

Reinforcement Learning for Automated Exploration and Detection of Cache-Timing Attacks in CPS Hardware

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HW Affects CPS Security

- CPS contains HW Parts
	- E.g., Micro-controller, micro-processor, DRAM
- HW vulnerabilities affect CPS
	- Cache side channels
	- Fault injection attacks
	- Row-hammer attacks
- CPS safety and privacy may be violated due to HW security issues
	- Side channel for tracking autonomous vehicles
	- Interrupt injection for manipulating robotic vehicles

Meltdown/Spectre

Tracking autonomous vehicle with cache timing channel [Luo, USENIX 2020]

Finding HW Vulnerabilities is Hard

- System is too complex
	- $-$ laptop processors have $\sim 20,000,000,000$ transistors
- Undefined system behavior
	- timing of a memory read is unspecified
	- speculative execution that are not committed
- Humans are slow and make mistakes
	- can we use **machine intelligence** to replace them?

A microprocessor

Meltdown/Spectre

Executive Summary

- Reinforcement learning (RL) can explore cache-timing attacks in processors automatically
	- without explicit specification of processors
	- without knowing existing attack sequences
- RL finds attacks
	- on diverse configurations of caches
	- on real hardware
	- discovers new attack patterns

Reinforcement learning scheme

Attack a processor

Cache-Timing Attack: Powerful and Stealthy

- Mechanism
	- sharing of caches by different processes
	- infer secret by observing cache timing
- Advantages
	- attacker is just a program, no physical access
	- does not violate any OS-level access control
- Leak important assets
	- cryptographic keys
	- VM/browser isolation
	- building blocks for Spectre/Meltdown

Why Finding new Cache-Timing Attack is Hard?

- Cache-timing attack is still developing
	- Traditional: prime+probe, flush+reload, evict+reload, etc
- Finding cache-timing attack is challenging
	- replacement policy complications
	- unknown microarchitectural states

Existing Tools to Find Vulnerabilities

- Fuzzing
	- pros:
		- require fewer human interventions
	- con:
		- have to deal with large search space
- Formal methods
	- pros:
		- can provably exclude possible vulnerabilities/attacks
	- cons:
		- require RTL of the processor
		- require human to rewrite/implement the formal models

Reinforcement Learning

- RL: a machine learning scheme
	- an agent generates an action sequence
	- maximizes long-term reward

- RL has been applied in game settings to show human-level performance
	- games like Atari (single party)
	- Chess, Go, etc. (two parties)

AlphaGo (Source: BBC)

Atari (source: OpenAI)

Reinforcement Learning

- Key notions
	- agent
	- environment (env)
	- action
	- observation
	- reward

- Advantages of RL
	- learns a sequence of actions \rightarrow cache-timing attack is a sequence
	- no dataset needed, just an env \rightarrow a simulator/a real processor

Outline

- RL formulation of cache-timing attack exploration
- RL finds attacks on diverse configurations of caches
- RL finds attacks on real-hardware

• RL discovers new attack patterns

Cache-Timing Attack as an RL Game

- Agent: Attacker
- Environment: Cache
	- architecture simulator
	- cache in the processor
- Actions
	- attacker makes an access
	- attacker waits for victim access
	- attacker guesses the secret
- Observation
	- latency of attacker accesses

Summary of actions of existing attacks

Cache-Timing Attack as a Game

- Reward
	- guess correct: positive reward
	- guess wrong: negative reward
	- each step: small negative reward
- Maximizing long-term reward
	- more correct guesses
	- fewer wrong guesses
	- fewer number of steps

Summary of actions of existing attacks

AutoCAT: A Simple Example

- **Settings**
	- 1 set 1-way cache
	- attacker can access address 1
	- victim secret: **access 0 (0) / no access (N)**
	- attacker want to infer whether victim secret **is 0/N** Reward during
- Attack found
	- step 1: attacker accesses 1
	- step 2: then wait for a while
	- step 3: attacker accesses 1 again
	- step 4: guess the secret **0/N**

AutoCAT: Framework Overview

Outline

- RL formulation of cache-timing attack exploration
- RL finds attacks on diverse configurations of caches
- RL finds attacks on real-hardware

• RL discovers new attack patterns

AutoCAT: Attacks on Diverse Configurations

- Number of sets/ways
- Type of caches
	- direct-map/fully-associative/setassociative
- Replacement policies
	- least recently used (LRU)/rereference interval prediction (RRIP)
- Prefetchers
	- none/stream/nextline
- Single-level/multi-level

AutoCAT: Attacks in Simulator

- Find attack patterns across 17 different configurations (No. 1-17)
	- including **direct-map, fully-associative, prefetchers, 2-level caches**

Excerpts from Table IV in the paper

Outline

- RL formulation of cache-timing attack exploration
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- RL finds attacks on real-hardware

• RL discovers new attack patterns

AutoCAT: Real Hardware

• AutoCAT finds attacks without knowing the replacement policy

Outline

- RL formulation of cache-timing attack exploration
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AutoCAT: A New Attack Pattern

- Setting:
	- 4-way cache
	- victim secret address from 0, 1, 2, 3
- Attack pattern:
	- attacker accesses 0, 1, 2, 3 first
	- victim accesses the secret address (always a hit)
	- attacker accesses 4, 0, 1, measure the timing of 0 and 1
	- depending on 0,1 hit/miss can infer the victim secret address

0 1 2 3 v? 4 loop **4 0 1** … …

New Attack Pattern: StealthyStreamline

- No victim cache misses
- Works across different processors
	- 4 different Xeon/Core processor tested
- Higher bandwidth than the LRU-based attack

StealthyStreamline bandwidth and error rate (top-left corner is better)

Cornell University

MACTA: A Multi-agent Reinforcement Learning Approach for Cache Timing Attacks and **Detection**

- Approach:
	- Multi-agent reinforcement learning (RL) for automatically exploring cache-timing attacks and detection schemes together.
- Key Findings:
	- Without any manual input from security experts,
		- the trained attacker is able to act more stealthily
		- the trained detector can generalize to unseen attacks
		- the trained detector is less exploitable to high-bandwidth attacks.

Multiagent RL Formulation

- To train a detector, we need both attacker scenario and benign Scenario.
- For each agent, there are observation, action, and rewards, respectively.

MACTA Results

- Without any manual input from security experts,
	- the trained MACTA detector can generalize to unseen attacks

Conclusions and Future Works

- Reinforcement learning shows promising results for exploring the attacks and detection HW vulnerabilities for CPS
- Would this method scale?
- How to understand the results of the model?
- How about other security problems?

Learn more at https://rl4cas.github.io

Acknowledgements

More in the Paper

- Bypassing defense and detection techniques
	- partition-locked (PL) cache
	- autocorrelation-based detection similar to CC-Hunter [MICRO14]
	- ML-based detection similar to Cyclone [MICRO19]
- Discussions
	- comparison with search algorithms
		- less number of steps compared with exhaustive search
	- future extensions
		- automated attack analysis
		- scalability of the RL model

Conclusion

- AutoCAT uses RL to explore cache-timing attacks in processors
	- without explicit specification of processor design
	- without knowing existing attack patterns
- AutoCAT found attack patterns
	- on many configurations in the cache simulator/real hardware
	- a new attack pattern: StealthyStreamline

Artifact available at: https://github.com/facebookresearch/AutoCAT

Introduction: Cybersecurity

- Vulnerability is everywhere
	- Stuxnet: nuclear power plant
	- Cambridge Analytica: social networks
	- Log4j: web infrastructure
	- Spectre/Meltdown: computer hardware
- Huge dollars spent
	- $-$ 2.5 trillion USD = GDP of UK (5th) largest country)
	- finding and resolving vulnerabilities

Growing Threat

Estimated increases in data-breach costs and global cybersecurity spending over the next five years

Annual cost of data breaches

Annual cybersecurity spending

Source: fair institute

0 1 2

Cache Defense Mechanism

- Partition
	- Attacker process and victim process uses their own cache lines without sharing with the others set 509 510 511
	- E.g., PLCache
		- Example: 4-way PLCache
			- Way 0: victim process exclusive
			- Way 1-3: attacker process exclusive
		- Can AutoCAT find attacks on PLCache?

AutoCAT's Attack on PLCache

Cache Timing Attack Detection

• The cache access pattern by the attacker have specific characteristics

AutoCAT can Bypass the Detection

- AutoCAT can generate attacks that bypass CC-Hunter
	- Textbook: prime+probe
	- RL_baseline: training without considering the CCHunter
	- RL_autocor: training with consider high autocor as penalty
- AutoCAT can generate attacks that evade SVM detection
	- RL_SVM: training with considering SVM detection penalty

TABLE IX: Comparison of bit rate, guess accuracy and detection rate by the SVM.

AutoCAT: A Simple Example

- Settings
	- 1 set 2 way cache LRU policy
	- address 0, 1, 2, 3 – Attacker can access
	- Victim can access 0 or 1
	- 0 or 1 uu whether victim accesses 21 C – Attacker want to infer an essential de la construction de
La construction de la construction
- Reward
	- Correct guess: 200
	- Wrong guess: -10,000

Covert and Side Channels

- Computation affects the physical world, and an observer can measure physical effects
- Confidential information may leak through physical properties not intended for communications
	- –Timing, power consumption, EM, temperature, acoustic, etc.
- Covert channels
	- –Use unintended physical properties to transmit information without the authorization or knowledge of a system
- Side channels
	- –Unintentional covert channels

Timing Channel Protection

- Completely remove timing dependence –Secure, but expensive
- More empirical protection
	- –Reduce the timing dependence (noise, coarser-grained resource allocation, etc)
	- –Detect an attack
	- –Less expensive, but difficult to provide a security guarantee
- Use ML to automatically generate attacks?
	- –A game between an attacker and a defender

Side-Channel Attack: An Example

- Infer secret information from target device by observing power consumption
- Threat models require physical access or proximity to device

Cache Timing Attack Detection

- CC-Hunter: calculate the autocorrelation of eviction encode
	- High autocorrelation \rightarrow likely an attack
	- Low autocorrelation \rightarrow likely a benign program
- **Cyclone**
	- Use SVM classifier to detect an attack

AutoCAT can Bypass the Detection

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Cache-Timing Attack as an RL Game

- Agent: Attacker
- Environment: Cache
	- architecture simulator
	- cache in the processor
- Actions
	- a1: attack makes an access
	- a2: wait for victim access
	- a3: guess the secret
- Observation
	- latency of attacker access

secret→ a3

Cache-Timing Attack as a Game

- Reward
	- guess correct: positive reward
	- guess wrong: negative reward
	- each step: small negative reward
- Maximizing long-term reward
	- More correct guess
	- Less wrong guess
	- $-$ Less number of steps \rightarrow shorter $_{510}^{509}$ attack sequence 511

P1 fills the P2 reads an cache→ a1 array → a2 data again→ a1 P1 reads its

secret→ a3

Cache Timing Attack

Executive Summary

- We use RL to automatically explore cache timing attacks in processors
- We find attacks on a diverse configurations of caches
	- Different replacement policies
	- Different defense mechanisms
- We discover StealthyStreamline attacks
	- Bypass performance counter-based detection
	- Higher bandwidth

Prior Work on ML for Side Channel

- Focuses on using ML to analyze existing power side-channel traces and predict secrets
	- –Use a supervised learning model to analyze traces
	- –Auto-encoder to learn representations