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A Hybrid Model to Detect Malicious Executables

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Abstract— **We present a hybrid data mining approach to detect malicious executables. In this approach we identify important features of the malicious and benign executables. These features are used by a classifier to learn a classification model that can distinguish between malicious and benign executables. We construct a novel combination of three different kinds of features: binary n-grams, assembly n-grams, and library function calls. Binary features are extracted from the binary executables, whereas assembly features are extracted from the disassembled executables. The function call features are extracted from the program headers. We also propose an efficient and scalable feature extraction technique. We apply our model on a large corpus of real benign and malicious executables. We extract the abovementioned features from the data and train a classifier using Support Vector Machine. This classifier achieves a very high accuracy and low false positive rate in detecting malicious executables. Our model is compared with other feature-based approaches, and found to be more efficient in terms of detection accuracy and false alarm rate.**

Keywords- disassembly, feature extraction, malicious executable, n-gram analysis.

I. Introduction

Malicious code is a great threat to computers and computer society. Numerous kinds of malicious code wander in the wild. Some of them are mobile, such as worms, and spread through the internet crashing thousands of computers worldwide. Other kinds of malicious code are static, like viruses, but sometimes deadlier than its mobile counterpart. Malicious code writers mainly exploit different kind of software vulnerabilities to attack host machines. There has been tremendous effort imparted by researchers to counter the attacks of malicious code writers. Unfortunately, the more successful the researchers become in cracking down malicious code, the more sophisticated mal-code appear in the wild, evading all kinds of detection mechanisms. Thus, the battle between malicious code writers and researchers is virtually a never-ending game.

Although signature based detection techniques are being used widely, they are not effective against "zero-day attacks" and various "obfuscation" techniques. Signature based technique is also hopeless against new attacks. So, there has been a growing need for fast, automated, and efficient detection technique that can also detect new attacks. Many automated systems [1-8] have already been developed by different researchers in recent years.

In this paper we describe our new model, the Hybrid Feature Retrieval (HFR) model, which can detect malicious executables efficiently. Our model extracts three different kinds of features from the executables and combines them into one feature set, which we call the *hybrid feature set* (HFS). These features are used to train a classifier using Support Vector Machine (SVM). This classifier is then used to detect malicious executables. The features that we extract are: i) binary features, ii) derived assembly features and iii) dynamic link library (DLL) call features. The binary features are extracted as binary *n*-grams (i.e., *n* consecutive bytes) from the binary executable files. This extraction process is explained in section III (A). Derived assembly features are extracted from disassembled executables. A derived assembly feature is actually a sequence of one or more assembly instructions. We extract these features using our sophisticated assembly feature retrieval (AFR) algorithm, explained in section IV (B). These derived assembly features are similar to, but not exactly the same as assembly *n*-gram features (explained in section III (B)). We do not directly use the assembly *n*-grams features in HFS, because we observe during our initial experiments [9] that derived assembly features perform better than assembly *n*-gram features. The process of extracting derived assembly features is not trivial, but involves a lot of technical challenges. It is explained in section IV. DLL call features are also extracted from the header of the disassembled binaries, and explained elaborately in section III (C). We show empirically that the combination of these three features is always better than any single feature in terms of classification accuracy. We discuss our results in section V.

Our contributions to this research work are as follows. First, we propose and implement our HFR model, which combines three types of features mentioned above. Second, we apply a novel idea to extract assembly features using binary features. A binary feature or binary *n*-gram may represent an assembly instruction, or part of one or more instructions, or even a string data inside the code block. Thus, a binary *n*-gram may represent some partial information. But we apply AFR algorithm to retrieve the most appropriate assembly instruction or instruction sequences corresponding to the binary n-gram. We call it the *most appropriate* assembly instruction sequence because there may be multiple possible assembly instruction sequences corresponding to a single binary *n*-gram, and AFR selects the most appropriate of them by applying some selection criteria. If the binary *n*-gram represents a partial assembly instruction or instruction sequence, then we find the corresponding complete instruction sequence, and use this as a feature. The net effect is that, we convert a binary feature to an assembly feature. We hope that the assembly feature would carry more complete and meaningful information than the binary feature. Third, we propose and implement a scalable solution to the *n*-gram feature extraction and selection problem in general. Our solution not only solves the limited memory problem but also applies efficient and powerful data structures to ensure fast running time. Thus, it is scalable to very large set of executables (in the order of thousands), even with limited main memory and processor speed. Fourth, we compare our results with a recently published work [10] that is claimed to have achieved high accuracy using only binary *n*-gram feature, and we show that our method is superior to that.

The rest of the paper is organized as follows: Section II discusses related works, Section III presents and explains different kinds of *n*-gram feature extraction methods, Section IV describes the HFR model, Section V discusses our experiments and analyzes results, Section VI concludes with future research directions.

II. RELATED WORK

There has been a significant amount of research in recent years to detect malicious executables. Researchers apply different approaches to automate the detection process. One of them is behavioral approach, which is mainly applied to mobile malicious code. Behavioral approaches try to analyze characteristics such as source and destination addresses, build statistical models of packet flow at the network level, consider email attachments etc. Examples of behavioral approaches are social network analysis [1, 2], and statistical analysis [3]. A data mining based behavioral approach for detecting email worms as been proposed by Masud et al. [4].

Another approach is content-based, which analyzes the content of the code. Some content based approaches try to generate signature automatically from network packets. Examples are EarlyBird [5], Autograph [6], and Polygraph [7]. Another kind of content-based approach extracts features from the executables and apply machine learning to classify malicious executables. Stolfo et al. [8] extract DLL call information using GNU Bin-Utils [11], and character strings using GNU *strings*, from the header of Windows PE executables. Also, they use byte sequences as features. They report accuracy of their features using different classifiers.

A similar work is done by Maloof et al. [10]. They extract binary *n*-gram features from the binary executables and apply them to different classification methods, and report accuracy. Our model is also content based. But it is different from [10] in that it extracts not only the binary *n*-grams but also assembly instruction sequences from the disassembled executables, and gathers DLL call information from the program headers. We compare our model's performance with [10], since they report higher accuracy than [8].

III. FEATURE EXTRACTION USING N-GRAM ANALYSIS

Feature extraction using *n*-gram analysis involves extracting all possible *n*-grams from the given dataset (*training set*), and selecting the best *n*-grams among them. We extend the notion of *n*-gram from bytes to assembly instructions, and to DLL function calls. That is, an *n*-gram may be either a sequence of *n* bytes or *n* assembly instructions, or *n* DLL function calls, depending on whether we want to extract features from binary or assembly program, or DLL call list. Before extracting *n*-grams, we preprocess the binary executables by converting them to hexdump files and assembly program files, as explained below.

A. *Binary n-gram feature*

We apply the UNIX hexdump utility to convert the binary files into text files ('hexdump' files), containing the hexadecimal number corresponding to each byte of the binary file. The feature extraction process consists of two phases: i) feature collection, and ii) feature selection, both of which are explained in subsequent paragraphs.

1) Feature Collection

We collect *n*-grams from the 'hexdump' files. As an example, the 4-grams corresponding to the 6 bytes sequence "a1b2c3d4e5f6" are "a1b2c3d4", "b2c3d4e5" and "c3d4e5f6", where "a1","b2",…etc are the hexadecimal representation of each byte.

N-gram collection is done in the following way: we scan through each file by sliding a window of *n* bytes. If we get a new *n*-byte sequence, then we add it to a list, otherwise we discard it. In this way, we gather all the *n*-grams. But there are several implementation issues related to the feature collection process. First, the total number of *n*-grams is very large. For example, the total number of 10-grams in 'dataset2' (see Section V(A)) is 200 million. It is not possible to store all of them in computer's main memory. Second, each newly scanned *n*-gram must be checked against the list. This requires a search through the entire list. If a linear search is performed, it will take a long time to collect all the *n*-grams. The total time for collecting all *n*-grams would be $O(N^2)$, where N is the total number of *n*-grams, which is very large when N=200 million.

In order to solve the first problem, we use disk I/O. We store the *n*-grams in the disk in sorted order to enable merging with the *n*-grams in the main memory.

In order to solve the second problem, we use a data structure called Adelson Velsky Landis (AVL) tree [12] to store the *n*-grams in memory. An AVL tree is a height-balanced binary search tree. This tree has a property that the absolute difference between the heights of the left sub-tree and the right sub-tree of any node is at most one. If this property is violated during insertion or deletion, a balancing operation is performed and the tree regains its height-balanced property. It is guaranteed that insertions and deletions are performed in logarithmic time. So, in order to insert an *n*-gram in memory, we now need only $O(\log_2(N))$ searches. So, the total running time is reduced to $O(N\log_2(N))$ from $O(N^2)$, which is a great improvement for N as large as 200 million.

2) Feature Selection

Since the number of extracted features is very large, it is not possible to use all of them for training because of the following reasons. First, the memory requirement would be impractical.

Second, training time of any classifier would be too long. Third, a classifier would be confused with such a large number of features, because most of the features would be noisy, redundant or irrelevant. So, we are to choose a small, relevant and useful feature set from the very large set. We choose information gain as the selection criterion, because it is one of the best criteria used in literature for selecting the best features from.

Information gain can be defined as a measure of the effectiveness of an attribute (i.e., feature) in classifying the training data [13]. If we split the training data on this attribute values, then information gain gives the measurement of the expected reduction in entropy after the split. The more an attribute can reduce entropy in the training data, the better the attribute in classifying the data. Information Gain of an attribute A on a collection of examples S is given by (1):

$$Gain(S, A) \equiv Entropy(S) - \sum_{V \in Values(A)} \frac{|S_v|}{|S|} Entropy(S_v) \quad \dots (1)$$

Where *Values*(*A*) is the set of all possible values for attribute *A*, and S_v is the subset of *S* for which attribute *A* has value *v*. In our case, each attribute has only two possible values (0, 1). If this attribute is present in an instance (i.e., executable) then the value of this attribute for that instance is 1, otherwise it is 0. Entropy of *S* is computed using the following equation (2):

$$Entropy(S) = -\frac{p(s)}{n(s)+p(s)}\log_2\left(\frac{p(s)}{n(s)+p(s)}\right) - \frac{n(s)}{n(s)+p(s)}\log_2\left(\frac{n(s)}{n(s)+p(s)}\right) \quad \dots (2)$$

Where *p*(*S*) is the number of positive instances in *S* and *n*(*S*) is the total number of negative instances in *S*. We denote the best 500 features, selected using information gain criterion, as the *Binary Feature Set* (BFS). We generate feature vectors corresponding to the BFS for all the instances in the training set. A feature vector corresponding to an instance (i.e., an executable) is a binary vector having exactly one bit for each feature, and a bit is 'one' if the corresponding feature is present in the example and 'zero' otherwise. Feature vectors are used to train classifier with SVM.

B. Assembly n-gram feature

We disassemble all the binary files using a disassembly tool called *PEDisassem* [14] that is used to disassemble Windows Portable Executable (P.E.) files. Besides generating the assembly instructions with opcode and address information, PEDisassem provides useful information like list of resources (e.g. cursor) used, list of DLL functions called, list of exported functions, and list of strings inside the code block and so on.

In order to extract assembly *n*-gram features, we follow a method very similar to the binary *n*-gram feature extraction. First we collect all possible *n*-grams, i.e., sequence of *n* instructions, and select best 500 of them according to information gain. We call this selected set of features as *Assembly Feature Set* (AFS). We face the same difficulties of limited memory and long running time as in byte *n*-grams, and solve them in the same way.

As an example of assembly *n*-gram feature extraction, assume that we have a sequence of 3 instructions:

"*push eax*"; "*mov eax, dword[0f34]*" ; "*add ecx, eax*";

and that want to extract all the 2-grams, which are:

(1) "*push eax*"; "*mov eax, dword[0f34]*";

and (2) "*mov eax, dword[0f34]*"; "*add ecx, eax*";

We adopt a standard representation of assembly instructions, which has the following format: *name.param1.param2*, where name is the instruction name (e.g., mov), param1 is the first parameter, and param2 is the second parameter. Again, a parameter is any one of the followings {*register*, *memory*, *constant*}. So, the second instruction in the above example: "*mov eax, dword[0f34]*", after standardization, becomes: "*mov.register.memory*".

We also compute binary feature vectors for the AFS. Please note that we do not use the AFS in our HFS. We use AFS only for comparison purposes.

C. DLL function call feature

We extract information about DLL function calls made by a program by parsing the disassembled file. We define the *n*-gram of DLL function call as a sequence of *n* DLL calls that appears in the disassembled file. For example, assume that the disassembled file has the following sequence of instructions (omitting all instructions except DLL calls):

"…"$^+$; "*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* "

After extracting the *n*-grams we select best 500 of them using information gain. We then generate the feature vectors in a similar way as explained earlier. We also compute binary feature vector for the selected DLL call features.

IV. The Hybrid Feature Retrieval Model

The Hybrid Feature Retrieval (HFR) Model is illustrated in fig. 1. It consists of different phases and components. Most of the components have already been discussed in details. Below is a brief description of the model.

A. Description of the Model

The Hybrid Feature Retrieval (HFR) Model consists of two phases: the training phase and the testing phase. The training phase is shown in Figure 1(a), and testing phase is shown in Figure 1(b).

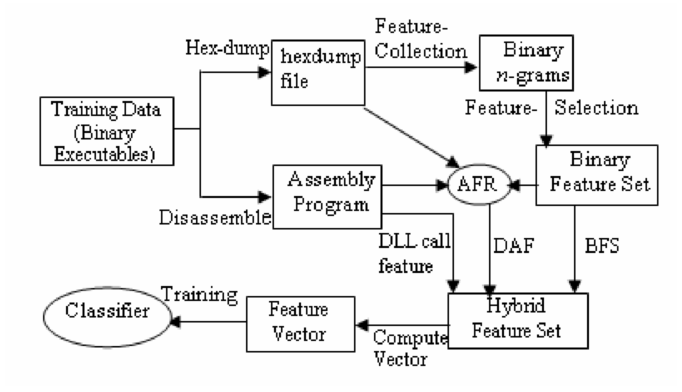


Figure 1(a). The Hybrid Feature Retrieval Model, training phase.

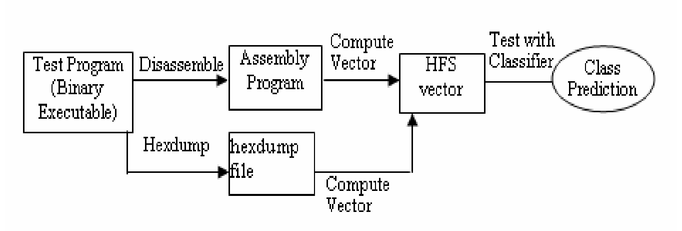


Figure 1(b). The Hybrid Feature Retrieval Model, testing phase.

In the training phase we convert binary executables into hexdump files and Assembly Program files using UNIX Hex-dump utility and the disassembly tool PEDisassem, respectively. We extract binary *n*-gram features using the approach explained in section III (A). We then apply AFR algorithm (to be explained shortly) to retrieve assembly instruction sequences, called the *derived assembly features* (DAF), that best represent the selected binary *n*-gram features. We combine these features with the DLL function call features, and denote this combined feature set as *Hybrid Feature Set* (HFS). We compute the binary feature vector corresponding to the HFS and train a classifier using SVM. In the testing phase, we scan the test file and compute the feature vector corresponding to the HFS. This vector is tested against the classifier. The classifier outputs the class prediction {benign, malicious} of the test file.

The main challenge that we face is that of finding DAF using the binary *n*-gram features. The main reason for finding DAF is that we observe that a binary feature may sometimes represent partial information. For example: it may represent part of one or more assembly instructions. Thus, a binary feature is sometimes a *partial feature*. We would like to find the *complete feature* corresponding to the partial one, which represents one or more whole instructions. We then use this complete feature instead of the partial feature so that we can obtain a more useful feature set.

B. The Assembly Feature Retrieval (AFR) algorithm

The AFR algorithm is used to extract derived assembly instruction sequences (i.e., DAF) corresponding to the binary *n*-gram features. As we have explained earlier, we do not use assembly *n*-gram features (AFS) in the HFS, because we observe that AFS performs poorer compared to DAF. Now we describe the problem with some examples and then explain how it has been solved.

The problem is: given a binary *n*-gram feature, how to find its corresponding assembly code. The code should be searched through all the assembly programs files. The solution consists of several steps.

First, we apply our *linear address matching* technique: we use the offset address of the *n*-gram in the binary file to look for instructions at the same offset at the assembly program file. Based on the offset value, one of the three situations may occur:

i. The offset is before program entry point, so there is no corresponding code for the *n*-gram. We refer to this address as *Address Before Entry Point* (ABEP).

ii. There is some data, but no code at that offset. We refer to this address as DATA.

iii. There is some code at that offset. We refer to this address as CODE.

Second, we select the best CODE instance among all instances. We apply a heuristic to find the best sequence, which we call the *Most Distinguishing Instruction Sequence (MDIS)* heuristic. According to this heuristic, we choose the instruction sequence that has the highest information gain. Due to the shortage of space, we are unable to explain details of our algorithm here. Please refer to [9] for a detailed explanation with examples of the AFR algorithm, and MDIS heuristics.

V. Experiments

We design our experiments to run on two different datasets. Each dataset has different sizes and distributions of benign and malicious executables. We generate all kinds of *n*-gram features (e.g. binary, assembly, DLL) using the techniques explained in section III. We also generate the HFS (see section IV) using our model. We test the accuracy of each of the feature sets using SVM, applying a three-fold cross validation. We use the raw SVM output (i.e., probability distribution) to compute the average accuracy, false positive and false negative rate, and Receiver Operating Characteristic (ROC) graphs (using techniques in [15]).

A. Dataset

We have two non-disjoint datasets. The first dataset (dataset1) contains a collection of 1,435 executables, 597 of which are benign and 838 are malicious. The second dataset (dataset2) contains 2,452 executables, with 1,370 benign and 1,082 malicious. So, the distribution of dataset1 is benign=41.6%, malicious=58.4%, and that of dataset2 is benign=55.9%, malicious=44.1%. We collect the benign executables from different Windows XP, and Windows 2000 machines, and collect the malicious executables from [16], which contains a large collection of malicious executables. We select only the Win32 executables in both cases. We would like to experiment with the ELF executables in future.

B. Experimental setup

Our implementation is developed in Java with JDK 1.5. We use the libSVM library [17] for SVM. We run C-SVC with a Polynomial kernel, gamma = 0.1, and epsilon = 1.0E-12. Most of our experiments are run on two machines: a Sun Solaris machine with 4GB main memory and 2GHz clock speed, and a LINUX machine with 2GB main memory and 1.8GHz clock speed. The disassembly and hex-dump are done only once for all machine executables and the resulting files are stored. We then run our experiments on the stored files.

C. Results

We first present classification accuracies, and the Area Under the ROC Curve (AUC) of different methods in Table-I, and Table-II respectively, for both datasets and different values of *n*.

From Table-I we see that the classification accuracy of our model is always better than other models, on both datasets. On dataset1, the best accuracy of the hybrid model is for *n*=6, which is 97.4, and it is 1.9% higher than BFS. On average, HFS's accuracy is 6.5% higher than BFS. Accuracy of AFS is always the lowest, and much lower than the other two. The average accuracy of AFS is 10.3% lower than HFS. The reason behind this poor performance is that Assembly features consider only the CODE (see IV-B) part of the executables. If any code is encrypted as data, it cannot be decrypted by our disassembly tool, and thus the whole encrypted portion is recognized as DATA and ignored by our feature extractor. Thus, AFS misses a lot of information and consequently the extracted features also have poorer performance. But BFS considers all parts of the executable and thus able to detect patterns from encrypted parts too. If we look at the accuracies of dataset2, we find that the difference between the accuracies of HFS and BFS is greater than that of dataset1. For example, the average accuracy of HFS is 8.6% higher. AFS again performs much poorer than the other two. It is interesting to note that HFS has an improved performance over BFS (and AFS) in dataset2, which has more benign examples than malicious. This is more likely in real world; we have a lot more benign examples than malicious ones. This implies that our model will perform much better in a real-world scenario, having larger number of benign executables in the dataset. One interesting observation from table-I is that accuracy for 1-gram BFS is very low. This is because a 1-gram is only a 1-byte long pattern, which is not long enough to be useful.

Figure 2 shows ROC curves of dataset1 for *n*=6 and dataset2 for *n* = 4. Note that ROC curves for other values of *n* have similar trends, except n = 1, where AFS performs better than BFS. It is evident from the curves that HFS is always dominant over the other two, and it is more dominant in dataset2. Table-II shows the AUC for the ROC curves of each of the features sets. A higher value of AUC indicates a higher probability that a classifier will predict correctly. Table-II shows that the AUC for HFS is the highest, and it improves (relative to other two) in dataset2, supporting our hypothesis that our model will perform better in a more likely real-world scenario, where benign executables occur more frequently.

Table III reports the false positive and false negative rate (in percentage) for each feature set. Here we also see that in dataset1, the average false positive rate of HFS is 5.4%, which is the lowest. In dataset2, this rate is even lower (3.9%). False positive rate is a measure of false alarm rate. Thus, our model has the lowest false alarm rate. We also observe that this rate decreases as we increase the number of benign examples. This is because the classifier gets more familiar with benign executables and misclassifies fewer of them as malicious. We believe that a large collection of training set with larger portion of benign executables would eventually diminish false positive rate towards zero. The false negative rate is also the lowest for HFS as reported in Table-III.

TABLE – I
CLASSIFICATION ACCURACY (%) OF SVM ON DIFFERENT FEATURE SETS

n	Dataset1			Dataset2		
	HFS	BFS	AFS	HFS	BFS	AFS
1	93.4	63.0	88.4	92.1	59.4	88.6
2	96.8	94.1	88.1	96.3	92.1	87.9
4	96.3	95.6	90.9	97.4	92.8	89.4
6	97.4	95.5	87.2	96.9	93.0	86.7
8	96.9	95.1	87.7	97.2	93.4	85.1
10	97.0	95.7	73.7	97.3	92.8	75.8
Avg	**96.30**	**89.83**	**86.00**	**96.15**	**87.52**	**85.58**

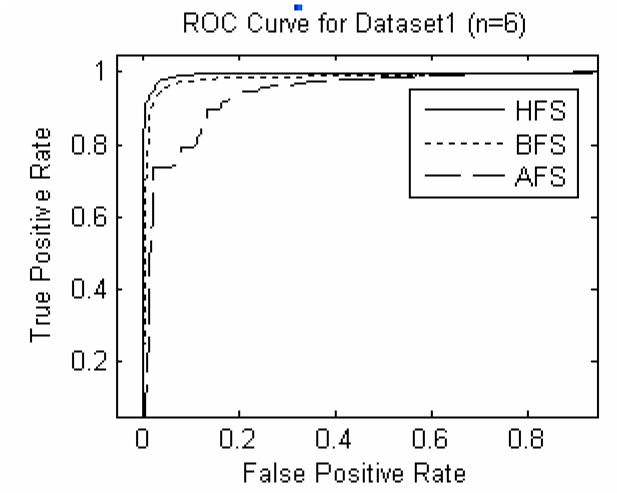
TABLE – II
AREA UNDER THE ROC CURVE ON DIFFERENT FEATURE SETS

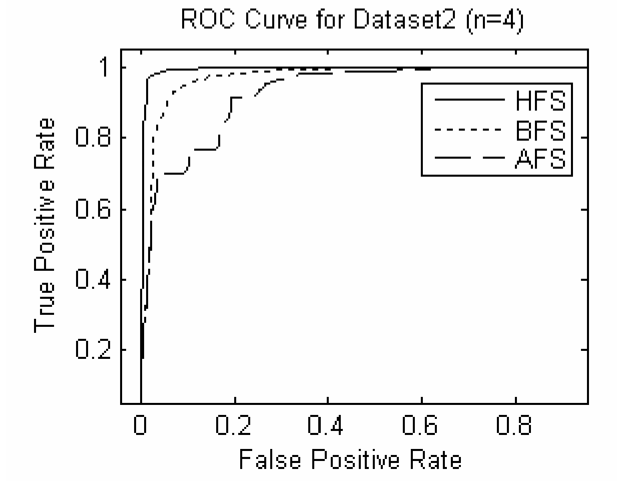
n	Dataset1			Dataset2		
	HFS	BFS	AFS	HFS	BFS	AFS
1	0.9767	0.7023	0.9467	0.9666	0.7250	0.9489
2	0.9883	0.9782	0.9403	0.9919	0.9720	0.9373
4	0.9928	0.9825	0.9651	0.9948	0.9708	0.9515
6	0.9949	0.9831	0.9421	0.9951	0.9733	0.9358
8	0.9946	0.9766	0.9398	0.9956	0.9760	0.9254
10	0.9929	0.9777	0.8663	0.9967	0.9700	0.8736
Avg	**0.9900**	**0.9334**	**0.9334**	**0.9901**	**0.9312**	**0.9288**

TABLE -III
FALSE POSITIVE AND FALSE NEGATIVE RATES ON DIFFERENT FEATURE SETS

n	Dataset1			Dataset2		
	HFS	BFS	AFS	HFS	BFS	AFS
1	8.0/5.6	77.7/7.9	12.4/11.1	7.5/8.3	65.0/9.8	12.8/9.6
2	5.3/1.7	6.0/5.7	22.8/4.2	3.4/4.1	5.6/10.6	15.1/8.3
4	4.9/2.9	6.4/3.0	16.4/3.8	2.5/2.2	7.4/6.9	12.6/8.1
6	3.5/ 2.0	5.7/3.7	24.5/4.5	3.2/2.9	6.1/8.1	17.8/7.6
8	4.9/1.9	6.0/4.1	26.3/2.3	3.1/2.3	6.0/7.5	19.9/8.6
10	5.5/1.2	5.2/3.6	43.9/1.7	3.4/1.9	6.3/8.4	30.4/16.4
Avg	**5.4/2.6**	**17.8/4.7**	**24.4/3.3**	**3.9/3.6**	**16.1/8.9**	**18.1/9.8**

To conclude the results section, we report the accuracies of the DLL function features. The 1-gram accuracies are: 92.8% for dataset1 and 91.9% for dataset2. The accuracies for higher grams are less than 75% and so we do not report them. The reason behind this is possibly that there is no distinguishing call-pattern, which can identify executables as malicious or benign.





VI. Conclusion

Our HFR model is a completely novel idea in malicious code detection. It extracts useful features from disassembled executables using the information obtained from binary executables. It then combines the assembly features with other features like DLL function calls and binary *n*-gram features. We have addressed a number of difficult implementation issues and provided very efficient, scalable and practical solutions. The difficulties that we have faced during implementation are related to memory limitations and long running times. By using efficient data structures, algorithms and disk I/O, we are able to implement a fast, scalable and robust system for malicious code detection. We run our experiments on two datasets with different class distribution, and show that a more realistic distribution improves the performance of our model.

Our model also has a few limitations. First, it is not effective against obfuscations as we do not apply any de-obfuscation technique. Second, it is an offline detection mechanism. Meaning, it cannot be directly deployed on a network to detect malicious code in real time.

We address these issues in our future work, and vow to solve these problems. We also propose several modifications to our model. For example, we would like to combine our features with run-time features of the executables. Besides, we propose building a feature-database that would store all the features and be updated incrementally. This would save a large amount of training time and memory.

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