Efficient and Interpretable Real-Time Malware Detection Using Random-Forest

NODENS

Scope

- Current State of Play
- Project Overview - NODENS
- Proposed Method
- Dataset
- Results
- Interpretability
- Further Work

Current State of Play

- Machine learning used in lots of proof-of-concept models or as augmentation
- Use of Machine-Learning that incorporate existing tools
  - Cuckoo, Sandbox, Anubis, HookMe
- High accuracy, but incur a time penalty
- Computationally expensive
- Little work on the interpretability of decisions

Project Overview – NODENS

- Malware detection system using Machine Learning
- Identify malware using ‘process signatures’
- Lightweight – can be deployed from a Pi (Tested on a Pi 2B)
- Interpretable output – without sacrificing speed or accuracy
- Average detection speed of 3 – 8 seconds
- Use of re-fitting and end user input

Proposed Method

- PowerShell was used to collect process data from the target VM.
  - Chosen as it could be ported between Windows and Linux systems
- Produces 64 features as raw output
- Reduced down to 22 used for classification
- During initial training a Legitimate label was appended to each process, to allow supervised training of the classifier(s)
- For each entry the process Name is used as the index

Proposed Method

- Features used during training

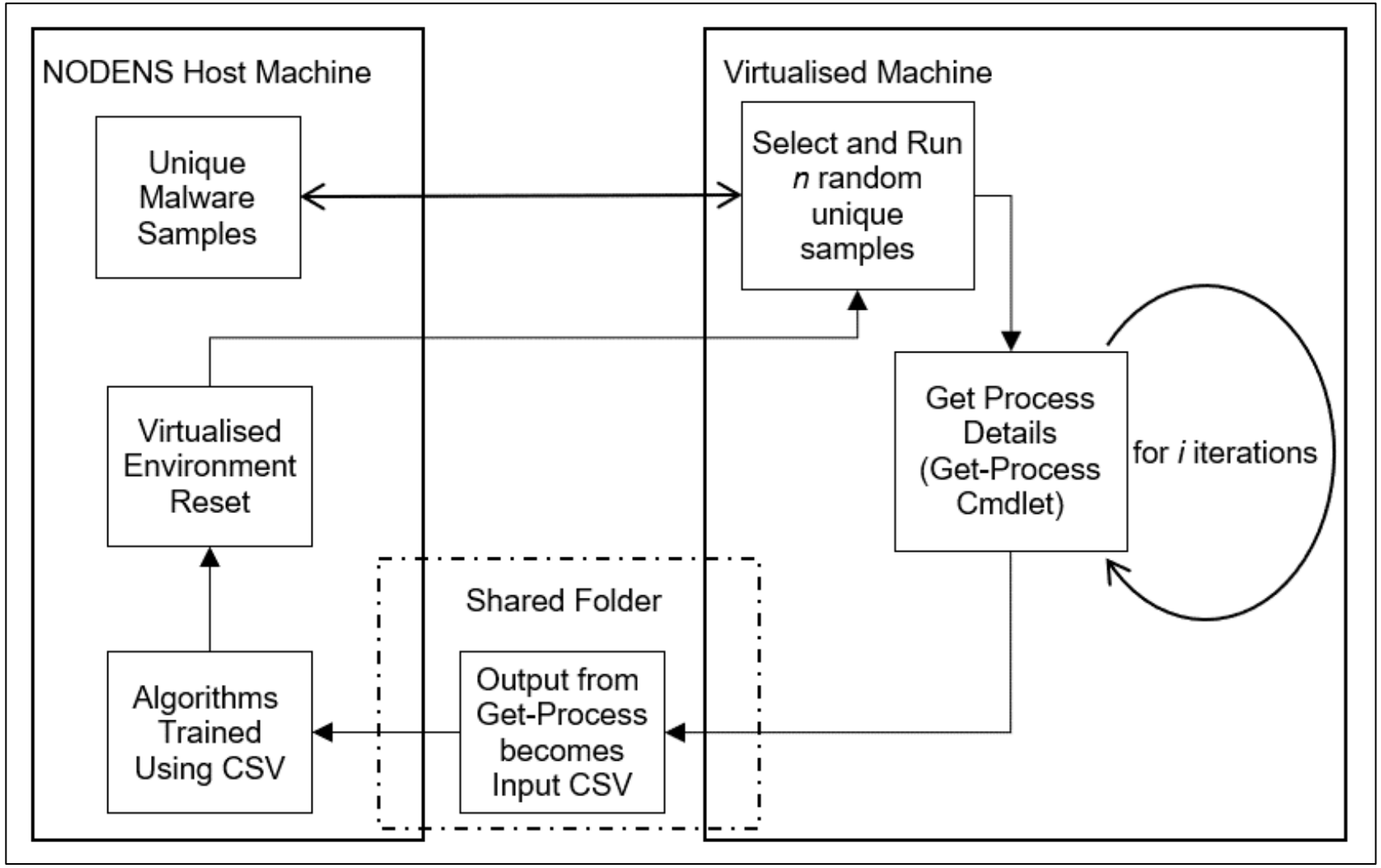
1. Handles
2. Path
3. Company
4. Description
5. Product
6. HasExited
7. Handle
8. HandleCount
9. NonpagedSystemMemorySize64
10. PagedMemorySize64
11. PagedSystemMemorySize64
12. PeakPagedSystemMemorySize64
13. PeakWorkingSet64
14. PeakVirtualMemorySize64
15. PrivateMemorySize64
16. PrivilegedProcessorTime
17. ProcessorAffinity
18. Responding
19. TotalProcessorTime
20. UserProcessorTime
21. VirtualMemorySize64
22. WorkingSet64

Proposed Method

- Multiple algorithms were tested against a pool of 55 malware samples
- *n* samples were randomly selected and run 10 times
- Each time the virtual environment was reset to a clean default state
- Features were captured, manually labelled and tested against:

Random-Forest	KNearestNeighbour	GradientBoosting
GNB	AdaBoost	LogisiticRegression
DecisionTree	SVC	OneClassSVM

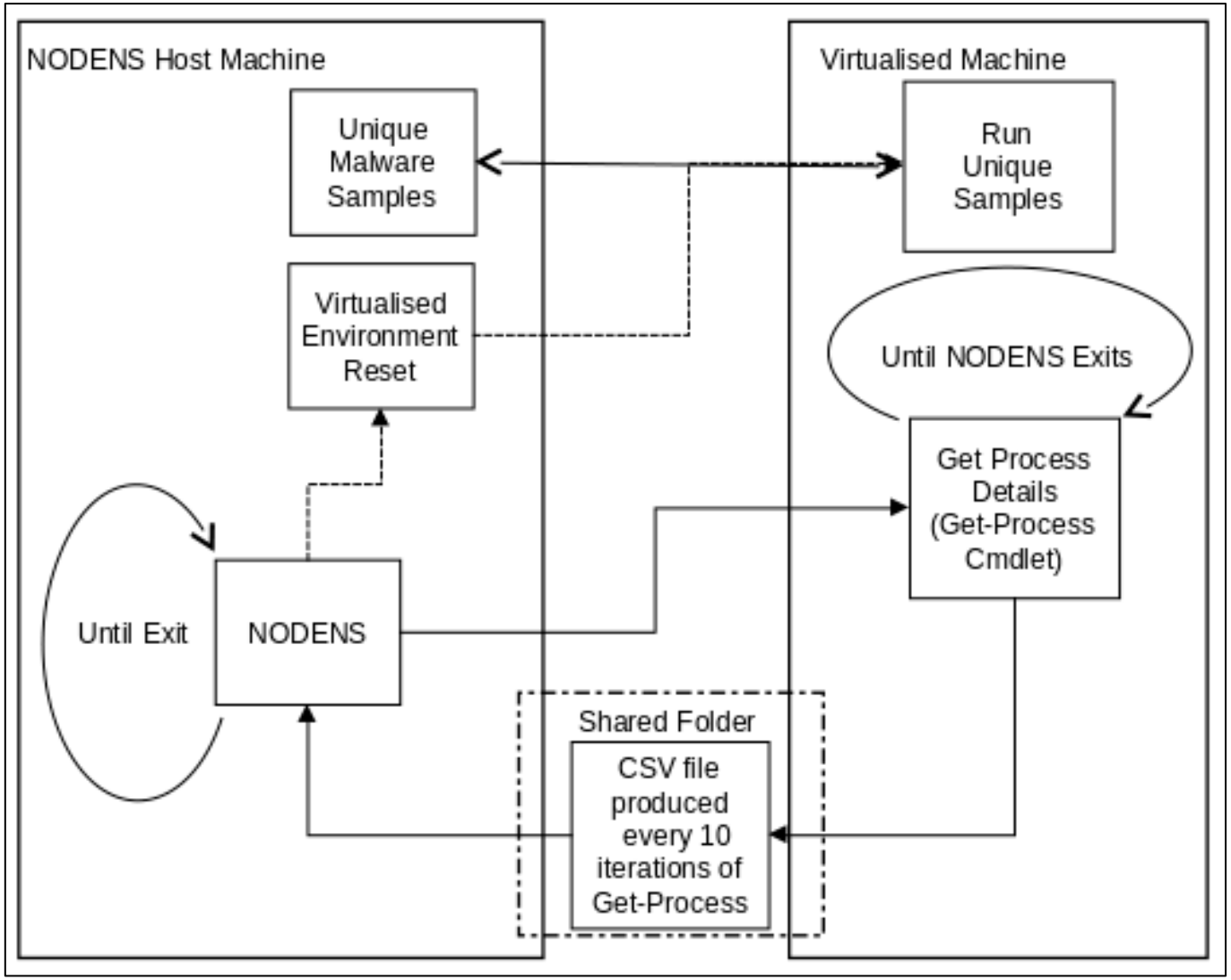
Proposed Method



Proposed Method

- A Random-Forest classifier was trained on all combined training data
- Live testing started, but with an initial detection delay of 30 seconds
- The classifier and supporting scripts were modified and the delay reduced to 3-8 seconds
- Feature selection was found to negatively effect accuracy, so removed and re-trained

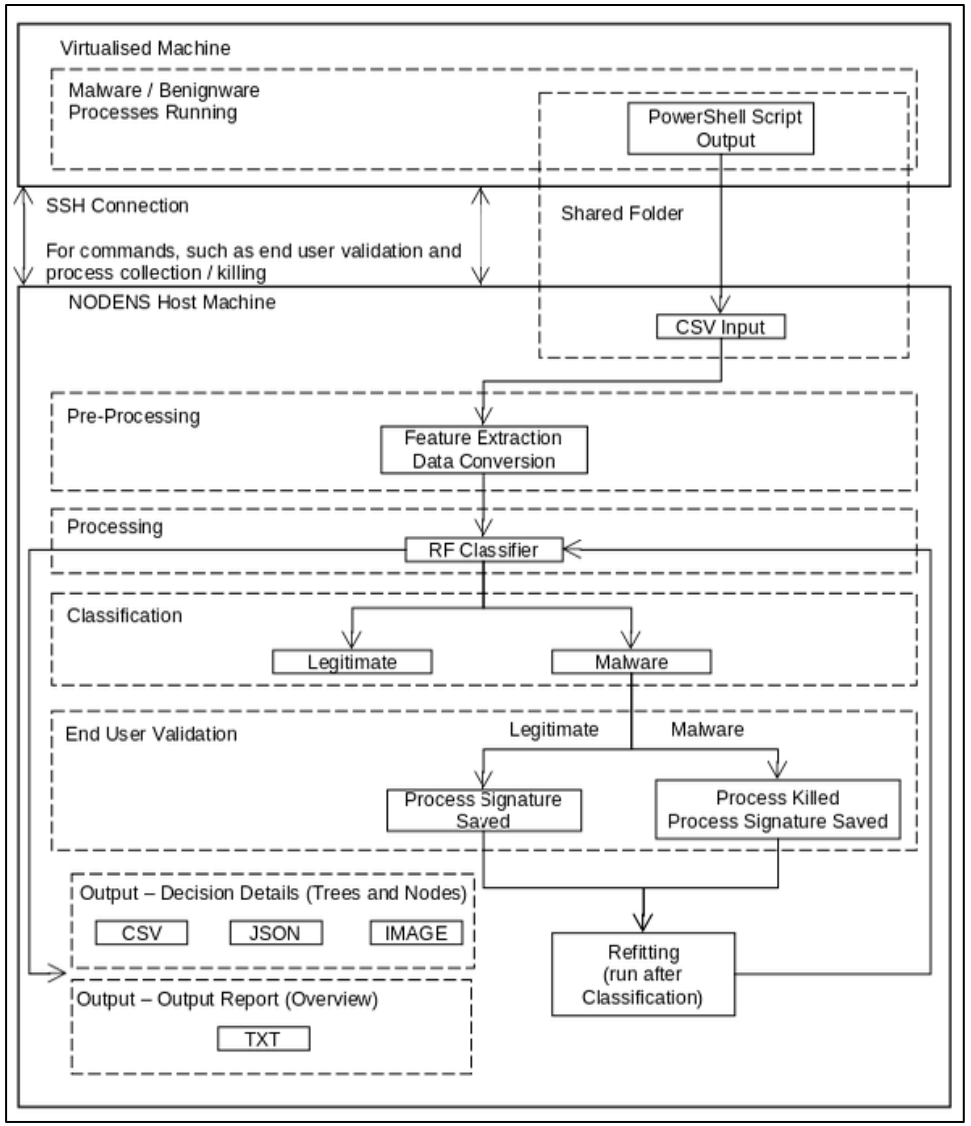
Proposed Method



Proposed Method

- Command line interface to allow for validation or countering of decisions
- Modular ‘plug-in’ scripts
  - Start and Stop data collection and detection
  - Termination of malicious processes
  - Re-fitting of classifier

Proposed Method



Dataset

- A total of 146 malware samples overall (all from OS repositories)
- A total of 1,048,575 processes

Process Classification	Number	Percentage
Malware	95,191	9%
Benignware	953,384	91%

- Malware processes were all PE32 (.exe)
- Benginware included
  - Background Processes
  - Third party software
  - Portable Apps

Dataset

Malware Classification	Number	Percentage
Trojan	47	93%
Ransomware	15	100%
Spyware	15	100%
RAT	7	100%
Bit Coin Miner	3	100%
Process Injector	3	100%
Virus	1	100%

Dataset – Refitting

- Refitting was included to allow NODENS to ‘learn’ from the malware data
- New process data was saved in a .csv and appended to the training dataset
  - This included benignware processes captured within the same time period
- Re-trained using a pickle warm-start
- As a result the training dataset is continually expanding

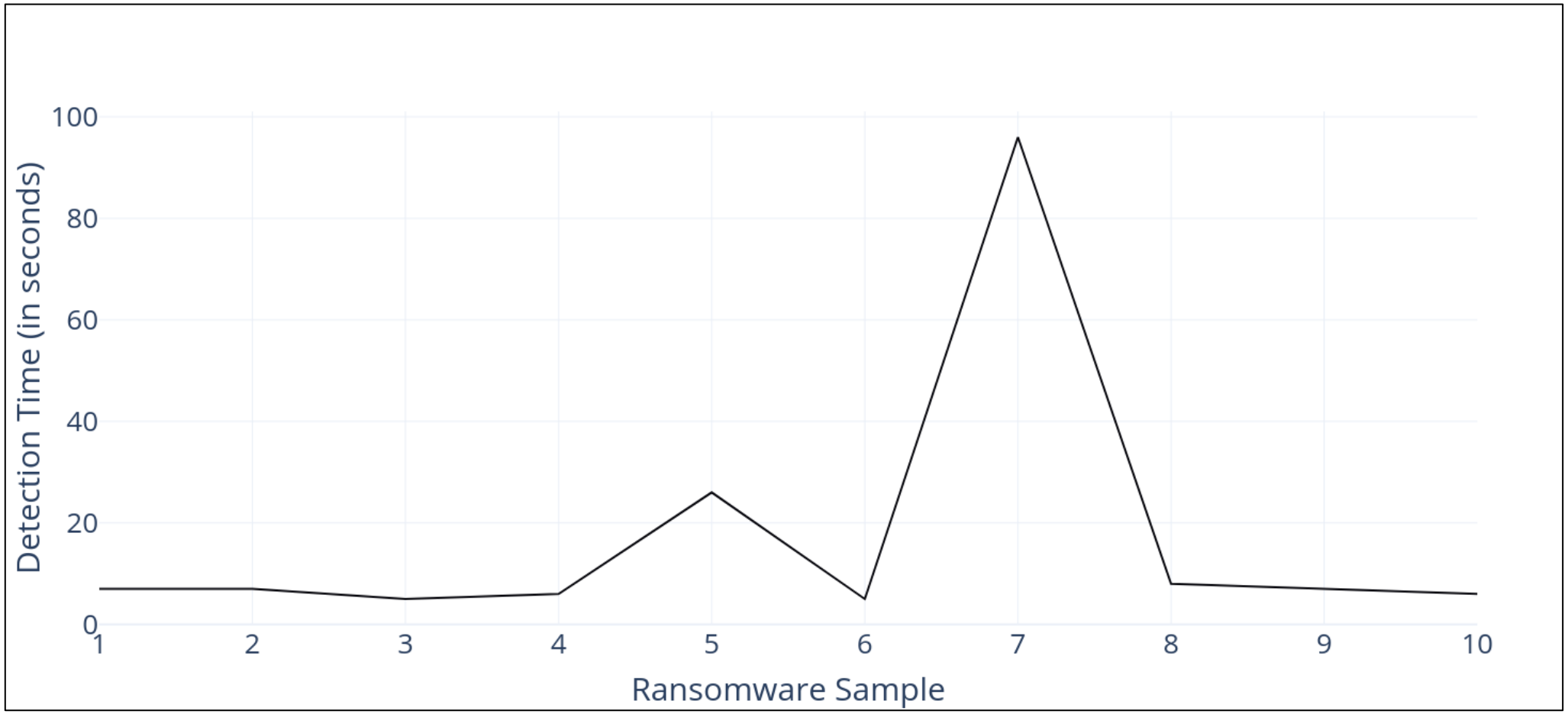
Dataset – Refitting

- Refitting was effective in two ways
    1. It showed that NODENS was able to ‘learn’, having identified 5 samples through refitting
    2. This indicates that (among the samples tested) there is an underlying pattern to behaviour which does indicate a process is malicious

Dataset – Ransomware

- Dedicated ransomware test was conducted
- 10 unique samples of ransomware
- On average detection was within 9 seconds
- Two outliers
    1. 96 seconds
    2. 30 seconds

Dataset – Ransomware



Dataset – Ransomware

- Ransomware was encrypting the CSV process details
- Each time NODENS was forced to wait for a new file
- More robust design is required

Dataset – Persistence

- In addition to OS malware NODENS was tested against custom malware
- Persistent malware created using msfvenom
- NODENS was able to detect all created malware
- It was unable to defeat persistence
  - Assessed to be linked to a lower memory footprint when re-initialised

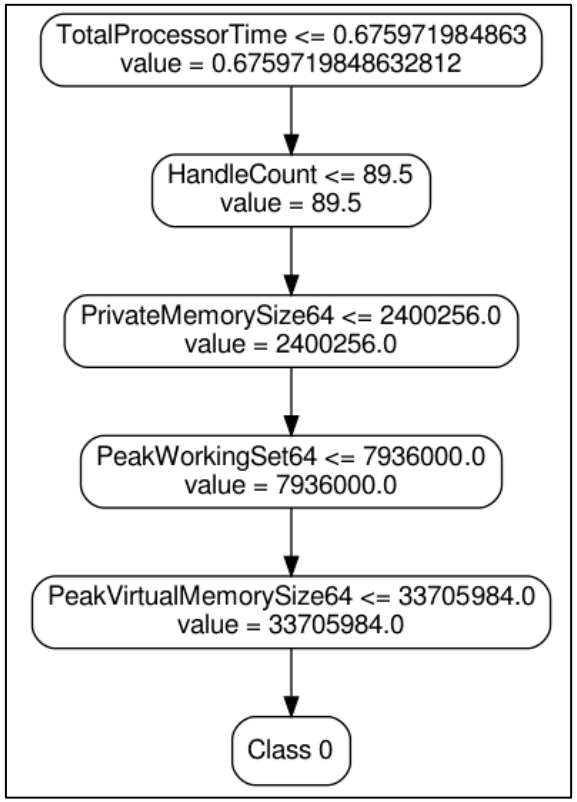
Interpretability

- Initially through manual interrogation of raw CSV process output
  - Removal of feature selection made this un-workable
- Modified to produce multiple output formats at point of decision
  - CSV
  - JSON
  - DOT
  - PNG

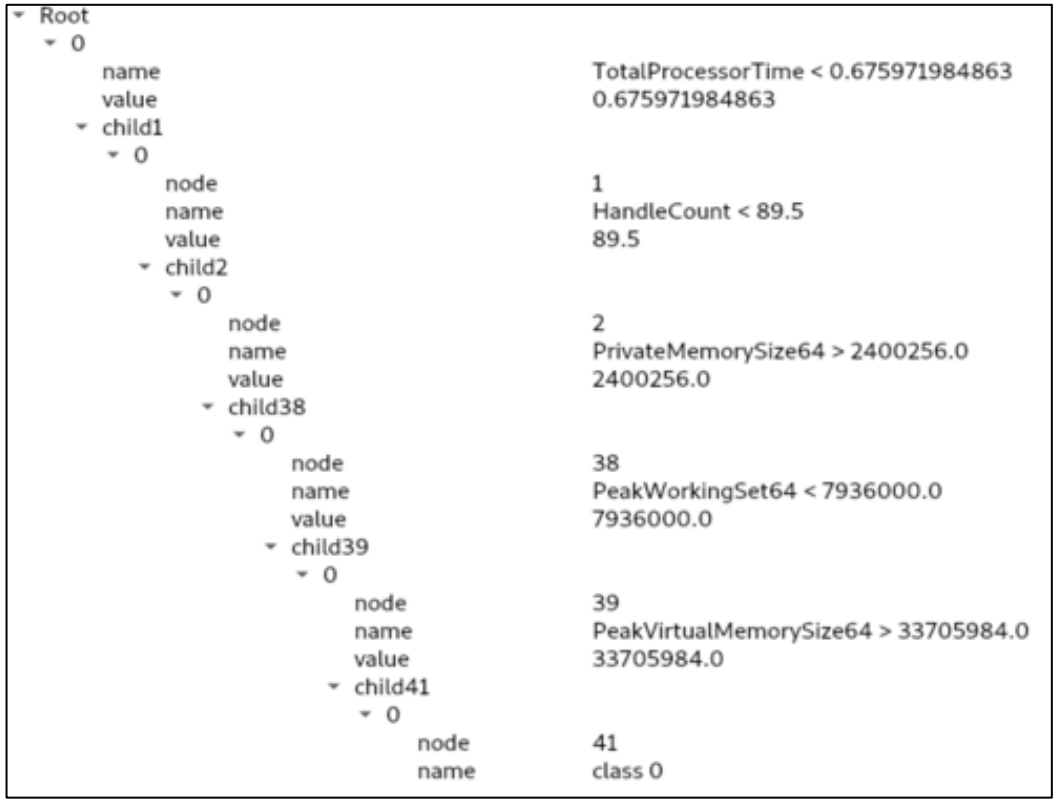
Interpretability

TREE: 41
0 NODE: feature[ProcessorAffinity] > 0.5 next=76
76 NODE: feature[HasExited] < 0.5 next=77
77 NODE: feature[PeakVirtualMemorySize64] < 94238720.0 next=78
78 NODE: feature[UserProcessorTime] < 0.0150215998292 next=79
79 NODE: feature[PagedSystemMemorySize64] < 103664.0 next=80
80 LEAF: return class=0
TREE: 42
0 NODE: feature[TotalProcessorTime] < 0.675971984863 next=1
1 NODE: feature[HandleCount] < 89.5 next=2
2 NODE: feature[PrivateMemorySize64] > 2400256.0 next=38
38 NODE: feature[PeakWorkingSet64] < 7936000.0 next=39
39 NODE: feature[PeakVirtualMemorySize64] > 33705984.0 next=41
41 LEAF: return class=0
TREE: 43
TREE: 44
0 NODE: feature[TotalProcessorTime] < 0.675971984863 next=1
1 NODE: feature[PrivilegedProcessorTime] > 0.00500719994307 next=71
71 NODE: feature[PeakVirtualMemorySize64] < 66170880.0 next=72
72 NODE: feature[NonpagedSystemMemorySize64] > 2316.0 next=84
84 NODE: feature[HandleCount] < 68.0 next=85
85 NODE: feature[PeakVirtualMemorySize64] < 53284864.0 next=86
86 NODE: feature[PeakWorkingSet64] < 5062656.0 next=87
87 NODE: feature[Description] < 0.5 next=88
88 LEAF: return class=0

CSV output

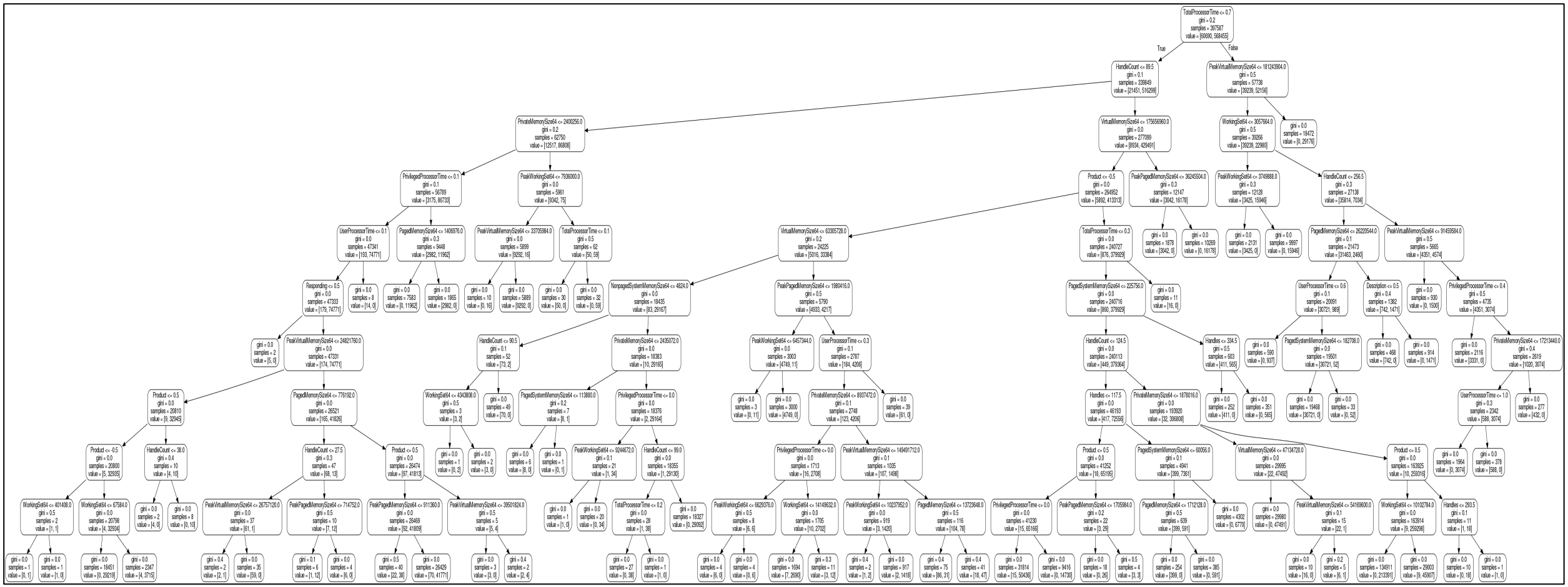


DOT output



JSON output

Interpretability



PNG output

Results

- Binary values
  - Benignware samples were largely True or False for all
  - Malware samples showed a greater variance
- Variable data
  - Benignware processes had on average a higher score
  - Some Malware and Benignware processes within the same ‘score bracket’
  - Malware processes had (on average) higher amounts of private data

Results

- Decision specific data allowed the confirmation of assessments from manual interrogation
- * These features appeared twice, with different threshold values

Root Node Feature	Frequency
Processor Affinity	20%
Total Processor Time	16%
User Processor Time	16%
Handle	13%
Path	12%
Product	10%
Privileged Processor Time	3%
Peak Virtual Memory Size64	2%
Paged System Memory Size64*	<=2%
Virtual Memory Size64	1%
Handle Count*	<=1%
Handles	< 1%
Working Set 64	< 1%

Results

- The highlighted features had previously been identified through feature selection
- This lent weight to previous assessments made during manual interrogation of the data

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Virtual Memory Size64	1%
Handle Count*	<=1%
Handles	< 1%
Working Set 64	< 1%

Results

- The use of multiple memory features lends weight to assessments regarding malwares unique memory footprint
- These features are used with low frequency other features are favoured
- This is assessed to be due to some ‘easy win’ metrics
  - Malware which deletes it’s own path
  - Malware which injects itself into another process

Further Work

- Increased sample size
  - Further sample testing
  - Bulk data
- Environmentally Aware malware
  - Virtually hardened system
  - Physical machine testing
- More robust processing system
  - Improve or remove shared folder system

Any Questions?