Reducing Unwanted Traffic in a Backbone Network

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Abstract

This paper studies the techniques a backbone ISP can employ to reduce unwanted traffic on its network. For this purpose, we extract likely sources of exploit (thus unwanted) traffic from packet traces collected on backbone links using an Internet traffic behavior profiling methodology we developed earlier. We first study the characteristics of exploit traffic from several aspects, such as network origins and severity. Based on these characteristics, we propose several heuristic rules that an ISP may pursue for reducing unwanted traffic, and evaluate their cost and performance. Using packet traces collected from backbone links, we demonstrate that simple blocking strategies could potentially reduce substantial exploit traffic in a backbone network.

1 Introduction

Recently we have seen a tremendous increase in unwanted or exploit traffic [1] [2] – malicious or unproductive traffic that attempts to compromise vulnerable hosts, propagate malware, spread spam or deny valuable services. A significant portion of this traffic is due to self-propagating worms, viruses or other malware; this leads to a vicious cycle as new hosts are infected, generating more unwanted traffic and infecting other vulnerable hosts. In addition to self-propagating malware, new variants of old malware or new exploits emerge faster than ever, producing yet more unwanted traffic. Current measures in stopping or reducing unwanted or exploit traffic[1] rely on various firewalls or similar devices deployed on the *end hosts* or at *stub networks* (i.e., networks such as enterprise or campus networks that do not provide *transit* services) to block such traffic. In this paper we are interested in the feasibility and effectiveness of stopping or reducing unwanted traffic from the perspective of transit networks or ISPs (Internet Service Providers), in particular that of a *backbone* ISP.

As a prerequisite to stop or reduce unwanted traffic at an ISP, we first need an effective and efficient mechanism to identify such traffic and its sources, especially using packet header information of one-way traffic only. In a recent work [3], we have developed a backbone traffic profiling methodology – using a combination of information-theoretical and data mining techniques – to automatically discover and classify interesting and significant communication patterns from largely unstructured traffic data. Using packet header traces of one-way traffic collected on Sprint backbone links, we have demonstrated that our methodology is capable of identifying canonical behavior patterns for well-known servers such as the HTTP, SMTP, and DNS, as well as for traffic generated by known or unknown exploits. In addition, our methodology also uncovers “unusual” behavior patterns that deviate from the canonical profiles and thus warrant further investigation by security analysts.

Given the exploit traffic thus identified, in this paper we consider blocking strategies an ISP may pursue to reduce unwanted traffic, by installing access control lists (ACLs) on routers at entry points of an ISP. Although most of exploit traffic is associated with a relatively small set of (destination) ports, simply blocking these ports from any source is, in general, infeasible for a backbone ISP. This is because many ports that are vulnerable to attacks such as port 1434 (Microsoft SQL server) [4] or port 139 (Common Internet File System for Windows) are also used by legitimate applications run by an ISP’s customers. An alternate approach is to block the specific offending sources (and the exploit destination ports) of exploit traffic. However, these sources can number in tens or hundreds of thousands for a large backbone network; hence there is a significant scalability problem (primarily due to overheads incurred in backbone routers for filtering traffic using ACLs) in attempting to block each and every one of these sources. Hence this approach is likely to be most cost-effective when used to block the top offending sources that send a majority of self-propagating exploit traffic, in particular, in the early stage of a malware outbreak, to hinder their spread.

The contributions of this paper are i) characterizing unwanted traffic in a backbone network in terms of their sources, severity and sequential activities; ii) devising and evaluating possible blocking strategies for reducing unwanted traffic in a backbone network.

The remainder of the paper is structured as follows. In section 2 we provide a short overview of the backbone traffic behavior methodology we have developed, and apply it to identify individual sources that generate a significant amount of exploit traffic in any 5-minute time period. In section 3 we study the characteristics of extracted exploit traffic from several aspects. In section 4 we propose several heuristic blocking rules for reducing exploit traffic and evaluate their efficacy and trade-offs. In section 5 we summarize our findings and outline the future work.

2 Profiling Behavior of Exploit Traffic

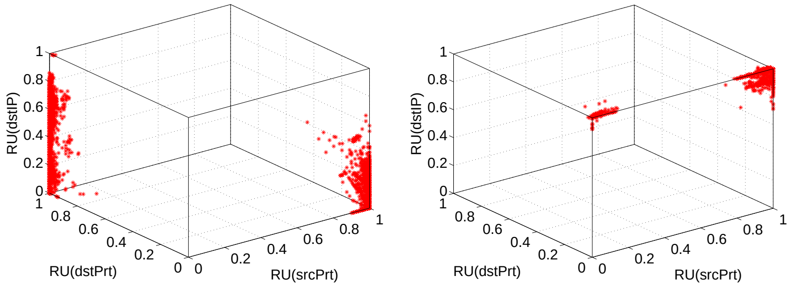
We provide a short overview of the backbone traffic behavior profiling methodology we have developed in [3]. By using a combination of information-theoretical and data mining techniques, the profiling methodology can identify several "canonical" behavior profiles such as "normal traffic" associated with typical servers and heavy-hitter client hosts, "unwanted" or exploit traffic, as well as rare or anomalous behavior patterns. The methodology is extensively evaluated and validated using packet header traces collected on backbone ISP links.

The behavior profiling works by examining communication patterns of end hosts (source and destination IP addresses) or ports (source and destination port numbers) that account for a significant number of flows in a time period (5-minute is used in this and our earlier studies). For example, for a given source IP address (`srcIP`) a, the profiling process includes i) extracting the 5-tuple flows whose `srcIP` is a in the 5-minute time period into to a cluster, C_a, referred to as the *srcIP* cluster (associated with a); ii) characterizing the communication patterns (i.e., behavior) of a using information-theoretical measures on the remaining three feature dimensions of the flows, i.e., source port (`srcPrt`), destination port (`dstPrt`) and destination IP address (`dstIP`). Note that the profiling process also works for `dstIP`, `srcPrt` or `dstPrt`.

We introduce an information-theoretic measure – *relative uncertainty*[2] (RU_X) – to provide an index of variety or uniformity on each of the three feature dimensions, X = {`srcPrt, dstPrt, dstIP`}. Based on this measure, we define an RU vector [RU_{srcPrt}, RU_{dstPrt} and RU_{dstIP}] to characterize the uncertainty of the three dimensions for each srcIP cluster. Hence each `srcIP` cluster can be represented as a single point in a 3-dimensional space of the RU vectors. This leads to a behavior classification scheme which classifies all srcIPs into various behavior classes based on their similarity/dissimilarity in the RU vector space. In particular, we identify three *canonical* behavior profiles, namely, server profile, heavy hitter profile, and exploit profile, to which most of `srcIP` clusters belong. We have applied the framework on a diverse set of backbone links and demonstrated the applicability of the profiling methodology to the problem of classifying distinct behavior patterns. For example, using the packet traces collected from an OC48 backbone link during a 24-hour period, we identified 418, 466 and 3728 distinct `srcIP`s with server, heavy hitter and exploit behavior profiles, respectively. Due to a lack of space, we will only show the results for this link, L, in this paper. The results for other links are presented in [5].

As an example to illustrate the distinct behaviors of *normal* vs. *exploit* traffic profiles, Figs. 1[a] and [b] plot the points in the RU vector space corresponding to the `srcIP`s belonging to the three canonical traffic profiles[3]. The points are clustered in three clearly separable groups. The points on the left side of Fig. 1[a] belong to the server profile, where they share a strong similarity in RU_{srcPrt} (low uncertainty) and RU_{dstPrt} (high uncertainty): a server typically talks to many clients using the same service `srcPrt` and randomly selected `dstPrt`'s. The cluster on the right side of Fig. 1[a] belong to the heavy hitter profile, where they share a strong similarity in RU_{srcPrt} (high uncertainty), RU_{dstPrt} (low uncertainty), and have *low-to-medium* uncertainty in RU_{dstIP}: a heavy-hitter client host tends to talk to a limited number of servers using randomly selected `srcPrt`'s but the same `dstPrt`. Closer inspection reveals that the `srcPrt`'s in the server profile almost exclusively are the well-known service ports (e.g., TCP port 80); whereas the majority of the `dstPrt`'s in the heavy-hitter profile are the well-known service ports, but they also include some popular peer-to-peer ports (e.g., TCP port 6346).

In contrast, the points in the exploit traffic profile (Fig. 1[b]) all have high uncertainty in RU_{dstIP} and low uncertainty in RU_{dstPrt}, and fall into two categories in terms of RU_{srcPrt}. Closer inspection [4] reveals that the `dstPrt`s include various known exploit ports (e.g., TCP ports 135, 137, 138, 445, UDP ports 1026-28) as well as a few high ports with unknown vulnerabilities. They also include some well-known service ports (e.g., TCP 80) as well as ICMP traffic ("port" 0). Fig. 2 plots the *popularity* of the exploit ports in L in the decreasing order, where the popularity of an exploit port is measured by the number of sources that have an exploit profile associated with the port. Clearly, a large majority of these ports are associated with known vulnerabilities



(a) srcIPs with normal behavior profiles

(b) srcIPs with exploit behavior profile

Figure 1: The RU vector distribution of the canonical behavior profiles for significant `srcIP`'s in L during a 24-hour period.

and widely used by worms or viruses, e.g., TCP port 135 (W32/Blaster worm), TCP port 3127 (MyDoom worm). Several well-known service ports (e.g., TCP port 80, UDP port 53, TCP port 25) are also scanned/exploited by a few sources. Most sources target a single exploit, however, a small number of sources generate exploit traffic on multiple ports concurrently. In most cases, these ports are associated with the same vulnerability, for instance, the port combination {TCP port 139, TCP port 445} associated with MS Window common Internet file systems (CIFS), and {UDP ports 1026-1028} associated with MS Window messenger pop-up spams.

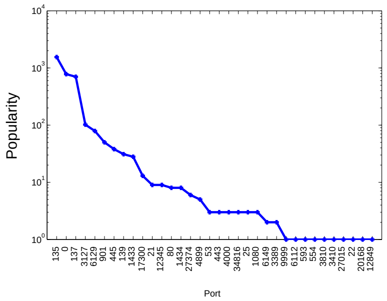


Figure 2: Port popularity of exploits traffic in L during a 24-hour period

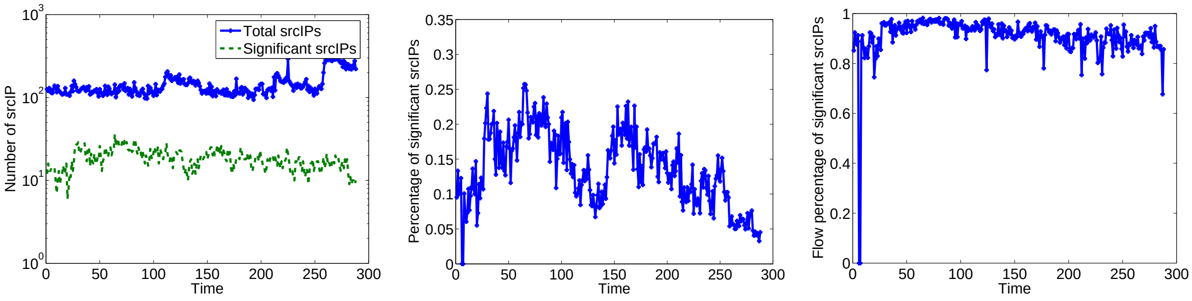
It is worth noting that our focus is on *significant* end hosts or services, so the sources we built behavior profiles are far less than the total number of sources seen in backbone links. Thus, it is not surprising that our behavior profiling framework identifies a subset of sources that send exploit traffic. However, these sources often account for a large percentage of exploit traffic. For example, Fig. 3[a] shows the total number of sources that send at least one flow on the most popular exploit port, port 135, as well as the number of significant sources extracted by our clustering technique that targeted port 135. As illustrated in Fig. 3[b], the percentage of such significant sources ranges from 0% to 26%. However, as shown in Fig. 3[c], these significant sources account for 80% traffic on TCP port 135 for most intervals. This observation suggests that our profiling framework is effective to extract most exploit traffic sent by a small number of aggressive sources.

3 Characteristics of Exploit Traffic

We study the characteristics of the exploit traffic from the sources profiled as exploits in section 2 in terms of network origins, their frequency, intensity and target footprints in the IP space. Our objective is to shed light on effective strategies we can explore for reducing such unwanted traffic.

3.1 Origins of Exploit Traffic

We first examine where the sources of exploit traffic are from, in terms of their origin ASes (autonomous systems) and geographical locations. Among the 3728 `srcIP`s in L during a 24-hour period, 57 are from the private RFC1918 space [6]. These source IP addresses are likely leaked from NAT boxes or spoofed. For the remaining `srcIP`'s, we search its network prefix using the *longest prefix* match in a snapshot of the BGP routing table of the same day from Route-Views [7], and obtain the AS that originates the prefix. These 3671 `srcIP`'s are from 468 different ASes. Fig. 4 shows the distribution of the exploit sources among these ASes. The top 10 ASes account for nearly 50% of the sources, and 9 out of them are from Asia or Europe.



(a) Significant sources of exploit

(b) Percentage of significant sources

(c) Flow percentage from significant sources

Figure 3: Aggregated traffic from significant sources of exploit on TCP port 135 over a 24-hour period (i.e., 288 five-minute periods.

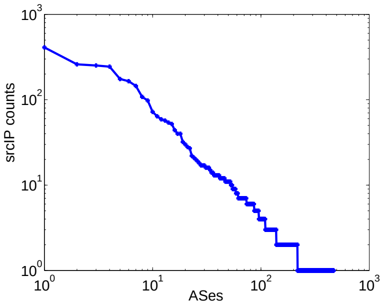


Figure 4: Distribution of srcIP counts across all ASes for 3728 sources of exploit in L during a 24-hour period.

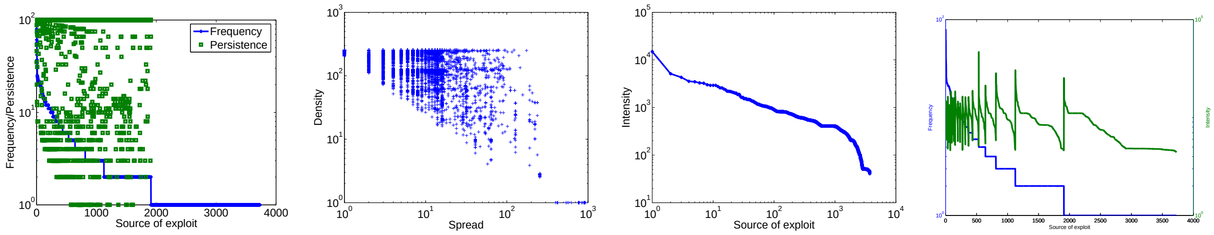
3.2 Severity of Exploit Traffic

We introduce several metrics to study the temporal and spatial characteristics of exploit traffic. The *frequency*, T_f, measures the number of 5-minute time periods (over the course of 24 hours) in which a source is profiled by our methodology as having an exploit profile. The *persistence*, T_p, measures (in *percentage*) the number of *consecutive* 5-minute periods over the total number of periods that a source sends significant amount of exploit traffic. It is only defined for sources with $T_f \geq 2$. Hence $T_p = 100(\%)$ means that the source continuously sends significant amount of exploit traffic in all the time slots it is observed. We use the *spread*, F_s, of the target footprint (i.e., destination IP address) to measure the number of $/24$ IP address blocks that a source touches in a 5-minute time period, and the *density* of the target footprint, F_d, to measure the (average) number of IP addresses within each $/24$ block that a source touches in the period. Finally, we use the *intensity*, I, to relate both the temporal and spatial aspects of exploit traffic: it measures the (average) number of distinct target IP addresses per minute that a source touches in each 5-minute period. Thus it is an indicator how fast or aggressive a source attempts to spread the exploit.

Figs. 5(a)(b)(c)(d) show the distributions of the frequency vs. persistence, a scatter plot of the spread vs. density of target footprint, the distribution of intensity, and the distributions of frequency vs. intensity for the 3728 exploit sources, respectively. From Fig. 5(a) we observe that frequency follows a power-law like distribution: only 17.2% sources have a frequency of 5 or more, while 82.8% sources have a frequency of less than 5. In particular, over 70% of them have frequency of 1 or 2. Furthermore, those 17.2% frequent ($T_f \geq 5$) sources account for 64.7%, 61.1% and 65.5% of the total flows, packets, and bytes of exploit traffic. The persistence varies for sources with similar frequency, but nearly 60% of the sources ($T_f \geq 2$) have a persistence of 100 (%): these sources continuously send exploit traffic over time and then disappear.

From Fig. 5(b) we see the exploit sources have quite diverse target footprints. In nearly 60% cases, exploit sources touch at least ten different $/24$ blocks with a density of above 20. In other words, these sources probe an average of more than 20 addresses in each block. However, in about 1.6% cases, the sources have a density of less than 5, but a spread of more than 60. In a sense, these sources are smart in selecting the targets as they have a low density in each block. As the rate of exploit seen from each destination network is slow [8], they may evade port scan detection mechanisms used, e.g., in SNORT [9], Bro [10] or [11]. Upon close examination we find that these sources employ two main strategies for target selections. One is to randomly generate targets (or to use a hit-list). The other is to choose targets like $a.b.x.d$ or $a.x.c.d$, instead of $a.b.c.x$, where x ranges from 1 to 255, and a, b, c, d take constant values.

The exploit intensity (Fig. 5(c)) also follows a power-law like distribution. The maximum intensity is 21K tar-



(a) Frequency (T_f) and persistence (T_p)

(b) Footprint (F_s vs. F_d)

(c) Intensity (I)

(d) Frequency (T_f) and intensity (I)

Figure 5: Temporal and spatial aspects of exploit traffic for the sources with exploit profiles in the backbone link during a 24-hour period. Note that (a) and (d) have the same index in x axis.

gets per minute, while the minimum is 40 targets per minute. There are only 12.9% sources with an intensity of over 500 targets per minute, while nearly 81.1% sources have an intensity of less than 500 targets per minute. Those 12.9% aggressive ($I \geq 500$) sources account for 50.5%, 53.3%, and 45.2% of the total flows, packets, and bytes of exploit traffic. However, as evident in Fig. 5(d), there is no clear correlation between frequency and intensity of exploit traffic: the intensity of exploit activities varies across sources of similar frequency.

In summary, we see that there is a relatively small number of sources that frequently, persistently or aggressively generate exploit traffic. They are candidates for blocking actions. Whereas a small percentage of sources are also quite smart in their exploit activities: they tend to come and go quickly, performing less intensive probing with wide-spread, low-density target footprint. These sources may be operated by malicious attackers as opposed to innocent hosts infected with malware that attempt to self-propagate. These sources need to be watched for more carefully.

4 Initial Assessment of Blocking Strategies

In this section, we propose several heuristic rules of blocking strategies based on characteristics of exploit activities and then evaluate their efficacy in reducing unwanted traffic.

In order to determine which sources to block traffic from, we use the behavior profiling technique outlined in section 2. For every five minute interval, we profile all sources and identify those that exhibit the exploit traffic profile. We then devise simple rules to select some or all of these sources as candidates for blocking. Instead of blocking all traffic from the selected sources, we consider blocking traffic on only the ports that a source seek to exploit. This is because exploit hosts may indeed be sending a mixture of legitimate and exploit traffic. For example, if an infected host behind a NAT box is sending exploit traffic, then we may observe a mixture of legitimate and exploit traffic coming from the single IP address corresponding to the NAT box.

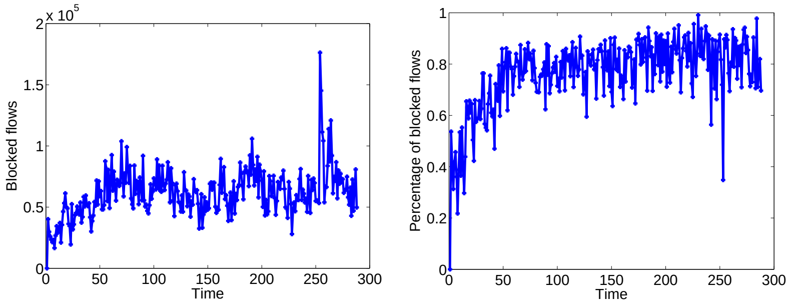
For our evaluation, we start with the following benchmark rule. If a source is profiled as an exploit source during any five minute interval, then all traffic from this source on vulnerable ports is blocked from then on. Fig. 6[a][b] illustrates the total blocked flows from sources of exploit every 5-minute interval in L, and the percentage of such flows over all traffic from these sources, respectively. Overall, the benchmark rule could block about 80% traffic from the sources of exploit. In other words, this rule may still not block all traffic from the source due to two reasons. First, the source might already have been sending traffic, perhaps legitimate, prior to the time-slot in which it exhibited the exploit profile. Second, as explained above, only ports on which we see exploit traffic are considered to be blocked.

While this benchmark rule is very aggressive in selecting sources for blocking, the candidate set of source/port pairs to be added to the ACLs of routers may grow to be very large across all links in a network. Therefore, we consider other blocking rules that embody additional (and more restrictive) criteria that an exploit source must satisfy in order to be selected for blocking.

- *Rule 2*: an ACL entry is created if and only if the source has been profiled with an exploit behavior on a port for n consecutive intervals. This rule is to block traffic from persistent sources;

- *Rule 3*: an ACL entry is created if and only if the source has an average intensity of at least m flows per minute. This rule is to block aggressive sources;

- *Rule 4*: an ACL entry is created if and only if the source is exploit one of the top k popular ports. This



(a) Blocked flows

(b) Percentage

Figure 6: a) blocked flows using the benchmark rule on L over a 24-hour period; b) percentage of blocked flows over the total flows from sources of exploit.

rule is to block exploit traffic of the popular ports;

- *Rule 5*: Rule 2 plus Rule 3.

We introduce three metrics, *cost*, *effectiveness*, and *wastage* to evaluate the efficacy of these rules. The cost refers to the overhead incurred in a router to store and lookup the ACLs of blocked sources/ports. For simplicity, we use the total number of sources/ports as an index of the overhead for a blocking rule. The effectiveness measures the reduction of unwanted traffic in terms of flow, packet and byte counts compared with the benchmark rule. The resource wastage refers to the number of entries in ACLs that are never used after creations.

Table 1 summarizes these rules of blocking strategies and their efficacy. The benchmark rule achieves the optimal performance, but has the largest cost, i.e., 3756 blocking entries[5]. *Rule 2* with $n = 2$ obtains 60% reductions of the benchmark rule with 1585 ACL entries, while *Rule 2* with $n = 3$ obtains less than 40% reductions with 671 entries. *Rule 3*, with $m = 100$ or $m = 300$ achieves more than 70% reductions with 2636 or 1789 entries. *Rule 4* has a similar performance as the benchmark rule, but its cost is also very high. The *Rule 5*, a combination of *Rule 2* and *Rule 3* has a small cost, but obtains about 40% reductions compared with the benchmark rule.

We observe that the simple rules, *Rule 3* with $m = 100$ or $m = 300$ and *Rule 2* with $n = 2$, are most cost-effective when used to block the aggressive or frequent sources that send a majority of self-propagating exploit traffic, in particular, in the early stage of a malware outbreak, to hinder their spread.

5 Conclusions and Ongoing Work

This paper studied the characteristics of exploit traffic using packet-level traffic traces collected from backbone links. Based on the insights obtained, we then investigated possible countermeasure strategies that a backbone ISP may pursue for reducing unwanted traffic. We proposed several heuristic rules for blocking most offending sources of exploit traffic and evaluated their efficacy and performance trade-offs in reducing unwanted traffic. Our results demonstrate that blocking the most offending sources is reasonably cost-effective, and can potentially stop self-propagating malware in their early stage of outburst. We are currently performing more in-depth analysis of exploit traffic, and correlating exploit activities from multiple links. Ultimately we plan to incorporate these mechanisms in a comprehensive security monitoring and defense system for backbone ISPs.

Acknowledgments

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Table 1: Simple blocking strategies and their efficacy.

Rule	Cost	Effectiveness (Reduction (%))			Wastage
		flow	packet	byte	
Benchmark	3756	-	-	-	1310
Rule 2 (n=2)	1586	63.0%	61.2%	56.5%	505
(n=3)	671	38.0%	36.0%	31.2%	176
Rule 3 (m=100)	2636	97.1%	94.0%	89.4%	560
(m=300)	1789	84.3%	80.4%	72.7%	302
(m=500)	720	57.6%	57.0%	53.1%	68
Rule 4 (k=5)	3471	87.4%	79.2%	77.5%	1216
(k=10)	3624	92.9%	85.5%	81.5%	1260
Rule 5 (n=2, m=300)	884	48.7%	44.0%	37.7%	163

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Notes

[1] Strictly speaking, in this paper we will use the term *exploit* traffic to mean traffic that is generated with the explicit intention to exploit certain vulnerabilities in target systems - a large subset of *unwanted* traffic, although frequently we do use the two terms interchangeably.

[2] Suppose the size of C_a is m and X may take N_X discrete values. Moreover, $P(X)$ denotes a probability distribution, and $p(x_i) = m_i/m, x_i \in X$, where m_i is the frequency or number of times we observe X taking the value x_i. Then, the RU of X for C_a is defined as $RU(X) := \frac{H(X)}{H_{max}(X)} = H(X)/\log\min\{N_X, m\}$, where $H(X)$ is the (empirical) *entropy* of X defined as $H(X) := -\sum_{x_i \in X} p(x_i)\log p(x_i)$.

[3] For clarity of presentation, points belonging to the *rare* behavior classes, i.e., those falling outside the three canonical behavior profiles, are excluded in both plots. These rare behavior classes tend to also contain anomalous or suspicious activities. See [3] for more details.

[4] Our profiling approach reveals the dominant activity of a given source, and not all activities. For example, an infect host, which sends a large number of exploit traffic, could also send legitimate web traffic.

[5] The cost exceeds the total number of unique sources of exploit since a few sources have exploit profiles on multiple destination ports.