Covert & Side Stories:
Threats Evolution in Traditional and Modern Technologies

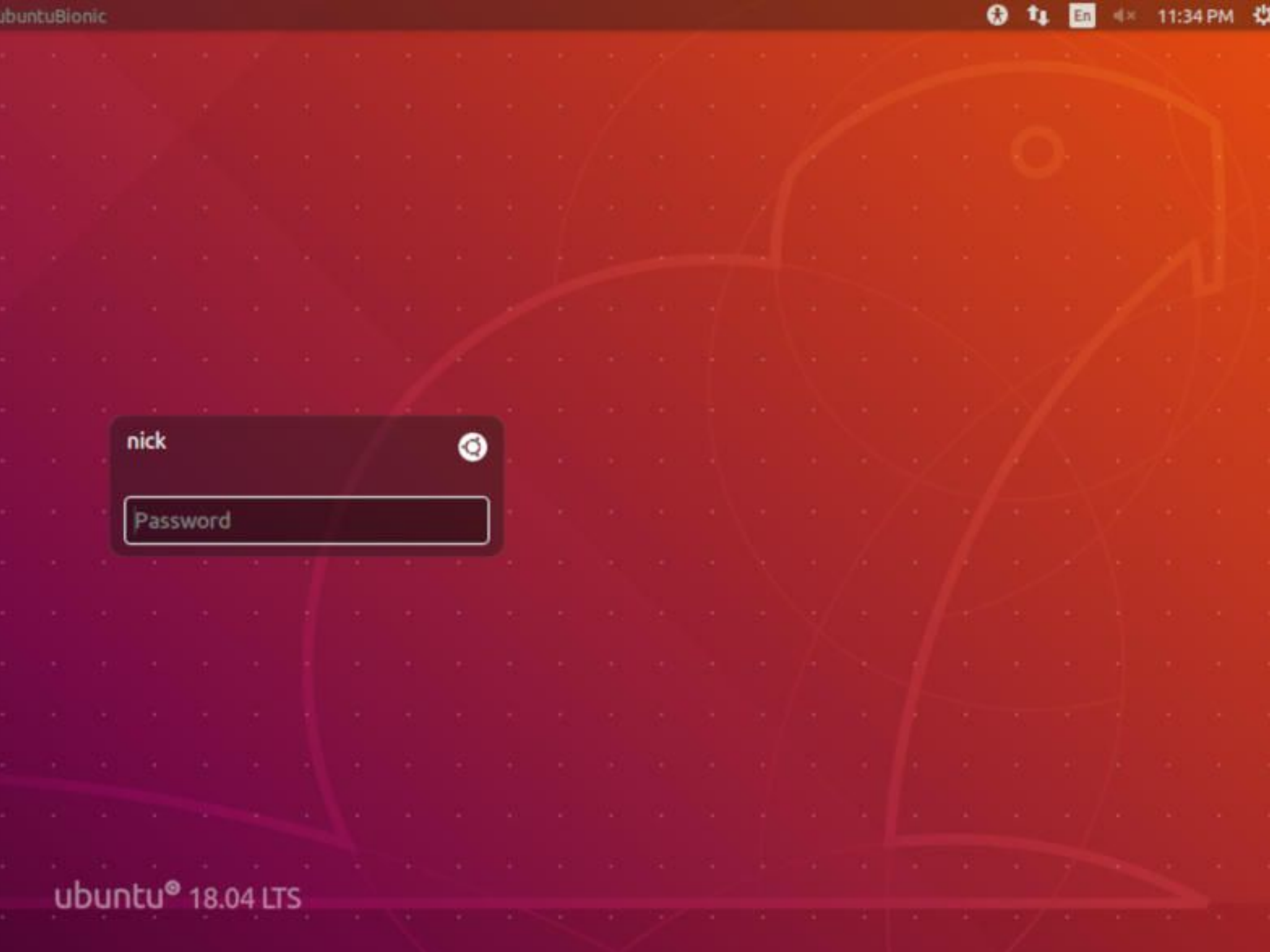
Mauro Conti

February 27, 2024

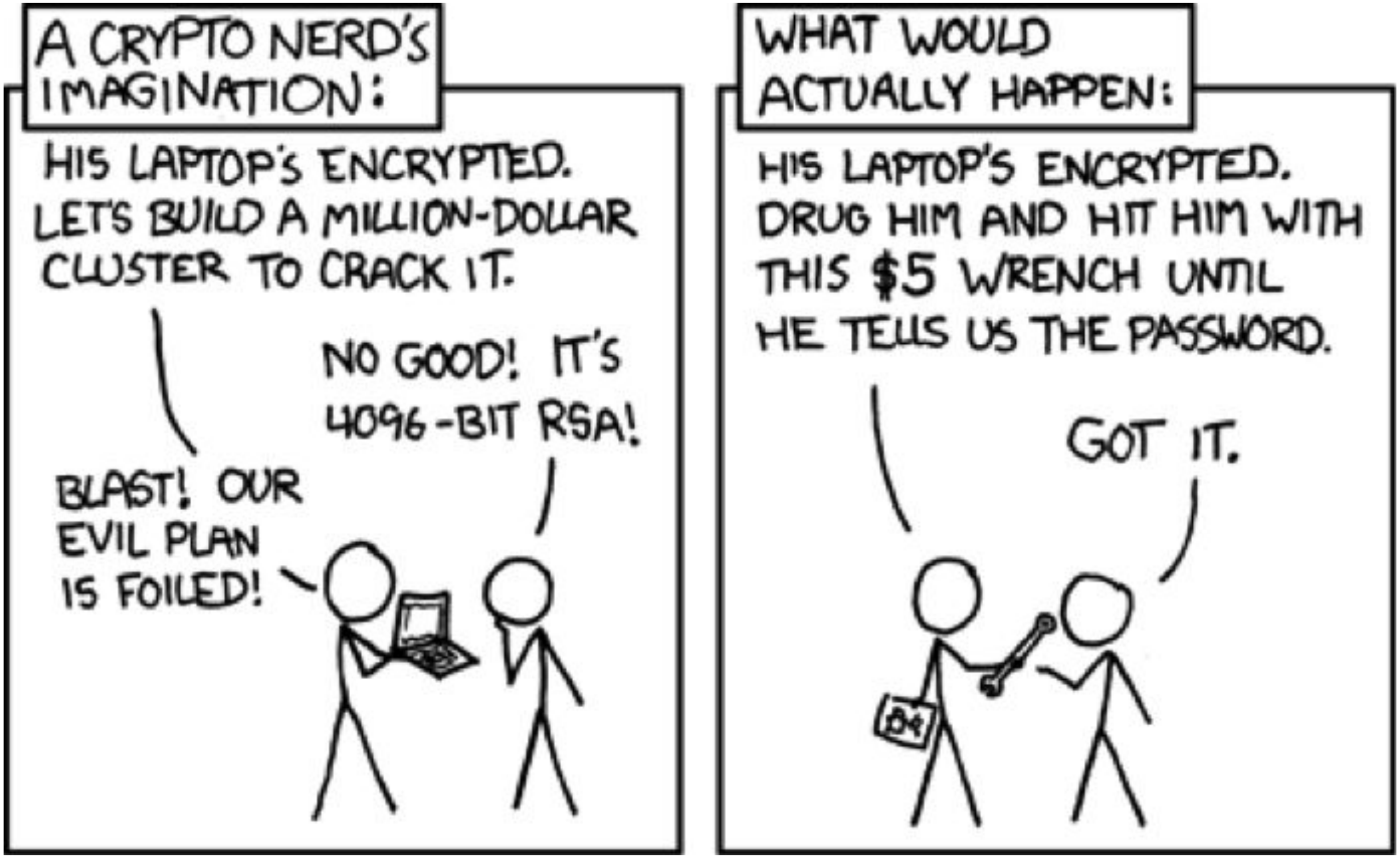
ICISSP 2024
10th International Conference on Information Systems Security and Privacy
ROME, ITALY | 26 - 28 February, 2024

SPRITZ
Security & Privacy
Research Group

Università
degli Studi
di Padova


ubuntuBionic
En
11:34 PM
nick
Password
ubuntu® 18.04 LTS

Outline



A CRYPTO NERD'S IMAGINATION:
HIS LAPTOP'S ENCRYPTED. LET'S BUILD A MILLION-DOLLAR CLUSTER TO CRACK IT.
NO GOOD! IT'S 4096-BIT RSA!
BLAST! OUR EVIL PLAN IS FOILED!
WHAT WOULD ACTUALLY HAPPEN:
HIS LAPTOP'S ENCRYPTED. DRUG HIM AND HIT HIM WITH THIS $5 WRENCH UNTIL HE TELLS US THE PASSWORD.
GOT IT.


DELL


SAFUEL
FAST CHARGE

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*

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*

Physical Property Leveraged

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*

Keystroke Inference

Outline

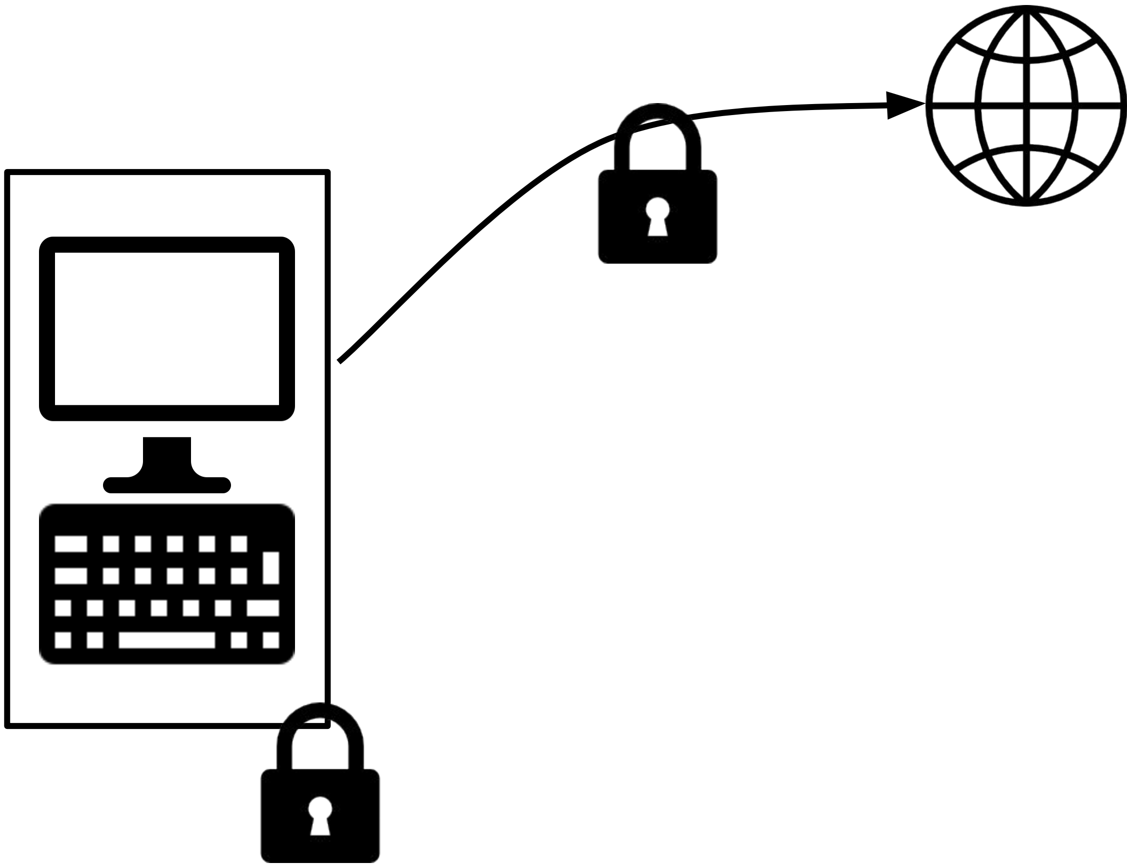
- **<u>Covert and Side Channels 101</u>**

- 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*

Side Channels

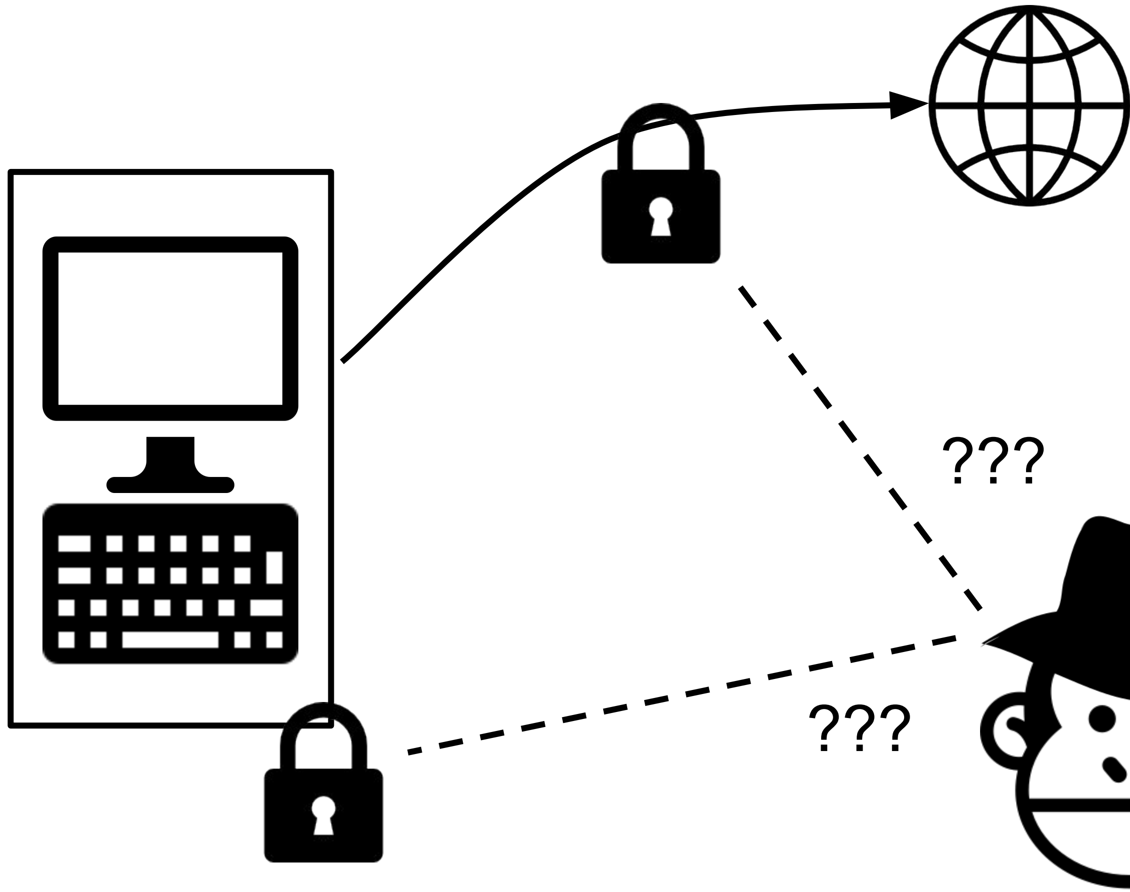
Devices, and network communication, are usually **protected** and **encrypted**



Side Channels

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

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



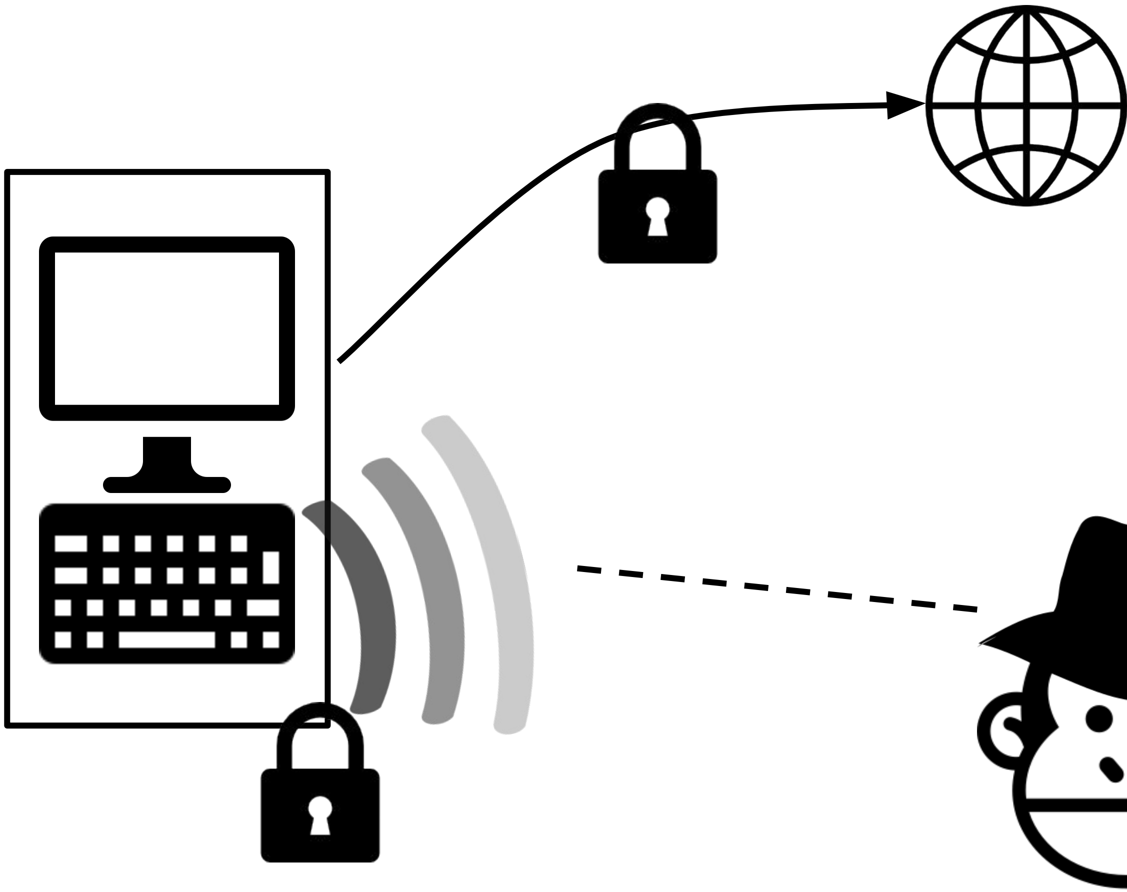
SPRITZ Security & Privacy Research Group
Università degli Studi di Padova

Side Channels

Observing emanations and patterns

Can reveal secrets!

This is called a **side channel**

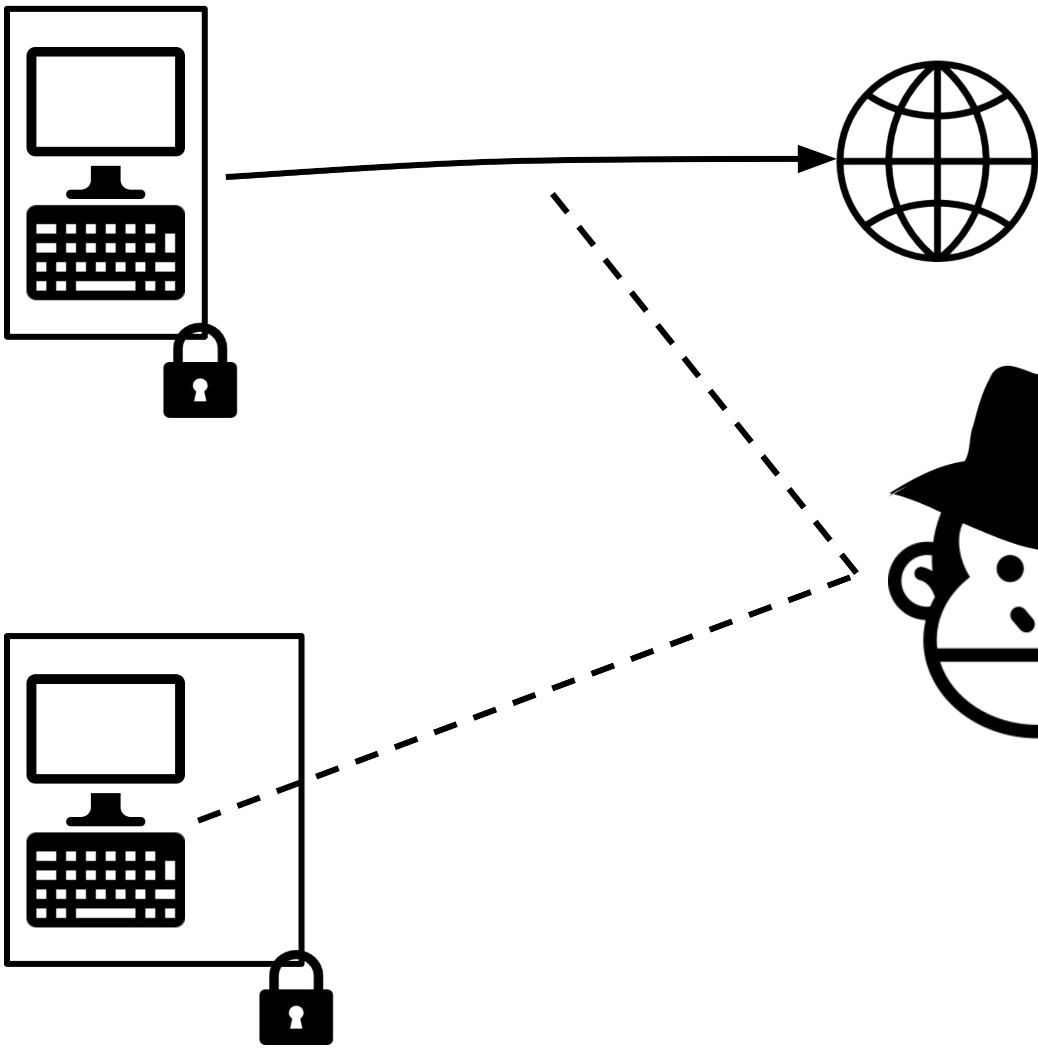


Covert Channels

Covert Channels are used to communicate stealthily.

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

…or to exfiltrate information.



Outline

- Covert and Side Channels 101
- **<u>Network Traffic Analysis</u>**
  - *<u>As a side channel: app and sensitive data inference</u>*
- 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*

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.

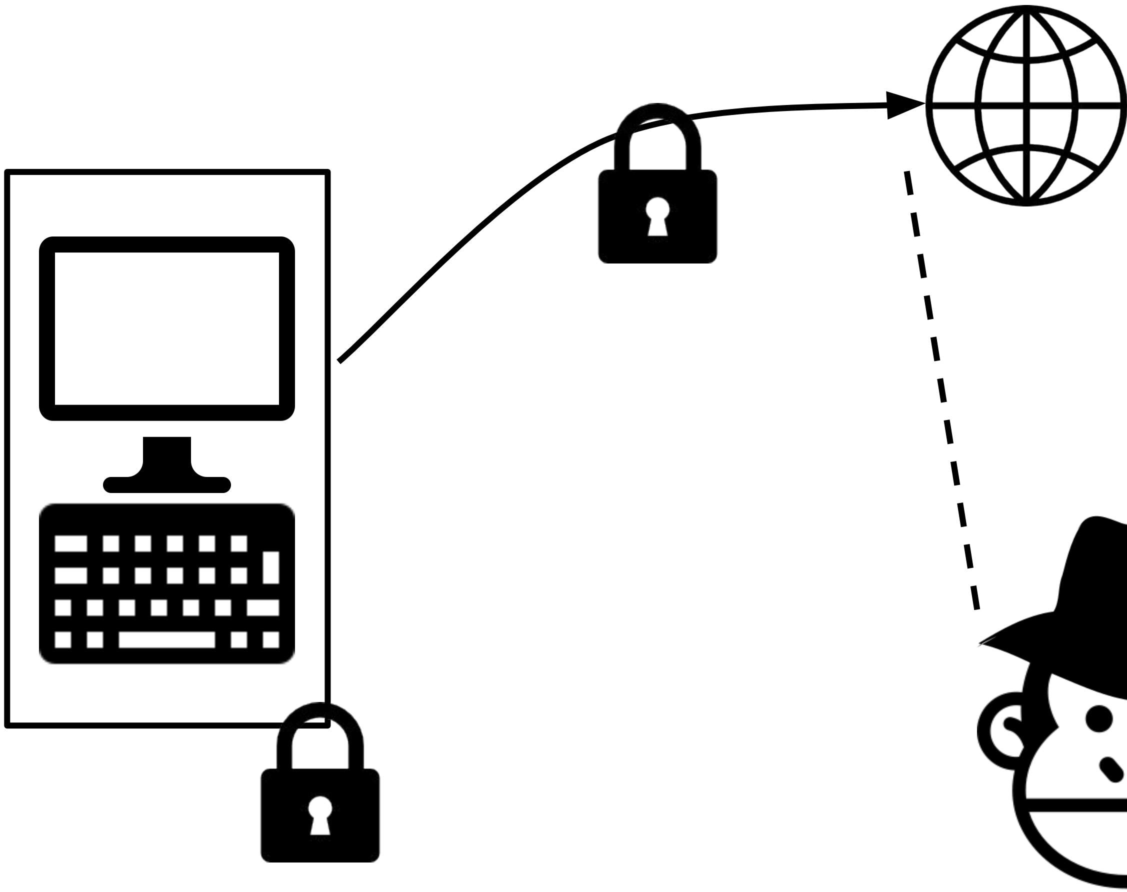
AppScanner: Automatic Fingerprinting of Smartphone Apps From Encrypted Network Traffic.

In IEEE EuroSP 2016

Traffic Analysis

Traffic patterns

Can reveal what we are doing!



Device-platform interaction reveals our actions

Called **traffic analysis**

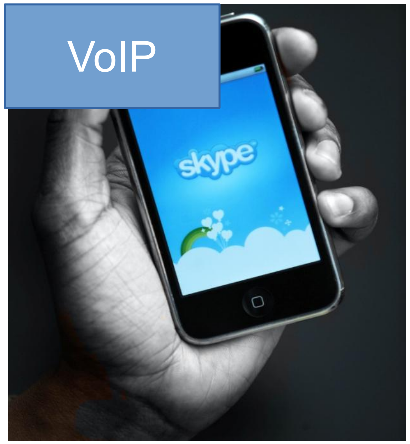
Motivation

Encryption is not enough!

SSH

[Song et al. '11]

VoIP



[Wright et al. '08]

Attacker's observations

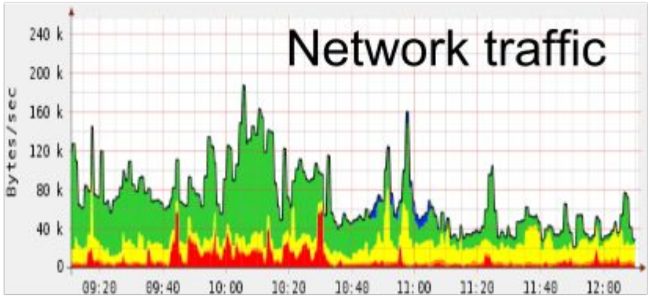
- Coarse features:
  - Packet lengths
  - Packet directions
  - Packet timings
  - ....

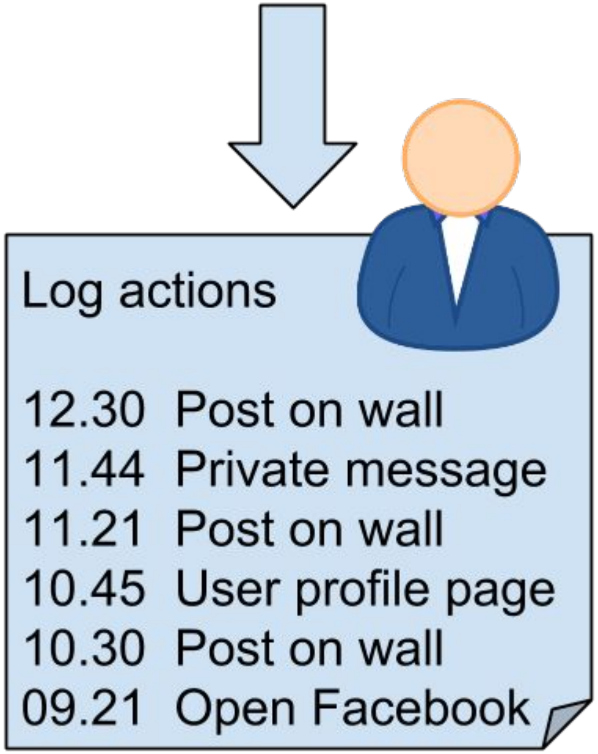
Enable Traffic Analysis Attacks

Attack scenario

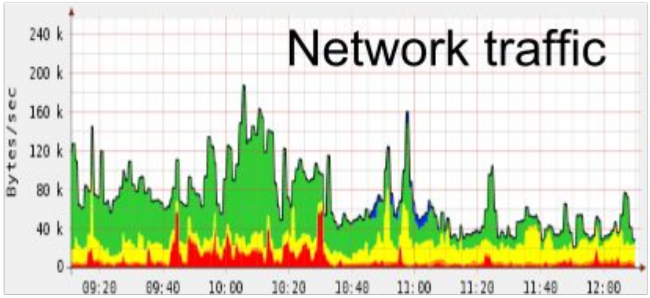
SPRITZ
Security & Privacy
Research Group

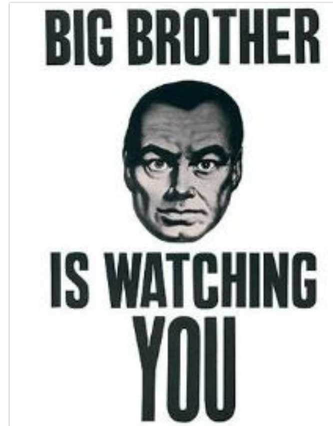
Università
degli Studi
di Padova





Attack scenario

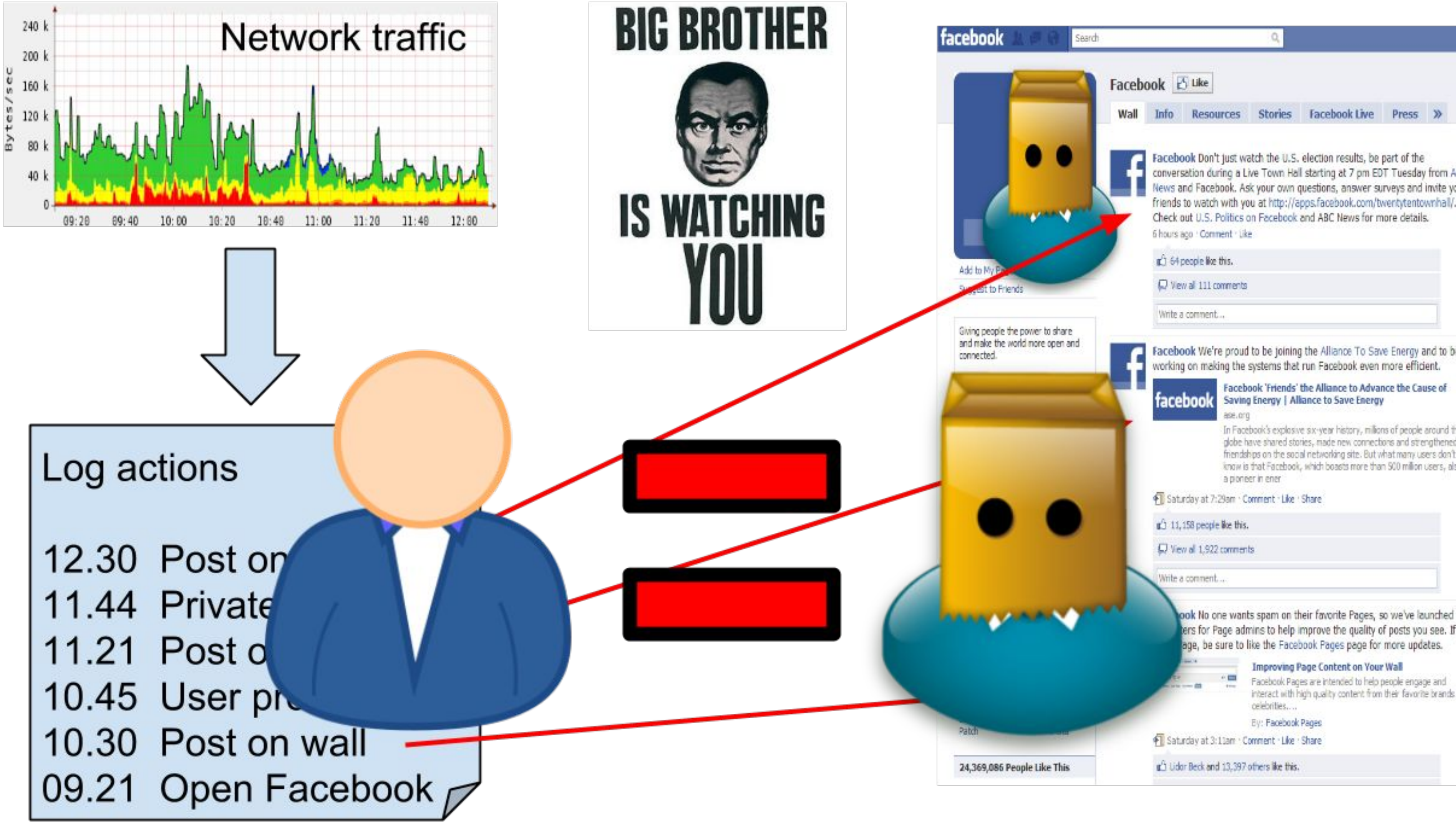




Log actions

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



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

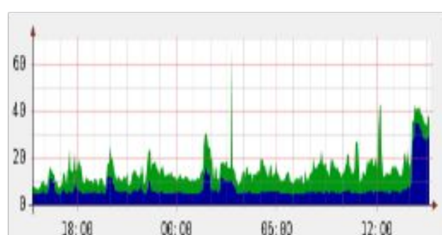
User actions

Operation on apps

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

produce

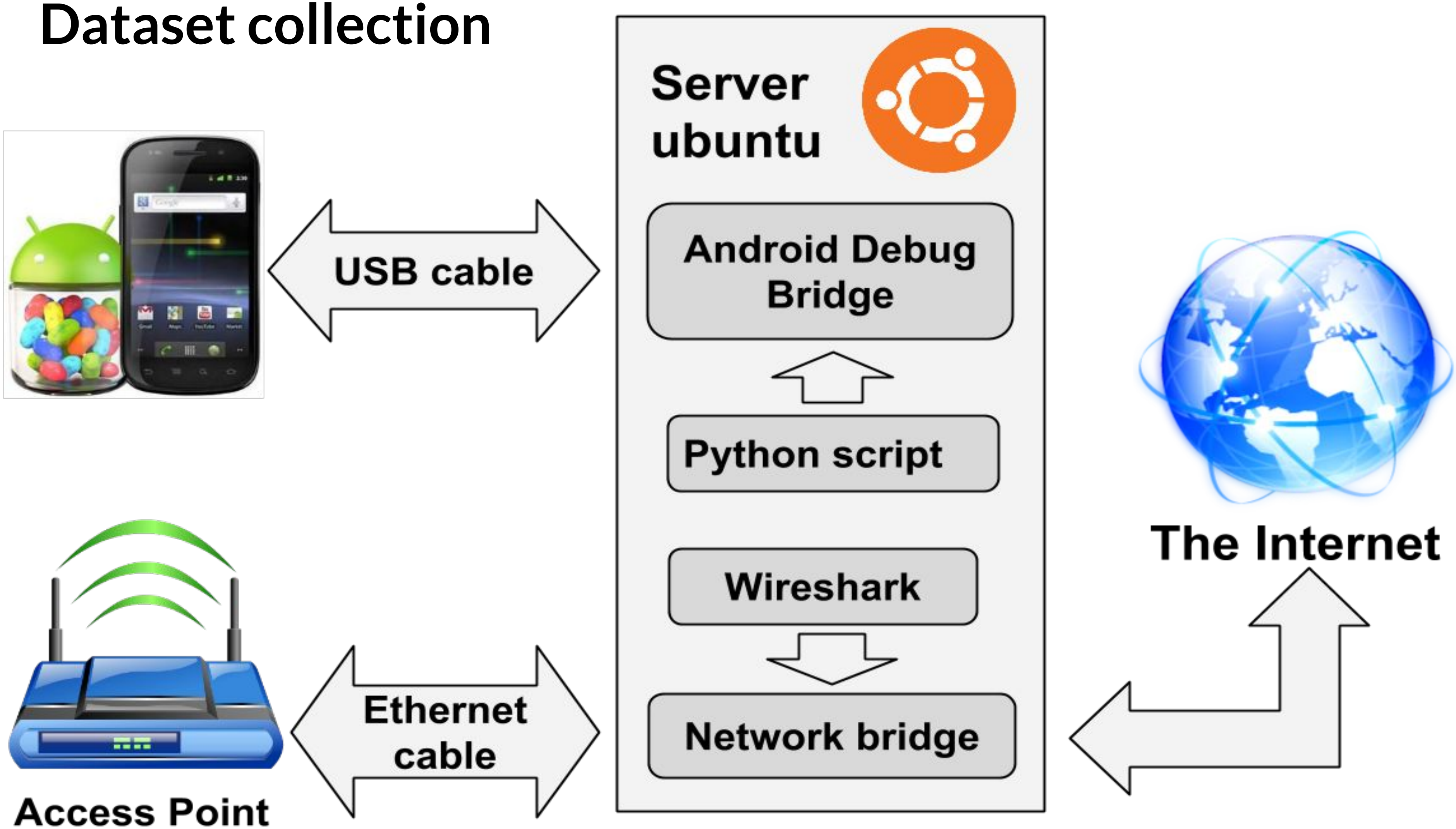
Network flows



Sequence of packets

Couple of IP addresses and ports

Dataset collection

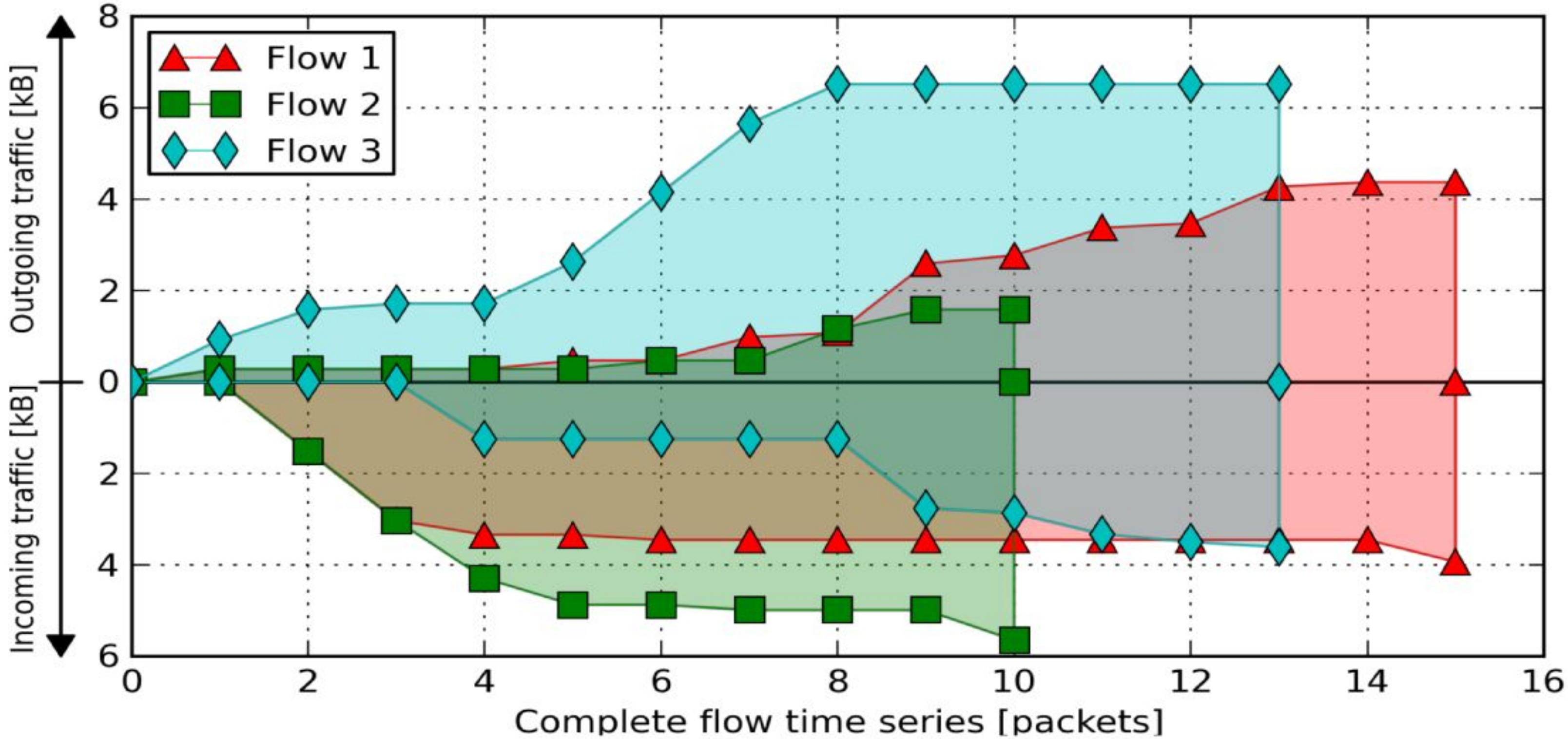


Can't you hear me knocking (CODASPY '14, TIFS '15)

SPRITZ Security & Privacy Research Group

Università degli Studi di Padova

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)

SPRITZ Security & Privacy Research Group

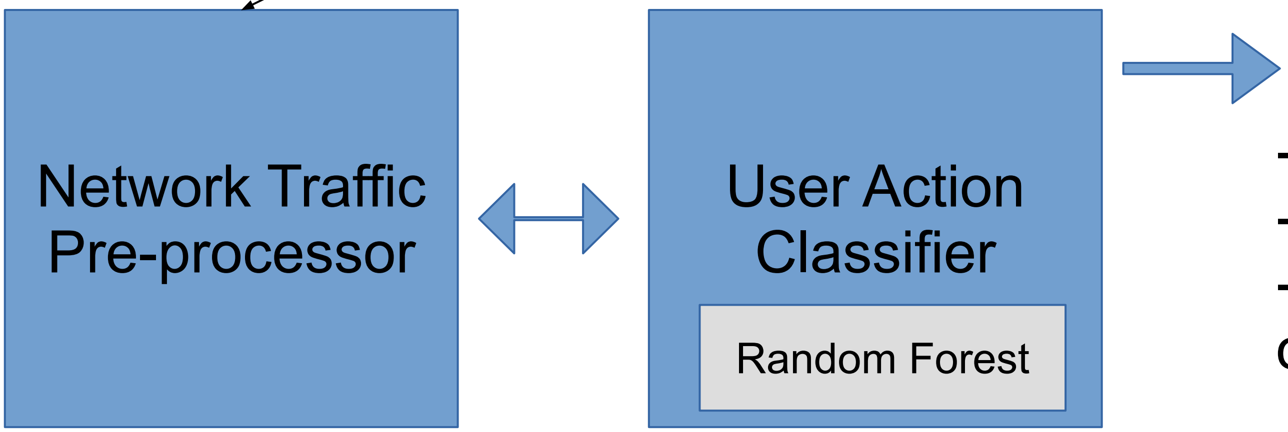
Università degli Studi di Padova

The framework

Labeled Dataset

Phase 1.
Training

Phase 2.
Testing



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

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

Training phase

1. Unsupervised learning →**Clusters** of similar flows
   - **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**

Evaluation phase

1. User actions produce **unseen flows**

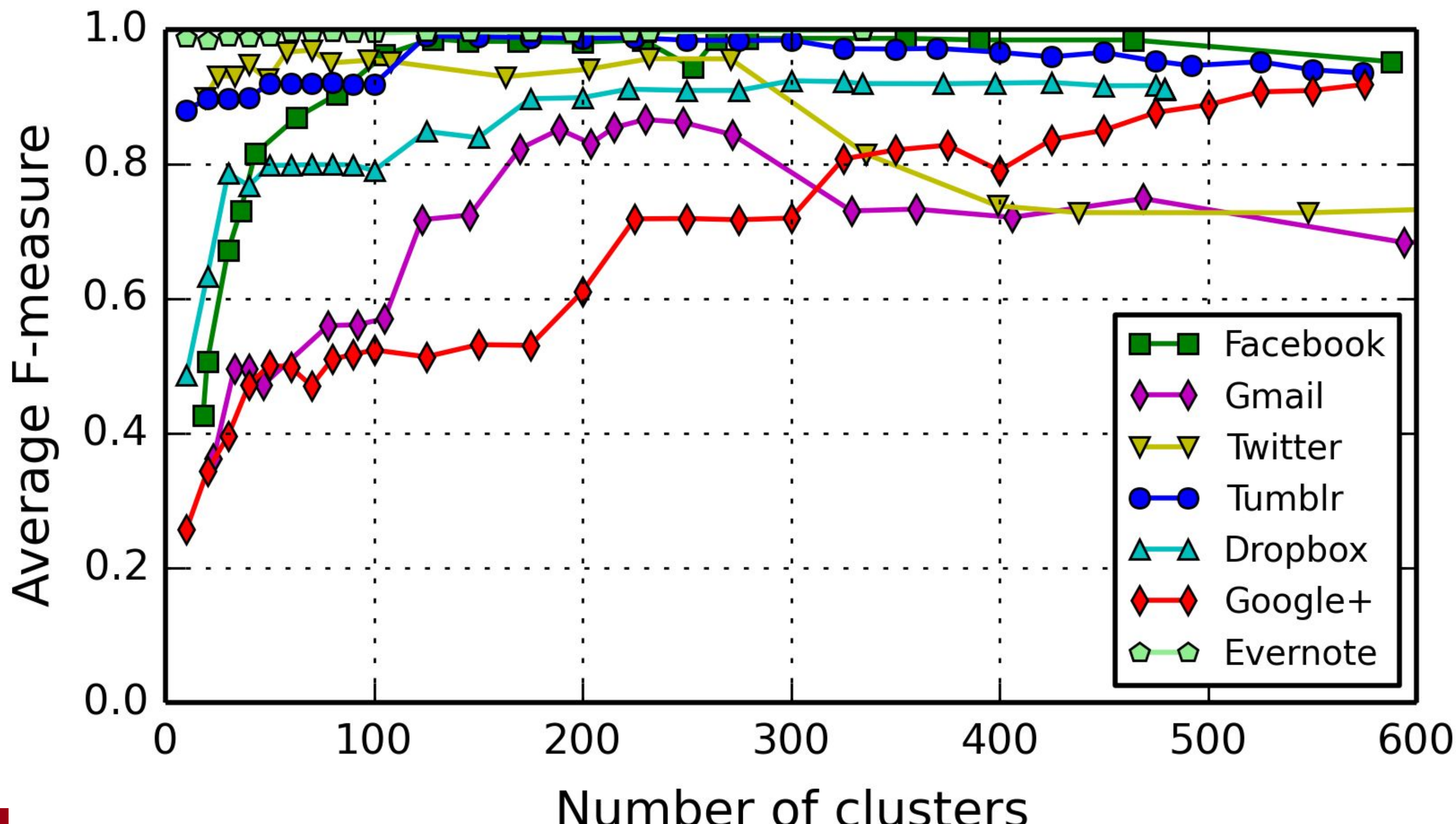
2. Assign each **unseen flow** to a **cluster**
   - clusters used in **training** phase and **DTW** as metric

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

4. User action **recognition**

© Ron Leishman * www.ClipartOf.com/439797

Accuracy vs. number of clusters

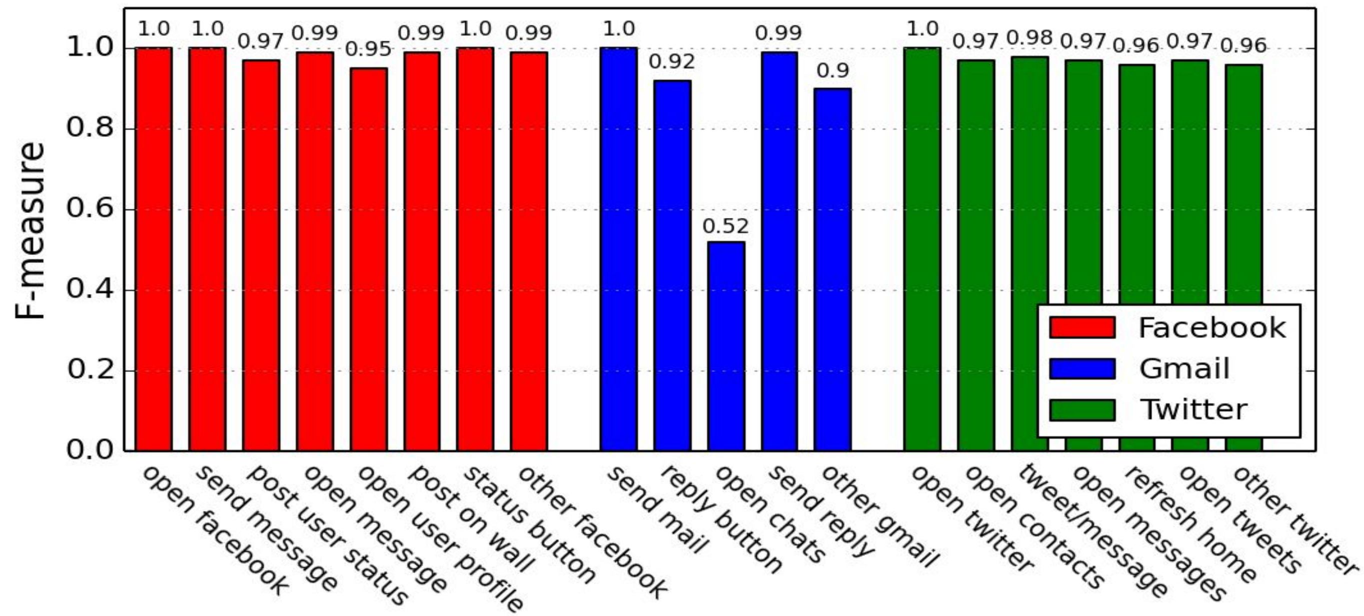


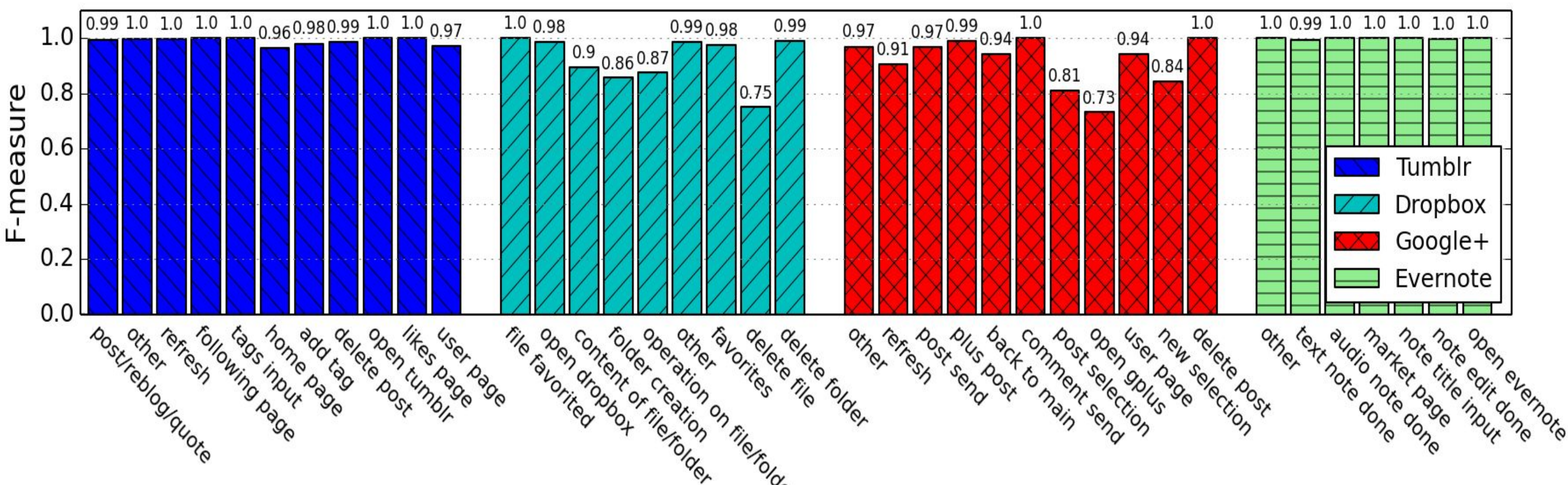
Can't you hear me knocking (CODASPY '14, TIFS '15)

SPRITZ Security & Privacy Research Group

Università degli Studi di Padova

Accuracy per user action





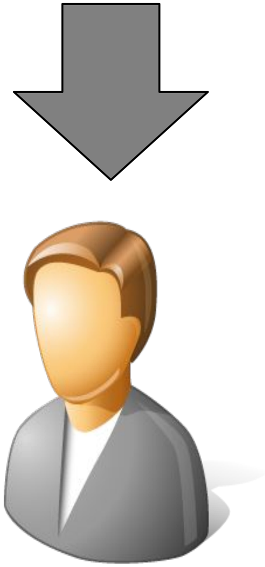
Conclusions

- 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

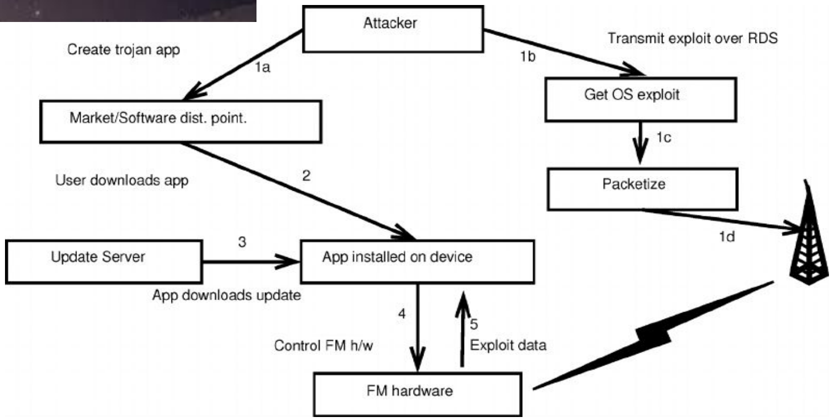


S. Seneviratne, A. Seneviratne, P. Mohapatra, A. Mahanti. "Predicting User Traits From a Snapshot of Apps Installed on a Smartphone" in ACM SIGMOBILE Mobile Computing and Communications Review 2014.

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

Motivation

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

It isn’t so easy!

Motivation

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

It isn’t so easy!

- Encryption → Payload inspection is not feasible

Motivation

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

It isn't so easy!

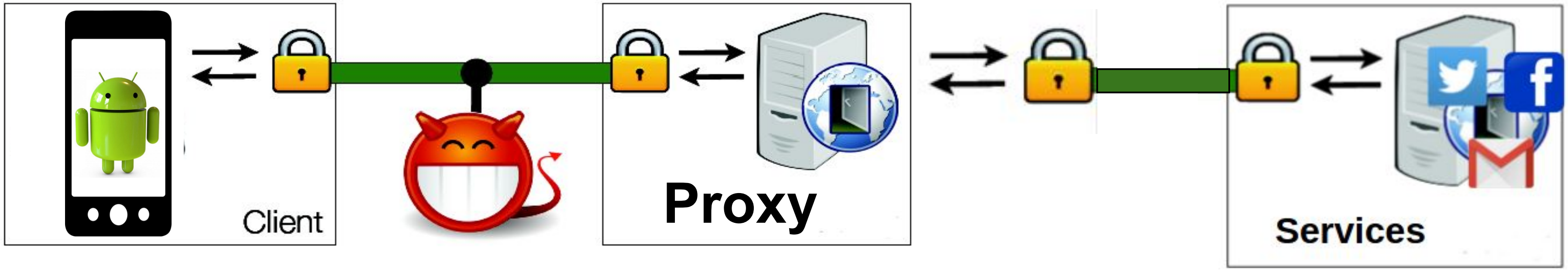
- Encryption → Payload inspection is not feasible
- Owner of Destination IP ≠ App
    - Content Delivery Network (CDN)
    - Proxy

SPRITZ Security & Privacy Research Group
Università degli Studi di Padova

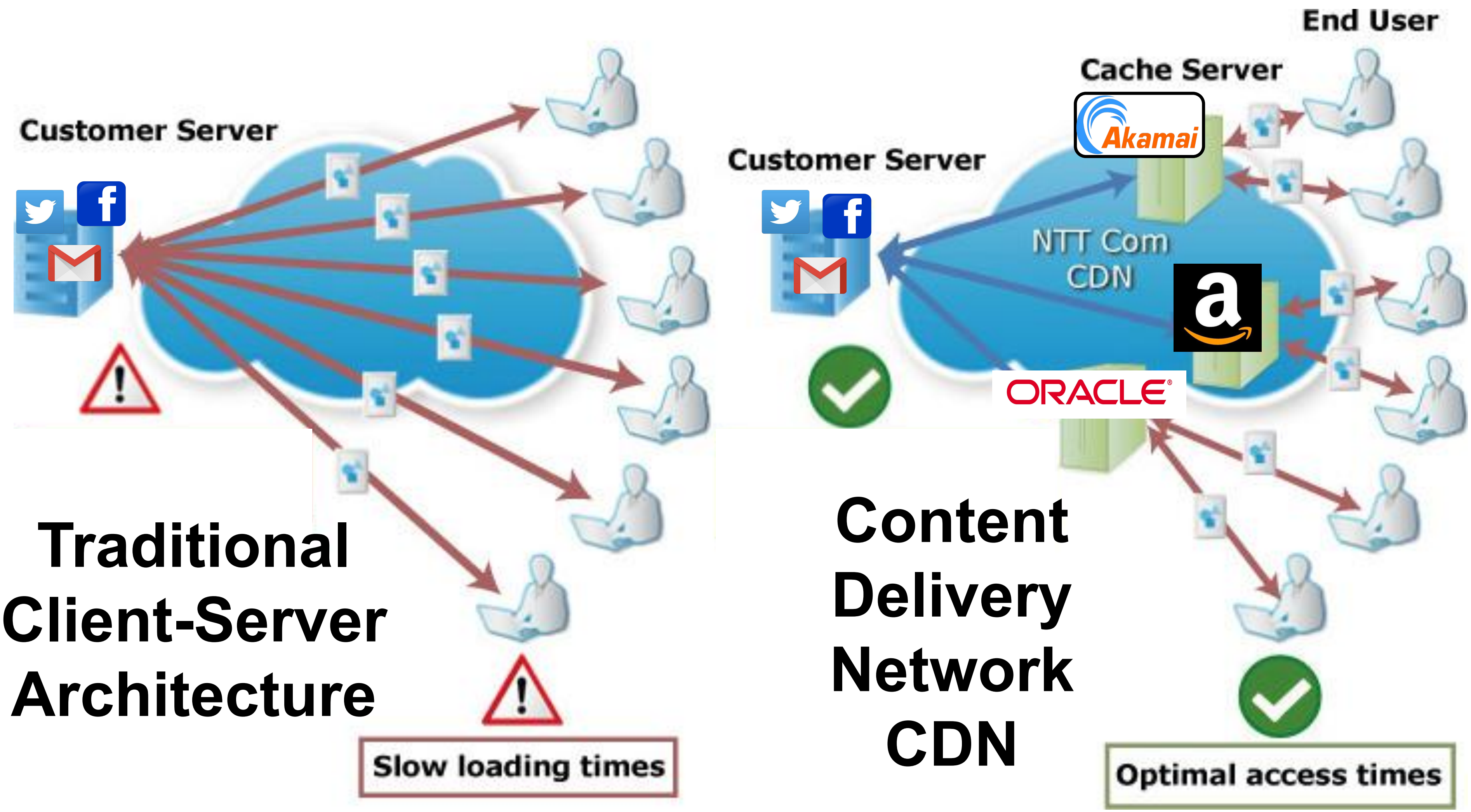
Attacker's observations (similarly to the previous work)

- Packet length
- Packet directions
- Packet timings

Enable Traffic Analysis Attacks



AppScanner
(IEEE EuroS&P '16)



Traditional Client-Server Architecture

Content Delivery Network CDN

Three different approaches proposed:

1. **Per flow Multi-class** length classification
   ○ A classifier for each length
   ○ No out-of-order packets resiliency, but fast

Three different approaches proposed:

AppScanner (IEEE EuroS&P '16)

SPRITZ Security & Privacy Research Group
Università degli Studi di Padova

Three different approaches proposed:

1. **Per flow Multi-class** length classification
   - A classifier for each length
   - No out-of-order packets resiliency, but fast

2. **Large Multi-class** classification
   - Uses statistics on network flows
   - It works on a **set of apps**
   - **High Accuracy** and out-of-order packets resiliency, but slow

AppScanner
(IEEE EuroS&P '16)

Three different approaches proposed:

1. **Per flow Multi-class** length classification
   - A classifier for each length
   - No out-of-order packets resiliency, but fast
2. **Large Multi-class** classification
   - Uses statistics on network flows
   - 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

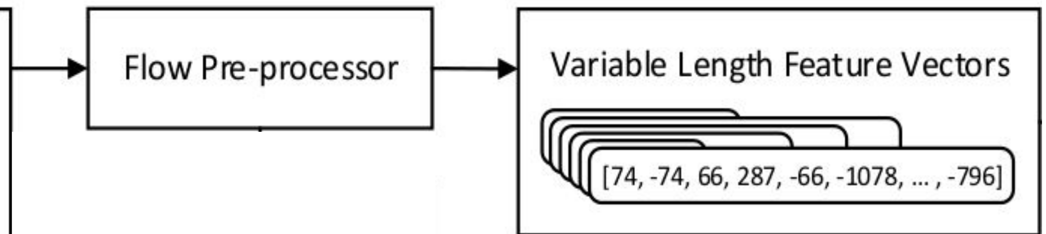
TCP Packets captured

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
23.23.162.140	192.168.137.2	TCP	1078
23.23.162.140	192.168.137.2	TLSv1	796

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
23.23.162.140	192.168.137.2	TCP	1078
23.23.162.140	192.168.137.2	TLSv1	796



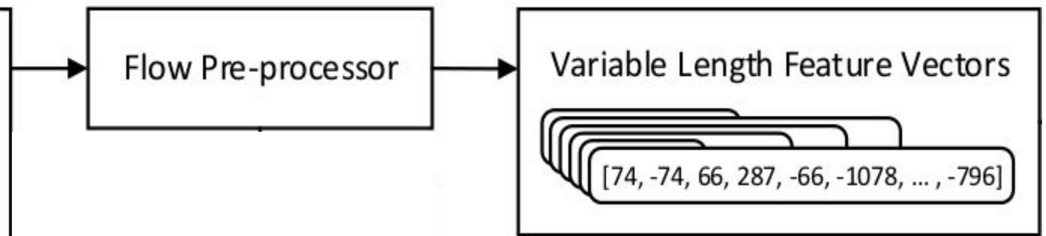
AppScanner (IEEE EuroS&P '16)

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
23.23.162.140	192.168.137.2	TCP	1078
23.23.162.140	192.168.137.2	TLSv1	796

Per Flow approach (1)



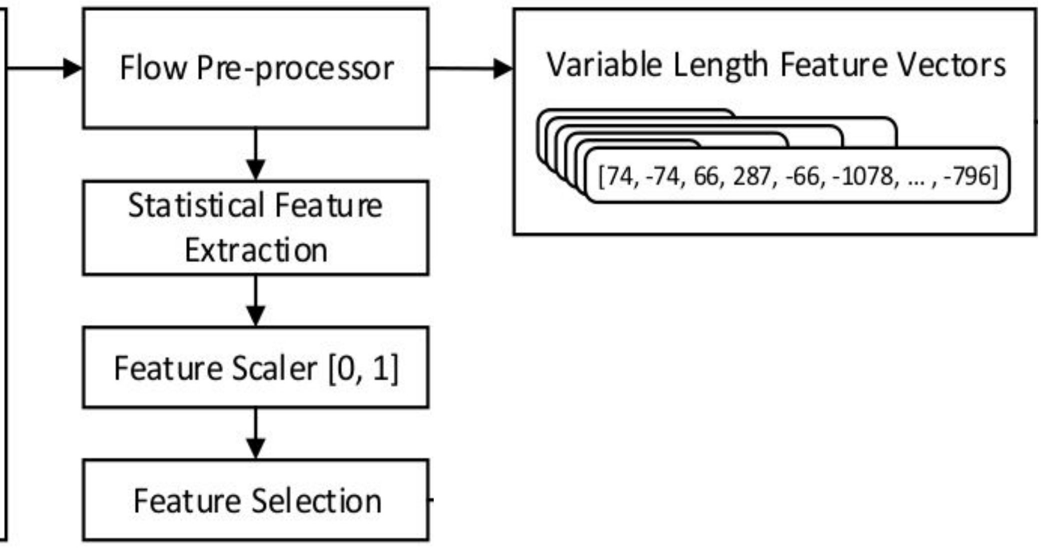
SPRITZ Security & Privacy Research Group
Università degli Studi di Padova

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
23.23.162.140	192.168.137.2	TCP	1078
23.23.162.140	192.168.137.2	TLSv1	796

Per Flow approach (1)



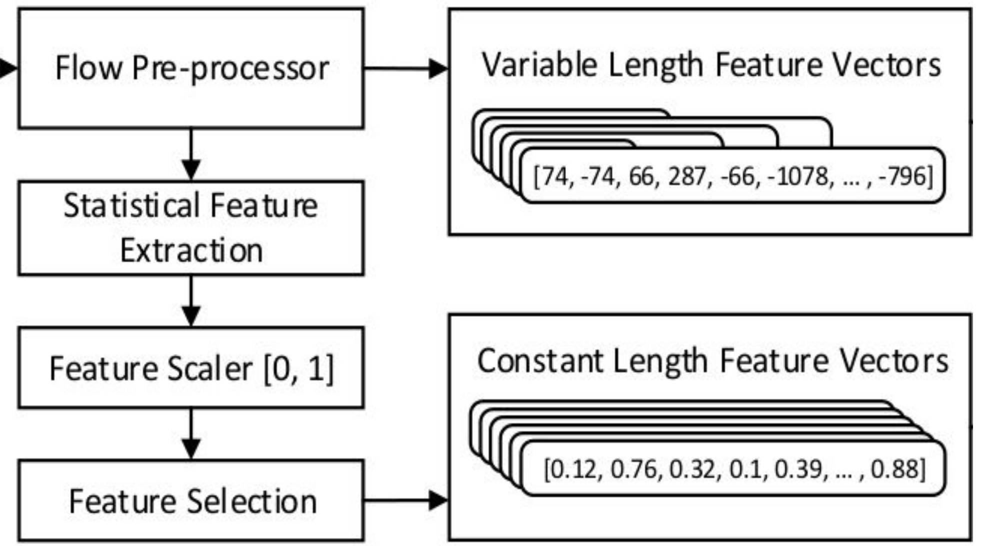
AppScanner (IEEE EuroS&P '16)

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
23.23.162.140	192.168.137.2	TCP	1078
23.23.162.140	192.168.137.2	TLSv1	796

Per Flow approach (1)



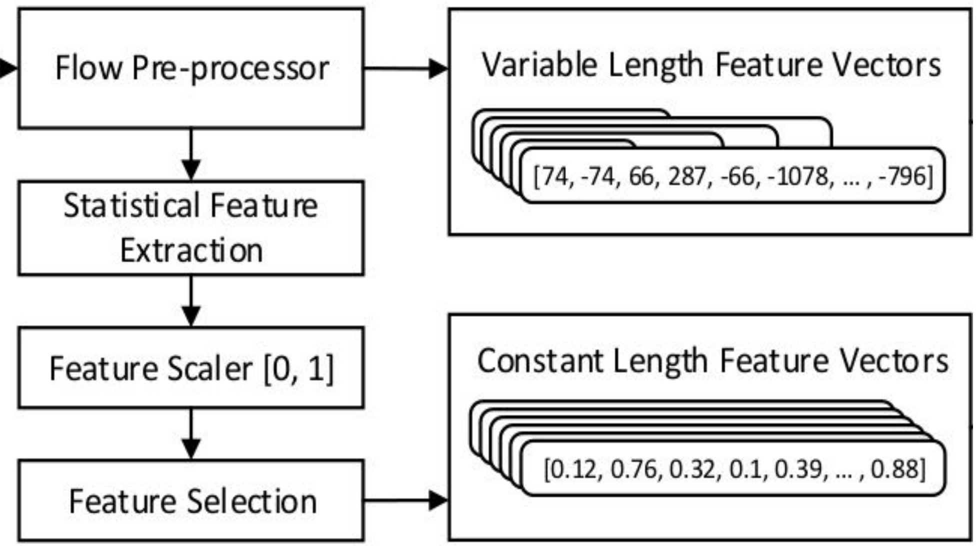
AppScanner (IEEE EuroS&P ‘16)

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
23.23.162.140	192.168.137.2	TCP	1078
23.23.162.140	192.168.137.2	TLSv1	796

Per Flow approach (1)



Statistical approaches (2, 3)

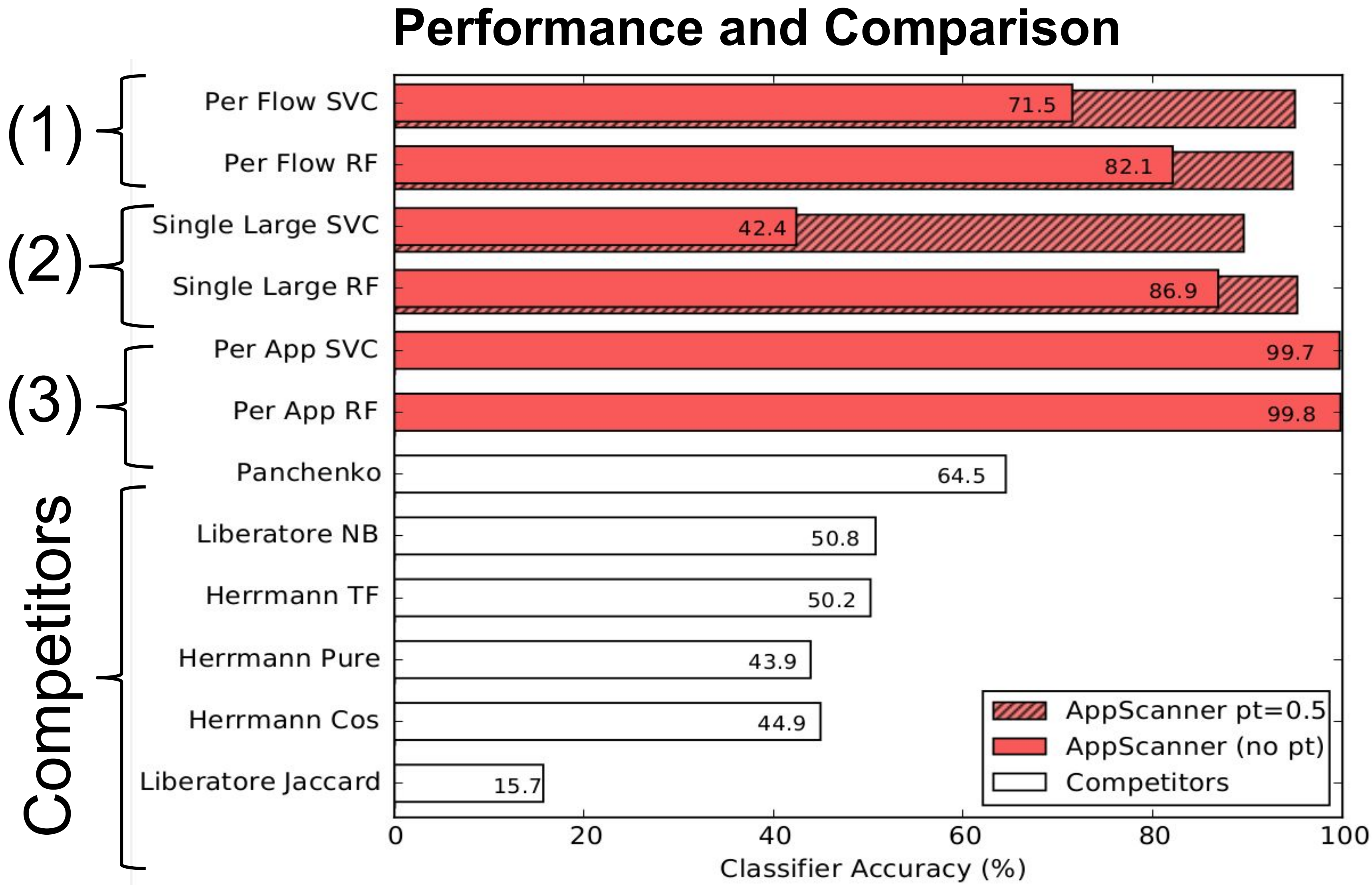
Improving the accuracy of AppScanner

- 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

AppScanner (IEEE EuroS&P '16)

SPRITZ Security & Privacy Research Group

Università degli Studi di Padova



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*


DELL

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

Mind The Plug! Laptop-User Recognition Through Power Consumption.

In ACM AsiaCCS 2016 workshop IoTPTS 2016

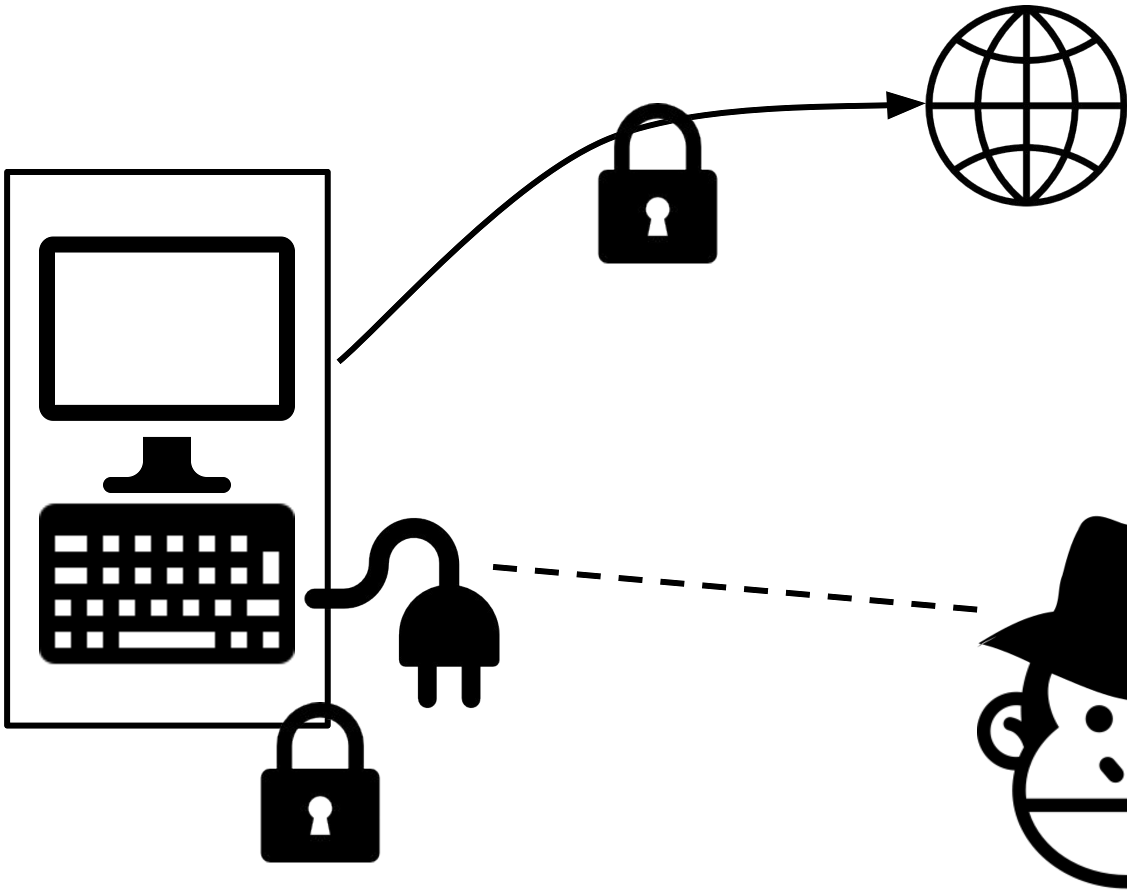
Power Consumption Side Channel

Power consumption

Can reveal what we are doing!

Device drains different power depending on our actions

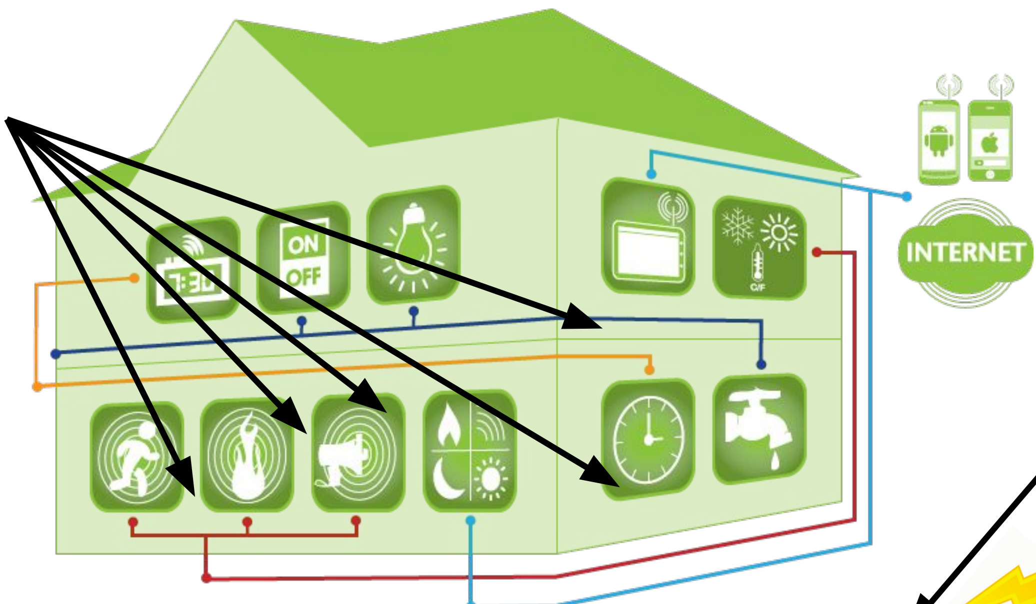
Works on **laptops** and **mobile**



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

Smartgrid

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

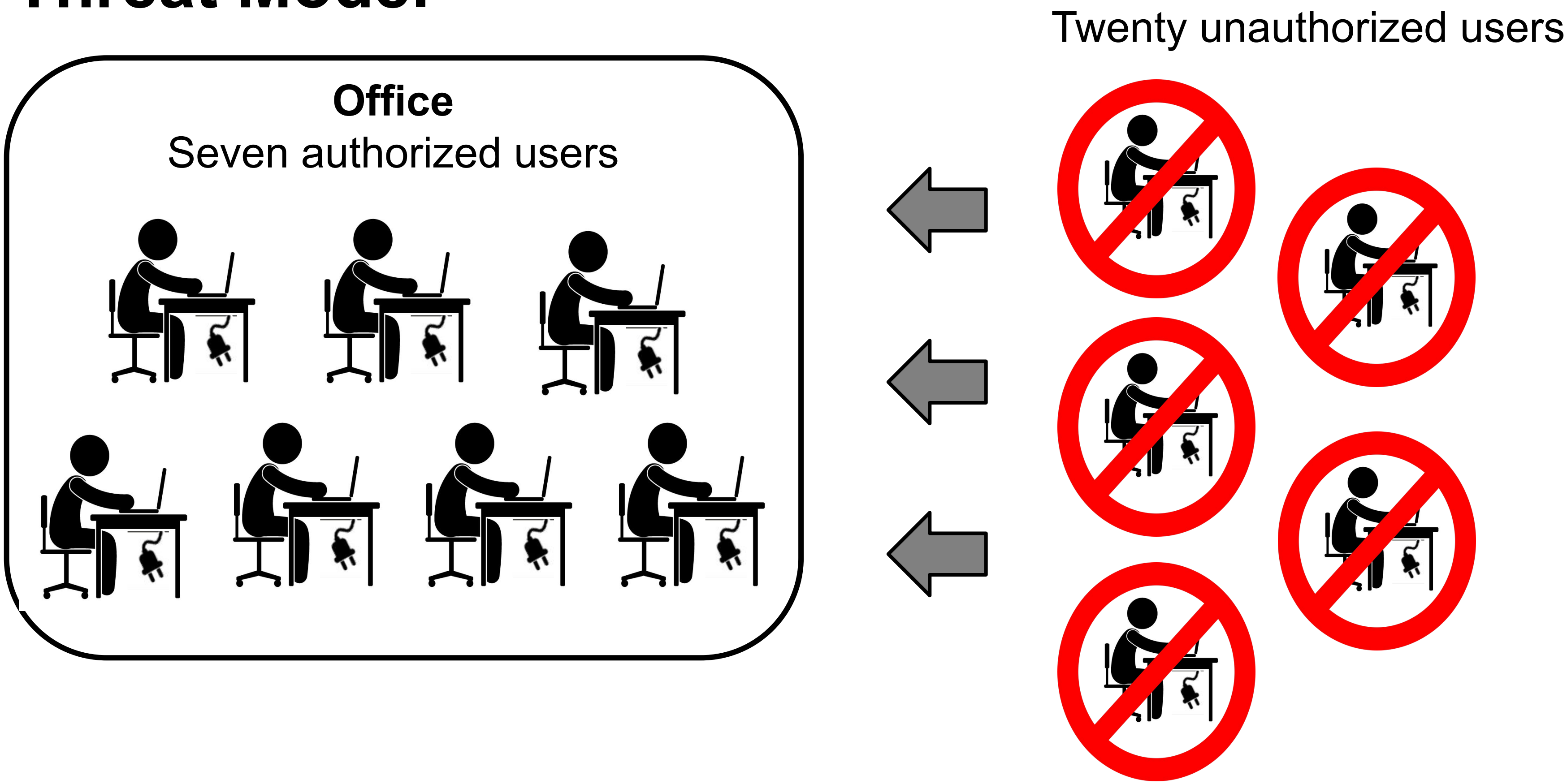
Goal & Motivation

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 <u>locate and trace a user</u>

Threat Model



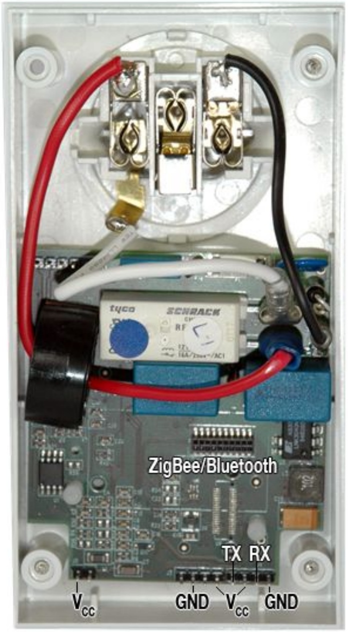
We aim to:

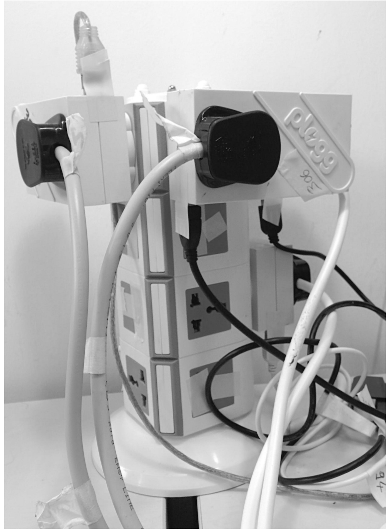
- Recognize whether the user is in the “authorized” set
- Identify the specific user in the “authorized” set

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)

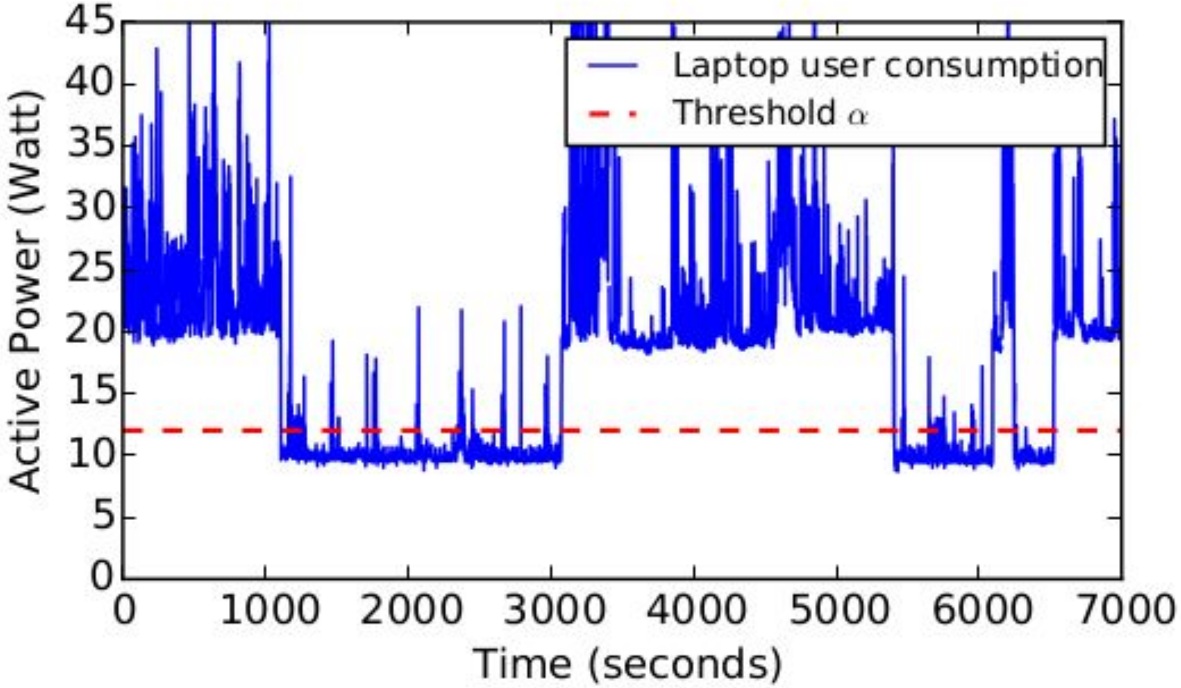
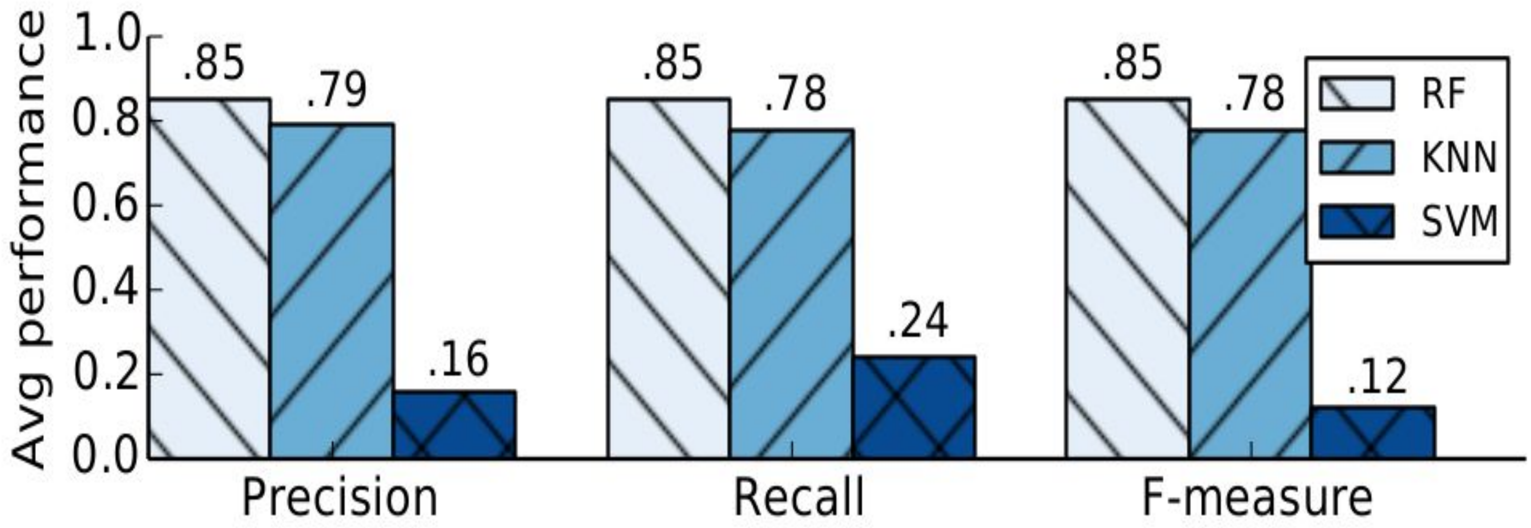


Figure 2: Example of *Active Power* trace (continuous blue line) and the lower-cutting threshold $\alpha = 12$ Watt (dashed red line). Samples under α are low-energy timespans in which the user does not use the laptop.

Mind the Plug! (IoTPTS @AsiaCCS ’16)

SPRITZ Security & Privacy Research Group

Università degli Studi di Padova



85% of F-measure with Random Forest classifier

Classification validation

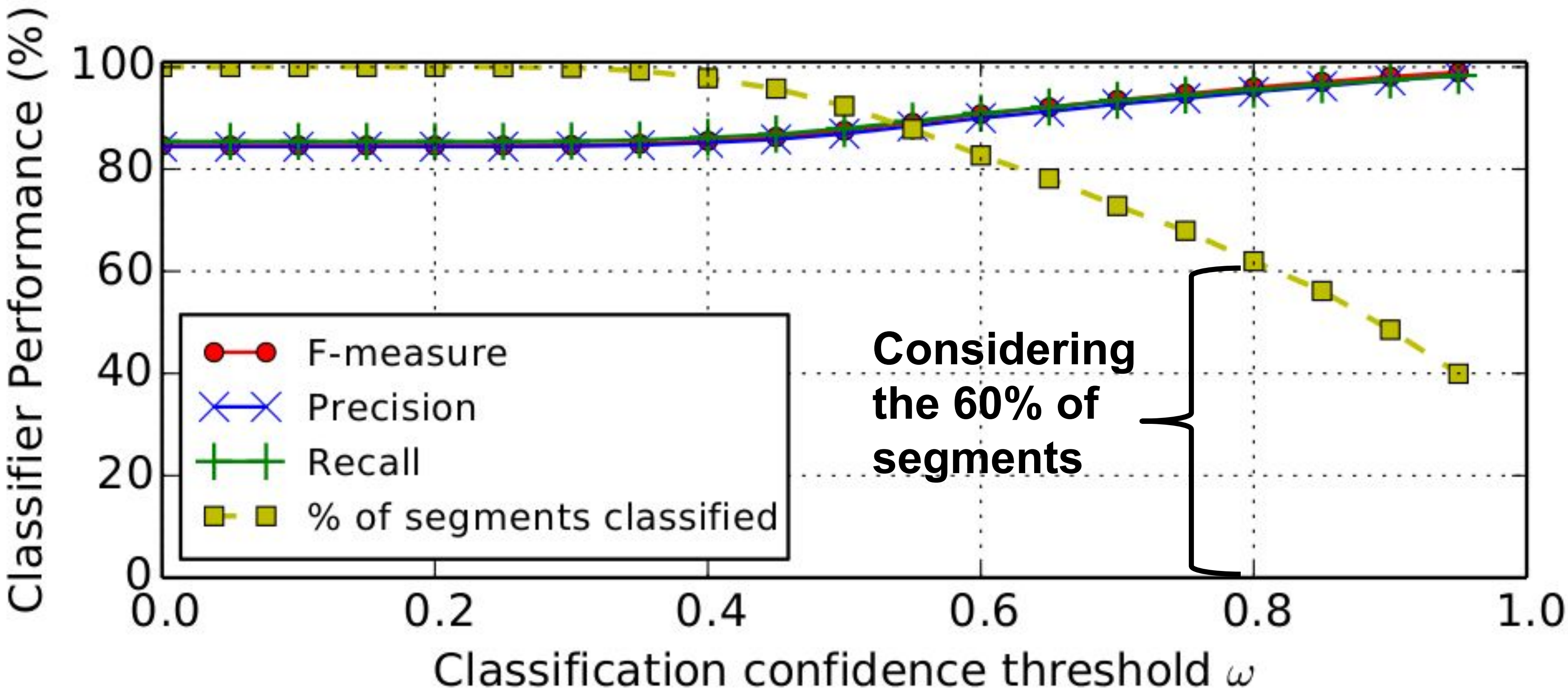
Classifiers label all segments in the testset
- Bad for False Positive rate (FPR)

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

Outline

- Covert and Side Channels 101
- Network Traffic Analysis
  - *As a side channel: app and sensitive data inference*
- **<u>Energy Consumption</u>**
  - *As a side channel: user and app inference*
  - ***<u>As a covert channel: data exfiltration</u>***
- 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*


DELL


SAFUEL
FAST CHARGE

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

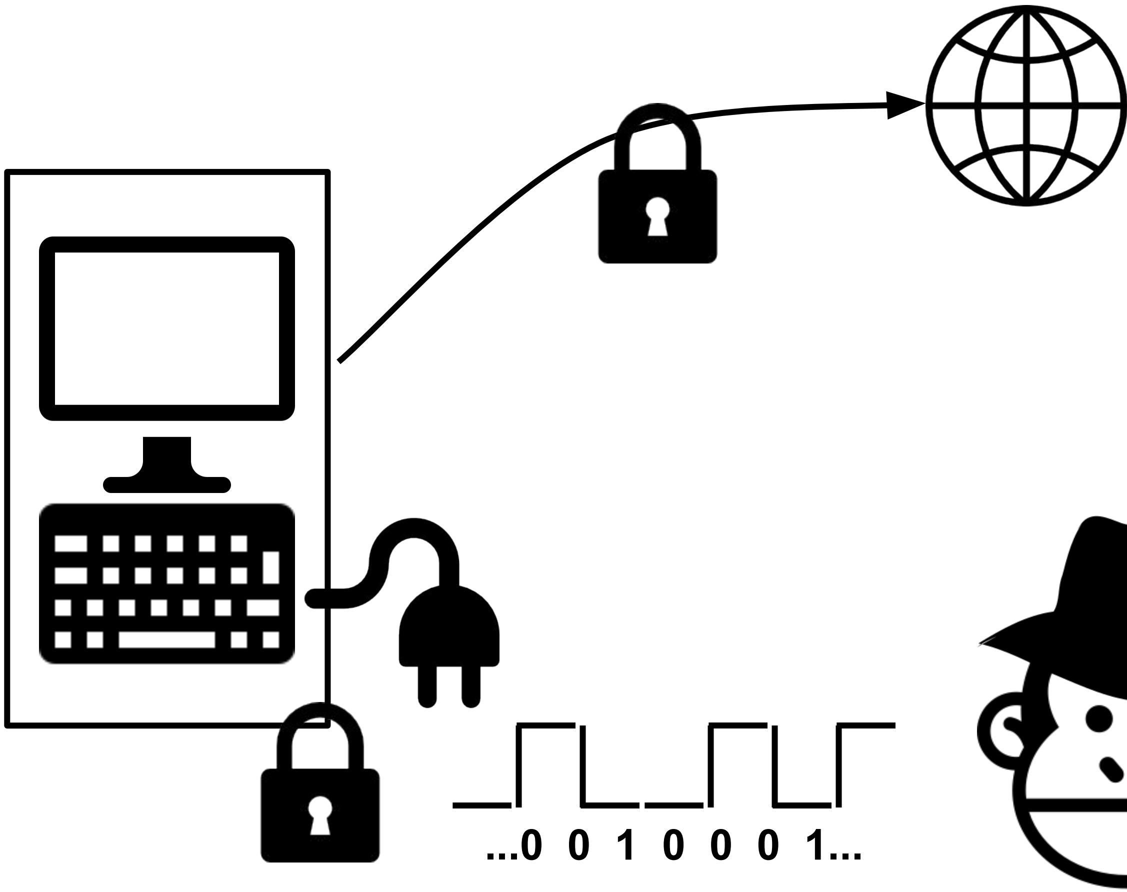
Presented at Black Hat Europe 2018

Power consumption

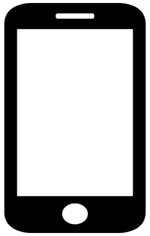
Can be used as a covert channel

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



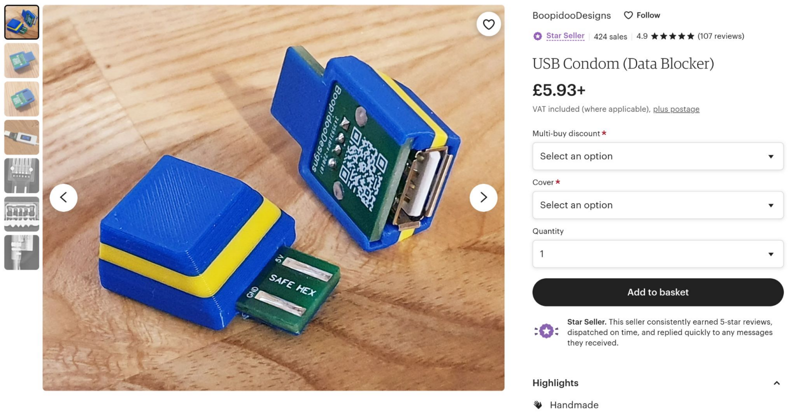
USB protection…

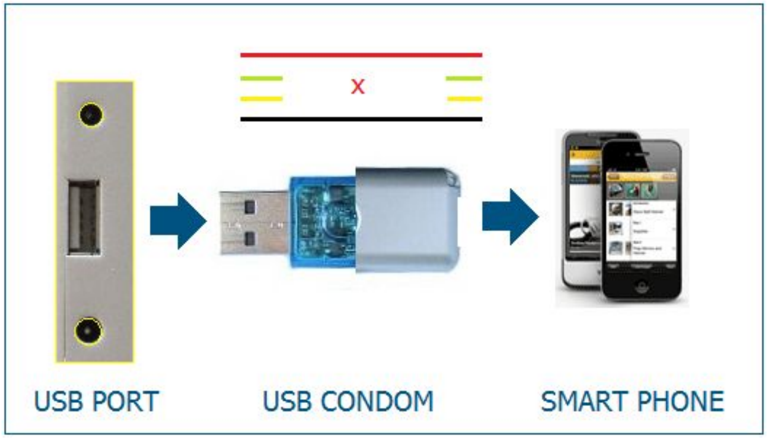
Protect your data

SyncStop prevents accidental data exchange when your device is plugged into someone else's computer or a public charging station. SyncStop achieves this by blocking the data pins on any USB cable and allowing only power to flow through. This minimizes opportunities to steal your data or install malware on your mobile device.

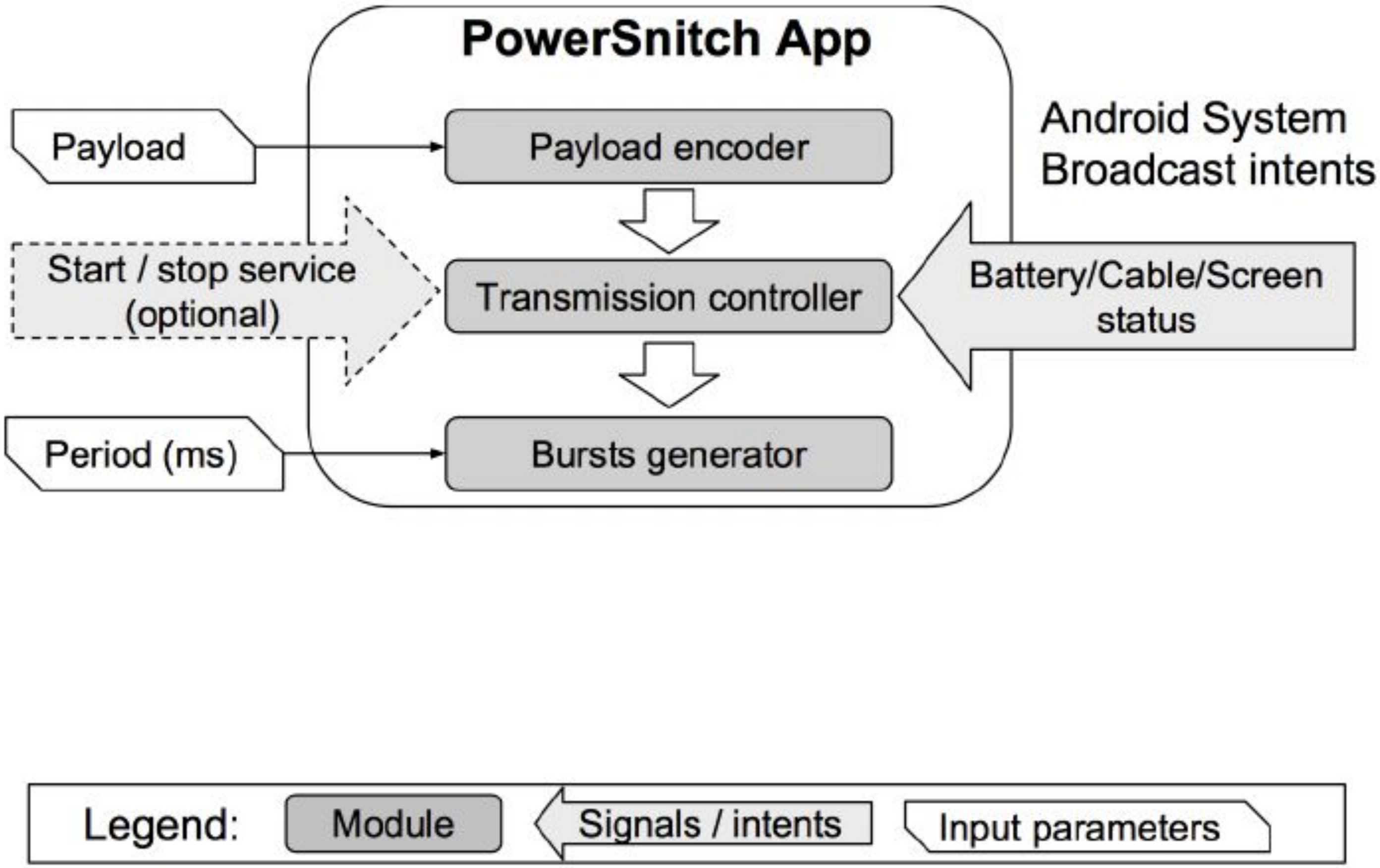
SyncStop is the 'cased' version of the original USB Condom. We listened and spent some time designing and manufacturing our own enclosure.

SyncStop works with any mobile device:



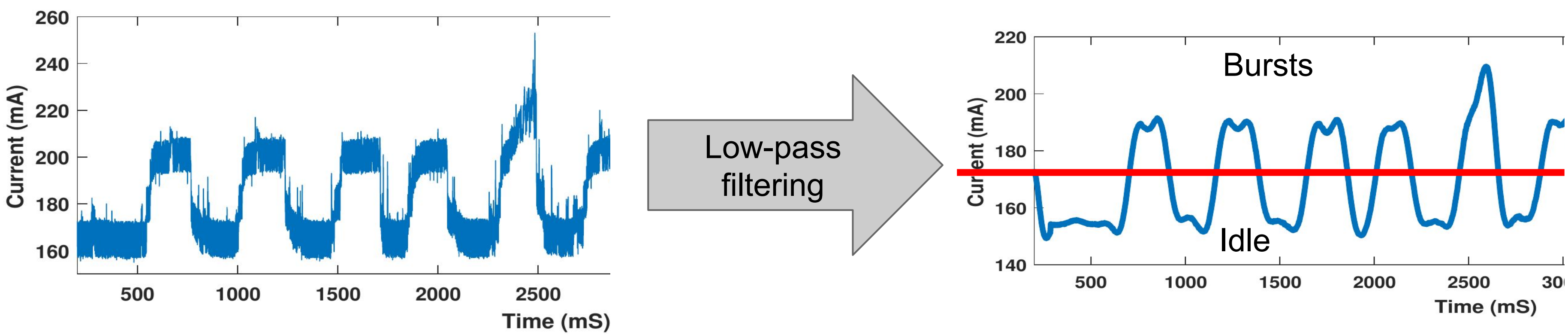


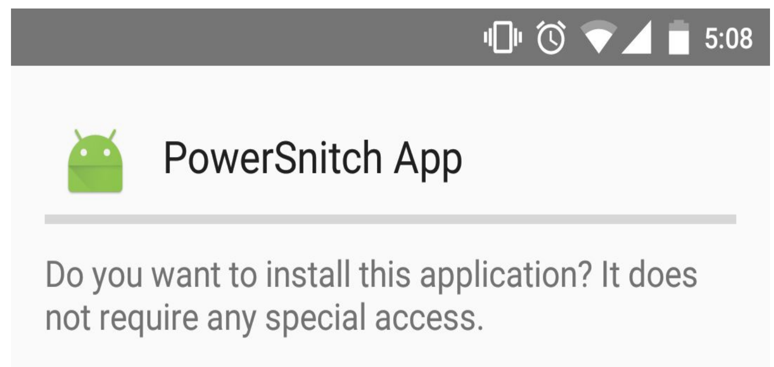
PowerSnitch Application



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

SPRITZ Security & Privacy Research Group
Università degli Studi di Padova





Results in terms of Bit Error Ratio (BER)

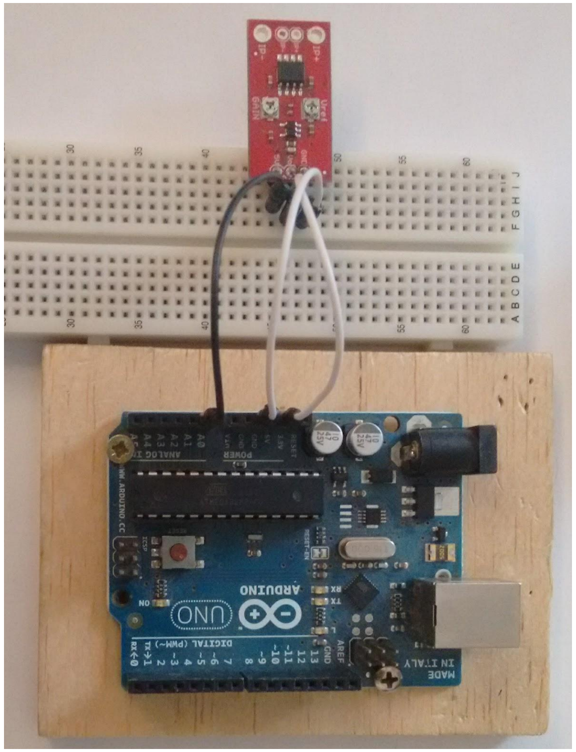
Device	Period (milliseconds)					
	1000	900	800	700	600	500
Nexus 4	13.5	0.78	0.0	0.0	13.33	16.21
Nexus 5	21.0	0.0	0.95	36.82	40.35	13.4
Nexus 6	1.07	0.0	0.21	0.0	4.05	7.42
Samsung S5	12.5	13.5	13.31	16.33	17.9	21.42

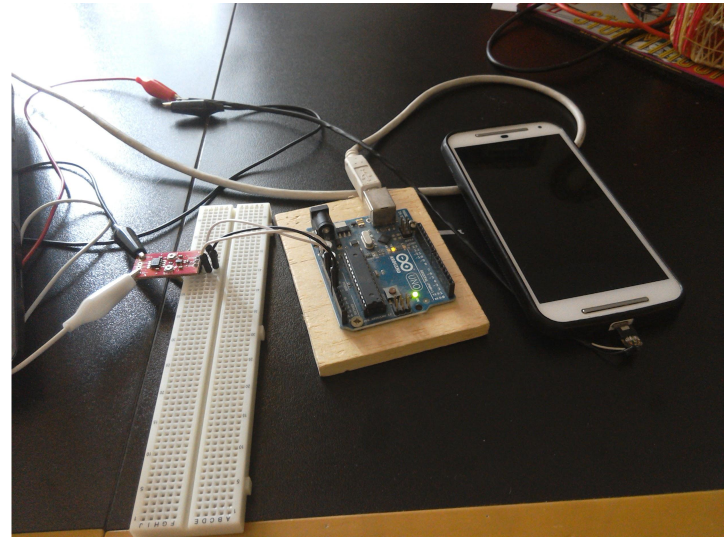
PowerSnitch app does not require any permission !!!

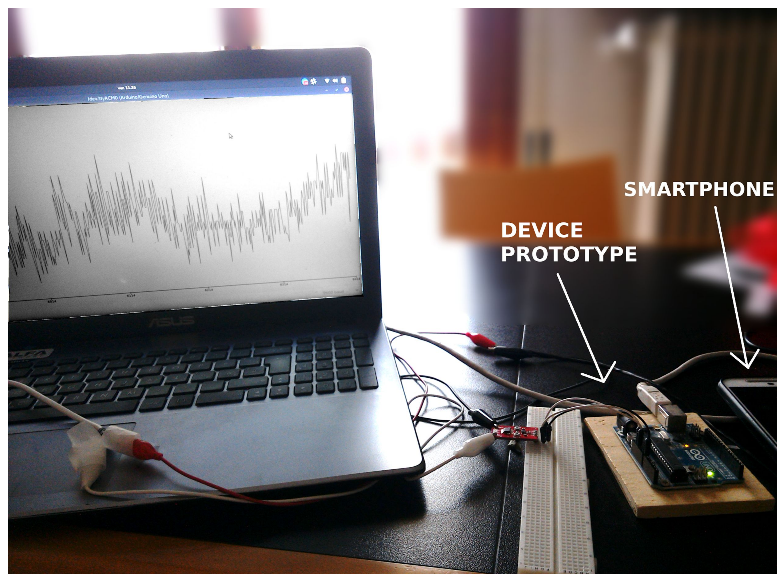
SPRITZ
Security & Privacy
Research Group

Università
degli Studi
di Padova

Power Bank Prototype







Power Bank - DEMO TIME

https://drive.google.com/file/d/1JXzoyOM3xpQqaM8exWF07htp67G5m82v/view?usp=sharing

Outline

SPRITZ Security & Privacy Research Group

Università degli Studi di Padova

- 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*

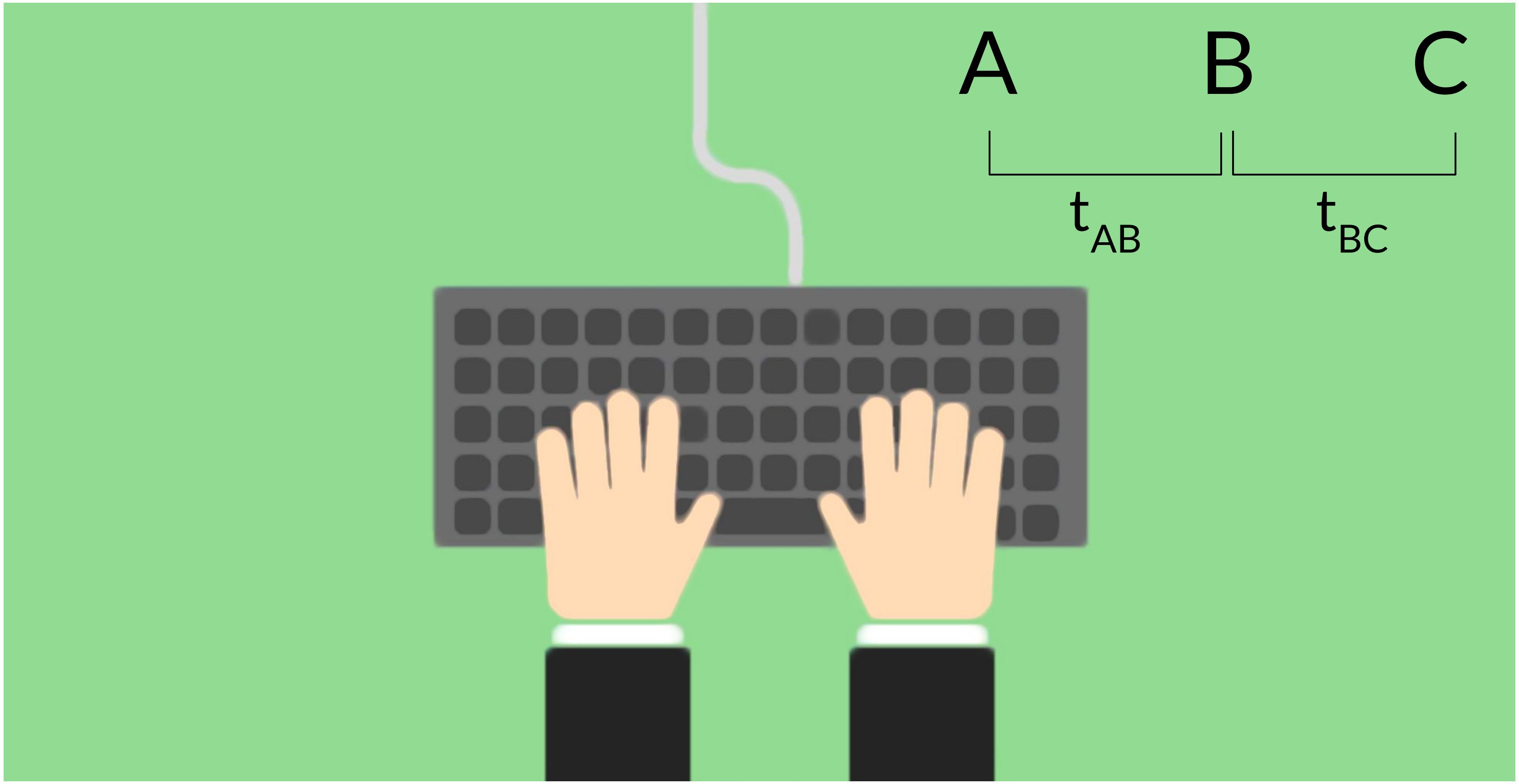
Keystroke Dynamics 101

Keystroke Dynamics 101

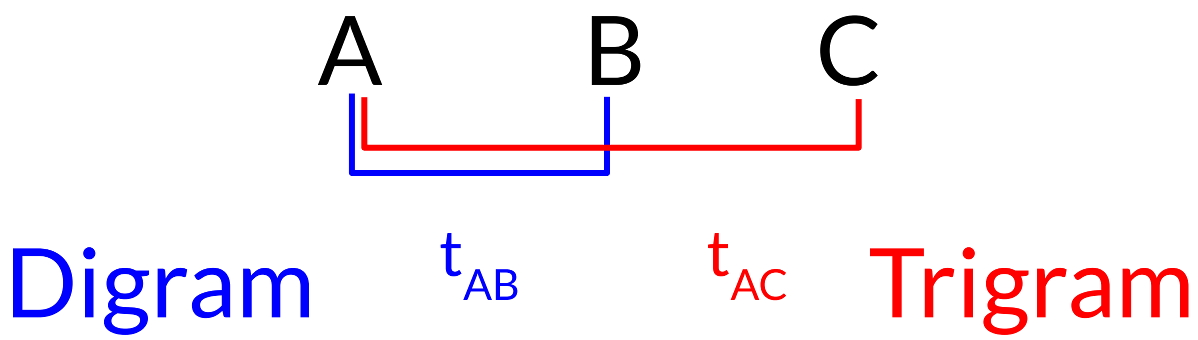
Keystroke Dynamics 101

Keystroke Dynamics 101

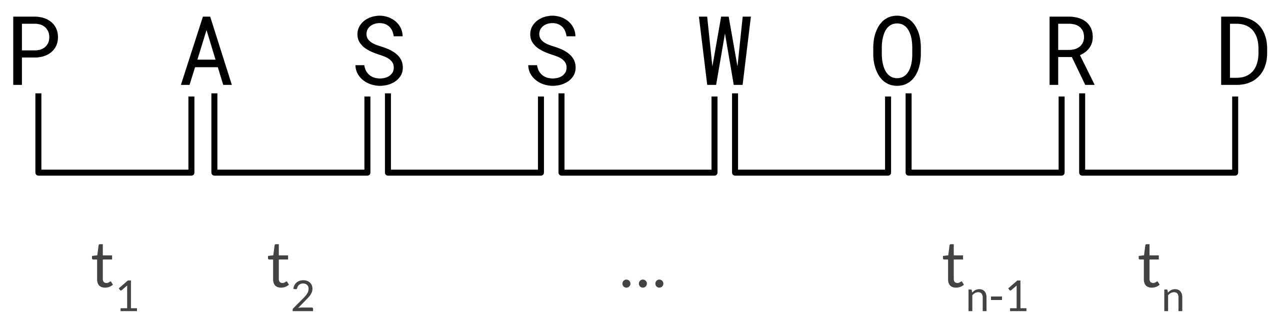
Keystroke Dynamics 101



Keystroke Dynamics 101



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

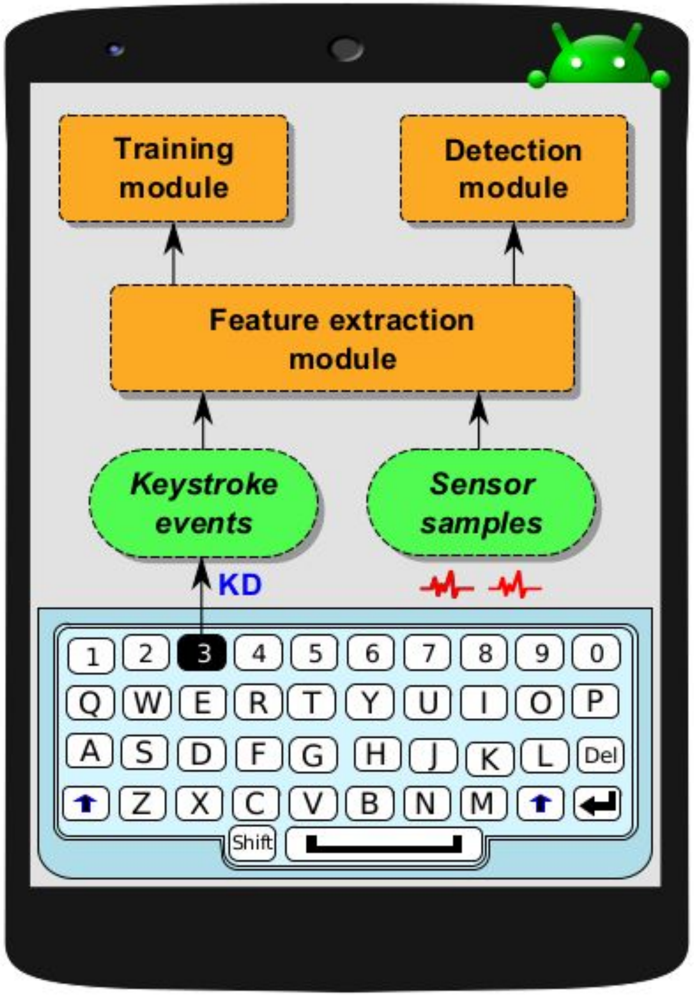
SPRITZ Security & Privacy Research Group

Università degli Studi di Padova

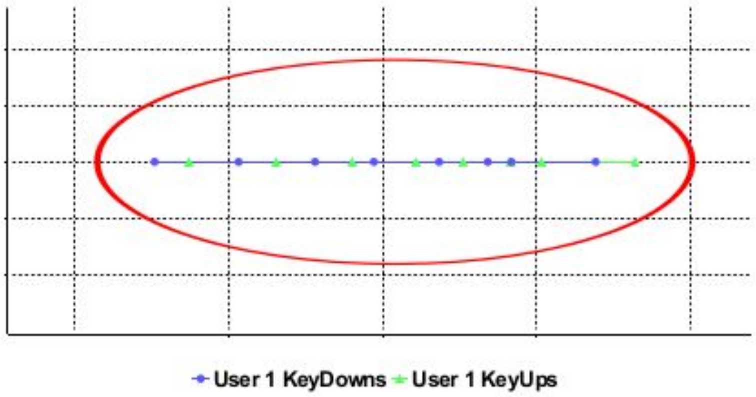
Our system: Unagi

User authentication with
Sensor enhanced
Keystroke Dynamics

Scenario: User typing 'HELLO'

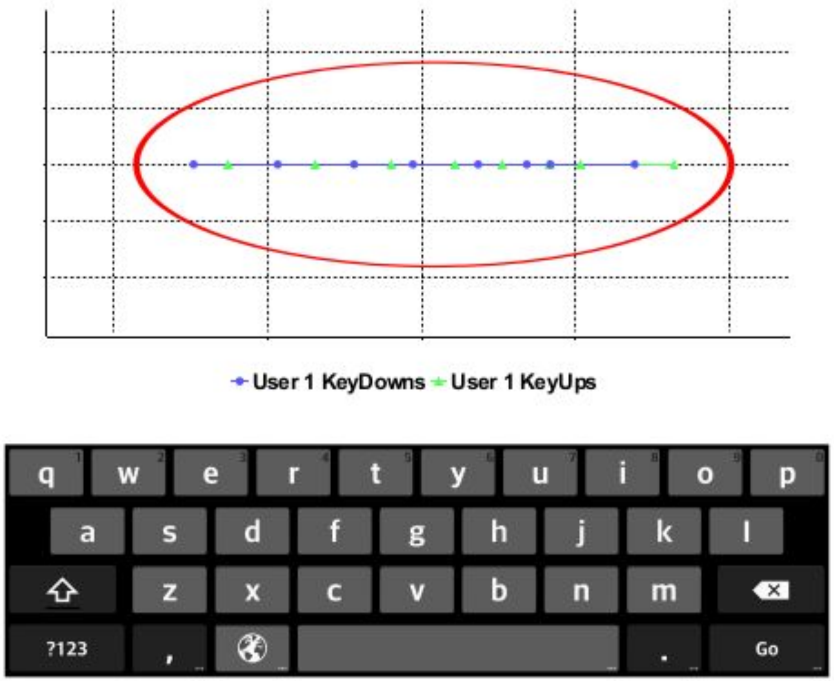


I Sensed It Was You

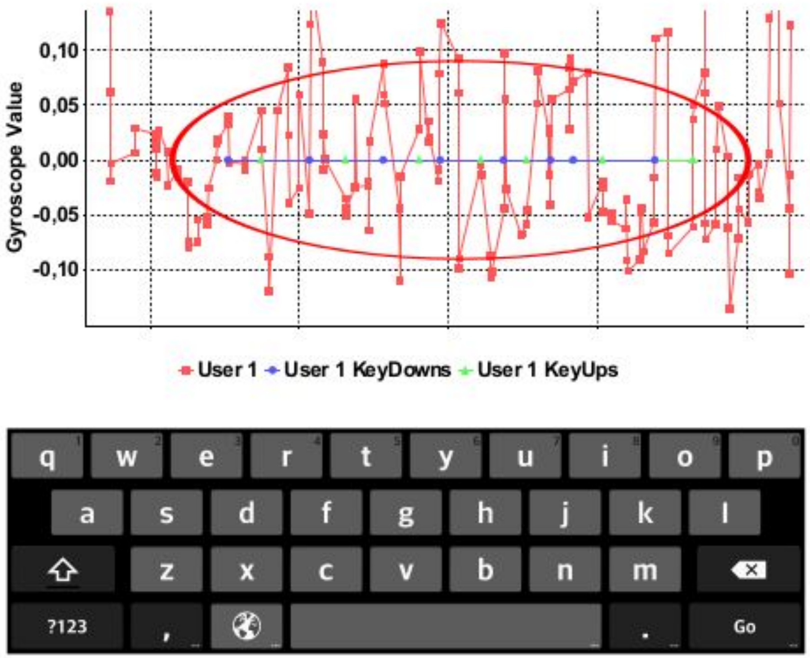


Keystroke dynamics

I Sensed It Was You



Keystroke dynamics

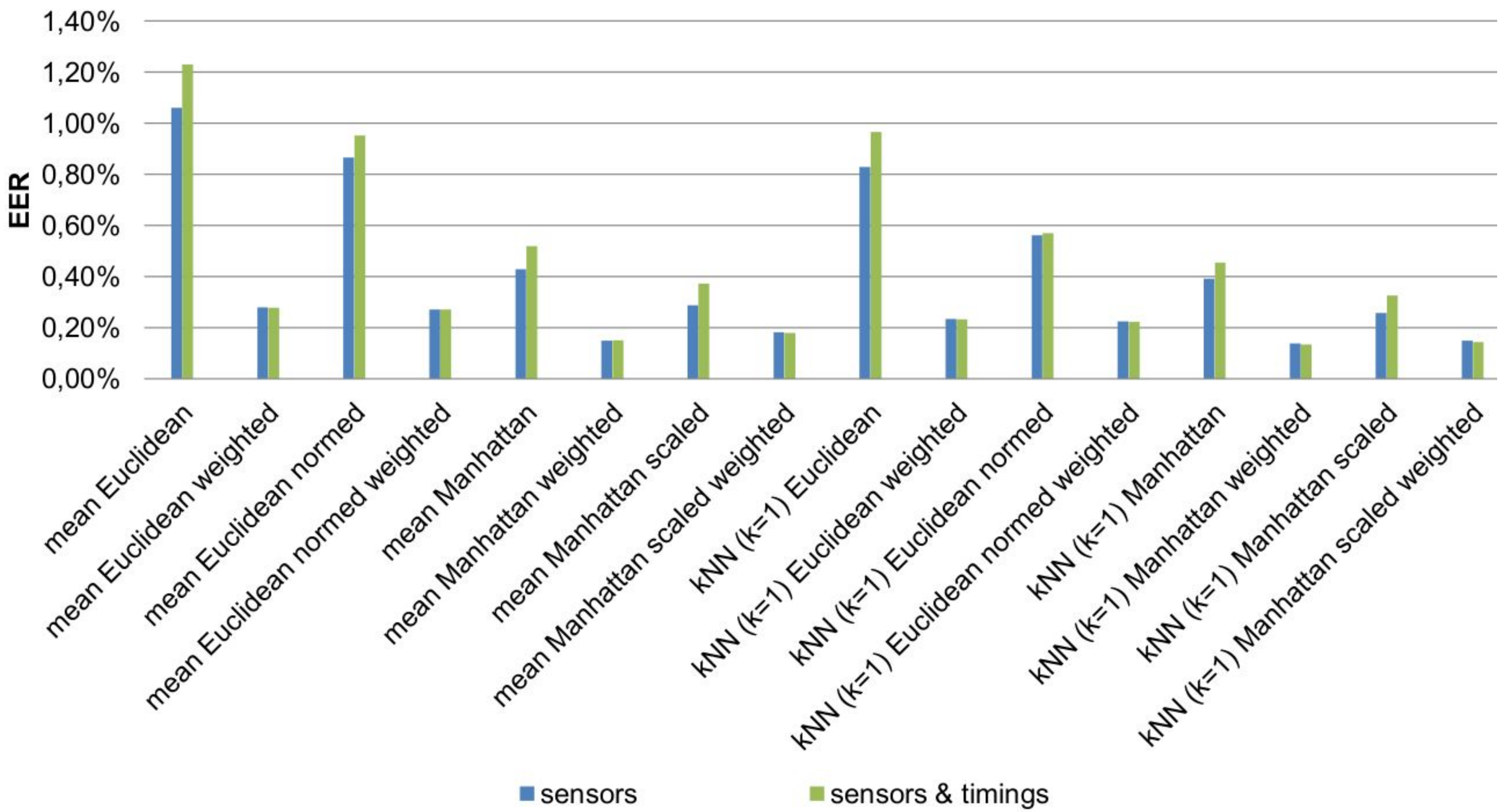


Sensor-enhanced keystroke dynamics

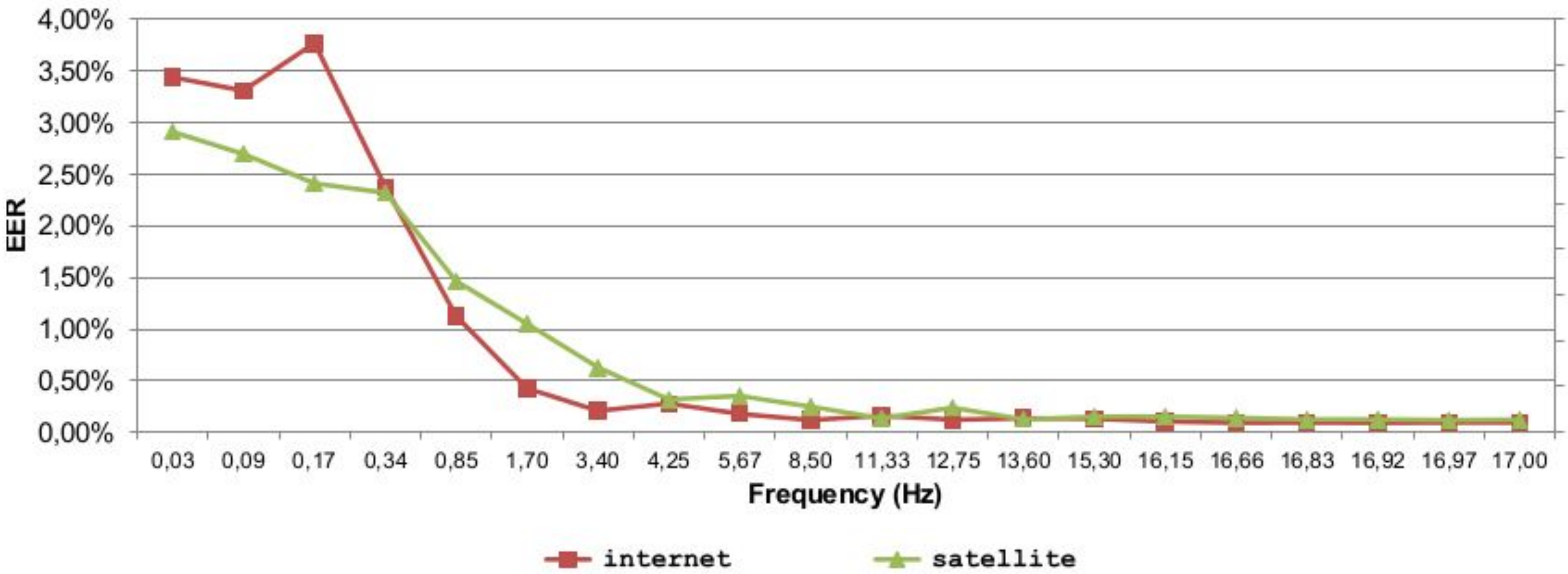
SPRITZ Security & Privacy Research Group

Università degli Studi di Padova

Accuracy (EER) for different considered algorithms



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

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*

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

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

SPRITZ
Security & Privacy
Research Group

Università
degli Studi
di Padova

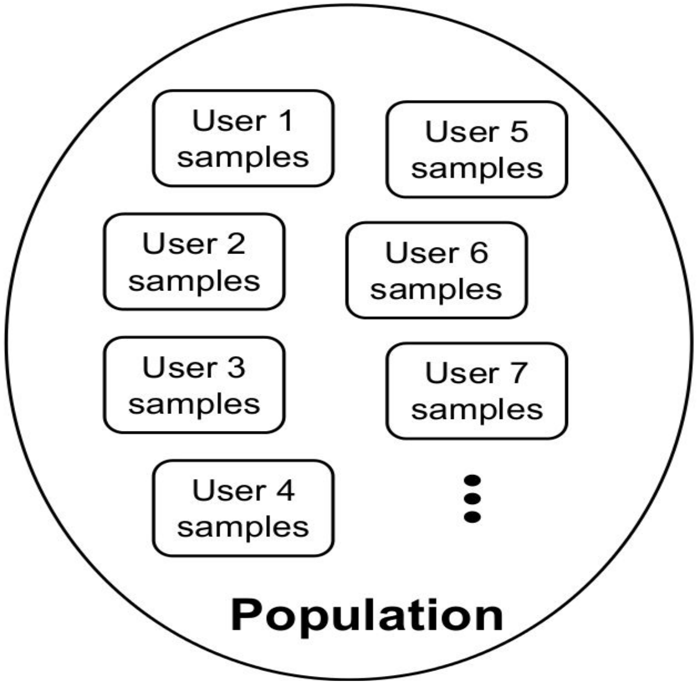
The previous **behavioral biometric authentication** system relies on:

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

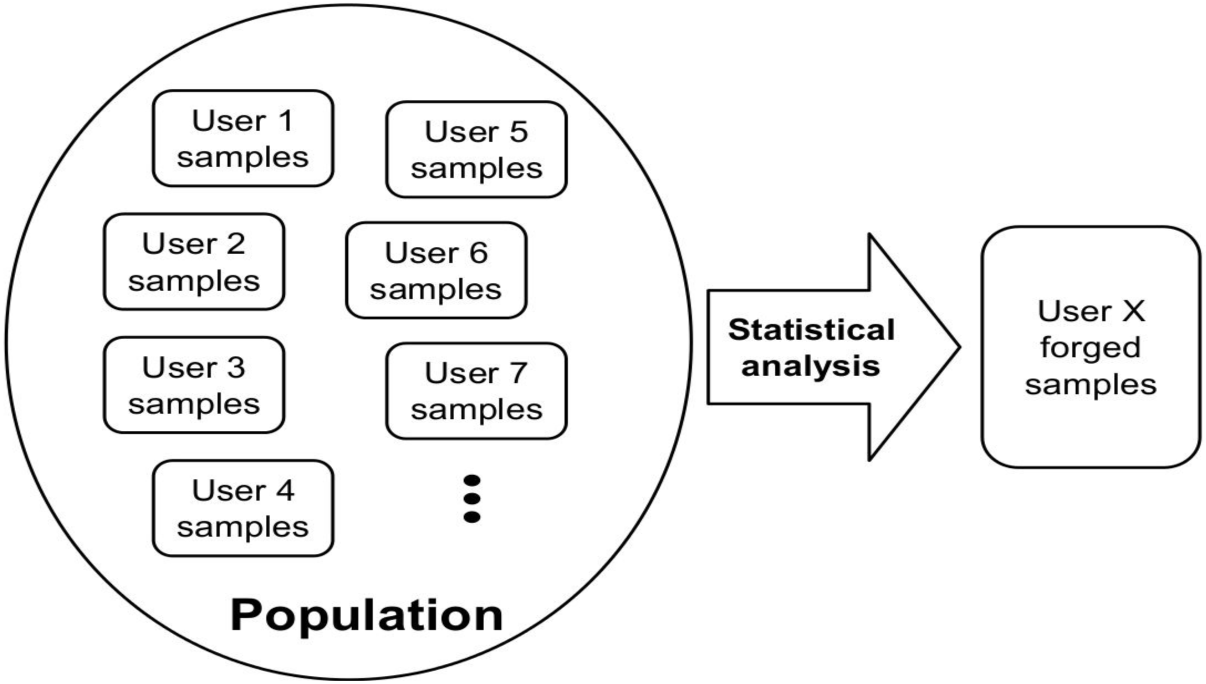
Previous work: we used kNN (with k=1) and mean values combined with several metrics (e.g., euclidean, Manhattan)

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

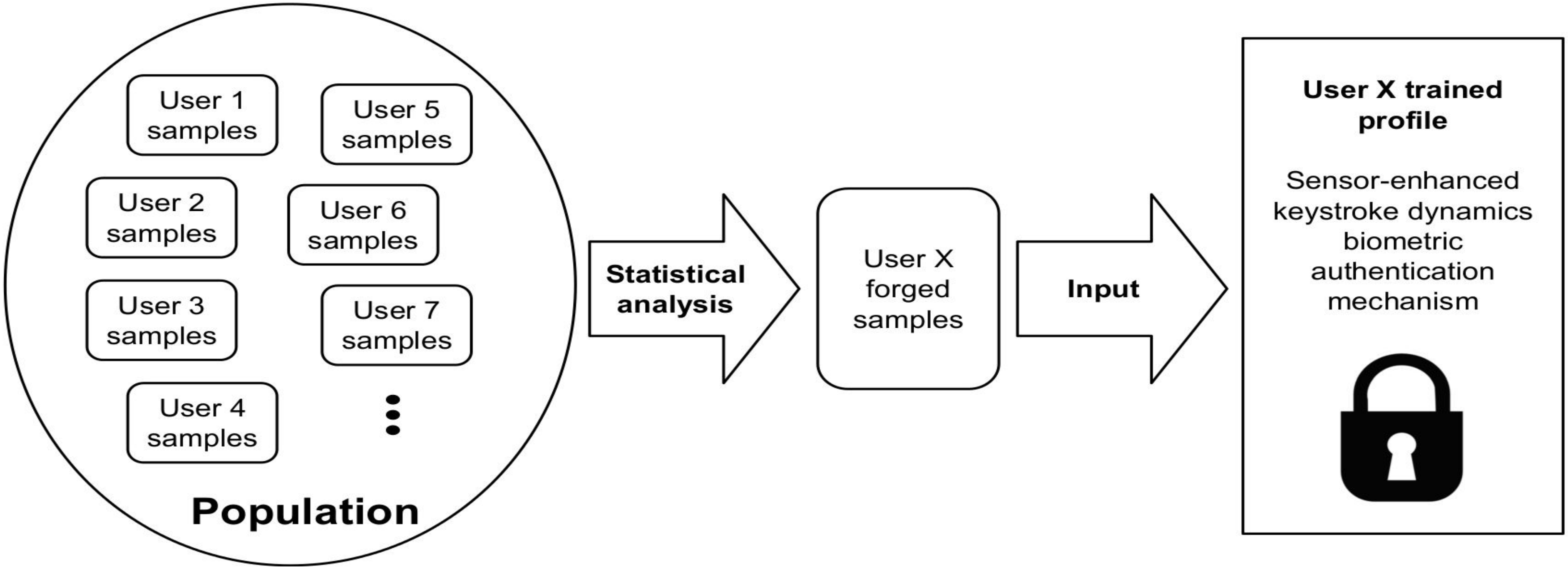
Statistical Attack



Statistical Attack

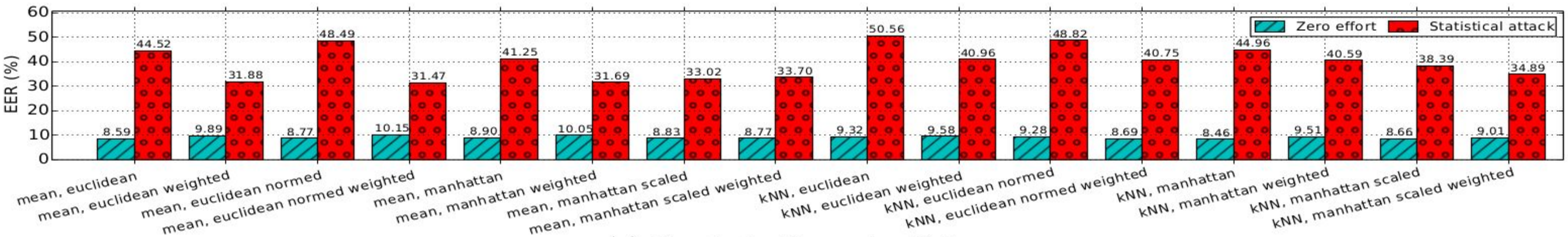


Statistical Attack

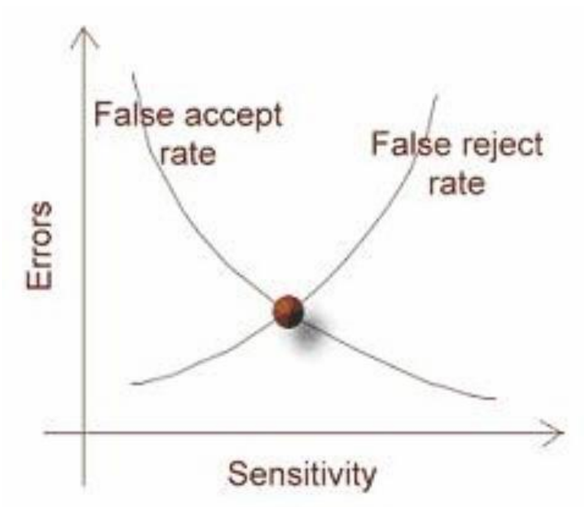


Results

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

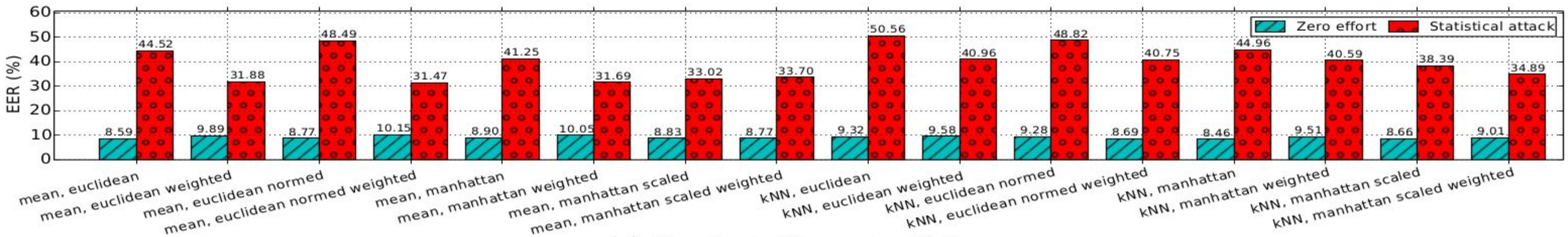


(a) Keystroke-Dynamics Only.

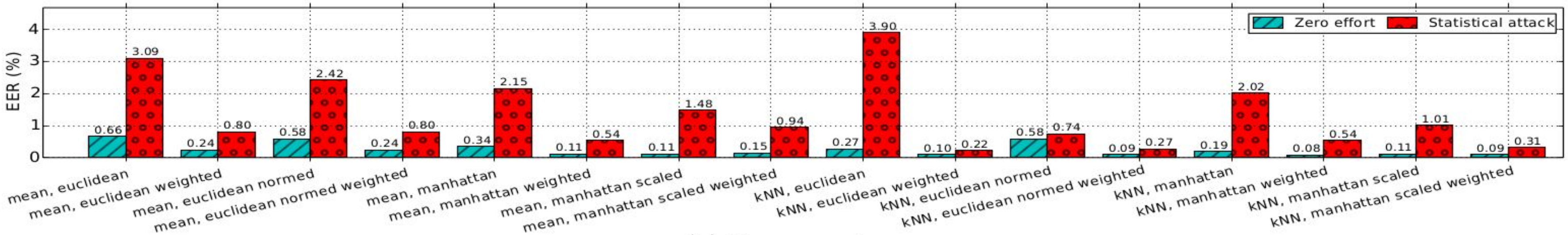


Results

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



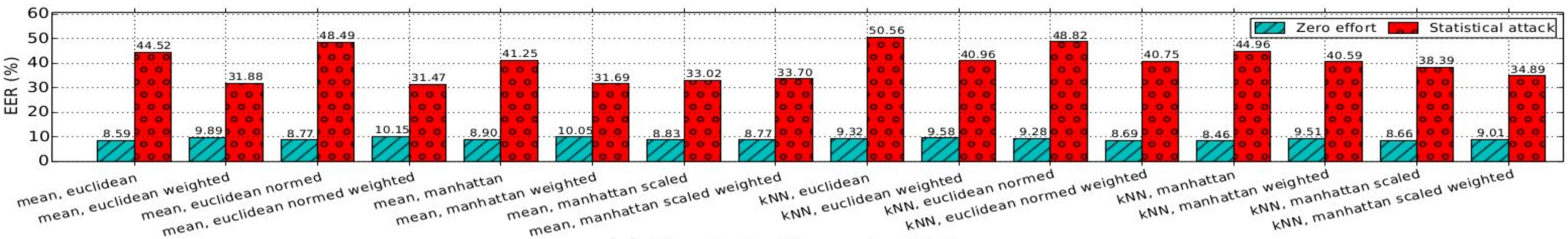
(a) Keystroke-Dynamics Only.



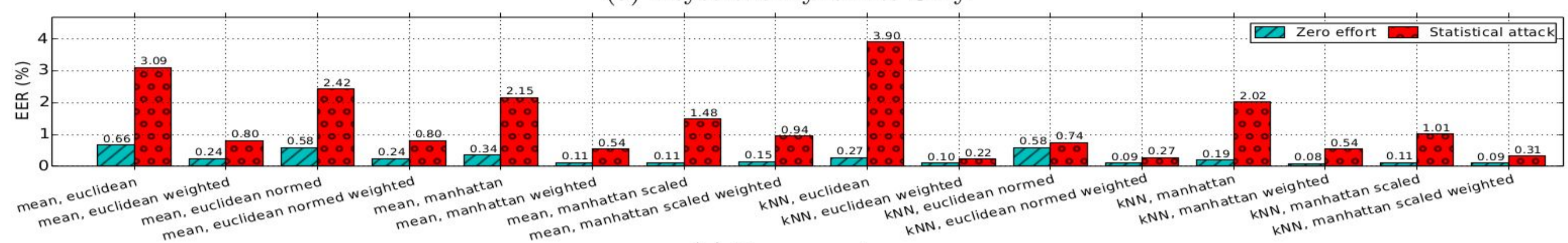
(b) Sensors only.

Results

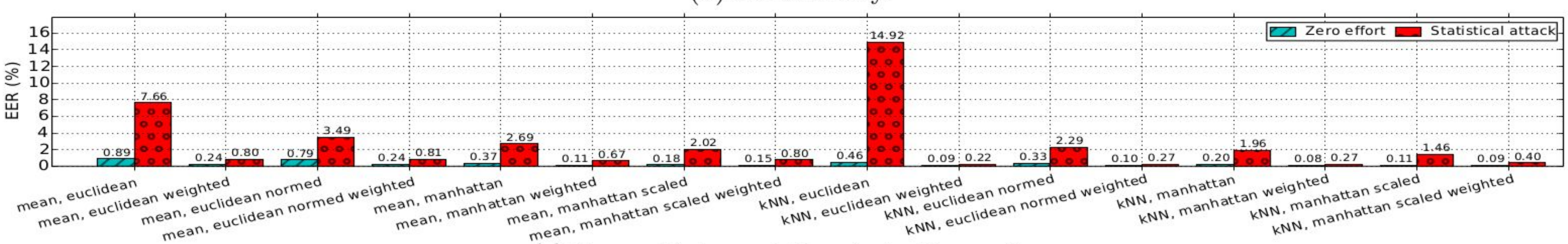
low Equal Error Rate (EER) == accurate authentication method



(a) Keystroke-Dynamics Only.



(b) Sensors only.



(c) Sensor-Enhanced Keystroke-Dynamics.

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*

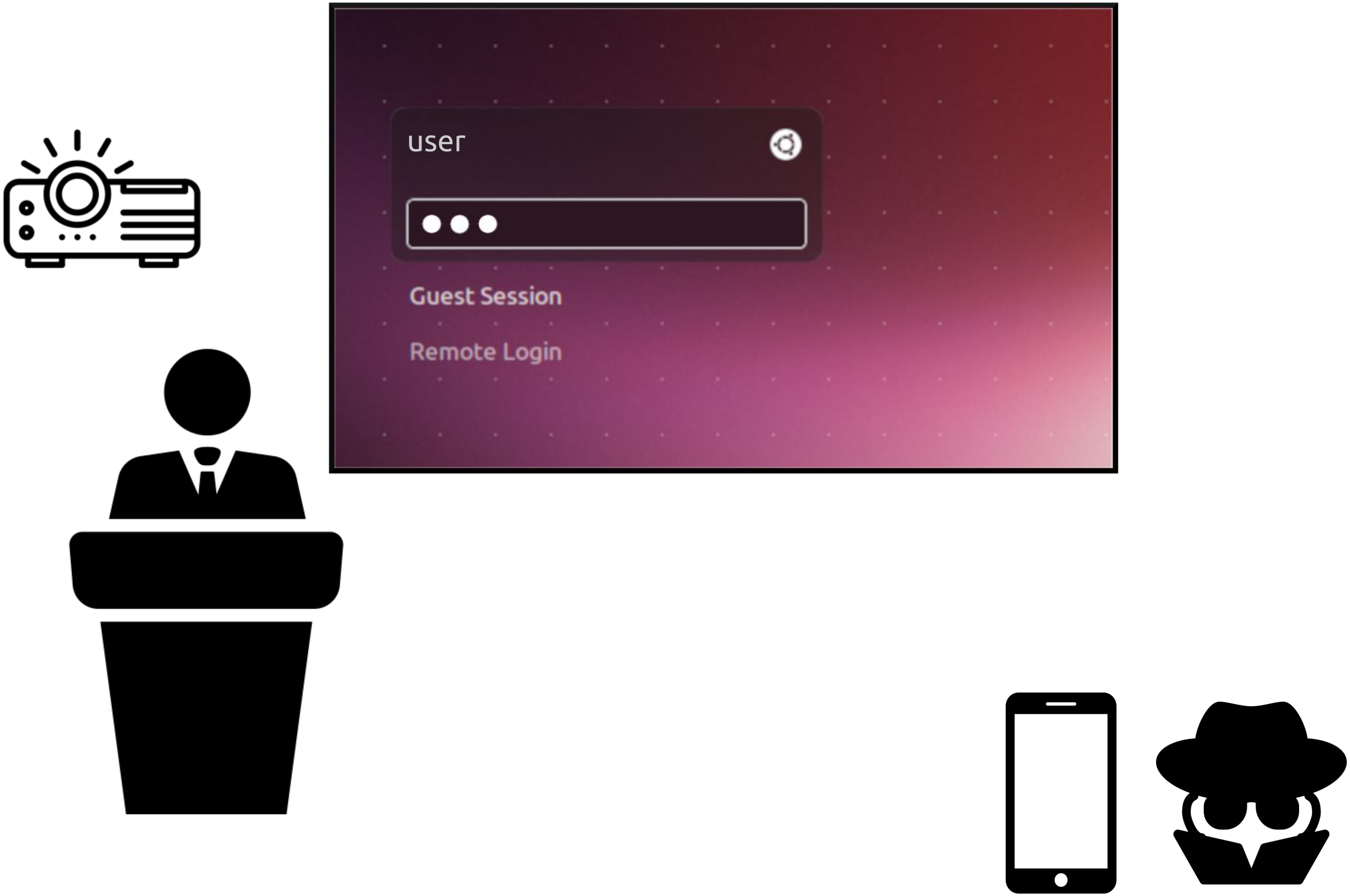
- Device Movement
  - *As a side channel: smartphone user authentication*
  - *Attacks against biometric authentication*
- **Keystroke Timing**
  - ***As a side channel: text typed on keyboards***
- Acoustic Emanations
  - *As a side channel: text typed on keyboards*

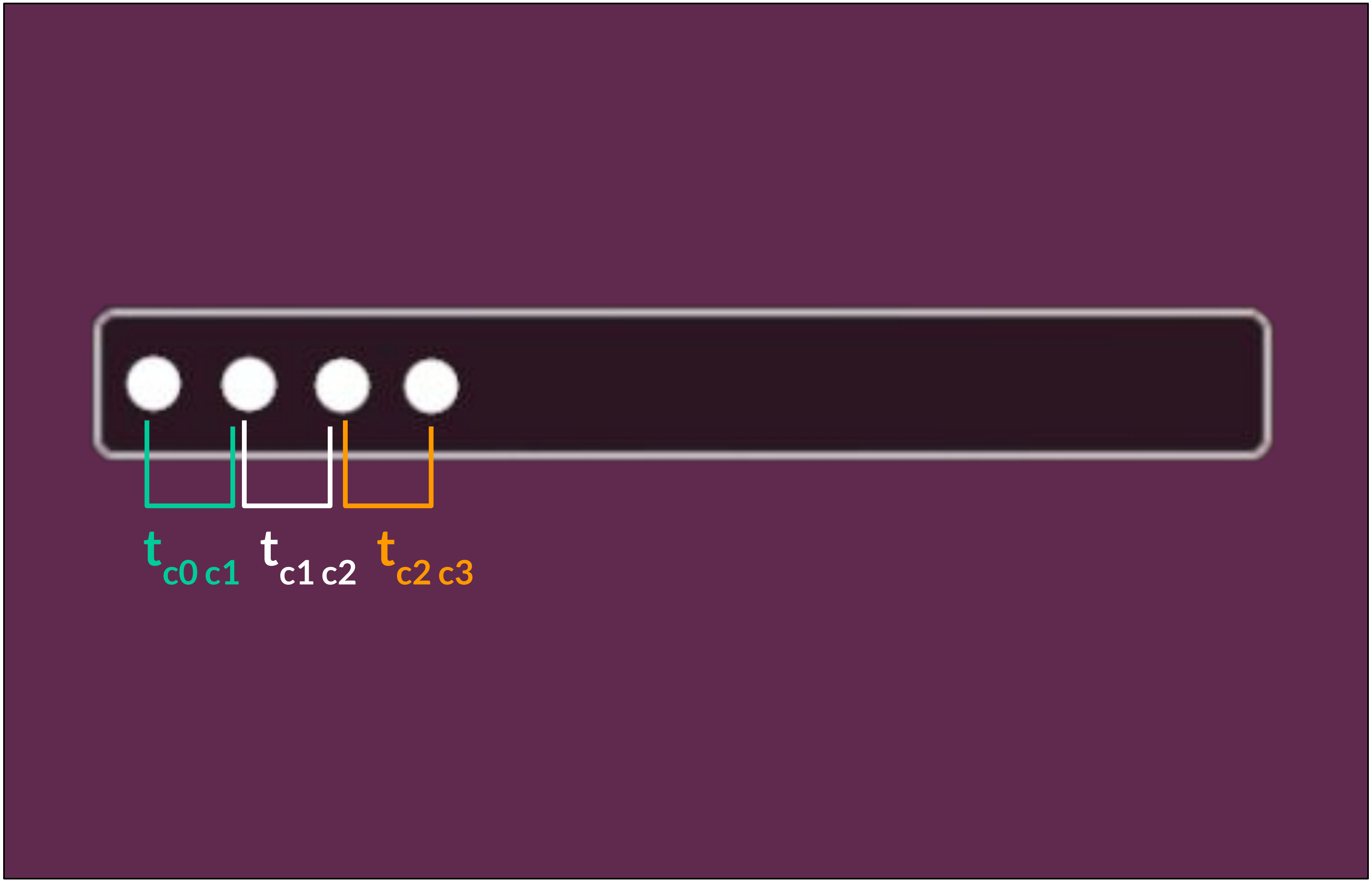
Kiran Balagani, Mauro Conti, Paolo Gasti, Martin Georgiev, Tristan Gurtler, Daniele Lain, Charissa Miller, Kendall Molas, Nikita Samarin, Eugen Saraci, Gene Tsudik, Lynn Wu

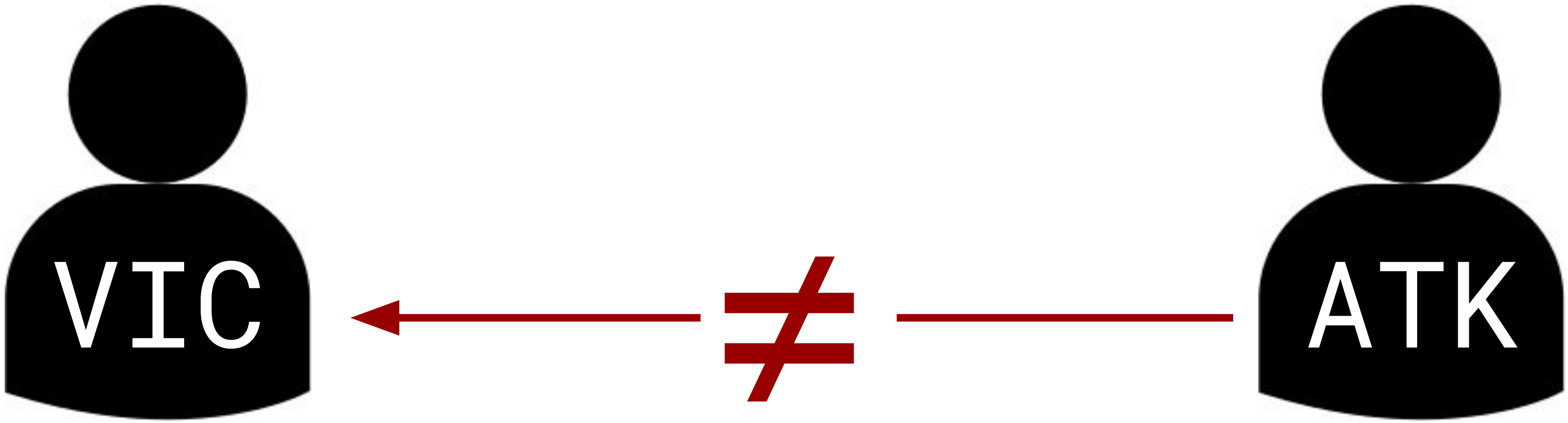
SILK-TV: Secret Information Leakage From Keystroke Timing Videos.

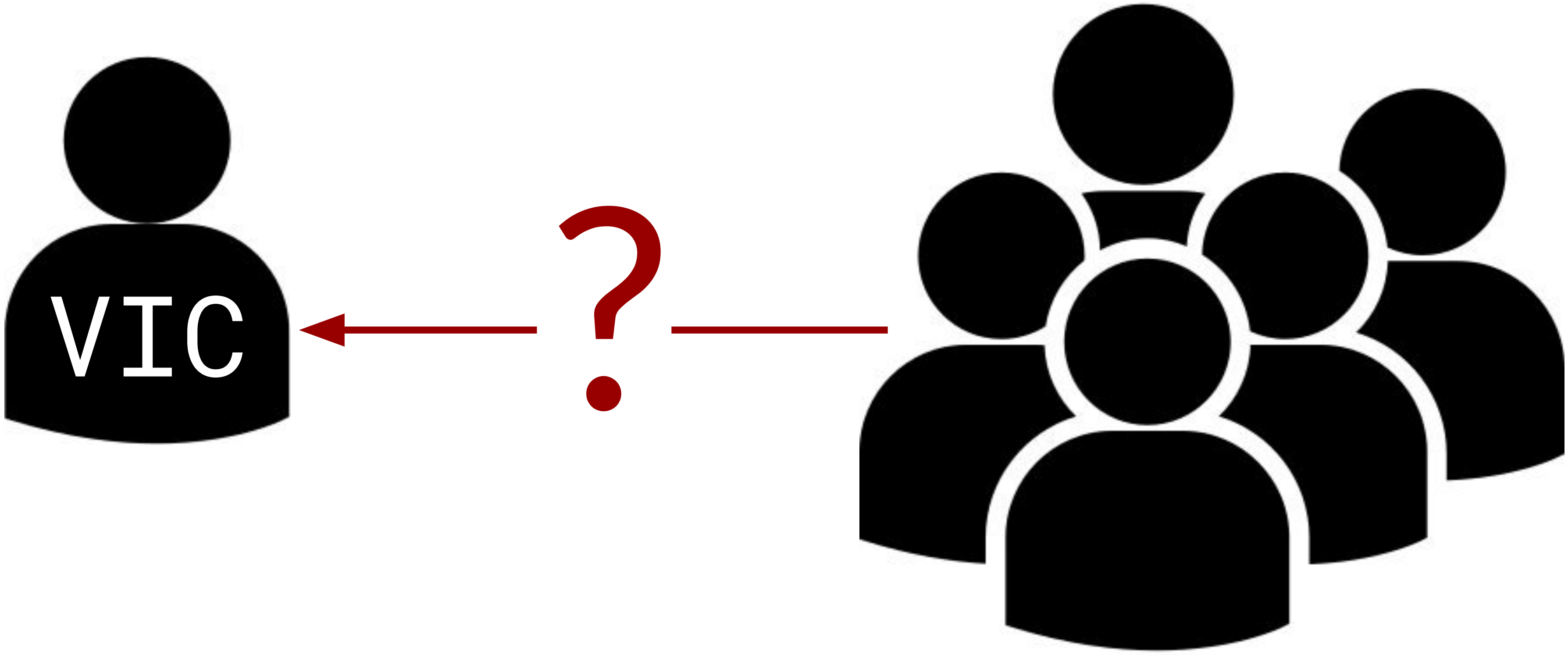
In ESORICS 2018

Timing Information Leak - 1




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

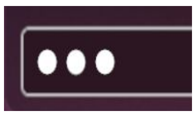

VIC
≠
ATK


VIC
?

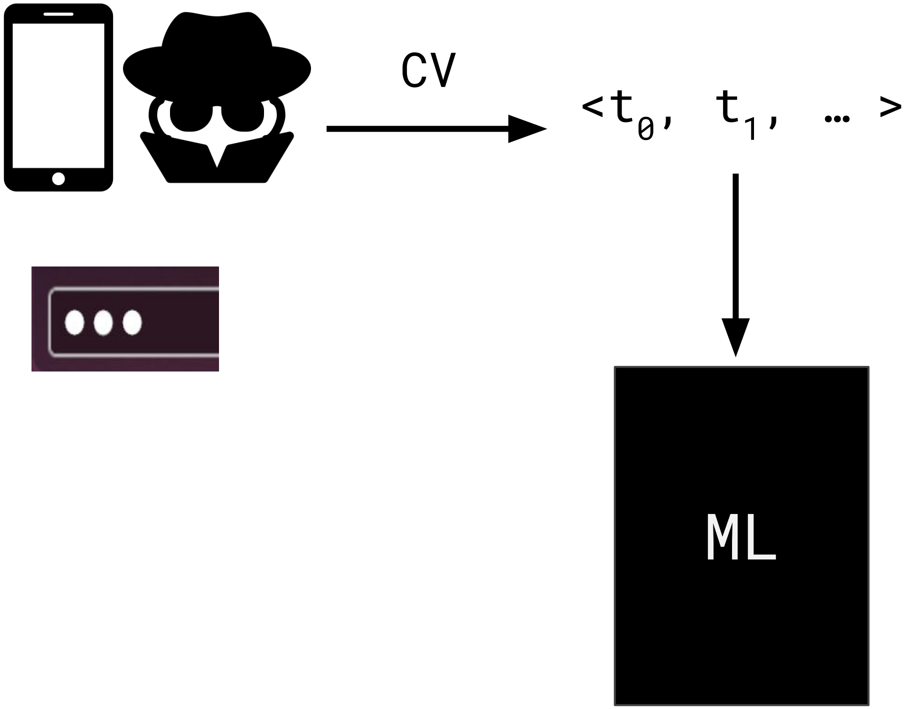
Contributions

- 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)*

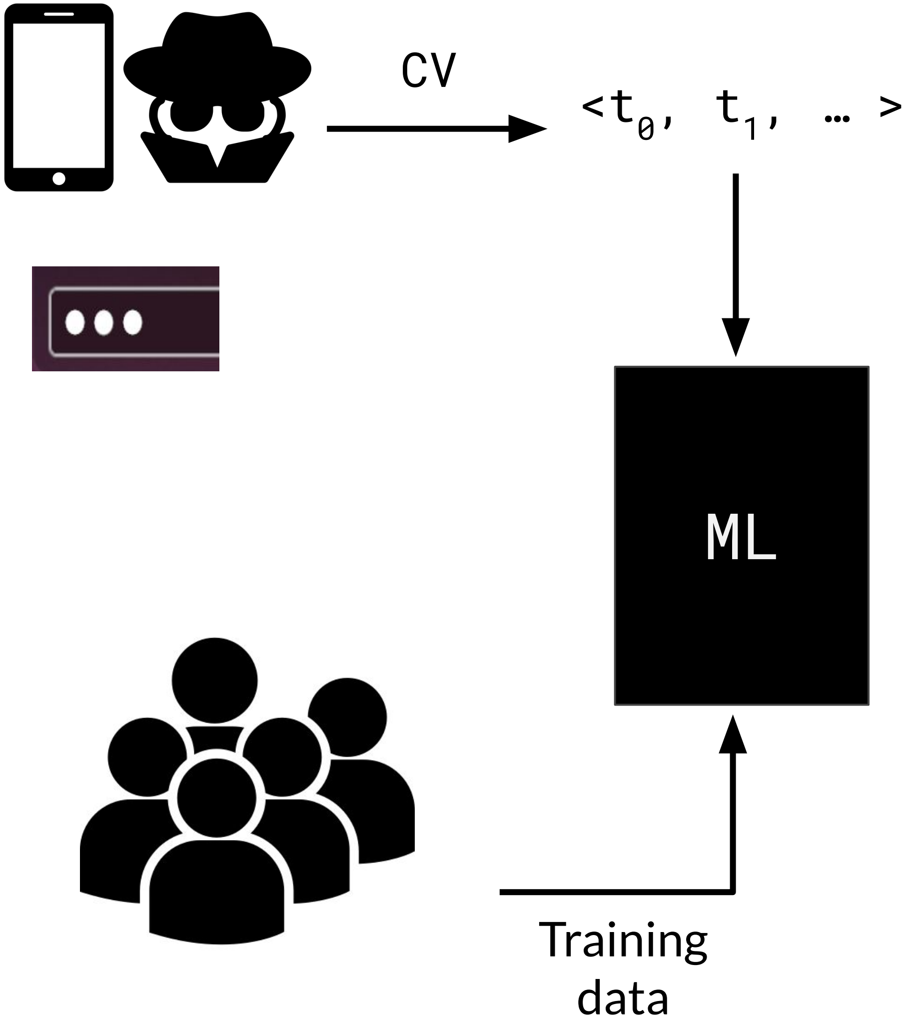
SILK-TV



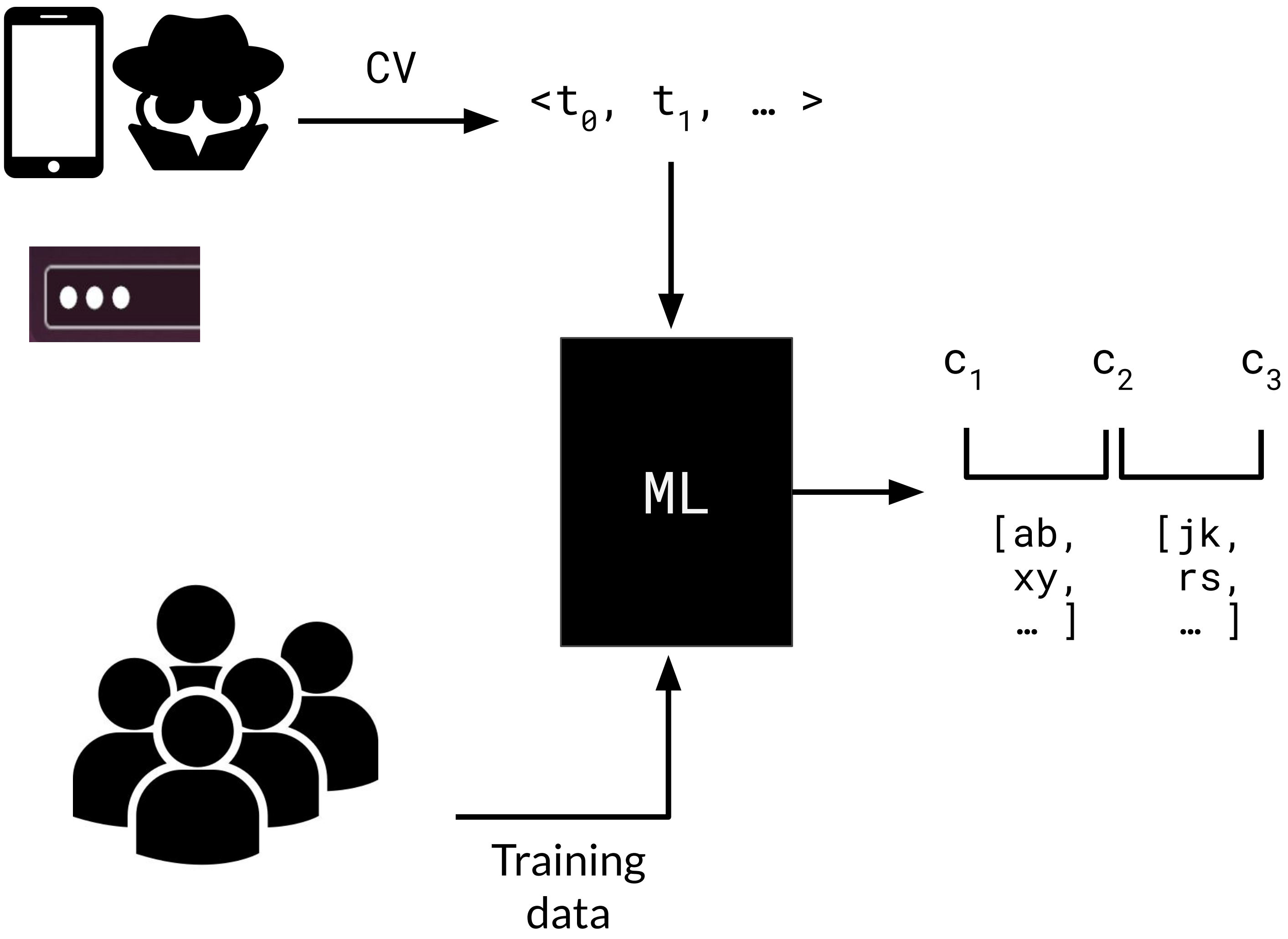
SILK-TV



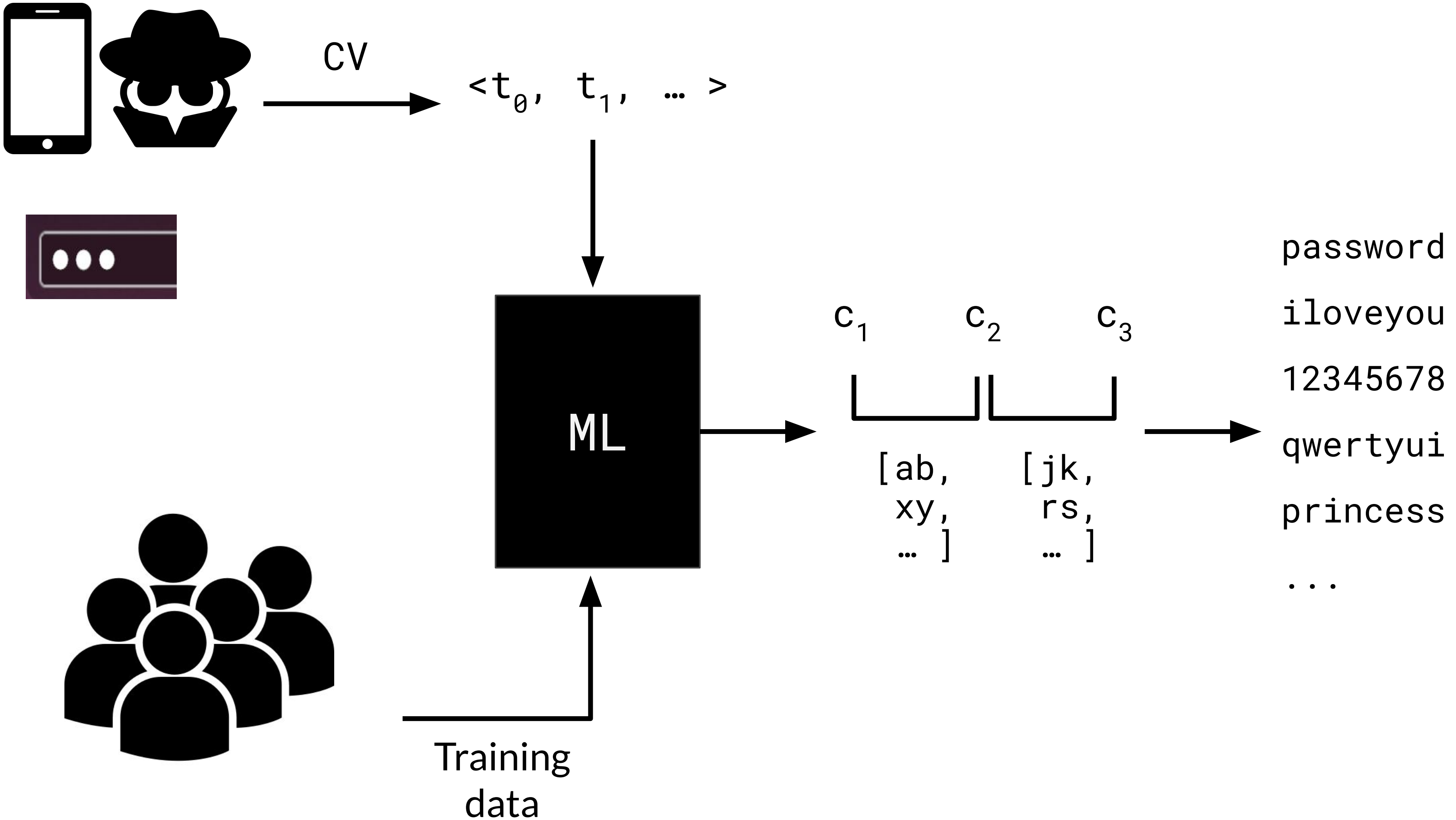
SILK-TV



SILK-TV



SILK-TV


CV
<t_0, t_1, … >
ML
c_1 c_2 c_3
[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

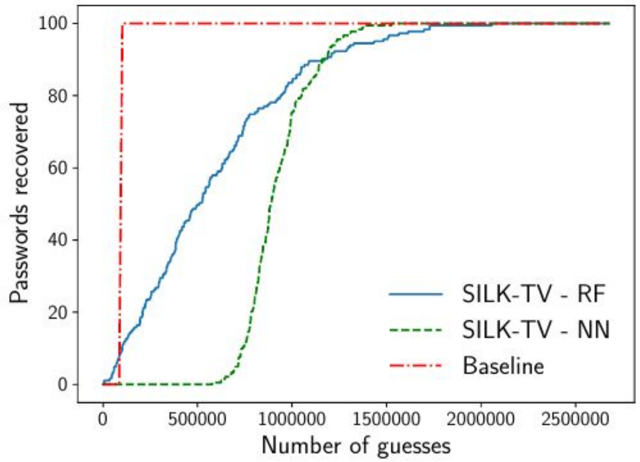
Evaluation - Passwords

- Baseline: password list sorted by frequency
  - *"Best" strategy for a zero-information attacker*

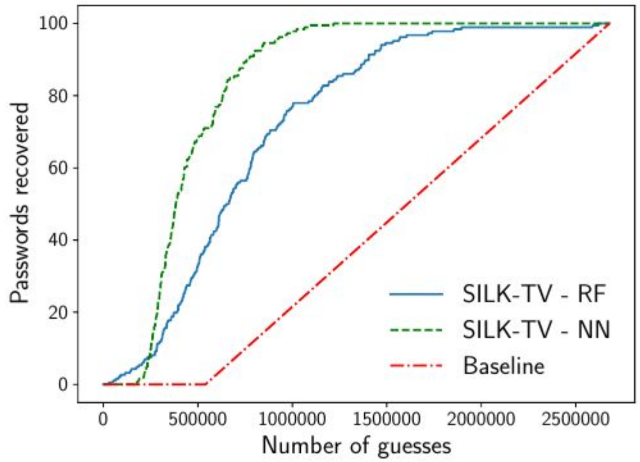
  - `123brian` - *93,874th*
  - `jillie02` - *1,753,571st*
  - `lamondre` - *397,213rd*
  - `william1` - *187th* ← *very frequent password*

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

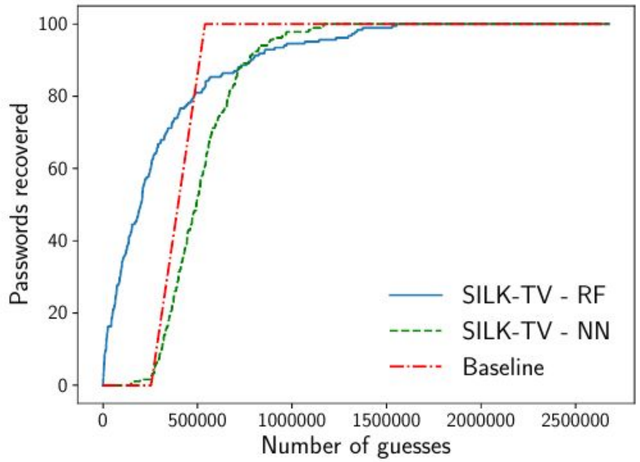
Password - “Single Shot” results



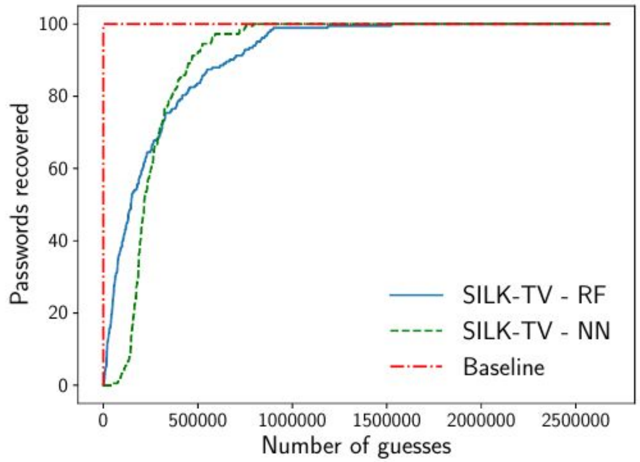
(a) **123brian** (183 auth. attempts).



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

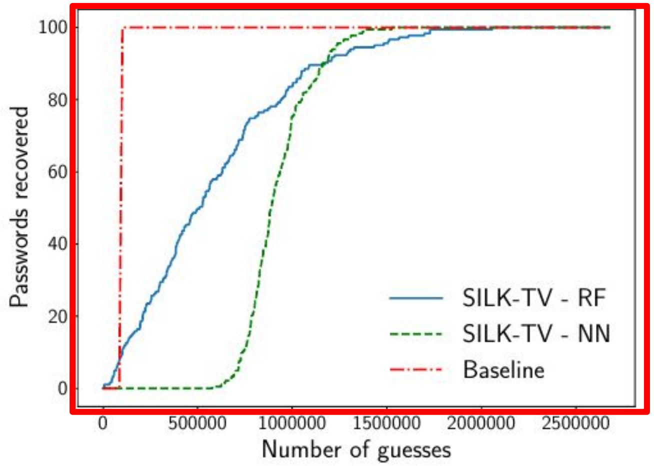


(c) **lamondre** (184 auth. attempts).

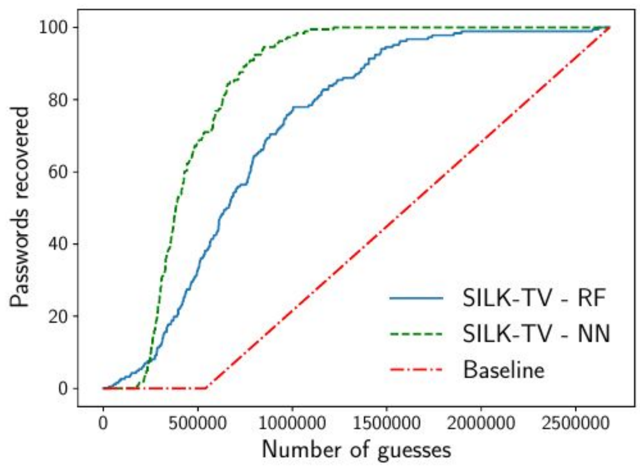


(d) **william1** (183 auth. attempts).

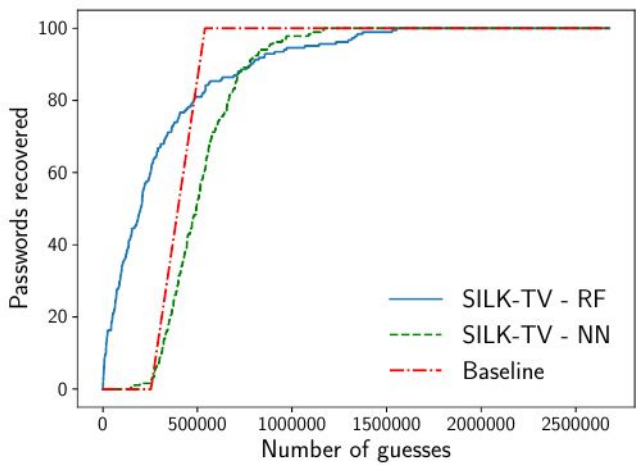
Password - “Single Shot” results



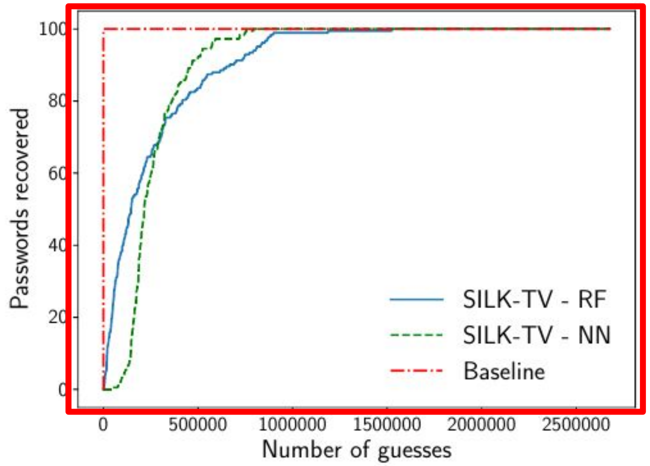
(a) 123brian (183 auth. attempts).



(b) jillie02 (186 auth. attempts).

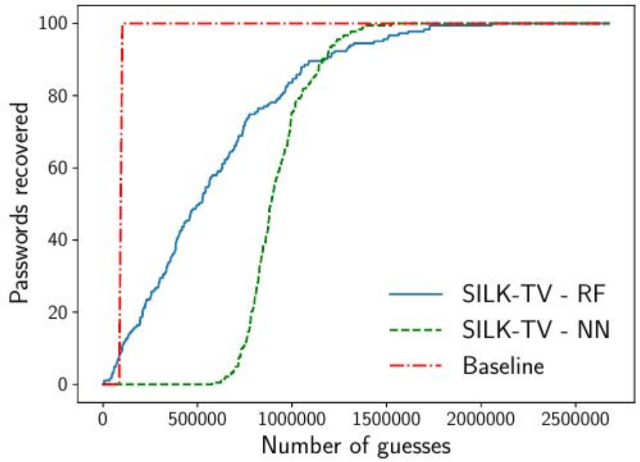


(c) lamondre (184 auth. attempts).

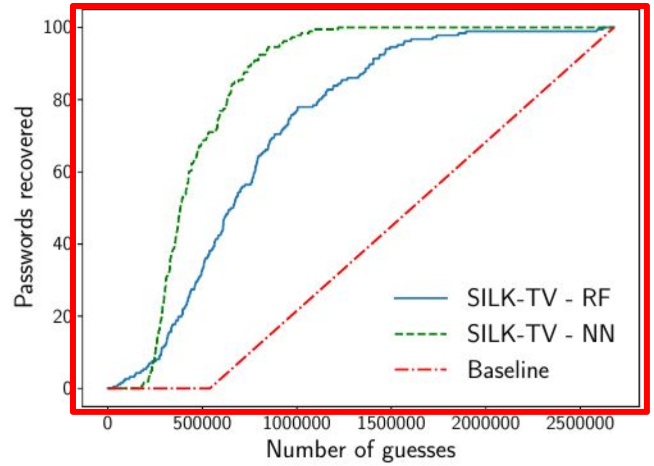


(d) william1 (183 auth. attempts).

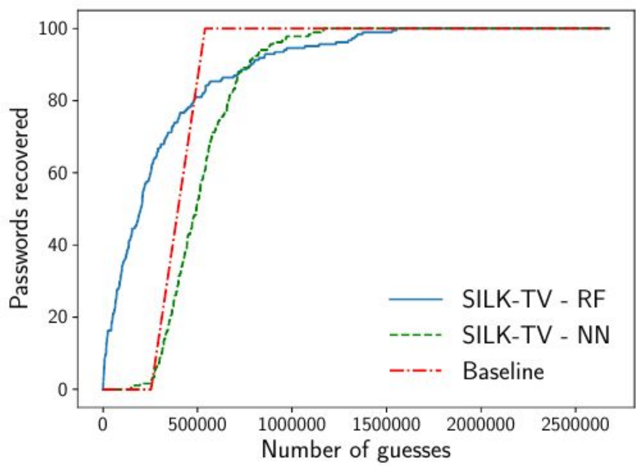
Password - “Single Shot” results



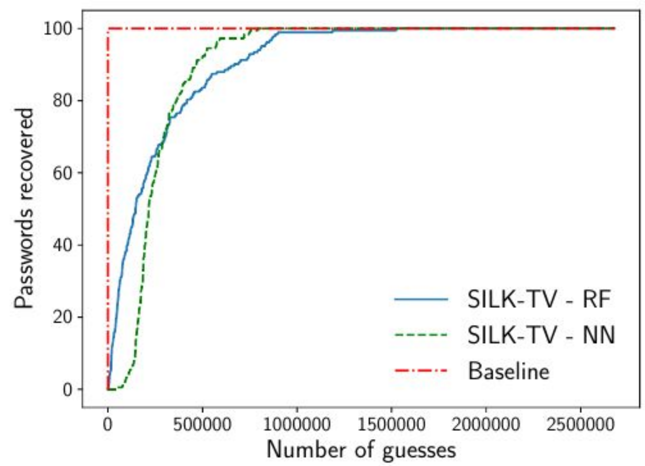
(a) **123brian** (183 auth. attempts).



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



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



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

Password - “Single Shot” results

	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*

Password - "Single Shot" results

	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*

Password - "Single Shot" results

	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*

Timing Information Leak - 2

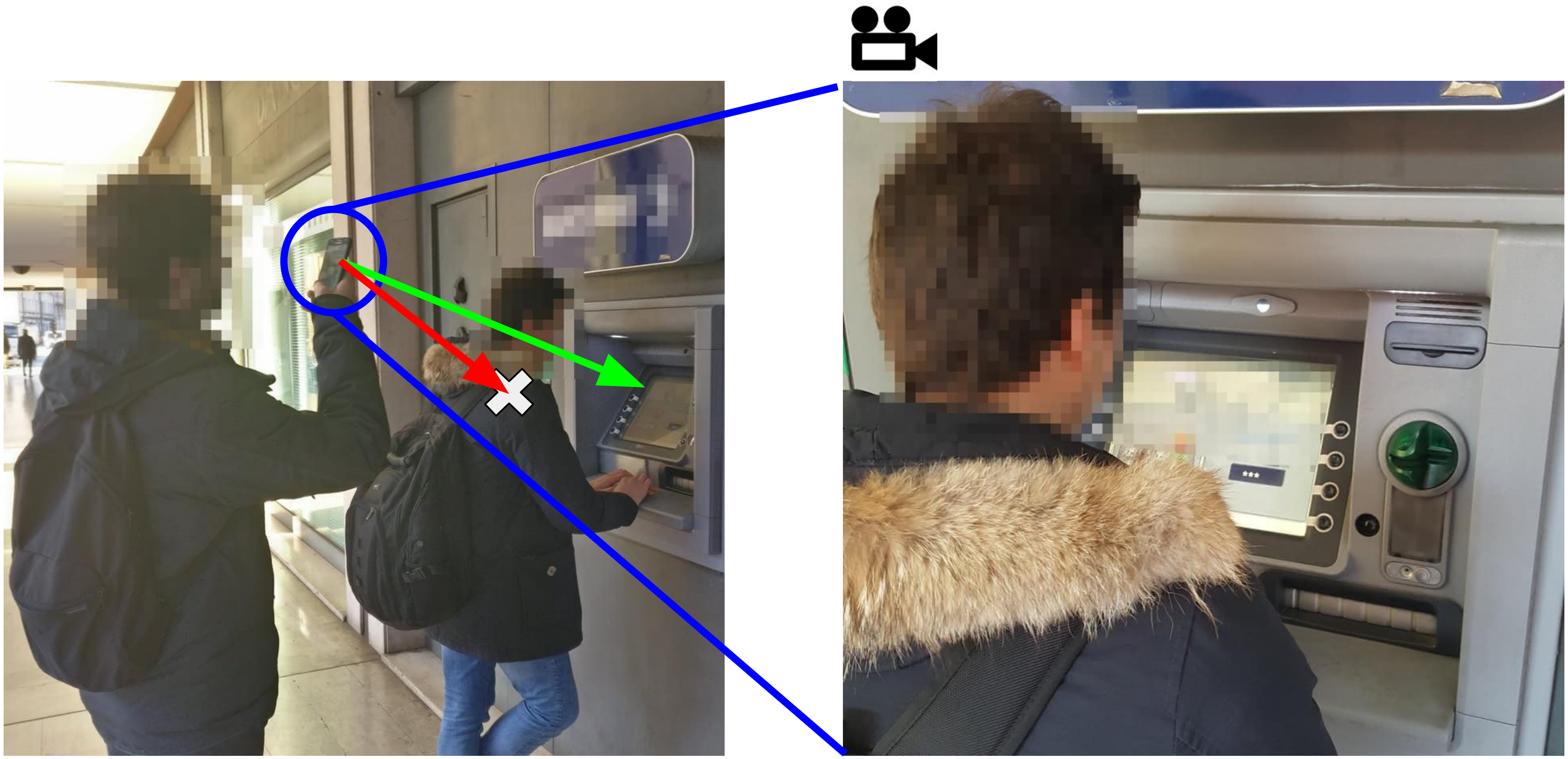
Keypad not visible - but the screen is!

Conclusions

- Timing information from videos is **accurate**
- Password masking leak timing → useful information
  - *Reduces number of attempts*
  - *More useful on **uncommon** passwords!*
- Performances on PIN… not great (close to random guess)

PIN Salabim

PIN Salabim



Keypad not visible - but the screen is!

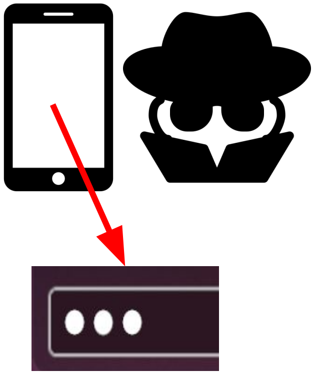
PILOT
Password and PIN Information Leakage from Obfuscated Typing Videos

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

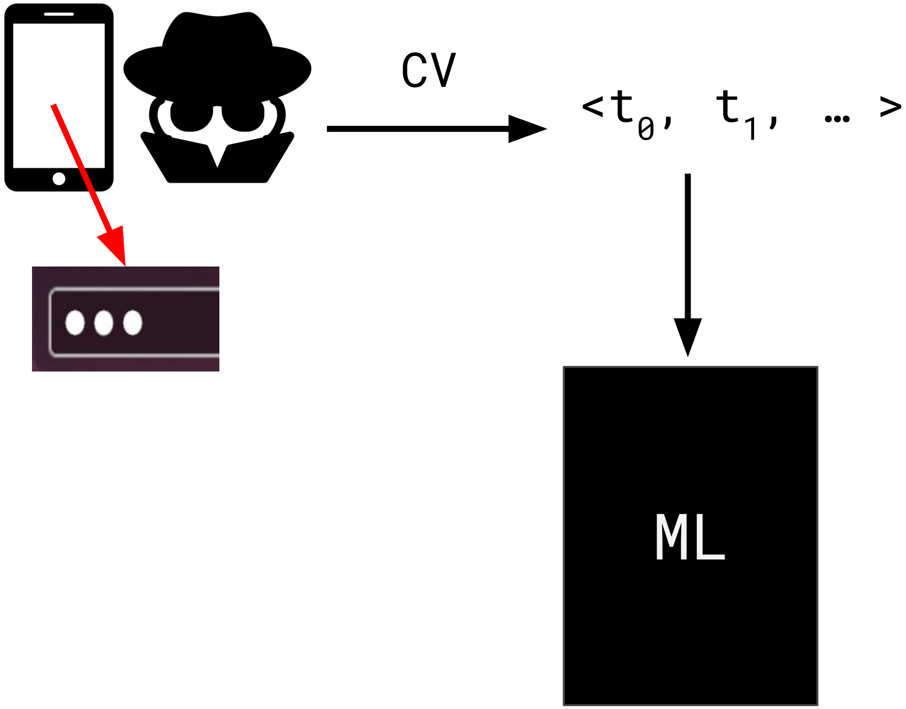
In Journal of Computer Security 2019

Università
degli Studi
di Padova
NYIT
New York Institute
of Technology
GFT
ETH zürich

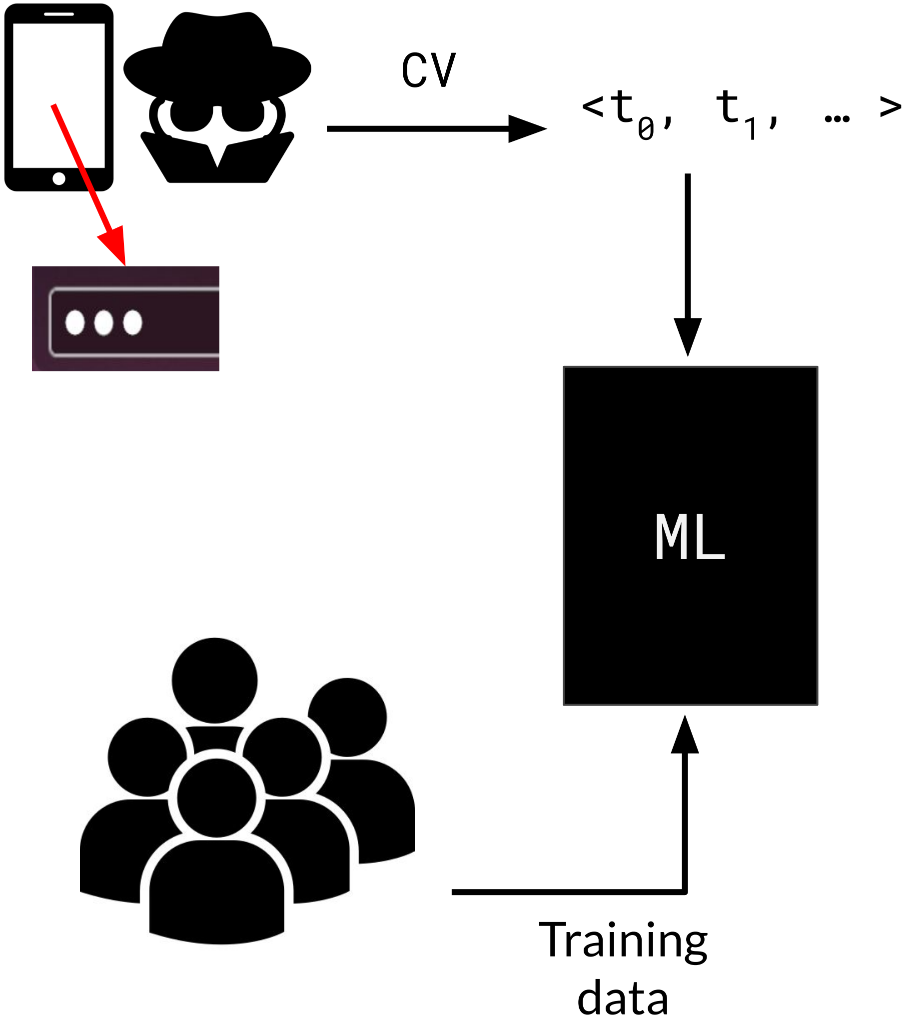
PILOT



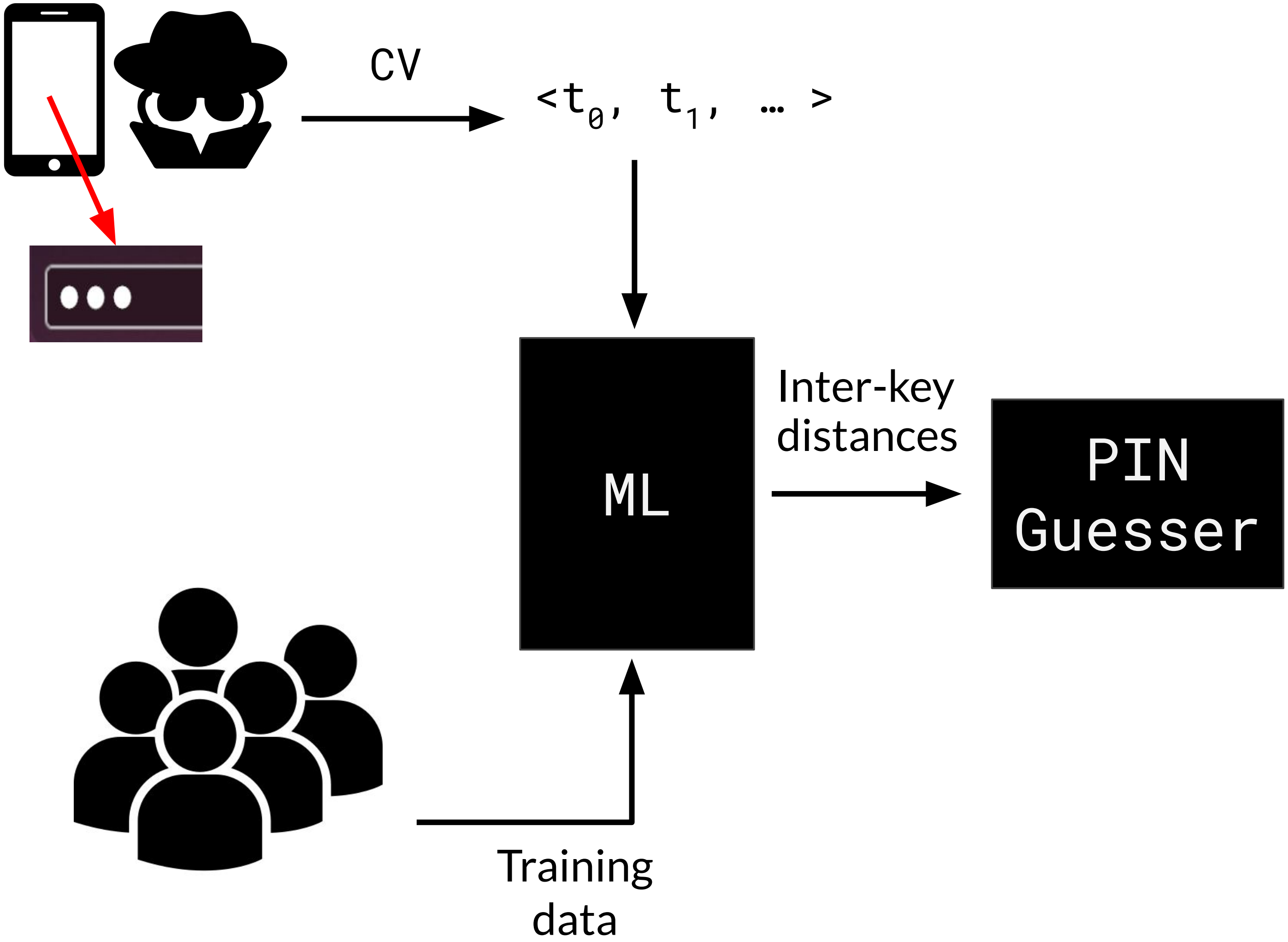
PILOT



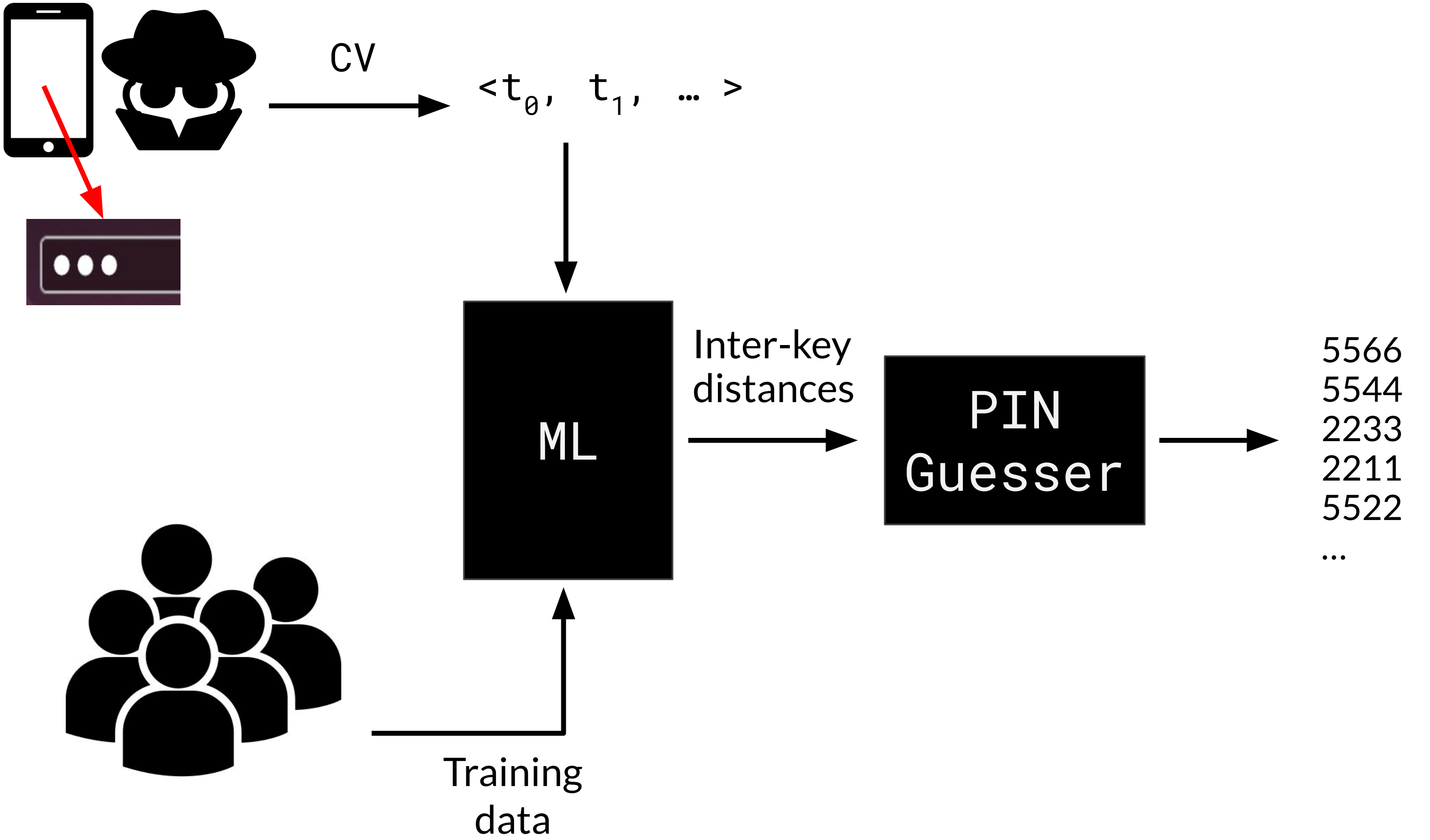
PILOT



PILOT



PILOT


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

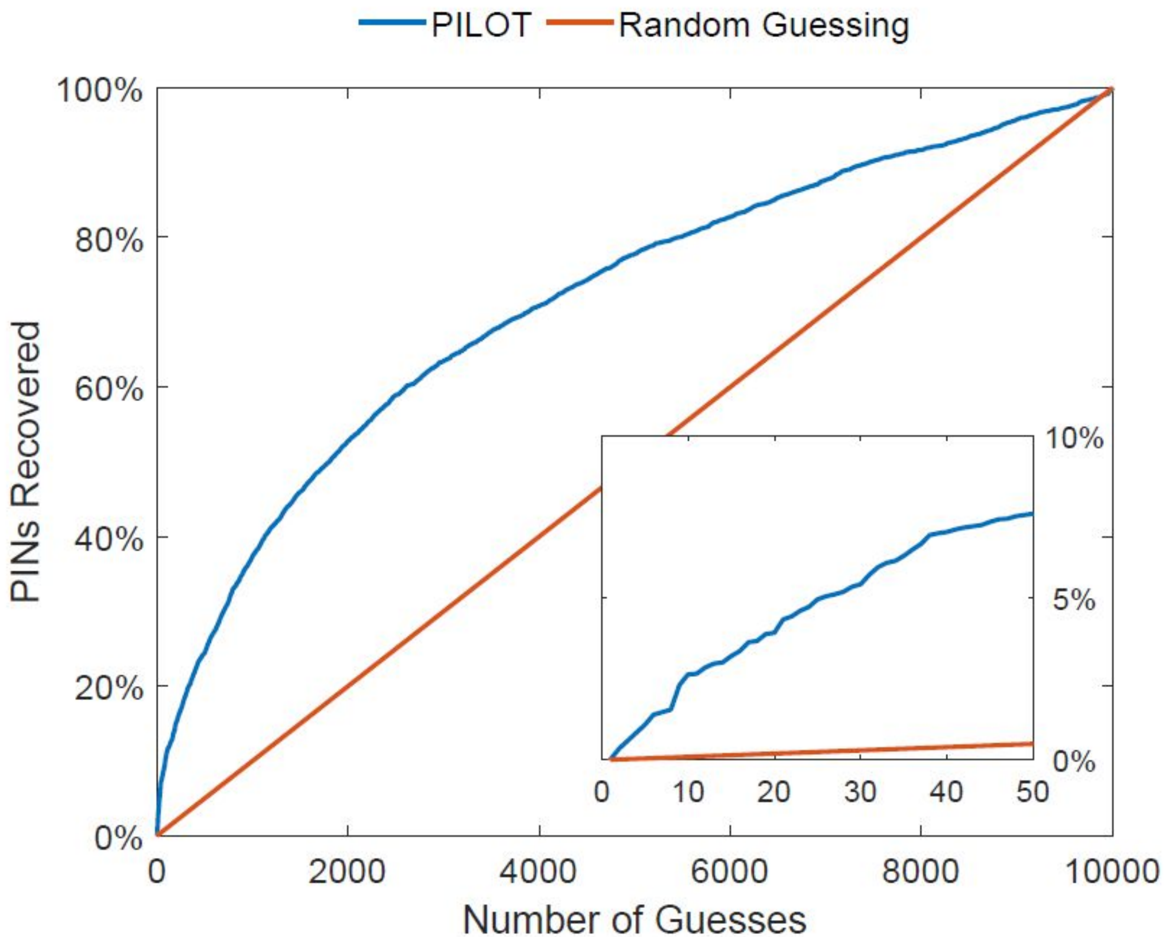
SPRITZ Security & Privacy Research Group

Università degli Studi di Padova

GFT

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

Università
degli Studi
di Padova
New York Institute
of Technology
GFT

Neither keypad nor screen are visible

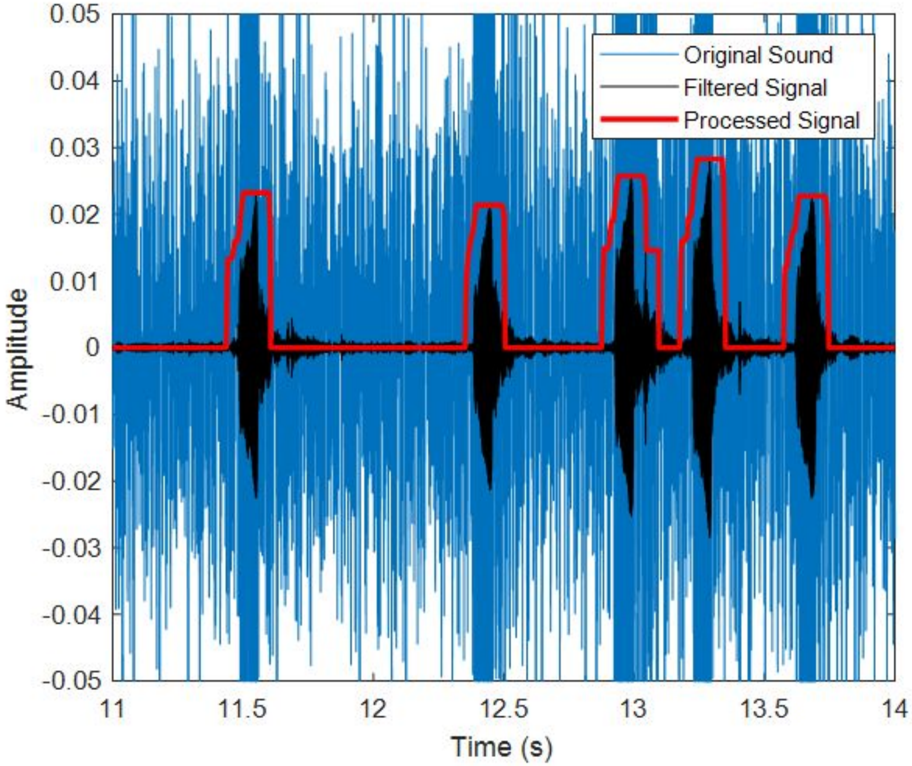
Inter-keystroke timing identification through sound analysis

- Signal filtering

  To extract feedback sound characteristic frequency

- Signal processing

  To remove residual noise and to identify time distance between peaks



Your PIN Sounds Good!

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*

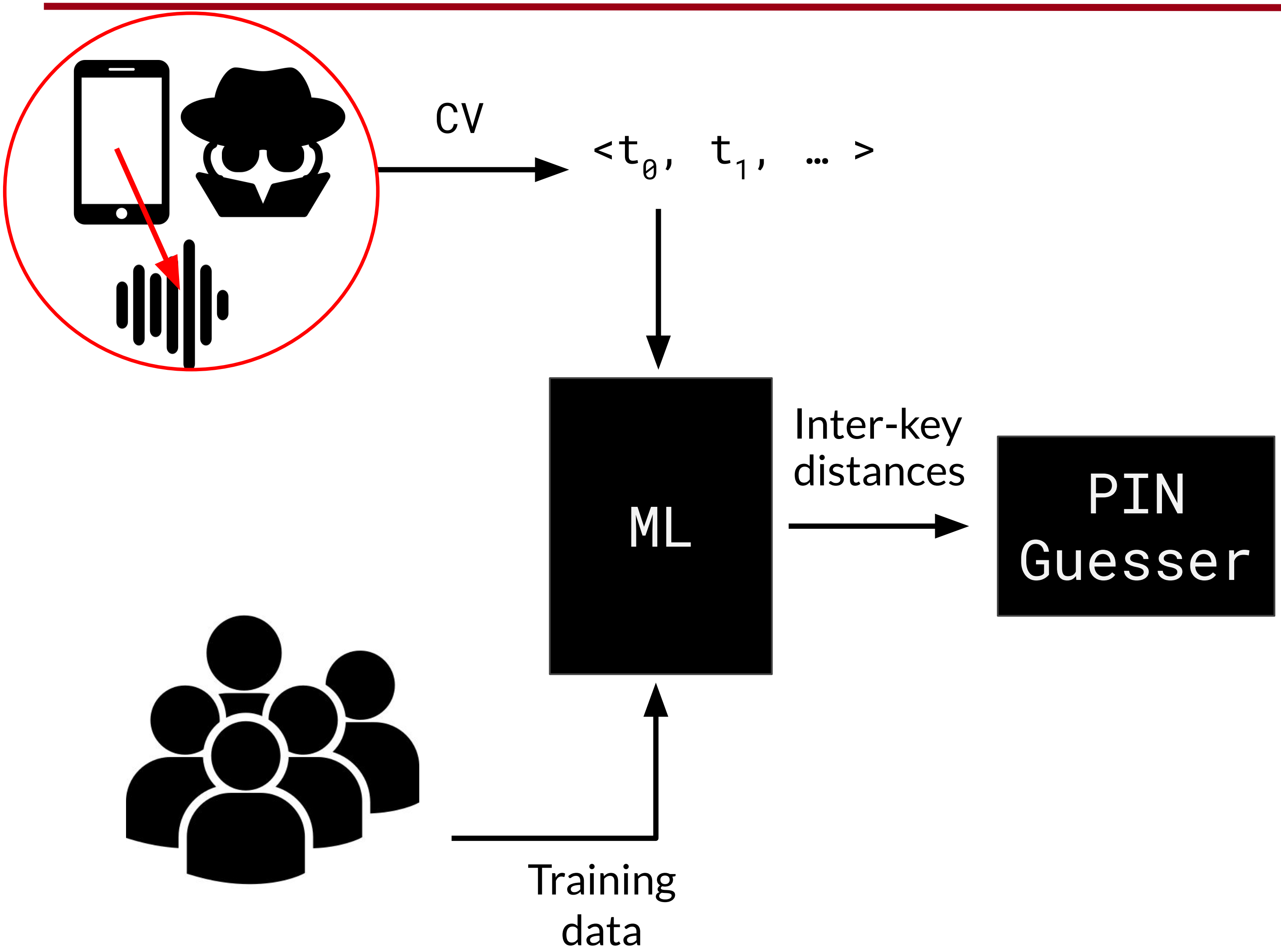
- **Heatmap**

  Adversary performs a ***thermal attack***

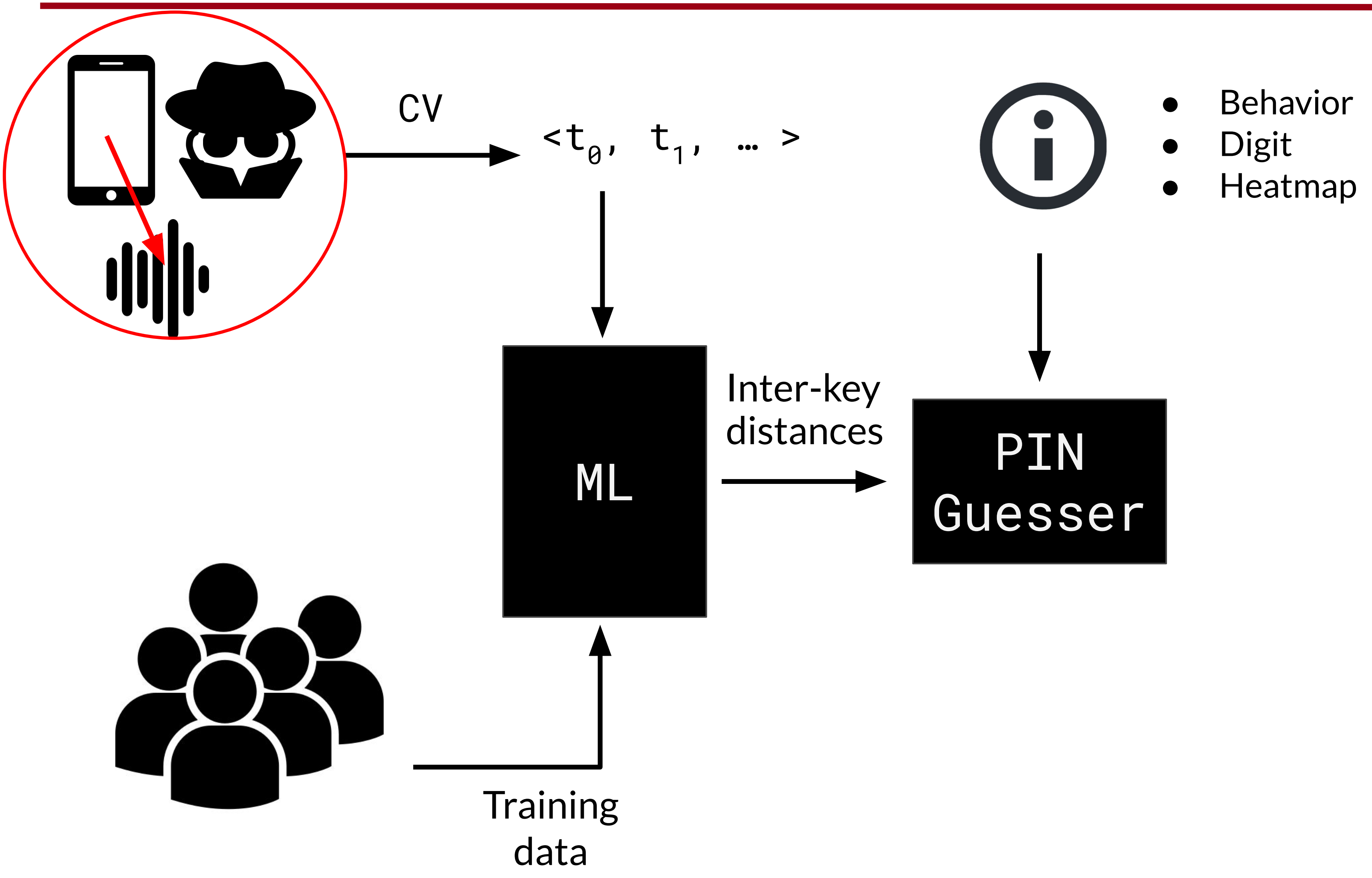
  - *Better on plastic and rubber*
    Not so good on metal

FLIR One PRO Lt iOS...
252 €
amazon

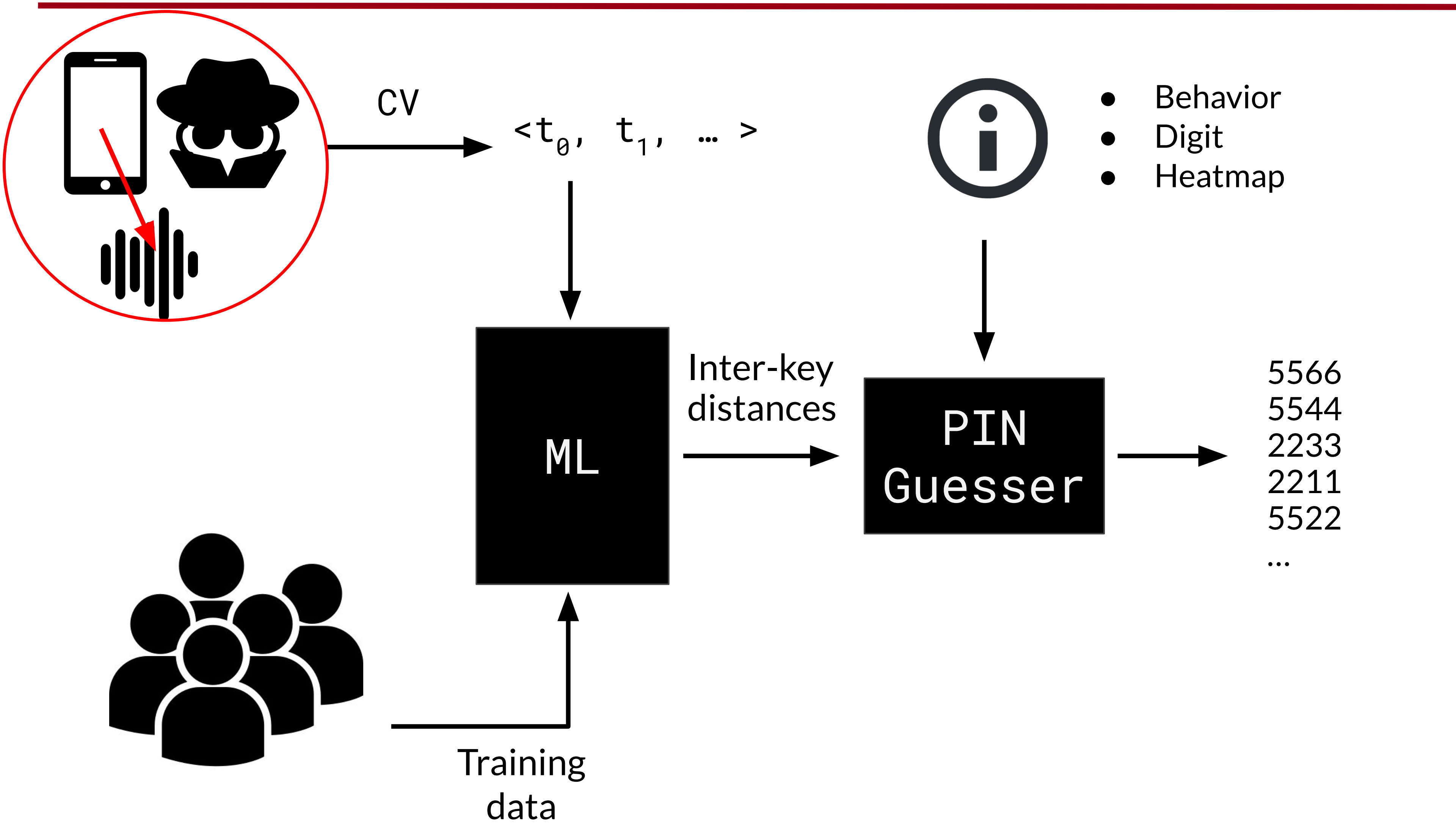
Your PIN Sounds Good!



Your PIN Sounds Good!



Your PIN Sounds Good!



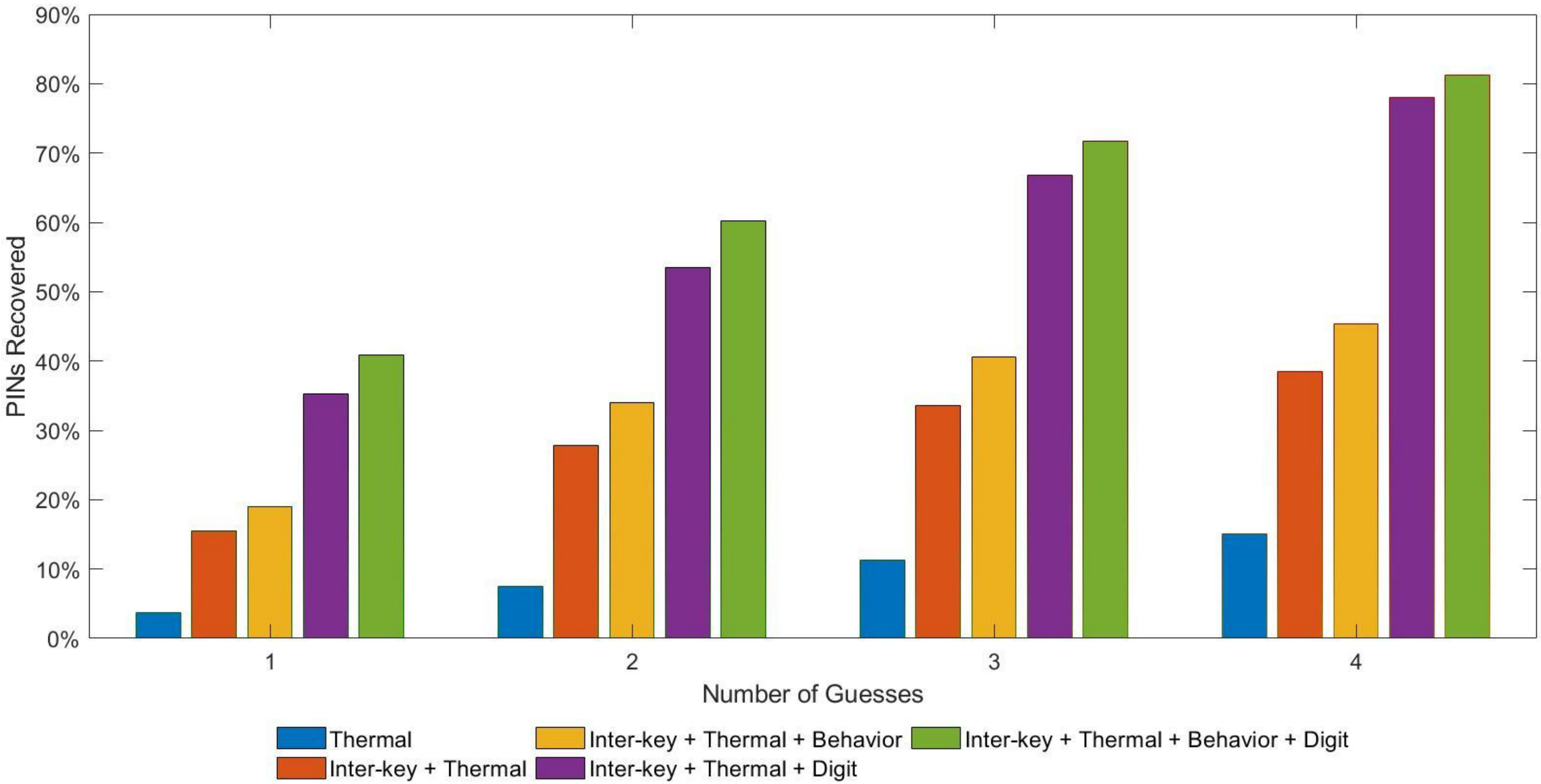
Your PIN Sounds Good!

SPRITZ
Security & Privacy
Research Group

Università
degli Studi
di Padova

GFT

% PINs recovered: inter-keystroke timing + other informations



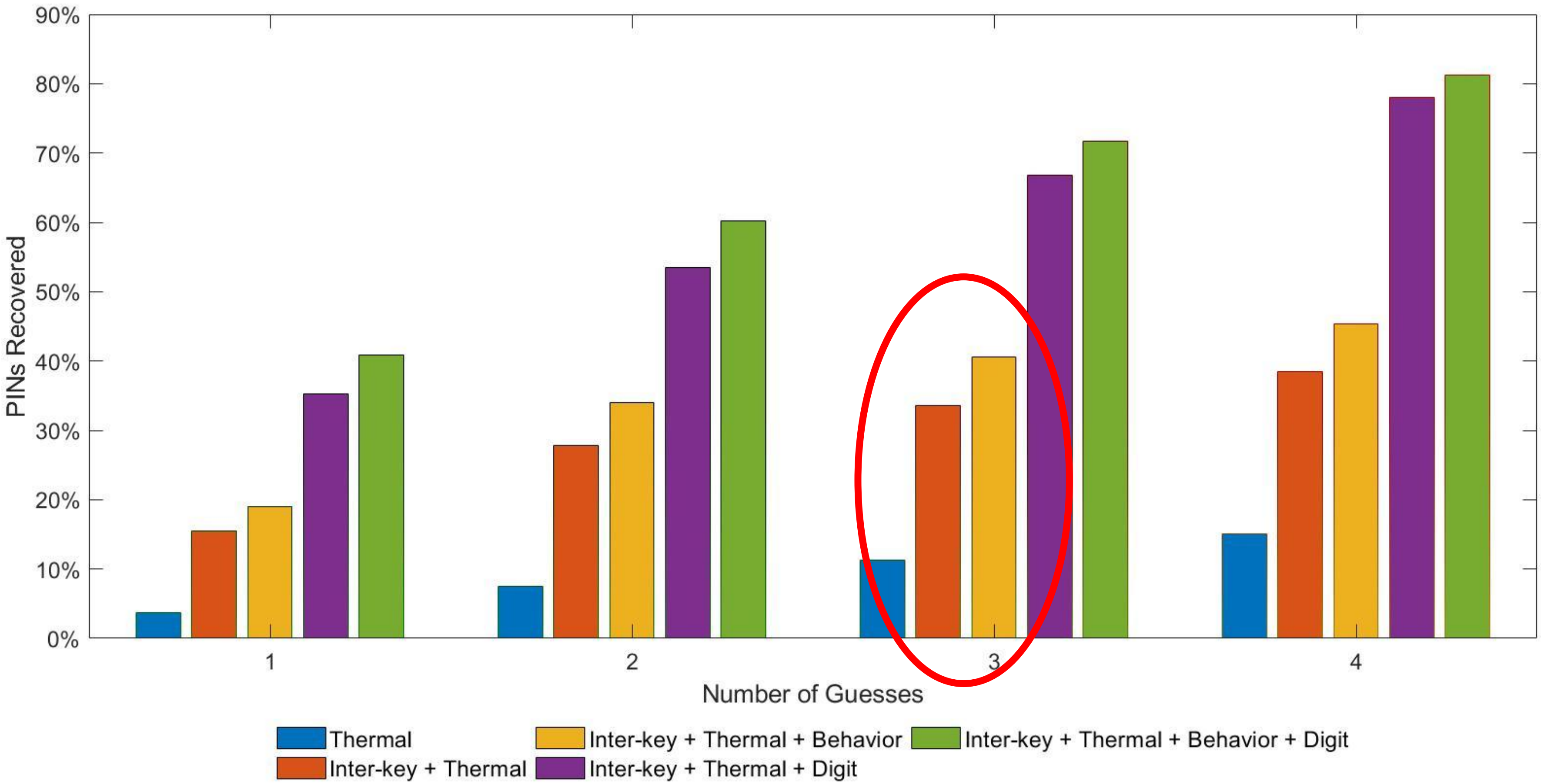
Your PIN Sounds Good!

SPRITZ
Security & Privacy
Research Group

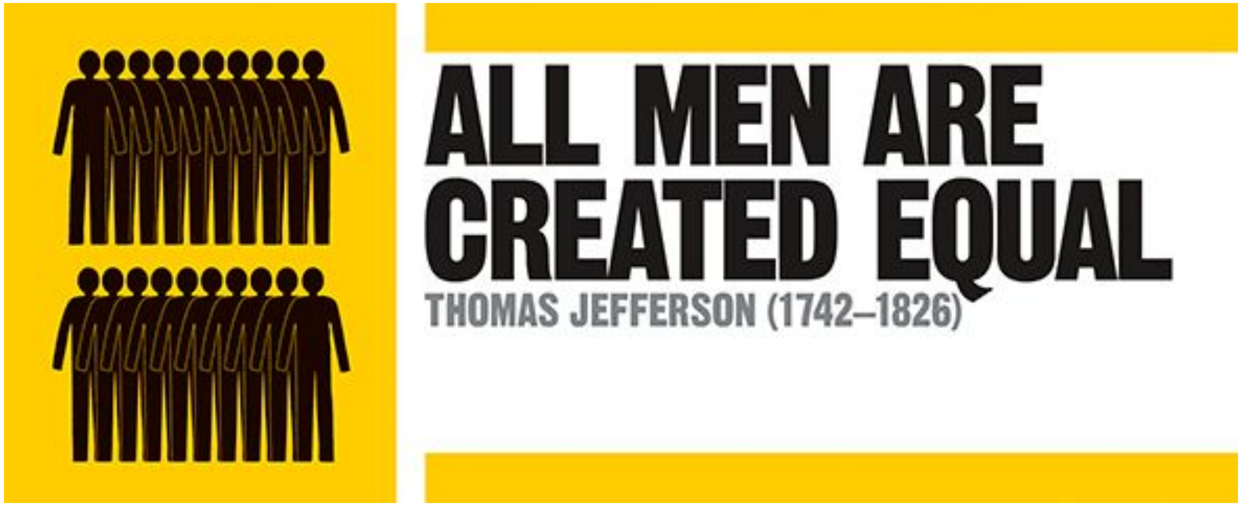
Università
degli Studi
di Padova

GFT

% PINs recovered: inter-keystroke timing + other informations

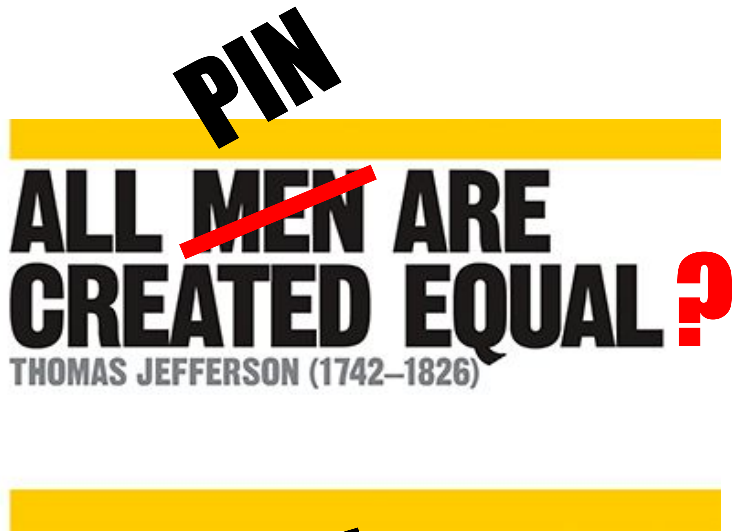


Your PIN Sounds Good!



Your PIN Sounds Good!

Your PIN Sounds Good!



User Chosen

Your PIN Sounds Good!

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

User Chosen

Random

Your PIN Sounds Good!

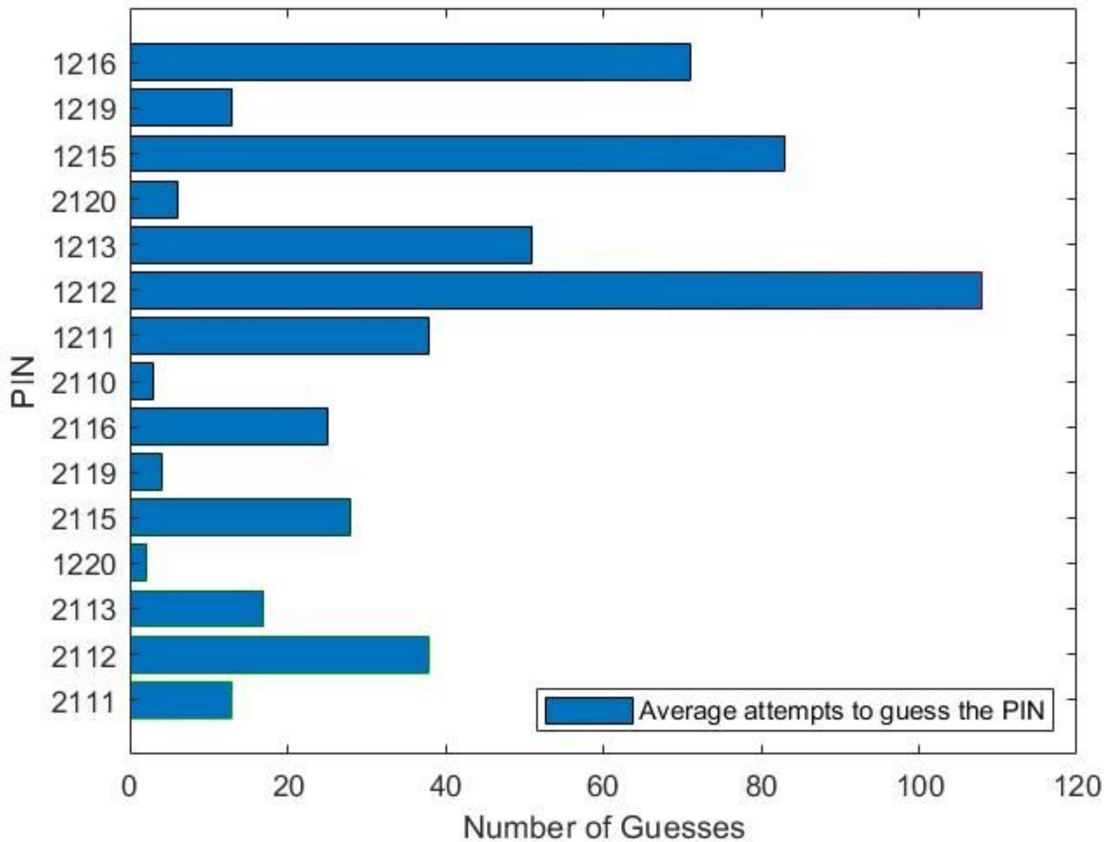
User Chosen

Random

DEFINITELY... NOT!

Not all PINs are born the same

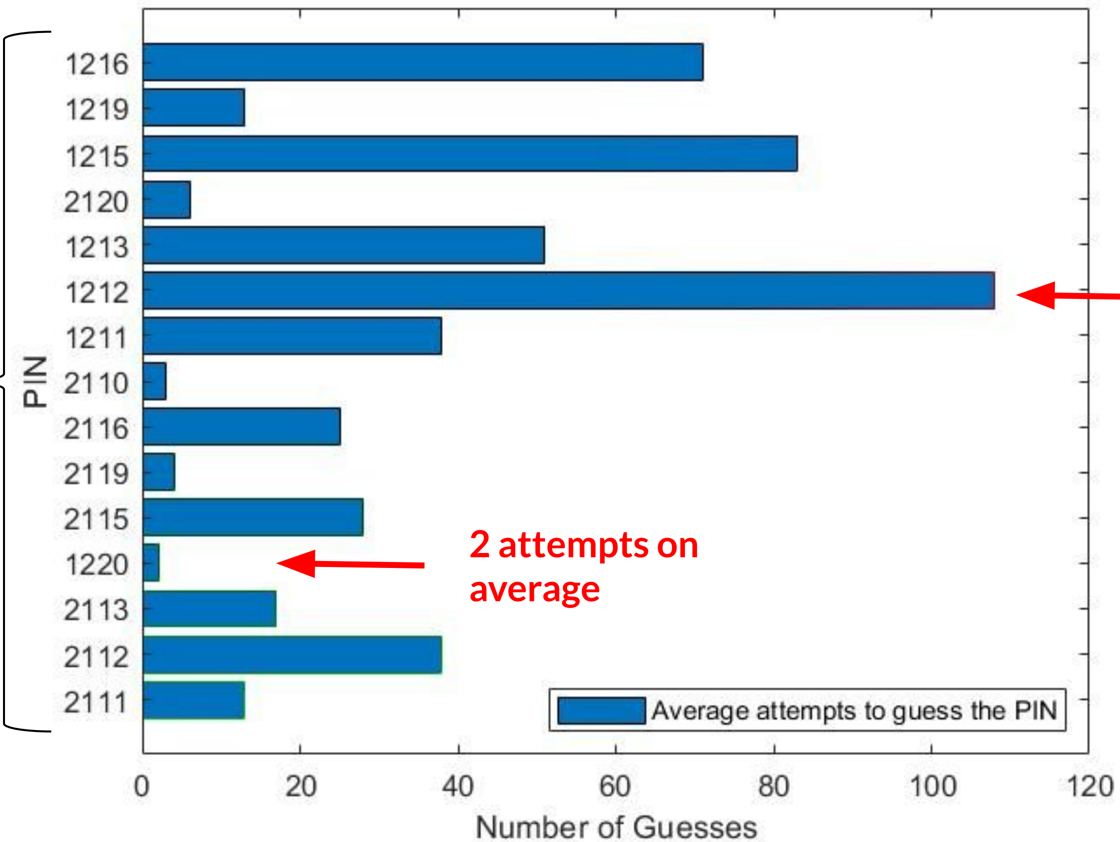
*Knowing **inter-key distance only***



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



128 attempts on average

2 attempts on average

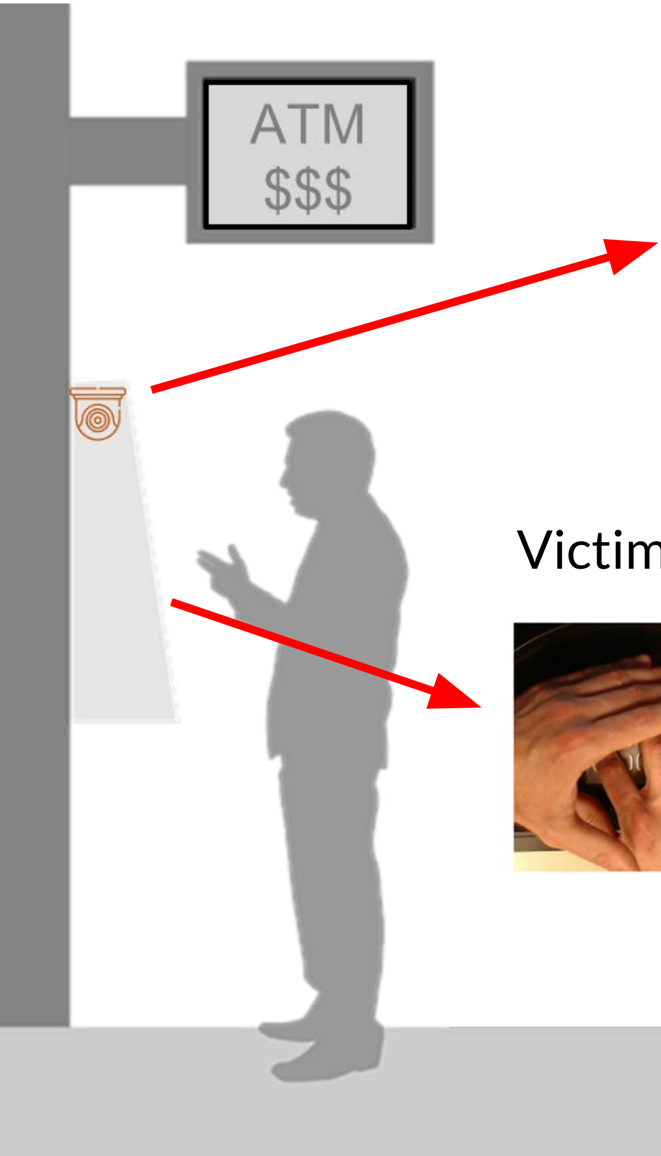
DEMO time!

Hand Me Your PIN!
Inferring ATM PINs of Users Typing with a Covered Hand

Matteo Cardaioli, Stefano Cecconello, Mauro Conti, and Simone Milani

In USENIX Security Symposium 2022

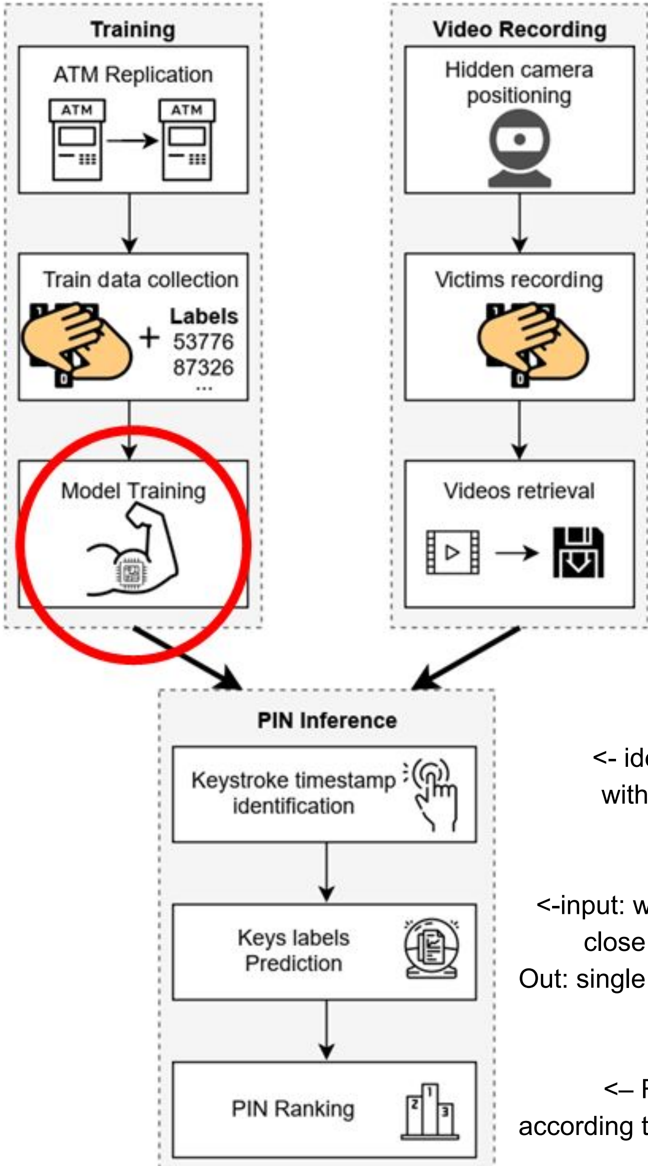
Hand me Your PIN



Hidden camera recording the PIN pad

Victim's covering strategy to avoid shoulder surfing attacks

Experimental Setting



<- identify frame
with "pressing"

<-input: window of frames
close to the press
Out: single keys probabilities

<– Rank PINS
according to single key prob.

Central camera

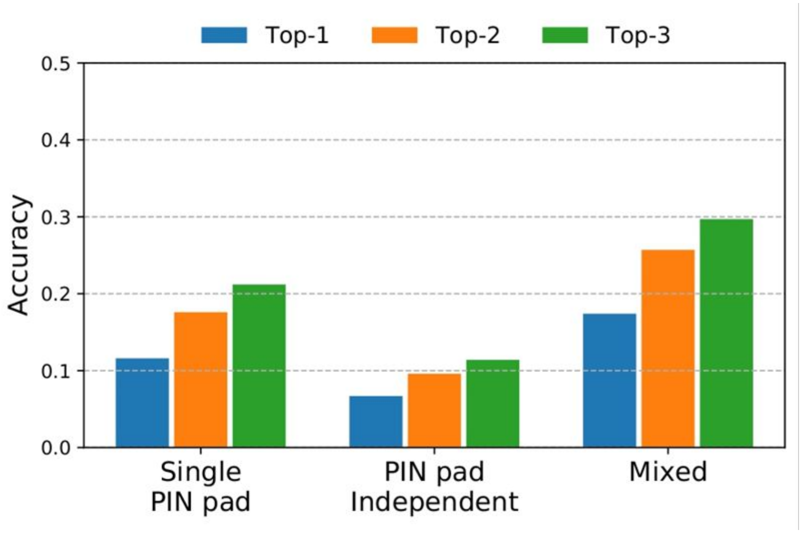
Left-corner camera

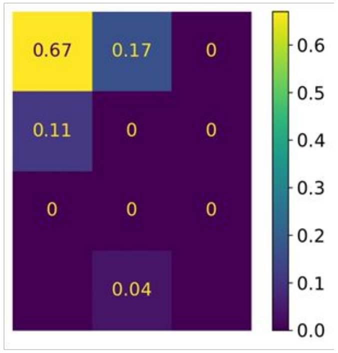
Right-corner camera

Results

Attack Scenarios

- **Single PIN pad:**
  - *the adversary knows the target PIN pad model and owns a copy*
- **PIN pad Independent:**
  - *the adversary trains the machine learning model on a **PIN pad with a similar (but not the same)** layout to the target one.*
- **Mixed:**
  - *the **adversary** owns both a copy of the target PIN pad and a PIN pad similar to the target one*





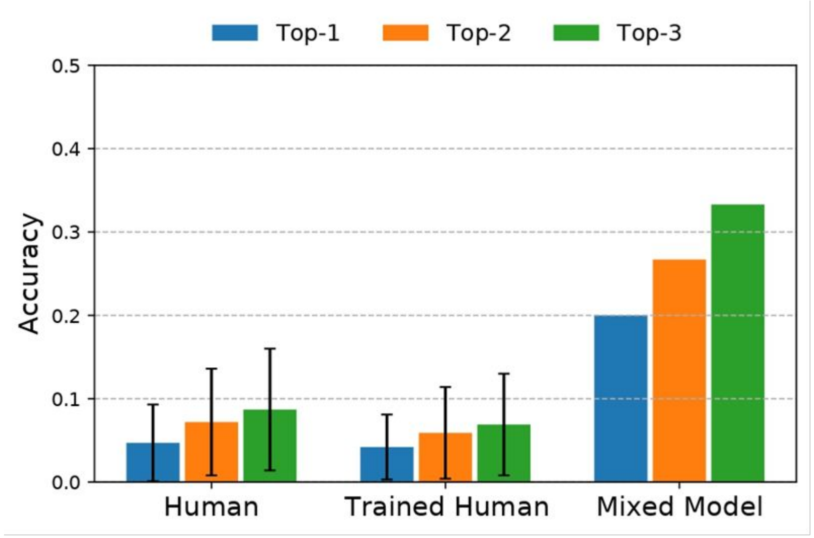
heatmap for prediction of Digit "1"

Results

Human Vs Machine assessment

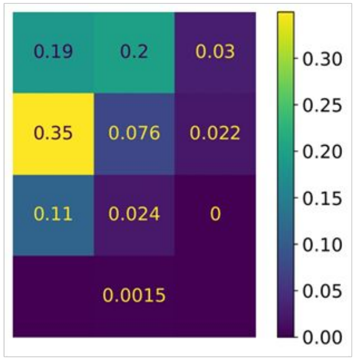
Survey:

- ***30 videos*** *of people entering* ***5-digit PINs*** *by covering the PIN pad with the non-typing hand*
- *Videos from the* ***Mixed scenario*** *test set (i.e., the only one including both PIN pads)*
- *Participants had to indicate* ***the three most likely*** *PINs*

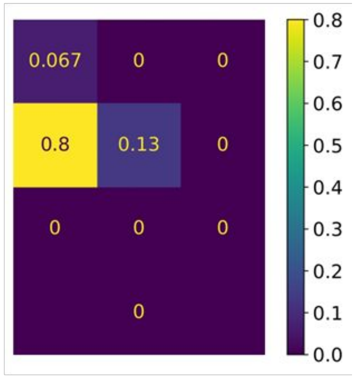


Participants:

- ***45*** *participants performed the questionnaire* ***without any training***
- ***33*** *participants* ***pre-trained*** *on other covered PIN videos from the test set.*

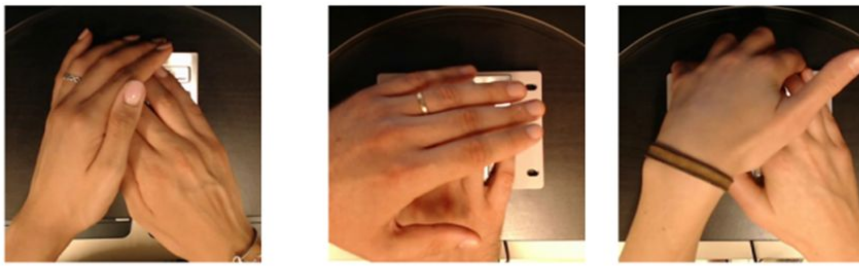


Human
(non trained)



Mixed Model

Results



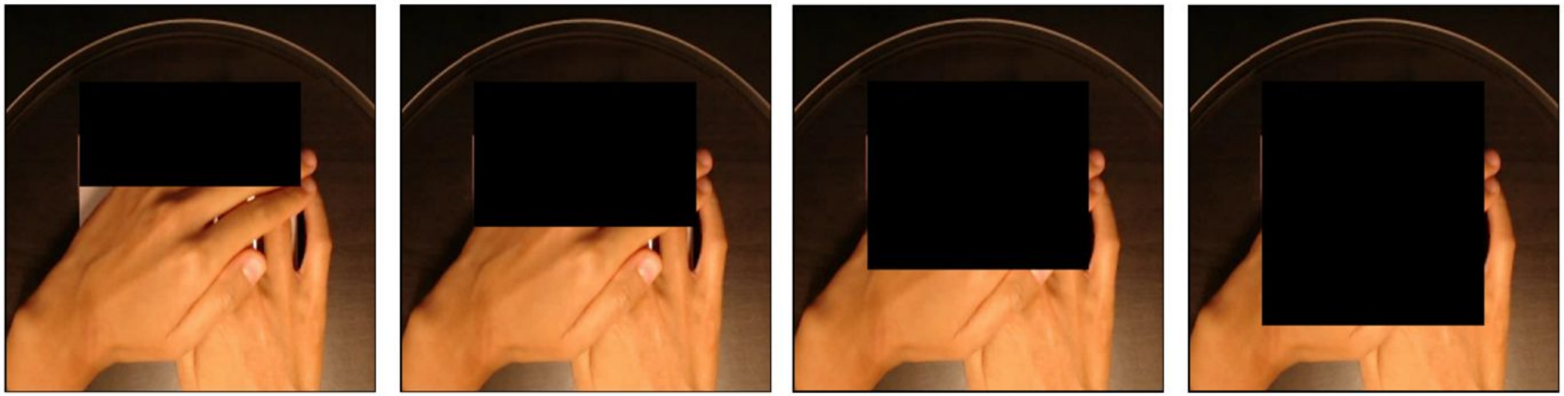
(a) *Side: hand resting on the side of the palm.* (b) *Over: raised hand not touching the surface.* (c) *Top: hand restin on fingers and ve tically covering th PIN pad.*

Covering strategy	Scenario	Key accuracy	PIN TOP-3 accuracy
Side	Single	0.64	0.30
	Independent	0.42	0.12
	Mixed	0.77	0.53
Over	Single	0.52	0.12
	Independent	0.31	0.10
	Mixed	0.46	0.07
Top	Single	NA	NA
	Independent	0.41	0.13
	Mixed	NA	NA

(a) *Left-corner camera.* (b) *Center camera.* (c) *Right-corner camera.*

Experiment	Key accuracy	PIN TOP-3 accuracy
Input resolution 125 x 125	0.55	0.23
Input resolution 64 x 64	0.47	0.15
Left-corner camera	0.46	0.10
Right-corner camera	0.62	0.31
Multi-camera training	0.53	0.22
No data augmentation	0.44	0.11
Blacklisted excluded in training	0.54	0.18

Countermeasures



(a) *25% of PIN pad surface covered (i.e., digits form 1 to 3).*
(b) *50% of PIN pad surface covered (i.e., digits form 1 to 6).*
(c) *75% of PIN pad surface covered (i.e., digits form 1 to 9).*
(d) *100% of PIN pad surface covered (i.e., no digit is visible).*

Coverage percentage	Key accuracy	PIN TOP-3 accuracy
25%	0.54	0.22
50%	0.55	0.22
75%	0.50	0.17
100%	0.33	0.01

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***

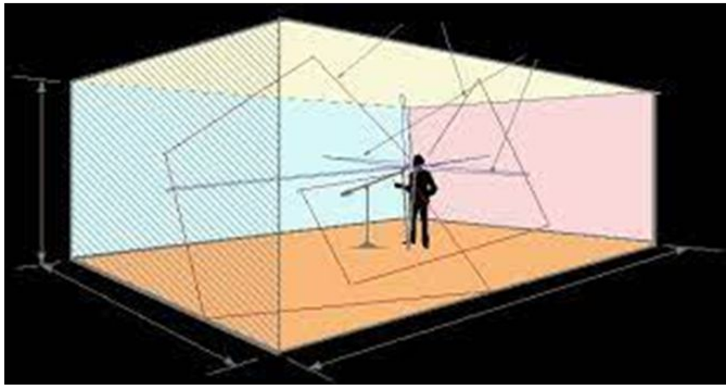
For your voice only
Exploiting side channels in voice messaging for environment detection

Matteo Cardaioli, Mauro Conti, and Arpita Ravindranath

In ESORICS 2022

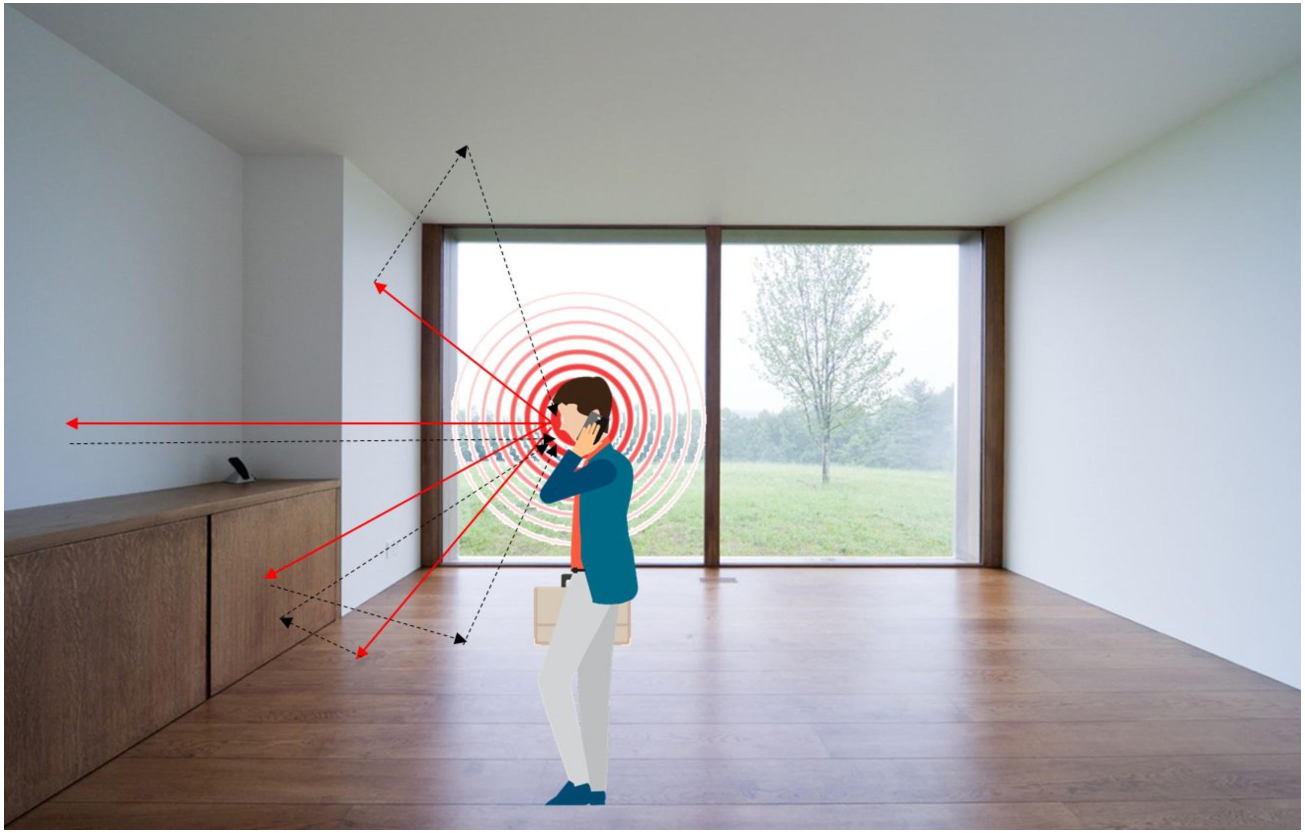
Università degli Studi di Padova
TU Delft
Delft University of Technology
GFT

Is GPS the only way to locate you?

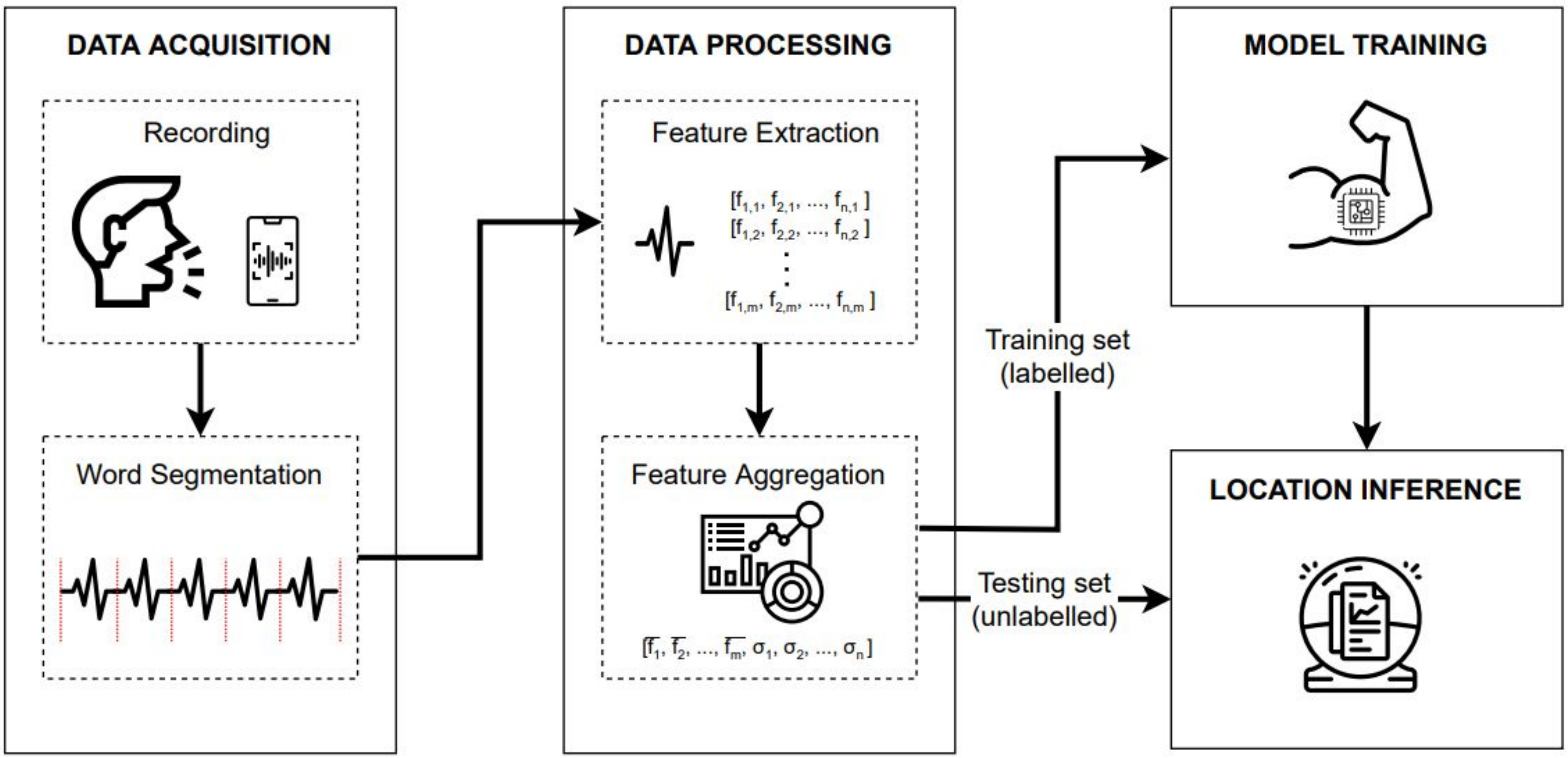


Can audio messages be used in identification of the location/room?

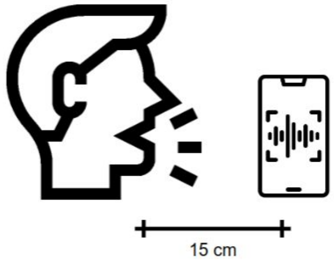
-

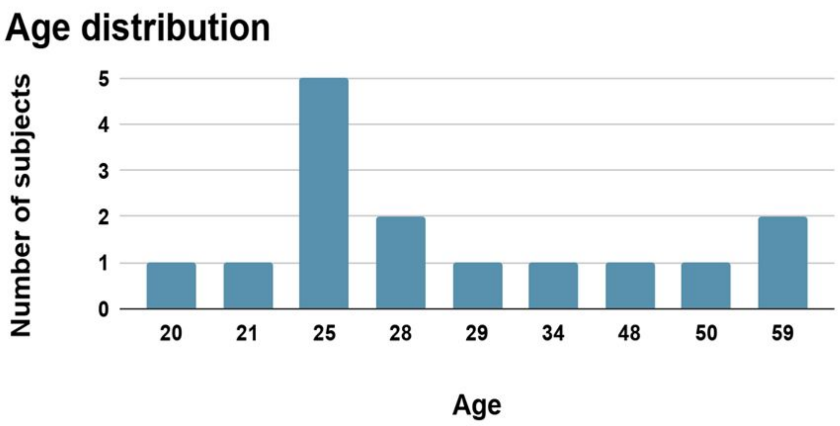


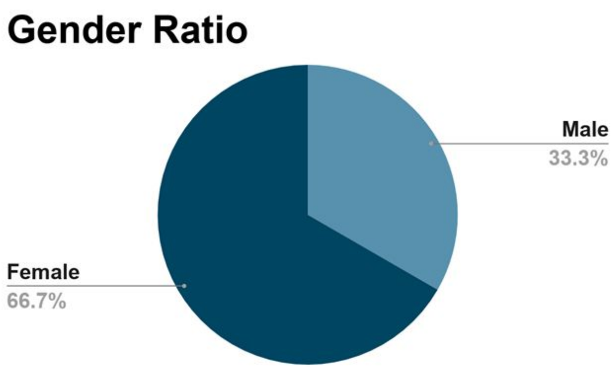
Experimental Setting



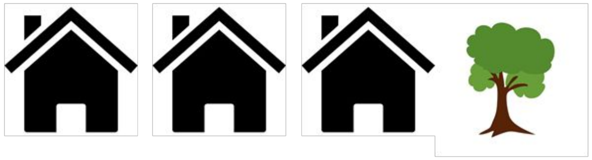
Experimental Setting







LOCATIONS :
3 INDOOR
1 OUTDOOR



AUDIO CONTENT/SYLLABLES :

AND OF THE

DEVICE: 14 DIFFERENT DEVICE MODELS {SAMSUNG, ONEPLUS, IPHONE,MOTO}

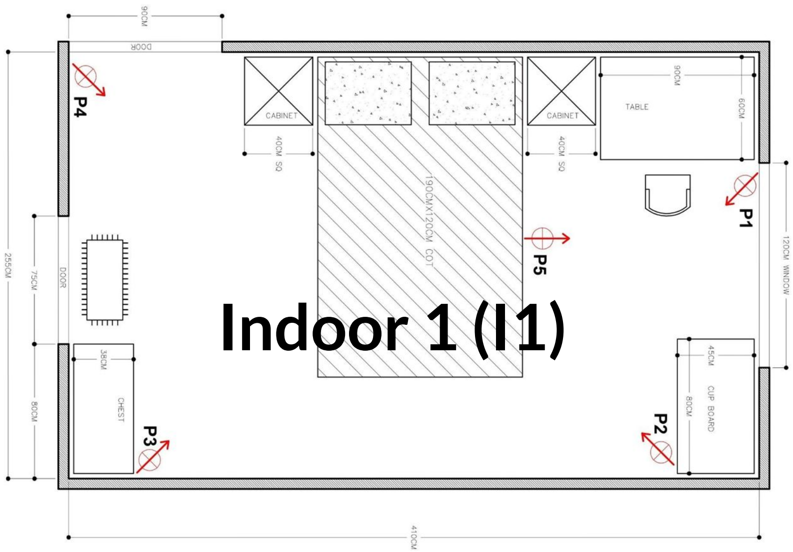
Experimental Setting

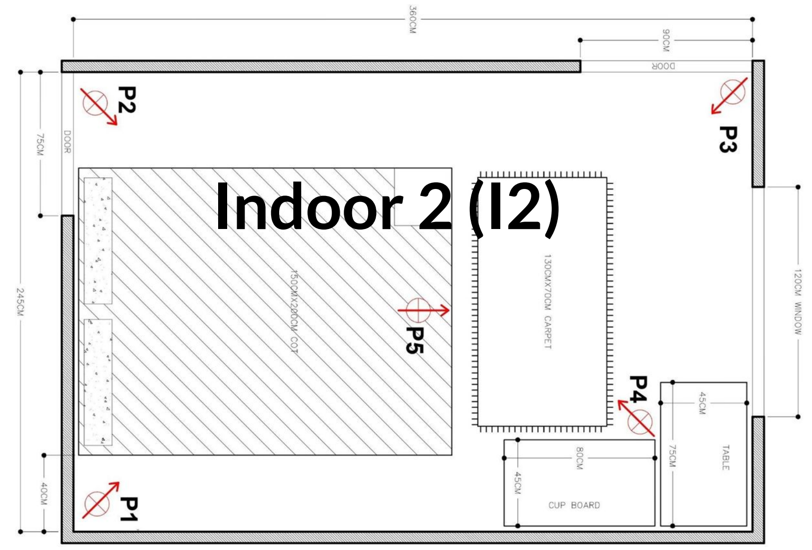
SPRITZ
Security & Privacy
Research Group

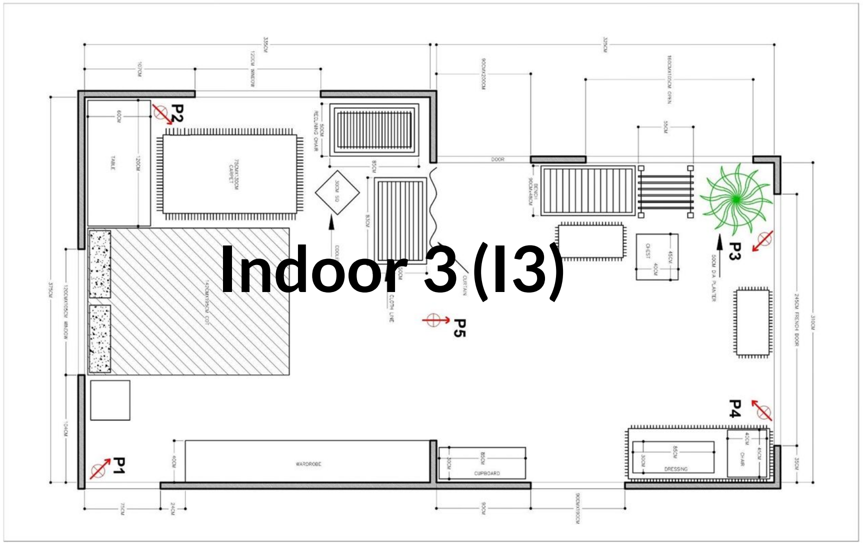
Università
degli Studi
di Padova

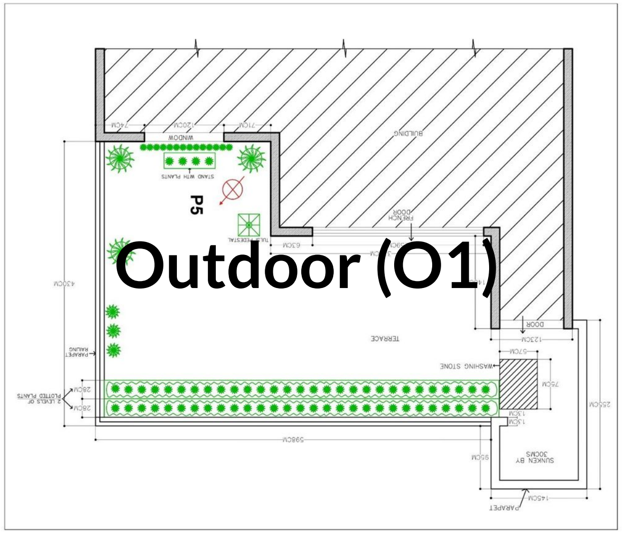
GFT

Experimental Setting

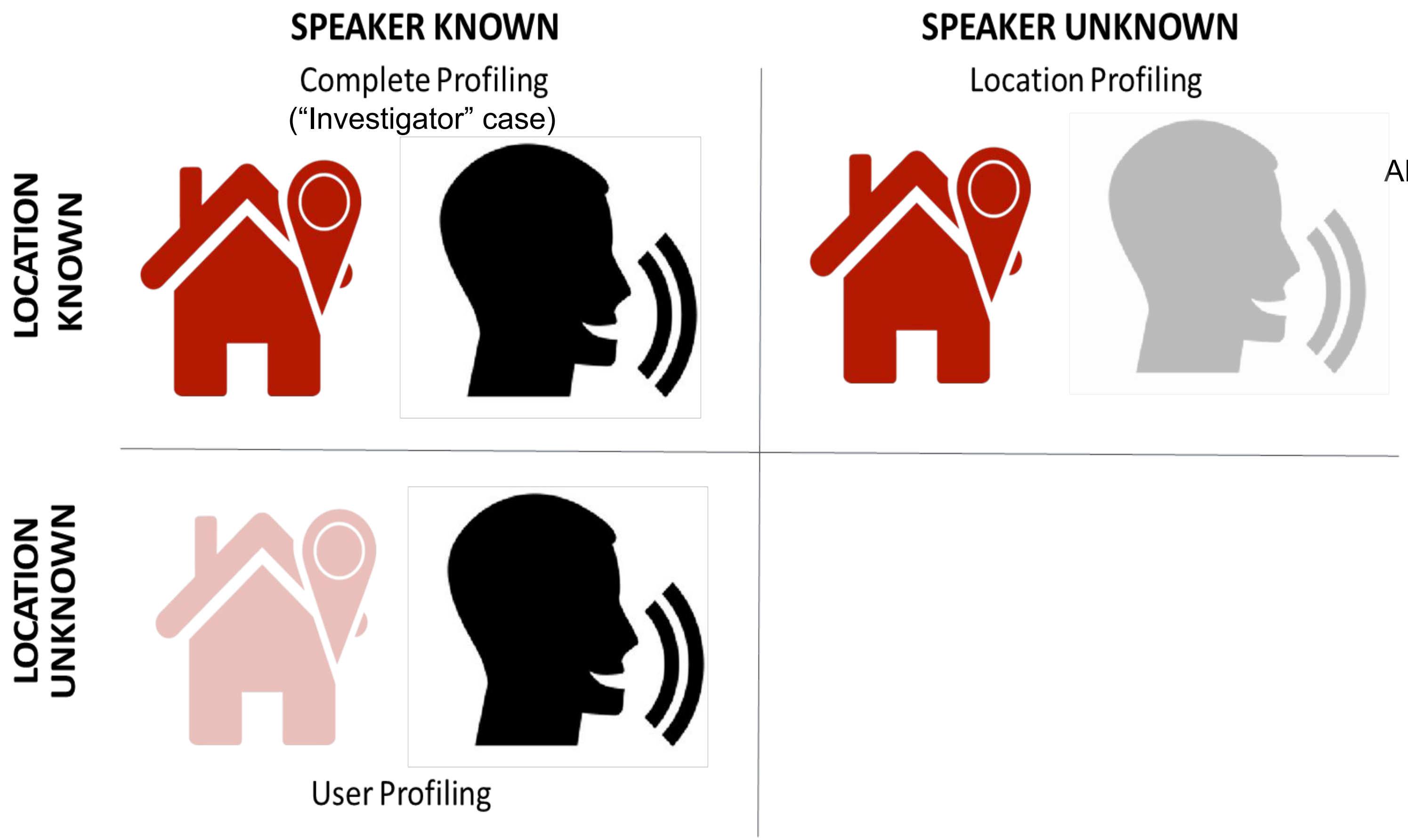








Scenarios



ADV has samples on
- ALL locations (room and specific position inside)
- but NOT from Victim

ADV has samples
- OF the victim
- In the correct room but in unknown specific position (inside that known room)

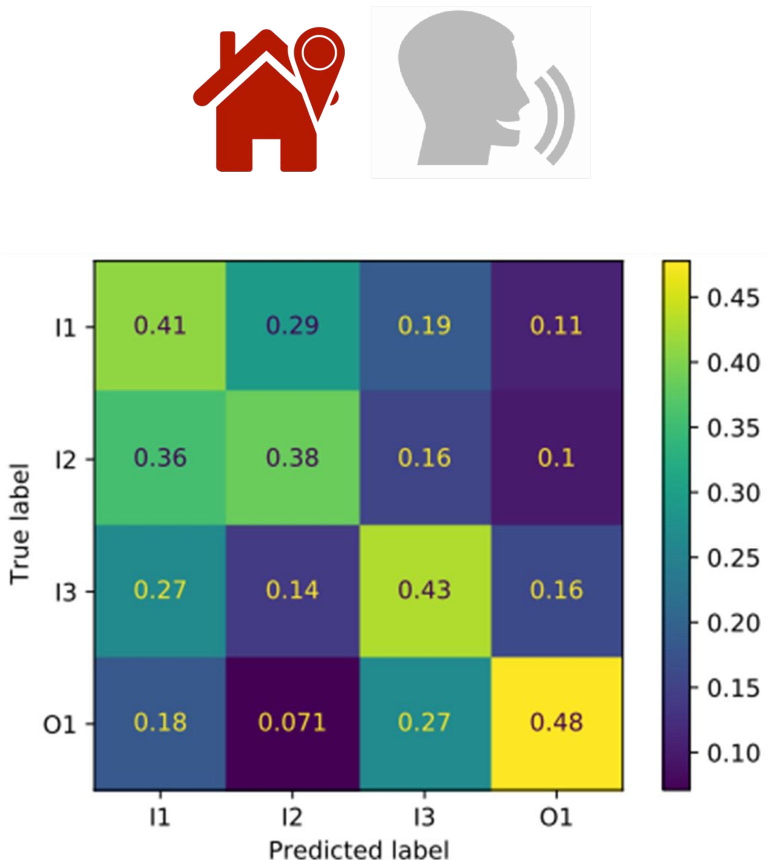
Scenarios (just in case…)

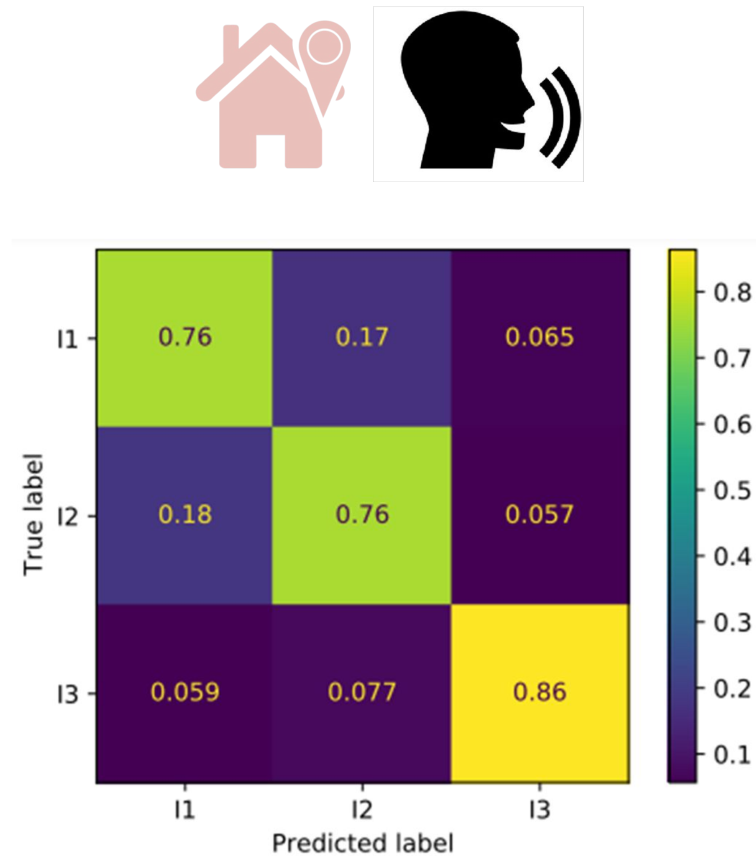
- *Complete Profiling*: This scenario occurs when the attacker asks the victim to send voice messages from specific locations. For example, an investigator (i.e., the attacker) might ask a suspect (i.e., the victim) to stand in a specific part of a room to verify that the suspect was there or elsewhere at the time a voice message was sent. In this scenario, the attacker has recordings of the victim in all the selected locations. Moreover, the attacker also knows the victim's specific position in the selected locations (e.g., a room corner). In this scenario, the attacker has the highest knowledge to execute his attack.

- *Location Profiling*: In this scenario, the attacker cannot access any of the victim's voice messages other than the one he wants to infer the location. The attacker knows that the victim has sent the voice message from a selected location (e.g., the attacker knows that the victim is in a specific building). Therefore, the attacker can have WhatsApp audio recordings of different speakers but the victim. The speakers are assumed to have recorded their messages at the same locations where the victim is sending the voice message. Hence, the victim is "unknown" while the location position is "known" to the attacker.

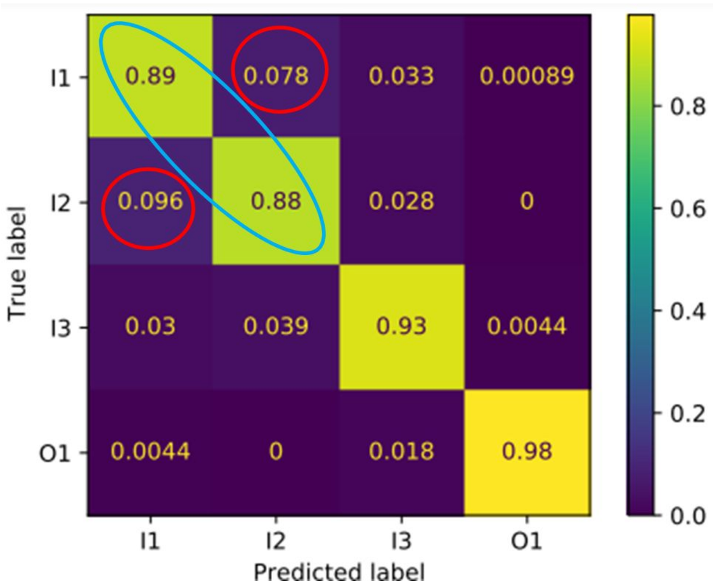
- *User Profiling*: This scenario occurs when the attacker owns the victim's voice messages and knows the recording location but does not know the specific position in the location (e.g., a corner of a room) from which they were recorded. The attacker wants to infer the location of a new voice message sent by the victim. Different from the *Complete Profiling* scenario, the attacker cannot ask the victim to send more voice messages from specific positions of the selected locations (e.g., the victim is no longer reachable). The victim is "known" while the position is "unknown" to the attacker in this situation.

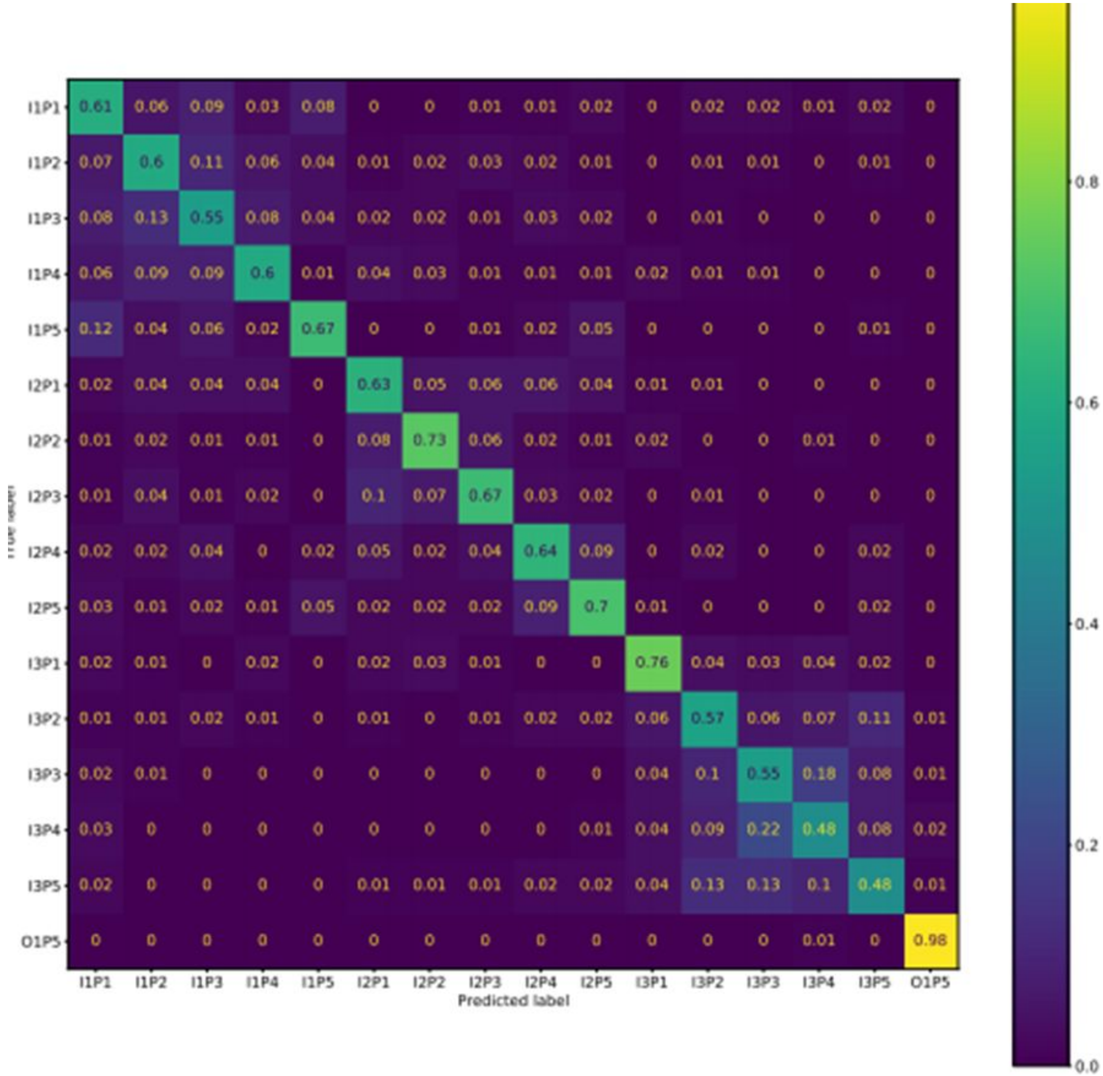
Results


I1 0.41 0.29 0.19 0.11
I2 0.36 0.38 0.16 0.1
I3 0.27 0.14 0.43 0.16
O1 0.18 0.071 0.27 0.48
I1 I2 I3 O1
Predicted label
True label
0.45 0.40 0.35 0.30 0.25 0.20 0.15 0.10


I1 0.76 0.17 0.065
I2 0.18 0.76 0.057
I3 0.059 0.077 0.86
I1 I2 I3
Predicted label
True label
0.8 0.7 0.6 0.5 0.4 0.3 0.2 0.1

Results


True label
Predicted label
I1 0.89 0.078 0.033 0.00089
I2 0.096 0.88 0.028 0
I3 0.03 0.039 0.93 0.0044
O1 0.0044 0 0.018 0.98
I1 I2 I3 O1
0.0 0.2 0.4 0.6 0.8


I1P1 0.61 0.06 0.09 0.03 0.08 0 0 0.01 0.01 0.02 0 0.02 0.02 0.01 0.02 0
I1P2 0.07 0.6 0.11 0.06 0.04 0.01 0.02 0.03 0.02 0.01 0 0.01 0.01 0 0.01 0
I1P3 0.08 0.13 0.55 0.08 0.04 0.02 0.02 0.01 0.03 0.02 0 0.01 0 0 0 0
I1P4 0.06 0.09 0.09 0.6 0.01 0.04 0.03 0.01 0.01 0.01 0.02 0.01 0.01 0 0 0
I1P5 0.12 0.04 0.06 0.02 0.67 0 0 0.01 0.02 0.05 0 0 0 0 0.01 0
I2P1 0.02 0.04 0.04 0.04 0 0.63 0.05 0.06 0.06 0.04 0.01 0.01 0 0 0 0
I2P2 0.01 0.02 0.01 0.01 0 0.08 0.73 0.06 0.02 0.01 0.02 0 0 0.01 0 0
I2P3 0.01 0.04 0.01 0.02 0 0.1 0.07 0.67 0.03 0.02 0 0.01 0 0 0 0
I2P4 0.02 0.02 0.04 0 0.02 0.05 0.02 0.04 0.64 0.09 0 0.02 0 0 0.02 0
I2P5 0.03 0.01 0.02 0.01 0.05 0.02 0.02 0.02 0.09 0.7 0.01 0 0 0 0.02 0
I3P1 0.02 0.01 0 0.02 0 0.02 0.03 0.01 0 0 0.76 0.04 0.03 0.04 0.02 0
I3P2 0.01 0.01 0.02 0.01 0 0.01 0 0.01 0.02 0.02 0.06 0.57 0.06 0.07 0.11 0.01
I3P3 0.02 0.01 0 0 0 0 0 0 0 0 0.04 0.1 0.55 0.18 0.08 0.01
I3P4 0.03 0 0 0 0 0 0 0 0 0.01 0.04 0.09 0.22 0.48 0.08 0.02
I3P5 0.02 0 0 0 0 0.01 0.01 0.01 0.02 0.02 0.04 0.13 0.13 0.1 0.48 0.01
O1P5 0 0 0 0 0 0 0 0 0 0 0 0 0 0.01 0 0.98
I1P1 I1P2 I1P3 I1P4 I1P5 I2P1 I2P2 I2P3 I2P4 I2P5 I3P1 I3P2 I3P3 I3P4 I3P5 O1P5
Predicted label
0.0 0.2 0.4 0.6 0.8


DELL

F. Marchiori, M. Conti

<u>Your Battery Is a Blast!</u>
<u>Safeguarding Against Counterfeit Batteries with Authentication</u>

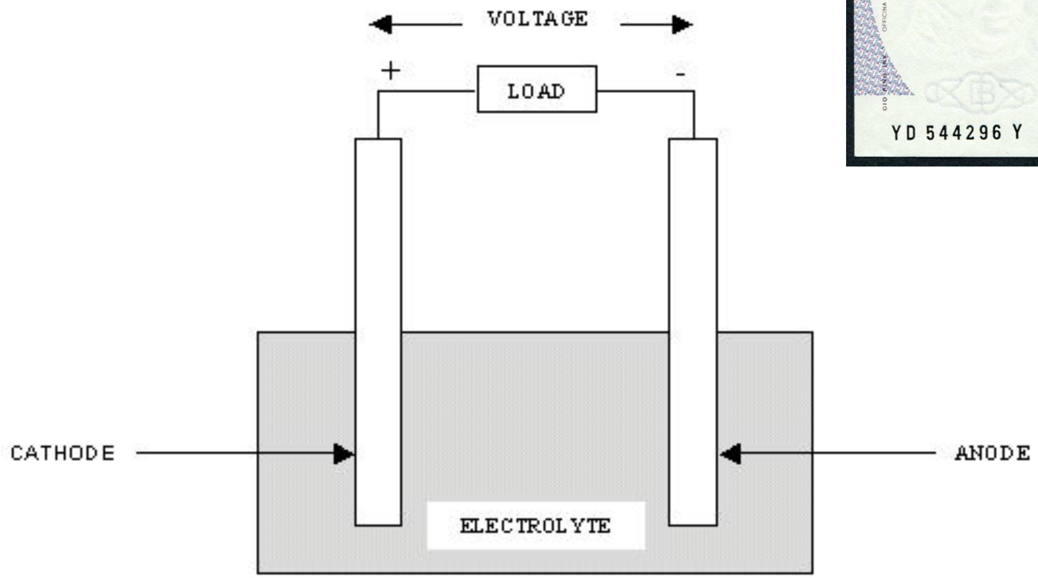
In ACM Conference on Computer and Communications Security (CCS' 23)

Battery Authentication

How many Lithium-ion batteries are around you right now?

Battery Authentication

- Store as chemical energy -> turned into electrical energy



Battery Authentication

How many **safe** Lithium-ion batteries are around you right now?

Lithium-ion (Li-ion) batteries market was estimated to be up to **48 billion U.S. dollars in 2022**

In 2003, roughly **5 million counterfeit cellular phone** batteries were seized worldwide.
https://www.wilsonelser.com/files/repository/PL_eNews0308_LithiumIonBatteries.pdf

In 2016, in a case related to hoverboards with counterfeit batteries, the U.S. customs and border protection agency seized over 16 thousand counterfeit hoverboards with an estimated value of over **USD 6 million**
https://www.cbp.gov/newsroom/local-media-release/cbp-seizes-record-amount-counterfeit-hoverboards

Battery Authentication

How have we checked it until now?
(tick means defence is successful)

Method	Attacks: **Cloning**	**Replay Attacks**	**Unscalability**	**Rewrapping**
Markings		✓	✓	
External Features		✓	✓	
Form Factor		✓	✓	
Resistor		✓	✓	
Chip	✓			
CR (in clear)	✓			
CR (encrypted)	✓	✓		
DCAuth	✓	✓	✓	✓
EISthentication	✓	✓	✓	✓

CR = Challenge and Response Protocols

Battery Authentication

Our **contribution**

DCAuth EISthentication

- Leverage only internal characteristics of the batteries
- Scalable to many models and architectures
- Small computational cost

We make dataset and code available.

https://github.com/Mhackiori/DCAuth

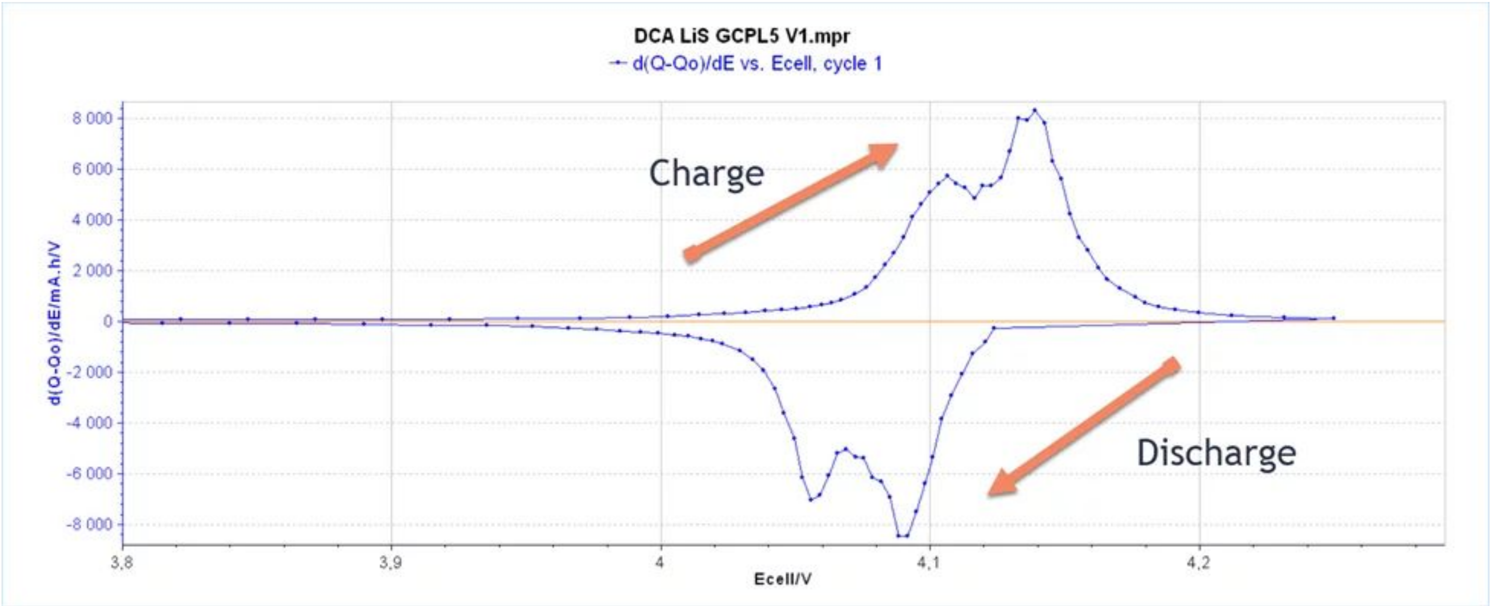
https://github.com/Mhackiori/EISthentication

SPRITZ Security & Privacy Research Group

Università degli Studi di Padova

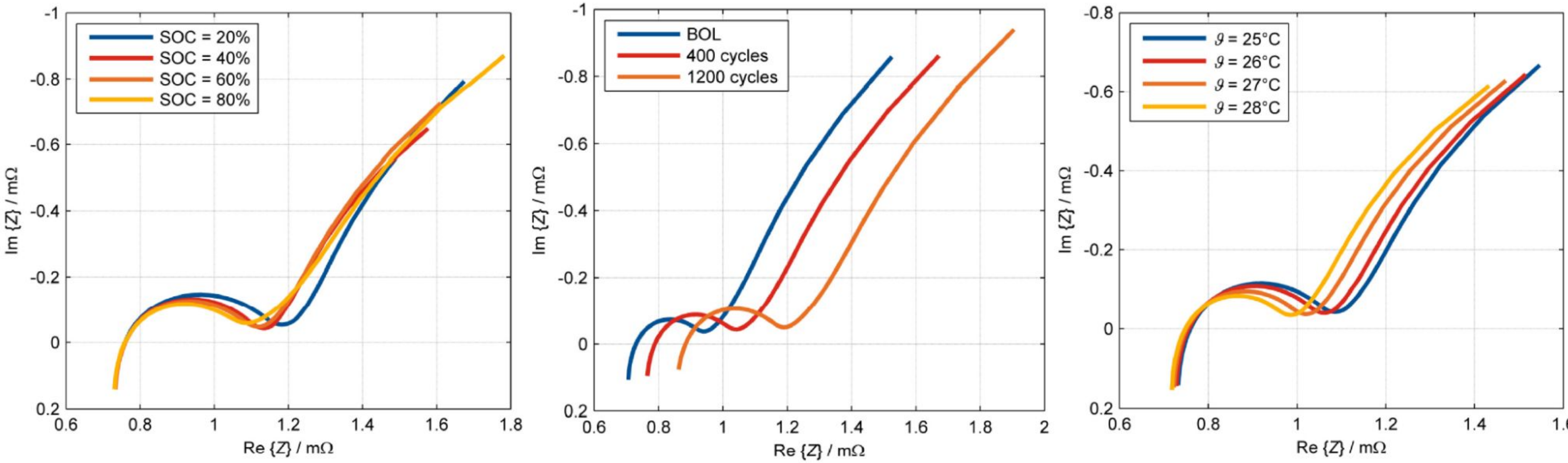
Differential Capacity Analysis (DCA)

- Measuring change in capacity response in the electrodes
- It tracks increase/decrease in capacity when charged/discharged
- Plot of differential capacity versus voltage



Electrochemical Impedance Spectroscopy (EIS)

- Analytical technique for electrochemical system characterization
- Measures the electrical impedance
- Dependance on several environment/external factor



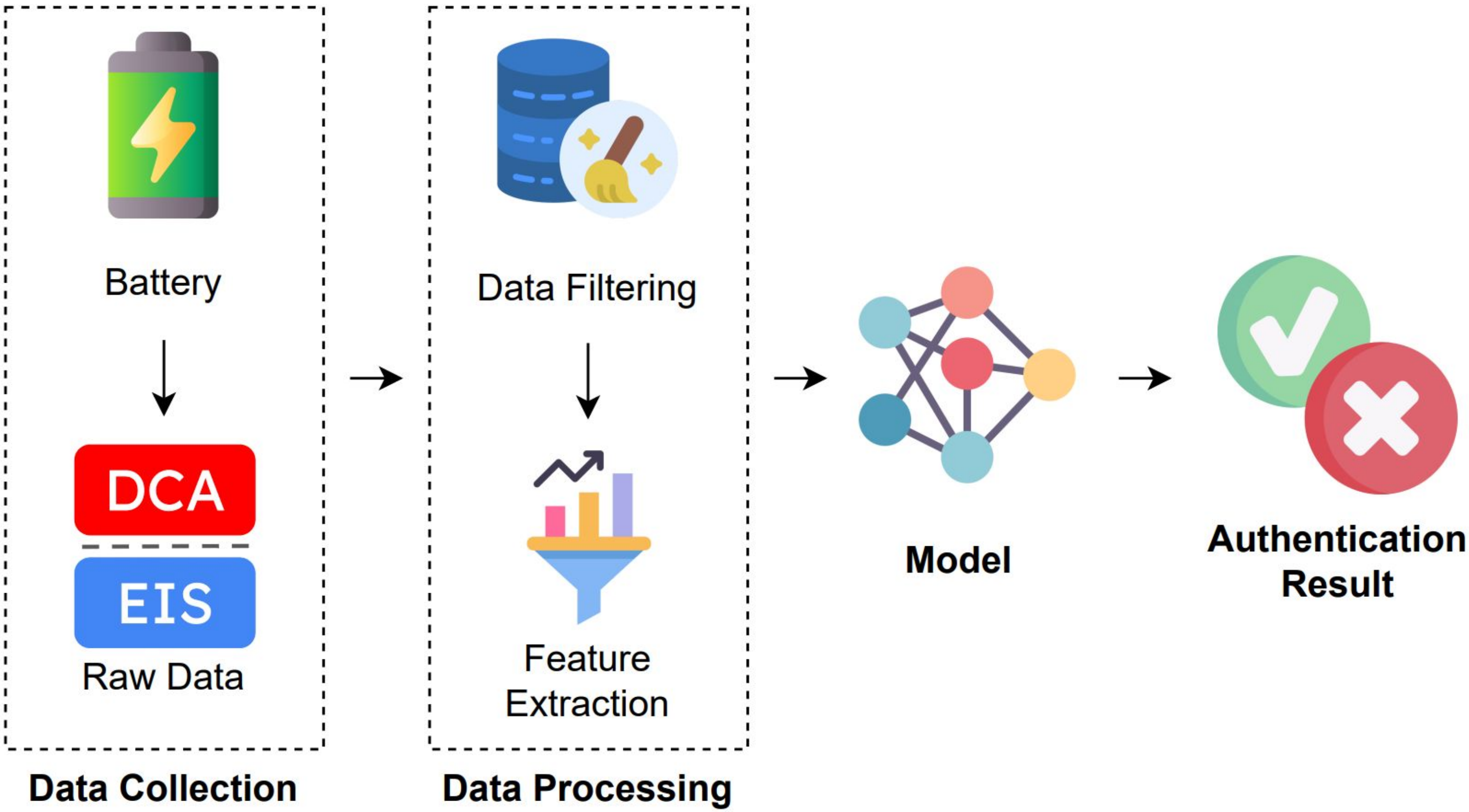
(a): Dependence on SOC.

(b): Dependence on SOH.

(c): Dependence on temperature.

Battery Authentication

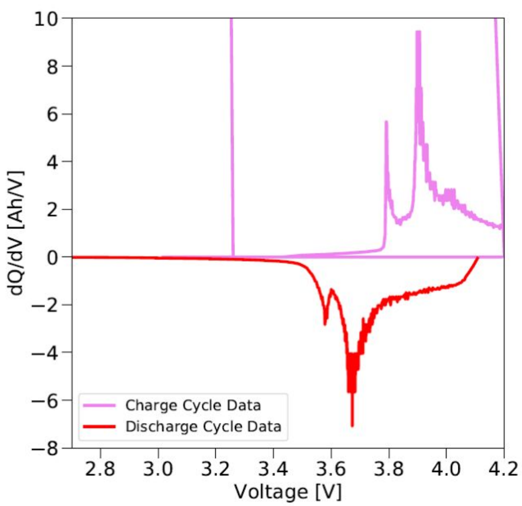
System Model



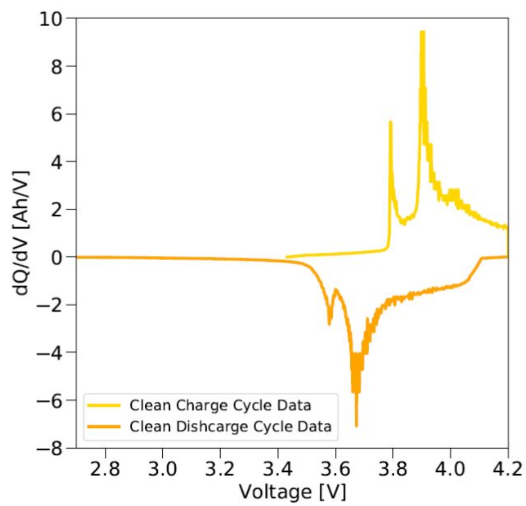
Datasets

- Issues in finding collaborations with companies or organization
- Collection of available datasets
- 20 datasets (17 for DCA, 3 for EIS)
    - *That includes 11 different models, 5 different architectures*

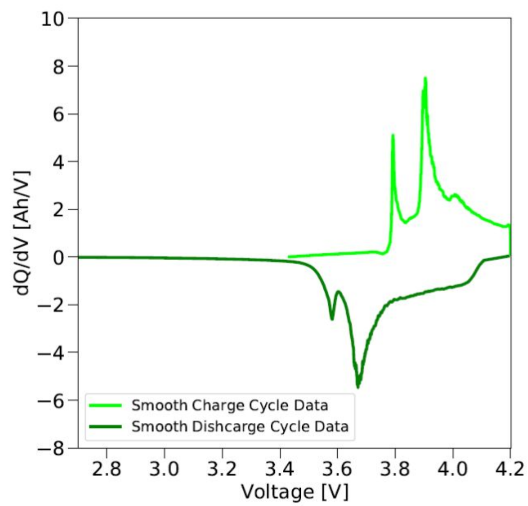
Processing (available on GitHub)



(a): Raw DCA plot.



(b): Clean DCA plot.



(c): Smooth DCA plot.

Battery Authentication

SPRITZ
Security & Privacy
Research Group

Università
degli Studi
di Padova

Models

- Machine Learning
- Avoiding complex DL to keep low computational cost
- Commonly used in literature

Models	Hyperparameters
AdaBoost (AB)	• Number of estimators
Decision Tree (DT)	• Criterion • Maximum Depth
Gaussian Naive Bayes (GNB)	• Variance Smoothing
Nearest Neighbors (KNN)	• Number of neighbors • Weight function
Neural Network (NN)	• Hidden layer sizes • Activation function • Solver
Quadratic Discriminant Analysis (QDA)	• Regularization Parameter
Random Forest (RF)	• Criterion • Number of estimators
Support Vector Machine (SVM)	• Kernel • Regularization parameter • Kernel coefficient

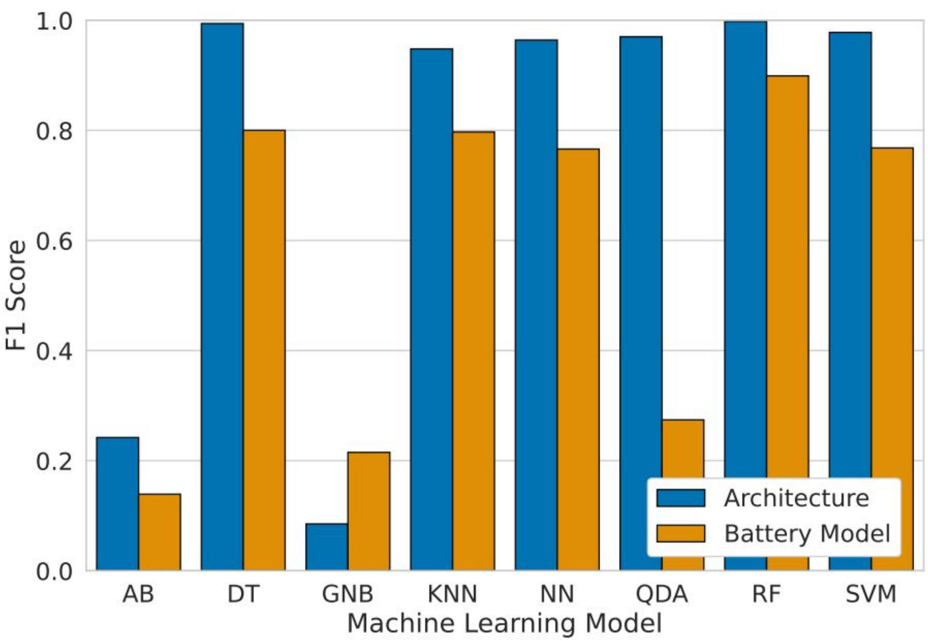
Evaluation Metrics

- Precision
- Recall
- F1 Score
- False Acceptance Rate (FAR)
- False Rejection Rate (FRR)

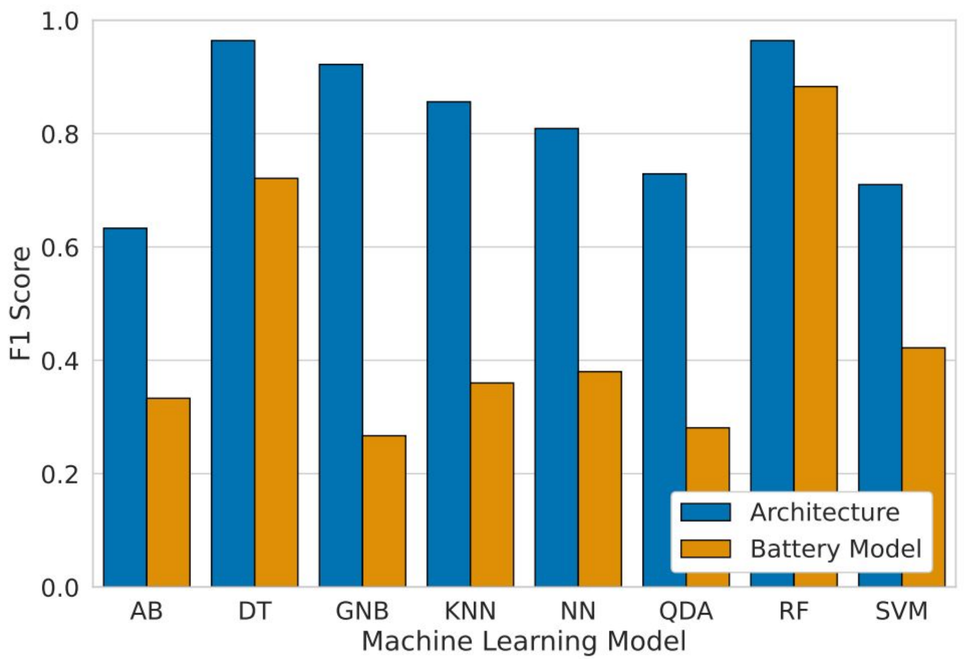
SPRITZ Security & Privacy Research Group

Università degli Studi di Padova

Results - Identification



DCAuth

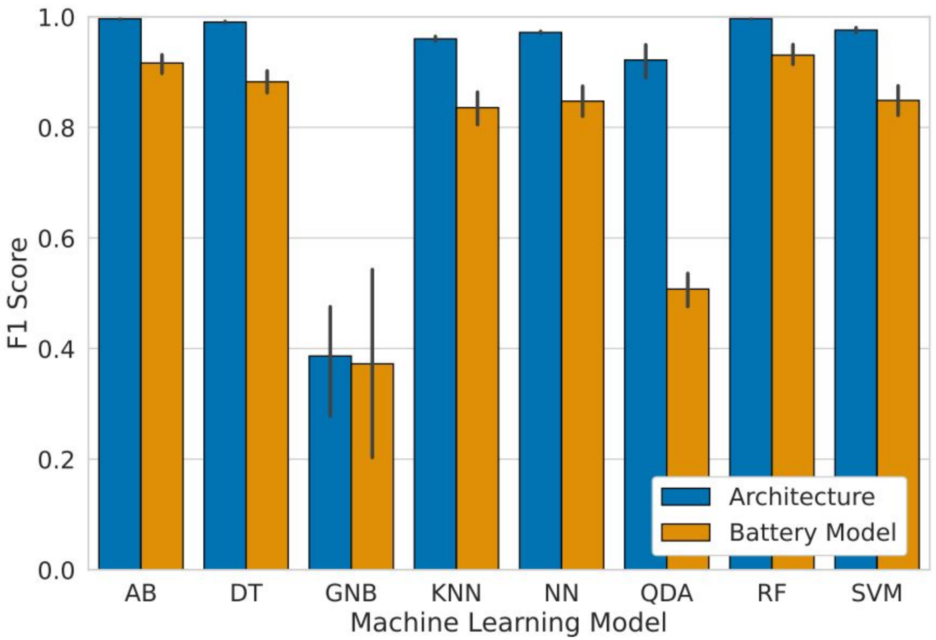


EISthentication

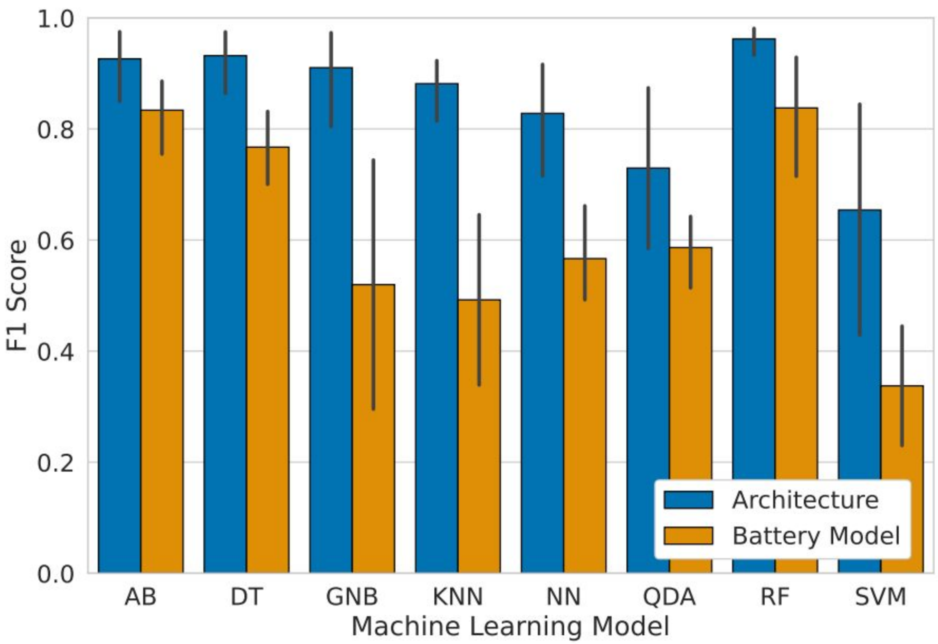
SPRITZ Security & Privacy Research Group

Università degli Studi di Padova

Results - Authentication

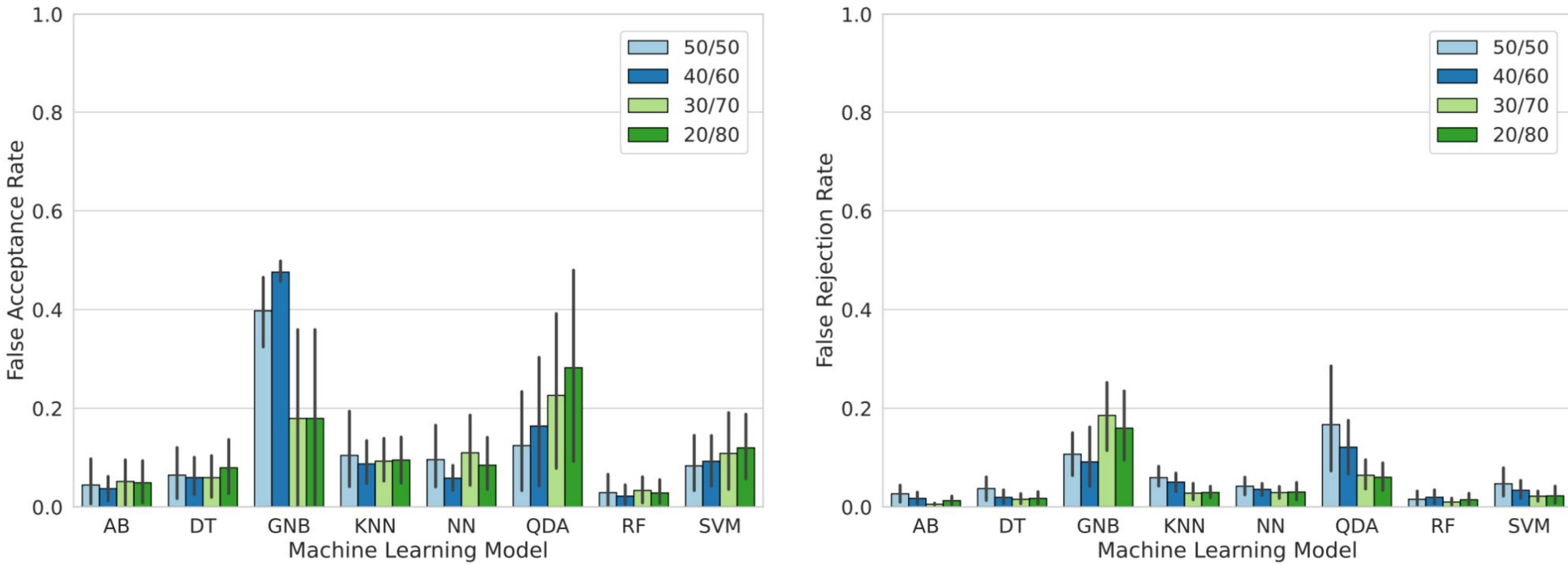


DCAuth



EIShentication

Results - FAR/FRR on Dataset Balance



DCAuth

Battery Authentication

Table 12: Complexity.

Model	Time_{DCA}	Size_{DCA}	Time_{EIS}	Size_{EIS}
AB	15.492 ms	75 kB	8.523 ms	59 kB
DT	3.892 ms	31 kB	2.881 ms	20 kB
GNB	4.687 ms	53 kB	3.192 ms	33 kB
KNN	12.951 ms	4800 kB	7.1 ms	263 kB
NN	4.595 ms	2600 kB	3.204 ms	1200 kB
QDA	7.856 ms	3100 kB	4.435 ms	271 kB
RF	13.661 ms	348 kB	13.288 ms	221 kB
SVM	9.854 ms	500 kB	2.99 ms	158 kB

Conclusions and Follow-ups

- Important issue to address for user safety
- More data can improve the methodology
- Collecting data in various condition can enhance the adaptability of the system

https://arxiv.org/abs/2309.03607


DELL

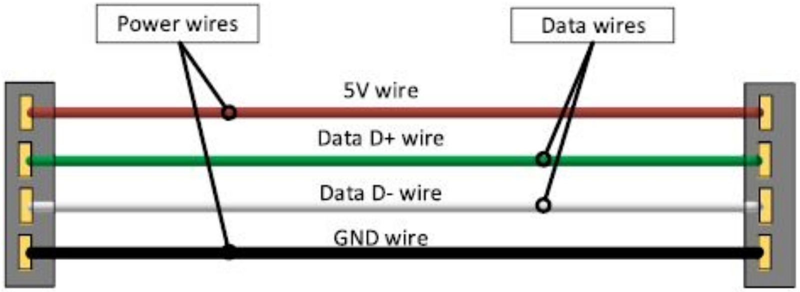
R. Spolaor, H. Liu, F. Turrin, M. Conti, X. Cheng

Plug and Power: Fingerprinting USB Powered Peripherals via Power Side-channel

In IEEE International Conference on Computer Communications (INFOCOM) 2023

USB Devices

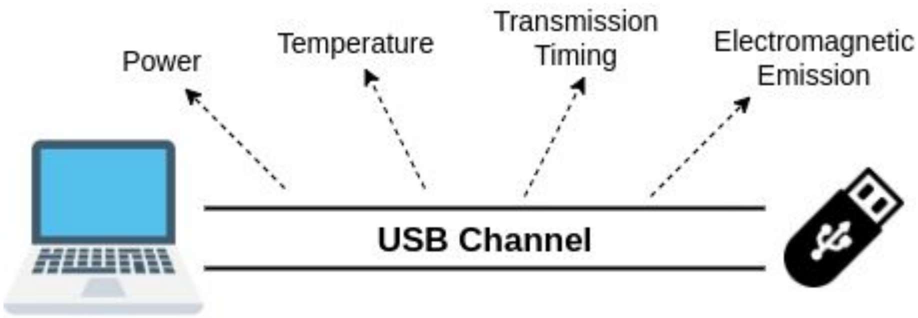
- Widely used in everyday life
  - Peripheral devices, smartphone, IoT
- Data Transfer + Power supply
- **<u>No security</u>** measure by design
- Common attack vectors
  - Malware, BadUSB, USBkill



Idea

Exploit Power Side-Channel to identify authorized devices

- Identification of **legitimate devices**
- Recognize **legitimate actions**
- Detect **malicious devices**



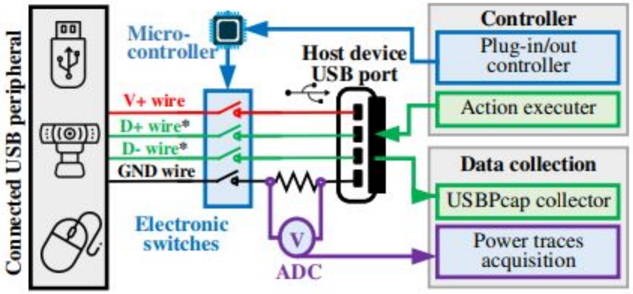
Use cases

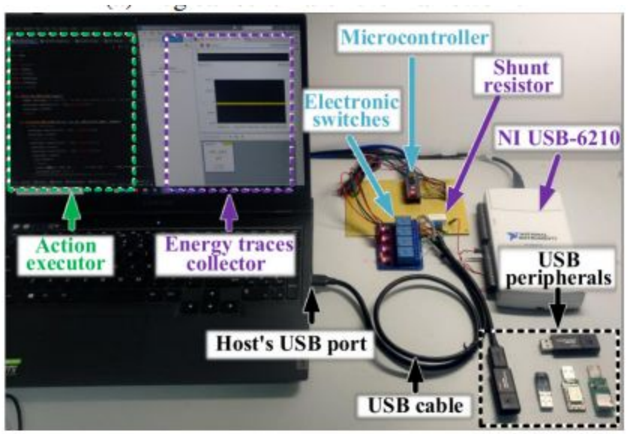
- End-user Personal Protection
- Organization Assets Protection

Data Collection

USB Power traces collection

- 82 different devices
    - 8 types
        - HDD, USB stick, WiFi & Bluetooth adapters, mouse, keyboard, webcam, microphone
    - 35 models
- Automated collection
- Different action
    - *Boot*
    - *On* (operating mode)
    - *Actions* (e.g., read, write, connect)
- Univariate time series

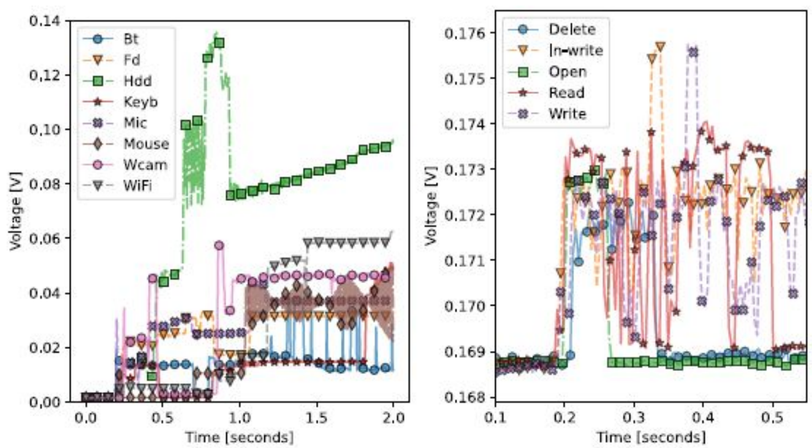




Analysis Goals

SPRITZ Security & Privacy Research Group
Università degli Studi di Padova

1. **Type** (during *Boot* and *On states)*
2. **Model** (*Boot* and *On)*
3. Specific **Device** among the ones with same model
4. **Action** given a device type
5. Given a type, **Device via action**
6. **Good vs. Bad** (malicious USB peripherals)



Boot *On*

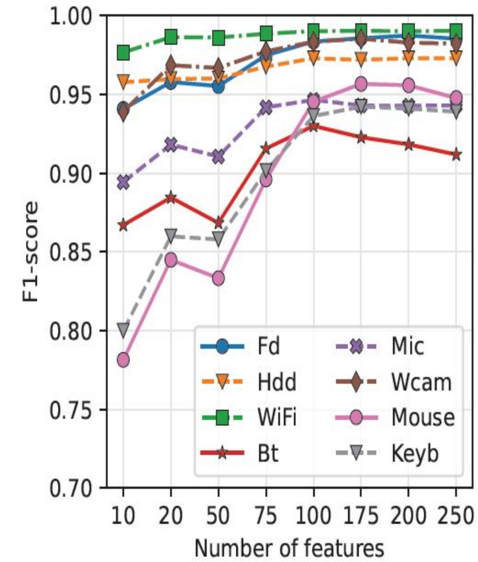
Pipeline

1) **Traces Preprocessing**
   a) Segmentation: sliding window (1 second with a 75% overlap)
   b) Feature extraction with tsfresh libraries (740 features per segment)
2) **Model tuning**
   a) Random Forest classifier (each task)
   b) 70% training, 10% validation, and 20% test (stratified)
   c) SMOTE to balance classes
3) **Classification approaches**
   a) Multiclass with "Other" class
   b) Binary (One-vs-All strategy) with Unknown devices in test
4) **Evaluation Metrics**: Precision, Recall, F1-Score, G-Mean, AUC

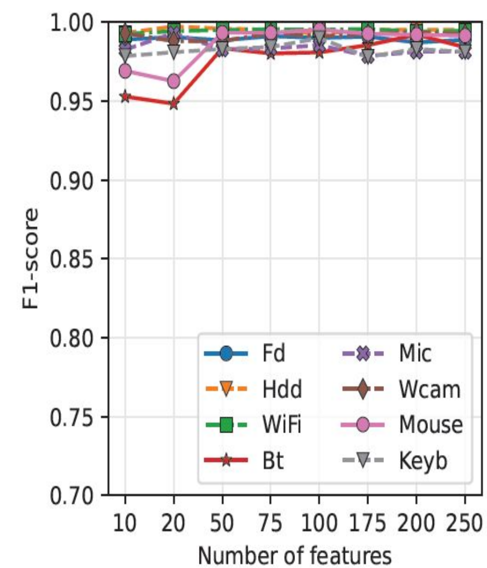
Type Recognition - Results (1/6)

- Recognize the type during *Boot* and *On* states
- *Multiclass* approach
  - 8 classes
  - *Other* includes random traces
- *Boot*: Mouse and Keyb (upon visual inspection)
  - Very quick (below 0.5 second)
  - LEDs may introduce noise
- *On*: simple to detect

State Boot



State On

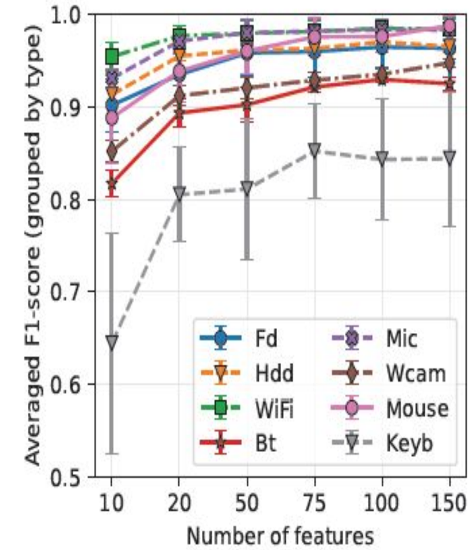


We can discriminate USB type for *Boot* and *On*

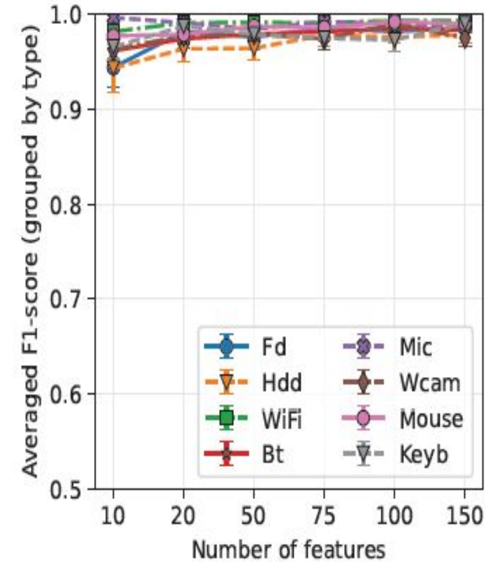
Model Recognition - Results (2/6)

- Recognize the model during *Boot* and *On* states
- *Multiclass* approach
  - *35 classes*
  - *Other* includes random traces
- *On*: high classification performance
- Keyb3 and Fd8 perform worst
  - *Very quick (below 0.5 second)*
  - *LEDs may introduce noise*
- Accurate fingerprint with 75 features both Boot and On

State Boot



State On

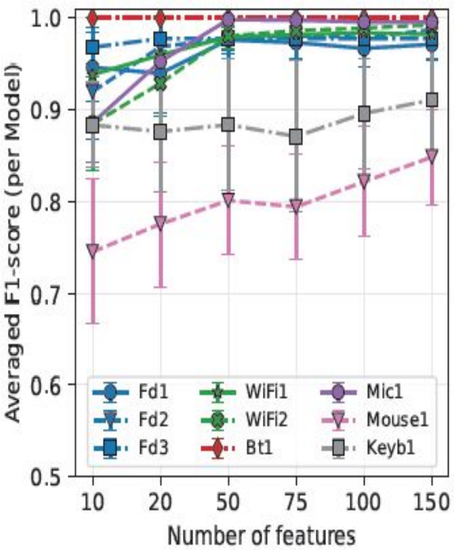


We can discriminate USB model for Boot and On

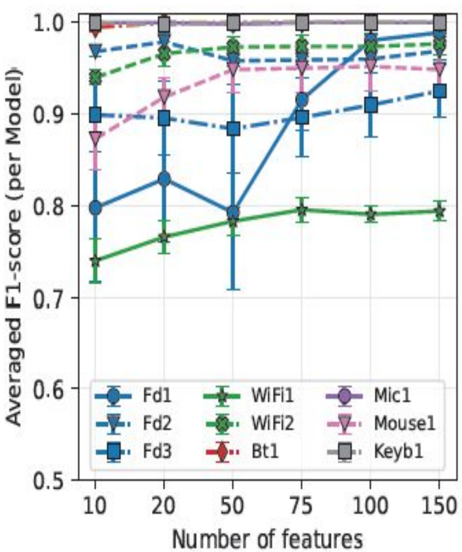
Device Recognition - Results (3/6)

- Given peripherals of the same model identify the specific device
    - *Models with # ≥ 4 individual devices*
- Binary approach
    - One random class not in Training set
- No good results on Mouse1 and Keyb1 state *Boot*
- WiFi1 model has the lowest score on state *On*
    - Models' traces are very similar

State Boot



State On

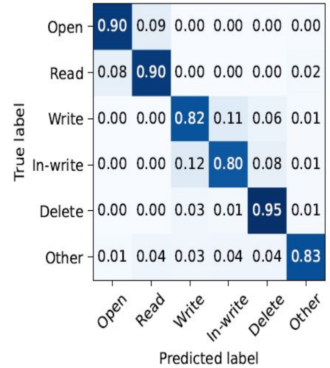


We can <u>almost</u> discriminate the specific USB device

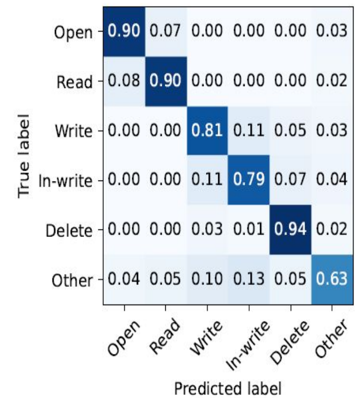
Action Recognition - Results (4/6)

- Recognize an ongoing action given a device type
- *Multiclass* approach
  - *Fd*, *Hdd*, and *WiFi*
  - *Other* includes random actions
- WiFi type have a clear fingerprint
- Miss-classification between Write and In-Write
  - *In-Write is derived by the combination of Read and Write*

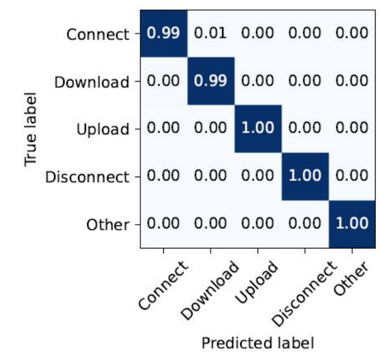
Flash Drive



HDD



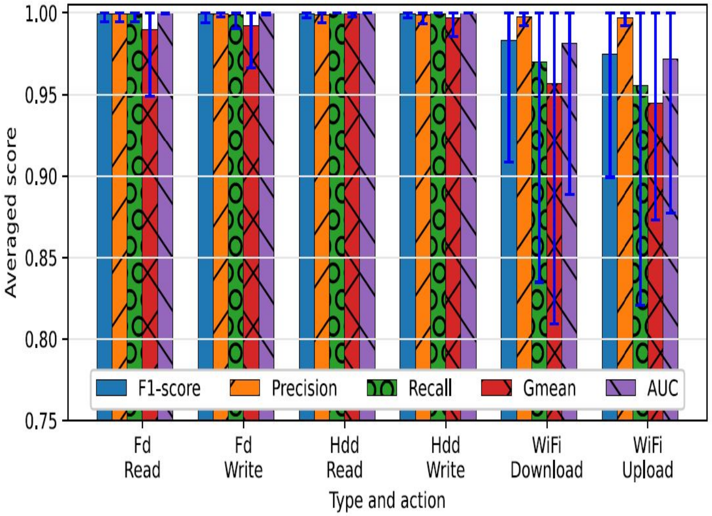
WiFi adapter



We can discriminate action given a type

Device via Action - Results (5/6)

- Given an action for a type , identify specific device
- *Binary* approach
  - Fd, Hdd, and WiFi types (46, 10, and 38 classes)
- Good performance for all the types and actions
- Fd and Hdd actions are distinguishable
- WiFi slightly lower performance (similar behavior)



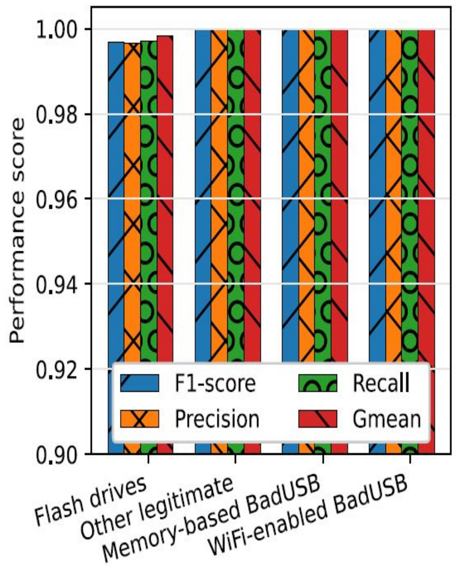
We can fingerprint an individual device from its actions

Bad vs. Good - Results (6/6)

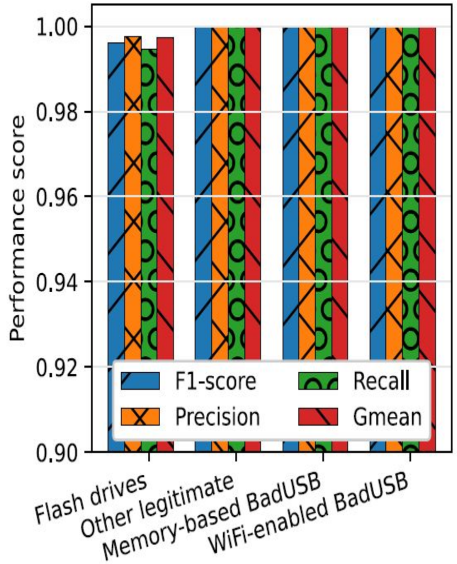
- Discriminate between
  - Flash Drives
  - Bad USBs
- *Multiclass* approach
  - 3 classes
  - *Other legitimate* includes other legitimate peripherals
- While collecting traces we run several attacks
  - command injection, WiFi scanning and connection
- Good scores according to all metrics

We can discriminate Bad USBs

State Boot



State On



Lesson Learned

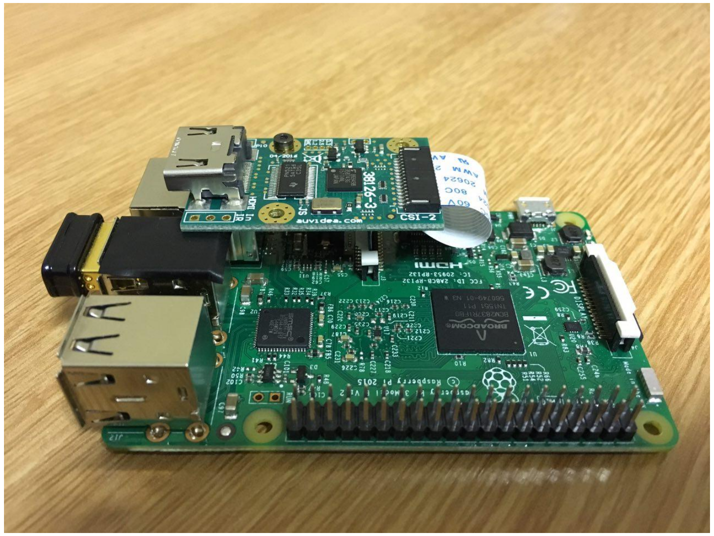
- USB devices are a still a common attack vector
- Evolution of the standard did not include any security
- Power consumption allows USB fingerprinting
  - *State*
  - *Type*
  - *Model*
  - *Specific device*
  - *Action*
  - *Malicious devices*
- Protect the host from USB-based threats
  - *Non Intrusive*
  - *Privacy preserving*


DELL

M. Conti, E. Losiouk, A. Visintin

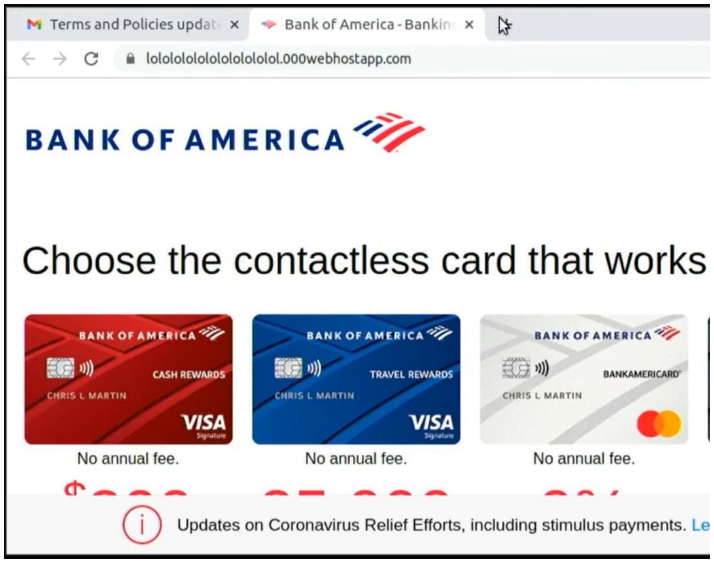
What You See is Not What You Get
A Man-in-the-Middle Attack Applied to Video Channels

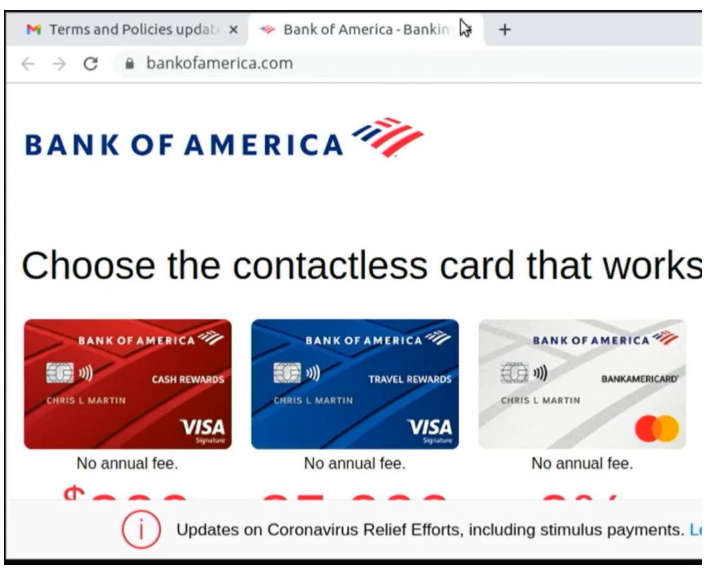
In ACM/SIGAPP Symposium On Applied Computing 2022



Man-in-the-Middle attack on a video channel.

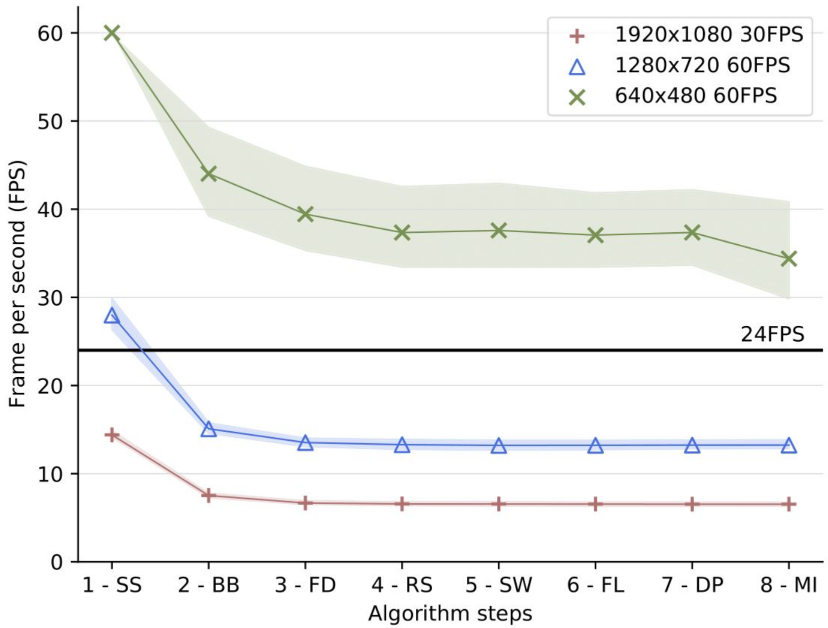
Using a Raspberry PI to modify in real-time the HDMI output before it is displayed.





Phishing replica of Bank of America website.

Raspberry PI detects and modify the URL into a legit one.



Measured performances show the practicality of the attack.

The frame rate can be substantially improved using dedicated hardware.

Attack demo available online.
https://www.youtube.com/watch?v=lvsoJdpNsZA&ab_channel=SPRITZResearchGroupvideos

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

Don’t Skype & Type! Acoustic Eavesdropping in Voice-over-IP.

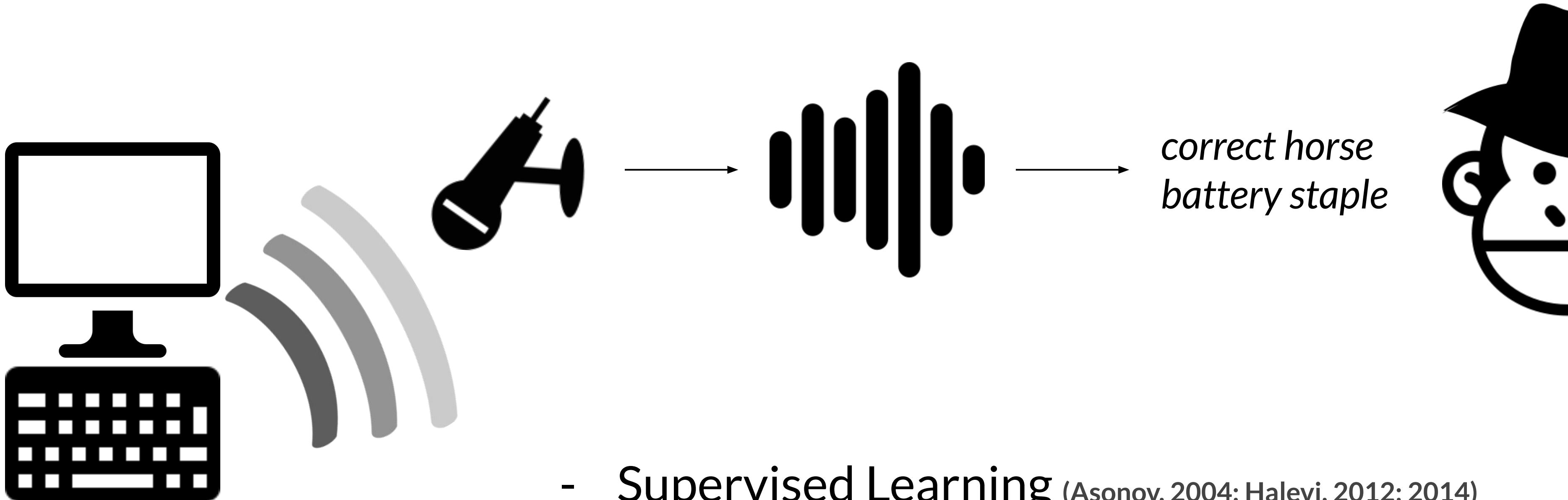
In ACM SIGSAC AsiaCCS 2017

Presented at Black Hat USA 2017

Keyboard Acoustic Eavesdropping

SPRITZ
Security & Privacy
Research Group

Università
degli Studi
di Padova



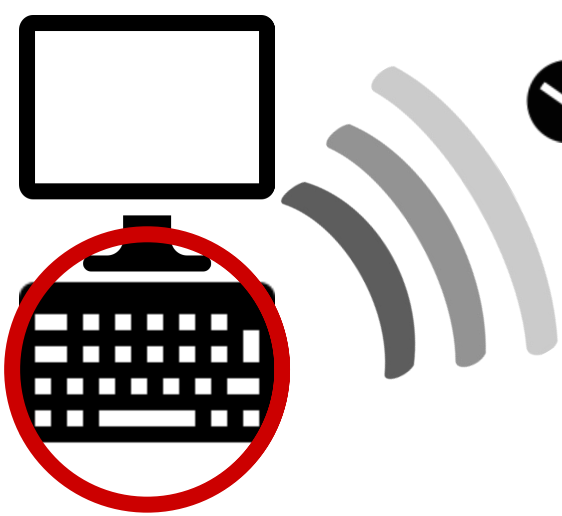
- Supervised Learning (Asonov, 2004; Halevi, 2012; 2014)
  Less input assumptions, more specific

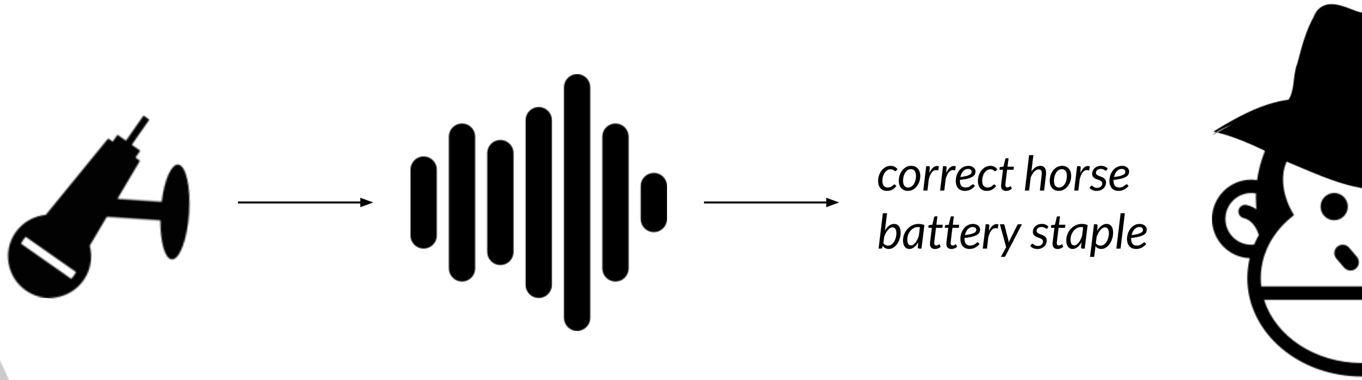
- Unsupervised Learning (Berger, 2006; Zhuang, 2009)
  More input assumptions, more general

Keyboard Acoustic Eavesdropping

SPRITZ
Security & Privacy
Research Group

Università
degli Studi
di Padova





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

Keyboard Acoustic Eavesdropping

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

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

Motivation

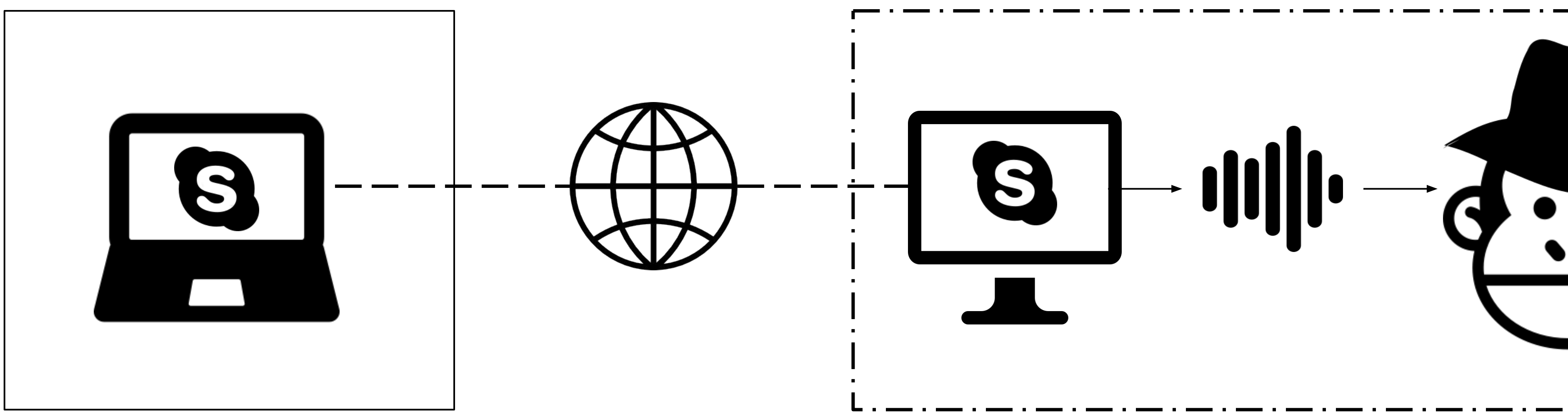
VoIP → one of the most used software: in academia, industry, at home

People type private stuff during Skype calls - it happens!

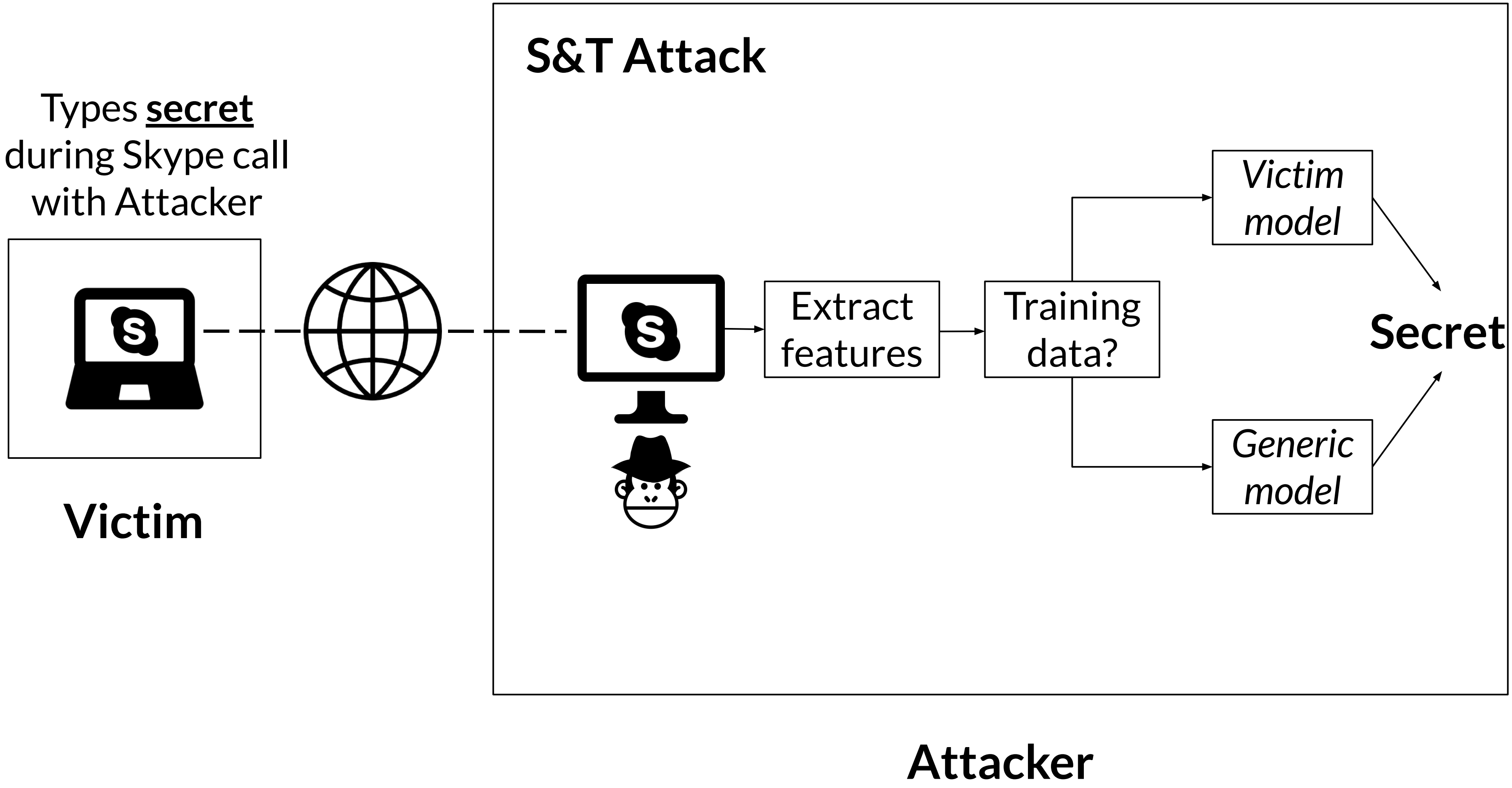
- *Login to websites*
- *Write a sensitive email*
- *Take notes*

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

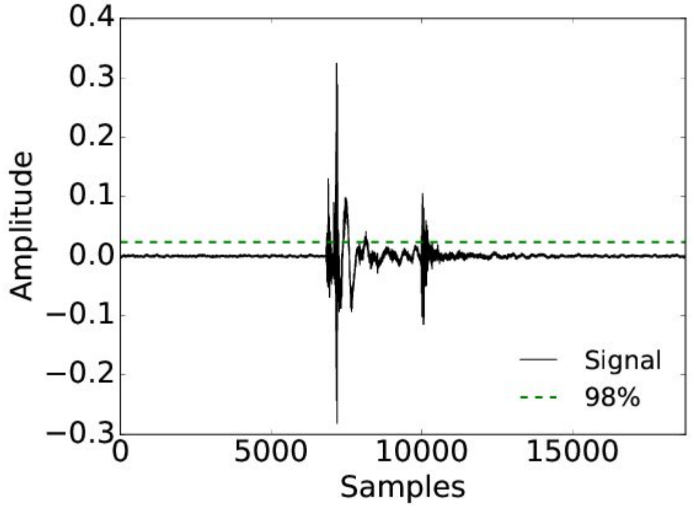
- Mel frequency cepstral coefficients

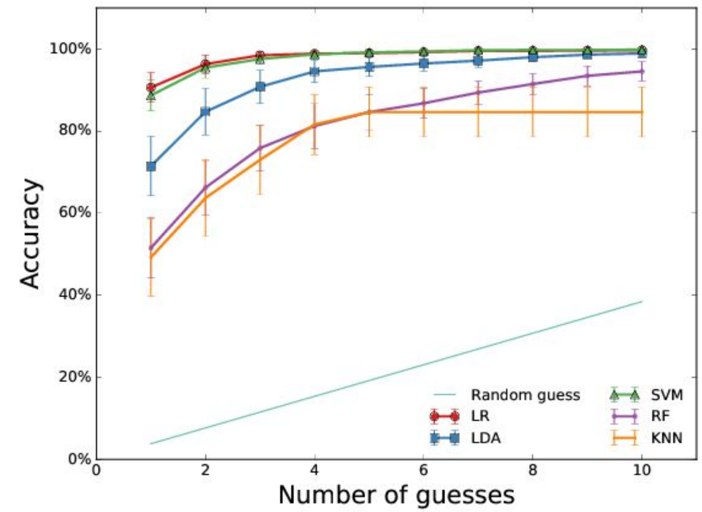
  Best performing and robust

- 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

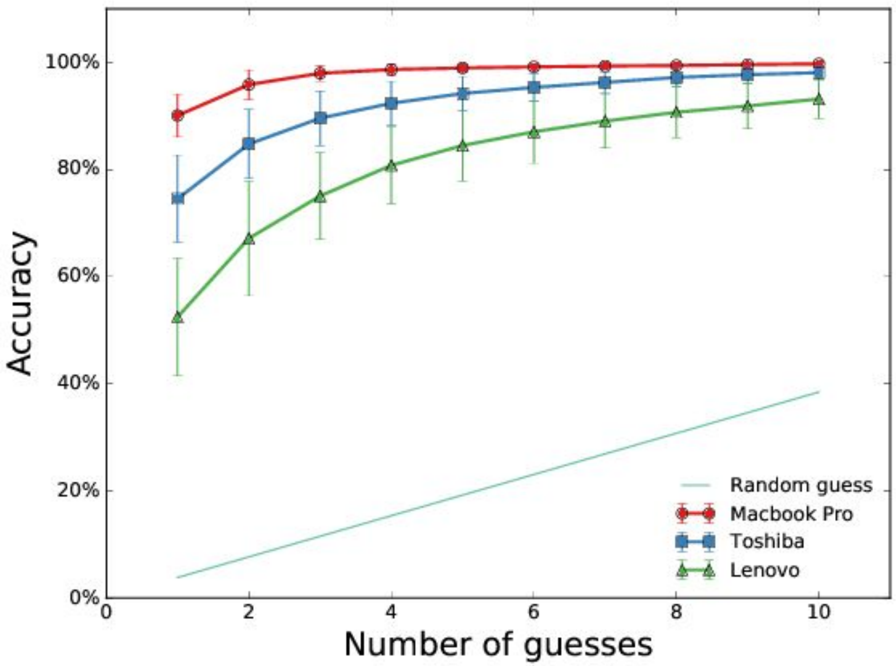
Evaluate the attack on two realistic scenarios

- 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*

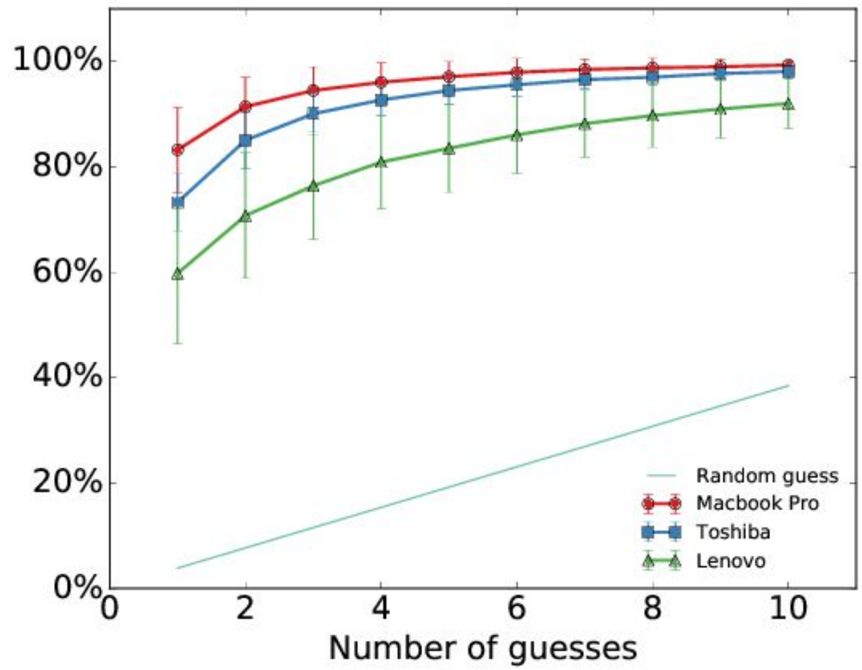
- (Laptop-)Model Profiling Scenario
  - *Profiled **a laptop of the same model on some users***
  - ***Victim is/can be unknown!***

Complete Profiling

Training set with the data the user disclosed



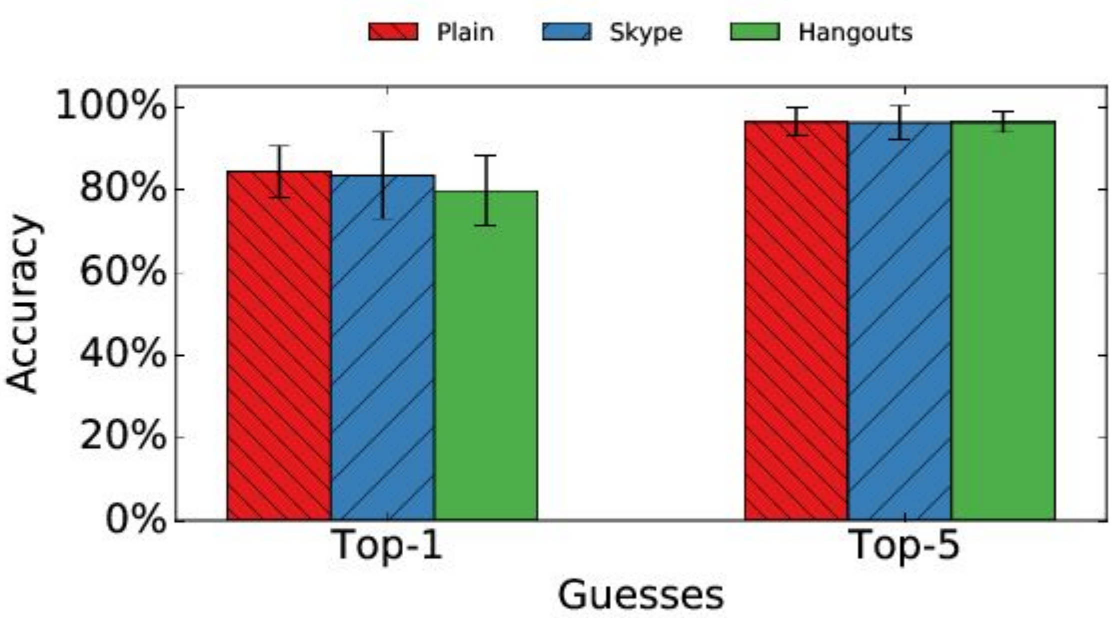
Hunt&Peck typing, unfiltered data



Touch typing, Skype filtered data

Complete Profiling

Is only Skype vulnerable to our attack?



No! It looks like a common problem for VoIP software

(Laptop-)Model Profiling Setup

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

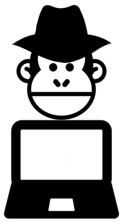
Someone the attacker does not know personally

First need to understand the laptop of the victim

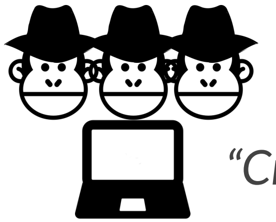
→ match it with a database of model signatures

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

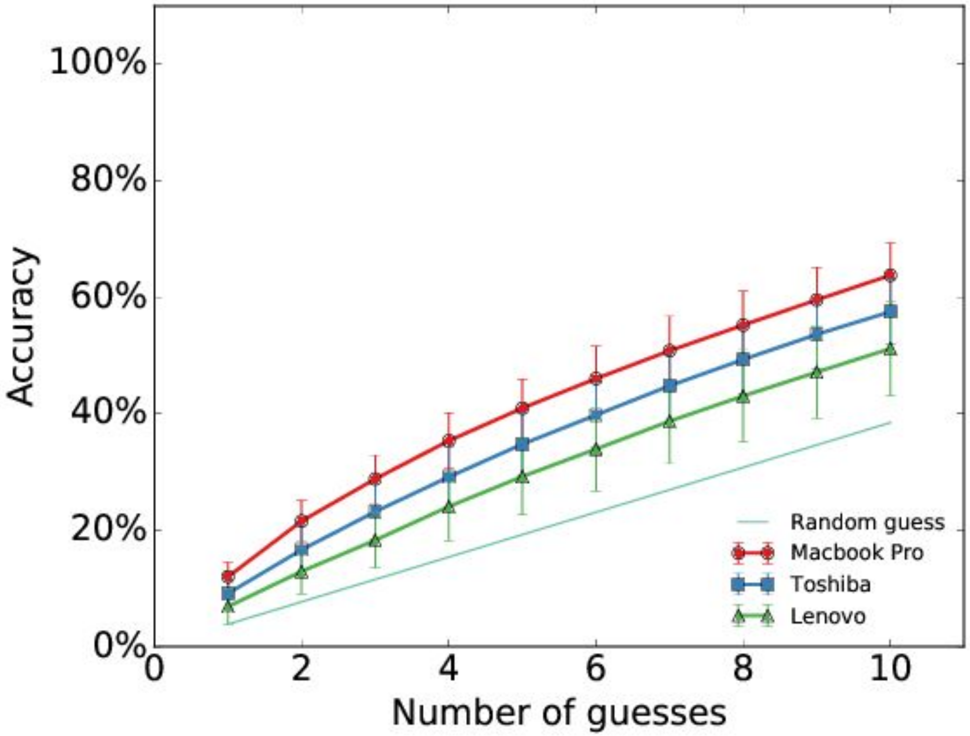
(Laptop-)Model Profiling

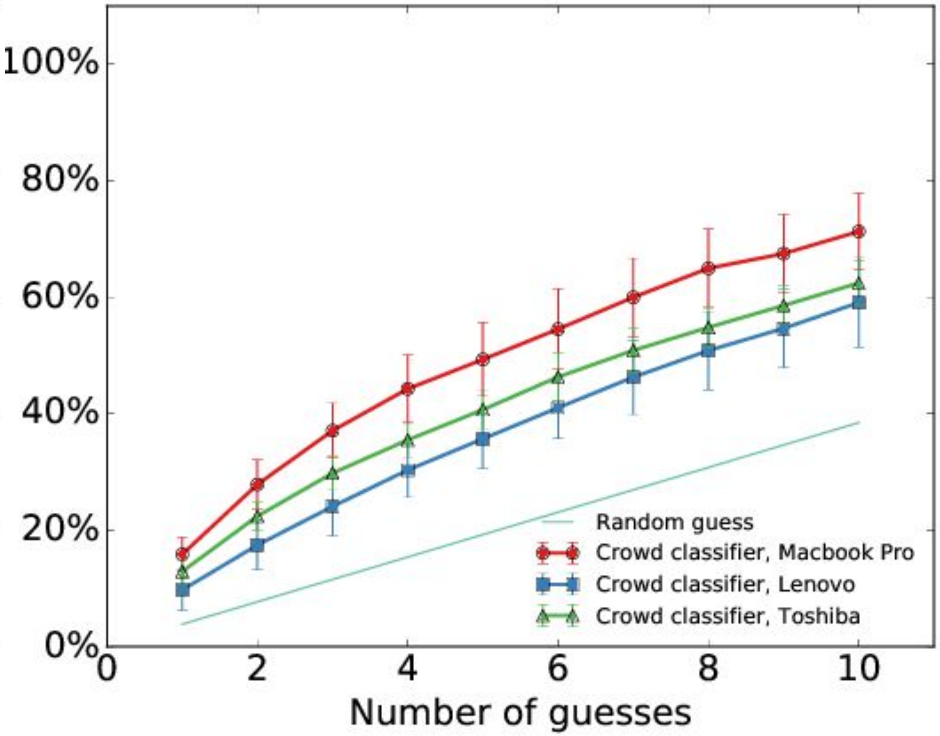


One user



“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*

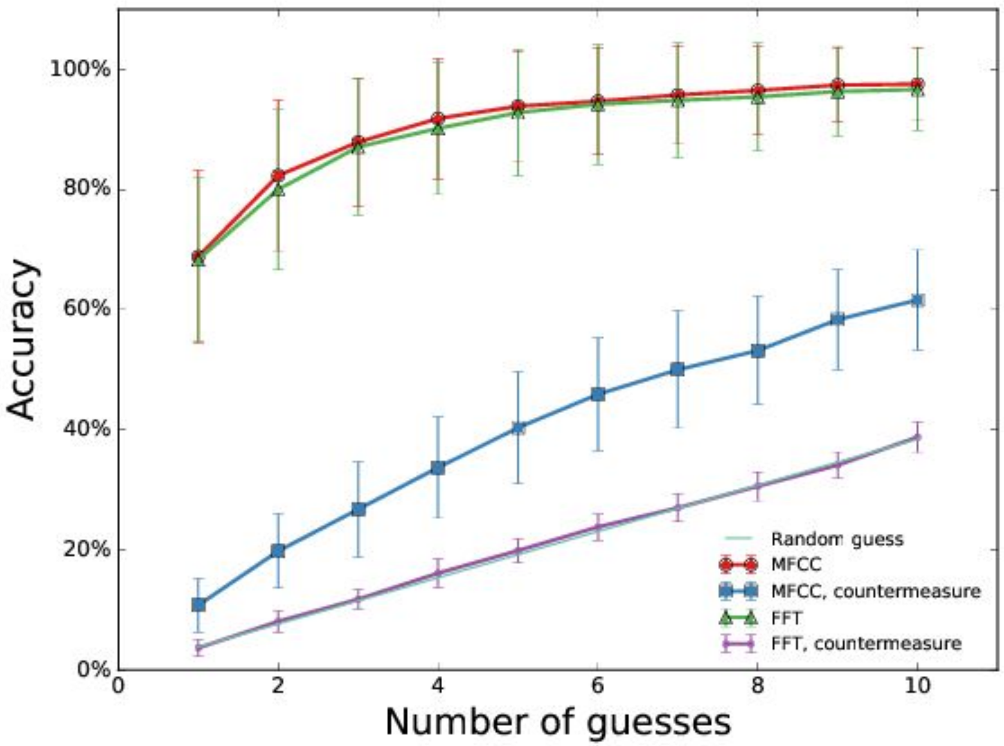
Countermeasures

- <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*

Conclusions & Future Work

- VoIP Keyboard acoustic eavesdropping a serious threat

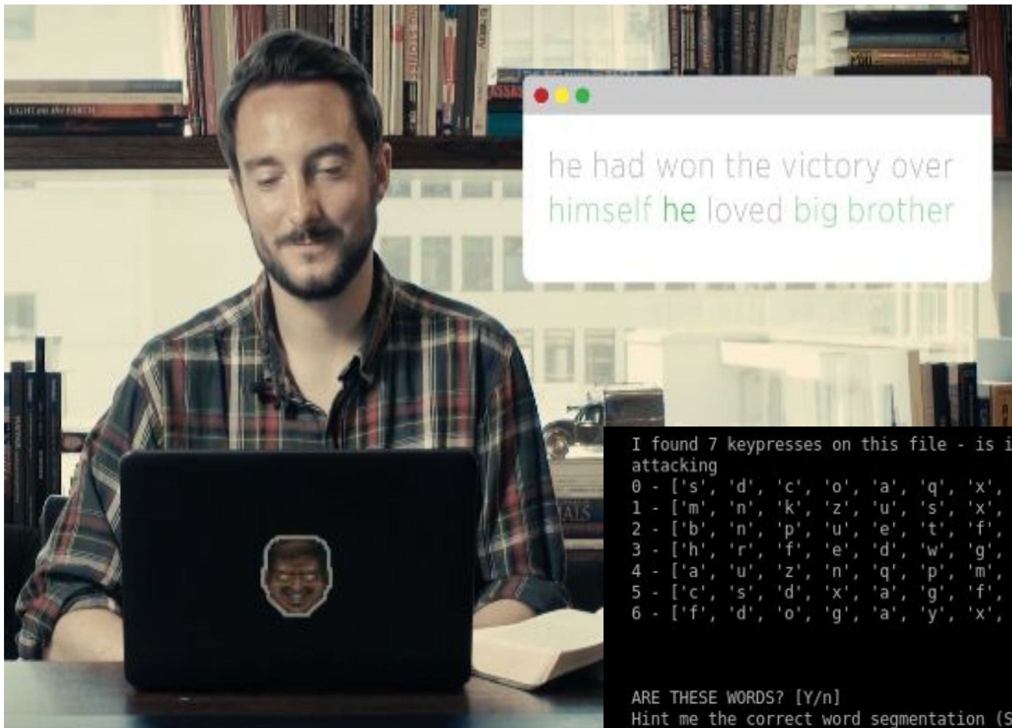
- Feasible and accurate:
  - *Realistic attack scenarios*
  - *91.71% on* ***Complete Profiling*** *scenario*
    - *Halevi (2012; 2014): 85.78%*
  - *41.89% on* ***Model Profiling*** *scenario*
    - *Novel attack vs. unknown victims*
  - *Robust to degradation and to voice*

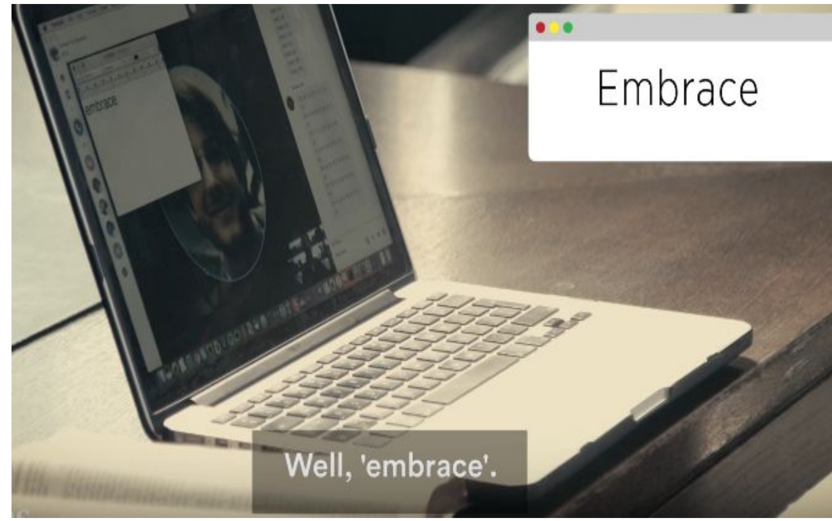
- Future work:
  - *Try more users and different keyboards, and on more VoIP software*
  - *Try to attack another user in the same room*
  - *Analyze and improve the countermeasures*

Does it **really** work?

SPRITZ
Security & Privacy
Research Group
Università degli Studi di Padova

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)]
```

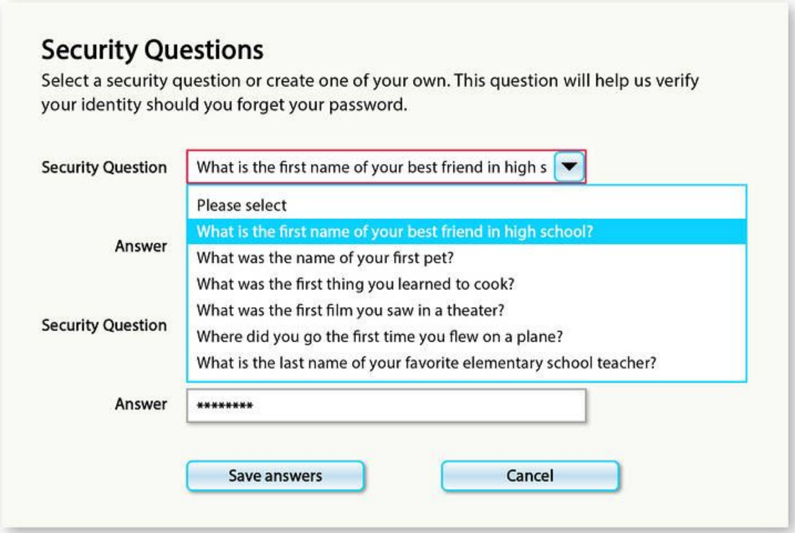
https://drive.google.com/file/d/1uLDDl_eESswOm6pQs59I4NeOjXwjOq1M/view?usp=sharing

Forbes Credits: https://www.forbes.com/sites/thomasbrewster/2017/07/06/skype-and-type-attack-steals-passwords

Thank you!

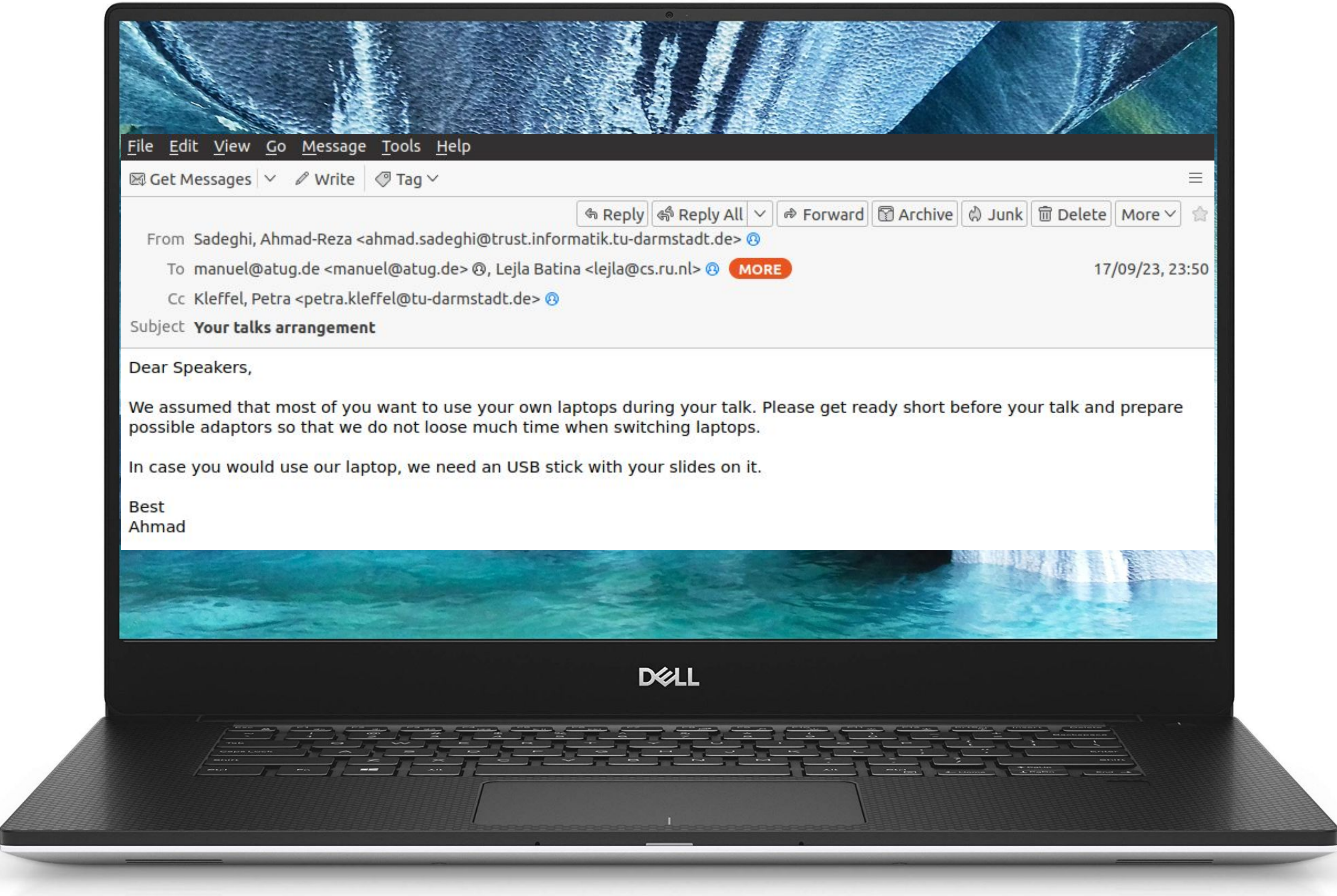
Questions?

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



This is the END!

Backup Slides
after this point… ;-)

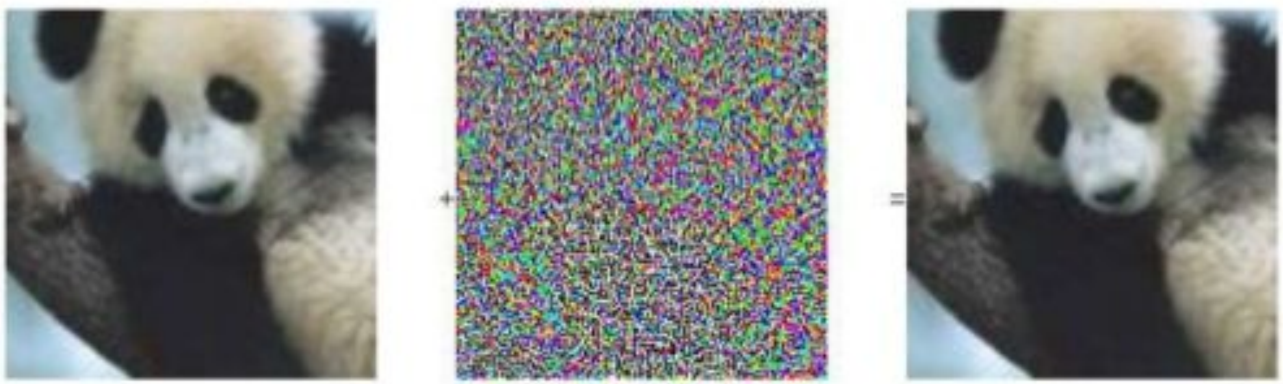

File Edit View Go Message Tools Help
Get Messages
Write
Tag
Reply
Reply All
Forward
Archive
Junk
Delete
More
From Sadeghi, Ahmad-Reza <ahmad.sadeghi@trust.informatik.tu-darmstadt.de>
To manuel@atug.de <manuel@atug.de>, Lejla Batina <lejla@cs.ru.nl>
MORE
17/09/23, 23:50
Cc Kleffel, Petra <petra.kleffel@tu-darmstadt.de>
Subject Your talks arrangement
Dear Speakers,
We assumed that most of you want to use your own laptops during your talk. Please get ready short before your talk and prepare possible adaptors so that we do not loose much time when switching laptops.
In case you would use our laptop, we need an USB stick with your slides on it.
Best
Ahmad
DELL

Adversarial Machine Learning

SPRITZ
Security & Privacy
Research Group

Università
degli Studi
di Padova

Adversarial Examples (Deep Learning/CNNs)



Original image classified as a panda with 60% confidence.

Tiny adversarial perturbation.

Imperceptibly modified image, classified as a gibbon with 99% confidence.

http://www.kdnuggets.com/2015/07/deep-learning-adversarial-examples-misconceptions.html

http://karpathy.github.io/2015/03/30/breaking-convnets/

Classification Accuracy

Classification Accuracy is what we usually mean, when we use the term accuracy. It is the ratio of number of correct predictions to the total number of input samples.

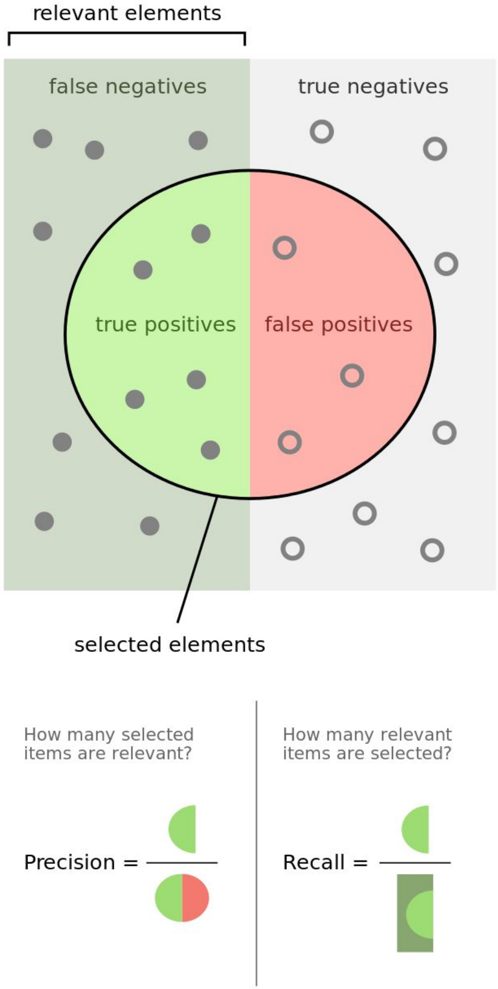
$$Accuracy = \frac{Number\ of\ Correct\ predictions}{Total\ number\ of\ predictions\ made}$$

It works well only if there are equal number of samples belonging to each class.

For example, consider that there are 98% samples of class A and 2% samples of class B in our training set. Then our model can easily get **98% training accuracy** by simply predicting every training sample belonging to class A.

When the same model is tested on a test set with 60% samples of class A and 40% samples of class B, then the **test accuracy would drop down to 60%.** Classification Accuracy is great, but gives us the false sense of achieving high accuracy.

- Precision, Recall, and F-measure



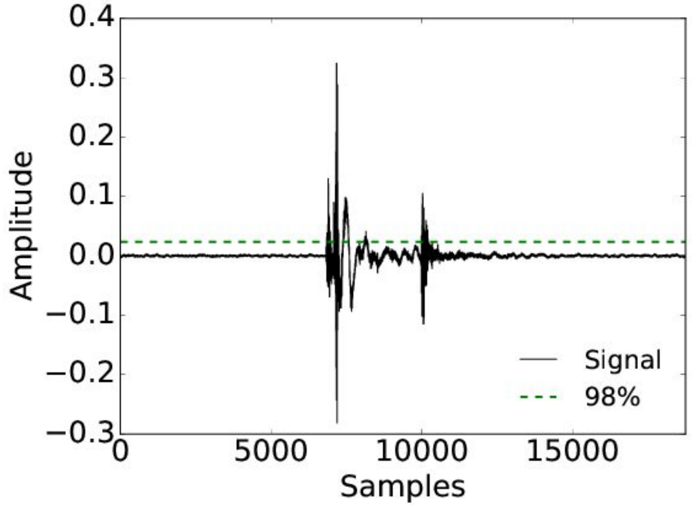
$$F_1 = 2 \cdot \frac{1}{\frac{1}{\mathrm{recall}} + \frac{1}{\mathrm{precision}}} = 2 \cdot \frac{\mathrm{precision} \cdot \mathrm{recall}}{\mathrm{precision} + \mathrm{recall}}$$

$$F_\beta = \frac{(1+\beta^2) \cdot \mathrm{true\ positive}}{(1+\beta^2) \cdot \mathrm{true\ positive} + \beta^2 \cdot \mathrm{false\ negative} + \mathrm{false\ positive}}$$

Attack - Data Processing

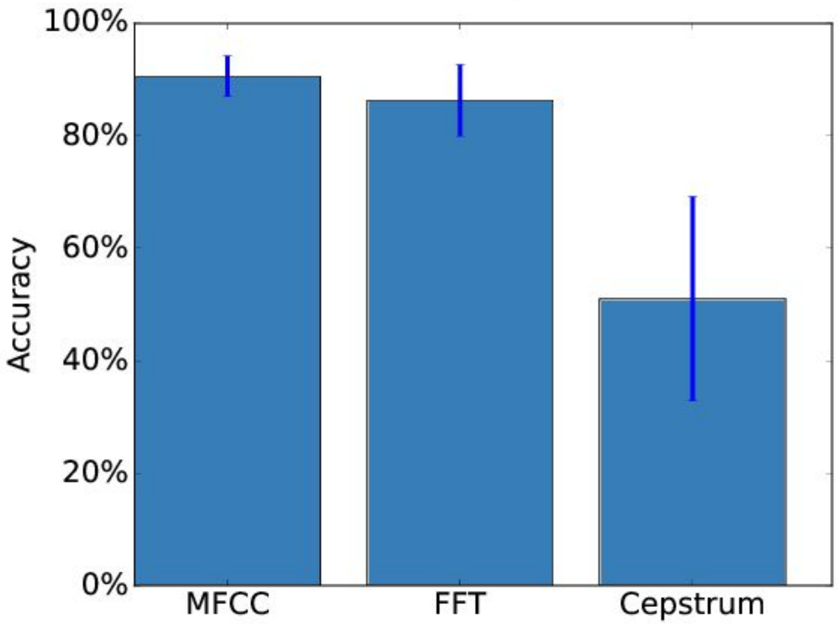
- Data windowing and segmentation

  To extract sound samples



- Feature extraction: *mel frequency cepstral coefficients*

  Selected with a preliminary experiment



Novelty - Attack Scenarios

Evaluate the attack on three different 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*

- User Profiling Scenario
  - *Profiled the user on a different laptop*
  - *Social engineering techniques*

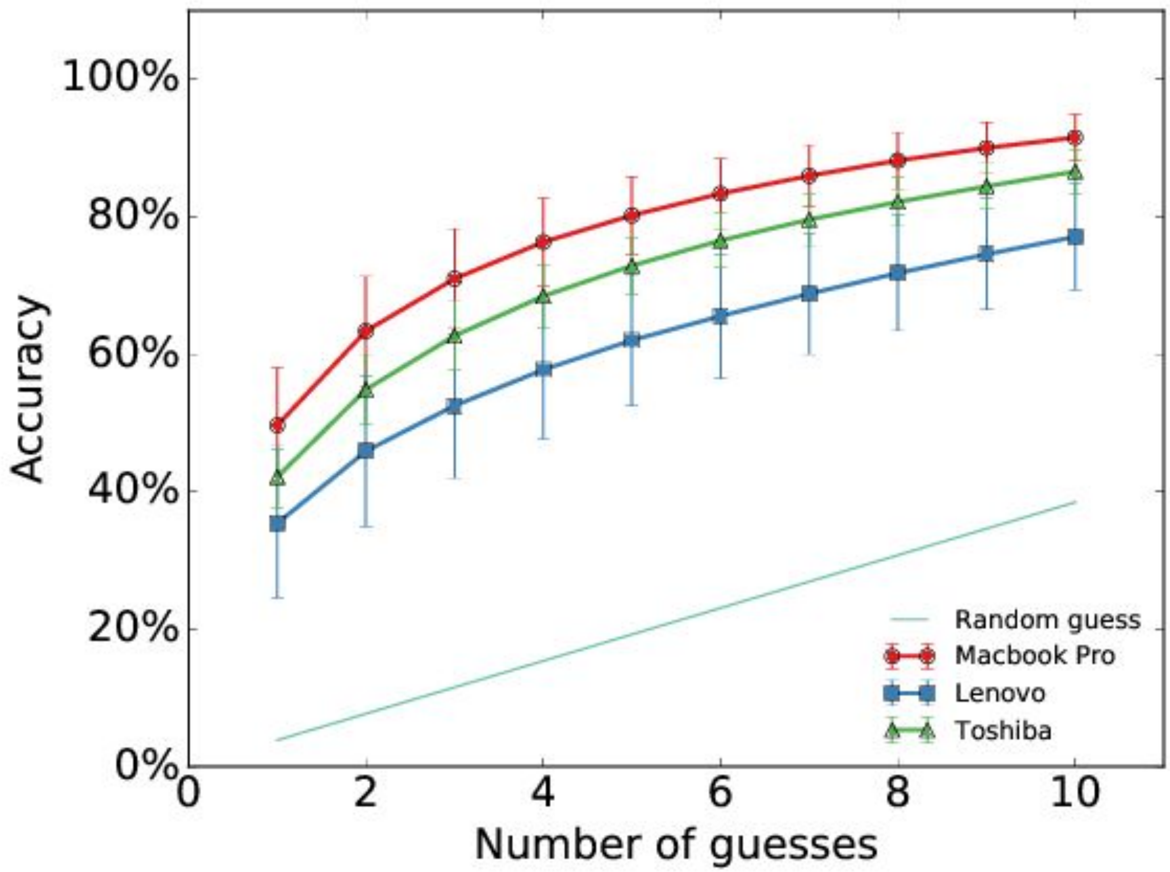
- Model Profiling Scenario
  - *Profiled a laptop of the same model on some users*
  - *The victim can be unknown*

Evaluation - Small Training Set

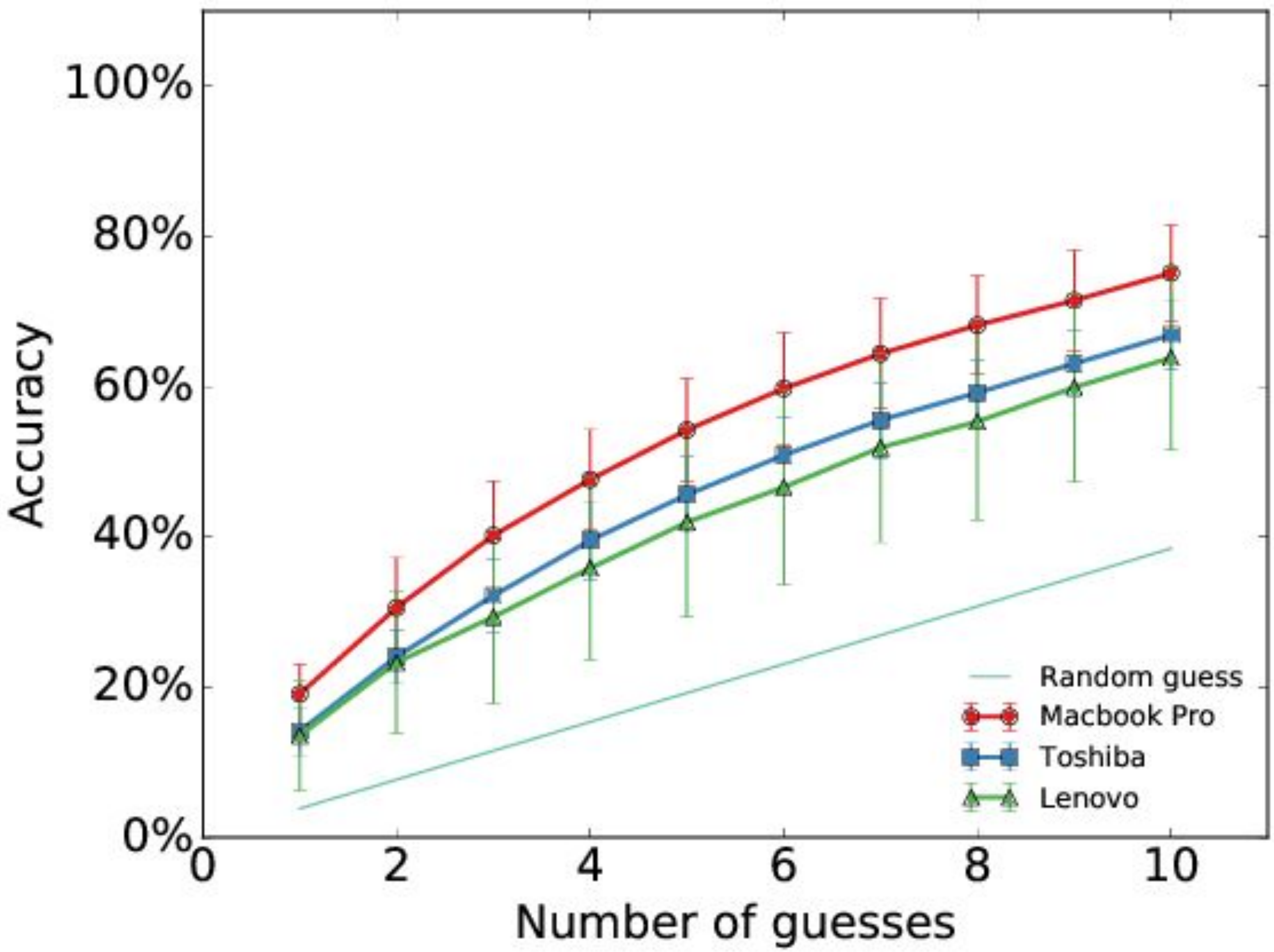
10 samples/character aren't your typical chat message

Training set *with realistic letter frequencies*
Test *against random password*

Character	*# Samples*
E	10
A	9
R	7
J	1
Z	1



Evaluation - User Profiling



Password Cracking

The goal was to crack the victim's random password

→ We need bruteforce techniques

Random password of 10 lowercase letters

- $\log_2(26^{10}) = 47$ bits of entropy

On the Complete Profiling Scenario (high accuracy)

- $\log_2(5^{10}) = 23.22$ bits of entropy

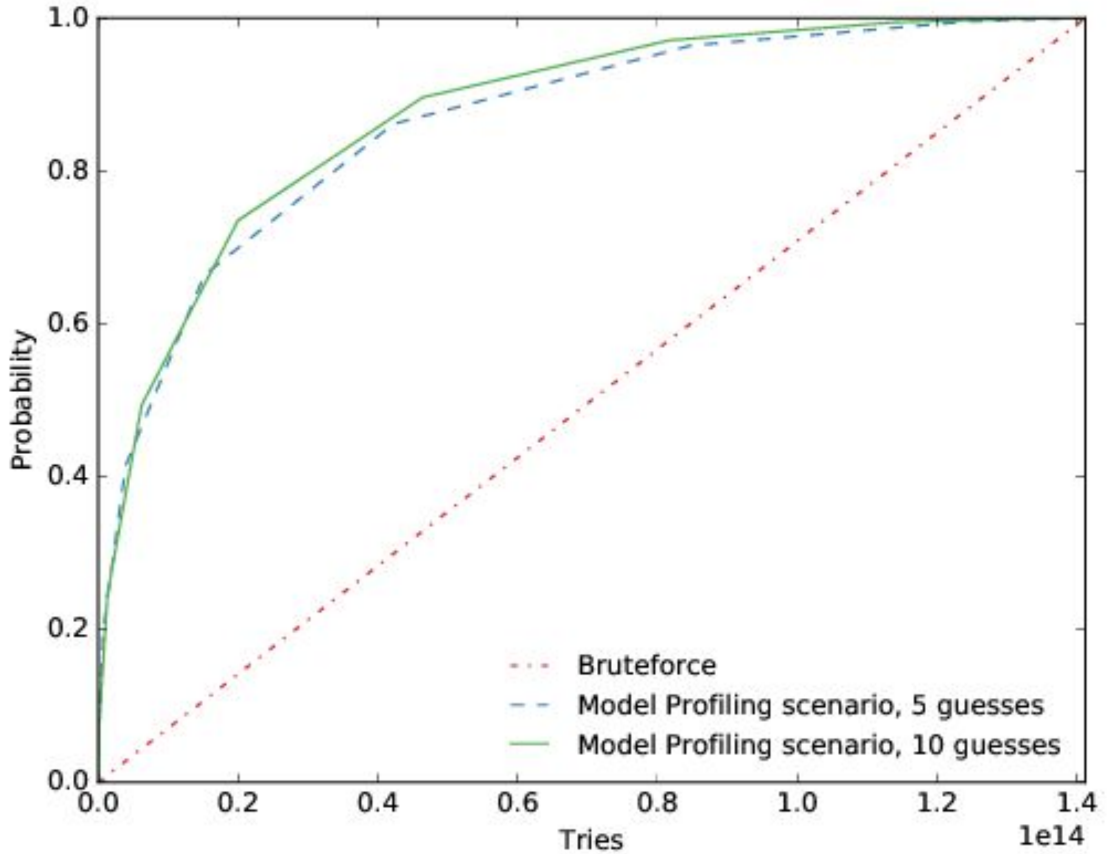
On the other scenarios - entropy is not meaningful

Password Cracking

Model Profiling Scenario → improved bruteforce

Take into account character probabilities

Evaluate the reduction of the average number of trials



Features

Fast Fourier Transform coefficients

$$S(f(t)) = 20\log_{10}\left(|\mathcal{F}(f(t))|\right)$$

$f(t) = \text{signal}$
$\mathcal{F} = \text{Discrete Fourier Transform function}$

Cepstrum coefficients

$$C(f(t)) = \left|\mathcal{F}^{-1}(S(f(t)))\right|^2$$

Mel frequency cepstral coefficients

$$MFC(f(t)) = DCT\left(\log_{10}\left(mel\{|\mathcal{F}(f(t))|\}\right)\right)$$

$$mel(f) = 2595\log_{10}\left(1 + \frac{f}{700}\right)$$

$DCT = \text{Discrete Cosine Transform}$

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

Mauro Conti

2020 WiseML @ WiSec

July 13 2020

SPRITZ
SECURITY & PRIVACY
RESEARCH GROUP

UNIVERSITÀ
DEGLI STUDI
DI PADOVA