DETECTING AND CHARACTERIZING MALICIOUS WEBSITES

APPROVED BY SUPERVISING COMMITTEE:

Shouhuai Xu, Ph.D., Chair

Tom Bylander, Ph.D.

Hugh B. Maynard, Ph.D.

Ravi Sandhu, Ph.D.

Maochao Xu, Ph.D.

Accepted:

Dean, Graduate School

DEDICATION

I dedicate my dissertation work to my wife Yang Juan and lovely son Xu Ding. A special feeling of gratitude to my loving parents, Xu Zuguo and Zheng Qiufen whose support during years of graduate work was essential. I also dedicate this dissertation to my sister Wan Xuan, brother-in-law Yang Shaoxiong and my parents-in-law who have never left my side.

DETECTING AND CHARACTERIZING MALICIOUS WEBSITES

by

LI XU, MS. C.

DISSERTATION
Presented to the Graduate Faculty of
The University of Texas at San Antonio
In Partial Fulfillment
Of the Requirements
For the Degree of

DOCTOR OF PHILOSOPHY IN COMPUTER SCIENCE

THE UNIVERSITY OF TEXAS AT SAN ANTONIO
College of Science
Department of Computer Science
August 2014

ACKNOWLEDGEMENTS

This dissertation would never have been completed without the help and support of Dr. Shouhuai Xu, my supervisor, who advised me and worked with me. My friends Zhenxin Zhan, Qingji Zheng and Weiliang Luo were also an invaluable helps many times. I also would like to thank my committee members: Dr. Tom Bylander, Dr. Hugh Maynard Dr. Ravi Sandhu, and Dr. Maochao Xu.

The research described in the dissertation was partly supported by Prof. Shouhuai Xu's ARO Grant # W911NF-12-1-0286 and AFOSR Grant # FA9550-09-1-0165. The studies were approved by IRB.

August 2014

DETECTING AND CHARACTERIZING MALICIOUS WEBSITES

Li Xu, Ph.D.
The University of Texas at San Antonio, 2014

Supervising Professor: Shouhuai Xu, Ph.D.

Malicious websites have become a big cyber threat. Given that malicious websites are inevitable, we need good solutions for detecting them. The present dissertation makes three contributions that are centered on addressing the malicious websites problem. First, it presents a novel cross-layer method for detecting malicious websites, which essentially exploits the network-layer "lens" to expose more information about malicious websites. Evaluation based on some real data shows that cross-layer detection is about 50 times faster than the dynamic approach, while achieving almost the same detection effectiveness (in terms of accuracy, false-negative rate, and false-positive rate). Second, it presents a novel proactive detection method to deal with adaptive attacks that can be exploited to evade the static detection approach. By formulating a novel security model, it characterizes when proactive detection can achieve significant success against adaptive attacks. Third, it presents statistical characteristics on the evolution of malicious websites. The characteristics offer deeper understanding about the threat of malicious websites.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

Chapter 1: INTRODUCTION

1.1 Problem Statement and Research Motivation

Today, many client-side attackers are part of organized crime with the intent to defraud their victims. Their goal is to deploy malware on a victim's machine and to start collecting sensitive data, such as online account credentials and credit card numbers. Since attackers have a tendency to take the path of least resistance and many traditional attack paths are barred by a basic set of security measures, such as firewalls or anti-virus engines, the "black hats" are turning to easier, unprotected attack paths to place their malware onto the end user's machine. They are turning to client-side attacks, because they can cause the automatic download and execution of malware in browsers, and thus compromise vulnerable computers [50]. The phenomenon of malicious websites will persevere at least in the foreseeable future because we cannot prevent websites from being compromised or abused. Existing approaches to detecting malicious websites can be classified into two categories:

- The *static* approach aims to detect malicious websites by analyzing their URLs [39, 40] or their contents [61]. This approach is very efficient and thus can scale up to deal with the huge population of websites in cyberspace. This approach however has trouble coping with sophisticated attacks that include obfuscation [54], and thus can cause high false-negative rates by classifying malicious websites as benign ones.

- The *dynamic* approach aims to detect malicious websites by analyzing their run-time behavior using Client Honeypots or their like [4, 5, 42, 58, 63]. Assuming the underlying detection is competent, this approach is very effective. This approach however, is inefficient because it runs or emulates the browser and possibly the operating system [14]. As a consequence, this approach cannot scale up to deal with the large number of websites in cyberspace.

Because of the above, it has been advocated to use a front-end light-weight tool, which is mainly based on static analysis and aims to rapidly detect suspicious websites, and a back-end more

powerful but much slower tool (e.g., dynamic analysis or even binary analysis), which conducts a deeper analysis of the detected suspicious websites. While conceptually attractive, the success of this *hybrid* approach fundamentally relies on the assumption that the front-end static analysis does have very low false-negative rates; otherwise, many malicious websites will not be detected even if the back-end dynamic analysis tools are powerful. However, this assumption can be easily violated because of the following.

First, in real life, the attacker could defeat pure static analysis by exploiting various sophisticated techniques such as obfuscation and redirection. Redirection technique was originally introduced for the purpose of making various changes to the web servers transparent to their users. Not surprisingly, this technique has also been abused to launch cyber attacks. Assuming the back-end detection tool is effective, the false-negative rate of the front-end static analysis tool determines the detection power (resp. scalability) of the hybrid approach. Therefore, in order to achieve high detection accuracy and high scalability simultaneously, the hybrid solution must have minimum false-negatives and false-positives. This requirement is necessary to achieve the best of both worlds — static analysis and dynamic analysis.

Second, the attacker can get the same data and therefore use the same machine learning algorithms to derive the defender's classifiers. This is plausible because in view of Kerckhoffs's Principle in cryptography, we should assume that the defender's learning algorithms are known to the attacker. As a consequence, the attacker can always act one step ahead of the defender by adjusting its activities so as to evade detection.

The above two issues lead to the following question: how can we achieve the best of both static and dynamic analysis, and go beyond? This question is clearly important and motivates the investigation presented in this dissertation. For solutions based on a hybrid architecture to succeed, a key factor is to reduce both false-positives and false-negatives of the static analysis tools. While intuitive, this crucial aspect has not been thoroughly investigated and characterized in the literature. This dissertation aims to take a substantial step towards the ultimate goal.

1.2 Dissertation Contributions

The first contribution is a novel cross-layer malicious website detection approach which analyzes network-layer traffic and application-layer website contents simultaneously. Existing malicious website detection approaches have technical and computational limitations in detecting sophisticated attacks and analyzing massive data. The main objective of our research is to minimize these limitations of malicious website detection. Detailed data collection and performance evaluation methods are also presented. Evaluations based on data collected during 37 days show that the computing time of the cross-layer detection is 50 times faster than the dynamic approach while detection can be almost as effective as the dynamic approach. Experimental results indicate that the cross-layer detection outperforms existing malicious website detection techniques.

The second contribution addresses the following question: What if the attacker is adaptive? We present three adaptation strategies that may be used by the attacker to launch adaptive attacks, and can be exploited by the defender to launch adaptive defense. We also provide two manipulation algorithms that attempt to bypass the trained J48 detection system. The algorithms demonstrate how easy it can be for an adaptive attacker to evade non-adaptive detection. We show how our defense algorithms can effectively deal with adaptive attacks, and thus make our detection system resilient to adaptive attacks. We characterize the effectiveness of proactive defense against adaptive attacks. We believe that this investigation opens the door for an interesting research direction.

The third contribution is the investigation of the "natural" evolution of malicious websites. We present characteristics of the evolution, which can be exploited to design future defense systems against malicious websites.

Chapter 2: DATA COLLECTION, PRE-PROCESSING AND FEATURE DEFINITIONS

We now describe the methodology underlying our study, including data collection, data pre-processing, evaluation metrics and data analysis methods. The methodology is general enough to accommodate single-layer analyses, but will be extended slightly to accommodate extra ideas that are specific to cross-layer analyses.

2.1 Data Collection

In order to facilitate cross-layer analysis and detection, we need an automated system to collect both the application-layer website contents and the corresponding network-layer traffic. The architecture of our automated data collection system is depicted in Figure 2.1. At a high level, the data collection system is centered on a crawler. The crawler takes a list of URLs as input, automatically fetches the website contents by launching HTTP requests and tracks the redirects that are identified from the website contents (elaborated below). The crawler also uses the URLs, including the input URL and the detected redirection URLs, to query the DNS, Whois, and Geographic services. This collects information about the registration dates of websites and the geographic locations of the URL owners/registrants. The application-layer website contents and the *corresponding* network-layer IP packets are recorded separately (where the IP packets are caused by application-layer activities), but are indexed by the input URLs to facilitate cross-layer analysis.

As mentioned above, the data collection system proactively tracks redirects by analyzing the website contents in a static fashion. Specifically, it considers the following four types of redirects. The first type is the server side redirects, which are initiated either by server rules (i.e., `.htaccess` file) or by server side page code such as `PHP`. These redirects often utilize HTTP 300 level status codes. The second type is JavaScript-based redirects. The third type is the refresh Meta tag and the HTTP refresh header, which allow the URLs of the redirection pages to be specified. The fourth type is the embedded file redirects. Some examples of this type are the following:

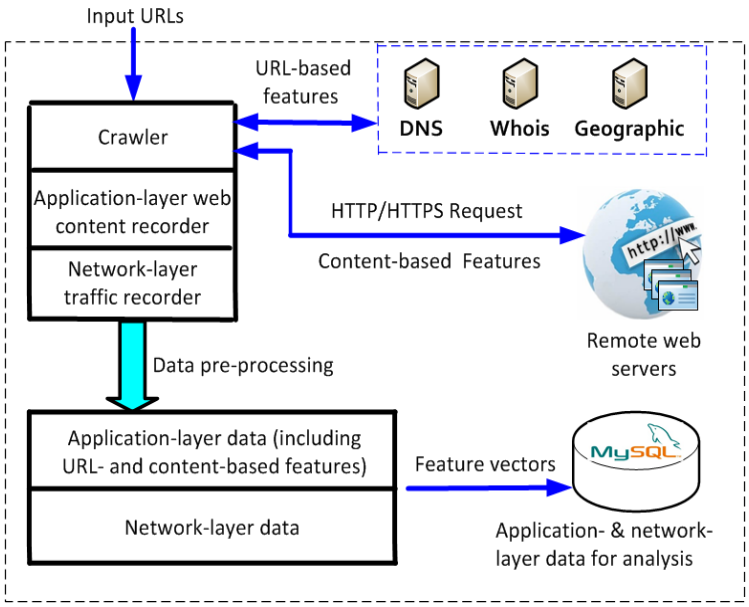


Figure 2.1: Data collection system architecture.

`<script src='badsite.php'> </script>`, `<iframe src='badsite.php' />`, and `<img src='badsite.php' />`.

The input URLs may consist of malicious and benign websites. A URL is malicious if the corresponding website content is malicious or any of its redirects leads to a URL that corresponds to malicious content; otherwise, it is benign. In this chapter, the terms *malicious URLs* and *malicious websites* are used interchangeably. In our experimental system for training and testing detection models, malicious URLs are initially obtained from the following blacklists: `compuweb.com/url-domain-bl.txt`, `malware.com.br`, `malwaredomainlist.com`, `zeustracker.abuse.ch` and `spyeyetracker.abuse.ch`. Since some of the blacklisted URLs are not accessible or malicious any more, we use the high-interactive client honeypot called Capture-HPC version 3.0 [58] to identify the subset of URLs that are still accessible and malicious. We emphasize that our experiments were based on Capture-HPC, which is assumed to offer the ground truth. This is a practical choice because we cannot manually analyze the large number of websites. Even if we could, manual analysis might still be error-prone. Note that any dynamic analysis system (e.g., another client honeypot system) can be used instead in a plug-and-play fashion. Pursuing a client honeypot that truly offers the ground truth is an orthogonal research problem. The benign

URLs are obtained from `alexa.com`, which lists the top 2,088 websites that are supposed to be well protected. The data was collected for a period of 37 days between 12/07/2011 and 01/12/2012, with the input URLs updated daily.

2.2 Data Pre-Processing

Each input URL has an associated application-layer raw feature vector. The features record information such as HTTP header fields, information returned by DNS, Whois and Geographic services, information about JavaScript functions that are called in the JavaScript code embedded into the website content, and information about redirects (e.g., redirection method, whether or not a redirect points to a different domain, and the number of redirection hops). Since different URLs may lead to different numbers of redirection hops, the raw feature vectors may not have the same number of features. In order to facilitate analysis, we use a pre-processing step to aggregate multiple-hop information into some *artificial* single-hop information. Specifically, for numerical data, we aggregate them by using their average instead; for boolean data, we aggregate them by taking the `OR` operation; for nominal data, we only consider the final destination URL of the redirection chain. For example, suppose the features of interest are: (`Content-Length`, "Does JavaScript function `eval()` exist in the code?", `Country`). Suppose an input URL is redirected twice to reach the final destination URL, and the raw feature vectors corresponding to the input, first redirect, and second redirect URLs are (100, `FALSE`, US), (200, `FALSE`, UK), and (300, `TRUE`, RUSSIA), respectively. We aggregate the three raw features into a single feature (200, `TRUE`, RUSSIA). After the pre-processing step, the application-layer data have 105 features, some of which will be elaborated below.

Each input URL has an associated network-layer raw feature vector. The features are extracted from the corresponding PCAP (Packet CAPture) files that are recorded when the crawler accesses the URLs. There are 19 network-layer features that are derived from the IP, UDP/TCP or flow level, where a flow is uniquely identified by a tuple (source IP, source port number, destination IP, destination port number, protocol).

Each URL is also associated with a cross-layer feature vector, which is simply the concatenation of its associated application-layer and network-layer feature vectors.

2.3 Data Description

The resulting data has 105 application-layer features of 4 sub-classes and 19 network-layer features of 3 sub-classes. Throughout the chapter, “average" means the average over the 37-day data.

2.3.1 Application-Layer Features

Feature based on the URL lexical information We defined 15 features based on the URL lexical information, 3 of which are elaborated below.

(A1): `URL_Length`. URLs include the following parts: protocol, domain name or plain IP address, optional port, directory file. When using HTTP Get to request information from a server, there will be an additional part consisting of a question mark followed by a list of “$key = value$" pairs. In order to make malicious URLs hard to blacklist, malicious URLs often include automatically and dynamically generated long random character strings. Our data showed that the average length of benign URLs is 18.23 characters, whereas the average length of malicious URLs is 25.11 characters.

(A2): `Number_of_special_characters_in_URL`. This is the number of special characters (e.g., ?, -, _, =, %) that appear in a URL. Our data showed that benign URLs used on average 2.93 special characters, whereas malicious URLs used on average 3.36 special characters.

(A3): `Presence_of_IP_address_in_URL`. This feature indicates whether an IP address is presented as the domain name in a URL. Some websites use IP addresses instead of domain names in the URL because the IP addresses represent the compromised computers that actually do not have registered domain names. This explains why this feature may be indicative of malicious URLs. This feature has been used in [14].

Features based on the HTTP header information We defined 15 features based on the HTTP header information, 4 of which are elaborated below.

(A4): `Charset`. This is the encoding charset of the URL in question (e.g., iso-8859-1). It hints at the language a website uses and the ethnicity of the targeted users of the website. It is also indicative of the nationality of the webpage.

(A5): `Server`. This is the server field in the http response head. It gives the software information at the server side, such as the webserver type/name and its version. Our data showed that the Top 3 webservers that were abused to host malicious websites are Apache, Microsoft IIS, and nginx, which respectively correspond to 322, 97, and 44 malicious websites on average. On the other hand, Apache, Microsoft IIS, and nginx were abused to host 879, 253, and 357 benign websites on average.

(A6): `Cache_control`. Four cache control strategies are identified in the websites of our data: no-cache, private, public, and cache with max-age. The average numbers of benign websites that use these strategies are respectively 444, 276, 67, and 397, whereas the average numbers of malicious websites that use these strategies are respectively 99, 46, 0.5, and 23.

(A7): `Content_length`. This feature indicates the content-length field of a HTTP header. For malicious URLs, the value of this field may be manipulated so that it does not match the actual length of the content.

Features based on the host information (include DNS, Whois data) We defined 7 features based on the host information, 5 of which are elaborated below.

(A8-A9): `RegDate` and `Updated_date`. These two features are closely related to each other. They indicate the dates the webserver was registered and updated with the Whois service, respectively. Our data showed that on average, malicious websites were registered in 2004, whereas benign websites were registered in 2002. We also observed that on average, malicious websites were updated in 2009, one year earlier than the average update date of 2010 for benign websites .

(A10-A11): `Country` and `Stateprov`. These two features respectively indicate the counter

and the location where the website was registered. These two features, together with the aforementioned `charset` feature, can be indicative of the locations of websites. Our data showed that the average numbers of benign websites registered in US, NL, and AU are respectively 618, 523, and 302, whereas the average numbers of malicious websites registered in US, NL, and AU are respectively 152, 177, and 98.

(A12): `Within_domain`. This feature indicates whether or not the destination URL and the original URL are in the same domain. Redirection has been widely used by both benign and malicious websites. From our data, we found that malicious websites are more often redirected to exploit servers that reside in different domains. Specifically, we found that 21.7% of malicious websites redirect to different domains, whereas 16.1% of benign websites redirect to different domains.

Features based on web content information (including HTML and Script source code) We defined 68 content-based features, 7 of which are described as follows.

(A13): `Number_of_redirect`. This is the total number of redirects embedded into an input URL. It is indicative of malicious URLs because our data showed that on average, malicious URLs have 0.67 redirects whereas benign URLs have 0.43 redirects. Note that this feature is unique at the application layer because it cannot be precisely obtained at the network layer, which cannot tell a redirect from a normal link.

(A14): `Number_of_embedded_URLs`. This feature counts the number of URLs that are embedded into the input URL and use external resources (e.g., image, voice and video). This feature can be indicative of malicious URLs because external URLs are often abused by attackers to import malicious content to hacked URLs.

(A15): `Content_length_valid`. This feature checks the consistency between the `HTTPHeader_content_Length` feature value (i.e., the value of the content length field in HTTP header) and the actual length of web content. It is relevant because the content length field could be a negative number, which may cause buffer overflow attacks. This feature has been used in [16].

(A16): `Number_of_long_strings`. This feature counts the number of long strings used in the JavaScript code that is embedded into the input URL. A string is considered long if its length is greater than 50. Because attackers try to encode some shell code into a string and then use heap-overflow to execute that shell code, this feature can be indicative of malicious URLs as suggested in [14]. Our data showed that the average `Number_of_long_strings` is 0.88 for malicious URLs and 0.43 for benign URLs.

(A17-A18): `Number_of_iframe` and `number_of_small_size_iframe`. These two features respectively count how many iframe and small size iframes are present in a webpage. If any iframe contains malicious code, the URL is malicious. A small size iframe is even more harmful because it imports malicious content that is invisible to the users.

(A19): `Number_of_suspicious_JS_functions`. This feature [28] indicates whether or not the JavaScript code is obfuscated. In the script block and imported JavaScript files, we check for suspicious JavaScript functions such as `eval()`, `escape()`, and `unescape()`. JavaScript functions are often used by attackers to obfuscate their code and bypass static analysis. For example, `eval()` can be used to dynamically execute a long string at runtime, where the string can be the concatenation of many dynamic pieces of obfuscated substrings at runtime; this makes the obfuscated substrings hard to detect by static analysis.

(A20): `Number_of_Scripts`. Number of scripts in a website (e.g., JavaScript). Script plays a very important role in drive-by download attack.

2.3.2 Network-Layer Features

Features based on remote server attributes **(N1):** `Tcp_conversation_exchange`. This is the total number of TCP packets sent to the remote server by the crawler. Malicious websites often use rich web resources that may cause multiple HTTP requests sent to the webserver. Our data showed the average `Tcp_conversation_exchange` is 73.72 for malicious websites and 693.38 for benign websites.

(N2): `Dist_remote_TCP_port`. This is the total number of distinct TCP ports that the remote

webserver used during the conversation with the crawler. Our data showed that benign websites often use the standard http port 80, whereas malicious websites often use some of the other ports. Our data showed the average `Dist_remote_TCP_port` is 1.98 for malicious websites and 1.99 for benign websites.

(N3): `Remote_ips`. This is the number of distinct remote IP addresses connected by the crawler, not including the DNS server IP addresses. Multiple remote IP addresses can be caused by redirection, internal and external resources that are embedded into the webpage corresponding to the input URL. Our data showed the average `Remote_ips` is 2.15 for malicious websites and 2.40 for benign websites.

Features based on crawler-server communication **(N4):** `App_bytes`. This is the number of Bytes of the application-layer data sent by the crawler to the remote webserver, not including the data sent to the DNS servers. Malicious URLs often cause the crawler to initiate multiple requests to remote servers, such as multiple redirections, iframes, and external links to other domain names. Our data showed the average `App_bytes` is 36818 bytes for malicious websites and 53959 bytes for benign websites.

(N5): `UDP_packets`. This is the number of UDP packets generated during the entire lifecycle when the crawler visits a URL, not including the DNS packets. Benign websites running an online streaming application (such as video, audio and internet phone) will generate numerous UDP packets, whereas malicious websites often exhibit numerous TCP packets. Our data showed the average `UDP_packets` for both benign and malicious URLs are 0 because the crawler does not download any video/audio stream from the sever.

(N6): `TCP_urg_packets`. This is the number of urgent TCP packets with the URG (urgent) flag set. Some attacks abuse this flag to bypass the IDS or firewall systems that are not properly set up. If a packet has the URGENT POINTER field set, but the URG flag is not set, this constitutes a protocol anomaly and usually indicates a malicious activity that involves transmission of malformed TCP/IP datagrams. Our data showed the average `TCP_urg_packets` is 0.0003 for

malicious websites and 0.001 for benign websites.

(N7): `Source_app_packets`. This is the number of packets send by the crawler to remote servers. Our data showed the average `source_app_packets` is 130.65 for malicious websites and 35.44 for benign websites.

(N8): `Remote_app_packets`. This is the number of packets sent by the remote webserver(s) to the crawler. This feature is unique to the network layer. Our data showed the average value of this feature is 100.47 for malicious websites and 38.28 for benign websites.

(N9): `Source_app_bytes`. This is the volume (in bytes) of the crawler-to-webserver communications. Our data showed that the average application payload volumes of benign websites and malicious websites are about 146 bytes and 269 bytes, respectively.

(N10): `Remote_app_bytes`. This is the volume (in bytes) of data from the webserver(s) to the crawler, which is similar to feature `Source_app_byte`. Our data showed the average value of this feature is 36527 bytes for malicious websites and 49761 bytes for benign websites.

(N11): `Duration`. This is the the duration of time, starting from the point the crawler was fed with an input URL to the point the webpage was successfully obtained by the crawler or an error returned by the webserver. This feature is indicative of malicious websites because visiting malicious URLs may cause the crawler to send multiple DNS queries and multiple connections to multiple web servers, which could lead to a high volume of communications. Our data showed that visiting benign websites caused 0.793 seconds duration time on average, whereas visiting malicious websites caused 2.05 seconds duration time on average.

(N12): `Avg_local_pkt_rate`. This is the average rate of IP packets (packets per second) that are sent from the crawler to the remote webserver(s) with respect to an input URL, which equals `source_app_packets/duration`. This feature measures the packet sending speed of the crawler, which is related to the richness of webpage resources. Webpages containing rich resources often cause the crawler to send a large volume of data to the server. Our data showed the average `Avg_local_pkt_rate` is 63.73 for malicious websites and 44.69 for benign websites.

(N13): `Avg_remote_pkt_rate`. This is the average IP packet rate (in packets per second) of

packets sent from the remote server to the crawler. When multiple remote IP addresses are involved (e.g., because of redirection or because the webpage uses external links), we amortize the number of packets, despite the fact that some remote IP addresses may send more packets than others back to the crawler. Websites containing malicious code or contents can cause large volume communications between the remote server(s) and the crawler. Our data showed the average `Avg_remote_pkt_rate` is 63.73 for malicious websites and is 48.27 for benign websites.

(N14): `App_packets`. This is the total number of IP packets generated for obtaining the content corresponding to an input URL, including redirects and DNS queries. It measures the data exchange volume between the crawler and the remote webserver(s). Our data showed the average value of this feature is 63.73 for malicious websites and 48.27 for benign websites.

Features based on crawler-DNS flows **(N15):** `DNS_query_times`. This is the number of DNS queries sent by the crawler. Because of redirection, visiting malicious URLs often causes the crawler to send multiple DNS queries and to connect multiple remote webservers. Our data showed the average value of this feature is 13.30 for malicious websites and 7.36 for benign websites.

(N16): `DNS_response_time`. This is the response time of DNS servers. Benign URLs often have longer lifetimes and their domain names are more likely cached at local DNS servers. As a result, the average value of this feature may be shorter for benign URLs. Our data showed the average value of this feature is 13.29 ms for malicious websites and is 7.36 ms for benign websites.

Features based on aggregated values **(N17):** `Iat_flow`. This is the accumulated inter-arrival time between consecutive flows. Given two consecutive flows, the inter-arrival time is the difference between the timestamps of the first packet in each flow. Our data showed the average `Iat_flow` is 1358.4 for malicious websites and 512.99 for benign websites.

(N18): `Flow_number`. This is the number of flows generated during the entire lifecycle for the crawler to download the web content corresponding to an input URL, including the recursive queries to DNS and recursive access to redirects. It includes both TCP flows and UDP flows, and is a more general way to measure the communications between the crawler and the remote

webservers. Each resource in the webpage may generate a new flow. This feature is also unique to the network layer. Our data showed the average `Flow_number` is 19.48 for malicious websites and 4.91 for benign websites.

(N19): `Flow_duration`. This is the accumulated duration of each basic flow. Different from feature `Duration`, this feature indicates the linear process time of visiting a URL. Our data showed the average `Flow_duration` is 22285.43 for malicious websites and 13191 for benign websites.

2.4 Effectiveness Metrics

In order to compare different detection models (or methods, or algorithms), we consider three effectiveness metrics: *detection accuracy*, *false-negative rate*, and *false-positive rate*. Suppose we are given a detection model (e.g., J48 classifier or decision tree), which may be learned from the training data. Suppose we are given test data that consists of d_1 malicious URLs and d_2 benign URLs. Suppose further that the detection model correctly detects d_1' of the d_1 malicious URLs and d_2' of the d_2 benign URLs. The detection accuracy is defined as $\frac{d_1'+d_2'}{d_1+d_2}$. The false-negative rate is defined as $\frac{d_1-d_1'}{d_1}$. The false-positive rate is defined as $\frac{d_2-d_2'}{d_2}$. A good detection model achieves high effectiveness (i.e., high detection accuracy, low false-positive and low false-negative rate).

Chapter 3: CROSS-LAYER DETECTION OF MALICIOUS WEBSITES

3.1 Introduction

Malicious websites have become a severe cyber threat because they can cause the automatic download and execution of malware in browsers, and thus compromise vulnerable computers [50]. The phenomenon of malicious websites will persevere in the future because we cannot prevent websites from being compromised or abused. For example, Sophos Corporation has identified the percentage of malicious code that is hosted on hacked sites as 90% [7]. Often the malicious code is implanted using SQL injection methods and shows up in the form of an embedded file. In addition, stolen ftp credentials allow hackers to have direct access to files, where they can implant malicious code directly into the body of a web page or again as an embedded file reference. Yet another powerful adversarial technique is obfuscation [54], which is very difficult to cope with. These attacks are attractive to hackers because the hackers can exploit them to better hide the malicious nature of these embedded links from the defenders.

Existing approaches to detect malicious websites can be classified into two categories: *static* approach and *dynamic* approach. How can we achieve the best of the static and dynamic approaches simultaneously? A simple solution is to run a front-end static analysis tool that aims to rapidly detect suspicious websites, which are then examined by a back-end dynamic analysis tool. However, the effectiveness of this approach is fundamentally limited by the assumption that the front-end static analysis tool has a very low false-negative rate; otherwise, many malicious websites will not be examined by the back-end dynamic analysis tool. Unfortunately, static analysis tools often incur high false-negative rates, especially when malicious websites are equipped with the aforesaid sophisticated techniques. In this paper, we propose a novel technique by which we can simultaneously achieve almost the same effectiveness of the dynamic approach and the efficiency of the static approach. The core idea is to exploit the network-layer or cross-layer information that somehow exposes the nature of malicious websites from a different perspective.

Our Contributions We propose an analysis of the corresponding network-layer traffic between the browser and the web server by incorporating the static analysis of website contents. The insight of this approach is that the network-layer may expose useful information about malicious websites from a different perspective. The cross-layer detection is further coupled with the trick of statically tracing redirects, which are embedded into the websites to hide the actual websites that disseminate malwares. That is, the redirection URLs are not obtained via dynamic analysis, but obtained by slightly extending the static analysis method. This allows us to consider not only redirection related features of the present website, but also the redirection website contents.

Evaluation of our approach is based on real data that was collected during the span of 37 days. We found that cross-layer detection can be almost as effective as the dynamic approach and almost as efficient as the static approach, where effectiveness is measured via the vector of (*detection accuracy*, *false-negative rate*, *false-positive rate*). For example, using the dynamic approach as effectiveness base, our data-aggregation cross-layer classifier achieved (99.178%, 2.284%, 0.422%), while the application-layer classifier only achieved (96.394%, 6.096%, 2.933%). Moreover, the `XOR`-aggregation cross-layer classifier can achieve (99.986%, 0.054%, 0.003%), while subjecting only 0.014% of the websites to the dynamic approach. We also discuss the deployment issues of the cross-layer detection approach. Since performance experiments in Section 3.3.4 show that cross-layer detection can be 50 times faster than the dynamic approach when processing a batch of URLs, the cross-layer detection approach is very suitable for deployment as a service. Moreover, cross-layer detection incurs no more than 4.9 seconds for processing an individual URL, whereas the dynamic approach takes 20 seconds to process a URL on average. This means that cross-layer detection would be acceptable for real-time detection.

The rest of the chapter is organized as follows. Section 3.2 investigates two single-layer detection systems. Section 3.3 presents our cross-layer detection systems. Section 5.6 discusses the related work.Section 5.7 concludes the present chapter.

Data Analysis Methods In order to identify the better detection model, we consider four popular machine learning algorithms: Naive Bayes, Logistic regression, Support Vector Machine (SVM) and J48. Naive Bayes classifier is a probabilistic classifier based on Bayes' rule [30]. Logistic regression classifier [36] is a type of linear classifier, where the domain of the target variable is $0, 1$. SVM classifier aims to find an maximum-margin hyperplane for separating different classes in the training data [17]. We use the SMO (Sequential Minimal-Optimization) algorithm in our experiment with polynomial kernel function [49]. J48 classifier is an implementation of C4.5 decision trees [52] for binary classification. These algorithms have been implemented in the Weka toolbox [27], which also resolves issues such as missing feature data and conversion of strings to numbers.

In order to know whether using a few features is as powerful as using all features and which features are more indicative of malicious websites, we consider the following three feature selection methods. The first method is Principle Component Analysis (`PCA`), which transforms a set of feature vectors to a set of shorter feature vectors [27]. The second feature selection method is called "`CfsSubsetEval` with best-first search method" in the Weka toolbox [27], or `Subset` for short. It essentially computes the features' prediction power according to their contributions [26]. It outputs a subset of features, which are substantially correlated with the class but have low inter-feature correlations. The third feature selection method is called "`InfoGainAttributeEval` with ranker search method" in the Weka toolbox [27], or `InfoGain` for short. Its evaluation algorithm essentially computes the information gain ratio (or more intuitively the importance of each feature) with respect to the class. Its selection algorithm ranks features based on their information gains [19]. It outputs the ranks of all features in the order of decreasing importance.

3.2 Single-Layer Detection of Malicious Websites

In this section, we investigate two kinds of single-layer detection systems. One uses the application-layer information only, and corresponds to the traditional static approach. The other uses the network-layer information only, which is newly introduced in the present paper. The latter was

motivated by our insight that the network layer may expose useful information about malicious websites from a different perspective. At each layer, we report the results obtained by using the methodology described in Chapter 2.

Table 3.1: Single-layer average effectiveness (Acc: detection accuracy; FN: false negative rate; FP: false positive rate)

Feature selection?	Naive Bayes			Logistic			SVM			J48		
	Acc	FN	FP	Acc	FN	FP	Acc	FN	FP	Acc	FN	FP
application-layer average detection effectiveness (%)												
none	51.260	11.029	59.275	90.551	22.990	5.692	85.659	55.504	3.068	96.394	6.096	2.933
PCA	67.757	9.998	38.477	91.495	20.526	5.166	89.460	30.031	5.189	95.668	9.537	2.896
Subset	77.962	35.311	18.162	86.864	37.895	6.283	84.688	51.671	5.279	93.581	15.075	3.999
InfoGain	71.702	19.675	30.664	84.895	43.857	7.097	83.733	52.071	6.363	94.737	12.148	3.390
network-layer average detection effectiveness (%)												
none	51.767	0.796	61.645	90.126	21.531	6.630	86.919	24.449	9.986	95.161	9.127	3.676
PCA	67.766	4.017	40.278	87.454	30.651	7.520	85.851	32.957	9.346	89.907	22.587	6.604
Subset	70.188	0.625	38.035	88.141	25.629	8.061	86.534	25.397	10.188	92.415	14.580	5.658
InfoGain	55.533	0.824	56.801	86.756	29.783	8.647	82.822	40.875	10.560	92.853	15.442	4.852

The application-layer and network-layer effectiveness results averaged over the 37 days are described in Table 3.1. For application-layer detection, we make two observations.

- J48 classifier is significantly more effective than the other three detection models, whether feature selection is used or not. However, J48 classifiers may incur somewhat high false-negative rates.

- Feature selection will significantly hurt detection effectiveness, which is true even for J48 classifiers. This means that conducting feature selection at the application layer does not appear to be a good choice.

For network-layer detection, we observe the following:

- J48 classifier is significantly more effective than the other three detection models, whether feature selection is used or not. Note that although Naive Bayes incurs a lower false-negative rate, it has a very low detection accuracy. Similar to what we observed at the application layer, J48 classifier also produces high false-negative rates, meaning that network-layer analysis alone is not sufficient.

- Overall, feature selection hurts detection effectiveness. This also means that conducting feature selection at the network layer is not a good approach.

By comparing the application layer and the network layer, we observed two interesting phenomena. First, each single-layer detection method has some inherent limitation. Specifically, since we were somewhat surprised by the high false-negative and false-positive rates of the single-layer detection methods, we wanted to know whether they are caused by some outliers (extremely high rates for some days), or are persistent over the 37 days. By looking into the data in detail, we found that the false-negative and false-positive rates are reasonably persistent. This means that single-layer detection has an inherent weakness.

Second, we observe that network-layer detection is only slightly less effective than application-layer detection. This confirms our original insight that the network-layer traffic data can expose useful information about malicious websites. Although network-layer detection alone is not sufficient, this paved the way for exploring the utility of cross-layer detection of malicious websites, which is explored in Section 3.3.

3.3 Cross-Layer Detection of Malicious Website

Having shown that network-layer traffic information can give approximately the same detection effectiveness as the application layer, we now show how cross-layer detection can achieve much better detection effectiveness. Given the pre-processed feature vectors at the application and network layers, we extend the preceding methodology slightly to accommodate extra ideas that are specific to cross-layer detection.

- Data-aggregation cross-layer detection: For a given URL, we obtain its cross-layer feature vector by concatenating its application-layer feature vector and its network-layer feature vector. The resultant feature vectors are then treated as the pre-processed data in the methodology described in Chapter 2 for further analysis.

- `OR`-aggregation cross-layer detection: For a given URL, if either the application-layer de-

tection model or the network-layer detection model says the URL is malicious, then the cross-layer detection model says the URL is malicious; otherwise, the cross-layer detection model says the URL is benign. This explains why we call this approach `OR`-aggregation.

- `AND`-aggregation cross-layer detection: For a given URL, if both the application-layer detection model and the network-layer detection model say the URL is malicious, then the cross-layer detection model says the URL is malicious; otherwise, the cross-layer detection model says the URL is benign. This explains why we call this approach `AND`-aggregation.

- `XOR`-aggregation cross-layer detection: For a given URL, if both the application-layer detection model and the network-layer detection model say the URL is malicious, then the cross-layer detection model says the URL is malicious; if both the application-layer detection model and the network-layer detection model say the URL is benign, then the cross-layer detection model says the URL is benign. Otherwise, the cross-layer detection model resorts to the dynamic approach. That is, if the dynamic approach says the URL is malicious, then the cross-layer detection model says the URL is malicious; otherwise, the cross-layer detection model says the URL is benign. We call this approach `XOR`-aggregation because it is in the spirit of the XOR operation.

We stress that the `XOR`-aggregation cross-layer detection model resides in between the above three cross-layer detection models and the dynamic approach because it partly relies on the dynamic approach. `XOR`-aggregation cross-layer detection is practical *only when* it rarely invokes the dynamic approach.

3.3.1 Overall Effectiveness of Cross-Layer Detection

The effectiveness of cross-layer detection models, averaged over the 37 days, is described in Table 3.2, from which we make six observations discussed in the rest of this section.

First, data-aggregation cross-layer J48 classifier without using feature selection achieves (99.178%, 2.284%, 0.422%)-effectiveness, which is significantly better than the application-layer J48 classi-

fier that achieves (96.394%, 6.096%, 2.933%)-effectiveness, and is significantly better than the network-layer J48 classifier that achieves (95.161%, 9.127%, 3.676%)-effectiveness. In other words, cross-layer detection can achieve significantly higher effectiveness than the single-layer detection models. This further confirms our motivational insight that the network-layer can expose useful information about malicious websites from a different perspective. This phenomenon can be explained by the low correlation between the application-layer feature vectors and the network-layer feature vectors of the respective URLs. We plot the correlation coefficients in Figure 3.1, which shows the absence of any correlation because the correlation coefficients fall into the interval of $(-0.4, 0.16]$. This implies that the application layer and the network layer expose different kinds of perspectives of malicious websites, and can be exploited to construct more effective detection models.

Table 3.2: Cross-layer average effectiveness (Acc: detection accuracy; FN: false-negative rate; FP: false-positive rate). In the `XOR`-aggregation cross-layer detection, the portions of websites queried in the dynamic approach (i.e., the websites for which the application-layer and cross-layer detection models have different opinions) with respect to the four machine learning algorithms are respectively: without using feature selection, (19.139%, 1.49%, 1.814%, 0.014%); using `PCA` feature selection, (17.448%, 1.897%, 3.948%, 0.307%); using `Subset` feature selection, (8.01%, 2.725%, 3.246%, 0.654%); using `InfoGain` feature section, (13.197%, 2.86%, 4.178%, 0.37%). Therefore, J48 classifier is appropriate for `XOR`-aggregation.

Layer	Feature selection?	Naive Bayes			Logistic			SVM			J48		
		Acc (%)	FN (%)	FP (%)	Acc (%)	FN (%)	FP (%)	Acc (%)	FN (%)	FP (%)	Acc (%)	FN (%)	FP (%)
Cross-layer (data-aggregation)	none	55.245	7.961	55.104	96.861	7.945	1.781	94.568	21.227	1.112	99.178	2.284	0.422
	`PCA`	72.084	4.124	34.659	97.582	5.740	1.481	96.014	9.330	2.492	98.807	3.007	0.692
	`Subset`	80.396	1.402	24.729	94.568	13.662	3.129	93.296	15.575	4.244	98.335	4.245	0.945
	`InfoGain`	73.146	1.342	34.069	90.703	22.267	5.693	88.297	26.562	7.571	97.365	6.052	1.685
Cross-layer (`OR`-aggregation)	none	40.286	0.162	76.437	91.565	6.116	9.104	88.517	7.858	12.542	97.101	0.054	3.708
	`PCA`	41.582	0.212	74.707	90.039	7.992	10.529	88.342	19.301	9.919	94.251	1.279	7.010
	`Subset`	57.666	0.065	54.162	88.493	11.460	11.554	86.958	14.154	12.770	94.263	2.615	6.622
	`InfoGain`	45.276	0.150	70.051	87.342	12.075	12.851	85.266	18.144	13.802	95.129	1.621	5.794
Cross-layer (`AND`-aggregation)	none	79.097	8.262	24.502	92.528	33.536	0.202	90.335	44.216	0.142	97.888	9.781	0.003
	`PCA`	79.918	12.428	22.355	90.437	43.244	0.192	85.642	66.755	0.005	94.524	24.998	0.037
	`Subset`	88.188	17.355	10.246	88.984	49.660	0.300	86.738	60.510	0.205	95.448	20.508	0.111
	`InfoGain`	83.719	14.269	16.888	87.625	55.774	0.293	84.313	71.175	0.265	95.496	20.685	0.023
Cross-layer (`XOR`-aggregation)	none	80.861	0.162	24.502	98.510	6.116	0.202	98.186	7.858	0.142	99.986	0.054	0.003
	`PCA`	82.552	0.212	22.355	98.103	7.992	0.192	96.052	19.301	0.005	99.693	1.279	0.037
	`Subset`	91.990	0.065	10.246	97.275	11.460	0.300	96.754	14.154	0.205	99.346	2.615	0.111
	`InfoGain`	86.803	0.150	16.888	97.140	12.075	0.293	95.822	18.144	0.265	99.630	1.621	0.023

Second, J48 classifier is significantly better than the other three classifiers, with or without feature selection. Since the above comparison is based on the average over 37 days, we wanted to know whether or not J48 classifier is consistently more effective than the other three classifiers. For this purpose, we looked into the data and found that J48 classifier is almost always more effective

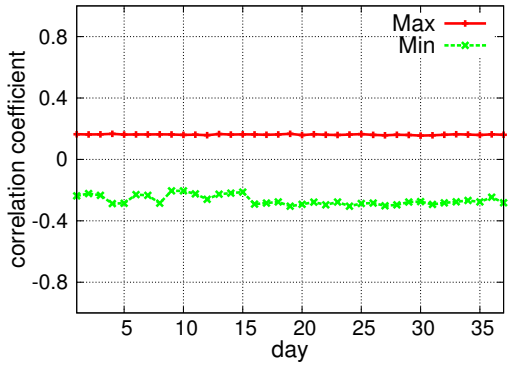


Figure 3.1: The max and min correlation coefficients between application-layer and network-layer feature vectors.

than the other three classifiers. Therefore, we recommend to use J48 classifier and will focus on J48 classifier in the rest of the chapter.

Third, looking into the day-by-day effectiveness of cross-layer detection models with respect to the `InfoGain` feature selection algorithm, we found the effect of feature selection to be persistent over the 37 days, especially for the `XOR`-aggregation cross-layer detection model. This further confirms that feature selection can be adopted in practice.

Fourth, the `OR`-aggregation cross-layer J48 classifier can achieve significantly lower false-negative rate than the data-aggregation cross-layer J48 classifier, at the price of a lower detection accuracy and a higher false-positive rate. On the other hand, the `AND`-aggregation cross-layer J48 classifier can achieve a significantly lower false-negative rate than the data-aggregation cross-layer J48 classifier, at the price of a lower detection accuracy and a higher false-negative rate. This phenomenon can be explained by using the definitions of the effectiveness metrics as follows. For a fixed population of d_1 malicious URLs and d_2 benign URLs, a lower false-negative rate $\frac{d_1-d_1'}{d_1}$ implies a higher d_1'. Since the detection accuracy $\frac{d_1'+d_2'}{d_1+d_2}$ slightly decreases when compared with the data-aggregation cross-layer detection, d_2' must decrease. This means that the false-positive rate $\frac{d_2-d_2'}{d_2}$ increases. In a similar fashion, we can deduce that an increase in false-positive rate can lead to a decrease in the false-negative rate. Thus, cross-layer classifiers offer a spectrum of deployment possibilities, depending on security needs (e.g., a preference for lower false-negative rate or lower false-positive rate). In Section 3.3.5, we will explore the deployment issues of the

cross-layer detection models.

Fifth, feature selection still hurts cross-layer detection effectiveness, but to a much lesser degree than without feature selection. Indeed, the data-aggregation cross-layer J48 classifier with feature selection is significantly better than the single-layer J48 classifier without using feature selection. Moreover, the data-aggregation cross-layer J48 classifier with feature selection offers very high detection accuracy and very low false-positive rate, the OR-aggregation cross-layer J48 classifier with feature selection offers reasonably high detection accuracy and reasonably low false-negative rate, and the AND-aggregation cross-layer J48 classifier with feature selection offers reasonably high detection accuracy and extremely low false-positive rate. When compared with data-aggregation cross-layer detection, OR-aggregation cross-layer detection has a lower false-negative rate, but a lower detection accuracy and a higher false-positive rate. This can be explained as before.

Sixth and lastly, XOR-aggregation cross-layer detection can achieve almost the same effectiveness as the dynamic approach. For example, it achieves (99.986%, 0.054%, 0.003%) effectiveness without using feature selection, while only losing 100-99.086=0.014% accuracy to the dynamic approach. This means that the J48 classifier with XOR-aggregation can be appropriate for real-world deployment. Also, note that the false-negative rate of the XOR-aggregation J48 classifier equals the false-negative rate of the OR-aggregation J48 classifier. This is because all of the malicious websites which are mistakenly classified as benign by the OR-aggregation J48 classifier are necessarily mistakenly classified as benign by the XOR-aggregation J48 classifier. For a similar reason, we see why the false-positive rate of the XOR-aggregation J48 classifier equals the false-positive rate of the AND-aggregation J48 classifier.

3.3.2 Which Features Are Indicative?

Identifying the features that are most indicative of malicious websites is important because it can deepen our understanding of malicious websites. Principal Components Analysis (PCA) has been widely applied to obtain unsupervised feature selections by using linear dimensionality reduction techniques. However, the PCA-based feature selection method is not appropriate to discover indi-

cations of malicious websites. Therefore, this research has focused on `Subset` and `InfoGain`.

The `Subset` feature selection algorithm This algorithm selects a subset of features with low correlation while achieving high detection accuracy. Over the 37 days, this algorithm selected 15 to 16 (median: 16) features for the `data`-aggregation cross-layer detection, and 15 to 21 (median: 18) features for both the `OR`-aggregation and the `AND`-aggregation. Since this algorithm selects at least 15 features daily, space limitation does not allow us to discuss the features in detail. Nevertheless, we will identify the few features that are also most commonly selected by the `InfoGain` algorithm.

The `InfoGain` feature selection algorithm This algorithm ranks the contributions of individual features. For each of the three specific cross-layer J48 classifiers and for each of the 37 days, we used this algorithm to select the 5 most contributive application-layer features and the 4 most contributive network-layer features, which together led to the detection effectiveness described in Table 3.2. The five most contributive application-layer features are (in descending order): (**A1**): `URL_Length`; (**A5**): `Server`; (**A8**): `RegDate`; (**A6**): `Cache_control`; (**A11**): `Stateprov`. The four most contributive network-layer features are (in descending order): (**N11**): `Duration`; (**N9**): `Source_app_byte`; (**N13**): `Avg_remote_pkt_rate`; (**N2**): `Dist_remote_TCP_port`.

Intuitively, these features are indicative of malicious websites because during the compromise of browsers, extra communications may be incurred for connecting to the redirection websites while involving more remote TCP ports. We observed that most of the HTTP connections with large (**N11**): `Duration` time are caused by slow HTTP responses. This is seemingly because malicious websites usually employ dynamic DNS and Fast-Flush service network techniques to better hide from detection. This would also explain why malicious websites often lead to larger values of (**N2**): `Dist_remote_TCP_port`. We also observed that malicious websites often have longer DNS query time (1.33 seconds on average) than benign websites (0.28 seconds on average). This can be because the DNS information of benign websites is often cached in local

DNS servers, meaning there is no need to launch recursive or iterative DNS queries. Moreover, we observe that malicious websites often incur smaller (**N13**): `Avg_remote_pkt_rate` because the average volume of malicious website contents is often smaller than the average volume of benign website contents. Our datasets show that the average volume of malicious website contents is about 36.6% of the average volume of benign website contents.

The most commonly selected features Now we discuss the features that are most commonly selected by both feature selection algorithms. On each of the 37 days, the `Subset` feature selection algorithm selected the aforesaid 15-21 features of the 124 features. Overall, many more features are selected by this algorithm over the 37 days. However, only 5 features were selected every day, where 4 features are from the application layer and 1 feature is from the network layer. Specifically, these features are: (**A1**): `URL_Length`; (**A5**): `Server`; (**A2**): `Number_of_special_characters_in_URL`; (**A13**): `Number_of_redirects`; (**N1**): `Duration`. These features are indicative of malicious websites because visiting malicious URLs may cause the crawler to send multiple DNS queries and to connect to multiple web servers, which could lead to a high volume of communications.

The `InfoGain` feature selection algorithm selected the aforesaid 15-16 features out of the 124 application-layer and network-layer features. Overall, only 17 of the 124 features were ever selected, where 6 features are from the application layer and the other 11 features are from the network layer. Three of the aforesaid features were selected every day: (**A1**): `URL_Length`, (**N1**): `Duration`, (**N9**): `Source_app_byte`. As mentioned in the description of the `InfoGain` feature selection algorithm, (**N1**): `Duration` represents one important feature of a malicious web page. As for the (**N9**): `Source_app_byte` feature, intuitively, malicious web pages that contain rich content (usually phishing contents) can cause multiple HTTP requests.

Overall, the features most commonly selected by the two feature selection algorithms are the aforementioned (**A1**): `URL_Length`, (**A5**): `Server` and (**N1**): `Duration`. This further confirms the power of cross-layer detection. These features are indicative of malicious websites as

explained before.

3.3.3 How Did the Network Layer Help Out?

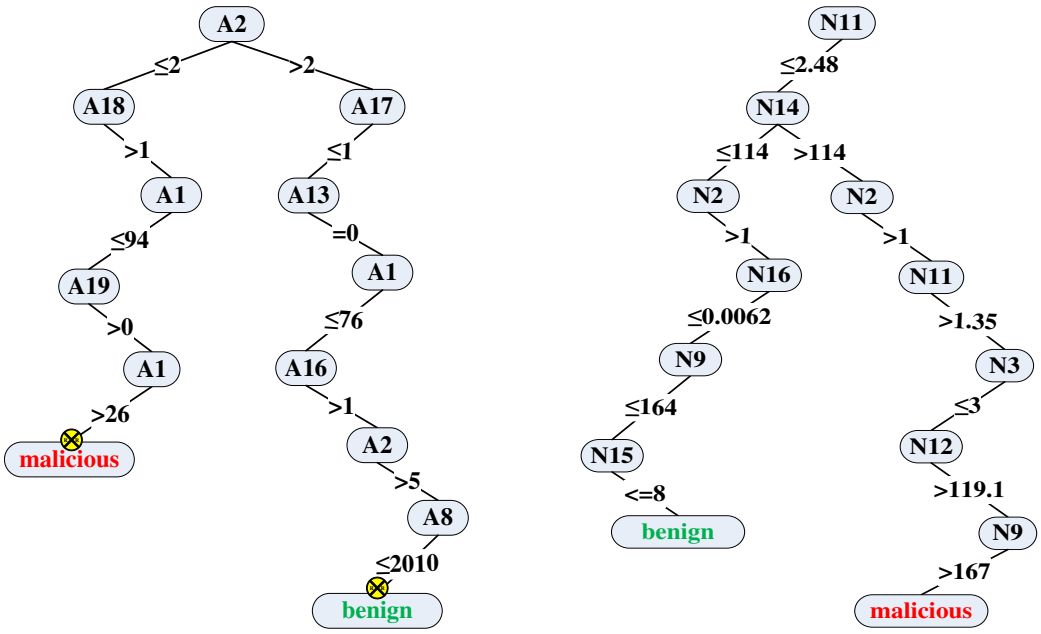
Previously, we observed the overall effectiveness of cross-layer detection, which at a high level can be attributed to the fact that the network-layer data has a low correlation with the application-layer data (i.e., the network-layer data does expose extra information about websites). Now we give a deeper characterization of the specific contributions of the network-layer information that leads to the correct classification of URLs.

Table 3.3: Breakdown of the average mis-classifications that were corrected by the network-layer classifiers, where N/A means that the network-layer cannot help (see text for explanation).

Cross-layer aggregation method	Average correction of FN	Average correction of FP
Data-aggregation	79.59	13.91
`OR`-aggregation	126.16	N/A
`AND`-aggregation	N/A	16.23
`XOR`-aggregation	126.16	16.32

Table 3.3 summarizes the average number of “corrections" made through the network-layer classifiers, where the average is taken over the 37 days. The mis-classifications by the application-layer classifiers are either false-negative (i.e., the application-layer classifiers missed some malicious URLs) or false-positive (i.e., the application-layer classifiers wrongly accused some benign URLs). Note that for `OR`-aggregation, the network-layer classifiers cannot help correct the FP mistakes made by the application-layer classifiers because the benign URLs are always classified as malicious as long as one classifier (in this case, the application-layer one) says they are malicious. Similarly, for `AND`-aggregation, the network-layer classifiers cannot help correct the FN mistakes made by the application-layer classifiers because (i) the malicious URLs are always classified as benign unless both kinds of classifiers think they are malicious and (ii) the application-layer classifier already says they are benign. We observe that the contributions of the network-layer classifiers for `XOR`-aggregation in terms of correcting both FP and FN (126.16 and 16.32, respectively) are strictly more significant than the contributions of the network-layer information for

data-aggregation (79.59 and 13.91, correspondingly). This explains why XOR-aggregation is more effective than data-aggregation.



(a) Two mis-classification examples by application-layer classifier

(b) Network-layer corrections of the two application-layer mis-classifications

Figure 3.2: Portions of the application-layer and network-layer classifiers corresponding to the two URLs.

In what follows we examine two example URLs that were mis-classified by the application-layer classifier but corrected through the network-layer classifier. The two examples are among the URLs on the first day data, where one example corresponds to the FP mistake (i.e., the application-layer classifier mis-classified a benign URL as malicious) and the other example corresponds to the FN mistake (i.e., the application-layer classifier mis-classified a malicious URL as benign). The portion of the application-layer classifier corresponding to the two example URLs are highlighted in Figure 3.2a, which involves the following features (in the order of their appearances on the paths):

(**A2**)	`Number_of_special_char`
(**A18**)	`Number_of_small_size_iframe`
(**A1**)	`URL_length`
(**A19**)	`Number_of_suspicious_JavaScript_functions`
(**A17**)	`Number_iframe`
(**A13**)	`number_of_redirect`
(**A16**)	`Number_of_long_strings`
(**A8**)	`register_date`

The portions of the network-layer classified corresponding to the two URLs are highlighted in Figure 3.2b, which involves the following features (in the order of their appearances on the paths):

(**N11**)	`Duration`
(**N14**)	`App_packets`
(**N2**)	`Dist_remote_TCP_port`
(**N16**)	`DNS_response_time`
(**N9**)	`Avg_local_pkt_rate`
(**N15**)	`DNS_query_times`
(**N3**)	`Remote_ips`
(**N12**)	`Source_app_bytes`

Note that some features can, and indeed often, appear multiple times on a single path.

For the FP mistake made by the application-layer classifier, the feature values are **A2**=0 (no special characters in URL), **A18**=2 (two small iframes), **A1**=61 (medium URL length) and **A19**=4 (four suspicious JavaScript functions), which lead to the left-hand path in Figure 3.2a. The application-layer mis-classification may be attributed to **A18**=2 and **A19**=4, while noting that benign websites also use the `eval()` function to dynamically generate code according to certain information about the browser/user and use obfuscation to hide/protect JavaScript source code. On the other hand, the relevant network-layer feature values are **N11**=0.89 seconds (close to 0.793 second, the average of benign URLs), **N14**=79 (close to 63.73, the average of malicious URLs), **N2**=5 (not

indicative because it is almost equally close to the averages of both benign URLs and malicious URLs), **N16**=13.11ms (close to 13.29, the average of malicious URLs), **N9**=113 (close to 146, the average of benign URLs), **N15**=6 (close to 7.36, the average of benign URLs). We observe that the three network-layer features, namely **N11**, **N9** and **N15**, played a more important role in correctly classifying the URL.

For the FN mistake made by the application-layer classifier, **A2**=7 (close to 3.36, the average of malicious URLs), **A17**=0 (indicating benign URL because there are no iframes), **A13**=0 (indicating benign URL because there are no redirects), **A1**=22 (close to 18.23, the average of malicious URLs), **A16**=2 (close to 0.88, the average of malicious URLs), and **A8**=2007 (indicating benign URL because the domain name has been registered for multiple years). The above suggests that **A17**, **A13** and **A8** played a bigger role in causing the mis-classification. On the other hand, the relevant network feature values are **N11**=2.13 (close to 2.05, the average of malicious URLs), **N14**=342 (close to 63.73, the average of malicious URLs), **N2**=7 (not very indicative because the respective averages of benign URLs and malicious URLs are about the same), **N3**=3 (close to 2.40, the average of benign URLs), **N12**=289 bytes (relatively close to 63.73, the average of malicious URLs), and **N9**=423 (relatively close to 269, the average of malicious URLs). The above suggests that the network-layer classifier can correct the mistake made by the application-layer classifier because of features **N11**, **N14**, **N12** and **N9**.

3.3.4 Performance Evaluation

As discussed in the Introduction, we aim to make our system as fast and scalable as the static approach while achieving as high an effectiveness as the dynamic approach. In the preceding, we have demonstrated that cross-layer J48 classifiers (indeed, all of the cross-layer detection models we investigated) are almost as effective as the dynamic approach. In what follows we report that the cross-layer J48 classifiers are much faster than the dynamic approach and almost as efficient as the static approach.

The time spent on running our system consists of three parts: the time spent for collecting

application-layer and network-layer data, the time spent for training the cross-layer J48 classifiers, and the time spent for using the J48 classifiers to classify websites. Since the training of cross-layer J48 classifiers is conducted periodically (e.g., once a day in our experiments), this time is not a significant factor and can be omitted. Nevertheless, we report that the time spent for learning data-aggregation cross-layer J48 classifiers is typically less than 10 seconds on a modest computer when the training dataset has thousands of feature vectors. The training time spent for learning `OR`-aggregation, `AND`-aggregation, or `XOR`-aggregation cross-layer J48 classifiers is about the same. Therefore, we will focus on the time spent for collecting the application-layer and network-layer data corresponding to a given URL and the time spent for classifying the given URL. These two metrics are the most important because they ultimately determine whether the cross-layer J48 classifiers can be deployed for the purpose of real-time detection.

In the afore-reported effectiveness experiments, the cross-layer J48 classifiers and the Capture-HPC client honeypot (as an example of the dynamic approach) were tested on different computers with different hardware configurations. Therefore, we cannot simply measure and compare their respective time complexities. In order to have a fair comparison, we conducted extra experiments by using two computers with the same configuration. One computer ran our cross-layer J48 classifiers and the other computer ran the Capture-HPC client honeypot. The hardware of the two computers is Intel Xeon X3320 4 cores CPU and 8GB memory. We used Capture-HPC version 3.0.0 and VMWare Server version 1.0.6. The Host OS is Windows Server 2008 and the Guest OS is Windows XP sp3. Our crawler was written in JAVA 1.6 and ran on top of Debian 6.0. We used IPTABLES [3] and a modified version of TCPDUMP [8] to parallelize the data collection system. The application-layer features were directly obtained by each crawler instance, but the network-layer features were extracted from the network traffic collected by the TCPDUMP software on the local host. IPTABLES were configured to log network flow information with respect to different processes, which correspond to different crawler instances. Since our crawler is light-weight, we ran 50 instances concurrently in our experiments, whereas we ran 5 guest Operating Systems to parallelize the Capture-HPC. Experimental results indicated that more guest Operating Systems

make the system unstable. Both computers used network cards with 100Mbps network cable.

Table 3.4: Measured performance comparison between the data-aggregation cross-layer J48 classifier and the dynamic approach (the Capture-HPC client honeypot) with 3,062 input URLs (1,562 malicious URLs + 1,500 Benign URLs)

Data-aggregation cross-layer J48 classifier	
Total data collection time	4 min
Total classification time	302 ms
Total time	≈ 4 min
Capture-HPC	
Total time	199min

Table 3.4 describes the performance of the cross-layer J48 classifier and of the Capture-HPC client honeypot. It took the data-aggregation cross-layer J48 classifier about 4 minutes to process the 3,062 input URLs, whereas it took the Capture-HPC 199 minutes to process the same 3,062 URLs. In order words, the cross-layer detection approach can be about 50 times faster than the dynamic approach, while achieving about the same detection effectiveness.

The preceding conclusion that the cross-layer detection approach is faster than the dynamic approach was based on batch processing of 3,062 URLs. To compare processing times for individual URLs, we approximately broke down the performance as follows, where *approximation* is caused by the concurrent executions of the respective systems. Specifically, the time for the data-aggregation cross-layer J48 classifier to determine whether a given website is malicious or not is calculated as $240/(3062/50) \approx 3.92$ seconds because each crawler actually processed 3062/50 URLs on average. Among the 3.92 seconds, on average 2.73 seconds were actually spent on downloading the website content, which means that 1.19 seconds were spent for feature extractions, etc. Similarly, the time for Capture-HPC to determine whether a given website is malicious or not is $(199 \times 60)/(3062/5) = 19.5$ seconds because 5 Capture-HPC instances ran concurrently. The reason why Capture-HPC is slow is because Capture-HPC spent much time on receiving all the diagnostic results caused by visiting URLs in the virtual machine and reverting the virtual machine back to a clean snapshot whenever a URL was deemed to be malicious. Moreover, the XOR-aggregation cross-layer J48 classifier without feature selection would only incur the dynamic

approach to analyze, on average, about $5.04\% \times 3062 \approx 154$ websites. This means that even for XOR-aggregation, the processing time per URL is no more than $3.92 + 19.5 \times 154/3062 \approx 4.9$ seconds. Therefore, we conclude that even if the cross-layer detection system runs within each individual computer, rather than a third-party server, it is about 4 times faster than the dynamic approach. In any case, 4 seconds waiting time is arguably acceptable, especially since we can let the browser start displaying the portions of website content that have no security concerns. This is reasonable because the same idea has been used to give users the illusion that website contents are displayed almost instantly, but actually it takes a few seconds to display the entire website contents. On the other hand, waiting for 19.5 seconds for the dynamic approach to test whether a website is malicious or not is not reasonable, which perhaps explains why the dynamic approach, while powerful, is not used for real-time detection in practice.

3.3.5 Deployment

Cross-layer detection offers a spectrum of deployment options. It can be deployed as a stand-alone solution because it is highly effective as analyzed before. Moreover, it can be deployed as a light-weight front-end detection system of a bigger solution (see Figure 3.3), which aims at detecting as many malicious websites as possible while scaling up to a large population of websites. For this purpose, the data-aggregation and the OR-aggregation method would be efficient. Moreover, the XOR-aggregation is particularly effective and should be deployed when it only incurs the back-end dynamic approach occasionally.

There are several ways to deploy the physical components of the cross-layer detection service. Recall that our system has three components: application-layer data collector (i.e., crawler), network-layer traffic recorder, and cross-layer data correlator. The crawler takes URLs as input, fetches the corresponding website contents, and conducts a light-weight analysis to identify the redirects that are embedded into the website contents. The traffic recorder collects the network traffic corresponding to the crawler's activities in fetching the website contents. The cross-layer data correlator relates the application-layer website contents to the corresponding network-layer

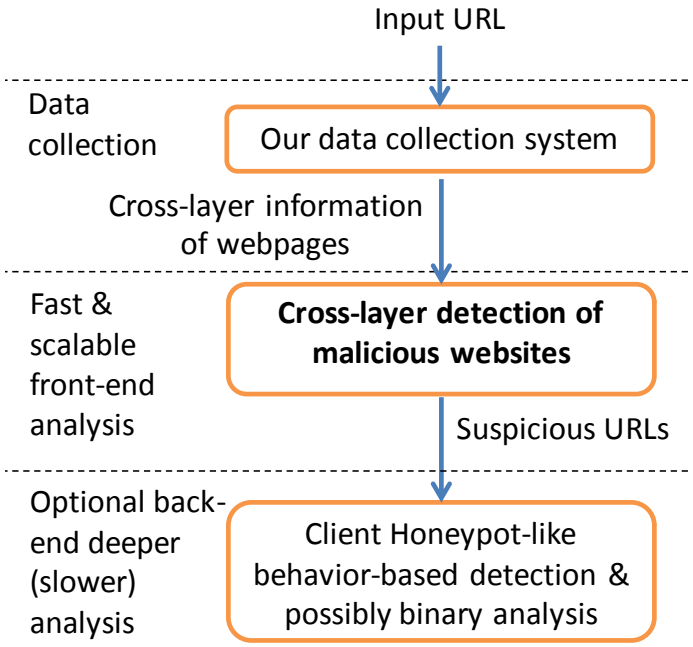


Figure 3.3: Example deployment of the cross-layer detection system as the front-end of a bigger solution because XOR-aggregation J48 classifiers achieve extremely high detection accuracy, extremely low false-negative and false-positive rates.

traffic via the input URLs. These components may or may not be deployed on the same physical computer, as the following scenarios demonstrate.

First, we can deploy the stand-alone cross-layer detection system as a web browser plug-in. In this case, the detection system can test whether the website is malicious or not before the browser actually displays the website content. If it is malicious, the browser can take appropriate actions according to a pre-determined policy (e.g., warning the user that the website is malicious). The plug-in should collect the network-layer traffic corresponding to the application-layer website content of the given URL. The plug-in also may act as the network-layer traffic collector and the cross-layer correlator. Moreover, network-traffic could be collected at some routers or gateways, from which the plug-in can obtain the traffic corresponding to the application-layer website content.

Second, we can deploy the cross-layer detection system as an online service. This service may be accessed by web browsers via the proxy or gateway technique. Specifically, when a user browser points to a URL, the corresponding website will be analyzed by the cross-layer detection service, which will then communicate the outcome back to the browser. The browser can take

appropriate actions based on its pre-determined policy (e.g., displaying the website or not).

Third, we can deploy the cross-layer detection system at the website hosting server itself. The website hosting service vendor might have the incentive for proactively examining whether the websites it hosts have been compromised, because this might enhance the reputation of the vendor. In this case, the vendor can deploy it as a front-end to a bigger detection system, or deploy it as a stand-alone system.

3.4 Related Work

Both industry and academia are actively seeking effective solutions to the problem of malicious websites. Industry has mainly offered their proprietary blacklists of malicious websites, such as Google's Safe Browsing [1] and Mcafee's SiteAdvisor [6]. Effectiveness of the blacklist approach is fundamentally limited by the frequency at which the blacklists are updated and disseminated. This justifies why we advocate pursuing light-weight real-time detection, which is the goal of the present paper.

Researchers have used logistic regression to study phishing URLs [24], which does not consider the issue of redirection. On the other hand, redirection has been used as an indicator of web spams [10,45,51,64]. Kurt et al. [61] presented a system for scalably detecting spam contents. Ma et al. [39, 40] studied how to detect phishing and spams based on URLs themselves.

In terms of detecting malicious websites that may host malwares, Choi et al. [16] investigated the detection of malicious URLs, and Canali et al. [14] presented the design and implementation of a static detection tool called Prophiler. However, these studies did not consider the usefulness of cross-layer detection. On the other hand, the back-end system for deeper analysis is also an active research topic [15, 18, 41, 67], because attackers have been attempting to circumvent dynamic analysis [31, 53].

3.5 Summery

A key limitation of the present study is that, as pointed out in [31, 53] , the (back-end) dynamic approach itself may have its own non-zero false-negative and false-positive rates. While studying the dynamic approach is an orthogonal issue, we suggest a future study on the impact of false-negatives and false-positives incurred in the dynamic approach, with an emphasis on Capture-HPC.

Another problem of interest for future work is to learn to what extent the effectiveness of cross-layer detection systems can be improved by incorporating new techniques such as those described in [18, 20, 46, 56].

Our cross-layer detection system provides a best-effort capability by statistically tracking the redirects that are embedded into the website contents. It is difficult to statistically detect obfuscated JavaScript-based redirects [22, 23]. Even though the effectiveness of our cross-layer detection system is almost as good as the dynamic approach, it would be useful in future work to determine the impact of progress made in the direction of detecting obfuscated JavaScript-based redirects. This is an important issue because, although our collected data hints that JavaScript-based redirection is widely used by malicious websites, it appears that JavaScript obfuscation may not have been widely used because our system can effectively detect the malicious URLs (almost as effectively as the dynamic approach which is capable of dealing with redirects). However, this may not remain true if in the future such redirects may be more widely exploited by the adversary. Fortunately, any progress in dealing with obfuscated redirects can be adopted by our system in a plug-and-play fashion.

To sum up, we presented a novel approach to detecting malicious websites based on the insight that network-layer traffic data may expose useful information about websites, which may be exploited to attain cross-layer detection of malicious websites. Experimental results showed that cross-layer detection can achieve almost the same detection effectiveness, but about 50 times faster than, the dynamic approach based on client honeypot systems. Moreover, the cross-layer detection systems can also be deployed to detect malicious websites in real time because the average

time for processing a website is approximately 4.9 seconds, which could be improved with some engineering optimization.

Chapter 4: PROACTIVE DETECTION OF ADAPTIVE MALICIOUS WEBSITES

4.1 Introduction

Compromising websites and abusing them to launch further attacks (e.g., drive-by-download [18, 50]) have become one of the mainstream attack methods. Unfortunately, it is infeasible, if not impossible, to prevent websites from being abused to launch attacks. This means that we must have competent solutions that can detect compromised/malicious websites as soon as possible. This is a difficult problem. Although client honeypots or their variants can detect malicious websites with high accuracy, this *dynamic* approach often is too resource-consuming to be scalable. On the other hand, the *static* approach aims to analyze the website contents without executing them in an (emulated) browser. This approach is very efficient but has limited success in dealing with sophisticated attacks. Recently, Xu et al. [65] (ACM CODASPY'13) proposed a promising cross-layer method, which enhances the static approach by exploiting the corresponding network-layer traffic that exposes some extra information about malicious websites. Using a dataset of 37 days, they showed that their solution can almost achieve the best of both static detection (i.e., efficiency and scalability) and dynamic detection (i.e., high accuracy, low false-positive, and low false-negative).

In this chapter, we investigate an inherent weakness of the static approach, namely that the attacker can adaptively manipulate the contents of malicious websites to evade detection. The manipulation operations can take place either during the process of, or after, compromising the websites. This weakness is inherent because the attacker controls the malicious websites. Furthermore, the attacker can anticipate the machine learning algorithms the defender would use to train its detection schemes (e.g., J48 classifiers or decision trees [52]), and therefore can use the same algorithms to train its own version of the detection schemes. In other words, the defender has no substantial "secret" that is not known to the attacker. This is in sharp contrast to the case of cryptography, where the defender's cryptographic keys are not known to the attacker. It is the secrecy

of cryptographic keys (as well as the mathematical properties of the cryptosystem in question) that allows the defender to defeat various attacks.

The above discussion leads to the following question: **how can we defeat adaptive attacks?** In this chapter, we make two contributions toward ultimately answering this question. First, we formulate a model of adaptive attacks. The model accommodates attacker's adaptation strategies, manipulation constraints, and manipulation algorithms. Experiments based on a dataset of 40 days show that adaptive attacks can make malicious websites easily evade both single- and cross-layer detections. Moreover, we find that the feature selection algorithms used by machine learning algorithms do not select features of high security significance. In contrast, the adaptive attack algorithms can select features of high security significance. Unfortunately, the "black-box" nature of machine learning algorithms still makes it difficult to explain why some features are more significant than others from a security perspective.

Second, we propose using proactive detection to counter adaptive attacks, where the defender proactively trains its detection schemes. Experiments show that the proactive detection schemes can detect manipulated malicious websites with significant success. Other findings include: (i) The defender can always use proactive detection without worrying about the side-effects (e.g., when the attacker is not adaptive). (ii) If the defender does not know the attacker's adaptation strategy, the defender should adopt what we call the `full` adaptation strategy, which appears (or is close) to be a kind of equilibrium strategy as our preliminary analysis suggests.

The rest of the chapter is organized as follows. Section 4.2 investigates adaptive attacks and their power. Section 4.3 explores proactive detection and its effectiveness against adaptive attacks. Section 5.6 discusses related work. Section 5.7 concludes the chapter with future research directions.

Metrics. To evaluate the power of adaptive attacks and the effectiveness of proactive detection against adaptive attacks, we mainly use the following metrics: *detection accuracy*, *trust-positive rate*, *false-negative rate*, and *false-positive rate*. Let $D_\alpha = D_\alpha.malicious \cup D_\alpha.benign$ be a set of feature vectors that represent websites, where $D_\alpha.malicious$ represents the malicious websites

and $D_\alpha.benign$ represents the benign websites. Suppose a detection scheme (e.g., J48 classifier) detects malicious $\subseteq D_\alpha.malicious$ as malicious websites and benign $\subseteq D_\alpha.benign$ as benign websites. Detection accuracy is defined as $\frac{|\mathsf{malicious} \cup \mathsf{benign}|}{|D_\alpha|}$, true-positive rate is defined as TP=$\frac{|\mathsf{malicious}|}{|D_\alpha.malicious|}$, false-negative rate is defined as TN=$\frac{|D_\alpha.malicious \setminus \mathsf{malicious}|}{|D_\alpha.malicious|}$, false-positive rate is defined as FP=$\frac{|D_\alpha.benign \setminus \mathsf{benign}|}{|D_\alpha.benign|}$. Note that TP+FN=1, but we use both for better exposition of results.

Notations. The main notations are summarized as follows.

MLA	machine learning algorithm
fv	feature vector representing a website (and its redirects)
X_z	feature X_z's domain is $[\min_z, \max_z]$
$M_0, \ldots, M_\gamma$	defender's detection schemes (e.g., J48 classifier)
D'_0	training data (feature vectors) for learning M_0
D_0	$D_0 = D_0.malicious \cup D_0.benign$, where malicious feature vectors in $D_0.malicious$ may have been manipulated
$D_0^\dagger$	feature vectors used by defender to proactively train $M_1, \ldots, M_\gamma$; $D_0^\dagger = D_0^\dagger.malicious \cup D_0^\dagger.benign$
$M_i(D_\alpha)$	applying detection scheme M_i to feature vectors D_α
$M_{0\text{-}\gamma}(D_\alpha)$	majority vote of $M_0(D_\alpha), M_1(D_\alpha), \ldots, M_\gamma(D_\alpha)$
ST, C, F	adaptation strategy ST, manipulation algorithm F, manipulation constraints C
$s \xleftarrow{R} S$	assigning s as a random member of set S
v	v is a node on a J48 classifier (decision tree), $v.feature$ is the feature associated to node v, and $v.value$ is the "branching" point of $v.feature$'s value on the tree

4.2 Adaptive Attacks and Their Power

4.2.1 Adaptive Attack Model and Algorithm

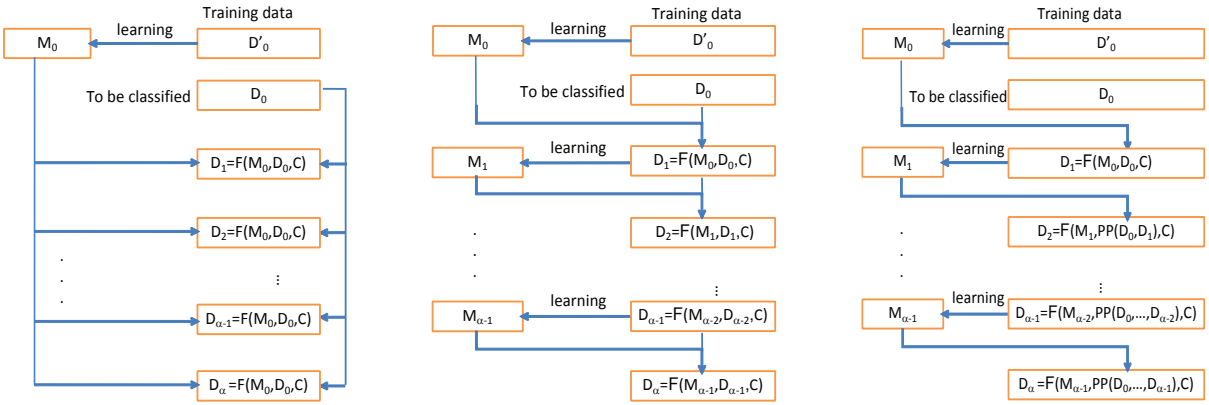
The attacker can collect the same data as what is used by the defender to train a detection scheme. The attacker knows the machine learning algorithm(s) the defender uses to learn a detection scheme (e.g., J48 classifier or decision tree [52]), or even the defender's detection scheme. To accommo-

date the worst-case scenario, we assume there is a single attacker that coordinates the compromise of websites (possibly by many sub-attackers). This means that the attacker knows which websites are malicious, while the defender aims to detect them. In order to evade detection, the attacker can manipulate some features of the malicious websites. The manipulation operations can take place during the process of compromising a website, or after compromising a website but before the website is examined by the defender's detection scheme.

More precisely, a website is represented by a feature vector. We call the feature vector representing a benign website *benign feature vector*, and *malicious feature vector* otherwise. Denote by D'_0 the defender's *training data*, namely a set of feature vectors corresponding to a set of benign websites ($D'_0.benign$) and malicious websites ($D'_0.malicious$). The defender uses a machine learning algorithm MLA to learn a detection scheme M_0 from D'_0 (i.e., M_0 is learned from one portion of D'_0 and tested via the other portion of D'_0). As mentioned above, the attacker is given M_0 to accommodate the worst-case scenario. Denote by D_0 the set of feature vectors that are to be examined by M_0 to determine which feature vectors (i.e., the corresponding websites) are malicious. The attacker's objective is to manipulate the malicious feature vectors in D_0 into some D_α so that $M_0(D_\alpha)$ has a high false-negative rate, where $\alpha > 0$ represents the number of rounds the attacker conducts the manipulation operations.

The above discussion can be generalized to the adaptive attack model highlighted in Figure 4.1. The model leads to adaptive attack **Algorithm 1**, which may call **Algorithm 2** as a sub-routine. Specifically, an adaptive attack is an algorithm $\mathsf{AA}(\mathsf{MLA}, M_0, D_0, \mathsf{ST}, \mathsf{C}, \mathsf{F}, \alpha)$, where MLA and M_0 and D_0 are described above, ST is the attacker's *adaptation strategy* specified below, C is a set of manipulation constraints (see Section 4.2.1), F is the attacker's (deterministic or randomized) *manipulation algorithm* (see Section 4.2.1), and $\alpha \geq 1$ is the number of rounds the attacker runs F. Also as highlighted in Figure 4.1, we consider three basic adaptation strategies.

Parallel adaptation strategy: The attacker sets the manipulated $D_i = \mathsf{F}(M_0, D_0, \mathsf{C})$, where $i = 1, \ldots, \alpha$, and F is a randomized manipulation algorithm, meaning that $D_i = D_j$ for $i \neq j$ is unlikely.



(a) Parallel adaptation strategy (b) Sequential adaptation strategy (c) Full adaptation strategy

Figure 4.1: Adaptive attack algorithm $\mathsf{AA}(\mathsf{MLA}, M_0, D_0, \mathsf{ST}, \mathsf{C}, \mathsf{F}, \alpha)$, where MLA is the defender's machine learning algorithm, D'_0 is the defender's training data, M_0 is the defender's detection scheme that is learned from D'_0 by using MLA, D_0 is the feature vectors that are examined by M_0 in the absence of adaptive attacks, ST is the attacker's adaptation strategy, C is a set of manipulation constraints, F is the attacker's (deterministic or randomized) manipulation algorithm that maintains the set of constraints C, α is the number of rounds the attacker runs its manipulation algorithms. D_α is the manipulated version of D_0 with malicious feature vectors $D_0.malicious$ manipulated. The attacker's objective is make $M_0(D_\alpha)$ have high false-negative rate.

Sequential adaptation strategy: The attacker sets the manipulated $D_i = \mathsf{F}(M_{i-1}, D_{i-1}, \mathsf{C})$ for $i = 1, \ldots, \alpha$, where detection schemes $M_1, \ldots, M_\alpha$ are respectively learned from $D_1, \ldots, D_\alpha$ using the defender's machine learning algorithm MLA (also known to the attacker).

Full adaptation strategy: The attacker sets the manipulated $D_i = \mathsf{F}(M_{i-1}, \mathsf{PP}(D_0, \ldots, D_{i-1}), \mathsf{C})$ for $i = 1, 2, \ldots$, where $\mathsf{PP}(\cdot, \ldots)$ is a pre-processing algorithm for "aggregating" sets of feature vectors $D_0, D_1, \ldots$ into a single set of feature vectors, F is a manipulation algorithm, $M_1, \ldots, M_\alpha$ are learned respectively from $D_1, \ldots, D_\alpha$ by the attacker using the defender's machine learning algorithm MLA. **Algorithm 2** is a concrete implementation of PP. Its idea is: since each malicious website corresponds to m malicious feature vectors that respectively belong to $D_0, \ldots, D_{m-1}$, PP randomly picks one of the m malicious feature vectors to represent the malicious website in $\mathcal{D}$.

Note that it is possible to derive some hybrid attack strategies from the above three basic strategies; we leave their study to future work. Note also that the attack strategies and manipulation constraints are independent of the detection schemes, but manipulation algorithms would be spe-

Algorithm 1 Adaptive attack $\mathsf{AA}(\mathsf{MLA}, M_0, D_0, \mathsf{ST}, \mathsf{C}, \mathsf{F}, \alpha)$

INPUT: MLA is defender's machine learning algorithm, M_0 is defender's detection scheme, $D_0 = D_0.malicious \cup D_0.benign$ where malicious feature vectors ($D_0.malicious$) are to be manipulated (to evade detection of M_0), ST is attacker's adaptation strategy, C is a set of manipulation constraints, F is attacker's manipulation algorithm, α is attacker's number of adaptation rounds
OUTPUT: D_α

initialize array $D_1, \ldots, D_\alpha$
for i=1 **to** α **do**
  if ST == `parallel-adaptation` **then**
    $D_i \leftarrow \mathsf{F}(M_0, D_0, \mathsf{C})$ {manipulated version of D_0}
  else if ST == `sequential-adaptation` **then**
    $D_i \leftarrow \mathsf{F}(M_{i-1}, D_{i-1}, \mathsf{C})$ {manipulated version of D_0}
  else if ST == `full-adaptation` **then**
    $\mathcal{D}_{i-1} \leftarrow \mathsf{PP}(D_0, \ldots, D_{i-2})$ {see **Algorithm 2**}
    $D_i \leftarrow \mathsf{F}(M_{i-1}, \mathcal{D}_{i-1}, \mathsf{C})$ {manipulated version of D_0}
  if $i < \alpha$ **then**
    $M_i \leftarrow \mathsf{MLA}(D_i)$ {$D_1, \ldots, D_{\alpha-1}, M_1, \ldots, M_{\alpha-1}$ are not used when ST==`parallel-adaptation`}
return D_α

Algorithm 2 Algorithm $\mathsf{PP}(D_0, \ldots, D_{m-1})$

INPUT: m sets of feature vectors $D_0, \ldots, D_{m-1}$ where the zth malicious website corresponds to $D_0.malicious[z], \ldots, D_{m-1}.malicious[z]$
OUTPUT: $\mathcal{D} = \mathsf{PP}(D_0, \ldots, D_{m-1})$

$\mathcal{D} \leftarrow \emptyset$
`size` $\leftarrow$ sizeof($D_0.malicious$)
for $z = 1$ **to** `size` **do**
  $\mathcal{D}[z] \overset{R}{\leftarrow} \{D_0.malicious[z], \ldots, D_{m-1}.malicious[z]\}$
  $\mathcal{D} \leftarrow \mathcal{D} \cup D_0.benign$
return $\mathcal{D}$

cific to the detection schemes.

Manipulation Constraints

There are three kinds of manipulation constraints. For a feature X whose value is to be manipulated, the attacker needs to compute $X.escape\_interval$, which is a subset of feature X's domain $domain(X)$ and can possibly cause the malicious feature vector to evade detection. Specifically, suppose features $X_1, \ldots, X_j$ have been respectively manipulated to $x_1, \ldots, x_j$ (initially $j = 0$), feature X_{j+1}'s manipulated value is randomly chosen from its $escapte\_interval$, which is calculated using **Algorithm 3**, while taking as input X_{j+1}'s domain constraints, semantics constraints

and correlation constraints and conditioned on $X_1 = x_1, \ldots, X_j = x_j$.

Algorithm 3 Compute X_{j+1}'s escape_interval
$\mathsf{Escape}(X_{j+1}, M, \mathsf{C}, (X_1 = x_1, \ldots, X_j = x_j))$

INPUT: X_{j+1} is feature for manipulation, M is detection scheme, C represents constraints, X_{j+1} is correlated to $X_1, \ldots, X_j$ whose values have been respectively manipulated to $x_1, \ldots, x_j$
OUTPUT: X_{j+1}'s $escape\_interval$

1: $domain\_constraint \leftarrow \mathsf{C}.domain\_map(X_{j+1})$
2: $semantics\_constraint \leftarrow \mathsf{C}.semantics\_map(X_{j+1})$ {$\emptyset$ if X_{j+1} cannot be manipulate due to semantics constraints}
3: calculate $correlation\_constraint$ of X_{j+1} given $X_1 = x_1, \ldots, X_j = x_j$ according to Eq. (4.1)
4: $escape\_interval \leftarrow domain\_constraint \cap semantics\_constraint \cap correlation\_constraint$
5: **return** $escape\_interval$

Domain constraints: Each feature has its own domain of possible values. This means that the new value of a feature after manipulation must fall into the domain of the feature. Domain constraints are specified by the defender. Let $\mathsf{C}.domain\_map$ be a table of $(key, value)$ pairs, where key is feature name and $value$ is the feature's domain constraint. Let $\mathsf{C}.domain\_map(X)$ return feature X's domain as defined in $\mathsf{C}.domain\_map$.

Semantics constraints: Some features cannot be manipulated at all. For example, `Whois_country` and `Whois_stateProv` of websites cannot be manipulated because they are bound to the website URLs, rather than the website contents. (The exception that the Whois system is compromised is assumed away here because it is orthogonal to the purpose of the present study.) Moreover, the manipulation of feature values should have no side-effect to the attack, or at least cannot invalidate the attacks. For example, if a malicious website needs to use some script to launch the drive-by-download attack, the feature indicating the number of scripts in the website content cannot be manipulated to 0. Semantics constraints are also specified by the defender. Let $\mathsf{C}.semantics\_map$ be a table of $(key, value)$ pairs, where key is feature name and $value$ is the feature's *semantics constraints*. Let $\mathsf{C}.semantics\_map(X)$ return feature X's semantics constraints as specified in $\mathsf{C}.attack\_map$.

Correlation constraints: Some features may be correlated to each other. This means that these features' values should not be manipulated independently of each other; otherwise, adaptive attacks can be defeated by simply examining the violation of correlations. In other words, when some

features' values are manipulated, the correlated features' values should be accordingly manipulated as well. That is, feature values are manipulated either for evading detection or for maintaining the constraints. Correlation constraints can be automatically derived from data on demand (as done in our experiments), or alternatively given as input. Let $\mathsf{C}.group$ be a table of $(key, value)$ pairs, where key is feature name and $value$ records the feature's correlated features. Let $\mathsf{C}.group(X)$ return the set of features belonging to $\mathsf{C}.group$, namely the features that are correlated to X.

Now we describe a method for maintaining correlation constraints, which is used in our experiments. Suppose $D_0 = D_0.malicious \cup D_0.benign$ is the input set of feature vectors, where the attacker knows $D_0.malicious$ and attempts to manipulate the malicious feature vectors (representing malicious websites). Suppose the attacker already manipulated D_0 into D_i and is about to manipulate D_i into D_{i+1}, where initial manipulation corresponds to $i = 0$. Suppose $X_1, \ldots, X_m$ are some features that are strongly correlated to each other, where "strong" means that the Pearson correlation coefficient is greater than a threshold (e.g., 0.7). To accommodate the worst-case scenario, we assume that the threshold parameter is set by the defender and given to the attacker. It is natural and simple to identify and manipulate features one-by-one. Suppose without loss of generality that features $X_1, \ldots, X_j$ ($j < m$) have been manipulated, where $j = 0$ corresponds to the initial case, and that the attacker now needs to manipulate feature X_{j+1}'s value. For this purpose, the attacker derives from data D'_0 a regression function:

$$X_{j+1} = \beta_0 + \beta_1 X_1 + \ldots + \beta_j X_j + \epsilon$$

for some unknown noise ϵ. Given $(X_1, \ldots, X_j) = (x_1, \ldots, x_j)$, the attacker can compute

$$\hat{x}_{j+1} = \beta_0 + \beta_1 x_1 + \ldots + \beta_j x_j.$$

Suppose the attacker wants to maintain the correlation constraints with a confidence level θ (e.g., $\theta = .85$) that is known to the defender and the attacker (for accommodating the worst-case sce-

nario), the attacker needs to compute X_{j+1}'s *correlation_interval*:

$$\left[\hat{x}_{j+1} - t_{\delta/2} \cdot \widehat{\mathsf{se}(\hat{x}_{j+1})}, \hat{x}_{j+1} + t_{\delta/2} \cdot \widehat{\mathsf{se}(\hat{x}_{j+1})}\right], \tag{4.1}$$

where $\delta = 1 - \theta$ is the significance level for a given hypothesis test, $t_\delta/2$ is a critical value (i.e., the area between t and $-t$ is θ), $\widehat{\mathsf{se}(\hat{x}_{j+1})} = s\sqrt{\mathbf{x}'(\mathbf{X}'\mathbf{X})^{-1}\mathbf{x}}$ is the estimated standard error for $\hat{x}_{j+1}$ with s being the sample standard deviation,

$$\mathbf{X} = \begin{bmatrix} x^0_{1,1} & x^0_{1,2} & \cdots & x^0_{1,j} \\ x^0_{2,1} & x^0_{2,2} & \cdots & x^0_{2,j} \\ \vdots & \vdots & \ddots & \vdots \\ x^0_{n,1} & x^0_{n,2} & \cdots & x^0_{n,j} \end{bmatrix}, \qquad \mathbf{x} = \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_j \end{bmatrix},$$

n being the sample size (i.e., the number of feature vectors in training data D'_0), $x^0_{z,j}$ being feature X_j's original value in the zth feature vector in training data D'_0 for $1 \leq z \leq n$, x_j being feature X_j's new value in the feature vector in D_{i+1} (the manipulated version of D_i), and $\mathbf{X}'$ and $\mathbf{x}'$ being respectively $\mathbf{X}$'s and $\mathbf{x}$'s transpose. Note that the above method assumes that the prediction error $\hat{x}_{j+1} - X_{j+1}$, rather than feature X_{j+1}, follows the Gaussian distribution.

Manipulation Algorithms

As mentioned in Section 2, we adopt the data-aggregation cross-layer J48 classifier method, where a J48 classifier is trained by concatenating the application- and network-layer data corresponding to the same URL. This method makes it much easier to deal with cross-layer correlations (i.e., some application-layer features are correlated to some network-layer features); whereas, the XOR-aggregation cross-layer method can cause complicated cascading side-effects when treating cross-layer correlations because the application and network layers have their own classifiers. Note that there is no simple mapping between the application-layer features and the network-layer features;

otherwise, the network-layer data would not expose any useful information beyond what is already exposed by the application-layer data [65]. Specifically, we present two manipulation algorithms, called F_1 and F_2, which exploit the defender's J48 classifier to guide the manipulation of features. Both algorithms neither manipulate the benign feature vectors (which are not controlled by the attacker), nor manipulate the malicious feature vectors that are already classified as benign by the defender's detection scheme (i.e., false-negative). Both algorithms may fail, while brute-forcing may fail as well because of the manipulation constraints.

The notations used in the algorithms are: for node v in the classifier, $v.feature$ is the feature associated to node v, and $v.value$ is $v.feature$'s "branching" value as specified by the classifier (a binary tree with all features numericalized). For feature vector fv, $\mathsf{fv}.feature.value$ denotes the value of feature $feature$ in fv. The data structure

$$S = \{(feature, value, interval, manipulated)\},$$

keeps track of the features that are associated to the nodes in question, $S.features$ is the set of features recorded in S, $S.feature.value$ is the $feature$'s value recorded in S, $S.feature.interval$ is the $feature$'s interval recorded in S, $S.feature.manipulated == \texttt{true}$ means $S.feature$ has been manipulated. A feature vector fv is actually manipulated according to S only when the manipulation can mislead M to misclassify the manipulated fv as benign.

Algorithm 4 describes manipulation algorithm $\mathsf{F}_1(M, D, \mathsf{C})$, where M is a J48 classifier and D is a set of feature vectors, and C is the manipulation constraints. The basic idea is the following: For every malicious feature vector in D, there is a unique path (in the J48 classifier M) that leads to a *malicious leaf*, which indicates that the feature vector is malicious. We call the path leading to malicious leaf a *malicious path*, and the path leading to a *benign leaf* (which indicates a feature vector as benign) a *benign path*. By examining the path from the malicious leaf to the root, say $malicious\_leaf \rightarrow v_2 \rightarrow \ldots \rightarrow root$, and identifying the first inner node, namely v_2, the algorithm attempts to manipulate $\mathsf{fv}.(v_2.feature).value$ so that the classification can lead

Algorithm 4 Manipulation algorithm $\mathsf{F}_1(M, D, \mathsf{C})$

INPUT: J48 classifier M (binary decision tree), feature vector set $D = D.malicious \cup D.benign$, manipulation constraints C
OUTPUT: manipulated feature vectors

for all feature vector $\mathsf{fv} \in D.malicious$ **do**
  $mani \leftarrow$ `true`; $success \leftarrow$ `false`; $S \leftarrow \emptyset$
  v be the root node of M
  while ($mani ==$ `true`) AND ($success ==$ `false`) **do**
    if v is an inner node **then**
      if $\mathsf{fv}.(v.feature).value \leq v.value$ **then**
        $interval \leftarrow [\mathsf{min}_{v.feature}, v.value]$
      else
        $interval \leftarrow (v.value, \mathsf{max}_{v.feature}]$
      if $\nexists(v.feature, \cdot, \cdot, \cdot) \in S$ **then**
        $S \leftarrow S \cup \{(v.feature,$
        $\mathsf{fv}.(v.feature).value, interval,$ `false`$)\}$
      else
        $S.(v.feature).interval \leftarrow interval \cap$
        $S.(v.feature).interval$
      $v \leftarrow v$'s child as determined by $v.value$ and $\mathsf{fv}.(v.feature).value$
    else if v is a malicious leaf **then**
      $v^* \leftarrow v.parent$
      $S^* \leftarrow \{s \in S : s.manipulated ==$ `true`$\}$
      $\{X_1, \ldots, X_j\} \leftarrow \mathsf{C}.group(v^*.feature) \cap S^*.features$, with values $x_1, \ldots, x_j$ w.r.t. S^*
      $esc\_interval \leftarrow \mathsf{Escape}(v^*.feature, M, \mathsf{C}, (X_1 = x_1, \ldots, X_j = x_j))$ {call **Algorithm 3**}
      if $esc\_interval == \emptyset$ **then**
        $mani \leftarrow$ `false`
      else
        denote $v^*.feature$ by X {for shorter presentation}
        $S.X.interval \leftarrow (esc\_interval \cap S.X.interval)$
        $S.X.value \overset{R}{\leftarrow} S.X.interval$
        $S.X.manipulated \leftarrow$ `true`
        $v \leftarrow v$'s sibling
    else
      $success \leftarrow$ `true` {reaching a benign leaf}
  if ($mani ==$ `true`) AND ($success ==$ `true`) AND ($\mathsf{MR}(M, \mathsf{C}, S) ==$ `true`) **then**
    update fv's manipulated features according to S
return set of manipulated feature vectors D

to $malicious\_leaf$'s sibling, say $v_{2,another\_child}$, which is guaranteed to exist (otherwise, v_2 cannot be an inner node). Note that there must be a sub-path rooted at $v_{2,another\_child}$ that leads to a $benign\_leaf$ (otherwise, v_2 cannot be an inner node as well), and that manipulation of values of the features corresponding to the nodes on the sub-tree rooted at $v_{2,another\_child}$ will preserve the postfix $v_2 \rightarrow \ldots \rightarrow root$. For each feature vector $\mathsf{fv} \in D.malicious$, the algorithm may successfully manipulate some features' values while calling **Algorithm 5** to maintain constraints, or fail because the manipulations cannot be conducted without violating the constraints. The worst-case time complexity of F_1 is $O(h\ell g)$, where h is the height of the J48 classifier, ℓ is the number of features, and g is the size of the largest group of correlated features. The actual time complexity is very small. In our experiments on a laptop with Intel X3320 CPU and 8GB RAM memory, F_1 takes 1.67 milliseconds to process a malicious feature vector on average over all malicious feature vectors and over 40 days.

Algorithm 5 Maintaining constraints $\mathsf{MR}(M, \mathsf{C}, S)$

INPUT: J48 classifier M, manipulation constraints C, $S = \{(feature, value, interval, manipulated)\}$
OUTPUT: `true` or `false`

$S^* \leftarrow \{s \in S : s.manipulated == \texttt{true}\}$
for all $(feature, value, interval, \texttt{true}) \in S$ **do**
  for all $X \in \mathsf{C}.group(feature) \setminus S^*.features$ **do**
    $\{X_1, \ldots, X_j\} \leftarrow \mathsf{C}.group(feature) \cap S^*.features$, whose values are respectively $x_1, \ldots, x_j$ w.r.t. S^*
    $escape\_interval \leftarrow \mathsf{Escape}(feature, M, \mathsf{C}, (X_1 = x_1, \ldots, X_j = x_j))$
    if $escape\_interval == \emptyset$ **then**
      return `false`
    else
      $X.interval \leftarrow escape\_interval$
      $X.value \overset{R}{\leftarrow} X.interval$
      $S^* \leftarrow S^* \cup \{(X, X.value, X.interval, \texttt{true})\}$
return `true`

Now let us look at one example. At a high-level, the attacker runs $\mathsf{AA}(\text{“}J48\text{”}, M_0, D_0, \mathsf{ST}, \mathsf{C}, \mathsf{F}_1, \alpha = 1)$ and therefore $\mathsf{F}_1(M_0, D_0, \mathsf{C})$ to manipulate the feature vectors, where ST can be any of the three strategies because they cause no difference when $\alpha = 1$ (see Figure 4.1 for a better exposition). Consider the example J48 classifier M in Figure 4.2, where features and their values are for illustration purpose, and the leaves are decision nodes with class 0 indicating *benign leaves* and 1

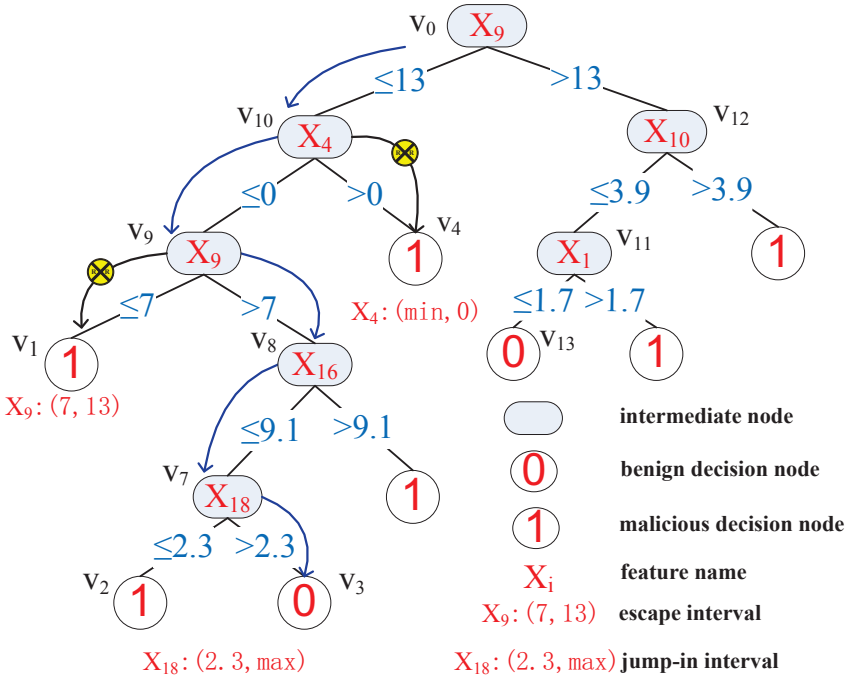


Figure 4.2: Example J48 classifier and feature manipulation. For inner node v_{10} on the $benign\_path$ ending at $benign\_leaf$ v_3, we have $v_{10}.feature =$ "X_4" and $v_{10}.feature.value = X_4.value$.

indicating *malicious leaves*. A website with feature vector

$$(X_4 = -1, X_9 = 5, X_{16} = 5, X_{18} = 5)$$

is classified as malicious because it leads to decision path

$$v_0 \xrightarrow{X_9 \leq 13} v_{10} \xrightarrow{X_4 \leq 0} v_9 \xrightarrow{X_9 \leq 7} v_1,$$

which ends at malicious leaf v_1. The manipulation algorithm first identifies malicious leaf v_1's parent node v_9, and manipulates X_9's value to fit into v_1's sibling (v_8). Note that X_9's *escape_interval* is as:

$$([\min_9, \max_9] \setminus [\min_9, 7]) \cap [\min_9, 13] = (7, 13],$$

where $Domain(X_9) = [\min_9, \max_9]$, $[\min_9, 7]$ corresponds to node v_9 on the path, and $[\min_0, 13]$ corresponds to node v_0 on the path. The algorithm manipulates X_9's value to be a random element from X_9's $escapte\_interval$, say $8 \in (7, 13]$, which causes the manipulated feature vector to evade detection because of decision path:

$$v_0 \xrightarrow{X_9 \leq 13} v_{10} \xrightarrow{X_4 \leq 0} v_9 \xrightarrow{X_9 > 7} v_8 \xrightarrow{X_{16} \leq 9.1} v_7 \xrightarrow{X_{18} > 2.3} v_3$$

and ends at benign leaf v_3. Assuming X_9 is not correlated to other features, the above manipulation is sufficient. Manipulating multiple features and dealing with constraints will be demonstrated via an example scenario of running manipulation algorithm F_2 below.

Algorithm 6 describes manipulation algorithm $\mathsf{F}_2(M, D, \mathsf{C})$, where M is a J48 classifier and D is a set of feature vectors, and C is the manipulation constraints (as in **Algorithm 4**). The basic idea is to first extract all benign paths. For each feature vector $\mathsf{fv} \in D.malicious$, F_2 keeps track of the mismatches between fv and a benign path (described by $P \in \mathcal{P}$) via an index structure

$$(mismatch, S = \{(feature, value, interval, manipulated)\}),$$

where $mismatch$ is the number of mismatches between fv and a benign path P, and S records the mismatches. For a feature vector fv that is classified by M as malicious, the algorithm attempts to manipulate as few "mismatched" features as possible to evade M. After manipulating the mismatched features, the algorithm maintains the constraints on the other correlated features by calling **Algorithm 5**. **Algorithm 6** incurs $O(m\ell)$ space complexity and $O(h\ell gm)$ time complexity where where m is the number of benign paths in a classifier, ℓ is the number of features, h is the height of the J48 classifier and g is the size of the largest group of correlated features. In our experiments on the same laptop with Intel X3320 CPU and 8GB RAM memory, F_2 takes 8.18 milliseconds to process a malicious feature vector on average over all malicious feature vectors and over 40 days.

To help understand **Algorithm 6**, let us look at another example also related to Figure 4.2.

Consider feature vector

$$(X_4 = .3, X_9 = 5.3, X_{16} = 7.9, X_{18} = 2.1, X_{10} = 3, X_1 = 2.3),$$

which is classified as malicious because of path

$$v_0 \xrightarrow{X_9 \leq 13} v_{10} \xrightarrow{X_4 > 0} v_4.$$

To evade detection, the attacker can compare the feature vector to the matrix of two benign pathes. For the benign path $v_3 \rightarrow v_7 \rightarrow v_8 \rightarrow v_9 \rightarrow v_{10} \rightarrow v_0$, the feature vector has three mismatches, namely features X_4, X_9, X_{18}. For the benign path $v_{13} \rightarrow v_{11} \rightarrow v_{12} \rightarrow v_0$, the feature vector has two mismatches, namely X_9 and X_1. The algorithm first processes the benign path ending at node v_{13}. For the benign path ending at node v_{13}, the algorithm manipulates X_9 to a random value in $[13, \max_9]$ (say 17), and manipulates X_1 to a random value in $X_1.interval = [\min_1, 1.7]$ (say 1.4). Suppose X_9, X_{10}, X_1 are strongly correlated to each other. the algorithm further calculates X_{10}'s escape interval according to Eq. (4.1) while considering the constraint $X_{10} \in [\min_{10}, 3.9]$ (see node v_{12}). Suppose X_{10} is manipulated to 3.5 after accommodating the correlation constraints. In this scenario, the manipulated feature vector is

$$(X_4 = .3, X_9 = 17, X_{16} = 7.9, X_{18} = 2.1, X_{10} = 3.5, X_1 = 1.4),$$

which is classified as benign because of path

$$v_0 \xrightarrow{X_9 > 13} v_{12} \xrightarrow{X_{10} \leq 3.9} v_{11} \xrightarrow{X_1 \leq 1.7} v_{13}.$$

Suppose on the other hand, that X_{10} cannot be manipulated to a value in $[\min_{10}, 3.9]$ without violating the constraints. The algorithm stops with this benign path and considers the benign path end at node v_3. If the algorithm fails with this benign path again, the algorithm will not manipulate

the feature vector and leave it to be classified as malicious by defender's J48 classifier M.

Algorithm 6 Manipulation algorithm $\mathsf{F}_2(M, D, \mathsf{C})$

INPUT: J48 classifier M, feature vectors $D = D.malicious \cup D.benign$, constraints C
OUTPUT: manipulated feature vectors

$\mathcal{P} \leftarrow \emptyset$ {$P \in \mathcal{P}$ corresponds to a benign path}
for all benign leaf v **do**
  $P \leftarrow \emptyset$
  while v is not the root **do**
    $v \leftarrow v.parent$
    if $\nexists(v.feature, interval) \in P$ **then**
      $P \leftarrow P \cup \{(v.feature, v.interval)\}$
    else
      $interval \leftarrow v.interval \cap interval$
  $\mathcal{P} \leftarrow \mathcal{P} \cup \{P\}$
for all feature vector $\mathsf{fv} \in D.malicious$ **do**
  $\mathcal{S} \leftarrow \emptyset$ {record fv's mismatches w.r.t. all benign pathes}
  for all $P \in \mathcal{P}$ **do**
    $(mismatch, S) \leftarrow (0, \emptyset)$ {S: mismatched feature set}
    for all $(feature, interval) \in P$ **do**
      if $\mathsf{fv}.feature.value \notin interval$ **then**
        $mismatch \leftarrow mismatch + 1$
        $S \leftarrow S \cup \{(feature, \mathsf{fv}.feature.value, interval, \texttt{false})\}$
    $\mathcal{S} \leftarrow \mathcal{S} \cup \{(mismatch, S)\}$
  sort $(mismatch, S) \in \mathcal{S}$ in ascending order of $mismatch$
  $attempt \leftarrow 1$; $mani \leftarrow \texttt{true}$
  while ($attempt \leq |\mathcal{S}|$) AND ($mani == \texttt{true}$) **do**
    parse the $attempt^{th}$ element $(mismatch, S)$ of $\mathcal{S}$
    for all $s = (feature, value, interval, \texttt{false}) \in S$ **do**
      if $mani == \texttt{true}$ **then**
        $S^* \leftarrow \{s \in S : s.manipulated == \texttt{true}\}$
        $\{X_1, \ldots, X_j\} \leftarrow \mathsf{C}.group(feature) \cap S^*$, their values are respectively $x_1, \ldots, x_j$ w.r.t. S^*
        $escape\_interval \leftarrow \mathsf{Escape}(feature, M, \mathsf{C}, (X_1 = x_1, \ldots, X_j = x_j))$ {call **Algorithm 3**}
        if $escape\_interval \cap S.feature.interval \neq \emptyset$ **then**
          $S.feature.interval \leftarrow (S.feature.interval \cap escape\_interval)$
          $S.feature.value \overset{R}{\leftarrow} S.feature.interval$
          $S.feature.manipulated \leftarrow \texttt{true}$
        else
          $mani \leftarrow \texttt{false}$
    if ($mani == \texttt{false}$) OR ($\mathsf{MR}(M, \mathsf{C}, S) == \texttt{false}$) **then**
      $attempt \leftarrow attempt + 1$; $mani \leftarrow \texttt{true}$
    else
      update fv's manipulated features according to S
      $mani \leftarrow \texttt{false}$
return manipulated feature vectors D

4.2.2 Power of Adaptive Attacks

In order to evaluate the power of adaptive attacks, we evalute $M_0(D_1)$, where M_0 is learned from D'_0 and D_1 is the output of adaptive attack algorithm AA. Our experiments are based on a 40-day dataset, where for each day: D'_0 consists of 340–722 malicious websites (with mean 571) as well as 2,231–2,243 benign websites (with mean 2,237); D_0 consists of 246–310 malicious websites (with mean 282) as well as 1,124–1,131 benign websites (with mean 1,127). We focus on the data-aggregation cross-layer method, while considering single-layer (i.e., application and network) method for comparison purpose. We first highlight some manipulation constraints that are enforced in our experiments.

Domain constraints: The length of URLs (`URL_Length`) cannot be arbitrarily manipulated because it must include hostname, protocol name, domain name and directories. Similarly, the length of webpage content (`Content_length`) cannot be arbitrarily short.

Correlation constraints: There are four groups of application-layer features that are strongly correlated to each other; there are three groups of network-layer features that are strongly correlated to each other; there are three groups of features that formulate cross-layer constraints. One group of cross-layer correlation is: the application-layer website content length (`Number_of_Content_length`) and the network-layer duration time (`Duration`). This is because the bigger the content, the longer the fetching time. Another group of cross-layer correlations is: the application-layer number of redirects (`Number_of_redirect`), the network-layer number of DNS queries (`Number_of_DNS_query`), the network-layer number of DNS answers (`Number_of_DNS_answer`). This is because more redirects leads to more DNS queries and more DNS answers.

Semantics constraints: Assuming the Whois system is not compromised, the following features cannot be manipulated: website registration date (`RegDate`), website registration state/province (`Stateprov`), website registration postal code (`Postalcode`), and website registration country (`Country`). For malicious websites that use some scripts to launch the drive-by-download attack,

the number of scripts contained in the webpage contents (`Number_of_Scripts`) cannot be 0. The application-layer protocol feature (`Protocol`) may not be arbitrarily changed (e.g., from ftp to http).

Table 4.1: Experiment results with $M_0(D_1)$ in terms of average false-negative rate (FN), average number of manipulated features (Number_of_MF), average percentage of failed attempts (FA), where "average" is over the 40 days of the dataset mentioned above.

	F_1			F_2		
	FN	Number_of_MF	FA	FN	Number_of_MF	FA
network-layer	94.7%	4.31	5.8%	95.3%	4.01	5.1%
application-layer	91.9%	6.01	8.6%	93.3%	5.23	7.1%
data-agg. cross-layer	87.6%	7.23	12.6%	89.1%	6.19	11.0%

Table 4.1 summarizes the results of adaptive attack $\mathsf{AA}(\text{“}J48\text{”}, M_0, D_0, \mathsf{ST}, \mathsf{C}, \mathsf{F}, \alpha = 1)$ based on the 40-day dataset mentioned above, where C accommodates the constraints mentioned above. The experiment can be more succinctly represented as $M_0(D_1)$, meaning that the defender is static (or non-proactive) and the attacker is adaptive with $\alpha = 1$, where D_1 is the manipulated version of D_0. Note that in the case of $\alpha = 1$, the three adaptation strategies lead to the same D_1 as shown in Figure 4.1. From Table 4.1, we make the following observations. First, both manipulation algorithms can effectively evade detection by manipulating on average 4.31-7.23 features while achieving false-negative rate 87.6%-94.7% for F_1, and by manipulating on average 4.01-6.19 features while achieving false-negative rate 89.1%-95.3% for F_2. For the three J48 classifiers based on different kinds of D_0 (i.e., network-layer data alone, application-layer data alone and cross-layer data-aggregation), F_2 almost always slightly outperforms F_1 in terms of false-negative rate (FN), average number of manipulated features (Number_of_MF), and average percentage of failed attempts at manipulating feature vectors (FA). Second, data-aggregation cross-layer classifiers are more resilient against adaptive attacks than network-layer classifiers as well as application-layer classifiers.

Now we ask: **Which features are often manipulated for evasion?** We notice that many features are manipulated over the 40 days, but only a few are manipulated often. For application-layer alone, F_1 most often (i.e., > 150 times each day for over the 40 days) manipulates the following five application-layer features: URL length (`URL_Length`), number of scripts con-

tained in website content (Number_of_Script), webpage length (Content_length), number of URLs embedded into the website contents (Number_of_Embedded_URL), and number of Iframes contained in the webpage content (Number_of_Iframe). In contrast, F_2 most often (i.e., > 150 times) manipulates the following three application-layer features: number of special characters contained in URL (Number_of_Special_character), number of long strings (Number_of_Long_strings) and webpage content length (Content_length). That is, Content_length is the only feature that is most often manipulated by both algorithms.

For network-layer alone, F_1 most often (i.e., > 150 times) manipulates the following three features: number of remote IP addresses (Number_of_Dist_remote_IP), duration time (Duration), and number of application packets (Number_of_Local_app_packet). Whereas, F_2 most often (i.e., > 150 times) manipulates the distinct number of TCP ports used by the remote servers (Number_of_Dist_remote_TCP_port). In other words, no single feature is often manipulated by both algorithm.

For data-aggregation cross-layer detection, F_1 most often (i.e., > 150 times each day for over the 40 days) manipulates three application-layer features — URL length (URL_Length), webpage length (Content_length), number of URLs embedded into the website contents (Number_of_Embedded_URLs) — and two network-layer features — duration time (Duration) and number of application packets (Number_of_Local_app_packet). On the other hand, F_2 most often (i.e., > 150 times) manipulates two application-layer features — number of special characters contained in URL (Number_of_Special_characters) and webpage content length (Content length) — and one network-layer feature — duration time (Duration). Therefore, Content_length and Duration are most often manipulated by both algorithms.

The above discrepancy between the frequencies that features are manipulated can be attributed to the design of the manipulation algorithms. Specifically, F_1 seeks to manipulate features that are associated to nodes that are close to the leaves. In contrast, F_2 emphasizes on the mismatches between a malicious feature vector and an entire benign path, which represents a kind of global

search and also explains why F_2 manipulates fewer features.

Table 4.2: Experiment results of $M_0(D_1)$ by treating as non-manipulatable the InfoGain-selected five application-layer features and four network-layer features. Metrics are as in Table 4.1.

	F_1			F_2		
	FN	Number_of_MF	FA	FN	Number_of_MF	FA
network-layer	93.1%	4.29	7.5%	95.3%	4.07	5.1%
application-layer	91.3%	6.00	9.2%	93.3%	5.28	7.1%
data-aggregation	87.4%	7.22	12.7%	89.1%	6.23	11.0%

Having identified the features that are often manipulated, the next natural question is: **Why them? Or: Are they some kind of "important" features?** It would be ideal if we can directly answer this question by looking into the most-often manipulated features. Unfortunately, this is a difficult problem because J48 classifiers (or most, if not all, detection schemes based on machine learning), are learned in a *black-box* (rather than *white-box*) fashion. As an alternative, we compare the manipulated features to the features that would be selected by a feature selection algorithm for the purpose of training classifiers. To be specific, we use the InfoGain feature selection algorithm because it ranks the contributions of individual features [65]. We find that among the manipulated features, `URL_Length` is the only feature among the five InfoGain-selected application-layer features, and `Number_of_Dist_remote_TCP_port` is the only feature among the four InfoGain-selected network-layer features. This suggests that the feature selection algorithm does not necessarily offer good insights into the importance of features from a security perspective. To confirm this, we further conduct the following experiment by additionally treating InfoGain-selected tops features as semantics constraints in C (i.e., they cannot be manipulated). Table 4.2 (counterparting Table 4.1) summarizes the new experiment results. By comparing the two tables, we observe that there is no significant difference between them, especially for manipulation algorithm F_2. This means that InfoGain-selected features have little security significance.

Table 4.3: Experiment results of $M_0(D_1)$ by treating the features that were manipulated by adaptive attack AA as non-manipulatable. Notations are as in Tables 4.1-4.2.

	F_1			F_2		
	FN	Number_of_MF	FA	FN	Number_of_MF	FA
network-layer	62.1%	5.88	41.6%	80.3%	5.07	21.6%
application-layer	68.3%	8.03	33.7%	81.1%	6.08	20.1%
data-aggregation	59.4%	11.13	41.0%	78.7%	7.83	21.5%

In order to know whether or not the adaptive attack algorithm AA actually manipulated some "important" features, we conduct an experiments by setting the most-often manipulated features as non-manipulatable. The features that are originally identified by F_1 and then set as non-manipulatable are: webpage length (`content_length`), number of URLs that are embedded into the website contents (`Number_of_Embedded_URLs`), number of redirects (`Number_of_redirect`), number of distinct TCP ports that are used by the remote webservers (`Dist_remote_tcp_port`), and number of application-layer packets (`Local_app_packets`). Table 4.3 summarizes the results. When compared with Tables 4.1-4.2, we see that the false-negative rate caused by adaptive attacks drops substantially: from about 90% down to about 60% for manipulation algorithm F_1, and from about 90% down to about 80% for manipulation algorithm F_2. This means perhaps that the features that are originally identified by F_1 are more indicative of malicious websites than the features that are originally identified by F_2. Moreover, we note that no feature is manipulated more than 150 times and only two features — `Number_of_Iframe` (the number of iframes) and `Number_of_DNS_query` (the number of DNS query) — are manipulated more than 120 times by F_1 and one feature — `Number_of_suspicous_JS_function` (the number of JavaScript functions) — is manipulated more than 120 times by F_2.

4.3 Proactive Defense against Adaptive Attacks

We have showed that adaptive attacks can ruin the defender's (non-proactive) detection schemes. Now we investigate how the defender can exploit proactive defense against adaptive attacks. We propose that the defender can run the same *kinds of manipulation algorithms* to *proactively* anticipate the attacker's adaptive attacks.

4.3.1 Proactive Defense Model and Algorithm

Proactive defense $\mathsf{PD}(\mathsf{MLA}, M_0, D_0^\dagger, D_\alpha, \mathsf{ST}_D, \mathsf{C}, \mathsf{F}_D, \gamma)$ is described as **Algorithm 7**, which calls as a sub-routine the proactive training algorithm PT described in **Algorithm 8** (which is similar to, but different from, the adaptive attack algorithm AA). Specifically, PT aims to derive detection

Algorithm 7 Proactive defense $\mathsf{PD}(\mathsf{MLA}, M_0, D_0^\dagger, D_\alpha, \mathsf{ST}_D, \mathsf{C}, \mathsf{F}_D, \gamma)$

INPUT: M_0 is learned from D_0' using machine learning algorithm MLA, $D_0^\dagger = D_0^\dagger.benign \cup D_0^\dagger.malicious$, D_α (α unknown to defender) is set of feature vectors (with $D_\alpha.malicious$ possibly manipulated by the attacker), ST_D is defender's adaptation strategy, F_D is defender's manipulation algorithm, C is set of constraints, γ is defender's number of adaptations rounds
OUTPUT: malicious vectors $\mathsf{fv} \in D_\alpha$

$M_1^\dagger, \ldots, M_\gamma^\dagger \leftarrow \mathsf{PT}(\mathsf{MLA}, M_0, D_0^\dagger, \mathsf{ST}_D, \mathsf{C}, \mathsf{F}_D, \gamma)$ {see **Algorithm 8**}
$\mathsf{malicious} \leftarrow \emptyset$
for all $\mathsf{fv} \in D_\alpha$ **do**
  if ($M_0(\mathsf{fv})$ says fv is malicious) OR (majority of $M_0(\mathsf{fv}), M_1^\dagger(\mathsf{fv}), \ldots, M_\gamma^\dagger(\mathsf{fv})$ say fv is malicious) **then**
    $\mathsf{malicious} \leftarrow \mathsf{malicious} \cup \{\mathsf{fv}\}$
return malicious

schemes $M_1^\dagger, \ldots, M_\gamma^\dagger$ from the starting-point detection scheme M_0. Since the defender does not know *a priori* whether the attacker is adaptive or not (i.e., $\alpha > 0$ vs. $\alpha = 0$), PD deals with this uncertainty by first applying M_0, which can deal with D_0 effectively. If M_0 says that a feature vector $\mathsf{fv} \in D_\alpha$ is malicious, fv is deemed malicious; otherwise, a majority voting is made between $M_0(\mathsf{fv}), M_1^\dagger(\mathsf{fv}), \ldots, M_\gamma^\dagger(\mathsf{fv})$.

Algorithm 8 Proactive training $\mathsf{PT}(\mathsf{MLA}, M_0, D_0^\dagger, \mathsf{ST}_D, \mathsf{C}, \mathsf{F}_D, \gamma)$

INPUT: same as in **Algorithm 7**
OUTPUT: $M_1^\dagger, \ldots, M_\gamma^\dagger$

$M_0^\dagger \leftarrow M_0$ {for simplifying notations}
initialize $D_1^\dagger, \ldots, D_\gamma^\dagger$ and $M_1^\dagger, \ldots, M_\gamma^\dagger$
for i=1 **to** γ **do**
  if $\mathsf{ST}_D ==$ `parallel-adaptation` **then**
    $D_i^\dagger.malicious \leftarrow \mathsf{F}_D(M_0^\dagger, D_0^\dagger.malicious, \mathsf{C})$
  else if $\mathsf{ST}_D ==$ `sequential-adaptation` **then**
    $D_i^\dagger.malicious \leftarrow \mathsf{F}_D(M_{i-1}^\dagger, D_{i-1}^\dagger.malicious, \mathsf{C})$
  else if $\mathsf{ST}_D ==$ `full-adaptation` **then**
    $\mathcal{D}_{i-1}^\dagger.malicious \leftarrow \mathsf{PP}(D_0^\dagger, \ldots, D_{i-2}^\dagger)$
    $D_i^\dagger.malicious \leftarrow \mathsf{F}_D(M_{i-1}^\dagger, \mathcal{D}_{i-1}^\dagger, \mathsf{C})$
  $D_i^\dagger.benign \leftarrow D_0^\dagger.benign$
  $M_i^\dagger \leftarrow \mathsf{MLA}(D_i^\dagger)$
return $M_1^\dagger, \ldots, M_\gamma^\dagger$

4.3.2 Evaluation and Results

To evaluate proactive defense PD's effectiveness, we use **Algorithm 9** and the metrics defined in Chapter 2: detection accuracy (ACC), trust-positive (TP), false-negative (FN), and false-positive (FP). Note that TP=1-FN, but we still list both for easing the discussion. When the other parameters are clear from the context, we use $M_{0\text{-}\gamma}(D_\alpha)$ to stand for $\mathsf{Eva}(\mathsf{MLA}, M_0, D_0^\dagger, D_0, \mathsf{ST}_A, \mathsf{F}_A, \mathsf{ST}_D, \mathsf{F}_D, \mathsf{C}, \alpha, \gamma)$. For each of the 40 days mentioned above, the data for proactive training, namely $D_0^\dagger$, consists of 333–719 malicious websites (with mean 575) and 2,236–2,241 benign websites (with mean 2,238).

The parameter space of Eva includes at least 108 scenarios: the basic adaptation strategy space $\mathsf{ST}_A \times \mathsf{ST}_D$ is 3×3 (i.e., not counting any hybrids of `parallel-adaptation`, `sequential-adaptation` and `full-adapatation`), the manipulation algorithm space $\mathsf{F}_A \times \mathsf{F}_B$ is 2×2, and the adaptation round parameter space is at least 3 ($\alpha >, =, < \gamma$). Since the data-aggregation cross-layer detection significantly outperforms the single layer detections against non-adaptive attacks [65] and is more resilient than the single layer detections against adaptive attacks as shown in Section 4.2.2, in what follows we focus on data-aggregation cross-layer detection. For the baseline case of non-proactive detection against non-adaptive attack, namely $M_0(D_0)$, we have average ACC = 99.68% (detection accuracy), TP =99.21% (true-positive rate), FN=0.79% (false-negative rate) and FP=0.14% (false-positive rate), where "average" is over the 40 days corresponding to the dataset. This baseline result also confirms the conclusion in [65], namely that data-aggregation cross-layer detection can be used in practice, and justifies why we use it in this chapter.

Table 4.4 summarizes the effectiveness of proactive defense against adaptive attacks. We make the following observations. First, if the defender is proactive (i.e., $\gamma > 0$) but the attacker is non-adaptive (i.e., $\alpha = 0$), the false-negative rate drops from 0.79% in the baseline case to some number belonging to interval $[0.23\%, 0.56\%]$. The price is: the detection accuracy drops from 99.68% in the baseline case to some number belonging to interval $[99.23\%, 99.68\%]$ the false-positive rate increases from 0.14% in the baseline case to some number belonging to interval $[0.20\%, 0.93\%]$,

Algorithm 9 Proactive defense vs. adaptive attack evaluation
$\mathsf{Eva}(\mathsf{MLA}, M_0, D_0^\dagger, D_0, \mathsf{ST}_A, \mathsf{F}_A, \mathsf{ST}_D, \mathsf{F}_D, \mathsf{C}, \alpha, \gamma)$

INPUT: detection scheme M_0 (learned from D_0', which is omitted), $D_0^\dagger$ is set of feature vectors for defender's proactive training, $D_0 = D_0.malicious \cup D_0.benign$, ST_A (ST_D) is attacker's (defender's) adaptation strategy, F_A (F_D) is attacker's (defender's) manipulation algorithm, C is the constraints, α (γ) is the number of attacker's (defender's) adaptation rounds
OUTPUT: ACC, FN, TP and FP

1: **if** $\alpha > 0$ **then**
2: $D\_\alpha \leftarrow \mathsf{AA}(\mathsf{MLA}, M_0, D_0, \mathsf{ST}_A, \mathsf{C}, \mathsf{F}_A, \alpha)$
{call **Algorithm 1**}
3: $M_1^\dagger, \ldots, M_\gamma^\dagger \leftarrow \mathsf{PT}(\mathsf{MLA}, M_0, D_0^\dagger, \mathsf{ST}_D, \mathsf{C}, \mathsf{F}_D, \gamma)$
{call **Algorithm 8**}
4: malicious $\leftarrow \mathsf{PD}(\mathsf{MLA}, M_0, D_0^\dagger, D_\alpha, \mathsf{ST}_D, \mathsf{C}, \mathsf{F}_D, \gamma)$
{call **Algorithm 7**}
5: benign $\leftarrow D_\alpha \setminus$ malicious
6: calculate ACC, FN, TP and FP w.r.t. D_0
7: **return** ACC, FN, TP and FP

and the proactive detection algorithm PD's running time is now $(\gamma + 1)$ times of the baseline case because of running $M_0(D_\alpha), M_1^\dagger(D_\alpha), \ldots, M_\gamma^\dagger(D_\alpha)$, which takes on average $0.54(\gamma+1)$ milliseconds to process a feature vector. Note that the running time of the proactive training algorithm PT is also $(\gamma + 1)$ times of the baseline training algorithm. This can be reasonably ignored because the defender only runs the training algorithms once a day. The above observations suggest: **the defender can always use proactive detection without worrying about side-effects (e.g., when the attacker is not adaptive)**. This is because the proactive detection algorithm PD uses $M_0(D_0)$ as the first line of detection.

Second, when $\mathsf{ST}_A = \mathsf{ST}_D$ (meaning $\alpha > 0$ and $\gamma > 0$), it has a significant impact whether or not they use the same manipulation algorithm. Specifically, proactive defense in the case of $\mathsf{F}_D = \mathsf{F}_A$ is more effective than in the case of $\mathsf{F}_D \neq \mathsf{F}_A$. This phenomenon also can be explained by that the features that are often manipulated by F_1 are very different from the features that are often manipulated by F_2. More specifically, when $\mathsf{F}_A = \mathsf{F}_D$, the proactively learned classifiers $M_1^\dagger, \ldots, M_\gamma^\dagger$ would capture the "maliciousness" information embedded in the manipulated data D_α; this would not be true when $\mathsf{F}_A \neq \mathsf{F}_D$. Moreover, the `sequential` adaptation strategy appears to be more "oblivious" than the other two strategies in the sense that D_α preserves less information

Table 4.4: Data-aggregation cross-layer proactive detection with $\mathsf{ST}_A = \mathsf{ST}_D$. For baseline case $M_0(D_0)$, ACC = 99.68%, true-positive rate TP =99.21%, false-negative rate FN=0.79%, and false-positive rate FP=0.14%.

Strat.	Manipulation algorithm	$M_{0\text{-}8}(D_0)$				$M_{0\text{-}8}(D_1)$				$M_{0\text{-}8}(D_9)$			
		ACC	TP	FN	FP	ACC	TP	FN	FP	ACC	TP	FN	FP
PAR	$\mathsf{F}_D = \mathsf{F}_1$ vs. $\mathsf{F}_A = \mathsf{F}_1$	99.59	99.71	0.29	0.39	95.58	92.03	7.97	3.62	95.39	92.00	8.00	3.83
	$\mathsf{F}_D = \mathsf{F}_1$ vs. $\mathsf{F}_A = \mathsf{F}_2$	99.27	99.77	0.23	0.77	78.51	25.50	74.50	9.88	78.11	32.18	67.82	11.48
	$\mathsf{F}_D = \mathsf{F}_2$ vs. $\mathsf{F}_A = \mathsf{F}_1$	99.16	99.76	0.24	0.93	76.33	19.32	80.68	11.17	78.96	39.77	60.23	12.14
	$\mathsf{F}_D = \mathsf{F}_2$ vs. $\mathsf{F}_A = \mathsf{F}_2$	99.59	99.62	0.38	0.39	93.66	90.25	9.75	5.59	96.17	92.77	7.23	3.08
SEQ	$\mathsf{F}_D = \mathsf{F}_1$ vs. $\mathsf{F}_A = \mathsf{F}_1$	99.52	99.69	0.31	0.45	93.44	77.48	22.52	3.05	92.04	59.33	30.67	2.99
	$\mathsf{F}_D = \mathsf{F}_1$ vs. $\mathsf{F}_A = \mathsf{F}_2$	99.23	99.70	0.30	0.82	74.24	20.88	79.22	14.06	79.43	30.03	69.97	9.38
	$\mathsf{F}_D = \mathsf{F}_2$ vs. $\mathsf{F}_A = \mathsf{F}_1$	99.27	99.67	0.33	0.80	77.14	29.03	70.97	12.33	82.72	40.93	59.07	7.83
	$\mathsf{F}_D = \mathsf{F}_2$ vs. $\mathsf{F}_A = \mathsf{F}_2$	99.52	99.53	0.47	0.50	93.44	78.70	21.30	2.10	92.04	62.30	37.70	2.11
FULL	$\mathsf{F}_D = \mathsf{F}_1$ vs. $\mathsf{F}_A = \mathsf{F}_1$	99.68	99.44	0.56	0.20	96.92	96.32	3.68	2.89	95.73	92.03	7.97	3.27
	$\mathsf{F}_D = \mathsf{F}_1$ vs. $\mathsf{F}_A = \mathsf{F}_2$	99.27	99.58	0.42	0.72	85.68	40.32	59.68	4.38	78.11	29.99	70.01	11.00
	$\mathsf{F}_D = \mathsf{F}_2$ vs. $\mathsf{F}_A = \mathsf{F}_1$	99.60	99.66	0.34	0.40	85.65	51.84	48.16	6.93	87.61	72.99	27.01	9.01
	$\mathsf{F}_D = \mathsf{F}_2$ vs. $\mathsf{F}_A = \mathsf{F}_2$	99.68	99.60	0.40	0.28	96.92	95.60	4.40	2.88	95.73	90.09	9.91	2.83

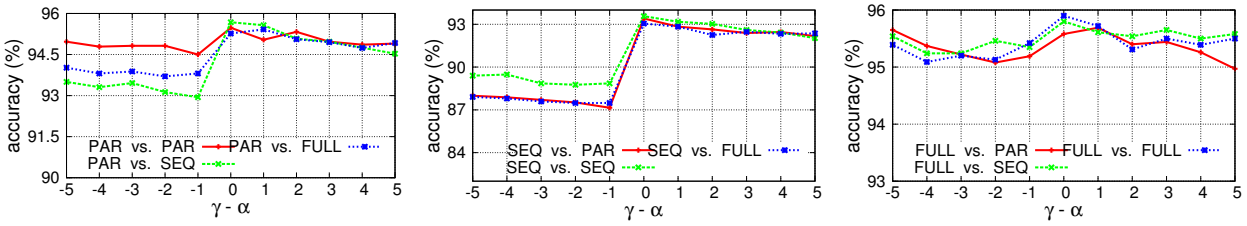
about D_0. This may explain why the false-negative rates when $\mathsf{ST}_A = \mathsf{ST}_D = \texttt{sequential}$ can be respectively substantially higher than their counterparts when $\mathsf{ST}_A = \mathsf{ST}_D \neq \texttt{sequential}$. The above discussions suggest the following: **If the attacker is using $\mathsf{ST}_A = \texttt{sequential}$, the defender should not use $\mathsf{ST}_D = \texttt{sequential}$.**

Table 4.5: Data-aggregation cross-layer proactive detection against adaptive attacks with $\mathsf{F}_D = \mathsf{F}_A$.

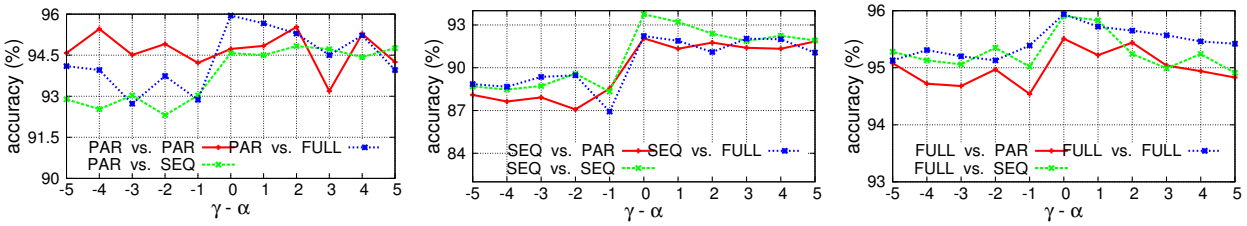
ST_D vs. ST_A	$M_{0\text{-}\gamma}(D_\alpha)$	$\mathsf{ST}_A = \texttt{parallel}$				$\mathsf{ST}_A = \texttt{sequential}$				$\mathsf{ST}_A = \texttt{full}$			
		ACC	TP	FN	FP	ACC	TP	FN	FP	ACC	TP	FN	FP
Manipulation algorithm $\mathsf{F}_D = \mathsf{F}_A = \mathsf{F}_1$													
$\mathsf{ST}_D = \texttt{PAR}$	$M_{0\text{-}8}(D_1)$	95.58	92.03	7.97	3.62	94.25	90.89	9.11	4.96	94.91	92.08	7.92	4.32
	$M_{0\text{-}8}(D_9)$	95.39	92.00	8.00	3.83	92.38	80.03	19.97	4.89	93.19	84.32	15.68	4.54
$\mathsf{ST}_D = \texttt{SEQ}$	$M_{0\text{-}8}(D_1)$	92.15	74.22	25.78	3.93	93.44	77.48	22.52	3.05	92.79	76.32	23.68	3.07
	$M_{0\text{-}8}(D_9)$	89.20	58.39	41.61	4.11	92.04	59.33	30.67	2.99	88.42	57.89	42.11	3.91
$\mathsf{ST}_D = \texttt{FULL}$	$M_{0\text{-}8}(D_1)$	96.24	94.98	5.02	3.42	96.46	94.99	5.01	3.15	96.92	96.32	3.68	2.89
	$M_{0\text{-}8}(D_9)$	94.73	90.01	9.99	4.21	94.70	90.03	9.97	4.23	95.73	92.03	7.97	3.27
Manipulation algorithm $\mathsf{F}_D = \mathsf{F}_A = \mathsf{F}_2$													
$\mathsf{ST}_D = \texttt{PAR}$	$M_{0\text{-}8}(D_1)$	93.66	90.25	9.75	5.59	94.25	88.91	11.09	3.98	94.91	89.77	10.23	3.53
	$M_{0\text{-}8}(D_9)$	96.17	92.77	7.23	3.08	92.38	77.89	22.11	4.32	93.19	81.32	18.68	3.38
$\mathsf{ST}_D = \texttt{SEQ}$	$M_{0\text{-}8}(D_1)$	90.86	70.98	29.02	4.82	93.44	78.70	21.30	2.10	92.79	72.32	27.68	4.02
	$M_{0\text{-}8}(D_9)$	88.43	53.32	46.68	3.97	92.04	62.30	37.70	2.11	88.42	57.88	42.12	3.17
$\mathsf{ST}_D = \texttt{FULL}$	$M_{0\text{-}8}(D_1)$	95.69	93.89	6.11	3.88	96.46	94.98	5.02	3.03	96.92	95.60	4.40	2.88
	$M_{0\text{-}8}(D_9)$	96.06	91.46	8.54	2.89	94.70	90.99	9.01	2.32	95.73	90.09	9.91	2.83

Third, what adaptation strategy should the defender use to counter $\mathsf{ST}_A = \texttt{sequential}$? Table 4.5 shows that the defender should use $\mathsf{ST}_D = \texttt{full}$ because it leads to relatively high detection accuracy and relatively low false-negative rate, while the false-positive rate is comparable to the other cases. Even if the attacker knows that the defender is using $\mathsf{ST}_D = \texttt{full}$, Table 4.5 shows that the attacker does not have an obviously more effective counter adaptation strategy. This hints

that the `full` strategy (or some variant of it) may be a kind of equilibrium strategy because both attacker and defender have no significant gains by deviating from it. This inspires an important problem for future research **Is the `full` adaptation strategy (or variant of it) an equilibrium strategy?**



(a) $\mathsf{F}_D = \mathsf{F}_A = \mathsf{F}_1$



(b) $\mathsf{F}_D = \mathsf{F}_A = \mathsf{F}_2$

Figure 4.3: Impact of defender's proactiveness γ vs. attacker's adaptiveness α on detection accuracy (average over the 40 days) under various "$\mathsf{ST}_D \times \mathsf{ST}_A$" combinations, where $\alpha \in [0, 8]$, $\gamma \in [0, 9]$, `PAR`, `SEQ` and `FULL` respectively stand for `paraleel`, `sequential` and `full` adaptation strategy, "`SEQ` vs. `APR`" means $\mathsf{ST}_D =$ `sequential` and $\mathsf{ST}_A =$ `parallel` etc.

Fourth, Table 4.4 shows that when $\mathsf{ST}_D = \mathsf{ST}_A$, the attacker can benefit by increasing its adaptiveness (i.e., increasing α). Table 4.5 exhibits the same phenomenon when $\mathsf{ST}_D \neq \mathsf{ST}_A$. On the other hand, by comparing Tables 4.4-4.5 and Table 4.1, it is clear that proactive detection $M_{0\text{-}\gamma}(D_\alpha)$ for $\gamma > 0$ is much more effective than non-proactive detection $M_0(D_\alpha)$ for $\gamma = 0$. In order to see the impact of defender's proactiveness as reflected by γ against the defender's adaptiveness as reflected by α, we plot in Figure 4.3 how the detection accuracy with respect to $(\gamma - \alpha)$ under the condition $\mathsf{F}_D = \mathsf{F}_A$ and under various $\mathsf{ST}_D \times \mathsf{ST}_A$ combinations. We observe that roughly speaking, as the defender's proactiveness γ increases to exceed the attacker's adaptiveness

α (i.e., γ changes from $\gamma < \alpha$ to $\gamma = \alpha$ to $\gamma > \alpha$), the detection accuracy may have a significant increase at $\gamma - \alpha = 0$. Moreover, we observe that when $\mathsf{ST}_D = \texttt{full}$, $\gamma - \alpha$ has no significant impact on the detection accuracy. This suggest that **the defender should always use the** `full` **adaptation strategy to alleviate the uncertainty about the attacker's adaptiveness** α.

4.4 Related Work

The most closely related work is the cross-layer framework for detecting malicious websites proposed by Xu et al. [65]. Their study appears to be motivated by the following observation: Static analysis technique (e.g., by analyzing URLs and/or webpage contents) for detecting malicious websites can achieve the highest performance and scalability, but not effective; whereas dynamic analysis technique (i.e., by analyzing the runtime behavior of website contents in monitored environment) can achieve the highest effectiveness, but not performance or scalability. They proposed exploiting the network "lens" (i.e., looking into the network-layer traffic that corresponding to their static data collection) to obtain extra information about the websites, where the extra information may be useful to enhance the effectiveness of static detection technique. The effectiveness metrics they consider are: detection accuracy, false-positive rate and false-negative rate. The showed indeed that by additionally taking advantage of the network "lens" they can almost achieve the best of both static detection technique (i.e., performance and scalability) and dynamic detection technique (i.e., effectiveness).

Another factor that may have contributed to the success and performance of their cross-layer detection is that they statically parse website contents to catch redirects. While static parsing can only achieve best-effort guarantee only because of the difficulty in dealing with obfuscated JavaScript-based redirects [23], which is nevertheless an orthogonal research problem and can benefit from any future studies in this category [66]. Finally, Invernizzi et al. [29] proposed a novel method for quickly identifying malicious websites, which can be used to replace the method of identifying malicious websites for training purpose — downloading blacklisted websites and analyzing their maliciousness using the dynamic approach — in a modular fashion.

Taking a broader view, the problem of detecting malicious websites have been investigated by both industry and academia. For example, industrial solutions include McAfee's Site Advisor [2] and Google's Safe Browsing [1]. Prior academic investigations on the detection of malicious websites include Prophiler [14] and others (e.g., [16]). Dynamic detection techniques such as Client Hopeypot have been investigated in [15, 18, 41, 67]. There are ongoing research activities on making dynamic analysis techniques resistant against sophisticated attacks [33, 53]. Loosely related to our study are the investigations on detecting Phishing websites [24, 39, 40], detecting spams [10, 39, 40, 45, 51, 61, 64], detecting suspicious URLs embedded in twitter message streams [57], and dealing with browser-related attacks [37, 59]. All these studies did not consider the idea of cross-layer detection introduced in [65].

Our study of proactive defense vs. adaptive attack is closely related to the problem of *adversarial machine learning*, where the attacker aims to evade an detection mechanism that is derived from some machine learning method [9, 62]. In the context of unsupervised learning for anomaly detection, Perdisci et al. [48] investigated how to make the detection harder to evade. In the context of supervised learning, existing studies fall into two categories. In the first category, the attacker can poison/manipulate the training data. Existing studies for tackling this problem include [44, 47, 55]. In the second category, the training data is not poisoned. There are two scenarios. First, the attacker has black-box access to the detection mechanism and attempts to evade detection after making, ideally, as few as possible queries to the detection mechanism. This setting has been studied in [38, 43]. Second, the attacker has access to the detection mechanism, which is true for our resilience study. Dalvi et al. [21] used Game Theoretic method to study this problem in the setting of spam detection. Our model actually gives the attacker more freedom because the attacker knows the data the defender collected.

4.5 Summary

We formulated a model of adaptive attacks by which the attacker can manipulate the malicious websites under its control to evade detection. We also formulated a model of proactive defense

against the adaptive attacks. Experimental results based on a 40-day dataset shows that adaptive attacks can easily evade non-proactive defense, but can be effectively countered by proactive defense.

This study introduces a set of interesting research problems: Is the `full` adaptation strategy indeed a kind of equilibrium strategy? What is the optimal manipulation algorithm (if exists)? How can we precisely characterize the evadability caused by adaptive attacks in this context?

Chapter 5: CHARACTERIZING AND DETECTING EVOLVING MALICIOUS WEBSITES

5.1 Introduction

Compromising websites and subsequently abusing them to launch further attacks (e.g., drive-by-download [18,50]) has become one of the mainstream attack vectors. Unfortunately, it is infeasible, if not impossible, to completely eliminate such attacks, meaning that we must have competent solutions that can detect compromised/malicious websites as soon as possible. It is therefore important to understand how the threats may evolve. In this chapter we present a statistical characterization of the evolution of malicious websites. Such characterization studies can lead to a deeper understanding about the threat landscape. More specifically, we focus on two aspects: What are the statistical evolution characteristics of malicious websites? For how long a newly learned detectin model will remain effective?

5.2 Our Contributions

We make the following contributions. First, we characterize the detection accuracy of $M_i(D_j)$, where M_i is the detection model trained using the data collected on day i, D_j is the (testing) data collected on day j. We find that despite that $M_i(D_i)$ is highly effective in terms of accuracy, false-positive rate, and false-negative rate, $M_i(D_j)$ for $i \neq j$ is not.

Second, we propose using online learning to cope with the evolution of malicious websites. Our experiments show that online learning can effectively deal with evolving malicious websites. We also develop an online learning algorithm with a real-time adaptation strategy, which automatically refreshes the training dataset when some criteria are met.

The rest of the chapter is organized as follows. Section 5.3 briefly describes the dataset we analyze. Section 5.4 investigates the evolution of malicious websites and the security implications. Section 5.5 characterize the distribution of D_i. Section 5.6 discusses related prior work. Section

5.7 concludes the chapter with future research directions.

5.3 Data Description

The input candidate URLs consist of two categories: malicious websites and benign websites. As defined in Chapter 2, a malicious website is a website that launches drive-by-download attacks (perhaps coupled with website redirects). The terms *malicious URLs* and *malicious websites* are used interchangeably. In this chapter, websites features are the application-layer and network-layer ones defined in Chapter 2.

The dataset consists of benign and malicious websites for a period of 160 consecutive days, between 09/19/2013 and 02/25/2013. On each day, our training data consists of 498–877 malicious websites (with mean 599) and 6798–6810 benign websites (with mean 6800); our cross validation data consists of 232–277 malicious websites (with mean 241) and 1880–1895 benign websites (with mean 1887); our test data consists of 232–277 malicious websites (with mean 241) and 1880–1896 benign websites (with mean 1887).

5.4 On the Evolution of Malicious Websites

In this section, we want to characterize that for how large ℓ, $M_i(D_{i+\ell})$ is still effective (i.e., high detection accuracy, low false-positive rate, low false-negative rate) when applying the model learned from the data collected on day i to classify the websites on day $(i + \ell)$?

5.4.1 Analysis Methodology

Our analysis methodology has three steps, which are equally applicable to both benign and malicious data.

Step 1: Preparation. This step resolves issues such as missing feature data. In particular, any feature with more than 100 missing data is removed from the analysis.

Step 2: Feature selection. Since there are 144 features in total, we may need to conduct feature

selection so that the selected (smaller number of) features may give more intuitive explanations of the results.

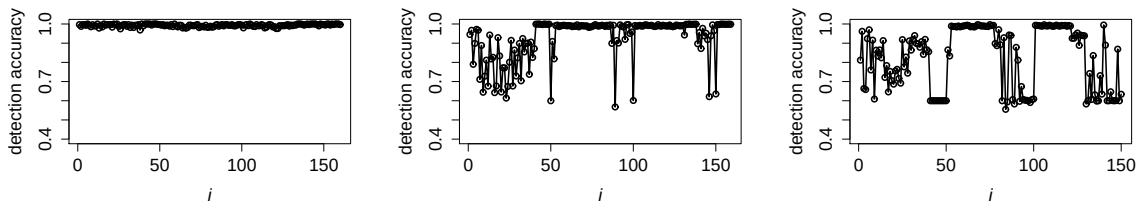
Step 3: Model learning and validation. Several learning logarithms are used, including Random Forest, Logistic and Adaboost. Logistic regression classifier [36] is one kind of linear classification, where the domain of the target variable is $[0, 1]$. Adaboost classifier aims to assign different weights to wrong classifications in each iteration. We use Random Forest in this chapter (instead of single decision tree) because it is more resilient against overfitting.

5.4.2 Characteristics of the Evolving Websites

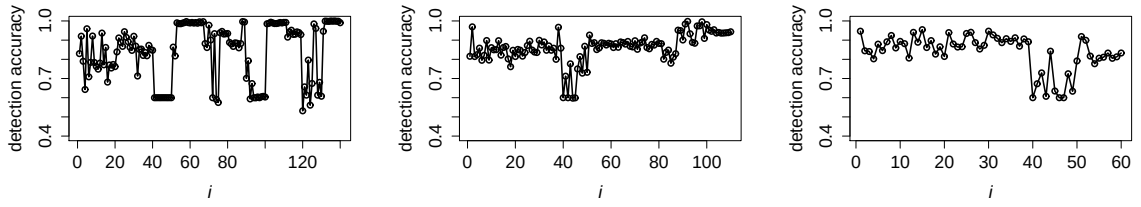
Website contents are dynamic, namely evolving with time. In previous two chapters, we find that J48 classifier is very effective when using the model learned from the training data collected on day i to classify the testing data collected on day i. In this chapter, we investigate the following. Let M_i be the classifier the defender learned from the training data collected on D_i, D_j be the (testing) data collected on day j. What is the effectiveness of $M_i(D_j)$, namely the effectiveness of applying model M_i to classify data D_j? In particular, we are interested in the case of $i < j$ as in this case $M_i(D_j)$ reflects the *predictive detection* power of M_i. Note that the scenarios corresponding to $i = j$ are investigated in the previous two chapters.

Figure 5.1 plots the detection accuracy of $M_i(D_j)$ for $j = i, i+1, i+10, i+20, i+50, i+100$, where M_i is learned using the random forest method. We observe the following. First, the detection accuracy of $M_i(D_j)$ for $i \neq j$ can be substantially lower than the detection accuracy of $M_i(D_i)$. This confirms the “natural" evolution of malicious (and benign) websites. Second, $M_i(D_j)$ can somtimes exhibit high detection accuracy when $j = i + 1$, $j = i + 10$ and $j = i + 20$.

Similarly, Figure 5.2 plots the detection accuracy of $M_i(D_j)$ for $j = i, i+1, i+10, i+20, i+50, i+100$, where M_i is learned using the adaboost method. We observe the following. First, the detection accuracy of $M_i(D_j)$ for $i \neq j$ are often substantially lower than the detection accuracy of $M_i(D_i)$. This further confirms the “natural" evolution of malicious (and benign) websites. Second, unlike in the case of using the random forest method, $M_i(D_j)$ rarely exhibits high detection

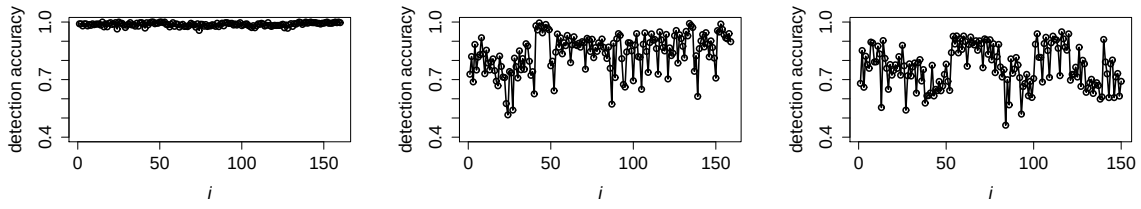


(a) Detection accuracy: $M_i(D_i)$ (b) Detection accuracy: $M_i(D_{i+1})$ (c) Detection accuracy: $M_i(D_{i+10})$

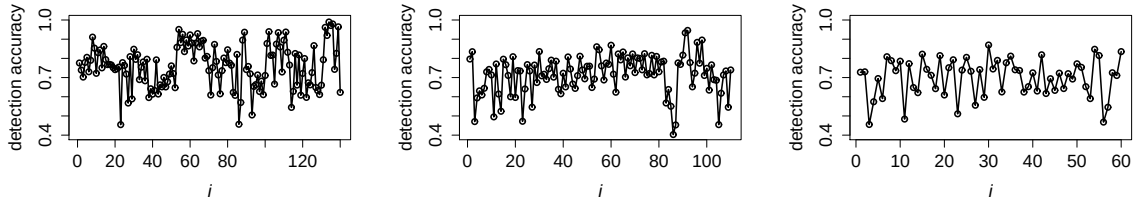


(d) Detection accuracy: $M_i(D_{i+20})$ (e) Detection accuracy: $M_i(D_{i+50})$ (f) Detection accuracy: $M_i(D_{i+100})$

Figure 5.1: Detection accuracy of $M_i(D_j)$ using the random forest method, where x-axis represents day i (from which model M_i is learned) and y-axis represents detection accuracy.



(a) Detection accuracy: $M_i(D_i)$ (b) Detection accuracy: $M_i(D_{i+1})$ (c) Detection accuracy: $M_i(D_{i+10})$



(d) Detection accuracy: $M_i(D_{i+20})$ (e) Detection accuracy: $M_i(D_{i+50})$ (f) Detection accuracy: $M_i(D_{i+100})$

Figure 5.2: Detection accuracy of $M_i(D_j)$ using the adaboost method, where x-axis represents day i (from which model M_i is learned) and y-axis represents detection accuracy.

accuracy when $j = i + 1$, $j = i + 10$ and $j = i + 20$.

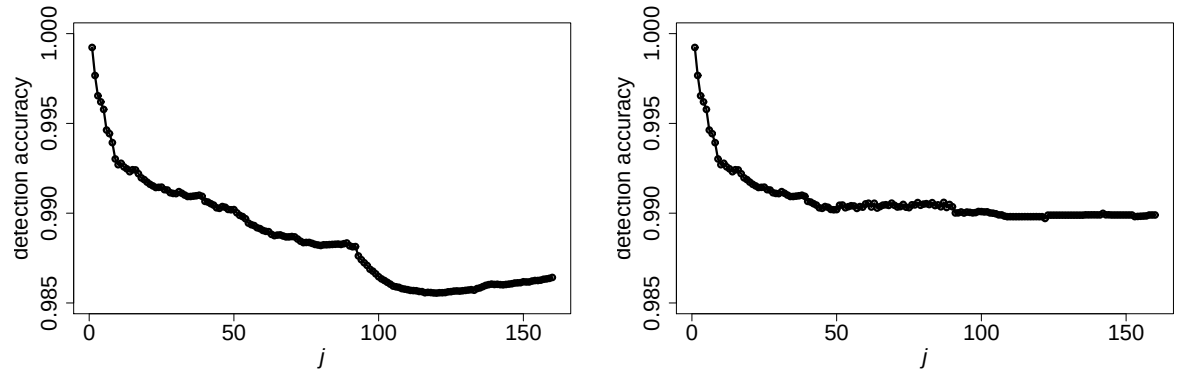
Explanations of these phenomena will be reported elsewhere.

5.5 Online Learning

Having identified that $M_i(D_j)$ for $i < j$ is substantially less effective than $M_i(D_i)$, we need to identify ways for effectively classify D_j. For this purpose, we propose using *online learning*. Vowpal Wabbit is an open source learning software system that includes a series of online machine learning algorithm. One representative online learning algorithm is *logistic regression with stochastic gradient descent* (LRsgd), where model parameters are updated incrementally by the gradients of feature vectors of benign/malicious URLs. It is worthy mentioning that online machine learning algorithm scans the training data once — a characteristic that nicely matches the problem of detecting malicious websites, which dynamically evolve.

The basic idea of online learning is described as follows. Suppose each website is represented as a feature vector X_i and has a label $y_i \in \{0, 1\}$ (i.e., benign or malicious). The online learning algorithm treats the training data as a stream. For each incoming feature vector X, the online learning algorithm using the currently classification model, say M, to classify x with label y. If M's classification is correct, there is no need to update M; otherwise, M is updated toward correctly classifying X.

Figure 5.3 compare the detection accuracies of random forest classification models obtained by using or without using online learning algorithm. Specifically, Figure 5.3a shows the detection accuracy rate for online learning with non-adpative strategy, meaning that the entire history of training data from $D_1, \ldots, D_j$ are used for learning $M_{1..j}$. We observe that the detection accuracy rate is almost 99.99% at day 0 and drop to 99.40% during the first five days. Then, the detection accuracy slowly decreases and reaches 98.40% on the 160th day. Figure 5.3b plots the the detection accuracy rate for online learning with adpative strategy, meaning that only partial history of training data from $D_i, \ldots, D_j$ are used for learning $M_{i..j}$. We observe that the detection accuracy is actually higher than that of the non-adaptive strategy. The reason is that the adaptive strategy can disregard



(a) Non-adaptive online learning strategy: $M_{1..j}(D_j)$ (b) Adaptive online learning strategy: $M_{i..j}(D_j)$

Figure 5.3: Detection accuracy of random forest classification models obtained by using online learning algorithm LRsgd with non-adaptive or adpative strategy, where x-axis represents j, y-axis represents the detection accuracy rate, $M_{1..j}(D_j)$ means that the model $M_{1..j}$ is learned from the entire history of training data from $D_1, \ldots, D_j$ (non-adaptive strategy), and $M_{i..j}$ means that the model $M_{i..j}$ is learned from partial history of trainig data from $D_i, \ldots, D_j$ (adaptive strategy).

data that is "old" enough to cause misclassifications on day j.

5.6 Related Work

Industrial products for detecting malicious websites include McAfee Site Advisor [2] and Google Safe Browsing [1]. Academic research efforts, which aim at more powerful techniques include [13–16, 18, 29, 32, 33, 37, 41, 53, 57, 59, 60, 65, 67]. For example, Kim and Leey [57] aim to detect suspicious URLs embedded in twitter message streams; Invernizzi et al. [29] aim to quickly identify malicious websites; Xu et al. [65] aim to use both application and network layers information to detect malicious websites; Gianluca et al. [60] aim to use redirection graphs to detect malicious webpages; Kapravelos et al. [32] aim to automatically detect evasive behavior in malicious JavaScript. To the best of our knowledge, the present chapter is the first systematic investigation of the "natural" evolution of malicious websites, and designing countermeasures against them.

5.7 Summery

We have showed that malicious websites are evolving. We also have presented online learning methods, especially adaptive online learning methods, for effectively dealing with evolving malicious websites. Experimental results based on a 160-day dataset shows that the resulting detection accuracy is very promising. We expect to report more detailed results of this research elsewhere shortly.

Chapter 6: CONCLUSION AND FUTURE WORK

In conclusion, we have investigated three aspects of an important problem: understanding and detecting malicious websites. While we have made a substantial step towards ultimately solving the problem, there are many interesting problems that are yet to be tackled before we can achieve the ultimate goal. Two representative research problems are highlighted below.

First, our current data collection system may not be able to deal with obfuscated JavaScript-based redirection, which is a challenging open problem [23]. Although our collected data hints that JavaScript-based redirection is widely used by malicious websites, it appears that JavaScript obfuscation may not have been widely used because our system can effectively detect the malicious URLs. However, this is not true in general and in the future because the fact — many malicious websites are using JavaScript-based redirection — does suggest that the attackers will likely continue using this redirection method, perhaps coupled with obfuscation. It is perhaps equally important to deal with encrypted web contents using light-weight extensions to the static analysis. Fortunately, any progress in these directions can be plugged into our system in a modular fashion. It is possible to enhance our static analysis system by incorporating new techniques such as those described in [18, 20, 46, 56].

Second, we consider a certain class of adaptive attacks that attempt to evade detection, which are equally used by both attacker and defender. There could be other classes of adaptive attacks that may be able to defeat our defense. Our artificial manipulation algorithms for mimicking adaptive attacks may or may not be truthful because when the algorithms changes the values of some application-layer features, some network-layer features may have to be changed correspondingly so as to make the cross-layer semantics consistent. This is a non-trivial problems because there is no simple mapping between the application-layer features and the network-layer features. Finally, our adaptive defense is reminiscent of the studies in robust classifiers [11, 12, 25, 34, 35], which suggests that our study will spark more investigations on the power and limitation of our defense.

BIBLIOGRAPHY

[1] Google safe browing, http://code.google.com/apis/safebrowsing/developers_guide_v2.html.

[2] *http* : *//en.wikipedia.org/wiki/url_redirection.*

[3] iptables 1.4.12.1 www.netfilter.org/projects/iptables.

[4] Know your enemy: Behind the scenes of malicious web servers. http://www.honeynet.org.

[5] Know your enemy: Malicious web servers. http://www.honeynet.org.

[6] Mcafee. siteadvisor. http://www.siteadvisor.com.

[7] Sophos corporation. security threat report update 07/2008. http://sophos.com/sophos/docs/eng/papers/sophos-security-report-jul08-srna.pdf.

[8] tcpdump 4.2.0 www.tcpdump.org.

[9] Marco Barreno, Blaine Nelson, Russell Sears, Anthony D. Joseph, and J. D. Tygar. Can machine learning be secure? In *ASIACCS'06*, pages 16–25, 2006.

[10] Andras A. Benczur, Karoly Csalogany, Tamas Sarlos, and Mate Uher. Spamrank - fully automatic link spam detection. In *AIRWeb*, 2005.

[11] Battista Biggio, Giorgio Fumera, and Fabio Roli. Multiple classifier systems under attack. In *MCS*, pages 74–83, 2010.

[12] Leo Breiman. Bagging predictors. *Machine Learning*, pages 123–140, 1996.

[13] Davide Canali and Davide Balzarotti. Behind the scenes of online attacks: an analysis of exploitation behaviors on the web. In *NDSS '13*.

[14] Davide Canali, Marco Cova, Giovanni Vigna, and Christopher Kruegel. Prophiler: a fast filter for the large-scale detection of malicious web pages. Proc. WWW'11, pages 197–206. ACM, 2011.

[15] Kevin Zhijie Chen, Guofei Gu, Jose Nazario, Xinhui Han, and Jianwei Zhuge. WebPatrol: Automated collection and replay of web-based malware scenarios. In *ASIACCS'11)*, 2011.

[16] Hyunsang Choi, Bin B. Zhu, and Heejo Lee. Detecting malicious web links and identifying their attack types. In *WebApps'11*, pages 11–11, 2011.

[17] Corinna Cortes and Vladimir Vapnik. Support-vector networks. In *Machine Learning*, pages 273–297, 1995.

[18] Marco Cova, Christopher Kruegel, and Giovanni Vigna. Detection and analysis of drive-by-download attacks and malicious javascript code. In *WWW10*, 2010.

[19] Thomas M. Cover and Joy A. Thomas. *Elements of information theory*. Wiley-Interscience, New York, NY, USA, 1991.

[20] Charlie Curtsinger, Benjamin Livshits, Benjamin Zorn, and Christian Seifert. Zozzle: fast and precise in-browser javascript malware detection. In *USENIX Security*, 2011.

[21] Nilesh Dalvi, Pedro Domingos, Mausam, Sumit Sanghai, and Deepak Verma. Adversarial classification. In *KDD'04*, pages 99–108, 2004.

[22] Andreas Dewald, Thorsten Holz, and Felix C. Freiling. Adsandbox: sandboxing javascript to fight malicious websites. In *SAC'10*, pages 1859–1864, 2010.

[23] Ben Feinstein and Daniel Peck. Caffeine monkey: Automated collection, detection and analysis of malicious javascript. In *DEFCON 15*, 2007.

[24] Sujata Garera, Niels Provos, Monica Chew, and Aviel D. Rubin. A framework for detection and measurement of phishing attacks. In *WORM'07*, pages 1–8, 2007.

[25] Amir Globerson and Sam T. Roweis. Nightmare at test time: robust learning by feature deletion. In *ICML*, pages 353–360, 2006.

[26] M. A. Hall. *Correlation-based Feature Subset Selection for Machine Learning*. PhD thesis, University of Waikato, Hamilton, New Zealand, 1998.

[27] Mark Hall, Eibe Frank, Geoffrey Holmes, Bernhard Pfahringer, Peter Reutemann, and Ian H. Witten. The weka data mining software: an update. *SIGKDD Explor. Newsl.*, pages 10–18, 2009.

[28] Yung-Tsung Hou, Yimeng Chang, Tsuhan Chen, Chi-Sung Laih, and Chia-Mei Chen. Malicious web content detection by machine learning. *Expert Syst. Appl.*, pages 55–60, January 2010.

[29] Luca Invernizzi, Stefano Benvenuti, Marco Cova, Paolo Milani Comparetti, Christopher Kruegel, and Giovanni Vigna. Evilseed: A guided approach to finding malicious web pages. In *Proceedings of the 2012 IEEE Symposium on Security and Privacy*, SP '12, pages 428–442.

[30] G. H. John and P. Langley. Estimating continuous distributions in Bayesian classifiers. *UAI*, pages 338–345, 1995.

[31] A. Kapravelos, M. Cova, C. Kruegel, and G. Vigna. Escape from monkey island: Evading high-interaction honeyclients. In *DIMVA'11*, 2011.

[32] A. Kapravelos, Y. Shoshitaishvili, M. Cova, C. Kruegel, and G. Vigna. Revolver: An automated approach to the detection of evasive web-based malware. In *Proceedings of the USENIX Security Symposium*, 2013.

[33] Alexandros Kapravelos, Marco Cova, Christopher Kruegel, and Giovanni Vigna. Escape from monkey island: Evading high-interaction honeyclients. In *DIMVA*, pages 124–143, 2011.

[34] Josef Kittler, Mohamad Hatef, Robert P. W. Duin, and Jiri Matas. On combining classifiers. *TPAMI*, pages 226–239, 1998.

[35] Aleksander Kolcz and Choon Hui Teo. Feature weighting for improved classifier robustness. In *CEAS*, 2009.

[36] S. le Cessie and J.C. van Houwelingen. Ridge estimators in logistic regression. *Applied Statistics*, pages 191–201, 1992.

[37] Guanhua Yan Lei Liu, Xinwen Zhang and Songqing Chen. Chrome extensions: Threat analysis and countermeasures. In *NDSS '13*.

[38] Daniel Lowd and Christopher Meek. Adversarial learning. In *KDD'05*, pages 641–647, 2005.

[39] Justin Ma, Lawrence K. Saul, Stefan Savage, and Geoffrey M. Voelker. Beyond blacklists: learning to detect malicious web sites from suspicious urls. In *KDD'09*, pages 1245–1254, 2009.

[40] Justin Ma, Lawrence K. Saul, Stefan Savage, and Geoffrey M. Voelker. Identifying suspicious urls: an application of large-scale online learning. In *ICML'09*, pages 681–688, 2009.

[41] Tilman Frosch Mario Heiderich and Thorsten Holz. Iceshield: Detection and mitigation of malicious websites with a frozen dom. In *RAID'11*, 2011.

[42] Jose Nazario. Phoneyc: A virtual client honeypot, 2009.

[43] Blaine Nelson, Benjamin I. P. Rubinstein, Ling Huang, Anthony D. Joseph, and J. D. Tygar. Classifier evasion: models and open problems. In *ECML PKDD 2011*, pages 92–98, 2011.

[44] James Newsome, Brad Karp, and Dawn Song. Paragraph: Thwarting signature learning by training maliciously. In *RAID06*, 2006.

[45] Yuan Niu, Yi min Wang, Hao Chen, Ming Ma, and Francis Hsu. A quantitative study of forum spamming using contextbased analysis. In *NDSS*, 2007.

[46] W Palant. Javascript deobfuscator 1.5.8. https://addons.mozilla.org/en-US/firefox/addon/javascript-deobfuscator/, 2010.

[47] Roberto Perdisci, David Dagon, Wenke Lee, Prahlad Fogla, and Monirul Sharif. Misleading worm signature generators using deliberate noise injection. In *Proc. S&P'06*, 2006.

[48] Roberto Perdisci, Guofei Gu, and Wenke Lee. Using an ensemble of one-class svm classifiers to harden payload-based anomaly detection systems. In *ICDM*, pages 488–498, 2006.

[49] J. Platt. Fast training of support vector machines using sequential minimal optimization. In *Advances in Kernel Methods – Support Vector Learning*, pages 42–65. 1998.

[50] Niels Provos, Panayiotis Mavrommatis, Moheeb Abu Rajab, and Fabian Monrose. All your iframes point to us. In *USENIX Security*, 2008.

[51] Zhiyun Qian, Zhuoqing Morley Mao, Yinglian Xie, and Fang Yu. On network-level clusters for spam detection. In *NDSS*, 2010.

[52] Ross Quinlan. *C4.5: Programs for Machine Learning*. San Mateo, CA, 1993.

[53] Moheeb Rajab, Lucas Ballard, Nav Jagpal, Panayiotis Mavrommatis, Daisuke Nojiri, Niels Provos, and Ludwig Schmidt. Trends in circumventing web-malware detection. Technical report, Google, 2011.

[54] Konrad Rieck, Tammo Krueger, and Andreas Dewald. Cujo: efficient detection and prevention of drive-by-download attacks. In *ACSAC'10*, pages 31–39, 2010.

[55] Benjamin I.P. Rubinstein, Blaine Nelson, Ling Huang, Anthony D. Joseph, Shing-hon Lau, Satish Rao, Nina Taft, and J. D. Tygar. Antidote: understanding and defending against poisoning of anomaly detectors. In *IMC'09*, pages 1–14, 2009.

[56] Chenette S. The ultimate deobfuscator. http://securitylabs.websense.com/content/Blogs/3198.aspx.

[57] Jong Kim Sangho Leey. Warningbird: Detecting suspicious urls in twitter stream. In *NDSS '12*.

[58] Christian Seifert and Ramon Steenson. Capture - Honeypot Client (Capture-HPC). `https://projects.honeynet.org/capture-hpc`, 2006.

[59] Vitaly Shmatikov Sooel Son. The postman always rings twice: Attacking and defending postmessage in html5websites. In *NDSS '13*, NDSS '13, 2013.

[60] Gianluca Stringhini, Christopher Kruegel, and Giovanni Vigna. Shady paths: leveraging surfing crowds to detect malicious web pages. CCS '13, pages 133–144.

[61] Kurt Thomas, Chris Grier, Justin Ma, Vern Paxson, and Dawn Song. Design and Evaluation of a Real-Time URL Spam Filtering Service. In *Proc. IEEE S&P'11*, 2011.

[62] Shobha Venkataraman, Avrim Blum, and Dawn Song. Limits of learning-based signature generation with adversaries. In *NDSS*, 2008.

[63] Yi-Min Wang, Doug Beck, Xuxian Jiang, and Roussi Roussev. Automated web patrol with strider honeymonkeys: Finding web sites that exploit browser vulnerabilities. In *NDSS'06*, 2006.

[64] Colin Whittaker, Brian Ryner, and Marria Nazif. Large-scale automatic classification of phishing pages. In *NDSS*, 2010.

[65] Li Xu, Zhenxin Zhan, Shouhuai Xu, and Keying Ye. Cross-layer detection of malicious websites. In *CODASPY*, pages 141–152, 2013.

[66] Wei Xu, Fangfang Zhang, and Sencun Zhu. Jstill: mostly static detection of obfuscated malicious javascript code. In *Proceedings of the third ACM conference on Data and application security and privacy*, CODASPY '13, pages 117–128, 2013.

[67] Junjie Zhang, Christian Seifert, Jack W. Stokes, and Wenke Lee. Arrow: Generating signatures to detect drive-by downloads. In *WWW*, pages 187–196, 2011.

VITA

Li Xu received his B.S. degree and M.SC. degree from China. He started his Ph.D. study at University of Texas at San Antonio from September 2008.