Hardware Malware Detectors

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Worms

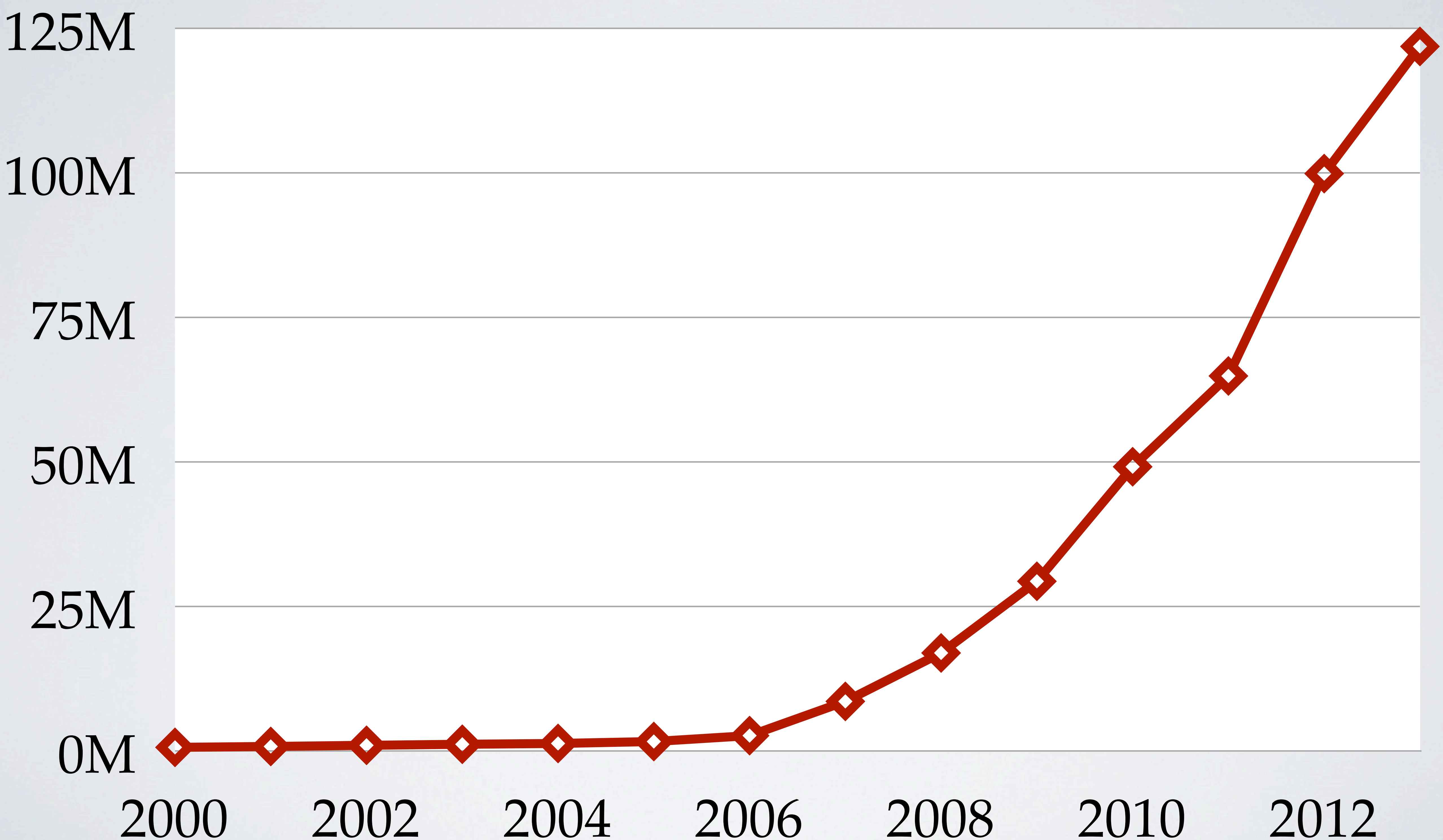
Trojan Horses

Botnets

Adware

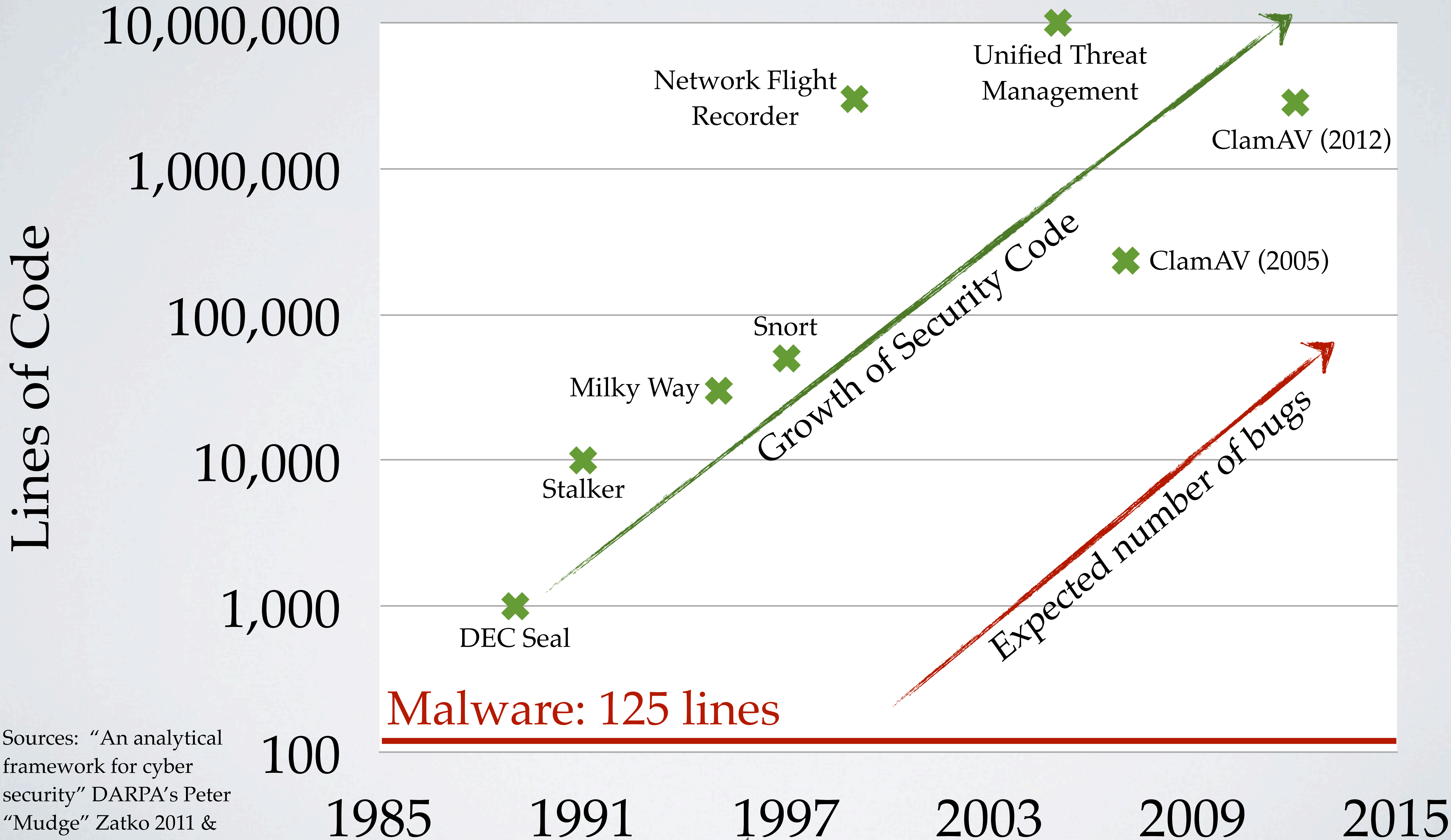
Spyware

Malware in the Wild



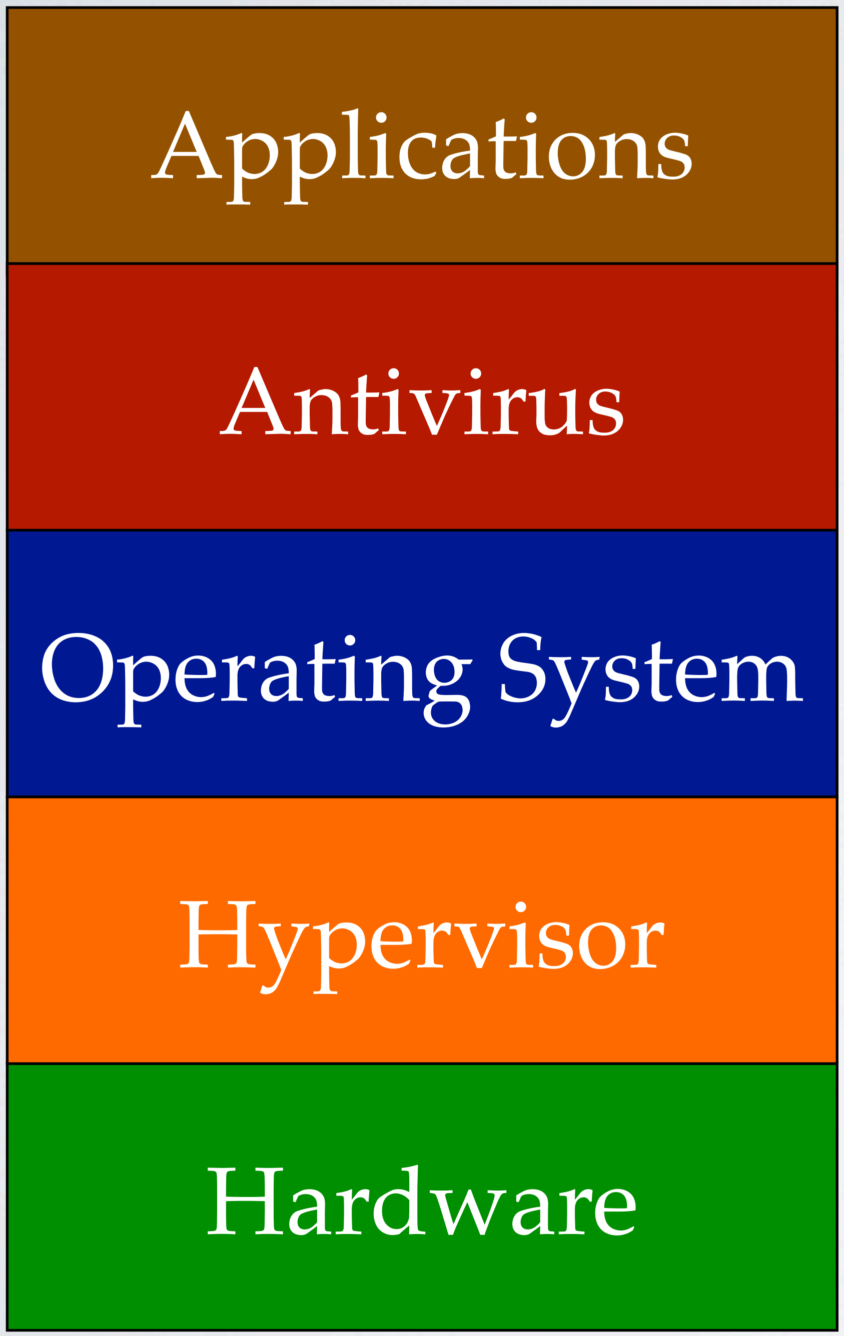
AVTest unique database entries (av-test.org)

Why we are losing the battle?



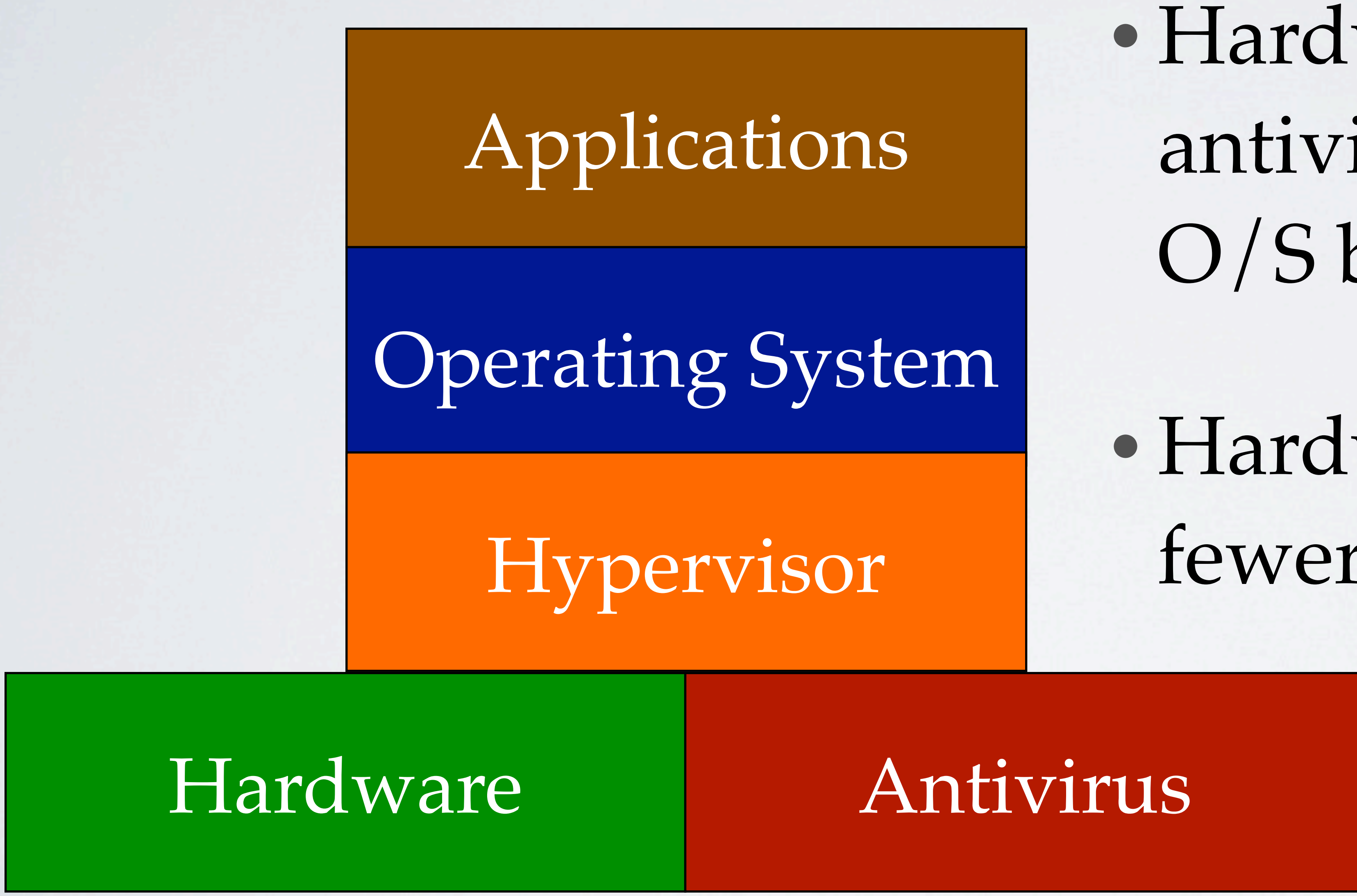
Sources: "An analytical framework for cyber security" DARPA's Peter "Mudge" Zatko 2011 & Ohloh.net

State of Practice



- Software-based antivirus runs above the O/S, hypervisor and hardware
- Operating systems and hypervisors have exploited bugs
- Software antivirus is vulnerable and can't help it!

Proposed Solution



- Hardware-based antivirus not susceptible O/S bugs
- Hardware tends to have fewer bugs & exploits

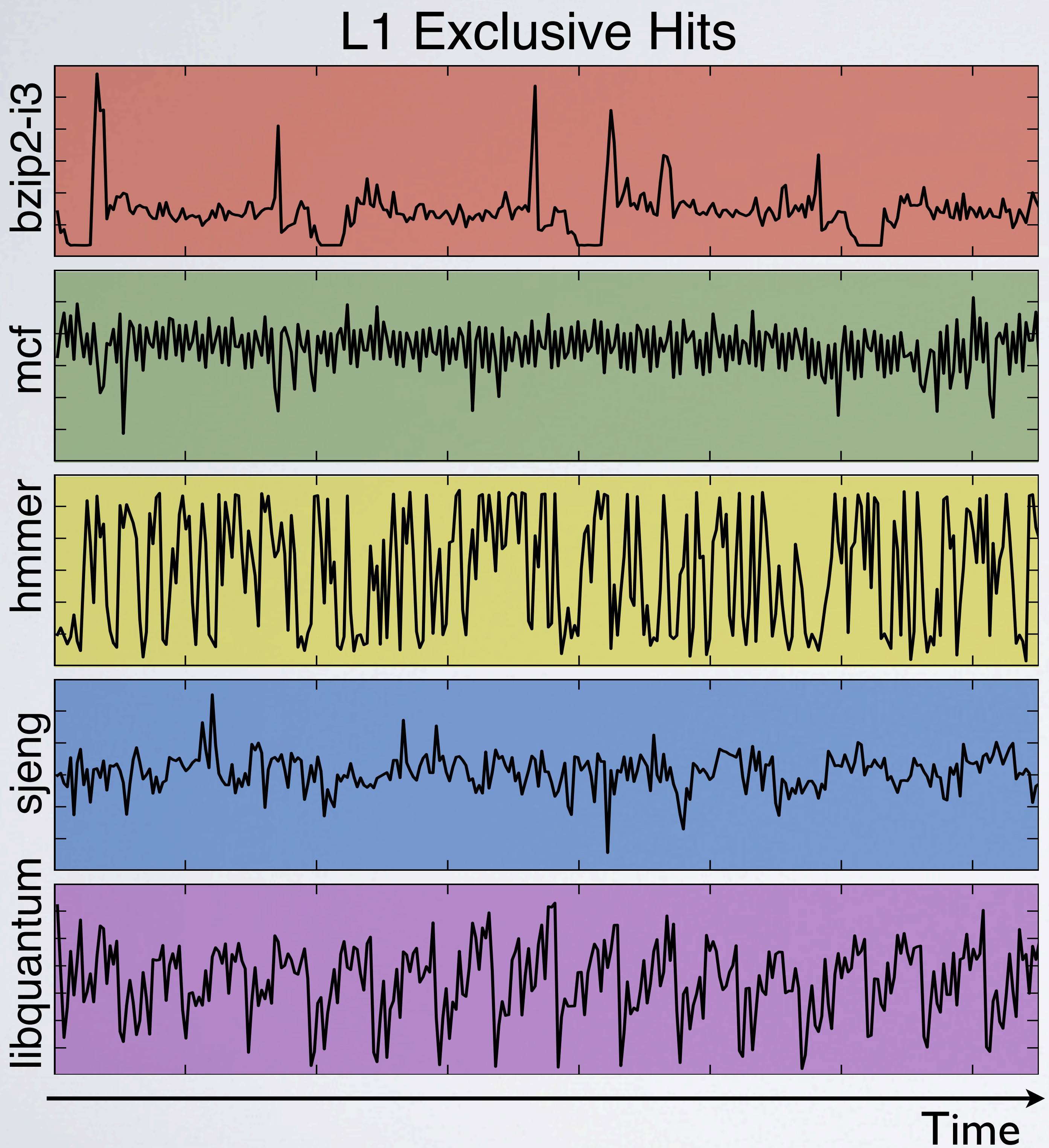
Outline

- Detecting malware with performance counters
  - ... using machine learning
  - Experimental setup
  - Results for Android
- An architecture for hardware antivirus systems

How do we build hardware A/V?

	Software	Hardware
Primitives	Files, Downloads, File Systems, Registry Entries, System Calls	Memory, Dynamic Instructions, uArch Events, System Calls
How it works	Scans downloads for static signatures	**?**

Programs have Unique μArch Signatures



Can μarch footprints uniquely identify malware during execution?

Could we build a database of malicious μarch signatures?

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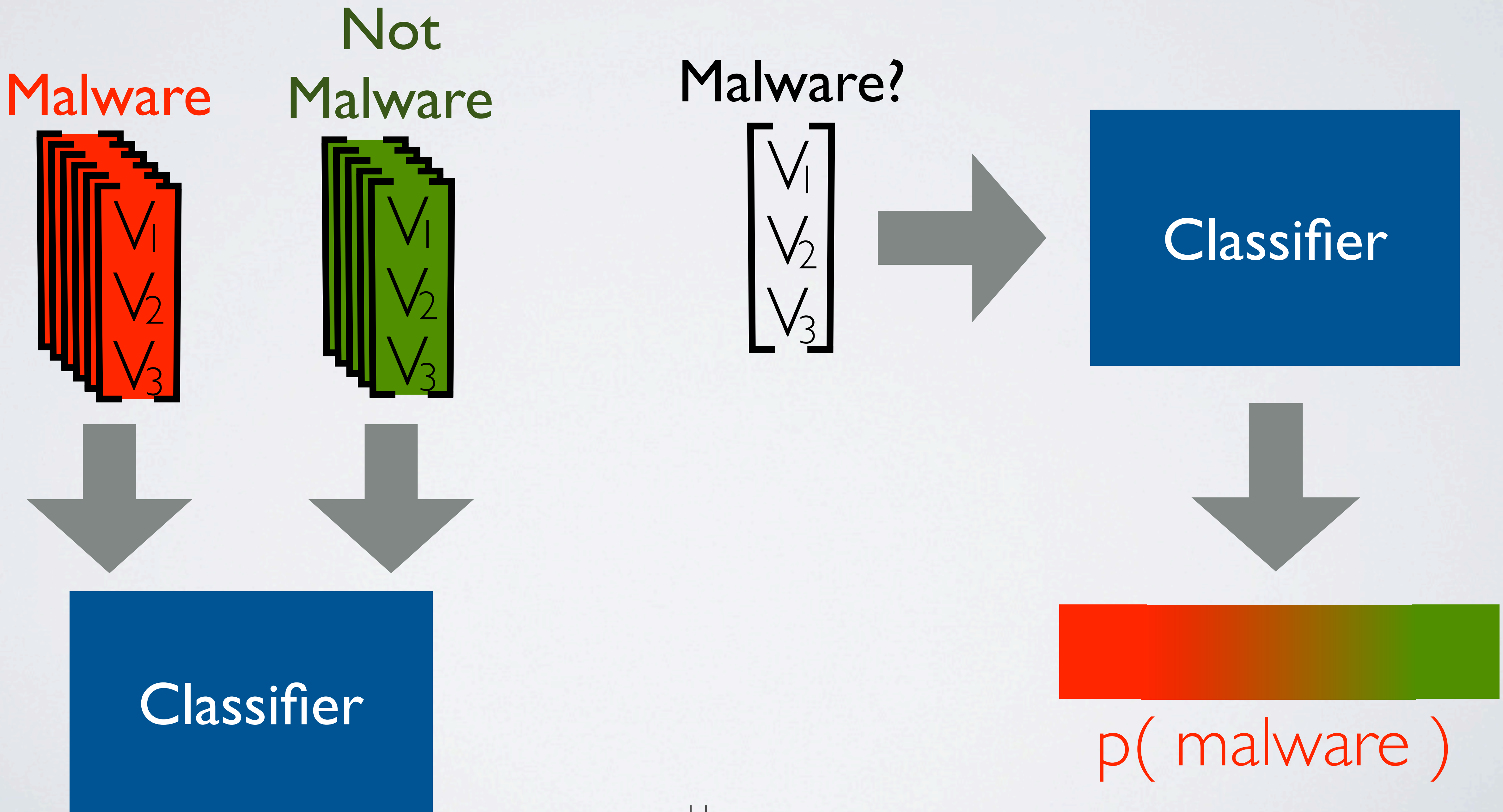
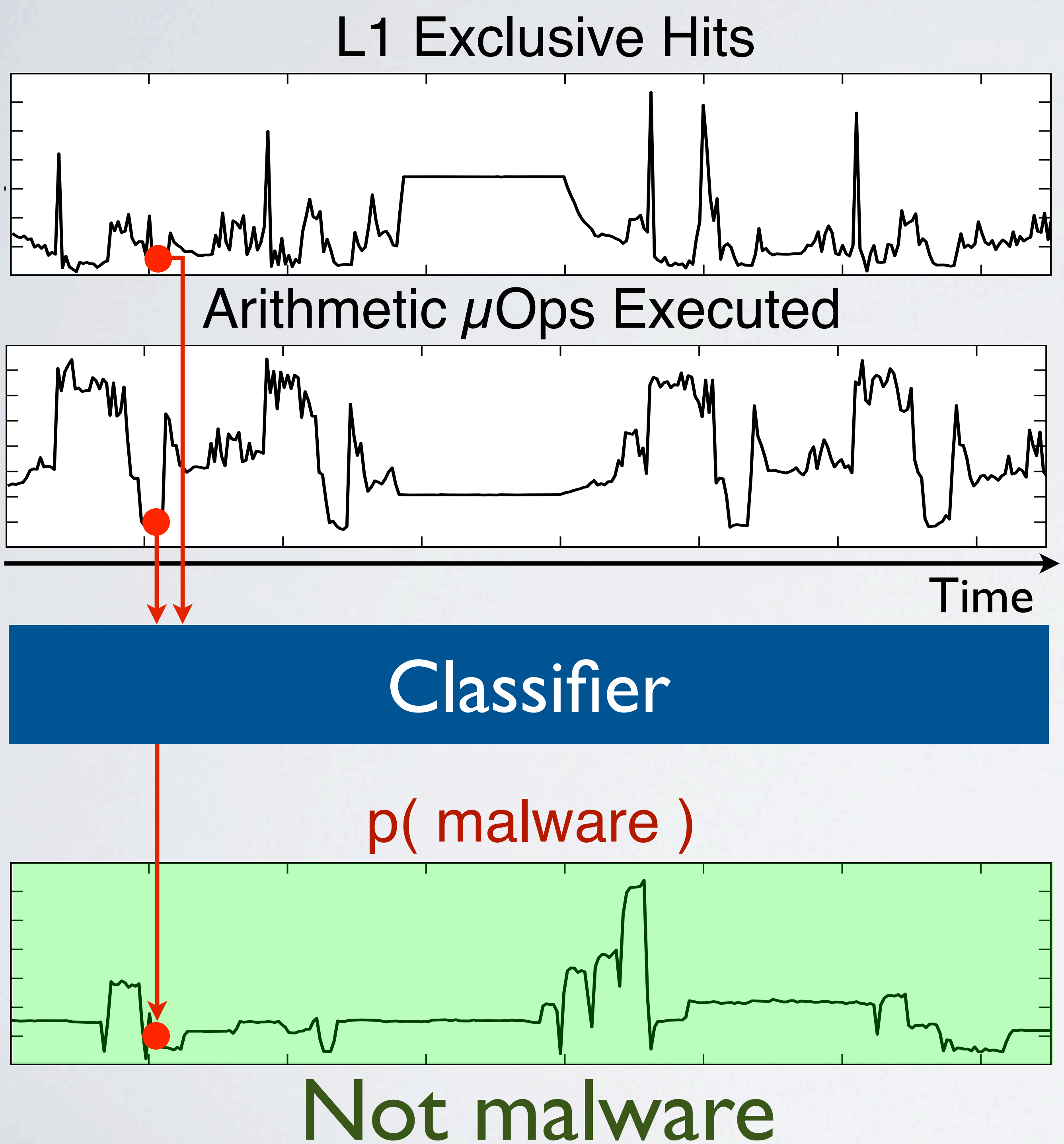
Machine Learning: Classifiers

Training
(at A/V Vendor)

Production
(on consumer device)

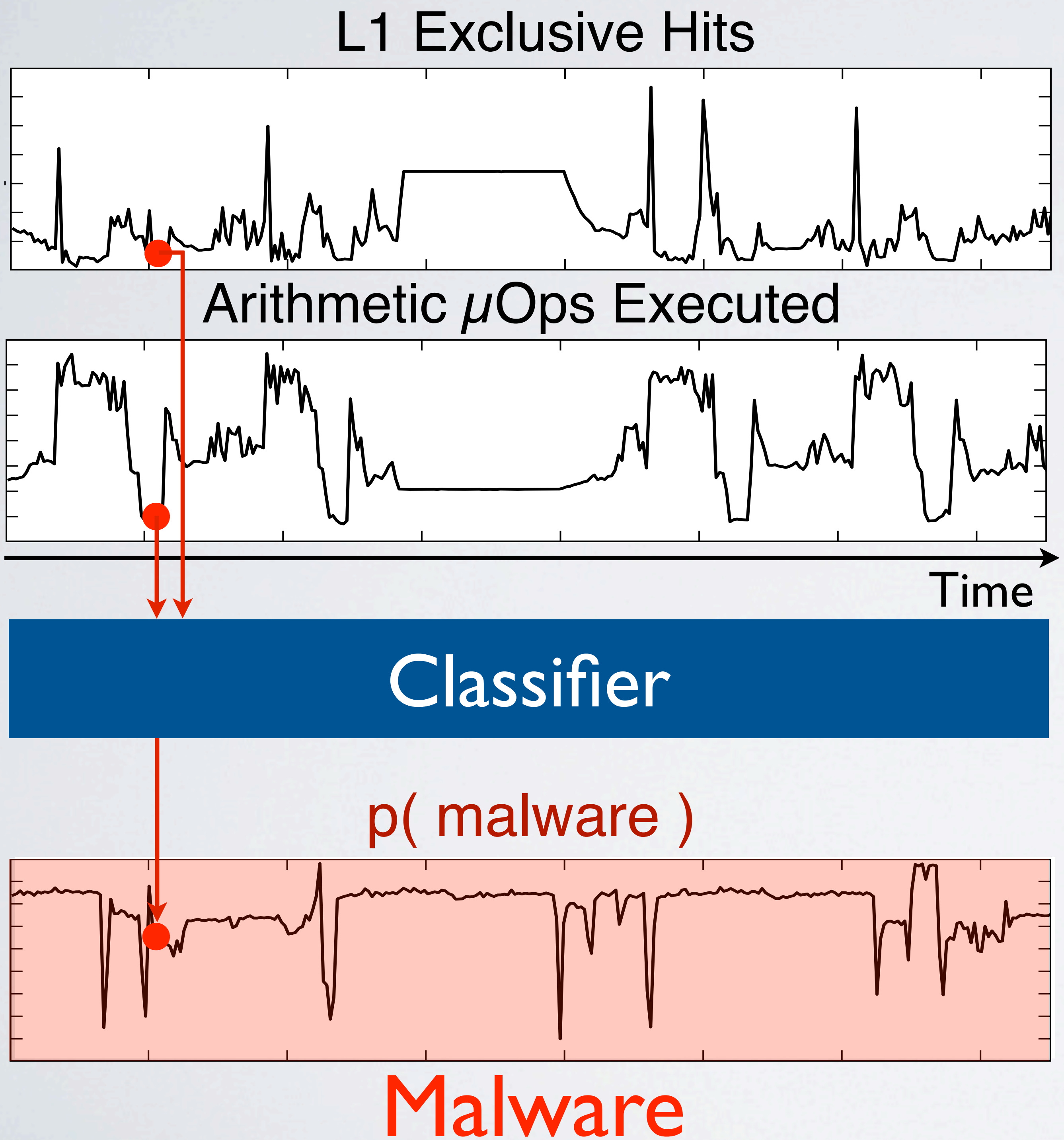


Machine Learning on μArch Events



- Microarchitectural event counts yield performance vectors over time
- Feed each vector into classifier, results in p(malware) over time
- Average over time, decide if malware or not with threshold

Machine Learning on μArch Events



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Android Malware Detection

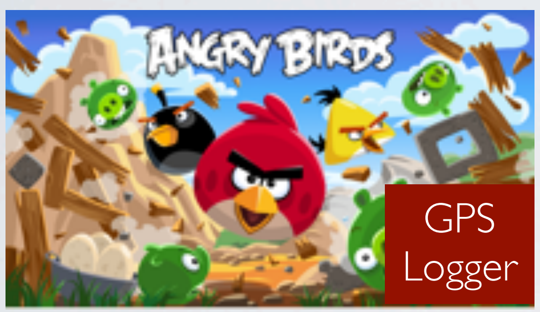
- 17x increase malware detections in 2012 ("Trends for 2013" ESET Latin America's Lab)
- Android 4.1 mobile O/S
- ARM/TI PandaBoard
  - 6 performance counters

Malware Families & Variants

GPS
Logger

- Family of variants which all do similar things
- Usually packaged with different host software
- Expectation: similar malicious code, different host code

Can we detect new variants after seeing only old ones?



Train classifier on these malware apps

Evaluate our classifier with *different* variants in the same family

Experimental Setup

- Tapsnake
- Zitmo
- Loozfon-android
- Android.Steek
- Android.Trojan.Qicsomos
- CruseWin
- Jifake
- AnserverBot
- Gone60
- YZHC
- FakePlayer
- LoveTrap
- Bgserv
- KMIN
- DroidDreamLight
- HippoSMS
- Dropdialerab
- Zsone
- Endofday
- AngryBirds-Lena.C
- jSMSHider
- Plankton
- PJAPPS
- Android.Sumzand
- RogueSPPush
- FakeNetflix
- GEINIMI
- SndApps
- GoldDream
- CoinPirate
- BASEBRIDGE
- DougaLeaker.A
- Newzitmo
- BeanBot
- GGTracker
- FakeAngry
- DogWars

- 503 Malware apps
  - 37 families
  - Taken from internet repository [1] and previous work [2]
- 210 Non-malware apps
  - Most popular apps on Google play
  - System applications (ls, bash, com.android.*)
- 3.68e8 data points total

[1] http://contagiominidump.blogspot.com/
[2] Y. Zhou and X. Jiang, "Dissecting android malware: Characterization and evolution," in Security and Privacy (SP), 2012 IEEE Symp. on, pp. 95 –109, may 2012.

Very Realistic, Noisy Data

- Network connectivity **allowed**:
  - Malware could phone home
  - Additional noise introduced
- Input bias **allowed**:
  - Multiple users conducted data collection
- Environmental noise **allowed**:
  - Malware ran with system applications, not isolated
- Contamination between training & testing data **prevented**:
  - Non-volatile storage wiped, eliminating 'sticky' malware
  - Training/testing split before data collection
- **Makes our task harder, better feasibility study**

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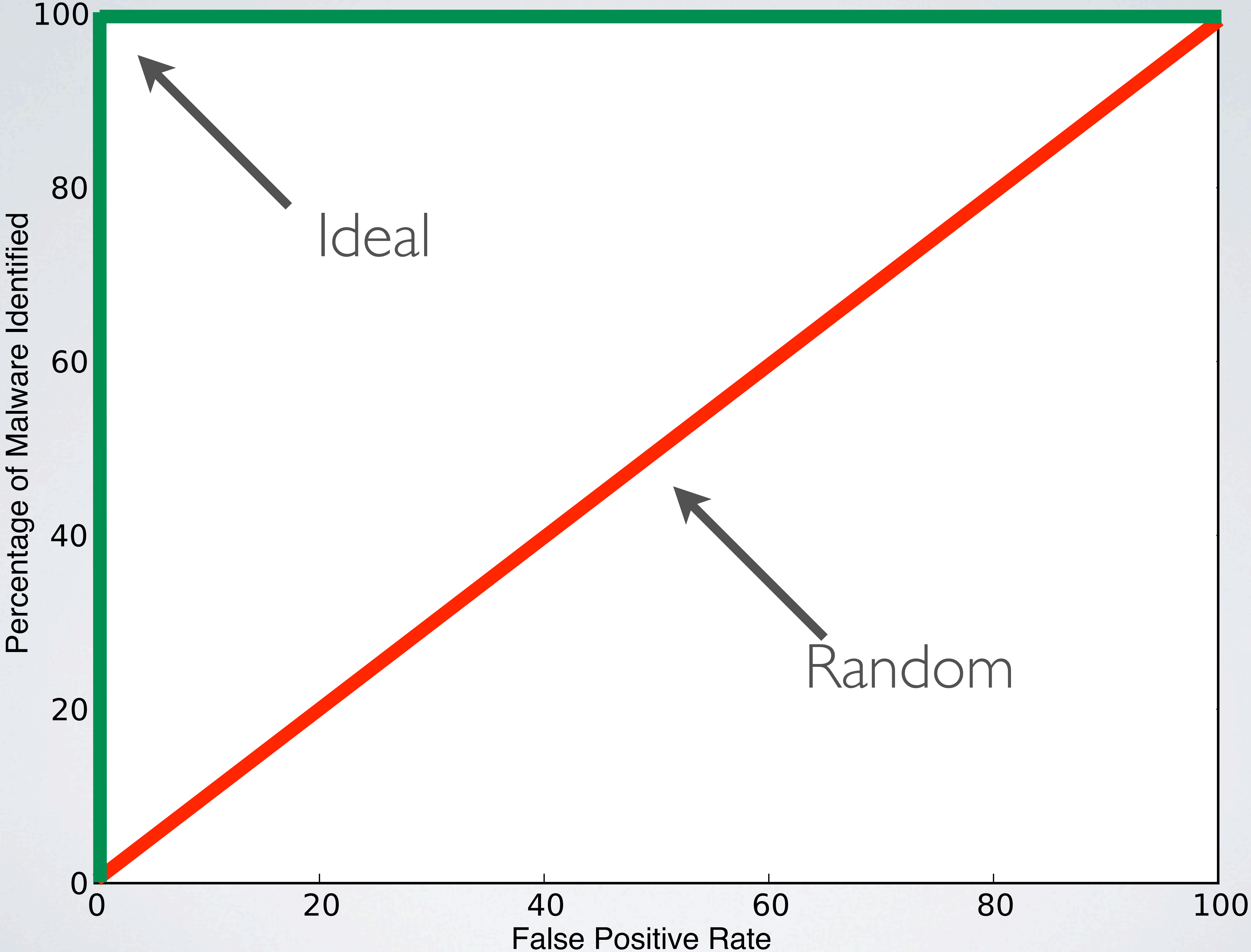
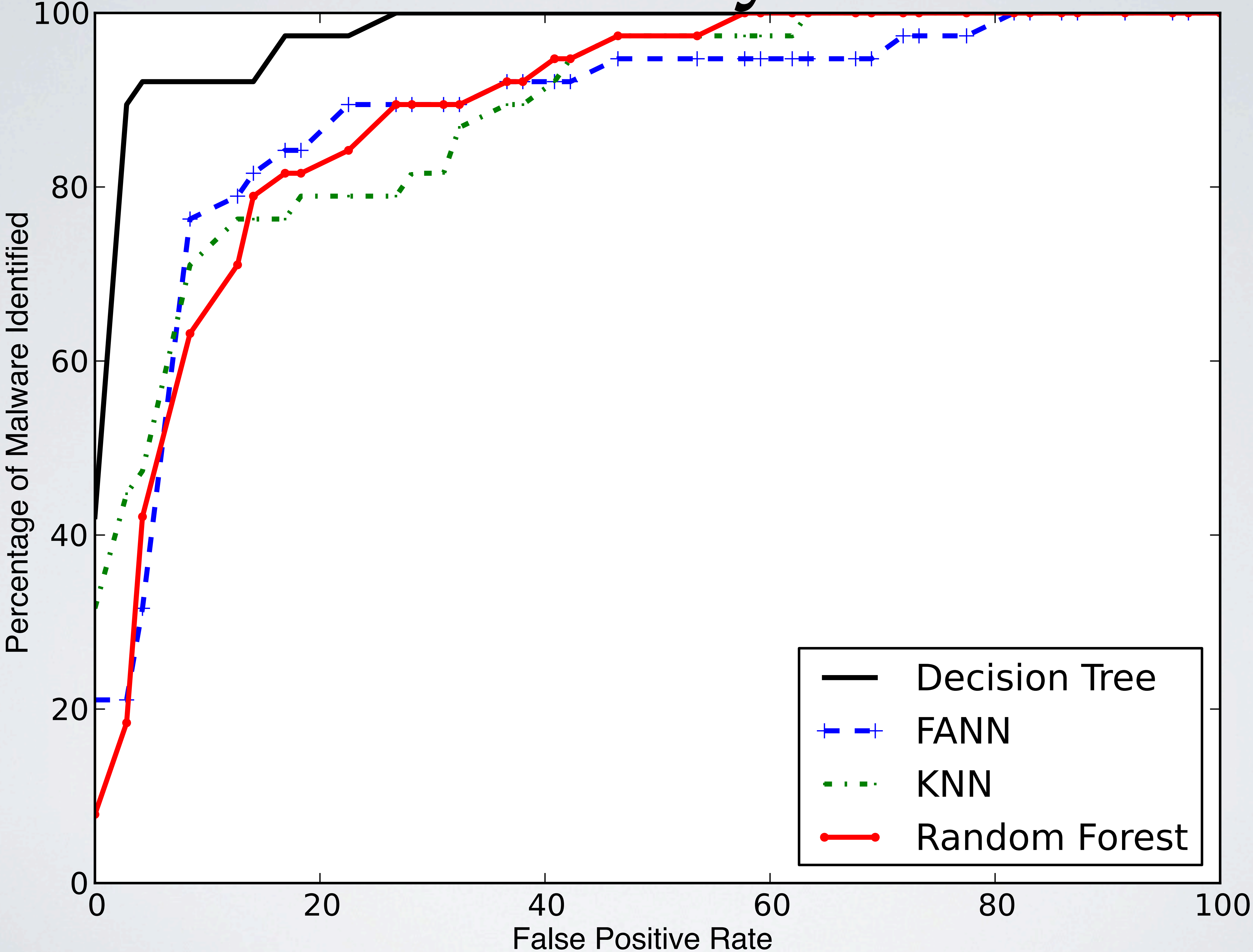
Experiments in Paper

- Detection of malicious packages on Android
- Detection of malicious threads on Android
- Linux rootkit detection
- Cache side-channel attack detection

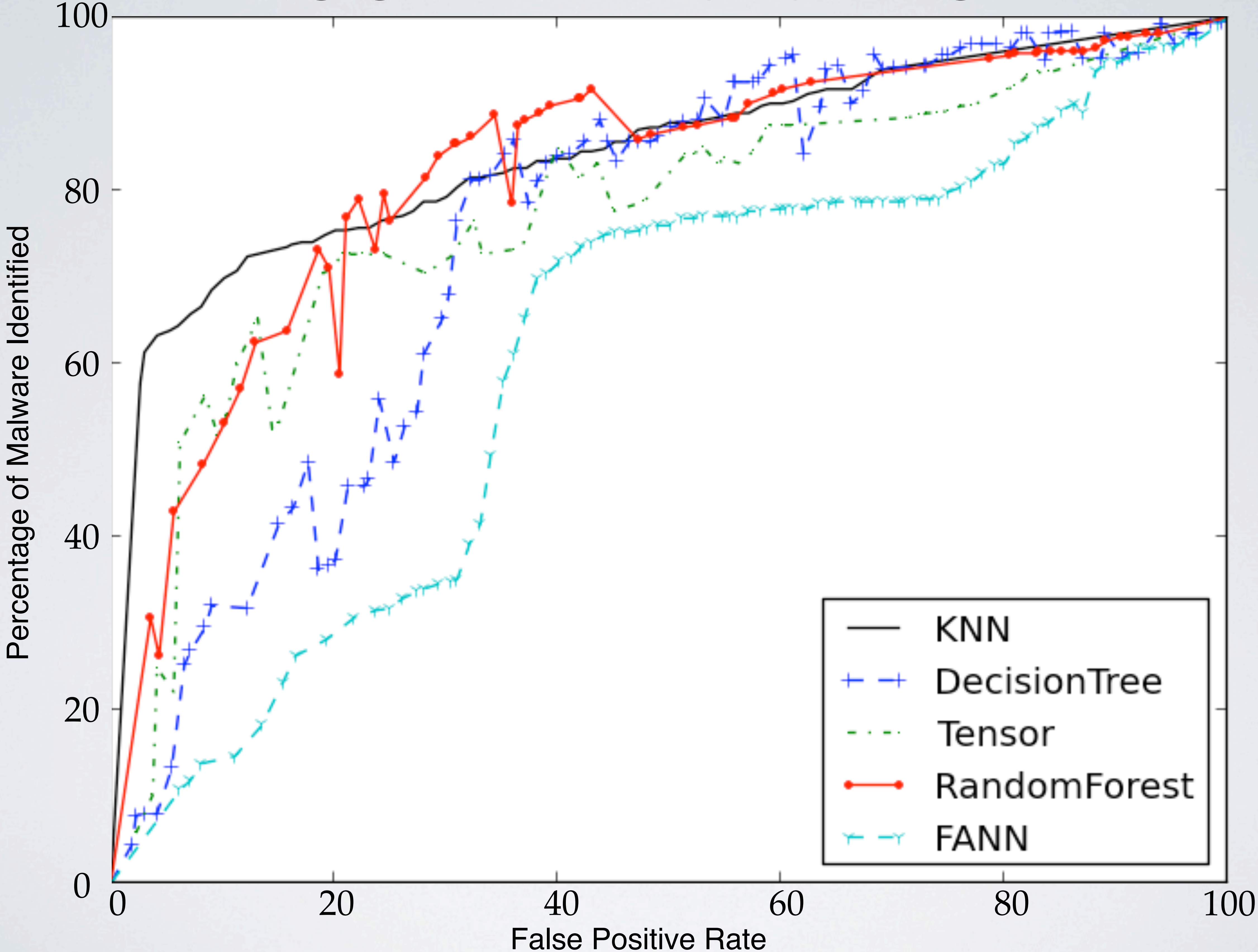
Detection Rates



Malware Family Detection



Rootkit Detection



Result Summary

- Detection of malicious packages on Android
  - 90% accuracy
- Detection of malicious threads on Android
  - 80% accuracy
- Linux rootkit detection
  - About 60% accuracy
  - Difficult problem; rootkits are tiny slices of execution
- Cache side-channel attack detection
  - 100% accuracy, no false positives

One Way to Improve Results

Android Software Package

- Malware writers package with non-malware.
- Problem: what's actually malware?
- Our (bad) solution: all of it
    - Raises false-positives

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Recommendations for Hardware A/V System Design

1. Provide strong isolation mechanisms to enable anti-virus software to execute without interference.
2. Investigate both on-chip and off-chip solutions for the AV implementations.
3. Allow performance counters to be read without interrupting the executing process.
4. Ensure that the AV engine can access physical memory safely.
5. Investigate domain-specific optimizations for the AV engine.
6. Increase performance counter coverage and the number of counters available.
7. The AV engine should be flexible enough to enforce a wide range of security policies.
8. Create mechanisms to allow the AV engine to run in the highest privilege mode.
9. Provide support in the AV engine for secure updates.

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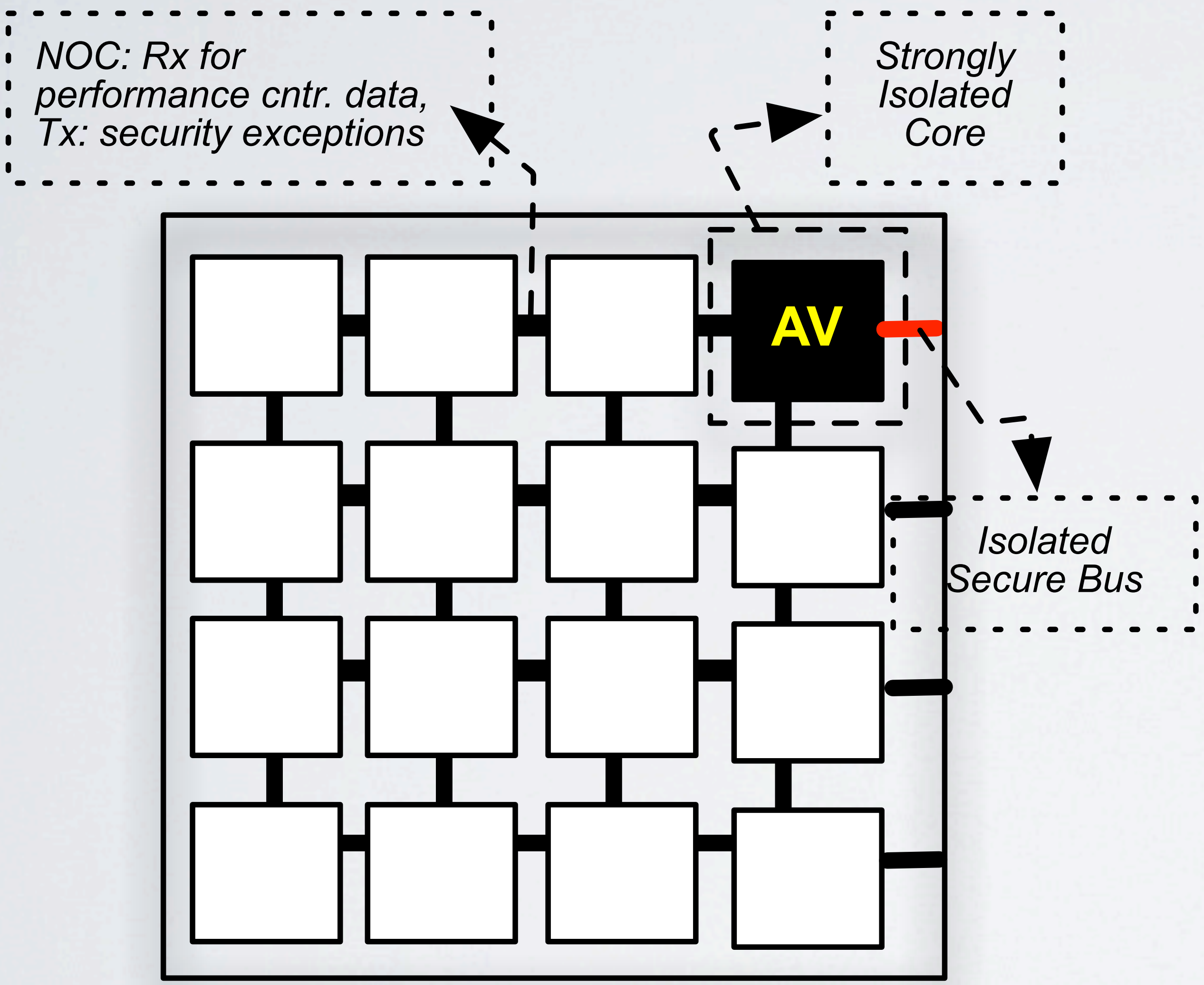
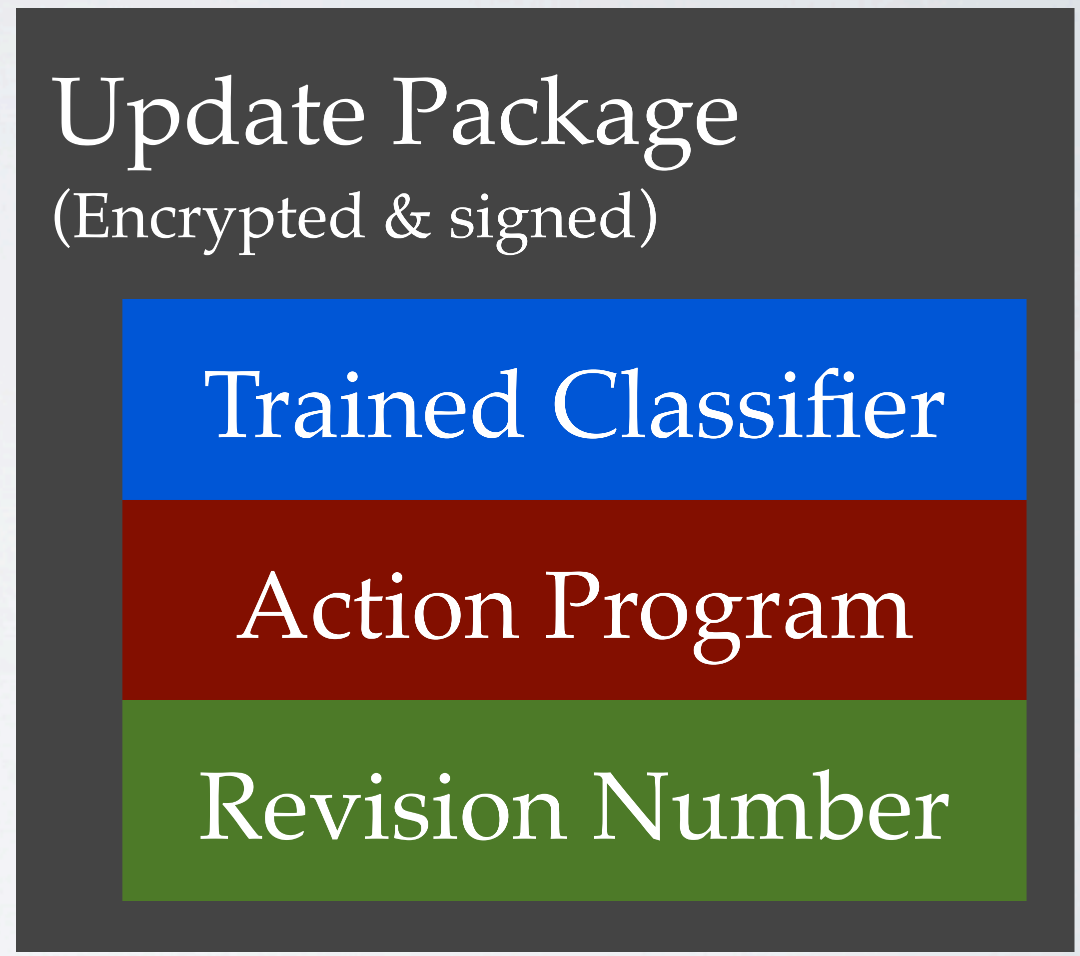
Strong isolation mechanisms enable anti-virus software to execute without interference



- Non-interruptable
- A/V requires data from cores
  - Starvation == exploit
- A/V uses off-die memory
  - Starvation == exploit

Allow Secure System Updates

- Update protocol:
  - Decrypt
  - Verify signature
  - Check revision number
- Disallows access to classifiers & action programs



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Contributions

(1) First hardware-based antivirus detection

- Promising results, reasons to believe results will improve
- First branch predictors started at 80% accuracy...

(2) Dataset available: http://castl.cs.columbia.edu/colmalset

Much to follow on: 0-day exploit detection, attacks, counterattack malware detection, better machine learning, precise training labels, ML accelerators, prototypes, etc.