DaDiDroid: An Obfuscation Resilient Tool for Detecting Android Malware via Weighted Directed Call Graph Modelling

Muhammad Ikram[1,3], Pierrick Beaume[2], and Mohamed Ali Kaafar[1,2]
[1]*Macquarie University,* [2]*Data61 CSIRO,* [3]*University of Michigan*
{*Muhammad.Ikram, Dali.Kaafar*}*@mq.edu.au, Pierrick.Beaume@data61.csiro.au*

Keywords: Malware, obfuscation, machine learning, android, mobile apps.

Abstract: With the number of new mobile malware instances increasing by over 50% annually since 2012 [25], malware embedding in mobile apps is arguably one of the most serious security issues mobile platforms are exposed to. While obfuscation techniques are successfully used to protect the intellectual property of apps' developers, they are unfortunately also often used by cybercriminals to hide malicious content inside mobile apps and to deceive malware detection tools. As a consequence, most of mobile malware detection approaches fail in differentiating between benign and obfuscated malicious apps. We examine the graph features of mobile apps code by building weighted directed graphs of the API calls, and verify that malicious apps often share structural similarities that can be used to differentiate them from benign apps, even under a heavily "polluted" training set where a large majority of the apps are obfuscated. We present DaDiDroid an Android malware app detection tool that leverages features of the weighted directed graphs of API calls to detect the presence of malware code in (obfuscated) Android apps. We show that DaDiDroid significantly outperforms MaMaDroid [24], a recently proposed malware detection tool that has been proven very efficient in detecting malware in a clean non-obfuscated environment. We evaluate DaDiDroid's accuracy and robustness against several evasion techniques using various datasets for a total of 43,262 benign and 20,431 malware apps. We show that DaDiDroid correctly labels up to 96% of Android malware samples, while achieving an 91% accuracy with an exclusive use of a training set of obfuscated apps.

1 INTRODUCTION

In recent years, Android OS and mobile applications (apps in short) have experienced an exponential growth with over 3 Million apps on Google Play [15] in 2017. This popularity naturally attracted malware developers leading to a continuous 50% yearly increase of the number of malware apps for over five years [25]. Several research studies (e.g., [20, 18, 12]) focused on dynamic runtime-network analysis to detect potential malicious behaviour of Android apps. Another line of research (e.g., [23, 4, 8, 1]) aimed to reduce the resources required to perform dynamic analysis by adopting static code analysis approaches [20, 19]. DroidAPIMiner [1], for instance, uses the frequency of API calls to classify malware apps. Recently, MaMaDroid [24] leverages the similarity in the code of apps as extracted from the transition probabilities between different API calls to build an efficient Android malware detection system. However, the increased code complexity and the use of obfuscation techniques as a way to protect apps from code theft, reverse engineering and code inspection, pose several challenges to static analysis of malware apps.

In this paper, we set the objective of building an effective mobile malware detection tool that is resistant to code obfuscation techniques. We propose DaDiDroid, a tool that runs static code analysis, leveraging apps' API call graphs to characterize the functional behaviour of apps and filter out malicious behaviour, even in presence of an obfuscated code. Specifically, DaDiDroid builds, for each Android app, the API families calls graph (e.g., API packages such as *android.util.log* are abstracted to *android*) and extracts the weighted directed graphs features (we use 23 unique graph features) to model the Android app behaviour. Using the graph features, we then rely on a classifier to establish whether or not the directed weighted graph belongs to a benign app.

This paper makes the following contributions:

Open Source Malware Detection Tool: We present our open source[1] malware detection tool, DaDiDroid, that leverages features from the weighted directed graph representation of apps' API calls (§ 3).

Efficacy of Graph Features: We empirically evaluate our proposed system and demonstrate the ef-

[1]For further research, we plan to release DaDiDroid to the research community.

ficacy of the graph features as peculiar features distinguishing between benign and malicious apps. We use a combination of six publicly available datasets to evaluate the effectiveness of DaDiDroid and determine that, in a clean environment (i.e., no obfuscation used by apps) it detects malware apps with an accuracy of 96.5%. We present the distributions of some selected graph features to show how they could be used as discriminating features of (obfuscated) malware and benign apps.

Comparison against MaMaDroid: We empirically show (cf. § 5 and § 5.3) that the accuracy of MaMaDroid, a recent static analysis mobile malware detection tool, is heavily dependent of the balance in the training dataset as captured by the ratio of benign versus malicious apps. In addition, we show that MaMaDroid is prone to obfuscation techniques with a generated false negatives as high as 86.3%.

DaDiDroid's Robustness Against Obfuscation: We show that DaDiDroid is robust against several code obfuscation techniques. With no obfuscated apps present in the training set, DaDiDroid accurately classifies 91.2% of all obfuscated apps[2], an average 17.7% higher success rates when compared to MaMaDroid.

2 OVERVIEW OF OBFUSCATION TECHNIQUES

An Android app package (i.e., APK) comes a compressed file containing all the module and content. Generally, the compressed APK include: four directories (*res*, *assets*, *lib*, and *META-INF*) and three files (*AndroidManifest.xml*, *classes.dex*, and *resources.arsc*). Among these components, *classes.dex* contains Java classes of an app, organized in a way the *Dalvik* virtual machine can interpret and execute.

In general, obfuscation attempts to obscure a program and makes the source code[3] more difficult for humans to understand, to evade malware detection tools, or both. Developers can deliberately obfuscate code (i.e., Java classes in *classes.dex*) to protect app's (malicious) logic or purpose, prevent tampering, or to deter reverse engineering efforts. Common obfuscation techniques used by apps include:

Call Indirection: This involves the manipulation of apps' call graphs by calling any two methods from each others. In essence, in this obfuscation technique, a method invocation is moved into a new method which, in turn, is invoked in place of the original method.

String Encoding and Encryption: Strings are very common-used data structures in software development. In an obfuscated app, strings could be encrypted to prevent information leakage. Based on cryptographic functions, the original plain texts are replaced by random strings and restore at runtime. As a result, string encryption could effectively hinder hard-coded static scanning.

Packing: In this obfuscation, an APK file is composed of an *origin* APK and a *wrapper* APK. Generally, a wrapper APK launches the origin APK into memory and executes it on Android devices. A wrapper APK may employ encryption to hide (or limit access to) the original APK which are decrypted at runtime thus often evade static code analysis.

Identifier Renaming: In software development, for good readability, code identifiers' names are usually meaningful, though developers may follow different naming rules. However, these meaningful names also accommodate reverse-engineers to understand the code logic and locate the target functions rapidly. Therefore, to reduce the potential information leakage, the identifier's name could be replaced by a meaningless string. Generally, with this obfuscation technique, a given API's name such as *myApp.net.myPackage* is transformed to at most three-letters words such as *a.bc.def*.

3 THE DADIDROID SYSTEM

Figure 1 depicts an overview of the four *steps* of the DaDiDroid's malware detection system. By leveraging source code analysis and graph theory, we extract APIs call graphs of Android apps (*step* 1) and then model the relationships among APIs (*step* 2). We use various graph features (*step* 3) and machine learning algorithms (*step* 4) to classify apps. We provide details of these steps in the following.

APIs Call Graph Extraction: We aim to model the behaviour of apps (benign and malware) from the API calls in the source code. To this end, the first step in DaDiDroid is to extract the apps' call[4] graphs by performing static analysis on the apps' APKs (Android Apps packages). We use Soot [30], a Java optimization and analysis framework, to extract API call graphs and then instrument FlowDroid (v2.5) [5] to extract dependencies among the APIs.

Our intuition is that malware may use calls for various operations, in a different graph structure, than be-

[2]Android apps that use several code obfuscation techniques, further reviewed in § 2 and discussed in § 5.3.

[3]Some obfuscation techniques may also attempt to transform *machine code*, however, in this work we consider source code obfuscation techniques.

[4]An Android often requires user's interactions to switch back to app's main GUI. The switching among apps GUIs as programming is termed method callback or simply *callback*. For ease of presentation, we use a generic term, "call", to also denote callback.

nign apps (further elaborated in Section 5.1). To ensure the benign graph structures are different enough from the malicious ones, we abstract API calls package to their respective families.

The APIs calls abstractions refers to all possible calls of APIs from every and each API present in the code. That is, for each app in our dataset (see Table 1), we determine all possible calls amongst the APIs. For instance, as depicted in Figure 1 (step 1), we find that the API call *com.fac.ex:Execute()* instantiates the functions *android.util.log:d()* and *java.lang.Throwable:getMessage()*. For the API family abstraction, we first derive the family names of the APIs and then construct the family call graphs. For example, from *android.net.http* and *java.sql* APIs we obtain API family names *android* and *java*, respectively and build the graph of calls based solely based on the family names of the APIs.

The abstraction provides resilience to API changes in the Android framework as families are often added and deprecated less frequently than single API calls. At the same time, this does not abstract away the behavior of an app. As families include classes as well as interfaces used to perform similar operations on set of similar objects, we can model the types of operations from the family names independently of modifications, if any, in the underlying classes and interfaces. For instance, we know that the *java.sql* package is used for database input, output, and update operations even though there are different classes and interfaces provided by the package for such operations.

Developer may extend the functionalities of their apps by importing a self-defined API. As mentioned earlier, developers also often resort to obfuscate the APIs in the source code. To capture the self-defined and obfuscated APIs in during our call graph extraction process, we rely on previous work [24] and introduce two types of family names in our APIs calls abstraction: self-defined and obfuscated. We rely on previous works [28] [24] to further determine the difference between these two APIs. In essence, we define that an API is obfuscated if either at least 50% of its functions or methods are at most *3 characters* (see § 5.3 for further details) or if we cannot tell what its class implements, extends, or inherits, due to identifier mangling [28]. When operating in API abstraction level, we abstract an API call to its package name using the list of Android packages, which as of Android OS v8.0 [16] includes 243 Android and 101 Google APIs.

DaDiDroid detects if malware developers attempt to define their "self-defined" APIs such as *com.google.MyMalware* with API names *com.google* (or family name *com*). The derived lists of Android and Google APIs and classes ensure the detection of any attempt that malware developers may perform to evade DaDiDroid by naming their self-defined APIs to legal *android* and *google* APIs such as *com.google.MyMalware* which could have been abstracted as *com.google* without APIs classes whitelist.

Overall, for Android API Level 26 [16], we obtain 387 distinct APIs and 12 different families (*Android*, *dalvik*, *java*, *javax*, *junit*, *apache*, *json*, *com*, *xml*, *google*, *self-defined*, and *obfuscated*). We evaluated DaDiDroid in family and API abstraction modes. We observe that DaDiDroid's results were similar to that of its operation in API abstraction mode. To ease presentation, in § 5, we present our analysis of DaDiDroid operating in family abstraction mode.

Graph Generation: *Next*, we model the relationships among API calls (resp. API families) in the Android apps as weighted, directed graph $G(\mathbf{V}, \mathbf{E}, \mathbf{W})$. As DaDiDroid uses static analysis, the graph obtained from Soot and FlowDroid represents the flow of functions that are potentially called by the app. Each node in $\mathbf{V}$ corresponds to a unique API call (resp. API family name) in the Android app. A directed link $(u, v) \in \mathbf{E}$ is presented in the graph if and only if an API, $u \in \mathbf{V}$, calls a method in another API, $v \in \mathbf{V}$. A weight $w \in \mathbf{W}$ represents the number of times u calls a method in v. Note that the links (u, v, w) and (v, u, w) may both exist if Android app's APIs are calling each other methods reciprocally.

For each Android app, we represent the relationships among API calls (resp. API families) as adjacency matrix containing the number of occurrence of possible transitions from v_i to v_j.

Features Extraction: *Next*, we leverage graph metrics (or *features*, listed in Table 4) to quantify the relationship among API calls. As some of the graph metrics, such as clustering coefficient, are defined only for undirected graphs, we first convert our directed graphs into a weighted, undirected graphs and then extract the corresponding graph metrics.

Classification: The last step in DaDiDroid is to perform classification, i.e., labelling apps as either benign or malware. To this end, we use a supervised two-class Support Vector Machine (SVM) classifier [26], k-Nearest Nighbours (k-NN) [2], and Random Forest [6], all implemented using *Weka* [17], an open source machine learning library in Java programming language.

We form two classes by labelling malware and benign apps' graph features (cf. Table 4) as positives and negatives, respectively. We use 80% of the instances for training and 20% for testing. For two-class SVM, appropriate values for parameters γ

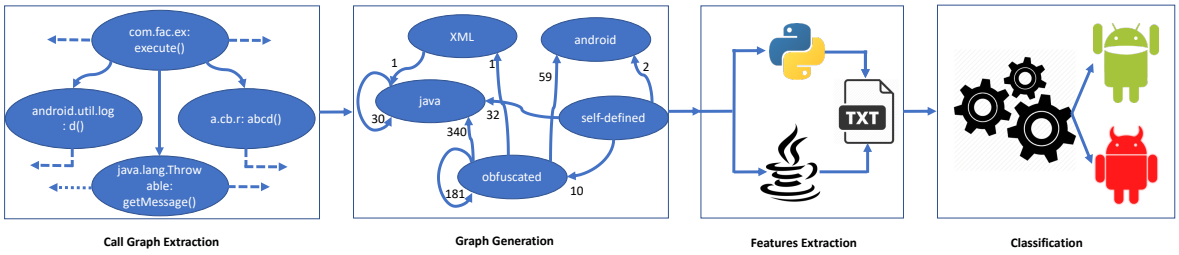


Figure 1: Overview of DaDiDroid: The dashed-arrows represent calls to other functions that are not shown in the figure.

(*radial basis function kernel* parameter [27]) and υ (SVM parameter) are set empirically by performing a greedy grid search on ranges $2^{-10} \leq \gamma \leq 2^{0}$ and $2^{-10} \leq \upsilon \leq 2^{0}$, respectively, on each training dataset. Likewise, for other classifiers, we perform empirical tests to set their parameters.

4 DATASET IN USE

Dataset: We use previously published datasets which include 63,693 Android apps (`apk` files) consisting of 43,262 benign and 20,431 malware samples. Table 1 summaries the dataset in use. We aim to verify that DaDiDroid is robust to the existence of a variety of Android malware samples as well as to heterogenous APIs. We then consider a dataset that includes a mix of obfuscated and non-obfuscated apps as well as newer and (relatively) older apps with a publication date ranging from August 2010 to June 2018. Our dataset consists of samples from the following data sources:

Marvin [22]. This source consists of a total of 38,740 apps, constituted from 28,181 benign apps and 10,559 malware samples.

Drebin [4]. It consists of 5,525 malware samples collected from August 2010 to October 2012.

Old Benign. This dataset includes a sample of 5,879 benign apps collected by PlayDrone [31] between April and November 2013 and published on the Internet Archive Machine [3].

New Benign. We use a customised crawler and unofficial Google Play API [14] to download a sample of 1,788 free apps, belong to 29 different categories, from the Google Play. We use VirusTotal to determine whether or not the app's embed in their source codes.

ObData I. We obtained this dataset from Garcia et al., [13] which consists of obfuscated apps employing various code transformation (i.e., obfuscation) techniques such as Encoding and Call Indirection (explained later in § 5.3).

ObData II. Apps developers often minify apps' source code by mapping the API names to names such as `myApp.net.myPackage` with at most three letters: `a.b.c` or `a.bc.def` (cf. § 5.3). By parsing the API names that correspond to a given Android app in the Marvin dataset, we construct a sample of 7,975 apps that employ source code minification technique.

Dataset	#Apps	# Benign	# Malicious	Date Range
Marvin [22]	38,740	28,181	10,559	06/12–05/14
Drebin [4]	5,525	-	5,525	08/10–10/12
OldBenign	5,909	5,909	-	04/13–11/13
NewBenign	1,788	1,788	-	06/17–06/17
ObData I [13]	883	-	883	06/12–05/14
ObData II [22]	7,975	5,884	2,091	05/13–03/14
PackedApps [11]	2,873	1,500	1,373	07/16–02/17
Total	63,693	43,262	20,431	08/10–06/18

Table 1: Overview of the datasets used in our analysis. We obtain two samples of obfuscated apps: We acquire "ObData I" from authors of [13] and use the Marvin dataset for obfuscated apps (cf. Section 5.3) to construct "ObData II".

PackedApps. We obtained this dataset from Dong et al., [11] which consists of 1,500 and 1,371 *packed*–original APK wrapped in another APK–benign and malicious APKs, respectively.

Datasets Annotation: To analyze the classification results of DaDiDroid, we annotate our datasets considering reports from VirusTotal [32]. VirusTotal is an online service that aggregates the scanning capabilities provided by more than 68 antivirus (AV) tools, scanning engines and datasets. It has been widely used in research literature to detect malicious apps, executables, software and domains [20]. After completing the scanning process for a given app, VirusTotal generates a report that indicates which of the participating AV scanning tools detected any malware activity in the app under consideration and the corresponding malware signature (if any). By parsing VirusTotal reports, we extract the number of affiliated AV tools that identified any malware activity and annotate each app in our dataset with the corresponding results.

5 EVALUATION OF DADIDROID

In this section, we present a detailed experimental evaluation of DaDiDroid.

5.1 The Intuition

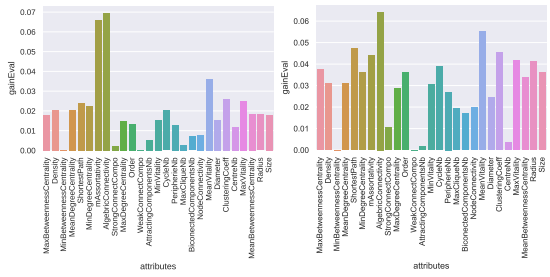
We first conduct preliminary experiments in order to verify our main intuition that graph features are valuable to differentiate benign and malicious apps.

To further analyze the importance of our features in classifying malware and benign apps, we use

an information-theoretic metric, *information gain ratio* [10]. This metric is used to quantify the differentiation power of features i.e., our graph metrics or features. In this context, information gain is the mutual information between a given graph metric X_i and the class label $C \in \{\text{Benign, Malware}\}$. Formally, for a given graph feature X_i and the class label C, the information gain of X_i with respect to C is defined as:

$$GainRatio(X_i, C) = \frac{(H(C) - H(C|X_i))}{H(X_i)} \quad (1)$$

where H(X_i) = $-\sum_{i \in N} p(x_i) log(p(x_i))$ denotes the marginal entropy of the graph feature X_i and H(C|X_i) represents the conditional entropy of class label C given graph feature X_i. In other words, information gain ratio quantifies the reduction in the uncertainty of the class label C given that we have the complete knowledge of feature X_i. Figure 2 shows the information gain ratio of our graph features extracted from the Marvin dataset and the Drebin dataset (cf. Table 1). We observe that the "algebraic connectivity" and the "assortativity" are the most distinct between benign and malicious apps. This analysis reveals that the minimum betweenness centrality (see Figure 2) and the number of weakly connected components (see Figure 2) are insignificant in classifying malware and benign apps that correspond to Marvin and Drebin dataset.



(a) Marvin Dataset (b) Drebin+Oldbenign

Figure 2: Information gain ratio of our graph features for the (a) Marvin dataset and (b) Drebin+Oldbenign dataset.

5.2 Effectiveness of DaDiDroid

Using the datasets summarised in Table 1, we perform experiments to analyze the effectiveness of DaDiDroid's classification on benign and malicious samples. We also study the effect of unbalanced training data on DaDiDroid's performance. We chose to compare to MaMaDroid, as the most recent work in the space, since MaMaDroid also aims to leverage API-calls to extract probabilistic-features building a Hidden Markov model of transitions between API calls.

To assess the accuracy of the classification, we use the standard F-measure = $2 \times (\frac{precision \times recall}{precision + recall})$, where *precision* = $\frac{TP}{TP+FP}$ and *recall* = $\frac{TP}{TP+FN}$. TP means *true positives* denoting the number of apps correctly classified as malicious. Likewise, FN (*false negatives*) and FP (*false positives*) indicate the number of samples mistakenly identified as benign and malicious, respectively. For all experiments, we perform 10-fold cross validation using at least one malicious and one benign dataset from Table 1.

Effectiveness of Classifiers: In order to generalize the classification of DaDiDroid, we use three machine learning classification algorithms: two-class SVM, k-NN, and Random Forest.

Table 2 summarizes the performance of the classifiers. Our results show that the Random Forest classifier achieves the highest accuracy with an accuracy of 90% and 96% in classifying malware and benign drawn from the Drebin+oldbenign and the Marvin datasets, respectively. Perhaps due to an overfitting effect in our dataset, two-class SVM showed poor results and may require further pruning and detailed analysis of parameters, as well as a selection of the optimal set of prominent features to improve the classification performances [21, 6]. We resort to the Random Forest classifier as our best classifier and use it next to compare against MaMaDroid and in our analysis of the effect of unbalanced training sets as well as the study of the resilience against the obfuscation techniques.

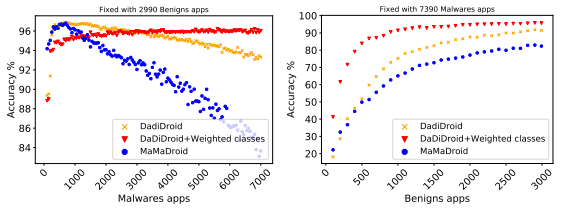
Dataset	Classifier	TP	FP	Precision	Recall	FM	Accuracy
Drebin+OB	RF	90.3%	9.7%	90.3%	90.3%	90.3%	90.1 %
	SVM	70.5%	29.2%	71%	70.5%	70.4%	71.4 %
	k-NN	86.8%	13.2%	86.8%	86.8%	86.8%	87.3 %
Marvin	RF	95.7%	6.6%	95.7%	95.7%	95.7%	96.5 %
	SVM	81.8%	32.4%	81.1%	81.8%	81.1%	82.7 %
	k-NN	94.1%	9.6%	94%	94.1%	94.1%	94.3 %

Table 2: Performance of our classifiers in classifying malware and benign drawn from Marvin [22] and Drebin+oldbenign (OB) datasets. Here RM means Random Forest while FM, TP, FP represent F1-Measure, True Positives rate and False Positives rate respectively.

Effectiveness of DaDiDroid with Unbalanced Training Dataset: In order to determine the minimum number of apps required to train DaDiDroid, we analyze several sets of training and testing datasets drawn from the Marvin dataset (see in Table 1). Figure 3 depicts the effect of unbalanced dataset on performance of DaDiDroid (with Random Forest). In the case of using fixed size of benign apps and various sets of malware apps (resp. benign apps) in the training phase, we observe that DaDiDroid outperforms MaMaDroid with on average 12% higher accuracy.

Moreover, the results also show that DaDiDroid

achieves higher accuracy (96%) in case of limited number (i.e, 1,500) of benign apps in training phase. In contrast, MaMaDroid [24] shows vulnerability to unbalanced training dataset. In Figure 3b, in the case of using fixed size of malicious apps and a set 1,500 of benign instances in the training phase, we observe that DaDiDroid outperforms MaMaDroid with on average 26% higher accuracy.



(a) (b)

Figure 3: Analyzing the effect of unbalanced dataset on the performance of DaDiDroid (with Random Forest in classification phase) and MaMaDroid: In (a) we use 2,990 benign apps and vary sets of malware apps to measure the *accuracy* while in (b) we use a fixed size of malware apps (7,390) and vary the set of benign apps.

5.3 Robustness Against Obfuscation Techniques

The main goal of obfuscation is to either secure apps' source codes or to hide apps' malware components. In this section, we evaluate the robustness of our proposed system against several types of obfuscation techniques.

Whitespace: To reduce the readability of source code, this (basic) obfuscation technique adds or removes white-spaces in apps source code. As DaDiDroid leverages API calls (and API family names) only, this obfuscation technique should have no effect on the accuracy of DaDiDroid.

Call Indirection (CI): This involves the manipulation of apps' call graphs by calling any two methods from each others. To measure the performance of DaDiDroid to Call Indirection, we use the Drebin and OldBenign datasets (cf. Table 1) for training our classifiers. We use NewBenign and 210 Call Indirecting malware apps drawn from ObData I [13] for testing. Table 3 shows the robustness of DaDiDroid against this type of obfuscation. We observe that 15 (7%) of apps, having Call Indirection obfuscation, were classified as benign. In contrast, MaMaDroid [24] misclassified 63 (30%) apps that employ Call Indirection obfuscation techniques.

String Encoding and Encryption (SEE): With this obfuscation technique, an app's developer encodes the used APIs to unintelligible ones. To evaluate the performance of DaDiDroid to String Encoding and Encryption, we use the Drebin and OldBenign datasets (cf. Table 1) for training our classifiers. We use NewBenign and 673 malware apps, with this obfuscation technique, drawn from ObData I [13] for testing. Table 3 shows the robustness of DaDiDroid against String Encoding and Encryption obfuscation. We found that 20% of apps, having String Encoding and Encryption obfuscation, were classified as benign. In contrast, MaMaDroid [24] results in 86% of false negatives.

Obf. Tech.	Scheme	TP	FP	P	R	FM	A
CI	DaDiDroid	92.9%	4.5%	70.7%	92.9%	80.2%	95.2%
	MaMaDroid [24]	70.0%	3.5%	70.0%	70.0%	70.0%	93.7%
SEE	DaDiDroid	79.5%	4.5%	86.9%	79.5%	83.1%	91.1%
	MaMaDroid [24]	13.7%	23.2%	59.4%	13.7%	22.2%	73.8%
Packing	DaDiDroid	98.4%	0.9%	97.9%	98.4%	98.2%	98.8%
	MaMaDroid [24]	98.4%	1.2%	97.5%	98.4%	97.9%	98.7%
IR	DaDiDroid	77.1%	7.1%	91.6%	77.1%	83.7%	95.2%
	MaMaDroid [24]	65.2%	2.2%	70.0%	96.8.0%	77.8%	65.2%
CI+SEE+Packing+IR	DaDiDroid	82.7%	4.5%	90.1%	82.7%	86.2%	91.2%
	MaMaDroid [24]	27.1%	3.5%	79.1%	27.1%	40.3%	73.5%

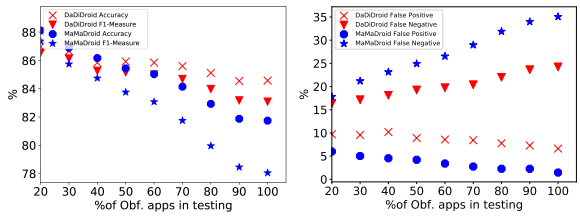
Table 3: Comparison of our proposed system, DaDiDroid, with MaMaDroid on obfuscated datasets (cf. Section 4). Here RM means Random Forest while P, R, and A represent precision, recall, and accuracy, respectively.

Packing: With this obfuscation technique, an app's developer wraps the original APKs inside another APKs. To evaluate the performance of DaDiDroid to packing obfuscation, we use 80% and 20% of the PackedApps dataset (cf. Table 1) for training and testing our classifiers, respectively, and use 10-fold cross validation in our experiments. Table 3 shows the robustness of DaDiDroid against Packing obfuscation. We found that 1.6% of apps, having Packing obfuscation, were classified as benign. In contrast, MaMaDroid [24] results in 1.2% of false positives.

Identifier Renaming: With Identifier Renaming, a given API's name such as *myApp.net.myPackage* is transformed to at most three-letters words such as *a.bc.def*. By parsing the API names that correspond to a given Android app in Marvin dataset, we determine this type of obfuscation in our datasets. In essence, leveraging previous works [28, 24], we define that an API is obfuscated if either at least 50% of its functions or methods are at most *3 characters* or if we cannot tell what its class implements, extends or inherits due to identifier mangling [28].

We draw apps with no Identifier Renaming from Marvin dataset to train MaMaDroid and DaDiDroid and use ObData II (cf. Table 2) to measure their robustness against minification. Once again, we use 80% and 20% of the data for training and testing, respectively, and use 10-fold cross validation in our experiments.

Table 3 overviews and Figure 4 further illuminates on the robustness of DaDiDroid against Identi-



(a) (b)

Figure 4: Robustness of DaDiDroid against Identifier Renaming (or minification): (a) F1-Measure and accuracy; and (b) false negatives and false positives.

fier Renaming. With increasing proportions of apps that employ Identifier Renaming, in Figure 4a, we observe a decreasing trend in DaDiDroid's and MaMaDroid's performance. When tested with 100% of ObData II, we observe that DaDiDroid outperforms MaMaDroid: F1-Measure of MaMaDroid drops from 87% to 78% whereas we notice merely 5% (from 88% to 83%) decrease in DaDiDroid's F1-Measure. In Figure 4b, we notice that minimification mainly affects the number of false negatives. With 83% of F1-Measure, DaDiDroid miss-classifies only 20% of the malware apps in testing dataset as benign. In contrasts, besides its lower F1-Measure (78%), MaMaDroid results in 35% of false negatives. Overall, for its high F1-Measure and low false negatives, DaDiDroid pays a very reasonable cost of 7% of false positives rate.

Overall, when tested on samples of benign and malware apps that involve four types obfuscation techniques, we observe (cf. Table 3) that DaDiDroid outperforms MaMaDroid with on average 46.2% and 17.7%, respectively, higher F1-Measure and accuracy, however, with a cost of 1% higher false positive rate than that of MaMaDroid.

6 RELATED WORK

A number of studies have characterised and detected malicious activities in Android apps. Several works [20, 18, 12, 9] rely on dynamic runtime-network analysis to detect potential malicious behaviour of Android apps. To reduce the resource required in performing dynamic analysis, a large body of works [23, 4, 8] perform static code analysis to detect malware component in Android apps. However, due recent development in obfuscation techniques and malware developers' affinity to obfuscate their apps [11], static analysis of Android malware apps is an active research topic. CrowDroid [7] performed dynamic analysis apps network traces to detect malware activities of Android apps. By collecting sequence of requests sent to remote servers, it built features vectors that consisted of number of calls of a specific API to differentiate malware apps from benign apps. Drebin [4] performed static analysis of API calls and requests to permission. It also analyzed hard-coded URLs in apps' source codes to determine apps' benign or malicious activities. DroidApiMiner [1] proposed a new approach by using the frequencies of API calls to sensitive APIs. StormDroid [8] improved the detection of DroidApiMiner by analyzing APIs calls sequences along with the API calls frequencies analysis.

Similarly, MaMaDroid [24] improved the inefficiency of both DroidAPIMiner and StormDroid [8] by using the transitions probabilities among API calls as features. However, we empirically analyzed that MaMaDroid is dependent on the type of data used for training (i.e., apps categories, ratio benign on malicious apps, and apps release dates) and is prone to obfuscation techniques (see Section 5.3) employed by malware apps. Overall, these techniques focused on sensitive API calls and privileged permissions that often lead to high false positives: a large number of benign apps often use sensitive API calls and request permissions for certain functionalities thus they are wrongly classified as malware. Moreover, these solutions seldom detect obfuscated malware components in apps, resulting in poor performance. Zhang et al., [33] used weighted graph models, extracted from Android apps' codes semantics, to quantify the similarities among malware apps. In contrast, we used metrics derived from weight directed graphs to differentiate among benign and malware apps. To analyze malicious software in desktop computing platform, GZero [29] collected the call sequences of software executables to build graph theoretic features. In the same spirit, in this work, we extracted an extended set of graph features and used showed the efficacy of graph theoretic metrics in classifying benign and malware apps. Moreover, we evaluate the robustness of our proposed scheme against unbalanced datasets as well as shown its resiliency against several type obfuscation techniques.

7 CONCLUSION

We presented DaDiDroid, an obfuscation resilient tool to detect Android malware based on modeling the API calls as a weighted, directed graph. We evaluated the effectiveness of DaDiDroid with several datasets and tested its robustness against different types of obfuscations. We shown that DaDiDroid classify up to 96.5% of benign and malicious apps. In worst case, when no obfuscated apps in training set and testing set contain all obfuscated apps (i.e., apps "Encoding" obfuscation technique), DaDiDroid achieved 91.2% of accuracy with only 17.3% of false negative rate

and 4.5 false positive rate. Moreover, DaDiDroid use small features vectors which can be customized with more or less features from the graph theory and even the extraction process depending on the context of the classification. We compared DaDiDroid to MaMaDroid [24], a Markov chain modeling tool for Android apps, showing that beside achieving similar high results on common datasets, DaDiDroid is much more resilient to changes in the datasets and especially to obfuscation techniques. In the future we plan to improve DaDiDroid by complementing features derived from dynamic runtime analysis of apps.

Acknowledgments

This work was partially supported by research grants from Macquarie University Deputy Vice-Chancellor Research (MQ-DVCR) and Optus Macquarie University Cyber Security Hub (OMUCSH). Any opinions, findings, and conclusions or recommendations expressed in this material are those of the authors or originators and do not necessarily reflect the views of the MQ-DVCR or of the OMUCSH. The authors would like to thank Minhui (Jason) Xue and the anonymous reviewers for their constructive feedback on the preparation of the final version of this paper.

REFERENCES

[1] Y. Aafer, W. Du, and H. Yin. Droidapiminer: Mining api-level features for robust malware detection in android. In *ICSPCS*. Springer, 2013.

[2] A. Andoni and P. Indyk. Near-optimal hashing algorithms for approximate nearest neighbor in high dimensions. *Communications of the ACM*, 2008.

[3] Archive. Playdrone apk's : Free software : Free download, borrow and streaming : Internet archive. https://archive.org/details/playdrone-apks, 2019.

[4] D. Arp, M. Spreitzenbarth, M. Hubner, H. Gascon, K. Rieck, and C. Siemens. Drebin: Effective and explainable detection of android malware in your pocket. In *NDSS*, 2014.

[5] S. Arzt, S. Rasthofer, C. Fritz, E. Bodden, A. Bartel, J. Klein, Y. Le Traon, D. Octeau, and P. McDaniel. Flowdroid: Precise context, flow, field, object-sensitive and lifecycle-aware taint analysis for android apps. In *PLDI*. ACM, 2014.

[6] L. Breiman. Random forests. *Machine Learning*, 2001.

[7] I. Burguera, U. Zurutuza, and S. Nadjm-Tehrani. Crowdroid: behavior-based malware detection system for android. In *WSPSMD*, pages 15–26. ACM, 2011.

[8] S. Chen, M. Xue, Z. Tang, L. Xu, and H. Zhu. Stormdroid: A streaminglized machine learning-based system for detecting android malware. In *CCS*, 2016.

[9] A. Continella, Y. Fratantonio, M. Lindorfer, A. Puccetti, A. Zand, C. Kruegel, and G. Vigna. Obfuscation-resilient privacy leak detection for mobile apps through differential analysis. In *NDSS*, 2017.

[10] T. M. Cover and J. A. Thomas. *Elements of information theory*. John Wiley & Sons, 2012.

[11] S. Dong, M. Li, W. Diao, X. Liu, J. Liu, Z. Li, F. Xu, K. Chen, X. Wang, and K. Zhang. Understanding android obfuscation techniques: A large-scale investigation in the wild. *arXiv preprint arXiv:1801.01633*, 2018.

[12] W. Enck, P. Gilbert, S. Han, V. Tendulkar, B.-G. Chun, L. P. Cox, J. Jung, P. McDaniel, and A. N. Sheth. Taintdroid: an information-flow tracking system for realtime privacy monitoring on smartphones. In *TOCS*, 2014.

[13] J. Garcia, M. Hammad, B. Pedrood, A. Bagheri-Khaligh, and S. Malek. Obfuscation-resilient, efficient, and accurate detection and family identification of android malware. *Department of Computer Science, George Mason University, Tech. Rep*, 2015.

[14] E. Girault. Google Play Unofficial Python API. https://github.com/egirault/googleplay-api, 2019.

[15] Google. Google Play Store. https://play.google.com, 2019.

[16] Google. Package Index (APIv26) — Android Developers. https://developer.android.com/reference/packages.html, 2019.

[17] M. Hall, E. Frank, G. Holmes, B. Pfahringer, P. Reutemann, and I. H. Witten. The weka data mining software: an update. *ACM SIGKDD Explorations*, 2009.

[18] P. Hornyack, S. Han, J. Jung, S. Schechter, and D. Wetherall. These aren't the droids you're looking for: Retrofitting android to protect data from imperious applications. In *CCS*, 2011.

[19] M. Ikram and M. A. Kaafar. A first look at mobile ad-blocking apps. In *Network Computing and Applications (NCA)*. IEEE, 2017.

[20] M. Ikram, N. Vallina-Rodriguez, S. Seneviratne, M. A. Kaafar, and V. Paxson. An analysis of the privacy and security risks of android vpn permission-enabled apps. In *IMC*, 2016.

[21] R. Kohavi and D. Sommerfield. Feature Subset Selection Using the Wrapper Method: Overfitting and Dynamic Search Space Topology. In *KDD*, 1995.

[22] M. Lindorfer, M. Neugschwandtner, and C. Platzer. Marvin: Efficient and comprehensive mobile app classification through static and dynamic analysis. In *COMPSAC*, 2015.

[23] C. Mann and A. Starostin. A framework for static detection of privacy leaks in android applications. In *ASAC*, 2012.

[24] E. Mariconti, L. Onwuzurike, P. Andriotis, E. De Cristofaro, G. Ross, and G. Stringhini. MaMaDroid: Detecting Android Malware by Building Markov Chains of Behavioral Models. In *NDSS*, 2017.

[25] McAfee. McAfee Labs Threat Report. https://www.mcafee.com/au/resources/reports/rp-quarterly-threats-sept-2017.pdf, 2017.

[26] K.-R. Müller, S. Mika, G. Rätsch, K. Tsuda, and B. Schölkopf. An Introduction to Kernel-based Learning Algorithms. *IEEE ToNE*, 12(2), 2001.

[27] B. Schölkopf, J. C. Platt, J. C. Shawe-Taylor, A. J. Smola, and R. C. Williamson. Estimating the support of a high-dimensional distribution. *Neural Computation*, 2001.

[28] P. Schulz. Code protection in android. In *Rheinische Friedrich-Wilhelms-Universitat Bonn, Germany*, 2012.

[29] Z. Shafiq and A. Liu. A graph theoretic approach to fast and accurate malware detection. In *IFIP Networking*, 2017.

[30] R. Vallée-Rai, P. Co, E. Gagnon, L. Hendren, P. Lam, and V. Sundaresan. Soot - a java bytecode optimization framework. In *CASCON*, 1999.

[31] N. Viennot. Github-nviennot/playdrone: Google play crawler, 2014.

[32] VirusTotal. VirusTotal. https://www.virustotal.com, 2019.

[33] M. Zhang, Y. Duan, H. Yin, and Z. Zhao. Semantics-aware android malware classification using weighted contextual api dependency graphs. In *CCS*, 2014.

Feature	Description
Graph Size	Denotes number of edges (i.e., relationships) of a node (i.e., API or family) in a graph.
Graph Order	Corresponds to the number nodes in a graph.
Number of Cycles	A cycle is a path of edges and vertices wherein a vertex is reachable from itself.
Degree Assortativity Coefficient	In a Directed graph, in-assortativity and out-assortativity measure the tendencies of nodes to connect with other nodes that have similar in and out degrees as themselves, respectively. To compute this feature we use the Pearson correlation approach which is way faster and provide representative results. Positive values of assortivity coefficient, r, indicates a correlation between nodes of similar degree, while negative values indicate relationships between nodes of different degree. In general, r lies between -1 and 1. When r = 1, the network is said to have *perfect assortative mixing patterns*, when r = 0 the network is *non-assortative*, while at $r = -1$ the network is completely *disassortative*.
Strongly Connected Components	The number of strongly connected components. A vertex v_i is said to be strongly connected if it is reachable from every other vertex v_k.
Weakly Connected Components	A weakly connected component is a maximal subgraph of a directed graph such that for every pair of vertices (u, v) in the subgraph, there is an undirected path from u to v and a directed path from v to u.
Node Connectivity	The node connectivity is the minimum number of nodes that must be removed to disconnect G.
Avg. Shortest Path Length	Average shortest path length is a concept in network topology that is defined as the average number of steps along the shortest paths for all possible pairs of network nodes.
Degree Centrality	The degree centrality a vertex v_i is the fraction of nodes it is connected to.
Betweenness Centrality	Measures the fraction of all pair shortest paths, except those originating or terminating at it, that pass through it, $\frac{2I(P_{jk},i)}{\|V\|(\|V\|-1)}$, where P_{jk} denote the shortest path from vertex v_j to vertex v_k, P_{jk} = $(v_j, v_l, v_m, v_n, ..., v_k)$ and $I(P_{jk}, i) = 1$ if $v_i \in P_{jk}$ otherwise $I(P_{jk}, i) = 0$ when v_i P_{jk}.
Vitality	Closeness vitality of a node is the change in the sum of distances between all node pairs when excluding that node.
Attracting Components	An attracting component in a directed graph G is a strongly connected component with the property that a random walker on the graph will never leave the component, once it enters the component.
Graph Density	It measures number of edges of graph is close to the maximum number of edges.
Clustering coefficient	It is a measure of the degree to which nodes in a graph tend to cluster together.
Algebraic connectivity	The algebraic connectivity (also known as Fiedler value or Fiedler eigenvalue) of a graph G is the second-smallest eigenvalue of the Laplacian matrix of G. This eigenvalue is greater than 0 if and only if G is a connected graph. This is a corollary to the fact that the number of times 0 appears as an eigenvalue in the Laplacian is the number of connected components in the graph.
Clique Number	It corresponds to the size (number of vertices V) of the largest clique of the graph. A clique C in an undirected graph is a subset of the vertices such that every two distinct vertices are adjacent.
Biconnected Components	They are maximal subgraphs such that the removal of a node (and all edges incident on that node) will not disconnect the subgraph.
Diameter	The diameter of a graph is the maximum eccentricity of any vertex in the graph. The eccentricity $\epsilon(v)$ of a graph vertex v_i in a connected graph G is the maximum graph distance between v_i and any other vertex v_j of G.
Radius	The radius r of a graph G is the minimum eccentricity of any vertex.
Center Number	The center is the set of nodes with eccentricity equal to radius, r.
Periphery Number	The periphery is the set of nodes with eccentricity equal to the diameter.

Table 4: List of our graph metrics (or *features*) to quantify the relationship among API calls as well API families.