

Detecting Anomalous Behaviors in Computer Infrastructures

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- ▶ (Mar 2008) **YouTube** stores more than 70 million videos and the most popular video has been viewed 112,486,327 times.

...unfortunately...

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Note: these only refer to the facts that have been **detected** and **reported**.

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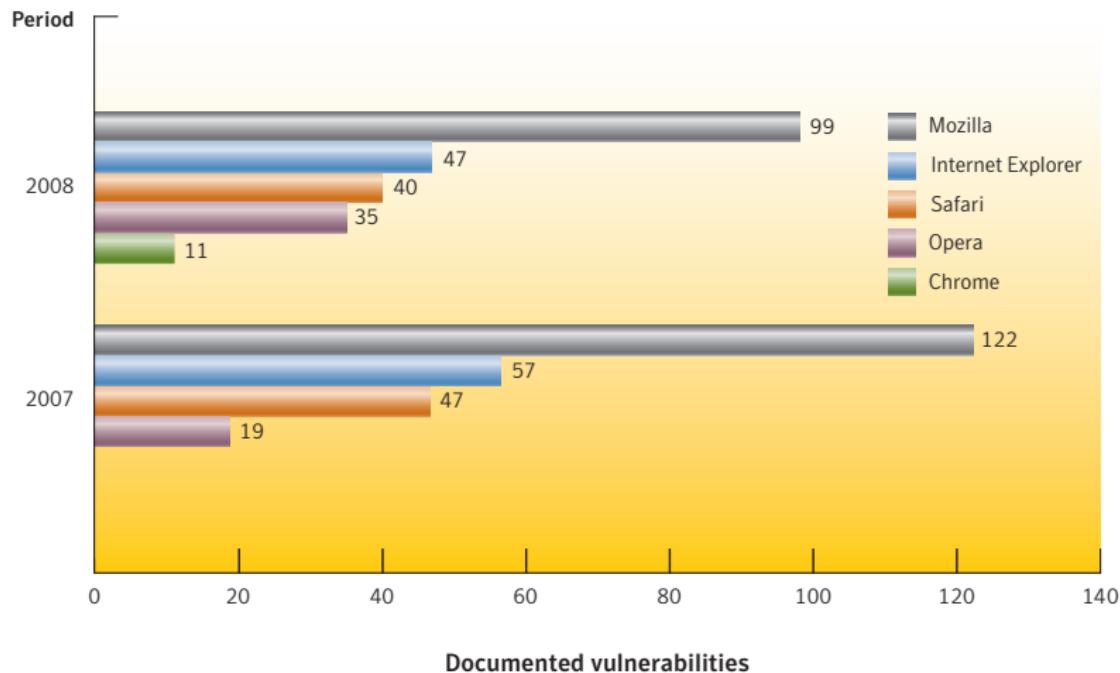
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This is actually a “lethal cocktail”: let's see why.

The most popular software tool is flawed

BTW, looks like MS IE is more secure than Mozilla :)



Actually, browsers do not really matter

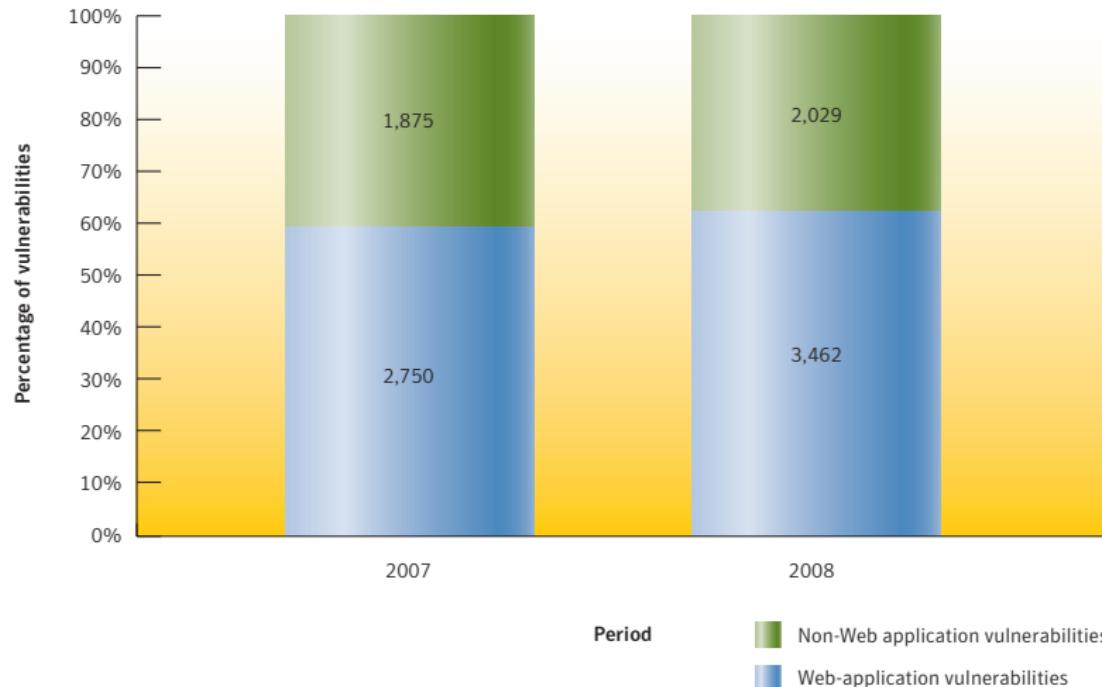
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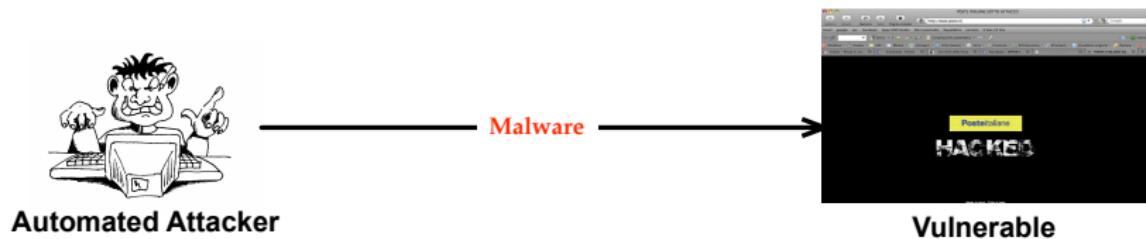
Plug-in	2008 Top Category	2007 Top Category
Adobe Acrobat Reader	Memory corruption	Memory corruption/content injection/command execution
Adobe Flash Player	Memory corruption/origin validation/elevated security context	Elevated security context
ActiveX	Memory corruption	Memory corruption
Java	Elevated security context	Elevated security context
Mozilla Extensions	Content injection	Content injection
QuickTime	Memory corruption	Memory corruption
Windows Media Player	Memory corruption	Memory corruption/DoS

The most accessible applications are flawed too

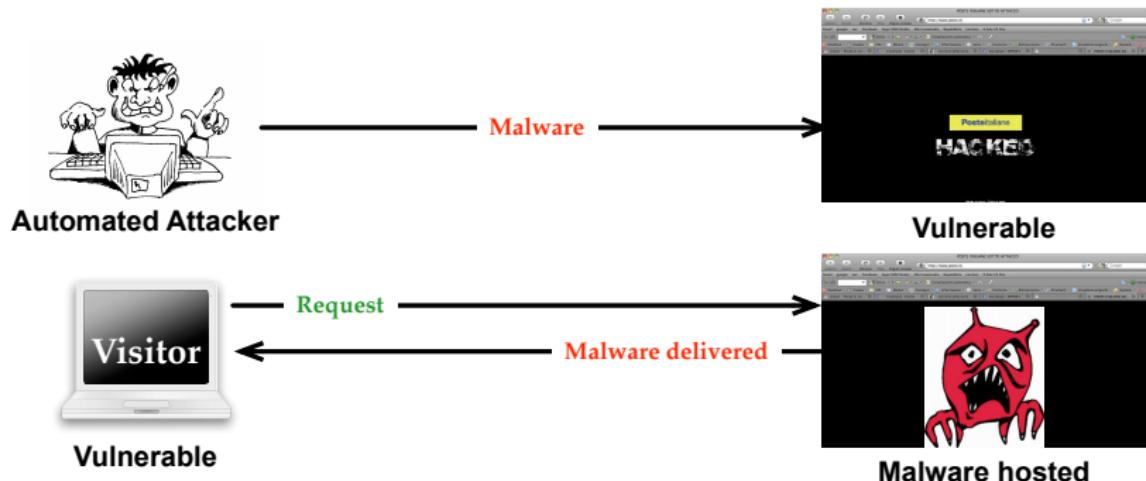


Overview of a modern exploitation work-flow

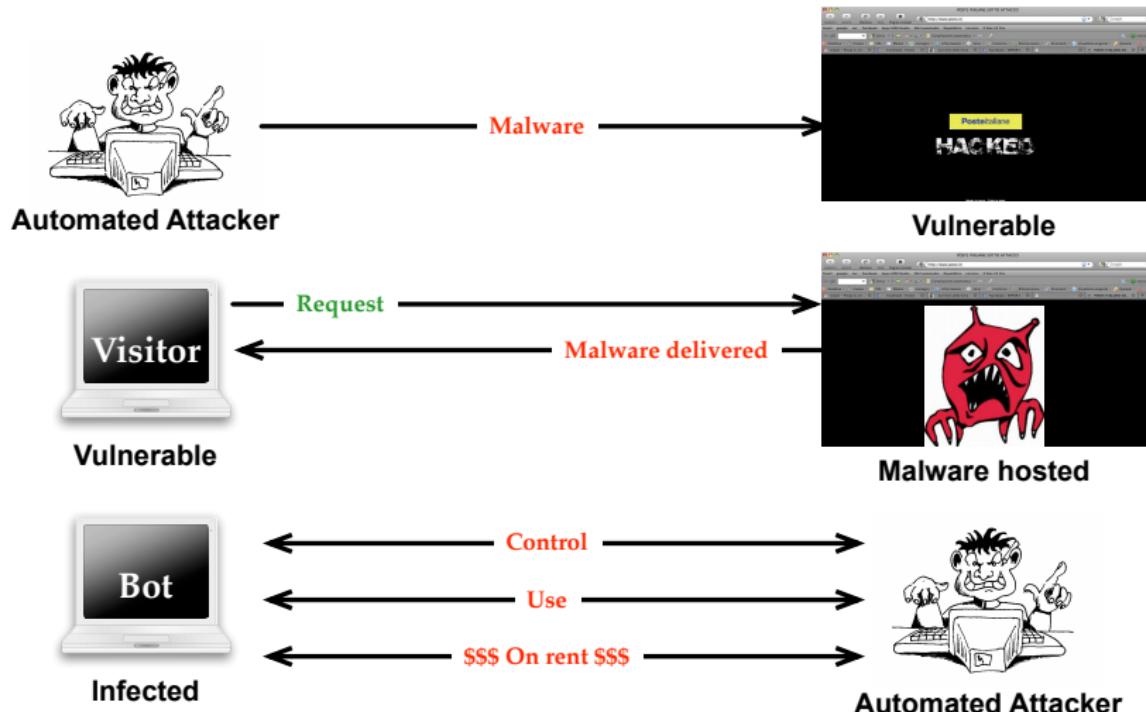
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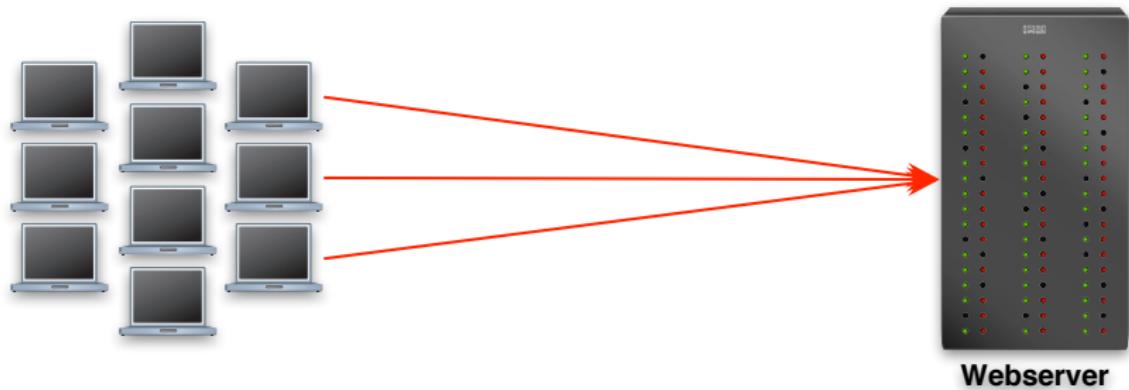
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 - ▶ Phishing campaigns
 - ▶ Spamming campaigns,
 - ▶ Scam web-sites design!

Pick your choice from the attack-as-a-service gourmet menu

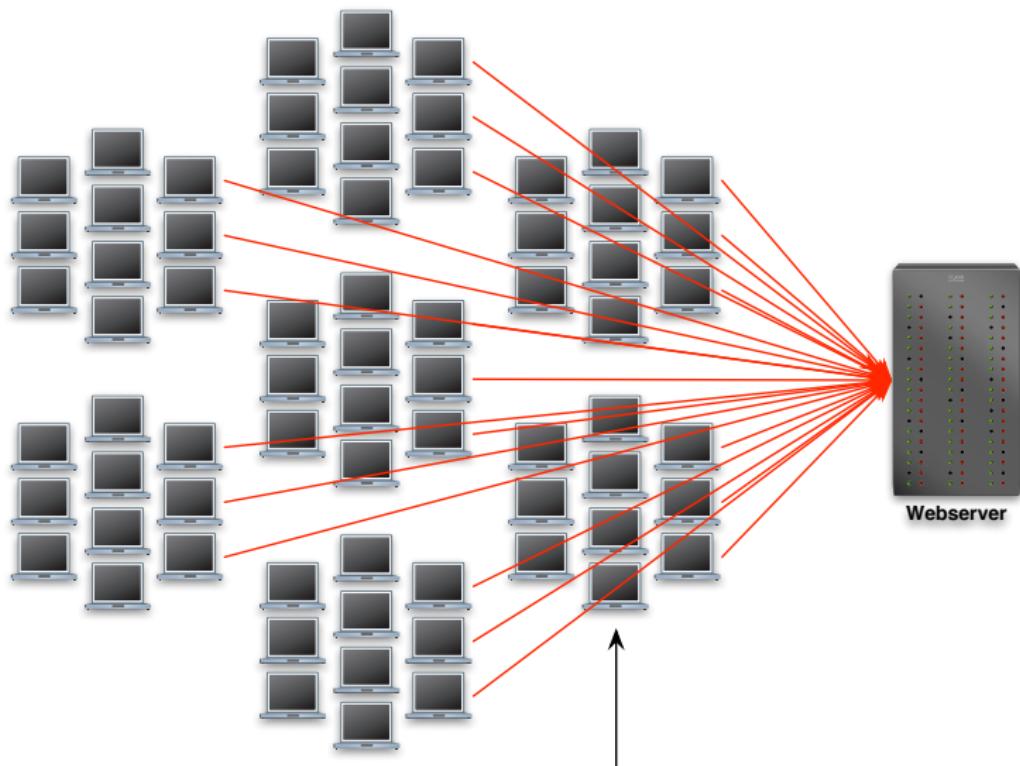
2008 Rank	2007 Rank	Item	2008 Percentage	2007 Percentage	Range of Prices
1	1	Credit card information	32%	21%	\$0.06-\$30
2	2	Bank account credentials	19%	17%	\$10-\$1000
3	9	Email accounts	5%	4%	\$0.10-\$100
4	3	Email addresses	5%	6%	\$0.33/MB-\$100/MB
5	12	Proxies	4%	3%	\$0.16-\$20
6	4	Full identities	4%	6%	\$0.70-\$60
7	6	Mailers	3%	5%	\$2-\$40
8	5	Cash out services	3%	5%	8%-50% or flat rate of \$200-\$2000 per item
9	17	Shell scripts	3%	2%	\$2-\$20
10	8	Scams	3%	5%	\$3-\$40/week for hosting, \$2-\$20 design

A few years ago...



...and nowadays

It's just a multiplication factor but it is damn significant!



Those hundreds of thousands infected machines. And own your PC.

...and they come with a sweet graphical user interface...

DDoS Create task SPAM Add file for Loads List bots Refresh Clear stats Clear

Search bot (mask: id, ip, country):

ID	Ver	Country	IP	Status	First
1	4	Brazil		Free	2008-12-20
2	4	Canada		Free	2008-12-20
3	4	Thailand		Free	2008-12-20
4	4	Kyrgyzstan		Free	2008-12-20
5	4	Russian Federation		Free	2008-12-20
6	4	Georgia		Free	2008-12-20

DDoS Create task SPAM List task Loads Stats botnet EXE Update build

Create new template for SPAM Generate template for SPAM

Tasks Stats Tasks

#	HOST	Bots	Type	Start
1	ya.ru	0/999	GET	2008-12-20
2	google.ru	0/666	GET	2008-12-31

Add new task Delete task Search host:

Add Task Loads

Name: Rules: File: Select file Add

Rules Country or/and Bot ID.
Examples:
1) US,UK,UZ
2) 23,3,9,133,98
3) 3,9,US,23,UK,133,98,UZ

Create new task

Host[:port]: Path: Referer: POST: Add

Page 1 of 1 View tasks

Add Template for SPAM Task

Name template: Enter name new template and upload files attach..
- Uploaded .txt file for text mail
- Uploaded .html,.htm file for html mail.
If html mail used image, css - upload auto attach in mail, and used name into html.
And upload pdf, zip, rar, doc, xls and etc. for attach in mail.

Update build

Version: 4 File: Select file

Add Generate subjects Cancel

Task SPAM

mail on one bot: for subject (split):
Select Senders List: Select Servers List: qwe1 Active

One possible Mitigation Strategy

Attacks generate anomalous behavior

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Simple example

HTTP messages (requests)

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/article/id/32

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/comment/<par1>/<par1-val>

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Simple example

HTTP messages (requests)

```
/article/id/32  
/comment/<par1>/<par1-val>  
/login/<par1>/<par1-val>/<par2>/<par2-val>  
...  
/<component1>/<par1>/<par1-val>/<par2>/<par2-val>
```

Simple example

HTTP messages (requests)

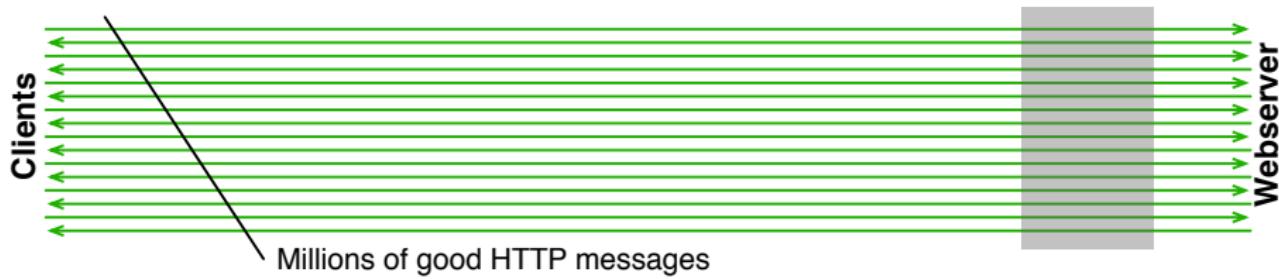
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...  
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/<component2>/<par1>/<par1-val>
```

Simple example

Anomaly detection

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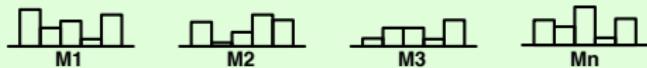
Simple example

Anomaly detection

Client

```
<component1>/<par1>/<par1-val>  
<component1>/<par1>/<par1-val>
```

Models of good messages



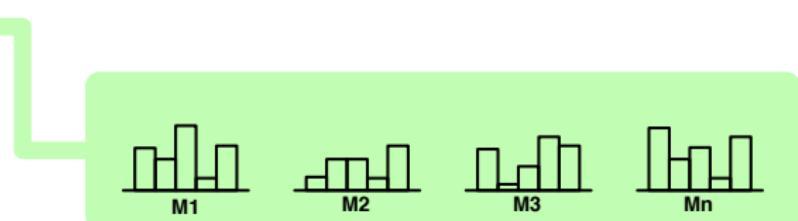
Webserver

Simple example

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Example of models

- parameter string length
- numeric range
- probabilistic grammar of strings
- string character distribution

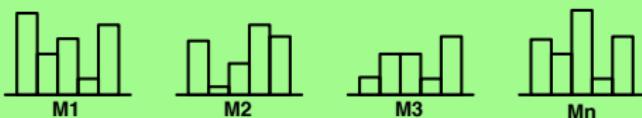
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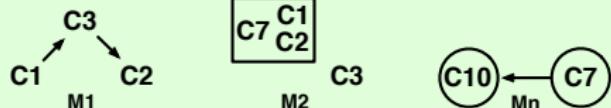
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Models of good sessions



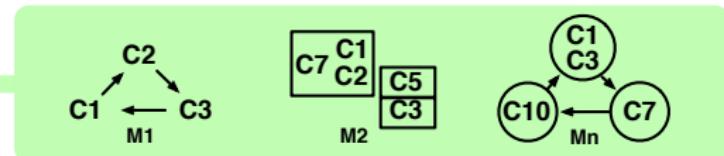
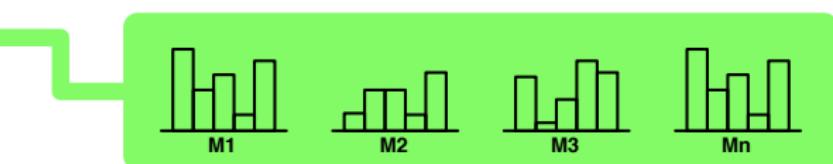
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Simple example

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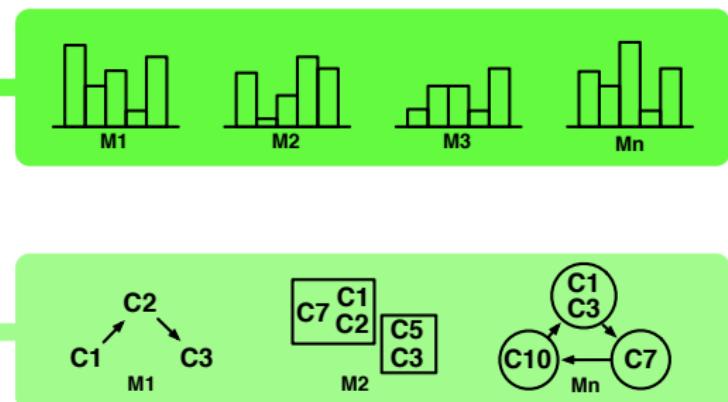
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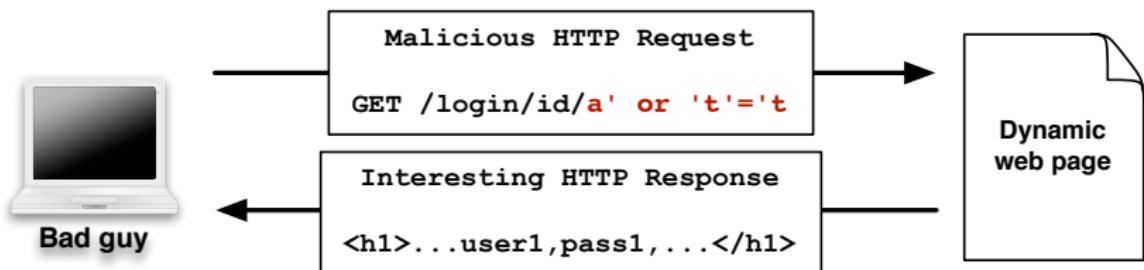
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Webserver

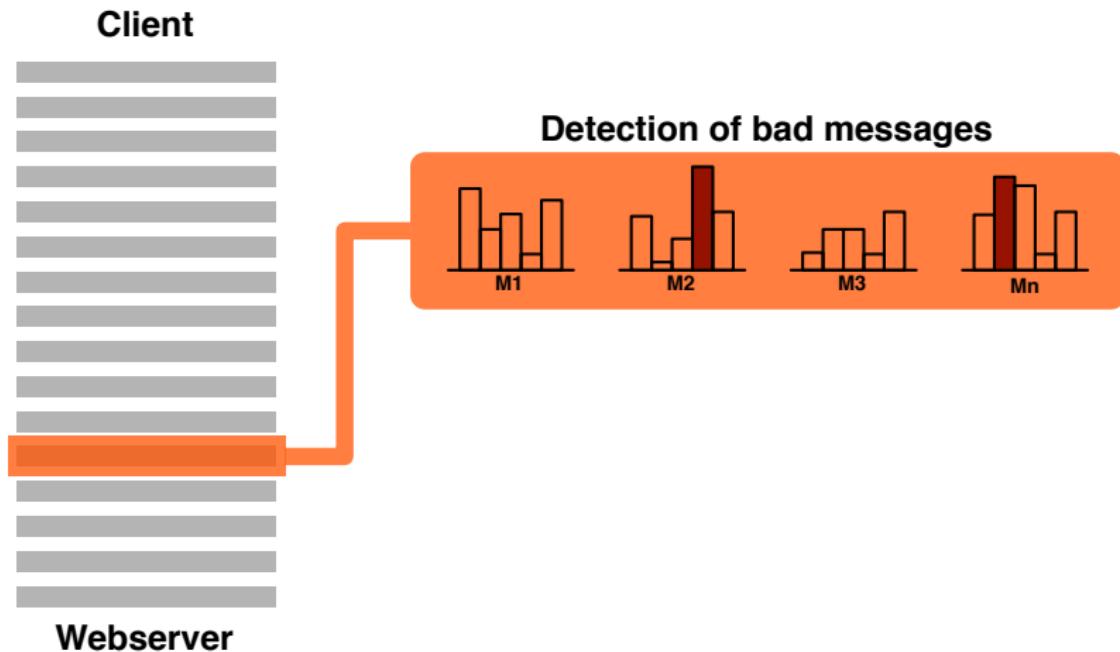
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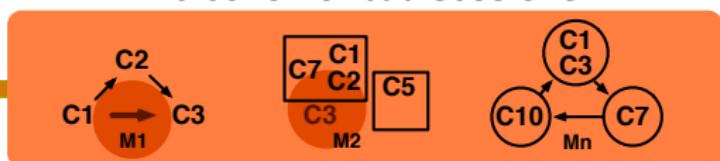
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Detection of bad sessions



Webserver

The same applies to any type of activity.
The **crucial** point is how to design **models**.

Our research

Three subjects

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1. HTTP interactions,

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2. operating system processes,
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3. combination of the two,
 - ▶ malicious network activity → malicious activity on the operating system.

1. HTTP interactions

Protecting web applications and clients

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Models of:

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Models of:

- ▶ HTTP requests,

to protect

Protecting web applications and clients

Models of:

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- ▶ **HTTP responses,**

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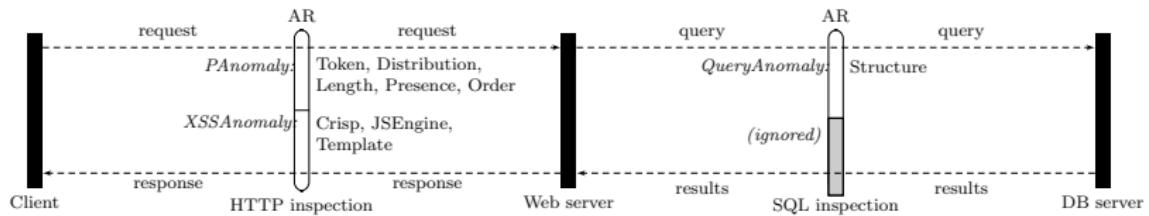
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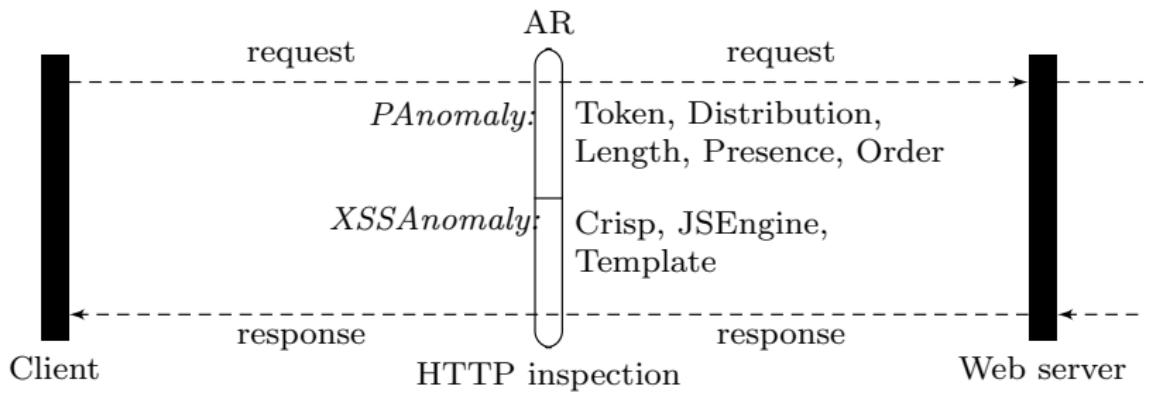
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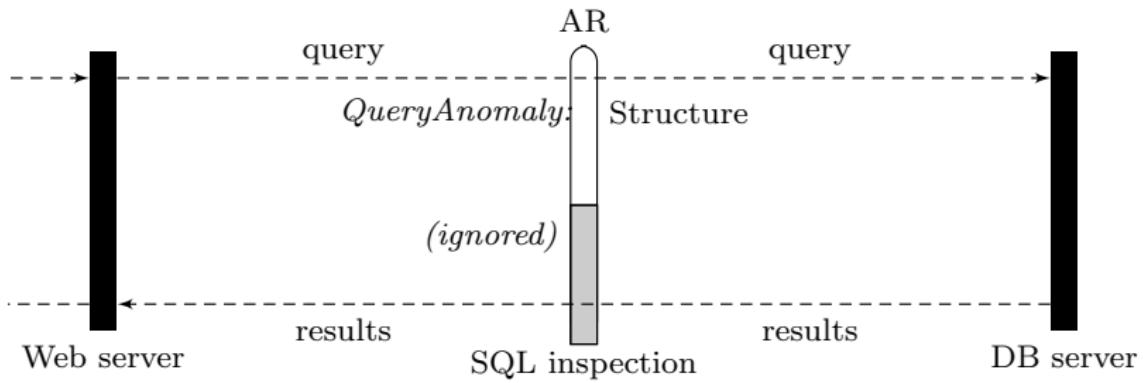
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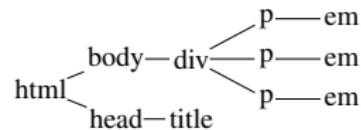
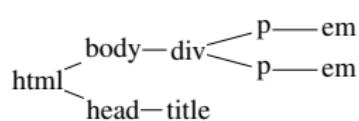
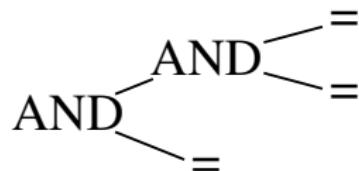




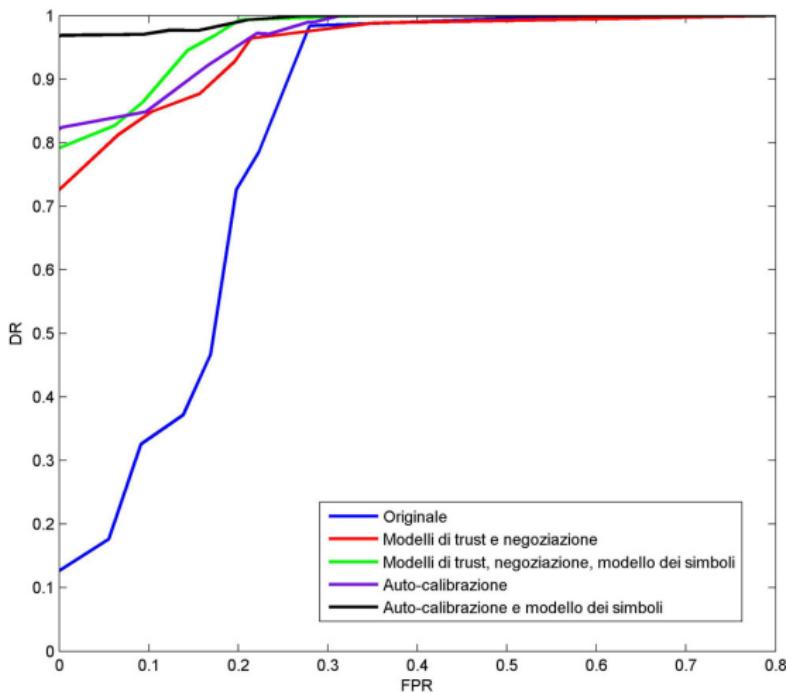


Example of very simple models

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Overall detection capabilities



Tested on about HTTP 8,000 requests, 3000 attacks. EC2ND 2009 [2].

Updating obsolete models dynamically

What if the website changes?

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- ▶ new parameter values → new training values.

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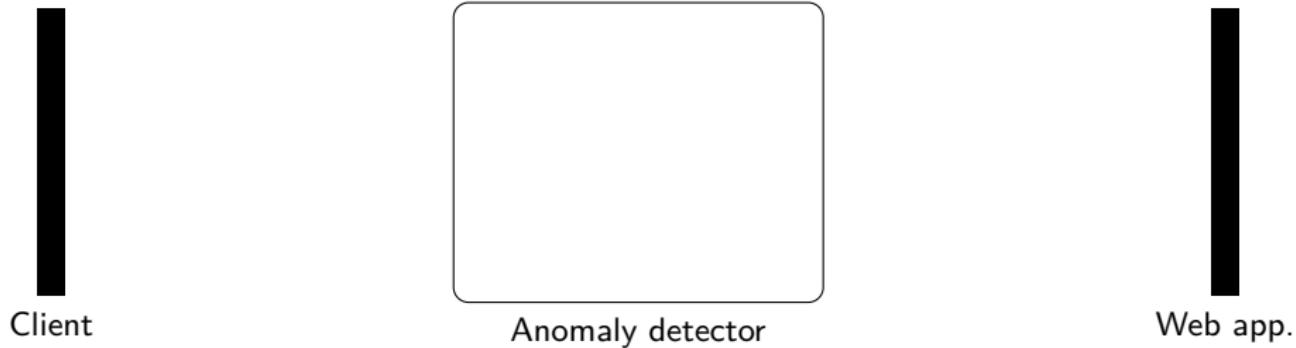
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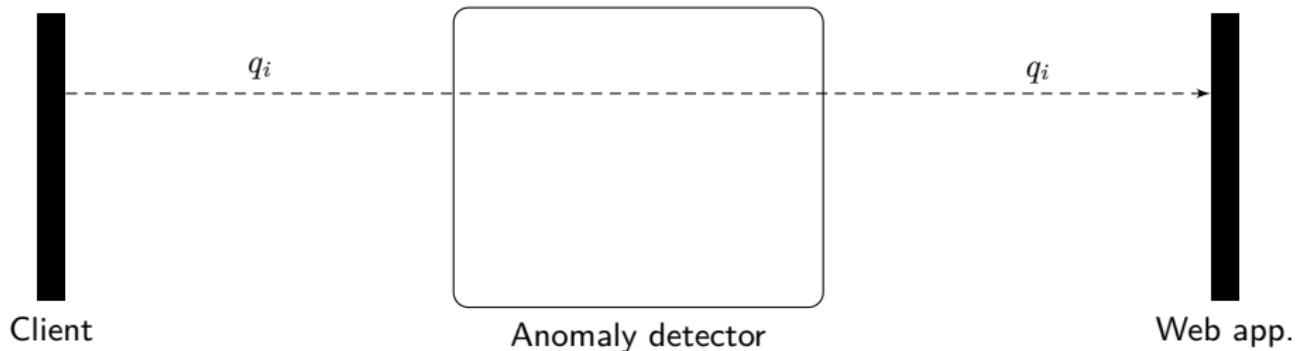
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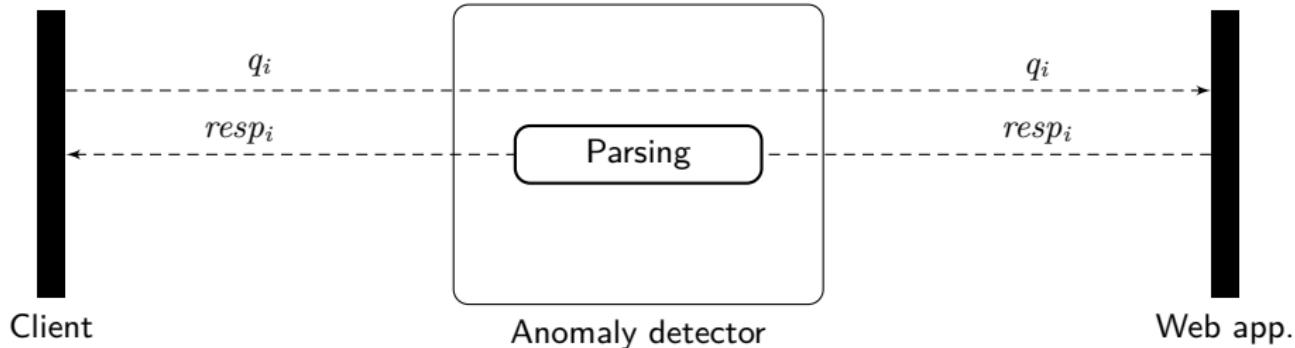


Parsing HTTP responses to update models



for each request q_i

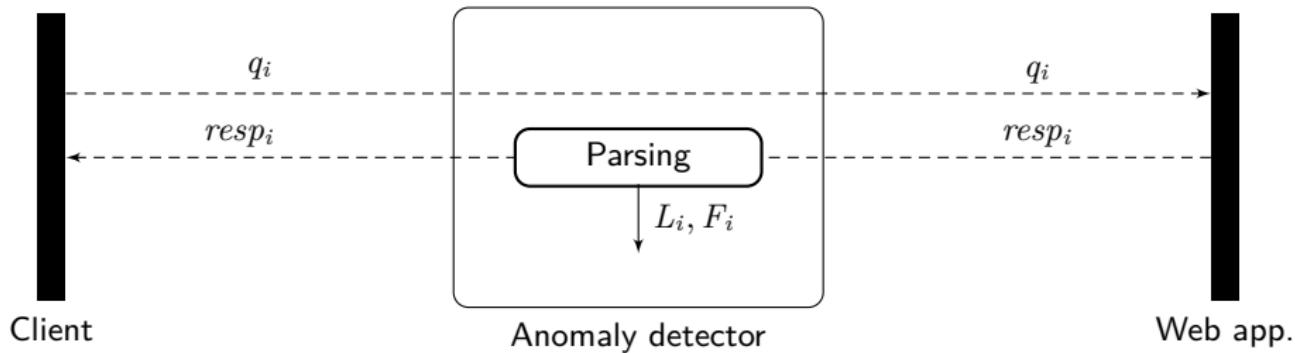
Parsing HTTP responses to update models



for each request q_i

intercept the corresponding response $resp_i$

Parsing HTTP responses to update models

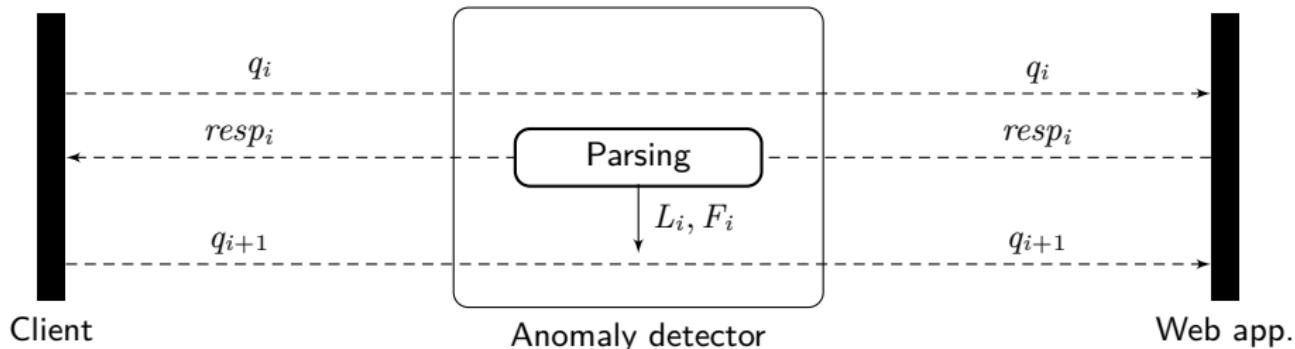


for each request q_i

intercept the corresponding response $resp_i$

extract parameters and values from links, forms, fields

Parsing HTTP responses to update models



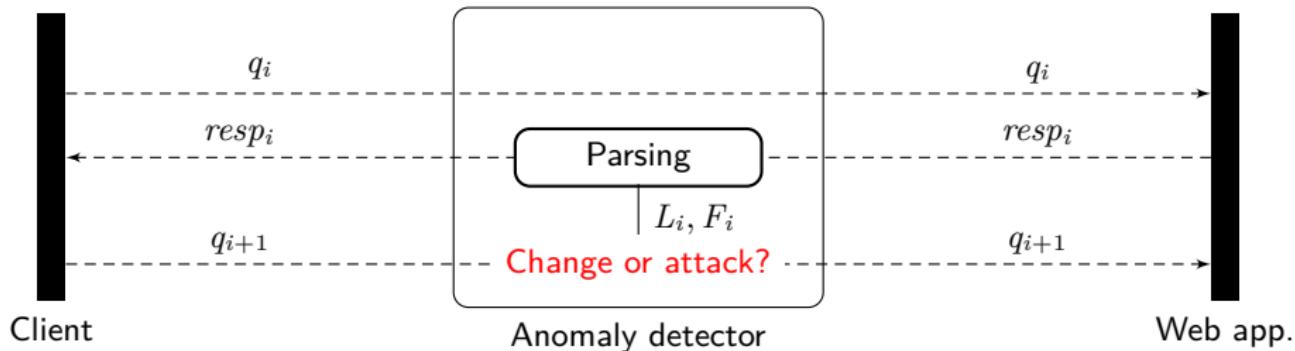
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at next request q_{i+1}

Parsing HTTP responses to update models



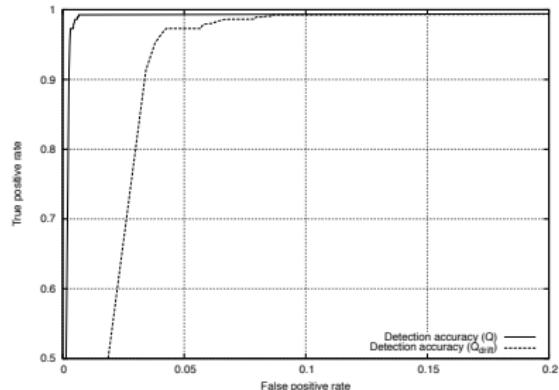
for each request q_i

 intercept the corresponding response $resp_i$

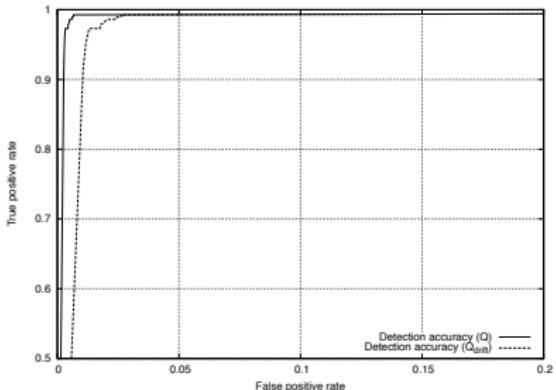
 extract parameters and values from links, forms, fields

at next request q_{i+1}

compare parameter and values to spot legit changes



(a) Response modeling disabled.



(b) Response modeling enabled.

Tested on 823 web applications, 58,732,624 HTTP requests, 1000 attacks. RAID 2009 [6] (w/ UC Santa Barbara).

Training with almost no data

Some pages are infrequently accessed

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Scarce HTTP interactions → scarce training data, but:

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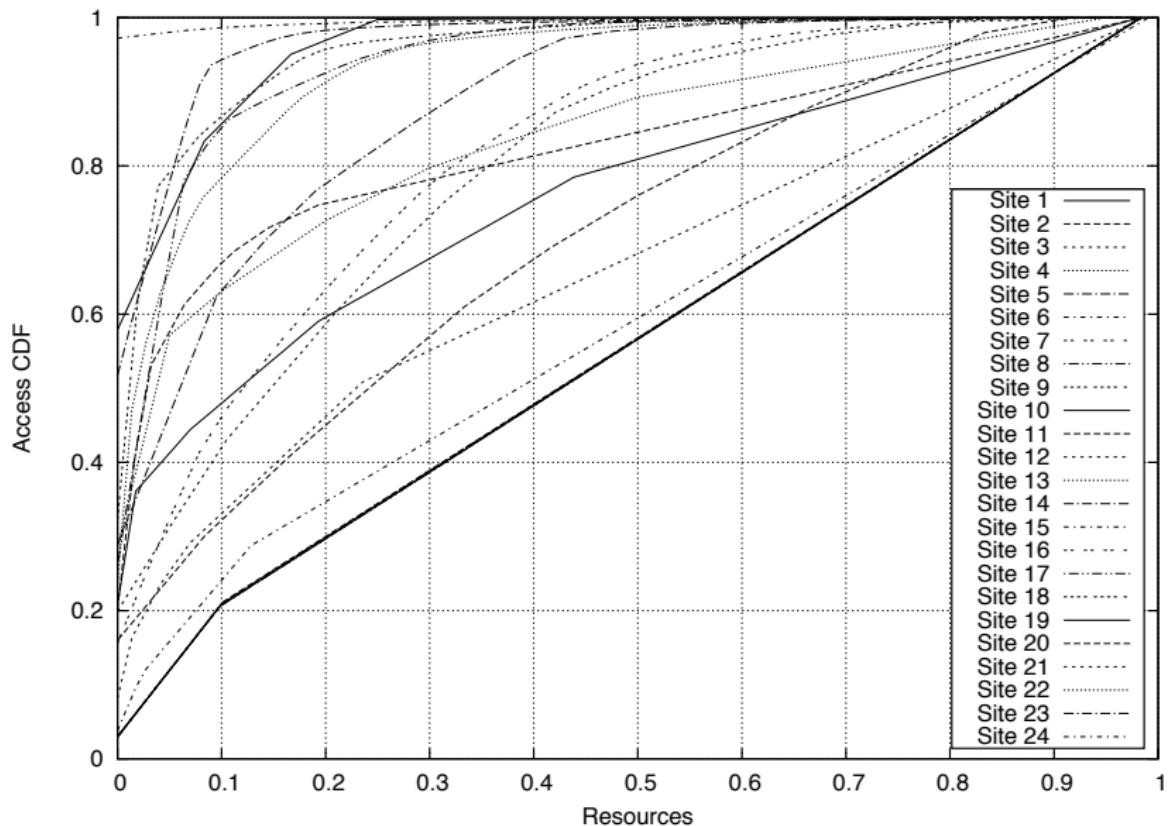
- ▶ similar models have (i.e., capture) similar characteristics,
- ▶ group similar models,
- ▶ rank models according to their completeness,

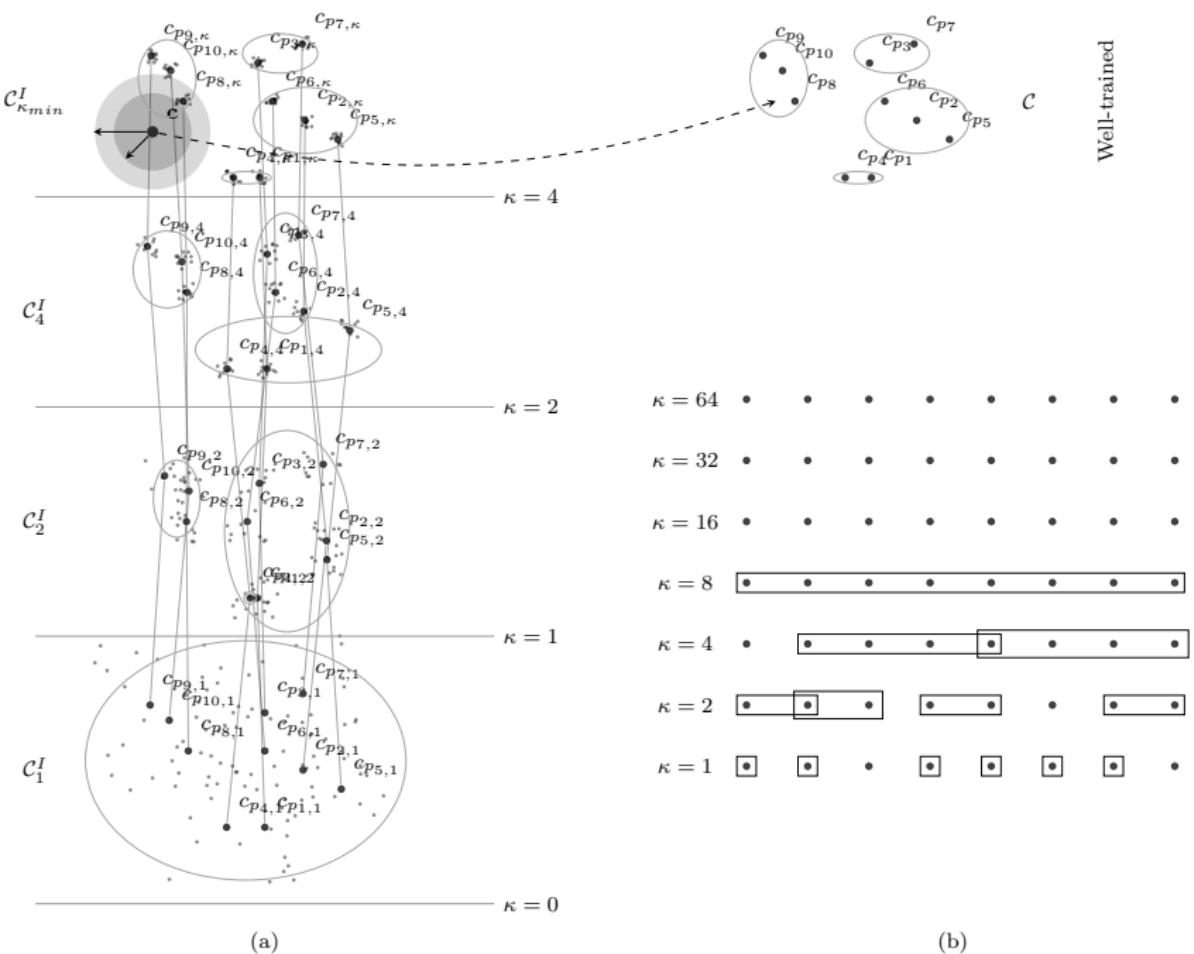
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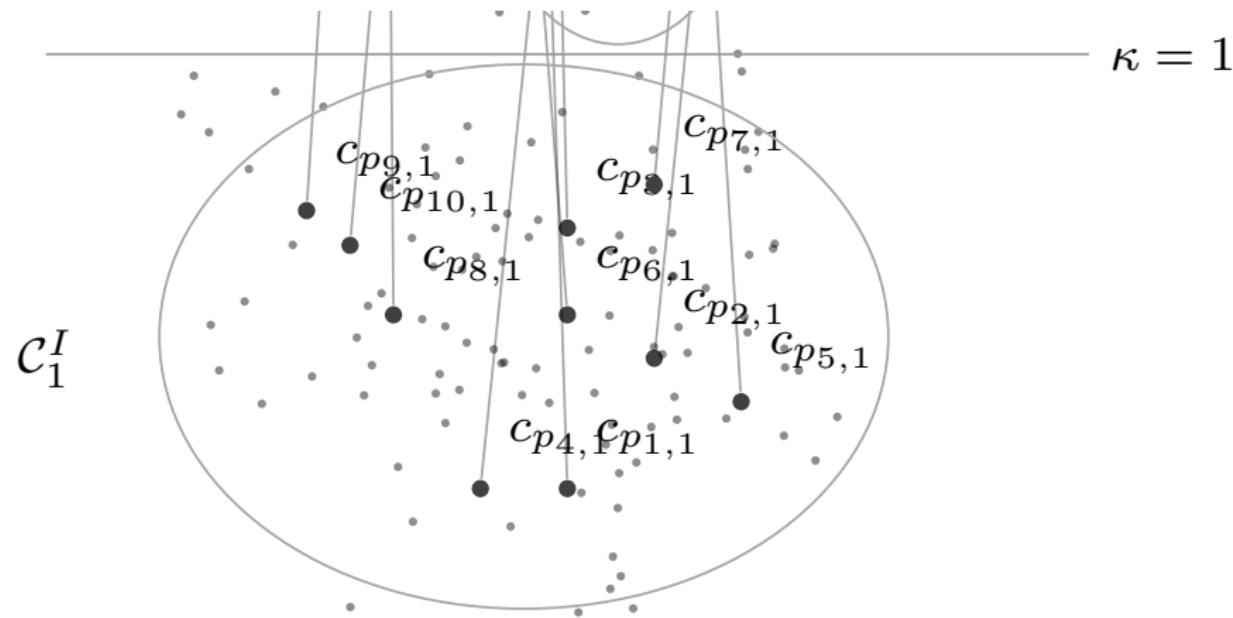
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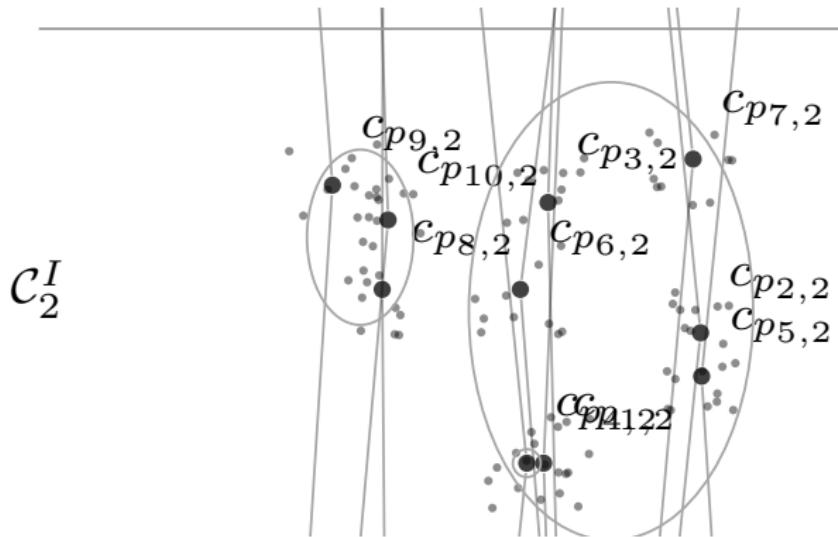
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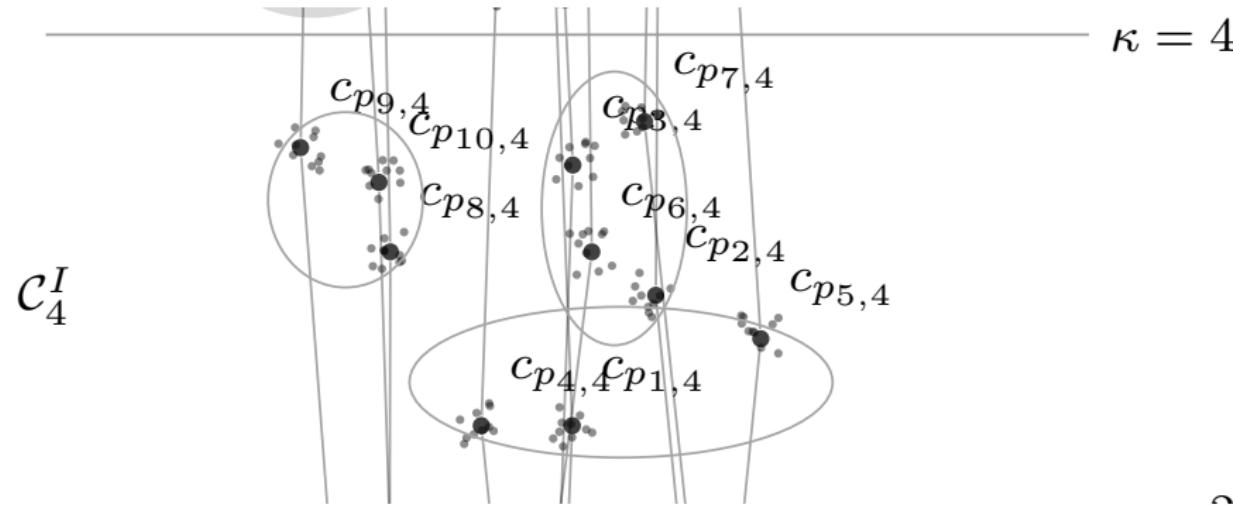
- ▶ similar models have (i.e., capture) similar characteristics,
- ▶ group similar models,
- ▶ rank models according to their completeness,
- ▶ substitute a poorly-trained model with a similar one, but well-trained.

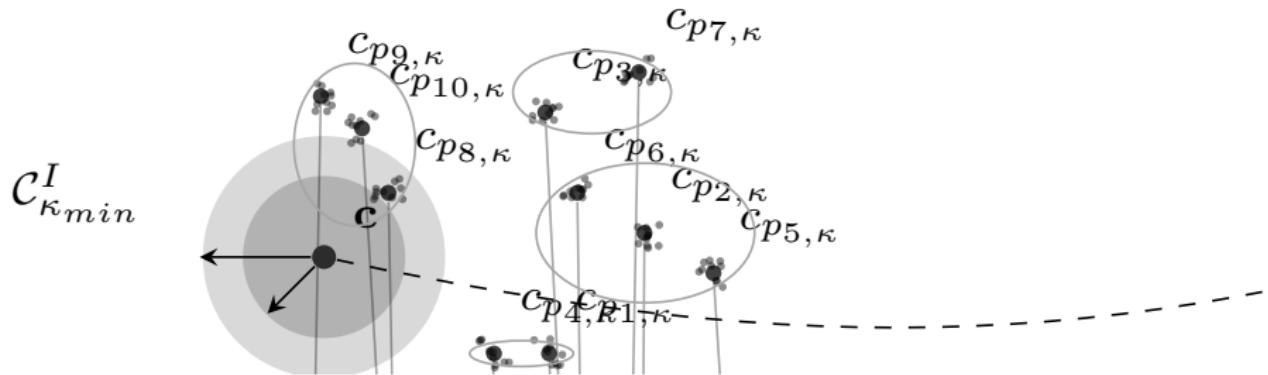






$\kappa = 2$ 

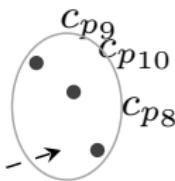
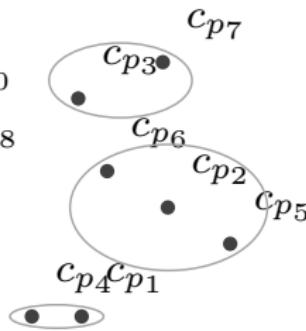


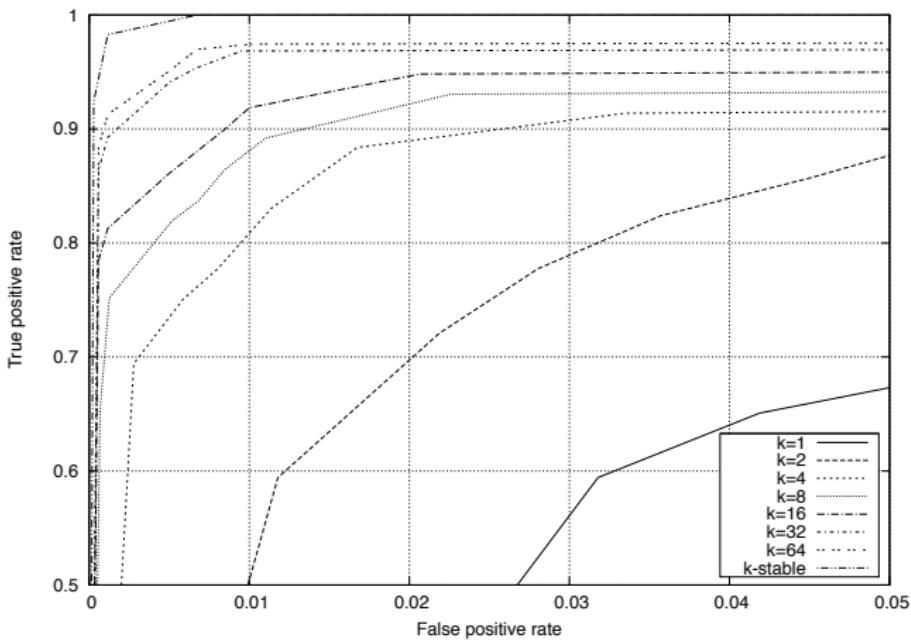
 $\kappa = \kappa_{min}$ 

$$\kappa_{stable} \gg \kappa_{min}$$

Well-trained

\mathcal{C}





Tested on 823 web applications, 58,732,624 HTTP requests, 1000 attacks. NDSS 2010 [10] (w/ UC Santa Barbara).

2. Operating system processes

Protecting the operating system

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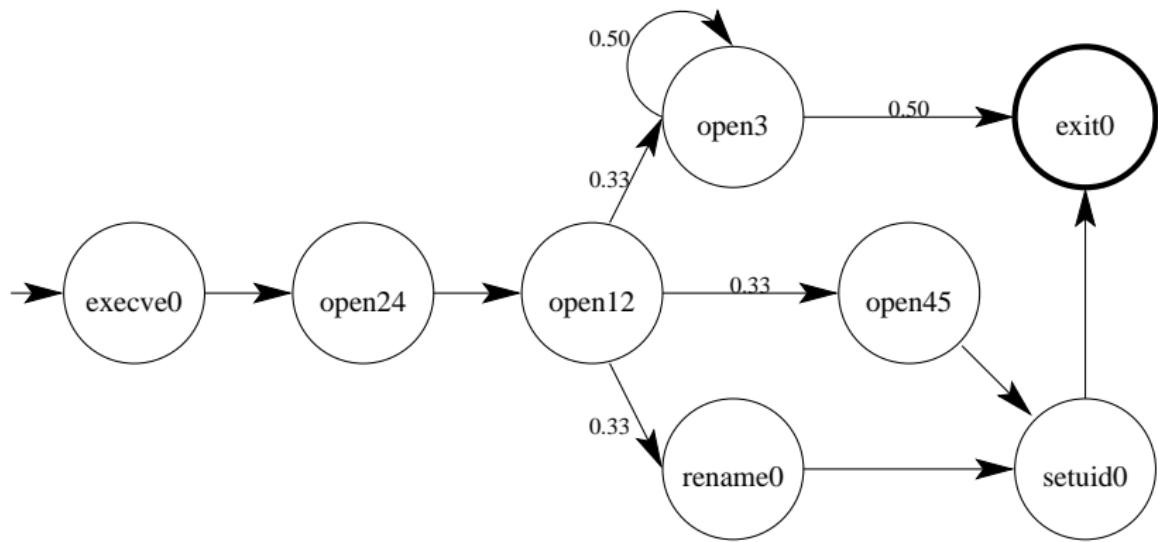
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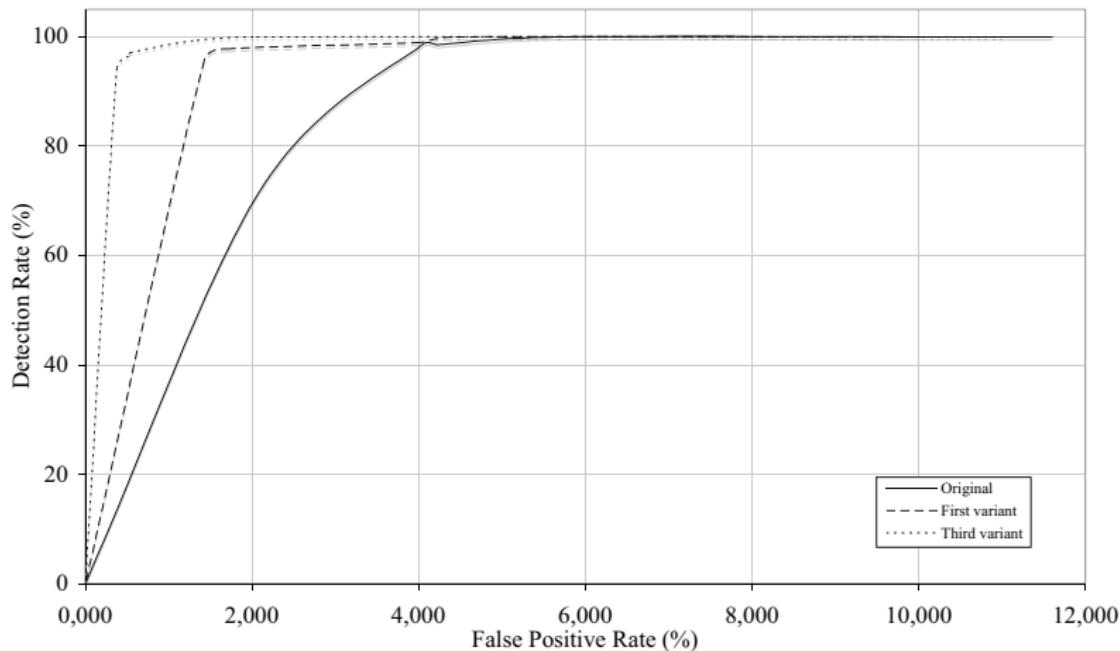
A process can be simplified as a sequence of system calls:

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- ▶ group similar calls to make the problem feasible,
- ▶ encode the sequence of classes of calls as a Markov chain,
- ▶ deviant process → malicious process.

Example of model



Overall detection capabilities



Tested on one week of kernel activity (about 100,000 syscalls/day),
142 attacks. IEEE Transaction on Dep. and Secure Systems [4],
ACM SIGOPS' O.S. Reviews [8].

Achieving better accuracy

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Tested on one day of kernel activity (about 145,000 syscalls), 5 attacks. DIMVA 2009 [3].

3. Combination of the two

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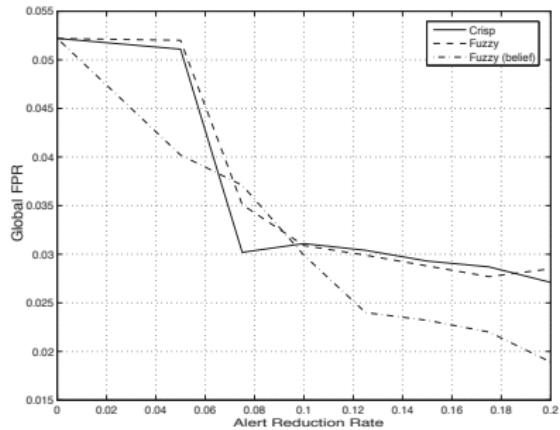
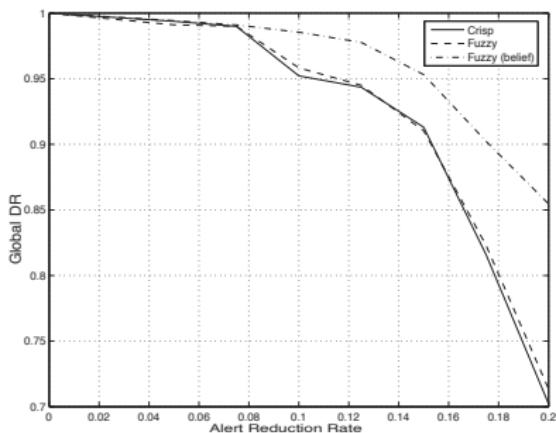
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Tested on about two weeks of detection resulting in about 2,000 alerts overall. Information Fusion, Elsevier [5].

Overall detection capabilities



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How to detect relationships?

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- ▶ matching series → related alerts.

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Conclusions and lesson learned during my PhD

- ▶ some of our systems require refactoring because performance was not our primary focus,
- ▶ the most difficult task ever, in our research area, is gathering **enough experimental data**,
- ▶ often, scientifically sound experiments are very difficult to prepare because data is also non-labeled,
- ▶ in our future research we really want to spend a considerable amount of time and efforts at designing **public data collection infrastructure**.

Obligatory Slide

Thanks!
Questions?

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