FROM RESEARCH TO INDUSTRY

Classifying Side-Channel Desynchronized Signals with Convolutional Neural Networks

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LETI ITSEF - Information Technology Security Evaluation Facility - CEA Grenoble

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2. Deep Learning against Misalignment

2.1 Neural Network Classifiers

2.2 Data Augmentation

2.3 Experimental Results

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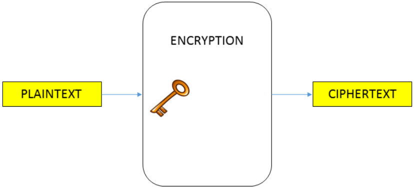
4. Conclusions

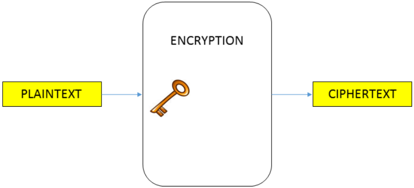
Side-Channel Vulnerability of Embedded Cryptography



Attack $\Longrightarrow$ a secret

Classical Attacks	Side-Channel Attacks
Mathematical vulnerability	
Black Box	

Side-Channel Vulnerability of Embedded Cryptography



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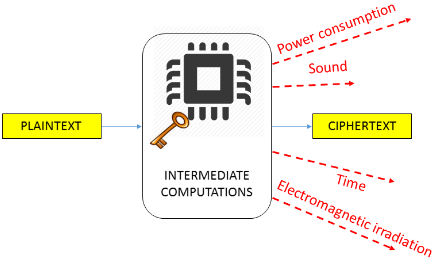
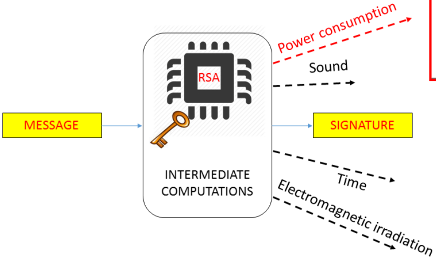
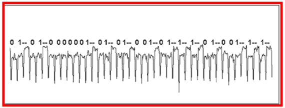


Attack $\Longrightarrow$ 

	Classical Attacks	Side-Channel Attacks
	Mathematical vulnerability	Physical vulnerability
	Black Box	Grey Box / Divide-and-conquer

Side-Channel Vulnerability of Embedded Cryptography





Source - Paul Kocher et al. "Introduction to differential power analysis".

Simple attack:
a single input

Attack $\Longrightarrow$ 

Classical Attacks	Side-Channel Attacks
Mathematical vulnerability	Physical vulnerability
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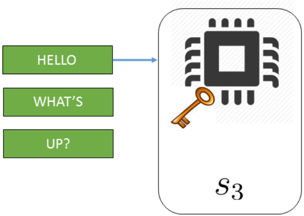
Advanced Side-Channel Attacks



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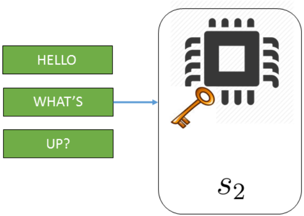

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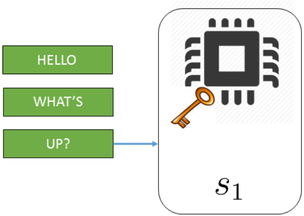

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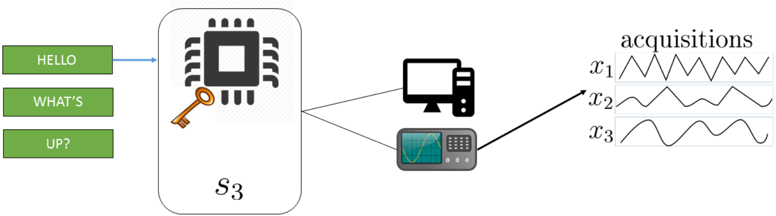

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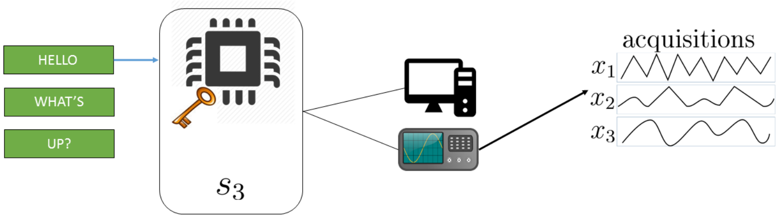

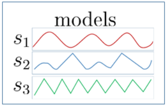

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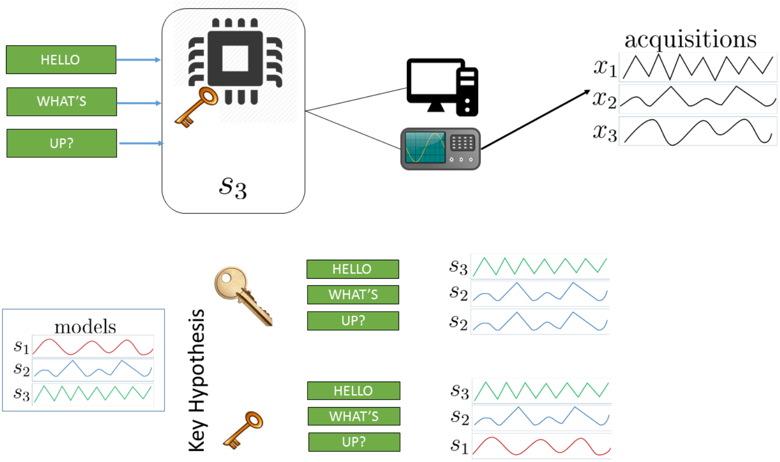

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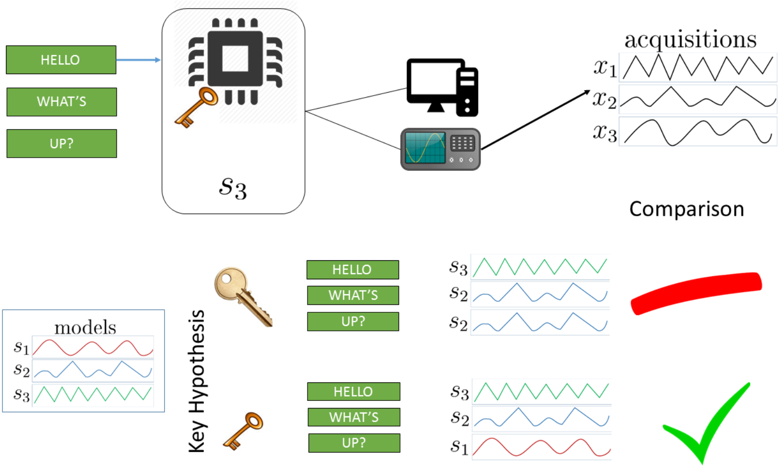

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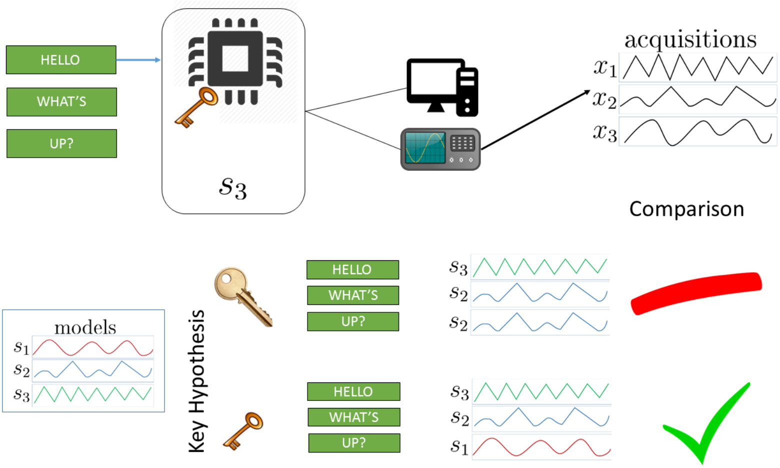
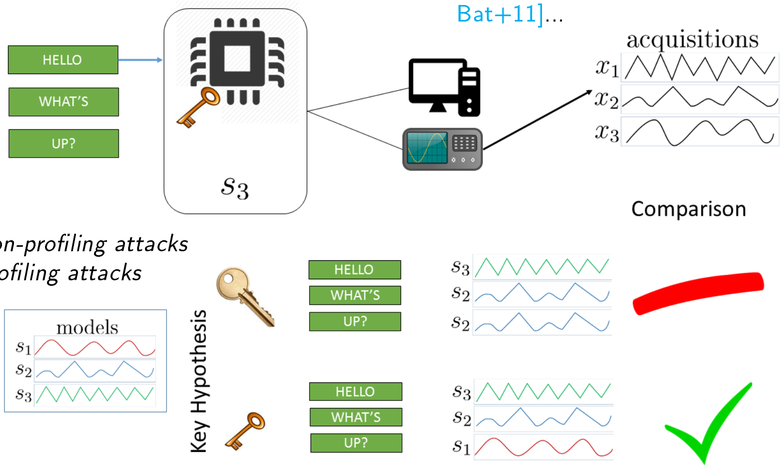


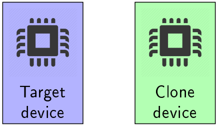
Advanced Side-Channel Attacks

Differential Power Analysis [KJJ99]
Correlation Power Analysis [BCO04]
Mutual Information Analysis [Gie+08; Bat+11]...

Non-profiling attacks
Profiling attacks



Profiling Attacks...Supervised Learning



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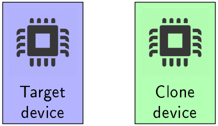
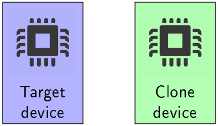


Machine Learning

Supervised Learning

Profiling Attacks...Supervised Learning



Machine Learning

Learn from data via statistic models
Task - Performance - Experience [TM97]

Supervised Learning

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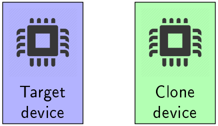


Machine Learning

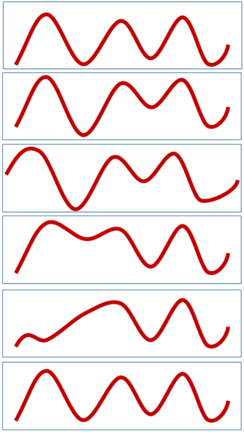
Learn from data via statistic models

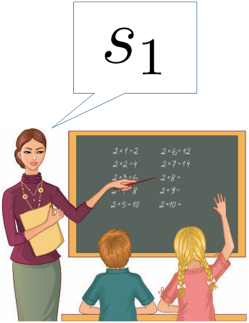
Task - Performance - Experience [TM97]

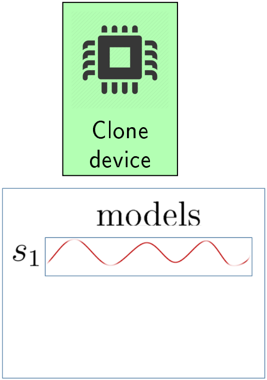
Supervised Learning

The *supervised* learning algorithms access to a dataset of examples, each associated in general to a *target* or *label*.

Classroom Side-Channel Attacks







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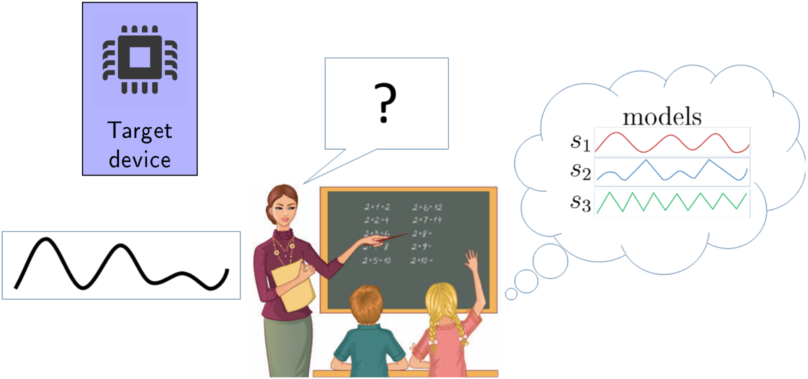

Classification

Classification problem

Assign to a datum $\vec{X}$ a label Z among a set of possible labels $\mathcal{Z} = \{s_1, s_2, s_3\}$, or probabilities.

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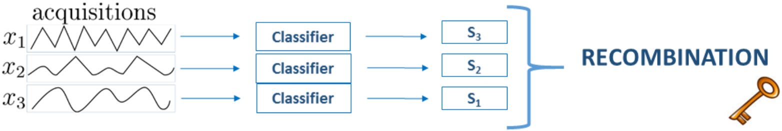
Advanced Attack as Multiple Classification Problems



Classification

Machine Learning classifiers in Side-Channel literature: SVM ([Hos+11; HZ12]), RF ([LBM14; LBM15])

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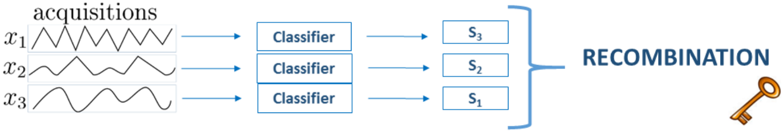

Notations

Notations and generalities

- Side-channel traces: realizations of a random vector $\vec{X} \in \mathbb{R}^D$
- D is the number of time samples (or features)
- Target: a *sensitive* variable $Z = f(\mathrm{e}, \mathrm{k})$ in $\mathcal{Z} = \{s_1, \ldots, s_{|\mathcal{Z}|}\}$

Profiling attack scenario

- labelled traces $\mathcal{D}_{\text{train}} = (\vec{x}_i, e_i, k_i)_{i=1}^{N}$, acquired under known secrets
- attack traces $\mathcal{D}_{\text{attack}} = (\vec{x}_i, e_i)_{i=1}^{N_a}$ acquired under unknown secrets

Profiling Attack

Profiling phase

- estimate
  - $p_{\vec{X} \mid Z=z}$

Attack phase

- Likelihood score for each key hypothesis k

$$d_k = p_{\vec{X} \mid Z}\left((\vec{x}_i)_{i=1,\dots,N_a}, (f(e_i, k))_{i=1,\dots,N_a}\right)$$

Profiling Attack

Profiling phase

- estimate
  - $p_{\vec{X} \mid Z=z}$ $p_{\vec{X}}$ p_Z (generative model)
  - $p_{Z \mid \vec{X}=\vec{x}}$ (discriminative model)

Attack phase

- Likelihood score for each key hypothesis k

$$d_k = p_{\vec{X} \mid Z}\left((\vec{x}_i)_{i=1,\dots,N_a}, (f(e_i,k))_{i=1,\dots,N_a}\right)$$

- A-posteriori probability score for each key hypothesis k

$$d_k = p_{Z \mid \vec{X}}\left(f\,(e_i,k)_{i=1,\dots,N_a}, (\vec{x}_i)_{i=1,\dots,N_a}\right) \ ,$$

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Profiling Attack

$\vec{X} \in \mathbb{R}^D$

Curse of dimensionality!

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Profiling phase

- estimate
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    - Gaussian hypothesis (**Template Attack**) [CRR03]
  - $p_{Z \mid \vec{X}=\vec{x}}$ (discriminative model)

Attack phase

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Profiling Attack

$\vec{X} \in \mathbb{R}^D$
Curse of dimensionality!

Profiling phase

- mandatory dimensionality reduction $[\mathcal{D}_{\text{train}} \longrightarrow \epsilon \colon \mathbb{R}^D \to \mathbb{R}^C]$
- estimate
  - $p_{\epsilon(\vec{X}) \mid Z=z}$ $p_{\epsilon(\vec{X})}$ p_Z (generative model)
    - Gaussian hypothesis (**Template Attack**) [CRR03]
  - $p_{Z \mid \epsilon(\vec{X})=\epsilon(\vec{x})}$ (discriminative model)

Attack phase

- Likelihood score for each key hypothesis k

$$d_k = p_{\epsilon(\vec{X}) \mid Z}\left(\left(\epsilon(\vec{x}_i)\right)_{i=1,\dots,N_a}, \left(f(e_i,k)\right)_{i=1,\dots,N_a}\right)$$

- A-posteriori probability score for each key hypothesis k

$$d_k = p_{Z \mid \epsilon(\vec{X})}\left(f\left(e_i,k\right)_{i=1,\dots,N_a}, \left(\epsilon(\vec{x}_i)\right)_{i=1,\dots,N_a}\right) \quad ,$$

Profiling Attack

$\vec{X} \in \mathbb{R}^D$

Curse of dimensionality!

Profiling phase

- manage desynchronization problem $[\mathcal{D}_{\mathbf{train}} \longrightarrow \rho \colon \mathbb{R}^D \to \mathbb{R}^D]$
- mandatory dimensionality reduction $[\mathcal{D}_{\mathbf{train}} \longrightarrow \epsilon \colon \mathbb{R}^D \to \mathbb{R}^C]$
- estimate
  - $p_{\epsilon(\rho(\vec{X}))\,|\,Z=z}\ p_{\epsilon(\rho(\vec{X}))}\ p_Z$ (generative model)
    - Gaussian hypothesis (**Template Attack**) [CRR03]
  - $p_{Z\,|\,\rho(\epsilon(\vec{X}))=\epsilon(\rho(\vec{x}))}$ (discriminative model)

Attack phase

- Likelihood score for each key hypothesis k

$$d_k = p_{\epsilon(\rho(\vec{X}))\,|\,Z}\left((\epsilon(\rho(\vec{x}_i)))_{i=1,\dots,N_a}, (f(e_i,k))_{i=1,\dots,N_a}\right)$$

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Mandatory Dimensionality Reduction

A vast domain

Features (Points of Interests - PoI) selection

- SOD [CRR03]
- SOST [BDP10]
- SNR [MOP08]/ NICV [Bha+14]
- t-test, F-test,... [GLRP06; CK14]

Feature extraction

- Principal Component Analysis (PCA) [Arc+06; BHW12]
- Linear Discriminant Analysis (LDA) [SA08; Bru+15]
- Projection Pursuits (PP) [Dur+15]

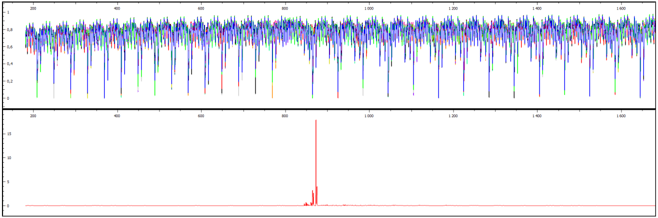

Figure: SNR computed on synchronized traces.

Manage desynchronization problem

Misaligning Countermeasures

- Random Delays, Clock Jittering, ...
- In theory: insufficient to provide security, since information still leak (somewhere)
- In practice: one of the main issues for evaluators

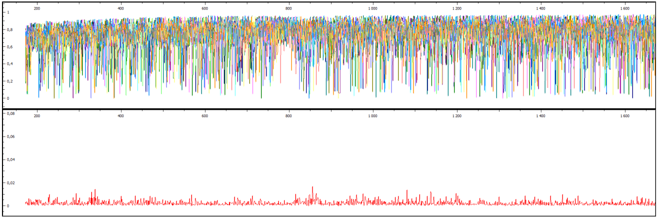

Figure: SNR computed on desynchronized traces.

Manage desynchronization problem

Misaligning Countermeasures

- Random Delays, Clock Jittering, ...
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Realignment

Mandatory realignment preprocessing

- not a wide literature
- in practice: evaluation labs home-made realignment techniques
- signal deformations or pattern extraction based on prior unverified assumptions
- Risks:
  - deformations $\rightarrow$ information degradation
  - pattern extraction $\rightarrow$ information loss

This talk

Profiling phase

- manage de-synchronization problem $[\mathcal{D}_{\text{train}} \longrightarrow \rho\colon \mathbb{R}^D \to \mathbb{R}^D]$
- mandatory dimensionality reduction $[\mathcal{D}_{\text{train}} \longrightarrow \epsilon\colon \mathbb{R}^D \to \mathbb{R}^C]$
- estimate
  - $p_{\epsilon(\rho(\vec{X}))\mid Z=z}$, $p_{\epsilon(\rho(\vec{X}))}$, p_Z (generative model)
    - Gaussian hypothesis (**Template Attack**)[CRR03]
- $p_{Z\mid\epsilon(\rho(\vec{x}))}$ (discriminative model)

This talk

Convolutional Neural Network: integrated approach (deal desynchronization + extraction feature + approximate a discriminative model)

This talk

Profiling phase

- manage de-synchronization problem $[\mathcal{D}_{\text{train}} \longrightarrow \rho\colon \mathbb{R}^D \to \mathbb{R}^D]$ DEEP LEARNING
- mandatory dimensionality reduction $[\mathcal{D}_{\text{train}} \longrightarrow \epsilon\colon \mathbb{R}^D \to \mathbb{R}^C]$
- estimate
  - $p_{\epsilon(\rho(\vec{X}))\mid Z=z}$, $p_{\epsilon(\rho(\vec{X}))}$, p_Z (generative model)
    - Gaussian hypothesis (**Template Attack**)[CRR03]
- $p_{Z\mid\vec{X}}$ (discriminative model)
  by means of a neural network $\hat{p}(\vec{x}, W) \approx p_{Z\mid\vec{X}=\vec{x}}$

This talk

Convolutional Neural Network: integrated approach (deal desynchronization + extraction feature + approximate a discriminative model)

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Multi-Layer Perceptron

In SCA litterature [MHM13; MZ13; MMT15; MDM16]

Multi-Layer Perceptron (MLP)

$$\hat{p}(\vec{x}, W) = s \circ \lambda_n \circ \sigma_{n-1} \circ \lambda_{n-1} \circ \cdots \circ \lambda_1(\vec{x}) = \vec{y} \approx p_{Z \mid \vec{X}=\vec{x}}$$

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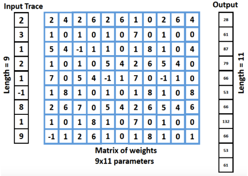
λ_i linear functions (linear combinations of time samples) depending on some **trainable weights** W



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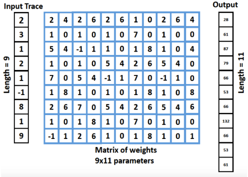
σ_i non-linear *activation* functions



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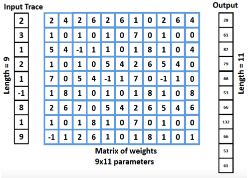
- s normalizing *softmax* function



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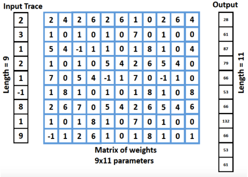
Architecture hyper-parameters



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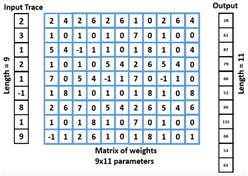
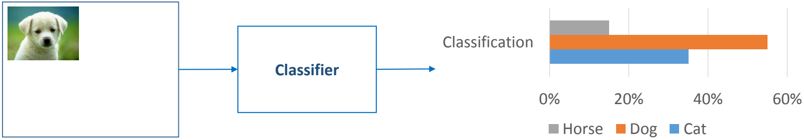
Architecture hyper-parameters

Universal approximation theorem



Convolutional Neural Networks

Translation-Invariance



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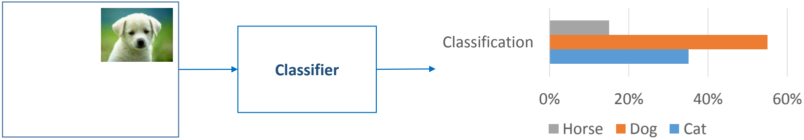
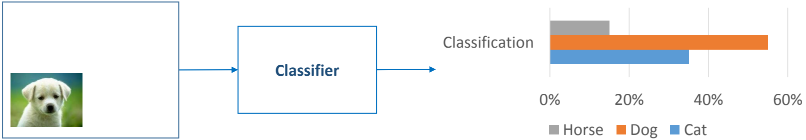


Convolutional Neural Networks

Translation-Invariance



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Convolutional Layers

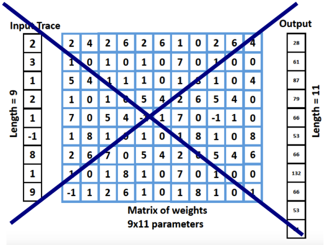


Figure: Linear layer in an MLP.

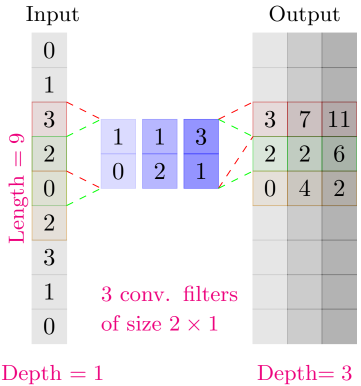
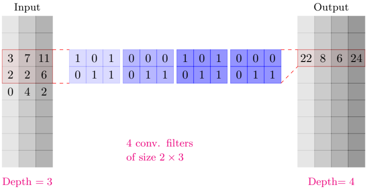


Figure: Convolutional layer in a CNN.

Pooling Layers



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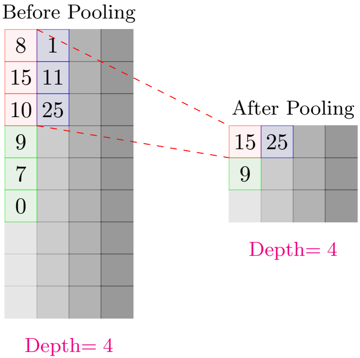
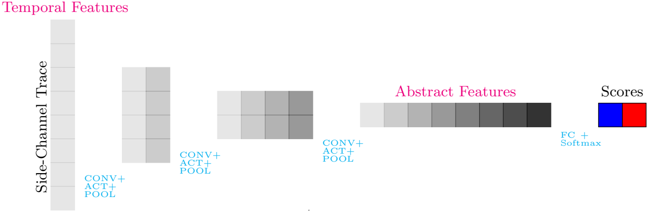


Figure: Pooling layer in a CNN.

A kind of CNN architecture



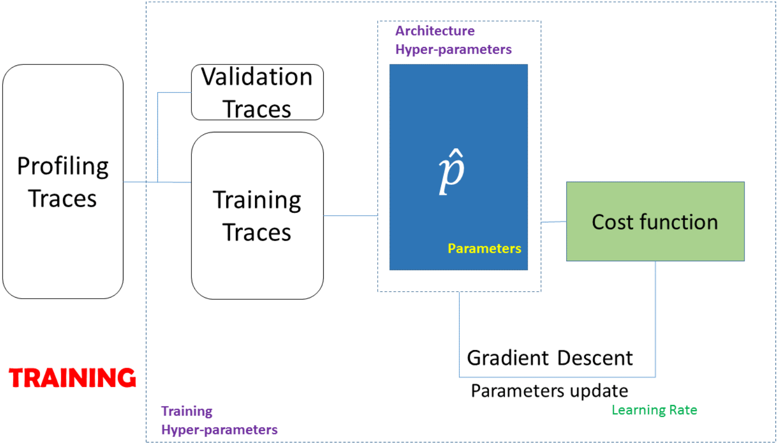
Architecture inspired by AlexNet [KSH12], VGG [SZ14], ResNet [He+16] design rules:

- Reduce temporal features to only one
- Maintain time complexity of each layer (one-half pooling when number of feature maps is doubled)

CHES 2017 - *Convolutional Neural Networks with Data Augmentation Against Jitter-Based Countermeasures - Profiling Attacks Without Pre-processing*. E. Cagli - C. Dumas - E. Prouff

- 4 Conv + Pool layers
- tanh activations
- batch normalisation [IS15]
- 1 *fully connected layer* + softmax

Training and Validation (1)



Cost function - Cross-entropy

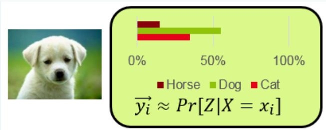
- batch of training data $(\vec{x}_i, z_i)_{i\in I}$, outputs of the current model $(\vec{y}_i)_{i\in I}$
- labels $z_i = s_j$ are *one-hot encoded*: $\vec{z}_i = \vec{s}_j = (0, \ldots, 0, \underbrace{1}_{j}, 0, \ldots, 0)$

Loss function

$$\mathcal{L} = -\frac{1}{|I|}\sum_{i\in I}\sum_{t=1}^{|\mathcal{Z}|}\vec{z}_i[t]\log\vec{y}_i[t] \qquad (1)$$

Maximum-*a-posteriori* or Cross-entropy

- $\vec{y}_i \approx \Pr[Z \mid \vec{X} = \vec{x}_i]$



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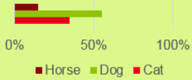
- $\vec{z}_i \approx \Pr[Z \mid Z = \vec{s}_j]$
- $\mathbb{H}(\vec{z}_i, \vec{y}_i) = \mathbb{H}(\vec{z}_i) + D_{KL}(\vec{z}_i || \vec{y}_i) = \mathbb{E}_{\vec{z}_i}[-\log \vec{y}_i] = -\sum_{t=1}^{|\mathcal{Z}|} \vec{z}_i[t] \log \vec{y}_i[t]$



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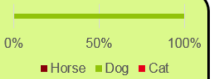

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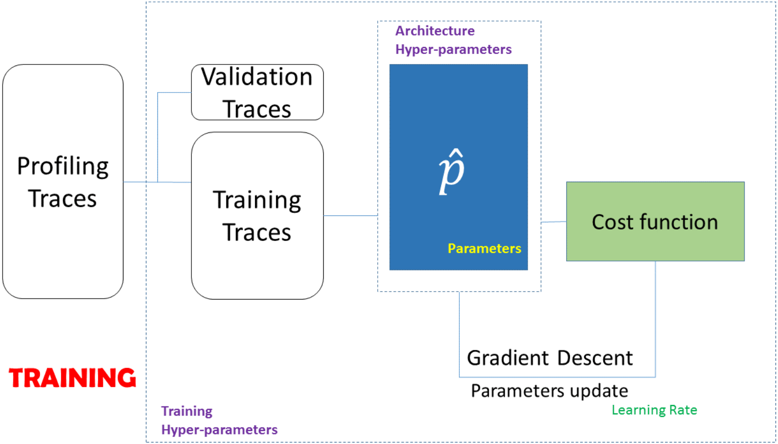

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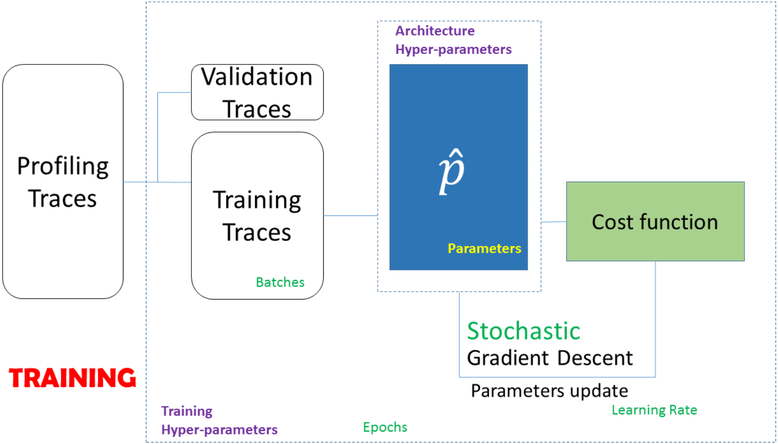

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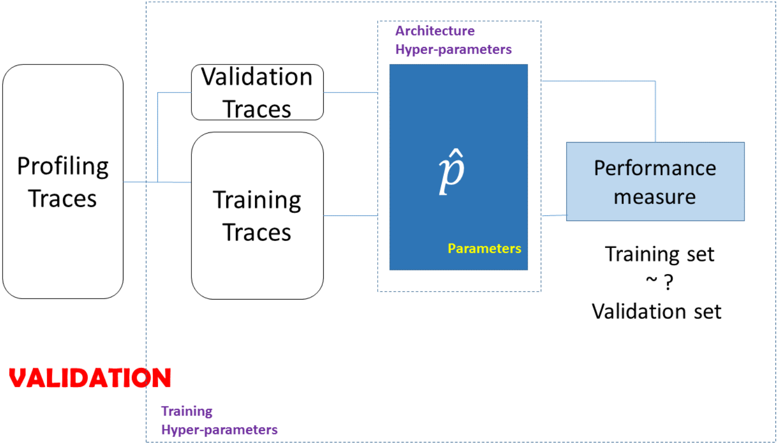

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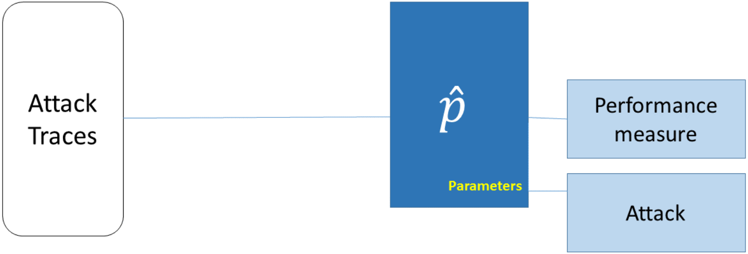


TEST

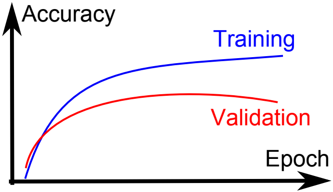
Overfitting

Accuracy

$$\frac{\text{Correct predictions}}{\text{Total predictions}}$$

Evaluate and compare training and validation accuracy

Learn by heart (**OVERFITTING**)



Overfitting

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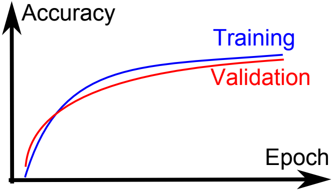
Evaluate and compare training and validation accuracy

Understand significant features



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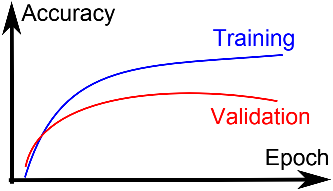

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Evaluate and compare training and validation accuracy

Why?
- Too complex model
- Not enough training data

Solution?
- Reduce model capacity
- Regularization
- Dropout
- Early-Stopping
- Data augmentation

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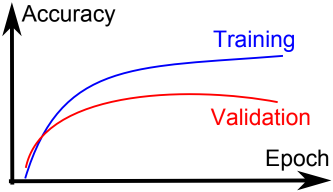

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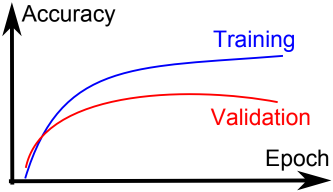
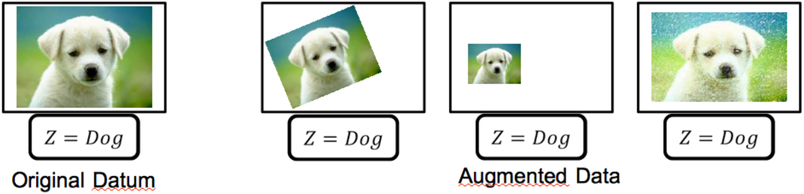


Data Augmentation

Data Augmentation

Artificially generate new training data by deforming those previously acquired,
Applying transformations that preserve the label Z



Side-Channel Data Augmentation

Countermeasure Emulation Idea

Emulate the effects of misaligning countermeasures to generate new traces

SHIFTING

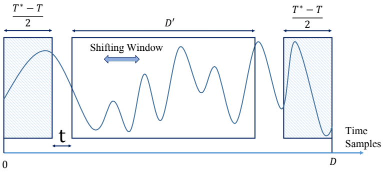


Figure: SH_T

ADD-REMOVE

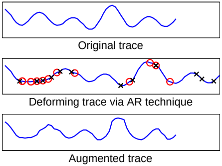


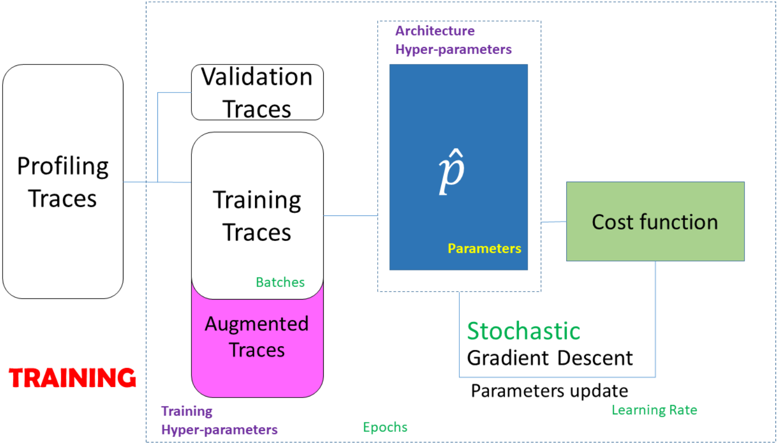
Figure: AR_R

Parameter T: $\sharp$ of possible positions

Parameter R: $\sharp$ of added and removed points

Data Augmentation techniques are applied online during training phase.

Training with Data Augmentation



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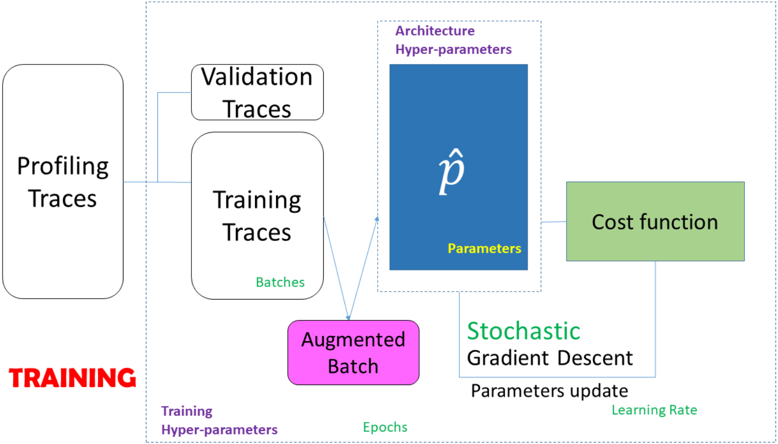

Experimental Results

- Random delays (software countermeasure)
- Artificial Jitter (simulated hardware countermeasure)
- Real Jitter (hardware countermeasure)

Keras 1.2.1 library with Tensorflow backend [Cho+15] (open source, today 2.2.4)

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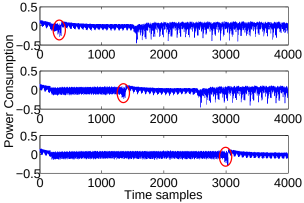


(a) One leaking operation

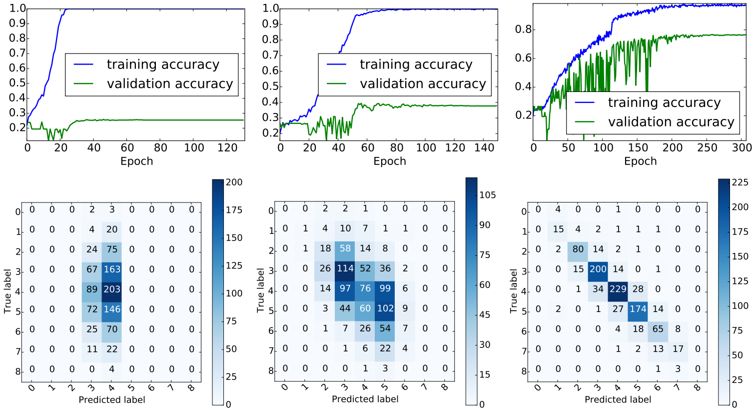
Setup

- Target Chip: Atmega328P
- Target Variable: $Z = \mathrm{HW}(\mathrm{Sbox}(P \oplus K))$
- Acquisition: through ChipWhisperer[OC14] platform, $\approx 4,000$ time samples
- Countermeasure: Random Delays - insertion of r *nop* operations, $r \in [0,127]$ uniform random
- $1,000$ training traces

Random delays

Data augmentation vs overfitting

Training



SH_0 SH_{100} SH_{500}

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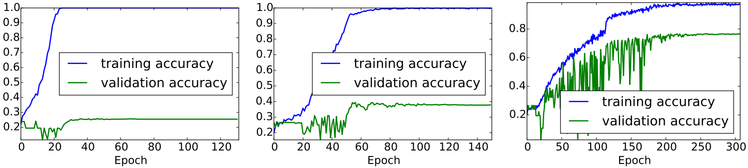


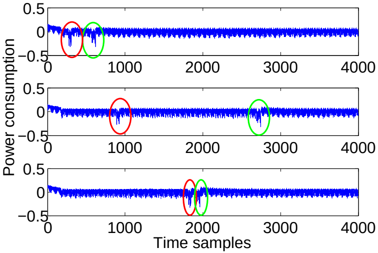
SH_0 SH_{100} SH_{500}

Attack

		SH_0		SH_{100}		SH_{500}	
Accuracy	$N^\star$	27.0%	$> 1,000$	31.8%	101	**78%**	**7**

Table: $N^\star$ = number of attack traces to have GE = 1.

Random Delays - Two Leaking Operations



Two leaking operations

First operation - Test acc: 76.8%, $N^{\star} = 7$
Second operation - Test acc: 82.5%, $N^{\star} = 6$

Conclusions about CNN

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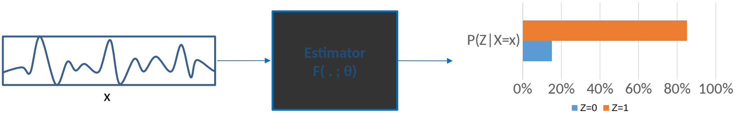
Among new problematics...

Deep Learning provides black-box models:



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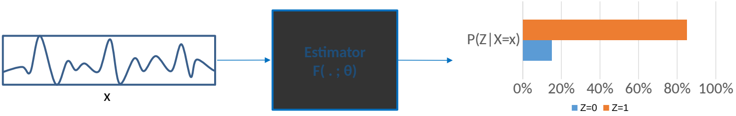

Lack of posterior knowledge: how did the model learn?

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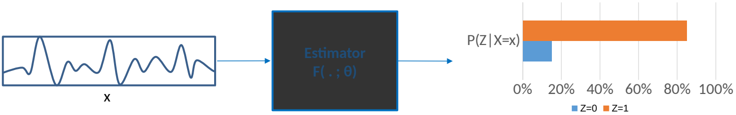

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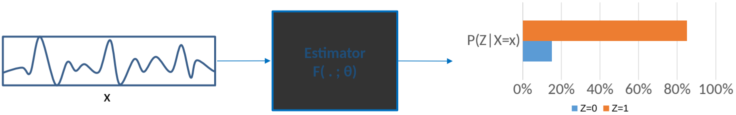

Lack of posterior knowledge: how did the model learn?
Lack of trust: where did the model get the information?
No hints to correct vulnerability

Contents

1. Context and State of the Art

2. Deep Learning against Misalignment

2.1 Neural Network Classifiers

2.2 Data Augmentation

2.3 Experimental Results

3. Gradient Visualization

4. Conclusions

Gradient Visualization

L.Masure *et al.*, *Gradient Visualization for General Characterization in Profiling Attacks*, COSADE 2019 (Darmstadt, 5th April 2019)

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- able to detect Points of Interest (PoIs) as long as the model has learned something
- already proposed in Image Recognition [SVZ13; Spr+14]
- starts to be used in SCA [Tim19; HGG19]

An ideal case

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

An example

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

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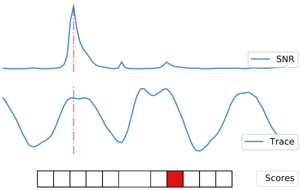

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- Assume the informative leakage is very localized (few PoIs)
- Consider a new trace and its label $\vec{x}, z$

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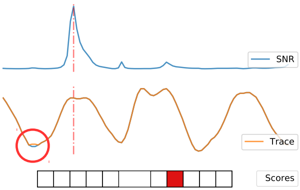

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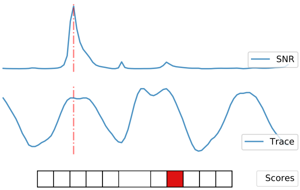

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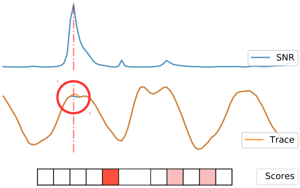

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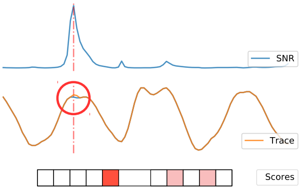

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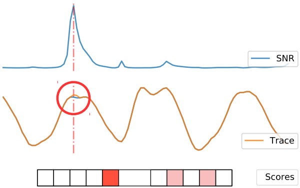

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Application on experimental data

Description

ASCAD dataset [Pro+18]: https://github.com/ANSSI-FR/ASCAD
50,000 traces, each of 700 points
Source codes of secure implementations of AES128 for public 8-bit architectures (https://github.com/ANSSI-FR/secAES-ATmega8515)
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

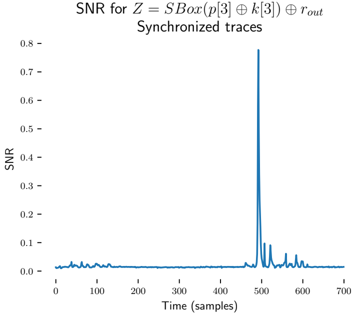

Figure: SNR

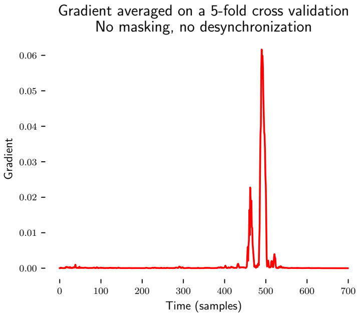

Figure: Gradient Visualization

Second experiment: with desynchronization

Average number of traces to recover the secret key: 3.6

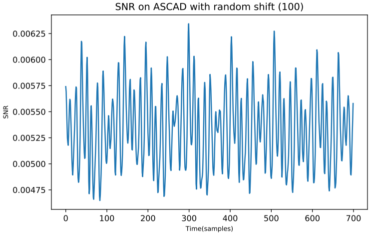

Figure: No PoI emphasized ☹

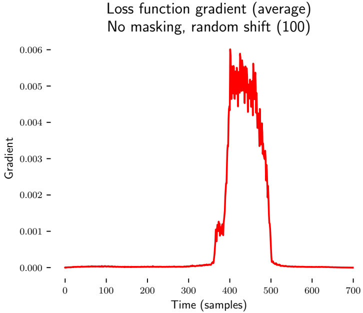

Figure: Band of peaks ☺

Second experiment: with desynchronization

Average number of traces to recover the secret key: 3.6

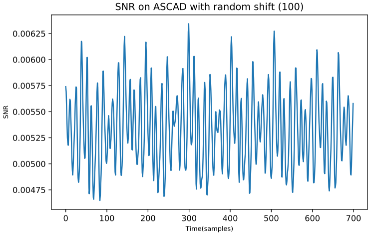

Figure: No PoI emphasized ☹

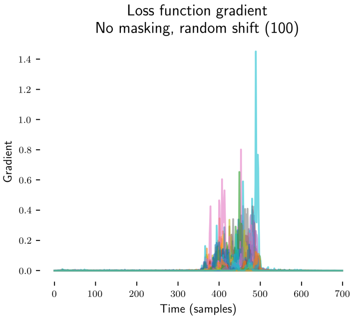

Figure: Characterization for each trace 🙂

Third experiment: with masking

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

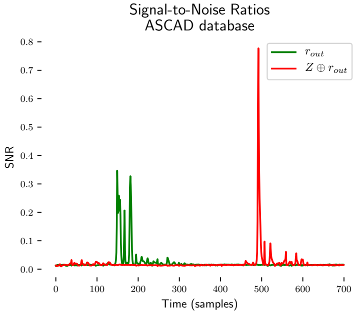

Figure: Requires knowledge of the masks ☹

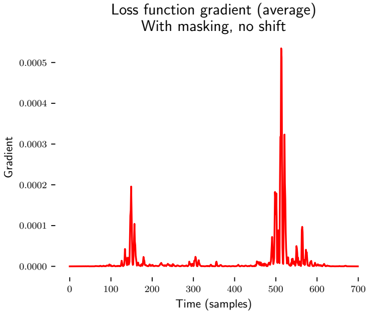

Figure: No knowledge required ☺

Be careful not to overfit !

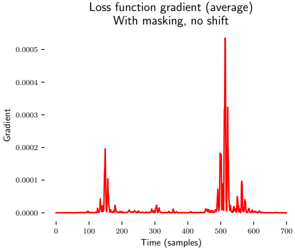

Figure: GV without overfitting 🙂

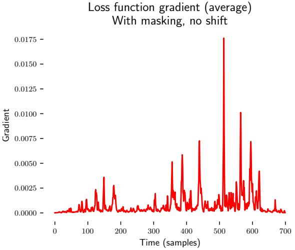

Figure: GV with overfitting ☹

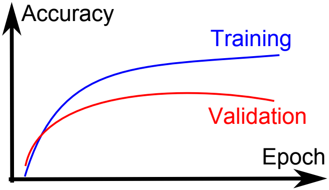

Figure: Solution: early-stopping

Conclusions on Gradient Visualization

- Reinforces trust into Deep Learning tools: in absence of overfitting information comes from well-identifiable regions of interest
- May be used to guide early-stopping and prevent overfitting
- Provides characterization of leakages, allows developpers to correct the vulnerability

Contents

1. Context and State of the Art

2. Deep Learning against Misalignment

2.1 Neural Network Classifiers

2.2 Data Augmentation

2.3 Experimental Results

3. Gradient Visualization

4. Conclusions

Conclusions

- Curse of dimensionality affects the potential optimality of profiling attacks
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- Beyond Classification
  - Collision attacks $\approx$ verification task (siamese network)
  - Does "accuracy" matter? Need for specifying a proper "Advanced-attack-oriented machine learning task" (SCA-specific loss functions and metrics)

Thank You!

- Eleonora Cagli, Cécile Dumas, Emmanuel Prouff: *Convolutional Neural Networks with Data Augmentation against Jitter-Based Countermeasures - Profiling Attacks without Pre-Processing -.* IACR Cryptology ePrint Archive 2017: 740 (2017) - CHES 2017:45-68
- Emmanuel Prouff, Remi Strullu, Ryad Benadjila, Eleonora Cagli, Cécile Dumas: *Study of Deep Learning Techniques for Side-Channel Analysis and Introduction to ASCAD Database.* IACR Cryptology ePrint Archive 2018: 53 (2018) `https://github.com/ANSSI-FR/ASCAD`
- Loïc Masure, Cécile Dumas, Emmanuel Prouff: *Gradient Visualization for General Characterization in Profiling Attacks* (COSADE 2019)

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