Mining malware specifications through static reachability analysis

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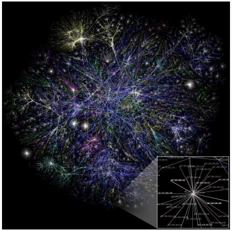
Motivation

Our goal: Malware detection!



Why? Social impact!

- Malware in the news!
- We are all collateral damage!

Huge technological challenge!

- 286 million new malware variants in 2010 ([Fossi et al.])

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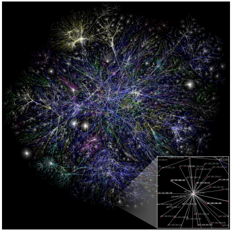

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Huge technological challenge!

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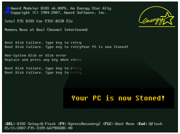
We need automation!

Existing anti-malware technology

Emulation based

- Time limited
- Behavior hiding



Signature matching based

- Easy to avoid detection by syntactic manipulation!

```
00000180  03 33 DB FE C1 CD 13 EB C5 07 59 6F 75 72 20 50  .3ÛþÁÍ.ëÅ.Your P
00000190  43 20 69 73 20 6E 6F 77 20 53 74 6F 6E 65 64 21  C is now Stoned!
000001A0  00 00 00 00 00 00 00 00 00 00 00 00 00 00 00 00  ................
```

Malware detection

More robust techniques

Solution

One needs to analyse the behavior not the syntax of the program without executing it!

Malware detection

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Model checking is a good candidate!

Model checking for malware detection

$$\text{Program} \quad \models \quad \text{Malicious behavior}$$

Model checking for malware detection

Program $\models$ Malicious behavior

Model?

Model checking for malware detection

$$\text{Program} \models \text{Malicious behavior}$$

Model?

Specification formalism
to describe behaviors?

Previous approaches on model checking for malware detection

Use finite state models

- (E.g. Kinder et al. [2010],Bonfante et al. [2008])
- But the model fails to capture stack behavior!

Why is the stack important?

Malware writers use the stack to obfuscate their behaviour.

Example of obfuscation

E.g. call obfuscation:

l_1 : push m
l_2 : push 0
l_3 : call *GetModuleFileName*
l_r : ...

l_1 : push m
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l_3 : push l_r
l_4 : jmp l_g
l_r : ...

Import address table	
l_g	*GetModuleFileName*

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Our solution is:

To use pushdown systems that is a finite state system + a stack

We use PDS (FSS + stack!)

Pushdown systems (**PDS**)

A **PDS** is a triple $\mathcal{P} = (P, \Gamma, \Delta)$ where:

- P is a finite set of control points,
- Γ is a finite alphabet of stack symbols, and
- $\Delta \subseteq (P \times \Gamma) \times (P \times \Gamma^*)$ is a finite set of transition rules.

Configurations

- A configuration $\langle p, \omega \rangle$ of $\mathcal{P}$ is an element of $P \times \Gamma^*$

PDS for malware detection

Since 2012 PDS have been used to perform malware detection!

- FM [Song and Touili, 2012b]
- TACAS [Song and Touili, 2012a]

POMMADE tool (FSEN [Song and Touili, 2013])

- Logic to specify malicious behaviors.
- Few malicious behaviors (discovered manually!)

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Our contribution in this work is to
Show how to automatically extract the malicious behaviors from a set of malware!

Model checking for malware detection

Program $\models$ Malicious behavior

PDS

Specification??

Example of an email worm behavior

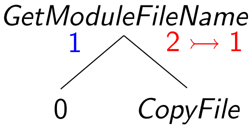
Assembly fragment from Bagle malware

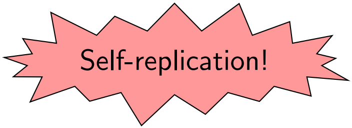
l_1 : push m
l_2 : push 0
l_3 : call *GetModuleFileName*
⋮
l_4 : push m
l_5 : call *CopyFile*

Self-replication!

System call dependency trees (SCDT)

l_1 : push m
l_2 : push 0
l_3 : call *GetModuleFileName*
⋮
l_4 : push m
l_5 : call *CopyFile*





Model checking for malware detection

To summarize

$$\text{Program} \models \text{Malicious behavior}$$

PDS

SCDT

Roadmap

Introduction

Mining specifications

Detecting malware

Results

How to automatically discover malicious SCDTs from programs?

Approach

Learning!

Given a:

- set of already known malicious programs
- set of already known benign programs

The goal is

To extract **SCDT**s and use statistical machinery to distinguish the malicious ones!

How to extract SCDTs from a program?

1. Model binaries as pushdown systems (mimic program behaviors)

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3. Extract behaviors (discover data flows encoded as trees)

Learning malicious trees

MalSCDT malicious behavior trees

A malicious behavior tree is a tree that occurs frequently in malware extracted **SCDT**s!

To compute frequent "subtrees" we use gSpan!

We specialize the frequent subgraph algorithm presented in [Yan and Han, 2002] to the case of trees.

Roadmap

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Model checking for malware detection

In summary we want to verify that:

Program $\models$ Malicious behavior

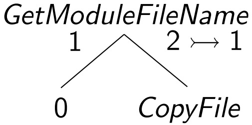
PDS

MalSCDT

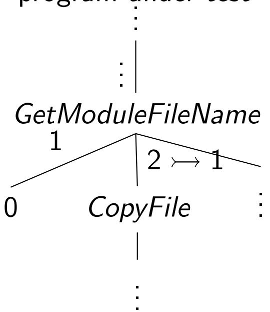
Recognizing **MalSCDT**

A problem!

MalSCDT



SCDT extracted from program under test



Use automata with regexps!

$GetModuleFileName(\mathrm{q}^{*}1(0)\mathrm{q}^{*}2 \rightarrowtail 1(\mathrm{CopyFile})\ \mathrm{q}^{*}) \rightarrow \mathrm{q}_{fin}$

Teaching computers to detect malware

Build malicious behaviors database

1. Build an hedge automaton $\mathcal{A}$ (recognizing **MalSCDT**)

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Malware detection

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3. Extract **SCDT** (discover data flows encoded as a tree)
4. Check wether **SCDT** belongs to $\mathcal{A}$

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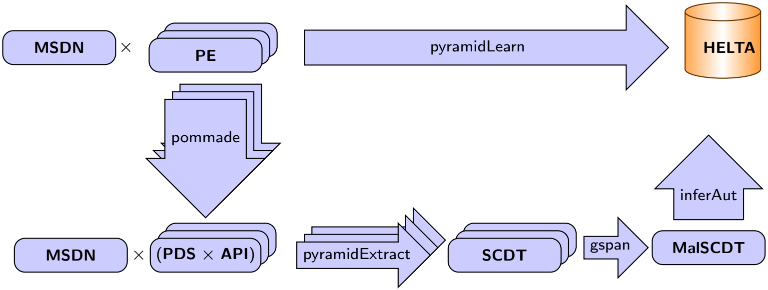
Results

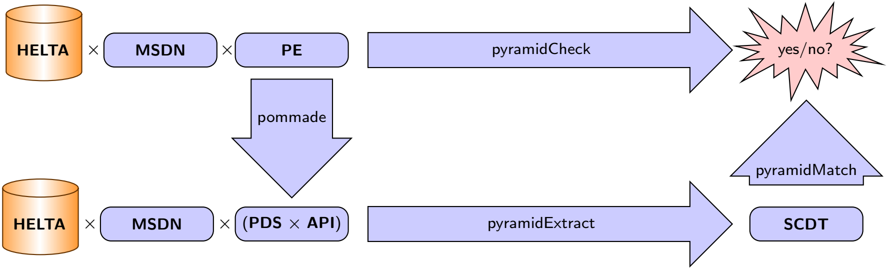
- Implemented the approach in a tool called **PYRAMID**
- Learned **MalSCDT** from a set of malware
- Tested them on another set of malware
- Compared the results with traditional antivirus

Implementation

PYRAMID in learning mode



PYRAMID in detection mode



Experimental results

Learning experimental phase

From 193 malware files we obtained 1026 **MalSCDT**

Detection experimental phase

- Detected 983 malware instances from 330 families (5$\times$ bigger)
- Detection in 2.15s in average
- Correctly classified as non-malware 250 benign programs files

Results comparison

Procedure

- Submitted the “malware” files to 48 antivirus tools
- Categorized the antivirus performance in 4 classes

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Outcome

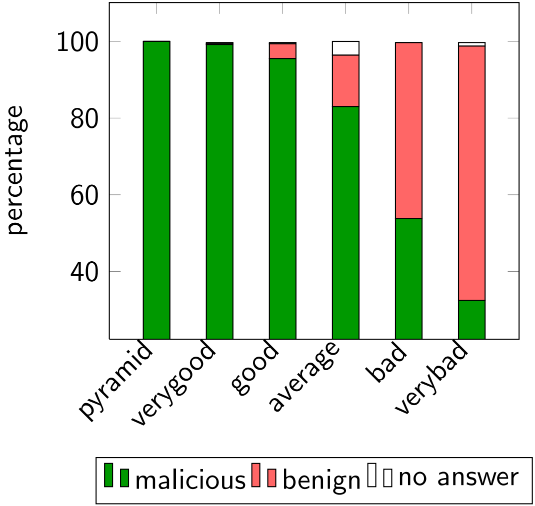
- 99% of the malware files were detected by the top 10% tools!
- Our tool detects real malware!
- In average the tools only detected 80% of the files!

Results comparison

Performance	#Antivirus	Detection range
very good	5	99.1% to 99.5%
good	19	95.0% to 99.1%
bad	19	40.0% to 95.0%
very bad	5	8.0% to 40.0%

Table: Performance categories

Results comparison



Thank you for your attention!

Bibliography

Guillaume Bonfante, Matthieu Kaczmarek, and Jean-Yves Marion. Morphological detection of malware. In *International Conference on Malicious and Unwanted Software*, 2008. doi: 10.1109/MALWARE.2008.4690851.

M. Fossi, G. Egan, K. Haley, E. Johnson, T. Mack, T. Adams, J. Blackbird, M.K. Low, D. Mazurek, D. McKinney, et al. Symantec internet security threat report trends for 2010.

Johannes Kinder, Stefan Katzenbeisser, Christian Schallhart, and Helmut Veith. Proactive Detection of Computer Worms Using Model Checking. *IEEE Trans. on Dependable and Secure Computing*, 2010.

Fu Song and Tayssir Touili. Pushdown model checking for malware detection. In *TACAS*, 2012a.

Fu Song and Tayssir Touili. Efficient malware detection using model-checking. In *FM*, 2012b.

Fu Song and Tayssir Touili. PoMMaDe: Pushdown model-checking for malware detection, 2013.

Experiments

Learning

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