A Comprehensive Study of Deep Learning for Side-Channel Analysis

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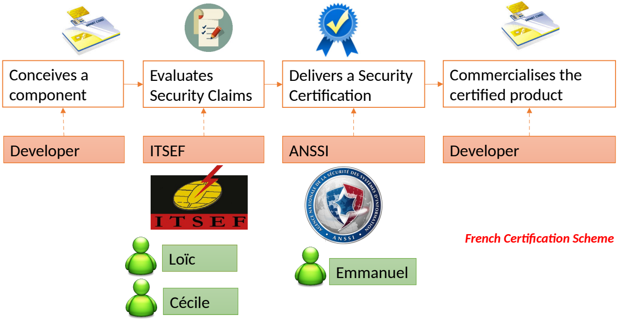
17/09/2020, CHES

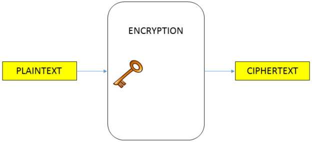
Outline

Who am I

- PhD student, studying Deep Learning (DL) for Side-Channel Analysis (SCA)



What is SCA?



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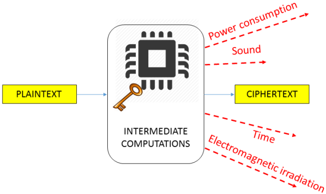
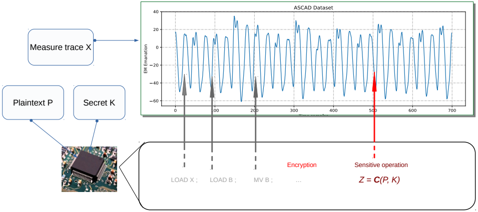

PLAINTEXT
INTERMEDIATE COMPUTATIONS
CIPHERTEXT
Power consumption
Sound
Time
Electromagnetic irradiation


Measure trace X
Plaintext P
Secret K
ASCAD Dataset
EM Emanation
LOAD X ;
LOAD B ;
MV B ;
...
Encryption
Sensitive operation
Z = C(P, K)

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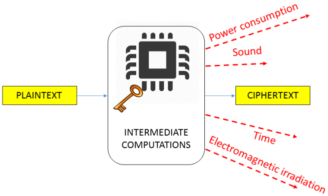

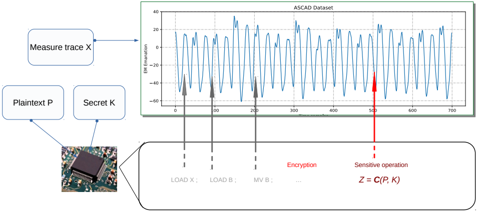

Profiling Attack

Attack using *open samples* similar to the target device – same code, same chip, *etc.* – with full knowledge of the secret key

Two steps:

- Profiling phase: P, K known $\implies$ Z known, $\mathbf{X}$ acquired on an open sample
- Attack phase: P known, $\mathbf{X}$ acquired on the *target* device, K guessed

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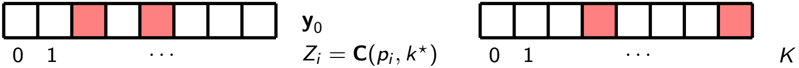
Outline

1. Context
2. SCA Optimization Problem versus Deep Learning Based SCA
3. NLL Minimization is PI Maximization
4. Simulation results
5. Experimental results

Profiling Attacks

Key Recovery (*i.e.* attack step)

Given N_a attack traces $\mathbf{x}_i$ with plaintext p_i, calculate *scores* $\mathbf{y}_i = F(\mathbf{x}_i)$



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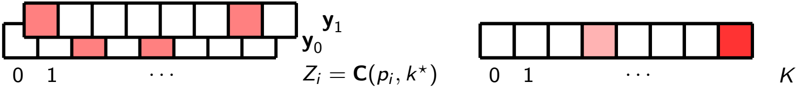

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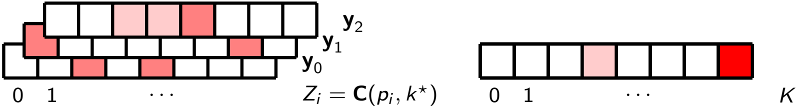

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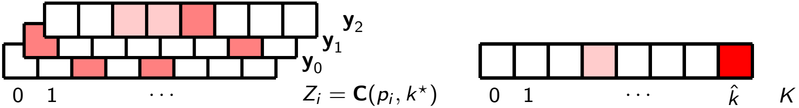

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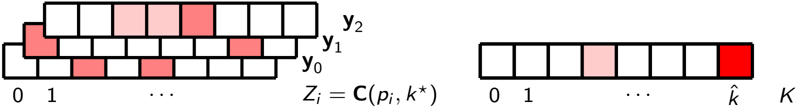

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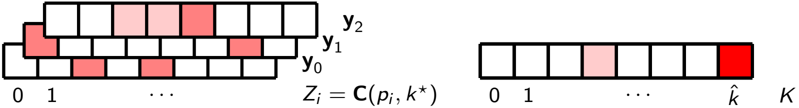

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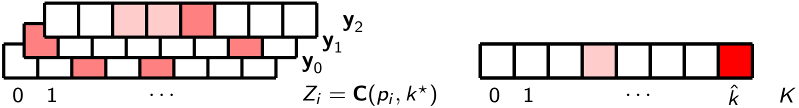

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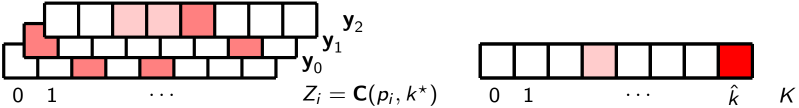

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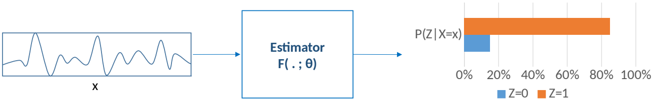
Requires to know the probability distribution $F^\star = \Pr[Z|\mathbf{X}]$
Reality: unknown for the evaluator/attacker. Estimation with parametric models $F(., \theta)$:



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Recent milestones about its effectiveness: more robust against counter-measures like masking [MPP16], jitter (misalignment) [CDP17], whether on software or FPGA [Kim+19]

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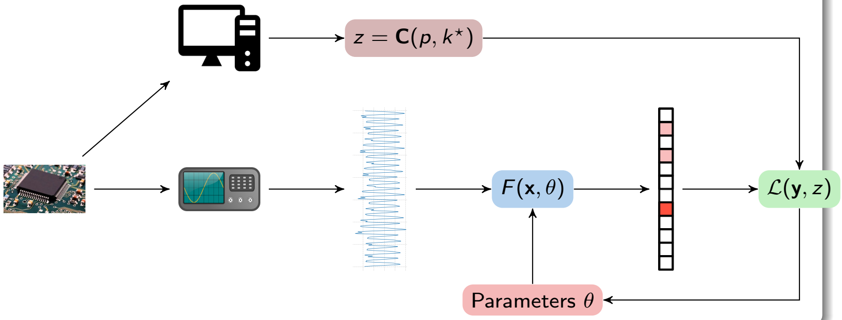

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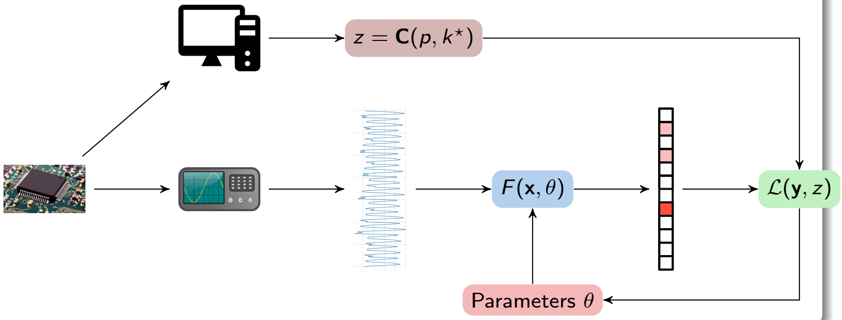

$\mathcal{L}$: performance metric (accuracy, recall, ...) or loss function (Mean Square Error, NLL, ...)

Open issue with Machine Learning based SCA[1]

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Accuracy: find β s.t. $N_a^\star = 1$

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Our claim: we can accurately estimate $N_a^\star$ with DL !

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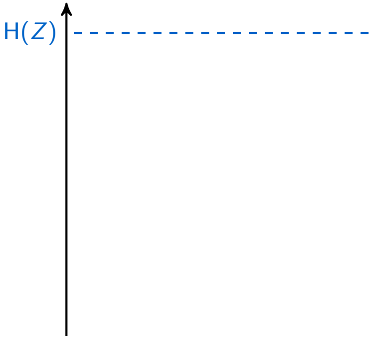

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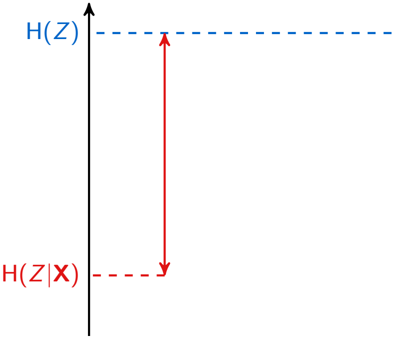

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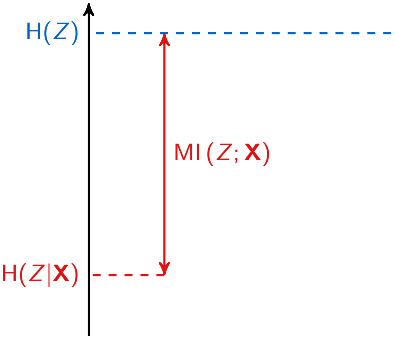

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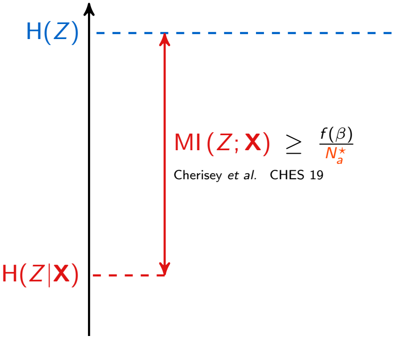

$$f(\beta) = n - (1-\beta)\log_2(2^n - 1) + \beta\log_2(\beta) + (1-\beta)\log_2(1-\beta)$$

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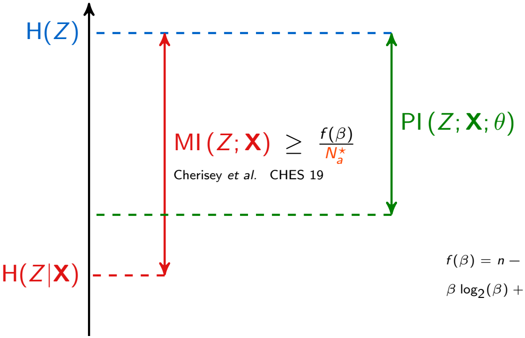

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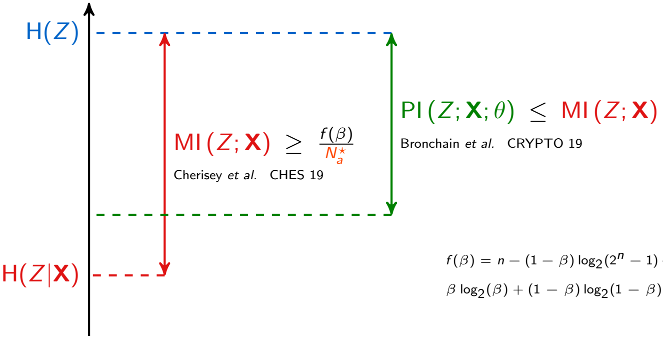

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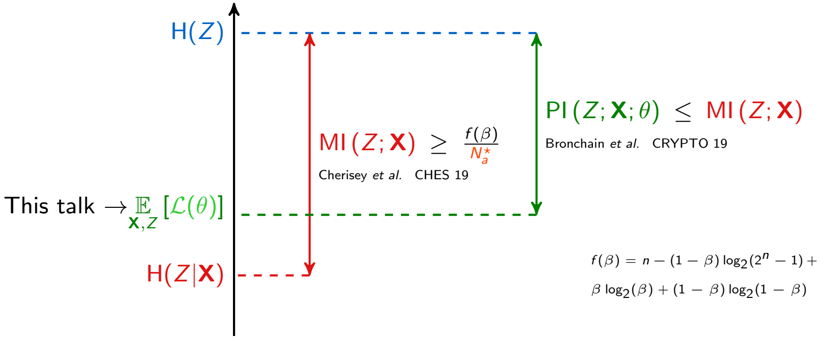
Bridging the gap between the loss function and the SCA metric

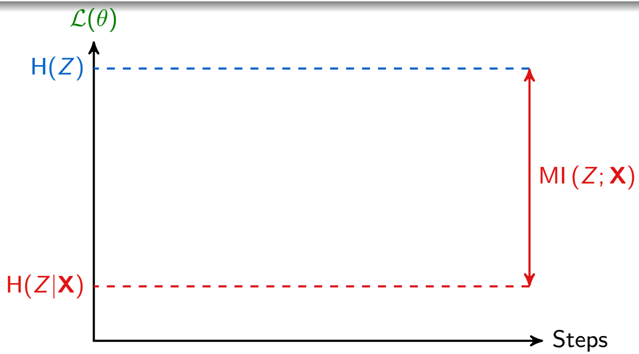
Training: minimization of the NLL *a.k.a.* Cross Entropy

$$\mathcal{L}(\theta) = \frac{1}{N_p}\sum_{i=1}^{N_p} -\log_2 F(\mathbf{x}_i, \theta)[z_i] = \mathrm{H}(Z) - \widehat{\mathrm{PI}_{N_p}}(Z; \mathbf{X}; \theta)$$



Main Result

Proposition



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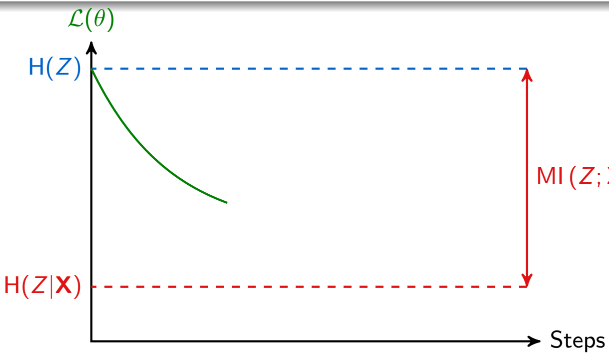

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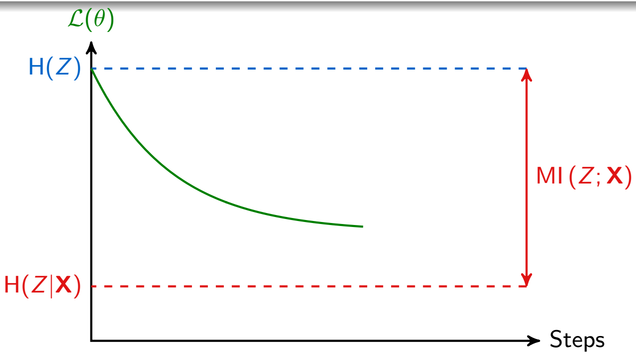

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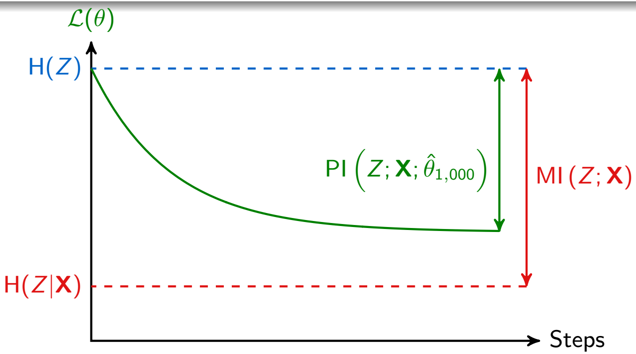

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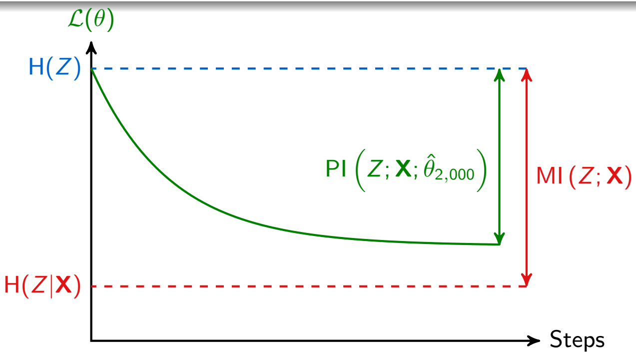

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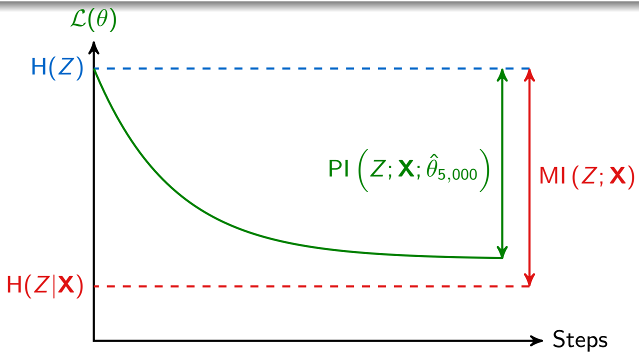

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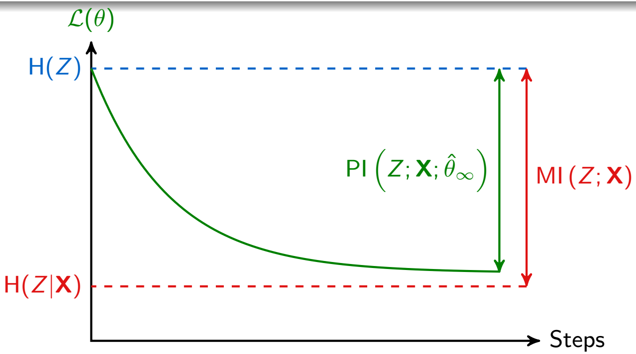

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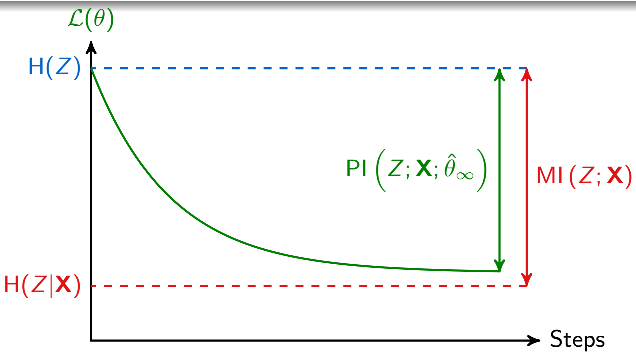
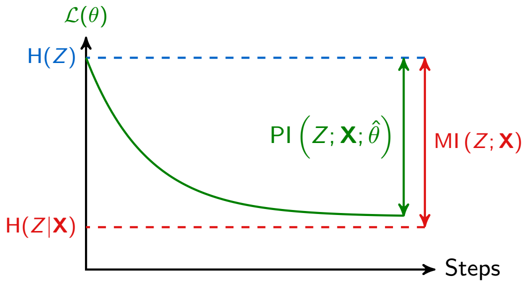
$$\mathrm{PI}\left(Z; \mathbf{X}; \hat{\theta}_{N_p}\right) \xrightarrow[N_p \to \infty]{\mathcal{P}} \sup_\theta \mathrm{PI}\,(Z; \mathbf{X}; \theta) \leq \mathrm{MI}\,(Z; \mathbf{X})$$



Tightness of the Lower Bound

To what extent the gap PI/MI is negligible?

Gap composed of three kinds of errors:



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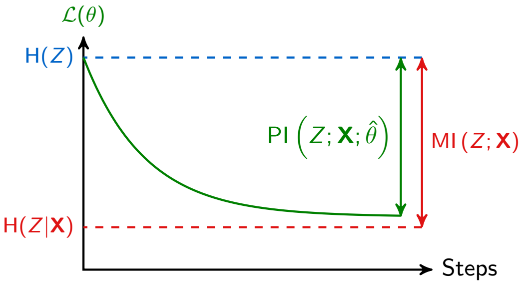

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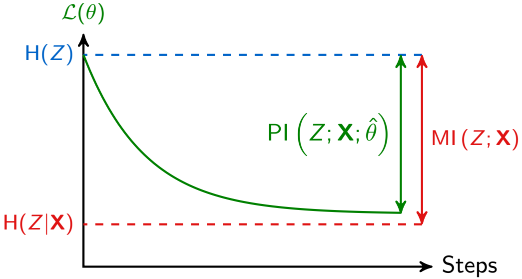

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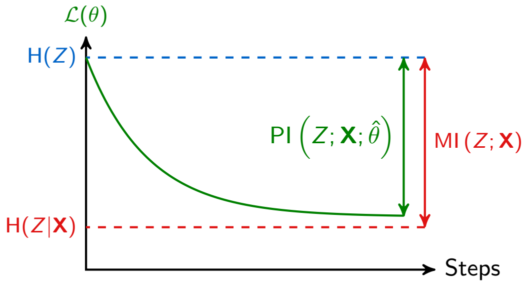

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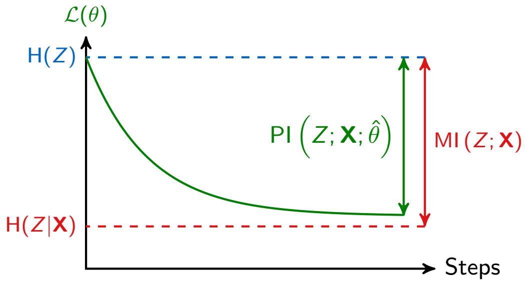
$\implies$ Ideally each error must be discussed through simulations and experiments



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Settings of the simulations

Leakage model

- Hamming weight with additive gaussian noise ($\sigma \in [0.01; 3.2]$)
- Draw an *Exhaustive* dataset: estimation error negligible

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Several case studies

- Higher-order masking: sensitive variable split into d independent parts
- Shuffling: independent operations (*e.g.* 16 SBoxes in SubBytes) randomly shuffled

Simulation results

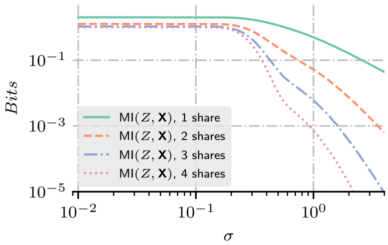
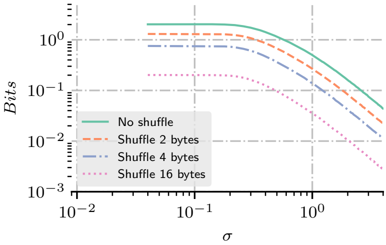


Figure: H-O masking, w.r.t. level of noise



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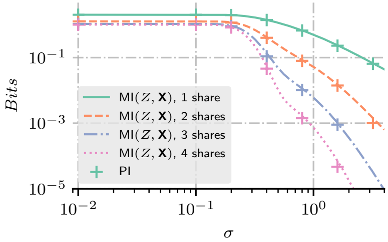

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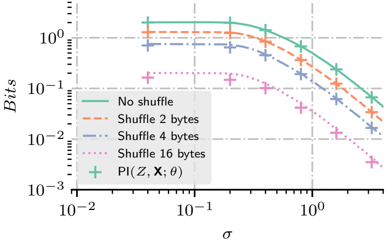

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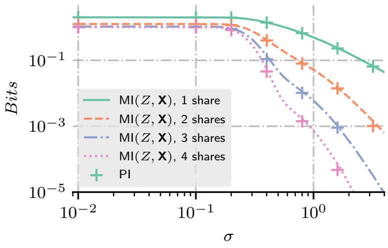

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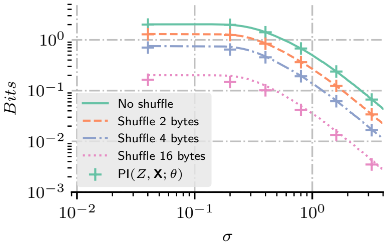

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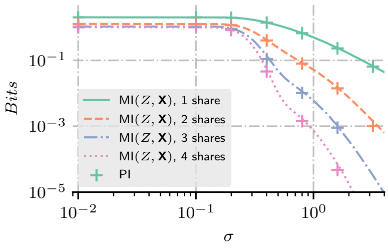

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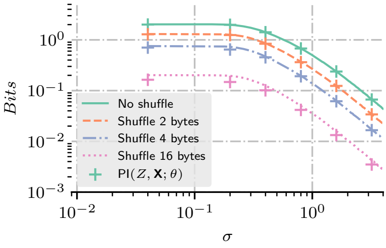

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- For a simple MLP, the approximation error and the optimization error are negligible
- Any more *complex* model should have a negligible approximation error too
- Empirical verifications: see appendix

Outline

1. Context

2. SCA Optimization Problem versus Deep Learning Based SCA

3. NLL Minimization is PI Maximization

4. Simulation results

5. Experimental results

Application on Public Datasets

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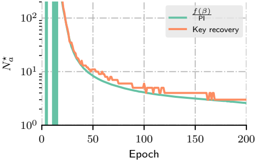
Micro-controller protected with misalignment



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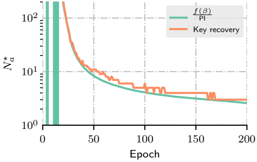

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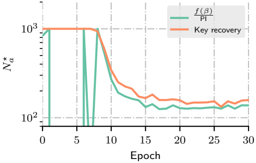

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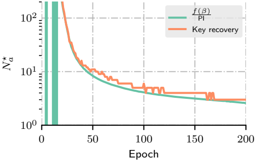

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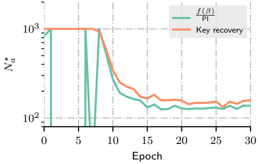

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Implementation on FPGA (no counter-measure)

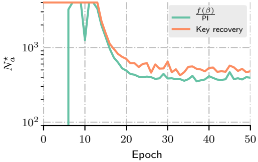

Figure: AES-HD: $\epsilon = 0.18$

Conclusion

Takeaway messages

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1. Minimizing the NLL loss $\equiv$ maximizing the PI $\implies$ tight lower bound of the MI $\implies$ accurate estimation of $N_a^\star$

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1. Minimizing the NLL loss $\equiv$ maximizing the PI $\implies$ tight lower bound of the MI $\implies$ accurate estimation of $N_a^\star$
2. NLL as a loss function is sound from an evaluator point of view
3. Enables to quantitatively measure the impact of counter-measures

Thank You!

Questions?

Looking for a postdoc candidate in machine-learning-based SCA? Hire me!

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Our home dataset

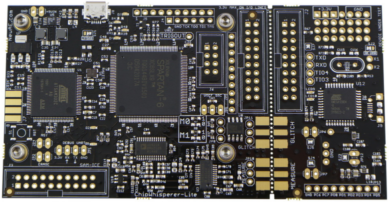

Figure: ChipWhisperer-Lite board

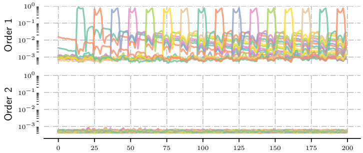

Figure: SNR at orders $d = 1, 2$

Algorithm 1 loadData

```
LD r0, X       ▷ Loads the first byte in r0
CLR r0         ▷ Clears the register
ST X, r0       ▷ Stores 0 in the plaintext array
LD r0, X       ▷ Do it again to clear the bus
CLR r0
ST X, r0
LD r0, X       ▷ One more time to be sure
CLR r0
ST X+, r0
```

Loads sequentially an array of 16 bytes into one register and clears it $\implies$ no joint leakage at order $d \geq 2$.
500, 000 traces acquired.
We only work on $n = 4$ bits, $|\mathcal{Z}| = 2^n = 16$.

Experiment on ChipWhisperer-Lite: masking

- Emulation of order d leakages: $Z = \bigoplus_{i \in [\![0,d]\!]} plain[i]$ for $d \in \{0, 1, 2\}$
- Extraction of PoIs according to SNR.
- Learning curve: $\mathrm{PI}\left(Z; \mathbf{X}; \theta_{SGD}\right)$ and $\widehat{\mathrm{PI}_{N_p}}\left(Z; \mathbf{X}; \theta_{SGD}\right)$ w.r.t. N_p $\Longrightarrow$ measures the estimation error.

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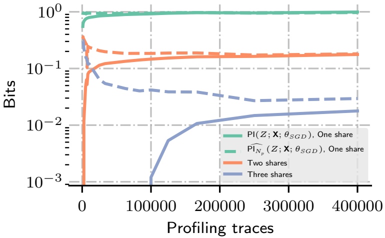

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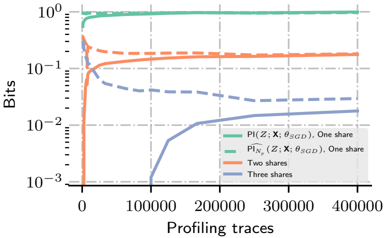

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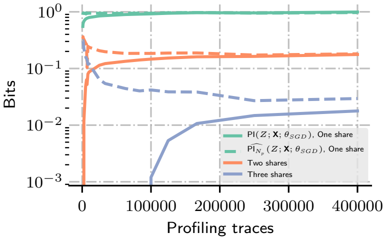

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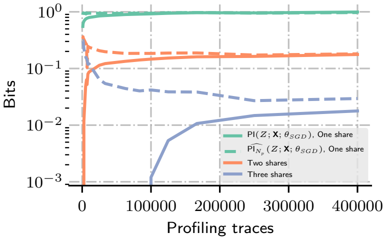

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- For $d = 3$, $N_p < 100,000$, no information !

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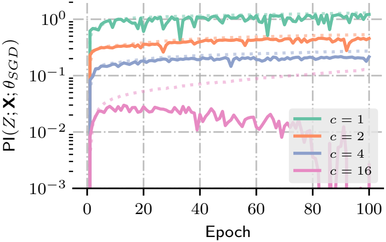

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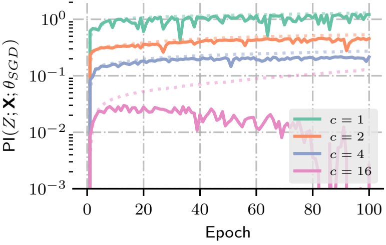

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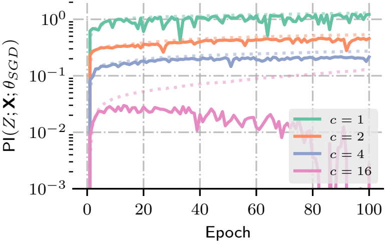

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What to interpret

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- Clearly over-fitting: the estimation error non-negligible