

# Behavioral Detection of Malwares: From a Survey Towards an Established Taxonomy

**JACOB Grégoire<sup>1/2</sup>, DEBAR Hervé<sup>1</sup>, FILIOL Eric<sup>2</sup>**

<sup>1</sup> *France Télécom R&D,  
Network and Service Security (MAPS/NSS).*

<sup>2</sup> *French Army Signal Academy,  
Cryptology & Virology Lab (ESAT).*

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research & development

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# summary

## 1 ■ Fundamental Aspects of Behavioral Detection

- Two strategies for detection
- Two opposite approaches

## 2 ■ General Description of Behavioral Detectors

- Sequential steps of the detection
- Important properties

## 3 ■ Taxonomy of the Behavioral Detectors

- Data capture conditions
- Matching algorithms and models
- Behavioral signature generation
- Synthesis on the classification

## 4 ■ Conclusions and perspectives

# 1

## Fundamental Aspects of Behavioral Detection

# 1.1 Two Strategies for Detection

## Appearance detection (form-based)

- Relies on syntactic markers
- Undecidable
- Problem of the signature extraction:  
cost and analysis delay / release speed and mutation mechanisms

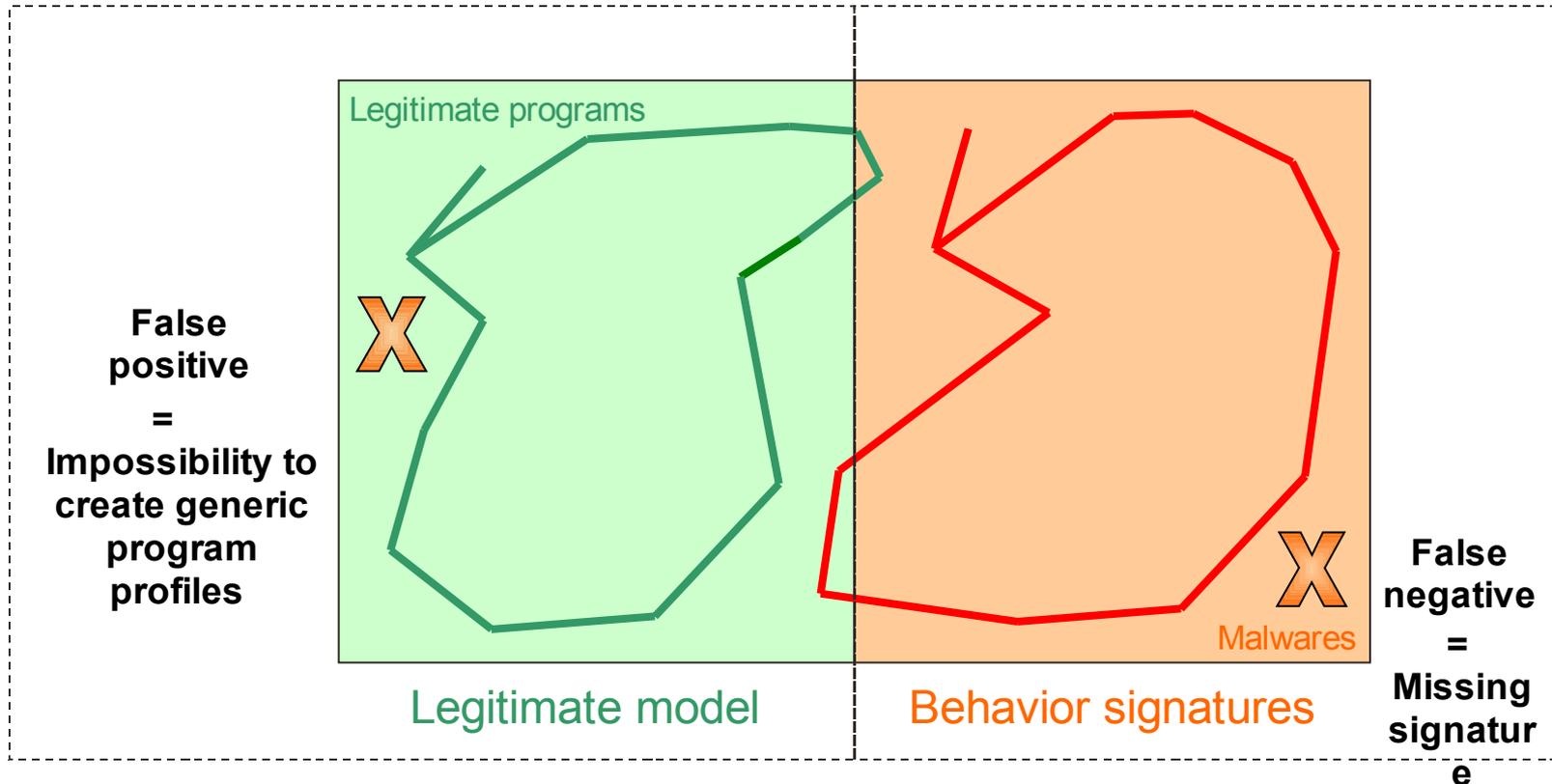
## Behavioral detection (function-based)

- Relies on the use of the system services and resources
- Undecidable since equivalent to syntactic analysis on request arguments
- Generic strategy more resilient to modifications, manual or automatic
- Recent interest because of the resources required once prohibiting

# 1.2 Two Opposite Approaches

Intrusion Detection (Vulnerabilities)

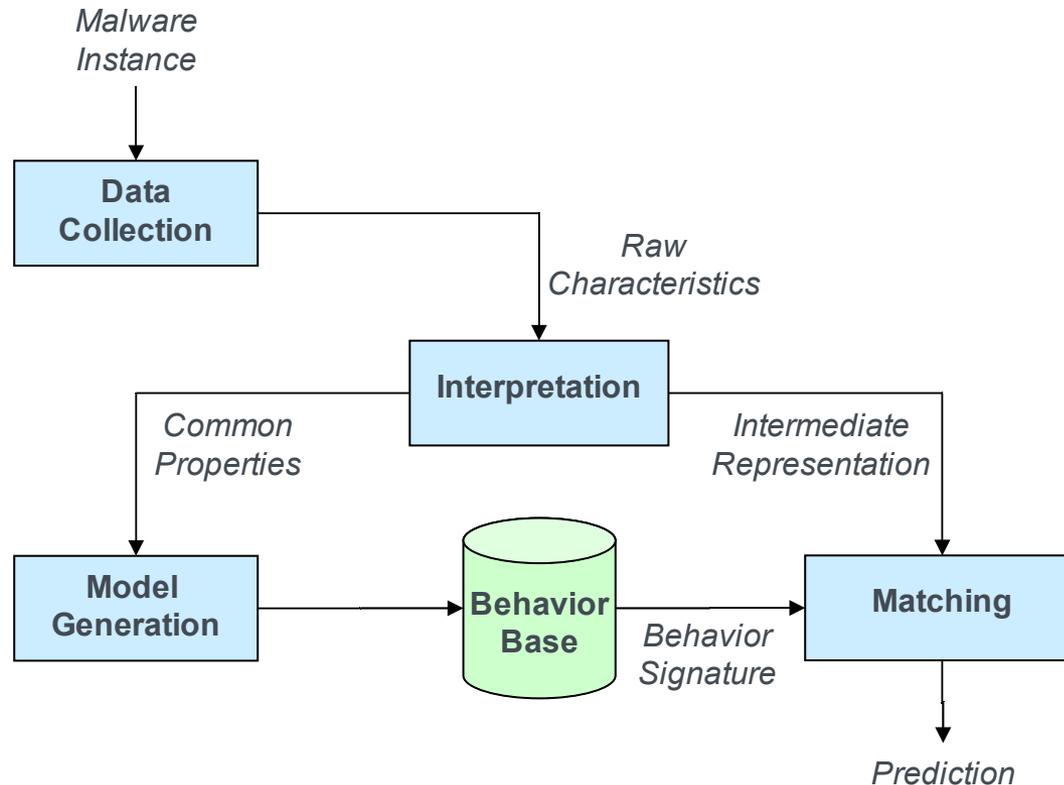
Virology



# 2

## Generic Description of Behavioral Detectors

# 2.1 Sequential Steps of the Detection



## 2.2 Important Properties

### Properties for assessment (AV Testing)

- Completeness / Accuracy / Adaptability:  
*False positives and negatives, adding new behaviors*
- Performance:  
*Complexity, overload introduced*
- Resilience to anti-analysis techniques:  
*Obfuscation, stealth*
- Unobtrusiveness / Fault-Tolerance (dynamic):  
*No perturbation introduced in the malware execution by the analysis and resistance to its proactive defenses*
- Timeliness (dynamic):  
*Detection reached before the point of no return*

# 3

## Taxonomy of the Behavioral Detectors

# 3.1 Data Capture Conditions

## Dynamic monitoring

- Sequences of discrete events (traces): *interruptions, system calls*
- Conditions:
  - real time with or without action recording  
*little overload but risky as effectively executed*
  - sandboxes and virtual machines  
*important overload, risk of detection or escape*

## Static Extraction

- Program structure: *control and data flow graphs*
- Conditions:
  - disassembly and debugging  
*hindered by obfuscation, anti debug, packing*

## 3.2 Matching Algorithms and Models

### Simulation-Based Detection

- Linked to dynamic monitoring for the simulation environment
- Black box approach
- Explore the current path during execution
- Matching of sequential models :  
*expert systems, heuristic engines, state machines*

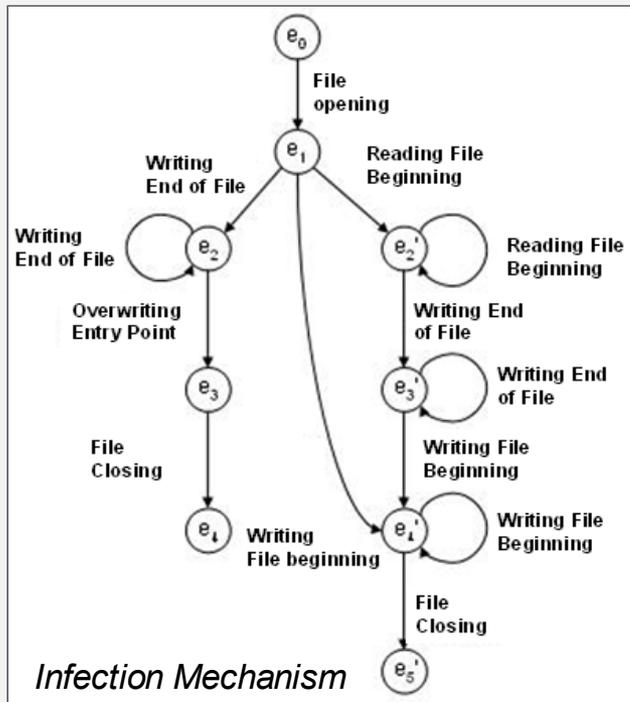
### Formal verification

- Linked to static extraction for the program abstraction
- White box approach
- Explore every possible path of execution
- Bisimulation between abstractions and specifications:  
*annotated graph isomorphism, model checking*

# 3.2 Matching Algorithms and Models

## Examples from both methods

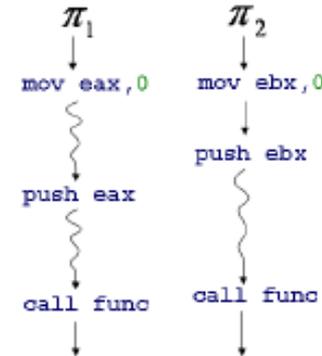
### ■ Deterministic finite automaton



### ■ Model checking

$$C_1 : \exists rEF(\text{mov}(r, 0) \wedge EF(\text{push}(r) \wedge EF(\text{call}(\text{func}))))$$

$$C_2 : \exists rEF(\text{mov}(r, 0) \wedge AX(\text{push}(r) \wedge EF(\text{call}(\text{func}))))$$



$E$  an existing path  
 $A$  any path  
 $F$  an undefined future step  
 $X$  the immediate following step

Quantifier operators

Temporal operators

## 3.3 Behavioral signature generation

### Manual generation

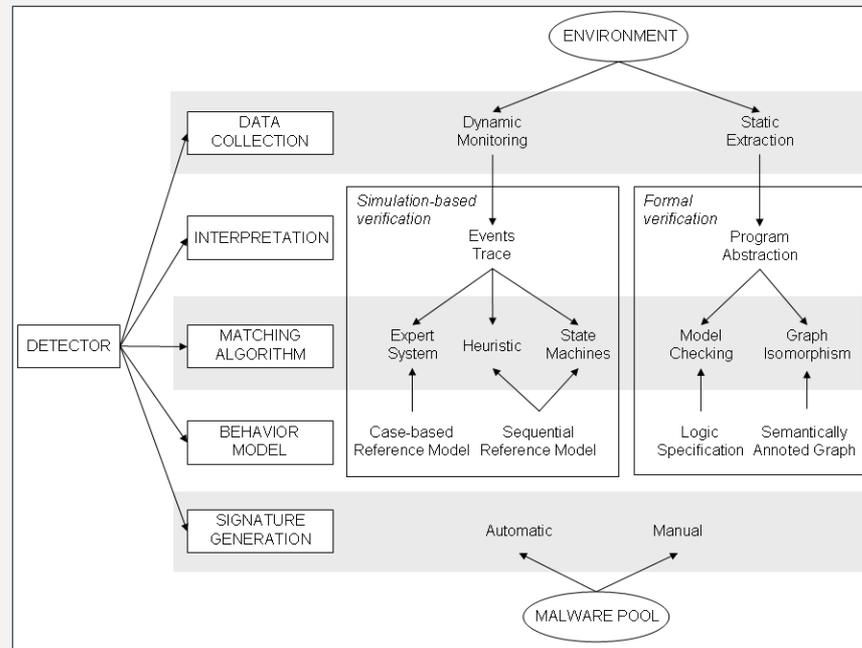
- Defined by a specialist based on its experience  
*Refined and deployable on any system*
- Defined by the user policy  
*Better adequacy but reserved to knowledgeable users*
- Time consuming and hardly evolving

### Automated generation

- Data mining and classifier
- Mainly three paradigms:  
Rules induction / Bayesian Statistics / Clustering
- Large, noise-free, learning and testing pools required

# 3.4 Synthesis on the Classification

## Classification scheme



## Major trends

- Expert system and heuristics with sandboxing in commercial products
- Classifiers with virtual machines / formal verification in research

# 4

## Conclusions and Perspectives

# 4. Conclusion and Perspectives

## Heterogeneity of the systems

- Model multiplication inducing vocabulary inconsistency  
*Explain the necessity of a taxonomy*  
*Need of a high level reference model for behaviors*

## Two main axes in the classification

- Choice between formal verification or simulation  
*Condition the capture, the model and associated matching algorithm*
- Complementary strength and weaknesses  
*Possible combination already explored*

Thank you for your attention,



Any questions?

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