Behavioral Analysis of Network Traffic for Detecting Advanced Cyber-threats

by

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(Under the Direction of Roberto Perdisci)

Abstract

Internet miscreants continue to spread malware on thousands of users' machines and they have become stealthier than ever before. Current prevention and detection technologies to protect users and networks from the threat of cyber attacks are lagging behind and becoming frustratingly useless. In this research, we tackle the problem of dealing with cyber criminals by introducing advanced and novel detection technologies. We present detailed measurement analysis of real-world malicious ecosystems that are utilized to distribute malware nowadays. In addition, we propose various state-of-the-art systems to fight against the spread of malice on the Internet, deploy our systems in real-world operative environments, and show the effectiveness and advantages of our design. We cover numerous aspects of today's security concerns ranging from P2P applications to malware downloads and Command and Control domains.

Index words: Network security and intelligence, Machine Learning, Large-scale data analysis, Malware, Botnet, P2P applications

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CHAPTER 1

INTRODUCTION AND LITERATURE REVIEW

1.1 Introduction

Despite extensive research efforts, malicious software (or malware) is still at large. In fact, numbers clearly show that malware infections continue to be on the rise. Because malware is at the root of most of today's cyber-crime, it is of utmost importance to persist in our battle to defeat it. Unfortunately, existing defense technologies (e.g., antivirus softwares or domain blacklists) have not been able to deal with new and sophisticated techniques utilized by the Internet miscreants to distribute and deploy their malware on thousands of users' machines. Nowadays, it is safe to say that we have reached a point where antivirus softwares simply don't work anymore. This is mostly due to the fact that the traditional antivirus systems rely on signature matching or static URL blacklisting, approaches that have long been counteracted by the criminals. In this research, we focus on studying and designing state-of-the-art prevention and detection models that are completely different from the ineffective, routine techniques to fight this uphill battle. The main theme of this work is, therefore, network security and machine learning with an emphasis on large-scale data analysis.

This study focuses on the behavior of malicious infrastructures as a whole, rather than having an individualistic approach on analysis of bad files or domains. It is next to impossible

to detect zero-day malwares installing and running themselves on victims' machines due to extreme obfuscation and code polymorphism techniques utilized by the malwares that conceal their existence. Nonetheless, a global understanding of distribution or control infrastructures of malwares hold promise, because it enables us to see the interaction patterns among the involved entities and to leverage these patterns in defusing the cyber threats. This idea forms the basis of this research and serves as the building block of this dissertation's chapters. More specifically, we researched behavioral models and graph-based learning algorithms that use a belief propagation strategy to enable detection. This work constitutes the design of distinct detection systems and measurement studies, each looking at the problem from a unique standpoint while carrying the core ideology, behavioral analysis. What follows is a summary of the chapters in this dissertation.

1.1.1 Behavior-based Classification of P2P Traffic

Peer2Peer (P2P) networks have been utilized greatly by criminals to facilitate their malware distribution efforts. A malicious P2P botnet is a network of infected machines, called bots, that are under the full control of an adversary, called a botmaster. The botmaster controls its army of bots through Command & Control (C&C) channels. Since in P2P networks there is no centralized and dedicated C&C servers to manage the bots, the P2P botnets are very hard to detect. In a novel research project, we studied P2P networks and designed a system for detection and categorization of P2P traffic [58]. The core idea behind this system is P2P behavioral analysis which involves investigation of different P2P networks' characteristics to be able to build profiles of their network activities. To generate the models, the traffic of numerous benign and malicious P2P applications were collected, and their key behavioral characteristics were extracted in terms of statistical feature vectors. These feature vectors were used to train an accurate classification system comprising a group of One-Class classifiers. Each One-Class classifier is basically an expert in classification of a specific P2P

application. When united, these distinct P2P profiles act in a collaborative fashion to reveal the true nature of P2P traffic crossing the boundaries of the network under surveillance. Chapter 2 provides a detailed discussion about this work.

1.1.2 Measuring the Properties of C&C Domains

While Chapter 2 focus is on P2P botnets, in Chapter 3 we study the properties of centralized botnets. So in a measurement study, we turn our attention to researching the malware-control domains (C&C servers) to obtain a better understanding of their life cycle. This work is a multiyear study of botnets that concerns the birth, growth, and death of their malicious infrastructure where we analyzed four years of DNS traffic related to known C&C servers. This project is based on a massive DNS traffic dataset that is unique in a sense that it is collected at upper DNS hierarchy that provides a global visibility into all domain resolutions from a few providers and their respective requesters. The C&C servers' lifetimes were modeled and their DNS resolutions were analyzed. The results help the security community to obtain an accurate understanding of how Internet miscreants manage their infrastructure and how agile they are in relocating their C&C servers. Chapter 3 contains details of this research study. Moreover, an interesting outcome of the study in Chapter 3 that involves further investigating the DNS resolution characteristics of inactive C&C servers is presented in Chapter 4.

1.1.3 Behavioral Graph-based Detection System Using Belief Propagation Strategy

Graph Learning is a novel approach that is introduced in two of our projects to detect malicious cyber contents. By building a behavioral graph, this method allows us to obtain

a global awareness related to the interaction among entities in a system, such as an ISP network or download patterns of users from various URLs.

Chapter 5 proposes a novel approach to detect malware-control (C&C) domains and Chapter 6 focuses on detecting the malware downloads from malicious domains.

Large-scale Detection of C&C servers

In this research project, we designed a novel detection system based on behavioral-graphs to identify new and previously unknown malware-control domains in live network traffic. A malware-control domain hosts malicious software with the sole purpose of distributing and installing it on users' machines. This system has been fully tested and deployed in real-world large ISP networks that serve millions of users in major cities in the United States where users visit hundreds of millions of domains daily. The system automatically learns how to discover new malware-control domain names by monitoring the DNS query behavior of both known malware-infected machines as well as benign, meaning non-infected, machines. Specifically, we build a machine-domain bipartite graph representing who is querying what. Based on the machine-domain bipartite graph, it is noticeable that unknown domains that are consistently queried only (or mostly) by known malware-infected machines are likely to be malware-related. In essence, we combine the machines' query behavior in terms of who is querying what with a number of other domain name features, such as IP resolution history and age, to compute the probability that a domain name is used for malware control or that a machine is infected. Refer to Chapter 5 for full details.

Detection of Malicious Files, URLs, and Vulnerable Users

In another novel research project, we use the same overall strategy to perform behavioral graph-based detection of malicious files, URLs, and vulnerable machines on a large scale. This study is based on a unique dataset containing download events of customers of a famous

antivirus company. The download events are 3-tuple of files, URLs, and user machines. Using this dataset, we build a tripartite graph which reveals the associations among the aforementioned three entities. Similar to the previous study, we propagate either goodness or badness information in the graph from labeled nodes towards unknown ones. The devised classification system measures the amount of information push from the neighbors of an unknown node towards making it either good or bad. The novelty and great advantage of this study is that, firstly, it takes into account only the relationships and associations among files, URLs, and machines and deduces based upon adjacencies (either direct or indirect) in the tripartite graph. It doesn't need to perform any deep file analysis, traffic monitoring, DNS query inspection, etc.. Secondly, the detection occurs in a unified manner. In other words, the system acts as a central defense and protection system that could detect malware downloads, identify infected machines, and automatically block malicious URLs at the same time. In fact, the detection result at each level in the graph assists in detection at other levels. In summary, we show that the system can detect malicious files and URLs days or even weeks before they are detected by antivirus softwares. This work is also partially similar to another URL reputation system which is published in [70]. This system explained fully in Chapter 6.

1.2 Literature Review

This section presents the state-of-the-art in network security and machine learning. The section is divided into two parts. The first part provides a clear picture of usage of various machine learning techniques in network security topics, including malware detection, intrusion detection systems, and spam detection. Machine learning is an integral part of this research and provides a framework to build and evaluate statistical models. The second part

of the literature review is designated to the review of some of the most recent studies that are closely related to each chapter of this dissertation.

1.2.1 Machine Learning and Security

One of the important applications of machine learning techniques is in security, where dealing with large datasets, for example, network or DNS traffic, and extracting the hidden knowledge in them is a challenge. In this section, we explore three major research areas of security, namely malware detection, intrusion detection systems, and spam detection. The papers discussed here are directly related to the research topics mentioned earlier, they also have great emphasis on machine learning. Moreover, a diverse group of different machine learning algorithms is discussed in the papers.

Malware Detection

Malicious code is "any code added, changed, or removed from a software system to intentionally cause harm or subvert the system's intended function" [44]. Anti-viruses alone are proved to be ineffective [61], and new techniques are required to fight against them [16]. Due to the sheer number of unknown files to be analyzed, manual methods cannot keep up, and, instead, machine learning methods hold promise to enable automatic detection and classification of malicious files [19]. Nonetheless, they come with their own unique challenges [10]. Malware distributors employ various techniques to install their malicious binaries into users' machines. In early days, the main distribution mean was the malicious email attachments. In this scenario, inexperienced or careless users were encouraged to open and run an attachment by utilizing social engineering methods. Once the attachment was run, the user's computer was infected. However, this method requires user's cooperation, which in turn makes the attacks less effective. Recently, a stealthier and more effective distribution attack vector has been used: Drive-by Downloads [37]. In this method, no user interaction is needed and,

in fact, merely visiting a malicious web site is enough to compromise the users' machines. Usually, upon visiting a page with drive-by download exploit code, an executable will run on the browser and forces it to download the malware automatically. The malware then will be installed and infects the host. After infection, the malware tries to communicate with a Command and Control channel (C&C) to update itself, download new binaries, upload stolen information, receive new orders, and etc.

Learning to Detect and Classify Malicious Executables in the Wild Kolter and Maloof [44] focus on detection of malware executables. Also they train models that are able to classify malwares based on their main operations (spamming, back door, etc.). A collection of 1,971 benign and 1,651 malicious executables were used. Then n-grams are extracted from the hex representation of these samples. Each n-gram represents a binary feature (same as text classification methods). The most informative ones were chosen by computing the information gain for each.

Multiple classification algorithms were used to train models to tell malware files apart from the legitimate ones. These algorithms are: 1) Instance-based Learner (including IBk, or k nearest neighbors), 2) Naive Bayes, 3) Support Vector Machines, 4) Decision Trees. Moreover, they also tried and evaluated classifier combination methods. Boosting is the used algorithm and it was performed on SVM, decision tress, and Naive Bayes.

The aforementioned classifiers are then trained using 10-fold cross validation, and their performance is evaluated by computing their ROC curve and the area under the ROC curve. There are a few variables that need to be determined before classifier evaluation. These variables are, the value of n in the n-grams, the number of n-grams to be used, and the size of the words. By performing some pilot experiments, they determine the optimal values for these variables. The evaluation results show that Boosting decision trees yields the best result, while Naive Bayes produces the worst performance.

Second part of the paper focuses on classifying the malwares based on what they do on the system. The approach used here is *one-versus-all* classifiers. In this method, instead of having one multi-class classifier, multiple binary classifiers are trained. Each binary classifier tells if the unknown input sample belongs to the class that is being represented by the classifier. For example, one classifier tells keyloggers apart from the rest, while another one separates backdoors from the rest. Since a single malware could perform multiple actions corresponding to different binary classifiers, multiples classifiers could produce a "hit" as output. A similar approach is also taken in [58]. The experimental evaluation suggests that the task of classifying malwares is a more difficult task than detecting malwares.

Automatic Analysis of Malware Behavior using Machine Learning The classification step presented in [44] works directly with the content of the binary files. Unfortunately, malware distributors utilize variety of techniques, such as code obfuscation, re-packing the files, self generating codes, and etc., to evade this method. Having this in mind, Reick et al. [61] employ another method for malware behavior classification. To analyze malwares behavior, they are run in controlled environment, sandbox, and the chain of operations performed, such as system calls, are logged. Instructions are then transformed into hex codes, and similar to [44], n-grams of them are considered. Finally, for the sake of using machine learning techniques, a malware's set of instruction n-grams is converted into a feature vector, where each element denotes the existence of a specific instruction. Now it would be possible to measure similarity of two sequences using simple means, for example, Euclidean distance.

Both clustering, for identification of similar and new behaviors among malwares, and classification, to assign a particular malware based on its operational characteristics to a known class, are studied in the paper. Hierarchical clustering algorithm is used to partition the feature vectors. The distance between the clusters is computed based on the complete linkage method that considers the distance of two farthest members of each cluster as the clusters distance. To perform classification, labeled data is required. To obtain the labeled

data, they use the clusters that are formed using their clustering method, and adopt k nearest neighbors algorithm to assign the closest cluster's label to instances.

Finally, the system is meant to be used in an incremental fashion, i.e. it gets updated when new instances become available through numerous feeds. A novel approach is taken here to incorporate new comers into the clusters. Upon receiving a new instance, the system checks if it matches one of the existing classes. In this case the new objects is absorbed. If it is not sufficiently close to one of the pre-established classes, it enters a clustering phase with other left out instances. If they bond well (i.e. could form a new cluster), then system has found a new cluster of malware behaviors that could correspond to a new operation, for example.

Large-scale Malware Classification Using Random Projections and Neural Networks The work presented in [19] also concerns with the detection and classification of malware. However, one interesting problem the authors try to tackle is to deal with a very large dataset of labeled instances where samples are represented with enormous number of features (179,000 features). In addition, one of their requirement is to produce an infinitesimal false positives rate, with reasonably low false negatives. In this large-scale setup it is very expensive to apply more sophisticated and effective classification algorithms. So another challenge is to properly get rid of the "curse of dimensionality".

The dataset used to train the models contains 1,843,359 labeled malware samples and 817,485 benign files. They also associated with each malware sample, a malware family. If malware family is not known for a malware sample, it is assigned a generic family class. The feature vectors in the labeled dataset, contain information from dynamic behavior of malwares. This information are captured via the system calls, and the 3-gram of them are considered as features (n-grams of system calls as features are also used in other studies, such as [61] and [44]). A simple feature selection technique is used to reduce the 50 million features generated by the tri-grams. This method reduces the dimensionality of the search

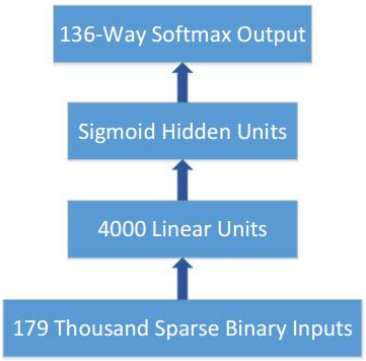

Figure 1.1: Architecture of the classifier system in [19]

space to 179 thousand. To train a Neural Network, however, the number of features are too many, and this makes the training too expensive. As a result, another feature selection method, called Random Projections, is used.

The classifier architecture is shown in Figure 1.1. It is composed of multiple steps and a combine classifier that comprises Neural Networks and multinomial logistic regression. The first step, as it was discussed above, is to reduce the dimensionality. The number of features in Neural Network input is 4,000. The output of the Neural Network layers is fed into the logistic regression classifier (the "softmax" layer), which in turn maps it to either of the malware family outputs or benign output (136 classes). Note that in this case, simple linear regression cannot be used, since it is a linear classifier, capable of only handling binary cases.

The proposed method is evaluated, and it is shown it can perform well. Specifically, multiple different configurations of the systems are tested. For example, different classification accuracies are reported for different number of hidden layers in the Neural Networks.

Polonium: Tera-Scale Graph Mining for Malware Detection A new malware detection approach is introduced by Polo et al. [16], called Polonium. It leverages a few simple intuitions about goodness and badness of the binary executables and utilizes statistical graphical models to build a reputation system. Having access to anonymous reports of

Symantec anti-virus about the users and the files on their computers, the system, first, builds a very large bipartite graph of machines and files, representing *who is running what*. The edges in this graph are drawn between a user's machine and a file, if the file exists on the machine. Belief Propagation algorithm is used to circulate information in this graph, to eventually compute the marginal probability of the files belonging to either good or bad classes. Machines reputation affects the reputation of the files associated with them, and similarly, files reputation impacts the machines' reputation. For example, a file is more likely good, if it appears on many machines, whereas a file that only exists on a very few machines is more likely malicious. Or an unknown file that mostly exists on infected hosts, and no other clean hosts, could be a malware. By using some ground truth about the files, machines and files are first labeled in the graph. Based on this labeling, an initial belief is associated with each node, denoting our prior knowledge about the true nature of the nodes. Then a repetitive message passing algorithm propagate the believes in the graph through weighted edges. Each incoming message to a node, carries the opinion of its neighbors about the nature of the node. For example, a malicious file's outgoing message to its machine neighbors pushes them toward badness. The aggregate of incoming messages to a node is used to update node's belief. The algorithm converges, if the changes of nodes' believes remain constant between iterations.

Large-Scale Malware Indexing Using Function-Call Graphs The goal of [33] is to have a mean to identify similar malwares. Since malwares often employ heavy polymorphism their contents in terms of bytes are different. But they are semantically the same. So the authors propose a malware database that provides an indexing mechanism that given a new graph of malware system calls, it finds most similar graphs in the database to the new sample. This method, first, generates the function call graph. A metric is defined to compare two graphs. This metric assigns a cost (an edit distance) to a series of operations required to convert one graph to another. Since computing the edit distance is expensive,

an optimization step is designed to give a close approximation of the real edit distance with less computational overhead. Having the more efficient edit distance, the next step is to build an index that can find a close neighbor to an input query. The indexing mechanism employs a multi-resolution search method. In a coarse-grained search, a B+-Tree is used to efficiently and quickly find groups of malware entities that are close enough to the input query. The leaves of the B+-Tree point to fine-grained VPT (Vantage Point Tree) indices. A VPT index is a tree where each node is an item in the database. Each node's children are groups of items that are within a specific range from their parent. For example, all nodes that have distance between x and y, where $x < y$, are grouped together in a child node. Given an input query and a distance threshold, the distance between the query and the root is computed and k nearest neighbors according to the computed distance and the distance threshold are explored recursively.

Nazca Nazca [37] is a malware distribution network detection system. That is, it does not analyze the malware binaries to extract signatures nor does take into account the provenance features of the source, such as the server host, network, etc. In contrast, Nazca takes a "zoomed out" approach where it considers the traits of malware distribution networks as a whole rather than single downloads or executables by monitoring the HTTP requests made by hosts in a network. The observation should have enough visibility to network traffic, e.g. at large ISP networks, universities, or large enterprise networks. One of the advantages of Nazca is that it can detect zero-day malware (new and previously unseen malware from unknown sources) better, because the origin of the file, and the file itself are not relevant to the system's operation.

In the first step, all HTTP communications that are related to fetching binaries are detected in the monitored network, and some relevant information (IPs, URIs, file hash, etc) are extracted from them. Next, from the set of all collected HTTP meta data, they select the ones that are likely related to malicious downloads using a few intuitive heuristics and

classifiers. One classifier designed to capture rapid file mutations (to avoid anti-viruses). Another classifier identifies malicious content providers and distinguishes them from benign ones. A decision tree with six features is trained and evaluated using leave-one-out cross validation. The third classifier detects dedicated malware hosts. Finally, the fourth classifier identifies exploit domains that infect users. Then a graph with heterogeneous nodes (host IPs, domains, files, etc) is generated over the suspicious events from the previous step that captures the correlated entities in a large scale. The goal here is to identify malicious candidates in this graph by a classifier that uses a specific metric. The metric is the strength and distance of candidates to other malicious entities. The evaluation on this part shows the classifier has low false positives, however, it also suffers from low detection rate.

Intrusion Detection Systems

Intrusion detection systems refer to a general class of security systems that identify malicious activities in a network under surveillance. They could be divided into anomaly detection systems that capture behaviors that deviate from normal and expected ones, and misuse detection systems that identifies predefined malicious activities [64]. From another view point, intrusion detection systems could be categorized into network-based and host-based intrusion detection systems, where the former considers network as a whole while looking for malicious traits, while the latter considers each individual host in the network as an entity, like [58].

Trust-Based Classifier Combination for Network Anomaly Detection This paper, [60], combines several intrusion detection methods and improve the quality of their decisions. It creates a model of the traffic in the network from the past observations, predicts the properties of current traffic, and identifies the potentially malicious actions. In another word, Net flows are aggregated over an observation period, relevant feature are extracted, and a conclusion (malicious flows, legitimate flows) is made. The paper defines Flow identity

(srcIP, srcPort, dstIP, dstPort, numPackets, ...) and Flow context (Features observed on the other flows in the same dataset. For example, number of similar flows from same srcIP). The flow identity and flow context collectively create the feature space. Several agents monitor the network flows and each one has a built in system to identify flows as legitimate or malicious. Each agent utilizes a different model, different detection method, and different flow context, i.e. different feature space, but all agents are given the same data which are the network flows in intervals. The detection process contains three stages. During the first stage each agent outputs a predicted anomaly value for each flow. Then the average of outputted values is taken. The aggregated anomaly then is fed into the agents feature space in the second stage. Each agent updates its model of the flows, and particularly updates its centroids, which are trustees of the model and are used to deduce the trustfulness of feature vectors in its vicinity. Finally, in stage three to determine the trustfulness of an individual flow, they aggregate the trustfulness associated with the centroids in the vicinity of flows feature vector.

In the experimental results of the paper a nice discussion is presented about why and how the proposed method helps to improve the results by decomposing the problem and letting each agent have a distinct insight into the problem, and, also how this method reduces the False Positives.

Outside the Closed World: On Using Machine Learning For Network Intrusion Detection Differences between usage of machine learning techniques in intrusion detection systems and other domains is studies in [64]. The authors discuss the unique challenges and difficulties that researches face when using machine learning methods in intrusion detection systems. These challenges are:

- Outlier Detection: In general machine learning algorithms and specially classification techniques require sufficient representatives of all classes in the training data. However,

one major challenge in intrusion detection systems is to identify new and previously unseen attacks.

- High Cost of Errors: False positives and false negatives in network intrusion detection systems are very costly compared to other areas (such as similar product recommendation of online merchants). For example, a system with even a very small false positive rate, could produce errors in its real deployment, and a security specialist should manually vet the output to make sure of its accuracy.

- Semantic Gap: A real-world deployment of intrusion detection systems poses the challenge of how to interpret the results. Does an anomaly mean an activity that is malicious, or does it simply mean that there is a new activity that was never seen before, but potentially legitimate?

- Diversity of Network Traffic: Intrusion detection systems have hard time dealing with the diverse types of traffic that could be observed in a network. Many variables play a part to make the same activity look different in distinct networks (such as bandwidth). Another issue is finding a stable definition of what is considered as "normal", because traffic in networks usually happens in burst intervals, i.e. for some periods of time a host's traffic might seem very heavy while in the next interval the traffic could be just a fraction of the previous interval. These all are normal, but how it could be represented to the algorithm?

- Difficulties with Evaluation: Evaluating intrusion detection systems poses another challenge. This challenge is two-fold: First, acquiring a valid, large enough, labeled dataset of network traffic is not easy. One problem here is how to find data for some anomaly that has not happened yet? Because the goal of the system is to identify new attacks. Is it a valid dataset if one synthetically simulate a few attacks? Second, how the output

of the classifier could be evaluated? Is telling what is normal from what is abnormal apart sufficient? (Please see the "Semantic Gap" challenge above)

Spam Detection

Spam Email Filtering The focus of [79] is on spam filtering. Many spam filtering techniques have been proposed. Many of them rely solely on blacklisting spammers, and others are content based filters which require constant maintenance. This paper proposes a filtering based approach using various machine learning techniques to distinguish spam emails from non-spam ones. The first step is to extract the message features. The words in the messages are features in this work which are extracted by, first, using word stemming to automatically remove suffixes. Then valuable features are extracted from the document by using a method called Mutual Information (MI), and features with highest MI are selected. Also two types of feature vectors that are used are Boolean and term frequency. One of the main contributions of the paper is introducing three information theoretic measures for evaluating the performance of spam categorization techniques in terms of False Positives and Negatives. These are, as they stated in[79]: "the remaining uncertainty after classifying a received message as non-spam or spam by a particular spam categorization technique, the uncertainty remaining after a message is classified as non-spam by the spam categorization technique under consideration, and the uncertainty remaining after a message is classified as spam, by the spam categorization technique under consideration".

The paper proposes a way to integrate two trained classification methods for spam classification, which one of them is expert with regards to False Positives while the other presents high accuracy with respect to False Negatives. Several classification methods have been used for this purpose which includes: Nave Bayes, AdaBoostM1, Classification Via Regression, MultiBoostAB, Random Committee, ADTree (Alternate Decision Tree), ID3-Tree, RandomTree.

		Integrity	*Availability*
Causative:	*Targeted*	Permit a specific intrusion	Create sufficient errors to make system unusable for one person or service
	Indiscriminate	Permit at least one intrusion	Create sufficient errors to make learner unusable
Exploratory:	*Targeted*	Find a permitted intrusion from a small set of possibilities	Find a set of points misclassified by the learner
	Indiscriminate	Find a permitted intrusion	

Figure 1.2: Threat model in [10]

Machine Learning and Security

Can Machine Learning Be Secure? Barreno et al. [10] try to answer the question in the title of the paper. More specifically, the authors explore the answers behind a few fundamental questions, such as how machine learning based classifiers could be evaded by attackers?, the degree of difficulty and effort required by the attackers to introduce noise in such a way that it makes the system unreliable?, can the learning algorithm be attacked?, and etc.

Usually, in security papers, a "threat model" is defined that enlists the abilities of the attacker. This model makes some assumptions about what an attacker could or could not do. The threat model discussed in this paper is given in Figure 1.2. Based on the threat model, possible defense mechanisms are discussed. Figure 1.3 shows a summary of techniques to prevent each attack from happening (The figures were directly copied from [10]).

The following provides a brief overview of the defense mechanisms. Regularization is one of the techniques that is beneficial against causative attacks, since it penalizes complexity, hence prevents overfitting. So it strengthens the robustness of the models. Detecting attacks from each of the categories is another defense strategy. For example, an exploratory attack is detectable by observing the classifier's output, and identify a cluster(s) of inputs that cause the system to output a decision near the decision boundary. This signals an attack on

		Integrity	*Availability*
Causative:	*Targeted*	• Regularization • Randomization	• Regularization • Randomization
	Indiscriminate	• Regularization	• Regularization
Exploratory:	*Targeted*	• Information hiding • Randomization	• Information hiding
	Indiscriminate	• Information hiding	

Figure 1.3: Defense mechanisms for the threat model in [10]

the classifier itself. Interestingly, the classifier could actually benefit from the exploratory attacks, by hiding information about its boundary decision, and therefore, confuse the attacker, the same way the attacker tried to confuse the classifier by probing the area near the classes boundary line. Randomization prevents the targeted attacks, because the randomization process affects the placement of the decision boundary, and therefore, it makes it harder for the attacker to predict a good few points to target one class of the model. Finally, the quality and quantity of the training data plays an important role. As more information become available for training, less open space will remain for the attacker to exploit. On the other hand, it could adversely damage the classifier's flexibility to generalize beyond the training set.

1.2.2 State-of-the-art in Analysis and Detection of Cyber-threats

For each chapter of this dissertation a few closely related research papers are discussed. The discussion of all the related work to each chapter is deferred to the respective chapters.

Detection and Classification of P2P Traffic (Chapter 2)

Except than port and application-layer signature based methods, which their ineffectiveness is known nowadays, the effectiveness of transport-layer heuristics on P2P traffic identification is shown by Madhukar et al. [49]. These methods are based on concurrent use of TCP and UDP and connection patterns for IP, Port pairs. This method could be useful in only determination of presence of P2P traffic, and not categorization of it. There are various limitations associated with transport-layer heuristics, and, moreover, identification of Skype and botnets are missing in this work.

Hu et al. [34] use flow statistics to build traffic behavior profiles for P2P applications. However, [34] does not attempt to separate P2P control and data transfer traffic. Because data transfer patterns are highly dependent on user behavior, the approach proposed [34] may not generalize well to P2P traffic generated by different users. Furthermore, [34] is limited to modeling and categorizing only two benign non-encrypted P2P applications (BitTorrent and PPLive), and does not consider at all malicious P2P applications.

A "zoomed-out" approach to identify P2P communities, rather than individual P2P hosts, is introduced by Li et al. [47]. Participating hosts in a P2P community use the same P2P application to communicate with each other. An unsupervised learning algorithm analyzes the graph of who-talks-to-whom and identifies the strongly connected parts of the graph as P2P communities. Although it is shown in [47] that P2P communities use the same P2P application, this method cannot determine the underlying P2P application, whereas PeerRush labels the P2P hosts.

In [30], Haq et al. discuss the importance of detecting and categorizing P2P traffic to improve the accuracy of intrusion detection systems. However, they propose to classify P2P traffic using deep packet inspection, which does not work well in case of encrypted P2P traffic. More recently, a number of studies have addressed the problem of detecting P2P

botnets [25, 76, 77]. However, all these works focus on P2P botnet detection, and cannot categorize the detected malicious traffic and attribute them to a specific botnet family.

Please see Section 2.5 for more related work and a detailed discussion of main differences of each work presented here from PeerRush. In summary, the differences of our work from the aforementioned studies are:

- Our analysis are based on traffic statistics without considering any information from packet payloads. This enables PeerRush to deal with encrypted traffic, too.
- PeerRush *detects* and *categorizes* P2P traffic, unlike the majority of the studies which only focus on detection.
- PeerRush not only detects and categorizes botnets, but also labels other legitimate P2P traffic. To the best of our knowledge all previous works only focused on either botnets or legitimate P2Ps, and not both.
- We evaluated our system using five legitimate P2P applications (including Skype), and three P2P botnets, unlike previous studies which used a few P2P applications.

Analysis and Measurement of Botnets and C&C Domains (Chapters 3 and 4)

One of the outstanding researches in studying botnets has been done by Dagon et al. [18]. In this paper, they have studied and described different topological structures of botnets. The main goal of this paper is to provide a taxonomy of botnets spotted in the wild to better understand the threat. By assigning a new botnet to a predefined taxonomy, defenders could better analyze the botnet, identify its characteristics, and adjust their remedial efforts to take down the botnet. Measuring the effectiveness of responses to each category of botnets is another contribution of this paper. To measure the robustness of botnets against the possible responses, they identify four network models for botnets including: Erdos-Renyi

random graph, Watts-Strogatz small world, barabasi-Albert scale free, and P2P models. For each model they also describe a specific response model. After analyzing the various response techniques, they provide some ideas and approaches for removing the attacks. For example, they show that botnets that are based on random models are usually harder to deal with, or targeted removals of C&C nodes on scale free botnets usually is the best response.

Detection of Malicious Domains (Chapter 5)

Recently, researchers have proposed domain name reputation systems [7, 12] as a way to detect malicious domains, by modeling historic domain-IP mappings, using features of the domain name strings, and leveraging past evidence of malicious content hosted at those domains. These systems mainly aim to detect malicious domains in general, including phishing, spam domains, etc. Notice that while both Notos [7] and Exposure [12] leverage information derived from domain-to-IP mappings, they do not leverage the query behavior of the machines "below" a local DNS server. As an example, domain reputation systems tend to classify as malicious those domains that resolve into IPs located in "dirty" networks (e.g., bullet proof networks), which may host spam URLs, phishing attacks, social engineering attacks, etc.

Kopis [8] has a goal more similar to ours: detect malware-related domains. However, Kopis's features (e.g., *requester diversity* and *requester profile*) are engineered specifically for modeling traffic collected at authoritative name servers, or at top-level-domain (TLD) servers, thus requiring access to authority-level DNS traffic [8]. This type of global access to DNS traffic is extremely difficult to obtain, and can only be achieved in close collaboration with large DNS zone operators. Furthermore, due to the target deployment location, Kopis may allow for detecting only malware domains that end with a specific TLD (e.g., `.ca`).

More recently, Antonakakis et al. have proposed Pleiades [9], which aims to detect machines infected with malware that makes use of domain generation algorithms (DGAs).

While Pleiades monitors the DNS traffic between the network users and their local DNS resolver, as we do, it focuses on monitoring non-existent (NX) domains, which are a side-effect of DGA-based malware.

For further discussion of the differences between the system presented in Chapter 5 and other related work see Section 5.8.

Detection of Malware Downloads (Chapter 6)

A few studies address the problem of detecting malicious files or URLs using the behavioral associations. [50] uses graphical models to detect malicious domains via loopy belief propagation [43]. However, the approach in [50] does not scale well to very large network log datasets that is the target of our work. The loopy belief propagation algorithm is quite expensive and takes very long time to run. Our goal in Chapter 6, however, is to provide online classification of files and URLs without long delays. Moreover, the work in [50] can only detect malicious binary files. In contrast, the system introduced in Chapter 6 enables the automatic and simultaneous detection of malicious files and URLs. Another work related to ours is Polonium [16], which similarly to [50], aims to detect malware files using graphical models.

A similar system called Amico [70] leverages a provenance based classifier to detect malware binary downloads in a monitored network. The classifier is trained based on the history of downloads by users in a network and takes into account the origin of the file downloads, such as the URL, domain, IP space, and etc. Google CAMP [59] is a system similar to [70] that detect malware files based on their origin reputation. However, this system only works with Google's web browser, and therefore, can only be used to monitor the users of the browser.

CHAPTER 2

PEERRUSH: MINING FOR UNWANTED P2P TRAFFIC[1]

[1]B. Rahbarinia, R. Perdisci, A. Lanzi, K. Li, Journal of Information Security and Applications, Volume 19, Issue 3, July 2014, Pages 194-208, DOI: 10.1016/j.jisa.2014.03.002.
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Abstract

In this paper we present PeerRush, a novel system for the identification of *unwanted* P2P traffic. Unlike most previous work, PeerRush goes beyond P2P traffic detection, and can accurately *categorize* the detected P2P traffic and attribute it to specific P2P applications, including malicious applications such as P2P *botnets*. PeerRush achieves these results without the need of deep packet inspection, and can accurately identify applications that use encrypted P2P traffic.

We implemented a prototype version of PeerRush and performed an extensive evaluation of the system over a variety of P2P traffic datasets. Our results show that we can detect all the considered types of P2P traffic with up to 99.5% true positives and 0.1% false positives. Furthermore, PeerRush can attribute the P2P traffic to a specific P2P application with a misclassification rate of 0.68% or less.

2.1 Introduction

Peer-to-peer (P2P) traffic represents a significant portion of today's global Internet traffic [49]. Therefore, it is important for network administrators to be able to identify and categorize P2P traffic crossing their network boundaries, so that appropriate fine-grained network management and security policies can be implemented. In addition, the ability to categorize P2P traffic can help to increase the accuracy of network-based intrusion detection systems [30].

While there exist a vast body of work dedicated to P2P traffic detection [24], a large portion of previous work focuses on signature-based approaches that require deep packet inspection (DPI), or on port-number-based identification [63, 31]. Because modern P2P applications avoid using fixed port numbers and implement encryption to prevent DPI-based detection [49], more recent work has addressed the problem of identifying P2P traffic based on statistical traffic analysis [40, 41]. However, very few of these studies address the problem of P2P traffic categorization [34], and they are limited to studying only few types of non-encrypted P2P communications. Also, a number of previous studies have focused on detecting P2P botnets [25, 76, 52, 17, 77], but with little or no attention to accurately distinguishing between different types of P2P botnet families based on their P2P traffic patterns.

In this paper, we propose a novel P2P traffic categorization system called PeerRush. Our system is based on a generic classification approach that leverages high-level statistical traffic features, and is able to accurately detect and categorize the traffic generated by a variety of P2P applications, including common file-sharing applications such as μTorrent, eMule, etc., P2P-based communication applications such as Skype, and P2P-botnets such as Storm [32], Waledac [55], and a new variant of Zeus [46] that uses encrypted P2P traffic. We would like to emphasize that, unlike previous work on P2P-botnet detection, PeerRush

focuses on accurately detecting and **categorizing different types of legitimate and malicious P2P traffic**, with the goal of identifying *unwanted* P2P applications within the monitored network. Depending on the network's traffic management and security policies, the unwanted applications may include P2P-botnets as well as certain specific legitimate P2P applications (e.g. some file-sharing applications). Moreover, unlike most previous work on P2P-botnet detection, **PeerRush can reveal if a host is compromised with a specific P2P botnet type** among a set of previously observed and modeled botnet families. To the best of our knowledge, no previous study has proposed a generic classification approach to accurately detect and categorize network traffic related to both legitimate and malicious P2P applications, including popular applications that use encrypted P2P traffic, and different types of P2P-botnet traffic (encrypted and non-encrypted).

Figure 2.1 provides an overview of PeerRush, which we discuss in detail in Section 2.2. The first step involves the identifications of P2P hosts within the monitored network. Then, the P2P traffic categorization module analyzes the network traffic generated by these hosts, and attempts to attribute it to a given P2P application by matching an *application profile* previously learned from samples of traffic generated by known P2P applications. If the P2P traffic does not match any of the available profiles, the traffic is classified as belonging to an "unknown" P2P application (e.g., this may represent a new P2P application release or a previously unknown P2P botnet), and should be further analyzed by the network administrator. On the other hand, if the P2P traffic matches more than one profile, an auxiliary *disambiguation* module is used to "break the tie", and the traffic is labeled as belonging to the closest P2P application profile.

The application profiles can model the traffic characteristics of legitimate P2P applications as well as different P2P-botnets. It is common for security researchers to run botnet samples in a controlled environment to study their system and network activities [20]. The traffic collected during this process can then be used as a sample for training a specific P2P-

botnet application profile, which can be plugged into our P2P traffic categorization module. In summary this paper makes the following contributions:

- We present PeerRush, a system for **P2P traffic categorization** that enables the accurate identification of *unwanted* P2P traffic, **including encrypted P2P traffic and different types of P2P botnet traffic**. To achieve these goals, we engineer a set of novel statistical features and classification approaches that provide both accuracy and robustness to noise.

- We collected a variety of P2P traffic datasets comprising of P2P traffic generated by five different legitimate P2P applications used in different configurations, and three different P2P botnets including a P2P botnet that employs encrypted P2P traffic. We are making these datasets *publicly available*.

- We performed an extensive evaluation of PeerRush's classification accuracy and noise resistance. Our results show that we can detect all the considered types of P2P traffic with up to 99.5% true positives and 0.1% false positives. Furthermore, PeerRush can correctly categorize the P2P traffic of a specific P2P application with a misclassification rate of 0.68% or less.

2.2 System Overview

PeerRush's main goal is to enable the discovery of *unwanted* P2P traffic in a monitored computer network. Because the exact definition of what traffic is unwanted depends on the management and security policies of each network, we take a generic P2P traffic categorization approach, and leave the final decision on what traffic is in violation of the policies to the network administrator.

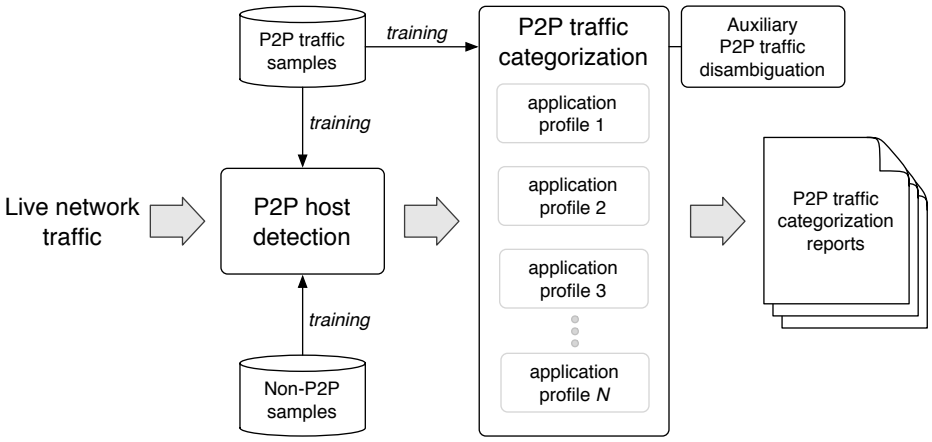


Figure 2.1: PeerRush system overview.

To achieve accurate P2P traffic categorization, PeerRush implements a two-stage classification system that consists of a *P2P host detection* module, and a *P2P traffic categorization* module, as shown in Figure 2.1. PeerRush partitions the stream of *live* network traffic into time windows of constant size W (e.g., $W = 10$ minutes). At the end of each time window, PeerRush extracts a number of statistical features from the observed network traffic, and translates the traffic generated by each host H in the network into a separate feature vector F_H (see Section 2.2.1 for details). Each feature vector F_H can then be fed to a previously trained statistical classifier that specializes in detecting whether H may be running a P2P application, as indicated by its traffic features within the considered time window. Splitting the traffic analysis in time windows allows to generate periodic reports and leads to more accurate results by aggregating outputs obtained in consecutive time windows (see Section 2.3.3).

The classifier used in the *P2P host detection* is trained using samples of network traffic generated by hosts that are known to be running a variety of P2P applications, as well as samples of traffic from hosts that are believed not to be running any known P2P application

(see Section 2.3.1). Once a host H is classified as a *P2P host* within a given time window W by the first module, its current network traffic (i.e., the traffic collected during the current analysis time window W) is sent to the *P2P traffic categorization* module. This module consists of a number of *one-class classifiers* [69], referred to as "application profiles" in Figure 2.1, whereby each classifier specializes in detecting whether H may be running a specific P2P application or not. Each one-class classifier is trained using only previously collected traffic samples related to a known P2P application. For example, we train a one-class classifier to detect Skype traffic, one for eMule, one for the P2P-botnet Storm, and etc. This allows us to build a new application profile independently from previously learned traffic models. Therefore, we can train and deploy a different optimal classifier configuration for each target P2P application and analysis time window W.

Given the traffic from H, we first translate it into a vector of categorization features, or *traffic profile*, P_H (notice that these features are different from the detection features F_H used in the previous module). Then, we feed P_H to each of the available one-class classifiers, and each classifier outputs a score that indicates how close the profile P_H is to the application profile that the classifier is trained to recognize. For example, if the Skype one-class classifier outputs a high score, this means that P_H closely resembles the P2P traffic generated by Skype. If none of the one-class classifiers outputs a high enough score for P_H, PeerRush cannot attribute the P2P traffic of H to a known P2P application, and the P2P traffic profile P_H is labeled as "unknown". This decision may be due to different reasons. For example, the detected P2P host may be running a new P2P application for which no traffic sample was available during the training of the application profiles, or may be infected with a previously unknown P2P-botnet.

Because of the nature of statistical classifiers, while a host H is running a single P2P application more than one classifier may declare that P_H is close to their application profile. In other words, it is possible that the *P2P traffic categorization* module may conclude that

H is running either Skype or eMule, for example. In these cases, to try to break the tie PeerRush sends the profile P_H to a disambiguation module, which consists of a multi-class classifier that specializes in deciding what application profile is actually the closest to an input profile P_H. Essentially, the output of the disambiguation module can be used by the network administrator in combination with the output of the single application profiles that "matched" the traffic to help in further investigating and deciding if the host is in violation of the policies.

In the following, we detail the internals of the P2P traffic detection and categorization modules. It is worth noting that while some of the ideas we use for the detection module are borrowed from previous work on P2P traffic detection (e.g., [77]) and are blended into our own P2P host detection approach, **the design and evaluation of the P2P traffic categorization component include many novel P2P traffic categorization features and traffic classification approaches**, which constitute our main contributions.

2.2.1 P2P Host Detection

Due to the nature of P2P networks, the traffic generated by hosts engaged in P2P communications shows distinct characteristics, which can be harnessed for detection purposes. For example, *peer churn* is an always-present attribute of P2P networks [65], causing P2P hosts to generate a noticeably high number of failed connections. Also, P2P applications typically discover and contact the IP address of other peers without leveraging DNS queries [73]. Furthermore, the peer IPs are usually scattered across many different networks. This makes P2P traffic noticeably different from most other types of Internet traffic (e.g, web browsing traffic). To capture the characteristics of P2P traffic and enable P2P host detection, PeerRush measures a number of statistical features extracted from a *traffic time window*. First, given the traffic observed during a time window of length W (e.g., 10 minutes), the network packets are aggregated into flows, where each flow is identified by a 5-tuple (`protocol`,

`srcip`, `srcport`, `dstip`, `dstport`). Then, to extract the features related to a host H, we consider all flows whose `srcip` is equal to the IP address of H, and compute a vector F_H that includes the following features:

Failed Connections: we measure the number of failed TCP and (virtual) UDP connections. Specifically, we consider as *failed* all TCP or UDP flows for which we observed an outgoing packet but no response, and all TCP flows that had a reset packet. We use two versions of the failed connection feature: (1) the number of failed connections as described above, and (2) the number of failed connections *per host*, where the failed connections to a same destination host are counted as one (i.e., we count the number of distinct `dstip` related to failed connections).

Non-DNS Connections: we consider the flows for which the destination IP address `dstip` was not resolved from a previous DNS query, and we measure two features: (1) the number of non-DNS connections, namely the number of network flows for which `dstip` was not resolved from a DNS query, and (2) non-DNS connections per host, in which all flows to a same destination host are counted as one (i.e., we count the number of distinct `dstip` related to non-DNS connections).

Destination Diversity: given all the `dstip` related to non-DNS connections, for each `dstip` we compute its `/16` IP prefix, and then compute the ratio between the number of distinct `/16` prefixes in which the different `dstips` reside, divided by the total number of distinct `dstips`. This gives us an approximate indication of the *diversity* of the `dstips` contacted by a host H. We consider `/16` IP prefixes because they provide a good approximation of network boundaries. In other words, it is likely that two IP addresses with different `/16` IP prefixes actually reside in different networks owned by different organizations. We define nine features divided in three groups:

1) *Successful Connections*: we measure the destination diversity of all successful connections, the number of distinct `dstips`, and number of distinct `/16` networks.

2) *Unsuccessful Connections*: we measure three features in a way analogous to the Successful Connections group above, except that in this case we only consider unsuccessful connections.

3) *All Connections*: again, we measure three features as for the other two groups, but in this case we do not discriminate between successful and unsuccessful connections.

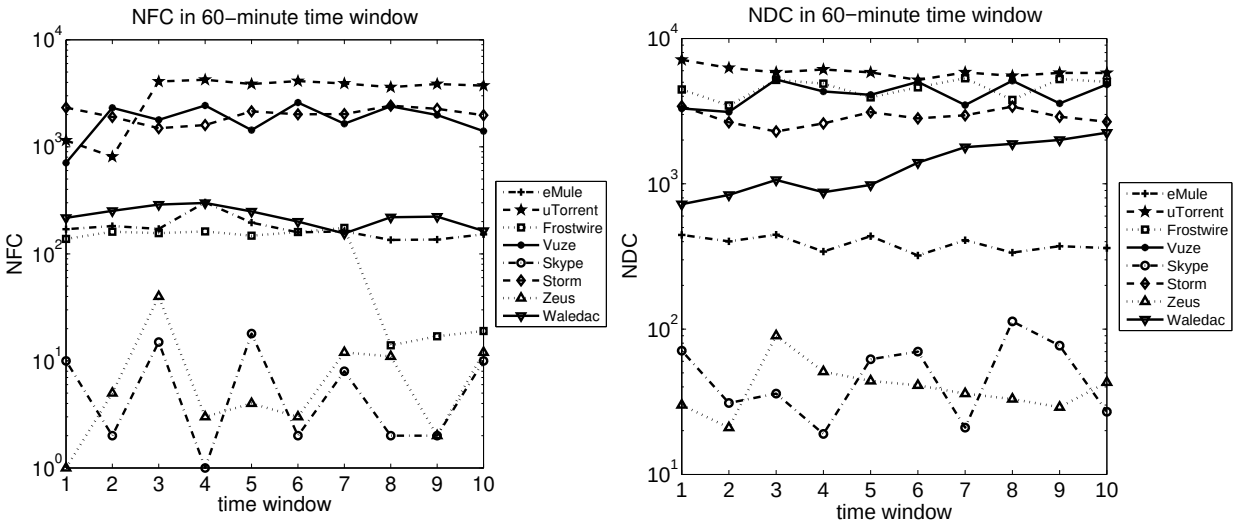
Figure 2.2 shows the numbers of failed connections (NFC) and Non-DNS connections (NDC) for various P2P applications and botnets in multiple 60 minutes time windows.

These three groups of features are designed to accurately pinpoint P2P hosts, since they capture the behavioral patterns of traffic generated by P2P applications. Therefore, the expectation is that the value of these features are higher for P2P hosts in comparison to non-P2P hosts. The time window size W is a configurable parameter. Intuitively, longer time windows allow for computing more accurate values for the features, and consequently yield more accurate results (in Section 2.3 we experiment with W ranging form 10 to 60 minutes).

To carry out the detection, at the end of each time window we input the computed feature vectors F_H (one vector per host and per time window) to a classifier based on decision trees (see Section 2.3.2 for details). To train the classifier, we use a dataset of traffic that includes non-P2P traffic collected from our departmental network, as well as the traffic generated by a variety of P2P applications, including Skype, eMule, BitTorrent, etc., over several days. The data collection approach we used to prepare the training datasets and assess the accuracy of the P2P host detection module is discussed in detail in Section 2.3.1.

2.2.2 P2P Traffic Categorization

After we have identified P2P hosts in the monitored network, the P2P traffic categorization module aims to determine what type of P2P application these hosts are running. Since



(a) (b)

Figure 2.2: An example of number of failed connections (NFC) and non-DNS connections (NDC) in ten 60-minute time windows

different P2P applications (including P2P-botnets) use different P2P protocols and networks (i.e., they connect to different sets of peers), they show distinguishable behaviors in terms of their network communication patterns. Therefore, we construct a classification system that is able to learn different P2P application profiles from past traffic samples, and that can accurately categorize new P2P traffic instances.

As shown in Figure 2.1, the categorization module consists of a number of *one-class classifiers* [69] that specialize in recognizing a specific application profile. For example, we train a one-class classifier to recognize P2P traffic generated by Skype, one that can recognize eMule, etc. Also, we build a number of one-class classifiers that aim to recognize different P2P-botnets, such as Storm, Waledac, and a P2P-based version of Zeus. Overall, in our experiments we build eight different one-class classifiers, with five models dedicated to recognizing five different legitimate P2P applications, and three models dedicated to categorizing different P2P-botnets (see Section 2.3.3). PeerRush can be easily extended to

new P2P applications by training a specialized one-class classifier on the new P2P traffic, and plugging the obtained application profile into the categorization module.

Given the traffic generated by a previously detected P2P host H, we first extract a number of statistical features (described below) that constitute the traffic profile P_H of H within a given time window. Then, we feed P_H to each of the previously trained one-class classifiers, and for each of them we obtain a detection score. For example, let s_k be the score output by the classifier dedicated to recognizing Skype. If s_k is greater than a predefined threshold θ_k, which is automatically learned during training, there is a high likelihood that H is running Skype. If no classifier outputs a score s_i (where the subscript i indicates the i-th classifier) greater than the respective application detection threshold θ_i, we label the P2P traffic from H as "unknown". That is, PeerRush detected the fact that H is running a P2P application, but the traffic profile does not fit any of the previously trained models. This may happen in particular if H is running a new P2P applications or an unknown P2P-botnet for which we could not capture any traffic samples to learn its application profile (other possible scenarios are discussed in Section 2.4).

Notice that the threshold θ_i is set during the training phase to cap the false positive rate to $\leq 1\%$. Specifically, the false positives produced by the i-th classifier over the traffic from P2P applications other than the one targeted by the classifier is $\leq 1\%$. Because of the nature of statistical classifiers, it is possible that more than one one-class classifier may output a score s_i greater than the respective detection threshold θ_i, thus declaring that P_H matches their application profile. In this case, to break the tie we use a *P2P traffic disambiguation* module that consists of a multi-class classifier trained to distinguish among the eight different P2P applications that we consider in our experiments. In this case, the multi-class classifier will definitely assign one application among the available ones, and the output of the multi-class classifier can then be interpreted as the most likely P2P application that is running on H. This information, along with the output of each single one-class classifier, can then

be used by the network administrator to help decide if H is in violation of the network management and security policies.

The main reason for building the application profiles using one-class classifiers, rather than directly using multi-class classification algorithms, is that they enable a modular classification approach. For example, given a new P2P application and some related traffic samples, we can separately train a new one-class classifier even with very few or no counterexamples (i.e., traffic samples from other P2P applications), and we can then directly plug it into the P2P traffic categorization module. Learning with few or no counterexamples cannot be easily done with multi-class classifiers. In addition, differently from multi-class classifiers, which will definitely assign exactly one class label among the possible classes, by using one-class classifiers we can more intuitively arrive to the conclusion that a given traffic profile P_H does not really match any previously learned P2P traffic and should therefore be considered as belonging to an "unknown" P2P application, for example.

Feature Engineering To distinguish between different P2P applications, we focus on their *management* (or control) traffic, namely network traffic dedicated to maintaining updated information about the overlay P2P network at each peer node [15]. The reason for focusing on management flows and discarding data-transfer flows is that management flows mainly depend on the P2P protocol design and the P2P application itself, whereas data flows are more user-dependent, because they are typically driven by the P2P application user's actions. Because the usage patterns of a P2P application may vary greatly from user to user, focusing on management flows allows for a more generic, user-independent P2P categorization approach. These observations apply to both legitimate P2P applications and P2P-botnets.

Management flows consist of management packets, such as keep-alive messages, periodically exchanged by the peers to maintain an accurate view of the P2P network to which they belong. In a way, the characteristics of management flows serve as a fingerprint for a

given P2P protocol, and can be used to build accurate application profiles. The first question, therefore, is how to identify management flows and separate them from the data flows. The answer to this question is complicated by the fact that management packets may be exchanged over management flows that are separate from the data flows, or may be embedded within the data flows themselves, depending on the specific P2P protocol specifications. Instead of making strong assumptions about how managements packets are exchanged, we aim to detect management flows by applying a few intuitive heuristics as described below.

We consider the outgoing flows of each P2P hosts (as detected by the P2P host detection module), and we use the following filters to identify the management packets and discard any other type of traffic:

1) *Inter-packet delays*: given a flow, we only consider packets that have at least a time gap $\delta > \theta_\delta$ between their previous and following packets, where θ_δ is a predefined threshold (set to one second, in our experiments). More precisely, let p_i be the packet under consideration within a flow f, and p_{i-1} and p_{i+1} be the packets in f that immediately precede and follow p_i, respectively. Also, let δ^- and δ^+ be the inter-packet delay (IPD) between p_{i-1} and p_i and between p_i and p_{i+1}, respectively. We label p_i as a management packet if both δ^- and δ^+ are greater than θ_δ. The intuition behind this heuristic is that management packets are exchanged periodically, while data packets are typically sent back-to-back. Therefore, the IPDs of data packets are typically very small, and therefore data packets will be discarded. On the other hand, management packets are typically characterized by much larger IPDs (in fact, a $\theta_\delta = 1s$ IPD is quite conservative, because the IPDs between management packets are often much larger).

2) *Duration of the connection*: P2P applications often open long-lived connections through which they exchange management packets, instead of exchanging each management message in a new connection (notice that UDP packets that share the same source and

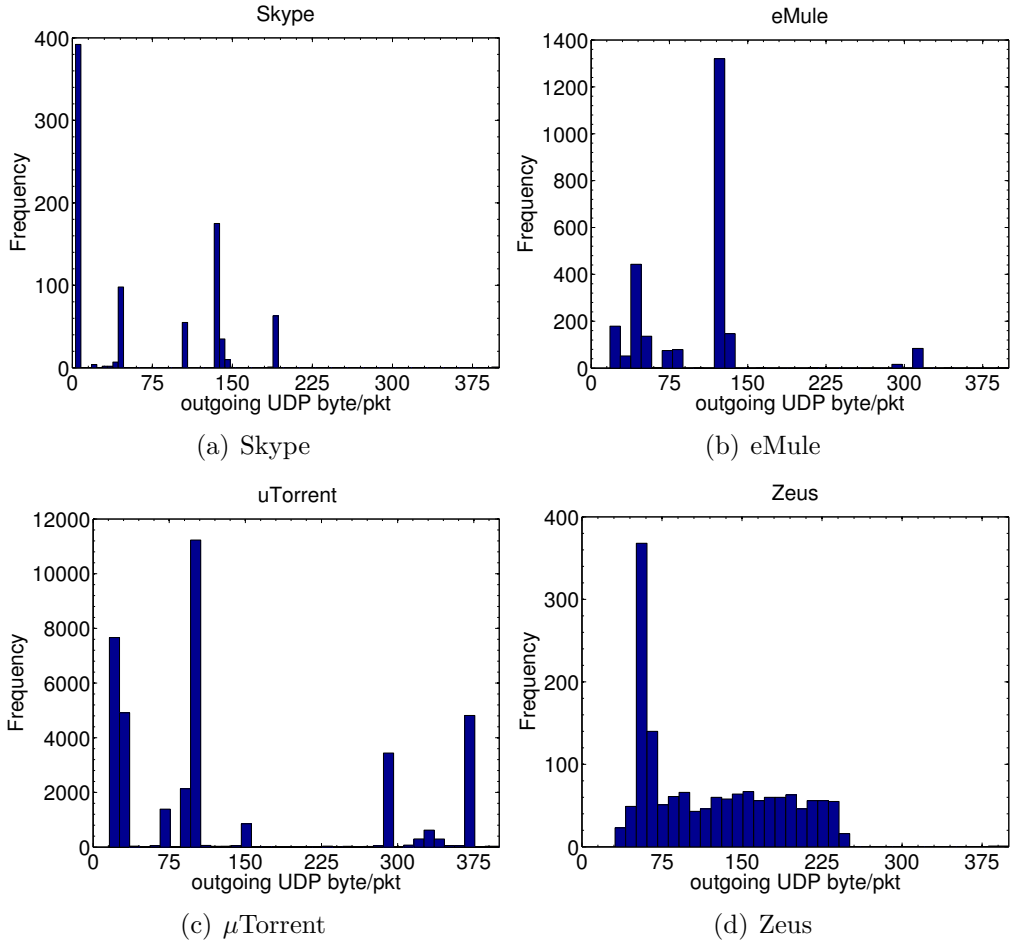
destinations IPs and ports are considered as belonging to the same virtual UDP connection). Therefore, we only consider flows that appear as *long-lived* relative to the size W of the traffic analysis time windows, and we discard all other flows. Specifically, flows that are shorter than $\frac{W}{3}$ are effectively excluded from further analysis.

3) *Bi-directionality*: this filter simply considers bi-directional flows only. The assumption here is that management messages are exchanged both ways between two hosts, and for a given management message (e.g., keep-alive) we will typically see a response or acknowledgment.

Notice that these rules are only applied to connections whose destination IP address did not resolve from DNS queries. This allows us to focus only the network traffic that has a higher chance of being related to the P2P application running on the identified P2P host. While a few non-P2P flows may still survive this pre-filtering (i.e., flows whose destination IP was not resolved from DNS queries, and that are related to some non-P2P application running on the same P2P host), thus potentially constituting noise w.r.t. the feature extraction process, they will be excluded (with very high probability) by the management flow identification rules outlined above.

After we have identified the management (or control) flows and packets, we extract a number of features that summarize the "management behavior" of a P2P host. We consider two groups of features: features based on the distribution of bytes-per-packet (BPP) in the management flows, and feature based on the distribution of the inter-packet delays (IPD) between the management packets. Specifically, given a P2P host and its P2P management flows, we measure eight features computed based on the distribution of BPPs of all incoming and outgoing TCP and UDP flows and the distribution of IPDs for all incoming and outgoing TCP and UDP packets within each management flow.

The intuition behind these features is that different P2P applications and protocols use different formats for the management messages (e.g., keep-alive), and therefore the distribution of BPP will tend to be different. Similarly, different P2P applications typically behave differently in terms of the timing between when management messages are exchanged between peers. As an example, Figure 2.3 reports the distribution of BPP for four different P2P applications. As can be seen from the figure, different applications have different *profiles*, which we leverage to perform P2P traffic *categorization*.



(a) Skype (b) eMule

(c) μTorrent (d) Zeus

Figure 2.3: Distribution of bytes per packets for management flows of different P2P apps.

To translate the distribution of the features discussed above into a pattern vector, which is a more suitable input for statistical classifiers, we proceed as follows. First, given a host H

and its set of management flows, we build a histogram for each of the eight features. Then, given a histogram, we sort its "peaks" according to their height in descending order and select the top ten peaks (i.e., the highest ten). By choosing only the top ten peaks, we aim to isolate possible noise in the distribution, focusing only on the most distinguishing patterns. For each of these peaks we record two values: the location (in the original histogram) of the peak on the x axis, and the its relative height compared to the remaining top ten peaks. For example, the relative height $\hat{h}_k$ of the k-th peak is computed as $\hat{h}_k = h_k / \sum_{j=1}^{10} h_j$, where h_j is the height of the j-th peak. This gives us a vector of twenty values for each feature, and therefore the overall feature vector contains 160 features.

This format of the feature vectors is used both as input to the application-specific one-class classifiers and the P2P traffic disambiguation multi-class classifier (see Figure 2.1). The learning and classification algorithms with which we experimented and the datasets used for training the P2P traffic categorization module are discussed in Section 2.3.3.

Although some of the features require fine grained information about the network packets, such as packet timings, we do not need to compute these features for the majority of the hosts in the network, because the traffic categorization module only deals with the P2P hosts identified by the first module. Moreover, we only focus on the management packets of the P2P hosts, and will not consider all the traffic generated by these hosts. This in turn hugely reduces the amount of network traffic for which traffic categorization module features should be computed.

2.3 Evaluation

2.3.1 Data Collection

PeerRush relies on three main datasets for the training of the P2P host detection and traffic categorization modules: a dataset of P2P traffic generated by a variety of P2P applications, a dataset of traffic from three modern P2P botnets, and a dataset of non-P2P traffic. In the next Sections, we will refer back to these datasets when presenting our evaluation results, which include cross-validation experiments. We plan to make our P2P traffic datasets openly available to facilitate further research and to make our results easier to reproduce[2].

(D1) Ordinary P2P Traffic To collect the P2P traffic dataset, we built an experimental network in our lab consisting of 11 distinct hosts which we used to run 5 different popular P2P applications for several weeks. Specifically, we dedicated 9 hosts to running Skype, and the two remaining hosts to run, at different times, eMule, μTorrent, Frostwire, and Vuze. This choice of P2P applications provided diversity in both P2P protocols and networks (see Table 2.1). The 9 hosts dedicated to Skype were divided into two groups: we configured two hosts with high-end hardware, public IP addresses, and no firewall filtering. This was done so that these hosts had a chance to be elected as Skype super-nodes (indeed, a manual analysis of the volume of traffic generated by these machines gives us reasons to believe that one of the two was actually elected to become a super-node). The remaining 7 hosts were configured using filtered IP addresses, and resided in distinct sub-networks. Using both filtered and unfiltered hosts allowed us to collect samples of Skype traffic that may be witnessed in different real-world scenarios. For each host, we created one separate Skype account and we made some of these accounts be "friends" with each other and with Skype instances running on machines external to our lab. In addition, using AutoIt [1], we created

[2]Please contact the authors to obtain a copy of the datasets.

a number of scripts to simulate user activities on the host, including periodic chat messages and phone calls to friends located both inside and outside of our campus network. Overall, we collected 83 days of a variety of Skype traffic, as shown in Table 2.1.

We used other two distinct unfiltered hosts to run each of the remaining legitimate P2P applications. For example, we first used these two hosts to run two instances of eMule for about 9 consecutive days. During this period, we initiated a variety of file searches and downloads. Whenever possible, we used AutoIt [1] to automate user interactions with the client applications. The files to be downloaded were selected among popular open-source software. However, because of a possible mismatch between file names and actual file contents, to avoid potential copyright issues we made sure to never store the downloads permanently. Furthermore, we set our packet capture tool to only capture part of the payloads, so to make it impossible to reconstruct the downloaded files from the collected traffic traces (notice that in this paper we do not use deep packet inspection for detection, only flow statistics). We replicated this process to collect approximately the same amount of traffic from FrostWire, μTorrent, and Vuze.

(D2) P2P Botnet Traffic In addition to popular P2P applications, we were able to obtain (mainly from third parties) several days of traffic from three different P2P-botnets: Storm [32], Waledac [55], and Zeus [46]. It is worth noting that the Waledac traces were collected before the botnet takedown enacted by Microsoft, while the Zeus traces are from a very recent version of a likely still active Zeus botnet that relies entirely on P2P-based command-and-control (C&C) communications. Table 2.1 indicates the number of hosts and days of traffic we were able to obtain, along with information about the underlying transport protocol used to carry P2P management traffic.

(D3) Non-P2P Traffic To collect the dataset of non-P2P traffic, we proceeded as follows. We monitored the traffic crossing our departmental network over about 5 days, and collected each packet in an anonymized form. Specifically, we wrote a sniffing tool based on `libpcap`

that can anonymize the packets "on the fly" by mapping the department IPs to randomly selected `10.x.x.x` addresses using a keyed hash function, and truncating the packets payloads. We leave all other packet information intact. Also, we do not truncate the payload of DNS response packets, because we need domain name resolution information to extract a number of statistical features (see Section 2.2). Because users in our departmental network may use Skype or (sporadically) some P2P file-sharing applications, we used a number of conservative heuristics to filter out potential P2P hosts from the non-P2P traffic dataset.

To identify possible Skype nodes within our network, we leverage the fact that whenever a Skype client is started, it will query domain names ending in `skype.com` [31]. Therefore, we use the DNS traffic collected from our department to identify all hosts that query any Skype-related domain names, and we exclude them from the traces. Obviously, this is a very conservative approach, because it may cause a non-negligible number of false positives, excluding nodes that visit the `www.skype.com` website, for example, but that are not running Skype. However, we chose this approach because it is difficult to devise reliable heuristics that can identify with high precision what hosts are running Skype and for how long (that's why systems such as PeerRush needed in the first place), and using a conservative approach gives us confidence on the fact that the non-P2P dataset contains a very low amount of noise. Using this approach, we excluded 14 out of 931 hosts in our network.

To filter out other possible P2P traffic, we used Snort [6] with a large set of publicly available P2P detection rules based on payload content inspection. We ran Snort in parallel to our traffic collection tool, and excluded from our dataset all traffic from hosts that triggered a Snort P2P detection rule. Again, we use a very conservative approach of eliminating *all* traffic from suspected P2P hosts to obtain a clean non-P2P dataset. The reason is that it is very hard to exactly identify for how long certain hosts ran a P2P application simply based on the Snort alerts. From a manual analysis of the Snort alerts, we suspect that some of the users of our network may only run P2P file-sharing applications (e.g., eMule or BitTorrent)

Table 2.1: P2P traffic dataset summary

Application	Protocol	Hosts	Capture Days	Transport
Skype	Skype	9	83	TCP/UDP
eMule	eDonkey	2	9	TCP/UDP
FrostWire	Gnutella	2	9	TCP/UDP
μTorrent	BitTorrent	2	9	TCP/UDP
Vuze	BitTorrent	2	9	TCP/UDP
Storm	-	13	7	UDP
Zeus	-	1	34	UDP
Waledac	-	3	3	TCP

for a short amount of time, perhaps because P2P traffic is not seen favorably by the network administrators, and users may not want to be reprimanded. Even using this conservative approach, we only filtered out 7 out of 931 IP addresses from our department traffic traces.

The heuristics-based traffic filtering approach discussed above aims to produce a dataset for which we have reliable *ground truth*. While our heuristics are quite conservative, and may erroneously eliminate hosts that are not actually engaging in P2P traffic, we ended up eliminating only a small fraction of hosts within our network. Therefore, we believe the remaining traffic is representative of non-P2P traffic in our department. Naturally, it is also possible that the non-P2P dataset may contain some P2P traffic (e.g., encrypted or botnet traffic) that we were not able to label using Snort or our heuristics, thus potentially inflating the estimated false positives generated by PeerRush. However, since this would in the worst case underestimate the accuracy of our system, not overestimate it, we can still use the dataset for a fair evaluation.

2.3.2 Evaluation of P2P Host Detection

Balanced Dataset To evaluate the P2P host detection module, we proceed as follows. We perform cross-validation tests using the datasets **D1**, **D2**, and **D3** described in Section 2.3.1. We then applied the process described in Section 2.2.1 to extract statistical features and translate the traffic into feature vectors (one vector per host and per observation time win-

Table 2.2: P2P Host Detection: results of 10-fold cross-validation using J48+AdaBoost

time window	TP	FP	AUC
60 min	99.5%	0.1%	1
40 min	99.1%	0.8%	0.999
20 min	98.4%	1.1%	0.999
10 min	97.9%	1.2%	0.997

dow). Because the volume of Skype-related traffic in **D1** was much larger than the traffic we collected from the remaining popular P2P applications, we under-sampled (at random) the Skype-related traffic to obtain a smaller, balanced dataset. Also, we under-sampled from **D3** to obtain approximately the same number of labeled instances derived from P2P and non-P2P traffic. Consequently, our training set for this module contains roughly the same number of samples from legitimate P2P applications and from the non-P2P traffic.

Cross-validation To perform cross-validation, we initially excluded **D2**, and only considered a balanced version of **D1** and **D3**. As a classifier for the P2P host detection module we used *boosted decision trees*. Specifically, we employ Weka [72] to run 10-fold cross-validation using the J48 decision tree and the AdaBoost meta-classifier (we set AdaBoost to combine 50 decision trees). We repeated the same experiment by measuring the features for different values for the time window length W ranging from 10 to 60 minutes. For $W = 60$ minutes, we had 1,885 P2P and 3,779 non-P2P training instances, while for 10 minutes we had 10,856 P2P and 19,437 non-P2P instances. The results in terms of true positive rate (TP), false positive rate (FP), and area under the ROC curve (AUC) are summarized in Table 2.2. As can be seen, the best results are obtained for the 60 minutes time window, with a 99.5% true positives and a 0.1% false positives. This was expected, because the more time we wait, the more evidence we can collect on whether a host is engaging in P2P communications. However, even at a 10 minutes time window, the classifier perform fairly well, with a true positive rate close to 98%, a false positive rate of 1.2%, and an AUC of 99.7%.

Table 2.3: P2P Host Detection: classification of P2P botnet traffic instances

Time Win.	**Botnet**	**Instances**	**TPs**	IPs detected
60 min	Storm	306	100%	13 out of 13
	Zeus	825	92.48%	1 out 1
	Waledac	75	100%	3 out 3
40 min	Storm	306	100%	13 out of 13
	Zeus	1,229	91.05%	1 out of 1
	Waledac	111	100%	3 out of 3
20 min	Storm	918	100%	13 out of 13
	Zeus	2,448	58.99%	1 out of 1
	Waledac	222	100%	3 out of 3
10 min	Storm	1,834	100%	13 out of 13
	Zeus	4,877	33.46%	1 out of 1
	Waledac	444	100%	3 out of 3

Botnets Besides cross-validation, we performed two additional sets of experiments. First, we train the P2P host detection classifier (we use J48+AdaBoost) using **D1** and **D3**, but not **D2**. Then, given the obtained trained classifier, we test against the P2P botnet traffic **D2**. The results of this experiments are summarized in Table 2.3 . As we can see, the P2P host detection classifier can perfectly classify all the instances of Storm and Waledac traffic. Zeus traffic is somewhat harder to detect, although when we set the time window for feature extraction to 40 minutes or higher we can correctly classify more than 90% of all Zeus traffic instances. We believe this is due to the fact that in our Zeus dataset the host infected by the Zeus botnet sometimes enters a "dormant phase" in which the number of established connections decreases significantly. Also, by considering traffic *over different time windows*, all the IP addresses related to the P2P botnets are correctly classified as P2P hosts. That is, if we consider the Zeus-infected host over a number of consecutive time windows, the Zeus P2P traffic is correctly identified in at least one time window, allowing us to identify the P2P host. Therefore, the 33.46% detection rate using 10-minute time windows is not as low as it may seem, in that the host was labeled as a P2P host at least once in every three time windows.

Table 2.4: P2P Host Detection: "leave one application out" test

	time window: 60 minutes			time window: 40 minutes		
Left out app.	**Test on left out app.**			**Test on left out app.**		
	Instances	**TPs**	**IPs detected**	**Instances**	**TPs**	**IPs detected**
Skype	16,534	95.11%	9 out of 9	24,795	94.64%	9 out of 9
eMule	386	100%	2 out of 2	386	100%	2 out of 2
Frostwire	386	100%	2 out of 2	386	100%	2 out of 2
μTorrent	339	100%	2 out of 2	339	100%	2 out of 2
Vuze	339	100%	2 out of 2	339	100%	2 out of 2
	time window: 20 minutes			**time window: 10 minutes**		
Left out app.	**Test on left out app.**			**Test on left out app.**		
	Instances	**TPs**	**IPs detected**	**Instances**	**TPs**	**IPs detected**
Skype	49,596	92.17%	9 out of 9	99,165	90.26%	9 out of 9
eMule	1,158	100%	2 out of 2	2,316	100%	2 out of 2
Frostwire	1,158	100%	2 out of 2	2,316	100%	2 out of 2
μTorrent	1,018	100%	2 out of 2	2,035	100%	2 out of 2
Vuze	1,018	100%	2 out of 2	2,035	100%	2 out of 2

Leave-one-out In addition, we performed a number of experiments to assess the *generalization ability* of our P2P host classifier. To this end, we again trained the classifier on **D1** and **D3**. This time, though, we train the classifier multiple times, and every time we leave out one specific type of P2P traffic from **D1**. For example, first we train the classifier while leaving out all Skype traffic from the training dataset, and then we test the obtained trained classifier on the Skype traffic that we left out. We repeat this leaving out from **D1** one P2P application at a time (as before, we did not include the P2P botnet traffic from the training dataset). The results of this set of experiments are reported in Table 2.4 . The results show that we can detect most of the left out applications perfectly in all time windows. In case of Skype, the classifier can still generalize remarkably well and correctly classifies more than 90% of the Skype instances using $W = 10$. Using larger time windows improves the results further, because the statistical features can be measured more accurately. Also, the *IPs detected* column shows that all IP addresses engaged in P2P communications are correctly classified as P2P hosts.

Other non-P2P instances Besides the cross-validation experiments, to further asses the false positives generated by our system we tested the P2P host detection classifier over

Table 2.5: P2P Host Detection: test of non-P2P traffic instances excluded from the training set (data collected across $\sim$ 5 days)

Time window	Instances	FP rate	FP IPs
60	18,892	0.29%	21 out of 527
40	18,449	1.08%	44 out of 502
20	51,875	0.45%	25 out of 537
10	97,185	1.14%	78 out of 559

the portion of the non-P2P traffic dataset that was left out from training (due to under-sampling). The results are reported in Table 2.5. Notice that the "FP IPs" column shows the number of distinct IP addresses for which at least one traffic instance (i.e., a small snapshot of its traffic) was at some point labeled as P2P traffic. The non-P2P traffic used for testing was collected over about 5 days, and therefore the average number of false positive IPs is approximately 2 per day. These false positives can be further reduced by flagging a host as P2P only if its traffic instances are classified as P2P by the P2P host detection module for more than one consecutive time window.

2.3.3 Evaluation of P2P Traffic Categorization

In this Section, we evaluate the P2P traffic categorization module. First, we separately evaluate the one-class classifiers used to learn single application profiles (**E1**) and the auxiliary P2P traffic disambiguation module (**E2**). Then, we evaluate the entire P2P traffic categorization module in a scenario that replicates the intended use of PeerRush after deployment (**E3**). Finally, given a separate new dataset of encrypted μTorrent traffic that we recently collected, we show that this new P2P traffic can be accurately detected by the P2P host detection module, and a new application profile can be readily built and plugged into the P2P traffic categorization module for accurate traffic labeling (**E4**).

In all our experiments, we translate a host's traffic into statistical features using the process described in Section 2.2.2. Similar to the evaluation of the P2P host detection module

presented in Section 2.3.2, we experiment with values of the time windows W ranging from 10 to 60 minutes.

(E1) P2P Application Profiles As mentioned in Section 2.2.2, each application profile is modeled using a one-class classifier. Specifically, we experiment with the Parzen, KNN, and Gaussian *data description* classifiers detailed in [69] and implemented in [68]. To build a one-class classifier (i.e., an application profile) for Skype traffic, for example, we use part of the Skype traffic from **D1** as a *target* training dataset, and a subset of non-Skype traffic from the other legitimate P2P applications (again from **D1**) as an *outlier* validation dataset. This validation dataset is used for setting the classifier's detection threshold so to obtain $\leq 1\%$ false positives (i.e., non-Skype traffic instances erroneously classified as Skype). Then we use the remaining portion of the Skype and non-Skype traffic from **D1** that we did not use for training and threshold setting to estimate the FP, TP, and AUC. We repeat the same process for each P2P application in **D1** and P2P botnets in **D2**. Each experiment is run with a 10-fold cross-validation setting for each of the considered one-class classifiers. The results of these experiments are summarized in Table 2.6. The "#Inst." column shows the overall number of *target* instances available for each traffic class.

Besides experimenting with different one-class classifiers, we also evaluated different combinations of features and different feature transformation algorithms, namely principal component analysis (PCA) and feature scaling (Scal.). The "Configuration" column in Table 2.6 shows, for each different time window, the best classifier and feature configuration. For example, the first row of results related to Skype reports the following configuration: "60min; KNN; 32 feat.; PCA". This means that the best application profile for Skype when considering a 60 minutes traffic time window was obtained using the KNN algorithm, 32 features (out of all possible 160 features we extract from the traffic characteristics), and by applying the PCA feature transformation. In the remaining rows, "Scal." indicates features scaling, while "-" indicates no feature transformation.

Notice that because we use one-class classifiers, each application profile can be built independently from other profiles. Therefore, we can train and deploy different optimal classifier configurations depending on the target P2P application and desired time window W for traffic analysis. For example, for a time window of 60 minutes, we can use a KNN classifier with 32 features transformed using PCA for Skype, and a Parzen classifier with 16 scaled features for eMule. This gives us a remarkable degree of flexibility in building the application profiles, compared to multi-class classifiers, because in the latter case we would be limited to using the same algorithm and set of features for all application profiles. Furthermore, using multi-class classifiers makes identifying P2P traffic that does not match any of the profiles (i.e., "unknown" P2P traffic) more straightforward.

Table 2.6 shows that for most applications we can achieve a TP rate of more than 90% with an FP rate close to or below 1%. In particular, all traffic related to P2P botnets can be accurately categorized with very high true positive rates and low false positives. These results hold in most cases even for time windows of $W = 10$ minutes, with the exception of Waledac, for which we were not able to build a comparably accurate application profile using a 10 minutes time window, since we did not have enough target instances to train a classifier (this unsatisfactory result is omitted from Table 2.6).

(E2) P2P Traffic Disambiguation When a traffic instance (i.e., the feature vector extracted from the traffic generated by a host within a given time window) is classified as *target* by more than one application profile, we can use the traffic disambiguation module to try to break the tie. while it is possible for a host to run more than one P2P application at the same time within a given time window, we can still apply the disambiguation module and send the output of the disambiguation results along with the output of each application profile to the network administrator for further analysis. Essentially, we want to provide the network administrator with two pieces of information: the fact that more than one

Table 2.6: One-Class Classification Results

App.	#Inst.	Configuration	TP	FP	AUC
Skype	526	60min; KNN; 32 feat.; PCA	96.54%	0.74%	0.998
	541	40min; Parzen; 8 feat.; PCA	100%	0.85%	1.000
	559	20min; KNN; 24 feat.; PCA	98.18%	0.88%	0.999
	579	10min; Parzen; 16 feat.; -	91.27%	1.00%	0.978
eMule	387	60min; Parzen; 16 feat; Scal.	90.64%	0.92%	0.989
	421	40min; Parzen; 16 feat.; Scal.	92.79%	0.90%	0.995
	448	20min; Parzen; 12 feat.; PCA	95.56%	0.90%	0.985
	483	10min; KNN; 8 feat.; PCA	88.40%	1.16%	0.961
Frostwire	382	60min; KNN; 12 feat.; PCA	85.58%	0.96%	0.966
	402	40min; Parzen; 8 feat.; -	90.81%	1.04%	0.975
	436	20min; Parzen; 8 feat.; PCA	87.12%	0.59%	0.963
	467	10min; KNN; 8 feat.; PCA	92.68%	1.25%	0.989
μTorrent	370	60min; KNN; 8 feat.; -	92.94%	1.30%	0.948
	431	40min; KNN; 4 feat.; Scal.+PCA	91.89%	1.14%	0.985
	509	20min; KNN; 8 feat.; -	93.25%	1.11%	0.962
	609	10min; Parzen; 4 feat.; Scal.	94.55%	1.24%	0.992
Vuze	376	60min; KNN; 8 feat.; -	91.92%	0.95%	0.979
	421	40min; KNN; 8 feat.; -	91.79%	1.06%	0.966
	462	20min; KNN; 12 feat.; PCA	95.44%	1.24%	0.992
	514	10min; KNN; 8 feat.; PCA	84.18%	1.17%	0.964
Storm	162	60min; Parzen; 16 feat.; -	100%	0%	1.000
	240	40min; Parzen; 16 feat.; -	99.29%	0%	0.993
	305	20min; Parzen; 16 feat.; -	99.62%	0.03%	0.996
	391	10min; Parzen; 12 feat.; PCA	100%	0%	1.000
Zeus	375	60min; KNN; 4 feat.; -	97.29%	0.99%	0.996
	426	40min; KNN; 4 feat.; PCA	94.80%	0.91%	0.991
	160	20min; Parzen; 8 feat.; PCA	98.71%	0.73%	0.987
	188	10min; KNN;12 feat.; -	94.53%	0.79%	0.976
Waledac	37	60min; Gaussian; 12 feat.; PCA	99.99%	0.90%	0.998
	42	40min; Gaussian; 12 feat.; PCA	95.00%	1.13%	0.999
	34	20min; Kmeans; 28 feat.; PCA	90.00%	1.07%	0.993

application profile "matched" the traffic instance, and the most likely (or "prevalent") P2P application according to the disambiguation module.

The disambiguation module (see Section 2.2) consists of a multi-class classifier based on the Random Forest algorithm combining 100 decision trees. In this case, we use all 160 features computed as described in Section 2.2.2 without any feature transformation, because even without applying any feature selection process we obtained high accuracy. We independently tested the disambiguation module using 10-fold cross-validation. On average, we obtained an accuracy (percentage of correctly classified instances) of 98.6% for a time window of 60 minutes, 98.3% for 40 minutes, 97.5% for 20 minutes, and 96.7% for 10 minutes.

Table 2.7: P2P Traffic Disambiguation: Results of 10-fold cross-validation

	time window: 60min			**time window: 40min**		
Application	**TP**	**FP**	**AUC**	**TP**	**FP**	**AUC**
Skype	99.8%	0.4%	1	99%	0.1%	1
eMule	99.5%	0.2%	1	100%	0.6%	1
Frostwire	96.1%	0.6%	0.998	95.5%	0.6%	0.998
μTorrent	99.7%	0%	1	99.5%	0%	1
Vuze	96%	0.3%	0.999	95.8%	0.3%	0.999
Storm	100%	0%	1	100%	0%	1
Zeus	99.5%	0%	1	100%	0.3%	1
Waledac	97.2%	0.1%	0.988	92.7%	0%	0.99
	time window: 20min			**time window: 10min**		
Application	**TP**	**FP**	**AUC**	**TP**	**FP**	**AUC**
Skype	99.6%	0.6%	1	99.3%	0.2%	1
eMule	96.7%	0.5%	0.999	98.1%	1.1%	0.997
Frostwire	96.1%	1.1%	0.997	94.8%	1.7%	0.99
μTorrent	99.2%	0.3%	1	98.7%	0.2%	0.999
Vuze	95.6%	0.4%	0.999	90.6%	0.6%	0.996
Storm	100%	0%	1	100%	0.1%	1
Zeus	96.9%	0.1%	1	96.3%	0%	0.998
Waledac	85.7%	1%	0.986	46.7%	0%	0.974

The detailed classification results obtained using 10-fold cross validation are reported in Table 2.7.

Note that the disambiguation module could be employed as the primary classification system for categorizing P2P flows, and it could eliminate the use of one-class classifiers. In fact, the accuracy of the categorization step will be enhanced by doing so (compare Tables 2.6 and 2.7). Nonetheless, we will loose the flexibility of PeerRush, and the advantage of having "unknown" as the classifier output, because the multi-class classifier should always output one of its classes as the answer, even in the case that an unknown input instance is fed to it.

The advantage of using one-class classifiers is that each could use a certain group of features that is more effective in detecting a certain P2P protocol. As a result, there is no general rule on which features are more or less useful. A certain group of features might be quite effective on categorizing Skype, while they might not do well on Zeus (see Table 2.6, column "Configuration").

(E3) Overall Module Evaluation In this section we aim to show how the P2P categorization module performs overall, and how robust it is to noise. To this end, we first split the **D1** dataset into two parts: (i) a training set consisting of 80% of the traffic instances (randomly selected) that we use for training the single application profiles, automatically learn their categorization thresholds, and to train the disambiguation module; (ii) a test set consisting of the remaining 20% of the traffic instances.

To test both the accuracy and robustness of PeerRush's categorization module, we also perform experiments by artificially adding noise to the traffic instances in the test dataset. In doing so, we consider the case in which non-P2P traffic is misclassified by the P2P host detection module and not completely filtered out through the management flow identification process described in Section 2.2.2. To obtain noisy traffic we processed the entire **D3** dataset (about 5 days of traffic from 910 distinct source IP addresses) to identify all flows that resemble P2P management flows. To simulate a *worst case scenario*, we took all the noisy management-like flows we could obtain, and randomly added these flows to *all* the P2P traffic instances in the 20% test dataset described above. Effectively, we simulated the scenario in which the traffic generated by a known P2P host is overlapped with non-P2P traffic from one or more randomly selected hosts from our departmental network.

For each test instance fed to the categorization module, we have the following possible outcomes: (1) the instance is assigned the correct P2P application label; (2) no application profile "matches", and the P2P traffic instance is therefore labeled as "unknown"; (3) more than one profile "matches", and the instance is sent to the disambiguation module. Table 2.8 and Table 2.9 report a summary of the obtained results related to the 20% test dataset with and without extra added noise, considering $W = 60$ minutes. For example, Table 2.9 shows that over 90% of the Skype-related traffic instances can be correctly labeled as being generated by Skype with 1.29% FP, even in the presence of added noise.

Overall, 45 out of 732 (6.15%) of the noisy test traffic instances were classified as "unknown", 32 instances were passed to the disambiguation module and all of them were classified perfectly. Finally, only 5 out of 732 instances were eventually misclassified as belonging to the wrong P2P application. It is worth noting that an administrator could handle the "unknown" and misclassified instances by relying on the categorization results for a given P2P host across more than one time window. For example, a P2P host that is running eMule may be categorized as "unknown" in one given time window, but has a very high chance of being correctly labeled as eMule in subsequent windows, because the true positive rate for eMule traffic is above 93%. In fact, in our experiments, by considering the output of the categorization module over more than one single time window we were always able to attribute the P2P traffic in our test to the correct application.

As we can see by comparing Table 2.8 and Table 2.9, the extra noise added to the P2P traffic instances causes a decrease in the accuracy of the P2P traffic categorization module. However, in most cases the degradation is fairly limited. The noise has a more negative impact on the categorization of Storm and Waledac, in particular. Notice, though, that the results reported in Table 2.9 are again related to single traffic instances (i.e., a single time window). This means that if a Storm- or Waledac-infected host connects to its botnet for longer than one time window, which is most likely the case since malware often makes itself permanent into the compromised systems, the probability of correct categorization would increase. Therefore, even in the scenario in which each P2P host is also running other network applications that may introduce noise in the management flow identification and feature extraction process, we can accurately detect the P2P traffic, and still achieve satisfactory categorization results.

We also wanted to determine how PeerRush's categorization module would deal with noise due to detection errors in the P2P host detection module. To this end, we further tested the classifier using traffic from the non-P2P traffic dataset that were misclassified as P2P by the

P2P host detection module. We found that considering a time window of 60 minutes, only 35 traffic instances misclassified by the P2P host detection module passed the management flow discovery filter. Of these, 33 were classified as "unknown" by the categorization module, one was misclassified as both Skype and μTorrent, and one was misclassified as Zeus.

Table 2.8: 80/20 experiments

time window: 60 minutes			
Application	**TP**	**FP**	**AUC**
Skype	100%	0.86%	1
eMule	93.59%	1.44%	0.9968
Frostwire	88.31%	0.97%	0.9873
μTorrent	96.97%	1%	0.9789
Vuze	93.1%	0.7%	0.9938
Storm	100%	0%	1
Zeus	96.69%	1.26%	0.9964
Waledac	57.14%	0.83%	0.9420

Classified as "unknown": 3.96% (29 out of 732)
Misclassified as other P2P: 0% (0 out of 732)
Disambiguation needed: 4.64% (34 out of 732)
· Correctly disambiguated: 33, Incorrectly disambiguated: 1
Total misclassified as other P2P: 0.14% (1 out of 732)

Table 2.9: 80/20 with extra noise

time window: 60 minutes			
Application	**TP**	**FP**	**AUC**
Skype	90.4%	1.29%	0.9891
eMule	94.87%	2.39%	0.9935
Frostwire	94.73%	0.48%	0.9927
μTorrent	98.99%	0.66%	0.9997
Vuze	93.22%	3.02%	0.9873
Storm	45.45%	0%	0.7273
Zeus	97.32%	0.72%	0.9991
Waledac	40%	0.8%	0.8610

Classified as "unknown": 6.15% (45 out of 732)
Misclassified as other P2P: 0.68% (5 out of 732)
Disambiguation needed: 4.37% (32 out of 732)
· Correctly disambiguated: 32, Incorrectly disambiguated: 0
Total misclassified as other P2P: 0.68% (5 out of 732)

(E4) Encrypted μTorrent Recently, we collected a separate trace of encrypted μTorrent traffic. First we tested the P2P host detection module on instances of encrypted μTorrent traffic where all instances were correctly classified as P2P traffic. So our focus in this section is to show how the new traffic profile of encrypted μTorrent could be easily added to the system as a plugin and how the proposed classification system could accurately label the new encrypted traffic. Note that encrypted μTorrent traffic statistical behavior is different

Table 2.10: Encrypted μTorrent 80/20 Experiments Results

Time Window: 60 minutes					
Application	**Target**	**Outlier**	**TP**	**FP**	**AUC**
Enc. μTorrent	9	732	9 (100 %)	0 (0 %)	1
Classified as Unknown			0 out of 741 (0 %)		
Mixed Enc. μTorrent	9	732	9 (100 %)	0 (0 %)	1
Classified as Unknown			0 out of 741 (0 %)		

from μTorrent even though they both are based on a same P2P protocol (perhaps due to changes in packet sizes as a result of encryption), so a new one-class classifier is required for the encrypted version.

To evaluate the P2P categorization module, we use a similar approach as **E3** experiments, and divide encrypted μTorrent traffic into training and testing sets consisting of 80% and 20% of all instances respectively. The training set is used to build a traffic profile for encrypted μTorrent, and the test set is used to evaluate the classifier. We also amalgamate the encrypted μTorrent test instances with noise from non-P2P traffic (as discussed in **E3** experiments section). The results of these experiments for time window $W = 60$ minutes are shown in Table 2.10. The 20% test set contains 9 instances (targets), and 732 outliers are the test instances from other P2P applications used in **E3** experiments. It is clear that newly introduced P2P application profile works perfectly and categorizes the encrypted μTorrent instances with 100% accuracy and without FPs, even in the presence of noise. The modular design of PeerRush enabled us to perform this addition without making any changes to other modules, especially the other traffic profiles. Had we used multi-class classifiers for P2P traffic categorization instead of one-class classifiers, we should have trained a new classifier with the newly added class. However, the disambiguation module still needs to be re-trained, in order to be able to break the tie in case of the new class. In this experiment, none of the other one-class classifiers identified encrypted μTorrent as their targets, so we did not need to utilize the disambiguation module.

2.4 Discussion

PeerRush is intentionally built using a modular approach, which allows for more flexibility. For example, as shown in Section 2.3, it may be best to use a different number of features and different classification algorithms to learn the traffic profile of different P2P applications. To build the profile for a new P2P application we can apply a model selection process, which is commonly used for other machine learning tasks, to find the best classifier configuration for the job, and then we can plug it directly into PeerRush.

One parameter that has direct influence on all the system modules is the observation time window used to split and translate the network traffic into instances (or feature vectors). It is important to notice that while different modules need to extract different statistical features from the same time window, all features can be extracted incrementally, and each given module can simply use the appropriate subset of all the extracted features for its own classification purposes. Also, while all modules perform quite well in most cases by setting the time window length to 10 minutes, the results tend to improve for larger time windows, because this allows the feature extraction process to *collect more evidence*. Therefore, fixing the observation time window at 60 minutes for all modules may be a good choice. However, this choice depends on the desired trade-off between the *detection time* and the *categorization accuracy*.

Classification systems, in general, always require a good number of labeled instances to build reliable models. This means if they encounter a new instance for which they did not have prior knowledge, they cannot reason about it by any means. One important advantage of PeerRush is the ability to provide the "unknown" answer, when is fed with a truly unknown traffic sample that does not have a designated one-class classifier. This by itself is enough to raise an alarm for network administrator to take a closer look at the traffic and analyze it further. So the new sample could be considered as "unwanted" right away, until further

information become available. Neither PeerRush, nor any other classification system could assign a label to an unknown sample it never have encountered. So in case there are one or more botnets appear at the same time they more likely will be detected as unknown P2P traffic, and according to the network policies, the network administrator might want to block them until their true nature is revealed.

It is possible that a host may be running more than one P2P application at the same time (or there may be a NAT device that effectively aggregates multiple single hosts), in which case the traffic patterns of these applications may overlap and prevent a match of the profiles. Therefore, PeerRush may categorize these cases as unknown P2P traffic. However, in many practical cases not all P2P applications will be *active* at the same time. Therefore, the analysis of traffic across different time windows applied by PeerRush may still allow for effectively distinguishing among P2P applications. However, notice that even in the cases when a host continuously runs more than one active P2P application at the same time, the host will be detected as a P2P host, although its P2P traffic may be classified as "unknown" and may therefore require further analysis by the network administrator.

Botnet developers could try to introduce noise (e.g., dummy packets or random padding) into the management flows to alter the distribution of BPP and IPDs. This may cause a "mismatch" with a previously learned application profile for the botnet. In this case, PeerRush would still very likely detect the P2P botnet hosts as running a P2P application, because the features used by the P2P host detection module are intrinsic to P2P traffic in general (see Section 2.2.1 and the results in Table 2.4) and are harder to evade. However, the P2P traffic categorization module may classify the P2P botnet traffic as "unknown", thus requiring further analysis to differentiate the botnet traffic from other possible types of P2P traffic. Because P2P botnet hosts may for example engage in sending large volumes of spam emails, be involved in a distributed denial-of-service (DDoS) attack, or download executable binaries to update the botnet software, one possible way to distinguish P2P traffic related

to botnets is to monitor for other suspicious network activities originating from the detected P2P hosts [25].

The developer of a new P2P application, including P2P botnets, may attempt to model its P2P traffic following the behavior of other legitimate P2P applications. Because some networks may consider most P2P applications (legitimate or not) as unwanted, the developer may be restricted to mimic a specific type of P2P traffic that is likely to be allowed in most networks (e.g., Skype traffic). However, while possible, morphing the traffic to mimic other protocols may require significant effort [51].

In order to deploy PeerRush, the classifiers could be trained at the vendors lab rather than the customers network, since the features are intrinsic to P2P applications and how they behave, and they are not dependent on specific network behaviors. The P2P host detection module binary classifier takes into account peer churn, non-DNS connection, and diversity of connected IPs of P2P applications. These are signatures of P2P applications regardless of the network they are used in. The P2P categorization module classifiers make their decisions based on the management flows of P2P applications as well, which are also protocol-dependent. As a result, PeerRush could easily be trained outside of the customers network, which facilitates the real deployment of the system.

2.5 Related Work

While P2P traffic *detection* has been a topic of much research, P2P traffic *categorization* has received very little attention. Because of space limitations, we cannot mention all related work here and we therefore refer the reader to a recent survey by Gomes et al. [24]. In the following, we limit our discussion to the most relevant work on P2P traffic categorization, and on P2P botnet detection.

Hu et al. [34] use flow statistics to build traffic behavior profiles for P2P applications. However, [34] does not attempt to separate P2P control and data transfer traffic. Because data transfer patterns are highly dependent on user behavior, the approach proposed [34] may not generalize well to P2P traffic generated by different users. Furthermore, [34] is limited to modeling and categorizing only two benign non-encrypted P2P applications (BitTorrent and PPLive), and does not consider at all malicious P2P applications. Unlike [34], PeerRush categorizes P2P applications based on an analysis of their P2P control traffic, which captures fundamental properties of the P2P protocol in use and is therefore less susceptible to different application usage patterns. Furthermore, we show that PeerRush can accurately categorize many different P2P applications, including encrypted traffic and different modern P2P botnets.

A "zoomed-out" approach to identify P2P communities, rather than individual P2P hosts, is introduced by Li et al. [47]. Participating hosts in a P2P community use the same P2P application to communicate with each other. An unsupervised learning algorithm analyzes the graph of who-talks-to-whom and identifies the strongly connected parts of the graph as P2P communities. Although it is shown in [47] that P2P communities use the same P2P application, this method cannot determine the underlying P2P application, whereas PeerRush labels the P2P hosts.

In [30], Haq et al. discuss the importance of detecting and categorizing P2P traffic to improve the accuracy of intrusion detection systems. However, they propose to classify P2P traffic using deep packet inspection, which does not work well in case of encrypted P2P traffic. More recently, a number of studies have addressed the problem of detecting P2P botnets [25, 76, 77]. However, all these works focus on P2P botnet detection, and cannot categorize the detected malicious traffic and attribute them to a specific botnet family. PeerRush is different because it focuses on *detecting and categorizing unwanted P2P traffic* in general, including a large variety of legitimate P2P applications and botnets.

Coskun et al. [17] proposed to discover hosts belonging to a P2P botnet from a *seed* of compromised hosts. Similarly, [52] analyzes communication graphs to identify P2P botnet nodes. Detecting botnets before they start their attacks (waiting stage), when bots maintain infrequent yet long-lived flows, is studied in [29]. These works focus solely on P2P botnets detection.

2.6 Conclusion

We presented PeerRush, a novel system for the identification of *unwanted* P2P traffic. We showed that PeerRush can accurately *categorize* P2P traffic and attribute it to specific P2P applications, including malicious applications such as P2P botnets. PeerRush achieves these results without the need of deep packet inspection, and can accurately identify applications that use encrypted P2P traffic. We implemented a prototype version of PeerRush and performed an extensive evaluation of the system over a variety of P2P traffic datasets. Our results show that PeerRush can detect all the considered types of P2P traffic with up to 99.5% true positives and 0.1% false positives. Furthermore, PeerRush can attribute the P2P traffic to a specific P2P application with a misclassification rate of 0.68% or less.

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CHAPTER 3

MEASURING THE PROPERTIES OF C&C DOMAINS[1]

[1]B. Rahbarinia, prepared for publication but not submitted.

Abstract

Botnets utilize Command & Control channels (C&C) to manage their malicious infrastructure. In centralized botnets, botmasters usually maintain one or more C&C servers and abuse Domain Name System (DNS). In order to better understand botnets activities and find efficient approaches to hinder their network, it is important to study the characteristics and life-time trends of these C&C servers. In this project, by harnessing a unique dataset of DNS query and responses that is collected from upper DNS hierarchy, we aim to measure the life-time traits of C&C servers. Our measurement results demonstrate some key behaviors of botnets life cycle.

3.1 Introduction

Every day, ISPs are facing with millions of cyber-attacks all around the world with different purposes including Botnets using Command and Control (C&C) domains. In the botnet attacks, criminals typically use bots to infect large numbers of computers which in result will form a network or botnet. In this type of attacks, criminals distribute the malwares through the network to infect machines and turn them into a bot or robot for sending out spam emails, spreading viruses, attacking computers and servers and stealing personal and private information [2].

In the past years, Domain Name System (DNS) has played an important role in propagating the malicious aim requests on Internet especially via C&C mechanism of botnets. In this mechanism the infected machines are a set of infected hosts which communicate with one or several C&C servers. The criminals use domains for C&C mechanism and to evade the countermeasure of blocking domains, create hundreds of domains every day.

In this paper we utilize a massive and unique dataset of historic DNS query and response which has been collected at an authoritative name server level during 4.5 years in which many malicious C&C domains reside. We aim to summarize C&C domains life cycle in terms of their requesters and their resolved IPs. That is, for domains' requesters, we form a time-series of their requesters (volume of queries) with epochs equal to one day. On each day of these domains' lives, we also extract their resolved IPs. We envision to plot C&C domains life cycles with respect to the volume of the queries. This presents an opportunity to study C&C domains in terms of botnets life cycle trends and shows how a malware started its malicious activity, how it reached its peak, and finally how it gradually died. The results of this study will help us devise more effective detection technologies, such as the one presented in Chapter 5.

In order to analyze this huge dataset, we employ Hadoop in a cluster with capacity of 472 mappers and 219 reducers. After processing the raw data, we study the resultant time-series of each C&C domain. More specifically, we do a clustering step to compare and group different C&C domains according to their life cycle trends, so we research possible techniques to cluster time-series data.

3.2 Related Work

One of the outstanding researches in studying botnets has been done by Dagon et al. [18]. In this paper, they have studied and described different topological structures of botnets. The main goal of this paper is to provide a taxonomy of botnets spotted in the wild to better understand the threat. By assigning a new botnet to a predefined taxonomy, defenders could better analyze the botnet, identify its characteristics, and adjust their remedial efforts to take down the botnet. Measuring the effectiveness of responses to each category of botnets is another contribution of this paper. To measure the robustness of botnets against the possible responses, they identify four network models for botnets including: Erdos-Renyi random graph, Watts-Strogatz small world, barabasi-Albert scale free, and P2P models. For each model they also describe a specific response model. After analyzing the various response techniques, they provide some ideas and approaches for removing the attacks. For example, they show that botnets that are based on random models are usually harder to deal with, or targeted removals of C&C nodes on scale free botnets usually is the best response.

3.3 The Approach and Goals

Studying botnets and analyzing their evolution during the years could reveal a lot about how attackers tend to organize their malicious infrastructure and how they launch their attacks.

This benefits large ISP network administrators as well as security researchers to be well prepared on their efforts to take down botnets or at least cripple their fundamental activities. This type of study, however, requires having access to a large historic botnet dataset that could be mined to extract useful information. In this paper, we utilize a massive and unique dataset that contains historic DNS query and responses collected on the authoritative DNS level during a period of 4.5 years (see section 3.4.1 for more details about the dataset). We use this dataset to acquire knowledge about hundreds of C&C domains from a dynamic DNS provider and their infection campaigns.

We perform a number of measurements on the botnets and their respective C&C domains. Each measurement aims to demonstrate some interesting observations about various aspects of C&C domains. We define two groups of measurements: i) individual C&C domains study, and ii) collective C&C studies. In the former, we present lifetime analysis of each individual C&C domain, while in the latter, we aim to study C&C domains trends in general, compare them, and discover methods to effectively group them.

3.3.1 Individual C&C Domains Study

In this group of measurements, we show how each individual C&C domain appears in the wild (the birth), how it extends its infection campaign (the growth), and how it eventually and gradually is ceased from existence (the death). To this end, we split each C&C domains' life into epochs. In our experiments we consider a day as our epoch. For each epoch, we record the domains requesters. Each requester is in fact a compromised host on the Internet that is infected with the same malware as to the domain under investigation. Each requester is identified by its IP address, and hence, could be mapped into distinct BGP prefixes (IP networks), Autonomous System numbers (ASN), and Country Codes (C&C). As a result, for each day of C&C domain's life, we can measure how many requester contacted the domain, and where these requester came from. The location of the requesters represents the type

of the botnet in general, in a sense that we could identify whether the C&C domain has a domestic or global infection breadth. More specifically, the requesters IP, BGP, ASN, and CC provide different levels of granularity for analyzing the infection campaign. In addition, for each epoch of C&C domain's life, we also extract its IP resolution to help identify how its malicious infrastructure moves. This kind of information manifests the C&C domains agility levels to avoid being trivially blacklisted. It also shows the mechanism that is common among C&C domains in changing their IPs, and the frequency of doing so. The results of this experiment and some implementation details are reported in section 3.4.2.

3.3.2 Collective C&C Domains Study

While the measurement explained in section 3.3.1 is useful in measuring single C&C domains lives in general, we also want to study the C&C domains trends in general. To do so we perform three different experiments as follows.

1. Study C&C domains with respect to their infection population (section 3.3.2).
2. Analyze the relationship between the C&C domains infection population and their lifetime duration (section 3.3.2).
3. Clustering C&C domains according to their lifetime patterns (section 3.3.2).

C&C Domains Sizes

Botnets come in different shapes and sizes according to their targets or based on their success. Botnets are the financial sources of their operators. So each botmaster endeavors to expand its botnet via recruiting more and more compromised machines, also known as bots. Recruiting happens through drive-by downloads in majority of the cases. Studying the various botnet sizes that appeared in the network in the past could provide crucial

information about the success rates of the botmasters in the respective network as well as prevalent trends in terms of infected population. Furthermore, it could give a good estimate of the number of current infected machines in the network. To perform this experiment, we estimated the size of each C&C domain in terms of its requesters. To do so, we considered the whole window in which we had full visibility of the C&C domain, and counted the unique number of requesters that ever contacted the domain during that window. The results of this experiment are reported in section 3.4.3.

C&C Domains Lifetime VS. Size

Security community have always speculated that smaller botnets tend to live longer than larger botnets. The reason behind this speculation is that they think larger botnets attract lots of attention and get noticed faster, and thus, are the targets of extensive take down efforts. On the other hand, smaller botnets could go unnoticed for a while before they are remediated. We put this thought into evaluation to confirm whether it is true or it is a myth. We chose those botnets that we had full visibility of their lifetime from birth to death phases. Then we estimated their population using the approach described in section 3.3.2. Our result that is presented in section 3.4.4, reveals a mixed phenomenon. We observed smaller botnets with both short and long lifetimes, and also larger botnets with varying lifetimes. This observation could be due to many reasons. For example, C&C domains could be used for a while and then before they give away the whole botnet, the attackers might decide to abandon them for another domain. As a result, it might appear that smaller C&C domains live shorter, even though the whole botnet's life might be longer simply because they used multiple C&C domains in their malicious campaign. Another reason for this mixed behavior could be C&C domains sinkholing that might fool us into believing that a large C&C domain is still alive and active while in fact it could be dead and sinkholed. These

and many other reasons that could be behind this phenomenon are beyond the scope of this paper and will not be discussed further.

C&C Domains Lifetime Trends

It is of great importance to be able to group C&C domains related to the same botnet family or same malware family, because it provides the following advantages:

- Often botnets constitute multiple C&C domains that attackers use either in order to avoid blacklisting or simultaneously to provide load balancing capabilities for their botnets. It is quite difficult to detect all these domains, since researchers run botnets' malware samples in sandboxes for a limited amount of time that does not allow the malware binary to contact all of the C&C domains. As a result, only a small number of C&C domains could be discovered using this method. By enabling C&C domain grouping, we can infer what other domains are part of the same botnet, and consequently could improve take down efforts.

- Attackers often use the same set of tools to come up with different variants of malware. Although these malwares are completely independent and are used by different attackers, they are semantically similar and show similar network behaviors. Now if security researchers already know how to deal with one specific botnet, they can extrapolate their methods to cope with other variants of the botnet developed using the same tool set given the domains from these botnets are grouped together using our technique.

- Different types of botnets may demonstrate the same lifetime patterns. For example, spamming botnets could show distinguishing patterns during their lifetime. Now if unknown domains show the same patterns, one could deduce that they are spamming botnets' C&C domains.

To enable the aforementioned advantages, we introduce a clustering technique for C&C domains according to their lifetime patterns. An overview of the clustering steps are summarized in Algorithm 1.

Algorithm 1: Clustering Algorithm

```
input  : C&C domains time series
output: Clustered C&C domains
begin
    for d in C&C domains time series do
        Smooth-out d time series using EWMA;
        Build a multi-dimensional time-series, in which each point is a feature vector
        containing the value of different "views" (requesters, BGPs, CCs, etc);
    end
    M_dist ← Apply distributed DTW to obtain a distance matrix;
    Apply hierarchical clustering given M_dist;
end
```

We start by converting each domain's lifetime into a time series vector, in which each element of the time series is the count of unique requesters for each epoch (e.g. day) in the C&C's life. In order to reduce noise in the requesters counts we apply a smoothing filter namely exponentially-weighted moving average (EWMA) [35]. EWMA filters out sudden jumps and deviations from the norm in the time series vectors. Then for each C&C domain we build a multi-dimensional time series by combining different values of different view granularities, namely requesters, BGP prefixes, ASNs, and CCs. As a result, each element of the multi-dimensional time series will contain the different counts for each epoch. Then we employ Dynamic Time Warping (DTW) [11] to compute the similarity between the pairs of C&C domains (a brief description of DTW is provided at the end of this section). The output of this step is a distance matrix. This matrix finally could be fed into the hierarchical clustering method [39] to generate clusters of similar C&C domain with different tunable distances between them. The details of clustering results as well as some implementation considerations are reported in section 3.4.5.

Dynamic Time Warping DTW is an algorithm for measuring similarity between two time series which may vary in length and time. It finds an optimal match between two given sequences, and outputs the best alignment between the two. Depending on how well the given time series are aligned, DTW also outputs a number representing the degree of similarity between the two time series.

3.4 Evaluation

This section is organized as follows: the details of our dataset is explained in section 3.4.1, measurement results corresponding to sections 3.3.1, 3.3.2, 3.3.2, and 3.3.2 are next, and finally, we perform some benchmarks on the Hadoop cluster that was available and utilized for the course of this project.

3.4.1 The Dataset

Our data is 4.5 years of DNS query responses from a dynamic DNS providers at the authoritative DNS level. To be more specific, for every domain that belongs to the this dynamic DNS provider our dataset contains the following: `<date, domain, requester IP, resolved IP>`. This dataset is unique in a sense that is collected at upper DNS hierarchy that provides a full visibility into all domain resolutions from the provider and their respective requesters. Figure 3.1 shows the difference between collecting data at the authoritative level and at the recursive DNS (RDNS) level. Table 3.1 shows more details about the dataset.

3.4.2 C&C Domains Lifetime Results

To parse the dataset, we employed Hadoop and used Python streaming [54]. For this project we had access to a large Hadoop cluster with hundreds of mapper and reducer nodes. In the Hadoop script, the mappers at first, parsed the data and while removing possible noise and

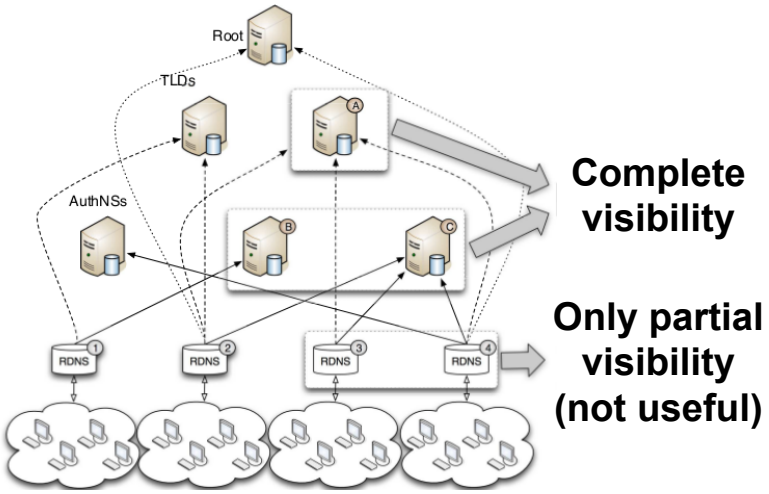

Figure 3.1: DNS data collected at authoritative level VS. RDNS level ([8])

Table 3.1: Experiment data: details of the dataset

Data	Size (GB)
2007	345.4
2008	240.0
2009	531.6
2010	664.5
2011	307.0

malformed records, output the following: `<date, domain, requester IP, resolved IP>`. We like this data to be partitioned based on domains while be sorted based on domain and date fields. To achieve that we set our partitioner key to be domain, and the secondary key (for the purpose of sorting to be domain and date combined) [4].

Figure 3.2 shows a sample of C&C domains lifetime plots. The X axis is the date in which we observed the domain, and the Y access is the volume of the requesters. For each domain we report different lifetime plots, each corresponds to volume of requesters from different views, namely unique IPs, BGP prefixes, ASNs, and CCs. We also incorporated the resolved IPs into the lifetime plots. Figure 3.3 is an example C&C domain. The Y axis in the right hand side of the lifetime plots reports different IP addresses that the domain resolved to during its lifetime.

3.4.3 C&C Domains Sizes Results

We combined the estimated population of all the C&C domains we observed in our dataset to cluster them accordingly. We plotted the histogram of C&C sizes for each distinct view point. Figure 3.4 reports the results. As it can be seen from the results, smaller C&Cs are more prevalent in our dataset, suggesting by and large C&C domains cannot grow extremely large.

3.4.4 C&C Domains Size VS. Life

To properly study the relationship between C&C domains size and lifetime we utilized the results of section 3.4.3, and used the same histograms reported in Figure 3.4, but this time, we replaced each bin of the histogram with min and max lifetime of domains that belong to that bin. As a result, each bar in Figure 3.5 reports the min and max of lifetime of domains that are grouped in that bin. We also augment each bar with mean and median of all C&C

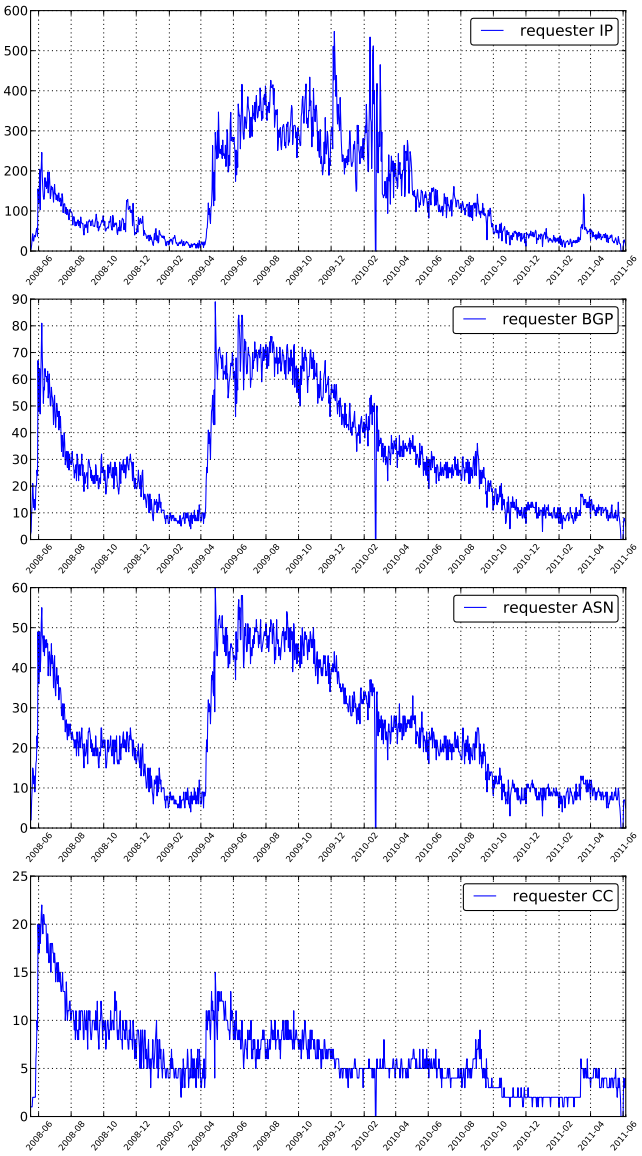

Figure 3.2: A sample C&C domain lifetime

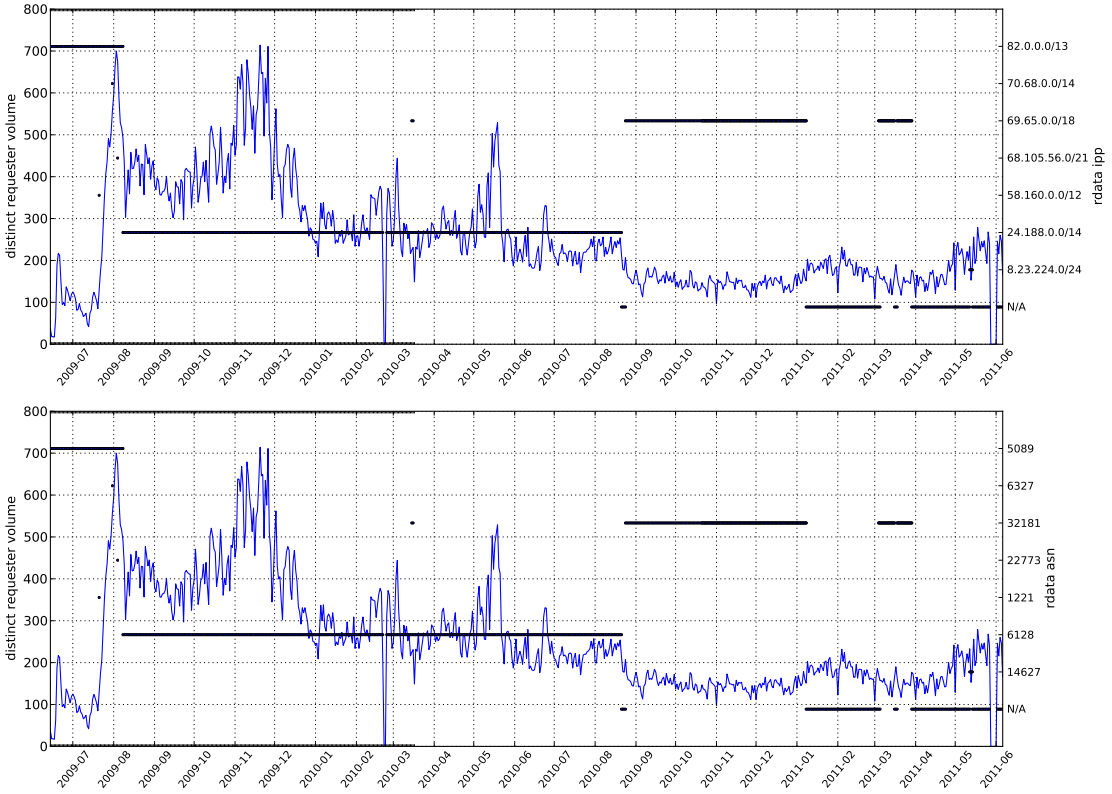

Figure 3.3: A sample C&C domain lifetime with incorporated IP resolution history

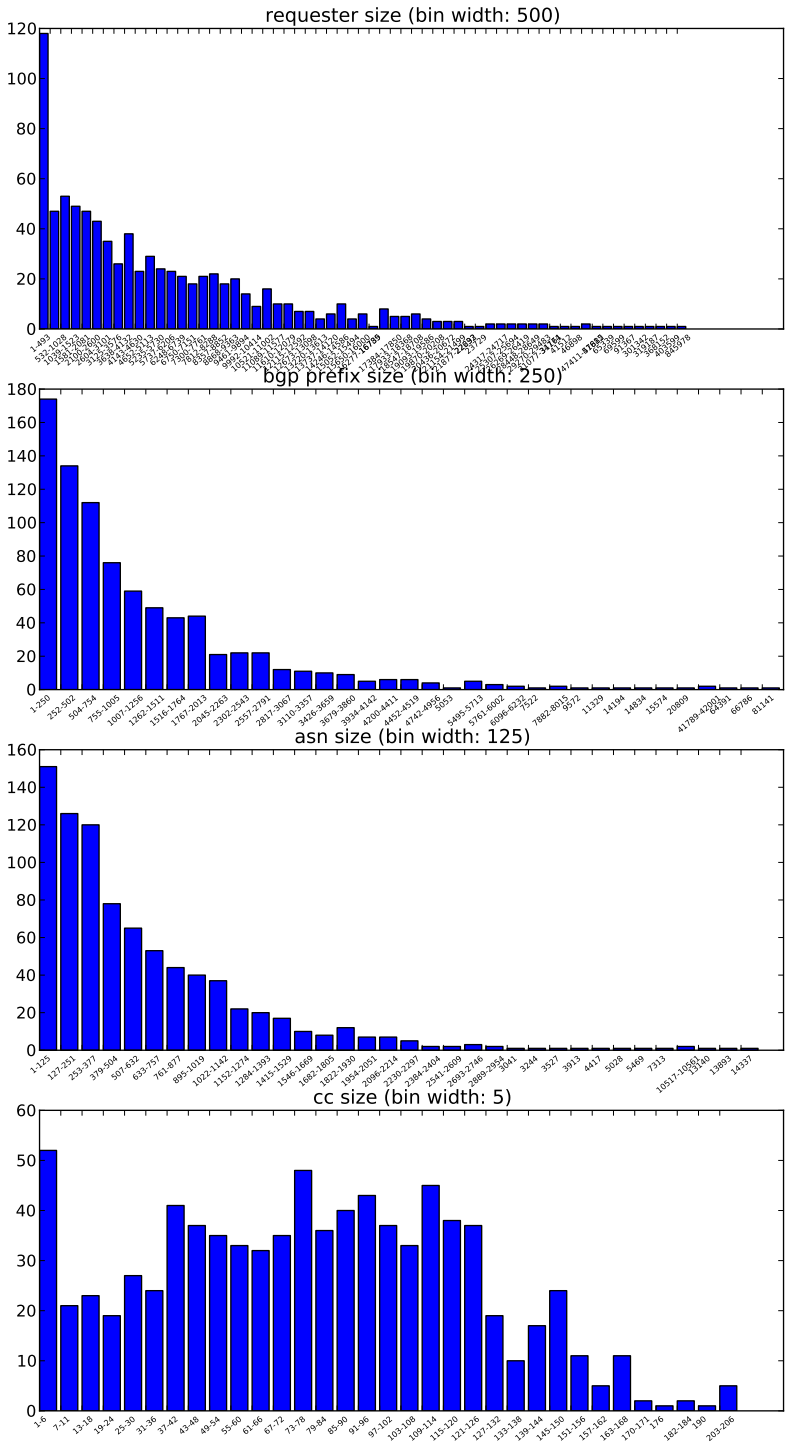

Figure 3.4: Categorization of C&C domains based on their infection population size

lifetimes present in that bin. The mean values in Figure 3.5 suggests a steady size to life relationship. These results that are backed up by 4.5 years of real DNS information shows that there is no apparent relationship between size and life of C&C domains.

3.4.5 C&C Domains Lifetime Trends Results

We implemented our version of EWMA and DTW using Python, however, DTW computation is quite time consuming. To speed things up, we implemented a distributed version of DTW. In this version, we again employed Hadoop in a map only fashion. Each mapper was responsible for computing a few DTW pairs, since each pair computation is completely independent of others, so it could be efficiently parallelized. This noticeably reduced the overall execution time. In our DTW implementation we experimented with various distance metrics, including Euclidean, Squared Euclidean, and Manhattan.

To perform the hierarchical clustering step, we used `hcluster` [5], a Python module. Figure 3.6 reports some of the clustering outputs that are computed based on 90 sample C&C domains. We performed numerous experiments using different hierarchical clustering configurations, however, the combination of Squared Euclidean metric with "complete" method to merge clusters almost always produced the best results, given its good intra-cluster similarity and inter-cluster dissimilarity measures. This is also visible by comparing different methods reported in Figure 3.6 (Figure 3.6(a) is the best result).

We further investigated the results of the clustering manually to confirm the similarity of domains in the same clusters, and was able to verify the C&C domains that are placed in the same cluster are indeed quite similar in majority of the cases.

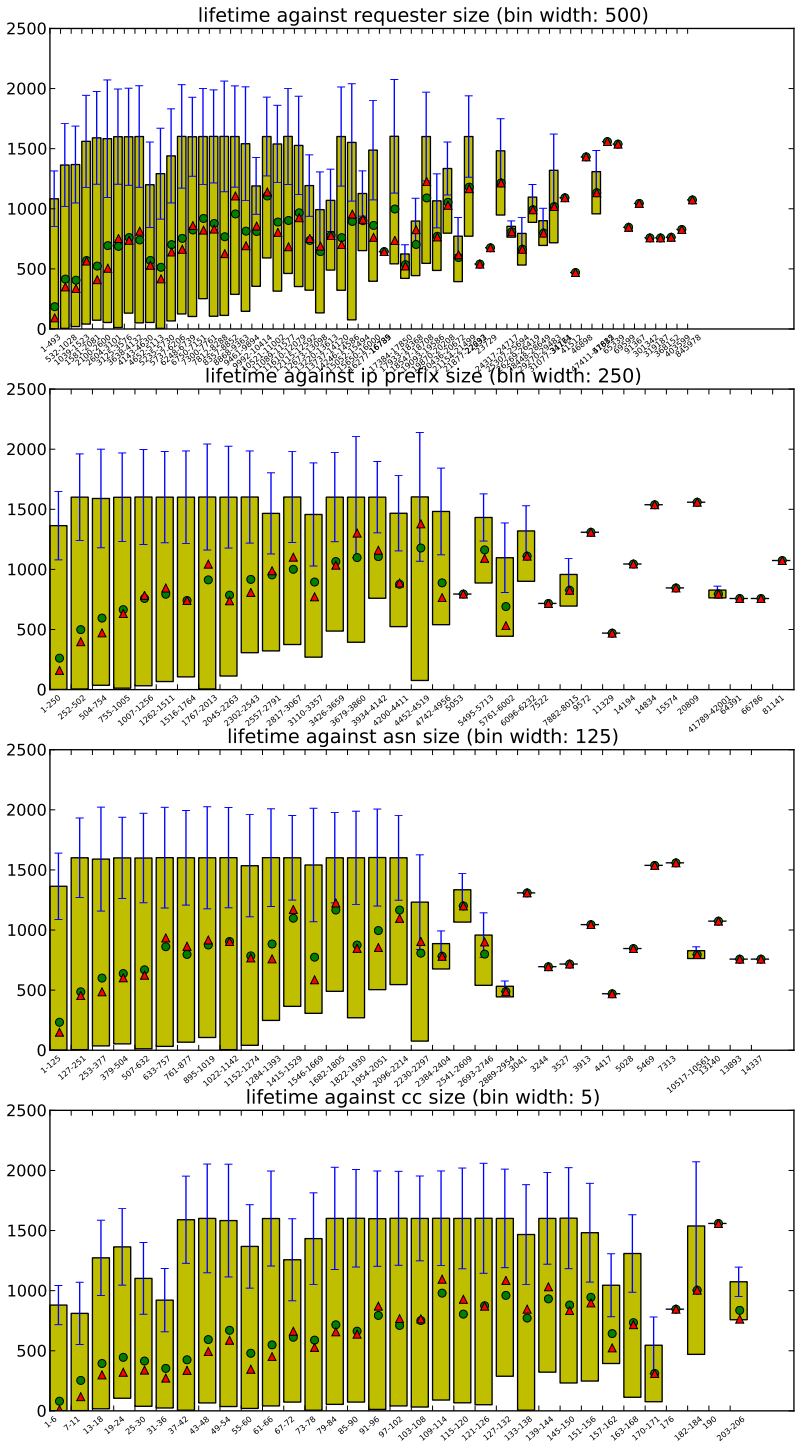

Figure 3.5: C&C domains life VS. Size

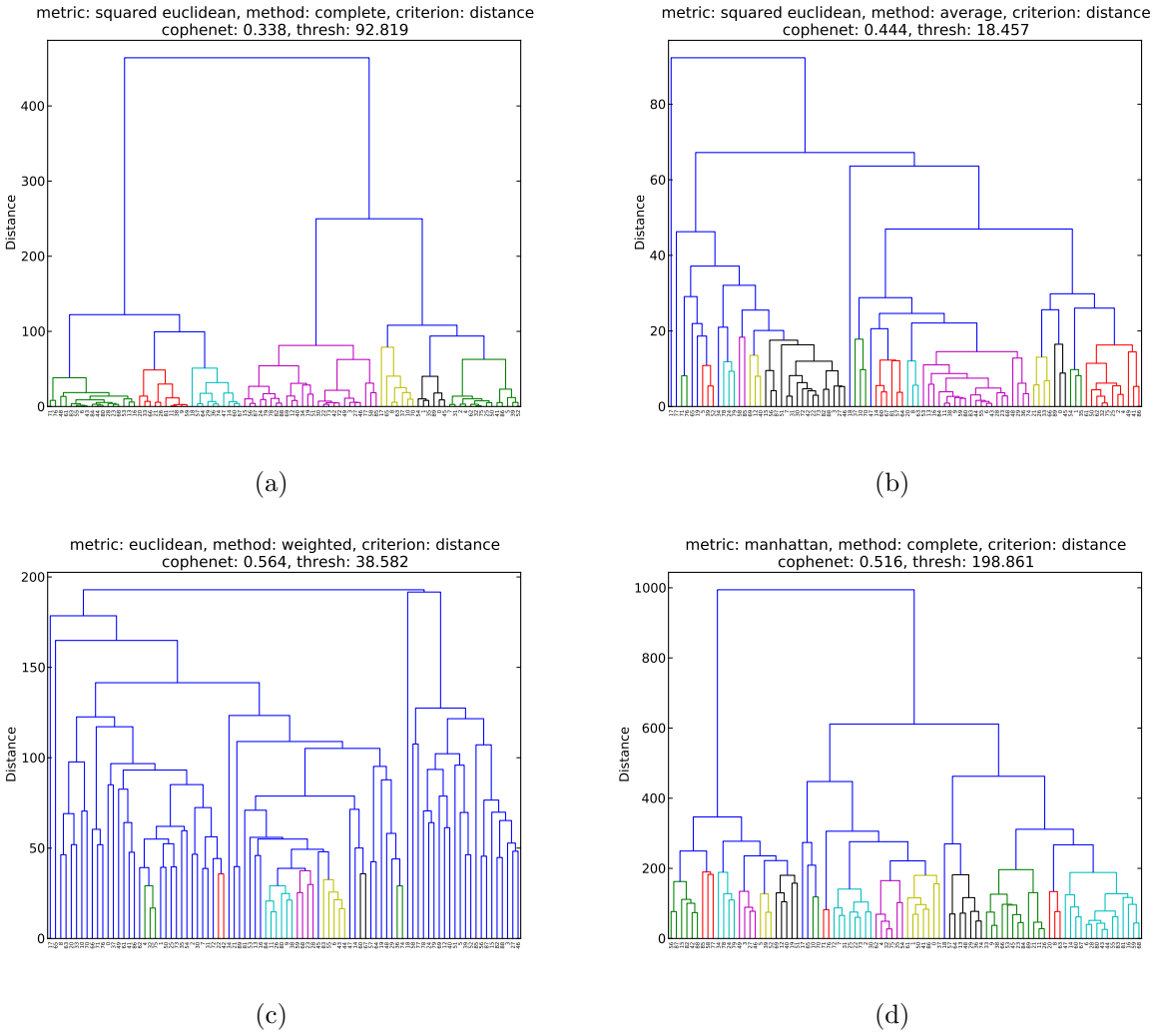

Figure 3.6: Hierarchical clustering results using various configurations

3.5 Conclusion

In this paper we studied botnet C&Cs in terms of their individual life cycles as well as analyzing their overall lifetime trends by considering groups of C&C domains. Using our historic DNS data and by employing Hadoop, we showed the type of botnets that existed in the wild. A clustering scheme, based on DTW for aligning C&C domains time series and hierarchical clustering, was discussed that provides a mean for grouping C&C domains together based on the similarity of their lifetime trends.

CHAPTER 4

SINKMINER: MINING BOTNET SINKHOLES FOR FUN AND PROFIT[1]

[1]B. Rahbarinia, R. Perdisci, M. Antonakakis, D. Dagon. 6th USENIX Workshop on Large-Scale Exploits and Emergent Threats, 2013.
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Abstract

Contrary to what security researcher have believed so far, C&C domains still have a mysterious journey after they die. Often their afterlife is filled with riddles that make it quite difficult to reason what really happens to them then. In this paper, we demystify the life of C&C domains after their death. Specifically, we turn our attention to sinkholed C&C domains which are malicious domains that are made inactive and their traffic is redirected to another IP address. We follow the chain of IP relocations to detect new sinkhole IPs. These IPs are of quite interest since their discovery could have benign and not-so-benign consequences. SinkMiner is a novel graph-based sinkhole IP discovery system that leverages a behavioral detection technology to enable the security community to better understand the afterlife of C&C domains.

4.1 Introduction

Botnets continue to pose a significant threat to Internet security, and their detection remains a focus of academic and industry research. Some of the most successful botnet measurement and remediation efforts rely heavily on *sinkholing* the botnet's command and control (C&C) domains [14]. Essentially, sinkholing consists of re-writing the DNS resource records of C&C domains to point to one or more *sinkhole IP addresses*, thus directing victim C&C communications to the *sinkhole operator* (e.g., law enforcement).

Sinkholes are typically managed in collaboration with domain registrars and/or registries, and the owner of the network range where the botnet C&C is sinkholed. Registrars often play a critical role in remediating abusive domains (e.g., by invoking rapid take-down terms commonly found in domain registration contracts, such as the "Uniform Rapid Suspension System" [36]). Collaboration with the sinkhole network range owners is needed to endure the possible IP reputation damage to their IP space, since sinkholes may appear as real C&Cs to others.

While some sinkhole IPs are publicly known or can be easily discovered (see Section 4.2.1), most are jealously kept as trade secrets by their operators, to protect proprietary black lists of remediated domains. Therefore, third-party researchers are often unable to distinguish between malicious C&C sites and remediated domains pointed to sinkholes.

In some cases, this stove-piping of sinkhole information can cause "friendly fire", whereby security operators or law enforcement may take down an already sinkholed C&C. This results in disrupting remediation efforts, and may in some cases bring more harm to the botnet victims (whose infected clients may turn to secondary or *backup C&C domains* not being remediated). It is therefore useful to build technologies capable of identifying whether or not a C&C domain and/or IP are part of a sinkholing effort.

In this paper, we present SinkMiner, a novel forensics system that enables the discovery of previously unknown sinkhole IPs and the related sinkholed domains by efficiently mining large passive DNS databases. Being able to discover "secretive" sinkhole operations has both benign and not-so-benign implications. On a purely benign side, labeling previously unknown sinkhole IPs may prevent "friendly fire," as mentioned above. Also, the discovery of sinkhole IPs may enable a much more precise measurement of the *effective lifetime* of C&C domains. On the other hand, the ability to identify sinkhole IPs may allow less-than-honest researchers to collect all related sinkholed domains, which could then be re-sold to third-parties as part of a domain blacklist, thus unfairly taking advantage of the often very meticulous and costly work done by the sinkhole operator.

Our system's ability to detect previously unknown sinkhole IPs is based on a somewhat surprising empirical observation: *sinkhole operators often relocate C&C domains from a sinkhole IP to another* (see Section 4.2.2). Therefore, given a small seed of known sinkhole IPs, we can leverage passive DNS databases to monitor the "behavior" or their sinkholed domains to track where they relocate — effectively discovering "by association" previously unknown sinkholes. This is in stark contrast with what common knowledge may suggest, namely that once a C&C domain falls into a sinkhole it will never escape until it expires or is "retired" by the sinkhole operator, making it "unresolvable".

In summary, we make the following contributions:

- We present SinkMiner, a novel forensics system for the identification of previously unknown C&C domain sinkholes.
- We provide insight and measurements on the "behavior" of sinkhole operators.
- We report preliminary results of our SinkMiner prototype, and show how our system can be used in practice to greatly expand on an initial list of known sinkhole IPs.

4.2 System Overview

The main goal of our system is to find new and previously unknown sinkhole IPs. We start with a list of few known sinkhole IPs, $\mathcal{S}$, which may be derived through manual investigation and/or personal communications with some sinkhole operators. Using a large passive DNS database (PDNS), we travel back in time and gather all the sinkholed domains $\mathcal{SD}$ historically related to IPs in $\mathcal{S}$. In other words, $\mathcal{SD}$ contains all domains that resolved to any of the IPs in $\mathcal{S}$ at least once during their lifetime (see Section 4.3 for more details). Next, we extract the full IP resolution history of the domains in $\mathcal{SD}$. One may expect that after a domain is sinkholed, it will continue to resolve to that sinkhole IP for the rest of its life. Nonetheless, we found numerous counterexamples. In practice, there exist many sinkholed domains that after pointing to an initial sinkhole IP later start to resolve to some other IPs, some of which are different known sinkholes whereas others are "unknown". Our goal is to properly label this set of unknown IPs, which we call $\mathcal{S}_{pot}$ (potential sinkholes).

We empirically found that the IPs in the set $\mathcal{S}_{pot}$ fall in one of the following categories:

1. *New Sinkhole*: These are IP addresses owned by security operators and used for the purposes of taking over and/or studying botnets. A previously sinkholed domain name may move to a new sinkhole IP due to a deliberate relocation decision performed by the sinkhole operator.

2. *Parking*: Parking IPs are typically used as a "traffic vacuum" [23]. Often, when a domain name registration expires, a registrar (or third-party) may take ownership of the expired domain, and point it to a parking IP. Machines (e.g., infected machines) that still query the now expired domain are redirected to websites that serve advertisement, thus generating revenue. Therefore, as a sinkholed C&C domain registration expires, the domain may later start resolving to one or more parking IPs.

3. *NX-Domain Rewriting*: Some ISPs generate revenue from advertisement by redirecting machines that query for non-existent (NX) domains, including some expired C&C domains, to an ad-populated web page [71]. To this end, the DNS resolver owned by the ISP performs an on-the-fly rewriting of the DNS response, injecting a valid resource record into the answer section.

Note that we do not make any claims about the IPs that the C&C domains resolved to *before* they were sinkholed. That is, the set $\mathcal{S}_{pot}$ only includes IP addresses resolved by domains that previously pointed to a known sinkhole. In the following sections, we address the problem of distinguishing new sinkhole IPs from parking and NX-domain rewriting IPs.

4.2.1 Preliminary Labeling

In this section, we describe two methods we use to perform a preliminary labeling of the potential sinkhole IPs ($\mathcal{S}_{pot}$).

Popularity-based labeling One thing that we observed while studying the characteristics of known sinkholes, is that sinkhole IPs are pointed to (in time) by relatively large numbers of domains (e.g., several thousands). Therefore, given the set $\mathcal{S}_{pot}$, we query the PDNS database, and rank the IPs by "popularity", and only consider IPs that in time were pointed to by more than θ_{pop} previously sinkholed domains.

Clearly, this subset of "popular" IPs may still include parking and NX-rewriting IPs. Therefore, we map the IPs to their autonomous system (AS) and consider as (highly likely) new sinkhole IPs only those addresses that are located within an IP space owned by well-known organization that are known to operate botnet sinkholes (e.g., Microsoft, Verisign, Google, ISC, etc.).

Name server-based labeling In addition, we consider the name server name associated with the remaining potential sinkhole IPs in $\mathcal{S}_{pot}$. This allows us to find additional sinkhole

IPs, and to also label a large number of known parking IPs. For example, we label as sinkhole IPs those that are resolved by name servers such as `torpig-sinkhole.org`, `ns1.sinkhole.ch`, `dns3.sinkdns.net`, `sinkhole-00.shadowserver.org`, etc. In general, we search the PDNS database for name server names that contain the keyword "sink", and then perform a quick manual analysis to only select names that are clearly related to botnet sinkhole operations.

Similarly, we label as parking those IPs resolved by name servers such as `dns1.ns-park.net`, `park1.dns.ws`, `nx1.dnspark.net`, `one.parkingservice.com`, etc. Again, we leverage the PDNS database to find name server names containing the word "park", and then perform a quick manual analysis to only select the most likely parking name servers.

Labeling popular NX-rewriting IPs is also feasible. For example, some ISP are very aggressive, and return an IP even for queries to invalid domain names, which should clearly return an NXDOMAIN error. Based on this and other empirical observations, we built a number of simple heuristics to automatically label the most likely NX-rewriting IP addresses.

4.2.2 Graph-based Labeling

While studying the "behavior" of botnet sinkholes, we noticed that in some cases sinkholed domains would be "relocated" from a known sinkhole IP to an uncategorized IP, and then back to another known sinkhole IP (not necessarily the original one). Other, more complicated patterns were also observed: some malware domains would relocate from a known sinkhole to an uncategorized IP, then to a different uncategorized IP, and so on, before moving back to a (possibly different) known sinkhole. While we are not entirely sure what drives this behavior, we believe sinkholes are sometimes relocated to enable some form of load balancing, or to isolate some botnets from each other, for the purpose of more precise measurements.

In other cases, sinkholed domains may "naturally" relocate to one or more parking or NX-rewriting IPs, as they expire without being reclaimed by the sinkhole operators. To efficiently distinguish among such behavioral patterns, we leverage the PDNS database to build a *graph database* around the set of known and potential sinkhole IPs, $\mathcal{S} \cup \mathcal{S}_{pot}$. Specifically, we build a weighted directed graph in which a node represents an IP address $p \in \mathcal{S} \cup \mathcal{S}_{pot}$. Given two nodes p_i and p_j, we draw an edge if there exists any domain name that, according to the PDNS database, first resolved to p_i and later started to resolve to p_j. The weight of the edge is equal to the number of such domains that transitioned from p_i to p_j during a given time window of interest.

Once the graph database is built, to discover new sinkholes we perform the following queries:

(1) $\mathcal{S} \rightarrow p_x \rightarrow \mathcal{S}$: We look for any node p_x "in between" known sinkhole IPs. In other words, we look for all cases in which there exist some domains that first pointed to a known sinkhole, then moved to p_x, and then relocated to another known sinkhole. Notice that as shown in Figure 4.1, there may be cases in which there are multiple domains that resolve to p_x, and these domains previously pointed to different sinkhole IPs. Similarly, domains that point to p_x may then relocate to different known sinkhole IPs.

In the context of the query, we also set some constraints on the edge weights: we only consider an IP address p_x as a new sinkhole IP if the edge weights (represented as occ_k, for "occurrences", in Fig.4.1) exceed a (tunable) threshold θ_w. We also require that the number of *distinct* "opening" and "terminal" $\mathcal{S}$ IPs that transit to/from p_x be above an adjustable threshold θ_n.

(2) $\mathcal{S} \rightarrow p_x \rightarrow p_y \rightarrow \mathcal{S}$: Similarly, we look for any pair of consecutive nodes p_x and p_y "in between" known sinkhole IPs. As for the previous query, we only consider p_x and p_y

as new sinkhole IPs if the edge weights and the number of opening and terminal IPs exceed the mentioned thresholds.

Essentially, we currently use the graph database as a forensic analysis tool, to make investigating the behavior of sinkhole IPs easier, and to discover previously unknown sinkhole operations. In our future work, we plan to explore other types of queries and to fully automate the sinkhole detection process.

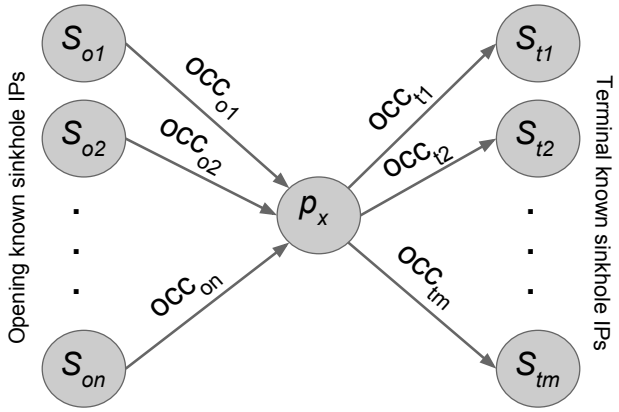

Figure 4.1: IP transitions from/to known sinkholes to/from an unknown IP

4.3 Preliminary Evaluation

To evaluate SinkMiner, we started from an initial list of 22 known sinkholes ($\mathcal{S}$) from 19 different Autonomous Systems (AS). Table 4.1 lists some of the ASes (we refrain from disclosing the initial sinkhole IPs, because they were provided to us by collaborators and are not part of our new discoveries). By querying our PDNS database, which contains historic DNS information that dates back to the start of 2011, overall we extracted 2,945,483 sinkholed domains. However, many of these domains appeared to be related to DGA-based botnets[2]. To eliminate this "DGA noise", we filtered out domain names that appeared in the PDNS

[2]DGA = domain generation algorithm.

Table 4.1: Examples of known sinkhole locations

ASN	Organization	Popularity	ASN	Organization	Popularity
14618	AMAZON-AES	46,959	1280	ISC	16,987
8069	MICROSOFT	16,522	2637	GEORGIATECH	15,390
30060	VERISIGN	11,168	15169	GOOGLE	630

database for less than three days. This reduced our set of sinkholed domains to 130,901. The "popularity" column of Table 4.1 shows the number of domains pointing to sinkholes in the listed ASes. As mentioned before, many C&C domains change resolved IPs after being sinkholed. We observed such behavior in 51,371 domains (39%). Overall, we collected 5,576 distinct IPs that appear after a known sinkhole, which represent our set $\mathcal{S}_{pot}$.

Among the $\mathcal{S}_{pot}$ IPs, using the approach described in Section 4.2.1, we were able to identify 23 new (highly likely) sinkhole IPs based on popularity, and 15 based on name server names, thus expanding our initial set of sinkholes from 22 to 60. In the process, we were also able to label 475 IPs as related to parking services, and 7 IPs related to NX-rewriting.

Our graph database (Section 4.2.2) is built over the set of both known and potential sinkholes ($\mathcal{S} \cup \mathcal{S}_{pot}$). As mentioned above, using the preliminary labeling approach we were able to label some of the graph nodes in $\mathcal{S}_{pot}$ as either "popular" sinkhole, parking or NX-rewriting. Overall, the graph consisted of 5,613 nodes and 164,344 edges.

To set the detection thresholds θ_w and θ_n described in Section 4.2.2, we fine-tuned them so to obtain no false positives (FP). Here, we consider an IP p_x classified as sinkhole through our graph as a FP if it was previously labeled as either parking or NX-rewiring. By leveraging the graph database queries defined in Section 4.2.2, we were able to label 49 highly likely new sinkhole IPs. In particular, by manual inspection we verified that query (1) yielded 12 highly likely new sinkhole IPs, whereas query (2) yielded 37 new potential sinkholes. In our future work we plan to seek further confirmation through a more direct collaboration with sinkhole operators.

Table 4.2: Examples of newly found sinkhole IPs

IP	ASN	Organization	Popularity
93.170.52.30	44557	DRAGONARA	817,563
216.239.32.21	15169	GOOGLE	535,638
69.25.27.173	10913	INTERNAP	347,902
208.91.197.101	40034	CONFLUENCE	337,539
174.129.212.2	14618	AMAZON	110,381
199.2.137.141	3598	MICROSOFT	1,367

To summarize, SinkMiner allowed us to find 87 new (highly likely) sinkholes, thus expanding our initial list of 22 known sinkhole IPs to 109. Overall, these 109 IPs were resolved by 3,443,344 distinct domains. This demonstrates the potential impact of discovering new sinkhole IPs using C&C domain intelligence.

4.4 Discussion

One of the limitations of our method is the lack of available labeled training dataset; we do not have any ground truth about the true nature of the IPs we found. Even though we are overly conservative in every step of our approach and tried to mark as sinkhole only the IPs that we are very confident about, there is no way for us to evaluate them against a known labeled test dataset. Moreover, in this paper we only executed two queries in our graph dataset that are intuitive and easy to understand. However, not only we could try many other queries (for instance, with more than two intermediate unknown IPs), we could also learn the queries themselves and evaluate them based on their performance in terms of true and false positives. A future work is required to explore these ideas further.

4.5 Conclusion

In this paper we presented SinkMiner, a novel system for the identification of previously unknown and secretive sinkhole IPs that utilizes a large dataset of historic DNS information. We also discussed the advantages and disadvantages that finding sinkholes could present. While some of the use cases we discussed are beneficial, some are malicious. Numerous approaches were also introduced to detect sinkholes IPs. To evaluate the system, we generated a large graph database of IP transitions associated with malicious domains, and showed SinkMiner could mark sinkhole IPs with high confidence and no false positives.

Acknowledgments

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CHAPTER 5

SEGUGIO: EFFICIENT BEHAVIOR-BASED TRACKING OF MALWARE-CONTROL DOMAINS IN LARGE ISP NETWORKS[1]

[1]B. Rahbarinia, R. Perdisci, M. Antonakakis. IEEE/IFIP International Conference on Dependable Systems and Networks, DSN 2015 (June).

Abstract

In this paper, we propose *Segugio*, a novel defense system that allows for efficiently tracking the occurrence of new *malware-control* domain names in very large ISP networks. Segugio passively monitors the DNS traffic to build a machine-domain bipartite graph representing *who is querying what*. After labeling nodes in this *query behavior* graph that are known to be either benign or malware-related, we propose a novel belief propagation strategy that allows us to accurately detect new, previously unknown, malware-control domains.

We implemented a proof-of-concept version of Segugio, and deployed it in three large ISP networks each serving millions of users. Our experimental results show that Segugio can track the occurrence of new malware-control domains with up to 94% true positives (TPs) at less than 0.1% false positives (FPs). In addition, we provide the following results: (1) we show that Segugio can also detect control domains related to new, previously unseen malware families, with 85% TPs at 0.1% FPs; (2) Segugio's detection models learned on traffic from a given ISP network can be deployed into different ISP networks and still achieve very high detection accuracy; (3) new malware-control domains can be detected days or even weeks before they appear in a large commercial domain name blacklist; and (4) we show that Segugio clearly outperforms Notos, a previously proposed domain name reputation system.

5.1 Introduction

Despite extensive research efforts, malicious software (or *malware*) is still at large. In fact, numbers clearly show that malware infections continue to be on the rise [67, 66]. Because malware is at the root of most of today's cyber-crime, it is of utmost importance to persist in our battle to defeat it, or at the very least to severely cripple its ability to cause harm by tracking and blocking its command-and-control (C&C) communications.

Our Research. In this paper, we propose *Segugio*[2], a novel defense system that allows for efficiently tracking the occurrence of new *malware-control* domain names in very large ISP networks. Segugio automatically learns how to discover new malware-control domain names by monitoring the DNS *query behavior* of both known malware-infected machines as well as benign (i.e., "non-infected") machines. Our work is based on the following simple but fundamental intuitions: (1) in time, as the infections evolve, infected machines tend to query new malware-control domains; (2) machines infected with the same malware, or more precisely malware family, tend to query the same (or a partially overlapping) set of malware-control domains; and (3) benign machines have no reason to query malware-control domains that exist for the sole purpose of providing malware C&C capabilities or other "malware-only" functionalities.

Segugio's main goal is to *track current malware infections* to discover where (i.e. to what new names) malware-control domains relocate. In addition, we will show that Segugio can also discover malware-control domains related to *new malware families* previously unseen in the monitored networks.

To put the above observations and goals into practice, we propose an efficient belief propagation strategy. First, Segugio passively observes the DNS traffic between the users' machines and the ISP's local DNS resolver to build an annotated bipartite graph representing

[2]The name *Segugio* refers to a hound dog breed.

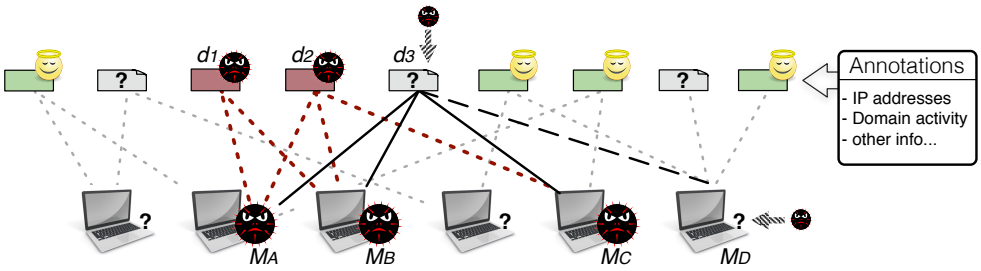


Figure 5.1: Machine-domain annotated graph. By observing *who is querying what*, we can infer that d_3 is likely a malware-related domain, and consequently that M_D is likely infected.

who is querying what, as shown in Figure 5.1. In this graph, nodes represent either machines or domain names, and an edge connects a machine to a domain if that machine queried the domain during the considered traffic observation time window. The domain nodes are augmented with a number of annotations, such as the set of IPs a domain resolved to, its domain activity (e.g., how long ago a domain was first queried), etc. Then, we label as *malware* those nodes that are already known to be related to malware control functionalities. For example, we can first label known malware C&C domains, and as a consequence also propagate that label to the machines, by marking any machine that queries a C&C domain as malware-infected. Similarly, we can label as *benign* those domains that belong to a whitelist of popular domains (e.g., according to `alexa.com`), and consequently propagate the *benign* label to machines that query *exclusively* known benign domains. All remaining machine nodes are labeled as *unknown*, because they do not query any known malware domain and query at least one *unknown* domain, whose true nature is not yet known. Segugio aims to efficiently classify these *unknown* graph nodes.

Approach. Based on the machine-domain bipartite graph (Figure 5.1), we can notice that *unknown* domains that are consistently queried only (or mostly) by known malware-infected machines are likely themselves malware-related, especially if they have been active only for a

very short time or point to previously abused IP space. In essence, we combine the machines' query behavior (i.e., who is querying what) with a number of other domain name features (annotated in the graph) to compute the probability that a domain name is used for malware control or that a machine is infected.

Main Differences w.r.t. Previous Work. Recently, researchers have proposed domain name reputation systems [7, 12] as a way to detect malicious domains, by modeling historic domain-IP mappings, using features of the domain name strings, and leveraging past evidence of malicious content hosted at those domains. These systems mainly aim to detect malicious domains in general, including phishing, spam domains, etc.

Notice that while both Notos [7] and Exposure [12] leverage information derived from domain-to-IP mappings, they do not leverage the query behavior of the machines "below" a local DNS server. Unlike [7, 12], our work focuses specifically on accurately tracking new "malware-only" domains by monitoring the DNS *query behavior* of ISP network users. In Section 5.6, we show that our approach yields both a lower false positive rate and much higher true positives, compared to Notos [7] (we perform a direct comparison to a version of Notos provided by the original authors of that system).

Kopis [8] has a goal more similar to ours: detect malware-related domains. However, Kopis's features (e.g., *requester diversity* and *requester profile*) are engineered specifically for modeling traffic collected at authoritative name servers, or at top-level-domain (TLD) servers, thus requiring access to authority-level DNS traffic [8]. This type of global access to DNS traffic is extremely difficult to obtain, and can only be achieved in close collaboration with large DNS zone operators. Furthermore, due to the target deployment location, Kopis may allow for detecting only malware domains that end with a specific TLD (e.g., `.ca`). Unlike Kopis, Segugio allows for efficiently detecting new malware-control domains regardless of their TLD, by monitoring *local* ISP traffic (namely, DNS traffic between ISP users and

their local DNS resolver). Therefore, Segugio can be independently deployed by ISP network administrators, without the need of a collaboration with external DNS operators.

More recently, Antonakakis et al. have proposed Pleiades [9], which aims to detect machines infected with malware that makes use of domain generation algorithms (DGAs). While Pleiades monitors the DNS traffic between the network users and their local DNS resolver, as we do, it focuses on monitoring non-existent (NX) domains, which are a side-effect of DGA-based malware. Our work is different, because we do not focus on DGA-based malware. In fact, Segugio only monitors "active" domain names, and aims to detect malware-control domains in general, rather than being limited to detecting only DGA-generated domains.

We further discuss the differences between Segugio and other related work in Section 5.8.

Summary of Our Contributions. In summary, with Segugio we make the following contributions:

- We propose a novel behavior-based system that can efficiently detect the occurrence of new malware-control domains by tracking the DNS query behavior of malware infections in large ISP networks.

- We implemented a proof-of-concept version of Segugio, and deployed it in three large ISP networks each serving millions of users. Our experimental results show that Segugio in average can classify an entire day worth of ISP-level DNS traffic in just a few minutes, achieving a true positive (TP) rate above 94% at less than 0.1% false positives (FPs).

- We provide the following additional results: (1) we show that Segugio can also detect malware-control domains related to previously unseen malware families, with 85% TPs at 0.1% FPs; (2) Segugio's detection models learned on traffic from an ISP network can be deployed into different ISP networks and still achieve very high detection accuracy;

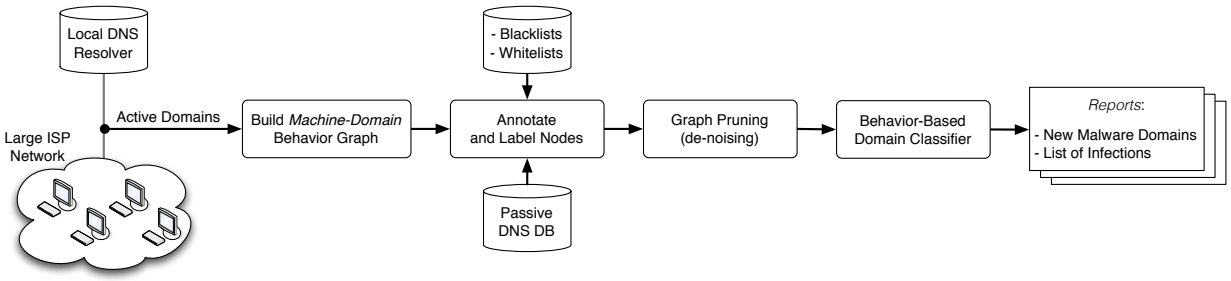


Figure 5.2: Segugio system overview.

(3) new malware-control domains can be detected days or even weeks before they appear in a large commercial domain name blacklist; and (4) we show that Segugio clearly outperforms Notos [7].

5.2 Segugio System Description

Segugio's main goal is to track the DNS query behavior of current malware infected machines to discover their new malware-control domains. In addition, in Section 5.5.4 we show that Segugio is also capable of discovering domains related to malware families previously unseen in the monitored networks. In this section, we first motivate the intuitions on which our system is based, and then describe Segugio's components.

Intuitions. As mentioned in Section 5.1, Segugio is based on the following main intuitions: (1) in time, infected machines tend to query new malware-related domains; (2) machines infected with the same malware family tend to query partially overlapping sets of malware-control domains; and (3) benign machines have no reason to query domains that exist for the sole purpose of providing "malware-only" functionalities.

We motivate the above three intuitions as follows (in reverse order), deferring a discussion of possible limitations and corner cases to Section 5.7. Intuition (3) is motivated by the fact

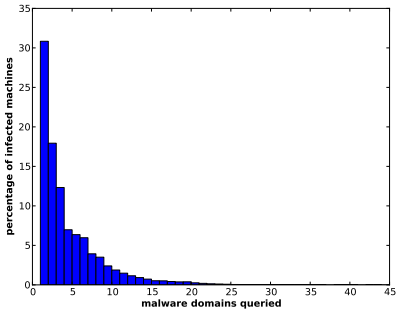


Figure 5.3: Distribution of the number of malware-control domains queried by infected machines. About 70% of known malware-infected machines query more than one malware domain.

that most malware-control domains host no benign content whatsoever, because they are often registered exclusively for supporting malware operations. This is particularly true for "recently activated" domains. Therefore, non-infected machines would have no reason to reach out to such domains. Intuition (2) relates to the fact that different variants of a same original malware are semantically similar, and will therefore exhibit similar network behavior. Finally, intuition (1) is motivated by the fact that malware needs to employ some level of network agility, to avoid being trivially blacklisted. To this end, malware-control servers will periodically relocate to new domain names and/or IP addresses. This intuition is further supported by the measurements on real-world ISP-level DNS traffic reported in Figure 5.3. During one day of traffic observation, roughly 70% of the malware-infected machines queried more than one malware-control domain name (Figure 5.3 also shows that it is extremely unlikely that an infected machine queries more than twenty malware-control domains in one day). We also verified that these results are consistent across different observation days and different large ISP networks.

5.2.1 System Components

We now describe the components of our Segugio system, which are also shown in Figure 5.2.

Machine-Domain Behavior Graph

As a first step, Segugio monitors the DNS traffic between the machines in a large ISP network and their local DNS server, for a given observation time window T (e.g., one day). Accordingly, it constructs a *machine-domain* graph that describes *who is querying what*. Notice that we are only interested in authoritative DNS responses that map a domain to a set of valid IP addresses.

Based on the monitored traffic, Segugio builds an undirected bipartite graph $\mathcal{G} = (M, D, E)$ that captures the DNS *query behavior* of machines in the ISP network. Nodes in the set M represent machines, whereas nodes in D represent domain names. A machine $m_i \in M$ is connected to a domain $d_j \in D$ by an edge $e_{ij} \in E$, if m_i queried d_j during the observation window T.

Node Annotations and Labeling. We augment each domain node $d_j \in D$ by recording the set of IP addresses that the domain pointed to during the observation window T (as collected from the live DNS traffic). In addition, we estimate how long ago (w.r.t. to T) the domain was first queried.

We then label machine and domain nodes as either *malware*, *benign*, or *unknown*. Specifically, by leveraging a small number of public and private malware C&C domain blacklists, we can first label known malware-control domains as *malware*. To label benign domains, we leverage the top one-million most popular second-level domains according to `alexa.com`. Specifically, we label as *benign* those domains whose effective second-level domain[3] consistently appeared in the top one-million `alexa.com` list for about one year (see Section 5.4 for

[3]We compute the effective second-level domain by leveraging the Mozilla Public Suffix List (*publicsuffix.org*) augmented with a large custom list of DNS zones owned by dynamic DNS providers.

details). These domains are unlikely to be used for malware control. Notice also that we take great care to exclude certain "free registration" second-level domains from our whitelist, such as dynamic DNS domains, blog domains, etc., because subdomains of these second-level domains can be freely registered and are very often abused. At the same time, we acknowledge that perfectly filtering the whitelist is difficult, and that some amount of noise (i.e., a few malicious domains) may still be present. In Section 5.5.5 we discuss the potential impact of such whitelist noise, which may cause us to somewhat overestimate our false positives.

All remaining domains are labeled as *unknown*, since we don't have enough information about their true nature. These *unknown* domains are the ones we ultimately want to classify, to discover previously unknown malware-control domains. Finally, we label machines as *malware*, if they query malware-control domains, in that they are highly likely infected. We can also label as *benign* those machines that query only known benign domains. All other machines are labeled as *unknown*.

Graph Pruning

Because we aim to monitor all DNS traffic in large ISP networks, our machine-domain graph $\mathcal{G}$ may contain several million machine nodes, hundreds of millions of distinct domain nodes, and potentially billions of edges. To boost performance and reduce noise, we prune the graph using the following conservative rules:

(R1) We identify and discard machines that are essentially "inactive", because it is unlikely that they can help our detection system. To be conservative, we only filter out machines that query $\leqslant 5$ domains.

(R2) In our ISP test networks, we observed a number of machine nodes that likely represent large proxies or DNS forwarders serving an entire enterprise network. Such devices appear as nodes with very high degree, and tend to introduce substantial levels of "noise".

We therefore filter them by discarding all machines that query $\geqslant \theta_d$ domains. Empirically setting θ_d to be the 99.99-percentile of the distribution of number of domains queried by a machine was sufficient to remove these outlier machines.

(R3) The graph $\mathcal{G}$ may contain a number of domain nodes that are queried by only one or very few machines. Because we are primarily interested in detecting malware domains that affect a meaningful number of victim machines, we discard all domain names that are queried by *only one* machine.

(R4) Very popular domains, i.e., domains that are queried by a very large fraction of all machines in the monitored network, are unlikely to be malware-control domains. For example, assume we monitor an ISP network serving three million users, in which a domain d is queried by one million of them. If d was a malware-control domain, this would mean that 1/3 of the ISP population is infected with the same malware (or malware family). By extrapolation, this would probably also mean that hundreds of millions of machines around the Internet may be infected with the same malware. While this scenario cannot be completely ruled out, such successful malwares are quite rare. In addition, due to the high number of victims, the malware would draw immediate attention from the security community, likely initiating extensive remediation and take down efforts. Therefore, we discard all domain names whose effective second-level domain is queried by $\geqslant \theta_m$ machines, where θ_m is conservatively set to 1/3 of all machines in the network, in our experiments.

To make our pruning even more conservative, we apply two small exceptions to the above rules. Machines that are labeled as *malware* are not pruned away by rule (R1), even if they query very few domains. The reason is that a machine may appear to be basically "inactive", but the malware running on the machine may periodically query a very small list (e.g., two or three) malware-control domains. We therefore keep those machine nodes,

as they may (slightly) help to detect currently unknown malware domains. Similarly, known malware-control domains are kept in the graph, even if they are queried by only one machine (exception to R3).

Behavior-Based Classifier

We now describe how we measure the features that describe *unknown* (i.e., to-be-classified) domains, which aim to capture the intuitions we outlined at the beginning of Section 5.2. Then, we explain how the behavior-based classifier is trained and deployed. We divide the domain features in three groups:

(F1) **Machine Behavior** (3 features):

Consider Figure 5.4. Let S be the set of machines that query domain d, $I \subseteq S$ be the subset of these machines that are known to be infected (i.e., are labeled as *malware*), and $U \subseteq S$ be the subset of machine labeled as *unknown*. We measure three features: the fraction of known infected machines, $m = |I|/|S|$; the fraction of "unknown" machines, $u = |U|/|S|$; and the total number of machines, $t = |S|$, that query d. These features try to capture the fact that the larger the total number t and fraction m of infected machines that query d, the higher the probability that d is a malware-control domain.

(F2) **Domain Activity** (4 features):

Intuitively, newly seen domains are more likely to be malware-related, if they are queried mostly by known malware-infected machines. Registration information may be of help, but some malware domains may have a long registration period and remain "dormant" for some time, waiting to be used by the attackers. Instead of measuring the "age" of a domain, we aim to capture its *domain activity*. Let t_{now} be the day in which the graph $\mathcal{G}$ was built, and t_{past} be n days in the past, w.r.t. t_{now} (e.g., we use

$n = 14$ in our experiments). We measure the total number of days in which d was actively queried within the time window $[t_{now} - t_{past}]$, and the number of consecutive days ending with t_{now} in which d was queried. We similarly measure these two features for the effective second-level domain of d.

(F3) **IP Abuse** (4 features):

Let A be the set of IPs to which d resolved during our observation window T. We would like to know how many of these IPs have been pointed to in the past by already known malware-control domains. To this end, we leverage a large passive DNS database. We consider a time period W preceding t_{now} (e.g., we set $W = 5$ months, in our experiments). We then measure the fraction of IPs in A that were associated to known malware domains during W. Also, for each IP in A we consider its `/24` prefix, and measure the fraction of such prefixes that match an IP that was pointed to by known malware domains during W. Similarly, we measure the number of IPs and `/24`'s that were used by *unknown* domains during W.

Past Feature Use. It is worth noting that while information similar to our *IP abuse* features (F3) has been used in previous work, e.g., in Notos [7] and Exposure [12], we show in Section 5.5.2 that those features are indeed helpful but not critical for Segugio to achieve high accuracy. In fact, the combination of our feature groups (F1) and (F2) by themselves already allows us to obtain quite accurate classification results. In addition, in Section 5.6 we show that by combining the *IP abuse* features with our *machine behavior* features, Segugio outperforms Notos.

Classifier Operation. To put Segugio in operation, we proceed as follows. Let $\mathcal{C}$ be Segugio's domain classifier trained during a traffic observation window T_1 (the training process is explained later in this section). Our main objective is to use $\mathcal{C}$ to classify *unknown* domains observed in DNS traffic from a different time window T_2. To this end, we first build a

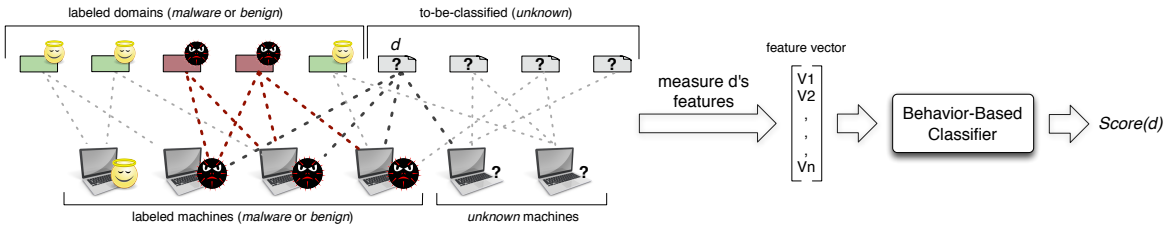


Figure 5.4: Overview of Segugio's feature measurement and classification phase. First domain d's features are measured, and then the feature vector is assigned a "malware score" by the previously trained classifier.

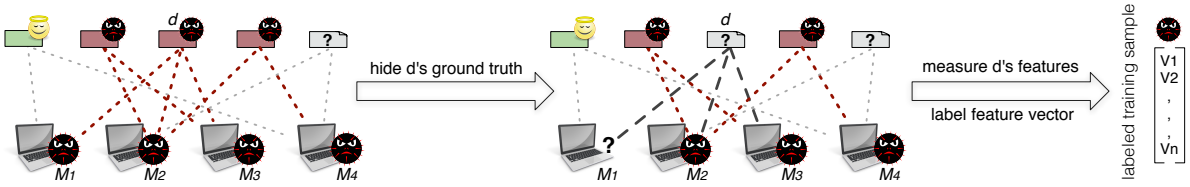


Figure 5.5: Training set preparation: extracting the feature vector for a known malware-control domain. Notice that "hiding" d's label causes machine M_1 to also be labeled as *unknown*, because in this example d was the only known malware-control domain queried by M_1. Machines M_2, M_3, M_4 queried some other known malware domains, and therefore keep their original labels.

machine-domain graph $\mathcal{G}_{T_2}$ on traffic from T_2. Then, for each *unknown* (i.e., to be classified) domain $d \in \mathcal{G}_{T_2}$, we measure the statistical features defined earlier, as shown in Figure 5.4. Then, we input d's feature vector into the previously trained classifier $\mathcal{C}$, which computes a *malware score* for d. If this score is above a (tunable) detection threshold, we label d as *malware*. The detection threshold can be chosen to obtain the desired trade-off between true and false positives, which we evaluate in Section 5.5.

Training Dataset. To obtain the dataset used to train the classifier $\mathcal{C}$, we proceed as follows (see Figure 5.5). Let T_1 be the "training time" (e.g., one day). For each *benign* or *malware* domain d observed during T_1, we first temporarily "hide" its true label, and then measure its features as defined earlier. The reason why we need to temporarily hide the ground truth

related to d is precisely to enable feature measurement. In fact, our definition of features (see above) applies to *unknown* domains only, because if a domain is already known to be malware, its first two machine behavior features, for example, would be by definition always one and zero, respectively.

Notice that hiding d's true label may have an impact on the label assigned to the machines that query it. For example, if d is a malware domain and there exists a machine that was labeled as malware *only* because it queried d, once we hide d's ground truth that machine should also be relabeled as *unknown*, as shown for machine M_1 in the example in Figure 5.5. After measuring the features, we label the obtained feature vector with d's original label (see Figure 5.5). By repeating this process for every *malware* and *benign* domain, we obtain a dataset that can be used to train the statistical classifier $\mathcal{C}$ (e.g., using Random Forest [13], Logistic Regression [21], etc.).

5.3 Summary of Results

To help the reader follow our evaluation, here we briefly summarize the most important results and refer to the related sections for details:

- *Cross-validation tests* (§5.5.1): We performed extensive 10-fold cross-validation tests in three separate large ISP networks and on multiple different days of traffic. Segugio can consistently achieve a true positive rate around 95% at 0.1% false positives.

- *Feature analysis* (§5.5.2): We show that each of the three groups of features we describe in Section 5.2.1 contributes meaningfully to Segugio's detection abilities, and at the same time that none of the feature groups by itself is absolutely critical to achieve high accuracy.

- *Cross-day and cross-network tests* (§5.5.3): Segugio can be trained on a given day of traffic from a given network, and can then be deployed in a separate network to accurately detect new malware-control domains on traffic observed even several days later.

- *Cross-malware family tests* (§5.5.4): We show that Segugio can also discover domains related to machines infected with malware families previously unseen in the monitored networks, achieving 85% true positives at a false positive rate of 0.1%.

- *Segugio's FP analysis* (§5.5.5): An analysis of possible causes of Segugio's false positives.

- *Additional results*: We provide the following additional results: (§5.5.6) by relying on public blacklist information, we can still accurately detect new malware-control domains; (§5.5.7) Segugio can detect new malware-control domains several days before they appear in malware C&C blacklists; and (§5.5.8) our system can classify one entire day worth of ISP-level DNS traffic in a few minutes.

- *Comparison with Notos* (§5.6): We show that, on the task of detecting malware-control domains, Segugio clearly outperforms Notos [7].

5.4 Experimental Setup

We deployed Segugio into three large regional ISP networks, one located in the South East, one in the North West Coast, and one in the West United States. We refer to these ISP networks simply as ISP_1, ISP_2, and ISP_3. Notice that this paper is part of an IRB-approved study; appropriate steps have been taken by our data provider to minimize privacy risks for the network users.

By inspecting the DNS traffic between the ISPs' customers and their local resolvers, we observed between roughly one to four million distinct machine identifiers per day (notice that the identifiers we were provided were stable, and did not appreciably suffer from DHCP effects, for example). Most of our experiments with Segugio were conducted in the month of April, 2013. In particular, we randomly sampled four days of traffic from that month, per each of the ISP networks. Table 5.1 summarizes the number of distinct machines and domains observed in the traffic, and the (randomly) sampled days used in our evaluation.

Domain and Machine Labeling. To label the known *malware* domain names, we check if its entire domain name string matches a domain in our C&C blacklist. We made use of a large commercial C&C domain blacklist containing tens of thousands of recently discovered malware-control domains (in Section 5.5.6 we also report on experiments using public blacklists). The advantage of using a commercial blacklist, is that domains are carefully vetted by expert threat analysts, to minimize noise (i.e., mislabeled benign domains). All machines that query a known C&C domain are also labeled as *malware*, because we assume benign machines would have no reason to query "malware-only" C&C domains (see Section 5.7 for possible limitations).

To label known *benign* domains, we collected a one-year archive of popular effective second-level domain (e2LD) rankings according to `alexa.com`. Specifically, every day for one year, we collected the list of top one million (1M, for short) popular domain names. Then, we searched this large archive for domain names that consistently appeared in the top 1M list for the entire year. This produced a list of 458,564 popular e2LDs, which we used to label benign domains. Accordingly, we label a domains d as benign if its e2LD matches the whitelist. For example, we would label `www.bbc.co.uk` as benign, because its e2LD is `bbc.co.uk`, which is whitelisted.

The reason why we only add "consistently top" e2LDs to our whitelist, is that sometimes malicious domains may become "popular" (due to a high number of victims) and enter the

top 1M list for a brief period of time. The vast majority of such domains can be filtered out by the filtering strategy described above. In addition, we filter out e2LDs that allow for the "free registration" of subdomains, such as popular blog-publishing services or dynamic DNS domains (e.g., `wordpress.com` and `dyndns.com`), as their subdomains are often abused by attackers. At the same time, as mentioned in Section 5.2.1, we acknowledge that perfectly filtering all such "special" e2LDs may be difficult, and some small amount of noise may remain in the whitelist. In Section 5.5.5 we discuss how the possible remaining noise may potentially inflate the number of false positives we measure. Notice that such whitelist noise may cause us to *underestimate* Segugio's true accuracy (i.e., the accuracy we could otherwise achieve with a perfectly "clean" whitelist), and we therefore believe this is acceptable because it would *not* artificially favor our evaluation.

Table 5.1 summarizes the number of benign and malware domains and machines we observed.

Table 5.1: Experiment data (before graph pruning).

Traffic Source	**Num. of Domains**			**Num. of Machines**		**Edges**
	Total	**Benign**	**Malware**	**Total**	**Malware**	
ISP_1, Day 1 (Apr.01)	~ 5.4M	~ 1.2M	12,120	~ 0.9M	32,327	~ 157.9M
ISP_1, Day 2 (Apr.12)	~ 8.7M	~ 1.8M	28,158	~ 2M	72,583	~ 345.9M
ISP_1, Day 3 (Apr.21)	~ 4.9M	~ 1.2M	13,005	~ 0.81M	27,907	~ 138M
ISP_1, Day 4 (Apr.30)	~ 6M	~ 1.3M	14,385	~ 0.84M	29,803	~ 157.5M
ISP_2, Day 1 (Apr.02)	~ 9M	~ 1.8M	13,239	~ 1.6M	50,339	~ 319.9M
ISP_2, Day 2 (Apr.15)	~ 9M	~ 1.9M	20,277	~ 1.6M	49,944	~ 324.2M
ISP_2, Day 3 (Apr.23)	~ 8.2M	~ 1.8M	18,020	~ 1.6M	47,506	~ 310.7M
ISP_2, Day 4 (Apr.28)	~ 10M	~ 1.9M	11,597	~ 1.6M	44,299	~ 312.3M
ISP_3, Day 1 (Apr.08)	~ 10.2M	~ 2M	15,706	~ 4M	78,990	~ 352.6M
ISP_3, Day 2 (Apr.20)	~ 9.8M	~ 2M	14,279	~ 3.9M	74,098	~ 347.1M
ISP_3, Day 3 (Apr.26)	~ 9.6M	~ 2M	36,758	~ 3.9M	69,773	~ 333.7M
ISP_3, Day 4 (Apr.30)	~ 10.6M	~ 2.2M	13,467	~ 4M	72,519	~ 355.6M

Domain Node Annotations. For each day of traffic monitoring, we build a machine-domain bipartite graph, as discussed in Section 5.2.1. Each domain node is augmented with information about the IP addresses the domain resolved to during the observation day, and its estimated activity. Given a machine-domain graph built on a day t_i, to estimate the

domain activity features (see Section 5.2.1) for a domain d we consider DNS queries about d within two weeks preceding t_i. For estimating the resolved IP abuse features, we leverage a large passive DNS (pDNS) database, and consider pDNS data stored within five months before t_i.

Graph Pruning. Following the process described in Section 5.2.1, we prune the graph by applying our set of conservative filtering rules (R1 to R4). In average, the pruning process reduced the number of domain nodes by 26.55%, and the machine nodes by 13.85%. Also, we obtained a 26.59% reduction of the total number of edges.

5.5 Experimental Results

5.5.1 Cross-Validation Tests

To evaluate Segugio's accuracy, we performed extensive 10-fold cross-validation experiments. Our main goal in setting up the experiments was to guarantee that no ground truth information about the domains to be classified is ever used to measure the features or derive the training dataset. Namely, all training and test instances are derived from a machine-behavior graph whose nodes (both domains and machines) are labeled by pretending that all the domains to be used for testing are *unknown*. To achieve this goal, we devised a rigorous procedure to build the training and test folds, as explained below.

Preparing the "10 folds". We now provide full details on the procedure we use to setup the cross-validation experiments over a machine-domain bipartite graph. A summary of what we discuss below is given as an algorithm in Figure 5.6.

Let $\mathcal{G} = (M, D, E)$ be the pruned machine-domain graph derived from a given ISP network based on one day of traffic observation. Also, let D_m, D_b, and D_u be the subsets of domain nodes in D that are either known *malware*, *benign*, or *unknown*, respectively.

Algorithm: Graph-based 10-fold Cross-Validation
$\mathcal{G} = (M, D, E)$
D_m: known *malware* domains
D_b: known *benign* domains
D_u: *unknown* domains
Result: 10-fold cross-validation results
$k = 10$
split D_m into k disjoint sets $\{D_m^{(1)}, \ldots, D_m^{(k)}\}$ s.t. $D_m = \bigcup_{i=1}^{k} D_m^{(i)}$
split D_b into k disjoint sets $\{D_b^{(1)}, \ldots, D_b^{(k)}\}$ s.t. $D_b = \bigcup_{i=1}^{k} D_b^{(i)}$
for $i \leftarrow 1$ **to** k **do**

build $\mathcal{G}_i = (M_i, D_i, E_i)$ by hiding the ground truth for $D_m^{(i)}$ and $D_b^{(i)}$
relabel M_i according to the new (partial) domain ground truth
$V_m^{(i)} = \{$set of feature vectors $\forall d \in D_m^{(i)}\}$
$V_b^{(i)} = \{$set of feature vectors $\forall d \in D_b^{(i)}\}$
$V^{(i)} = V_m^{(i)} \cup V_b^{(i)}$ (i-th fold test data)

$W_m^{(i)} = \{$set of feature vectors $\forall d \in D_m^{(\neg i)} = \bigcup_{j \neq i} D_m^{(j)}$
computed by temporarily hiding d's true label$\}$
$W_b^{(i)} = \{$set of feature vectors $\forall d \in D_b^{(\neg i)} = \bigcup_{j \neq i} D_b^{(j)}$
computed by temporarily hiding d's true label$\}$
$W^{(i)} = W_m^{(i)} \cup W_b^{(i)}$ (i-th fold training data)

$\mathcal{C}^{(i)} \leftarrow$ train a classifier on $W^{(i)}$
$P^{(i)} \leftarrow$ classify feature vectors in the test set $V^{(i)}$ using $\mathcal{C}^{(i)}$
store their *malware* scores
end for
$(TPs, FPs) \leftarrow$ set the detection threshold based on all scores in $P = \bigcup_{i=1}^{k} P^{(i)}$ to obtained the desired trade-off between true and false positives
return P and (TPs, FPs)

Figure 5.6: Graph-based 10-fold Cross-Validation Algorithm

First, we take the labeled domain sets D_m and D_b, and randomly partition them into $k = 10$ different disjoint subsets. For example, we split the set of known malware-control domains D_m into k subsets $\{D_m^{(1)}, \ldots, D_m^{(k)}\}$. We do the same for the set of known benign domains, D_b. Then, we build k new machine-domain graphs $\{\mathcal{G}_1, \ldots, \mathcal{G}_k\}$, where domain nodes of $\mathcal{G}_i$ that belong to the sets $D_m^{(i)}$ and $D_b^{(i)}$ are labeled as *unknown*. All other remaining domain nodes in $D_m^{(j)}$ and $D_b^{(j)}$, $\forall j \neq i$, are labeled according to their true labels, i.e., as *malware* and *benign*, respectively. Finally, all domains in D_u remain labeled as *unknown*. In other words, graph $\mathcal{G}_i$ is built by "hiding" our ground truth about domains in $D_m^{(i)}$ and $D_b^{(i)}$, and labeling all domain nodes according to this new "partial" ground truth. Afterwards, we also label the machine nodes according to the new ground truth. For example, all machines

that query any domain in $D_m^{(j)}$, $\forall j \neq i$, are labeled as *malware*, because, as mentioned earlier, we assume that machines that query known malware-control domains are infected. On the other hand, machines that queried one or more domains in $D_m^{(i)}$ but never queried any domain in $D_m^{(j)}$, $\forall j \neq i$, are labeled as *unknown*, because the ground truth associated to $D_m^{(i)}$ is "hidden" (it will be used only to compute the true positives during the test phase).

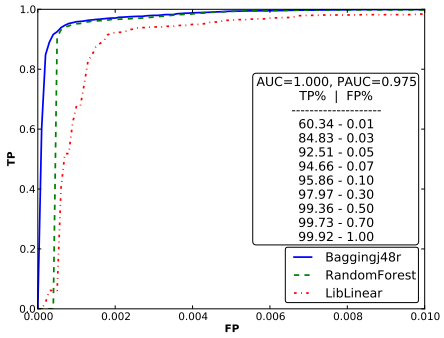
Feature measurement and test set preparation. Now, let us consider one of these k graphs, say $\mathcal{G}_i$. Our test data is represented by all nodes (i.e., all domains) in $D_m^{(i)}$ and $D_b^{(i)}$, whose true labels we want to recover by using our behavior-based classifier (remember that nodes in $\mathcal{G}_i$ are labeled after "hiding" the ground truth in $D_m^{(i)}$ and $D_b^{(i)}$).

To this end, for each domain node in $D_m^{(i)}$ and $D_b^{(i)}$, we measure the statistical features as defined in Section 5.2.1 (see also Figure 5.4). Let $V_m^{(i)}$ and $V_b^{(i)}$ be the set of all feature vectors derived from the domains in $D_m^{(i)}$ and $D_b^{(i)}$, respectively. While for the purpose of feature measurement we pretend the domains are *unknown*, we do know their true labels, and therefore we can eventually label their vectors, thus obtaining the desired labeled test set $V^{(i)} = V_m^{(i)} \cup V_b^{(i)}$. By applying this process for each $i = 1, \ldots, k$, we obtained the required $k = 10$ different test datasets, one per each fold.

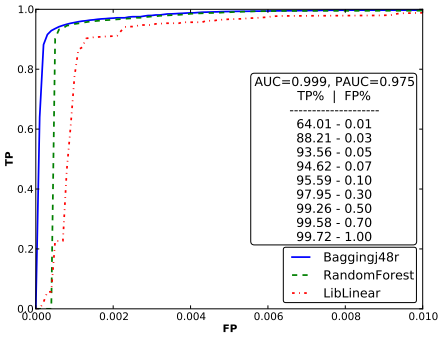
Training set preparation. To prepare the training dataset for the i-th cross-validation fold, we proceed as follow. We consider the pruned graph $\mathcal{G}_i$, and the set of its labeled domain nodes $D_m^{(\neg i)} = \bigcup_{j \neq i} D_m^{(j)}$ and $D_b^{(\neg i)} = \bigcup_{j \neq i} D_b^{(j)}$, namely all *malware* and *benign* domains excluding the "test domains" in $D_m^{(i)}$ and $D_b^{(i)}$ (which, as explained earlier, we pretend are labeled as *unknown*). Then, we apply the training dataset preparation procedure explained in Section 5.2.1 (see also Figure 5.5), thus obtaining the i-th fold's training dataset.

10-fold cross validation results. Given one day of traffic from an ISP network, we prepare the training and test sets as explained above, and then applied the standard cross-validation procedure to evaluate our classifier. For each fold, we compute the ROC curve by varying the detection threshold on the classifier's output scores, the area under the curve (AUC), and

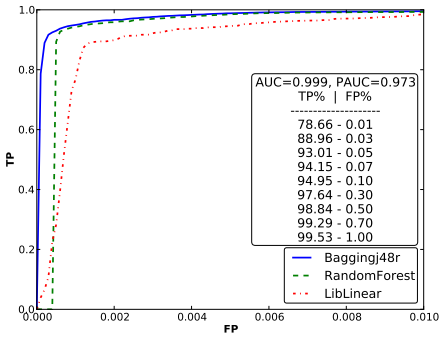
the *partial* AUC (PAUC). Notice that the PAUC is computed by measuring the area under the ROC curve in a range of false positive between 0% and 1%, and by normalizing this measure to obtain a value in $[0, 1]$. In essence, the PAUC highlights the classifier's trade-off between true positives (TP) and false positives (FP) at very low FP rates. We then average these results across all folds.



(a) ISP_1



(b) ISP_2



(c) ISP_3

Figure 5.7: Cross-validation results for three different ISP networks (with one day of traffic observation; FPs in $[0, 0.01]$)

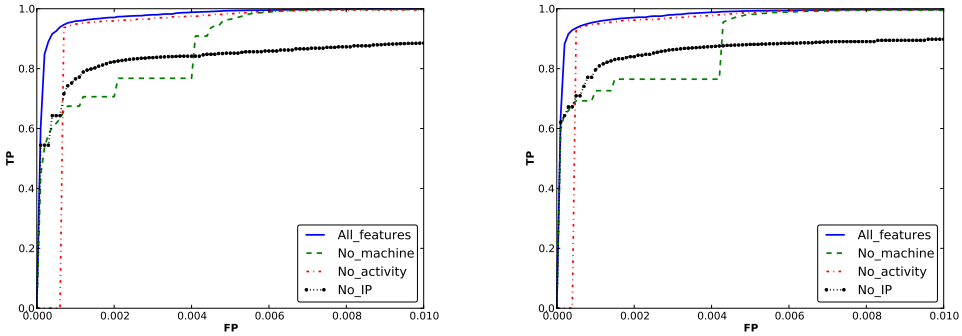
Figure 5.7 shows results obtained for each of the three ISP networks available to us. We conducted our experiments by building the machine-domain graphs based on one day of DNS traffic, and by comparing three different learning algorithms: a multiple-classifier system built using bagged decision trees [45] (BaggingJ48), the Random Forest algorithm by Breiman [13] (RandomForest), and an efficient implementation of Logistic Regression with

$\mathcal{L}_1$ regularization [21] (LibLinear). As shown in Figure 5.7, we consistently obtained the best results with BaggingJ48, achieving an AUC close to 100% and a PAUC above 97.5%. Also, the TP-FP trade-off tables embedded in the graphs show that we can achieve above 95% true positives at a false positive rate of 0.1%. These results are consistent across all ISP networks and days of traffic we had available.

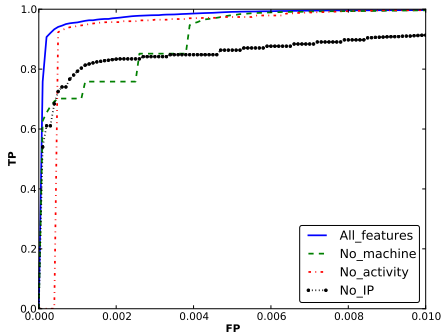
5.5.2 Feature Analysis

We repeated the cross-validation experiments described in Section 5.5.1 (using BaggingJ48) to perform a detailed analysis of our statistical features. To this end, we first trained our classifier by completely *removing one of the three feature groups* described in Section 5.2.1 at a time. For example, in Figure 5.8 the "No IP" ROC curves (dashed black line) refer to a statistical classifier learned without making use of the *IP abuse* features (F3). As we can see, even without the IP abuse features, Segugio can consistently achieve more than 80% TPs at less than 0.2% FPs. Also, we can see from the "No machine" line that removing our *machine behavior* (F1) features (i.e., using only domain activity and IP abuse features) would cause a noticeable drop in the TP rate, for most FP rates below 0.5%. This shows that our machine behavior features are needed to achieve high detection rates at low false positives. Overall, the combination of all three feature groups yields the best results.

Figure 5.9 shows the ROC curves obtained by *using only one group of features* at a time. The figure shows that at low FPs the IP abuse features by themselves yield a worse TP rate than using the *machine behavior* or *domain activity* features. (see the "IP" ROCs, which refer to cross-validation results obtained with a classifier trained using *only* the IP abuse features).



(a) ISP_1 (b) ISP_2



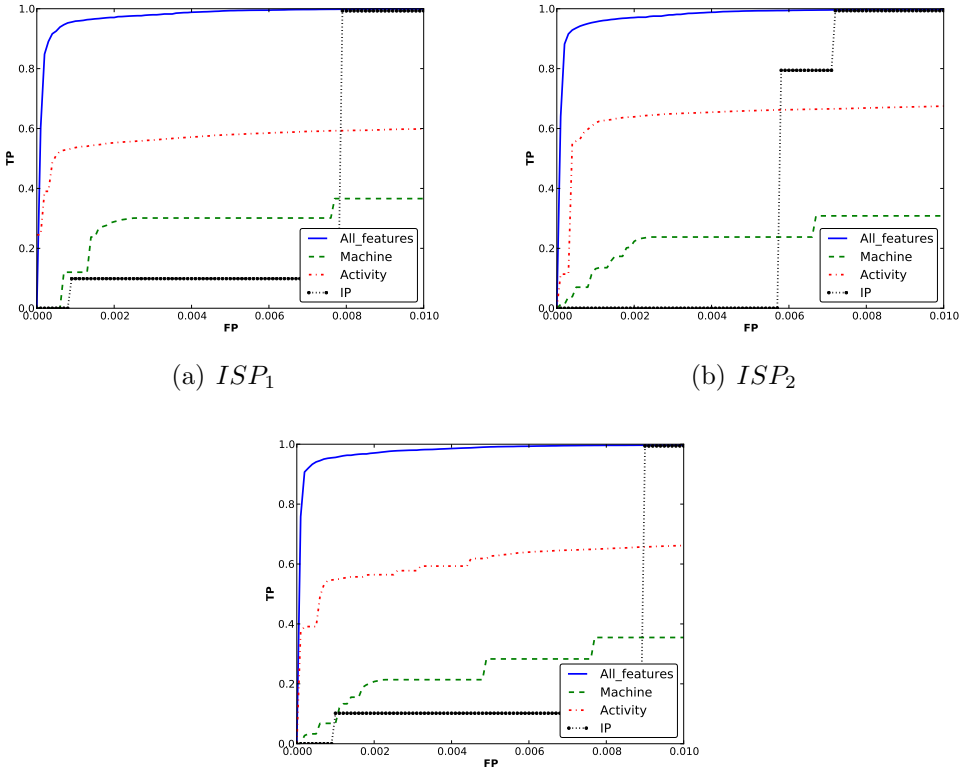
(c) ISP_3

Figure 5.8: Feature analysis: results obtained by excluding one group of features at a time, and comparison to using all features (FPs in $[0, 0.01]$)

5.5.3 Cross-Day and Cross-Network Tests

In this section we aim to show that Segugio's classifier learned on a given day can be successfully deployed in a different ISP network, and can accurately classify new malware-control domains observed several days after the training was completed.

Training and Test set preparation. To prepare the training and test sets, we consider two days of traffic observed at two different networks. We use the DNS traffic from the first day for training purposes, and then test our Segugio classifier on the second day of traffic



(a) ISP_1 (b) ISP_2

(c) ISP_3

Figure 5.9: Feature analysis: results obtained by using only one group of features at a time, and comparison with results obtained using all features (FPs in $[0, 0.01]$).

(observed at a different network). We devised a rigorous procedure to make sure that no ground truth information about the test domains is ever used during training and feature measurement.

Training set preparation. To prepare the training and test sets, we first built the machine-domain graphs $\mathcal{G}_{t_1}$ and $\mathcal{G}_{t_2}$ according to the DNS traffic observed at two different ISP networks on two different days, t_1 and t_2, respectively. These two days of traffic do not need to be consecutive, and in fact in our experiments they are separated by a gap of several days. Our main goal in preparing the training set was to make sure that a large subset of the known

malware and benign domains that appear in day t_1 and day t_2 are *excluded* from training, and are used only for testing. This allows us to evaluate the classifier's generalization ability, and how accurately we can detect previously unknown malware and benign domains.

To achieve this goal, we proceeded as follows. Let $D_m^{t_1}$ and $D_m^{t_2}$ be the sets of known malware-control domains that were "visible" in the traffic (i.e., that were queried at least once) on day one and day two, respectively. Similarly, let $D_b^{t_1}$ and $D_b^{t_2}$ be the sets of known benign domains observed in the traffic on the two different days. First, we computed the set intersections $D_m^{t_{12}} = D_m^{t_1} \cap D_m^{t_2}$, and $D_b^{t_{12}} = D_b^{t_1} \cap D_b^{t_2}$. In other words, we find all known malware and benign domains that were queried both in day one and day two. Then, we randomly "hide" the ground truth for half of the malware-control domains in $D_m^{t_{12}}$, effectively re-labeling them as *unknown*. We do the same for the benign domains in $D_b^{t_{12}}$, and call $D_m^{t_{12;50\%}}$ and $D_b^{t_{12;50\%}}$ the resulting sets of domains whose ground truth was "hidden". The reason why we "hide" the true label of domains in these two sets is that we will later use them for testing. Therefore, we need to effectively remove them from the labeled training set.

Let $\mathcal{G}_{t_{1;50\%}}$ be the graph $\mathcal{G}_{t_1}$ relabeled by excluding the ground truth for domains in $D_m^{t_{12;50\%}}$ and $D_b^{t_{12;50\%}}$ (i.e., those domain nodes are re-labeled as *unknown*, and the machines that query them are re-labeled accordingly). For each remaining labeled domain node in this new graph, we measure its features as explained in Section 5.2.1 (see also Figure 5.5) to obtain the training dataset.

Test set preparation. To prepare the test set we consider graph $\mathcal{G}_{t_2}$, which was built on day two. Let $N_m = D_m^{t_2} - D_m^{t_{12}}$ be the set of "new" known malware domains that we observed in the traffic of day t_2, but not in t_1 (i.e., those domains that where queried on day two but not on day one). Similarly, let $N_b = D_b^{t_2} - D_b^{t_{12}}$ be the set of "new" benign domains. We first randomly split N_m and N_b in half, obtaining two sets $N_m^{50\%}$ and $N_b^{50\%}$ by picking one of

the halves per set. Then, we "hide" the true labels of domains in these two sets, effectively pretending they are labeled as *unknown*.

Now, we form our test dataset of malware domains as $T_m = N_m^{50\%} \cup D_m^{t_{12};50\%}$, and $T_b = N_b^{50\%} \cup D_b^{t_{12};50\%}$ for the benign domains. Namely, we obtain a large set of domain names for which we know the ground truth, but whose ground truth is never used to train Segugio or to measure the features. Then, given graph $\mathcal{G}_{t_2}$, we relabel it according to all the available ground truth excluding all domains in T_m and T_b, thus obtaining a new labeled graph that we can use for testing purposes. We use this new (partially labeled) graph to measure the features for and classify each test domain in T_m and T_b, following the process described in Section 5.2.1 (see also Figure 5.4). This allows us to estimate the true and false positive rates.

Ultimately, the experimental approach outlined above allows us to obtain a large labeled test dataset of domains that were never used for training and whose true labels are never used during the feature measurement process. The number of test samples we obtained this way are reported in Table 5.2. The experimental results are discussed in Section 5.5.3.

Table 5.2: Cross-day and cross-network test set sizes (includes the total size and the size of the test subsets).

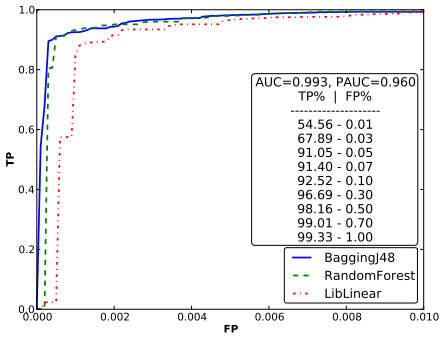
Experiment	T_m	T_b	$D_m^{t_{12};50\%}$	$D_b^{t_{12};50\%}$	$N_m^{50\%}$	$N_b^{50\%}$
ISP_1,ISP_2	6,390	748,093	2,021	322,982	4,369	425,111
ISP_1,ISP_3	6,490	820,219	2,234	372,803	4,256	447,416
ISP_2,ISP_3	6,477	879,328	2,165	406,558	4,312	472,770

Cross-day and cross-network test results. We used multiple training and test sets to evaluate our behavior-based classifier on all three ISP networks, and on several combinations of different networks and dates for traffic days t_1 and t_2. Table 5.3 reports the number of malicious and benign test domains for three representative experiments. For example, in the first experiment we train Segugio on traffic from ISP_1 and test it on domains seen in ISP_2.

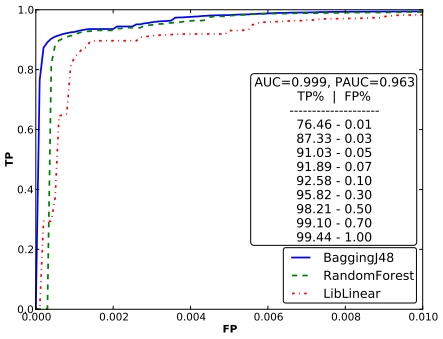
The classification results for these three experiments are reported in Figure 5.10. Segugio was able to consistently achieve above 92% TPs at 0.1% FPs.

Table 5.3: Cross-day and cross-network test set sizes.

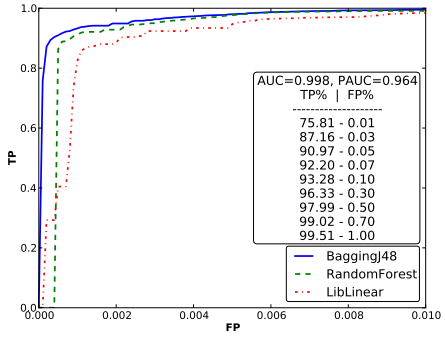
Test Experiment	**malicious domains**	**benign domains**
ISP_1,ISP_2 (1 day gap)	6,390	748,093
ISP_1,ISP_3 (14 days gap)	6,490	820,219
ISP_2,ISP_3 (15 days gap)	6,477	879,328



(a) Train on ISP_1, test on ISP_2, 1 day gap



(b) Train on ISP_1, test on ISP_3, 14 days gap



(c) Train on ISP_2, test on ISP_3, 15 days gap

Figure 5.10: Cross-day and cross-network test results for three different ISP networks (FPs in $[0, 0.01]$)

5.5.4 Cross-Malware Family Tests

While Segugio's main goal is to discover the occurrence of new malware-control domains by tracking known infections, in this section we show that Segugio can also detect domains related to malware families previously unseen in the monitored networks. Namely, no infection related to those families was previously known to have occurred in the monitored networks.

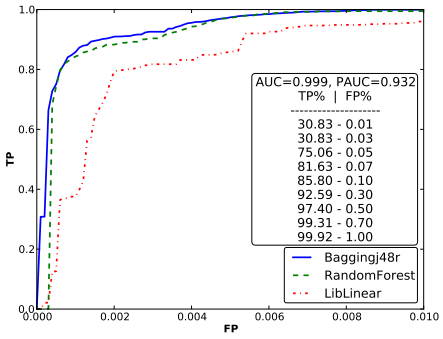
To this end, we performed a set of cross-validation experiments by splitting our dataset of known blacklisted C&C domains *according to their malware family*, rather than at random as in Section 5.5.1. The source of our commercial blacklist was able to provide us with malware family labels[4] for the vast majority of blacklisted domains (less than 0.1% of blacklisted domains were excluded form these experiments). Overall, the blacklist consisted of tens of thousands of C&C domains divided in more than one thousand different malware families.

To prepare our new tests, we partitioned the blacklisted domains into *balanced sets of malware families*. Namely, each fold contained roughly the same number of malware families. The net result is that the domains used for test always belonged to malware families never used for training. Said another way, *none of the known malware-control domains used for training belonged to any of the malware families represented in the test set.*

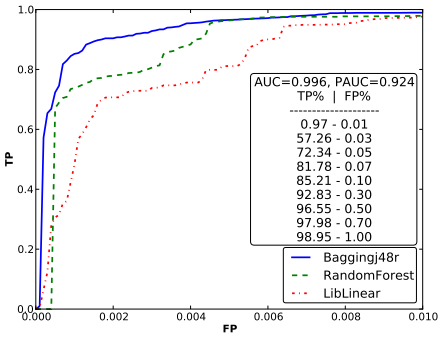
The results are reported in Figure 5.11. As we can see, Segugio is able to discover domains related to new malware families with more than 85% TPs at 0.1% FPs. To explain this result, we performed a set of feature analysis experiments (similar to Section 5.5.2) using the new experiment settings. We found that if we remove the (F1) group of *machine behavior* features, the detection rate drops significantly. In other words, our machine behavior features are important, because using only feature groups (F2) and (F3) yields significantly lower detection results for low FP rates.

[4]Often, the labels were more fine-grained than generic malware families, and associated domains to a specific cyber-criminal group.

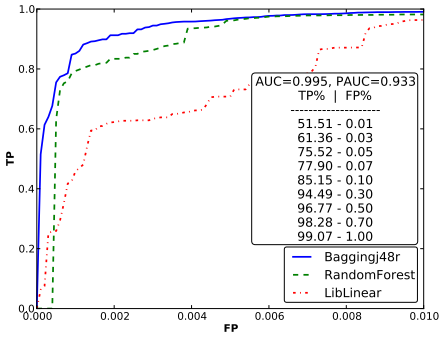
One reason for the contribution of our machine behavior features (F1) is the existence of *multiple infections*. Some machines appear to be infected with multiple malware belonging to different families, possibly due to the same vulnerabilities being exploited by different attackers, to the presence of malware droppers that sell their infection services to more than one criminal group, or because of multiple infections behind a NAT device (e.g., in case of home networks). Also, the domain activity features (F2) may help because the new domains were only recently used. Finally, the IP abuse features (F3) may help when new malware families point their control domains to IP space that was previously abused by different malware operators (e.g., in case of the same bulletproof hosting services used by multiple malware owners).



(a) ISP_1



(b) ISP_2



(c) ISP_3

Figure 5.11: Cross-malware family results for three different ISP networks (with one day of traffic observation; FPs in $[0, 0.01]$)

5.5.5 Analysis of Segugio's False Positives

We now provide an analysis of domains in our top Alexa whitelist that were classified as *malware* by Segugio. It is worth remembering that the whitelist we use contains only effective second-level domains (e2LDs) that have been in the top one million list for an entire year (see Section 5.4 for more details). During testing, we count as false positive any fully qualified domain (FQD) classified by Segugio as *malware* whose e2LD is in our whitelist.

By analyzing Segugio's output, we found that most of the false positives are due to domains related to personal websites or blogs with names under an e2LD that we failed to identify as offering "free registration" of subdomains. As discussed in Section 5.4, such e2LDs may introduce noise in our whitelist, and should have been filtered out. For example, most of Segugio's false positives were related to domain names under e2LDs such as `egloos .com`, `freehostia .com`, `uol.com.br`, `interfree.it`, etc. Unfortunately, these types of services are easily abused by attackers. Consequently, many of the domains that we counted as false positives may very well be actual malware-control domains. Figure 5.12 shows an example subset of such domains.

```
thaisqz.sites.uol.com.br
jkishii.sites.uol.com.br
sjhsjh333.egloos.com
ivoryzwei.egloos.com
dat007.xtgem.com
vk144.narod.ru
jhooli10.freehostia.com
7171.freehostia.com
cr0s.interfree.it
cr0k.interfree.it
id11870.luxup.ru
id23166.luxup.ru
...
```

Figure 5.12: Example set of domains that were counted as false positives. The effective 2LDs are highlighted in bold.

We now provide a breakdown of the false positives generated by Segugio during the three different cross-day and cross-network tests reported in Section 5.5.3 and in Figure 5.10 (a), (b), and (c). Table 5.4 summarizes the results. For example, experiment (a) produced 724 distinct false positive FQDs, using a detection threshold set to produce at most 0.05% FPs and $> 90\%$ TPs. Many of these FP domains shared the same e2LD. In fact, we had only 401 distinct e2LDs. Of these, the top 10 e2LDs that contributed the most FQDs under their domain name caused 32% of all FPs.

Table 5.4: Analysis of Segugio's FPs

Test Experiment	(a) ISP_1-ISP_2	(b) ISP_1-ISP_3	(c) ISP_2-ISP_3
Absolute number of false positives for overall 0.05% **FPs and** $> 90\%$ **TPs**			
Fully qualified domains (FQDs)	724	807	786
Effective second-level domains (e2LDs)	401	410	451
Contribution of top 10 e2LDs	230 (32%)	308 (38%)	247 (31%)
Feature Contributions			
$> 90\%$ infected machines	73%	71%	55%
Past abused IPs	86%	85%	80%
Active for ≤ 3 days	26%	20%	27%
Evidence of Malware Communications (sandbox traces)			
Domains queried by malware	21%	23%	19%

Table 5.4 also shows that 73% of all false positive domains were queried by a group of machines of which more than 90% were known to be infected. Also, 86% of the FP domains resolved to a previously abused IP addressed, and 26% of them were active for only less than three days. Finally, using a separate large database of malware network traces obtained by executing malware samples in a sandbox, we found that 26% of the domains that we counted towards the false positives had been contacted by known malware samples.

To summarize, our experiments show that Segugio's false positive rate is low (e.g., $\leq$ 0.05% FPs at a TP rate $\geq 90\%$) and FPs may also be somewhat overestimated. In general, Segugio yields much lower FPs than previously proposed systems for detecting malicious domains (see Section 5.6 for a comparison to Notos [7]). Even so, we acknowledge that some false positives are essentially inevitable for statistical detection systems such as Segugio.

Therefore, care should be taken (e.g., via an additional vetting process) before the discovered domains are deployed to block malware-control communications.

5.5.6 Experiments with Public Blacklists

To show that Segugio's results are not critically dependent on the specific commercial malware C&C blacklist we used as our ground truth, we also performed a number of experiments using public blacklist information.

Cross-Validation Tests. We repeated the cross-validation experiments on machine-domain graphs labeled using exclusively known malware-control domains collected from public blacklists. More specifically, we collected domains labeled as malware C&C (we excluded other types of non-C&C malicious domains) from the following sources: `spyeyetracker.abuse.ch`, `zeustracker.abuse.ch`, `malwaredomains.com`, and `malwaredomainlist.com`. Overall, our public C&C domain blacklist consisted of 4,125 distinct domain names. We then used this blacklist to label the *malware* nodes in the machine-domain graph, and then performed all other steps to conduct cross-validation experiments using the same procedure described in Section 5.5.1 (the only change was the blacklist).

Figure 5.13 reports the results on traffic from ISP_3 (results for other ISP networks and day of traffic are very similar). Segugio was able to achieve over 94% true positives at a false positive rate of 0.1%.

Cross-Blacklist Tests. To further demonstrate Segugio's ability to discover new malware-control domains, we conducted another experiment by using our commercial C&C blacklist (described in Section 5.4) for training purposes, and then testing Segugio to see if it would be able to detect new malware-control domains that appeared in the public blacklists but were not in our commercial blacklist (and therefore were not used during training). By inspecting a day of traffic from ISP_3, we observed 260 malware control domains that matched our public blacklist. However, of these 260 domains, 207 domains already existed in our

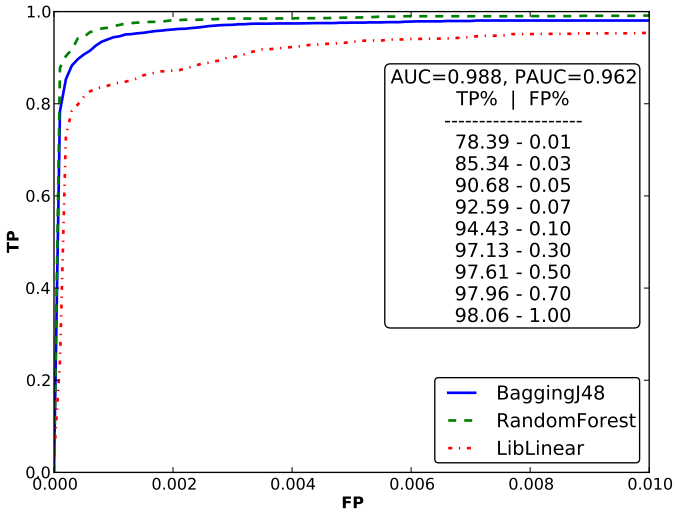


Figure 5.13: Cross-validation results using only public blacklists

commercial blacklist as well. Therefore, we used only the remaining 53 new domains that matched the public blacklist (but not the commercial blacklist) to compute Segugio's true positives. We found that Segugio could achieve the following trade-offs between true and false positives: (TPs=57%, FPs=0.1%), (TPs=74%, FPs=0.5%), and (TPs=77%, FPs=0.9%). While the TP rate looks somewhat lower than what obtained in other tests (though still fairly good, considering the low FP rates), we believe this is mainly due to the limited test set size (only 53 domains) and noise. In fact, we manually found that the public blacklists we used contained a number of domains labeled as C&C that were highly likely benign (e.g., `recsports.uga.edu` and `www.hdblog.it`), and others that were likely not related to malware-control activities (though possibly used for different malicious activities), which would not be labeled as *malware* by Segugio.

5.5.7 Early Detection of Malware-Control Domains

We also performed experiments to measure how early Segugio can detect malware-control domains, compared to malware domain blacklists. To this end, we selected four consecutive days of data from each of the three ISP networks (12 days of traffic, overall). For each day, we trained Segugio and set the detection threshold to obtain $\leq 0.1\%$ false positives. We then tested the classifier on all domains that on that day were still labeled as *unknown*. Finally, we checked if the new malware-control domains we detected appeared in our blacklists in the following 35 days. During the four days of monitoring, we found 38 domains that later appeared in the blacklist. A large fraction of these newly discovered domains were added to the blacklist many days after they were detected by Segugio, as shown in Figure 5.14.

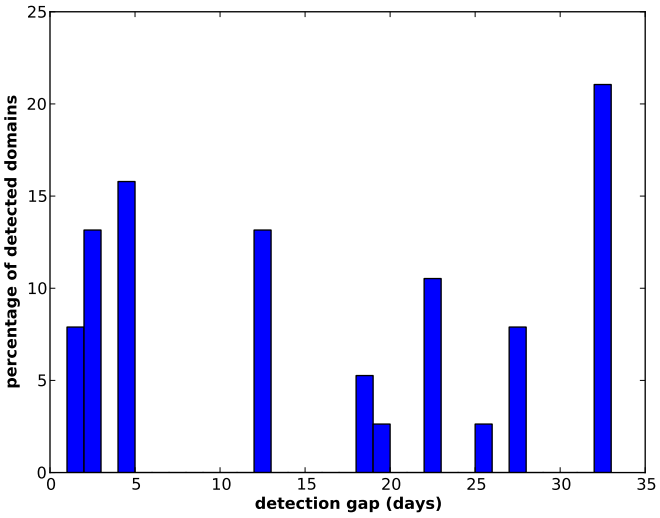
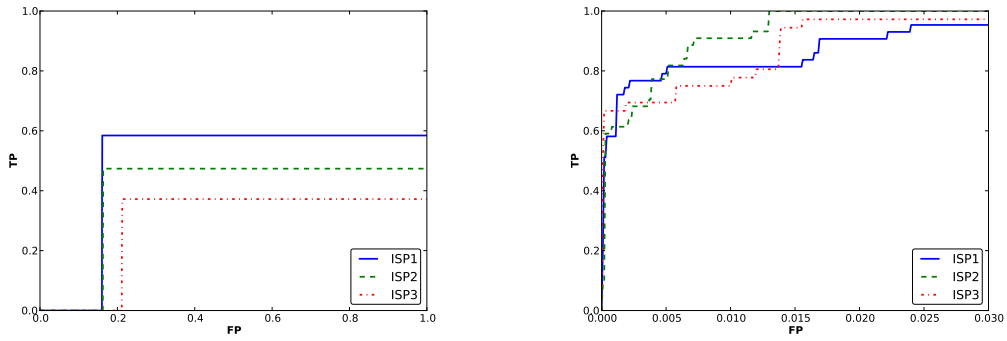


Figure 5.14: Early detection results: histogram of the time gap between Segugio's discovery of new malware-control domains and the time when they first appeared on the blacklist.

5.5.8 Segugio's Performance (Efficiency)

Segugio is able to efficiently learn the behavior-based classifier from an entire day of ISP-level DNS traffic, and can classify all (yet unknown) domains seen in a network in a matter of a few minutes. To show this, we computed the average training and test time for Segugio across the 12 days of traffic used to perform the *early detection* experiments discussed in Section 5.5.7. In average the learning phase took about 60 minutes, for building the machine-domain graph, annotating and labeling the nodes, pruning the graph, and training the behavior-based classifier. The feature measurement and testing of all *unknown* domains required only about 3 minutes.

5.6 Comparison with Notos



(a) Notos (b) Segugio

Figure 5.15: Comparison between Notos and Segugio (notice that the range of FPs for Notos is $[0, 1.0]$, while for Segugio FPs are in $[0, 0.03]$)

In this section, we aim to compare our Segugio system to Notos [7], a recently proposed domain reputation system. As mentioned in Section 5.1, Notos' goal is somewhat different from ours, because domain reputation systems aim to detect malicious domains in general, which include phishing and spam domains, for example. On the other hand, we focus

on a behavior-based approach for accurately detecting *malware-control domains*, namely "malware-only" domains through which attackers provide control functionalities to already infected machines. Nonetheless, Notos could be also used to detect malware-control domains, and therefore here we aim to compare the two systems.

Experimental setup. We have obtained access to a version of Notos built by the original authors of that system. The version of Notos available to us was trained using a very large blacklist of malicious domains, and a whitelist consisting of the top 100,000 most popular domains according to Alexa. We were able to verify that the blacklist they used to train Notos was a proper superset of the blacklist of malware-control domains we used to train Segugio. In addition, we made sure to train Segugio using only the top 100,000 Alexa domains, as done by Notos, thus allowing for a balanced comparison between the two systems.

To compute the false positives, we used the whitelist detailed in Section 5.4 (domains that were consistently very popular for at least one year), from which we removed the top 100,000 Alexa domains used during the training of Notos and Segugio. As mentioned earlier, we acknowledge that our whitelist may contain some small amount of noise. Later in this section we discuss how we further aggressively reduce such noise to obtain a more precise estimate of the false positives.

The version of Notos to which we were given access was trained on October 8, 2013, which we refer to as t_{train}. Therefore, we trained Segugio on traffic from the very same day t_{train}, and labeled malware domains using our blacklist updated until that same day. In other words, both Notos and Segugio were trained using only ground truth gathered before t_{train}. Then, we tested both Notos and Segugio on each of the three ISP networks, using one entire day of traffic from November 1, 2013, which we refer to as t_{test}. To compute the true positives, we considered as ground truth only those new confirmed malware-control domains that were added to our blacklist between days $(t_{train} + 1)$ and t_{test}. Overall, during that

period we had 43, 44, and 36 new blacklisted malware-control domains that appeared (i.e., were queried) in ISP_1, ISP_2, and ISP_3, respectively.

Results. Figure 5.15 shows the detection results for the two systems. In particular, Figure 5.15(a) shows that the detection threshold on Notos's output score needs to be increased significantly, before the new malware-control domains (i.e., the ones blacklisted after t_{train}) are detected. Unfortunately, this causes a fairly high false positive rate (16%, 16.23%, and 21.11%, respectively, for the three ISP networks). In addition, only less than 58% of the newly blacklisted domains are detected in the best case (ISP_1 in Figure 5.15(a)). Notice that the version of Notos given to us employed a "reject option" whereby the system may avoid classifying an input domain, if not enough historic evidence about its reputation could be collected. This explains why Notos is not able to detect all malware-control domains even at the highest FP rates.

According to Figure 5.15(b) (where FPs are in $[0, 0.03]$), Segugio was able to detect respectively 81.39%, 90.9%, and 75% of new malware-control domains with less than 0.7% of false positives. This shows that Segugio outperforms Notos, even considering that we had 24 days of gap between the training and test phases.

Braking down the FPs. To better understand why Notos produced a high false positive rate, we investigated the possible reasons why many of our whitelisted domains were assigned a low reputation (see Table 5.5). After adjusting the detection threshold so that Notos could detect the blacklisted domains (i.e., produce the true positives), Notos classified as malicious 13,432 of the whitelisted domains that were "visible" in the ISP_1 traffic on day t_{test} (see Figure 5.15(a)). Among these, 1,826 domain names (or 13.6% of the FPs) were related to adult content, and probably hosted in what we could consider as "dirty" networks. For other 234 domain names (1.7% of the FPs), we have evidence that they were queried at least once by malware samples executed in a sandboxed environment. We know that malware samples often query also popular benign domains. However, a domain queried by malware may be

considered as "suspicious", and that is probably why Notos assigns them a low reputation, though it does not necessarily mean that these domains are malware-related. Another 2,011 domain names (or 15% of the FPs) resolved to IP addresses that were contacted directly by malware samples in the past. Overall 7,341 domains (54.7% of FPs) resolved into a /24 network which hosted IPs contacted by at least one malware sample in the past. Finally, we are left with 2,020 domains (or 15% of the FPs) for which no evidence is available to infer why Notos classified them as malicious.

To summarize, this means that potentially the actual number of "reputation-based" false positives could be less than 15% of the 13,432 domains that Notos classified as malicious, which correspond to 2.94% of all whitelisted test domains. In other words, even considering these filtered results, Notos would still generate 2.94% FPs. Therefore, overall our experiments show that, on the task of discovering new malware-control domains, Segugio clearly outperforms Notos.

Table 5.5: Break-down of Notos's FPs

All Notos's FPs	13,432
Explicit evidence	
Suspicious content	1,826 (13.6%)
Domains queried by malware	234 (1.7%)
Domains with IPs previously contacted by malware	2,011 (15%)
Implicit evidence	
Domain names in /24 networks used by malware	7,341 (54.7%)
No evidence	
Potential reputation FPs	2,020 (15%)

5.7 Limitations and Discussion

Segugio requires preliminary ground truth to label known malware and benign nodes. This is fundamental to apply our belief propagation strategy. Fortunately, some level of ground truth is often openly available, like in the case of public C&C blacklists and popular domain

whitelists, or can be obtained for a fee from current security providers (in the case of commercial blacklists). In Section 5.5.6 we show that even using only ground truth collected from public sources, Segugio can still detect new malware-control domains. Notice also that while the ground truth may contain some level of noise, it is possible to apply some filtering steps to reduce its impact (see discussion in Section 5.4, for example).

Because Segugio focuses on detecting "malware-only" domains, an attacker may attempt to evade Segugio by somehow operating a malware-control channel under a legitimate and popular domain name. For example, the malware owner may build a C&C channel within some social network profile or by posting apparently legitimate blog comments on a popular blog site. While this is possible, popular sites are often patrolled for security flaws, which exposes the C&C channel to a potentially more prompt takedown. This is one of the reasons why attackers often prefer to point their C&C domains to servers within "bullet proof" hosting providers.

A possible limitation of Segugio is that a malware-control domain that is never queried by any of the previously known malware-infected machines is more difficult to detect, using a belief propagation strategy. However, in Section 5.5.4 we showed that by combining the *machine behavior* features (defined in Section 5.2.1) to the *domain activity* and *IP abuse* features, Segugio is still able to detect many such new domains.

Another possible challenge is represented by networks that have a high DHCP churn, if source IP addresses are used as the machine identifiers. High DHCP churn may cause some inflation in the number of machines that query a given (potentially malware-related) domain. However, we should consider that Segugio can independently be deployed by each ISP. Therefore, for deployments similar to ours, the ISP's network administrators may be able to correlate the DHCP logs with the DNS traffic, to obtain unique machine identifiers that can be used for building the machine-domain graphs.

Segugio's detection reports are generated after a given observation time window (one day, in our experiments). Therefore, malware operators may try to change their malware C&C domains more frequently than the observation window, so that if the discovered domains are deployed into a blacklist, they may be of less help for enumerating the infected machines in a network. However, it is worth noting that Segugio can detect both malware-control domains and the infected machines that query them at the same time. Therefore, infections can still be enumerated, thus allowing network administrators to track and remediate the compromised machines.

Some ISP networks may host clients that run security tools that attempt to continuously "probe" a large list of malware-related domains, for example to actively keep track of their activities (e.g., whether they are locally blacklisted, what is their list of resolved IPs, their name server names, etc.). Such clients may introduce noise into our bipartite machine-domain graph, potentially degrading Segugio's accuracy and performance. During our experiments, we used a set of heuristics to verify that our filtered graphs (obtained after pruning, as explained in Section 5.2) did not seem to contain such "anomalous" clients.

5.8 Related Work

In Section 5.1 we have discussed the main differences with recent previous work on detecting malicious domains, such as [7, 12, 8, 9]. In this section, we discuss the differences between Segugio and other related works.

Botnet/Malware detection: Studies such as [27, 28, 26, 76, 78] focus on detecting bot-compromised machines. For example, BotSniffer [28] and BotMiner [26] look for similar network behavior across network hosts. The intuitions is that compromised hosts belonging to the same botnet share common C&C communication patterns. These systems typically require to monitor all network traffic (possibly at different granularities) and are therefore

unlikely to scale well to very large ISP networks. Our work is different, because we focus on a more lightweight approach to detecting malware-control domains by monitoring DNS traffic in large ISP networks.

A large body of work has focused on detecting malware files. One work related to ours is Polonium [16], which aims to detect malware files using graphical models. Our work is different from Polonium in many respects. We focus on detecting new malware-control domains, rather than malware files. In addition, Polonium employes a very expensive loopy belief propagation algorithm on a graph with no annotations. Furthermore, through pilot experiments using GraphLab [48] we found that the inference approach used in Polonium would result in a significantly lower accuracy for Segugio with a huge negative impact on performance.

Malware C&C modeling and tracking. Wurzinger et al. [74] propose to first detect malicious network activities (e.g., scanning, spamming, etc.) generated by malware executed in a controlled environment (see [20]), and then to analyze the network traffic "backwards" to find what communication could have carried the command that initiated the malicious activities. Jackstraws [38], executes malware in an instrumented sandbox to generate "behavior graphs" for system calls related to network communications. These system-level behavior graphs are then compared to C&C graph templates to find new C&C communications. Our work is different, because we don't rely on performing detailed malware dynamic analysis in a controlled environment. Rather, we focus on detecting new malware-control domains via passive DNS traffic analysis in live ISP networks.

In [62], Sato et al. performed a preliminary study of unknown domains that frequently co-occur with DNS queries to known C&C domains. While the co-occurrence used in [62] has some resemblance to Segugio's machine behavior features, our work if different from [62]. For example the system presented in [62] suffers from a large number of false positives, even at a fairly low true positive rate. Furthermore, unlike Segugio, [62] is not able to detect new C&C

domains that have low or no co-occurrence with known malicious domains. Importantly, [62] has been evaluated only at a very small scale. In contracts, we performed a thorough evaluation of Segugio in many different settings, including cross-validation, cross-day and cross-network tests, feature analysis, performance evaluation, and direct comparison with Notos [7]. All our experiments were conducted at large scale, via a deployment in multiple real-world ISP networks hosting millions of users.

Signature-based C&C detection. Researchers have recently proposed a number of studies that focus on a signature-based approach to detect malware C&C communications, and the related malware C&C domains. For example, Perdisci et al. [56] proposed a system for clustering malware that request similar sets of URLs, and to extract token-subsequences signatures that may be used to detect infected hosts. ExecScent [53] is a new signature-based C&C detection system that builds control protocol templates (CPT) of known C&C communications, which are later used to detect new C&C domains. Another recent signature generation system, called FIRMA [57], can be used to detect C&C communications and the related malware-control domains.

The signature-based approaches outlined above typically require access to all TCP traffic crossing a network, to enable the detection of C&C communications. Instead, our system is based on a much more lightweight monitoring of DNS traffic only.

Other related work. Karagiannis et al. consider *who is talking to whom* to discover communities among hosts for flow classification purposes [42]. In a related study [75], Xu et al. use a bipartite graph of machine-to-machine communications. They use spectral clustering to identify groups of hosts with similar network behaviors. Coskun et al. [17] use a graph-based approach to discover peer nodes in peer-to-peer botnets. While we also leverage bipartite graphs, our work is very different from [42, 75, 17] in both the goals and approach. Felegyhazi et al. [22] take a proactive blacklisting approach to detect likely new malicious domains by leveraging domain registration information. Our work is different in

that Segugio mainly focuses on detecting new malware-control domains based on *who is querying what*. While we use information such as domain activity, Segugio does not rely on domain registration records.

5.9 Conclusion

In this paper, we presented *Segugio*, a novel defense system that is able of efficiently discover new *malware-control* domain names by passively monitoring the DNS traffic of large ISP networks.

We deployed Segugio in three large ISP networks, and we showed that Segugio can achieve a true positive rate above 94% at less than 0.1% false positives. In addition, we showed that Segugio can detect control domains related to previously unseen malware families, and that it outperforms Notos [7], a recently proposed domain reputation systems.

CHAPTER 6

BEHAVIORAL GRAPH-BASED DETECTION OF MALICIOUS FILES AND URLS IN LARGE SCALE

6.1 Introduction

Today drive-by downloads are one of the most effective ways for malware distributors to infect thousands of users' machines. Unfortunately, the infection can occur by merely visiting malicious URLs, in which case malwares automatically install themselves on vulnerable machines. Current defense technologies, such as antivirus softwares or URL blacklisting, are quite ineffective in preventing the infection. Antivirus softwares cannot deal with sophisticated, polymorphic malwares due to the fact that antivirus softwares employ signature based methods. Moreover, URL blacklists struggle to keep up with the agility of the Internet miscreants.

While in Chapter 5 we focused on the detection of malware-control domains, in this Chapter we study how do malwares infect the machines and introduce a novel protection system that enables the simultaneous detection of malware file downloads and malicious URLs. This system uses the same overall strategy of Segugio, introduced in Chapter 5, to perform behavioral graph-based detection of malicious files, URLs, and vulnerable machines on a large scale. This study is based on a unique dataset containing download events of customers of a famous antivirus company. The download events are 3-tuple of files, URLs,

and user machines. Using this dataset, we build a tripartite behavioral graph which reveals the associations among the aforementioned three entities. then we propagate either goodness or badness information in the graph from labeled nodes towards unknown ones. The devised classification system measures the amount of information push from the neighbors of an unknown node towards making it either good or bad. The novelty and great advantage of this study is that, firstly, it takes into account only the relationships and associations among files, URLs, and machines and deduces based upon adjacencies (either direct or indirect) in the tripartite graph. It does not need to perform any deep file analysis, traffic monitoring, DNS query inspection, etc.. Secondly, the detection occurs in a unified manner. In other words, the system acts as a central defense and protection system that could detect malware downloads, identify infected machines, and automatically block malicious URLs at the same time. In fact, the detection result at each level in the graph assists in detection at other levels.

Summary of our contributions follows.

- We propose a novel detection system that leverages behavioral graphs for identification of malicious files and URLs.
- Our system enables simultaneous detection of files and URLs and generates online classification reports.
- By implementing a prototype of our system, we show that it can detect malicious files and URLs with very high true positive rate even at extremely low false positive rates.

6.2 System Overview

6.2.1 Approach Outline

The main goal of this system is to automatically detect malware files and malicious URLs. This goal is achieved by passively monitoring *download events* that are triggered by users (machines). A download event occurs when a machine downloads a file from a URL and is denoted as a 3-tuple of <SHA1, URL, GUID>, where SHA1 is the hash of the binary file downloaded and GUID is the unique ID of monitored machines.

The detection is based on the associations and behavioral patterns of the download events. That is, we reason about an unknown item in a download event by analyzing the behavior of other entities in other download events that are somehow related and interact with the unknown item in question. Our belief about the interacting entities with an unknown node as well as their true nature, if known, lead the system to a conclusion regarding the unknown item. In general, to reason about an unknown file, the system performs an analysis of *where* this file is downloaded from and *who* is downloading the file. If the origin source of this file is historically associated with malicious file downloads or if the machine that downloaded the file is known to be a vulnerable machine the system could detect the file as a malware. On the other hand, a known legitimate source or a secure and clean machine will less likely cause a malicious file download. Similarly, an unknown URL could be labeled by our system by monitoring *what* files have been downloaded from the unknown URL in the past and *who* has accessed this URL previously. If a URL is hosted in a domain or network that was the source of many malware downloads, and numerous queries were made to this URL from susceptible machines, the system will likely label the URL as malicious. In our analysis we don't limit ourselves to association related to URLs only, instead, the association analysis is

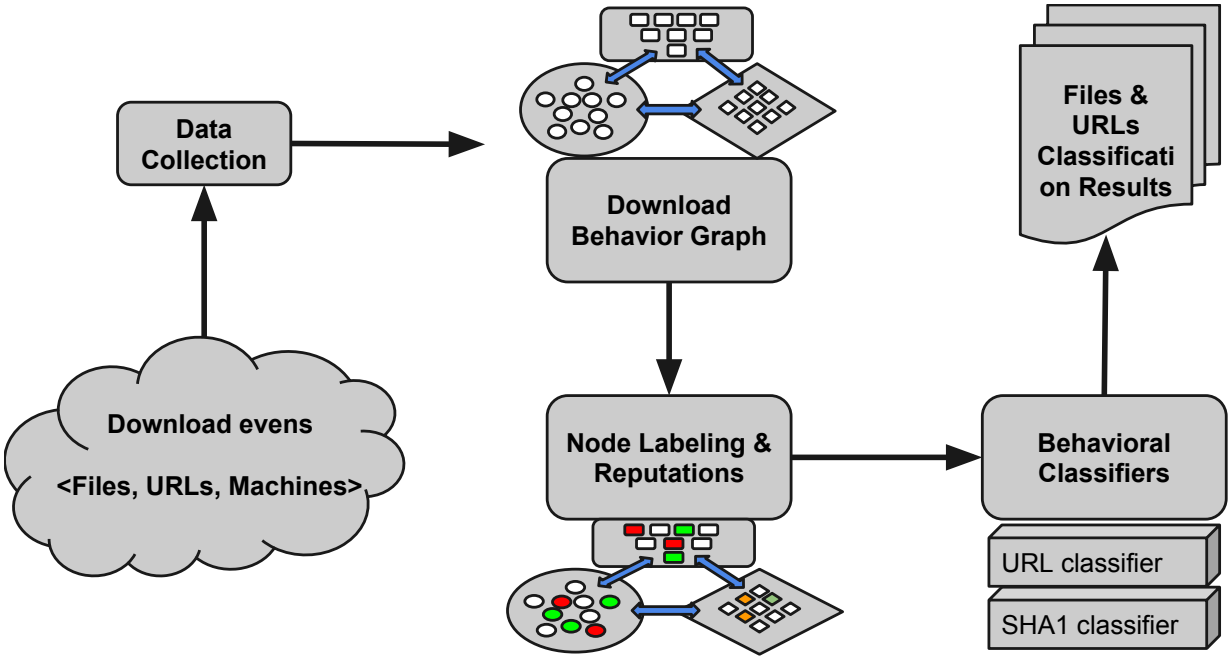


Figure 6.1: System Overview

expanded to relationships among files, machines, URLs' domains, paths, query strings, IPs, and etc.

An overview of the system is given in Figure 6.1. First, download events are monitored and are used to generate a large tripartite graph. Then, by using our ground truth, the graph nodes are partially labeled as either malicious, benign, or unknown. Next, based on the labeled graph, behavioral classifiers are trained to build detection models. Finally, these classifiers are used to provide classification of unknown nodes in the graph.

6.2.2 Download Behavior Graph

We first build a tripartite graph that reveals the associations among the three entities of all download events, namely SHA1s, URLs, and GUIDs, in an observation time window, T. The graph is denoted as $\mathcal{G} = (V, E)$ where V is the nodes and E the edges. The nodes include

the items of download events $V = \{S, U, G\}$, where S, U, and G are the set of all SHA1s, URLs, and GUIDs, respectively. A relationship between two nodes in V, such as a SHA1 downloaded from a URL, or a GUID downloads a SHA1s, is represented by an edge in E.

Each node in $\mathcal{G}$ is augmented with other information. The nodes in S have file name, size, prevalence (number of times this SHA1 was seen during T), first seen and last seen, and etc. The nodes in G have information of the operating system running on the machine. The nodes in U have the resolved IP addresses and prevalence. In addition, each node in U is annotated by the information about the URL itself which include the fully qualified domain name (FQD) and effective second level domain name (e2LD) of the domain portion of the URL, and the path and query string components of the URL. As a result, the graph not only shows the relationship between URLs and SHA1s or GUIDs, but it also shows the relationships between different URL components and SHA1s or GUIDs.

Furthermore, each download event is also augmented with additional information which include the timestamp of the event and details related to the process on the machine that triggered the event, such as the SHA1 of the downloading process.

6.2.3 Graph Node Labeling and Reputations

Using our partial ground truth about some of the nodes in the graph, we label $\mathcal{G}$ and assign reputation scores to nodes. A badness reputation score, $\mathcal{R}$, is in range $[0, 1]$ where 1 means maximum badness, 0 means maximum goodness, and 0.5 means unknown node. If a node's $\mathcal{R}$ is above a badness threshold, the node will be labeled as known bad, while if the reputation is below a certain threshold, the node will be labeled as known good. In all other cases the node will be labeled as unknown. The badness reputation scores for nodes in each layer of the graph are assigned as follows.

SHA1s Ground truth could be collected for some of the SHA1s in $\mathcal{G}$ using various sources, such as VirusTotal. If available, we use the assigned labels of reputable and well-known

antivirus companies to compute reputation scores for SHA1s. We also use a proprietary list of known benign files to further enhance the SHA1 reputation computation.

Our list of ten well-known antivirus softwares include Trend Micro, Microsoft, Symantec, McAfee, Kaspersky, AVG, Avast, ESET Nod32, BitDefender, and Sophos, and we refer to this list as trusted AVs. Our confidence a of SHA1 being bad depends on the number of AVs from the trusted AVs list that label the SHA1 as malicious, and, therefore, it determines the $\mathcal{R}$ for the SHA1. The more trusted AVs have a bad label for a SHA1 the higher the badness score will become. On the other hand, if no AV (either trusted or not) have a bad label for a SHA1, a low $\mathcal{R}$ and consequently a good label will be given to the SHA1. In addition, we utilize a proprietary list of known benign files to refine $\mathcal{R}$.

URLs We leverage black and whitelists of URLs and domains to gather ground truth regarding URLs. While some of the sources that we use are private, the majority are publicly available, such as list of popular domains according to Alexa and a blacklist of malicious domains according to Google Safe Browsing (GSB) [3]. To assign a good label to URLs, we maintain a list of domains that consistently appeared in top 1 million Alexa list for about a year. These domains are very unlikely to be malicious. Nonetheless, we acknowledge that there might be not-so-benign domains in this list. Thus, we consult multiple whitelists to eliminate noise from the Alexa list and to adjust the reputation of URLs as follows. If the e2LD of a URL appears in our Alexa list and the URL itself also belongs to a proprietary list of known benign URLs, the URL will receive a low $\mathcal{R}$, i.e. a score close to 0, indicating the URL is likely benign and, therefore, a good label. A URL will be assigned an $\mathcal{R}$ close to 1 (maximum badness), if GSB and our private blacklist have that URL as a malicious URL, and so a bad label will be assigned. In all other cases, $\mathcal{R}$ will be a number close to 0.5, and an unknown label will be assigned.

GUIDs The reputation computation of machines in $\mathcal{G}$ is somewhat different in terms of meaning from SHA1s and URLs, as benign and malicious labels for these group of nodes

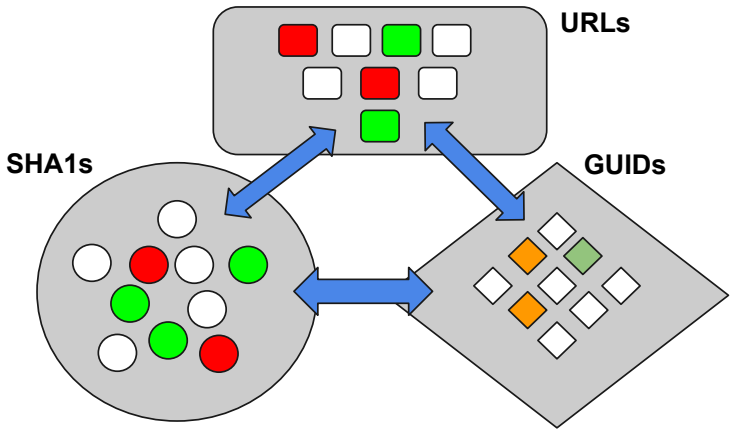
don't necessarily denote a good or a bad machine per se. Instead, a malicious label for a machine signifies a vulnerable machine that historically is known to download malwares and contact malicious URLs and a benign label represents a machine that seemed not associated with malicious content when looking at its activities in the past.

To compute a machine's $\mathcal{R}$, we consider the history of this machine's activities in a time window. We average the three highest $\mathcal{R}$ of SHA1s, the three highest $\mathcal{R}$ of URLs, and the three highest $\mathcal{R}$ of processes that are associated with the download events of the GUID. Then we take the max of these three averages and use it as $\mathcal{R}$ of the GUID. The intuition is if a GUID during a time period does not download bad SHA1s, contact bad URLs, or run bad processes, it is likely that the GUID is a clean machine. In contrast, a GUID will be assigned a high $\mathcal{R}$ if in the past downloaded enough bad SHA1s, contacted some bad URLs, or had malware processes running. In this case, it is likely that this GUID will access malicious content again in the future.

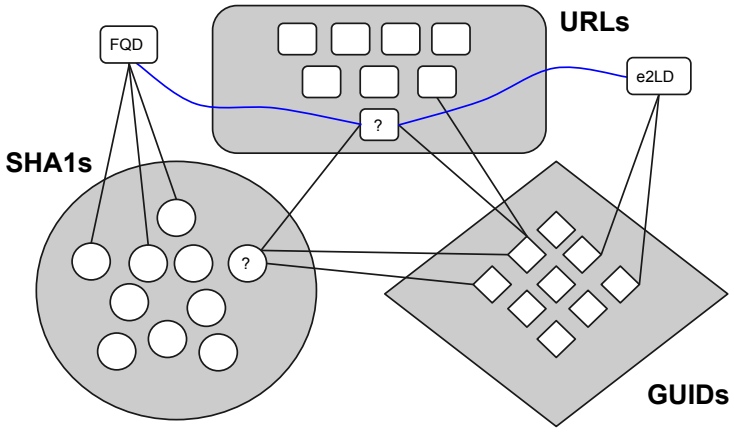
An example of a download behavior graph is shown in Figure 6.2(a) where some of the nodes are labeled (colored nodes indicating good and bad items). In addition, Figure 6.2(b) depicts a URL example in the download behavior graph and two of its components (FQDs and e2LDs). Each of the URL components are also connected to SHA1s and GUIDs.

6.2.4 Behavioral Graph-based Classifier

We use statistical classifiers that harness behavioral patterns among the nodes in the graph as well as the partially available ground truth from known nodes to detect malware file downloads and malicious URLs. More specifically, each layer in the graph (SHA1s and URLs) have their own behavioral classifiers. The classifiers in each layer receive a statistical feature vector as input for an unknown node, n, and output a badness score. The badness score is checked against an automatically learned detection threshold to label n. Each layer's classifier uses a set of statistical features to enable the detection. The classifier features in



(a) A download behavior graph with labeled nodes



(b) A URL example and two of its components

Figure 6.2: An example download behavior graph and components of URLs

each layer could be divided into two groups. A set of behavioral-based features and a set of intrinsic features. Behavioral-based features in each layer are the ones that describe the goodness or badness of related nodes connected to an unknown node. These features can only be computed by using the graph nodes and edges. The intrinsic features, on the other hand, are the features that could be computed without the graph, such as a SHA1's file size.

First, we describe the intrinsic features of nodes for each layer in the download behavior graph.

Intrinsic Features

SHA1s

- Size: The file size of the SHA1.
- Extension: This feature tries to capture malware binary downloads that have an unusual extension, such as `jpg`, to deceive users.
- Lifetime: The time difference between the last time and first time of seen date for a file.
- Prevalence: The number of downloads of a file by unique machines.
- Packed: This feature identifies whether files are packed by a packer or not.
- Signed: This feature identifies whether files are signed or not.
- Number of countries: The number of unique countries that downloaded the file.
- Java or Acrobat Reader downloading process: If the downloading process of a SHA1 is Java (`java.exe`) or Acrobat Reader (`acrord32.exe`) and the download URL is not `oracle.com` or `acrobat.com`, then this feature will be set to true. The reason is

usually the downloads that are triggered by the Java or Acrobat Reader processes are malicious.

URLs

- URL age: This feature determines how long ago the URL was first seen in a time window.
- FQD age: Same as URL age, but for FQD of URLs.
- e2LD age: Same as URL age, but for e2LD of URLs.

Note that we don't have a classifier for GUID layer, however, we use GUIDs as a support layer in our graph to compute the behavioral-based features for the other two layers as it is described in the following section.

Behavior-based Features

The behavior-based features for nodes in a layer of the download behavior graph, e.g. URLs, are computed based on the badness reputation, $\mathcal{R}$, of nodes in the other two layers.

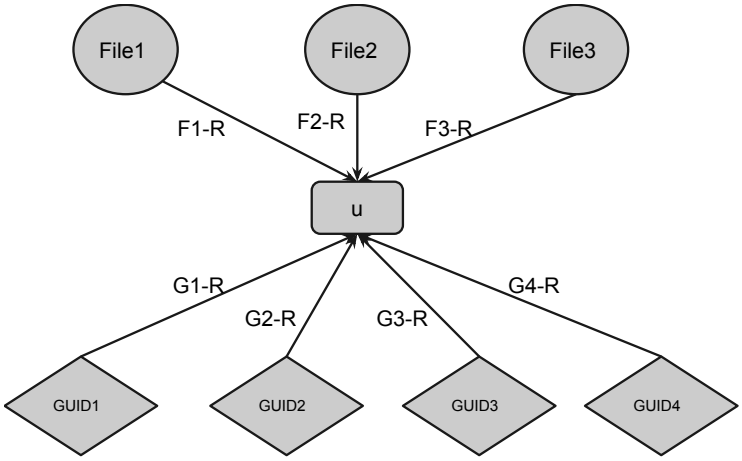
URLs To compute the behavior-based features for a URL, u, we first find the set of all SHA1s and GUIDs in the graph that are connected to u. Assume the set of connected SHA1s to u is S_u with m members and the set of connected GUIDs to u is G_u with n members. Then we compute min, max, average, median, and standard deviation of the following and use these numbers as features of u.

- Badness reputation, $\mathcal{R}$, of all SHA1s for each $s_i \in S_u$ where $i = 1 \cdots m$.
- Badness reputation, $\mathcal{R}$, of all GUIDs for each $g_i \in G_u$ where $i = 1 \cdots n$.
- Number of trusted AVs that labeled each $s_i \in S_u$ where $i = 1 \cdots m$.
- Number of all AVs that labeled each $s_i \in S_u$ where $i = 1 \cdots m$.

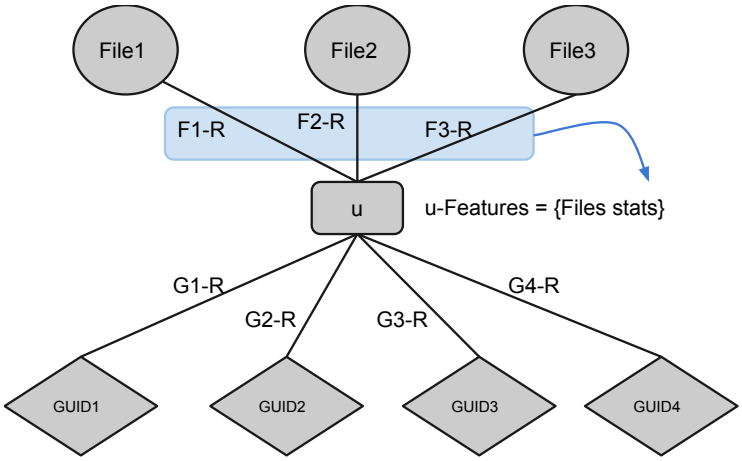
Figure 6.3 shows how the mentioned behavior-based features are computed for a sample URL u that is connected to three files and four GUIDs. Each file and GUID in Figure 6.3 *sends* its $\mathcal{R}$ to u for feature computations. $\mathcal{R}$ of files and GUIDs are shown on the edges.

It is important to note that as mentioned in Section 6.2.2, we can also find the set of all SHA1s and GUIDs in the graph that are connected to different components of u, such as FQD, e2LD, path, etc. For each of these components we also repeat the computation of features. That is we gather $\mathcal{R}$ and AV labels of all SHA1s that are connected to FQD of u, $\mathcal{R}$ of all GUIDs that are connected to FQD of u, and so forth for other components. For a given URL, u, these components are:

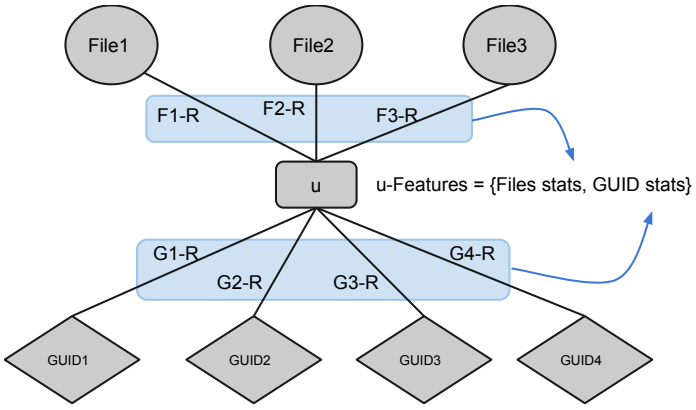
- FQD
- e2LD
- Path
- Path pattern: This is an advanced regular expression for u's path. To generate it, we identify sequences of letters, digits, and hexadecimal numbers in a path, and generalize them while keeping non-alphanumeric characters. For example, if a path is `/sample/123/DA10/install.exe`, then the generated path pattern would be `/S6/D3/H4/S7.S3`, which represents a path that contains a sequence of letters of length 6, a sequence of digits of length 3, a sequence of hexadecimal digits of length 4, a sequence of 7 letters, and a sequence of 3 letters.
- Query string
- Query string pattern: This is defined and generated in a similar fashion as path patterns.
- IP: This is the set of IP addresses that u resolved to during the observation time window.



(a) An example URL, u, connected to three SHA1s and four GUIDs

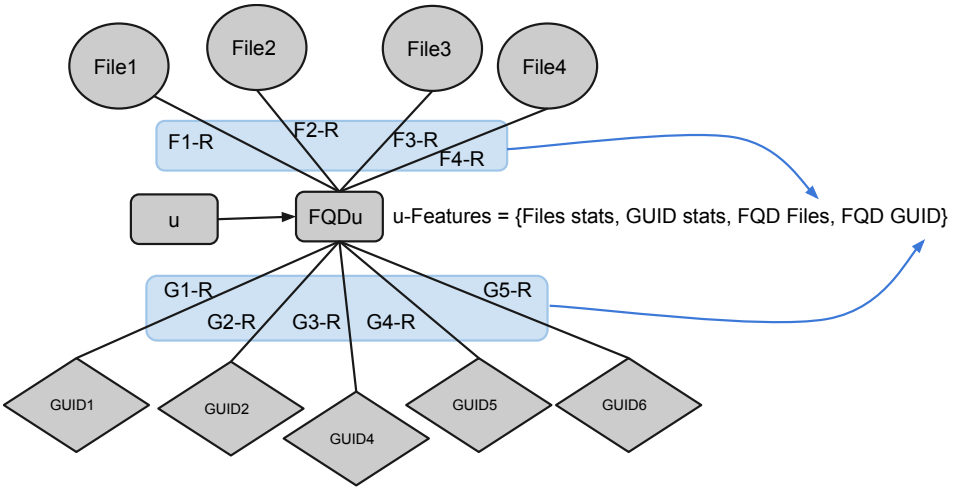


(b) SHA1 behavior-based features of u

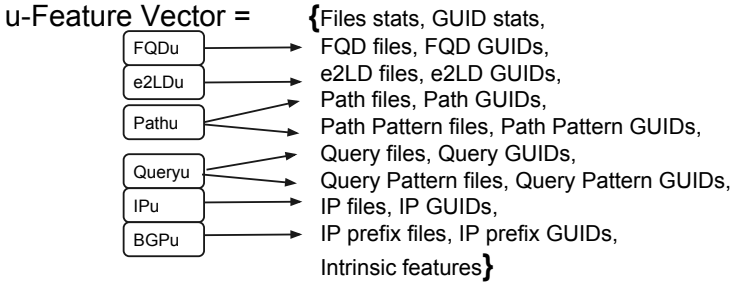


(c) GUID behavior-based features of u

Figure 6.3: Computation of SHA1 and GUID behavior-based features for a URL, u



(a) FQD of u behavior-based features



(b) Complete list of feature groups for u

Figure 6.4: An example of behavior-based feature computation for a URL, u

- IP/24: This is the set of IP/24 networks that u resolved to during the observation time window.

Figure 6.4(a) shows an example of computing features for FQD of u, which is connected to four SHA1s and five GUIDs. Furthermore, the complete list of feature groups for u is shown in Figure 6.4(b). Note that the complete feature vector for u includes behavior based features of SHA1s layer, URLs layer, URL components, and intrinsic features.

SHA1s The behavior-based features of the SHA1s is computed in a similar way as in URLs. For example, for a SHA1, s, we gather all the connected nodes from the URLs and

GUID layers to compute the features. Note that the connected nodes from the URLs layer also include FQDs, e2LDs, paths, path patterns, etc. So part of a SHA1's, s, behavior-based features are actually statistics of connected URL components to s. Thus, the components of the URLs should also have $\mathcal{R}$ values, since these reputations will be used to compute SHA1s behavior-based features. For a given component of a URL, such as path pattern, we average $\mathcal{R}$ of all URLs that share the same component, i.e. the path pattern. Moreover, for those FQDs and e2LDs that are extremely popular, we override the averaged $\mathcal{R}$ with a badness reputation score of 0.5, indicating that these URL components are most likely not malicious, but might not be completely benign either. To be conservative with this rule, we sort the FQDs and e2LDs based on their popularity (the number of unique machines that contact them) and apply the rule to 99-percentile of the sorted list. That is only 0.01% of FQDs' and e2LDs' $\mathcal{R}$ will be overridden by a value of 0.5.

6.3 Experimental Setup

6.3.1 The Data

As discussed in Section 6.2.1, our approach is based on download events which are 3-tuples of <SHA1, URL, GUID>. This data is provided to us through Trend Micro and is collected by monitoring the download events of customers of Trend Micro. This work is based the data that is collected from Dec 18, 2013 through Apr 5, 2014. Note that each record in the data (3-tuples) is also associated with other useful information. The following reports the details of data for each layer of the download behavior graph which are used to compute the features:

SHA1 This layer includes the following information.

- SHA1

- SHA1 location (this filed is anonymized in our dataset)
- SHA1 name
- SHA1 size
- downloading process SHA1
- downloading process location (this filed is anonymized in our dataset)
- downloading process name
- downloading process size
- prevalence
- first seen
- last seen
- list of countries
- packers
- signers
- first submission
- last submission
- known benign (true/false based on a private whitelist of SHA1s)
- AV labels
- last scan time

URL This layer includes the following information.

- URL
- resolved IP
- prevalence

GUID This layer includes the following information.

- GUID
- operating system

each download events also has a timestamp that indicates the time and date of the record.

6.3.2 System Operation

In this section we describe how the behavioral classifiers are trained and how the system operates. This system is intended to provide real-time classification results for SHA1s and URLs observed on daily basis. In other words the system automatically classifies any new items (SHA1 and URL) on the current day harnessing historical knowledge gathered from the previous days in a time window T. The historical knowledge is, in fact, the augmented download behavior graph that associates the items of download events together where all nodes are assigned an $\mathcal{R}$ value. We keep a sliding window over all the download events and set $T = 1 - month$. That is, the beginning of T is set to a month before the start of current day, d_c, for which we are interested to classify any unknown items using the download behavior graph that is generated by considering all download events during T.

For any unknown node in d_c, we compute its feature vector by following the procedure described in Section 6.2.4, and feed the feature vector of the unknown item to the related behavioral classifier, i.e. an unknown SHA1 will be fed to the SHA1s classifier and an unknown URL will be fed to the URLs classifier. The classifier in return produces a score which will be compared against a previously learned detection threshold. If the produced score is above the detection threshold the unknown item will be labeled as malicious. Figure 6.5 shows how does the system operate by keeping a sliding window over all the 3-tuples during T and using them to generate a download behavior graph and train behavioral classifiers.

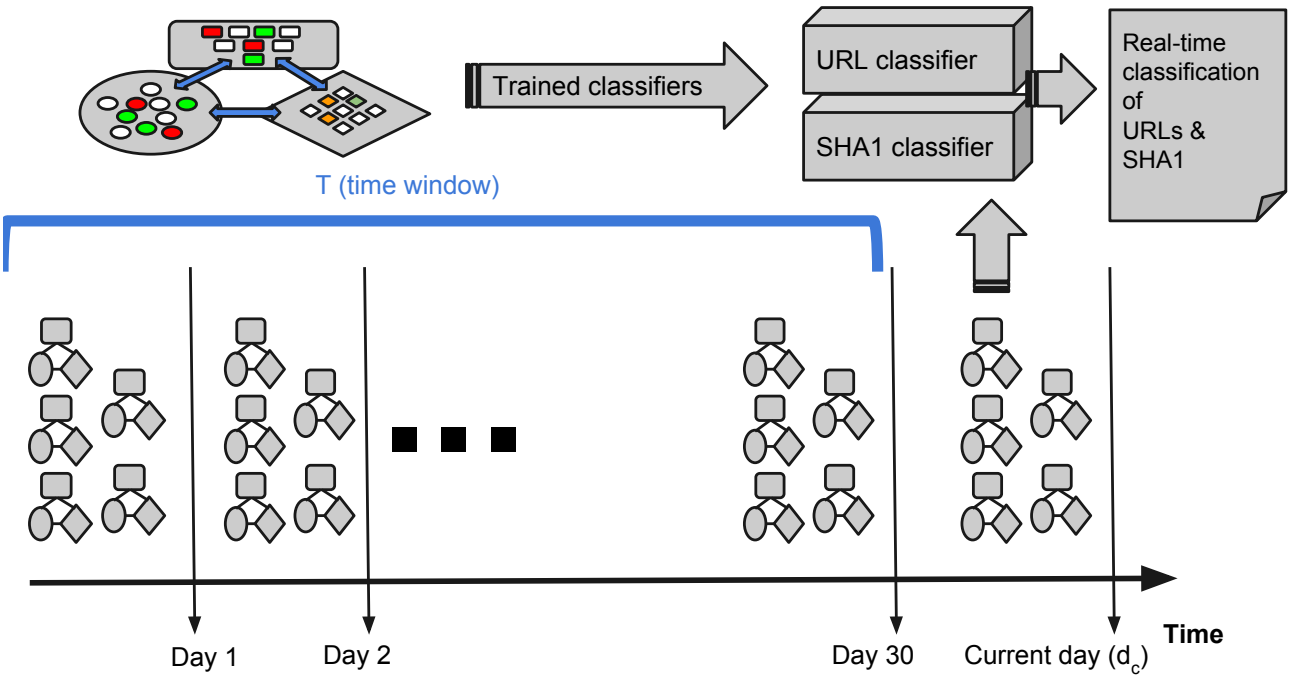


Figure 6.5: System Operation

6.3.3 Training the Classifiers

We train the SHA1 and URL behavioral classifiers using a training dataset of known bad and good SHA1s and URLs. In order to properly train classifiers to be used for detection in current day, d_c, we use the knowledge from previous days during T in the graph. To this end, we identify all known bad and good SHA1s and URLs during T and use them to obtain a labeled training dataset. More specifically, we take every labeled node in the graph, and compute a feature vector for them. For a labeled node n, we consider all of its download events during a training time window, T_{tr}, which starts a month before the last time n was seen. As a result, for every labeled node in the download behavior graph of time window T, a training time window T_{tr} is considered to compute the features.

Computing Behavior-based Features During Training

We need to compute the behavior-based features for SHA1s and URLs fairly that resembles the real-world operation of the system. Especially, part of the behavior-based features for SHA1s and URLs are based on $\mathcal{R}$ of GUIDs connected to them. However, the $\mathcal{R}$ of GUIDs was computed originally according to the SHA1s and URLs that are connected to GUIDs. As a result, if we simply use the assigned $\mathcal{R}$ of GUIDs to compute the behavior-based features for the SHA1s and URLs layer during training, we actually unfairly give the classifier an advantage. To resolve this issue and in order to compute behavior-based features for a labeled node, n, to be included in the training dataset, we recompute $\mathcal{R}$ of the GUIDs connected to n while pretending we don't know the true $\mathcal{R}$ (hence the label) of n temporarily and replace the true value of $\mathcal{R}$ with 0.5. In this way, the true nature of n will not have any effect on $\mathcal{R}$ of the GUIDs. This replicates the real-world operation of the system when an unknown node's $\mathcal{R} = 0.5$ is used to compute reputation of the connected GUIDs. Conservatively, to compute behavior-based features of a URL, u, we actually hide $\mathcal{R}$ of any URLs that share the same e2LD with u from the connected GUIDs.

6.3.4 Statistics of Download Behavior Graphs

Tables 6.1 and 6.2 summarize some simple statistics related to the download behavior graphs generated during different T_{tr} (the last day of T_{tr} is shown in column "Date").

Table 6.1: Sample Statistics of Experiment Data - Nodes Info

Date	SHA1s			URLs			GUIDs		
	Total	**Benign**	**Malware**	**Total**	**Benign**	**Malware**	**Total**	**Vulnerable**	**Clean**
Feb 24	355,011	5,637	2,513	308,736	101,777	33,498	288,970	901	66,201
Feb 26	352,325	5,732	2,438	306,474	100,495	34,213	287,787	852	63,766
Mar 12	310,729	4,775	1,784	271,422	90,050	31,697	252,192	822	64,393

Table 6.2: Sample Statistics of Experiment Data - Graph Info

Date	Download events	Edges
Feb 24	491,761	5,835,537
Feb 26	473,344	5,788,903
Mar 12	410,703	5,063,351

6.4 Evaluation

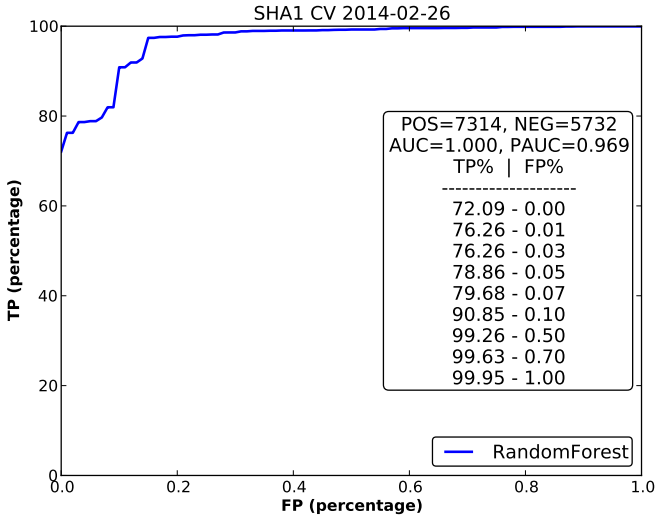
We performed numerous experiments to fully evaluate the system. In this section, first we explain our cross-validation experiment (CV), then we discuss the details of various other testing scenarios, and finally we report the result of analyzing our features.

6.4.1 Cross-Validation

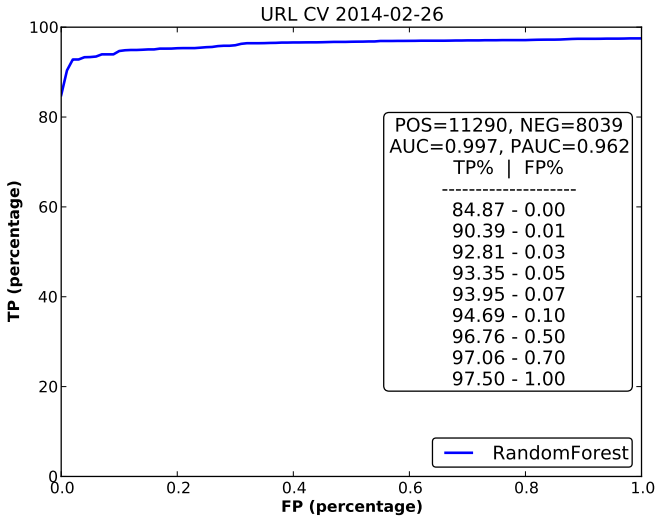
To perform cross-validation, we pick a date, d_{tr} from the data that marks the end of the training time window, T_{tr}. Then we generate a download behavior graph from all the events with timestamps during T_{tr}. Finally, we generate a training dataset using all the known nodes in the graph by following the procedure detailed in Section 6.3.3. The training dataset is used to perform standard 10-fold CV experiments.

Figure 6.6 shows the result of CV for SHA1s and URLs layer during T_{tr} ending on Feb 26. We compute the ROC curve by varying the detection threshold on the classifier's output scores, the area under the curve (AUC), and the *partial* AUC (PAUC). Notice that the PAUC is computed by measuring the area under the ROC curve in a range of false positive between 0% and 1%, and by normalizing this measure to obtain a value in $[0, 1]$. In essence, the PAUC highlights the classifier's trade-off between true positives (TP) and false positives (FP) at very low FP rates. In practice, if PAUC is close to 1, it means that the classifier

yields close to 100% true positives at low false positive rates. The small table embedded in the figures reports various points on the ROCs.



(a) SHA1s CV



(b) URL CV

Figure 6.6: Cross-validation results for SHA1s and URLs layer on Feb 26

6.4.2 Train and Test Experiments

In this section we show the evaluation result of system operation as it was discussed in Section 6.3.2. To this end we have defined a sliding time window, T, which keeps track of all download events that happened during T. We are interested to use trained classifiers based on labeled nodes in the download behavior graph during T to enable detection of new and unknown items on the current day, d_c. First, we discuss how do we prepare our training and test datasets and then present the results.

Training and Test Datasets

The training dataset is generated in a same manner as the training dataset that is used in Section 6.4.1, in which all known nodes during T in the graph will be used for training the behavioral classifiers. To prepare the test datasets and to replicate the real-world operation of the system we proceed as follows. We consider the labeled nodes on d_c that were not present during T for evaluating the classifiers. This ensures that no information regarding the test samples were ever used during training and properly simulates the operative mode of the system where we are only interested to label new and unknown nodes on d_c. We prepare three different test datasets using the labeled nodes on d_c as follows:

New items (I_{tst}) These are labeled nodes that only appear on d_c and not during T.

New events (E_{tst}) These are labeled nodes that are subset of I_{tst} and are part of download events where none of the three entities of the download events were seen during T.

New unknown events (UE_{tst}) These are labeled nodes that are subset of E_{tst} and are part of download events where all the entities of the download event are unknown, except, of course, the labeled node that is used for testing purposes.

Train and Test Evaluation Results

We perform train and test experiments to evaluate the generalization capabilities of our behavioral classifiers. First, we create the three test datasets, I_{tst}, E_{tst}, UE_{tst}, for SHA1s and URLs in the download behavior graph. Then we evaluate the performance of our trained classifiers on the test datasets.

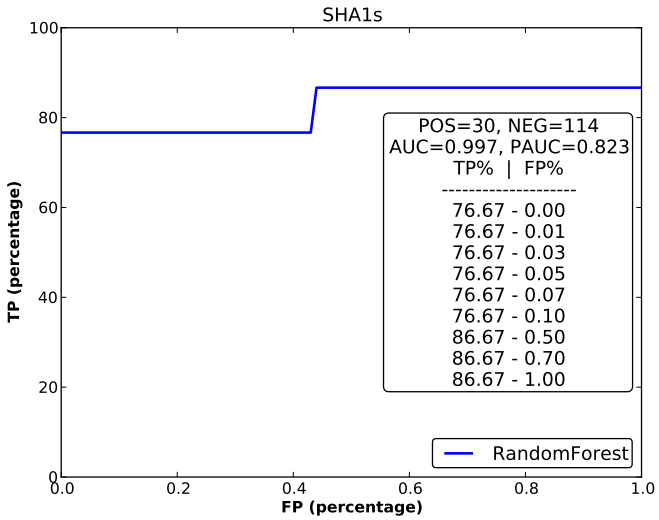
Figures 6.7, 6.8, and 6.9 show the result of train and test on Feb 25 (one day after the CV experiments) for SHA1s and URLs using I_{tst}, E_{tst}, and UE_{tst} datasets.

6.4.3 Early Detection of Malwares

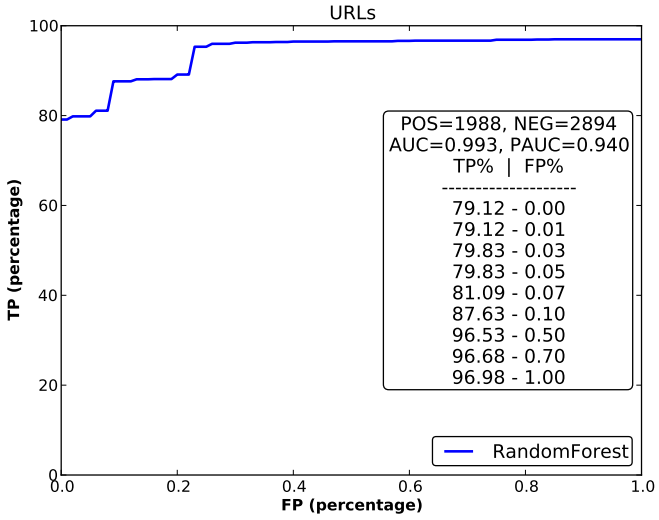
We also performed experiments to measure how early the system can detect malware binaries, compared to antivirus softwares. To this end, we trained a SHA1 classifier and used it to label all files that were unknown to antivirus companies on Feb 27 but later on received a label. Finally, we evaluated the performance of our system on these files. Figure 6.10 shows the result of this experiment.

6.5 Conclusion

In this paper, we presented a novel system that is able of efficiently detecting new malware files and malicious URLs by passively monitoring the download events of users of a famous antivirus company. We developed a proof-of-concept prototype of the system and evaluated it using real-world data. Our evaluation results show that the system can detect malware files and malicious URLs while only incurring less than 1% false positives, respectively. In addition, we showed that the system can detect unknown files many days before they are labeled by antivirus companies.

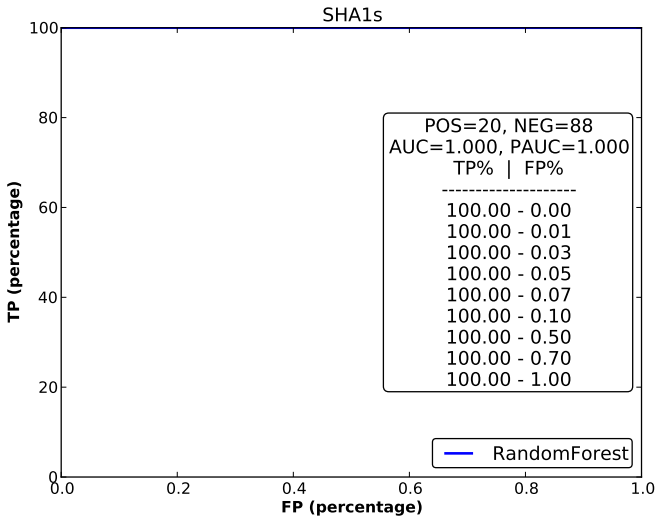


(a) SHA1s

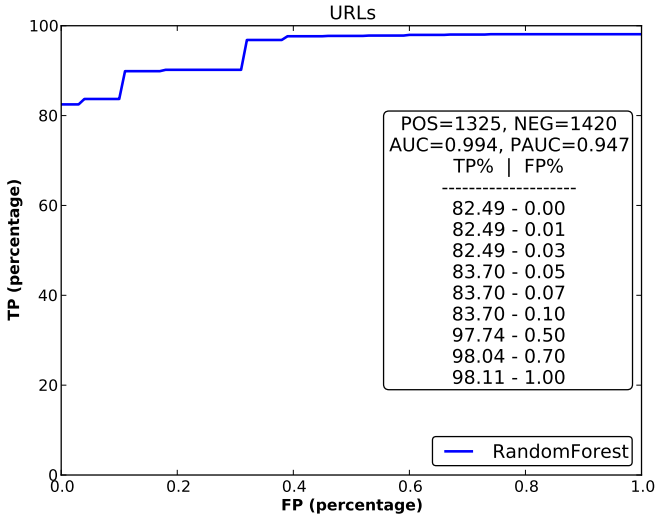


(b) URL

Figure 6.7: Train and test experiment on Feb 26 for SHA1s and URLs using I_{tst}

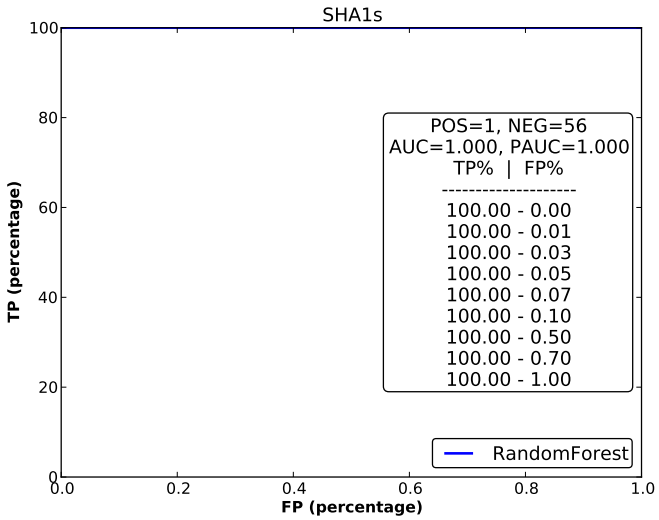


(a) SHA1s

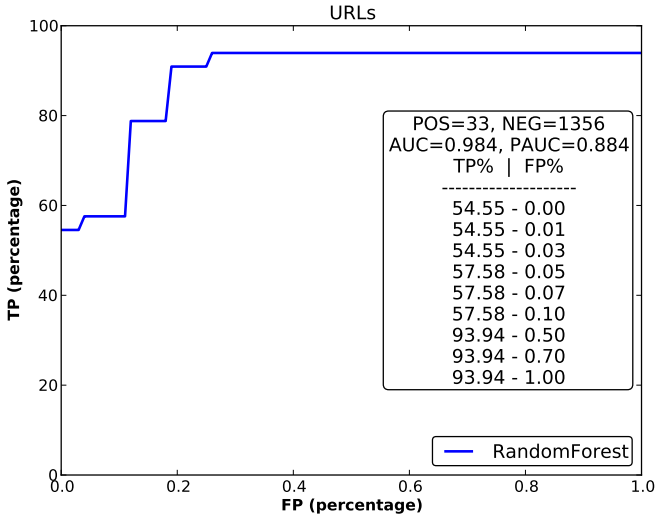


(b) URL

Figure 6.8: Train and test experiment on Feb 26 for SHA1s and URLs using E_{tst}



(a) SHA1s



(b) URL

Figure 6.9: Train and test experiment on Feb 26 for SHA1s and URLs using UE_{tst}

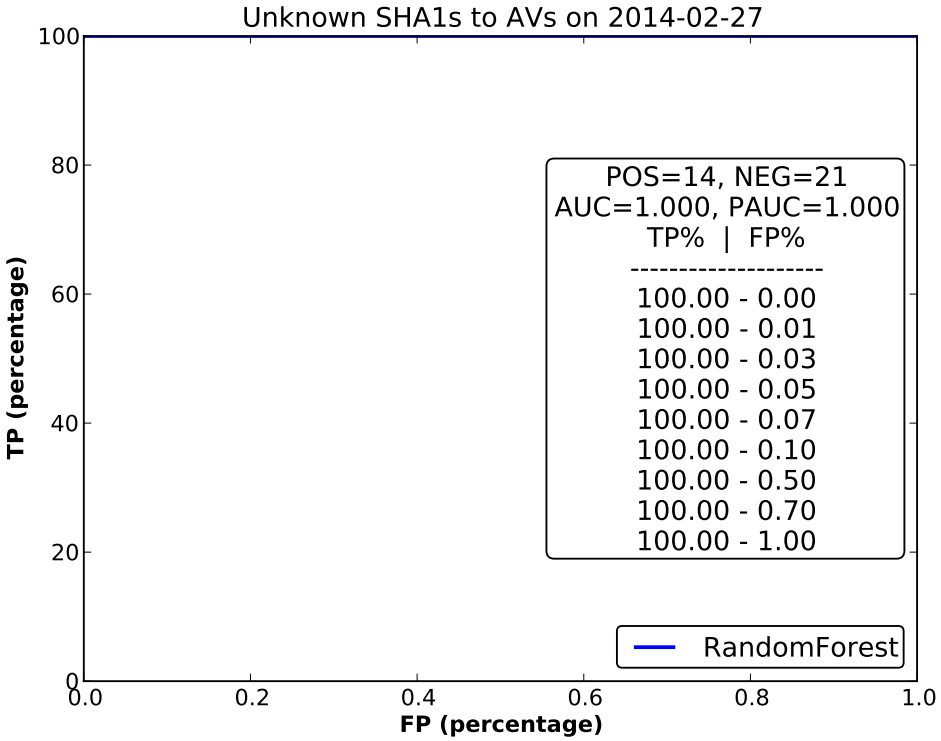


Figure 6.10: Early Detection of Malwares

CHAPTER 7

CONCLUSION

In this dissertation we focused on detection and analysis of advanced cyber threats. Various novel research studies were conducted to help us better understand how Internet miscreants manage their malicious infrastructures. These projects also provide us with state-of-the-art detection technologies to protect our networks against the cyber attacks. Behavioral analysis and detection of these threats was the main focus of our work. More specifically, PeerRush was presented in Chapter 2 where we introduced a novel system for the identification of *unwanted* P2P traffic. We showed that PeerRush can accurately *categorize* P2P traffic and attribute it to specific P2P applications, including malicious applications such as P2P botnets. PeerRush achieves these results without the need of deep packet inspection, and can accurately identify applications that use encrypted P2P traffic. We implemented a prototype version of PeerRush and performed an extensive evaluation of the system over a variety of P2P traffic datasets. Our results show that PeerRush can detect all the considered types of P2P traffic with up to 99.5% true positives and 0.1% false positives. Furthermore, PeerRush can attribute the P2P traffic to a specific P2P application with a misclassification rate of 0.68% or less.

In an attempt to understand how botmasters manage their botnets, in Chapter 3, we studied the lifetime traits of C&C servers in terms of their individual life cycles as well as analyzing their overall lifetime trends by considering groups of C&C domains. Using our

historic DNS data and by employing Hadoop, we showed the type of botnets that existed in the wild. A clustering scheme, based on DTW for aligning C&C domains time series and hierarchical clustering, was discussed that provides a mean for grouping C&C domains together based on the similarity of their lifetime trends.

Our findings and new results in Chapter 3 led to another project which aims to demystify the afterlife of C&C servers, i.e. when they die. As a result, in Chapter 4 we presented SinkMiner, a novel system for the identification of previously unknown and secretive sinkhole IPs that utilizes a large dataset of historic DNS information. We also discussed the advantages and disadvantages that finding sinkholes could present. While some of the use cases we discussed are beneficial, some are malicious. Numerous approaches were also introduced to detect sinkholes IPs. To evaluate the system, we generated a large graph database of IP transitions associated with malicious domains, and showed SinkMiner could mark sinkhole IPs with high confidence and no false positives.

After analyzing the C&C domains characteristics in the previous two chapters, we turned our attention towards detecting C&C servers while they are active to be able to track the relocations of these domains and identify the ones that were unknown previously. So we introduced Segugio, a novel defense system that is able of efficiently discover new *malware-control* domain names by passively monitoring the DNS traffic of large ISP networks. Segugio monitors *who is querying what* to build a machine-domain bipartite graph. First, we label some of the nodes in the graph using prior knowledge of benign and malware-control domains names (e.g., domain whitelists and C&C domain blacklists). Then, Segugio applies a novel belief propagation strategy to accurately detect previously unknown malware-control domains. We deployed Segugio in three large ISP networks, and we showed that Segugio can achieve a true positive rate above 94% at less than 0.1% false positives. In addition, we showed that Segugio can detect control domains related to previously unseen malware families, and that it outperforms Notos [7], a recently proposed domain reputation systems.

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