On the use of Machine Learning techniques to detect Malware in Android Operative System: *A survey*

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Abstract—**In this survey we explore the most novel approaches for malware detection in Android Operative System using Machine Learning techniques. Specifically, we reviewed the published works from 2012 to 2016. The target audience is machine learning researchers, therefore we first provide a substantial general overview on mobile device security, as well as on Android Operative System and security. The survey is organized by the type of analysis that is performed: static, dynamic, permission-based or hybrid. Along with a description of each work, we analyze Machine Learning relevant elements: the features, the dataset, the models and the performance results. We additionally provide a comparative table with all the surveyed works with additional elements (such as the scope, type of malware, monitoring environment and type of learning), which can be consulted *here*. We conclude the survey with some opportunity areas regarding a Machine Learning approach for Android malware detection, together with interesting venues of work regarding a general approach to detect Android malware.**

***Index Terms*—*Malware detection, Android security, Android Operative System, Security in mobile devices, Machine Learning, Classification, Clustering, Dimensionality Reduction, Static Analysis, Dynamic Analysis, Permissions-based analysis*.**

I. Introduction

Mobile Devices are the fastest growing consumer technology, with 1.9 billion worldwide users in 2014, surpassing for the first time PC users, according to Morgan Stanley Research report.

In addition to the impressive number of users, people is spending more time on the devices: in 2011, for the first time ever, people on average spent more time using mobile applications (81 minutes) than browsing the web (74 minutes) [Rashidi and Fung2015].

In contrast to conventional PCs, Applications are essential for the *mobile device experience* as they provide entertainment, productivity, healthcare, online dating, home security and business management. Hence, mobile device applications are becoming increasingly sophisticated, robust, life-engaging and also privacy-intrusive [Rashidi and Fung2015]. So, while once limited to simple voice communication, the mobile device now allows multiple functionalities. Hence, very sensitive personal, financial and laboral information such as contacts, messages, photos, secret company information, banking and company passwords, etc. Users are careless, treating the mobile device as the simple communication device it was years ago. This landscape provides a very attractive field for security attacks [Rashidi and Fung2015].

For example, malicious software such as Malware can not only steal private information such as contact list, text messages or location, but also cause financial loss of the users by making secretive premium-rate phone call and text messages and stealing credit card information [Rashidi and Fung2015]. Initially created to attain notoriety or for fun, malware development today is mostly motivated by financial gains [Demme et al.2013].

Android is currently the most popular smartphone operating system: 1.1 billion devices running on Google's Android Operating System in 2014, marking its >80% of mobile market share. Additional to the number of users, the number of Android appplications reached 1.6 million in early 2015, surpassing its major competitor, Apple Apps Store [Rashidi and Fung2015].

It is prohibitive for app marketplaces such as Google App Store, to thoroughly verify if an app is legitimate or maliciuos. Mobile users are left to decide for themselves whether an app is safe to use [Rashidi and Fung2015]. The problem is that users are neither informed nor attentive: in a survey of 308 Android users they showed low attention and comprehension rates as 17% of participants paid attention to permissions during installation, and only 3% of Internet survey respondents could correctly answer all three permission comprehension questions [Felt et al.2012]. These results also showed that Android's permission system, intended to inform users about the risks of installing applications, was not effective in helping the user make correct security decisions. Also, unlike iPhone Operative System users, Android Operative System users do not have to root or jailbreak their devices to install apps from unknown sources.

On the one hand, even though important advances have been made on malware detection in traditional personal computers during the last decades, adopting and adapting those techniques to smart devices is a challenging problem. For example, power consumption is one major constraint that makes unaffordable to run traditional detection engines on the device, while externalized (i.e., cloud-based) techniques rise many privacy concerns [Suarez-Tangil et al.2014b].

On the other hand, relying on currently developed approaches is not sufficient, given that intelligent malware keeps modifying rapidly and as a result becomes more difficult to detect [Narudin et al.2016]. For example, traditional approaches such as the antivirus is not very effective since it requires continuous signature database updating and mobile malware is constantly modified to circumvent the detection methods [Sohr et al.2011]. Additionally, antivirus solutions tend to have high rates of resource consumption and software complexity [Narudin et al.2016].

Therefore we need automatic, scalable and reliable mechanisms. Machine learning classifiers have played a part in the development of intelligent systems for many years. They acquire a labelled dataset and produce a model as output, which can handle new data. Classifiers learn from an abundance of input and labelled output to build a model. As such, adopting machine learning classifiers is proven to enhance detection accuracy [Narudin et al.2016].

In response to these needs, in this survey we explore the most novel approaches for malware detection in Android Operative System using Machine Learning techniques from 2012 to 2016. The target audience is machine learning researchers, therefore we first provide in *Section II* a substantial general overview on mobile device security, as well as on Android Operative System and security. The user that is acquainted with such overview can skip this section. The surveyed techniques come in *Section III*; they are organized by the type of analysis that is performed: static, dynamic, permission-based or hybrid. Along with a description of each work, we analyze Machine Learning relevant elements: the features, the dataset, the models and the performance results. We additionally provide a comparative table with all the surveyed works with additional elements (such as the scope, type of malware, monitoring environment and type of learning), which can be consulted *here*. We conclude in *Section IV* with some opportunity areas regarding a Machine Learning approach for Android malware detection, mainly regarding the following: the small size of the datasets, the imbalance class problem, the extremely high number of features, the lack of consistency of the evaluation metrics and error analysis and the need of integrating clustering, dimensionality reduction and classficiation methods into one single model. Also we suggest interesting venues of work regarding a general approach to detect Android malware including: bigger malware datasets, a comprehensive understanding of the currently available datasets, more approaches than integrate the three types of analysis, more hardware-based approchaes, the additional classification of types of malware (trojans, worms rootkits, etc), discussion on the usability, scalability and compatibility with other Operative Systems, consideration of computational complexity, overhead and efficiency, which are specially critical for mobile devices.

II. Mobile device security and Android Operative System and security overview

A. *Mobile device security*

According to NIST Computer Security Handbook, *Computer Security* is defined as the protection afforded to an automated information system in order to attain the applicable objectives of preserving the *integrity, availability, and confidentiality* of information system resources (includes hardware, software, firmware, information/data, and telecommunications) [Stallings2007].

The *OSI security architecture* helps to organize the task of providing security using the following concepts [Stallings2007]:

- Security attack/threat: any action that compromises the security of information.
- Security mechanism: a process that is designed to detect, prevent, or recover from a security attack.

Perhaps the most sophisticated threats to computer systems are programs that exploit vulnerabilities in computing systems. Such threats are referred to as malicious software, or **malware**. In this context, we are concerned with threats to application programs, utility programs and kernel-level programs [Stallings2007].

The most important examples of malware in mobile devices are virus, worms, Trojans, rootkits and botnets. Virus injects malicious code into existing programs that is replicated to other programs when the code is executed. Worms are spread over the network and exploit vulnerabilites on the computers that are connected to the network. Trojans appear to provide functionality to hide its malicious content. Rootkit directly infects the Operative System, so they can operate freely and for longer periods; usually they hide malicious user-space processes/files, installing Trojans or disabling firewalls[1] and antiviruses. Finally, botnet is a network of infected devices under command and control of an attacker [Stallings2007]

[1]A firewall is a barrier that dictates which traffic is authorized to pass in each direction. It can operate at the level of IP packets, or at a higher protocol layer [Stallings2007].

[La Polla et al.2013]; usually they are used to send spam or perform Denial of Service attacks (DoS)[2].

Mobile malware can propagate through various vectors, such as an spam SMS with a link to a website where a user can download the malicious code, an spam MMS with infected attachments, or infected programs received via Bluetooth [La Polla et al.2013].

Some malware fill devices with unwanted advertisements to gain revenue for the malware creator. Others can dial and text so-called " services resulting in extra phone bill charges. Some other malware is even more insidious, hiding itself (via rootkits or background processes) and collecting private data like GPS location or confidential documents. [Demme et al.2013].

Malware detection techniques can be classified in *Static Analysis, Dynamic Analysis and Permission-based Analysis*. Is it also possible to have an hybrid of them [Amos et al.2013].

- *Static Analysis:* inspects software properties and source code without executing the application, so it is performed using parameters such as code analysis, taint tracing and control flow dependencies [Dua and Bansal2014]. It is **inexpensive**, thus amicable to memory-limited mobile devices, but obfuscation, polymorphism and encryption techniques embedded in software makes it difficult. For example, software typically use static characteristics of malware such as suspicious strings of instructions in the binary to detect threats. Unfortunately, it is quite easy for malware writers to produce many diferent code variants that are functionally equivalent, both manually and automatically- For instance, one malware family in the AnserverBot dataset of [Demme et al.2013] had 187 code variations. It also produces less information, thus limiting the extraction of possible features that can be used by machine learning algorithms [Narudin et al.2016]. This type of analysis can be classified according to the way of detection [Dua and Bansal2014]:
  - Misuse detection: uses a signature for detection of malware based on security policies and rule-sets by matching of signatures.
  - Anomaly detection: uses algorithms to identify malware based on certain features, so signatures are not needed. Surprisingly, Machine Learning algorithms commonly appear in this class because they are useful to *learn* the features or characteristics of known malwares and predict unknown malware based on this learning [Dua and Bansal2014].
- *Dynamic Analysis:* it monitors malware behaviour when the application is executed. It can be performed using parameters such as native code, system calls [3], network traffic[4], used memory and user interaction [Dua and Bansal2014]. It also produces more information than static analysis, which can be used to build or enrich features [Narudin et al.2016]. Obviously this comes with the associated overhead [Demme et al.2013], which is an important shortcoming for mobile devices resource-constrained nature. Hence, dynamic analysis commonly is **expensive** and more difficult to scale. Additionally, some malwares even perform transformation attacks that changes not only their code but also its behavior during runtime [Wu and Hung2014].
- *Permission-based analysis* can be done with the help of permissions specified in the manifest file.
  Permission-based: Permissions are listed in some file and control the access to several types of resources in the device. Users have the right to allow or deny the installation of applications but the individual permissions are already defined. It is possible to detect malware using the permissions in the Manifest.xml.

It is important to point out that security tools and mechanisms used in computers are not feasible for applying on mobile devices due to its excessive resource consumption and battery depletion [Burguera et al.2011].

B. Android Operative System

Like all operating systems, Android enables applications to make use of the hardware features through abstraction and provide a defined environment for applications [Brahler2010].

Android Operating System is a stack of software components. Its source code is released by Google under open source licenses [Brahler2010]. Its architecture is formed by 4 main layers placed one on top of each other that can be visualized in Figure 1 (taken from [Rashidi and Fung2015]):

1) *Linux Kernel*: placed at the base, is the base Operating System. This means that all requests made from upper layers pass through the kernel using a system call interface before they're executed in hardware [Burguera et al.2011].
2) *Libraries and runtime environment:* Android runtime combines the core libraries of the Java Virtual Machine and Dalvik Virtual Machine, which is responsible for running Android applications in the operating system.
3) *Application Framework:* forces a structure on developers, it doesn't have a main() function or single entry point for execution, instead developers must design

[2]In a DoS, the attacker seeks to make a network resource unavailable to its intended users -for example an online store) by disrupting the services of a host connected to the Internet

[3]A system call is how a program requests a service from the operating system's kernel, so, analyzing this may help to identify unauthorized requests.

[4]The idea is that almost every every application, malign or benign must connect no the network. So network traffic may help to identify malign behaviour

applications in terms of components, wich can be seen in Figure 1 [Enck et al.2009].

4) *Applications:* they are written in Java and executed in its own Dalvik Virtual Machine. They comprise both the pre-installed applications provided with a particular Android implementation and third-party applications developed by individuals -hence unofficial- app developers [Rashidi and Fung2015].

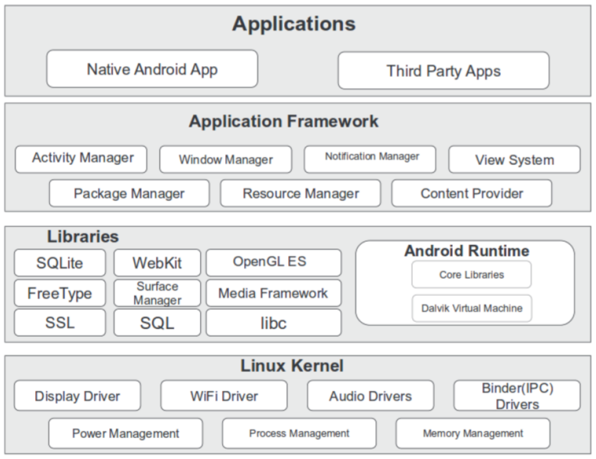

Fig. 1. Android operating system architecture (taken from [Rashidi and Fung2015])

We briefly describe Android's application structure with focus on the important files [Peiravian and Zhu2013]:

- Android Application Package file (APK). Each Android application is compiled and packaged in a single file that includes all of the application code (.dex files), resources, assets, and manifest file. The application package file can have any name but must use the .apk extension.
- Android Manifest file: Commonly refered as AndroidManifest.xml, is one of the most important files. It contains all necessary information about the Application. Once an application is launched, the first file the Android system seeks is the Manifest file. It is a roadmap to ensure that each application can function properly in the Android system. It is worth noting that Android system will not allow an application to access resources, permissions, and features that are not specified in the AndroidManiefest file. So AndroidManifest.xml provides the first hand information to understand the characteristics and security settings of the Apps. To see a more detailed explanation on Android Manifest file, please refer to [Enck et al.2009].

C. *Security in Android*

Android applications make use of advanced hardware, software and data with the objective of bringing innovation and value to the consumers. The platform must offer an environment that guarantees the security of users, data, applications, the device and the network. Despite the fact that Android is based on Linux, it is not straightforward to take the same desktop analysis approach for Android malware [Yan and Yin2012].

There are several reasons of why Android security is specially critical [Rashidi and Fung2015]:

- Number of users of Android OS: 1.1 billion devices running on Google's Android Operating System were shipped in 2014, marking its >80% of mobile market share.
- Number of Android Applications: 1.6 million in early 2015, surpassing its major competitor, Apple Apps Store [Rashidi and Fung2015].
- Number of Android-targeted malware: In 2013 F-secure reported 827 new families or variants of mobile malware; most of them were based on Android platform [Kang et al.2015].
- Number of Android threats and vulnerabilities: [Felt et al.2011] found that one of the main threats posed by malicious Android applications are privacy violations which leak sensitive information such as location information, contact data, pictures, SMS messages, etc. to the attacker. But even applications that are not malicious and were carefully programmed may suffer from such leaks, for instance when they contain advertisement libraries. Additionallt, threats can occur in any of the above-mentioned layers of Android OS stack, such as application or framework layer.
- Third-party market applications: since Android OS is an open source platform, it allows the installation of third-party applications, with regional and international app-stores.
- Developers decision power: few of them fully understand their privacy implications [Arzt et al.2014].
- Users decision power: on whether an app is safe to use. This puts too much responsibility on the end users.
- Android specific characteristics: android systems are different in several ways: application framework,touch-screen based graphical user interface, and management of personal data [Wu and Hung2014].

Android protects applications and data through a combination of two enforcement mechanisms, one at the system level placed on the Linux Kernel base of Figure 1 and the other as a middleware placed between the Kernel and the Application level. This middleware defines the core Android security framework but it builds on the guarantees provided by the underlying Linux system [Enck et al.2009].

Android security model can be considered system centric [Shabtai et al.2012] as it highly relies on permission-based mechanism. There are about 130 permissions that govern access to different resources. An Android application requires several permissions to work. Applications statically identify the permissions that govern the rights to their data and interfaces at installation time [Peiravian and Zhu2013]. However, the application/developer has limited ability thereafter to govern to whom those rights are given or how they are later exercised. Consequently, an essential step to install an Android application into a mobile device is to allow all permissions requested by the application. Before an application is being installed, the system prompts a list of permissions requested by the application and asks the user to confirm the settings for installation.

Although permission requests are useful for users to prevent possible misuse of resources by applications, users often have rare knowledge to determine if permissions might be harmful or not. The application may request network access, including Wifi and SMS service, which are normal requests, whereas some malware steal bandwidth or other useful information. So it's very difficult for users to determine, at the first place, whether an App is a malware by using the permission request exclusively [Peiravian and Zhu2013].

At the system level, Google announced that a security checking mechanism is applied to each application uploaded to their market. The open design of the Android operating system allows a user to install any applications downloaded from an untrusted source. Nevertheless, the permission list is still the minimal defense for a user to detect whether an application could be harmful. For example, users can choose to not install an application if they see the App unnecessarily requests permission to user's personal contact [Peiravian and Zhu2013].

Google further classifies adds permission protection levels and categorize the application into normal, dangerous, signature, and signature/system [Huang et al.2013]. However, this baseline security framework has not prevented the proliferation of malicious applications on Android Operative System. For a more exhaustive explanation of additional security refinements taken by Android, check the following sections from [Enck et al.2009]: public vs private components, broadcast intent permissions, content provider permissions, service hooks, protected APIs, pending intents and URI permissions.

III. Survey

In addition to the mechanism to detect malware, a critical challenge is the need for the collection and experimentation with a large dataset for training malware classifiers [Amos et al.2013]. Is difficult to collect *real* Android malware mainly for two reasons: 1. Android malware is a novel research area and 2. Due to the malign nature of this type of data, labelled examples are not commonly relased. So, before 2011 there have been no tangible datasets available to the whole research community. Researchers used to build their own artificial malware or used a crawler to collect apps from the internet. [Burguera et al.2011] presented a crowd-sourcing system to collect real samples of application execution traces. Also, in 2012 it was published a comprehensive dataset called MalGenome that comprises of 49 different Android malware families with a total of 1,260 malware samples [Narudin et al.2016].

Moreover, malware classifiers must be trained and evaluated in a repeatable and consistent manner with large-scale experimentation and automation infrastructure [Amamra et al.2012].

Due to the relevance of the problem, several surveys on mobile security threats and mechanisms have been published. Such mechanisms are different in nature and can be classified into different categories. We can mention some of the most recent works: [Sujithra and Padmavathi2012], [Amamra et al.2012], [La Polla et al.2013], [Dua and Bansal2014], [Rashidi and Fung2015], [Faruki et al.2015], [Khan et al.2015]. Some are focused specifically on Android, for example [Faruki et al.2015] and [Rashidi and Fung2015], and some others are broader, such as [La Polla et al.2013] and [Suarez-Tangil et al.2014b]. In these works, authors have organized and classified their work using: feature misuse, attack goals, distribution, infection, privilege acquisition, type of analysis, type of detection [Faruki et al.2015]. As of our knowledge, there is no published survey that is focused on a **machine learning analysis** of the defense mechanisms against Android threats. We choose to classify the survey using the sype of analysis that is performed, i.e. static, dynamic, hybrid or permission-based, instead of a machine-learning type classification because we realized that an analysis approach is widely used by researchers in the malware detection literature, so will give us more insights on how and where the machine learning techniques are really being used.

Static analysis utilizes the manifest file of the Android applications discussed above and retrieves information such as permissions and API calls to detect malware. Dynamic analysis focuses on the run-time behaviors and the system metrics of the applications. Most of the dynamic analysis methodologies involves executing applications in the emulator to obtain the run-time information [Wu and Hung2014].

A. Machine Learning for Static Analysis

[Arp et al.2014] was published in response to heavy applications that were prohibitive for mobile devices. It collects permissions, hardware access, API calls, network address, etc. Dataset consists of 123,453 benign applications and 5,560 malware samples were collected. They used a Support Vector Machine achieving 94% of accuracy. On five popular smartphones, the method requires 10 seconds for an analysis on average, rendering it suitable for checking downloaded applications directly on the device. While this approach tackles the overhead and efficiency problem, which is loosely tackled in many works, it is unable to detect malwares that use obfuscation techniques. It also provides accuracy to measure the classification performance, hence it is difficult to compare with other approaches.

[Arzt et al.2014] introduced FLOWDROID an static taint-analysis mechanism for Android applications. FLOWDROID is capable of modelling Android-specific challenges like the application lifecycle or callback methods, reducing missed leaks or false positives. Novel on-demand algorithms help FLOWDROID maintain high efficiency and precision. The authors also proposed DROIDBENCH, an Android-specific platform to evaluate the effectiveness and accuracy of taint-analysis tools for apps. FLOWDROID was tested using DROIDBENCH, achieving 93% recall and 86% precision. FLOWDROID found leaks in a subset of 500 apps from Google Play and about 1,000 malware apps from the VirusShare project.

[Hanna et al.2012] presented Juxtapp, a scalable infrastructure to perform automatic code similarity analysis on Android applications. It can determine if apps contain copies of buggy code, have significant code reuse that indicates piracy, or are instances of known malware. They used feature hashing to reduce the dimensionality of the feature set and Jaccard similarity between the feature sets together with agglomerative hierarchical clustering to group the applications. The system was evaluated using more than 58,000 Android applications and demonstrated that it scales well and is effective. The results show that Juxtapp is able to detect: 1) 463 applications with confirmed buggy code reuse of Google-provided sample code that lead to serious vulnerabilities in real-world apps, 2) 34 instances of known malware (trojans) and 13 variants of the GoldDream malware, and 3) pirated variants of a popular paid game with significant code variation from the original.

[Aafer et al.2013] propose DroidAPIMiner, a robust and lightweight detection mechanism. The selected features are gathered using API level information within the bytecode since it conveys substantial semantics about the apps behavior. The features include critical API calls (choosing the most frequent), their package level information, as well as some dangerous parameters. The dataset has 20,000 benign apps, 3,987 malware apps obtained from McAfee and Android Malware Genome Project. They used Decision trees, k-nn and SVM. The results showed that KNN achieves an accuracy of 99%, and a TPR of 97.8%, meaning that the Miss rate is just 2.2 %. A potential shortcoming of this proposal is that new malware might easily introduce more benign API calls into their code to camouflage their malign behaviour.

[Kang et al.2015] propose a detection and classification system that uses serial number information from the certificate as a feature. It mainly checks a serial number, checks suspicious behavior of SMS hiding, detects the malicious system commands in the code, and analyzes the suspicious permission requests. The features include serial number, information of the certificate, the application name, requested permission, component, and intent. 51,179 applications were downloaded from Google Play and 4,554 malicious applications were downloaded from Share, Contagio Mobile, and Malware.lu. They used a Bayesian classification model. The classifier classified the 20 kinds of malware families with 90% accuracy. Additionally, the system can help analysts to react efficiently from Android malware's threats by detecting and classifying with high accuracy in a reasonable time. One potential problem of this approach is that they they assume that $P(c_i = malicious) = P(c_i = benign)$, i.e. is equally likely that the the category of the application is malicious than benign, regardless of the imbalance status of the dataset (much more benign apps than malign).

[Yerima et al.2014a] proposed a static analysis of Android malware using Bayesian classification models built from mining data generated by automated reverse engineering of the Android application packages using a Java implemented custom package analyzer. The three models were built using the following combination of features: standard Android permissions in the Manifest files, code properties indicative of potential malicious payload and both standard permissions and code properties. The models were built by extracting these properties from a set of 1000 samples of 49 Android malware families together with another 1000 benign applications across a wide variety of categories. Evaluation was performed using the confusion matrix usual metrics. Results showed that mixed-based and code property-based models are a better choice than the permissions-only model. Specifically, the mixed-based approach reached a AUC of 0.977. This model can be used as a complementary tool to more robust techniques, specifically as a prefilter to more complex analysis.

[Suarez-Tangil et al.2014a] proposed a text mining approach to automatically classify malware samples and analyze families based on the code structures. They performed a statistical analysis of the distribution of such structures over a large dataset of real examples. They found strong resemblances to some questions arising in automated text classification and other information retrieval tasks, so they adapting the standard Vector Space Model commonly used in these domains (i.e. vector embeddings), they measured similarity among malware samples and classified unknown samples into known families. Te technique is fast, scalable and achieved an accuracy of. They additionally used hierarchical clustering to derive dendograms to analyze the relationships among families, the existence of common ancestors, the prevalence and/or extinction of certain code features. One of the main shortcomings of this approach is that they have too many features, namley 84,854 and about 600 malware instances. Another disadvantage is that obfuscation strategies modify the code structures (sintaxis) of a malware instance while preserving its intended purpose. A semantic approach to this purpose may be used.

[Huang et al.2013] They used an approach with features from the corresponding application package (APK) file. applied several machine learning classifiers: AdaBoost, Naive Bayes, Decision Tree and Support Vector Machine. The dataset consisted of 124,769 benign and 480 malign applications. Rule-based was used then for clustering. The results were 81% in F-measure naive bayes (label 2), 96% precision SVM with label 2, 9% in false positive rate with naive bayyes (dataset 3) and 81% TPR bayes (label 3). 81% accuracy is low, so it must be used as a quick filter to identify malicious applications. It still re-quires a second pass to make complete analysis to a reported malicious application. Also, labeling is rule based, so it is difficult to scale.

While most of the work on machine learning static analysis uses traditional machine learning algorithms for classification problems (decision trees, kNN, logistic regression, support vector machine), a minority uses novel approaches such as Bayesian classification models, neural networks and text-mining approaches ([Yerima et al.2014b] and [Suarez-Tangil et al.2014a]). As of the clustering approaches we can mention the Agglomerative Code similarity and the hierarchical clustering ([Hanna et al.2012] and [Suarez-Tangil et al.2014a]), respectively).

B. Machine Learning for Dynamic Analysis

[Burguera et al.2011] proposed Crowdroid, a dynamic analysis system that examines application behaviour to detect malware (specifically trojans) in Android by monitoring Linux Kernel system calls and report them to a centralized server. This framework is able to detect self-written malware. They cluster each dataset using k-means clustering to differentiate between benign and malicious applications. They collected system call traces from an unlimited number of real users based on crowdsourcing yielding 20 feature vectors. The authors recognize that if applying this system in a mobile device, it might have an extra overhead in the processor, hence this approach may lack of usability.

[Narudin et al.2016] evaluates the effectiveness of anomaly-based Intrusion Detection Systems in malware detection (mainly mobile bots) using network traffic. They assess five classifiers namely the decision tree (J48), Bayes network, multi-layer perceptron, k-nearest neighbours and random forest using 1,000 malware samples from Android Malware Genome Project. For this task they use 11 features from 4 groups: basic information, content-based, time-based and connection-based. The results showed that Bayes network and random forest classifiers produced more accurate readings, with a 99.97% true positive rate as opposed to the multi-layer perceptron with only 93.03%. A shortcoming is that the detection process must be run using cloud services, whereby network traffic is analyzed remotely. However this helps to reduce the overhead.

[Ham and Choi2013] defined novel features examining the structural features of Android architecture (defined above in Figure 1) and selecting the optimal to detect mobile malware. The features include diverse categories: Network, SMS, CPU, Power monitor the usage rate of allocated resources when an app is started; Process category consists of features for checking the unique ID and the name of currently running process; Memory category is mainly divided into Native, Dalvik and Other; finally Virtual Memory[5]. The performance was tested using four machine learning algorithms: RF, SVM, Logistic Regression and Naive Bayes. RF achieved the highest TPR and FPR.

[Yuan et al.2014] proposed a Deep Learning method[6] that utilizes more than 200 features extracted from both static and dynamic analysis of Android app. The features fall into three types: required permissions, sensitive API and dynamic behavior. The required permissions and the sensitive API are analyzed using the .apk file of an Android app yielding 184 features. The dynamic behavior is tested running the .apk file in a sandbox named DroidBox[7] yielding 18 features. The deep learning algorithm has 2 phases: the unsupervised pretraining phase and the supervised back-propagation phase and a Deep Belief Network was used for both tasks [8] The model achieved a 96% accuracy with real-world Android application sets, above traditional machine learning models (SVM, Naive Bayes, Linear Regression, Multilayer Perceptron).

[Wu and Hung2014] proposed a dynamic malware analysis using application instrumentation, emulation, GUI testing, feature extraction, and machine learning. Automatic testing tools were used to extract useful static and dynamic features from a training dataset composed with 32,000 benign and 32,000 malicious applications and a testing set of 1,000 and 1,000 respectively. There are 56,354 features obtained from event combinations of logged data. The results showed that the prediction accuracy reaches 86.1% and F-score reaches 0.857. As the dataset increases, the accuracy of detection increases significantly, which makes this methodology promising. The framework can be used in conjunction with other existing works to improve the detection rate.

[Dini et al.2012] presented MADAM, a Multilevel Anomaly Detector for Android Malware. MADAM concur-

[5]When an app is started in Android, only a part of the program is placed in the memory and a part of the hard disk is used by making it into virtual memory. Accordingly, peak memory size allocated to virtual memory and shared memory size are also counted as monitoring features

[6]Deep Learning is a subfield of Machine Learning that aims to model high level abstractions in data using deep neural networks. It has been successfully applied to AI-hard problems such as speech and image recognition.

[7]DroidBox collects the runtime activities including incoming/outgoing network data, file read and write operations, started services and loaded classes, information leaks via the network, SMS, etc.

[8]This Deep Learning model is composed of multiple layers of hidden units with connections between the layers but not between units within each layer. When used for pretraining, it can learn to probabilistically reconstruct its inputs.

rently monitors Android at the kernel-level (system calls, running processes, free RAM, CPU usage) and user-level (idle/active, key-stroke, called numbers, sent/received SMS, Bluetooth/WI-FI analysis) to detect real malware infections using machine learning techniques to distinguish between standard behaviors and malicious ones. The training dataset had 900 standard vectors and 100 malicious ones, which were defined manually. The first prototype of MADAM is able to detect several real malware found in the wild. The device usability is not affected by MADAM due to the low number of false positives and the overall performance overhead is acceptable.

[Shabtai et al.2012] proposed Andromaly, a dynamic detection system that monitors both the smartphone and user's behaviors by observing several parameters, spanning from sensors activities to CPU usage. It is lightweight in terms of CPU, memory and battery consumption. 88 features are used to describe these behaviors that include CPU consumption, number of sent packets through the Wi-Fi, number of running processes battery level, system and usage parameters, changed as a result of specific events. 10 datasets were formed from two different devices by activating 44 applications for 10 min. They reduced the dimensionality of the dataset using Chi-Square, Fisher Score and Information Gain. For the classification they tried k-Means, Logistic Regression, Decision Tree, Bayesian Networks and Naïve Bayes. The best results for the experiment 1 are Decision Tree AUC, TPR and Accuracy > 0.999, FPR 0%. Experiment 2: Decision tree 0.8-0.9 in AUC, TPR and Accuracy. Experiment 3: Naive Bayes AUC > 0.84. Experiment 4: Naive Bayes >0.88 in AUC. One interesting characteristic of Andromaly is that it is open and modular, hence, can easily accommodate multiple malware detection techniques.

[Wu et al.2012] is system to characterize the applications using the following features: requested permissions, Intent messages passing from each application's manifest file, and regards components such as activity, service, receiver as entry points drilling down for tracing API Calls related to permissions. Next, it applies K-means algorithm that enhances the malware modeling capability. The number of clusters are decided by Singular Value Decomposition (SVD) method on the low rank approximation. Finally, it uses kNN algorithm to classify the application. The dataset consists of 1500 benign and 238 malign from Contagio Mobile platform. The approach obtained 97.8% of accuracy.

[Amos et al.2013] introduced a system that collects a number of features such as battery, memory, network and permission yielding 6,832 feature vectors. STREAM framework, which was developed to enable rapid large-scale validation of mobile malware machine learning classifiers. They used Random forest, naive bayes, multilayer perceptron, bayes net, logistic and J48 into a dataset with 1330 malicious and 408 benign applications. However, the authors used Android emulator to collect selected features, which was proved not as accurate as a real device and claimed that using a real device was impossible. The approach also suffers from a high number of features, which may imply poor generalization.

[Demme et al.2013] examined the feasibility of building a malware detector in hardware using existing performance counters. The underlying assumption is that runtime behavior captured using performance counters can be used to identify malware and that the minor variations in malware that are typically used to foil signature AV software do not significantly interfere with our detection method. They built a multidimensional time series data with the count events together with used KNN or Decision Trees, Random Forest, ANN using 503 malware and 210 non-malware programs from both Android ARM and Intel X86 platforms, achieving a high area under the ROC curve result.

[Yerima et al.2015] proposes an approach that utilizes ensemble learning for Android malware detection. It combines advantages of static analysis with the efficiency and performance of ensemble machine learning to improve Android malware detection accuracy. The machine learning models are built using a large repository of malware samples and benign apps from a leading antivirus vendor. Experimental results and analysis presented shows that the proposed method which uses a large feature space to leverage the power of ensemble learning is capable of 97.3% to 99% detection accuracy with very low false positive rates.

As we have seen, the dynamic approaches extract features including logged behavior sequence, system calls, tainting Data flow and Control flow and power consumption. They tend to run heavy, sometimes requiring to run some processes and analysis in external servers. They also tend to have too many features, with the associated overfitting and curse of dimensionality disadvantage. Finally, we only found one hardware-based approach, namely [Demme et al.2013]. A novel approach, namely, [Yerima et al.2015] uses a new approach to learning, ensemble learning.

C. Machine Learning for Permission Analysis

[Sanz et al.2013] proposed PUMA, a method for detecting malicious Android applications through machine learning techniques by analysing the extracted permissions from the application itself. 1,811 beningn Android Application samples and 239 malware samples were collected. The features of the dataset were the collected permissions from the Android Manifest file. The results using cross-validation showed a 0.92 area under the ROC curve with the random forest classifier, 86.37% of accuracy but 19% TPR.

[Peng et al.2012] introduce the notion of risk scoring and ranking for Android apps in order to achieve an effective risk communication. They propose to use probabilistic generative models for risk scoring schemes based on permissions[9], ranging from the simple Naive Bayes (PNB), to advanced hierarchical mixture models (HMNB). The Benign Dataset is composed of 2 datasets from Google Play 157,856 apps for training and testing, 324,658 apps for validation. The Malware dataset of 378 unique .apk files that are known to be malicious. The features of the dataset are the permissions from the Android Manifest file. The results showed that all three generative models achieve an area under the ROC curve above 0.94, HMNB achieving the highest score. However, PNB is more suitable because it has the monotonicity property of the ranking scheme (i.e. removing a permission always reduces the risk value of an app).

[Aung and Zaw2013] implement a framework that extracts several permission features from several downloaded applications from android markets. The features were collected from the corresponding APK file. For each application, the authors identified real permissions required by the application using a binary label. The used two datasets of 500 and 200 applications with 160 features each. They applied dimensionality reduction of the space of variables using Information Gain method followed by k-means clustering and finally, classification using three tree-based approaches. The results showed that the Random Forest achieves 92% accuracy and TPR. The paper doesn't provide details on the results of the clustering algorithm. For example, we would like to know how balanced were the resulting classes in order to be able to interpret the confusion matrix results. Also, the False Negative Rate is high: 8%, which implies that 8% of the time, the algorithm classifies a malign application as benign.

[Frank et al.2012] used a probabilistic model to mine permission request patterns from Android and Facebook applications. They used a method for Boolean matrix factorization to find overlapping clusters of permissions. They found that the permission requests of low-reputation applications differ from the permission request patterns of high-reputation applications. This may indicate that permission request patterns can be used as part of a risk metric or soft prediction of the quality of new applications. For Android, they found that there is a relationship between permission request patterns and categories. One shortcoming of this approach is that it outputs a risk metric, not a classification, thus it serves much more as way to identify user satisfaction rather than application maliciousness.

In addition to the already mentioned shortcomings of each one of the discussed proposals, the permission-based warning mechanisms have the following disadvantages [Aafer et al.2013]:

- As we've seen, the existence of a certain permission in the app manifest file does not necessarily mean that it is actually used within the code. Many Android apps are over-privileged.
- A large number of requested permissions -specially the critical ones- are actually not used within the application's code itself, instead they are required by the advertisement packages.
- Malware is able to perform malicious behavior without any permission.

D. Machine Learning for hybrid analysis

In this subsection we present the works that hybrid approaches to detect malware.

[Spreitzenbarth et al.2015] present Mobile-Sandbox, a static and dynamic analyzer. In the static analysis a parse of the application's Manifest file and decompilation of the application is done. In the static phase, the application determines if the application is suspicious looking permissions or intents. Then the sandbox performs the dynamic analysis executing the application in order to log all performed actions including those stemming from native API calls. Finally they combine all of these results and try to detect malicious applications with the help of machine-learning techniques. The dataset consists of 69,223 apps from the most important Asian markets and 6,162 malicious samples from different malware families. The features were transformed into a bag-of-words representation. The classification algorithm used was Support Vector Machine achieving an accuracy of 94% of the malware an a FPR of 1%. An interesting characteristic of Mobile-Sandbox is that it can track native API calls, and is easily accessible through a web interface.

[Peiravian and Zhu2013] validated the combined use of permissions and API calls of Android applications and build high dimension feature vectors. The permission is extracted from each App's profile information and the APIs are extracted from the packed App file by using packages and classes to represent API calls. Experiments on real-world data demonstrate the good performance of the frame-work for malware detection. The dataset consists of 1200 real-word benign apps and 1200 malware apps. They used SVM, decision trees (J48) and Bagging[10]. Bagging has the best performance in classifying all created data sets with respect to AUC (>96%). Because permission settings and APIs are always available for each application, this system can be generalized to other mobile devices in addition to Android.

[9]So they assume that some parametrized random process generates the app datasets and learn the parameter value θ that best explain the data. Next, for each application they compute $p(a_i|\theta)$, the probability that the app's data is generated by the model.

[10]Bootstrap-based ensemble method that creates a number of base classifiers for its ensemble by training each base classifier using random redistribution of the training set

IV. Conclusions and future work

Along this survey, we have identified some opportunity areas regarding a machine learning approach to detect malware in Android mobile devices:

- As we have seen through this work, malicious individual data is is very hard to sample. Also, malicious activities can last very little. So there is insufficient data to learn from or detect.
- As there are not enough malicious applications to use in the training phase, most of the presented methods suffer from class imbalance. Many papers reported Accuracy as a means to evaluate their models. The problem is that a dataset suffering from class imbalance will be uninformative in terms of Accuracy. These observations were very rarely discussed in the papers.
- Many papers collected a very high number of features (i.e. dimensions) combined with very few observations. This yields to the well-known problem of the curse of dimensionality: when the dimensionality increases, the volume of the space increases so fast that the available data become sparse. The amount of data needed to achieve significance grows exponentially with the dimensionality. The curse of dimensionality also implies that the model will generalize poorly, i.e. often over-fitting on the training set and achieving poor performance in unseen observations.
- More exploration of techniques for dimensionality reduction. Most of the works that performed dimensionality reduction used methods based on Information Theory (i.e. Information Gain), but there exist many other methods, such as Principal Component Analysis and t-distributed stochastic neighbor embedding (see [Maaten and Hinton2008]).
- None of the revised works included an error analysis, i.e. an analysis that helps to understand why the algorithm performed successfully in some observations and unsuccessfully in others. This also includes understanding which are the features that contribute more to the performance (for example using an incremental analysis). This endeavour is key to really understand the models and to produce better ones.
- The need of more approaches that integrate clustering methods, dimensionality reduction and classification methods. First, clustering can help to obtain labeled datasets (i.e. benign and malware) if the underlying dataset do have both types of observations (regardless of the researcher ignoring the true labels). Once the dataset is labelled, a dimensionality reduction and classification schemes may follow.
- The malicious behavior may vary between attacks, resulting in many types of malicious behaviors. The learnt algorithms are not definite and final, so a continuously adapting machine learning scheme should be implemented. This implies much more overhead than initially considered, potentially making the scheme unaffordable due to the mobile device particular resource constriction.
- There is not an standardized way to measure the performance of the models. While some papers present many classification metrics such as Accuracy, TPR, FPR, TNR, area under the ROC curve, etc, some others only present the accuracy, which, as we have seen, es misleading.
- There is not a clear description of the dataset used to evaluate the performance of the models. While some papers report using Cross validation techniques and others splitting the dataset into training and test, some others omit this explanation.

With the objective of improving the malware detection models for Android devices (not necessarily with a machine learning perspective), the author of this survey can identify the following interesting venue of work:

- The need of bigger malware datasets. This will condition the advancement of the models themselves, as they are not only evaluated, but also trained using the available data.
- A comprehensive understanding of the currently available datasets. This will guide the work towards the needs in this area.
- The need of more approaches that integrate the three types of analysis (dynamic, static and permissions-base) in a modular approach.
- Most of the machine learning methods will fail to detect instantaneous and abrupt attacks, so it may be worthwhile to combine machine learning detectors with misuse-based detectors, which are rule-based or knowledge-based.
- The need of more hardware-based approaches, as they tend to be more efficient than software-based. We only found one such type of work, e.g. [Demme et al.2013].
- The need of models that, in addition to identify malware, are also able to classify the malware by type/family.
- Discussion on the usability, scalability and compatibility with other Operative Systems.
- While there are consistently reported classification metrics i.e. effectiveness of the detection, we did not find this for the computational and mobile device efficiency side, for example, a classic computational complexity measure, mobile device resource-consumption metrics (for example CPU, memory and battery consumption), overhead metrics, etc. Many proposals claim to be “very efficient" but they rely on external applications to perform certain tasks and analysis (mostly dynamic-oriented analysis, for example sandboxes or emulators). Hence, currently this is a very vague notion as it is really hard to compare the proposals in this dimension. This will impact the real scalability of the systems and will guide the needs in this path.

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