Unknown Malcode Detection Using OPCODE Representation

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Abstract. The recent growth in network usage has motivated the creation of new malicious code for various purposes, including economic ones. Today's signature-based anti-viruses are very accurate, but cannot detect new malicious code. Recently, classification algorithms were employed successfully for the detection of unknown malicious code. However, most of the studies use byte sequence n-grams representation of the binary code of the executables. We propose the use of (Operation Code) OpCodes, generated by disassembling the executables. We then use n-grams of the OpCodes as features for the classification process. We present a full methodology for the detection of unknown malicious code, based on text categorization concepts. We performed an extensive evaluation of a test collection of more than 30,000 files, in which we evaluated extensively the OpCode n-gram representation and investigated the imbalance problem, referring to real-life scenarios, in which the malicious file content is expected to be about 10% of the total files. Our results indicate that greater than 99% accuracy can be achieved through the use of a training set that has a malicious file percentage lower than 15%, which is higher than in our previous experience with byte sequence n-gram representation [1].

Keywords: Malicious Code Detection, OpCode, Classification.

1 Introduction

The term malicious code (malcode) commonly refers to pieces of code, not necessarily executable files, which are intended to harm, generally or in particular, the specific owner of the host. Malcodes are classified, based mainly on their transport mechanism, into five main categories: worms, viruses, Trojans and a new group that is becoming more common, which is comprised of remote access Trojans and backdoors. The recent growth in high-speed internet connections and in internet network services has led to an increase in the creation of new malicious codes for various purposes, based on economic, political, criminal or terrorist motives (among others). Some of these codes have been used to gather information, such as passwords and credit card numbers, as well as behavior monitoring.

Current anti-virus technology is primarily based on two approaches: signature-based methods, which rely on the identification of unique strings in the binary code; while

being very precise, they are useless against unknown malicious code. The second approach involves heuristic-based methods, which are based on rules defined by experts that define a malicious behavior, or a benign behavior, in order to enable the detection of unknown malcodes [2]. Other proposed methods include behavior blockers, which attempt to detect sequences of events in operating systems, and integrity checkers, which periodically check for changes in files and disks. However, besides the fact that these methods can be bypassed by viruses, their main drawback is that, by definition, they can only detect the presence of a malcode after it has been executed.

Generalizing the detection methods to be able to detect unknown malcodes is therefore, crucial. Recently, classification algorithms were employed to automate and extend the idea of heuristic-based methods. As we will describe in more detail shortly, the binary code of a file is represented by OpCode or n-grams, and classifiers are applied to learn patterns in the code and classify large amounts of data. A classifier is a rule set that is learnt from a given training set, including examples of classes, both malicious and benign files in our case. Recent studies, which we survey in the next section, and our experience [1], have shown that using byte sequence n-grams to represent the binary files yields very good results. A recent survey[1] done by McAfee indicates that about 4% of search results from the major search engines on the web contain malicious code. Additionally, [3] found that above 15% of the files in the KaZaA network contained malicious code. Thus, we assume that the percentage of malicious files in real life is about or lower than 10%, but we also consider other percentages.

In this study, we present a methodology for malcode categorization based on concepts from text categorization. We present an extensive and rigorous evaluation of many factors in the methodology, based on eight types of classifiers. The evaluation is based on a test collection ten times larger than any previously reported, containing more than 30,000 files. We introduce the imbalance problem, which refers to domains in which the proportions of each class instance is not equal, in the context of our task, in which we evaluate the classifiers for five levels of malcode content (percentages) in the training set and 17 (percentages) levels of malcode content in the test set. We start with a survey of previous relevant studies. We describe the methods we used, including: concepts from text categorization, data preparation, and classifiers. We present our results and finally discuss them.

2. Background

2.1 Detecting Unknown Malcode using Byte Sequence N-Grams

Over the past five years, several studies have investigated the direction of detecting unknown malcode based on its binary code. The authors of [4] were the first to introduce the idea of applying machine learning (ML) methods for the detection of different malcodes based on their respective binary codes. Three different feature

[1] McAfee Study Finds 4 Percent of Search Results Malicious,By Frederick Lane,June 4, 2007 [http://www.newsfactor.com/story.xhtml?story_id=010000CEUEQO]

extraction (FE) approaches were used: program header, string features and byte sequence features, to which they applied four classifiers: a signature-based method (anti-virus), Ripper – a rule-based learner, Naïve Bayes, and Multi-Naïve Bayes. The study found that all of the ML methods were more accurate than the signature-based algorithm. The ML methods were more than twice as accurate when the out-performing method was Naïve Bayes, using strings, or Multi-Naïve Bayes using byte sequences.

Abou-Assaleh et al. [5] introduced a framework that uses the common n-gram (CNG) method and the k nearest neighbor (KNN) classifier for the detection of malcodes. For each class, malicious and benign, a representative profile was constructed and assigned a new executable file. This executable file was compared with the profiles and matched to the most similar. Two different datasets were used: the I-worm collection, which consisted of 292 Windows internet worms and the win32 collection, which consisted of 493 Windows viruses. The best results were achieved by using 3-6 n-grams and a profile of 500-5000 features. [6] presented a collection that included 1971 benign and 1651 malicious executables files. N-grams were extracted and 500 features were selected using the information gain measure [7]. The vector of n-gram features was binary, presenting the presence or absence of a feature in the file and ignoring the frequency of feature appearances (in the file). In their experiment, they trained several classifiers: IBK (KNN), a similarity based classifier called the TFIDF classifier, Naïve Bayes, SVM (SMO) and Decision tree (J48). The last three of these were also boosted. Two main experiments were conducted on two different datasets, a small collection and a large collection. The small collection included 476 malicious and 561 benign executables and the larger collection included 1651 malicious and 1971 benign executables. In both experiments, the four best-performing classifiers were Boosted J48, SVM, boosted SVM and IBK. Boosted J48 out-performed the others. The authors indicated that the results of their n-gram study were better than those presented by [4].

Kolter and Maloof [8] reported an extension of their work, in which they classified malcodes into families (classes) based on the functions in their respective payloads. In the categorization task of multiple classifications, the best results were achieved for the classes' mass mailer, backdoor and virus (no benign classes). In attempts to estimate their ability to detect malicious codes based on their issue dates, these techniques were trained on files issued before July 2003, and then tested on 291 files issued from that point in time through August 2004. The results were, as expected, not as good as those of previous experiments. Those results indicate the importance of maintaining the training set by acquisition of new executables, in order to cope with unknown new executables. [9] presented a hierarchical feature selection approach which makes possible the selection of n-gram features that appear at rates above a specified threshold in a specific virus family, as well as in more than a minimal amount of virus classes (families). They applied several classifiers: ID3, J48 Naïve Bayes, SVM- and SMO to the dataset used by [4] and obtained results that were better than those obtained through traditional feature selection, as presented in [3], which focused mainly on 5-grams. However, it is not clear whether these results are reflective more of the feature selection method or of the number of features that were used.

Recently, Moskovitch et al. [1] reported a study consisting of the largest test collection currently reported, including more than 30,000 files, in which the files were represented by byte sequence n-grams. In addition to an extensive evaluation of 3 to 6 n-grams, three feature selection methods and eight classifiers, an investigation of the imbalance problem, on which we elaborate later, was demonstrated. In this paper we present the results of an alternative representation of the executable files using OpCodes.

2.2 Representing Executables through OpCodes

The main contribution and novelty of this study is in the representation of executable files by OpCodes expressions, through streamlining an executable into a series of *OpCodes*. This technique has first been suggested in [10] An OpCode is the portion of a machine language instruction that specifies the operation to be performed. A complete machine language instruction contains an OpCode and, optionally, the specification of one or more operands—upon what data the operation should act. Some operations have implicit operands, or indeed none. The operands upon which OpCodes operate may, depending on CPU architecture, consist of registers, values in memory, values stored on the stack, I/O ports, the bus, etc. The operations of an OpCode may include arithmetic, data manipulation, logical operations, and program control.

Our approach stems from the idea that there exist families of malware, such that two members of the same family share a common "engine." Moreover, there exist malware generation utilities which use a common engine to create new malware instances; this engine may even be used to polymorph the threat as it propagates. When searching for such common engines among known malwares, one must be aware that malware designers will strive to hide such engines using a broad range of techniques. For example, these common engines may be located in varying locations inside the executables, and thus may be mapped to different addresses in memory or even perturbed slightly. To overcome such practices, we suggest inspecting only the sequence of OpCodes in the executable, disregarding any parameters of the OpCodes. We conjecture that such an approach would lead to a detection of a large number of malwares of the same family and even future members of the same family.

2.3 The Imbalance Problem

The class imbalance problem was introduced to the machine learning research community about a decade ago. Typically it occurs when there are significantly more instances from one class relative to other classes. In such cases the classifier tends to misclassify the instances of the less represented classes. More and more researchers realized that the performance of their classifiers may be suboptimal due to the fact that the datasets are not balanced. This problem is even more important in fields where the natural datasets are highly imbalanced in the first place [11], as in the problem we describe. However, in our problem, unlike in other problems, the data are imbalanced not in the training set, but rather in real life conditions, which we reflect by the test set. Thus, we don't need an algorithm to overcome the imbalanced data,

but rather to understand the optimal construction of a training set to achieve the best performance in real life conditions.

3 Methods

3.1 Text Categorization

For the detection of unknown malicious code we suggest using the well-studied field of *text categorization*. Salton presented the *vector space model* [12] to represent a textual file as a *bag of words*. After parsing the text and extracting the words, a vocabulary, of the entire collection of words is constructed. Each term in the vocabulary can be described by its frequency in the entire collection, often called *document frequency*, which is later used for the term weighting. For each document a vector of terms in the size of the vocabulary is created, such that each index in the vector represents the *term frequency* (TF) in the document. Equation 1 shows the definition of a normalized TF, in which the term frequency is divided by the maximal appearing term in the document with values in the range of [0-1]. An extended representation is the TF *Inverse Document Frequency* (TFIDF), which combines the frequency of a term in the document (TF) and its frequency in the documents collection, denoted by Document Frequency (DF), as shown in Equation 2, in which the term's (normalized) TF value is multiplied by the IDF = log (N/DF), where N is the number of documents in the entire file collection and DF is the number of files in which it appears.

$$TF = \frac{term\ frequency}{\max(term\ frequency\ in\ document)} \tag{1}$$

$$TFIDF = TF * \log(\frac{N}{DF}) \tag{2}$$

The TF representation is actually the representation which was used in previous papers in our domain of malicious code classification [4,5,6]. However, in the textual domain it was shown that the tfidf is a richer and more successful representation for retrieval and categorization purposes [12], and thus, we expected that using the tfidf weighting would lead to better performance than using the tf.

3.2 Dataset Creation

We created a dataset of malicious and benign executables for the Windows operating system, which is the system most commonly used and most commonly attacked nowadays. The collection, which, to the best of our knowledge, is the largest ever assembled and used for research, was used in [1]. We acquired the malicious files

from the VX Heaven website[2]. The dataset contains 7688 malicious files. To identify the files, we used the Kaspersky[3] anti-virus and the Windows version of the Unix 'file' command for file type identification. The files in the benign set, including executable and DLL (Dynamic Linked Library) files, were gathered from machines running the Windows XP operating system on our campus. The benign set contained 22,735 files. The Kaspersky anti-virus program was used to verify that these files do not contain any malicious code. However, after converting the files into OpCode representation we had 5677 malicious and 20416 benign files (total of 26093 files), since part of the files could not be disassembled.

3.3 Data Preparation and Feature Selection

To classify the files we had to convert them into a vectorial representation. We had two representations, the known one, often called n-grams, which consists of byte sequences of characters extracted from the binary code [1], and the OpCodes, which were represented by sequences of OpCodes. We extracted a sequence of OpCodes from each file representing execution flow of machine operations, using a dis-assembler program. Later, several n-gram lengths were considered where each n-gram was composed of *n* sequential OpCodes.

The process of streamlining an executable starts with *disassembling* it. The disassembly process consists of translating the machine code instructions stored in the executable to a more human-readable language, namely, *Assembly* language. The next, and final, step in streamlining the executable is achieved by extracting the sequence of OpCodes generated during the disassembly process, in the same logical order in which the OpCodes appear in the executable, disregarding the extra information available (e.g., memory location, registers, etcetera).

Although, such a process seems trivial, malware writers often try to prevent the successful application of the disassembly process, to prevent experts from analyzing their malwares. In this study we used IDA Pro[4], which is the most advanced commercial disassembly program available today. IDA Pro implements sophisticated techniques which enabled us to successfully disassemble our entire malware collection.

In the second form of the representation we extracted sequences of OpCode expressions, which we term OpCode-n-grams. The vocabularies extracted were of 515, 39,011, 443,730, 1,769,641, 5,033,722 and 11,948,491, for 1-gram, 2-gram, 3-gram, 4-gram, 5-gram and 6-gram, respectively. Later TF and TFIDF representations were calculated for each n-gram in each file.

In machine learning applications, the large number of features (many of which do not contribute to the accuracy and may even decrease it) in many domains presents a huge problem. Moreover, in our problem, the reduction of the amount of features is crucial, but must be performed while maintaining a high level of accuracy. This is due to the fact that, as shown earlier, the vocabulary size may exceed thousands of features, far

2 http://vx.netlux.org
3 http://www.kaspersky.com
4 http://www.hex-rays.com/idapro/

more than can be processed by any feature selection tool within a reasonable period of time. Additionally, it is important to identify those terms that appear in most of the files, in order to avoid vectors that contain many zeros. Thus, we first extracted the features having the top 1000 *document frequency* (Equation 2) values, on which three feature selection methods were later applied. For the representation of the OpCode n-grams, we suggest using well-studied concepts from information retrieval (IR) and more specific text categorization. In our problem, binary files (executables) are disassembled and parsed, and n-grams are extracted. Each n-gram term in our problem is analogous to a word in the textual domain.
We used a filters approach, in which the measure was independent of any classification algorithm, to compare the performances of the different classification algorithms. In a filters approach, a measure is used to quantify the correlation of each feature to the class (malicious or benign) and estimate its expected contribution to the classification task. We used three feature selection measures. As a baseline, we used the document frequency measure DF (the amount of files in which the term appeared in), Gain Ratio (GR) [7] and Fisher Score (FS) [13].

3.4 Classification Algorithms

We employed four commonly used classification algorithms: Artificial Neural Networks (ANN) [14], Decision Trees (DT) [15], Naïve Bayes (NB) [16], and their boosted versions, BDT and BNB, respectively consisting of the Adaboost.M1 [17]. We used the Weka [18] implementation of these methods.

4 Evaluation

4.1 Research Questions

We wanted to evaluate the proposed methodology for the detection of unknown malicious codes through two main experiments, by answering five questions:
1. Which weighting formula is better: *tf* or *tfidf*?
2. Which n-gram is the best: *1, 2, 3*, *4*, *5* or *6*?
3. Which *top-selection* is the best: *50*, *100*, *200* or *300* and which features selection: *DF*, *FS* and *GR*?
4. Which classifier is the best: ANN, DT, BDT, NB or BNB?
5. What is the best MFP in the training set for varying MFPs in test set?
After determining the optimal settings when using the OpCode representation, we wanted to compare the achieved accuracy to the character representation, based on the top features used. Additionally, we investigated the imbalance problem to determine the optimal settings of the training set for each classifier in varying "real-life" conditions.

4.2 Evaluation Measures

For evaluation purposes, we measured the *True Positive Rate (TPR)* measure, which is the number of *positive* instances classified correctly, as shown in Equation 5, *False Positive Rate (FPR)*, which is the number of *negative* instances misclassified (Equation 5), and the *Total Accuracy*, which measures the number of absolutely correctly classified instances, either positive or negative, divided by the entire number of instances shown in Equation 6.

$$TPR = \frac{|TP|}{|TP| + |FN|}; \quad FPR = \frac{|FP|}{|FP| + |TN|} \tag{5}$$

$$Total\ Accuracy = \frac{|TP| + |TN|}{|TP| + |FP| + |TN| + |FN|} \tag{6}$$

5 Experiments and Results

5.1 Experiment 1

To answer the first four questions presented earlier, we designed a wide and comprehensive set of evaluation runs, including all the combinations of the optional settings for each of the aspects, amounting to 720 runs in a 5-fold cross validation format for all eight classifiers. Note that the files in the test set were not in the training set presenting unknown files to the classifier.

5.1.2 Feature representation vs n-grams

First we wanted to find the best terms representation, tf vs tfidf. Figure 1 presents the mean accuracy of the combinations of the term representations and n-grams. In general the tf was slightly better than the tfidf, which is good since maintaining the tfidf requires some computational efforts. Interestingly the best n-grams of OpCodes was the 2-grams, which means that the sequence of the OpCodes is more representative than single OpCodes; however, for longer grams decreased the accuracy, which might be explained by fewer appearances in many files, thus creating zeroed representation vectors.

5.1.3 Feature Selections and Top Selections

To identify the best feature selection method and the top amount of features, we calculated the mean accuracy of each option, as shown in Figure 2. Generally, the Fisher score was the best method, mainly whe, using a large number of top features, while the DF performed very well, especially when fewer features were used. While the DF is a simple feature selection method which favors features that appear in most of the files it performed well. This can be explained by its criterion, which has an advantage for fewer features. In other methods, the lack of appearances in many files might create zeroed vectors which might lead to a lower accuracy level.

5.1.4 Classifiers

For the comparison of the classifiers' performance we selected the settings that had the highest mean accuracy of all the classifiers, which was: 2-grams, tf, using 300 features selected by the DF measure. The results of each classifier are presented in Table 1.

Table 1. The BDT, DT and ANN out-performed, while maintaining low levels of false positives.

Classifier	Accuracy	FP	FN
ANN	92.13	0.04	0.21
Decision Tree	93	0.04	0.17
Boosted DT	94.43	0.03	0.15
Naïve Bayes	84.53	0.06	0.48
Boosted NB	84.53	0.06	0.48

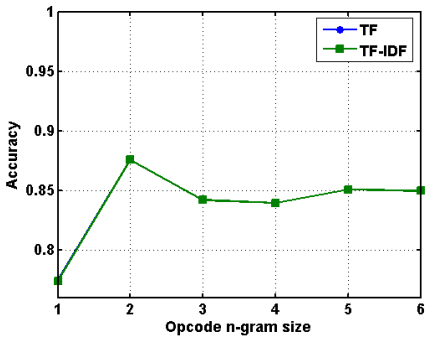

Figure 1. While the mean accuracies of the tf and tfidf were quite identical, the mean accuracy of the 2-grams outperforms all the other n-grams.

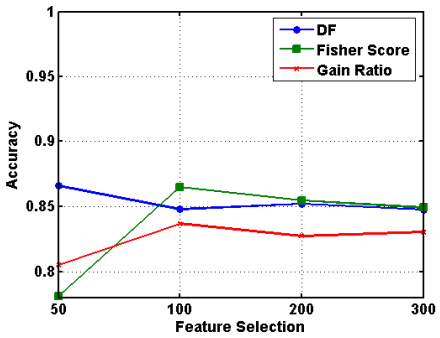

Figure 2. The Fisher score was very accurate for most of the top features, while the DF performed very well on average as well.

5.1 Experiment 2 – The imbalance problem

In the second experiment we created five levels of Malicious Files Percentage (MFP) in the training set (5, 10, 15, 30, 50%). For example, when referring to 15%, we mean that 15% of the files in the training set were malicious and 85% were benign. The test set represents the real-life situation, while the training set represents the set-up of the classifier, which is controlled. We had the same MFP levels also for the test sets. Thus, eventually we ran all the product combinations of five training sets and five test sets for a total of 25 runs for each classifier. We created two sets of datasets in order to perform a 2-fold cross validation-like evaluation to render the results more significant.

Training-Set Malcode Percentage. Figure 3 presents the mean accuracy (for all the MFP levels in the test-sets) of each classifier for each training MFP level. DT and BDT were non reactive to the MFP in the training set and out-performed, especially for the 30% MFP level, exceeding 99% accuracy. The Boosted version of the NB had

the same performance as the NB, which was generally low, and the ANN dropped significantly for 50% MFP in the training set.

10% Malcode Percentage in the Test Set. We consider the 10% MFP level in the test set to be a reasonable real life scenario, as explained in the introduction. Figure 4 presents the mean accuracy in the 2-fold cross validation of each classifier for each MFP in the training set, with a fixed level of 10% MFP in the test set. These results are quite similar in their magnitude to the results in Figure 3, although here the performance was higher. However, for the DT and BDT the higher performance was for 10% and 15% of MFP in the training set, which is more similar to the MFP in the test set.

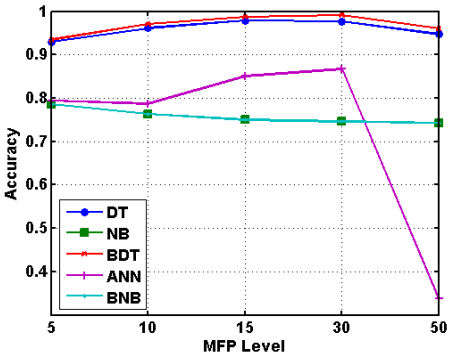

Fig. 3. Mean accuracy for various MFPs in the test set for each MFP in the training set. DT and BDT out-performed, with consistent accuracy, across the varying MFPs.

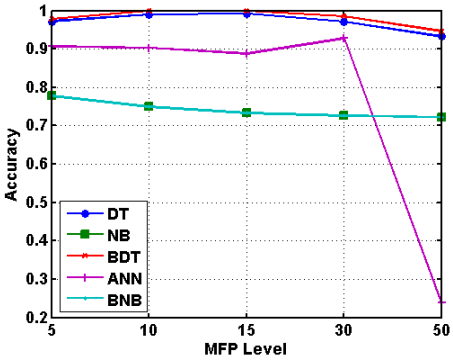

Fig. 4. Detection accuracy for 10% MFP in the test set, for varying MFPs in the training set. Greater than 99% accuracy was achieved for MFPs below 15% in the training set.

Comparison to byte n-grams [1]. In Figures 5 and 6 we present the results of [1], in which we used byte sequences n-gram and performed similar experiments (out of the MFP levels range and granularity), which are related to Figures 3 and 4, respectively. The results of the current study in the use of OpCode n-grams achieves better results than the byte n-grams, in which the highest accuracy level was about 96%.

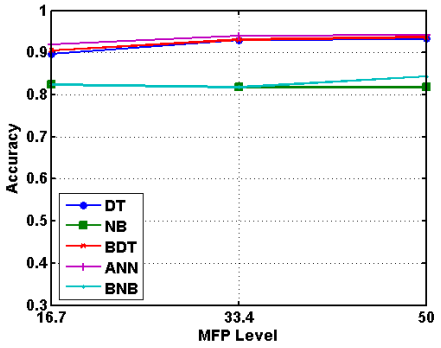

Fig. 5. Mean accuracy for various MFPs in the test set. The highest accuracy exceeds 96% (from [1]), which is less than in the current study (fig3).

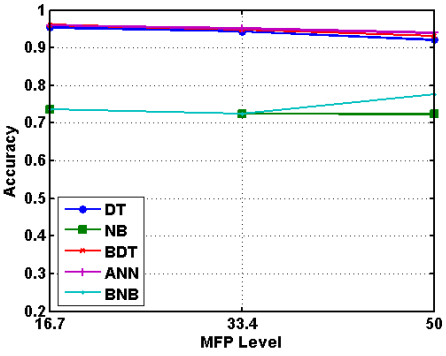

Fig. 6. Detection accuracy for 10% Malcode in the test set for varying MFPs in the training set, performs less than in the current study, with slightly more than 95% (from [1]).

Relations among MFPs in Training and Test Sets. To further our presentation of the mean accuracy from the training set point of view (Figures 3 and 4), we present a detailed description of the accuracy for the MFP levels in the two sets in a 3-dimensional presentation for each classifier (Figures 7-10). Similarly to Figures 3 and 4, DT, BDT, NB and BNB's (which had the same results) performance was quite stable for any MFP level, while the ANN was better for similar levels of MFP in the training sets and test sets.

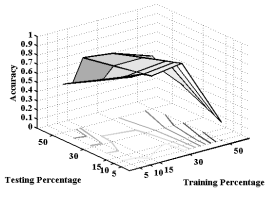

Fig 7. ANN

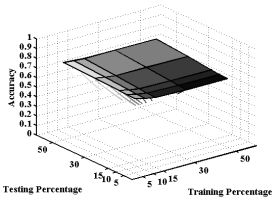

Fig 8. NB and BNB

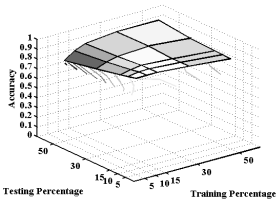

Fig 9. DT

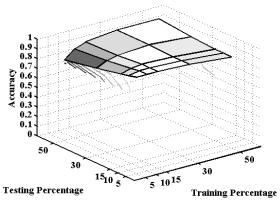

Fig 10. BDT

6 Discussion and Conclusions

We presented a methodology for the representation of malicious and benign executables for the task of unknown malicious code detection through OpCode. This presentation, which has not previously been proposed, makes possible the highly accurate detection of unknown malicious code, based on previously seen examples, while maintaining low levels of false alarms. In the first experiment, we found that the TFIDF representation has no added value over the TF, which is not the case in information retrieval applications. This is very important, since using the TFIDF representation introduces some computational challenges in the maintenance of the collection when it is updated. In order to reduce the number of n-gram features, which ranges from thousands to millions, we first used the DF measure to select the top 1000 features. The 2-gram OpCodes outperformed the others, and the Fisher Score and the DF feature selection were better than the Gain Ratio.

In the second experiment, we investigated the relationship between the MFP in the test set, which represents real-life scenario, and in the training-set, which is used for training the classifier. In this experiment, we found that there are classifiers which are relatively non-reactive to changes in the MFP level of the test set. In general, the best mean performance (across all levels of MFP) was associated with a 30% MFP in the training set (Figure 3). However, when setting a level of 10% MFP in the test set, illustrating a real-life situation and using several levels of MFP in the training set, a high level of accuracy (above 99%) was achieved when 15% of the files in the training set were malicious, while for specific classifiers, the accuracy was poor at all MFP levels (Figure 4). In comparison to our previous experience with byte sequences n-grams [1] (Figures 5 and 6), the OpCode n-grams achieved a higher performance level with the same classifiers. However, as we described earlier the limitation of the OpCodes is that not all the files can be disassembled, and thus, we suggest classifying

first using the OpCode representation and then if needed using the byte sequence representation. Finally, we presented a 3-dimensional representation of the results at all the MFP levels for each classifier (Figures 5-10). Most of the classifiers, out of the ANN, were non-reactive to the varying levels of MFP, and especially the DT and BDT yielded stable high accuracy levels.

Based on our extensive and rigorous experiments, we conclude that when one sets up a classifier for use in a real-life situation, one should use first the OpCode representation and, if the disassemble is not feasible, use the byte sequence representation. In addition, one should consider the expected proportion of malicious files in the stream of data. Since we assume that, in most real-life scenarios, low levels of malicious files are present, training sets should be designed accordingly.

References

[1] R. Moskovitch, D. Stopel, C. Feher, N. Nissim and Y. Elovici, Unknown Malcode Detection via Text Categorization and the Imbalance Problem, IEEE Intelligence and Security Informatics, Taiwan, 2008.

[2] Gryaznov, D. Scanners of the Year 2000: Heuritics, The 5th International Virus Bulletin, 1999.

[3] S. Shin, J. Jung, H. Balakrishnan, Malware Prevalence in the KaZaA File-Sharing Network, Internet Measurement Conference (IMC), Brazil, October 2006.

[4] Schultz, M., Eskin, E., Zadok, E., and Stolfo, S. (2001) Data mining methods for detection of new malicious executables, in Proceedings of the IEEE Symposium on Security and Privacy, 2001.

[5] Abou-Assaleh, T., Cercone, N., Keselj, V., and Sweidan, R. (2004) N-gram Based Detection of New Malicious Code, in Proceedings of the 28th Annual International Computer Software and Applications Conference (COMPSAC'04).

[6] Kolter, J.Z. and Maloof, M.A. (2004). Learning to detect malicious executables in the wild, in Proceedings of the Tenth ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, 470–478. New York, NY: ACM Press.

[7] Mitchell T. (1997) Machine Learning, McGraw-Hill.

[8] Kolter J., and Maloof M., Learning to Detect and Classify Malicious Executables in the Wild, Journal of Machine Learning Research 7 (2006) 2721-2744.

[9] Henchiri, O. and Japkowicz, N., A Feature Selection and Evaluation Scheme for Computer Virus Detection. Proceedings of ICDM-2006: 891-895, Hong Kong, 2006.

[10] S Dolev, N Tzachar, Malware signature builder and detection for executable code, patent application.

[11] Chawla, N. V., Japkowicz, N., and Kotcz, A. (2004) Editorial: special issue on learning from imbalanced data sets. SIGKDD Explorations Newsletter 6(1):1-6.

[12] Salton, G., Wong, A., and Yang, C.S. (1975) A vector space model for automatic indexing. Communications of the ACM, 18:613-620.

[13] Golub, T., Slonim, D., Tamaya, P., Huard, C., Gaasenbeek, M., Mesirov, J., Coller, H., Loh, M., Downing, J., Caligiuri, M., Bloomfield, C., and E. Lander, E. (1999) Molecular classification of cancer: Class discovery and class prediction by gene expression monitoring, Science, 286:531-537

[14] Bishop, C. (1995) Neural Networks for Pattern Recognition. Clarendon Press, Oxford..

[15] Quinlan, J.R. (1993) C4.5: programs for machine learning. Morgan Kaufmann Publishers, Inc., San Francisco, CA, USA.

[16] Domingos, P., and Pazzani, M. (1997) On the optimality of simple Bayesian classifier under zero-one loss, Machine Learning, 29:103-130.

[17] Y Freund, R E. Schapire, A brief introduction to boosting, International Joint Conference on Artificial Intelligence, 1999.

[18] Witten, I.H., and Frank, E. (2005) Data Mining: Practical machine learning tools and techniques, 2nd Edition, Morgan Kaufmann Publishers, Inc., San Francisco, CA, USA.