

# The Far Side of DNS Amplification: Tracing the DDoS Attack Ecosystem from the Internet Core

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## ABSTRACT

In this paper, we shed new light on the DNS amplification ecosystem, by studying complementary data sources, bolstered by orthogonal methodologies. First, we introduce a passive attack detection method for the Internet core, *i.e.*, at Internet eXchange Points (IXPs). Surprisingly, IXPs and honeypots observe mostly disjoint sets of attacks: 96% of IXP-inferred attacks were invisible to a sizable honeypot platform. Second, we assess the effectiveness of observed DNS attacks by studying IXP traces jointly with diverse data from independent measurement infrastructures. We find that attackers efficiently detect new reflectors and purposefully rotate between them. At the same time, we reveal that attackers are a small step away from bringing about significantly higher amplification factors (14×). Third, we identify and fingerprint a major attack entity by studying patterns in attack traces. We show that this entity dominates the DNS amplification ecosystem by carrying out 59% of the attacks, and provide an in-depth analysis of its behavior over time. Finally, our results reveal that operators of various .gov names do not adhere to DNSSEC key rollover best practices, which exacerbates amplification potential. We can verifiably connect this operational behavior to misuses and attacker decision-making.

## CCS CONCEPTS

• Security and privacy → Denial-of-service attacks; • Networks → Naming and addressing; *Public Internet*.

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## 1 INTRODUCTION

Denial of Service (DoS) attacks pose a major, omnipresent threat to the stability of the Internet. About one-third of the active /24 networks on the Internet received DoS attacks over a two-year period [20], and 90% of attacks mitigated at a large IXP involved reflection attacks [41]. To bring about reflection, attackers spoof source IP addresses to send request packets that supposedly originate from an intended victim, and abuse the infrastructure that replies to these requests (*e.g.*, open DNS resolvers). Amplification is successful if the responses are larger than the requests.

The DNS is a core Internet component. It primarily operates over the transport-layer protocol UDP. Due to its stateless nature, UDP is particularly susceptible to spoofing, and at least 14 protocols that work on top of UDP allow for reflection attacks [52]. The Network Time Protocol (NTP) and DNS are (currently) the most-abused protocols [20, 23, 41].

Notably, amplification attacks are not limited to UDP. Poor implementations of network stacks allow attackers to use TCP as well [31]. A recent DNS amplification attack exploits inefficient resolver implementations and works regardless of the underlying transport-layer protocol [2]—DNS amplification remains one of the most popular attack vectors, despite recent changes such as DNS-over-TLS [18] and DNS-over-HTTPS [16].

Expert measurement methods are essential to observe global attack activities. Having a thorough understanding of attack dynamics and the abused infrastructure is crucial to effectively mitigate DNS-based attacks and to reduce the opportunity for infrastructure abuse. Several efforts exist to monitor amplification attacks on a global scale. Primarily, the monitoring infrastructures are implemented with the help of honeypots [26, 46, 59]. In such works, careful assumptions are made about the share of global attacks that honeypots account for [26, 59] because the amplification ecosystem consists of a large number of amplifiers [57] with high churn rates [30]. Moreover, sophisticated attackers learn about the location of honeypots and exclude them [50].

In this paper, we extend the understanding of the DNS amplification ecosystem by jointly analyzing results from four complementary measurements, including the Internet edge and core. First, we introduce a method to infer DNS amplification attacks at Internet eXchange Points (IXPs). We exploit the central position of the IXP to comprehend abused infrastructure dynamics and explore opportunities to fingerprint attack origins. Second, we use a

large, distributed honeypot platform to infer whether the IXP and honeypots observe the same set of attacks, and to investigate if attackers appear to exclude honeypots from attacks. Figure 1 visualizes our extended perspective on inter-domain DNS amplification attacks. Note that we anticipate attackers to abuse infrastructure that responds to DNS queries, which includes DNS forwarders and recursive resolvers. Third, we compare our observations with data from Internet-wide open resolver scans, allowing us to assess the extent of existing views on abusable infrastructure. Last, we consider comprehensive DNS measurement data to gain insights into the type of DNS infrastructure abused (*i.e.*, open resolver versus authoritative nameserver) as well as the amplification potential of attacks.

**In detail, we address three key research questions:**

**Question 1 (Section 5).** *Does an IXP-centric view contribute additional insights into DNS amplification attacks?*

As we will show, passive observations of DNS-based reflection and amplification attacks at an IXP can identify misused query names and abused infrastructure beyond honeypot-based inferences. Surprisingly, with an overlap of only  $\sim 4\%$ , IXPs and honeypots detect mostly disjoint sets of attacks. In total, we find 24k new attacks over the course of 3 months, which were not observed by the honeypots.

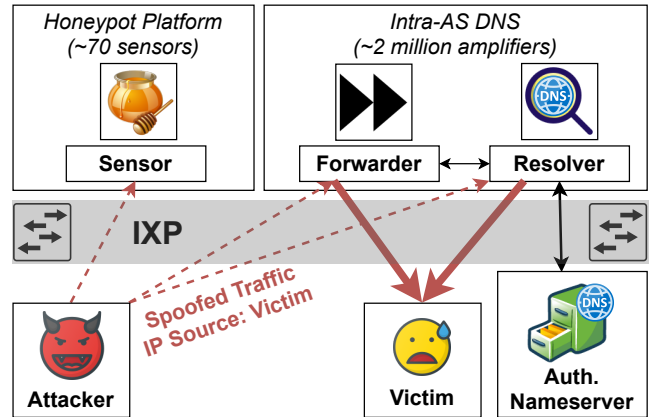
**Question 2 (Section 6).** *Can we fingerprint outstanding attackers within the DNS amplification ecosystem?*

We fingerprint a larger attacking entity by correlating the use of .gov names and static DNS transaction ID behavior. The entity in question is demonstrably dominant and responsible for 59% of inferred attacks. Our data suggests two topological changes (*i.e.*, relocation) of the attacking infrastructure within one year, indicated by shifts in network layer observables. We observe that the entity frequently changes abused amplifiers. Moreover, we recognize patterns in misused query names that strongly suggest attempts by the entity to improve the overall amplification factors.

**Question 3 (Section 7).** *How efficient is the current exploitation of the DNS, meaning: (i) how are the amplifiers misused; and (ii) can the amplification factor still be improved?*

We are able to pinpoint the abuse of at least 10 to 1000 amplifiers in most events. Our results show that attackers mainly misuse legitimate .gov names in spoofed DNS queries, which is likely, because names under the .gov zone are DNSSEC signed. Bilateral clustering also shows that only 2% of attacks use static amplifier lists. 95% of the amplifiers for which we observe abuse are also found by a large-scale platform that scans for abusable infrastructure, which suggests that attackers use mostly well-known, publicly documented amplifiers. Nevertheless, we reveal that 2% of amplifiers are abused before they show up in public scan data, suggesting that attackers also employ alternative methods to find amplifiers.

Overall, our observations show that attackers exploit amplifiers effectively, and the turnover makes fine-grained source-IP filtering much harder. In spoofed requests, attackers also misuse query names that lead to significant amplification factors. After inspecting 440 million domain names in DNS measurement data, we detect only 9000 names with larger amplification potential. At the same time, our estimation of DNS response sizes for these names reveals



**Figure 1: Vantage points and stakeholders of distributed, inter-domain DNS amplification attacks.**

that they could cause up to  $14\times$  more amplification. This shows that attackers do not fully exploit the DNS-based attack vector.

In the remainder of this paper, we present background and related work in Section 2. We outline four viewpoints from the complementary measurements in Section 3, and introduce our DNS attack detection method for an IXP in Section 4. We then proceed to answer our research questions in Section 5–Section 7, summarize discussions in Section 8, and conclude in Section 9.

## 2 BACKGROUND AND RELATED WORK

**Reflective Amplification Attacks and Honeypots.** Reflection and amplification attacks [54] are traditionally observed with honeypots [43], which apply straightforward thresholds to infer attack activity and to discern mere scanning for reflectors [26, 46, 59]. The advantage of using honeypots is that all incoming requests are likely part of attacks or scans since legitimate DNS services do not send DNS queries to those sensors. Honeypots, however, cannot infer the extent to which other infrastructures are involved (*e.g.*, public DNS resolvers) and are therefore limited in the assessment of general attack properties such as intensity. An additional challenge arises because the number of attacks visible to honeypots appears to converge quickly with only a few sensors deployed. Deploying more sensors does not necessarily increase the breadth of observation. This effect was shown with fewer than 10 sensors [26]. Thomas *et al.* [59] use a capture-recapture approach to estimate a 85%–97% visibility into UDP reflection attacks.

The research community has so far shown a tendency towards detection techniques for edge networks [36, 52]. We instead centre on IXP-based detection at the Internet core. Only NTP-based attacks have been studied at IXPs [24] by explicitly launching attacks via an attacking infrastructure. We focus on attacks in the wild and on DNS-based reflection, which requires a comprehensive detection mechanism. We also consider four Internet-scale, complementary data sources to investigate attack visibility and attacker behaviour. Our approach allows us to refute the common assumption that (sizable) honeypot infrastructures offer a near complete view on DNS-based reflection attack activity.

Recent prior work [23] started to compare attacks seen at an IXP and a honeypot using a flow- and volume-based DoS classification. The authors found little overlap (8.18%) between both vantage points. Following up on this, we present the first in-depth comparison between various DDoS ecosystem viewpoints, precisely targeting DNS.

**DNS Amplifier Ecosystem.** A DNS infrastructure that responds to *all* incoming requests is prone to be abused for reflection. This includes resolvers, forwarders, and authoritative nameservers [6, 35, 42]. DNS is the second most-common amplification vector, although its amplification potential is  $\sim 10\times$  smaller compared to NTP [6, 10] and it has the highest churn in reflectors among protocols susceptible to reflection. Kühner *et al.* [29, 30] show that this is mainly caused by open resolvers in access networks, *e.g.*, home routers, where dynamic address allocation leads to the quick disappearance of about 50% of identified amplifiers, when indexed by IP address.

Anecdotal evidence suggests that attackers abandon reflectors once response rate limiting (RRL) is detected [64]. Due to ample availability of DNS reflectors (2.1M in 2021 [42]), RRL can be counteracted [52] by scaling. High reflector churn as well as RRL force attackers to maintain and frequently update sizable amplifier lists. This aligns with the observation that DNS exhibits the highest daily rate of unique scanners [59]. Exploiting our IXP-centric view, we follow the abuse of amplifiers over a three-month measurement period, allowing us to unveil how efficiently attackers deal with churn. Honeypot-based studies have to date not been able to do so.

**Forged DNS Queries and Names.** The query name and type in DNS queries affect the amplification factor. Historically, the most common queries included unpremeditated as well as crafted domain names, which were set up and used for amplification attacks immediately after registration [26]. ANY is an evident query type, yet querying for specific records can equally lead to large responses [14, 26]. DNSSEC is a DNS extension that enables verification of DNS content but at the same time significantly increases the potential for amplification due to larger response sizes [6, 61]. Consequently, benign `.gov` names, which are subject to a DNSSEC mandate [58], started being misused in amplification attacks [59].

We shed light on how attackers select names and study effective amplification in attack traffic at the Internet core. We also analyze large-scale DNS measurement data to estimate the amplification potential of other names, allowing us to reveal that while attackers are prudent in selecting names, other choices would lead to higher amplification.

**Origins of DNS-Based Attacks.** As reflection and amplification attacks involve IP spoofing, attack attribution is challenging [13, 15, 33, 40]. In the case of NTP and its moderate amplifier churn, considering the set of abused NTP servers has shown utility towards attributing attacks to a DDoS-for-hire service [24]. However, other research shows that overlap in underlying infrastructure can exist, in addition to other obstacles to fingerprinting [55]. Not all honeypot sensors are necessarily used by attackers at the same time and attackers can choose to abuse a subset of available reflectors in subsequent attacks. Nevertheless, clustering methods such as KNN allowed researchers to fingerprint a few major attacking entities and attribute attacks to them [21, 28]. Another commonly

used feature is the IP Time-To-Live (TTL) field, which was used to narrow down attack origins [7, 27].

Despite challenges in fingerprinting attackers, we successfully use network and application layer data to fingerprint a major attack entity, responsible for over half of the attacks detected at the IXP. We follow this entity for over 9 months.

### 3 COMPLEMENTARY DATA SOURCES

We involve diverse and largely independent data from four data sources, bolstered by orthogonal methods. We next provide an overview of our main data to further comprehend the DNS amplification ecosystem. Our starting point is data from an Internet eXchange Point (IXP) for a three-month measurement period (2019-06-01 – 2019-08-31).

#### 3.1 Traces from a Large, Regional IXP

IXPs are a key component of the Internet to interconnect Autonomous Systems (AS) without introducing high costs. Observing traffic at a popular IXP provides a similar vantage point to that of large transit providers [4]. We use traffic captures from a large, regional IXP in Europe. Our IXP connects over a hundred member networks and observes traffic peaks of 600 Gbps. We now detail how we identify and sanitize DNS data in IXP traffic, before using the data for attack detection.

**Identifying DNS Traffic at IXPs.** Our traces involve 1:16k packet sampling and packets are truncated after 128 bytes, which can be challenging with respect to analysis of higher-layer (*e.g.*, application-level) protocols. On the upside of things, DNS usually operates with single UDP packets, hence packet sampling has no adverse effect as we do not need to observe complete flows. Moreover, the first 128 bytes of packets are sufficient to analyze DNS query packets. On the downside, in terms of analyzing DNS answers, response data is usually only partially visible (about 2 resource records per packet on average), since each DNS response contains request as well as answer data. Even though large UDP packets might be truncated and we cannot see the full answer data, we are still able to infer response packet sizes from the UDP length field, which precedes the DNS header.

Please note that we focus on DNS over UDP because TCP-based amplification attacks do not exploit features of DNS but only inefficient implementations of transport-layer sockets [31]. Also, even though stubs and forwarders use more recent DNS variants (DNS over TCP/TLS/HTTP) to contact resolvers, a recursive resolver usually still uses UDP to reach authoritative nameservers. TCP attacks use unencrypted traffic [3]. During our measurement period, only 1.25% of unencrypted DNS packets are based on TCP as a transport layer.

We use Tshark’s DNS packet filter and dissector for protocol identification and empirically verify that truncated DNS packets are identified correctly. In the case of a UDP packet that leads to IP fragmentation, only the first fragment is identified as it contains the DNS header. This effectively avoids double counting of fragmented DNS answers. Overall, we find 33 million sampled DNS packets

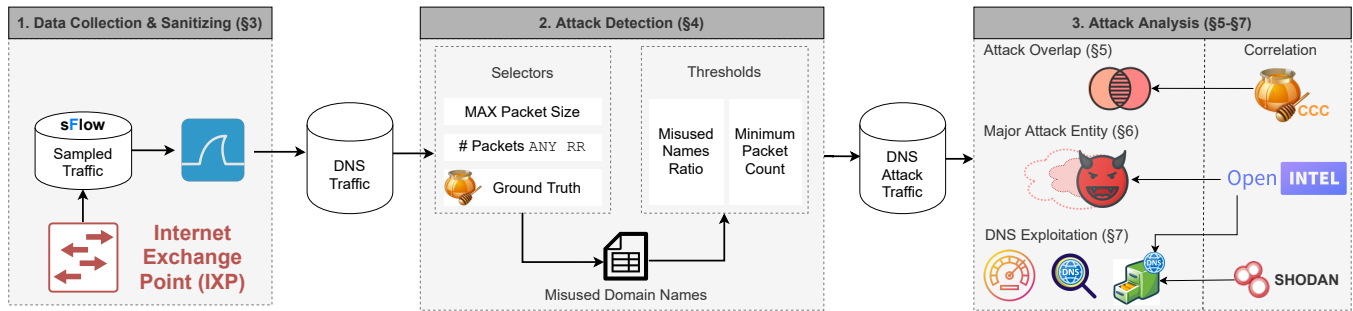


Figure 2: Overview of our data sources and attack inference steps.

from June to September 2019, which correspond to a total of 528 billion DNS packets.

**Sanitizing and Annotating DNS traffic.** We only consider packets that include: (i) IP and UDP headers; and (ii) well-formed values for IP addresses, UDP length, DNS query types and names, *i.e.*, values allowed and standardized by the respective RFCs. In the process, we disregard 3% of previously identified DNS traffic. In the resulting data set, we observe slightly more requests than responses per day (60% are requests). Daily aggregate packet counts follow a weekly pattern with small changes during the weekends. The most and second most common DNS query types are A (57%) and AAAA (13%) records. Using public routing data [44] and IXP member information we map the origin AS for 99% of packets, and the peering hop AS for 96%. For each query and answer packet, we also note the client and server IP addresses.

### 3.2 Additional Data Sources

**Honeypot Data.** We use data from the *Cambridge Cybercrime Center (CCC)* honeypots [59], which are distributed and capture reflection attacks at the Internet edge. This honeypot infrastructure has various features: (i) it provides topological diversity by using 80 active sensors that are distributed across 62 IP prefixes and 15 ASes; and (ii) it emulates open DNS resolvers, which are responsive to reflection attempts, while not harming the Internet. We learn 31k DNS reflection attacks from the CCC data during the same 3 months.

It is worth noting that we carefully verified that the CCC platform is able to make similar observations compared to related honeypot platforms (for details see Appendix B).

**Large-scale, Active DNS Measurements.** To investigate to what extent attackers might achieve amplification, we involve a longitudinal data source of daily DNS measurements that accounts for names that are not necessarily misused in amplification attacks (yet). We use data provided by the OpenINTEL project, which actively measures about 65% of the global DNS namespace, using well over 1200 zonefiles as a starting point [60]. OpenINTEL queries for

Table 1: Our various data sources backed by complementing methods to analyze DNS amplification attacks.

Data Source	Type	Viewpoint
IXP	Traffic	Transit, Internet core
CCC Honeypot	Traffic	Amplifier, edge network
OpenINTEL	Scans	DNS TLD zone walking
Shodan	Scans	Complete IP address space

a set of common resource record types, which allows us to map amplifier IP addresses to DNS infrastructure and to estimate response sizes (*i.e.*, amplification factors).

**Internet-wide Scans.** To verify whether an end host provided DNS services in the past, we use data from the Shodan search engine [57]. These data include daily scans of the complete IPv4 address space to discover Internet services per IP address.

We summarize our data sources in Table 1. Data sources of the category *scans* are based on active measurement methodologies, whereas *traffic* is brought about by passive observations. The complementary viewpoints allow us an in-depth understanding of effects observed for the DNS amplification ecosystem, as we show in the following sections.

## 4 INFERRING DNS AMPLIFICATION ATTACKS AT AN IXP

We first introduce our methods to infer misused DNS names and DNS amplification attacks in IXP traffic traces. We then briefly report about using these methods for live monitoring. Figure 2 shows an overview of our processing steps.

### 4.1 Identifying Misused Names

In DNS reflection attacks, queries for the right combinations of domain names and resource record types can trigger large responses and hence lead to sizable amplification. For this reason, attackers are likely to use effective names recurrently. Based on this assumption we find a list of suspicious DNS query names.

We develop the list of names using three so-called selectors. Two of our selectors consider features in the IXP data. The third selector involves the CCC honeypot data. The CCC data accounts for a

**Table 2: Distribution of attacks and attack traffic for misused names. .gov names that dominate amplified DNS traffic.**

TLD	.gov	.za	.cc	.pl	.cz	.com	.org	.se	.eu	.be	root(.)	.br	.ru
# Names	17	1	1	1	1	2	2	1	1	1	1	1	2
% Packets	74.92	1.32	3.92	1.1	1.17	1.31	0.99	0.54	0.38	6.23	6.73	1.38	0.005
# Attacks	22758	3969	3863	3732	3712	3388	3316	2663	2385	1551	1120	184	2
Max. Size [B]	8069	5155	4408	5954	5881	10270	6090	5535	4096	8199	4098	3893	–

substantial number of reflection attacks for which we may observe attack traffic at the IXP.

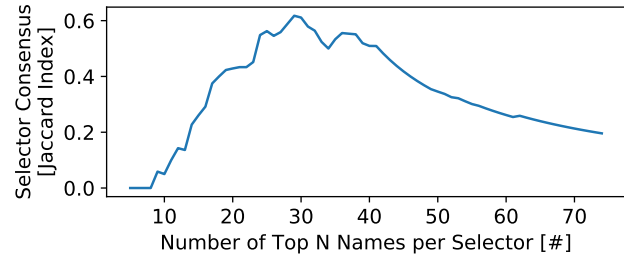
**Selector 1: Max Packet Size.** Our first selector considers the maximum (response) packet size of each and every query name observed at the IXP. Note that the response size per name may vary over time and also depends on the query type. We rank query names such that the first selector can pick, *e.g.*, the top-ten names in terms of max packet size. Large DNS responses may lead to IP fragmentation. Even in the presence of fragmentation, the UDP header, however, allows us to determine the size of the DNS response (see Section 3.1). The largest response of more than 10k bytes was triggered by an RRSIG query, the remaining top-ten largest responses are triggered by ANY queries.

**Selector 2: Number of ANY Packets.** The ANY query type is a convenient way to bring about DNS amplification, provided that ANY queries are not restricted by the authoritative nameserver of the chosen query name. This is why our second selector considers names that most appear in ANY query packets. The ten top-ranked names according to Selector 2 are used almost exclusively for ANY queries. Considering A, AAAA, and ANY packets, the share of type ANY packets is higher than >99.99% for all names but for the root (.) name (97%).

**Selector 3: Query Names Used Against Reflected DDoS Victims.** For our third selector we start by extracting all DNS attack victim IP addresses and timestamps from the CCC sensor data. Next, we search for the IXP DNS traffic associated with the attacks. Selector 3 then chooses the most common names used in the traffic in question. We find DNS attack traffic for 16% of all CCC DNS attack events ( $\approx$  4.4k victim IP addresses). We identify two reasons for invisible CCC attack traffic at the IXP: (i) The traffic is not routed via the IXP, and (ii) the traffic is routed via the IXP but the packets are not sampled (given our 1 : 16k sampling rate). The ground truth attack traffic consists almost exclusively of ANY packets (99%) and we observe only 482 unique names with this selector.

We consider the IXP DNS traffic associated with victim IP addresses at the time of an attack as *ground truth*. We later use this ground truth to validate detection thresholds. It is worth noting that the CCC data also provides query names, however, we decide to not use them in favour of selecting names that are actually visible from the perspective of the IXP in ground truth attacks.

**Number of Names per Selector.** The number of names chosen per selector is configurable. To determine the highest similarity, we calculate the Jaccard index for the three sets of names using increasing set sizes. We observe a high consensus for 29 names per selector (see Figure 3), which shows that the first 29 names chosen by each selector are almost the same, but with a different ordering.



**Figure 3: Our selectors detect the same names with a different ordering up to a set size of 29 names. These names are most likely to be misused in attacks.**

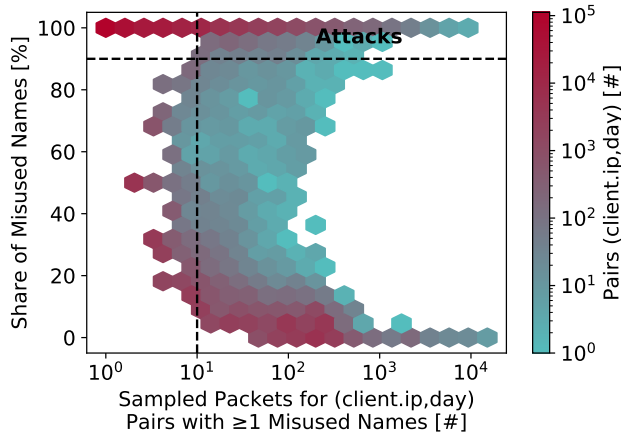
Note that selecting the point of highest consensus is a conservative measure for two reasons. First, this reduces the number of distinct names but chooses names for which up to three selectors agree. And second, the selector results follow a long-tail distribution with the knee points before the consensus point, which means that selecting more names would lead to adding *insignificant* names. All things considered, we set the size to detect misuse at 29 names per selector.

Finally, we merge the three selector sets of names to create our final list of names. The union combined with the high consensus point allows for a conservative name selection while still keeping significant names detectable only by a single selector. Our final list contains 34 names. For 32 of these names (94%), we detect attack traffic (see Section 4.2), which demonstrates the effectiveness of the selectors in identifying misused names. Table 2 shows properties of the considered names, most of which are part of the .gov zone. 21 names are mutually detected by all 3 selectors. The intersection of Selector 1 and 3 contains three names, and the intersection of Selector 2 and 3 contains five names. We find two exclusive names with Selector 1. Overall, the IXP and the first two selectors are sufficient to create our list. The CCC data does not add any names compared to the unions and intersections of all three sets. Using the honeypot-based selector is a good verification of the first two selectors, though, since it is based on ground truth attack traffic.

## 4.2 Attack Detection with Misused Names

Using the previously introduced list of misused names, we now further analyze DNS packets that contain queries or answer data for these names. This will allow us (i) to define two thresholds for the detection of attacks at the IXP, and (ii) to group related packets into attacks.

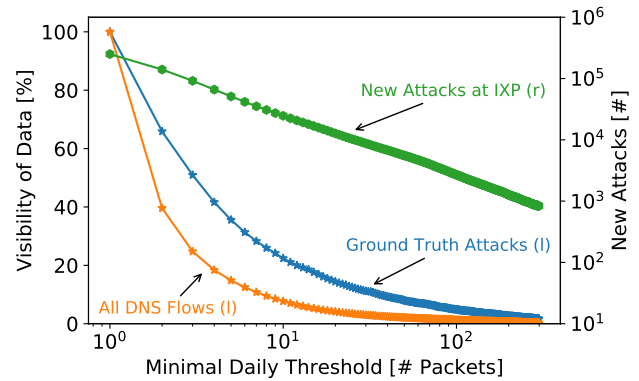
**Threshold 1: Traffic Share of Misused Names.** We calculate the daily “traffic share” of suspicious packets for client IP addresses



**Figure 4: Share of misused names compared to overall traffic. Many clients exchange DNS traffic with only misused names, which aids attack detection.**

(*i.e.*, supposed DNS query originators). A high share can indicate attack activity. Please note that the client IP address denotes the source IP address of DNS requests and the destination IP address of DNS responses. The share of suspicious packets is calculated for each unique (*client.ip, day*) pair for which at least 1 suspicious packet was observed. This excludes unrelated DNS activity, *i.e.*, clients which exchange traffic for only benign names on a given day. Then, we visualize the share of misused names for each (*client.ip, day*) in Figure 4. This reveals that with an increasing packet count a bimodal distribution becomes more pronounced, *i.e.*, even though clients exchange large numbers of DNS traffic, the related traffic consists of only misused names or almost none. The low shares occur due to the fact that one of the misused names is the root ( $.$ ) name, which is also a very common name for legitimate DNS traffic. This distinctive distribution allows for the introduction of thresholds to detect attacks. With our first threshold, we define that a client is under attack if the share of misused names exceeds 90% on a given day. This finds extreme cases of suspicious traffic shares but still allows for a small error margin, *i.e.*, we might observe other names due to legitimate DNS traffic of the client. Note that for clients with a low traffic volume (*e.g.*, 1 sampled packet), this single threshold is not enough since it most-likely leads to many false positives. We therefore set a minimum packet count threshold at the beginning of the bi-modal distribution (details see Threshold 2). With respect to the minimum packet count threshold, the traffic share threshold of 90% accounts for the smallest possible error, *i.e.*, exactly 1 sampled legitimate packet.

We argue that the high traffic share of misused names is a strong indicator of attack traffic. To illustrate this argument consider ten sampled packets, our sampling rate of 1:16k, and a misused name share of 90%. This would correspond to 144k packets with only misused names. No client should reasonably exchange so much

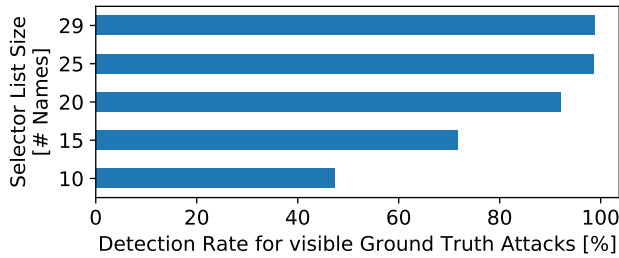


**Figure 5: Visibility of all DNS flows and ground truth attack flows depending on the number of packets considered. Number of detected DNS attacks at the IXP based on the thresholds are shown on the right  $y$ -axis.**

DNS traffic for legitimate reasons, especially in the presence of DNS caches.

**Threshold 2: Minimum Packet Threshold.** We now explore the effects of a minimum packet threshold at the IXP, in particular we analyze the trade-off between the detection of all attacks (*visibility*) and reducing false positives. To this end, we use our ground truth attack events that we found at the IXP with the help of CCC sensor data. We count the number of packets for these attack events and plot the fraction of visible events w.r.t. minimal packet count, see Figure 5. To provide a reference point, we also include the visibility of DNS traffic for all (*client.ip, day*) pairs. Overall, this plot demonstrates which share of DNS traffic remains visible at the IXP if a minimum packet threshold is applied. We find that 22% of visible ground truth attacks exhibit at least 10 sampled packets, *i.e.*, they remain detectable while applying a minimum packet threshold of 10 packets. Note that for all (*client.ip, day*) pairs, the visibility for 10 packets is, as expected, much lower (8%), since regular DNS flows only consist of significantly fewer packets. Looking at the total number of additionally detected attacks at the IXP (secondary  $y$ -axis), the threshold of 10 packets at minimum strongly limits the number of detected attacks. We argue that this significantly reduces false positives (or at least vague cases) but still allows us to find over 24k new, significant attack events at the IXP. Again, these attacks were not observed by the honeypots, hence provide an opportunity for new insights.

**Validation.** A sound attack detection mechanism should be able to detect attacks for which we know to be visible in the sampled IXP traces. Given this notion, we now investigate the detection rate for visible CCC attacks, based on the defined thresholds and a varying number of names for our selectors. This allows us to verify whether precision of our attack detection would increase by adding more misused names. Figure 6 shows that the detection rate converges at 99% with 29 names per selector for our threshold configuration. This clearly illustrates that we do not need to fine tune our detection method further. Also, this result is coherent with



**Figure 6: Attack detection rate based on selector list sizes and 2 thresholds. We reach 99% for visible ground truth attacks and see a convergence around 29 names.**

the selector consensus, which, again, suggests that adding more misused names does not have a beneficial effect.

**First Glimpse into Detected Attacks.** At the IXP, we found 25.7k attacks to 19k unique client IP addresses, which includes 24.6k new attacks (as previously mentioned). The detected attacks are dominated by traffic created by misusing .gov names, see Table 2. The attack durations match the observations of security reports [45, 47] with many short-lived attacks (25% shorter than 7 minutes 50% shorter than 33 minutes). One third (36%) of the total attack traffic is sent towards victims in ISP networks, which is the largest victim group after content networks (24%).

We see no signs of NXNS attacks [3]. Those rely on responses including NS referrals with many NS names (>30) but no glue records. In our data, 70% of the responses include at most 1 NS entry and 90% at most 10 NS entries. Recently detected attack vectors (*i.e.*, SRV, URI), which also offer a 10× amplification factor [37], are also not used, yet.

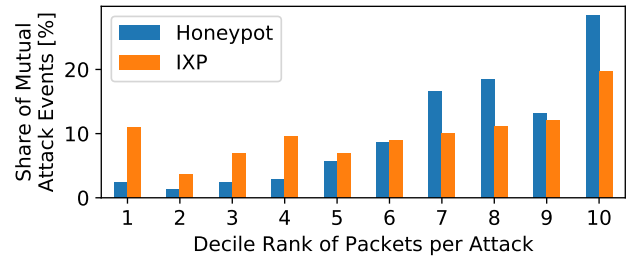
### 4.3 Live Monitoring

We deployed our method at the IXP to verify online detection capabilities in realistic settings. Our prototype consists of two building blocks: (i) A module that identifies potentially misused names in near real-time. (ii) A module that continuously analyzes changes compared to the previous day. Without advanced performance optimizations, we are able to identify misused names within a maximum delay of 5 minutes, on commodity hardware.

We utilize our deployment to assess victim and name fluctuations. Overall, we see quite stable numbers of unique victims and also very stable lists of misused names. On average, we observe 631 unique victim /24-prefixes (492 /16-prefixes and 121 /8-prefixes) per day. The name lists have a mean Jaccard index of 0.96 in comparison to the respective previous day. This suggests that daily updates for misused names are not necessary; we keep them to identify changes quickly.

## 5 COMPARING IXP AND HONEYPOT DATA

We now present basic properties from attacks inferred at the IXP and compare the observations to honeypots. We find that the IXP and the honeypot sensors observe a vastly disjoint set of attacks. Both vantage points share only 1.1k attack events, which corresponds to 4.2% of all events at the IXP and to 3.5% of 31k attack



**Figure 7: Attacks detected by the IXP and honeypots (1098) differ in relative attack intensity score: Mutual attacks are rather strong honeypot attacks, but medium-sized IXP attacks.**

events at the honeypots. This is a surprising result, given that prior work [26, 59] assumed that a distributed honeypot, such as ours, can capture a large percentage of global reflection attacks. We consider an IXP vantage point to be an opportunity to observe DNS amplification attacks which have been so far invisible to the research community, and potentially provide new insights, *e.g.*, for attacks that deliberately exclude honeypot platforms.

While the overlap is small, we now check, for comparative purposes, whether the honeypots and the IXP agree on the observations for mutual attacks. To this end, we calculate a relative attack intensity score for all attacks that have been identified by each type of vantage point. We do this by sorting all attacks by the total packet count and calculating the deciles. Then, we rank each attack with the decile score of 1 to 10. We plot the relative distribution of intensities for mutual attacks in Figure 7. Overall, honeypots are rather sensitive vantage points: the mutual attacks are mostly strong honeypot attacks (with a mean intensity of 7.7) and medium-sized IXP attacks (with a mean intensity of 6.3). We argue that this is due to packet sampling and our thresholds, which make smaller attacks invisible at an IXP. Hence, honeypots are good vantage points to detect small-sized attacks, *if* they are abused by the attacker as reflector. IXPs, on the other hand, show that a substantial number of large attacks occur, which were not observed by the honeypots. They are likely to see even more small attacks but this would require significantly smaller sampling, which is uncommon in practice. We will leave this for future work.

## 6 TRACING A MAJOR ATTACK ENTITY

In this section, we reveal a major attacking entity, which is responsible for 59% of all attacks at the IXP. To this end, we identify recurring patterns based on the selection of domain names, the creation of DNS requests, and the selection of amplifiers. Our method does not depend on our specific vantage point but can be generalized to other inter-domain data sets.

We link multiple independent events to an attack entity. We explicitly use the abstract term *entity* as we do not refer to a specific botnet, booter website *etc.* but to the essence that maintains an infrastructure to select names and amplifiers to launch attacks.

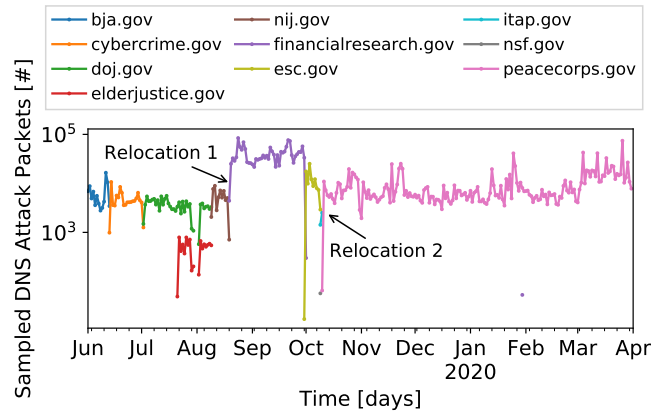
### 6.1 Fingerprinting Using Domain Names

We conduct a time series analysis of the misuse of names. Our results reveal a clear transition between names for selected .gov names (see Figure 8(a)), which contribute 59% of the overall attack traffic. Names appear to be chosen in lexicographical order, except for few weeks in which two names were used concurrently.

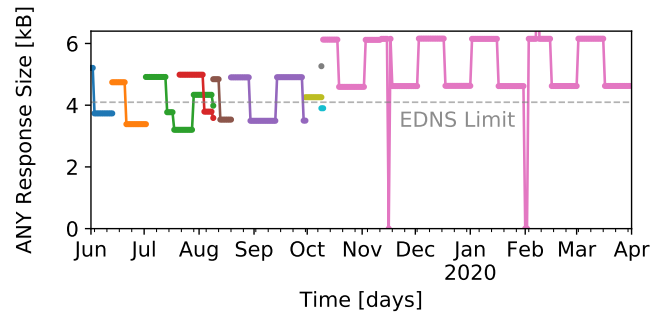
The transition pattern between names strongly suggests that a specific entity is involved in the attacks. Independent misuse of the same domain would not lead to clear, abrupt transitions. Interestingly, we observe an increase in attack traffic at the IXP following changes in misused name. This hints at a driving factor behind the transitions in lexicographical order. To further investigate this observation, we analyze the expected response sizes offered by names, as this is crucial for amplification attacks. Figure 8(b) depicts the ANY response sizes of each name inferred from the OpenINTEL data set, which provides us with historical DNS data. The dashed line indicates the recommended maximum payload size (4096 bytes) of EDNS [11], the extension mechanism in DNS to carry, e.g., DNSSEC data. **We observe that the expected response sizes change while names are actively misused in attacks, and also that transitions to other names follow drops in sizes.** Further analysis of the OpenINTEL data set reveals that the plateaus in response sizes—which last two weeks—relate to DNSSEC key rollovers. When a new zone signing key (ZSK) is introduced, an increase in response size can be expected, as multiple DNSKEY records are present at the same time. ZSK rollovers can be completely automated in software, which explains the regular patterns. RFC 6781 [22] recommends two rollover schemes, pre-publish and double-signature. Pre-publish introduces only the new key in stand-by mode, i.e., the key is not yet used to sign RRSets. This allows resolvers to learn about the new key before it is actively used. This scheme, however, is prone to race-conditions and misconfigurations [9] which impair the validation process. To overcome the challenges of pre-publishing, the double-signature scheme has been introduced. Double-signature allows two active ZSKs and generates two (redundant) RRSIG records signatures. The old ZSK can then be retired at any given time. On the downside, this scheme doubles the number of signatures in a zone. Although both rollover schemes are proposed in RFC 6781 [22], pre-publish has been established as a de-facto standard. It was used 4x more often than double-signature in 2016 [9, 48], and 8x more often in 2020 [48]. Also, it is recommended by various DNS software vendors [48].

We only observe double-signature schemes for the misused .gov names. This leads us to conclude that **operators of these .gov names, many of which are US federal government domain names, do not only not adhere to best practices, which exacerbates amplification, but also that these decisions introduce misuse by others.** A recent (Q2 2021) sample of DNSSEC records for nsf.gov and doj.gov shows that the rollover practices did not change.

Even though we observe transitions after a (variable) number of days when the expected size is below the recommended EDNS limit (see the valleys in Figure 8), we cannot reasonably infer the decision making process behind. Either the attack entity completely understands DNSSEC mechanics or simply observes < 4096 byte responses and then (manually) transitions to the next name.



(a) Attack traffic volume of misused names based on IXP data.



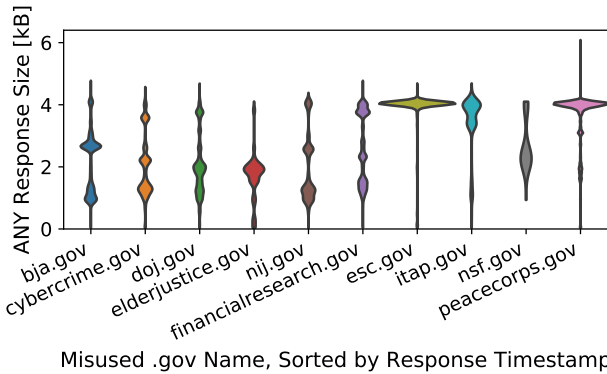
(b) Estimated ANY response sizes of currently misused names based on OpenIntel data set. Plateaus indicate DNSSEC key rollovers. Cutoff of a single anomaly (value of 12.5kB) for better readability.

**Figure 8: Time series of synchronized names misused by major attack entity.**

By analyzing the packet sizes in the sampled IXP data, we can confirm that the attack entity achieves effective amplification factors. In contrast to Figure 8(b), which exhibits the potential maximum ANY response sizes, Figure 9 shows the relative frequency of the actual response sizes observed at the IXP and extracted from the UDP headers, grouped by each name. Please note that we consider all DNS query types for the misused names. In the attack traffic, however, we only observe the type ANY for these names. Most names exhibit a bi- or tri-modal distribution. The observed clusters of response sizes near the theoretical limit highlight that the attack entity succeeds in finding names (and related authoritative name-servers) as well as amplifiers that still allow ANY requests. Closer investigation reveals that smaller response sizes appear rather at the end of a name’s life cycle. This bolsters our result that the entity observes the current effective amplification factor and updates misused names upon a decline.

**Additional Fingerprinting Features.** To verify that we can link multiple events to a single entity, we seek other features that may indicate uncommon consistency over time. To this end, we perform an entropy analysis of packet header fields that usually should show





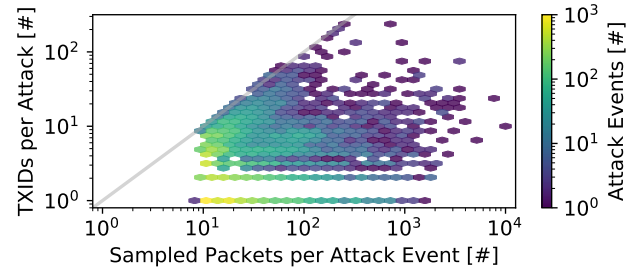
**Figure 9: Violin plot of the observed DNS response sizes at the IXP for the major attack entity.**

high randomness. If they do not, we suppose the deployment of the same attack tool. Pre-built headers and usage of raw sockets may lead to such consistent behavior, for example.

For each attack event, we check whether the number of distinct values of a specific feature grows linearly with the total packet count. We investigate header fields such as IP . ID, UDP . SRCPORT, and DNS . ID. As network and transport layer features change after reflection, we consider only DNS queries (*i.e.*, packets that are sent before amplification) here.

Unfortunately, all features in the network and transport layer headers exhibit a linear growth and hence a high entropy. Fortunately, we detect a low randomness for the DNS transaction ID, a feature in the application header. The number of IDs in use is usually 1-2 orders of magnitude smaller than the total packet count, see Figure 10. The low entropy gives good reasons to manually inspect the DNS IDs. We found that 91% of attack events have only a (seemingly random) selection of odd or even IDs. With respect to the minimal number of sampled packets containing misused names (9), the probability for this observation with random DNS IDs is  $2 \cdot (1/2)^9 = 0.4\%$ . Also, we rule out measurement artifacts such as a synchronization between traffic and sampling, since sampling selects 1 out of 16k and not every 16kth packet. Hence, we argue that we found an arithmetic structure and not only a random phenomenon. For the remaining 9% of attack events we observe two phases with odd and even IDs, respectively, and a distinct shift. Indeed, the overall selection of IDs for the attack events with synchronized names follows a two-day rhythm, alternating between odd and even DNS transaction IDs every 48 hours, independent of other features. The selection of IDs is probably seeded with timestamps and not linked to the properties of the victim.

In summary, we are able to fingerprint a major attack entity based on two properties: (i) its selection of names and (ii) the implementation details of the attack tool (selection of DNS IDs). Both features are part of the application header, which means that we can link attack traffic to this entity even after the reflection occurred. Similar to our observations in Section 5, the fingerprint of this attack entity is only visible for  $\leq 0.6\%$  of the attacks detected by the honeypot, *i.e.*, the attack entity is only clearly visible at the IXP.

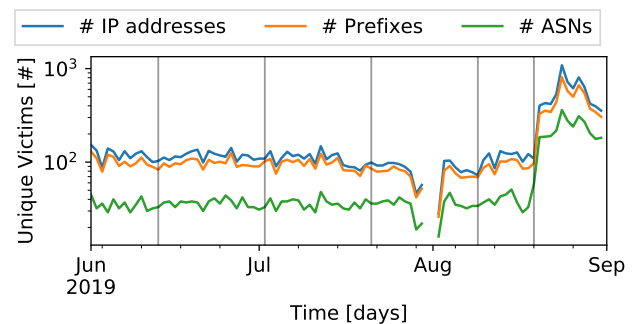


**Figure 10: Entropy check: # of unique DNS transaction IDs and packets for all packets from attack entity. A limited number of DNS IDs indicates pre-built queries.**

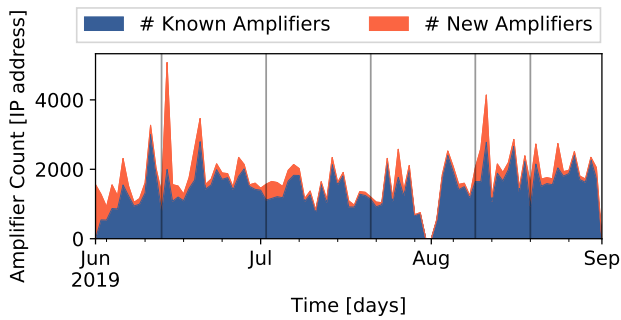
## 6.2 Attacked Victims, Misused Amplifiers

We now describe the executed attack events as well as reconfigurations and relocations controlled by the attacker. The attacks we associate with this entity are distributed. We observe almost as many victim destination IP addresses as covering victim prefixes per day, see Figure 11. In this plot, we highlight the transitions between misused names with vertical lines. The number of victims remains stable until the transition to the last name occurs. Then, the number of victims increases by almost an order of magnitude. The increase also correlates with the total number of packets (compare Figure 8(a)).

We check whether the attacker reconfigures only the list of misused names or also the list of misused amplifiers. To this end, we count the daily number of new and known amplifiers, *i.e.*, amplifiers that have been already misused at least once, see Figure 12. This plot introduces two findings. First, although the number of total attacks increases, the number of misused amplifiers remains stable. This suggests that the entity misuses only a specific set of amplifiers per day. Random subsets, however, are selected per attack event, which we will show in detail in Section 7. Second, periods with significantly more new amplifiers usually follow name transitions, indicating that names as well as the amplifier list were updated at the same time. Nevertheless, new amplifiers appear almost daily,



**Figure 11: Number of unique victims identified by IP address, prefix, and AS numbers. Vertical lines highlight transitions of misused names.**



**Figure 12: Known and new amplifiers used by the major attack entity. Bursts of new amplifiers correlate loosely with name transitions (vertical lines).**

revealing a more continuous update behaviour, which is necessary due to IP churn of DNS hosts.

In order to understand the increased number of attacks, we continue investigating other features. We find that starting with the peak mid of August, the DNS request-response ratio for this entity shifts dramatically. Before, we observe almost purely amplified DNS traffic, *i.e.*, DNS responses. The absolute numbers of responses remain stable, however, we see a stark increase in requests. Now,  $\sim 85\%$  of attack traffic consists of requests. Moreover,  $99.8\%$  of the requests originate from the same ingress AS and exhibit the same IP TTL of 250. Seeing such a concentration from a single ingress AS indicates a centralized attack infrastructure, because botnets are usually distributed across multiple networks. Such infrastructures are usually the hidden back-end of booter websites. Unfortunately, the customer cone of this ingress AS contains more than 16k ASes, so we are not able to fully trace back the infrastructure. We do not find topological changes at the IXP that would justify the shift in attack traffic properties, *i.e.*, we do not find any new members and the ingress network has been already a member during the whole measurement period. Also, it is unlikely that this shift is caused by unrelated routing updates as the paths to all amplifiers would have to change simultaneously for such a homogeneous effect. Instead we argue that since the shift occurred concurrently with a name transition, this effect is triggered by the attack entity itself, namely due to a relocation into the ingress cone of the IXP member. We define relocation as the topological transition of a centralized attack infrastructure into another network. We later observe a second relocation in mid October.

To sum up, by revisiting the main measurement period with a fingerprint in hand, we were able to identify reconfigurations of names and amplifiers, and a relocation of the attacking infrastructure. We were able to do this on the basis of network and application layer information visible at an IXP.

## 7 UNVEILING DNS ATTACK PRACTICE

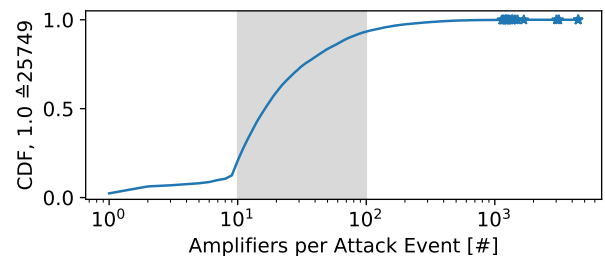
In our last analysis, we use our inter-domain IXP perspective to disclose the abused infrastructure. Also, we analyze how (all) attackers perform in terms of amplification efficiency.

### 7.1 Amplification Ecosystem

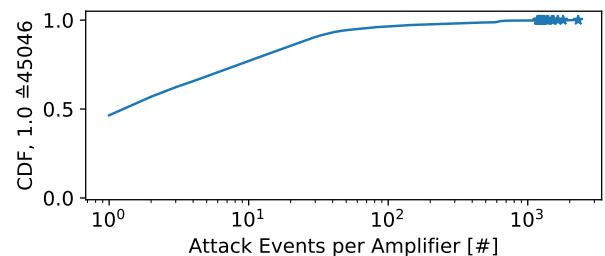
We start by investigating whether attackers continue to abuse the same reflectors across attacks. Repeatedly using a stable infrastructure may make attackers (i) fingerprintable and (ii) susceptible to frequent re-addressing of edge resolvers.

**How many amplifiers are used in attacks? And in how many attacks do particular amplifiers appear?** The OpenINTEL data accounts for a large number of authoritative nameservers active during our main measurement period: approximately 4.2 million NS names that together map to well over a million IP addresses. We use these data to associate amplifier IP addresses observed at the IXP with authoritative nameservers, where applicable.

We find that only 908 authoritative nameservers are abused in attacks—about 2% of all amplifiers observed at the IXP. By exclusion, we conclude that the vast majority of abused DNS amplifiers are open resolvers or forwarders. We discuss further a classification of forwarders and resolvers in Appendix C. This does not come as a surprise, because authoritative servers should not recursively resolve DNS queries, which makes them less attractive reflectors. Root-query-based attacks, however, utilize  $4\times$  more authoritative nameservers, which can be linked to attacks misusing misconfigured root hint-files [19], [5, Chapter 4]. We observe that 80% of attack events use between 10 and 100 amplifiers (numbers not extrapolated by sampling rate), *cf.* Figure 13(a). Also, Figure 13(b) shows 23% of amplifiers that participate in more than ten attacks.

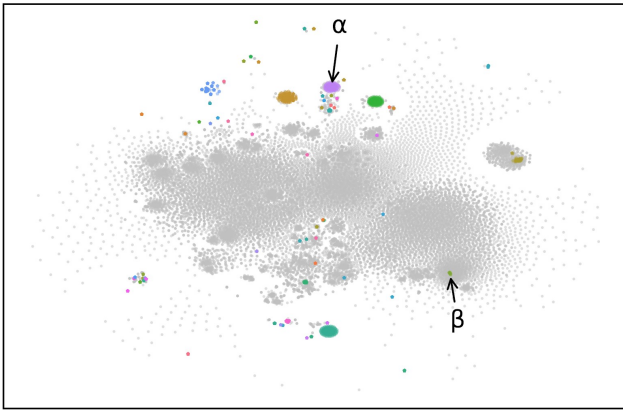


(a) Number of amplifiers per attack: Most victims are attacked by 10 to 100 amplifiers.



(b) Number of attacks per amplifier: 50% of the amplifiers participate in more than one attack, even 23% of amplifiers in more than ten attacks.

**Figure 13: Distributions of amplifier involvement in attacks. Last 20 data points are highlighted.**



**Figure 14: T-SNE visualization of attack events based on Jaccard distance over the amplifier sets. DBSCAN clusters marked with colors (gray being not classifiable). Both clustering algorithms agree on the dissimilarity of attack events.**

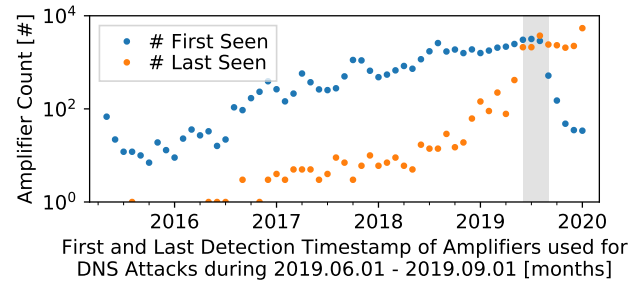
Such recurrent use of amplifiers may allow for fingerprinting attackers.

**Do attack entities work with stable lists of amplifiers?** After observing recurrent amplifiers, we now investigate whether attackers use relatively static amplifier sets. As the DNS is subject to high amplifier churn [30] from home gateways with 24h IP address lease times [29], we expect sets to exist for short time spans, only.

We approach our analysis by quantifying the (dis)similarity of two attacks from measuring the Jaccard distance over its respective sets of amplifiers. A group of similar attacks (*i.e.*, cluster) with a low Jaccard distance among each other indicates a fixed list. We use a bilateral clustering method by using two well-known algorithms: T-Distributed Stochastic Neighbor Embedding (T-SNE) [34] and Density-Based Spatial Clustering of Applications with Noise (DBSCAN) [12]. We compute both algorithms independently to exclude a biased result from a single clustering method.

T-SNE allows us to visualize high-dimensional data on a two-dimensional plane. Similar attacks are moved towards each other and dissimilar attacks are moved apart. We observe very stable results for different perplexity parameters. The clustering results are visualized in Figure 14, each gray scatter point represents a single attack event. T-SNE indicates a strong dissimilarity between most events, with some noticeable clusters. DBSCAN groups nearby neighbors into clusters and marks non-classifiable outliers within low-density regions. We next combine both clustering results in the single Figure 14. DBSCAN cluster IDs are encoded with colors, the non-classifiable outliers in gray.

We see 67 clusters while  $\sim 92\%$  of attack events remain outliers. We inspect clusters of at least 5 attacks and 5 amplifiers to find stable sets. Here, the most static amplifier set ( $\alpha$ ) was used for 177 attacks during 40 days without any change. The largest set ( $\beta$ ) uses  $\sim 527$  amplifiers per attack while always introducing a small, steady change. We can attribute in total only 2% of attack events to fixed sets. Attackers seem to steadily use a random combination of known and new amplifiers. This reinforces our previous findings



**Figure 15: Number of Shodan first and last interaction with reflectors that were observed by us during the attacks at the IXP. Timerange of attacks highlighted in gray.**

that attackers leverage the amplification ecosystem and that source-based filtering is infeasible to mitigate DNS amplification attacks.

**Do attack entities recruit new amplifiers?** Since our results suggest that attackers steadily vary their amplifier sets, we question which amplifiers are used over time. To this end, we use the Shodan historic lookup, which allows to retrieve its complete scan history for a given IP address. Shodan omits transparent DNS forwarders. It lists currently around 2 million recursive DNS resolvers, which all can be abused for reflection. Next, we perform a historic IP address lookup for all 45k amplifiers observed at the IXP.

We find that 95% of these amplifiers are reported by Shodan to serve recursive DNS at some point in time. This finding grants two insights: (i) it confirms independent observations that although most amplifiers are known to the community, we fail to remove these amplifiers ultimately [42, 49]; (ii) attackers do not use private but mostly publicly indexed amplifiers. Scan results can differ even for Internet-wide measurements, *e.g.*, due to the origin of the scanner [62]. However, both Shodan and attackers observe a very similar set of DNS-amplifiers.

To examine the age of an amplifier that was abused during our measurement period, we determine its first and last successful detection by Shodan in Figure 15. A significant number of amplifiers was first seen during six months preceding the attack, *i.e.*, attackers mostly use amplifiers that are not older than six months. Also, many amplifiers are observed for the last time during or right after our main measurement period indicating that (i) operators change the inadvertently open state of their resolvers; or (ii) the amplifiers churned because of a dynamic IP address. Notably around 850 reflectors (2%) appeared in attacks before discovery by Shodan. This suggests that some attackers run their own scanning engines with a higher scan frequency or accuracy than Shodan.

At this point, our methodology allows to passively identify DNS amplifiers as they are abused, even before other measurement efforts succeed. Overall, we observe substantial DNS amplifier churn at the IXP but discern no downside for attackers. Note that we observe actual amplifier abuse at the IXP, not the churn in amplifier reachability (which scans can reveal). Although the total number of abused amplifiers remains stable between attacks, we see on average only 45% of abused amplifiers in subsequent ( $\text{day}_i, \text{day}_{i+1}$ ) pairs. Comparing the first and last day of our three-month measurement period, only 20% of amplifiers still make an appearance.

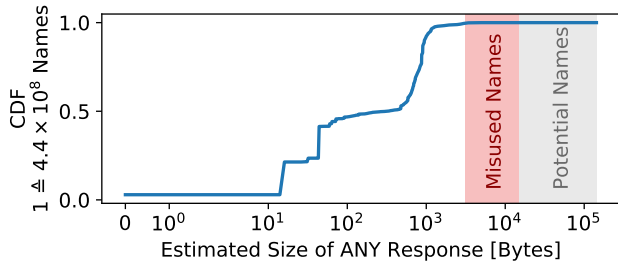


Figure 16: Estimated ANY response sizes for names measured by OpenINTEL. We highlight the range for currently misused names (red), and show the range of potential names (only 9048 distinct names) to increase the amplification factor (gray).

This observation suggests that attackers effectively detect—and purposefully rotate—new DNS amplifiers.

## 7.2 Potential Amplification Factors

**Do attackers select names that maximize amplification?** We investigate whether attackers inquire names for maximizing amplification, or whether there is an unused threat potential. Using the OpenINTEL data, we estimate the response sizes of ANY queries of 440 million domain names and plot the CDF, see Figure 16. Please note that we calculate the response sizes based on the cumulative resource record sizes stored in the DNS and ignore common software or protocol limits (4096 bytes for EDNS and 65,536 bytes for UDP).

The names previously observed in misuse exhibit a response size highlighted in the red area. Overall, only 9048 domains show a higher amplification factor than the highest ranked, misused name—about 0.002% of all names (gray area in Figure 16). This suggests that attackers attempt to cherry-pick names for high amplification factors without being optimal. Our estimated largest response size is 142,855 bytes, whereas the largest we actually observed is 14× smaller.

**Can we expect larger attacks in the future?** Frighteningly, we find that ~92,000 names (0.02%) in the OpenINTEL data set may lead to a response size larger than 4096 bytes. Even though EDNS [11] recommends to not send larger replies, our measurements reveal that the DNS infrastructure frequently does so in practice (see Section 6.1).

Visible DNS attack events contribute a substantial amount of DNS attack traffic to the Internet core. Notably, the overall attack traffic at the IXP accounts for 5% of the total DNS packets and 40% of the total DNS traffic volume. This trend becomes even more apparent when only ANY traffic is considered: 68% of ANY packets and 78% ANY bytes are part of attacks. The situation will grow worse when attackers begin to use the names with a higher amplification factor.

## 8 DISCUSSION

**Is the observation of the major attack entity a bias of our vantage point?** Despite being a central element of today’s Internet,

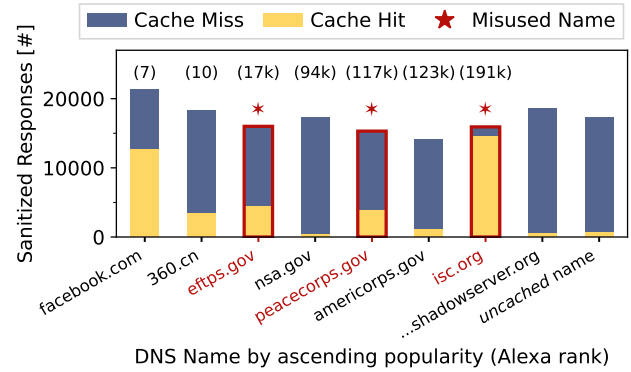


Figure 17: DNS cache hits for a set of arbitrary names and misused names. Names with a low popularity in the Alexa ranking but high cache hit rates indicate world-wide usage of the names for other reasons.

most IXPs still operate locally to interconnect networks. To verify that our observations are not a local phenomena based on our large, regional IXP, we assume that popular names are likely to be cached in the DNS. To quantify world-wide usage of names, we apply a modified cache snooping analysis. In a nutshell, we resolved misused names as well as a set of arbitrary names via all public resolvers and compare whether the names were cached or not (details see Appendix C). We correlate the cache hits and misses with popularity of the names in the Alexa ranking. For reference purposes we created a name only for this study (*i.e.*, a name that was not cached before).

Figure 17 shows that misused names (highlighted in red and with a ★) have a similar cache hit ratio as very popular western and eastern names, even though our misused names exhibit much lower popularity based on the Alexa ranking. The results indicate that the misused names are resolved frequently but not because of common (Web) services. Hence, we argue that the IXP and our methodology give insights into behavior of global scale.

Our results are further substantiated by a recent study published by an anti-DDoS provider [32]. Labovitz [32] confirms that one of the misused names identified by us (peacecorps.gov) has been utilized by the booter *SynStresser* to perform attacks. Also, some of our attack events correlate with publicly documented attacks [53].

**Would authoritative name servers provide a complete picture?** No. 98% of open DNS amplifiers are forwarders and not recursive resolvers [42]. This means that the majority of amplifiers do not communicate with authoritative servers. Also, recursive resolvers will contact an authoritative server only when the name is not locally cached. Cached responses, however, are common because they make DNS scalable. TTLs may range between 1 hour up to days [38]. We observed the impact of caching in the bi- and tri-modal distributions of attack traffic at the IXP (see Section 6). Furthermore, our data corpus includes individual resolvers that serve up to 20k DNS amplifiers, which illustrates that caching is more likely and, thus, requests less visible at the authoritative servers.

Hence, neither the misuse of a name nor the complete attacking infrastructure might be visible to an authoritative server.

**What can operators do to improve the situation?** Operators can help by configuring their authoritative nameservers or recursive resolvers to (i) block ANY requests completely, (ii) respond to ANY requests only via TCP or with a minimal subset [1], (iii) deploy rate limiting. Similar recommendations have been proposed for years [61], unfortunately DNS amplifiers still exist. Our observations suggest that those countermeasures are still helpful because an attack is based on a relatively stable set of queries. In case advanced query patterns [3] are issued in the future, which our method would detect, the deployment of filters that focus on names or observations across multiple resolvers are options. As we found that some few resolvers serve a significant amount of amplifiers (i.e., forwarders), educating those first will have larger impact.

To the best of our knowledge, this is the first paper that shows the adverse impact of DNSSEC key rollovers in the context of amplification attacks (see Section 6.1). Double-signature rollovers temporarily create a second, superfluous set of signatures, which makes these names more attractive to attackers. Operators should pay attention to misuse during rollovers for their zones. Overall, we recommend pre-publish rollovers which currently are best practice [48].

**Advantages of IXPs?** IXPs are considered to be central vantage points [8]. We introduced methods to leverage IXPs to shed new light on DNS amplification attacks. We found that honeypot platforms see less compared to what was assumed before, extending recently observed trends [23]. To achieve a similar coverage compared to large, regional IXPs, honeypots require broader distribution. What concerns us most is that honeypots are easy to detect [39, 50, 63], either because they deploy (for good reasons) rate limiting [26, 59] or they expose other features such as delays that enable fingerprinting. Prior work clearly indicated that malware adapts and hides [17]. In contrast to honeypots, IXPs are native part of the Internet infrastructure. They do not need to deploy detection schemes that expose to an attacker. They allow for monitoring of Internet traffic where networks intertwine, which also simplifies operational maintenance of a monitoring system.

## 9 CONCLUSION AND OUTLOOK

We studied the DNS amplification ecosystem from the Internet core, in combination with complementary data sources.

Our attack detection method for public peering points has enabled us to unveil distributed inter-domain attacks. Our results show that the DNS attack vector is more popular than previously captured by (even distributed) honeypots, a common vantage point in the context of reflection and amplification attacks. We were successful in tracking a prominent attack entity and identifying concrete attack patterns. Our study reveals that attackers are able to detect new abusable amplifiers quickly and reasonably change which infrastructure they abuse. At the same time, we find that attackers could achieve higher amplification by choosing (query) names more prudently, especially in the case of attacks utilizing spoofing and highly variable amplifier sets.

Our study also reveals that operators of various US federal government domain names break from recommended DNSSEC key

rollover practices, which does not only exacerbate the amplification potential of various .gov names, but which our results can also tie to amplification attacks and attacker decision-making. For future work we plan to extend our methods to cover a larger number of protocols and explore the fine-tuning of our thresholds to identify more subtle attacks.

## ACKNOWLEDGMENTS

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## A ETHICS

Our research may raise the following ethical concerns.

**Privacy Invasion through Deep Packet Inspection.** Our IXP vantage point provides a view into application-layer payloads. These data are particularly sensitive as they can contain personal information, or reveal the interests of users (e.g., visited websites). However, we do not use the data to identify or study users. We also present only aggregated views, eliminating the possibility for third-parties to infer privacy-sensitive information. Finally, we focus on attack traffic, which consists of misused query names that do not disclose the interests of particular users.

**Educating Attackers.** This paper presents misused query names in clear view, effectively showing the attackers suitable names for amplification. We argue that these names are already extensively misused in attacks, hence publishing them will not reveal new information. At the same time, we identified over 9000 names that can offer higher amplification than what we witness in practice. We will not divulge these names.

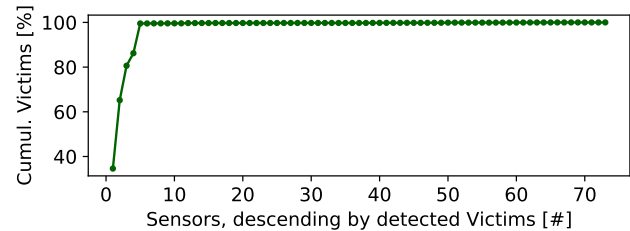
**Alerting the Major Attack Entity.** Releasing a DNS signature as detailed as presented in Section 6 could warn the attack entity responsible for more than half of the attacks. We argue, however, that publishing this information can do more good than harm as it will assist mitigation efforts by the research community.

## B VALIDATION OF THE CCC HONEYPOT PLATFORM

To verify that the CCC honeypot used in this paper makes similar observations compared to previous honeypot studies, we compare various attack thresholds and analyze the convergence of our honeypot platform. CCC infers attacks using a threshold of 5 requests per sensor with no gap of more than 900 seconds before stop replying to requests. This is in contrast to other honeypots that set higher thresholds (i.e., 100 packets and no gap of more than 3600 seconds [26] or 600 seconds [46]). Therefore, CCC applies a more sensitive attack detection, which becomes apparent by a slightly higher number of reported DNS attacks for similar time ranges [26, 59].

A major property of honeypot platforms is the convergence of visible attacks by deploying a small number of sensors [26]. We reproduce the convergence analysis of prior work [26] for our data gathered at the CCC platform and make very similar observations. 99.5% of victims are already visible with only 5 sensors, see Figure 18. However, we require 50 sensors to cover 99.9% of victims due to a long-tail distribution. It is worth noting that the CCC platform is assumed to capture most DNS attacks (between 85.1% and 96.6%) on the basis of a capture-recapture statistical technique [59].

Overall, these results suggest that our honeypot platform behaves similar to related projects. The sensitive thresholds and convergence behavior suggest the observation of all DNS attacks, which we refute in Section 5.



**Figure 18: Honeypot convergence for the CCC platform. We observe a similar behavior compared to related projects.**

## C CACHE SNOOPING TO CHECK NAME POPULARITY

To verify whether a name is frequently resolved globally, we use a modified cache snooping (CS) analysis. CS exploits the fact that popular names remain in DNS caches. Cached responses are identified by TTLs which are smaller than the default TTL defined by the authoritative nameservers. CS has been used to scrutinize the caching behavior at large public DNS resolvers [51]. Today, there is relatively little guidance backed by research about how to set TTLs, so operators usually reuse the same TTLs (e.g., 5 minutes, 1 hour, 1 day) [38], which makes this analysis easier.

**Phase 1: Identifying DNS Resolvers.** We perform a scan of the complete public IPv4 address space and search for DNS amplifiers. Simply initiating DNS queries to all potential amplifiers and checking whether the DNS TTLs comply with default TTLs does not yield accurate results. This is due to the common DNS deployment, in which a DNS forwarder uses a recursive resolver and thus inherits current TTLs from this resolver. Hence, we first need to exclude forwarders from CS.

To identify DNS resolvers, we operate our own name and authoritative DNS server that responds with an A record set to the IP address of the resolver that directly queries our authoritative nameserver. By comparing both the IP address of the A record and target with the source IP address of the respond, we can distinguish resolvers (addresses match) and forwarders (addresses differ), details see [42]. This method allows for fast scanning with pre-built DNS queries and also limits the traffic at our authoritative nameserver since forwarders using the same resolver will return a cached entry. The relation between forwarders and resolvers has been measured before, but the previous methodologies [6, 25, 56] embed the IP address of each target into the subdomain. This embedding requires the analysis of queries at the authoritative nameserver, which impedes reproducibility.

**Phase 2: Assessing Name Popularity.** After isolating the resolvers, we now can initiate a CS ANY scan to find uncommon cache activities. The reasoning here is that misused names are uncommonly often present in caches although being not popular, as

measured by *e.g.*, the Alexa Rank. We find recently misused names with the help of our long-term monitoring tool. We sanitize responses by removing (i) answers with erroneous flags and codes (*e.g.*, rcode REFUSED), (ii) responses from obvious DNS manipulators, (*i.e.*, sources that change the TTLs or A records), (iii) duplicate responses from a single source. Then, we classify a response as a cache miss if all answer resource records contain a default TTL, a cache hit otherwise.

We focused our analysis on similarly popular .gov names. Please note that `americops.gov` also has a larger (+25%) maximum TTL than `peacecorps.gov`, so it would be expected to produce more cache hits.

We utilize two anchor names to verify the correctness of this measurement. First, we reuse a name from Shadowserver which has well-documented, daily scanning times and TTLs. We initiate our scans *after* the daily expiration time to showcase correct cache evictions. Second, right before our CS scan, we create a completely new name, which should produce cache misses only. Still, the anchor names reveal a small amount of cache hits. We consider these cache hits to be the error rate of our measurements. We assume mutual resolver caches and DNS optimizers responsible for these errors.