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A Quantitative Study of Accuracy in System Call-Based Malware Detection

Davide Canali, Andrea Lanzi, Davide Balzarotti, Christopher Kruegel, Mihai Christodorescu, Engin Kirda

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UC SANTA BARBARA
engineering

IBM

Northeastern University

Agenda

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- Malware Detection approaches
- Goals and Contributions
- Model Specification
- Evaluation
- Results
- Pitfalls

Malware Detectors

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- Code signatures
  - Strings or RegExps at the byte level
  - Easy to evade (packing, obfuscation)
  - Still the most widely used in the AV industry
- Behavioral signatures
  - Based on high-level, abstract, behavior representations
  - Usually based on system calls
  - Harder to evade

Behavior-based Malware Detectors

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- Different models have been considered, but:
  - It's very difficult to understand when, and why, one should be preferred to another
  - They all lack a solid evaluation
    - Tested on very limited datasets
      - Often extracted in controlled environments, from one machine only
      - Tens of malware samples, few benign apps
- Starting to be adopted by the AV industry as well
  - Very few (if any) details available

Goals and Contributions

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MAIN GOAL

- Creating a benchmark for designing and testing common behavioral malware detectors

CONTRIBUTIONS

- Development of a systematic testing technique to evaluate the quality of behavioral-based malware detectors
- Creation of a comprehensive dataset for validating experiments
- Evidence that the empirical evaluation of a malware detection model is fundamental

Model specification - Atoms

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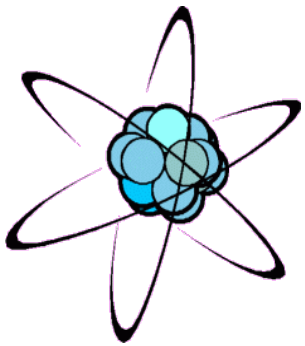
1. Behavioral Atom
   - Represents the fundamental behavioral element that appears in a program syscall trace
     - System call → *NtOpenFile, NtClose, ...*
     - Action: high-level operation (“read file”, …) → *ReadFile, LoadLibrary, ...*
     - With and without parameters
   - Limited to what can be collected efficiently at runtime
     - No instruction-level tracking
     - No data-flow / taint information



Model specification - Structures

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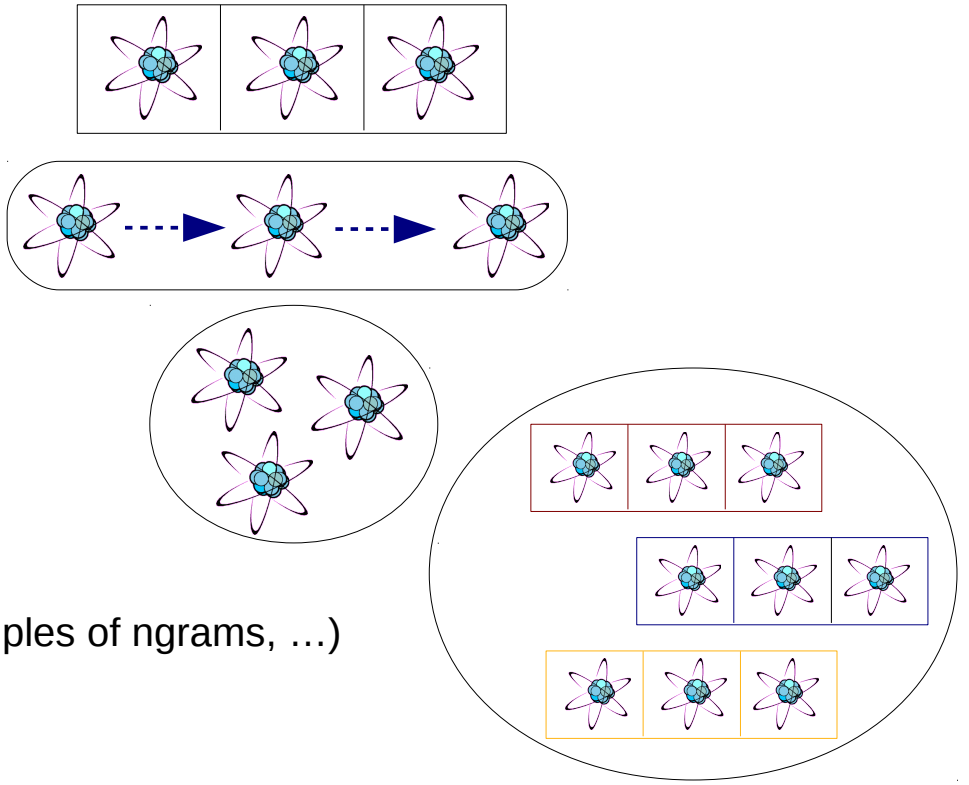
2. Signature Structure

- Describes how the atoms are combined together
  - » Sequences (n-grams)
  - » Tuples (ordered set)
  - » Bags (unordered set)
  - » Recursive structures
    (bags of sequences, tuples of ngrams, …)



Model specification – Structures

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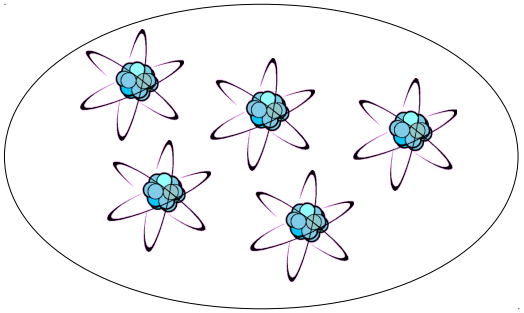
3. Signature Cardinality
   - Defines how many atoms are included in the structure
     - » Bounded by the maximum number of atoms in the sample
     - » In practice, limited to the range 2-100



Model specification – Alert threshold

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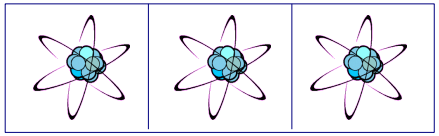
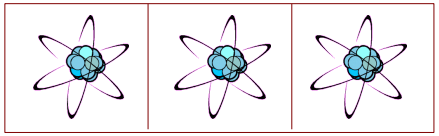
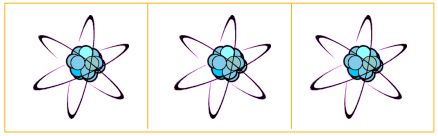
4. Alert Threshold

- How many different signatures must be matched by a program before an alert is raised
- Signatures are matched in no particular order







Too Simple?

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- Why only sequences, tuples, and bags?
  - Because it is important to assess the limitations of basic models before new research delves into increasingly more complex models
  - Because they are the basic blocks to compose more complex models
- What about complex structures?
  (previous studies often adopted tree or graph-like structures)
  - Combinations of basic structures (n-grams, bags, and tuples) have the same expressive power of DAG
  - For example, it is possible to use sequences to enumerate all paths in a tree or loop-free graph

Experiment Goals

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- Are programs' behaviors better characterized by complex structures, or simple ones?
- How do different parameters affect the models ability to distinguish between benign and malicious behaviors?
- Does moving to more abstract atoms improve detection?
- Which is the best combination of parameters, that:
  - maximizes the detection rate?
  - minimizes the false positives?

Datasets

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`[malware]` – 6,000 malware traces from Anubis
(training for malicious behavior)

`[goodware]` – the 180GB of traces collected with our collector
(training for benign behavior and testing for FP)

`[anubis-good]` – traces of 36 benign apps run in Anubis
(filtering Anubis-specific artifacts)

`[mal-test]` – 1,200 malware traces from a *different* Anubis machine
(used for testing the detection rate)

Datasets

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`[malware]` – From all existing malware categories (botnets, worms, trojans, droppers)

`[goodware]` – the 180GB of traces collected with our collector (training for benign behavior and testing for FP)

`[anubis-good]` – traces of 36 benign apps run in Anubis (filtering Anubis-specific artifacts)

`[mal-test]` – 1,200 malware traces from a *different* Anubis machine (used for testing the detection rate)

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Datasets

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`[malware]` – 6,000 malware traces from Anubis
(training for malicious behavior)

`[goodware]` – Kernel module that intercepts syscalls and extracts all the parameters
Collected on 10 real user machines (not under our control) for about a week: 1.56 billions syscalls, 242 unique benign applications, 362,000 process executions

`[anubis-good]` – traces of 36 benign apps run in Anubis
(filtering Anubis-specific artifacts)

`[mal-test]` – 1,200 malware traces from a *different* Anubis machine
(used for testing the detection rate)

Datasets

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Signature Generation

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For each model (e.g., “7-bags of syscalls with parameters”):

1. We extract ALL possible combinations from the `malware` dataset
   - May include pruning (see following slides)
2. We remove the ones that match the `anubis-good` dataset
3. We create the signatures by removing all the ones that match 9 out of 10 `goodware` machines
4. We test the false positives of the signature set on the 10th machine, and the detection rate on the `malware-test` dataset
   - Results are extracted for all possible values of the matching threshold
5. We repeat from step 3 for a total of 10 times (for each excluded machine) and we compute the average between all runs

Signature Generation

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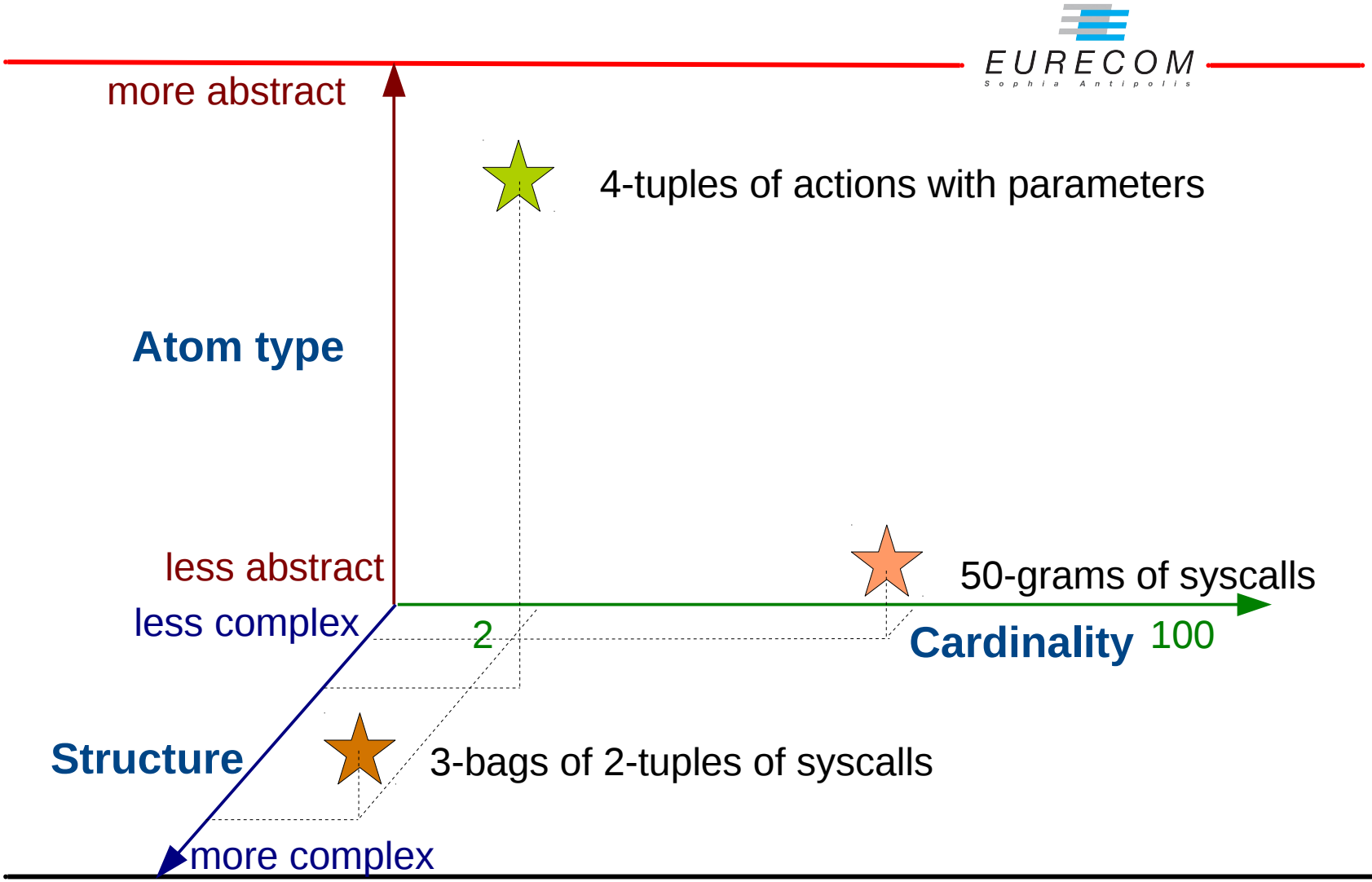
- For certain models, extracting all the possible combinations is computationally infeasible
  - e.g., extracting 3-tuples from a sample of 5000 atoms:

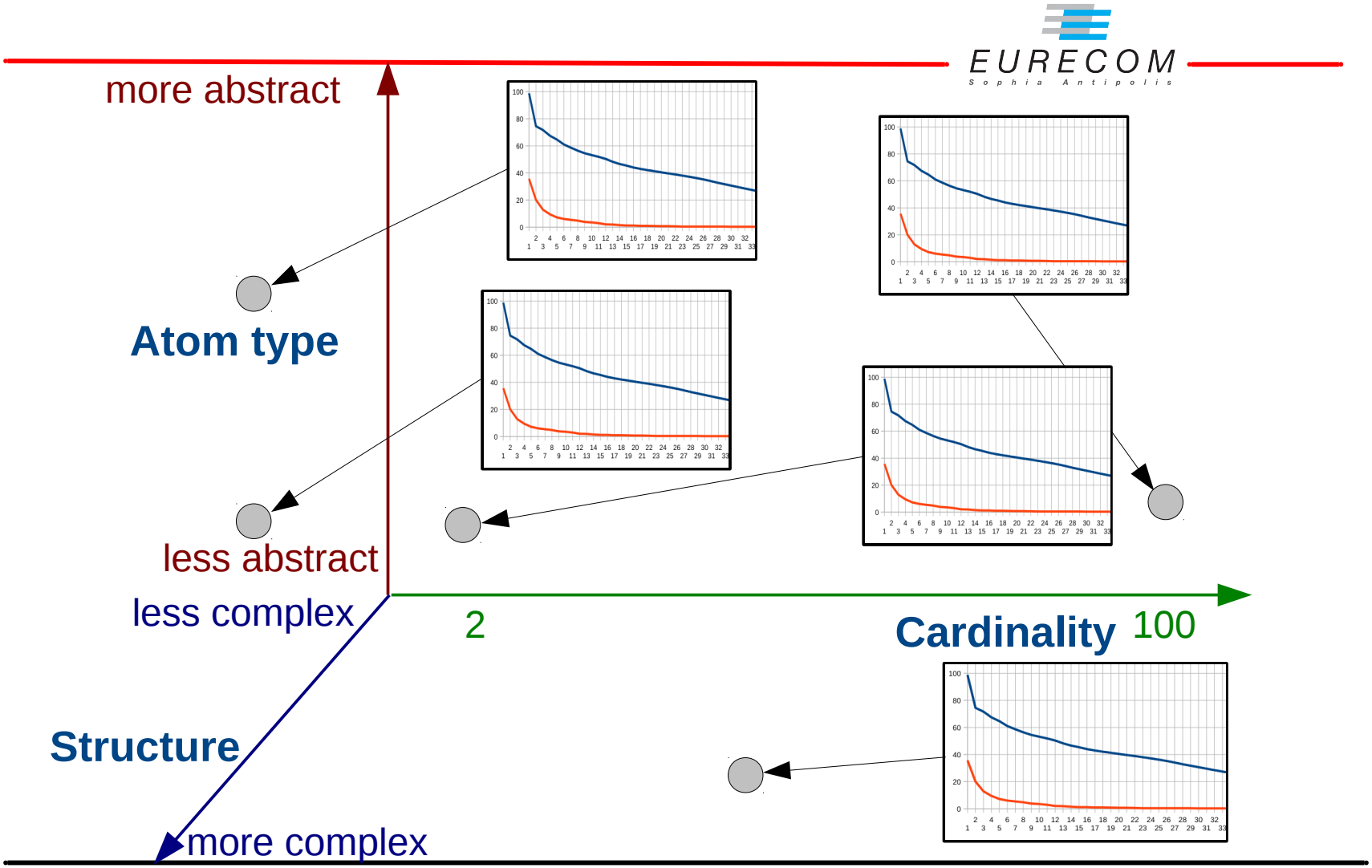
$$\binom{5000}{3} \approx 20.8 \times 10^{9} \text{ combinations!}$$

- Pruning. A combination is generated only if:
  - It covers a minimum of 5 malware samples that are not already covered by at least 20,000 other signatures
    - The first threshold prevents overfitting
    - The second threshold prevents the generation of too many signatures for the same sample
- It is a greedy approach... it does not guarantee an optimal result

Exploring the Model Space



What happens if we move along the axes?



Key Indicators

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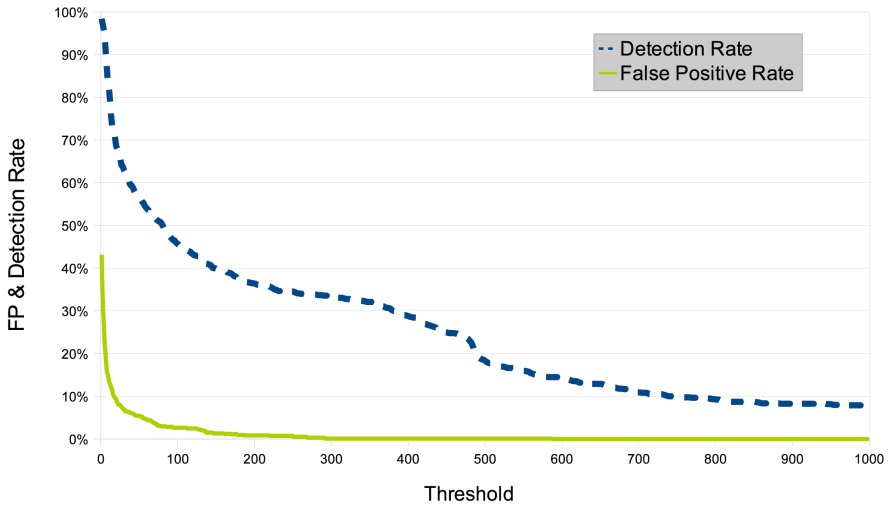
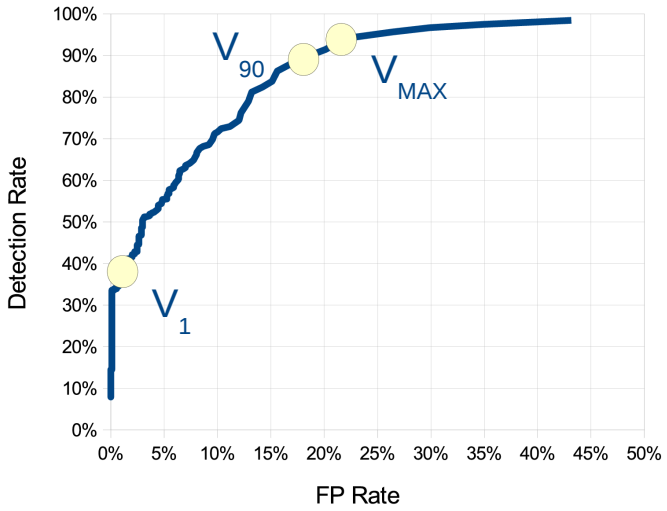
Used to compare the models





V_1 – point in which the model provides 1% FP rate

V_{90} – point in which the model provides 90% detection

V_{MAX} – point in which the area under the ROC curve is max

Evaluation

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- We explored all the significant points in the model space
  - Some points are not significant, e.g. “n-grams of bags” would not make any sense
  - We stopped increasing the cardinality once we saw the detection rate of the model was always decreasing and V_{MAX} dropped below 0.2
- 215 different detection models analyzed
- More than 220 million signatures generated

General Results

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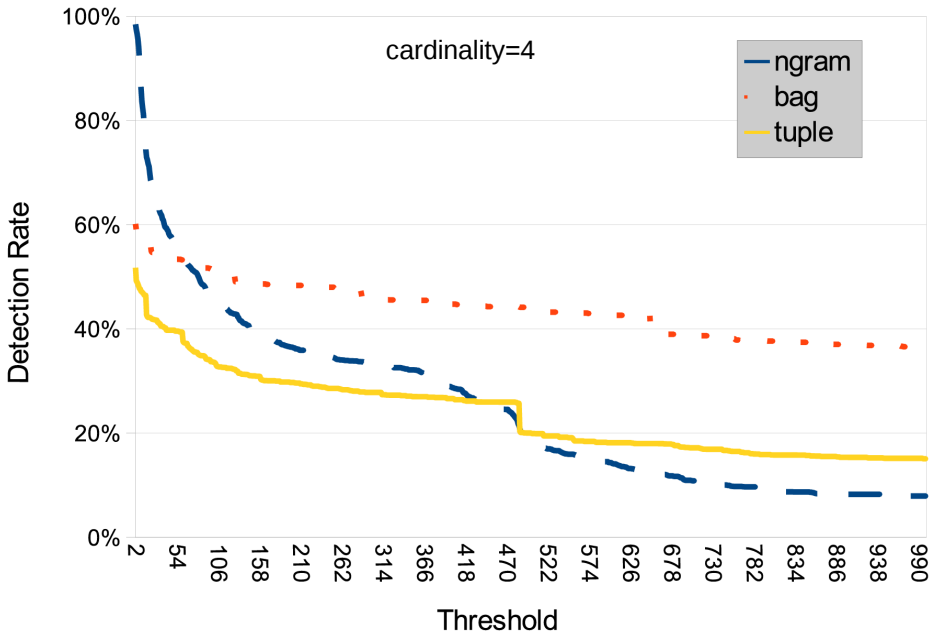
- Signature extraction
  - Extraction times ranged between 20 minutes and 2 days per model (on a 4-core Xeon machine with 16GB of RAM)

- Findings:
  - All models without parameters perform really bad (too generic)
  - Also signatures with high cardinality perform quite bad
    - But remember that we are looking for “general” signatures that can match multiple samples
  - The best model is “2-bags of 2-tuples of actions, with parameters”: 99% detection with 0.4% FP (variance of 0.00016)

Table 3: Evaluation summary of different types of models.

Model	Cardinality Range	V_{max}	Best Cardinality	V_{90}	V_1
n-grams of syscalls	2–40	0.615	10	31.7%	4.1%
n-grams of syscalls with args	2–40	0.775	3	15.8%	43.3%
n-grams of action	2–75	0.423	15	62.2%	0.4%
n-grams of action with args	2–75	0.737	2	27.1%	45.9%
bags of syscalls	1–10	0.127	3	–	12.8%
bags of syscalls with args	1–20	0.736	1	26.4%	43.3%
bags of actions	1–10	0.004	1	–	–
bags of actions with args	1–15	0.970	4	0.4%	97.3%
tuples of syscalls	2–10	–	–	–	–
tuples of syscalls with args	2–10	0.616	2	–	28.0%
tuples of actions	2–10	–	–	–	–
tuples of actions with args	2–10	0.987	2	0.0%	99.2%
bags of n-grams of syscalls	2–4/2–4	0.500	2/2	–	8.2%
bags of n-grams of syscalls with args	2–4/2–4	0.648	2/4	–	30.2%
bags of n-grams of action	2–4/2–4	0.111	3/4	–	–
bags of n-grams of action with args	2–4/2–4	0.529	2/3	–	22.0%
bags of tuples of syscalls	2-4/2-4	–	–	–	–
bags of tuples of syscalls with args	2-4/2-4	0.497	2/2	–	33.8%
bags of tuples of action	2-4/2-4	–	–	–	–
bags of tuples of action with args	2-4/2-4	0.990	2/2	0.42%	–
tuples of n-grams of syscalls	2-4/2-4	0.509	2/2	–	2.9%
tuples of n-grams of syscalls with args	2-4/2-4	0.624	2/3	–	26.5%
tuples of n-grams of action	2-4/2-4	0.142	3/4	–	0.1%
tuples of n-grams of action with args	2-4/2-4	0.536	2/2	–	24.9%
tuples of bags of syscalls	2-4/2-4	–	–	–	–
tuples of bags of syscalls with arguments	2-4/2-4	0.480	2/2	–	32.4%
tuples of bags of actions	2-4/2-4	–	–	–	–
tuples of bags of actions with arguments	2-4/2-4	0.873	2/2	–	–

Impact of Matching Threshold



- Both the detection rate and the false positives decrease when the matching threshold is increased
  - The drop is faster for models based on a semantically rich set of atoms (e.g., syscalls with parameters)

Impact of Signature Cardinality

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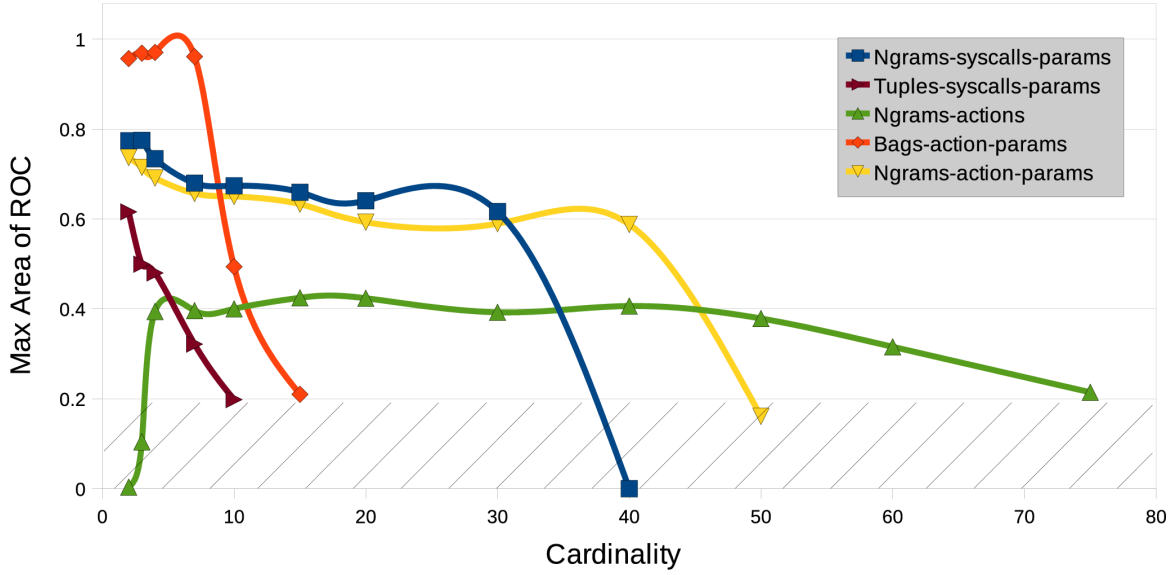
- For low values of the cardinality, adding atoms to the signatures can improve the results
  - Increasing the cardinality above 10 generates signatures that over-fit the malware training dataset, thus decreasing detection (too specific)
  - Recursive structures show similar trends, but drop faster than simple ones



Impact of Atoms and Signature Structure

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- Models based on low-level atoms (syscalls)
  - n-grams > bags > tuples
- Models based on high-level atoms (actions)
  - tuples > bags > n-grams

- Recursive structures
  - Tuples and bags provide better results than n-grams
  - Best with high-level atoms (actions) with parameters

Impact on Performances

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- Prototype testing on 12 hours of user activity
  - In python → can be implemented more efficiently

Number of signatures	Memory consumption	CPU time		
		ngrams	bags	tuples
250,000	144.7 MB	25 min	26 min	29 min
1,000,000	359.6 MB	31 min	32 min	35 min
5,000,000	1.0 GB	43 min	46 min	58 min

- High numbers of signatures lead to high memory consumption
  - The number of signatures is related to the signature cardinality
  - Signatures of high cardinality may be difficult to employ in real world deployments

Limits of Analytical Reasoning

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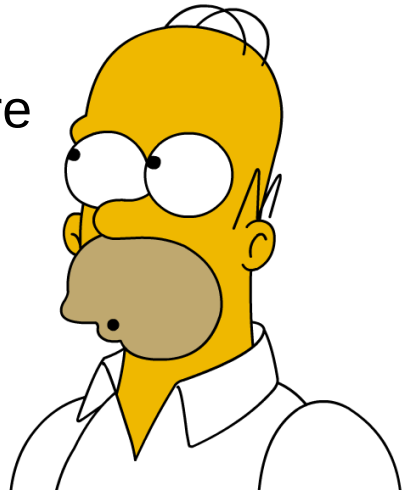
- It is very tempting to propose rules, based on intuitions, about the models and their accuracy
- Example:
  - Increasing the cardinality makes the signatures more specific and, therefore, less likely to match on both the goodware and the malware datasets
  - Therefore, a model based on 3-grams should generate less false positives than a model based on 2-grams
  - Similarly a model based on 3-bags generates more false positives than one based on 3-grams



Wrong!

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- Extending the property of a signature to the property of the models based on that signature is a very common pitfall
  - Changing a parameter does not only change the matching, but also the number of signatures extracted!
  - Against common sense, making the signatures more specific can, in some cases, increase the FP of the entire model

Malware: (a1, a2, a3, a4, a5)
Goodware: (a3, a1, a2, a5, a4, a2, a3)
Signatures:
  2-grams: ?
  3-grams: ?
  k-bags: ?

Wrong!

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Malware: (a1, a2, a3, a4, a5)
Goodware: (a3, a1, a2, a5, a4, a2, a3)
Possible combinations from malware trace:
2-grams: [a1,a2] [a2,a3] [a3,a4] [a4,a5]
3-grams: [a1,a2,a3] [a2,a3,a4] [a3,a4,a5]
2-bags: {a1,a2} {a1,a3} {a1,a4} {a1,a5} {a2,a3} {a2,a4} {a2,a5} {a3,a4} {a3,a5} {a4,a5}

Wrong!

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Malware: (a1, a2, a3, a4, a5)
Goodware: (a3, a1, a2, a5, a4, a2, a3)
Signatures:
2-grams: ~~[a1,a2]~~ ~~[a2,a3]~~ [a3,a4] [a4,a5]
3-grams: [a1,a2,a3] [a2,a3,a4] [a3,a4,a5]
2-bags: ~~{a1,a2}~~ ~~{a1,a3}~~ ~~{a1,a4}~~ ~~{a1,a5}~~ ~~{a2,a3}~~ ~~{a2,a4}~~ ~~{a2,a5}~~ ~~{a3,a4}~~ ~~{a3,a5}~~ ~~{a4,a5}~~

(same for 3-bags)

Wrong!

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- Extending the property of a signature to the property of the models based on that signature is a very common pitfall
  - Changing a parameter does not only change the matching, but also the number of signatures extracted!
  - Against common sense, making the signatures more specific can, in some cases, increase the FP of the entire model

Malware: (a1, a2, a3, a4, a5)
Goodware: (a3, a1, a2, a5, a4, a2, a3)
Signatures:
2-grams: [a3,a4] [a4,a5]
3-grams: [a1,a2,a3] [a2,a3,a4] [a3,a4,a5]
k-bags: none

Conclusions

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- The three indicators (V_1, V_{90}, V_{max}) don't always provide consistent results
  - The best model depends on the optimization goal

- Empirical testing is fundamental
  - We showed it's easy to fall in common pitfalls when trying to generalize results
  - Future works should be supported by strong evaluation
    - » Avoid a-priori rules!

Thank you

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For further questions, suggestions, comments:

andrew@iseclab.org

Backup Slides

Behavioral Detection (in Academia)

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- "Static-Aware Malware Detection" -
  - Model: templates based on instruction sequences where variables and symbolic constant are used
  - Generation: Manual
  - Dataset: 2 templates tested on 3 malware families
    200k small benign executables (less than 1.5KB each)
  - Assume it is possible to reliably disassemble the programs
- "Mining Specifications of Malicious Behavior" - FSE 07
  - Model: DAG of syscalls (no parameters) generated by comparing benign and malicious programs executions
  - Generation: Automatic
  - Dataset: 16 malware samples, 4 benign applications run for 1 minute each

Behavioral Detection (in Academia)

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- "Effective and Efficient Malware Detection at the End Host" - Usenix 09
  - Model: graph of syscalls + program slices to compute the parameter t ransformations to infer data-flow
  - Generation: Automatic
  - Dataset: 563 malware samples belonging to 6 families, 5 goodware, 1 machine
  - Result: 92% detection on same families, 23% otherwise (5% to 40% overhead)
- "A layered Architecture for Detecting Malicious Behaviors" - RAID 08
  - Model: 3-layer graph (syscalls, similar actions, aggregate/composite effects) for 7 suspicious behaviors (e.g., download and execute, data leak, tcp proxy, ...)
  - Generation: Manual
  - Dataset: 7 malware, 11 goodware
  - Performance: require QEMU + taint analysis + mouse/keyboard tracking
    Up to 34x slowdown

Behavioral-Based Models (AV Companies)

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- Very few (if any) details available
- Often mentioned in web-pages and press releases
  - Not much against evasions, but more as a "*Signature-less technique to detect unknown malware*"
- Adopted (?) by all vendors...
  - Sana Security SafeConnect (2005?)
    - » Acquired by AVG in 2009
  - Symantec SONAR (2007)
  - Panda TruePrevent (2007)
  - NovaShield (2008)

Extracting Signatures

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```
NtOpenKey("SYSTEM\Cu ... 70B}", 131097)
NtQueryValueKey(1640, "EnableDHCP", 2)
NtQueryValueKey(1640, "DhcpServer", 2)
NtQueryValueKey(1640, "DhcpServer", 2)
NtClose(1640)
NtCreateFile("\\Device\...", 3, 0)
NtClose(1641)
```

Extracting Signatures

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```
NtOpenKey("SYSTEM\Cu ... 70B}", 131097)
NtQueryValueKey("SYS...", "EnableDHCP", 2)
NtQueryValueKey("SYS...", "DhcpServer", 2)
NtQueryValueKey("SYS...", "DhcpServer", 2)
NtClose("SYS...")
NtCreateFile("\\Device\...", 3, 0)
NtClose("\\Devi...")
```

Normalization

Extracting Signatures

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```
NtOpenKey("SYSTEM\Cu ... 70B}", 131097)
NtQueryValueKey("SYS...", "EnableDHCP", 2)
NtQueryValueKey("SYS...", "DhcpServer", 2)
NtQueryValueKey("SYS...", "DhcpServer", 2)
NtClose("SYS...")
NtCreateFile("\\Device\...", 3, 0)
NtClose("\\Devi...")
```

S1: `NtOpenKey("SYSTEM\Cu …", 131097)`

S2: `NtQueryValueKey, NtQueryValueKey, NtQueryValueKey`

S3: `ReadKeyValue("SYSTEM\Cu …\EnableDHCP")`

Goodware Dataset

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- Kernel module to intercept syscalls and extract all the parameters
  - 79 different system calls in 5 categories (filesystem, networking, registry, memory)
- Collected on 10 real user machines (not under our control) for about a week
  - 1.56 billions syscalls
  - 242 unique benign applications
  - 362,000 process executions
  - 180 GB of execution traces

Data Collection (goodware)

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- We run our module on 10 real user machines (not under our control) for about a week
  - 4 Home/Laptop machines
  - 1 Office
  - 1 Lab
  - 2 production
  - 2 development
- Collected data:
  - 1.56 billions syscalls
  - 242 unique benign applications
  - 362,000 process executions
  - 180 GB of execution traces

Data Collection (malware)

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- Malicious samples extracted from Anubis
  - 6000 random samples of active malware
  - From all existing malware categories
    - Botnets
    - Worms
    - Trojans
    - Droppers
    - ...

Normalization datasets

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- 1200 additional samples from Anubis
  - Extracted from a different machine than the ones used in production
  - Still from multiple malware families
  - Named 'malware-test'
- 36 execution traces of benign applications
  - Executed under Anubis
  - Named 'anubis-good'
- Purpose of these two datasets:
  - Eliminating any machine-specific artifacts that may introduce noise in our evaluation results

Impact of Pruning Techniques

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- Our pruning approach is greedy
  - The extracted signatures depend on the order of the samples in the training set
- We picked one model, and built signatures with 3 different orderings of the training samples, with any cardinality
  - Different orderings sensibly affect the number of extracted signatures
  - The 3 key indicators are only marginally affected
    - Fluctuations of 3% max.
  - The trends between different models were not affected

Impact on Performances

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- Prototype testing on 12 hours of user activity
  - In python → can be implemented more efficiently

Number of signatures	Memory consumption	CPU time		
		ngrams	bags	tuples
250,000	144.7 MB	25 min	26 min	29 min
1,000,000	359.6 MB	31 min	32 min	35 min
5,000,000	1.0 GB	43 min	46 min	58 min

- High numbers of signatures lead to high memory consumption
  - The number of signatures is related to the signature cardinality
  - Signatures of high cardinality may be difficult to employ in real world deployments

Number of Signatures

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- Extracting and matching signatures that contain a large number of elements is extremely time consuming
- n-grams
  - Signature numbers keep growing linearly with cardinality
  - Those that actually contribute to detection decrease for cardinalities higher than 10 (overfitting)
- Bags
  - Very high number of signatures (because too general)
- Sequences
  - Similar to n-grams, but more matching signatures

Insights on Signatures

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- Most of the FPs are generated by signatures related to registry operations
  - Top ten registry keys associated to autostart locations were more often a cause of false positives than detection
- The “best” signatures often contained the `LoadLibrary` action
- Tuples perform better than bags not because of their ordering, but because they can model repetitions

Table 3: Evaluation summary of different types of models.

Model	Cardinality Range	V_{max}	Best Cardinality	V_{90}	V_1
n-grams of syscalls	2–40	0.615	10	31.7%	4.1%
n-grams of syscalls with args	2–40	0.775	3	15.8%	43.3%
n-grams of action	2–75	0.423	15	62.2%	0.4%
n-grams of action with args	2–75	0.737	2	27.1%	45.9%
bags of syscalls	1–10	0.127	3	–	12.8%
bags of syscalls with args	1–20	0.736	1	26.4%	43.3%
bags of actions	1–10	0.004	1	–	–
bags of actions with args	1–15	0.970	4	0.4%	97.3%
tuples of syscalls	2–10	–	–	–	–
tuples of syscalls with args	2–10	0.616	2	–	28.0%
tuples of actions	2–10	–	–	–	–
tuples of actions with args	2–10	0.987	2	0.0%	99.2%
bags of n-grams of syscalls	2–4/2–4	0.500	2/2	–	8.2%
bags of n-grams of syscalls with args	2–4/2–4	0.648	2/4	–	30.2%
bags of n-grams of action	2–4/2–4	0.111	3/4	–	–
bags of n-grams of action with args	2–4/2–4	0.529	2/3	–	22.0%
bags of tuples of syscalls	2-4/2-4	–	–	–	–
bags of tuples of syscalls with args	2-4/2-4	0.497	2/2	–	33.8%
bags of tuples of action	2-4/2-4	–	–	–	–
bags of tuples of action with args	2-4/2-4	0.990	2/2	0.42%	–
tuples of n-grams of syscalls	2-4/2-4	0.509	2/2	–	2.9%
tuples of n-grams of syscalls with args	2-4/2-4	0.624	2/3	–	26.5%
tuples of n-grams of action	2-4/2-4	0.142	3/4	–	0.1%
tuples of n-grams of action with args	2-4/2-4	0.536	2/2	–	24.9%
tuples of bags of syscalls	2-4/2-4	–	–	–	–
tuples of bags of syscalls with arguments	2-4/2-4	0.480	2/2	–	32.4%
tuples of bags of actions	2-4/2-4	–	–	–	–
tuples of bags of actions with arguments	2-4/2-4	0.873	2/2	–	–