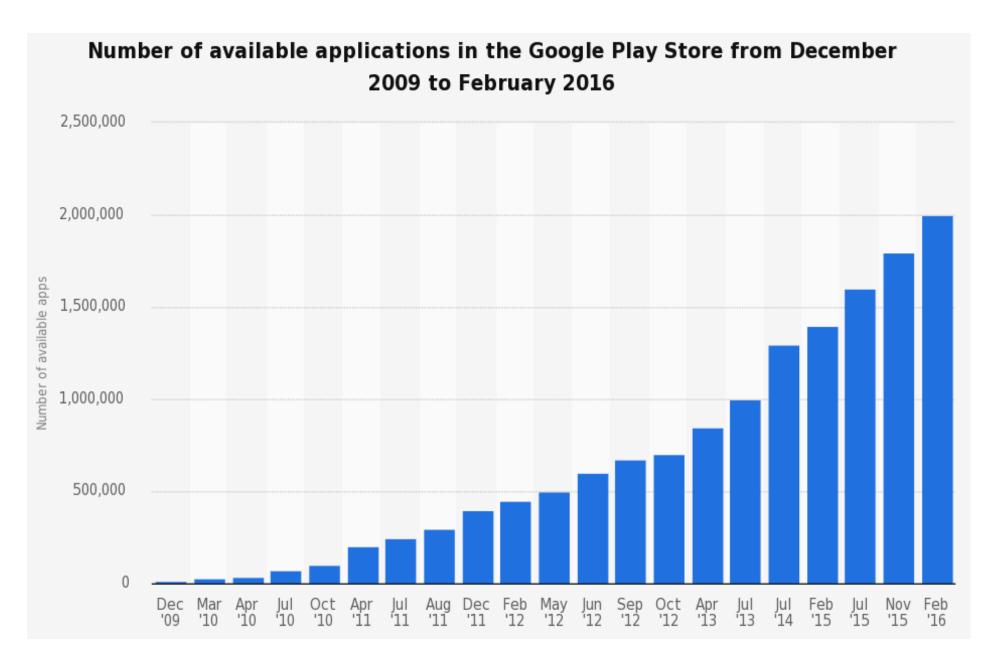
Mobile App Security: Detection and Family Identification of the Malice in Your Pocket

Sam Malek

Associate Professor
Institute for Software Research
University of California, Irvine
malek@uci.edu





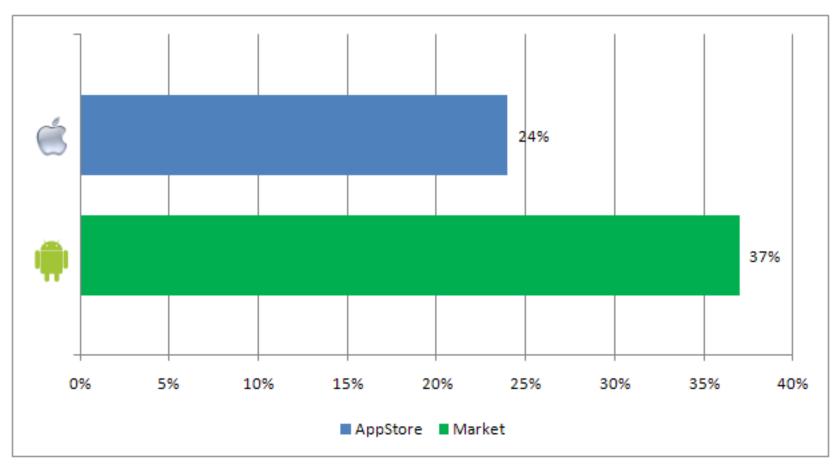


Source: Statista 2016

Typical App Developer



Many Low Quality Apps



Source: Research2Guidance

Potentially have Access to Lots of Private Data

- Camera
- Microphone
- Accelerometer
- Gravity sensor
- Linear acceleration sensor
- Magnetic field sensor
- Orientation sensor
- Gyroscope
- Light sensor
- Proximity sensor
- Temperature sensor
- Pressure sensor



Perfect Storm

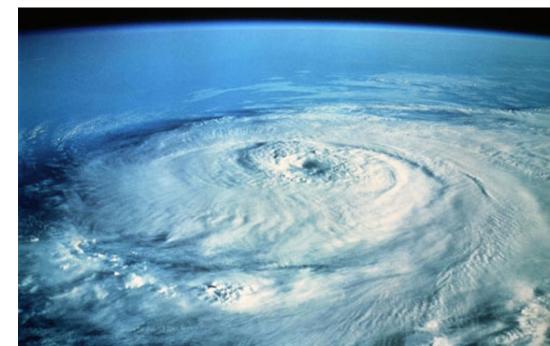
App markets

 best tool ever known to attackers for delivering malicious payload

Market operators are challenged by the limitations of program analysis

- Halting problem
- Lots of riches to be gained
 - Premium numbers
 - Adware

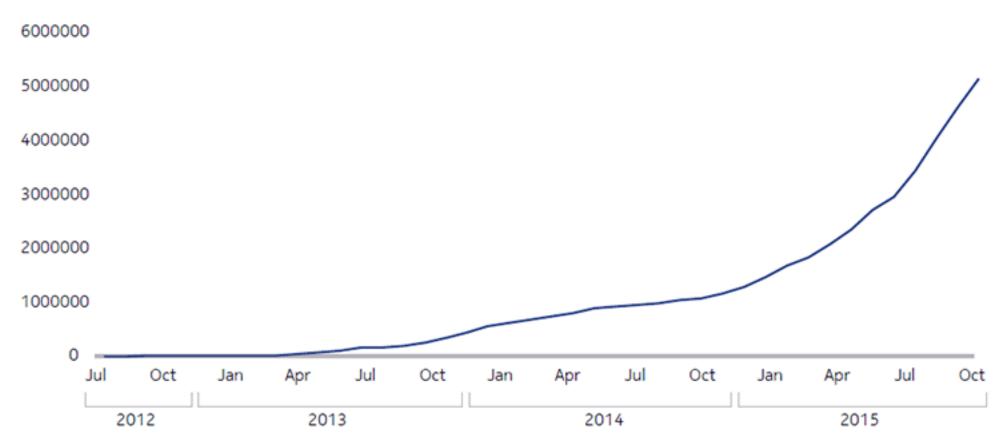
— ...



Malicious Android Apps



- Immense number of Android malware apps
 - 342% growth in 2015



Source: Calyptix Security

Malware Family

- GingerMaster
 - First Android malware using root exploit
 - Steal sensitive info (IMEI, SIM card number, etc.)
- DroidJack
 - No root access required
 - Remote Access Tool
 - Update itself
 - Record phone calls and audio
 - Steal sensitive info



•

Detection and removal



Detection and removal is not enough



Detection and removal is not enough---identify families



- Detection and removal is not enough---identify families
- Malware likes to hide



- Detection and removal is not enough---identify families
- Malware likes to hide
- Catch them fast



Our Research

1. Is it possible to learn what makes an app malicious?

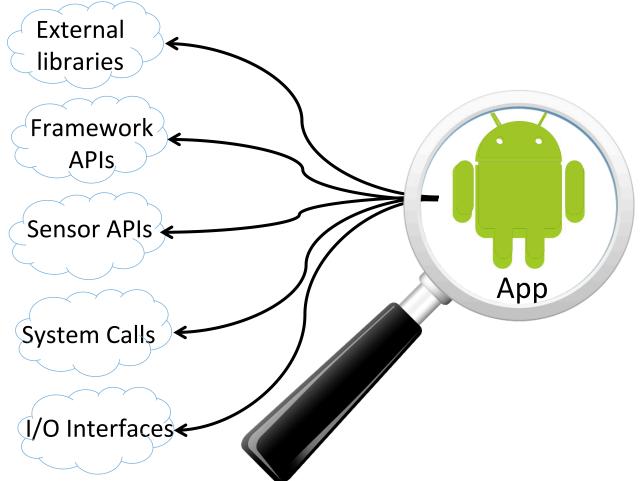
2. If so, is it possible to automatically learn the family of malicious apps?



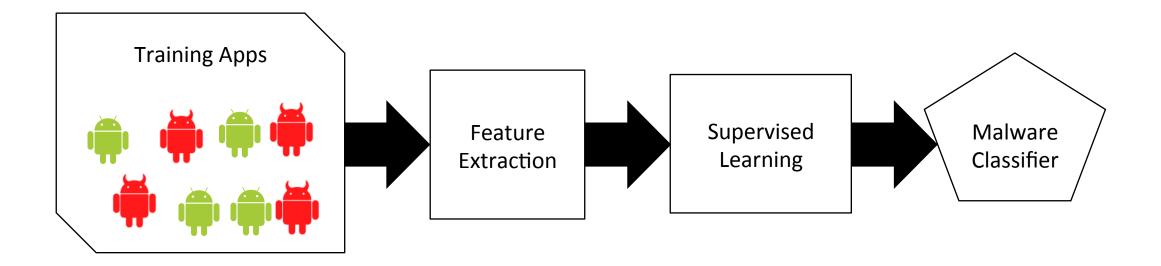
RevealDroid

 A machine learning-based approach for malware detection and family identification

- Accurate
- Highly efficient
- Obfuscation-resilient



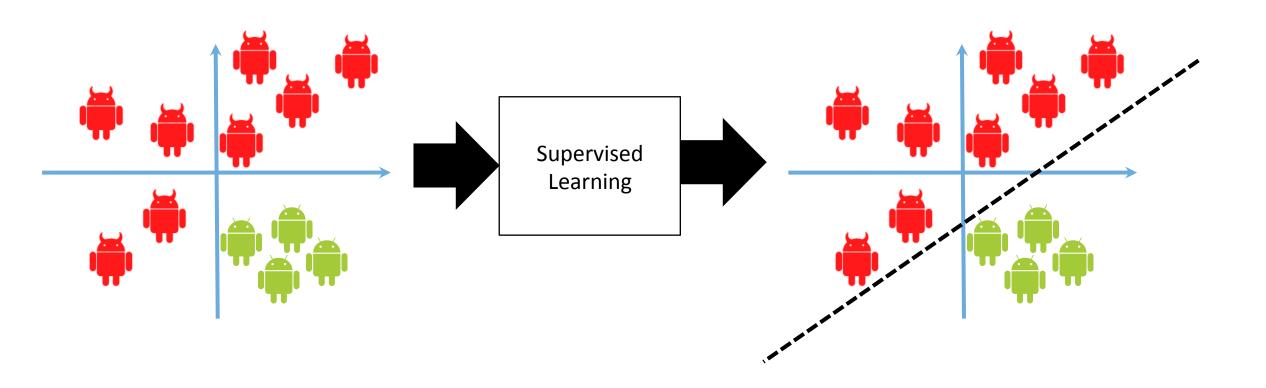
Classifier Construction for Malware Detection



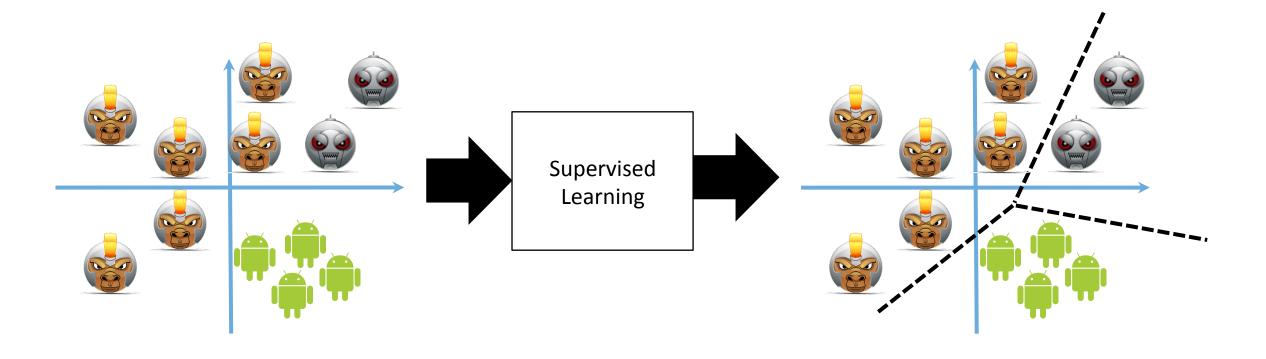
App Representation for Supervised Learning

Арр	Feature1	Feature2	Feature3	Feature4	Label
	1	0	0	0	Malicious
	0	1	0	0	Malicious
	0	0	1	1	Benign
	0	0	1	0	Benign

Supervised Learning for Malware Detection



Supervised Learning for Family Identification



Feature Selection

	Perm	Comp	IFilters	Flows	UAPI	PAPI	SAPI	IActions	Reflection	Native
Accuracy	X	X	X	V	V	V	V	V	V	V
Efficiency	/	V	V	X	X	~	V	V	/	/
Obfuscation	V	X	X	X	V	~	V	X	/	V

Feature Examples: Package API (PAPI)

- Numbers of Android API methods invoked by app per package
 - android.telephony
 - TelephonyManager.getCellLocation()
 - CellIdentityLte.getCi()

	telephony	location	sqlite	Fam
mal1	8	0	2	jSMSHider
mal2	0	12	0	Geinimi
mal3	2	0	7	BaseBridge

Feature Examples: Reflective Calls

- Apps may dynamically load libraries/classes through reflection
 - Used frequently to obfuscate malicious behavior

```
ClassLoader cl = MyClass.getClassLoader();
try { Class c = cl.loadClass("MyActivity");

Method m = c.getMethod("onPause",...);

m.invoke(...); }

catch { ... }
```

Feature Examples: Native Calls

- Apps can make system calls and calls to native binaries
 - Analysis of native binaries requires disassembly of ELF files

```
1 99ec: e59d0010 ldr r0, [sp, #16]
2 99f0: e59f13c0 ldr r1, [pc, #960]
3 99f4: ebfffc3e bl 8af4 <chmod@plt>
```

Code segment where *chmod* is invoked in *GingerBreak* malware

Labeling and Classifier Selection

- Classifier for detection
 - 2-way classifier with labels "benign" or "malicious"
 - Support Vector Machine (SVM)
- Classifier for family identification
 - n-way classifier where n = the number of families
 - Classification and Regression Trees (CART)

Experiments



Experimental Setup

- Prototype built using open-source software
 - Java-based
- Over 23,300 benign and 28,100 malicious apps
 - Collected from Malware Genome, Drebin, and Virus Share repositories
- 68 different malware families

Detection accuracy on non-obfuscated apps

	Precision	Recall	F1
Benign	95%	85%	90%
Malicious	89%	96%	92%
Average	92%	91%	91%

Greater than 90% precision and recall

Family identification accuracy on non-obfuscated apps

	No. Apps	No. Families	Correct Classification Rate
Malware Genome	1,250	49	92%
Virus Share	18,065	68	87%

A random classifier would obtain only 1.5% correct classification rate

Detection accuracy on obfuscated apps

- Testing apps were obfuscated using DroidChameleon
 - Shown to evade all commercial antivirus products
 - String/Array encryption, class renaming, call indirection, etc.

	Precision	Recall	F1
Benign	96%	70%	81%
Malicious	82%	98%	89%
Average	89%	84%	85%

Family identification accuracy on obfuscated apps

	No. Apps	No. Families	Correct Classification Rate
Malware Genome	1,188	49	94%

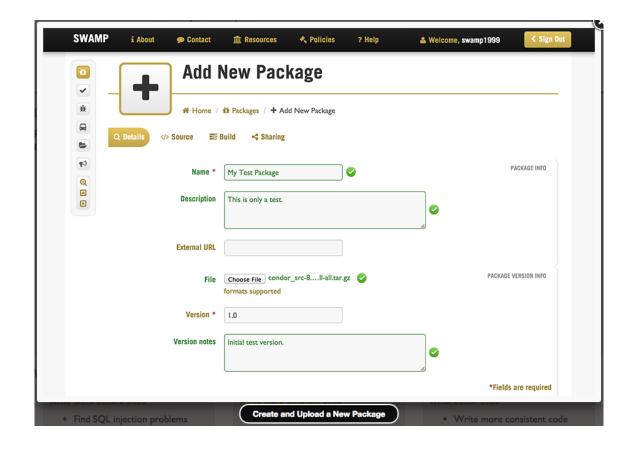
Performance

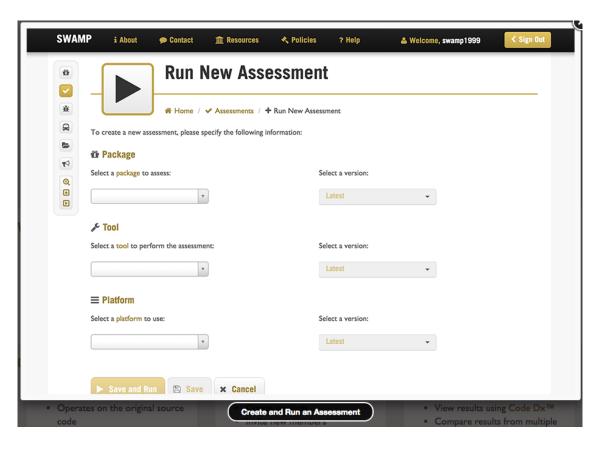
		Classification		
No. of apps	Native (s)	Reflection (s)	PAPI (s)	(s)
100 randomly selected	18	31	24	2

It takes around 30 seconds to run RevealDroid on an app

Department of Homeland Security

- Available for use through the SWAMP portal
 - https://continuousassurance.org/





Conclusion



RevealDroid

- A machine-learning based approach for malware detection and family identification
- Highly accurate, obfuscation resilient, and fast

Acknowledgement

- Joshua Garcia
- Mahmoud Hammad
- Kari Nies







Backup

Mobile Software Ecosystems

- Successful software platforms open themselves to third party developers, resulting in massive product lines
 - E.g., Android app ecosystem



