Gradient Visualization for General Characterization in Profiling Attacks

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FROM RESEARCH TO INDUSTRY

cea tech

leti

Outline

1. Context
2. The Neural Networks paradigm
3. Characterization with gradient visualization
4. Experimental results

Context

About me: PhD student, working on Statistical Learning applied to Side Channel Analysis

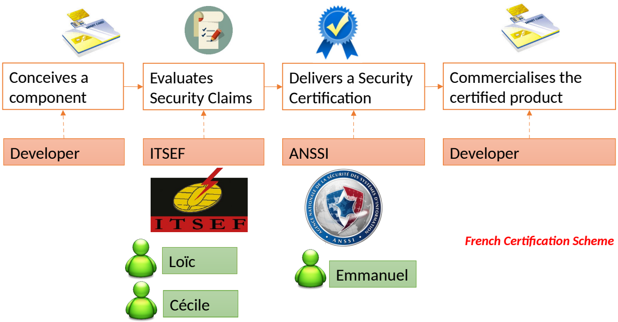

Figure: French certification scheme

Evaluating Side-Channel Vulnerabilities

Evaluating worst-case scenarios from a developer point of view.

Open samples

- *Open samples* are admitted for evaluation
- They are used to previously characterize the behaviour of the device $\Rightarrow$ *Profiling Attacks*

Profiling: two steps

1. Characterization with statistical tools (SNR, T-Test, χ^2, ...)
2. Profiling with Generative models: Template Attacks

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Profiling **with Deep Learning**: two steps

1. Characterization with statistical tools (SNR, T-Test, χ^2, ...)
2. Profiling with **Discriminative** models: **Convolutional Neural Networks**

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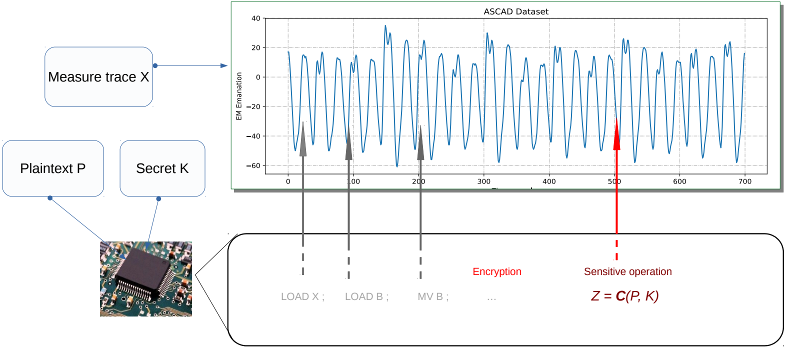
Notations in Side-Channel Analysis



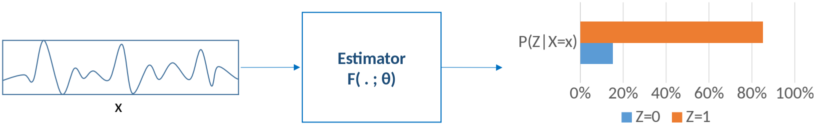
Profiling Attacks

Profiling step

Follows Maximum Likelihood principles

Requires to know the probability distribution $F^* \triangleq \Pr[Z|\mathbf{X}]$

Reality: unknown for the evaluator/attacker. Estimation with parametric models $F(., \theta^*)$!



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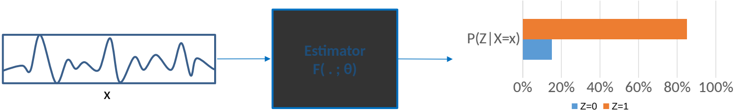
New problematics

Deep Learning provides black-box models:



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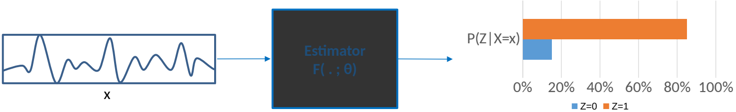

Lack of posterior knowledge about the learned leakage model: how did the model learn?

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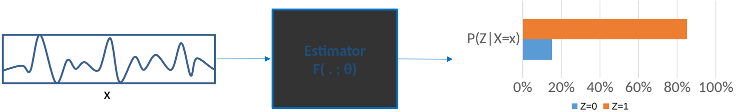

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Lack of trust on the Deep Learning tools: where did the model get the information?

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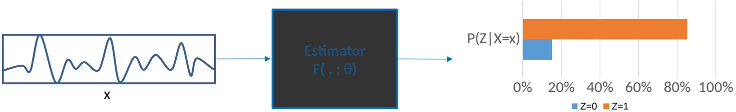

Lack of posterior knowledge about the learned leakage model: how did the model learn?
Lack of trust on the Deep Learning tools: where did the model get the information? **Issue addressed in this talk!**

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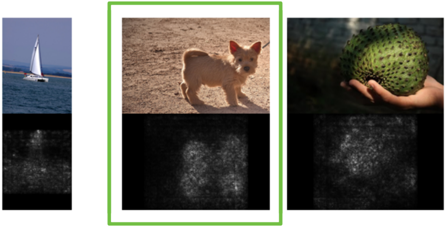

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Not at the state of the art in Image Recognition. So why such a choice for Side Channel Analysis?

Let us start with an ideal case

Ideal case: we know $F^* = \Pr[Z|\mathbf{X}]$ (*i.e.* $F^* : \mathbb{R}^D \to \mathcal{P}(\mathcal{Z}) \subset [0,1]^{|\mathcal{Z}|}$)

An example

An explanation

- Assume the informative leakage is very localized (few PoIs)

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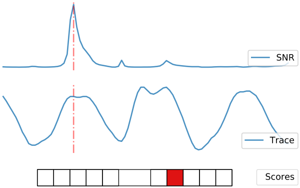

An explanation

- Assume the informative leakage is very localized (few PoIs)
- Consider a new trace and its label $\mathbf{x}, z$

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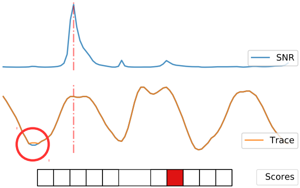

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- Assume the informative leakage is very localized (few PoIs)
- t_0 non informative: $\mathbf{x}[t_0] \mapsto \mathbf{x}[t_0] + \epsilon$ not sensitive
- In other words, t_0 non informative $\to \frac{\partial}{\partial \mathbf{x}[t_0]} F^*(\mathbf{x})[z] \approx 0$

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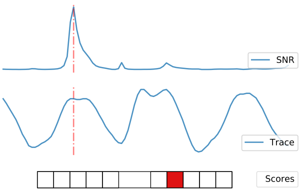

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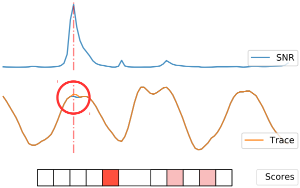

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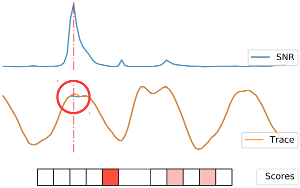

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If t is a PoI, then it should be seen in the gradients $\nabla_{\mathbf{x}} F^*(\mathbf{x})[z]$

Q: Why such a choice for Side Channel Analysis?

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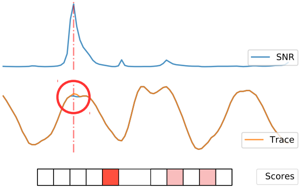

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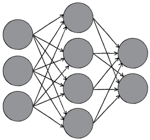
What is the link with Deep learning?

We do not know F^*, but we can replace it with a Deep Neural Net

Deep Neural Networks

Composition of simple operations (a.k.a layers), alternating between linear (λ) and non-linear (σ) layers. Linear layers are parametrized by real values gathered into a vector θ



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Can we approximate F^* with $F(., \theta^*)$ with an arbitrary uniform precision?

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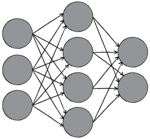

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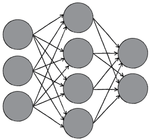

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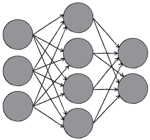

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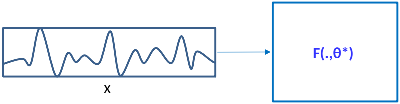

Learning θ...

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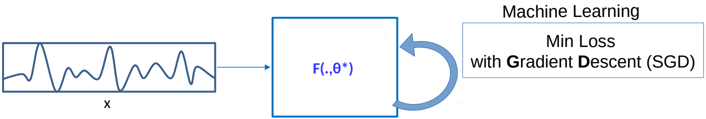

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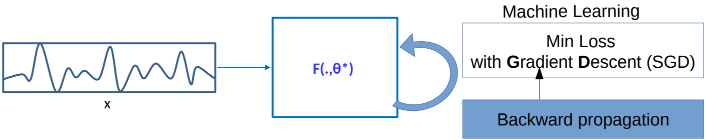

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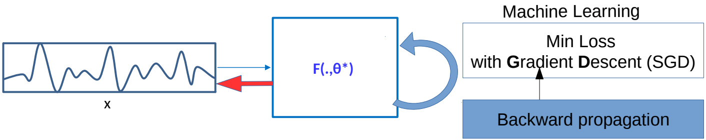

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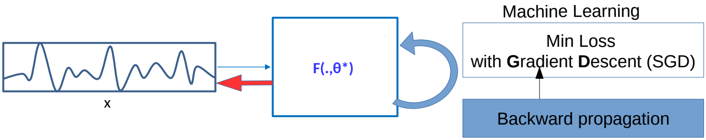

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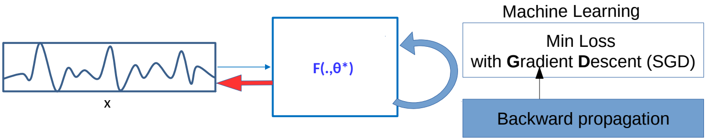

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A: Yes !
Both are equivalent.

Concretely, how to implement this method?

Very straightforward in Pytorch [Noa]:

```
def gradient_viz(model, x, z):
  """
  Generates the gradient visualization from a trace or
  a batch of traces.
  """
  # Enables x to store its gradient during the backprop
  x.requires_grad_()

  # Forward pass
  probas = model(x)
  loss = lossFunc(probas, z)

  # Gradient initialization
  model.zero_grad()

  # Backward pass
  loss.backward()

  # Post-processing of the gradient
  gradients = x.grad.abs()
  return gradients
```

With Tensorflow: tf.abs(tf.gradients(probas[:,Z], X)).

Outline

Application on experimental data

Description

ASCAD dataset [Pro+18]: $50,000$ traces, each of 700 points
Corresponds to the first AES round
Three cases studied:

1. **No countermeasure**: synchronized traces, no masking
2. **Artificial random shift**
3. **Synchronized traces, boolean masking (unknown masks)**

Trained model

CNN with a VGG-like architecture
Grid search of hyperparameters
Best model: minimal trace number when the guessing entropy reaches 2

First experiment: no countermeasure

Average number of traces to recover the secret key: 3

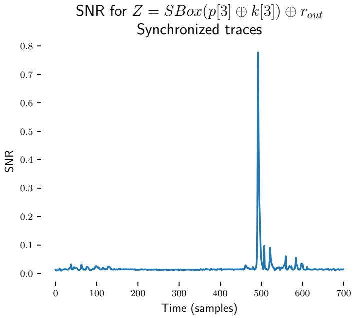

Figure: SNR

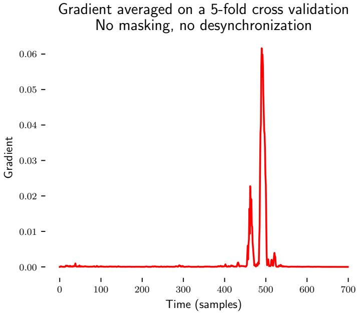

Figure: Gradient Visualization

Second experiment: with desynchronization

Average number of traces to recover the secret key: 3.6

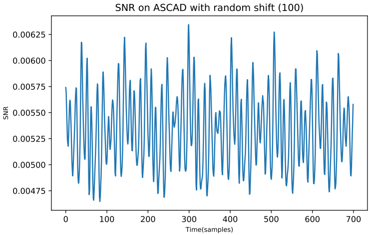

Figure: No PoI emphasized ☹

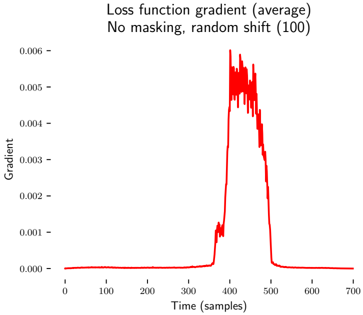

Figure: Band of peaks ☺

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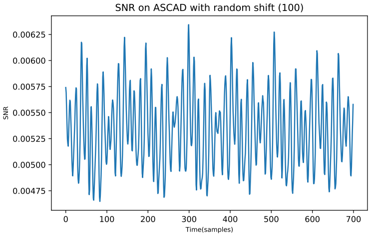

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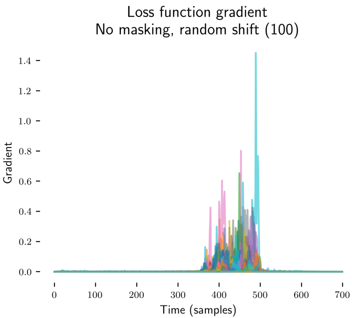


Figure: Characterization for each trace ☺

Third experiment: with masking

Average number of traces to recover the secret key: ≈ 100

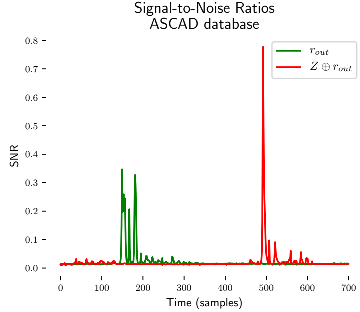


Figure: Requires knowledge of the masks ☹

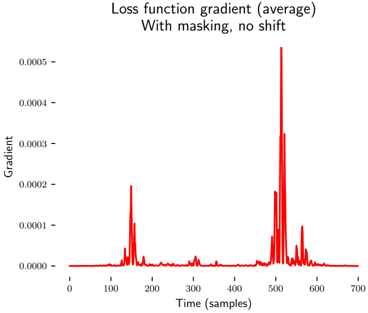


Figure: No kowledge required ☺

Be careful not to overfit !

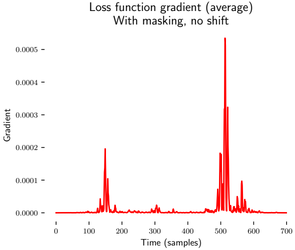
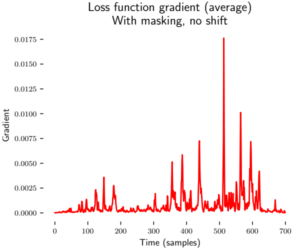


Figure: GV without overfitting 🙂



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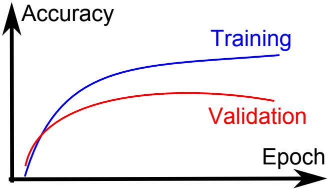

Figure: Solution: early-stopping

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Thank You!

Questions?

References I

[HGG19] Benjamin Hettwer, Stefan Gehrer, and Tim Güneysu. *Deep Neural Network Attribution Methods for Leakage Analysis and Symmetric Key Recovery*. 143. 2019. URL: https://eprint.iacr.org/2019/143 (visited on 02/21/2019).

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Analysis of overfitting

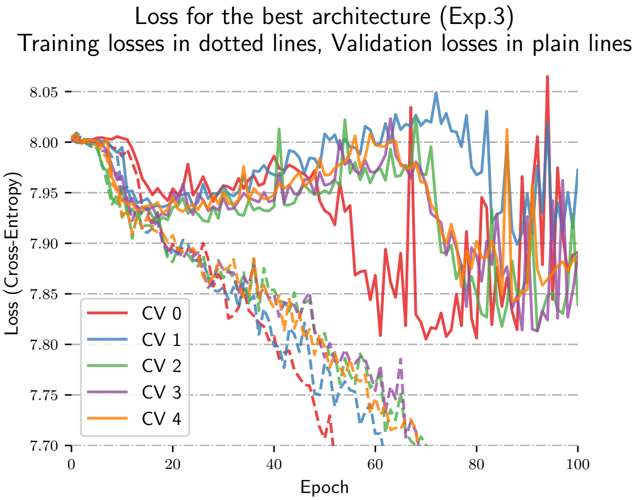

Figure: The loss during training.

Illustration on simulated data

Description

Simulation on $n = 4$ bits.
One or several shares that leak in a Hamming weights model with white Gaussian noise, mixed with fool points (same marginal pdf).
Training with a *small* Multi-Layer Perceptron with *exhaustive* data to guess the xor of the shares.

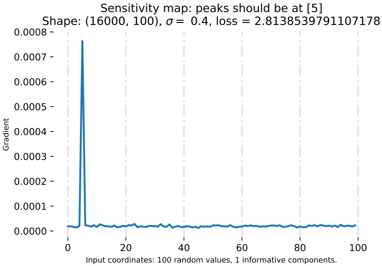

Figure: Average Gradient of the loss function w.r.t. the simulated traces.

Illustration on simulated data

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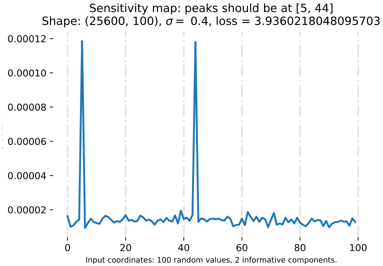

Figure: Average Gradient of the loss function w.r.t. the simulated traces.

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One or several shares that leak in a Hamming weights model with white Gaussian noise, mixed with fool points (same marginal pdf).
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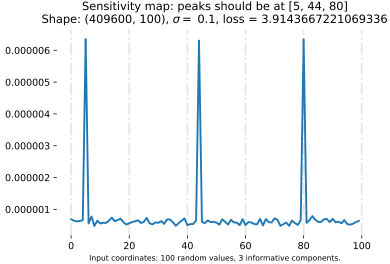

Figure: Average Gradient of the loss function w.r.t. the simulated traces.

Wait, this is not exactly what we were looking for !

We wanted $\nabla_{\mathbf{x}} F(\mathbf{x}, \theta^*)[z]$ but we got $\nabla_{\mathbf{x}} \ell(F(\mathbf{x}, \theta^*), z)$.

1. **What is the link between the two terms?**

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1. **What is the link between the two terms?**
   The loss gradient can be computed from the Jacobian matrix with the chain rule for derivatives:

$$\nabla_{\mathbf{x}} \ell(F(\mathbf{x}, \theta), z) = J_F(\mathbf{x}, \theta)^T \nabla_{\mathbf{y}} \ell(F(\mathbf{x}, \theta), z). \tag{1}$$

2. **Why not giving the Jacobian matrix directly?**

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   Surprisingly, the Deep Learning frameworks compute the loss gradient more efficiently. The Jacobian is not even explicitly computed !
3. **Should we be concerned about that?**

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1. **What is the link between the two terms?**
   The loss gradient can be computed from the Jacobian matrix with the chain rule for derivatives:
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2. **Why not giving the Jacobian matrix directly?**
   Surprisingly, the Deep Learning frameworks compute the loss gradient more efficiently. The Jacobian is not even explicitly computed !
3. **Should we be concerned about that?**
   No. Remind that $J_F(\mathbf{x}, \theta)$ is made with the $\nabla_{\mathbf{x}} F(\mathbf{x}, \theta^*)[s], s \in \mathcal{Z}$. Furthermore, $\nabla_{\mathbf{y}} \ell(F(\mathbf{x}, \theta), z)$ is actually proportional to the one-hot vector encoding z. It follows that $\nabla_{\mathbf{x}} \ell(F(\mathbf{x}, \theta), z) \propto \nabla_{\mathbf{x}} F(\mathbf{x}, \theta^*)[z]$.

Remark: It is still possible to get the Jacobian matrix.

The Jacobian matrix in practise

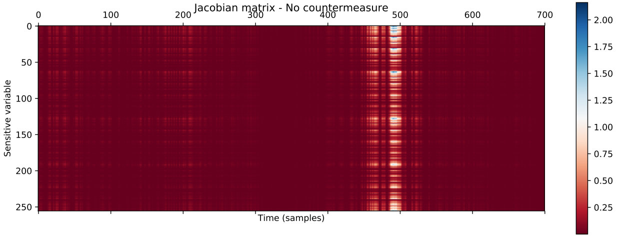

Figure: The Jacobian matrix in Experiment 1