



PREEMPT: PReempting Malware by Examining Embedded Processor Traces

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Virus vs. Anti-Virus Software (AVS)

- Malware is a catch-all term for any type of malicious software designed to harm or exploit any programmable device, service or network.
- Anti-Virus Software (AVS) tools are used to detect Malware in a system
- Software-based Anti-Virus Softwares are extremely vulnerable to attacks from Malware and viruses
- A malicious entity can exploit these vulnerabilities to subvert an Anti-Virus Software



The Ugly Truth Behind Anti-Virus Softwares

- Anti-Virus Softwares have lots of software vulnerabilities.
- According to a recent study, a stealthier Malware can always be created to circumvent a top of the line Anti-Virus Software
- Most Anti-Virus Softwares use static signatures to detect Malware, however, Malware can have multiple executable formats to circumvent these signatures
- Because AVS is a software, it is slow, which results in high latency for Malware detection



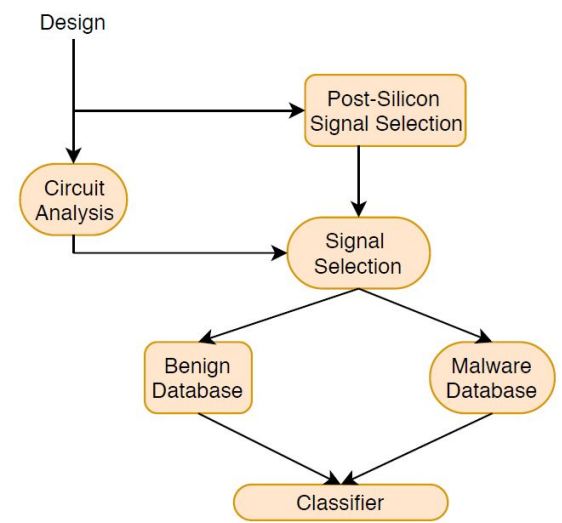


HPCs – High Performance Counters

- Researchers have started using on-chip hardware components like HPCs to detect Malware in a system
- Researchers think that although an Anti-Virus Software can be circumvented by variations in Malware code, it is difficult to subvert a hardware-based detector, since the Malware function will remain the same
- Although what seemed like a good idea, HPC-based Malware detection has an unacceptably high false positive rate (FPR) of 15%

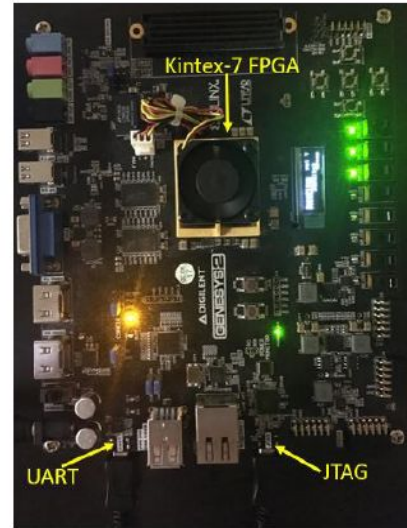
What is PREEMPT?

- PREEMPT stands for PReempting Malware by Examining Embedded Processor Traces
 - Essentially, a malware bounty hunter, hardware antivirus
1. It selects the trace signals from the embedded trace buffer, which controls and monitors the internal activities of a chip AKA ETB
 2. Then analyzes the circuit to remove any redundant signals, and creates a database of traces for the benign programs and malware, which are inputs for the ML classifier
 3. Finally, An ML-based classifier is used to distinguish between malware and benign classes, predicting the probability the new data it is fed belongs to a particular bin

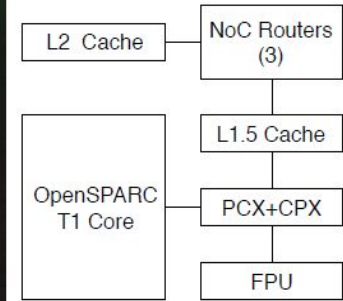


How it works – 1

- The researchers downloaded 300 samples from two different types of malware families
- After running benign and malware programs on an OpenPiton platform, ETB trace signals from the cache core crossbar are analyzed
- Classifiers distinguish malware traces from the benign by analyzing the cache-lines and the instructions
- The traces are now pre-processed in two stages
 - Cleanup of reset values – registers initialized to reset states
 - Cleanup of benign traces – 2 benign traces, 1 in benign programs and 1 in benign functions within the malware; the former is removed



(a)



(b)



How it works – 2

- There are 4 classifiers that are used to test for the traces
 - KNN – K-nearest neighbor
 - RF – Random forest
 - DT – Decision Tree
 - NN – Neural Networks
- Each classifier is trained from data of both classes – benign and malware
- Then it predicts the probability that a new trace is from a particular class



Strengths of the paper

- Use of pictures and figures
 - Helps with outlining the results
 - Enhances understanding of the topic's methodology
- Detailed paper format outline
 - Dives into inner workings of what each component will do
 - Steps through each step in the method

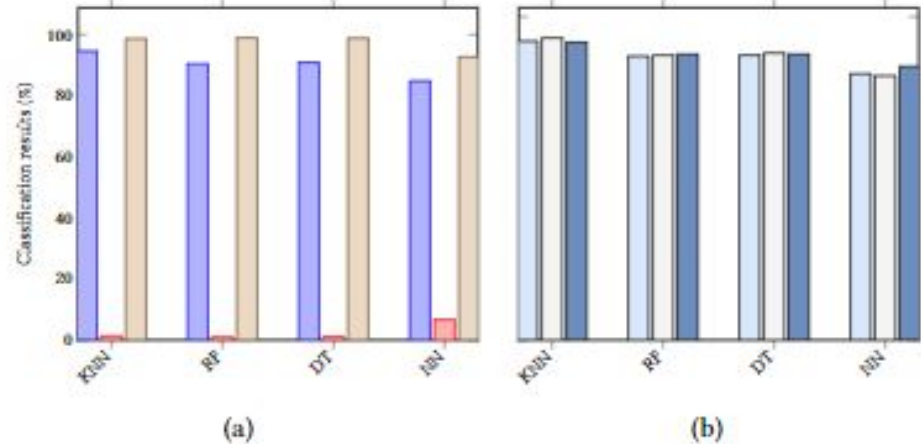


Weaknesses of the paper

- Only 2 families of malware
 - Lack of experimentation
 - More explanation as to why other types were not used
 - Experiment specific to board and processor
- Speculative conclusion
 - Mentioning this beforehand is helpful
 - Implies that its experiment is flawed

Classifiers Results

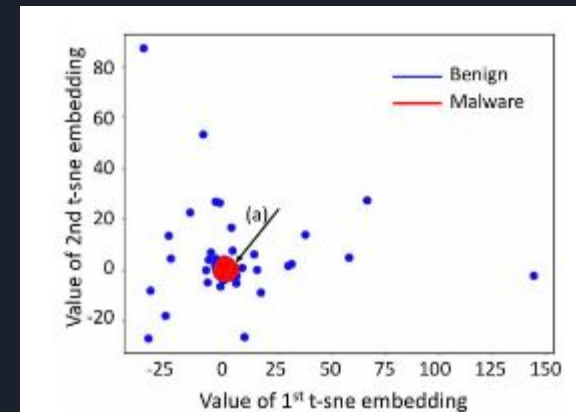
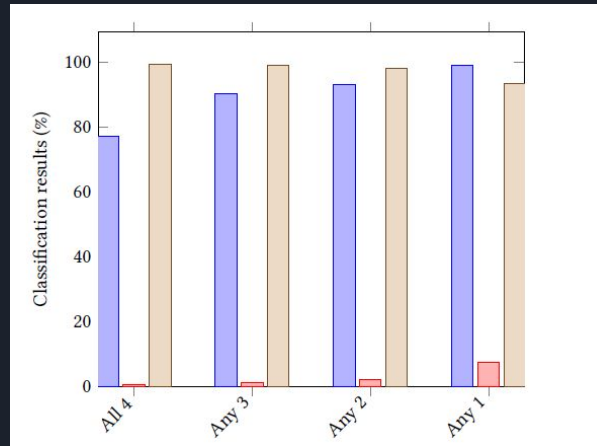
- Figure a all 4 classifiers surpass the 90% mark of finding malware traces
- Figure b reports cross-validation accuracy when tested against additional unknown malware
- KNN is the best.



Other Results

- Factor: speed – Malicious traces were detected within 600 cycles; table
- When combined with other classifiers, TP increases, but FP worsens
- Scatter plot shows big red dot which is malware
 - Blue dots are benign programs

| Malware Sample | Malicious trace (cycles) | | | |
|----------------|--------------------------|-----|-----|-----|
| | KNN | RF | DT | NN |
| 1 | 118 | 118 | 118 | 118 |
| 2 | 50 | 50 | 50 | 50 |
| 3 | 42 | 42 | 42 | 42 |
| 4 | 211 | 528 | 528 | 528 |
| 5 | 266 | 266 | 266 | 266 |
| 6 | 138 | 138 | 138 | 248 |
| 7 | 0 | 0 | 0 | 0 |
| 8 | 98 | 98 | 98 | 98 |
| 9 | 4 | 4 | 4 | 4 |
| 10 | 56 | 56 | 56 | 56 |
| 11 | 272 | 272 | 272 | 439 |
| 12 | 97 | 97 | 97 | 97 |
| 13 | 93 | 94 | 94 | 93 |
| 14 | 29 | 29 | 29 | 29 |
| 15 | 463 | 463 | 463 | 463 |





Conclusion

- PREEMPT uses ML to detect malware at the hardware level with a high TP value, while keeping a low FP, re-using debug data to find these malicious traces.
- We think that the benefits outweigh the paper's weaknesses and the topic's methodology
- The technique is still waiting to be built into modern processors; however, we are sure that some variation of PREEMPT will be implemented soon.