Kullback-Leibler Divergence Based Detection of Repackaged Android Malware

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ABSTRACT: *Android applications are widely used by millions of users to perform many activities. Unfortunately, legitimate and popular applications are targeted by malware authors and they repackage the existing applications by injecting additional code intended to perform malicious activities without the knowledge of end users. Thus, it is important to validate applications for possible repackaging before their installation to safeguard end users. This paper presents the detection of repackaged malware application based on Kullback-Leibler Divergence (KLD) metric. Our approach builds the population distribution of a legitimate and suspected repackaged malware application based on a set of Smali opcode. A high KLD value indicates that an application is dissimilar compared to an original application, hence likely a repackaged application. The approach has been validated based on real-world malware samples and repackaging them to a legitimate application. The results indicate that KLD values remain high for all the malware when repackaged within a legitimate application, and hence can be used as a suitable metric for detection of new malware.*

Keywords: Android Malware, Repackaging, Decompliler, Kullback-leibler Divergence, Smali Opcode, Information Theory

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1. Introduction

Android is an open source operating system for mobile devices. Currently Android occupies close to 80% of mobile device market share [1]. We now highly dependent on Android devices as well as the applications that run on the platform. In particular, many useful activities such as phone call, message sending, and game playing are performed with applications. End users rely on Android market to obtain legitimate applications and install in their devices.

Unfortunately, popular Android applications are becoming the target of malware authors. In particular, there exists available open source tools that can be used to download legitimate applications, disassemble these applications, insert with additional malicious code intended to perform unauthorized activities, repackage the modified applications, and finally lure or distribute to potential victims to download the applications and install in their devices. The modified and repackaged application if installed by a victim in his/her phone, unwanted malicious activities take place without his/her knowledge.

A detailed study of a large set of malware applications and characteristics revealed that most of the well-known malware samples belong to few popular legitimate applications available in the market [2]. In particular, three common types of malicious functionalities are added during repackaging (i) leveraging root level exploits to compromise Android security such as changing device password, (ii) communicating with external servers controlled by attackers (in botnet) through SMS messages sent to premium numbers, and (iii) making phone calls without user awareness. Given this, it is very important to check the possibility of a repackaged application before an application is installed. This paper proposes an offline analysis for detecting repackaged application given that we have an access to a legitimate application.

A large number of literature works have recently addressed Android malware from the perspective of classification [6, 7, 8] and detection [9-19] based on anomalous activities or permission sets present in suspected applications. However, very few research works [22, 23, 24] have addressed the issue of detecting repackaged Android malware applications considering the availability of legitimate applications. Existing approaches statically analyzes the assembly code. These approaches suffer from false positive warnings or generating numerous hashes based on opcode sets resulting in significant computation time. In this paper, we propose metric-based detection of repackaged malware. In particular, we apply a popular measurement brought from information theory called Kullback-Leibler Divergence (KLD) [25].

A repackaged application when compared to its original version of the application is different compared to the set of available functionalities. We capture the difference by proposing a set of opcode (Smali) to compute needed population sets as part of KLD. Our proposed opcodes consider the existing knowledge from malware detection domain such as method call invocation that may send a message sneakingly as part of malware application functionality. To perform computation for missing elements of a population set, we rely on back-off smoothing algorithms.

The approach has been performed for a number of malicious and repackaged android applications and compared with the known legitimate version of the applications. The results seem promising, KDL values between malware and known good application differs significantly.

The paper is organized as follows. Section II provides an overview of Android application packaging and related work. In Section III, the proposed approach is discussed in details. Section IV discusses the experimental evaluation. Section V draws the conclusions and discusses future work.

2. Overview and Related Work

2.1 Android Application Repackaging

Android application developer can package an application during release time by signing with a chosen private key that may include a developers or organization identity [3]. The signature file stored in the package can be extracted to view the finger prints such as MD5 and SHA1 hashes using toolsets (keytool, Jarsigner). An Android application is distributed as an apk file, which can be later unzipped.

The zipped APK file includes the application code in DEX format (Dalvik Executable) which is similar to an assembly language called Smali [30]. There exists open source tools (*e.g.*, dex2jar[5], java decompiler [20], apktool [21]) that enables anyone to disassemble an apk file and retrieve the opcode or Java source code from DEX to inspect, modify, and repackage with additional code. Below we describe the steps to repackage an application using the apktool.

Step 1: Create a malicious application that implements an intended functionality. The attacker (malware author) then attempts to invoke the functionality either due to system level event (*e.g.*, receiving a phone call) or user level event (e.g., initiate a phone call). The malicious application is converted to an apk file format.

Step 2: Use the apktool to disassemble the malicious applications and extract the directory containing classes implementing malicious functionalities (all class files are present in the smali folder). The classes are represented as opcode format [30].

Step 3: Identify a suitable legitimate application to inject malicious activities. The legitimate application is disassembled using the same tool, and the classes that perform malicious activities are inserted in appropriate directories. If additional permission or library support is needed, the manifest file (*AndroidManifest.xml*) is modified appropriately. The modified application is assembled again with the apktool and signed with a new key.

Step 4: The repackaged application is distributed over the network and potential victims are lured to install the malware on their devices.

2.2 Related Works on Android Malware Detection

Crusselle *et al.* [22] detect repackaged applications by computing the data dependency graph (DDG) statically for each of the methods statically. The graphs are compared for similarity for a known application to identify possible deviation due to additional methods part of a repackaging malware application.

Li *et al.* [23] propose feature hashing-based technique. They first identify k-grams of various opcode sequence patterns within each basic block and consider them as features. The presence or absence of each features in dex files are encoded in a vector. All vectors obtained from files are merged to obtain the fingerprint of each application.

Zhou *et al.* [24] computes hash values for each local unit of opcode sequence of the classes (dex files). The long opcode is handled by splitting into small units and computing hashes for each split unit. Finally, all individual hashes are combined into one hash values. This way any additional inserted code is detected not only for the overall application, but locating the files or specific instruction sets that are inserted by malware authors. The approach suffers from false positive if inserted dummy opcode does not have any negative impact.

In contrast to these efforts, our proposed technique relies on metrics and computes them at application runtime in sandbox.

We are aware of several works that classify malware applications and their detection technique. Amamra *et al.* [7] perform a survey on malware detection approaches highlighting two broader classes of malware detection: signature and anomaly-based. Porter *et al.* [6] performed a survey on malicious characteristics for mobile device malware in 2011. Cooper *et al.* [8] classify android malware detection techniques and comparatively identify the advantages and disadvantages including static analysis, sandboxing, and machine learning approaches. Tanh et al. [29] characterize malware and demonstrate what end users can do to check the presence of malware and prevent them.

Enck *et al.* [9] analyzed a large set of android applications and identified dataflow, structure, and semantic patterns. The dataflow patterns identify whether any sensitive data information piece should not be sent to outside (*e.g.*, IMEI, IMSI, ICC-ID). Enck *et al.* [10] proposed a rule-based certification technique to check the presence of undesirable properties in applications suspected as malware. The approach starts from general functionality requirements and then analyze whether required permissions can create conflicting operations that are used in malware operations. Batyuk *et al.* [11] perform static analysis on binary code of android applications (after decompressing APK and decoding Java bytecode into Smali assembly language. They look for the presence of APIs that may be relevant of reading sensitive information (e.g., IMEI or device identifier, IMSI or subscriber identifier, phone number, writing information to output stream). Yang *et al.* [16] detect money stealing malware by examining the manifest file of android applications to see if billing permission is present. They look for specific method calls or APIs that perform SMS messaging or calls to premium phone numbers. Permission files are analyzed in some approaches as part of malware mitigation. Barrera *et al.* [12] apply selforganizing map-based learning to cluster permission sets. The study and findings cannot be suitably applied for detecting malware as both malicious and benign applications may have similar type of permissions. Similarly, Felt *et al.* [13] compared the permission system between Google Chrome and Google Android, and performed a subjective analysis for improving permission model in general for security and user level awareness.

Nevertheless, detection technique of repackaged malware is still needed to identify malicious behaviors of malware, and our approach is complementary to these earlier efforts.

Several works rely on live analysis of applications running in a sandbox environment. Enck *et al.* [14] analyze the dataflow of Android application to detect privacy leak (whether sensitive data are being transferred to third parties related to advertisement services). Blasing *et al.* [15] also develop a sandbox to perform dynamic analysis of suspected applications in an isolated environment. They first perform static analysis to identify suspected APIs such as loading of a library method and class, retrieving a list of directory, issuing a system level command like file deletion. The sandbox environment is used to launch necessary activity to confirm those behaviors as part of malware detection. All these earlier efforts are complementary to our proposed approach intended to build defense in-depth against repackaged malware.

3. Proposed Detection Approach

3.1 Kullback-Leibler Divergence (KLD) Computation

The Kullback-Leibler Distance (KLD) computes the divergence or distance between two given probability distributions. Let us assume that P and Q represent two probability distributions, where $P = \{p_1, ..., p_n\}$ and $Q = \{q_1, ..., q_n\}$. Then, the KLD is defined as follows [25]:

$$KLD\ (P, Q) = \sum_i p_i * log_2\ (p_i / q_i) \ldots (i)$$

Here, the following two constraints (Equations (ii) and (iii)) are satisfied:

$$\sum_i p_i = 1 \ldots \text{(ii)}$$
$$\sum_i q_i = 1 \ldots \text{(iii)}$$

The KLD can be viewed as the additional message-length required when using a code based on the target distribution (Q) compared to using a code based on the true distribution (P). Therefore, KLD is also denoted as the relative entropy between P and Q in information theory. Note that KLD is not symmetric (i.e., $KLD\ (P, Q) \neq KLD\ (Q, P)$). Also, $KLD\ (P, Q) = 0$, iff $P = Q$.

We start with a hypothesis that the Kullback-Leibler Divergence (KLD) between an original and repackaged malware application should be a high number. On the other hand, the KLD among 2 legitimate applications from the same source, KLD value should be very low.

To compute the KLD between two population sets (or probability distributions) need to be defined at the beginning. We focus on a set of well-known opcode that may be common in both legitimate and repackaged malware applications. A set of opcode elements are extracted from a known legitimate application to build P set. Now, given that we have a new application (Q), we extract the similar opcode occurrence probability distribution and compute the divergence to detect possible repackaged application.

The challenge of computing $KLD\ (P, Q)$ is the term $p_i * log_2\ (p_i / q_i)$. It can be rewritten as subtraction of two terms: $p_i * log_2(p_i) - p_i * log_2(q_i)$. If p_i or q_i is zero (no occurrence of a specific opcode is observed), then the term becomes infinite, which results in $KLD\ (P, Q)$ to be infinite as well.

Name	Smalie opcode	Description
f_1	invoke-super {parameter},methodtocall	Invokes the virtual method of the immediate parent class
f_2	invoke-static {parameters}, methodtocall	Invokes a static method with parameters.
f_3	invoke-direct {parameter},methodtocall	Invokes a method with parameters without the virtual method resolution
f_4	invoke-virtual {parameter},methodtocall	Invokes a virtual method with parameters.
f_5	const-string vx,string_id	Puts reference to a string constant identified by string_id into vx.
f_6	new-instance vx, type	Instantiates an object type and puts the reference of the newly created instance into vx

Table 1. Description of opcode for population set

To address this issue, we propose to apply a well-known smoothing technique known as constant back-off [26]. Here, all zero probability values in both *P* and *Q* are replaced with a very negligible constant probability value and all the nonzero values are equally subtracted with the same constant value proportionally so that Equations *(ii)* and *(iii)* are still satisfied. This simple step results in two smoothed probability distributions that we denote as *P′ (*derived from *P*) and *Q′ (*derived from *Q*). So, we essentially compute *KLD* (*P′*, *Q′*) to avoid infinity problem instead of KLD (*P*, *Q*).

3.2 Elements of Population Set for KLD Computation

Table 1 shows a set of Smali opcode that we propose to build population elements ($f_1 - f_6$). We consider six opcode: *invokesuper*, *invoke-static*, *invoke-direct*, *invoke-virtual*, *conststring*, and *new-instance*. A description of the opcode is provided in Table 1.

For example, *invoke-direct* opcode invokes a method specified in the second argument while supplying a set of parameter specified in the first argument. We choose these opcodes based on the literature knowledge that injected code by malware authors are mostly doing a set of operations such as sending of SMS messages to premium numbers, probing device id and

```
public class HelloWorldActivity extends Activity {
@Override
public void onCreate(Bundle savedInstanceState) {
super.onCreate(savedInstanceState);
TextView text = new TextView(this);
text.setText("Hello World, Android");
setContentView(text);
}
}
```

Figure 1. Example Java code for legitimate application (P)

```
…
# virtual methods
.method public onCreate(Landroid/os/Bundle;)V
…
invoke-super {p0, p1}, Landroid/app/Activity;-
>onCreate(Landroid/os/Bundle;)V
new-instance v0, Landroid/widget/TextView;
invoke-direct {v0, p0}, Landroid/widget/TextView;-
>(Landroid/content/Context;)V
.local v0, text:Landroid/widget/TextView;
const-string v1, "Hello World, Android"
invoke-virtual {v0, v1}, Landroid/widget/TextView;-
>setText(Ljava/lang/CharSequence;)V
invoke-virtual {p0, v0},
Lcom/test/helloworld/HelloWorldActivity;-
>setContentView(Landroid/view/View;)V
…
.end method
```

Figure 2. Example opcode for the legitimate application (P)

sending the information over the network. All these operations require method call invocation as well as often defining constant string values (*const-string* opcode) that may store attacker supplied information such as phone number.

3.3 Example of repackaged Malware Detection

We consider a legitimate example of Android application that is intended to display a simple message "*hello world*" in an Activity class as shown in Figure 1. In this example, the *onCreate*() method displays the message by accessing the *TextView* object and invoking the *setText*() method call.

```
public class HelloWorldActivity extends Activity {
public void onCreate(Bundle savedInstanceState) {
super.onCreate(savedInstanceState);
TextView text = new TextView(this);
text.setText("Hello World, Android");
setContentView(text);
SmsManager smsManager =
SmsManager.getDefault();
String phone = "1-900-222-3333";
smsManager.sendTextMessage (phone, null, "sms",
null, null);
}
}
```

Figure 3. Example Java code for a legitimate Android application (P)

Figure 2 shows a snapshot the Smali opcode that can be obtained based on a suitable reverse engineering tool such as apktool [21]. We display and highlight the relevant opcode as part of population set (*e.g.*, invoke-super) for the *onCreate()* method call only due to space limitation.

Opcode	**Occurrence (p_i)**	**Smoothed (p_i')**
invoke-super (f_1)	1/4	1/4 - e/5
invoke-static (f_2)	0/4	2e/4
invoke-direct (f_3)	1/4	1/4 - e/5
invoke-virtual (f_4)	2/4	2/4 - 2e/5
const-string (f_5)	1/4	1/4 - e/5
new-instance (f_6)	0/4	2e/4

Table 2. Occurrence of population element from legitimate application (*P*)

Opcode	**Occurrence (q_i)**	**Smoothed (q_i')**
invoke-super (f_1)	1/8	1/8 - e/8
invoke-static (f_2)	1/8	1/8 – e/8
invoke-direct (f_3)	1/8	1/8 - e/8
invoke-virtual (f_4)	2/8	2/8 - 2e/8
const-string (f_5)	3/8	3/8 - 3e/8
new-instance (f_6)	0/8	e

Table 3. Occurrence of population element from repackaged malware application (*Q*)

```
…
# virtual methods
.method public onCreate(Landroid/os/Bundle;)V
…
invoke-super {p0, p1}, Landroid/app/Activity;-
>onCreate(Landroid/os/Bundle;)V
…
new-instance v0, Landroid/widget/TextView;
…
invoke-direct {v0, p0}, Landroid/widget/TextView;-
>(Landroid/content/Context;)V
.local v0, text:Landroid/widget/TextView;
…
const-string v1, “Hello World, Android”
…
invoke-virtual {v0, v1}, Landroid/widget/TextView;-
>setText(Ljava/lang/CharSequence;)V
…
invoke-virtual {p0, v0},
Lcom/test/helloworld/HelloWorldActivity;-
>setContentView(Landroid/view/View;)V
…
invoke-virtual {p0}, Lcom/android/telephony/SmsManager;-
>getDefault () Landroid/content/Context;
const-string v1, “1-900-222-3333”
const/4 v2, 0x0
const-string v3, “sms”
const/4 v4, 0x0
const/4 v5, 0x0
invoke-static {v1, v2, v3, v4, v5},
Landroid/telephony/SmsManager;->sendTextMessage();
…
.end method
```

Figure 4. Example opcode of repackaged Android malware (Q)

Let us assume that a malware author injects an SMS message sending operation to a premium number right after the hello world message display operation. The added Java code is shown and highlighted in Figure 3. Here, the *SmsManager* object is first retrieved followed by invocation of the *sendTextMessage()* method call having five arguments including a premium phone number (1-900-222- 3333) and a message (sms). Figure 4 shows the Smali opcode for the malware activity of sending a SMS message to a premium number with the population elements highlighted (*e.g.*, *const-string*, *invoke-virtual*).

Element (i)	***p'$_i$***	***q'$_i$***	***$log_2(p'_i)$***	***$log_2(q'_i)$***	***$p'_i * log_2(p'_i / q'_i)$***
invoke-super (f_1)	0.25000	0.12500	-2.00001	-3.00001	0.25000
invoke-static (f_2)	0.00001	0.12500	-17.60964	-3.00001	-0.00007
invoke-direct (f_3)	0.25000	0.12500	-2.00001	-3.00001	0.25000
invoke-virtual (f_4)	0.50000	0.25000	-1.00001	-2.00001	0.50000
const-string (f_5)	0.25000	0.37500	-2.00001	-1.41505	-0.14624
new-instance (f_6)	0.00001	0.00001	-17.60964	-16.60964	-0.00001
Sum ($p'_i * log_2(p'_i / q'_i)$)					0.85367

Table 4. Computation of KLD (*P'*, *Q'*)

Based on Figure 2, we develop the occurrence probability of the population element to build P set as follows in Table 2. We also show the smoothed probability values due to missing elements (f_2, f_4). Here, we assume *e* is a very small number having the value of 0.00001. Similarly Table 3 computes Q set based on the repackaged application opcode with necessary smoothing.

Now, Table 4 shows the detailed steps of computing KLD (*P'*, *Q'*). The last row shows the value of KLD as 0.85367, which we can consider high.

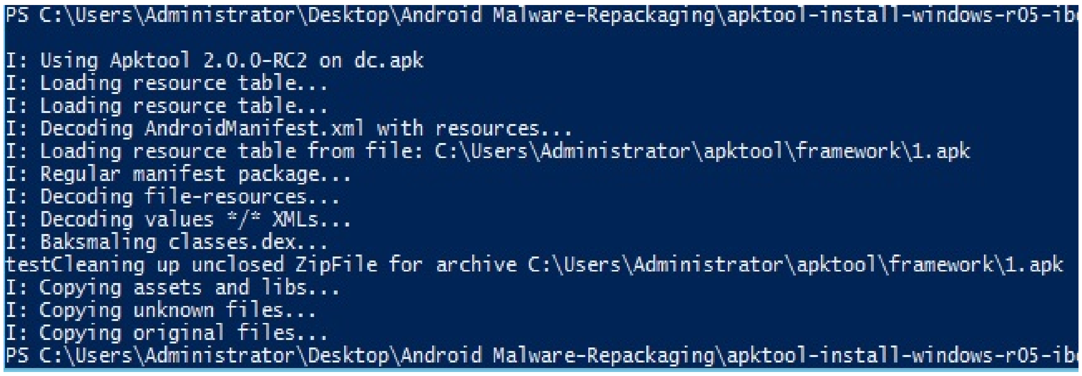
4. Evaluation

We evaluated our approach by using a set of malware samples obtained from the authors of [28] (Malgenomre project dataset). The same benchmark has been widely used for related research work as well. From the benchmark, we randomly choose samples from three malware families: *DroidDream*, *Gone60*, and *Plankton*. Table 5 shows brief characteristics of the malware family along with number of samples we evaluate from each of the families. For example, *DroidDram* malware attempts to obtain product ID, device type, language, country, and send them to a remote server via text message.

Malware family	**Characteristics**	**# of samples**
DroidDream	• Steal IMEI, IMSI, and phone number • Send information to remote server via SMS messages	16
Gone60	• Steal IMEI, IMSI and phone number • Steal phone's state: calls log, SMS, contacts, account • Send information to remote server via SMS messages	9
Plankton	• Change or copy file in external storage • Download and install apps • Stolen location information: GPS, Google, Country code • Send information to remote server via SMS messages	11

Table 5. Occurrence of population element from repackaged malware application (*Q*)

We first use the apktool to disassemble the obtained samples. Figure 5 shows an example snapshot of deassembling using the apktool. We then search if original application for a given malware family is available in the Google market place or any sources or not. Since all the legitimate applications infected with the three malware malware have been removed already from market place, we build a small benign Android application (tip calculator that computes tip amount based on user supplied inputs). We disssemble it and compute the *P* set. We then use the same apktool and inject the malware classes and add needed opcode to trigger the classes, and then compute *Q* set from the new application package. We implement a Java class to automate the computing of population set occurrence probability along with KLD computation.



```
PS C:\Users\Administrator\Desktop\Android Malware-Repackaging\apktool-install-windows-r05-ib

I: Using Apktool 2.0.0-RC2 on dc.apk
I: Loading resource table...
I: Loading resource table...
I: Decoding AndroidManifest.xml with resources...
I: Loading resource table from file: C:\Users\Administrator\apktool\framework\1.apk
I: Regular manifest package...
I: Decoding file-resources...
I: Decoding values */* XMLs...
I: Baksmaling classes.dex...
testCleaning up unclosed ZipFile for archive C:\Users\Administrator\apktool\framework\1.apk
I: Copying assets and libs...
I: Copying unknown files...
I: Copying original files...
PS C:\Users\Administrator\Desktop\Android Malware-Repackaging\apktool-install-windows-r05-ib
```

Figure 5. Example run of apktool for decompling malware

Figure 6 shows an example of Smali code from a sample of Plankton malware application. Here, the opcode **invokevirtual** (highlighted) are used to read information from an input stream and send it to an output file stream, which was part of downloading application from network stream to a local storage of the Android device.

```
line 163
.local v0, "b":[B
invoke-virtual {v3, v0}, Ljava/io/InputStream;->read([B)I
.line 164
invoke-virtual {v2, v0}, Ljava/io/FileOutputStream;-
>write([B)V
```

Figure 6. An example of Smali code from a Plankton sample

We now discuss the obtained results. Figure 7 shows the histogram representing the population element set occurrence for *P*.

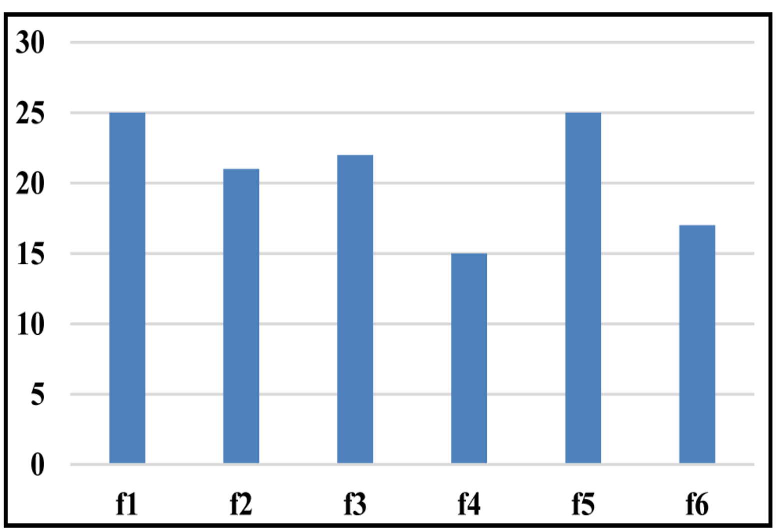


Figure 7. Population element distribution for P

Figure 8 shows the population element distribution ($f_1 - f_6$) for all 16 samples of the DreamDroid family after they are injected into P. For each of the repackaged applications, the occurrence of population elements ($f_1 - f_6$) increases significantly compared to the legitimate application.

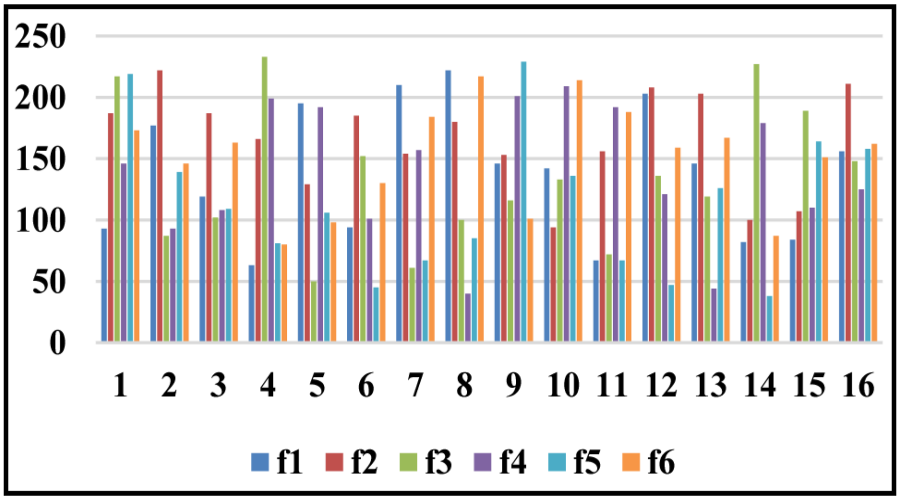


Figure 8. Population element distribution of DreamDroid samples (Q)

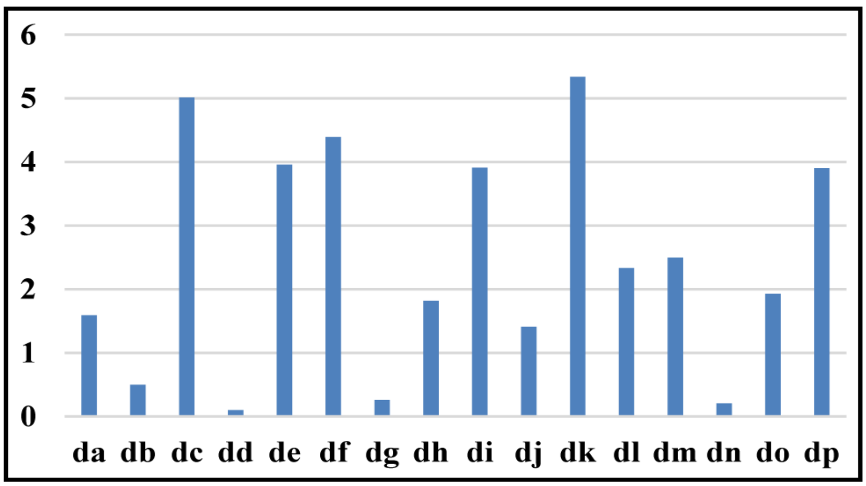


Figure 9. KLD values for various DreamDroid samples

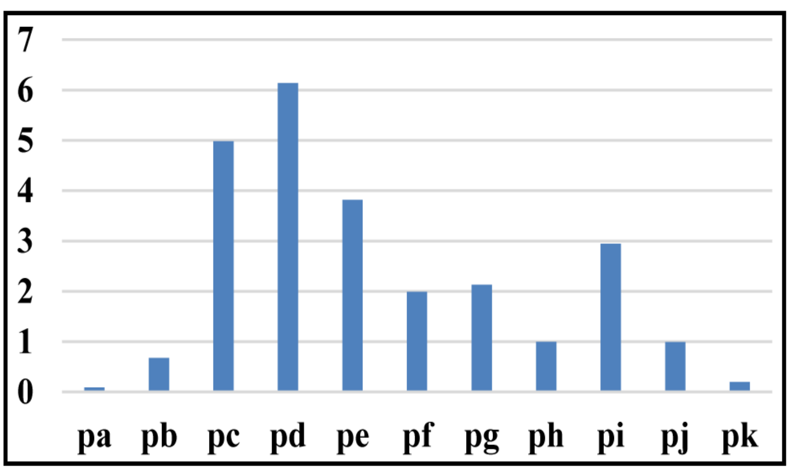


Figure 10. KLD values for Plankton family samples

Figure 9 shows KLD (*P*, *Q*) values as part of detecting repackaged applications having *DreamDroid* malware. We rename 16 different malware samples from *da-dp* for reader's convenience. Note that the highest KLD we observed was for the dc sample (5.3382) and the lowest value was for the dd sample (0.1003). Similarly, Figures 10 and 11 display the obtained KLD values as we detect the repackaged malware from *Plankton* and *Gone60* family. The highest and lowest KLD values for Plankton family were 0.01968 and 6.1368, respectively. The highest and lowest KLD values for *Gone60* family were 0.01484 and 4.1396, respectively.

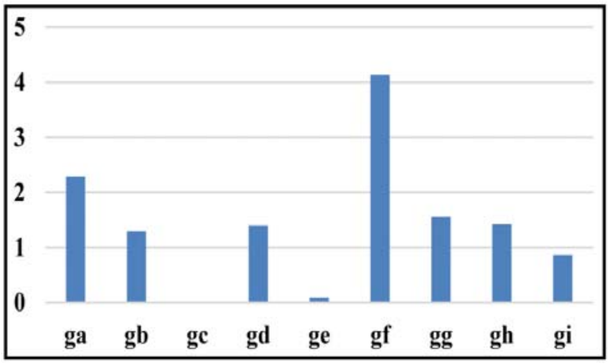


Figure 11. KLD values for malware samples of Gone60

From the obtained data, a KDL threshold value can be chosen to detect new repackaged application. We suggest choosing KLD values above zero.

5. Conclusions and Future Work

Repackaging tools are now highly available in today's application development market and malware authors are taking full advantages by downloading legitimate Android applications, injecting additional code, repackaging and luring potential victims to install the modified applications in their devices. This paper proposes a metric-based approach using Kullback-Leibler Distance (KLD) to identify altered legitimate applications and warn users for possible repackaging. We propose a set of population element features to compute the occurrence probability of specific Smali opcode that may indicate likely malicious activities such as method call invocation performing a message sending operation. The approach has been evaluated with a set of sample malware applications from a real-world benchmark suite and the initial obtained results look promising. For all the repackaging cases, we find that the KLD value exceeds zero and a higher number frequently appears. Our approach can provide the footstep for developing more metric-based solution to combat against repackaged malware detection.

Our future works remains to include more elements for population building set as well as validating with more sample malwares. We also plan to develop a network-based online detection approach to validate whether an application is repackaged or not for a given legitimate application based on other suitable metrics from information theoretic and data compression domains.

References

[1] Lomas, N. (2014). Android Still Growing Market Share By Winning First Time Smartphone Users, May 2014, Accessed from from http://techcrunch.com/2014/05/06/android-still-growingmarket- share-by-winning-first-time-smartphone-users/

[2] Zhou, Y., Jiang, X. (2012). Dissecting Android Malware: Characterization and Evolution, *In*: Proceeding of IEEE Symposium on Security and Privacy, Oakland, CA, USA, May, p. 95-109.

[3] Signing Android Applications, Accessed from http://developer.android.com/tools/publishing/appsigning. html

[4] Repackaged Applications, Blog report from University of Lousiana at Lafayette, Accessed from http://ulsrl.org/repackaged-applications/

[5] Dex2jar, Accessed from https://code.google.com/p/dex2jar/

[6] Felt, A., Finifter, M., Chin, E., Hanna, S., Wagner, D. (2011). A Survey of Mobile Malware in the Wild, *Proc. of the ACM Workshop Security and Privacy in Mobile Devices (SPMD)*, 2011, p. 3-14.

[7] Amamra, A., Talhi, C., Robert, J. (2012). Smartphone Malware Detection: From a Survey Towards Taxonomy, *Proc. of 7th International Conference on Malicious and Unwanted Software (MALWARE)*, October 2012, Puerto Rico, USA, p. 79-86.

[8] Cooper, V., Shahriar, H., Haddad, H. (2014). A Survey of Android Malware Characteristics and Mitigation Techniques," *Proc. of the* 11th *International Conference on Information Technology: New Generations (ITNG)*, IEEE CPS, Las Vegas, USA, April 2014, p. 327-332.

[9] Enck, W., Octeau, D., McDaniel, P., Chaudhuri, S.(2011). A Study of Android Application Security, *Proc. of USENIX Security Symposium*, August.

[10] Enck, W., Ongtang, M., McDaniel, P., On Lightweight Mobile Phone Application Certification, *Proc. 16th ACM Conf. Computer and Communications Security (CCS 09)*, ACM, 2009, p. 235-245.

[11] Batyuk, L., Herpich, M., Camtepe, S., Raddatz, K., Schmidt, A., Albayrak, S. (2011). Using Static Analysis for Automatic Assessment and Mitigation of Unwanted and Malicious Activities within Android Applications, *In:Proceedings of* 6th *International Conference on Malicious and Unwanted Software (MALWARE)*, October, p. 66-72.

[12] Barrera, D., Kayacik, H., Oorchot, P., Somayaji, A. (2010). A Methodology for Empirical Analysis of Permission-Based Security Models and Its Application to Android, *In: Proceeding* 17th *ACM Conf. Computer and Communications Security (CCS)*, p. 73-84.

[13] Felt, A., Greenwood, K., Wagner, D. (2011). The Effectiveness of Application Permissions, *In:Proceedings of the* 2nd *USENIX Conference on Web Application Development (WebApps)*.

[14] Enck, W., Gilbert, P., Chun, B., Cox, L., Jung, J., McDaniel, P., Sheth, A. (2010). TaintDroid: An Information-Flow Tracking System for Real-Time Privacy Monitoring on Smartphones, *Proc. 9th USENIX Symposium Operating Systems Design and Implementation (OSDI)*.

[15] Blasing, T., Batyuk, L., Schmidt, A., Camtepe, S., Albayrak, S. (2010). An Android Application Sandbox System for Suspicious Software Detection, *In*: *Proceedings of 5th IEEE Malicious and Unwanted Software*, p. 55-62.

[16] C. Yang, V. Yegneswaran, P. Porras, and G. Gu, "Detecting Money-Stealing Apps in Alternative Android Markets, *In: Proceedings of the* 2012 *ACM Conference on Computer and Communications Security (CCS)*, October 2012, Raleigh, North Carolina, USA, p. 1034-1036.

[17] Zhou, Y., Jian, X. (2013). Detecting Passive Content Leaks and Pollution in Android Applications, *In*: Proceedings of 20th Annual Network and Distributed System Security Symposium, NDSS 2013, San Diego, California, USA, February 24-27, 2013.

[18] Grace, M., Zhou, Y., Wang, Z., Jiang, X. (2012). Systematic Detection of Capability Leaks in Stock Android Smartphones, *In*: *Proceedings of the* 19th *Annual Symposium on Network and Distributed System Security*, NDSS.

[19] Bugiel, S., Davi, L., Dmitrienko, A., Fischer, T., Sadeghi, A.-R., Shastry, B. (2012). Towards Taming Privilege-Escalation Attacks on Android, *In*: *Proceedings of the* 19th *Annual Symposium on Network and Distributed System Security*, NDSS.

[20] Java decompiler, Accessed from http://jd.benow.ca/

[21] Android-apktool, https://code.google.com/p/android-apktool/

[22] Crussell, J., Gibler, C., Chen, H. (2012). Attack of the clones: Detecting cloned applications on android markets. *In: Proceedings of ESORICS*, p 37–54.

[23] Li, S. (2012). Juxtapp: A scalable system for detecting code reuse among android applications. Master's thesis, EECS Department, University of California, Berkeley, May. http://www.eecs.berkeley.edu/Pubs/TechRpts/2012/EECS- 2012-111.html

[24] Zhou, W., Zhou, Y., Jiang, X., Ning, P. Detecting repackaged smartphone applications in third-party android marketplaces, *Proc. of the* 2nd *ACM conference on Data and Application Security and Privacy* (*CODASPY*), p. 317–326.

[25] Cover, T., Thomas, J. (2006). *Elements of Information Theory*, John Wiley and Sons.

[26] Brigitte Bigi, (2003). Using Kullback-Leibler Distance for TextCategorization, *Lecture Notes in Computer Science (LNCS)*, 2633, p. 305-319.

[27] Huang, H., Zhu, S., Liu, P., Wu, D. (2013). A Framework for Evaluating Mobile App Repackaging Detection Algorithms, Trust and Trustworthy Computing, *Lecture Notes in Computer Science*, 7904, 2013, p 169-186.

[28] Zhou, Y., Jiang, X. (2012). Dissecting android malware: Characterization and evolution, In: Proceedings of IEEE Symposium on Security and Privacy (SP), Oakland, CA, USA, May, p. 95–109.

[29] Thanh, H. (2013). Analysis of Malware Families on Android Mobiles: Detection Characteristics Recognizable by Ordinary Phone Users and How to Fix It, *Journal of Information Security*, 4, p. 213-224.

[30] Smali opcode, Acessed from http://pallergabor.uw.hu/androidblog/dalvik_opcodes.html