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Mining permission patterns for contrasting clean and malicious android applications

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HIGHLIGHTS

- A pattern mining algorithm is proposed to identify contrast permission patterns.
- We collected a new dataset with 1227 clean Android applications.
- We considered both required and used permission.
- Biclustering method has been employed to provide visualization.
- The permission patterns show big contrasts between clean apps and malware.

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ABSTRACT

An *Android* application uses a permission system to regulate the access to system resources and users' privacy-relevant information. Existing works have demonstrated several techniques to study the required permissions declared by the developers, but little attention has been paid towards used permissions. Besides, no specific permission combination is identified to be effective for malware detection. To fill these gaps, we have proposed a novel pattern mining algorithm to identify a set of contrast permission patterns that aim to detect the difference between clean and malicious applications. A benchmark malware dataset and a dataset of 1227 clean applications has been collected by us to evaluate the performance of the proposed algorithm. Valuable findings are obtained by analyzing the returned contrast permission patterns.

1. Introduction

Smartphone is used to describe a mobile device equipped with enhanced computing capability and connectivity [1], such as *Nexus* by *Google* [2], *iPhone* by *Apple* [3], *Blackberry* by *RIM* [4] and *Windows Phone* by *Microsoft* [5]. In the past few years, the global telephony industry has witnessed an upsurge in the sales of smartphones. A smartphone is usually sold with an in-built mobile operating system (OS) together with a number of pre-installed "applications" packaged by the device manufacturer. An *application*, the software running on smartphones, enhances the smartphone's functionality and supports the interaction with end users to accomplish their tasks. *Calendar*, *address book*, *alarm clock*, *media player* and *web browser* are the common applications provided by the device manufacturers, but one important application exists on every smartphone—the "*application store*", which allows end users to access *online application markets* to browse and download additional applications of their choice.

Every device manufacturer hosts an application market for its own OS platform, such as *Apple*'s *App Store* [6], *Blackberry*'s *App World* [7] and *Google Play* [8]. However, far before the first *official application markets* were introduced in 2008 by *Apple*, smartphone application distribution was highly dependent on *third-party* sources, where individual application developers were free to upload their products. Due to a huge number of low-price applications being available, there is still a large group of end users who prefer visiting *third-party application markets*, but not all the applications from markets are "*safe*". The software that is specially designed to harm a device, its OS or other software is called "*Malware*", which stands for *mal*icious soft*ware* [9]. The increasing sales of smartphones has pushed the rapid growth of mobile malware.

As pointed out by Zhou and Jiang [10], malware or malicious applications might cause a series of user unexpected operations, for example, stealing user's personal information, making calls or sending an SMS without the user's knowledge. Such malicious behaviors not only cost users extra data usage, but also potentially bring privacy issues. Furthermore, the users may not be aware of

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running malware on their smartphones because in many cases the malware are downloaded and/or installed without authorization. Accordingly, an efficient and effective malware detection technique is highly demanded to protect smartphone users from the potential prevalence.

To effectively detect malware from millions of applications available on official and third-party markets, many efforts have contributed to studying the nature of smartphone platforms and their applications in the past decade. As the most popular mobile platform, *Google*'s *Android* overtook others to be the top mobile malware platform. The *Android* platform employs the permission system to restrict applications' privileges to secure the users' privacy-relevant resources [11]. An application needs to get a user's approval for the requested permissions to access the privacy-relevant resources. Thus, the permission system was designed to protect users from applications with invasive behaviors, but its effectiveness highly depends on the user's comprehension of permission approval. We refer to the permissions that are requested during application installation as *required permissions*. Unfortunately, not all the users read or understand the warnings of required permissions shown during installation. To improve this situation, many researchers have tried to interpret *Android* permissions and their combinations [12–15]. Frank et al. [11] proposed a probability model to identify the common required permission patterns for all *Android* applications. Zhou and Jiang [10] listed the top required permissions for both clean and malicious applications, but only individual permissions were considered by frequency counting. A problem is still remaining of whether the patterns in a permission combination can provide better performance for malware detection. Furthermore, in the existing literature, only the required permissions are considered in permission pattern mining, no work has incorporated the *used permissions* that are extracted from static analysis by the *Andrubis* system (http://anubis.iseclab.org) [16]. Therefore, we are the first group to explore both the required and used permissions. Accordingly, our aim is *to propose an efficient pattern mining method to identify a set of contrast permission patterns that effectively distinguish malware from the clean applications*.

By using a pattern mining technique to identify the desired permission patterns, we need two datasets: one has only clean *Android* applications and the other contains all malicious ones. In 2012, Zhou and Jiang [10] published the first benchmark dataset of malicious applications in 49 malware families, which was collected from third-party markets between August 2010 and October 2011. This is an ideal malware dataset for our experiments. On the other hand, due to the lack of a dataset of clean applications published at the same time period as Zhou and Jiang's, we collected our own clean dataset. The clean applications were collected from two popular third-party *Android* applications markets: *SlideME* (http://slideme.org) and *Pandaapp* (http://android.pandaapp.com). We sorted the collected applications based on the times of their download and the ratings given by the users, and only the top ones were picked. Each application was scanned by forty-three antivirus engines on *VirusTotal* (https://www.virustotal.com) [17], and only the ones that passed all virus tests were considered as "clean" and kept to form the clean dataset. These clean applications do not impede on the smooth execution of the OS. Like Zhou and Jiang, we represent applications in the collected clean dataset using a vector of 130 binary values, each of which is associated with one of the 130 official *Android* permissions. A value 1 is assigned to a permission only if it is required or used by an application, otherwise, 0 is given instead.

The novelty and contributions of this work can be summarized as follows:

- We collected a new dataset that contains 1227 clean applications that were uploaded to third-party markets from August 2010 to October 2011.
- Beyond the current studies that focused on *required permissions* only, we also considered the *used permissions*.
- We utilized a hierarchical *Biclustering* method to initially analyze both clean and malware datasets. The obtained resulting figures provided a straightforward preview of the data distribution, from which we built up our model of mining a set of permissions rather than using individual permissions as the patterns.
- We proposed a contrast permission pattern mining algorithm to identify the interesting permission sets that can be used to distinguish applications from malicious to clean.
- Our demonstration of the proposed *Contrast Permission Pattern Mining* proved that both required and used permissions should be considered in late malware detection tasks.

The rest of the paper is organized as follows: Section 2 briefly reviews the concepts of the *Android* platform, its applications, the permission system and the current research work in malware detection. In Section 3, we present our initial analysis on the collected datasets using a statistical method and *biclustering* followed by the proposed contrast pattern mining algorithm. The experiments and the obtained results are then reported in Section 4 followed by a further discussion on findings. Finally, Section 5 concludes the entire paper together with our future work.

2. Background and related work

2.1. Android

Android is a Linux-based OS which was designed and developed by the *Open Handset Alliance* in 2007 [18]. The *Android* platform is made up of multiple layers consisting of the OS, the Java libraries and the basic built-in applications [19]. Additional applications can be downloaded and installed from either official or third-party markets.

Google provides the application developer community with a *Software Development Kit* (SDK) [20] to build *Android* applications and it includes a collection of Java libraries and classes, sample applications and developer documentations. The SDK can be used as a plug-in for Eclipse IDE [21] and therefore allows developers to code their applications in a rich Java environment. One particularly useful feature of the SDK is the *Android emulator* which allows developers to test their applications in virtual devices on various versions of *Android* OS.

An *Android* application includes two folders and one file: (i) Class, (ii) Resources and (iii) AndroidManifest.xml. The Class folder contains the application's source code in Java; the Resources folder stores the multimedia files; and the `AndroidManifest.xml` file lists the required permissions that are declared by the developer. After the Java source code is done, it is then compiled and converted into Dalvik byte code [22] and bundled with the Resources folder and `AndroidManifest.xml` file to generate the *Android Application Package* (APK). Finally, before the APK can be installed on a device or emulator, the develop has to generate a key and sign the application.

Android developers can upload their applications to either the official market, *Google Play* [23], or any third-party market. To secure the privacy-relevant resources for its users, *Google* provides automatic antivirus scanning [24]. The applications will be rejected from *Google Play* if any malicious content is detected. From 2012, *Google* has extended its antivirus service on the new *Android* 4.2 OS, which is claimed to be able to scan applications before they are installed on the device [25].

2.1.1. Android permission system

Google applies the permission system as a measure to restrict access to privileged system resources. Application developers have to explicitly mention the permissions that need user's approval

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in the `AndroidManifest.xml` file. *Android* adopts an 'all-or-nothing' permission granting policy. Hence, the application is installed successfully only when the user chooses to grant access to all of the required permissions.

There are currently 130 official *Android* permissions that are categorized into four types: *Normal*, *Dangerous*, *Signature* and *SignatureOrSystem* [26]. *Normal* permissions do not require the user's approval but they can be viewed after the application has been installed. *Dangerous* permissions require the user's confirmation before the installation process starts; these permissions have access to restricted resources and can have a negative impact if used incorrectly. A permission in the *Signature* category is granted without the user's knowledge only if the application is signed with the device manufacturer's certificate. The *SignatureOrSystem* permissions are granted only to the applications that are in the *Android* system image or are signed with the device manufacturer's certificate. Such permissions are used for special situations where the applications, built by multiple vendors, are stored in one system image and share specific features.

After an application is installed, a set of application programming interfaces (APIs) are called during the runtime. Each API call is associated with a particular permission. When an API call is made, the *Android* OS checks whether or not its associated permission has been approved by the user. Only a match result will proceed to execute the certain API call. In this way, the required permissions are able to protect the user's privacy-relevant resource from the unauthorized operations. However, it cannot fully stop the malware developers who can declare any required permissions for their applications. With this reason, several studies have tried to identify the common required permissions that are frequently declared by *Android* application developers.

By applying the *Self-Organizing Map* (SOM) algorithm, Barrera et al. [12] studied the trends of permission requests from a dataset of 1, 100 applications downloaded from the official market. Frank et al. [11] selected 188,389 applications from the official market and analyzed the combinations of permission requests by these applications. A probabilistic method was proposed to deduce the popular permission patterns based on the applications' popularity (ratings together with number of reviews), that is, the deviation of permission requests for high- and low-ranked applications. Bartel et al. [27] proposed an automated tool that can statistically analyze the methods defined in an application and subsequently generate the permissions required by the application. This in turn ensures that the user does not grant access to unnecessary permissions when installing the application. A model designed by Sanz et al. [28] is based on features which comprised solely of *Android* permissions. These works studied the applications that were collected mainly from the official market. The results and findings help us to understand the *Android* permission system and the patterns for normal permission requests. However, comparing with the clean applications, we are more interested in the abnormal permission requests, which are considered as more valuable to help detect the malware and their malicious behaviors.

2.2. Android malware detection with permissions

Malware detection is an emerging topic in *Android* application study with many successful achievements, but not much attention has been paid to detection using permission patterns. Rassameeroj and Tanahashi [29] used visualization techniques and clustering algorithms to reveal normal and abnormal permission request combinations. They evaluated their methodology on a dataset comprising of 999 applications. After analyzing the extracted permission combinations, they claimed that nearly 8% of the applications were potentially malicious. Chia et al. [15] argue that the current user-rating system is not a reliable source of measurement to predict whether or not an application is malicious. Their dataset consisted of 650 applications from the official market and 1,210 applications from a third-party market. The required permissions were extracted from the dataset, together with other application-related information to develop a risk signal mechanism for detecting malware. Sahs and Khan [30] focused on feature representation as one of the challenges of malware detection. The features to be represented included: (i) permissions extracted from manifest files and (ii) control flow graphs for each method in an application. Each feature was processed independently using multiple kernels and a one-class *Support Vector Machine* to train the classifiers was applied. However, the evaluation results showed that the common features existing in both clean and malware datasets cause a detection error rate. Wu et al. [31] put forward a static feature-based technique that can aid towards malware detection. First, they apply *K-means* algorithms to generate the clusters and use *Singular Value Decomposition* to determine the number of clusters. In the second step, they classify clean and malicious applications using the *k-Nearest Neighbor* (kNN) algorithm. Zhou et al. [32] proposed a two-layered system known as, *DroidRanger* that makes use of "permission-based behavioral foot-printing and heuristics-based filtering". The authors observed that the permissions extracted from the `AndroidManifest.xml` files of malicious applications gave an insight into uncommon permission requests by some malware families. In Sanz et al.'s work [28], they extracted the permissions and the hardware features to build the feature set. As a result, clean applications require two to three permissions on average, but some of malicious applications only have one permission and are still able to carry out the attack.

Most of the work extracted a feature set to represent the applications. The information carried by those features was different from work to work. There is no evidence to show which features give the best detection result, but required permissions are considered in each study. Accordingly, we are interested in taking the permissions as the only features to represent the applications and expect to find specific permission patterns to show the difference between clean and malicious applications.

2.3. Summary

Malware proliferation is rising exponentially and the attack vectors used by malware authors are getting more sophisticated. Current solutions proposed to thwart attacks by malicious applications will struggle to keep up with the increase of malware. The *Android* platform relies heavily on its permission system to control access to restricted system resources and private information stored on the smartphone. As demonstrated by [11,33,34], permissions that are requested by applications during installation can be helpful in identifying permission patterns.

However, we identify the following problems in the existing literature:

Problem 1 What required permission patterns can be used to detect malicious applications?
Problem 2 What used permission patterns can be used to detect malicious applications?
Problem 3 Can we extract useful information by incorporating used permissions into the permission patterns?
Problem 4 What method can we use to identify these expected permission patterns?

In this paper, we aim to extend the current statistical method used for identifying permission patterns in *Android* applications by applying pattern mining techniques to a set of clean and malicious applications in order to better understand the similarities and differences between these two datasets. With the help of visualization

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Table 1
Top 20 required permissions by clean and malicious applications.

Clean applications		Malicious applications	
Required permission	Frequency	Required permission	Frequency
INTERNET	1121 (91.36%)	INTERNET	1199 (97.72%)
ACCESS_NETWORK_STATE	663 (54.03%)	ACCESS_COARSE_LOCATION	1146 (93.40%)
READ_PHONE_STATE	391 (31.87%)	VIBRATE	994 (81.01%)
WRITE_EXTERNAL_STORAGE	362 (29.50%)	WRITE_EXTERNAL_STORAGE	823 (67.07%)
ACCESS_COARSE_LOCATION	236 (19.23%)	READ_SMS	779 (63.49%)
VIBRATE	210 (17.11%)	WRITE_SMS	762 (62.10%)
WAKE_LOCK	188 (15.32%)	READ_CONTACTS	680 (55.42%)
ACCESS_FINE_LOCATION	162 (13.20%)	BLUETOOTH	633 (51.59%)
GET_TASKS	125 (10.19%)	WRITE_CONTACTS	542 (44.17%)
SET_WALLPAPER	102 (8.31%)	DISABLE_KEYGUARD	491 (40.02%)
ACCESS_WIFI_STATE	64 (5.22%)	WAKE_LOCK	471 (38.39%)
RECEIVE_BOOT_COMPLETED	60 (4.89%)	RECORD_AUDIO	461 (37.57%)
READ_CONTACTS	58 (4.73%)	ACCESS_FINE_LOCATION	446 (36.35%)
WRITE_SETTINGS	45 (3.67%)	ACCESS_NETWORK_STATE	416 (33.90%)
CAMERA	43 (3.50%)	READ_PHONE_STATE	414 (33.74%)
CALL_PHONE	42 (3.42%)	SET_ORIENTATION	413 (33.66%)
SEND_SMS	34 (2.77%)	CHANGE_WIFI_STATE	384 (31.30%)
RESTART_PACKAGES	32 (2.61%)	READ_LOGS	361 (29.42%)
RECEIVE_SMS	31 (2.53%)	BLUETOOTH_ADMIN	342 (27.87%)
RECORD_AUDIO	27 (2.20%)	RECEIVE_BOOT_COMPLETED	325 (26.49%)

graphs, we establish possible connections between required permissions and used permissions in order to extrapolate emerging permission patterns that are frequently requested by applications. Then, we apply contrast set mining on the permissions patterns from clean and malicious applications to identify which patterns are most prevalent in each dataset.

3. Mining permission patterns

The common methods used widely to analyze *Android* permissions are statistical ones, such as frequency counting by Zhou and Jiang [10], and the probabilistic model by Frank et al. [35]. Thus, we started our work from an initial analysis on the clean and malware datasets using frequency counting following Zhou and Jiang's work and extend it to explore used permissions. As inspired by the work of Barrera et al. [12] who utilized SOM for application clustering and visualization, we would like to employ the *Biclustering* algorithm to group not only the applications but also the permissions. Finally, a novel contrast permission pattern mining algorithm is presented to identify specific permission patterns that help to distinguish clean and malicious applications.

3.1. Classic statistical analysis on android permissions

We employed statistical analysis to study both required and used permissions for clean applications as well as malicious ones, so four sub-datasets were further extracted: (1) Required permissions for clean applications; (2) Required permissions for malicious applications; (3) Used permissions for clean applications; and (4) Used permissions for malicious applications. Direct frequency counting is employed on all four sub-datasets to find out the most popular permissions required or used by clean and malicious applications.

By comparing the top 20 required permissions for clean and malicious applications listed in Table 1, we found that malicious applications requested a total of 14,758 permissions, which was much more than clean applications (4,470 permissions). Among these permissions, we found some of them only appeared in one dataset, that is, those permissions are only requested or used by clean applications but not malicious ones, and vice versa. We call these permissions 'unique permissions'. Similarly, we name those permissions that appear in both clean and malware datasets as 'common permissions'. Totally, there are 33 unique required permissions for clean applications and 20 for malicious ones; and also 70 common required permissions. Another 5 permissions have never been requested by any application. For used permissions, there are 9 unique ones for clean applications and only 4 for malicious ones. The number of commonly used permissions drops to 28, and a large number of 87 permissions have never been used by any application. Four common permissions were most frequently required by both clean and malicious applications: `INTERNET`, `ACCESS_COARSE_LOCATION`, `WRITE_EXTERNAL_STORAGE` and `VIBRATE`. In contrast, there were nine out of twenty required permissions that appeared frequently in the malware dataset than in the clean one. Malicious applications need permissions to read or write an SMS rather than clean applications which prefer to get the approval of sending an SMS. `BLUETOOTH`-related permissions are also popular for malicious applications as well. In addition, malicious applications have a greater desire to get access to change data on smartphones than clean applications, for example, they request more to write contacts, to set orientation, and to change WiFi state. On the other hand, by listing the top 20 used permissions for clean and malicious applications, there is a small difference that can be observed from Table 2. Sixteen out of twenty popular used permissions are commonly existing in both datasets.

A classic statistical method like direct frequency counting is good at identifying single permissions that are popular in each sub-dataset respectively. However, it still needs manual checking to compare the obtained permission lists for clean and malicious applications. Moreover, the counting process becomes complicated and time-consuming in order to consider permission combinations instead of single permissions. Therefore, we continued the analysis of *Android* permissions with the *biclustering* algorithm in the next step, which is able to provide a visualization of the relationship between permissions and applications.

3.2. Visualization using biclustering

Biclustering [36] is a special cluster analysis method, which applies classic clustering to both rows and columns simultaneously in a two-dimensional data matrix. In this work, *biclustering* can help group applications that request or use different permission combinations as well as show us the clusters of permission combinations based on the various applications associated with them.

The *biclustering* is achieved by performing *Agglomerative Hierarchical Clustering* (AHC) [37,38] on both dimensions of the data matrix. The *AHC* is first applied along the columns of the data

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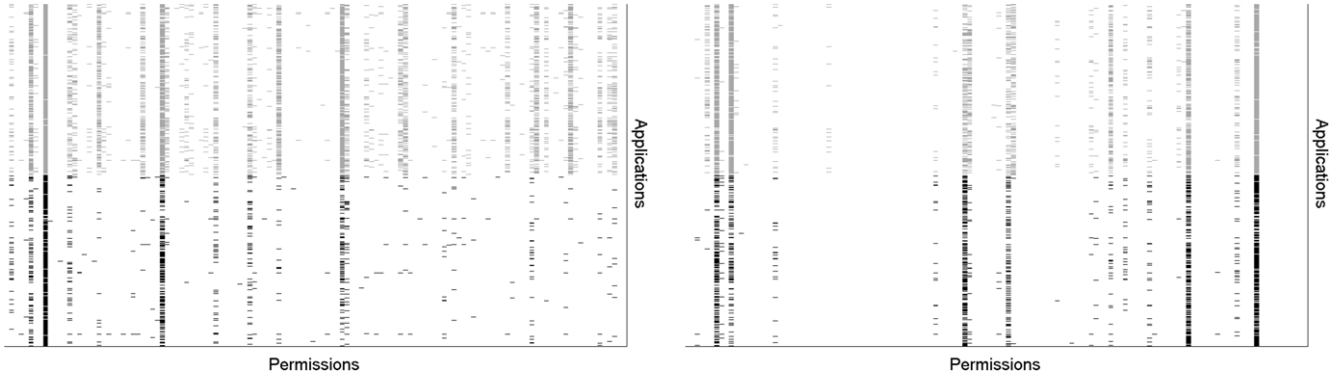
Table 2
Top 20 used permissions by clean and malicious applications.

Clean applications		Malicious applications	
Used permission	Frequency	Used permission	Frequency
INTERNET	1029 (83.86%)	INTERNET	1161 (94.62%)
WAKE_LOCK	816 (66.50%)	ACCESS_COARSE_LOCATION	1125 (91.69%)
ACCESS_NETWORK_STATE	738 (60.15%)	VIBRATE	954 (77.75%)
VIBRATE	608 (49.55%)	WAKE_LOCK	826 (67.32%)
READ_PHONE_STATE	457 (37.25%)	ACCESS_WIFI_STATE	584 (47.60%)
ACCESS_COARSE_LOCATION	372 (30.32%)	ACCESS_NETWORK_STATE	519 (42.30%)
SET_WALLPAPER	126 (10.27%)	READ_SMS	473 (38.55%)
ACCESS_FINE_LOCATION	116 (9.45%)	WRITE_CONTACTS	426 (34.72%)
GET_ACCOUNTS	98 (7.99%)	READ_PHONE_STATE	354 (28.85%)
ACCESS_WIFI_STATE	85 (6.93%)	RECORD_AUDIO	319 (26.00%)
READ_SMS	82 (6.68%)	SET_WALLPAPER	297 (24.21%)
RESTART_PACKAGES	65 (5.30%)	ACCESS_FINE_LOCATION	199 (16.22%)
GET_TASKS	61 (4.97%)	GET_ACCOUNTS	178 (14.51%)
CHANGE_CONFIGURATION	55 (4.48%)	GET_TASKS	124 (10.11%)
RECEIVE_SMS	37 (3.02%)	RECEIVE_BOOT_COMPLETED	111 (9.05%)
FLASHLIGHT	37 (3.02%)	ACCESS_CACHE_FILESYSTEM	101 (8.23%)
WRITE_CONTACTS	34 (2.77%)	WRTIE_OWNER_DATA	59 (4.81%)
RECEIVE_BOOT_COMPLETED	23 (1.87%)	CHANGE_CONFIGURATION	52 (4.24%)
WRTIE_OWNER_DATA	12 (0.98%)	READ_HISTORY_BOOKMARKS	49 (3.99%)
WRITE_SETTINGS	10 (0.81%)	EXPAND_STATUS_BAR	41 (3.34%)



(a) Required permissions.

(b) Used permissions.

Fig. 1. Visualization of sub-datasets for biclustering: white for 0s; gray for 1s in clean applications; and black for 1s in malicious applications.

matrix, and then is applied along the rows of the row-clustered data matrix.

Unlike the common clustering methods which identify a single set of clusters, the *AHC* is a bottom-up clustering method that seeks to identify clusters with sub-clusters. It forms a multilevel hierarchical clustering tree where lower level clusters are joined to form higher level clusters. The procedures are given as follows:

Step 1: Generate the Disjoint Clusters—The *AHC* starts with every single data object, i.e. each data object is assigned to a separate cluster.
Step 2: Form a Distance Matrix—The pairwise distances between the disjoint clusters are calculated using the *Ward's linkage* [39] and are used to initialize the distance matrix.
Step 3: Merge two Closest Clusters—Based on the distance matrix, each cluster is merged with another one that has the shortest distance between them.
Step 4: Update the Distance Matrix—After the merging, the distance matrix needs to be updated by calculating the new distances between every two merged clusters.
Step 5: Obtain the Hierarchical Clustering Tree—The steps 3 and 4 are repeated until all clusters are merged into one large single cluster. By recording the mergence in each iteration, a complete hierarchical clustering tree is then presented.

We applied the above *biclustering* procedures on two separate sub-datasets extracted from the malware dataset and our collected clean one. One sub-dataset contains all clean and malicious applications with required permissions (see Fig. 1(a)); the other has the same applications but with used permissions (see Fig. 1(b)).

As a result, we had two output matrices, the required permissions are shown in Fig. 2 and the used permissions are in Fig. 3. Based on the statistical analysis presented in Section 3.1, there exist unique and common permissions for either clean or malicious applications. As binary values are shown in these matrices, we manually picked up four colors to mark the values to visualize different types of permissions for clean and malicious applications:

- Black shows *Common permissions* for clean applications;
- Light Grey shows *Common permissions* for malicious applications;
- Dark Grey indicates *Unique permissions* for clean applications; and
- Grey indicates *Unique permissions* for malicious applications.

From these two figures, we can easily observe that more permissions are declared as required than are actually used, which matches our statistical analysis results. Malicious applications either request or use many more permissions than clean applications. In normal cases, the unique permissions should perform better than the common permissions to detect a contrast between clean and malicious applications. However, from the resulting matrices, we have a few unique permissions shown in Grey and Dark Grey colors, but a large set of common permissions. Therefore, it is easy to ignore those unique permissions due to their low frequency using classic statistical methods. A challenge is then raised.

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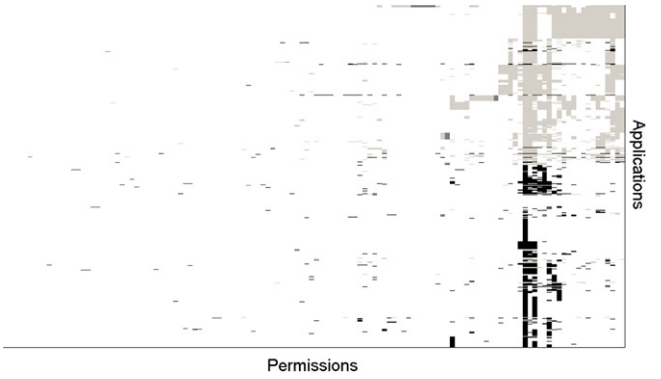

Fig. 2. Resulting matrix for required permissions by biclustering. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

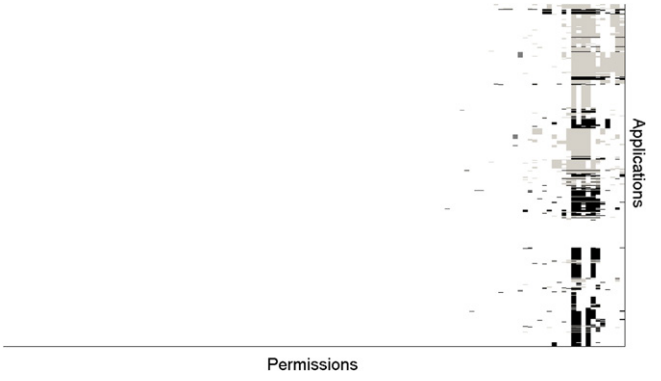

Fig. 3. Resulting matrix for used permissions by biclustering. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

How can we take use of these rare but unique permissions for contrast detection? Furthermore, it is obvious to see the color blocks in both figures, which indicate specific permission combinations have a potential capability to group applications in separate clusters. How we can find out these permission combinations and use them as the patterns for malware detection is the second challenge to be solved in the next step of our work.

3.3. Contrast permission pattern mining

In order to find the answers to the two challenges from the *biclustering* results in previous subsection, the *Contrast Permission Pattern Mining* (CPPM) is proposed. The output permission patterns were expected to have the ability to indicate the difference between the clean and malicious applications. *CPPM* was designed to process more than one dataset and take both frequent and infrequent permissions and their combinations into consideration. Two major processes are involved in *CPPM*: (1) candidate permission itemset generation, and (2) contrast permission pattern selection.

3.3.1. Candidate permission itemset generation

The purpose of this process is to obtain a number of candidate permission combinations that have the potential to be the expected contrast patterns. *CPPM* takes at least two datasets as input. In this case two datasets are loaded, each of which contains either clean or malicious applications. We generate the candidate permission itemsets from every dataset using the same procedure, which can be described in two steps:

Apriori-based Itemset Enumeration Given *Dx* is one of the input datasets with either required or used permissions, which contains n application examples. Let $I = \{A, B, C \ldots\}$ be the set of possible items (or permissions requested or used by the applications) in *Dx*. The *Apriori-based* approach [40], enumerates a candidate itemset from the simplest structure with only a single item. Based on this single item, a more complex itemset is then obtained by adding new items. This joining operation is repeated continuously to increase the number of the items in the itemsets. In each iteration, only one item is added into the existing candidate itemset. One item will not appear twice in one itemset. However, the *Apriori-based* approach has an obvious weakness that a large number of candidate itemsets will be generated with high computational cost. To solve this problem, we employ a support-based pruning technique to cut the number of candidate itemsets and reduce the cost.

Support-based Candidate Pruning Support is usually used to measure the occurrence frequency of a certain item or itemset in a dataset. Let A, $B \subseteq I$ be two items, and $\{A, B\}$ forms a candidate itemset. The support of the candidate itemset $\{A, B\}$ can be calculated by:

$$\text{supp}(A, B) = \frac{\text{number of applications that contain } A \text{ and } B \text{ in } Dx}{\text{total number of applications in } Dx}. \quad (1)$$

The candidate itemset $\{A, B\}$ is considered as *frequent* only if $\text{supp}(A, B) \geq \delta_{\text{supp}}$, where δ_{supp} is a user-specified minimum *support* threshold. In classic pattern mining methods, only the frequent itemset is considered. Any itemset with a lower support than the pre-determined threshold is treated as *infrequent* and discarded immediately. However, in our case, both the statistical analysis and *biclustering* results show most of the unique permissions are requested or used by few applications. Their supports are definitely low. With the idea of avoid missing any valuable patterns, we decide to take both frequent and infrequent candidate itemsets, but only use frequent ones to generate new candidate itemsets to cut down the computational cost.

3.3.2. Contrast permission pattern selection

The permission itemsets obtained from the previous steps are still the candidates which need to be finally selected according to pre-defined selection criteria. This process guarantees that the output itemsets are highly contrasted between clean and malicious applications. The contrasts are shown by the different occurrence behaviors in two datasets. If one permission itemset is frequent in one dataset, it is often considered to carry more common features than the infrequent ones. Therefore, the selection of a specific contrast permission pattern is based on comparison of its supports in both datasets. The bigger the distance shown in supports, the greater contrast the permission pattern has.

Given one candidate permission itemset $\{A, B\}$ and its supports in clean and malware datasets, $\text{supp}(A, B)_{\text{clean}}$ and $\text{supp}(A, B)_{\text{malicious}}$, calculate the difference by $\text{diff}(A, B) = \text{supp}(A, B)_{\text{clean}} - \text{supp}(A, B)_{\text{malicious}}$. $\{A, B\}$ is identified as a contrasted permission pattern only if $\text{diff}(A, B) \geq \delta_{\text{diff}}$, where δ_{diff} is a user-specified *minimum support difference*. All the candidate permission itemsets need to be tested using this approach, and the ones with big support difference will be selected as the final output contrast permission patterns.

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Table 3
Four sub-datasets used in contrast permission pattern mining experiments.

	Dataset	Permission involved	Permission discarded
1	Clean_Required	103	27
2	Malicious_Required	90	40
3	Clean_Used	37	93
4	Malicious_Used	31	99

Table 4
Permission index.

Permission category	Permission ID	Permission name
Normal	*pms*0001	INTERNET
Normal	*pms*0006	ACCESS_NETWORK_STATE
Normal	*pms*0007	VIBRATE
Normal	*pms*0012	RESTART_PACKAGES
Normal	*pms*0013	RECEIVE_BOOT_COMPLETED
Normal	*pms*0023	ACCESS_WIFI_STATE
Dangerous	*pms*0002	ACCESS_FINE_LOCATION
Dangerous	*pms*0003	WAKE_LOCK
Dangerous	*pms*0004	WRITE_EXTERNAL_STORAGE
Dangerous	*pms*0005	READ_PHONE_STATE
Dangerous	*pms*0008	READ_CONTACTS
Dangerous	*pms*0011	READ_LOGS
Dangerous	*pms*0020	ACCESS_COARSE_LOCATION
Dangerous	*pms*0021	SEND_SMS
Dangerous	*pms*0022	GET_TASKS
Dangerous	*pms*0024	CHANGE_WIFI_STATE
Dangerous	*pms*0028	WRITE_CONTACTS
Dangerous	*pms*0029	RECEIVE_SMS
Dangerous	*pms*0030	READ_SMS
Dangerous	*pms*0031	WRITE_SMS
Dangerous	*pms*0036	CALL_PHONE
Signature	*pms*0010	FACTORY_TEST
SignatureOrSystem	*pms*0052	INSTALL_PACKAGES

4. Experiments and results

4.1. Experiment settings

According to the statistical analysis and *biclustering* resulting figures, not all the permissions are required or used. In the experiment to evaluate the proposed Contrast Permission Pattern Mining algorithm, we ignore the permissions that are not required or used in each sub-datasets respectively. Table 3 gives more details of the four new sub-datasets.

The statistical analysis results also show that only a small set of permissions have support that are greater than 0.1 (10%), so we follow the previous studies [41–43] to set 0.05 as an acceptable value for minimum support threshold for all four sub-datasets in *CPPM*. The minimum support difference threshold is set to be 0.15 (15%) and is applied to filter out itemsets that are highly contrasted between clean and malicious applications.

4.2. Contrast permission patterns

Among the permission patterns that were generated, we found that 23 distinct permissions were present in the highly contrasted permission combinations as listed in Table 4. We classified the permissions based on the following permission categories: *normal*, *Dangerous*, *Signature* and *SignatureOrSystem*. We recorded 6 permissions belonging to the *Normal* category, 15 permissions for the *Dangerous* category and 1 permission each for the *Signature* and *SignatureOrSystem* category.

We found that the generated permission combinations are correlated and differed between clean and malicious applications. Based on the experimental results, we recorded 56 required permission patterns that are unique to the malware dataset, 31 used permission patterns that only appear amongst malware, 17 required permission patterns and 9 used permission patterns that are present in both clean and malware dataset. These findings are formed as permission combinations which are listed in Tables 5–13, and summarized with respect to the usage type of the permission as follows:

Table 5
Unique required permission sets in malware dataset (*normal permissions*).

Permission set	Support		Permission set
	Clean	*Malware*	ID
*pms*0001, *pms*0005, *pms*0023	0	0.6309	$URPSet_1$
*pms*0001, *pms*0006, *pms*0023	0	0.6031	$URPSet_2$
*pms*0001, *pms*0013	0	0.5542	$URPSet_3$
*pms*0006, *pms*0013	0	0.5168	$URPSet_4$
*pms*0006, *pms*0031	0	0.4964	$URPSet_5$
*pms*0001, *pms*0021	0	0.4312	$URPSet_6$
*pms*0013, *pms*0023	0	0.4263	$URPSet_7$
*pms*0021, *pms*0029	0	0.3701	$URPSet_8$
*pms*0004, *pms*0013	0	0.3660	$URPSet_9$
*pms*0001, *pms*0005, *pms*0020	0	0.3562	$URPSet_{10}$
*pms*0001, *pms*0005, *pms*0006, *pms*0007	0	0.3497	$URPSet_{11}$
*pms*0001, *pms*0004, *pms*0020	0	0.3122	$URPSet_{12}$
*pms*0023, *pms*0024	0	0.3097	$URPSet_{13}$
*pms*0006, *pms*0008	0	0.2975	$URPSet_{14}$
*pms*0013, *pms*0031	0	0.2943	$URPSet_{15}$
*pms*0006, *pms*0036	0	0.2869	$URPSet_{16}$
*pms*0013, *pms*0021	0	0.2804	$URPSet_{17}$
*pms*0007, *pms*0036	0	0.2494	$URPSet_{18}$
*pms*0012, *pms*0021	0	0.2405	$URPSet_{19}$
*pms*0013, *pms*0036	0	0.2380	$URPSet_{20}$
*pms*0006, *pms*0012	0	0.2372	$URPSet_{21}$
*pms*0012, *pms*0029	0	0.2282	$URPSet_{22}$
*pms*0012, *pms*0013	0	0.2234	$URPSet_{23}$
*pms*0012, *pms*0036	0	0.2119	$URPSet_{24}$
*pms*0001, *pms*0004, *pms*0005, *pms*0007	0	0.2014	$URPSet_{25}$

Table 6
Unique required permission sets in malware dataset (*ACCESS_FINE(COARSE)_LOCATION*).

Permission set	Support		Permission set
	Clean	*Malware*	ID
*pms*0002, *pms*0005, *pms*0020	0	0.2690	$URPSet_{26}$
*pms*0002, *pms*0004, *pms*0020	0	0.2576	$URPSet_{27}$
*pms*0002, *pms*0005, *pms*0023	0	0.2307	$URPSet_{28}$
*pms*0002, *pms*0004, *pms*0023	0	0.2234	$URPSet_{29}$

4.2.1. Unique Required Permission (URP) Patterns

From Tables 5–10, we present the permission patterns that were frequently required by the applications in our dataset. It is worth noting that these required permission patterns were unique to the malware dataset only; hence the support value for the clean applications is 0.

In Table 5, we list the top 25 permission combinations where the first permission in the listed patterns belongs to the *normal* permissions category. The permission combinations from $URPSet_1$ and $URPSet_2$ were both required by more than 60% of the malware. In fact, we found that the `INTERNET` permission (*pms*0001) is frequently requested along with other permissions and their support value are relatively high. The permission combination, `INTERNET` and `RECEIVE_BOOT_COMPLETED` were present in 55% of the malware dataset. Other such patterns involving the `INTERNET` permission are listed in Table 5.

In Tables 6–10, we present the permission patterns that can have an impact on the following actions: access location information, read/write/send and receive SMS, access to contact list, write to external storage and access to phone state.

4.2.2. Unique Used Permission (UUP) Patterns

In Table 11, we list the combinations of the used permissions that are unique to the malware dataset only. It can be noted that

Table 7
Unique required permission sets in malware dataset (*SMS*).

Permission set	Support		Permission set
	Clean	*Malware*	ID
*pms*0030, *pms*0036	0	0.3228	$URPSet_{30}$
*pms*0021, *pms*0036	0	0.3163	$URPSet_{31}$
*pms*0031, *pms*0036	0	0.2690	$URPSet_{32}$
*pms*0029, *pms*0036	0	0.2674	$URPSet_{33}$
*pms*0021, *pms*0028	0	0.2519	$URPSet_{34}$

Table 8
Unique required permission sets in malware dataset (*CONTACTS*).

Permission set	Support		Permission set
	Clean	*Malware*	ID
*pms*0008, *pms*0030	0	0.3269	$URPSet_{35}$
*pms*0008, *pms*0021	0	0.2894	$URPSet_{36}$
*pms*0008, *pms*0031	0	0.2649	$URPSet_{37}$
*pms*0008, *pms*0029	0	0.2429	$URPSet_{38}$
*pms*0028, *pms*0036	0	0.2413	$URPSet_{39}$
*pms*0008, *pms*0028	0	0.2282	$URPSet_{40}$
*pms*0008, *pms*0013	0	0.2250	$URPSet_{41}$
*pms*0028, *pms*0029	0	0.2128	$URPSet_{42}$

Table 9
Unique required permission sets in malware dataset (*WRITE_EXTERNAL_STORAGE*).

Permission set	Support		Permission set
	Clean	*Malware*	ID
*pms*0004, *pms*0006, *pms*0023	0	0.4475	$URPSet_{43}$
*pms*0004, *pms*0030	0	0.3896	$URPSet_{44}$
*pms*0004, *pms*0005, *pms*0020	0	0.3106	$URPSet_{45}$
*pms*0004, *pms*0021	0	0.2462	$URPSet_{46}$
*pms*0004, *pms*0020, *pms*0023	0	0.2258	$URPSet_{47}$
*pms*0004, *pms*0029	0	0.2022	$URPSet_{48}$

Table 10
Unique required permission sets in malware dataset (*READ_PHONE_STATE*).

Permission set	Support		Permission set
	Clean	*Malware*	ID
*pms*0005, *pms*0013	0	0.5453	$URPSet_{49}$
*pms*0005, *pms*0031	0	0.5094	$URPSet_{50}$
*pms*0005, *pms*0021	0	0.4190	$URPSet_{51}$
*pms*0005, *pms*0029	0	0.3798	$URPSet_{52}$
*pms*0005, *pms*0008	0	0.3538	$URPSet_{53}$
*pms*0005, *pms*0036	0	0.3350	$URPSet_{54}$
*pms*0005, *pms*0028	0	0.2934	$URPSet_{55}$
*pms*0005, *pms*0012	0	0.2560	$URPSet_{56}$

the INTERNET permission is included in the top 3 permission combinations, $UUPSet_1$ to $UUPSet_3$ and appears in over 40% of the malware samples. The combination of INTERNET and READ_PHONE_STATE permission is another frequent permission pattern, as depicted by $UUPSet_{21}$ and $UUPSet_{30}$.

Another interesting observation is the presence of the READ_LOGS (*pms*0011) permission in one-third of the permission patterns presented in Table 11. It is often combined with the INTERNET (*pms*0001) and ACCESS_FINE_LOCATION (*pms*0002) permissions. The remaining patterns include combinations of network-related and SMS permissions.

4.2.3. Common Required Permission (CRP) Patterns

Previously, we presented the permission patterns that were unique to malicious applications only. In Table 12, we list the permission combinations that appear in both clean and malware datasets. However, it can be observed based on the support value difference that the permission patterns are more prevalent in the malware dataset, as shown by the negative support difference values.

Table 11
Unique used permission sets in malware dataset.

Permission set	Support		Permission set
	Clean	*Malware*	ID
*pms*0001, *pms*0005, *pms*0006, *pms*0007	0	0.5542	$UUPSet_1$
*pms*0001, *pms*0005, *pms*0011	0	0.4687	$UUPSet_2$
*pms*0001, *pms*0006, *pms*0011	0	0.4320	$UUPSet_3$
*pms*0005, *pms*0006, *pms*0011	0	0.4312	$UUPSet_4$
*pms*0001, *pms*0007, *pms*0011	0	0.4149	$UUPSet_5$
*pms*0005, *pms*0007, *pms*0011	0	0.4133	$UUPSet_6$
*pms*0006, *pms*0007, *pms*0011	0	0.3855	$UUPSet_7$
*pms*0001, *pms*0002, *pms*0005, *pms*0007	0	0.3423	$UUPSet_8$
*pms*0001, *pms*0021	0	0.3358	$UUPSet_9$
*pms*0005, *pms*0021	0	0.3236	$UUPSet_{10}$
*pms*0001, *pms*0002, *pms*0011	0	0.2845	$UUPSet_{11}$
*pms*0002, *pms*0005, *pms*0011	0	0.2845	$UUPSet_{12}$
*pms*0001, *pms*0002, *pms*0006, *pms*0007	0	0.2829	$UUPSet_{13}$
*pms*0002, *pms*0005, *pms*0006, *pms*0007	0	0.2829	$UUPSet_{14}$
*pms*0002, *pms*0006, *pms*0011	0	0.2755	$UUPSet_{15}$
*pms*0007, *pms*0021	0	0.2723	$UUPSet_{16}$
*pms*0001, *pms*0020	0	0.2600	$UUPSet_{17}$
*pms*0005, *pms*0020	0	0.2600	$UUPSet_{18}$
*pms*0002, *pms*0007, *pms*0011	0	0.2568	$UUPSet_{19}$
*pms*0006, *pms*0020	0	0.2511	$UUPSet_{20}$
*pms*0001, *pms*0005, *pms*0010	0	0.2421	$UUPSet_{21}$
*pms*0001, *pms*0007, *pms*0010	0	0.2413	$UUPSet_{22}$
*pms*0005, *pms*0007, *pms*0010	0	0.2413	$UUPSet_{23}$
*pms*0011, *pms*0020	0	0.2380	$UUPSet_{24}$
*pms*0001, *pms*0006, *pms*0010	0	0.2372	$UUPSet_{25}$
*pms*0005, *pms*0006, *pms*0010	0	0.2372	$UUPSet_{26}$
*pms*0006, *pms*0007, *pms*0010	0	0.2364	$UUPSet_{27}$
*pms*0006, *pms*0021	0	0.2348	$UUPSet_{28}$
*pms*0007, *pms*0020	0	0.2266	$UUPSet_{29}$
*pms*0001, *pms*0003, *pms*0005, *pms*0007	0	0.2258	$UUPSet_{30}$
*pms*0002, *pms*0020	0	0.2185	$UUPSet_{31}$

We identify four permissions: INTERNET (*pms*0001), READ_PHONE_STATE (*pms*0005), ACCESS_NETWORK_STATE (*pms*0006) and ACCESS_WIFI_STATE (*pms*0023) that are present in different permission combinations and appear in more than 40% of the malware dataset. One interesting observation is $CRPSet_{14}$ which comprises of a combination of four permissions and appear in a significant 40% of the malicious applications.

4.2.4. Common Used Permission (CUP) Patterns

In Table 13, we present the used permission combinations that appeared in both the clean and malware datasets. We note that although both datasets have the same permission patterns, the ones in the malware dataset have higher support values.

The permissions included in the patterns are INTERNET (*pms*0001), READ_PHONE_STATE (*pms*0005), ACCESS_NETWORK_STATE (*pms*0006), VIBRATE (*pms*0007) and READ_LOGS (*pms*0011). It is also worth noting that $CUPSet_1$ and $CUPSet_2$ have almost the same support difference, hence indicating that the occurrence of these permission combinations are highly relevant. Moreover, we observed that even though READ_LOGS (*pms*0011) permission did not appear in the common required permission patterns, but it appeared in three common unique permission patterns READ_LOGS, $CUPSet_7$–$CUPSet_9$.

4.3. Discussion

The *Android* smartphone has gained in popularity in the past few years. Two main factors that contributed towards this change is the open-source nature of the platform and the flexibility provided to users and developers alike when downloading and developing *Android* applications, respectively. However, not all applications present on the application markets, both official and third-party, are clean. Previous work showed that malware authors take advantage of the *Android* permission system to entice users

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Table 12
Common required permission sets in both clean and malware datasets.

Permission set	Support		Difference	Permission set ID
	Clean	Malware		
*pms*0001, *pms*0005	0.3121	0.9307	−0.6186	$CRPSet_1$
*pms*0005	0.3187	0.9340	−0.6153	$CRPSet_2$
*pms*0005, *pms*0023	0.0236	0.6308	−0.6072	$CRPSet_3$
*pms*0030	0.0147	0.6210	−0.6064	$CRPSet_4$
*pms*0001, *pms*0023	0.0505	0.6349	−0.5844	$CRPSet_5$
*pms*0023	0.0522	0.6349	−0.5827	$CRPSet_6$
*pms*0006, *pms*0023	0.0399	0.6031	−0.5632	$CRPSet_7$
*pms*0005, *pms*0006	0.2421	0.7905	−0.5485	$CRPSet_8$
*pms*0001, *pms*0005, *pms*0006	0.2421	0.7897	−0.5477	$CRPSet_9$
*pms*0001, *pms*0004, *pms*0005	0.1328	0.6544	−0.5216	$CRPSet_{10}$
*pms*0004, *pms*0005	0.1337	0.6553	−0.5216	$CRPSet_{11}$
*pms*0013	0.0489	0.5542	−0.5053	$CRPSet_{12}$
*pms*0031	0.0106	0.5159	−0.5053	$CRPSet_{13}$
*pms*0001, *pms*0004, *pms*0005, *pms*0006	0.1149	0.5623	−0.4474	$CRPSet_{14}$
*pms*0004, *pms*0005, *pms*0006	0.1149	0.5623	−0.4474	$CRPSet_{15}$
*pms*0004, *pms*0023	0.0293	0.4637	−0.4344	$CRPSet_{16}$
*pms*0021	0.0277	0.4417	−0.4140	$CRPSet_{17}$

Table 13
Common used permission sets in both clean and malware datasets.

Permission set	Support		Difference	Permission set ID
	Clean	*Malware*		
*pms*0001, *pms*0005	0.2991	0.9152	−0.6161	$CUPSet_1$
*pms*0005	0.3032	0.9169	−0.6137	$CUPSet_2$
*pms*0001, *pms*0005, *pms*0006	0.2363	0.7718	−0.5355	$CUPSet_3$
*pms*0005, *pms*0006	0.2363	0.7718	−0.5355	$CUPSet_4$
*pms*0001, *pms*0005, *pms*0007	0.2168	0.6512	−0.4344	$CUPSet_5$
*pms*0005, *pms*0007	0.2192	0.6528	−0.4336	$CUPSet_6$
*pms*0005, *pms*0011	0.0538	0.4686	−0.4148	$CUPSet_7$
*pms*0011	0.0693	0.4760	−0.4067	$CUPSet_8$
*pms*0001, *pms*0011	0.0685	0.4711	−0.4026	$CUPSet_9$

into installing unsafe applications. As such, this study aims to understand required and used permissions by *Android* applications by applying data mining techniques to find emerging permission patterns that can be used to contrast clean and malicious applications.

4.3.1. Observations from statistical analysis

Our proposed methodology considers the patterns of both required and used permissions. From our statistical analysis in Section 3.1, we observe that the `INTERNET` permission remains the most required (97.72%) and used (94.62%) permission in our experimental dataset. We also find, from Tables 1 and 2, that there is a significant difference in the frequencies of required and used permissions for the clean and malware datasets. This observation aligns with the one made by Felt et al. in [33] and therefore, demonstrates that both clean and malicious applications can be over-privileged. Until, most of the proposed solutions have only considered required permissions which are extracted from the `AndroidManifest.xml` files. From our statistical results, we argue that used permissions should also be considered as part of the feature set and as such, can aid towards malicious application detection.

Additionally, in order to have a comparative distribution of required and used permissions, we extend the statistical analysis by applying the *biclustering* algorithm to generate visualization maps. It should be noted that we apply *biclustering* mainly to visualize the distribution of required and used permissions. Thus, we do not aim to identify clusters of permissions. As expected, since applications generally request more permissions than are actually used, the distribution of required permissions for clean and malware datasets is sparser than that of used permissions—as shown in Figs. 2 and 3, respectively. The visualization maps provide researchers and analysts alike with a first-hand overview of permissions that are common and unique between clean and malicious applications. Furthermore, the maps can be used as a substitution for statistical analysis as it is a time-consuming process and requires little or no margin of error. As Zhou et al. [44] pointed out in their work, the increasing number of malicious applications is mostly due to how easy it is to produce repackaged applications. These applications can contain additional advertising libraries, malicious code and most importantly, additional permissions that were previously not present in the original applications. The maps can outline these differences in permissions for clean and malicious applications. Subsequently, the permission distribution visuals can also portray required and used permissions for different variants belonging to the same malware family. Hence, the maps can be used for a preliminary analysis of zero-day samples detected by antivirus companies.

4.3.2. Analysis of permission visualizations

From the *biclustering* results, we observed that several applications, clean or malicious, have more than one (required and used) permission in common between them. Conversely, we also noticed similar observation for unique required and used permissions for the two datasets. In general, existing works [11,32,29] consider only individual permissions when studying permission request patterns. Therefore, we put forward a method that considers co-dependencies between permissions that are unique and common amongst clean and malicious applications. In our paper, we apply a data mining technique known as contrast mining to generate permission sets that constitute multiple permissions and can be used to reinforce similarities and contrasts between clean and malicious applications.

From our findings, we observe that 23 permissions (as shown in Table 4), out of a total of 128 permissions that were extracted from our dataset, appear frequently in the permission sets. It is also worth noting that two of the *Dangerous* permissions,

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WRITE_EXTERNAL_STORAGE (*pms*0004) and READ_PHONE_STATE (*pms*0005) can be implicitly granted to an application that utilizes API level 3 or lower, as described in [26]. This implies that if these two permissions are not recorded as required permissions, they can still be present as used permissions. Upon further investigation, we found that whilst the number of required permissions for WRITE_EXTERNAL_STORAGE exceeds that of used permissions, the same observation cannot be made for READ_PHONE_STATE. From Tables 1 and 2, it can be noticed that the number of clean applications (391) which *required* READ_PHONE_STATE is less than the number of clean applications (457) that *used* this permission. Although we do not keep a record of the API level information for the applications in our dataset, in this case we can deduce that some clean applications from the set of 457 applications were implicitly granted the READ_PHONE_STATE permission. This permission can have nefarious ramifications on users' private information as it allows an application to read unique device identifiers such as, *International Mobile Equipment Identity* (IMEI), *International Mobile Subscriber Identity* (IMSI) and the *SIM* serial number, as shown by [45].

4.3.3. Analysis of contrast permission patterns

In Section 4.2, we present the most significant permission sets generated by contrast mining. Based on our experimental results, we found that a large number of required and used permission sets were unique in malicious applications only. This is a good indication that the permission sets can be further applied during the malware detection phase to identify malicious applications. For *normal* required permissions, we observed from Table 5 that the permission set IDs, $URPSet_1$ and $URPSet_2$ were required by 63% and 60% of the malicious applications in our dataset, respectively. We deduce that this might be the case due to the fact that 25% of our experimental malware samples (malicious applications) belong to the *DroidKungFu3* malware family. As demonstrated in [46], malware samples classified under *DroidKungFu3* attempt to extract device ID, network-related information and send all information back to the attacker's server.

As for the *Dangerous* required permission sets included in Tables 6–10, we notice several interesting permission sets on which we provide further explanation. For permission set IDs $URPSet_{26}$ and $URPSet_{27}$, we find that 25% of malicious applications require both ACCESS_FINE_LOCATION (*pms*0002) and ACCESS_COARSE_LOCATION (*pms*0020) permissions. While ACCESS_COARSE_LOCATION grants access to GPS location sources, ACCESS_COARSE_LOCATION is used for location information related to network sources. However, the documentation [47] provided by *Google* specifies that if a developer requires network and GPS location information, they do not need to include both permissions in the application; only requesting ACCESS_FINE_LOCATION should suffice. The presence of unused permissions can be exploited via permission inheritance during inter-component communications, as explained in [48].

Moreover, we observe that for SMS-related permissions: SEND_SMS (*pms*0021), RECEIVE_SMS (*pms*0029), READ_SMS (*pms*0030) and WRITE_SMS (*pms*0031), as shown in Table 7, the CALL_PHONE (*pms*0036) permission is associated with these four permissions in over 25% of the malicious applications in our dataset. The CALL_PHONE permission allows an application to proceed with making a phone call without going through the usual dialer interface. Some malware samples exploit the aforementioned permission combinations to make premium calls and send text messages to premium numbers.

As for the used permission sets that are unique in our malware dataset (Table 11), we observed that the permission set: INTERNET (*pms*0001), READ_PHONE_STATE (*pms*0005), ACCESS_NETWORK_STATE (*pms*0006), VIBRATE (*pms*0007) with permission set ID $UUPSet_1$ was used by 55% of the malware samples. Interestingly, we also found that the same permission set was present in Table 5 under the permission set ID $URPSet_{11}$, with the only exception that it was required by only 35% of the malware samples. We attribute this 20% difference to the observation made in Section 4.3.2, on the READ_PHONE_STATE permission. Moreover, it can be noted from Table 11 that the READ_LOGS (*pms*0011) permission is frequently associated with the permission sets and appeared in 25%–50% of the malware dataset. There was previously no indication that (*pms*0011) was a highly used permission among malicious applications as the permission did not appear in the Top 20 most used permissions in Table 2. This further consolidates our argument that permission patterns cannot be generated by only considering the number of frequencies for that particular permission.

Furthermore, we also noted that there are several permission sets which appeared in both clean and malware datasets, shown in Tables 12 and 13. The negative support difference given in the table shows that the permission sets are more prevalent in malicious applications than in clean ones. We observed that the top two permission sets, $CRPSet_1$ and $CRPSet_2$ in Table 12 and $CUPSet_1$ and $CUPSet_{11}$ in Table 13 are the same. However, we noted some discrepancies for permissions such as READ_LOGS (*pms*0011) and VIBRATE (*pms*0007). Similar to our previous observations, it appears that the above two permissions are not recorded during the generation of required permission sets but for used permission sets, their high support values indicate that they are highly significant.

5. Conclusion

In this paper, we studied the *Android* permission system as the smartphone platform makes use of permissions to regulate access to system resources and users' private information. In order to understand and identify permission patterns, the existing work considers only those permissions that are declared in the AndroidManifest.xml files. We refer to those permissions as 'required' permissions. However, there is another permission check that takes place after an application has been installed and is executed by the smartphone OS. We refer to such permissions as 'used permissions'.

In our work, we considered the implications of incorporating used permissions in permission patterns and determined their usefulness in contrasting between clean and malicious applications. We proposed an efficient pattern mining method to generate a set of emerging contrast permission patterns for our clean and malware dataset. Based on our experimental results, we observed that there are several permissions that do not appear in the required permission sets but are present in the used permission sets. We found out that there is a discrepancy in the official documentation that allows for application with API level 3 or level to implicitly inherit certain permissions—although they are not declared in the AndroidManifest.xml file.

Additionally, the patterns obtained from our proposed methodology ensures that the permission sets were not generated by chance as we used support values to measure and rank the patterns. This is an improvement over Frank et al.'s work [11] where the authors had to simulate permission request data to test their generated patterns. Last but not least, since obfuscation methods cannot be applied to *Android* permissions, the generated permission sets can be used to contrast clean and malicious applications. In the future, we would like to work on finding contrasting patterns that can differentiate between an original application and a repackaged one.

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