FROM RESEARCH TO INDUSTRY

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SORBONNE UNIVERSITÉ
CRÉATEURS DE FUTURS DEPUIS 1257

LIP6

Feature Extraction for Side-Channel Attacks

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LIP6 - Laboratoire d'Informatique de Paris 6

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Contents

Secure Component and Embedded Cryptography

Secure Component and Embedded Cryptography

- Sensitive applications
- Pervasive aspect
- Hostile environment

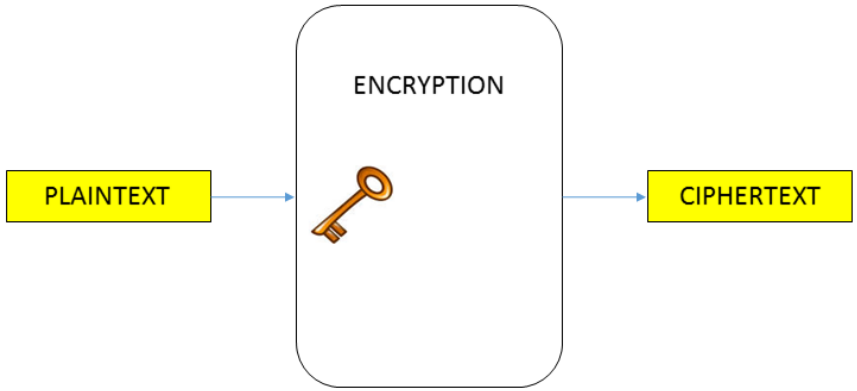
⇒ Requires protection against very high-level attacker

Secure Component and Embedded Cryptography

- Sensitive applications
- Pervasive aspect
- Hostile environment

$\Rightarrow$ Requires protection against very high-level attacker

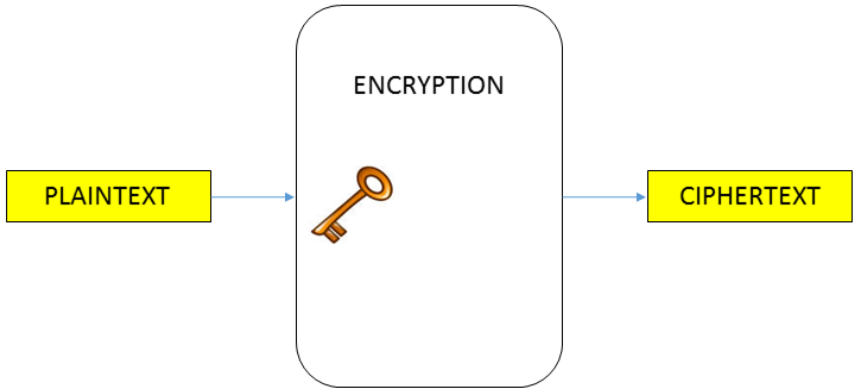
Side-Channel Vulnerability of Embedded Cryptography



Attack $\Longrightarrow$ a secret

	Classical Attacks	**Side-Channel Attacks**
Mathematical vulnerability		
Black Box		

Side-Channel Vulnerability of Embedded Cryptography



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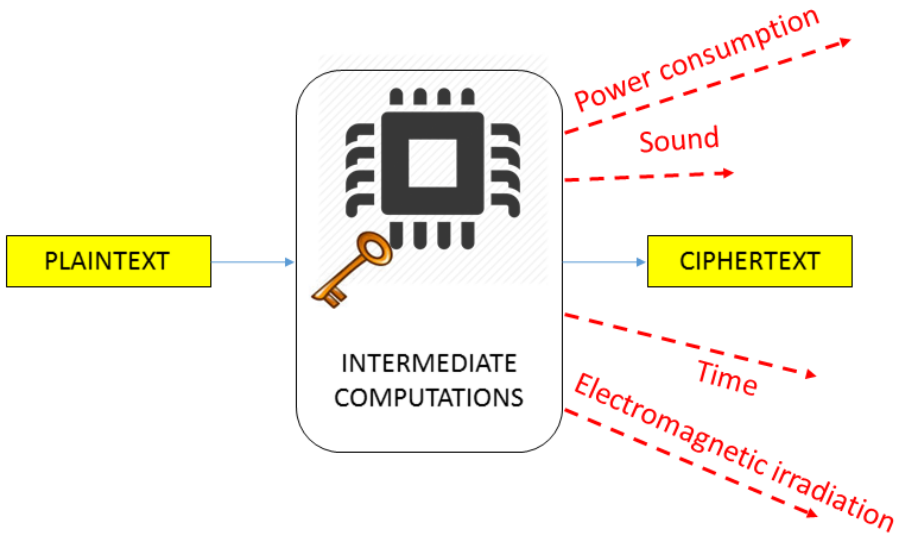
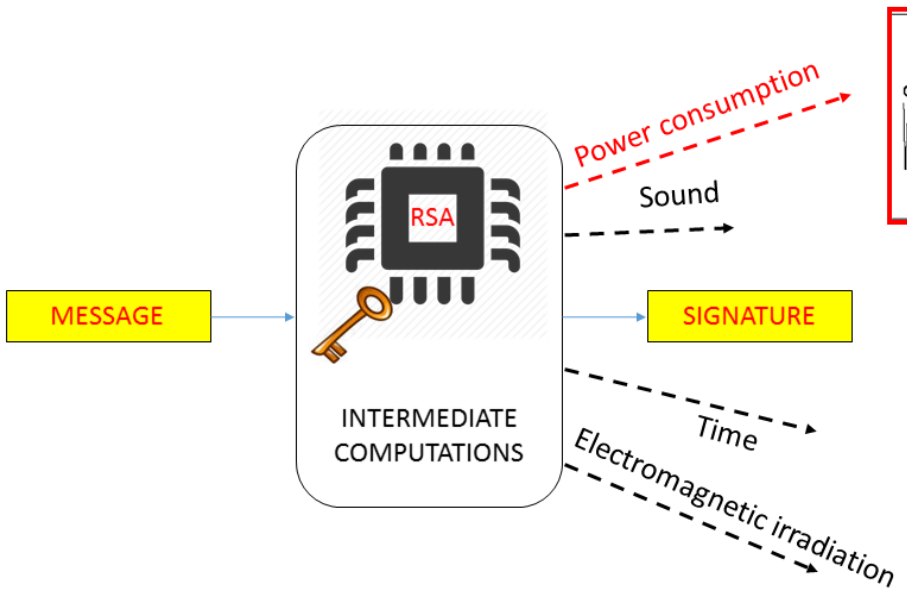
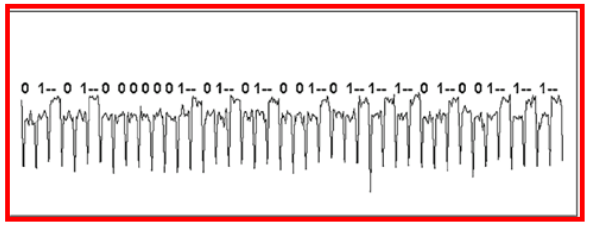


Attack $\Longrightarrow$ 

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

Side-Channel Vulnerability of Embedded Cryptography





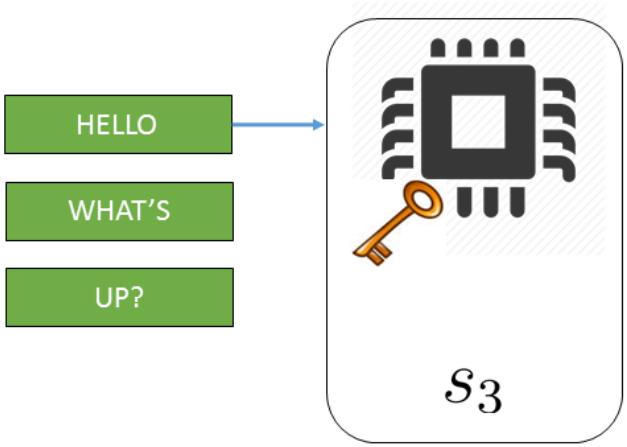
Source - Paul Kocher et al. "Introduction to differential power analysis".

Simple attack:
a single input

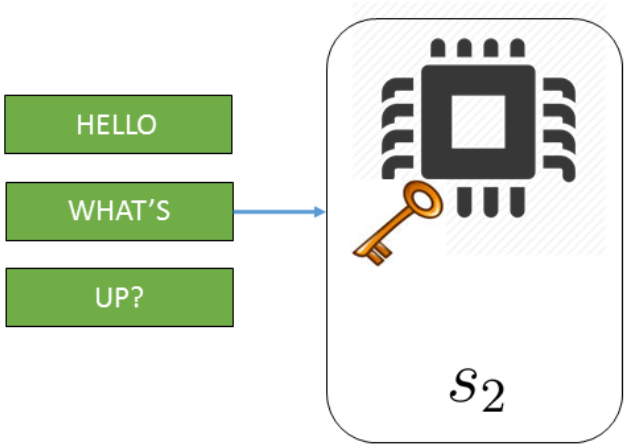
Attack $\Longrightarrow$ 

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

Advanced Side-Channel Attacks



Advanced Side-Channel Attacks



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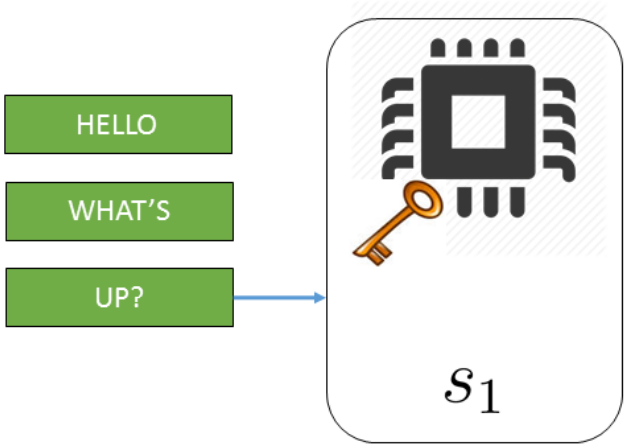

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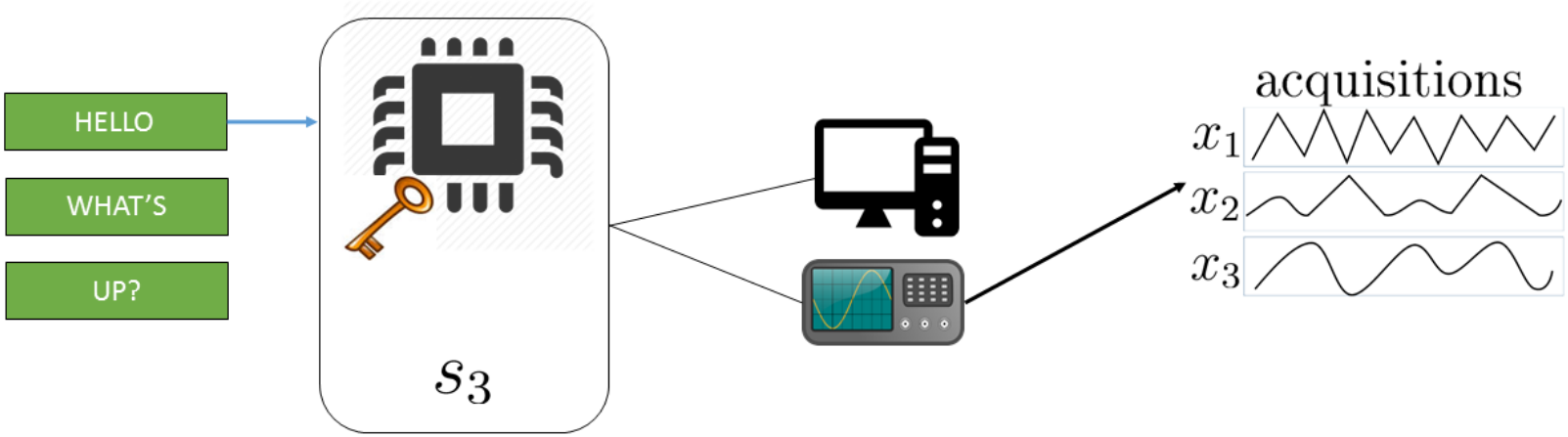

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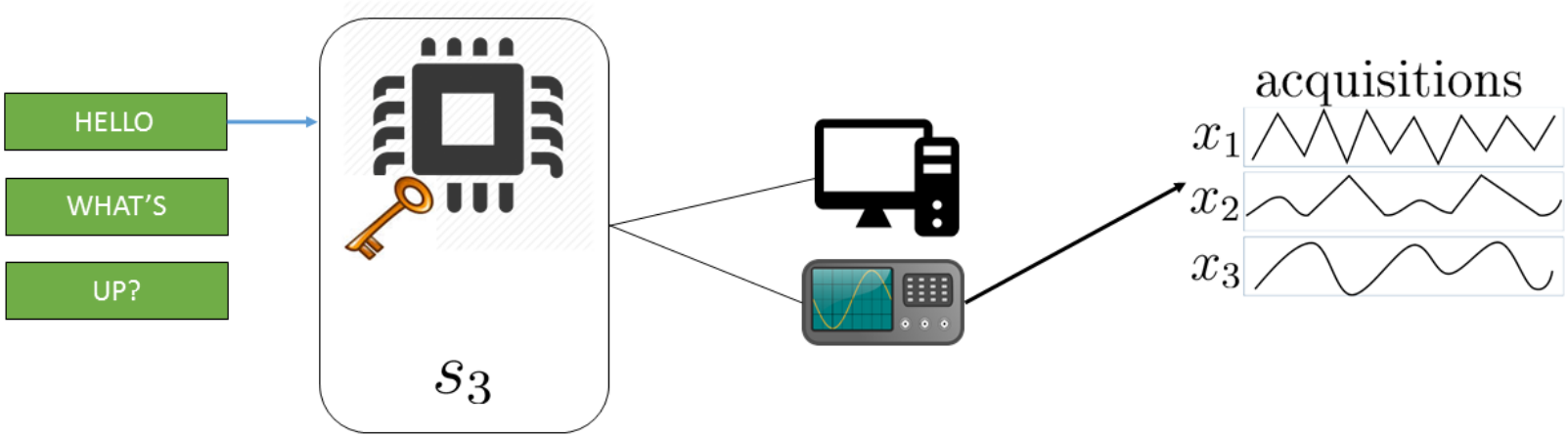

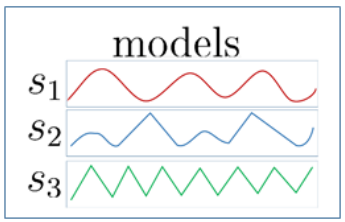

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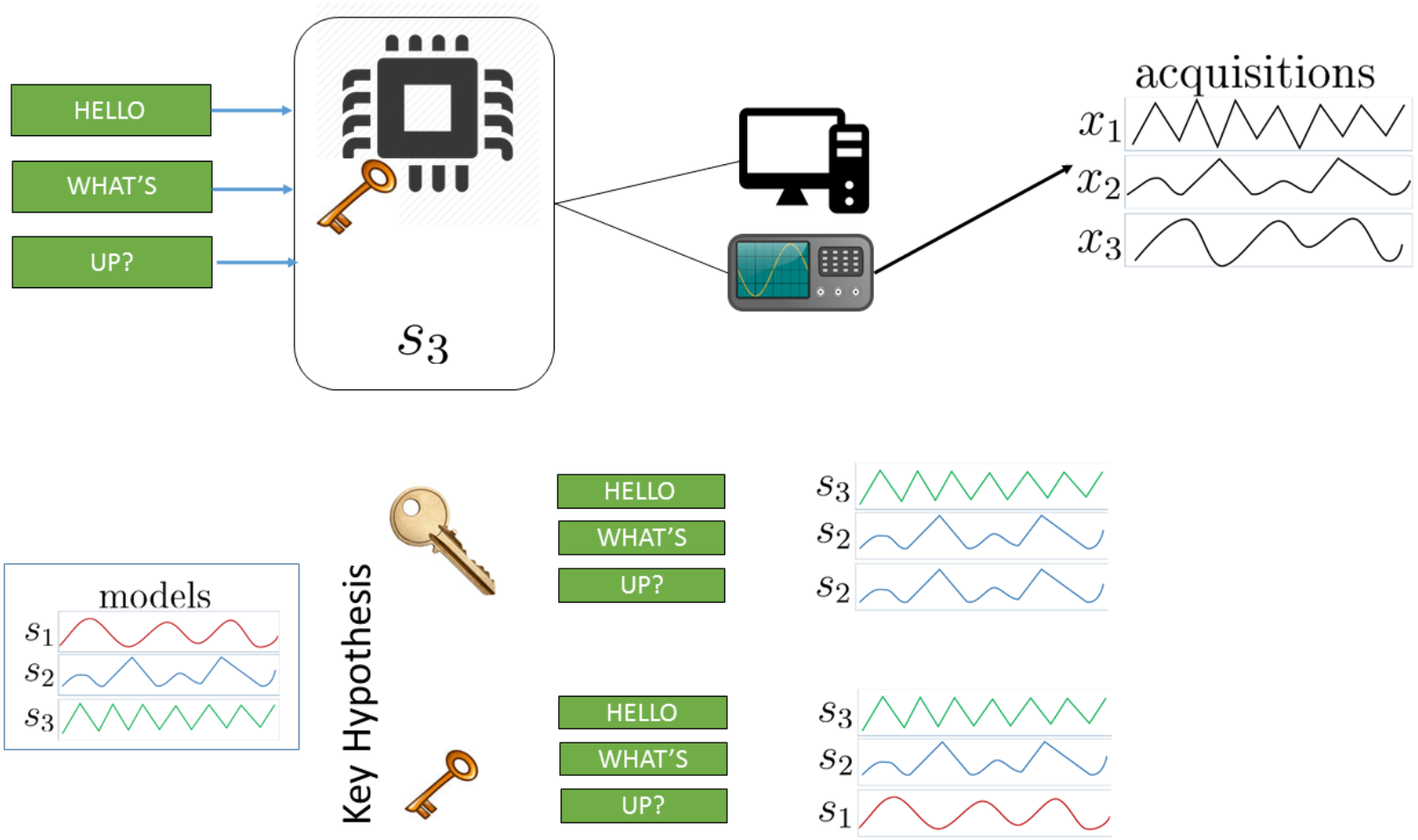

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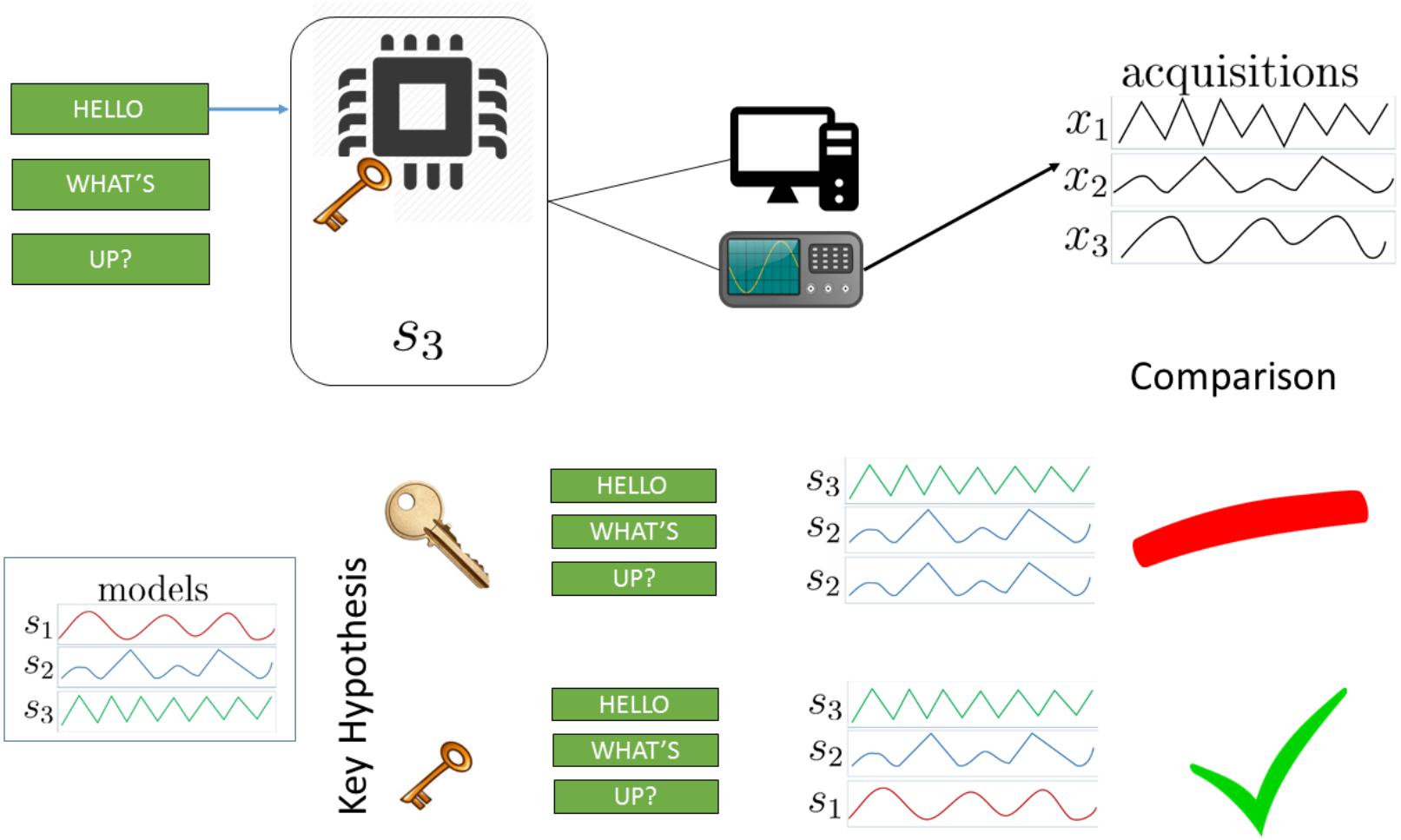

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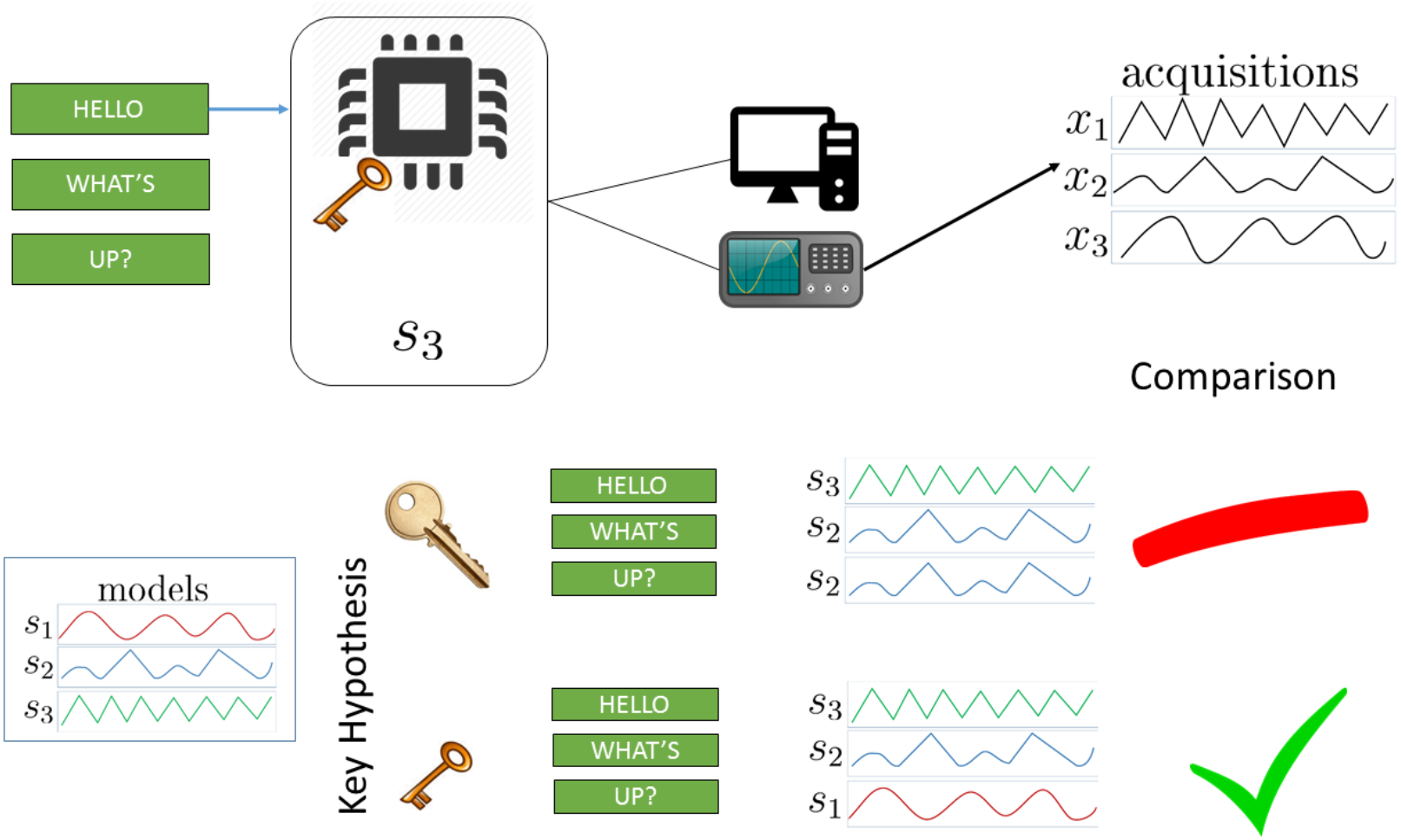
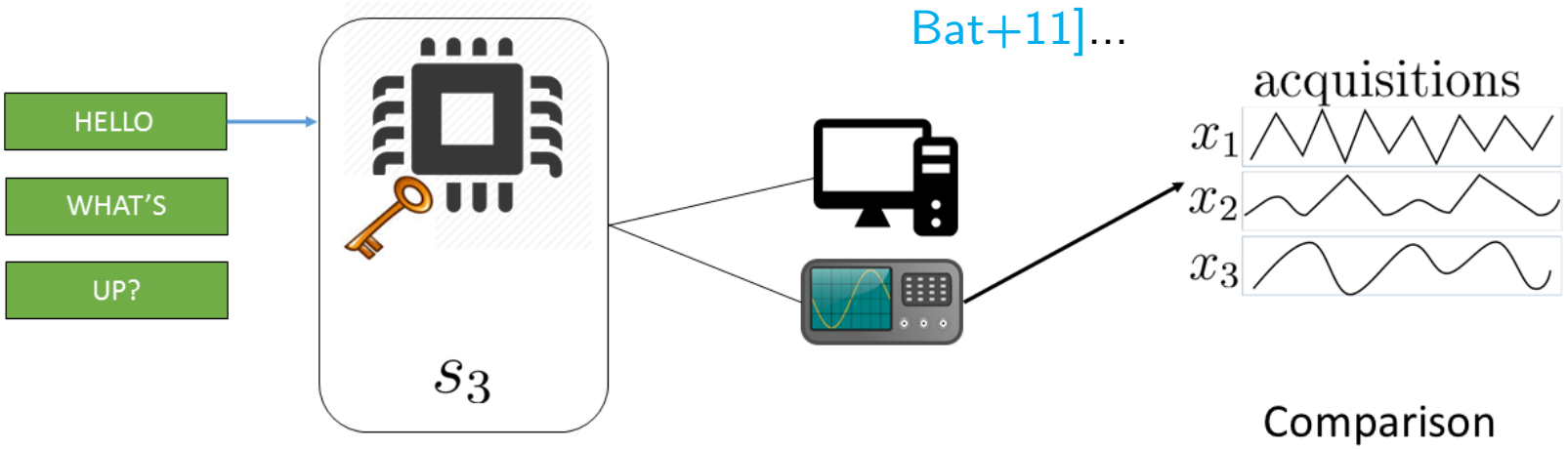
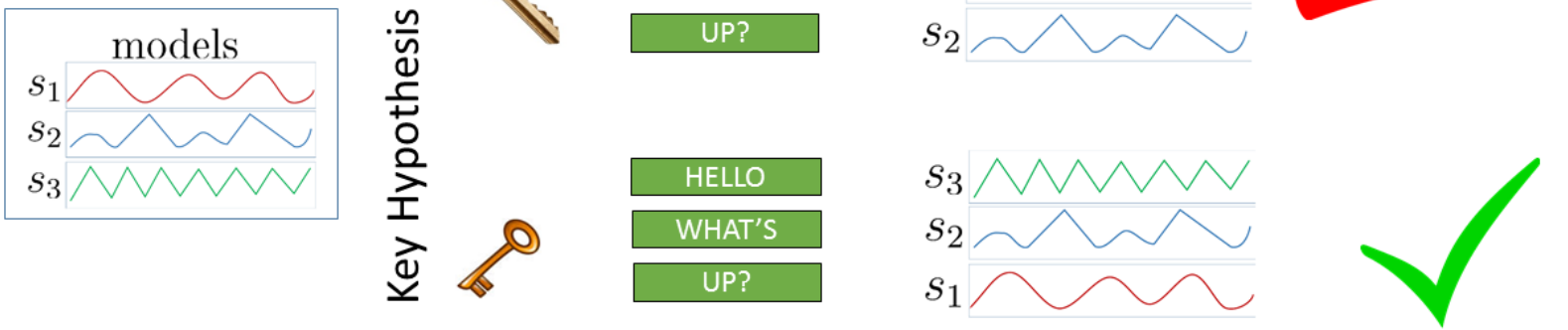


Advanced Side-Channel Attacks

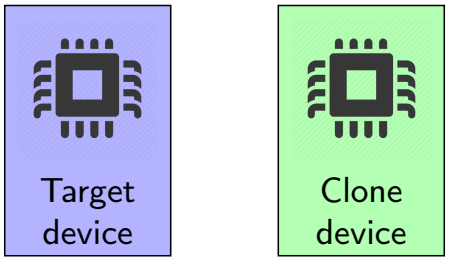
Differential Power Analysis [KJJ99]
Correlation Power Analysis [BCO04]
Mutual Information Analysis [Gie+08; Bat+11]...



Non-profiling attacks
Profiling attacks



Profiling Attacks...Supervised Learning



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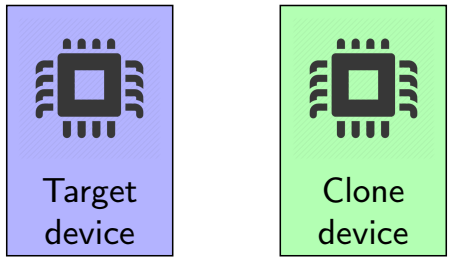
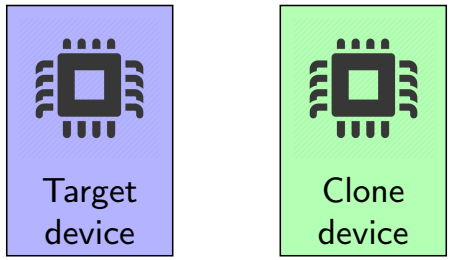


Machine Learning

Supervised Learning

Profiling Attacks...Supervised Learning

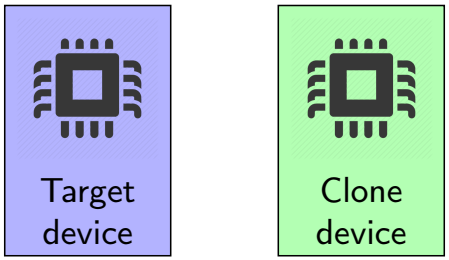


Machine Learning

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

Supervised Learning

Profiling Attacks...Supervised Learning



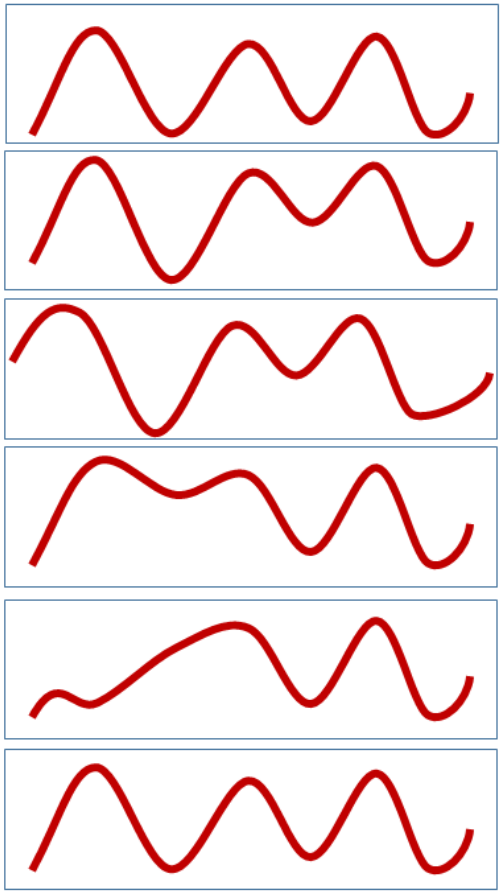
Machine Learning

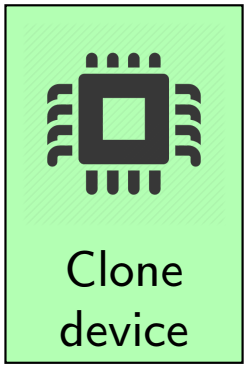
Learn from data via statistic models
Task - Performance - Experience [TM97]

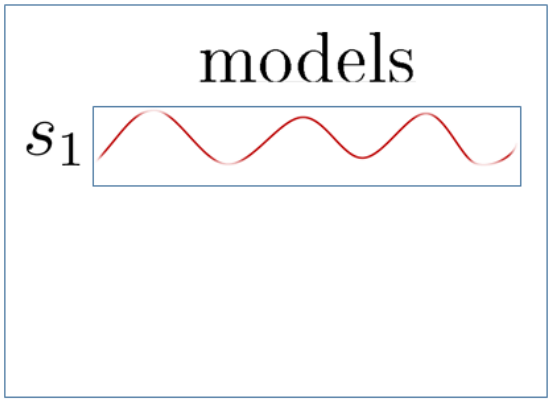
Supervised Learning

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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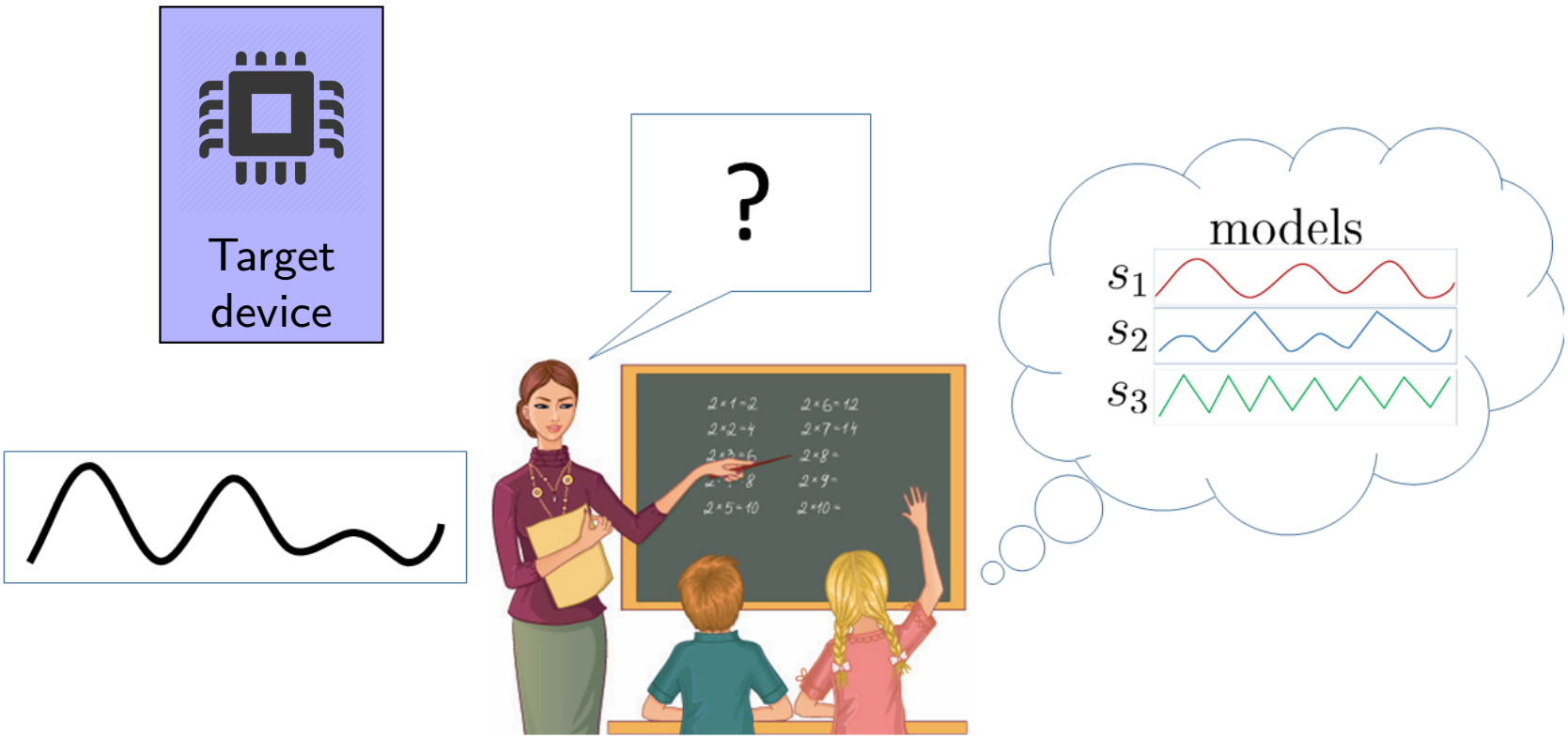
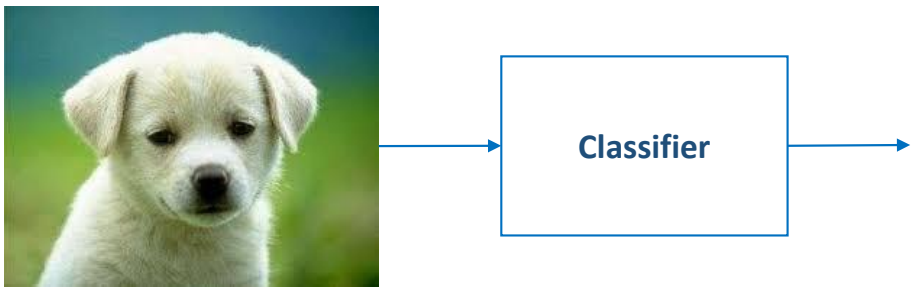


Classification

Classification problem

Assign to a datum $\vec{X}$ (e.g. an image) a label Z among a set of possible labels $\mathcal{Z} = \{\mathrm{Cat}, \mathrm{Dog}, \mathrm{Horse}\}$



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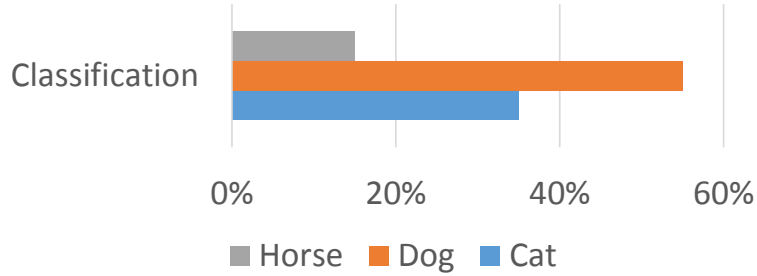

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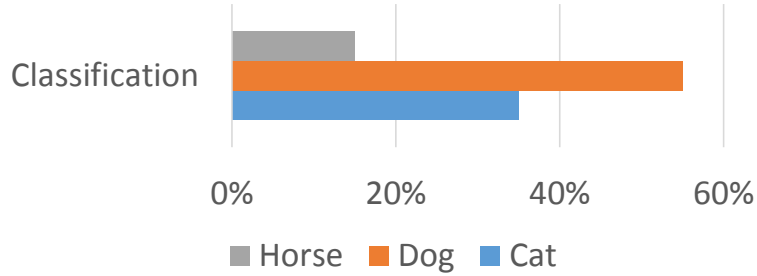
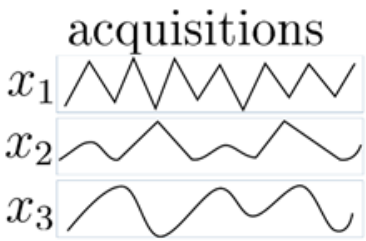
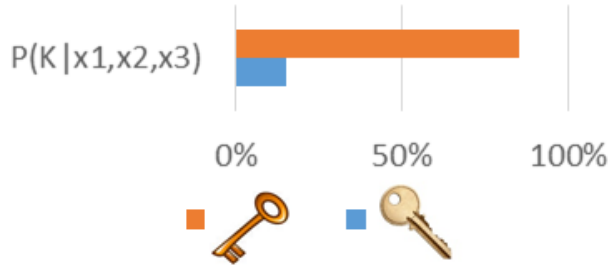


Advanced Attack as a Classification Problem





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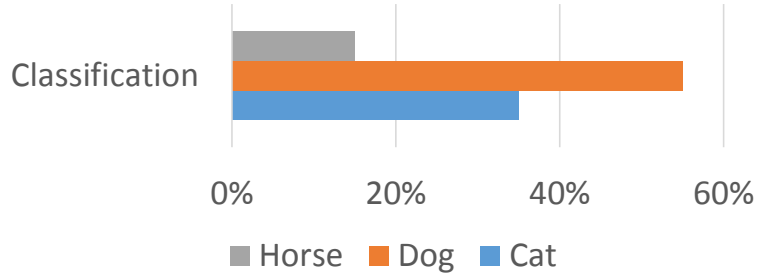
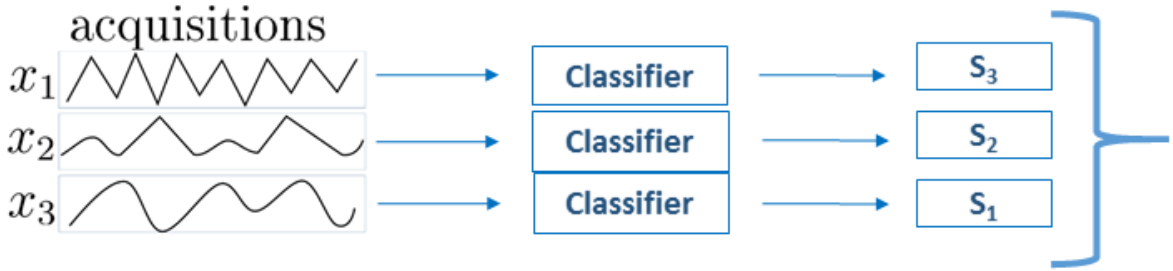


Advanced Attack as Multiple Classification Problems



Classification

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

Classification problem

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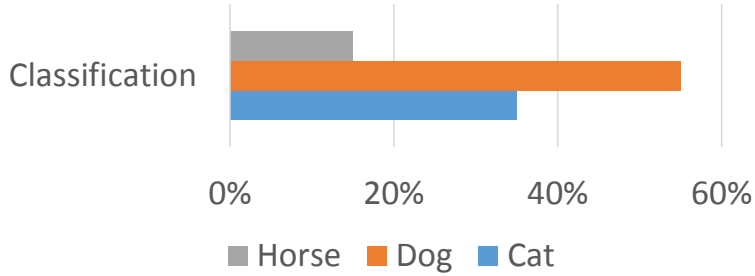

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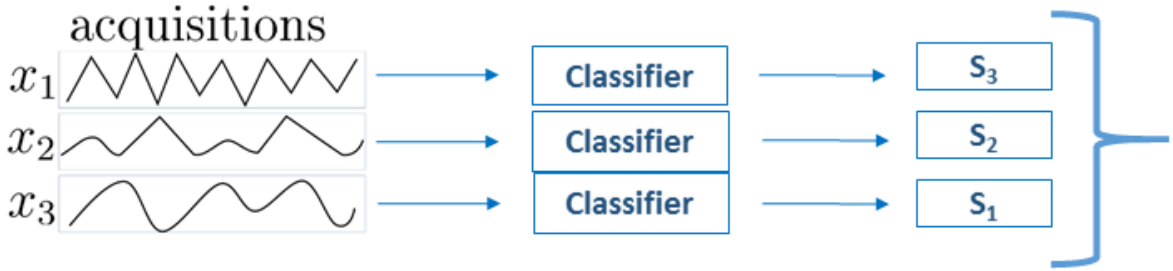

Contents

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

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

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

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

- A-posteriori probability score for each key hypothesis k

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

Profiling Attack

Profiling phase

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Profiling Attack

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

Curse of dimensionality!

Profiling phase

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

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Profiling Attack

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

Curse of dimensionality!

Profiling phase

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

Attack phase

- Likelihood score for each key hypothesis k

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

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Profiling Attack

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

Curse of dimensionality!

Profiling phase

- mandatory dimensionality reduction $[\mathcal{D}_{\text{train}} \longrightarrow \epsilon : \mathbb{R}^D \to \mathbb{R}^C]$
- 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

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

- A-posteriori probability score for each key hypothesis k

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

Profiling Attack

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

Curse of dimensionality!

Profiling phase

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

Attack phase

- Likelihood score for each key hypothesis k

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

- A-posteriori probability score for each key hypothesis k

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Objectives

Profiling phase

- manage de-synchronization problem [$\mathcal{D}_{\text{train}} \longrightarrow \rho : \mathbb{R}^D \rightarrow \mathbb{R}^D$]
- mandatory dimensionality reduction [$\mathcal{D}_{\text{train}} \longrightarrow \epsilon : \mathbb{R}^D \rightarrow \mathbb{R}^C$]
- estimate
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    - Gaussian hypothesis (**Template Attack**) [CRR03]
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Profiling phase

- manage de-synchronization problem $[\mathcal{D}_{\text{train}} \longrightarrow \rho : \mathbb{R}^D \rightarrow \mathbb{R}^D]$
- mandatory dimensionality reduction $[\mathcal{D}_{\text{train}} \longrightarrow \epsilon : \mathbb{R}^D \rightarrow \mathbb{R}^C]$
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DEEP LEARNING

Objectives

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- More generally, ameliorate the profiling attack strategy

Dimensionality Reduction: State of the Art

Dimensionality Reduction

$$\epsilon : \mathbb{R}^D \rightarrow \mathbb{R}^C$$
$$\vec{x} \mapsto \epsilon(\vec{x})$$

- Feature selection (Points of Interest selection)
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  - PCA, choise of components ELV
  - LDA in case of undersampling
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  - discriminative model by means of neural network classifiers
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$(d-1)$th-order Sharing (or Masking)

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- Random *masks*: $M_1, \ldots, M_{d-1}$
- *Masked* variable: $M_d = Z \oplus M_1^{-1} \oplus \cdots \oplus M_{d-1}$

Shares are handled at time samples

$$t_1, \ldots, t_d \qquad \text{(in general different if software countermeasure)}$$

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$\Rightarrow$ extract features containing $\vec{X}[t_1]\vec{X}[t_2]\ldots\vec{X}[t_d]$ **(Necessary condition)**

How to detect the d-tuple $t_1, \ldots, t_d$?

Feature selection

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- SOD [CRR03]
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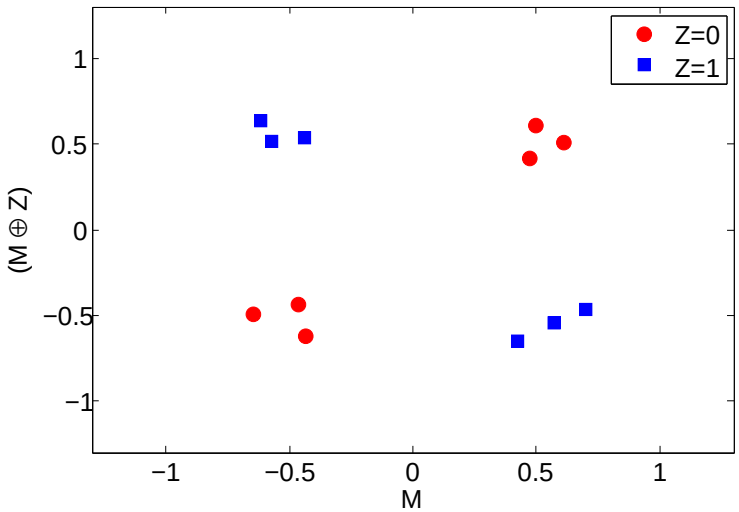

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t_1: $M + n$, $n \sim \mathcal{N}(0, 0.1)$

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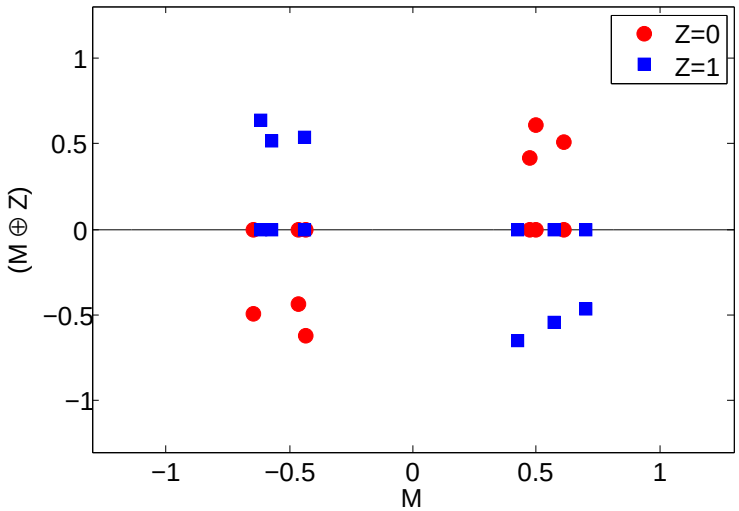

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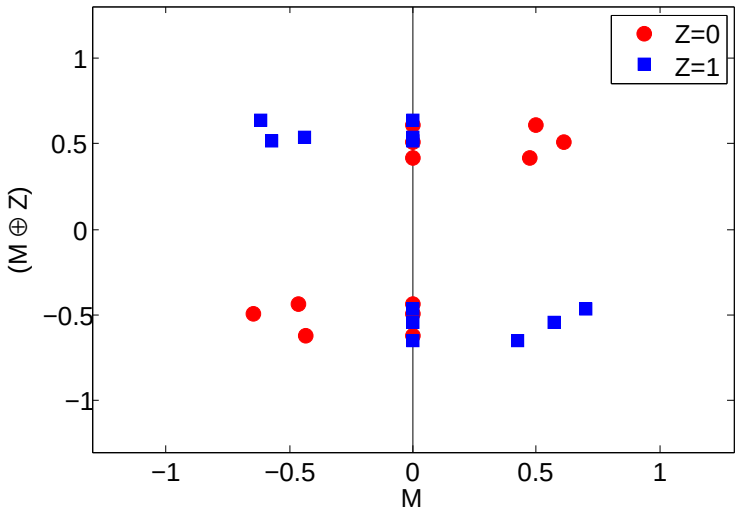

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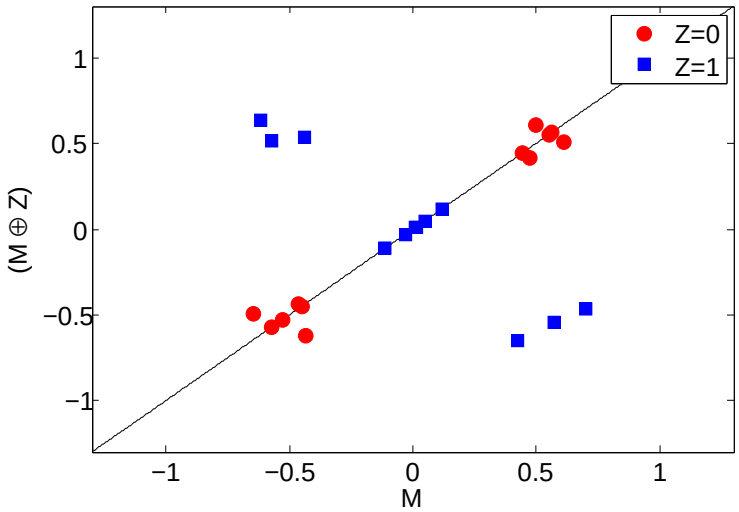

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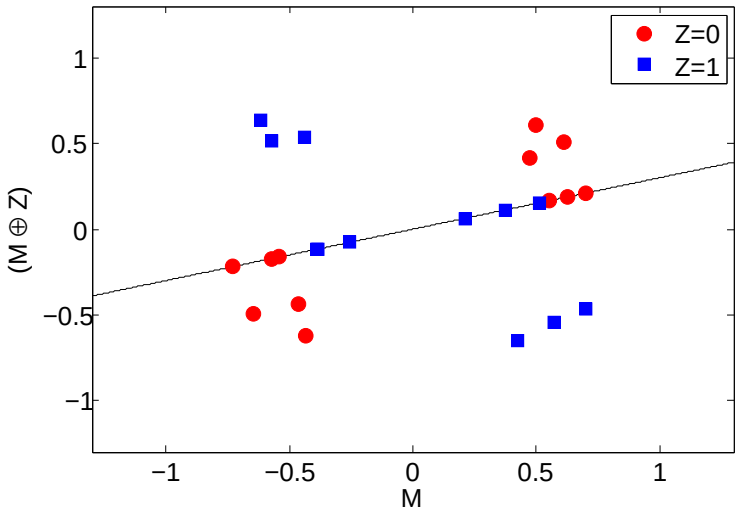

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PoIs Research

A lacking literature

- many HO attacks papers assume the knowledge of $t_1, \ldots, t_d$
- PoI research exploiting the masks knowledge in profiling phase
- Hand selection via educated guess [Osw+06]
- Feature Selection for Higher-Order Attacks $\longrightarrow$ Projection Pursuits [Dur+15]

Kernel Discriminant Analysis starting point

Naive strategy: infer over all possible d-tuples

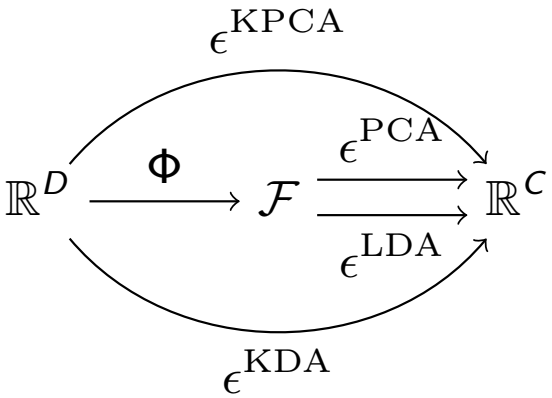
KDA: the purpose

Problem

All dth-degree monomials in the trace coordinates lie in:

$$\mathcal{F} = \mathbb{R}^{\binom{D+d-1}{d}} \qquad \textit{feature} \text{ space}$$

⚠ Dimension increasing combinatorially with d and D



Φ non-linear function

KDA

KDA allows performing LDA in $\mathcal{F}$, remaining in $\mathbb{R}^D$.

KDA: an intuition

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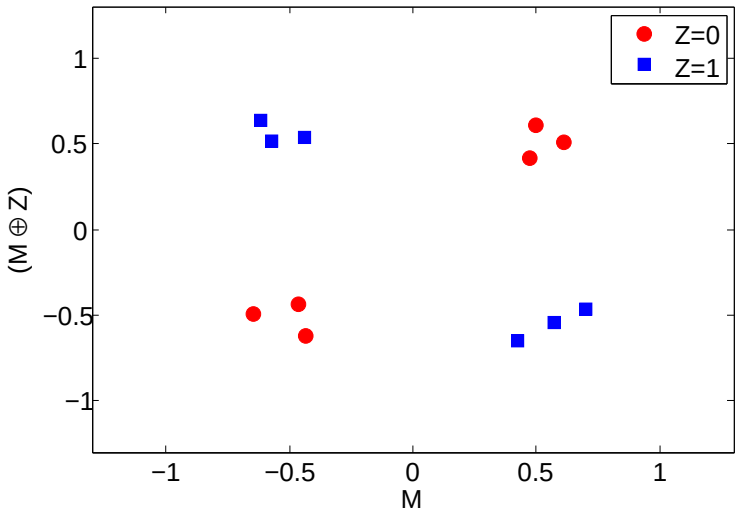

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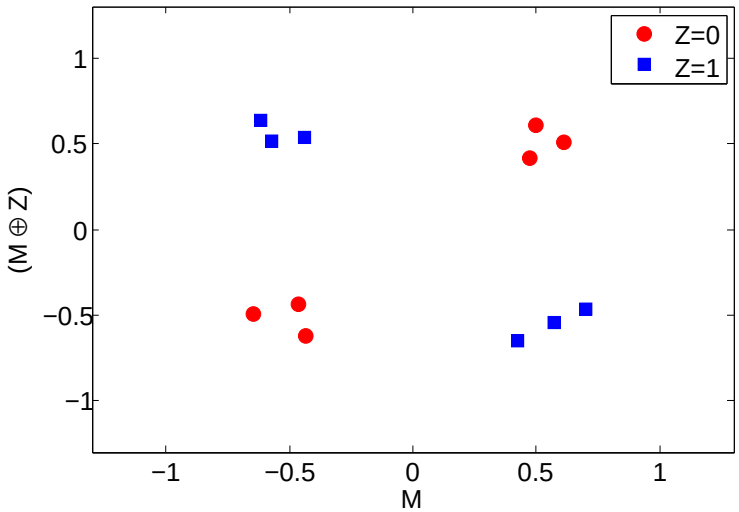

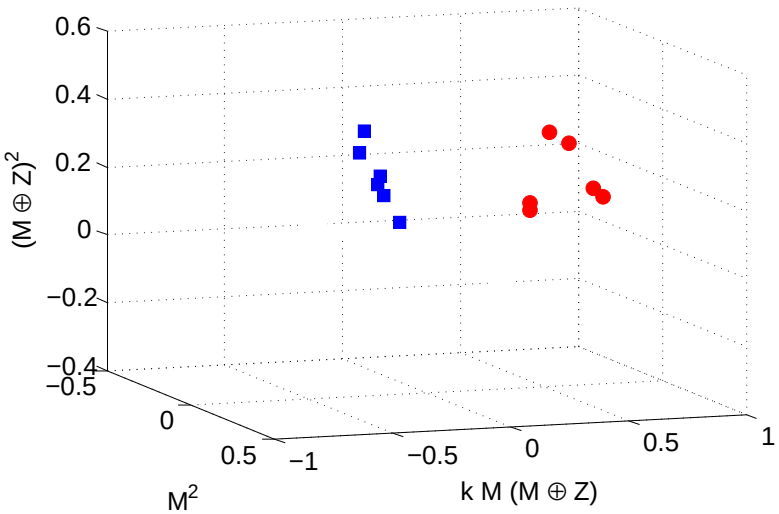

$$\Phi : \mathbb{R}^D \rightarrow \mathbb{R}^{\binom{D+d-1}{d}}$$
$$\Phi(t_1, t2) = (t_1^2, t_2^2, kt_1t_2)$$

KDA: an intuition

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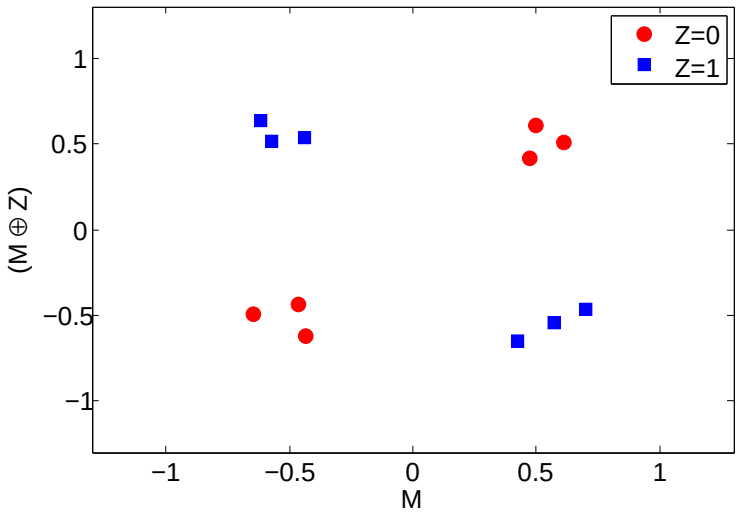

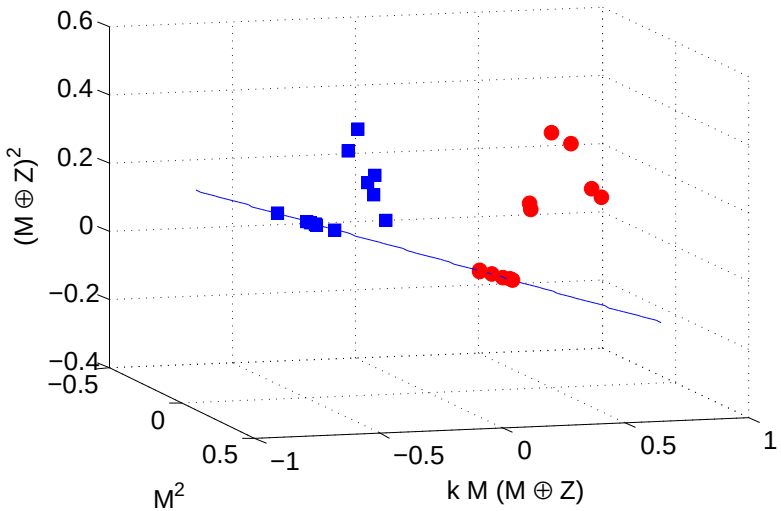

$\Phi \longrightarrow$ LDA

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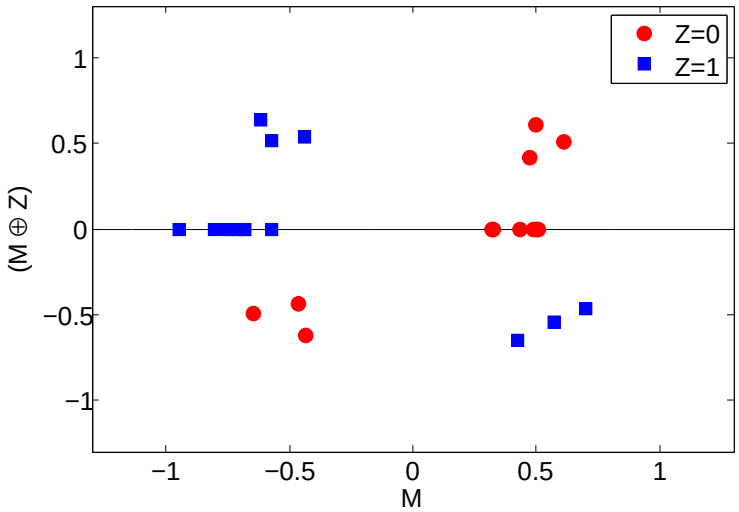
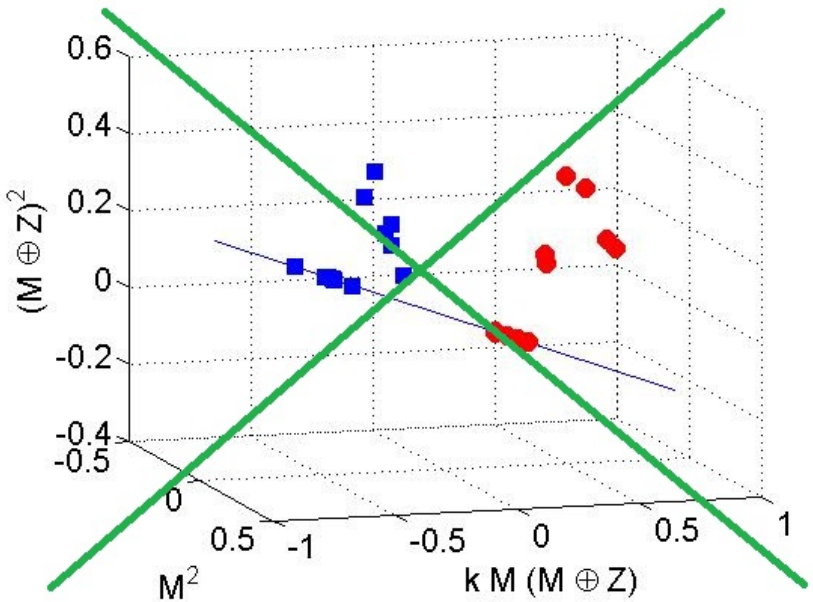
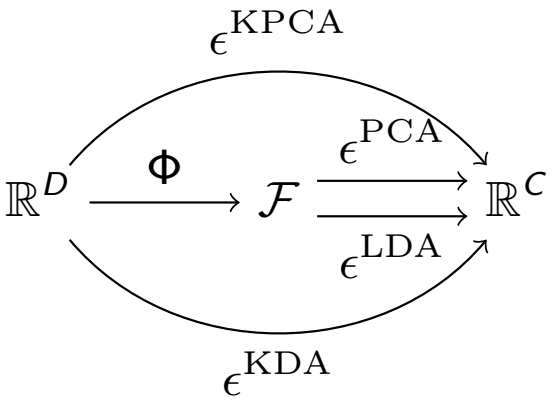


KDA
remains in $\mathbb{R}^D$



Kernel Function



Φ non-linear function

Kernel Function

$K : \mathbb{R}^D \times \mathbb{R}^D \to \mathbb{R}$

$$K(\mathbf{x}_i, \mathbf{x}_j) = \Phi(\mathbf{x}_i) \cdot \Phi(\mathbf{x}_j) \tag{1}$$

d th-degree Polynomial Kernel Function

$K(\mathbf{x}_i, \mathbf{x}_j) = (\mathbf{x}_i \cdot \mathbf{x}_j)^d \quad \leftrightarrow \quad \Phi : \mathbb{R}^D \to \mathcal{F} \subset \mathbb{R}^{\binom{D+d-1}{d}}$ all dth-degree monomials

KDA - the training

"Fisher Discriminant Analysis with Kernels"([SM99])

Between-class (inter-class) Covariance Matrix

LDA

- $\mathbf{S_B} = \sum_{z \in \mathcal{Z}} N_z (\vec{\mu}_s - \bar{\vec{x}})(\vec{\mu}_s - \bar{\vec{x}})^\intercal$

KDA

- $\mathbf{M} = \sum_{z \in \mathcal{Z}} N_z (\vec{M}_s - \vec{M}_T)(\vec{M}_s - \vec{M}_T)^\intercal$ [1]
-

[1] $\vec{M}_s$ and $\vec{M}_T$ are two N-sized column vectors whose entries are given by: $\vec{M}_z[j] = \frac{\mathbf{1}}{N_z} \sum_{i:z_i=z}^{N_z} K(\mathbf{x}_j^{z_j}, \mathbf{x}_i^{z_i})$, $\vec{M}_T[j] = \frac{\mathbf{1}}{N} \sum_{i=\mathbf{1}}^{N} K(\mathbf{x}_j^{z_j}, \mathbf{x}_i^{z_i})$.

[2] $\mathbf{I}$ is a $N_z \times N_z$ identity matrix, $\mathbf{I}_{N_z}$ is a $N_z \times N_z$ matrix with all entries equal to $\frac{\mathbf{1}}{N_z}$ and $\mathbf{K}_z$ is the $N \times N_z$ sub-matrix of $\mathbf{K} = (K(\mathbf{x}_i^{z_i}, \mathbf{x}_j^{z_j}))_{\substack{i=\mathbf{1},\dots,N \\ j=\mathbf{1},\dots,N}}$ storing only columns indexed by the indices i such that $z_i = z$

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- $\mathbf{S_W} = \sum_{z \in \mathcal{Z}} \sum_{i=1}^{N_z} (\mathbf{x}_i^z - \vec{\mu}_s)(\mathbf{x}_i^z - \vec{\mu}_s)^\intercal$

KDA

- $\mathbf{M} = \sum_{z \in \mathcal{Z}} N_z (\vec{M}_s - \vec{M}_T)(\vec{M}_s - \vec{M}_T)^\intercal$ [1]
- $\mathbf{N} = \sum_{z \in \mathcal{Z}} \mathbf{K}_z (\mathbf{I} - \mathbf{I}_{N_z}) \mathbf{K}_z^\intercal$ [2]
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[2] $\mathbf{I}$ is a $N_z \times N_z$ identity matrix, $\mathbf{I}_{N_z}$ is a $N_z \times N_z$ matrix with all entries equal to $\frac{\mathbf{1}}{N_z}$ and $\mathbf{K}_z$ is the $N \times N_z$ sub-matrix of $\mathbf{K} = (K(\mathbf{x}_i^{z_i}, \mathbf{x}_j^{z_j}))_{\substack{i=\mathbf{1},\dots,N \\ j=\mathbf{1},\dots,N}}$ storing only columns indexed by the indices i such that $z_i = z$

KDA - the training

"Fisher Discriminant Analysis with Kernels"([SM99])

Eigenvector problem

Computational Complexity $O(D^3)$

LDA

- $\mathbf{S_B} = \sum_{z \in \mathcal{Z}} N_z (\vec{\mu}_s - \overline{\vec{x}})(\vec{\mu}_s - \overline{\vec{x}})^\intercal$
- $\mathbf{S_W} = \sum_{z \in \mathcal{Z}} \sum_{i=1}^{N_z} (\mathbf{x}_i^z - \vec{\mu}_s)(\mathbf{x}_i^z - \vec{\mu}_s)^\intercal$
- $\vec{\alpha}_i$ eigenvectors of $\mathbf{S_W}^{-1}\mathbf{S_B}$ $[D \times D]$

Computational Complexity $O(N^3)$

KDA

- $\mathbf{M} = \sum_{z \in \mathcal{Z}} N_z (\vec{M}_s - \vec{M}_T)(\vec{M}_s - \vec{M}_T)^\intercal$ [1]
- $\mathbf{N} = \sum_{z \in \mathcal{Z}} \mathbf{K}_z (\mathbf{I} - \mathbf{I}_{N_z}) \mathbf{K}_z^\intercal$ [2]
- $\vec{\nu}_i$ eigenvectors of $\mathbf{N}^{-1}\mathbf{M}$ $[N \times N]$
-

---

[1] $\vec{M}_s$ and $\vec{M}_T$ are two N-sized column vectors whose entries are given by: $\vec{M}_z[j] = \frac{1}{N_z} \sum_{i:z_i=z}^{N_z} K(\mathbf{x}_j^{z_j}, \mathbf{x}_i^{z_i})$, $\vec{M}_T[j] = \frac{1}{N} \sum_{i=1}^{N} K(\mathbf{x}_j^{z_j}, \mathbf{x}_i^{z_i})$.

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KDA - the training

"Fisher Discriminant Analysis with Kernels"([SM99])

New trace projection

Computational Complexity $O(D^3)$

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- $\mathbf{S_W} = \sum_{z\in\mathcal{Z}} \sum_{i=1}^{N_z}(\mathbf{x}_i^z - \vec{\mu}_s)(\mathbf{x}_i^z - \vec{\mu}_s)^\intercal$
- $\vec{\alpha}_i$ eigenvectors of $\mathbf{S_W}^{-1}\mathbf{S_B}$ $[D \times D]$
- $\epsilon_\ell^{LDA}(\vec{x}) = \sum_{i=1}^{D} \vec{\alpha}_\ell[i]\vec{x}[i]$

Computational Complexity $O(N^3)$

KDA

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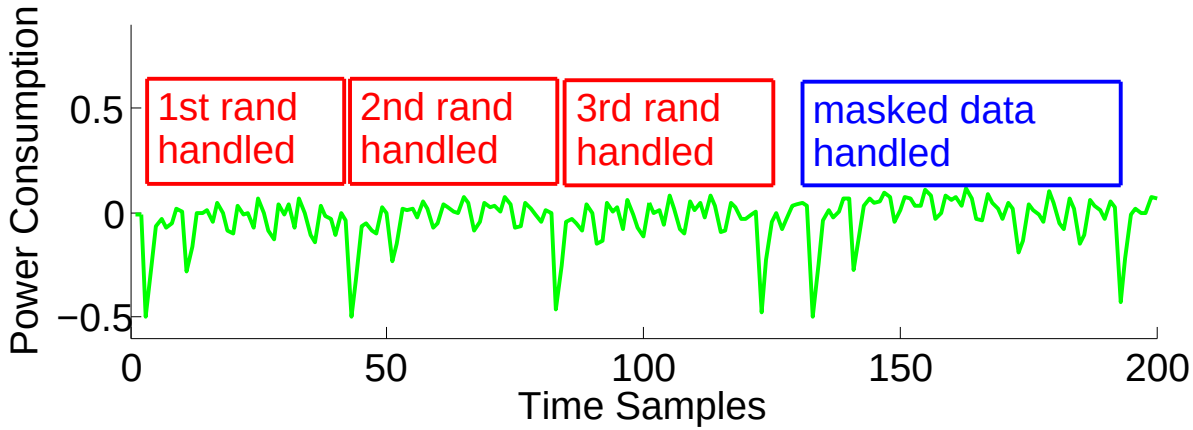
Experimental setup

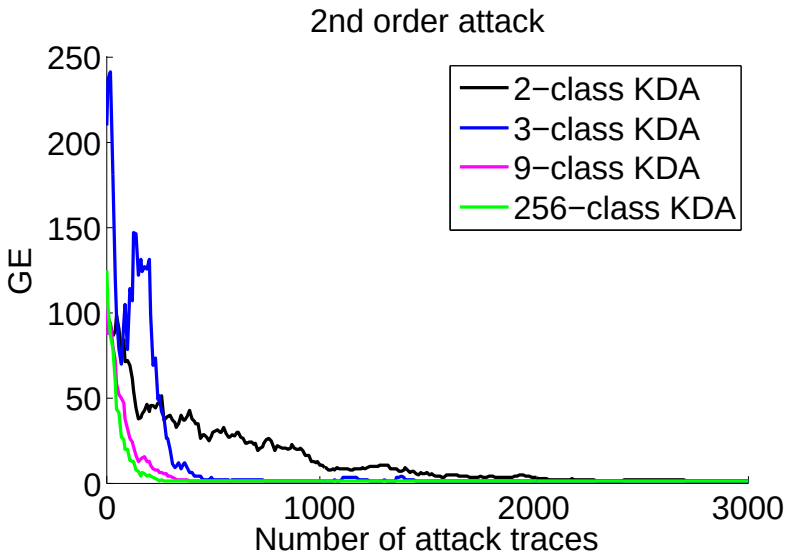
Target device and acquisitions:

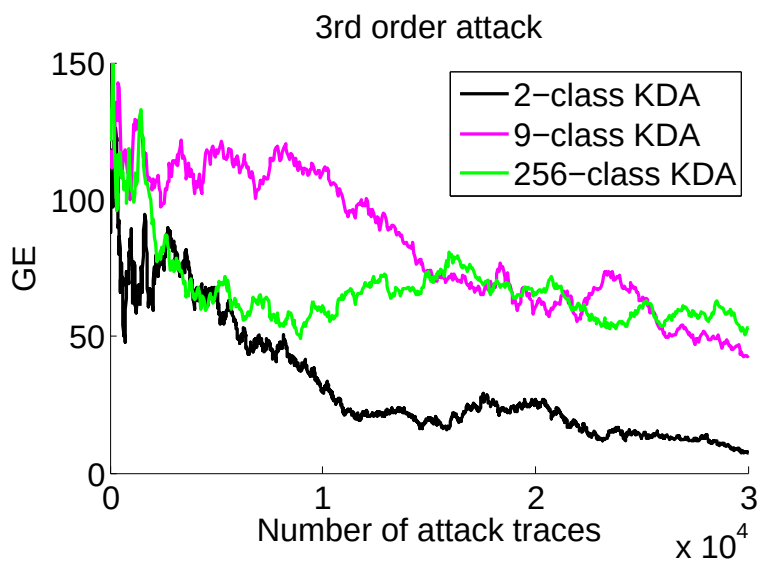
- 8-bit AVR microprocessor Atmega328P
- power-consumption acquired via the ChipWhisperer [OC14] platform
- $D = 200$, 4 clock-cycles are selected
- $9,000$ KDA training traces

Sensitive variable: $Z = \mathrm{Sbox}_{\mathrm{AES}}(P \oplus K^{\star})$
One byte: 256 classes



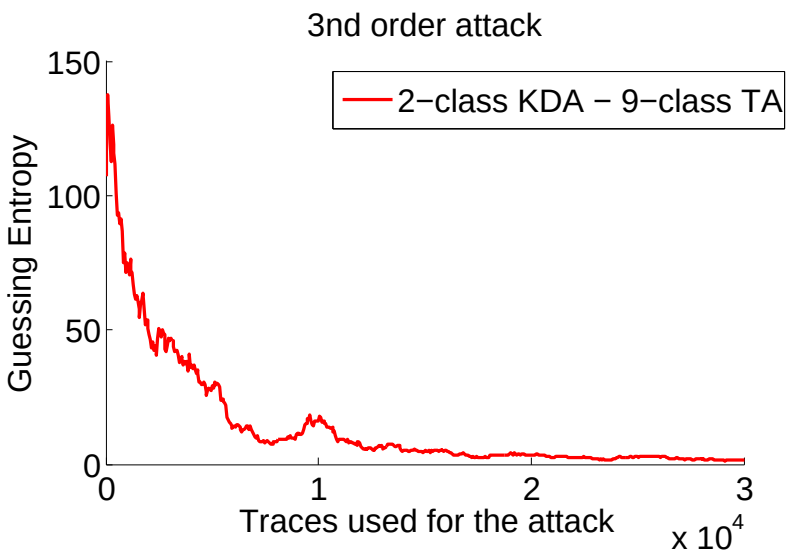
Second and third order

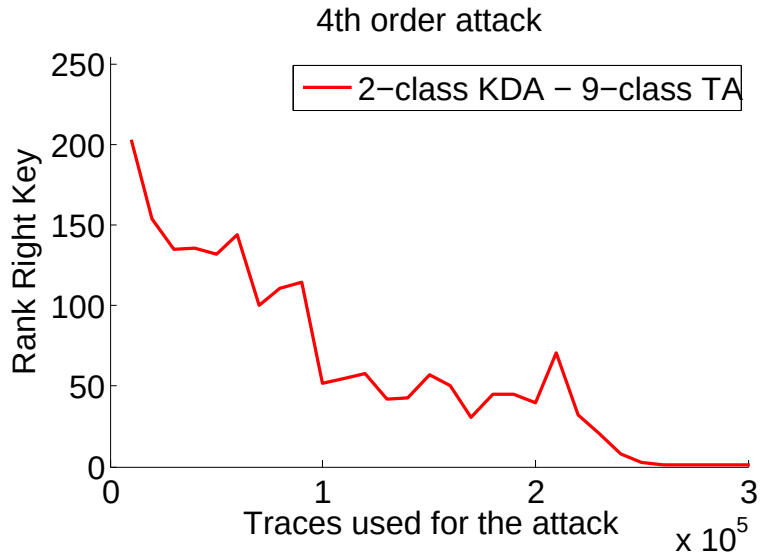




GE = Guessing Entropy (mean rank of the right key candidate)

Third and Fourth Order





- $d = 2 \longrightarrow \mathcal{F} = \mathbb{R}^{\binom{200+2-1}{2}} \Rightarrow 20,100$ implicit coefficients
- $d = 3 \longrightarrow \mathcal{F} = \mathbb{R}^{\binom{200+3-1}{3}} \Rightarrow 1,353,400$ implicit coefficients
- $d = 4 \longrightarrow \mathcal{F} = \mathbb{R}^{\binom{200+4-1}{4}} \Rightarrow 68,685,050$ implicit coefficients

Same time of execution of the KDA algorithm!

Conclusions on KDA

Strong points

- KDA with d-th degree polynomial kernel function is suitable to attack $(d-1)$th-order masking
- KDA computational complexity is independent from the order d
- Tested and effective on a real case, positively compared to PP

	2nd order	3-rd order	4th order
KDA	✓	✓	✓
PP	✓	–	–

Limits and drawbacks

- Memory-based $[\epsilon_\ell^{\mathrm{KDA}}(\vec{x}) = \sum_{i=1}^{N} \vec{\nu}_\ell[i] K(\mathbf{x}_i^{z_i}, \mathbf{x})]$

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- No localisation of PoIs

Contents

Motivations

Profiling phase

- manage de-synchronization problem $[\mathcal{D}_{\text{train}} \longrightarrow \rho : \mathbb{R}^D \rightarrow \mathbb{R}^D]$
- mandatory dimensionality reduction $[\mathcal{D}_{\text{train}} \longrightarrow \epsilon : \mathbb{R}^D \rightarrow \mathbb{R}^C]$
- 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)

Many independent preprocessing steps and assumptions

Motivations

Profiling phase **DEEP LEARNING**

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

Many independent preprocessing steps and assumptions
$\longleftrightarrow$ integrated and agnostic approach

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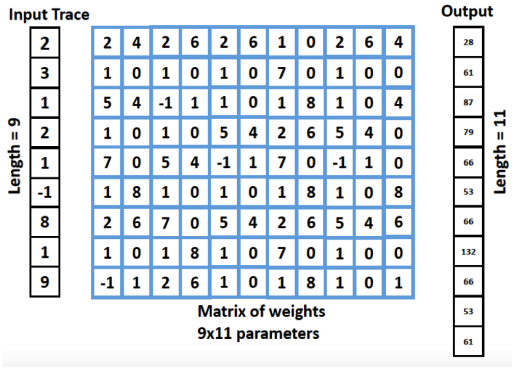
λ_i linear functions (linear combinations of time samples) depending on some **trainable weights** W



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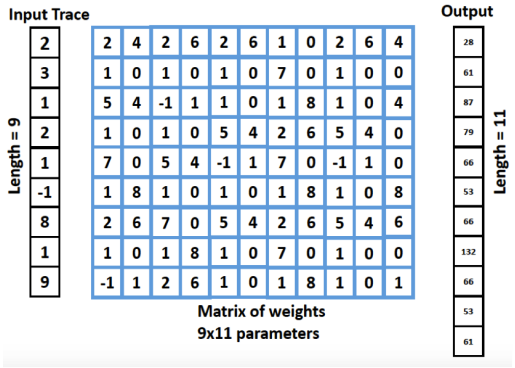
σ_i non-linear *activation* functions



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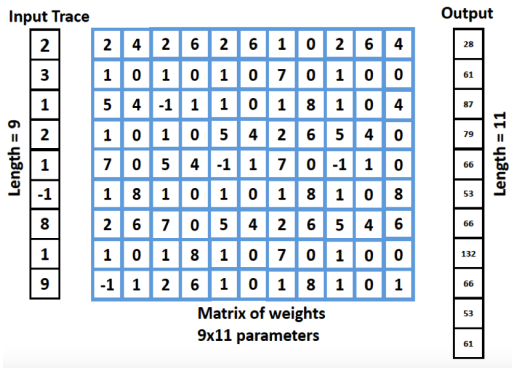

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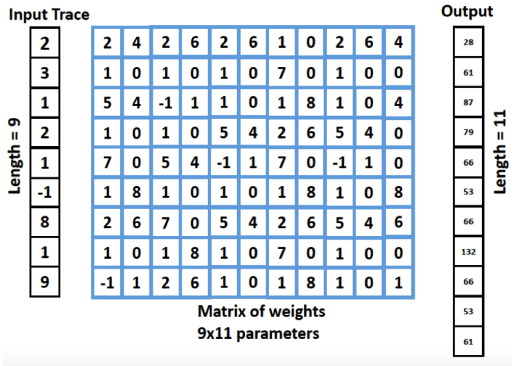
Architecture hyper-parameters



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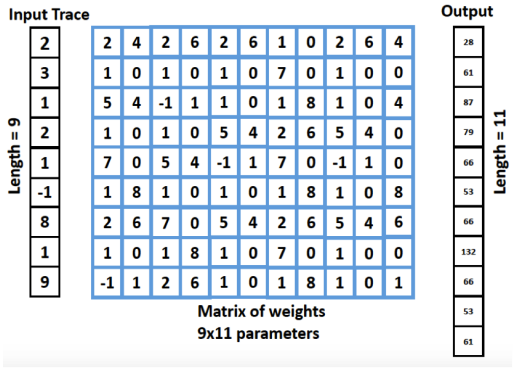
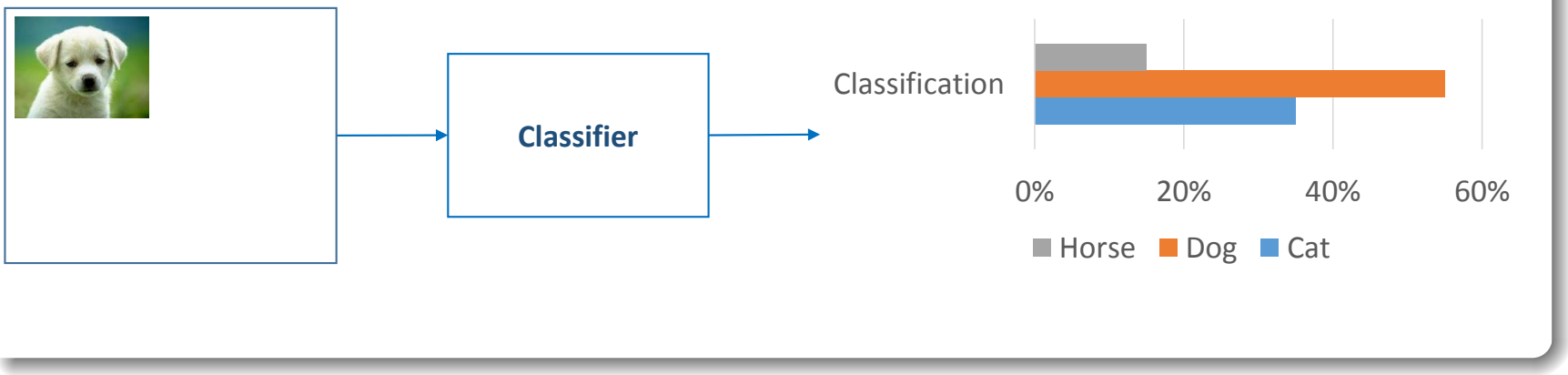
s normalizing *softmax* function — Architecture hyper-parameters

Universal approximation theorem



Convolutional Neural Networks

Translation-Invariance



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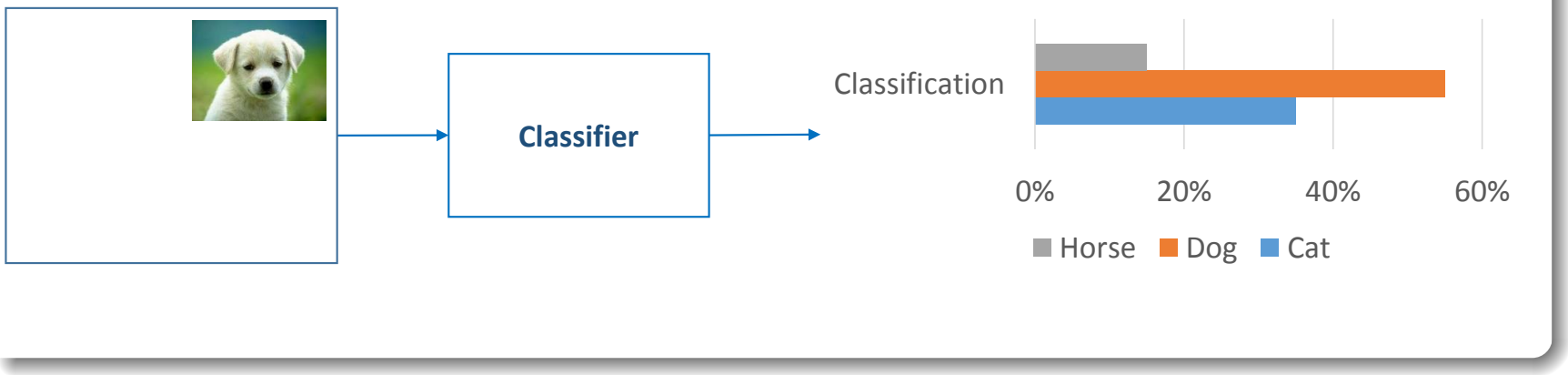

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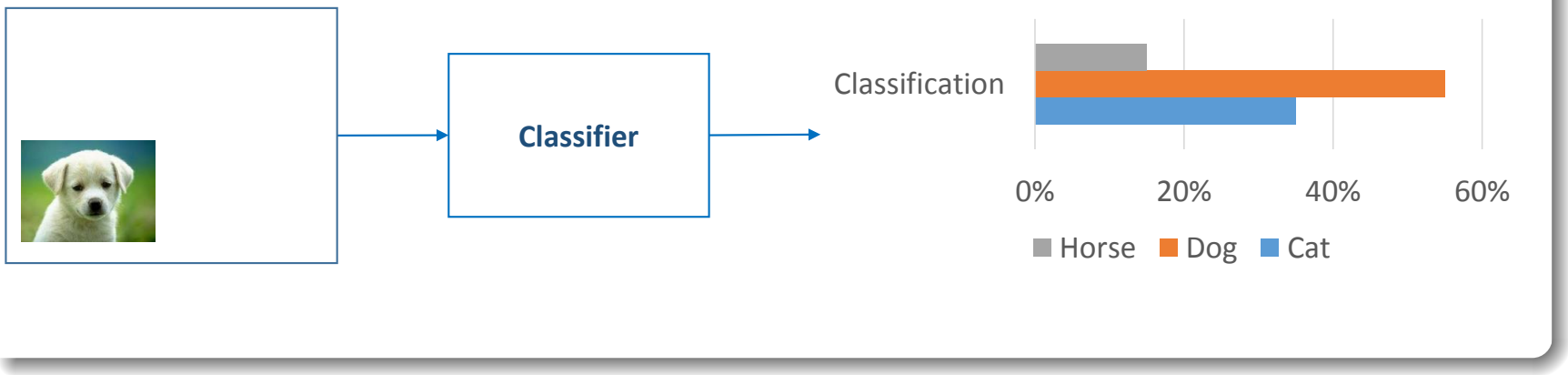


Convolutional Neural Networks

Translation-Invariance

Convolutional Neural Networks

Translation-Invariance

Convolutional Neural Networks

Translation-Invariance

Convolutional Layers

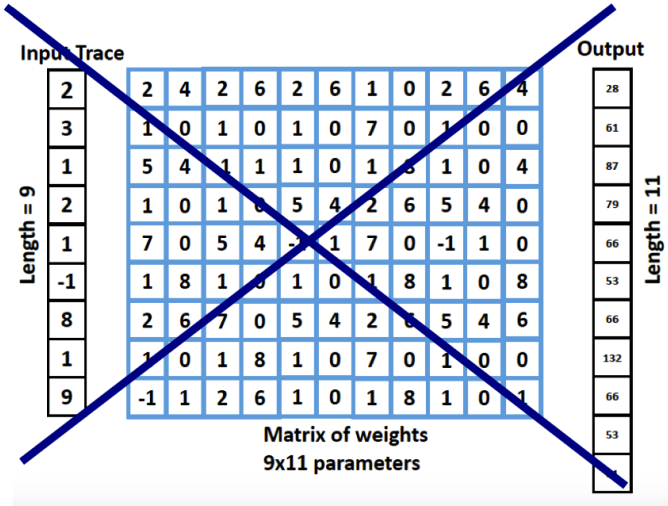


Figure: Linear layer in an MLP.

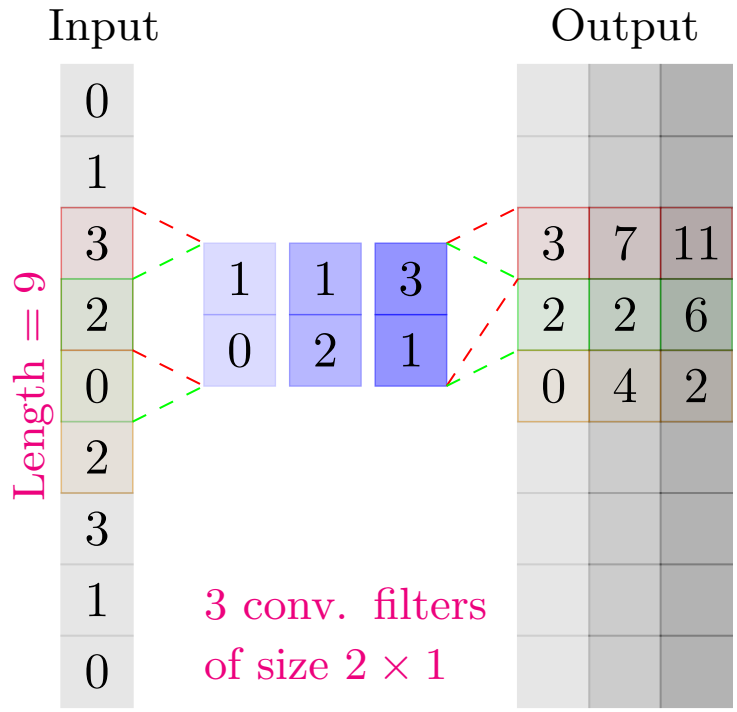
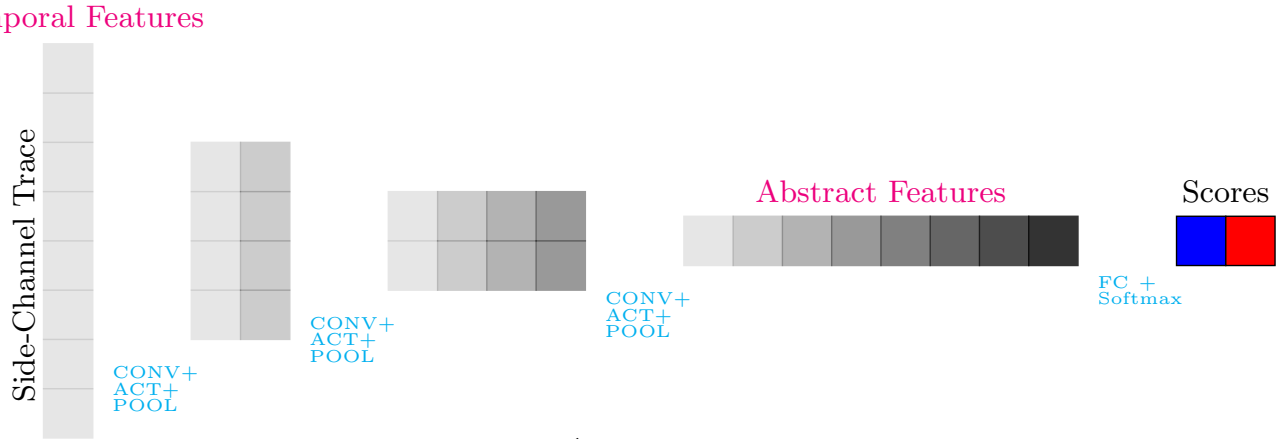


Figure: Convolutional layer in a CNN.

A kind of CNN architecture



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

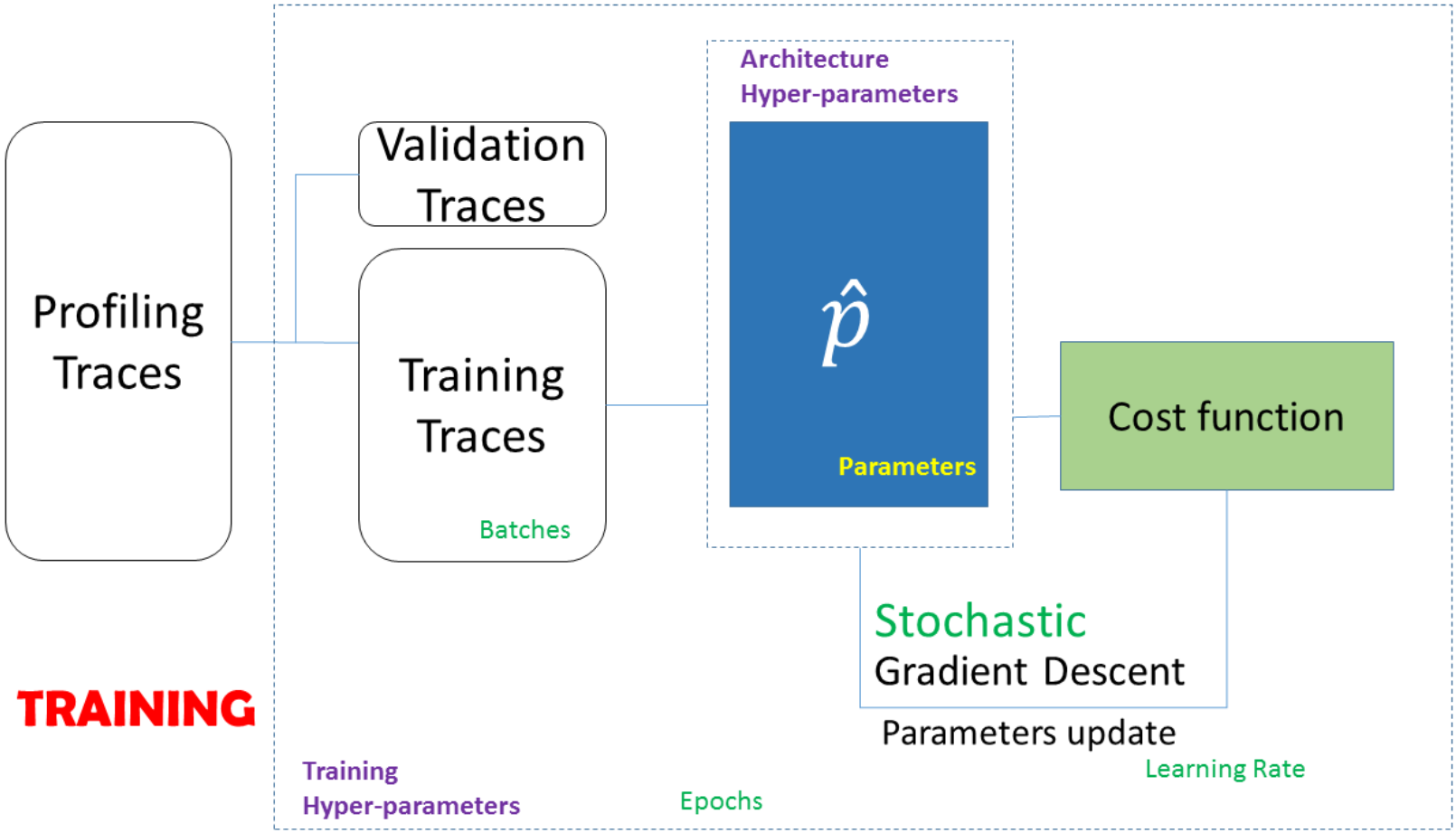
- Reduce temporal features to only one
- Maintain time complexity of each layer (one-half pooling when number of feature maps is doubled)

Model used in our experiments

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

Training and Validation

Training and Validation



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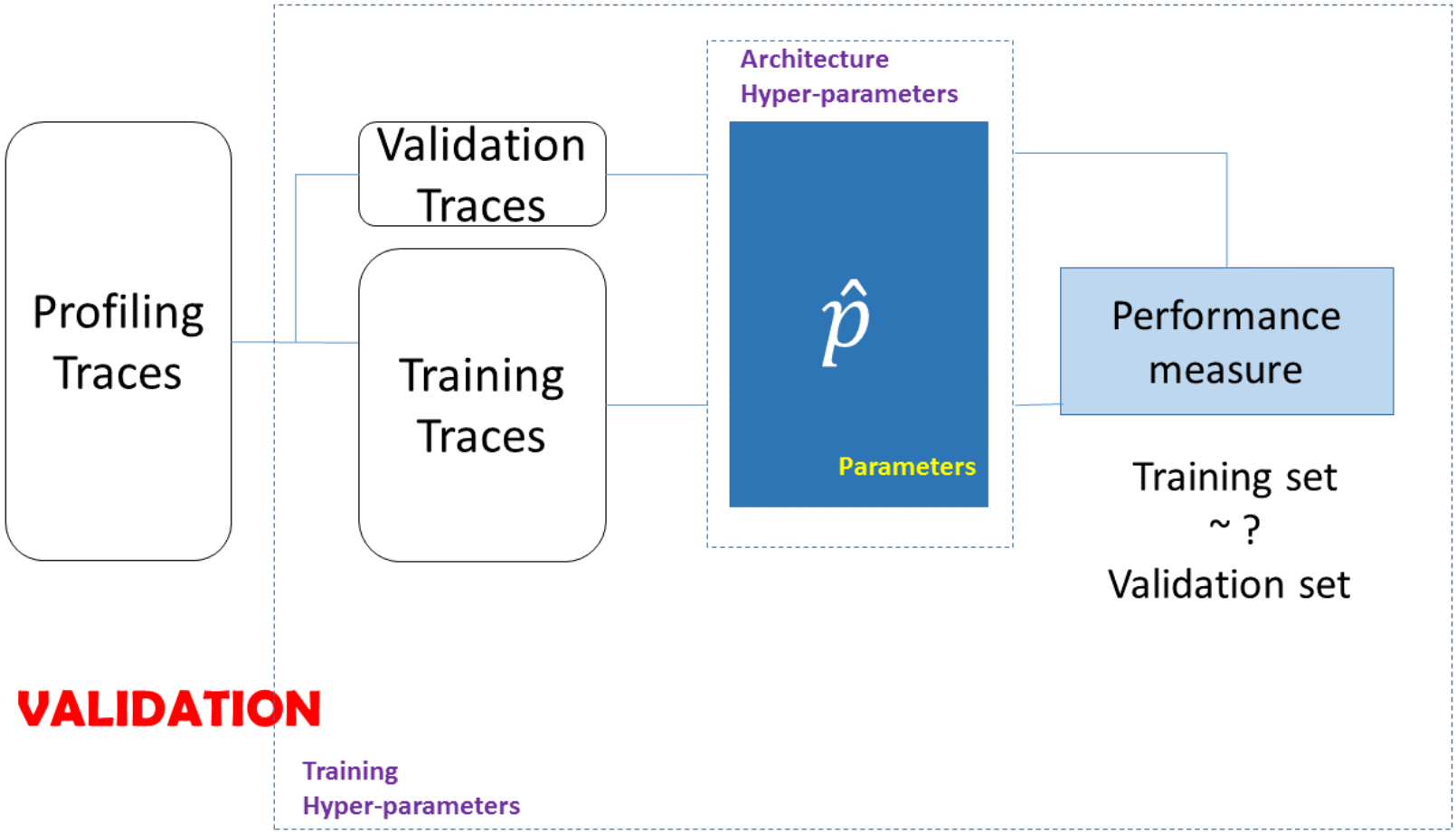
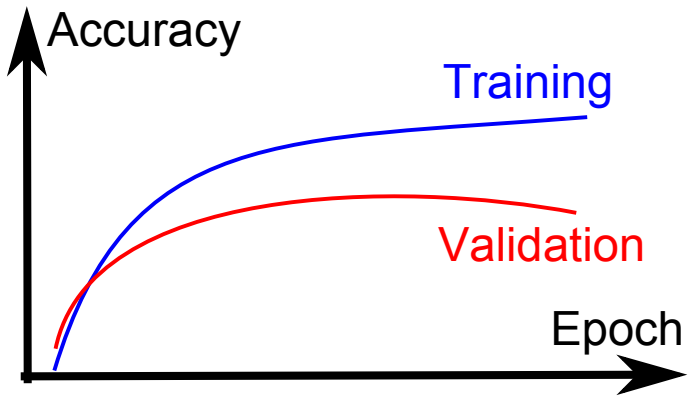


Overfitting

Evaluate and compare training and validation accuracy

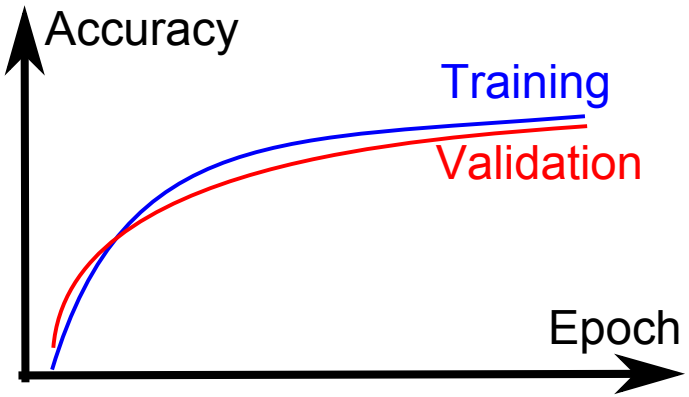
Learn by heart (**OVERFITTING**)



Overfitting

Evaluate and compare training and validation accuracy

Understand significant features



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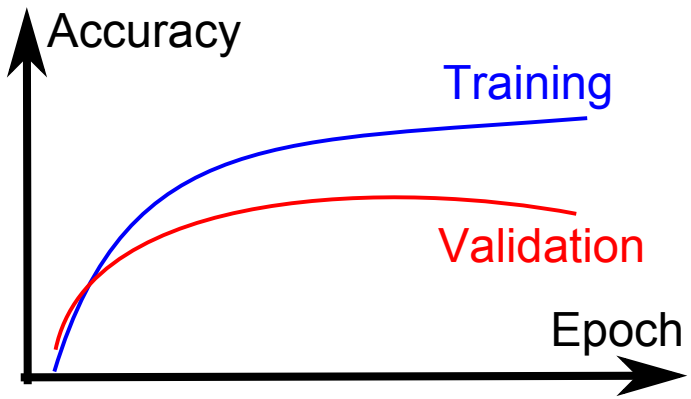

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Why?

- Too complex model
- Not enough training data

Solution?

- Reduce model capacity
- Regularization
- Dropout
- Data augmentation

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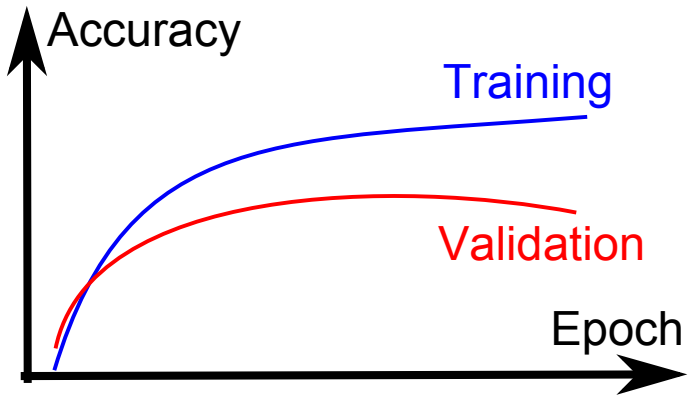

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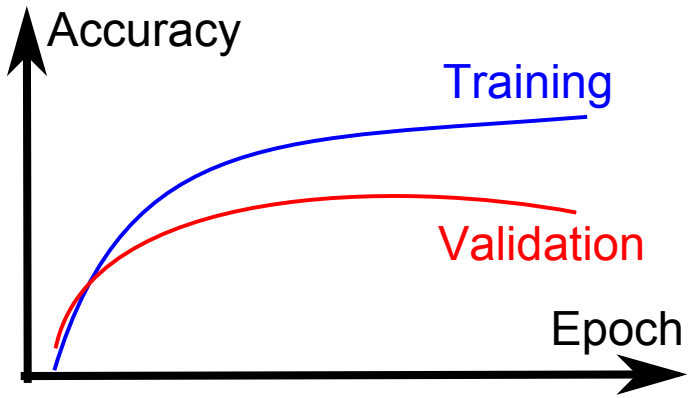

Data Augmentation

Data Augmentation

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

Countermeasure Emulation Idea

Emulate the effects of misaligning countermeasures to generate new traces

SHIFTING

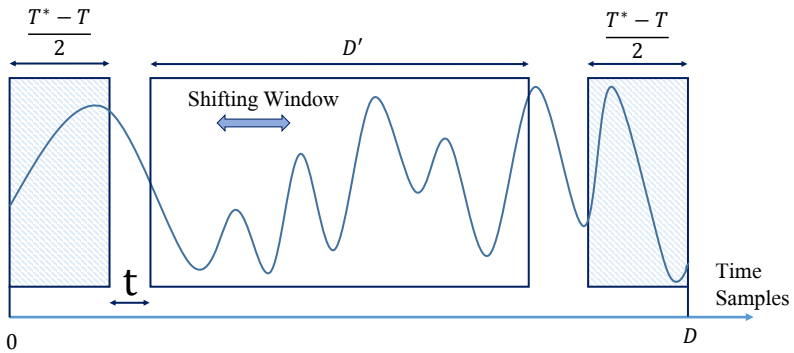

Figure: SH_T

ADD-REMOVE

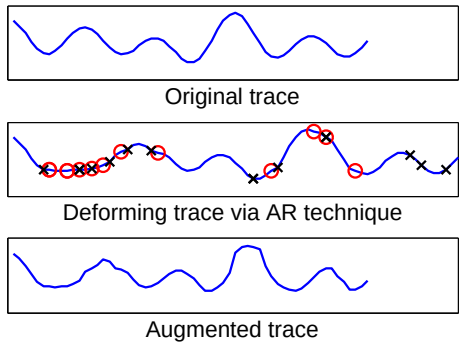

Figure: AR_R

Parameter T: ♯ of possible positions
Parameter R: ♯ of added and removed points
Data Augmentation techniques are applied online during training phase.

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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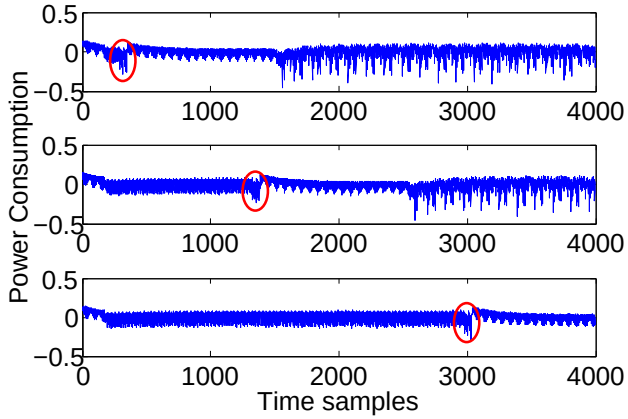
Random delays



(a) One leaking operation

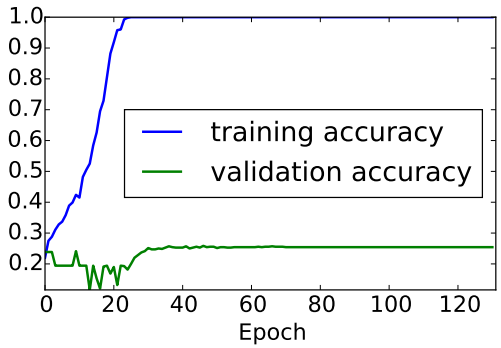
Setup

- 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

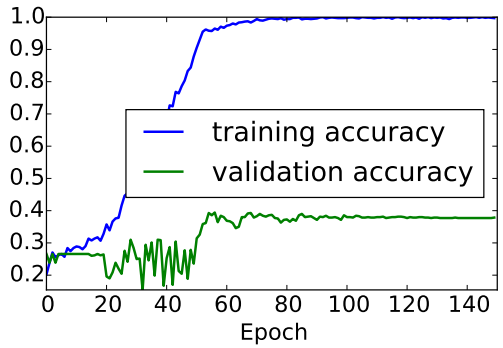
Random delays

Data augmentation vs overfitting

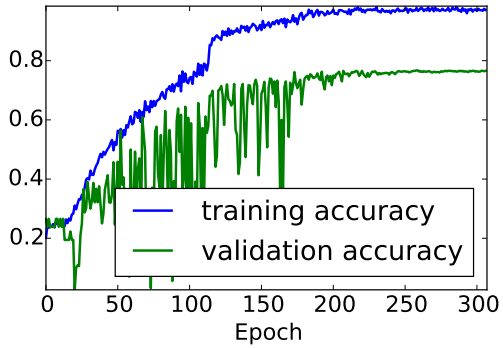
Training



SH_0



SH_{100}

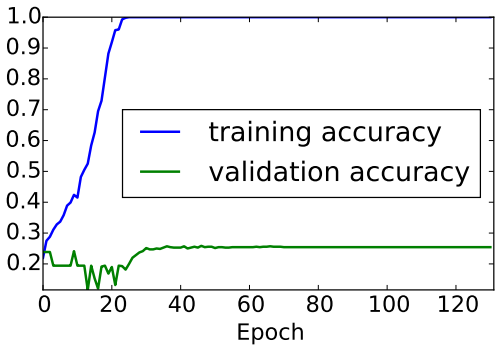


SH_{500}

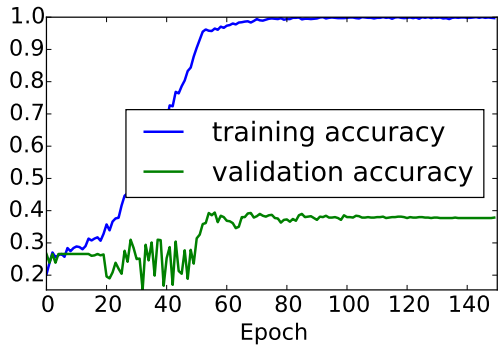
Random delays

Data augmentation vs overfitting

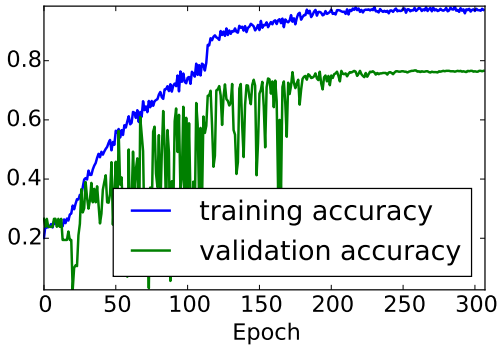
Training



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.

Conclusions about CNN

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Contents

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- In many domains Machine Learning solutions are used to tackle it
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- From CNN to PoIs, visualizing techniques
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Thank You!

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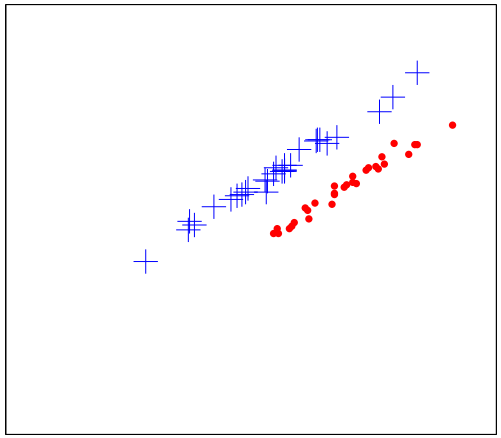
LDA: an optimal binary linear classifier



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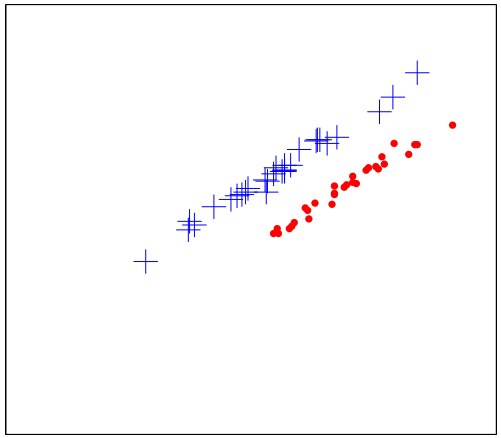

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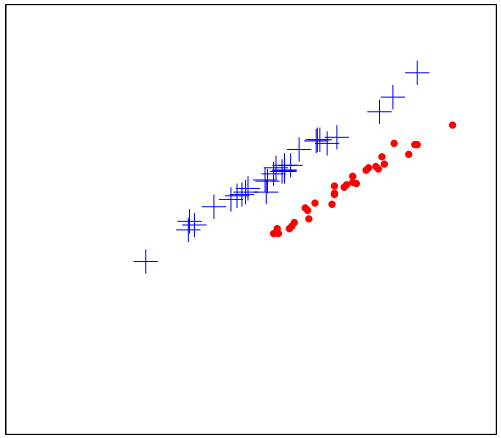

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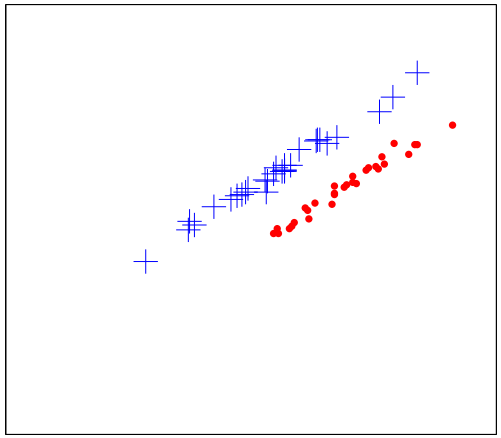

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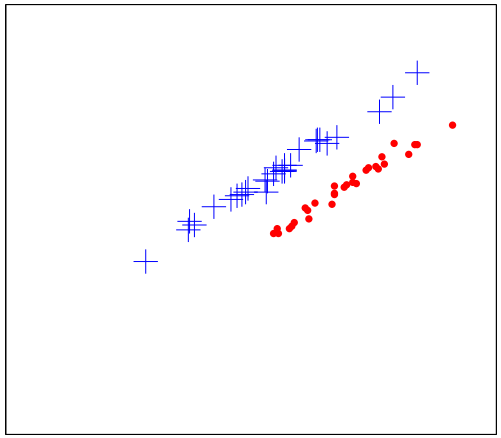

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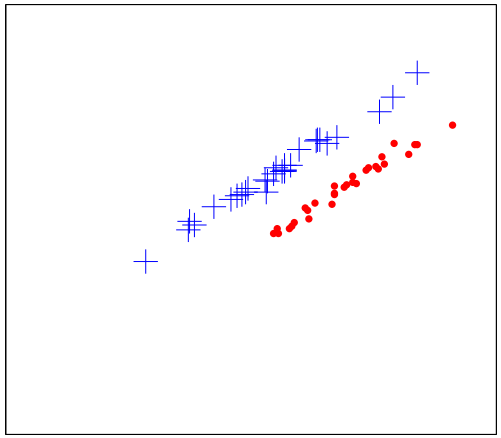

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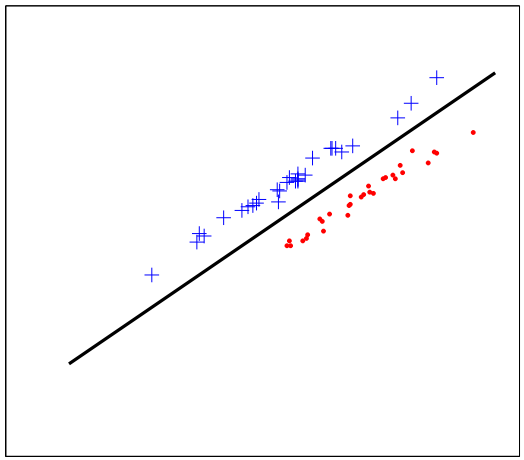
Generalised linear discriminative model

$$\Pr(s_1 \mid \vec{x}) = \sigma(\vec{w}^\intercal \vec{x} + w_0) \text{ ,where } \sigma(a) = \frac{1}{1+e^{-a}} \textit{ logistic sigmoid} \qquad (2)$$

LDA and Fisher Criterion



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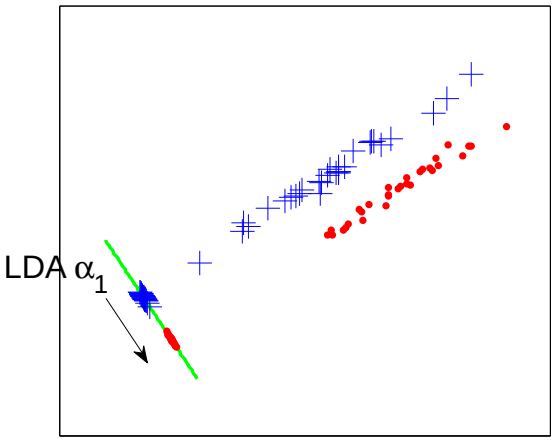

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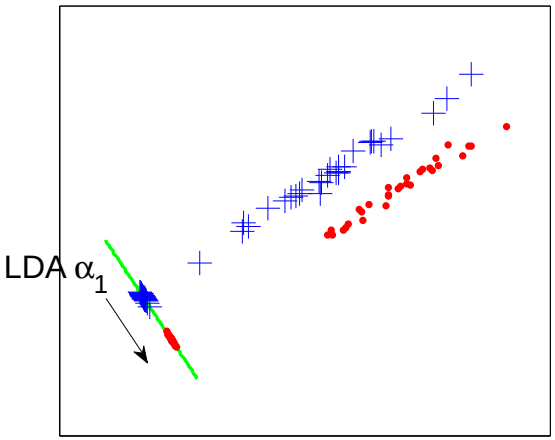

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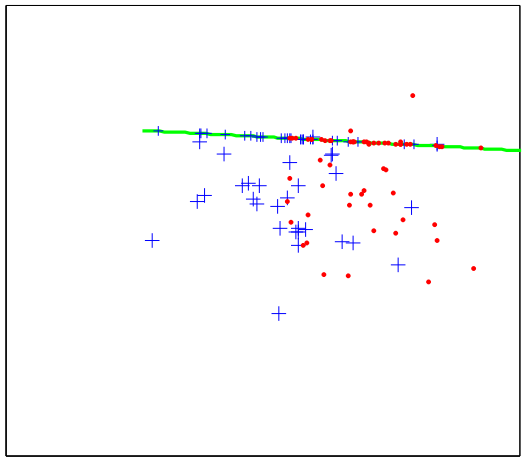
Fact, abuse and preference for the dimensionality reduction formulation

- When LDA assumptions are met, the solution $\vec{\alpha}_1$ of the Fisher's criterion is orthogonal to $\vec{w}$.
- assumption not required
- naturally multi-class

Linear separability

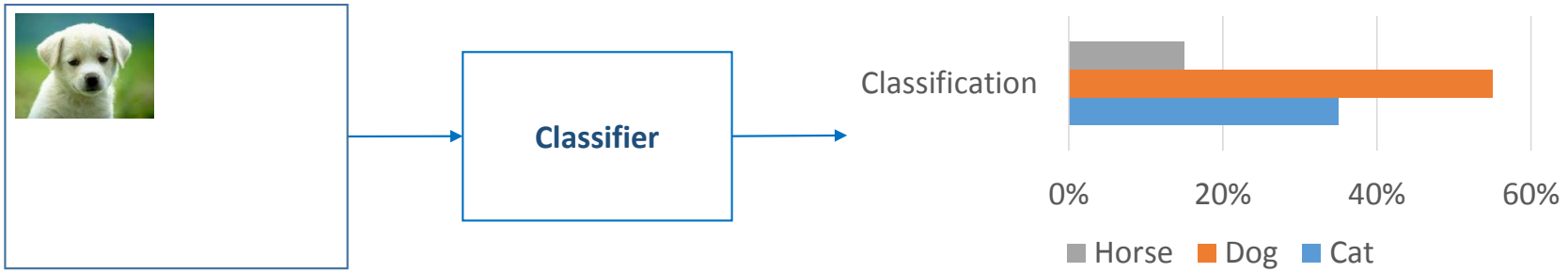


LDA: linear decision boundary $a = \vec{w}^{\intercal}\vec{x} + w_0$ $(\vec{w} = \Sigma^{-1}(\mu_1 - \mu_2))$

What if $\mu_1 = \mu_2$?

Convolutional Neural Networks

Translation-invariance



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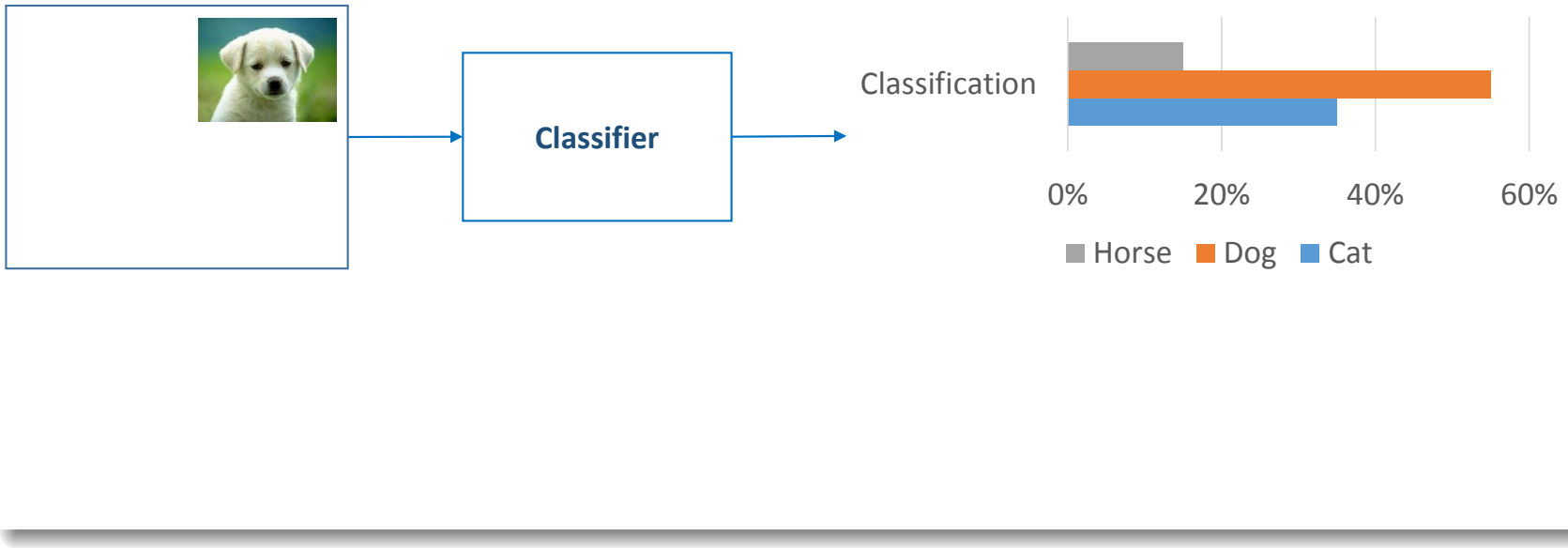
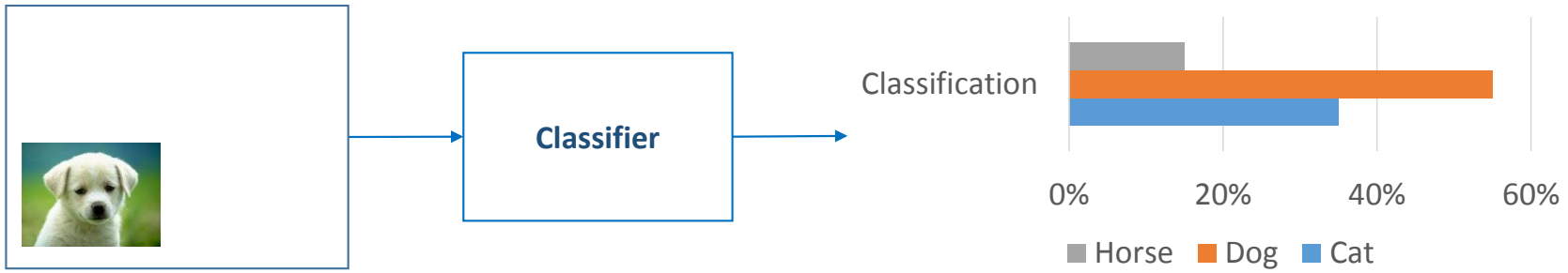


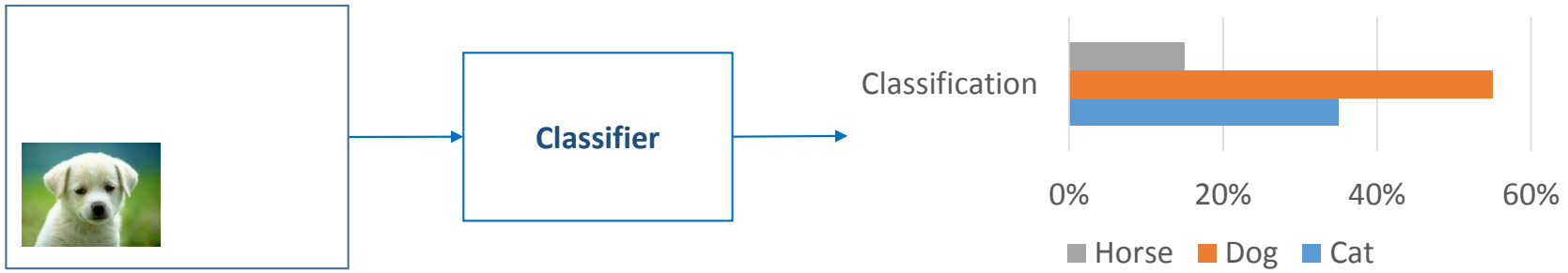
Convolutional Neural Networks

Translation-invariance



Convolutional Neural Networks

Translation-invariance



It is important to explicit the data translation-invariance

Convolutional Neural Networks

Translation-invariance

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Translation-invariance

It is important to explicit the data translation-invariance
Convolutional Neural Networks: share weights across space

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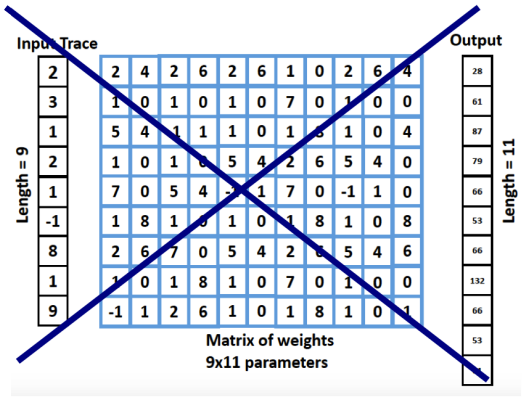


Figure: Linear layer in an MLP (*Fully Connected layer*)

Convolutional Neural Networks

Translation-invariance

It is important to explicit the data translation-invariance
Convolutional Neural Networks: share weights across space

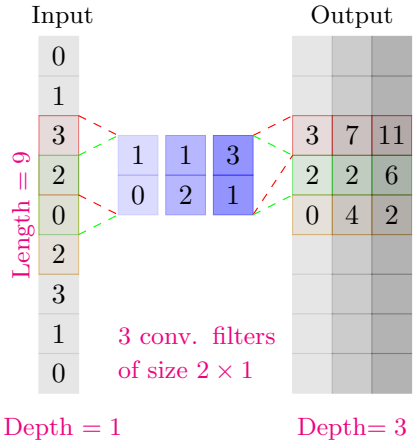
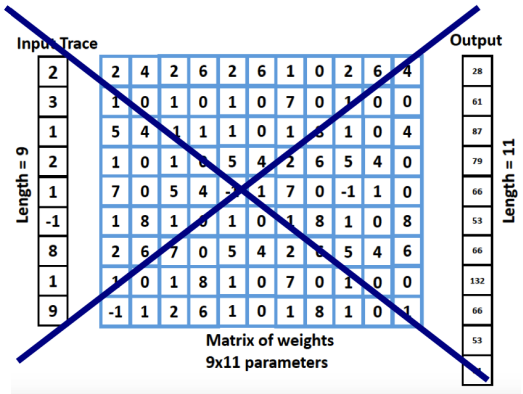


Figure: Linear layer in a ConvNet (*Convolutional Layer*)



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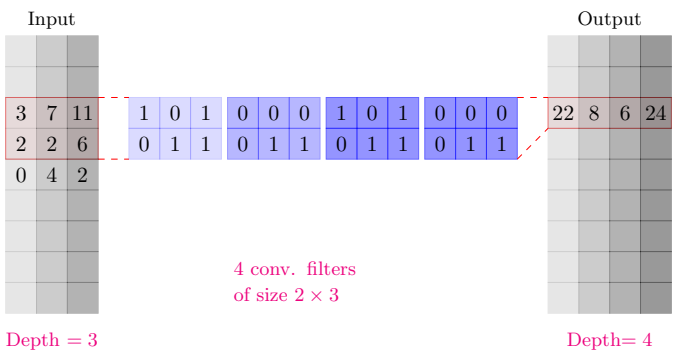

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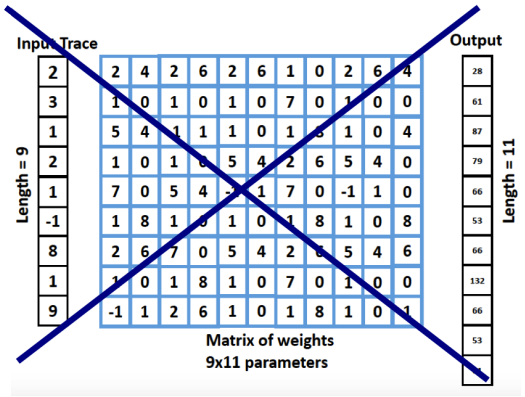

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Convolutional Neural Networks

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Convolutional Neural Networks: share weights across space

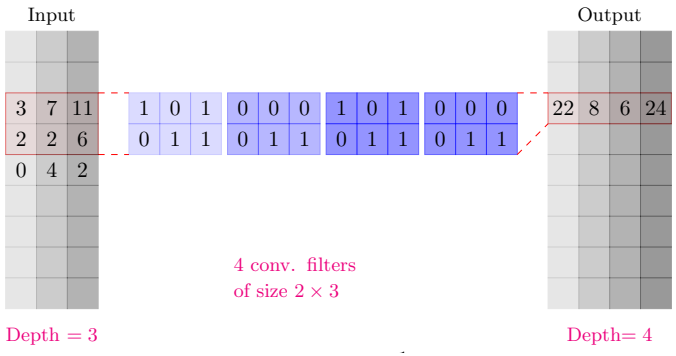


Figure: Linear layer in a ConvNet (*Convolutional Layer*)

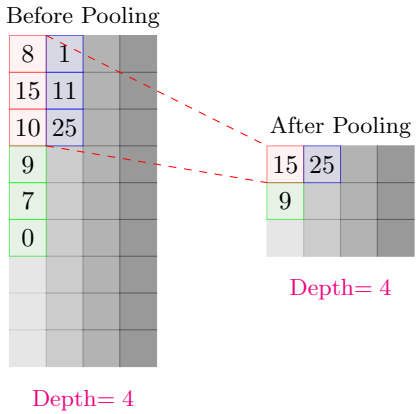


Figure: Max Pooling Layer

Cost function - Cross-entropy

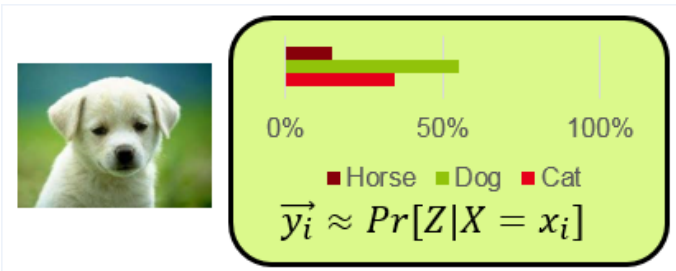
- batch of training data $(\vec{x}_i, z_i)_{i \in I}$, outputs of the current model $(\vec{y}_i)_{i \in I}$
- labels $z_i = s_j$ are *one-hot encoded*: $\vec{z}_i = \vec{s}_j = (0, \ldots, 0, \underbrace{1}_{j}, 0, \ldots, 0)$

Loss function

$$\mathcal{L} = -\frac{1}{|I|} \sum_{i \in I} \sum_{t=1}^{|\mathcal{Z}|} \vec{z}_i[t] \log \vec{y}_i[t] \tag{3}$$

Maximum-*a-posteriori* or Cross-entropy

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



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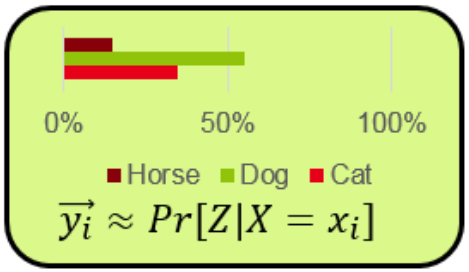
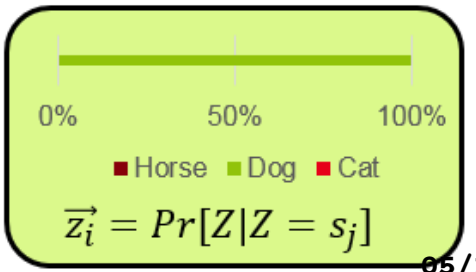
Maximum-*a-posteriori* or Cross-entropy

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





Regression example

Performance metric: Mean Square Error (MSE)

MSE_train=44.228280, MSE_test=330.984916

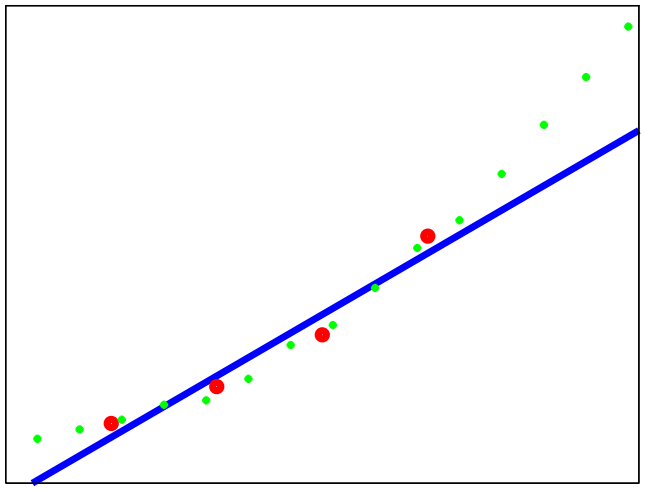


Figure: Linear regression → underfitting

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Performance metric: Mean Square Error (MSE)

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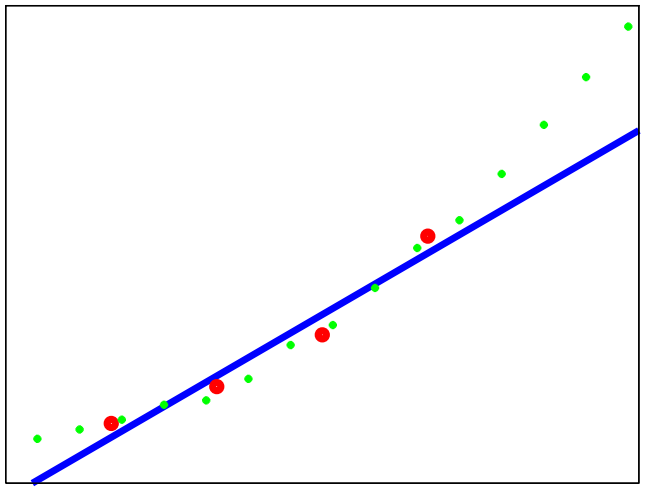


Figure: Linear regression → underfitting

MSE_train=2.243097, MSE_test=61.891672

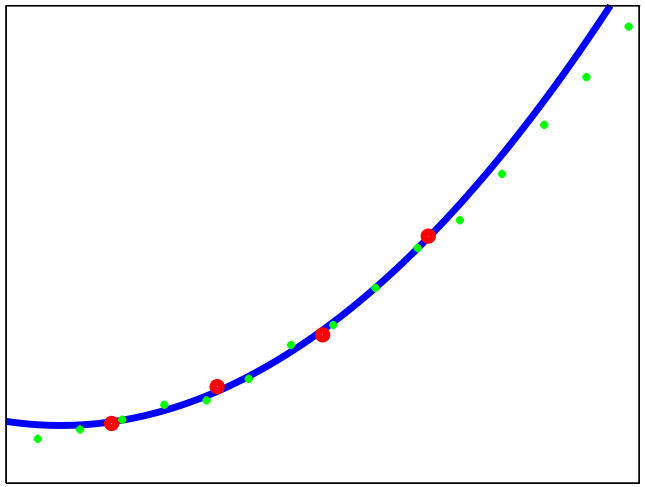


Figure: Quadratic regression → fits

Regression example

Performance metric: Mean Square Error (MSE)

MSE_train=0, MSE_test=970.081580

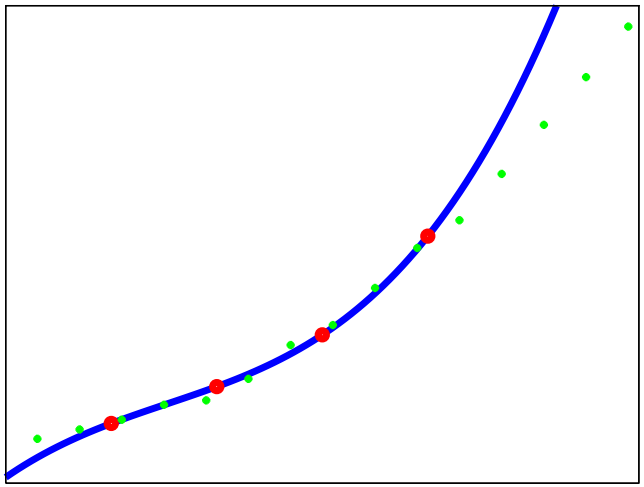
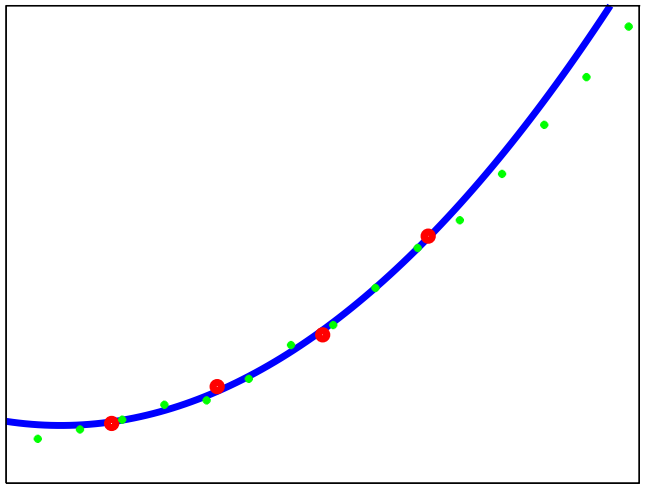


Figure: Cubic regression → overfitting

MSE_train=2.243097, MSE_test=61.891672



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Regression example

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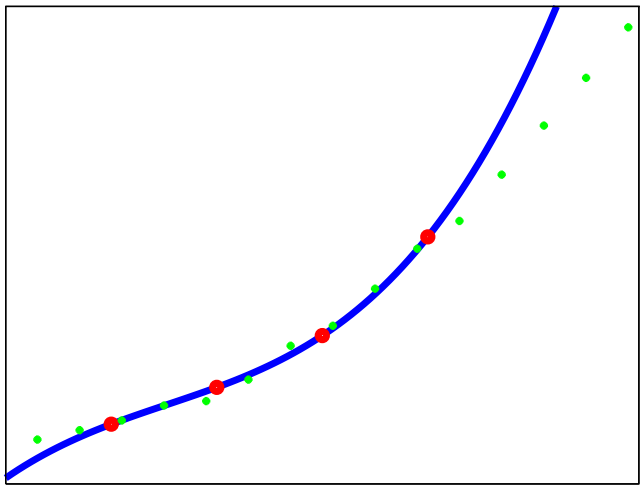


Figure: Cubic regression → overfitting

MSE_train=3.040333, MSE_test=58.377719

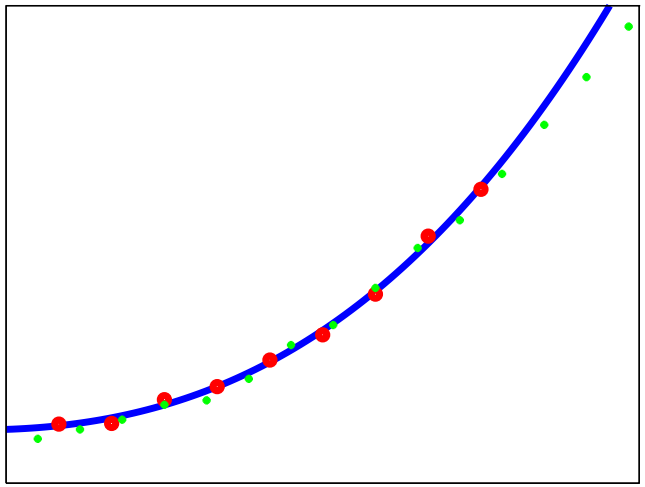


Figure: Cubic regression with more training data

Capacity-Overfitting-Regularization

Regression example

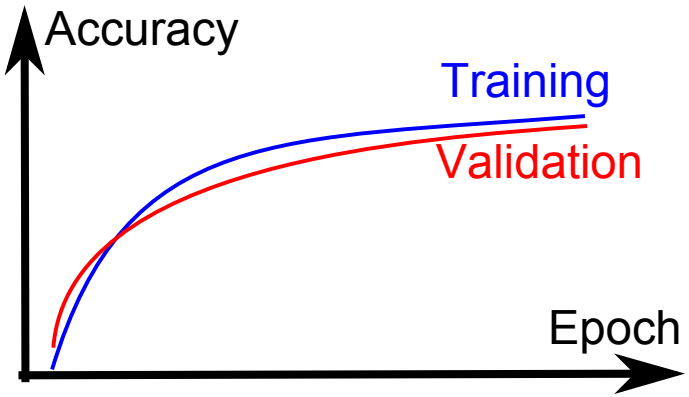
Performance metric: Mean Square Error (MSE)

Classification via Neural Network

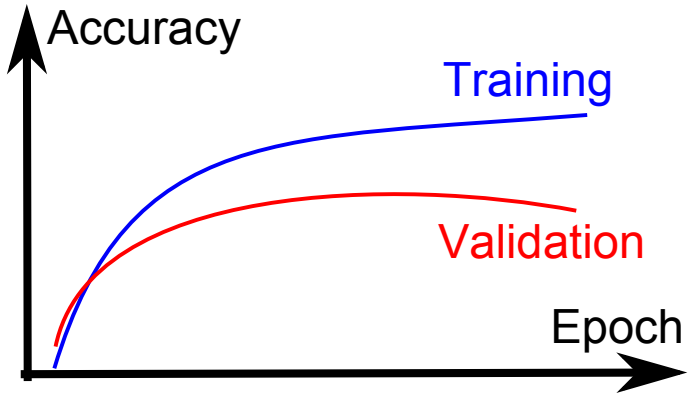
Performance measure: Accuracy (Classification rate)

Evaluate and compare training and validation accuracy

Understand significant features



Learn by heart (**OVERFITTING**)



Capacity-Overfitting-Regularization

Regression example

Performance metric: Mean Square Error (MSE)

Classification via Neural Network

Performance measure: Accuracy (Classification rate)

Evaluate and compare training and validation accuracy

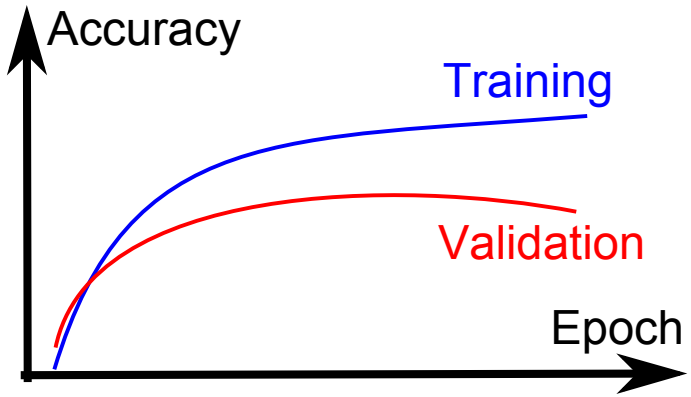
Learn by heart (**OVERFITTING**)

Why?

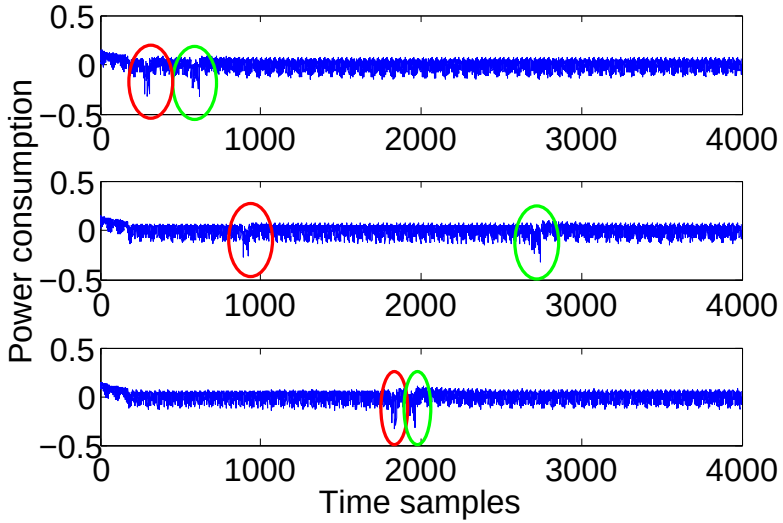
- Too complex model
- Not enough training data

Solution?

- Data augmentation



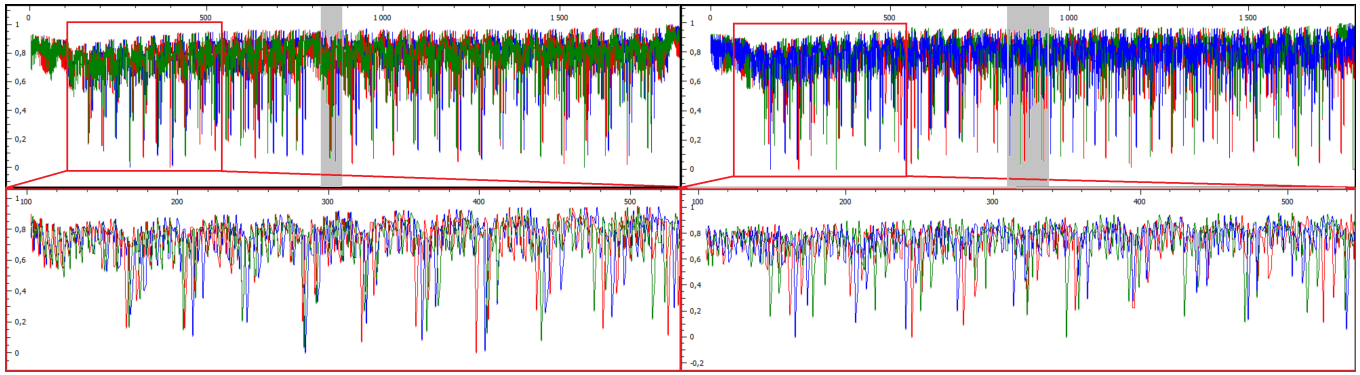
Random Delays - Two Leaking Operations



Two leaking operations

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

Artificial Jitter



(a) Low artificial jitter (b) High artificial jitter

Target

- Target Variable: $Z = \mathrm{HW}(\mathrm{Sbox}(P \oplus K))$
- $\approx$ 2000 time samples
- Countermeasure: artificial signal treatment simulating clock jitter
- 10000 training traces

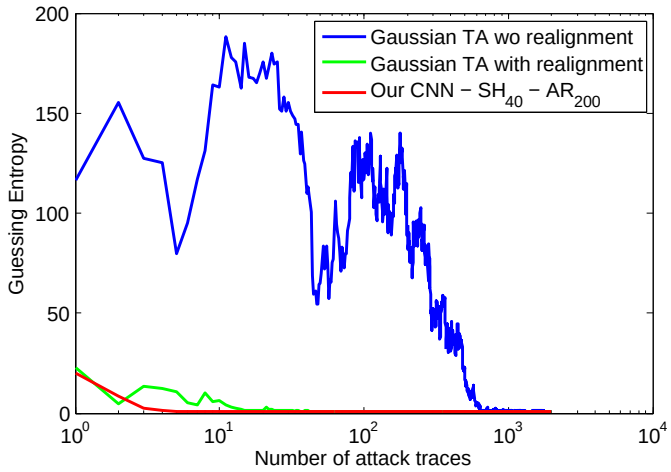
Artificial Jitter (2)

Low_jitter

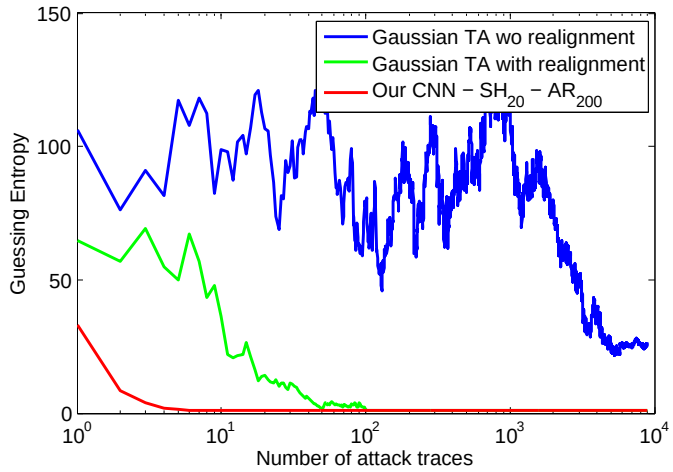
Acc	$N^\star$	SH_0		SH_{20}		SH_{40}	
AR_0		57.4%	14	82.5%	6	83.6%	6
AR_{100}		86.0%	6	87.0%	5	87.5%	6
AR_{200}		86.6%	6	85.7%	6	**87.7%**	5

High_jitter

Acc	$N^\star$	SH_0		SH_{20}		SH_{40}	
AR_0		40.6%	35	51.1%	9	62.4%	11
AR_{100}		50.2%	15	72.4%	11	73.5%	9
AR_{200}		64.0%	11	**75.5%**	8	74.4%	8



(c) Low Jitter



(d) High Jitter

Artificial Jitter

DS_low_jitter									
a / *c*	*b* / *d*	SH_0		SH_{20}		SH_{40}		SH_{200}	
AR_0		100.0%	68.7%	99.8%	86.1%	98.9%	84.1%		
		57.4%	14	82.5%	6	83.6%	6		
AR_{100}		87.7%	88.2%	82.4%	88.4%	81.9%	89.6%		
		86.0%	6	87.0%	5	87.5%	6		
AR_{200}		83.2%	88.6%	81.4%	86.9%	80.6%	88.9%		
		86.6%	6	85.7%	6	87.7%	5		
AR_{500}								85.0%	88.6%
								86.2%	5

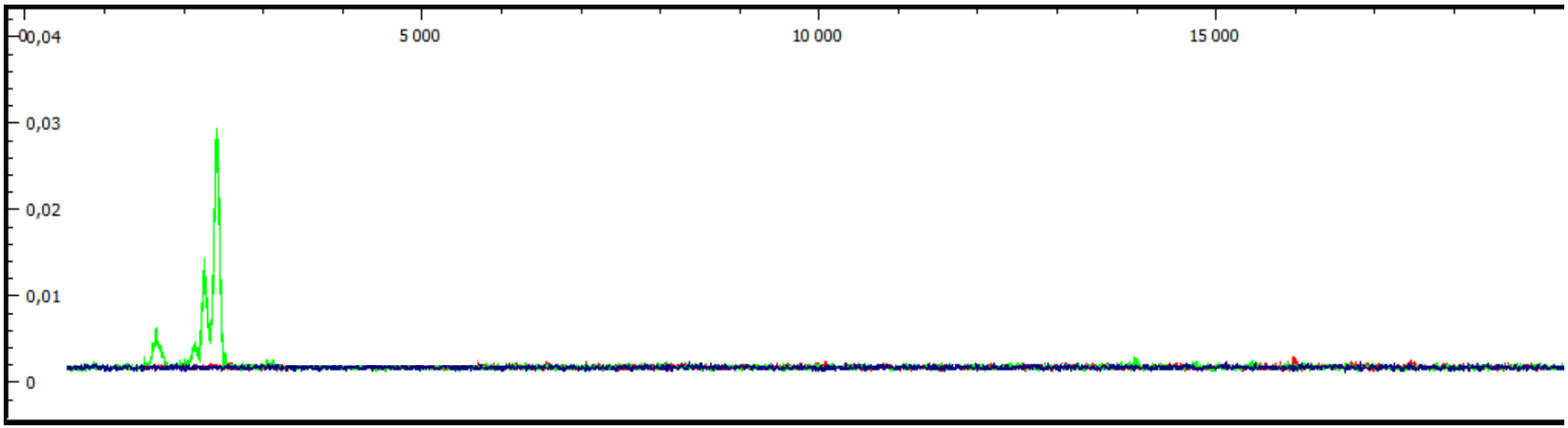
DS_high_jitter									
a / *c*	*b* / *d*	SH_0		SH_{20}		SH_{40}		SH_{200}	
AR_0		100%	45.0%	100%	60.0%	98.5%	67.6%		
		40.6%	35	51.1%	9	62.4%	11		
AR_{100}		90.4%	57.3%	76.6%	73.6%	78.5%	76.4%		
		50.2%	15	72.4%	11	73.5%	9		
AR_{200}		83.1%	67.7%	82.0%	77.1%	82.6%	77.0%		
		64.0%	11	75.5%	8	74.4%	8		
AR_{500}								83.6%	73.4%
								68.2%	11

Real Jitter (1)

Target

- AES hardware implementation
- strong jitter effect
- Target Variable: $Z = \mathrm{Sbox}(P \oplus K)$
- $2,500$ selected time samples
- $99,000$ training traces

SNR first Sbox



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Target

- AES hardware implementation
- strong jitter effect
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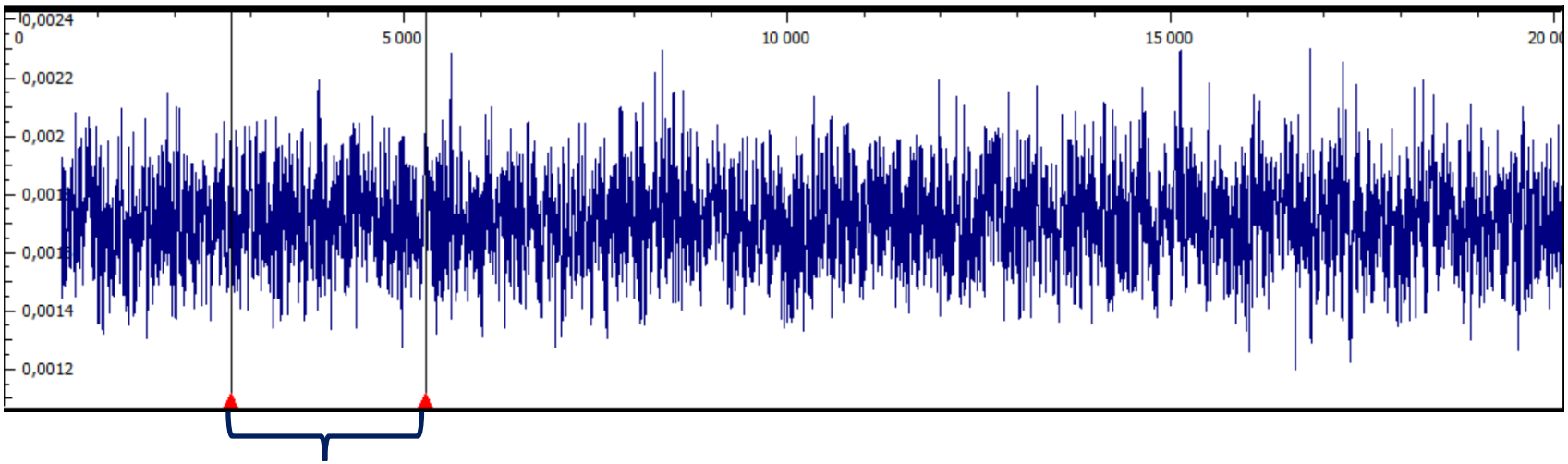
- $2,500$ selected time samples
- $99,000$ training traces

SNR second Sbox without realignment



Entry region for CNN (2,500 pts)

Real Jitter (2)

		SH_0AR_0		$SH_{10}AR_{100}$		$SH_{20}AR_{200}$	
Acc	$N^\star$	1.2%	137	1.3%	89	1.8%	54

Real Jitter (2)

		SH_0AR_0		$SH_{10}AR_{100}$		$SH_{20}AR_{200}$	
Acc	$N^\star$	1.2%	137	1.3%	89	1.8%	54

SNR second Sbox with realignment