

Mobile Malware Detection using Op-code Frequency Histograms

Gerardo Canfora, Francesco Mercaldo and Corrado Aaron Visaggio

Department of Engineering, University of Sannio, Benevento, Italy

Keywords: Malware, Android, Security, Testing, Static Analysis.

Abstract: Mobile malware has grown in scale and complexity, as a consequence of the unabated uptake of smartphones worldwide. Malware writers have been developing detection evasion techniques which are rapidly making anti-malware technologies ineffective. In particular, zero-days malware is able to easily pass signature based detection, while dynamic analysis based techniques, which could be more accurate and robust, are too costly or inappropriate to real contexts, especially for reasons related to usability. This paper discusses a technique for discriminating Android malware from trusted applications that does not rely on signature, but on identifying a vector of features obtained from the static analysis of the Android's Dalvik code. Experimentation accomplished on a sample of 11,200 applications revealed that the proposed technique produces high precision (over 93%) in mobile malware detection, with an accuracy of 95%.

1 INTRODUCTION

A recent report from Gartner (Gartner, 2014) shows that the worldwide sales of mobile phones totaled 301 million units in the third quarter of 2014; in addition, it estimates that by 2018 nine out of ten phones will be smartphones. Accordingly, the number of smartphone applications is explosively growing. Unfortunately, such popularity also attracts malware developers, determining an increased production of malware for the Android platform. Not only official marketplaces, such as Google Play (GooglePlay, 2014), but a number of third-party marketplaces (AppBrain, Ap-toide, Blackmart Alpha) provide smartphone applications: anecdotal evidence shows that these markets are very likely to contain malware.

In February 2011, Google introduced Bouncer (GoogleMobile, 2014) to screen submitted apps for detecting malicious behaviors, but this has not eliminated the problem, as it is discussed in (Oberheide and Miller, 2012). Existing solutions for protecting privacy and security on smartphones are still ineffective in many facets (Marforio et al., 2011), and many analysts warn that the malware families and their variants for Android are rapidly increasing. This scenario calls for new security models and tools to limit the spreading of malware for smartphones.

The Fraunhofer Research Institution for Applied and Integrated Security has performed an evaluation of antivirus for Android (Fedler et al., 2014): the con-

clusion is there are many techniques for evading the detection of most antivirus. An example is repackaging (Zhou and Jiang, 2012): the attacker decompiles a trusted application to get the source code, then adds the malicious payload and recompiles the application with the payload to make it available on various market alternatives, and sometimes also on the official market. The user is often encouraged to download such malicious applications because they are free versions of trusted applications sold on the official market.

Signature-based malware detection, which is the most common technique adopted by commercial anti-malware for mobile, is often ineffective. Moreover it is costly, as the process for obtaining and classifying a malware signature is laborious and time-consuming.

There is another problem affecting the ability to detect malware on Android platform. Antivirus software on desktop operating system has the possibility of monitoring the file system operations. In this way, it is possible to check whether some applications assume a suspicious behavior; for example, if an application starts to download malicious code, it will be detected immediately by the anti-virus responsible for scanning the disk drive.

Android does not allow for an application to monitor the file system: any application can only access its own disk space. Resource sharing is allowed only if expressly provided by the developer of the application.

Therefore antivirus software on Android cannot monitor the file system: this allows applications to download updates and run new code without any control by the operating system. This behavior will not be detected by antivirus software in any way; as a matter of fact, a series of attacks are based on this principle (this kind of malware is also known as ‘downloader’).

This paper proposes a technique for malware detection, which uses a features vector, in place of the code signature. The assumption (that will be demonstrated with the evaluation) is that malicious applications show values for this features vector which are different from the values shown by trusted applications.

The vector includes eight features obtained by counting some Dalvik op-codes of the instructions which form the smali code (smali, 2014) of the application. Specifically, we analyze some op-codes which are usually used to change the application’s control flow, as these op-codes can be indicators of the application’s complexity. The underlying assumption is that the business logic of a trusted application tend to be more complex than the malware logic, because the trusted application code must implement a certain set of functions. On the contrary, the malware application is required to implement just the functions that activate the payload.

An approach commonly used for generating computer malware, consists of decomposing the control flow in smaller procedures to be called in a certain order, instead of following the original flow (Attaluri et al., 2008; Baysa et al., 2013). This technique is called ‘fragmentation’, and is intended to circumvent signature based antivirus or those kinds of antivirus which attempt to analyze the control flow for detecting malware.

The first six features aim at characterizing the fragmentation of the control flow, and compute, respectively, the number of the ‘move’, the ‘jump’, the ‘packed-switch’, the ‘sparse-switch’, the ‘invoke’ and the ‘if’ op-codes, singly taken, divided by the overall sum of the occurrences of all these six Dalvik op-codes.

The last two features are based on another assumption. The classes of a trusted application tend to exhibit an intrinsic variability, because each class is designed to implement a specific part of the business logic of the overall application. Such a variability should be reflected in the distribution of the op-codes, so the same op-code should occur with different frequencies in different classes. Conversely, as the malware has not an articulated business logic except for the malicious payload, this difference among its classes tend to be less evident than in trusted appli-

cations. For evaluating such a difference in op-codes distribution among the different classes forming the final application we use two features, which are two variants of the Minkowski distance (Rad and Masrom, 2010): the first one is represented by the Manhattan distance, the second one by the Euclidean distance. All the features are used to build a classifier which is then used to discriminate an Android malware from a trusted Android application. An advantage of using a classifier, removes the need to continuously collect malware signatures. However, this requires a sample of malware and a sample of trusted applications for training the classifier. Of course, the training can be run with new samples after a certain period of usage, in order to improve the accuracy and make the classifier robust with respect to the new families of malware that arise over time.

The paper poses two research questions:

- RQ1: are the features extracted able to distinguish a malware from a trusted application for Android platform?
- RQ2: is a combination of the features more effective than a single feature to distinguish an Android malware from a trusted application?

The main contribution of this paper can be resumed in the following points:

- we provide a set of features that have been never applied to the detection of Android malware;
- the set of features consists of occurrence frequency of some specific op-codes, so the extraction of such features is easy to reproduce and does not require a great use of resources;
- we discuss extensive experimentation that shows how our detection technique is very effective in terms of precision and recall, especially if compared with the antagonist methods presented in the literature.

The rest of the paper is organized as follows: the next section provides an overview of related work; the following section illustrates the proposed features and the detection technique; the fourth section discusses the experimentation, and, finally, conclusion and future works are given in the last section.

2 RELATED WORK

Several works address the problem of features extraction using dynamic and static analysis.

Counting op-codes is a technique used in previous works for the detection of virus: it revealed to

be successful with several variants of the W32.Evol metamorphic virus (Choucane and Lakhotia, 2006).

Bilar (Bilar, 2007) proposes a detection mechanism for malicious code through statistical analysis of op-codes distributions. This work compares the statistical op-codes frequency between malware and trusted samples, concluding that malware opcode frequency distribution seems to deviate significantly from trusted applications. We accomplish a similar analysis, but for Android malware. In reference (Rad and Masrom, 2010; Rad et al., 2012) the histograms of op-codes are used as a feature to find whether a file is a morphed version of another. Using a threshold of 0.067 authors in reference (Rad and Masrom, 2010) correctly classify different obfuscated versions of metamorphic viruses; while in reference (Rad et al., 2012) the authors obtain a 100% detection rate using a dataset of 40 malware instances of NGCVK family, 40 benign files and 20 samples classified by authors as other virus files.

In the literature there are a number of solutions for the detection of malicious behaviors which do not exploit op-codes occurrences.

A number of papers deals with privacy leakage, such as Pios (Chandra and Franz, 2007), AndroidLeaks (Gibler et al., 2012) and TaintDroid (Enck et al., 2010).

The purpose of TaintDroid (Enck et al., 2010) is to track the flow of privacy sensitive data, and monitor how the applications access and manipulate users personal data, in order to detect when sensitive data leave the system through untrusted applications. Authors monitor 30 third-party Android applications, founding 68 potential misuses of private information on 20 applications.

PiOS (Chandra and Franz, 2007) and AndroidLeaks (Gibler et al., 2012) perform static analysis for detecting privacy leaks in smartphones. The aim is to detect when sensitive information is collected by applications with malicious intents.

Canfora et al. (Canfora et al., 2013) propose a method for detecting mobile malware based on three metrics, which evaluate: the occurrences of a specific subset of system calls, a weighted sum of a subset of permissions that the application requires, and a set of combinations of permissions. They obtain a precision of 0.74 using a balanced dataset composed by 200 trusted and 200 real malware applications.

Sahs et al. (Sahs and Khan, 2012) use a control flow graph to detect Android Malware; their work is based on AndroGuard (Androguard, 2014), a tool useful to extract a series of features from mobile applications in order to train a One-Class Support Vector Machine. They validate the proposed method on

2,081 benign and 91 malicious application, concluding that the trusted sample size combined with a fixed malicious sample size causes precision to decrease as the benign sample increases.

Desnos (Desnos, 2012) presents an algorithm to detect an infected Android application using similarity distance between two applications. The similarity distance seems to be an useful index to determine whether a version of an application has potentially been pirated.

Mobile Application Security Triage (MAST) (Chakradeo et al., 2013) ranks the maliciousness of apks by using a set of attributes, like intent filters and native code. MAST uses Multiple Correspondence Analysis to measure the correlation between declared indicators of functionality required to be present in the packages of the analyzed applications. Conversely, in this paper we focus on a set of op-codes.

CopperDroid (Reina et al., 2013) recognizes Android malware through a system call analysis: the solution is based on the observation that such behaviors are however achieved through the system calls invocation, using a customized version of the Android emulator to enable system call tracking and support system call analyses.

Wu et al. (Wu et al., 2012) propose a static feature-based mechanism that considers the permission, the deployment of components, the intent messages passing and API calls for characterizing the Android applications behavior. Zheng et al. (Zheng et al., 2013) propose a signature based analytic system to automatically collect, manage, analyze and extract Android malware. Arp et al. (Arp et al., 2014) propose a method to perform a static analysis of Android applications based on features extracted from the manifest file and from the disassembled code (suspicious API calls, network addresses and other). Their approach uses Support Vector Machines to produce a detection model, and extracts a set of features which is different from the one presented in this paper. Their dataset is composed by 5,560 malware applications and 123,453 trusted one obtaining a detection rate equal to 93.9%.

As emerges from this discussion and at the best knowledge of the authors, the set of features considered in this paper was never used in any of the works on Android malware in literature.

3 THE PROPOSED FEATURES

We classify malware using a set of features which count the occurrences of a specific group of op-codes

extracted from the smali Dalvik code of the application under analysis (AUA in the remaining of the paper). Smali is a language that represents disassembled code for the Dalvik Virtual Machine (dalvik, 2014), a virtual machine optimized for the hardware of mobile devices.

We produce the histograms of a set of op-codes occurring in the AUA: each histogram dimension represents the number of times the op-code corresponding to that dimension appears in the code. The collected op-codes have been chosen because they are representative of the alteration of the control flow. The underlying assumption is that a trusted application tend to have a greater complexity than a malicious one. We consider 6 op-codes:

- Move: which moves the content of one register into another one.
- Jump: which deviates the control flow to a new instruction based on the value in a specific register.
- Packed-Switch: which represents a switch statement. The instruction uses an index table.
- Sparse-Switch: which implements a switch statement with sparse case table, the difference with the previous switch is that it uses a lookup table.
- Invoke: which is used to invoke a method, it may accept one or more parameters.
- If: which is a Jump conditioned by the verification of a truth predicate.

In order to compute the set of features, we follow two steps. The first step consists of preprocessing the AUA: we prepare the input data in form of histograms. It is worth observing that the histogram dissimilarity has been already applied with success in malware detection in (Rad and Masrom, 2010; Rad et al., 2012).

At the end of this step, we have a series of histograms, a histogram for each class of the AUA; each histogram has six dimensions, each dimension corresponds to one among the six op-codes included in the model. In the second step, we compute two forms of the Minkowski distances.

In the preprocessing step, we disassemble the executable files using APKTool (apktool, 2014), a tool for reverse engineering Android apps, and generating Dalvik source code files. After this, we create a set of histograms that represent the frequencies of the six op-codes within each class.

Fig. 1 shows the process of program disassembly and the corresponding breakdown into histograms.

Fig 2 represents an example of a class histogram.

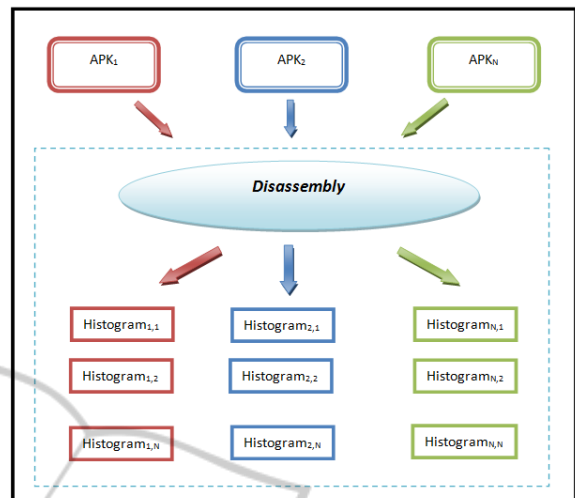


Figure 1: A graphical representation of AUA analysis' step 1, which consists of the AUA disassembly and histograms generation.

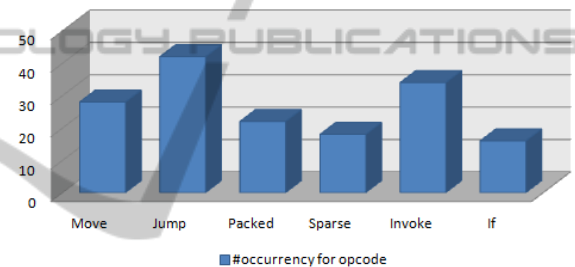


Figure 2: An example of a histogram generated from the n-th class of the j-th AUA obtained with the processing of the step 1.

The second step comprises the computation of the distances between the various histograms obtained with the step 1.

The first six features are computed as follows; let X be one of the following values:

- M_i : the number of occurrences of the 'move' op-code in the i-th class of the application;
- J_i : the number of occurrences of the 'jump' op-code in the i-th class of the application;
- P_i : the number of occurrences of the 'packed-switch' op-code in the i-th class of the application;
- S_i : the number of occurrences of the 'sparse-switch' op-code in the i-th class of the application;
- K_i : the number of occurrences of the 'invoke' op-code in the i-th class of the application;
- I_i : the number of occurrences of the 'if' op-code in the i-th class of the application.

Then:

$$\#X = \frac{\sum_{k=1}^N X_k}{\sum_{k=1}^N (M_i + J_i + P_i + S_i + K_i + I_i)}$$

where X is the occurrence of one of the six op-codes extracted and N is the total number of the classes forming the AUA.

Before explaining the last two features, it will be useful to recall the Minkowski distance.

Let's consider two vectors of size n, $X = (x_1, x_2, \dots, x_n)$ and $Y = (y_1, y_2, \dots, y_n)$, then the Minkowski distance between two vectors X and Y is:

$$d_{X,Y}^r = \sum_{k=1}^N |x_k - y_k|^r$$

One of the most popular histogram distance measurements is the Euclidean distance. It is a Minkowski distance with $r = 2$:

$$d_{X,Y}^E = \sqrt{\sum_{k=1}^N (x_k - y_k)^2}$$

Another popular histogram distance measurement is Manhattan distance. Even the Manhattan distance is a form of the Minkowski distance, in this case $r = 1$:

$$d_{X,Y}^M = \sum_{k=1}^N |x_k - y_k|$$

The last two features are Manhattan and Euclidean distance, computed with a process of three steps. Given an AUA containing N classes, the AUA will have N histograms, one for each class, where each histogram H_i will be a vector of six values, each one corresponding to an op-code of the model ('move', 'jump', 'packed-switch', 'sparse-switch', 'invoke', 'if').

As an example, we will show an application of the model to a simplified case, in which the model has only three classes and two op-codes. Let's assume that the AUA's histograms are $H_1 = \{4, 2\}$, $H_2 = \{2, 1\}$, $H_3 = \{5, 9\}$.

- *Step 1*: the Minkowski distance is computed among each pair H_i, H_j with $i \neq j$ and $1 \leq i, j \leq N$. In the example we will have $d_{1,2} = 3$; $d_{1,3} = 2$; $d_{2,3} = 11$. We do not compute $d_{2,1}$, $d_{3,1}$ and $d_{3,2}$ because Minkowski distance is symmetric, i.e. $d_{i,j} = d_{j,i}$ for $1 \leq i, j \leq N$. For simplicity we consider only the Manhattan distance in the example;
- *Step 2*: the vector with all the distances is computed for each AUA, $D = \{d_{i,j} \mid i \neq j \text{ and } 1 \leq i \leq N, 2 \leq j \leq N\}$. Each dimension of the vector corresponds to a class of the AUA. In the example $D = \{3, 2, 11\}$.
- *Step 3*: the max element in the vector is extracted, which is $M_{AUA} = \text{MAX}(D[i])$. In the example

M_{AUA} is 11.

Finally the last two features are the values M_{AUA} computed, respectively, with Manhattan and Euclidean distance. Thus, M_{AUA} is a measure of dissimilarity among the classes of the AUA.

4 EVALUATION: STUDY DESIGN

We designed an experiment in order to evaluate the effectiveness of the proposed technique, expressed through the research questions RQ1 and RQ2, stated in the introduction.

More specifically, the experiment is aimed at verifying whether the eight features are able to classify a mobile application as trusted or malicious. The classification is carried out by using a classifier built with the eight features discussed in the previous section. The evaluation consists of three stages: (i) a comparison of descriptive statistics of the populations of programs; (ii) hypotheses testing, to verify if the eight features have different distributions for the populations of malware and trusted applications; and (iii) a classification analysis aimed at assessing whether the features are able to correctly classify malware and trusted applications. The classification analysis was accomplished with Weka, a suite of machine learning software (weka 3, 2014), largely employed in data mining for scientific research.

The dataset was made by 5,560 Android trusted applications and 5,560 Android malware applications: trusted applications of different categories (call & contacts, education, entertainment, GPS & travel, internet, lifestyle, news & weather, productivity, utilities, business, communication, email & SMS, fun & games, health & fitness, live wallpapers, personalization) were downloaded from Google Play (Google-Play, 2014), while the malware applications belong to the collection of the Drebin project (Arp et al., 2014; Spreitzenbarth et al., 2013). The Drebin project is a dataset that gathers the majority of existing Android malware families. The dataset includes different types of malware categorized by installation methods and activation mechanisms, as well as the nature of carried malicious payloads, in particular the dataset includes 179 Android malware families.

With regards to the hypotheses testing, the null hypothesis to be tested is:

H_0 : 'malware and trusted applications have similar values of the features'.

The null hypothesis was tested with Mann-Whitney (with the p-level fixed to 0.05) and with Kolmogorov-Smirnov Test (with the p-level fixed to

0.05). We chose to run two different tests in order to enforce the conclusion validity.

The purpose of these tests is to determine the level of significance, i.e. the risk (the probability) that erroneous conclusions be drawn: in our case, we set the significance level equal to .05, which means that we accept to make mistakes 5 times out of 100.

The classification analysis was aimed at assessing whether the features were able to correctly classify malware and trusted applications.

Six algorithms of classification were used: J48, LadTree, NBTree, RandomForest, RandomTree and RepTree. These algorithms were applied separately to the eight features and to three groups of features.

The first group includes the move and the jump features, the second group includes the two distances, and the third group includes all the four features (move, jump, Manhattan and Euclidean features). The features grouping is driven by the goal to obtain the best results in classification, as discussed later in the paper.

5 EVALUATION: ANALYSIS OF DATA

For the sake of clarity, the results of our evaluation will be discussed reflecting the data analysis' division in three phases: descriptive statistics, hypotheses testing and classification.

5.1 Descriptive Statistics

The analysis of box plots (shown in figure 3) related to the eight features helps to identify the features more effective to discriminate malware from trusted applications. The differences between the box plots of malware and trusted applications for the 'move' and 'jump' features suggest that the two populations could belong to different distributions. A huge part of the trusted sample (between the second and the third quartile) has values greater than the 75% of the malware sample for this couple of features. The reason may reside, as conjectured in the introduction, in the fact that in trusted applications these op-codes are used for implementing a certain business logic (whose complexity may vary a lot), while in the malware they can be only employed basically for code fragmentation.

This hypothesis will be confirmed by the hypothesis testing, as discussed later.

The distributions of 'sparse-switch' and 'packed-switch' op-codes seem to show a difference in the two

samples, too, which is more relevant for the 'sparse-switch' box plots. This evidence strengthens the starting assumption of the paper, that will be confirmed by the results of the hypotheses testing. Switch constructs are frequently used for implementing the business logic of remote control (command and control malware are very widespread) of a victim device, or the selection criteria for activating the payload.

Instead, the box plots related to the features 'invoke' and 'if' do not produce significant differences between malware and trusted samples.

Finally, the differences between the box plots of trusted applications and malware for the Manhattan and the Euclidean distance are much more pronounced than the previous cases, suggesting that the two populations could belong to different distributions. It is interesting to observe how in both the cases the third percentile of the malware sample is lower than the first percentile of the trusted sample.

The very tight box plots of the distances for malware, especially the one associated to the Manhattan distance, confirm the assumption that malware code has a lower variability (in terms of business logic) than trusted applications.

Remark 1: From descriptive statistics we find out that trusted applications boxplots (for 'move' and 'jump' opcodes, and for the two distances) range in a wider interval than the malware ones. This may reveal the fact that malware applications implement little business logic with respect to the trusted ones, and identifies these four features as good candidates for the classification phase. This result will be confirmed by the hypotheses testing and by the classification analysis.

5.2 Hypothesis Testing

The hypothesis testing aims at evaluating if the features present different distributions for the populations of malware and trusted applications with statistical evidence.

We assume valid the results when the null hypothesis is rejected by both the tests performed.

Table 1 shows the results of hypothesis testing: the null hypothesis H_0 can be rejected for all the eight features. This means that there is statistical evidence that the vector of features is a potential candidate for correctly classifying malware and trusted applications.

This result will provide an evaluation of the risk to generalize the fact that the selected features produce values which belong to two different distributions (i.e. the one of malware and the trusted one): those features can distinguish those observations. With the classification analysis we will be able to establish the

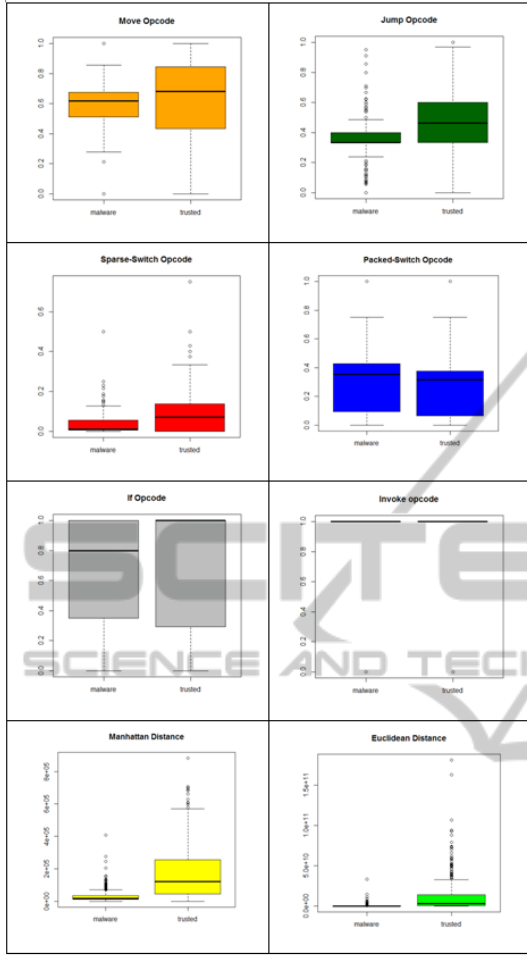


Figure 3: Box plots for the features extracted.

accuracy of the features in associating any applications to a sample, malware or trusted.

Remark 2: the malware and trusted samples (produced with all the eight features) show a statistically significant difference by running both the tests.

5.3 Classification Analysis

The classification analysis consisted of building a classifier, and evaluating its accuracy. For training the classifier, we defined T as a set of labelled mobile applications (AUA, l), where each AUA is associated to a label $l \in \{trusted, malicious\}$. For each AUA we built a feature vector $F \in R_y$, where y is the number of the features used in training phase ($1 \leq y \leq 8$). To answer RQ1, we performed eight different classifications, each one with a single feature ($y=1$), while for answering RQ2 we performed three classifications with $y>1$ (classifications with a set of features).

For the learning phase, we use a k-fold cross-

 Table 1: Results of the test of the null hypothesis H_0 .

Variable	Mann-Whitney	Kolmogorov-Smirnov
Move	0,000000	$p < .001$
Jump	0,000000	$p < .001$
Packed	0,000240	$p < .001$
Sparse	0,000000	$p < .001$
If	0,000000	$p < .001$
Invoke	0,000000	$p < .001$
Manhattan	0,000000	$p < .001$
Euclidean	0,000000	$p < .001$

validation: the dataset is randomly partitioned into k subsets. A single subset is retained as the validation dataset for testing the model, while the remaining $k-1$ subsets of the original dataset are used as training data. We repeated the process for k times; each one of the k subsets has been used once as the validation dataset. To obtain a single estimate, we computed the average of the k results from the folds.

We evaluated the effectiveness of the classification method with the following procedure:

1. build a training set $T \subset D$;
2. build a testing set $T' = D \div T$;
3. run the training phase on T ;
4. apply the learned classifier to each element of T' .

We performed a 10-fold cross validation: we repeated the four steps 10 times varying the composition of T (and hence of T').

The results that we obtained with this procedure are shown in table 2. Three metrics were used to evaluate the classification results: recall, precision and roc area.

The precision has been computed as the proportion of the examples that truly belong to class X among all those which were assigned to the class. It is the ratio of the number of relevant records retrieved to the total number of irrelevant and relevant records retrieved:

$$Precision = \frac{tp}{tp+fp}$$

where tp indicates the number of true positives and fp indicates the number of false positives.

The recall has been computed as the proportion of examples that were assigned to class X , among all the examples that truly belong to the class, i.e. how much part of the class was captured. It is the ratio of the number of relevant records retrieved to the total number of relevant records:

$$Recall = \frac{tp}{tp+fn}$$

Table 2: Classification Results: Precision, Recall and RocArea for classifying Malware and Trusted applications, computed with the single features, with the algorithms J48, LadTree, NBTree, RandomForest, RandomTree and RepTree.

Features	Algorithm	Precision		Recall		RocArea	
		Malware	Trusted	Malware	Trusted	Malware	Trusted
move	J48	0.905	0.714	0.885	0.757	0.856	0.856
	LADTree	0.81	0.714	0.887	0.742	0.858	0.858
	NBTree	0.81	0.713	0.887	0.742	0.859	0.859
	RandomForest	0.926	0.69	0.867	0.821	0.802	0.802
	RandomTree	0.924	0.695	0.866	0.817	0.88	0.88
	RepTree	0.904	0.715	0.886	0.755	0.886	0.886
jump	J48	0.872	0.706	0.896	0.651	0.858	0.858
	LADTree	0.866	0.732	0.91	0.626	0.875	0.875
	NBTree	0.853	0.753	0.925	0.575	0.861	0.861
	RandomForest	0.887	0.735	0.903	0.697	0.876	0.876
	RandomTree	0.886	0.736	0.904	0.695	0.868	0.868
	RepTree	0.885	0.713	0.893	0.695	0.871	0.871
invoke	J48	0.765	0.598	0.935	0.227	0.569	0.569
	LADTree	0.765	0.598	0.935	0.227	0.569	0.569
	NBTree	0.765	0.598	0.935	0.227	0.569	0.569
	RandomForest	0.765	0.598	0.935	0.227	0.578	0.578
	RandomTree	0.765	0.598	0.935	0.227	0.569	0.569
	RepTree	0.765	0.598	0.935	0.227	0.569	0.569
packed	J48	0.67	0.576	0.937	0.201	0.619	0.619
	LADTree	0.751	0.512	0.938	0.161	0.715	0.715
	NBTree	0.732	0.373	0.95	0.059	0.635	0.635
	RandomForest	0.768	0.557	0.918	0.254	0.64	0.64
	RandomTree	0.759	0.569	0.935	0.201	0.725	0.725
	RepTree	0.752	0.531	0.936	0.107	0.697	0.697
sparse	J48	0.846	0.731	0.919	0.555	0.747	0.747
	LADTree	0.834	0.718	0.92	0.501	0.826	0.826
	NBTree	0.828	0.702	0.921	0.489	0.801	0.801
	RandomForest	0.831	0.747	0.932	0.493	0.855	0.855
	RandomTree	0.824	0.767	0.941	0.462	0.849	0.849
	RepTree	0.837	0.723	0.921	0.52	0.836	0.836
if	J48	0.766	0.6	0.935	0.229	0.621	0.621
	LADTree	0.766	0.596	0.934	0.232	0.71	0.71
	NBTree	0.765	0.595	0.926	0.227	0.71	0.71
	RandomForest	0.771	0.596	0.928	0.216	0.726	0.726
	RandomTree	0.771	0.596	0.928	0.216	0.72	0.72
	RepTree	0.768	0.598	0.932	0.241	0.708	0.708
Manhattan	J48	0.856	0.844	0.934	0.575	0.843	0.843
	LADTree	0.854	0.848	0.956	0.556	0.868	0.868
	NBTree	0.838	0.888	0.969	0.5	0.854	0.854
	RandomForest	0.885	0.783	0.921	0.686	0.852	0.852
	RandomTree	0.889	0.789	0.918	0.7	0.809	0.809
	RepTree	0.861	0.842	0.953	0.591	0.849	0.849
Euclidean	J48	0.833	0.934	0.98	0.478	0.71	0.71
	LADTree	0.836	0.908	0.974	0.489	0.869	0.869
	NBTree	0.833	0.934	0.98	0.478	0.854	0.854
	RandomForest	0.88	0.771	0.918	0.702	0.854	0.854
	RandomTree	0.891	0.765	0.915	0.706	0.811	0.811
	RepTree	0.851	0.829	0.951	0.558	0.852	0.852

where fn is the number of false negatives. Precision and recall are inversely related. The Roc Area is defined as the probability that a positive instance randomly chosen is classified above a negative randomly chosen.

The classification analysis suggests several considerations. With regards to the precision:

- All the algorithms are able to effectively classify both trusted applications and malicious applications (with the exception of the 'packed-switch' feature that exhibits a value of precision in the trusted classification lower than 0.5 with the NBTree classification algorithm).
- The features 'move' and 'jump' return the best results for the classification of malware applications (in particular, the precision of the 'move' is equal to 0.926 with RandomForest classification algorithm), the features Manhattan distance and Euclidean distance appear to be the best to classify trusted applications (in particular precision of the Euclidean distance for the trusted applications amounted to 0.934 with J48 and NBTree classification algorithms).
- The 'Invoke', 'Packed', 'Switch' and 'If' features are characterized by precision values smaller than the other features analyzed, but exhibit much better results with regard to the classification of malware, if compared to trusted applications. However, in any case, these values are lower than the features 'move' and 'jump' for detecting malware and Manhattan and Euclidean distance, for classifying the trusted applications.

With regards to the recall:

- All the algorithms are able to classify effectively malware (with the exception of the 'packed-switch', 'invoke' and 'if' features that exhibit a value of recall lower than 0.5 in the trusted classification).
- The recall presents high values for malware detection (the Euclidean distance allows for a recall equal to 0.98 with J48 and NBTree classification algorithms), while the trusted applications detection appears to be weaker if compared to the malware detection, in fact the maximum recall value for trusted applications distribution is equal to 0.821 (corresponding to the 'move' feature with RandomForest algorithm).
- The other features have lower values of recall for both the distributions.

With regards to the roc area:

- The performances of all the algorithms are pretty the same for malware and trusted applications.

- The 'move' feature presents the maximum rocaea value equal to 0.892 with RandomForest algorithm.
- The 'invoke' feature presents the lowest values of roc-area.

Relying on this first classification, we selected those features which had the best performance, in order to investigate if grouping them could increase the accuracy of the classification obtained with single features.

The following three groups of features were identified: (i) 'move-jump', in order to obtain the maximum precision value for detecting malware; (ii) 'Manhattan-Euclidean', in order to obtain the maximum precision value in the detection of trusted applications, and (iii) 'move-jump-Manhattan-Euclidean', in order to combine the characteristics of the two sets of features previously considered.

The classification accomplished by using these groups of features confirms our expectations: we obtained results significantly better than in the case of the classification with single features, as table 3 shows.

The group of features 'move-jump' allows for a precision equal to 0.939 by performing the classification of malware with the J48 algorithm, while the precision of the classification of trusted applications is equal to 0.782 using the J48, the RandomForest and the RandomTree algorithm.

Combining the two features produces an improvement on the detection of malware (0.939), in fact by using only the 'move' the precision is equal to 0.926, by using the algorithm RandomForest; while the single 'jump' feature reaches a precision equal to 0.886, by using the algorithm RandomTree.

The recall is 0.911 in the classification of malware, when using the algorithm RandomForest and RandomTree, while for the classification of trusted applications is 0.853 by using the J48 algorithm.

The maximum value of rocaea is equal to 0.928 by using the algorithm RandomForest.

The group of the features 'Manhattan-Euclidean' presents a precision in the detection of malware equal to 0.912, by using the algorithm RandomForest, while with regard to the trusted applications a value equal to 0.935 is obtained by using the algorithms J48 and NBTree. Combining these two features produces an improvement for the detection of the trusted applications: in fact, the precision of the feature 'Manhattan' for trusted applications is equal to 0.888 with the algorithm NBTree, for the feature 'Euclidean' is equal to 0.934 with the algorithm J48 and NBTree .

The recall is 0.961 in the classification of malware using the algorithm J48, while in the trusted applica-

Table 3: Classification Results: Precision, Recall and RocArea for classifying Malware and Trusted applications, computed with the three groups of features, with the algorithms J48, LadTree, NBTree, RandomForest, RandomTree and RepTree.

Features	Algorithm	Precision		Recall		RocArea	
		Malware	Trusted	Malware	Trusted	Malware.	Trusted
move-jump	J48	0.939	0.782	0.909	0.853	0.917	0.917
	LADTree	0.8	0.723	0.896	0.708	0.877	0.877
	NBTree	0.912	0.748	0.9	0.775	0.909	0.909
	RandomForest	0.931	0.782	0.911	0.828	0.928	0.928
	RandomTree	0.929	0.782	0.911	0.824	0.892	0.892
	RepTree	0.93	0.748	0.894	0.83	0.916	0.916
Manhattan-Euclidean	J48	0.855	0.935	0.961	0.569	0.841	0.841
	LADTree	0.85	0.853	0.958	0.551	0.868	0.868
	NBTree	0.84	0.935	0.956	0.515	0.855	0.855
	RandomForest	0.906	0.83	0.938	0.746	0.897	0.897
	RandomTree	0.912	0.807	0.927	0.77	0.849	0.849
	RepTree	0.871	0.854	0.954	0.626	0.854	0.854
Move-Jump Manhattan-Euclidean	J48	0.916	0.852	0.945	0.777	0.897	0.897
	LADTree	0.885	0.803	0.933	0.682	0.911	0.911
	NBTree	0.922	0.738	0.891	0.806	0.925	0.925
	RandomForest	0.931	0.902	0.971	0.821	0.946	0.946
	RandomTree	0.931	0.894	0.958	0.812	0.8	0.8
	RepTree	0.997	0.876	0.955	0.746	0.904	0.904

tions detection is equal to 0.77 using the algorithm RandomTree. The maximum value of rocaea is equal to 0.897 using the algorithm RandomForest.

The classification of the combination of the four features leads to optimal results for the detection of both malware and trusted applications: in fact, the value of precision for the detection of malware is equal to 0.931 by using the algorithm RandomForest and 0.902 for the trusted applications, by using the algorithm RandomForest. The recall is 0.961 using the algorithm RandomForest in the case of malware, and 0.821 using the algorithms RandomForest and RandomTree. The rocArea is maintained equal for the detection of both trusted applications and malware, using the algorithm RandomForest. This result is particularly valuable: tests producing values of ROCArea greater than 0.9 are usually considered optimal in terms of accuracy.

Remark 3: The classification analysis suggests that the features are effective to detect mobile malware. The multi-features classification improves the detection capability, with a very high level of accuracy.

6 CONCLUSIONS AND FUTURE WORKS

The aim of this work is to understand whether a features vector obtained by the counting of some op-

codes occurrences can be used to classify a mobile application as malware or trusted.

The experiment allowed us to provide the following answers to the research questions we posed:

- RQ1: the features extracted are able to discriminate malware from trusted applications. In particular, the features ‘move’ and ‘jump’ produced values of precision equal to 0.9 in the identification of malware, while the ‘Manhattan’ and ‘Euclidean’ distance revealed to be the best ones for detecting the trusted applications.
- RQ2: grouping the features may increase precision and accuracy of classification. In fact the classification with all the features allows for benefits for both malware and trusted applications classification, achieving a precision of 0.931 in the detection of malware and 0.902 in detection of trusted applications. Additionally, the accuracy of the tests is equal to 0.95, which is considered optimal.

Unfortunately code morphing techniques could be employed in order to alterate op-codes histograms. This is usually accomplished by adding junk code which does not alter the behaviour of malware, but just the distribution of op-codes.

This evasion technique can be contrasted by two ways: first, by applying methods for finding junk code within malware, which is part of future work. Second, by identifying precise patterns and sequences of op-

codes that could be recurrent in malicious malware's code. This latter technique could also help to understand which is the family each malware instance belongs to, which is a further improvement of interest in the area of malware detection.

An undeniable advantage of this technique is the easiness of implementation and the correspondent lightness in terms of requested resources: basically the proposed method needs to extract the occurrence frequency of a set of op-codes. The method can be straightforward reproduced and this fosters the replications of our study for confirming the outcomes or finding possible weakness points.

We can compare our work with (Arp et al., 2014) and (Peng et al., 2012), as these are the closest works to ours for technique among the considered related works. Arp et al. (Arp et al., 2014) obtained a precision (94%) which is almost identical than the one obtained with our approach (93.9%), while Peng et al. (Peng et al., 2012) reported a ROC AREA of 95%, which coincides with our best ROC AREA (95.6%). The best deployment of the proposed classifier is a client-server architecture, where the classifier resides in a server and a client app is installed on the user device and requires the analysis of a certain app to the server.

The main limitation of the evaluation stands in the external validity, as we have considered a sample of applications collected in 2012. Running our method on newest samples could produce different results. However, some mitigation factors must be taken into account for this experimental threat. First, we have considered a large set of samples, amounting to 11,200 units. This could assure a wide coverage of many kinds of malware and trusted applications, so the sample could be considered well representative of the original population. Additionally, in order to enforce the validity of the used dataset, we should consider that malware traditionally evolves by improving existing malware with (a few) new functions, or merging fragments of existing malware applications.

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