

Detecting Malicious Activity with DNS Backscatter

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ABSTRACT

Network-wide activity is when one computer (the *originator*) touches many others (the *targets*). Motives for activity may be benign (mailing lists, CDNs, and research scanning), malicious (spammers and scanners for security vulnerabilities), or perhaps indeterminate (ad trackers). Knowledge of malicious activity may help anticipate attacks, and understanding benign activity may set a baseline or characterize growth. This paper identifies *DNS backscatter* as a new source of information about network-wide activity. Backscatter is the reverse DNS queries caused when targets or middleboxes automatically look up the domain name of the originator. Queries are visible to the authoritative DNS servers that handle reverse DNS. While the fraction of backscatter they see depends on the server's location in the DNS hierarchy, we show that activity that touches many targets appear even in sampled observations. We use information about the queriers to classify originator activity using machine-learning. Our algorithm has reasonable precision (70–80%) as shown by data from three different organizations operating DNS servers at the root or country-level. Using this technique we examine nine months of activity from one authority to identify trends in scanning, identifying bursts corresponding to Heartbleed and broad and continuous scanning of ssh.

Categories and Subject Descriptors

C.2.3 [Computer-Communication Networks]: Network Operations—*Network monitoring*

General Terms

Measurement

Keywords

Internet; Domain Name System; DNS; network activity; scanning

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IMC'15, October 28–30, 2015, Tokyo, Japan.

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ACM 978-1-4503-3848-6/15/10 ...\$15.00.

DOI: <http://dx.doi.org/10.1145/2815675.2815706>.

1. INTRODUCTION

Network-wide activity is when one computer (the *originator*) touches many others (the *targets*). Malicious activity is a growing problem in the Internet. *Spammers* exploit compromised computers to send mail, one part of the gray-market ecosystem [30]. *Scanners* walk the IP address space, for research [25, 19], in academic [18] or commercial [35] vulnerability scanning, as cyber criminals searching for vulnerabilities [17] (or joyriding [6]), or as nation-states espionage [24, 28]. Knowledge of malicious activity may help anticipate attacks [12]. Non-malicious activity is of concern as well: ad trackers and content-delivery networks (CDNs) also interact with many computers. Studies of benign activity help set a baseline [54] or characterize growth (results like Calder et al. [10], but without active probing).

Unfortunately, it is difficult to understand the scope of these potential threats because of the Internet's decentralization. While firewalls observe activity directed at one network, and a few security providers aggregate data from a few hundreds [3], by design the Internet has no central vantage point to detect widespread activity. Prior work has used Domain Name System (DNS) traffic to assess misbehavior seen in specific networks or resolvers [56, 26, 40, 55, 2], but this work does not generalize to network-wide activity. Darknets [37, 34, 54, 13, 14, 17] and honeypots (for example, [41]) are effective at understanding network-wide activity, but they miss targeted scans (scanning only Alexa top websites [17]), and new large darknets are unlikely given IPv4 full allocation and the huge IPv6 space. Search engines gather information about activity that appears in the public web, but information is unstructured and may be delayed by indexing [48]. (§ 6 has detailed related work.)

This paper identifies a new source of information on network-wide activity: *DNS backscatter*, the reverse DNS queries triggered by such activity (Figure 1 as explained in § 2). Activities of interest are those that touch many Internet devices, including malicious or potentially malicious activity such as spamming and scanning, as well as widespread services such as CDNs, software updates, and web crawling. These activities trigger *reverse DNS queries* as firewalls, middleboxes, and servers (*queriers*) resolve map the IP address of the originator to DNS name in the process of logging or host-based authentication. Authoritative DNS servers provide a point of concentration of these queries that allows detection of large activities. Since backscatter occurs mostly as automated processes, and we consider only originators with many queriers, our approach avoids traffic from individuals and so has minimal privacy concerns. Since

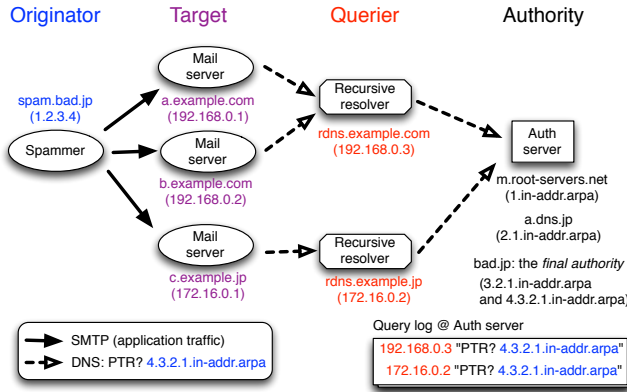


Figure 1: The process behind a DNS backscatter sensor: an originator sends mail to targets, causing queries that are observed at the authority.

backscatter is generated by the targets of network activity, not the originator, an adversarial originator cannot prevent its generation.

The contribution of this paper is to identify DNS backscatter as a new concentrator of information about network-wide activity (§ 2). We show that this source is noisy and attenuated by caching, but careful interpretation of aggregate queriers allows construction of a new type of sensor (§ 3) that detects large, automated activities that touch many targets. We use machine learning to classify the originators of each activity into broad groups (spammers, scanners, and several types of commercial activity) with reasonable precision (70–80%) and robustness (§ 4). Finally, we use backscatter and classification to examine world-wide scanning activity from three sources and up to nine months (§ 5). We characterize the “natural footprint” of different activities for two days at two sensors at the DNS root and one national-level server. We also examine nine months of data, showing that there is a continuous background of scanning, and identifying increased scanning following announcements of vulnerabilities such as Heartbleed [38]. Through this study, our work helps characterize scanning and other network-wide activity; our approach may also serve to support detection and response.

2. DNS BACKSCATTER’S POTENTIAL

DNS backscatter is the set of reverse DNS queries observed by a DNS *authority* as the result of a *network-wide activity*. In such activity, an *originator* interacts with many *targets*. Targets usually do not directly interact with the authority, but do so through a *querier* that acts on their behalf. Figure 1 shows these players. We use DNS backscatter observations to identify and classify the originators.

Origination of Network Activity: We look for network activity that affects many targets. An *originator* interacts with many *target* hosts, for purposes that are legitimate (large mailing lists and web crawlers), malicious (spam), or perhaps in between (scanning and peer-to-peer sharing). Our goal is to infer and classify the originator (§ 3) and to understand the size of its *footprint* (from [47])—how many targets it touches. In Figure 1, the originator is `spam.bad.jp` from IP address 1.2.3.4, and it sends spam

emails to (`a.example.com` and its neighbors; our goal is to identify an otherwise unknown originator).

An originator is a single IP address that touches many targets. In the application classes we study, originators interact with their targets. In principle the originator could be the victim of spoofed traffic (such as a DNS server as part of an amplification attack); we have not identified such originators in our data. (For a few application classes, such as software update service, ad-trackers, and CDNs, the activity is initiated by the target and some other service co-located with the target does a reverse-DNS query.)

At the Target: The activity prompts the target’s interest in discovering the originator’s domain name from its IP address: a reverse DNS mapping that causes a *querier* to make a reverse query if the result is not already cached. This query may be for logging (as by firewalls), to perform domain-name based access control, or to characterize the originator (for example, mail servers that consider the sender’s hostname as part of anti-spam measures). The querier is defined as the computer that does resolution of the reverse name. That the target and the querier may be the same computer, or the querier may be a dedicated recursive resolver shared by several targets.

A reverse DNS query will have the query name (QNAME `4.3.2.1.in-addr.arpa` in Figure 1) with the reversed IP address of the originator, and will ask for a reverse Internet name (QTYPE PTR, QCLASS IN). In this example, this query returns `spam.bad.jp`, but we do not use this response or even depend on the existence of a reverse name for the originator.

At the Authority: An authoritative DNS nameserver (the *authority*) will reply to this query. We analyze DNS traffic at the authority to infer information about the originator.

DNS is a hierarchical, distributed database with many authoritative servers that cover different levels and parts of the namespace. In addition, DNS uses aggressive caching at nearly all levels of the system. These factors mean that there are multiple authorities that will see different reverse-DNS traffic with different amounts of sampling due to caching and coverage.

The ideal place to observe reverse queries is the *final authority* directly responsible for the originator. In typically the originator’s company or ISP (serving `3.2.1.in-addr.arpa` in our example), the final authority will see *all* queriers. However, authorities higher in the DNS hierarchy will see some attenuated fraction of queriers and can discover unknown originators. We consider several authorities: a national-level, top-level server (we examine Japan), and root nameservers (we consider B and M, two of the 14), as well as a final authority. Our national-level view sees traffic only for originators in address space delegated to that country (perhaps `2.1.in-addr.arpa` in our example). Roots potentially see all originators, but caching of the top of the tree (`in-addr.arpa` and `1.in-addr.arpa`) filters many queries, and visibility is affected by selection algorithms that favor nearby DNS servers. Some *recursive* servers, such as those run by large ISPs or large open DNS providers, will also have broad visibility.

Backscatter Evaluation: We observe reverse queries at the authority and use this backscatter to identify the originator’s application. Queries directly provide the IP address of the originator, but we use that only to group queriers (we

ignore the originator reverse DNS record, if any). Instead we use information about *queriers* to suggest the originator’s application. Each individual query has little information, but the *collective behavior* of all queriers generating backscatter indicates the nature of an originator’s activity. For example, spammers send mail to many mail servers, generating backscatter from these servers and anti-spam middleboxes. Similarly, large-scale network scanning causes firewalls at targets log the originator’s domain name.

The number of reverse queriers also provides a rough idea of the size of the originator’s activity. Unfortunately, the DNS’s caching policies make it extremely difficult to quantify originator traffic rates—we caution that querier counts only *approximate* activity sizes.

An adversarial originator may seek to hide its activity. Spreading activity over many originators will reduce detection, but other aspects of our approach depend on targets and thus are outside the control of the originator.

Privacy: Analysis of DNS traffic raises potential privacy issues, since much DNS traffic originates from activity by individuals. Our approach minimizes these concerns for several reasons. First, the data sources we use intrinsically mask the visibility and identity of individuals. Caching heavily attenuates all queries seen by the authority, and a shared cache obscures the identity of any individual. We see network-wide activity only because of its many targets, while activity of any given individual is extremely unlikely to appear. Second, authorities have little or no direct contact with individuals due to indirection from recursive resolvers. Finally, while raw data at an authority is a mix of individual and automated traffic, the reverse queries we consider is nearly all automated. Humans typically use DNS to map names to addresses; almost all reverse queries are from automated sources. (As evidence, we examined ten minutes of B-Root queries in B-post-ditl. Using not-found replies [NXDomain] as evidence of typos, only 8 of 126,820 reverse queries against `in-addr.arpa` are not-found, while about half of the forward queries for IP addresses are not-found.)

Our analysis and its output also raise minimal concern. Our automated analysis effectively anonymizes its input through abstraction and aggregation, as input becomes feature vectors about collective queriers. It identifies and classifies originators in bulk, and we consider only originators in the top fraction of network-wide activity—a set that is necessarily automated to reach that scope. Finally, when examining specific originators to validate our results, we would anonymize any that present personally-identifiable information (PII). None so far show any PII.

Our work has been institutionally reviewed and approved as non-human-subjects research (USC IIR00001718). We see minimal privacy risk in this work, and substantial benefit in better understanding the scope of network-wide activity such as scanning.

3. METHODOLOGY: BACKSCATTER TO ACTIVITY SENSOR

We next summarize our approach to make DNS backscatter a sensor for network-wide activity: collecting DNS data at the authority, classifying data for each originator with features based on the queries and queriers, and then clustering originators into activities.

3.1 Data Collection: Queries at the Authority

We begin with data collection at the authority. We observe all DNS queries at arrival and retain only reverse DNS queries (PTR queries made against `in-addr.arpa`). Each query results in an (originator, querier, authority) tuple; we identify the originator from the QNAME, and the querier and authority are the source and destination of the DNS packet.

Queries may be obtained through packet capture on the network or through logging in DNS server itself. DNS packet capture techniques are widely used [51, 20]. DNS logging is supported in most servers, and tools such as dnstap define standard logging formats [50]. Centralized DNS information is available today through services such as SIE [45]. We describe the datasets used in this paper in § 3.6.

3.2 Interesting and Analyzable Originators

We want to focus our classification on only those originators that are *interesting*, carrying out activities that affect large parts of the network, and that are *analyzable*, providing enough information from queriers that we can reasonably classify them.

We identify these originators by analyzing data over time intervals that are long enough to include a significant number of analyzable originators, and then identifying the most interesting among them based on how many targets they touch.

We generate a *feature vector* v^o for each originator o over some time interval lasting d days. The time interval under consideration must be long enough that the originator touches enough targets to allow inference of the originator’s application class. We consider 20 or more unique queriers per originator to be sufficient for analysis. We select the time interval for each dataset to meet this goal (details of the datasets are shown in § 3.6). DITL datasets [16] last 1–2 days, and for each we generate one feature vector for each originator across the whole dataset (d is the dataset duration, 36 or 50 hours). For the M-sampled dataset we use $d = 7$ days, thus generating an array of feature vectors v_i^o where $i \in [0, 35]$.

Originators that touch many targets have larger, more interesting activities. To identify the most prolific originators we record the number of unique (originator, querier) combinations in each time interval. We rank originators by number of unique queriers in the time interval and retain only the N originators with the most unique queriers. When we count originators (§ 5.3) we take all originators with more than 20 unique queriers.

3.3 Queries to Originator Features

We define static and dynamic features for each originator. *Static* features are derived from the domain names of the queriers, using differences in which targets different originators touch to infer the originator’s intentions. *Dynamic* features use spatial and temporal patterns in queries.

Querier domain names provide these static features, often determined by specific keywords:

home computers with automatically assigned names like `home1-2-3-4.example.com`. The name includes digits of the IP address and a keyword: ap, cable, cpe, customer, dsl, dynamic, fiber, flets, home, host, ip, net, pool, pop, retail, user.

mail mail servers like `mail.example.com`. Keywords: mail, mx, smtp, post, correo, poczta, send*, lists, newsletter, zimbra, mta, pop, imap.

ns nameservers like `ns.example.com`. Keywords: cns, dns, ns, cache, resolv, name.

fw firewalls like `firewall.example.com`. Keywords: firewall, wall, fw.

antispam anti-spam services, like `spam.example.com`. Keywords: ironport, spam.

www web servers like `www.example.com`

ntp NTP servers like `ntp.example.com`

cdn CDN infrastructure, including suffix of Akamai, Edgecast, CDNetworks, LLNW.

aws Amazon AWS, including suffix of amazonaws.

ms Microsoft Azure, checked with web page.

google IP addresses assigned to Google, as confirmed by SPF record in DNS.

other-unclassified a name not matching the categories above.

unreach cannot reach the authority servers.

nxdomain no reverse name exists.

Domain names may match multiple static features (for example, `mail.google.com` is both google and mail). We match by component, favoring matches by the left-most component, and taking first rule for components with multiple keywords. (Thus both `mail.ns.example.com` and `mail-ns.example.com` are mail).

The static portion of the feature vector for an originator is the fraction of queriers that match each of the features. For example, an originator where all queriers have “mail” in their domain names would have the mail feature as 1 and all others as zero. Another where a quarter have “mail” and the rest have “firewall” would have feature vector with (mail=0.25, firewall=0.75). We use the fraction of queriers rather than absolute counts so static features are independent of query rate.

We use these dynamic features to capture temporal and spatial aspects of the queries:

queries per querier (temporal) As a *rough* query rate we compute the mean number of queries per querier. Differences in caching and TTLs prevent generate an exact rate, but this metric is roughly proportional to query rate.

query persistence (temporal) To show how often an originator is active we count the number of 10-minute-long periods that include the originator.

local entropy (spatial) To see if an activity affects many people we compute the Shannon entropy of /24 prefixes of all queriers.

global entropy (spatial) We compute the Shannon entropy of the /8 prefix of all querier IP addresses. Since /8 prefix are assigned geographically, wide variation here shows global activity.

unique ASes (spatial) the number of ASes across all queriers normalized by the total number of ASes that appear in the time interval. (ASes are from IP addresses via whois.)

unique countries (spatial) the number of countries across all queriers, normalized by the total number of countries that appear in the time interval. We determine country from the IP using MaxMind GeoLiteCity database [32].

queriers per country (spatial) unique queriers per country.

queriers per AS (spatial) unique queriers per AS.

To avoid excessive skew of querier rate estimates due to queriers that do not follow DNS timeout rules [52, 11] we eliminate duplicate queries from the the same querier in a 30s window. Some variation remains due to different caching times (TTLs) for different portions of the namespace. In some cases, such as fast flux domains, low TTLs will assist detection.

We selected the features and classes (in this section and the next) after iteration with our several datasets. Different features and classes will produce different results (for example, although we omit details due to space, we see higher accuracy with fewer application classes), but our results show the general approach is sound.

3.4 Originator Features to Application Classes

Finally we classify each originator based on its feature vector using machine learning. We use several standard machine-learning algorithms: a decision tree (Classification And Regression Tree; CART) [8], random forest (RF) [7], and kernel support vector machines (SVM) [43]. For non-deterministic algorithms (both RF and SVM use randomization), we run each 10 times and take the majority classification. These algorithms classify each originator into one of the following classes:

ad-tracker Servers implementing web-bugs (objects in embedded in web pages) to track user for advertising.

cdn Computers that are part of public content delivery networks (Akamai, CDNetworks, etc.)

cloud Front-end hosts of cloud service such as Google map, Goggle drive, and Dropbox.

crawler Web crawlers by Google, Bing, Baidu, etc.

dns Large DNS servers

mail Mail servers that send mail to large mailing lists and webmail service

ntp Large Network Time Protocol (NTP) servers

p2p End-user computers that participate in peer-to-peer file sharing. (We added this late in our work; our analysis of root servers does not include it.)

push Push-based messaging services for mobile phones (Android and iPhone); typically TCP port 5223.

scan Internet scanners using ICMP, TCP, or UDP.

spam Computers (end-user or mail servers) that send spam to many destinations.

update Servers for software update distribution run by OS, computer, and printer vendors

Data over time: For short datasets, each originator has one feature vector and one class. For longer datasets we see an array of feature vectors (v_i^o) and a time-specific class c_i^o . Because our observations are incomplete and classification is imperfect, an originator may change class over time, so our final step is to identify the originator as the most common class seen over all time (the statistical mode of c_i^o). We divide the M-sampled data into 35 week-long periods; all other datasets are analyzed as one period of 1–2 days. Longer observations for the M-sampled data partially compensate for attenuation in the data due to its 1:10 downsample (see also § 3.6).

Training: Classification requires training. We label a subset of each dataset as ground truth, manually identifying the application class of 200–300 originators in each dataset. Traffic seen by each authority is different for many reasons: placement in the DNS hierarchy, size, physical location, use of anycast, and possible use of sampling (for M-sampled). For this reason, we currently train for each dataset separately, although in some cases originators appear in multiple datasets and so we can reuse labeled ground-truth. (Studying of training portability and its effects on accuracy is ongoing.)

We do training by generating feature vectors as described above, then feed this input and known output into each ML algorithm.

3.5 Constraints in Backscatter as a Data Source

While DNS backscatter provides a new tool to identify network-wide activity, it is an incomplete source about originators and their activity.

First, querier domain-names only provide limited information about targets. Domain names may be overly general, unavailable, or never assigned. Currently we see 14–19% of queriers without reverse names, and the fraction serves as a classification feature, but if *all* queriers lacked reverse names our approach would not work. Other network services use reverse names, such as anti-spam and network reputation services, finding as we do that they are imperfect but still useful. Our results use only backscatter, but we show that applications will benefit from combining it with other sources of information (such as small darknets) to overcome the limitations of querier names alone.

Second, the signal provided in DNS backscatter is spread over many authorities by DNS anycast, attenuated by caching in recursive DNS resolvers, and complicated by caching durations (TTLs) that differ across the DNS hierarchy. These challenges prevent us from getting strong estimates on the rates of originator activity, but we show that they do not prevent their identification or classification.

Finally, an adversarial originator may try to defeat our analysis. As with spam, spreading traffic from an activity across many separate originating IP addresses or longer durations disperses the signal. We cannot prevent this countermeasure, but it greatly increases the effort required by an adversarial originator. Fortunately our classification depends on queriers (not originators), and they cannot be manipulated by the originator.

In this paper we show that querier provides reasonable classification accuracy and backscatter’s signal identifies hundreds of originators. We are working to refine our estimates of accuracy and sensitivity, and of course additional data sources, larger labeled ground-truth, and more refined classes may improve on our work.

3.6 Datasets

This paper uses DNS datasets from three authorities: one national-level top-level domain, operators of two root servers as shown in Table 1.

JP-DNS operates the `.jp` country code domain for Japan; we have data from all seven of their anycast sites. We obtained data from two root server operators: B is a single site in the US west coast, and M operates 7 anycast sites in Asia, North America, and Europe. We use root datasets from the short-term, complete (unsampled) observations taken as

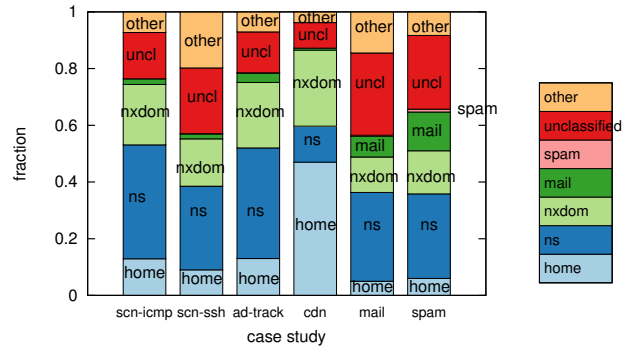


Figure 2: Static features for case studies, derived from querier domain names. (Dataset: JP-ditl.)

part of the 2014 DITL collection [16] (for B-Root, shortly after 2014 DITL). We also use data for M-Root’s 2015 DITL collection (§ 4.4). These root datasets are available to researchers through DNS-OARC.

For longitudinal analysis we draw on 9 months of data taken at the M-Root server. This dataset (M-sampled) is sampled with only 1 out of every 10 queries in deterministic manner; this sampling decreases our sensitivity but is part of their policy for long-term collection. We also use an 5-month unsampled dataset (B-long) taken from B-Root to evaluate for controlled experiments (§ 4.4).

4. VALIDATION

Classification with machine learning requires appropriate features and accurate training data. Here we illustrate our features with several different type of originators, then identify external sources we use to label the ground truth for training and validation. Finally, we validate our approach by training on a random portion of the ground truth and testing the remainder.

4.1 Distinguishing Different Classes of Originators

We first illustrate how the DNS backscatter allows us to differentiate the activity of six different originators: scan-icmp, scan-ssh, ad-tracker, cdn, mail, and spam. Figure 2 and Table 2 show their static and dynamic features.

Static features: Static features (Figure 2) distinguish several cases. We examine two scanners: *scan-icmp* is the Japanese site for a research scanner doing outage detection [42], while *scan-ssh* is an unknown party probing ssh (TCP port 22) on all computers. Scanners trigger many queries from shared nameservers (NS), as well as nxdomain, home, and static addresses. We believe this mix results from scanners walking all IP addresses and triggering firewall and logging reverse queries; the large number of NS queriers suggest these services often use an ISP’s shared resolver, but not always.

Ad-trackers are servers triggered by user’s web behavior. While similar to scanners, this classes see more shared nameservers, perhaps because it is queried by end-users’s web browsers.

Our *cdn* case is an Akamai server based in Japan. It shows a *much* higher fraction of home queriers than others. We believe this shift results from heavy CDN use at homes.

type	dataset	operator	start (UTC)	duration	sampling	queries ($\times 10^9$)		qps ($\times 10^3$)	
						(all)	(reverse)	(all)	(reverse)
ccTLD	JP-ditl	JP-DNS	2014-04-15 11:00	50 hours	no	4.0	0.3	22	1.8
root	B-post-ditl	B-Root	2014-04-28 19:56	36 hours	no	2.9	0.04	22	0.2
root	B-long	B-Root	2015-01-01	5 months	no	290*	5.14	22*	0.39
root	M-ditl	M-Root	2014-04-15 11:00	50 hours	no	8.3	0.06	46	0.3
root	M-ditl-2015	M-Root	2015-04-13 11:00	50 hours	no	9.9	0.07	55	0.4
root	M-sampled	M-Root	2014-02-16	9 months	1:10	36.2	1.5	1.6	0.07

Table 1: DNS datasets used in this paper.

case	queries/ querier	global entropy	local entropy	queriers/ country
scan-icmp	3.3	0.83	0.92	0.006
scan-ssh	4.7	0.84	0.96	0.006
ad-track	2.3	0.85	0.94	0.017
cdn	4.4	0.48	0.97	0.018
mail	1.7	0.71	0.94	0.009
spam	3.4	0.85	0.95	0.005

Table 2: Dynamic features for case studies.

Finally, *mail* and *spam* both show a much higher fraction of the mail feature, consistent with application. Although hard to see on the graph, spam shows more than twice the fraction of spam-related queriers (0.1% compared to 0.03%), indicating heavier involvement of spam-filtering and logging systems.

Dynamic features: Table 2 lists the distribution of some dynamic features for the six originators. As described in § 3.3, query counts only approximate true rates because of caching, but we believe relative comparisons are appropriate for classification.

We see that the queries:querier ratio helps distinguish mail from spam. Global entropy demonstrates geographic dispersion of the queriers. Low global entropy for *cdn* reflects CDN selection algorithms that associate our Japan-based CDN server with Asian clients. Similarly, the global entropy *mail* is lower because the language of this specific list is Japanese. Queries per country also reflects geographic coverage, with high values of *ad-tracker*, *cdn*, and *mail* suggesting geographically constrained targets.

The examples in § 3.3 illustrate how these features help identify our application classes, and their overlap suggests the potential for machine learning as a framework to interpret them optimally. We quantify our approach in § 4.3.

4.2 Confirming Labeled Ground-Truth

We require ground truth with originators labeled into our twelve application classes (§ 3.4) both to train our classifier and to evaluate its accuracy (§ 4.3).

In labeling ground truth we strive for *accuracy* over quantity because a mix of inaccurate originators will mis-train our classifier. We draw on multiple sources of external data (blacklists, darknets, and manual investigation) to get reasonable coverage of most application classes, with 180 to 700 samples depending on the dataset (Table 3).

We generate moderate to large lists of potential IP addresses in each application class from external sources (described below), then intersect it with the top-10000 originators in dataset by the number of queriers. We then verify the intersection manually. We determine the verifying application class of each originator manually using the methods described below. We added two categories (push and up-

date) after examining all of the top 100 and 1000 largest originators, respectively.

Validation for each class is as follows:

ad-tracker We identify servers associated with advertising affiliation and tracking systems (such as [doubleclick.net](#) and [kauli.net](#)) by crawling around 20 blog pages. We also registered with ad affiliation programs for four services and added the servers they recommended.

cdn We identified content-distribution networks for several large providers (Akamai, Edgecast, CDNetworks, ChinaCache, and, CloudFlare) based on their reverse domain names and WHOIS on their IP addresses.

cloud We crawled IP addresses of front-end hosts for Google services such (map, drive, and news) and Dropbox from Japan and the US.

crawler We confirm web crawler IP addresses from UserAgent strings in web server logs of NII, originator reverse domain names, and <http://botvsbrowsers.com>.

dns We started with all root DNS servers, country-code TLD servers, then we added servers for large Japanese ISPs that had large originator footprints.

mail We confirm mail originators by examining over 100 Japanese mailing lists operated by mail ASPs and companies themselves. We see about 300 IP addresses over about three months in 2014. We also identify mail originators for cloud-based mail including Google, Microsoft, Apple, Facebook, LinkedIn, and Amazon, as confirmed by domain names in e-mail message headers.

ntp We consider well-known Stratum 1 servers and crawled IP addresses of NTP servers in Open NTP project (at *.pool.ntp.org).

push We list IP addresses that send packets with TCP port 5223 (Lync mobile client push), as observed in sampled netflow traffic from the University of Tokyo.

p2p We identify IP addresses running DHT-based BitTorrent from htindex.com in fall 2014 (As of 2015, this service no longer operates).

scan We confirm scanners by looking at traffic in two darknets (one a /17 and the other a /18 prefix) located in Japan. A confirmed scanner sends TCP (SYN only, not SYN-ACK), UDP, or ICMP packets to more than 1024 addresses in at least one darknet, or is a known research scanner (such as Trinocular [42] and shadowserver [46]).

spam We confirm spammer IP addresses with data from DNS blacklists (DNSBL) run by 9 organization (badips, barracuda, dnsbl.sorbs, inps.de, junkemail, openbl, spamhaus, spamrats, spam.dnsbl.sorbs); we consider only the spam portion of blacklists that distinguish spam from others such as ssh-brute force.

dataset	ad-track	cdn	cloud	crawler	dns	mail	ntp	p2p	push	scan	spam	update	total
JP-ditl	15	8	-	-	26	44	10	37	-	25	64	6	235
B-post-ditl	13	29	16	17	16	46	5	-	12	29	35	-	214
M-ditl	13	36	16	16	17	50	8	-	12	33	43	-	240
M-sampled	54	81	82	35	52	111	-	-	73	124	136	-	746

Table 3: Number of examples of each application class in labeled ground-truth, per dataset.

dataset	algorithm	accuracy	precision	recall	F1-score
JP ditl	CART	0.66 (0.05)	0.63 (0.08)	0.60 (0.06)	0.61 (0.06)
	RF	0.78 (0.03)	0.82 (0.05)	0.76 (0.06)	0.79 (0.05)
B post- ditl	SVM	0.73 (0.04)	0.74 (0.05)	0.71 (0.06)	0.73 (0.05)
	CART	0.48 (0.05)	0.48 (0.07)	0.45 (0.05)	0.46 (0.05)
M ditl	RF	0.62 (0.05)	0.66 (0.07)	0.60 (0.07)	0.63 (0.07)
	SVM	0.38 (0.11)	0.50 (0.14)	0.32 (0.13)	0.39 (0.13)
M sampled	CART	0.53 (0.06)	0.52 (0.07)	0.49 (0.06)	0.51 (0.06)
	RF	0.68 (0.04)	0.74 (0.06)	0.63 (0.05)	0.68 (0.05)
	SVM	0.60 (0.08)	0.68 (0.10)	0.52 (0.08)	0.59 (0.09)
	CART	0.61 (0.03)	0.65 (0.04)	0.58 (0.04)	0.61 (0.04)
	RF	0.79 (0.02)	0.82 (0.02)	0.77 (0.03)	0.79 (0.02)
	SVM	0.72 (0.02)	0.76 (0.03)	0.70 (0.03)	0.73 (0.02)

Table 4: Validating classification against labeled ground-truth.

update We identified 5 large software update services hosted in Japan corresponding to computer and printer vendors such as Sony, Ricoh, and Epson.

We identified these classes after iteration and manual examination of data, traces, and applications. They share in common that a single originator touches many targets that make reverse DNS queries, but activity is sometimes initiated by the originator (spam, mail, and scan) and other times likely a side effect of activity at the target (such as update, ad-tracker, and cdn).

4.3 Classification Accuracy and Algorithm Choice

We next carry out cross-validation, using random subsets of labeled ground-truth to test the classification accuracy and to compare three classification algorithms: Classification And Regression Tree (CART), Random Forest (RF), and Kernel Support-Vector Machines (SVM).

Classification accuracy: To evaluate a particular machine-learning algorithm, for each dataset we pick a random 60% of the labeled ground-truth for training, then test on the remaining 40% of data. We repeat this process 50 times, testing each subset with all three algorithms. For each run we compute accuracy $((tp + tn)/all)$, precision $(tp/(tp + fp))$, recall $(tp/(tp + fn))$, and F1-score $(2tp/(2tp + fp + fn))$, where tp : true positive, tn : true negative, fp : false positive, fn : false negative. Table 4 shows the mean of each metric over the 50 iterations, with standard deviations in smaller type.

Overall, we find that RF outperforms SVM and CART in most metrics. The accuracy of the best algorithm over each dataset is 0.7 to 0.8, suggesting classification from our limited data is not easy, but fairly strong given 12 categories (thus an expected 0.08 accuracy for guessing). We see mislabeling of application classes where the training data is sparse: *ntp*, *update*, *ad-tracker*, and *cdn* for JP-ditl. In particular, the classification ratio of *update* events is very low. Reducing the number of classes would improve accuracy, at the cost of less useful results. Improving the accuracy of

rank	JP-ditl		M-ditl	
	feature	Gini	feature	Gini
1	mail(S)	8.4	mail(S)	12.5
2	home(S)	7.9	ns(S)	8.3
3	spam(S)	6.3	unreach(S)	7.0
4	nxdomain(S)	6.2	query rate(D)	6.2
5	unreach(S)	5.2	home(S)	6.0
6	global entropy(D)	5.0	nxdomain(S)	5.8

Table 5: Top discriminative features. Classifier: RF.

classification across multiple classes with unbalanced training data is an active area of research in machine learning. Our current results show promise and will improve as the field progresses.

Similarly, for JP-ditl, *p2p* is sometimes misclassified as scan. Manual inspection shows that misclassified *p2p* actually sent traffic to dynamically-assigned ports in our dark-nets as well. We conclude that they are mis-behaving P2P-clients [31, 9] and these random probes are triggered by software bugs or by injection of random IP addresses by anti-P2P services.

Choice of authority: While accuracy is good, accuracy for B post-ditl and M-ditl are slightly poorer (60–75%) because roots are attenuated and these datasets are short. M-sampled does better because it uses longer observations (7 days, not 2). JP accuracy is highest because it is unsampled and lower in hierarchy. We conclude that approach can be strong, but one must be careful to match the quality of the signal and training data.

Feature choice: In evaluating classification, we naturally would like to know what features are most discriminative. Random Forest provides this information, and Table 5 lists the top discriminative features for two datasets, as determined by Gini coefficient [53]. Larger Gini values indicate features with greater discriminative power. We see that *mail*, *home*, *nxdomain*, and *unreach* are important static features in both datasets. *Query rate* and *global entropy* are important in different datasets, perhaps reflecting M-ditl’s weaker global signal and JP-ditl’s more regional signal. These results are consistent with intuitive case studies (§ 4.1).

Algorithm choice: Since Random Forest provides the best accuracy and is consistent (small standard deviations), we use that algorithm to characterize originators in the next section, after retraining with the full labeled ground-truth data.

4.4 Controlled Experiments to Evaluate DNS Caching

Attenuation from DNS caching makes interpreting backscatter challenging. Such caching is difficult to model: first, the DNS resolver infrastructure can be quite complex [44]. Second, DNS caches are kept for varying durations and caching

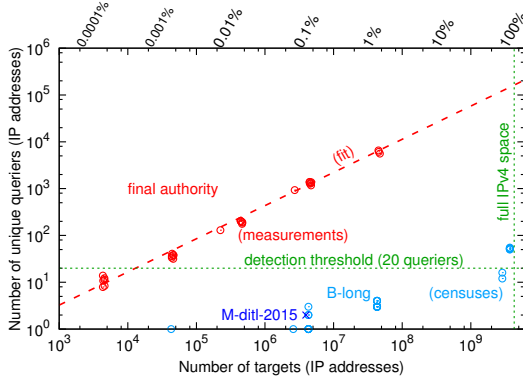


Figure 3: Size of footprint of random network scans at the final authority. (Datasets: B-long and M-ditl.)

of the resolution tree (`in-addr.apra`) will be caused by many competing users.

Attenuation: To estimate the number of queriers that respond to a large network event we conducted a controlled experiment where we probe a fraction of the IPv4 Internet from a host where we can monitor queries sent to the final reverse DNS server for the prober. We set the TTL of the reverse DNS record (PTR) to zero to disable or minimize caching (some resolvers force a short minimum caching period), thus we should observe all queriers triggered in response to our scan. We scan several protocols (ICMP, TCP port 22, 23, 80, and UDP port 53, 123) using ZMap [19], varying the fraction of the address space we scan from 0.0001% (4k addresses) to 0.1% (4M addresses) of the whole IPv4 space. The time required for the biggest scan (0.1%) was 13 hours. We run each scan up to 5 times. We also examine 8 full-internet scans (nearly 100% of unicast IP) taken with Trinocular [42], starting at two different months (January and April 2015) from four different sites [49].

Figure 3 shows the number of queries we see as we grow the size of the scan. Circles represent experimental trials measured at the final authority (slightly jittered). The diagonal line represents a best fit: roughly 1 querier per 1000 targets, but actually a power-law fit with power of 0.71. We also examine M-sampled and B-long, reporting what they see for 0.1% and 1% ZMap scans and the 100% Trinocular scans. This large reduction in responses at root servers is due to both DNS caching and because not all targets are actually interested in the scanner.

False negatives: Our controlled experiments can evaluate false negatives (missed network-wide events). The horizontal line at 20 queriers is our detection threshold, so we see that the final authority will detect all events scanning 0.0001% of the Internet or more.

We expect greater caching at higher levels of the DNS hierarchy. To measure this, we examined M-ditl-2015 data for evidence of these trials. Only two trials overlap with this datasets: one for 0.01% and the other for 0.1%. Of these, we find two queriers for the 0.1% trial (the blue X) in Figure 3. Greater attenuation at higher levels of DNS means that it will detect only much larger (space) or longer (in time) activity. (We are currently extending this study to trials at larger percentages.)

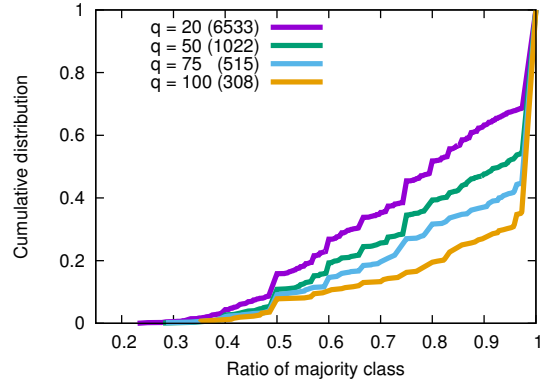


Figure 4: CDF of r , the fraction of the most common class over all weeks with q or more queriers per originator. (Dataset: M-sampled.)

This experiment shows that backscatter is highly attenuated due to disinterested targets and DNS caching, but responses follow the number of targets.

4.5 Sensitivity of Results

Finally, we use M-sampled to evaluate the sensitivity of our conclusions by looking at when or if classifications change over time. We current vote on classifications of each originator over all weeks. To estimate degree of consensus in a vote, we define r as the fraction of weeks when the preferred class (the most common response) occurred of all weeks that originator appeared. When r is near one, we see consistent activity, but when $r < 0.5$ it seems likely that either the originator is changing activity over time (perhaps different machines behind a NAT, or a botnet node being repurposed), or doing two things concurrently, or we classify variations in behavior differently, suggesting an incomplete training set or indistinguishable classes.

Figure 4 shows the cumulative distribution of the ratio r , looking at subsets of data with at least q queriers per originator. To avoid overly quantized distributions we show only originators that appear in four or more samples (weeks). Requiring more queriers per originator (larger q) reduces the number of eligible originators, but the number of samples (shown in parenthesis in the legend) are all large enough to be robust.

We see that more queriers (thus more data for classification) provide more consistent results, since with $q = 100$, about 60% of originators are strongly consistent. Even with a threshold of 20 querier per originator, 30% of originators are consistent. In addition, almost all originators (85–90%, depending on q) have a class that has strict majority ($r > 0.5$). Thus our approach almost always (85–90%) provides a consistent result.

For the few where the strongest class is only a plurality ($r \leq 0.5$), we wanted to see if there are two nearly equally strong classes. We examined the entropy for originators in this case: we find that usually there is a single dominant class and multiple others, not two nearly equally common classes.

These initial results suggest our approach is consistent for observers with at least 20 queriers, although noise grows as queriers approach that threshold.

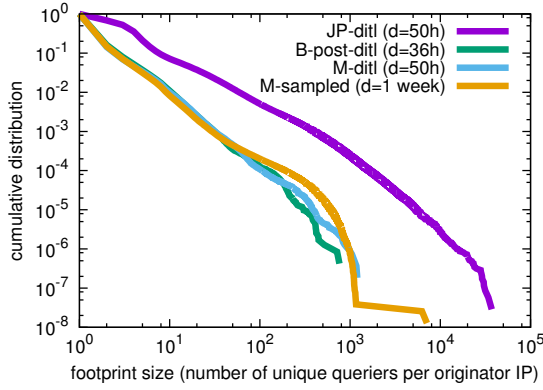


Figure 5: Distribution of originator footprint size.

5. RESULTS

We next study network-wide activities with our method, identifying large network events and trends in different applications and over time. Since our approach is based on feedback from targets, our results complement prior studies (such as darknets) and will observe targeted events will not appear in darknets.

5.1 Sizes of Originator Footprints

We estimate the footprint of each originator as the number of unique queriers per originator. Figure 5 shows the fraction of originators with each footprint size a log-log scale for each of our three datasets.

Our data suggests *there are hundreds of originators that touch large parts of the Internet*. Our controlled trials (§ 4.4) show high attenuation at root servers, yet hundreds of originators have footprints suggesting they scan most or all of the Internet (590 in M-ditl and 298 in B-post-ditl have footprints larger than 10^2).

The *distributions* of footprints is consistent across our datasets. (We cannot directly compare footprint sizes due to variation in duration and sampling.) As one would expect, they are a heavy-tailed, with some originators triggering queries from 10k queriers. We focus the remainder of our analysis of the originators with the largest footprints, typically the top-10000 (about 0.5% of each dataset), or the top-1000 or -100. Considering only large originators will miss those that are intentionally trying to be stealthy, but many scanners make no such attempt [17], and we expect commercial large services to also be open.

The largest footprints here are larger than those we observe in controlled trials at M-Root (Figure 3). Those scans were quite short (a few to a dozen hours), while here we aggregate data over one or two days. In addition, our trials used random targets, most of which are unoccupied (only 6–8% respond, as seen before [25]); many real-world scans are targeted, resulting in higher responses rates and thus greater backscatter.

5.2 Observability and Size of Application Classes

We next classify the top originators. Our goal is to understand what activity is taking place and approximately how aggressive they are. Our key observations are: there are *thousands* of originators causing network-wide activity,

different *authorities* see different applications, and we see evidence of team of coordinated scanners even with no direct information from originators.

Size of application classes: There are *thousands* of unique originators that touch large parts of the Internet. Table 6 shows how many originators we see in each originator class for each dataset, with classes with counts within 10% of the largest count in bold. We use our preferred classifier (RF) with per-dataset training over the entire ground-truth. Classes that lack ground truth for some dataset have no matches (a “-”).

Applications vary by authority: The classes of applications seen at *different authorities* vary considerably. For JP-ditl, *spam* is the most common class of originator. Although Japan hosts computers for most major CDNs, the size of the *cdn* class seen from backscatter is small because CDNs often use address space assigned by other registrars (we verify this statement for Akamai and Google with geolocation, whois and prior work [21]). The *update* class is exactly those in labeled ground-truth. We identified this class in examining the data (not from an external source), and lack of additional examples suggests either class has insufficient training data to avoid over-fitting, or update servers are rare.

Both unsampled root servers (B-post-ditl and M-ditl) show similar distributions of activity, with *mail* the most common and *spam* and *cdn* both close. The larger number of CDNs in at M-Root is due to 300 *cdn* originators located in two Chinese ISPs and interacting with queriers in China. Classification appears correct (they do not send traffic to darknets, nor appear in spam blacklists), but the originators lack domain names and we cannot identify them. Such originators appear only in M-ditl, suggesting that their queriers may be using DNS resolvers that prefer nearby authorities, since M-Root is well provisioned in Asia while B-Root is only based in North America.

Long-term, sampled root data (M-sampled) has some important differences from short term (M-ditl). Consider relative sizes of classes (since absolute counts vary due to dataset duration), we see many more scanner and spammers in long-term data. We believe the size of these categories reflect churn in the population carrying out the activity. We expect churn in spamming where computers known for spamming are less effective. We measure churn directly for scanners in § 5.3.

Big footprints can be unsavory: The mix of applications varies as we examine originators with smaller footprints, but we see that *big footprints are often unsavory activity*. Figure 6 shows how originator classes change as we look at more originators with smaller footprints (from Figure 6a to Figure 6c).

The largest footprints are often spammers (in JP-ditl) or scanners (for B and M). By contrast, we see that *mail* appears only in the top-1000 and top-10000, suggesting that legitimate mail servers may service large mailing lists (to many targets), but spammers touch many more targets. For B and M, more spammers rise in Figure 6c, suggesting spreading of traffic over many smaller originators to evade filtering.

By contrast, large but not top originators are often infrastructure: *cloud*, *mail*, *ad-tracker*, and *crawler*. In general, we find that application classes have a “natural” size, with some favoring origins with large footprints (prominent in

data	ad-track	cdn	cloud	crawl	dns	mail	ntp	p2p	push	scan	spam	update
JP-ditl	210	49	-	-	414	1412	237	2235	-	355	5083	6
B-post-ditl	72	1782	168	361	76	3137	8	-	318	1228	2849	-
M-ditl	76	2692	135	557	258	2750	67	-	119	983	2353	-
M-sampled	1329	17,708	2035	885	1202	14,752	-	-	3652	47,201	34,110	-

Table 6: Number of originators in each class for all datasets. (Classifier: RF.)

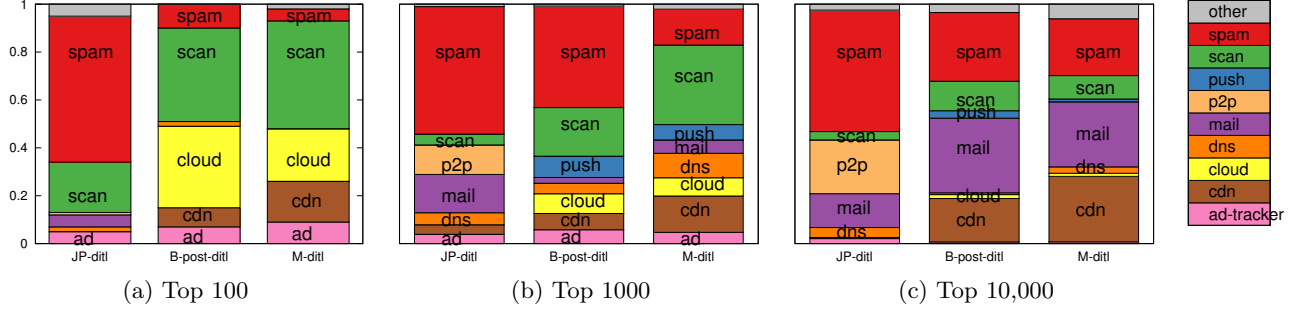


Figure 6: Fraction of originator classes of top- N originators. (Dataset: JP-ditl, B-post-ditl, M-ditl; classifier: RF.)

Figure 6a), while others favor smaller footprints and so are more common in Figure 6c.

The *ad-tracker* class is most common in the prominent in top-most originators (a larger red *ad-tracker* fraction in Figure 6a compared to to Figure 6c). There are relatively a few originators (we see 5 companies as 22 unique originating addresses for top-100/JP-ditl). Unlike spam, they need not hide, and are likely prominent because tracking needs little traffic (a few originators can support a network-wide service), and because they use DNS records with short cache lifetimes (small TTLs). *Cloud* follows this pattern as well; 1 company across 21 distinct originating IPs for top-100 in M-ditl.

The *crawler* class shows the opposite behavior: most crawlers appear only in the top-10000, with few in top-1000 (554 vs. 3). This shift is consistent with web crawlers being data intensive, operating across many distributed IP addresses in parallel.

We also see that the physical location of the authority influences what they see. We earlier observed how differences in *cdn* for M-Root and B-Root are explained by their physical location to CDNs in China. B-Root’s U.S.-only location may place it closer to more services in *cloud* (see Figure 6a) compared to M-Root’s locations mainly in Asia and Europe.

New and old observations: A new observation in our data is *potential teams of scanners*. We have manually identified several /24 address blocks where many addresses are engaged in scanning, suggesting possible parallelized scanning. Without direct scan traffic, we cannot confirm coordination, but backscatter suggests networks for closer examination. To understand with scope of potential collaborative teams, we start with a very simple model where a team is multiple originators in the same /24 IP address block. In M-sampled we see 5606 unique scan originators (by IP address), across 2227 unique originating /24 address blocks. Of these, 167 blocks have 4 or more originators, suggesting a potential team of collaborators. While 128 of these blocks have multiple application classes, suggesting against collaboration (or

possibly mis-classification), we see 39 blocks with 4 or more originators all with the same application class. Such blocks warrant closer examination.

We also confirmed prior observations that clients linger on retired services. Originators we find include four retired root DNS servers (B, D, J, L), two prior cloud-based mail servers, and one prior NTP server. These cases show our methods can be used to systematically identify overly-sticky, outdated clients across many services, automating prior reports of clients that stick to retired servers in DNS [29] and NTP [39].

Classification on originator actions: An important benefit of our approach is that we classify on *indirect actions caused by the originator, with no direct information from the originator*. In fact, about a quarter of the originators in JP-ditl and half of those in the root datasets have no reverse domain names, but originator omissions have no affect on our approach because we do not observe *any* traffic or reverse names of originators. This separation makes it more difficult for adversarial originators to conceal their activities.

5.3 Trends in Network-Wide Activity

We next look for long-term trends in our data. We believe this is the first longitudinal study of network-wide activities such as scanning (prior work focused on specific events [17]). Our goal is to understand the ebb and flow of network-wide activity, so rather than examine the N largest originators, we count all originators with footprints of at least 20 queriers (see also Figure 5). While we see no growth in network-wide events, we see *peaks that respond to security events* and a *core of slow-and-steady scanners*.

Peaks in numbers of originators: The top *all* line in Figure 7 shows the absolute number of originators over time, each class (the lower, colored lines) and total (the top, black line). There are fairly large week-by-week changes, showing churn in the number of active originator activities,

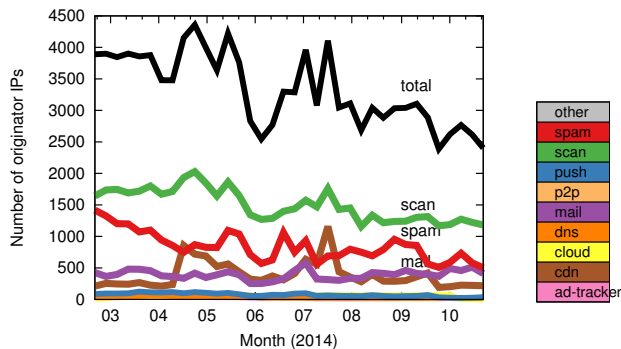


Figure 7: Number of originators over time. (Dataset: M-sampled; classifier: RF.)

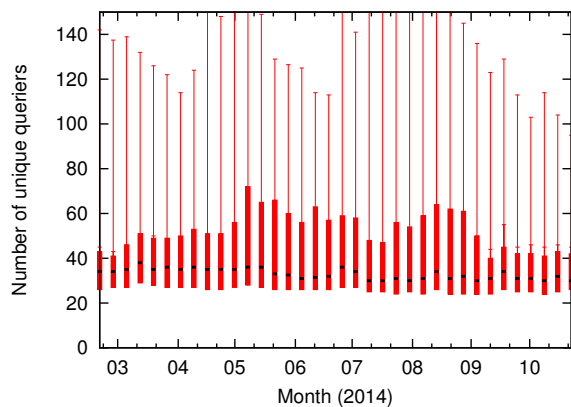


Figure 8: Box plot of originator footprint (queriers per scanner) over time; whiskers: 10%ile/90%ile. (Dataset: M-sampled.)

and peaks that can be explained by reactions to network security events.

To understand how network activity results from real-world events we next look the *scanner* application class. Our observation period includes public announcement of the Heartbleed vulnerability on 2014-04-07 [38], and we know that there were multiple research [1, 18], commercial, and presumably government scanning activities triggered by that announcement. The green scanner line in Figure 7 shows more than a 25% increase in scanning by mid-April, from 1400 originator IPs per week to 1800 at its peak. While this change is noticeable, it is smaller than we might expect. Instead, it shows that reaction to Heartbleed is small compared to the *large amount of scanning that happens at all times*—the 1200–1400 scanners we saw in March, and the 1000–1200 scanners that are present from June to October.

Churn: To understand long-term scanning, Figure 8 shows the distribution of footprint sizes over time for class *scan*. While the median and quartiles are both stable over these 36 weeks, but the 90th percentile varies considerably. This variation suggests a few very large scanners that come and go, while a core of slower scanners are always present.

We illustrate this observation with three different scanners that appear in both M-sampled and our darknet data

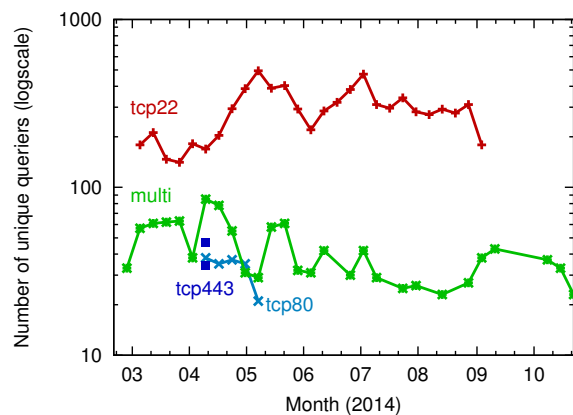


Figure 9: Three example originators with application class *scan*. (Dataset: M-sampled with darknet.)

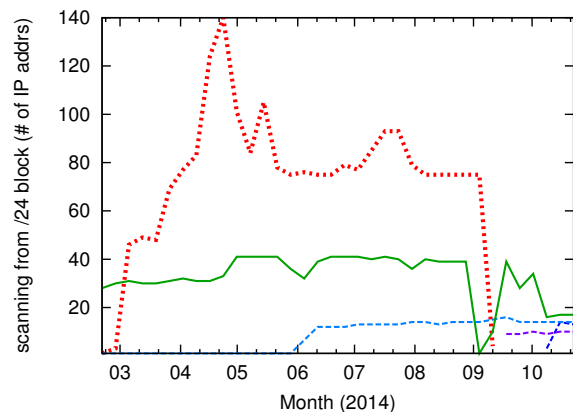


Figure 10: Five example blocks originating scanning activity. (Dataset: M-sampled.)

(Figure 9). Two are long-lived (the top “tcp22” line scanning ssh, and the middle line scanning multiple ports), while the tcp80 scanner occurs in April and May. Furthermore, two tcp443 scans only appear in one week in April (shown as dark squares), suggesting they are Heartbleed-related. We also see that tcp22 has a bigger footprint than the others, and it looks a part of a big campaign whose 140 IP addresses belong to the same /24 block. Using our darknets, we confirm 164 scanners for TCP ports 22, 80, or 443, and while there is no “typical” scanner, these variations are common.

Our approach also *identifies networks supporting scanners*. For each /24 block, we count the number of IP addresses in class *scan* over time; Figure 10 shows five of these blocks. The top dotted line is a block with large scanning peaks corresponding with Heartbleed and Shellshock, ending in September. The solid line shows a block that scans continuously, while the three dotted lines are blocks that start scanning during our observation.

To understand if *who* scans changes over time, Figure 11 measures week-by-week change in scanner IP addresses. The bar above the origin shows the number of scanners each week, showing both new originators (top, dark) and con-

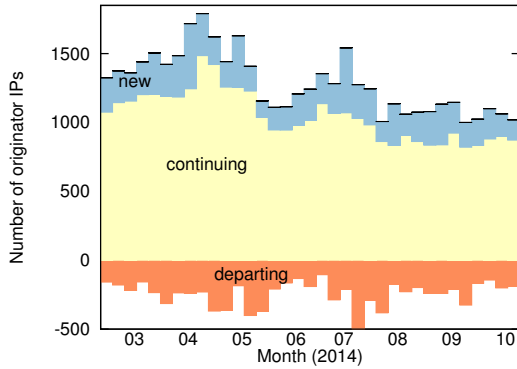


Figure 11: Week-by-week churn for originators of class *scan*. (Dataset: M-sampled.)

tinuing originators (middle, light) The red bar below the origin shows scanners that were lost from the prior week. While there are always scanners coming and going (about 20% turnover per week), this data confirms that there is a stable core of scanners that are consistently probing, week-after-week.

6. RELATED WORK

We next review prior work in both DNS- and non-DNS-based sensors and analysis. Overall, our contribution is to show that reverse DNS queries can identify network-wide behavior. Prior work instead considers forward DNS traffic and typically applies it to specific problems, or uses non-DNS sensors such as darknets and search engines.

DNS-specific sensors: Several groups use forward DNS queries to identify spam [56, 27], fast-flux [56, 26], automatically generated domain names [55], and cache poisoning [2]. Like our work, several of these approaches use machine learning to classify activity. However, this prior work focuses on *forward* DNS queries, while we consider *reverse* queries. Moreover, many use algorithms optimized to detect specific malicious activities, while we detect a range of network-wide behavior.

Recent work has used DNS to infer the structure of CDN networks [4] or internal to DNS resolvers [44]. They infer specific services from DNS traffic, we search for network-wide events from reverse queries.

An earlier work uses targeted scan and DNS backscatter for detecting Tor exit routers peeking POP3 authentication information [33], an earlier use of DNS backscatter de-anonymization; we generalize this use to detect scanners.

Plonka and Barford use machine-learning-based clustering and visualization to identify undesirable activity from local DNS traffic [40]. They use DNS traffic from an organization’s recursive resolver to infer activity about that organization. Overall, our approach provides larger coverage, both by using data from authoritative DNS servers that aggregate queries from many organizations, unlike their single organization, and by examining trends in ten months of data, unlike their week-long analysis.

Antispam software has long used reverse DNS lookups to directly classify sources of mail. We use the domain names of queriers to indirectly classify originators.

Non-DNS Passive sensors: Darknets (or network telescopes) are a commonly used passive technique to characterize large-scale network activity [37, 34, 54, 13, 14, 17]. By monitoring a large, unoccupied blocks of addresses, darknets see active probes from viruses and scanners, queries from misconfiguration, and backscatter from spoofed traffic; traffic that can predict global malware, and its absence, network outages. Our analysis of DNS backscatter shares the goal of understanding network-wide activity from a simple, passive observer, but we observe at DNS authorities rather than large ranges of addresses. Like Durumeric et al. [17], we seek to enumerate scanners, but our use of DNS backscatter will see targeted scans that miss their darknet, and our study considers eight months of activity, not just one.

Some security services use middleboxes with deep-packet inspection to passively monitor large ISPs [3]. They observe all traffic from multiple points, while we monitor DNS backscatter from a single provider only.

Staniford monitored network traffic for scanners [47], and Gates emphasized rapid detection with scanner modeling [23]. Rather than protecting a single network, we look for network-wide activity with a simple observer.

Honeypots (for example, [41]) are a form of application-level darknet. By interacting with originators they see attacks darknets miss, but they miss attacks that probe specific targets (such as Alexa top sites). Interactivity also makes them fewer because of deployment expense. DNS backscatter uses information from existing servers.

Unconstrained endpoint profiling [48] uses search engines to gather information on addresses that leak into the public web, possibly complementing network flow data. We both seek to understand network-wide activity, but we use different data sources and methods. They use largely unstructured information from the web, while we infer features from semi-structured domain names and also traffic patterns. Their work depends on the speed of search engine indexing, while our work can provide rapid feedback given data from a DNS authority.

General DNS traffic analysis and privacy: Finally, a wide body of work has explored DNS traffic in general (examples include [15, 52, 11, 22]). Their work seeks to understand DNS, while we instead study what reverse DNS tells us about network-wide activities.

Work in DNS privacy focuses on client-to-recursive resolvers for end-users (examples include [36, 57], and proposals in the IETF DPRIVE working group). Our use of reverse queries from automated systems triggered by originators should see almost no human-triggered, end-user queries (§ 2). Use of query minimization [5] at the queriers will constrain the signal to only the local authority (that immediately serving the originator’s reverse address).

7. CONCLUSION

We identified DNS backscatter as a new source of information about benign and malicious network-wide activity, including originators of mailings list traffic, CDN infrastructure, spammers and scanners. Their activity triggers reverse DNS queries by or near their targets, and we show that classification of these queriers allows us to identify classes of activity with reasonable precision. We use our approach to identify trends in scanning across nine months of data from one data source, and we characterize several kinds of activ-

ity for two days over three data sources. Our work provides a new approach to evaluate classes of network-wide activity.

Acknowledgments: We thank Yuri Pradkin for B-Root data collection, Akira Kato for M-Root data, and Yoshiro Yoneya and Takeshi Mitamura for JP data. We thank Xun Fan for input about Google and Akamai sites in Japan. We thank Terry Benz, Kenjiro Cho, Ethan Katz-Bassett, Abdul Qadeer, and John Wroclawski comments on this paper.

Kensuke Fukuda's work in this paper is partially funded by Young Researcher Overseas Visit Program by Sokendai, JSPS KAKENHI Grant Number 15H02699, and the Strategic International Collaborative R&D Promotion Project of the Ministry of Internal Affairs and Communication in Japan (MIC) and by the European Union Seventh Framework Programme (FP7/2007- 2013) under grant agreement No. 608533 (NECOMA). The opinions expressed in this paper are those of the authors and do not necessarily reflect the views of the MIC or of the European Commission.

John Heidemann's work in this paper is partially sponsored by the Department of Homeland Security (DHS) Science and Technology Directorate, HSARPA, Cyber Security Division, via SPAWAR Systems Center Pacific under Contract No. N66001-13-C-3001, and via BAA 11-01-RIKA and Air Force Research Laboratory, Information Directorate under agreement number FA8750-12-2-0344. The U.S. Government is authorized to make reprints for Governmental purposes notwithstanding any copyright. The views contained herein are those of the authors and do not necessarily represent those of DHS or the U.S. Government.

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