Identifying malicious hosts involved in periodic communications

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***Abstract*—After many research efforts, Network Intrusion Detection Systems still have much room for improvement. This paper proposes a novel method for automatic and timely analysis of traffic generated by large networks, which is able to identify malicious external hosts even if their activities do not raise any alert by existing defensive systems. Our proposal focuses on periodic communications, since our experimental evaluation shows that they are more related to malicious activities, and it can be easily integrated with other detection systems. We highlight that periodic network activities can occur at very different intervals ranging from seconds to hours, hence a timely analysis of long time-windows of the traffic generated by large organizations is a challenging task in itself. Existing work is primarily focused on identifying botnets, whereas the method proposed in this paper has a broader target and aims to detect external hosts that are likely involved in any malicious operation. Since malware-related network activities can be considered as rare events in the overall traffic, the output of the proposed method is a manageable graylist of external hosts that are characterized by a considerably higher likelihood of being malicious compared to the entire set of external hosts contacted by the monitored large network. A thorough evaluation on a real large network traffic demonstrates the effectiveness of our proposal, which is capable of automatically selecting only dozens of suspicious hosts from hundreds of thousands, thus allowing security operators to focus their analyses on few likely malicious targets.**

***Index Terms*—beaconing, periodicity, graylist, clustering**

I. Introduction

The defense of large information systems is characterized by two major problems. On one hand, attackers are capable of performing attacks spanning over long periods of time and employing advanced techniques, allowing them to avoid detection [1]; on the other hand, security analysts are overwhelmed by the huge volume of logs generated daily by network traffic [2]. Furthermore, the majority of Network Intrusion Detection Systems (NIDS) are unable to detect novel forms of attacks [1] or tend to raise several false alarms [3]. Proposals to increase the efficacy of NIDSs are oriented to improve their ability to detect attacks [4], or to provide security analysts with concise information about ongoing attacks [5]–[8]. Other solutions rely on prioritization techniques of likely infected internal hosts [9].

978-1-5386-1465-5/17/$31.00 ©2017 European Union

This paper is focused to support automatic security analyses by identifying *external* hosts that are performing attacks against the monitored network, even if their activities do not raise any NIDS alert. The proposed method analyzes network flows and is able to automatically generate a graylist of few external hosts characterized by a likelihood of being malicious that is several orders of magnitude greater with respect to all the external hosts contacted by the monitored network. The goal is to identify hosts involved in periodic communications (also referred to as *beaconing*) at different time intervals. The detection of malicious beaconing activities is still an open research problem [10]–[12], which is further complicated in large networks due to the difficulty of performing accurate and timely analyses of huge volumes of network traffic. Moreover, we have experimentally verified that external hosts exhibiting periodic connections present a higher rate of malicious behaviors when compared to hosts with irregular communication patterns. Our novel algorithm detects periodic behaviors by analyzing network flows. It is capable of labeling as periodic even communications that do not display a strict periodic pattern, thus allowing the detection of possible evasion attempts.

Our proposal is evaluated with a thorough set of experiments performed on a large, real network without the creation of any synthetic traffic.

This paper is structured as follows. Section II discusses related literature. Section III describes the proposed method. Section IV presents an extensive evaluation of the performance and efficacy of our proposal. Section V reports conclusions and future work.

II. Related Work

We present a novel method for automatically generating a graylist of external hosts with a higher probability of being involved in malicious beaconing activities with respect to the entire set of external hosts contacted by the monitored organization. Our proposal leverages clustering techniques applied to network flows. There are two main areas of related work: NIDS alarm optimization and detection of malicious beaconing activities.

Each NIDS generates huge amounts of alerts whose manual inspection is often unfeasible for human operators, hence several solutions aim to improve the information presented to security analysts by presenting shorter, comprehensive records. The authors in [6] discuss an algorithm to reduce the volume of alarms produced by multiple NIDSs through clustering alerts raised by similar malicious actions. Other papers, such as [5], propose to cluster alarms to detect their root-causes. Valeur et al. [7] transform groups of correlated alarms into intrusion reports. More recent works propose prioritization techniques for *internal* hosts. Authors of [13] and [8] focus on multistep attacks. The proposal in [14] leverages the alarms raised by the most critical assets. In [9] an architecture that prioritizes internal hosts upon their likelihood of being involved in several kinds of malicious cyber-attacks is proposed. All these papers share the broad goal of supporting security analysts by allowing them to focus on the most relevant alarms detected by a NIDS. In contrast, our proposal combines intrusion alerts together with network flow analyses and clustering algorithms to identify the most suspicious *external* hosts even if their actions do not raise any NIDS alert.

The detection of malicious beaconing activities is a well known problem in the field of botnet detection. Gu et al. [15] devise a framework for detecting internal hosts belonging to botnets through clustering of network traffic, based on the assumption that bots belonging to the same botnet have similar network behaviors. Authors of [16] plan to discover botnet infected hosts through supervised machine learning algorithms applied to network flows by identifying the key features of Command and Control communications. A similar solution is proposed in [12], although its main focus is on detecting Command and Control servers instead of bots.

Our method is not limited to detecting botnet-related malware, but extends to any possible external threat that is performing beaconing activities. Unlike botnet-related proposals, we do not make any assumption about the characteristics displayed by the analyzed traffic. Related work, such as [10], inspects DNS logs to discover malicious beaconing activities performed by internal hosts, whereas the proposal in [11] relies on the analysis of both DNS and web-proxy logs. On the other hand, we aim to detect malicious external hosts, which is a tougher problem because a large organization may contact hundreds of thousands of external hosts daily.

Moreover, our proposal is based on the analysys of network flows, which can be easily gathered and stored [17], leverages an unsupervised machine learning algorithm (unlike [12], [16]), and its execution time on a large network is compatible to online traffic analyses.

III. Identification of malicious external hosts

This section begins with a high level description of the proposed approach, and offers details of each processing module in the other subsections.

A. Overview

The main objective is to provide a graylist of external hosts involved in periodic communications with a high likelihood of being malicious. The basic assumption is that although novel variants of attacks are likely to evade NIDS detection [18], some features of malware network behavior persist and can be used to identify likely malicious activities.

The proposed method works on two inputs that can be easily obtained in modern infrastructures: network flows related to communications between internal and external hosts, and security alerts generated by a signature-based NIDS. These inputs are processed by the three modules shown in Figure 1. The *Periodicity Detector* is responsible for identifying network communications between internal and external hosts occurring at regular intervals. The *Behavioral Aggregator* clusters periodic connections according to their network behavior. The *Graylist Builder* creates the final graylist of suspicious external hosts.

As the number of connected devices in enterprise networks continues to increase, the detection of periodic activities is becoming a challenging task, since they can occur at different degrees of granularity spanning from few seconds to hours. Instead of looking for periodicities in raw traffic, we consider network flows which offer aggregated metadata summarizing relevant network traffic features. Each flow record is defined as an unidirectional sequence of packets that share specific network properties, such as source/destination IP address, transport layer protocol type, and source/destination port. Using network flows as input source is a popular choice in the cybersecurity domain [17], as they lower the amount of storage space required, make analyses faster, and reduce

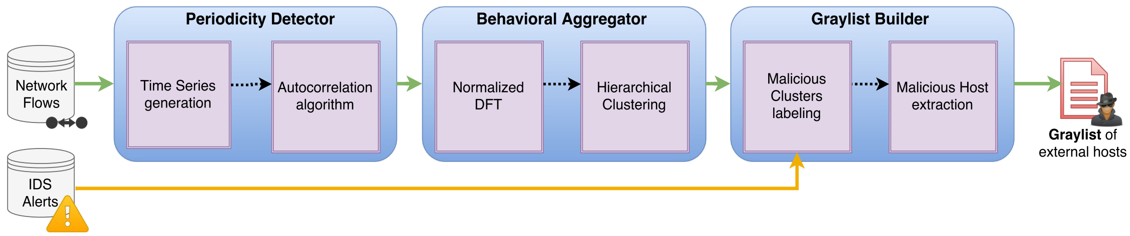


Fig. 1. Workflow of the proposed method.

privacy concerns due to the absence of packet-specific payloads.

NIDSs are a valuable asset for detecting malicious activities, but they are unable to detect novel malware variants that do not contain any known signature. However, some characteristics of malware behavior, such as beaconing, are stable across a wide array of automatically generated malware variants, thus resulting in similar communication patterns. Since our approach clusters network communications that share similar periodic behaviors, different variants of the same piece of malware are likely to be clustered together. Our approach only requires that a single malware variant generates a NIDS alert to pinpoint as suspicious the entire cluster of periodic communications containing that variant.

B. *Periodicity Detector*

The Periodicity Detector module detects periodic communications from network flows in two phases: first, it generates time series from the network flows; then, it analyzes these time series through an autocorrelation algorithm to determine whether they are periodic or not. The adopted techniques are robust and tolerate possible pertubations caused by noise or introduced by an attacker to escape detection.

The sequence of network flows among two hosts represents an unevenly spaced time series, which cannot be immediately used to detect periodic communications. Hence, we initially compute one evenly spaced time series for each pair of internal and external hosts exchanging packets within a time window W. Given a sampling period P, this time series contains a total of W/P elements. Each element is built by aggregating all the network flows between the involved hosts occurring within the same sampling period. As beaconing activities require repeated exchanges of some data, to capture these data transfers we compute each element of the time series by adding together the amount of bytes exchanged between the involved hosts within the related sampling period. This design choice allows us to better differentiate beaconing activities that exchange different volumes of data. After this phase, each pair of internal and external hosts is associated to one time series.

Then, we adopt autocorrelation to detect periodicities in each time series because this technique can signal time series exhibiting more than one period [19]. By computing the autocorrelation on a time series we obtain an autocorrelation function (ACF) containing W/P elements, each one representing the similarity of the time series with a delayed copy of itself. The analysis of the local maxima of the ACF determines whether a time series exhibits or not periodicities. In particular, looking for periodicities in the ACF involves determining the coordinates of local maxima, since strictly periodic time series tend to have local maxima with high amplitude at the beginning of the related ACF. Existing works relying on this technique for detecting periodicities in time series (e.g., [20]) are only able to identify strictly periodic time series. The problem is that skilled attackers may insert some perturbations to avoid detection, either by delaying or anticipating the communications, or by changing the volume of data exchanged during each interaction by random amounts. Moreover, network traffic may be subject to noise induced by inactivity periods, temporal disconnections, or by the presence of packets retransmissions and other network-related artifacts. To address these issues, we propose an innovative algorithm that is capable of labeling as periodic even time series that do not display a strictly periodic pattern. The main intuition is that restricting the analysis of the ACF only on the first very high local maxima does not allow to identify noisy periodic time series: time series with noisy periodicities are characterized by a limited amplitude of local maxima, hence they cannot be detected by conventional approaches. However, with respect to aperiodic time series, they present several local maxima with a similar amplitude, as well as high amplitudes between a local maximum and its next local minimum. To achieve a more flexible algorithm to detect noisy periodicities, we introduce two thresholds in the ACF:

- the *local maximum-location threshold* τ identifies the initial set of local maxima, splitting the ACF into

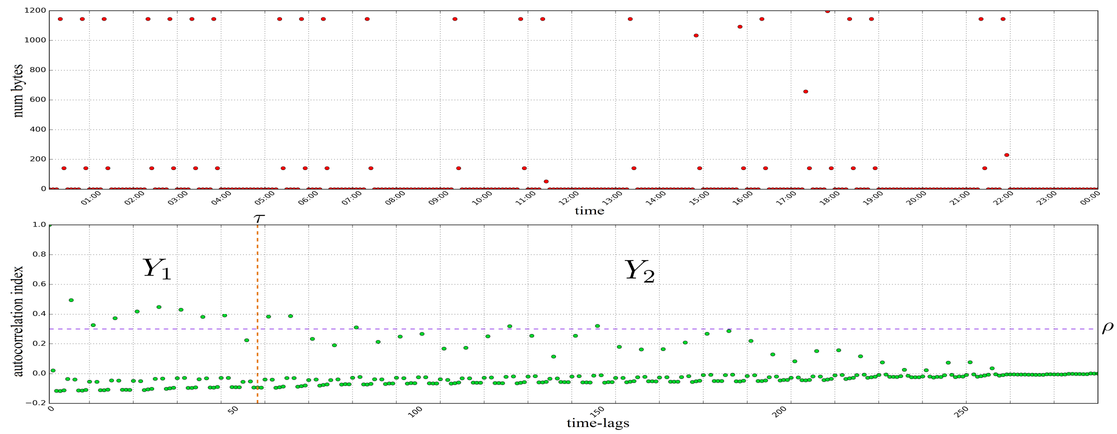


Fig. 2. Example of time series and related ACF generated by two host with a noisy periodic behavior.

two subseries: Y_1, containing all the first τ elements of the ACF and determining the initial set of local maxima; and Y_2, containing all the other elements, determining the remaining set of local maxima;

- the *local maximum-amplitude threshold* ρ is used to determine the amplitude required for an ACF element to be considered a local maximum: we consider those elements whose value is greater than ρ as local maxima, and those elements whose value is lower than $\frac{\rho}{2}$ as local minima.

To illustrate the idea, we report in Figure 2 the time series and its related ACF obtained from the communications between two hosts. We observe the existence of two noisy periodic behaviors in the time series, evidenced by the exchange of about 1.1KB and 180B of data every 30 minutes. For the ACF plot, we represent τ and ρ with a vertical and horizontal dashed line, respectively. We note that the amplitude of the local maxima in the ACF decreases irregularly, caused by the presence of noise in the original time series; furthermore, the initial local maxima set has a similar amplitude as the remaining set.

Our algorithm labels as periodic those time series whose ACF satisfy at least one of the following criteria:

- Y_2 has at least d elements $\geq \rho$ **and** Y_1 has at least $2d$ elements $\leq \frac{\rho}{2}$;
- Y_1 has at least r elements $\geq \rho$ **and** Y_1 has at least r elements $\leq \frac{\rho}{2}$.

Where d is the *period duration sensitivity* and r is the *periodic rate sensitivity* that must be chosen manually. Higher values of d imply that those time series that are labeled as periodic are characterized by periods of shorter length; higher values of r result in periodic time series whose periodicities occur for longer time-frames. We remark that the first and second criteria are designed to detect time series with periods of greater and shorter length, respectively. Upon the completion of this phase, all those time series that have been labeled as periodic are forwarded to the Behavioral Aggregator module.

C. Behavioral Aggregator

The Behavioral Aggregator clusters periodic communications exhibiting similar patterns. Although clustering techniques have already been employed in the information security field, to the best of our knowledge this is the first paper that proposes the leveraging of clustering algorithms to detect communications with a similar periodic behavior. This task is performed in two phases: we compute the Discrete Fourier Transform (DFT) for each periodic time series to obtain its spectrogram; then, these spectrograms are used as input for a hierarchical clustering algorithm.

By applying the DFT to a periodic time series it is possible to generate a spectrogram. This representation is useful to describe the behavior of network communications, since periodic time series that are out of phase may look very different, while their spectrograms exhibit the same profile. The problem is that the shape of each spectrogram also depends on the amounts of bytes exchanged between the involved hosts. For example, two hosts that regularly exchange 1MB of data will have a spectrogram with a smaller amplitude than a different pair of hosts that regularly exchange 10MB, although their frequency components are the same. To address this issue we normalize the amplitudes of each spectrogram between 0 and 1.

Then, each spectrogram is used as input for a hierarchical clustering algorithm, an unsupervised machine learning algorithm that takes as its input a matrix of distances. We create this distance matrix by means of the Pearson correlation coefficient [21], which is computed among all the normalized spectrograms. The output of the hierarchical clustering algorithm is a dendrogram. By cutting the dendrogram at a given height h, it is possible to create clusters of objects that are similar to each other. We tune the parameter h as to minimize intra-cluster variance and maximize the inter-cluster variance. At the end of this phase we obtain a variable number of clusters of periodic communications with similar behaviors, which are used as input for the Graylist Builder module.

D. Graylist Builder

The final graylist of malicious external hosts is produced by the Graylist Builder module. It initially identifies malicious clusters of periodic communications by mapping NIDS alerts into clusters of similar periodic communications. More specifically, those clusters containing at least one communication that has raised a NIDS alert are labeled as malicious; this process allows us to detect malicious hosts that are not signaled by the NIDS. Then, this module extracts all the external hosts belonging to malicious clusters and uses them to populate the final graylist.

IV. Experimental Evaluation

A. Experimental testbed

The proposed method is validated on real traffic generated by a large network of nearly ten thousand hosts during an entire week, consisting of about half a billion of network flows. The outgoing traffic has been monitored by a NIDS equipped with Suricata [22], used and configured by security operators with the most recent rulesets [23]. Table I reports the most meaningful metrics of the testbed for the different days of the considered week. The second and third days, marked with an asterisk, represent weekend days and are characterized by a lower activity.

Table I
Traffic information of each day of the dataset.

Day	Distinct external hosts	Distinct time series	Network flows
1	296 945	1 915 186	109 302 224
2*	105 884	541 844	53 500 389
3*	89 283	393 077	47 789 977
4	298 241	1 835 351	101 314 287
5	314 313	1 935 982	110 875 503
6	249 768	1 667 168	99 359 716
7	258 439	1 789 238	106 304 916

All the experiments discussed in this section refer to a time window set to one day ($W = 1$d), while network flows are sampled every five minutes ($P = 300$s). The parameters of the autocorrelation algorithm are determined through a comprehensive sensitivity analysis performed through multiple executions of the algorithm, and the resulting values are summarized in Table II. The values of the parameters ρ and τ are chosen equal to those suggested by the literature on periodicity evaluation in time series [19]. The height at which the dendrogram is cut to generate the clusters is set to $h = 0.95$, because sensitivity analyses show that this value minimizes intra-cluster variance and maximizes inter-cluster variance for the monitored environment.

Table II
Parameter values used as input.

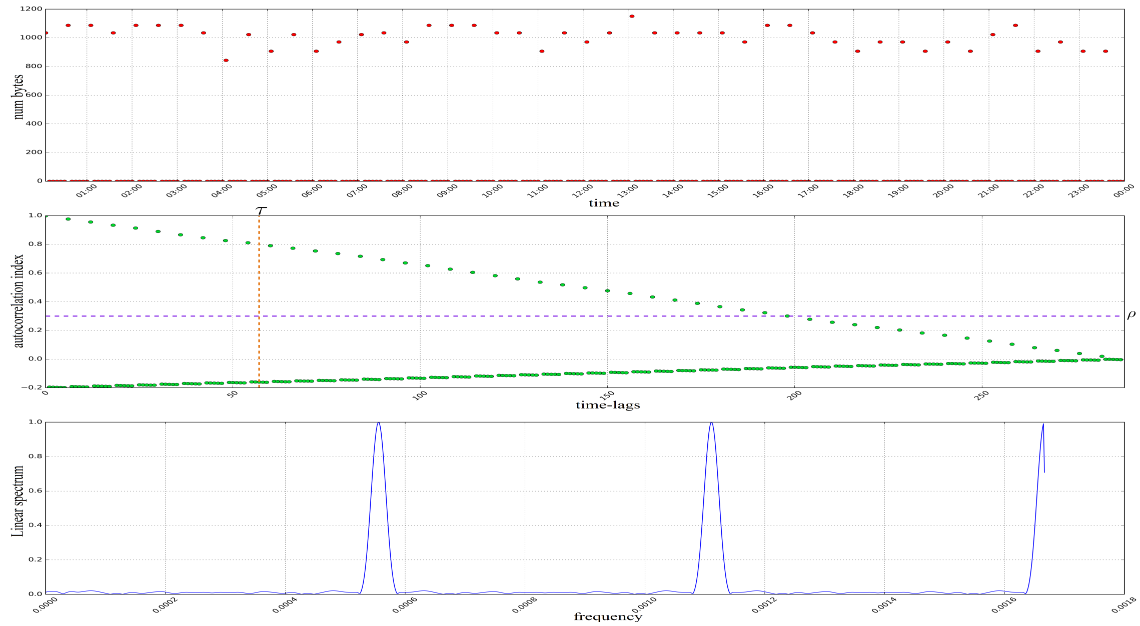
Symbol	Description	Value
ρ	Local maximum-height threshold	0.30
τ	Local maximum-location threshold	$\frac{W}{5P}$
d	Period duration sensitivity	6
r	Periodic rate sensitivity	2

B. Experimental Results

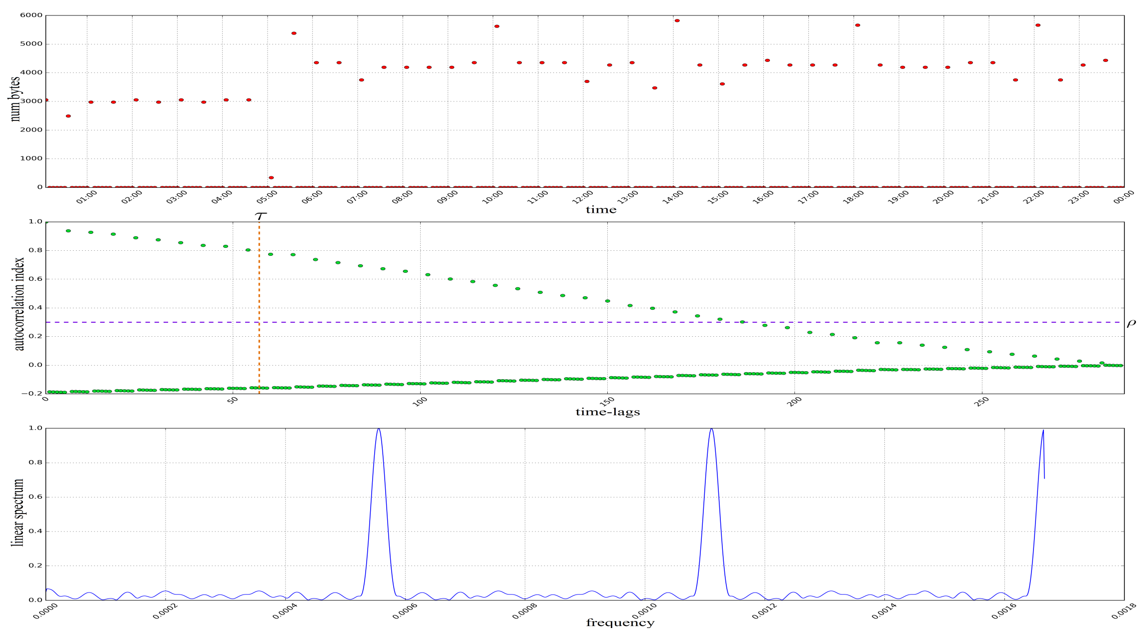
The detection framework is executed every day. The goal is to demonstrate its capability of producing a manageable graylist of external hosts with a considerably higher likelihood of being malicious when compared to the original set of contacted external hosts. In addition we show that the rate of malicious external hosts performing periodic communications is considerably higher with respect to those involved in aperiodic communications. Finally, we demonstrate that the graylist includes even external hosts that did not raise a NIDS alert, and that the execution time of our method is compatible with online traffic analyses.

We initially assess the amount of malicious external hosts in the entire set of external hosts that have been contacted by the monitored network. Then, we let the Periodicity Detector module generate time series and determine which of them are periodic. We remark that our analyses are executed on the unmodified network traffic produced by a large organization: we did not inject synthetic attacks or malicious traffic, but we leverage the APIs provided by VirusTotal [24] to validate malicious external hosts. More specifically, we consider an external host to be malicious if it has been signaled by more than half of the sources queried by VirusTotal.

To demonstrate that the rate of malicious external hosts involved in periodic communications is considerably higher than the rate of malicious hosts involved in aperiodic communications, we present the results of the validation process performed on these two sets of hosts in Table III. For each column, the rows with gray and white background report the number of external hosts involved in periodic and aperiodic communications, respectively. We observe that the average ratio of



(a) Communications involving a malicious external host with one periodic behavior.



(b) Communications involving a malicious external host with three periodic behaviors.

Fig. 3. Time series, ACF and normalized spectrogram of two communications involving distinct malicious external hosts.

malicious external hosts exhibiting periodic communications is 2.7%, whereas the one of hosts involved in irregular communications is 0.51%. These results show that periodic communications display a greater rate of maliciousness with respect to aperiodic communications, thus supporting our decision to focus on this set of hosts. Furthermore, these results indicate that malicious external communications can be considered as rare events in the overall traffic, and motivates our effort of building a manageable graylist in which the likelihood of finding a malicious host is higher.

To illustrate that our method is capable of detect-

Table III
VALIDATION OF EXTERNAL HOSTS INVOLVED IN PERIODIC (GRAY) AND APERIODIC (WHITE) COMMUNICATIONS.

Day	External hosts	Malicious external hosts
1	3139	97 (3.09%)
	293 806	1224 (0.42%)
2*	2284	59 (2.58%)
	103 600	785 (0.76%)
3*	2123	53 (2.49%)
	87 160	603 (0.69%)
4	3194	74 (2.31%)
	295 047	1198 (0.41%)
5	3288	91 (2.77%)
	311 025	1153 (0.37%)
6	3044	80 (2.63%)
	246 724	1202 (0.48%)
7	3034	90 (2.97%)
	255 405	1283 (0.50%)

ing periodicities, we execute the Behavioral Aggregator module and we report in Figures 3 the time series, ACF and normalized DFT pertaining to communications belonging to the same cluster and involving two distinct malicious external hosts. The first and second plots in each figure display the time series and related ACF, while the third plot displays the normalized spectrogram of the DFT. We observe that both time series exhibit a periodic behavior, although some noise is present. More specifically, the hosts associated to the first time series exchange about 1KB of data every 30 minutes; whereas those associated to the second time series present three periodical behaviors, evidenced by the exchange of about 3KB and 4KB of data every 30 minutes, and of about 5.5KB of data every 4 hours. These results demonstrate that our algorithm is able to identify even periodic communications affected by some perturbations. Moreover, we observe that the spectrograms of Figures 3 are very similar despite featuring different data exchanges, leading to their inclusion in the same cluster. This result indicates that our approach based on normalized DFT provides a good representation of the periodic behavior of a time series and is robust against alterations in exchanged data volume.

Table IV
COMPARISON OF THE AMOUNT OF EXTERNAL HOSTS.

Day	All external hosts	External hosts with periodic behavior	External hosts in graylist
1	296 943	3139	127
2*	105 884	2284	90
3*	89 283	2123	70
4	298 241	3194	31
5	314 313	3288	120
6	249 768	3044	119
7	258 439	3034	115

Finally, we generate the graylists by executing the Graylist Builder module for each day of the dataset. We present in Table IV the amount of hosts included in our graylists alongsisde both the entire set of hosts that have been contacted and the number of hosts displaying a periodic behavior. We appreciate that our graylists comprise about one hundred of entries down from the initial set of hundreds of thousands hosts, thus allowing further security inspections to focus on a restricted amount of external threats.

Table V
VALIDATION OF THE GRAYLIST AND COMPARISON WITH NIDS.

Day	Malicious hosts in graylist	Malicious hosts detected by NIDS
1	19 (14.96%)	3 (2.36%)
2*	17 (18.89%)	3 (3.33%)
3*	6 (8.57%)	3 (4.29%)
4	3 (9.68%)	3 (9.68%)
5	17 (14.17%)	4 (3.33%)
6	7 (5.58%)	3 (2.52%)
7	15 (13.04%)	4 (3.48%)

The evaluation of the graylist produced by our method is performed by determining the rate of malicious graylisted hosts, and by showing that the graylist contains even malicious hosts that do not raise NIDS alarms. The results are reported in Table V, where the first column indicates different days while the second and third columns show the number of malicious hosts included in the graylist and the number of malicious hosts that raised a NIDS alarm, respectively.

By correlating the values of Table V with those presented in Table III, we understand that the ratio of malicious hosts in our graylist is an order of magnitude greater than the ratio of malicious host in the entire set of contacted hosts. Moreover, by comparing the values of the second and third column of Table V we understand that our method is capable of graylisting up to six times as many malicious hosts with respect to those detected by the NIDS.

These results indicate that our method is able to produce a manageable graylist consisting of about one hundred of entries, down from the original set of hundreds of thousands entries, which is characterized by a ratio of malicious hosts that is an order of magnitude greater and containing malicious hosts that do not raise any NIDS alarm. Validating several dozens of IP addresses through external public APIs only requires few minutes, whereas the validation of hundreds of thousands of addresses requires almost one week. Finally, we remark that all these analyses are performed on real network traffic, as we did not inject any artificial attack.

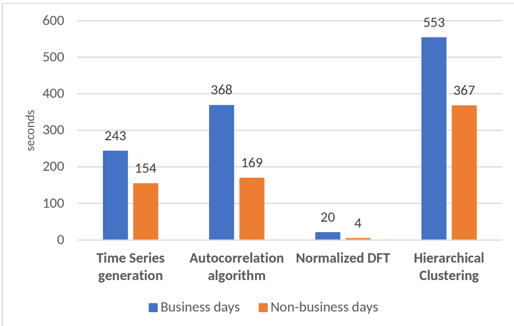


Fig. 4. Average execution time of the main phases of the proposed method for 24 hours of traffic.

Early detection of ongoing attacks is of paramount importance for modern organizations. Hence, we evaluate the execution time of the proposed method for each day of the dataset by distinguishing business and weekend days. The results are illustrated in Figure 4, where each pair of histograms represents the average execution time (in seconds) for a different phase of the proposed method, calculated for business days (left rectangle) and non-business days (right rectangle). For the sake of completeness, we report that these analyses have been performed on a COTS server equipped with an Intel Xeon E5-2609 v2 CPU with 4 physical cores and 4 threads, and 128GB RAM. It is important to observe that the execution time for the analysis of 24 hours of traffic is below 20 minutes even for contexts generating hundreds of millions of network flows daily. In particular, we note that the longest phase (Hierarchical Clustering) requires less than 10 minutes. Hence, by pipelining our algorithms, it is possible to obtain detailed reports once every $\sim$10 minutes. These results prove that the proposed method is applicable to online security analyses.

V. Conclusions

This paper presents an innovative method for automatically identifying malicious periodic communications with external hosts. The output is a manageable graylist of external hosts characterized by a considerably higher likelihood of being malicious compared to the entire set of contacted hosts, allowing security analysts to focus only on a limited amount of targets. Extensive evaluation on real traffic data of a large organization validated through external sources demonstrates the efficacy of our proposal, which is capable of identifying even malicious hosts that do not raise any NIDS alarm. The proposed method can be deployed even on very large networks, can be integrated in any detection system, and can be easily combined with other detection algorithms. Finally, its execution time is compatible with online analyses for timely detection of external threats performing periodic communications.

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