Tracking and Characterizing Botnets Using Automatically Generated Domains

Hack In The Box
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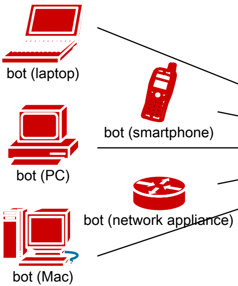
Introduction

Botnet: Definition

Network of **malware-infected devices** under the control of an external entity.



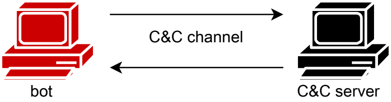
Compromised devices are employed for **malicious purposes**:

information harvesting: login credentials, credit card numbers,

distributed computations: spamming, DDOS attacks.

Command&Control Channel

It is the channel employed for bot-botmaster communications.



It is **logically bidirectional**:

botmaster $\rightarrow$ bot: commands to execute, attacks to launch,

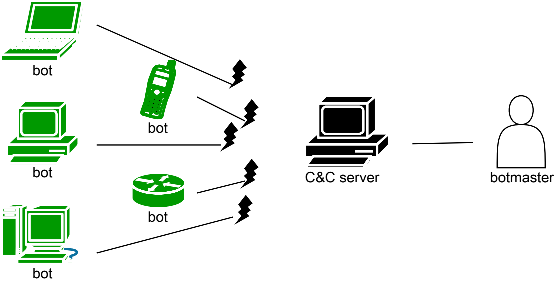
bot $\rightarrow$ botmaster: harvested information, feedbacks.

Single Point of Failure

If bots cannot communicate with their master, they are **innocuous** and **do no produce profit**.

The C&C channel is **single point of failure** of the whole botnet.

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 Mechanisms

Rallying Mechanism: Definition

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 address.

Many mechanisms exist, with different **security properties**.

Hardcoded IP: Functioning

The bot **knows the address** of its botmaster.

Actually, the bot can have **a list of addresses**.

Moreover, it can be instructed to **learn new rendezvous addresses** when necessary, with a **migration-by-delegation**.

Hardcoded IP: Problems

The rendezvous IP is **written in the malware code**: it can be leaked through **reverse engineering**.

If we sinkhole that address:

- the bots **cannot reach their master**,
- the bots are left **without a backup plan**.

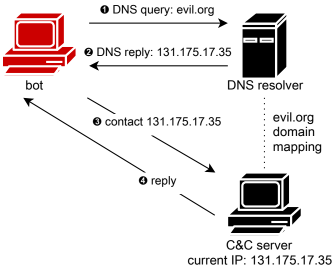
A precise defensive action would **disable the whole botnet**.

Hardcoded Domain: Functioning

The bot resolves a domain `evil.org` and discovers the IP address of the C&C server.

The resulting architecture is **extremely more flexible**.

There is no more vulnerability to IP sinkholing.



Hardcoded Domain: Problems

But actually, **we just moved the single point of failure**: Now it is the domain `evil.org`.

Nevertheless, **sinkholing a domain is much harder** than sinkholing an IP address [Jiang et al. 2012].

General Issues

The aforementioned schemes fail 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.

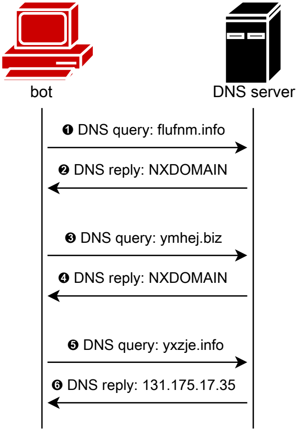
Domain Generation Algorithms

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

The DGA mechanism **does not allow proactive defense strategies** and does not have obvious vulnerabilities.

It is necessary to study defensive solutions that allow to **identify and block** DGA-related domains (**AGDs**) 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]

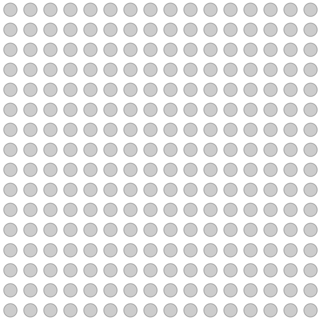
They leverage the fact that malicious domains tend to **exhibit different patterns** with respect to benign domains:

- Behavior over time
- TTL values
- Domain-IP mappings
- ...

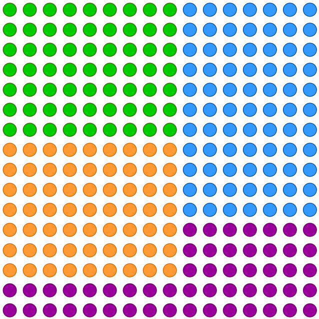
Domain Reputation Systems: Drawbacks I

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

256 malicious domains



4 distinct threats



Domain Reputation Systems: Drawbacks II

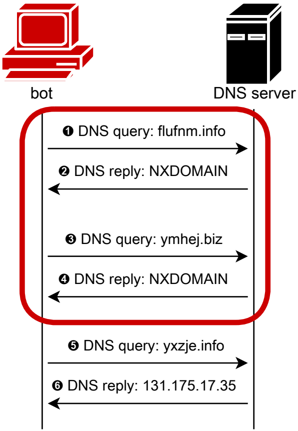
They even fail in providing information about the **specific malicious activity** related to each domain.

- Command&Control of botnets?
- Phishing?
- Drive-by download?

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].

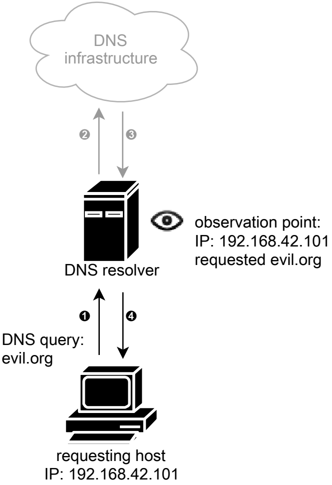
They are driven by the hypothesis that malware-infected machines operating a DGA **generate huge amounts of NXDOMAIN** DNS replies.



DGA Detection Systems: Drawbacks

Nevertheless, they require access to network data that:

- violates users' **privacy**,
- leads to non-repeatable experiments.



Objectives and Challenges

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**.

Challenges

Studying DGAs translates into **analyzing DNS traffic**.

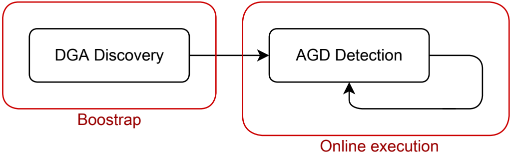
- Where to collect the traffic?
- How to process such **high-volume** and **high-volatility** data?

No ground-truth information is available about DGAs, if not months after they have been employed.

System Description

Overview

Phoenix works in two phases:



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

AGD Detection: Detects **previously-unseen AGDs** and assigns them to a specific DGA.

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

DGA Discovery

AGD Filtering: Rationale

AGDs 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 automatize the process of **recognizing the randomness** of domain names.

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

AGD 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 HGD

$d = \texttt{pub03str.info}$

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

likely AGD

AGD 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 HGD

$d =$ `aawrqv.com`

aa	aw	wr	rq	qv
4	45	17	0	0

mean: $S_2 = 13.2$

likely AGD

AGD 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 (AGD)

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

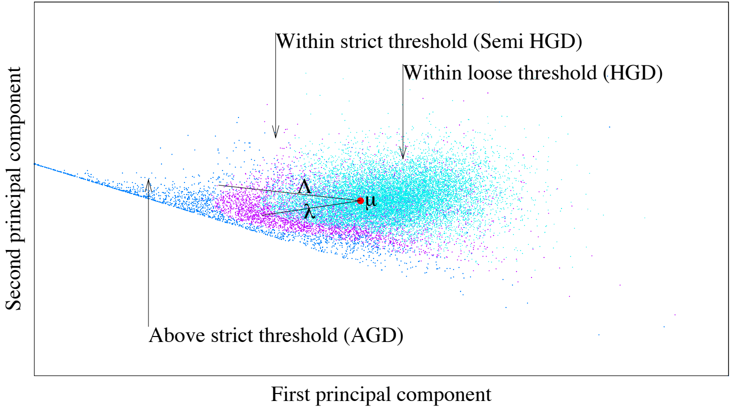
AGD Filtering: Distance and Thresholds Identification I

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

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

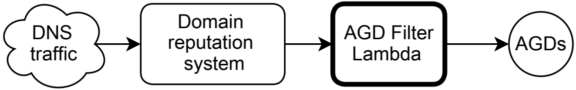
We set the thresholds by **deciding *a priori* the amount of error** we wish to allow.

AGD Filtering: Distance and Thresholds Identification II



Identifying AGDs Between Malicious Domains

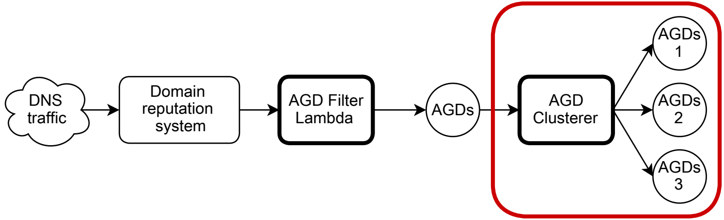
Starting from a *flat* list of malicious domains (e.g., Exposure), we identify those **malicious and automatically generated** (with strict threshold).



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

AGD Clustering

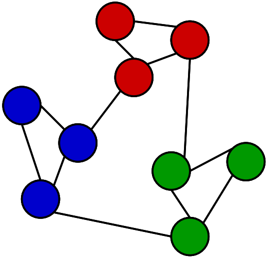
It is possibile to leverage historical DNS network traffic to **cluster together domains employed by the same botnet**.



AGD Clustering: Approach

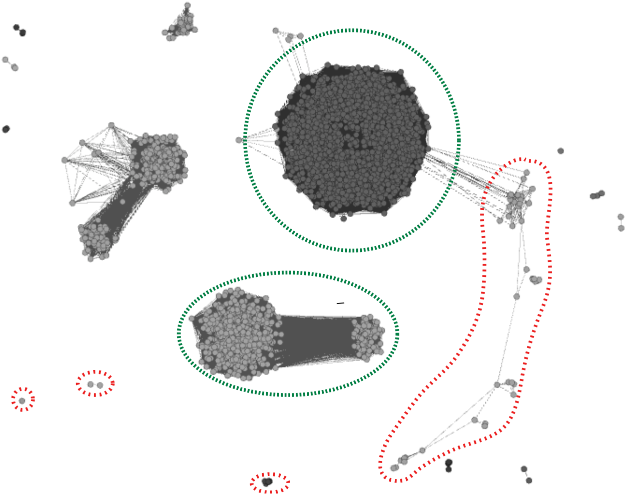
We build a **graph** such that

- every AGD 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.

AGD Clustering: Example



AGD 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:

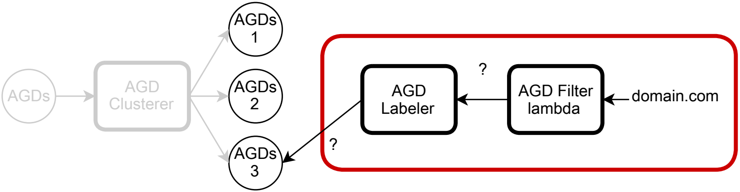
- TLD employed,
- linguistic features (e.g., length, character set),
- C&C IP addresses associated to the botnet.

AGD 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 AGD**.

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 AGDs

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

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

DGA Discovery

AGD Filter Evaluation: Dataset

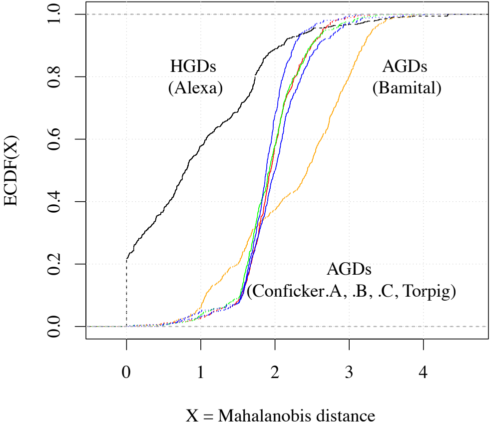
We employ AGDs of **known botnets of the past** to verify the accuracy of the filter.

Specifically, we use the AGDs of:

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

AGD Filter Evaluation: Distance ECDF

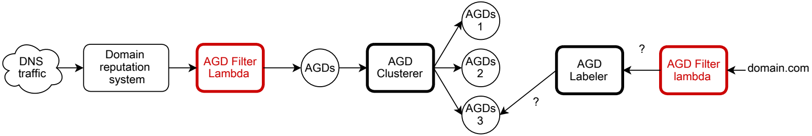
First, we show that the distance from the reference we employed **discriminates well** between HGDs and AGDs.



AGD 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%**



AGD Clustering Evaluation

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

We verify the correspondence 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.

AGD Detection

Detection of Previously-unseen Domains

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

We show that it identifies AGDs 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

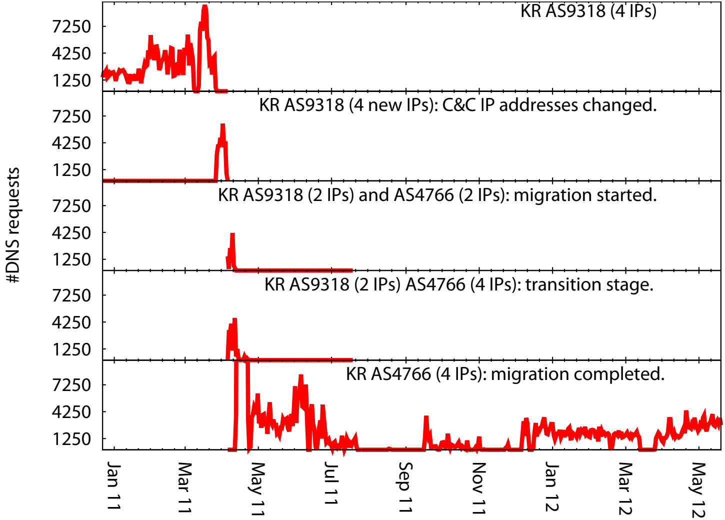
Intelligence and Insights

We produced **novel blacklists of AGDs**.

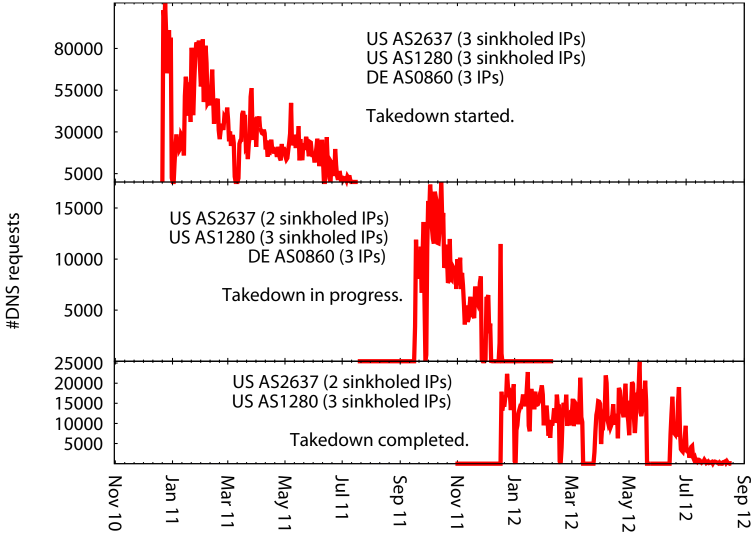
We discovered **C&C servers** employed by each botnet

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

- Chinese domains? Swedish domains?
- Non-ASCII domains?
  - π`.com`
  - $\clubsuit \rightarrow \heartsuit \rightarrow \spadesuit \rightarrow \diamondsuit \rightarrow$`.com`

Phoenix **may not provide warnings earlier** than similar systems employing NXDOMAIN replies:

- it is fed with data that **take longer to be collected**,
- nevertheless, this makes our system **easier to deploy** and more **privacy-preserving**.

Conclusions

Phoenix gives the following contributions:

1. it **identifies groups of AGDs** 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 AGD 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.

Publish our findings and allow users to navigate the data (almost there... :-)

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

Let's keep talking on Twitter (@raistolo) or on email (stefano.zanero@polimi.it)

Acknowledgments

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