Glassbox: Dynamic Analysis Platform for Malware Android Applications on Real Devices

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1. INTRODUCTION

Android is the most widely used smartphone OS with 82.8% market share in 2015 [1]. It is therefore the most widely targeted system by malware authors. To detect these malicious applications before they are installed on users phones, we need an automated analysis. Researchers rely on dynamic analysis to extract malware behaviors and often use emulators to do so. However, using emulators lead to new issues. Currently emulators cannot emulate SIM card, camera and microphone - components that are likely to be used by malware applications. Moreover, malware may detect emulation and as a result it does not execute the payload to prevent the analysis. Finally, emulation suffers from inherent slowness and causes more application crashes than real devices. Dealing with virtual device evasion is a never-ending war and comes with a non-negligible computation cost [2]. To overcome this state of affairs, we propose a system that does not use virtual devices for analysing malware behavior.

Glassbox is a functional prototype for the dynamic analysis of malware applications. It executes applications on real devices in a monitored and controlled environment. It is a fully automated system that installs, tests and extracts features from the application for further analysis. The environment is controlled in a way that Glassbox neither suffers from malware nor becomes an infection vector through the control of web requests, calls and SMS/MMS. The features extracted are Java calls, system calls and both encrypted and non encrypted web requests. In this paper, we present the architecture of the platform and we compare it with existing Android dynamic analysis platforms.

Lastly, we evaluate the capacity of Glassbox to trigger application behaviors by measuring the average coverage of basic blocks on the AndroCoverage dataset [3]. We show that it executes on average 13.52% more basic blocks than the Monkey program.

Keywords
dynamic analysis; Android; malware detection; automatic testing

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ysis platform for Android malware applications on real devices. Glassbox is an environment for the controlled execution of applications, where the Android OS and the network are monitored and have the capacity to block some actions of the analyzed application. This environment is paired with Smart Monkey, a program that automates the installation, the testing of applications and the cleaning of the environment afterwards. The objective of Glassbox is to collect features for machine learning algorithm, to classify applications as malware or as benign. In the following sections we will present the related work about dynamic analysis systems, we will expose the architecture of both Glassbox and Smart Monkey. Finally, we will present the average coverage of basic blocks of Smart Monkey on the AndroCoverage Dataset [3].

2. RELATED WORK

Such dynamic analysis systems started being designed since 2010 [7] by the academic research, to circumvent the limitations of static analysis - namely, code morphism and obfuscation. Since that time, many systems have been released. For this study we have built a classification of a part of these systems, presented in Figure 1 and Figure 2. The classification takes into account three categories: the dynamic features collected by the analysis, the strategies set in order to automate application testing and finally the use of real devices in dynamic analysis systems history. We discuss the results on the following sub-sections.

2.1 Features Analyzed

Since the rise of Android dynamic analysis systems, the use of system calls have been the leading approach. System calls are the functions of the kernel space, available to the user space. It gives the capacity to manipulate hard drive files or to control processes. System calls can describe a program behaviors, from a low level perspective. The retrieval of those calls can be achieved in two ways, mainly:

- **Virtual Machine Introspection** - This is a technique available for emulators, which enables the host to monitor the guest. It cannot be detected by the guest since it is out of its reach and it is therefore convenient for security analysis. Andrubis [2], CopperDroid [14] and DroidScope [10] take advantage of VMI to retrieve, unseen by the target malware, all system calls done by the guest Android virtual machine.

- **Strace/ptrace** - Strace is a Linux utility for debugging processes. It can monitor system calls, signal deliveries and changes of process state. Strace use the ptrace system call to monitor another process memory and registers. This second method is by far the simplest and the most straightforward one as the only task here is the automation of the strace execution. Moreover, it targets directly the system calls of the application we need to. That is why this method has been adopted in most of the literature, namely Crowdroid [8], HADM [15], Maline [16] and [13]. We have also chosen to use the strace utility for system calls monitoring. Despite the theoretical possibility of a malware to detect that it is being debugged, we found no evidence about this.

System calls seem to give great results for classification. Maline reported 96% accuracy rate and HADM 87.3% both with syscalls frequencies only. Actually syscalls capture low level behaviors of both Java code and native code.

The second most collected feature is taint tracking information as it reveals data leakage. It works by the instrumentation of the Dalvik VM interpreter. The information we do not want to leak is called a source. Some source of personal data are tainted, like the phone number or the contacts list. Each time a tainted source or value is used in a method call, the DVM interpreter taints the returned value. With this simple mechanism, we can observe the propagation of the tainted information regardless of its transformations. A function that enable to transmit an information outside of the system is called a sink, like network requests or SMS. If a tainted value is used in a sink, it means data source has leaked. It enables to detect data leakage even if this data have been ciphered or encoded. An application that leaks data is not necessarily a malware, as data leakage is the business of both malware and user tracking frameworks in commercial applications - which constitutes essentially a large part of “goodware” applications. Whereas this feature gives useful insights on the application behaviors for manual analysis, its utility for automatic malware detection needs to be proved. Moreover the implementation and execution of taint tracking is costly, which leads us not to choose this feature for now.

Java calls is another feature of interest as it captures an explicit behavior of the application. There are several ways to collect them:

- **Application instrumentation** - This strategy does not need any modification of the Android source code and is not dependent on Android version. The application can be modified in order to dump targeted method parameters and return values. APImonitor [18] is a tool that enables the instrumentation of targeted Java calls. It reverses the application into smali, a human friendly format equivalent to the Java bytecode, with the baksmali [19] utility. Then, it adds monitor routines around the targeted calls and it compiles the code with the smali [19] utility. This strategy is used by the authors of [13].

- **DVM/ART instrumentation** - The DVM (Dalvik Virtual Machine) or ART (Android RunTime, Android API version ≥ 4.4) is the system that interprets and executes all the application instructions. All Java calls converge to this component. Hence, by hooking the execution of DVM/ART, one can monitor and control all Java calls, their arguments and their return values. That implies the modification of Android source code and its compilation to a custom ROM. This is the strategy we chose to use for collecting Java calls. We prefer this method for keeping the application behaviors pristine, and particularly not inducing additional bugs. Andrubis [2] and DroidScope [10] use similar approaches for tracing method calls.

For the last features, they are highly marginal. Here, Andrubis reported the retrieval of targeted shared library calls. Another data are the network communications. Only Andrubis reported the utilization of features from network communications, but without any further details. Our system
| Reference                        | Tool name       | Dynamic features used                          | App testing strategies | Objectives & comments                  |
|---------------------------------|-----------------|------------------------------------------------|------------------------|----------------------------------------|
| Thomas Blasing et al. 2010      | AASandbox       | System calls (name)                            | Monkey                 | Data for malware/benign classification |
|                                 |                 | System calls (name)                            |                        | # Virtual device                        |
| Iker Burguera et al. 2011       | Crowdroid       | System calls (name)                            | Crowdsourced app interactions | Data for malware/benign classification |
|                                 |                 | System calls (name)                            |                        | # Real device                           |
| Cong Zheng et al. 2012          | SmartDroid      | Taint tracking, +?                             | UI brute force          | Data for classification or manual analysis |
|                                 |                 |                                                  | Restriction of execution to targeted activities | # Virtual device                        |
| Lok Kwong Yan et al. 2012       | DroidScope      | System call (all content)                      | Monkey                 | Data for classification or manual analysis |
|                                 |                 | Java calls (all content)                       |                        | # Virtual device                        |
|                                 |                 | Taint tracking                                  |                        |                                        |
| Vaibhav Rastogi et al. 2013     | AppsPlayground  | Taint tracking                                 | Monkey                 | Malware/benign classification           |
|                                 |                 | Targeted Android API Java calls                |                        | # Virtual device                        |
|                                 |                 |                                                  |                        |                                        |
| Martina Lindorfer et al. 2014   | Andrubis        | App Java calls (all content)                   | Monkey                 | Data leaks detector                     |
|                                 |                 | System calls (name, +?)                        |                        | # Symbolic execution                    |
|                                 |                 | Shared libraries targeted calls (name, +?)     |                        |                                        |
|                                 |                 | Taint tracking Deng/HTTP/FTP/SMT/IRC (all content) |                        |                                        |
|                                 |                 |                                                  |                        |                                        |
| Mingyuan Xia et al. 2015        | AppAudit        | Taint tracking                                 | ~                      | Malware/benign classification           |
|                                 |                 |                                                  |                        | # Virtual device                        |
|                                 |                 |                                                  |                        |                                        |
| Vitor Monte Alonso et al. 2014  | -               | Targeted Android API Java calls (name) System calls (name) | Monkey                 | Malware/benign classification           |
|                                 |                 |                                                  |                        | 96.6% accuracy # Virtual device         |
| Kimberly Tam et al. 2015         | CopperDroid     | System calls (all content) Binder data          | Broadcast events       | Data for classification or manual analysis |
|                                 |                 |                                                  | Text fields filling, +? | # Virtual device                        |
|                                 |                 |                                                  |                        |                                        |
| Lifan Xu et al. 2016            | HADM            | System call (name)                             | Monkey                 | Malware/benign classification           |
|                                 |                 |                                                  | Broadcast events       | 87.3% accuracy # Virtual device         |
|                                 |                 |                                                  | Text fields filling     |                                        |
| Marko Dimjasević et al. 2016    | Maline          | System call (name)                             | Monkey                 | Malware/benign classification           |
|                                 |                 |                                                  | Broadcast events       | 96% accuracy # Virtual device           |
|                                 |                 |                                                  |                        |                                        |
| Michelle Y. Wong et al. 2016    | IntelliDroid    | Taint tracking                                 | Targeted inputs leading to suspicious Android API calls | Data for classification or manual analysis |
|                                 |                 |                                                  |                        | # Virtual device                        |
|                                 |                 |                                                  |                        |                                        |
|                                 | Glassbox        | Java calls (name) System calls (name) HTTP/HTTPS requests (all content) | Monkey                 | Data for malware/benign classification |
|                                 |                 |                                                  |                        | # Real device                           |

**Figure 2: Comparative state of the art of dynamic analysis systems - legend.**

| +? | The paper is not clear enough on those details and we cannot be sure that it is an exhaustive list |
|----|--------------------------------------------------------------------------------------------------|
| #  | Only the name of the call is used, in order to get the appearance frequency                       |
| ~  | No data                                         |

Note on the difference between *data for classification* and simply *classification* on the *objectives* column:
Many papers, as ours, only present the dynamical analysis system but do not present an analysis of the results on collected features. This can be postponed for another paper or made by other researchers. For this kind of papers, the objective of the system presented is to produce *data for classification*. For the other ones the data is used on a classification algorithm and the results are presented in the paper.

makes use of *Panoptes* [20] for gathering plain text and encrypted web communications, the process will be described in the *Network control & monitoring* part.

2.2 Automated Testing Strategies
Dynamic analysis does not consist of launching the application and waiting the malware to show its malicious behaviors off. Malware are using logic bombs for hiding the payload. Logic bombs are a malicious piece of code that is executed after a condition is triggered. It means we need to test each application as a real user could have done it. For achieving this objective, several strategies have been used in the past:

- **Black Box testing strategies** - This class of strategies does not take the application source code into account; it focuses on sending inputs in the application without any prior information. This is the commonly used strategy. *Monkey* [21] is a dedicated tool
created by Google for this task. It generates random events in a fast pace. Events range from system events (home/wifi/bluetooth/sound volume etc.) to navigation events (motion, click). Because of its capacity to quickly explore applications activities, it has been used by most of dynamic analysis systems (AAASandbox [7], AppsPlayground [11], Andrubis [2], [13], HADM [15], Maline [16]). Monkey is sometimes confused with Monkey Runner [22] in the literature, which is a python library for writing Android test routines.

- **White Box testing strategies** - This class of strategies takes the application source code into account. It focuses on sending specific inputs in the application for triggering targeted code paths. It requires the information from the static analysis of the application. Parsing the code is needed, to find the target methods and all their triggering conditions. SmartDroid [9] and IntellIDroid [17] determine all paths to sensitive API calls, then execute one of the paths to the target with dynamic analysis. Another kind of White Box testing strategy is **symbolic execution** where dynamic analysis is done by simulating the execution of the application static code. AppAudit [12] uses this technique for finding data leaks with symbolic taint tracking.

- **Grey Box testing strategies** - This class of strategies partially takes the applications source code into account. It focuses on testing all visible inputs the application declares or displays (UI). It usually takes the output of the application to generate the next inputs. Andrubis uses a Grey Box strategy when it tests all possible application services and activities, because they get the information from the application manifest. AppsPlayground also uses Grey Box testing with its **Intelligent Execution** where windows, widgets, and objects are uniquely identified to know when an object has already been explored. We use a similar strategy in Glassbox.

### 2.3 Real Devices

The use of real devices for dynamic analysis started with Crowdroid [8], a crowdsourced based analysis. Whereas this approach give good results, one cannot ask users to execute real malware on their personal device. So this system can only be an option, when we have already a trained machine real malware on their personal device. So this system can approach give good results, one cannot ask users to execute Crowdroid [8], a crowdsourced based analysis. Whereas this

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### 3. ARCHITECTURE OVERVIEW

Glassbox (Figure 3) is a modular system distributed among one or several phones and a computer. Each part is detailed in the following sections.

### 3.1 Android Instrumentation

A custom Android OS has been made, based on the Android Open Source Project (AOSP) [27]. The objective here is to log dynamically each Java call of a targeted application. This involves hooking these calls, at a point where all of them pass through. We instrumented ART (Android RunTime) [28], the Android managed runtime system that executes application instructions. With the default parameters, we found that ART (at least until Android Marshmallow) have the following important behaviors for our study:

- The first time Android is launched, Java Android API libraries and applications are optimized and compiled to a native code format called OAT [29].
- Each time a new application is installed, it is optimized and compiled to OAT format.
- Java methods can be executed in three ways: by an OAT JUMP instruction to the method address, by the ART interpreter for non-compiled methods (debugging purposes mostly), or via the Binder for invoking a method from another process or with Java Reflection. Details on the Android Binder can be found in [30] chapter 4.

A straightforward way of hooking Java calls is to instrument the ART interpreter. Unfortunately only a few calls are executed through it because most of the code is compiled into OAT and therefore it is not interpreted. We forced all calls to be interpreted by disabling several optimizations. The first one is the disabling of the compilation to OAT. That leads calls to be interpreted before executed. But others optimizations mechanisms comes into play, namely direct branching and inlining.

The boot classpath contains the Android framework (Figure 4) and core libraries. They are always compiled in OAT resulting in a boot.oat file. This file is mapped into memory by the Zygote process, started at the initialisation of Android. For launching an application, the main activity is given at Zygote in parameters. When Zygote is called that way, it forks and starts the given activity. It means that any application has access to same instance of the Android framework and core libraries.** Direct branching** is an optimisation that replaces framework/core method calls by their actual address in memory. So the calls does not pass through the interpreter. That optimisation is disabled.

Then inlining is an optimisation that replaces short and frequently used methods with their actual code. Although, it slightly increases the application size in memory, runtime performance are increased. As there is no method any more, it cannot be hooked in the ART interpreter. That optimisation is also disabled.

A monitoring routine is added to ART interpreter that logs any method call from a targeted application. A sample of a capture of Java calls is shown in annexes. All these modifications overload the global execution of Android. Whereas it is not noticeable for most of the applications, on gaming applications are visibly slow down by this approach.

Lastly the phone is shipped with a real SIM card for luding malware payloads with SMS/MMS/Calls. Many malware may use it for stealing money with premium numbers, and because we use a real SIM card it would actually cost us money. We modified the telephony framework of the Android API to reject all outgoing communications except for
our own phone number. When a forbidden call is made, the calling UI pops and closes after one second around. This way does not crash applications that rely on calls and SMS.

### 3.2 Network Control & Monitoring

All communications of the instrumented phone pass through a transparent SSL/TLS interception proxy behind a wifi access point. This is set by Panoptes [20]. To understand how it works we need to describe a part of the TLS handshake. Here is the regular behavior of a https request on Android:

Android have a keystore of all root certificates the system trusts. When a SSL/TLS request is initialized, the requested server send its certificate. It contains identifying informations - like the domain name that must verify the contacted domain name - and a signature that can only be decrypted with the right root CA. The server certificate is tested with each trusted root CA, and if one matches the communication is accepted. Extended information on the TLS handshake can be found with the RFC 2246 memo [31].

For our interception system to work, a SSL/TLS root certificate from a custom certification authority (CA) is implanted in the keystore of Android. When the device requests a https web page, the request goes through the proxy. It is parsed and a new one is initialised to be sent to the original recipient. The response is encapsulated in a new
SSL/TLS response signed by our custom certificate. This custom certificate is dynamically generated with the recipient identifying informations and our custom root CA private key. As the communication is signed by an authority of certification that is known by the client, Android accepts it without any warning. Finally, all HTTP/HTTPS communications are logged and a report can be generated which is convenient for manual analysis if needed.

This system has been extended to support manipulation of requests. The objective is to restrict the proliferation of malware and the damage that it may produce. As Glassbox runs malware, it may have a negative impact on its environment. An extreme mean could be to disconnect the system from internet but we would see less or no malicious behavior at all for numerous applications. Our design is a trade-off between safety and behavior detection:

- **ClamAV** [24] is used to detect known malware sent through network. If a malware is detected, the payload is removed from the request and is redirected to Inetsim [26], a network services simulation server that replies consistently to the requests. It forbids the communication between the application and internet without crashing it.

- For all other requests, we assess the reputation of the domain name or IP address with the Web of Trust (WoT) [25] API. WoT is a browser extension that filters urls based on different reputation rating. These rating come mainly from the users. If the request contacts a known address with a good reputation, we forbid the application under test to reach it, then it is redirected to Inetsim. The advantages are twofold. The application cannot damage a respectable website, and it pre-filters behaviors for classification.

Finally features from communications content are collected and the WoT reputation scores as well. A sample of a network capture is shown in the annexes.

### 3.3 Automated Application Testing

*Smart Monkey* is an automated testing program based on Grey Box strategies. The context of the application is determined at runtime for the automatic exploration. We use *UIautomator* [32], a tool that can dump the hierarchy tree of the current UI elements present on screen. It enable us to monitor variables of each UI element at runtime. For a smart exploration, we need to know if we have already processed an element. Unfortunately, elements do not carry such an unique identifier. Nonetheless, we found that elements can be identified to some degree:

- **Strong identification** - Elements can have an associated ID string that developers set. Concatenated to the current activity name we have robust identification, but for most of the elements this field is empty. With the same method, a content description is sometimes associated with the element. We can also use this for strong identification.

- **Partial identification** - If we do not have access to previous values, which happens most of the times, we can use lesser discriminative values. Textfields can be set with an initial value, or a printed text can be associated to it. With no better available options we use the element dimensions to identify it. Obviously, when an element is partially identified, a risk of false positive is possible.

Moreover each element carries a list of actions it can trigger. Our automatic exploration consists of systematically triggering all actions of all elements for all activities. We do not try each combination of actions as it would not scale and be mostly redundant. To this basic general process we add targeted actions to trigger more sophisticated behaviors:
Some textfields of interest are detected like phone number, first or last name, email address, IBAN, country, city, street addresses, password or pin code. These textfields are filled with consistent values accordingly. For this task, we use databases of realistic data (samples can be found in the annexes). Uncategorised textfields are filled with a pseudo-random string.

The order of actions done matters. For example login and password textfields must be filled before validating. In the exploration, filling textfields and checkboxes takes precedence over the rest.

An application can register a receiver for a broadcast Android event like the change of phone state or wifi state. It can be done statically in the application manifest or dynamically. Those dynamical receivers could be hidden from static analysis with obfuscation. To trigger the receivers code, we test applications with a list of broadcast events that are often used by malware (a partial list is given in annexes). Moreover, real SMS and phone calls are sent to the real device own number.

We finally use the Monkey [21] program during the analysis. It can help to trigger behaviors requiring complex inputs combination that Smart Monkey could miss. At the end comes the cleaning phase. For our real device we keep a white list of regular processes and installed applications - regular, system and device administrator applications. Non-authorised processes are killed and applications uninstalled. Important phone configurations like wifi, data network and sounds are reset to a predefined value.

4. DISCUSSION

Toward the standardization of the evaluation of automated testing methods for Android.

Research community used different strategies for automated application testing, with different evaluation methods and different datasets. To promote the successful strategies for future researches on the domain, we need a standard for the experimentation. Otherwise, we cannot compare the results objectively. The research titled Automated Test Input Generation for Android: Are We There Yet? [33] shows the re-evaluation on the same ground of 5 published automated testing tools for Android. The experimental results found is far from what have been claimed in the published papers. Moreover, according to this study Monkey program have the best performances above all at around 53% average coverage of statements on 68 selected applications. It could question the contribution of the main researches papers to the field. However, we believe the evaluation method lacks pertinence.

To summarize, these observations reveal several problems on the experimental results:

- (1) They are currently not reproducible.
- (2) They cannot be compared to each other.
- (3) They do not highlight the contribution of the tested tool compared to Monkey program.

To answer those problems, we propose the following rules:

- (2) A common performance measure. We propose the average coverage of basic blocks (this measure is described in the Experimentation part). Statement coverage (also called line coverage) is considered as the weakest code coverage measure by specialists in software testing. This metric should not be used when another one is available. For an argued reflection about coverage metrics, we refer to the paper What is Wrong with Statement Coverage [34];

- (1) A common dataset and common tools for instrumenting the applications. We propose the AndroCoverage Dataset [3];

- (1) A common configuration - Monkey arguments, a fixed seed for every random number generator used and application versions. These information are either present in annexes of this document or on the AndroCoverage Github web page.

- (3) To assess the performance of the combination of both Monkey and the evaluated tool. Comparing separately, the performance of Monkey and the tested tool does not highlight new code paths that have been triggered by the evaluated tool. A complex method would not seem successful whereas it would have triggered complex conditions that Monkey could never find. Moreover, the Monkey program is embedded in every Android device (real and virtual), it interacts in a very fast pace with the application and it produces good results. Then, on an operational situation, it makes sense to use it in addition to any research tool.

5. EXPERIMENTATION

We use the AndroCoverage Dataset [3] for our experimentation. It contains 100 applications from F-Droid, which is a repository of free and open source (FOSS) applications. They have been manually selected with the following criteria for each application:

- It does not depend on a third party library or application as an automatic tool would be unable to install it.
- It does not depend on root privilege. To meet the requirement of a maximum of testing tools configuration, we stick with regular privilege.
- It does not depend on local or temporary remote data. We want the application to be usable worldwide and in the long-term. This category excludes applications for a temporary event or a specific country.

Our goal is to use applications which show a large variety of different and steady behaviors. It is why we predict that performance on the AndroCoverage Dataset will be overestimated compared to the average of real applications. This dataset is to be used to compare the performance of different automated testing tools on the same ground.

The AndroCoverage Dataset is supplied with tools which instruments the application, adding monitoring routines for code coverage. We used them for comparing the performance between Monkey and Smart Monkey. These tools are partially founded on BBoxTester [35], a tool for measuring the code coverage for Black Box testing of Android.
applications. Smart Monkey runs Monkey at the beginning of the analysis. For a fair trial, we tested the performance of its code coverage with and without Monkey. The configuration of the Monkey tool has been described in annexes. The results are presented on Figure 5.

The Monkey program tends to generate bugs with the instrumentation. For a significant amount of applications we are unable to get the coverage rate. We note that the same applications crash between Monkey and Smart Monkey so the crash rate has no effect on the comparison of performance between both programs.

For the analysis of the results, we focus mainly on the average coverage of basic blocks, as it is the most significant measure. Here are definitions of the vocabulary used in the experimentation:

- A basic block is an uninterrupted or continuous section of instructions. It means that when the first instruction of a basic block is executed, all other instructions of the block will also be executed, only one time. A basic block begins at the start of the program or at the target of a control transfert instruction (JUMP/-CALL/RETURN). It ends at the next control transfert instruction.

- The basic block coverage for an application is the number of unique basic blocks executed at runtime divided by the number of unique basic blocks present in the source code.

- The average coverage of basic blocks, is the sum of the basic block coverage of all applications divided by the number of applications.

The results shows Monkey and Smart (Smart Monkey without Monkey) do not trigger the same code paths. They have approximately the same performance but their combination leads to an increase of 13.52% of average coverage of basic blocks \( \frac{smartMonkey + smartMonkeyAuc}{monkeyAuc} = 1.1352 \) compared to the Monkey program only.

6. LIMITATIONS

Dynamic analysis systems that allows internet communications are vulnerable to fingerprinting. Our platform is not an exception. For example Bouncer have been the target of remote shell attacks \[36\] that enabled the fingerprinting of the system. The malware gets some information on the system and sends it to a command and control server. Hence, the malware author can reshape trigger conditions of the logic bomb. We accepted this risk for now. A solution halfway between shutting down all communications and no filtering at all could be to strip all outgoing information - POST request contents/GET url variables/Cookies/Meta-data fields. This could lead to a loss of behaviors and the negative impact of such solution needs to be measured. Anyway a smart malware author will eventually find a way to leak remote shell outputs.

The network monitoring has limitations. First, it cannot currently handle all protocols like POP, IMAP and FTP so these protocols are simply blocked. In fact the communications are parsed, to get its content, the destination and the metadata. So this parsing needs to be changed for each protocol. It is an impossible task of adding one by one all protocols, so we would need to measure the protocol usage and implement the most used ones. At last, there is a countermeasure to our SSL/TLS interception, namely certificate pinning. The requipement of the interception is the implantation of a custom root certificate in the Android keystore of trusted certificates. An application can choose to discard the Android keystore and to embed its own. Therefore when a communication, encrypted with our custom certificate, is checked, the communication is rejected. This technique is used in many banking applications \[20\]. In fact the point of view of the bank is: the user OS cannot be trusted. Although we have no evidence that it happens for malware, it may be used by an avant-gardist malware and other would follow the trail. It is inconvenient for malware authors to buy a certificate signed by an authority of certification, as a payment trace could identify them. Despite of that, it is possible to get a valid certificate from Let’s Encrypt \[37\], or to control a legitimate server via hacking and use it as a relay for the C&C server. In these cases, certificate pinning could be used for hiding communications from analysts or interception systems. A counter to this technique is instrumentation. By monitoring arguments of the SSL/TLS encryption method, one can get the plaintext communications. We have done it manually for some banking applications \[20\] with APImonitor \[18\], but doing it automatically is another issue. Applications that use certificate pinning generally embed their own library for SSL/TLS encryption, so detecting dynamically which call is the SSL/TLS encryption method can be challenging.

Last, the cleaning phase of Glassbox fits the security needed for a prototype. However, to move to an operational situation with malware that could execute 0-day root exploits, we need a real factory-reset of the phone. This is why we plan to integrate the open source project BareDroid as a part of Smart Monkey, for its factory-reset capability on real device.

7. CONCLUSION & FUTURE RESEARCH

This paper contributes to the domain of dynamic analysis system for Android in three ways. First, we presented Glassbox a functional prototype of a platform that uses real devices, controls network and GMS communications to some extends and monitors Java calls, systems calls and network communication content. Second, we experimented Smart Monkey, an automatic testing tool with a Grey Box testing strategy. We showed that it enhances the application code coverage compared to the common Black Box testing tool called Monkey. Last, we presented a method of evaluation of automated testing tools to research community. This method covers the problems of reproducibility, the comparison with other works and of the contribution measurement of the tool. We made the dataset available on Github under the name AndroCoverage.

The next step is to use Glassbox on malware/benigne applications and to use the features found on a machine learning algorithm. We are working on the classification of these data with a neural network.

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### Figure 5: Code coverage results.

| Method       | Classes average coverage | Methods average coverage | Blocks average coverage | Crash rate |
|--------------|--------------------------|--------------------------|-------------------------|------------|
| Monkey       | 32.93%                   | 35.05%                   | 36.32%                  | 16%        |
| Smart        | 34.84%                   | 36.68%                   | 37.73%                  | 0%         |
| Smart Monkey | 37.12%                   | 41.0%                    | 41.23%                  | 16%        |

### Annexes

**Data samples used in Smart Monkey**

```shell
$> head first-names.txt
Aaren
Aarika
Abagael
Abagail
Abbey
Abbi
Abbie
Abby
Abbye

$> head random-iban.txt
AL94283405797977629281563659
AL607261223500546547899947
AL2379384960503665784521815
AL9108126476354620659672884
AL1109262957032338172366593
AL4093472087593458598788
AL13434083187544897640510833
AL0431672587884613781699980
AL79290673310314808303011517
AL97147262313758527061137496

$> head broadcast-events.txt
android.intent.action.ACTION_POWER_CONNECTED
android.bluetooth.device.action.ACL_CONNECTED
android.bluetooth.device.action.ACL_DISCONNECTED
android.intent.action.ACTION_POWER_DISCONNECTED
android.net.conn.CONNECTIVITY_CHANGE
android.intent.action.BATTERY_CHANGED
android.intent.action.USER_PRESENT
android.intent.action.GTALK_CONNECTED
android.intent.action.GTALK_DISCONNECTED
android.intent.action.BOOT_COMPLETED
android.intent.action.BATTERY_CHANGED
android.intent.action.ON_BOOT_COMPLETED
android.intent.action.ACTION_POWER_CONNECTED
android.intent.action.ACTION_POWER_DISCONNECTED

$> logcat
[...]
java.lang.StringBuilder.<init>
java.lang.StringBuilder.java.lang.StringBuilder.append
java.lang.StringBuilder.java.lang.StringBuilder.toString
void com.energysource.szj.android.Log.i
android.osLooper.android.os.Looper
android.osLooper.android.os.Looper grassroots
void android.os.Handler.<init>
```

**Sample of a network capture**

```text
<header>
<method>R0VU</method>
<scheme>http</scheme>
<host>MTE1LjE4Mi4zMC42OA==</host>
<port>0DA==</port>
<path>L0dldEluZm8uU29t</path>
</header>
```

**Sample of a network capture**

```text
<content/>
```

**Sample of a Java calls capture**

```java
void java.lang.StringBuilder.<init>
java.lang.StringBuilder.java.lang.StringBuilder.append
java.lang.StringBuilder.java.lang.StringBuilder.toString
void com.energysource.szj.android.Log.i
android.osLooper.android.os.Looper
android.osLooper.android.os.Looper grassroots
void android.os.Handler.<init>
```

NB: all field values are encoded in base 64
Monkey configuration

```
monkey -s 0 --pct-syskeys 0 --pct-appswitch 0 --throttle 50 -p <package-name> -v 500
-\s 0: The seed of the random number generator is fixed to 0
--pct-syskeys 0: No system key events are sent, such as Home, Back, Start Call, End Call, or Volume inputs.
--pct-appswitch 0: No startActivity() are issued as calling the instrumentation activity another time breaks it.
--throttle 50: The delay between events is fixed to 50 milliseconds.
500: A total of 500 events are sent.
```

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