Radbound University

Side-channel analysis of cryptographic implementations: Lessons learned and future directions

BFA, Voss, Norway
September 7, 2023

Lejla Batina

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Radboud University
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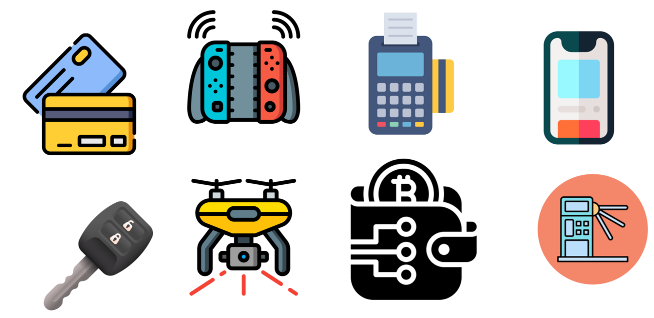
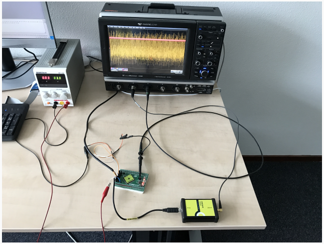
Outline

Intro to side-channel analysis

Known challenge: embedded crypto devices



Implementation attacks



Relevance

October 3, 2019

Researchers Discover ECDSA Key Recovery Method

October 3, 2019 • Add Comment • by Emma Davis

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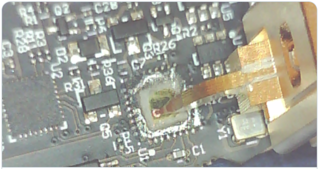

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October 3, 2019 • Add Comment • by Emma Davis

March 16, 2023

No, AI did not break post-quantum cryptography

16/03/2023

Lejla Batina (Guest author) Stjepan Picek (Guest author)

Bas Westerbaan

January 7, 2021

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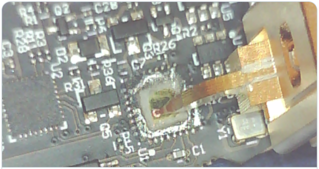
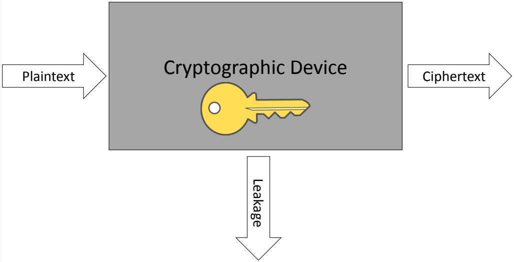


Side-channel Analysis (SCA) Attacks and Countermeasures

Greybox/Whitebox scenario



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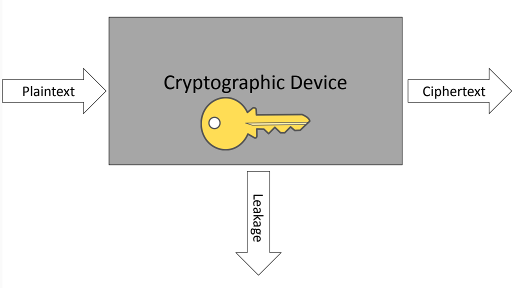

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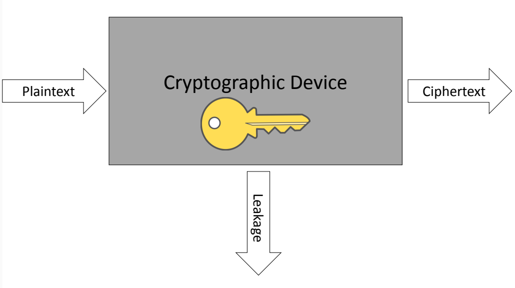

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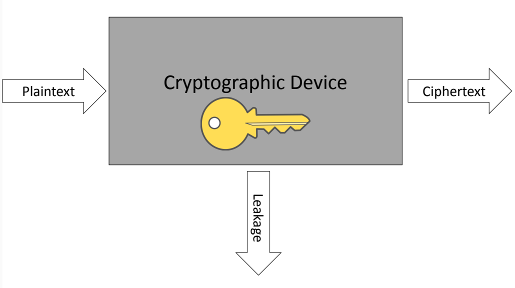

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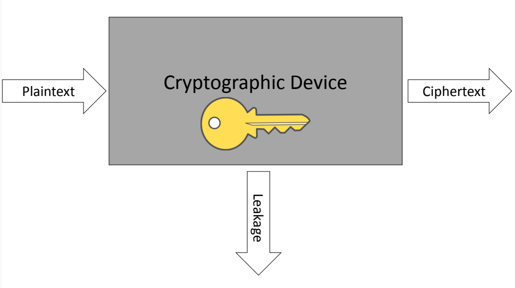

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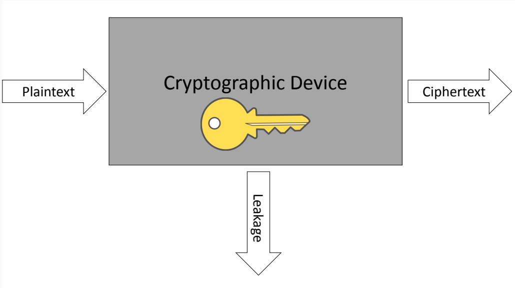

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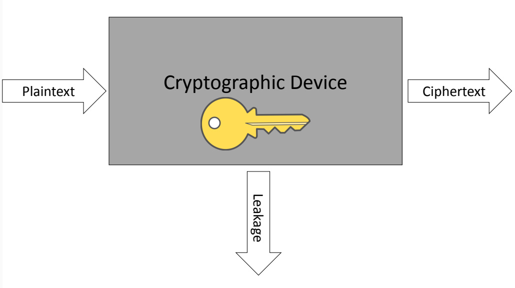

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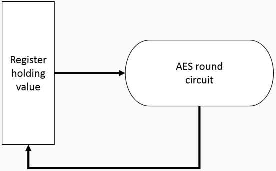
- Algorithms and implementation details are (partially) known
- Adversary's goal: secret key or message recovery by observing input/output pairs while trying all known attacks

Power side-channel: Modeling the leakage

- The Hamming distance model counts the number of $0 \to 1$ and $1 \to 0$ transitions
- Example 1: Assume a hardware register R storing the result of an AES round. The register initially contains value v_0 and gets overwritten with value v_1



- The power consumption because of the register transition $v_0 \to v_1$ is related to the number of bit flips that occurred
- Thus it can be modeled as $\text{HammingDistance}(v_0, v_1) = \text{HammingWeight}(v_0 \oplus v_1)$

- Example 2: In a microcontroller, assume register A with value v_0 and an assembly instruction that moves the contents of register A to register B

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mov rB, rA
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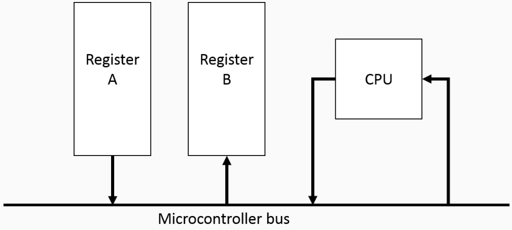

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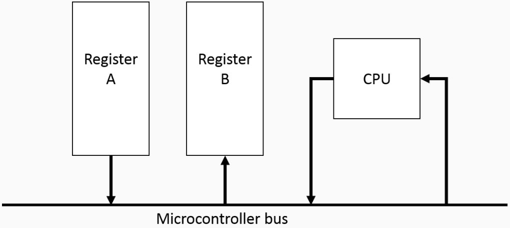

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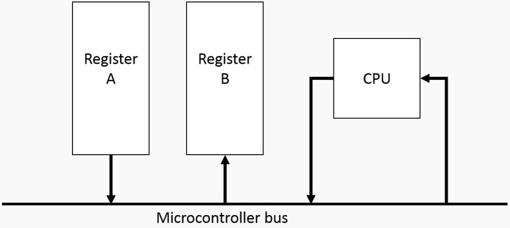

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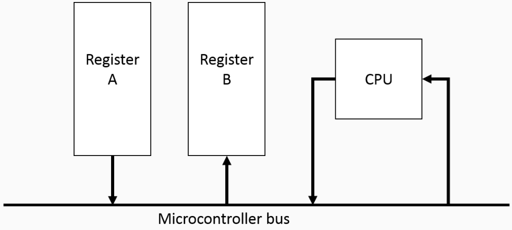

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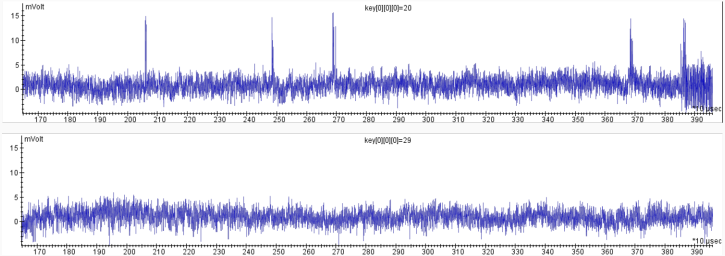
- The power consumption of the assembly instruction can be modeled as $\text{HammingDistance}(\text{busInitialValue}, v_0) = \text{HammingWeight}(v_0 \oplus 0) = \text{HW}(v_0)$

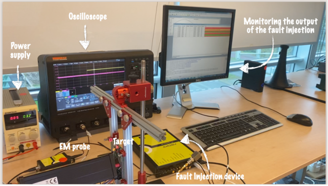
Differential Power Analysis (DPA)



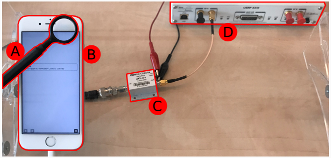
- The most popular side-channel attack
- Aims at recovering the secret key by using a large number of power measurements (traces)
- Nowadays often combined/replaced with a leakage evaluation methodology such as Test Vector Leakage Assessment (TVLA)

Actual setups

FA setup



Tempest



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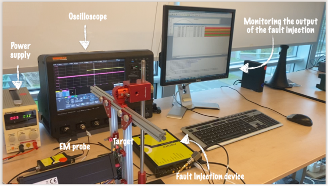

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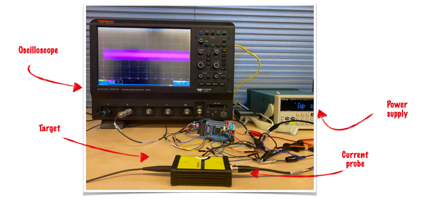

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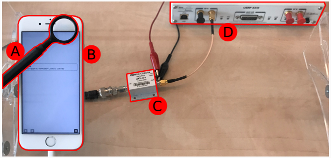

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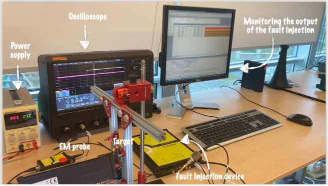

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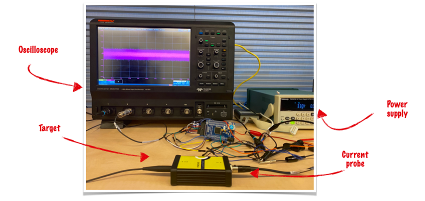

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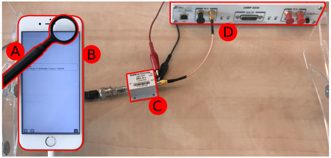

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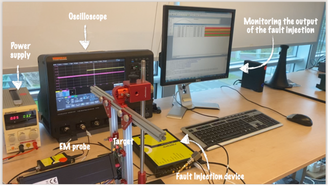
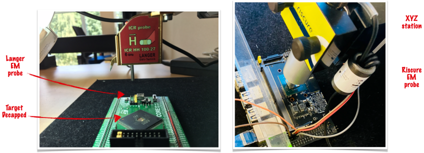


EM setups



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Countermeasures: main idea

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- Hiding: power consumption is independent of the intermediate values and of the operations

Masking

Boolean masking: a dth-order (Boolean) masking scheme splits an internal sensitive value v into $d+1$ shares $(v_0, v_1, ..., v_d)$, as follows:

$$v = v_0 \oplus v_1 \oplus \cdots \oplus v_d$$

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Probing-secure scheme. We refer to a scheme that uses certain families of shares as $d-$probing-secure iff any set of at most d intermediate variables is independent from the sensitive values.

Consequently, the leakage of up to d values does not disclose any information to the attacker.

Masking in practice: unintended interactions between values in the processor cause leakage in 1st order (caused often by transitional effects and glitches).

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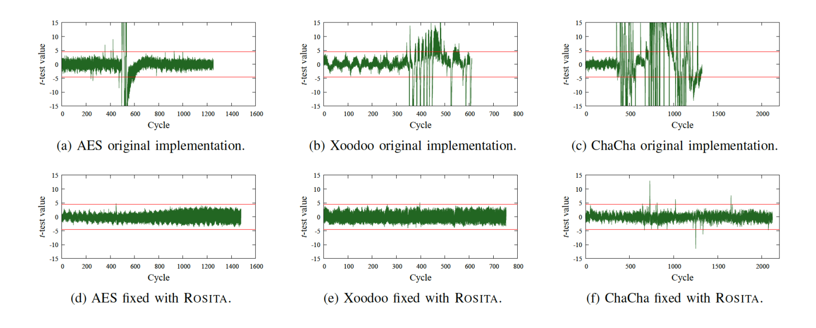
Actually, Balasch et al. show [BGGRS14] that unintended interactions typically halve the number of intermediate values the adversary needs to acquire.

Test Vector Leakage Assessment (TVLA)

- Leakage assessment of a device is very important for the semiconductor and the security evaluation industries
- Number of attacks to check the device's resistance against keeps on growing
- Various attackers' models possible but security evaluation often goes for the strongest adversary
- It is using Welch's t-test to differentiate between two sets of measurements, one with fixed inputs and the other with random inputs
- Leakage from combining multiple points is not detected

TVLA on masked implementations



The slowdowns of the "fixes" for ChaCha, Xoodoo and AES are 61% (1 322 vs. 2 122 cycles), 18% (637 vs. 753 cycles) and 15% (1 285 vs 1 479).

M. A. Shelton, N. Samwel, L. Batina, F. Regazzoni, M. Wagner, Y. Yarom: Rosita: Towards Automatic Elimination of Power-Analysis Leakage in Ciphers. NDSS 2021.

SCA and AI

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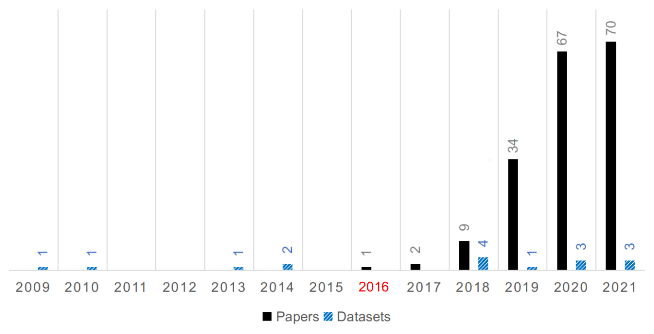
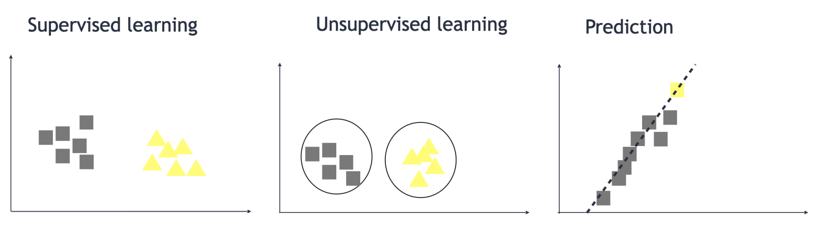
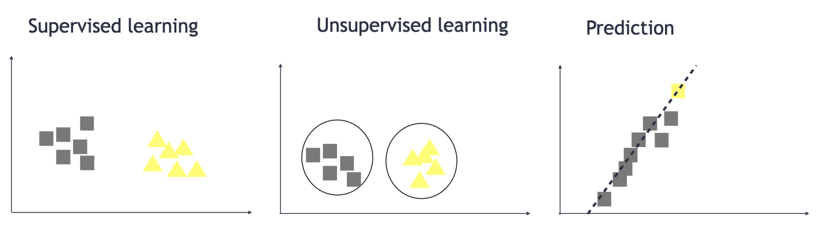


Figure: **Deep learning papers and datasets**.

S. Picek, G. Perin, L. Mariot, L. Wu and L. Batina, SoK: Deep Learning-based Physical Side-channel Analysis, `https://eprint.iacr.org/2021/1092`, ACM Comput. Surv. 55(11): 227:1-227:35 (2023)


Supervised learning
Unsupervised learning
Prediction

Applications for machine learning



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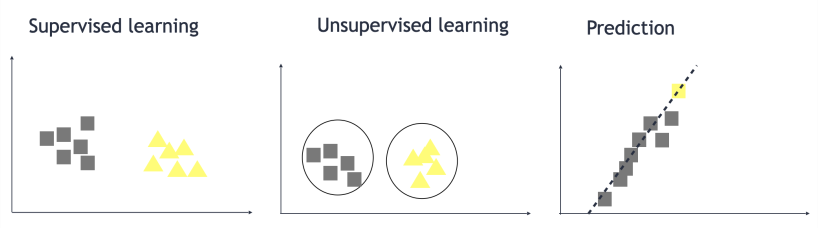

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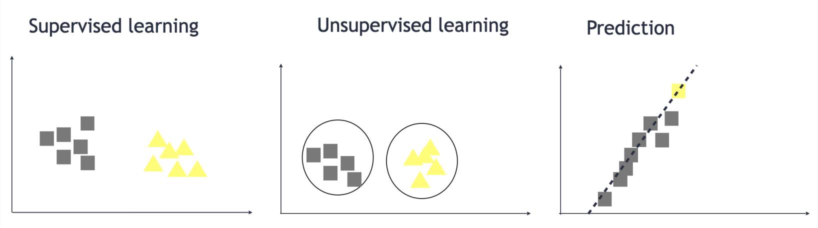

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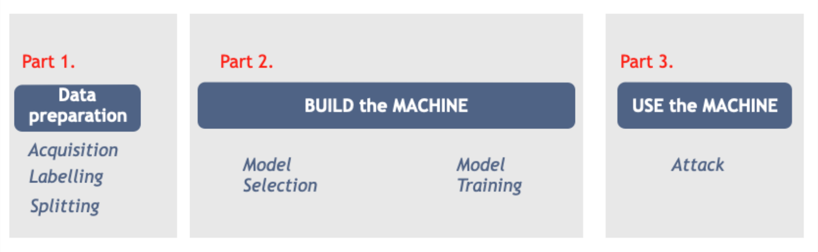
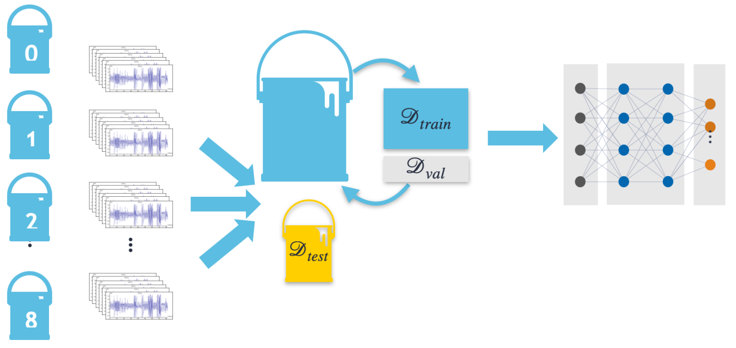
Workflow machine learning



A visual overview of how data is split:



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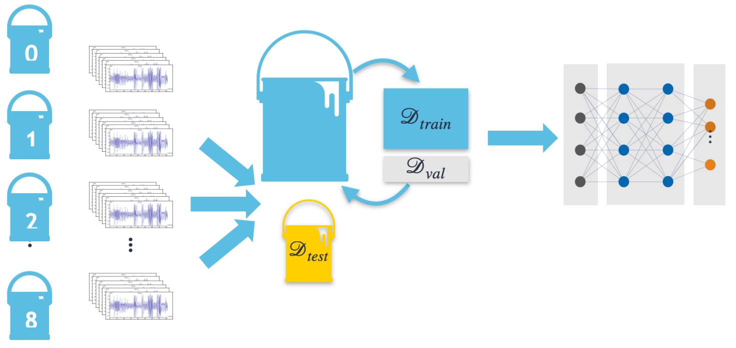

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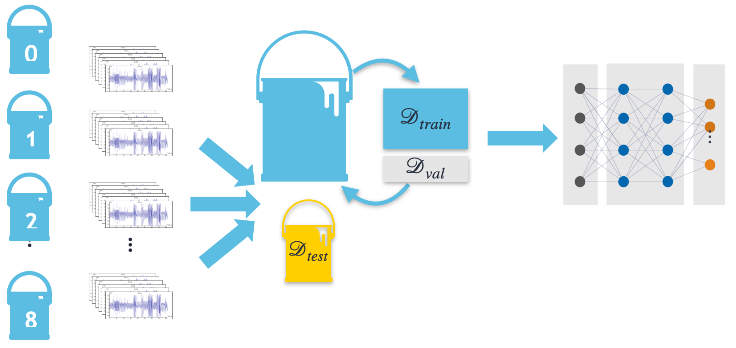

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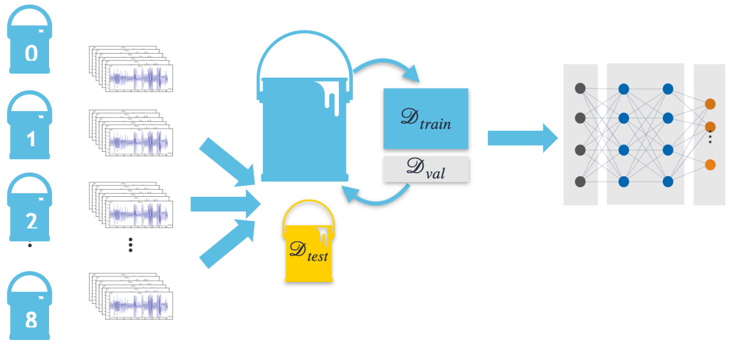

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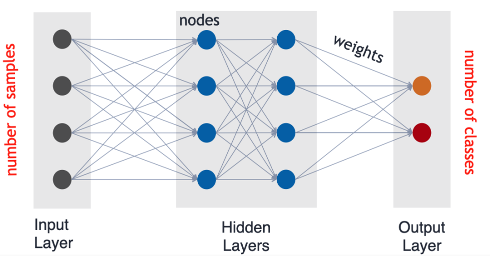

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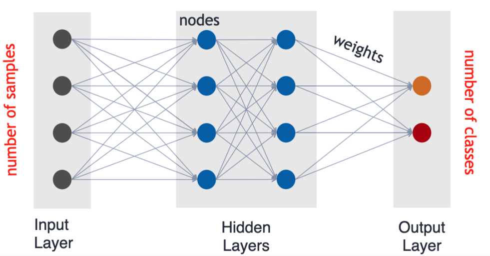

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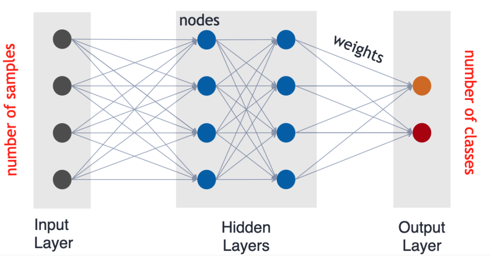

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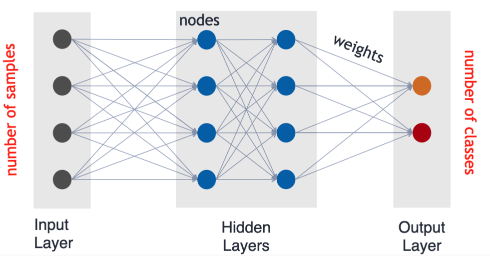

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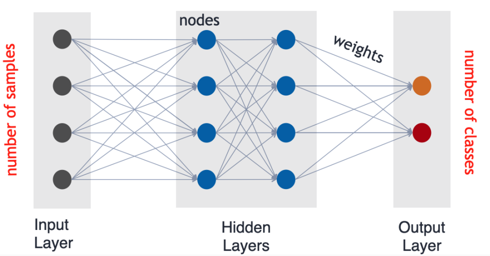

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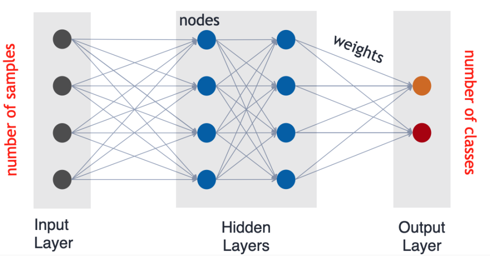

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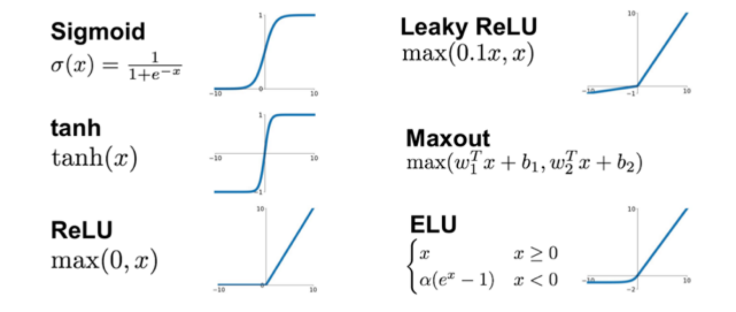

SCA of PQC Implementations

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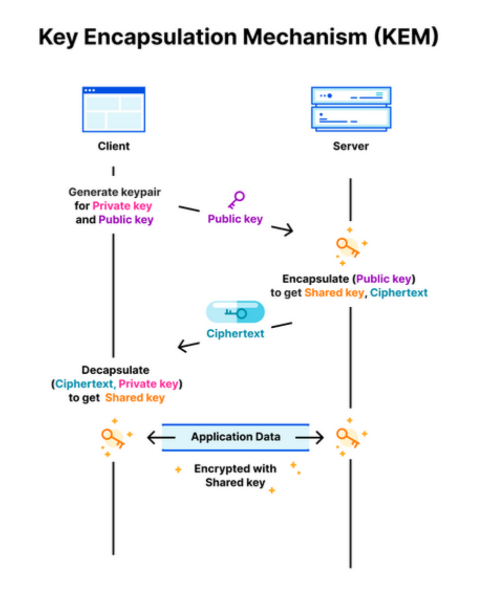
Attacking (lattice-based) PQC

- Due to the NIST PQC competition a lot of research is done on implementations
- Implementation attacks on all finalists were discussed
- Algorithm-specific and other countermeasures proposed
- SCA attacks on implementations protected against higher order attacks found to be feasible
- Deep learning attacks made a difference $\rightarrow$ profiling attacks

Example: Kyber



SCA attacks on Kyber

- SCA attack goals: msg recovery $\rightarrow$ secret-key recovery
- Attacks focus:
  - decapsulation step i.e. re-encryption step (encoding the key into a polynomial), tricky to mask, assuming chosen ciphertext attack
  - leakage in the Number-Theoretic Transform (NTT)
- Recent DL attacks broke a 6-shares implementation
- Countermeasures deemed very expensive

Screen Gleaning

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- Provide a testbed and parameterized attacker model for further research

Screen gleaning (Theory)

Screen gleaning (Practice)

The signal we observe is, in most cases, not interpretable to the human eye.

Attacker model: Motivating story and assumptions

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- The attacker can collect electromagnetic traces from the target device (representing the image displayed on the screen)

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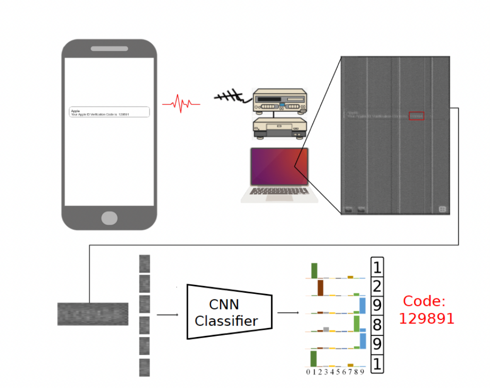

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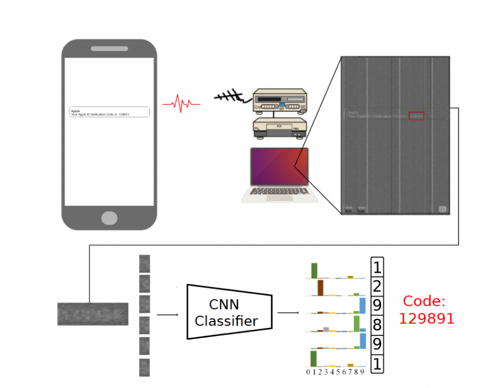

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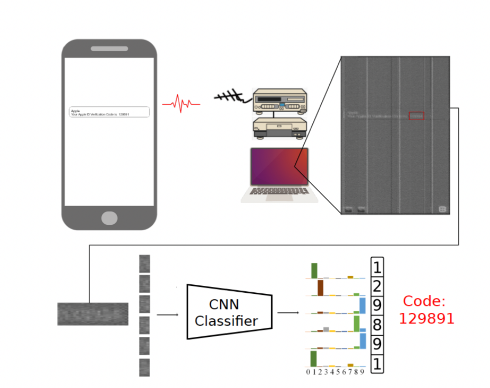

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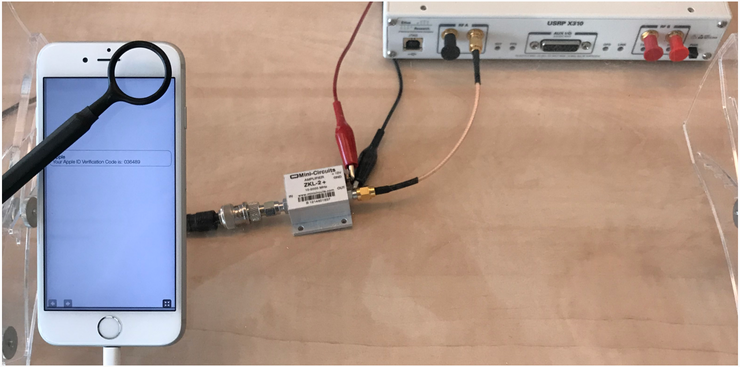
- From emage, the 6-digit security code is cropped and fed into a CNN classifier for recognition

Screen gleaning setup



Security code results

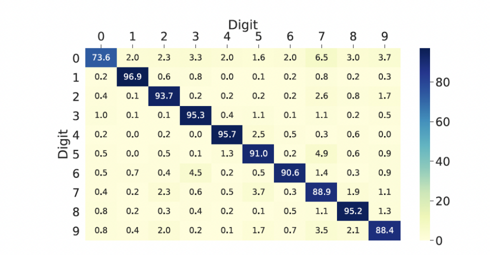


Figure: Confusion matrix of the inter-session accuracy of the security.

Digits	0	1	2	3	4	5	6	7	8	9	All
Acc. (%)	87.2	86.8	97.4	75.8	99.1	97.4	95.1	93.1	82.5	86.1	89.8

Table: Accuracy with respect to different digits (0-9) and overall accuracy in our security code attack.

	6 digits	$\geq$ 5 digits	$\geq$ 4 digits
Acc. (%)	50.5	89.5	99.0

Table: Accuracy of predicting partial security code correctly.

Security code results

- Attack on different phones of the same model
  E.g., cross-device accuracy of 61.5%, where the classifier is trained and tested on two distinct iPhone 6.
- Attack on different phone of different model
  E.g., accuracy of 74.0% on Huawei Honor 6X.
- Attack at a greater distance (through a magazine)
  E.g., 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.

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Reverse Engineering of NN Architectures Through SCA

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- Implementations on those platforms are common targets for side-channel adversaries

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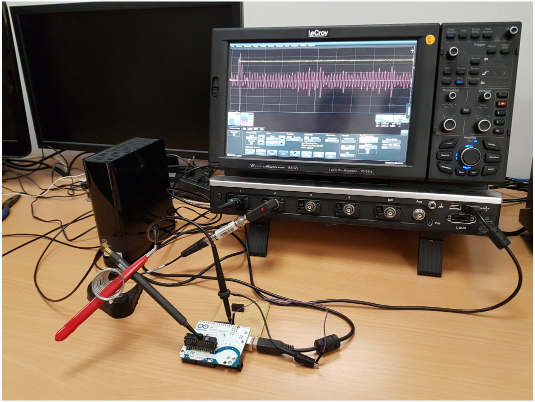
LeCroy

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- Examples: Sigmoid, tanh, softmax, ReLU

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Timing behavior can be observed directly from the EM trace

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Table: Minimum, Maximum, and Mean computation time (in *ns*)

Activation Function	Minimum	Maximum	Mean
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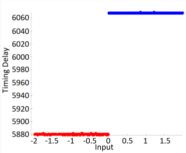
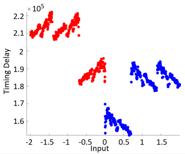
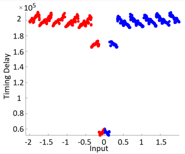


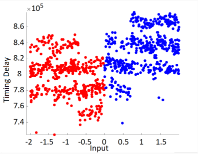
(a) **ReLU**



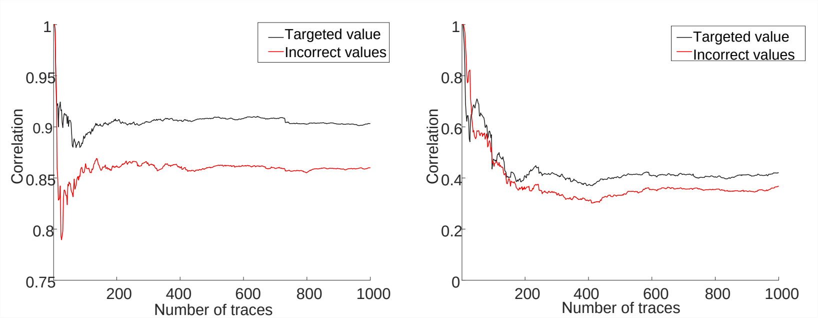
(b) **Sigmoid**



(c) **Tanh**

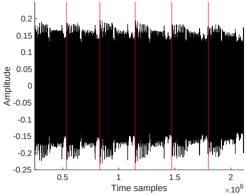


(d) **Softmax**

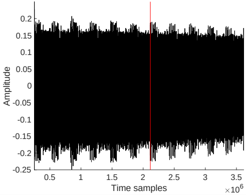


(a) First byte recovery (sign and 7-bit exponent) **(b) Second byte recovery (lsb exponent and mantissa)**

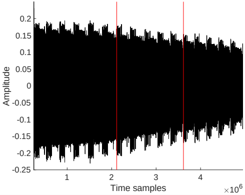
SEMA on hidden layers



(a) One hidden layer with 6 neurons



(b) 2 hidden layers (6 and 5 neurons each)



(c) 3 hidden layers (6,5,5 neurons each)

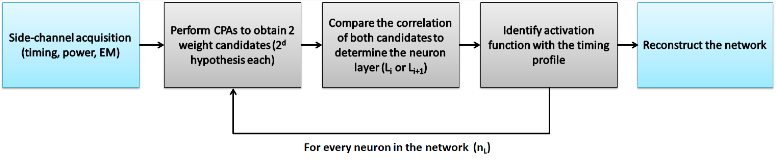


Figure: Methodology to reverse engineer the target neural network

ARM Cortex M-3 and MLP

- Tests with MNIST and DPAv4 datasets

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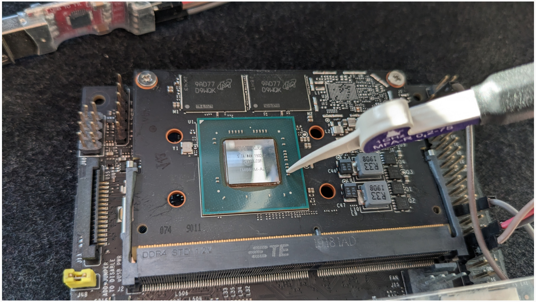
- DPAv4: the original accuracy equals 60.9% and the accuracy of the reverse engineered network is 60.87%
- MNIST: the accuracy of the original network is equal to 98.16% and the accuracy of the reverse engineered network equals 98.15%, with an average weight error converging to 0.0025

Lejla Batina, Shivam Bhasin, Dirmanto Jap, Stjepan Picek: CSI NN: Reverse Engineering of Neural Network Architectures Through Electromagnetic Side Channel. USENIX Security Symposium 2019: 515-532.

Recent work: reverse engineering commercial GPUs



- Architecture recovery from NVIDIA Jetson Nano device with 128-core GPU
- Weights recovery
- Known input assumption

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Lessons learned

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- But we should not give up on theory
- AI-assisted SCA attacks are more powerful in some use cases
- But, in many SCA evaluations "classical" techniques could be more efficient
- SCA and AI are getting more and more intertwined

Thank you for your attention!

https://cescalab.cs.ru.nl/