Side and Covert Channels: *the Dr. Jekyll and Mr Hyde of Modern Technologies*

Mauro Conti, University of Padua

Università degli Studi di Padova

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Security & Privacy
Research Group


Log on to this computer
Username
Password
Use NMAS for Windows Logon
Log on to: testpc1
Log on to another domain
Network Logon
Switch User
Windows 7 Professional

Outline

- Covert and Side Channels 101
- Network Traffic Analysis
  - *As a side channel: app and sensitive data inference*
- Energy Consumption
  - *As a side channel: user and app inference*
  - *As a covert channel: data exfiltration*
- Device Movement
  - *As a side channel: smartphone user authentication*
  - *Attacks against biometric authentication*
- Keystroke Timing
  - *As a side channel: text typed on keyboards*
- Acoustic Emanations
  - *As a side channel: text typed on keyboards*

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Physical Property Leveraged

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Keystroke Inference

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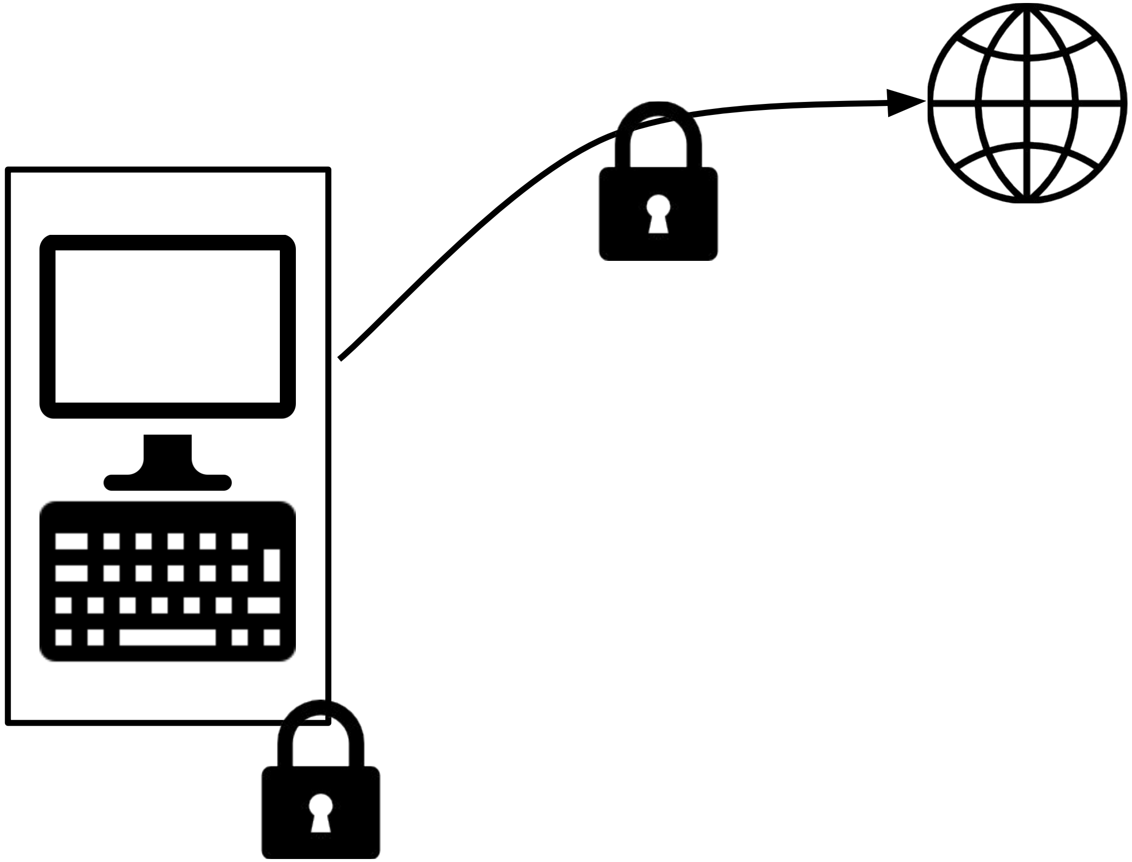
Side Channels

Devices, and network communication, are usually **protected** and **encrypted**



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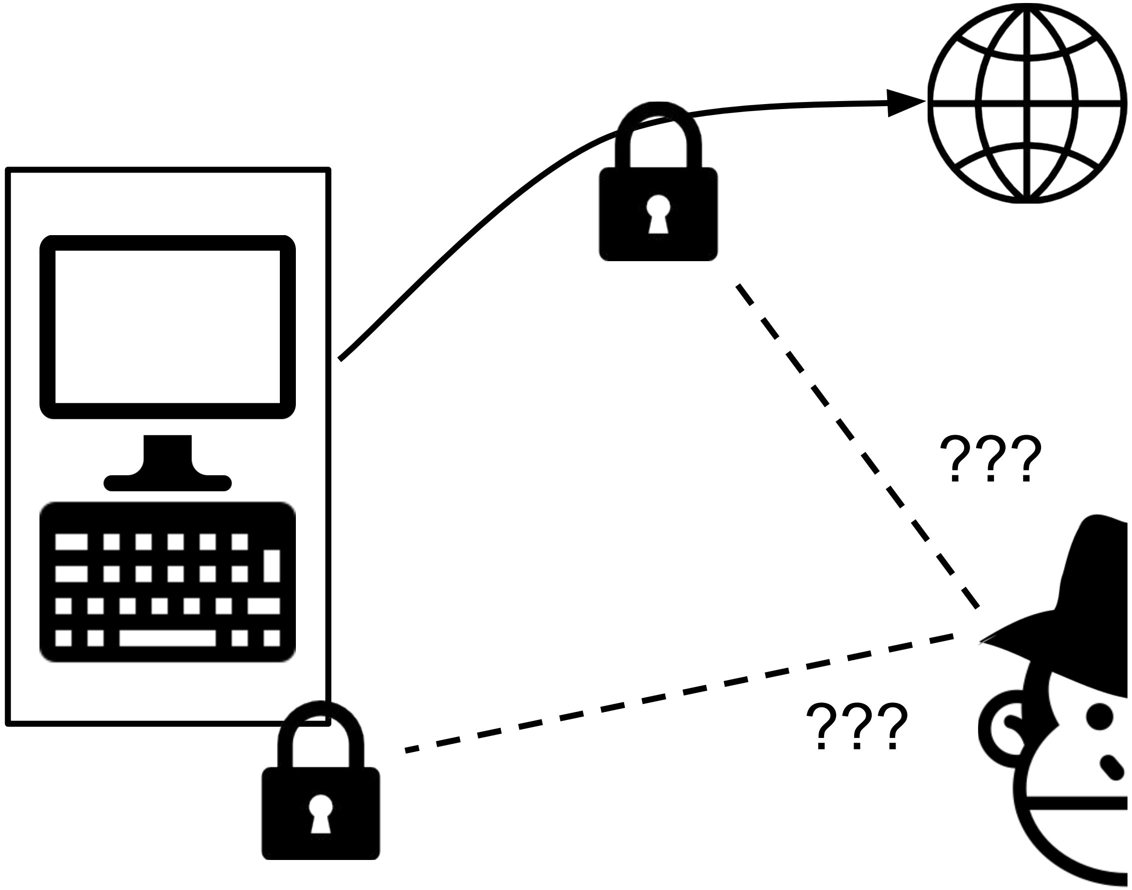
Devices, and network communication, are usually **protected** and **encrypted**

→ Difficult for **Attackers** to violate such protecion

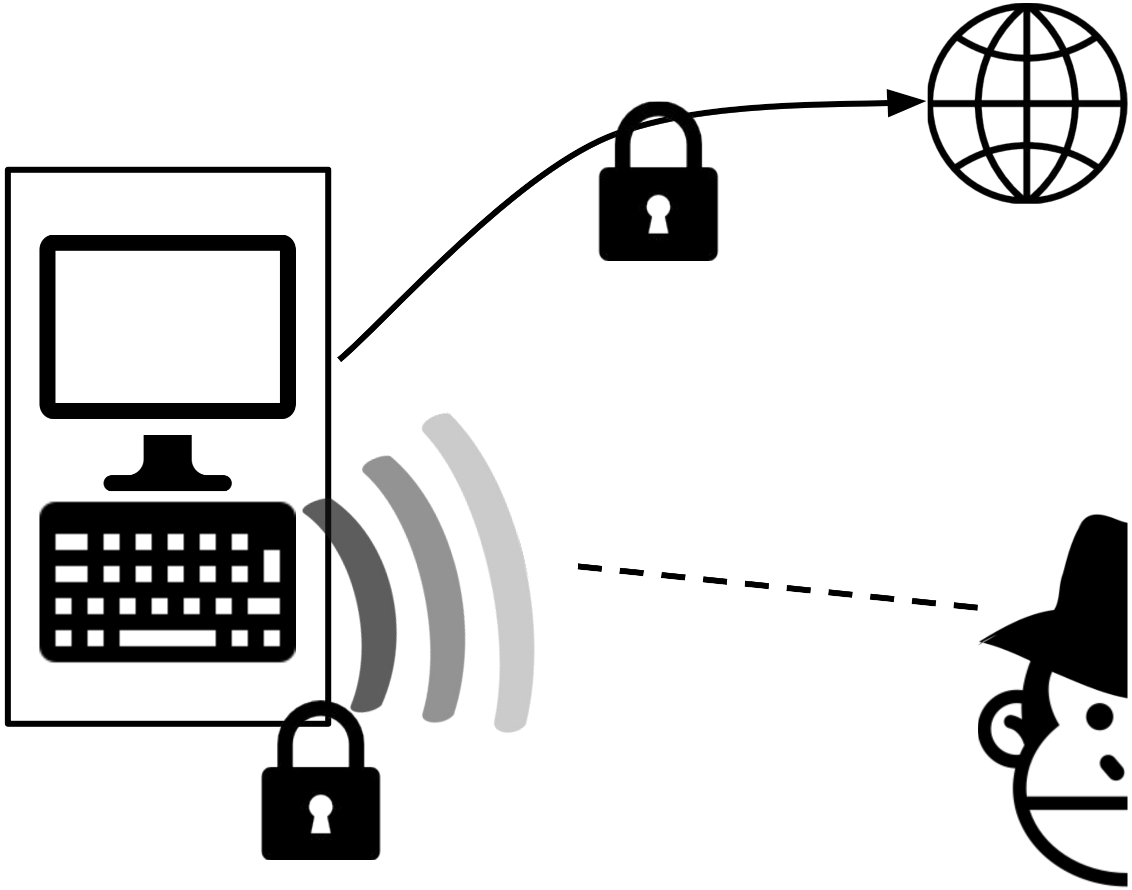


Side Channels

Observing emanations and patterns

Can reveal secrets!

This is called a **side channel**

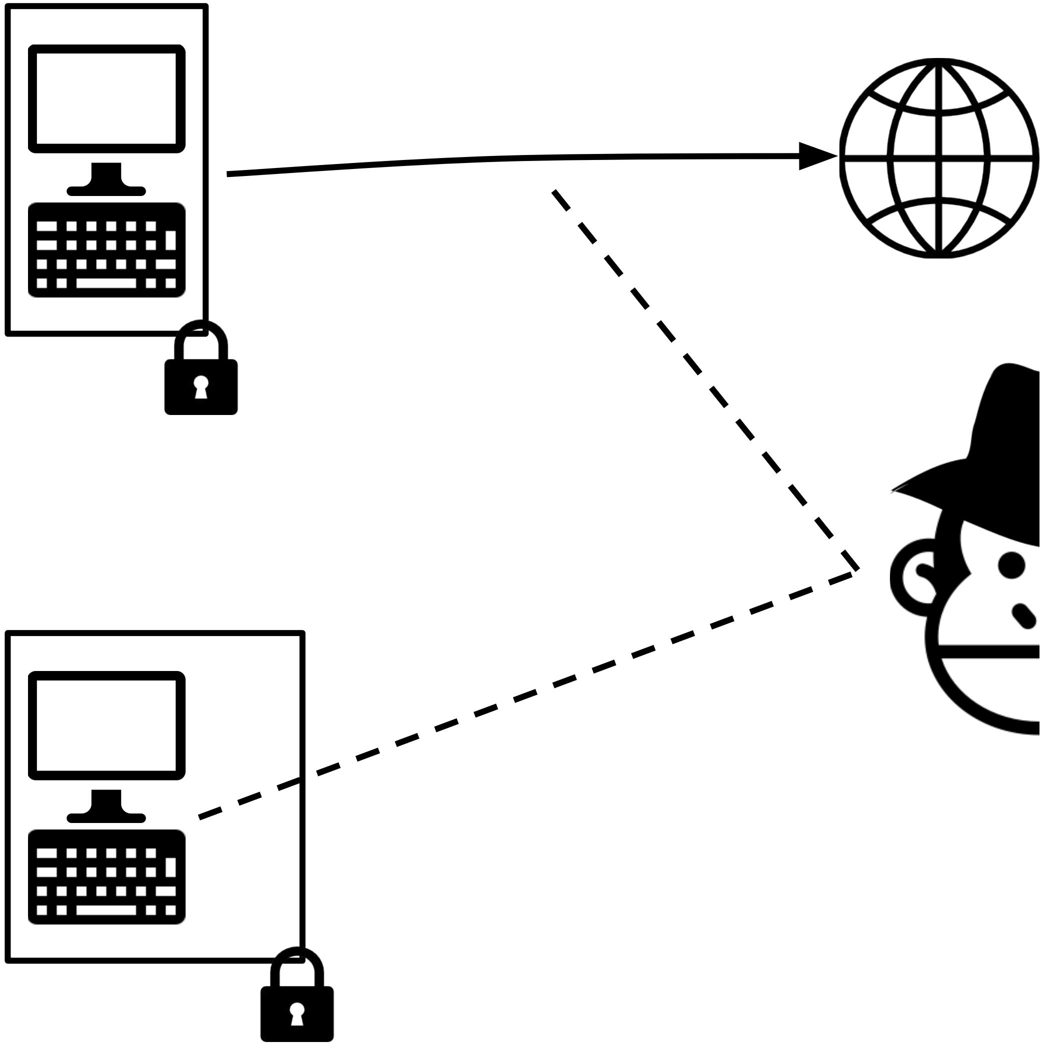


Covert Channels

Covert Channels are used to communicate stealthily.

Either to **avoid listeners in the middle**...

...or to exfiltrate information.



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M. Conti, L. V. Mancini, R. Spolaor, N. V. Verde.

Can't you hear me knocking: Identification of user actions on Android apps via traffic analysis.

In ACM SIGSAC CODASPY 2015

V. F. Taylor, R. Spolaor, M. Conti, I. Martinovic.

AppScanner: Automatic Fingerprinting of Smartphone Apps From Encrypted Network Traffic.

In IEEE EuroSP 2016

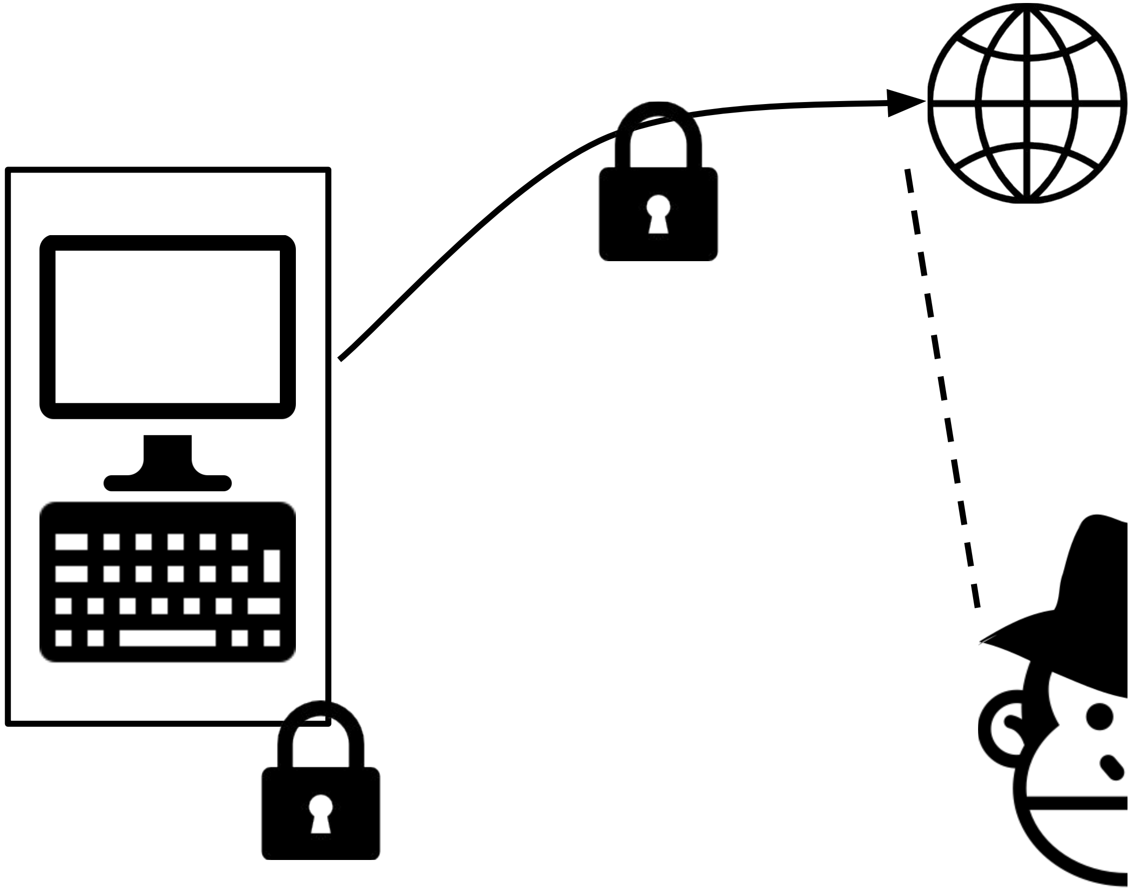
Traffic Analysis

Traffic patterns

Can reveal what we are doing!

Device-platform interaction reveals our actions

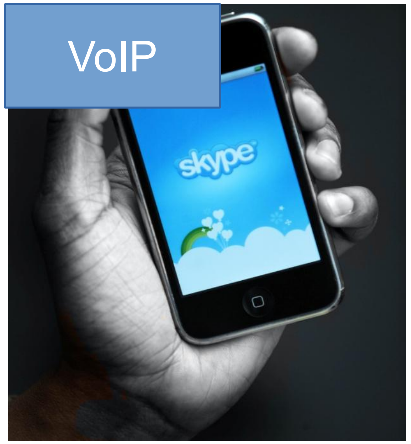
Called **traffic analysis**



Motivation

Encryption is not enough!

[Song et al. '11]



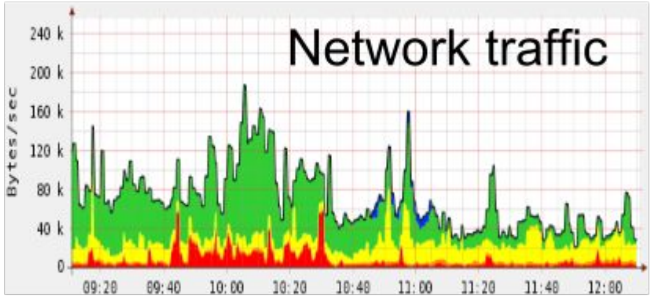
[Wright et al. '08]

Attacker's observations

- Coarse features:
  - Packet lengths
  - Packet directions
  - Packet timings
  - ....

Enable Traffic Analysis Attacks

Attack scenario

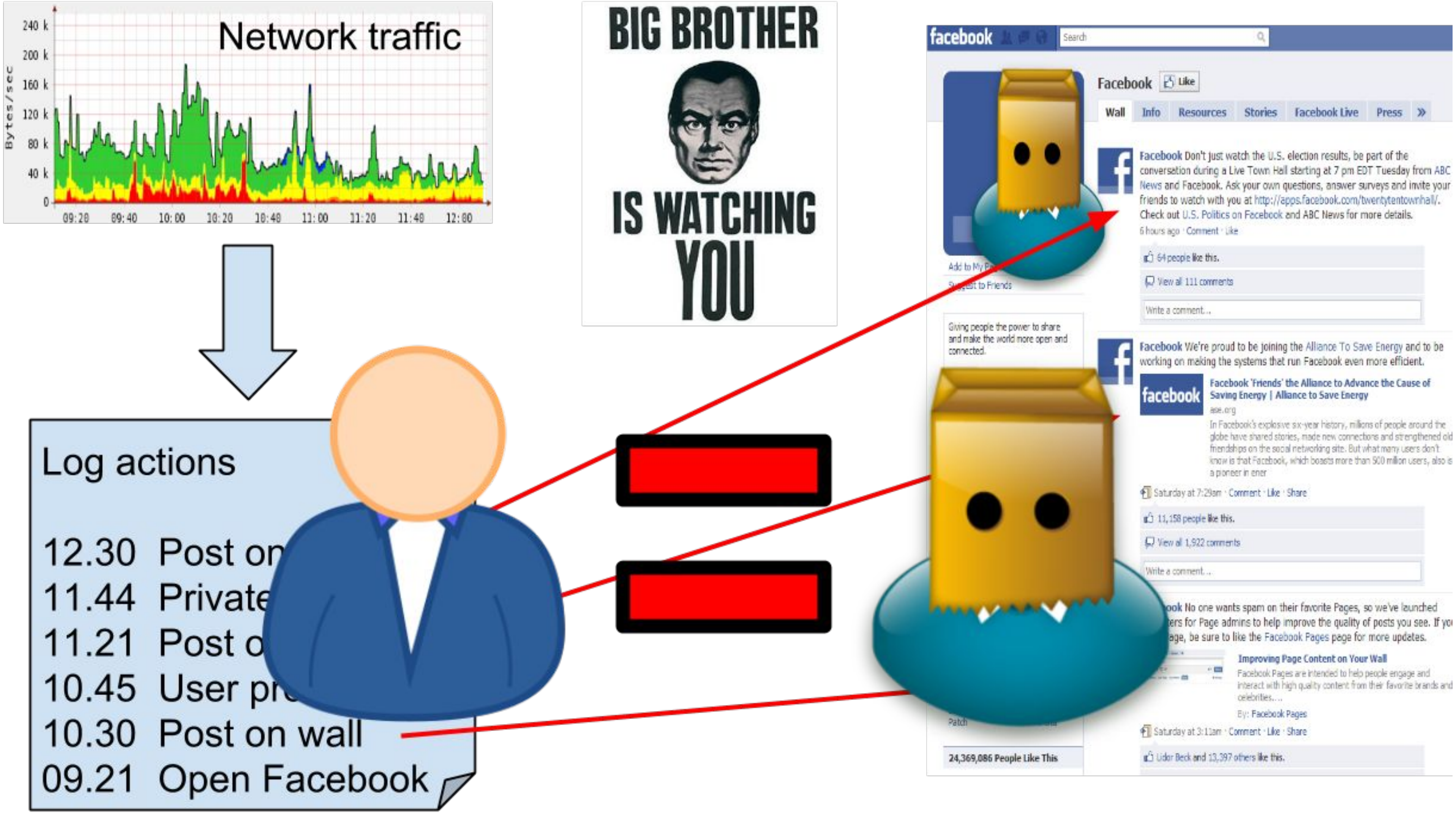


Log actions

12.30 Post on wall
11.44 Private message
11.21 Post on wall
10.45 User profile page
10.30 Post on wall
09.21 Open Facebook

Attack scenario

Attack scenario



Other attack scenarios

- **To identify communicating parties**
  - **from sending/receiving pattern**

- **Behavioural profiling**
  - **to improve fingerprintings**
  - **for marketing reasons**
  - **...**

The goal

Can an attacker recognize actions that a user performs on some android app by analyzing the **encrypted network traffic**?

Contribution

- We prove that it is possible, with an accuracy $> 95\%$
- Traffic analysis using **machine learning** techniques

Can't you hear me knocking (CODASPY '14, TIFS '15)

Key Concepts

Interactions

Input on a device

E.g., tap, swipe, key press

used to achieve

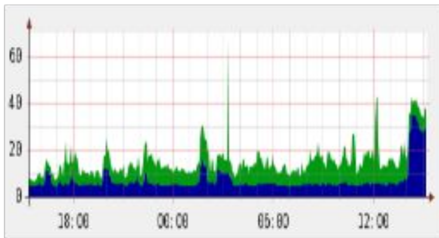
User actions

Operation on apps

E.g., send an email, open a page

produce

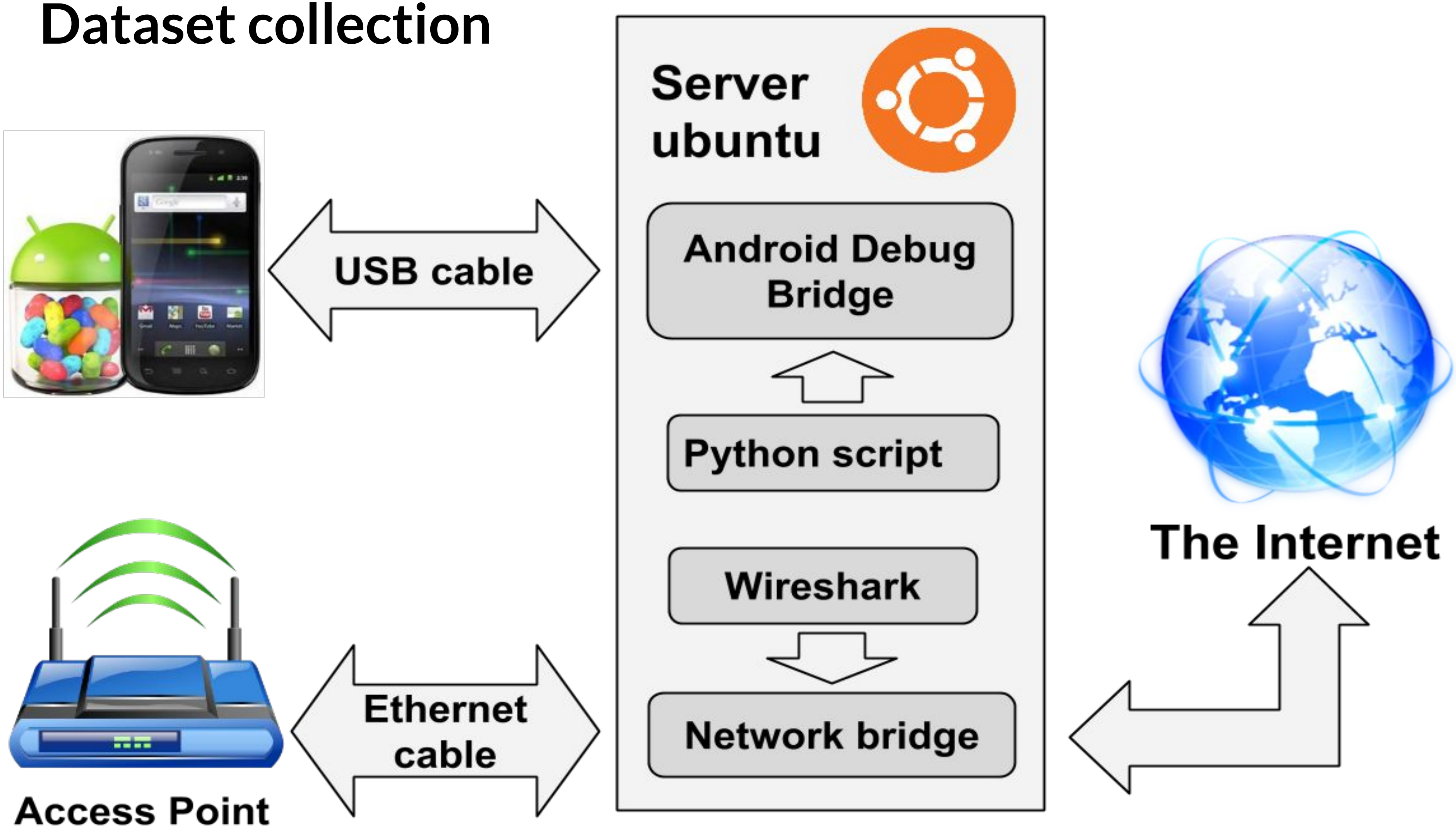
Network flows



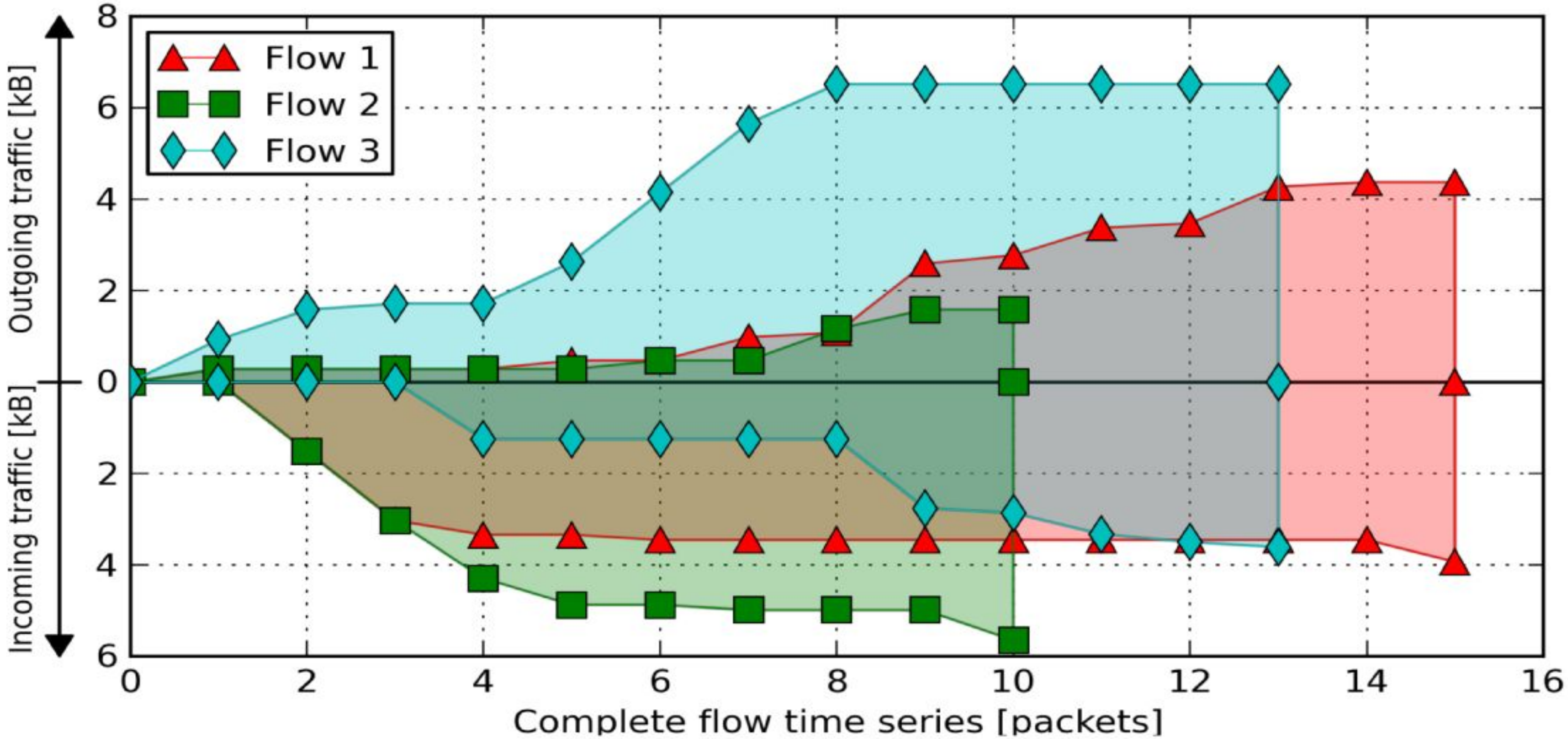
Sequence of packets

Couple of IP addresses and ports

Dataset collection



Network Traffic Flows Representation



Flow ID	Flow time series
Flow 1	[282, -1514, -1514, -315, 188, -113, 514, 96, 1514, 179, 603, 98, 801, 98, -477]
Flow 2	[282, -1514, -1514, -1266, -582, 188, -113, 692, 423, -661]
Flow 3	[926, 655, 136, -1245, 913, 1514, 1514, 863, -1514, -107, -465, -172, -111]

Can’t you hear me knocking (CODASPY ‘14, TIFS ‘15)

The framework

Labeled Dataset

Phase 1.
Training

Phase 2.
Testing

Network Traffic Pre-processor

User Action Classifier

Random Forest

Predictions

- Tweet sent
- email answered
- tweeter contact opened...

Training phase

1. Unsupervised learning →**Clusters** of similar flo
    - **Dynamic Time Warping** (DTW) [Müller 2007] as metric
    - The **number of clusters** is a parameter to tune

2. Training set building
    - User actions → Classes
    - Cluster labels → Features

IDs	user actions	cluster 0	cluster 1	...	cluster k	....	cluster N-1	cluster N
001	send mail	0	1	...	1	...	0	0
002	send mail	0	1	...	1	...	0	0
003	send reply	1	0	...	2	...	1	0
....	...	...	...	...	...	...	...	...

3. Supervised learning → Random Forest **classifier**

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Evaluation phase

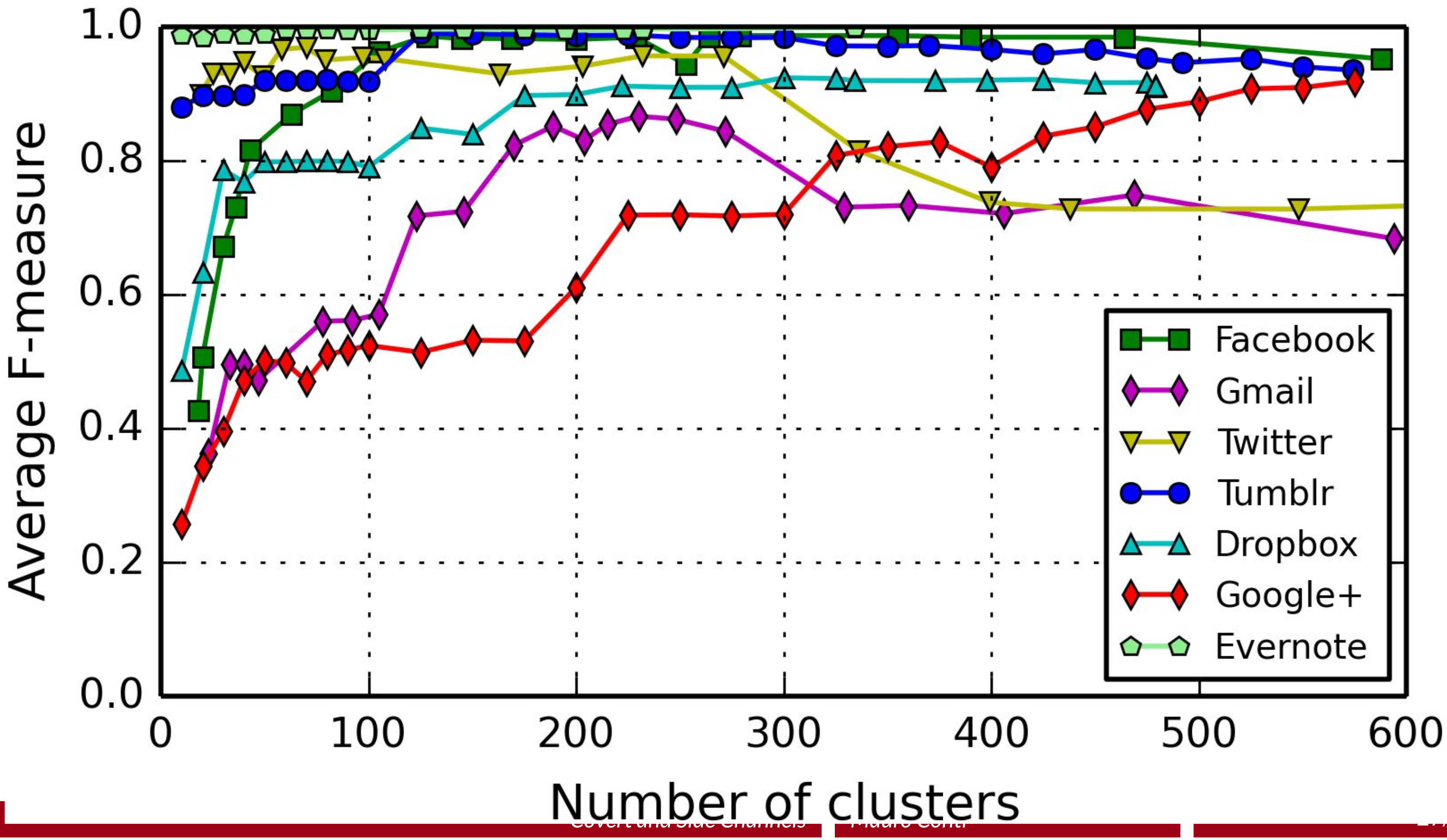
1. User actions produce **unseen flows**

2. Assign each **unseen flow** to a **cluster**
   - clusters used in **training** phase and **DTW** as metric

3. Test set building
   - (similarly to training set)
   - User actions → **unknown classes**
   - Cluster labels → Features

4. User action **recognition**

Accuracy vs. number of clusters



Can't you hear me knocking (CODASPY '14, TIFS '15)

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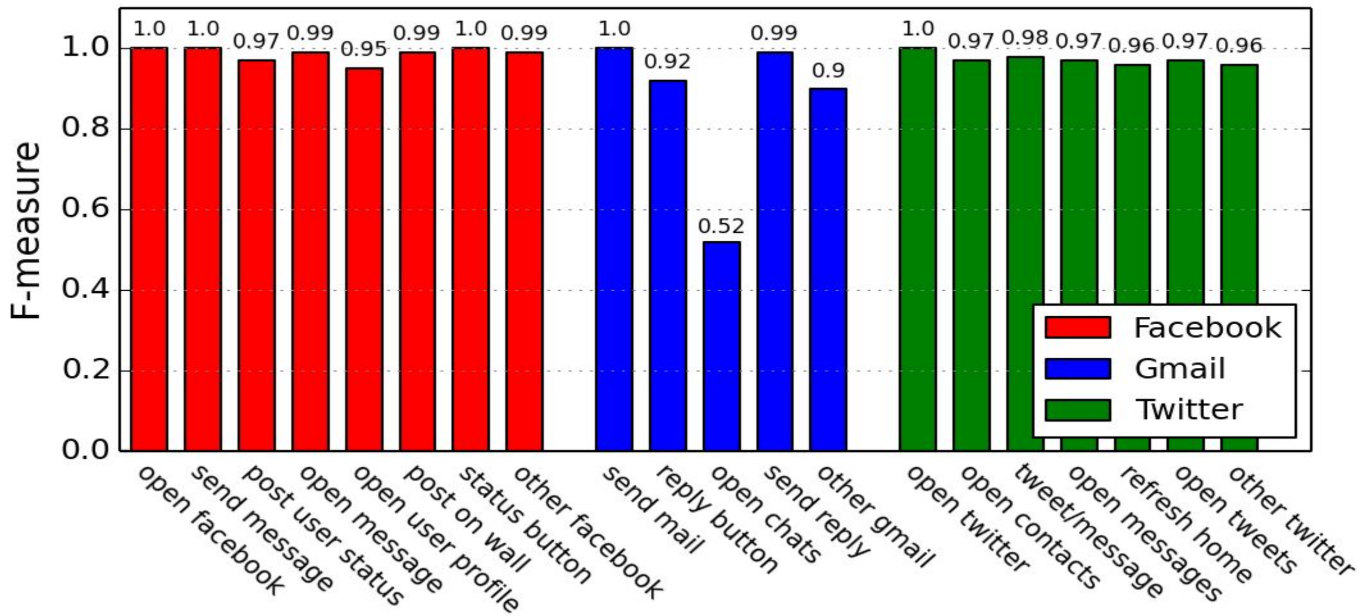
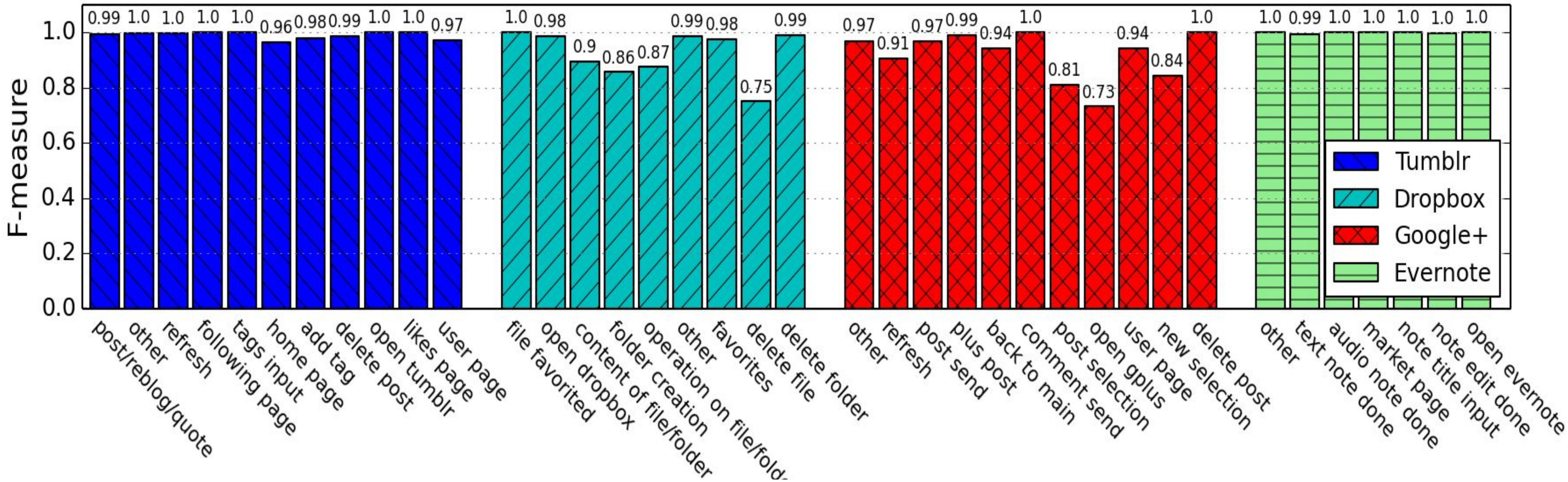
Accuracy per user action





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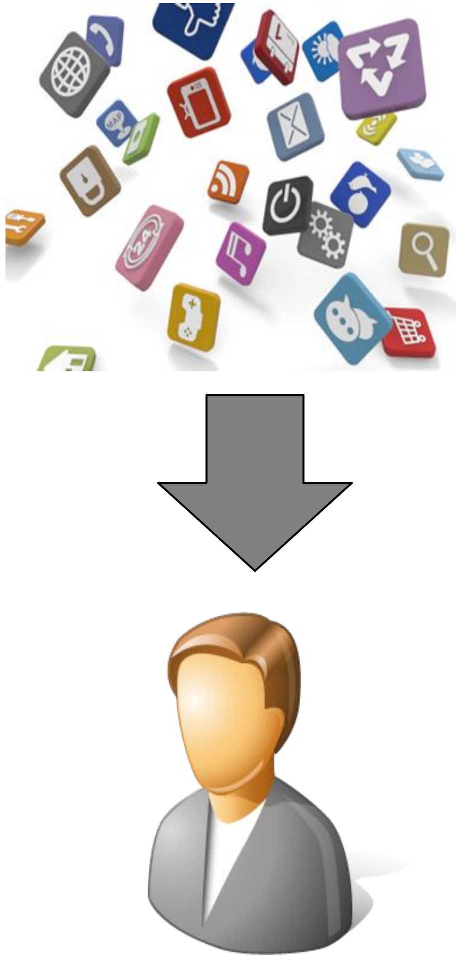
Conclusions

- Encryption does not hide communication patterns
  - We shown that user actions performed on *A*ndroid apps can be detected by analyzing the encrypted network traffic
- Attackers can leverage our framework to undermine user privacy:
  - Learn user habits
  - *G*ain commercial or intelligence advantage against some competitor
  - *A*ttribution of social network pseudonyms
- Countermeasures to this type of attacks are needed...

Motivation (1)

From the set of **apps installed** on a device can be inferred private information about her **owner:**

- Age
- Sex
- Religion
- Relationship status
- Spoken languages
- Countries of interest

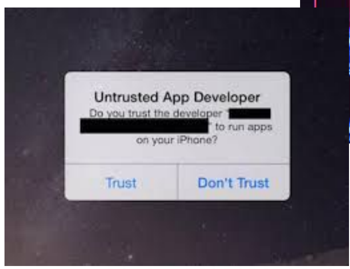


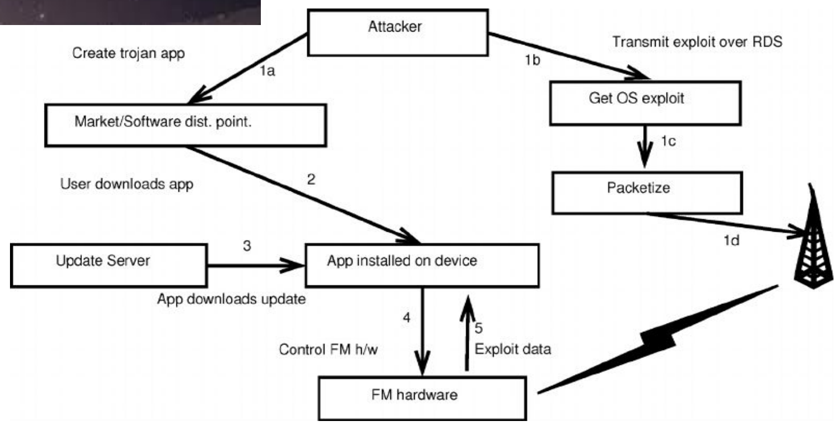
S. Seneviratne, A. Seneviratne, P. Mohapatra, A. Mahanti. "Predicting User Traits From a Snapshot of Apps Installed on a Smartphone" in ACM SIGMOBILE Mobile Computing and Communications Review 2014.

Motivation (2)

Knowing a presence of a specific app
- Hence specific vulnerabilities

Possible ad-hoc attacks
- E.g., zero day exploits





Motivation

- Given a target app X
- Identify the presence of X in a mobile device
- Using network traffic analysis

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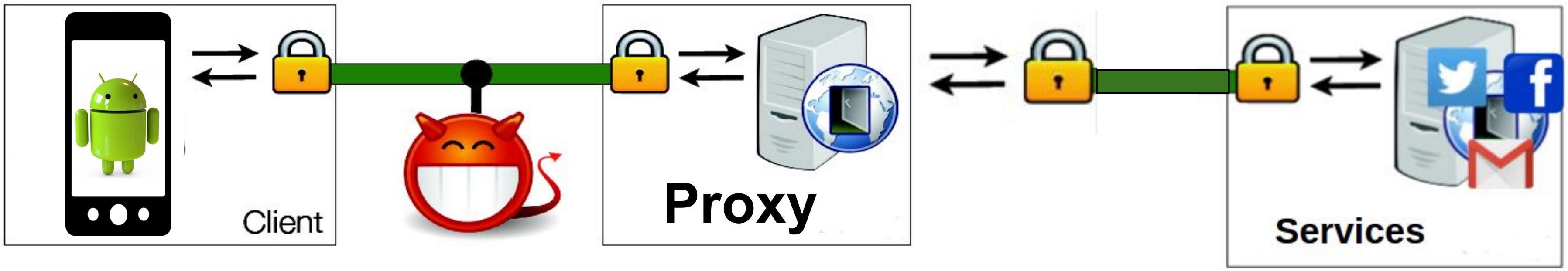
It isn't so easy!

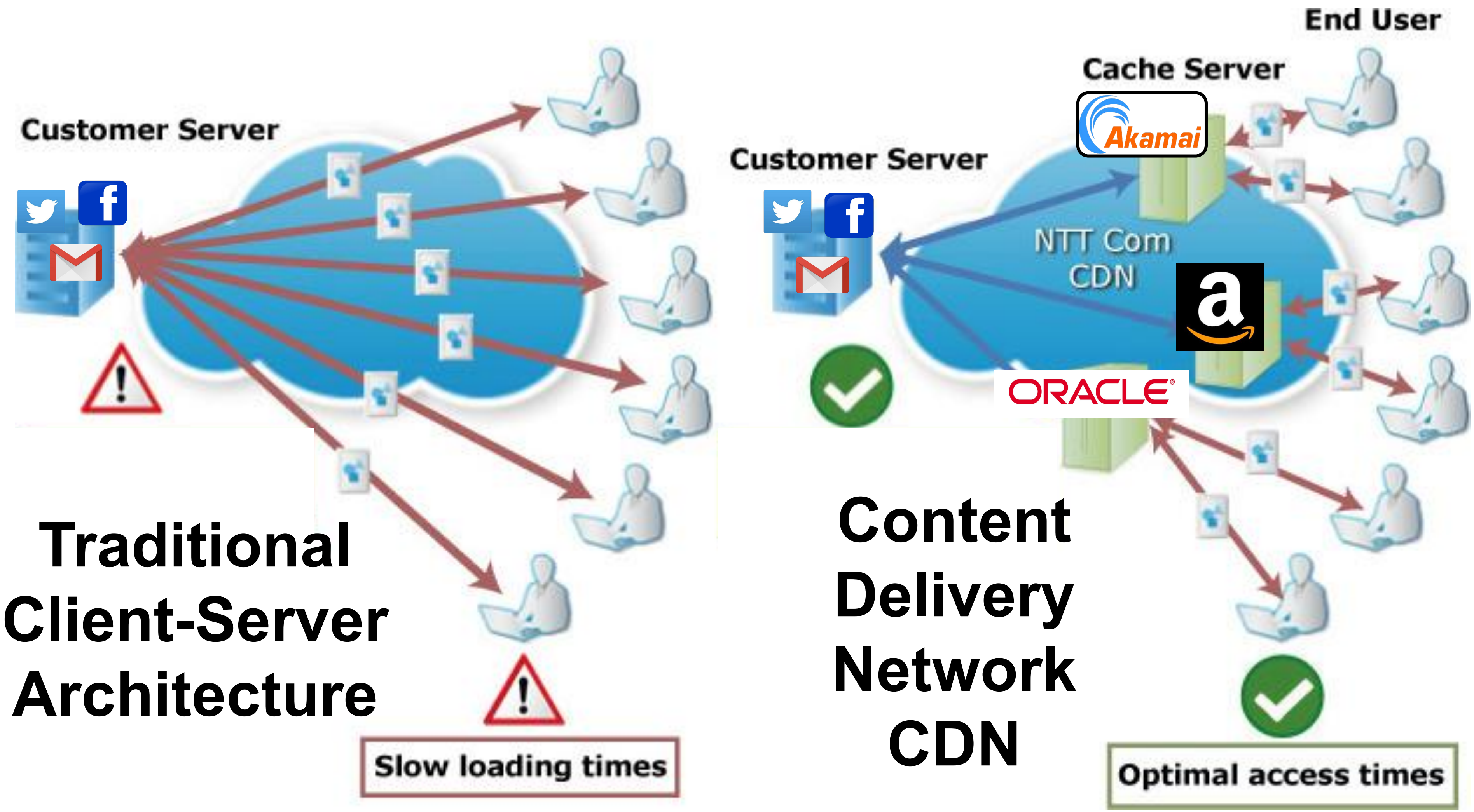
- Encryption → Payload inspection is not feasible
- Owner of Destination IP ≠ App
  - Content Delivery Network (CDN)
  - Proxy

Attacker's observations (similarly to the previous work)

- Packet length
- Packet directions
- Packet timings

Enable Traffic Analysis Attacks





Customer Server
Traditional Client-Server Architecture
Slow loading times
End User
Cache Server
Akamai
Customer Server
NTT Com CDN
ORACLE
Content Delivery Network CDN
Optimal access times

Three different approaches proposed:

AppScanner
(IEEE EuroS&P '16)

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1. **Per flow** length classification
   - A classifier for each length
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   - It works on a **set of apps**
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   - It works on a **set of apps**
   - **High Accuracy** and out-of-order packets resiliency, but slow
3. **Per App** classification
   - Uses statistics on network flows
   - It focuses on a **specific app**
   - Binary classification (app is present of not)

Building the dataset

TCP Packets captured

SOURCE_IP	DEST_IP	PROTO	LEN
192.168.137.2	23.23.162.140	TCP	74
23.23.162.140	192.168.137.2	TCP	74
192.168.137.2	23.23.162.140	TCP	66
192.168.137.2	23.23.162.140	TLSv1	287
23.23.162.140	192.168.137.2	TCP	66
23.23.162.140	192.168.137.2	TLSv1	1078
23.23.162.140	192.168.137.2	TCP	1078
23.23.162.140	192.168.137.2	TCP	1078
23.23.162.140	192.168.137.2	TCP	1078
23.23.162.140	192.168.137.2	TCP	114
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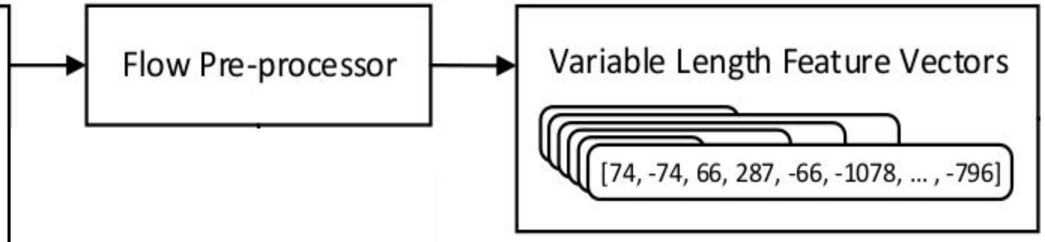

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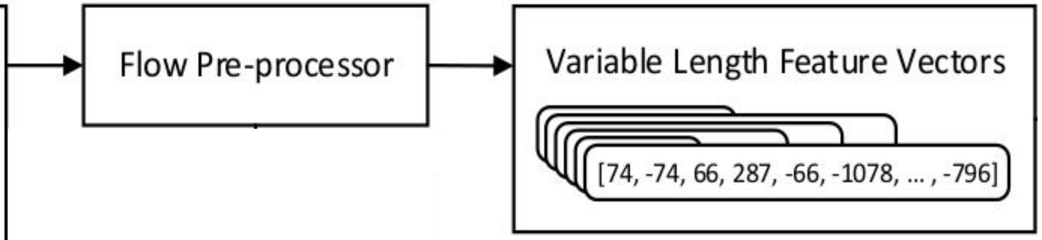
Per Flow approach (1)



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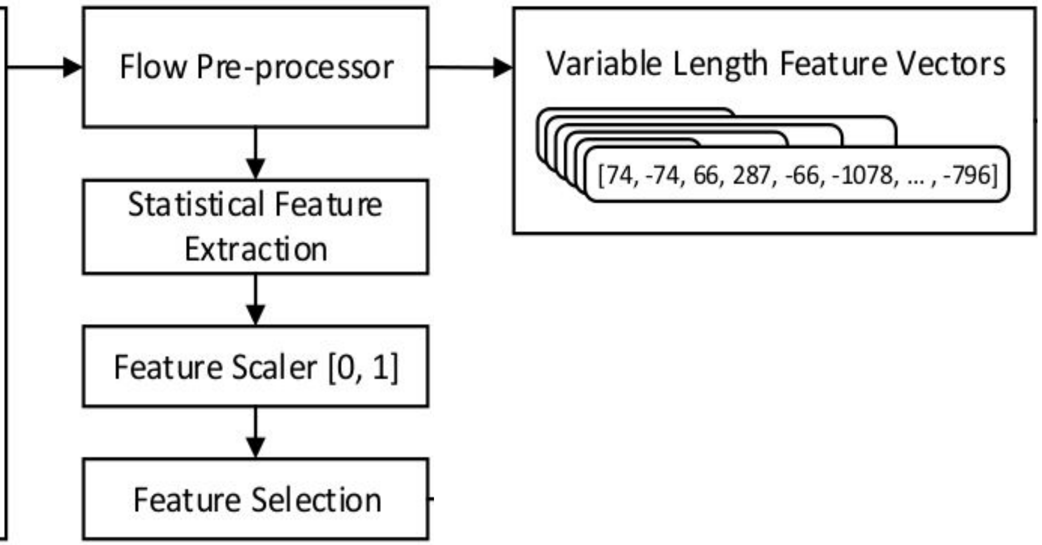

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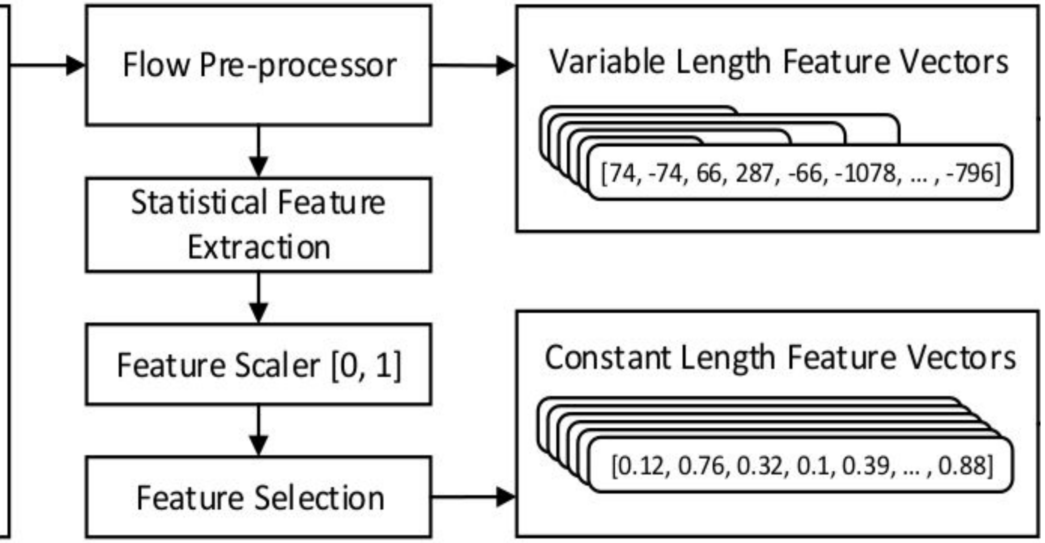

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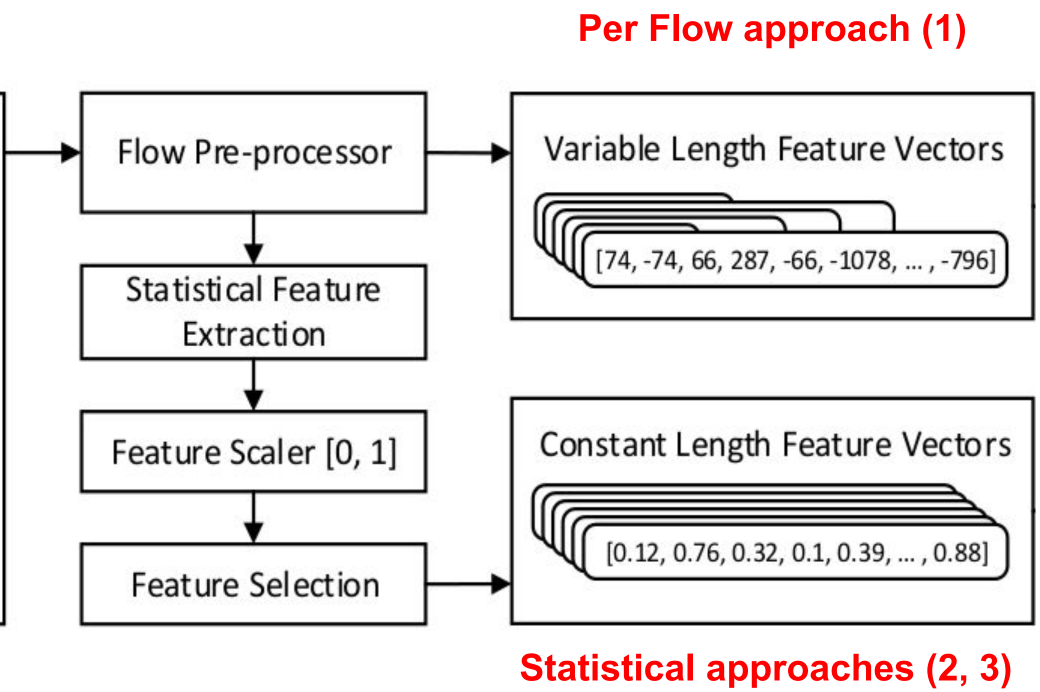

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Improving the accuracy of AppScanner

- Classification performed on **each** network traffic flow
- We aim to identify an app →many flows available
- Flow →Classifier prediction → (App, Probability of prediction)
- Applying a **probability threshold** (PT)
  - Filter out flows with **uncertain predictions**
  - Increase classification accuracy tuning PT

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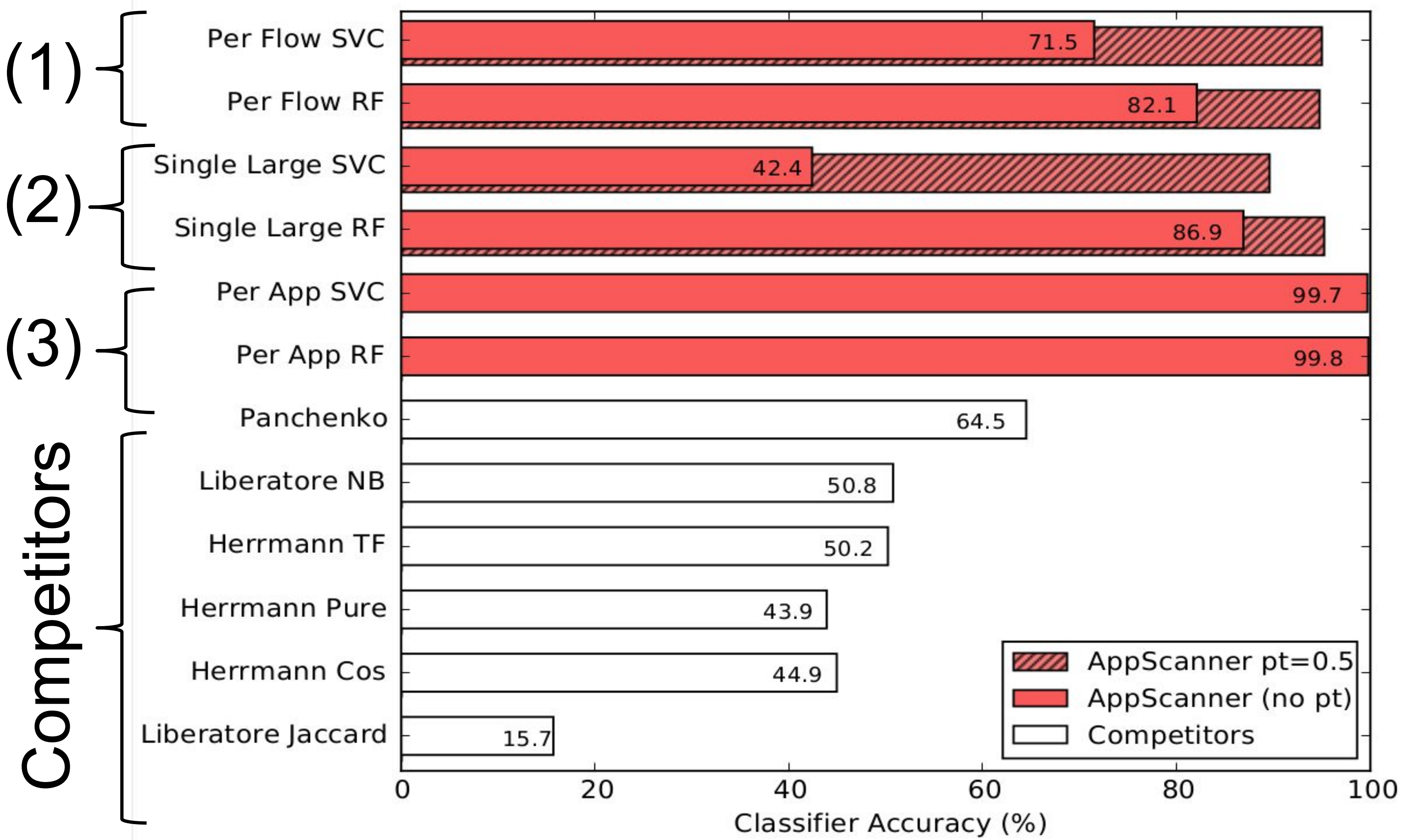
Performance and Comparison



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M. Conti, M. Nati, E. Rotundo, R. Spolaor.

<u>Mind The Plug! Laptop-User Recognition Through Power Consumption.</u>

In ACM AsiaCCS 2016 workshop IoTPTS 2016

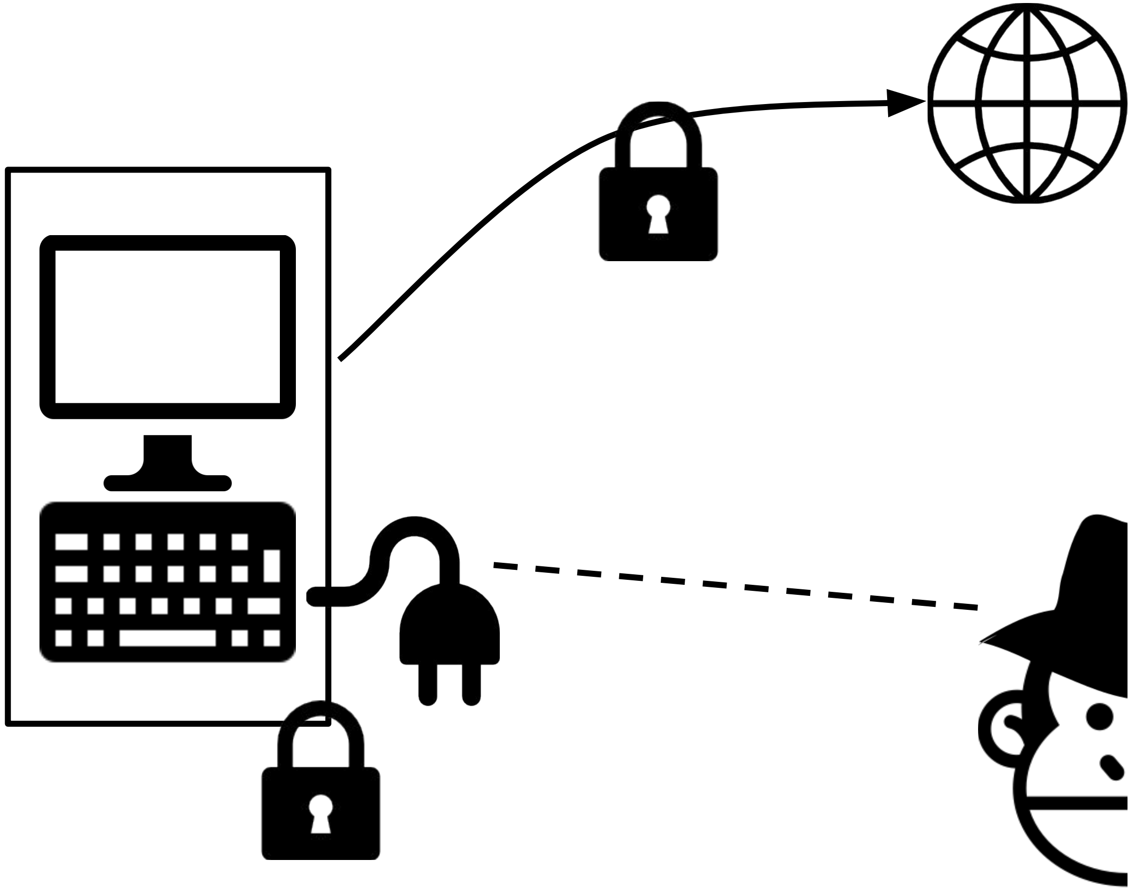
Power Consumption Side Channel

Power consumption

Can reveal what we are doing!

Device drains different power depending on our actions

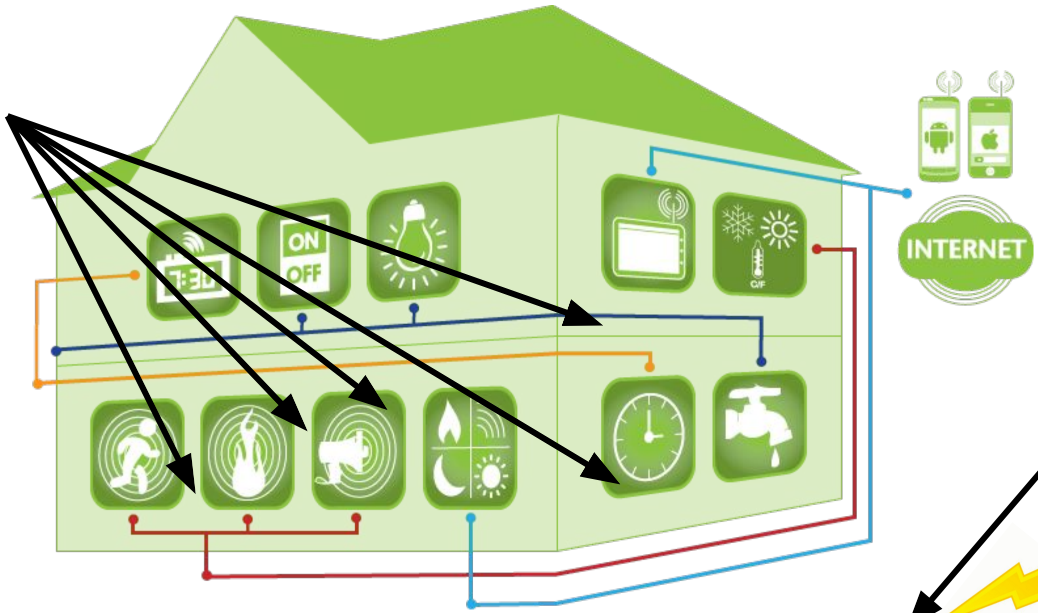
Works on **laptops** and **mobile**



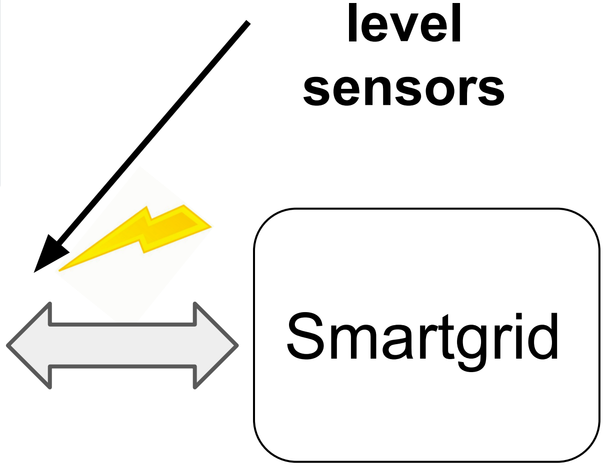
Smartbuilding

Internet of Things applied not only to industry, but also to buildings, such as houses and **offices**

Wall-socket level sensors



household level sensors



Wall-socket smartmeters

- Smartmeters are able to measure the electric quantities of the plugged appliances
  - **Reactive Power**
  - **RMS Current**
  - **Voltage**
  - **Phase**

- IoT testbed in University of Surrey (UK)

- Limitation:
  - only **<u>1Hz</u>** of sampling rate

Definition of "Laptop-User"

A **Laptop-user** is made of the **combination** of:

- Laptop
- Software installed and running
- User behavior

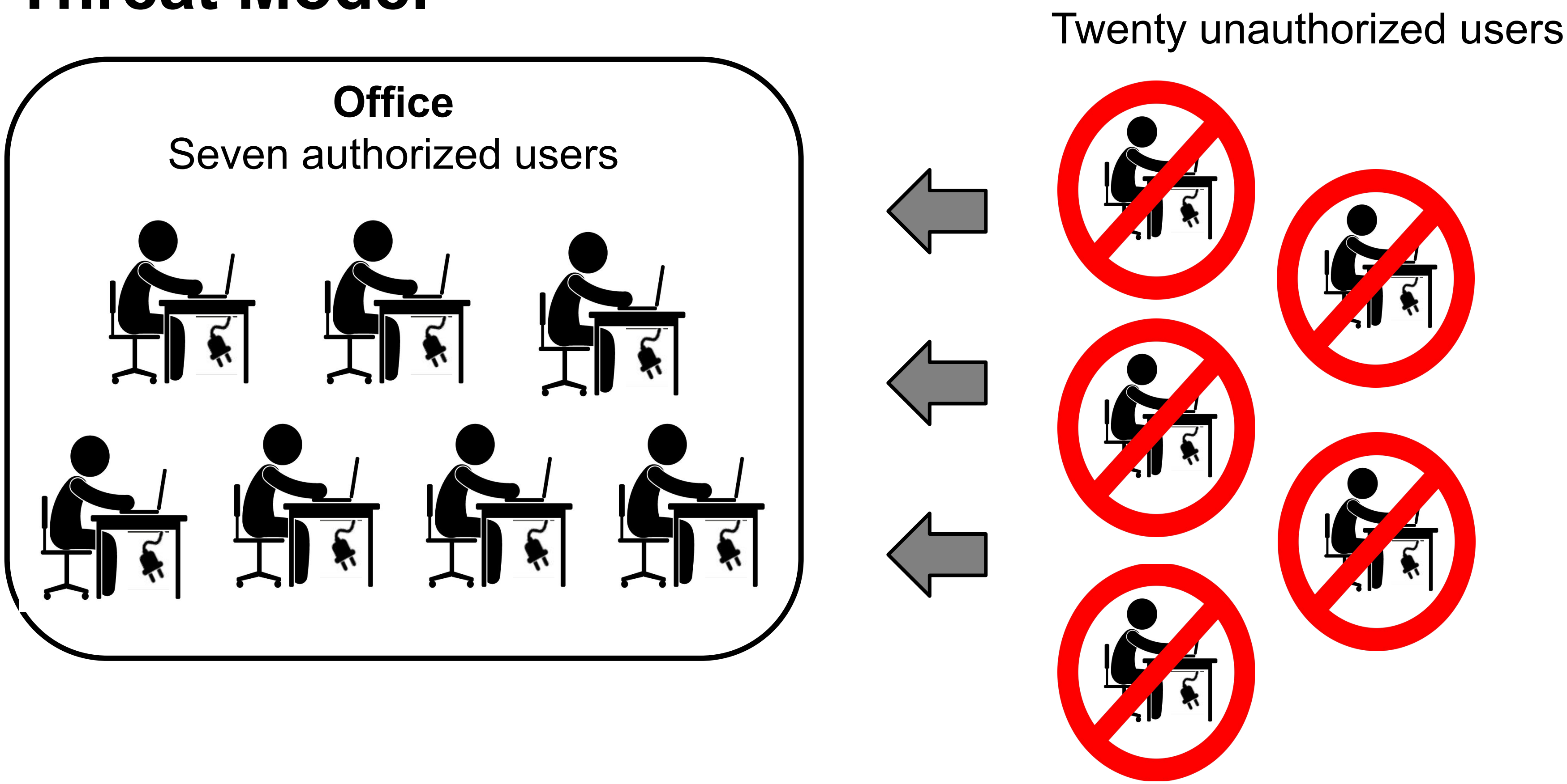
Goal & Motivation

Is it possible to recognize a **Laptop-user** from its energy consumption?

This can bring:

- **Benefit on smartbuilding automation**,
    - context-aware environments can automatically adjust and trigger predefined actions or services
        - e.g., according to the presence of a specific user
    - Detect un-authorized users
- **Threat to user privacy**,
    - it is possible to locate and trace a user

Threat Model



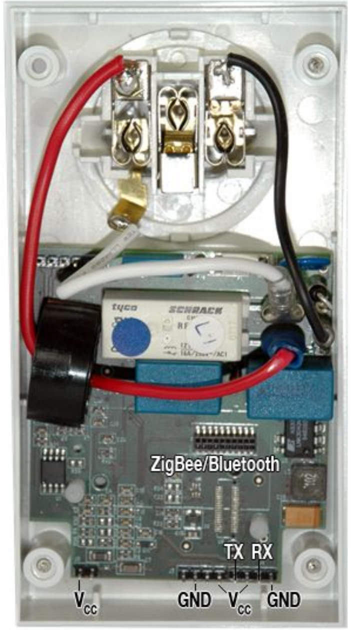
We aim to:

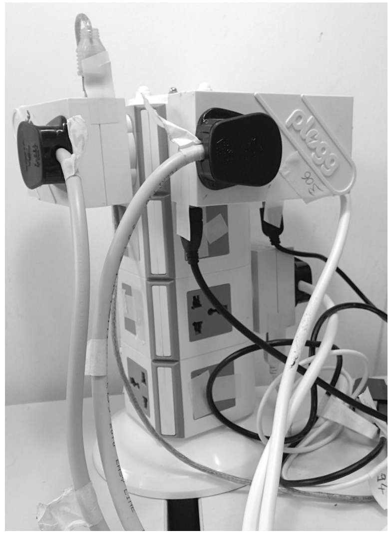
- Recognize whether the user is in the "authorized" set
- Identify the specific user in the "authorized" set

Laptop-users Recognition

Multiclass classification (8 classes)

- The **seven authorized** laptop-users
- The **intruders** (as a single class)





Classification in three steps:

1. 10-fold cross validation for **parameters selection**
2. Performance **evaluation** on a disjoint test set
3. Classification **validation**

Mind the Plug! (IoTPTS @AsiaCCS '16)

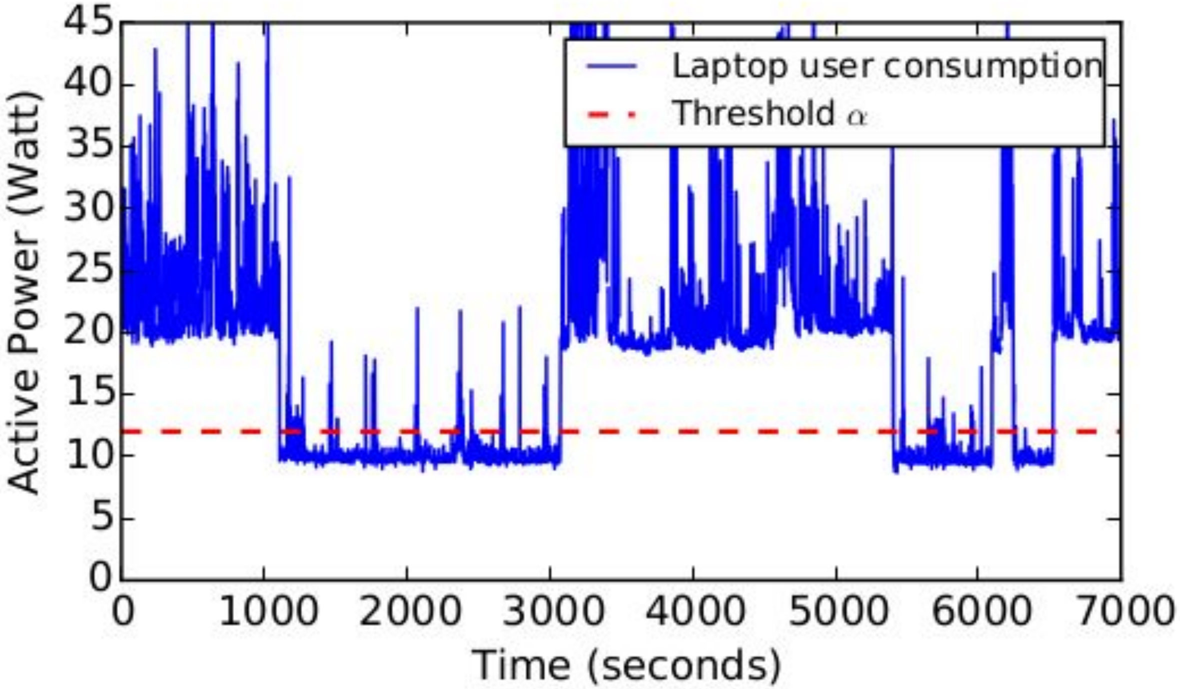
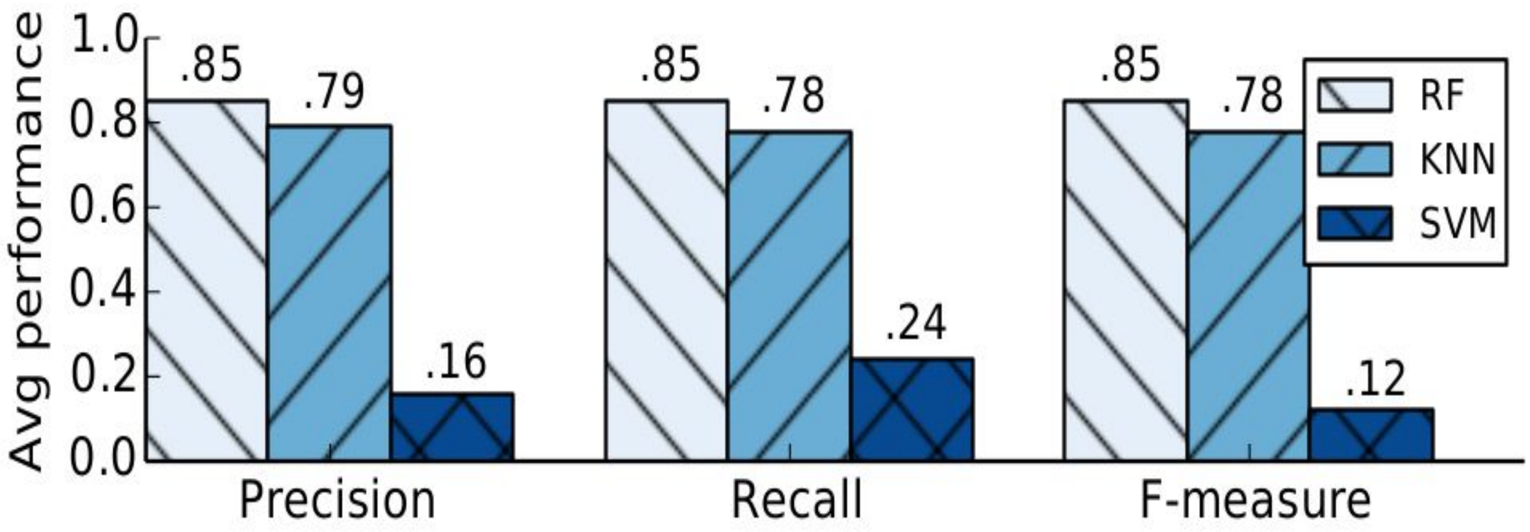


Figure 2: Example of *Active Power* trace (continuous blue line) and the lower-cutting threshold $\alpha = 12$ Watt (dashed red line). Samples under α are low-energy timespans in which the user does not use the laptop.



85% of F-measure with Random Forest classifier

Classification validation

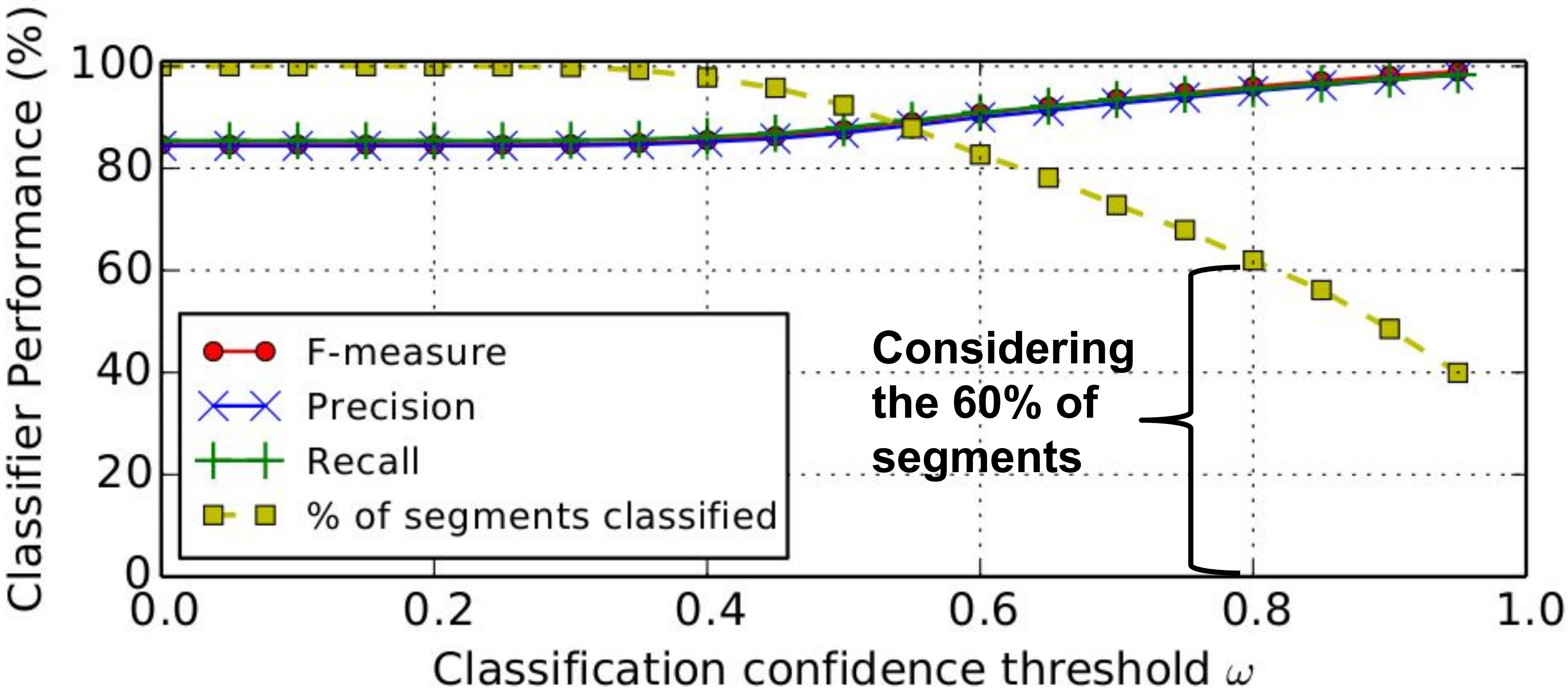
Classifiers label all segments in the testset
- Bad for False Positive rate (FPR)

We can leverage also the prediction probability
- Since classifiers output also their **confidence**

Tuning prediction probability threshold
- It can reduce False Positives

Other implications:
- MTPlug can be more conservative
- May take more segments to identify some laptop-user

Classification validation results



Limitations and Future work

Structural limitation: The plogg wall-socket sensors have a low sampling rate
Solution: Adopt a new generation wall-socket sensors

Data limitation: we collected data of seven users (office)
Solution: Collect more data in order to assess the feasibility of authentication system based on energy consumption

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  - *As a side channel: text typed on keyboards*
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  - *As a side channel: text typed on keyboards*

R Spolaor, L Abudahi, V Moonsamy, M Conti, R Poovendran.

No Free Charge Theorem: a Covert Channel via USB Charging Cable on Mobile Devices.

In ACNS 2017

Presented at Black Hat Europe 2018

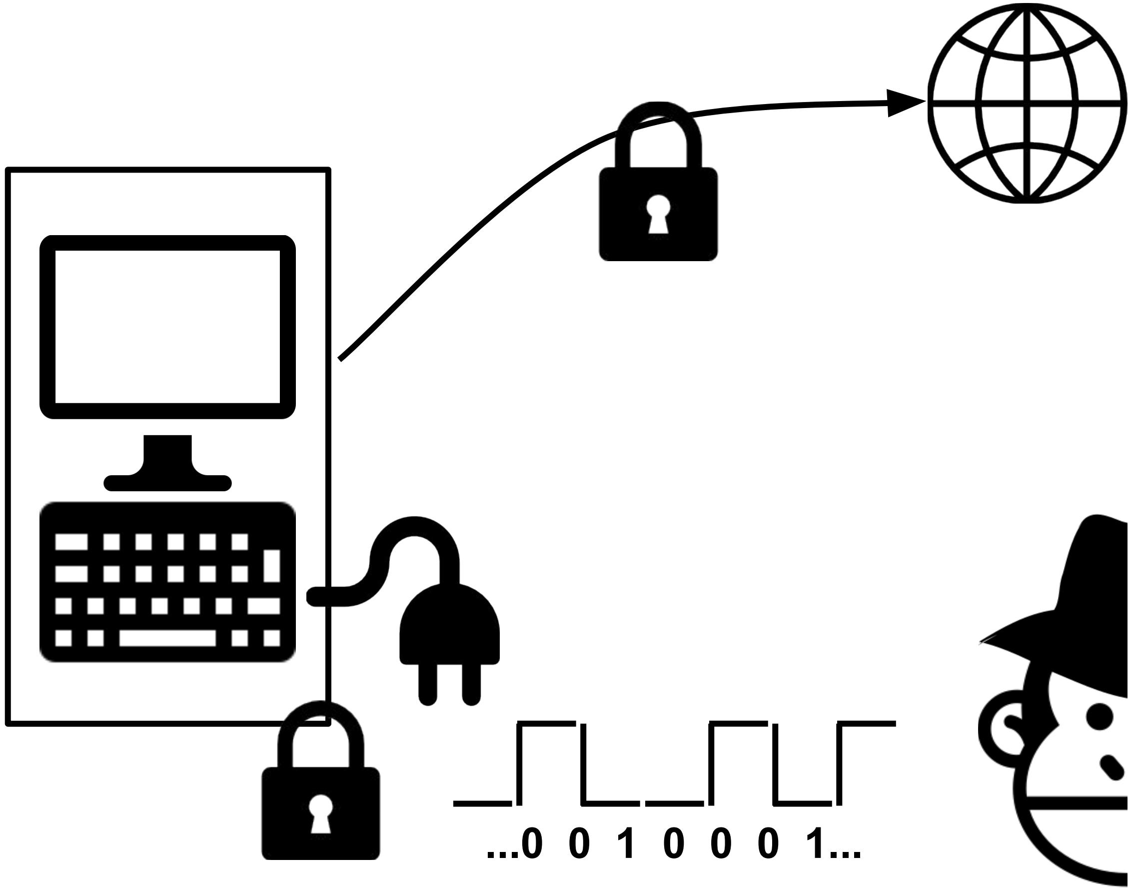
Power Consumption Covert Channel

Power consumption

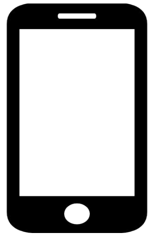
Can be used as a covert channel

Malware makes device drain more/less power to communicate with a **malicious power outlet**

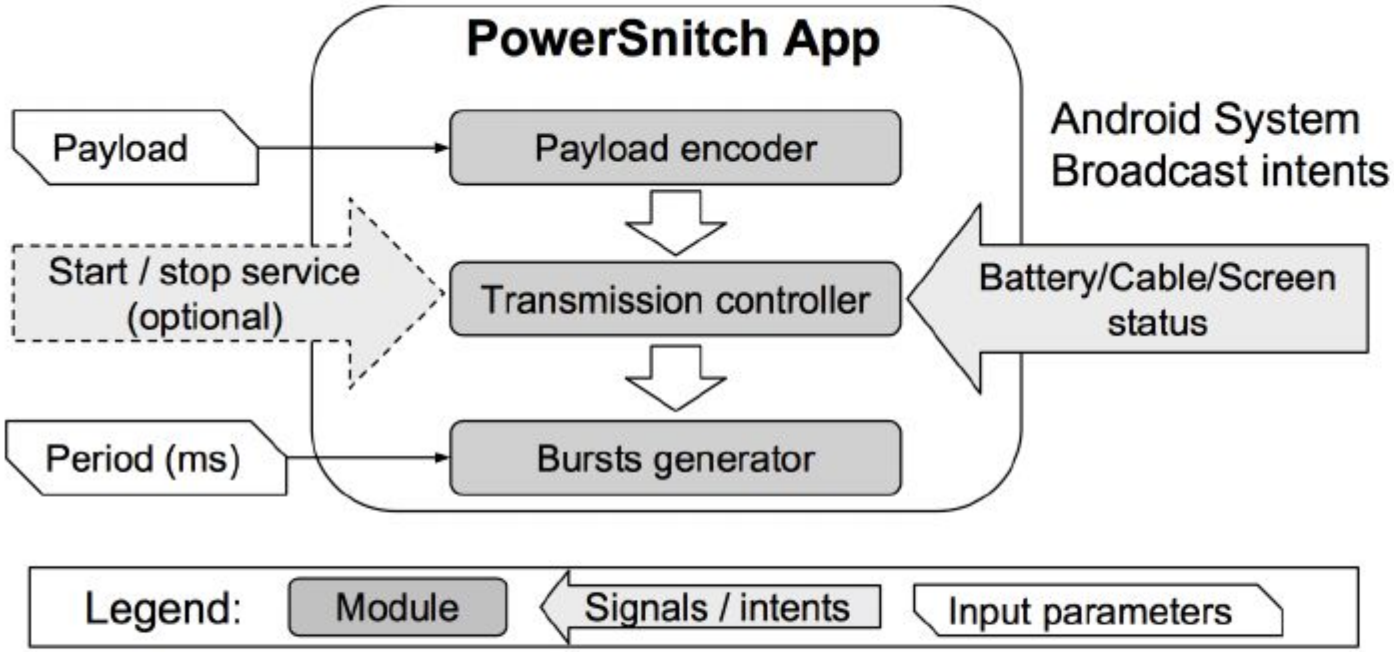
Thus **exfiltrating secrets**



No Free Charge Theorem: a Covert Channel via USB Charging Cable on Mobile Devices



PowerSnitch Application



No Free Charge Theorem: a Covert Channel via USB Charging Cable on Mobile Devices

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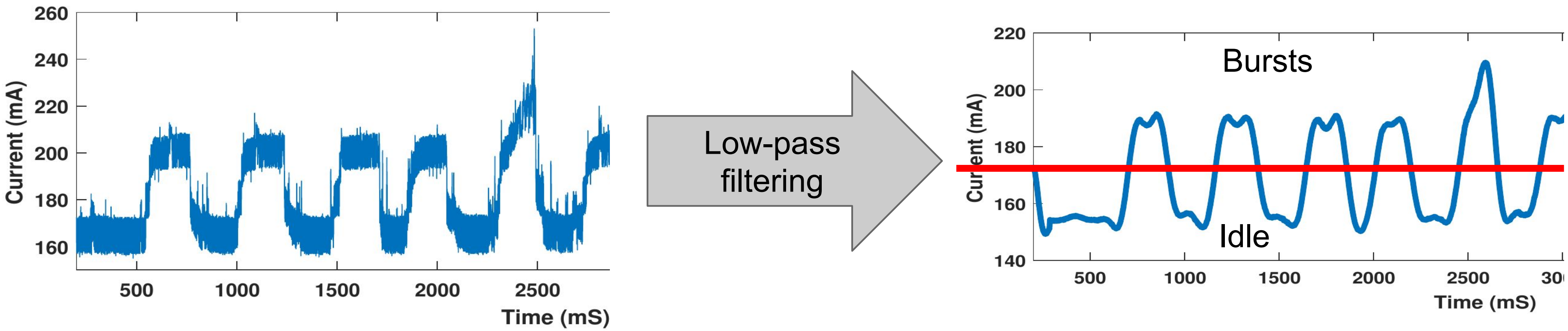
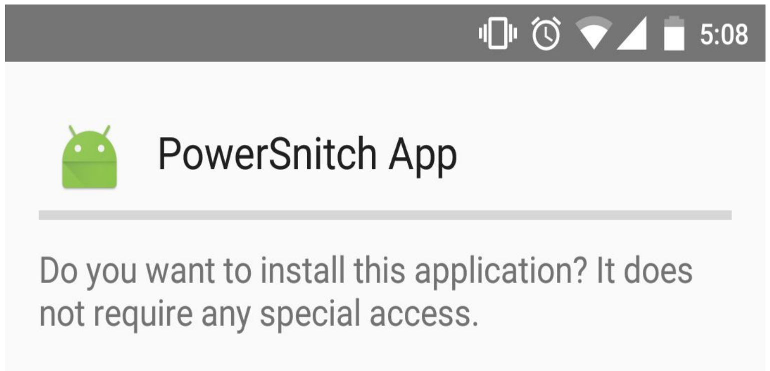


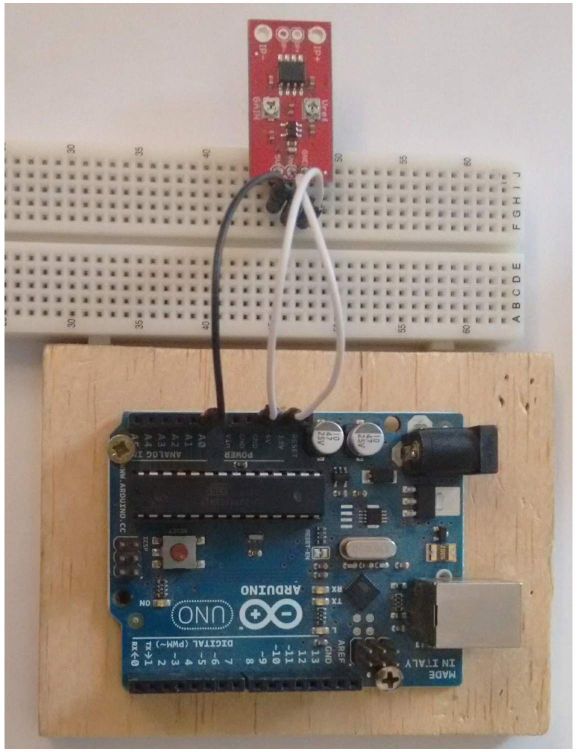


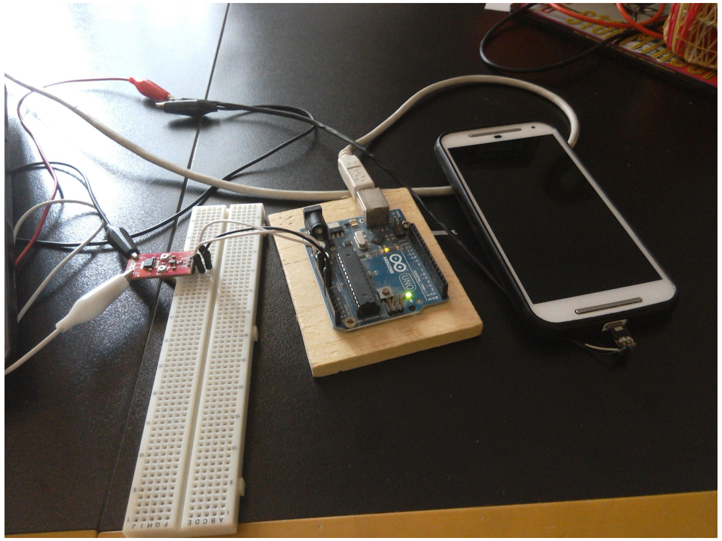
PowerSnitch app does not require any permission !!!

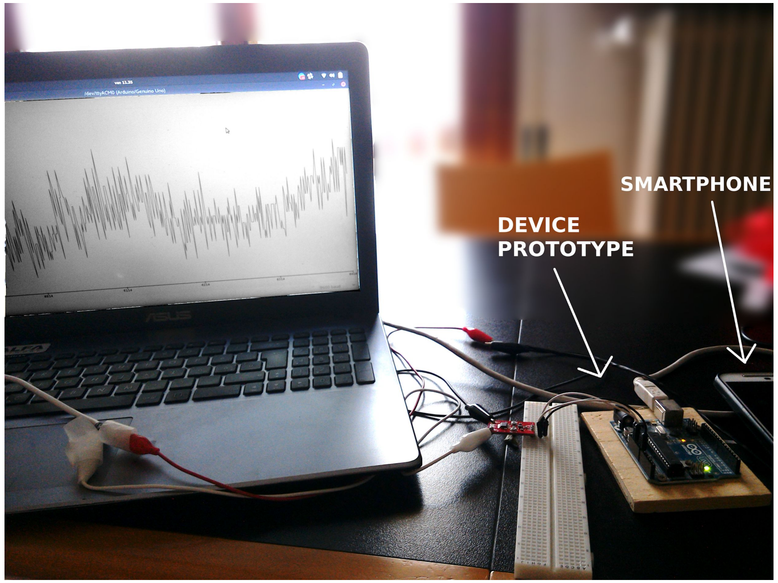
Results in terms of Bit Error Ratio (BER)

Device	Period (milliseconds)					
	1000	900	800	700	600	500
Nexus 4	13.5	0.78	0.0	0.0	13.33	16.21
Nexus 5	21.0	0.0	0.95	36.82	40.35	13.4
Nexus 6	1.07	0.0	0.21	0.0	4.05	7.42
Samsung S5	12.5	13.5	13.31	16.33	17.9	21.42

Power Bank Prototype







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Keystroke Dynamics 101

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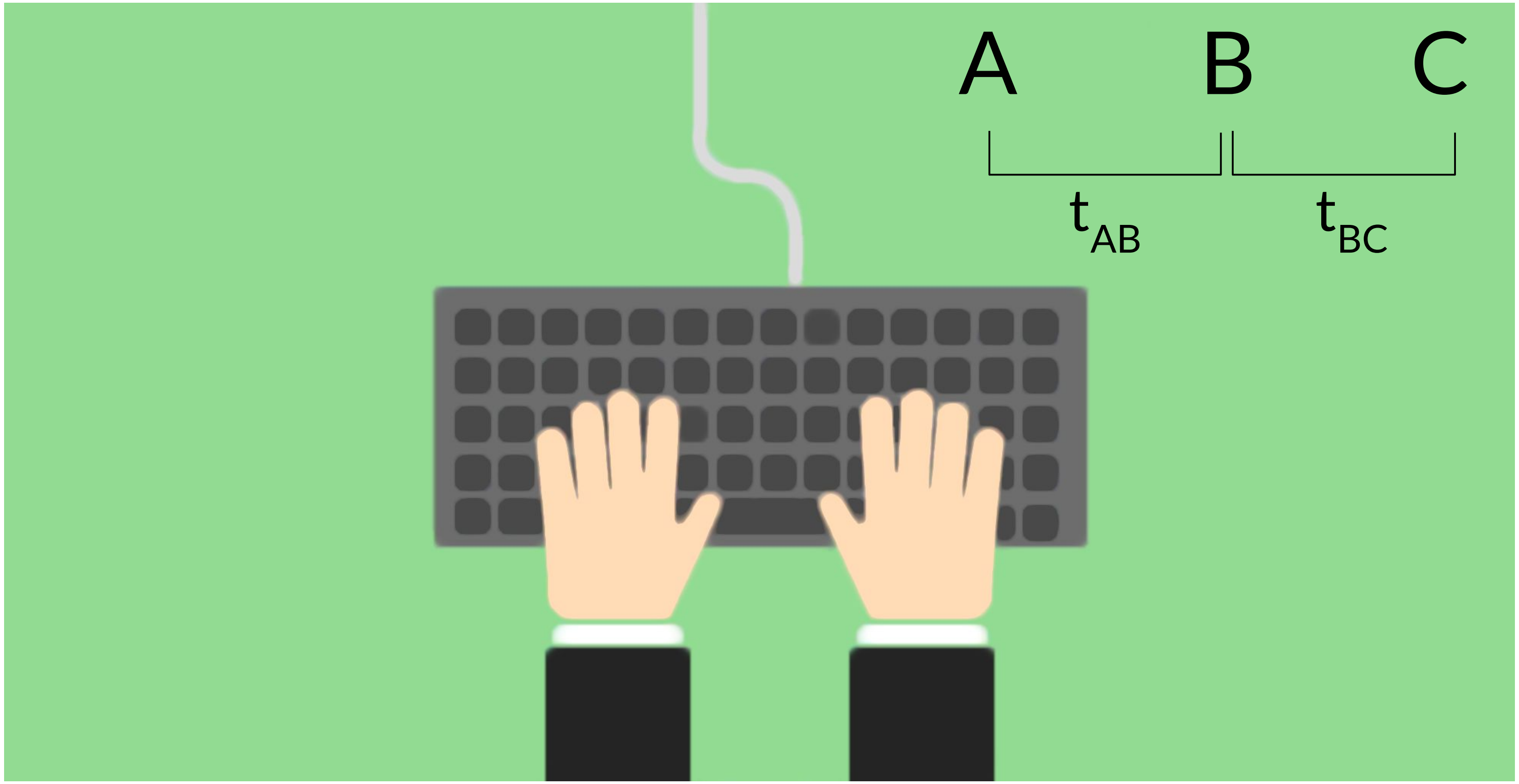
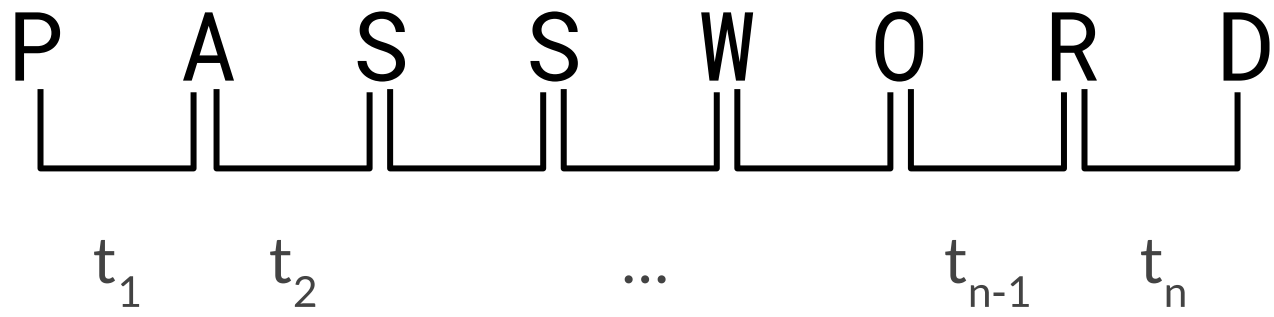


Keystroke Dynamics 101

A B C

Digram t_{AB} t_{AC} Trigram

Keystroke Dynamics 101



- Inter-keystroke times as a personal *signature*
- Used as biometric in authentication systems

Kamil Majdanik, Cristiano Giuffrida, Mauro Conti, Herbert Bos.

I Sensed It Was You: Authenticating Mobile Users with Sensor-enhanced Keystroke Dynamics.

In DIMVA 2014

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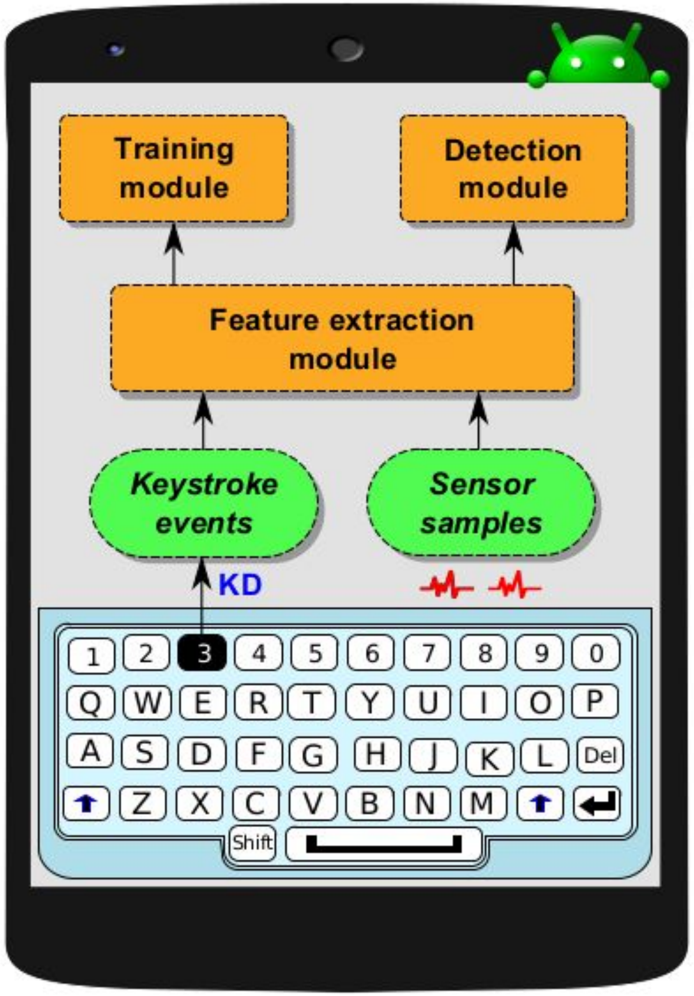
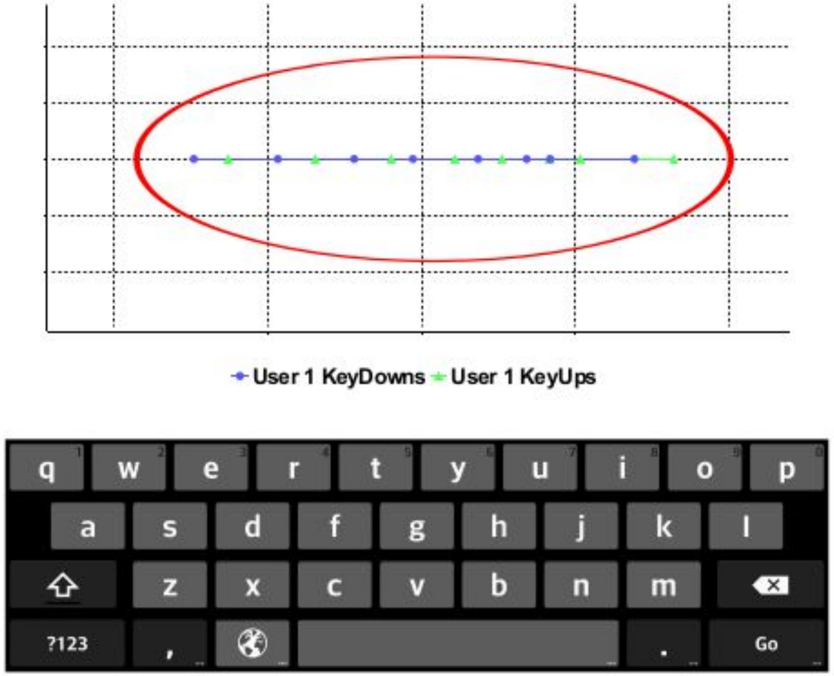
Our system: Unagi

User authentication with Sensor enhanced Keystroke Dynamics

Scenario: User typing 'HELLO'

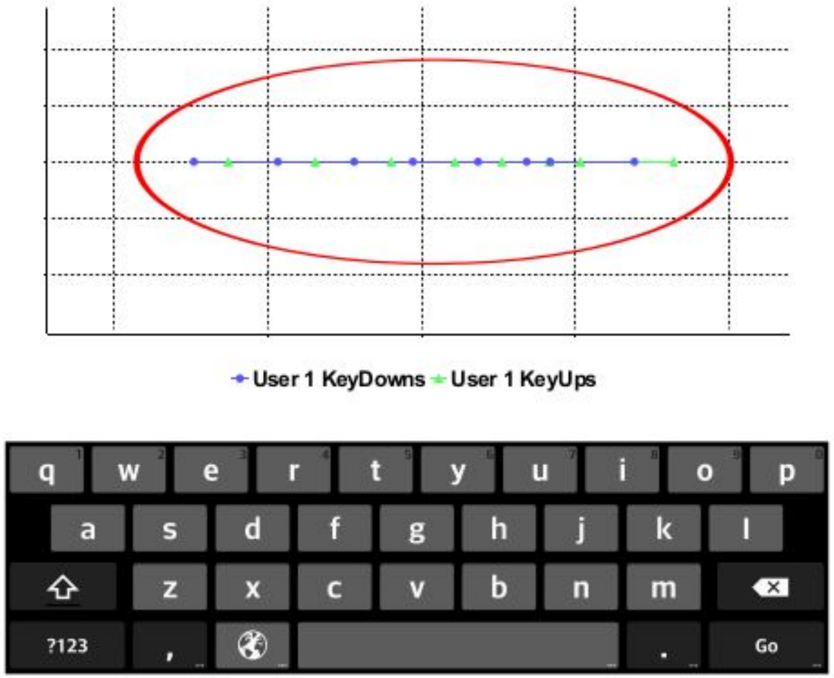


I Sensed It Was You

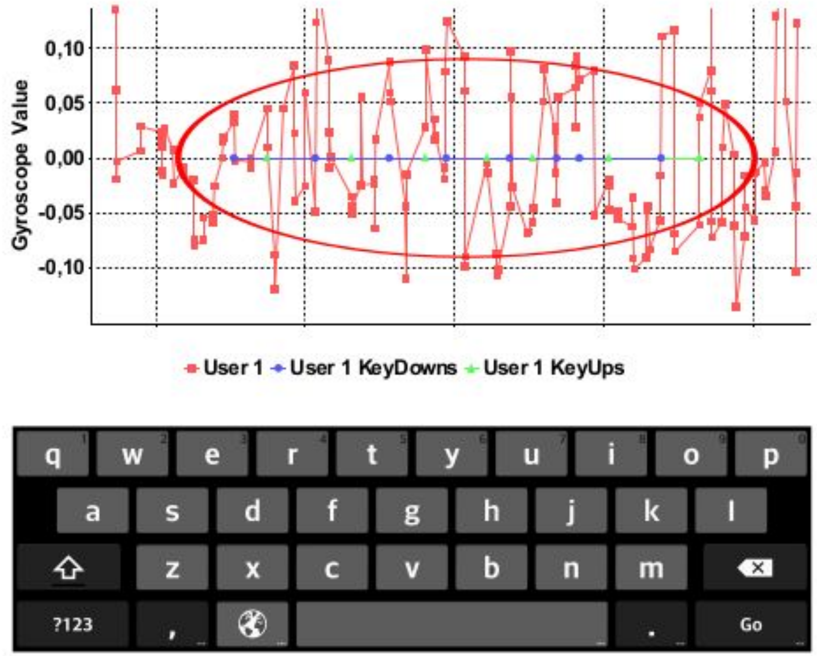


Keystroke dynamics

I Sensed It Was You

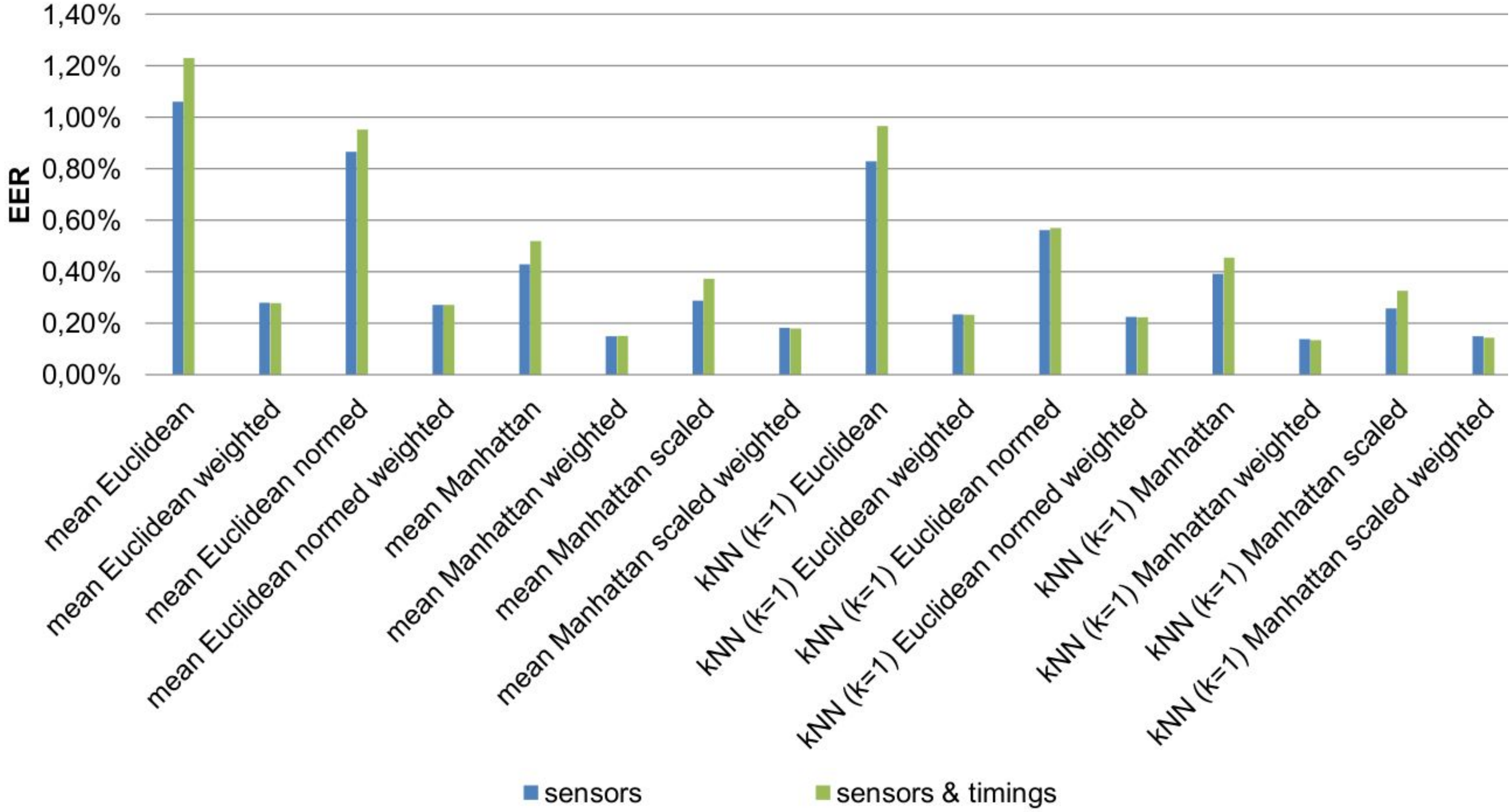


Keystroke dynamics



Sensor-enhanced keystroke dynamics

Accuracy (EER) for different considered algorithms



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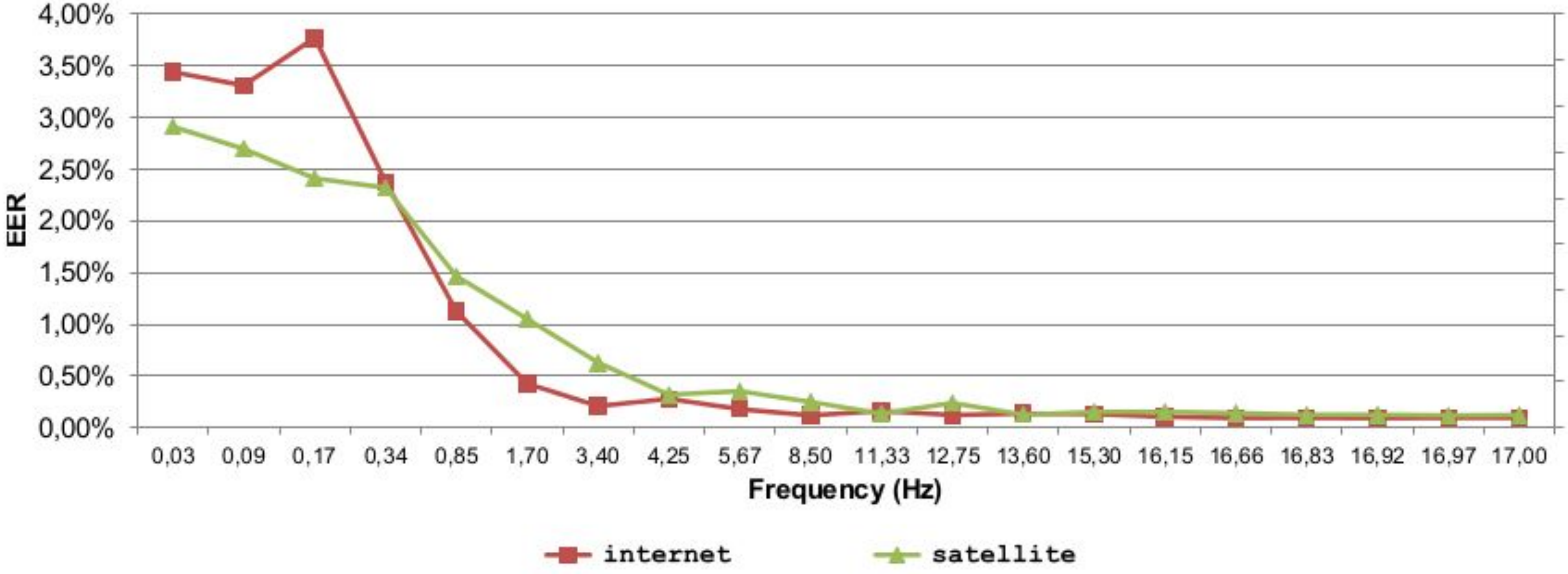
Accuracy vs. Sensors Sampling Frequency



EER - Equal Error Rate (rate at which both acceptance and rejection errors are equal)

Key Results

- Movement sensors are suitable for biometric authentication
- Sensors can dramatically enhance keystroke dynamics accuracy
- Effective even with short passwords and low sampling frequencies

Future work

- Applicability to free-text authentication
- Robustness against statistical attacks

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V. D. Stanciu, R. Spolaor, M. Conti, C. Giuffrida

On the Effectiveness of Sensor-enhanced Keystroke Dynamics Against Statistical Attacks

in ACM CODASPY 2016

Previous work - Drawbacks

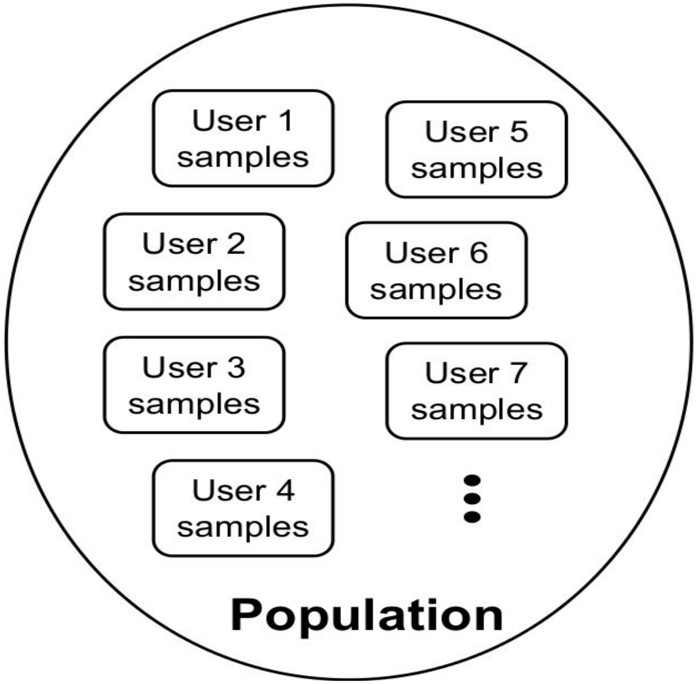
The previous **behavioral biometric authentication** system relies on:

- Secret of the password
- **Keystroke dynamics** (touch gestures)
- **Accelerometer** and **Gyroscope** sensors data

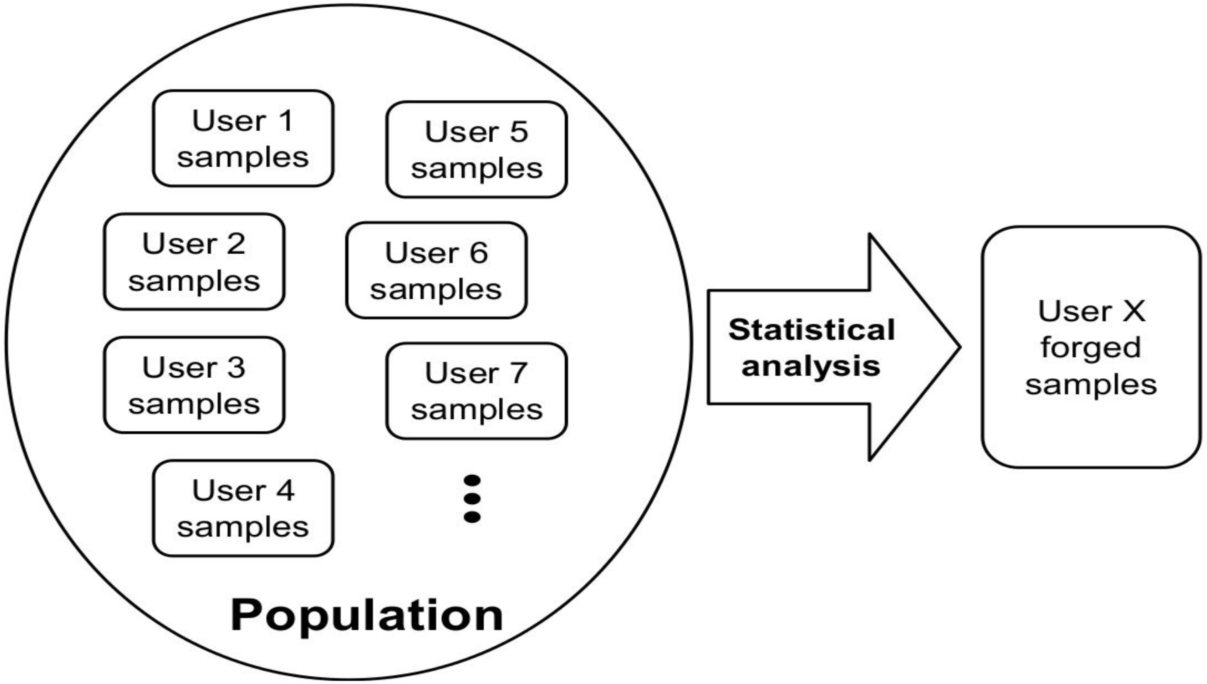
Previous work: we used kNN (with k=1) and mean values combined with several metrics (e.g., euclidean, Manhattan)

Question: is our system resilient to **Statistical attacks**?

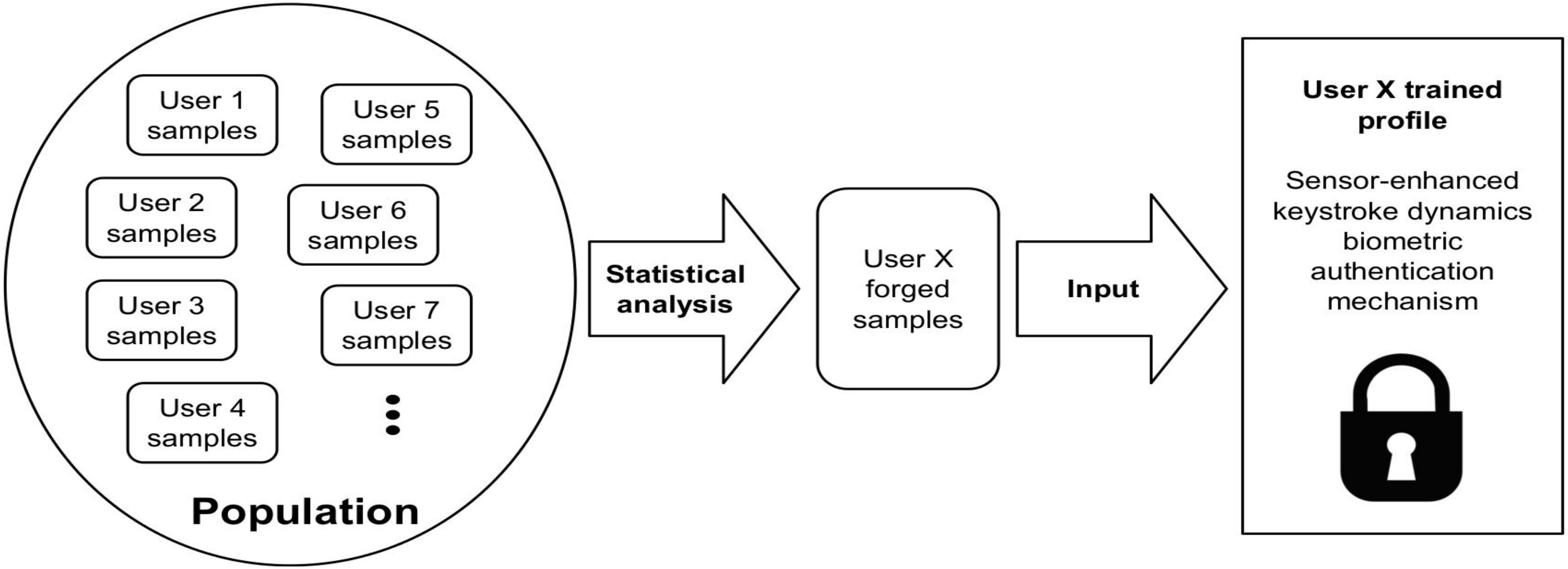
Statistical Attack



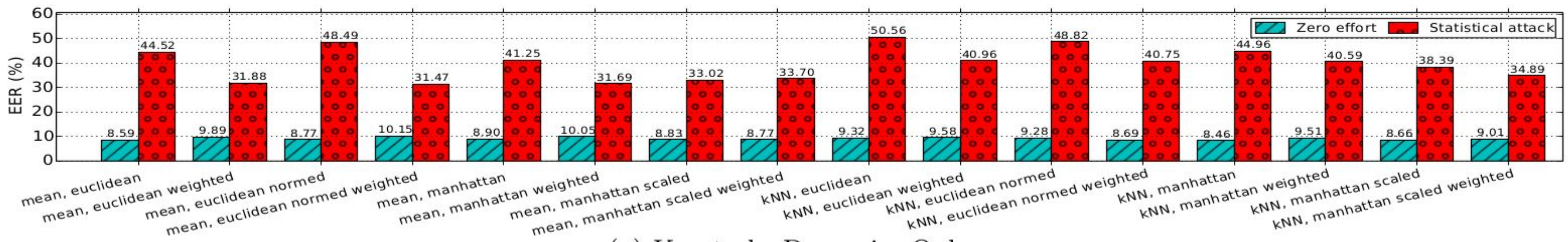
Statistical Attack



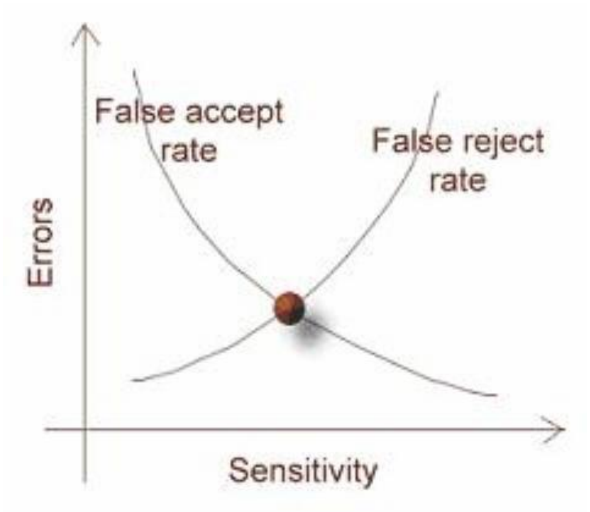
Statistical Attack



low Equal Error Rate (EER) == accurate authentication method

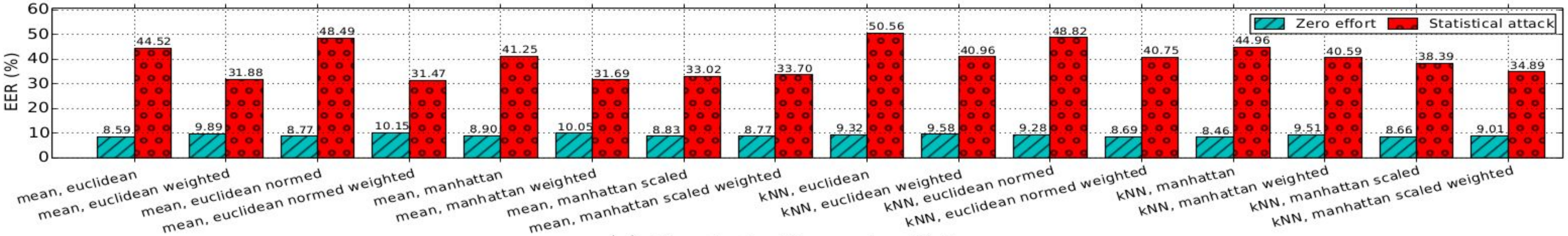


(a) Keystroke-Dynamics Only.

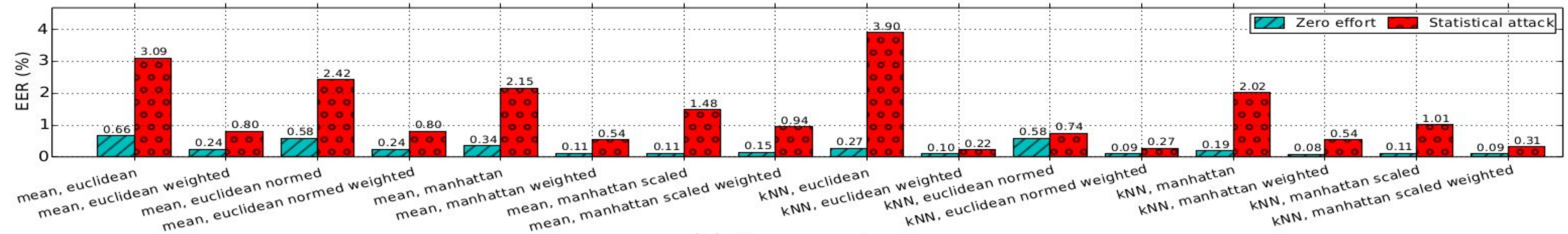


Results

low Equal Error Rate (EER) == accurate authentication method



(a) Keystroke-Dynamics Only.



(b) Sensors only.

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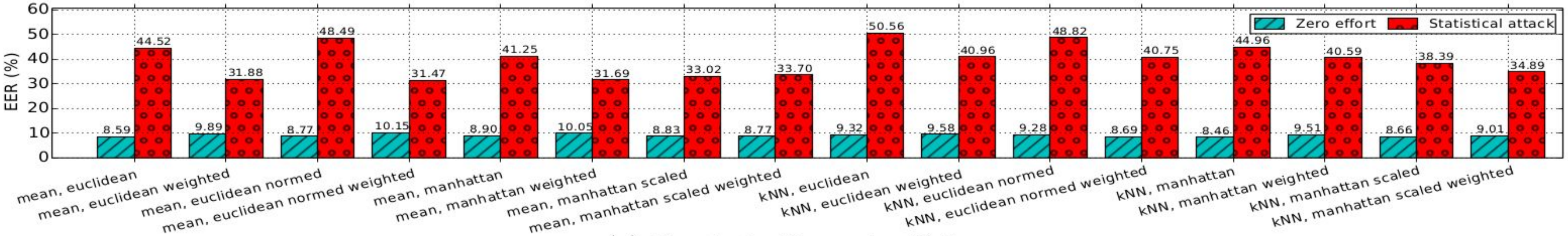
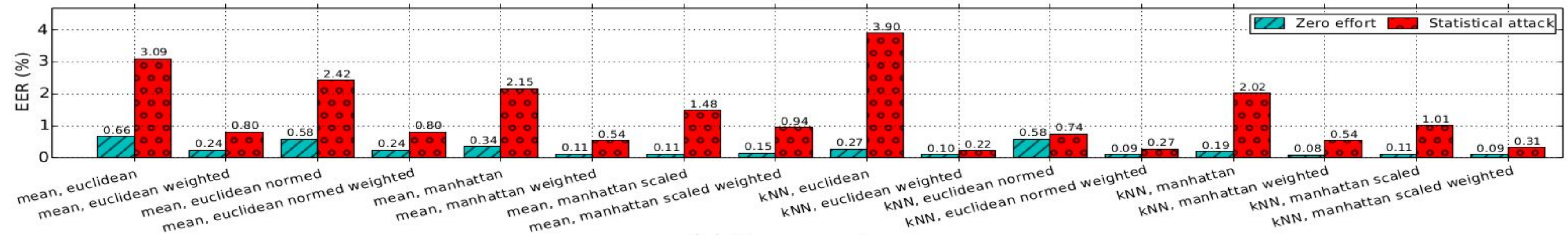
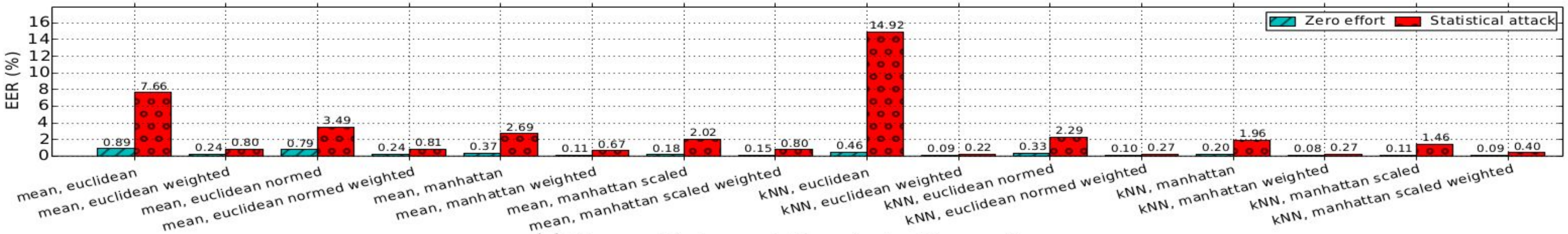


(a) Keystroke-Dynamics Only.



(b) Sensors only.



(c) Sensor-Enhanced Keystroke-Dynamics.

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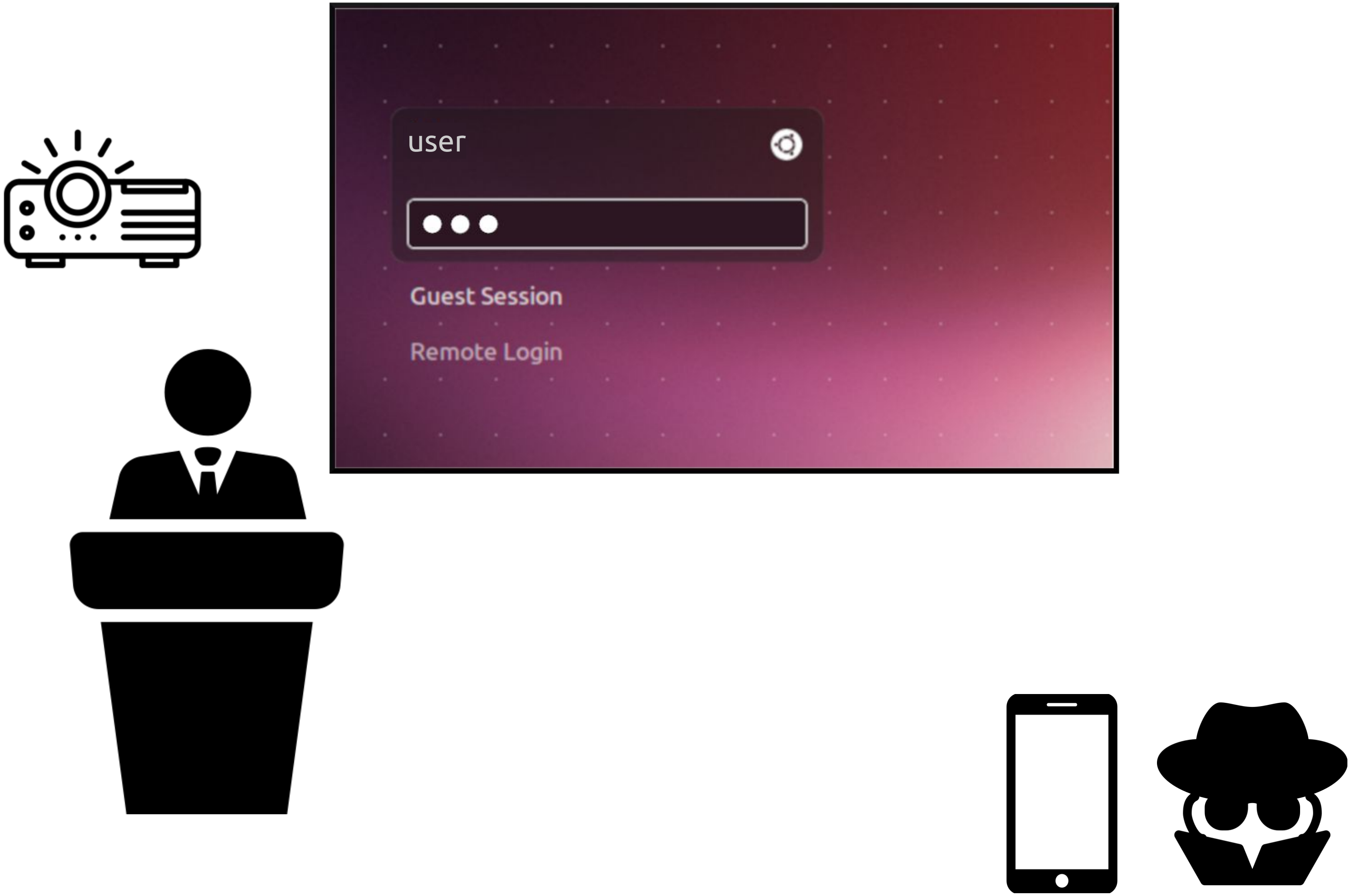
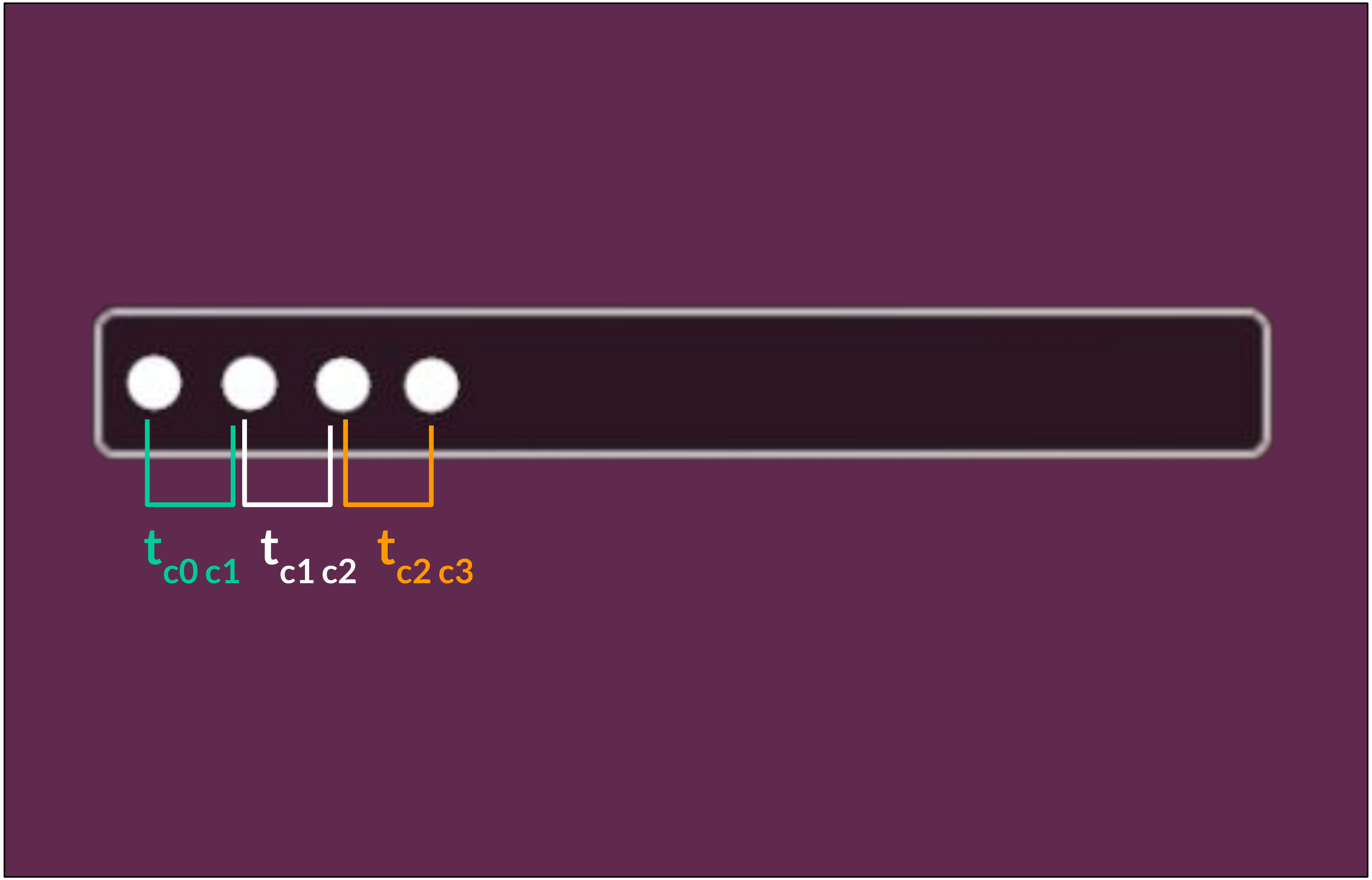
Kiran Balagani, Mauro Conti, Paolo Gasti, Martin Georgiev, Tristan Gurtler, Daniele Lain, Charissa Miller, Kendall Molas, Nikita Samarin, Eugen Saraci, Gene Tsudik, Lynn Wu

SILK-TV: Secret Information Leakage From Keystroke Timing Videos.

In ESORICS 2018

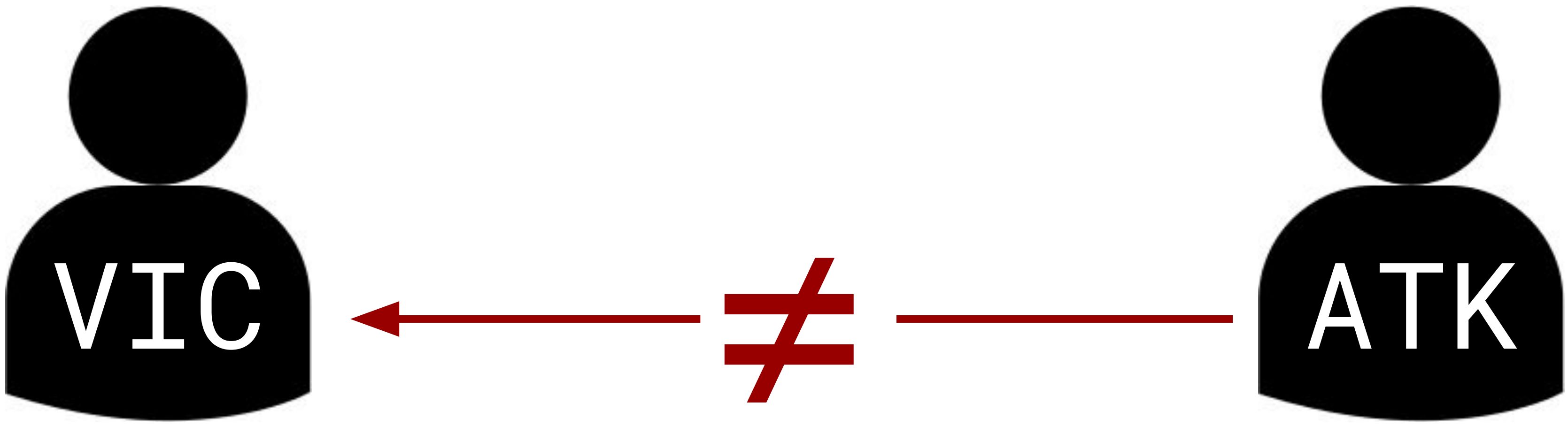
Timing Information Leak - 1

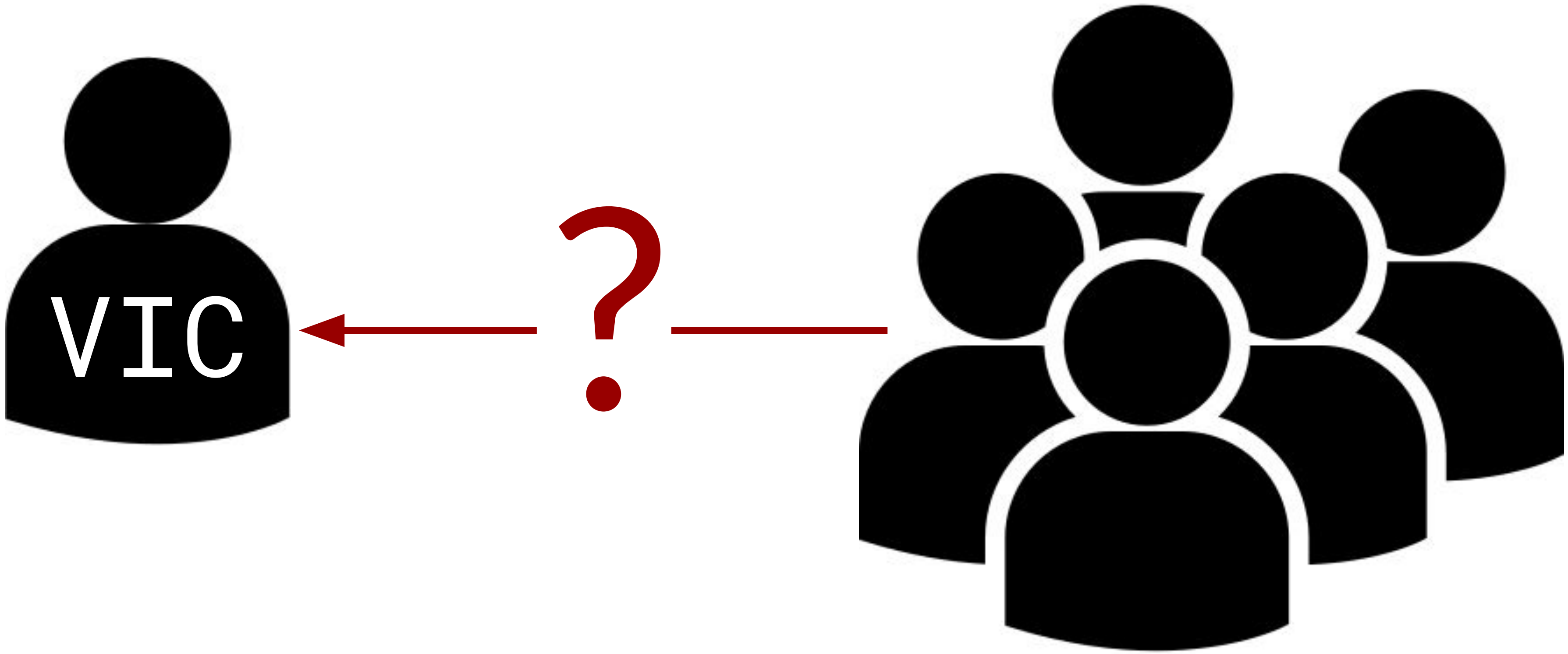



$t_{c0\ c1}$
$t_{c1\ c2}$
$t_{c2\ c3}$

Timing Information Leak - 2

Keypad not visible - but the screen is!

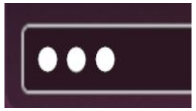

VIC
≠
ATK


VIC
?

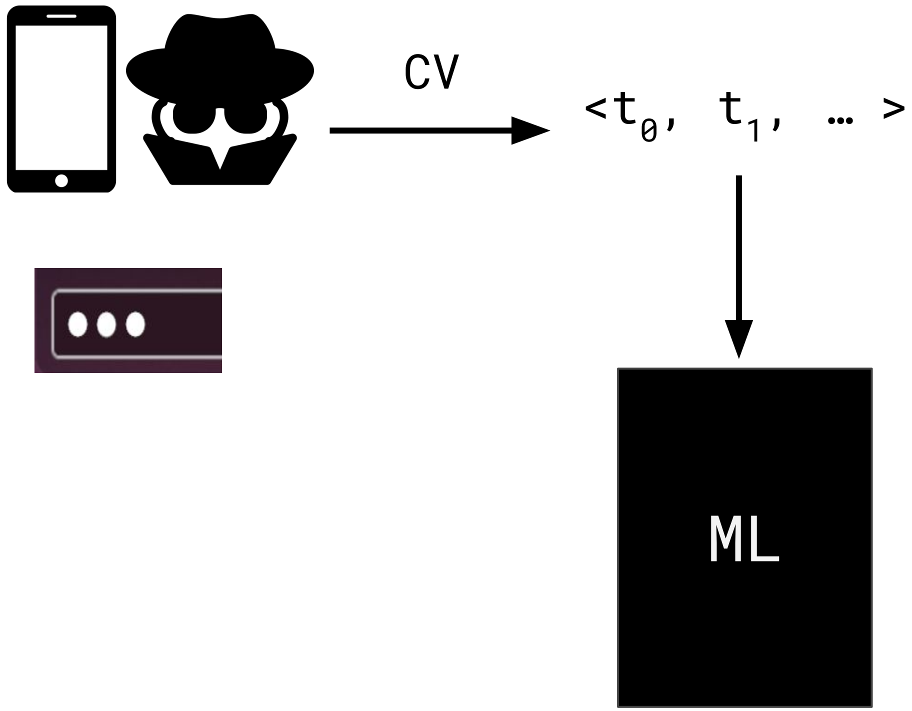
Contributions

- Quantify information leakage of on-screen keystroke feedback
- Novel attack: *SILK-TV*
  - *Uses public datasets only from multiple sources ("population data")*
  - *Machine Learning to guess typed text (passwords and PINs)*

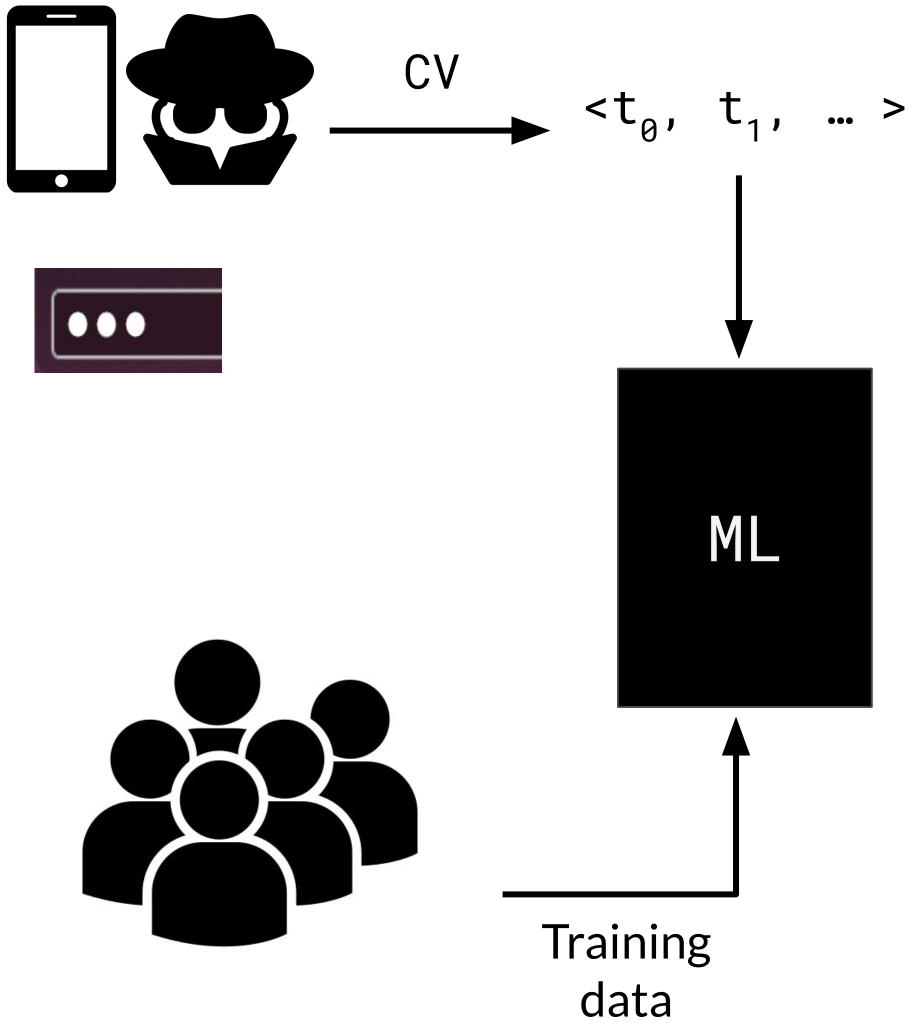
SILK-TV



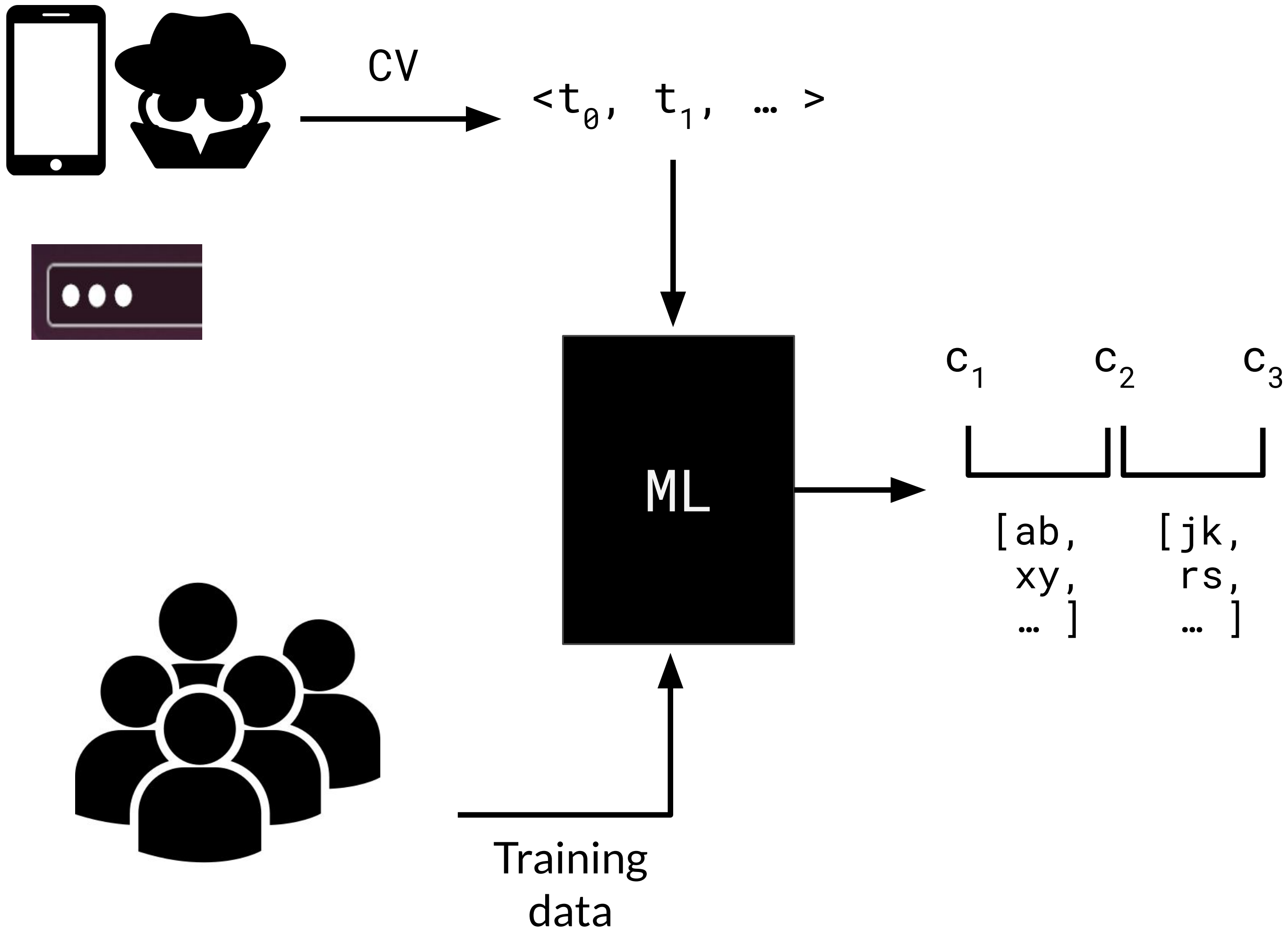
SILK-TV



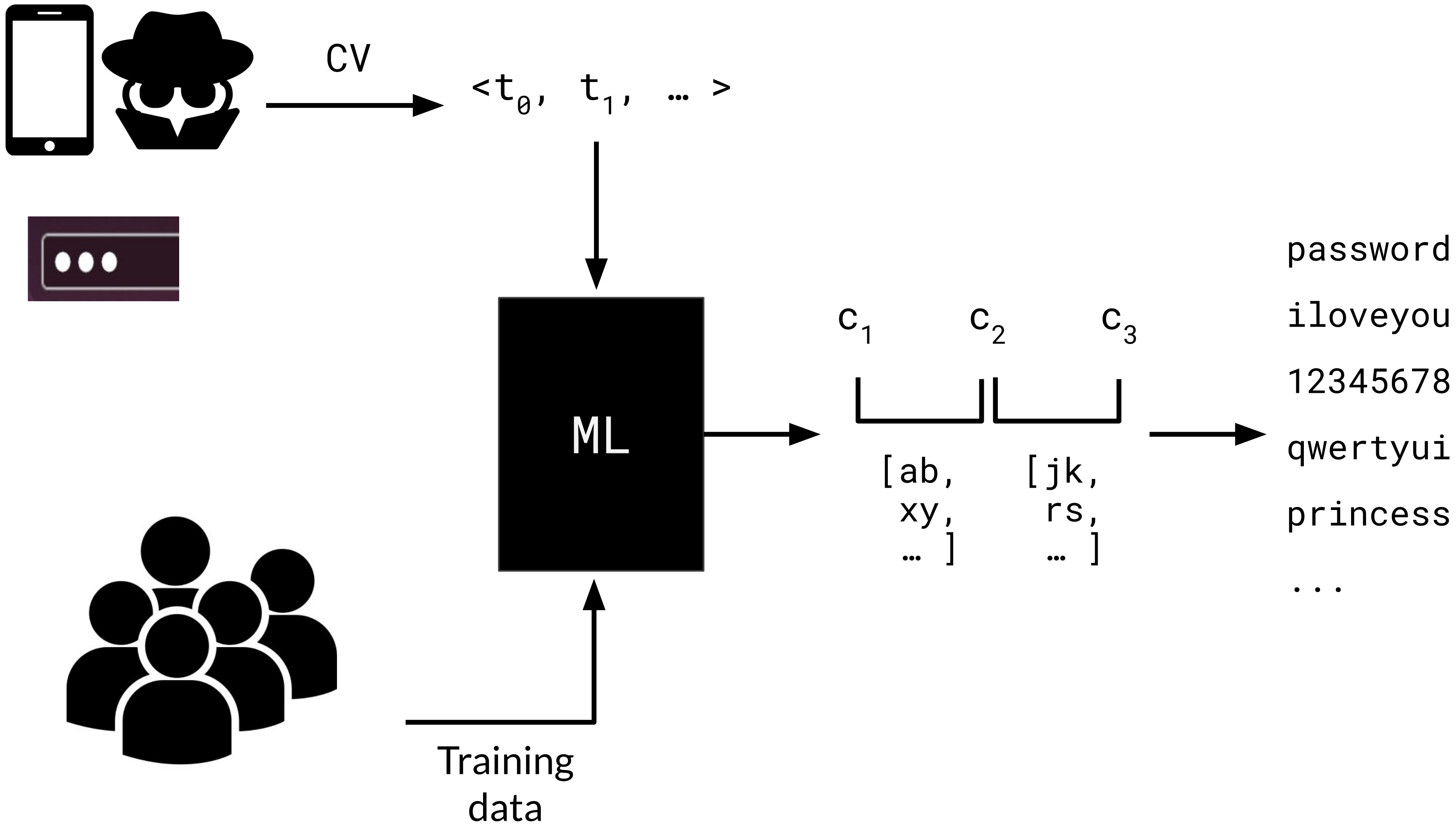
SILK-TV



SILK-TV



SILK-TV


CV
<t0, t1, … >
ML
c1 c2 c3
[ab, xy, …]
[jk, rs, …]
password
iloveyou
12345678
qwertyui
princess
...
Training data

Data Collection - Passwords

- Data from **projector** and **laptop screen** @ 60Hz
- Recorded with a smartphone
- 62 users - 3 times each pwd - ***touch* typing** on keyboard
- Randomly selected 4 passwords from `rockyou`[1]
  - *`123brian, jillie02, lamondre, william1`*

1 - http://downloads.skullsecurity.org/passwords/rockyou.txt.bz2

Evaluation - Passwords

- Baseline: password list sorted by frequency
  - *"Best" strategy for a zero-information attacker*
  - `123brian` - *93,874th*
  - `jillie02` - *1,753,571st*
  - `lamondre` - *397,213rd*
  - `william1` - *187th* ← *very frequent password*

- Evaluation scenarios
  - *"Single shot"*
  - *"Multiple recordings" (e.g., professor at lectures)*

Password - “Single Shot” results

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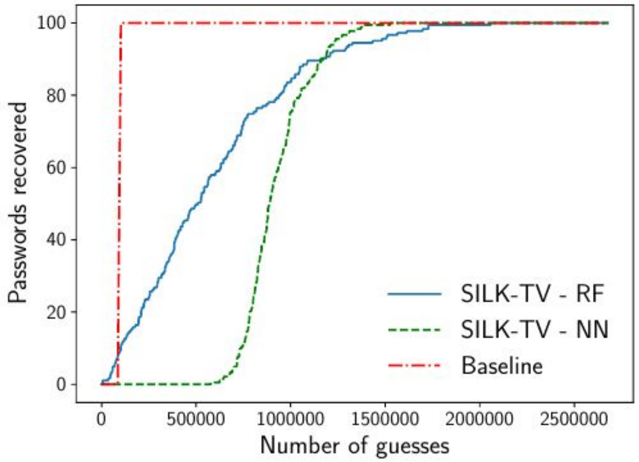
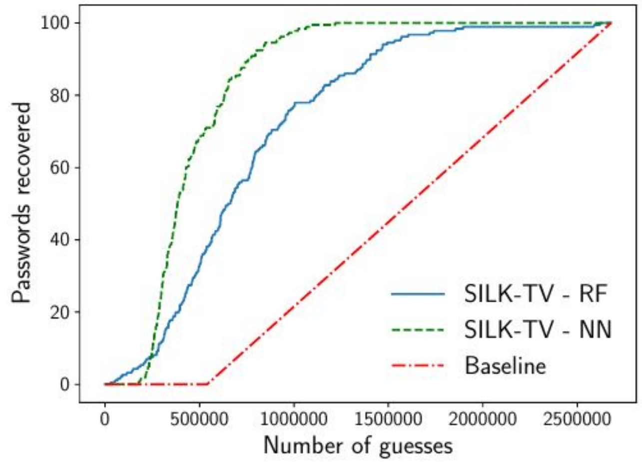
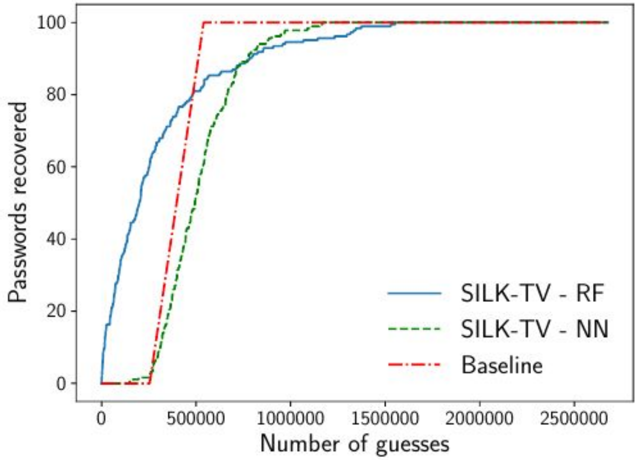


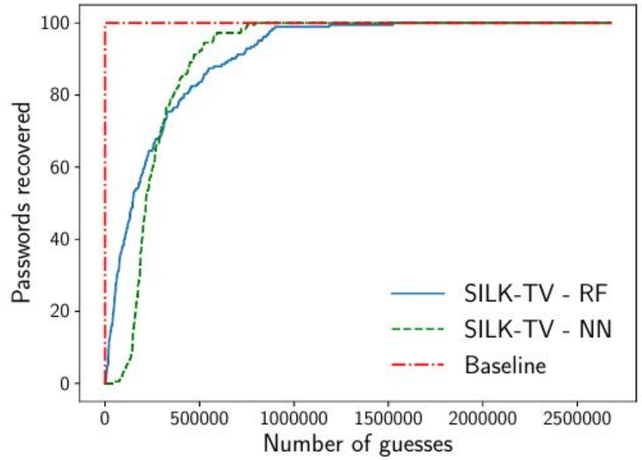
(a) `123brian` (183 auth. attempts).



(b) `jillie02` (186 auth. attempts).

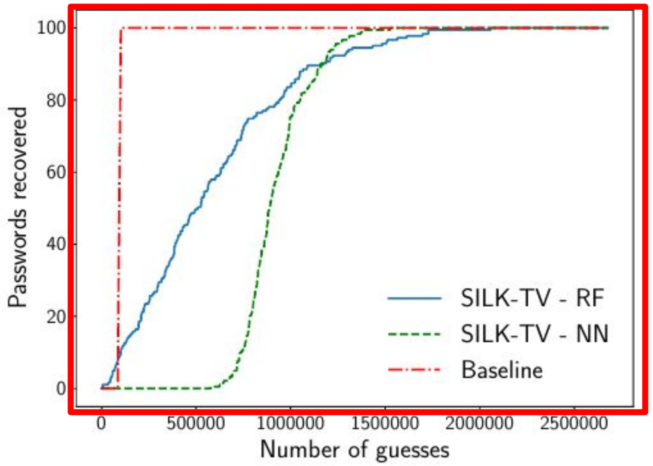


(c) `lamondre` (184 auth. attempts).

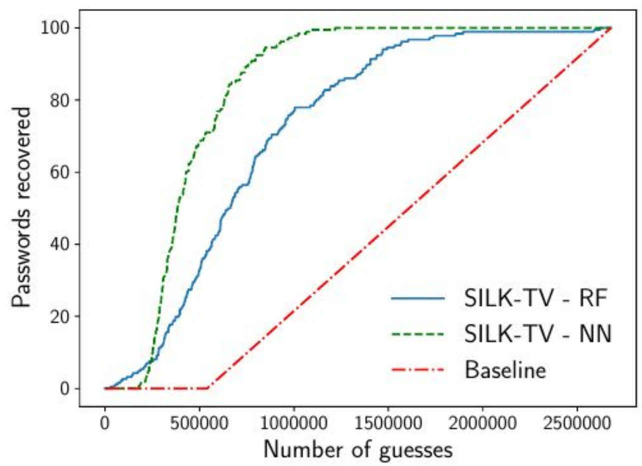


(d) `william1` (183 auth. attempts).

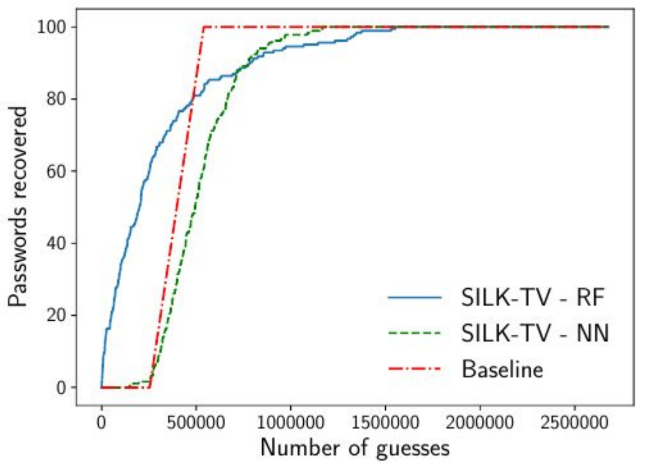
Password - “Single Shot” results



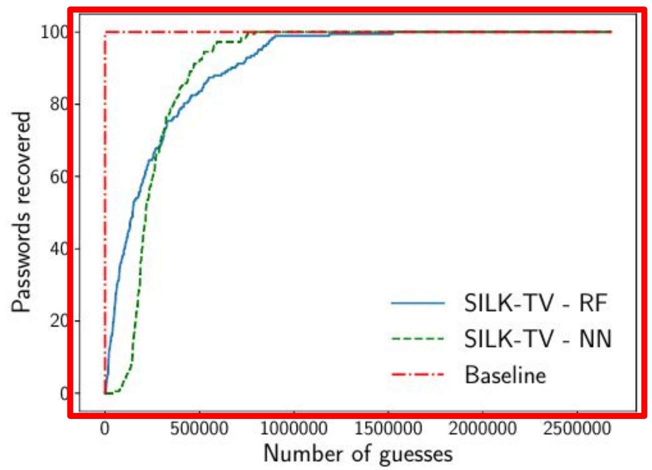
(a) `123brian` (183 auth. attempts).



(b) `jillie02` (186 auth. attempts).



(c) `lamondre` (184 auth. attempts).



(d) `william1` (183 auth. attempts).

Password - “Single Shot” results

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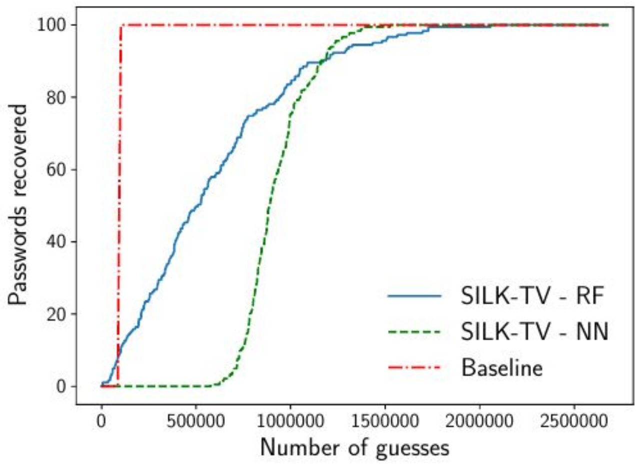
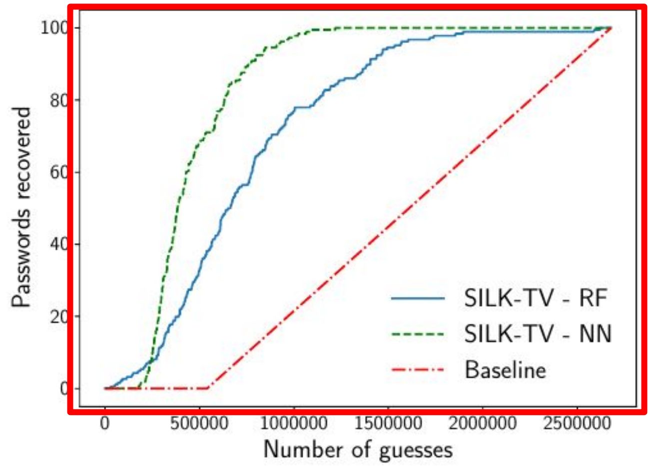


(a) **123brian** (183 auth. attempts).



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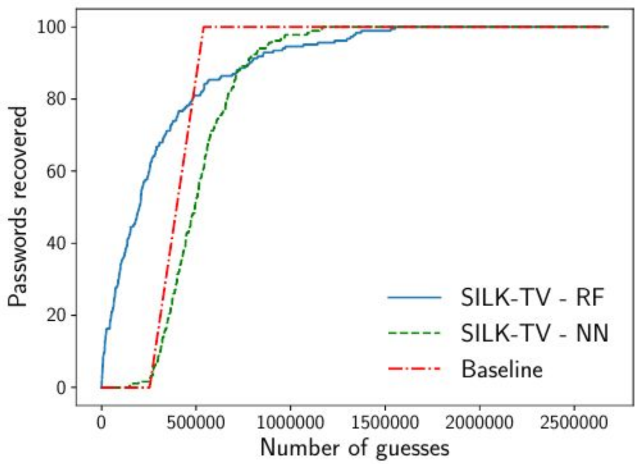

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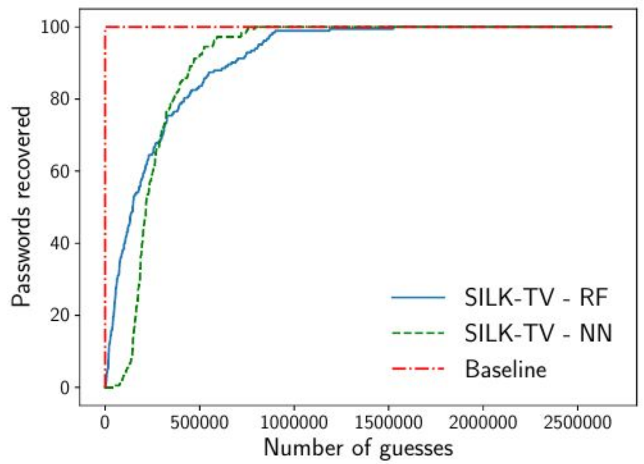

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Password - “Single Shot” results

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	Avg	Stdev	Med	Rnd	<Rnd	Best	<20k	<100k
Random Forest								
123brian	581,743	414,761	508,332	93,874	8.7%	5,535	1.1%	9.3%
jillie02	749,718	448,319	656,754	1,753,571	97.8%	28,962	0.0%	2.7%
lamondre	301,906	334,681	199,344	397,213	75.0%	145	13.0%	33.7%
william1	246,437	264,090	145,966	187	0.5%	68	10.9%	39.9%
Neural Network								
123brian	923,534	165,454	886,802	93,874	0.0%	577,739	0.0%	0.0%
jillie02	456,811	210,512	383,230	1,753,571	100.0%	164,754	0.0%	0.0%
lamondre	517,472	189,355	493,713	397,213	28.8%	148,403	0.0%	0.0%
william1	265,813	140,753	215,840	187	0.0%	45,176	0.0%	3.8%

`Avg, Stdev, Median` *of SILK-TV cracking attempts*

`Rnd` *average baseline cracking attempts*

`<Rnd, Best, <20k, <100k` *highlights of SILK-TV performance*

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`Avg, Stdev, Median` *of SILK-TV cracking attempts*

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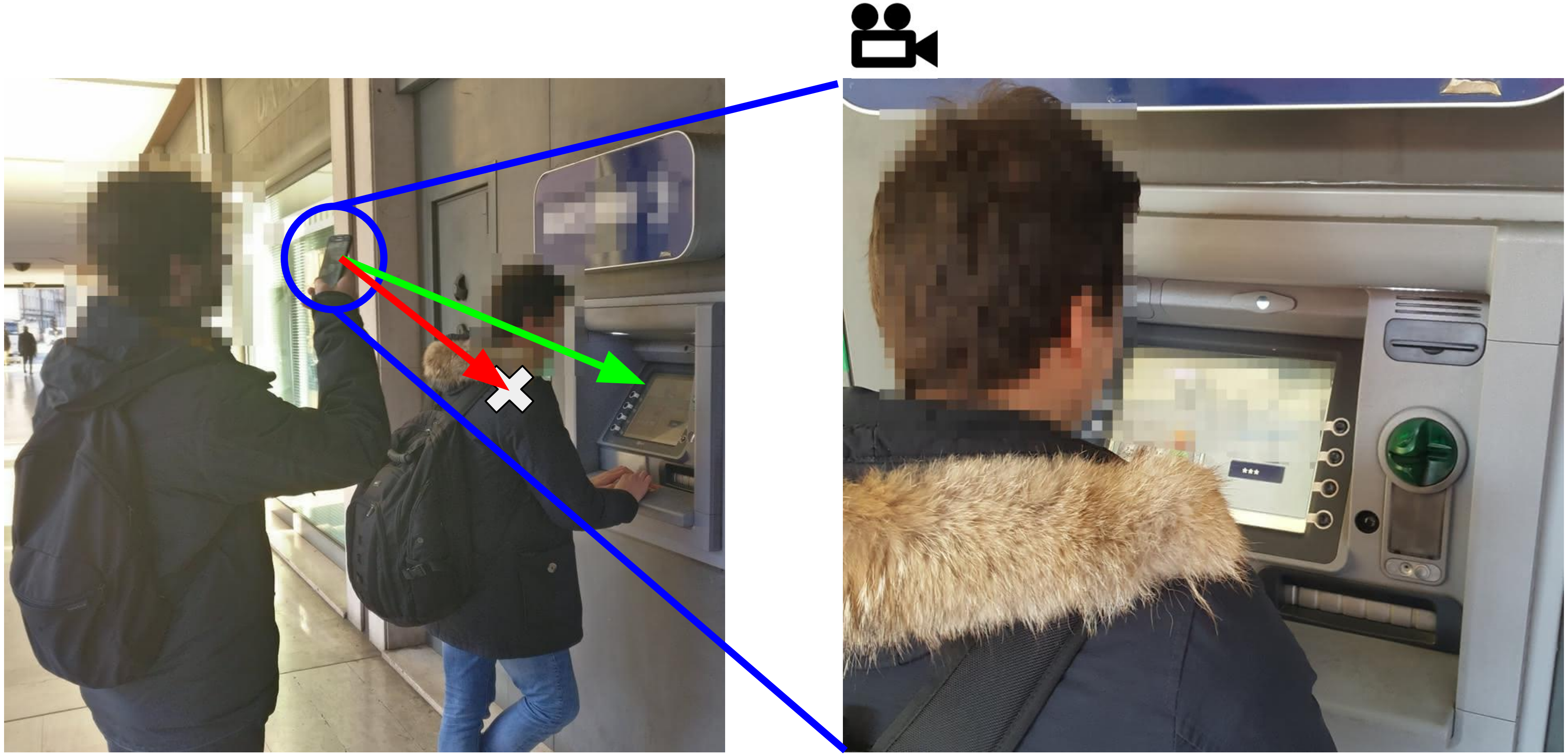
`<Rnd, Best, <20k, <100k` *highlights of SILK-TV performance*

Conclusions

- Timing information from videos is **accurate**
- Password masking leak timing → useful information
  - *Reduces number of attempts*
  - *More useful on **uncommon** passwords!*

PIN Salabim

PIN Salabim



Keypad not visible - but the screen is!

PILOT
Password and PIN Information Leakage from Obfuscated Typing Videos

Kiran Balagani, Matteo Cardaioli, Mauro Conti, Paolo Gasti, Martin Georgiev, Tristan Gurtler, Daniele Lain, Charissa Miller, Kendall Molas, Nikita Samarin, Eugen Saraci, Gene Tsudik, and Lynn Wu

In Journal of Computer Security 2019

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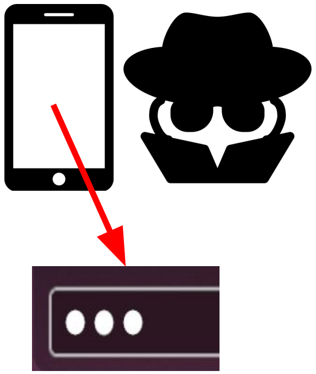
NYIT
New York Institute
of Technology

GFT

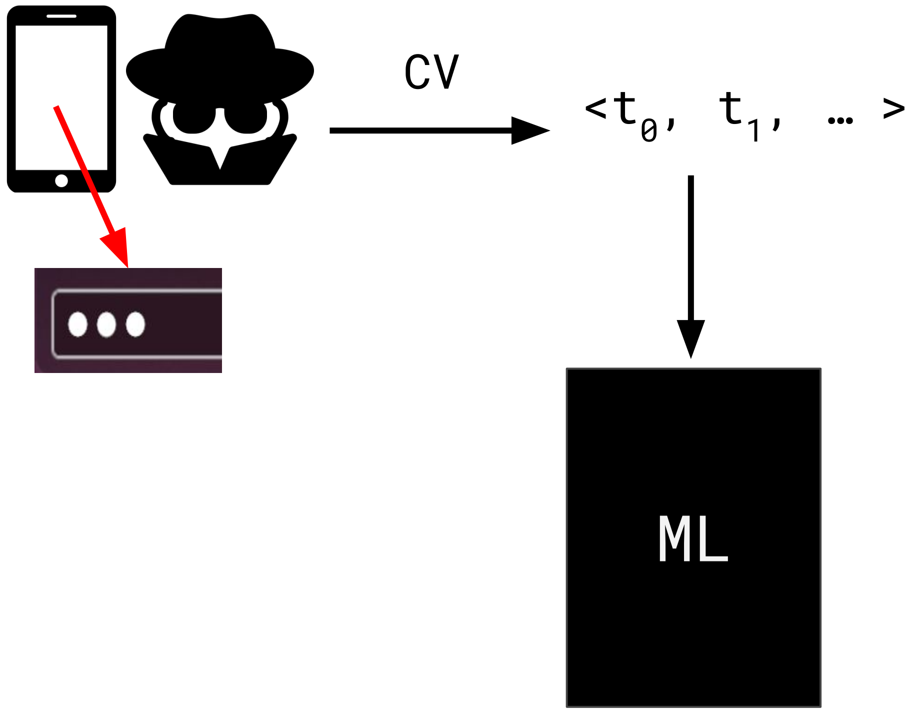
The University of California Irvine
Let there be light

ETH zürich

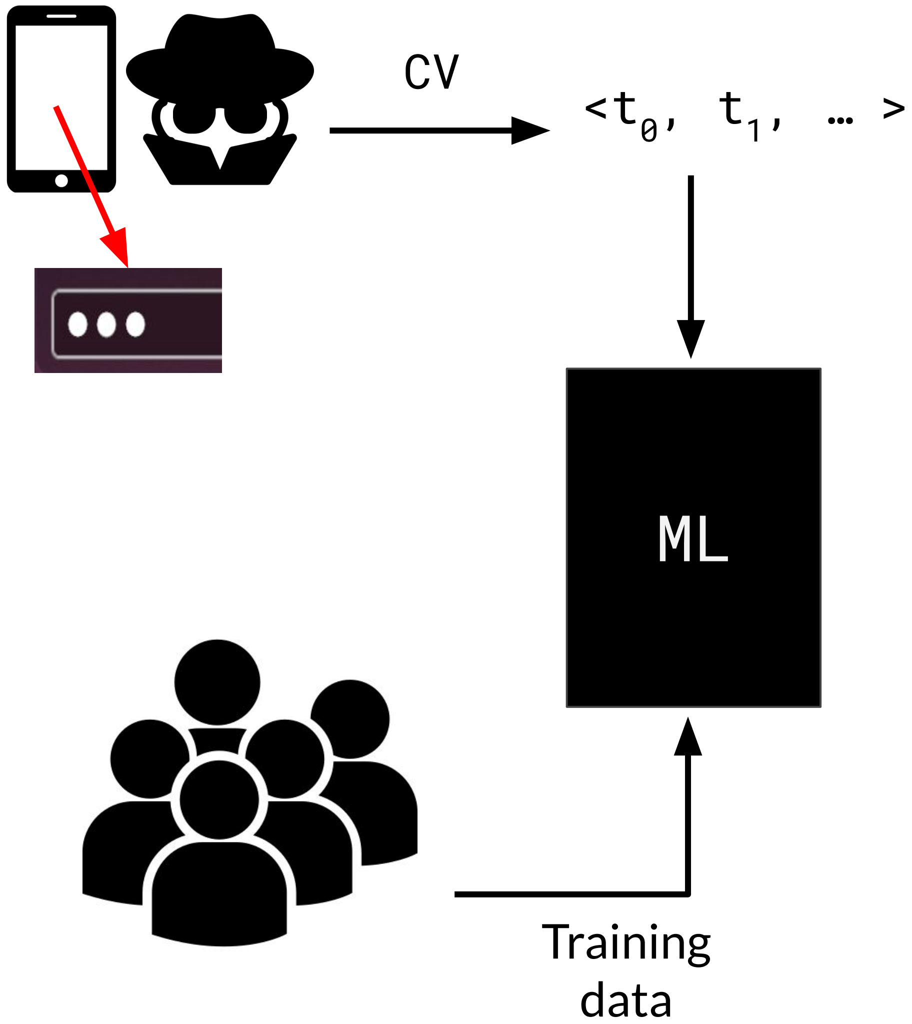
PILOT



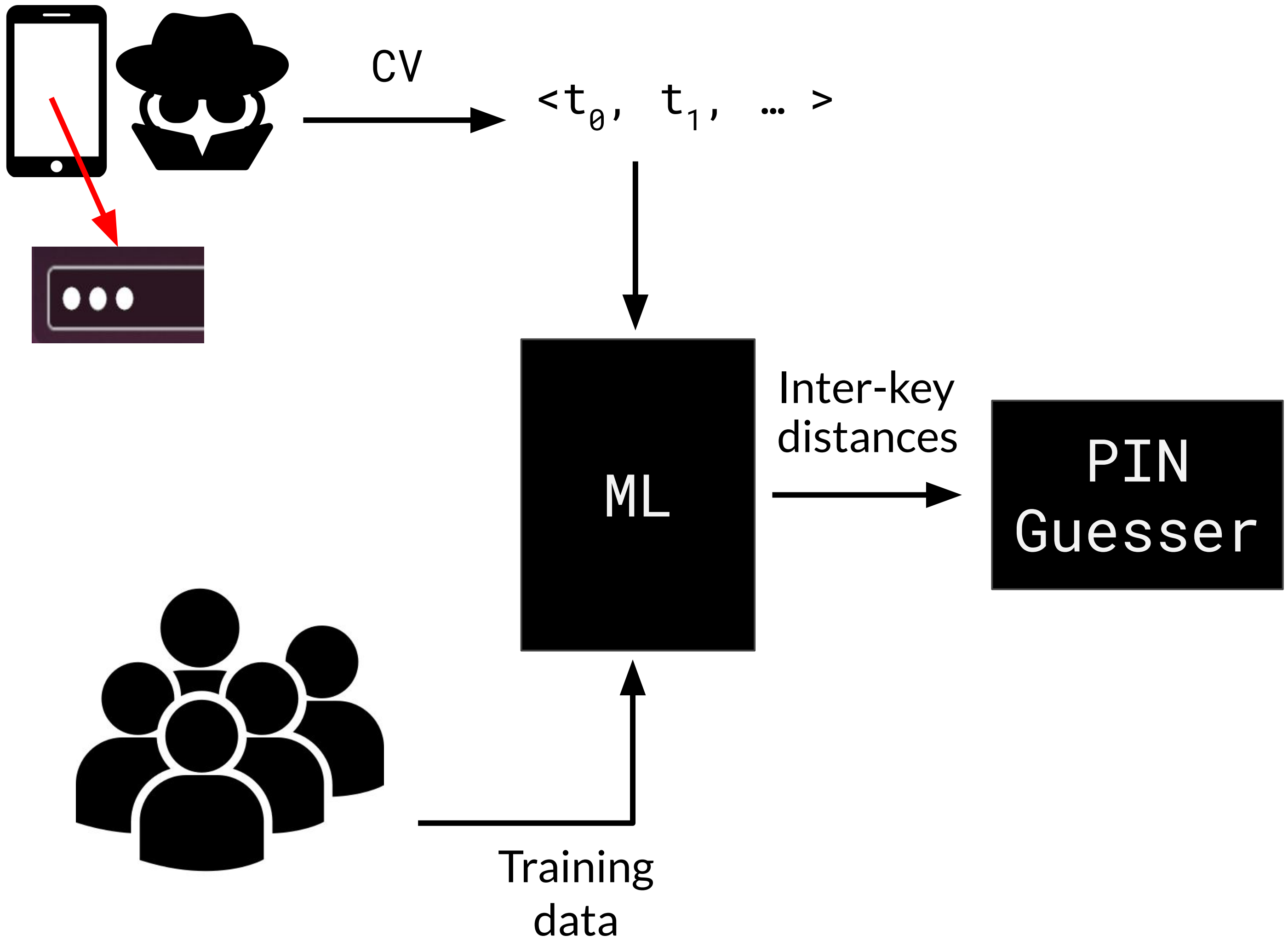
PILOT



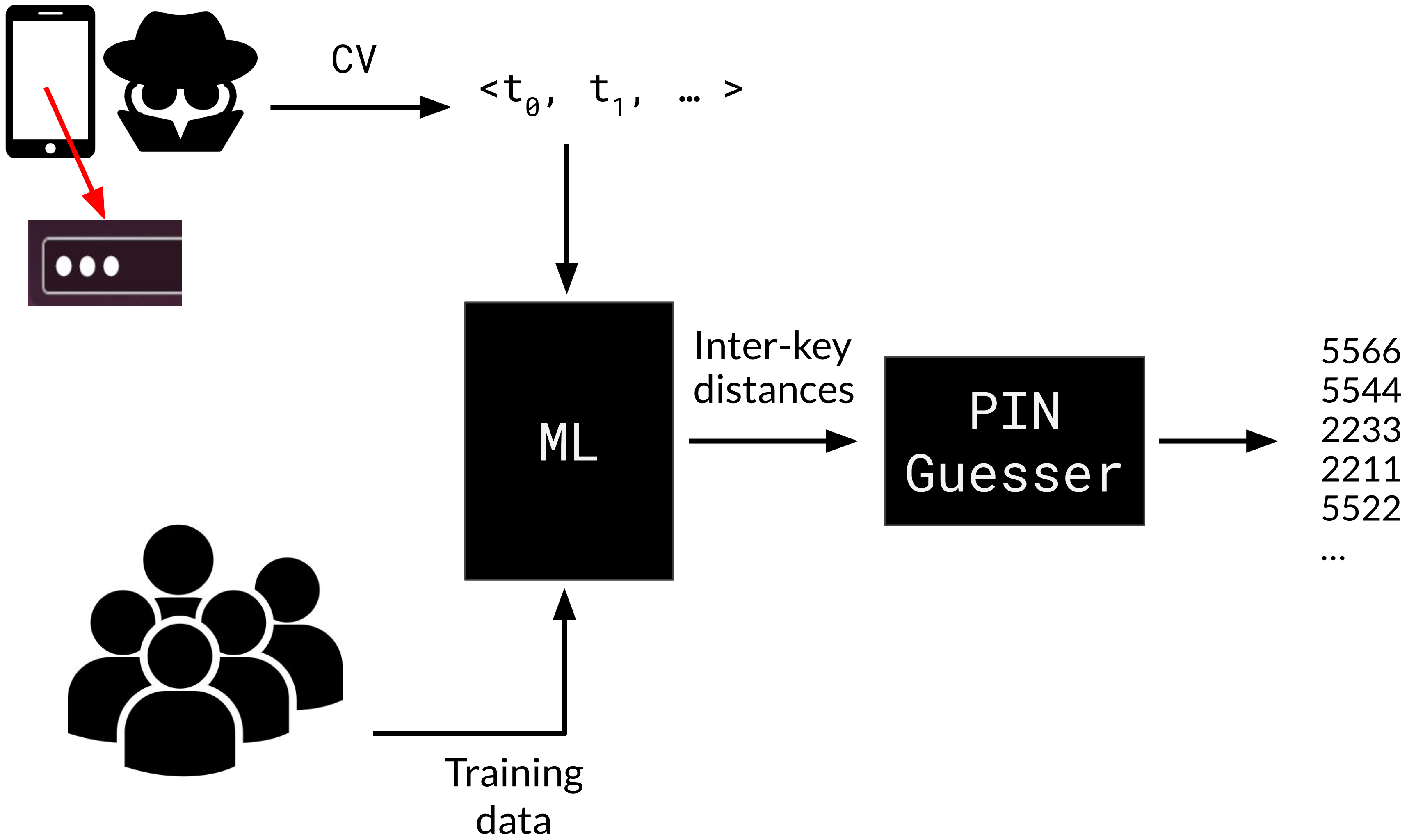
PILOT



PILOT



PILOT


CV
<t0, t1, … >
ML
Inter-key
distances
PIN
Guesser
5566
5544
2233
2211
5522
…
Training
data

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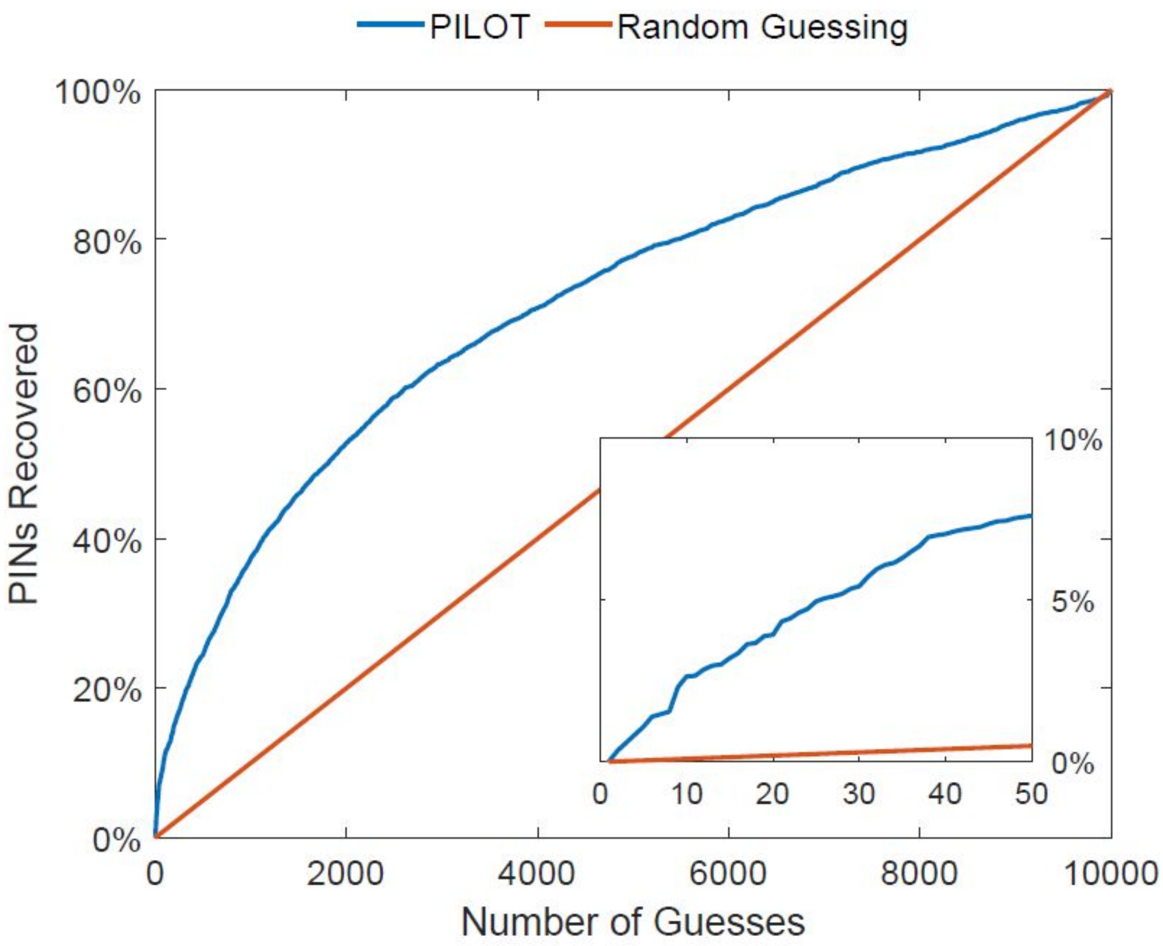
Percentage of PINs recovered with PILOT vs Random Guessing

- 4 digit PIN (USA ATM card)



Your PIN Sounds Good!
On The Feasibility of PIN Inference Through Audio Leakage

Matteo Cardaioli, Mauro Conti, Kiran Balagani, and Paolo Gasti

IEEE Transactions on Information Forensics and Security 2019 (Submitted)
https://arxiv.org/abs/1905.08742

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Neither keypad nor screen are visible

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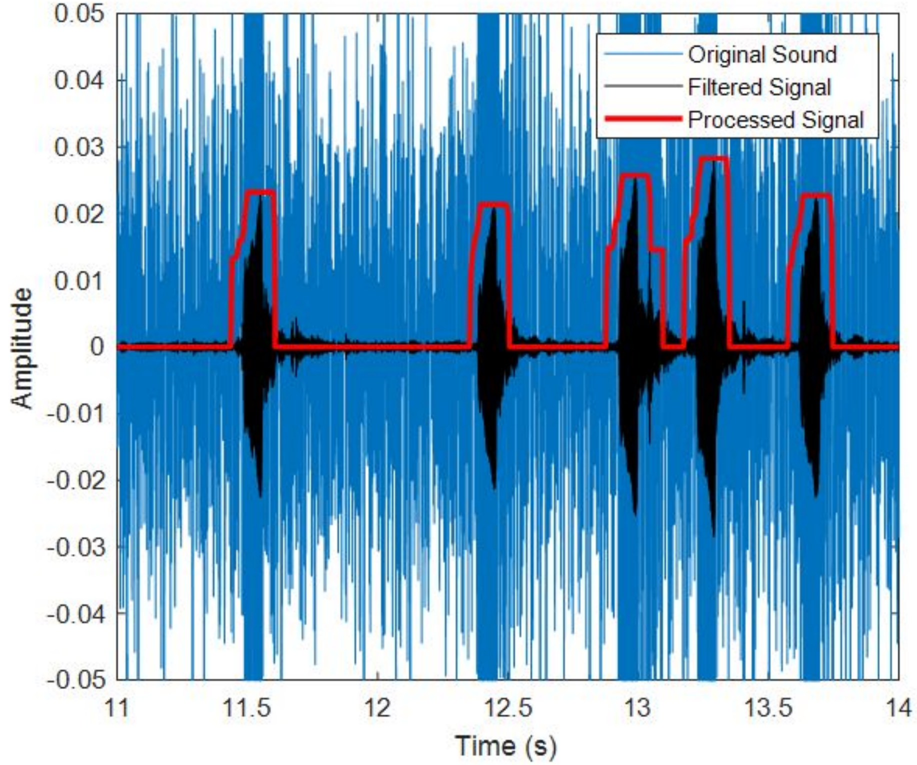
Inter-keystroke timing identification through sound analysis

- Signal filtering

  To extract feedback sound characteristic frequency

- Signal processing

  To remove residual noise and to identify time distance between peaks



Adversarial **additional knowledge** about the user or the PIN

- Knowledge of **typing behavior**

  Hunt-and-peck *vs.* ***touch typing***

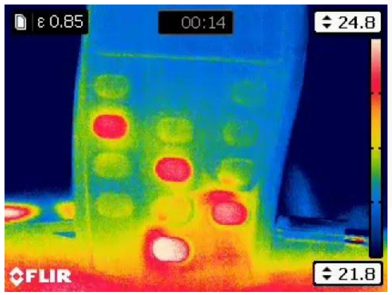
- Knowledge of **a digit**

  Adversary ***knows one digit*** *of the PIN*

- **Heatmap**

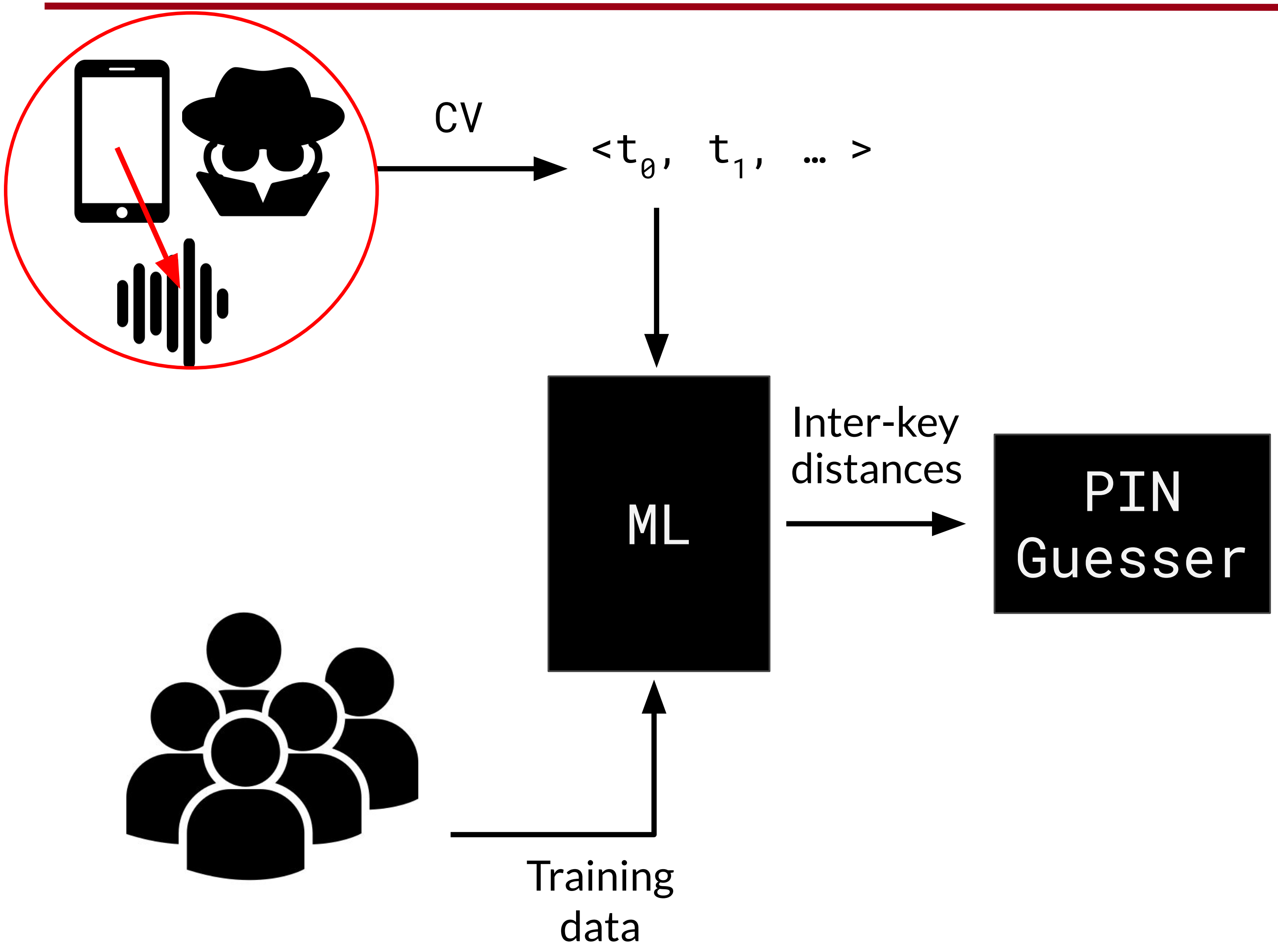
  Adversary performs a ***thermal attack***

  - *Better on plastic and rubber*
    Not so good on metal

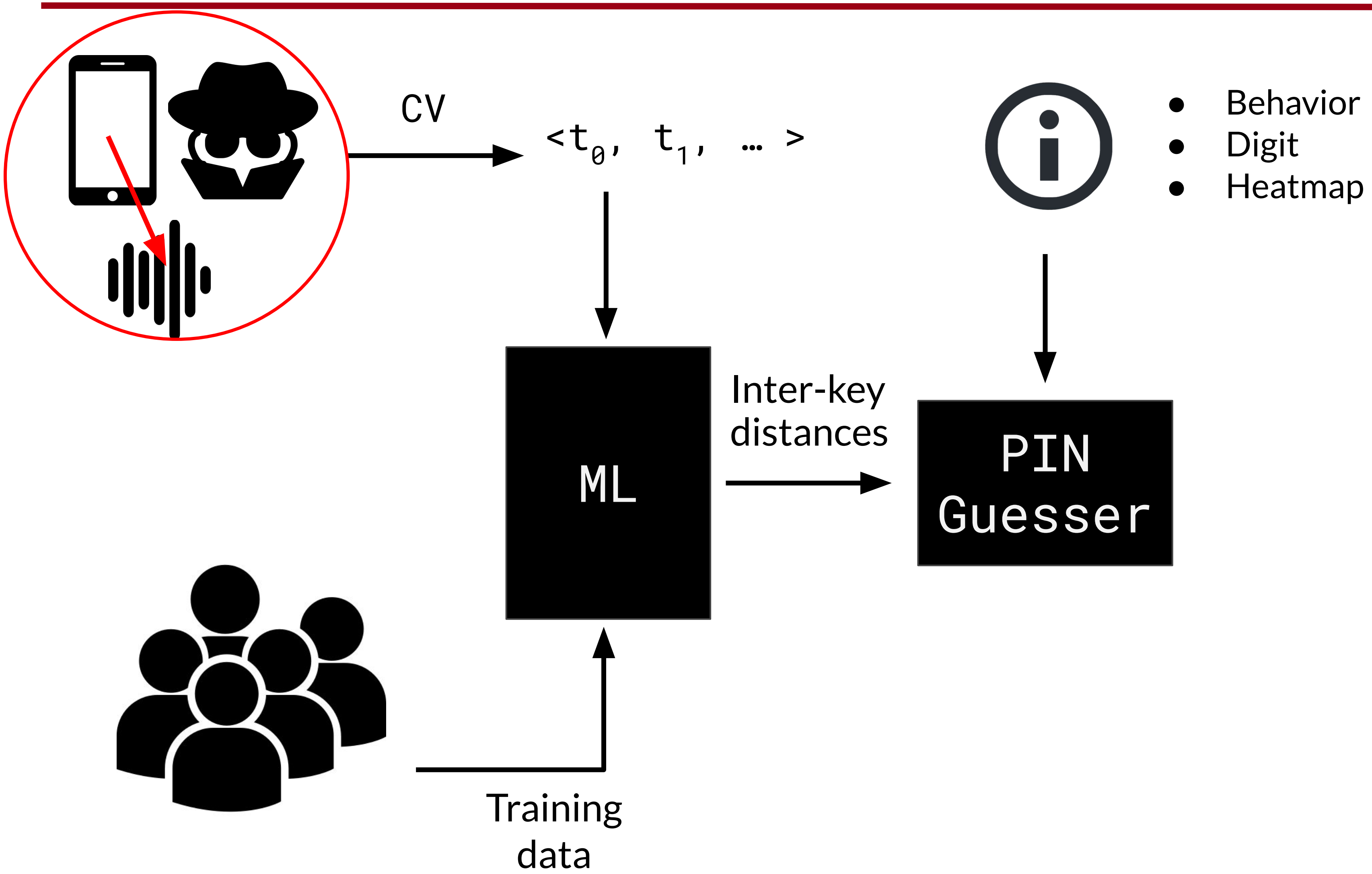


FLIR One PRO
Lt iOS...
252 €
amazon

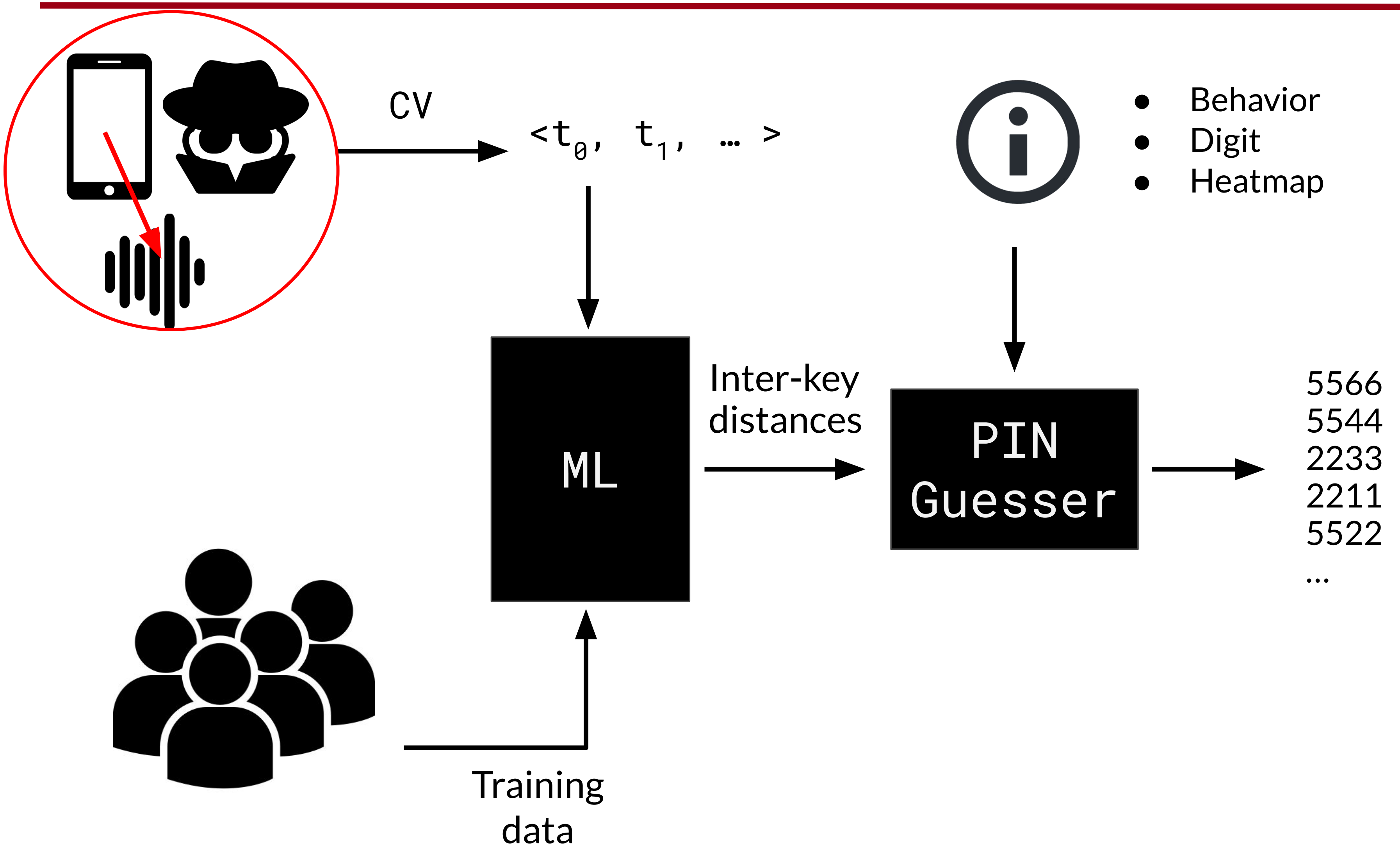
Your PIN Sounds Good!



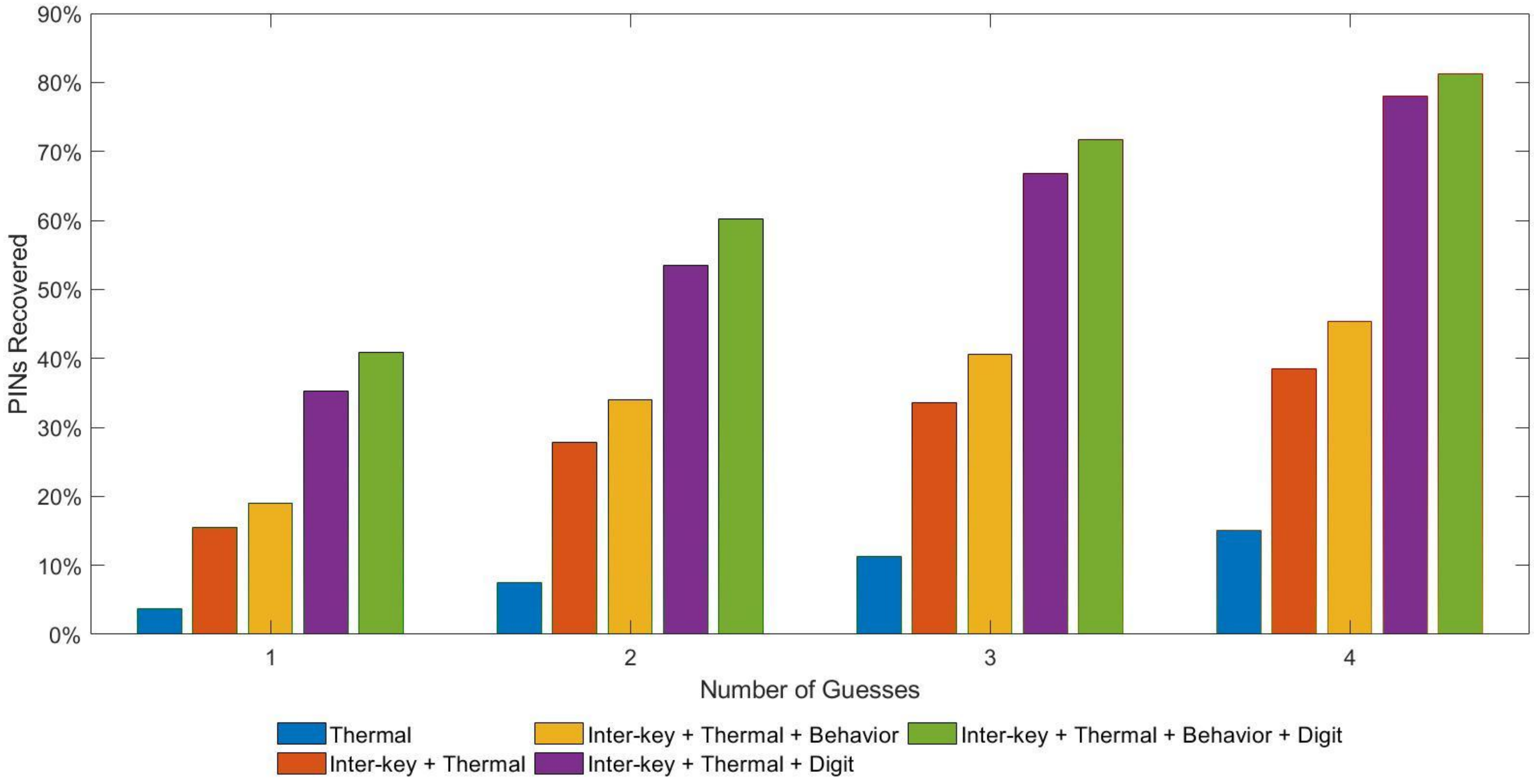
Your PIN Sounds Good!



Your PIN Sounds Good!



% PINs recovered: inter-keystroke timing + other informations



Your PIN Sounds Good!

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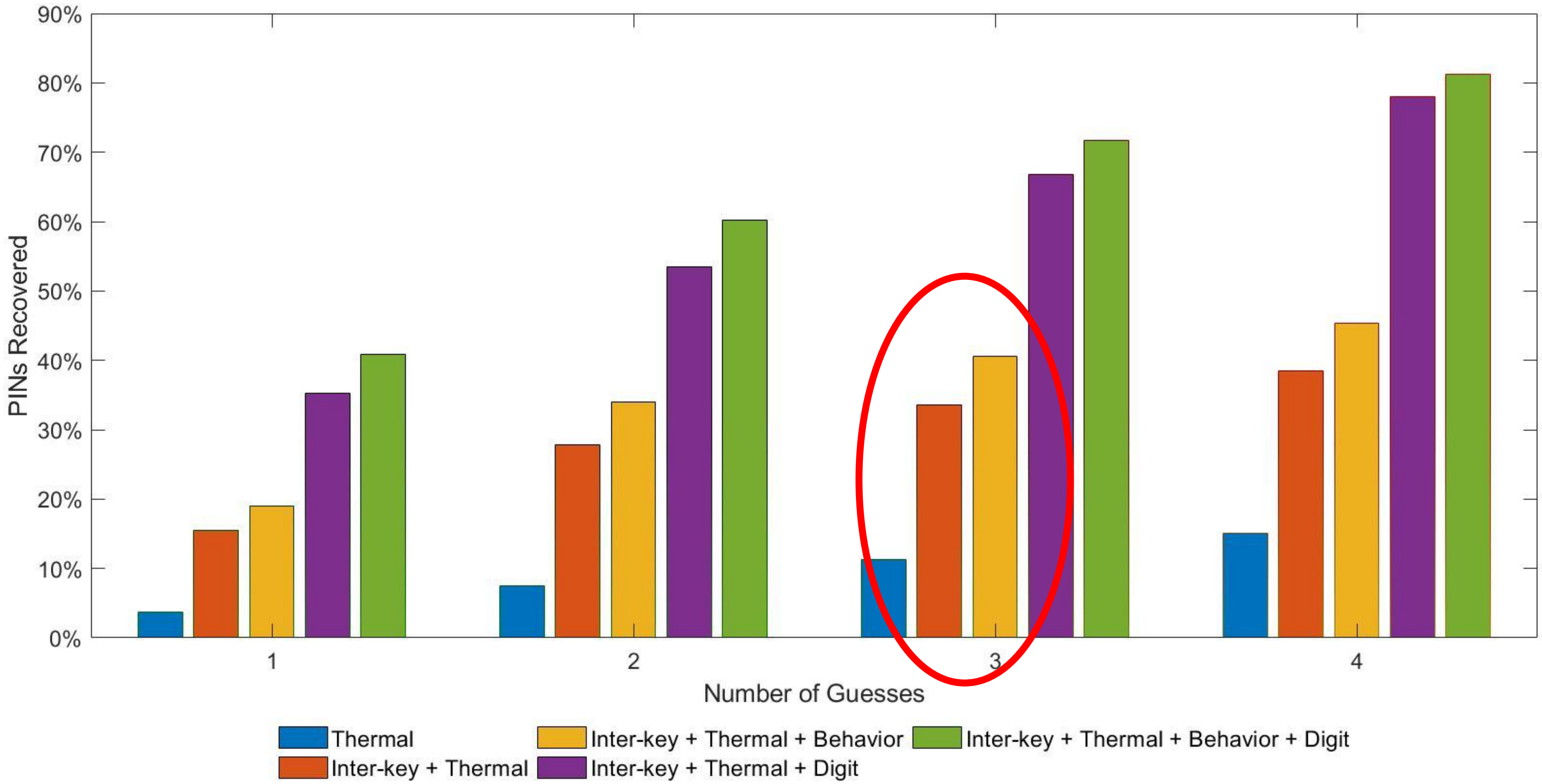
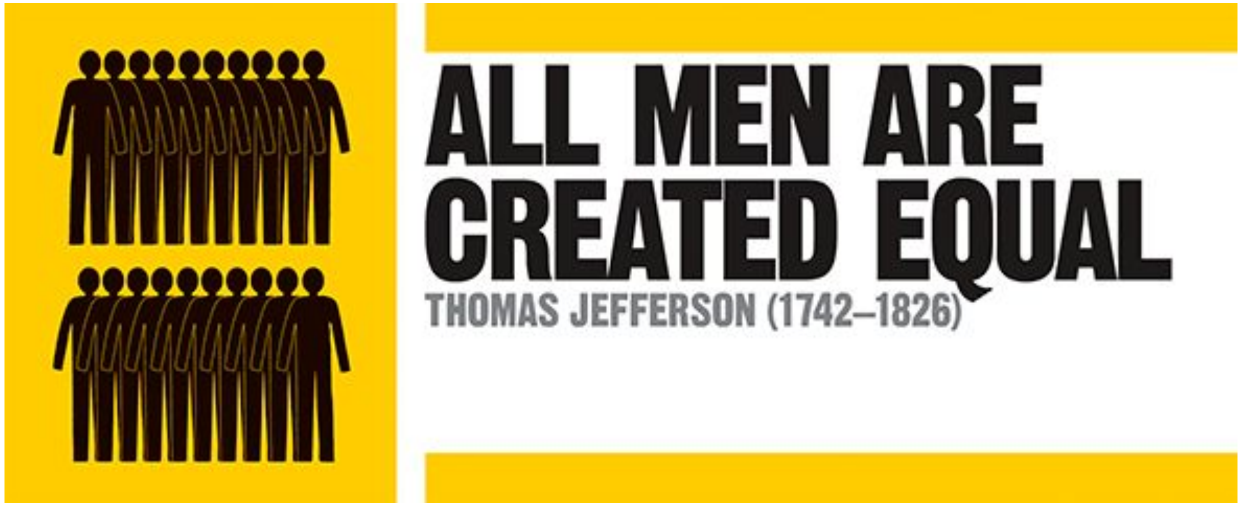
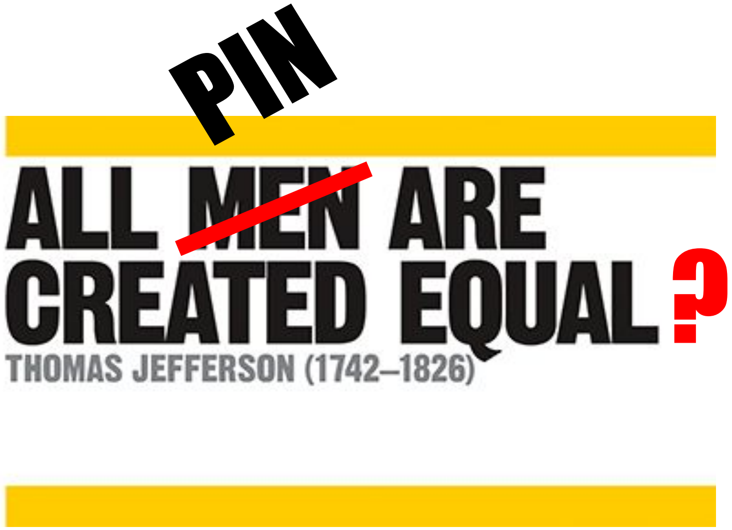



ALL MEN ARE
CREATED EQUAL
THOMAS JEFFERSON (1742–1826)

Your PIN Sounds Good!




PIN
ALL ~~MEN~~ ARE
CREATED EQUAL ?
THOMAS JEFFERSON (1742–1826)

User Chosen


5555
1122
4321
1212
0000
1004
6666
8888
2222
1234
4444
2000
9999
7777
2001
6969
3333
1111
1313
1010

User Chosen

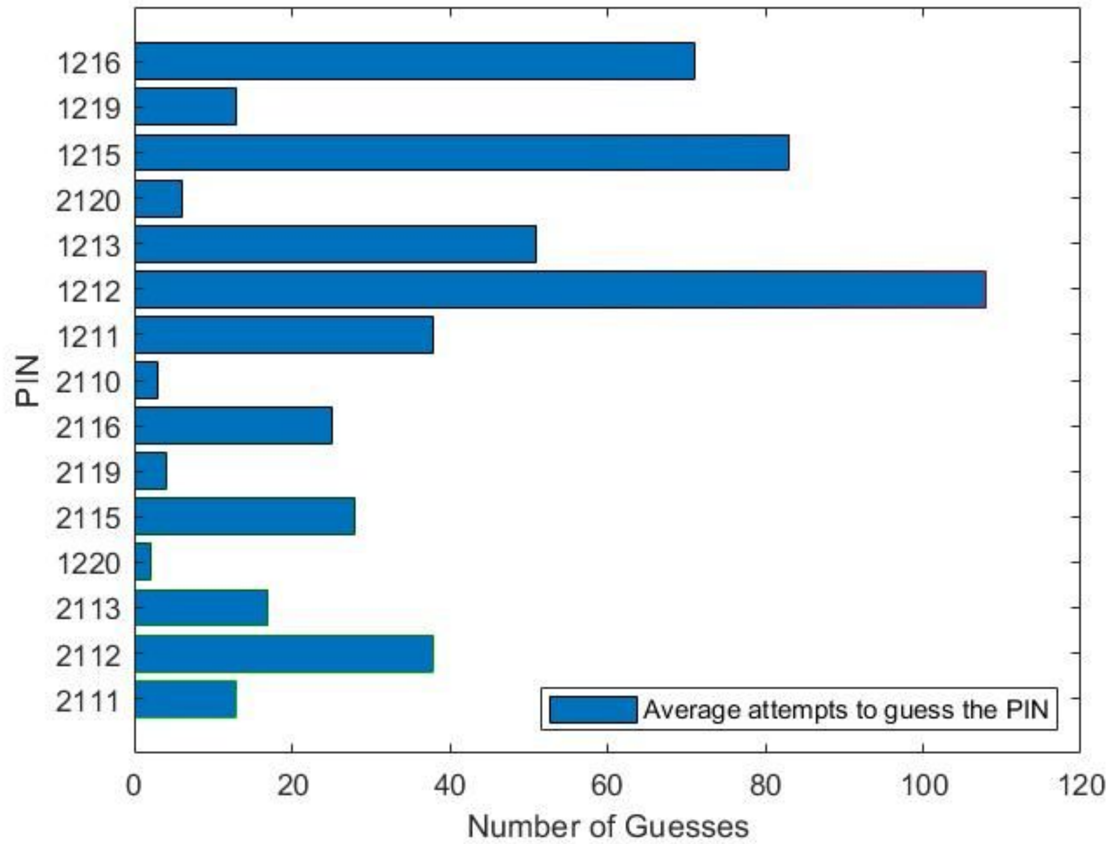
Random

Your PIN Sounds Good!

DEFINITELY... NOT!

Not all PINs are born the same

*Knowing **inter-key distance only***



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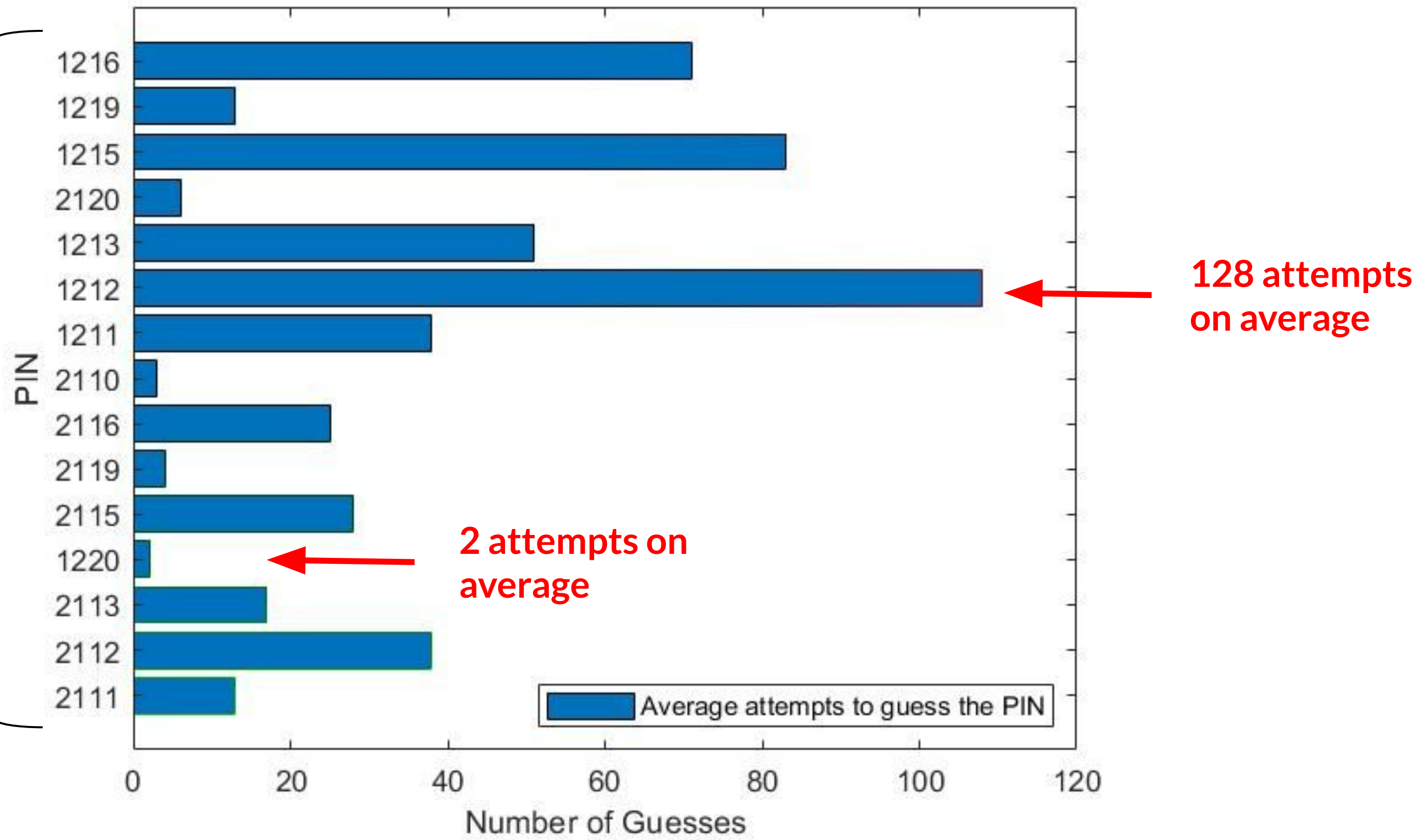
Not all PINs are born the same

*Knowing **inter-key distance only*** → *PINs probability distribution is **no longer uniform***

Showing just a subset of PINs



DEMO time!

Outline

- Covert and Side Channels 101

- Network Traffic Analysis
  - *As a side channel: app and sensitive data inference*
- Energy Consumption
  - *As a side channel: user and app inference*
  - *As a covert channel: data exfiltration*

- Device Movement
  - *As a side channel: smartphone user authentication*
  - *Attacks against biometric authentication*
- Keystroke Timing
  - *As a side channel: text typed on keyboards*
- **Acoustic Emanations**
  - ***As a side channel: text typed on keyboards***

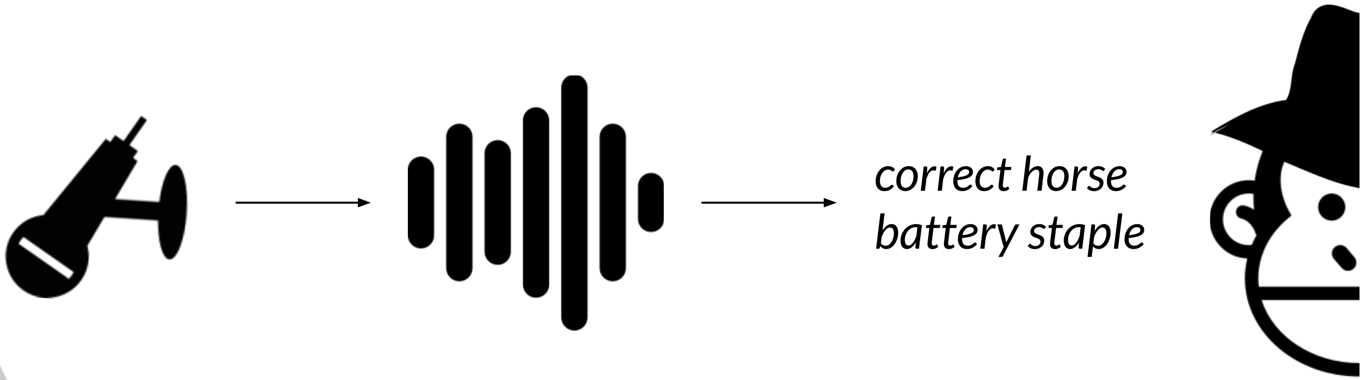
A. Compagno, M. Conti, D. Lain, G. Tsudik

<u>Don't Skype & Type! Acoustic Eavesdropping in Voice-over-IP.</u>

In ACM SIGSAC AsiaCCS 2017

Presented at Black Hat USA 2017

Keyboard Acoustic Eavesdropping



- Supervised Learning (Asonov, 2004; Halevi, 2012; 2014)
  Less input assumptions, more specific

- Unsupervised Learning (Berger, 2006; Zhuang, 2009)
  More input assumptions, more general

Keyboard Acoustic Eavesdropping

1 - How to get either:

- A lot of data
- Some labeled data

Keyboard Acoustic Eavesdropping

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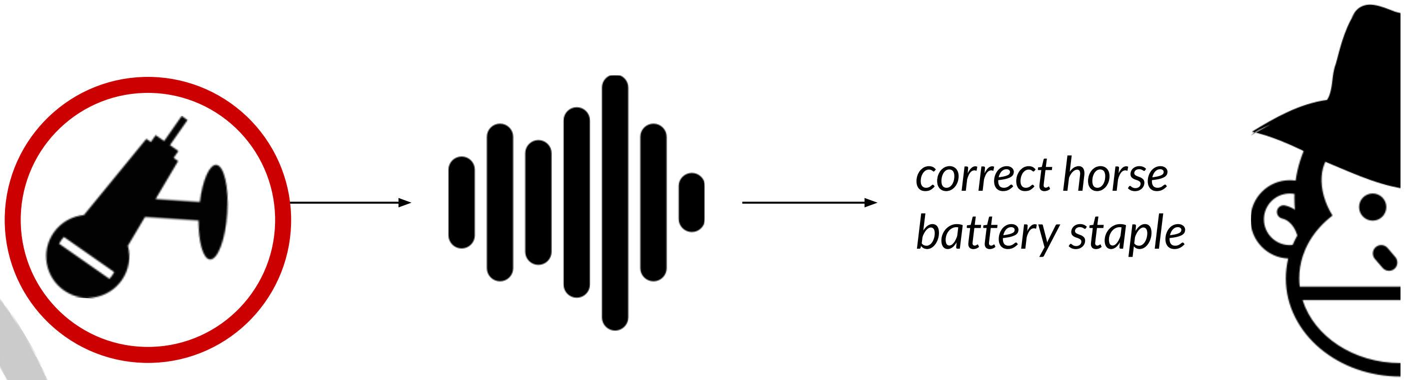


1 - How to get either:
- A lot of data
- Some labeled data

2 - How to place a compromised microphone close to my victim?

Motivation

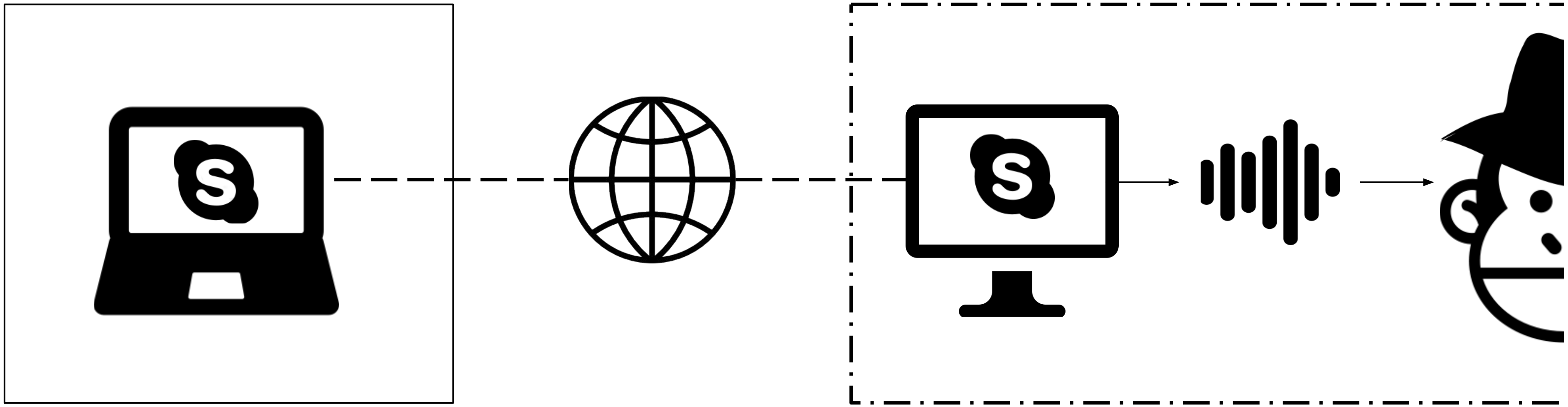
VoIP → one of the most used software: in academia, industry, at home

People type private stuff during Skype calls - it happens!

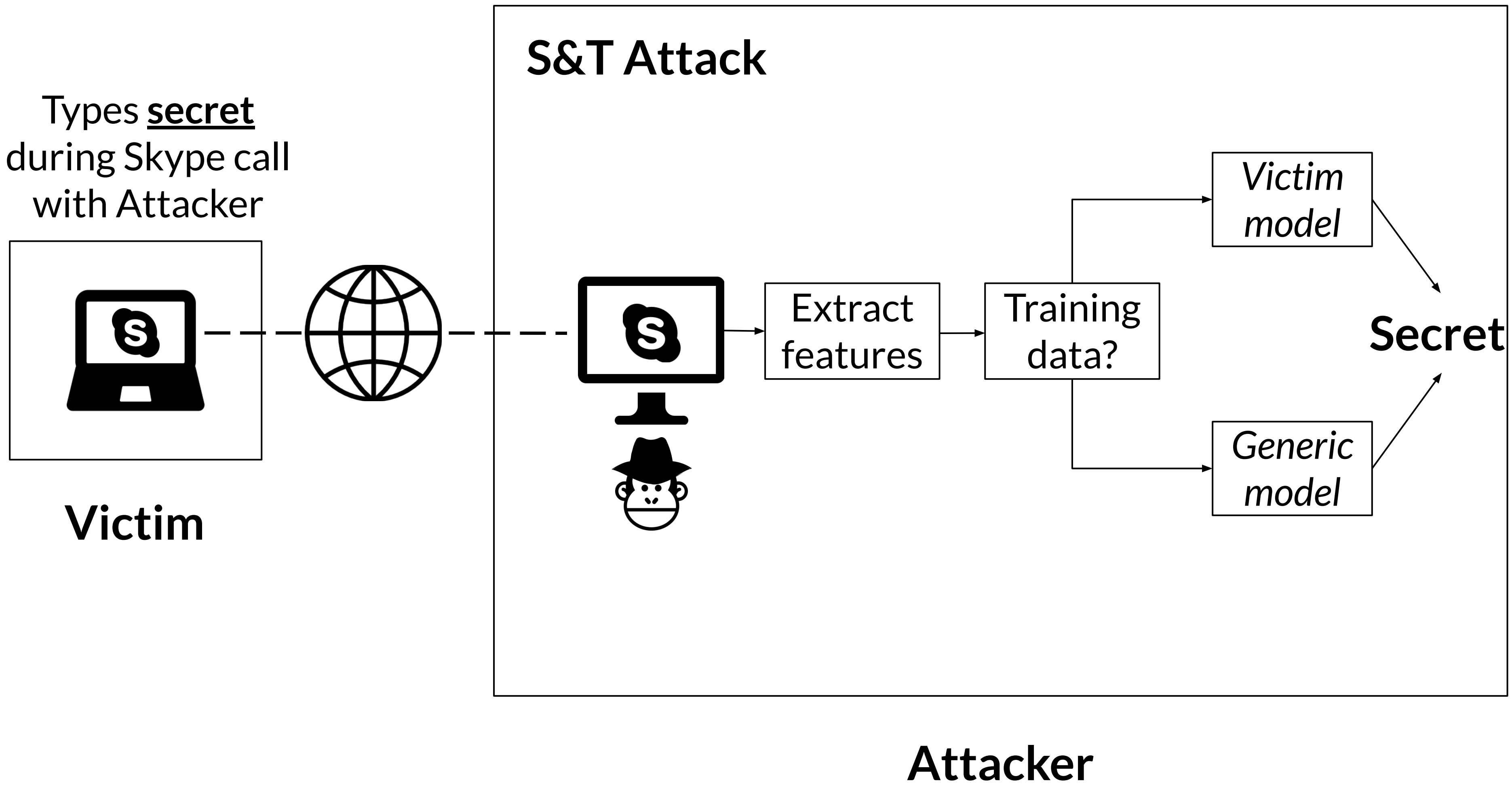
- *Login to websites*
- *Write a sensitive email*
- *Take notes*

We hear the keys' noise and use it to understand typed text

- *Victim is willingly giving us access to his microphone*



Skype&Type Attack



S&T - Tools

- Data windowing and segmentation

  To extract sound samples

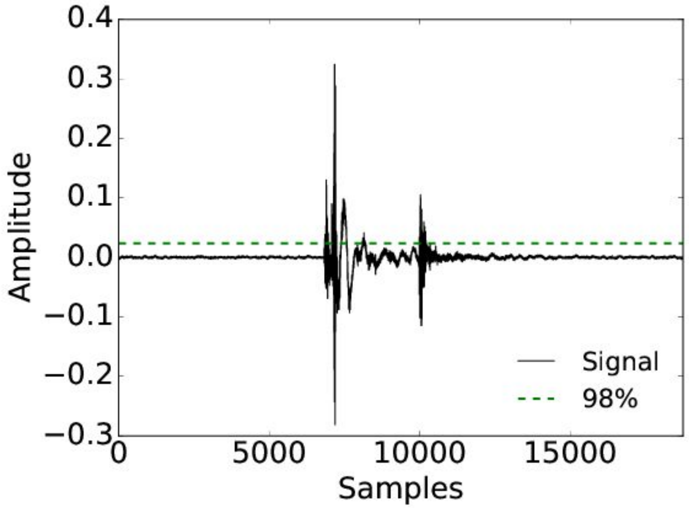
- Mel frequency cepstral coefficients

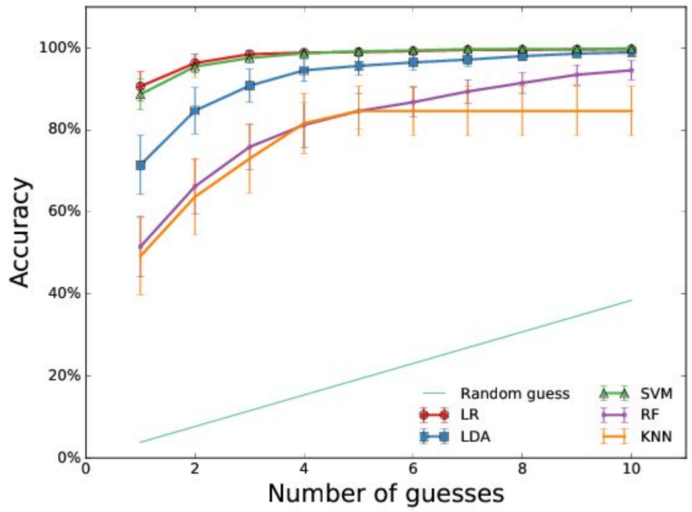
  Best performing and robust

- Supervised learning paradigm

  Target text can be possibly:
  - *Short (no clustering)*
  - *Random (no dictionary)*

- Logistic Regression classifier





Data Collection

- Try S&T in many scenarios
  - *With **5** different users over **Skype*** *(Google Hangouts also vulnerable)*
  - *Using **3** different common laptops: Macbook Pro, Lenovo, Toshiba*
  - *With **2** typing styles: single finger, and natural "touch" typing*

- Evaluate top-n accuracy of character recognition

  as a function of the number of guesses, focus on top-1 and top-5 accuracy

- Against a "dumb" random guess

  Might be a random password -- we can not use "smarter" approaches

Attack Scenarios

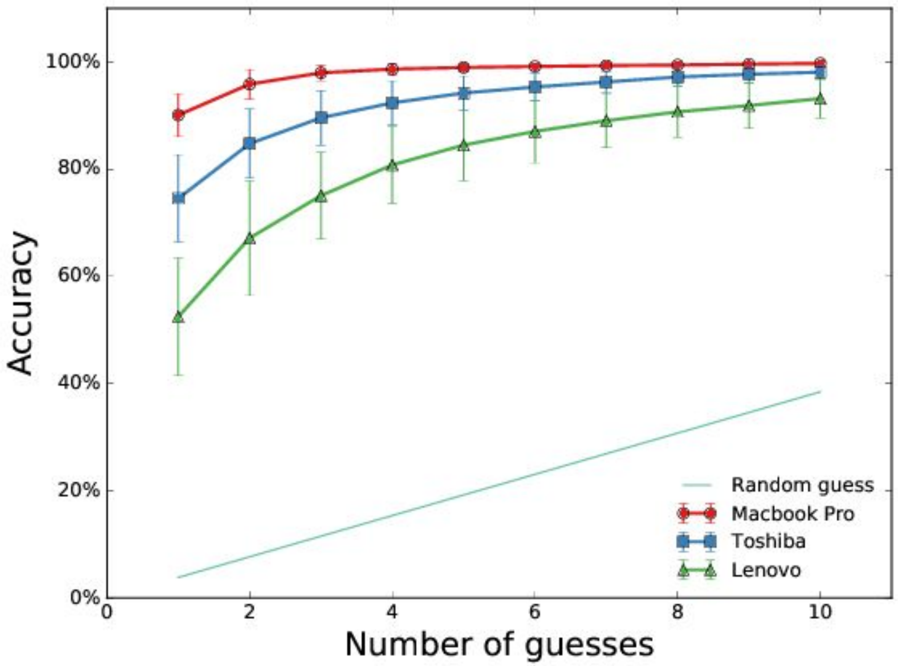
Evaluate the attack on two realistic scenarios

- Complete Profiling Scenario **(Asonov, 2004; Halevi, 2012; 2014)**
  - *Profiled the user on his laptop → specific training set*
  - *Ground truth disclosure, e.g., a short chat message*

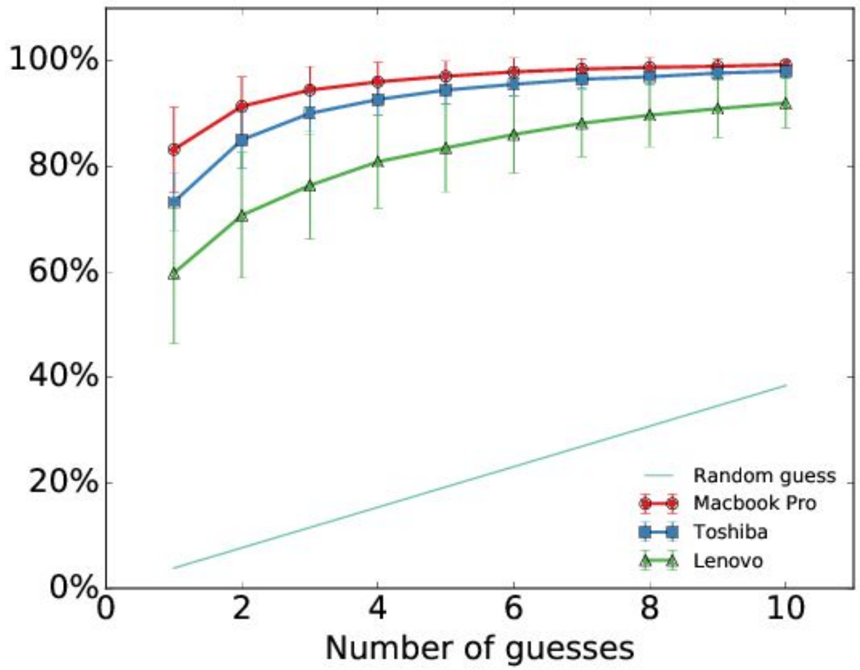
- Model Profiling Scenario
  - *Profiled a laptop of the same model on some users*
  - ***Victim is/can be unknown!***

Complete Profiling

Training set with the data the user disclosed



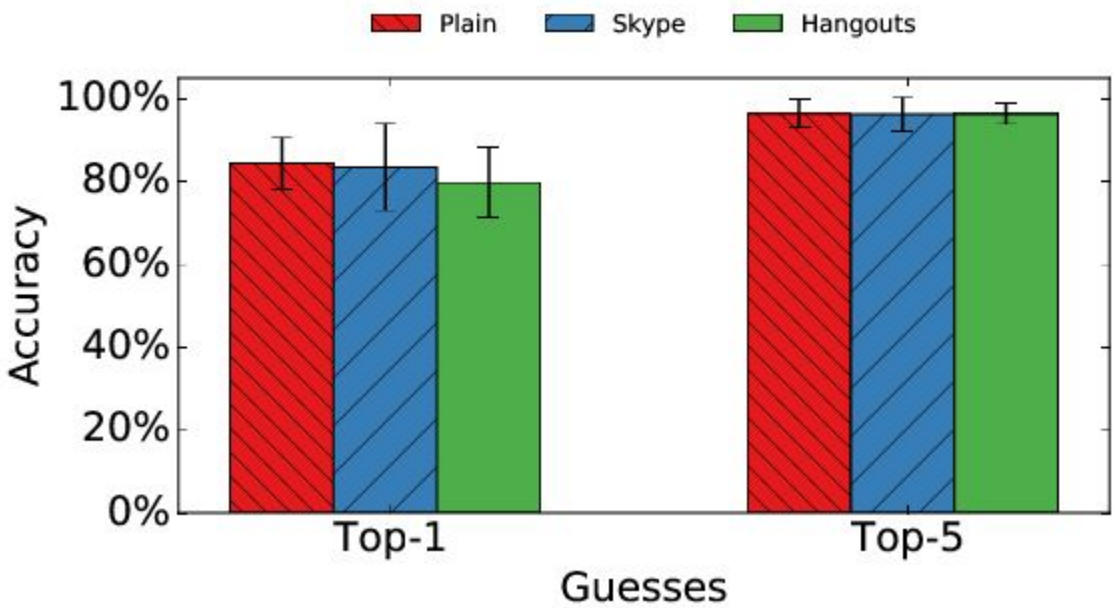
Hunt&Peck typing, unfiltered data



Touch typing, Skype filtered data

Complete Profiling

Is only Skype vulnerable to our attack?



No! It looks like a common problem for VoIP software

Model Profiling Setup

On the *Model Profiling* Scenario, the victim can be unknown

Someone the attacker does not know personally

First need to understand the laptop of the victim

→ match it with a database of model signatures

- Guess correctly **93%** of the times if the model is known
- Statistical measures if the model is unknown

Model Profiling

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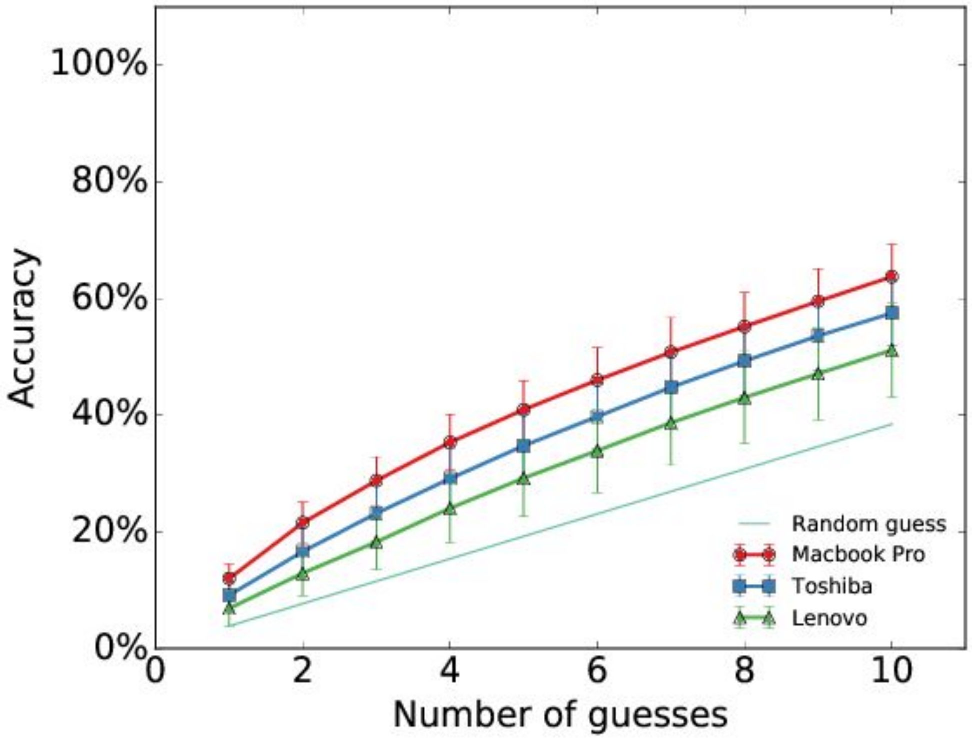
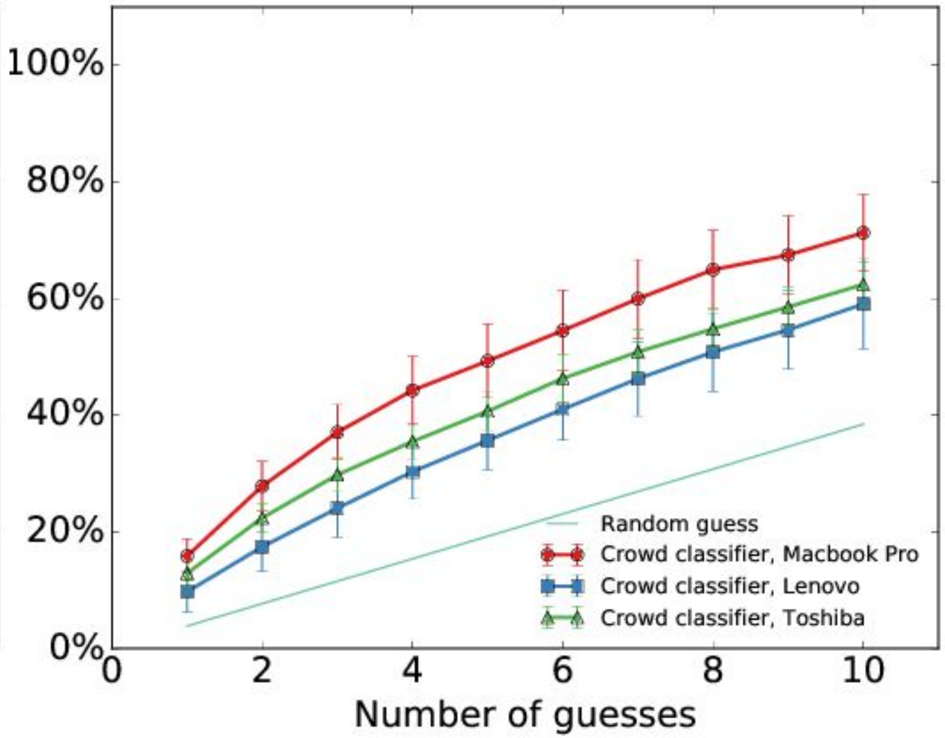
One user

"Crowd" of multiple users





Summing Up Our Results

- Recognize a single character
  - *Complete Profiling: 90%+ accuracy*
  - *Model Profiling: 40%+ accuracy*

- Recognize a single word
  - *Complete Profiling: 98% correct letters*
  - *Model Profiling: 50% correct letters*

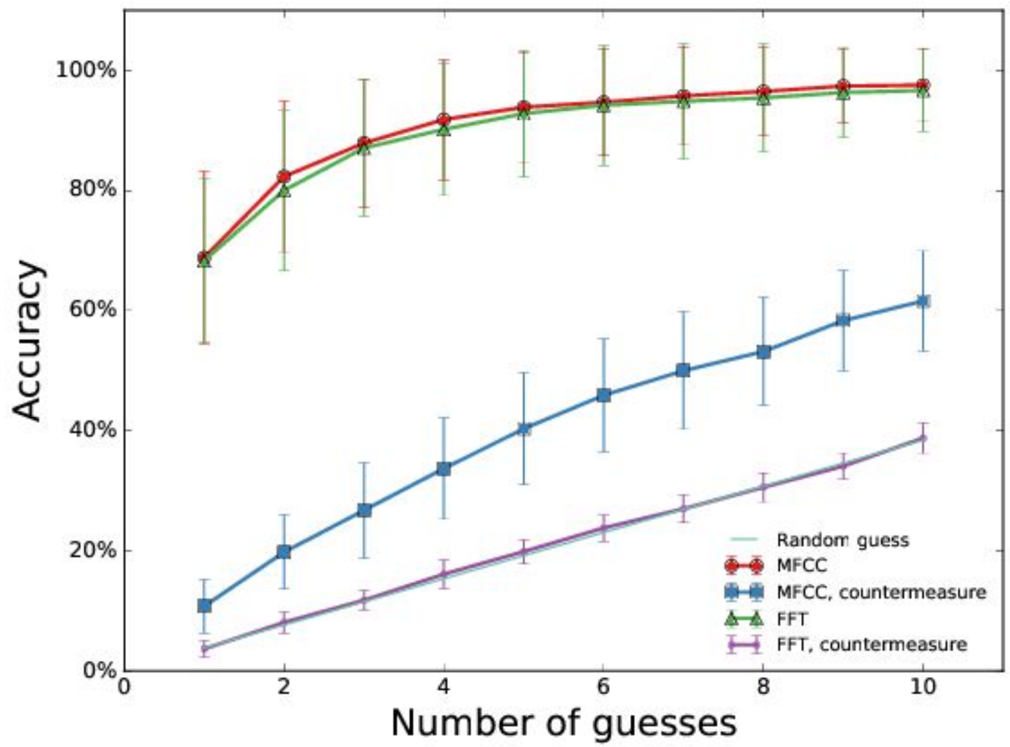
- Recognize a random password
  - *Improves 1-5 orders of magnitude time needed to guess the password*
  - *From 50 days to 42 seconds on a domestic PC*

Countermeasures

- <u>Don't Skype & Type</u>

- Remove volume when we detect a keypress sound
  - *Impacts voice, greatly degrades call quality*

- Disrupt spectral features with random equalization
  - *Assess impact on voice, real time feasibility*



Conclusions & Future Work

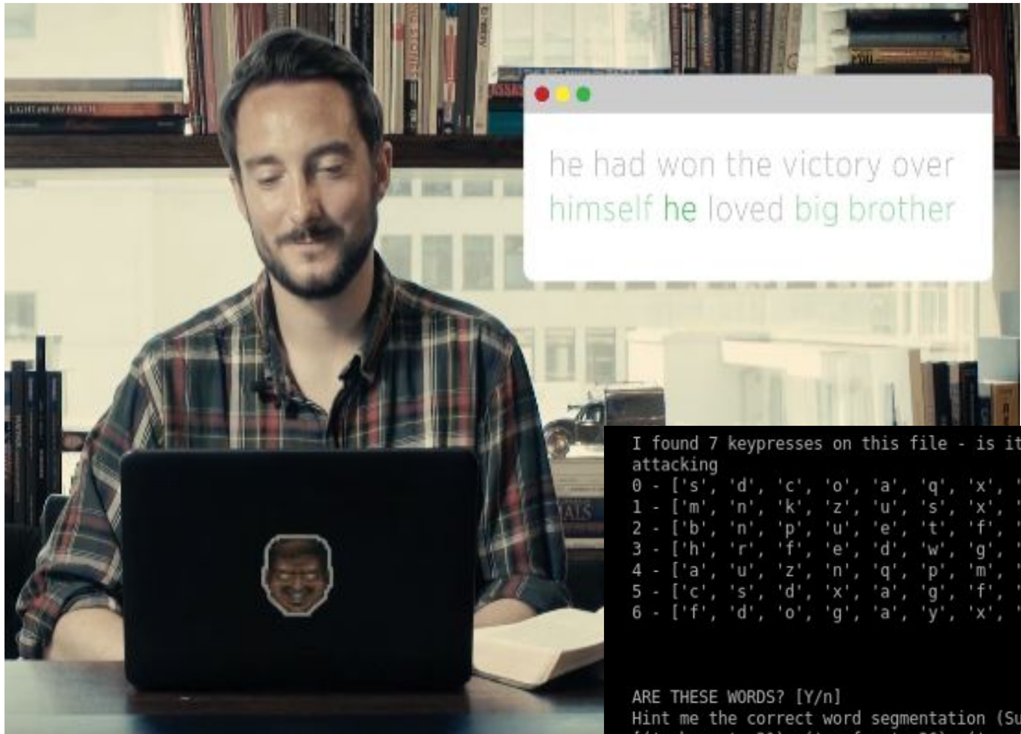
- VoIP Keyboard acoustic eavesdropping a serious threat

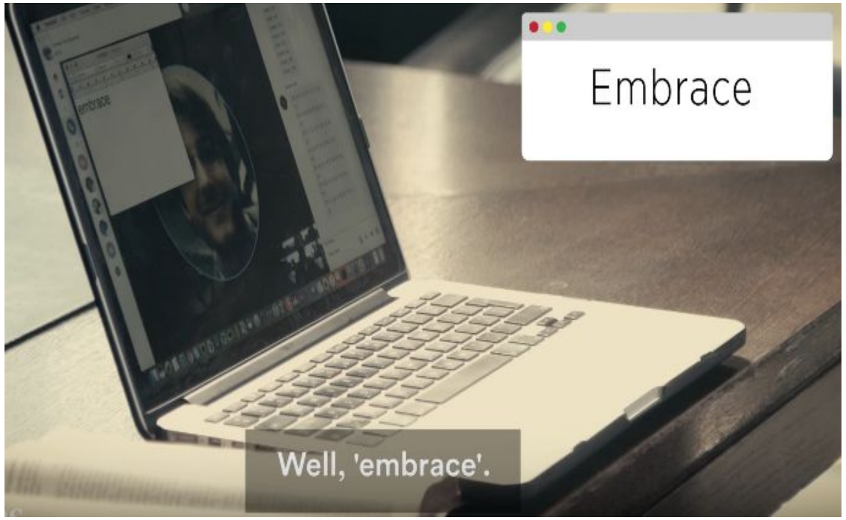
- Feasible and accurate:
  - *Realistic attack scenarios*
  - *91.71% on **Complete Profiling** scenario*
    - *Halevi (2012; 2014): 85.78%*
  - *41.89% on **Model Profiling** scenario*
    - *Novel attack vs. unknown victims*
  - *Robust to degradation and to voice*

- Future work:
  - *Try more users and different keyboards, and on more VoIP software*
  - *Try to attack another user in the same room*
  - *Analyze and improve the countermeasures*

Does it **really** work?

vs Forbes, 1984 & the Bible






```
I found 7 keypresses on this file - is it correct? [Y/n]
attacking
0 - ['s', 'd', 'c', 'o', 'a', 'q', 'x', 'f', 'g']
1 - ['m', 'n', 'k', 'z', 'u', 's', 'x', 'i', 'a']
2 - ['b', 'n', 'p', 'u', 'e', 't', 'f', 's', 'v']
3 - ['h', 'r', 'f', 'e', 'd', 'w', 'g', 'p', 'c']
4 - ['a', 'u', 'z', 'n', 'q', 'p', 'm', 'c', 's']
5 - ['c', 's', 'd', 'x', 'a', 'g', 'f', 'k', 'z']
6 - ['f', 'd', 'o', 'g', 'a', 'y', 'x', 'h', 'c']



ARE THESE WORDS? [Y/n]
Hint me the correct word segmentation (Suggested spaces in []):
[('embrace', 21), ('surface', 26), ('conduct', 28), ('disease', 29), ('attract', 30), ('courage', 31), ('fantasy', 32), ('contact', 3
3), ('intense', 33), ('library', 33), ('silence', 33), ('already', 34), ('average', 34), ('defense', 34), ('impress', 34), ('subject'
, 34), ('suppose', 34), ('discuss', 35), ('expense', 35), ('offense', 36), ('science', 36), ('storage', 36), ('absence', 37), ('stoma
ch', 37), ('finance', 38), ('operate', 38), ('overall', 38), ('suspect', 38), ('century', 39), ('funding', 39)]
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Credits: https://www.forbes.com/sites/thomasbrewster/2017/07/06/skype-and-type-attack-steals-passwords

Thank you!

Questions?

(if you do not have one, please find some suggestions below)