



第六届“山海论坛”-大数据与高性能计算

Mobile Offloading for Cloud-based Malware Detections with Learning

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Outline

- Background & motivation
- Cloud-based malware detection for mobile devices:
 - Challenges & opportunities by big data
- Nash equilibrium (NE) of the cloud-based malware detection game:
 - Competition & cooperation among mobile devices
- Reinforcement learning based cloud malware detection
- Conclusions

Motivation

- Malware: Viruses, trojans, spywares and other intrusive codes
 - Aim to disrupt operations, access private information, display unwanted advertising, etc
- Hummingbad malware that generates fake clicks for adverts infected 10 million Android smartphones and made \$300,000/mon for the attacker
- The average smartphone infection rate increased 96% in the first half of 2016, compared to the second half of 2015

Malware
Infected Apps

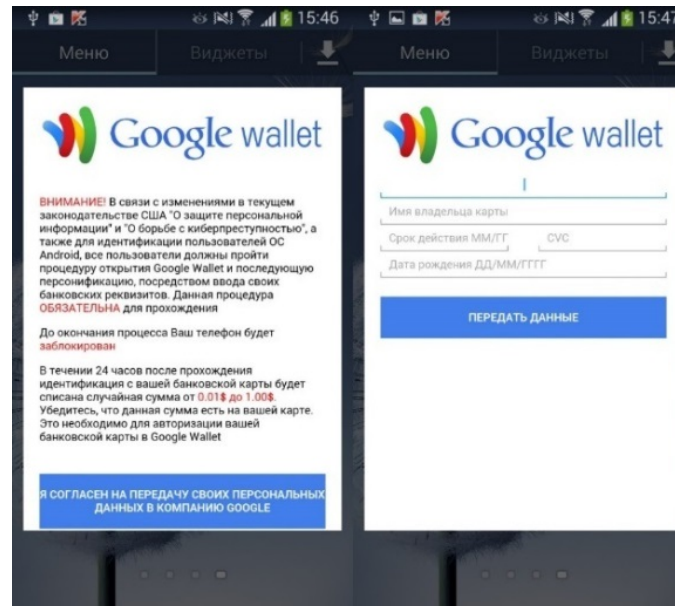
download

Mobile devices

- Backdoor
- Rootkit
- Worm
- Virus
- ...



3



Malware hits millions of Android phones

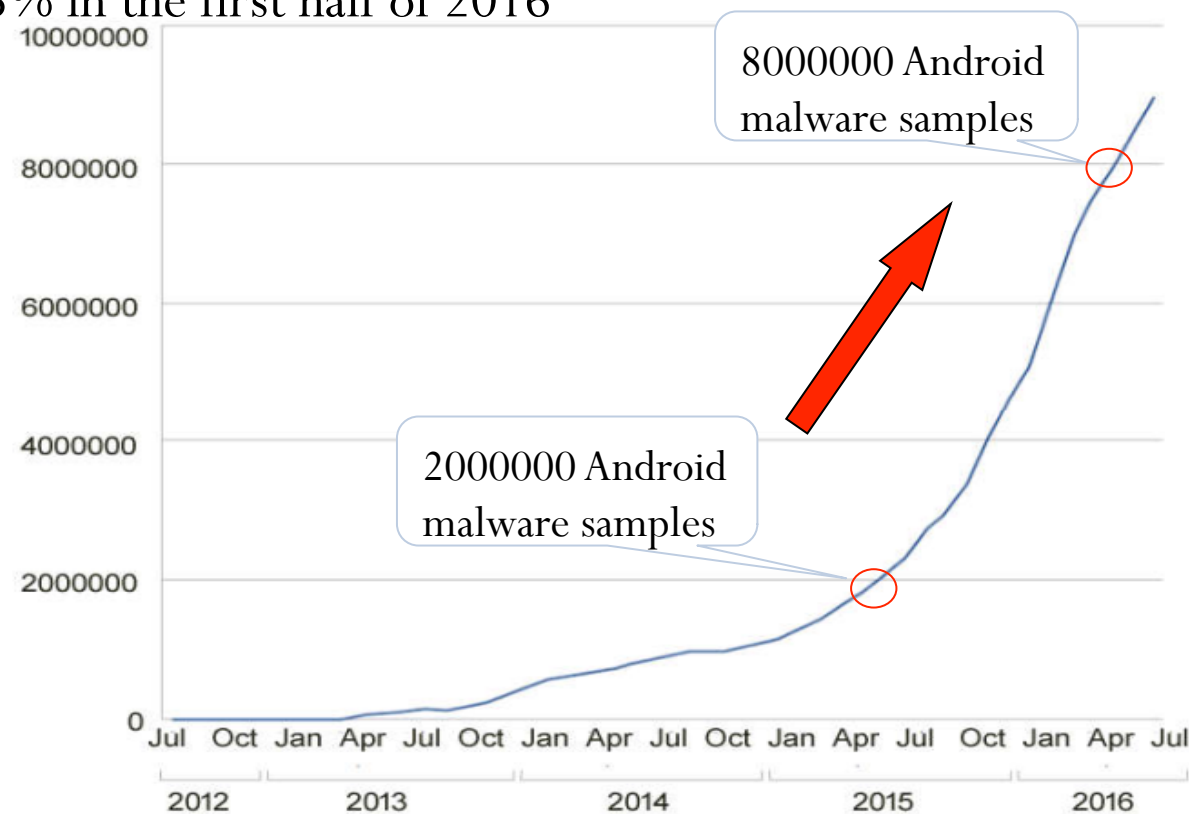
8 July 2016 | Technology



Older versions of Android are vulnerable to being infected by the Hummingbad malware

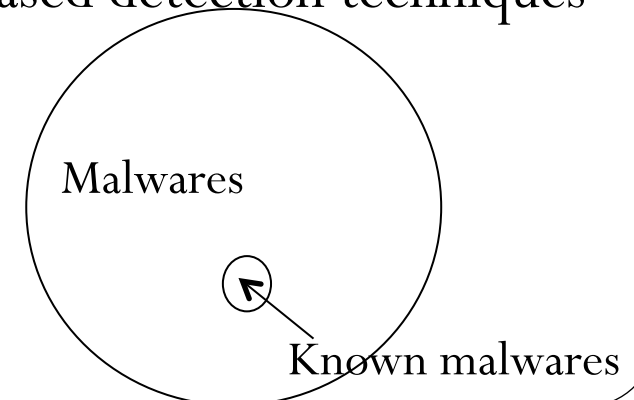
Big Data in Malware Detections

- In 2015, 144 million new malwares were found: 274 new unknown malware were produced and launched in every minute
- The number of Android malware samples in Nokia malware database increased by 75% in the first half of 2016



Malware Detections

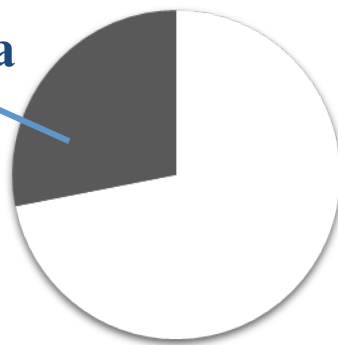
- Signature-based detection: Identify malwares by their signatures
 - Rely on human expertise in creating labels for malicious behaviors
 - Low computational complexity and low false alarm rate
 - Vulnerable to zero-day attacks
- Anomaly-based detection: Use the knowledge of normal behavior
 - Detect new malwares
 - Large sample size required in the training phase
 - High computation complexity & high false alarm rate
- Hybrid detection: Signature-based + anomaly-based detection techniques



Malware Detection at Mobile Devices

- Big data in malware detection: A large number of traces generated by the applications run at a mobile device
- Challenges:
 - High storage cost
 - Long detection delay
 - Zero-day malware attacks: Attack signatures not downloaded in time
- Benefits: Detection accuracy depends on the size of the virus database downloaded from security servers

117903 lines of log data



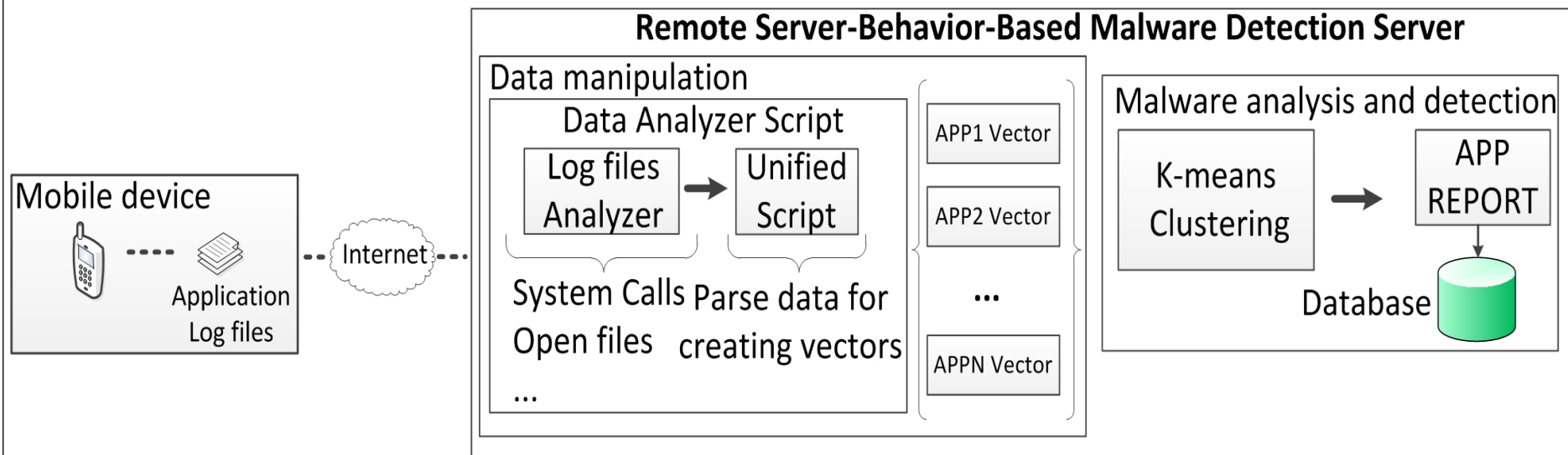
□ Size of the whole operation data

■ Size of the generated log data

**The log data evaluated in
Norton security application**

Cloud-based Malware Detection System

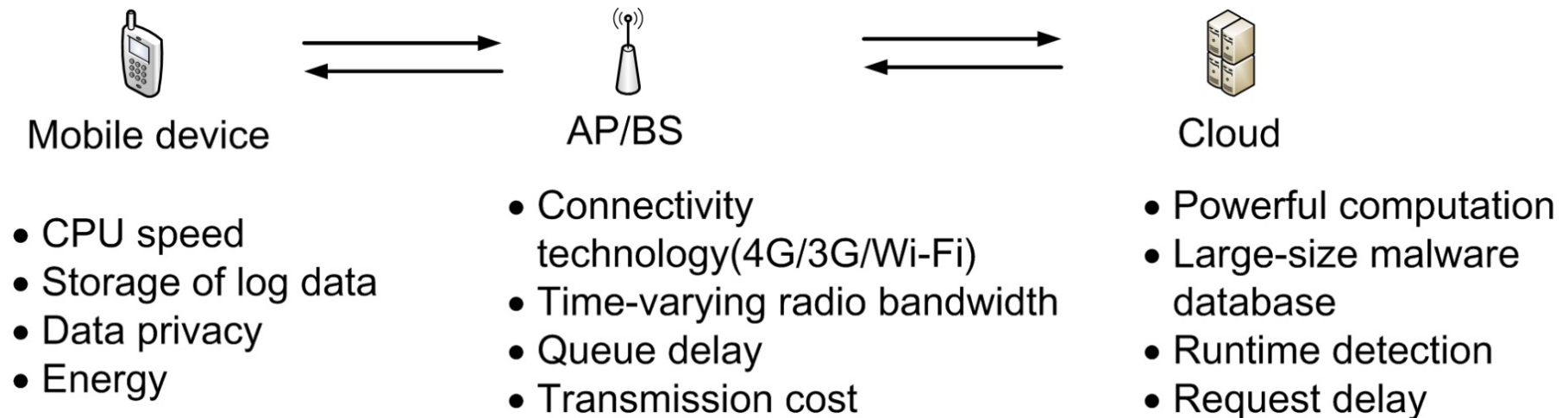
- Behavior-based malware detection system: k-means clustering [Iker'11]
- Online cloud anomaly detection: SVM [Watson'16]



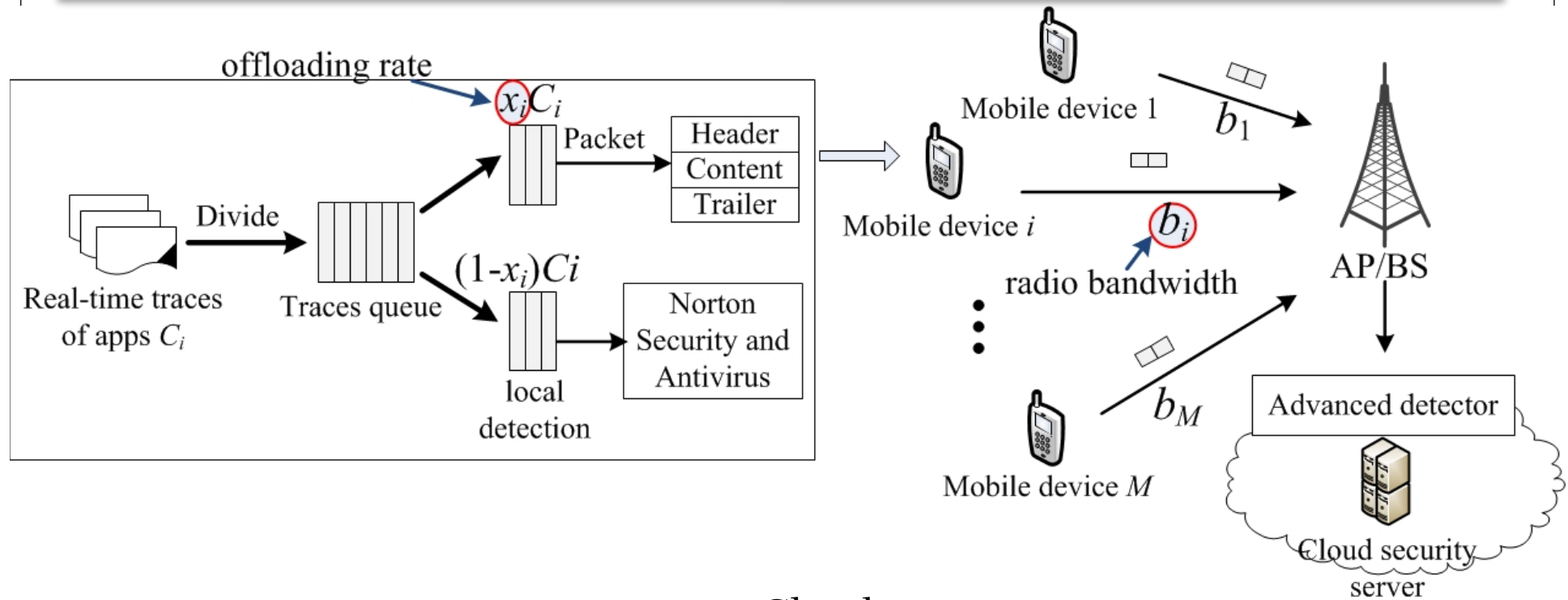
- Advantages:
 - Fast computation to run more advanced and complex detection algorithms
 - More accurate detection with a large-size signature database
 - Address zero-day vulnerabilities

Mobile Offloading in the Malware Detection

- Cloud-based malware detection vs. local detection
 - Transmission delay, computation speed, detection accuracy, storage cost
- User competition vs. cooperation in the malware detection
 - Compete for the limited network bandwidth
 - Contribute the malware signature database to improve the malware detection accuracy at the cloud



Mobile Offloading Game



$$u_i(x_i, \mathbf{x}_{-i}) = \left(\frac{R}{\sum_{m=1}^M x_m C_m} - \frac{\omega}{b_i} \right) x_i C_i + \gamma \sum_{m=1}^M x_m C_m$$

The equation defines the utility function $u_i(x_i, \mathbf{x}_{-i})$ for mobile device i . The components are labeled as follows:

- x_i : Offloading rate
- \mathbf{x}_{-i} : Amount of app traces
- R : Cloud computation capacity
- ω : Unit transmission cost
- b_i : radio bandwidth
- γ : Accuracy coefficient
- $\sum_{m=1}^M x_m C_m$: Amount of app traces
- $x_i C_i$: Amount of app traces
- $\sum_{m=1}^M x_m C_m$: Amount of app traces

Static Cloud-based Detection Game

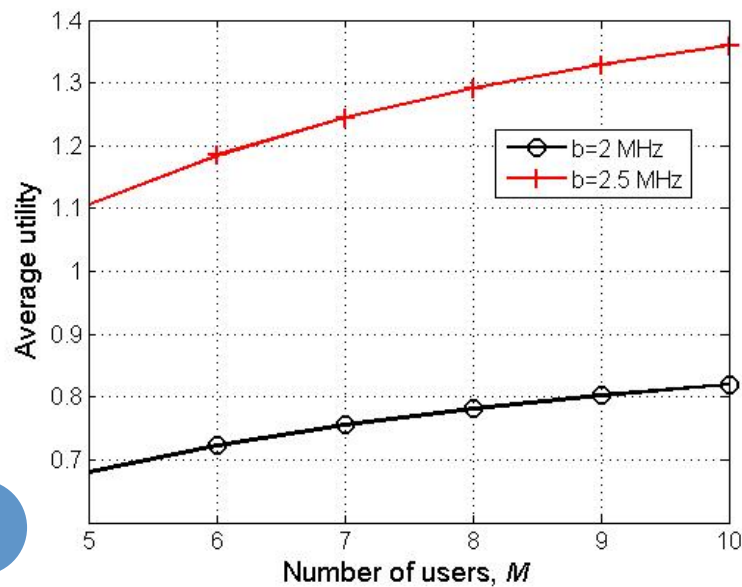
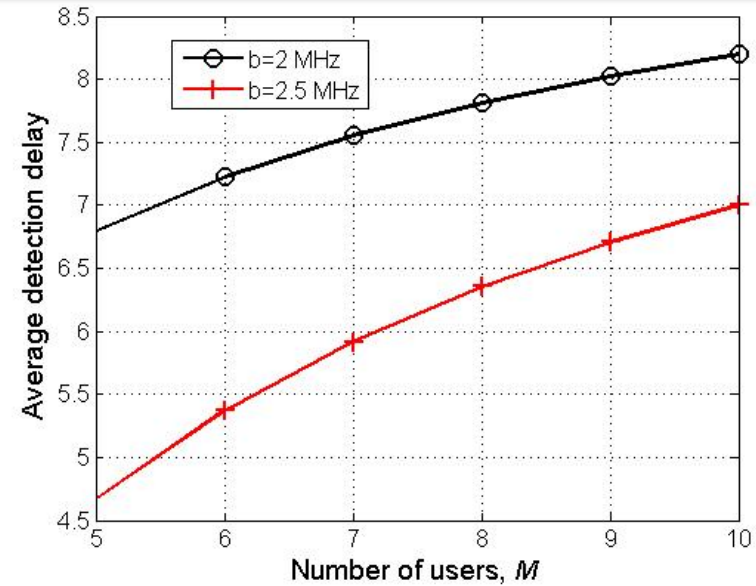
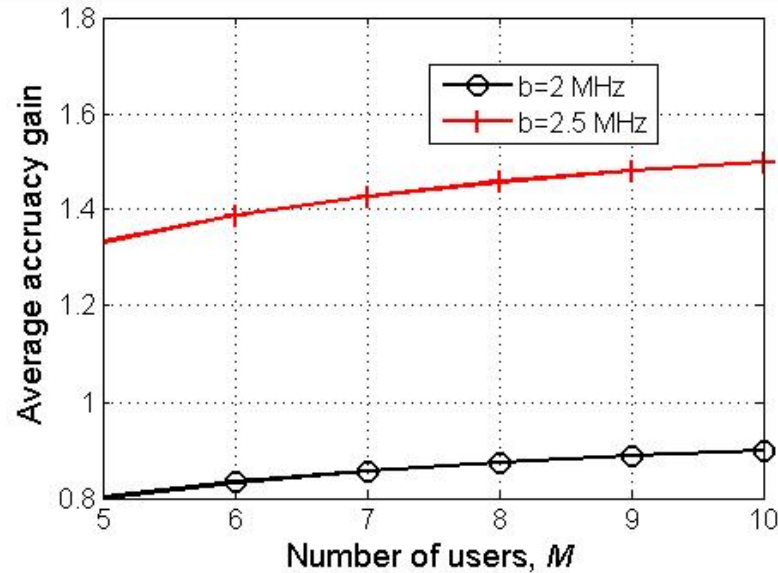
- NE of the static game: No mobile station can benefit by unilaterally leaving the NE strategy $u_i(x_i^*, \mathbf{x}_{-i}^*) \geq u_i(x_i, \mathbf{x}_{-i}^*), \forall \mathbf{x}_{-i}^*$

$$x_i^* = \begin{cases} 0, & \text{if } \frac{Rb_i}{\omega - \gamma b_i} < \sum_{m \neq i} x_m C_m \\ 1, & \left(\sum_{m \neq i} x_m C_m \right)^2 + \left(2C_i - \frac{Rb_i}{\omega - \gamma b_i} \right) \sum_{m \neq i} x_m C_m + C_i^2 < 0 \\ \frac{1}{C_i} \left(\sqrt{\frac{Rb_i \sum_{m \neq i} x_m C_m}{\omega - \gamma b_i}} - \sum_{m \neq i} x_m C_m \right), & \text{otherwise,} \end{cases}$$

Severe shadow fading

Light communication overhead

Detection Performance at the NE



Cloud computation resource=1 Gbps

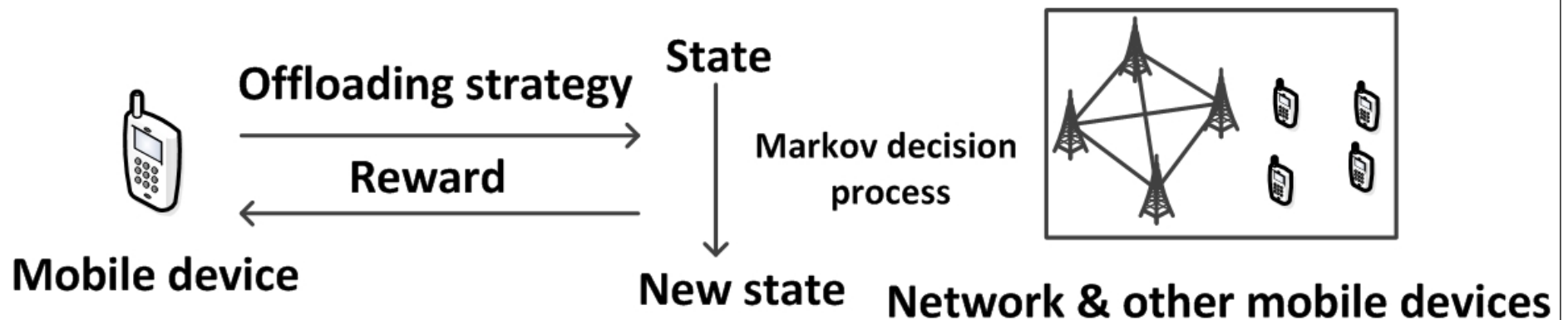
Trace generation speed=1 Mbps

Transmission cost factor=0.2

Accuracy coefficient=0.5

Dynamic Malware Detection Game

- Dynamic cloud-based malware detection game: Repeated interactions among mobile devices in time-variant network environments
- Q-learning based malware detection: Offloading rate is chosen without knowing the network model and the app trace generation model
- A model-free reinforcement learning algorithm for an agent to derive the optimal strategy via trial-and-errors in a dynamic game



Q-Learning Based Malware Detection

- State: Network bandwidth and the offloading rates of the other mobile devices at last time, $s_i^k = [\mathbf{x}_{-i}^{k-1}, b_i^k]$
- Q-function: Estimated discounted long-term utility for each state-action pair
 - Update via iterative Bellman equation:

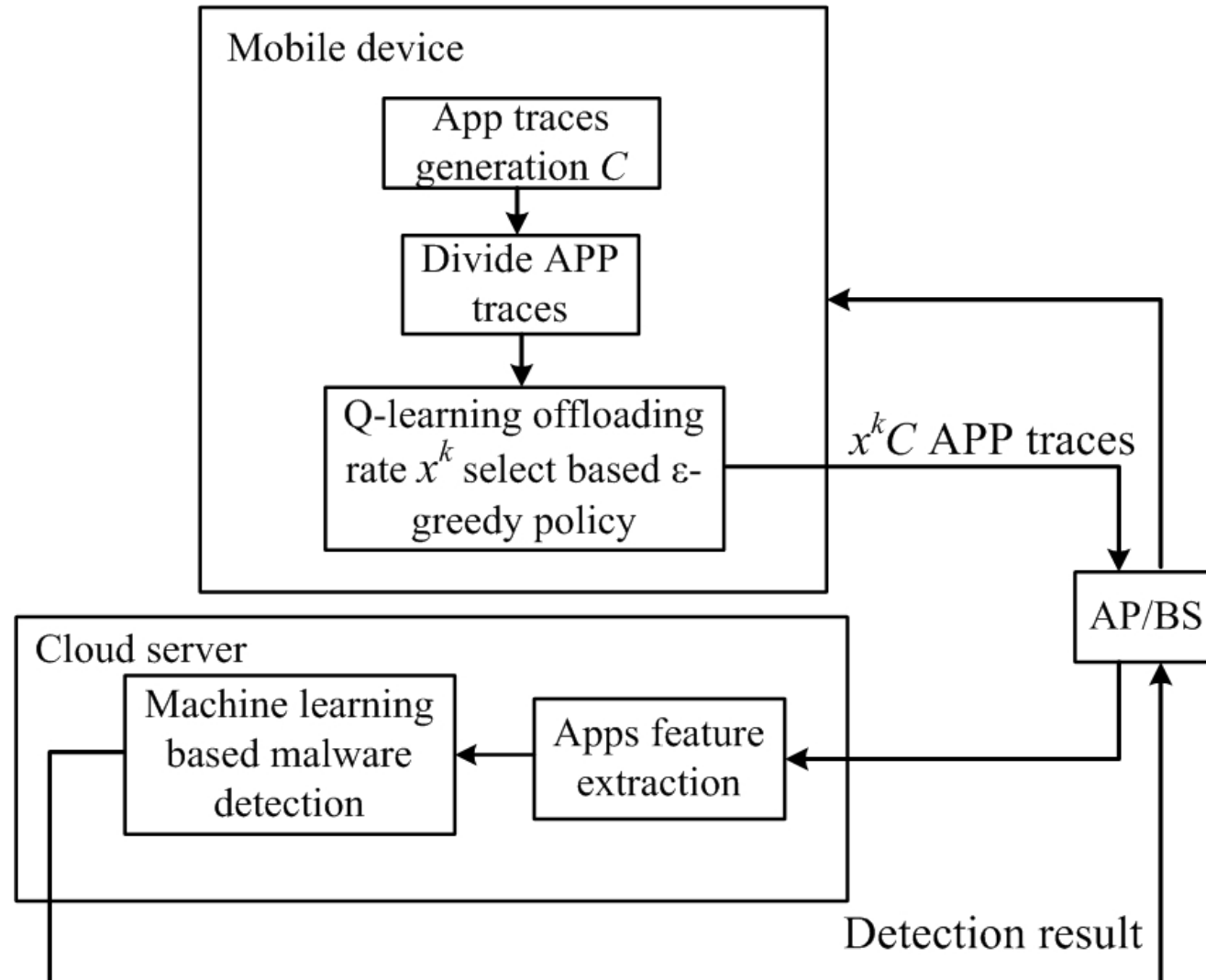
$$Q(s^k, x^k) \leftarrow (1 - \gamma)Q(s^k, x^k) + \gamma(u_i(s^k, x^k) + \delta \max_{\mu \in \mathbf{x}} Q(s^{k+1}, \mu))$$

Learning rate: Weigh the current Q-function

Discount factor: Uncertain future reward

- Encourage exploration with ϵ -greedy policy: Not trapped in the local optimum at the beginning of the game

Q-Learning Based Offloading in Malware Detections



Simulation Results

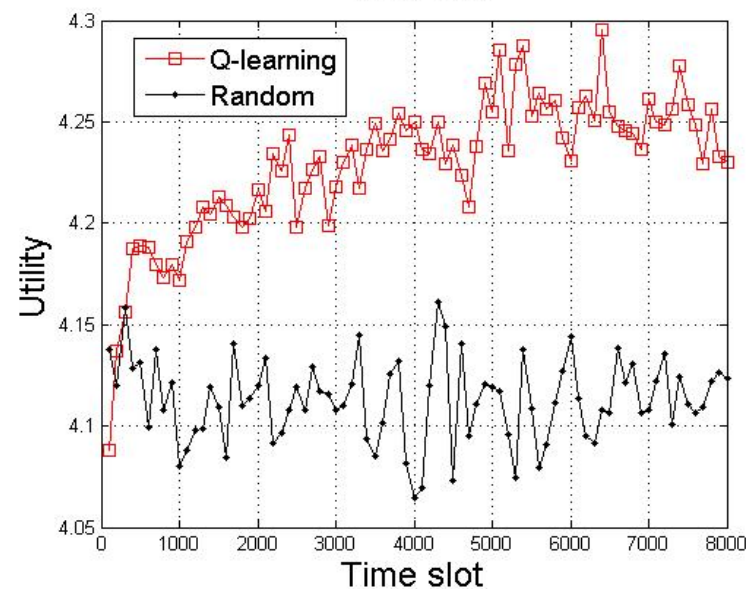
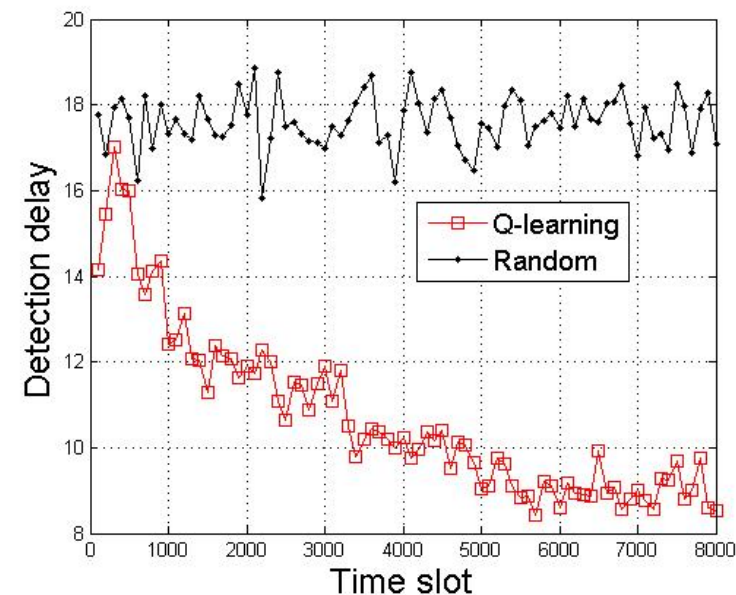
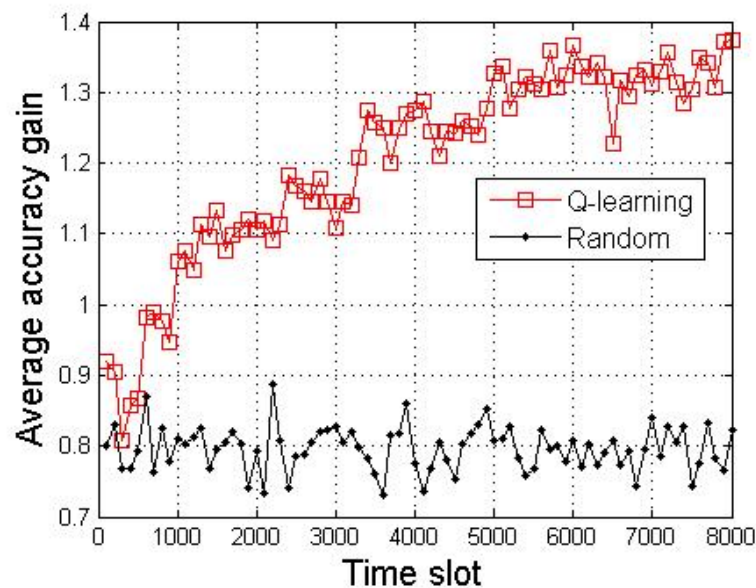
Cloud computation resource=8Gbps

Trace generation speed=1Mbps

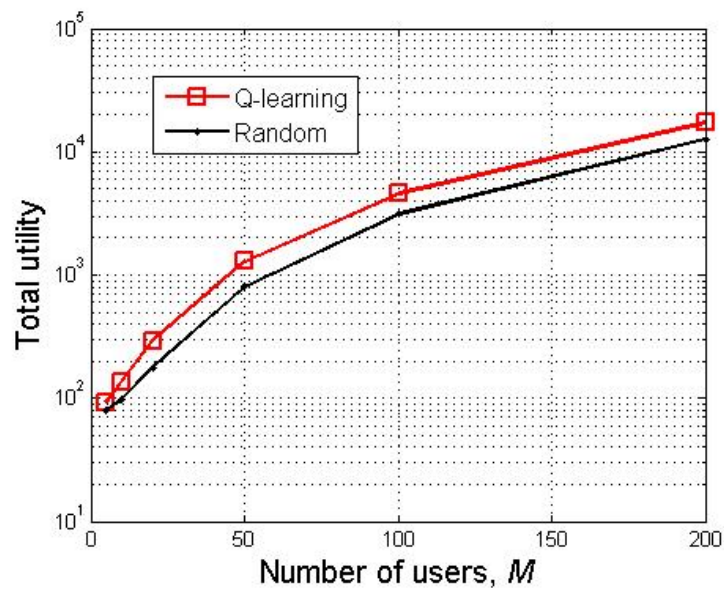
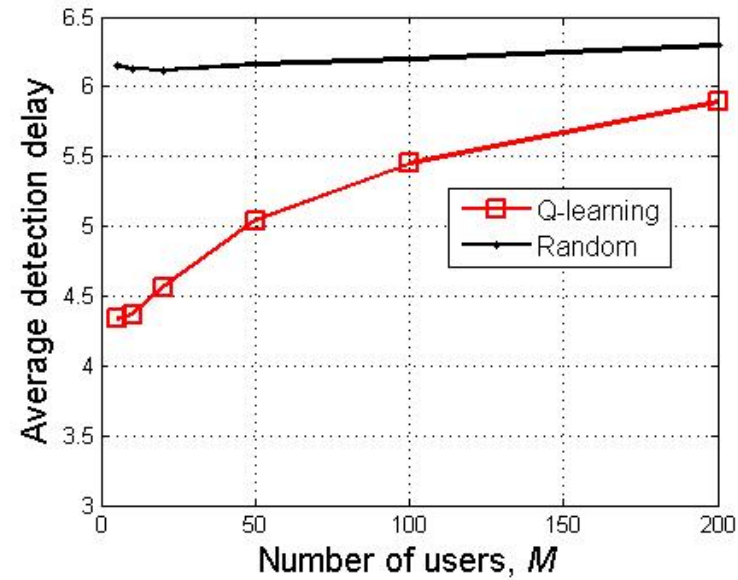
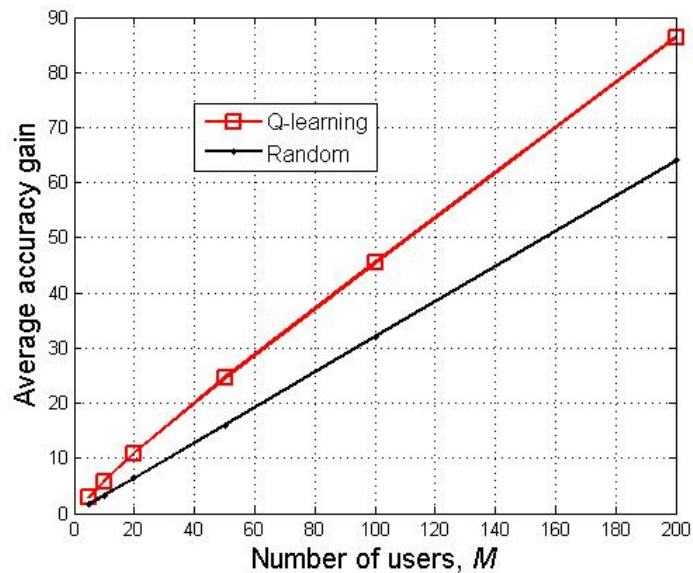
Transmission cost factor= 0.1

Accuracy coefficient= 0.8

Radio bandwidth $\in \{1/6, 1/5, 1/4\} * 10\text{MHz}$



Average Performance



[Xiao, Li, INFOCOM –BigSecurity'15]

Conclusion

- We formulated a cloud-based malware detection game and provided the NE of the game to investigate the user cooperation and competition
- A Q-learning based malware detection strategy was proposed in the dynamic game with time-variant radio networks
 - Reduce the detection delay of mobile users by 33%
 - Increase the detection accuracy gain by 40%
- Further work:
 - Improve the cloud-based malware detection game model
 - Improve the performance of the Q-learning based malware detection with deep learning and data mining in dynamic environments
 - Build prototype and evaluate the performance via experiments

Questions?

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