ADDRESSING INSIDER THREATS FROM SMART DEVICES

A Dissertation

by

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ABSTRACT

Smart devices have unique security challenges and are becoming increasingly common. They have been used in the past to launch cyber attacks such as the Mirai attack. This work is focused on solving the threats posed to and by smart devices inside a network. The size of the problem is quantified; the initial compromise is prevented where possible, and compromised devices are identified.

To gain insight into the size of the problem, campus Domain Name System (DNS) measurements were taken that allow for wireless traffic to be separated from wired traffic. Two-thirds of the DNS traffic measured came from wireless hosts, implying that mobile devices are playing a bigger role in networks. Also, port scans and service discovery protocols were used to identify Internet of Things (IoT) devices on the campus network and follow-up work was done to assess the state of the IoT devices.

Motivated by these findings, three solutions were developed. To handle the scenario when compromised mobile devices are connected to the network, a new strategy for steppingstone detection was developed with both an application layer and a transport layer solution. The proposed solution is effective even when the mobile device cellular connection is used. Also, malicious or vulnerable applications make it through the mobile app store vetting process. A user space tool was developed that identifies apps contacting malicious domains in real time and collects data for research purposes. Malicious app behavior can then be identified on the user's device, catching malicious apps that were overlooked by software vetting. Last, the variety of IoT device types and manufacturers makes the job of keeping them secure difficult. A generic framework was developed to lighten the management burden of securing IoT devices, serve as a middle box to secure legacy devices, and also use DNS queries as a way to identify misbehaving devices.

DEDICATION

To my beloved wife Faith.

CONTRIBUTORS AND FUNDING SOURCES

Contributors

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All the remaining work for this dissertation was conducted by the student.

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NOMENCLATURE

AIDL	Android Interface Definition Language [1].
ANM	App Network Monitor (see page 60).
API	Application Program Interface.
ARPA	Address and Routing Parameter Area [2].
CDF	Cumulative distribution function.
CDN	Content Delivery Network.
CPU	Central Processing Unit.
C&C	Command and Control.
DDoS	Distributed Denial of Service.
DGA	Domain Generation Algorithms.
DHCP	Dynamic Host Configuration Protocol [3].
DNP3	Distributed Network Protocol Version 3.
DNS	Domain Name System [4, 5].
DNS-SD	Domain Name System Service Discovery [6].
DVR	Digital Video Recorder.
ENUM	E.164 to Uniform Resource Identifiers [7].
FTP	File Transfer Protocol [8].
GPS	Global Positioning System.
HTTP	Hypertext transfer protocol [9].
HTTPS	Hypertext transfer protocol over SSL or TLS.

HTTP-RT	Hypertext transfer protocol Response Time Method (see subsection 4.2.2).
IMAP	Internet Message Access Protocol [10].
IoT	The Internet of Things.
IP	Internet Protocol [11].
IPC	Interprocess Communication.
IPP	Internet Printing Protocol [12].
IPsec	Internet Protocol Security [13].
JSD	Jensen Shannon Divergence (see page 40).
KVM	Keyboard Video and Mouse.
LAN	Local Area Network.
LDAP	Lightweight Directory Access Protocol [14].
Mbps	Megabits per Second, 1,000,000 Bits per Second [15].
mDNS	Multicast DNS [15].
MMD	Mean Minimum Distance (see page 41).
MPGS	Mean Pairwise Gaussian Similarity (see page 41).
MTU	Maximum Transmission Unit.
NAT	Network Address Translation [16].
NAS	Network Attached Storage.
NFC	Near Field Communication.
OS	Operating System.
PBX	Private Branch Exchange.
PDL	Page Description Language.
POP2	Post Office Protocol Version 2 [17].

POP3	Post Office Protocol Version 3 [18].
RFU	Remote Firmware Update.
ROC	Receiver Operating Characteristic.
RTT	Round Trip Time.
SCADA	Supervisory Control and Data Acquisition.
SDN	Software-Defined Networking.
SIP	Session Initiation Protocol [19].
SLD	Second Level Domain.
SMTP	Simple Mail Transfer Protocol [20, 21].
SOA	Start of Authority.
SOAP	Simple Object Access Protocol [22].
SOCKS	Socket Secure [23].
SSDP	Simple Service Discovery Protocol [24].
SSH	Secure Shell [24].
SSL	Secure Socket Layer.
TCP	Transmission Control Protocol [25].
TCP-DD	Transmission Control Protocol Delay Distribution Method (see subsection 4.2.1).
TLD	Top Level Domain.
TLS	Transport Layer Security [26].
TTL	Time to Live.
UID	User Identification.
UPnP	Universal Plug and Play.
UPS	Uninterrupted Power Supply.

URI	Uniform Resource Identifier [27].
URL	Uniform Resource Locator [28].
VoIP	Voice Over IP.
VM	Virtual Machine.
VNC	Virtual Network Computing [29].
VPN	Virtual Private Networking.
WAN	Wide Area Network.
WPA	Wi-Fi Protected Access.
WEP	Wired Equivalent Privacy.
μ	Mean, Average.
σ	Standard Deviation.

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1. INTRODUCTION

The development of computers has had a profound and far reaching effect on society. This development is ongoing, and with innovation comes many new challenges. While the new technology has benefitted society, it has also created problems that need to be addressed. Though the Internet provides unprecedented opportunity for freedom of expression, learning, and trade, some would use it as a weapon or to take advantage of others. Computer and network security deals with the protection of users from malicious attacks.

When dealing with security threats, two factors that can maximize the positive impact are: (1) How widespread is the threat? (e.g. How many devices and people are affected?) (2) How severe is the impact of the threat? (e.g. Is it life threatening? Could it cause a company to go bankrupt?) Based on these factors, this work is focused on smartphones and smart devices because they have widespread usage and can be found in safety critical environments such as hospitals.

Mobile devices are gaining increased attention because laptops and mobile handsets are ubiquitous. Three-quarters of the US population own one [30], and the global median for adult smartphone ownership of a country is 43% [31]. These devices are brought along with the user and come in contact with a variety of networks and devices such as public Wi-Fi hotspots, bluetooth headsets, home networks, and office networks. Since these devices are not tied down within a secure domain, they can carry infections and other malware from outside into a protected network. When these devices are brought back into the network, the network provider has more to worry about than just the vulnerabilities of these mobile devices. They also need to protect the desktops, servers and other equipment that remains within the protected domain. Thus, smartphones are attractive targets and need appropriate protection.

People store significant personal data on their phones. Some examples include contact information, personal calendars, personal photos, and payment information. In addition, smartphones can use services like GPS, the Cellular network, and Wi-Fi to locate and track the device. This information is vulnerable when malicious applications are present on the user's smartphone. The major smartphone app stores police the apps they host as a measure to prevent the spread of malware. Android even can remove malicious apps installed on user devices remotely. However, some malicious apps end up on user devices either by being preinstalled, by using an exploit, or by masquerading as a benign application. Malicious behavior may not be evident until long after an app was originally installed for various reasons. Apps can download new instructions to execute at runtime, they can detect when they are being observed, and they can have zero day vulnerabilities. Therefore, monitoring can play a crucial role in identifying malicious activity on the end-user device.

In addition to smartphones, many other devices are being connected to networks and are already widespread in medical, educational, and industrial facilities. While smart devices offer new features and remote management capability, these conveniences come with added complexity and management burden. Handling one device may not be that much trouble; however, it becomes a challenge when scaled up to a variety of device types and vendors. In addition these devices pose new challenges to providing protection from attacks because most have no capability to run third party security applications. When these devices are medical equipment or are used at medical facilities, they can become safety critical.

These challenges justify research effort to identify and address potential security risks. Ideally, solutions to important issues would be found and deployed before there is an opportunity for known vulnerabilities to be exploited by attackers. First, mobile devices provide attackers with a way to avoid detection at the network edge. Second, malicious behavior needs to be detected on mobile devices even with policing at the app store. Third,

monitoring and deploying patches to each device is difficult and motivates solutions that require less effort and upkeep.

This dissertation addresses security issues related to mobile and non-compute devices on the network, and has two main parts. The first two chapters are measurement studies that cover the security considerations and prevalence of non-compute devices such as smartphones and IoT devices. The last three chapters cover solutions to inside network threats posed by non-compute devices.

The first measurement study investigates wireless vs. wired DNS traffic and analyzes DNS traffic for suspicious traffic. The second measurement study investigates non-compute devices that have open ports. Findings from these studies show that wireless devices (such as smartphones) dominate the DNS traffic (chapter 2) and that IoT devices outnumber the compute devices with open services (chapter 3). These results motivate the study of potential security problems that can arise from these smart devices.

First, chapter 4 presents a solution to the problem of securing sensitive internal services from compromised mobile devices. Second, solutions for detecting malicious smartphone apps are covered in chapter 5. Third, chapter 6 details a solution for securing and managing IoT devices.

Before developing a solution to a problem, it helps to understand the size of the problem as well as any previously unnoticed cravats. The first measurement study utilizes Domain Name System (DNS) traffic. The Domain Name System (DNS) is fundamental to the day-to-day operation of the Internet. As new uses for DNS are introduced and the ways people use the Internet change, the impact on existing network utilities and services need to be continuously studied and evaluated. We present a study of the DNS traffic on a large campus network (chapter 2) that is based on an investigation of wireless and wired traffic and the impact of new applications of DNS. We look into the differences in DNS traffic from wired hosts and Wi-Fi hosts. In addition, we study various aspects of DNS traffic

including the network sources, application sources, and especially the various sources of DNS nonexistent domain responses. Our results indicate that non-negligible fraction (10-15%) of DNS queries result in nonexistent domain responses, many new applications have come to rely on DNS as a side channel through network firewalls and that wireless DNS traffic can exceed the wired DNS traffic.

DNS traffic is a sign of devices communicating with the Internet, but some devices primarily have local communication. Smart devices such as printers, VoIP phones, and IP cameras host services but typically generate few DNS queries or none. These devices are still important from a security perspective. The infamous Mirai attack [32] which hijacked nearly half a million Internet connected devices demonstrated the widespread security vulnerabilities of the Internet-of-Things (IoT). In chapter 3 a set of active and passive observation methods are employed to discover the security vulnerabilities of IoT devices within a university campus. We show that (a) the number of non-compute devices dominates the number of compute devices with open ports in a campus network; (b) 58.9% or more devices do not keep up-to-date firmware and 51.3% or more do not have a user defined password; and (c) the number of devices together with the diversity of device ages and vendors make the protection of IoT devices a difficult problem.

Since mobile devices outnumbered wired devices in the DNS study, this work was focused on attacks enabled by the unique properties of mobile devices. Smartphones can connect over both Wi-Fi and Cellular interfaces allowing data to be funneled off of a network without it passing through the network edge. When compromised they can be used by attackers as steppingstones for accessing sensitive or protected information. We propose a class of detection methods based on anomaly detection at the service and present two lightweight methods of detecting proxies at the service: one for TCP and one for the application layer. These methods can potentially be deployed to monitor connections in real time so attackers may be stopped before accessing sensitive data. We evaluate these

methods on local and wide area networks, with different proxy applications, and under different load conditions to show that the proposed techniques can provide high detection rates at low false positive rates. Our techniques are effective even when the client to proxy connections are out of scope of surveillance and resilient to attacks even during training[1].

In addition to detecting proxies, other strategies can be used for identifying malicious activity on smartphones. Some malicious apps for smartphones have been already identified, and there is a need to have the capability to quickly identify attacks and respond in ways that minimize the damage they cause. Mobile apps are checked for malicious behavior before being published on app stores, but this does not catch all the malicious or vulnerable apps. In addition to determining aspects of the future behavior of an app, malicious activity can be detected on users' devices in real time. Chapter 5 expounds methods for creating a controlled test environment that runs untrusted Android apps for security research. These methods were used to determine that 20 out of the top 100 most popular apps on the Google play store access the Internet regardless of user activity. This makes the presence of periodic network traffic a poor indicator of malicious apps. A platform was constructed for using DNS traffic to identify malicious apps. This platform also enables data collection to gain new insights into the domains accessed by different apps with a goal of detecting previously unknown malicious activity.

Smartphones are not the only new growing area that needs to be addressed. Smart devices such as printers, VoIP phones, IP cameras, and other network enabled devices also can be compromised. Motivated by the findings in chapter 3 we developed the IoTAegis framework, which offers device-level protection to automatically manage device configurations and security updates. With cloud-based device profile updates, the development effort to use IoTAegis to handle one device can be shared by all other users of the frame-

[1] © 2016 IEEE. Reprinted, with permission, from Allen T. Webb and A. L. N. Reddy, Finding proxy users at the service using anomaly detection, 2016 IEEE Conference on Communications and Network Security (CNS), October, 2016.

work. Our solution is shown to be effective, scalable, lightweight, and can be deployed in different forms and network types. The above solutions together constitute solutions to insider threats posed by smart devices.

2. THE TWO FACES OF DNS TRAFFIC

2.1 Introduction

The availability of low cost and portable computers such as laptops, smart phones, and tablets has introduced new variation into the way networks are used. One window for observing changes in usage is the DNS requests made by different classes of devices. The Domain Name System (DNS) [4, 5] provides a mapping from human readable names into Internet Protocol addresses that can be routed to specific endpoints on the Internet (e.g. www.domain.tld). It serves as a distributed database for records identified with a multi-part name where DNS servers have authority over subsets of names delegated to them. In this way the administrative burden of updating records is spread across organizations that have authority over particular domains. DNS traffic is typically allowed through firewalls; thus, many new services use DNS infrastructure as a means of communicating information.

DNS traffic has been widely studied to understand network traffic at large. It provides a view into traffic patterns [33] and popular domains. DNS responses give a view into the mechanisms of load balancing [34] [35] and how Content Delivery Networks (CDNs) function [36]. DNS traffic has recently been used to provide a view into botnet behavior, by distinguishing the botnet generated DNS query traffic from human generated query traffic [37]. Collecting and analyzing DNS traffic is more scalable than carrying out similar analysis on all the network traffic.

This study is motivated by two trends in network usage. First, usage of mobile and wireless devices is the growing. Users have started replacing desktop computers with laptops and other devices; the widespread adoption of smartphones with Wi-Fi capabilities is changing the network usage patterns. The introduction of mobile devices brings several aspects to the study of DNS traffic. The network traffic can be different because of differ-

ences in application usage, network usage, and the different resources in the devices. The application usage on mobile devices may include more frequent accesses to social networking and video sites. The wireless devices on a campus that has wide Wi-Fi coverage allow for more continuous or longer usage of network resources compared to desktop devices. Mobile devices with limited resources (and hence lower caching) may also generate more traffic than desktop devices.

Second, DNS is now used as a side channel by many applications. Most campus and enterprise networks are protected by firewalls at the edge. These firewalls restrict the flow of traffic between the protected network and the outside world. However, most network firewalls typically allow communication on a few designated ports. The ports for HTTP and DNS are commonly open, and a number of applications rely on these open ports for getting through the firewalls. This is significant because attackers may utilize DNS for this same purpose. DNS is being used by a number of applications from spam checkers to anti virus software as a side channel to contact outside servers to provide their service. Other new services we observed are ENUM over DNS (section 2.4), and the ICANN name collision block list. ENUM is an important part of the VoIP infrastructure that enables one type of smart device, VoIP phones, to perform their intended function. New services that make use of the Domain Name System (DNS) infrastructure change the nature of DNS queries.

This chapter studies the DNS traffic to observe and understand the impact of these two trends. We collect and analyze DNS traffic at an educational institution to understand any differences in mobile device traffic over wired devices. A better understanding of spam DNS traffic improves decision-making in the area of how much monitoring is warranted to stop outbreaks of malicious software and detect intrusions while protecting individual privacy. A better picture of DNS traffic will also help gain an understanding of scalability and other issues. For example, DNS traffic has been recently used as a means to identify

botnet C&C (command and control) [38, 39], and [40]. Specifically, these earlier studies have used DNS nonexistent domain responses as a means of identifying potential botnet traffic. Many new applications such as spam checkers and antivirus tools that use DNS as a side channel generate a significant number of nonexistent domain responses as part of their legitimate service. Understanding and separating this traffic is important for continuing to provide security of the networks.

This chapter makes the following significant contributions: (1) Collects and analyzes the DNS traffic over several days at a campus network, separating the traffic from wired networks and wireless networks; (2) Shows that wireless networks are starting to dominate the campus traffic, leading to implications on scalability and throughput of these networks; (3) Shows that mobile devices have much less failed DNS queries than wired devices. Some of this traffic is originating from new services exploiting DNS as a side channel. These increased failure traffic increase the processing burden for separating legitimate traffic from malicious traffic; (4) Shows that the application usage across wireless and wired networks leads to different network accesses.

2.2 Datasets / Methods

Our measurements were taken from a campus of about 60,000 users. We collected all the DNS traffic from three time periods: the summer of 2014, the fall semester of 2014, and the spring semester of 2015. Our data includes requests for which the campus DNS servers are the start of authority (SOA) and also local queries which were recursively resolved. The size of the datasets and some basic statistics about their constituents can be found in Table 2.1.

To collect our data we tapped DNS traffic directed to the campus DNS resolvers. We excluded traffic involved in the process of recursive DNS resolution. Thus, each dataset contains those DNS requests made to the local campus resolvers, as well as the correspond-

		Dataset 1	Dataset 2	Dataset 3	Dataset 4
Time Period		Summer	Fall Semester	Spring Sem. Weekend	Spring Sem. Week
Start Date		June 19, 2014	Sep. 9, 2014	Jan. 16, 2015	Jan. 22, 2015
Duration (days)		13.07	10.26	2.26	7.02
Requests	Total	2.02E+09	2.57E+09	2.36E+08	1.82E+09
	% No Error	70.11%	92.02%	86.35%	91.10%
	% Error	29.89%	7.43%	13.00%	7.99%
Unique Domains	Total	9.22E+06	9.08E+06	1.08E+06	4.81E+06
	% Resolved	47.10%	57.72%	76.67%	76.66%
	% Not Res.	52.90%	42.28%	23.33%	23.34%
Unique IPs	Total	1.77E+05	1.66E+05	9.65E+04	1.78E+05
	% Wired	42.96%	29.63%	24.74%	26.59%
	% Wi-Fi	57.04%	70.37%	75.26%	73.41%

Table 2.1: Volume of traffic present in each dataset. It should be noted that for Dataset 1, which was during the summer, and Dataset 3, which was during a weekend, there are fewer students on campus than the other datasets. This provides a variety of different conditions to observe the unique and common features across the datasets.

ing responses from the resolver back to the requester. These traces were then processed afterward. DNS names longer than the 255 byte limit are included in the count as an empty domain, “”. These made up 0.05% to 0.18% of the total requests.

It is notable that in Table 2.1 between 7.43% and 29.89% of the DNS requests failed across the datasets. The DNS failure rates were higher during the summer and weekends. The hosts that filter out Spam emails generate a higher ratio of failed to successful DNS responses than typical users. When there are more typical users such as the university students during the semester or week, the relative contribution of the Spam filter traffic is less. In dataset 1 the hosts that accessed Spam blacklists had a 50.7% DNS error rate and were responsible for 37.5% of the total DNS responses. We found that four forwarding nameservers were responsible for the much larger nonexistent domain percentage in dataset 1. For datasets 2 and 4 the error rates of hosts accessing Spam blacklists were between 16.4% and 19.0%, while for dataset 3 the error rate was 29.4%. The higher error rate for dataset

3 is due to the volume of DNS errors remaining relatively flat across the week while the successful traffic is more dependent on the time of day and day of the week, see Figure 2.3.

Also of note, is the difference in percentages of domains that resolved versus domains that did not resolve. Domains that resolved had at least one successful DNS response while domains that didn't resolve had no successful DNS responses. There were a higher percentage, 70.11% to 92.02%, of successful DNS responses than resolved domains, 47.10% to 76.66%. This means there was a higher proportion of non-existent domains than requests of non-existent domains. This can be attributed to Spam and URL blacklists as well as the fact that a few domains account for a large percentage of the total requests (see 2.2).

The unique IPs in Table 2.1 show the change in relative percentage of IP addresses between the wired and Wi-Fi networks during the summer when students were away versus during the semesters when students were present. Between datasets 1 and 2 this difference was 13.33%.

2.3 Wired vs. Wi-Fi DNS Traffic

By observing how DNS traffic from wired vs Wi-Fi hosts differ, the top potential security issues facing mobile devices in particular can be found. Along with the DNS traces we identified the IP addresses that had server related ports including FTP, SSH, Telnet, SMTP, DNS, DHCP, HTTP, Kerberos, POP2, POP3, IMAP, LDAP, and secure versions of these protocols. This set of hosts represents 2.52% of the total hosts and 9.46% of the wired hosts. These hosts received 15.28% of all the successful DNS responses and 46.39% of the successful DNS responses to wired hosts. This suggests that server traffic is a significant fraction of the wired network even though they constitute a small fraction of the number of machines. More and more, the wired and wireless networks are becoming "server" networks and "client" networks.

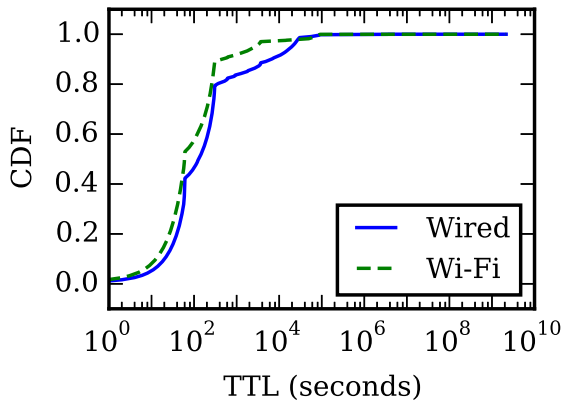


Figure 2.1: CDF of DNS Address Record TTL Values

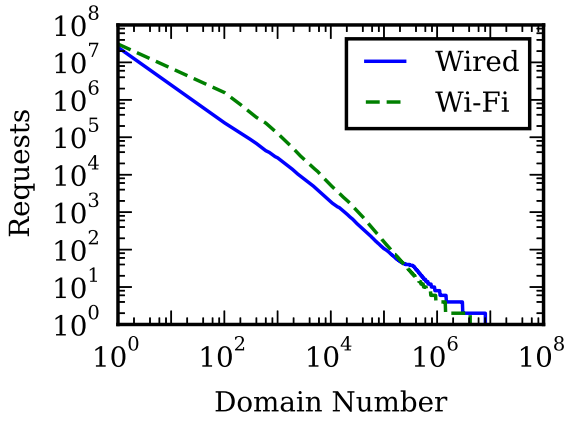


Figure 2.2: Volume of DNS Requests for Each Domain

Four second level domains were responsible for 21.93% of all the successful DNS requests, and of these 83.30% of the requests originated from Wi-Fi IP addresses. This shows that a small subset of domains are responsible for a significant bias in the amount of successful DNS queries between wired and Wi-Fi devices. In Table 2.2 the top 25 most requested second level domains are listed. Only successful requests are counted in this table. The *% All* column is the percentage of all successful DNS requests that match the

specified second level domain. The *Wi-Fi %* column is the fraction of successful DNS requests for the specified second level domain that originate from Wi-Fi IP addresses.

The Time to Live (TTL) value of a DNS record conveys how long the record should be cached before expiring. More information can be inferred from the TTL values as they reflect a trade off between DNS server load and update response time. A record with a higher TTL is cached longer and is requested less frequently as a result. Web services that depend heavily on load balancing to provide better quality-of-service such as video streaming use small TTLs to allow for faster control over which servers receive new clients. Fast-fluxing DNS botnets use small TTL values to make it more difficult to blacklist all their IP addresses and domain names. The TTL CDF plots for are shown in Figure 2.1. More than 80% of the domains ranked 51st through 500th had TTL values of 60 seconds or fewer. For the top 25 domains almost half of the requests had TTL values between 60 seconds and 5 minutes. The remaining domains had more of a spread over the different TTL values with about half having TTL values 60 seconds or fewer. Figure 2.1 shows the CDF of the TTL values of address records for Wi-Fi and wired devices. We saw that more of the TTL values of DNS address records requested by Wi-Fi devices were sixty seconds or fewer than 5 minutes. Other common TTL values include three hours and one day. This suggests that users of Wi-Fi devices requested more CDN hosted content such as online videos than users of wired devices. Table 2.2 confirms that several well-known CDN domains (`akadns.net`, `akamai.net`, `akamaihd.net`, `amazonaws.com`, etc.) were requested more often by Wi-Fi hosts.

Figure 2.2 shows that the volume of requests of domains is nearly linear on a log-log plot. This resembles a distribution following a power law [41]. However, there is a slight curve that suggests that it is actually a power law with exponential cutoff or a log-normal distribution. The distribution of requests from wired devices is more linear on the log-log plot than from Wi-Fi devices. Wired devices made more requests to domains with less than

SLD	Wi-Fi %	% All	μ_{TTL}	SLD	Wi-Fi %	% All	μ_{TTL}
apple.com	92.44%	8.61%	5495.2	yahoo.com	74.98%	1.32%	756.2
<local #1>	9.41%	8.34%	14719.4	icloud.com	89.83%	1.23%	37210.6
google.com	73.27%	7.67%	31188.1	twitter.com	77.10%	1.16%	50.7
akadns.net	86.10%	6.12%	90.5	yahooapis.com	92.52%	1.01%	194.8
facebook.com	85.36%	3.52%	1255.7	gstatic.com	65.12%	0.99%	175.7
groupme.com	96.32%	2.48%	31.6	doubleclick.net	71.63%	0.97%	20786.8
amazonaws.com	77.87%	2.14%	455.7	googleapis.com	82.27%	0.76%	6167
akamaihd.net	79.19%	2.06%	179.4	microsoft.com	48.95%	0.74%	1819.8
flurry.com	94.92%	1.99%	31.5	bing.com	86.50%	0.64%	1493.3
instagram.com	94.56%	1.90%	108.1	yahoodns.net	76.79%	0.60%	148.9
akamai.net	61.62%	1.74%	37	cloudfront.net	66.25%	0.55%	64.6
akamaiedge.net	67.12%	1.45%	37.2	google-analytics .com	81.85%	0.55%	49556.4
in-addr.arpa	16.89%	1.40%	15423.3				

Table 2.2: 25 Second-level Domains (SLD) with the Most Error-free Responses. The *Wi-Fi %* column shows what percentage of these requests came from Wi-Fi IP addresses. The *% All* column shows the percentage of total valid requests were for this domain. The average TTL values are shown in the μ_{TTL} column.

100 requests each and significantly more to domains with only 2 requests. This shows the wired network accesses were more diverse than the wireless network accesses.

From Table 2.2 the top three SLDs, *apple.com*, *<local #1>* and *google.com*, make up a very large percentage of the successful DNS responses, about one quarter. This can be explained by synchronization or other mobile device features on devices running iOS and Android, as well as local services such as authentication servers. Contributing factors to the results include cache misses due to smaller TTL values and unique subdomains. The more unique subdomains a SLD has, the more requests and cache entries will be. In Table 2.2 only *<local #1>* and *in-addr.arpa*, have more DNS requests from wired hosts than Wi-Fi hosts.

Figure 2.3 shows the number of DNS responses with and without errors per five minute interval. The data showed a different diurnal cycle for wired versus wireless hosts especially for DNS error responses. This difference is likely due to the Wi-Fi devices being

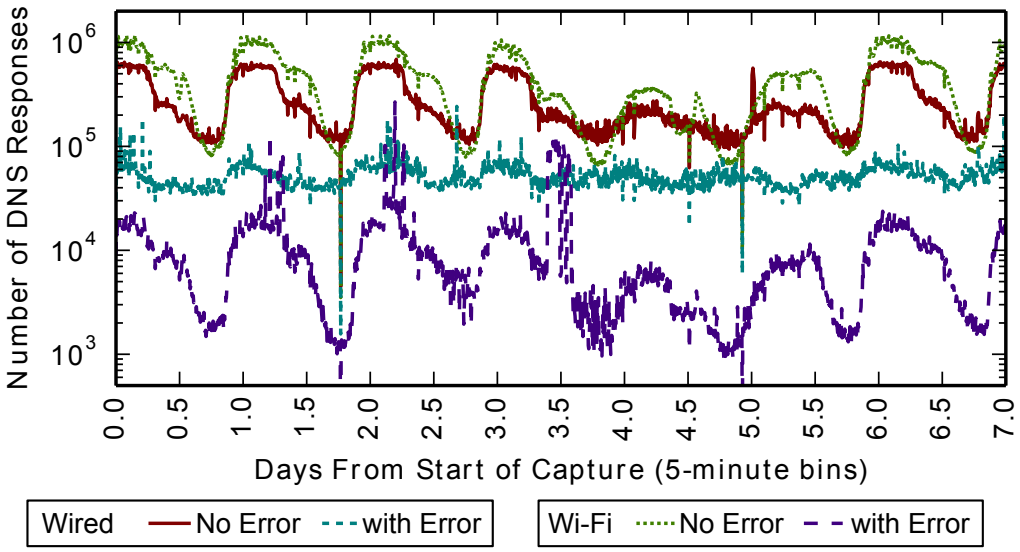


Figure 2.3: Wired vs. Wi-Fi DNS Response Volume

used after work hours for personal use, but the wired devices mostly being used during work hours. Typically, the wired hosts see a drop-off in activity after 5-6PM and the wireless hosts were active until 10-11PM.

The volume of DNS errors for Wi-Fi hosts more closely follows the volume of DNS successes. The relatively flat error response volume for wired hosts in Figure 2.3 is due to the requests from Spam filters which are related to the volume of email traffic. The Wi-Fi hosts are responsible for more successful DNS responses than the wired hosts, but the Wi-Fi hosts produce less failed responses than the wired hosts. The spikes in Wi-Fi error responses on Figure 2.3 result from anomalous traffic.

One interesting feature in Figure 2.3 is centered 4.5 days after the start of the trace. There was a football game during this time that resulted in less than half the Wi-Fi DNS responses on each side of the valley. The DNS responses from wired hosts did not have a noticeable change in the volume.

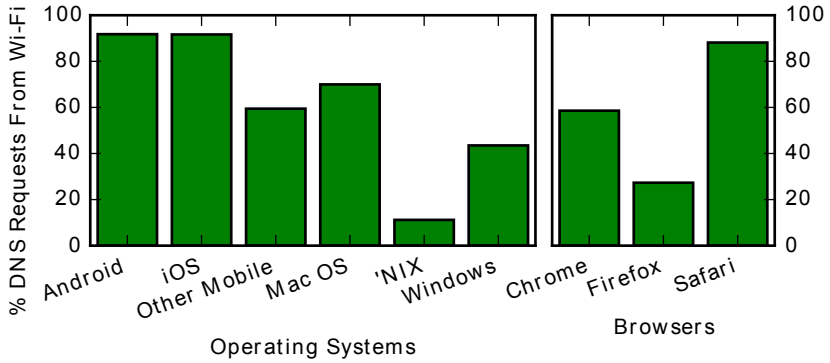


Figure 2.4: Percent of Total DNS Requests from Wi-Fi Hosts for Software Specific Domain Names (Dataset 4)

It is possible to predict when students are between classes by changes in the volume of traffic. There are regular peaks on the Wi-Fi DNS responses without errors in Figure 2.3 during the breaks between classes.

Figure 2.4 shows the percentages of DNS requests made for software specific domain names. The particular domains chosen were those used for software updates and account synchronization. An example software specific domain is *android.clients.google.com*, which is used by android to download application updates and to access the Google Play API. As expected Android and iOS DNS requests predominantly originated from Wi-Fi IP addresses. Rogue access points are one source of mobile specific domains being accessed from wired IP addresses. There is a strong bias toward mobile traffic originating from Wi-Fi IPs, so by observing the Wi-Fi tendencies we can infer mobile usage trends. Windows was split about evenly between the Wi-Fi and wired IP addresses; however, Mac OS had a higher number of requests from Wi-Fi IP addresses. Safari is closely tied to iOS and Mac OS so its percentage lied between the two operating systems. Requests from Firefox were more common from wired hosts; requests from Chrome was more common on Wi-Fi hosts. These percentages are from the raw total number of requests.

Dataset		1	2	3	4
api.*	RF	2.46%	3.63%	4.68%	5.71%
	W	0.61%	1.19%	0.64%	1.02%
m.*	RF	0.42%	0.38%	0.34%	0.30%
	W	0.26%	0.29%	0.18%	0.24%
mobile.*	RF	0.12%	0.18%	0.22%	0.21%
	W	0.03%	0.06%	0.03%	0.05%
*.mobi	RF	0.11%	0.18%	0.17%	0.18%
	W	0.01%	0.03%	0.01%	0.02%

Table 2.3: Mobile Domain Responses Wired (W) and Wi-Fi (RF) IPs

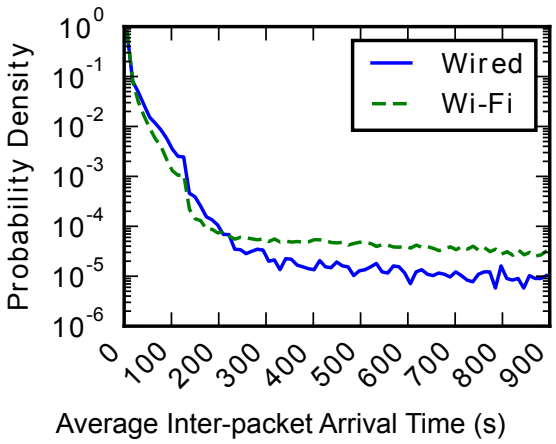


Figure 2.5: Distribution of Average Delay Between DNS Requests

Mobile devices such as smart-phones and tablets are increasingly common. These devices typically connect to local networks through Wi-Fi. Separate web sites are provided for these devices because they have touch screens instead of a mouse and keyboard. Also, their screens may be much smaller so that a different layout is preferable than for desktops or laptops. Domains of the following formats are associated with mobile devices: (1) ***.mobi** is a TLD dedicated to mobile websites. (2) **api.*** are for web and mobile application programming interfaces. (3) **m.***, and **mobile.*** are for websites formatted for mobile devices.

The *api.** subdomains made up the largest percentage of the responses with no error with between 0.61% and 1.19% for wired hosts and between 2.46% and 5.71% for Wi-Fi hosts. Although we did observe requests made to other mobile related domains (*mini.**, *palm.**, *pda.**, *wap.**, *wireless.**, and *xhtml.**), these made up less than 0.005% of the total requests. Table 2.3 shows that the mobile handsets are not necessarily always visiting mobile domains. The *api.** domain group is commonly used with mobile applications instead of websites in a browser. Not all mobile websites use mobile domains; some share the same domain as the website formatted for desktops. Also, many websites are designed using a "responsive design" [42] which is shared across different devices and screen formats. Although there are still hits for older style mobile domains such as *palm.**, *pda.**, *wap.**, and *xhtml.**, these domains make up a very small percentage of the total responses.

Besides differences in the domains being queried, there were also rate differences between wired and Wi-Fi hosts. We observed higher DNS packet rates on wired hosts vs Wi-Fi hosts based sessions defined by a 15-minute separation between packets for a given IP address shown in Figure 2.5. To exclude the bias introduced by the edge of the session window we calculated the mean time between packets to be the time of the last packet minus the time to the first packet divided by the total number of packets minus one. Wi-Fi IP addresses had a higher likelihood of long periods of time between DNS requests than wired IP addresses. Wi-Fi devices may be used more intermittently than wired devices. Wired IP addresses with multiple simultaneous hosts through NAT, and higher demand from DNS dependent services such as Spam filtering contribute to the higher rate on wired IP addresses.

We found that across all four datasets 16.53% of all the DNS responses had the error flag set, while only 28.55% of these came from Wi-Fi hosts. Furthermore, 23.00% of all the error responses were for the ARPA TLD, and only 1.69% of these were from Wi-Fi

Dataset	1	2	3	4
Number of blocked domains	1	772	45	427
Number of blocked TLDs	0	24	7	39
TLDs with any DNS record	420	354	132	335

Table 2.4: ICANN Name Collision Block List Stats

hosts. We attributed 13.42% of the error responses to local domains either the campus domain or domains with the local, and localdomain TLDs. Wi-Fi hosts were recipients of 20.11% of this traffic. DNS Service Discovery made up 8.43% of the DNS error responses 18.08% of which went to Wi-Fi hosts. Lastly, anti-virus and spam blacklists made up 7.90% of the total error responses, but only 4.79% were for Wi-Fi hosts.

2.4 Other Observations

In investigating top level domains that were coming back as having IP addresses we found some with records to *127.0.53.53*. Since, August 2014 this address has been purposed for ICANN name collision management. Table 2.4 shows the number of unique domains returning *127.0.53.53* versus the total number of requests for a domain name with only a top level that returned an IP address.

Several malicious and compromised machines were detected through the analysis of failed DNS queries. However, this analysis is increasingly becoming difficult with several applications generating nonexistent domain responses as part of their operation. We did observe fast fluxing DNS responses, and suspicious DNS traffic likely related to botnets. Some suspicious traffic appeared to be aggregated either by NAT or a DNS forwarder. Of the domains with DNS failures 89.11% to 99.53% of them had an edit distance greater than two to the nearest valid domain. The remaining percentage includes those typos where in one or two instances a letter is omitted, different, or inserted.

Examples of domains we identified that indicate the presence of malware include:

`bvkaymxoioe.www.game499.com.2014-12-30.pw`

`bvkcrzkdcsb.www.gannme499.com`

`looooplollokp80.com`

With each example the bold part of the domain name was constant while the rest of the domain had variation. The last example was accompanied by several requests to the same prefix with different numbers at the end. This is an attempt to lower the edit distance between requests and avoid detection.

One source of a large volume of nonexistent domains was the *nrenum.net* second level domain. Nrenum provides an ENUM database over DNS for participating universities. ENUM provides a way for E.164 numbers to be converted to a URI [7]. Protocols such as SIP and H.323 then provide a way of initiating the voice communication. 99.98% of the nonexistent ENUM domain responses were for a single host. In Dataset 4 for every successful lookup this host had 9.67 failures, but the next most common requester had more than 350 successful lookups for every failure. This appears to be a brute force search of the entire ENUM database. The results of this kind of search could be used to associate IP addresses with VoIP phone numbers, or determine what numbers are active for purposes like robo-callers, etc. One technique to mitigate this kind of attack is to impose rate limiting per IP by the number of unique ENUMs requested with a higher penalty for non-existent numbers. Heavy offenders could be blacklisted, and legitimate services that require higher rates could be white-listed.

2.5 Related Work

DNS traffic has been widely studied to understand network traffic at large. It provides a view into traffic patterns [33], popular domains and through responses a view into the

mechanisms of load balancing [34] [35] and the functioning of Content Delivery Networks (CDNs) [36].

DNS traffic in cellular networks has been recently studied [36]. They investigate the impact on CDN load balancing performance from using a single DNS server for a geographically diverse set of mobile devices. DNS has been widely used for load balancing and reducing delays over wide area networks through redirection [34] and [35]. It has also been used as a way to measure delays across the internet [43]. DNS measurement studies have been conducted in the past from the point of view of a root DNS server [33]. This study identified violations of the DNS standard, reflection attacks, and divided up DNS failure responses by the reasons they failed.

Domain registration has been studied for the possibility of identifying spammers early in [44]. DNS behavior has been studied from several vantages to understand the global DNS query patterns that can be used to detect malicious domain groups [45].

DNS traffic has recently been used to provide a view into botnet behavior, by distinguishing the botnet generated DNS query traffic from human generated query traffic. In [46, 38, 39], and [40] non-existent domain queries are used to identify botnets that use domain generation algorithms (DGA) for locating the C&C channel. The query rates for bots were observed to be high, occurring over a short period, and generating nonexistent domain responses in [46]. DNS error responses were classified using the type of error, query entropy over the number of requests per local resolver and authoritative name server, and query content in [47]. They found a string of malicious domains copying strings from common social network domains. In [48] and [37] rather than focusing on DGA, a classification scheme is developed for malicious domains. [37] makes use of timing information, address record IP related information, reverse record information, TTL statistics, and domain name features to perform the classification.

The possibility of information being leaked through DNS is investigated in [49]. Several services now use DNS for purposes beyond looking up the address record of a server by name. In addition to intentional leakage of information, the architecture of a network can be inferred through DNS traffic. The problem of remotely identifying the type of DNS client infrastructure is addressed in [50]. They perform this classification by probing for DNS servers by issuing requests to an authoritative name server they control.

DNS traffic can be analyzed to identify the operating systems of hosts. DNS query traffic has been employed to carry out passive OS fingerprinting in [51] using OS-specific DNS queries and timing of DNS queries. They also estimated the number of devices generating the queries.

Work has been done to evaluate the performance of DNS caches in [41]. In their study DNS traffic was collected along with TCP `SYN`, `FIN`, and `RST` packets. They investigated the relationship between TTL and DNS cache hit rate and found that most of the DNS cache hits occur within minutes of the initial miss.

Other work has investigated the difference in usage patterns between traditional computers such as desktops and mobile devices [52]. This work makes no mention of DNS but instead relies on other measurements. Our work seeks to gain insights into mobile device usage with only a subset of the network traffic.

2.6 Summary

We collected DNS traffic from a campus over several days distinguishing wireless from wired traffic. We compared DNS usage between wired and Wi-Fi hosts. The wireless hosts were responsible for close to two-thirds of the DNS traffic. Most of the popular domains received more DNS requests from wireless devices. The traffic could loosely be categorized into traffic from server machines and traffic from users. The Wi-Fi hosts generated the bulk of the traffic and servers contributing half the traffic from wired IP ad-

dresses. More and more, the wired and wireless networks are becoming "server" networks and "client" networks. Also, we have investigated network sources, application sources, and sources of nonexistent domain responses that account for a significant percent of the traffic (10-15%). Many of these were from applications that use DNS as a side channel through network firewalls. This increase in failures makes it more difficult to identify malicious traffic. DNS traffic analysis has proved useful in identifying several anomalies and infected machines on the network. This investigation of the contributing sources of DNS traffic provides insight into DNS and its relationship to the Internet as well as how new technologies influence this relationship.

3. IOT MEASUREMENT STUDY

The infamous Mirai attack which hijacked nearly half a million Internet connected devices demonstrated the widespread security vulnerabilities of the Internet-of-Things (IoT). This study employs a set of active and passive observation methods to discover the security vulnerabilities of IoT devices within a university campus. We show that (a) the number of non-compute devices dominates the number of compute devices with open ports in a campus network; (b) 58.9% or more devices do not keep up-to-date firmware and 51.3% or more do not have a user defined password; and (c) the number of devices together with the diversity of device ages and vendors make the protection of IoT devices a difficult problem.

3.1 Introduction

Network connected sensors and devices are being used in several application domains from inventory tracking to smart automation of buildings and other applications. Connected printers, smart lightbulbs, VoIP phones, web cameras, and smart appliances (televisions, refrigerators, washers, etc) are commonly seen IoT devices. Other common examples include smart meters, gas pumps, medical equipment, and industrial devices. These devices employ different types of technologies such as Bluetooth [53], Wi-Fi, Near Field Communication (NFC) [54], or Ethernet to improve their functionality and performance.

However, the lack of adequate security awareness in IoT deployment has led to widespread cybersecurity vulnerabilities that threaten to undermine individuals, companies, and national infrastructures. In recent years, the IoT has become a ripe target of hackers. For example, lightbulbs have been shown to be hackable via a drone [55], smart TVs could be eavesdropping people's conversations [56], and vulnerable Internet-connected printers can leak sensitive documents from print jobs [57]. In addition, IoT devices could

be leveraged to launch disreputable attacks against other infrastructures. The recent DDoS attack against DynDNS [58] was launched from nearly half a million Mirai-powered IoT devices (mostly IP cameras and DVRs).

While computer security has received significant attention, the security of non-compute devices or IoT devices is only beginning to receive a similar level of attention. A number of studies disclose the security vulnerabilities of individual IoT devices. In [59] static analysis is performed and the permission granularity is exploited to craft a number of proof-of-concept attacks against smart home components. They were able to secretly plant door lock codes, extract the current door lock codes, disable the home's "vacation mode," and set off the fire alarm. Vulnerabilities were disclosed for a home sensor monitor platform and smart meter in [60]. The insecurity of baby monitors was demonstrated in [61]. Authors in [62] employ SHODAN [63] to reveal the scale of vulnerable IoT devices and identify ones with default passwords. Another work [64] provides details of an IoT honeypot and sandbox to analyze Telnet-based attacks against various IoT devices. These studies focus on narrow domains of IoT devices with limited services, but a complete vulnerability disclosure of IoT devices is still unknown.

This chapter discovers security vulnerabilities of various IoT device types. In contrast to previous study [62] that uses SHODAN search engine [63] to identify Internet-connected IoT devices, we employ a set of active and passive observation methods to discover a complete-as-possible list of IoT devices within a university campus. Our datasets include not only IoT devices that can be directly visited by external hosts, but also devices that are only visible to hosts within their subnet. Next, we evaluate the security of these devices where we mainly focus on default/weak credentials and unpatched firmware or software.

3.2 Survey

In order to understand the scope of the IoT security problem, we carried out a measurement study of a campus network. This study is expected to provide an understanding of the relative number of computers versus other non-compute devices on a typical campus network. Second, we expect this study to reveal the status of the IoT devices in a well managed network. Third, we expect this study to point to potential security problems from IoT devices since the security practices for them may be different from the computers e.g., the operating system software (or the firmware) may not be automatically updated on these devices and they may not be protected by anti-virus software.

The section below covers the methodology used and our findings on the security issues of IoT devices.

3.2.1 Methodology

We employed two primary strategies for device discovery: port scanning and use of service discovery protocols.

Devices that advertise through service discovery protocols are only visible within a subnet. Thus, we walked through the campus to collect data across a random sample of the subnets in a university campus. Our dataset includes computing devices, IP phones, printers, NAS, network infrastructure, cameras and surveillance equipment, industrial control devices used in electrical grid and water distribution facilities, scientific measurement equipment, and other less common equipment.

Port scanning. Nmap [65] and Zmap [66] are both open source utilities for network discovery and security auditing. In our study, Nmap was used to identify non-SCADA devices with TCP ports 80 and 443 open, as well as SCADA devices with open TCP port 502 (Modbus protocol), TCP port 20,000 (DNP3 protocol) and UDP port 47,808 (BACnet protocol). This data can be combined with external scripts [67] to retrieve additional

device information such as firmware version, device ID and operating status. Both DNS resolution and host discovery were disabled to minimize the impact on the network. The landing pages for devices with a service running on port 80 or 443 were downloaded using curl. The resulting pages were clustered using unique strings and each group was manually identified. Figure 3.1 shows the distribution of IoT devices across the different categories.

Service discovery protocols. DNS-SD (DNS Service Discovery) and UPnP (Universal Plug and Play) SSDP (Simple Service Discovery Protocol) are two different technologies both designed to allow devices to easily discover and browse other devices on the local network so that the average user does not have to deal with the complexities of IP addresses, ports, and protocols. DNS-SD [6] uses multicast [15] instead of broadcast for cross communication and leverages the DNS protocol to advertise services available on each host as part of zeroconf (Zero Configuration Networking). UPnP's SSDP uses HTTP and SOAP (Simple Object Access Protocol) for host and service discovery instead of DNS.

3.2.2 Findings

We found 1828 index pages from unique hosts with port scan and 584 unique hosts from the service discovery technique. There were 13 hosts that were common to both datasets, so the total number of unique hosts from both datasets is 2399. One dataset was a port scan of a random sample of the hosts on all the subnets on the campus network. The other dataset was a random sample of subnets on the campus that were scanned using service discovery protocols. The port scan data revealed that IoT devices with open services are about three times more common than compute devices such as servers, desktops, laptops and smartphones. The results of the classified data from the port scan are shown in Figure 3.1. 34 different manufacturers were represented in the sample, some spanning more than one device category. Among all hosts from both datasets, we grouped all the computing devices into one category that had 692 devices making up 28.8% of the total.

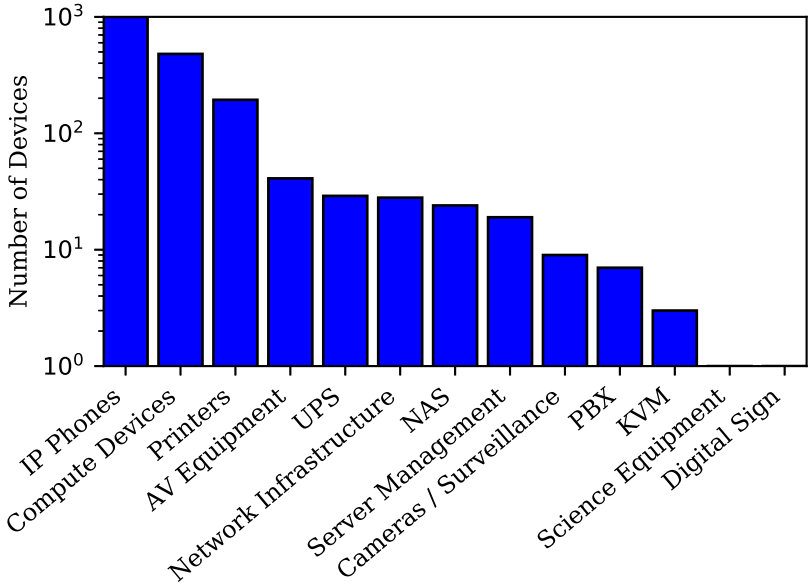


Figure 3.1: Categorized Sample of Devices from the Port Scan.

The non-compute or IoT devices are represented as separate categories. IP phones comprised the largest group with 1001 unique devices and 41.7% of the total. The next largest category was printers with 194 devices followed by AV (Audio/Video) equipment with 41 devices. Uninterrupted power supplies (UPS), network infrastructure such as router and wireless access points, network attached storage (NAS), server remote management cards, private branch exchanges (PBX), keyboard video and mouse (KVM) switches, a piece of science equipment and a digital sign each had less than 30 devices.

While some of these devices are less critical such as KVM switches, others such as NAS, UPS and network infrastructure could lead to serious problems if compromised. Critical data could be leaked or lost, critical systems could be powered off on demand, or parts of the network could be cut off. Each brand has one or more unique administration pages for their devices, so the variety of IoT devices increases the difficulty of managing them all.

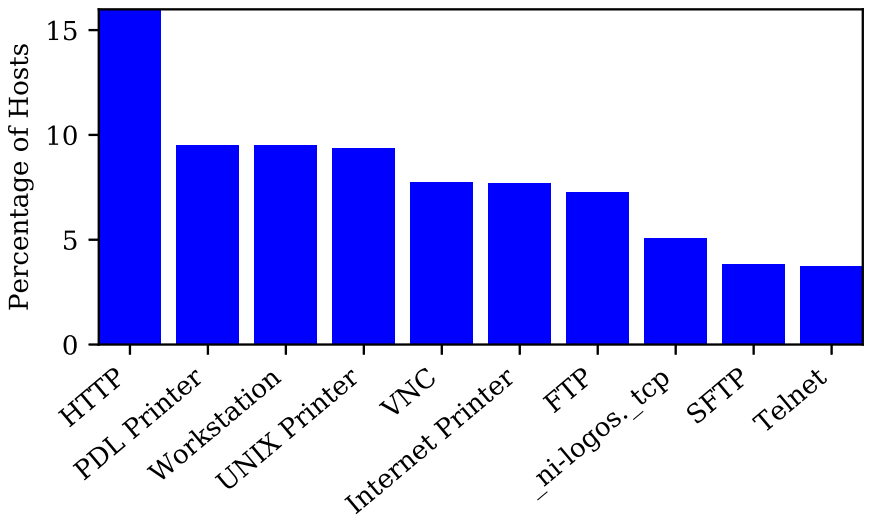
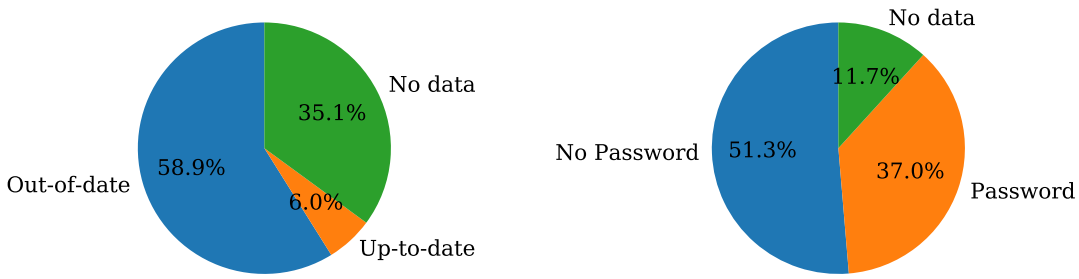


Figure 3.2: Top Ten Identified Services

The service discovery based dataset included 78 different services. Fig. 3.2 shows the top ten identified services. The most common service was `_http._tcp` or web services that account for 16.00% of the unique devices identified. These web services have a wide variety of uses ranging from public web sites to administration interfaces for IoT devices such as printers, cameras, network attached storage, and more. Therefore, the presence or absence of the HTTP service is not enough to classify a device. Page description language (PDL) printers, workstations, and UNIX printers each account for about 9% of the devices; VNC, Internet printers, FTP services were identified in about 7% of the unique devices. Of these services workstation and virtual network computing (VNC) are associated with compute devices. For this dataset compute devices represent 36.1% of the included hosts.

Printers. We identified printers from 11 different manufacturers. The presence of custom passwords and the firmware dates for printers were obtained using web scraping scripts. Of all the printers identified, we confirmed 51.3% had no password ever specified

by the user (see Figure 3.3b). The no data percentage is different between the two plots because for some printers with a password set the firmware version is inaccessible.



(a) Printer Firmware (b) Printer Passwords

Figure 3.3: Security Readiness of Printer Sample

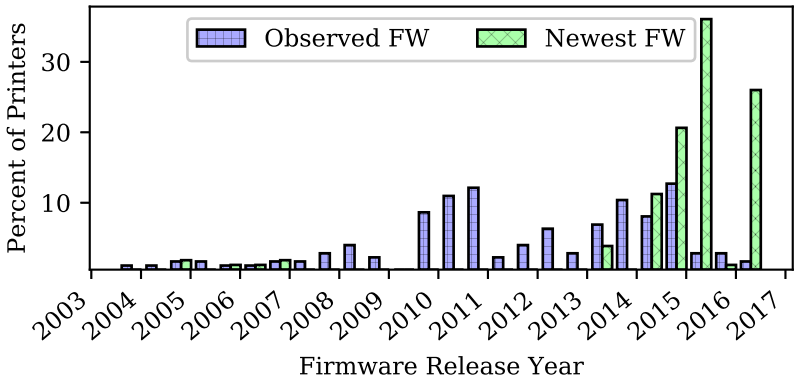


Figure 3.4: Printer Firmware (FW) Release Dates

Figure 3.3a shows the percentage of printers identified known to have out-of-date firmware 58.9% as well as the 6.0% that were known to have up-to-date firmware. The

devices in the *no data* category timed out while trying to access the HTTP index page or had a password preventing access to the firmware date. Figure 3.4 is a histogram of the dates of the firmwares installed on printers we observed along with the dates of the latest firmwares available for those printers. There is a cluster of printers with firmwares made in 2010 and the first half of 2011. The newest firmware available for 12.5% of the printers was from 2014 or before. This data points to the fact that the firmware on these devices is both not being updated by the manufacturers and not being updated by the users even when new version of firmware is available. This shows that even on a well managed network IoT devices like printers may be overlooked, receive minimal initial configuration, and fall behind in updates. We did observe newer devices that automatically update their firmware.

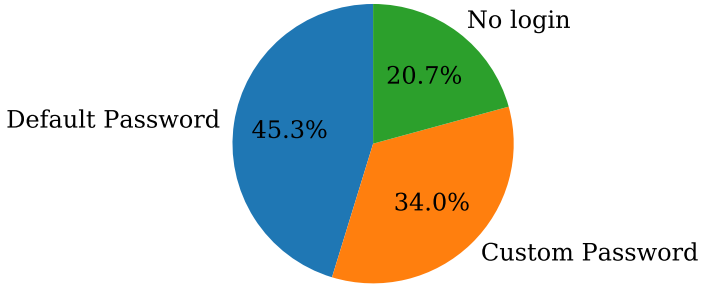


Figure 3.5: Authentication for VoIP Phone Administration

VoIP Phones. VoIP (Voice over Internet Protocol) telephones can be connected to a Private branch exchange (PBX) through a local area network (LAN). Given an VoIP phone with minimal custom configuration, the default admin password will be known [68]. Using this access the SIP configuration can be changed to launch a man in the middle attack. This

enables attackers to record calls, and keep track of call log information. If the attacker manages to steal the SIP authentication data, they can place calls from the victim's phone number.

The VOIP phones dominated the sample of devices scanned on port 80 prompting us to conduct a more in-depth scan of the VOIP subnet. We found a total of 6999 VoIP phones from the focused port scan. Only about a third of the VoIP phones were protected with a custom admin password (see: Figure 3.5) None of the VoIP phones had the newest firmware. One brand of VoIP phone had no password authentication for the HTTP management page and represented 20.7% of the VoIP phones. This data strengthens the point that some IoT devices do not receive the same attention to configuration and security updates as compute devices.

SCADA devices. We have identified a total of 415 SCADA devices that are used across building automation networks, water metering system and electrical grid. This includes 197 BACnet field panels and workstations, 188 water system meters and 30 DNP3 devices. Security vulnerabilities have been identified among these devices. However, due to security reasons, we are not allowed to further discuss these vulnerabilities in this chapter.

We also identified a piece of scientific measurement equipment that could be tampered with over the network interface. Adjusting the default configuration of the device with awareness of the potential problems could go a long way toward securing the scientific measurements. Ideally, the network access to the device would be restricted through a VPN to only authorized individuals.

3.3 Summary

The infamous Mirai attack has shown that many IoT devices do not have adequate security protections and can be leveraged to cause significant damage. In this chapter, an IoT

security disclosure is provided that shows that about 58.9% devices do not keep up-to-date firmware and 51.3% or more do not have a user defined password. Our measurements also indicate that the number of non-compute devices may dominate the number of compute devices in a typical campus network. This work motivates the solution proposed in chapter 6.

4. FINDING PROXY USERS AT THE SERVICE USING ANOMALY DETECTION

4.1 Introduction

A proxy server is a software that forwards network traffic. HTTP and SOCKS proxies [23] are used to hide the identity of the source by relaying data through the server. A typical configuration of how a proxy may be used by an attacker is shown in Figure 4.1. The three hosts shown are a sensitive service, a proxy server (a compromised machine), and a proxy client. The sensitive server provides some service the attacker has interest in. Some examples are internal databases, online banking websites, or corporate file servers. The proxy server acts as a middle man and initiates a connection to the sensitive service on a request from the proxy client. The proxy client connects to the proxy server to communicate with the sensitive service anonymously. From the point of view of a service, the IP address of the requester and TCP parameters may be identical between direct traffic and tunneled traffic. Although proxy servers have legitimate uses, they can also be utilized by those with malicious intent.

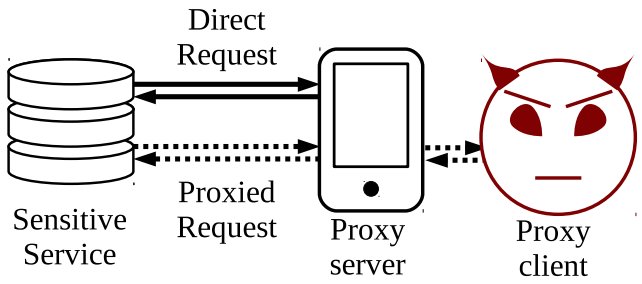


Figure 4.1: Direct Traffic vs. Socket Proxy Backdoor

Trojans and backdoors provide attackers a foothold on the network. Even with anti-virus software, firewalls, and intrusion detection, new threats emerge that have been tailored to disable the protection and/or evade detection. Once a machine is compromised, it can be used for detrimental purposes. For example, the machine could be used as an inside proxy, a steppingstone, that allows an attacker access to sensitive internal network resources. The trusted machine may even connect to the sensitive network remotely through VPN. It then operates in the role of the proxy server in Figure 4.1 and may still issue legitimate direct requests along with proxy requests. The attackers can then create a covert channel from which they can probe the network, steal private information, compromise other systems, and cause service outages. Preventing the systems from being compromised is preferable, but expecting attacks never to succeed is unreasonable. Thus, we focus on identifying and stopping unauthorized access to services.

Open proxy servers are available on the Internet, and blacklists of their IP addresses are also available [69]. Information from logs of VPN servers and proxy servers can be useful in tracing abusers back to their original IP address. However, when the proxy server is hosted by the attackers themselves on a compromised machine, the attackers are free to implement the proxy servers as they choose. Proxy logs will likely not exist in this case, so there is a need for additional measures to identify attackers in these cases. All this is done after the fact. Would it not be better to prevent leaking information first?

Whenever information systems are managed by a third party such as a cloud provider, the cloud user may have limited ability to enhance the security of their services beyond what is already provided by the third party. Attacks can be detected without collaboration with the service provider by developing methods that operate at the service rather than the network infrastructure. The level of difficulty required for an attacker to compromise a service can be increased by writing security-aware services that have built in detection strategies requiring only a small amount of data. These detection schemes would aim to

detect or deter attackers with minimal impact on performance and with minimal increase to the attack surface of the service.

Although there are methods to detect the channels by which an attacker can funnel information outside the network, most rely on having access to more than one flow of that traffic [70] and [71]. In cases where a virtual private network (VPN) is used, the attacker could funnel the data through a side channel without passing it back through the VPN. Examples of channels which an attacker might use to avoid monitoring include Bluetooth, cellular data, air-gap techniques, and third party infrastructure. In other words the attacker could create a proxy to services using a compromised host's VPN and connect to that proxy through a side channel such as cellular data. This scenario is of interest because it bypasses typical intrusion detection systems, which typically need to have access to the proxy-to-client traffic. Our work specifically investigates techniques for identifying covert proxy traffic at the sensitive server or network resource. Although the proposed detection methods do not provide the originating IP address of the attacker, they do point out that a particular machine is being used as a proxy. Once a compromised machine is detected, attention can be focused on that machine's traffic to identify the attacker and clean off any malicious software or additional security checks can be required.

Our approach employs timing information, specifically delays at the transport layer and application layer measured at the sensitive server to distinguish direct traffic from proxy traffic. The chapter makes the following significant contributions: (1) Proposes a new class of steppingstone detection methods based on anomaly detection. Two examples are provided, one at the TCP layer and another at the application layer. These anomaly detection based methods have the following properties: (1a) Only the traffic at the server is required. (1b) The traffic may or may not be interactive (1c) Detection can be performed near real-time allowing for intervention. (1d) Training is per endpoint and detection is per flow thus reducing the computational complexity of network traffic analysis. (2) Pro-

poses a technique for hardening the training process against manipulation by attackers. (3) Shows that the proposed techniques are lightweight and can be effective with a very small number of samples enabling them to detect attacks in real-time.

4.2 Detection Methods at the Service

Previous work, [72] and [73], has made progress in detecting abuse of privileges. We consider the scenario in which the attacker is stealing data from a service. Our methods can identify tunnels and proxies at the sensitive service providing a way to log, limit, or deny access after detection.

Our approach relies on network delay measurements. Rather than depending on the contents of the traffic, which may be controlled by the attacker, this method relies on properties of the network path and timing of the traffic. Our hypothesis is that the RTT measurements of traffic when the service is accessed by the attacker through the proxy will be different from the RTT measurements when the service is accessed by the proxy machine directly.

Let d_{sp} denote the variable RTTs observed between the server and the proxy, d_{spa} the variable RTTs observed when the service is accessed by the attacker through the proxy, $\{d_u\}$ a set of unlabeled measurements (one that may contain either d_{sp} or d_{spa}), and $\{d_{tr}\}$ a collection of training measurements of d_{sp}. Our hypothesis is that d_{sp} and d_{spa} will have different distributions and will be distinguishable.

Several techniques and measurements can be employed to distinguish d_{sp} and d_{spa}. Our goal is that given training data, $\{d_{tr}\}$, we can identify and assign an accurate label to $\{d_u\}$. In addition, the delays themselves can be measured at different levels to provide different levels of protection.

In this chapter, we consider two types of delay measurements, one at the transport layer and the second at the application layer. The transport layer approach has the advantage of

not having to modify or enhance the applications whereas the application layer approach can leverage application semantics to enable the design of a better tool.

We present two detection methods: the TCP Delay Distribution (TCP-DD) method, which relies on timing information from TCP packets; and the Application Layer Response Time (AL-RT) method, which leverages data dependencies in the application layer. Many machine learning algorithms require training data for each label. Our detection methods fall into the category of anomaly detection because we only have access to training data for one label, direct traffic. Direct traffic from trusted machines can be observed before an attack. Prior measurements for tunneled traffic can only be obtained after an attack has been carried out and identified. Our goal is to identify an attack as it is being carried out to prevent it from being successful. Requests classified as proxy traffic can be required to go through additional security checks or can be denied access to sensitive network services. This method has the flexibility of being deployed as part of an intrusion detection system or as part of a service.

4.2.1 TCP Delay Distribution Method

We measure TCP delays at the transport layer. A set of training samples are employed to indicate the characteristics of direct traffic. TCP delays are constantly measured and compared against the training set to see if proxy traffic is originating from the machine. This method does not require modifications to the server or client software. Because it does not require access to the client machine, the detection does not require changes to the application layer software, and it supports the commonly used protocol, TCP. If the intrusion detection system controls a dynamic firewall, unwanted TCP flows could be interrupted or blocked. If this is integrated into a service, the service could limit, or block access to TCP flows or SSL sessions that are not classified as direct traffic. Note that once

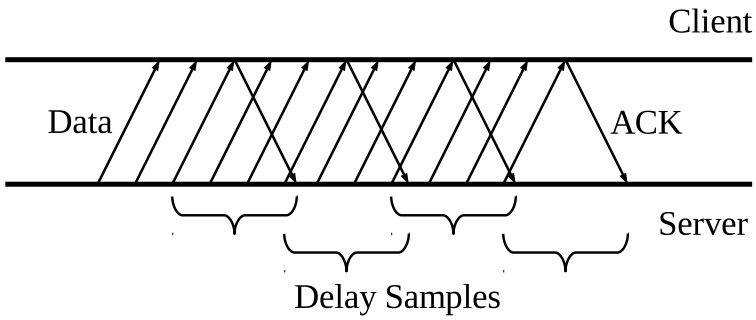


Figure 4.2: TCP Delay Distribution Measurements

a session is classified initially, it still may be monitored because sessions can be hijacked [74].

Here is an examination of how this method works (see Figure 4.2): Consider the instantaneous delay between the server resource and the proxy server for direct traffic, d_{sp}, and the instantaneous delay between the proxy and the client, d_{pa}. Although the round trip time for acknowledgments will follow d_{sp} for the most part, the timing of acknowledgments is typically also affected by techniques to reduce the number of acknowledgments sent such as Nagle's algorithm and TCP large segment offload. As long as these techniques are dependent on whether there is new data to send, there will be information leakage from d_{pa} to the server resource.

Although TCP timestamps could be used instead of measuring the delay, the TCP timestamp fields could be forged by the attacker; the attacker could send a future timestamp. It is conceivable that the attacker could use a custom implementation of TCP to have more control over the distribution of delays between packets and their corresponding acknowledgments. For the attacker to successfully launch an attack, they would need to know the characteristics of direct traffic observed from the service and have a way to replicate them.

The mean values of d_{sp} and d_{spa} could appear to be the same. However, functions other than the mean could reveal differences between d_{sp} and d_{spa}. TCP-DD has the following procedure: Record the delays between a TCP `ACK` and the most recent TCP segment it acknowledges to obtain an unlabeled set of measurements, d_u, for the RTT. Compute a function on the timings, d_u, such as a binned distribution estimate, a density estimate, the variance, etc. Compare the result with training data for d_{sp} and classify the connection as normal or anomalous.

One category of statistical measures we used provided a comparison of empirical distributions or densities. A simple way to obtain an empirical distribution is binning, the technique used to generate histograms. After binning, the probability mass function is obtained by dividing the value of each bin by the sum of the values of all the bins. Also, a smoothing function such as the Gaussian function (see Equation 4.2) can be applied to the histogram to obtain a density estimate from sparse data. An expected distribution can be constructed by aggregating all the training data into one distribution.

Raw JSD: The similarity of distributions can be measured using the Jensen–Shannon divergence (JSD) [75]. The JSD is shown in Equation 4.1 where p_1 and p_2 are the distributions, and X is the set of bins. This allows for the measurements of one trial to be compared to the expected distribution. To identify when a measurement is anomalous it is necessary to have some notion of what range of values the data should have. This can be obtained by using the JSD to calculate a distance between the distribution estimates for each trial and the distribution estimates for the aggregate of the training data. The JSD becomes undefined whenever there is at least one bin with a zero value, the solution we used was to initialize the bins to a very small positive number before performing binning.

$$JS_{\pi}(p_1, p_2) = \sum_{x \in X} \left[\frac{p_1(x)}{2} \log \frac{p_1(x)}{p_2(x)} + \frac{p_2(x)}{2} \log \frac{p_2(x)}{p_1(x)} \right] \tag{4.1}$$

For simple binning and JSD there is an order $O(n + m)$ computation cost that scales with the number of samples, n, and the number of bins, m.

Smooth JSD: If a Gaussian (see Equation 4.2) smoothing filter is applied to the binned results to obtain a different density estimate before using the JSD, it has an order $O(n + m \times l)$ computation cost that scales with the number of samples, n, and the number of bins, m, times the number of filter taps, l.

$$G(x) = \frac{1}{\sigma\sqrt{2\pi}} e^{\frac{-(x-\mu)^2}{2\sigma^2}} \tag{4.2}$$

Variance: Another statistic measure that we found to distinguish d_{sp} from d_{spa} is the variance. Although the mean between d_{sp} and d_{spa} could be too similar to distinguish them, the variance may not be. Training data isn't needed to show the separability of the variances calculated for the direct traffic trials from the variances calculated for the tunneled traffic, but it is necessary for anomaly detection. This is an order $O(n)$ computation cost that scales with the number of samples, n.

MPGS: The mean pairwise Gaussian similarity (MPGS) also can be used. The Gaussian similarity [76] can be described as a measure of closeness and could be compared with the inverted squared Euclidean distance. The mathematical formulation for this measure is shown in Equation 4.3. This is calculated for each pair of a training sample with an unlabeled data sample. The results are averaged to obtain the MPGS that is compared against the MPGS values for the trials in the training data. The computational cost for calculating the MPGS is $O(n \times k)$ where n is the number of samples in d_u, and k is the number of training samples.

$$\text{MPGS}(d_u) = \frac{1}{|d_u||d_{tr}|} \sum_{x \in d_u, y \in d_{tr}} \frac{1}{\sigma\sqrt{2\pi}} e^{\frac{-(x-y)^2}{2\sigma^2}} \tag{4.3}$$

Mean distance measures are another way to distinguish the direct and tunneled traffic. The mean minimum distance (MMD) from the inter-arrival times, d_u, in an unlabeled set to the times in the training data can also be used. The L1 norm was used for the distance. It is the absolute value of the difference between the values being compared, $|a - b|$. We took the mean of the lower quartile of the distance values. The computation cost depends on the implementation but costs of $O(n \log k)$, and $O(n \log n + k)$ can be achieved where n is the number of samples in d_u, and k is the number of training samples. This was chosen because it uses the k-distance measure, which is part of the formulation for the Local Outlier Factor [77].

4.2.2 Application Layer Response Time Method

This method estimates the round-trip-time by measuring the end-to-end delay at the application layer. Socket proxies may hide the RTT at the transport layer, but they forward the unmodified application layer data. One potential way of identifying tunneled traffic is to measure the RTT at the application layer. Ideally, this would be done without requiring changes to the application layer protocol. Many applications have data dependencies between served content and requests. The time delay between a message being sent and the receipt of the first dependent message can be used to bound the round trip time between the server and client applications. For this to be an effective way of detecting a tunnel, the attacker should not be able to send the dependent message early. This challenge can be solved by requiring a sufficiently hard to guess random token in the dependent message.

In this chapter we use HTTP to validate the concept of the Application Layer Response Time Method. HTTP serves pages typically containing references to additional content such as images, scripts, styles, or frames with other pages. The HTTP example for determining if a visitor to a website is using a proxy or not is as follows: Create a chain of iframes such that a browser will not cache the iframes (they will be loaded every time), and

the delay between HTTP requests is logged. Nonces are used to ensure that each iframe in the chain must be loaded one after the other. This establishes a data dependency which is used to measure the delay from the browser to the web server. We can then compare a function of the delays between requests for the iframes to training data to determine if they are anomalous. Although we focus on HTTP in this chapter here, it is possible to extract delays at the application layer similarly with other protocols.

Iframes were chosen because they allow for chaining multiple measurements one after the other even when JavaScript is disabled. Figure 4.3 shows how embedded iframes can be used to create data dependencies for measuring the end-to-end RTT. If only one measurement is needed, an image or style file could be used instead.

An attacker may employ an application-layer proxy server. This would potentially defeat TCP-DD; however, without prefetching the proxy server would still leak the end-to-end time to HTTP-RT. Prefetching proxy servers neglect images by default because of the cost of prefetching all the images on all related pages, so images could be incorporated into the HTTP-RT method to prevent prefetching of certain resources. The access times of these non-prefetched resources would then be used in the HTTP-RT measurements.

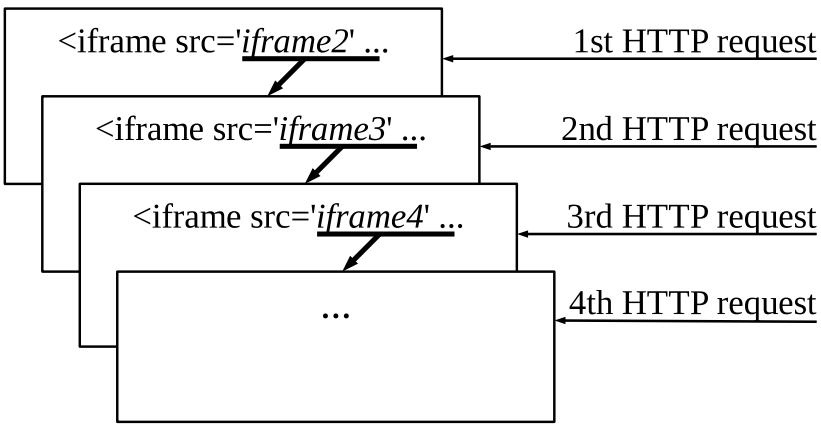


Figure 4.3: HTTP Response Time Method

For HTTP-RT the absolute minimum round trip time between the service resource and the proxy server is a lower bound; attackers cannot cross except in highly improbable situations: Assume a set of nonces is chosen randomly from a set such that the chance of guessing each nonce is much smaller than the number of times the valid user connects. A nonce is sent as part of a URL for the destination of a resource such as an iframe. Each resource loads another resource at a URL including the next nonce. The first nonce isn't known until after the first page loads, the second until after the first resource loads, the third until after the second resource loads, and so on. For the attacker to request the next resource they must know (or guess) the nonce. An incorrect guess identifies an attack. The probability of the attacker correctly guessing all the nonces in a chain of dependent resources quickly drops off to zero. The chain provides more data points to reduce the effects of noise. If the attacker receives the nonce through the proxy server, the delay will be greater than the delay between the proxy server and the requested service.

4.2.3 Identifying proxies during training

Adaptive methods or retraining open up the possibility of the attacker manipulating the results of the training data. Any classification method that uses training data is sensitive to the quality or truthfulness of that data. When these methods are put into a situation with adversaries, one might ask whether an adversary has the ability to taint the training data to thwart the classification method. We propose a solution to prevent attackers from being able to manipulate the training data. Training data from similar network paths can be cross checked to notify the administrator when retraining falls outside the acceptable limits. An example definition of a similar network path is one that is only different in at most the first and last links of the path. Using this definition we tested the similarity of the distributions of training data across similar paths as well as with the proxy data. We collected additional data from Planetlab for groups of nodes which are hosted by the same organization. The

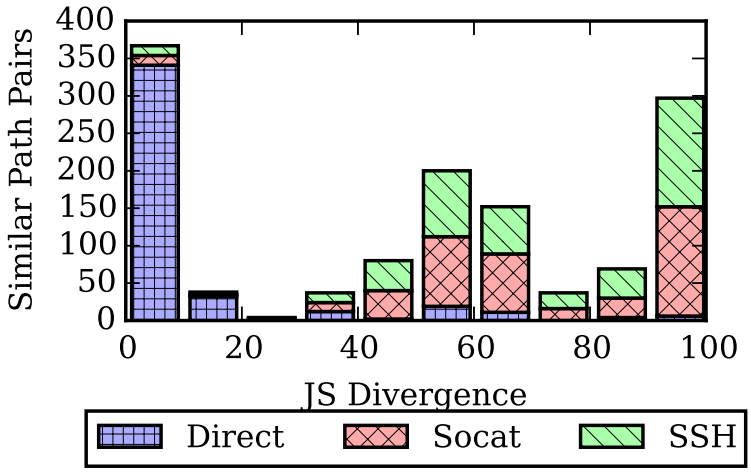


Figure 4.4: Jensen Shannon Divergence Between Training Data from Similar Paths. Note that the proxy data, SSH and Socat, are included to show where an attacker's distribution would fall, but these would not be available as training data.

results for HTTP-RT are shown in Figure 4.4. We include the proxy traffic represented by socat and SSH on the plot to show how the attacker's distributions compare with the direct traffic. Ideally the direct traffic would be clustered together, and the proxy traffic would not overlap with the direct traffic. In most cases the direct traffic has a lower Jensen-Shannon Divergence with the similar paths than the proxy traffic. For TCP-DD the results are much less spread, but the direct and proxy traffic were completely separable for 77% of the groups of similar paths. This cross-check method for verifying the training data increases the difficulty the attacker faces. Either they will have to compromise more hosts to launch a successful attack, or they will be limited in how much their attack traffic can vary from hosts on similar paths.

4.3 Experimental Evaluation

We evaluated our approach in three settings. The first setting employed PlanetLab [78] with the sensitive server, proxy and the attacker location distributed across the globe.

The second setting considered attacks within a local area network where all three parties, sensitive server, proxy and attacker, all reside on the same network. The two settings provide different vantage points with wide-delay measurements and tight-delay measurements. Third we tested the sensitivity of the results to various parameters such as CPU load.

As part of our evaluation we compared the accuracy of different statistical measures for the function computed on d_u. On one hand, this shows that using the RTT measurements has some flexibility. On the other hand, the comparison shows which measures might be best in deploying TCP-DD.

We considered different download intensive communication models that the attacker could employ. With *socat* the traffic is passed unencrypted to the proxy client, whereas with *ssh* the traffic is encrypted between the proxy and the proxy client. Transparent proxies that work by network address translation (NAT) will not hide the end-to-end RTT so they were not tested because the end-to-end RTT should be enough to distinguish direct and tunneled traffic.

4.3.1 Wide Area Network Measurements

PlanetLab offers a network testbed spanning diverse geographic locations. Our slice provided 80 active nodes covering different continents with which we conducted our measurements. Figure 4.1 shows the basic setup we used for each trial. One node functions as the service. It hosts the web server and records access times and packet traces. Another node functions as the proxy server. It hosts proxies both through *socat* [79] and *SSH* [24]. It also makes a direct request to the web server. The last node functions as the proxy client and makes requests to the web server both through the *socat* and *ssh* proxies.

Combinations of three nodes were randomly selected. For each combination all permutations were tested. 1727 working configurations were tested for the 80 PlanetLab

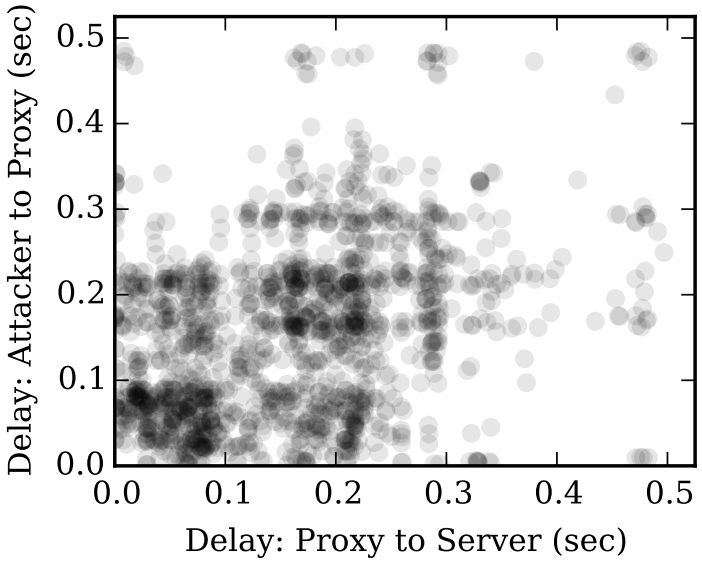


Figure 4.5: Path Pings of Each Set of Selected PlanetLab Nodes

nodes. Groups of nearby nodes were also selected to allow for measuring the accuracy when network distances were smaller. Figure 4.5 shows the delays between nodes in each working configuration tested. Notice there is a good spread; in some cases the attacker is closer to the proxy than the proxy is to the server and vice versa. The measurements were taken once every thirty minutes over a 24-hour period.

The separability between the proxy traffic and the direct traffic can be seen in the ROC (Receiver operating characteristic) area plots in Figure 4.6 and Figure 4.7. ROC plots are typically used to show how well a communication channel operates. In our case we are plotting the percentage of true positives achievable by selecting a specific threshold for a percentage of false positives. An ROC area of 1.0 is ideal where all the true positives can be included by a threshold without including any false positives.

Figure 4.6 and Figure 4.7 show the results of our experiments using both TCP-DD and HTTP-RT methods and different measures in the PlanetLab setting. Figure 4.6 shows the

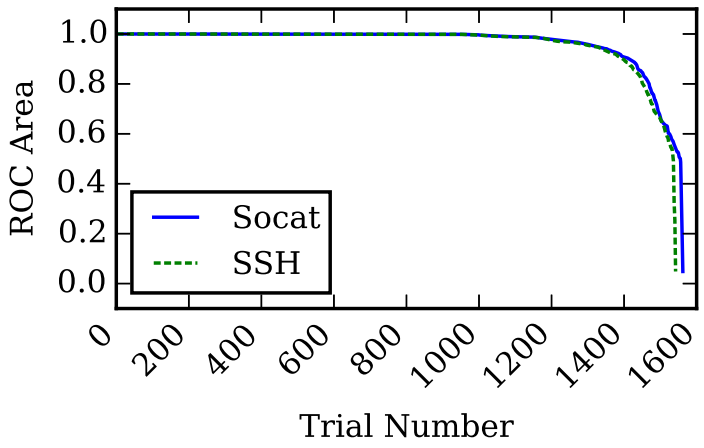


Figure 4.6: Performance Comparison of Implementation Options: ROC Area of Each TCP-DD Trial Using Smoothed JSD Listed in Descending Order

TCP-DD measure with the highest accuracy, smoothed JSD. A maximum of forty-eight training points were used when training data was needed in the TCP-DD measures. After analyzing how many training points are needed for smoothed JSD, we found that with five trials most of the separation between the direct traffic and proxy traffic was already achieved. Different training points (d_{sp}) are needed for each pair of a service host with a proxy host because they represent different possible paths. The true positives of the ROC plot are $min(\{d_{sp}\})$ for each trial and the false positives are $min(\{d_{spa}\})$ for each trial. Figure 4.7 shows the HTTP-RT measure with the highest accuracy, the minimum RTT.

The results between the unencrypted and encrypted socket tunnel implementations, *socat* and *ssh*, are almost the same with *ssh* having a few more measurement failures resulting in fewer trials. The majority of trials had a close to ideal separation. In each of these cases a threshold could be chosen for TCP-DD using smoothed JSD in those trials to distinguish the direct traffic from the tunneled traffic.

In Figure 4.8 the separability of different functions are used over the samples collected for each trial for TCP-DD. These functions are discussed in more detail earlier in subsec-

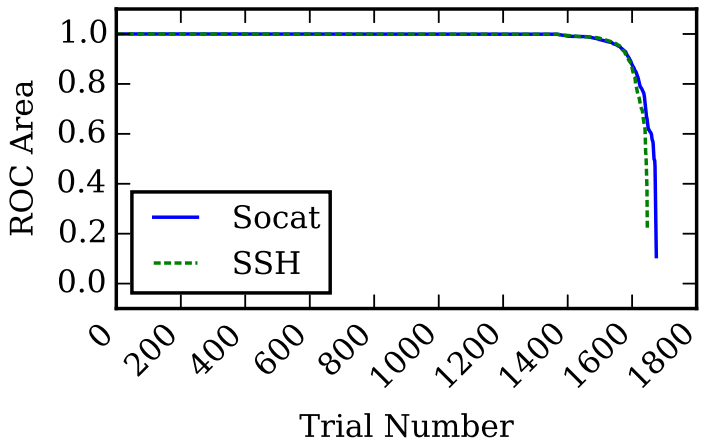


Figure 4.7: Performance Comparison of Implementation Options: ROC Area of Each HTTP-RT Trial For Three Samples Using Minimum Listed in Descending Order

tion 4.2.1. "MMD." represents mean minimum distance for the highest quartile. "Raw JSD" represents binning the inter-arrival times to obtain a distribution estimate and using the Jensen–Shannon Divergence (JSD). "MPGS" represents using the Mean Pairwise Gaussian Similarity (MPGS). Bins of 25 milliseconds were used, but further optimization could be done for this parameter. "Variance" represents taking the variance of the measurements within a trial. The variance values were then compared across trials to test for separability. "Smooth JSD" represents first binning to obtain a density estimate. The result is smoothed using a Gaussian smoothing filter that is truncated to 4 standard deviations of 1250 μ-seconds. Lastly, then the JSD is used to compare the smoothed density of the training data with the one for the unlabeled data.

The results show that both TCP-DD and HTTP-RT can separate the direct traffic from proxy traffic. Figure 4.8 and Figure 4.9 show the percentage of trials that had ROC areas above 0.9, 0.99, and 0.999. From these figures it is clear that HTTP-RT outperforms TCP-DD for the configurations tested. An ROC area of 0.90 can be likened to a 90% true positive detection rate for 0% false positives. It does not correspond directly because an

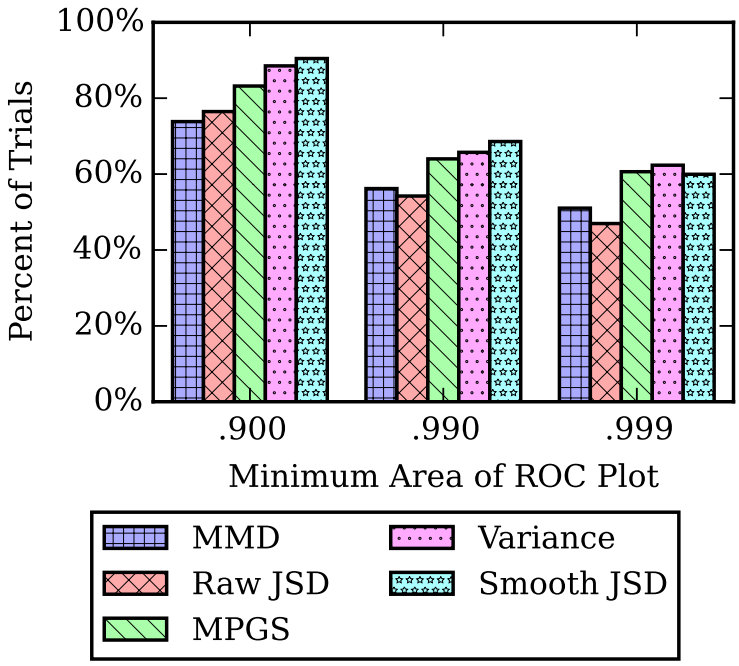


Figure 4.8: Performance Comparison of Implementation Options: TCP-DD Processing Method Comparison with *Socat* and *SSH* Combined

ROC area of 0.90 may have different shapes. For the rightmost bar of HTTP-RT using the minimum of the measurements, an ROC area of 0.999 and above was achieved for more than 80% of the trials.

For Figure 4.9 the measured round trip times differ between the direct and proxy traffic, but there is noise present. Three samples of round trip times were used for the HTTP-RT classification. "Mean" represents taking the average of the samples in a trial, "Prod" represents multiplying the samples, and "Min." represents taking the minimum of the samples. All these functions have $O(n)$ complexity over the n samples per trial. Out of all the methods, the minimum function resulted in the greatest separability.

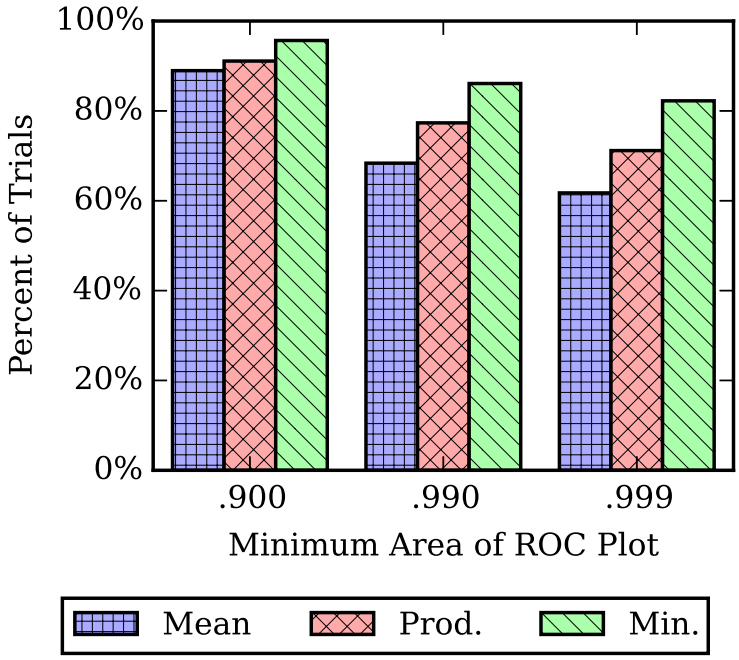


Figure 4.9: Performance Comparison of Implementation Options: HTTP-RT Processing Method Comparison with *Socat* and *SSH* Combined

From Figure 4.8 and Figure 4.9 it is clear that HTTP-RT outperforms TCP-DD in the tested configurations. Tests were also run for more than one proxy node to confirm that adding more nodes increases the detection accuracy for both methods.

4.3.2 Local Area Network Measurements

In a local setting the distances are much shorter, the links are more reliable, and the bandwidth limitations are less. We expected to have a more difficult time detecting the tunnels when the proxy server and client were on the same local network. A single host was used to provide the service. Two different proxy servers were used in different locations. Four different proxy client locations were used with both a Wi-Fi and wired host each. The measurements were recorded every five minutes for at least two and a half hours yielding 30 or more data points for each trial. In this experiment the packets were processed in real

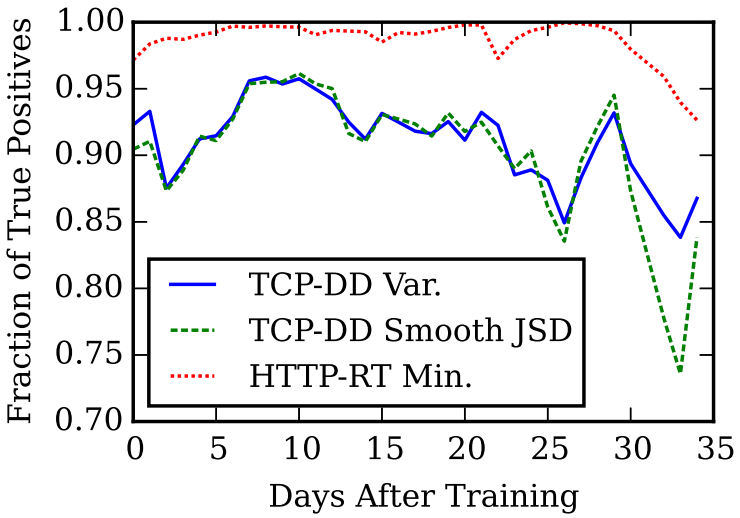


Figure 4.10: True positives of Direct Traffic Over Time After Initial Training Averaged Across Trials

time to obtain the TCP `ACK` delays and iframe delays. In this dataset about twelve TCP `ACK` delays were recorded per measurement

A good separability was achieved in all the trials. The direct traffic was completely separable from the tunneled traffic in more than half of the trials. For the local measurements TCP-DD outperformed HTTP-RT.

4.3.3 Sensitivity

Planetlab measurements were taken over a 34-day period to determine how often retraining is needed. The measurements were taken every 30 minutes, and only the first 24 were used as training data. Figure 4.10 shows the fraction of true positives out of direct measurements averaged across trials plotted over time. HTTP-RT Min. had over a 97% true positive rate after a month. The true positive accuracy of TCP-DD degraded after 20 days. The decision to retrain can be made on a per host basis once the false positive rate is high enough.

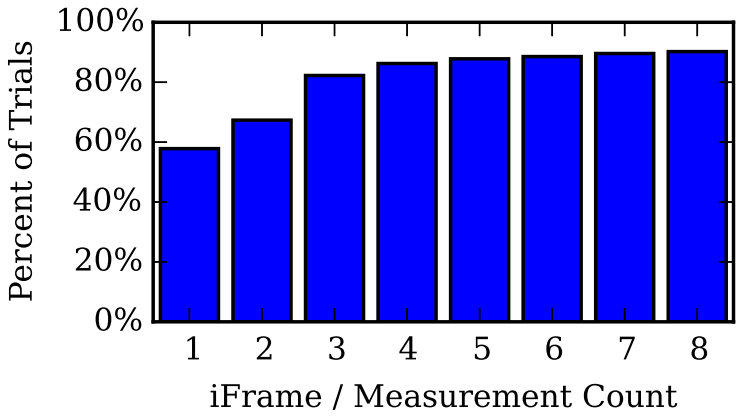


Figure 4.11: Percent of HTTP-RT Trials with ROC Area Above 0.999

How many measurements are warranted for HTTP-RT? Figure 4.11 shows the relationship between separability and the number of measurements used. A higher percentage corresponds to better separation between the direct traffic and the tunneled traffic. At three measurements three iframes are loaded after the initial page load. It is observed that most of the separability is achieved within 3 measurements. Since the cost in terms of delay to the user increases linearly with the number of measurements, three is probably the best number of measurements to take based on our results.

Figure 4.12 shows the classification accuracy using separate training data and direct measurements from the PlanetLab data. In these experiments, the measured data contains both direct traffic and proxy traffic. These experiments are designed to see if presence of proxy traffic can be detected when the compromised machine is being used both for direct and proxy communications. Up to 48 training points were used to find the mean and standard deviation of each measure. The accepted range was defined as $\mu \pm 2\sigma$ for the training data. Separate direct measurements and proxy measurements for both *socat* and *ssh* were tested to determine the experimental true positive and true negative rates. Note that the performance of TCP-DD using the variance is poor in this case even though it has

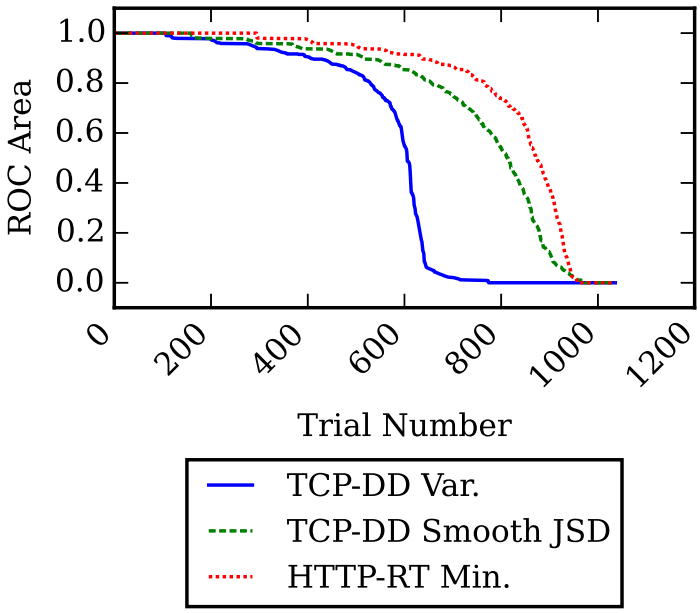


Figure 4.12: Classifiers Using $\mu \pm 2\sigma$

a high separability in Figure 4.8. We then used the true positive percentage times the true negative percentage as the ROC area in the plot. Again HTTP-RT outperforms TCP-DD. It is observed that the proposed techniques provide very high detection rates with very low false positive rates across the many experiments.

To investigate the effects of CPU load on TCP-DD we conducted an experiment using *iperf3* [80] under different load conditions. We used the tool in download mode because the traffic from the server to the proxy is what generates the TCP acknowledgments used in TCP-DD. These tests were done with three machines connected through a single switch to eliminate uncontrolled network factors. This allowed us to observe the difference in the steady state delay distribution for different amounts of CPU load. We tested the effects of CPU load at both the server and the proxy. The results are shown in Figure 4.13.

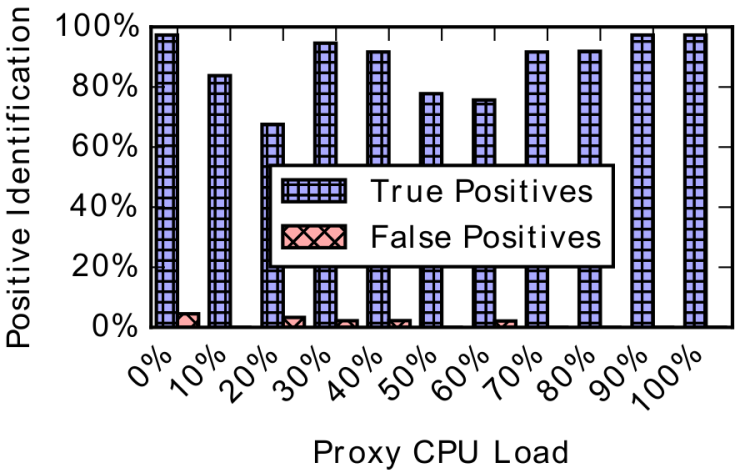
Varying the load on the proxy case does introduce variance into the detection rates as shown in Figure 4.13a. There is a noticeable degradation of performance in the server

case Figure 4.13b. The loss is about 2% less true positives for every 10% point increase of Server CPU usage. Since, the CPU load on the server can be measured training could be done across different CPU load regions to increase detection performance if needed. It is noted that even when tested against different loads from the training loads, the proposed methods provide reasonable detection rates.

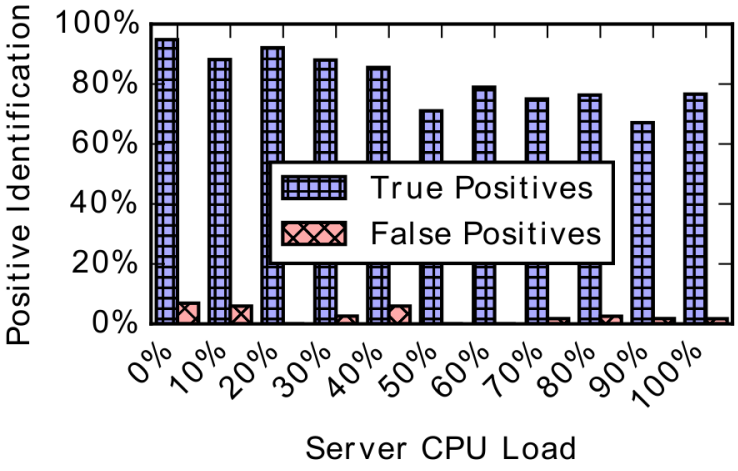
4.4 Related Work

A body of work exists for detecting steppingstones. Recently proxy detection at the service has started to get attention. In [81] motivated by Nagle's algorithm the size of segments and inter arrival times were used to identify proxies. They rely on a steady stream of small segments to detect proxies, while TCP-DD works for download intensive streams which may have segments at the MTU. They achieved a 94.0% true positive rate with a false positive rate ranging from 0.8% to 85.4% averaging 10.2% across all their trials. This corresponds to an ROC area of 0.844. Machine learning is used for proxy detection in [82]. Their method works well for the proxy server configurations they tested (squid) with a 94.1% true positive rate and a 7.9% false positive rate for distinguishing proxy traffic from direct traffic. This corresponds to an ROC area of 0.867. Using a $\mu \pm 2\sigma$ classifier, HTTP-RT using the minimum has a greater ROC area in 67.4% of our trials, and TCP-DD using smooth JSD in 56.8% of our trials. While they employ timing features for classification, they do not contrast delay distributions as employed in our approach. We chose to use anomaly detection to avoid requiring labeled proxy data which targets the classification on particular proxy implementations and behaviors.

Prior steppingstone detection techniques fall into one of three categories: (1) content based methods, which require clear text or the same content across the observed flows[83] and [84]; (2) passive time based methods, which rely on the assumption of a maximum tolerable delay [84], [85], [86], and [87]; and (3) active time based methods often called



(a) Effect of Proxy Loading



(b) Effect of Server Loading

Figure 4.13: Identification of Direct Traffic Across Load Using TCP-DD Smooth JSD. For each plot a $\mu \pm 2\sigma$ classifier was trained using the data for 0% load. Measurements were conducted using 10 second *iperf3* traces at 100Mbps for each load level. The traces were partitioned into sets of 100 measurements for the classification. Each trace had about 50 partitions.

watermarking [88] and [89]. The typical threat model used by the above steppingstone detection papers assume all the traffic on the network is being monitored and that the attackers do not have access to an alternative unmonitored Internet connection. Our work

does not make these assumptions. Instead of tracing the attack back to an IP address at the edge of the network, we identify connections that have steppingstones. These methods rely on correlating two or more connections to identify steppingstones and thus cannot detect a steppingstone that has only one visible connection. For this reason we argue steppingstone detection at the service can be applied in addition to the previous methods to detect steppingstones that would not be detected otherwise.

Timing of packets has already been shown to betray information in the past such as keystrokes over SSH in [90]. TCP jitter has been used as a means of identifying rogue Wi-Fi access points on a network [91]. It has also been used to defeat location spoofing VPNs in [92].

Work has been done to identify the destination of encrypted HTTP traffic (over WPA and WEP) by using statistical analysis, lengths of the packets, and the distribution of interarrival times [93]. Statistical measures of packet lengths [94] and information theoretic measures [95] have been employed to classify TCP flows and to detect anomalous traffic.

Detection of middleboxes such as NATs has been explored through observation of instant messaging traffic [96]. Tracetcp, [97], uses TCP `SYN` packets and TTL values to perform a traceroute over TCP ports. It can identify transparent TCP tunnels and proxies, but is designed for the client side. It is also dependent on the proxy forwarding the TTL values, which is up to the proxy implementation. Our methods handle proxies at the server side and are not dependent on TTL values.

Work has been done to identify tunnels through application layer protocols such as HTTP [70] and [71]. These are aimed at detecting information leakage from a network, whereas we are addressing the problem of whether trusted clients are compromised and are serving as a proxy.

In [98] HTTP proxy traffic is detected to find attempts to circumvent firewalls, and spyware back channels. This work focuses on detecting anomalies using a variety of

different techniques such as the HTTP header fields, request sizes, request rates, bandwidth usage, and request interarrival times. Our goal is to find proxies on trusted nodes rather than find trusted nodes that are accessing proxies. A key difference in our work is that instead of using interarrival times to look for periodic traffic, we are estimating the end-to-end RTT or comparing interarrival time distributions.

There are existing methods for HTTP client fingerprinting that can serve to distinguish proxy clients. Client side Javascript is used for detection in [99]. SSL handshakes are used to fingerprint clients in [100]. A survey of these methods is provided in [101]. If a machine is compromised, metrics used in fingerprinting such as screen resolution, browser plugins, etc. may be determined and spoofed by the attacker. Even the IP address of the machine can be used by the attacker through proxies. Our work seeks to address this issue.

4.5 Summary

This chapter proposed using anomaly detection as a new class of steppingstone detecting methods by monitoring traffic at the server. These methods handle the case when an attacker has access to unmonitored communication channels, which thwart previous detection techniques. Although compromised machines may be used as proxies, we have presented techniques that can be used to identify such proxies at the service. We have shown two working examples of these methods work on actual networks both on a global scale and a local scale. Our results show that the proposed techniques can provide very high detection rates of up to 99% with very low false positive rates. In addition, we show that comparing training data from similar paths can be used to harden the method against manipulation of the training data. The methods we present may also be combined with other features as part of a machine learning system for proxy detection, or used as an early detection system to supplement more computationally expensive post processing methods.

5. IDENTIFYING MALICIOUS ACTIVITY FROM ANDROID APPS

5.1 Introduction

Smartphones are widely used and have become an attractive target to cyber thieves. These devices often contain sensitive information such as the owner's location, contacts, emails and login credentials. They can be tied to payment methods such as credit cards and may have apps related to banking. Examples of malicious apps for smartphones have already been discovered. Thus, there is a need to develop the tools necessary to identify attacks as quickly as possible and to minimize the damage they cause. We present methods for creating a controlled test environment that runs untrusted Android apps for security research.

Four main approaches are used to analyze applications to find malicious behavior. First, static analysis is performed on the compiled code of an app to determine as much as possible. However, this doesn't always capture dynamically loaded code, which may be downloaded or decrypted at runtime. Second, dynamic analysis involves executing all or part of the app and using predefined rules. By running the app in a test environment, malicious behavior can be observed rather than inferred. Third, manual inspection is performed when static and dynamic methods fail since attackers change their techniques to avoid detection. Lastly, data about application behavior can be collected from devices in the field. This has the potential for providing the best picture about the behavior of malicious apps because it uses the same environment the attacker is targeting. However, it also is the most difficult because the data collection must not noticeably impact performance, and a large enough user-base is needed to collect meaningful data.

When an app is in use, user actions can trigger network traffic. During startup apps may check for updated resource files. As the user navigates a web based app, web pages will be

accessed and downloaded. Other examples of network activity from user actions include taking sending an email or taking a photograph which is backed up online. Network traffic outside of user activity results from background services such as email apps polling for new emails, messaging apps checking for messages, or the system checking for app updates.

In a test environment, we captured traffic from 100 of the most downloaded apps from the Google Play Store as well as samples of known malicious applications. From these traces we were able to identify what domains each app was contacting, when they were contacting them, and how often the app was sending traffic. Although we expected that most activity from benign applications would coincide with user activity, we found that ad networks commonly generate network traffic during times when the user is not interacting with that particular app or the device.

We also used the test environment to determine if the malicious apps were trying to make use of the Bluetooth on the device by monitoring Interprocess Communication (IPC). This method could also be used to catch malicious activity that involves IPC such as exploiting flaws in other apps or using other communication methods that interact with apps through IPC.

Finally, we developed a method for collecting the domain names requested by each app without requiring root access on Android devices. We built an Android app, App Network Monitor (ANM), using this method and deployed it on the Google Play Store. Three malicious domains were identified from the data collected. Two of them could be traced back to the original app. This work is ongoing.

5.2 Dynamic Analysis Test Platform

One challenge faced in providing tools for monitoring the behavior of potentially malicious applications is the time required for setup and execution. While ARM emulators are

available, they have a higher performance overhead than running a virtual machine (VM). Android ARM code can be executed on x86 architecture using helper libraries [102]. Another challenge is to make the environment as authentic as possible. Attackers can avoid detection when they are able to distinguish a test environment from a real phone (e.g. by relying on user input). To make this as difficult as possible, the test environment should not have any differences that are detectable by the app being tested.

Finally, the test environment should be setup to prevent harm that results from executing malicious apps. This is difficult to achieve because Internet access may be needed in order for an app to function properly; however, unrestricted Internet access could allow a malicious app to communicate with its author. Also, the app would be free to carry out any instructions it was given such as participating in denial of service attacks. We present a method for isolating the test environment while giving the phone the illusion of Internet connectivity. This method can also allow for connectivity to authorized sites.

Our goal is to determine if there are network features we can identify that distinguish known malware samples from the top 100 Android apps on the Google play store. We also wanted to obtain the interprocess communication (IPC) from malicious apps to search for interesting features. Ideally, these features would help find malicious apps that had not been classified as malicious.

5.2.1 Methods

Mobile devices favor maximizing efficiency over performance because they rely on batteries for power. The x86_64 architecture provides low-cost high-performance hardware, hypervisors, and virtual machines. This gap leads to interesting opportunities and challenges when executing Android apps on x86_64. To retrieve the domains accessed by Android apps in a scalable way, the amount of human intervention should be minimized. Malicious apps are sometimes used to launch attacks on remote computers and networks,

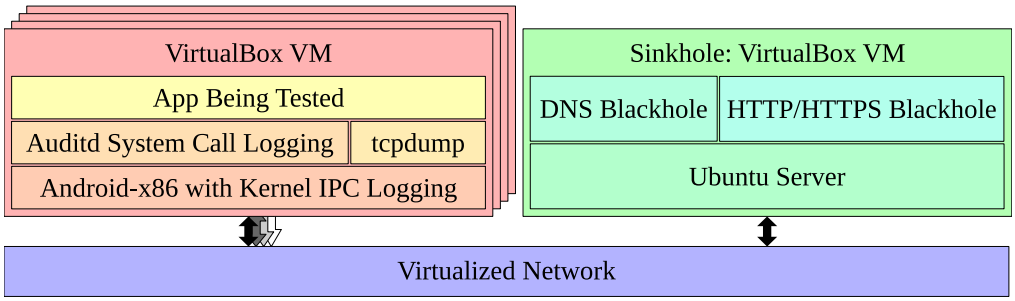


Figure 5.1: Basic Architecture of the Experimental Setup

so the testbed setup should prevent this from taking place. There are trade-offs to allowing some Internet traffic, but for the purpose of this work, the testbed did not have access to the Internet during the testing.

A general view of the testbed setup is shown in Figure 5.1. Each Android x86 VM is created as a clone of a preconfigured VM with Android x86 [103] installed along with the base Android Google apps. Any high popularity app with access to personal accounts, data, or sensitive permissions would be an attractive target for IPC attacks. With this in mind, we preloaded the base Google apps that are commonly included on most Android phones.

The base Android x86 kernel was modified to add logging to Binder IPC transactions (see Source Code A.1). If the transactions were intercepted at another layer (e.g. by modifying the Java Binder implementation), it would be tricky to guarantee that all the transactions were being logged since Android has a mix of Java and native code. Later versions of the kernel used by Android have a hook that can be used by kernel modules to audit or log Binder IPC. These IPC transaction logs include the time, the sending and receiving process id, a transaction code, and a data field (that has the interface name and optional arguments). For these logs to be useful, the process IDs need to be converted to the package name strings that identify the apps; the Binder interface name needs to

be extracted from the data field; and the code needs to be converted to the corresponding function for the particular Binder interface. Additionally, the remaining data could be parsed into the transaction arguments in the form of a Parcel, but that was left for future work. To convert the process ID to package name of the application, the process name can be used since Android uses the package name as the process name. It is recommended to double check the user ID of the process and its associated package name to make sure they match. A mismatch would be suspicious.

Converting a Binder transaction code from a log entry is an involved process. Code was written to scrape the android source code for AIDL files (Android Interface Definition Language [1]) as well as Java and C/C++ files that inherit from `IBinder` (Source Code B.3). These files need to be parsed to infer the association between transaction codes and interface function calls. This association is then used to translate an (interface, code) pair into an (interface, function) pair.

Auditd was configured to log `SYS_LISTEN` and `SYS_CONNECT` socketcalls using the script in Source Code 5.1. While `tcp`, `tcp6`, `udp`, and `udp6` can be monitored without requiring root privileges in `/proc/net/`, they must be polled whereas *auditd* provides event driven results. Unfortunately, the logged arguments for socket call include a pointer that would need to be dereferenced during runtime to determine what was being connected to or which port was being opened.

```
1 #!/system/xbin/sh
2 auditctl -e 0 # Disable auditing
3 # Close the auditd service
4 kill `cat /data/local/tmp/auditd.pid`
5 auditctl -D    # Clear all rules
6 auditctl -b 320
7 # Log socketcalls for SYS_LISTEN
8 auditctl -a exit,always -S socketcall -F a0=4
9 # Log socketcalls for SYS_CONNECT
```

```
10 auditctl -a exit,always -S socketcall -F a0=3
11 auditctl -e 1  # Enable auditing
12 # Start the auditd service
13 auditd
14 auditctl -l    # List all rules
```

Source Code 5.1: "start_auditd.sh"

It is possible to use a single virtual machine for multiple Android apps and still attribute all the traffic back to each app in the following way. The following commands can be executed to add *iptables* rules that log new TCP connections along with their user identification (UID).

```
1 iptables -I OUTPUT 1 -j LOG -m state --state NEW --
    log-prefix "[IPT_LOG] " --log-level 4 --log-uid
2 iptables -I INPUT 1 -j LOG -m state --state NEW --log
    -prefix "[IPT_LOG] " --log-level 4 --log-uid
```

On Android each UID usually corresponds to a single application. The option:

`-m state -state NEW`

can be replaced to monitor individual packets instead of new connections if needed.

The sinkhole server is configured to be the default gateway for the virtualized network so that all traffic from the Android x86 VMs is routed through it. It also fills the roles of the DHCP server and DNS recursive resolver. As the DHCP server, it supplies the default DNS server and gateway addresses. As the DNS server, it has a wildcard record that directs all domain names to itself. A network address translation (NAT) firewall rule is set up to redirect all non-local IP addresses to the sinkhole server.

The HTTP server (with HTTPS too) is configured to accept requests from any domain name, and the private key of the webserver can be imported into Wireshark to decrypt SSL sessions. This allows the hostname, the path, any custom headers, `GET` the parameters, `POST` the data, and the uploaded files to be recorded for requests initiated by the client application. This configuration could be modified to create a more sophisticated setup that

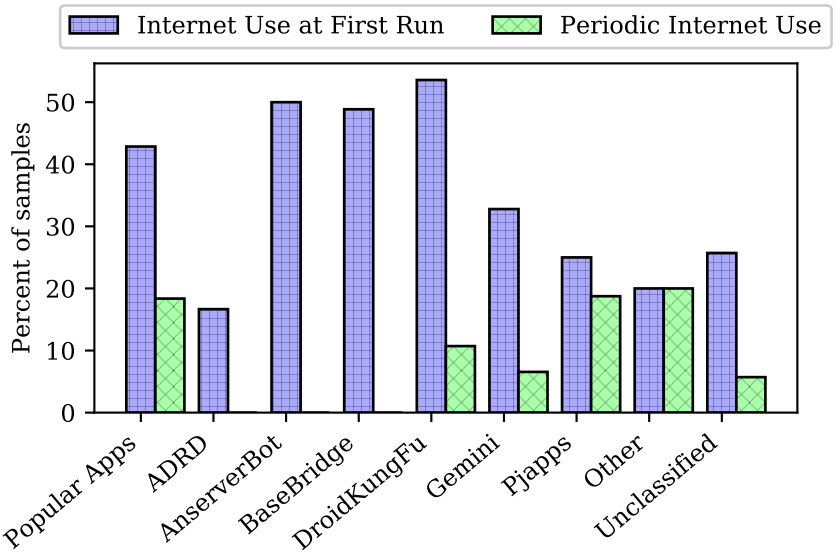


Figure 5.2: Internet Usage Timing

would allow partial connections to the Internet. Another option would be to serve cached copies of pages with the goal of getting apps to expose more of their behavior.

5.2.2 Results

The network usage measurements are summarized in Figure 5.2. The data was collected over 4-hour time windows, so periods larger than 4 hours would not show up in the results. Almost 20% of the top 100 Android apps on the Google Play store periodically accessed the Internet in the background after simply installing the app and running it once. Three of the six malware families did not show periodic background Internet usage during the 4-hour monitoring period. This suggests that identifying malware based on Internet usage when the user isn't actively using the device is not feasible.

Figure 5.3 shows an example Binder IPC graph from a clean Android system. Though we did not find any evidence of Bluetooth usage by the malicious applications in our

dataset, we were able to collect the IPC data from the various apps that could be further investigated.

5.3 App Network Monitor: A DNS Based Device Hygiene Solution

Aside from a data usage chart, Android does not have features to help a user police how apps use the Internet Users can decide whether to remove an app if it uses too much data, but nothing is provided to indicate what is being sent or received. Similarly, if the user wants to limit network access on the device, they have fairly coarse-grained control. They can turn the Wi-Fi or Cellular data on or off, but that affects the entire device. Android 6.0 and newer OS versions allow permissions to be granted or denied to apps, but this feature does not include the network access permission. When a user installs an app that requests Internet or network access, they grant it permission simply by installing the app.

The Linux kernel that Android is based on has support for `iptables`, but modifying the firewall rules requires root access. However, Android does provide an API (application program interface) for setting up virtual private network (VPN) client applications. This API provides a way to read and write the packets that normally would travel over the device's network interfaces. We developed ANM using the Android VPN API.

5.3.1 Implementation

Figure 5.4 shows an overview of how ANM is able to collect statistics on the domains accessed by each app to determine which apps are malicious. At a high level, the DNS traffic is handled by the Pseudo VPN service while the rest of the network traffic isn't touched by the VPN service. The mapping of IP address to UID for open sockets is recorded from entries in the path `/proc/net/`. These entries are linked with the DNS responses and the mapping of each UID to a package name to determine the domains accessed by each app. This information is aggregated at a statistics server to establish the

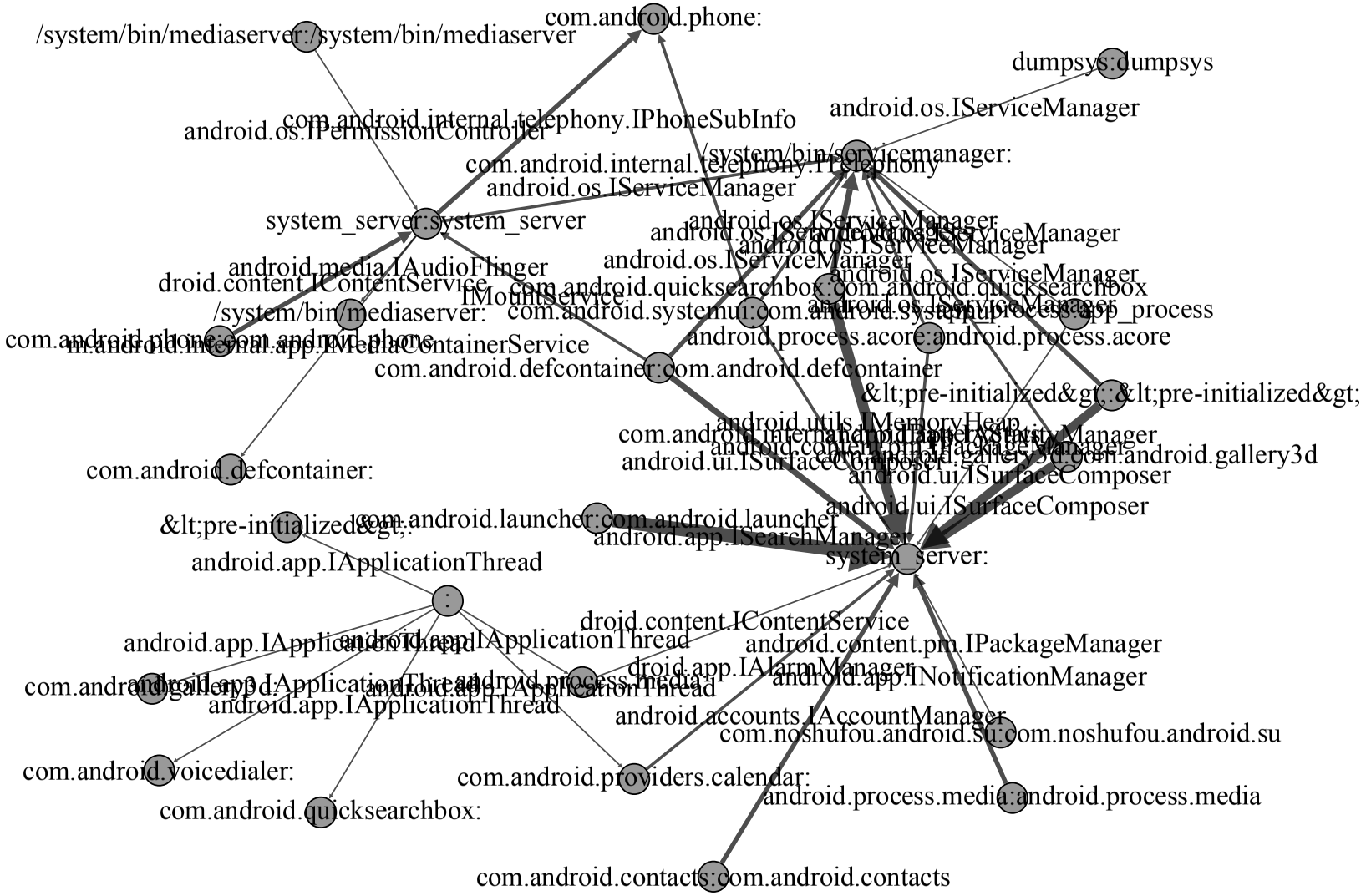


Figure 5.3: Example Weighted Binder IPC Graph. The nodes represent Android processes labeled by package name. The edges represent Binder connections and are weighted by the volume of transactions. This graph was generated using Gephi [104].

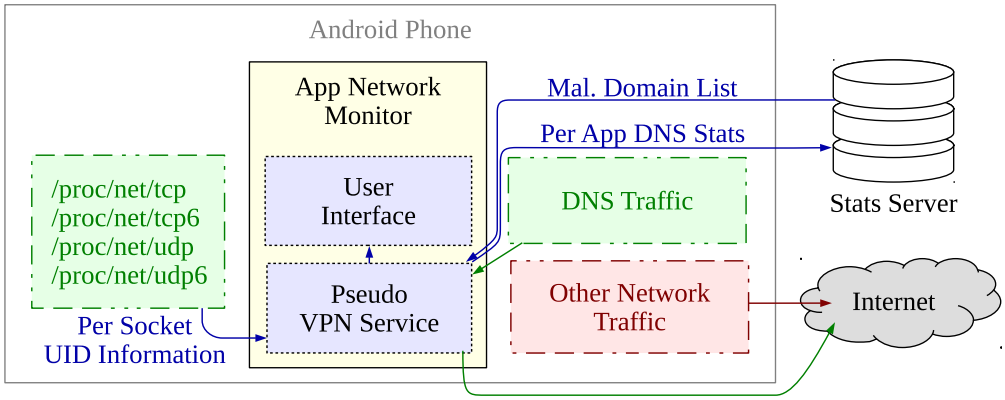


Figure 5.4: App Network Monitor Overview

domain access patterns of apps regardless of variations in user behavior so that malicious apps can be identified.

The VPN API allows for specification of custom routes to filter which traffic is selected to pass through the VPN. Routes were added for the DNS server IP addresses so that domain name resolution requests and responses could be captured by ANM. These packets include information about what domains are being accessed and can be checked against a list of known malicious domains such as Google Safe Browsing [105]. ANM uses much less system resources than solutions that monitor all the network traffic. This is true because DNS traffic makes up a small percentage of the total number of network packets. The downside of this is that contents of connections such as HTTP request headers cannot be checked.

Implementing this technique required (1) parsing the IP and UDP headers of the DNS requests; (2) sending them over datagram sockets to each DNS server; and (3) generating new IP and UDP headers for the DNS responses. This functionality replaces the VPN client, tunnel, and server with network address translation performed by the application. DNS requests are sent to the virtual DNS server IP address provided by the pseudo VPN

service. These requests are forwarded to the actual DNS server. The responses are then forwarded back as if they were sent from the virtual DNS server IP address.

The DNS packets do not indicate which app initiated the request. To obtain this information the pseudo files `tcp`, `udp`, `tcp6`, and `udp6` from `/proc/net/` are polled at least once per minute to record the UID to destination address information for each socket connection. The destination addresses are then checked to find the most recent matching DNS record from the answer section of a response. This circumstantially implies the domain that was requested to initiate the socket connection and thus the UID associated with the domain.

There are some challenges faced by this method. First, DNS records are cached for a period specified by a TTL value, so not every socket connection will have a DNS request. Second, multiple domain names can be associated with a single IP address so it is possible to have multiple answer records pointing to the same domain name. HTTP requests can be sent for both domains to the same IP address causing a possible confusion of the domain that was being accessed by an app. Third, when an domain request results in an error, there is no way to associate the original request with a UID. This makes it difficult to attribute the original request to the app that initiated it.

While it is possible to create a scenario where multiple domain name requests are answered with records to the same IP address, the risks of this scenario can be mitigated in a variety of ways depending on the goal. If the goal is to identify suspicious apps, all the matching domains could be attributed to all the matching apps making the requests. This data could then be checked across devices to eliminate the false positives.

DNS errors are useful in detecting the presence of malware that uses DGAs (domain generation algorithms). While it isn't possible to directly attribute requests to non-existent domains to the app which made the request, it is possible to monitor these requests to

establish patterns across devices. It is also possible to guess the format of the DGA, check for domain requests that succeeded, and match the same pattern.

The UID to app relationship is strong on Android. Apps are assigned a unique UID when they are installed. A notable exception occurs when the app writer specifies a shared UID to use for a group of applications. Apps can also be assigned to a group belonging to system apps, which are part of the original software on the system partition. In this case, the malicious behavior could be traced to the shared UID, which would point to the publisher responsible for the app. There is the possibility of malicious apps trying to hide their behavior by using an Android *intent* to open a malicious URI from whichever app is configured to accept that specific content type. However, the malicious app would still need to be able to access the data that was retrieved in order to use this for a C&C channel.

For the user interface, we chose to warn the user when an app accesses a known malicious domain. This gives the user an opportunity to decide if they want to navigate away from that page, avoid clicking on a malicious ad, or uninstall an app that frequently accesses malicious domains. The user is also given access to the complete list of domains accessed by each app on their device.

5.3.2 Results

We deployed ANM on the Google play store and had 550 unique installs over a six-month period. Only about a fifth of those opted in to the study and provided meaningful data. The summary statistics of the dataset are shown in Table 5.1. The dataset includes 4885.6 device hours of network activity that was calculated by merging the overlapping connection intervals so that the time shared over several connections is only counted once per device. There were 10963 unique domains resolved in the dataset and 1443 domain requests that resulted in errors.

	Total	Mean	Std.
Unique Packages Installed	7542	293.1	111.0
Unique Domains Successfully Resolved	10963	183.6	406.1
Unique Domains with Error Responses	1443	23.6	39.8
Device×Hours of Network Activity	4885.6 hours	44.4 hours	141.4 hours

Table 5.1: ANM Data Set Statistics

We found three different malicious domains that were each accessed on a different device. Google Safe Browsing classified two of the domains as hosting malware and one of the domains as being a social engineering platform. We were able to trace two of the domains back to the apps which accessed them. One was a text messaging app, and the other was confirmed to be a malicious app by AVG.

In one case we found domain errors for IP version 6 records that appeared to be from a DGA. However, matching records were received for the IP version 4 addresses. We traced back the IP version 4 address to a Internet security company and suspect they are using the DNS for checking signatures against a cloud-based threat database.

We plan to continue the development of ANM and expand its user base to get further insight into the behavior of malicious apps.

5.4 Related Work

There is already work which was concurrently developed in [106] that also uses a user-space solution for monitoring network traffic. Their work focuses on privacy and loss of personal information. They also monitor all the network traffic and even intercept encrypted TLS streams adding significant overhead. This imposes a latency overhead that has trade-offs with CPU usage. During active network usage they see a 9% increase in CPU overhead. ANM avoids this problem by only monitoring the DNS traffic. Thus,

ANM only has added latency to the DNS lookup, and other traffic has no performance penalty.

5.5 Summary

We found that network activity during the times a device isn't being used does not give a good indication of whether an app is malicious.

However, we developed a lightweight method for identifying malicious activity without requiring root access on Android devices. We deployed this method and were able to identify malicious activity through an analysis of DNS requests of Apps. This work is ongoing and will be continued by other students.

6. IOTAEGIS: A SCALABLE FRAMEWORK TO SECURE THE INTERNET OF THINGS

Motivated by the findings in chapter 3 we developed the IoTAegis framework, which offers device-level protection to automatically manage device configurations and security updates. It also acts as a middle-box to protect legacy devices that no longer receive updates and leverages DNS to identify when a device has been compromised With cloud-based device profile updates, the development effort to use IoTAegis to handle one device can be shared by all other users of the framework. Our solution is shown to be effective, scalable, lightweight, and can be deployed in different forms and network types.

6.1 Introduction

The protection of IoT devices is a challenging research topic because of the diversity of IoT device types, communication media, protocols, and network topologies. A number of solutions [107, 108, 109, 110, 111] already exist for securing IoT devices, but the expertise and management burden of applying these fixes has led to this problem of IoT devices left insecure. These solutions can be classified into two categories: device level and network level. At the network level, the Norton Core [112] identifies unpatched or unsecured IoT devices in a home network. In [110], an SDN platform is applied to identify suspicious network behavior and dynamic security rules are enforced on IoT devices. At device level, authors in [111] propose a secure authentication algorithm to verify the identities of clients and servers in a CoAP-based IoT environment. Studies in [107] and [108] focus on the security of IoT apps. We developed a framework to effectively secure IoT devices from the device level: it checks the unsecured IoT devices in the network and updates their firmwares, passwords, and configurations. It also includes a network based option to provide extra security for devices which are no longer supported, and a DNS based

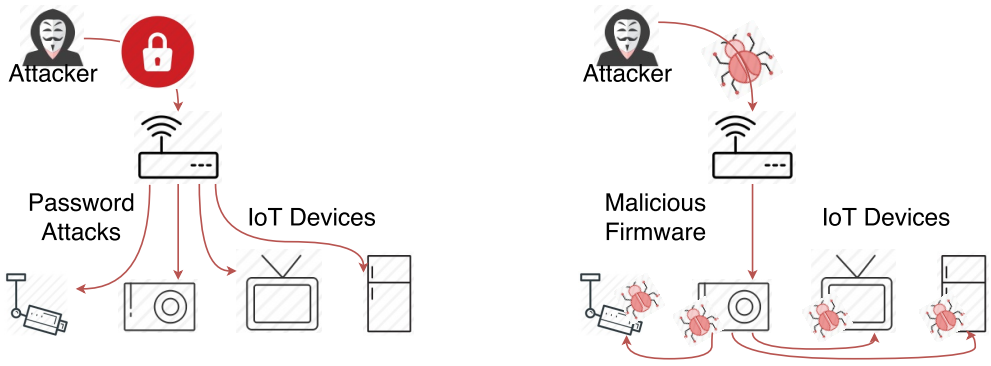
option to identify when devices are behaving strangely. Norton Core focuses on securing IoT devices at the network level leaving firmware and configuration vulnerabilities on the end devices. By focusing on the problem at the device level, we aim to have an approach that works for any size network ranging from small home networks to large campus or enterprise networks. The framework is applicable to different types of IoT devices and easy-to-scale. It can be deployed on a dedicated device, integrated with network routers, or as a standalone application. We developed a prototype and showed that our framework can automatically update firmwares for HP printers as well as apply a non-default password.

Traditional *Anti-Virus* or *Internet Security* solutions on compute devices rely on being able to run as third party applications. However, you cannot load third party applications onto an IoT device. In the case of IoT devices, the solution must accomplish the same goals by interacting with the device specific management interfaces. This problem is compounded by the wide variety of management interfaces. Our approach can be seen as a "device hygiene" approach, and our solution is implemented centrally within an administrative network (campus or home). While the current solution works as a software running on a workstation within a campus network, a future version of this software can run as an app within a home network or as a service on a consumer router.

6.2 Attacker Model

In this chapter we try to prevent the compromise of IoT device in the first place instead of focusing on solutions to prevent various network-level attacks. We are interested in developing a solution to prevent attackers from gaining unauthorized control of the devices of interest. Thus, we consider two different attacks in the exploitation stage: *configuration attacks* and *firmware attacks*, see Figure 6.1.

Assumptions. Without loss of generality, we focus on IoT devices that communicate through a wired or wireless network connection. Media such as Bluetooth [53], Zig-



(a) Configuration Attacks (b) Firmware Attacks

Figure 6.1: Exploitation Attacks Considered in the Chapter

Bee [113], Z-Wave [114], 6LowPAN [115] are not considered in this chapter. However, they could easily be addressed when the device supports these protocols in addition to an IP-based network connection. We assume attackers do not have physical access to IoT devices, but can access the devices over the local network within any firewalls.

Configuration Attacks. Attackers may launch password attacks that take advantage of IoT devices with weak or no password protection, *e.g.* brute force attacks and dictionary attacks. Once they have access, attackers may further modify the devices' configuration to prevent authorized users from accessing or controlling the devices. IoT devices provide some services without authentication by default, providing opportunities to the attackers.

Firmware Attacks. Attackers may launch firmware attacks to infect IoT devices by exploiting outdated firmware with design or implementation flaws. We assume patches already exist in the newest firmware version and attackers cannot exploit the latest firmware with 0-day attacks. In addition, some devices (such as HP printers before 2011) support remote firmware update without checking the signature of the firmware to be installed [116]. Attackers who have network access to the target devices may infect the devices by

uploading a malicious firmware. Exploitation may also result from unsecured protocols such as Telnet or SNMP and from flawed parsers for data like postscript print jobs.

Once the IoT devices have been exploited, attackers may launch (a) *actuation attacks*: change the state of an IoT device with malicious intent, *e.g.* false command injection attacks; (b) *data acquisition attacks*: obtain a user's sensitive data such as print jobs or phone calls; (c) *data integrity attacks*: send false sensor data or status information to a server or other IoT device; and (d) *Botnet attacks*: leverage the infected IoT devices to attack other hosts, *e.g.* Mirai attacks.

6.3 Solution

From the results of our measurement study outlined in chapter 3, it is clear that the number of IoT devices could be more than that of compute devices. While compute devices are generally protected by Antivirus and security patches are regularly updated, many IoT devices are not adequately protected. Specifically, while firmware updates may be available, 58.9% or more of the devices were not kept up-to-date. In addition, 51.3% or more devices did not have a user defined password. This problem has been recognized by others [62, 117]. The solution is made difficult by the number of devices on the network, their age range, and the number of vendors supplying these devices. Thus, we developed IoTAegis to address these identified problems directly while simultaneously reducing the management burden. The IoTAegis provides a central tool for keeping firmware up-to-date and device configurations secure.

An overview of IoTAegis is shown in Figure 6.2. The framework discovers hosts, identifies device types and supported services. Then, it can perform tasks needed to update the devices to the newest firmware and address security holes in the device configuration. In this way an application or system service uses the framework to manage the network devices and handle security issues as they are detected. Ideally, checks will be performed

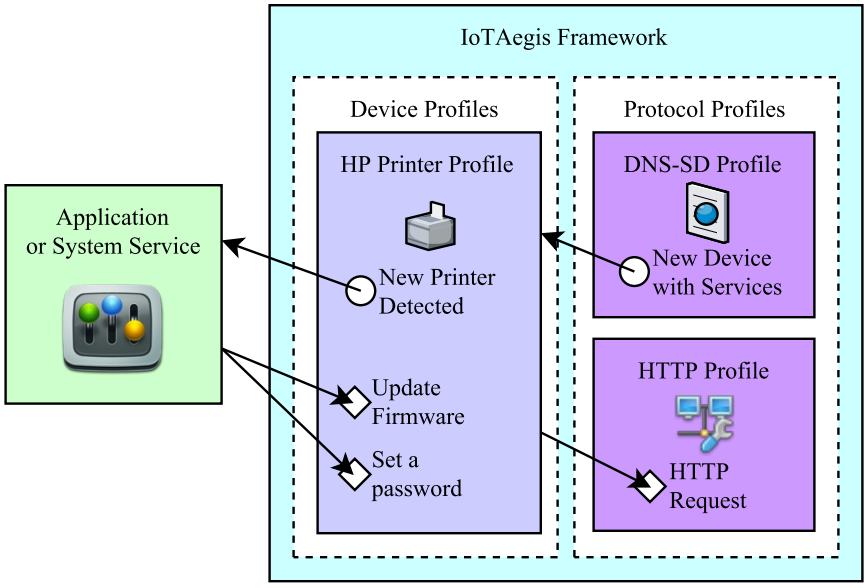


Figure 6.2: An Overview of Our Solution—IoTAegis

as soon as a new IoT device is connected to the network. Rather than introducing another network protocol to handle these attacks, we propose a methodology that could be drafted into a standardized API. Our proposed methodology consists of two types of profiles: one for handling network protocols and the other for handling devices. These profiles could be likened to device drivers used by an operating system. Device and protocol profiles can be downloaded and updated from a cloud-based provider, so the solution would accommodate new devices. Writing a profile for one device or manufacturer would apply to other devices of the same model or manufacturer. Large networks with a variety of devices reduce to a configuration for each device type because the profiles abstract a configuration task.

Each network protocol profile fulfills two primary roles. First, it defines "requests" that are abstracted from the underlying protocol and can be used by device profiles. An example of a request would be downloading an index page over HTTP. Second, the network protocol profile defines events. These events are tied to activity at the protocol level which should be handled by listeners defined in device profiles. An example of an event

would be the discovery of a new device and its services over mDNS. The DNS-SD profile includes the logic needed to discover devices using mDNS and generate events whenever a service advertisement is received.

Each device profile depends on network protocol requests or events to provide the logic required to perform a set of standard tasks. Some tasks are device specific, but here are a few key examples: discovering the device, identifying the device model and state, defining the password, checking what the latest available firmware is, checking the firmware version on the device, applying a secure set of configuration options, recommending restrictive firewall rules. Not all tasks will apply to every device.

IoTAegis uses an event driven architecture where protocols such as DNS-SD over mDNS produce events. These events are multiplexed by their service discovery data to the appropriate handlers. For example an IoT printer may advertise the `_http._tcp`, and `_printer._tcp` services. The `_printer._tcp` service includes a `TXT` record with information about the printer that aids in the identification of the printer manufacturer and model number. At this point the appropriate device profile can be notified through its registered event listener. Based on these events, follow-up requests are made to query the firmware version of the new printer and check if the new printer has a custom password set. Further execution on that event tree can be halted, and the tasks registered for that device would then be made available to the application or system service. These tasks could be executed once on demand, periodically, or as updates are released for the device.

A device-centric solution requires the following key functions (a) host discovery, (b) device identification, (c) configuration management, and (d) firmware updates.

Host Discovery. Several well-known techniques can be leveraged for host discovery, as discussed in Section 2. IoTAegis uses the Avahi-client library [118] in our framework to construct a DNS-SD profile. When new devices are services are discovered events are

generated by the framework. Next, we aggregate the list of services advertised by each host.

Device Identification. IoTAegis matches service strings with different types of devices and automatically identifies IoT device types. Specifically, `_printer._tcp` corresponds to a Unix printer, `_pdl-datastream._tcp` to a Page Description Language (PDL) printer, `_ipp._tcp` to an Internet Printing Protocol (IPP) printer, `_ipps._tcp` and `_ipp-tls._tcp` to IPP printers using HTTPS. Within the DNS-SD `TXT` records are key-value-pairs, one of which describes the product by including the brand and model number.

Devices with insufficient identifying information or no DNS-SD advertisement may require a request to be made through a protocol profile. For example, a check could be performed on their HTTP index page to match against signatures. Additional protocol profiles can be provided to expand the capabilities of the framework as necessary, and new device profiles would provide the logic required to identify more devices. Ideally, a standard API could be drafted and the device manufacturer would provide its own device profiles, but third parties could develop them as well.

Configuration Management. Some printers for example do not have an administrative password set by default or have a default password that is easy to look up. When devices use simple HTTP authentication, IoTAegis sets a header with the default authentication information. If a page requiring authentication can be accessed with the default username and password, it is clear the device needs to have a custom password set. The user can be prompted or an automatic password can be generated, set, and stored in a password manager where both the security framework and the user can access it as needed.

In addition to problems with the default password configuration, tasks defined in the device profile can address extraneous services enabled by default or device specific security considerations. Thus, a device profile for IoTAegis can serve as a replacement for the

vendor specific device configuration software that is shipped with IoT devices. This provides the end user with a common place and interface to manage a wide variety of devices connected to their home or business network in contrast to needing to use each device's individual management interface.

Firmware Updates. While newer devices may include automatic firmware updates, our survey demonstrates there are plenty of devices running old firmware versions. To update the firmware of an HP printer IoTAegis downloads the appropriate remote firmware update (RFU) file and transmits it using TCP to the raw print port of the printer (9100). The latest update can be found by querying an FTP site for a matching RFU file with the greatest version number of date code. Some logic may be required to update very old firmware to intermediate versions prior to updating to the latest version. This logic can be included in the device profile, but in general the devices should be at most one version behind. In this case, the latest supported firmware version will install without requiring intermediate updates. Once the firmware is downloaded and transmitted, the printer executes the update commands contained in the RFU file that perform the update using the self-contained data without user intervention. Thus, the devices on the network can be kept up-to-date with the latest firmware versions available to prevent attackers from exploiting known vulnerabilities that have already been patched.

Middle-box Solution for Vulnerable Devices. Some devices are old enough that they no longer receive updates from the manufacturer. Any vulnerabilities on these devices will remain and may be exploited by attackers. A solution to this scenario requires preventing exploits from reaching the vulnerable device. This is achieved by (1) using a managed switch or user access control to prevent direct access to the vulnerable service on the device; and (2) implementing a transparent proxy with signature detection to block exploits. The signatures are included in the device profile.

This feature is more costly in terms of performance because it requires funneling all the traffic to the affected devices through the middle box. As long as the usage of these devices doesn't saturate the network link and the cost of running the signature checks doesn't saturate the CPU, the cost of this feature will be negligible. If these limits are reached, one option would be to run additional middle boxes and another option would be to replace the legacy hardware with newer hardware that doesn't need the middle box feature.

DNS-based Compromise Detection. IoT devices have a very limited set of behaviors compared to compute devices. Thus, it is easier to establish a pattern of network access behavior such as DNS lookups. These DNS lookups can provide insight into whether the devices are properly configured and detect malicious behavior when the devices have abnormal accesses.

For example, VoIP phones connect through a PBX which is configured on the device. If the VoIP phones only access the domains for the proper PBX server, it demonstrates the phone is configured correctly. If the phone accesses other domains or doesn't look up the proper PBX server, its configuration should be reset.

Printers were observed accessing vendor specific domains and performing reverse lookups for local IP addresses. Any other DNS accesses would be suspicious and suggest a printer was compromised.

IoTAegis can be integrated with the local DNS server to check the domain lookups against the expected behavior defined in the device profile. This provides a way to know when devices have been compromised, so proper action can be taken.

6.4 Evaluation

We tested the features of IoTAegis on an HP 2055x printer. We first verified that the firmware files downloaded by IoTAegis matched the ones downloaded through a browser.

Then, we successfully updated the firmware twice by applying the next newest update and an update to the newest version. The initial firmware datecode was 20120615, the intermediate datecode was 20131112, and the final datecode was 20141201. The before and after screenshots of the device configuration administration page hosted by the printer for the last update are displayed in Figure 6.3. We hid most of the identifying information, but the last few digits of the serial number and hardware address are shown to validate that the screenshots were taken from the same device.

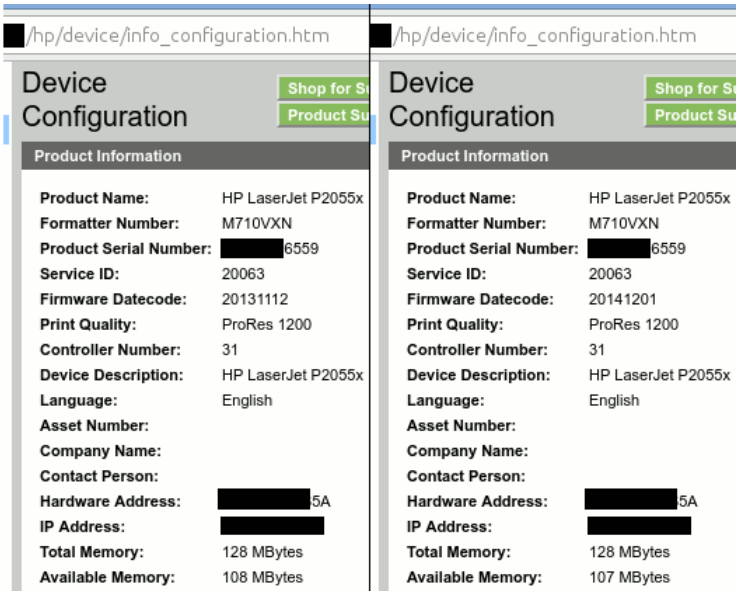


Figure 6.3: Printer Configuration Page Before (Left) and After (Right) IoTAegis Downloaded and Updated the Firmware.

IoTAegis also successfully configured the printer to use custom password. Figure 6.4 shows the authentication prompt when attempting to access a sensitive part of the printer's administration page. We envision IoTAegis being integrated with a password manager of the user's choice. This gives the user easy access to the passwords in a secure place, and

IoTAegis can retrieve the passwords when future configuration or firmware updates are needed.

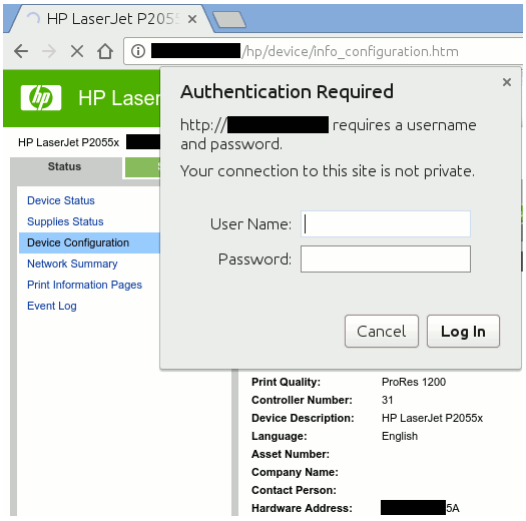


Figure 6.4: Authentication Prompt When Accessing a Sensitive Page After IoTAegis Set a Password.

These demonstrations show that IoTAegis is able to solve the two primary channels of attack motivated by our survey data. Attackers will not be able to exploit known vulnerabilities in out-of-date firmware or gain control of devices through insecure configurations such as default passwords.

Solution Costs We implemented a proof-of-concept framework and demonstrated that we are able to automatically check passwords on IoT devices and update firmware on HP printers. We tested the proof-of-concept on an Intel Core i5-3330 CPU at 3.00GHz running Ubuntu 16.10 and recorded the CPU time as well was the network usage for the first 60 seconds of operation. The test subnet had 67 compute devices and 25 printers. The network usage by protocol is shown in Figure 6.5, where the mDNS traffic was generated by the avahi library for service discovery and the HTTP traffic was used to obtain

the firmware and password state information from the detected printers. Also, the peak network usage was about 350kBps (2.8Mbps), and most of the traffic occurred in the first 20 seconds of operation.

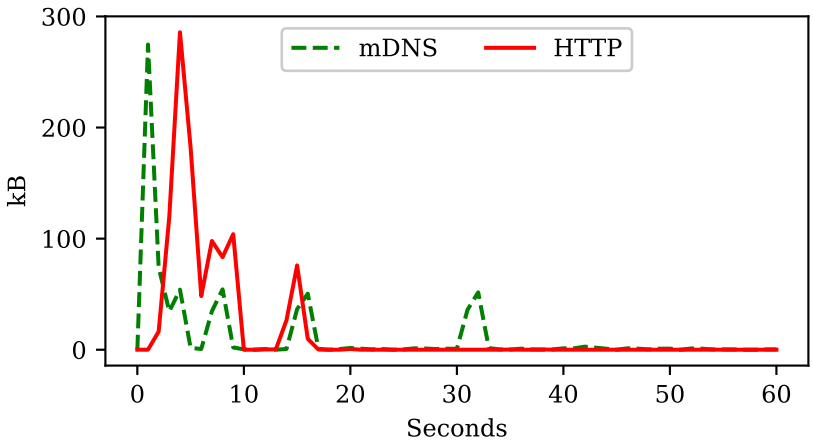


Figure 6.5: Network Usage During the First 60 Seconds of Operation

During the 60-second test interval the service avahi-daemon used 1.34 seconds of CPU time in user mode and 0.32 seconds in kernel mode. The proof-of-concept app used 0.51 seconds of CPU in user mode and 0.08 seconds in kernel mode. This amounts to a utilization of 3.75% of one core during the 60-second test period. The utilization would be 11.25% if we assume all the activity took place in the first 20 seconds. The peak memory usage of the proof-of-concept app was 99.6MB, but with rate limits on the DNS-SD queries and optimization this number could be brought down to a number that would be practical for consumer grade routers.

Our password update demonstration only requires a single HTTP request. This should apply in most cases unless an initial request is required to obtain a nonce to use the submission form. Verification that the update succeeded requires an additional request. One

limitation of the firmware updates is the printer being updated must be in the "ready" state for the update to complete—there can be no paper jams or active print jobs.

Scalability and Scope. While our proof-of-concept is limited in scope because of the limited protocol and device profiles it contains, the general principles behind its design can be applied to a wide variety of IoT devices. The primary requirement for IoTAegis to work with an IoT device is it must have the appropriate device profile network protocol profile and the network profile dependencies. Protocol profiles can be created for Bluetooth and near field communications to support non-IP-based devices.

IoTAegis can be easily deployed in different forms such as a phone app, a browser extension, or as a feature of a network device or home router. It is already suitable for both wired and wireless Ethernet interfaces. The development of a standardized API would make it easier for device manufacturers and third parties to develop profiles supporting more IoT devices. This also enables alternative, but compatible, framework implementations to be developed that can use the same profiles.

6.5 Related Work

IoT Defense Solutions. A number of solutions have been proposed to secure IoT devices through a security framework [109], SDN (software-defined networking) [110], and authentication [111].

ZENworks [119] is an effective security and configuration management solution for compute devices. Symantec Norton Core Router [112] aims to protect IoT devices in a home network from network-level perspective. It detects suspicious activities within a home network, and quarantines infected connected devices, but does not handle updates to the device firmware or changes to the device configuration. IoTAegis solves the problem from device level and provides a general framework that can be applied to different IoT devices regardless of their type, manufacturers, and network interfaces (wired and wireless).

Our solution also provides password checks and automatic firmware updates to prevent potential exploits.

Jia et. al [107] provide a taxonomic IoT attack app dataset based on reported IoT attacks and constructing new IoT attacks. They also propose a context-based access control system for IoT devices. This system supports fine-grained context identification and runtime prompts with rich context information to help users authenticate sensitive actions and perform access control.

Fernandes et al. [108] propose the FlowFence framework that enforces the declared data flow patterns within IoT apps for sensitive data and prevent all other flows. The solution can be incorporated with existing IoT apps with small overhead.

6.6 Summary

The infamous Mirai attack has shown that many IoT devices do not have adequate security protections and can be leveraged to cause significant damage. To solve the problems uncovered in chapter 3, we developed IoTAegis to offer device-level security protection for various IoT devices. Having one management interface for all IoT devices and device profile updates via the cloud, significantly decrease the management burden for securing the IoT. By incorporating a middle box feature, older IoT devices that no longer receive updates are secured. The DNS traffic from IoT devices is used to verify that they are behaving as expected. Our framework is effective, scalable, easy-to-deploy with low computational cost. It enables the development of a single management platform for configuring and securing the IoT.

7. CONCLUSIONS

In order to identify and solve internal network threats related to non-compute devices, this work includes quantitative studies of the number of devices and their condition. It also includes three solutions to handle security issues present in non-compute devices in particular smartphones and the IoT.

In chapter 2 we found that two-thirds of the DNS traffic came from wireless hosts. This shows that mobile devices are playing a bigger role in networks. Also, DNS was being used as a side channel to access data even through firewalls, and anomalous requests that pointed to infected machines on the network were found. While these results apply to both mobile and non-mobile devices, they show that DNS traffic can provide enough information to identify malicious activity.

After performing measurements to estimate the impact of IoT devices on the network in chapter 3, we found that 58.9% of printers had out-of-date firmware and 51.3% did not have a user-defined password. The discovered VoIP phones composed the largest category of IoT devices, and 45.3% of them had default passwords. At least 34 different manufacturers were represented in the data, which included at least 12 different device types. Each manufacturer had unique management interfaces, and some even had several for each device type. This poses a significant challenge in securing and configuring all these devices.

Mobile devices often have multiple connectivity options, which leads to novel security challenges. While previous steppingstone detection techniques rely on correlating multiple network flows, mobile devices can be steppingstones with only one observable flow. Solutions were developed to this problem and are presented in chapter 4. One solution uses

timing measurements at the transport layer and the other at the application layer. These solutions provide very high detection rates and low false positive rates.

Two different solutions for identifying malicious apps were tried in chapter 5. First, we expected to see most of the harmful network activity happen regardless of whether a user was interacting with the device; however, we did not expect to see a significant percentage of benign apps actively using the Internet during this time. We found that contrary to expectation, 20% of the 100 most popular Android apps exhibited periodic background network activity when neither that app nor the device were in use. The second solution was App Network Monitor, an Android app that monitors which domains are accessed by each app and warns the user when malicious domains are accessed. This also allows the malicious activity to be attributed to the app responsible. From the preliminary data collected, we identified three malicious domains and one malicious app. This work will be continued by other students.

Finally, the IoTAegis framework is presented in chapter 6. It addresses the challenge of securing and configuring the wide variety of non-compute devices in a scalable way. A proof of concept app was used to demonstrate the IoTAegis framework by updating the firmware of a printer and setting a non-default password.

The aforementioned work contributes to the well-being of society by addressing insider attacks that are enabled by the rise of non-compute devices such as smartphones and the Internet of Things.

7.1 Future Work

7.1.1 Proxy Detection

The proxy detection methods worked well, but there are some additional improvements which can be investigated. For example, other features could be investigated to determine if the classification accuracy may be improved. Along with new features, methods that

perform anomaly detection across a combination of features can be evaluated. Investigation could be done to find a method for preventing the case when an attacker does not use a tunnel but instead funnels the information first to the compromised machine and later extracts it. IPsec [120] could be investigated to see if similar results could be achieved at the network layer. Also instead of group of similar paths merely to detect compromised hosts during training, training could be performed for each of these groups. This would reduce the amount of training needed. Lastly, this method could be tested on a service with fewer controls to see how it performs and to solve any challenges that did not come up in the previous measurements.

7.1.2 App Network Monitor

There are two main tasks that would increase the benefit of the App Network Monitor. First, work needs to be done to expand the userbase of the app to collect more data. More data will provide the opportunity to establish patterns of app behavior across devices. Second, changes can be made to the app so it can notify users of malicious domains without having to wait for updated domain lists. This would simultaneously reduce the effort required to upkeep the app and make the app more useful.

7.1.3 IoTAegis

IoTAegis would be even more beneficial with the following future contributions. First, the IoTAegis framework can be extended to include additional network based protection (firewall rules), support other IoT devices. Firewall rules can be used to add additional protection to devices which do not include access control features. Second, the middle box functionality could be further developed to allow for reprocessing of application specific data such as print jobs to strip out common attack vectors. This would act as a more proactive preventative measure then blocking data sent to IoT devices based on signatures. Signatures require analysis on known malware samples while the reprocessing task will

validate and translate the input into a trusted format. Lastly, a flexible API can be extracted from IoTAegis to aid in the development of third party protocol and device profiles that may serve as the basis of a standardized API.

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APPENDIX A

ANDROID LINUX KERNEL MODIFICATIONS FOR BINDER IPC LOGGING

The patch below contains a change that adds kernel logging of Binder IPC transactions. The log lines are appending to a ring buffer which is accessible at the path `/proc/kmsg`.

```
diff --git a/drivers/staging/android/binder.c b/drivers/staging/android/binder.c
index e13b4c48340..b94502d3f2e 100644
--- a/drivers/staging/android/binder.c
+++ b/drivers/staging/android/binder.c
@@ -357,6 +357,89 @@ struct binder_transaction {
     uid_t   sender_euid;
 };

+char lookup_table[] = {'0','1','2','3','4','5','6','7','8','9','A','B','C','D','E','F'};
+
+void append_to_logfile(struct binder_transaction* t) {
+    if (t->buffer == NULL) {
+        printk(KERN_WARNING
+            "%d: %p from %d:%d to %d:%d code %x flags %x pri %ld r%d buffer free\n",
+            t->debug_id, t,
+            t->from ? t->from->proc->pid : 0,
+            t->from ? t->from->pid : 0,
+            t->to_proc ? t->to_proc->pid : 0,
+            t->to_thread ? t->to_thread->pid : 0,
+            t->code, t->flags, t->priority, t->need_reply);
+    } else{
+//        const int len=t->buffer->data_size<65?t->buffer->data_size+1:65;
+//        int x, x2, val;
+//        char data_str[len];
```

```
25 +//         x=0;
26 +//         for(x2=0; x2<len-1; x2+=2){
27 +//             data_str[x+1]=lookup_table[0x000f & t
   ->buffer->data[x]];
28 +//             data_str[x]=lookup_table[0x000f & (t->
   buffer->data[x] >> 4)];
29 +//             x++;
30 +//         }
31 +//         data_str[len-1]=0;
32 +         int str_len = t->buffer->data_size >= t->
   buffer->offsets_size+12?*((const uint32_t*)(t->
   buffer->data+4)):0;
33 +         const uint16_t *unicode = (const uint16_t*)(
   t->buffer->data+t->buffer->offsets_size+8);
34 +         int num_unicode=0, x, ind;
35 +         if(str_len){
36 +             int offset = ((str_len+1) << 1)+t->
   buffer->offsets_size+8;
37 +             if(t->buffer->data_size<(offset) || t->
   buffer->data[offset-1]!=0 ||
38 +                     t->buffer->data[offset-2]!=0){
39 +                 str_len=0;
40 +             }
41 +             for (x = 0; x < str_len; x++) {
42 +                 if(unicode[x]>(uint16_t)0x00ff){
43 +                     num_unicode++;
44 +                 }
45 +             }
46 +         }
47 +         const int len = str_len+1+num_unicode*5;
48 +         char data_str[len];
49 +   ind=0;
50 +         for(x = 0; x < str_len; x++) {
51 +             if(unicode[x]>(uint16_t)0x00ff){
52 +                 data_str[ind  ]='\\';
53 +                 data_str[ind+1]='u';
54 +                 data_str[ind+2]=lookup_table[0x000f
   & (unicode[x] >> 12)];
55 +                 data_str[ind+3]=lookup_table[0x000f
   & (unicode[x] >> 8)];
56 +                 data_str[ind+4]=lookup_table[0x000f
   & (unicode[x] >> 4)];
```

```
57 +                data_str[ind+5]=lookup_table[0x000f
   & (unicode[x])];
58 +                ind+=6;
59 +            } else {
60 +                data_str[ind] = (char)(unicode[x]);
61 +                ind++;
62 +            }
63 +        }
64 +        data_str[len-1] = 0;
65 +        if (t->buffer->target_node){
66 +            printk(KERN_WARNING
67 +                "%d: %p from %d:%d to %d:%d code %x
   flags %x pri %ld r%d node %d size %zd:%zd data (%s
   )\n",
68 +                t->debug_id, t,
69 +                t->from ? t->from->proc->pid : 0,
70 +                t->from ? t->from->pid : 0,
71 +                t->to_proc ? t->to_proc->pid : 0,
72 +                t->to_thread ? t->to_thread->pid :
   0,
73 +                t->code, t->flags, t->priority, t->
   need_reply,
74 +                t->buffer->target_node->debug_id,
75 +                t->buffer->data_size, t->buffer->
   offsets_size,
76 +                data_str/*t->buffer->data*/);
77 +        } else {
78 +            printk(KERN_WARNING
79 +                "%d: %p from %d:%d to %d:%d code %x
   flags %x pri %ld r%d size %zd:%zd data (%s)\n",
80 +                t->debug_id, t,
81 +                t->from ? t->from->proc->pid : 0,
82 +                t->from ? t->from->pid : 0,
83 +                t->to_proc ? t->to_proc->pid : 0,
84 +                t->to_thread ? t->to_thread->pid :
   0,
85 +                t->code, t->flags, t->priority, t->
   need_reply,
86 +                t->buffer->data_size, t->buffer->
   offsets_size,
87 +                data_str/*t->buffer->data*/);
88 +        }
```

```
89  +    }
90  +}
91  +
92   static void
93   binder_defer_work(struct binder_proc *proc, enum
        binder_deferred_state defer);
94
95  @@ -1736,6 +1819,9 @@ static void binder_transaction(
       struct binder_proc *proc,
96       list_add_tail(&t->work.entry, target_list);
97       tcomplete->type =
            BINDER_WORK_TRANSACTION_COMPLETE;
98       list_add_tail(&tcomplete->entry, &thread->todo);
99  +
100 +    append_to_logfile(t);
101 +
102      if (target_wait)
103          wake_up_interruptible(target_wait);
104      return;
105 @@ -1763,7 +1849,8 @@ err_bad_call_stack:
106  err_empty_call_stack:
107  err_dead_binder:
108  err_invalid_target_handle:
109 -err_no_context_mgr_node:
110 +err_no_context_mgr_node:
111 +    append_to_logfile(t);
112      binder_debug(BINDER_DEBUG_FAILED_TRANSACTION,
113                   "binder: %d:%d transaction failed %d,
                        size %zd-%zd\n",
114                   proc->pid, thread->pid, return_error,
```

Source Code A.1: “android-x86-ics-kernel.patch”

APPENDIX B

CODE FOR CREATING A DATABASE OF BINDER TRANSACTION CODES

The first two source files are perquisites and the third source file does the work if populating a database with the Android binder transaction codes.

```
1  #!/usr/bin/python
2  #sudo pip install --upgrade sqlalchemy sqlalchemy-ext
3
4  import os
5
6  from sqlalchemy import create_engine, MetaData,
       Column, ForeignKey, Integer, String
7  from sqlalchemy.ext.declarative import
       declarative_base
8  from sqlalchemy.orm import backref, relationship,
       sessionmaker
9
10 from xml.sax.saxutils import escape
11
12 android='ics'
13 android_src_path='../android-x86-ics'
14
15
16 aidl_filename_list=os.path.join(os.path.dirname(
       __file__),android,'aidl-list.txt')
17 cpp_filename_list=os.path.join(os.path.dirname(
       __file__),android,'aidl-cpp-list.txt')
18 java_filename_list=os.path.join(os.path.dirname(
       __file__),android,'aidl-java-list.txt')
19
20 # engine = create_engine('sqlite:///:memory:', echo=
       False)
21
22 engine = create_engine('sqlite:///%s/aidl.db' % (os.
       path.join(os.path.dirname(__file__),android)))
23 Base = declarative_base()
```

```
24
25 class AndroidInterface(Base):
26   __tablename__ = 'aidl_files'
27
28   id = Column(Integer, primary_key=True)
29   name = Column(String)
30   filepath = Column(String)
31   functions = relationship("InterfaceFunction",
        order_by='InterfaceFunction.code',
32                 backref='function')
33
34   def __repr__(self):
35     contents = ["<AndroidInterface id='%s' name='%s'
          filepath='%s'>" % (
36       str(self.id), escape(self.name), escape(self.
           filepath))]
37     for function in self.functions:
38       contents.append('  '+function.__repr__())
39     contents.append("</AndroidInterface>")
40     return '\n'.join(contents)
41
42 class InterfaceFunction(Base):
43   __tablename__ = 'function'
44
45   id = Column(Integer, primary_key=True)
46   code = Column(Integer)
47   name = Column(String)
48
49   interface_id = Column(Integer, ForeignKey('
        aidl_files.id'))
50   interface = relationship("AndroidInterface",
        backref=backref('function', order_by=code))
51
52   def __repr__(self):
53     return "<InterfaceFunction id='%s' code='%x' name
          ='%s' interface='%s' />" % (
54       str(self.id), self.code, escape(self.name), str
           (self.interface_id) )
55
56 def reset_database():
57   meta = MetaData(engine)
58   meta.reflect()
```

```
59    for tbl in reversed(meta.sorted_tables):
60      engine.execute(tbl.delete())
61    Base.metadata.create_all(engine)
62
63  Session = sessionmaker(bind=engine)
```

Source Code B.1: “common.py”

```
1   #!/usr/bin/python
2   #sudo pip install --upgrade sqlalchemy
3
4   import os, subprocess, sys
5
6   import common
7
8   output = sys.stdout
9
10  if not os.path.isdir(common.android_src_path):
11    raise ValueError('android_src_path, "%s", is not a
        directory!' % (common.android_src_path))
12
13  if not os.path.exists(common.android):
14    output.write('Creating "%s"\n' % (common.android))
15    os.mkdir(common.android)
16
17  if not os.path.isdir(common.android):
18    raise ValueError('destination path, "%s", is not a
        directory!' % (common.android))
19
20  init_filename = os.path.join(common.android,'__init__
      .py')
21
22  if not os.path.exists(init_filename):
23    with file(init_filename,'w'):
24      None
25
26  out_path = os.path.abspath(common.android)
27  subprocess.call(['bash','-c','cd %s; find . -iname
      "*.aidl" > %s/aidl-list.txt'
28      % (common.android_src_path,out_path)])
29
30  out_file = '%s/aidl-cpp-list.txt' % (out_path)
```

```
31 if os.path.isfile(out_file):
32   os.unlink(out_file)
33 subprocess.call(['bash','-c','cd %s; find . -iname
     "*.cpp" -print0 | xargs -0 -n1 -P8 grep -l "
     IBinder::FIRST_CALL_TRANSACTION" >> %s'
34   % (common.android_src_path,out_file)])
35
36 out_file = '%s/aidl-java-list.txt' % (out_path)
37 if os.path.isfile(out_file):
38   os.unlink(out_file)
39 subprocess.call(['bash','-c','cd %s; find . -iname
     "*.java" -not -path "./out/*" -print0 | xargs -0 -
     n1 -P8 grep -l "IBinder.FIRST_CALL_TRANSACTION" >>
      %s'
40   % (common.android_src_path,out_file)])
41
42 import generate_add_custom_file
43 with open(os.path.join(out_path,'custom.py'),'w') as
     out_file:
44   generate_add_custom_file.output = out_file
45   generate_add_custom_file.generate_add_custom_file()
```

Source Code B.2: “do_setup.py”

```
1  #!/usr/bin/python
2  #sudo pip install --upgrade sqlalchemy
3
4  import importlib, os, re, sys
5
6  import common
7  custom = importlib.import_module('%s.custom' % (
     common.android))
8
9  #setup filename lists
10 aidl_filenames=[]
11
12 with open(common.aidl_filename_list) as f:
13   aidl_filenames = f.readlines()
14
15 #regular expressions
16 whitespace = re.compile('\\s+',re.MULTILINE)
```

```
17 comments = re.compile('(?:/\\*(?:[^*]|(?:\\*+[^*/]))
     *\\*+/)|(?://.*$)',re.MULTILINE)
18
19 package_name = re.compile('package\\s+([a-zA-Z_]{1}[a
     -zA-Z0-9_]*(?:\\.[a-zA-Z_]{1}[a-zA-Z0-9_]*)*)\\s*;
     ',re.MULTILINE)
20 interface_spec = re.compile('interface\\s+([a-zA-Z_
     ]{1}[a-zA-Z0-9_]*)\\s*(?:\\{([^}]*)\\})?',re.
     MULTILINE)
21 parcel_name = re.compile('parcelable\\s+([a-zA-Z_
     ]{1}[a-zA-Z0-9_]*(?:\\.[a-zA-Z_]{1}[a-zA-Z0-9_]*)
     *)\\s*;',re.MULTILINE)
22
23 function_def = re.compile('([a-zA-Z_]{1}[a-zA-Z0-9_
     ]*(?:\\.[a-zA-Z_]{1}[a-zA-Z0-9_]*)*(?:\\s*<(?:[a-
     zA-Z_]{1}[a-zA-Z0-9_]*\\.)*[a-zA-Z0-9_<>\\[\\]]*>)
     ?(?:\\s*\\[\\])?)\\s+([a-zA-Z_]{1}[a-zA-Z0-9_]*)\\
     s*\\(([^)]*)\\)\\s*;',re.MULTILINE)
24
25 #parser functions
26 def parse_aidl_file(filepath):
27   interfaces=[]
28   abs_path = os.path.abspath(os.path.join(common.
       android_src_path,filepath))
29   if not os.path.isfile(abs_path):
30     raise ValueError("expecting a path to a valid
         file!")
31   with open(abs_path) as aidl_file:
32     contents = aidl_file.read()
33     contents = re.sub(comments, '', contents)
34 #     print "<<%s>>" % (abs_path)
35 #     print contents
36 #     raw_input("<<press enter to continue>>")
37     results = re.search(package_name,contents)
38     if results is None:
39       raise ValueError("cannot find package name in
           aidl file!")
40     package = results.group(1)
41     results = re.finditer(interface_spec,contents)
42     count=0
43     if not results is None:
44       count+=1
```

```
45        for result in results:
46          name = result.group(1)
47          interface_dbo = common.AndroidInterface(name=
               "%s.%s" % (package,name),filepath=filepath
               )
48          num_sresults=0
49          if not result.group(2) is None:
50            sub_results = re.finditer(function_def,
                 result.group(2))
51            if not sub_results is None:
52              for sub_result in sub_results:
53                num_sresults+=1
54                interface_dbo.functions.append(common.
                     InterfaceFunction(name=re.sub(
                     whitespace,' ',sub_result.group(0)),
                     code=num_sresults))
55  #               print "   %s" % (sub_result.group(0))
56            num_scolon=result.group(2).count(';')
57            if num_sresults!=num_scolon:
58              print "Warning: %d functions found, but %
                   d semicolons in interface definition."
                    % (num_sresults,num_scolon)
59              print "   in: %s interface %s" % (
                   abs_path,name)
60  #             print result.group(2)
61          else:
62            print "Warning interface %s.%s empty!" % (
                 package, name)
63          print "%s.%s (%d)" % (package, name,
               num_sresults)
64  #         print "<<%s>>" % (abs_path)
65  #         print result.group(2)
66  #         raw_input("<<press enter to continue>>")
67          interfaces.append(interface_dbo)
68      results = re.finditer(parcel_name,contents)
69      if not results is None:
70        count+=1
71        for result in results:
72          name = result.group(1)
73          print "%s.%s (parcelable)" % (package, name)
```

```
74          interfaces.append(common.AndroidInterface(
               name="%s.%s" % (package,name),filepath=
               filepath))
75      if count==0:
76        print "Warning didn't find any interfaces in: "
              + abs_path
77    return interfaces
78
79  common.reset_database()
80  custom.addCustom(common)
81  for aidl_file in aidl_filenames:
82    try:
83      session = common.Session()
84      interfaces = parse_aidl_file(aidl_file.strip())
85      for interface in interfaces:
86        session.add(interface)
87  #       print interface
88      session.commit()
89    except ValueError as ve:
90      print "%s: %s" % (aidl_file.strip(),ve.message)
```

Source Code B.3: "populate_database.py"