MORTON: Detection of Malicious Routines in Large-Scale DNS Traffic

Hen Tzaban
Akami Technologies Inc.
htzaban@akamai.com

Yael Daihes
Akami Technologies Inc.
ydaihes@akamai.com

Asaf Nadler
Akamai Technologies Inc. and
Ben Gurion University of the Negev
anadler@akamai.com

Asaf Shabtai
Ben Gurion University of the Negev
shabtaia@bgu.ac.il

Abstract—In this paper, we present MORTON, a system that identifies compromised enterprise devices (bots) without relying on malicious domain name detection. To achieve this goal, MORTON processes DNS requests made by enterprise devices in order to identify routine communication to disreputable host names. With its compact representation of the input data and use of efficient signal processing and a neural network for classification, MORTON is designed to be accurate, robust, and scalable. We evaluate MORTON using a large dataset of corporate DNS logs and compare MORTON to two recently proposed systems aimed at detecting malware communication. The results demonstrate that while MORTON’s accuracy is comparable to that of the two systems for beaconing detection, it outperforms the systems in terms of its ability to detect sophisticated bot communication techniques such as multi-stage channels, as well as its robustness and efficiency. MORTON was also deployed to monitor real-world DNS traffic made by nine worldwide enterprise over the course of 30 days. The real-world results include previously unreported threats, and a low false positive rate, thus demonstrating the effectiveness of MORTON for real-world, unlabeled environments.

Keywords—DNS, PSD, Neural Networks, Botnet

I. INTRODUCTION

Enterprise networks are prominent targets of malware and potentially unwanted application (PUA) downloads [12]. After malware or a PUA has been downloaded and executed on an enterprise device, the device becomes compromised and effectively becomes part of a bot network (botnet) controlled by a remote attacker. The attacker exchanges control messages with the bots it controls through a command and control (C&C) channel, by which the attacker instructs the bots to carry out attacks, such as data theft [22], [23] and DDoS attacks [35].

To protect against these attacks, numerous studies have focused on the detection of bots that attempt to communicate with their C&C, and in many studies this was achieved by processing the domain name system (DNS) protocol logs [7], [4], [14].

The DNS protocol is a core component of the Internet whose primary goal is to translate a host name (e.g., google.com) to its hosting IP address (e.g., 8.8.8.8) [21]. Bots often rely on the DNS protocol to acquire the hosting IP address of their C&C server, because the IP address can be changed whenever the existing hosting becomes blocked or suspect. Modern botnets frequently change their C&C servers’ hosting IP addresses and domain names using techniques, such as fast flux [10], and domain generation algorithms (DGA) [24], in order to avoid being detected and blocked. The fact that in many cases the botnet infrastructure utilizes the DNS protocol has led to extensive research on detecting malicious domain names in DNS logs by tracking patterns of fast flux and DGA techniques, and identifying devices that query these domain names as bots [39]. Despite the fact that the practice of classifying bots based on the DNS protocol through malicious domain name detection has been widely adopted, it fails to detect all botnet communication, and less than 20% of all malicious domain names are reported and eventually added to DNS blacklists [13]. Given this, the primary aim of this study is to explore and evaluate systems for classifying bots in large-scale enterprise DNS traffic that complement malicious domain name detection but don’t rely on it. More specifically, we are interested in system methods that detect bots by identifying routine communication to disreputable host names.

Prior studies [11], [30] that attempted to identify bots without relying on malicious domain name detection focused on a bot communication technique called “beaconing.” Beaconing refers to a bot communication technique in which a recurring message is sent from bots to a constant, predetermined host name (i.e., domain name) so that a bot herder can know the latest time at which a bot was available. This goal is achieved by applying periodicity detection on DNS connection pairs — the outgoing DNS queries from a specific device to a specific host name. Connection pairs that exhibit periodicity are suspected as botnet communication which should be investigated by an enterprise’s CERT team and/or by using automated techniques.
Existing beaconing detection systems for identifying bots suffer from several limitations. First, the number of connection pairs in large-scale enterprises might significantly exceed the number of devices, and therefore, the systems rely heavily on eliminating less suspicious host names prior to classification to provide acceptable performance and a low false alarm rate. Second, the classification of each connection pair often involves periodicity detection algorithms that strongly favor accuracy over run-time due to the underlying assumption that many connection pairs will be eliminated. Lastly, attackers may communicate with their bots through multiple host names, which, despite being recurring, aren’t captured within any single connection pair. One notable example of a bot communication technique that involves multiple host names is multistage channels [19], in which a bot communicates with a set of host names throughout its lifecycle; for instance, the TrickBot and Emotet banking Trojans, which are considered major business security threats [27], [32], [26], make use of multistage channels, thus demonstrating the importance of identifying bot communication that involves multiple host names.

In this paper, we present MORTON: a system for malicious routine detection on large-scale DNS traffic. MORTON analyzes DNS communication logs of enterprise devices in large-scale corporate networks and identifies devices that periodically communicate with a set of disreputable domains. In contrast to prior studies, MORTON does not rely heavily on elimination to reduce the number of connection pairs examined, because it classifies the outgoing DNS requests made by a device directly, rather than indirectly classifying connection pairs. Direct classification of devices as bots has two main advantages. First, direct classification is faster, because it involves less classification tasks (i.e., the number of enterprise devices is significantly smaller than the number of connection pairs). Second, direct classification can be used to detect malicious routines that include multiple host names, such multistage and multihop attacks.

The evaluation in this study compares MORTON with Baywatch [11] and the adaption of WARP [9] to DNS logs as proposed by Shalaginov et al. [30], two recently proposed systems designed to identify malware beaconing. The dataset used in the evaluation consists of real DNS logs that were collected from 16,000 managed devices of eight worldwide corporate networks over the course of a week. The devices in the dataset are assumed not to be bots due to the scarcity of C&C communication on managed enterprise devices. To obtain malicious labels (i.e., bots), we select a subset of the devices in the dataset into which we inject DNS queries of malware beaconing and multistage channel communication. The labeled dataset is used to evaluate three important aspects of bot detection methods: accuracy, robustness to noise, and scalability.

Our results demonstrate that malware beaconing is successfully detected by all of the evaluated methods ($AUC > 0.85$), however multistage channels are detected by MORTON ($AUC > 0.85$) but overlooked by the other two methods ($AUC < 0.72$). We measure robustness using a score that embodies the detection rate as a function of unobserved traffic (i.e., noise). For beaconing detection, MORTON and Baywatch are tied for the highest robustness score, but for multistage channels, MORTON dominates the other methods. Moreover, we found that it only took MORTON 70 seconds to be applied on the entire test set (containing 700,000 connection pairs), a rate which was almost a hundred times faster than Baywatch and an even more impressive thousand times faster than WARP.

MORTON was also deployed to monitor nine large-scale enterprise network environments for a period of 30 days. The results of MORTON throughout the deployment time consist of several case studies that are manually investigated and analyzed by experts. The case studies include a bot that uses a multi-stage channel technique, namely IsErik [1], and other bots, namely Nestha [31] and uBlock [3], that demonstrate the practicality of MORTON in a real-world, unsupervised environment.

We summarize our papers contributions as follows:

1) We introduce MORTON, an accurate, robust, and efficient system to detect routine bot communication in large-scale DNS traffic. MORTON is capable of detecting bot communication techniques that were thus far overlooked by other periodicity detection systems (e.g., multistage channels).

2) We provide a comparison of MORTON and recently proposed methods on a large-scale DNS dataset to evaluate accuracy, robustness to noise, and efficiency.

3) We present the results of MORTON on real-world, large-scale DNS logs that were produced by nine worldwide enterprises over the course of a month. The results include several case studies that are investigated and analyzed by experts to demonstrate the practicality of MORTON in a real-world, unsupervised environment.

II. BACKGROUND

A bot can communicate with its C&C server using various techniques, that may involve either a single host name or multiple host names. A bot communication technique that uses a single host name for C&C communication is easier to set up and less expensive compared to one that uses multiple host names. Traditionally, bot communication techniques have often been taken place through a single host name. Notable examples of such techniques include malware beaconing established for local scheduling [18], scheduled file transfers [20], connectivity checks, and automated exfiltration [15], [22].

The primary drawback of bot communication techniques that use a single host name is their lack of robustness. This is because the single host name is effectively a single point of failure for the botnet infrastructure. If the host name is unavailable for any reason, then the bot herder cannot control its bots. An additional drawback is that a single host
name may also be less covert. For instance, in the case of DNS data exfiltration, every exfiltration message is sent to an attacker host name. Host names that get a large volume of exfiltration messages become more detectable by security systems \[22\]. Therefore, bots that split their volume of DNS exfiltration messages and send them to multiple host names, makes the multiple host names more covert than a single host name. These drawbacks are addressed by bot communication techniques that use multiple host names.

The most well-known use of multiple host names for botnet communication is through domain generation algorithms (DGAs) which have been used by over 40 known botnets \[24\]. DGAs are used by bots and attackers to generate and select the domain names used to establish the C&C communication channel. Most bots that use DGAs generate new domain names on a daily basis \[24\], thus pointing to the importance of detecting bot communication that use multiple domain names.

Multistage channels are another bot communication technique in which multiple host names are used. When a bot is first installed onto a compromised device, the bot is referred to as the first stage of the infection. Throughout the first stage, the bot communicates with its C&C through either a single host name or a multiple host name. However, the host names will change when the first stage bot requires an upgrade. A bot upgrade typically involves communicating with a new host name to download a module that enhances the bot with additional capabilities. The upgraded bot is now referred to as the second stage of the infection. The multistage channel bot communication technique often involves several stages, and therefore, multiple host names to gradually upgrade their bots. The use of multistage channels improves the robustness of a botnet’s infrastructure, because security researchers cannot easily identify the different host names that will be used by a botnet in order to shut down its operation (i.e., preventing bots from upgrading).

Other cases of bot communication techniques in which multiple host names are used include fallback channels \[17\] and multi-hop proxies. In fallback channels, a bot that fails to communicate with its C&C host name attempts to communicate to the host name next in line, based on a prioritized list of host names. Multi-hop proxies is a bot communication technique in which the C&C channel is established through a series of proxy servers that are associated with different host names. The series of proxy servers between bots and their C&C servers prevents security researchers from easily matching a bot its C&C server based on network logs.

Figure \[1\] illustrates bot communication techniques that use a single host name or conversely, multiple host names. The first example (top) includes the malware beaconing technique with a single host name C&C communication. The second example (middle) includes a multistage channel technique in which a different host name is used in each stage. The last example (bottom) includes a DGA-based technique where various different host names are used each day for bot communication.

III. RELATED WORK

The detection of compromised devices over DNS has been thoroughly studied over the last decade. In the most commonly studied approach, malicious domain names are detected in the DNS traffic, and devices that query these malicious domain names are assumed to be compromised \[39\]. Malicious domain name detection is extremely effective against botnets that use DGAs \[4, 24, 33\]. Fast-flux \[7, 10\], and DNS data exfiltration \[22, 23\]. Nevertheless, identifying compromised devices based only on their access to malicious domain names is limited, thus driving further research aimed at detecting compromised devices without evidence about the malicious domain names they access.

A complementary approach, which is the subject of this study, is to explore the periodicity of communication between devices and disreputable host names on the Internet, based on the assumption that bot devices must consistently communicate with their C&C servers.

Hu et al. adapted a general periodicity detection scheme called AUTOPERIOD \[34\] for the network security domain, proposing Baywatch \[11\], a system that detects malware beaconing over the DNS protocol. The Baywatch system works by grouping DNS logs into connection pairs of devices and host names, eliminating pairs with reputable host names, and applies the AUTOPERIOD scheme with additional hypothesis testing to the logs of every remaining pair. The hypothesis testing is conducted by generating $m$ (typically set to 100) random permutations of the DNS logs of every connection pair, so that the periodicity of every connection pair’s DNS logs is evaluated in comparison to its permutations. Generating $m$ permutations for every connection pair and comparing their periodicity to the original connection pair is a quite inefficient task. Therefore, the primary drawback of Baywatch is that unless the elimination of reputable host names dramatically reduces the number of connection pairs, then the system becomes inefficient and can’t properly scale for an increased number of enterprise devices. An additional drawback is that because Baywatch applies periodicity detection for connection pairs, it is inherently less effective against bot communication that involves multiple host names like multi-stage channels, multi-hop proxies, and fallback channels.

Research performed by Shalaginov et al. \[30\] also proposes a beaconing detection system that classifies connection pairs. In contrast to Baywatch which uses hypothesis testing, Shalaginov et al. proposed representing the DNS logs of connection pairs as symbols that match smoothed inter-arrival times (e.g., two messages 10-20 seconds apart would be replaced with the symbol ‘a’). The characters representation enabled Shalaginov et al. to integrate an existing variety of periodicity detection algorithms that identify character repetitiveness \[9, 25, 8\] into their system. Similarly to Baywatch, the system proposed by Shalaginov et al. eliminates connection pairs with reputable host names, but it also goes further and eliminates connection pairs with verbose communication. Accordingly, the system
proposed by Shalaginov et al. is expected to suffer from the same drawbacks as Baywatch (i.e., poor scalability if the number of connection pairs is not dramatically reduced and the inherent inability to identify bot communication that goes through multiple host names), because it indirectly classifies connection pairs.

MORTON addresses the drawbacks of Baywatch and the system proposed by Shalaginov et al. by directly classifying the outgoing DNS queries made by a device rather than an indirect classification of connection pairs. The benefits of direct classification is that its efficiency is independent in the number of connection pairs, and it is more suitable for detecting botnet communication that goes through multiple host names.

In several other studies [6], [2], [5], the authors used periodicity detection to identify bots, but also leveraged additional information that is not available in DNS requests to provide accurate results (e.g., NetFlow logs). Despite reporting accurate results, they are not applicable on DNS logs on their own.

IV. MORTON

A. Overview

MORTON consists of two main phases: data processing and classification. The data processing phase (see Section IV-C) part transforms the input, a time series of outgoing DNS queries, to a power spectral density (PSD) vector that characterizes the intensity of periodic communication at various frequencies. The transformation starts by filtering the time series of DNS queries from reputable host names that aren’t relevant for bot communication. Then, the filtered time series of DNS queries are counted based on equal-length time frames. The data processing ends by applying discrete Fourier transform (DFT) on the DNS query counts to produce the PSD vector. In the classification phase a neural network classifies the PSD vector based on whether the device that made the DNS queries is a bot or not.

B. Definitions

An outgoing DNS query \((Q)\) that is made by internal device \((D)\) to a host name \((H)\) at time \((T)\) is represented as a tuple that appears in Equation 1.

\[
Q = < D, H, T >
\]

The device \(D\) can be represented using a string ID (e.g., “b1ec3636” or “cbb6d92”). The host name can include the DNS resource record type (see [21]) because a different resource record type can be regarded as an entirely different service from a bot communication perspective. For instance: a bot communication that uses the DNS query “example.com., A” is not necessarily related to a DNS query “example.com., MX” that is made by legitimate services to learn about e-mail services. The time \(T\) can be represented in various forms, but for consistency, we refer to it as Unix time in milliseconds, which is defined as the number of milliseconds that have passed since January 1, 1970 [37]. For example, the tuple

\(< b1ec3636, \text{“example.com., A”}, 159593003000 >\)

represents an outgoing DNS query of type A to resolve the host name “example.com.” at time 159593003000 (July 28, 2020).
The input to MORTON is a series of DNS queries that were made by a specific device \( (D_i) \) within a predetermined time frame that starts at \( T_s \) and ends at \( T_e \). The input is formally defined in Equation 2:

\[
I_{(D_i,T_s,T_e)} = \{ Q \mid (D = D_i) \land (T_s \leq T < T_e) \}
\]  

In this manner, MORTON can process and classify whether a device “b1ec3636” is a bot or not, based on its series of outgoing DNS queries, as they appear in the example below:

\[
\{ <b1ec3636, \text{"example.com."}, A^\prime, 1595933003000 > \}
\]

\[
\ldots
\]

\[
\{ <b1ec3636, \text{"example.net."}, AAAA^\prime, 1595933005301 > \}
\]

C. Data processing

1) Filtering: MORTON’s input might contain a large number of queries to host names that are assumed to be trusted. Accordingly, the goal of the data filtering part is to remove queries to reputable host names from the input in order to decrease the processing time and improve the accuracy. These benefits make data filtering processes very common in methods that attempt to detect malicious routines [11], [30].

The data filtering process that is applied in MORTON is standard and is based on the ideas of global and local reputation ranking that appear in [11]. Global reputation dictates that a host name is reputable, and therefore should be trusted, if it is listed in publicly available lists that are often associated with benign host names (e.g., the Alexa Top 1M list). Local reputation complements global reputation by dictating that the host names are also regarded as trusted if they are queried by a sufficiently large portion of devices in the network.

We define a filtering function \( C \) that outputs a true value indicating if a \( Q \) should remain. The filtering function respects both the global reputation and the local reputation using special parameters, \( \phi_G \) and \( \phi_L \). \( \phi_G \) defines the number of highest-ranking Alexa top 1M domains that are regarded as trusted. \( \phi_L \) defines the minimal rate of querying devices to consider a host name as trusted. For instance, if \( \phi_G \) is set to 100,000 and \( \phi_L \) is set to 0.3, then host names that are ranked below 100,000 in the Alexa top 1M list or are accessed by at least 30% of the devices within the observed time frame are regarded as trusted and are filtered away from the input. Both \( \phi_G \) and \( \phi_L \) are listed as MORTON’s parameters in Table I.

Formally, the filtering is applied to the input using the filtering function as defined in Equation 3 which results in a filtered input.

\[
I'_{(D_i,T_s,T_e)} = \{ Q \mid (D = D_i) \land (T_s \leq T < T_e) \land (C(Q) \text{ is True}) \}
\]  

2) DNS Query Counts: The DNS query counts part transforms a filtered input, a series of outgoing DNS queries, into a series of DNS queries count that are associated with equal length time frames. Counting results in a loss of information, but it has several important advantages. First, the resulting counts are dramatically smaller than the filtered input, thereby reducing the processing time. Second, counting reduces the size of the data to a constant size, regardless of the filtering...
function configuration, therefore allowing MORTON to efficiently process a large number of disreputable host names. Lastly, an aware bot herder can design its bots so they wait for a random period of time before every communication so as to appear less periodic and evade periodicity detection. The use of counting results in discrete time frames (e.g., hourly query counts) which limits an aware bot herder in evading detection. For instance, an aware bot herder that knows MORTON was configured to use hourly time frames, would have to choose between communicating within an hour of the communication time and becoming detected, or delaying communication by between communicating within an hour of the communication

Formally, the counting of the filtered input is defined in Equation 4, where \( t_i \) represents the number of overall DNS queries that were made in the \( i \)-th time frame, and \( N \) is the overall number of time frames of length \( \lambda \) seconds.

\[
T_{(D_i,T_s,T_e)} = (t_1, t_2, t_3, \ldots, t_i, \ldots, t_N)
\]

MORTON can be configured to use different values of \( N \) and \( \lambda \) (see Table I). Lower \( \lambda \) values will result in shorter time frames that provide better data granularity for accuracy, while higher values will result in longer time frames that provide greater efficiency through a smaller representation. Higher \( N \) values will result in the system inspecting more time frames, thus making it more sensitive to detections that occur over a period of time, but less efficient, because the input becomes larger.

The following example demonstrates how the DNS query counts are computed. Consider an enterprise that decides to deploy MORTON to produce hourly classifications. In this case, the enterprise will use time frames of one hour (i.e., \( \lambda = 3600 \) seconds) and the total number of time frames for one week (i.e., \( N=168 \)). Every hour, the series of DNS queries that are performed by each user during the last week are counted into \( N = 168 \) time frames of \( \lambda = 3600 \) seconds, that represent the number of DNS requests made to disreputable host names. The resulted DNS query counts will be of the form:

\[
(t_1 = 0, t_1 = 4, t_2 = 0, \ldots, t_{167} = 4)
\]

For brevity, for the remainder of the paper we refer to the DNS query count \( T_{(D_i,T_s,T_e)} \) simply as \( T \).

3) Power spectral density (PSD) computation: A power spectral density (PSD) vector is a common data representation form in the field of periodicity detection. The PSD vector is defined as the squared magnitude of the discrete Fourier transform (DFT) coefficients for a given input. PSD vectors are used to estimate the spectral density within a time series signal, which later allows classifiers to more easily identify periods in which a repetitive behavior takes place. Intuitively, a PSD vector can be thought of as the “intensity” of the rate of events at particular time frequencies. Accordingly, a frequency entry within the PSD vector that has a high value indicates that a routine event with that frequency.

First, DFT is applied to the DNS query counts \( T \) as shown in Equation 5.

\[
DFT(T, k) = \sum_{n=0}^{N-1} t_n e^{-j2\pi \frac{k}{N}}
\]

where \( k = 0, 1, \ldots, N - 1 \).

By definition, every PSD vector entry (frequency) is defined as described in Equation 6.

\[
F_i = \| DFT(T,0) \|^2
\]

resulting in a PSD vector of the form 7.

\[
PSD(T) = (F_0, F_1, \ldots, F_{N-1})
\]

For example, if the number of time frames is \( N = 168 \), then the output PSD will have \( \frac{N-1}{2} = 83 \) entries, as shown below:

\[
(F_0 = 0.145, F_1 = 0.03, \ldots, F_{82} = 0.01)
\]

4) Normalization: The values of the PSD vectors are unbounded and of different magnitudes, and therefore they must be normalized prior to classification. The normalization of PSD vectors in MORTON scales the amplitude of every frequency to a value between zero and one, which is proportional to the original values that appear in the training set. The resulting normalized PSD vector is guaranteed to maintain the same “distribution of energy” for every frequency and a consistent scale for classification. The normalized PSD vector is henceforth referred to as \( \overline{PSD}(T) \).

| Parameter     | Description                | Possible Values                        |
|---------------|----------------------------|----------------------------------------|
| \( \phi_C \)  | Global reputation max rank | Integer between 0 and 1,000,000.       |
| \( \phi_L \)  | Local reputation percentile| [0,1].                                  |
| \( \lambda \)  | A time frame length in seconds | Non-negative integer                |
| \( N \)       | Number of time frames      | Non-negative integer                |

D. Classification

MORTON trains a vanilla feedforward neural network; this type of neural network is commonly used for classification tasks with well structured input due to its performance. The feedforward network parameters (\( \theta \)) are learned in advanced, and the network is applied as a function (\( F \)) on the normalized PSD to output a classification result (\( Y \)), as specified in Equation 8.

\[
Y = F(\theta, \overline{PSD}(T))
\]

The result (\( Y \)) is a continuous value ranging from zero to one, where higher values indicate greater certainty that the input series of DNS queries was made by a bot or not.
TABLE II: Examples of log lines

| DNS Query Timestamp | Device     | Host               |
|---------------------|------------|--------------------|
| 1585633874000       | b1ec3636   | google.com, A      |
| 1585633874013       | b1ec3636   | malicious.net, A   |
| 1585633874024       | cbb62d92   | facebook.com, AAAA |

V. Evaluation

A. Dataset

The dataset used for the evaluation is based on real DNS logs from Akamai’s DNS traffic that cover eight enterprise networks. The DNS logs are all from the week beginning January 1, 2020, and include 16,000 devices used in a variety of time zones. Every DNS log line matches the input format that is defined in Section IV-B, using three fields: the DNS request timestamp, a unique identifier that is associated with a device, and a host name. The DNS request timestamp is represented in epochs using a millisecond resolution. The unique identifiers for devices are provided using a client-side agent that is installed on the devices, thus guaranteeing that every outgoing DNS query is correctly associated with its sending device. The host name is listed alongside the DNS resource record type (e.g., a DNS request for the google.com IPv4 record will be listed as “google.com, A”). Three examples of log lines in the dataset can be seen in Table II.

The dataset is supervised, and therefore every device must be labeled as either a benign device, or alternatively, a bot. Our main assumption is that managed enterprise devices are rarely part of a botnet. Therefore, we label all of the devices in the dataset as benign, except for a subset of devices (5%) into which we inject malicious bot communication traffic.

The malicious bot communication traffic that was injected is characterized using three variables:

1) The time interval (in minutes) between consecutive malicious queries,
2) The number of DNS queries that are sent in every interval, and
3) The malicious host name (or names) to which the DNS queries are sent.

The time interval is an integer number, and it is sampled uniformly with possible values ranging from 120 minutes (i.e., communicate every two hours) to 720 minutes (i.e., communicate every 12 hours). The number of queries made for each interval is also sampled uniformly with values ranging from 5 to 15. For the beaconing detection experiment, the malicious domain name is set to a single host name that doesn’t appear in the dataset. For the multistage channel detection experiment, we compile a set of six host names that do not appear in the dataset. Then, we select the number of host names to be used (between three and six), and for every DNS query we select random host names from the set.

The 16,000 devices are split into a training set of 10,000 devices and a test set of 6,000. Both the training set and the test set include a similar proportion of malicious devices (5%). Dataset filtering is performed using the following configuration: $\phi_G = 500,000$ and $\phi_L = 0.03$, i.e., only the top 500,000 host names on the Alexa Top 1M list and host names that are queried by at least 3% of the devices throughout the past week are assumed reputable. This configuration is conservative in the sense that the Alexa Top 1M list is not free of malicious domains, especially its lower ranked host names [29], and therefore it cannot be fully trusted. The dataset is described in Table III.

B. Evaluation environment

The entire evaluation is conducted on a cloud computing instance (AWS EC2 c5.x18 xlarge), with extensive computational and memory resources, to correctly simulate the hardware of a large-scale enterprise network. The specification of the instance includes 72 virtual CPUs (vCPU), 144 GB of memory, and a 550GB EBS disk.

C. Methods compared

The experiment compares the following systems: MORTON, Baywatch [11], and WARP as proposed by Shalaginov et al. [30] on detecting beaconing and multistage channels. The Baywatch system in particular is evaluated using two different settings, namely a fast setting and an accurate setting, to account for the range of achievable results by the system. The comparison of the systems focuses on the accuracy of detection, robustness to noise in the data, and the run-time performance.

1) MORTON: The neural network architecture with which MORTON performed best consists of the following:

1) An input layer with a number of units to match the number of PSD values,
2) A hidden layer with 25 neurons with a ReLU activation function and L2 regularization,
3) A hidden layer with 55 neurons with a ReLU activation function,
4) A hidden layer with 25 neurons with a ReLU activation function, and
5) A output layer with a sigmoid activation function.

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5) A output layer with a sigmoid activation function.

TABLE III: Dataset properties

|               | Training set | Test set |
|---------------|--------------|----------|
| # Devices     | 10,000       | 6,000    |
| % Bot class   | 5%           | 5%       |
| # Connection pairs | 1,149,635 | 743,586  |
| # Unique domain names | 736,181   | 526,346  |
| # Worldwide corporations | 8         | 8        |

1 https://aws.amazon.com/ec2/instance-types/c5/
Our evaluation and the results presented are based on this architecture.

The training of the neural network is conducted with a dropout setting on the dense layer with a rate of 0.1; this is done to regulate the training so it will use all of the neurons and achieve its optimal performance. Early stopping is defined so that if the validation loss remains roughly unchanged for five consecutive epochs, the training stops. The Adam optimizer is used to minimize the binary cross-entropy loss.

2) Baywatch: The Baywatch system has exactly two parameters, $C$ and $m$, both of which are explained below, because they significantly affect the trade-off between the run-time of the system and the desired level of confidence. The $C$ parameter is a continuous value between zero and one, and it is used to indicate the level of certainty. The $m$ parameter is a discrete positive value that is used to construct a baseline of $m$ non-periodic signals, based on which the system is able to establish the significance of the periodicity signal observed. For every connection pair between a device and a queried domain name, Baywatch generates $m$ random permutations of the input time series. Then, if the maximal value of the PSD belonging to the original time series is within the $C$ percentile of the maximal value of the PSD belonging to the $m$ random permutations of the time series, the connection pair of the machine and queried domain name is classified as a pair that is engaged in a periodic communication channel. Based on this behavior, assignments of higher $m$ values would produce a more robust baseline to assure more accurate results while increasing the run-time of the overall autocorrelation function (ACF) linearly. Accordingly, the evaluation includes two different settings to best reflect Baywatch’s performance: an accurate setting ($m = 100$), as was evaluated in the original study, and a fast setting ($m = 10$). For each of these settings, we evaluate different confidence values that are commonly used for a low false alarm rate in security systems, i.e., $C = 0.9, 0.99, 0.999$. For the sake of brevity, we henceforth refer to the two settings as Baywatch-10 and Baywatch-100.

3) WARP: Shalaginov et al. presents a general system for periodicity detection. Within the general system, connection pairs of internal devices and external host names are extracted and processed to return the length of the minimal periodic cycle. Processing specific connection pairs consists of computing the time difference between consecutive DNS queries, smoothing the time difference, and replacing the smoothed time difference values with unique symbols that form a string. The string formed is provided to an underlying periodicity detection algorithm that process strings. Shalaginov et al. propose four potential underlying periodicity detection algorithms, and our implementation relies on one of them, namely “WARP” [9]. The other periodicity detection algorithms that were mentioned in the study require parameter settings that were not provided in the paper; WARP is the only algorithm that we could guarantee would perform similar to the version evaluated by Shalaginov et al.. Our beaconing and multistage experiments consist of a repeating query with a constant inter-arrival time. Therefore, if the returned minimal periodic cycle is one, we classify the connection pair as periodic, because all time differences between consecutive queries are equal after smoothing. Otherwise, we classify the connection as non-periodic. The smoothing variance is defined by a parameter $s$, so that the modulo of the time difference from $s$ is removed. Accordingly, higher $s$ values make the classification more sensitive (i.e., having a higher recall score, but a lower precision score).

D. Evaluation results

1) Classification accuracy comparison: Our first experiment deals with the accuracy of the evaluated systems by analyzing receiver operating characteristic (ROC) curves that describe the systems detection rates on the test set. The ROC curves for detecting beaconing and multistage channels are
presented in Figure 3. The graphs are analyzed from two perspectives:

1) The area under the curve (AUC), which provides a single scalar value to represent the trade-off between the false positive rate (FPR) and true positive rate (TPR);

2) The TPR for a fixed and low FPR (1%), which is often the setting in automated cybersecurity systems in order to reduce the number of false alarms that must be investigated by an enterprise CERT.

For beaconing detection, WARP is the most accurate system (AUC=0.97), followed by MORTON (AUC=0.85) and Baywatch-100 (AUC=0.85), and finally by the fast Baywatch-10 (AUC=0.64). The AUC scores show that all systems are capable of detecting beaconing with high accuracy, with WARP performing best. Despite that, for a low FPR value of 1%, only MORTON was able to produce adequate results with a TPR value of 77%, compared to the rest of the systems that weren’t able to produce any detection with the low FPR value. For Baywatch, setting the confidence parameter C to 1.0 resulted in a minimal FPR of 14.4%, thus reflecting Baywatch’s lack of sensitivity, which is addressed by the authors who mention the need to apply additional methods to reduce the FPR further. For WARP, the lowest s value of zero (i.e., highest confidence) results in a minimal FPR of 3%, which is more sensitive than Baywatch but less sensitive than MORTON. Effectively, the automated use of these systems to detect beaconing with an acceptable FPR of less than 3% can only be achieved by either using MORTON on its own or by applying one of the other two methods with additional filtering to reduce the FPR after detection.

For multistage channel detection, MORTON (AUC=0.85) is the most accurate system; it is followed by the accurate Baywatch-100 (AUC=0.72), Shalginov-WARP (0.58), and the fast Baywatch-10 (0.56). Similarly to the beaconing experiment, systems other than MORTON weren’t able to produce any detection when configured to a low FPR value of 1%. The lowest possible FPR value for which the system produced a detection were FPR=14.4% for Baywatch and FPR=3% for WARP. In contrast to the beaconing accuracy test, MORTON dominates the accuracy evaluation for multistage channels, with higher TPR values for every FPR value, thus making MORTON more suitable for the detection of multistage channels in general and for automatic detection in particular.

2) Robustness: Bots that are configured to periodically communicate with their C&C server aren’t always able to do so. For instance, the act of turning off a compromised device will immediately prevent an installed bot from communicating. Accordingly, an important aspect to consider when evaluating bot communication detection systems is their ability to detect bots even when some of their routine communication logs are lacking. An additional important example in which the routine communication may be lacking is due to an attacker that attempts to evade detection systems by preventing an install bot from sending some of the communication.

We refer to this aspect as the robustness of a periodicity detection method. To evaluate the robustness, we create an experiment that simulates dropped communication and define a new metric that we refer to as the robustness score, which is explained in detail below.

The experiment for evaluating robustness draws similarity to the experiment for evaluating accuracy except for two modifications. First, we define the notion of a drop rate – the rate of malicious DNS queries to drop from the dataset. This experiment was conducted with 10 different drop rate values ranging from 0% (i.e., no drop) and increasing by 10% until a 90% drop is reached. Second, we define a acceptable false positive rate that applies for all of the systems, which is crucial for the detection rate to be comparable. The acceptable false positive rate is determined to be 0.144, because it is the lowest FPR value for which all of the systems are capable of detecting at least one bot in the test set (see Figure 3). Eventually, the rate of bots that were successfully detected while respecting the acceptable FPR, are reported as the detection rate.

The experiment results in a function that maps drop rate values to detection rates, which is henceforth referred to as the robustness function. The area that is captured between the robustness function and the x-axis is referred to as the robustness score. The robustness score is a scalar that describes the level of robustness provided by a system that detects periodic signals. The score ranges between zero and one, and a perfect score of one signifies a system with a perfect detection rate when dealing with varying rates of dropped traffic. Accordingly, the evaluation of robustness deals with the robustness score of the different systems for both beaconing and multistage channels.

The robustness scores of all of the systems evaluated are presented in Figure 4. For beaconing detection, the highest robustness score (0.697) was achieved by both MORTON and Baywatch, whereas WARP received a score of 0.402. For multistage channels, MORTON (0.697) performed best and was followed by Baywatch (0.393) and WARP (0.211).

3) Run-time performance comparison: To better understand the relationship between the number of devices in the dataset and the run-time performance of the compared systems, we select subsets of the original dataset where the number of machines varies. This sampling results in 11 subsets of the original datasets with $2^1,2^2,2^4,...,2^{10}$, and $2^{11}$ machine IDs that were randomly selected from the original dataset. The systems compared are then implemented on each of the datasets sampled to estimate the total number of seconds required for bot communication detection. The results are portrayed in Figure 5. The largest sample consisted of 2048 devices, and slightly more than 700,000 connection pairs. For that amount of devices and connection pairs, MORTON was the fastest at bot communication detection. When MORTON was applied on the entire test set, it took slightly more than 70 seconds to complete. The fast Baywatch-10 took 16 minutes.
(100x), the accurate Baywatch-100 took almost three hours (1000x), and WARP took almost 24 hours (10000x). The number of devices within a large enterprise network can be significantly larger than 2048 devices thus resulting in even greater differences.

4) Summary of results: A summary of the evaluation results is presented in Table IV.

VI. REAL-WORLD ANALYSIS

A. Overview

In this section, we present the results of MORTON on real-world, large-scale DNS logs that were produced by nine worldwide enterprises over the course of a month. The results are manually validated by cybersecurity experts who analyzed the data to validate MORTON’s practicality in a real-world, unsupervised environment.

The setup for the deployment consists of a neural network architecture and training data similar to that described in Section V. Throughout the deployment period, MORTON was applied on DNS logs that were collected from Akamai servers who monitors DNS traffic for large enterprise networks. Because of the unsupervised nature of the data (i.e., unlabeled) cybersecurity experts needed to validate the data. A manual validation requires extensive time, and therefore, the experts were asked to validate only a limited sample of the DNS logs. The limited sample consists of DNS requests obtained from 10,000 devices that belong to nine large enterprise networks. All of the DNS requests in the sample were made on 30 days starting at May of 2020. The size of the sample is sufficiently large to capture the threat landscape, while also being manageable for manual analysis.

The analysis methodology relies on a majority vote by a team of three cybersecurity experts. Each of the experts was provided with a set of enterprise devices that were classified as bots by MORTON within a specific week. The experts had access to the set of outgoing DNS queries made by the bot-classified devices for that week. Based on the logs, as well as open-source tools (e.g., VirusTotal), an expert had to label each classified device as either:

1) A bot, which is verified as malicious.
2) A bot, which is unverified as malicious.
3) Not a bot (i.e., a false positive).

Manual analysis of cybersecurity data presents challenges due to incomplete and unavailable data. We therefore anticipated cases in which an expert would be unable to make a conclusive classification. False positives in security systems are often
considered to have a worse impact compared to false negatives, and therefore, we asked the experts to label a device as a non-bot in a case of uncertainty. This decision guarantees that the false positive rate is overestimated, rather than underestimated.

MORTON identified an average of 36 of the 10,000 (0.36%) devices as bots each week. The vast majority (61.1%) of the classified devices were verified as malicious bots; this was followed up by bots that could not be verified (32.65%). The effective false positive rate, i.e., rate of non-bot detection was 2.25 out of 10,000 devices per week on average (0.03%). The real-world results are summarized in Table V.

### B. Case studies

1) uBlock: One of the verified malicious bots detected was uBlock [3] [33], which is a malicious add-on for the Chrome browser that is disguised as an ad blocker. uBlock uses code that was cloned to mimic a legitimate ad blocker and includes a malicious backdoor for cookie stuffing [36], which is a technique used to commit ad fraud. The outgoing DNS traffic of uBlock routinely acquires the hosting IP of its servers by using the DNS protocol. After that, uBlock sends a heartbeat (beacon) to its servers using an HTTPS GET request to various URLs that start with “https://ublockerext.com/heartbeat.” uBlock uses a single host name (ublockertext[.]com) with whom it communicates every 15 minutes (see Figure 6). The uBlock case study demonstrates MORTON’s ability to identify bot communication to a single host name, as shown in Section V.

2) Neshta: Neshta is spyware that connects to a remote server in Russia and uses HTTP POST to upload information gathered from the infected system, such as currently installed applications, running programs, and SMTP email accounts [31]. The experts identified a device as a Neshta bot after observing routine communication to the host name “oneclient[.]sfx[.]ms” (see Figure 6). The host name is legitimate and owned by Microsoft. However, only one other device issued periodic DNS requests to this host name, in contrast to 1500 other devices within the same enterprise network that queried the host name on the DNS but did not do so periodically. In a more in depth analysis of Neshtas operations, our experts learned that devices infected with it are very likely to be performing routinely beaconing to the CNC.
hosts, therefore, the communication to “oneclient[.]sfx[.]ms” is assumed to be a connectivity test performed by the bot. The Neshta case study demonstrates the importance of processing a large number of disreputable host names, which is limited in systems that indirectly classify connection pairs rather than directly classifying devices as proposed in MORTON.

3) IsErik: IsErik [1] is a sophisticated and modular adware (sometimes referred to as DealPly or ManageX) that uses a multistage channel to communicate with its servers. IsErik’s infection process involves the automated and periodic execution of code through WScript on a victim device. The code execution includes communication to a variety of host names and is described in a special report issued by security vendor, Bitdefender [1], as well as a report issued by Trend Micro [28]. The latter even refers directly to the constant time intervals between consecutive communication, which is the same signal that MORTON targets to identify bots. The expert that examined MORTON’s detection of IsErik identified host names that were publicly reported by the security community in the VirusTotal platform. Notably, the expert also identified host names that were accessed periodically but never reported publicly. A time series plot of the DNS queries made by IsErik to its servers is presented in Figure 7. The IsErik case study demonstrates the importance of the ability of a bot detection system to detect routine communication to multiple host names, rather than a single host name.

Exploring the falsely detected devices uncovered two trends. The first trend has to do with the false detection of a periodic routine which was labeled as ”Not a bot.” This type of false positive could be automatically removed by a post-detection filtering mechanism that would remove detections for which a greedy algorithm would not have been able to retrieve the periodicity from the original signal, based on the detected interval. Such an algorithm could be tweaked with thresholds to minimize the false positive rate as desired. The second trend has to do with the correctly detected bot activity that is unverifiable as malicious and therefore would be considered a false positive as a security threat. In this setting, where a detection is made from the network’s point of view rather than the endpoint’s perspective, it is significantly harder to trace back the threat name that is responsible for the observed activity. Although this task is extremely challenging, it must be successfully performed in a real-world setting, in order to ensure that the detection is actionable and enables the device owner to mitigate the security threat based on the detection. Although the algorithm correctly detected the periodic routine, and it is visibly a bot (and therefore labeled as ”Bot”), our team of three cybersecurity experts was unable to identify an external source to explain this activity. This trend of unverifiable detections could lead to a possible automatic and relaxed operation to mimic the analysis conducted by our experts. Automatic crossing with open-source databases, such as VirusTotal, could create an automated approach for eliminating false positives. While this might be a more difficult threshold than the one applied by our experts, it would be a fair relaxation and provide a fully automated false positive removal methodology.

The difference between the simulated experiment and the real-world results merits a discussion on the subject. Bot detection in real-world DNS traffic is a more challenging task, mainly because of the noise within the traffic, which is characterized by time shifting, drops, and predefined “sleeps,” etc. This is in contrast to the supervised and semi-synthetic dataset, where we control the noise by injecting malicious traffic. This difference reflects the importance of employing a robust system for detection, as evaluated in Section V-D2.

To summarize, the results obtained on real-world DNS traffic demonstrate the effectiveness of MORTON for malicious bot detection in a real-world, unlabeled environment. The importance of not considering a large number of host names to reputable (e.g., everything in the Alexa top 1M list) is demonstrated in the Neshta use case, while the importance of the ability to detect multistage channels and communication that uses multiple host names in general is illustrated in the IsErik use case. The false positive rate of the real-world analysis was reasonable for our experts (up to 3 out of 10,000 devices on a weekly basis and less than 0.03% of the devices on average), but as mentioned, MORTON can be configured for a lower acceptable false positive rate if required for a small CERT team with less resources.

VII. CONCLUSIONS

In this paper, we present MORTON, a system that detects bots by analyzing DNS communication logs and identifying routine DNS queries to disreputable host names that are queried by a bot on behalf of an enterprise device. MORTON is designed for large-scale corporate networks, and accordingly, it was evaluated on a large-scale DNS dataset and compared to the recently proposed systems, Baywatch proposed by Hu et al. [11] and WARP as proposed by Shalaginov et. al [30] which were also designed for large-scale networks. The evaluation
indicates that MORTON is comparable to the two recently proposed systems in terms of accuracy for detecting malware beaconing but outperforms those methods when detecting bots that communicate using advanced techniques such as multistage channels. Additionally, MORTON was found to be more robust and efficient than the other methods evaluated. MORTON was also deployed in a real-world scenario, and was applied on DNS logs that were produced by 10,000 devices that belong to nine enterprise networks. The real-world results of MORTON were manually verified by cybersecurity experts, and are analyzed by use cases that show previously unreported threats and a reasonably low rate of false positives. The latter demonstrate the effectiveness of MORTON for real-world, unlabeled environments.

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