# How Dangerous Is Internet Scanning?

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## A Measurement Study of the Aftermath of an Internet-wide Scan

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**Abstract.** Internet scanning is a de facto background traffic noise that is not clear if it poses a dangerous threat, i.e., what happens to scanned hosts? what is the success rate of scanning? and whether the problem is worth investing significant effort and money on mitigating it, e.g., by filtering unwanted traffic? In this work we take a first look into Internet scanning from the point of view of scan repliers using a unique combination of data sets which allows us to estimate how many hosts replied to scanners and whether they were subsequently attacked in an actual network. To contain our analysis, we focus on a specific interesting scanning event that was orchestrated by the Sality botnet during February 2011 which scanned the entire IPv4 address space. By analyzing unsampled NetFlow records, we show that 2% of the scanned hosts actually replied to the scanners. Moreover, by correlating scan replies with IDS alerts from the same network, we show that significant exploitation activity followed towards the repliers, which eventually led to an estimated 8% of compromised repliers. These observations suggest that Internet scanning is dangerous: in our university network, at least 142 scanned hosts were eventually compromised. World-wide, the number of hosts that were compromised in response to the studied event is likely much larger.

**Keywords:** Botnet Characterization, Network Scanning, IDS, Netflow

## 1 Introduction

Botnets of up to millions of compromised computers are presently the most widely-used cyberweapon for executing criminal activities, such as fraud, sensitive data leakage, distributed denial-of-service attacks, and spam. Botnets engage into large-scale scanning to enumerate vulnerable hosts for targeted criminal activities or simply propagation [6, 26]. A recent study showed that scanning accounts for 34-67% of all connection attempts in an academic ISP [15]. Besides, recent advances in scanning software make it possible to scan the entire IPv4 address space in less than 45 minutes [10], simplifying further the execution of aggressive scanning attacks. In spite of the prevalence of scanning, it is difficult to assess how dangerous it is, i.e., is it simply an innocent background traffic

noise or a dangerous threat that is worth investing effort and money for blocking it?

In this work we take a novel look into Internet scanning from the point of view of scan repliers. We combine unsampled Netflow records and IDS alerts collected from a university network to assess the aftermath of a specific scanning event. In particular, we focus on the "sipscan", an Internet-wide scanning event orchestrated from the Sality botnet over 12 days in February 2011 that was analyzed by Dainotti *et al.* [9]. This event had several interesting characteristics: 1) it used a well-orchestrated stealth scanning strategy; 2) it originated from 3 million IP addresses; 3) it is believed that it scanned the entire Internet address space; and 4) it targeted Session Initiation Protocol (SIP) [25] servers.

We show that this scanning event escalated into persistent exploitation attempts towards the hosts that replied to the sipscan. We use our data to assess the effectiveness of scanning in terms of scan repliers and hosts that were eventually compromised. We find that 2% of the scanned IP addresses replied and at least 8% of the repliers were eventually compromised. Besides, our analysis shows that scanners originated primarily from Eastern countries, while the subsequent exploitation attempts originated from Western countries. This suggests that information about scan repliers was communicated to the subsequent attackers (likely through underground channels). Moreover, we observe 352,350 new scanner IP addresses and show that the sipscan was largely undetected by the IDS used in the observed network, which only raised alerts for 4% of the scan probes.

In summary, our work makes the following contributions:

- We conduct a first measurement study about Internet scanning focusing on scan repliers and the aftermath of scanning.
- We show that significant exploitation activity followed a specific scanning event and estimate the success rate.
- We provide new insights about Internet scanning and the sipscan: 1) we observe a segregation of roles between scanners and exploiters; and 2) that the sipscan originated from 352,350 new IP addresses.

The rest of the paper is structured as follows. We first discuss related research in Section 2. In Section 3 we describe the used data-sets. Then, Section 4 presents how unsampled NetFlow records were used to detect the sipscan and measure scan repliers. Then, in Section 5 we characterize the exploitation activity that followed based on our IDS data. Finally, Section 6 discusses the impact of false-positive IDS alerts on our analysis and Section 7 concludes our paper.

## 2 Related Work

A long line of measurement studies has analyzed botnets over the last years, following their evolution from centralized IRC-based [8, 7] to fully decentralized C&C architectures [17]. The goal of these efforts has been to characterize botnet activities [24], analyze C&C communication methods [8], and estimate the

respective botnet size and geographical properties [27]. Their observations have been used to fine tune network defences [14] and tailor novel detection mechanisms [16].

One of the most integral aspects of botnet activity is scanning. Since scanning is widespread [15] and regularly captured by monitoring infrastructures [5, 7], it is imperative for security analysts to have a measure regarding its severity and impact on the victim population. However, few studies have focused on the probing characteristics of botnets. In [28] Paxson *et al.* analyzed traffic captured at honeynets in order to study the statistical properties of 22 large-scale scanning events. In a followup study, Li *et al.* [20] extracted botnet scan traffic from honeynet data and used it to infer general properties of botnets, such as population characteristics, blacklisting effectiveness, dynamics of new bot arrivals and scanning strategies. Finally, Yegneswaran *et al.* [7] analyzed the source code of a widely-used botnet malware, revealing the scanning capabilities of basic IRC bots.

Most related to our work, Dainotti *et al* [9] discovered an interesting stealthy scan of the entire IPv4 address space that was carried out by the Sality botnet and analyzed the different phases of the event. However, this study was based solely on packet traces collected at the UCSD network telescope and does not provide insights regarding the effectiveness of scanning and its followup activity. In our work, we detect the sipscan in a large ISP with live hosts, identify the set of hosts that replied to scanners, and analyze the targeted exploitation activity that followed. This way, we provide new insights about the escalation of this event and the effectiveness of scanning in terms of turnover.

## 3 Monitoring Infrastructure and Data Collection

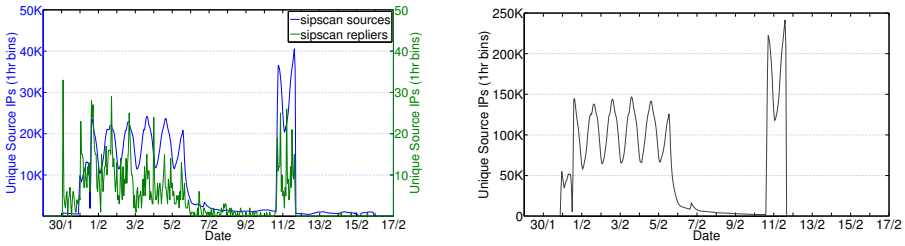
In this section, we describe the monitored network and the data we use in this study. We collected our measurements from the network of the main campus of the Swiss Federal Institute of Technology at Zurich (ETH Zurich). The ETH Zurich network is large and diverse. During our data collection period, which spanned 5 months (between the 1st January and the 31th of May 2011), we observed in total 79,821 internal hosts. On these hosts, the IT policy grants full freedom to users regarding the software and services they can use.

We select two data sources that provide complementary views into the studied event. First, we collect unsampled NetFlow data from the only upstream provider of ETH Zurich. Netflow produces summary records for *all* flows crossing the monitoring point. However, Netflow lacks context, since it does not provide information regarding the type of activity that triggered a flow. To fill this gap, we use IDS data collected from a Snort sensor, which captures and analyzes all traffic crossing our infrastructure's border router. Snort uses signature-based payload matching to perform protocol analysis, revealing more information about the type of activity that triggered an observed packet sequence. The two passive monitoring data sets complement each other, since they capture flow summaries for all traffic and finer (payload/header) details for packets that trigger IDS sig-

natures. A detailed description of our data collection methodology can be found in our accompanying technical report [11].

## 4 Sipscan Detection

To extract sipscan traffic from NetFlow data, we rely on heuristics introduced by Dainotti *et al.* [9], which are based on the analysis of the payload of sipscan packets. However, because flow data do not include packet payload contents, we adapted the extraction rules. We focus on the UDP part of sipscan traffic, which is sufficient to detect sipscan activity and identify sipscan sources. Specifically, we identify a sipscan flow as a single-packet one-way flow towards port 5060/udp having a size in the range of 382 to 451 bytes.




(a) ETH Zurich (NetFlow trace) (b) UCSD (full packets trace)

Fig. 1: Number of IP addresses per hour sourcing or replying to scan flows in ETH Zurich and in the UCSD network telescope.

In Figure 1a, we highlight how the host population sourcing attacks towards the SIP service port evolved over 16.7 days (from 31/01/2011 to 16/02/2011). In Figure 1b, we illustrate how the same event was captured by the UCSD network telescope. Note that Dainotti *et al.* [9] used full packet traces collected at the network telescope in order to estimate the scanning population. The similarity in these two patterns, indicates that our heuristic adapted to Netflow records, is able to capture the same phenomenon as seen on our network. We observe two major sipscan outbreaks in terms of participating attackers along with a minor fraction of hosts engaged continuously in SIP scanning. The first outbreak starts at 2011.01.31 21:30 UTC and lasts until approximately 2011.02.06 22:40, while the second outbreak starts at 2011.02.11 14:10 and lasts until 2011.02.12 15:00 UTC. In total, 952,652 scanners participated in the scan. A significant number (352,350) of hosts targeting our infrastructure were not observed in the population of Sality scanners detected by the UCSD network telescope, which were 2,954,108 [9]. This finding indicates that the size (expressed in terms of source IP addresses) of the botnet was at least 11.9% larger than the lower bound estimated in the previous work. At the victim side, 77,158 hosts within

ETH Zurich were scanned at least once during the 16.7 days period, meaning that the coverage of the scan in our infrastructure was 96.6%. The scan was largely stealthy, in terms of generated alerts from the IDS, since only 4% of the respective probing flows triggered a scan-related IDS signature.

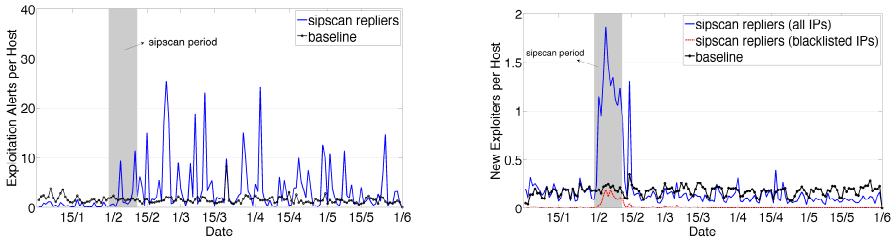
In contrast to [9], our data set allows us to identify those target hosts that reply to the sender of a sipscan flow. For this purpose, we search for two-way flows matching a relaxed filter (i.e., requiring port 5060/UDP only). Additionally, we look at the number of attacker-victim host pairs where a sipscan flow is answered with an ICMP flow. For this answer type, we see a weak correlation of ICMP flow counts with the two sipscan outbreaks. On the other hand, when looking at host pairs where we have biflows, we observe a strong correlation of biflow counts with the sipscan outbreaks indicating that sipscan attacks significantly result in bidirectional communication between attacker and victim. In Figure 1a we present the number of unique internal IP source addresses responding to the sipscan. In total, we identify 1,748 sipscan repliers, whereas during the scan we find 3.8 new unique internal IPs responding to the scan every hour. For 80.2% of the repliers we detected a TCP reply originating from the respective host, whereas for 8.3% of the repliers, the sipscan was answered with an ICMP flow. 0.2% of the replies involved both a TCP and an ICMP flow, while the remaining 11.5% used neither TCP or ICMP.

## 5 Aftermath of the Sipscan

### 5.1 Inbound exploitation attempts

In this section, we study the impact of the sipscan on the target host population within ETH Zurich. We first investigate if scanning was a precursor of subsequent exploitation attempts targeting hosts that replied to the scanners. Recall that our IDS data cover 5 months, including one month before the beginning of the sipscan (31/01/2011) and approximately 3.5 months after its end (16/02/2011).

In Figure 2a, we show how the daily number of exploitation alerts per target host triggered by inbound traffic changed after the sipscan. We consider alerts of the VRT rule sets *exploit.rules*, *exploit-kit.rules*, and *indicator-shellcode.rules* and of the ET rule set *emerging-exploit.rules*. These rule sets [11] are tailored to detect exploit activity, including buffer overflow attacks, remote command execution, brute force authorization and privilege escalation attempts. In Figure 2a, we also show the daily number of exploitation alerts per target host for the *baseline*, i.e., the ETH Zurich hosts that did not reply to the scanners according to our data. The *baseline* accounts for 78,073 hosts, whereas the number of sipscan repliers is 1,748. In the pre-sipscan period sipscan repliers were involved on average in 122 exploitation alerts per day. During the sipscan period we see that this number increases to 842 alerts per day, whereas after the sipscan it remains high at 931 alerts per day. In sharp contrast, the inbound exploitation activity associated with the *baseline* remains low after the sipscan. On average, each host is a target to 1.2 alerts per day, which is a baseline noise caused by automated threats attempting to propagate and false alerts. The respective



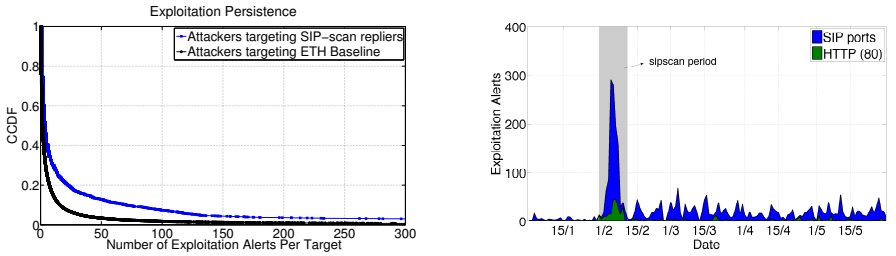

(a) Inbound exploitation alerts (b) New offending IPs

Fig. 2: Daily number of inbound exploitation alerts and new offending IPs per target host over a period of 5 months. The shaded region marks the duration of the sipscan.

noise level for the sipscan repliers in the pre-sipscan period is 0.4 alerts per day. After the sipscan, this number increases to 3.7 alerts per day. The high number of exploitation alerts towards sipscan repliers persists even 4 months after the end of the sipscan, although it is more intense during the first two months (from 31/1 to 28/2), when 68% of the total exploitation alerts are triggered. Out of the 1,748 sipscan repliers, we observe that 852 were involved in inbound exploitation alerts.

Next, we study whether the observed increase in exploitation activity comes from new offenders. Figure 2b illustrates the daily number of new offending IP addresses per target host for sipscan repliers and for the baseline. We report IP addresses that appear in exploitation alerts, however we consider an address new only when it has not previously appeared in the entire alert trace. A baseline host records a new external attacker approximately every four days consistently throughout the 5-month period. However, this number increases sharply for sipscan repliers during the sipscan, when each victim is attacked on average by 1.4 new IP addresses per day. Moreover, we investigate whether these IP addresses are known blacklisted hosts using four public blacklists [1, 3, 2, 4]. Figure 2b shows that only 7% of the new offenders were already blacklisted, while this number drops to almost 0 before and after the sipscan period.

In addition, we explore how persistent the attacking hosts are in terms of generated exploitation alerts, and examine whether the attackers targeting the sipscan repliers are more persistent compared to the ones targeting the baseline. In Figure 3a, we compare the average number of exploitation alerts per target for sipscan repliers and baseline attackers, respectively. We see that the former group tends to be more persistent triggering in the median case 4 exploitation alerts per target, whereas the same number for the latter group is 2 alerts. The increased persistence towards sipscan repliers is more prominent in the tails of the distributions. We see that the top 10% most active attackers towards sipscan repliers launch up to 73 alerts on average per target, whereas the respective number for the baseline is only 21 alerts.




(a) Persistence of exploitation attackers (b) Exploitation attempt alert volume

Fig. 3: Persistence of exploitation attackers and alert volume for exploitation attempts targeting SIP related ports.

Table 1: Top 10 countries used by the sipscanners compared to the respective countries for exploitation attack originators. Geo location data for sipscan sources and exploitation attack originators was obtained using the MaxMind GeoIP Lite Database[21].

| | *sipscanners CAIDA* | | *sipscanners ETH* | | *Exploiters ETH* | |
|---|---|---|---|---|---|---|
| Rank | % | Country | % | Country | % | Country |
| 1 | 12.55 | Turkey | 10.06 | Indonesia | 27.11 | United States |
| 2 | 12.54 | India | 9.72 | Turkey | 12.70 | Canada |
| 3 | 8.64 | Brazil | 7.32 | China | 9.90 | China |
| 4 | 7.23 | Egypt | 6.86 | Brazil | 7.01 | Switzerland |
| 5 | 5.77 | Indonesia | 6.52 | Egypt | 4.98 | Germany |
| 6 | 5.59 | Romania | 5.94 | India | 4.78 | Taiwan |
| 7 | 5.58 | Russian Federation | 4.80 | Thailand | 4.31 | Japan |
| 8 | 5.36 | Vietnam | 4.06 | Philippines | 3.31 | India |
| 9 | 5.10 | Thailand | 3.71 | Russian Federation | 2.95 | Russian Federation |
| 10 | 3.01 | Ukraine | 3.20 | Romania | 2.88 | Brazil |

We also investigate the similarity between the IP addresses of scanners (extracted from NetFlow) and of exploiters (extracted from Snort alerts towards sipscan repliers). Surprisingly, we observe that out of 6,676 exploiter and 1.3 million scanner IP addresses, only 17 are in common. This suggests that there is a clear separation between scanners and bots wielded to exploit target hosts. In Table 1, we compare the geographical distribution of the scanners detected in our infrastructure and in the UCSD network telescope [9] with the exploiters targeting the ETH Zurich sipscan repliers. The geographical distribution of scanners seen in the UCSD network telescope and in ETH Zurich is very similar with the exception of China. In our data set China is a significant source of SIP scanning accounting for 7.32% of the total scanners population. On the UCSD data set China is ranked 27th. More importantly, the geographical distribution of exploiters is particularly interesting, since it is dominated by Western countries and United States in particular, which is the most strongly represented country with 27.11% of the exploiters. In contrast, the geographical distribution of scan-

ners is dominated by Eastern countries. US is not sourcing sipscanning, which is remarkable since the analysis of the botnet has shown a strong presence in the United States [13]. This observation shows that information about scan repliers was communicated from scanning to attacking bots through unknown channels.

Finally, we examine the exploitation activity on port numbers related to SIP. Figure 3b shows the number of exploitation alerts targeting sipscan repliers on ports 5060, 5061, 5070 and 80. Ports 5060, 5061 and 5070 are used by SIP for control and data traffic. Moreover, the sipscan binary attempts to open a connection and gain administration privileges on port 80, where an HTTP server may provide remote administration to SIP servers [12]. Figure 3b shows a sharp increase of exploitation activity targeting SIP ports during and after the sipscan. Before, the sipscan we observe on a daily basis less than 12 exploitation alerts targeting SIP ports and 3 alerts targeting port 80. During the sipscan period, these numbers jump to 135 and 27, respectively, exhibiting approximately a ten-fold increase. Moreover, during the sipscan period 22% of all inbound exploitation alerts are on SIP ports. In the post-scan period we observe that these values drop, but still remain significant compared to the pre-sipscan period. Specifically, the daily number of exploitation alerts targeting SIP ports and port 80 are 5 and 21, respectively.

To summarize the key findings of this section, we first observe a steep increase in exploitation alerts against sipscan repliers right after the sipscan, which is associated only with sipscan repliers and not with other hosts in the monitored infrastructure. Second, we observe that the attackers associated with the increase appear for the first time during the sipscan and were not active before. Third, we observe a sharp increase in exploitation alerts towards SIP ports and show that these exploitation attempts happen in close temporal proximity to the sipscan. We believe these findings constitute sufficient evidence that the sipscan was the precursor of a subsequent large-scale exploitation activity targeting sipscan repliers.

### 5.2 Sality alert classification and outbound exploitation activity

In Sections 4 and 5.1, we analyzed the inbound scanning and exploitation activity towards the monitored network. In this section, we shift our attention to IDS alerts raised by outbound traffic originated by sipscan repliers, and analyze the new behavioral patterns that emerge. A comprehensive overview of the activity exhibited by the Sality bot based on the forensics investigation of compromised hosts can be found in our technical report [11].

In Table 2, we list the Snort identifiers (SIDs) and their official short description for relevant signatures that are triggered in our data. To compile the list, we manually analyzed the outbound alerts generated by sipscan repliers. We found the new types of alerts that emerged in the post-scan period and inspected their signatures in order to identify specific behaviors. We group signatures into four categories shown in Table 2.

Signatures in the group *C&C Communication* detect the activity triggered by a bot when calling its controller for instructions. In the case of the HTTP

Table 2: Snort signatures related to Sality bot lifecycle.

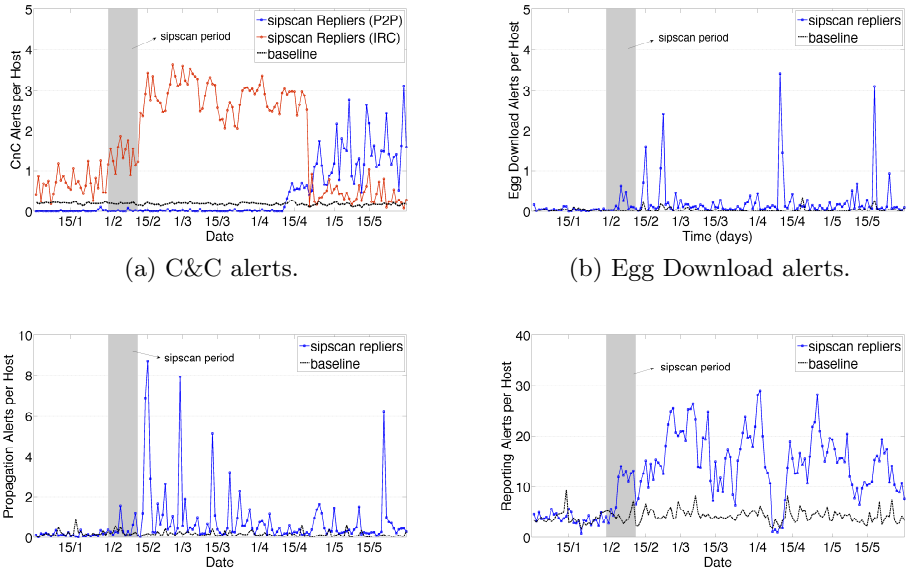
| SID | Signature Description |
|---|---|
| [**C&C Communication**] Communication with botnet controller. | |
| 2404138:2404156 | ET DROP Known Bot C&C Server Traffic TCP/UDP |
| 2000348 | ET ATTACK_RESPONSE IRC - Channel JOIN on non-std port |
| 2000334 | ET P2P BitTorrent peer sync |
| 2009971 | ET P2P eMule KAD Network Hello Request |
| 2008581 | ET P2p BitTorrent DHT ping Outbound |
| 2010142 | ET P2P Vuze BT UDP Connection Outbound |
| 2008584 | ET P2P BitTorrent DHT announce_peers request |
| 2181 | P2P BitTorrent transfer |
| [**Exfiltration**] Possible leakage of sensitive user data. | |
| 5 | SENSITIVE-DATA Email Addresses Outbound |
| 2006380 | ET Policy Outgoing Basic Auth Base64 HTTP Password detected unencrypted |
| 2010784 | ET CHAT Facebook Chat POST Outbound |
| 2000347 | ET ATTACK_RESPONSE IRC - Private message on non-std port |
| 1463 | CHAT IRC message Outbound |
| [**Propagation**] Attempted infection of vulnerable hosts. | |
| 2007695,2008070 | ET User-Agent Malware overflow attempt |
| 4060 | POLICY RDP attempted administrator connection request |
| 2006546 | ET SCAN LibSSH Based SSH Connection - BruteForce Attack |
| 2002383 | ET SCAN Potential FTP Brute-Force attempt |
| 3817 | TFTP GET transfer mode overflow attempt |
| 2010643 | ET SCAN Multiple FTP Administrator Login Attempts- Brute Force Attempt |
| 2001972 | ET SCAN Behavioral Unusually fast Terminal Server Traffic, Potential Scan or Infection |
| 2001569 | ET SCAN Behavioral Unusual Port 445 traffic |
| [**Egg Download**] Possible download of malicious executable. | |
| 2009897 | ET MALWARE Possible Windows Executable sent when remote host claims to send a Text File |
| 19270 | POLICY attempted download of a PDF with embedded Javascript |
| 15306 | WEB-CLIENT Portable Executable binary file transfer |
| 2003546 | ET USER Agents Suspicious User agent Downloader |
| 2007577 | ET TROJAN General Downloader Checkin URL |
| 2012648 | ET Policy Dropbox Client Downloading Executable |
| 2009301 | ET Policy Megaupload file download service access |

version of the Sality bot, the signatures in the SID range *(2404138:2404156)* are triggered when a set of known blacklisted C&C servers are contacted, whereas the signature *(2000348)* detects the setup of an IRC channel, which is used by the bot and the controller to communicate. The remaining alerts are related to the P2P version of the bot and are triggered when the bot is either attempting to join the P2P network, instantiating a new P2P connection, or fetching the latest peers list.

Signatures in the group *Exfiltration* are tailored to detect the exfiltration of confidential data. The SIDs *(5,2006380)* are triggered when passwords or email addresses are sent from the intranet unencrypted. The signature *(2010784)* is triggered when the bot is attempting to leak sensitive information using Facebook's POST mechanism. This alert should be expected to generate a significant amount of false positives, since it is also triggered when a user sends a legitimate Facebook message. However, a sudden sharp increase in the amount of Facebook POST operations could signify a malicious activity. The signatures with SIDs *(2000347,1463)* are triggered when information is exfiltrated using an IRC channel.

Signatures in the group *Propagation* are generated when the bot is attempting to infect exposed vulnerable hosts. The main targeted vulnerabilities are the

MS-LSASS buffer overflow and the MS-WebDav vulnerability related to services used for accessing remote network shares. The set of signatures shown in Table 2 are fine-tuned to detect brute force privilege escalation attacks (*4060,2006546, 2002383,2010643*), buffer overflow exploitation attempts (*2007695,2008070, 3817*), and targeted scanning on these services (*2001972 ,2001569*).




(a) C&C alerts.

(b) Egg Download alerts.

(c) Propagation alerts.

(d) Exfiltration alerts.

Fig. 4: Daily number of different types of alerts per host for sipscan repliers and for baseline hosts over a period of 5 months.

Finally, signatures in the group *Egg Download* correspond to attempts made by the bot to fetch a malicious binary from a remote domain. The downloaded executable can be either an update of Sality's own code or can correspond to a new malware pushed to the infected population. Signatures with SIDs (*15306,2003546,2007577*) detect the activity of Sality's downloader module when attempting to check a suspicious URL or when a binary download is initiated. Sality tries to obfuscate the downloaded binary by hiding it in seemingly legitimate files, such as Text and PDF documents. This activity is detected by signatures with SIDs (*2009897,19270*). The obfuscation is used to evade detection by cloud providers, such as Dropbox and Megaupload, which are exploited in order to host the malicious content. Signatures with SIDs (*2012648,2009301*) detect the download of executables from these sites.

Figure 4a shows the average number of C&C alerts triggered by sipscan repliers and baseline hosts. For sipscan repliers, we differentiate between IRC

and P2P C&C alerts, whereas for the baseline we include both types of alerts. After the sipscan, we see a sharp increase in the IRC C&C alerts, which indicates that hosts are attempting to contact known malicious IRC servers operating as controllers. This behavior continues for approximately two months, during which we see daily on average 2.4 C&C alerts per sipscan replier. However, on April 11 (day 111) there is a clear shift in the pattern of triggered signatures: the volume of IRC alerts suddenly drops, while the volume of P2P alerts rises. This signifies a likely upgrade in the mode of C&C communication of the Sality botnet.

Figure 4b illustrates the daily number of *Egg Download* alerts per sipscan replier and baseline host. After the sipscan, we observe 4 malware downloading spikes, during which the daily alert count ranges from 1.6 to 3.4 per sipscan replier. The spike that occurs on April 11 (day 111), seems to be associated with the shift in the communication method used to contact the controller shown in Figure 4a. We believe that during that event the Sality botnet pushed a major update to the infected population, upgrading itself from the centralized HTTP to the fully decentralized P2P version.

In Figure 4c, we show the daily number of *Propagation* alerts per local host for sipscan repliers and baseline hosts. We see that after the sipscan the number of outbound exploitation attempts originating from the sipscan repliers increases drastically, exhibiting an average daily value of 1.2 alerts per host compared to only 0.21 alerts per baseline host. The most dominant alerts of this group are the privilege escalation attempts with SIDs *(4060,2006546,2002383,2010643)* accounting for 72% of the observed activity.

Finally, Figure 4d illustrates the daily number of information leakage alerts per local host for sipscan repliers and baseline hosts. Again we see a sharp increase in the number of exfiltration alerts for sipscan repliers in the post-sipscan period, where the daily average increases from 4.7 to 18.2 alerts per host. The triggered alerts are dominated by the signature *ET CHAT Facebook Chat POST Outbound*, which accounts for 83% of all alerts. However, this signature is also triggered by legitimate user activity and may introduce a significant number of false positives. This is reflected in the high baseline in the pre-sipscan period, which accounts on average for 4.7 alerts per host. Although the baseline for this alert group is high, we can still see a clear increase in the post-sipscan period when its alert volume quadruples. Summarizing the key finding, we discovered major changes in the alert patterns of sipscan repliers that correlate with the behavior of the Sality bot.

### 5.3 Sality-bot infections

In this section, we build a heuristic to identify this behavioral shift and extract likely Sality infections. We use our heuristic to conservatively estimate a lower bound on the success rate of the sipscan in terms of infected hosts. Note, that we do not have the goal to build a general purpose detector, but rather a systematic way to identify infected sipscan repliers in the monitored network.

Our heuristic is summarized in Algorithm 1. We focus on sipscan repliers that were subsequently attacked. Then we find repliers that exhibit a persistent

increase in outbound exploitation activity for the four signature classes listed in Table 2, while their respective activity in the pre-sipscan period is low. In particular, for the four classes in Table 2, we first compute the number of alerts per day each internal host generates. Our heuristic then finds and keeps hosts that trigger in the pre-sipscan period fewer alerts per day than the corresponding baseline of that day plus a tolerance of 1.5× the inter-quartile range of the baseline. If a host has more alerts per day even for a single day, then it is discarded from further consideration because it is either already infected or it generates a large number of false positives. Second, our heuristic makes the same comparison in the post-sipscan period. If the daily alert count is consistently above the tolerance threshold, then it constitutes an indication of compromise activity. To assess whether this increase persists, we count the number of daily bins where it is above the threshold and tolerate only 5% of the post-sipscan bins where this condition is not met. We consider only the bins in which a host has generated at least one alert of any type.

**Input**:
$B_T^S$ : mean count of S type alerts generated by Baseline hosts on day T
$I_T^S$ : IQR of S type alerts generated by Baseline hosts on day T
$R_T^S$ : mean count of S type alerts generated by sipscan repliers on day T
$S$={CnC Communication, Reporting, Propagation, Egg Download}
**Result**: Returns *true* if the examined host is infected, *false* otherwise.
**foreach** *alert type S* **do**
  $BelowThreshCount = 0$;
  **for** $T_i$ = *1:*$T_{max}$ **do**
    **if** *isHostActiveAt(*$T_i$*) eq* false **then** *next;*
    $SignificanceThresh = B_{T_i}^S + 1.5 * I_{T_i}^S$;
    **if** $T_i \leq T_{scan}$ **then**
      **if** $R_{T_i}^S > SignificanceThresh$ **then**
        return *false*;
      **end**
    **else**
      **if** $R_{T_i}^S \leq SignificanceThresh$ **then**
        $BelowThreshCount$ += 1;
      **end**
    **end**
    **if** $BelowThreshCount/(T_{max} - T_{scan}) > 0.05$ **then**
      return *false*;
    **end**
  **end**
**end**
return *true*;

**Algorithm 1:** Pseudo-code for identifying Sality-bot infections

Our heuristic takes a conservative approach by introducing several conditions to make a Sality infection assessment. It is possible, however, that a Sality bot exhibits some of the post-sipscan behaviors presented in Section 5.2, but not all. For example, some examined hosts show persistent signs of C&C communication and attempts to propagate, but do not attempt to leak data. Others attempt to exfiltrate data, but do not frequently visit malicious domains to fetch malware. By tailoring our heuristic to only make an assessment if all alert types in the post-

sipscan period exhibit a persistent increase, we attempt to minimize possible false positives even if we introduce a number of false negatives. This way, we believe we can estimate a lower bound of the Sality infections that occurred in our infrastructure.

Our heuristic identified a total of 142 Sality infections in our IDS data set. In the first stage of reconnaissance, 77,158 exposed ETH Zurich IPs were scanned. Out of these only 1,748 (2%) hosts replied to the scanners. Almost half of the sipscan repliers, specifically 48%, were subsequently the targets of inbound exploitation attacks. Based on our heuristic we identified that 142 hosts showed persistent signs of infection during the post-sipscan period. Therefore, the sipscan turnover, i.e. the percentage of hosts that were infected out of the sipscan repliers, was 8%.

## 6 Discussion about IDS false positives

The quality of IDS alerts we study in Section 5 heavily relies on the accuracy of the inferences made by the Snort sensor deployed in our infrastructure. Snort has been criticized for generating an excessive number of false positives, often exceeding 99% [18, 19]. Such high false positive rates can introduce significant bias in our measurements, resulting in skewed results. However, in this work we have focused on signatures which, based on our previous work [22, 23], were shown to be reliable, generating only a small number of false positives. Specifically, in [22] we performed a thorough evaluation of the alerts being triggered by Snort in our infrastructure and identified signatures that generate a large number of false positives. These alerts have been excluded from the current work. Moreover, in [23] we introduced a complexity criterion to evaluate the effectiveness of a Snort signature in terms of correctly identifying malicious activity. The alerts analyzed in Section 5 are triggered by highly complex signatures, which our analysis in [23] has shown to be more reliable, generating a low number of false positives.

## 7 Conclusions

In this work, we analyzed the aftermath of an Internet-wide scanning event [9] in a university network focusing on scan repliers. Using a unique combination of unsampled Netflow records and IDS alerts we found that the sipscan was followed by significant exploitation activity that led to at least 142 infected hosts in the studied network and likely many more worldwide. The effectiveness of scanning in terms of targeted hosts that replied and repliers that were eventually compromised was 2% and at least 8%, respectively. We also observed a segregation of roles between scanners and exploiters, which originated from different geographical locations. We therefore conclude that Internet scanning is dangerous as it leads to many compromised hosts. Understanding how these observations differ across networks and scanning events is an interesting subject for future research.

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