基于用户意图的异常检测
User Intention Based Anomaly Detection

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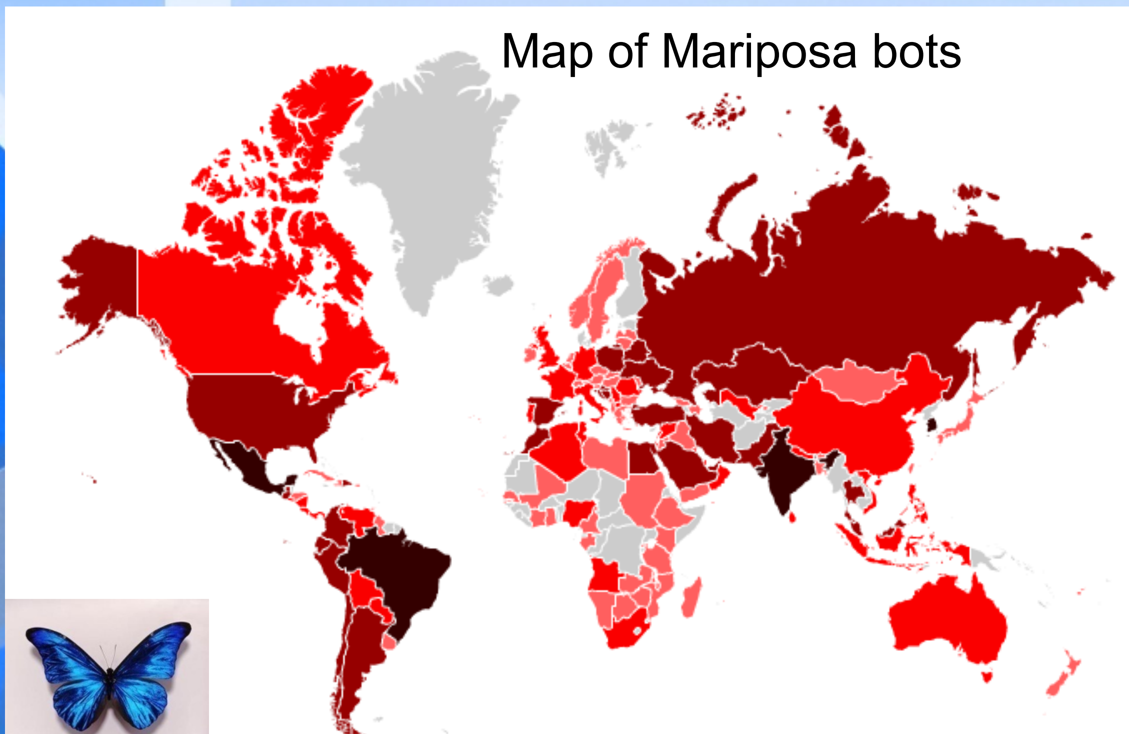
Tianjin University June 2012

Botnet threats are pervasive



llion bots found by AT&T,
ted by botnets [GTISC 08]

nes
nfo

Corporate

Financial loses
IP theft

Individual

Identity theft
Financial loses

Mariposa botnet 12 million IPs;
Stolen data belonging to 800K users;
Malware changes every 48 hours;
Attacker uses real name in DNS

Malware installation

E.g., **drive-by downloads**: 450,000 out of 4.5 millions URLs [Google 08]

Source: GTISC, PandaSolution

Evolving landscape of attacks

[1980’s - early 1990’s]

Curiosity fueled hacking: capability demonstration of hackers

[late 1990’s – early 2000]

Financial driven attacks: spam, stealing credit cards, phishing, large-scale botnets

[late 2000 – present]

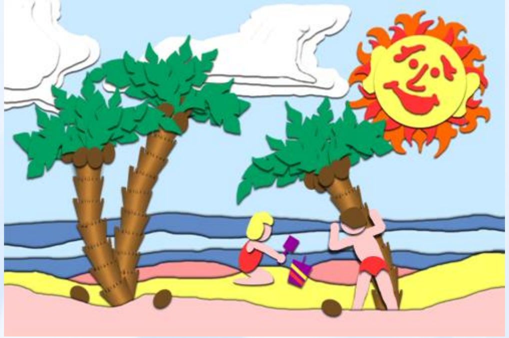
Targeted attacks: stealing proprietary information, information warfare

Challenges caused by:

Scale, complexity, anonymity

Internet was a friendly place. Security problem then was a day at the beach.

-- Barbara Fraser ‘08



Detecting malware – code vs. behavior

First academic use of term *virus* by Fred Cohen in 1984, who credits advisor Len Adleman with coining it

Signature based scanning

- Analyze malware samples, extract signatures, and statically scan the file system for malicious code

But malware may encrypt/obfuscate itself

- To detect malware behaviors at run time (dynamically)
- E.g., system call execution, memory/stack access

But what about zero-day malware/exploit?

- Anomaly detection

But how to define the normalcy of a program?

D. Denning '87: anomaly detection

Problem: how to ensure system integrity （系统完整性）?

Challenges in Winning Bot Wars

Our approach: host-based bot detection by enforcing normal system and network patterns

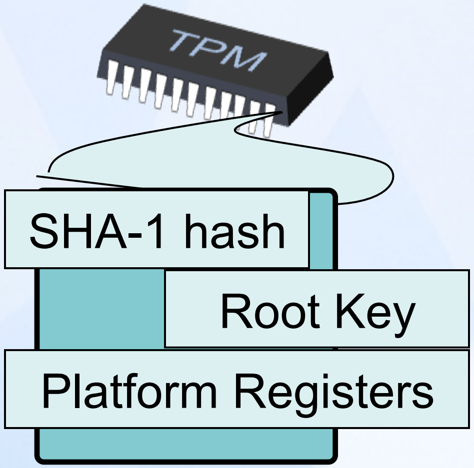
Motivation: Humans and bots have distinct patterns when interacting with computers

Challenge 1: How to find robust features?

User inputs and activities

Challenge 2: How to prevent bot forgery?

Trusted computing platform



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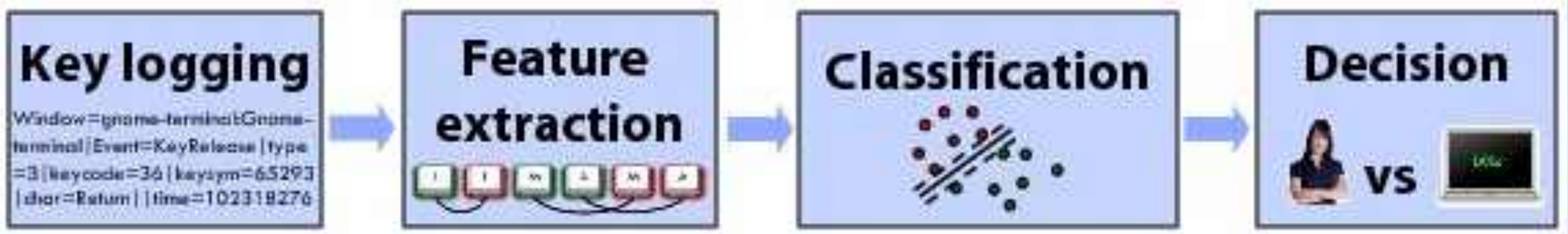
Using our user-intention based anomaly detection techniques, a PC owner wants to know:

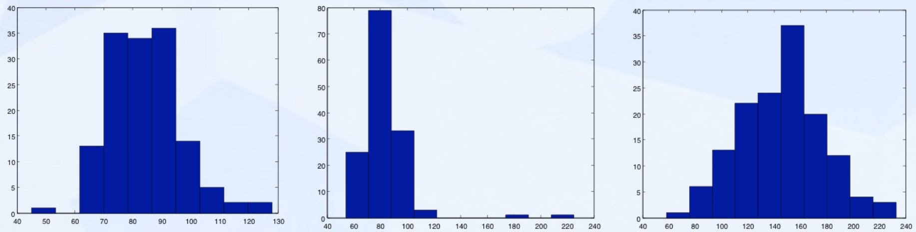
- Who is using the computer
- Where the keystroke is from
- Where the packet is from
- What/who causes outbound traffic
- What/who downloads files on the computer
- Whether or not the apps behave

→ **For preserving system integrity**

Know who is using the computer

Keystroke Dynamics Based Authentication





Keystroke timing follows a Gaussian distribution

Related keystroke dynamics [MRW CCS 99] [MR CCS 97]

TUBA (Telling hUman and Bot Apart)

Use Scenario

1. *Training Phase:* user keystroke data collected
2. *TUBA challenge:* asks user to prove identity by typing a string

Used support vector machine (SVM) for classification, 92.26% TP, 3.39% FP

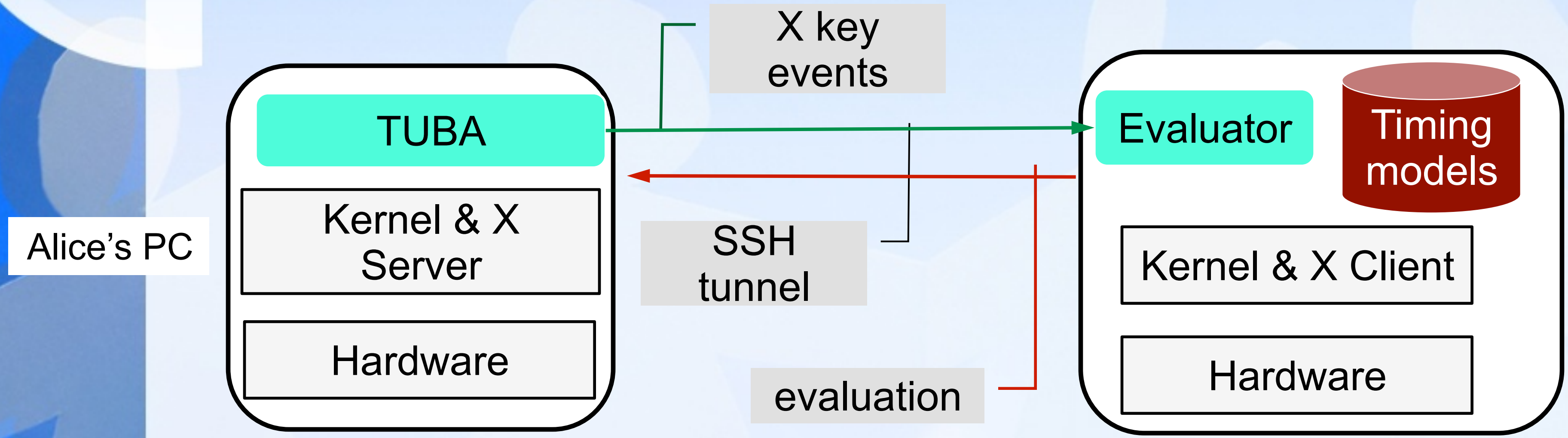
TUBA challenge is personalized

How robust is keystroke dynamics based authentication against forgery attacks?

Our Architecture and Adversary Model

Client-server architecture

Data collection & processing on a trusted server



Adversary model

- Infect the user's computer
- Monitor, intercept and modify network traffic
- Collect and inject keystroke information of the general public, *except* the owner

Can also support a stand-alone architecture

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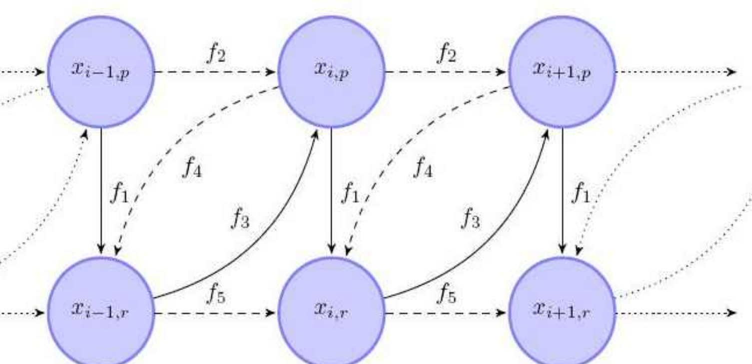
Human vs. Bots

20 users: 10 males 10 females, ages [18-23]
Session time [20 min – 1 hr]
Collected samples: 6 words, 35 samples of each

String	GaussianBot		NoiseBot	
	TP	FP	TP	FP
www.cooper.edu	96.29%	2.00%	100.0%	0.00%
1calend4r	93.74%	3.43%	97.71%	1.43%
deianstefan@gmail.com	96.57%	1.71%	99.71%	0.29%



Assuming first-order Markov model

Duration of i-th character as random variable $X_i > 0$

1. Gaussian distribution with mean μ_i and variance σ_i^2:

   $X_i \sim N(\mu_i,\sigma_i^2)$ -- **GaussianBot**

2. Constant with additive uniform noise:

   $X_i \sim \mu_i + U(-\eta_i; \eta_i)$ -- **NoiseBot**

Summary: Keystroke timing analysis is robust against statistical bots studied

Keystroke dynamics authentication work appeared in:

Deian Stefan, Xiaokui Shu, and Danfeng Yao.
Robustness of Keystroke-Dynamics Based Biometrics Against Synthetic Forgeries.
***Computers & Security*. 31. 109-121. 2012. Elsevier.**

Know where your keystroke is from

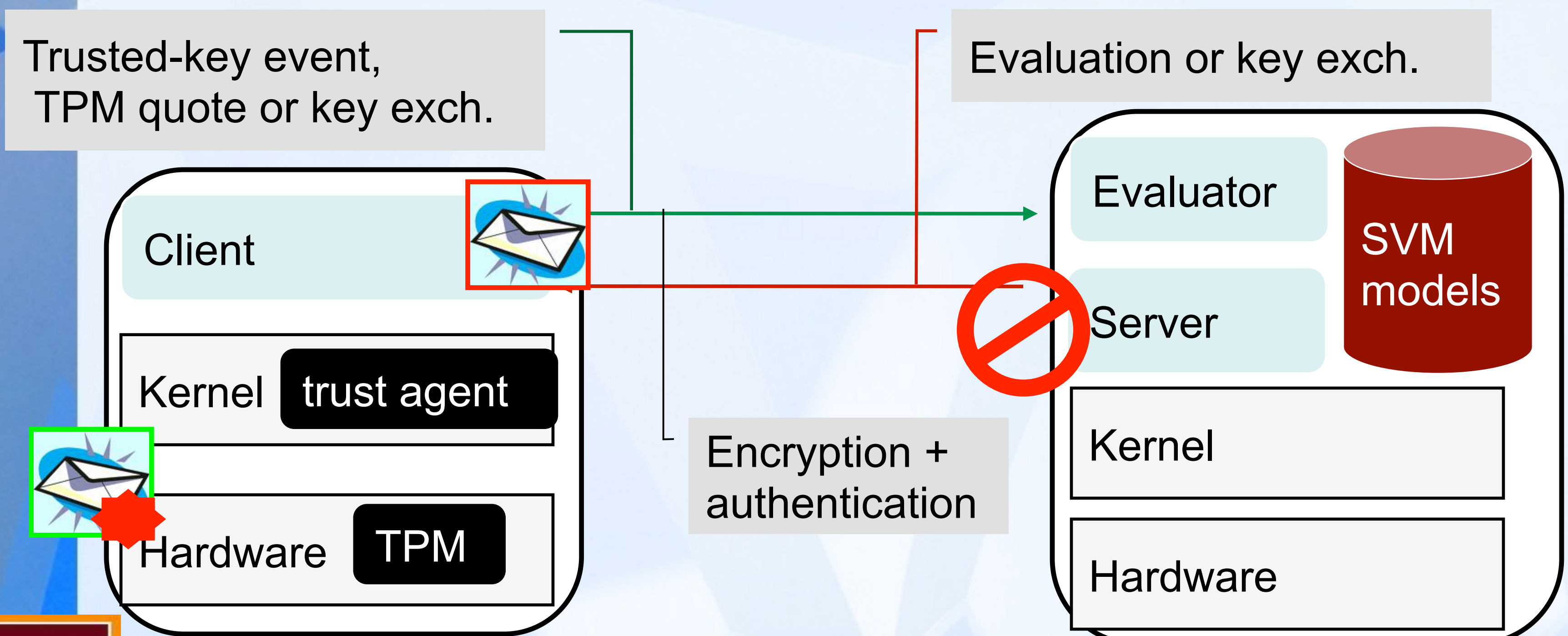
Preventing Stronger Adversaries With TPM

A stronger adversary may:

- Gain root on the computer
- Collect the owner's keystroke information
- Tampering TUBA client

Our prototype on Intel Core 2 Duo (INT-C0-102) following TPM Interface Spec 1.2

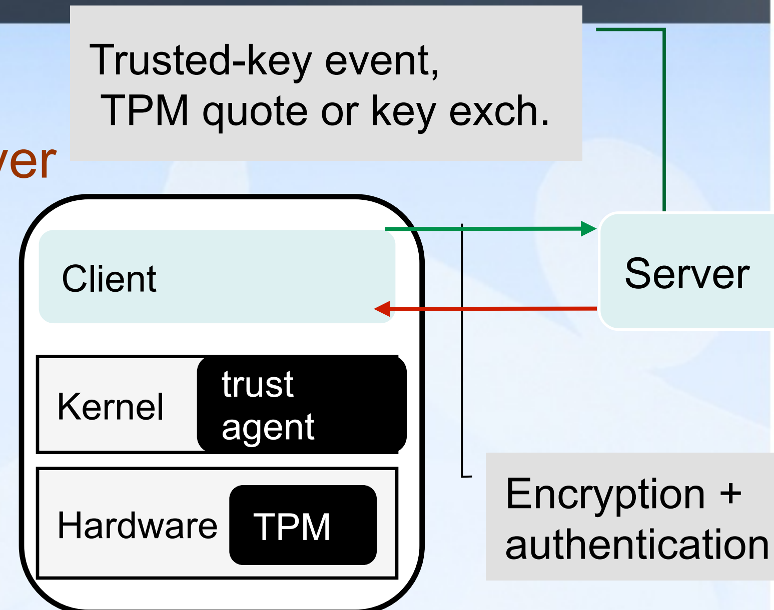
Our goal: to prevent fake key event injections & tampering TUBA



Related TCB/TPM work [MPR NDSS 09] [GBMR, NSDI 08] [MPPRI, EuroSys 08]

Highlights in TUBA Integrity Service

1. Server verifies trusted boot of client
2. Key exchange between agent & server
3. Trust agent signs keystroke events
4. Client relays signed events



Secrecy of Signing key is guaranteed

Sign a packet (SHA1) with a 256-bit key: 18.0 usec

Encrypt a packet (AES-CBC) with a 256-bit key: 67.6 usec

(Averaged on 1312 keystroke events with TPM key initiation.)

Bandwidth (i.e., communication overhead): 13 KBps

Summary: Robust TUBA introduces minimal overhead and practically causes no delay even for a fast typist

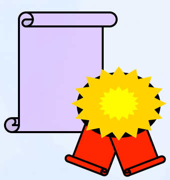
Our Approach: Cryptographic Provenance Verification (CPV)

Data-provenance integrity – origin of kernel-level data not spoofed

CPV - a robust attestation mechanism that ensures true origin of data

TUBA embodies our CPV approach

CPV differs from traditional digital signatures



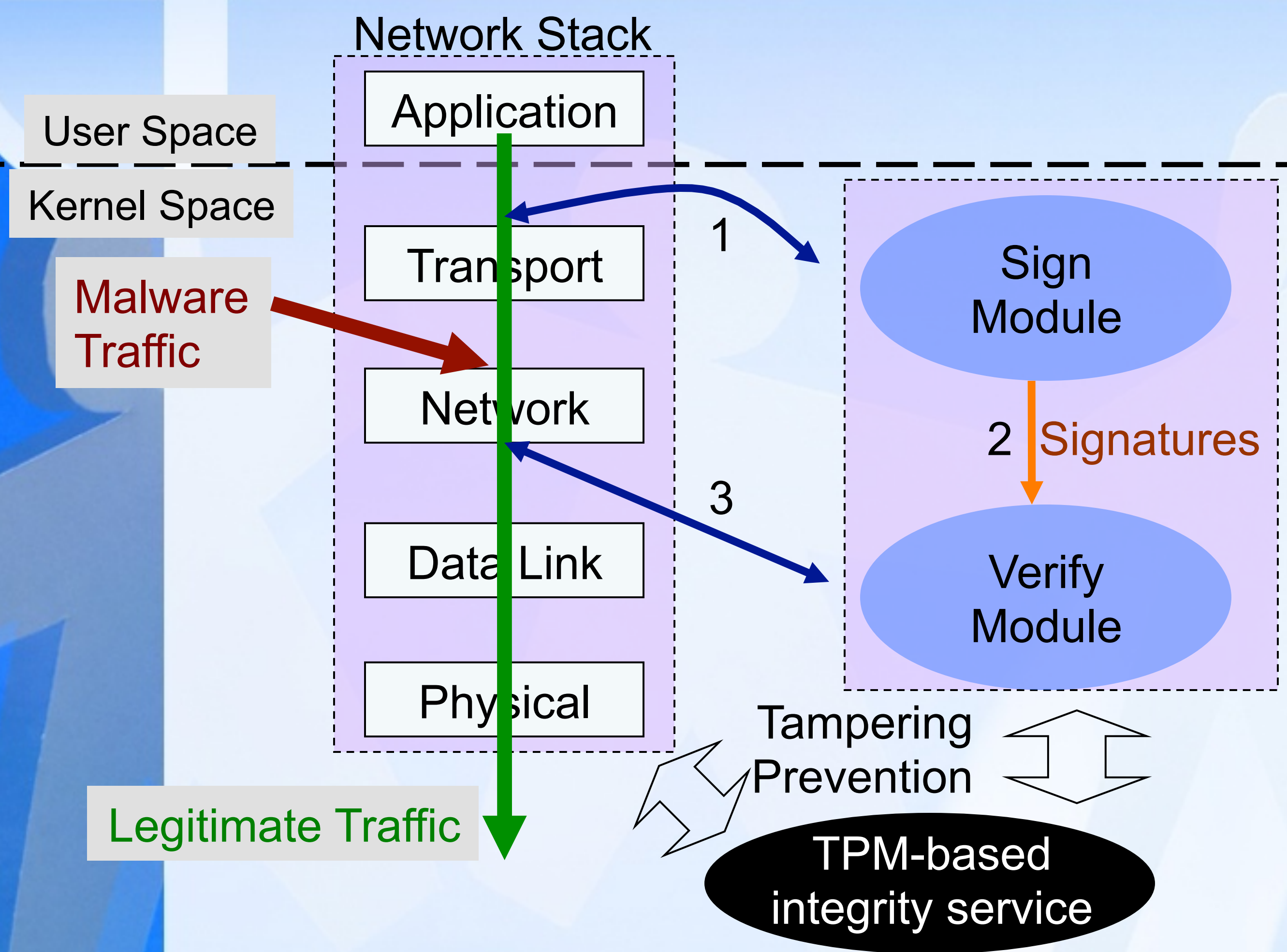
Signs a document

Signer knows what to sign and what not

Know where your outbound network packet is from

i.e., to catch all outbound traffic from a host for inspection

Apply Cryptographic Provenance Verification to Network Stack



2 Kernel Modules:
- Sign Module
- Verify Module

Key management:
- Key derived from TPM

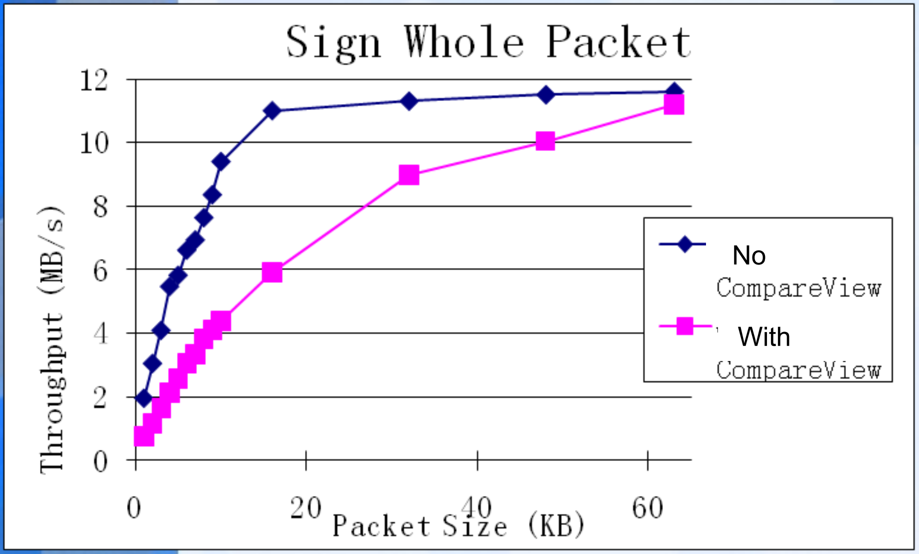
Technicalities:
- Defragmentation
- Signature transfer

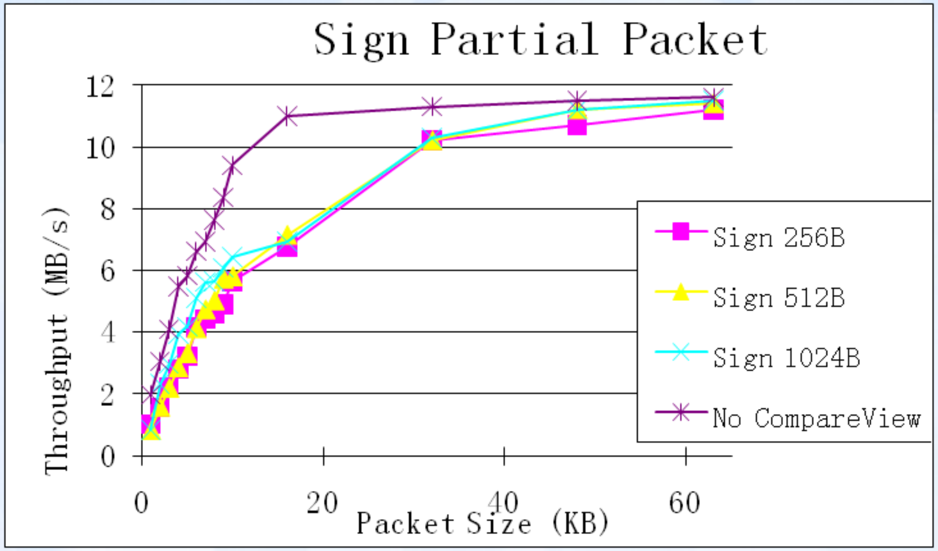
Prototype in Windows

Our solution enables advanced traffic inspection – no packet left behind

Throughput Analysis in CompareView

- As packet size increases, overhead decreases
- < 5% overhead for 64KB packet size
- Signing partial packet reduces overhead





Successfully detected several real-world and synthetic rootkit-based malware

Fu_Rootkit, hxdef, AFXRootkit, our proof-of-concept rootkit

Summary: Our work enables robust personal firewall

Cryptographic provenance verification work appeared in:

Kui Xu, Huijun Xiong, Chehai Wu, Deian Stefan, and Danfeng Yao. **Data-Provenance Verification For Secure Hosts.** ***IEEE Transactions of Dependable and Secure Computing (TDSC).*** 9(2), 173-183. March/April 2012.

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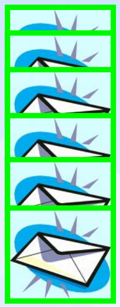
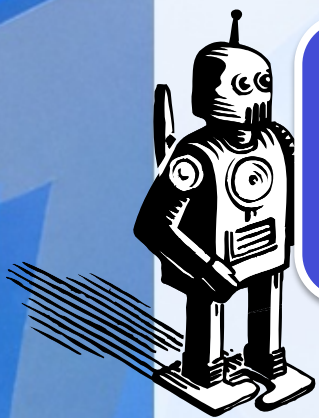
Know what/who causes your outbound traffic

Motivation for traffic anomaly detection on a host





How to distinguish the malicious outbound packets from the legitimate ones on a host?

Our approach for traffic anomaly detection

To enforce ***dependence*** properties among outbound network requests of a host

Key observation

- User inputs trigger outbound network packets

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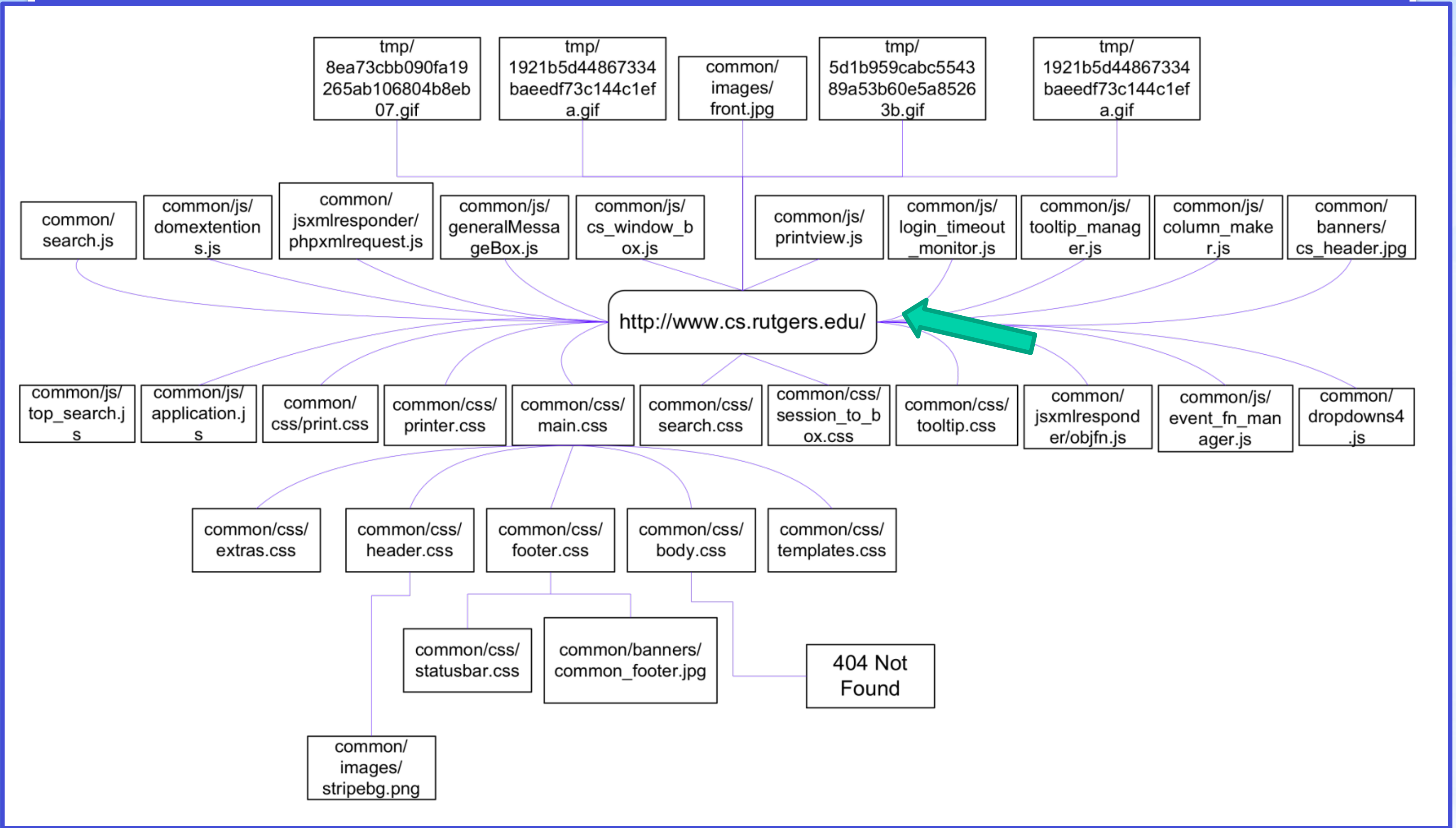
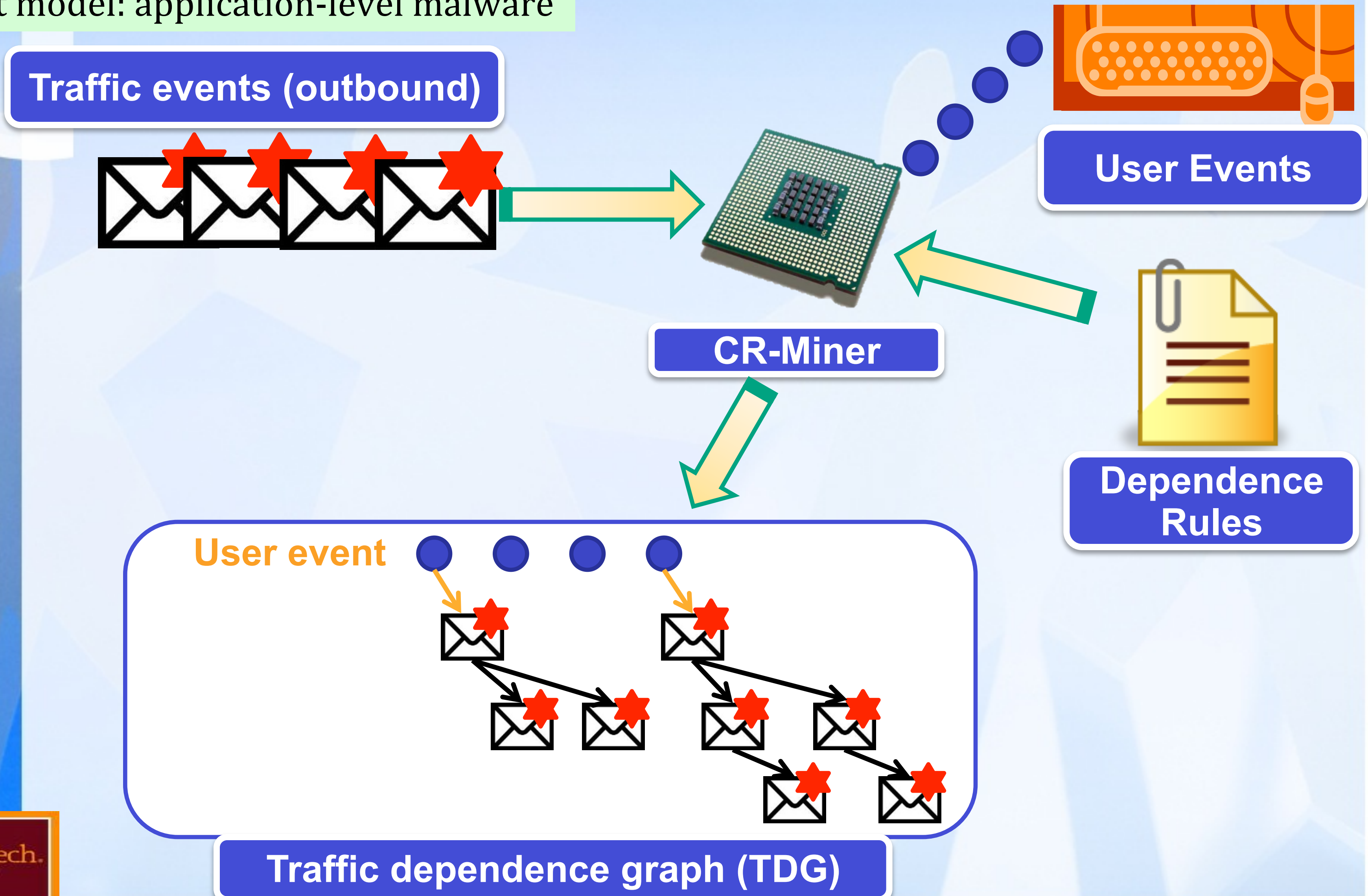
A Technical Challenge



Work Flow of CR-Miner

Threat model: application-level malware



Events and their attributes

Dependence rules specify relations of attributes of dependent events

User events

	Timestamp	Event Name	Value	URL
A	0:0:01.077	KeyDown	Return	http://www.engadget.com/
B	0:0:02.910	MouseClick - Left	X=1069 Y=474	http://www.cnet.com/
C	0:0:03.000	Wheel	-120	N/A

Traffic events

	Timestamp	Object Requested	Remote Domain Name	Referrer
1	0:0:02.863	/	www.engadget.com	http://www.engadget.com/
2	0:0:02.873	/media/main.css	www.engadget.com	http://www.engadget.com/...
3	0:0:03.113	/	www.cnet.com	null

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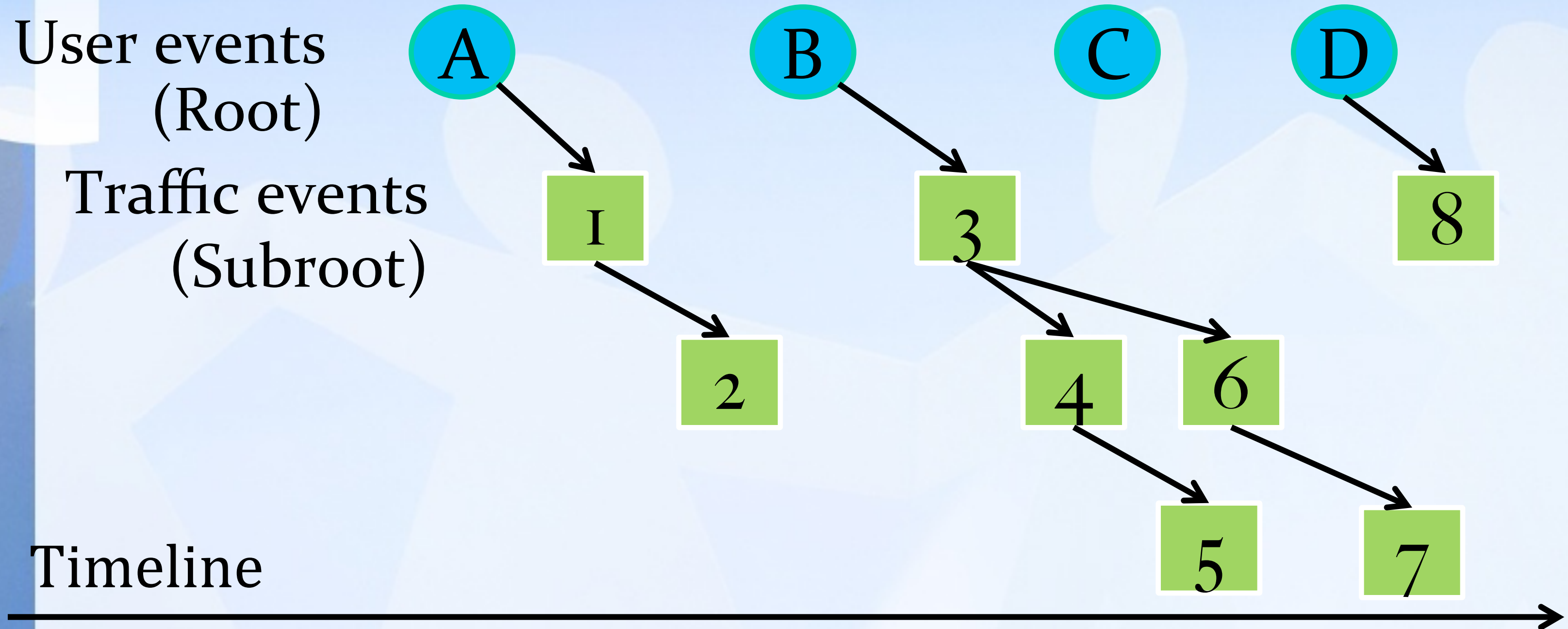
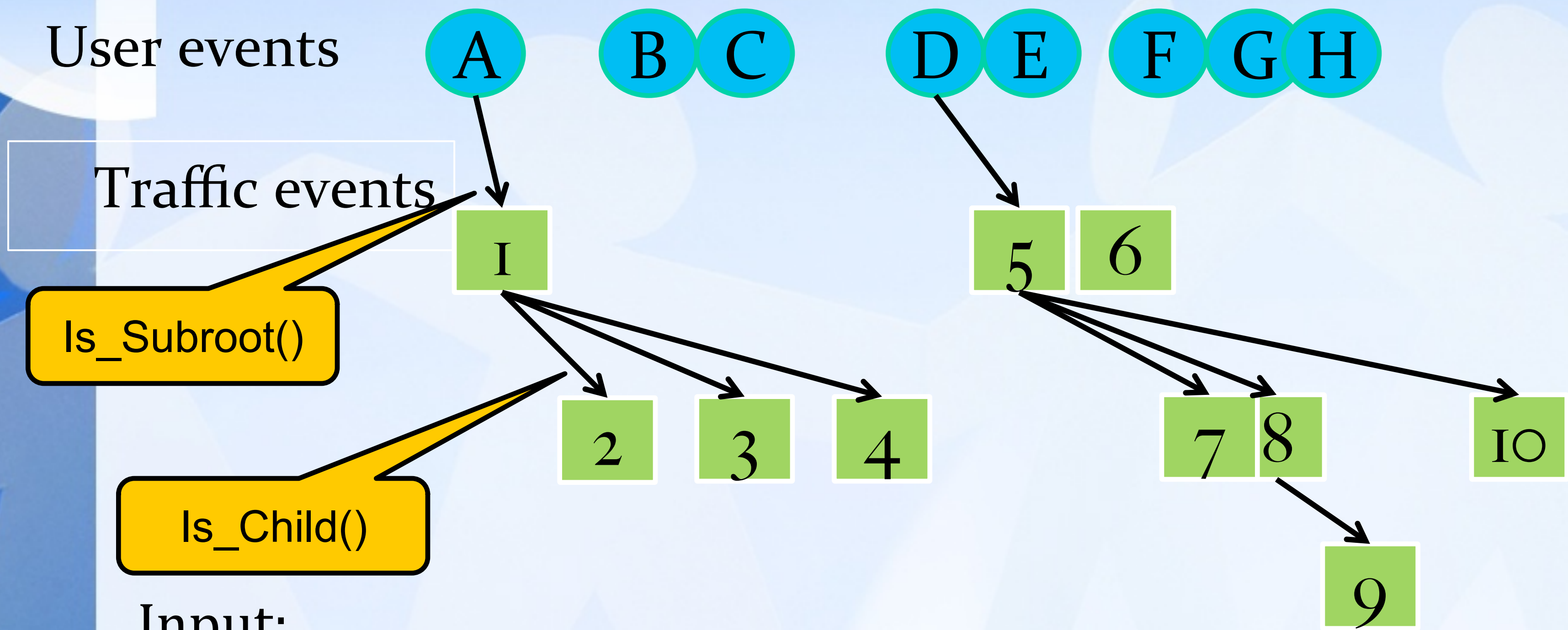
Definitions in Our Traffic Dependency Graph (TDG)



Definition of security: a legitimate traffic event belongs to a tree in a TDG that is rooted at a legitimate user event.

Vagabond traffic event

Our BFS-Based Algorithm to Construct Traffic Dependence Graph

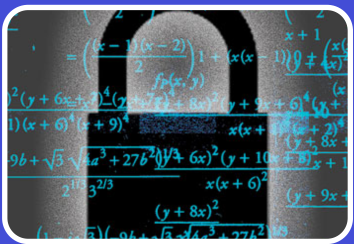


Input:
- an existing TDG (trees of events, which root at user events)
- a new outbound traffic event ***q***

Output: - whether or not ***q*** is legitimate

Security Analysis

- Forgery of events and defense
- Piggybacking attack and defense

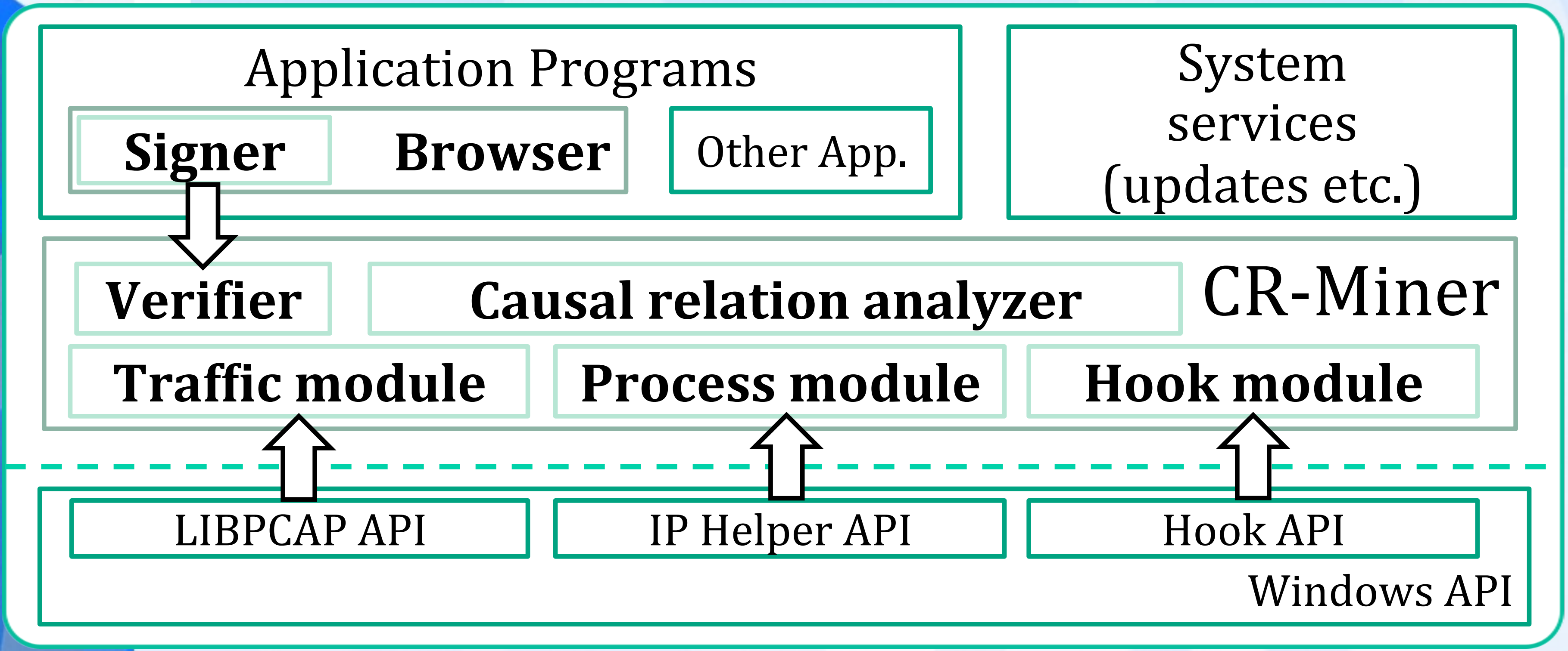


Integrity of traffic information

- Signer and verifier
- Add a message authentication code (MAC)

Implementation Architecture

Our prototype in Windows is called CR-Miner.



Questions to be answered in experimental evaluation

- Can we detect real-world stealthy malware traffic?
- How accurate is the dependency inference algorithm?
- How efficient is the BFS (breath-first search) based dependency inference algorithm?
- Does the inference accuracy suffer in noisy traffic?

User study with 20 participants

A 30-minute surfing session for each user

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Experiments

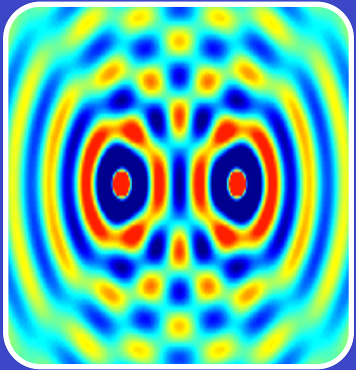
Hit rate r = percentage of traffic events whose causal relations are identified by CR-Miner

Hit Rate	# of User Cases	Percentage (%)
$0.98 \le r < 0.985$	1	5
$0.985 \le r < 0.99$	2	10
$0.99 \le r < 0.995$	4	20
$0.995 \le r < 1$	10	50
$r = 1.00$	3	15

High hit rate: ≥ 0.98 for all user cases.

Are the vagabond traffic events that we found real, i.e., malicious?

Experiments cont'd



Does the inference accuracy suffer in noisy traffic?

- Accuracy = 99.2% in merged data set

Spyware detection

- Infostealer and a trojan
- Proof-of-concept password sniffier

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Traffic dependency work appeared in:

Hao Zhang, Danfeng Yao, Naren Ramakrishnan, and Matthew Banick. User Intention-Based Traffic Dependence Analysis for Anomaly Detection.
Workshop on Semantics and Security (WSCS), in conjunction with the *IEEE Symposium on Security and Privacy*. San Francisco, CA. May 2012.

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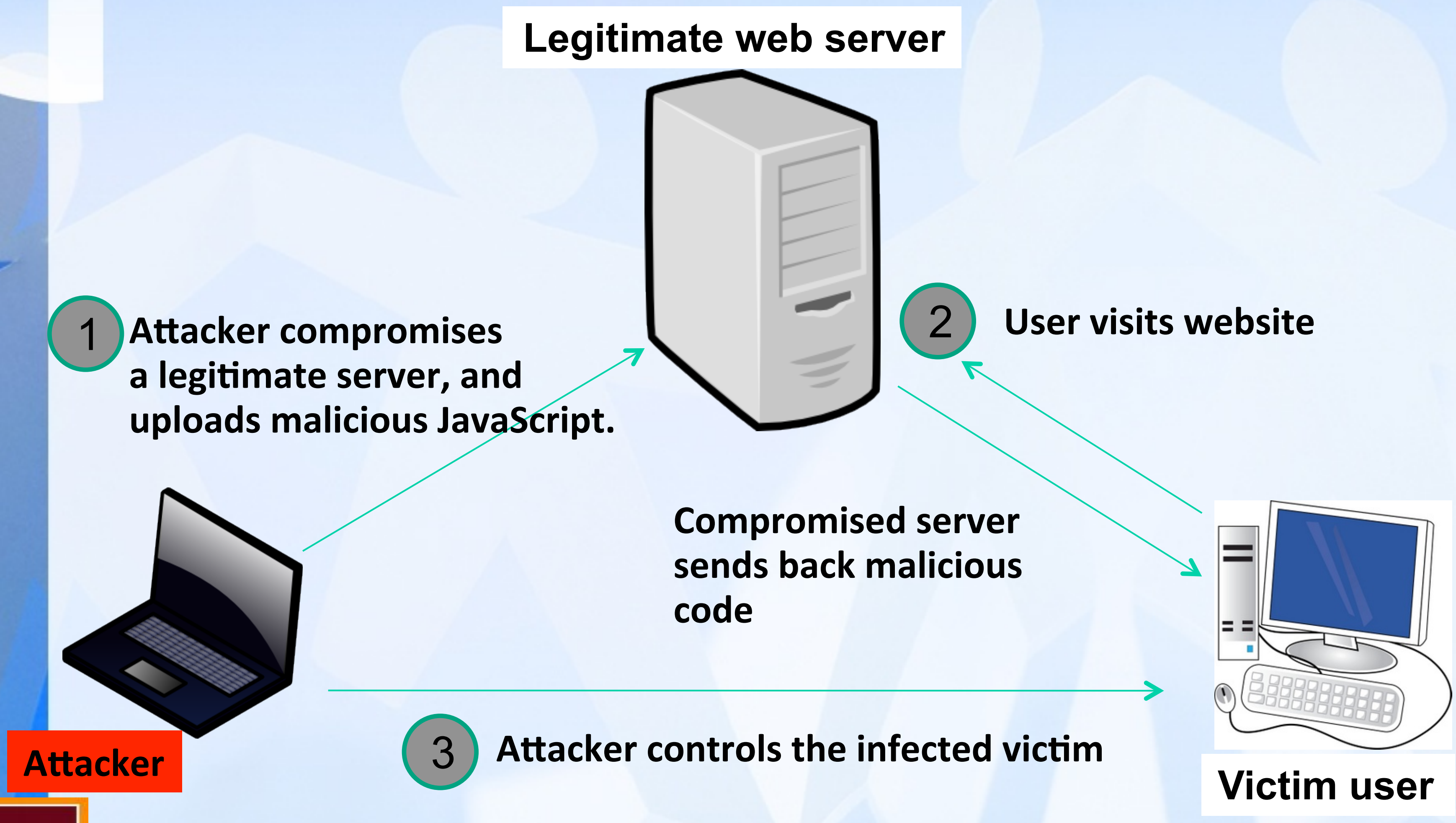
Know what/who downloads files on your computer

Drive-by Download Attacks

Steps of malicious code injection & host infection

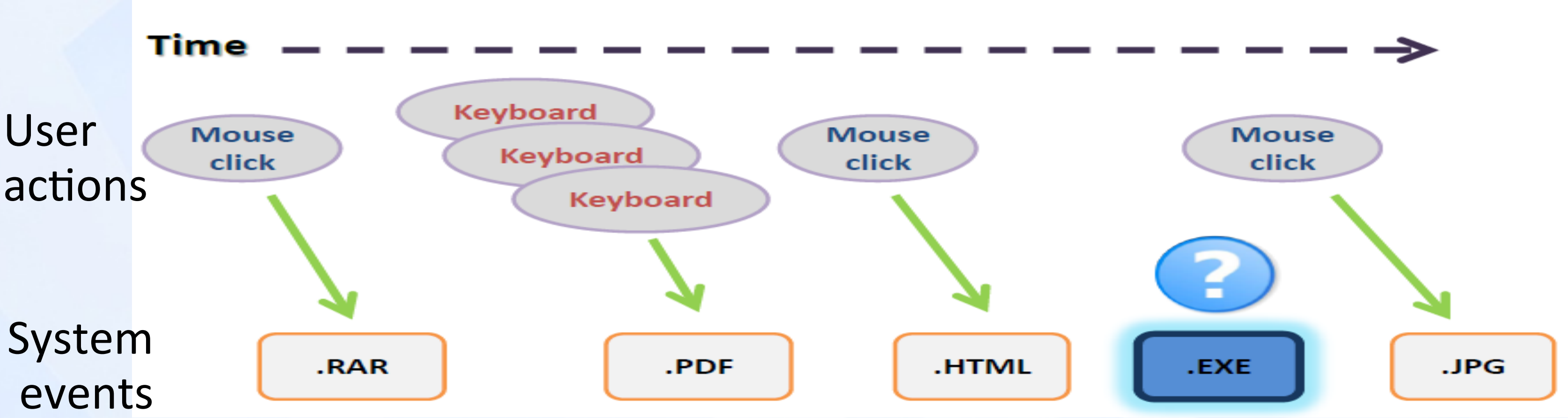


Our User Intention Based DBD Detection

Key Observation:
Legitimate system events should be triggered by users' actions.

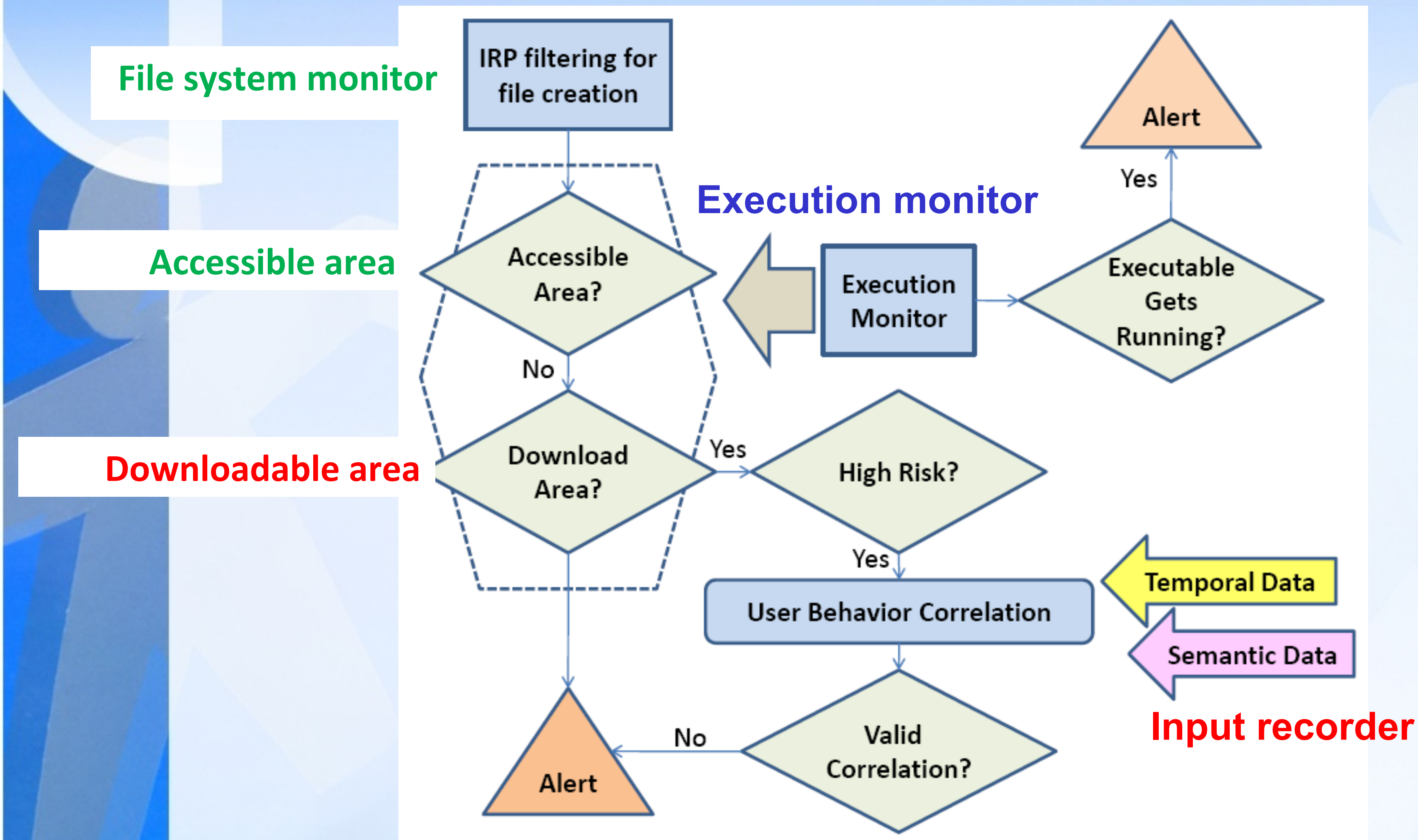
Our approach for DBD detection:

– Monitor file-creation events and user actions
– Identify the dependency between them



Challenge: Browser automatically creates files
E.g., a user indirectly triggers 482 file creation in ***Temporary Internet Files*** folder and 47 in ***Cookies*** directory within 30 minutes of surfing.

Components and work flow



DeWare prototype in Windows 7 Ultimate edition

Dependency Rules Among Events

A file creation event and its triggering user event need to satisfy dependency rules

- ***Rule 1 File properties of events match.***
  - The file user confirms to create should be same as the one actually created.
- ***Rule 2 URLs match.***
  - The file should be downloaded from the URL that user requests.
- **Rule 3 Process properties of events match.**
  - The process that receives input should be the one creating the file.
- **Rule 4 Temporal constraint is satisfied.**
  - A legitimate file creation event should take place within a short threshold after a valid user-input event.

Evaluation of detection ability (2)

Against popular DBD exploits:

– **We successfully detected the lab reproduced exploits:**

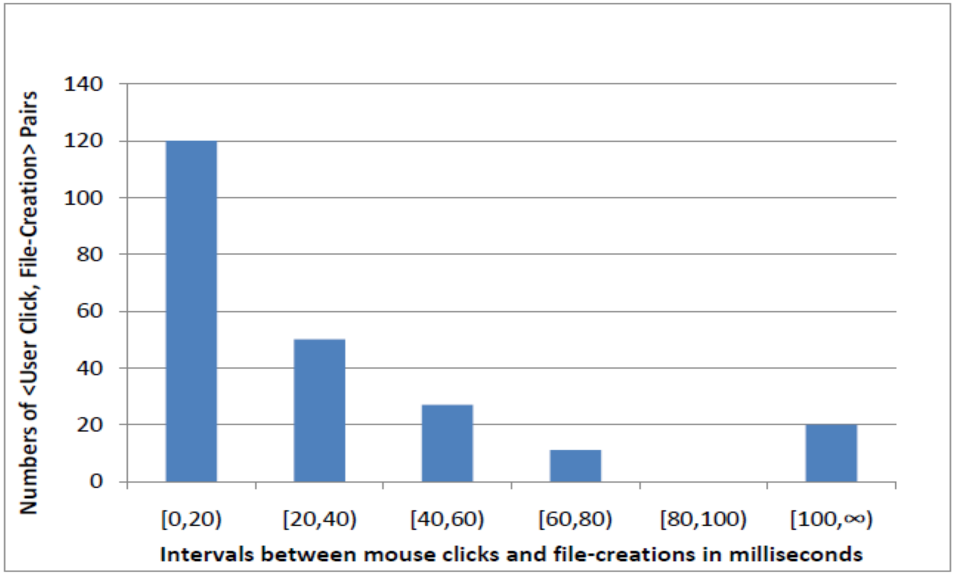
- *Heap Feng Shui attack* 風水
- *HTML Object Memory Corruption Vunerability*
- *Superbuddy through AOL activeX control*
- *Adobe Flash player remote-code execution*
- *Microsoft Data Access Component API misuse*
- *DBD exploiting IE 7 XML library*

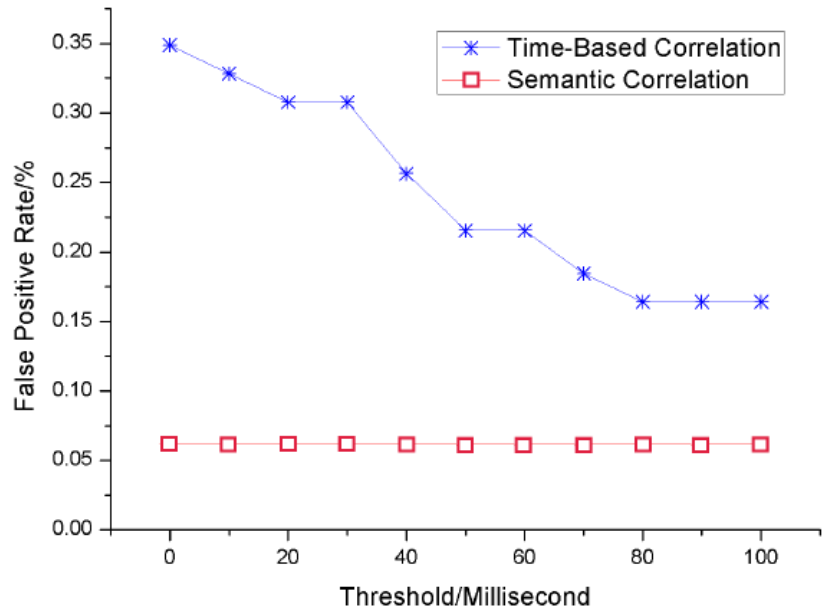
Evaluation of DBD detection ability (1)

Against real-world malicious websites

- 84 out of 142 malicious websites were detected by DeWare
  - Some websites track incoming requests and a second visit would not trigger exploit
- Malicious websites download .exe and/or .dll files
  - E.g., to \Temp folder
- Popular exploit kits are used:
  - Phoenix exploit kit
  - Eleonore exploits pack
  - Targeting at multiple vulnerabilities including Flash, PDF, Java, and browser

False positive evaluation





(b)

False positive analysis is based on the temporal correlation is performed on the 21 user study data.

The number of false alarms is small, less than 1%.

Evaluations on commodity software on IE 7 XML DBD attacks

McAfee, Kaspersky, AVG

Security Software			Reaction
Product	Driver Engine Version	Definition	
Trend Micro Internet Security Pro	v8.952	Pattern version 6.289	No detection
		Pattern version 6.587.50	No detection
Microsoft Security Essentials		Virus Definition 1.69.825 Spyware Definition 1.69.825	Detected. User clicked clean the threats, but DBD files were still downloaded and not deleted by MSE.
360 Safeguard	v3.0	.1112	No detection
	360 v6.0.1	2008-6-16	No detection
	360 v6.0.1	2008-10-27	No detection
	360 v6.0.2	2009-10-14	Detected Heap Spray attack, shutdown iexplorer.exe
Zonealarm Pro	7.0.483	Anti-spyware engine 5.0.189	Captured a.exe trying to access internet. Clicked "Deny", but H.exe was still downloaded successfully
	8.0.400	Anti-spyware engine 5.0.209	
	9.1.008	Anti-spyware engine 9.1.008	

Drive-by download detection work appeared in:

Kui Xu, Danfeng Yao, Qiang Ma, and Alexander Crowell. Detecting Infection Onset With Behavior-Based Policies. In ***Proceedings of the Fifth International Conference on Network and System Security (NSS)***. Milan, Italy. Sep. 2011.

Know whether or not your apps behave

We have provided a white-box approach

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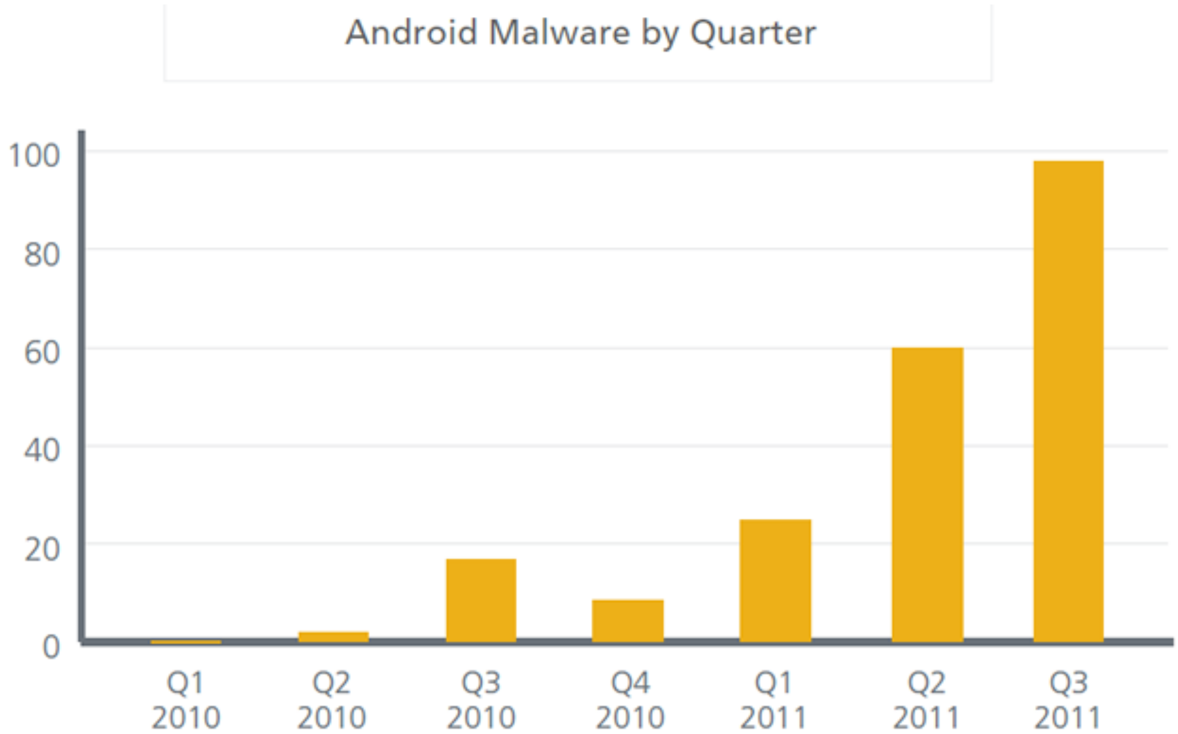
Legitimate or Malicious: an app-classification problem

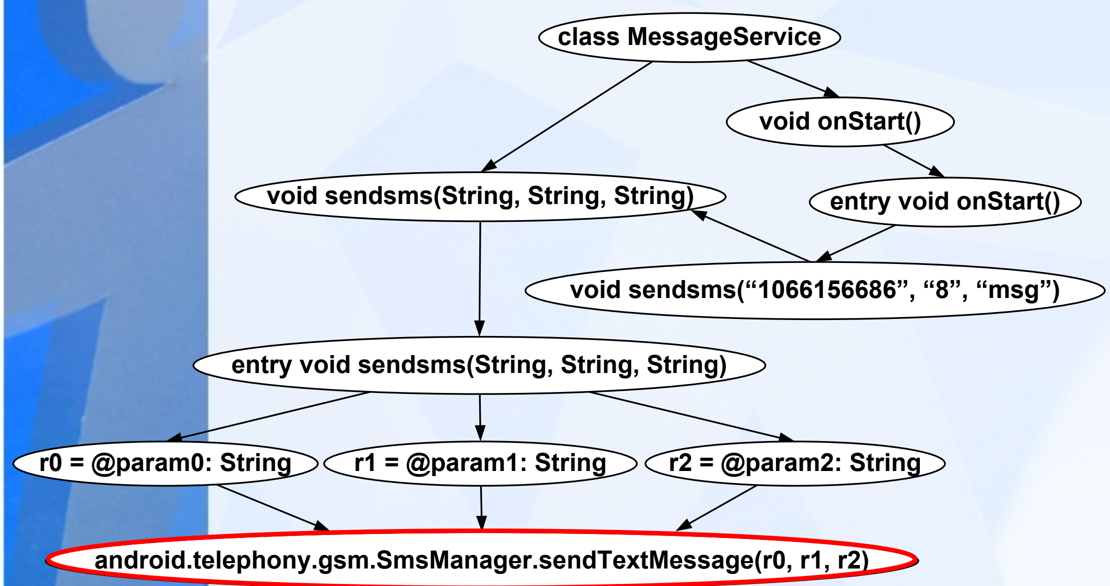


Problem: How to classify unknown apps as benign or malicious?

Source: http://news.cnet.com/8301-1009_3-57328575-83/androids-a-malware-magnet-saysmcafee/?tag=mncol;topStories

Example of Malicious App: HippoSMS

This malware sends SMS messages to a hard-coded premium-rated number without the user's awareness



A Data Dependence Graph

```
public class MessageService{
   .....
     public void onStart(){
        sendsms("1066156686", "8", "");
     }
     public void sendsms(param1,
param2, param3){
        .....

localSmsManager.sendTextMessage(
        param1, param2, param3);
     }
}
```

Malicious code

What is the norm? How to enforce it?

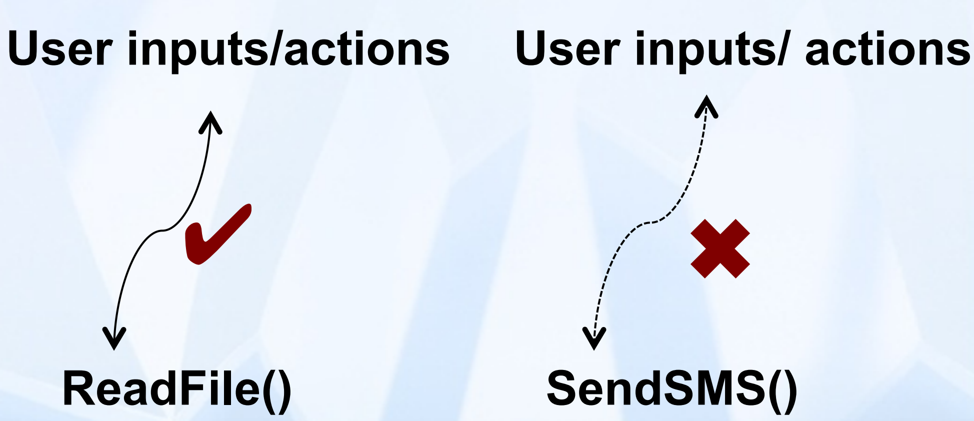
Requests to access system resources should be based on user inputs / actions

Our approach:

Identify the dependency relation between critical system events and user-initiated events in programs

Resources to protect from malicious programs:

- File system access
- Network access
- Sensitive/personal data



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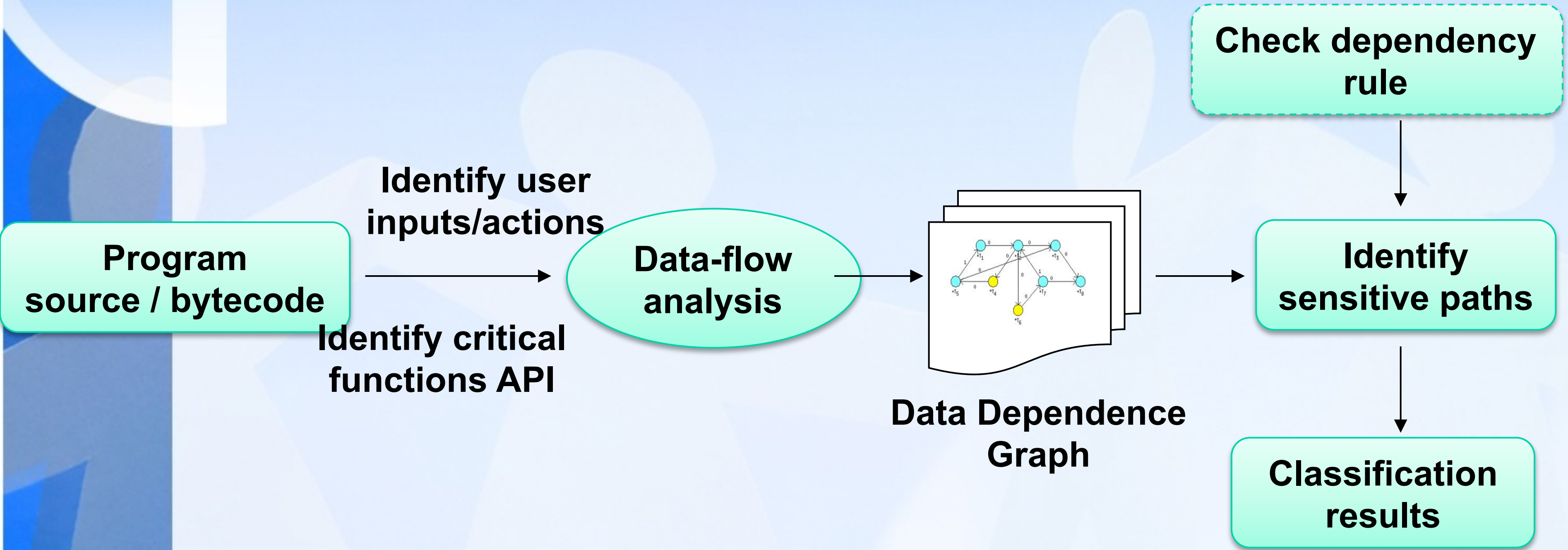
Our User-Centric Dependence Based Anomaly Detection Approach



Our Static Analysis Tool:

We utilize definition-use structures provided by Soot (a static analysis toolkit for Java)

Our tool can analyze Java bytecode / source code

Evaluation Results on Legitimate and Malicious Android Apps

Most malware apps tested do not satisfy our data dependence requirement

	App/Malware Name	# of User Inputs/ Actions (Source)	% of Sensitive Func. Calls without User Inputs	Library of Sensitive Function Calls
Legitimate	SendSMS	3	0%	android.telephony.gsm
Legitimate	BMI Calculator	2	0%	android.app.Activity
Legitimate	BluetoothChat	2	0%	java.io.OutputStream
Legitimate	SendMail	4	0%	android.app.Activity
Legitimate	Tip Calculator	4	0%	android.widget
Malicious	GGTracker.A	0	100%	org.apache.http.impl.client
Malicious	HippoSMS	0	100%	android.telephony.gsm android.content.ContentResolver
Malicious	Fakeneflic	3	0%	org.apache.http.impl.client
Malicious	GoldDream	0	100%	android.content.Context java.io.FileOutputStream
Malicious	Walk & Text	0	100%	android.content.ContentResolver org.apache.http.impl.client
Malicious	RogueSPPush	0	100%	android.telephony.gsm android.content.ContentResolver
Malicious	Dog Wars	0	100%	android.telephony.gsm android.content.ContentResolver

Security Analysis

Attacks	Countermeasures
Phishing apps / social engineering apps	Site authentication and user education
Using superfluous user inputs and actions	Easy to detect by using our approach to track the dependency
Code obfuscation or Java reflection	Dynamic taint analysis

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Program analysis work appeared in:

Karim Elish, Danfeng Yao and Barbara Ryder.
User-Centric Dependence Analysis For Identifying Malicious Mobile Apps.
In ***Proceedings of the Workshop on Mobile Security Technologies (MoST)***, in conjunction with the IEEE Symposium on Security and Privacy.
San Francisco, CA. May 2012.

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Using our user-intention based anomaly detection techniques, we know:

- Who is using the computer
- Where the keystroke is from
- Where the packet is from
- What/who causes your outbound traffic
- What/who downloads files on your computer
- Whether or not your apps behave

→ **For preserving system integrity**

Conclusions and Future Work

User-intention based anomaly detection is a promising approach; we've demonstrated its use in detecting anomalies in

- network traffic,
- file system events,
- apps,
- keystrokes …

Future work:

More investigation on white box anomaly detection and analysis

Android based mobile system integrity

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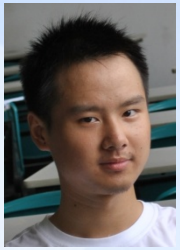
Personnel in Yao group

Current Ph.D. students


Kui Xu


Huijun Xiong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