Metric design for Botnet Infection problem

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I. Introduction

It is impractical and very expensive to defend against every possible vulnerability [1]. Therefore, decision-makers must design and implement effective security strategies about where and when to invest time and money [2]. To make decisions on security investments, models are used and these models are build on security metrics [3]. Since the definition of these metrics are the basis of a good security model and therefore, they are a key element to produce valuable information for the decision-makers. For example, not all vulnerabilities will be attacked, thus knowing the most likely attack vectors is key in planning effective security measurements [1].

One way of gathering attacker information is by using *honeypots*. Honeypots are isolated and monitored systems that emulate to be vulnerable in order to attract attackers and track their behavior [4], i.e., attack attempt data could be used to define metrics that capture different aspects of attacker behavior. In particular we take a closer look to *Elastichoney* [3] project. It emulate to be a elasticsearch server suffering of a remote code execution (RCE) vulnerability identified as CVE- 2015-1427. This vulnerability allow attackers to execute Java based code by querying the server [5]. Furthermore, the Elastichoney project have gathered data over two months and tracked about 8k attempts to attack from over 300 unique IP addresses [3].

In Elastichoney logs the major security issue that can be found is *Botnet Infection* attempts, i.e. when a botnet machine is trying propagate the botnet by infecting another machine.

In this work we take a look to two different parties who have great incentive to know about the attacking behavior of botnet infection, namely *Internet Service Providers (ISP's)* and *Enforcement agencies*.

Botnet infection is a major security issue for ISP's, because 27% of the overall unwanted traffic on the Internet can be attributed to botnet-related spreading activity [6]. And this is a great loss in productivity for ISP's. On the other hand, law enforcement agencies (LAE) would counter this security issue, because botnets are heavily used as a platform for various criminal business models like sending spam, committing click fraud, harvesting account credentials, launching denial-of-service attacks, installing scareware and phishing [7].

In the rest of this paper we discuss ideal and state-of-the-art metrics that measure different aspects of botnet infection and how these metrics can be used by ISP's and enforcement agencies to make effective security investments. Finally, we propose, implement compare and evaluate our own metrics.

II. Ideal metrics

What would be the ideal metrics for security decision makers? The security issue defined in section I have distinct effects depending on the issued party. For each party, we identify how the botnet infection (BNI) is negatively influencing their interests, as well as a set of ideal metrics which could help each party to be able to explain and react in a more informed fashion against the BNI issue, and therefore, derive better decisions to take the more effective counter measures to mitigate this problem while maximizing the return on security investment.

a) ISP: For this party it is of main interest to avoid misuse of resources i.e. the ISP would like to block not legitim incoming traffic to its network while the botnet's victim would like to maintain availability of its resources.

- *BN propagation.* The growth and propagation trend are an ideal tool to quantify and predict the cost of malicious activity within the ISP network.
- *Resources (un)availability cost.* The ISP would like to know how much traffic of botnet infection activity is passing through his network. If is able to distinguish botnet activity from user activity he could measure how much resources are being misused and estimate the cost of having botnet inside his network and therefore justify the investment on security countermeasures.
- *Network infection rate.* The ISP could quantify his subnet infection rate prevention and reaction policies would be better targeted, i.e., if the subnet x.x.x.0 is heavy infected the ISP could target only this portion his network.

b) LAE: This party is interested in prevent, prosecute and punish the entity behind a security issue, i.e., to prevent BNI is of main interest to transfer the risk from the BN victims to the ISP and/or to encourage the zombies machines to increase their security protection, while for prosecution and punishment it is important to have mechanisms to understand and hunt down the BN.

- *BN geographical and digital location.* With geographical and digital location metrics the interested party could measure the infected population in a particular region either in the physical or digital world, i.e. how many infected machines are in the south of Chine, or how many infected machine does a ISP have.
- *BNI target machines.* By characterizing which kind of machines are the weakest link in a network, the LAE could launch prevention campaigns describing which kind of machines are more probable to become part of a botnet, i.e., operative system version, browser, etc.

III. State-of-the-art metrics

In the previous section we have seen which kind of metrics would be ideal for different parties facing the botnet issue.

Before going to the metrics proposed for each party by this paper, first a list is presented of metrics that are already used by honeypots for botnet detection:

c) Network Telescope: This is a control metric.

A block of Ip addresses from the entire range of IPv4 addresses are unassigned to hosts. This network is called "darknet". These block of ip addresses are still advertised on the internet through Border gateway(BGP) protocol making it BGP reachable. If any host from anywhere in the world(on the internet) sends a packet to one of these addresses, this packet would travel all over the world, would reach the router that advretises this routes, would be silently dropped (without any repsonses) but this would be logged. Network telescopes would be used to observe this internet traffic. By definition, this traffic is unsolicited since it does not have any hosts assigned to the addreses.Most of this unsolicted traffic would be malicious i.e traffic from malware, traffic from infected hosts that randomnly scan entire internet address space and so on [8].

Enforcement agencies use this to create metric out of samples of telescope data containing security event signatures. This metric would inform about possible network attacks, botnet activities and other misconfigurations.

d) Network Fingerprinting: This is a control metric.

With this method, one can create a metric that states which hosts communicates to which hosts. For example, one can track all the IP addresses , the honeypot communicates to. The honeypots will only communicate to the controller and in a peer to peer botnet , the honeypots will create multiple other members of the botnet [9].

Enforcement agencies use this to create metric which contains information of traffic logs that are automatically processed to extract a network fingerprint, the targets of any DNS requests, the destination IPaddresses, the contacted ports (and protocols), and whether or not default scanning behavior was detected. This would be used to differentiate between different types of botnets for example if the honeypot is part of a traditional command and control botnet [6].

e) IRC related features: This is a control metric.

With this method, one can create metric that differentiates between a member of a IRC type botnet and a non-infected member because these type of botnets send and receive signature commands over IRC channels [6].

Enforcement agencies use this to create metric which contains information of initial password to establish an IRC session with the server, the format of the nickname and username chosen by the bot, the particular modesset, and which IRC channels are automatically joined (with associated channel passwords).This is used to identify infected members(botnet) in the network [6].

Network fingerprinting and IRC related features provide enough information to join a botnet in the wild [6].

f) Longitudinal tracking: This is an incident metric.

With this method, one can create metric where you can visualise the number of attacks originating from a particular geographical location [6].

Enforcement agencies use this to create metrics containing information about geographical location to track the location of origination of a specific botnet.

g) DNS tracking: This is an incident metric. This method is almost the same as Longitudinal tracking, but instead of tracking the geographical location, this method tracks the domain names [6].

Enforcement agencies use this to create metrics containing information about domain names. This is used to probe the caches of a large number of DNS servers in order to infer the footprint of a particular botnet (total number of DNS servers giving cache hits) [6].

h) Botnet resources tracking: This is an incident metric.

In figure 1,you can see different resource aspects of botnet and each of these resources can be used to create metrics which differentiates between different types of botnets [9].

Enforcement agencies uses this to create metrics for each resource to characterize different botnets. It contains information about distinguishing characteristics. For example, peer-to-peer botnets would have network characteristics like distinctive communication graph, higher command latency and so on [9].

i) Signature tracking: This is a prevented losses/impact metrics.

Enforcement agencies uses this to create a metric that tracks the infection rate of a specific botnet by using the signature of a specific botnet, for example a trojan horse and its backdoor port as signature [10].

IV. Proposed metrics

In this section, we propose a number of metrics that can be used to extract valuable information from the *Ellastichoney* dataset. For each metric we define its input, output and the utility for the interested party mentioned in section II. For each ideal metric that we define in section II we name some metric implementations that help us to extract valuable information from the dataset in use.

A. BN propagation

1) BN growth: It measures the number new IPs where the BNI attempts are being performed. It is useful to see the aggregate growth of the BN, and to help to infer a BNI rate.

2) BNI attempts: It measures the number of attacks executed daily. We will use this data to analyze the BN activity. This metric could be useful to measure the effectiveness of mitigating controls.

B. Network infection rate

By summarizing the number of attacks that a particular IP perform and listing all the IP within a network, we can assign certain subnetworks an infection rate. I.e. Number infected IPs vs total IPs in a certain subnetwork.

C. BN geographical and digital location.

The input for this metric will include the number of attacks coming from various counties and also pinpointing the regional locations according to cities. This metric will help measure the scale of attacks coming from a particular geographical location. Furthermore, we can assess to block the IP ranges as per the geographical source of the attack coming from to mitigate the risk of potential impacts to critical infrastructure.

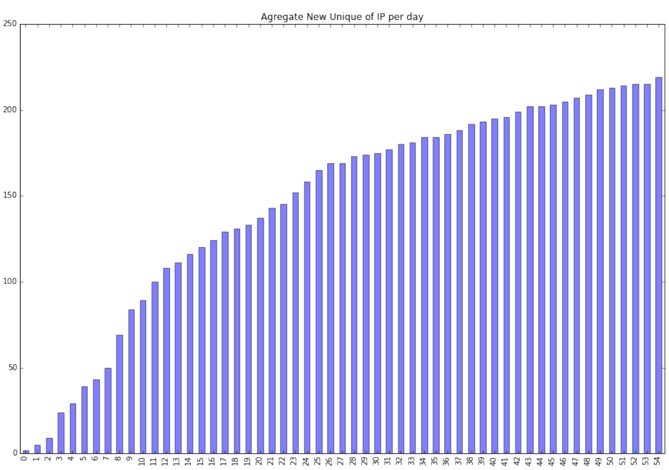
V. RESULTS EVALUATION AND CONCLUSION

The evaluation and results of the metrics defined in section IV is presented in this section. We highlight the most useful metrics, however a previous and complete statistical analysis of the variables in the dataset have been performed. I.e., over 93% of the BNI attempts are coming from China, more than 90% of the requests were done via GET method,etc.

A. BN propagation

In figure 1 we can see the aggregate growth of unique IP addresses per day. As we can see, the number of IPs used to try propagate the BN(s) increments daily. Even when we know that ISPs use dynamic IP allocation and therefore, by itself it is not Personal-identifiable information (PII), this metric provide a rough idea of the BNI success and of the size of the problem that is being faced. Similarly, figure 2a presents the number of unique IP per day and figure 2b show the BNI attempts or BN activity in terms of number of requests per day. To compute the relation between this two metrics we have performed a Person's correlation resulting on a 0.5, suggesting that this two analysis are *strongly correlated* [11]. Consequently, the growth of the BN is strongly correlated with the increment of attacks, thus, or the BNI is succeeding and/or the BN activity is increasing and with this informations an interested party could motivate the investment on security countermeasures.

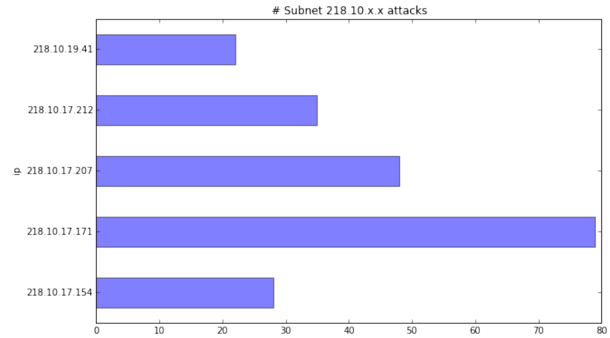
Fig. 1: BN growth



B. Network infection radio

An example of this kind of analysis is shown in figure 3, we list all the infected IPs in a subnetwork of an ISP, i.e. we have assumed that the ISP has class B IPs and one of his subnetwork is 218.10.0.0. Therefore, for each subnetwork within an ISP network we can see the activity of infected IPs and the infection radio of the subscribers in this network. Further analysis can be done by the ISP since he can use other data sources to get PII from the IPs and therefore compute this metric in a more accurate fashion.

Fig. 3: Subnet 218.10.0.0 attacks



C. BN geographical and digital location.

Geographical and digital location analysis is shown in figures 4 and 5. In figure 4 we show the geographical distribution of the BNI attempts

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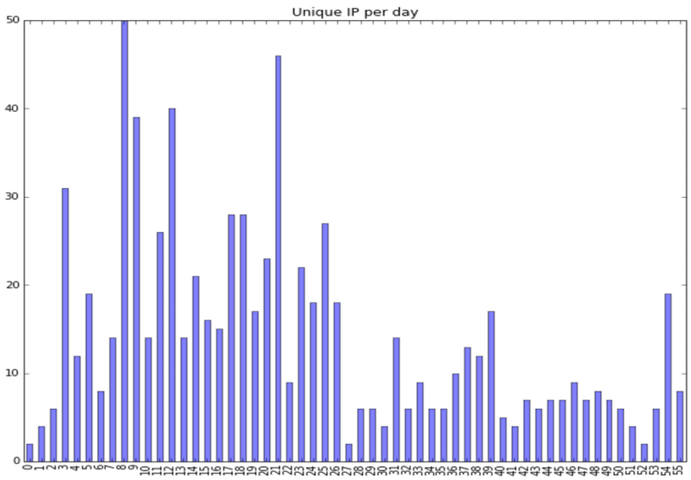
(a) Unique IP per day



(b) BNI attempts

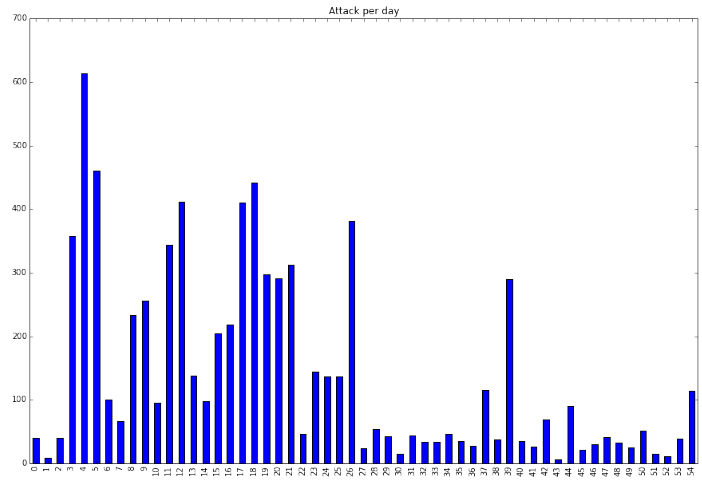
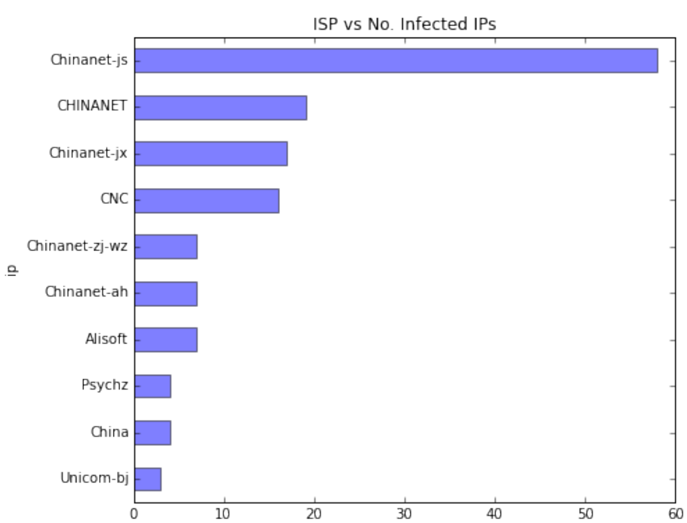


Fig. 4: BNI geolocation [12]

Fig. 5: ISP analysis

(a) Infected IPs per ISP



(b) BNI attempts per ISP