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Challenges in Android Malware Detection

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Contents

Android

Android in one minute

- A complete Software Stack
- Linux based Kernel + custom (Non POSIX) Libc
- Dalvik Virtual Machine
- Userland Apps written in Java, and compiled to Dalvik ByteCode
- Self-contained Applications packaged in One file
- Solid User Base (Billion)
- Strong ecosystem (Millions of Apps)
- + *alternative* markets (AppChina, Amazon, Opera, GetJar, etc.)

With great market shares comes great risks

Android is becoming Ubiquitous

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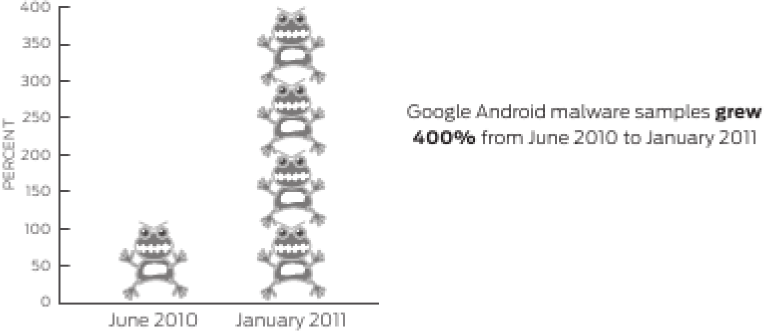
- A lot of device types (Media Players, STBs, DECT Phones, etc.)
- Huge amounts of personal data on each device
- Connected to both the phone network and the Internet

A target of choice for attackers

The Rise of the Malware



[1]

- Bank Phishing Apps (2010)
- Botnet (2010)
- GPS tracking disguised as a game (2010)
- SMS Trojan, SMS Leakage, Contacts Leakage, etc.
- Without using any Exploit (i.e. without breaking the permission-based security model)

[1] *Malicious Mobile Threats Report 2010/2011*, Juniper Networks, 2011

Research Question

Android Malware Detection

- How can we detect Malware Applications?

Android Malware Detection I

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The traditional Antivirus method

- Collect supicious samples
- Analyze each sample (Static and/or dynamic analysis)
- Extract a *signature*

What I'm trying to do

- Given a set of known malware
- And given a set of known goodware
- Use Data Mining to detect unknown malware samples

Android Malware Detection II

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Machine-Learning Android Malware : A Recipe

- Extract a Feature Vector from each known Malware sample;
- Extract a Feature Vector from each known Goodware sample;
- Extract a Feature Vector from an unknown Android App;
- Add some Machine Learning Magic.

Machine Learning I

Feature Vector…

- A *Feature* is just a characteristic, a property, a trait
- Example for Human Beings: Age, Gender, Height, Weight, Skin color, Eye color, Hair color, etc.
- Can you spot correlations between those variables?
- Can you spot variables that would allow to guess the variable *Gender*?

  $\rightarrow$ **Machine Learning finds correlations between variables**
- Machine Learning will spot that on average, men are taller than women

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Feature Matrix

Example with 2 Features and One class:

Height	Weight	Gender
185.42	70.3	male
172.72	60.3	female
185.42	70.3	male
157.48	49.9	female
180.34	68.0	male
170.18	68.0	female
172.72	70.3	male
156.845	48.9	female
⋮	⋮	⋮

Back to Android Malware

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What Features to detect Malware ?

→Put everything you can think of that *may* be statistically different for malware.

Back to Android Malware

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!TROLL ALERT! Have no idea at all ?

- You don't know what you're doing ?
- YOLO ?

Back to Android Malware

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- You don't know what you're doing ?
- YOLO ?
- "Deep Learning" is made for you !

Two Families of features

Static Analysis

- +Can be fast
- +Can be relatively simple
- −Blind to many things

Dynamic Analysis

- +Can see more things (like downloaded code)
- −Can see more things (so much data)
- −Cannot be fast
- −Exercising apps ? Fuzzing a GUI is highly inefficient, and not necessarily effective

Given the cost in time and CPU of dynamic Analysis, most researchers go the static Analysis way

Evaluation

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But features are just the first step

- Now you need to evaluate the performance of your malware detecor…
- That's incredibly hard to do properly

A few examples of issues…

What is a Malware?

Remember the scary Juniper graph?

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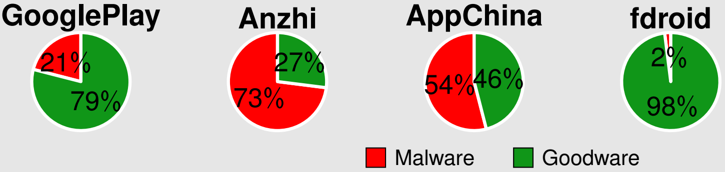
I can do scary graphs as well



(Malware == detected by at least 1 Antivirus)

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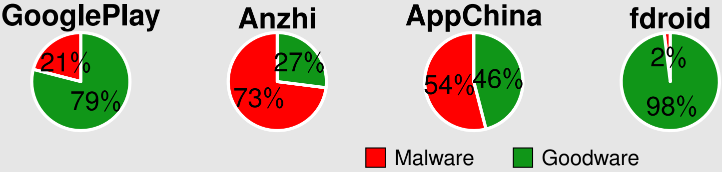

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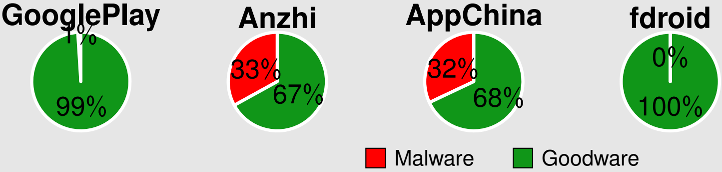
That one is slightly less scarry



(Malware == detected by at least 10 Antivirus)

Ground-truth

To do Machine Learning, we need:

- A set of known Malware
- A set of known Goodware

There are a few (small) sets of known Malware.
Interestingly, there is no set of known Goodware.

Using AntiVirus Products

- Not every AV agree

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Using AntiVirus Products

- Not every AV agree
- Well. . . All AVs Disagree
- Some flag Adware
- Some Don't
- Some Do Sometimes

→ **AVs do NOT share a common definition of what is a Malware**

AVs

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!TROLL ALERT! Increase your performance

AVs

!TROLL ALERT! Increase your performance

By choosing the definition that makes your detector look good.

In-the-Lab vs in-the-Wild

Size does matter

- Malware Detectors are often tested on very small datasets
- Their performance may be over-estimated

In-the-Lab vs in-the-Wild

Size does matter

- Malware Detectors are often tested on very small datasets
- Their performance may be over-estimated
- By a Whole lot

Data Leakage: The Time issue

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One slight methodology problem. . .

- We don't know the future.

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Data Leakage: The Time issue

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One slight methodology problem…

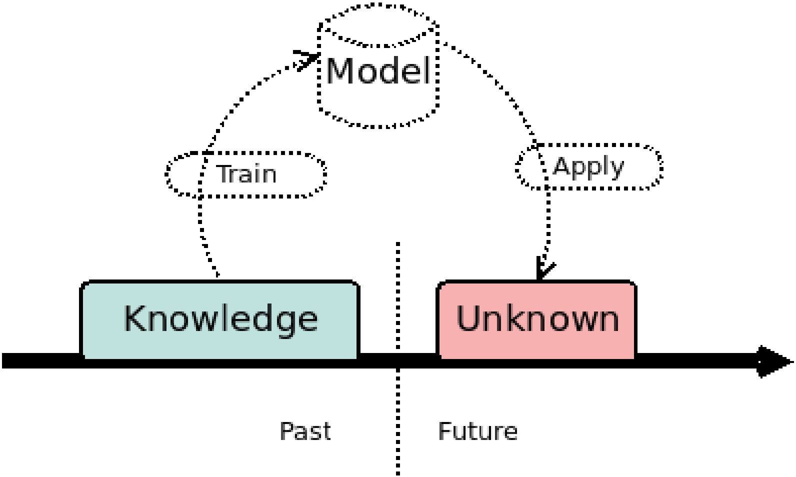
- We don't know the future.
- Yes, I learned that during my PhD
- "Science is a slow process"

The Time Issue: [*Back To The Future* Style]

- Testing an approach in an historically Incoherent way tells us:
  a) How this approach would perform Now on Malware from the Past
  or
  b) How this approach would have performed in the Past with (then-)Present Malware if it has had access to the (then-)Future
- However, it does Not tell us how it would perform Now on Present Malware

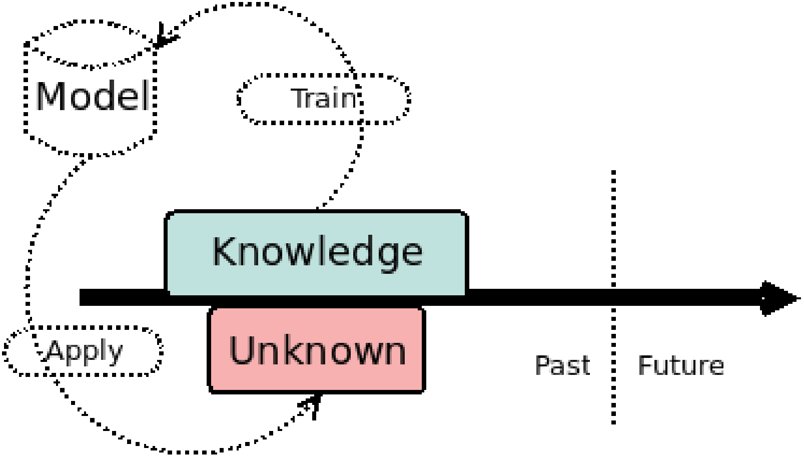
Does your brain hurt ?

Use-Cases I



Filtering / Finding brand new Malware

Use-Cases II



Cleaning Markets

State of the Art ?

- Nearly everyone does the time in-coherent way
- Knowing the Future helps a lot!
- I guess those two things are unrelated...

History Matters!

- History should be taken into account when evaluating a Malware detector;
- Approaches whose evaluation ignores History may actually perform badly where we need them most;

Conclusion

Automatic Malware Detection? We're not quite there...

What is needed ?

- Dependability, Dependability, Dependability
  Increase trust in Machine Learning-based malware detectors ?
  → Predicting performance where it cannot be assessed yet
  → Explanation
- Practicality
  How to tune an approach to match its user needs ?

Thank You!

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Questions?