both known and the classification model can be trained by the attacker. After the attacker modifies the malicious executables, the classification model remains and will not be re-trained using the modified data.

1.4 Result Summary

Our results show that our scheme works well and can truly fool the detector.

2 Background

The author of the dataset we used generated the dataset based on the n-gram feature set construction from Masud et al.'s paper [6]. In this paper, they proposed a new way to construct features for binary files, called N-gram Features. An n-gram may be either a sequence of n bytes or n assembly instructions, or n DLL function calls, depending on whether they want to extract features from binary or assembly program, or DLL call list. For example, the 3-grams corresponding to the 4 bytes sequence "a1b2c3d4" are "a1b2c3" and "b2c3d4". They constructed Binary/Assembly/DLL N-gram feature set, and proposed a hybrid model to combine the three feature sets. Then, they choose best 500 features for each set based on entropy gain. Later on, they use LibSVM to test their models. The hybrid model works best for both datasets (Accuracy:96.30%, 96.15%).

There is an older paper about detecting malicious executables by Schultz et al. [7]. In their paper, they constructed DLLs, GNU Strings, and Byte Sequence features. The DLL and Byte Sequence features are similar to the way of constructing our dataset, but they did not use N-gram feature. They further tested their features using different machine learning algorithms, i.e., RIPPER, Naive Bayes, and Multi-Naive Bayes. The best one (Multi-Naive Bayes) can achieve 97.76% detection rate.

3 Methodology

3.1 Tools

3.1.1 LibSVM

LibSVM [1] is an open-source software that implements Support Vector Machine (SVM) algorithm [3]. It is one of the most popular tools when it comes to SVM implementation. It is the main tool that we use to test the performance our evasion scheme.

3.1.2 Weka

Weka [4] is a collection of machine learning algorithms for data mining tasks. It has a nice GUI interface and can accept different file inputs (e.g, .arff, .csv, etc.). In our project, our main task is to find important features to add or delete (feature selection). Therefore, we use Weka as a tool for feature selection and compare the performance with our feature selection scheme.

3.2 Algorithms

3.2.1 SVM

SVM [3] is a supervised learning model that analyzes data for classification or regression. Provided with a set of training examples, which are marked with their belonging categories, a SVM algorithm performs to build a model so as to recognize and assign testing examples to the predicted categories.

3.2.2 Correlation-based Feature Selection

We choose the `weka.attributeSelection.CfsSubsetEval` module as the feature selection method to compare with our scheme. It implements correlation-based feature selection, which evaluates the worth of a subset of attributes by considering the individual predictive ability of each feature along with the degree of redundancy between them [5].

3.2.3 LibSVM Feature Selection

We also use a feature selection python script in LibSVM to compare with our scheme. The script implements several feature selection methods, such as `F-score + Random Forest`, which are originally from a paper [2].

3.2.4 Relative Ratio Feature Selection

In this project, we came up with a novel way to select features to modify, which is specific to this project only. We will propose our method in detail in Section 4.

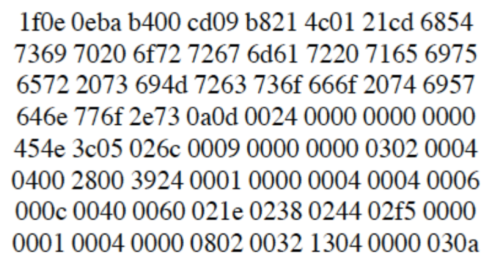
4 Experiments

4.1 Original Dataset

The dataset includes instances of malicious executables (computer virus) as well as non-malicious executables (normal programs). The features are extracted from real-world malicious and non-malicious executables. The dataset was published in March 2016 in UCI Machine Learning Repository. Within one year, the web hits of the dataset has already reached over 200,000. It is obvious that the dataset arouses great interest in the machine learning community.

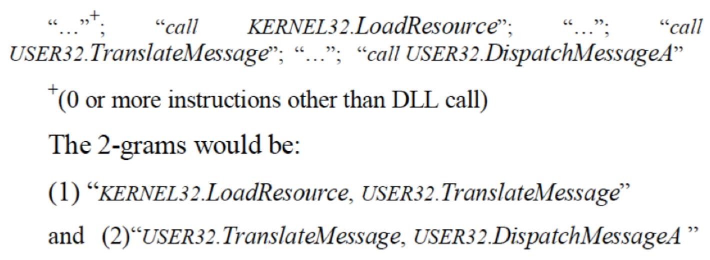
The dataset consists of 373 instances, of which 301 are malicious and 72 are benign. Each instance has 500 hex features and 30 DLL features. Examples of hex features and DLL features are shown in Fig. **??**. Notice that on the UCI webpage it claims that there are 13 DLL features but we found from the raw data that there are actually 30 of them. All the attributes are binary, meaning a certain feature exists or not.

However, the primary weakness of the dataset is that the sample number is relatively low. However, the goal of our project is not to exhaustively find the best machine learning model to classify malicious and non-malicious executables. Thus we think the low sample amount is tolerable. In addition, after searching online, the UCI dataset is the only dataset available that do not require extracting features by ourselves.



```
1f0e 0eba b400 cd09 b821 4c01 21cd 6854
7369 7020 6f72 7267 6d61 7220 7165 6975
6572 2073 694d 7263 736f 666f 2074 6957
646e 776f 2e73 0a0d 0024 0000 0000 0000
454e 3c05 026c 0009 0000 0000 0302 0004
0400 2800 3924 0001 0000 0004 0004 0006
000c 0040 0060 021e 0238 0244 02f5 0000
0001 0004 0000 0802 0032 1304 0000 030a
```

(a) Hex Feature



"…"+; "*call KERNEL32.LoadResource*"; "…"; "*call USER32.TranslateMessage*"; "…"; "*call USER32.DispatchMessageA*"

+(0 or more instructions other than DLL call)

The 2-grams would be:

(1) "*KERNEL32.LoadResource, USER32.TranslateMessage*"

and (2)"*USER32.TranslateMessage, USER32.DispatchMessageA* "

(b) DLL Feature

4.2 Workflow

The whole experiment is made up of four steps. We will go through each step in detail.

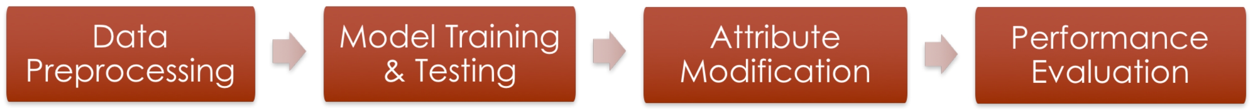


Figure 2: Workflow

4.2.1 Data Preprocessing

The raw data is generally LibSVM-format conformant. The class attribute at the beginning of an instance marks whether it is benign or malicious. -1 stands for a malicious instance and +1 means benign. However, at the end of each instance there is an additional -1. We need to remove it before passing it to LibSVM as input.

4.2.2 Model Training & Testing

After data preprocessing, we pass the training set to LibSVM to train a classification model. In 1.3, we mentioned that the model is known to the attacker, and it will not change when the test set changes.

Given a trained classification model, we apply it to the test set first and get the test results as a criterion for later evaluation. With the unmodified test set, we expect the performance of the model to classify malicious instances to be high enough. Otherwise, the model itself does not make sense and it is pointless to fool an inaccurate classification model.

4.2.3 Attribute Modification

Now that we have a model, we can apply different attribute modification methods to the test set. Notice that only malicious instances are modified since our only goal is to disguise a malicious executable as a benign one. More specifically, we use different feature selection methods to find the right attributes to modify (add or delete attributes). With different modified test sets, we re-do the testing phase with unmodified classification model.

4.2.4 Performance Evaluation

In the end, we compare the new test result with the original one and see whether the detection rate drops. Moreover, we compare the escape results of different modification methods to find which one performs best.

4.3 Relative Ratio Feature Selection

At first, we chose to modify only one attribute. We modified each of the 530 attribute (add or delete), but none of them affected the performance of the original model. We cannot simply choose any two of them, because there are too many combinations. To solve this problem, we came up with a novel way to perform the feature selection, and we call it Relative Ratio feature selection. In this part, we will introduce this method in detail.

For every attribute X (1 530) in the training set, first, we compute the `Positive Ratio (PR)` using the following equation:

$$PR(X) = \frac{\text{benign instances that have attribute X}}{\text{total benign instances}} \tag{1}$$

Similarly, we also compute the Nagative Ratio (NR) using the following equation:

$$NR(X) = \frac{\text{malicious instances that have attribute X}}{\text{total malicious instances}} \tag{2}$$

Then, the `Relative Ratio (RR)` is defined as follows:

$$RR(X) = PR(X) - NR(X) \tag{3}$$

Here, if an attribute X has high `RR`, it means that attribute X appears more often in benign samples; On the other hand, if an attribute X has low `RR`, it means that attribute X appears more often in malicious samples.

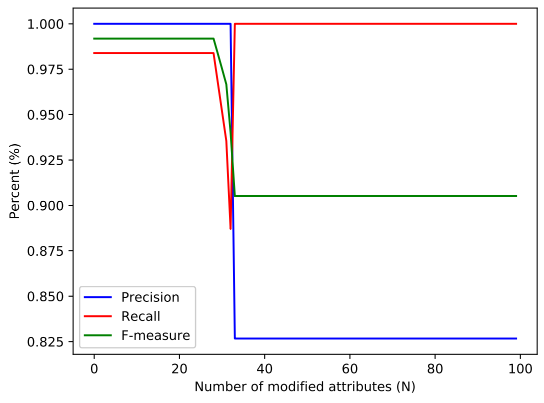
After calculating `RR` for all 530 attributes, we sort them in descending order and obtain an attribute list, `RRList`. In `RRList`, if attribute X appears earlier than Y, it means that X has larger `RR` values than Y. Then, we can perform two kinds of modification strategies:

1. Adding attributes. We can add top N attributes in `RRList` to the malicious samples. By adding N attributes that have high `RRs`, we make the viruses become more like benign samples.
2. Removing attributes. We can remove last N attributes in `RRList` to the malicious samples, should they have such attributes. By removing N attributes that have low `RRs`, we make the viruses become less like malicious samples.

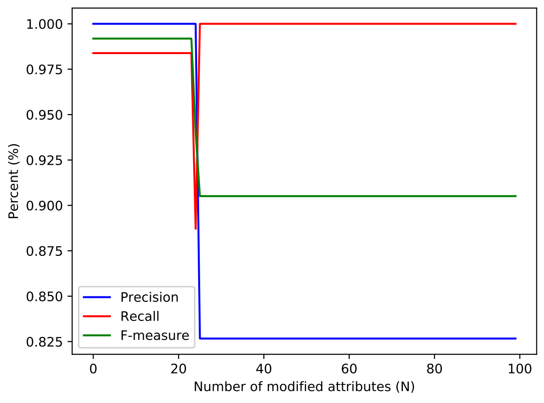
4.4 Relative Ratio Evaluation

4.4.1 Adding Attributes

The first strategy we tried was to add the top N attributes according to their RR. We tried different N numbers and evaluated how they performed with precision and recall. As shown in figure xx and figure yy, there is an obvious performance drop when N reaches about 35?. When less than 25? attributes are added, the classifier stays robust to the changes and the malicious instances are not able to escape the detection. However, take N=35? as a threshold, when more than threshold attributes are added, almost all the malicious instances successfully fool the classifier to think they are benign.



(a) Add attributes



(b) Remove attributes

Figure 3: Relative Ratio Evaluation

4.4.2 Removing Attributes

Similar to adding attributes, we did experiments on removing them as well. We tried different N numbers and evaluated how they performed with precision and recall. The evaluation result is also close to adding them. When removing less than threshold number of attributes, none of the malicious instances are misclassified. But when the number of removed attributes increases to over threshold, all of them succeeds in escaping the detection.

If we do further comparison between adding and removing attributes, as shown in figure zz, the threshold of removing attributes turns out to be lower than that of adding attributes. This suggests that removing attributes is easier to fool the classification-based virus detector than adding attributes.

4.5 Comparison with Existing Feature Selection Methods

In order to compare our RR-based feature selection with other approaches, we specified the same number of attributes to be added/deleted and applied the different feature selection methods. Then we record and compare the performance of the classifier towards the different modified test set. The results are shown in Table 1 and Table 2. `LibSVM-FS` stands for LibSVM feature selection, and `CB-FS` stands for correlation-based feature selection. `RR-FS` is our method.

Table 1 shows the result of adding N attributes. When N = 30, the performance of our `RR-FS` begins to drop. When N = 40, it reaches the lowest point (baseline). For `LibSVM-FS`, it does not change when N ¡= 50; but when N = 60, it also hits the baseline. However, for `CB-FS`, the performance never drops when N ¡= 70.

Table 2 shows the result of deleting N attributes. According to 3, we know that deleting features works better than adding them. Not surprisingly, the performance of `LibSVM-FS` starts to decrease when N = 50, which is earlier than adding. Still, for `CB-FS`, the performance does not change at all. Our `RR-FS` remains efficient and touches baseline when N = 40.

N	LibSVM-FS	CB-FS	RR-FS
20	0.992	0.992	0.992
30	0.992	0.992	0.984
40	0.992	0.992	0.905
50	0.992	0.992	0.905
60	0.905	0.992	0.905
70	0.905	0.992	0.905

Table 1: F-measure: Adding N Attributes

N	LibSVM-FS	CB-FS	RR-FS
20	0.992	0.992	0.992
30	0.992	0.992	0.905
40	0.992	0.992	0.905
50	0.984	0.992	0.905
60	0.905	0.992	0.905
70	0.905	0.992	0.905

Table 2: F-measure: Deleting N Attributes

5 Discussion

5.1 Real-world Feasibility

In this section we briefly discusses the feasibility of our modification towards the malicious executables and compare them with existing anti-antivirus methods deployed by real-world virus.

In reality, it is much more difficult to remove features than to add features. The features to remove mostly denote the malicious behavior of a virus and are thus hard to take out. In contrast, we can easily add features as dummy code that will never be executed.

Our modification schemes in fact serves as a combination of two existing anti-antivirus methods. The first is to disguise as popular file formats such as .pdf or .docx or programs such as calc.exe or notepad.exe. The second is polymorphic virus. It mutates on each copy by adding different types of NOP instructions.

5.2 Feature Selection Algorithms

In our project, our method works better because it is specifically designed for this project. It does not indicate that other feature selection methods are not good. Also, we notice that LibSVM feature selection result is actually the combination of features that have high and low `RRs`, which means our method does have similarity with modern feature selection algorithms.

6 Conclusion

By modifying the top N attributes according to our self-defined `RR` values, we are able to fool the given SVM model into mistakenly classifying malicious executables as benign ones. Removing attributes works better than adding them, but in practice the difficulty of adding features is lower than that of removing. In real world scenario, our hiding scheme serves as the combination of two existing schemes. Thus it is feasible in real world under the given assumptions.

References

[1] Chih-Chung Chang and Chih-Jen Lin. LIBSVM: A library for support vector machines. *ACM Transactions on Intelligent Systems and Technology*, 2:27:1–27:27, 2011. Software available at `http://www.csie.ntu.edu.tw/~cjlin/libsvm`.

[2] Yi-Wei Chen and Chih-Jen Lin. Combining svms with various feature selection strategies. In *Feature extraction*, pages 315–324. Springer, 2006.

[3] Corinna Cortes and Vladimir Vapnik. Support-vector networks. *Machine learning*, 20(3):273–297, 1995.

[4] Mark Hall, Eibe Frank, Geoffrey Holmes, Bernhard Pfahringer, Peter Reutemann, and Ian H Witten. The weka data mining software: an update. *ACM SIGKDD explorations newsletter*, 11(1):10–18, 2009.

[5] Mark A Hall. *Correlation-based feature selection for machine learning*. PhD thesis, The University of Waikato, 1999.

[6] Mohammad M Masud, Latifur Khan, and Bhavani Thuraisingham. A hybrid model to detect malicious executables. In *Communications, 2007. ICC'07. IEEE International Conference on*, pages 1443–1448. IEEE, 2007.

[7] Matthew G Schultz, Eleazar Eskin, F Zadok, and Salvatore J Stolfo. Data mining methods for detection of new malicious executables. In *Security and Privacy, 2001. S&P 2001. Proceedings. 2001 IEEE Symposium on*, pages 38–49. IEEE, 2001.