Robustness of Microarchitecture Attacks/Malware Detection Tools against Adversarial Artificial Intelligence Attacks

Group: 16
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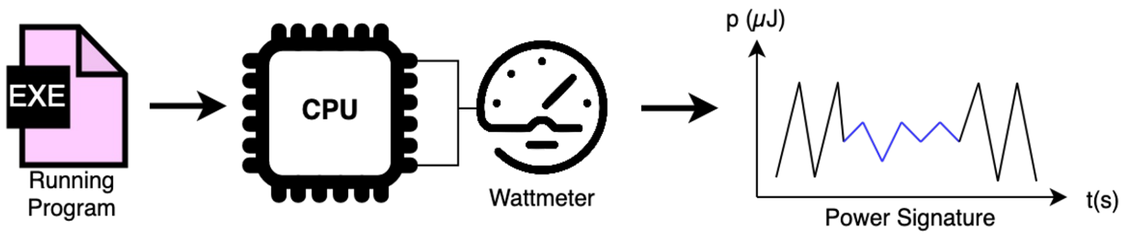
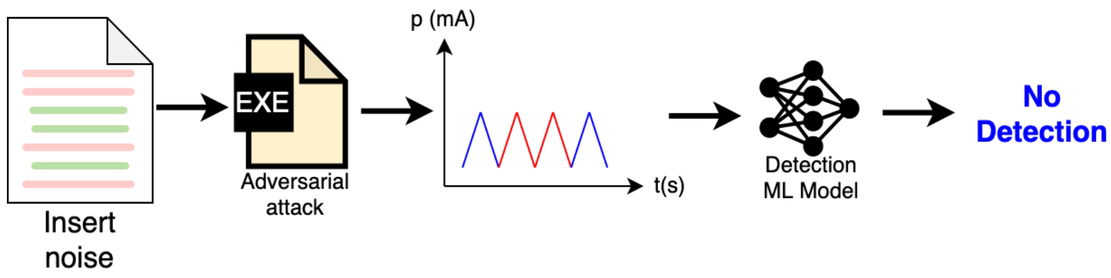
Introduction

- Malware exploiting underlying hardware implementation, or **microarchitecture attacks**, are tough to detect with traditional anti-malware solutions.
- One detection method involves using an AI to monitor CPU power consumption for malicious patterns of energy consumption called **power signatures** [1].



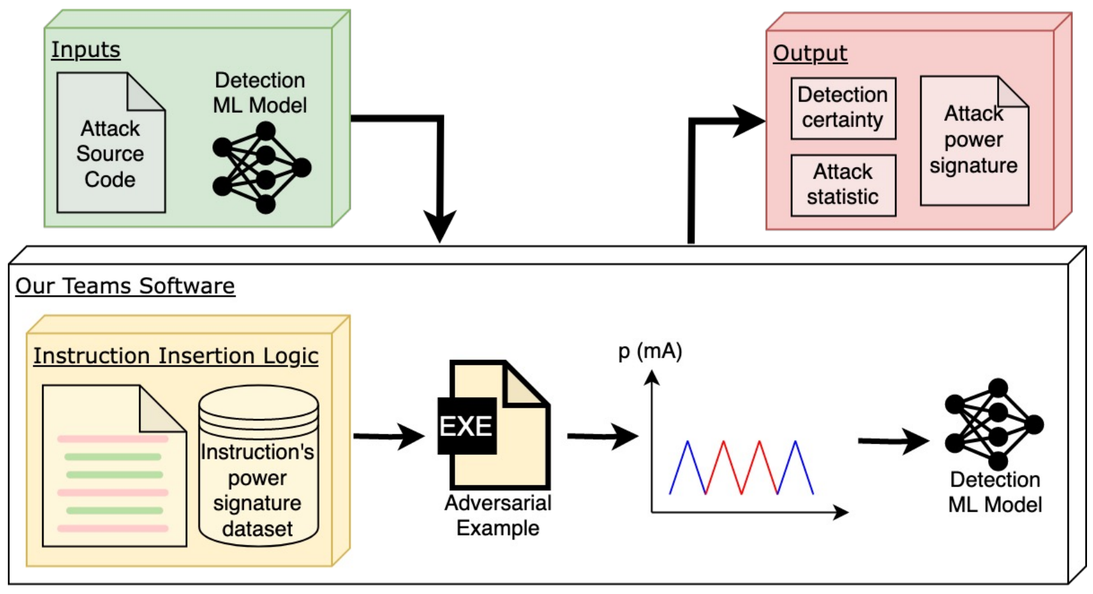
- Detection systems need to be resistant to evasive malware that uses **adversarial examples** to alter power consumption patterns and evade detection.



- We want to design software that will test these system's robustness with adversarial examples.

Overview

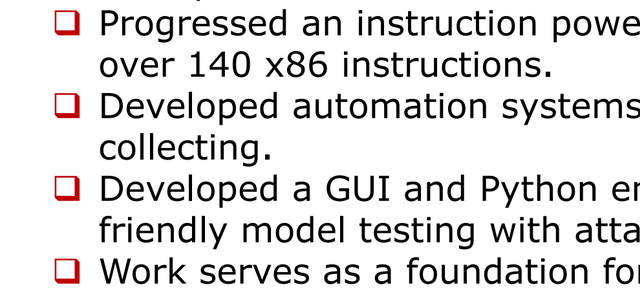
- Our software will help automate the current manual process of assessing the robustness of malware detection systems.
- Features a simple and user-friendly graphical user interface
- It can be used by researchers or developers to efficiently generate adversarial examples and test the robustness of their detection system.

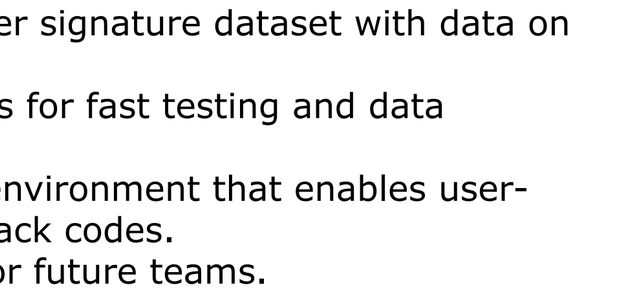


Results and Impact

- Achieved an original goal to create a time-efficient adversarial example that can fool the ML model.
- Progressed an instruction power signature dataset with data on over 140 x86 instructions.
- Developed automation systems for fast testing and data collecting.
- Developed a GUI and Python environment that enables user-friendly model testing with attack codes.
- Work serves as a foundation for future teams.

Instruction	Time (ms)	Instructions (M)	Avg. Power	# Power Values	Inst. / ms (K)
add i r16	458.31	450	7400.04	3917	981.86
add i r32	223.73	450	8493.38	1644	2011.33
add i r64	267.95	450	8828.76	1923	1679.41
dec r64	136.29	450	7656.22	1162	3301.88
cmp i r64	272.54	450	8616.44	1967	1651.16
imul i r64 r64	274.20	450	8760.30	2008	1641.11
mulx r32 r32 m	241.22	960	8382.29	2415	3979.69
mov r64 m	231.46	153	6878.65	2308	661.01
mov r64 r64	259.51	2700	7791.87	2576	10404.09
prefetchw	807.28	200	7479.29	8294	247.74
rdtsc	898.44	136	8112.16	9336	151.37
sleep	1001.32	0	6081.71	9826	N/A
spectre	807.91	0	5939.56	8319	N/A





Methodology

Step 1: **Learn attack codes for insight into limits and requirements**

- Each microarchitecture attack has its own structure and set of instructions that can't be altered.
- A deep understanding of the attack is crucial so **noise** (x86 instructions) can be inserted in optimal positions.

Step 2: Create scripts and configure systems for efficient data collection/analysis

- Configure servers for diverse operations.
- A program that can efficiently interact with these machines to collect and analyze data is necessary for both the backend side of the project for further experiments and research.

Step 3: **Implement user interface**

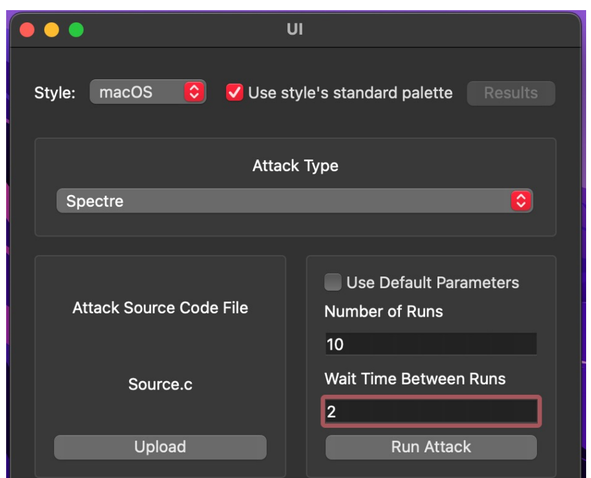
- A graphical user interface built on top of the underlying systems provides a user-friendly way to launch tests and view the results in a convenient format.

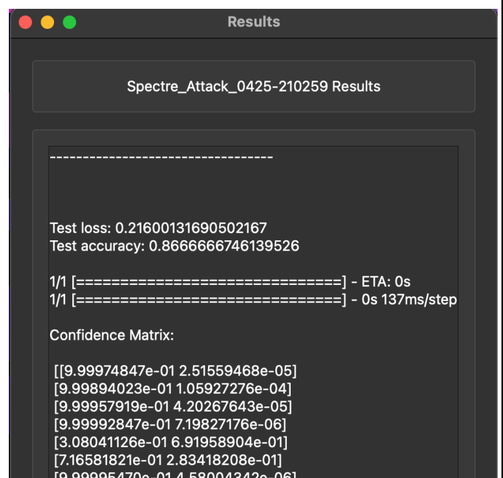
Step 4: Profile instruction's power consumption and changes on power signatures

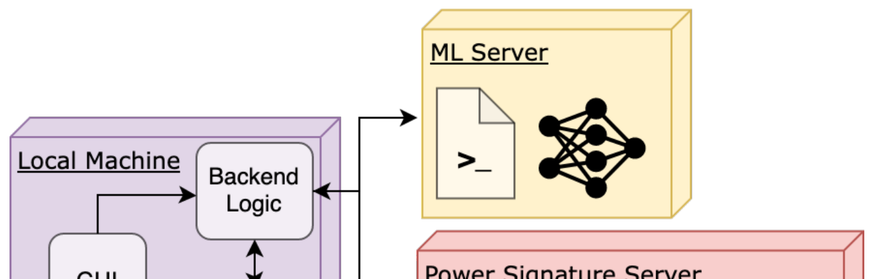
- We must find out how each x86 instruction affects the power consumption so we can freely manipulate the power signature with precise **noise**.
- It requires research and experimentation to understand how instructions correlate to the power signature.

Implementation

- The GUI is implemented using python and PyQt6 GUI Framework. As well as internal logic on the local machine
- The backend logic uses SSH to establish communication channels with the machine learning (ML) and power signature server to collect and analyze data
- The servers are configured with Bash scripts that provide the following functionality
  1) Test an attack's ability to fool the ML model
  2) Collect statistics about an attack
  3) Profile an instruction's power consumption







Conclusion

- UI successfully automated the old system that enabled users to test adversarial examples on the detection ML model.
- Manually created adversarial examples that exposed security vulnerabilities in the ML model.
- Advanced the effort towards comprehensively understanding the effects of x86 instructions on power signatures.
- Established groundwork for future team progress.

[1] *Dipta, Debopriya Roy and Berk Gülmezoglu. "MAD-EN: Microarchitectural Attack Detection through System-wide Energy Consumption." ArXiv abs/2206.00101 (2022): n. pag.*