Catching the Cyber Criminals

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Revealing Malicious Infrastructures with OpenDNS

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Abstract



Cyber Criminals are increasingly exploiting the Internet to build agile and resilient infrastructures, and consequently to protect themselves from being exposed and taken over.

The **Internet** is an open system, meaning that the **information** to expose those infrastructures is available somewhere. The challenge is that fragments of data broken up and spread across the web are not immediately visible.

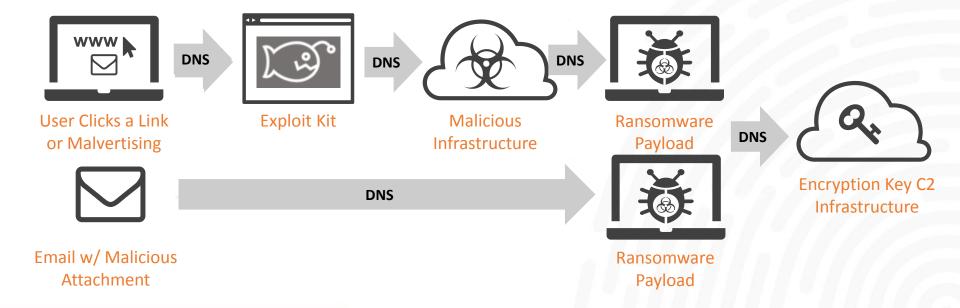
Connecting the dots, being able to analyze a diverse set of information made of billions of pieces of discrete data allows us to build maps that reveal where malicious infrastructure is hidden and where attacks are being staged. This turns the tables on traditional security with a new approach where the defender takes the upper hand on the attacker, being able to pivot through criminal infrastructure.



Ransomware Kill Chain with DNS

Elements of the infrastructure are involved in each phase



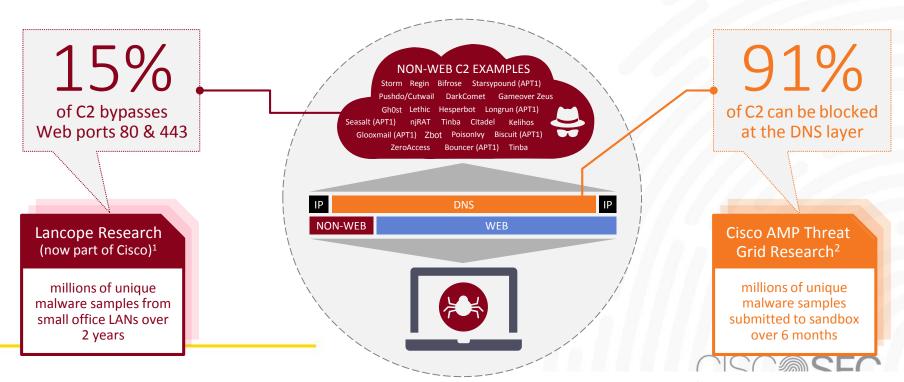




Why leverage DNS to Detect and Block Threats

Most attacker C2 is initiated via DNS lookups with some non-Web callbacks





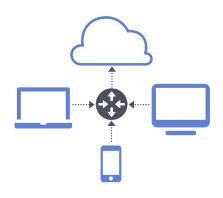
NOTE1: Visual Investigations of Botnet Command and Control Behavior ($\underline{\text{link}}$)

- malware reached out to 150,000 C2 servers over 100,000 TCP/UDP ports
- malware often used 866 (TCP) & 1018 (UDP) "well known" ports, whereas legitimate traffic used 166 (TCP) & 19 (UDP) ports

NOTE2: 2016 Cisco Annual Security Report

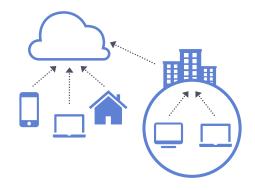
- 9% had IP connections only and/or legitimate DNS requests
- 91% had IP connections, which were preceded by malicious DNS lookups
- very few had no IP connections

DNS is *Used by Every Device* on Your Network



ANY OWNER

network's DHCP tells every connected device where to point DNS



ANY TOPOLOGY

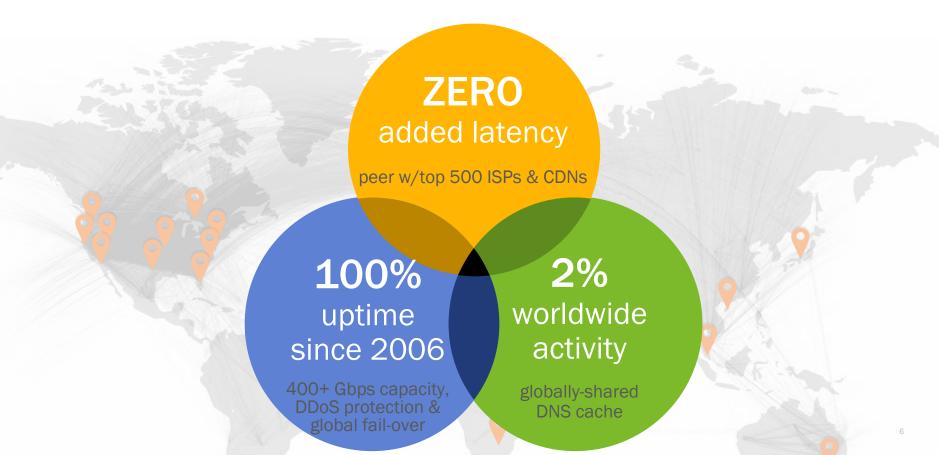
no matter how your LAN or WAN is set up, it simply works



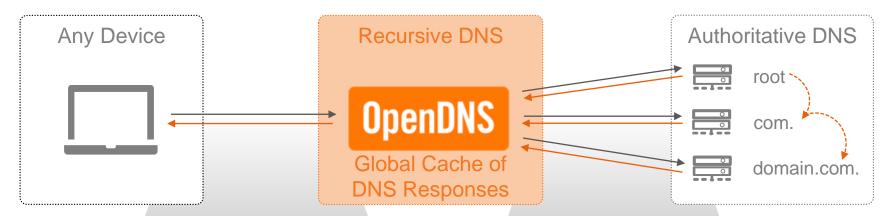
ANY OPERATING SYS

Win, Mac, iOS, Android, Linux, custom app servers, and even IoT

Global Network Built Into the Fabric Of the Internet



Gather Intelligence At the DNS Level



Request Patterns

Used to detect:

- Compromised systems
- · Command & control callbacks
- Malware & phishing attempts
- Algorithm-generated domains
- · Domain co-occurrences
- Newly registered domains

Authoritative Logs

Used to find:

- Newly staged infrastructures
- · Malicious domains, IPs, ASNs
- DNS hijacking
- · Fast flux domains
- Related domains

Some Security Graph Metrics

GLOBAL NETWORK

- 90B+ DNS requests/day
- 65M+ biz & home users
- 100% uptime
- Any port, protocol, app



UNIQUE ANALYTICS

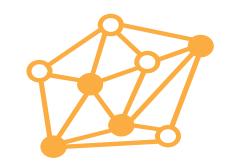
- security research team
- · automated classification
- BGP peer relationships
- 3D visualization engine



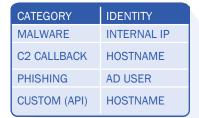


SECURITY GRAPHS

- > 10 TB/day
- ~46M nodes per day
- ~174M edges per day



What does OpenDNS Provide







(

SECURITY LABS



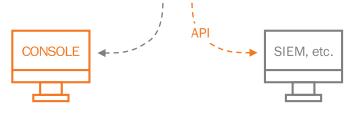


STATUS & SCORES
CO-OCCURRENCES
RELATIONSHIPS
ATTRIBUTIONS
PATTERNS & GEOS



208.67.222.222 DOMAIN, IP, ASN, EMAIL, HASH





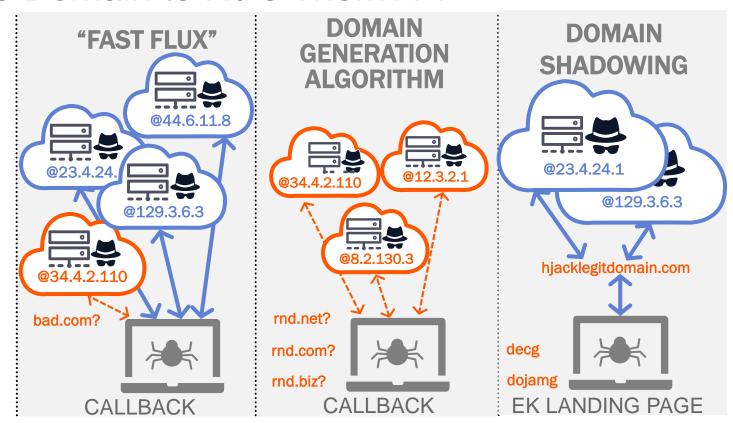


Traditional Domain Reputation Techniques Are No Longer Effective

- Domain Reputation is not effective on Identifying certain groups of threats such as Exploit Kits or Domain Shadowing
 - Malicious domains move quickly from IP to IP
 - Legitimate domains may be compromised to distribute malware
 - Malware can use DGA/Domain Shadowing
- Conceived for an Internet of 10 years ago



One Domain to Rule Them All!

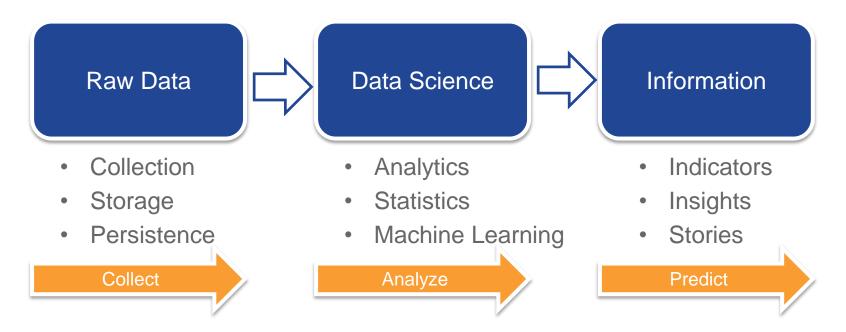


Who Says That a Crystal Ball Is the Only Way to Predict Cyber Attacks?

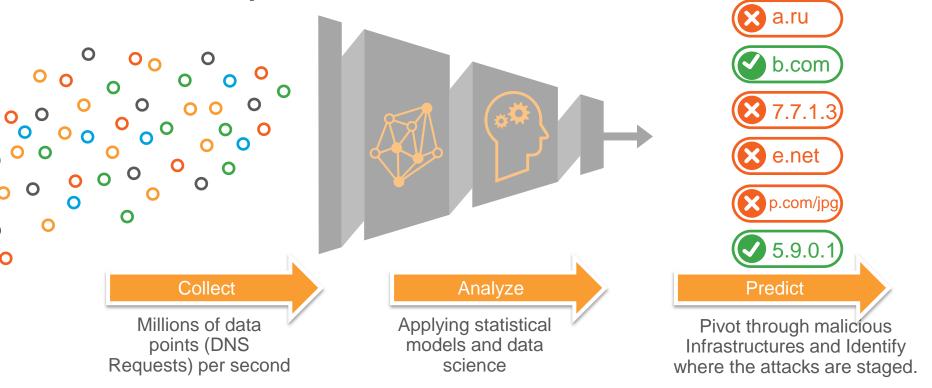
A Diamond (And a Bunch of Math) Can Help!

$$T(x) \cdot \frac{\partial}{\partial \theta} f(x, \theta) = V(x, \theta) \cdot \int_{\partial \theta} \ln L(x, \theta) \int_{R_{\star}} T(x) \cdot \left(\frac{\partial}{\partial \theta} \ln L(x, \theta) \right) \int_{R_{\star}} T(x) \cdot \left(\frac{\partial}{\partial \theta} \ln L(x, \theta) \right) \int_{R_{\star}} T(x) \cdot \left(\frac{\partial}{\partial \theta} \ln L(x, \theta) \right) \int_{R_{\star}} T(x) \cdot \left(\frac{\partial}{\partial \theta} \ln L(x, \theta) \right) \int_{R_{\star}} T(x) \cdot \left(\frac{\partial}{\partial \theta} \ln L(x, \theta) \right) \int_{R_{\star}} T(x) \cdot \left(\frac{\partial}{\partial \theta} \ln L(x, \theta) \right) \int_{R_{\star}} T(x) \cdot \left(\frac{\partial}{\partial \theta} \ln L(x, \theta) \right) \int_{R_{\star}} T(x) \cdot \left(\frac{\partial}{\partial \theta} \ln L(x, \theta) \right) \int_{R_{\star}} T(x) \cdot \left(\frac{\partial}{\partial \theta} \ln L(x, \theta) \right) \int_{R_{\star}} T(x) \cdot \left(\frac{\partial}{\partial \theta} \ln L(x, \theta) \right) \int_{R_{\star}} T(x) \cdot \left(\frac{\partial}{\partial \theta} \ln L(x, \theta) \right) \int_{R_{\star}} T(x) \cdot \left(\frac{\partial}{\partial \theta} \ln L(x, \theta) \right) \int_{R_{\star}} T(x) \cdot \left(\frac{\partial}{\partial \theta} \ln L(x, \theta) \right) \int_{R_{\star}} T(x) \cdot \left(\frac{\partial}{\partial \theta} \ln L(x, \theta) \right) \int_{R_{\star}} T(x) \cdot \left(\frac{\partial}{\partial \theta} \ln L(x, \theta) \right) \int_{R_{\star}} T(x) \cdot \left(\frac{\partial}{\partial \theta} \ln L(x, \theta) \right) \int_{R_{\star}} T(x) \cdot \left(\frac{\partial}{\partial \theta} \ln L(x, \theta) \right) \int_{R_{\star}} T(x) \cdot \left(\frac{\partial}{\partial \theta} \ln L(x, \theta) \right) \int_{R_{\star}} T(x) \cdot \left(\frac{\partial}{\partial \theta} \ln L(x, \theta) \right) \int_{R_{\star}} T(x) \cdot \left(\frac{\partial}{\partial \theta} \ln L(x, \theta) \right) \int_{R_{\star}} T(x) \cdot \left(\frac{\partial}{\partial \theta} \ln L(x, \theta) \right) \int_{R_{\star}} T(x) \cdot \left(\frac{\partial}{\partial \theta} \ln L(x, \theta) \right) \int_{R_{\star}} T(x) \cdot \left(\frac{\partial}{\partial \theta} \ln L(x, \theta) \right) \int_{R_{\star}} T(x) \cdot \left(\frac{\partial}{\partial \theta} \ln L(x, \theta) \right) \int_{R_{\star}} T(x) \cdot \left(\frac{\partial}{\partial \theta} \ln L(x, \theta) \right) \int_{R_{\star}} T(x) \cdot \left(\frac{\partial}{\partial \theta} \ln L(x, \theta) \right) \int_{R_{\star}} T(x) \cdot \left(\frac{\partial}{\partial \theta} \ln L(x, \theta) \right) \int_{R_{\star}} T(x) \cdot \left(\frac{\partial}{\partial \theta} \ln L(x, \theta) \right) \int_{R_{\star}} T(x) \cdot \left(\frac{\partial}{\partial \theta} \ln L(x, \theta) \right) \int_{R_{\star}} T(x) \cdot \left(\frac{\partial}{\partial \theta} \ln L(x, \theta) \right) \int_{R_{\star}} T(x) \cdot \left(\frac{\partial}{\partial \theta} \ln L(x, \theta) \right) \int_{R_{\star}} T(x) \cdot \left(\frac{\partial}{\partial \theta} \ln L(x, \theta) \right) \int_{R_{\star}} T(x) \cdot \left(\frac{\partial}{\partial \theta} \ln L(x, \theta) \right) \int_{R_{\star}} T(x) \cdot \left(\frac{\partial}{\partial \theta} \ln L(x, \theta) \right) \int_{R_{\star}} T(x) \cdot \left(\frac{\partial}{\partial \theta} \ln L(x, \theta) \right) \int_{R_{\star}} T(x) \cdot \left(\frac{\partial}{\partial \theta} \ln L(x, \theta) \right) \int_{R_{\star}} T(x) \cdot \left(\frac{\partial}{\partial \theta} \ln L(x) \right) \int_{R_{\star}} T(x) \cdot \left(\frac{\partial}{\partial \theta} \ln L(x) \right) \int_{R_{\star}} T(x) \cdot \left(\frac{\partial}{\partial \theta} \ln L(x) \right) \int_{R_{\star}} T(x) \cdot \left(\frac{\partial}{\partial \theta} \ln L(x) \right) \int_{R_{\star}} T(x) \cdot \left(\frac{\partial}{\partial \theta} \ln L(x) \right) \int_{R_{\star}} T(x) \cdot \left(\frac{\partial}{\partial \theta} \ln L(x) \right) \int_{R_{\star}} T(x) \cdot \left(\frac{\partial}{\partial \theta} \ln L(x) \right) \int_{R_{\star}} T(x) \cdot \left(\frac{\partial}{\partial \theta} \ln L(x) \right) \int_{R_{\star}} T(x) \cdot \left(\frac{\partial}{\partial \theta} \ln L(x) \right) \int_{R_{\star}} T(x) \cdot \left(\frac{\partial}{\partial \theta} \ln L(x) \right) \int_{R_{\star}} T(x) \cdot \left(\frac{\partial}{\partial \theta} \ln L(x) \right) \int$$

Making Sense of Data



How Security Classification Works



Predictive Detectors Used by OpenDNS

- SecureRank
- Co-Occurrences
- NLPRank
- DGA Detectors
- Spike Detectors
- Predictive IP Space Monitoring



SecureRank

- Abstract DNS traffic in a bipartite graph
- Color the graph with different shades of "red" to indicate bad domains, and "green" for good ones.
- There are clusters of 'red' separated from "green" zones with few intra links.
- Domains requested by known infected clients but never requested by clean ones are most likely to be bad.
- SecureRank2 is designed to identify these domains



Assigning a Score to Malicious Domains

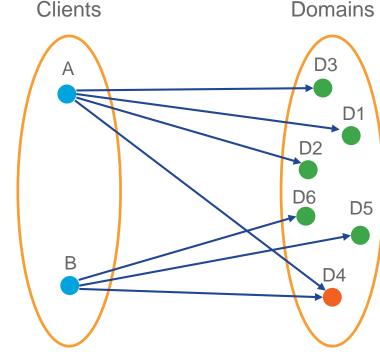
$$SR_{Domain} = \sum \frac{SR_{Client}}{L_{Client}}$$

$$SR_{Client} = \sum \frac{SR_{Domain}}{L_{Domain}}$$

$$SR_{C}(A) = SR_{D}(D_{1}) + SR_{D}(D_{2}) + SR_{D}(D_{3}) + \frac{SR_{D}(D_{4})}{2}$$

$$SR_{C}(B) = \frac{SR_{D}(D_{4})}{2} + SR_{D}(D_{5}) + SR_{D}(D_{6})$$

$$Next$$
Interaction
$$SR_{D}(D_{4}) = \frac{SR_{C}(A)}{A} + \frac{SR_{C}(B)}{2}$$



https://labs.opendns.com/2013/03/28/secure-rank-a-large-scale-discovery-algorithm-for-predictive-detection/

The Algorithm in Action

Link Analysis March through global DNS query data and map the requestor-requestee pairs as a graph.

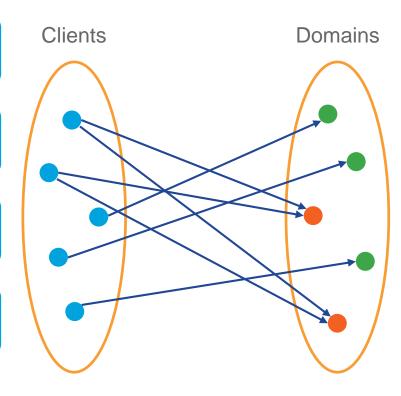
Initialize

 Negative ranks to known blacklisted domains and positive ranks to known whitelisted domains.

Iteration

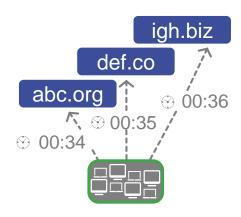
• Run The Algorithm through different iterations

Final Rank • Final ranks are generated when the ranks converge after a number of iterations.



Co-Occurrences

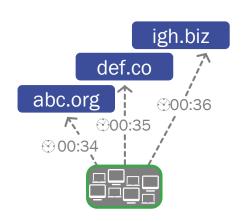
- Sequence of DNS requests to domains that co-occur within seconds of each other across a statistically significant number of streams.
- For a domain, being a co-occurrence is not necessarily a bad thing.
- But what if one of the domains involved is part of a malicious campaign?



CO-OCCURRENCES

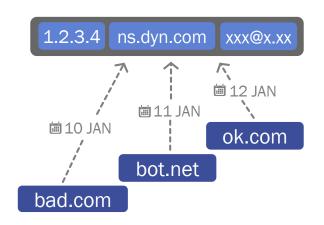
domain-to-domain request sequences via recursive DNS

Co Occurrences can be correlated with more "traditional" Techniques



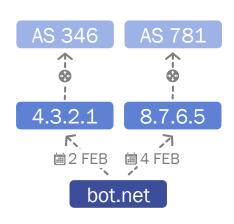
CO-OCCURRENCES

domain-to-domain request sequences via



PASSIVE DNS & WHOIS

present & past relationships for domains-to-IP/nameserver/email via authoritative DNS & DNS registrars



INFRASTRUCTURES

domain-to-IP-to-AS relationships via graphing BGP routing data

NLPRank

Identifies malicious domain-squatting and targeted C2 or phishing domains



Read APT reports





Patterns in domains used in attacks

- Domain spoofing used to obfuscate
- Often saw brand names and terms like "update"
- Examples: update-java[.]net adobe-update[.]net



Checked data & confirmed intuition

- Dictionary & company names merged
- Change small # of characters to obfuscate
- Domains hosted on ASNs unassociated w/company
- Different webpage fingerprints



Built model and continue to tune

 Detects fraudulent brand domains:





NLPRank Detections: DarkHotel

adobeupdates[.]com

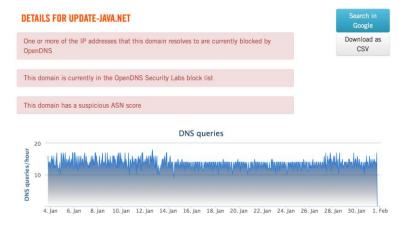


microsoft-xpupdate[.]com

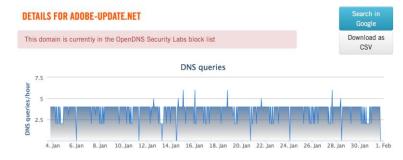


NLPRank Detections: Carbanak

update-java[.]net



adobe-update[.]net



DGA Detection

Identifies malicious domain-squatting and targeted C2 or phishing domains

"N-gram" analysis

Do sets of adjacent letters match normal language patterns?

yfrscsddkkdl.com

qgmcgoqeasgommee.org

iyyxtyxdeypk.com

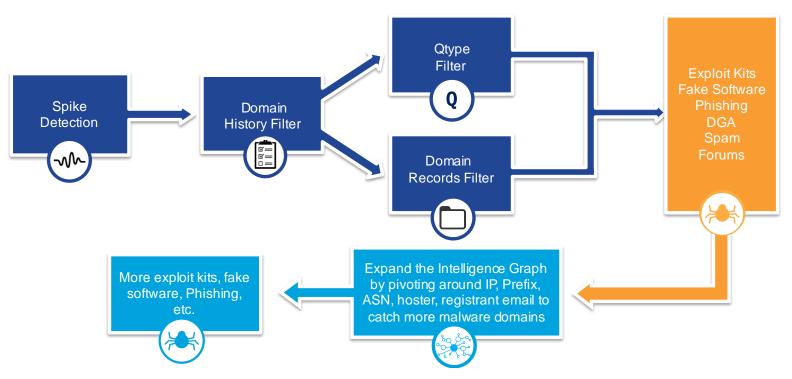
diiqngijkpop.ru

Entropy analysis

Does the probability distribution of letters appear random?

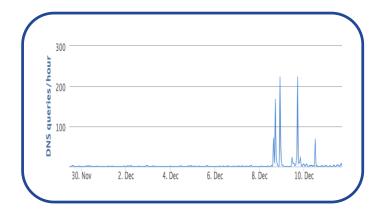
SPRank

SPRank detects domains showing as a sudden surge, or a spike, in DNS queries



What Does a Malicious Connection Sounds Like?

What if we could model the traffic spikes as sound waves and identifies "spike behavior" typical of domains used for malware campaigns such as exploit kits, DGAs, fake software, phishing, etc...

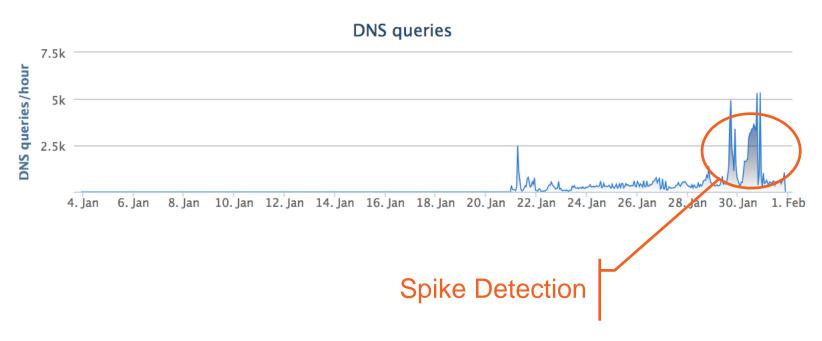


Example of An Exploit Kit



Example of a DGA

Example of a DGA



Spike Detection

- New Series of threats such as Exploit Kits or Domain Shadowing make many of the classical domain reputation or IP reputation methods ineffective.
- Spike defined as a jump in traffic over a two hour window.
- Use predetermined threshold. Helps filter out Google, Facebook, etc.
- Use a MapReduce algorithm to calculate domains that spike.
- Output 50-100k domains each hour.



Domain History Filter

- Past query history is used to help remove benign domains and focus in Exact Domain Match ones.
- Allows to eliminate all domains with more than X consecutive non-zero hours of traffic.
- Based on current EK domains traffic patterns, only keep domains that feature Y consecutive most recent non-zero hours of traffic.



Query Type Filter

- Look at past history, DNS Qyery types, all existing DNS records of a domain, unique IPs, unique resolvers, etc.
- Partition based on Query types Distribution:
 - ✓ 1 A Record
 - √ 15 MX Record
 - √ 16 TXT Record
 - ✓ 99 SPF Record
 - ✓ 255 ANY Record



Domain Records Filter

- Check for all DNS records available for a domain: the existence/non-existence
 of certain records helps narrow down the purpose of a domain.
- Partition based on DNS records:
 - A
 - MX
 - TXT
 - CNAME
 - NS, specific name servers, indicative of compromise or malware



Empirical Data on the Model Efficacy

On Average, only

16%

of security vendors catch the domains identified by SPRank.

Of the 200 domains, observed in a one hour period,

70

of the compromised domains had not been identified by any other vendor. SPRank has a

100%

success rate of discovering malicious domains before other security vendors (tested hourly against VirusTotal).

https://blog.opendns.com/2015/11/19/opendns-cracks-predictive-security/

Predictive IP Space Monitoring

Predictive IP Space Monitoring is used to further drill into associated indicators by analyzing 8 different recorded hosting patterns:

- Compromised domains, i.e. "domain shadowing"
- Domain shadowing on multiple hosting IPs
- Sibling peripheral ASNs and bulk malware IP setup
- Leaf ASNs
- Offshore registration and diversification of IP space
- Rogue ASN and affiliated hosters
- Abuse of large hosting providers
- Shady hosts within larger hosting providers



Expanding The Selection

Predictive IP Space Monitoring expands the selection of SPRank, to determine which domains will be the source of future malicious activity.

For

1

malicious domain identified by SPRank, Predictive IP Space Monitoring predicted

340

Additional domains

https://blog.opendns.com/2015/11/19/opendns-cracks-predictive-security/

Pivoting Through the Attack Infrastructure with Just one Piece of Information (1/2) **Analysis of IP Requester Location**

Alerts and risk scores

Summarise the suspicious activity identified for the domain



Global Requests Patterns

Shows an abnormal spike in traffic, which highlights when the attack launched



Shows the vast majority of requests for this domain are coming from people located in a certain country, which could signify a more targeted attack



Domain Tagging

Shows history of when the malware was associated with malware or botnet activity

DOMAIN TAGGING				
Period	Category	URL		
Sep 23, 2015 - Current	Botnet			

IP Geography Analysis

Reveals the domain is hosted by IP addresses on different networks in more than 20 countries, which, for instance, is unusual for legitimate country code toplevel domains.



WHOIS Record Data

Shows the domain was recently created and registered by someone who used the same email address to register other malicious domains



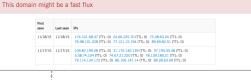
Pivoting Through the Attack Infrastructure with Just one Piece of Information (2/2) Related Domains and Co-Occurrences

Mappings of IP prefixes and ASNs Highlights where the domain is hosted and confirm it's a "bad neighbor" of many other malicious domains. Pivot on the IP or ASN for more details.



Anomaly Detection

Identifies that this is a fast flux domain, a technique used to hide malware sites behind IPs that are constantly changing



Related Domains and Co-Occurrences Identify other domains that were queried with a high statistical frequency right before or after this one and are likely related to the same attack.

CO-OCCURRENCES

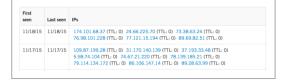
www.dondetucompras.es (46.33) aondeconvem.com.br (31.02) corporate.doveconviene.it (22.65)

RELATED DOMAINS

www.dondetucompras.es (13) aondeconvem.com.br (9) 123contactform.com (7) corporate.doveconviene.it (6) www.dondelocompro.mx (5) forms.doveconviene.it (3) cdn.iubenda.com (3)

Passive DNS Data

Provides insight into the history of the mapping between domains and IPs: this domain was associated with different IPs when detected the first time.



Named Threat Attribution

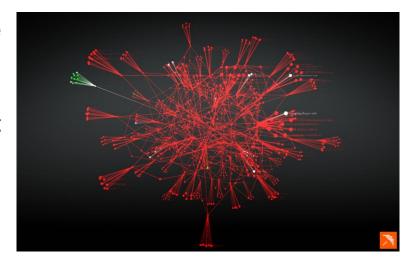
Confirms that the domain was associated with a particular malware family or botnet C&C.

This domain is associated with the following attack: ZBot Fast Flux Botnet

Starting from a single piece of data, it is possible to quickly investigate the domain leveraging a single, correlated source and speed up incident response.

Visualizing Data with OpenGraphiti

- OpenGraphiti, is the Open Source interactive data visualization engine developed by OpenDNS.
- Used by security analysts and researchers, it pairs visualization and Big Data to create 3D representations of threats.
- The basic concept is that information is processed more efficiently when it is presented in visual rather than text form.
- OpenGraphiti can uncover sophisticated behaviors and relationships associated with cyber-attacks.



Using Semantic Networks to Visualize Threats

- Graph = Set of Nodes
- Node = Concept, Edge = Relationship
- · Agents populate the graph
- A semantic network can be represented as a graph connecting any kind of information by any kind of relationship
- They can be used to model nearly everything and can be applied to a wide range of problems













199.10.130.230

Public DNS providers struggle to resolve websites amid the @Dyn DDoS. OpenDNS is holding up. Here's servers trying to resolve Twitter

Agent 183-scottlinux Location US - Fremont Network Abovenet Comm (AS17025)	208.67.222.222	OpenDNS, LLC (AS36692)	~	14 ms	199.16.156.198 199.16.156.102 expand
	74.207.242.5	Linode, LLC (AS63949)	×	64 ms	expand
	45.33.58.84	Linode, LLC (AS63949)	×	66 ms	expand
	8.8.8.8	Google Inc (AS15169)	×	2 ms	expand
Agent 187-TWCRR-AS10796 Location = US - Cleveland Network Time Warner C (AS10796)	209.18.47.62	Time Warner C (AS7843)	×	13 ms	expand
	208.67.222.222	OpenDNS, LLC (AS36692)	•	26 ms	199.16.156.102 199.16.156.198 199.16.156.70 199.16.156.230 expand
	209.18.47.61	Time Warner C (AS7843)	×	22 ms	expand
	8.8.8.8	Google Inc (AS15169)	×	37 ms	expand
Agent 188-STLMO Location = US - St. Louis Network Charter Commu (AS20115)	8.8.8.8	Google Inc (AS15169)	×	26 ms	expand
	208.67.222.222	OpenDNS, LLC (AS36692)	~	40 ms	199.59.150.7 199.59.148.10 199.59.149.198 199.59.148.82 expand
	24.196.64.53	Charter Commu (AS20115)	×	42 ms	expand
Agent 190-ATT-AS7018 Location = US - Cleveland Network AT&T Services (AS7018)	208.67.222.222	OpenDNS, LLC (AS36692)	~	28 ms	199.16.156.230 199.16.156.198 199.16.156.102 199.16.156.70 expand
	8.8.8.8	Google Inc (AS15169)	×	37 ms	expand
	68.94.157.1	AT&T Services (AS7018)	×	21 ms	expand
	68.94.156.1	AT&T Services (AS7018)	×	960 ms	expand

Predict and Prevent Attacks Before They Happen

- With its 90+ Billion DNS requests analyzed per day OpenDNS has a comprehensive and privileged view of the Internet
- The analysis of this massive and diverse dataset allows to build models and detectors able to identify where attacks are staged.
- Starting from a single piece of information it is possible to pivot through the malicious infrastructure, exposing attackers and predicting their moves before they happen
- On the other hand, the Internet is not unlimited, so there are zones more prone to be exploited by criminals, or even recycled.

Start your Free Trial Now

CISCO

https://signup.opendns.com/freetrial/

www.opendns.com labs.opendns.com opengraphiti.com





Thank you

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