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Control Flow Graph Based Multiclass Malware Detection Using Bi-normal Separation

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ABSTRACT

Control flow graphs (CFG) and OpCodes extracted from disassembled executable files are widely used for malware detection. Most of the research in static analysis is focused on binary class malware detection which only classifies an executable as benign or malware. To overcome this issue, CFG based multiclass malware detection system that automatically classifies the malware into their respective families is proposed. The use Bi-normal separation (BNS) as a feature scoring metric. Experimental results show that proposed method using BNS outperforms compared to hitherto use technique of document Frequency for multiclass metamorphic malware detection and achieves detection accuracy of 99.5 per cent.

Keywords: Bi normal separation, control flow graph, machine learning, malware detection

1. INTRODUCTION

Malware is an all-encompassing term which encapsulates all program created with intent to cause harm to computer systems and includes viruses, worms, trojans among others. The loss caused to the computer systems and their users due to these malware can be in the form of loss of sensitive information, system downtime, reduced performance and loss of reputation.

Most of the antivirus softwares use signature based techniques for malware detection that involves matching the files to be checked for infection against a database containing the malware signatures. This requires a signature to be generated for each malware and can be easily evaded. The newest forms of malware employ code obfuscation techniques such as register renaming, code reordering, instruction replacement, garbage code insertion and semantic nops which change the signature of the malware while keeping the intended functions intact. This helps the malware to evade the antivirus software and continue spreading till such time its signature is generated. These types of malwares are called as metamorphic malware and have metamorphing engines built in their code allowing the malware to create multiple variants of it. Detection of metamorphic malwares is still an open challenge.

To overcome the challenges posed by metamorphic malware, research has been done for their detection through various techniques. Some of these techniques focused on API calls, some on function calls made by malware while some used control flow graphs. All these techniques can be broadly classified into dynamic and static detection techniques. Dynamic detection techniques involve executing the malware in a protected environment and examining its run-time behaviour. The focus is on analysis of API calls made, actions being taken by the malware such as create process, registry changes, file changes etc. Such detection techniques can examine packed or polymorphic malware. Static detection techniques involve examining the malware without executing the program. Static detection analyse the content using header information, control flow graphs, opcodes and API call graphs etc and ensures complete code coverage and can reveal all possible actions a malware may carry out; while dynamic detection will only reveal information about what the malware is doing at that time. Existing CFG and Opcodes sequence based malware detection methods either cannot accurately describe the behaviours of the original executables or based on binary classification only. The remarkable growth in malware and benign apps needs automated analysis of potentially dangerous apps to aid malware analysts. In the real world scenario, it would be extremely helpful to be informed of the type as well as the family of the malware. The groupings of the samples into families in turn help to establish the relationships among them, identify the potential source of infection, detect the newer variants and study the advancement of the a variety of known malwares.

2. RELATED WORK

Use of machine learning technique for malware detection was proposed by Schultz[1], *et al.* Their experimental results indicated to achieve good detection rates compared to the traditional signature based methods. Kolter[2], *et al.* improved the results by using n-grams of the opcode sequences as features which are extracted from executables. Bruschi[3], *et al.* first proposed the use of CFG for detection of self-mutating malware along with graph matching techniques. Bilar[4], *et al.* proposed malware detection method based on opcode distributions in malware and benign which differed significantly. Igor[5], *et al.* and Robert[6], *et al.* used opcode sequences to represent program

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behaviour and applied machine learning methods for malware detection. Igor[5], *et al*. used static analysis to extract opcode sequences in the order of their appearance in a decompiled executable.

Zhao[7], *et al*. has extracted all opcode sequences from basic blocks of an executable. They separated a decompiled executable into basic blocks, and then extracted the opcode sequences from basic blocks. These opcode sequences were used to represent program behaviour and the authors used machine learning to detect malware. However, as the basic blocks were only considered and not the execution order among these basic blocks, the control flow information was not captured in its entirety[8].

Ding[8], *et al*., considered opcode sequences from all execution paths (path from root to leaf) and extracted n-grams from the opcode stream. For feature extraction, unique n-grams are used as features. Machine learning is used to detect malware by using document frequency threshold for feature selection. Their malware detection model is designed for binary class detection wherein the files get classified as malware or benign. This may not completely useful in the real world scenario where the user has to be informed of the type as well as the family of the malware, to help identify the potential source of infection and also to detect the newer variant of an existing malware.

Forman[9], proposed the use of Bi normal separation as a feature selection metric for text classification. BNS is used for feature scaling for text classification[10]. The experimental results showed that use of BNS provided better results over TF-IDF for text classification especially in skewed class datasets where number of samples for one class was very large as compared to the samples in the other class.

Authors research closely follows the work of Ding[8], *et al*. and employs the use of BNS for feature scoring and using chi-square test for feature selection to detect malware families. This helps in to differentiate between the families and detect unknown variant of a known malware. They concentrated their efforts towards detecting malware in the Windows OS.

3. PROPOSED MODEL

The proposed multiclass malware detection system consists of training and testing phase as shown in Fig. 1.

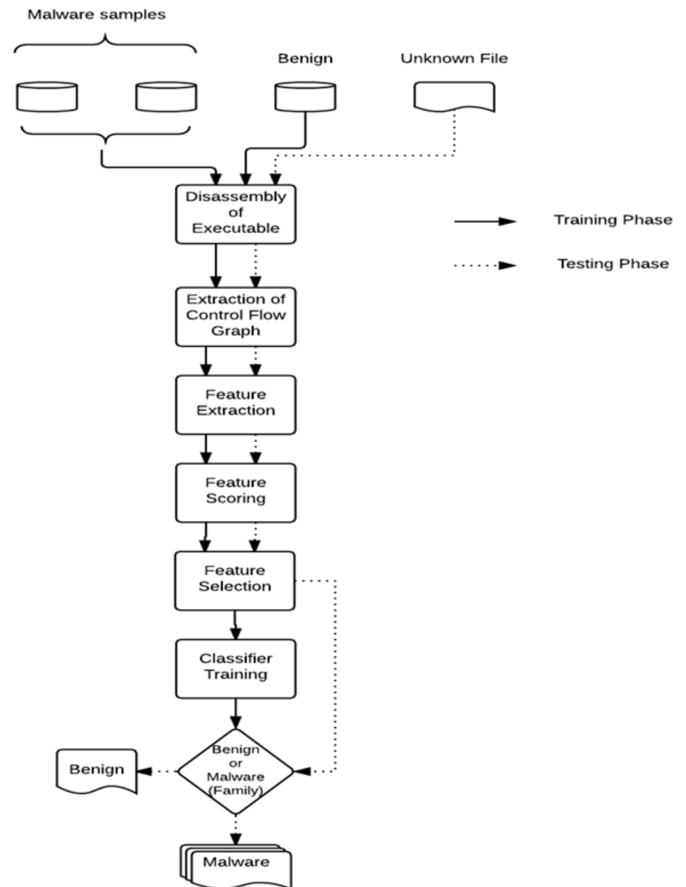

Figure 1. Flow chart of proposed model.

3.1 Disassembly of Executable

Before any executable file is analysed, it needs to be disassembled first. We used IDA Pro[15], a commercially available recursive loop disassembler to disassemble the executable. Since, static analysis cannot be done on packed files, we need to check whether the file is packed i.e. either compressed or encrypted or both, as a packed file will reveal no information. We used PEId software[16], to check for packing as well as the type of packer used. If a file is found to be packed, it is first unpacked using corresponding unpacker eg UPX[17], before it is disassembled.

3.2 Control Flow Graph Extraction

Most of the programs including malware run by executing instructions, making API calls, calling subroutines and making changes to the system, either temporary or permanent. The instructions executed by a program can be broadly classified based on the type of actions being performed by them, some move data between various locations, some carry out mathematical operations while some transfer the control between different blocks of code. The class of instructions that transfers the control between different blocks of code within the program helps in creation of control flow graphs.

Proposed system uses IDA pro to disassemble the file and generate the control flow graph of the executable with each basic block having a unique block id, start and end addresses and its successors if any. Generated CFG represents all paths which can be traversed through a program during execution and is a weighted directed graph. It contains nodes and edges, where each node contains the instructions to be executed while edges denote the transfer of control between two blocks of code. If control can be passed from one node to another, then there exists an edge between the two nodes with direction of the edge indicating the flow of control.

Each node in the control flow graph is known as a basic block. A basic block has the property of having single entry and exit points. It implies that if the first instruction of the basic block is executed then all the instructions of the block will be executed sequentially. Figure 2 shows a portion of the control flow graph of calculator program (benign file) from the system 32 folder of Windows 7 OS.

By analysing the control flow graph, we can capture the behaviour of an executable. After a file has been disassembled,

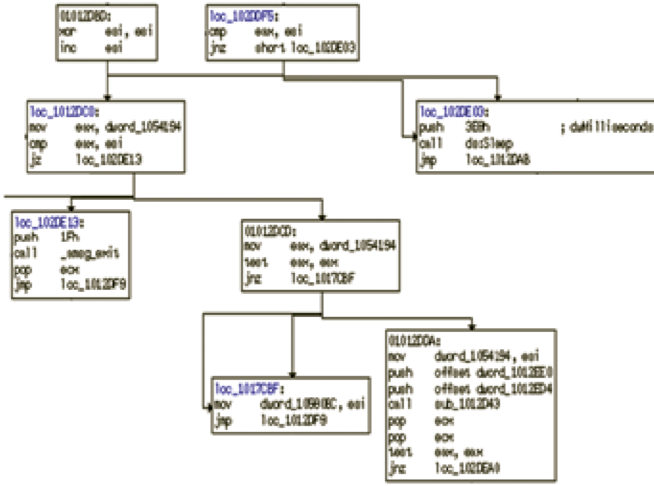

Figure 2. Control flow graph of calc.exe.

the control flow information needs to be extracted. The information is extracted from IDA Pro using a custom script written in Python which accesses IDA Pro APIs to extract the information which includes unique id of each basic block, its start and end addresses, all the instructions contained in the basic blocks and its successor blocks. Once the information about the basic block is extracted, a tree is created to depict its control flow and all possible execution traces recorded. It is important to avoid loops as considering loops will lead to indefinitely long execution paths. Capturing all possible execution traces provides us the correct behaviour of the executable. These execution traces are then concatenated and saved as the execution profile of the executable. A data structure is used to store basic block information as shown below:

$$ClassTreeNode\begin{Bmatrix} BlockID(Numeric) \\ StartAddr(Hex) \\ EndAddr(Hex) \\ LeftChild(Pointer) \\ RightChild(Pointer) \end{Bmatrix}$$

The *Tree Nodes* stores *BlockID*, which is the unique ID for each Basic block of the executable. *StartAddr* and *EndAddr* store the starting and end address of the particular basic block. *LeftChild* and *RightChild* store the pointers to the successor nodes, if any of that block. Besides these, certain methods were defined to initialise the node with the relevant information, a method to read all the instructions and a method to store the pointers to the successor nodes.

To extract the control flow and all the possible execution traces a modified depth-first tree traversal algorithm is used which apart from storing all the traversed nodes also carried out the check for loops and discard them as and when encountered. The pseudo code is depicted as Algorithm 1.

$Algorithm1: ExtractExecutionPath$

$Input: Start_{Node}(Basic\ BlockID)$

$Output: ArrayofExecutionTrace(Basic\ BlockIDs)$

$DefineArrays: Stack[], Curr_{ExecPath}[], Total_{ExecPath}[]$

$Algorithm:$

1. $Counter = 0$
2. $Push\quad Start_{Node}\quad on\quad Stack$
3. $While\quad Stack\,!= Empty\quad do$
4. $Pop\quad Stack$
5. $Curr_{ExecPath} = Curr_{ExecPath} \cup Basic\ BlockID$
6. $Counter = Counter + 1$
7. $If\quad Exists(RightChild)\quad and\quad RightChild \not\subset Curr_{ExecPath}$
8. $Push\quad RightChild\quad on\quad Stack$
9. $Path_{Len} = Path_{Len} + Counter$
10. $endif$
11. $If\quad NotExists(LeftChild)\quad and\ LeftChild \subset Curr_{ExecPath}$
12. $Total_{ExecPath} = Total_{ExecPath} + Curr_{ExecPath}$
13. $Delete_nodes_from\quad Curr_{ExecPath}\quad till_last_added\ RightChild$
14. $Adjust_Counter$
15. $Elseif\quad Exists(LeftChild)\quad and\ LeftChild \not\subset Curr_{ExecPath}$
16. $Push\quad LeftChild\quad on\quad Stack$
17. $endif$
18. $endwhile$
19. $Return\quad Total_{ExecPath}$

Figure 3 shows the basic block IDs of the execution trace of sample control flow graph. All the execution paths are concatenated. The numbers shown are the IDs of the basic blocks executed in order

```
7, 10, 32, 11, 12, 16, 17, 18, 19, 21, 25, 23, 24, 0, 1, 28, 29, 3, 4, 26, 6, 8, 9, 10, 32, 11,
, 6, 8, 9, 10, 32, 11, 12, 16, 17, 18, 19, 21, 25, 23, 35, 37, 39, 0, 1, 28, 29, 3, 4, 26, 6, 8
, 6, 8, 9, 10, 32, 11, 12, 16, 17, 18, 21, 22, 23, 35, 36, 37, 39, 0, 1, 28, 29, 3, 4, 26, 6, 8
4, 26, 6, 8, 9, 10, 32, 11, 12, 16, 17, 18, 21, 25, 23, 24, 0, 1, 28, 29, 3, 4, 26, 6, 8, 9, 1
4, 26, 6, 8, 9, 10, 32, 11, 12, 16, 17, 18, 21, 25, 23, 35, 37, 39, 0, 1, 28, 29, 3, 4, 26, 6,
10, 32, 11, 12, 16, 18, 19, 21, 22, 23, 24, 0, 1, 28, 29, 3, 4, 26, 6, 8, 9, 10, 32, 11, 12, 16
```

Figure 3. Execution trace of calc.exe shown by basic block IDs.

The opcode sequence trace are extracted from the execution trace by traversing through each basic block in the order of its execution as extracting all the while discarding any operands as shown in Fig. 4. The process of extracting the complete execution trace is computationally intensive which requires machine with good processing capabilities.

```
'inc', 'jmp', 'call', 'push', 'push', 'call', 'xor', 'mov', 'mov', 'lea', 'push', 'call', 'mov', 'mov', 'mov',
'jnz', 'xor', 'inc', 'mov', 'cmp', 'jz', 'mov', 'test', 'jnz', 'mov', 'push', 'push', 'call', 'pop', 'pop', 't
'pop', 'pop', 'mov', 'test', 'jnz', 'push', 'push', 'call', 'cmp', 'jnz', 'mov', 'mov', 'mov', 'mov', 'cmp', '
'push', 'call', 'pop', 'test', 'jnz', 'inc', 'jmp', 'call', 'push', 'push', 'call', 'xor', 'mov', 'mov', 'lea'
'push', 'push', 'push', 'call', 'test', 'jnz', 'xor', 'inc', 'mov', 'cmp', 'jz', 'mov', 'test', 'jnz', 'mov',
'mov', 'cmp', 'jnz', 'push', 'push', 'call', 'pop', 'pop', 'mov', 'test', 'jnz', 'push', 'push', 'call', 'cmp'
'test', 'jz', 'cmp', 'jnz', 'cmp', 'jz', 'movzx', 'push', 'call', 'pop', 'test', 'jnz', 'inc', 'mov', 'jmp', '
'mov', 'mov', 'lea', 'push', 'call', 'mov', 'mov', 'mov', 'mov', 'mov', 'push', 'push', 'push', 'call', 'test'
```

Figure 4. Opcode sequences extracted from the execution trace.

3.3 Feature Extraction

Manning[11], *et al*. had proposed the use of n-grams as features and the same is a widely used technique in natural language processing as well as document classification. n-gram method means selecting a group of words as features for classification or sentiment analysis with n representing the number of words in each feature. 3-grams (trigrams) as for features as experimentally shown to be most effective[8]. For

feature extraction we use sliding window approach, as used by[8] and generate the trigrams, Figure 5. Each of these trigrams is a feature with all the trigrams of an executable being the feature vector. Two different approaches for feature set are used. In the first approach all trigrams from the execution trace were considered and in the second approach only the unique trigrams were taken. These extracted trigrams form text documents for corresponding malwares.

```
'cmp jnz push', 'jnz push call', 'push call pop', 'call pop test', 'pop test jz', 'test jz mov', 'jz mov mov', 'mov mo
jbe', 'cmp jbe test', 'jbe test jz', 'test jz cmp', 'jz cmp jnz', 'cmp jnz mov', 'jnz mov test', 'mov test jz', 'test
jnz', 'test jnz push', 'jnz push pop', 'push pop push', 'pop push push', 'push push push', 'push push push', 'push pus
cmp jnz', 'cmp jnz cmp', 'jnz cmp jnz', 'cmp jnz mov', 'jnz mov mov', 'mov mov jmp', 'mov jmp call', 'jmp call retn',
push', 'push push call', 'push call xor', 'call xor mov', 'xor mov mov', 'mov mov lea', 'mov lea push', 'lea push call
mov', 'mov mov mov', 'mov mov mov', 'mov mov push', 'mov push push', 'push push push', 'push push call', 'push call te
```

Figure 5. Extracted 3-grams to be used as features.

3.4 Feature Scoring

Before classification, these documents need to be converted from text form to vector space representation in matrix form where each row represents a document and each column represents the features. The total number of columns is the total number of features extracted from the documents.

To enable classifier to effectively differentiate between the various classes, feature scaling is done to give a numerical value to each of these features. Various techniques are used for feature scaling. Some of the techniques are defined as follows.

Document frequency (DF) of a feature fives the number of documents the feature occurs in a class of documents[12], and is given by the Eqn. (1):

$$DF(f_i, C_j) = \frac{\lg|C_p|}{\lg|C_j|} \tag{1}$$

where $DF(f_i, C_j)$ is document frequency of the ith feature in j^{th} class of documents, C_p: Number of documents of class *j,* which contain the feature. C_j: Number of documents of class *j,* i : index of the feature extracted $(i \in N)$, N is the total number of features. j : Number of classes ie. Benign and different malware families.

Bi-normal separation (BNS) measures the importance of a feature based on its presence in different classes of documents[9,10] and is given by Eqn. (2):

$$BNS(f_i) = \left| F^{-1}\left(\frac{C_p}{C_j}\right) - F^{-1}\left(\frac{C_N}{C_{j^{-1}}}\right) \right| \tag{2}$$

where F^{-1} is the inverse cumulative probability function of standard normal distribution.

$\left(\frac{C_p}{C_j}\right)$: True positive rate for a feature.

$\left(\frac{C_N}{C_{j^{-1}}}\right)$: False positive rate for the feature.

Since *BNS* scores are calculated over binary classes, one vs rest all classes approach to signify positive and negative classes is used. It is important to note that the *BNS* score will tend to ∞ if either of the true positive rate or false rate becomes 1 or 0, Hence they are restricted between 0.0005 and 1-0.0005 as proposed[9,10].

Term frequency-inverse document frequency (*tfidf*), is a numerical statistic to find out how important a word is in a set of documents. It is obtained by multiplying the term frequency of the feature with the inverse of its document frequency and is given by the Eqn. (3):

$$tfidf(f_i) = tf(f_i, d_j) \times idf(f_i, D) \tag{3}$$

where

$tf(f_i, d_j)$ Number of times a feature is present in the document d_j.

$idf(f_i, D)$ Inverse of the document frequency given by $\log\left(\frac{N}{D}\right)$

N Total number of documents.

D Number of documents in which feature f_i is present.

Term frequency Bi-normal separation (TF.BNS) proposed[10], is calculated by multiplying the term frequency of the feature with its BNS score as given in Eqn. (4):

$$TF.BNS(f_i) = tf(f_i, d_j) \times BNS(f_i) \tag{4}$$

Ding[8], *et al*. used DF for feature scoring and selected the top features based on document frequency score for each class after filtering out any features common to both classes. In our view, mere presence of a feature in different classes is not enough for it to be discarded and may lead to loss of some good features. We assign score to each feature and use an independent metric for feature selection. This has shown good results in the classification results.

3.5 Feature Selection

Feature selection is carried out to convert the feature set to a manageable size and reduce the dimensionality of the features set to remove redundant and noisy feature which reduce the performance of the classification. Here, we carry out feature selection via filtering and have used two feature selection metrics which are commonly used. They are defined as:

Information gain (IG), gives out the decrease on entropy for any feature caused due to it being present or absent in a document class and is widely used as feature selection metric[7,8,13]. It is given by Eqn. (5):

$$IG(f_m, C) = \sum_{i=0}^{j} -C_j \ln C_i - \sum_{q=\{0,1\}} \frac{|C_{q|}|}{|C|} \sum_{i=0}^{j} -C_i \ln C_i \tag{5}$$

where

f_m m^{th} feature.

C Number of documents.

j Number of classes.

C_i Number of documents belonging to class *i*.

$C_{q|}$ Number of documents containing the feature f_m

C_i Number of documents of class *i* containing f_m.

q Presence or absence of a feature. It can be either 0 if absent or 1 if present.

Chi-Square (χ^2) test : The χ^2 test is used to test the

independence of two variables. The χ^2 test measures the independence of a feature and a category. Features with the higher χ^2 values are less independent for a category, and bound to perform better for classification[13]. It is given by the Eqn. (6).

$$\chi^2(f_i) = \sum_{i=1}^{n} \frac{(O_i - E_i)^2}{E_i} \quad (6)$$

where O_i is observed value of feature i, E_i is expected value of feature i.

3.6 Training and Testing

The detection method uses machine learning for classifying a file into benign or the respective malware family. The process consists of two steps: training and testing. In the training phase, the classifier requires to be trained to be able to differentiate between malware and benign files and involves using a training dataset of feature vectors to be used alongwith the class labels for building the classification model. In the testing phase, unlabelled dataset is passed to trained model to evaluate the performance of the classification model.

For the purpose of evaluating our approach, we used two different techniques for training and testing the classifiers. In the first approach we split up the dataset set into training and testing dataset with 80 per cent samples being used to train the classifier and rest 20 per cent for testing the classifier. We also used 10 fold cross validation where the entire dataset is randomly split up into 10 blocks with 9 blocks being used for training and the remaining block used for testing. This is then repeated 10 times.

We use multiple classifiers in our research. Some of the classifiers are as follows:

Naïve Bayes Classifier: It uses probabilistic methods to assign classes to a document and is used in fields of information retrieval, text classification. We used two algorithms for the classifier using Gaussian distribution and multinomial distribution[1].

Support Vector Machines[14]: They are non-probabilistic classifiers and used binary classification. We used one vs rest approach for multiple class classification as well as two class classification. Support Vector Machines (SVM) classify by representing features as points in multidimensional space and then separates out the different classes using maximum margin hyperplanes. We used three kernel functions for the SVM and include linear, polynomial and radial basis function.

Random Forest Tree Classifier (RF Tree): It is an ensemble classifier which classifies by creating multitude of decision trees with features selected randomly from the feature space. We implemented our approach using python and made use of sklearn[21], machine learning package of python. To compare the results with Ding[8], *et al*, a well-known data mining tool Weka[18] was used.

4. EXPERIMENTATION

4.1 Experimental Setup

To check the effectiveness of proposed method a number of experiments were carried on a machine with Intel i5 processor @ 3.1GHz clock speed, with 4GB RAM and windows 7 OS with Weka and Python interpreter installed.

4.2 Data Set Collection

For the experimentation, we collected 266 files from the system 32 folder of a freshly installed win 7 OS. The files were checked for any infection by uploading them to virustotal.com which checks the files uploaded using a number of antivirus software. The 133 malware samples were downloaded from vxheavens[19] and openmalware[20] repositories. The samples consisted of metamorphic virus, worms and generic Trojan agents. Two datasets were created for the experimentation. Dataset1 consisted of 266 benign and 105 metamorphic malware samples belonging to different families and Dataset2, created to check the performance of the proposed model against generic malware included generic Trojans apart from those in Dataset1.

4.3 Evaluation Criteria

Both 10 fold cross validation as well standard split dataset techniques to measure the performance of the proposed model using BNS against DF for feature scaling were employed. Cross validation was done primarily to compare results of our model with the model proposed by Ding[8], *et al*.

The performance of classifier was measured using three metric: accuracy, precision and recall. The same are defined as follows.

Accuracy: It is the ratio of correct results against the total results and calculated using Eqn. (7):

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (7)$$

Precision: Also known as positive predictive value, it gives ability of the classifier to correctly label the positive classes. It is calculated using Eqn. (8).

$$Precision = \frac{TP}{TP + FP} \quad (8)$$

Recall: It gives the sensitivity of the classifier and signifies the ability of the classifier to find all positive samples. It is calculated using the Eqn. (9).

$$Recall = \frac{TP}{TP + FN} \quad (9)$$

where TP is number of positive classes correctly classified as positive, FP is number of negative classes incorrectly classified as positive, TN is number of negatives classes correctly classified as negative, FN is number of negatives classes incorrectly classified as positive.

4.4 Experimental Results

The malware detection method explained in Section 3 was implemented in python language. As mentioned earlier, we created two datasets for evaluating our approach. Extracted the features using the technique similar to Ding[8], *et al*. From the execution trace, extracted all trigrams as well as unique trigrams. The dataset containing all trigrams was used for calculation of TF.BNS and TF-IDF scores, while unique trigrams were used for calculation of BNS and DF scores.

Ding[8], *et al*. had selected features based on information gain (IG) and DF threshold. Classification results obtained

when using IG, DF threshold, and Chi-square test as feature selection technique are compered. Tables 1 - 3 show the average accuracy, precision and recall rates from different classifiers on Dataset1 over 5 iterations when using 80 per cent of the data set for training and 20 per cent for testing. We used chi square test for feature selection when using TF-IDF, TF.BNS, BNS and IG, Chi-square and DF threshold when using DF. The classifiers were trained and tested on different number of features to evaluate the performance of the classifier when using different number of features.

In the Tables 1 - 3; GNB, MNB, LSVC, PSVC, RBF and RF depict the classifiers Gaussian Naïve Bayes, Multinomial Naïve Bayes, Linear SVM, Polynomial SVM, SVM using Radial Basis function, and Random forest trees. The rates shown are expressed in percentage.

Table 1. Accuracy rates for Dataset1

	GNB	MNB	LSVC	PSVC	RBF	RF
TF.IDF	98.02	81.44	99.61	68.85	68.85	93.37
TF.BNS	98.36	74.42	99.9	68.85	99.71	98.71
BNS	98.7	98.46	99.54	90.28	99.41	98.73
DF-IG	93.64	94.49	93.18	86.20	92	91.03
DF-CHI	93.67	94.8	93.41	86.76	91.78	90.88
DF	90.14	94.2	94.36	80.28	80.28	94.36

Table 2. Precision rates for Dataset1

	GNB	MNB	LSVC	PSVC	RBF	RF
TF.IDF	98.22	82.45	99.64	47.41	47.41	98.34
TF.BNS	98.99	70.85	99.9	68.85	94.73	98.24
BNS	98.85	99.12	99.57	91.60	99.17	98.76
DF-IG	95.5	95.3	93.8	89.2	92.88	92.08
DF-CHI	95.2	95.25	94	88.9	92.69	91.99
DF	90.14	94.9	94.7	80.3	64.5	94.7

Table 3. Recall rates for Dataset1

	GNB	MNB	LSVC	PSVC	RBF	RF
TF.IDF	98.02	81.44	99.61	68.85	88.85	98.37
TF.BNS	98.36	74.42	99.9	68.85	94.71	98.17
BNS	98.70	98.46	99.54	90.28	99.11	98.73
DF-IG	93.67	95	93.16	87.26	92.02	91.01
DF-CHI	93.65	94.87	93.42	86.78	91.8	91.3
DF	90.10	94.2	94.4	64.5	80.3	94.4

TF-IDF, TF.BNS, and BNS with chi-square feature selection gave best results with linear SVM giving accuracies of 99.61 per cent, 99.9 per cent, and 99.54 per cent, respectively with similar precision and recall rates, while DF with IG, chi-square and threshold as frequency selection metrics had best results with Multinomial Naïve Bayes classifier, giving accuracy results of 94.49 per cent, 94.8 per cent, and 94.2 per cent.

Tables 4 - 6 show the accuracy precision and recall rates for the same classifiers on Dataset2.

The performance for all feature scoring techniques dipped for Dataset2 due to addition of generic malware Trojans which did not belong to any family. However, TF-IDF, TF.BNS and BNS still performed better than DF by around 3 per cent improvement in accuracy rates.

Table 4. Accuracy rates for Dataset2

	GNB	MNB	LSVC	PSVC	RBF	RF
TF-IDF	90.70	73.26	92.94	52.86	70.04	89.10
TF.BNS	92.58	63.24	92.81	52.86	87.89	89.19
BNS	91.34	91.17	91.86	85.10	91.28	89.30
DF-IG	87.50	89.71	87.90	60	84.52	87.71
DF-CHI	86.30	89.99	87.71	60.57	84.85	87.90
DF	81.4	90.1	88.57	60	60	88.57

Table 5. Precision rates for Dataset2

	GNB	MNB	LSVC	PSVC	RBF	RF
TF-IDF	94.49	75.28	93.18	27.94	63.33	90.80
TF.BNS	93.92	56.22	93.64	27.94	90.19	90.70
BNS	92.45	91.18	92.91	88.40	92.51	91.3
DF-IG	92.6	90.82	86.50	36	82.60	86.7
DF-CHI	91.81	91.59	86.24	36.9	81.2	86.84
DF	82.5	90	88.57	36	36	87.5

Table 6. Recall rates for Dataset2

	GNB	MNB	LSVC	PSVC	RBF	RF
TF-IDF	90.70	73.26	92.24	52.86	70.04	89.10
TF.BNS	92.58	63.24	92.81	82.86	87.89	89.25
BNS	91.34	91.17	91.86	85.10	91.28	89.35
DF-IG	87.5	89.69	87.90	60	84.67	87.72
DF-CHI	86.45	89.57	87.41	54.18	84.86	87.1
DF	81.4	90.1	88.1	60	60	88.6

It can be seen, that TF-IDF and TF.BNS showed slightly better results as compared to BNS and DF. However, they both suffer from additional computational and storage overheads incurred while storing and processing all the trigrams present. Hence, it is recommended to use only unique trigrams extracted. For the next set of experimentation by means of 10 fold cross-validation, we used only BNS and DF for classification tests. Figures 6 and 7 give the accuracy rates for BNS using chi square test for feature selection and DF scoring using DF threshold for feature selection[8], using Gaussian Naïve Bayes, Linear SVM, SVM with radial basis function as kernel functions for dataset1 and dataset2, respectively.

It is seen from the figures above that BNS has performed consistently better than DF for multi-class malware detection, with average accuracies for BNS with GNB, LSVC and RBF being 97.38 per cent, 95.9 per cent, and 96.9 per cent, respectively for Dataset1 and 90.93 per cent, 92.33 per cent, and 93.2 per cent, respectively for Dataset2. Yuxin[8], *et al.* had developed the model for only binary class classification. Our model when tested on binary class classification with all malwares combined into a single class gave average accuracy rates of 99.2 per cent with Gaussian

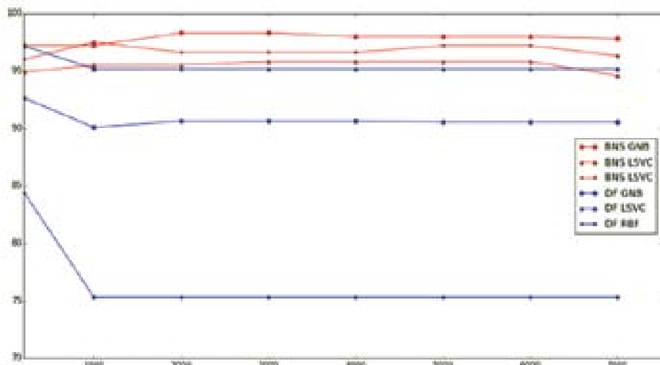

Figure 6. Comparative accuracy rates for Dataset1.

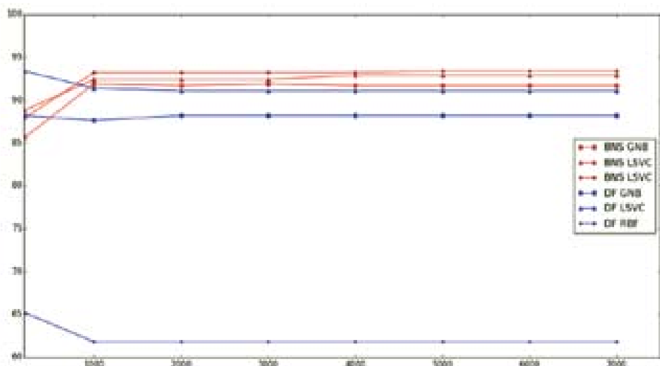

Figure 7. Comparative accuracy rates for Dataset2.

Naïve Bayes and SVM classifiers, indicating that most of misclassifications in our took place between different malware classes. The same was also confirmed by analysis of the confusion matrix generated at each stage.

The learning curves for Gaussian Naïve Bayes and Linear SVM classifiers for the experiments involving BNS as feature scoring technique are shown by Figs. 8 and 9, respectively. Both the curves show that the classifiers have been trained and the test accuracy scores will improve as more samples are added. This will result in further improvement in detection accuracy as the number of malware samples increases.

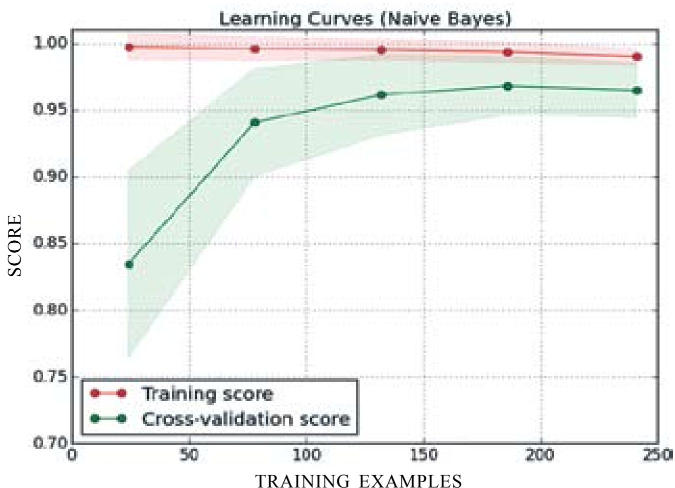

Figure 8. Learning curve for Gaussian Naïve Bayes classifier.

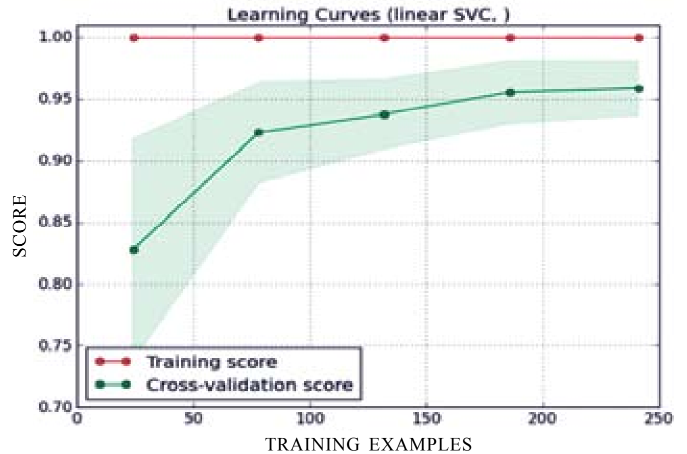

Figure 9. Learning curve for Linear SVM classifier.

5. CONCLUSIONS

Existing CFG and Opcodes Sequence based malware detection methods either cannot accurately describe the behaviors of the original executables or based on binary classification only. In this research paper, we have proposed an automated multiclass malware detection method using opcodes generated from CFGs and BNS for feature scoring. Our experimental results show an improvement of up to 4 per cent in accuracy, precision and recall rates over DF when tested over multiple classifiers. The proposed detection model also showed accuracy rates of 99.2 per cent for two class malware detection when using Gaussian Naïve Bayes and Support Vector Machines, which is much higher than what could be achieved using Document Frequency. The technique of scoring features performs better for classification than the filtering method of removing any features common to different classes of samples. Besides good performance, our proposed model achieves automatic classification of unknown malware samples into candidate families. This feature could be remarkably useful for malware analysts. Proposed method is bounded by the limitations that of any static detection technique.

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