Signature Generation for Sensitive Information Leakage in Android Applications

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Abstract—In recent years, there has been rapid growth in mobile devices such as smartphones, and a number of applications are developed specifically for the smartphone market. In particular, there are many applications that are "free" to the user, but depend on advertisement services for their revenue. Such applications include an advertisement module - a library provided by the advertisement service - that can collect a user's sensitive information and transmit it across the network. Such information is used for targeted advertisements, and user behavior statistics. Users accept this business model, but in most cases the applications do not require the user's acknowledgment in order to transmit sensitive information. Therefore, such applications' behavior becomes an invasion of privacy. In our analysis of 1,188 Android applications' network traffic and permissions, 93% of the applications we analyzed connected to multiple destinations when using the network. 61% required a permission combination that included both access to sensitive information and use of networking services. These applications have the potential to leak the user's sensitive information. Of the 107,859 HTTP packets from these applications, 23,309 (22%) contained sensitive information, such as device identification number and carrier name. In an effort to enable users to control the transmission of their private information, we propose a system which, using a novel clustering method based on the HTTP packet destination and content distances, generates signatures from the clustering result and uses them to detect sensitive information leakage from Android applications. Our system does not require an Android framework modification or any special privileges. Thus users can easily introduce our system to their devices, and manage suspicious applications' network behavior in a fine grained manner. Our system accurately detected 94% of the sensitive information leakage from the applications evaluated and produced only 5% false negative results, and less than 3% false positive results.

Index Terms—Security, Smartphone, Privacy

I. INTRODUCTION

With the increasing popularity of smartphones and tablets, development for mobile device operating systems (particularly for Apple's iOS and Google's Android, which are the most popular choices) has drastically increased, especially the development of applications for sale in the providers online marketplaces such as the AppStore and Google Play, respectively. In May 2012, Google Play alone had 500,000 applications. Applications are categorized as free or paid. In this work, we are primarily interested in free applications, since these often come with an advertising module.

A smartphone retains various kinds of personal information, such as the contents of the user's address book, location tracking data, and the unique device identifier. In order to

decouple the features of the device (ie, network access, the camera, the previously discussed sensitive information), and thus maintain security, Android provides a framework which requires applications to have specific permissions for accessing restricted resources. However, the Android permission framework does not completely protect the user's sensitive information: applications or advertising modules send the user's sensitive information to the outside servers using the network [1], [2], [3], [4]. While this information is generally used for targeted advertising, it can also be discovered and used by malicious parties without the original user's awareness to combat this threat [5], [6]. Various methods, employing tracking information flow and privilege separation, have been examined [7], [8], [9], [10], [11]. These approaches could effectively expose a sensitive information leakage, but they all would require extensive modifications to the Android framework. We think it is sufficient to force applications to notify users of information usage details, thus enabling the user to dynamically control the handling of sensitive information. Our goal is a practical method that can identify a sensitive information leakage in applications without an Android framework modification. A user can easily add our system to his device and use it to manage the transmission of sensitive information by applications. In this way, the user can reduce the possible violations of his privacy.

In this paper, we present a novel method of clustering that uses selected HTTP packets to generate signatures which can accurately identify new HTTP packets that contain sensitive information. Our primary concern is not malware, but free applications which risk leaking sensitive information. In many cases, malware is detected by the anti-virus software. If free software is not malware but causes a sensitive information leakage. We postulate that software is the new threat for the user. In our evaluation, we analyzed 1,188 free Android applications from the Top 100 list and the Recent Uploads list in Google Play Japan and collected 107,859 HTTP packets that these applications generated. We examined the number of HTTP packets that included sensitive information and sent it to outside servers. Of our trace, 23,309 HTTP packets contained such information. We then applied clustering to a sample of the refined data the packets containing sensitive information to generate signatures, and re-applied these signatures to the entire dataset. This method result in a high percentage of true positives, and a low percentage false positives. Thus, we conclude that our generated signatures have sufficient

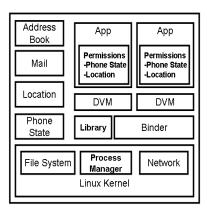


Fig. 1. Overview of Android architecture

accuracy for detecting of sensitive information transmission in applications.

We consider the main contributions of this paper to be:

- a novel clustering method using HTTP packet distance that identifies the similarity between the two of Android application network packets
- a system, using that the proposed method followed by signature generation, that can detect sensitive information leakage without altering the Android framework.

The rest of this paper is organized as follows. In Section II, we explain the Android architecture and permission framework. We describe the Android application permission pattern can be a problem and show the practical validity of this problem with an analysis of applications network behavior in Section III. We present our algorithms for the HTTP packet clustering and signature generation in Section IV. We evaluate our approach using an HTTP packet dataset in Section V. We review related work, discuss our results, and the limitations of this approach in Section VI Finally, we conclude and suggest directions for future work in Section 8.

II. BACKGROUND

A. Android Architecture

Figure 1 shows an overview of Android architecture. Android consists a Linux kernel, Middleware, Android applications, and sensitive information (Address Book, GPS, Mail, Phone State are shown). Middleware includes the Binder, the Library framework, and one Dalvik Virtual Machine (DVM) per application.

The Linux kernel provides some fundamental features for the upper layers: process management, file system and network services. Middleware provides DVMs, which are used run applications as well as the Binder, which supports IPC and checks an application's permission list when it tries to access sensitive information via the Library. Applications on Android have a unique Linux UID and the associated permissions. This environment paradigm is called sand-boxing. The application can only access resources within the bounds of its privileges.

B. Android Permissions

Android provides the permission framework for managing of an application's privileges. In order to access resources on Android, an application needs a specific set of permissions which link to the resources. For instance, the **INTERNET** permission can connect to any outside server using network. The **READ_PHONE_STATE** permission can get the unique device identifier and line number on the device. At the present time there are 125 privileges permissions defined by Android API Level 15 [12]. When an application accesses a controlled resource object, the Binder takes charge of the reference monitor to manage the application's request. The Binder verifies that the application has the appropriate permissions to bind to the requested resource.

III. PROBLEM DESCRIPTION

In this section, we explain how particular combinations of application permissions can allow a violation of user privacy. Then, we use our analysis of the network traffic of 1,188 free applications - how many servers are connected to by an application; what, if any, sensitive information is included in the traffic - to show that this problem is a practical concern.

A. Application Request Permissions

Previous studies show that many applications require the **INTERNET** permission [13]. Table I shows the permissions held by our collected 1,188 applications. 302 applications (25%) require only the **INTERNET** permission, while 727 applications (61%) require the **INTERNET** and some combination of sensitive information permissions. We consider sensitive information permissions to include **LOCATION**, **READ_PHONE_STATE**, and **READ_CONTACTS**. Those 727 applications can access sensitive resources on the device and send information gathered from those sensitive resources using the network feature, all without user confirmation, putting the user's privacy at risk.

In Android's current model, an application requests permissions once, on installation. Once the application is installed, all its transmissions are opaque to the user, who has no way of determining if sensitive information is present in his network traffic. He may wish to use an application without interruption when it is only transmitting benign data, but to be prompted for confirmation when the application wishes to send sensitive information over the network.

B. Application Traffic Analysis

It has been shown that some applications transmit sensitive information to external servers [1], [2]. One of the main reasons for this is that developers build an advertisement module into the free version of their applications for revenue. In order to collect statistical information of the device usage and to provide a targeted advertisements for users, advertisement modules take advantage of their ability to access sensitive information.

Unique device identifiers (UDIDs) are most commonly used by advertisement modules [3]. The types of UDIDs include Number of applications with dangerous permission combinations. Out of 1,188 applications total, 61% (the four lower rows in this table) REQUIRED BOTH THE **INTERNET** AND ATLEASET ONE PERMISSION FOR SENSITIVE INFORMATION.

INTERNET	LOCATION	PHONE_STATE	CONTACTS	# Apps
X				302
X		X		329
X	X	X		153
X	X			148
X	X	X	X	23

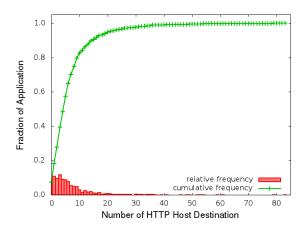


Fig. 2. Frequency Distribution of HTTP Host Destinations. Out of 1,188 applications total, 81 (7%) have 1 destinations, 885 (74%) have up to 10 destinations, and average number of destinations was 7.9.

the Android ID, the International Mobile Equipment Identity (IMEI), the International Mobile Subscriber Identity (IMSI) and the SIM Serial ID. Additionally, some modules compute UDID's hash with a cryptographic hash function at the time of transmission [4]. These UDIDs are immutable and linked to a user's real name and bank account. Unlike Internet cookies and IP addresses, UDIDs are hard (if not impossible) to change or erase, so it can be very dangerous for a user to have an advertisement module leaking his UDIDs. If an advertisement module generates a UDID's hash value from only a UDID, the hash value is same all the time, thus the user cannot change the UDID's hash value without changing the original UDID, so the hash values have similar security problems. We believe that an advertisement module should use an application's unique user ID value (i.e UUID value) rather than its UDID. If UUIDs (which are mutable) were used instead of UDIDs, harvested information would be restricted to the transmitting application, and the user would have the ability to alter his device's ID if he were concerned by the accumulation of information.

We selected 1,188 free applications from the popular ranking in Japan's Google Play from January to April, 2012. Since many users choose their applications from this ranking, we consider this to be a good sample of applications used in Japan. We investigated the network traffic generated by these applications. The applications sent 107,859 GET/POST HTTP packets. The Experiment environment was a Galaxy Nexus S, Android 2.3.4.

Table II shows the number of HTTP packets destined for the most common hosts and the number of applications that send to each destination domain. Note that many applications send HTTP packets to the same destinations, and that some of these domains, such as "admob.com" and "ad-maker.info", are clearly advertisement services. Other domains are Web API service providers. We can see that many of our applications send information to advertisement servers. We noticed during this experiment that several applications have multiple advertisement modules (ie. AdMob, AdMaker, Adlantis, and MicroAd). We suspect that those applications switch from one module to another, depending on the user's device environment such as country or carrier, to improve the revenue.

Figure 2 shows the cumulative frequency distribution of HTTP host destinations of our applications. From this, we can confirm that most of the targeted applications connect to multiple servers. In our examination of the HTTP host destinations, we found that 81 applications (7%) have 1 destination, 885 applications (74%) have up to 10 destinations, and 1,006 (90%) application have up to 16 destinations. The average number of destinations was 7.9. One application included an embedded browser, and thus had the largest number of destinations at 84.

Table III shows the number of HTTP packets, applications, and HTTP host destinations that are touched by sensitive information, where sensitive information is considered to be: UDIDs (IMEI, IMSI, SIM Serial ID, and Android ID), UDIDs hashed values, and CARRIER names. IMEI refers to the assigned device number, IMSI to the assigned telephone service subscriber number in the SIM card, SIM Serial ID to the assigned SIM card number, and the Android ID to the assigned Android instance number, which is generated at Android's initial boot. The Android ID is the most frequently used identifier. We also found many examples of sensitive information being sent to the same destination. For example: "ad-maker.info", "mydas.mobi", "medibaad.com", and "adlantis.jp" expect IMEI and Android ID; "zqapk.com" expects IMEI, and SIM Serial ID, and Carrier name; and "googlesyndication.com" and "admob.com" expect only Android ID.

From these results, we can see that the user's sensitive information is accessed by applications, which send it to outside servers via the network. Since Android does not provide the usage history of runtime applications' permissions, the users can not observe the application's network behavior, and thus can not prevent the sensitive information leakage.

TABLE II

HTTP packet destinations. This table shows the number of packets sent to each HTTP Host destination, and the number of Applications that send packets to each HTTP Host destination.

HTTP Host Destination	# Packets	# Apps
doubleclick.net	5786	407
admob.com	1299	401
google-analytics.com	3098	353
gstatic.com	1387	333
google.com	3604	308
yahoo.co.jp	1756	287
ggpht.com	940	281
googlesyndication.com	938	244
ad-maker.info	3391	195
nend.net	1368	192
mydas.mobi	332	164
amoad.com	583	116
flurry.com	335	119
microad.jp	868	103
adwhirl.com	548	102
i-mobile.co.jp	3729	100
adlantis.jp	237	98
naver.jp	3390	82
adimg.net	315	72
mbga.jp	1048	63
rakuten.co.jp	502	56
fc2.com	163	52
medibaad.com	1162	49
mediba.jp	427	48
mobclix.com	260	48
gree.jp	228	45

TABLE III

Sensitive Information. This table shows for each type of information considered sensitive the number of packets containing the information, the number of application that send those packets, and the number of destinations to which those packets go.

Sensitive Information	# Packets	# Apps	# HTTP Host Destinations
ANDROID ID	7590	21	75
ANDROID ID MD5	10058	433	21
ANDROID ID SHA1	1247	47	12
CARRIER	2095	135	44
IMEI (Device ID)	3331	171	94
IMEI MD5	692	59	15
IMEI SHA1	1062	51	13
IMSI (Subscriber ID)	655	16	22
SIM Serial ID	369	13	18

IV. APPROACH

We present the following HTTP packet clustering and signature generation methods to address the problem described in Section III. The objective of our work is to, without an Android framework modification, detect suspicious network behavior specifically the transmission of sensitive information by an application to an outside server. Additionally, our system should be practical and lightweight for users to apply, and should not require any special device privileges. Ideally, users would install our application component to handle all the network transmissions generated by other applications.

Our approach is to collect network traffic and generate signatures from the clustering of the traffic. If sensitive information is sent unencrypted over the network, it is a fairly simple matter to detect such transmission. However, the signature generation can help to counteract leakage in polymorphic and obfuscation traffic. It is also effective against encrypted traffic that uses the same encryption key over a

variety of modules or applies a cryptographic hash function to sensitive information.

A. Overview

Figure 3 shows our approach, which consists of two parts. First, a separate server (shown in Figure 3a) collects application traffic, clustering the data and generating signatures. Second, an information flow control application on the user's device (shown in Figure 3b) fetches signatures from the servers and manages the transmission of other applications' network traffic.

The server generates signatures by the following process. First, it generates a payload check, which separates application network traffic into two groups: one containing packets with sensitive information, and the other not. Second, the server clusters the group containing sensitive information based on packet destination distance and contents distance, and constructs a set of signatures using conjunction signatures [14]. This process is most effective with accurate patterns of

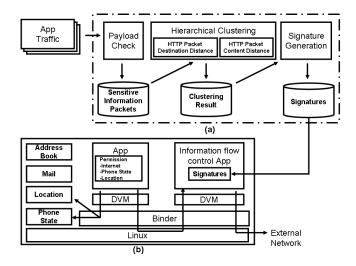


Fig. 3. (a) The architecture of our clustering and signature generation system. (b) The information flow control application that uses the signatures generated by (a).

sensitive information leakage, and our clustering and signature choices reflect that. Using the HTTP packet distance is emphasizes patterns in HTTP packets, allowing us to distinguish trends and distributions of HTTP packets. Thus a packet with sensitive information will be clustered with other packets containing sensitive information, generating a useful signature. In order to generate such useful signatures, we define distance to include both packet content and packet destination. This broader definition causes results sent to the same server to be clustered together, creating advertisement module specific signatures. The information flow control application inspects network traffic using the Android API and detects sensitive information leakage using the our server generated signatures. It does not require any special privileges.

B. HTTP Packet Destination Distance

The HTTP packet destination distances are calculated by the packets' destination IP addresses, port numbers, and HTTP host domains. Given two HTTP packets p_x and p_y , we define the HTTP packet destination distance as

$$d_{dst}(p_x, p_y) = d_{ip}(p_x, p_y) + d_{port}(p_x, p_y) + d_{host}(p_x, p_y).$$

Let HTTP packet p_n destination be defined as $p_n = \{ip_n, port_n, host_n\}$, where ip_n is a destination IPv4 address, $port_n$ is the port number, $host_n$ is HTTP host. The distance in the above equation are defined as follows:

Destination IP Address Distance: The distance between destination IP addresses' high bit is the longest matching prefix of the binary representations. IPv4 addresses have a 2³² bit space, and IP address blocks are denoted approximately by the upper 8 bit range. IP address blocks are allocated to organizations by the National Internet Registry and if the upper bits of IP addresses match on separate packets, there is a high possibility that the two destinations are managed by the same organization.

Therefore, we define the destination IP address distance on packets p_x , p_y as

$$d_{ip}(p_x, p_y) = lmatch(ip_x, ip_y)/32 \in [0, 1]$$

where lmatch is a function returns a number of common upper bits in two IP address.

Port Number Distance: The distance between port numbers is a Boolean (matching or not). Port numbers have a 2¹⁶ bit space, and usually, specific port number is reserved for services. We define the port number distance on packets p_x, p_y as

$$d_{port}(p_x, p_y) = match(port_x, port_y) \in \{0, 1\}$$

where match is a function returns 1 on matching ports, and 0 on different ports.

• HTTP Host Distance: We define the HTTP host as the character string of the FQDN. Thus, the distance between HTTP host domains can be computed using the generality method to determine their edit distance. We define the HTTP Host distance on packets p_x , p_y as

$$d_{host}(p_x, p_y) = \frac{ed(host_x, host_y)}{max(len(host_x), len(host_y))} \in [0, 1]$$

where ed is a function which returns an edit distance result, len is a function which returns a length of character strings, and max is a function which returns the greater of its two input values.

C. HTTP Packet Content Distance

The HTTP packet content distance is computed using the request-line, cookie, and message-body fields of the HTTP header. Given two HTTP packets p_x and p_y , we define the HTTP content distance $d_{header}(p_x, p_y)$ as

$$d_{header}(p_x, p_y) = d_{rline}(p_x, p_y) + d_{cookie}(p_x, p_y) + d_{body}(p_x, p_y).$$

Let HTTP packet p_n contents be defined as $p_n = \{rline_n, cookie_n, body_n\}$, where $rline_n$ is request-line, $cookie_n$ is cookie, $body_n$ is message-body. These contents are character or binary strings. In order to accurately compute a distance, we apply the normalized compression distance (NCD) [15] algorithm, which is based on Kolmogorov's complexity, to calculate the closeness of two strings without any context dependency. The NCD of any two character strings is defined as

$$ncd(x,y) = \frac{C(xy) - min(C(x), C(y))}{max(C(x), C(y))}$$

where C(x) is a function which compresses a character string x, then returns its length. We define the distance between content components of HTTP packets p_x , p_y as

$$d_{data}(p_x, p_y) = ncd(data_x, data_y) \in [0, 1]$$

where data corresponds to request-line, cookie, and messagebody respectively. After each data has been computed, they are combined into the overall distance.

D. Hierarchical Clustering

Hierarchical clustering uses group averages for iterative calculation and computes the proximity of clusters with HTTP packet distance (HTTP packet destination distance and HTTP packet content distance) as a heuristic. It then assigns a cluster to each HTTP packet, and iteratively composes new clusters from the nearest distance of HTTP packet pairs until there is only one cluster. Given two HTTP packets p_x and p_y , we define the HTTP packet distance as

$$d_{pkt}(p_x, p_y) = d_{dst}(p_x, p_y) + d_{header}(p_x, p_y)$$

using the formulae from sections IV-B, IV-C to compute d_{dst} and d_{header} . Given two clusters C_x and C_y , group average distance is defined as

$$d_{group}(C_x, C_y) = \frac{1}{|C_x||C_y|} \sum_{p_x \in C_x} \sum_{p_y \in C_y} d_{pkt}(p_x, p_y).$$

In a dataset of N HTTP packets $\mathbf{H} = \{p_i\}_{i=1..N}$, we apply hierarchical clustering to a subset \mathbf{P} of size $M: \mathbf{P}_{j,j=1..M} \subset \mathbf{H}$, using the following method:

- 1) Assign each HTTP packet $p_k \in \mathbf{P}$ to cluster C_k . At the end of this step, $\mathbf{C} = \{C_k\}_{k=1..M}$ is the set of defined clusters.
- 2) Chose any cluster $C_x \in \mathbf{C}$, and compute the distance to all other clusters $C_{y,y=1..M} \in \mathbf{C}, x \neq y$ using the cluster distance d_{group} .
- 3) Select the cluster C_y that is the closest to C_x . Create a new cluster $C_z = \{C_x, C_y\}$ and add it to ${\bf C}$, then remove C_x and C_y
- 4) Repeat until C has one cluster.

E. Signature Generation

We generate a conjunction signature set from the hierarchical clustering result, which is a dendrogram of the HTTP packet group. A conjunction signature set contains the invariant tokens that describe the longest common substrings in the dendrogram. Signatures each represent a feature of the cluster. That is, they reflect sensitive information as a invariant token. Given a dataset of N HTTP packets $\mathbf{H} = \{p_i\}_{i=1..N}$ and a subset $\mathbf{P}_{j,j=1..M} \subset \mathbf{H}$ used to generate (as described in Section IV-D) dendrogram \mathbf{C} , which has the nesting structure characteristic of clusters, we generate the conjunction signature set using the following process:

- 1) Select the top of cluster $C_i \in \mathbf{C}$.
- 2) Compute a signature S_i as longest common strings of HTTP contents in C_i .
- 3) Remove C_i from C and repeat for all clusters in C.

V. EVALUATION

A. Experimental Setup

We collected network traffic from 1,188 free applications running on an Android 2.3.6, Galaxy Nexus S, from January to April, 2012. The application set was as previously described in Section III. Each application was run manually for 5 to 15 minutes on the device. We attempted to test a every possible

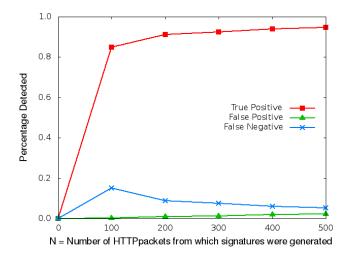


Fig. 4. Detection Rate of Sensitive Information Leakage

application function. We generated the data manually, since it is difficult to automatically test an application that requirs user interaction such as entering passwords and other user identification, or correct screen taps for a game.

The resulting dataset of application network traffic contained 107,859 GET/POST HTTP packets. For this experiment, we manually separated the dataset into a suspicious group and a normal group for the evaluation of our signatures' detection rate. The suspicious group consisted of packets containing sensitive information. The normal group was made up of those containing non-sensitive information. Again we considered UDIDs (Android ID, IMEI, IMSI, and SIM Serial ID), hashed UDIDs (MD5, SHA1), and Carrier names to be sensitive information.

In this experiment, we were not concerned with encrypted packets and obfuscation packets except the hashes mentioned above. Consequently, the normal group contained these packets. The suspicions group consisted of 23,309 HTTP packets, and the normal group contained 84,550 HTTP packets. The details of the suspicious group are shown in Table III. We selected N HTTP packets at random out of the suspicious group for signature generation, where N was increased from 0 up to 500 in intervals of 100. Finally, we applied the generated signatures to the dataset in its entirely to see how accurately they could identify packets containing sensitive information. We evaluate signatures for accuracy detection rate.

B. Experimental Results

Figure 4 shows the results of our experiment, approach. We evaluated the percentage of true positives, false positives and false negatives for varying values of N.

True Positive: a correctly detected packet containing sensitive information. The percentage of true positives was calculated according to the following equation:

$$\text{TP} = \frac{\text{\# of detected sensitive information packets} - N}{\text{\# of sensitive information packets} - N}$$

There were 23,309 sensitive information packets in the dataset for our evaluation. Our system produced 85% true positives at sampling size N=100. It grew beyond 90% by N=200, with the best result being 94% at N=500. These results show that true positives rise with an increasing number of signature generating sensitive information packets, therefore, signatures generated from more packets cover a wider common pattern of information leakage.

False Negative: a sensitive packet that was not correctly detected. We calculated the percentage of false negative results using following equation:

$$\text{FN} = \frac{\text{\# of undetected sensitive information packets}}{\text{\# of sensitive information packets} - N}$$

As stated above, there were 23,309 sensitive packets in our dataset. In this experiment, there were 15% false negatives at N=100, only 8% or less at more than N=200, and finally 5% at N=500. Thus, effective detection of information leakage is improved by increasing the number of sensitive information packets used for generating signatures.

False Positive: a non-sensitive packet incorrectly detected as sensitive. We calculated the percentage of false positives using following equation:

$$\text{FP} = \frac{\text{\# of detected non-sensitive information packets}}{\text{\# of non-sensitive information packets} - N}$$

This value is important for an evaluation of our system's signatures detection rate in terms of usefulness. If our system produces many false positives, users will be continually bothered by unnecessary warnings and prompts. This dataset had 84,550 non-sensitive information packets. The signatures from this dataset produced 0.3% false positives at $N=100,\,0.9\%$ at $N=200,\,$ and eventually 2.3% at N=500. We can see that verbose signatures are generated by increasing the number of clustering packets. We postulate that large signature generating sets produce signatures that detect packets without relation to their information leakage.

VI. RELATED WORK AND DISCUSSION

Other approaches to preventing sensitive information leakage include taint tracking and permission framework modifications. In this section, we compare our approach with current research results, and discuss the limitations of our scheme.

Several studies have analyzed the security and privacy concerns of the potential sensitive information leakage in Android and iOS applications [1], [2], [16], [17]. Other works have focused specifically on advertisement modules' access to device identification number and location information and their ability to send it over the network [3], [4]. To address this problem, fine-grained access control techniques have been proposed. These projects implement enhancements to the Android permission policy [18], [19], [20]. Taint tracking can also accurately detect sensitive information leakage and control the information flow of applications [1], [7]. These approaches have shown that dynamic analysis of the trace details of applications' behavior on the Android framework

can ameliorate the problem. It has the advantage of having low overhead with very few false positives, minimizing the notifications issue to the users. Separating the advertisement module's permissions from application's can also reduce the privacy risk [10], [11]. If the user does not grant permissions to the advertisement module, he can be sure that advertisement module does not access sensitive information on the device and send it over the network. However, all these approaches require Android framework modifications. Our approach of generating signatures that can identify sensitive packets with a small percentage of false positives does not require any modifications to the Android framework, or any escalation of user privilege on the Android device, making our system simple and immediately applicable. It can also be used with previous works should the proposed modifications be implemented or with anti-virus applications which are designed to detect malware.

Generating signatures from clustering is not a new idea. Previous work on signature generation used clustering focused on the similarity of network traffic or on the characteristics of applications, specifically, targeting malware and malicious network traffic [21], [22], [23], [24], [25], [26], [27]. Other proposals regarding clustering network destination and traffic individually intend to comprehend some aspect of an application's behavior [28], and signature generation uses include computing HTTP packet statistics contents to improve detection rates [29], similar to our approach.

Clustering in general is useful for pulling together patterns in large amounts of data, but the number of the generated signatures tend to increase with cluster size, and can produce signatures that match most network packets (e.g POST *, GET *, * HTTP/1.1), if the signature generation is applied carelessly. For this reason, it has been difficult for a signatures approach to achieve high detection rates using a real dataset. Probabilistic signatures [14], [30], [31] might improve detection of information leakage on Android applications, and we hope to include them in our scheme in future work. Currently our use of HTTP packet destination distance allows us to generate more useful signatures. A concern with using the destination distance is that two HTTP packets may have close IP addresses but be owned different organizations, thus generating an erroneously small distance is still very small. While our current implementation does not specifically handle this case, we feel that using a registration information process such as WHOIS could be helpful for the verification of IP addresses and domain names, which could be used to confirm the distances. Our current approach also does not focus on encrypted or obfuscated traffic. It can be difficult to detect sensitive information in SSL traffic but if an advertisement module uses one encryption key among applications or applies a cryptographic hash function to sensitive information, our approach can detect it.

Privacy preserving advertisement approaches which do not collect users' behavioral information from devices for targeted advertising have also been proposed [32], [33]. In spite of these proposals reducing users' privacy risks, they are not being

utilized practically.

VII. CONCLUSION

Advertisement services are widely accepted among application developers. However it is still important to investigate the behavior of an application with regards to security and privacy. We have shown that many Android applications require permissions for sensitive information access and network features, and that among them are applications that connect to many outside servers without the user's acknowledgment. Furthermore, we have observed that applications' network behavior includes a large amount of sensitive information, particularly, UDIDs and Android ID which are immutable identifiers. We have proposed a novel clustering method using HTTP packet distances which include both the distance between HTTP packet destinations and between HTTP packet contents. Using that clustering method in combination with signature generation in our dataset of 1,188 applications and 107,859 packets, which included 23,309 sensitive information packets, we were able to achieve 94% accurate detection of packets containing sensitive data with only 3% false positives.

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