Illegal But Not Malware: An Underground Economy App Detection System Based on Usage Scenario

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Abstract—This paper focuses on mobile apps serving the underground economy by providing illegal services in the mobile system (e.g., gambling, porn, scam). These apps are named as \textit{underground economy apps}, or UEware for short. As most UEware do not have malicious payloads, traditional malware detection approaches are ineffective to perform the detection.

To address this problem, we propose a novel approach to effectively and efficiently detect UEware by considering the transition orders of the user interfaces (UIs), which determine the \textit{usage scenarios} of these apps. Based on the proposed approach, we design a system named DeUEDroid to detect the UEware via scene graph. To evaluate DeUEDroid, we collect 26,591 apps to evaluate DeUEDroid and build up the first large-scale ground-truth UEware dataset (1,720 underground economy apps and 831 legitimate apps). The evaluation result shows that DeUEDroid can construct scene graph accurately, and achieve the accuracy scores of 77.70\% on the five-classification task (i.e., gambling game, porn, financial scam, miscellaneous, and legitimate apps), reaching obvious improvements over the SOTA approaches. Running further on 24,017 apps, DeUEDroid performs well in the real-world scenario to mitigate the threat. Specifically, by using DeUEDroid, we found that UEware are prevalent, i.e., 61\% apps in the wild and 21\% apps in the app stores are UEware (with over 72\% accuracy after the manual investigation). We will release our dataset and system to engage the community after been accepted.

1. Introduction

Mobile apps have been an indispensable part of our daily life, from online shopping, entertainment, and even financial business \cite{7}. At the same time, apps that serve the underground economy by providing illegal services \cite{25} are prevalent in the wild nowadays \cite{4}, \cite{10}, \cite{55}, and thereby lead to serious damages. For example, the porn scam apps caused more than $304 million losses in 2020 \cite{5}. Meanwhile, the gambling apps made more than $53 billion revenue in the US in 2021 \cite{13}, \cite{14}. As an essential role in reported losses \cite{4}, these apps serve the underground economy by providing illegal services in the mobile system (e.g., gambling, porn, scam). In this study, we call them \textit{underground economy apps}, or UEware for short.

Unlike the traditional malware (e.g., backdoor, trojan, spyware), UEware are characterized based on the \textit{legitimacy of the services}, while (most of) them do not necessarily engage malicious payloads. As the concept of UEware is (partially) orthogonal to that of the malware, it is possible to give a more comprehensive categorization for mobile apps by considering the combination of the existence of the malicious payloads and the legitimacy of the services. As such, apps could be further categorized into four categories, i.e., \textit{legitimate apps}, \textit{malware}, \textit{malware & UEware} and UEware, respectively, as shown in Figure 1. Obviously, UEware consist of both the third and the fourth categories; while the majority of UEware fall into the fourth category, occupying over 80\% (see Section 8.3) among all UEware.

The proliferation of UEware calls for effective solutions to mitigate this threat. Specifically, there is a great demand for an efficient detection technique due to the large volume of apps that need to be verified. For instance, there were over two million new apps released on GooglePlay in 2021 \cite{12}. However, only a few previous studies \cite{24}, \cite{32}, \cite{46}, \cite{47} have focused on UEware by analyzing some special sort of them (i.e., gambling and scam) and proposing some recommendations to users and legal authorities. Nonetheless, none of the existing works propose feasible detection approaches.

Furthermore, the malware detection approaches could not be applied to identify UEware. Specifically, as most UEware do not have malicious payloads, those static detection methods \cite{29}, \cite{44}, \cite{61}, \cite{65} focusing on the malicious payloads will inevitably lead to high false negative rates.
mate apps, UEware opt to serve as single-purpose apps, i.e., most underground loan apps are used for only one purpose, respectively (see Section 8). Unlike the legitimate apps, UEware opt to serve as single-purpose apps.

Our approach. In this paper, we propose a novel approach to effectively and efficiently detect UEware by considering the transition orders of the user interfaces (UIs), which determine the usage scenarios of these apps. Specifically, for a given app, the service is presented to the users through multiple UIs in a specific order. These ordered UIs are aware of the usage scenarios, which further constitute a scene-aware UI transition graph. In the following context, this graph is named as scene graph for short.

Our approach is based on two key observations. First, the scene graphs of UEware are different from those of the legitimate apps. On average, UEware have fewer transition pairs and UI widgets than legitimate apps, i.e., 11 vs. 22 and 29 vs. 227, respectively (see Section 8). Unlike the legitimate apps, UEware opt to serve as single-purpose apps.

For example, most underground loan apps are used for only one purpose, i.e., loan application. On the contrary, normal financial apps not only serve for loan applications, but also for financial derivatives purchasing, asset evaluation, and other purposes. Second, the scene graphs of the same type of UEware are extremely similar, while the scene graphs of different types of UEware vary from each other. For instance, underground loan apps have a similar scene graph, such as the transition from the personal page to loan apply, as shown in Figure 2. Note that, this scene graph is different from that of other types, e.g., the gambling apps, as shown in Figure 3.

However, identifying UEware based on scene graph is a challenging task. First, it is difficult to build a precise scene graph, which requires effectively: (i) identifying the UI widgets and their attributes; and (ii) determining the UI transition orders. However, the existing UI analysis studies [39], [53] only focus on native widgets (i.e., XML widget and dynamic widget) but omit web widgets (i.e., Webview).

Meanwhile, the existing transition identification studies [50] only focus on the Inter-Component Communication (ICC) of the activity but ignore the processing of fragment and navigation. Second, it is hard to directly leverage scene graph to perform the detection. A scene graph is expressed via a mixture of graph topology and unstructured UI attributes, and the correlations of them cannot easily be applied as an effective representation.

This work. We design a system named DeUEDroid to detect UEware by addressing the above challenges. DeUEDroid consists of three modules: (i) scene graph builder, which is used to construct a precise scene graph. This module consists of two phases, i.e., UI widget identification and UI transition determination. Specifically, in the first phase, DeUEDroid proposes a hybrid widget identification approach, which covers both the native widgets and the web widgets by properly integrating two previous studies, i.e., SOTA UI analysis tool [31] and network imprint [23]. While in the second phase, DeUEDroid proposes a new activity transition graph (ATG) construction algorithm to accurately capture UI transition pairs. By doing so, DeUEDroid is capable of building scene graph in a precise manner. (ii) scene graph feature extractor, which is responsible for extracting the feature from the scene graph. Specifically, DeUEDroid follows the success of graph embedding, and adopts the self-supervised graph auto encoder (GAE) to combine the scene graph topology and UI attributes together as the scene graph representation. (iii) UEware detector. The detector leverages the self-supervised representation learning to detect and classify UEware based on the scene graph features.

To evaluate the effectiveness and efficiency of DeUEDroid, we build up three datasets, containing 26,591 apps. First, we use 23 open-source apps to evaluate the effectiveness of scene graph construction. The evaluation result suggests that DeUEDroid can construct accurate scene graph, which can accurately identify transition pairs (over 72%) and imprint tokens (over 90%). Then, we build up the ground-truth UEware dataset, which is the first large-scale ground-truth dataset (2,551 apps) of UEware, to evaluate the effectiveness of UEware detection. The evaluation result shows that DeUEDroid can detect discrepancies with accuracy values 77.70% for demystifying gambling game, porn, underground loan, financial scam, and legitimate apps. Our system has a significant effect on improving detection.
We build up a ground-truth UEware dataset with accuracy. Finally, we perform a large-scale experiment on 24,017 apps collected from app stores (and the wild), to measure the effectiveness and efficiency of large-scale UEware detection. The evaluation result demonstrates that DeUEDroid achieves good performance to mitigate the real-world threats. By using DeUEDroid, we found that UEware are prevalent, i.e., 61% apps in the wild and 21% apps in the app stores are UEware (with over 72% accuracy after the manual investigation).

Contributions. We make the following contributions:

- We proposed a novel approach to detect UEware based on scene graph. This approach first builds scene graph for the training APKs, and then extracts features of scene graph. After that, it applies a machine learning method to train the classifier to detect UEware. We proposed and implemented a prototype system named DeUEDroid to perform the detection. The evaluation results demonstrate the effectiveness and efficiency of the proposed system.

- Based on DeUEDroid, we found that the UEware is proliferating, which occupies 61% apps in the wild. What’s more, even in the app stores, there are still a lot of undetected UEware (21% of all apps).

- We built up a ground-truth UEware dataset with 2,551 Android apps. To our best knowledge, this is the first large-scale UEware dataset. We will release our system and datasets to engage the community.

2. Background

In this section, we introduce the usage service of the Android app, which consists of user interfaces (UI) and their transitions. Then we describe the definition of the Android scene graph. For better understanding, we show a core scene graph of an underground loan app in Figure 2 as an example (the real screenshots are in Figure 13 in appendix).

2.1. User Interface

The UI is responsible for communicating with users, which shows the contents of the app. Specifically, UI consists of the UI widgets on the same activity/fragment. And it is worth noting that all widgets depend on activity or fragment for drawing.

First, the activity is the fundamental component for drawing the UI widgets with which users can interact with. And since Android 3.0, fragments can also render the UI widgets. However, the fragment is a portion of the activities, which can not exist independently. Second, the UI widget is the fundamental accessible view for the users that contains data or functionality. All widgets inherit from the view class, such as TextView and LinearLayout. The widget can be dived into two types: native widget and web widget. The native widgets are statically recorded in the XML file or dynamically added in code. But the web widgets are loaded from a web URL.

2.2. User Interface Transition

An android app is consist of multiple UIs for handling complex business requirements. When some special conditions are triggered, the app will transit from one UI to another. Specifically, UI is rendered on activity/fragment, so these UI transitions are triggered in three ways: (i) triggered by explicitly invoking activity transition API, e.g., the StartActivity, StartActivityResult; (ii) triggered by implicitly invoking conversions, e.g., Android Inter-Component Communication (ICC); (iii) triggered by invoking system listener, e.g., onKeyDown. The activity transition is closely integrated with Android lifecycle, i.e., the target activity will gain the focus and invoke OnCreate and OnStart while the origin one lose the focus and invoke the OnPause or onStop.

Besides, the fragment navigation also reflects the UI transition within an activity. The navigation consists of three key parts: (i) Navigation graph, an XML resource that contains all navigation-related information. (ii) NavHost, an empty container that displays navigation graph. (iii) NavController, an object that manages navigation within a NavHost. Fragment navigation extremely improves the flexibility of transitions, and has been widely used in recent years.

2.3. Formal Definition of Scene Graph

For a given app, its service is presented to the users through multiple user interfaces (UIs) in a specific order. These specific ordered UIs are aware of the app usage scenarios, which further constitute a scene-aware UI transition graph, or scene graph for short.

Definition 1: A scene graph is a directed graph \( G = (V, E) \) in a node attribute space \( \Omega \), where: 1. \( V \) is a node set, with each node being an activity/fragment; 2. Each node is assigned UI attribute labels in \( \Omega \), e.g., layout, widget type, button, and network imprint. 3. Directed edge set \( E \subseteq V \times V \) is a set of transitions between activity/fragment and \( e \) is the single edge within the \( E \).

3. Motivation

In this section, we first illustrate the limitation of the traditional malware detection approaches. Specifically, we summarize the features adopted by representative systems/tools to detect malware, which cannot be applied to detect UEware. After that, we detail the feasibility of our approach by demonstrating the validity of the key observations.

3.1. Limitation of the Traditional Approaches

Features used by those traditional malware detection approaches can be categorized into the following three categories: code, UI, and Manifest, as shown in Table 1. Specifically, they mainly focus on code features at the
method granularity. In addition, a few studies focus on UI features for XML widgets, while some other studies make extensive use of the Manifest information, including app name, package name, developer signatures, and permissions. However, all of these features are ineffective to detect UEware due to the following reasons:

- Lack of malicious payload. Most UEware do not have any malicious payloads, which inevitably leads to the failure of control flow based detection approaches (e.g., API flow).
- Incomplete UI content. Nowadays, the dynamic loading and web widgets are widely adopted by UEware. As a result, those approaches [21], [67] that only analyze XML widgets become ineffective due to the low identification coverage. On the other side, the UI content (e.g., pictures, videos) is always downloaded from the remote server at runtime. Obviously, the detection approaches based on native resources [22], [43], [48] are not feasible due to the high false negative rate.
- Ineffective Manifest. The Manifest information cannot be used as the unique features to detect UEware. Specifically, the permissions acquired by UEware are similar to those of legitimate apps [32], while the developer signatures can always be arbitrarily customized (in Android).

### 3.2. Feasibility of Our Approach

As mentioned in Section 1, our approach is based on two key observations:

- **Observation-I**: the scene graphs of UEware are different from those of the legitimate apps.
- **Observation-II**: the scene graphs of the same type of UEware are extremely similar, while the scene graphs of different types of UEware vary from each other.

As the first observation can be concluded from the statistical result, hence here we mainly focus on the second observation by providing two concrete examples.

To demonstrate that the scene graphs of the same type of UEware are extremely similar, we randomly choose two loan apps (with different Manifest information) that serve the underground loan application. The runtime screenshots of these two apps are shown in Figure 13 (in appendix) and Figure 14 (in appendix), respectively. Although the texts and images of these two screenshots are different from each other, they share the same (core) scene graph, as shown in Figure 2.

![Figure 4: The design overview of DeUEDroid.](image)

To demonstrate that the scene graphs of different types of UEware vary from each other, we additional use a gambling app to perform the comparison. The runtime screenshot and the core scene graph of the gambling app are shown in Figure 15 (in appendix) and Figure 3, respectively. Obviously, the (core) scene graph of the gambling app is different from that of the loan app, i.e., Figure 3 vs. Figure 2.

### 4. Design Overview

Based on the proposed approach, we design a system named DeUEDroid to detect the UEware via scene graph. Specifically, DeUEDroid first builds scene graph for the training APKs, and then extracts features of scene graph. After that, it applies a machine learning method (i.e., self-supervised representation learning) to train the classifier to detect UEware.

Figure 4 shows the architecture of DeUEDroid. There are three modules, i.e., Scene Graph Builder, Scene Graph Feature Extractor and UEware Detector, as follows:

- **Scene Graph Builder**: This module accepts Android APK files as the input, and outputs the scene graphs. It consists of two phases: **UI widget identification** and **UI transition determination**. Specifically, in the first phase, the builder covers both the native widgets and the web widgets by properly integrating two previous studies, i.e., SOTA UI analysis tool [51] and network imprint [23]. While in the second phase, the builder considers all transition types and proposes a new ATG construction algorithm to accurately capture UI transition pairs.
- **Scene Graph Feature Extractor**: Based on the scene graphs, this module combines both graph topology and UI attributes together and outputs the scene graph representation.
representation. Specifically, it leverages the Graph Automatic Encoder (GAE) [38] with a 2-layer GCN [25] to embed scene graph. In particular, before the graph embedding, the DeUEDroid additionally adopts the Mask strategy to enhance the embedding robustness.

- **UEware Detector.** Based on the scene graph features, this module leverages the self-supervised representation learning to train a UEware classifier, which will be used to perform the detection. Note that the scene graph based approach allows further classifying the apps into different categories of UEware. Hence currently fives categories, including gambling game, porn, financial scam, Miscellaneous and legitimate apps, are supported by the system.

The detailed design of these three modules will be illustrated in Section 5, Section 6 and Section 7 respectively.

5. Scene Graph Builder

In this section, we describe the design of scene graph builder by first providing the module overview, and then introducing the two phases of this module one after another.

5.1. Module Overview

This module has two phases: (i) UI widget identification, and (ii) UI transition determination, as shown in Figure 5. All phases take an Android APK file as the input. The output of UI widget identification is a set of UI widgets and their attributes. Notably, the native widget attributes are well collected, such as widget layout, types, and button listener. And the web widget (e.g., WebView) attributes are represented by their network imprints. The output of UI transition determination is a directed graph representing the transition relationship between activities/fragments, also called the activity transition graph (ATG). In the end, the scene graph of apps is well constructed as a directed graph, in which each node is an activity/fragment, and each directed edge describes a transition from one activity to another.

5.2. UI Widget Identification

In Android, the UI widgets are rendered on an activity or a fragment, and can be dived into native widgets and web widgets. Specifically, DeUEDroid proposes different analysis methods for two different types of widgets.

Native Widgets. As mentioned in Section 2, the native widgets can be statically recorded in the XML file or dynamically added at runtime. Generally speaking, XML file are loaded through API calls like “setContentView” or “inflate”. And the XML widgets can be loaded via API calls such as “findViewById”. The dynamic loading widgets will be identified in code (e.g., new TextView()), directly, and be attached to some existing layout. And through these API calls, we map the widget to their corresponding activity.

To perform native widgets analysis, we adopt FrontMatter [39], the SOTA static UI analysis tool, to figure out the native widgets. Considering the lifecycle of Android, the FrontMatter only restores the UI creation process within the “OnCreate” phase. This design improves the analysis speed and is suitable for massive dataset situations.

The analysis performs on XML files to identify the widget types (e.g., ImageView, ConstraintLayout), the widget layout, the widget icon (e.g., @drawable/ic_button), and the event listeners (e.g., OnClick). And the analysis also performs on code and leverages taint flow analysis to identify the dynamic widget attributions. Finally, it combines the results on both the XML files and the code to identify all native widgets and their attributes. In addition, based on the special API calls, we analyze relationships between activities/fragments and widgets to map the activities and their native widgets together.

Web Widgets. Nowadays, the hybrid development paradigm is commonly used in app development, occupying 74% top 50 apps in markets [9]. These hybrid apps acquire remote resources through web widgets. Specifically, the WebView starts a local browser and invokes the “LoadURL” API with a java.lang.String type parameter. Then the URL corresponding to the parameter will be shown in the local browser. For these web widgets, the essential part is the URL parameter.

However, it’s nearly impossible to get the accurate network URL in static analysis [20]. So we refer to the previous studies [23] and generate the network im-
print of web widgets instead. The network imprint consists of any field token with invariant content (e.g., IP address, hostname, key, and value) to identify the web widget. To generate imprint, there are two key observations we leverage for variable identification: (i) the URL parameter of WebView and its related tokens are all in string type (i.e., java.lang.String, java.lang.StringBuilder and java.lang.StringBuffer). (ii) almost always, a parameter related token originates from some constant values within the program, such as constants, XML resources, and Manifest. Based on the two key observations, we propose a special backward taint analysis scheme. Specifically, we only focus on the variables in string type and methods related to string (e.g., duplicate(), add(), replace()) to reduce the magnitude of taint analysis. We then instantiate variables from constant values and discard runtime-generated variables (e.g., user input).

Here we use an example (Figure 6) to present the whole backward taint process. First, the program loads activities/fragments, and searches special API calls (e.g., WebView.loadURL()). Once the sink statement is found in Class Y method C, the sink variable is url. Then the program will perform backward taint analysis to check whether any variable affect url. After running, v4 and X.B() is determined to affect url using java.lang.StringBuilder.append() method. And the v4 is considered that unrelated to any invariant source within the app but instantiated from runtime-generated variables, which can not be determined in static analysis, so we discard the v4. Turn to the X.B(), since it is an inter-procedure call, the program additionally loads Class X and sink the v2. Going further, the program finds that A() and v3 affect the v2. At this time, v3 is determined to be an ImmediateBox variable, so the program instantiates v3 with a concrete value. At last, program finds that A() is assigned by v1 from XML resource (R.stringbaseUrl). In this sample, the variable is from res/values/string.xml, which will be dynamically loaded by the program and instantiated with a concrete value. To sum up, v1,v3 are instantiated as constant variables, v4 is instantiated as runtime-generated variable and discarded. In the end, the program outputs a set of tokens (e.g., [v1,v3]) and removes some common tokens (e.g., github). These tokens are used as network imprints to identify web widget attributes.

| Top-Class Name | Run Method | Start Method |
|----------------|------------|--------------|
| AsyncTask      | doInBackground | onPostExecute |
| Runnable       | run        | start        |
| Message        | handleMessage | sendMessage |

**TABLE 2:** The implicit run and start pairs.

5.3. UI Transition Determination

As mentioned in Section 2.2, the UI transition can be triggered by multiple methods. And it is worth noting that fragments have become an essential part of transition relationships, with independent transition functions and UI widgets. However, previous studies [19], [22], [50] have overlooked this part, leading to some omissions. To build up an appropriate UI transition graph, we propose a new Activity Transition Constriction (ATG) Algorithm 1. Specifically, we first initialize Nodes and Edges as empty sets, which stores the activity/fragment and their transition relationships respectively. Then we generate the call graph (cg) of the given APK, and fetch out all classes defined in the Manifest. Notably, considering there are some implicit run and start pairs (see in Table 2) in Android, which will affect the integrity of the call graph. We manually add these pairs and complete the call graph in our studies.

To each class in APK, we judge whether they inherit from activity or fragment, and if so, add them to the Nodes set. Then for all methods in each class, we get all units according to the previous call graph. To these units, we judge...
whether they have transition movements. As mentioned in Section 2.2, the explicitly transition and implicitly transition have special APIs (e.g., $StartActivity(), Intent()$). By comparing the API signatures, we can locate the translation units. Besides the special APIs, we analyze the navigation by searching special structures (e.g., $NavController$) defined in classes. Finally, we monitor whether the activity has overloaded system-level calls, such as $onKeyDown()$, to implement the transition.

If there lives an activity transition unit, we first get the target activities (callee) by analyzing the unit arguments based on taint analysis. Due to the difficulty in handling conditional judgments, all possible target activities/fragments are included. Then we get the source activities (callers). Specifically, three different processing methods are adopted according to the class type: (i) If the class is a fragment, the callers are the union of this fragment and all activities that own this fragment. (ii) If the class is an inner class, the callers are the union of the outer classes of this inner class. (iii) Else, the caller is the current class itself. Finally, for the callers and callees found by a transition, we traverse all callers and callees and add all pairs (caller → callee) to the $Edges$ set. The activity transition graph consists of the nodes in $Nodes$ and the local edges in $Edges$.

6. Scene Graph Feature Extractor

In this section, we describe the design and implementation of scene graph feature extractor. We first provide the module overview, and then introduce the detail of Mask strategy, the GAE, and the loss calculation.

6.1. Module Overview

The overview of this module is shown in Figure 7. For an input APK, its scene graph is produced from the previous module, and the scene graph definition is shown in Sec 2. We first encode the activity’s UI attributes $\Omega$ into UI matrix $X$ and adopt the Mask strategy to mask the graph to produce two masked graphs $G$ and $\hat{G}$. We then use GAE with 2-layer GCN to combine the graph $G$ and UI matrix $X$ into a feature representation $Z$ as the node embedding. Note that even UI properties and graph topology can be seen as independent features of the apps, the correlation information will be ignored, resulting in the loss of accuracy. Consequently, we correlate these two features together as a joint feature. Finally, to improve the quality of the embedding, we calculate the decode loss, which consists the global contrastive loss between the two masked graphs and the local reconstruction loss within the same map.

6.2. Mask Strategy

In the underground economy, developers always generate new apps by modifying parts of the code or functions of existing apps to improve development efficiency. To counteract the impact of code modifications, it requires a high robustness of the graph embedding model. To this end, we find that the Mask strategy is very suitable. First, the Mask strategy can be viewed as an adversarial attack that provides a new view of the graph as data augmentation. Second, according to previous work [41], masking a certain part of the fringe edges/nodes can significantly reduce the redundancy of two paired subgraphs, thereby avoiding trivial overlapping subgraphs. Furthermore, previous empirical evidence [52] shows that fringe information is often redundant for downstream tasks such as node classification. In general, Mask strategies can be divided into Edge-wise random masking and Path-wise random masking. In this study, we adopt the Edge-wise random masking, which is defined as:

$$\varepsilon_{mask} \sim \text{Bernoulli}(p)$$

where $\varepsilon$ denotes the edge within the $E$. We use the Bernoulli random function to mask a part of edges as the input for the next stage.

6.3. Graph Auto Encoder

Autoencoders [34] are designed to reconstruct certain inputs given the contexts and do not enforce any decoding orders. In this study, our encoder $f_o$ (parameterized by $\theta$) is 2-layer graph convolutional networks (GCN) [25], a well-established GNN architecture widely used in literature [53]. Specifically, the encoder first calculate $\hat{A} = D^{-\frac{1}{2}}AD^{-\frac{1}{2}}$ in the pre-processing step, where $\hat{A}$ is the adjacency matrix of the graph $G$ with added self-connections, $I_N$ is the identity matrix, and $D$ stands for the degree matrix of $G$. The forward model then takes a simple form:

$$Z = f(X,A) = \text{softmax}(\hat{A}\text{ReLU}(\hat{A}XW^{(0)})W^{(1)})$$

Here, $W^0 \in \mathbb{R}^{C \times H}$ is an input-to-hidden weight matrix for a hidden layer with $H$ feature maps, while $W^{(1)} \in \mathbb{R}^{H \times F}$ is a hidden-to-output weight matrix. The softmax activation function, defined as $\text{softmax}(x_i) = \frac{1}{\sum_i \exp(x_i)}$ with $Z = \sum_i \exp(x_i)$, is applied row-wise.

The decoder aggregates pairwise node representations as link representations to decode the graph. There are several decoders in previous literature, such as inner product or a neural network. We define the structure decoder $h_w$ with parameters $\omega$ as:

$$h_w(z_i, z_j) = \text{Sigmoid}(\text{MLP}(z_i^T \circ z_j))$$

where MLP denotes a multilayer perceptron and $\circ$ denotes an element-wise product.

6.4. Loss Calculation

Our loss calculation consists of two parts: local reconstruction loss $L_{\text{local}}$ and global contrastive loss $L_{\text{global}}$. For the masked graph, we divide the edges as remaining edges and masked edges. The masked edges are selected as positive samples, while the disconnected node’s edges are selected as negative samples. For the embeddings from the
decoder, we calculate their inner product as the probability of the edge existing.

\[ \mathcal{L}_{\text{Local}} = - \frac{1}{|\mathcal{E}^+|} \sum_{(u, v) \in \mathcal{E}^+} \log h_{w}(z_u, z_v) \]
\[ + \frac{1}{|\mathcal{E}^-|} \sum_{(u', v') \in \mathcal{E}^-} \log (1 - h_{w}(z_u', z_v')) \]  \hspace{1cm} (4)

where \( \mathcal{Z} \) is the graph embedding result from the encoder; \( \mathcal{E}^+ \) is a set of positive edges while \( \mathcal{E}^- \) is a set of negative edges sampled from the graph.

Further, we calculate the distance between the two representations \( \mathcal{Z}, \hat{\mathcal{Z}} \) as the global contrastive loss. Specifically, we leverage the MSE to normalize the loss value into the range of \([0, 1]\) to facilitate model optimization.

\[ \mathcal{L}_{\text{Global}} = \frac{1}{N} \sum_{i=1}^{N} (z_i - \hat{z}_i)^2 \]  \hspace{1cm} (5)

Finally, we combine the global loss and local loss into the total loss and use gradient descent to minimize it.

\[ \mathcal{L}_{\text{Total}} = \mathcal{L}_{\text{Local}} + \alpha \mathcal{L}_{\text{Global}} \]  \hspace{1cm} (6)

Where \( \alpha \) denotes a non-negative hyperparameter trading off two terms.

7. **UEware Detecting**

In the above sections, the system has constructed scene graph and extracted scene graph representation. In this section, we describe the design and implementation of UEware detector, especially the classifier.

7.1. **Module Overview**

The UEware detector leverages the self-supervised representation learning \([41]\), which is widely adopted in previous studies \([33, 58]\). In detail, it consists of two stages:

- **Self-supervision Training Task**: This stage is used to train the encoder \( f_0 \) and decoder \( \psi \). It leverages the self-supervision training task, and downstream training task, see Figure 8. The self-supervised training task refers to the algorithm in the previous scene graph feature extractor (see Section 6), however, their inputs and outputs are different. In detail, the scene graph feature extractor accepts the scene graph topology \( \mathcal{G} \) and the UI attributes \( X \) to trains the scene graph encoder \( f_0 \). But the self-supervision training task accepts the APK relation graph \( \mathcal{H} \) and the APK feature \( X \), and trains the encoder \( f_\psi \). Referring to previous studies \([69]\), the APK relation graph \( \mathcal{H} \) is an undirected graph, while the node of the graph is APK, and the edge of the graph is the overlap strong features (i.e., PackageName, AppName, signature) between APKs. Meanwhile, the APK feature \( X \) is the scene graph representation produced by encoder \( f_\theta \).

- **Downstream Task**: The downstream task uses the encoder \( f_\psi \) and to train the classifier \( q_\psi \) for UEware detection.

7.2. **Classifier**

The APK encoder \( f_\psi \) learned from self-supervision training is set frozen and directly introduced into the downstream task. According to this frozen encoder, the downstream task then calculates the \( \mathcal{Z} \). Finally, the classifier \( q_\psi \) (also called the downstream decoder) is trained based on the labeled dataset. In this study, we leverage a linear classifier (i.e., a logistic regression model) and the labeled information is the app types (i.e., gambling game, porn trading, invest-
ment scam, miscellaneous and legitimate apps). Specifically, the detection task decoder parameter is calculated as:

\[
\psi = \arg\min_{\mathcal{L}_{\text{sup}}} (f_\psi, q_\psi, \mathcal{H}, y)
\]  

(7)

where \(\mathcal{H}\) is the APK relation graph and \(y\) is the label of UEware.

In the end, when input test APKs, the DeUEDroid first combine the test APKs and training APKs together to construct a new graph \(\mathcal{H}\). And then, the DeUEDroid labels the test APKs through the encoder \(f_\psi\) and decoder \(q_\psi\).

8. Evaluation

In this section, we evaluate the performance of DeUEDroid based on the following three research questions:

- **RQ1**: How effective is DeUEDroid in scene graph construction?
- **RQ2**: How effective is DeUEDroid in UEware detection?
- **RQ3**: How effective and efficient is DeUEDroid in large-scale UEware detection?

8.1. Evaluation Setup

For RQ1, we investigate the capability of scene graph construction. To evaluate the capability, we build up the Open-source Dataset, consisting of 20 open-source self-developed apps and 3 real-world open-source apps. Specifically, we self-developed 5 initial apps as our ground-truth benchmark, which covers different transitions (i.e., the transitions between activity - activity, activity - fragment, fragment - fragment, and navigation) and widgets. Then, to investigate the anti-obfuscation capability, we perform popular obfuscation techniques (i.e., rename [5], code [11], reflect [16] on the initial 5 apps to generate another 15 obfuscated apps. We claim that this solution is the only way to accurately understand the ground truth of transitions and widgets, and this solution has been widely used in previous studies [22]. In addition, to strengthen the conviction of our experiments, we additionally compare the SOTA work IC3 [50] and analyze several famous open-source apps (i.e., org.woheller69.weather [4], site.leos.setter [5], de.digisocken.antherrss [6]). Note that there are some studies [22, 23] mentioned about static transition identification or imprint generation, we have no way to compare with them since they do not release code or dataset.

For RQ2, we evaluate the capability in UEware detection. To the best of our knowledge, there is no released dataset of UEware. To perform our evaluation, we first put a lot of effort into building up the Ground-truth Dataset. This dataset is built up by our group of four members who have worked on easing the underground economy for at least two years. We first collect the apps from the wild, and then manually inspect whether these apps are UEware. Specifically, each app is assigned to four members for them to mark independently. And we will decide which attribute to apply based on the majority rule. If a consensus cannot be reached, we will exclude this sample. Finally, the ground-truth dataset consists of 1,720 UEware (i.e., 470 gambling game apps, 497 porn apps, 300 investment scam apps, 453 miscellaneous) and 831 legitimate apps. Notably, DeUEDroid is not limited to the UEware types in our ground-truth dataset. The coverage of DeUEDroid depends on the training dataset. But in this study, due to the limited time and human resources of our team, we mainly focus on these most common UEware types. We randomly select 70% of them as the training input, 20% as the validation set, and 10% as the test set.

For RQ3, we conduct a large-scale evaluation to test the performance of DeUEDroid on the real-world large-scale tasks. For this goal, we first implement a web crawler to collect real-world apps and setup the Large-scale Dataset. Based on the source of acquisition, we divide these apps into two categories: AppStore apps and wild apps. The AppStore apps are collected from formal app markets, such as Mi Store, 360 Software Manager. In contrast, wild apps are collected from covert channels, such as social platforms or websites. In total, the large-scale dataset consists of 13,460 wild apps and 10,557 market apps. After setup the dataset, we evaluate the DeUEDroid’s performance by investigating the UEware detection rate, and the time consumption. What’s more, we perform a measurement on the large-scale dataset based on DeUEDroid analysis.

In total, we setup three datasets (i.e., open-source dataset, ground-truth dataset, and large-scale dataset) containing 26,591 android apps, see details in Table 3. Note that all hardened apps that cannot be analyzed have been removed from our dataset. To the best of our knowledge, this is the first large-scale ground-truth UEware dataset, and we will release our datasets.

8.2. Implementation

To implement scene graph builder, we perform taint analysis based on Soot [56] and flowdroid [18]. We decode apps using ApkTool [6], and leverage Frontmatter [39] for UI analysis. In network imprint analysis, we additionally adopt Java string analysis techniques [26], and customize the

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Table 3: The dataset for evaluation.

| Dataset            | Component                           | Setup Time | Detail | Number |
|--------------------|-------------------------------------|------------|--------|--------|
| Open-source Dataset| Self-Developed                       | July, 2022 | No Obfuscation Apps | 5      |
|                    |                                     |            | Removing Obfuscation Apps | 5      |
|                    |                                     |            | Code Obfuscation Apps | 3      |
|                    |                                     |            | Reflect Obfuscation Apps | 3      |
|                    | Real-world                           | 2021-2022  | site.leos.setter | 1      |
|                    |                                     |            | de.digisocken.antherrss | 1      |
|                    |                                     |            | org.woheller69.weather | 25     |
| Ground-truth Dataset| UEware                              | June, 2022 | Gambling Game | 470    |
|                    |                                     |            | Porn | 497    |
|                    |                                     |            | Investment Scam | 300    |
|                    |                                     |            | Miscellaneous | 831    |
|                    | Total                                |            |        | 2,391  |
| Large-scale Dataset| Wild                                | June-July, 2022 | Apps from websites | 11,460 |
|                    | Appstore                             | June-July, 2022 | Apps from AppStore | 10,557 |
|                    | Total                                |            |        | 21,217 |
8.3. Evaluation Result

8.3.1. For RQ1. As mentioned in Sec 5, our scene graph builder has two phases: (i) UI widget identification, and (ii) UI transition determination. Note that the native widget analysis is implemented by Frontmatter [39], a SOTA GUI analysis framework that covers 84.7% native widgets. We only evaluate the effectiveness of imprint generation for web widgets and UI transition determination, which are implemented by ourselves.

First, for the imprint generation of the web widget, we list our evaluation result in Table 4. For the self-developed apps, the token number is clearly identified by our developers. In total, the App1-App5 have 36 tokens, such as IP host, domain name, and keyword. In the end, DeUEDroid identifies 37 tokens from the self-developed apps, with 3 false positive and 8 false negative (F1-score is 84.3%). For the real-world apps, we first identify the real tokens used by their web widgets. In order to guarantee the accuracy of identification, we combine dynamic and static analysis. Specifically, we first insert some logging code (i.e., logging.log()) in the source code after the network API, which does not affect the functionality of the app. Then we run the app dynamically to generate the log, and also manually analyze the source code to get the final token. The F1-score of real-world apps are range from 90.01% to 95.00%, which shows that our imprint generation is accurate with sufficient coverage.

Second, for the UI transition determination, we list our evaluation result in Table 5. Specifically, these self-developed apps are designed to be developed by certain transition types. The App1 to App4 consist of single transition type (e.g., Activity - Fragment) to evaluate the accuracy of different transition types, and App5 is implemented by all transition types to mimic the real development scenario. It can be seen from the evaluation results that IC3 can accurately identify the transition between Activity, but cannot accurately identify the transition between Activity and Fragment, nor can it handle the transition between Fragment and Navigation. What’s more, the real-world apps, the IC3 is ineffective and even can not get the result within 30 minutes. In contrast, DeUEDroid can identify all transition types and is more accurate than IC3 (97.6% vs 57.4%). To real-world apps, DeUEDroid also receives high accuracy and even the lowest F1-score is more than 72.7%.

Finally, we evaluate the anti-obfuscation capability of DeUEDroid (i.e., rename, code, reflect obfuscation). The evaluation result shows that DeUEDroid has an extremely good anti-obfuscation ability, see Table 4 and Table 5. The F1-scores of imprint generation (84.3%) and UI transition determination (97.6%) are not affected by the obfuscation techniques.

The results demonstrate the effectiveness of DeUEDroid in scene graph construction. We further explain the evaluation results. First, since we take into account all transition types rather than only activity transitions, DeUEDroid can label all kinds of sensitive APIs and perform a more accurate algorithm to identify the transition pairs. It results in the high accuracy of UI transition determination. Second, because the obfuscation (e.g., renaming, code obfuscation) has no impact on atomic APIs (e.g., transition APIs, network APIs), our UI transition determination and imprint generation are not affected by the obfuscation techniques. The well anti-obfuscation ability shows our system is enough robust against adversarial. Finally, to ensure the efficiency of our system, we set a maximum taint depth and it leads to some omissions of transition and token identification. For example, we show a mission edge in the evaluation, the mission edge consists of a long call chain (i.e., onClick() • funct1() • func2() • ... • func9() • actionStart() • startActivity()) that beyond our maximum recursion. At the same time, due to the nature of the static analysis, false positives are inevitable.

Answer RQ1: DeUEDroid is effective in scene graph construction, which can accurately identify transition pairs (over 72%) and imprint tokens (over 90%). Besides, DeUEDroid is obfuscation-resilient.

| Dataset Component | Transition Identified (F1-score) |
|-------------------|---------------------------------|
| Type              | # | IC3 | DeUEDroid |
| Self-Developed App | All | 62 | 97.6% |
| ⊢ # No Obfuscation | 1 | 96.0% |
| ⊢ # App1          | 13 | 96.3% |
| ⊢ # App2          | 13 | 92.3% |
| ⊢ # App3          | 13 | 100% |
| ⊢ # App4          | 12 | 100% |
| ⊢ # App5          | 11 | 100% |
| ⊢ # Code Obfuscation | All | 62 | 97.6% |
| ⊢ # Reflect Obfuscation | All | 62 | 97.6% |

| Real-World App    | Transition Identified (F1-score) |
|-------------------|---------------------------------|
| ⊢ # site.leos.setter | All | 5 | 72.7% |
| ⊢ # de.digisocken.anotherrss | All | 4 | 80.0% |
| ⊢ # org.woheller69.weather | All | 12 | 91.7% |

1. Act. means Activity, and Frag. means Fragment.
2. IC3 timed out within the 30 minute time limit.

TABLE 4: The evaluation of imprint generation.

TABLE 5: The evaluation of UI transition determination. The boldfaced score denotes the best result.
To observe the effectiveness of scene graph features, we compare the accuracy rate between column#3 and column#4-6. The result shows that these features can improve the detection performance of all algorithms individually. In addition, from the comparison between column#7 and column#4-6, the scene graph features perform much better than all individual features. It further demonstrates that scene graph can synthesize these individual features well, with outstanding accuracy improvement across all algorithms (ranging from 12.63% to 19.05%). The effectiveness of the scene graph features is shown by the outstanding improvement of the comparative experiments.

To observe the effectiveness of DeUEDroid algorithm, we comparing the accuracy scores of DeUEDroid line#7 with other algorithms line#2-6. And our system achieves leading performance among all algorithms, which on average exceeds the supervised algorithm 11.26% and exceeds GAE 2.26%. Note that the comparison with GAE proves that our Mask strategy can improve the robustness of our detection model. This proves that our algorithm is effective and can better handle the scene graph information.

Further, since we introduce the GAE and masking strategy, we show the Alpha and mask ratio effect of our detection results in Figure 9. From the alpha ratio effect in Figure 9, we can see that by increasing the alpha ratio from 0.0001 to 100, the accuracy first smoothly improves to 78.43% and declines then to 77.61%. The gap of ratio influence fluctuates very little, only around 0.82%. And the same to the masking ratio, the ratio influence gap is around 1.26%. The ratio effect indicates that our model is very stable and insensitive to the influence of hyper-parameters, which can guarantee stable detection results.

To show more details, we present our case study in appendix A.
There are more than half of apps (as shown in Figure 10. First, we observe the detection results on the large-scale dataset to evaluate the detection capability on real-world large-scale tasks. The detection results are astounding, though the app stores have manually checked their apps, we still find that there are some undetected UEware (21% of all apps) in AppStore.

**Answer RQ2:** DeUEDroid is effective in UEware detection, achieving 77.70% accuracy rate. Specifically, the scene graph features improve the detection capability of all algorithms (ranging from 12.63% to 19.05%), and the DeUEDroid algorithm also has a better performance than others STOA algorithms. Besides, DeUEDroid is stable and insensitive to the hyper-parameters.

**8.3.3. For RQ3.** We perform our system on the large-scale dataset to evaluate the DeUEDroid in the reality. We first observe the detection result and the performance of DeUEDroid. And then, we conduct a measurement on the scene graph.

**Detection Result.** After demonstrating the detection effectiveness of DeUEDroid, we perform our system on the large-scale dataset to evaluate the detection capability on real-world large-scale tasks. The detection results are astounding, as shown in Figure [10]. First, we observe the detection results of wild apps. There are more than half of apps (61%) in the wild are UEware (i.e., 12% of gambling, 9% of porn, 19% of investment scam, and 21% of miscellaneous), and only 39% apps are legitimate ones. Then we observe the detection results of the AppStore apps. Unexpectedly, we find the apps in the AppStore are not completely safe. Specifically, there are 21% apps in the AppStore are UEware (i.e., 2% gambling game, 1% porn, 8% investment scam and 10% miscellaneous).

To further confirm the effect of our system, we additional select detected UEware from the two dataset components for manual review. In the wild dataset, we review a total of 200 UEware, 156 apps are consistent with the manual review results, and the main inconsistency occurred in the judgment of investment scam and miscellaneous. In addition, we review 200 detected UEware in the AppStore dataset, 132 apps are consistent with the manual inspection results. In conclusion, the manual review shows DeUEDroid is effective, with the accuracy above 72%.

Further, we explain the reason why the classification accuracy of the large-scale dataset is lower than the ground-truth dataset (5% lower than the ground-truth dataset). Due to the huge difference between the UEware distribution of the ground-truth dataset and the large-scale dataset, the Out-of-distribution (OOD) of our detection model is unavoidable, and thus causes a lower accuracy rate.

Finally, the detection result shows that DeUEDroid is effective for large-scale UEware detection tasks (achieving over 72% accuracy rate after manual investigation). Even if the app stores have manually checked their apps, we still find that there are some undetected UEware (21% of all apps) in AppStore.

**Performance.** In addition, we evaluate the time consumption of our system. Overall, each app costs about 213 seconds on average, ranging from 9 seconds to 2,347 seconds. We show the average time consumption of different app sizes in Figure [11]. We can see that the time consumption increases with the size of the app. However, the time increase is stable that the time consumption fluctuation in the range of 15M-57M is within 67s. The performance results show that DeUEDroid is large-scale resilient, which is important for real-world tasks.

We further explain that the stable time consumption is attributed to scene graph based detection method. Since the app size is mainly determined by its resource files, the increase in source code (especially activity-level) is modest. Our detection method is less affected by app size, resulting the stable time consumption.

**Measurement.** In Section [3], we have an insight that the UEware are different from legitimate apps, and opt to serve as single-purpose applications. To confirm our insight, we investigate the scene graphs produced by our system, including the number of transition pairs, the widgets, and the imprint tokens, shown in Figure [12]. Specifically, the UEware are the detected ones from the large-scale dataset, while the legitimate apps are the remaining ones.

The investigation shows that the services of UEware and legitimate apps are significantly different in statistics. First, the median of transition pairs is only 71 in UEware, while there is 91 in legitimate apps. And the average transition pairs in legitimate apps are twice as many as UEware (22 in legitimate apps vs. 11 in UEware). Second, the average number of widgets owned by legitimate apps is much higher than that of UEware (227 in legitimate apps vs. 29 in UEware). Finally, turning to the network imprint. We find that their hybrid ratios are nearly the same (30% in legitimate apps vs. 29% in UEware). But the average number of tokens owned by legitimate apps is higher than that of UEware (211 in legitimate apps vs. 121 in UEware). In general, when a service is complex and multi-purpose, more transition pairs, widgets, and imprint tokens are required. So the statistical result proves that UEware is more simple.
Answer RQ3: DeUEDroid is effective and efficient in large-scale detection. One one side, the detection accuracy is 72% after manually investigating 400 detected UEware in AppStore and wild. On the other side, DeUEDroid is large-size resilient. Besides, the result suggests that 61% apps in the wild and 21% apps in the AppStore are UEware.

9. Discussion

Scene Graph Construction. As scene graph is built using static analysis, apps may leverage app harden techniques to disrupt static analysis. In addition, even though the static analysis takes into account the major factors introduced by Android (i.e., multi-threading, lifecycle, and ICCs), apps may evade our analysis by invoking sensitive APIs via reflections, native libraries, and Jbridge. In the future, we plan to incorporate dynamic analysis techniques to deal with the app harden techniques, reflections, and native libraries. Moreover, the static analysis can produce incorrect associations between activities and UIs due to its overapproximations. We plan to mitigate such issues using dynamic techniques to filter out false associations.

Network Imprint. Since DeUEDroid is built upon static techniques, it uses network imprints to identify the network features rather than fetching the real remote resources. While the network imprints are highly malleable, they are still inaccurate compared to real remote resources. In the future, we plan to combine dynamic analysis techniques to capture real network remote resources. And further, use the network discovery technology to fetch more network information.

Anti Adversary. Our model is learned from the behaviors of the ground-truth UEware dataset. To avoid our detection, adversaries may download our dataset and find patterns of behavior that are not covered in it. For example, they can use native reflections and specially designed activity transformations to mislead our detection model. And we admit that these adversaries against the dataset cannot be prevented due to our limited dataset. Since the dataset is collected manually by our team, the number and coverage of samples are limited.

However, we claim that enterprises can supplement the dataset by themselves to improve the coverage, thereby improving the accuracy and avoiding attacks on the model coverage. What’s more, to improve our model robustness, we have introduced many techniques, such as anti-obfuscation, and Mask strategy. Due to our anti-adversary techniques, designing a UEware pretending to be normal from the learned model are non-trivial. As a result, our technique significantly raises the bar for potential attacks.

10. Related Work

Android Static Analysis. To better analyze the Android app, existing works [18], [59], [63] have made a lot of work on building up the call graphs. Since the complex Android environment, they connect edges by enumerating all possible combinations within lifecycle methods. Due to the addition of taint analysis, it consumes too much time and is unavoidable to have a high false positive when introduced in UI handler analysis. Meanwhile, to build up an accurate call graph, the ICC requires additional solutions. There are some works [49]–[51] focused on the ICC analysis by leveraging the taint analysis and program analysis techniques. And some works [70] leveraged machine learning approaches. In addition, considering the impact of multi-threading, some works [61], [62] connected certain multi-thread handles, so as to better improve the accuracy of the call graph. Then based on the call graph, Azim et al. [19] first present the activity transition graph, Chen et al. [22] took into account the inner class extra. However, their activity transition graphs lacked consideration for system-level callback listener and fragment navigation. Our static analysis is based on the above-mentioned works, and has supplemented some shortcomings.

Android GUI Analysis. Yang et al. [63], [64] leveraged context-sensitive analysis of callback methods and developed a client analysis that builds a static GUI model and window transition graph. StoryDroid [22] recorded all XML layout code and dynamic view binding code, rebuild a new app based on this code, and finally took a snapshot. StoryDroid used these screenshots as the representation of the GUI. AppIntent [65] used the taint analysis from the UIs to analyze the location that may cause sensitive data leakage. AsDroid [36] compares the GUI attribution and code behavior to find out the stealthy behavior against the normal GUI attribution. UIPicker [48] extracted UI layout resources and program code, and further analyzed them for the sensitive information locations. PERUIM [43] focused on the permissions used behind the UIs, and connected the UIs with their handlers.

Malware Detection. Arora et al. [17] proposed a detection model by extracting the permission pairs from the Manifest file. Chen et al. [20] characterized existing Android ransomware and proposed a real-time detection system by monitoring the user interface widgets. DeepReflect [28] focused on malicious functionalities based upon binary, improved the robust of malware detection. Zhang et al. [68] proposed a enhanced framework to help AI-based module detect evolved Android malware.
11. Conclusion

In this study, we have proposed a novel UEware detection approach based on the scene graph. This approach first builds scene graph for the training APKs, and then extracts features of scene graph. After that, it applies a machine learning method to train the classifier to detect UEware. We then proposed and implemented a prototype system named DeUEDroid to perform the detection. Our evaluation demonstrates that DeUEDroid is efficient and effective. First, DeUEDroid can accurately construct the scene graph, which can accurately identify transition pairs (over 72%) and imprint tokens (over 90%). Then the evaluation result shows that DeUEDroid can detect discrepancies with accuracy values 77.70% for demystifying gambling game, porn, underground loan, financial scam, and legitimate apps. Our system has a significant effect on improving detection accuracy. Finally, DeUEDroid is effective and efficient for large-scale tasks. By using DeUEDroid, we found that UEware are prevalent, i.e., 61% apps in the wild and 21% apps in the app stores are UEware (with over 72% accuracy after the manual investigation).

References

[1] https://www.gamblingsites.org/apps/popularity June 2012. Accessed June 2012.
[2] https://developer.android.com/guide/components/activities/intro-activities November 2021. Accessed November 23, 2021.
[3] Bbc report about romance scammer. https://edition.cnn.com/2021/02/21/us/losses-to-romance-scams-trnd/index.html January 2021. Accessed January 1, 2021.
[4] China gambling report. http://english.www.gov.cn/statecouncil/Bbc report about romance scammer. https://edition.cnn.com/2021/02/21/us/losses-to-romance-scams-trnd/index.html January 2021. Accessed January 1, 2021.
[5] Reflect obfuscation technique. https://allatori.com, June 2022. Accessed June 4, 2022.
[6] Apktool—a tool for reverse engineering android apk files. https://developer.android.com/studio/build
[7] Apps for economy. https://42matters.com/blog/?p=
[8] Fragment navigation. https://developer.android.com/guide/navigation/getting-started, June 2022. Accessed June 4, 2022.
[9] Android studio r8. https://venturebeat.com/2020/11/23/shrink-code?hl=zh-cn June 2022. Accessed June 4, 2022.
[10] State of mobile in 2022. https://www.data.ai/en/go/state-of-mobile-2022 June 2022. Accessed June 8, 2022.
[11] Us gambling report. https://www.forbes.com/sites/willyakowicz/2022/02/15/us-gambling-revenue-hit-record-53-billion-in-2021/?sh=7a270758fd50 June 2022. Accessed June 6, 2022.
[12] Us gambling report. https://www.forbes.com/sites/willyakowicz/2022/02/15/us-gambling-revenue-hit-record-53-billion-in-2021/?sh=7a270758fd50 June 2022. Accessed June 6, 2022.
[13] Hybrid app percentage in app-store. https://venturebeat.com/2020/11/23/why-74-of-the-top-50-retail-apps-are-hybrid-apps-not-native-apps/ June 2022. Accessed August 8, 2022.
[14] Why 74% of the top 50 retail apps are hybrid-apps-not-native-apps/ June 2022. Accessed August 8, 2022.
[15] Faraz Ahmed, Haider Hameed, M Zubair Shafiq, and Muddassar Farooq. Using spatio-temporal information in api calls with machine learning algorithms for malware detection. In Proceedings of the 2nd ACM Workshop on Security and Artificial Intelligence, pages 55–62, 2009.
[16] Simone Aonzo, Gabriel Claudiu Georgiuc, Luca Verderame, and Alessio Merlo. Obfuscapk: An open-source black-box obfuscation tool for android apps. SoftwareX, 11:100403, 2020.
[17] Anshul Arora, Sateesh K Peddoju, and Mauro Conti. Permpair: Android malware detection using permission pairs. IEEE Transactions on Information Forensics and Security, 15:1968–1982, 2019.
[18] Steven Arzt, Siegfried Rasthofer, Christian Fritz, Eric Bodden, Alexandre Bartel, Jacques Klein, Yves Le Traon, Damien Octeau, and Patrick McDaniel. Flowdroid: Precise context, flow, field, object-sensitive and lifecycle-aware taint analysis for android apps. Acm Sigplan Notices, 49(6):259–269, 2014.
[19] Taznirul Azim and Julian Neamtiu. Targeted and depth-first exploration for systematic testing of android apps. In Proceedings of the 2013 ACM SIGPLAN international conference on Object oriented programming systems languages & applications, pages 641–660, 2013.
[20] Jing Chen, Chiheng Wang, Ziming Zhao, Kai Chen, Ruiying Du, and Gail-Joon Ahn. Uncovering the face of android ransomware: Characterization and real-time detection. IEEE Transactions on Information Forensics and Security, 13(5):1286–1300, 2017.
[21] Kai Chen, Peng Wang, Yeonjoon Lee, Xiaofeng Wang, Nan Zhang, Heqiang Huang, Wei Zou, and Peng Liu. Finding unknown malware in 10 seconds: Mass vetting for new threats at the {Google-Play} scale. In 24th USENIX Security Symposium (USENIX Security 15), pages 659–674, 2015.
[22] Sen Chen, Lingling Fan, Chunyang Chen, Ting Su, Wenhe Li, Yang Liu, and Lihua Xu. Storydroid: Automated generation of storyboard for android apps. In 2019 IEEE/ACM 41st International Conference on Software Engineering (ICSE), pages 596–607. IEEE, 2019.
[23] Yi Chen, Wei You, Yeonjoon Lee, Kai Chen, Xiaofeng Wang, and Wei Zou. Mass discovery of android traffic imprints through instantiated partial execution. In Proceedings of the 2017 ACM SIGSAC Conference on Computer and Communications Security, pages 815–828, 2017.
[24] Zhuo Chen, Lei Wu, Jing Cheng, Yubo Hu, Yajin Zhou, Zhushou Tang, Yexuan Chen, Jinku Li, and Kui Ren. Lifting the grey curtain: A first look at the ecosystem of culpritware. arXiv preprint arXiv:2106.05756, 2021.
[25] Wei-Lin Chiang, Xuanying Liu, Si Si, Yang Li, Samy Bengio, and Cho-Jui Hsieh. Cluster-gcn: An efficient algorithm for training deep and large graph convolutional networks. In Proceedings of the 25th ACM SIGKDD international conference on knowledge discovery & data mining, pages 257–266, 2019.
[26] Aske Simon Christensen, Anders Møller, and Michael I. Schwartzbach. Precise analysis of string expressions. In Proc. 10th International Static Analysis Symposium (SAS), volume 2694 of LNCS, pages 1–18. Springer-Verlag, June 2003. Available from http://www.brics.dk/JSA/.
[27] Feng Dong, Haoyu Wang, Li Li, Yao Guo, Tagawendé F Bissyandé, Tianming Liu, Guoai Xu, and Jacques Klein. Frauddroid: Automated ad fraud detection for android apps. In Proceedings of the 2016 26th ACM Joint Meeting on European Software Engineering Conference and Symposium on the Foundations of Software Engineering, pages 257–268, 2018.
[28] Evan Downing, Yisroel Mirsky, Kyuhong Park, and Wenke Lee. Deeprefect: Discovering malicious functionality through binary reconstruction. In 30th {USENIX} Security Symposium ({USENIX} Security 21), 2021.
[29] William Enck, Machigār Ongtang, and Patrick McDaniel. On lightweight mobile phone application certification. In Proceedings of the 10th ACM conference on Computer and communications security, pages 235–245, 2009.
[30] Parvez Faruki, Vijay Laxmi, Ammar Bharmal, Manoj Singh Gaur, and Vijay Ganmoor. Androsimilar: Robust signature for detecting variants of android malware. Journal of Information Security and Applications, 22:68–80, 2015.

[31] Tatiana Frenklach, Dvir Cohen, Asaf Shabtai, and Rami Pazis. Android malware detection via an app similarity graph. Computers & Security, 109:102386, 2021.

[32] Yuhao Gao, Haoyu Wang, Li Li, Xiapu Luo, Guoai Xu, and Xuanzhe Liu. Demystifying illegal mobile gambling apps. In Proceedings of the Web Conference 2021, pages 1447–1458, 2021.

[33] Kaveh Hassani and Amir Hosein Khasahmadi. Contrastive multi-view representation learning on graphs. In International Conference on Machine Learning, pages 4116–4126. PMLR, 2020.

[34] Geoffrey E Hinton and Richard Zemel. Autoencoders, minimum description length and helmholtz free energy. Advances in neural information processing systems, 6, 1993.

[35] Yangyu Hu, Haoyu Wang, Yajin Zhou, Yao Guo, Li Li, Bingxuan Luo, and Fangyen Xu. Dating with scambots: Understanding the ecosystem of fraudulent dating applications. IEEE Transactions on Dependable and Secure Computing, 2019.

[36] Jianjun Huang, Xiangyu Zhang, Lin Tan, Peng Wang, and Bin Liang. Android: Detecting stealthy behaviors in android applications by user interface and program behavior contradiction. In Proceedings of the 36th International Conference on Software Engineering, pages 1036–1046, 2014.

[37] Taeguen Kim, Boojooong Kang, Mina Rho, Sakir Sezer, and Eul Gyu Im. A multimodal deep learning method for android malware detection using various features. IEEE Transactions on Information Forensics and Security, 14(3):773–788, 2018.

[38] Thomas N Kipf and Max Welling. Variational graph auto-encoders. arXiv preprint arXiv:1611.07030, 2016.

[39] Konstantin Kaznetsow, Chen Fu, Song Gao, David N Jansen, Li-jun Zhang, and Andreas Zeller. What do all these buttons do? statically mining android user interfaces at scale. arXiv preprint arXiv:2105.03144, 2021.

[40] Jin Li, Lichao Sun, Qiben Yan, Zhiquiang Li, Witawas Srisa-An, and Eric Bodden. A multimodal deep learning method for android malware detection using various features. IEEE Transactions on Information Forensics and Security, 14(3):773–788, 2018.

[41] Konstantin Kaznetsow, Chen Fu, Song Gao, David N Jansen, Li-jun Zhang, and Andreas Zeller. What do all these buttons do? statically mining android user interfaces at scale. arXiv preprint arXiv:2105.03144, 2021.

[42] Li Li, Tegawendé F Bissyandé, and Jacques Klein. Simidroid: Identifying and explaining similarities in android apps. In 2017 IEEE TrustCom/BigDataSE/ICESS, pages 136–143. IEEE, 2017.

[43] Yu Rong, Wenbing Huang, Tingyang Xu, and Junzhou Huang. Drope-dge: Towards deep graph convolutional networks on node classification. arXiv preprint arXiv:1907.10903, 2019.

[44] Atanas Rountev and Dacong Yan. Static reference analysis for gui objects in android software. In Proceedings of Annual IEEE/ACM International Symposium on Code Generation and Optimization, pages 143–153, 2014.

[45] Petar Veličković, Guillem Cucurull, Arantxa Casanova, Adriana Romero, Pietro Lio, and Yoshua Bengio. Graph attention networks. arXiv preprint arXiv:1710.10903, 2017.

[46] Fengguo Wei, Ninad Kulkarni, and Xinxuan Ou. Amdroid: A precise and general inter-component data flow analysis framework for security vetting of android apps. In Proceedings of the 2014 ACM SIGSAC Conference on Computer and Communications Security, pages 1329–1341, 2014.

[47] Michelle Y Wong and David Lie. Intellidroid: A targeted input generator for the dynamic analysis of android malware. In NDSS, volume 16, pages 21–24, 2016.
Appendix

Case Study To better illustrate the effectiveness of our proposed method, we show some example details. First, we use the visualization technology TSNE to show the clustering result through manifest feature (i.e., app name, package name, certificate, app size), and clustering result through scene graph, as shown in Figure 17. Specifically, we take two same type apps as an example (com.a0gq1n.dpoe9, com.a16gpj.y8or7). Their manifest information is different, which leads to a long distance in the manifest clustering. However, since their scene graph embeddings are highly similar, we can attribute them to the same type in scene graph clustering.

Figure 17: The clustering comparison between manifest based and scene graph based.

Notably, web widget feature is valid for hybrid apps. We show some cases implemented by a single activity and several webview widgets (e.g., antv.com, chunyuzb.com). These cases cannot be accurately identified by graph topology and UI widgets, as their implementation relies mainly on webview and lacks scene graph information (only 3 transition pairs and 2 webview widgets). But since we generated their imprint tokens (e.g., 1080kan.cc, api/ui/share, 91porn), we can well identify such UEware based on their token similarity.
Figure 13: The screenshots of an underground loan App#1.

Figure 14: The screenshots of an underground loan App#2.

Figure 15: The screenshots of a gambling App.
Figure 16: The design overview of App5. The edge label
1 means transition between Activity, 2 means transition
between Activity-Fragment, 3 means transition between
Fragment.