







Your PIN Sounds Good! Augmentation of PIN Guessing Strategies Through Audio Leakage

Matteo Cardaioli

Topics:

Authentication, Side-Channel, Behavioral









Master's Degree in Bioengineering

Ph.D. student in Brain, Mind and Computer Science at University of Padova (Italy)

SPRITZ (Security and Privacy Research Group) member

Project Developer @GFT Italy

Research Activities

My research activity focuses on the study and the development of new methods for analysing and **detecting patterns of suspicious behaviors**, **authentication** procedures to detect and mitigate identity fraud and on the implementation of the so called "**predictive security**" of critical financial infrastructures.













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









PIN















PIN







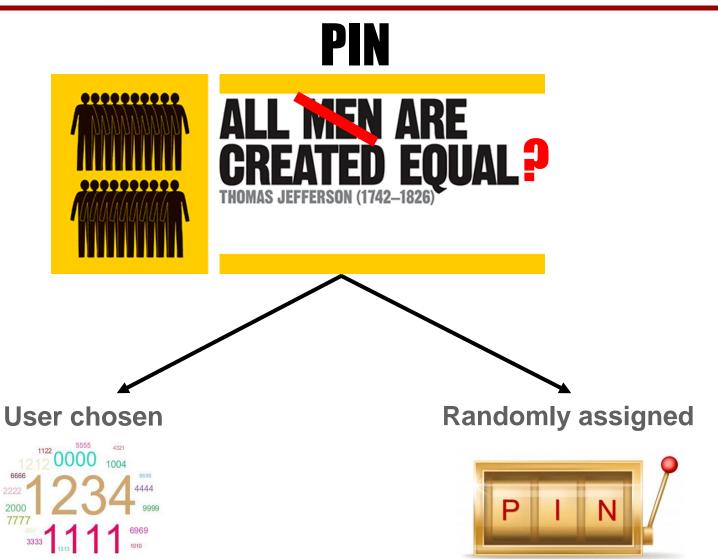












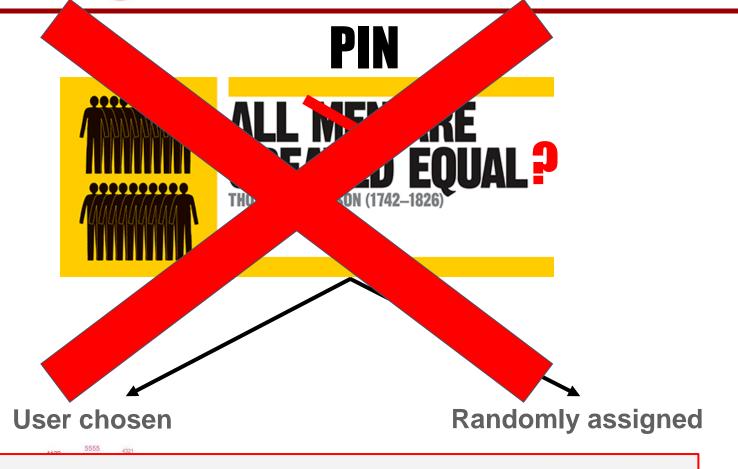




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DEFINITELY... NOT!











User chosen passwords

In December 2017 4iQ discovered, scanning the dark web, a single file containing a database of 1.4 billion credentials in clear.

None of the database passwords are encrypted and most of them have been verified as true.

This collection contains 252 already known breaches (like Linkedin) and other new ones like Netflix, Last.FM, Zoosk or YouPorn.

https://4iq.com/wp-content/uploads/2018/05/2018_IdentityBreachReport_4iQ.pdf











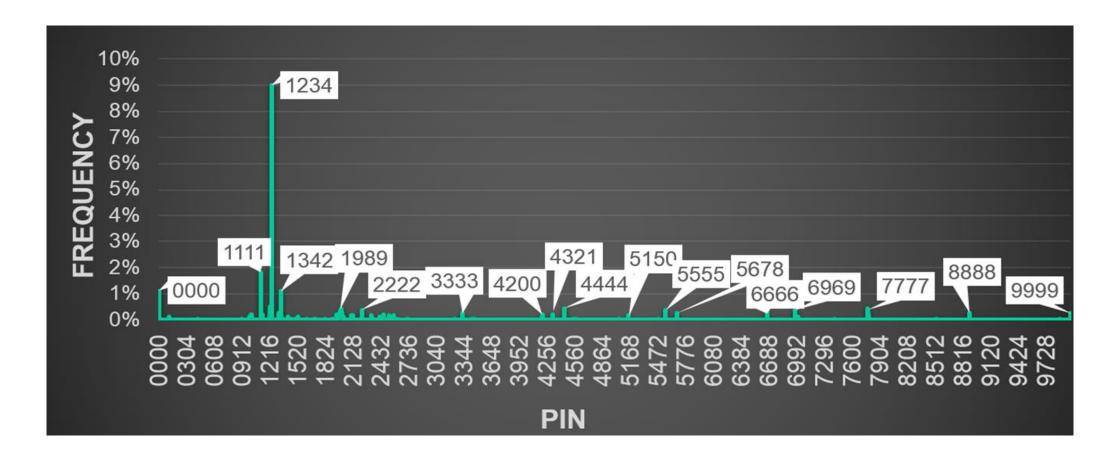
What about PINs?











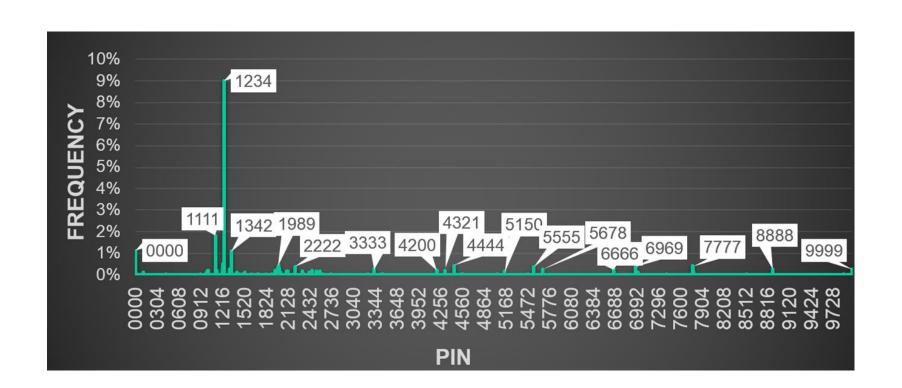












WORST 10 PINs

PIN	FREQ
1234	9.00%
1111	1.83%
0000	1.13%
1342	1.10%
1212	0.50%
4444	0.43%
1989	0.43%
1986	0.42%
7777	0.41%
2222	0.37%

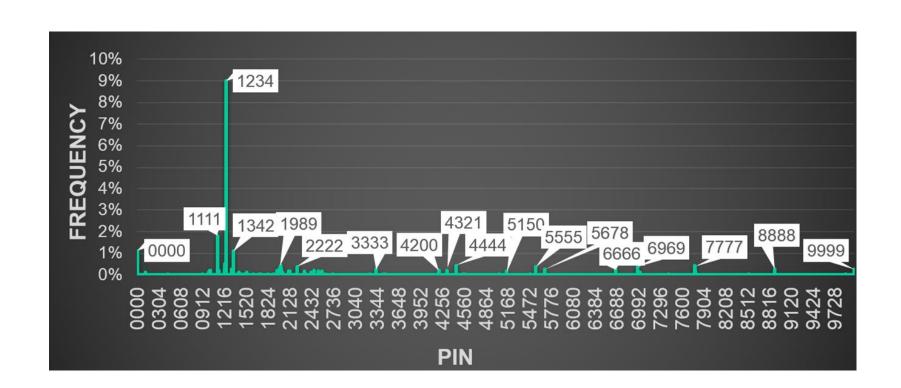












BEST 10 PINs

0.0014%
0.0014%
0.0014%
0.0014%
0.0013%
0.0013%
0.0013%
0.0013%
0.0012%
0.0009%











In this scenario, 20% of PINs can be guessed by trying the 20 most common combinations chosen by the user

If these 20 4-digit PINs were distributed uniformly and randomly, they would represent only 0.2% of the total



WORST 10 PINs

PIN	FREQ
1234	9.00%
1111	1.83%
0000	1.13%
1342	1.10%
1212	0.50%
4444	0.43%
1989	0.43%
1986	0.42%
7777	0.41%
2222	0.37%





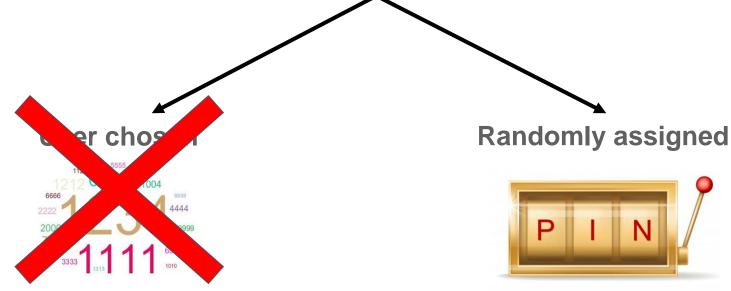




PIN

















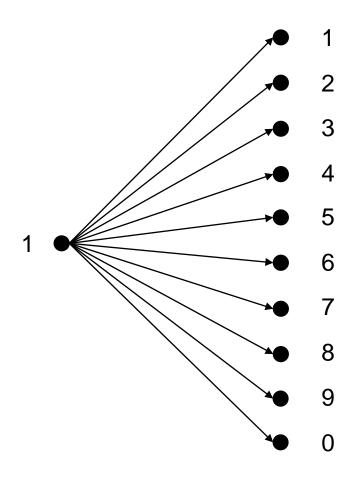












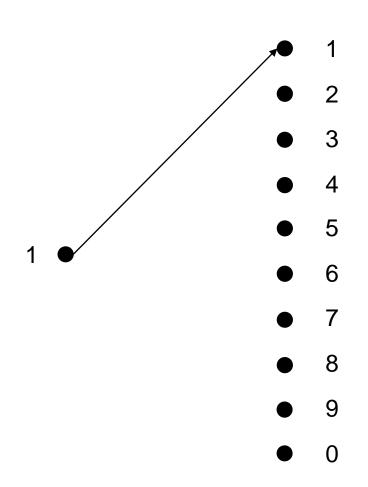












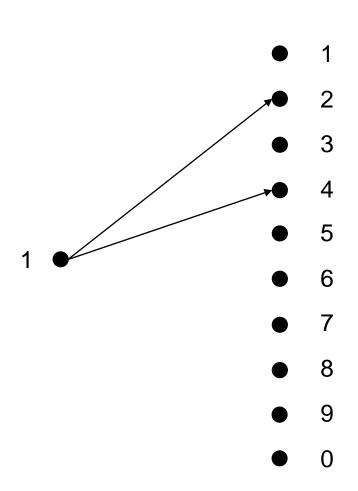
Distance 0 11** 22** 55** 00**











Distance 1

12**

14**

45**

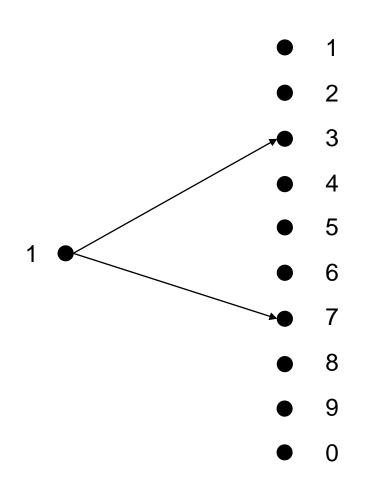












Distance 2

13**

17**

28**

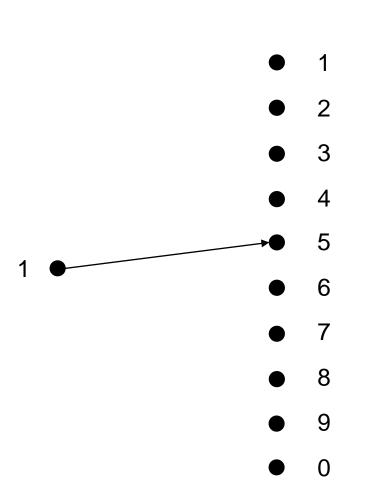












Distance D1

15**

57**

70**

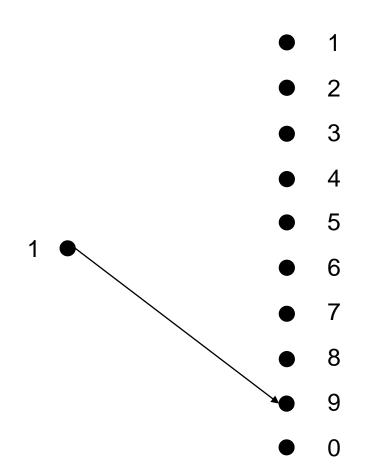












19** 73**

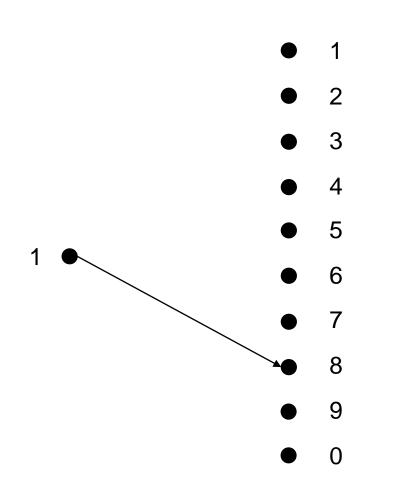












Distance DS

18**

29**

40**

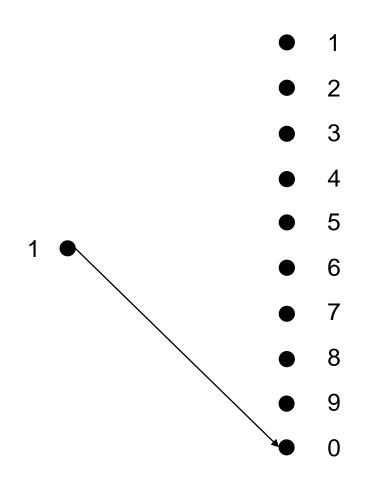












Distance DL01**
30**











1

0

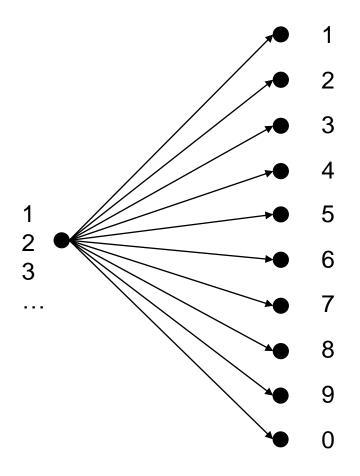
Distance 3 20**

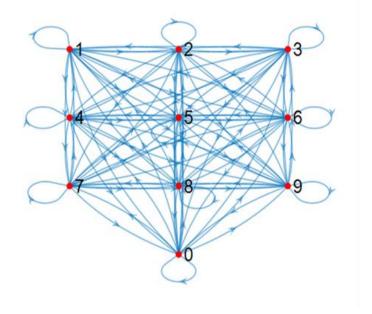




















How much does the knowledge of the distance affect PIN security?

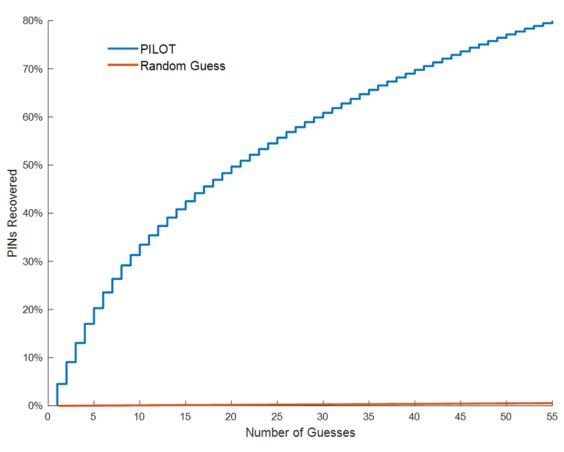








How much does the knowledge of the distance affect PIN security?



Balagani, Kiran, et al. "PILOT: Password and PIN information leakage from obfuscated typing videos." Journal of Computer Security.



Your PIN Sounds Good!









Knowing the physical distance between keys poses another significant security problem ...

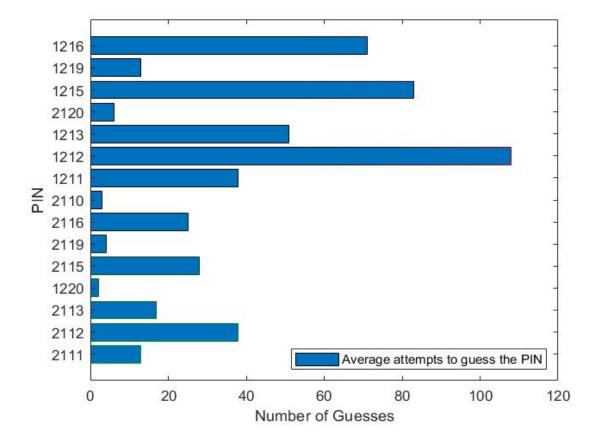








Although distributed randomly and uniformly, some subsets of PINs may be more likely than others



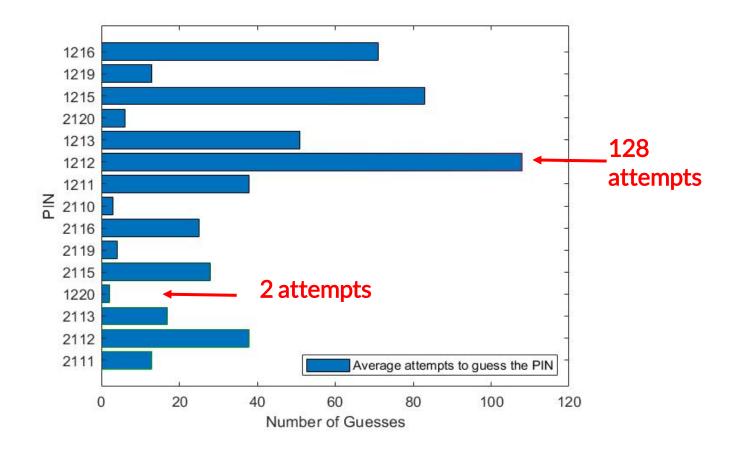








Although distributed randomly and uniformly, some subsets of PINs may be more likely than others













Is it possible to deduce the distances between keys using environmental information?









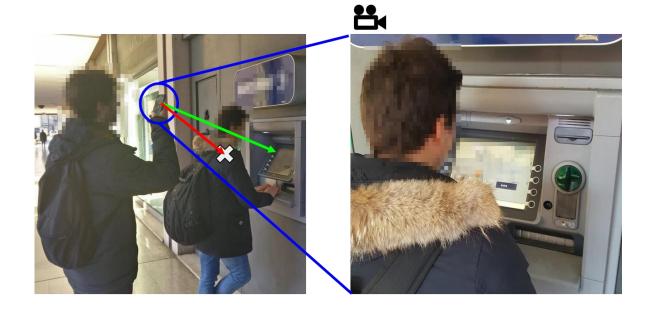






If the screen is visible, we can record the asterisk sequence ...











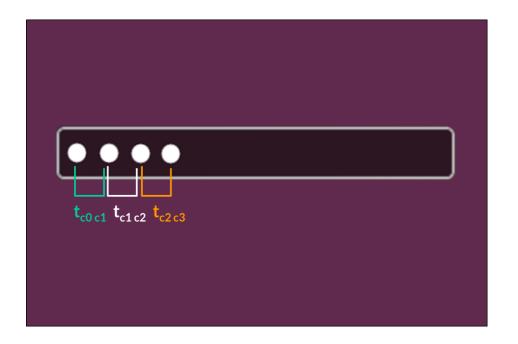






... and deduce the inter-keystroke timing















The audio signal can be used to get a lot of information about the sequence of the keys pressed ...













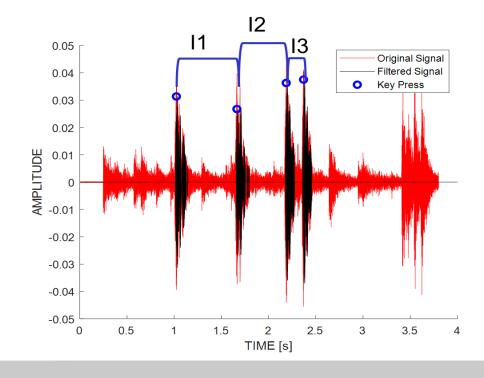






Filtering the audio it is possible to trace back to the instant in which the key was pressed, even in noisy environments



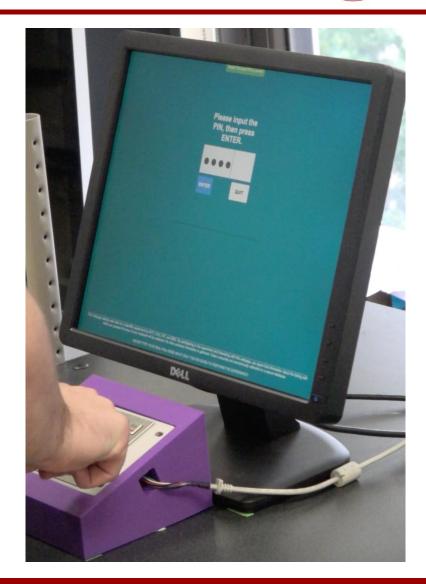












Dataset

- 22 participants recorded with a camera located at a distance of 1.5 meters
- 15 different 4-digit PINs entered 12 times per session
- 19 participants completed 3 sessions
- 3 participants completed 1 session

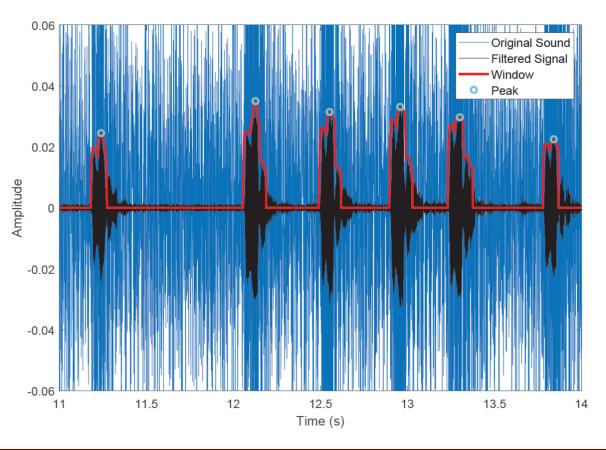








Inter-keystroke timing extraction



- Linear normalization of the audio recording amplitude in the interval [-1; 1]
- 16-order Butterworth band-pass filter centered in 5.6 kHz to isolate the feedback sound frequency
- Samples with an amplitude below 0.01 were "muted"
- Maximum samples amplitude in a sliding window of 1200 samples (25 milliseconds)

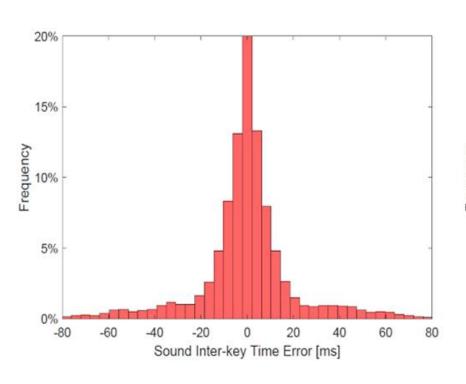


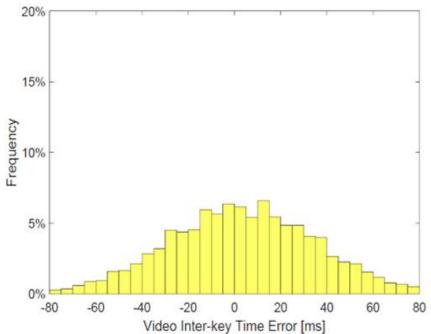






Sound vs Video Inter-keystroke timing







37 of 54



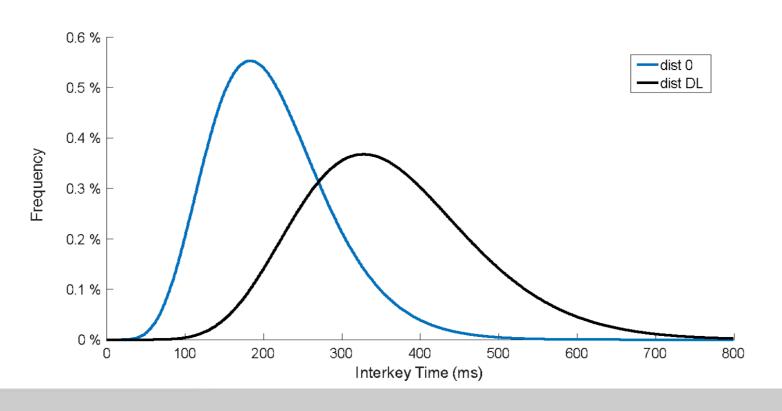






Inter-keystroke timing difference between distance 0 (11**, 00**) and distance DL (10**, 30**)





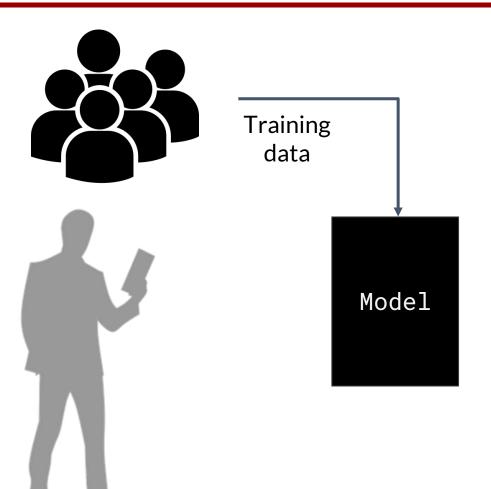












- 11 Users
- 5195 PINs

Test set

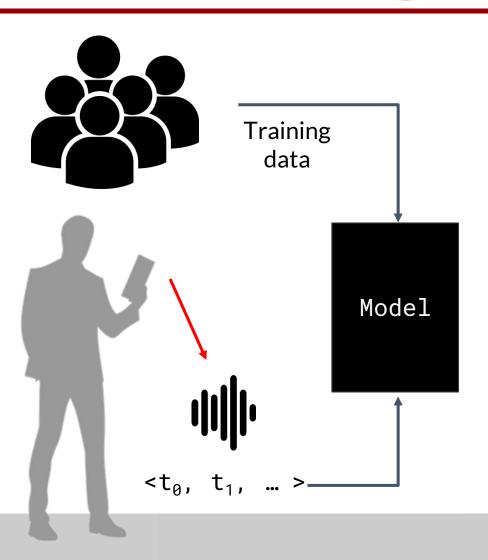
- 11 Users
- 5135 PINs











- 11 Users

- 5195 PINs

Test set

- 11 Users

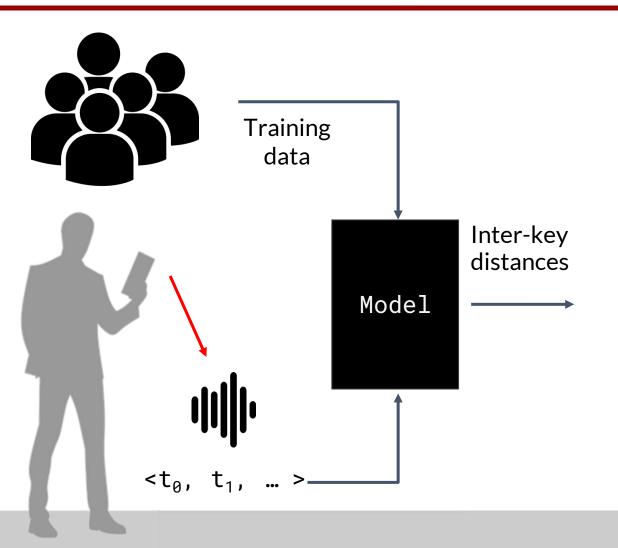












- 11 Users

- 5195 PINs

Test set

- 11 Users

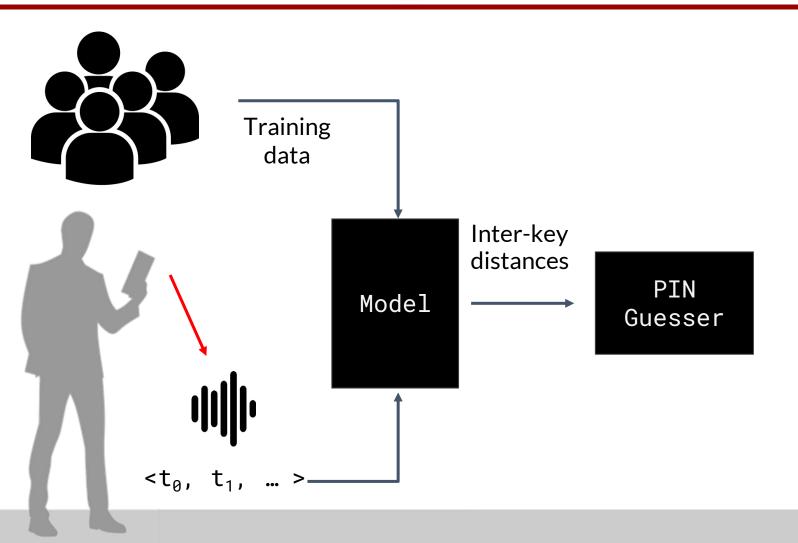












- 11 Users

- 5195 PINs

Test set

- 11 Users

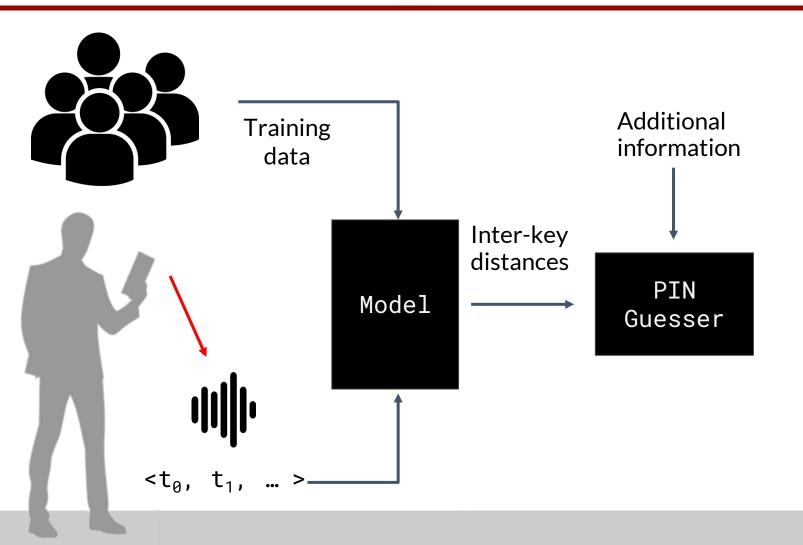












- 11 Users

- 5195 PINs

Test set

- 11 Users

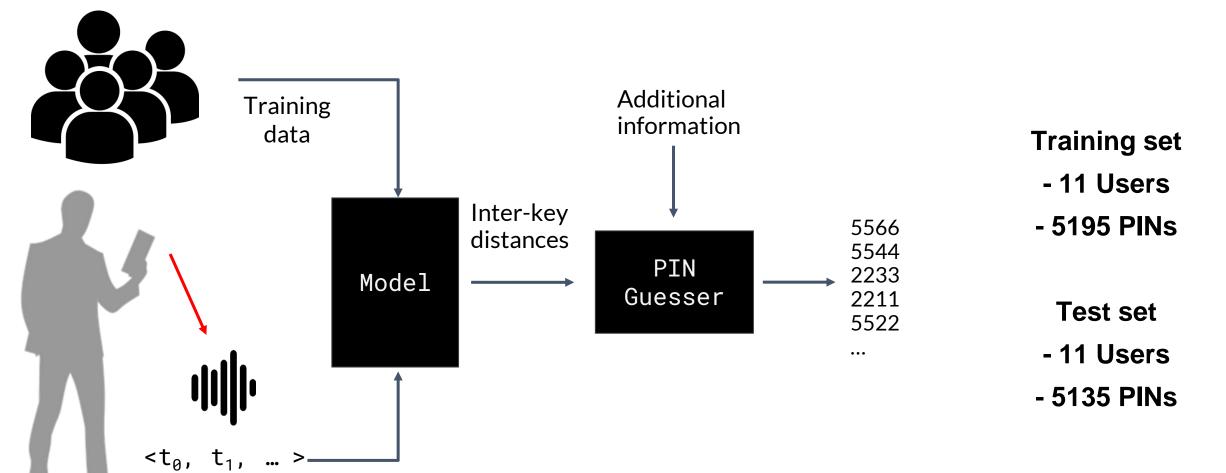












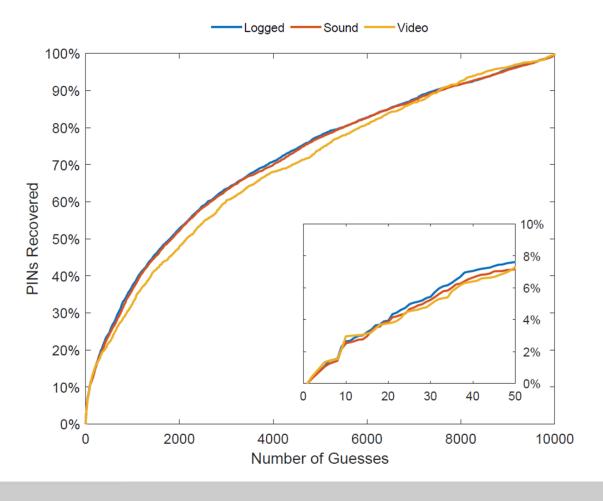
























Does the way we type the PIN provide useful information?







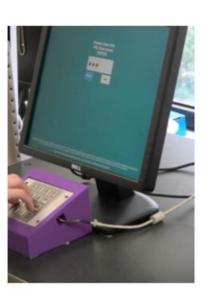






"Single finger PIN" (SFP) represent 70% of the total, 92% of them is entered using the index while 8% is typed with the thumb.











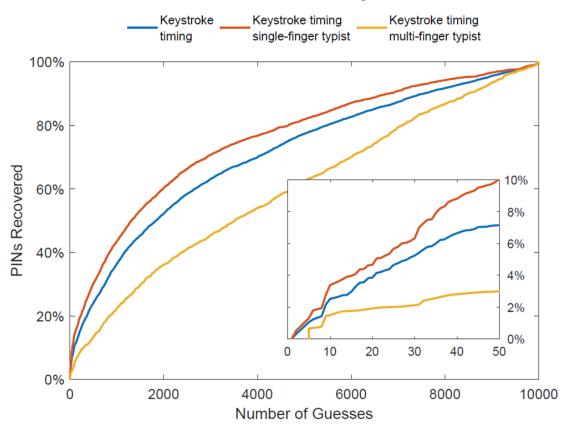






There is a correlation between distance and PIN entry method















Can we get information even after entering the PIN?







Your PIN Sounds Good!

















Seek Thermal Termocamera CompactPRO FF MicroUSB -40 fino a +330 °C 320 x 240 Pixel 15 Hz

498,04€

✓prime Spedizione GRATUITA venerdì 8 novembre





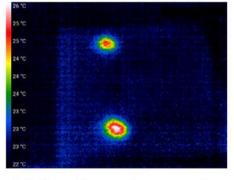




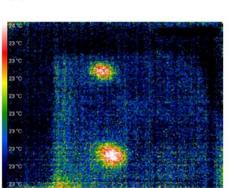


Using a thermal camera it is possible to identify the thermal trace left on

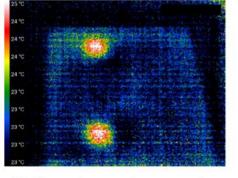
the keypad



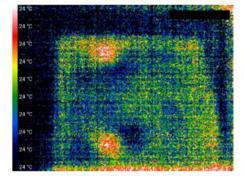
(a) Thermal trace after 2 seconds.



(c) Thermal trace after 10 seconds.



(b) Thermal trace after 7 seconds.



(d) Thermal trace after 15 seconds.







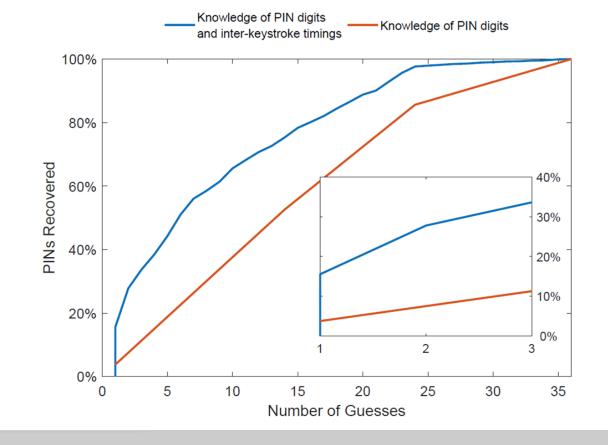




S\$

Using a thermal camera it is possible to identify the thermal trace left on

the keypad







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Information				PINs Guessed Within Attempt				
Keystroke Timing	Single Finger	First Digit	PIN Digits	1	2	3	5	10
				0.01%	0.02%	0.03%	0.05%	0.10%
		o		0.10%	0.20%	0.30%	0.50%	1.00%
0				0.02%	0.31%	0.70%	1.05%	2.51%
0	o			0.03%	0.52%	0.91%	1.30%	3.38%
0		o		3.02%	3.72%	4.36%	6.97%	11.04%
o	О	o		3.73%	4.13%	5.43%	8.73%	14.01%
			O	3.76%	7.52%	11.28%	18.80%	37.60%
O			o	15.54%	27.79%	33.63%	44.25%	65.57%
O	o		O	19.04%	34.01%	40.60%	50.74%	71.31%
		o	0	13.27%	26.62%	39.88%	66.40%	92.80%
0		o	О	35.27%	53.46%	66.84%	86.76%	98.99%
o	o	o	o	40.86%	60.24%	71.77%	89.19%	99.28%













- It is possible to retrieve accurate inter-keystroke timing information from audio in a real context
- Inter-keystroke timing inferred from audio feedback emitted by standard PIN pads can be effectively used to reduce the attempts to guess a PIN
- Compared to prior sources of keystroke timing information, audio feedback is easier to collect
- The typing behavior affects the adversary's ability to guess PINs
- Inter-keystroke timing can be combined with other information to drastically reduce the number of attempts required to guess a PIN







Thank you!

Matteo Cardaioli

matteo.cardaioli@phd.unipd.it







GFT ■

Backup slides



Use case...











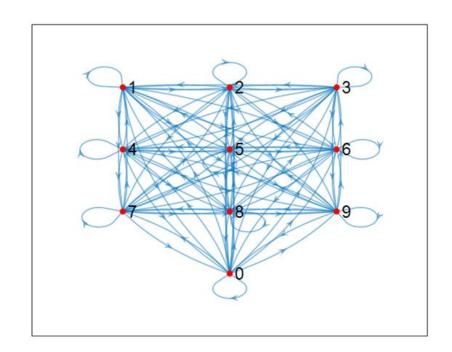
Use case... Let's try to guess the PIN 1077





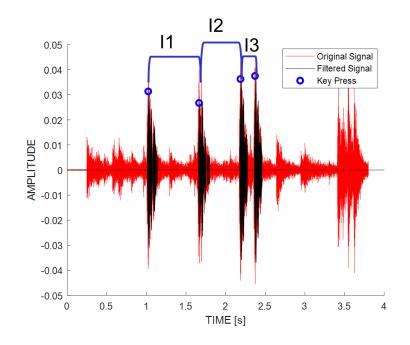
Use case... Let's try to guess the PIN 1077







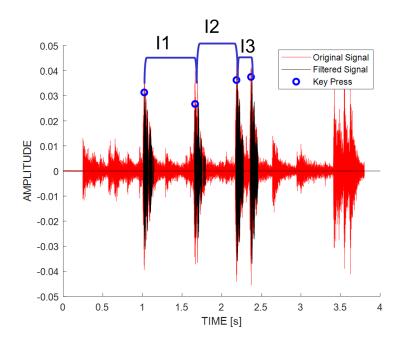
The first step is to filter the audio signal to extract the inter key timing





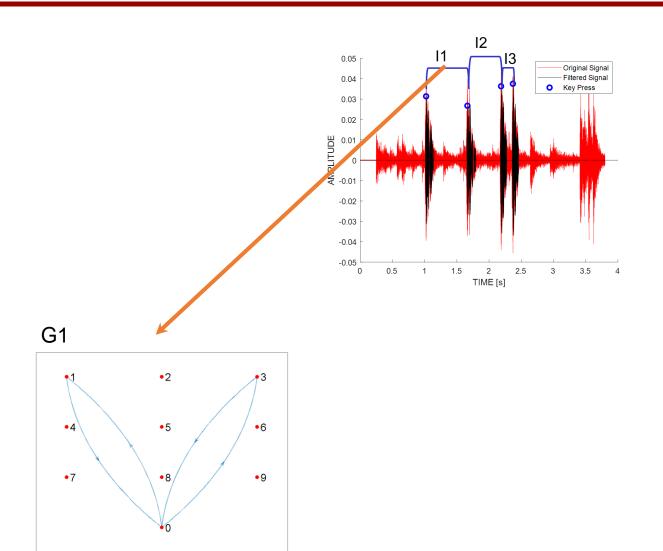


From the inter-keystroke timing, the ML model tells us which physical distances are most likely for each consecutive pair of keys



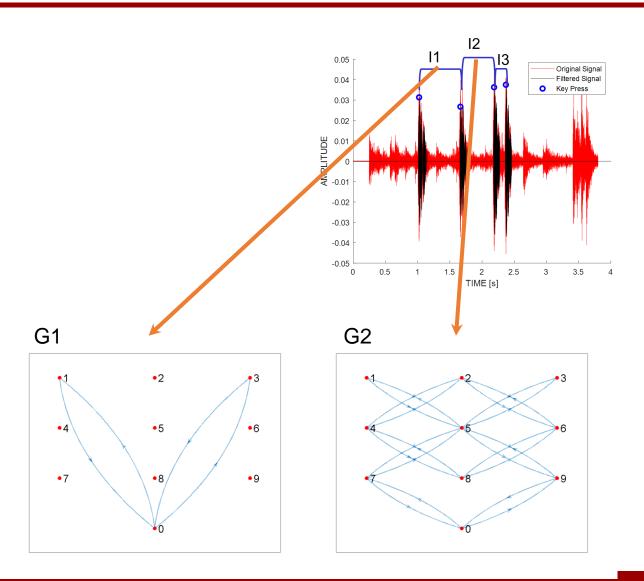




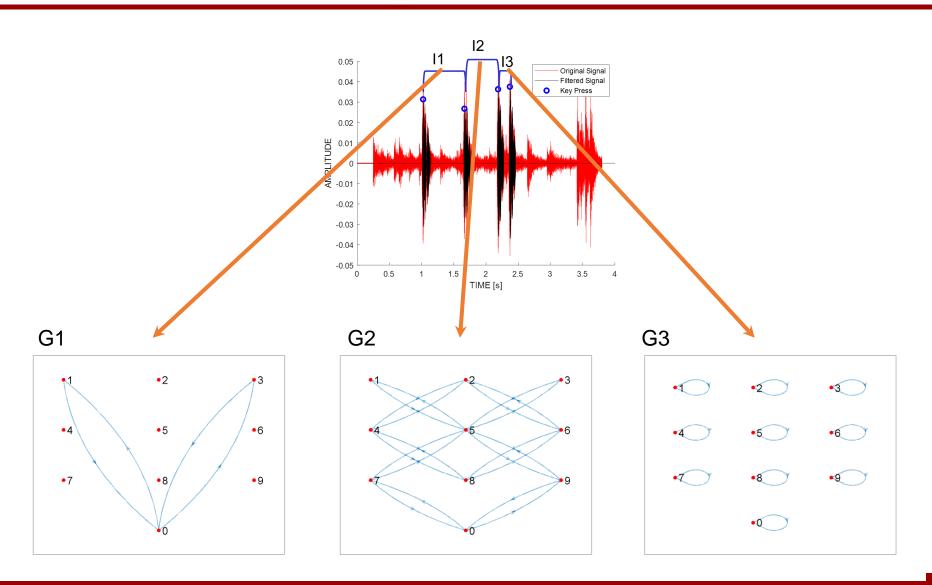










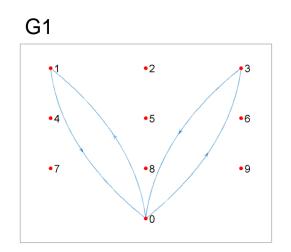


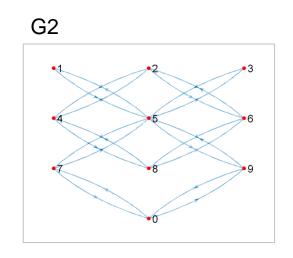


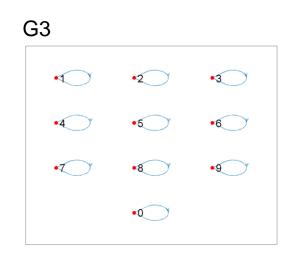




The subgraphs obtained are processed by an algorithm that identifies all possible patterns









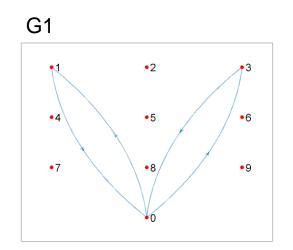


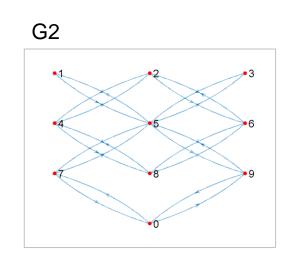


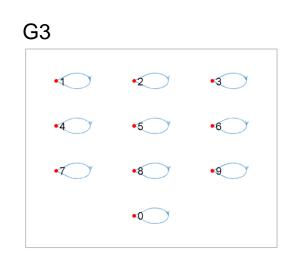




From G1 we know that the first two digits will be 1-0, 0-1, 0-3 or 3-0









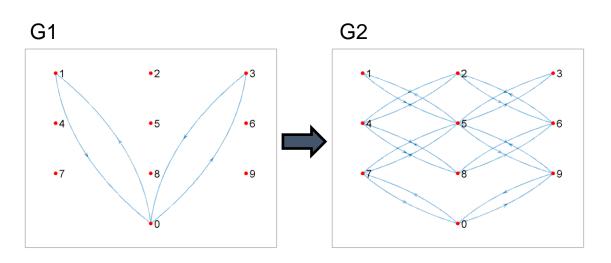


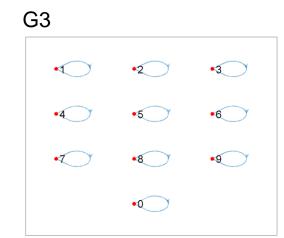




From G1 we know that the first two digits will be 1-0, 0-1, 0-3 or 3-0

Merging this information with that provided by G2, we can exclude some combinations like 1-0-5 or 0-3-6







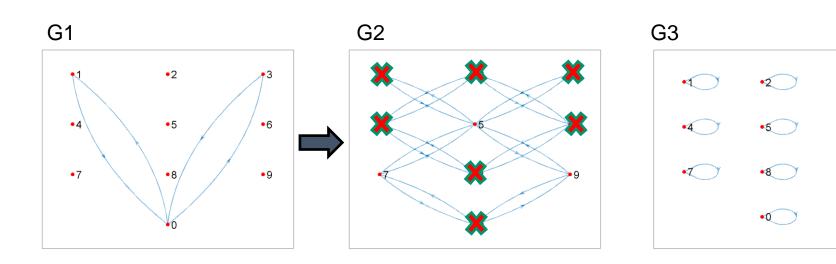






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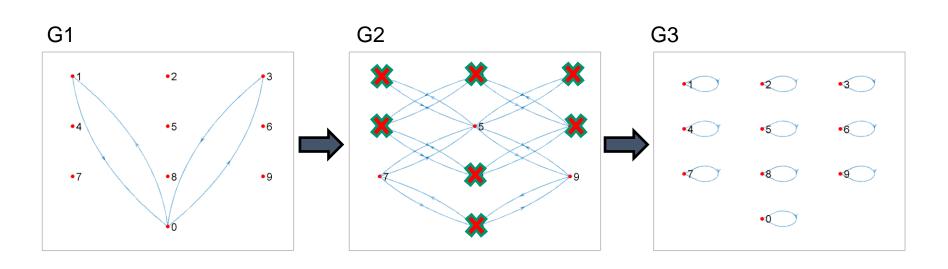
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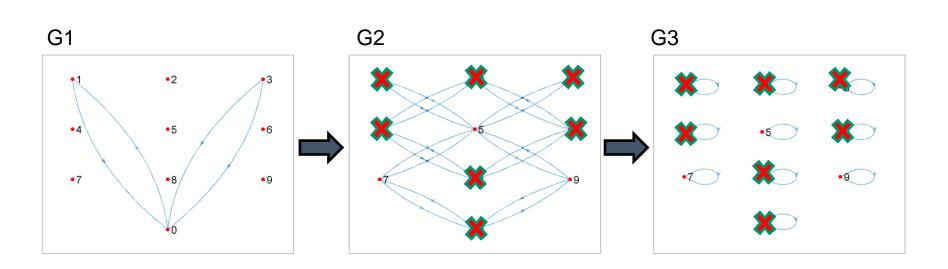
Similarly, the same process is done by combining the information derived from G1 and G2 with that provided by G3





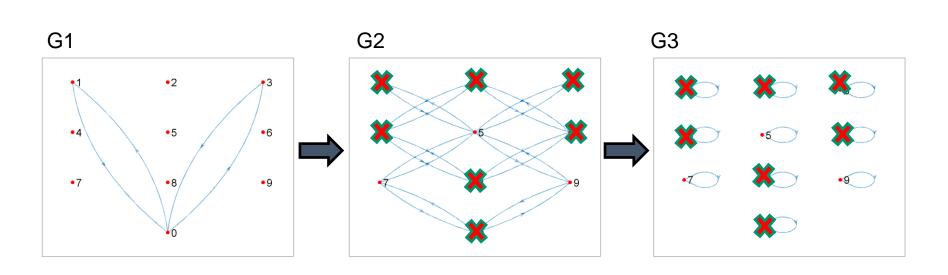


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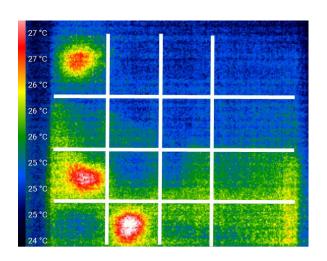






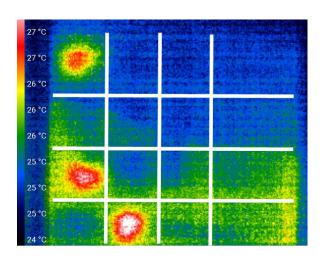






Analyzing the thermal trace we know that the user has entered the numbers 1,7,0 ... But not the order





Analyzing the thermal trace we know that the user has entered the numbers 1,7,0 ... But not the order

We note that there is only one PIN that satisfies all the features

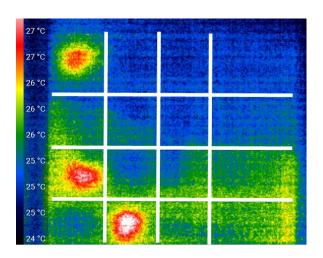








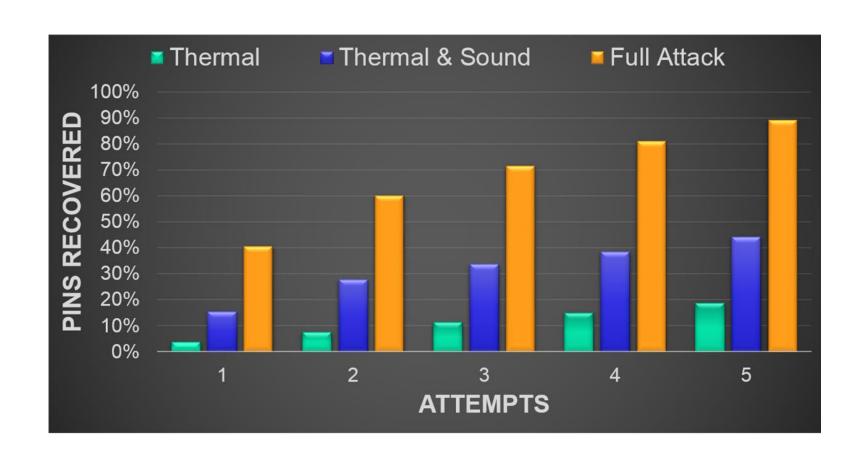




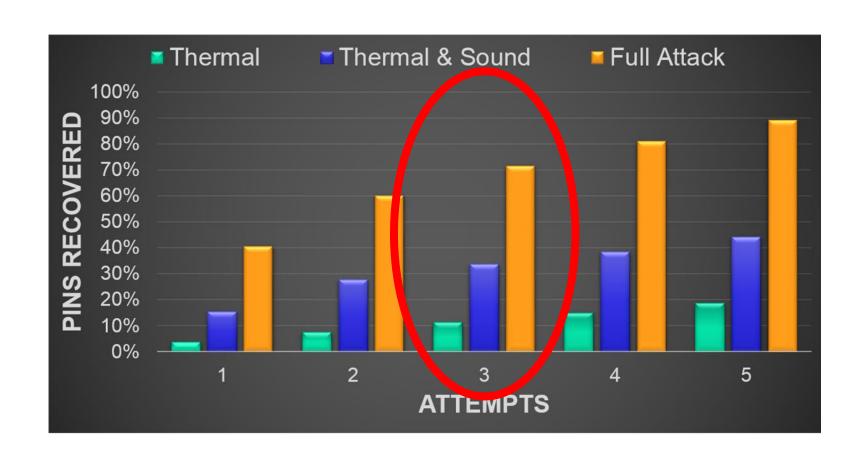
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Thank you!

Matteo Cardaioli

Brain, Mind and Computer Science University of Padua, Italy matteo.cardaioli@phd.unipd.it

Topics:

Authentication, Side-Channel, Behavioral