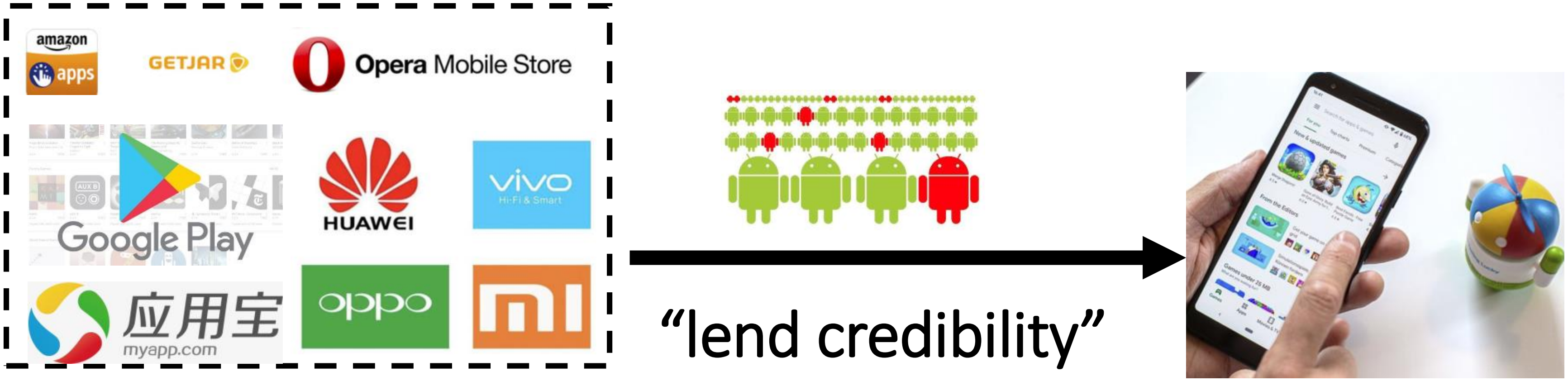
<EURO/SYS'20>

Experiences of Landing Machine Learning onto Market-Scale Mobile Malware Detection

Liangyi Gong, Zhenhua Li, Feng Qian, Zifan Zhang,
Qi Alfred Chen, Zhiyun Qian, Hao Lin, Yunhao Liu

Mobile Malware Detection

- **Android App Markets**

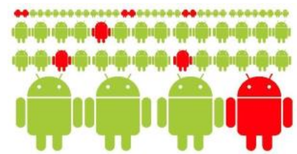


Mobile App Markets

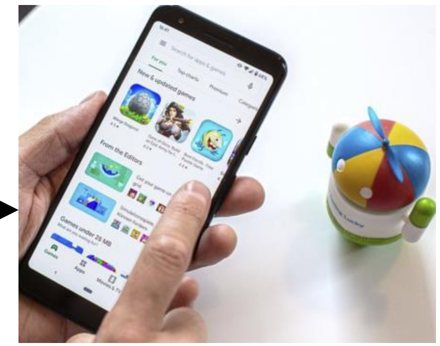
Mobile Users

Mobile Malware Detection

- **Android App Markets**



“lend credibility”



Mobile App Markets

Mobile Users

- **ML-based Mobile App Review Techniques**

- Fingerprint-based Antivirus Checking
- Static Code Inspection
- Dynamic Behavior Analysis

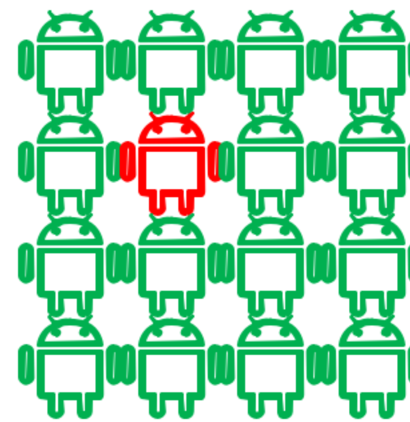
ML-based Detection at Market Scales

Widely explored in the past decade

Real-world Challenges?

No existing report of the effectiveness

ML-based Malware Detection

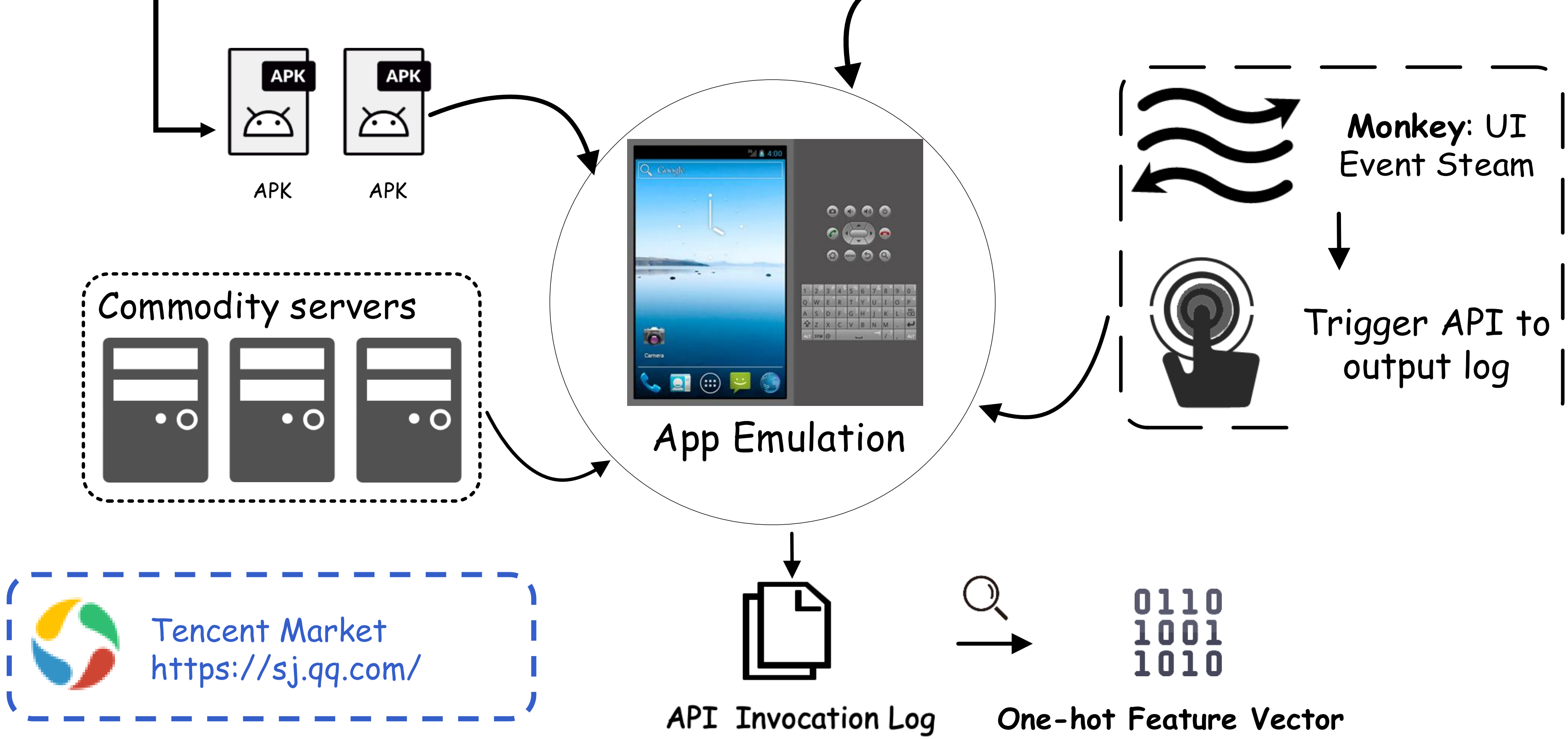


ML-based Solutions at Market Scales

Large-scale Dataset: API-centric, Dynamic

- 500K apps submitted to Tencent Market
- From March to December 2017
- Containing apps' malice labels

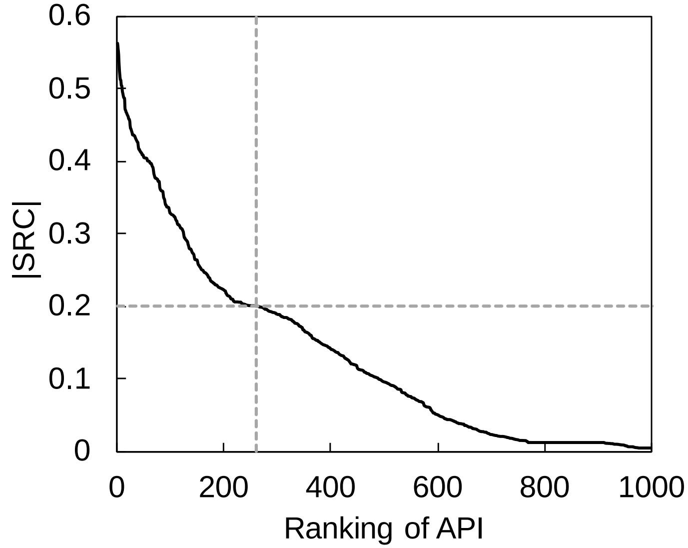
Xposed



API Selection: Correlation

- **APIs' correlations with the malice of apps**

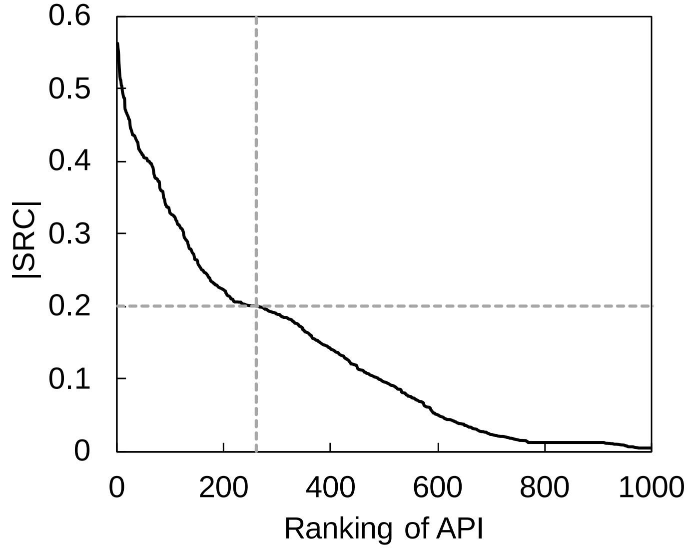
  - Using SRC (*Spearman's rank correlation coefficient*) to evaluate APIs' correlation with apps' malice
  - 260 APIs pose non-trivial correlation ($|SRC| \geq 0.2$)



API Selection: Correlation

- **APIs' correlations with the malice of apps**

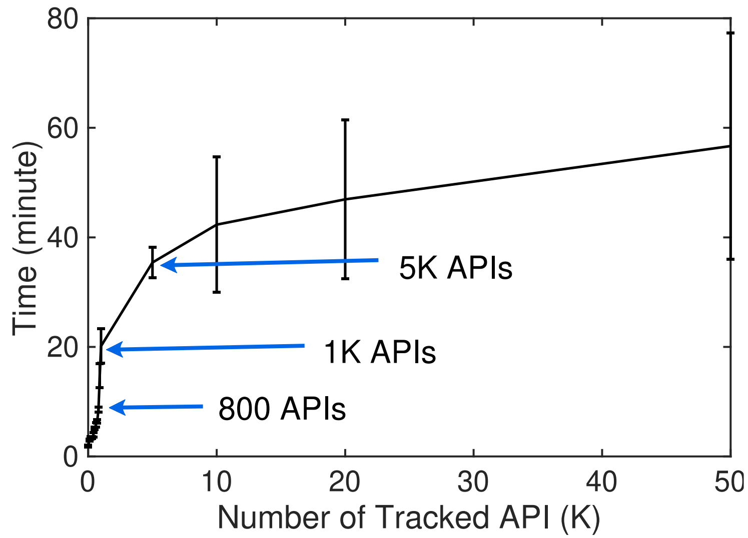
  - Using SRC (*Spearman's rank correlation coefficient*) to evaluate APIs' correlation with apps' malice
  - 260 APIs pose non-trivial correlation ($|SRC| \geq 0.2$)



- **Time consumption of tracking different API sets**

  - Fitting a tri-modal distribution
  - Indicating a complex relationship

$$t = \begin{cases} a_1 \cdot n + b_1, & n \in [1, 800); \\ a_2 \cdot n^{b_2}, & n \in [800, 1K]; \\ a_3 \cdot log(n) + b_3, & n > 1K. \end{cases}$$



API Selection: Model & Accuracy

- **Machine Learning Model & Detection Accuracy**

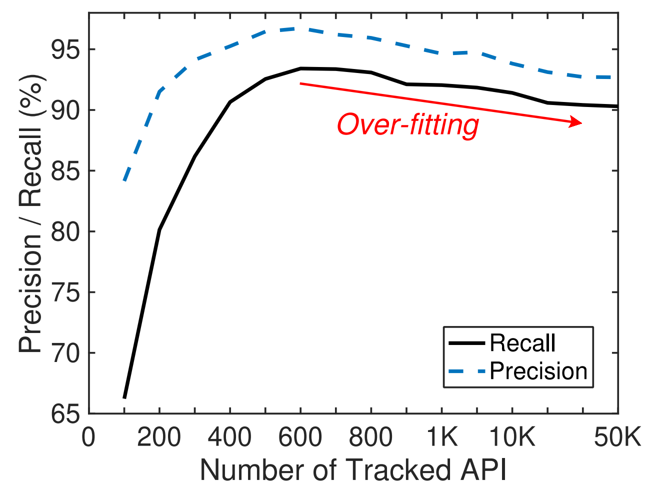
Model	Precision	Recall	Training Time
Naive Bayes	60.4%	59.6%	3.6 min
LR	81.2%	70.3%	10.4 min
SVM	87.9%	71.6%	~27K min
GBDT	88.4%	74.3%	364 min
kNN	86.5%	83.7%	~1.8K min
CART	87.6%	84.3%	11.6 min
ANN	90.8%	89.9%	~1.2K min
DNN	91.5%	90.9%	~1.9K min
Random Forest	91.6%	90.2%	29.1 min

API Selection: Model & Accuracy

- **Machine Learning Model & Detection Accuracy**

Model	Precision	Recall	Training Time
Naive Bayes	60.4%	59.6%	3.6 min
LR	81.2%	70.3%	10.4 min
SVM	87.9%	71.6%	~27K min
GBDT	88.4%	74.3%	364 min
kNN	86.5%	83.7%	~1.8K min
CART	87.6%	84.3%	11.6 min
ANN	90.8%	89.9%	~1.2K min
DNN	91.5%	90.9%	~1.9K min
Random Forest	91.6%	90.2%	29.1 min

Tracking top-490 correlated APIs achieves the highest precision/recall



Tracking fewer APIs benefits both detection accuracy and speed!

Key API Selection Strategy

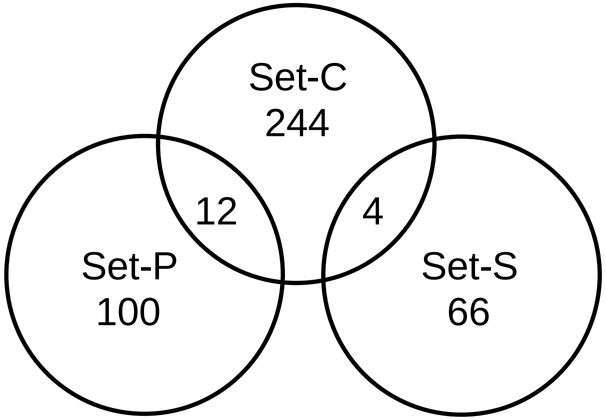
- **Step 1. Selecting APIs with the highest correlation with malware (Set-C).**
- **Step 2. Selecting APIs that relate to restrictive permissions (Set-P).**
- **Step 3. Selecting APIs that perform sensitive operations (Set-S).**
- **Step 4. Combining the above.**

Key API Selection Strategy

- **Step 1. Selecting APIs with the highest correlation with malware (Set-C).**
- **Step 2. Selecting APIs that relate to restrictive permissions (Set-P).**
- **Step 3. Selecting APIs that perform sensitive operations (Set-S).**
- **Step 4. Combining the above.**

Performance:

- **Analysis time: 4.3 minutes**
- **Precision/Recall: 96.8% / 93.7%**
- **Training time: 14.4 seconds**



Further Enriching the Feature Space

- **Hidden features – API invocation hidden by certain techniques**

Hidden and internal APIs
triggered by special techniques like Java reflection

Checking Permissions

IPC through intents
leveraging other apps/services to perform sensitive actions

Checking Used Intents

Further Enriching the Feature Space

- **Hidden features – API invocation hidden by certain techniques**

Hidden and internal APIs
triggered by special techniques like Java reflection

Checking Permissions

IPC through intents
leveraging other apps/services to perform sensitive actions

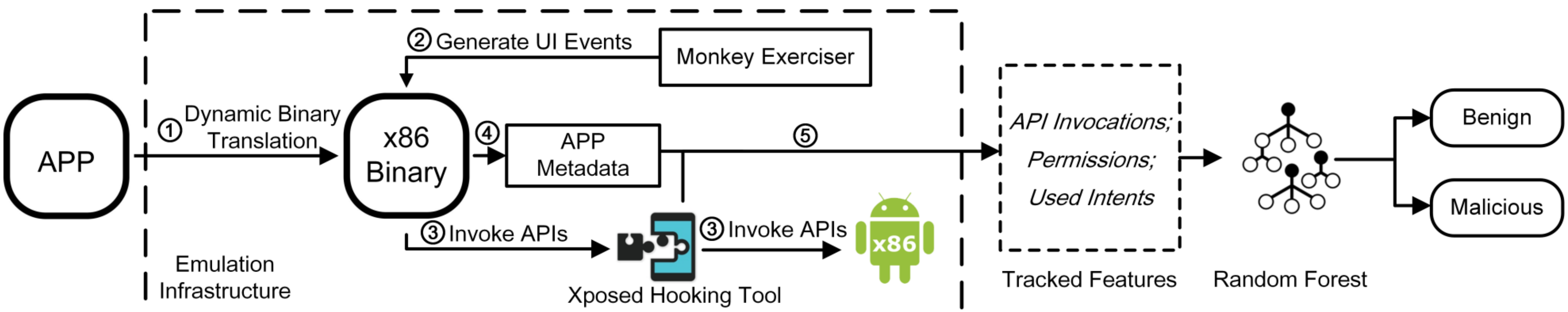
Checking Used Intents

Key APIs alone
- Precision: 96.8%
- Recall: 93.7%

API + Permission + Intents
- Precision: 98.6%
- Recall: 96.7%

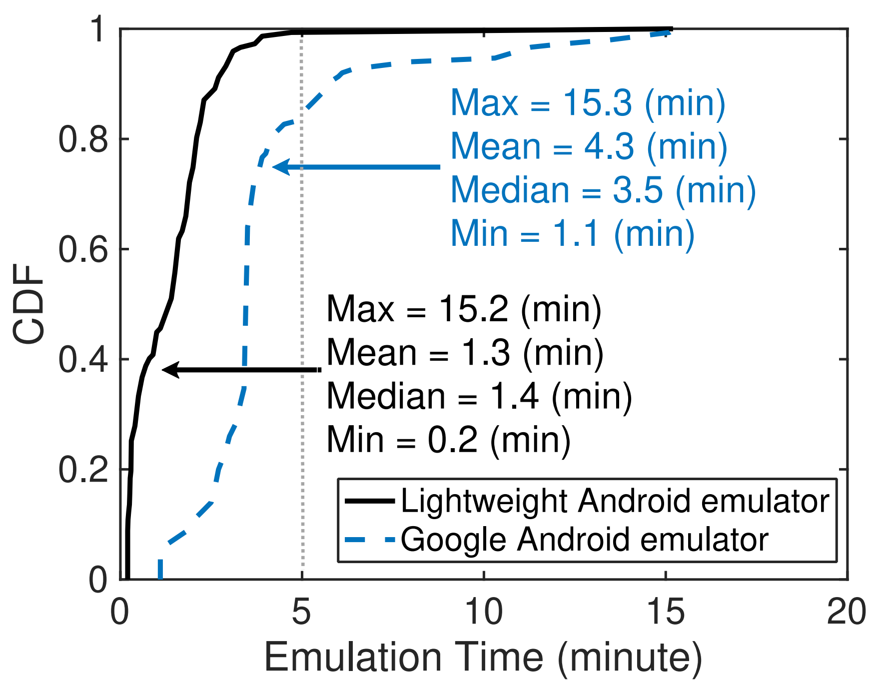
System: Emulation Optimization

- Default Google Android Emulator: full-system emulation
- Result: 30% of apps require ≥5-minute analysis time
- Solution: lightweight emulation on powerful x86 server
- Architect: native x86 Android + Dynamic Binary Translation



System: Emulation Optimization

- Configuration: 5x4-core x86 server with CPU pinning
- Compatibility: ≤1% incompatible apps
- Roll back to the Google Emulator for incompatible apps
- Performance: saving around 70% of the detection time

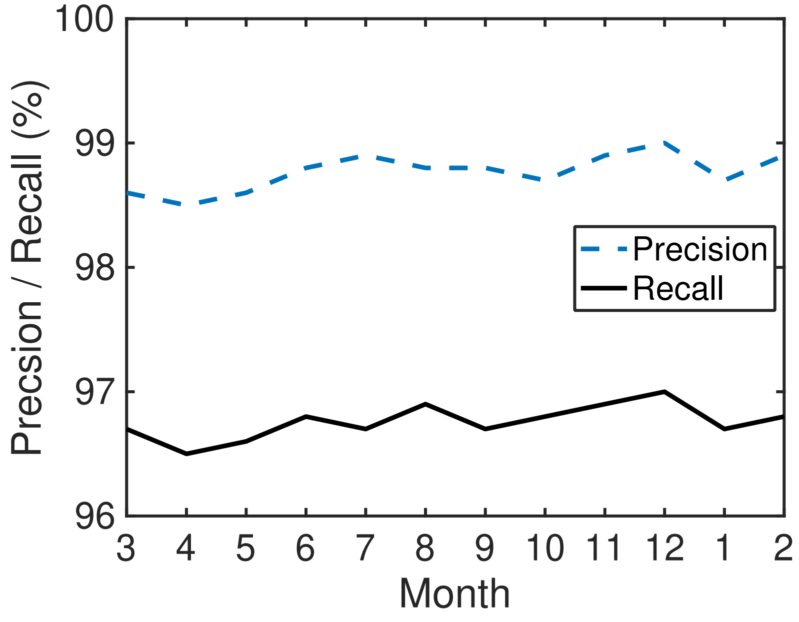


Able to analyze an app in around 1.3 minutes

System: Real-world Deployment

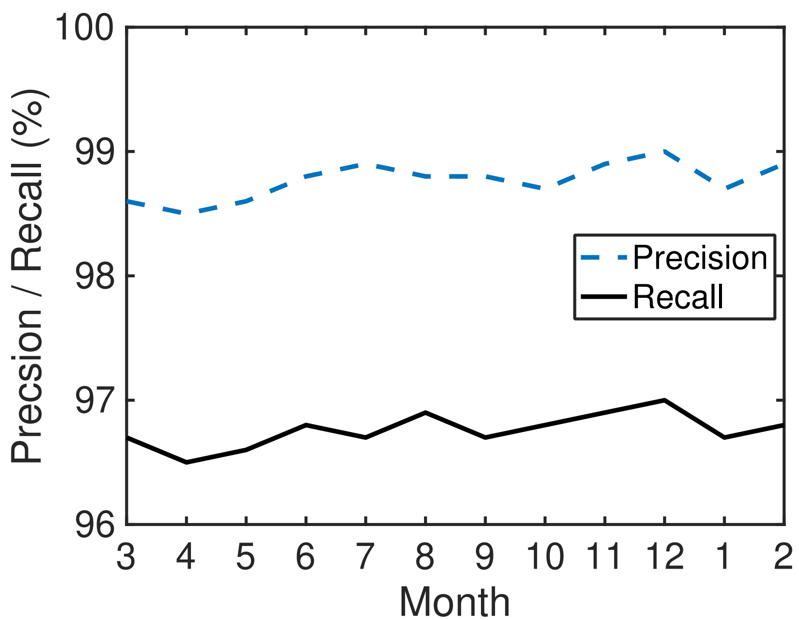
- **Integration to Tencent Market**

  - Running since March 2018
  - Checking ~10K apps per day using a single commodity server
  - Over 98%/96% online precision/recall

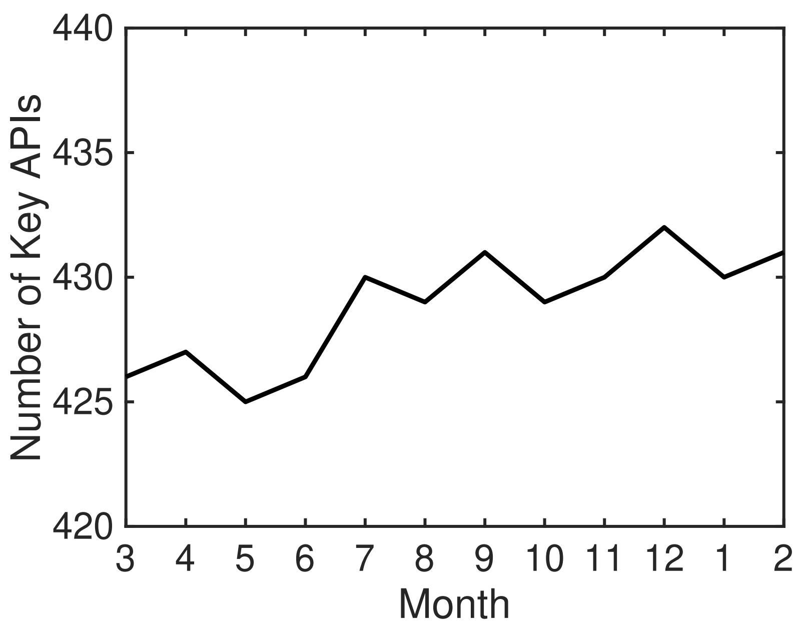


System: Real-world Deployment

- **Integration to Tencent Market**
  - Running since March 2018
  - Checking ~10K apps per day using a single commodity server
  - Over 98%/96% online precision/recall



- **System Evolution**
  - Monthly updating the key APIs with the original dataset and newly submitted apps
  - Fluctuating between 425 and 432



System: Addressing FPs & FNs

- **False Positives**

  - 2% FP apps as complained by developers
  - All using a few top-ranking APIs
  - Most are quickly vetted based on previous versions

Manual Inspection: acceptable workload

Active & complete avoidance of FPs

System: Addressing FPs & FNs

- **False Positives**
  - 2% FP apps as complained by developers
  - All using a few top-ranking APIs
  - Most are quickly vetted based on previous versions

Manual Inspection: acceptable workload

Active & complete avoidance of FPs

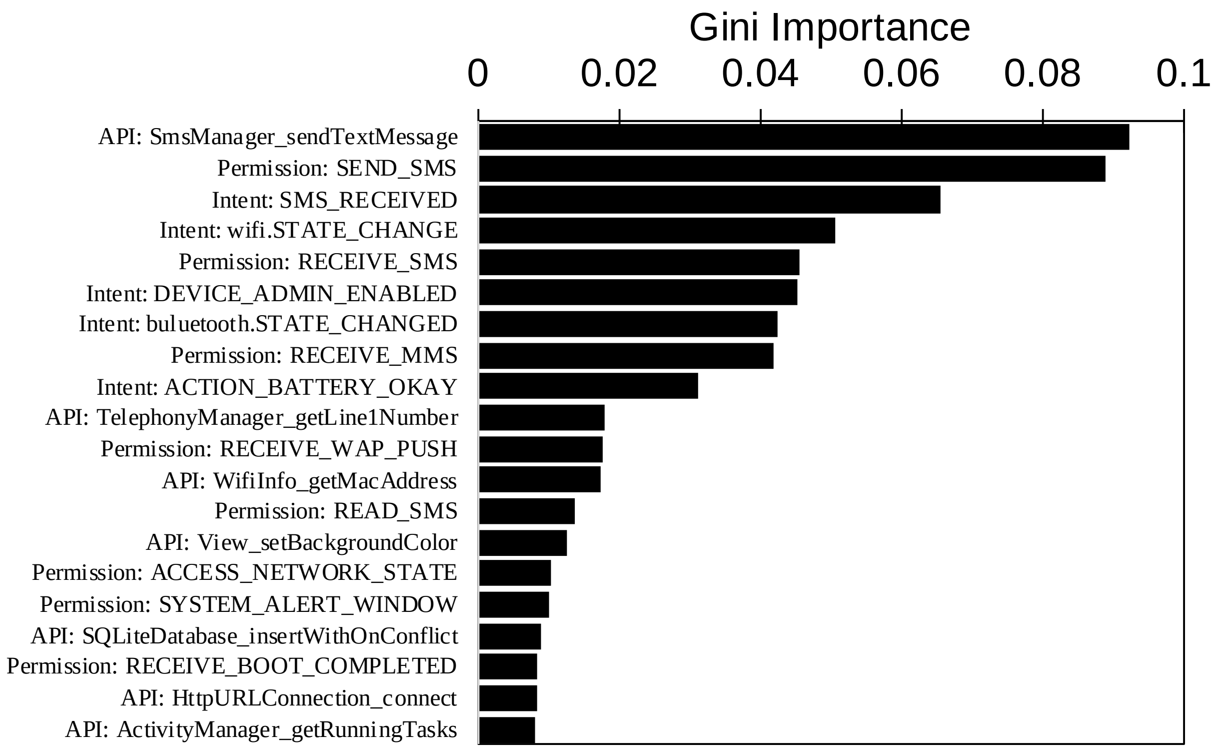
- **False Negatives**
  - 4% FN apps reported by end users
  - Hard to avoid
  - Most (87%) barely use key APIs
  - They have fairly simple functionalities, posing little threat

Report-driven: mild impact on users

Passive mitigation of FNs

Revealed Important Features

- Attempting to acquire privacy-sensitive information of user devices
- Tracking or intercepting system-level events
- Enabling certain types of attacks such as overlay-based attacks



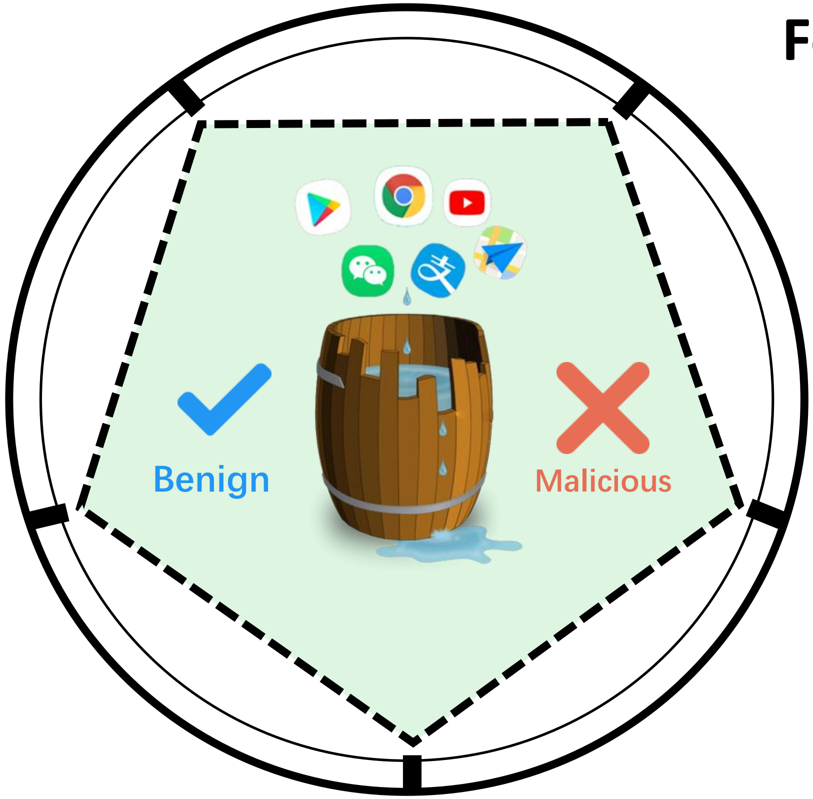
Experiences of APIChecker

Feature Selection

Principled, data-driven

Feature Engineering

Adversary's perspective



Analysis Speed

Efficient app emulation on powerful x86 servers

Model Evolution

Monthly update with novel apps & SDK APIs

Developer Engagement

Active & complete avoidance of FPs vs. Passive mitigation of FNs

Conclusion & Dataset

- We conduct a large-scale study to understand and overcome real-world challenges of developing ML-based malware detection solutions at market scales.

- We showcase several key design decisions we make towards implementing, deploying, and operating a production market-scale mobile malware detection system – APICHECKER.

- Our system has been operational at Tencent Market since March 2018, vetting around 10K apps per day on a single commodity server.

Dataset & tool release: https://apichecker.github.io/

Countering Emulator Detection

- Strategies:
  - changing the default configurations of emulators
  - tuning the execution parameters of Monkey
  - replaying traces of sensor data collected from real devices
  - obfuscating the existence of Xposed
- Experiment on real devices, original and enhanced emulator:
  - original emulator: 86.6% apps invoke the same amount of APIs
  - enhanced emulator: 98.6% apps invoke the same amount of APIs

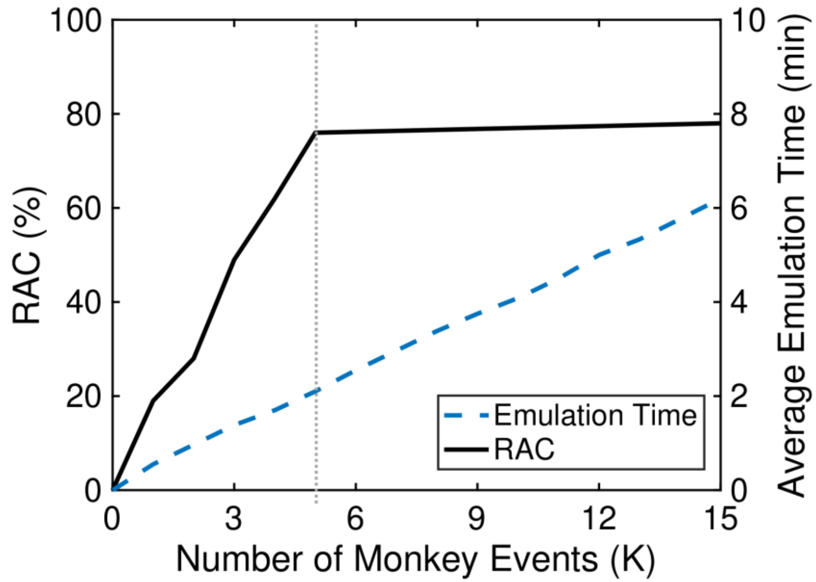
Comparison with Other Work

- Differences:
  - the scale of studied apps is much larger
  - innovations in API selection, identifying hidden features
  - optimization in dynamic emulation infrastructure
  - commercial deployment result & online model evolution

API Selection Strategy	Related Work	Analysis Method	Analysis Time per App	# APIs Used	# Apps Studied	Precision, Recall
Statistical Correlations	Sharma *et al.* [35]	static	- -	35	1,600	91.2%, 97.5%
	DroidAPIMiner [1]	static	25 sec	169	~20K	- -
Restrictive Permissions	Stowaway [15]	static	- -	1,259	964	- -
	DroidMat [43]	static	- -	- -	1,738	96.7%, 87.4%
	Yang *et al.* [46]	dynamic	1080 sec	19	~27K	92.8%, 84.9%
Sensitive Operations	RiskRanker [20]	static	41 sec	- -	~118K	- -
	DroidCat [9]	semi-dynamic	354 sec	27	~34K	97.5%, 97.3%
	IntelliDroid [42]	static + dynamic	138.4 sec	228	2,326	- -
	Droid–Sec [49]	static + dynamic	- -	64	250	- -
	DroidDolphin [44]	dynamic	1020 sec	25	64K	90%, 82%
Hybrid	DREBIN [6]	static	10 sec	- -	~128K	- -
	APICHECKER	**dynamic**	**78 sec**	**426**	**~500K**	**98.6%, 96.7%**

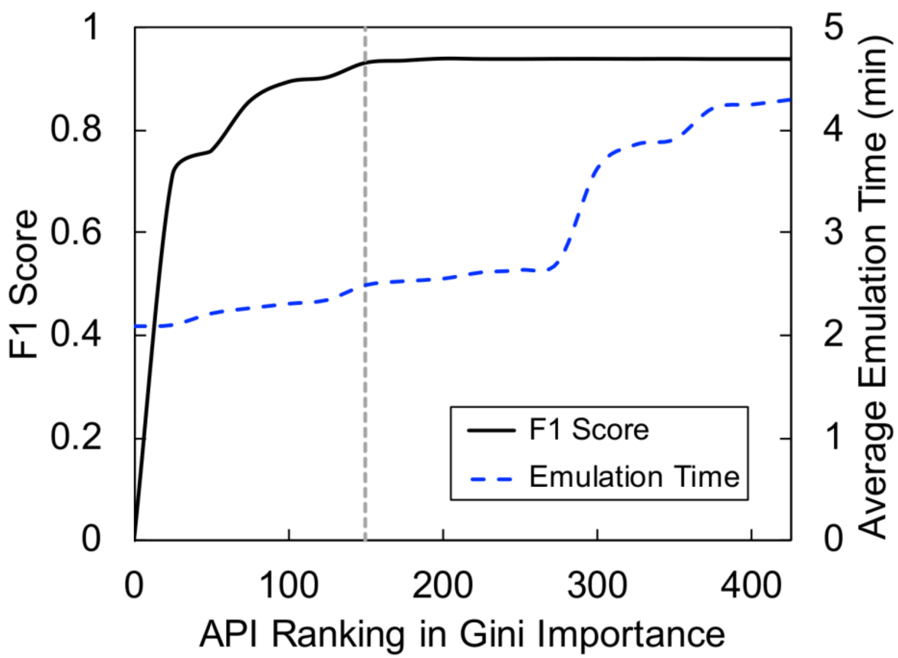
UI Exploration & Coverage

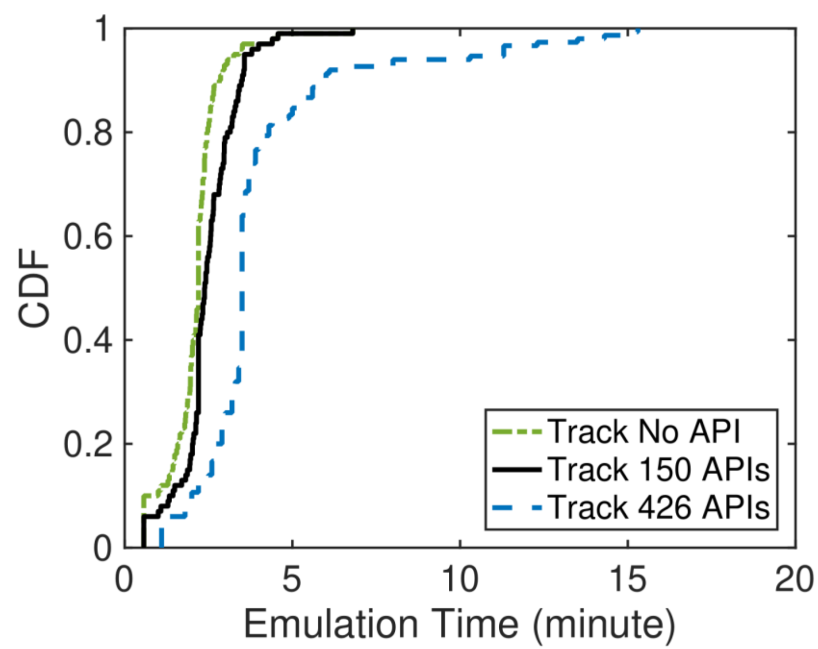
- Activity Coverage: pessimistic, only 88% of defined activities are actually referred in source code
- New metric: Referred Activity Coverage (RAC)
- Tradeoff: 5K *vs.* 100K Monkey Events, sacrificing a small fraction (9.5%) of RAC to largely reduce (94%) of the emulation time



A Smaller API set?

- API selection can affect both the detection accuracy and speed
- Most of key APIs slightly affect accuracy, greatly impacts speed
- Tracking top-150 *vs.* Tracking top-426:
  - Precision/Recall: 98.3%/96.6% *vs.* 98.6%/96.7%
  - Analysis Time: 2.5 m *vs.* 4.3 m (without efficient emulation)





Integration to Other Markets

- Expected to be a easy process
- Implementation: mature analysis tool chain + machine learning
- Training: APKs + ground-truth data
- Possible for large markets to distribute pre-trained models

Robustness of APICHECKER

- Our key API set: 426 APIs, 0.85% of the 50K APIs in SDK
- 4,816 APIs depend on the key APIs, a total of 5,242 (10.5%) APIs
- Reimplementing all the APIs: high technical bar
- Possible workaround – NDK: high usage is also an indicator

Online Evaluation & Evolution

- Evaluation:
  - based on other components in T-Market's app review process
  - ≥4 SOTA fingerprint-based antivirus checking (all claim ≤5% FP)
  - expert-informed API inspection
  - user-report-driven manual examination
- Evolution:
  - dataset: original dataset & newly submitted apps
  - labels: flagged by both APICHECKER and manual inspection