# Phoenix: DGA-based Botnet Tracking and Intelligence

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# Introduction

# Botnets

A **largely widespread** and **highly lucrative** criminal activity.

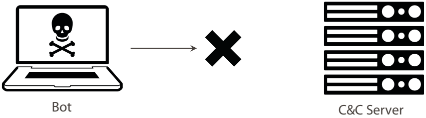
Four examples:

- Flashback: year 2012, **600K** compromised Macs, credentials stealing
- Grum: from 2008 to 2012, **840K** compromised devices, **40bln/mo** spam emails
- TDL-4: from 2011, **4,5M** victims in the first 3 months, known as *"indestructible"*.
- Gameover ZeuS from 2011, **500K - 1M** infections as of last month, huge effort and collaboration to take down.

# C&C Channel

It's the logical communication channel used by the botmaster to communicate with his bots.

Security **defenders strive to disable C&C channels** as means to disable botnets without sanitizing the infected machines.



# C&C Channels Security

Botnet architects need to buid ***sinkholing-proof*** C&C infrastructures.

No perfect solution exists, but sinkholing can be made **hard** or **antieconomic**.

Employing **P2P architectures** helps, but these are difficult to manage and provide little guarantees.

Client-server C&C infrastructures can be effective if a **strong rallying mechanism** is employed.

# Rallying Mechanism

The process with which a bot looks up for a **rendezvous point** with its master, before starting the actual communication.

The rendezvous point can be:

- an IP address,
- a domain name.

In the most basic scenario, the IP addresses or domain names are **hardcoded in the binary**.

## General Issues

Hardcoding IP addresses or domain names is not great because:

1. **the rendezvous coordinates can be leaked** by the malware binary through reverse engineering;
2. a rendezvous point change needs an **explicit agreement**.

The mechanism of **domain generation algorithms (DGAs)** targets and solves these issues.

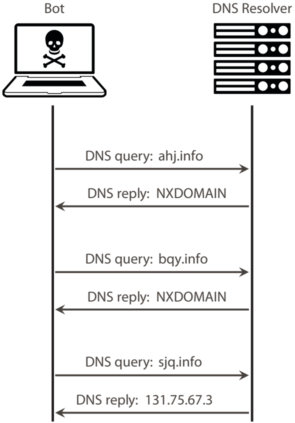
# Domain Generation Algorithms

# Domain Generation Algorithms: Functioning

Every day the bots generate a **long list of pseudo-random domains**, with an unpredictable seed (e.g., Twitter TT).

The botmaster **registers one of them**.

When the bots find it, **they find the rendezvous point**.



# Domain Generation Algorithms: Properties

Malware code is **agnostic**: reverse engineering it is useless.

There is an **asymmetry in the costs and efforts**:

botmaster: needs to register **one domain** to talk to his bots,

defender: needs to register all the **domain pool**, to avoid it.

Migrations of C&C servers **do not need explicit agreement**.

# Domain Generation Algorithms: Defense

It is necessary to study defensive solutions that allow to **identify and block** DGA-related domains timely.

The natural observation point is the **DNS infrastructure**.

# State of the Art and Motivation

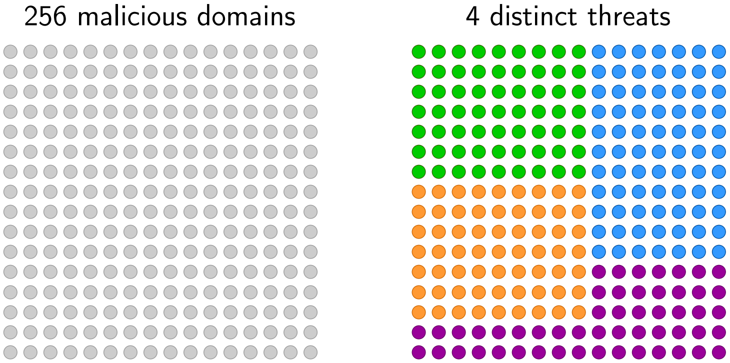
# Domain Reputation Systems

Domain reputation systems exist able to **tell malicious and benign domains apart**.

Some exist that do so by **mining DNS network traffic**, e.g., **Exposure** [Bilge et al. 2011], **Kopis** [Antonakakis et al. 2011], **Notos** [Antonakakis et al. 2010]

# Domain Reputation Systems: Drawbacks

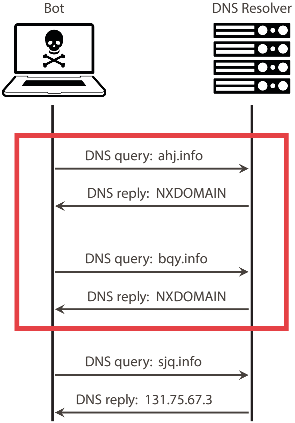
They **fail in correlating** distinct yet related domains.



# DGA Detection Systems

Detection systems exist that **specifically identify active DGAs** and related domains [Yadav et al. 2010, Yadav and Reddy 2012, Antonakakis et al. 2012].

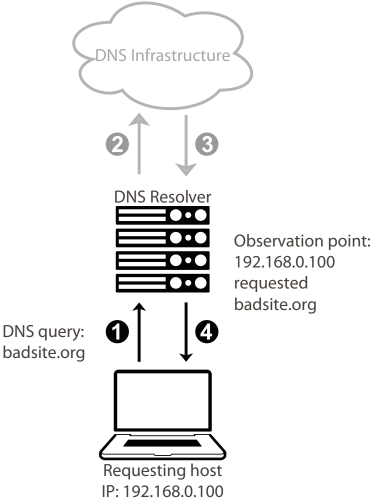
They are driven by the hypothesis that malware-infected machines operating a DGA **generate huge amounts of NX-DOMAIN** DNS replies.



# DGA Detection Systems: Drawbacks

Nevertheless, they require access to network data that:

- is not publicly available to academics, because of **privacy** concerns,
- leads to non-repeatable experiments.



# Objectives

# Objectives

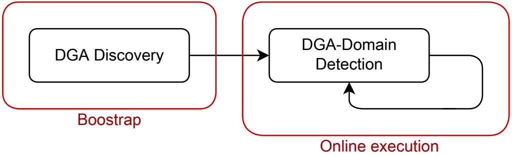
Given the limitations of the state-of-the-art systems, we propose **Phoenix**, which:

1. **identifies active DGAs** and the related domains with realistic hypoteses,
2. **correlates the activities of different domains** related to the same DGAs.
3. produces **novel knowledge** and **intelligence insights**.

# System Description

# Overview

Phoenix works in two phases:




DGA Discovery: Discovers **DGAs active in the wild** and characterizes the generation processes.

DGA-Domain Detection: Detects **previously-unseen DGA-domains** and assigns them to a specific DGA.

During its execution, it produces **novel intelligence knowledge**.

# DGA Discovery

# DGA-Domain Filtering: Rationale

DGA-domains are the result of **randomized computations**. They look like **"high-entropy" strings**:

| | | |
|---|---|---|
| `vljiic.org` | `vitgyyizzz.biz` | `79ec8...f57ef.co.cc` |
| `f0938...772fb.co.cc` | `nlgie.org` | `gkeqr.org` |
| `jyzirvf.info` | `aawrqv.biz` | `xtknjczaafo.biz` |
| `hughfgh142.tk` | `yxipat.cn` | `yxzje.info` |
| `fyivbrl3b0dyf.cn` | `rboed.info` | `ukujhjg11.tk` |

We automate the process of **recognizing the randomness** of domain names.

We do so by computing **linguistic-based features**.

# DGA-domain Filtering: Features I

$R$: percentage of symbols of the domain name $d$ composing **meaningful words**.

For instance:

$d = \texttt{facebook.com}$

$$R(d) = \frac{|\texttt{face}| + |\texttt{book}|}{|\texttt{facebook}|} = 1$$

likely humanly-generated domain

$d = \texttt{pub03str.info}$

$$R(d) = \frac{|\texttt{pub}|}{|\texttt{pub03str}|} = 0.375.$$

likely DGA-domain

# DGA-Domain Filtering: Features II

$S_n$: **popularity** of the $n$-grams of domain $d$.

For instance:

$d =$ `facebook.com`

| fa | ac | ce | eb | bo | oo | ok |
|---|---|---|---|---|---|---|
| 109 | 343 | 438 | 29 | 118 | 114 | 45 |

mean: $S_2 = 170.8$

likely humanly-generated domain

$d =$ `aawrqv.com`

| aa | aw | wr | rq | qv |
|---|---|---|---|---|
| 4 | 45 | 17 | 0 | 0 |

mean: $S_2 = 13.2$

likely DGA-domain

# DGA-Domain Filtering: Construction

Every domain $d$ is assigned a vector of linguistic features

$$f(d) = [R(d), S_1(d), S_2(d), S_3(d)]^T$$

We compute the values of $f$ for the **100,000 most popular domains** according to Alexa, and we use them as **reference**.

**Automatically Generated Domain**

A domain $d'$ is *automatically generated* when $f(d')$ significantly diverges from the reference.

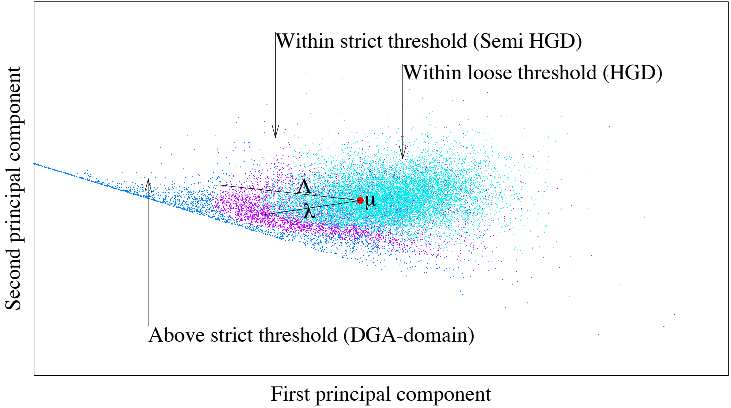
# DGA-Domain Filtering: Distance and Thresholds I

We define the distance from the reference through the **Mahalanobis distance**.

We set two divergence thresholds $\lambda < \Lambda$, a **strict** and a **loose** one.

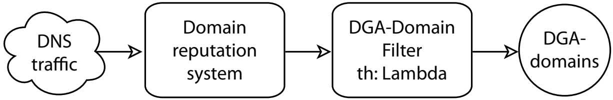
We set the thresholds by **deciding** ***a priori*** **the amount of error** we wish to allow.

# DGA-Domain Filtering: Distance and Thresholds II



# Identifying DGA-Domains Between Malicious Domains

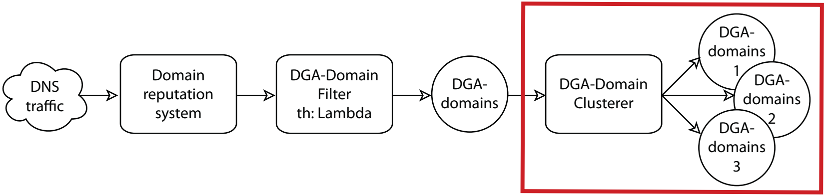
Starting from a *flat* list of malicious domains (e.g., Exposure), we identify those **malicious and automatically generated** (with strict threshold).




These domains are the result of different **generation mechanisms**, and thus have been employed by **different botnets**.

# DGA-Domain Clustering

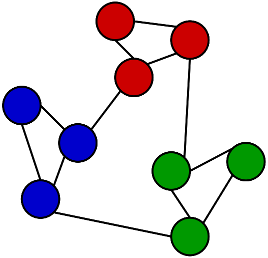
It is possibile to leverage historical DNS network traffic to **cluster together domains employed by the same botnet**.



# DGA-Domain Clustering: Approach

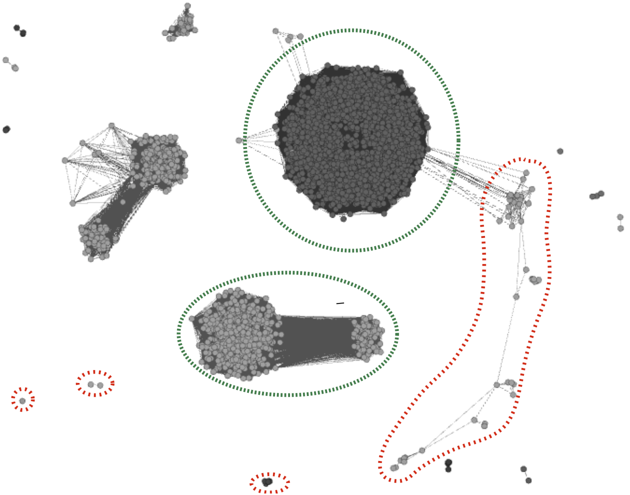
We build a **graph** such that

- every DGA-domain is a node,
- an edge exists if two nodes resolved to the same IP,
- the stronger the peculiarity of the shared IP, the stronger the weight of the edge.



The resulting graph is a **social network**.
We wish to isolate the communities.

# DGA-Domain Clustering: Example



# DGA-Domain Fingerprinting

The communities correspond to **families of domains**. Each family corresponds to a generation algorithm.

| | | | |
|---|---|---|---|
| sbhecmv.tk | sedewe.cn | caftvmvf.org | zsx.net |
| dughuhg39.tk | lomonosovv.cn | gkeqr.org | vkh.net |
| dughuhg27.tk | jatokfi.cn | xtknjczaafo.biz | ypr.net |
| hughfgh142.tk | yxipat.cn | yxzje.info | vqt.org |
| ukujhjg11.tk | fyivbrl3b0dyf.cn | rboed.info | uon.org |

We extract **characterizing fingerprints** from each family:

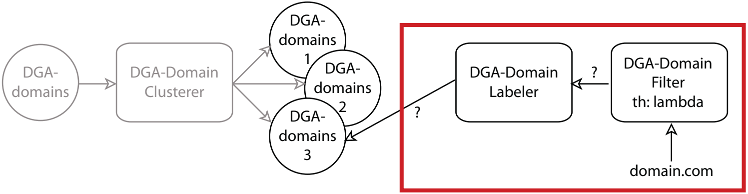
- TLD employed,
- linguistic features (e.g., length, character set),
- C&C IP addresses associated to the botnet.

# DGA-Domain Detection

# Classification of Previously-unseen Domains I

We leverage the fingerprints to **classify previously-unseen domain**, so to extend the blacklist we employed during the bootstrap.

# Classification of Previously-unseen Domains II




Given a previously-unseen domain, we answer the questions:

1. does it look like it was **automatically generated** (with loose threshold)?
2. can we associate it with one of the **known domain families**?

If yes, then we found a **new malicious DGA-domain**.

# System Evaluation

# Approach to Validation

Validating Phoenix is far from trivial, as it **produces novel knowledge**.

For instance, no information is available about the membership of a given malicious domain to one family of DGA-domains.

In **lack** of an established **ground truth**, we:

- run **quantitative tests** to valide each module,
- provide a **qualitative validation** of the whole approach.

# DGA Discovery

# DGA-Domain Filter Evaluation: Dataset

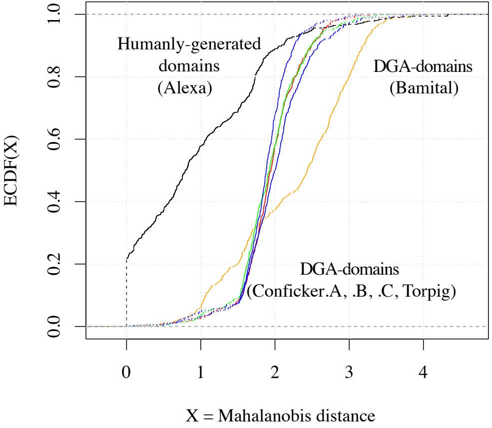
We employ DGA-domains of **known botnets of the past** to verify the accuracy of the filter.

Specifically, we use the DGA-domains of:

- Conficker.A (7,500),
- Conficker.B (7,750),
- Conficker.C (1,101,500),
- Torpig (420),
- Bamital (36,346).

# DGA-Domain Filter Evaluation: Distance ECDF

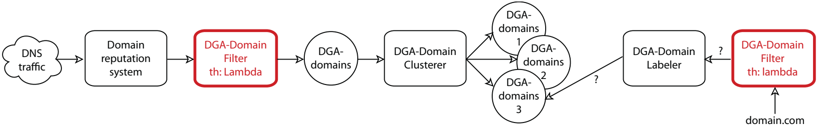
First, we show that the distance from the reference we employed **discriminates well** between HGDs and DGA-domains.



# DGA-Domain Filtering Evaluation: Recall

Then, we **validate the recall** of the filter, with both the thresholds.

| | $d_{Mah} > \Lambda$ | $d_{Mah} > \lambda$ |
|---|---|---|
| | Pre-clustering selection | Recall |
| **Conficker.A** | 46.5% | **93.4%** |
| **Conficker.B** | 47.2% | **93.7%** |
| **Conficker.C** | 52.9 % | **94.8%** |
| **Torpig** | 34.2% | **93.0%** |
| **Bamital** | 62.3% | **81.4%** |



# DGA-Domain Clustering Evaluation

We show that the clustering based on DNS features **partitions well** the DGA-domains according to **DGA-dependent features** (e.g., TLD, domain length).

We verify the correspondance between the families we isolate and some active botnets: **Conficker**, **Bamital**, **SpyEye**, **Palevo**.

Moreover, we **verify the sensitivity** of the clustering from the **configuration thresholds**, and we evaluate them automatically.

# DGA-Domain Detection

# Detection of Previously-unseen Domains

We feed Phoenix with a **previously-unseen DNS traffic dump**.

We show that it identifies DGA-domains and associates each of them to a specific family.

| Previously-unseen domains | | |
|---|---|---|
| hy613.cn | 5ybdiv.cn | 73it.cn |
| 69wan.cn | hy093.cn | 08hhwl.cn |
| hy673.cn | onkx.cn | xmsyt.cn |
| watdj.cn | dhjy6.cn | algxy.cn |

| Previously-unseen domains | | |
|---|---|---|
| dky.com | ejm.com | eko.com |
| efu.com | elq.com | bqs.com |
| bec.com | dpl.com | eqy.com |
| dur.com | bnq.com | ccz.com |

Cluster A

| | | |
|---|---|---|
| pjrn3.cn | 3dcyp.cn | x0v7r.cn |
| 0bc3p.cn | hdnx0.cn | 9q0kv.cn |
| 5vm53.cn | 7ydzr.cn | fyj25.cn |
| qwr7.cn | xq4ac.cn | ygb55.cn |

Cluster B

| | | |
|---|---|---|
| uon.org | jhg.org | eks.org |
| mzo.net | zuh.com | bwn.org |
| zuw.org | ldt.org | lxx.net |
| ntz.com | cbv.org | iqd.com |

# Intelligence and Insights

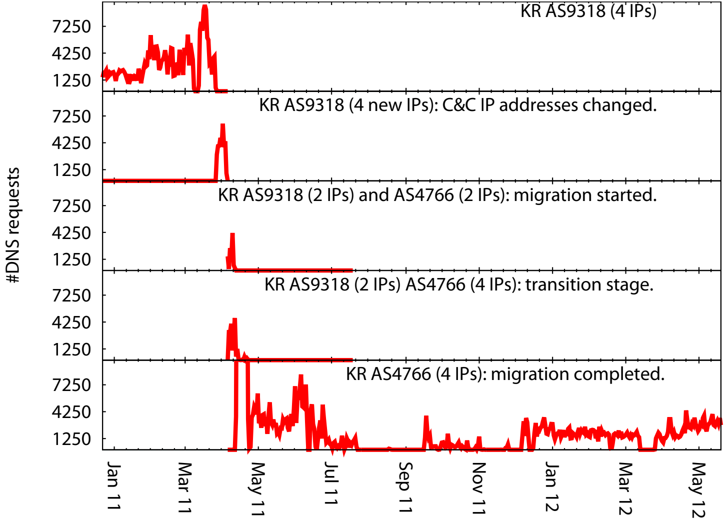
# Intelligence and Insights

We produced **novel blacklists of DGA-domains**.

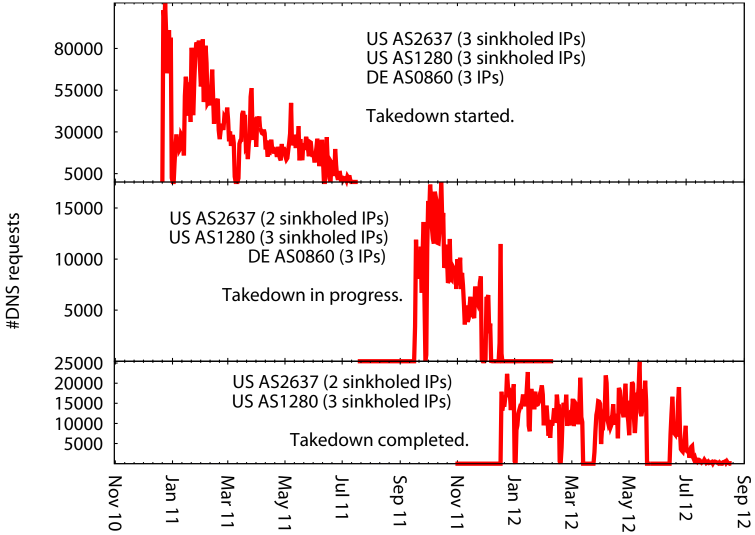
We discovered **C&C servers** employed by each botnet.

We processed data in a way which allows us to **follow the evolution of each botnet** over time.

# Botnet Evolution Tracking: C&C Migration



# Botnet Evolution Tracking: C&C Takedown



# Conclusions

# Limitations

The DGA-Domain Filter of Phoenix assumes to be always dealing with **domains targeting an English-speaking population**.

- Chinese domains? Swedish domains?
- Non-ASCII domains?
  - `camtasia教程网.com`
  - $\pi$`.com`
  - ♣→♡→♠→♢→`.com`

# Conclusions

Phoenix gives the following contributions:

1. it **identifies groups of DGA-domains** between malicious domains and characterizes the generation processes under **more realistic hypoteses** with respect to similar approaches;
2. it **identifies previously-unseen malicious domains** and associates them to the activity of a specific botnet;
3. it produces novel knowledge, which allows—for instance—to **track the evolution of a botnet** over time.

# Future Work

**Reduce the bias** of the DGA-domain Filter from the English language:

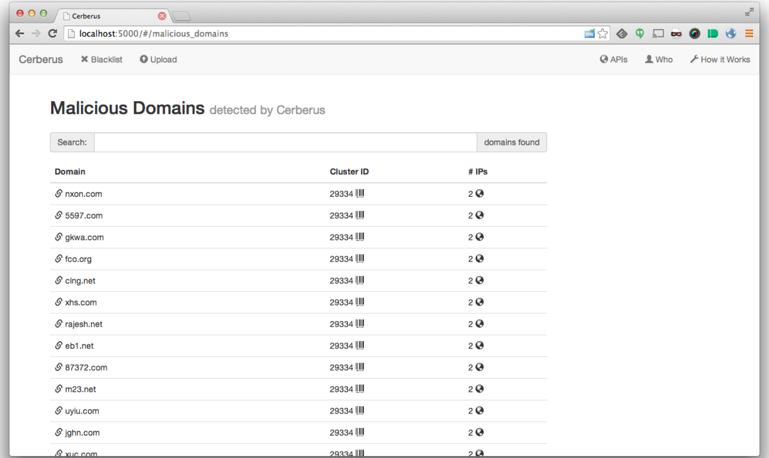
- try to **capture the language target** of each domain,
- evaluate its "randomness" according to that language.

Implement an **incremental** version of the clustering algorithm.

Add low-false-positives **whitelisting filter** to avoid expensive analysis of obviously-benign domains.

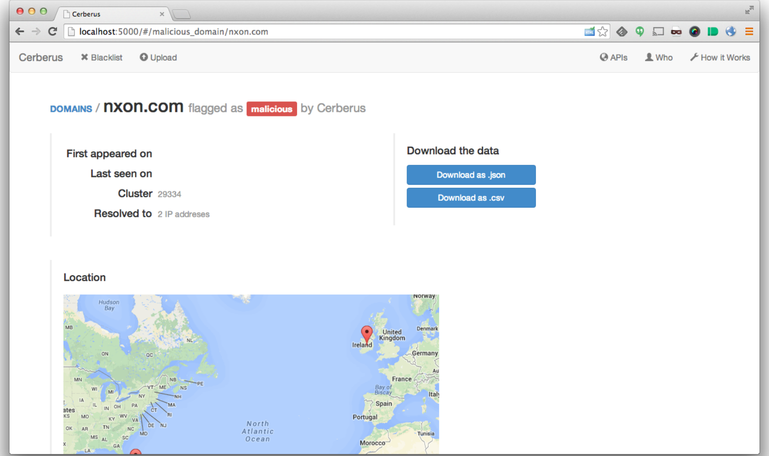
Finally, **publish our findings** and allow users to navigate the data.

# Future Work




(Acks: Edoardo Colombo)

# Future Work




(Acks: Edoardo Colombo)

Thank you for your attention. **Questions?**

# Acknowledgments

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Nominet and HP Labs Bristol are collaborating on the follow-up of Pheonix.

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