Tracking and Characterizing Botnets Using Automatically Generated Domains

Stevens
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Introduction

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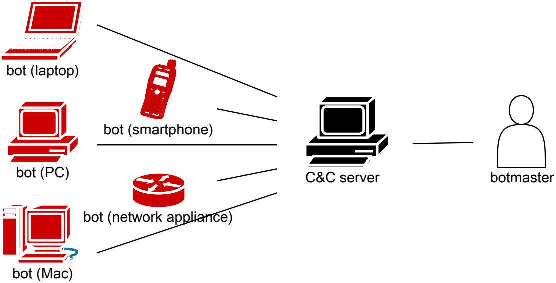

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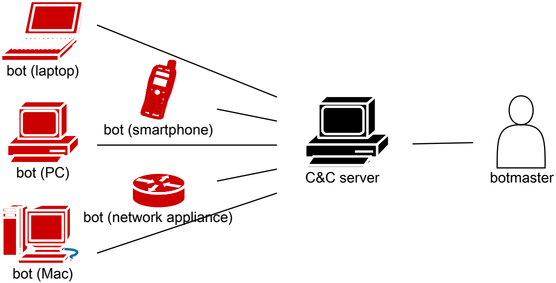

Compromised devices are employed for **malicious purposes**:

information harvesting: login credentials, credit card numbers,

distributed computations: spamming, DDOS attacks.

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Three 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"*.

Command&Control Channel

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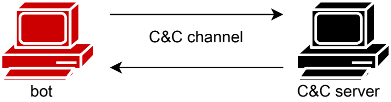

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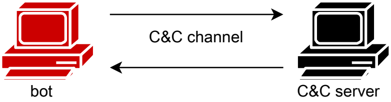

It is **logically bidirectional**:

botmaster → bot: commands to execute, attacks to launch,

bot → botmaster: harvested information, feedbacks.

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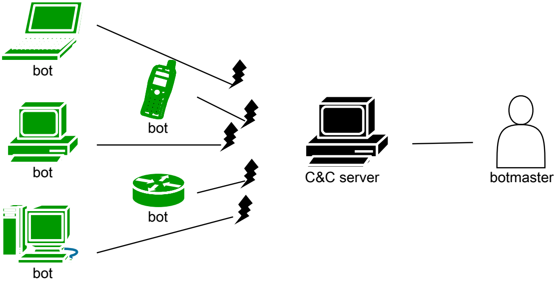
Security **defenders strive to disable C&C channels** as means to disable botnets without sanitizing the infected machines.



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

Rallying Mechanisms

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

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

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

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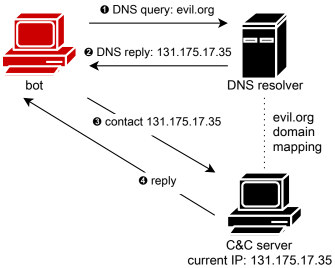
The bot resolves a domain `evil.org` and discovers the IP address of the C&C server.



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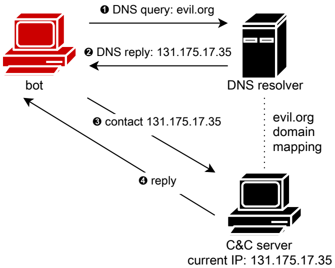

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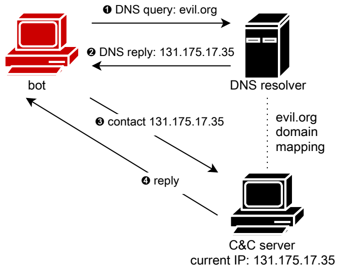
There is no more vulnerability to IP sinkholing.



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

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

Domain Generation Algorithms

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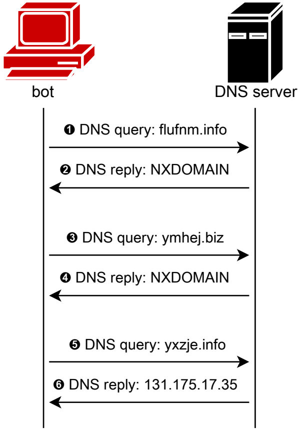

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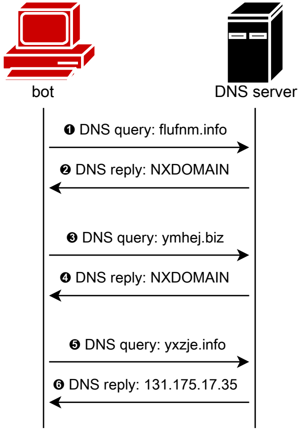

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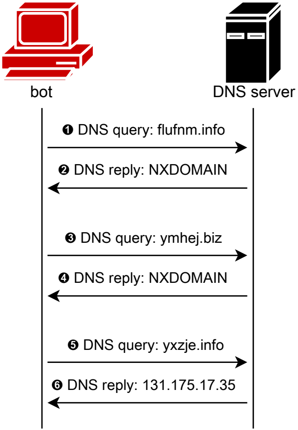

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Migrations of C&C servers **do not need explicit agreement**.

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

State of the Art and Motivation

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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
- ...

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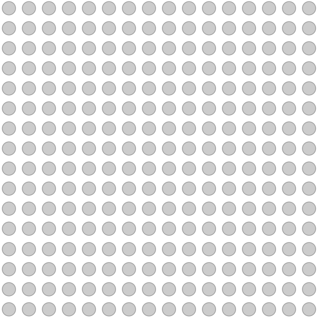

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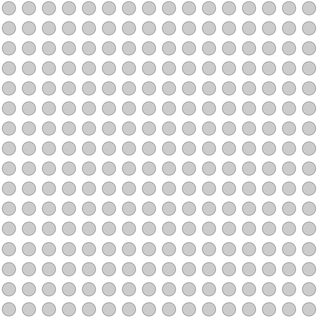
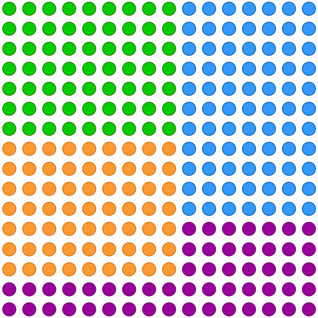


4 distinct threats



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

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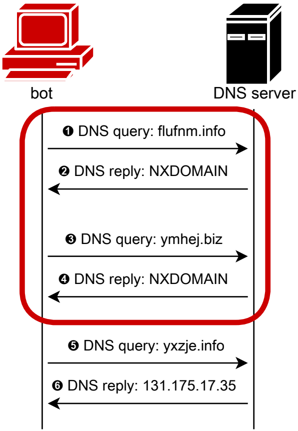
They are driven by the hypothesis that malware-infected machines operating a DGA **generate huge amounts of NXDOMAIN** DNS replies.



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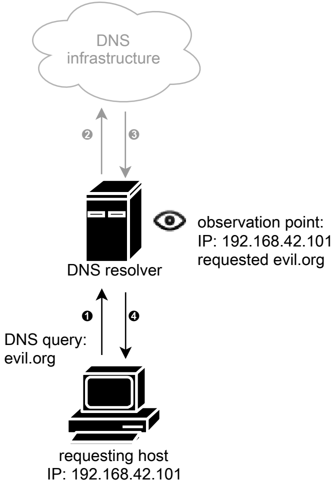

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2. **correlates the activities of different domains** related to the same DGAs.
3. produces **novel knowledge** and **intelligence insights**.

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

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

System Description

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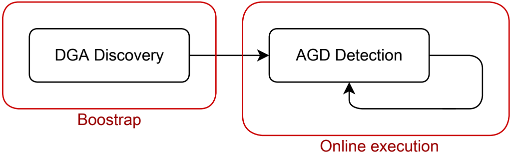

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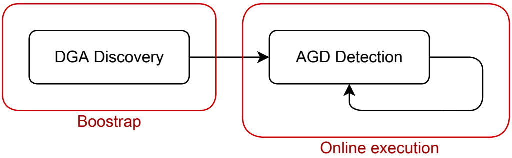

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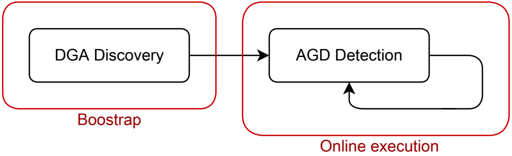

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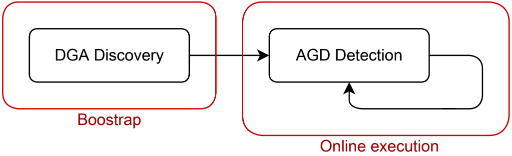

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AGD Detection: Detects **previously-unseen AGDs** and assigns them to a specific DGA.

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

DGA Discovery

AGD Filtering: Rationale

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

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`f0938...772fb.co.cc`	`nlgie.org`	`gkeqr.org`
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We do so by computing **linguistic-based features**.

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

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$d = \texttt{pub03str.info}$

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

likely AGD

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$d =$ `aawrqv.com`

aa	aw	wr	rq	qv
4	45	17	0	0

mean: $S_2 = 13.2$

likely AGD

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Every domain d is assigned a vector of linguistic features

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Automatically Generated Domain (AGD)

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

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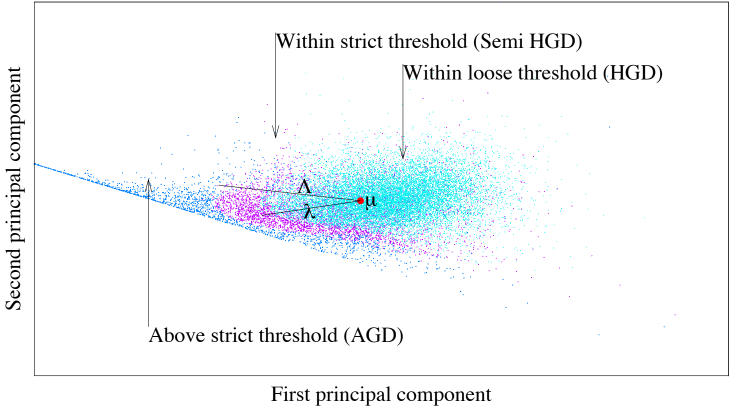
We set the thresholds by **deciding *a priori* the amount of error** we wish to allow.

AGD Filtering: Distance and Thresholds Identification II



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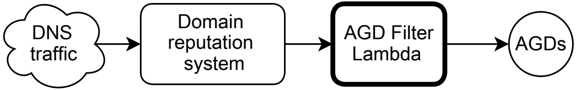

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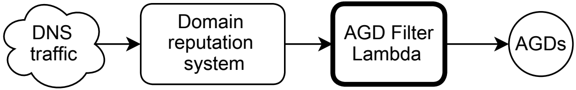

These domains are the result of different **generation mechanisms**, and thus have been employed by **different botnets**.

AGD Clustering

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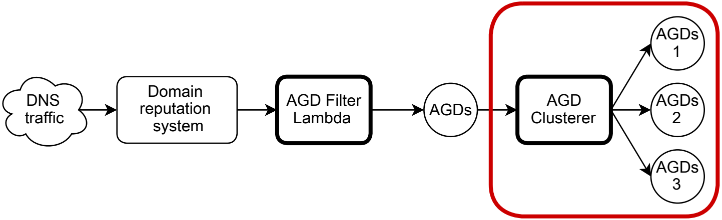
It is possibile to leverage historical DNS network traffic to **cluster together domains employed by the same botnet**.



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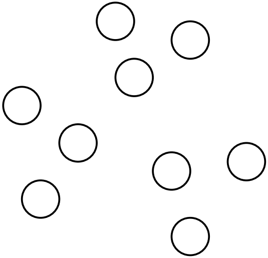

AGD Clustering: Approach

We build a **graph** such that

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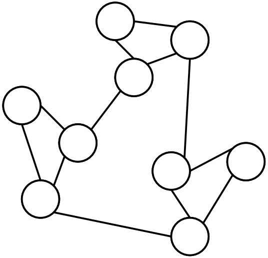
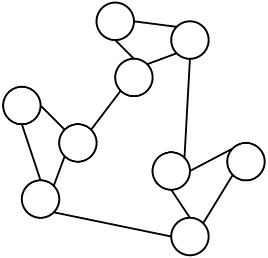
- an edge exists if two nodes resolved to the same IP,



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.



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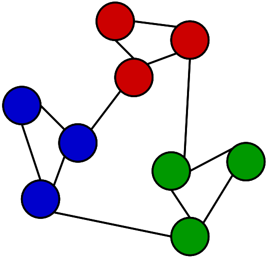

The resulting graph is a **social network**.
We wish to isolate the communities.

AGD Clustering: Example

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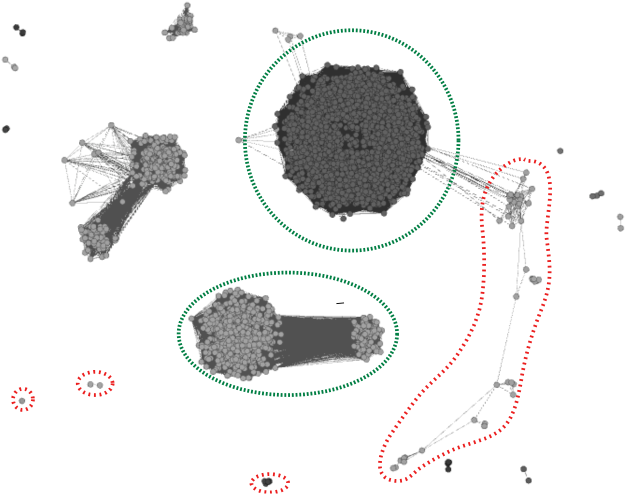

AGD Fingerprinting

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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

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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

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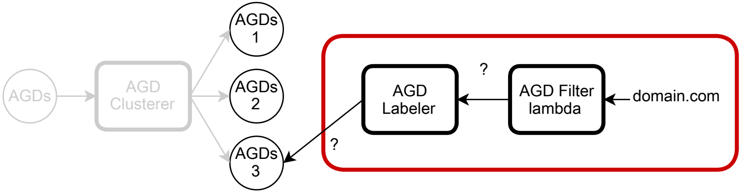
We leverage the fingerprints to **classify previously-unseen domain**, so to extend the blacklist we employed during the bootstrap.

Classification of Previously-unseen Domains II



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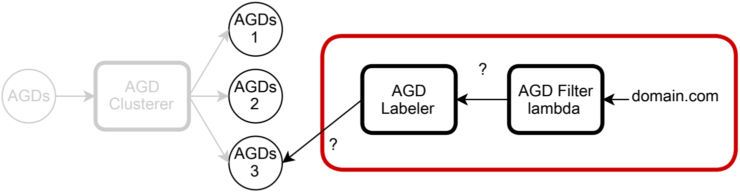
Classification of Previously-unseen Domains II



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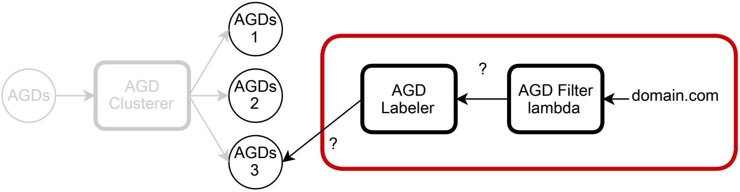

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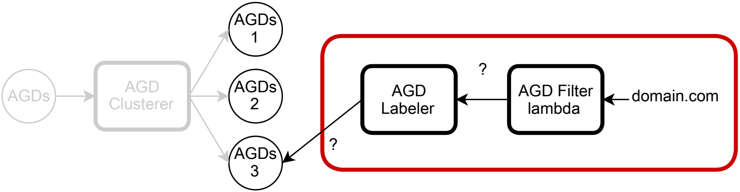

Given a previously-unseen domain, we answer the questions:

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

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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

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

AGD Filter Evaluation: Dataset

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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

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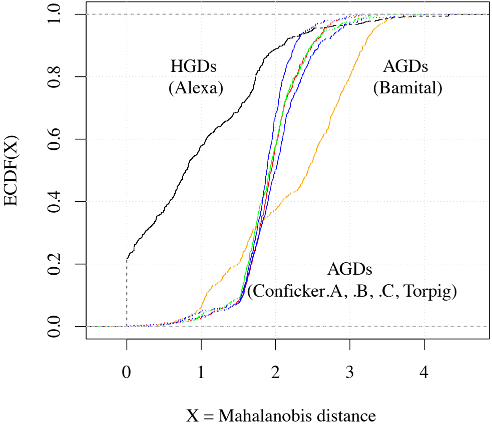

AGD Filtering Evaluation: Recall

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

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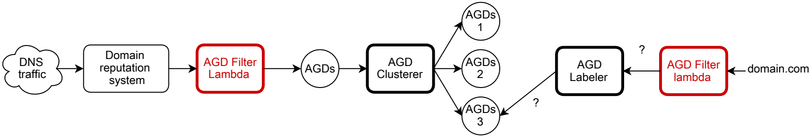
	$d_{Mah} > \Lambda$	$d_{Mah} > \lambda$
	Pre-clustering selection	Recall
Conficker.A	46.5%	**93.4%**
Conficker.B	47.2%	**93.7%**
Conficker.C	52.9 %	**94.8%**
Torpig	34.2%	**93.0%**
Bamital	62.3%	**81.4%**



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

AGD Detection

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Previously-unseen domains		
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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

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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

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 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

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

Botnet Evolution Tracking: C&C Migration

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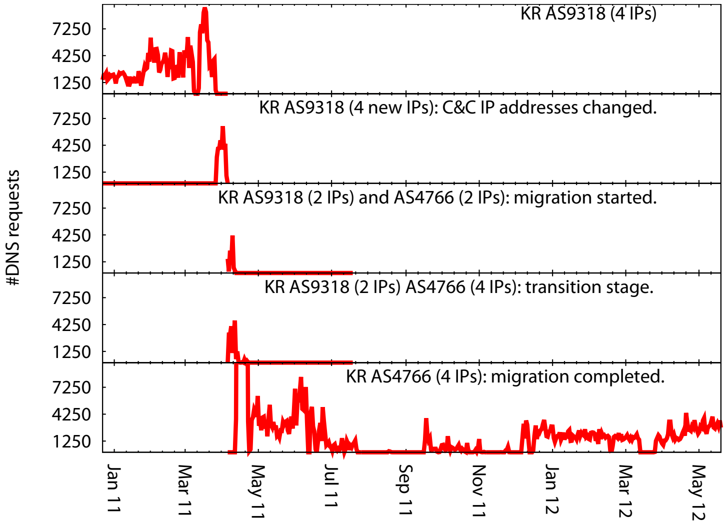

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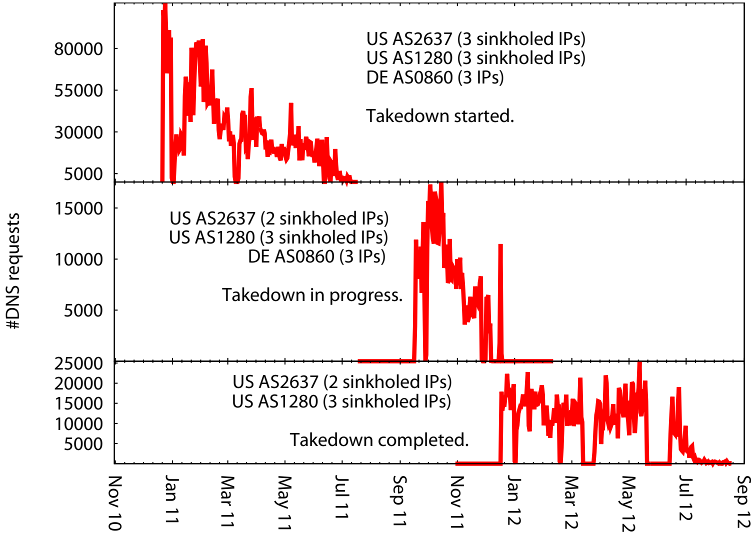

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Phoenix **may not provide warnings earlier** than similar systems employing NXDOMAIN replies:

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

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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

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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

The work has been partially funded by the EPSRC-funded project "Mining the Network Behaviour of Bots", under research agreement EP/K033344/1, and by the European Union Seventh Framework Programme (FP7/2007-2013) under grant agreement n° 257007 "SysSec"

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