

Toward a Trustworthy Android Ecosystem

Yan Chen

Lab of Internet and Security Technology (LIST)

Northwestern University, USA



Smartphone Security

- Ubiquity - Smartphones and mobile devices

Worldwide smart phone and client PC shipments

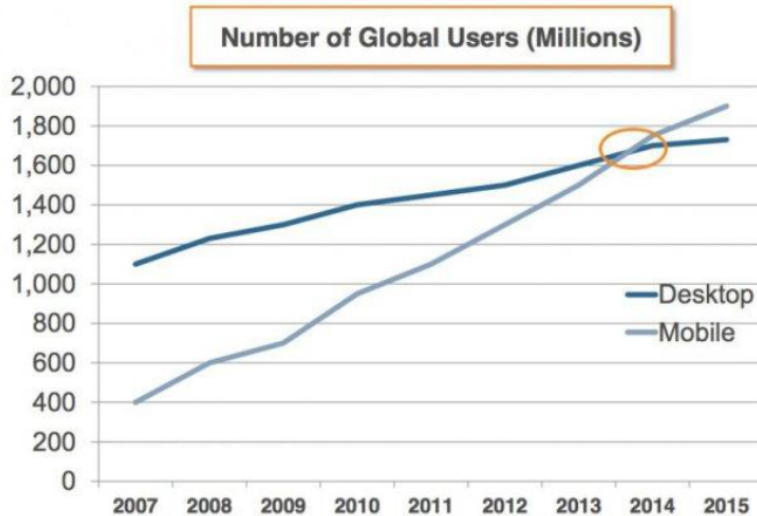
Shipments and growth rates by category, Q4 2011 and full year 2011

Category	Q4 2011 shipments (millions)	Growth Q4'11/Q4'10	Full year 2011 shipments (millions)	Growth 2011/2010
Smart phones	158.5	56.6%	487.7	62.7%
Total client PCs	120.2	16.3%	414.6	14.8%
- Pads	26.5	186.2%	63.2	274.2%
- Netbooks	6.7	-32.4%	29.4	-25.3%
- Notebooks	57.9	7.3%	209.6	7.5%
- Desktops	29.1	-3.6%	112.4	2.3%

Source: Canalys estimates © Canalys 2012



Mobile Devices (apps) Dominate



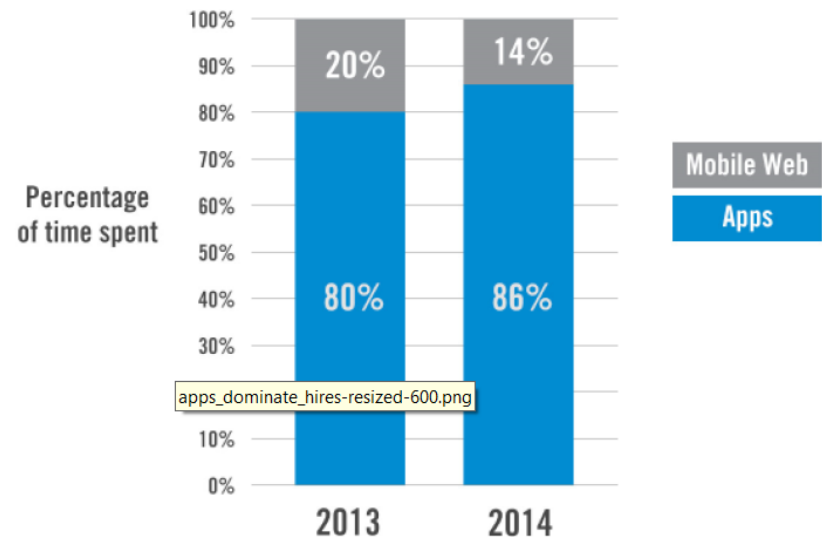
comSCORE.

© comScore, Inc. Proprietary and Confidential.

24

Source: Morgan Stanley Research

Apps Continue to Dominate the Mobile Web



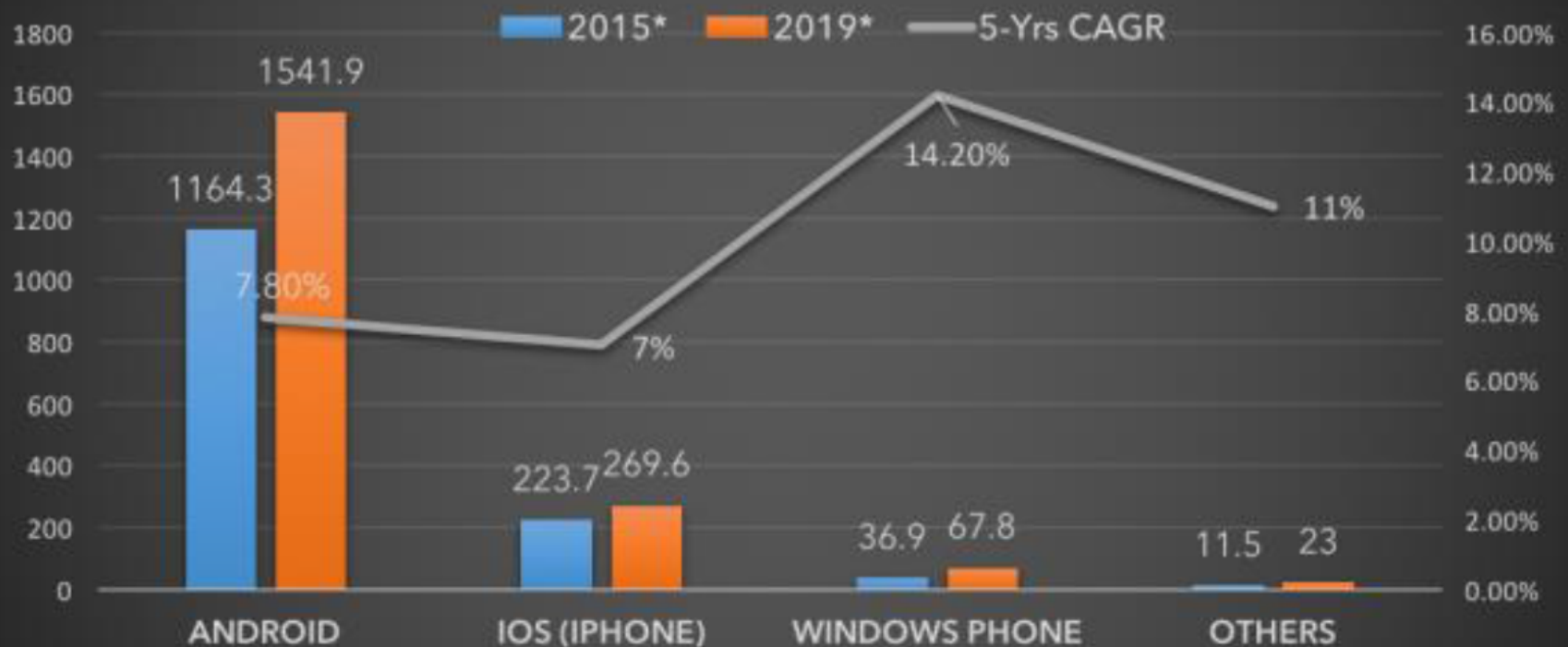
FLURRY

Source: Flurry Analytics



Android is Leading the Pack

WORLDWIDE SMARTPHONE SHIPMENTS FORECAST BY OS



SOURCE: IDC TRACKER, AUGUST 2015

NOTE: FIGURES IN MILLIONS

DAZEINFO



Android Ecosystem

Carriers



Vendors



Application Stores

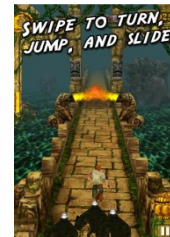


Google play

Google



Applications



Devices and OS



Security Vendors

Users



Developers





Android Threats



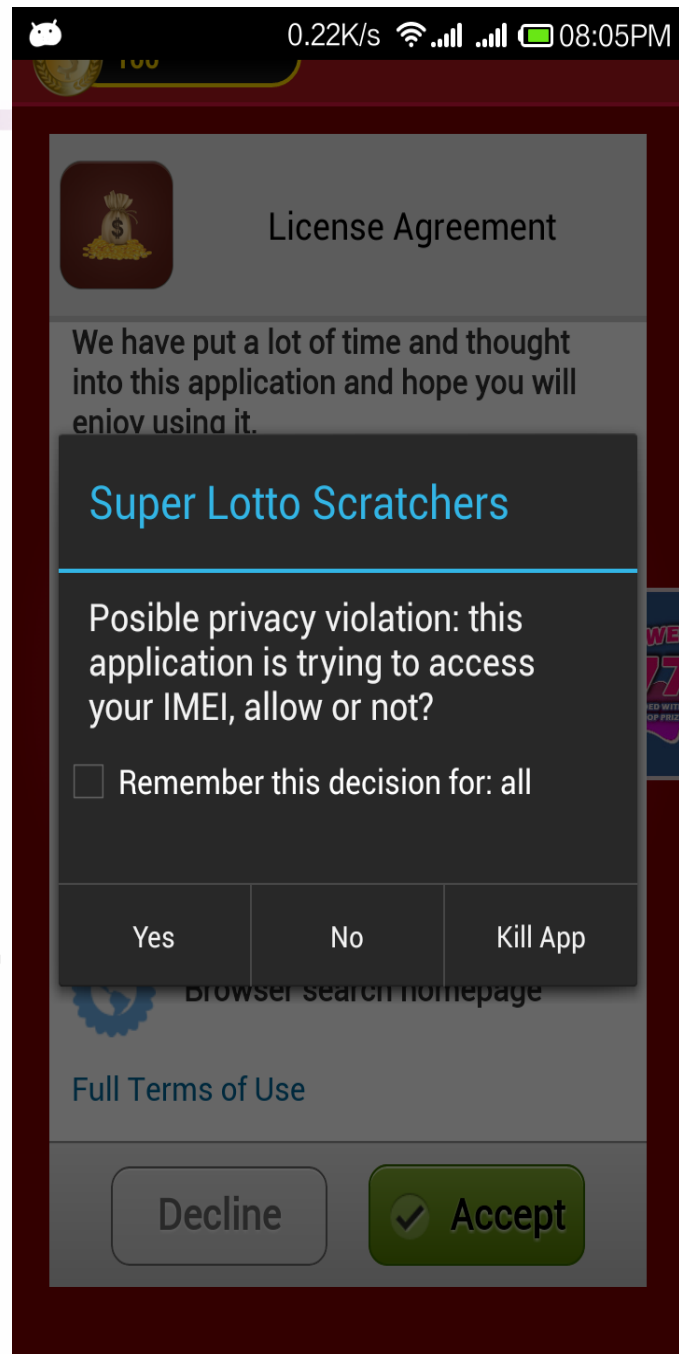
[flickr.com/photos/panda_security_france/](https://www.flickr.com/photos/panda_security_france/)

- Malware and vulnerabilities
 - The numbers are increasing consistently
 - Anti-malware ineffective at catching zero-day and polymorphic malware
- Information Leakage
 - Users have no way to know when and what info is being leaked out of their device to whom
 - Even legitimate apps leak private info though the user may not be aware
- Fraud activities (esp. for mobile payment)



Privacy Leakage

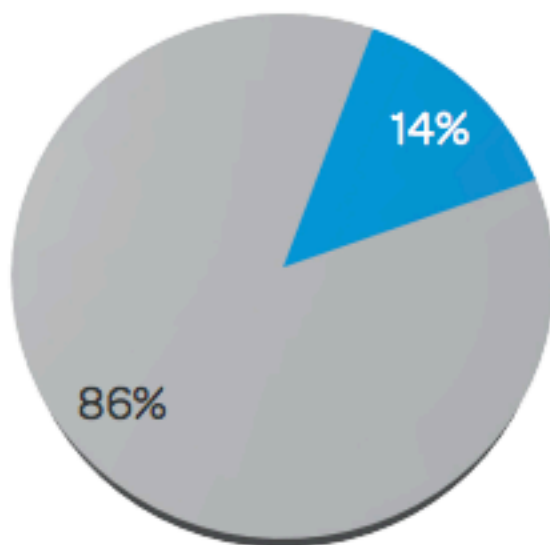
- Android permissions are insufficient
 - User still does not know if some private information will be leaked
- Information leakage is more dangerous than information access
 - Example 1: popular apps (e.g., Angry Birds) leak location info with its developer, advertisers and analytics services
 - Even doesn't need it for its functionality!
 - Example 2: malware apps may steal private data
 - A camera app trojan send video recordings out of the phone



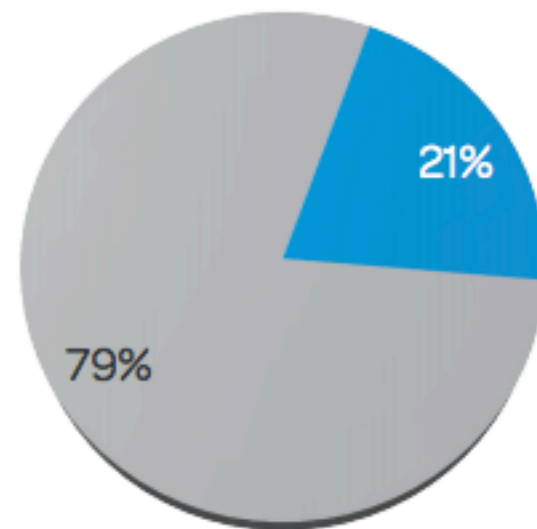


Fraudulent Mobile Transactions

Total Transactions



Fraudulent Transactions



■ Mobile payments ■ All other payments

123,255 eCommerce customers with >\$0 fraud in March 2014, by LexisNexis



New Challenges & Opportunities

- Centralized control
 - Vet applications before they enter store
 - Carriers may have more complete pictures of users and traffic
- Apps are much easier to analyze statically
 - Use of Dalvik bytecode instead of x86
- Constrained environment
 - CPU, memory, battery
 - User perception



Problems and Our Solutions

- Issues for existing mobile anti-virus systems
 - Easy to evade [DroidChamelon]
 - Unable to detect native malware [DroidNative]
 - Unable to detect malware in ads or dynamically loaded content [AdShield]
- Privacy leakage detection and prevention
 - How to find questionable sensitive permissions [AutoCog]
 - Real time tracking & preventing privacy leakage on phone
 - Consumer [PrivacyShield]
 - Enterprise Mobility Management (EMM) [AppShield]
- Fraud detection mostly with app-level risk management [DroidCog]
 - Duplicate detection
 - Privacy infringement



Systems Developed

- AppsPlayground [ACM CODASPY'13]
 - Automatic, large-scale dynamic analysis of Android apps
 - System released with hundreds of download
- DroidChameleon [ACM ASIACCS'13, IEEE Transaction on Information Forensics and Security 14]
 - Evaluation of latest Android anti-malware tools
 - All can be evaded with transformed malware
 - System released upon wide interest from media and industry

Impact of DroidChameleon



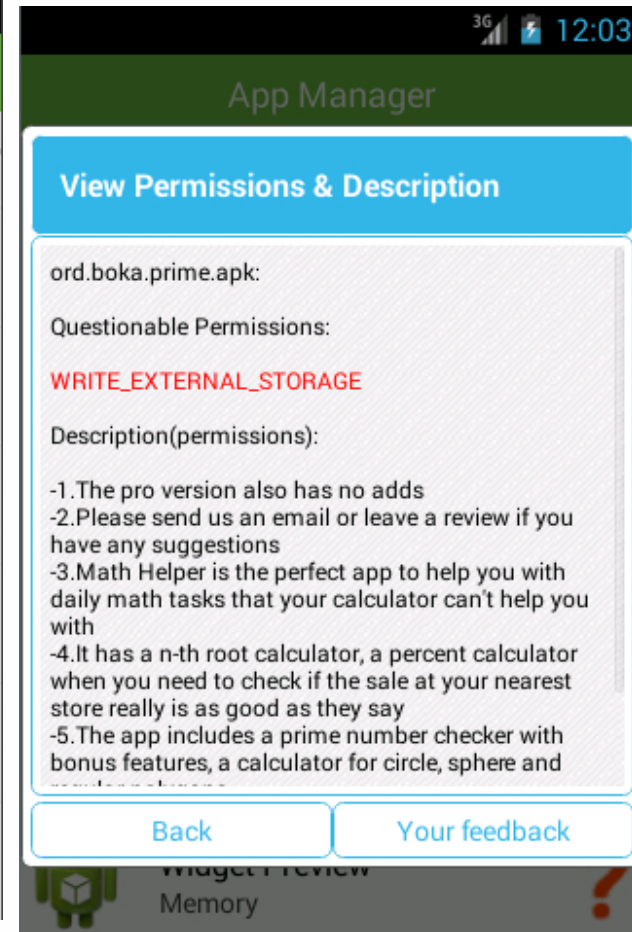
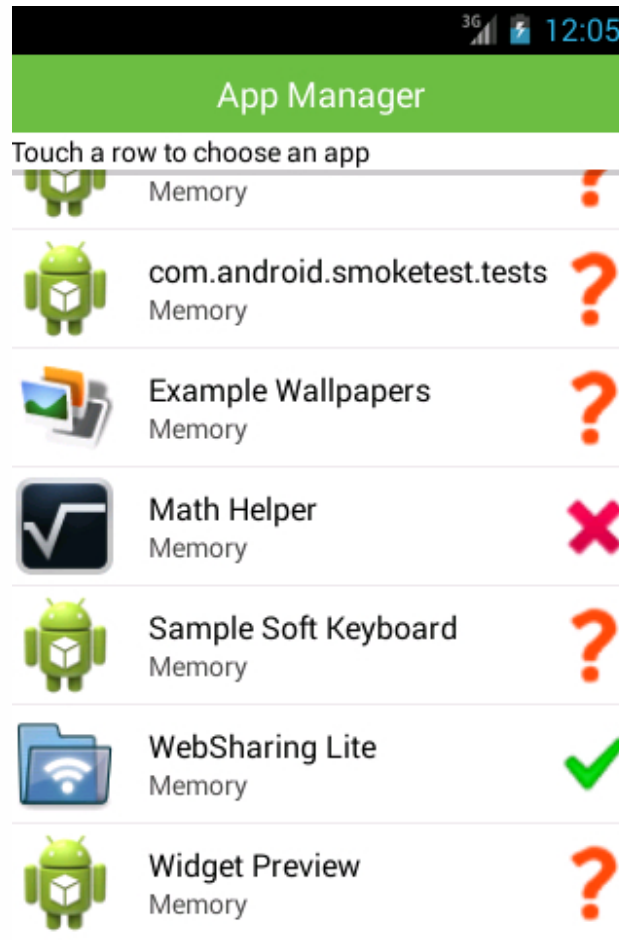
Interest from vendors





System Developed: AutoCog

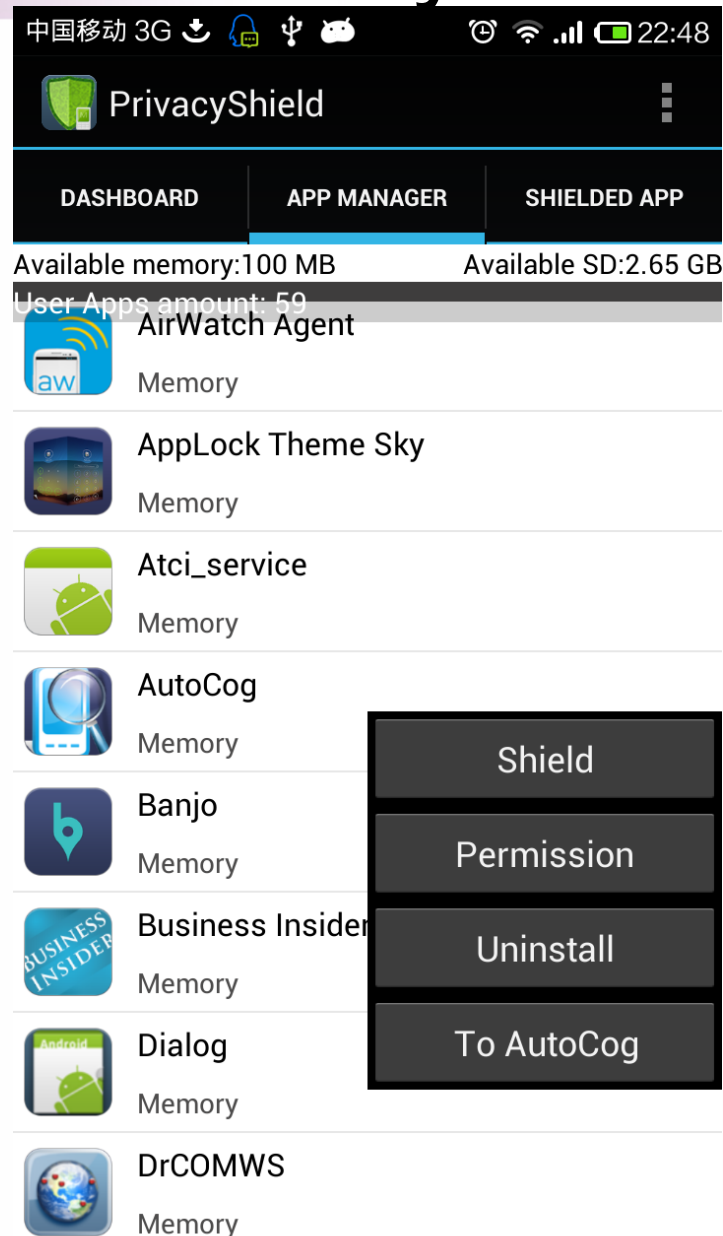
Check whether sensitive permissions requested by apps are consistent with its natural-language description





Systems Developed: PrivacyShield

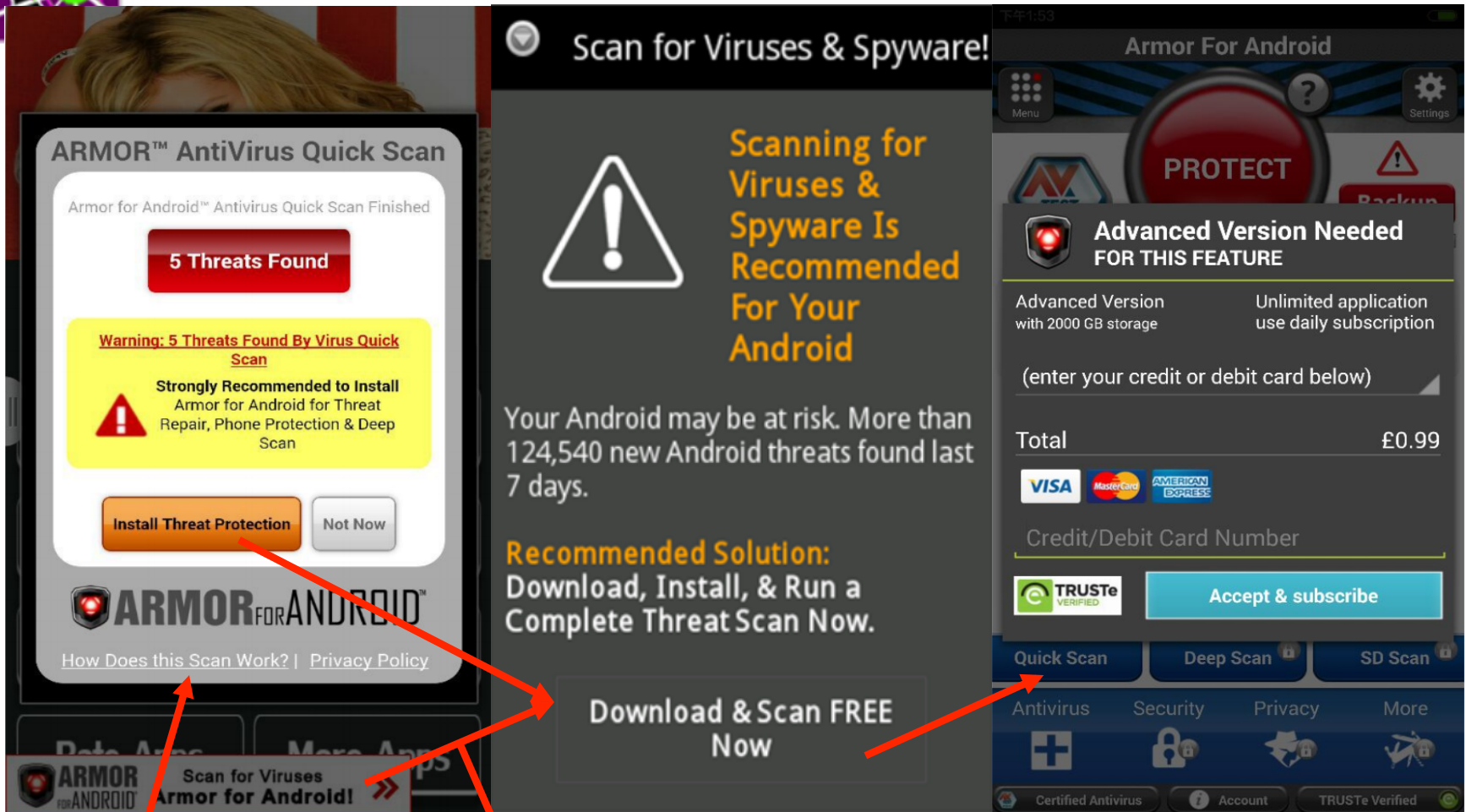
- Real-time information-flow tracking for privacy leakage detection
- App instrumentation, with zero platform modification
- App released in Google play and Baidu stores





ARE THESE ADS SAFE: DETECTING HIDDEN ATTACKS THROUGH MOBILE APP-WEB INTERFACES

Consider This...



Faked threat report

Click on the buttons

Downloaded phishing
app



The Problem

- Enormous effort toward analyzing malicious applications
- App may itself be benign
 - But may lead to malicious content through links
- ***App-web interface***
 - Links inside the app leading to web-content
 - Not well-explored
- Types
 - Advertisements
 - Other links in app



Outline



App-Web Interface Characteristics

Solution

Results

Conclusion



Outline

App-Web Interface Characteristics

Solution

Results

Conclusion



App-Web Interface Characteristics

- Can be highly dynamic
- A link may recursively redirect to another before leading to a final web page
- Links embedded in apps
 - Can be dynamically generated
 - Can lead to dynamic websites
- Advertisements
 - Ad libraries create links dynamically
 - Ad economics can lead to complex redirection chains

Advertising Overview



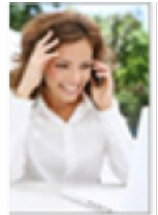
ADCOLONY

admob

millennialmedia

友盟 UMENG

inMOBI



Advertisers

Ad networks

Apps / Developers

Users



Ad Networks

- Ad libraries act as the interface between apps and ad network servers
- Ad networks may interface with each other
 - Syndication – One network asks another to fill ad space
 - Ad exchange – Real-time auction of ad space
- App or original ad network may not have control on ads served



Outline

App-Web Interface Characteristics

Solution

Results

Conclusion

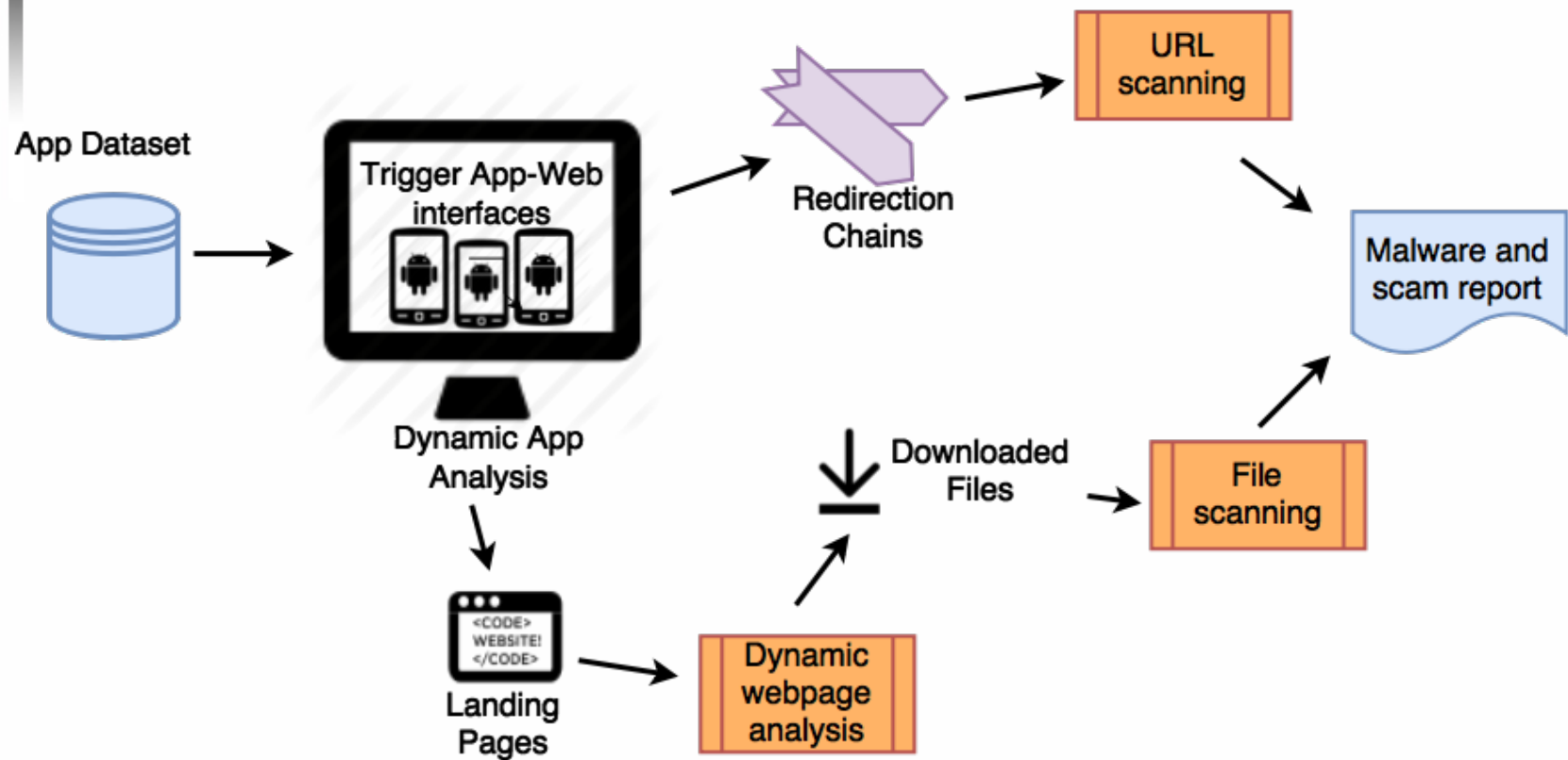


Solution Components

- **Triggering:** Interact with app to launch web links
- **Detection:** Process the results to identify malicious content
- **Provenance:** Identify the origin of a detected malicious activity
 - Attribute malicious content to domains and ad networks



Solution Architecture





Triggering

- Use AppsPlayground¹
 - A gray box tool for app UI exploration
 - Extracts features from displayed UI and iteratively generates a UI model
- A novel computer graphics-based algorithm for identifying buttons
 - See widgets and buttons as a human would

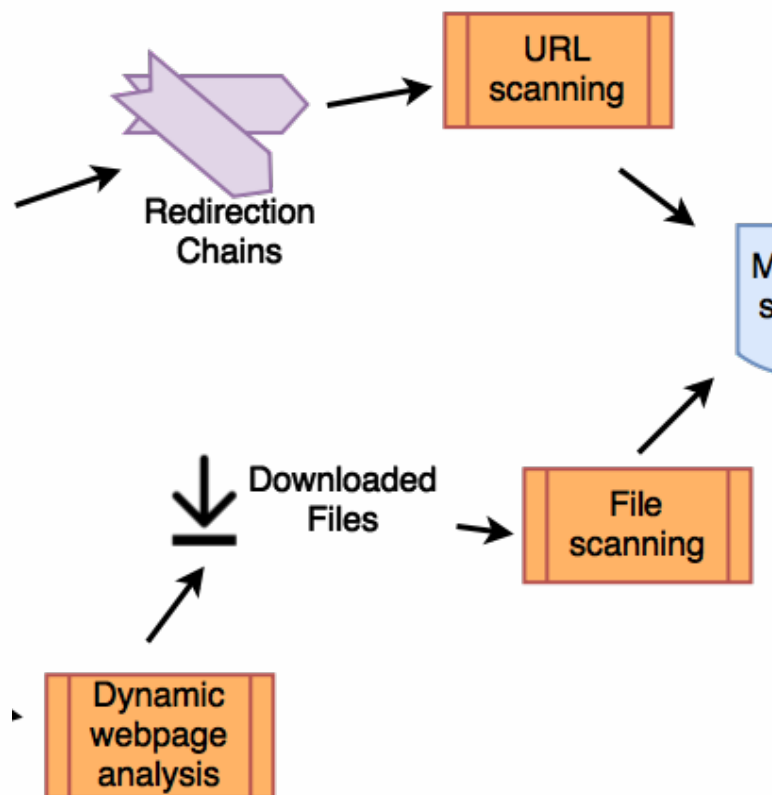


¹Rastogi, Vaibhav, Yan Chen, and William Enck. "AppsPlayground: automatic security analysis of smartphone apps." In *Proceedings of the third ACM conference on Data and application security and privacy*, pp. 209-220. ACM, 2013.



Detection

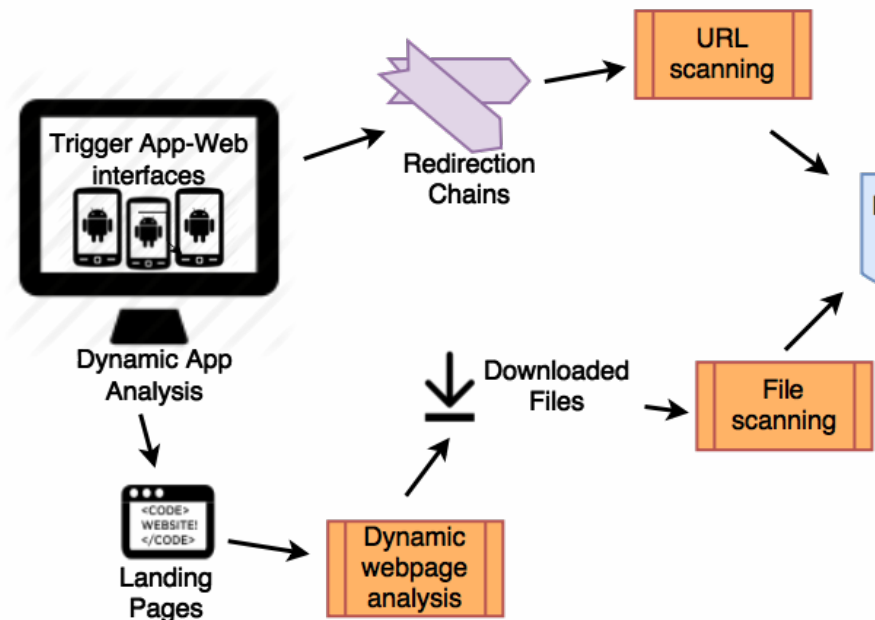
- Automatically download content from landing pages
- Use VirusTotal for detecting malicious files and URLs





Provenance

- How did the user come across an attack?
- Code-level attribution
 - App code
 - Ad libraries
 - **Identified 201 ad libraries**
- Redirection chain-level attribution
 - Which URLs led to attack page or content





Outline

App-Web Interface Characteristics

Solution

Results

Conclusion



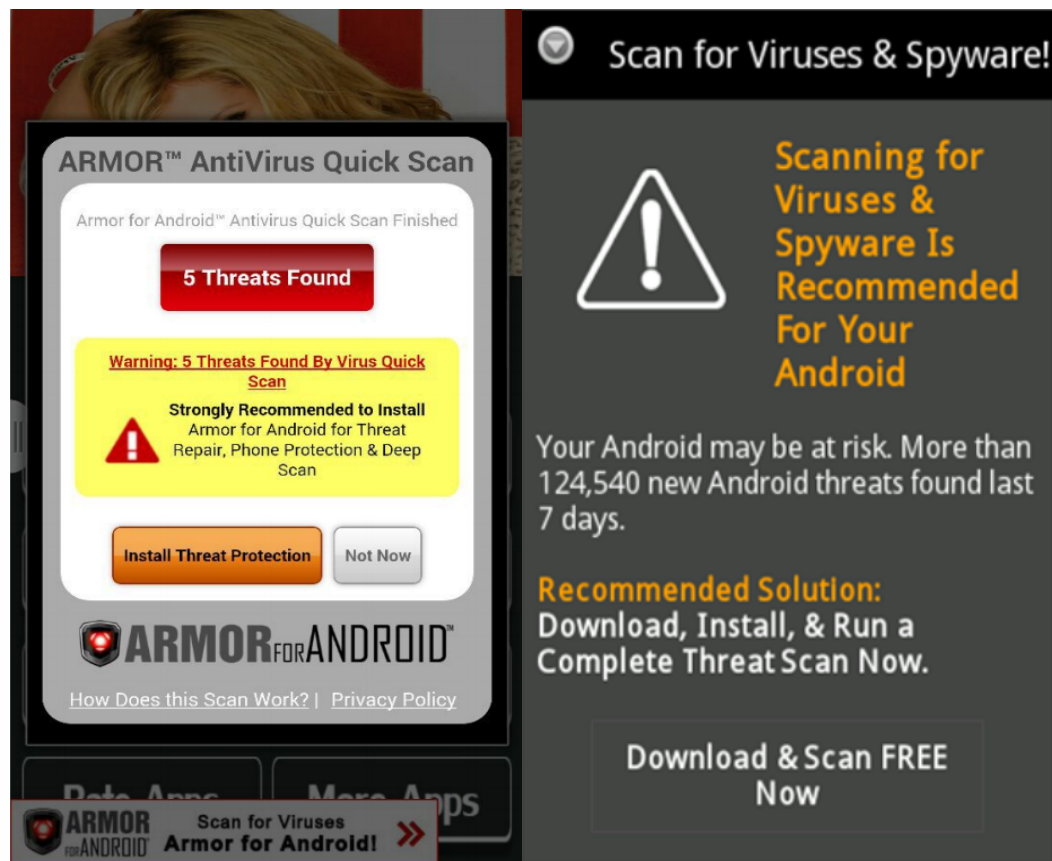
Results

- Deployments in US and China
- 600 K apps from Google Play and Chinese stores
 - 91, Anzhi (安智), AppChina(应用汇), Mumayi (木蚂蚁)
- 1.4 M app-web links triggered
- 2,423 malicious URLs
- 706 malicious files



Case Study: Fake AV Scam

- Multiple apps, one ad network: Tapcontext
- Ad network solely serving this scam campaign
- Phishing webpages detected by Google and other URL blacklists about 20 days after we detected first instance





Case Study: Free iPad Scam

- Asked to give personal information without any return
- New email address receiving spam ever since
- Origins at Mobclix and Tapfortap
 - Ad exchanges
 - Neither developers nor the primary ad networks likely aware of this

Lucky Visitor!




You've been randomly selected to qualify for a special offer!

Your phone has been randomly selected. You have the opportunity to get 1 of 3 offers listed below! Participation Required: [Read terms.](#)

Choose now:

Select a special offer below to continue...

Get now before we give the offer to another eligible visitor.

	iPad Air Available Select
	Samsung Note 4 Not Available Select
	new iPhone 6 Available

Congratulations!



Your iPhone 6 has been reserved. Follow the instructions below in order to continue.

Click "CONTINUE" and claim your prize.

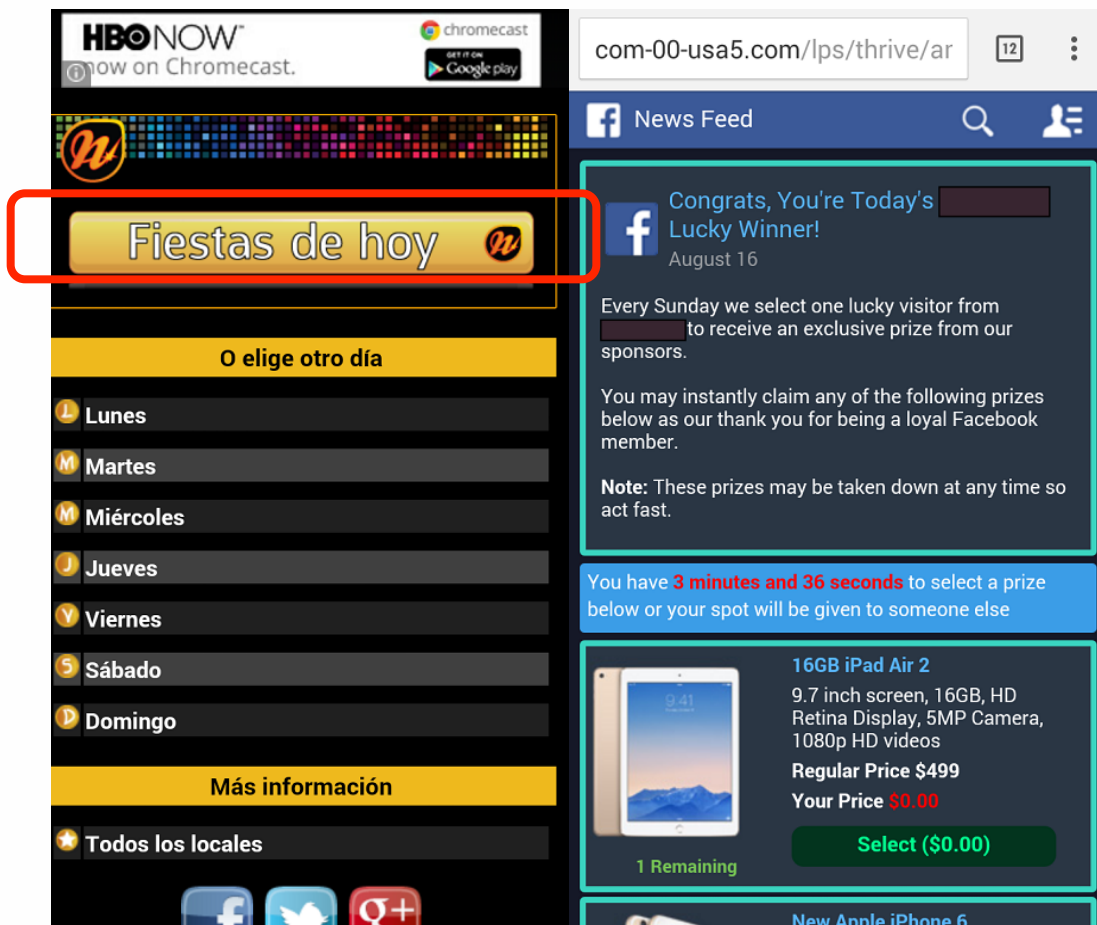
CONTINUE

This offer is valid for **300** seconds.



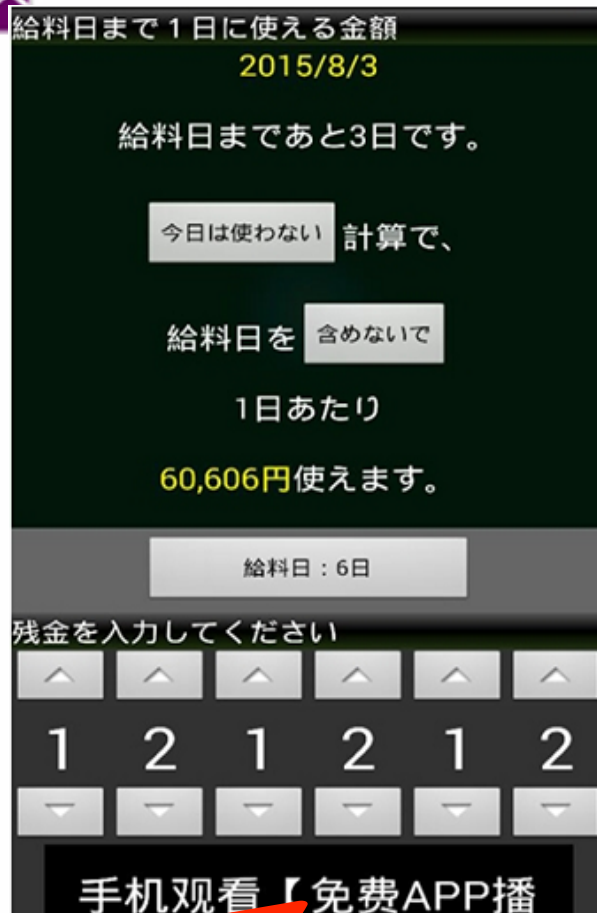
Case Study: iPad Scam from static link

- Another Scam, this time through a static link embedded in app
- Link target opens in browser and redirects to scam
- Not affiliated with Facebook





Case Study: SMS Trojan Video Player



Click on ad



- Ad from nobot.co.jp leads to download a movie player
- Player sends SMS messages to a premium number without user consent



Outline

App-Web Interface Characteristics

Solution

Results

Conclusion



Limitations

- Incomplete detection
 - Antiviruses and URL blacklists are not perfect
 - Our work DroidChameleon² shows this
- Incomplete triggering
 - App UI can be very complex
 - May still be sufficient to capture advertisements

²Rastogi, Vaibhav, Yan Chen, and Xuxian Jiang. "Catch me if you can: Evaluating android anti-malware against transformation attacks."

Information Forensics and Security, IEEE Transactions on 9.1 (2014): 99-108.



Conclusion and Ongoing Work

- Benign apps can lead to malicious content
- First large scale study to detect malicious ads on Android
- Making it a 24 * 7 service
- Working with ad network providers (e.g., Baidu and Google) and CNCERT for defense
- Only the tip of iceberg, security issues on dynamic code loading (DCL)
 - Detected malware and vulnerabilities that Google Bouncer missed



DROIDCOG: DEVICE-LEVEL MOBILE RISK MANAGEMENT



Motivations

- The growing popularity of mobile payment

- Attack surface financial

- Countermeasures

- G1: authentication

- G2: risk

- Heavy

- Application

US Proximity Mobile Payment User Penetration, by Age, 2014-2019

% of smartphone users

	2014	2015	2016	2017	2018	2019
14-17	5.3%	7.0%	9.5%	13.0%	17.0%	22.0%
18-24	12.3%	15.5%	24.0%	33.0%	37.0%	43.0%
25-34	14.0%	17.5%	29.0%	37.0%	40.0%	45.0%
35-44	11.3%	14.5%	22.5%	28.0%	32.0%	36.0%
45-54	9.3%	12.3%	16.5%	20.0%	23.0%	27.0%
55-64	7.3%	9.0%	11.5%	14.7%	18.0%	21.0%
65+	2.1%	3.5%	5.1%	6.3%	7.5%	10.4%
Total	10.0%	12.7%	19.0%	24.0%	27.0%	31.0%

Note: includes point-of-sale transactions made by using mobile devices as a payment method; excludes transactions made via tablet

Source: eMarketer, Oct 2015

198682

www.eMarketer.com



(安卓版隐私门)

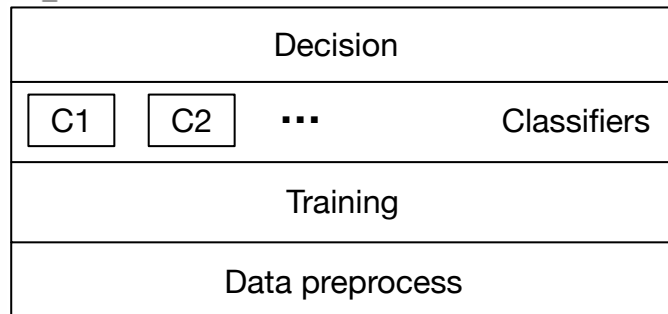
Payment detection



Goal

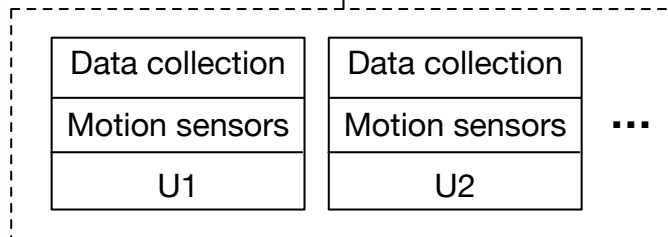
- A learning-based mechanism for user fraud detection
 - Least user privacy required, high detection accuracy
 - Device-level approach: only one copy of data is uploaded
 - Robust, hard to evade

Goal

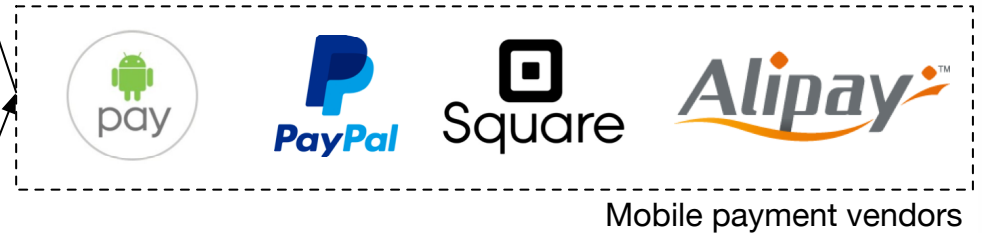


Server

Periodical upload



Client





Problem Statement



Fingerprinting Bob's
usage manner



Verify based on classification results





Challenges

- Lack of features
- Data availability
- Imbalanced dataset
- Noise surrounding
- Unlabeled data



Challenges

- Lack of features
 - Only based on acceleration sensor and gyroscope sensor
 - Feature selection (6 values \rightarrow 64 features)
- Data availability
- Imbalanced dataset
- Noise surrounding
- Unlabeled data



Challenges

- Lack of features
- Data availability
 - Periodical data collection
 - User activity detection
- Imbalanced dataset
- Noise surrounding
- Unlabeled data



Challenges

- Lack of features
- Data availability
- Imbalanced (classification) dataset
 - Control of distribution of training set
 - Random selection & stratified sampling
- Noise surrounding
- Unlabeled data



Challenges

- Lack of features
- Data availability
- Imbalanced dataset
- Noise surrounding
 - Calibrate sensor data based on gravity direction
 - Identify user motion state: static or in motion?
- Unlabeled data



Challenges

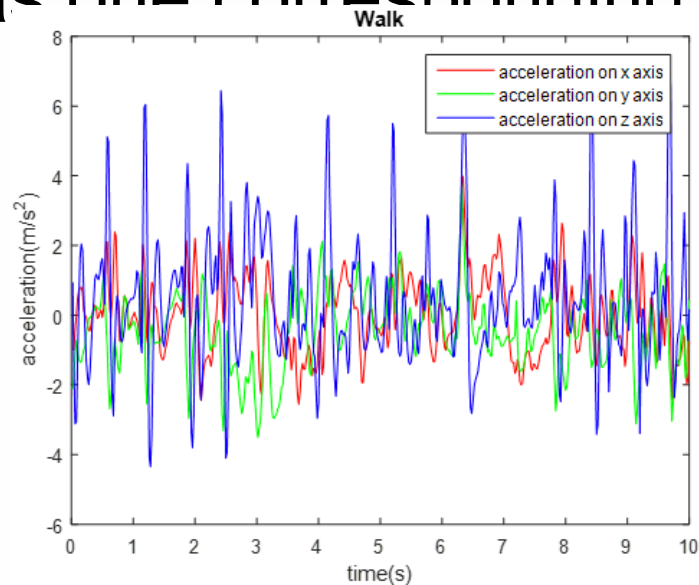
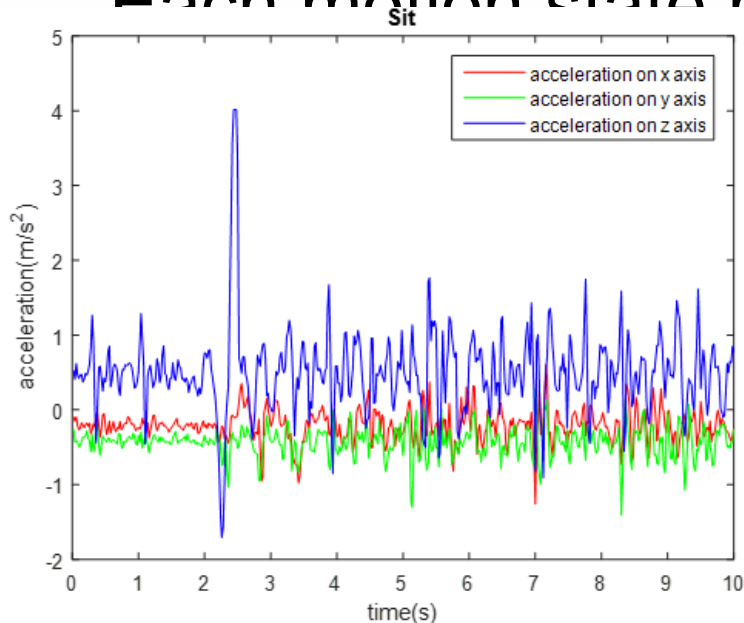
- Lack of features
- Data availability
- Imbalanced dataset
- Noise surrounding
- Unlabeled data
 - Semi-supervised online learning



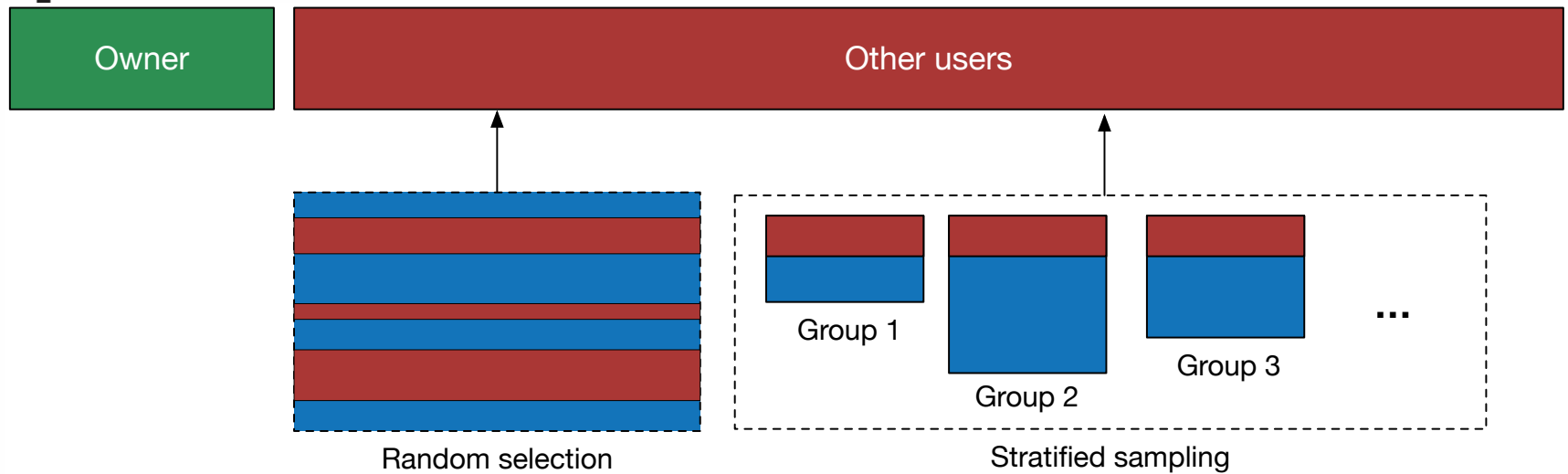
Data Preprocessing

- Filter useless data on client side
 - The device is put on a flat plane
- Identify motion state on server

Each motion state has one corresponding



Training Set Construction

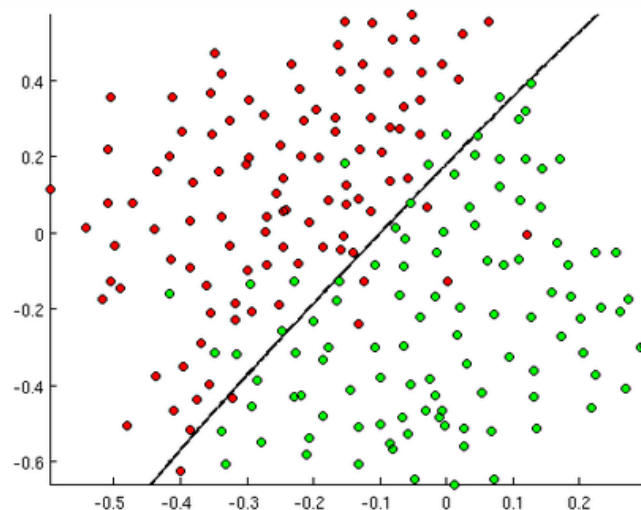
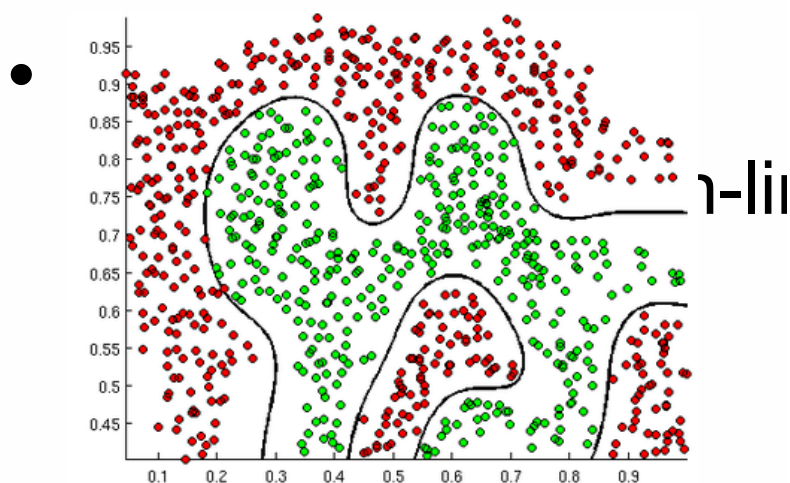


- Random selection v.s. stratified sampling
 - Similar performance
 - No cost of grouping user data for random selection



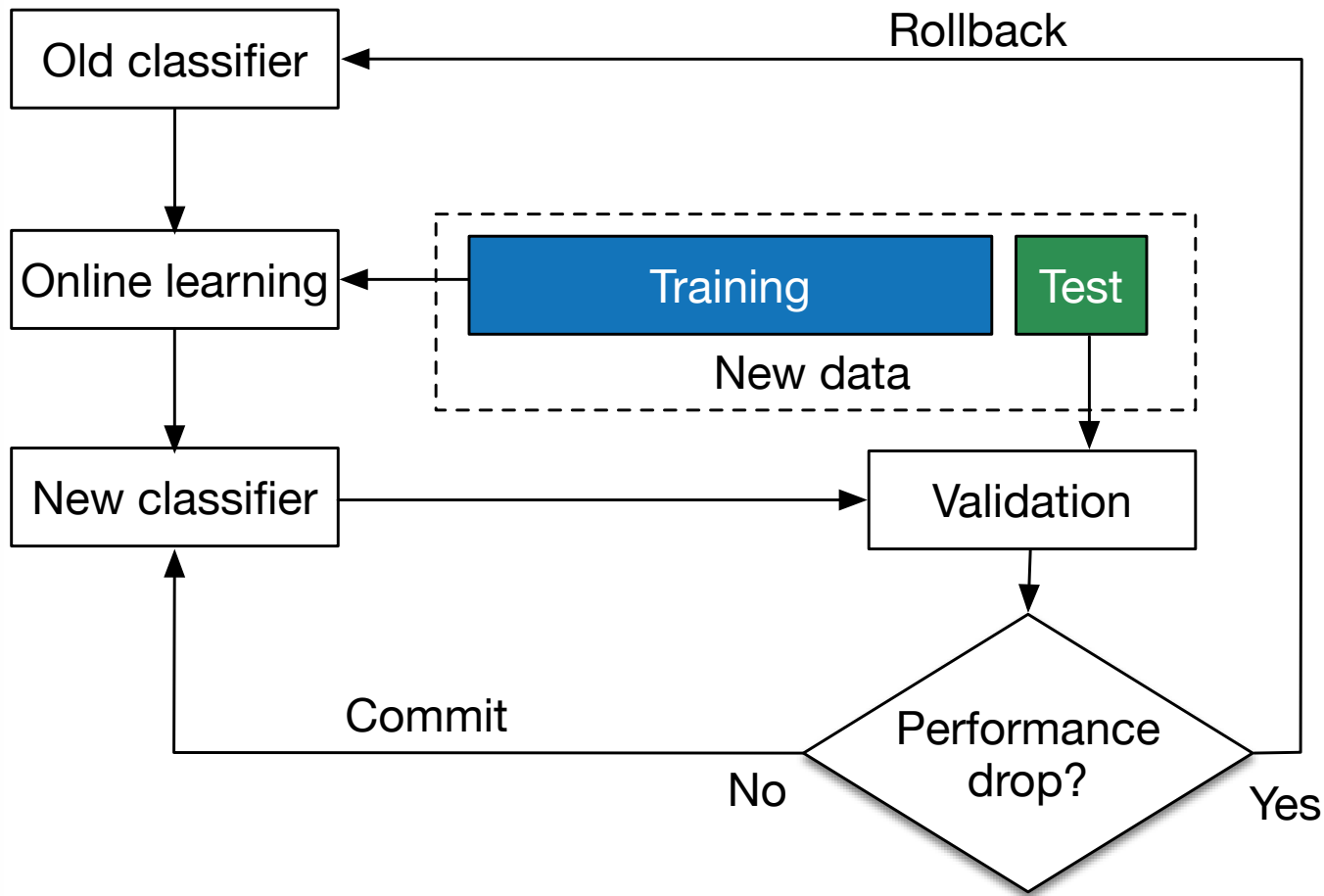
ML Algorithm Selection

- Expectation Maximization (EM): slow
- J48 decision tree: training set over fit, extra cost of tree pruning
- Logistic regression: cannot handle non-linear boundary





Semi-supervised Online Learning





Preliminary Evaluation

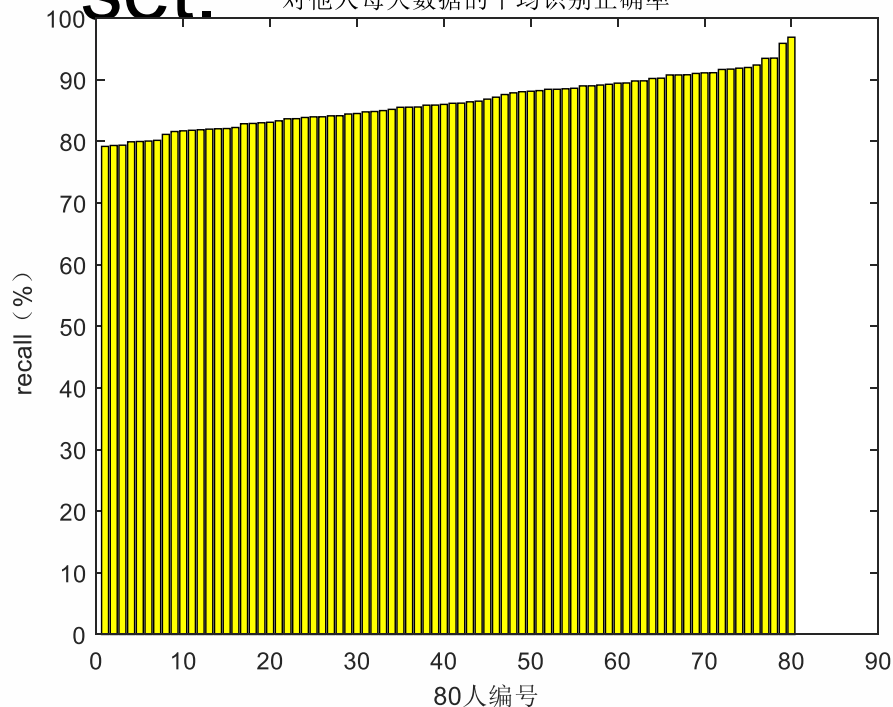
- Data
 - Collected with “Phone manager” (手机管家) by Tencent
 - 1st batch dataset: 210 users
 - 2nd batch dataset: 1516 users
- Metrics
 - Accuracy
 - True positive: owner is correctly identified
 - False positive: other is incorrectly identified as owner
 - False negative: owner is incorrectly identified as other
 - True negative: other is correctly identified
 - $R_{\text{owner}} = \text{TP}/(\text{TP}+\text{FN})$, $R_{\text{other}} = \text{TN}/(\text{TN}+\text{FP})$
 - ROC curve
 - Overhead
 - Robustness



Accuracy

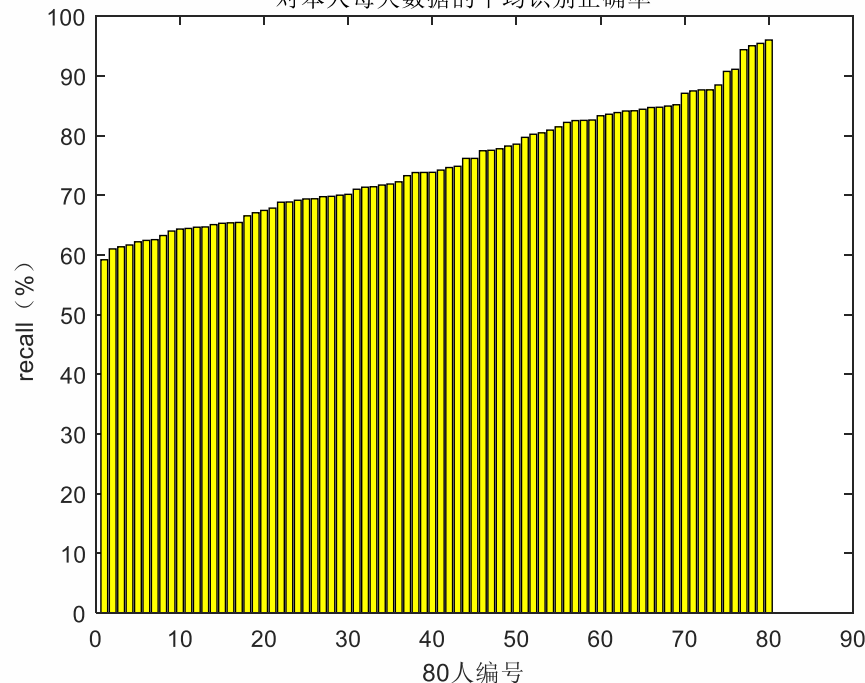
- 80 users with full data; each user has 4K samples in training set and 1.2K samples in test set.

对他人每天数据的平均识别正确率



R_{other} : 86.44%

对本人每天数据的平均识别正确率



R_{owner} : 75.50%



Overhead

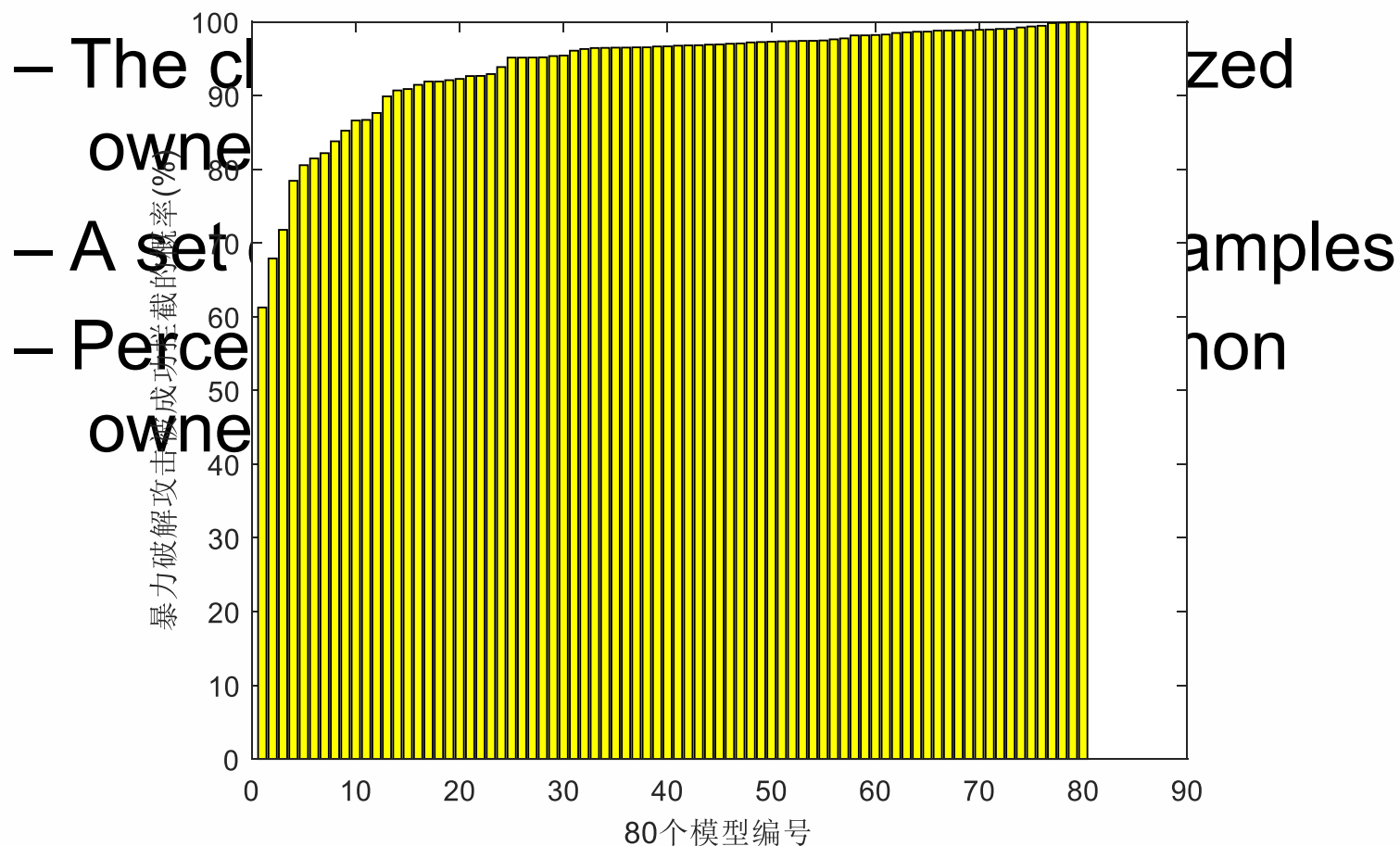
- Upload traffic
 - Around 300KB each time, compressed to 90KB.
- Latency (average over 210 users)

#Samples in training set	Training time (s)	#Samples in test set	Test time (s)
13203	18.415	52065	0.639



Robustness

- Brute-force attack

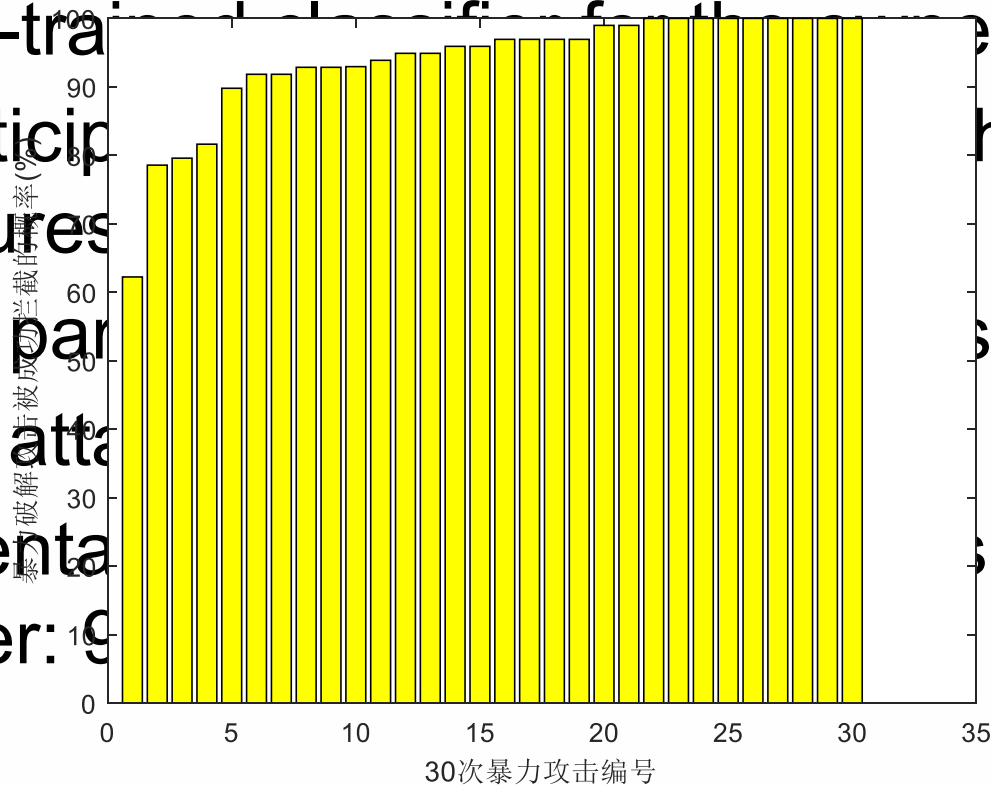




Robustness

- Human attack

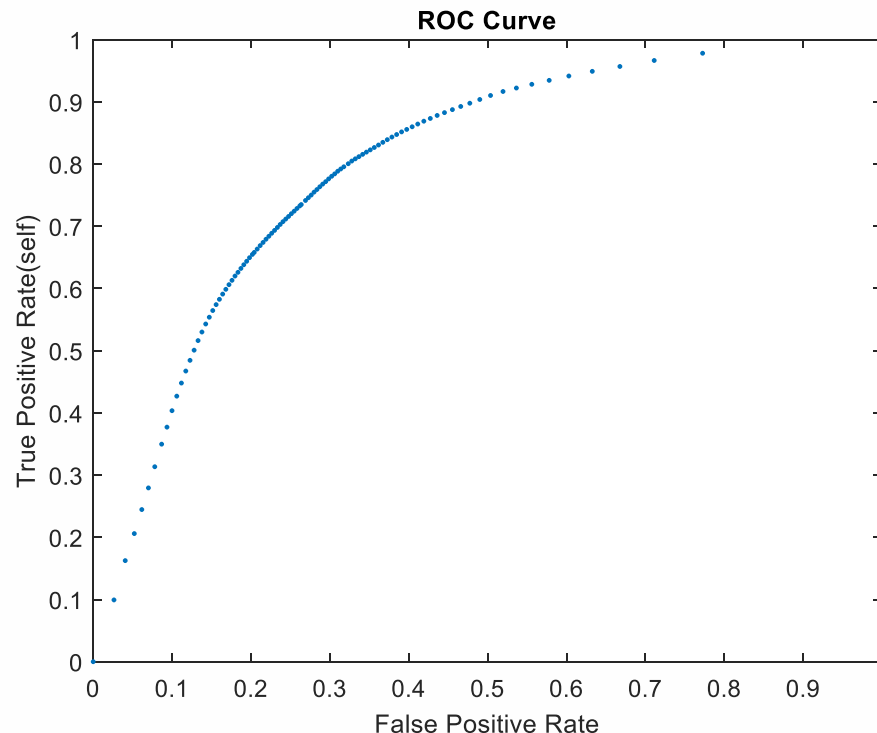
- A pre-trained model is used to detect the attack with various gestures
- Each participant performs 30 attacks
- Each attack is recorded
- Percentage of successful attacks is calculated for each participant





ROC Curve

- True positive rate v.s. False positive rate
 - $TPR = TP / (TP + FN)$, $FPR = FP / (FP + TN)$
 - Changes the classification threshold (0-1)





Conclusion and Ongoing Work

- DroidCog: The first device level user identification system with wild collected sensor data
- Deploy detection system on the phone
- Improve the classification accuracy
 - Explore more usable but privacy insensitive features (e.g. widely used IP address)
- Combine with existing risk management
- Theme of RSA 2016: Connect to Protect



Summary

<http://list.cs.northwestern.edu>

- Issues for existing mobile anti-virus systems
 - Easy to evade [DroidChamelon]
 - Unable to detect native malware [DroidNative]
 - Unable to detect malware in ads or dynamically loaded content [AdShield]
- Privacy leakage detection and prevention
 - How to find questionable sensitive permissions [AutoCog]
 - Real time tracking & preventing privacy leakage on phone
 - Consumer [PrivacyShield]
 - Enterprise Mobility Management (EMM) [AppShield]
- Fraud detection mostly with app-level risk management [DroidCog]
 - Duplicate detection
 - Privacy infringement