Optimizing Re-Evaluation of Malware Distribution Networks

by

Kyle Zeeuwen

A THESIS SUBMITTED IN PARTIAL FULFILLMENT OF
THE REQUIREMENTS FOR THE DEGREE OF

MASTER OF APPLIED SCIENCE

in

The Faculty of Graduate Studies

(Electrical and Computer Engineering)

THE UNIVERSITY OF BRITISH COLUMBIA

(Vancouver)

October, 2011

Abstract

The retrieval and analysis of malicious content is an essential task for security researchers. Security labs use automated HTTP clients known as client honeypots to visit hundreds of thousands of suspicious URLs daily. The dynamic nature of malware distribution networks necessitate periodic re-evaluation of a subset of the confirmed malicious sites, which introduces two problems: 1) the number of URLs requiring re-evaluation exhaust available resources, and 2) repeated evaluation exposes the system to adversarial blacklisting, which affects the accuracy of the content collected. To address these problems, I propose optimizations to the re-evaluation logic that reduce the number of re-evaluations while maintaining a constant sample discovery rate during URLs re-evaluation.

I study these problems in two adversarial scenarios: 1) monitoring malware repositories where no provenance is available, and 2) monitoring Fake Anti-Virus (AV) distribution networks. I perform a study of the adversary by repeatedly content from the distribution networks. This reveals trends in the update patterns and lifetimes of the distribution sites and malicious executables. Using these observations I propose optimizations to reduce the amount of re-evaluations necessary to maintain a high malicious sample discovery rate.

In the first scenario the proposed techniques, when evaluated versus a fixed interval scheduler, are shown to reduce the number of re-evaluations by 80-93% (assuming a re-evaluation interval of 1 hour to 1 day) with a corresponding impact on sample discovery rate of only 2-7% percent. In the second scenario, optimizations proposed are shown to reduce fetch volume by orders of magnitude and, more importantly, reduce the likelihood of blacklisting.

During direct evaluation of malware repositories I observe multiple instances of blacklisting, but on the whole, less than 1% of the repositories studied show evidence of blacklisting. Fake AV distribution networks actively blacklist IPs; I encountered repeated occurrences of IP blacklisting while monitoring Fake AV distribution networks.

Preface

This chapter documents the external contributions to this research.

Statement of Co-Authorship

Virus Bulletin 2011: Section 5.2.2, Section 5.2.3, Chapter 6 and Chapter 7 present materials from analysis of Fake Anti-Virus Malware Distribution Networks that has been submitted for publication [KZRB11]. This analysis and resulting write up was performed in collaboration with Onur Komili, Matei Ripeanu, and Konstantin Beznosov and included in this thesis as well as the Virus Bulletin paper. The data was collected and analyzed using the Tachyon Detection Grid (TDG) (Section 4.1), a system I was solely responsible for building (with contributions noted in the Preface). Onur's analysis of the data identified the Malware Distribution Networks (MDNs), which led to joint development of analysis scripts to produce the statistics presented. The proposed optimizations and simulation methodology were both my work. Onur wrote the initial drafts of Section 5.2.2; however after 4 rounds of collaborative revision we both can safely claim authorship. Matei Ripeanu contributed to a final revision of the sections mentioned above.

O. Komili, K. Zeeuwen, M. Ripeanu, and K. Beznosov. Strategies for Monitoring Fake AV Distribution Networks. In Virus Bulletin 2011. Virus Bulletin, October 5-7, 2011.

WebQuality 2011: A preliminary study of zero provenance malware repositories using my experimental apparatus was published in [ZRB11]. The results presented in this paper are not directly reproduced in this thesis, however much of the approach is the same and the content in the background and approach section of the WebQuality Paper may appear throughout the thesis.

K. Zeeuwen, M. Ripeanu, and K. Beznosov. Improving Malicious URL Re-Evaluation Scheduling Through an Empirical Study of Malware Download Centers. In WebQuality 2011. ACM, April 28, 2011.

Hardware and software support from Sophos

This section documents the contributions to this work made by SophosLabs [Sop11] and specific individuals within the Lab. The first version of the Tachyon Detection Grid (TDG) was hosted entirely on two virtual servers provisioned by a company called Linode [Lin11]. This became costly and the experiment quickly outgrew this infrastructure. The second version was hosted on SophosLabs hardware. Once inside the SophosLabs infrastructure, I was able to leverage several technologies, allowing me to focus on the research aspects of the system. The specific contributions of SophosLabs to this research are listed below:

Hardware In the second version of the TDG, the central server was hosted on SophosLabs hardware. All communication to and from the central server ran over SophosLabs bandwidth.

Apache QPID Message Broker Sean Macdonald wrote the perl AMQP bindings and deployed the Apache QPID messaging broker. This broker provided the communication mechanism between all persistent processes on the central server.

NodeJS Key-Value Store Sean Macdonald wrote the REST based key-value store used by the TDG. This software was used in a separate project and was adopted for use in the TDG with very minimal modifications.

High Interaction Honey Client The initial work to set up Virtual Box and develop scripts to control Firefox was performed by Onur Komili and Jeff Leong. I modified their prototype to interact with the TDG and performed several subsequent improvements. The Sikuli script to emulate human interaction with the browser was developed by Jeff Leong and updated by Onur Komili.

Analysis and Interpretation of Fake AV crawling In early June 2011, Onur Komili began actively participating in the Fake AV experiments. The work was very much a collab-

orative effort and I am grateful for his contributions. This specific subset of the research will be presented at Virus Bulletin in October, 2011 [KZRB11] in a paper co authored by Onur. This is addressed separately in the Statement of Authorship.

AV Detection Filter Lists For several analysis tasks it was necessary to infer a sample category (malicious executable, malicious web content, suspicious, application control) based on an AV detection. Human maintained lists for Sophos and other vendor detections were made available by SophosLabs. These are discussed in Section 4.2.

Table of Contents

List of Tables

List of Figures

Glossary

AV Anti Virus

AIR Adversarial Information Retrieval

CDF Cumulative Distribution Function

DB Database

DNS Domain Name System

FP False Positive

HC Honey Client

HIHC High Interaction Honey Client

HTML Hypertext Markup Language

HTTP Hypertext Transfer Protocol

IP Internet Protocol

JS Java Script

LIHC Low Interaction Honey Client

LWP Perl WWW Library

MDN Malware Distribution Network

MIHC Medium Interaction Honey Client

NAT Network Address Translation

RFC Request for Comment

RRT Repository Re-Evaluation Threshold

SEO Search Engine Optimization

SQL Structured Query Language

SSH Secure Shell

TCP/IP Transmission Control Protocol/Internet Protocol

TDG Tachyon Detection Grid

TDS Traffic Direction System

TLD Top Level Domain

URL Uniform Resource Locator

WWW World Wide Web

Acknowledgments

Thanks to everyone in SophosLabs for their invaluable expertise and constant feedback during my research. Specifically Onur, Dmitry, Mike, Mike, Mike, Dave, David, Jeff, Sean, and Brett. Thanks to SophosLabs for all the hardware, bandwidth, and time off to complete the work.

Thanks to my supervising professors: Konstantin Beznosov and Matei Ripeanu. Without their wisdom and guidance this would not be possible. Thanks to Yazan Boshmaf for his feedback on the thesis.

Thanks to the anonymous reviewers at WebQuality2011.

Thanks to my parents and my awesome syster.

Chapter 1

Introduction

The installation of malicious software, or *malware*, on computers is a profitable activity for criminal organizations [FPPS07, SGAK+11]. The web has become one of most effective mechanisms for the installation of malware. This shift to the web as the delivery mechanism of choice is attributed to three trends: the increasing prevalence of perimeter network security devices, the increasing complexity of modern web browsers, and the abundance of insecure web servers on the Web [PMRM08].

Given this shift to the malware delivered over the web, information security researchers constantly download web content and system executables from the Internet looking for new threats. I refer to the systems used to accomplish this task as Adversarial Information Retrieval (AIR) systems. The typical goal in this information retrieval scenario is to get the same treatment as the average Internet user: that is, to receive a malicious executable, often via a path of redirections, culminating in a browser exploit or social engineering trick to initiate the download of a malicious executable file onto the victim computer [PMRM08]. The data collected by security researchers is used to update Uniform Resource Locator (URL) blocklists[1] and anti-virus detections for malicious executable files and web content.

The task of studying MDNs is adversarial in nature: behind the networks and the binaries is a group of humans that change their behaviour to counter the efforts of security researchers. The adversarial nature of the problem introduces several challenges to effective AIR on the web. *The first challenge is the dynamic nature of MDNs.* These networks are typically composed of multiple layers of servers, each playing a different role in the malware delivery chain. The links between servers, and the content served by each server, including the malicious binary, are constantly updated to evade the efforts of security researchers. *The second challenge is*

[1] Terminology clarification: a blocklist is a list of resources to block. Blacklisting is the act of using a blocklist to change a response.

the adversarial countermeasure of blacklisting, where an MDN identifies the components of a security AIR system and alters its behaviour when studied by the AIR system. These challenges lead to two problems in AIR system design, which this research addresses:

1. **Scalability: There are too many URLs to evaluate.** The volume of new URLs is such that AIR systems are in a constant state of work; there is always a backlog of URLs awaiting initial or subsequent evaluation. New suspicious URLs are constantly discovered, and confirmed malicious URLs must be periodically re-evaluated for content updates, due to the dynamic nature of MDNs.

2. **Accuracy of Content: URL evaluation can be tainted by blacklisting.** Blacklisting occurs because the AIR system repeatedly visit the same servers, and they visit many different servers controlled by the same organization. This repetitive downloading leaves patterns in HTTP server logs that can be identified by malicious adversaries. If a client has been identified, the MDN can alter content, which limits the effectiveness of the AIR system.

I attempt to address these problems by reducing the number of re-evaluations necessary to discover the same amount of new malicious content. My research takes the following approach:

- Systematically study malicious web sites over time to identify the distribution and prevalence of MDN update behaviours.

- Develop and evaluate optimizations to the re-evaluation logic of AIR systems based on update behaviours observed.

- Identify the prevalence of IP blacklisting by malware networks, and propose strategies to cope with blacklisting of AIR resources.

I studied this problem within the context of two common AIR scenarios: (1) investigating malware repositories with no associated provenance[2], and (2) MDNs serving fake anti-virus (Fake AV) software. I developed a research focused AIR system capable of controlling multiple HTTP clients and performing precise URL re-evaluations over long periods of time. This system

[2]Provenance refers to the history of ownership. It is used in sensor network and security research to refer to the source of information. I adopt it to refer to the sites that lead to a malware repository.

produced a corpus of over 500,000 *Hypertext Transfer Protocol (HTTP) Traces*[3] from over 9000 malicious URLs over a period of two months. I analyze this corpus to determine MDN update patterns, which are presented in detail. Based on the observed update behaviours, multiple optimizations to the AIR system re-evaluation component are proposed and then evaluated. Throughout the data collection phase, I monitored for signs of blacklisting, and discard any data that is potentially tainted by blacklisting.

Through simulation I show that the optimizations in the *zero provenance malware repository* scenario reduce the number of URL re-evaluations by 80-93% (depending on the re-evaluation interval), with a corresponding drop in malware discovery rate of only 2-7%. The optimizations in the *Fake AV MDN* scenario reduce the number of re-evaluations by over 90% with small reductions in malware discovery rates that vary depending on the update behaviour of the MDN.

This thesis provides the following contributions:

- I propose and evaluate three optimization techniques that apply to the case of directly re-evaluating malware repositories. These techniques can reduce the required fetch volume by 80-93% (depending on the re-evaluation interval) with a corresponding impact on sample discovery rate of only 2-7% compared to a fixed-interval scheduler with no optimizations applied.

- I propose and evaluate two optimization techniques that apply to the specific case of monitoring MDNs used to distribute Fake Anti Virus (AV) malware. These techniques can reduce fetch volume by over 90% with a sample discovery rate drop of under 10% compared to fixed-interval scheduler that re-evaluates all landing pages of a single MDN independently.

- I provide fresh data that contributes to the study of a challenging adversary in the security community: fake AV distributors. My study confirms that several of the statistical observations provided by Rajab *et al.* in [RBM+10] are still valid, over 18 months after their study. Analysis of the data I collected provides new insights with regards to unique

[3] I adopt the terminology used by Zhang *et al.* in [ZSSL11]. An HTTP Trace is a log of all HTTP traffic generated by visiting a URL, which typically includes meta data about how the trace was generated. Note that I use the terms *fetch log* and HTTP Trace interchangeably.

affiliate behaviours and the use of IP blacklisting countermeasures.

The thesis is organized into the following chapters. Chapter 2 provides necessary background information and also incorporates a survey of related work. Chapter 3 discusses AIR systems, focusing on the two problems identified above, and proposes optimizations to address these problems. Chapter 4 presents the system that collected data and the approach I used to analyze the data and perform simulations. Chapter 5 presents results of data collection and analysis. Discussion of these results is provided in Chapter 6, and Chapter 7 concludes.

Chapter 2

Background

This chapter provides background on the problem space. Section 2.1 provides a brief overview of Internet technologies. Section 2.2 discusses the exploitation of these technologies to spread malware. Section 2.3 introduces the use of AIR systems to monitor malware on the web, Section 2.4 provides an overview of related work, and Section 2.5 summarizes the chapter.

2.1 Mechanics of the World Wide Web

The World Wide Web (WWW) is a collection of technologies built on top of the Internet that allows the delivery of a wide range of services to web users. Web browsing is one of the most common user tasks on the WWW and is the focus of this section. Each WWW resource is identified by a unique Uniform Resource Locator (URL) [BLMM94]. Web users employ web browsers (e.g., Microsoft Internet Explorer, Mozilla Firefox, Google Chrome) to retrieve content from the web. Web browsers use several technologies to achieve this task. The steps (and enabling technologies) taken by a web browser to retrieve content given a URL are listed below. The technologies listed are briefly described in Section 2.1.1; a detailed treatment of these technologies (i.e., TCP/IP, DNS, and HTTP) can be found in [KR07].

1. The URL is separated into domain, path and query components.
2. The Internet Protocol (IP) address of the domain is determined by making a Domain Name System (DNS) query.
3. A Transmission Control Protocol/Internet Protocol (TCP/IP) connection is established with the web server.
4. An HTTP GET request is sent to the web server.

5. The content is extracted from the HTTP response.

6. The content is displayed by the browser, or a plugin is invoked to interpret the content, depending on the content-type header.

2.1.1 Essential Web Protocols

Web browsers use many technologies to communicate with web servers. This section focuses on the essential protocols used during basic browsing. When a browser is instructed to fetch a URL the browser first extracts the domain from the URL. A URL is decomposed into several components, which are shown in Figure 2.1. The *domain* component can be an IP address or one or more dot-separated domain names. An IP address is required to locate a web server via the TCP/IP protocol; if the URL does not include an IP address, then the IP address must be retrieved by making a request to the Domain Name System (DNS) using the domain names provided.

Once an IP address has been determined for the web server, a TCP/IP session is established, which provides a reliable mechanism to transmit packets between the web browser and the web server. The TCP/IP protocol takes care of packet (de)composition and network reliability issues, which keeps HTTP (and other application level IP protocols) relatively simple. HTTP communication takes place in *request/response* pairs. An example *request/response* pair is shown in Figure 2.2. HTTP headers are used in the request and response to communicate information between the client and server. Several of these headers are relevant to this work. The HTTP *response code* is used to succinctly communicate the success or failure of the request. I frequently refer to the *response code* in subsequent chapters; a summary of the different *response code* values and their meanings is provided in Table 2.1. The full list of HTTP response codes can be found in the HTTP RFC [FGM+99]. The *user-agent* request header identifies the type of web client making a request. In the case of a redirection or a user following an outbound link from a site, the HTTP *initial-referer*[sic] header is used to communicate what site a client is coming from when browsing to a new site.

$$scheme : //domain : port/path?query\_string\#fragment\_id$$

Figure 2.1: The components of a Uniform Resource Locator (URL)

```
GET / HTTP/1.1
Host: google.com
User-Agent: Mozilla/5.0 ...

HTTP/1.1 301 Moved Permanently
Location: http://www.google.com/
Content-Type: text/html; charset=UTF-8

GET / HTTP/1.1
Host: www.google.com
User-Agent: Mozilla/5.0 ...

HTTP/1.1 200 OK
Date: Thu, 30 Jun 2011 05:31:35 GMT
Content-Type: text/html; charset=UTF-8
```

Figure 2.2: The example above shows two abridged request/response header pairs generated as a result of a web request to *google.com*. The initial request results in a redirect to *www.google.com* via a HTTP 302 response. The response content and non-essential headers are stripped for brevity.

2XX Successful: Codes 200-206 indicate the request has been received, is well formed, and is accepted

3XX Redirection: Codes 300-307 indicate that the resource is available but further action - typically a subsequent request to a new location - is required by the client

4XX Client Error: Codes 400-417 indicate that the client has likely committed an error, most commonly by requesting an non-existent or forbidden resource, or has left out a required component in the request

5XX Server Error: Codes 500-505 indicate that the server has made an error

Table 2.1: The HTTP Response code groups and their respective meanings.

2.1.2 Web Browsers

Web browsers provide the user with a way to interact with the WWW. Early browsers were relatively simple applications that fulfilled the client role of the HTTP exchange and rendered basic Hypertext Markup Language (HTML) content to the user. The browsers of 2011, such as Microsoft Internet Explorer, Mozilla Firefox, Google Chrome, and Apple Safari, render a wide variety of content and perform complex client side operations encoded in ECMAScript [Ass99] based languages (e.g., JavaScript). To handle increasingly complex and diverse content types, web browsers use code *plug-ins* to handle specific content types. These extensions are often written and maintained by third-party organizations.

2.2 Malware on the World Wide Web

The installation of malicious software on computers has become a profitable activity for criminal organizations [FPPS07, SGAK+11]. The means to perform this installation have evolved over time. In the earliest days of malware a virus would embed itself in files on the local system and wait to be transferred to new hosts by natural propagation of the infected files (e.g., removable media, network file transfer). These viruses had no means of self-propagation. With the increasing connectedness of computing systems came the rise of network worms, which exploited vulnerabilities in network services to spread from host to host [CER01a, CER01b, CER03a, CER03b]. The exploitation of vulnerable network services as a means to spread malware has become less effective due to the increased deployment of Network Address Translation (NAT) and firewalls, which prevent untrusted incoming network traffic [PMM+07].

At this point, the web became, and is still currently, the delivery mechanism of choice for malware distributors. The increasing prevalence of perimeter network security devices coincided with the increasing complexity of modern browsers mentioned in Section 2.1.2. This increasing complexity and reliance on externally developed code plugins has greatly increased the attack surface of the web browser. The SANS Top Cyber Security Risks report [SAN09] consistently lists "web browsers and client side applications that can be invoked by web browsers" as some of the most exploited client side applications.

The tactics of any single instance of a web-based malware infection vary in several ways,

but several common trends can be identified. All of them involve one or collaborating malicious agents, which are serving in a Malware Distribution Network (MDN). In all cases the victim visits a web server hosting malicious code and in most cases the end result is the execution of a malicious executable binary on the victim computer. Section 2.2.1 discusses MDNs and how users are lured into visiting them, and Section 2.2.2 discusses the mechanisms used to infect a victim computer upon arrival at the *malware repository*. This attack scenario is depicted in Figure 2.3.

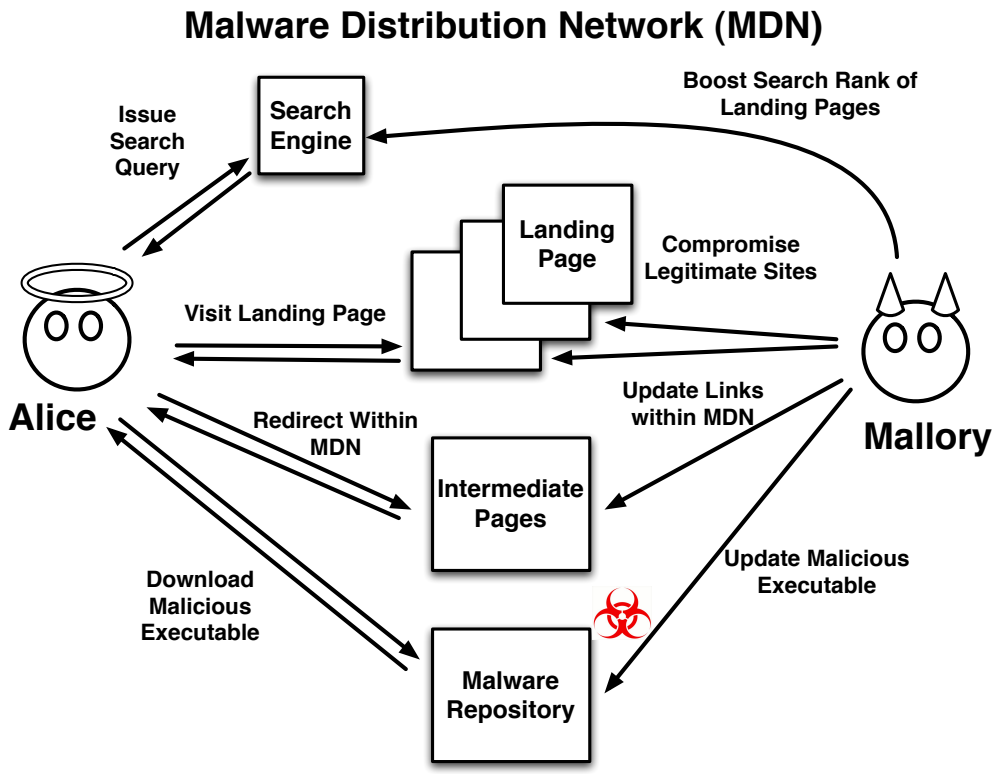
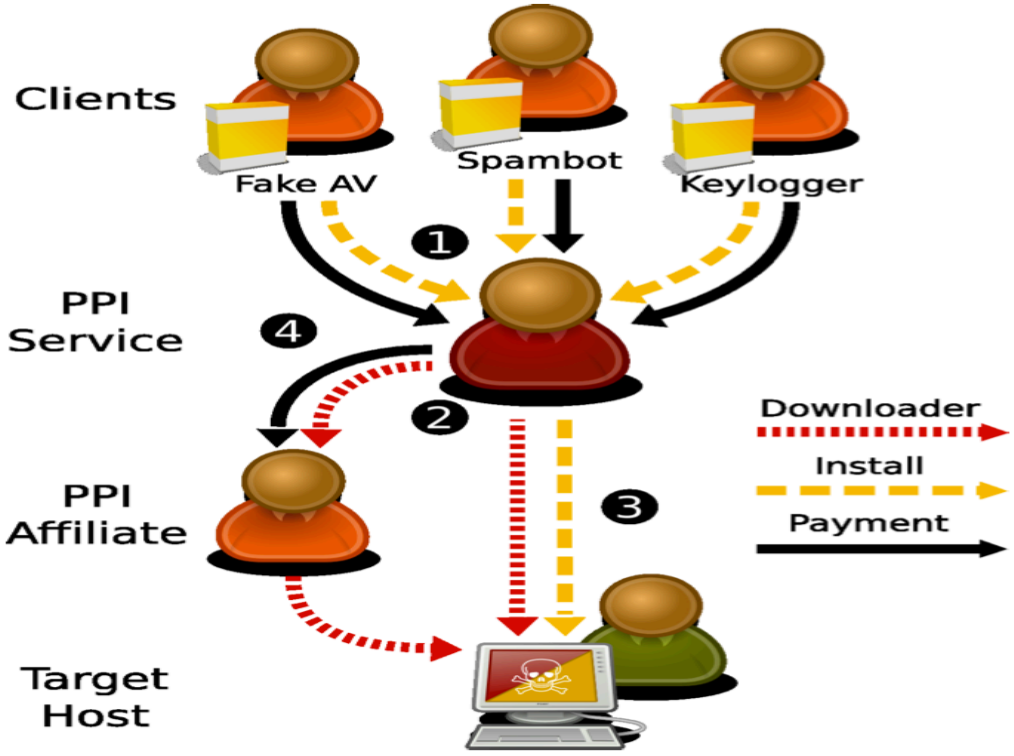


Figure 2.3: Attack scenario showing different roles in a Malware Distribution Network (MDN). Alice, an average Internet user, issues a search query that returns a result set containing a link to a compromised landing page. Alice visits the compromised site, which redirects her into the core of the MDN. At this point, depending on the specific MDN, her browser will be redirected through zero of more intermediate sites, eventually arriving at a malware repository. Once at the malware repository an exploit or a social engineering scam will be attempted, both potentially resulting in the download and installation of a malicious executable binary. Mallory, the *malware distributor*, is actively maintaining the MDN. This is described in detail in Section 2.2.1.

2.2.1 Malicious Distribution Network

Malware distributors on the web, like so many in e-commerce, live and die by click traffic [Sam09]. Irrespective of the sophistication of the malicious binary or the exploit used to trigger the binary download, the MDN will experience no success unless there is a stream of victims entering the network. It is worth briefly noting that there is a trend toward specialization of certain parts of the *malware delivery chain* [CGKP11, Rad09]. The individuals compromising web servers in order to redirect to a *malware repository* are not necessarily the same individuals maintaining the binary at the repository. This roles identified by Cabalerro *et al.* [CGKP11] are shown in Figure 2.4. This noted, for the duration of the paper I refer to the amorphous conglomerate of individuals responsible for an infection as a single entity: the *malware distributor*.



. **J. Caballero, C. Grier, C. Kreibich, and V. Paxson. Measuring pay-per-install: The commoditization of malware distribution. In Proceedings of the 20th USENIX Security Symposium, San Francisco, CA, USA, August 8 - 12 2011. USENIX Association.**

Figure 2.4: The typical transactions in the Pay Per Install (PPI) market. PPI clients provide software they want to have installed, and pay a PPI service to distribute their software (1). The PPI service conducts downloader infections itself or employs affiliates that install the PPI's downloader on victim machines (2). The PPI service pushes out the client's executables (3). Affiliates receive commission for any successful installations they facilitated (4). Image and caption from [CGKP11].

The *click traffic* (i.e., a users web browser being directed into the network) is achieved through the control of landing pages. The remainder of this section discusses landing pages, and the structure and dynamic nature of MDNs.

Landing Pages

Toward the goal of click traffic the malware distributor has two options: create or compromise. Both strategies are used on the WWW and worth briefly describing.

Software is available (e.g., 'jonn22') to aid malware distributors in quickly generating content that ranks high in web searches [Sam09]. The distributor can link their pages together in order to boost the search rank and resultant click volume. Compared to the *compromise* option, creating is more expensive in terms of time and money, and search engines are becoming more tuned to detect and punish *auto-generated* pages [Cut11]. For these reasons, it is more common for a malware distributor to inject code into a legitimate site and leverage the existing reputation and popularity of the site.

There are multiple means in which a legitimate site can be made to serve as a *landing page* in a malicious network. There are many commercial and open source HTTP servers available, most popular being Apache and Microsoft IIS [Net11]. On top of these software packages are content management platforms such as Drupal [Dru11] and WordPress [Wor11]. Each of these widely deployed components, the content management platforms in particular, contain *bugs*, some of which become *vulnerabilities* once a means is discovered to *exploit* the *bug*. Exploit kits (e.g., phoenix exploit kit [Vil11], blackhole exploit kit [Puz11]) are available that contain exploits targeting specific versions of vulnerable software. These kits often include the search terms that can be used to find vulnerable servers [JYX+11]. Once a server is found the kit code makes execution of the exploit trivial, allowing attackers to add and alter content on the legitimate site. In much the same manner as the *create* scenario described above, attackers commonly deploy Search Engine Optimization (SEO) kits in order to automatically generate popular content and cross-link with other compromised sites, further boosting traffic to the compromised site [HK10].

It is not necessary for the attacker to fully compromise the web hosting software in order to inject content. Many sites rely on user submitted content and advertising networks for

content. This provides two new vectors for an attacker to inject code into the rendered content presented to a web user upon visiting the site. Sites that rely upon user content often store this data in a Database (DB) and generate the web markup dynamically by querying the DB. The attacker can inject the redirection code into the content DB by exploiting one of many known SQL injection vulnerabilities [MIT11], and it will be rendered to users by the content management platform when they visit the page. This type of injected content is harder for web administrators to detect because it cannot be caught when inspecting the static content of a web site.

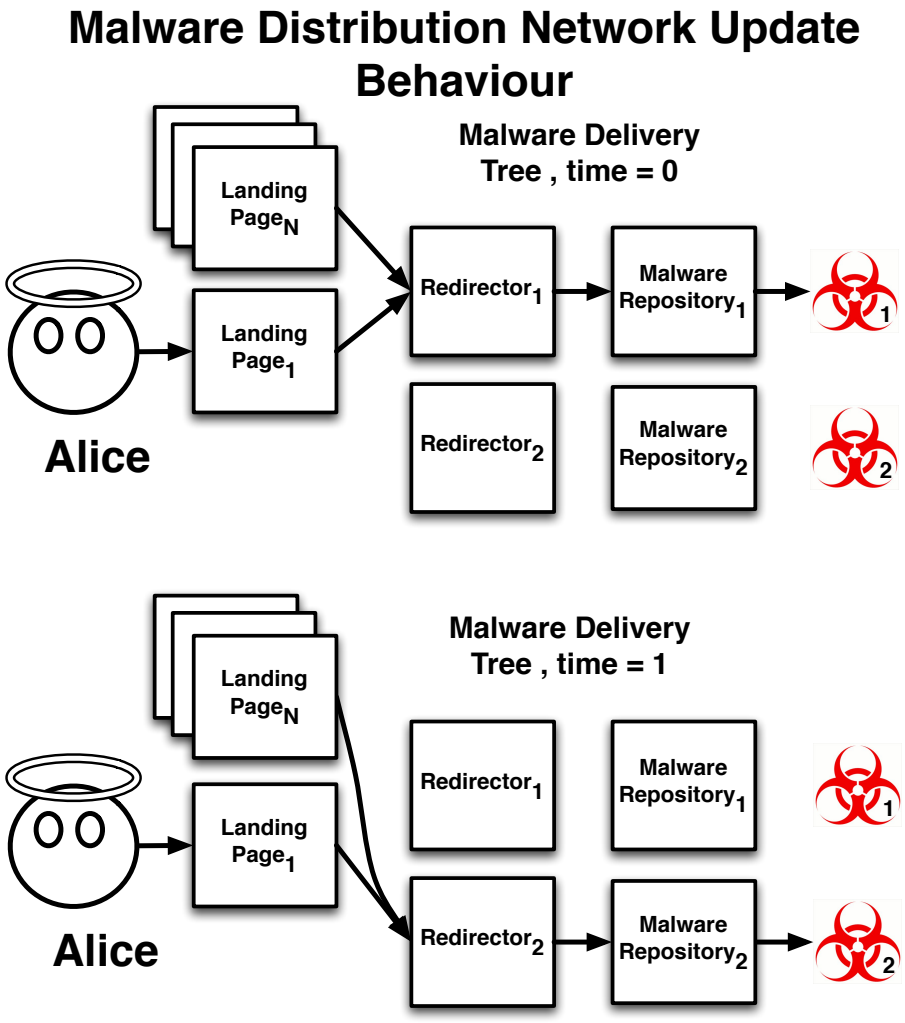


Figure 2.5: When Alice, an average Internet user, visits a landing page at time 0, she is redirected through a specific set of servers to a malware repository hosting a malicious executable. If Alice visits the same landing page at time 1 she is directed along a different set of servers to a different repository hosting a different malicious executable.

The *landing page* is rarely the same page used to deliver the exploit or perform the social engineering scam. The injected code on the *landing page* is most commonly a small piece of code that will either redirect the browser (henceforth referred to shorthand as *redirection*) to another site or cause the browser to download content through the use of embedded elements such as *iframe* or *img* tags (henceforth referred to as *embedding*). The *redirection/embedding* will lead directly or indirectly (in some cases there are multiple intermediate servers that redirect the victim) to a *malware repository* responsible for carrying out the actual attack. This attack scenario is depicted in Figure 2.3. The differences between *redirection* and *embedding* are not relevant to this research and are used interchangeably for the remainder of the paper.

Structure

MDNs are composed of several components and are sometimes very dynamic in nature: the path of redirection from the landing page to the malicious executable (i.e., the *malware delivery tree* or the *malware redirection chain*), as well as the malware executables themselves, are frequently updated. Figure 2.5 shows how the malware delivery chain changes between two visits to the same MDN.

Two factors contributing to the dynamic nature are:

1. URL Blocklists and AV Detection: An MDN must constantly change domains to avoid URL blocklists and takedown requests. Executables are constantly modified to evade AV detections.

2. Pricing Differentials: A single MDN can serve as an affiliate for multiple PPI providers (see Figure 2.4 for list of PPI roles). Each provider has a different price payment scheme, and certain traffic (e.g., a Canadian IP address) will be more valuable to one PPI provider.

Several features of the MDN change over time:

Landing Pages

Each compromised landing page is kept active as long as possible. The churn in landing pages over time is primarily based on newly compromised sites entering the network and site disin-

fections removing landing pages from the network.[4].

Intermediate Sites

Not all MDNs have intermediate hops between the landing page and the distribution site. Research suggests the intermediate sites are likely a Traffic Direction System (TDS), that routes traffic to maximize profit based on the current click-traffic market [CGKP11]. If this is the case, the lifetime is hard to predict for the intermediate elements.

Malware Repositories

The full URL and domains used for the repositories are rotated to avoid URL blocklists and the samples are frequently updated to avoid AV detections. The update frequency of the malicious executable (I interchangeably use the terms binary, executable, and sample to refer to the malicious executable) served by a malware repository varies depending on the MDN. I classify a repository into three categories of sample update behaviours:

Single Sample Repository A repository that does not update the malicious executable for the lifetime of the repository.

Multiple Sample Repository A repository that performs updates to the malicious executable over time, but is not generating the samples for each request.

Polymorphic Repository A repository that produces a unique malicious executable for every download request. [She08].

Several combinations of MDN components have been identified in [SASC10]. This is shown in Figure 2.6. The MDNs that I study all show a fan-in arrangement. In this arrangement, the *fan-in factor* of the MDN at a given time is the ratio of the number of active landing pages to the number of active repositories.

2.2.2 Infection Vectors

The previous section detailed the techniques used to capture the users traffic and redirect them to a malware repository. Once at this server, the techniques used to deliver the malware

[4]In many cases a disinfection does not fix the vulnerability, and the site becomes compromised again.

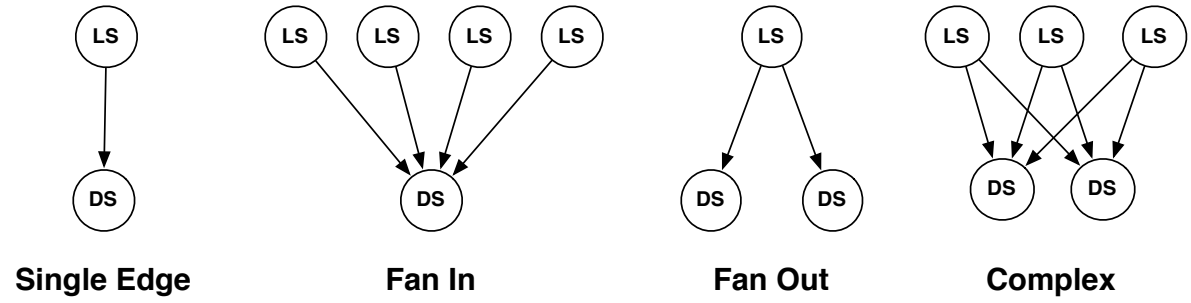


Figure 2.6: Simplified MDN configurations showing relationship between landing sites (LS) and malware repositories (MR). These patterns disregard the intermediate sites if any are encountered. Image from [SASC10].

can be broadly divided into two categories [PMRM08]: social engineering and vulnerability exploitation.

First a brief terminology clarification: in some work a social engineering based attack that tricks the victim into willfully downloading a virus has been referred to as a *drive by download*. I reject this terminology. A *drive by download* is an attack that requires no user interaction; it is a download that is triggered via the successful exploitation of a vulnerability in the browser or a plugin that causes the download and execution of a malicious binary. The *vulnerability* chosen is most frequently a memory corruption vulnerability that allows *arbitrary code execution*. The injected code, referred to as *shellcode*, causes the browser to download and execute a malicious binary, thus infecting the victim PC.

In the social engineering scenario the user willingly downloads the malicious executable, thinking that it is a legitimate software program, such as anti-virus software or a video codec. At time of writing Fake AV scareware is by far the most common and effective social engineering trick used by malware authors [RBM+10]. In the Fake AV scenario, a user is redirected to a web server that displays content resembling the Windows *My Computer* page[5], and informs the user that their computer is infected with many viruses. The user is prompted to download a tool to remove all the viruses.

2.3 Adversarial Information Retrieval Systems

[5]Variations of the web content have emerged mimicking the *look and feel* of Windows 7 and Mac OSX

Given the prevalence of malicious web content on the Internet, Anti Virus (AV) firms must continually identify MDNs and harvest their content. In this research I refer to the systems that are responsible for this task as Adversarial Information Retrieval systems. I divide the discussion of these systems into *why* evaluate (and re-evaluate) URLs (Section 2.3.1), *which* URLs to evaluate (Section 2.3.2), and *how* to evaluate URLs (Section 2.3.3). Answering the question of *when* to evaluate URLs, more precisely when to *re*-evaluate, is the fundamental question addressed in this thesis; thus this is addressed separately in Chapter 3.

2.3.1 Adversarial Information Retrieval Objectives

The evaluation of URLs by security vendors is necessary to support several objectives, which are detailed below:

Collect new malicious binaries to update detections strategies

Malicious binaries are periodically updated in response to AV detections. In some cases new URLs are used to host the updated binaries, in other cases the same URL is used to host a new binary. The latter case necessitates the periodic re-evaluation of confirmed malicious URLs in order to harvest new malicious binaries.

Collect new malicious web content to update detection strategies

Many AV products include detection for malicious web content as well as malicious executable content. This provides an additional layer of protection to users; often an attack will be stopped by the identification of malicious web content before a user's browser is compromised and made to download a malicious executable. This content, like the malicious binaries, is updated to counter AV detection strategies [How10], so a persistent effort to collect and analyze new malicious web content is necessary.

Maintain a blocklist of malicious URLs

URL blocklists provide an additional layer of protection. Even if an update to malicious content by malware distributors breaks AV detection, if the malicious content is hosted on a blocklisted domain or IP then the user is still protected. Populating and maintaining blocklists of network elements (domains, name servers, IPs, rDNS patterns, ASs) requires collection and inspection

of content from these respective network components.

Avoid false positives

The classification of benign content as malicious is referred to as a False Positive (FP). This is a constant risk in any system that classifies content. The use of blocklists introduces a new FP concern: the listing of a legitimate but compromised site for longer than necessary. The initial decision to list a legitimate site that has been compromised is itself contentious; putting this contention aside, once a legitimate site is blocklisted, the site must be monitored for signs of clean up so that the site can be subsequently removed from the blocklist.[6]

2.3.2 What to Harvest

Assuming unlimited resources, from a protection standpoint the best strategy is to repeatedly crawl everything on the Internet. For all but the largest technology firms, this is not feasible. Given this reality, what URLs should an AV firm harvest? There are several common sources of suspicious URLs processed in security labs:

Following trending search terms

The use of Search Engine Optimization (SEO) poisoning to generate traffic to malicious networks is a common tactic [PMRM08]. It is possible to identify trending search terms and then execute searches for these terms. The results currently[7] contain landing pages that lead to MDNs.

Searching for vulnerable strings

Vulnerable web hosting platforms can be identified by footers containing the version string (e.g., powered by Wordpress v 2.3.3). Searching for these yields potentially compromised sites. These sites can be used as anchors in subsequent searches (using search operators such as *inurl* [Goo11]), yielding potential landing pages.

[6] A separate policy issue is how to handle legitimate sites that are repeatedly infected and cleaned up without sufficient patching taking place. Is an AV vendor being negligent by removing the site from a list too early? Are they being unnecessary harsh towards the owners of the site by permanently listing them?

[7] This is another example of an AIR scenario: search providers (e.g., Google) change heuristics to filter SEO poisoned content from search results, the techniques to boost search rank change to counter the heuristics and the results once again become tainted. At time of writing, searches for trending terms still yield many compromised landing pages.

Searching for known kit patterns

Many exploit kits will generate URLs that have known patterns (e.g., bad.com/bad.php?. . . &page=[0-9]). Search modifiers can be used to identify URLs matching these patterns, yielding potential landing pages.

Static and dynamic analysis of executable files

URLs can be retrieved from the static strings contained in malicious executable binaries, as well as from monitoring the runtime behaviour of a sample.

Product Feedback

An excellent real-time source of malicious URLs come from modern security products that report detection incidents back to the vendor. Many feedback strategies are possible, this research uses feedback from web content filters that report URLs classified as malicious based on content inspection.

Strategic Relationships

There are symbiotic relationships possible where a non-security firm with unique visibility (e.g., search engines, social networks, telecommunications firms) use augmented security products to identify malicious networks affecting the partner. In exchange the partner delivers threat intelligence that was gained using the security product.

Cooperative Industry Exchanges

It is common practise in industry to share confirmed malicious executables and URLs between AV labs and security researchers. These feeds are of various composition and quality and must typically be verified upon receipt.

2.3.3 How to Harvest

In order to collect samples of malicious web content and binaries, security researchers have developed custom HTTP clients that automatically collect content for analysis. These systems are commonly referred to as *client-side honeypots*, or *honey clients*. The Honey Client (HC) is responsible for content retrieval and monitoring system state after download and malware

installation. This section provides an overview of honey client technologies, focusing on the content retrieval phase.

HCs vary widely in terms of their implementation and feature set. Similar to honeypots, honeyclients are commonly classified into high and low interaction varieties [PH08]. Fundamentally, a high interaction honeypot uses the actual vulnerable software (in this case the browser and plugin), whereas a low interaction honeypot will emulate the vulnerable software. In the description below I have added a third category, the Medium Interaction Honey Client (MIHC). Each are described below.

Low Interaction Honey Clients (LIHCs) (e.g., GNU Wget [GNU11], Heretrix [Her11]) implement the HTTP protocol and are capable of downloading content and following basic HTTP redirection. They do not interpret the downloaded content in the same manner as a web browser. This means that Java Script (JS) or HTML redirections will not be followed, and embedded content will not be retrieved. The upside to a LIHC is that they are typically light weight in terms of resource use, and the state of the downloader does not need to be reset between fetch attempts (as in the case of a HIHC). Therefore, a LIHC can download at a higher rate than a MIHC or a HIHC.

Medium Interaction Honey Clients (MIHCs), such as jsunpack [jsu11] or Wepawet [CKV10], add additional functionality to interpret the content and emulate certain browser features towards the goal of identifying malicious behaviours. For example, jsunpack mimics ActiveX plugins, which allows the software to identify exploits targeting specific plugins. The analysis and interpretation features of a MIHC add an additional resource cost compared to a MIHC, but they do not need to reset state, so there is still a time savings compared to a HIHC.

High Interaction Honey Clients (HIHCs), such as Microsoft's HoneyMonkey [WBJ+06], use an automated web browser in a sand-boxed environment to perform the URL evaluation. The operating system is monitored for unexpected state changes, such as file downloads or process creation that indicate the system has been infected with malware. The main advantage of a HIHC is the full fidelity of the environment; a real browser is used to perform the sequence of HTTP requests, and all content interpretation is performed by the browser. Some honey clients monitor the post infection behaviour of the malware, providing additional insight and confidence in any subsequent malicious classification. The design and maintenance of a HIHC is

more complex simply due to the amount of components involved. Another downside is the time required to restore state between download attempts. The HIHC may become compromised during a download attempt, therefore it is necessary to reset the HIHC to a known clean state between downloads. Without this reset, the results of one download could potentially taint subsequent downloads.

A fundamental decision in AIR system design is which type of honey client to use to download a URL. A HIHC can handle a wider range of URLs than a LIHC; however, HIHCs are typically orders of magnitude slower and more expensive than a LIHC. If the resources are available, it makes sense to harvest everything with HIHCs. When this is not feasible a mix of high and low interaction honey clients is most appropriate [CCVK11].

An HIHC is necessary when a MDN uses a browser or plugin exploit, or when the network uses crawler evasion techniques (Section 2.3.4) that prevent study by a LIHC. URL streams received from external sources typically do not contain enough provenance to determine the expected content *a priori*. By performing a preliminary fetch with a LIHC one can identify URLs that require analysis by a HIHC. For URLs that are discovered through in house sources (e.g., searching for SEO poisoned links) origin is known and there is an expectation that a HIHC is needed. In these cases the initial LIHC fetch should be skipped.

This research uses both high and low interaction honey clients to download web content. The choice to use both is based on the availability of resources. It should be noted that the HIHC I used did not perform post HTTP operations, such as monitoring for system changes.

2.3.4 Adversarial Concerns

The study of malware on the web is complicated by several countermeasures employed by adversaries. These include anti-crawler content and blacklisting, which are each described below:

Anti Crawler Content

I consider any use of technology towards the objective of complicating the task of a honey client an anti-crawling technique. There are many content-based techniques that must be considered when designing AIR systems. The most common is the use of obfuscated Javascript. This

technique is widely deployed [How10] to complicate the task of content interpretation. Simple Javascript functions (e.g., 'window.location') are layered with multiple layers of encoding to prevent simple crawlers from interpreting their intent (typically redirect or exploit). This area is highly adversarial (rapid updates on both sides of the problem). As a result, the techniques used to prevent crawlers are evolving quickly to include multiple cooperating scripts, use of DOM content in decryption loops, checking for the presence or absence of cookies, and other nasty tricks.

Blacklisting

There is little published information on the use of blacklisting by malicious networks [ZRB11, Woo11, Sob11, CGKP11]; however, it is a commonly accepted belief in the security community that certain malware networks engage in this behaviour. The act of blacklisting in the context of malicious networks can be broken into two steps: identification of honey clients, and altering responses to honey clients. These are discussed below.

Identifying Honey Clients

Honey clients are identifiable because they repeatedly visit web servers, and they visit many web servers controlled by the same organization. This repetition of the download operation creates a fingerprint of the honey client that can be identified by malicious adversaries. Identifiable characteristics include: the IP address, TCP/IP characteristics, HTTP characteristics, frequecny of requests, and volume of requests.

In addition to the "do it yourself" approach to identifying honey clients, there are also a number of sources of pre-compiled lists of IP addresses used by security researchers [Web11, AV 11, Sob11], search engine crawlers, [Fan11], and anonymizing proxy networks [Blo11].

Altering Responses To Honey Clients

Once a honey client has been identified, the malware distributor has a number of options available:

HTTP 500 In this scenario a malware network simply refuses to deliver content to the honey client.

Benign Content In this scenario the malware network will deliver content or redirect to a benign website, such as cnn.com [HK10].

Old Content In this scenario a malware network will continue to serve malware to the honey client, however the rendered content will be an older version of malware.

Tarpit The use of tarpitting was originally deployed to mitigate the effects of network worms [Tar11]. the MDN deliberately holds the TCP/IP connection open as long as possible, delivering content at a very low rate, or not delivering content at all.

2.4 Related Work

The research in this paper evaluates optimizations to the re-evaluation logic of AIR system towards the goal of reducing the overall fetch volume of the system. To the best of my knowledge this is the first research to address this specific issue. However; there are several areas of related research. This chapter surveys this work.

2.4.1 Studies of Malware on the Web

The study of malware on the web has been an active area of research for several years. Stokes *et al.* [SASC10] provide an effective classification of the existing approaches to malware discovery into *top down* and *bottom up* approaches. In the top down approach [MBGL06, PMM+07, PMRM08, WBJ+06] suspicious URLs are evaluated, the malware delivery tree is traversed, and the malware is collected and in some cases executed. This research takes a top down approach, but is different from previous works in that I focus on the re-evaluation of known malicious networks to collect new data instead of the initial discovery and classification of the malicious components. The work by Provos *et al.* [PMM+07] includes statistics on the distribution of binaries across URLs, but does not provide a detailed treatment on the update behaviours. My work is similar to theirs, but studies a smaller amount of MDNs in greater detail, focusing specifically on the MDN update behaviour and strategies to use resources more efficiently.

In the bottom up approach [SASC10, ZSSL11], data from many HTTP Traces is aggregated in an offline process to discover a larger percentage of the components of MDNs. This is similar

to the approach I use to group landing pages and repositories into MDNs. Their approach incorporates more network information to identify MDNs and also provides a degree of automation to the process through the use of *AutoRE* [XYA+08]. Our work differs from theirs in that we use the identification of MDNs to adjust and optimize re-evaluation logic, whereas they used the identification of MDNs to retroactively identify malicious fetch logs to improve URL blocklists.

2.4.2 Study of Blacklisting Techniques

The web spam technique of *cloaking*, that is to return altered content to search engine crawlers for the purpose of search engine optimization (SEO), became a popular research topic around 2005. Wu and Davison [WD05, WD06] performed several studies of sites that performed *semantic cloaking*. They impersonate regular Internet users as a baseline as well as automated crawlers by varying the user agent. Niu *et al.* [NWC+07] performed a similar study focusing on the problem of forum-based spamming as a black SEO technique. They identified a new type of cloaking known as *click through cloaking* that differentiates user from crawler based on the value of the HTTP referrer. They trigger the cloaking by varying the HTTP referrer and use the presence of cloaking as a spam sign to aid in URL classification. I am monitoring for blacklisting caused by repeated evaluations of malicious sites, as opposed to blacklisting based on characteristics of the client. Further, they do not propose strategies to reduce the likelihood of blacklisting.

2.4.3 Fake AV Malware Distribution Networks

Rajab *et al.* [RBM+10] specifically addressed Fake AV distribution networks. Their results were consistent with the observations made in my research: Fake AV MDNs are updating the malware repositories and malicious payloads on a frequent basis, and there is still a strong fan in factor from the landing pages to the malware repository. While their analysis typically presents results at the macro scale, something only possible with the visibility of an organization like Google, I provide a very focused study of several MDNs and specific strategies for identifying and re-evaluating these MDNs. Recent work by Stone-Gross *et al.* [SGAK+11] also focused on Fake AV networks, however their work focused primarily on the payment systems in place to monetize the infections, whereas I focus on the delivery networks.

2.5 Summary

In this chapter I presented relevant background and related work. Section 2.1 presents background on the World Wide Web (WWW). Section 2.2 describes the rise of malware on the Web. In Section 2.3 I discuss the role of Adversarial Information Retrieval (AIR) systems in web security research. In the next chapter I discuss how high rates of suspicious incoming URLs and the threat of blacklisting challenge the success of deployed AIR systems. I motivate the need for further research into this area and propose several optimizations to re-evaluation logic that help to address these challenges.

Chapter 3

Preliminaries

The previous chapter provided background on Internet technologies, the rise of malware on the web, and the use of AIR systems to monitor MDNs. This chapter discusses several problems faced by AIR systems and proposes solutions.

AIR systems must cope with a large volume of URLs. Industry sources estimate between 600,000 - 1,000,000 new unique potentially malicious URLs are reported daily [Dun11]. Additionally, to satisfy the goals outlined in Section 2.3.1, a proportion of these URLs must be periodically re-evaluated. However, the questions of which URLs to re-evaluate, and for how long to re-evaluate the URLs, are not adequately addressed in the current body of research.

Not all URLs will provide an "additional gain" from subsequent evaluation. If an MDN does not update the redirection chain or if a malware repository does not update the malicious binary, then the subsequent visits to these malicious resources serves no purpose. Unfortunately, it is not easy to determine which URLs will provide additional gain on re-evaluation without actually conducting the re-evaluation. As a result, all URLs must be re-evaluated, which greatly increases the work load of the AIR system.

This naive re-evaluation strategy is a significant contributor to AIR system workload. Any AIR system that implements a naive re-evaluation algorithm will be in a perpetual state of work. That is, the percentage of time that the system spends in an idle state is negligible; there is always a list of URLs that need evaluation. Given this reality, techniques are necessary to cope with the daily volume of URLs. However, there is insufficient research publicly available to make improvements on the naive approach without performing a study of the problem space.

In addition to system load, re-evaluation of MDNs increases the probability of blacklisting, which is discussed in Section 2.3.4. When AIR resources are identified, each of the objectives

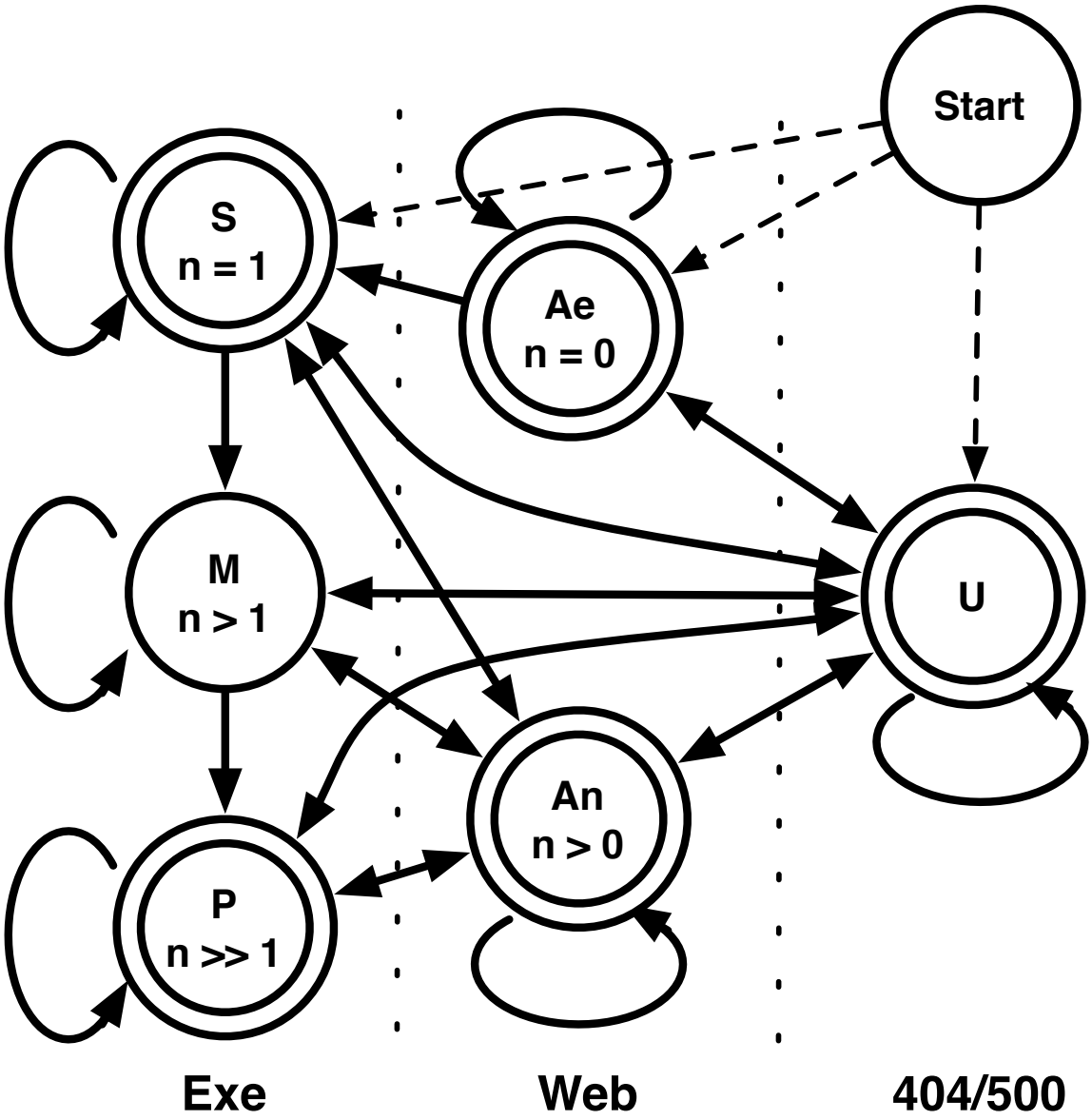
listed in Section 2.3.1 are impacted. It is therefore important to: 1) limit the opportunity for blacklisting by reducing the number of times the AIR resources are exposed to MDNs, and 2) detect the blacklisting when it occurs.

In order to reduce the load on AIR systems caused by re-evaluation of URLs, this research studies the problem space and proposes techniques to identify which URLs do not require subsequent re-evaluation.

I pursue these research objectives in two distinct adversarial scenarios that are commonly encountered by security vendors:

1. Evaluating zero-provenance malware repositories
2. Evaluating Fake AV MDNs

I take the following approach: first I build a corpus of data by collecting data from active malicious networks. Next I analyze the data looking for optimization points. Finally, I simulate re-evaluation algorithms on the data collected to evaluate the proposed optimizations. The results of data collection and simulation are presented in Chapter 5. The proposed optimization are presented in the sections that follow.



	S	-	single sample server
	M	-	multiple sample server
	P	-	polymorphic server
Legend	Ae	-	active no exe ever
	An	-	active no exe right now
	U	-	unresponsive
	n	-	number unique executable samples from URL

Figure 3.1: This state diagram is used to track the current state of malware repositories. The proposed optimizations control when to discontinue evaluation in each of the double edged terminal states shown above. The state transitions take place when n changes (i.e., new executable samples are discovered) or when active content type changes (i.e., between *Exe*, *Web*, *404/500*).

3.1 Evaluating Zero-Provenance Malware Repositories

Malware repositories are typically discovered by following a malware redirection chain and arriving at a repository. When a malware repository has no associated information about the upstream links in the MDN, I refer to it as having zero provenance. This situation arises when processing URLs found in cooperative industry exchanges or other external sources of suspicious URLs. It is not possible to study these sites by entering the MDN from the landing page, because this information is not available. Therefore, a direct evaluation of the repository is necessary in order to retrieve content from these URLs. My primary interest when studying malware repositories in this manner is to determine if the repository is delivering malicious binaries and if the repository will serve multiple executables over time. I want to discontinue re-evaluations of the repository once it is no longer useful.

To reduce the total volume of evaluations performed by an AIR system, I propose several optimizations to reduce the number of re-evaluations performed on malware repositories while maintaining a constant rate of malicious executable discovery.

The optimizations are based on the state model shown in Figure 3.1. In this model I introduce 5 terminal states where re-evaluation is discontinued. All of the optimizations share the goal of reducing the amount of resources (i.e., re-evaluations) spent on malware repositories in one of these 5 states. The three optimizations are introduced below, followed by a more detailed treatment of each state in Section 3.1, focusing on why to "discontinue" re-evaluation of a zero provenance malware repository in each of these states.

Cutoff optimizations (ct): After each re-evaluation, the scheduling component of the AIR system checks the current state of the repository. If the repository is in one of the five terminal states and has been in that state longer than a threshold value (each state has a distinct threshold), then discontinue re-evaluation.

Backoff optimizations (bk): After each re-evaluation, the scheduling component of the AIR system checks the current state and the transition (or lack of transition) that just occurred as a result of the most recent evaluation. If the repository has not transitioned and is in one of the following states: *single sample* (S), *active no exe right now* (An), and *active*

no exe ever (Ae), then increase the re-evaluation interval by a fixed increment.[8]

In each of these states, re-evaluations are not forwarding the goal of sample collection, but re-evaluation must continue for a period to prevent missed samples. Increasing the re-evaluation interval reduces the number of re-evaluations spent waiting for the cutoff threshold to be reached.

Initial Detection optimizations (cp): Assuming that the same "distribution strategy" is used by a given family of malware over time (I provide results towards this assertion in Section 5.1.3), then it is possible in some cases to predict the update behaviour of a new malware repository based on the "family" of malware that is initially downloaded from the repository. If a family *known* to use single server repositories is downloaded, immediately discontinue re-evaluating a repository. In the same manner, if a family of malware has a history of being served from multiple sample repositories that update at a periodic interval, this interval is used to seed the initial re-evaluation interval.

The implementation of this optimization requires two thresholds for each optimization: the minimum probability, and the minimum data points (also referred to as the minimum confidence) that contribute to the probability score: $n(d)$. For example, assume for the single sample conditional probability optimization I use a minimum probability of 0.7 and a minimum confidence of 5. I would only apply the optimization to a repository with an initial detection of d if: (1) at least 5 repositories with initial detection d have been previously studied (i.e., $n(d) \geq 5$), and 2) the current $P(S|d)$ is greater than or equal to 0.7.

States

The significance and unique considerations for each of the states are discussed below.

Unresponsive (U)

There are multiple causes for a server to appear inactive. In the experiments performed I treat all of these conditions as equivalent negative responses:

[8] In [ZRB11] I explore different functions to update the re-evaluation interval. In the thesis work I constrain my evaluation to using a function that increases the re-evaluation interval by a fixed increment.

1. There is no DNS record available for the URL
2. The server refuses to initiate a TCP connection
3. The server sends no data during the entire TCP conversation (then a timeout occurs)
4. The server responds with a negative HTTP response (i.e., 40X or 50X)

When a consecutive run of negative responses exceeding some threshold is observed, the server is considered inactive and re-evaluation should be discontinued.[9] Repeatedly querying inactive servers does not advance the goal of content discovery, and detracts from the goal of resource conservation and blacklisting avoidance. It is therefore desirable to discontinue attempts to fetch from inactive servers. This objective - to discontinue attempts to fetch content from inactive servers - is complicated by a characteristic exhibited by some malicious networks: intermittent availability. Some malicious networks appear to be inactive, only to become active at a later time. The consequence of categorizing an intermittently available malicious repository as inactive is missed sample updates.

Active No Exe (Ae,An)

Note this section covers both *Active No Exe Ever* and *Active No Exe Right Now*. When a LIHC visits a suspected malware repository and receives non executable content, typically HTML content, two things should be done:

1. This URL should be revisited by a HIHC for more thorough analysis, as the URL content may be using crawler evasion techniques or hosting an exploit that will not function unless in the context of a browser.
2. The URL should be removed from subsequent evaluation by the LIHC as this serves no value unless the URL begins serving executable content at a later date.

Single Sample (S)

Towards the goal of content discovery there is no benefit to repeatedly downloading the same

[9] A variation of this strategy is to reschedule an evaluation in the distant future (e.g., several weeks or even months) to see if the server becomes active again. I do not evaluate the merits of this variation.

sample. Additionally, repeatedly downloading the same sample detracts from the goals of resource conservation and blacklisting avoidance. However, the only way to determine that a server is a single sample repository is to make multiple requests to the server over time. Making too many observations wastes network resources and increases blacklisting probability. Taking too few observations and incorrectly classifying a periodic updater as a single sample repository will result in missed sample updates.

Polymorphic Server (P)

Dealing with purely polymorphic servers is a challenging task that is not fully addressed in this research. Every evaluation of a polymorphic server contributes to new content discovery, but at a diminishing rate. The cost of sample collection, in addition to AIR system resources, is non-zero and must be considered. A more detailed treatment is provided in Chapter 6. To summarize, a polymorphic server should be dealt with using a separate iterative approach allowing human or automated action between batches.

3.2 Evaluating Fake AV Malware Distribution Networks

Fake AV is actively being distributed using sophisticated MDNs (shown in Chapter 5). These networks engage in IP blacklisting behaviour, the repositories and malicious executables are frequently updated, and the distribution network is sophisticated in terms of the countermeasures in place to thwart security researchers.

This represents a worse case scenario where information needs to be frequently collected from the MDN in order to actively protect users, but there is also need to limit the exposure of AIR resources through the act of collection.

To balance the conflicting objectives of discovery[10] *and blacklisting avoidance, I propose several techniques to reduce AIR client exposures to the network, which I assume will reduce blacklisting, while maintaining a relatively high discovery rate.*

The first technique leverages the high degree of fan in from landing page to malware repository. My data indicates that all landing pages in a MDN redirect to a single repository at a

[10] discovery of the MDN network topology and malicious executables

given time. For any MDN that satisfies this condition (i.e., one active repository at a time), a visit to a single landing page in the MDN will yield the active malware repository at a given time, and no immediate evaluations are necessary to the other known landing pages in the MDN.

The second technique reduces the number of exposures to the repository, at the cost of greater uncertainty about the malicious executable being served by the repository. I propose the addition of a decision point during the evaluation of a MDN landing page. If the landing page redirects (directly or indirectly) to a known malware repository, and the repository has been *recently* visited, then the HTTP client should not make a HTTP request to the repository. This requires a threshold value to control when to re-evaluate the repository. I refer to this threshold as the *repository re-evaluation threshold* (RRT). The application of this optimization saves one exposure to the malware repository. This technique will be effective if at least one of two conditions is met; note the second condition only applies when approaching the problem from the perspective of a security vendor.

1. The lifetime of an active repository in the MDN is long compared to the lifetime of a specific malware binary.

2. The ability of a vendor to proactively detect the malicious binaries (i.e., already detected upon initial discovery) is "good enough"; revisiting the repository to collect a new malicious executable on every evaluation of the MDN is unnecessary. In this scenario, the MDN is being monitored to add the repositories to blocklists and periodically check that the malicious samples are proactively detected.

3.3 Summary

This chapter provided a more detailed presentation of the problem addressed by this research, and proposed optimizations in each of the two adversarial scenarios that are addressed by this research.

Chapter 4

Approach

The previous chapter provided an overview of the problem space and the two adversarial scenarios that are addressed in this research. This chapter presents the approach taken to study these scenarios: I collected data from suspicious URLs, analyzed the data, proposed optimizations, and then evaluated the optimizations by simulation using the collected data. Section 4.1 provides an overview of the major system components used during the data collection phase of my research. Section 4.2 discusses data validity concerns, and Section 4.3 presents the simulation and measurement methodology used to evaluate the proposed optimizations.

4.1 The Tachyon Detection Grid

To study the behaviour of malware distribution networks over time, I built a framework that supported multiple distributed honey clients and pluggable scheduling and data analysis components. I named the framework TDG, which is a geeky Star Trek reference.[11] Figure 4.1 shows the TDG architecture. The TDG system consists of a single central server and multiple clients that execute instructions from the server. The system was implemented in Perl 5.8 [The11] running on Gentoo Linux [Gen11]. All major components were implemented as objects. The central server consists of persistent perl processes that communicate with each other using an Apache QPID [Mes11] message broker. Persistent data storage was realized using MySQL [MYS11] for relational data storage and a REST based key/value store implemented using Node.js [Nod11]. A more detailed presentation of the TDG is provided in Appendix A.1.

[11] In StarTrek: The Next Generation, the Federation deploys a Tachyon Detection Grid to detect cloaked Romulan vessels [Tac11]. My initial research objective was to study the use of cloaking by malware networks, and so a name was given to a bunch of code.

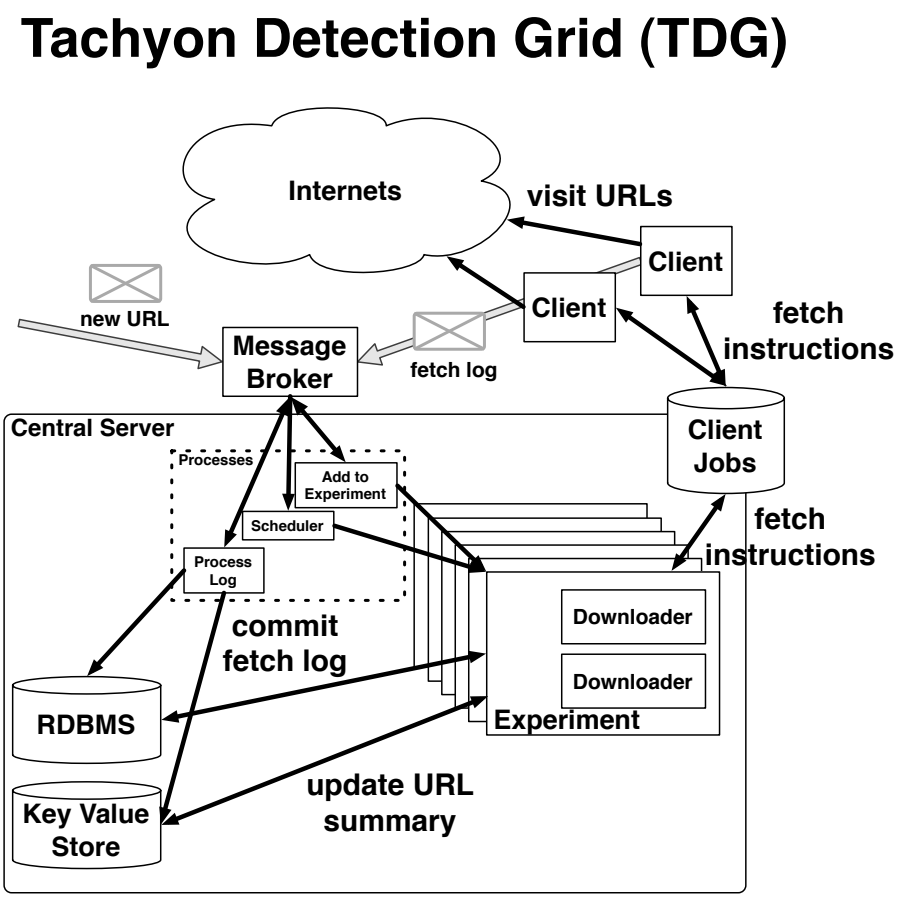


Figure 4.1: Architecture of the Tachyon Detection Grid. New URLs are added to the system and added to one or more experiments. The experiments delegate the role of fetching to its downloaders. The downloaders send command to the clients, which execute the HTTP requests. New fetch results are sent back to the central sever, where the experiment is invoked to process the new fetch.

4.2 Data Validity Concerns

Several factors must be accounted for when collecting and analyzing results. Each of these factors can potentially bias the conclusions drawn from the results. These factors, and my approach to dealing with them, are presented in the sections that follow.

Blacklisting

As discussed in Section 2.3, when honey clients revisit confirmed malicious websites they expose themselves to potential blacklisting. Many of the experiments I performed in this research involve sustained re-evaluation of malware repositories to determine the prevalence of various

update patterns, so there is a chance that blacklisting could occur. To account for this in the LIHC experiments, I harvested content from URLs using multiple downloaders. In each experiment there were one or more high volume fetchers distributed across multiple IP addresses, at least one low volume downloader, often using a pool of IP addresses, and a reserve downloader, which did not execute any fetches unless there was suspected blacklisting. There are two forms of blacklisting that I detect: reactive content denial blacklisting and proactive content denial blacklisting. Any URL that triggers either blacklisting heuristic was discarded from the evaluation phase of the approach. This was done to prevent results tainted by blacklisting from affecting the statistical distributions and evaluation results.

Reactive Content Denial Blacklisting

I define *reactive blacklisting* as an adversarial response from a specific *repository* after a honey client has made one or fetch attempts to the site. In the case of *reactive content denial blacklisting*, the response by the adversary is to deny access to content, via a HTTP response in the 400 or 500 group (HTTP response code groups are detailed in Figure 2.2). The approach I used to identify this form of blacklisting relies on the URL state model presented in Figure 3.1. Every time a high volume downloader transitioned into an inactive state, I enqueued a fetch attempt using a reserve downloader. If the reserve downloader received a positive response, I considered this evidence of reactive content denial blacklisting.

Proactive Content Denial Blacklisting

I define *proactive content denial blacklisting* as an adversarial response from a specific *adversary* after a honey client has made requests to multiple repositories under the control of the adversary. The adversary blacklists the client, and then all subsequent requests, even the *first* request to a new repository, will be denied, via a HTTP response in the 400 or 500 group. The approach I used to identify this form of blacklisting also relies on the URL state model (Figure 3.1). If a high volume downloader transitioned directly from start to unresponsive, and other high or low volume downloaders received positive responses, I considered this proactive content denial blacklisting.

Sample Truncation

When a download is terminated before a file transfer is completed, the result is a truncated version of the complete file. If this condition is not detected by the honey client, incorrect observations can be made regarding the update behaviour of a malware network. Indeed, this was the case for results that were gathered[12] - and presented - from the TDG before May 22, 2011 [ZRB11]. This premature download termination has two main causes: artificial client side timeouts, and server side timeouts or connection resets.

Some malware distribution networks appear to suffer from performance issues.[13] In all experiments conducted during this research, I consistently encountered repositories that delivered samples at rates under 1 KB / second. In other cases the server paused for multiple seconds in the middle of a file download, sometimes recovering, and in other cases never resuming the data transmission. The net result of these intermittent behaviours was a "download time" distribution with a very long tail. Another cause of sample truncation is server timeouts. In some instances the server stopped uploading in the middle of a download. In this scenario, regardless of the client side timeout, a full sample cannot be downloaded.

To cope with these phenomena, a difficult design decision had to be made on whether to place an artificial upper limit on the time spent per download. Without the upper limit, the experiment throughput would degrade significantly if repeated download attempts take an extended period of time. Worse still, a small number of adversaries that identify the clients and tarpit (see Section 2.3.4) download attempts would impact the study of all malware repositories. On the other hand, introducing the upper limit inhibits the ability to collect samples from networks that suffer from connectivity and bandwidth issues. In order to keep the experiments running without constant supervision and maintenance (e.g., trimming experiment size to cope with backlogs caused by slow servers) I chose to introduce an artificial client side cutoff threshold of 10 minutes.

[12]The results presented in [ZRB11] suggest a ratio of *single sample* to *multi sample* repositories were 1.67:1, whereas the dataset used in this thesis suggests 10:1. The discrepancy was confirmed to be due to sample truncation in the earlier data set. The scheduling algorithms presented in my previous work still provide gain but the numbers presented are skewed by the data collection fault. None of the data from the flawed set is used in this thesis.

[13]It is unclear whether the network issues were a deliberate action of the adversary to thwart security researchers, a deliberate action of the hosting provider to throttle downloads, or a legitimate issue with the hosting infrastructure.

Of the approximately 750,000 low interaction HTTP Traces used in this work, 4687 hit the 10 minute download timeout threshold. These 4687 requests that hit the timeout were made to 456 distinct domains; 5% of the total in the set. As mentioned above, sample truncation can occur even if the client side timeout is not reached. To account for this, post processing of the downloaded content was necessary to prevent truncated samples from biasing results. I used an algorithm to identify files whose entire byte sequence is a subset of another file collected from the same URL. This approach identified and eliminated 2430 truncated samples from the corpus used in Chapter 5. The algorithm is presented in Algorithm 4.1. The effectiveness of this approach relies on two assumptions:

1. Sample truncation is highly unlikely to produce the same truncated sample more than once. This would require a download to be terminated at the same point twice.

2. It is unlikely to see two files a and b where $b > a$ and $sha1(0, size_a, a) = sha1(0, size_a, b)$ but a is not a truncated version of b.

3. If the entire byte sequence of file a is the starting byte sequence of a larger file b, it is highly likely that a is a truncated version of b.

Algorithm 4.1 This algorithm is run on a set of samples downloaded from a specific repository to identify and exclude truncated samples from the experiment results.

let S_T = set of all samples downloaded from URL U_i
let S_M = set of all samples downloaded from URL U_i multiple times
let S_S = set of all samples downloaded from URL U_i once
let $size(F)$ return the size in bytes of sample F
let $sha1(A, B, F)$ return the SHA1 signature of the byte sequence A to B taken from sample F

for all $s : s \in S_S$ **do**
  $size_s = size(s)$
  for all $m : m \in S_M$ **do**
    $size_m = size(m)$
    if $size_m > size_s$ AND $sha1(0, size_s, m) = sha1(0, size_s, s)$ **then**
      sample s is a truncated version of m. **goto** next s
    end if
  end for
end for

Benign Binaries

There is a risk that a server is not actually malicious. I took several steps to ensure benign URLs were not included in my results. Essentially, I only added confirmed malicious URLs to the experiments, and then discarded results from any URL that I could not confirm as malicious *during* the experiment.

The experiments were only run on confirmed malicious URLs. The URLs were confirmed to be malicious by 1) a production system in SophosLabs that downloads URL content and scans the content using a Sophos AV scanner, or 2) a trusted external feed. Despite this preliminary filtering, some URLs did not yield confirmed malicious executables during the course of study. All downloaded content was AV scanned with a multi vendor scanning system immediately before generating results. For the older experiments included in the results, the time interval between sample collection and final scan is more than a month. This re-scanning step is important (according to Rajab *et al.* [RBM+10]), because AV detections are always being updated, thus malware undetected at initial download time may be detected at the final scan time. Any URL that did not serve at least one detected executable was excluded from the results.

Relying on detections to filter results introduces the chance that a URL serving malicious but undetected samples will be incorrectly filtered from the results. To minimize this risk I used AV detection results from eight vendors: Sophos, Microsoft, Kaspersky, Symantec, McAfee, TrendMicro, K7, and Avira. If a sample was detected as malicious by at least one vendor, then the URL that served the sample is included in the dataset.

Finally, the presence of an AV detection string does not always indicate that a sample is malware. This is particularly true for the scanning products I used, which are batch-mode, "on-demand" scanners[14] as opposed to the persistent "on-access" scanners deployed on customer PCs. A final step was applied to filter out detections that are weak, policy based, or are otherwise not strong indicators of a sample's maliciousness (e.g., Symantec's "Joke Program" detection). This filtering was accomplished using vendor specific *detection filter lists* provided by Sophos. Using these lists, I was able to classify each detection into one of the following categories: (malicious, suspicious, application, internal, informational, warning, packed file,

[14]The batch mode scanners used in this research are 1) more verbose in output and 2) running in diagnostic modes, so they reported on files that would be allowed to run by an "on-access" scanner.

ignorable, checksum/weak detection). If at least one vendor produced a *malicious* detection for at least one sample from a URL, then all of the data gathered from the URL was included in the results.

4.3 Simulation Methodology

In order to evaluate the proposed optimizations I use simulation to determine the data that would have been collected using different combinations of the proposed optimizations. This section provides an overview of the simulation and measurement methodology, focusing on decisions made that may impact results.

4.3.1 Pre-Simulation Data Processing

There were several processing steps necessary before a simulation was performed. First, URLs that were a) benign, b) polymorphic, or c) blacklisting the apparatus, were identified and excluded (these are each discussed in Section 4.2). Second, data tuples[15] representing the state of repositories and landing pages are prepared and stored for subsequent use. The information required varies between the two adversarial scenarios. For the evaluation of *zero provenance malware repositories*, a single set of tuples, with one or more records for each repository, is necessary:

```
(repository, SHA1, content_type, HTTP code, start, end)
```

Each tuple represents a period in time from *start* to *end* when the repository responded with a *HTTP code* and specific content, identified by the *SHA1* checksum of the content. The zero provenance malware repository optimizations also require detection information for samples. This data was precomputed using the cross scanning system discussed in Section 4.2 and made available to the simulation.

Simulation of Fake AV MDN re-evaluation required an additional set of tuples recording the history of links from landing pages to malware repositories over time. The application of two simplifying assumptions during the pre-simulation data processing steps were also necessary for

[15]The data tuple storage was implemented using a MySQL database.

Fake AV MDN simulation. First, for each HTTP trace I reduced the network at that moment to a landing page and a repository; I disregard the intermediate components of the network for the simulation. Next, I assumed the strong fan in property applies to all MDNs in my data set. That is, I assumed that at a given time, all landing pages point to a single repository. Note that all the data I collected shows this assumption to be true for the MDNs studied in this research.

4.3.2 Performing the Simulation

Multiple re-evaluation algorithms, each with a different combination of initial re-evaluation interval, optimizations and parameters, were simulated. The simulation runs over a specified period of time (e.g., May 23, 2011 - July 5 2011) and requires a set of URLs and the initial discovery time for each URL. The re-evaluation algorithms selects times when the URL should be evaluated. The simulation engine determines the content that would be retrieved at that time. The time requested will either a) overlap with a record, which requires no interpolation, or b) fall between two records, which requires data interpolation. When data interpolation is required, the nearest record, according to time, is selected and that response is used. Note that interpolation will be inaccurate for polymorphic servers. This is one of the primary reason why these servers are excluded from simulation.

4.3.3 Measuring Re-Evaluation Improvements

Each simulation produced three measurements: the number of evaluations performed (*numF*), the number of unique executables discovered (*numS*), and the number of unique detection families discovered (*numFm*). The Fake AV MDN simulations also produced measurements of the number of malware repositories discovered (*numR*), and break down the number of evaluations into the number of client exposures to the landing pages (*numExpLP*) and to the malware repositories (*numExpR*).

I developed a single success score to combine the metrics from the zero-provenance malware repository simulations.[16] Conceptually, the objective of the optimizations is to reduce the number of evaluations while maintaining a high sample discovery rate. There are additional

[16] I felt that a similar metric for the Fake AV MDN re-evaluation simulations was unnecessary. The Fake AV MDN results are much easier to interpret than the zero provenance malware repository results.

considerations, such as avoiding downloading many polymorphic samples (unless this is an objective), and finding as many distinct malware families as possible, however I did not attempt to model these additional objectives in my success metric. Based on this simple objective statement, I derived the following success metric: $success = \alpha \times numSamples - numFetches$, where α is a subjective metric used to express the relative cost of sample discovery in terms of fetching resources.

The success metric above provides an absolute measurement of the success of a particular set of optimizations. During my analysis of the results I found it easier to draw conclusions when using a normalized success metric ($nSuccess$). The normalization process is based on several insights:

1. The *re-evaluation interval* (i.e., time to wait between consecutive evaluations) has a big impact on the results of the simulation. The initial re-evaluation is a another highly environment-sensitive parameter. I want to eliminate the impact of the initial re-evaluation interval from the normalized success score.

2. The *initial evaluation* (i.e., the first evaluation) of the repository is a strong contributor to the number of samples detected, and this initial evaluation is constant across the simulations. I want to eliminate the results of the initial evaluation from the normalized success score.

Based on these insights, I derived the following metrics to compare the different simulation results. In the formula below $numF_{Base}$ and $numS_{Base}$ are the simulated fetch and sample counts for a re-evaluation algorithm using the same initial interval and no optimizations. $numF_{initial}$ and $numS_{initial}$ are the number of fetches performed and the number of samples discovered on the initial evaluation of each URL.

$$fetchReduction_A = 1 - \frac{numF_A - numF_{initial}}{numF_{Base} - numF_{initial}} \tag{4.1}$$

$$sampleCost_A = 1 - \frac{numS_A - numS_{initial}}{numS_{Base} - numS_{intitial}} \tag{4.2}$$

$$nSuccess_A = (numF_{Base} - numF_A) - \alpha \times (numS_{Base} - numS_A) \tag{4.3}$$

Determining α

The α value introduced above represents the relative cost of each new sample discovered in terms of the number of fetches spent to get that sample. This is a very subjective value, and the means to properly calculate this value for a given environment is not something addressed by this research. I conducted a survey of SophosLabs analysts and developers, asking the following question: "How many fetches would you spend to get a single sample we have not seen before?". The average from a collection of 18 valid responses was 8.2 (standard deviation was 11.9); full details of the survey are available in Appendix A.5. In Chapter 5, I present normalized success scores for each of the following α values: 8.2, 100, 1000, and 10000.

Chapter 5

Results

I performed multiple experiments using data collected by the Tachyon Detection Grid (TDG) between May 2011 and July 2011. This section presents the results and analysis of these experiments. Section 5.1 presents analysis of the data collected from the zero provenance malware repositories and an evaluation of the proposed optimizations. Section 5.2 presents analysis of the data collected from Fake AV MDNs and an evaluation of the proposed optimizations.

5.1 Optimizing Re-Evaluation of Zero Provenance Malware Repositories

This section analyzes the data gathered from repeatedly making requests to known malware repositories. The composition of the data set is provided in Section 5.1.2. In Section 5.1.3 I present results from analysis of the collected data. In Section 5.1.4 I evaluate the optimizations proposed in Section 3.1 and quantify the improvements provided.

5.1.1 Simulation Terminology

These terms are used in the sections that follow.

Conditional Probability of Repository Update Behaviours

I present calculations to determine the conditional probability of repository update behaviour given the initial detection values. The following terms are used:

$P(S|d)$ The probability that a URL is a *single sample repository* given the initial detection d

$P(M|d)$ The probability that a URL is a *multiple sample repository* given the initial detection d

$P(P|d)$ The probability that a URL is a *polymorphic repository* given the initial detection d

Zero Provenance Malware Repository Re-Evaluation Optimizations

I apply eight distinct optimizations, grouped into three types: *state-based cutoffs* (ct), *state-based backoffs* (bk), and *conditional probability* (cp) optimizations, all of which are presented in Section 3.1. When referring to a simulation that used all optimizations in a group I use the $\forall$ symbol to indicate that all the optimizations in this group were applied (e.g., $ct(\forall)$ indicates all of the state-based cutoffs were applied to the simulation). When a single optimization is applied, a short hand notation, enumerated below, is used (e.g., $ct(s)$ refers to a simulation where only the state based cutoff for the single sample state was used).

$cp(s)$ *single sample* conditional probability optimization

$cp(m)$ *multiple sample* conditional probability optimization

$ct(i)$ *unresponsive* cutoff optimization

$ct(s)$ *single sample* cutoff optimization

$ct(ae)$ *active no exe ever* cutoff optimization

$ct(an)$ *active no exe right now* cutoff optimization

$bk(s)$ *single sample* backoff optimization

$bk(ae)$ *active no exe ever* backoff optimization

$bk(an)$ *active no exe right now* backoff optimization

5.1.2 Malware Repository Data Set

This data set is composed of fetches to confirmed malware repositories. For future reference I refer to this as the *low interaction repository* data set. 728325 fetches were made to 8539 URLs between May 23, 2011 and July 6, 2011. The data set was further filtered (details and motivation of filtering are provided in Section 4.2) to eliminate 1457 URLs that served

executables but could not be confirmed to be malicious and 21 URLs that exhibited evidence of blacklisting behaviours. The resulting set contained 6816 URLs from 3183 distinct domains, and 151 Top Level Domains (TLDs). The re-evaluation frequency of URLs in this set ranges from 15 - 60 minutes.

5.1.3 Malware Repository Data Analysis

In this section I analyze the collected data to determine the relative prevalence of the different repository update behaviours and the time spent in each state of the model presented in Figure 3.1.

Conditional Probability of Update Behaviours Given Initial Detection

I used the malware repository state model presented in Figure 3.1 to classify the update behaviours of servers in the *low interaction repository* data set. The resulting distribution of update behaviours is presented in Table 5.1.

URL Update Behaviour	Count
Inactive on Arrival	1239
Zero Executables	1618
Single Executable	3561
Multiple Executables	305
Polymorphic URL	93
Total	6816

Table 5.1: Distribution of Update Behaviours for URL in the *Low Interaction Repository* dataset.

I used the detection results from the multi vendor scanning system (described in Section 4.2) to compute $P(B_U|d_U)$ for each detection in the data set, which is the conditional probability that a URL U will exhibit a specific update behaviour B given the detection (d) of the first downloaded executable sample. The full result set and a summary table are included in Appendix A.2.1.

Only 10.1% of the malware repository URLs studied produce a sample update. When the subset of malware repositories serving Fake Anti-virus malware[17] is considered in isolation, the

[17] A limitation of this approach is that we are relying on AV detection to identify a family. This is discussed further in Chapter 6

probability of sample update increases to nearly 30%. The conditional probability analysis revealed 89 distinct detection groups that triggered on malware from repositories that showed sample update behaviour. For 54 of these detection types $P(M|d)$ was over 50%. However, this observation is limited by our small data set and the challenges of grouping malware by detection name: of the 54 detections exhibiting a high probability of sample update behaviour, only 5 of these detections were observed from at least 5 distinct domains (i.e., $n(d) \geq 5$). Indeed, from the 3959 URLs in this corpus that served at least one piece of malware, there were 1470 unique initial detections, even after I made efforts to group different sample variants into the same family (e.g., Mal/Bad-A and Mal/Bad-B are combined to make the Mal/Bad family).

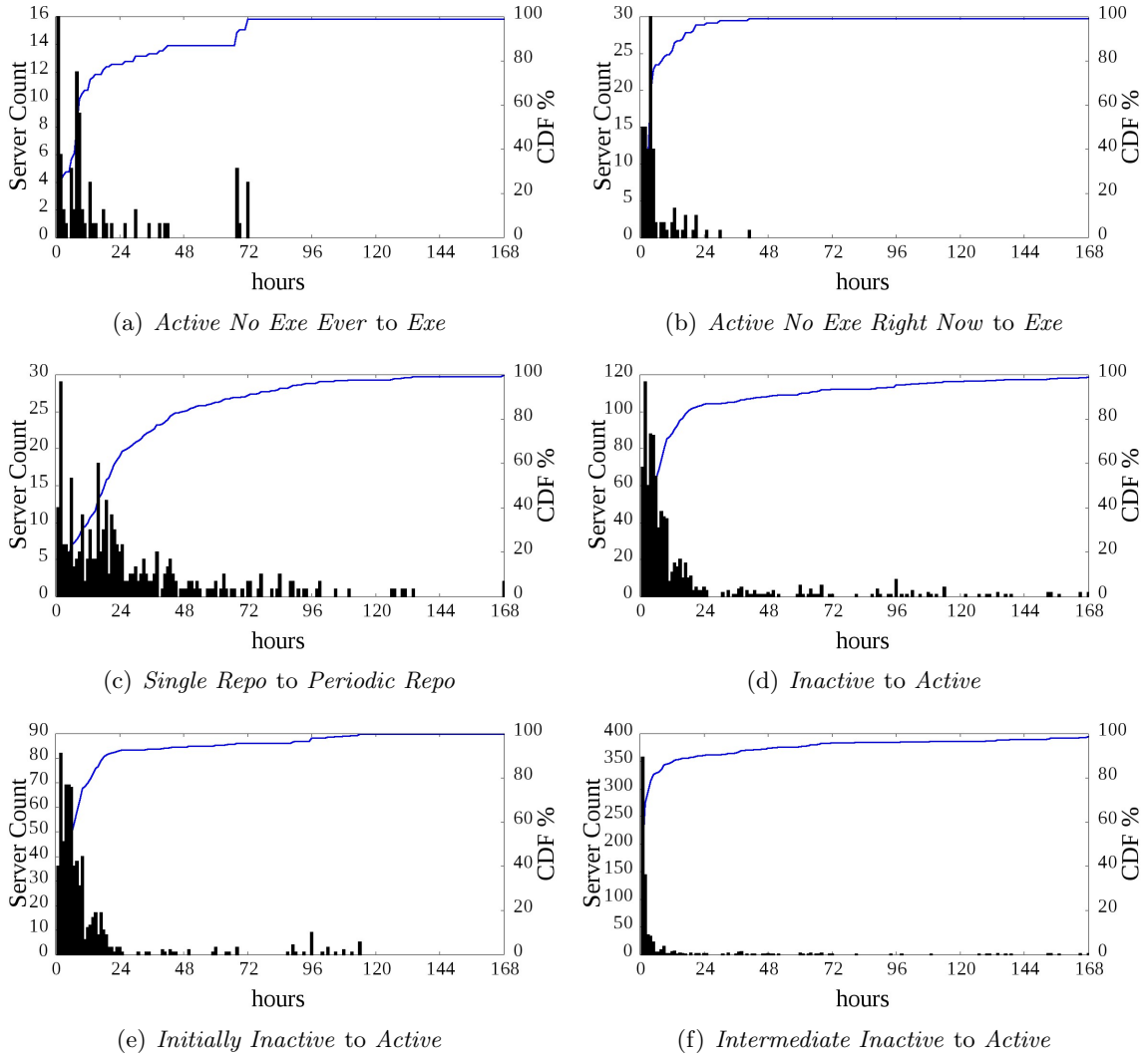
There were many malware families that were served almost exclusively from single sample repositories. Nearly 50% of the corpus can be mapped to 113 distinct detections whose $P(S|d)$ value was over 70%. This suggests that the early cutoff based on $P(S|d)$ computations can provide substantial resource savings.

Malware Repository State Transition Thresholds

In this section I analyze the data collected looking for the most appropriate thresholds for several re-evaluation cutoff decisions. The malware repository state model (Figure 3.1) shows six[18] subjective state transitions to the "stop fetching" state. The state diagram and motivation for each of these cutoffs are rooted in the AIR goals presented in Chapter 3. Essentially, repositories in each of these states are not "interesting", so I want to stop wasting resources on them; however, some repositories will transition from these uninteresting states back to interesting ones. If I discontinue evaluation too soon I lose interesting data. If I wait too long, I waste resources unnecessarily.

To determine appropriate thresholds to discontinue fetching at each of these states, I analyzed the *low interaction repository* dataset looking for repositories that entered into one of the uninteresting states and then transitioned back to an interesting state. For example, for the *active no exe ever* state, I looked for repositories that transitioned from this state into any of the "Exe" states. For each repository that makes one of these transitions, I recorded the max-

[18] Figure 3.1 shows 5 subjective transitions but I have split the inactive transition into 'Initial' and 'Intermediate' as they produced distinct distributions.



(a) *Active No Exe Ever* to *Exe*

(b) *Active No Exe Right Now* to *Exe*

(c) *Single Repo* to *Periodic Repo*

(d) *Inactive* to *Active*

(e) *Initially Inactive* to *Active*

(f) *Intermediate Inactive* to *Active*

Figure 5.1: Each figure above contains a histogram and an overlaid CDF for one of the 6 'subjective' transitions shown in Figure 3.1. The figures are derived from the HTTP Traces in the *low interaction repository* set.

imum time spent in the uninteresting state. I used these data points to generate a distribution of the maximum time spent in each uninteresting state before transitioning to an interesting state. These distributions are shown in Figure 5.1. From these distributions I derived the 80% and 90% CDF points. These sets, presented in Table 5.2, are used in the next section to seed simulation parameters.

Transition	80% Base (Hours)	90% Base (Hours)
Single Server to *Multi Server*	42	68
Active No Exe Ever to *Exe*	29	68
Active No Exe Right Now to *Exe*	8	16
Inactive to *Active*	16	47
Initial Inactive to *Active*	14	19
Intermediate Inactive to *Active*	5	24

Table 5.2: **Seed Parameters for Malware Repository Simulation derived from *low interaction repository* dataset** Each set of cutoffs (i.e., 80% and 90%) are derived from the CDF distributions presented in Figure 5.1. As an example, 80% of the URLs in the set that had a transition from single sample to multiple sample updater made this transition in less than 42 hours of the Initial Fetch.

5.1.4 Evaluation of Optimizations

In this section I evaluate the impact of the optimizations proposed in Section 3.1. A brief review of the proposed optimizations is provided. There are three types of optimizations applied; each is intended to discontinue re-evaluation of a repository when it is unlikely to further useful information (i.e., new malicious binaries). Some optimizations can be applied to multiple repository states; a total of eight optimization points are simulated. The *conditional probability* optimizations discontinue evaluation of a repository when the first malicious executable downloaded from the repository provides a strong indicator (based on previous study of repositories that served similar malware) that the repository will not update the malicious executable. The *cutoff* optimizations discontinue evaluation when a repository remains in a specific state (based on state model in Figure 3.1) for a period of time. The *backoff* optimizations increase the re-evaluation interval (i.e., the time between subsequent HTTP requests to a repository) every time a repository is observed in a specific state.

I simulated multiple combinations of these optimizations using data from the *low interaction repository* dataset[19]. Each simulation produced three values: the number of fetches performed (*numF*), the number of malicious binaries downloaded (*numS*), and the number of unique detections on those binaries (*numFm*). The actual values from the data collection phase are: 502391 fetches, 4786 malicious binaries, and 1813 unique detections. For each simulation,

[19]Note the results from the 95 URLs of polymorphic repositories were excluded from this evaluation. The re-evaluation of polymorphic servers is outside the scope of this research, for reasons discussed in Section 3.1.

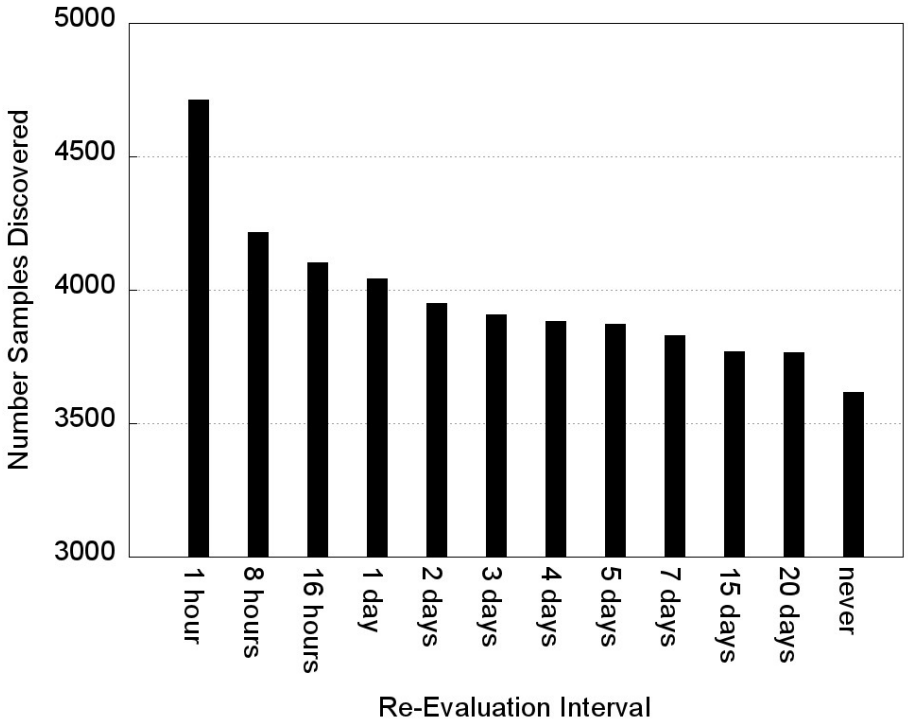


Figure 5.2: **Impact of Re-Evaluation Interval on Sample Discovery Rate** Varying the re-evaluation interval with no optimizations produces a predictable trend of increased resource savings at the cost of a lower rate of sample discovery. When no re-evaluations are performed, 3616 samples are still discovered, or 75.5% of the total corpus. The full set of data for this experiment is presented in Table A.3.

I combined these three metrics to compute the normalized success metric ($nSuccess(\alpha)$, or $nS(\alpha)$), the $fetchReduction$ (fR), and the $sampleCost$ (sC) values. The formulas for these metrics are discussed in Section 4.3.

I began the evaluation by running several simulations with no optimizations enabled and only varied the re-evaluation interval. I varied the re-evaluation interval from one hour to *infinity* (i.e., no re-evaluation; only evaluate each URL once). These results are shown in Figure 5.2. This shows that performing no re-evaluations, that is to perform 6816 fetches (i.e., once per URL) still results in 3616 unique binary downloads (i.e., 75.5% of the total set), representing 1649 (i.e., 90.9%) distinct detections observed. This represents a worst case for any re-evaluation algorithm: no matter how poor the optimizations perform, they should be able to collect at least 3616 binaries. These values provide the $numF_{initial}$ and $numS_{initial}$ values and are used to compute the $fetchReduction$ and $sampleCost$ for subsequent simulations.

To better understand the impact of each optimization, I compared the results of each of the optimizations proposed in Section 3.1 against a naive fixed interval scheduler, and also evaluated the cumulative impact of several optimization combinations. I chose a relatively low initial re-evaluation interval of 1 hour for these simulations in order to maximize the differences in fetch volume produced between different simulations. This allows better understanding of the individual contribution of each optimization. The results are shown in Figure 5.3.

The results show a wide range of fetch savings depending on the optimization combination used. The single sample cutoff optimization ($ct(s)$) and the single sample backoff optimization ($bk(s)$) provide the largest individual reduction in fetch volume: 53% and 61% respectively. The single sample conditional probability optimization ($cp(s)$) also produced a significant reduction in fetch volume (i.e., 21%), however this optimization produced a much larger cost in samples versus the previous two single optimizations (i.e., 29% sample loss vs 1-4%). In terms of optimization combinations, "all on" produced the largest fetch reduction but also had the largest cost in terms of sample discovery. When the conditional probability optimizations were removed the simulation produced a fetch reduction of 93% with a relatively small sample cost of 7%.

Next I determine if the initial re-evaluation interval has an effect on the optimizations. I simulated each optimization combination with re-evaluation interval values of 1 hour, 8 hours, 16 hours, and 1 day. For each re-evaluation interval, I select the top 4 optimization combinations and present the fetch reduction versus the sample discovery, and the normalized success scores, in Figure 5.4. For all initial re-evaluation intervals, when α is set low (e.g., 8.2), which corresponds to a bias toward fetch reduction, the full set of optimizations produced the best normalized success score. As α increases, more conservative set of optimizations produce better normalized success scores. For all re-evaluation intervals that were simulated, the $ct(\forall)$ simulation group produced the highest normalized success score when α is at the highest value simulated (i.e., 10000). Another factor dependant on the initial re-evaluation interval is the impact of the optimizations: the normalized fetch reduction and sample cost of the backoff optimizations drop as the initial re-evaluation interval increases. These values remain relatively constant or the cutoff optimizations.

Finally, I explore the impact of the varying the threshold values for each of the three

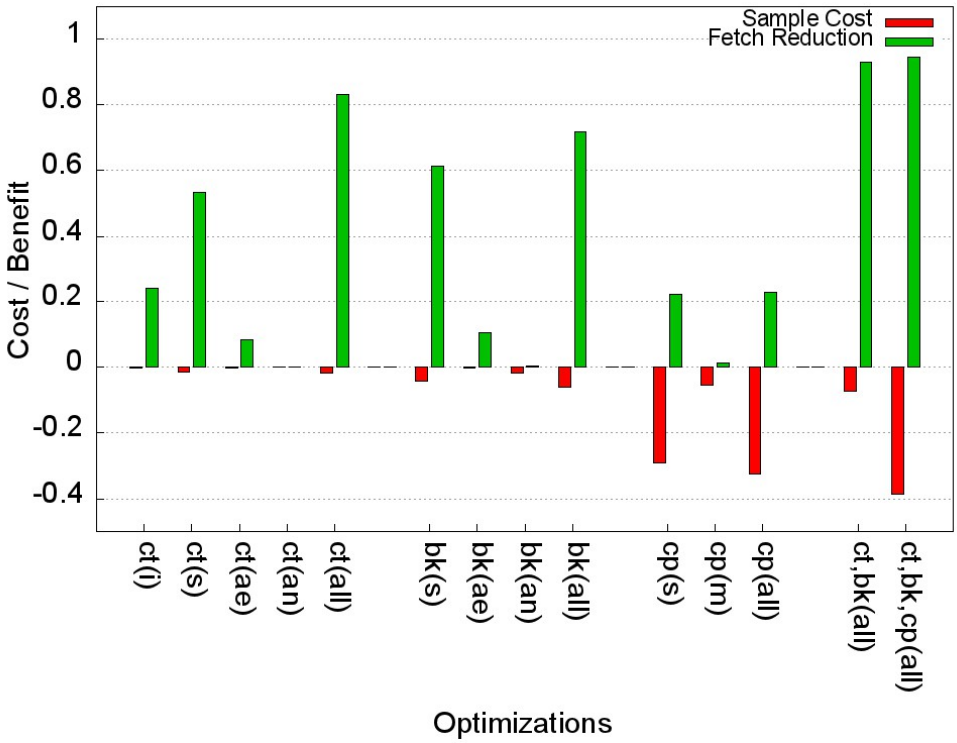
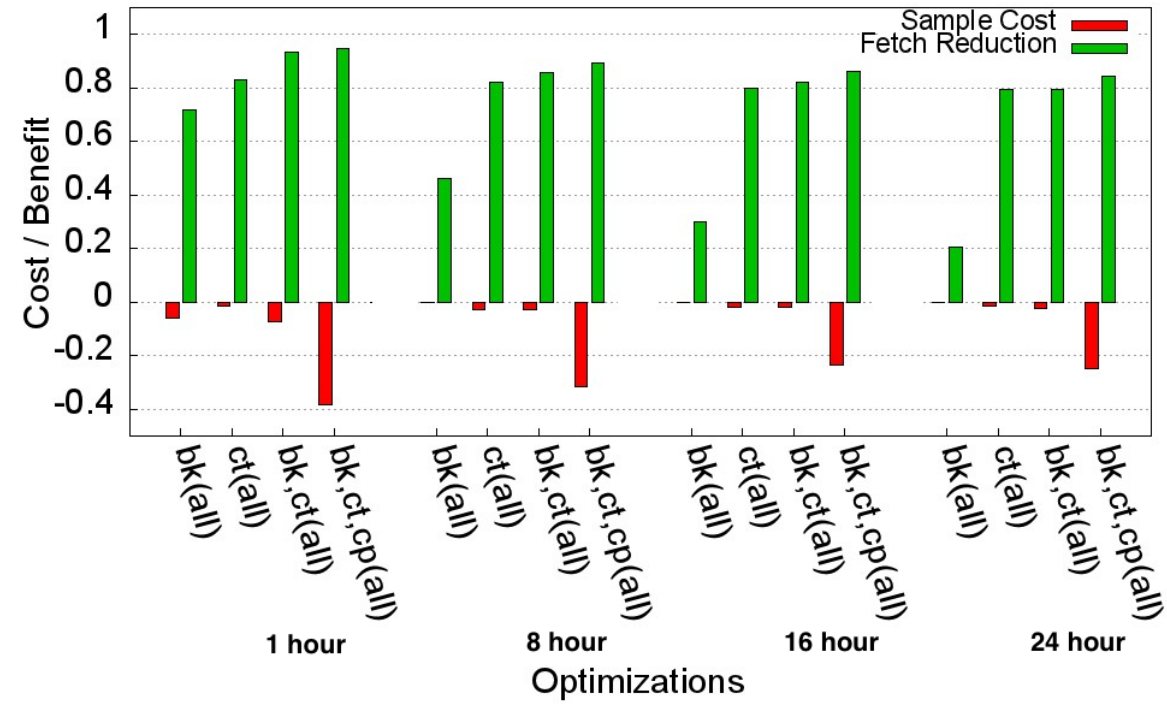
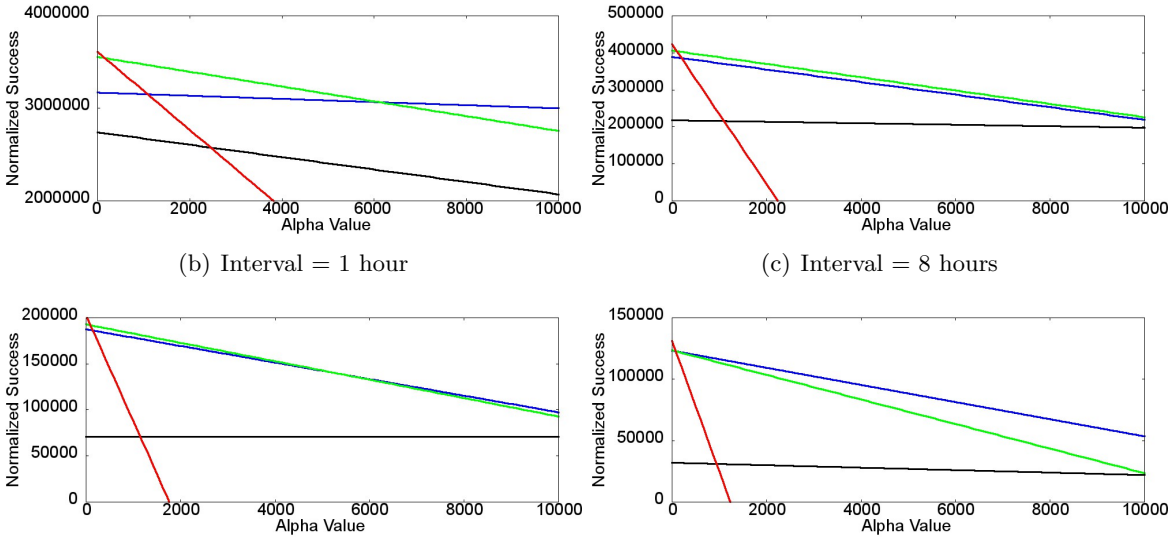


Figure 5.3: **Malware Repository Simulation: Optimization Results at Low Fetch Interval (1hr)** The results show a wide range of fetch savings are possible depending on the optimization combination used. The single sample cutoff optimization ($ct(s)$) and the single sample backoff optimization ($bk(s)$) provide the largest individual reduction in fetch volume: 53% and 61% respectively. The conditional probability ($cp(s)$) also produced a significant reduction in fetch volume (i.e., 21%), however this optimization produced a much larger cost in samples versus the previous two hilighted optimizations (i.e., 29% sample loss vs 1-4%). The full set of data for this experiment, including normalized success scores for multiple values of α, are presented in Table A.4.

optimization types. Table A.6 shows the impact of varying the probability and confidence thresholds for the $cp(s)$ and $cp(m)$ optimizations. Compared to the other optimization types, the conditional probability optimizations produced the least impressive results: any reduction in fetch volume produces a larger cost in terms of sample discovery rate. Table A.7 shows the results of 4 simulations with varied state cutoff thresholds and Table A.8 shows three simulations with varied state based re-evaluation backoffs. In both result sets, the use of more aggressive cutoff values produced further reductions in fetch volumes with a predictable loss in sample discovery rate.



(a) Fetch Reduction Versus Sample Cost



(b) Interval = 1 hour

(c) Interval = 8 hours

(d) Interval = 16 hours

(e) Interval = 24 hours

Figure 5.4: **Best Optimizations At Different Re-Evaluation Intervals** In all cases a low α results in the selection of the full optimization set. At higher α values more conservative sets are chosen, although the specific set of optimizations chosen ata given α varies with the interval. As the initial re-evaluation interval is increased the savings as well as the cost, in effect the impact, of the backoff optimizations lessens. The full set of data for this experiment is presented in Table A.5.

5.1.5 Summary

Analysis of the *low interaction repository* data set showed that only 10% of the active repositories served more than one malicious executable. Evaluation of the proposed optimizations using the collected data showed that the state based *cutoff* and *backoff* optimizations provide large reductions in fetch volume with a small reduction in sample discovery rate. The use of *conditional probability* optimizations introduced a large reduction of sample discovery rate. The effectiveness of the *conditional probability* optimizations may have been compromised by my inability to identify malware families using anti-virus detections; this is discussed further in Chapter 6.

5.2 Optimizing Re-Evaluation Fake AV Distribution Networks

This section analyzes the data gathered from malware networks distributing Fake AV by repeatedly visiting the landing pages and following the path of redirects using a HIHCs. The composition of the data set is provided in Section 5.2.1. In Section 5.2.2 I present results from analysis of the collected data. In Section 5.2.3 I evaluate the optimizations that were proposed in Section 3.2.

5.2.1 Fake AV Data Set

The data set includes high interaction fetches originating at the landing pages of Fake AV distribution networks advertised by SEO poisoning. The landing pages in this data set were taken from Sophos product feedback: any URL visited by a Sophos customer that triggers a web content detection is sent back to Sophos for analysis. I selected URLs from this feedback that triggered specific detections on known landing page content. For future reference I refer to this as the *Fake AV* data set.

The data set consists of 22,393 fetch logs. After filtering out fetch logs that did not yield a binary executable, 5,075 fetch logs remain. This dataset includes 634 URLs from 608 domains across 65 TLDs. Each site was confirmed to be serving as a landing page in a Fake AV MDN before being included in the dataset. The re-evaluation frequency in this set ranges from 2 - 4 hours for landing pages and 10 - 30 minutes for malware repositories.[20]

5.2.2 Fake AV Data Analysis

Our[21] analysis produced results consistent with previous Fake AV studies [RBM+10] performed by Rajab *et al.* in 2009 : Fake AV MDNs are updating the malware repositories and malicious payloads on a frequent basis, and there is still a strong fan in factor from the landing pages to the malware repository. This section describes our solution to identify each Fake AV MDN and presents the behavioural differences between the different MDNs.

[20] Whenever possible the malware repositories were directly evaluated from separate pools of IP addresses at higher frequency to supplement the data set.

[21] Section 5.2.2 and Section 5.2.3 contain analysis of the *Fake AV* data set that was printed verbatim in [KZRB11]. This analysis and resulting write up was performed in collaboration with Onur Komili, and included in this thesis as well as the Virus Bulletin paper. See the Statement of Authorship for more details.

Identifying Fake AV MDNs

Our focused analysis was able to identify multiple distinct update patterns in our data, which we attribute to distinct affiliate groups using the same set of resources (e.g., malware, packers, web content kit). The distinct subsets were identifiable by several dependant factors:

1. Each MDN we identified cycled through repository domains in a time sequential order with only one repository active at a given time. Figure 5.6(b) shows this temporal correlation between repositories belonging to the same MDN.

2. The malware repository URLs contain patterns that are distinct for each MDN. The patterns for each MDN are provided in Figure 5.5.

3. The injected redirection code at the landing page was distinct for each MDN.

Using only the second technique applied to the repositories above we identified four[22] MDNs in our data set. The landing pages in each MDN contained injected redirection code that was distinct for each MDN. Further, the observed lifespans of the repositories in each MDN had strong temporal correlations: only one repository was active at a given time for each MDN we identified. To illustrate the organizing effect of this procedure, we graphed the repository and sample lifetimes for the entire dataset as a whole and then separately for each MDN. This is shown in Figure 5.6. Based on the fact that the MDNs were organized using only one of the three factors, and the resulting sets were also organized according to the remaining two factors, we are confident that our identification approach was accurate for the data in the *Fake AV* data set.

```
MDN1 : /\.info/fastantivirus2011\.exe/
MDN2 : /^[^\/]+\.(findhere\.org|rr\.nu)\//
MDN3 : /^(?:188\.229\.|31\.44\.)/
MDN4 : /^(?:[^\.]+\.)+.+cdn[^\.]*\.info\//
```

Figure 5.5: **Fake AV MDN Repository Patterns** Each pattern above was applied to Fake AV malware repositories in our data set to identify the MDN to which the repository belongs.

[22]Six unique groups were identified, but two are discounted because they were only seen for a brief period.

ID	# LP	# Repo	# Exe	Average Repo LT (s)	Average Exe LT (s)
MDN_1	347	193	64	4874	19936
MDN_2	39	118	59	3783	10063
MDN_3	19	12	333	156492	10
MDN_4	8	12	17	69766	10879

Legend: LP - Landing Page, Repo - Malware Repository, LT - Lifetime

Table 5.3: **Fake AV MDN Statistics** Using the patterns for each family we subdivide the fetch logs into groups and find four distinct MDNs in our data.

Behavioural Characteristics of Fake AV MDNs

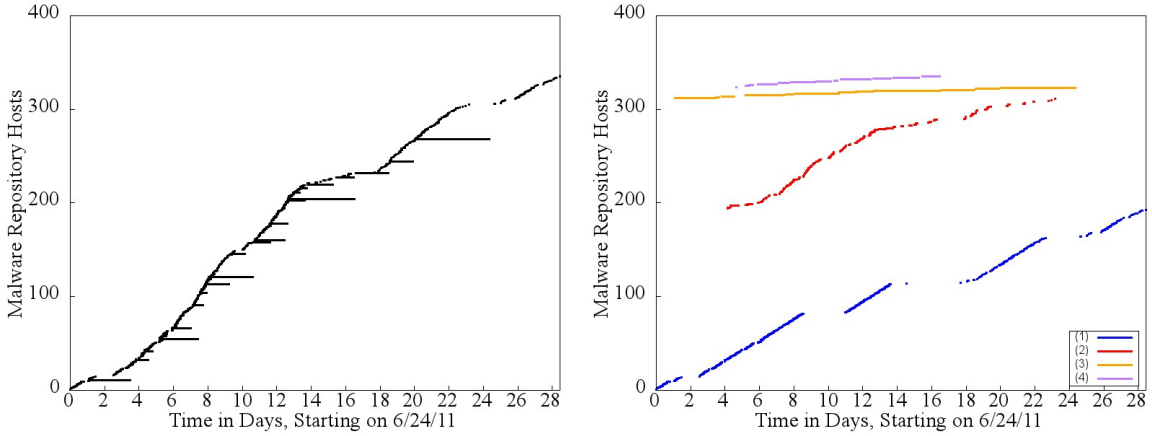
The statistics for each family are provided in Table 5.3. Of the four MDNs, MDN_1 was by far the most wide spread in terms of infected landing page counts. Compared to the next highest MDN, MDN_1 was almost 9 times more prevalent based on our customer feedback results. We present the distinct behaviours of the MDNs in terms of three characteristics: (1) The observed lifetime of the repositories; (2) The observed lifetime of the binaries, which indicates the degree of polymorphism employed by the MDN; and (3) Whether a particular MDN appears to do blacklisting, and if so what is the observed blacklisting response.

Repository Update Behaviours

We found two distinct patterns in the malware repository lifetimes. MDN_1 and MDN_2 took the approach of frequently changing the host of the malware repository, rotating them once every one to two hours, while MDN_3 and MDN_4 updated far less frequently, every half day to two days.

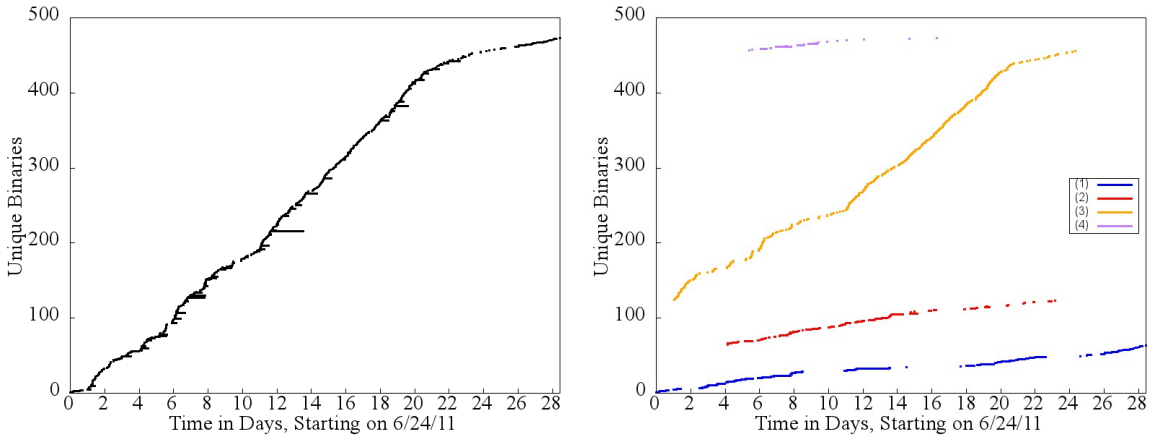
Sample Update Behaviours

We found that all MDNs periodically updated their binaries. MDN_3 appears to be using server side polymorphism, as every request to their active repository results in a new binary executable. We manually verified this in case the lifetime was simply shorter than our re-fetch interval but greater than zero, and found that the binaries were in fact dynamically generated. MDN_3 produced 333 of the 473 samples collected for all MDNs, despite having the fewest malware repositories with the longest average repository lifetime. The other three MDNs showed average binary lifetime of between two to six hours.



(a) Repo Lifetime (Unsorted)

(b) Repo Lifetime (Sorted)



(c) Sample Lifetime (Unsorted)

(d) Sample Lifetime (Sorted)

Figure 5.6: The graphs above show the lifetime of the malware repositories on the top row and the executable sample on the bottom row. The Y axis in all cases is discrete; each Y value represents a single repository/sample. The Y-axis for graphs on the left are ordered by the first seen time of the repo/sample. The Y-axis for graphs on the right are first ordered by MDN, and then ordered by first seen value, which reveals distinct patterns in the data set. It appears each family has different repository and sample update patterns. This is confirmed when looking at this data in Tabular form in Table 5.3

```
document.write(
 "<img src='//counter.yadro.ru/hit;JohnDeer?t52.6;r"
 +escape(document.referrer)
 +((typeof(screen)=="undefined")?"":";s"
 +screen.width+"*"+screen.height+"*"
 +(screen.colorDepth?screen.colorDepth:screen.pixelDepth))
 +";u"+escape(document.URL)
 +";"+Math.random()
 +""+"border='0' width='88' height='31'>"
);
```

Figure 5.7: **Fake AV MDN Screen Profiling Code Sample**. The execution of this Javascript snippet will cause the browser to make a HTTP request to *counter.yadro.ru* that contains information about the HTTP client and the current request. Note I applied wrapping and indentation to enhance readability.

Blacklisting Behaviours

Several MDNs showed signs of blacklisting. MDN_3 was an interesting case as it showed some indications of potential for blacklisting, though we never actually observed the blacklisting response. Figure 5.7 shows a snippet of Javascript code from an infected landing page used in MDN_3 that creates an image tag on the web page. When this image is requested by the browser, it will send a finger print of the client back to *yadro.ru* that contains the referrer used and the screen resolution and pixel depth. A virtualized fetcher running in headless mode will produce a pixel depth of 0. This is a clear indication to anyone monitoring server logs that an automated bot has visited the landing page. The use of JohnDeer in the path is note worthy but inconclusive.[23] Note that our experiments did not run in headless mode and therefore were not susceptible to this form of crawler fingerprinting.

MDN_1 exhibited blacklisting behaviours and was worth investigating further. We ran a separate experiment, using a new IP, that would fetch a landing page from MDN_1, as often as possible for two purposes: first, it provided more accurate measures of the repository and binary lifetimes, and second, this aggressive re-evaluation interval was more likely to trigger a blacklisting response. We started the experiment on the afternoon of June 30th. The lifetime of malware repositories throughout the experiment remained fairly consistent; a consistent update pattern is visible until July 2nd. At around 14:00 PDT the MDN began appending the query

[23] I speculate that "JohnDeer" could be a reference to John Deere, a manufacturer of heavy machinery used to *harvest*, which is a common industry term for collecting malware samples.

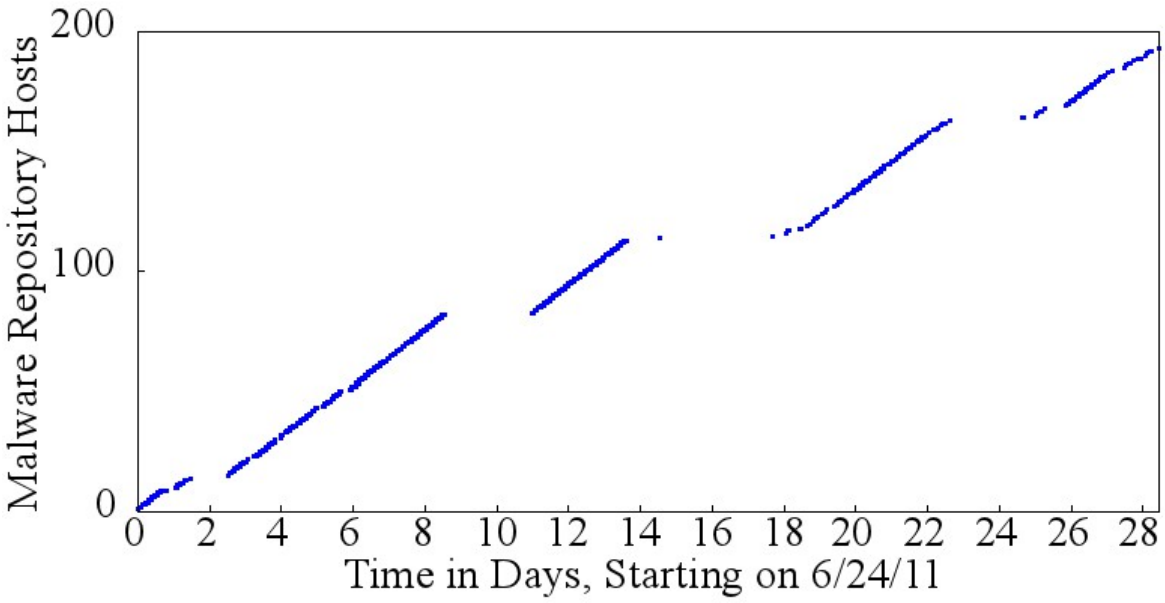


Figure 5.8: The malware repository lifetime of MDN_1, all gaps throughout the experiment occurred as a result of blacklisting. We responded to each blacklisting incident by rotating our proxy IP pool, which allowed successful monitoring to resume.

parameter *'?q=av-sucks'*, to the normal server side 302 redirects. We speculate that, in addition to encouraging us (i.e. the Anti-Virus industry), this query parameter was meant to fingerprint requests from our clients. Twelve hours later that they had fully prevented us from accessing the malware repository; that is, the landing page would no longer redirect into the MDN. We tried changing a number of variables such as the referrer string, user agent, browser plug-ins installed, HTTP request headers, but none resulted in a successful fetch. At the same time, requests from different IP pools were successful, so we conclude that blacklisting was IP based. In addition to the blacklisting incident described above, the same MDN blacklisted our IP pools on several other occasions. Figure 5.8 illustrates the time line of these incidents; each can be seen as a gap.

The other two MDNs did not appear to do any sort of blacklisting, though there were times when they redirected us to non-Fake AV content including sites trying to sell generic pills and other pay-per-click link sites. At no point did they stop serving us content altogether, and often the content served to us would randomly rotate through Fake AV, pills, and link sites.

5.2.3 Fake AV Network Re Evaluation Optimizations

To evaluate the proposed techniques from Section 3.2, we simulated the re-evaluation decisions that would be made when the optimizations were applied. First, a brief review of the optimizations is provided. Once an MDN is identified, all of the landing pages of the MDN should be pooled and tracked collaboratively. Instead of re-evaluating each landing page, only one landing page should be visited, and the results should be used to infer the state of all the landing pages of the MDN. The second optimization can be applied once an MDN has been studied for a sufficient period to determine the update frequency of the malicious executables. If the update period can be determined, and if a landing page redirects to a malware repository that has been recently evaluated (within the expected update window) then do not visit the repository and assume the sample has not been updated.

In order to perform this simulation we had to apply our assumption, that all landing pages in an MDN redirect to same repository at a given time, in order to interpolate the state of an MDN at a given time. As an example, assume an MDN having two landing pages, LP_1 and LP_2 and two repositories R_1 and R_2, and that we have data points showing that at time 10 $LP_1 \rightarrow R_1$ and at time 20 $LP_2 \rightarrow R_2$. It is possible during simulation that an algorithm makes a fetch to LP_2 at time 10 and to LP_1 at time 16. The simulation will return $LP_2 \rightarrow R_1$ at time 10 (based on evidence from the LP_1 observation at time 10), and $LP_1 \rightarrow R_2$ at time 16 (based on the nearest data point: LP_2 at time 20).

For each simulation we calculated the number of fetches that would be performed, the number of exposures to the landing pages and the repositories, the number of repositories discovered, and the number of executables discovered. Figure 5.9 shows the simulation results of a fixed interval scheduler that does not implement the proposed techniques. For each simulation the re-evaluation interval is increased. We see that the coverage (i.e., the number of repositories and binaries discovered) drops off quickly as the re-evaluation interval increases. This firmly establishes the need for frequent re-evaluation of the MDN in order to maintain coverage of the repositories and executables.

Figure 5.10 shows the impact of the first optimization techniques. A naive algorithm with a re-evaluation interval of 1 hour makes 276161 requests during the simulation, versus only 2905

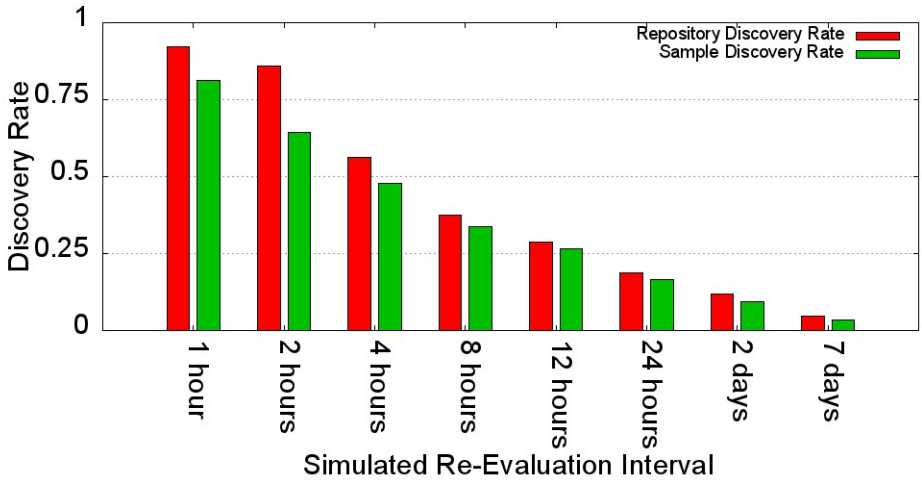


Figure 5.9: This set of simulation results illustrates the impact of increasing the re-evaluation interval on the repository and executable discovery rates. This shows that for Fake-AV MDNs the network coverage drops significantly as the re-evaluation interval is increased. This is due to the highly dynamic nature of the MDNs used to spread Fake AV. The full set of data for this experiment is presented in Table A.9.

requests made by a re-evaluation algorithm that uses knowledge of the MDN when re-evaluating landing pages. The cost of this optimization is a loss of 5 samples. When both optimizations are applied, as shown in Figure 5.11, the number of exposures to the repositories drops by as much as 50% versus using just the first optimization; however, it is clear that the second optimization comes with a cost in terms of sample discovery. The impact of the reduced discovery rate on the vendor depends on the specifics of their products, which will be discussed in Chapter 6.

In all simulations using the second optimization, the Repository Re-Evaluation Threshold (RRT) for MDN_3 was set to 0 (i.e., the second optimization is not applied to MDN_3) to account for the polymorphic nature of this MDN. For the simulation marked with the $*$, RRT for MDN_3 is set to 2 hours. The reader will note the drop in sample discovery rate that results when optimization two is applied to an MDN that has polymorphic malware repositories. This is is discussed further in Chapter 6.

5.2.4 Summary

Analysis of the *Fake AV* dataset revealed four distinct MDNs in the dataset, each exhibiting unique update behaviours. I present evidence showing that at least one MDN blacklisted my clients during data collection. This supports the assertion that reducing the number of re-

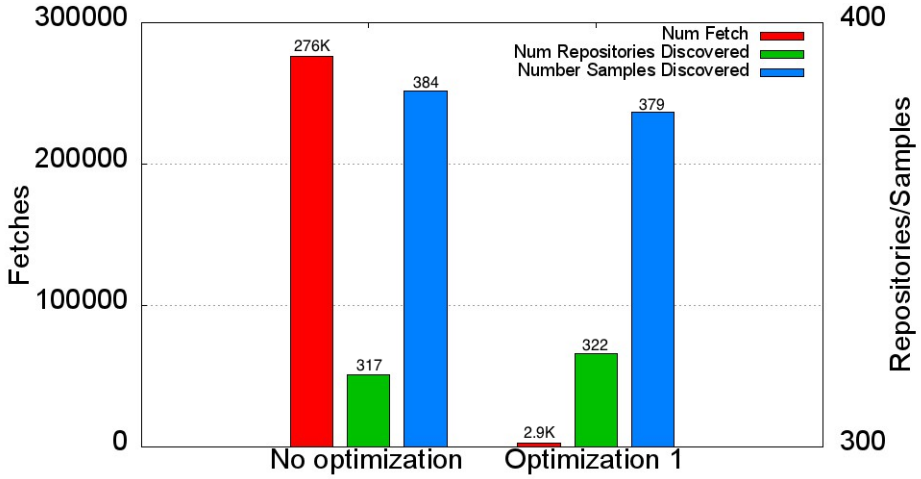


Figure 5.10: **MDN Re-Evaluation Optimization 1** The first optimization produces a 92% reduction in re-evaluations with a corresponding loss of only 5 samples. Due to changes in the sampling phase between the two simulations, there was actually an increase in the number of repositories once the optimization was applied. The full set of data for this experiment is presented in Table A.10.

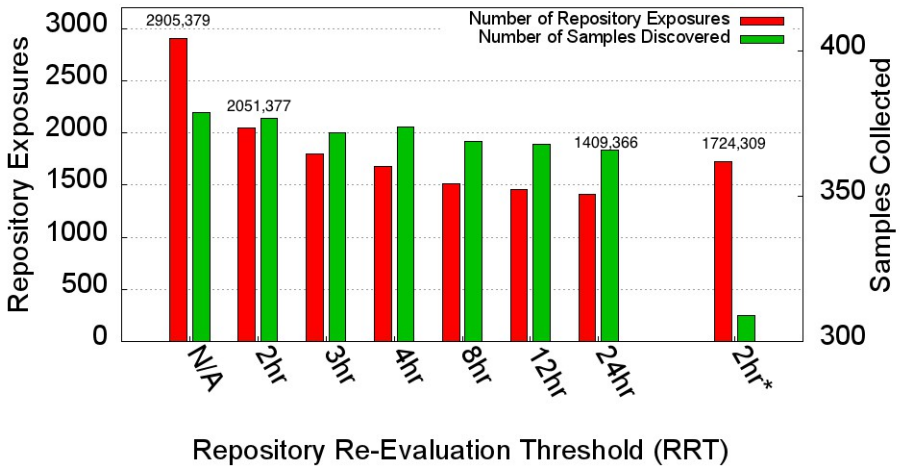


Figure 5.11: **MDN Re-Evaluation Optimization 2** This graph demonstrates the effects of applying the second optimization in addition to the first optimization, while using a one hour re-evaluation interval. Note that for all but the simulation marked with a '*', the second optimization is not applied to MDNs with polymorphic repositories (i.e., RRT=0 for all repositories in MDN_3). The second optimization produces as much as a 50% reduction in exposures to repositories, at a low sample cost (i.e., up to 11 samples). The full set of data for this experiment is presented in Table A.10.

evaluations is necessary (assuming that reducing the number of re-evaluations will reduce the likelihood of blacklisting). Evaluation of the proposed optimizations shows large reductions in fetch volume compared to a fixed interval re-evaluation algorithm that is not grouping URLs into MDNs.

Chapter 6

Discussion

In previous chapters I proposed and evaluated several optimizations to the re-evaluation logic for two distinct AIR scenarios: zero-provenance malware repositories, and landing pages that lead to Fake AV distribution networks. The key difference between these two scenarios is the missing provenance data; in the first scenario, a malware repository is investigated without knowledge of the larger MDN in which it participates. In this chapter I present the key findings from my investigation, the applications of these findings to the design of AIR systems, and the limitations of this study and the proposed optimizations.

6.1 Zero Provenance Malware Repositories

My ability to fully understand these repositories is limited by a fundamental property of the data set: the repositories do not have any provenance information; that is, I do not know the full malware delivery tree that leads to the repository. This limitation is not unique to my experiments; the majority of suspicious URL feeds available to researchers do not contain this essential context information. With this in mind, I explore the noteworthy properties of this data set and then draw conclusions from the evaluation that was performed.

6.1.1 Composition of Data Set

Analysis of the data collected showed that single sample repositories accounted for 50% of the total data set and 90% of the repositories that yielded at least one executable during study. This was an unexpected result that requires further consideration. There are several explanations I present to explain the high percentage of single sample repositories.

The first is that I am evaluating repositories that were part of an MDN before the period of

my study, and these repositories have been *abandoned* by the MDN. It is possible that malware repositories in this data set are no longer being linked to by active malware delivery trees. The MDN that the repository once participated in has shifted to new repositories that are not part of my data set, and the repository that I am studying is left active serving the same binary, even though the repository is not being used in active attacks. A troubling thought: in this scenario all of the traffic to an abandoned repository will be generated by AIR systems, providing the malware distributor a form of honeypot! A full 18% of the URLs in the dataset were inactive on the first and all subsequent requests. This large number is consistent with the assertion that many repositories in my data set were part of MDNs that actively shift repositories; the repositories studied were already abandoned when the URL enters the system.

Another possibility is that this data is representative of the overall update behaviour of malware distributors. This would suggest that 90% of the malware being distributed on the Internet does not use frequently updating distribution networks. This supports the assertion of several analysts at SophosLabs: a lot of malware distributors are lazy and unsophisticated.[24] There is much research done on the new and interesting threats that uncovers unprecedented levels of sophistication emerging in the underground malware community [SGAK+11, CGKP11, ZSSL11]. None of this research refutes the possibility that a lot of malware is distributed by very basic mechanisms.

The high rate of single sample malware repositories in my data set suggests limited value in repository re-evaluation; 75% of the malware collected in the study was collected on the first visit to a repository. However; it is clear (see Table A.2) that some types of malware consistently favor repositories that engage in sample updating, such as Fake AV (25% in the *low interaction repository* data set, and 100% in the *Fake AV* data set) and banking trojans (42% in the *low interaction repository* data set). This motivates two assertions made in this discussion: 1) there is a need for re-evaluation of some zero provenance malware repositories, and 2) optimizations should be used to reduce the number of re-evaluations per repository.

Figure 5.1 shows that the majority of state transitions take place within the first day of studying a given repository. This property of the data set allows the relatively high gains offered by the state based cutoff optimizations. Several of these distributions have long tails: 4

[24] Malware distributors: please do not take offense. Many analysts at Sophos are also lazy and unsophisticated.

of the six transitions have 90% CDF point that is more than double the 80% CDF point (see Table 5.2). Care must be taken to choose thresholds that are consistent with the preferences (fetch savings versus sample discovery) of the maintainers of the AIR system.

6.1.2 Performance of Optimizations

Of all the optimization types simulated, those that reduced the number of re-evaluations to single sample repositories offered the most savings (i.e., $cp(s)$, $ct(s)$, and $bk(s)$). This is consistent with, and likely caused by, the large percentage of single sample repositories in the data set. The conditional probability optimization produced the least impressive results: in all cases the normalized sample loss rate was higher than the normalized fetch reduction. Even with high confidence and probability thresholds (i.e., 20 and 0.9 respectively) the conditional probability optimization resulted in a sample loss of 26%. While the fetch reduction appears to quickly taper out as these thresholds are made more conservative,[25] the sample loss remains relatively high. I suspect this is due to a few high volume detections that cover a large range of samples that have nothing in common. This artificially inflates the confidence on these detections, even though they have no ability to predict the malware family. The limitations of my malware family grouping technique are discussed shortly; in short my inability to properly group malicious samples into families was the most likely cause of the poor performance of the conditional probability optimizations.

The state based cutoff and re-evaluation backoff optimizations both showed very promising results. With an unrealistically high re-evaluation interval of 1 hour the cutoff optimizations produced a normalized fetch reduction of 83% with only a 1% drop in sample discovery, while the backoff thresholds provided a 72% fetch reduction with a corresponding 6% drop in sample discovery. When the re-evaluation interval is raised to 1 day, the numbers are still high with cutoff optimizations yielding a 79% fetch reduction and the backoff optimizations providing a 21% fetch reduction. The drop in savings from the backoff optimizations as the re-evaluation interval increases is likely due to the ratio between the back offs and interval: for an interval of 1 hour the ratio is 1:1 whereas at 1 day the ratio is 1:24. I did not simulate with a one day

[25] On my use of *conservative* and *aggressive* in this discussion: conservative choices favor sample discovery, whereas aggressive choices favour greater reductions in the number of re-evaluations.

interval and backoff values of more than 1 hour. A final note on these optimizations is that they appear to be complementary. When both optimization sets are combined in a simulation with a re-evaluation interval of 1 hour, the fetch reduction increases to 93% with a sample loss of 7%. This leads to the third assertion: 3) The combined use of state based cutoff and backoff thresholds is an effective mechanism to reduce fetch volume while maintaining a high sample discovery rate.

Varying the α value, which balances sample discovery rate and fetch reduction in the success function, causes different sets of optimizations to provide the best results. In my opinion the α value of 8.2, which was an average derived from a survey, was too low for most environments. Inspecting Figure 5.4 shows that an α of 8.2 consistently favours evaluations that use all optimizations. Applying the conditional probability optimization on top of the cutoff and backoff optimizations produces an incremental fetch reduction of only 1-5% (depending on the re-evaluation interval) with a corresponding sample discovery cost of 31-22%. The combined cutoff and backoff optimization provides a much better tradeoff, this optimization combination is favored when α is set to between 100-1000, depending on the re-evaluation interval.

I observed two relationships between the initial re-evaluation interval and the optimizations. First, the overall impact of the optimizations, both in terms of fetch reduction and sample discovery cost, decreases as the initial re-evaluation increases. This observation is intuitive: as the interval increases there are less fetches to reduce and less samples to miss. Second, as the initial re-evaluation interval increases, the α values at which more conservative optimizations begin producing higher normalized success scores decreases. The final assertion from this section: 4) As the re-evaluation interval for a system increases, more conservative optimizations should be used.

The biggest lesson to take away from analysis of the zero provenance malware repositories study is that maintainers of AIR systems should aggressively constrain the amount of resources spent on zero provenance malware repositories. A full 75% of the samples can be discovered on the initial visit to the repository. Focusing on the full malware delivery tree, as shown by the Fake AV MDNs studied in this research, is preferable wherever possible. The optimizations studied in this research, particularly the state based cutoff and backoff optimizations, provide the means to quickly filter out repositories that provide no subsequent value on re-evaluation.

6.1.3 Limitations

The URLs studied were sourced exclusively from SophosLabs, who were in turn collecting this data from multiple locations, as discussed in Section 2.3.2. It is possible this feed of data is not representative of the overall behaviour of zero provenance malware repositories. Further, this study took steps to filter out landing pages and other suspicious URLs from the data set; these steps may have biased the selection of malware repositories.

The zero provenance malware repositories in this study were primarily sourced from co-operative URL exchanges between Sophos and many AV firms and security researchers. The URLs from these feeds are arriving at varying frequency (1-24 hours) and the initial delay before sharing varies with each feed. As a result, the distribution of state transition timing will likely vary between implementations.

The approach to group malware samples into families was ineffective. Due to this limitation I was unable to draw conclusions on the effectiveness of using the malware family as a predictor of repository update behaviour. The detection names assigned by vendors are a poor indicator of the malware family. Proper identification of malware families is a difficult problem,[26] and not a direct focus of this research.

In order to better group the malware executables, I would generate feature sets for each malicious executable from static analysis, emulation, and behavioural analysis, in particular the *file download tree* [CGKP11] (i.e., a dependence graph representing which samples install other samples after execution). I suspect the download tree and network behaviour will be helpful for grouping samples downloaded from the web because these samples are typically 'droppers' (i.e., their role is to avoid and/or disable AV detection, then install the 'payload') and one of their primary goals is to download subsequent malware from the pay per install infrastructure. While many droppers appear similar in terms of features, they will differ in the networks that they contact, and the malware that they install after execution. One potentially predictive factor of the MDN that is found in the dropper is the affiliate identifier, which should be common[27]

[26] David Cornell, Software Development Manager at SophosLabs Vancouver, on the difficulty of grouping malware: "It's like trying to group criminals into thieves, murderers, etc by how they are dressed".

[27] Common, but not unique: Caballero *et al.* [CGKP11] show evidence that affiliates sometimes distribute droppers for multiple PPI services, and in some case use custom droppers to install malware from multiple PPI services simultaneously.

among all droppers downloaded from a specific network.

6.2 Fake AV Malware Distribution Networks

Our analysis of known Fake AV landing pages revealed several distinct MDNs. All of the MDNs exhibited strong fan-in characteristics from landing pages to single repositories. This property can be exploited to drastically reduce the amount of re-evaluations needed to track each MDN over time.

6.2.1 Benefits of Identifying MDNs

There are several benefits to tracking the relationship between malware samples and the originating MDN, as well as tracking the update behaviours of the MDN.

Tracking the binary updating behaviour of each MDN in conjunction with current detection rate of downloaded executables can improve the detection triage process. When detection drops on samples from a purely polymorphic MDN, this requires immediate analyst attention. Any automated checksumming strategy will be ineffective as the samples are unique on every request. When detection dips on an MDN whose samples are longer lived, then an automated checksum approach is sufficient to reduce the urgency of the incident while analysts address the drop in detection rate by updating detections.

Grouping executable samples by MDN helps vendors identify patterns to improve detections. For MDN_1, 100% of the binaries are detected by a single Sophos detection. However, the samples from the other MDNs were detected by no less than six distinct Sophos detections. After providing the grouped samples to analysts, they were able to quickly produce single detections for each MDN.

The landing pages of MDNs that exhibit strong fan in can be grouped and re-evaluated using the proposed optimizations. This reduces the resources required to monitor each MDN, and reduce the chance of being blacklisted.

Blacklisting is a real threat and is being actively applied by the administrators of MDNs. This is an important phenomenon to consider when designing a system to monitor MDNs. In the same way that security vendors monitor threats and blacklist large IP ranges, so too can

malware distributors. Repeated visits to MDNs from IP addresses in the same range are easy to spot in server logs. During the data collection phase of this research, I observed the blacklisting response occur in under a week. It is important for security vendors to use large pools of IP addresses spread across disparate networks.

6.2.2 Limitations

In order to realize any of the benefits discussed above, MDNs must be constantly identified via human or automated means. Of the six MDNs that were identified, two were already gone from our incoming feed at the time of identification. One changed bulk subdomain providers during the middle of the experiment, from using *findhere.org* to using *rr.nu*. An additional two disappeared towards the end of our data collection. Only one MDN exhibited a predictable pattern for more than a month. If a human approach is taken, adequate data visualization must be provided to analysts if they are to sift through fetch logs looking for patterns. Towards automated identification, promising research [ZSSL11] has been recently presented toward this direction and future research is necessary in this area.

The optimizations presented rely on the *strong fan-in* assumption: all of the landing pages in the MDN at any given time redirect to a single repository. All of my data supported this assumption; however, there is nothing to prevent an MDN from using a compartmentalized strategy, where multiple repositories are active at once and the landing pages are split between the active repositories at any given time. The application of the proposed optimizations to a *compartmentalized* MDN would produce a drop in repository and sample discovery rates. A simple adjustment to the optimized approach would address the issue: instead of fetching only one landing page, perform a sampling of landing pages. If the sampled landing pages all redirect to a single repository, discontinue evaluation. If they do not, continue sampling landing pages until no new repositories are discovered.

6.3 Design Considerations

The state based *cutoff* and *backoff* optimizations require state to be maintained for each URL in the system. The TDG maintains a summary object for each URL studied. This proved to

be very helpful, not only for maintaining state, but also for purposes of maintaining summaries that represent data from multiple fetches, for the purposes of data visualization. However; the TDG was not built with scalability in mind. Maintaining state per URL may lead to system bottlenecks that prevent the number of concurrent clients from properly scaling horizontally. Investigating these issues is left as future work.

The MDN fan-in based optimizations require a system abstraction *greater* than the URL summary: the MDN abstraction. This abstraction exists as an object that URLs are added to when they are discovered to be part of the group. Once in the group, a single re-evaluation algorithm controls evaluations of all of the URLs in the set.

6.4 Monitoring Polymorphic Repositories

At several points throughout the previous chapters I note that dealing with polymorphic malware repositories is a difficult problem and then defer to the discussion. Here are my thoughts on how to deal with polymorphic repositories. Note that this is not a focus of this research and none of these strategies have been evaluated.

Resist the urge to collect polymorphic sample unnecessarily. Every request to a polymorphic server results in a new sample. It seems useful to collect as many samples as possible from a research and protection standpoint, however the probability that the exact samples downloaded will be used to infect a victim PC is negligible, therefore each sample is only valuable as a contribution to a corpus of similar malware, and by extension valuable as a contribution to improvements in understanding the malware and protecting against infection. There are several costs associated with downloading the sample, in addition to the AIR system cost. Every executable that enters a security lab is stored, processed by automated systems, potentially shared to other labs and repeatedly scanned in the future to test for detection regression. If the sample is not detected on entry or after automated analysis, it adds to the queues of undetected samples that must be triaged for manual analysis.

An iterative approach to sample collection from polymorphic servers that allows for analyst or automated systems to act between batches of sample collection is necessary. Once a polymorphic family has been identified, the honey client will gather a batch of specified size from

the site and then suspend further fetching. Anti-virus scans are run across the set of samples to determine the current detection rate. If the detection rate is below a specified threshold, anti-virus detections are updated, by analysts, to bring detection for this batch of samples above the threshold. Another batch of samples is downloaded, and the process is repeated, until the detection rate of new batches rises above the threshold.

Chapter 7

Conclusion

This research studies two AIRs scenarios commonly faced by security researchers: collecting data from *zero provenance malware repositories*, and collecting data from *Fake AV MDNs*. Through analysis of the behaviour of malicious networks, I propose and evaluate optimizations to the re-evaluation algorithm of AIR systems. I show through simulation that in the *zero provenance malware repositories* scenario, a combination of state based cutoff and state based backoff optimizations is able to reduce fetch volume by 80-93% (depending on the re-evaluation interval), with a corresponding drop in sample discovery rate of only 2-7%. In the *Fake AV MDN* scenario, I show through simulation that incorporating knowledge of the underlying MDN into the re-evaluation algorithm produces drastic (i.e., >90%) reductions in fetch volume compared to an approach that does not take advantage of this knowledge.

7.1 Future Work

There are several avenues for future research on re-evaluation strategies and blacklisting mitigation. I provided improvements by grouping landing pages and applying a scheduler to the group. There have been more sophisticated means of grouping recently demonstrated [ZSSL11, CGKP11]. Exploring the implications of this new research on system design in general and re-evaluation algorithms specifically offers an interesting angle for future research.

Toward zero provenance data feeds, I am interested in what can be gained from the URLs serving web content. A percentage of these will lead to landing pages of unknown distribution networks. There are several challenges to processing heterogeneous sets of suspicious URLs; the distribution networks encountered require various degrees of *simulated human interaction* and *patch levels* to trigger a malicious download. Acquiring and maintaining old versions of vulnerable software (i.e., OS, browser, and plugins) is a time consuming task, and there are a

growing number of unique human interaction tasks that some attacks require. In my research I used a basic sikuli [Pro11] script to 'say yes' to Fake AV pop-ups. Developing and maintaining simulated human computer interaction (HCI) is highly adversarial. Any techniques to bypass this adversarial game represent a valuable contribution to the field.

I observed that the technique of blacklisting is a real threat and is actively applied by the administrators of MDNs. There are several avenues to address the blacklisting problem. Any organization that deploys security software (or hardware) at user locations can attempt, with consent, to use user IP addresses as proxies. This would provide security researchers access to pools of IP address space for the purpose of malware sample collection. In this scenario adversarial blacklisting is turned on its head: when a user IP address is blacklisted it is essentially protected. Of course there are legal ramifications to be analyzed, as well as the risk of customers being targeted by MDNs in a retaliatory manner.

Another approach to the problem of blacklisting is increased collaboration among security vendors to share resources and eliminate duplicated data collection effort. URL and sample sharing among security vendors is already common practice; however, these arrangements do nothing to actually pool resources and reduce the overall number of exposures to the MDNs. It is unclear that such collaboration will naturally emerge, especially since some vendors might view their ability to crawl from a large pool if IPs as their competitive advantage.

A final avenue worth pursuing is increased cooperation with organizations that have Internet level views, such as ISPs or large research organizations. It has been shown that some MDNs pre-compute their repositories in advance. However, in other cases landing pages are periodically updated, via a pull or push mechanism, with the new repository. If these flows could be identified through passive network analysis, this would provide yet another means to reduce exposure to the MDN.

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Appendix A

Appendix

A.1 Tachyon Detection Grid Architecture

To study the behaviour of malware distribution networks over time, I built a framework that supported multiple distributed honey clients and pluggable scheduling and data analysis components. I named the framework TDG, which is a geeky Star Trek reference[28]. The TDG system consists of a single central server and multiple clients that execute instructions from the server. The system was implemented in Perl 5.8 [The11] running on Gentoo Linux [Gen11]. All major components were implemented as objects. The central server consists of persistent perl processes that communicate with each other using an Apache QPID [Mes11] message broker. Persistent data storage is realized using MySQL [MYS11] for relational data storage and a REST based key/value store implemented using Node.js [Nod11]. The architecture diagram from Section 4.1 is reproduced in Figure A.1 for easier reference. Section A.1.1 lists the conceptual components of the system and presents their responsibilities. Section A.1.2 describes the system events and how these events propagate through the components of the system.

A.1.1 System Components

Experiments

The experiment object is a high level abstraction that specifies system behaviour over a period of time. An example experiment definition is show in Figure A.2. An experiment defines a set of URLs to study, specifies the period over which to study these URLs, and defines one or more downloaders to repeatedly retrieve the URLs.

[28] In StarTrek: The Next Generation, the Federation deploys a Tachyon Detection Grid to detect cloaked Romulan vessels [Tac11]. My initial research objective was to study the use of cloaking by malware networks, and so a name was given to a bunch of code.

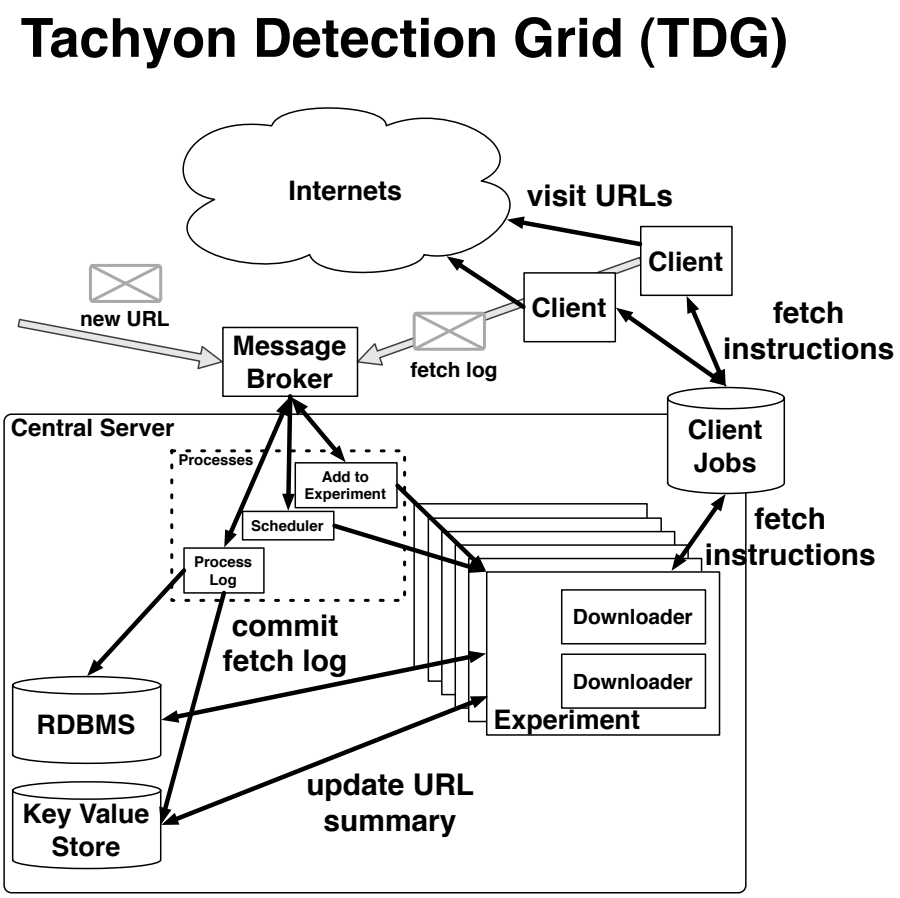

Figure A.1: Architecture of the Tachyon Detection Grid. New URLs are added to the system and added to one or more experiments. The experiments delegate the role of fetching to its downloaders. The downloaders send command to the clients, which execute the HTTP requests. New fetch results are sent back to the central sever, where the experiment is invoked to process the new fetch.

Downloaders

The downloader is another high level abstraction. The downloader is not the component that actually makes HTTP requests to the URLs, this is done by the clients. Each downloader instance specifies a client to use to make the HTTP request, the specific behaviour that the client should use while making the request (e.g., User Agent, Initial-Referer, timeouts, proxy settings), and the rescheduling behaviour to use for the duration of the experiment.

Example Experiment Definition

```
<experiment example>
 experiment_start  DATE
 experiment_end    DATE
 max_per_day       100
 max               4000

 <criteria>
  url.attr.sophos_detection = qr/SOME_FILTER/
 </criteria>

 <downloader high_volume1>
  type    TYPE
  role    high_volume
  client  CLIENT

  <fetcher_profile>
   profile LWP_IE6
   proxy          proxy1
   proxy          proxy2
   rotate_proxies 1
  </fetcher_profile>

  <scheduler>
   initial_offset 0
   initial_jitter 1200
   interval       3600
   jitter         900
  </scheduler>
 </downloader>
</experiment>
```

Figure A.2: Example Experiment Definition. The experiment above uses a single downloader. The downloader instructs *CLIENT* to use multiple proxies and impersonate Internet Explorer 6 (*IE6*) while harvesting URLs once every hour. Up to 100 URLs are added to the experiment until the max of 4000 is reached. The experiment will accept URLs that have the *sophos_detection* attribute set to a value that matches the regular expression */SOME_FILTER/*. Once experiment_end transpires, no more fetches will be executed and no further URLs will be added.

URL State

One URL state object is maintained for each downloader-URL pair. That is, if an experiment has three downloaders and a URL is added to that experiment, the TDG will maintain three URL states for the URL. Maintaining separate URL states for each downloader allows us to detect when one downloader is being blacklisted. Example URL summaries are provided in Figure A.3. The URL summary contains a historical summary of the fetch results and state transitions over the course of the experiment. The URL state model is an important component of the system that facilitates analysis of URLs. These states are used for several proposed optimizations, which are discussed in Section 3.1.

Fetch Log

Every time a client fetches a URL, a Fetch Log object is created by the client and processed by the central server. The fetch log contains a list of all the URLs visited during a fetch, all URL relationships, a snapshot of the DNS information for each URL visited, and a link to the content retrieved from each URL.

Clients

The clients receive fetch instructions from the central server and perform HTTP get requests to the server. The TDG is agnostic of the client implementation details. Any client that can: 1) retrieve commands from a MySQL server and 2) transfer files via SSH push or pull operations, can be used by the TDG. This flexibility allowed me to quickly add a HIHC late in the results gathering phase to test new hypotheses. Two honey clients are used to generate the results presented in this paper:

Low Interaction Honey Client (LIHC)

The LIHC is implemented using a wrapped version of the Perl WWW Library (LWP) package. Notable feature additions include the ability to interpret and follow HTTP redirects, and modify HTTP headers such as the User-Agent and Referer. The generation of the fetch log was trivial given the client is implemented for this project and I control the HTTP client code base - this is

Example URL Summary

```
<summary>
 <exe_counts>
  <exe_occurances>
   A = 13
   B = 19
  </exe_occurances>
  max_exe_occurances = 19
  max_sha1           = B
  num_fetches        = 32
  sum_exe_occurances = 32
  unique_exes        = 2
 </exe_counts>
 seed_url => "1.2.3.4:88/hs/12.exe",
 <state_history>
  (state:START, count:1, first:TS, last:TS),
  (state:SINGLE_SAMPLE, count:13, first:TS, last:TS),
  (state:PERIODIC_SAMPLE:19, first:TS, last:TS),
 </state_history>
 <download_history>
  <urls>
   <69.197.39.24:88/hs/12.exe>
    (code:200,ct:EXE,first:TS,last:TS,count:13,sha1:A)
    (code:200,ct:EXE,first:TS,last:TS,count:19,sha1:B)
   <69.197.39.24:88/hs/12.exe>
  </urls>
 </download_history>
</summary>
```

Figure A.3: Example URL Summary. The summary above is for a URL that served two executables over the investigation period. Note that URL Summaries are stored in JSON format; this example was converted to a more readable format.

not the case for the HIHC.[29] This client does not follow HTML or JS redirects, and is therefore limited to the study of URLs that directly host malicious binary executables. The bulk of the results presented are generated by this client.

High Interaction Honey Client (HIHC)

The HIHC is implemented using Virtual Box [Vir11] running a Windows XP2 guest image. An instance of Firefox is controlled using VBoxManage commands and directed to visit URLs. All redirection and content interpretation is handled by Firefox, thus the resulting fetch log is very close to the use experience when visiting the URL. Human interaction with the web server is simulated using Sikuli [Pro11], a software for automating human computer interaction using images.

Generation of the fetch log is a more complicated task compared to the LIHC because I cannot easily modify Firefox to generate this data. To generate the fetch log, I use tcpdump [TCP11] to capture all TCP/IP traffic generated by the Windows guest image, and then process the resulting packet capture file using a modified version of jsunpack [jsu11].[30] The HIHC is used to harvest known *landing pages* in Fake AV distribution networks. These landing pages are initially discovered by processing feedback from Sophos product feedback.

A.1.2 System Events

The components of the central server are organized in a hierarchical structure with the *experiment* object at the top. *Experiments* contain one or more *downloaders*, which contain one scheduling component and are linked to one client. The main scheduling process starts by instantiating all *experiments*, then enters an event processing loop. When an event arrives, via the QPID messaging broker, the event will either be passed to every experiment or to a specific experiment, depending on the type of event. Both the experiment and downloader objects have handlers for each event type. The events propagate down the hierarchical structure from the experiment down to the downloaders. The different event types are discussed in the following subsections.

[29] Firefox is the browser used in the HIHC. Modifying Firefox is a more complex task than modifying a small Perl code base.

[30] The modifications to jsunpack were minor; I added routines at the end of the execution to write the URL to URL and URL to file relationships to a file.

(www.badurl.com/foo, sophos_detection, Mal/SuperBad),
(www.badurl.com/bar, behavioural_http_request, *file_id*)

Figure A.4: Example URL Attribute Tuples: The first tuple communicates the Sophos AV detection of the contents of the URL *www.badurl.com/foo*. The second tuple communicates that a sample made a HTTP request to the URL www.badurl.com/bar during behavioural analysis.

New Candidate URLs

New URLs are sent to the TDG in batches by external systems. The characteristics of the URLs contained in these feeds are detailed in Section 5.1.2 and Section 5.2.1. Each message contains a list of URL attribute tuples, where each tuple contains a URL, an attribute identifier, and a value for the attribute. Several example URL attribute tuples are shown in Figure A.4. Each URL attribute tuple is processed by the experiment objects for potential inclusion. If the URL meets the criteria for inclusion it will be added to the experiment for subsequent analysis. Every time a URL is accepted, an *Experiment Accepts URL* event is emitted.

Experiment Accepts URL

When an experiment accepts a URL, each of the experiment downloader objects schedules an initial fetch at a time determined by the scheduling class. The fetch profile is generated for the fetch and added to the job instructions that are sent to the client.

New Fetch Result

A separate process periodically retrieves new fetch results from the clients and uploads the results to the data store. Once this is complete, a new fetch event is emitted. This event is handled by a single experiment object, which in turn passes the event to the downloader that created the fetch job. The downloader passes the fetch log object to the URL summary object, which then updates state. If a state transition occurs, the transition is handled. Example action taken on transition include a halt of subsequent fetches, a change in the subsequent fetching pattern, the queueing an intermediate URL in a separate experiment, or a test fetch to identify blacklisting (see Section 4.2).

A.2 Zero Provenance Malware Repositories Tabular Data

The raw data used to compute the figures and metrics in Section 5.1 are included in this appendix.

A.2.1 Probability of Update Behaviour Given Initial Detection

I used the detection results from the multi vendor scanning system (described in Section 4.2) to compute $P(B_U|d_U)$ for each detection in the data set, which is the conditional probability that a URL U will exhibit a specific update behaviour B given the detection (d) of the first downloaded executable sample. The full set of $P(B_U|d_U)$ values is provided in Table A.1. A summary of the results are provided in Table A.2.

When multiple vendors reported a *malicious* detection, the following vendor ordering was used to choose a detection: TrendMicro, Symantec, Sophos, Microsoft, Kaspersky, Avira, McAfee, K7. This order was chosen by arranging the vendors in ascending order by the number of unique detections that each vendor produced on the corpus. The implied logic is that better grouping will be produced by favoring vendors that produce fewer distinct detection names.

Table A.1 Detection vs Update Behaviour ($P(B|d)$)

Detection (d)	Vendor	DP	$P(S\|d)$	$P(M\|d)$	$P(P\|d)$
Trojan (0027f95b1)	K7	1	0.00	0.00	1.00
the Artemis!BB1B45B1DEB0 trojan	McAfee	4	0.00	0.00	1.00
Trojan (6f824de80)	K7	17	0.00	0.00	1.00
the Downloader-CEW.ay trojan	McAfee	3	0.00	0.33	0.67
the Generic FakeAlert.ama trojan	McAfee	3	0.33	0.00	0.67
TR/Jorik.Skor	Avira	3	0.33	0.33	0.33
the Downloader-CEW.ba trojan	McAfee	11	0.09	0.64	0.27
Trojan.Win32.Menti	Kaspersky	24	0.00	0.88	0.12
Trojan.FakeAV	Symantec	41	0.51	0.37	0.12
Hoax.Win32.ArchSMS	Kaspersky	91	0.45	0.47	0.08

Continued on next page

Table A.1 – continued from previous page

Detection (d)	Vendor	DP	$P(S\|d)$	$P(M\|d)$	$P(P\|d)$
TROJ_FAKEAV	Trend	32	0.50	0.44	0.06
Mal/FakeAV	Sophos	160	0.84	0.15	0.01
Trojan (0026d08f1)	K7	1	0.00	1.00	0.00
the W32/Autorun.worm!mw virus	McAfee	1	0.00	1.00	0.00
Trojan-Downloader (0026d80e1)	K7	1	0.00	1.00	0.00
Trojan (002709841)	K7	1	0.00	1.00	0.00
Trojan-Downloader (0026d41f1)	K7	2	0.00	1.00	0.00
Trojan (0f3455440)	K7	1	0.00	1.00	0.00
Riskware (971f13f40)	K7	1	0.00	1.00	0.00
the W32/Pinkslipbot.gen.ae virus	McAfee	1	0.00	1.00	0.00
the Generic.dx!zrv trojan	McAfee	3	0.00	1.00	0.00
Trojan (16c7f9920)	K7	2	0.00	1.00	0.00
Trojan (00268a191)	K7	7	0.00	1.00	0.00
Hoax.Win32.FlashApp	Kaspersky	1	0.00	1.00	0.00
Trojan (72cb44930)	K7	3	0.00	1.00	0.00
Trojan (0027f95a1)	K7	1	0.00	1.00	0.00
Trojan-Downloader (002700861)	K7	1	0.00	1.00	0.00
the Generic Downloader.x!fxu trojan	McAfee	2	0.00	1.00	0.00
Backdoor (e98cee350)	K7	1	0.00	1.00	0.00
trojan or variant New Malware.j	McAfee	1	0.00	1.00	0.00
the Generic Downloader.x!fys trojan	McAfee	2	0.00	1.00	0.00
Trojan (0026dded1)	K7	1	0.00	1.00	0.00
Trojan (002811911)	K7	3	0.00	1.00	0.00
Riskware (8a8f1f650)	K7	1	0.00	1.00	0.00
Riskware (d05016e90)	K7	1	0.00	1.00	0.00
Trojan (0b98dbf20)	K7	1	0.00	1.00	0.00

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Table A.1 – continued from previous page

Detection (d)	Vendor	DP	$P(S\|d)$	$P(M\|d)$	$P(P\|d)$
TR/Menti.gnip	Avira	1	0.00	1.00	0.00
Backdoor (0026fab61)	K7	1	0.00	1.00	0.00
Unwanted-Program (4d907a180)	K7	1	0.00	1.00	0.00
Riskware (d445829e0)	K7	1	0.00	1.00	0.00
the ProcKill-FQ trojan	McAfee	1	0.00	1.00	0.00
TR/Dynamer.dtc	Avira	2	0.00	1.00	0.00
the Artemis!43DCF5419A07 trojan	McAfee	1	0.00	1.00	0.00
Backdoor (001a67301)	K7	2	0.00	1.00	0.00
the Artemis!C2BA4B7834EB trojan	McAfee	2	0.00	1.00	0.00
Riskware (82c9a6270)	K7	1	0.00	1.00	0.00
Trojan (0026e48d1)	K7	1	0.00	1.00	0.00
Infected: TrojanDropper:Win32/Malf.gen	Microsoft	1	0.00	1.00	0.00
TR/Soduc.A	Avira	3	0.33	0.67	0.00
the Generic Downloader.x!dwg trojan	McAfee	8	0.38	0.62	0.00
Riskware (23c807e00)	K7	2	0.50	0.50	0.00
Spyware.Keylogger	Symantec	2	0.50	0.50	0.00
Trojan (0026e2b51)	K7	2	0.50	0.50	0.00
TR/Spy.Gen	Avira	2	0.50	0.50	0.00
the Artemis!EB107E3752CD trojan	McAfee	2	0.50	0.50	0.00
Mal/Banker	Sophos	16	0.56	0.44	0.00
TROJ_FAKEAL	Trend	81	0.58	0.42	0.00
Trojan (fa64a74e0)	K7	5	0.60	0.40	0.00
Riskware (eca15ce20)	K7	77	0.64	0.36	0.00
TR/ATRAPS.Gen	Avira	3	0.67	0.33	0.00
Trojan-Banker.Win32.Banker	Kaspersky	3	0.67	0.33	0.00
the Generic Malware.co trojan	McAfee	43	0.72	0.28	0.00

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Table A.1 – continued from previous page

Detection (d)	Vendor	DP	$P(S\|d)$	$P(M\|d)$	$P(P\|d)$
Riskware (c2ab9b1b0)	K7	4	0.75	0.25	0.00
Trojan (002812b01)	K7	4	0.75	0.25	0.00
Trojan-Downloader (85360ede0)	K7	4	0.75	0.25	0.00
Infected: TrojanDownloader:Win32/Agent	Microsoft	4	0.75	0.25	0.00
Infected: Rogue:Win32/FakeRean	Microsoft	13	0.77	0.23	0.00
Virus (e9ad17b50)	K7	5	0.80	0.20	0.00
Infected: Rogue:Win32/FakeRean	Microsoft	13	0.77	0.23	0.00
Trojan (72cb44930)	K7	3	0.00	1.00	0.00
Mal/HckPk	Sophos	11	0.91	0.09	0.00
Virus (e9ad17b50)	K7	5	0.80	0.20	0.00
Mal/Agent	Sophos	5	0.80	0.20	0.00
the trojan	McAfee	17	0.82	0.18	0.00
Riskware (42eab5340)	K7	19	0.84	0.16	0.00
Trojan-Downloader (c7a4d3720)	K7	7	0.86	0.14	0.00
Trojan (f1000f011)	K7	8	0.88	0.12	0.00
Spyware (0000b17b1)	K7	9	0.89	0.11	0.00
Mal/EncPk	Sophos	9	0.89	0.11	0.00
Trojan-Downloader.Win32.NSIS	Kaspersky	9	0.89	0.11	0.00
Riskware (92215c660)	K7	9	0.89	0.11	0.00
HEUR/Crypted	Avira	9	0.89	0.11	0.00
TR/Crypt.XPACK	Avira	10	0.90	0.10	0.00
TR/Dropper.Gen	Avira	22	0.91	0.09	0.00
Riskware (1e20d6d00)	K7	11	0.91	0.09	0.00
Mal/HckPk	Sophos	11	0.91	0.09	0.00
Mal/Emogen	Sophos	29	0.93	0.07	0.00
Virus (00001b791)	K7	15	0.93	0.07	0.00

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Table A.1 – continued from previous page

Detection (d)	Vendor	DP	$P(S\|d)$	$P(M\|d)$	$P(P\|d)$
Riskware (0015e4f11)	K7	61	0.93	0.07	0.00
Riskware (0015e4f01)	K7	102	0.94	0.06	0.00
Trojan (f10005021)	K7	38	0.95	0.05	0.00
Riskware (f9b383990)	K7	19	0.95	0.05	0.00
Riskware (3c86d9f30)	K7	142	0.96	0.04	0.00
Virus (00001b711)	K7	92	0.98	0.02	0.00
Mal/Generic	Sophos	76	0.99	0.01	0.00
Mal/Behav	Sophos	89	0.99	0.01	0.00
Trojan (0001140e1)	K7	114	0.99	0.01	0.00
Riskware (0015e4f21)	K7	74	1.00	0.00	0.00
PE_SALITY	Trend	63	1.00	0.00	0.00
Trojan (001c45ea1)	K7	62	1.00	0.00	0.00
Trojan (00071a9a1)	K7	50	1.00	0.00	0.00
EmailWorm (0006f2d01)	K7	47	1.00	0.00	0.00
Trojan (00071a9b1)	K7	34	1.00	0.00	0.00
the Artemis!CEA29C3F8D2A trojan	McAfee	26	1.00	0.00	0.00
Unwanted-Program (4ea219740)	K7	22	1.00	0.00	0.00
Troj/FakeAV	Sophos	22	1.00	0.00	0.00
Virus (00001b701)	K7	19	1.00	0.00	0.00
Trojan (0020fd751)	K7	19	1.00	0.00	0.00
Trojan-Downloader (dd62c54e0)	K7	17	1.00	0.00	0.00
Virus (00001b6e1)	K7	16	1.00	0.00	0.00
Riskware (2d8224700)	K7	14	1.00	0.00	0.00
Spyware (0004ee611)	K7	14	1.00	0.00	0.00
Riskware (444b28a80)	K7	13	1.00	0.00	0.00
Trojan (0006f5451)	K7	11	1.00	0.00	0.00

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Table A.1 – continued from previous page

Detection (d)	Vendor	DP	$P(S\|d)$	$P(M\|d)$	$P(P\|d)$
Riskware (b3e6b1d30)	K7	11	1.00	0.00	0.00
Trojan (0024f7fb1)	K7	11	1.00	0.00	0.00
the Generic.dx trojan	McAfee	10	1.00	0.00	0.00
Trojan (8f7a56420)	K7	10	1.00	0.00	0.00
6 detections w/ no update	n/a	9	1.00	0.00	0.00
10 detections w/ no update	n/a	8	1.00	0.00	0.00
10 detections w/ no update	n/a	7	1.00	0.00	0.00
19 detections w/ no update	n/a	6	1.00	0.00	0.00
18 detections w/ no update	n/a	5	1.00	0.00	0.00
34 detections w/ no update	n/a	4	1.00	0.00	0.00
60 detections w/ no update	n/a	3	1.00	0.00	0.00
198 detections w/ no update	n/a	2	1.00	0.00	0.00
1233 detections w/ no update	n/a	1	1.00	0.00	0.00

Table A.1: This table presents the probability of repository update behaviour given the detection of the first executable sample downloaded from the repository.

Set	URLs	P(S)	P(M)	P(P)
All URLs	3959	89.9%	7.7%	2.4%
Fake AV URLs	353	71%	25.5%	3.4%
Banker Trojan URLs	19	57.9%	42.1%	0

Criteria	Detections	URLs
$n(d) > 10$ & $P(s\|d) \geq 0.7$	41	1648
$n(d) > 10$ & $P(s\|d) \geq 0.8$	39	1592
$n(d) > 10$ & $P(s\|d) \geq 0.9$	36	1369
$n(d) > 10$ & $P(s\|d) \geq 1.0$	21	565
$n(d) > 5$ & $P(s\|d) \geq 0.7$	113	2126
$n(d) > 5$ & $P(s\|d) \geq 0.8$	111	1592
$n(d) > 5$ & $P(s\|d) \geq 0.9$	99	1804
$n(d) > 5$ & $P(s\|d) \geq 1.0$	84	973
$n(d) > 5$ & $(P(m\|d) + P(p\|d)) \geq 0.1$	27	742
$n(d) > 5$ & $(P(m\|d) + P(p\|d)) \geq 0.2$	16	476
$n(d) > 5$ & $(P(m\|d) + P(p\|d)) \geq 0.3$	12	410
$n(d) > 5$ & $(P(m\|d) + P(p\|d)) \geq 0.4$	10	292
$n(d) > 5$ & $(P(m\|d) + P(p\|d)) \geq 0.5$	5	67

Table A.2: **Summary of Update Behaviour Probability**. The top table shows the overall distribution of update behaviours among the repositories that served at least one malicious binary. When the set is limited to Fake AV or Banking Trojans, the distribution changes significantly. The bottom table summarizes the results provided in Table A.1. Each row provides stats on how many different detection and URLs satisfy certain criteria. The $n(d)$ value represents the number of URLs that contribute to the probability computation. For example, there were 41 distinct detections, seen on 1648 different URLs where the $P(s|d)$ was over 0.7 and there were at least 10 data points (i.e., URLs) supporting the $P(s|d)$.

A.2.2 Evaluation of Optimizations

LIHC Simulation Varying Re-evaluation Interval						
Interval	numF	numS	numFm	fetch Δ	sample Δ	family Δ
Actual Data	502391	4786	1813	n/a	n/a	n/a
1 hour	3822679	4711	1813	-6.7	0.064	0
8 hours	480016	4216	1785	0.045	0.487	0.171
16 hours	241682	4103	1772	0.526	0.584	0.25
1 day	162157	4041	1761	0.687	0.637	0.317
2 days	82785	3949	1740	0.847	0.715	0.445
3 days	56239	3908	1733	0.9	0.75	0.488
4 days	43351	3884	1725	0.926	0.771	0.537
5 days	34642	3872	1721	0.944	0.781	0.561
7 days	18778	3829	1710	0.976	0.818	0.628
15 days	13425	3768	1690	0.987	0.87	0.75
20 days	10955	3766	1690	0.992	0.872	0.75
never	6816	3616	1649	1	1	1

Table A.3: Varying the fetch interval with no optimizations produces a predictable trend of increased fetch savings at the cost of sample coverage. For this set of results the cost metrics are computed versus the actual data set. In all other result sets presented, the values above are used as the baseline to compute cost metrics. The last row of data presents results from a simulations where no re-evaluations are performed. In this scenario, 3616 samples are still discovered, or 75.5% of the total corpus.

Malware Repositories Simulation: Optimization Results at Low Fetch Interval (1hr)						
Optimizations	fR	sC	nS(8.2)	nS(100)	nS(1000)	nS(10000)
None	3822679	4711	n/a	n/a	n/a	n/a
$cp(s)$	**0.222**$^{\natural}$	0.291	845355	816078	528978	-2342022
$cp(m)$	0.015	0.055	55816	50309	-3691	-543691
$ct(i)$	0.24	0.002	914584	914400	912600	894600
$ct(s)$	**0.534**†	0.013	2037365	2036080	2023480	1897480
$ct(ae)$	0.086	0.001	329066	328974	328074	319074
$ct(an)$	0.003	0	10939	10939	10939	10939
$bk(s)$	**0.615**‡	0.043	2345313	2340999	2298699	1875699
$bk(ae)$	0.105	0.002	400514	400330	398530	380530
$bk(an)$	0.005	0.016	19245	17593	1393	-160607
$cp(\forall)$	0.229	0.324	872815	840234	520734	-2674266
$ct(\forall)$	0.831	0.016	3170616	3169056	3153756	**3000756**
$bk(\forall)$	0.718	0.061	2740810	2734661	2674361	2071361
$ct(\forall) + bk(\forall)$	0.932	0.073	3555654	3548312	**3476312**	2756312
ALL	0.946	0.385	**3607778**	**3569048**	3189248	-608752
Legend: fR - fetch Reduction, sC - sample cost, nS - success metric. See Section 4.3.3.						

Table A.4: The results show a wide range of fetch savings are possible depending on the optimization combination used. The single sample cutoff optimization† and the single sample backoff optimization‡ provide the largest individual reduction in fetch volume. The $cp(s)^{\natural}$ also produced a significant reduction in fetch volume, however this optimization produced a much larger cost in samples versus the previous two hilighted optimizations (i.e., 29% sample loss vs 1-4%). The highest normalized success value for each α value are presented in bold face. This data is graphed in Figure 5.3

LIHC Simulation: Best Optimization Combination For Intervals									
Optimizations	Interval	numF	numS	fR	sC	nS(8.2)	nS(100)	nS(1000)	nS(10000)
$bk(\forall)$	3600	1081318	4644	0.718	0.061	2740810	2734661	2674361	2071361
$ct(\forall)$	3600	651923	4694	0.831	0.016	3170616	3169056	3153756	**3000756**
$ct(\forall) + bk(\forall)$	3600	266367	4631	0.932	0.073	3555654	3548312	**3476312**	2756312
ALL	3600	211431	4289	0.946	0.385	**3607778**	**3569048**	3189248	-608752
$bk(\forall)$	28800	262165	4214	0.46	0.003	217835	217651	215851	197851
$ct(\forall)$	28800	90872	4199	0.822	0.028	389004	387444	372144	219144
$ct(\forall) + bk(\forall)$	28800	73873	4198	0.858	0.03	405995	404343	**388143**	**226143**
ALL	28800	56646	4027	0.895	0.315	**421816**	**404470**	234370	-1466630
$bk(\forall)$	57600	170643	4103	0.302	0.000	71039	71039	71039	71039
$ct(\forall)$	57600	54191	4094	0.798	0.018	187417	186591	178491	**97491**
$ct(\forall) + bk(\forall)$	57600	48800	4093	0.821	0.021	192800	**191882**	**182882**	92882
ALL	57600	38897	3988	0.863	0.236	**201839**	191285	87785	-947215
$bk(\forall)$	86400	130161	4040	0.206	0.002	31988	31896	30996	21996
$ct(\forall)$	86400	38742	4034	0.794	0.016	123357	**122715**	**116415**	**53415**
$ct(\forall) + bk(\forall)$	86400	38630	4031	0.795	0.024	123445	122527	113527	23527
ALL	86400	31129	3935	0.843	0.249	**130156**	120428	25028	-928972

Table A.5: In all cases a low α results in the selection of the full optimization set. At higher α values more conservative sets are chosen, although the specific set of optimizations chosen seems to vary with the interval. As the initial re-evaluation interval is increased the savings as well as the cost, in effect the impact, of the optimizations lessens. The highest normalized success value for each α value are presented in bold face. This data is graphed in Figure 5.4

LIHC Simulation: Different Conditional Probability Parameter Sets							
$CP(S\|d)$	$CP(M\|d)$	fR	sC	nS(8.2)	nS(100)	nS(1000)	nS(10000)
$CP_S(20, 0.7)$	$CP_M(5, 0.1)$	0.121	0.267	457484	430685	167885	-2460115
$CP_S(20, 0.9)$	$CP_M(5, 0.1)$	0.122	0.267	463535	436736	173936	-2454064
$CP_S(10, 0.7)$	$CP_M(5, 0.1)$	0.166	0.275	632856	605231	334331	**-2374669**
$CP_S(10, 0.9)$	$CP_M(5, 0.1)$	0.174	0.308	660467	629538	326238	-2706762
$CP_S(5, 0.9)$	$CP_M(5, 0.1)$	0.229	0.324	872815	840234	520734	-2674266
$CP_S(5, 0.7)$	$CP_M(5, 0.1)$	0.232	0.342	881869	847452	509952	-2865048
$CP_S(4, 0.9)$	$CP_M(5, 0.1)$	0.247	0.363	938713	902185	543985	-3038015
$CP_S(4, 0.7)$	$CP_M(5, 0.1)$	0.251	0.396	952764	912932	522332	-3383668
$CP_S(3, 0.9)$	$CP_M(5, 0.1)$	0.266	0.373	1013228	975783	608583	-3063417
$CP_S(3, 0.7)$	$CP_M(5, 0.1)$	0.27	0.406	1027271	986430	585930	-3419070
$CP_S(2, 0.9)$	$CP_M(5, 0.1)$	0.298	0.392	1131837	1092464	706364	-3154636
$CP_S(2, 0.7)$	$CP_M(5, 0.1)$	0.301	0.426	1145879	1103111	683711	-3510289
$CP_S(1, 0.9)$	$CP_M(5, 0.1)$	0.372	0.489	1414338	1365237	**883737**	-3931263
$CP_S(1, 0.7)$	$CP_M(5, 0.1)$	0.375	0.522	**1427507**	**1375010**	860210	-4287790
$CP_S(5, 0.9)$	$CP_M(5, 0.1)$	0.229	0.324	872815	840234	**520734**	**-2674266**
$CP_S(5, 0.9)$	$CP_M(4, 0.1)$	0.23	0.33	875179	842047	517147	-2731853
$CP_S(5, 0.9)$	$CP_M(3, 0.1)$	0.231	0.333	877208	843709	515209	-2769791
$CP_S(5, 0.9)$	$CP_M(2, 0.1)$	0.231	0.341	880173	845940	510240	-2846760
$CP_S(5, 0.9)$	$CP_M(1, 0.1)$	0.232	0.357	**883411**	**847526**	495626	-3023374
Legend: $CP_X(A, B)$: A - confidence threshold, B - probability threshold, S - single, M - multi							

Table A.6: Varying the $P(M|d)$ cutoffs produced little effect. Interestingly, varying the $P(S|d)$ thresholds from 90% to 70% also had little impact. Increasing the required confidence for the $P(S|d)$ cutoff from 5 to 10 produced a decrease in sample cost by 2-7%, depending on the probability threshold. The highest normalized success value for each α value are presented in bold face.

LIHC Simulation: Different State Cutoff Thresholds						
Parameter Set	fR	sC	nS(8.2)	nS(100)	nS(1000)	nS(10000)
90-base	0.831	0.016	3170616	3169056	3153756	**3000756**
80-base	0.894	0.047	3409804	3405123	3359223	2900223
oneday	0.909	0.069	3468156	3461181	3392781	2708781
aggressive	0.924	0.079	**3527052**	**3519159**	**3441759**	2667759
oneday parameters: ct(i) - 24 hr, ct(s) - 24 hr, ct(ae) - 6 hour, ct(an) - 24 hr						
aggressive parameters: ct(i) - 24 hr, ct(s) - 12 hr, ct(ae) - 6 hour, ct(an) - 24 hr						

Table A.7: Different parameter sets for the state cutoff values are simulated with a re-evaluation interval of one hour. Using aggressive cutoffs reduces the fetch volume with a predictable drop in sample discovery rate. The 80 and 90 base sets are derived in the previous section and presented in Table 5.2. The highest normalized success value for each α value are presented in bold face.

LIHC Simulation: Different State Backoff Parameters						
Backoff Increment	fR	sC	nS(8.2)	nS(100)	nS(1000)	nS(10000)
onehour	0.718	0.061	2738174	2732025	2671725	**2068725**
twohour	0.733	0.101	2795845	2785658	2685758	1686758
fourhour	0.743	0.121	**2835433**	**2823318**	**2704518**	1516518

Table A.8: Several different values were used to increment the re-evaluation interval used by the state based backoff optimizations. The sample cost appears to rise at a faster rate than the fetch reduction as the re-evaluation increment is increased. The highest normalized success value for each α value are presented in bold face.

A.3 Fake AV MDN Tabular Data

Impact of Re-Evaluation Interval on MDN Coverage					
Interval	Fetches	LP Exp	R Exp	numR	numS
Actual Data	22393	22393	22393	344	473
1 hour	276161	276161	276161	317	384
2 hour	138254	138254	138254	295	304
4 hour	69310	69310	69310	194	226
8 hour	34842	34842	34842	129	159
12 hour	23119	23119	23119	99	126
1 day	11762	11762	11762	64	79
2 days	6074	6074	6074	41	45
7 days	1999	1999	1999	16	16
Legend: LP - landing page, R - repo, Exp - exposures, S - samples					

Table A.9: This set of simulation results illustrates the impact of increasing the re-evaluation interval on the repository and executable discovery rates. This shows that for Fake-AV MDNs the network coverage drops significantly as the re-evaluation interval is increased. This is due to the highly dynamic nature of the MDNs used to spread Fake AV.

Evaluation of FakeAV MDN Re-Evaluation Optimizations							
Opts	Interval	RRT	Fetches	LP Exp	R Exp	numR	numS
Actual Data			22393	22393	22393	344	473
00	1 hour	-	276161	276161	276161	317	384
01†	1 hour	-	2905	2905	2905	322	379
11	1 hour	2 hours	2905	2905	2051	322	377
11	1 hour	2 hours‡	2905	2905	1724	322	309
11	1 hour	3 hours	2905	2905	1795	322	372
11	1 hour	4 hours	2905	2905	1676	322	374
11	1 hour	8 hours	2905	2905	1512	322	369
11	1 hour	12 hours	2905	2905	1455	322	368
11	1 hour	24 hours	2905	2905	1409	322	366
Legend: LP - landing page, R - repo, E - exposures, S - samples RRT - Repository Re-evaluation Threshold							

Table A.10: The application of the first proposed optimization (†) results in a drastic (99%) reduction in the fetch volume required to profile the MDN. The second optimization further reduces the number of exposures to the malware repositories; however, the second optimization does have a small cost in terms of missed samples.

A.4 Blacklisting Case Studies

The LIHC study of repositories did not show any sign of closed loop blacklisting systems (i.e., a fully automated process to identify and block researcher IPs); however, I did observe several malware servers blacklist my honey clients.

The examples below were identified automatically by the TDG by monitoring for unexpected differences in URL state between different downloaders used to monitor malware repositories. The downloaders operate on different IP addresses and have very different download frequencies. The assumption is that not all downloaders will be simultaneously blacklisted, and the high volume downloaders will be blacklisted first. As discussed in Section 4.2, once a potential case of blacklisting is discovered, a reserve downloader (i.e., a downloader using idle IP addresses) issues a HTTP request to determine the *true* state of the repository. I found that this eliminated most of the false positives caused by this method of blacklisting identification; in the new data captured after April 2011 (after DB purge) 182 URLs triggered the initial blacklisting alarm, 161 were discarded after the reserve fetcher received negative results. Of the 21 cases that remained there were several interesting cases; these are documented below. Note that in only one case is there *definitive* evidence of blacklisting; all other cases are circumstantial at best. They are included to illustrate some of the challenges that arise when trying to pinpoint incidents of blacklisting.

A.4.1 Reactive Blacklisting of a Client IP - ZBot

In this example a MDN serves executables to multiple clients - one high volume and several low volume - fetching successfully for a week and then the high volume client is blacklisted. The details are presented below:

From January 26 - Feb 2, 2011 an MDN was studied that spread over 100 IPs hosting at least three *.ru* domains and one *.in* domain serving executables at */au.exe* (and one other path), confirmed to be Zbot variants. The domains had similar WHOIS traits including registration date and stated nameserver[31]. The high volume client downloaded the executables 1500 times. Within a 10 minute period all IPs in the MDN servers began denying all requests from the high

[31] The nameservers were ns[1|2].laptoptamer.net, a reference to a botherder.

volume client. Executables were downloaded from the same URLs using low volume clients for as long as 30 hours after the alleged blacklisting event.

A.4.2 Assigning a single sample to each client IP - Swizzor

In essence this malware family was assigning a specific sample to each visiting client, and then responding to all requests from known clients with the original chosen sample. If two clients visit one of these servers, each client will get a different sample (e.g., A and B). All subsequent requests from client 1 will result in a download of sample A, and all subsequent requests from client 2 will result in a download of sample B. I speculate that this is a deliberate technique intended to limit the ability of a security researcher to collect a large corpus of samples from the *swizzor* family of malware. This countermeasure is different from traditional blacklisting in that it does not rely on identification of security honey clients in order to protect the malicious samples. The details are presented below.

In January 2011 four different malware repositories with a similar URL structure ($< IP >$ */path.int*? $< query >$) were fetched over 2000 times by LIHCs over a week long period. There were two clients being used (C1 and C2), each with a different IP address. Three of the malware servers consistently served sample A to C1 and B to C2. The fourth server consistently served sample C to C1 and sample D to C2.

A.4.3 Planet Lab Block

Between May 30, 2011 and June 1, 2011, the TDG studied 10 URLs from the domain *3-a.net*, with similar subdomain and path parameters. *3-a.net* is a dynamic DNS provider that simply redirects requests to another domain. Requests to *3-a.net* from linode servers resulted in a HTTP 500 (connection refused) with no redirects. Requests to *3-a.net* from any planetlab proxy resulted in a HTTP 302 redirect to the planetlab abuse page (*http://planetflow.planet-lab.org*). Upon time of investigation the sites were all down so further investigation was not possible.

A.4.4 Inconsistent DNS Responses

Between May 29, 2011 and June 1, 2011, the TDG studied URLs from the domain *videotech-pro.in*, with similar path parameters. For one high volume linode HTTP client, the domain resolved to 66.45.243.36 and the server responded with polymorphic malicious samples of unknown family. During the same period, seven other clients received DNS responses indicating the server was hosted on IP address 7.7.7.7 (which is registered by the U.S Department of Defense). All requests to 7.7.7.7 failed as there is no route to the IP address 7.7.7.7. Several other domains, (*smallsrv.com*, *duote.com.cn*, *3ddown.com*) exhibit similar inconsistent DNS resolution results, however no strong conclusions can be drawn without further investigation. Unfortunately, the temporal nature of DNS and malware repositories makes further investigation of these domains infeasible.

A.4.5 Negative Responses to High Volume Client

The URL *yy.lovegua.com:12345/windosys.exe* was studied for 5 days in early June. One high volume linode server received HTTP 500 (connection refused) for the full duration of study. Seven other clients were able to download malicious executable content for the duration of the study period.

A.5 Survey Question and Answer

A survey was sent out to get a seed value for the α parameter (see Section 4.3). Members of SophosLabs were asked the following question: "How many fetches would you spend to get a single sample we have not seen before?". The full survey question, which was sent over email, is included below:

```
I would like to conduct a very brief
survey to help choose a number in my
research that is highly subjective.
Try not to think too hard, and any
answer over 10 words will be thrown in the garbage.
```

```
I would be blessed if you all responded ASAP.

The question:
How many fetches would you spend to
get a single sample we have not seen before?

Examples of unacceptable answers:
Well you see Kyle that depends on:
blah blah lbahalabh lblah

Examples of acceptable answers:
X, where X is a positive integer.

Thanks,
You are all highly talented individuals
and I appreciate your feedback.

Kyle
```

The results of the survey are presented in Table A.11 in chronological order of response with any comments included. The average was 8.2 with a standard deviation of 11.9. My initial guess was 100, based on the first success formula I used:

$$S = 100 \times numS + 1000 \times numFm - numF \tag{A.1}$$

Note that I do not include my initial guess in the computed average. Any incidents of anchoring, that is, a survey response that was sent to the entire group before they could answer - clearly I should used a proper opaque survey tool instead of email - are noted in the Table.

Response	Reply All	Comment
50		manual 4 automated 50
4		
10	Y	do you guarantee a success? N 10 y 200
1		
3		it will come to us quickly enough
10		
2		Twice from different clients
4		
3		Assuming all are identical
3		
1		
NaN		
3		
5		
10		the likelihood of another URL serving the same payload is high, so why beat on a broken door when you have 100 more to knock on
1		
3		with different configs, for single sample sites
10		
25		
Average		8.2
Standard Deviation		11.9

Table A.11: α **value Survey Results**. Results are presented in chronological order with incidents of anchoring noted.