

# Everything Everywhere AI: Securing next-generation embedded devices

Lejla Batina  
Radboud University



**KIVI JAARCONGRES**  
**TU/e, March 11, 2026**

# Outline

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- (Embedded) crypto is everywhere
- Side-channel analysis (SCA) attacks are a relevant threat today
- What AI has to do with it?
  - Example 1: Screen Gleaning
  - Example 2: Attacking AI using side-channel analysis
- Where do we go from here?

# Our world is digital



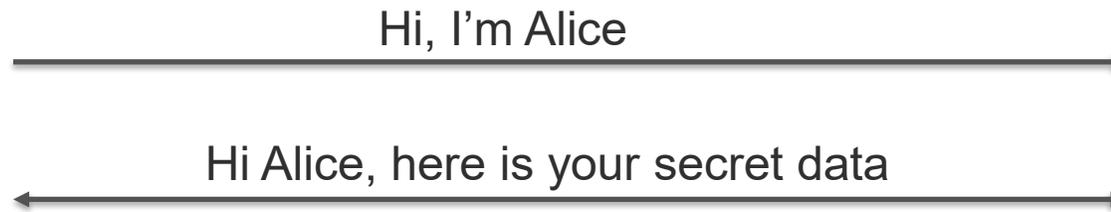
and with crypto we  
try to make it secure

# Schoolbook cryptography

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Alice

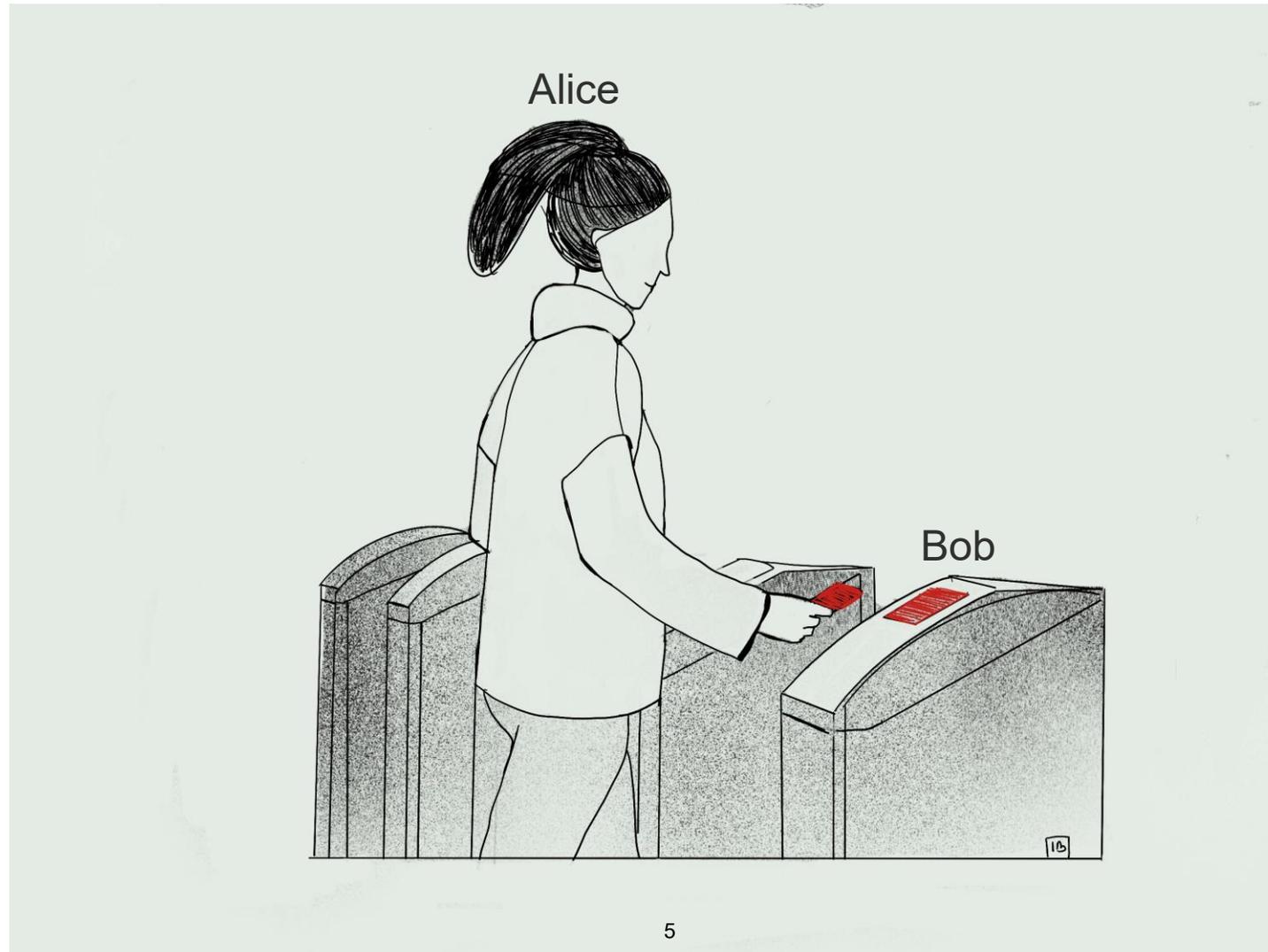


Bob



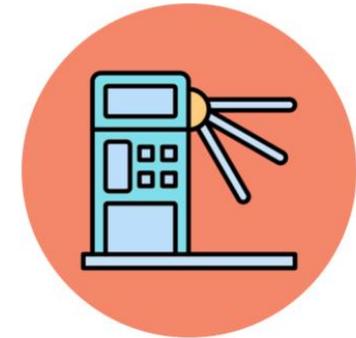
Eve

# Crypto in the real world

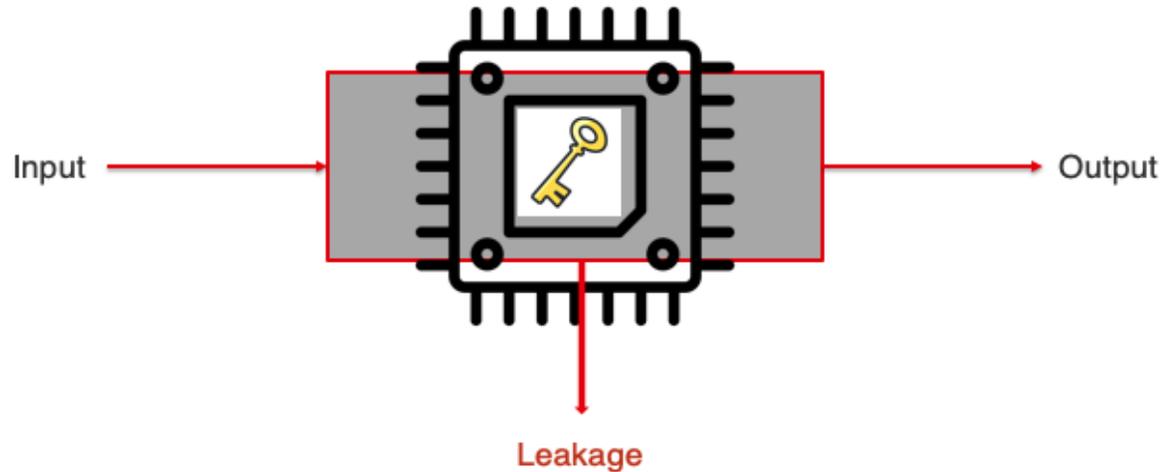


drawing by  
Ileana Buhan

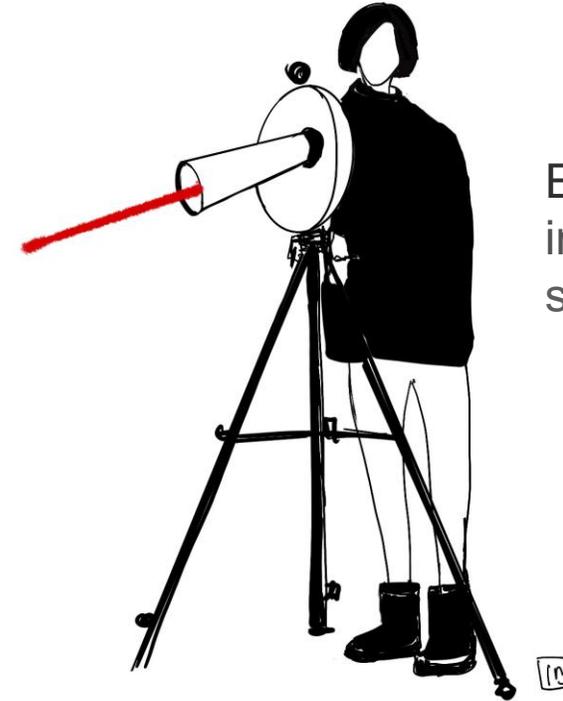
# Devices with embedded crypto



# Side-channel analysis (SCA)



Eve **passive**, can measure and process signals



Eve **active**, can insert her own signals

- Crypto is implemented on **real** devices such as microcontrollers and chips
- **Eve's goal**: secret key, message, IP, ...

# Relevance

## AI researchers claim 93% accuracy in detecting keystrokes over Zoom audio

Mitigating factors include typing style, multi-case passwords, uncommon laptops.

KEVIN PURDY - 8/7/2023, 8:17 PM



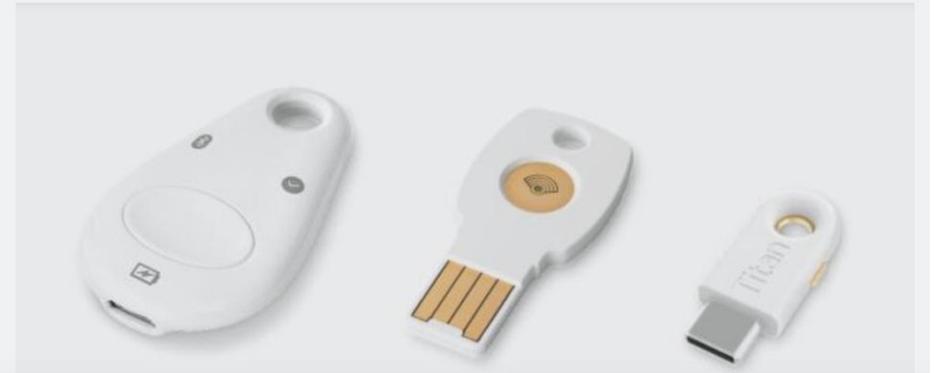
<https://arxiv.org/pdf/2308.01074.pdf>

SEND IN THE CLONES —

## Hackers can clone Google Titan 2FA keys using a side channel in NXP chips

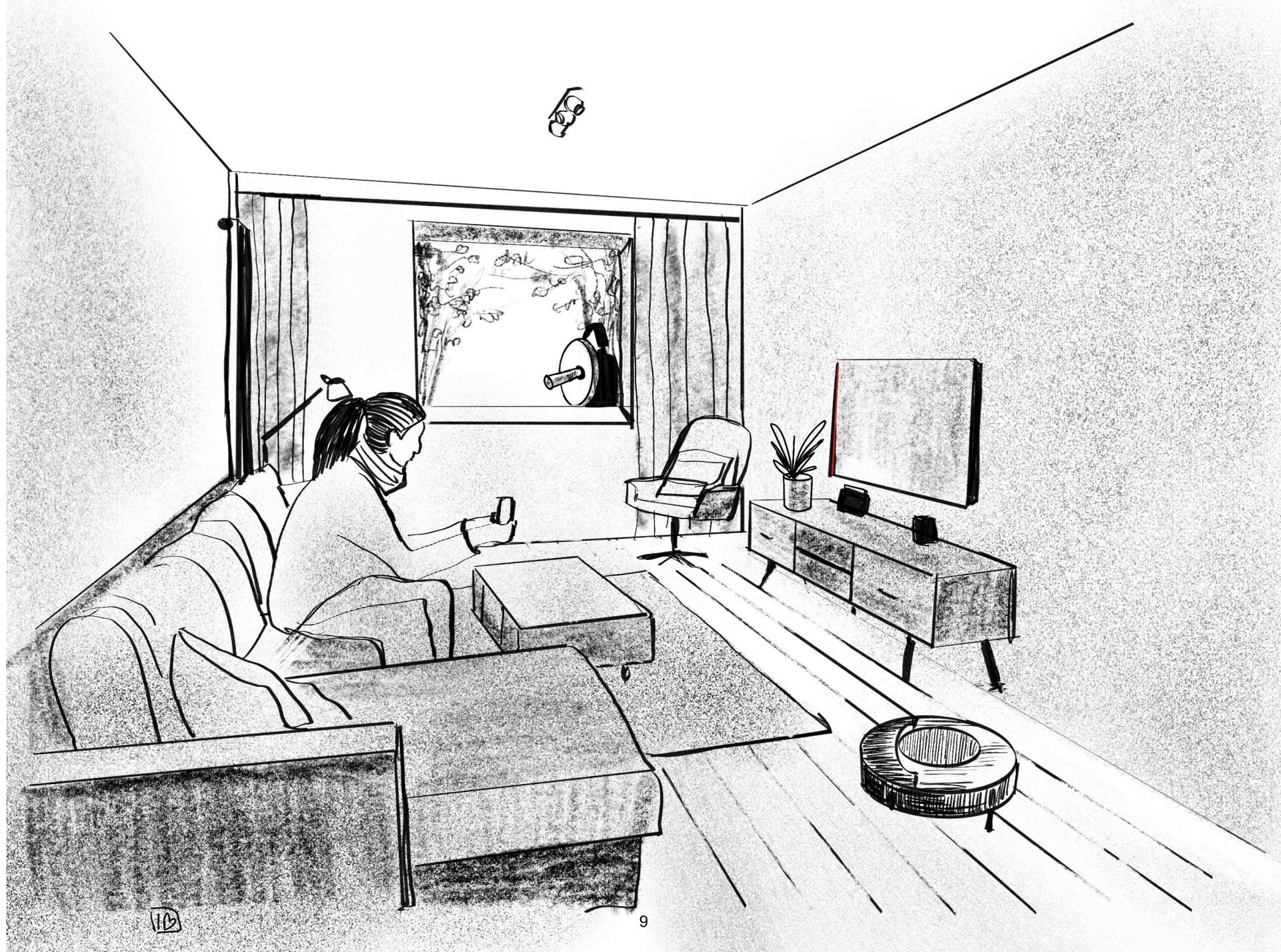
Yubico and Feitian keys that use the same chip are likely susceptible, too.

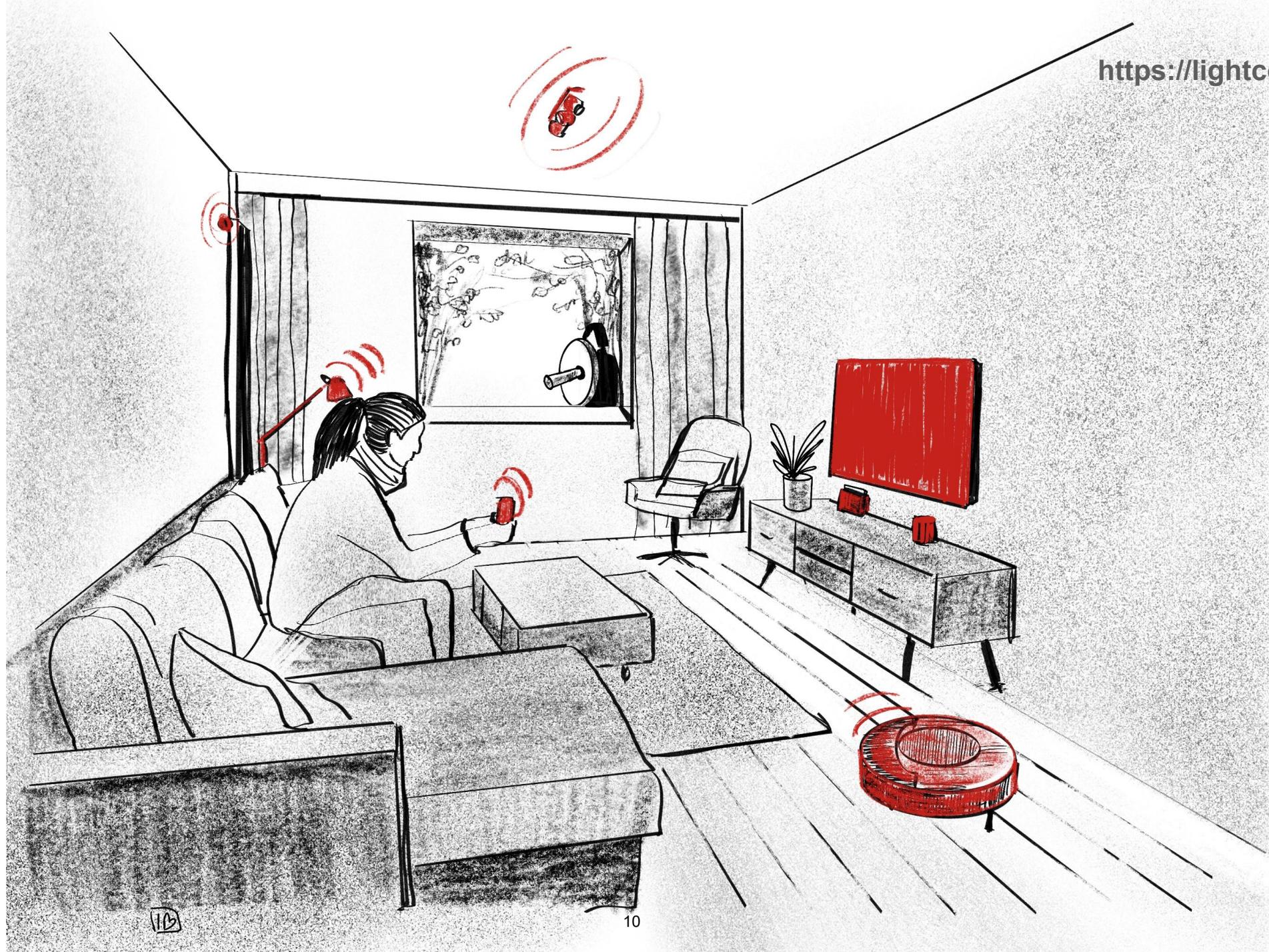
DAN GOODIN - 1/8/2021, 1:59 PM



<https://ninjalab.io/a-side-journey-to-titan/>

Side-channel attacks exploit weaknesses in implementations.





# AI and Security

- Machine Learning (ML) applications: image recognition, natural languages, robotics, gaming etc.
- ML in IoT devices for image and speech recognition
- AI in small devices manipulating our data and affecting our privacy



But, can we trust it?

# AI and SCA: How it all started

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- Machine learning (ML) for SCA was introduced 15 years ago
  - In collaboration with Data Science@RU and Riscure/Keysight (a.o.)
- Deep learning (DL) for SCA became a very active research topic:
  - Neural nets (NNs) for SCA attacks
  - TEMPEST-like techniques e.g. screen gleaning
- SCA attacks on implementations of neural nets:
  - Reverse engineering and stealing IP
  - Input recovery from NN implementations

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# Ex. 1: Screen Gleaning

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**SCREEN GLEANING: A SCREEN READING TEMPEST ATTACK ON MOBILE DEVICES EXPLOITING AN ELECTROMAGNETIC SIDE CHANNEL**

**Z. LIU, N. SAMWEL, L. WEISSBART, Z. ZHAO, D. LAURET,  
L. BATINA, M. LARSON**



# TEMPEST: eavesdropping on screens



# TEMPEST history

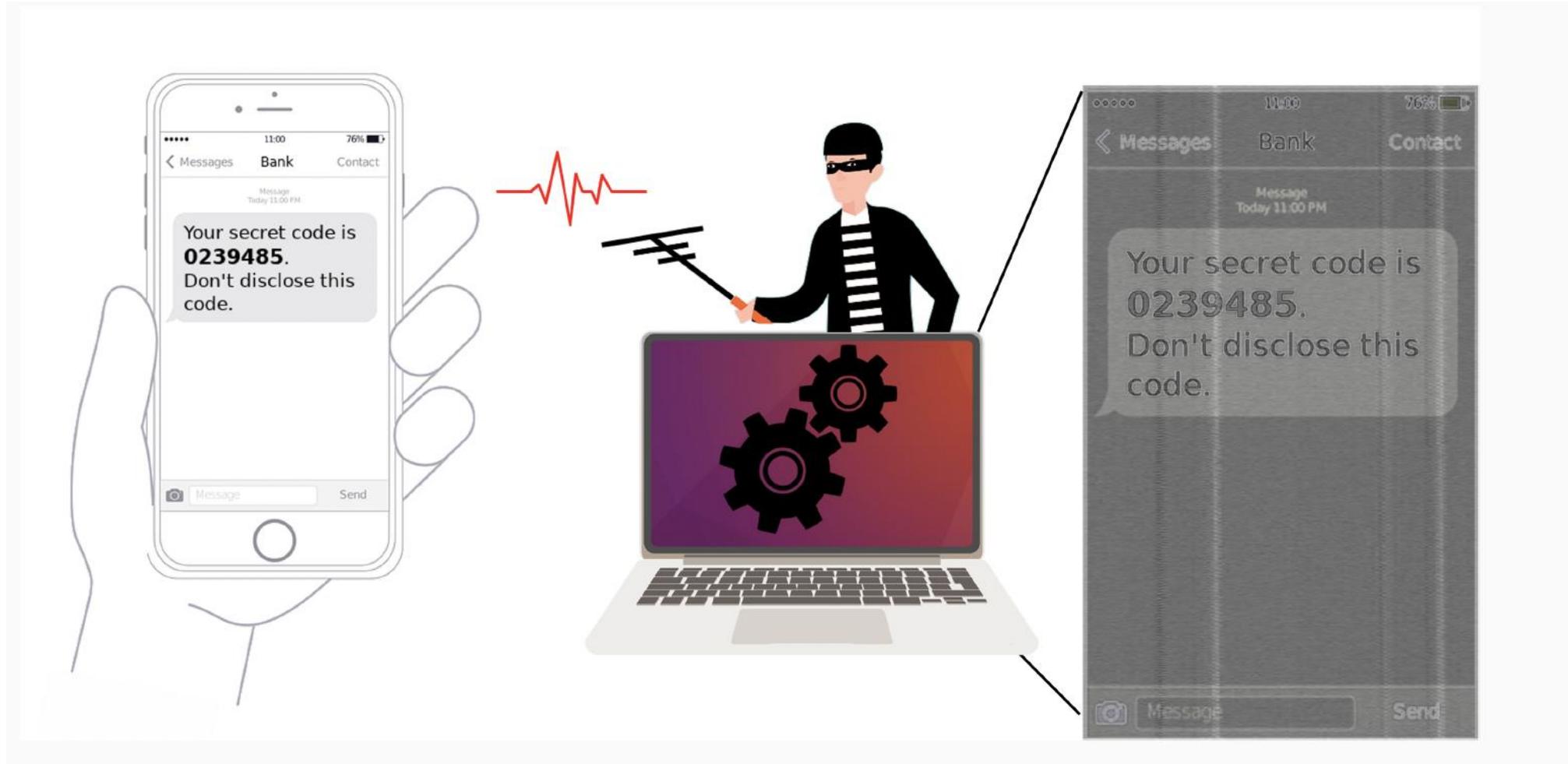
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- WWII: Bell Labs noticed that messages from teleprinter communications can be recovered
- 1982: NSA published TEMPEST Fundamentals
- 1985: “Van Eck phreaking” the first unclassified analysis of the security risks of emanations from PC monitors



Source: Tomorrow's world BBC

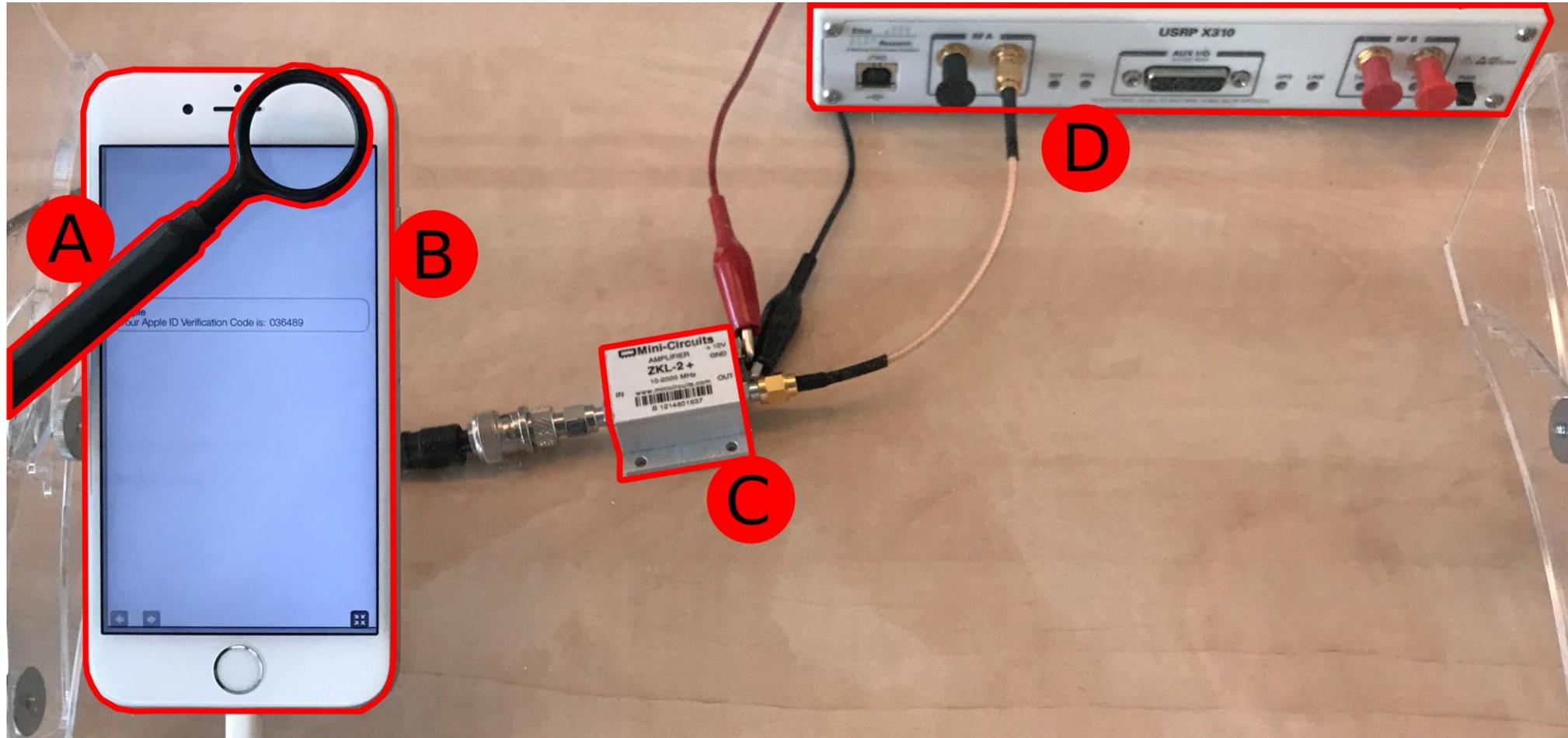
# Modern TEMPEST: Screen gleaning on mobile phones



# Screen gleaning in practice



# Screen gleaning setup

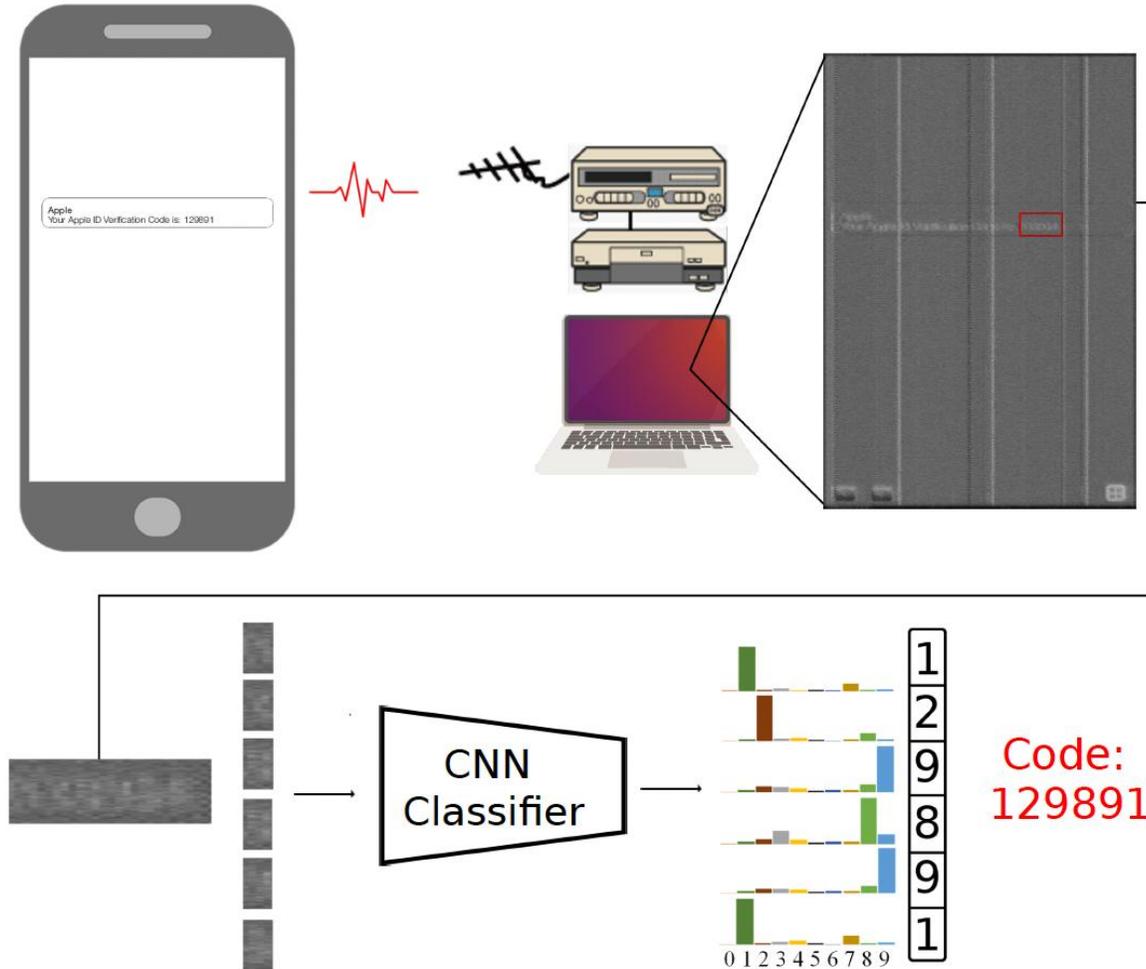


# Motivating story and assumptions



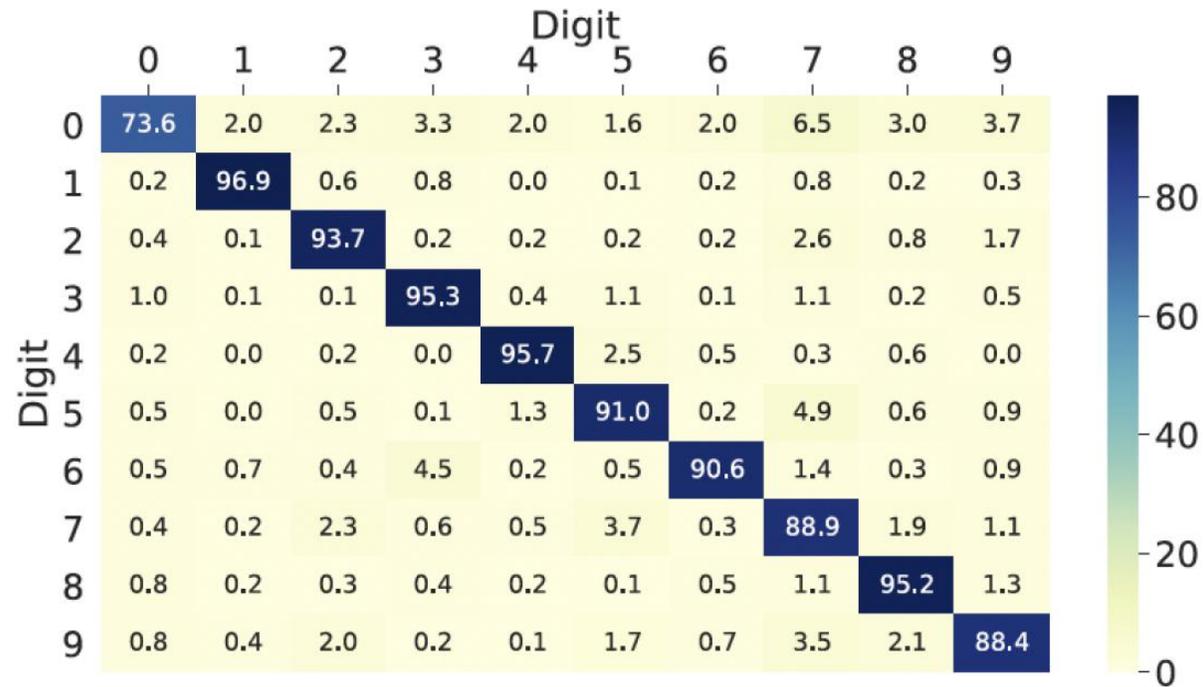
- The attacker has access to a profiling device that is “similar” to the target device
- The set of symbols displayed on the phone are digits only
- The attacker can collect EM traces from the target as representation of the image displayed on the screen

# The attack model



- The target emits EM signal intercepted by antenna connected to SDR
- The leaked information is collected and reconstructed as a gray-scale image (emage)
- From emage, the 6-digit security code is cropped and fed into a CNN classifier

# Security code results



|          | 6 digits | ≥ 5 digits | ≥ 4 digits |
|----------|----------|------------|------------|
| Acc. (%) | 50.5     | 89.5       | 99.0       |

# More results

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- Attack on different phones of the same model e.g. iPhone 6
  - ❖ Cross-device accuracy of 61.5% when the classifier is trained and tested on two different phones
- Attack on a different phone
  - ❖ Accuracy of 74% on Huawei Honor 6X
- Attack at a greater distance (through a magazine)
  - ❖ Accuracy of 65.8% on Huawei Honor 6X through 200 pages

Z. Liu, Niels Samwel, L. Weissbart, Z. Zhao, D. Lauret, L. Batina, M. Larson, Screen Gleaning: A Screen Reading TEMPEST Attack on Mobile Devices Exploiting an Electromagnetic Side Channel, NDSS 2021.

# CSI NN: REVERSE ENGINEERING OF NEURAL NETWORK ARCHITECTURES THROUGH ELECTROMAGNETIC SIDE CHANNEL

L. BATINA, S. BHASIN, D. JAP, S. PICEK



## Ex. 2: Rev engineering of NNs

BARRACUDA: GPUS DO LEAK DNN WEIGHTS

P. HORVATH, L. CHMIELEWSKI, L. WEISSBART, L. BATINA, Y. YAROM



# Everything Everywhere embedded AI



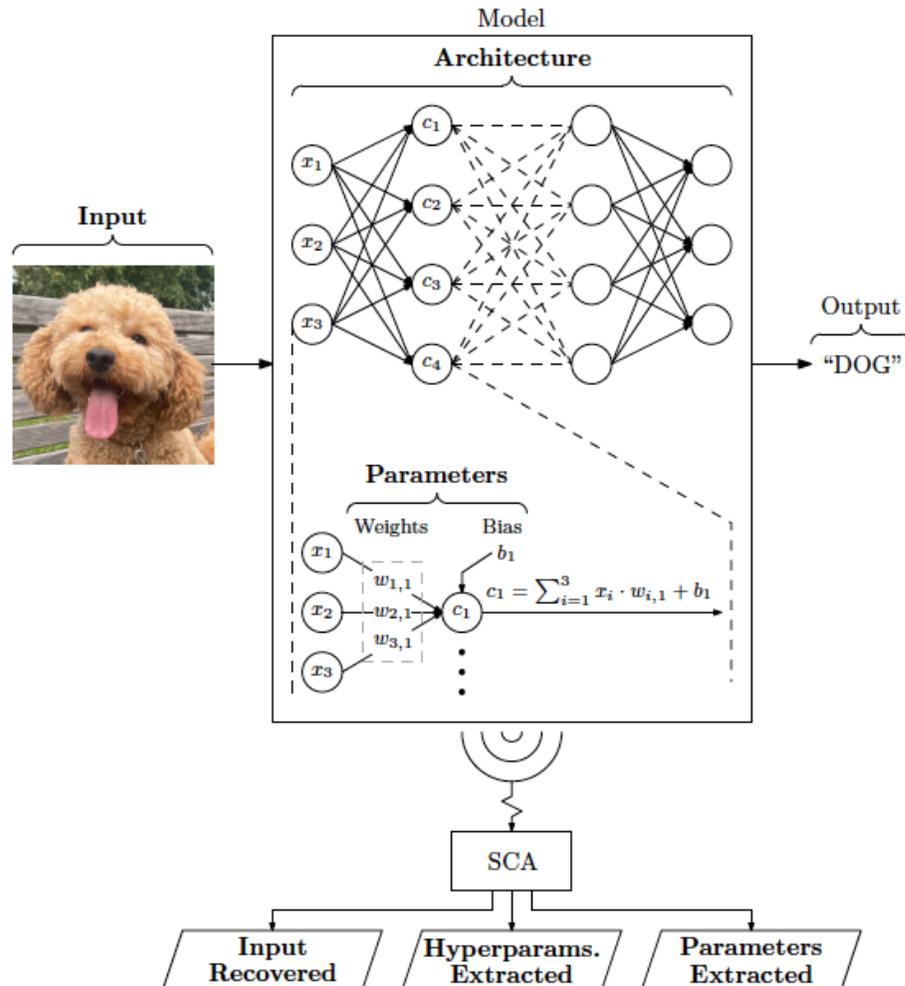
# Motivation

- Well-trained models are valuable for some industries
- Neural nets are being deployed on various platforms, some of those are constrained
- This makes the NN architectures and their parameters target for adversaries



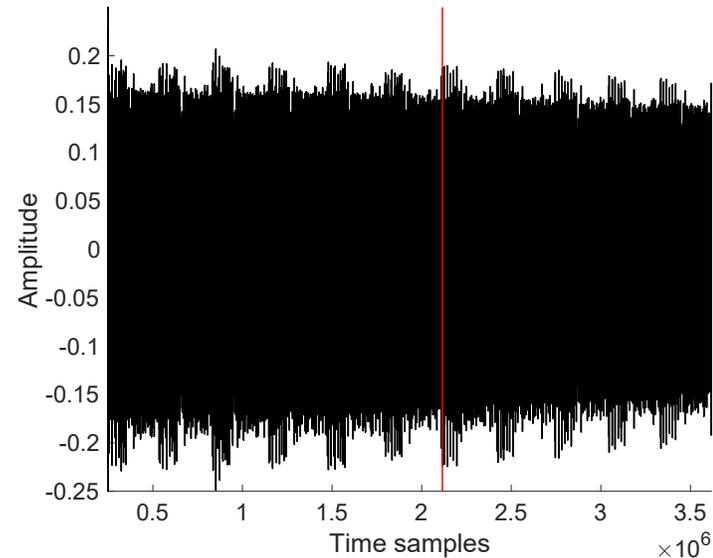
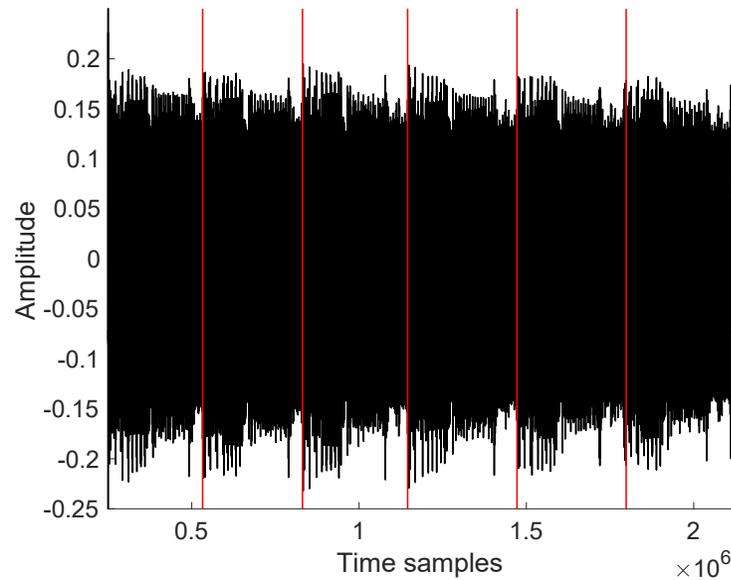
S. Picek and L. Batina: Cybersecurity and Artificial Intelligence: A Perfect Couple?  
DATA, CYBERSECURITY & PRIVACY 03-2024 #15

# New field: Physical SCA on neural nets

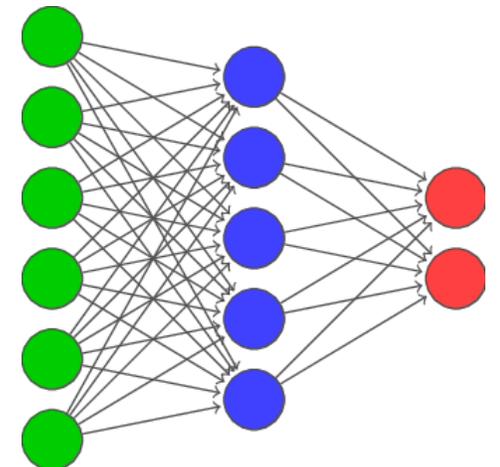


- Main components of interest for adversaries:
  - architecture and hyperparameters, including activation function
  - trained parameters
  - input (image or text)

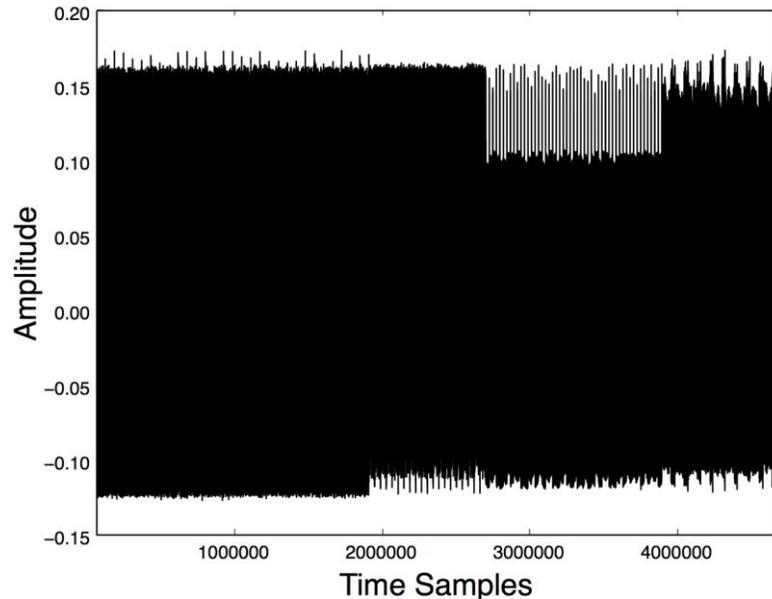
# Simple EMA on neurons



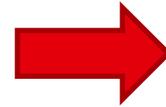
- 6 neurons = 6 repeating patterns
- Each neuron executes a number of multiplications, followed by activation f.



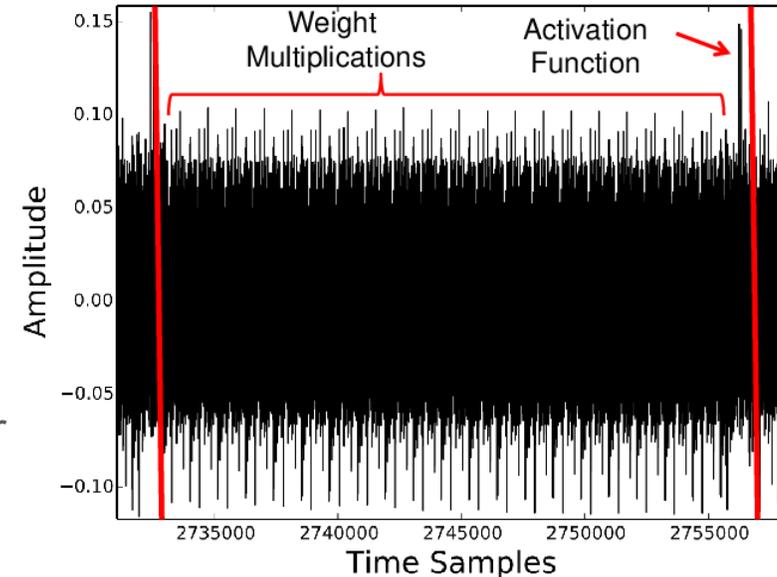
# Results for MLP on ARM Cortex-M3



Four hidden layers (50, 30, 20, 50)



Zoom in one  
neuron in 3<sup>rd</sup> layer

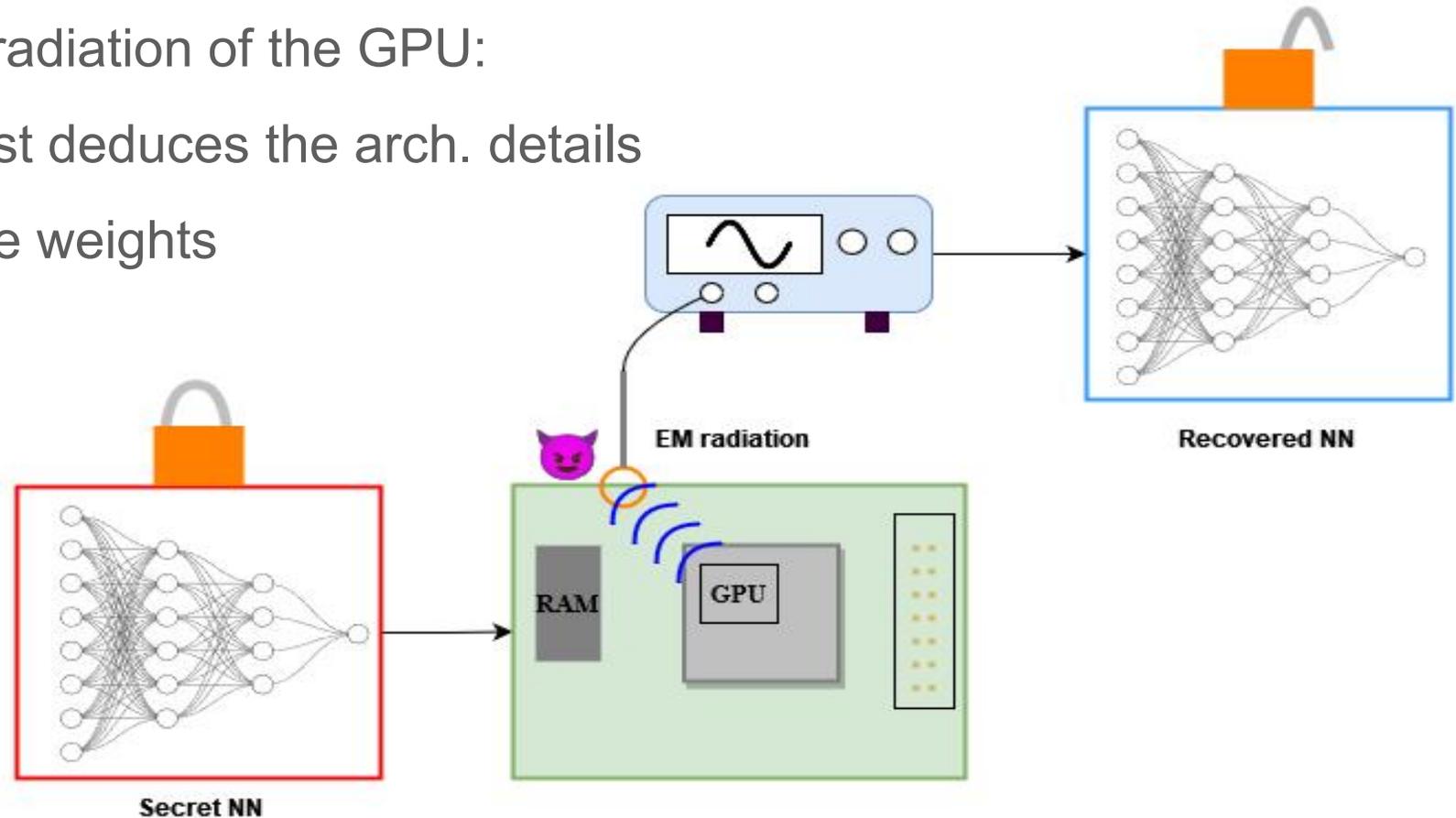


One neuron in 3<sup>rd</sup> hidden layer: 20  
multiplications and 1 ReLU

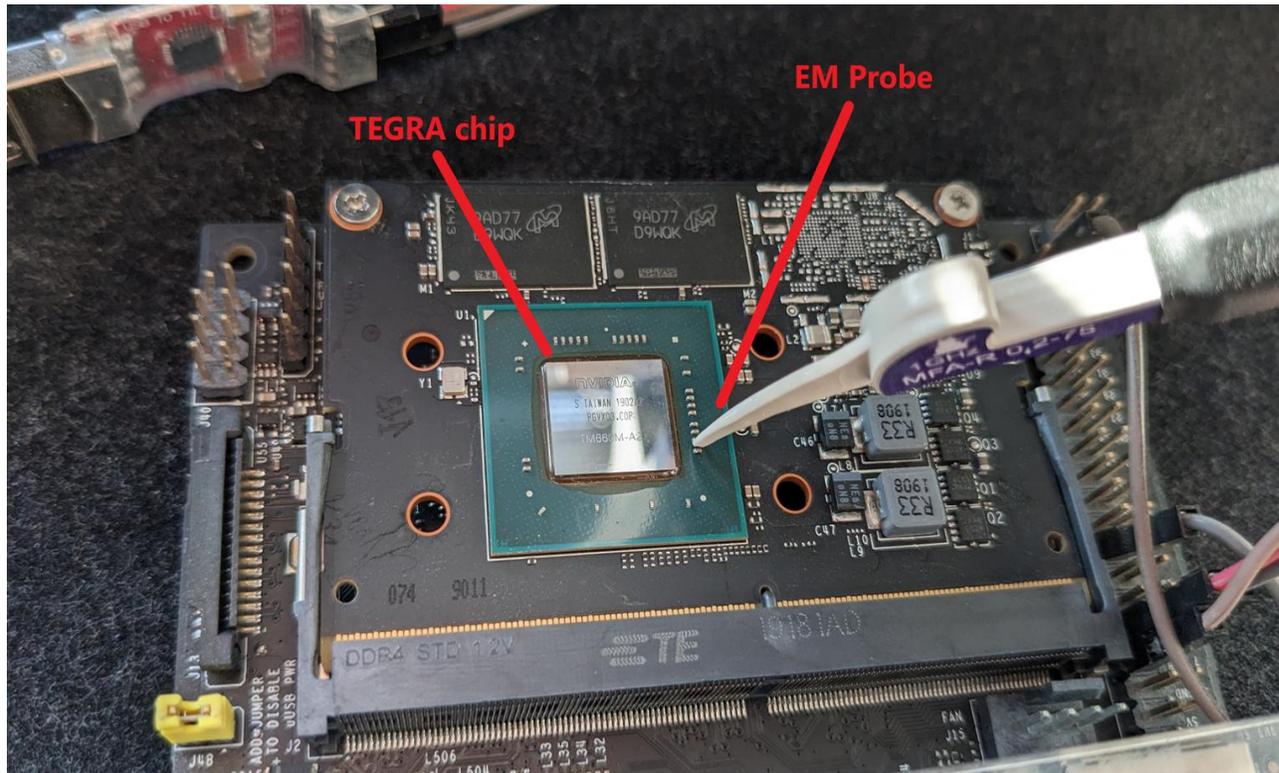
**With MNIST: Accuracy 98.16% (original) vs 98.15% (reverse engineered)  
Average weight error: 0.0025.**

# New attack BarraCUDA: Attacking Nvidia GPUs

- **Goal:** recover the trade secrets encoded in NNs parameters from an ML model
- By monitoring the EM radiation of the GPU:
  - the adversary first deduces the arch. details
  - then recovers the weights

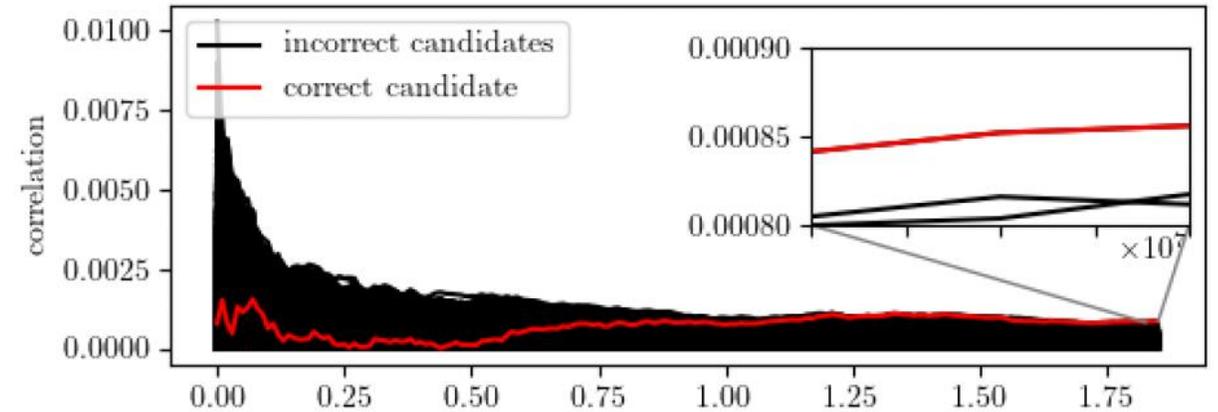
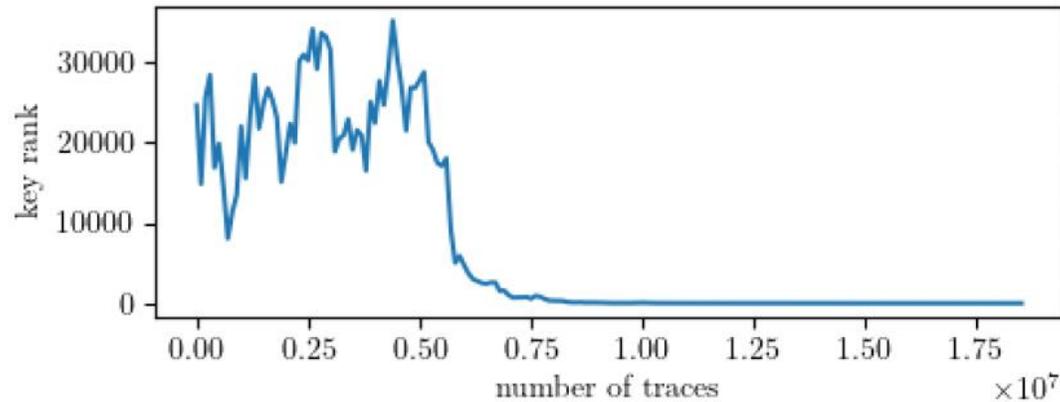


# Setup and the threat model



- Attacker learned the architecture details by using SCA techniques
- Attacker has a physical access to the device and can monitor EM during the inference for known inputs

# Results for weights recovery



Key rank and correlations of the 9<sup>th</sup> weight in the first layer in the real-world CNN architecture.

P. Horvath, L. Chmielewski, L. Weissbart, L. Batina, Y. Yarom. BarraCUDA: GPUs do Leak DNN Weights, USENIX Security Symposium, 2025.

# BarraCUDA: What is new

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- Performed **parameter extraction** from the EfficientNet model running on an industry-strength Jetson Nano device
- Reverse engineering the **closed source** TensorRT library
- Attack has a large complexity, which required developing a special **CUDA-based attack implementation**
- The attack on Jetson Nano requires **11-12 days** (traces collection and alignment), and the parameters are recovered in **6 min per weight**, but the results improved a lot on Jetson Orin

# AI and Security: Where do we go from here?

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- AI can improve side-channel and fault attacks on embedded devices
- Security and privacy vulnerabilities when implementing AI should be considered
- Other topics:
  - Security and privacy of AI
  - Malware recognition
  - Fuzzing
  - Network intrusion detection

# CESCA group @Radboud University



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Thank You!

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