RegionDroid: A Tool for Detecting Android Application Repackaging Based on Runtime UI Region Features

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***Abstract*—With the rapid development of mobile devices, Android applications (apps) are universally used. However, attackers repackage Android apps and release them to the markets for illegal purposes, which brings great threats to the Android ecosystem. To leverage the popularity of original apps, they keep similar software behaviors to confuse app users. Furthermore, repackaged apps can be obfuscated or encrypted to avoid being detected. Besides, hybrid mobile apps, built by combining web technology and native elements, are becoming a preferred choice for developers. The structure of hybrid apps differs a lot from that of native apps which would raise great challenges to repackaging detection. Existing works still have some limitations in detecting repackaging from obfuscated and encrypted apps. Besides, few of them can deal with hybrid apps. In this paper, we proposed an approach based on the app UI regions extracted from app's runtime UI traces. We also implement a tool named RegionDroid based on the approach. We apply RegionDroid to tree datasets with totally 369 apps. It successfully finds all the 98 obfuscated or encrypted repackaged pairs in dataset S_1. It also shows good credibility in distinguishing another 114 commercial apps in dataset S_2. We also test our approach in dataset S_3 with 157 hybrid apps by comparing them pairwisely and the false positive rate is 0.016%.**

***Index Terms*—Android application, Repackaging detection, User interface, Obfuscation resilient, Hybrid application**

I. Introduction

The number of mobile apps increases explosively in recent years. There were more than 3.6 million apps available in the Google Play market by February 2018 [1]. However, Android apps can be easily *repackaged*. Attackers firstly download apps from Android app markets, decompile these apps by reverse engineer tools (e.g., Apktool [2], dex2jar [3], and Soot [4]). After modification (e.g. adding some malicious payloads, changing advertisement account, etc.) and rebuilding, they repackage apps and release them to Android markets. Moreover, another reason for the dramatic growth of app repackaging is because of the lack of effective supervision in the unofficial and third-party markets. It is shown that 5% to 13% of apps were plagiarisms in Android markets [5] and 1083 of the analyzed 1260 malware samples were repackaged versions of legitimate apps with malicious payloads [6].

To detect Android repackaging, there have been several approaches proposed. Exacting software birthmarks [7] from apps and comparing birthmarks to measure apps similarities is a common way for repackaging detection. Birthmarks are unique and native characteristics to identity the apps [7]. According to the way of birthmark generation, current works can be divided into two types, static and dynamic. Static birthmarks [5], [8]–[15] are generated by analyzing static code and resources. However, since apps are often obfuscated or encrypted, the features extracted from these apps with static analysis will be heavily affected. In such cases, static birthmarks may hardly work [16], [17]. To deal with app obfuscation and encryption, dynamic birthmarks [18]–[20] have been proposed. The work of [18] executes apps with the testing tool Monkey [21] and generates birthmarks from runtime API sequences during the executions. The work of [19] executes apps by starting all of activities and analyze UI information collected at runtime. Its birthmark is a vector where each element in the vector represents the frequency count of a unique combination of the view class, selected attribute and value of the selected attribute. Repdroid [20] generates layout-group graph through runtime UI traces during apps execution as the birthmark. It traverses the apps by simulating user interactions with a heuristic strategy. Although these approaches improve their resistance to obfuscation, there are still some limitations. The first two works can be heavily affected by some semantic-preserving obfuscation and encryption [20]. Repdroid tries to traverse the whole app. However, when it traverse into a deep part of layout, it may be trapped into it. If Repdroid runs several times for the same app, it may lead to different birthmarks. Besides, since it relies on the type of views, and view types in the webviews (core elements in hybrid apps) are mostly identical, Repdroid could be inaccurate when dealing with hybrid apps.

To cover these shortages, in this paper, we propose an approach for app repackaging detection based on a dynamic birthmark, region-group graph (RGG). Like most existing works, our approach is based on the observation that repackaged apps should behave similar with original ones to leverage the their popularity. Although app obfuscation and encryption may change its static features but will not affect its runtime UI features. As a result, without knowing the source code or professional knowledge, app users can figure out whether two apps are repackaged easily by comparing the UI features between them. Another observations is that, intuitively speak-

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ing, when users try to tell whether two apps are a repackaged pair, they often check the first adequate layouts, rather than comparing apps in every corner. We do not have to traverse the whole app which can reduce the time consumption of birthmark generation without affecting accuracy (introduced in Section IV by the experiment). To model the UI features, we propose the RGG as the dynamic birthmark of an app. The graph is generated from app runtime UI traces. Besides, the RGG is based on extracting features from skeletons (defined as regions) of layouts instead of view types, which can still work when it comes to hybrid apps.

In summary, the main contributions of this paper are:

- We propose a dynamic app birthmark extracted from the skeletons of layouts called region-group graph (RGG). RGG is generated by partially traversing the app with a limited depth.
- We implemented a tool RegionDroid based on our approach by which we can extract the birthmark RGG and detect app repackaging.
- We conducted experiments to evaluate the effectiveness of RegionDroid on 3 datasets with totally 369 apps. RegionDroid successfully finds all the 98 obfuscated or encrypted repackaged pairs in dataset S_1 and has good credibility in dataset S_2 with 114 commercial apps. In dataset S_3, it also compares 157 hybrid apps pairwisely and the false positive rate is 0.016%.

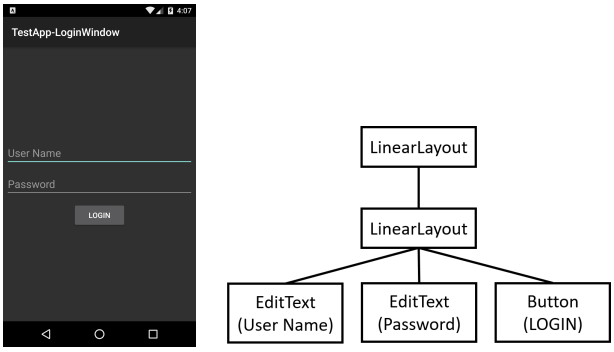
The rest of this paper is organized as follows: Section II introduces the background of Android and related works. Section III presents the methodology of our approach. Section IV evaluates our tool, along with Repdroid, by applying them to three different data sets. Section V discusses RegionDroid and shows its limitations and our future works. At last, we conclude the paper in Section VI.

II. Background

A. Android Applications

Most Android apps are usually developed with Java programming languages. The Java program code is compiled into a *.dex* file by Android SDK tools. The *.dex* file along with related data and resource files are finally packaged into an *apk* file. Each app project must have an *AndroidManifest.xml* file which describes the essential information about the app, including package name, launcher activity, permissions requested during app runtime, etc [22].

Android app UI is drawn into a container *window*. A window is often full-screen, but can also be floated on other windows or embedded inside of another window. UI elements drawn in a window consists of several different kinds of *views*, which are rectangular spaces and some of them can be interacted by users [23]. The views are organized in a *tree*. For instance, Fig. 1a shows a screen capture of an example login window. The views and their structure are shown in Fig. 1b. Besides the visible views (two *EditTexts* and a *Button*), there are another two views named *LinearLayout*. *LinearLayout* is used to arrange its child views horizontally or vertically.



(a) (b)

Fig. 1. The structure of views in the login window. Fig. 1a shows the screen capture of a login window. Fig. 1b shows the view structure.

More specifically, those views which can contain children (e.g. LinearLayout) are called *view groups*. We use the single word *layout* to define the visual structure for a UI [24].

B. Hybrid Applications

Nowadays, Android fragmentation becomes a serious problem for Android app developers [25]. Developers should design their apps carefully so that apps can be compatible with different versions of Android systems and devices, which bring developers great burdens. However, web technologies, such as HTML, css, or Javascript, have good cross-platform features. Developers only need to change the native shells, which are used to present web contents, for specific platforms, rather than redesign the whole projects. Hybrid apps, which combine native elements with web technologies, have become a trend for mobile development. A survey of more than 13,000 community developers shows that 55.5% of their apps were hybrid and 64.4% of them expected to develop hybrid apps in the future [26]. There have been many hybrid app frameworks which are used to help develop hybrid apps efficiently, e.g. ionic [27], phonegap [28], framework7 [29], appcelerator [30], etc. Typical hybrid Android apps utilize the key view *WebView*, which can be treated as a browser embed in the native apps. Running on Android with API level higher than 17, the content of webview can be dumped like native views. An example is shown in Fig. 2. The left picture of the figure shows a screen capture of a layout in a hybrid app. The right part of the figure shows the dumped layout structure of this browser. The node named 'android.webkit.WebView' is the main element of this layout, inside which most of the elements (e.g. the 'LOGIN' and 'SIGN UP' buttons) are described as 'view's, rather than varied kinds of view types in native apps ('android.widget.Button' will be used in most cases for these two buttons). In summary, the views in webviews are weakly typed.

C. Related Work

1) Static Birthmarks: DroidMOSS [5] applies a fuzzy hashing as the birthmark to localize and detect the changes from app-repackaging behavior. It calculates the similarity of birthmarks by edit distance. DNADroid [8] compares program de-

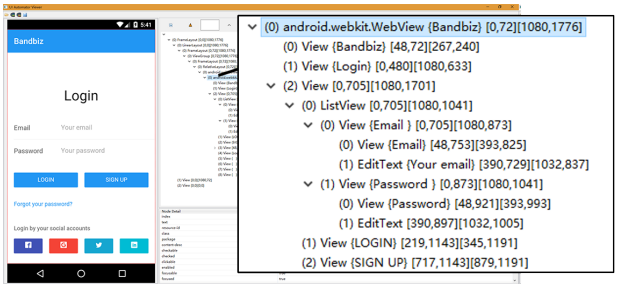


Fig. 2. Dumped layout of a hybrid app

pendency graphs (PDGs) between methods in candidate apps and measure the graphs by VF2 subgraph isomorphism [31]. AnDarwin [9] computes an undirected PDG of each method in the app to extract semantic vectors. It identifies similar code by local sensitive hashing on the semantic vectors. Besides, AnDarwin does not compare apps pairwisely, which increases its scalability. Juxtapp [10] uses k-grams of opcode sequences extracted from compiled applications and feature hashing to efficiently tackle the problem at large-scale. PiggyApp [11] divides an apps code into primary and non-primary modules. It extracts various semantic features from primary modules and converts them into feature vectors for comparison. Centroid [12] extracts methods from apps and encode a porjection from of 3D control flow graphs (3d-CFGs) to get the "centroid" geometry characteristic. It use the centroid-based comparison to measure the similarity between apps. Wukong [32] identifies suspicious apps by comparing light-weight static semantic features, and a ne-grained phase to compare more detailed features for only those apps found in the rst phase. Viewdroid [13] captures users' navigation behavior across app views and generate view graphs. By analyzing the API method invoking, it collects information about the activity transitions. Viewdroid also uses VF2 subgraph isomorphism to calculate the similarity between graphs. Work [33] applies machine-leaning-based detection relied on semantic features of apps to achieve better efficiency in detection. HookRanker [34] identifies the two types of hooks that trigger the execution of rider code and thereby ungrafting the malicious rider code. It outputs two recommended hook lists which can be applied for other implications such as malware detection.

Static birthmarks are usually credible, however, they may not resist code obfuscation and could even hardly work when it comes to app encryption.

2) Dynamic Birthmarks: There have been a few works on dynamic birthmarks of Android apps. Kim et al. [18] execute apps by testing tool Monkey and collect the execution API call traces. To calculate the similarity of traces, they generate all the k-length sequences from traces and use Jaccard index as a measure of similarity.

Soh et al. [19] detect repackaging based on the analysis of UI information collected at runtime. They leverage on the multiple entry points feature of Android applications and start each activities for the UI information. It generate vectors via counting the frequencies of certain selected attributes of views. To compute similarities, they first use local sensitive hashing to find the near neighbors for all activities. Then they apply the Hungarian algorithm to find the pairs of activities that will result in the highest similarity score.

Repdroid [20] is an automated tool to detect Android app repackaging. Repdroid uses *layout* to name the view structure of a window. It proposed the layout-group graph (LGG) as dynamic birthmark of an app. LGG is constructed based on the runtime UI traces. The vertexes of LGG are layout groups (the sets where similar layouts are grouped) and the edges are the group transitions. The reason why LGG does not simply use layout as vertex of graph is that app users consider layouts with little different views are the same layouts. Repdroid models this observation and group similar layouts together. To generate LGG, Repdroid executes each app and collects runtime UI trace by traversing the app. The traverse process is in a loop that for each round, a view in current shown layout is selected to interact with, and an action (e.g. Click, ScrollBackward, Back, etc.) associated with the selected view is selected to trigger. After triggering the selected action on selected view, LGG will be updated by the UI state at that time. Besides, Repdroid describes that when app users try to traverse an app, they often prefer to interact with the views which can lead to the new layouts that they have not arrived at yet. So Repdroid assigns a new attribute *weight* to each view of layouts and updates their weights during runtime execution. The larger the view's weight is, the more possibly it will be chosen.

Compared to static birthmarks, dynamic birthmarks focus on the characteristic at runtime, which can be an effective way to deal with app obfuscation. However, there are still some limitations. For example, the work of [19] still relies on some static features (activity lists by analyzing APKs), which can be affected by inserting unused activities. Some encrypted apps (e.g. encrypted by Ijiami [35]) partially run with the native binary instead of Android API. As a result, the work of [18] can not collect correct API traces for extracting birthmarks. Repdroid relies on view types in the layouts, while hybrid apps are weakly typed so that Repdroid can hardly deal with them. Besides, Repdroid tries to traverse the whole app, it may be trapped into a deep part of layout and affect the accuracy of the birthmarks.

III. Methodology Overview

Like most existing works, our methodology is based on the observation that the repackaged apps should share similar software behaviors (e.g. visual presentations, user interactions). Since the app obfuscation and encryption will heavily affect static analysis, we try to model dynamic UI as the birthmark for each app. Moreover, as the UI layouts of hybrid apps are weakly typed, we do not focus on the view types like Repdroid. Instead, we pay our attention to the view's visual presentation itself. Views in the layouts are in the shape of a rectangles, in which different contents (e.g. colors, texts, or images) are drawn. Modifying these contents, such as

changing the color of buttons or the background image of a layout) can maintain the similar visual presentations. The skeleton of layouts (i.e. the size and position of view rectangles in each layout) are hardly affected by these modifications. As a result, we can extract birthmarks by analyzing these view rectangles of layouts.

The overview of our approach is shown in Fig. 3. Our approach is divided into two main parts, RGG generation and birthmark similarity calculation. RGG is used as the birthmark of an app (introduced in Section III-A). Given an APK, we generate RGG during app execution (Section III-C). After RGGs are generated, we construct a bipartite graph for each pair of RGGs which are to be compared. Then we use bipartite graph's maximum weight matching algorithm to calculate the similarity score between RGG pairs (Section III-D), which can be used to detect app repackaging. Specifically, if the similarity score of a pair is larger than a threshold δ_s, we consider this pair of apps is repackaged.

A. The Region-group Graph (RGG)

For a clear introduction to our approach, we define some key concepts as follows.

Definition 1 (Region): A layout contains several views and each view is in the shape of a rectangle. A region r is defined as a rectangle set. Each of the rectangles is corresponding to a view in the layout. A region describes the skeleton area of a layout.

Definition 2 (Region Group): A region group g is defined as a region set in which similar regions are grouped.

Definition 3 (RGG): A RGG is defined as a directed graph $RGG = (G, E)$ where G is a set of region groups, edges $e \in E \subseteq G \times G$. $e = g_1 \rightarrow g_2$ means a transition from group g_1 to g_2.

An example of region group is shown in Fig. 4. Supposing we have a layout shown in the screen capture (Fig. 4a), the skeleton area of the layout is shown in Fig. 4b. Each rectangle in the region represents a view in the layout. Then we group the similar region into a region group (Fig. 4c).

B. Region Similarity Calculation

A region of the app layout consists of several rectangles. We measure the similarity of regions by calculating the spatial overlapping of rectangles in each region.

Firstly, we define the rectangle similarity with Jaccard distance [36]. Given two rectangles r_1 and r_2, their corresponding sizes (width×height) are $size_1$ and $size_2$, and their overlapped size is $size_o$ (see Fig. 5). The similarity of these two rectangles is shown in Equation 1.

$$Sim_r(r_1, r_2) = \frac{r_1 \cap r_2}{r_1 \cup r_2} = \frac{size_o}{size_1 + size_2 - size_o} \quad (1)$$

We then construct a R-tree [37] from the rectangles of the region. Each region is corresponding to a R-tree. R-tree is a tree data structure for indexing multi-dimensional information (rectangles can be treated as 2-dimension, width and height). R-tree groups nearby objects and represent them with their minimum bounding rectangle (MBR). An example is shown in Fig. 6. Fig. 6a is a screen capture of a demo layout. We mark the views in the layout with numbers. Fig. 6b is a visualization of R-tree constructed from this layout. The whole layout is covered by bound rectangle MBR_0, which is not shown in the figure. Fig. 6c shows the specific tree nodes of R-tree. From the figure we can see that the layout MBR_0 is divided into 3 parts, each part is the minimum bounding rectangle of 3 or 4 views. R-tree is a balanced search tree so it has good performance to search a given rectangle input.

Lastly, we calculate the similarity of two R-trees (supposing $tree_1$ and $tree_2$ extracted from $region_1, region_2$) as the similarity between $region_1, region_2$ by Algorithm 1. Since repackaged apps try to keep their looking similar with original apps, we consider that the positions and sizes of views in repackaged apps should be slightly changed, which means the corresponding rectangles can have high similarity scores. As a result, for each rectangle $rect_1$ in $tree_1$, we search the rectangle in $tree_2$ which has the most rectangle similarity score with $rect_1$. We use the average of these scores to measure the similarity of the two regions.

Algorithm 1 Region Similarity

```
1:  procedure RegionSimilarity(region_1, region_2)
2:      tree_1, tree_2 extracted from region_1 and region_2
3:      sum ← 0, n ← 0
4:      for all rect_1 ← tree_1 do
5:          rect_2 ← arg max_{r∈tree_2} Sim_r(rect_1, r)
6:          sum ← sum + Sum_r(rect_1, rect2)
7:          n ← n + 1
8:      end for
9:      sim_n ← sum/n
10:     return sim_n
11: end procedure
```

Additionally, supposing regions $r_i \in g_1.R, r_j \in g_2.R$, the similarity between groups g_1 and g_2 is shown in Equation 2.

$$Sim_g(g_1, g_2) = \max \text{RegionSimilarity}(r_i, r_j) \quad (2)$$

C. Graph Generation

We generate our RGG based on the graph generation method in Repdroid [20]. Repdroid constructs a graph called layout-group graph (LGG) as the birthmark of an app. It executes an app with a heuristic strategy by assigning weight properties to views and action types, and collect the runtime UI trace by traversing the app. When traversing an app, it prefers to interact with views which can lead to the layouts that they haven't arrived at. However, there are opportunities for optimizations. Firstly, Repdroid tries to traverse the whole app, it may be trapped into a part of the app and could lead to different birthmarks if we run Repdroid several times for the same app. Intuitively speaking, when users try to tell whether two apps are a repackaged pair, they often check the first several layouts shown in each app, rather than comparing apps in every corner. We just need to reach the initial part of app to

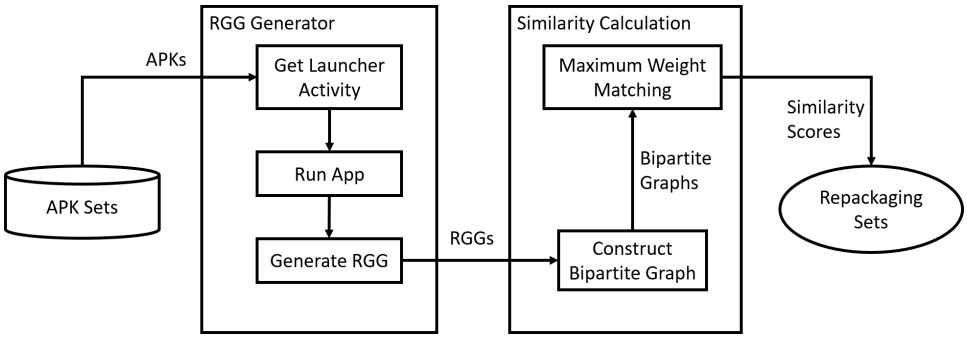
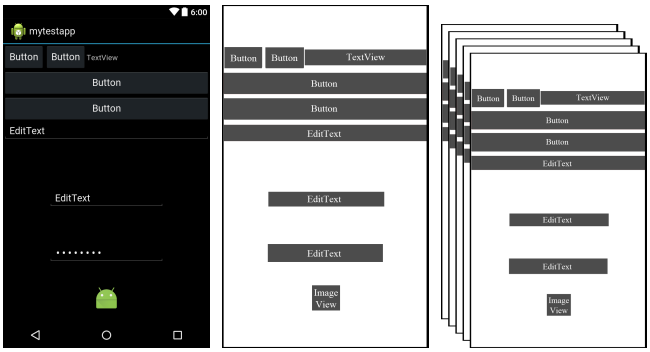


Fig. 3. The overview of our approach



(a) (b) (c)

Fig. 4. An example of region group.

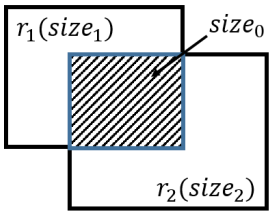
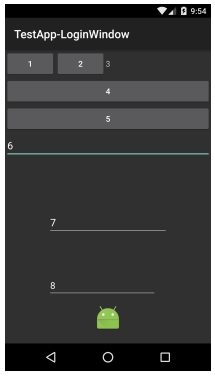
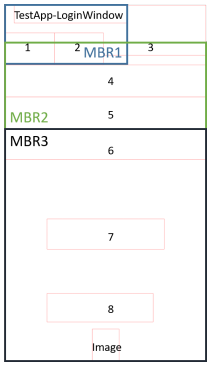


Fig. 5. Rectangle similarity



(a)



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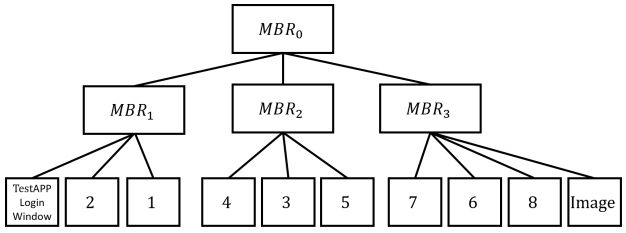


(c)

Fig. 6. An example of R-tree. Fig. 6a is a screen capture of a demo layout. Fig. 6b is a visualization of R-tree constructed from this layout. Fig. 6c shows the specific tree nodes of R-tree.

generate a partial graph which is credible for app birthmark. Secondly, not all the triggered action types are necessary. In fact, only triggering *click* action is enough for generating good enough birthmark for repackaging detection.

As a result, we propose a strategy to generate RGG shown in Algorithm 2. The inputs of the algorithm are apk, d_m, r_m, c_m. Here, apk is the target APK file, d_m means the maximum depth of region allowed to reach, r_m means the maximum rounds the main loop allowed to take, c_m means the maximum allowed rounds that the RGG does not change after a $click$ action triggered. Firstly, we get the launcher activity, install apk and start the app. The launcher activity is also known as an entry point of an app. It should be declared clearly so that Android system can know where to start the app. So no matter how an app is obfuscated of encrypted, we can always get this configuration. Then we get current region r_c and group g_c by calling GETCURRENTREGION. GETCURRENTREGION returns current region of app and the group which the region belongs to. We mark r_c as the launcher region, and g_c as the launcher group. Then we run into the main loop (Line 7) to generate the graph. r represents current rounds the loop has taken. c counts the current rounds that the RGG does not change after $click$. If any of them is larger than the maximum threshold (i.e. d_m, r_m, c_m), the loop will break and the graph will be returned (Line 27).

For each round in the main loop, we first select a rectangle $rect_s$ at current region according to rectangles' weights. The larger the weight is, the more likely the rectangle will be selected. Then we trigger $click$ action on $rect_s$. Although the layout of app may or may not change after the action, we always get the current region r and its group g. Afterwards, we get the depth d of group g by calculating distance between

g_s (the launcher group) and g. If d is larger than d_m (Line 12), we will try to trigger $back$ action to decrease current depth. Sometimes, a $back$ action may not successfully make app back to the previous layout due to the app designing. In this case, we will restart app and traverse app from beginning, i.e. the current depth will be reset to 0 and current group will be the launcher group g_s. If d is not larger than d_m (Line 15), we will insert new vertex or edge if we find new group or transaction accordingly after triggering $click$ action. If so, we increase the selected rectangle $rect_s$'s weight and reset c. Otherwise, $rect_s$'s weight decreases and the count c increases one.

Algorithm 2 Graph Generation Strategy

```
1:  procedure GraphGeneration(apk, d_m, r_m, c_m)
2:      RGG ← ∅
3:      Get launcher activity from apk
4:      Install apk and start launcher activity
5:      [g_c, r_c] ← GetCurrentRegion()
6:      g_s ← g_c, r ← 0, c ← 0
7:      while r ≤ r_m ∧ c ≤ c_m do
8:          rect_s ← WeightedSelectRect()
9:          Do click action on rect_s
10:         [g, r] ← GetCurrentRegion()
11:         d ← distance between g_s and g
12:         if d > d_m then
13:             Try to go back or restart app
14:             c ← c + 1
15:         else
16:             Update RGG
17:             if RGG's vertex or edge count changed then
18:                 rect_s.w ← rect_s.w + 1
19:                 c ← 0
20:             else
21:                 rect_s.w ← rect_s.w − 1
22:                 c ← c + 1
23:             end if
24:         end if
25:         r ← r + 1
26:     end while
27:     return RGG
28: end procedure
```

D. Graph Similarity Calculation

After we generate the RGGs from apps, we need to calculate the similarity between them to detect repacked apps. A common approach for graph comparison is the subgraph isomorphism algorithm. However, the subgraph isomorphism algorithm is not suitable for compare RGGs. Firstly, we do not try to traverse the whole apps and the generated RGGs are generally not complete but partial. Secondly, the subgraph isomorphism is time-consuming. Instead, we adopt the way proposed by Repdroid [20] with some improvement and try to find the matchings of elements in two RGGs. We first construct a bipartite graph from two RGGs and then use maximum weight matching to find the best matching in the bipartite graph. The matching score is used to measure the similarity of two RGGs.

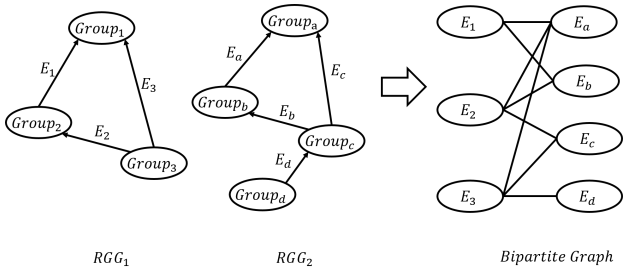


Fig. 7. Bipartite graph constructed from RGGs

More specifically, given two RGGs RGG_1 and RGG_2, we construct a bipartite graph (shown in Fig. 7). A bipartite graph has two parts of vertexes P_{left}, P_{right}, which are corresponding the edge sets of RGG_1 and RGG_2. This means edges in RGGs are the vertexes in the bipartite graph. Edges rather than vertexes in RGGs are used here because edges contain information about groups and their transitions. For example, in Fig. 7, E_1, E_2, E_3 make up the left part of the bipartite graph, and E_a, E_b, E_c, E_d make up the right part. Then, we need to construct the edges in bipartite graph. Since we do not know which vertex in left part should match which one in the right, all of vertexes were supposed to be connected. Given an edge $e = v_1 \rightarrow v_2$, the weight is calculated by Equation. 3. In fact, we do not need to connect all the vertexes in bipartite graph after we get the weights of all vertex pairs. Unlike Repdroid, we add a filter to reduce the complexity of the bipartite graph for improvement: If the weight of two vertexes is smaller than 0.5, we believe they are too 'different' to be a matching candidate and we will drop this edge connecting these two vertexes.

After bipartite graph is constructed, we use Kuhn-Munkres algorithm [38] to calculate the maximum weight matching. Without loss of generality, we assume the amount of vertexes in P_{left} is no larger than that in P_{right} and find the vertexes in P_{right} which match vertexes in P_{left}. Then we get the matching score M. Finally, we normalize the matching score as the graph similarity by Equation. 4, where N is the size of vertexes in P_{left}.

$$w(v_1, v_2) = \frac{sim_g(v_1.g_1, v_2.g_1) + sim_g(v_1.g_2, v_2.g_2)}{2} \quad (3)$$

$$Sim_G = norm(M) = \frac{M}{N} \quad (4)$$

If the similarity between two graphs is larger than a threshold δ_s, the corresponding pair of these two apps is considered as a repackaged pair.

IV. Implementation and Evaluations

To evaluate the proposed approach for generating and comparing the dynamic birthmark RGG, we implemented a tool name RegionDroid to generate RGGs and calculate the

similarities among RGGs. In RegionDroid, we use adb [39] tool to control the Android system and app runtime execution, such as installing APKs, triggering click actions, etc. We also use UIAutomator [40] tool to dump layouts to analyze the runtime UI.

We conducted the experiments on Genymotion [41] virtual device with Android 6.0 (API 23). The virtual device is configured with 4GB memory, and 1080*1920 resolution. We set thresholds $d_m = 2, r_m = 1000, c_m = 200$ and the graph similarity threshold δ_s is 0.78. The following two properties are used to evaluate the birthmarks [7].

Property 1: (*Resistance*) If program p' is obtained from p by any program semantic preserving transformation, the birthmarks of both p' and p should be the same. Obfuscation and encryption, should not affect the birthmarks of the transformed programs.

Property 2: (*Credibility*) For program p and q implementing the same specifications, if p and q are written independently, the birthmarks of p and q should be different.

A. Datasets

We design our experiment with two parts. In the first part, we use datasets S_1 and S_2 from Repdroid [20] to evaluate the credibility and resistance when apps are obfuscated or encrypted. In the second part, we apply both RegionDroid and RepDroid to a dataset S_3 consisting of 157 hybrid apps to compare their performances.

1) S_1 and S_2: In dataset S_1, there are 98 pairs of Android apps. Each pair is an original app from F-Droid and the corresponding obfuscated or encrypted app. 20 apps are downloaded from F-droid, and they are obfuscated by 2 different obfuscation tools (*FakeActivity*, and *NestedLayout*, both implemented by Repdroid's work) and encrypted by *AndroCrypt* [18]. These original and corresponding apps make up totally 60 pairs. The rest 38 apps are download from Wandoujia and they are encrypted by *Ijiami* [35]. In dataset S_2, there are 125 real world apps from Wandoujia and all of them are the top ranked apps from 8 categories.

FakeActivity repackages apps with useless activities by Soot [4]. These activities will never be started during apps' normal execution *NestedLayout* modifies layout files by inserting nested views such as *LinearLayout, FrameLayout*. With nested views attributes set properly, the repackaged apps still look the same as the original ones, but their layout XMLs are quiet different.

AndroCrypt encrypts the original APK as an asset file and pack it into a new shelled Android app. When new app is running, it dynamically decrypt and load original APK asset as if original app was running. *IJiami* is a commercial encryption tool, which has similar theory with *AndroCrypt*. However, *IJiami* loads assets by native operation while *AndroCrypt* uses Android APIs (e.g. *dalvik.system.DexClassLoader*).

2) S_3: In dataset S_3, we downloaded 117 hybrid apps from *androzoo* [42]. AndroZoo is a collection of Android apps collected from several sources, including the official Google Play app market. We select hybrid apps from androidzoo datasets by checking whether the layouts of apps contain element 'webview' or HTML, css files. Besides, since many developers build their apps with development frameworks, we also downloaded 40 hybrid apps from the showcases of 7 hybrid frameworks (shown in Table I). To sum up, we have 157 hybrid apps for dataset S_3 in total.

TABLE I
APKS DOWNLOADED FROM 7 HYBRID FRAMEWORKS.

Hybrid Framework	Apk Count
Appcelerator [30]	9
Framework7 [29]	7
Ionic [27]	4
Mobile Angular UI [43]	5
Onsen UI [44]	8
PhoneGap [28]	4
Xamarin [45]	3
Total	40

B. Resistance and Credibility

1) Resistance: To evaluate the resistance of RegionDroid, we extract RGGs from 98 pairs of apps in S_1. An original app and the corresponding obfuscated or encrypted app are defined as a RGG pair. For each pair, we calculate the similarity to detect whether they are repackaged. With the threshold δ_s 0.78, we can detect all repackaging pairs. Fig. 8 shows the distribution graph of the similarity. The distribution of RGG size is shown in Fig. 10a. We use the vertex count of graphs as the size of RGG. There are 156 RGGs generated in total, which are 20 graphs from F-droid apps, 20 graphs each from 3 kinds of obfuscation and encryption, 38 from apps in Wandoujia and 38 from their encrypted apps by Ijiami.

2) Credibility: To evaluate the credibility, we extract RGGs from S_2, and compare these RGGs pairwisely. Since Android version is different from that in Repdroid, we only successfully run 114 apps in our experiment. We applied RegionDroid to these apps and there about to be 6441 similarity scores. Like Repdroid did, we also filter the pairs that the differences between the amount of their groups are more than two times. The similarities of filtered pairs are set 0 directly. The distribution graph of similarity is shown in Fig. 9. There are 4 pairs found 'repackaged' with threshold δ_s 0.78. We check these pairs manually, and all of these 4 pairs are real repackaged pairs. Fig. 10b shows the distribution of RGG size in S_2.

C. Hybrid Applications

To evaluate RegionDroid for hybrid applications, we compare apps in S_3 pairwisely like in S_2, and with threshold δ_s 0.78, three pairs are found 'repackaged'. We check these three pairs manually. One of them is the real repackaged pair. The other 2 pairs are false positives. The first false-positive pair is because one of the app is a game which failed to run in our virtual device and the dumped layout is almost empty. The other app also has only one simple layout coincidentally, which make their similarity score high. The second false-positive pair is because they use same UI framework without much changes. They only changes some texts and the corresponding links to

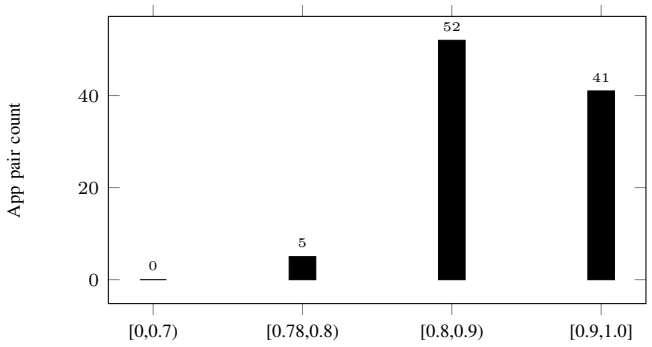


Fig. 8. The distribution graph of the similarity (Dataset S_1)

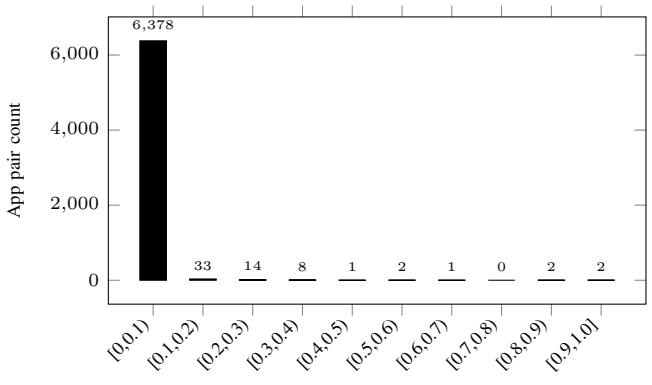


Fig. 9. The distribution graph of the similarity (Dataset S_2)

their own websites (shown in Fig. 11). Fig. 10c shows the distribution of RGG size in S_3.

D. Comparison with Repdroid

We applied S_3 to Repdroid to evaluate the performance when it comes to hybrid applications. Since Repdroid is implemented in Android 4.2.2, where contents of webviews can not be dumped. For the sake of fairness, in our experiment, Repdroid also runs on Android 6.0 so that the content of webview can be dumped. Besides, all parameter configurations of Repdroid are reserved. The comparison between RegionDroid and Repdroid is shown in Table II.

In Repdroid, 10 false-positives are found. Among these false-positives, 6 are raised because the layouts of corresponding apps are simple and the number of layouts is small (less than 2). The other 4 pairs are due to the identical class types of views. These apps consist of webviews and the view types in webviews are mostly 'view's, which affect the accuracy of similarity calculation in Repdroid. Moveover, dataset S_3 has a repackaged pair but Repdroid does not find it out. We check the result of this pair and find that the similarity between the two apps is larger than the threshold, but the group numbers of their LGGs are 2 more times different so that Repdroid filter this pair. Repdroid does not limit the depth of graph generation, it is trapped into different parts of app layouts and the number of traversed layouts can be greatly different by chance. Since we often generate birthmarks for each app just once in practice, this uncertainty will heavily affect the accuracy of repackaging detection.

Table II shows that the birthmark generation in RegionDroid (3.12 minutes on average) takes much shorter time than Repdroid does (14.09 minutes on average). The limited depth of graphs also helps speed up the similarity calculation because fewer groups in RGGs are compared during calculation.

E. Action Type and Graph Depth

We mentioned that our approach only use action *click* and do not traverse the whole app. To prove that it is reasonable, we conduct the experiment on Repdroid with the data set S_2. Two parts of Repdroid have been modified: 1)We only trigger *click* action during the graph generation strategy. 2)We only gereate LGG with certain depth. We run Repdroid with different depth thresholds as those in original Repdroid. The result of experiment is shown int Table. III. From the table we find that different depth of graph can significantly affect the time consumption of graph generation, while rarely affect the accuracy of repackaging detection.

F. Threats to Validity

We have tried to design our experiments for the representative evaluations, but there are still some threats which may affect the validity. Firstly, we have tried to find hybrid apps built by famous hybrid frameworks as many as possible. However, the showcases of these frameworks contains few apps and some of them failed to run in our virtual devices. Apps built from same framework may have features in common, which can be a testpoint for evaluating credibility. So the lack of such kinds of apps may affect the representativeness of our work. Secondly, we selected hybrid apps by statically checking whether the layouts of apps contain element 'webview' or HTML, css files. Such kinds of layouts may be in a deep position, i.e. the depth of them is larger than the threshold. We can not guarantee that RegionDroid will certainly visit the layouts which contain these web elements during executions of all apps.

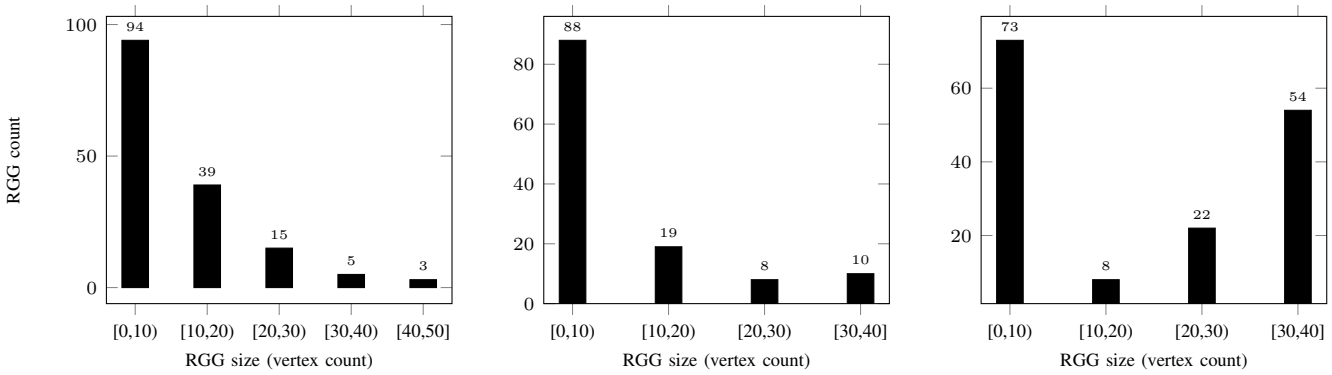
V. Discussion

A. Attacks and Defenses

Generally speaking, the Android app repackaging attacks can be classied into the three categories [13], lazy attack, amateur attack, and malware.

1) Lazy attack: Lazy attackers often modify apps with automatic code obfuscation tools and does not change the functionality of original apps. They may also change the information of apps, such as author name, company name, etc. However, these changes will not affect the UI features and the execution traces. Our birthmark will not be affected and the repackaging detection is still effective.

2) Amateur attack: Amateur attackers will make modifications on the functionalities or UI layouts. Parts of code or resources will be modified, added, or deleted for attackers' certain purposes. For example, they may try to add a new layout to lead users to browsing attackers' advertisements.



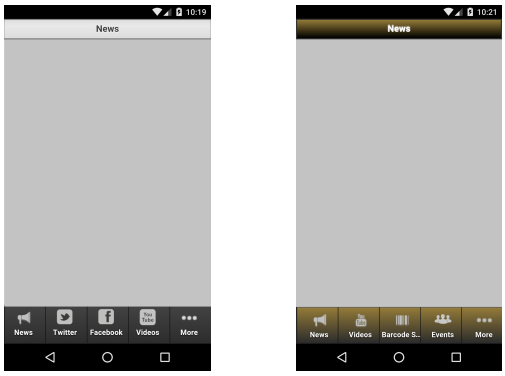
(a) Dataset S_1. (b) Dataset S_2. (c) Dataset S_3.

Fig. 10. The distribution graphs of the RGG size.

TABLE II
COMPARISON RESULTS

	S1	S2	S3		Average Time Consumption (S3)	
	FN Count	FP Count	FN Count	FP Count	Birthmark Generation	Similarity Calculation
RegionDroid	0	0	0	2	3.12 min	0.011 sec
Repdroid	0[1]	6[1]	1	10	14.09 min	0.021 sec

[1] Results are from the paper of Repdroid [20].



(a) (b)

Fig. 11. A false positive in S_3.

TABLE III
RESULTS WITH DIFFERENT DEPTH THRESHOLDS

Depth	Time consumption (minutes)	False positives
2	5.11	4
	5.38	4
	6.08	5
	5.25	4
3	7.31	5
	7.03	4
	6.23	4
	6.85	4
4	8.21	5
	9.34	4
	8.81	4
	8.78	4
5	15.77	4
	13.65	4
	12.32	5
	14.22	4

However, to leverage the popularity of the original app, the remaining parts of repackaged app should be similar as the original one. As a result, the similarity score can still be high and the repackaging can be detected as well.

3) Malware: Malware attackers will insert malicious code into apps. For example, they may upload user privacy information, damage device system, or hijack and tamper web links. Malwares often try to hide themselves to avoid being discovered, and it will not affect app UI features. So RegionDroid still works for this kind of attack.

4) Other Potential Attacks: There are other potential attacks against our approach. Firstly, attackers can obfuscate UI layouts far different from the original ones but still ensure that the runtime presentation does not change. For example, they can add a completely transparent layout overriding the original one. The looking of current layout is still the same as original one, but the contents dumped is replaced by the transparent layout. However, to make apps behave similarly, they need to handle the event listeners so that the transparent layout can response to user interface correctly. As a result, such attacks may be a great burden for repackaging. Secondly, attackers may change the positions and size of views in layouts. If the changes are small or the numbers of changed layouts are small, the overall similarity can still be high and our approach can tolerate such changes. If attackers tries to re-design the apps' layouts but make layouts still look similar (e.g. symmetrical views to the center), it could affect our work and can be a potential threat. However, as far as we know, there are no such automatic tool for this kind of attack. Attackers need to modify XML or HTML files carefully so that new layout can be similar enough to confuse users.

B. Limitations and Future Works

Firstly, since our approach is based on UI regions, if the app have few layouts, e.g. service apps which almost run in the background, we can not detect repackaging over these kinds of apps. Secondly, like most existing works, RegionDroid can not reach the layouts which need specific user input, such as password authentication. However, since repackaged apps try to maintain the same behaviors with the original ones, if layouts in original apps are unaccessible, the corresponding layouts in repackaged apps are also unaccessible. As a result, the RGG extracted from runtime UI features can still share similar characteristics. Thirdly, our approach can not deal with the apps where graphic UI are designed by OpenGL directly, e.g. most of games. The runtime dumped contents do not reflect the UI view hierarchies of current layout, not to mention analyzing their features. Lastly, third-party webview bring some troubles to RegionDroid. Since hybrid apps are becoming more and more popular, some organizations or companies have developed third-party webviews for hybrid app developers, such as CrossWalk [46] and TBS [47]. They contribute to their webviews for better app performance. Although Android native webview (since Android 4.4) has been replaced by Chromium, which is a powerful open-source webview core for hybrid apps (CrossWalk is no longer updated due to this replacement [48]), there are still apps embedded with third-party webviews. We can not dump contents from third-party webviews easily with existing tools for analysis. Although it does not affect the model of our approach itself, it is still a challenge for repackaging detection which can be our future works.

VI. Conclusion

In this paper, we proposed a dynamic birthmark RGG based on UI region features to detect Android app repackaging. Our approach execute apps automatically and analyze the runtime UI of apps. We partially traverse apps within a limited depth and focus on the region of layouts to deal with weakly typed views in hybrid apps. We also implement the tool RegionDroid based on RGG and conducted the experiment to evaluate our approach. The experiment shows that our approach has good credibility and resistance when it comes to the obfuscated and encrypted apps. Additionally, our approach also has good performance in detecting repackaging among hybrid apps.

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