

FROM RESEARCH TO INDUSTRY

cea tech



Feature Extraction for Side-Channel Attacks

Eleonora Cagli

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CESTI - Centre d'Évaluation de la Sécurité des
Technologies de l'Information - CEA Grenoble

LIP6 - Laboratoire d'Informatique de Paris 6

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PhD Supervisor : Emmanuel Prouff
(ANSSI)
CEA Supervisor : Cécile Dumas
(CESTI - CEA Grenoble)

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2. State of the Art, Objectives, Contributions
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 - 3.1 Kernel Discriminant Analysis
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5. Conclusions

Secure Component and Embedded Cryptography

Secure Component and Embedded Cryptography

- ▶ Sensitive applications
- ▶ Pervasive aspect
- ▶ Hostile environment



⇒ Requires protection against very high-level attacker

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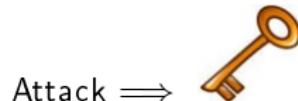
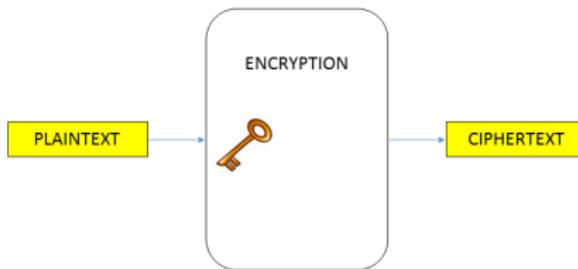
Side-Channel Vulnerability of Embedded Cryptography



Attack \implies a secret

Classical Attacks	Side-Channel Attacks
Mathematical vulnerability	
Black Box	

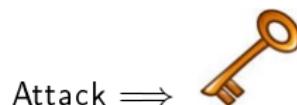
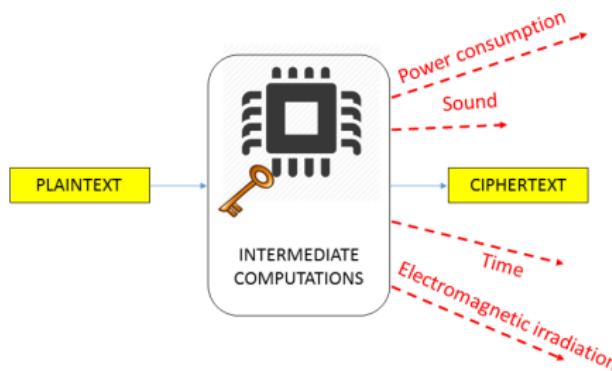
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Classical Attacks	Side-Channel Attacks
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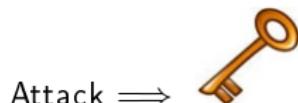
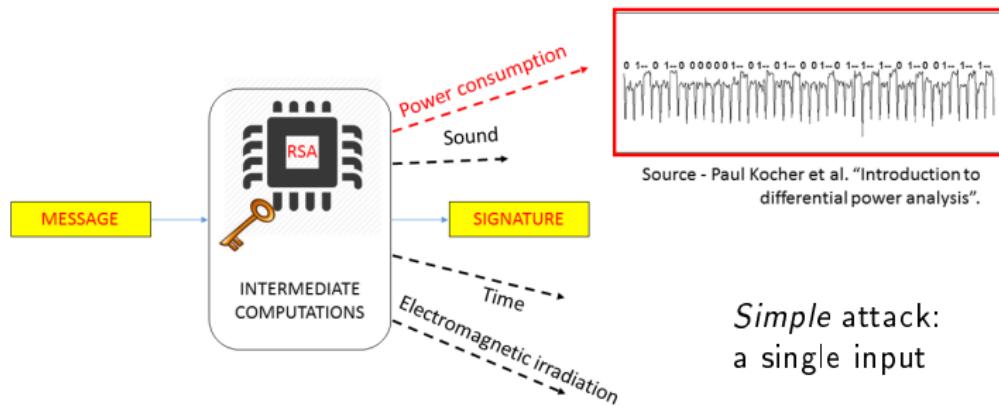
Mathematical vulnerability
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Side-Channel Vulnerability of Embedded Cryptography



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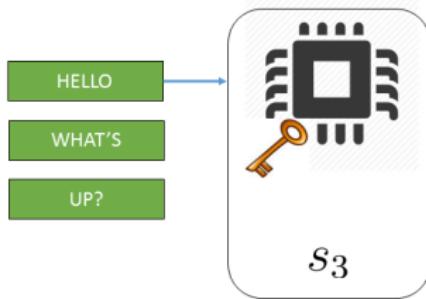
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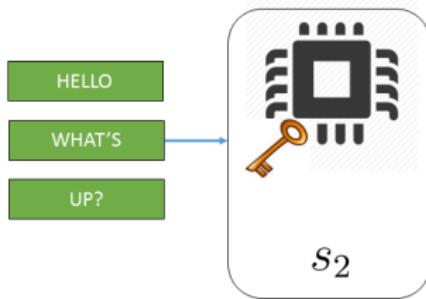
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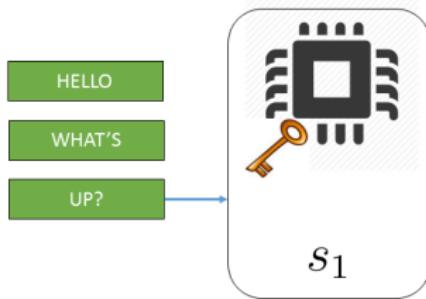
Advanced Side-Channel Attacks



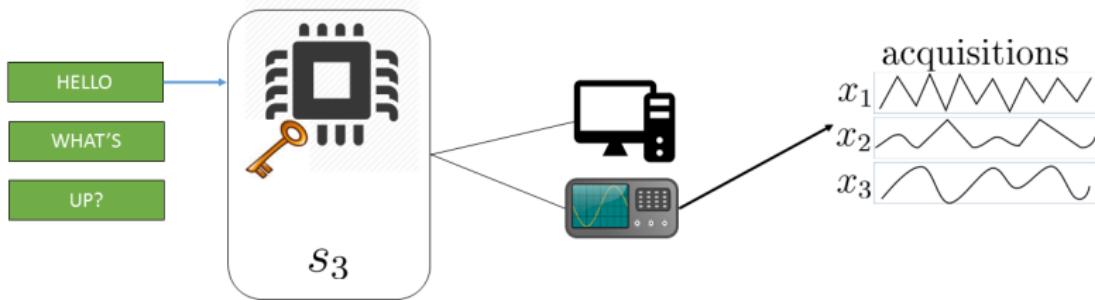
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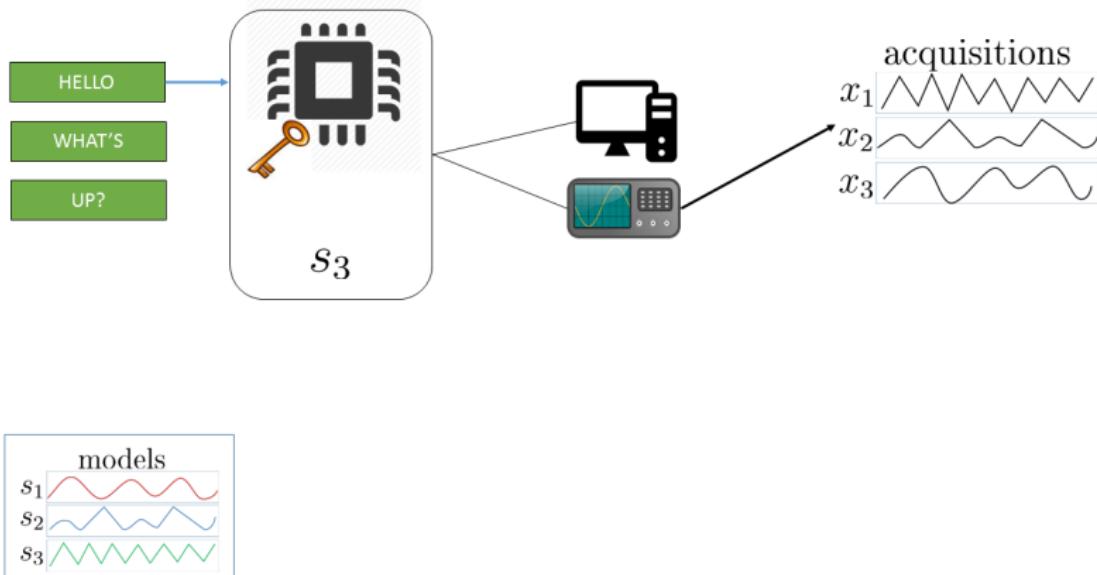
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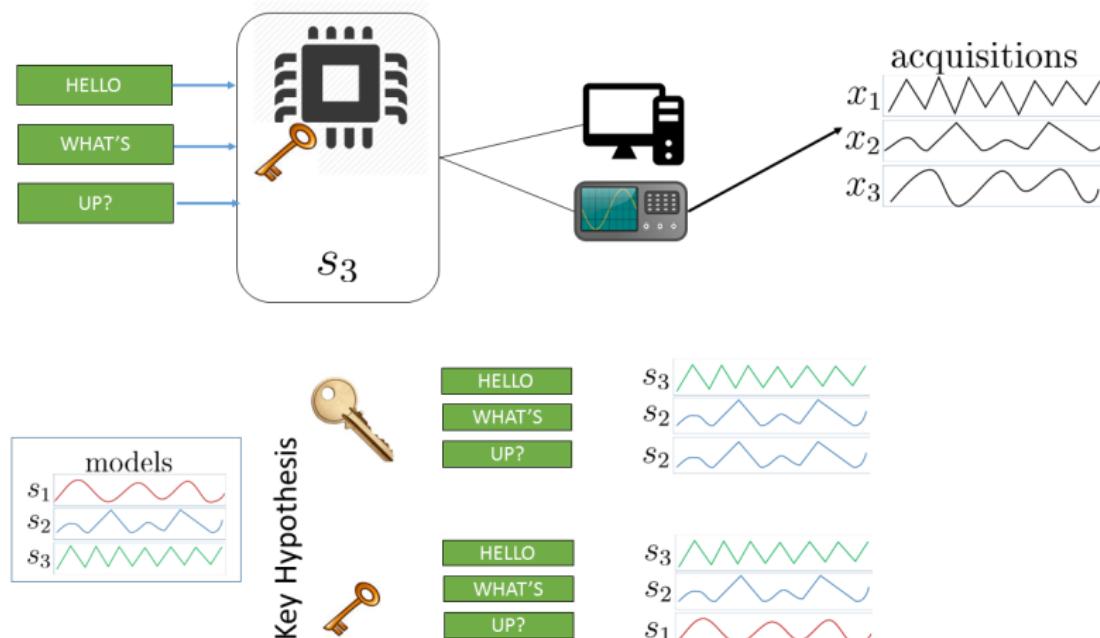
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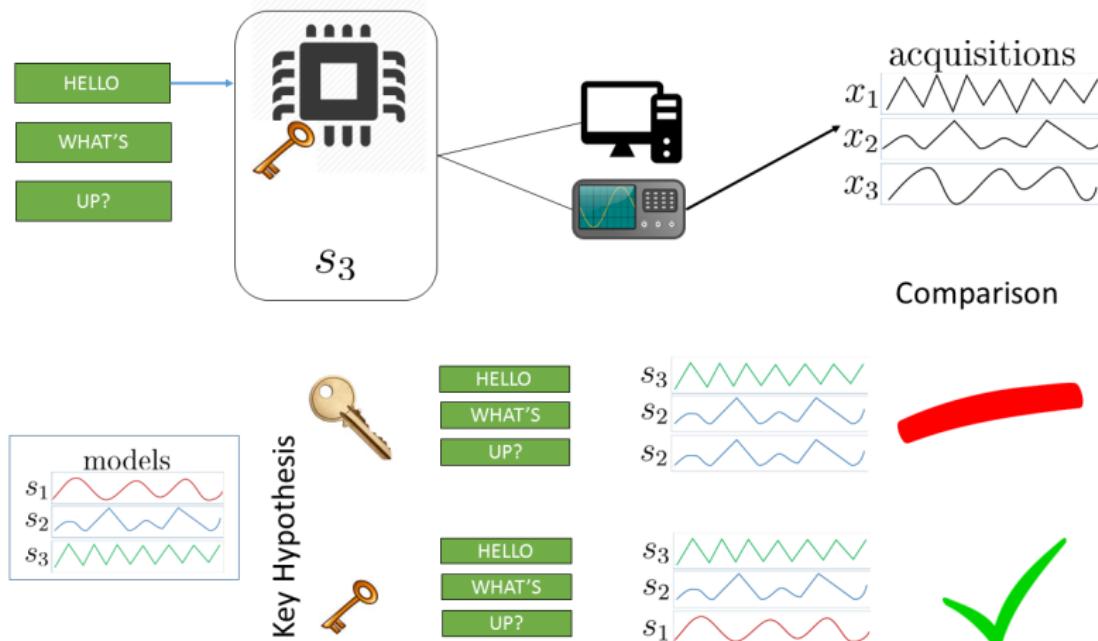
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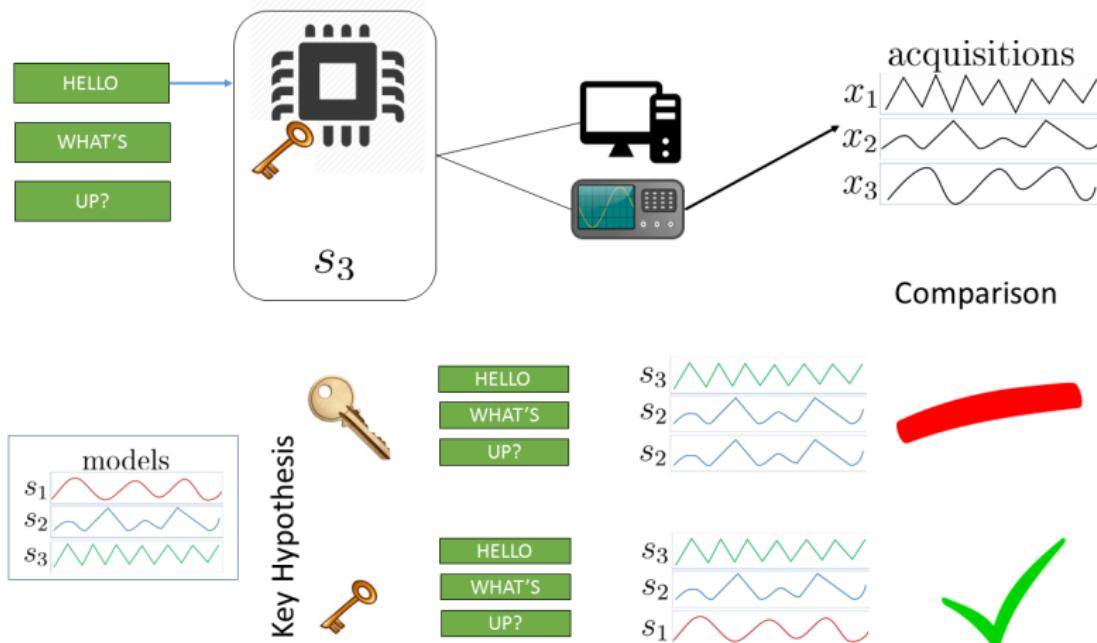
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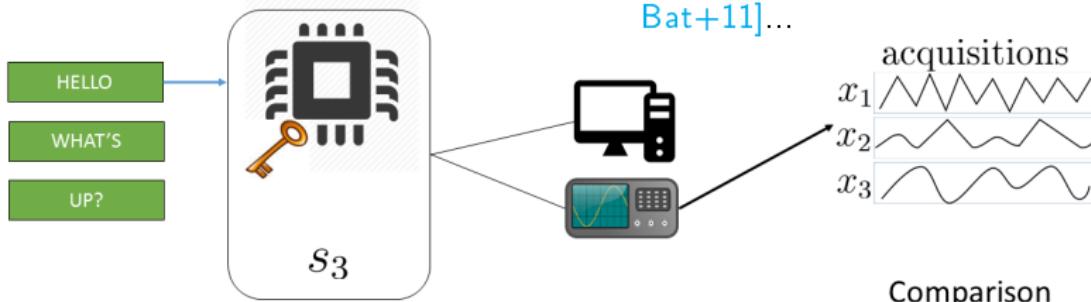
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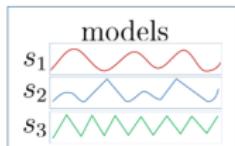


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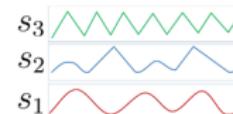
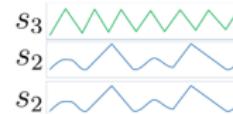


Non-profiling attacks

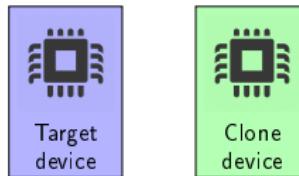
Profiling attacks



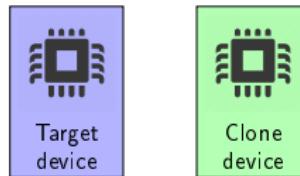
Key Hypothesis



Profiling Attacks...Supervised Learning



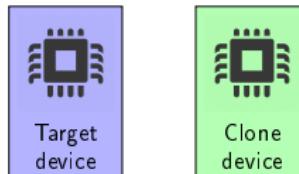
Profiling Attacks...Supervised Learning



Machine Learning

Supervised Learning

Profiling Attacks...Supervised Learning



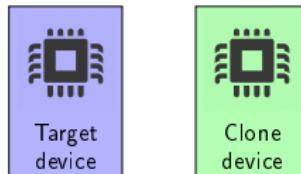
Machine Learning

Learn from data via statistic models

Task - Performance - Experience [TM97]

Supervised Learning

Profiling Attacks...Supervised Learning



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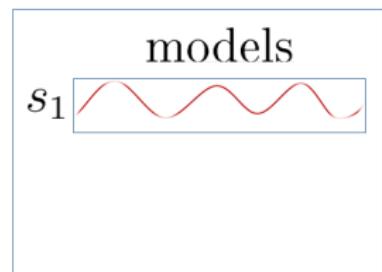
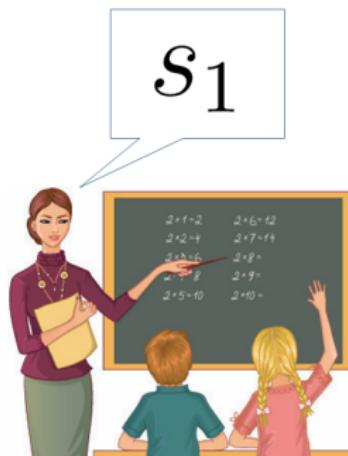
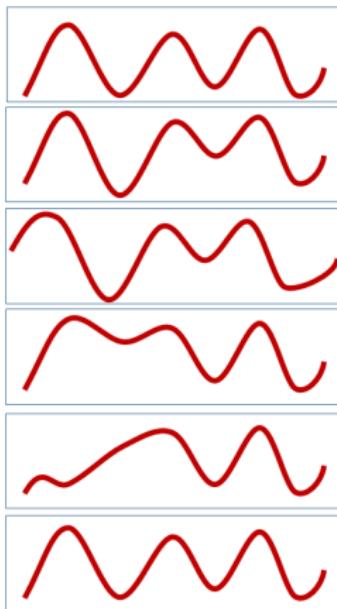
Task - Performance - Experience [TM97]

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



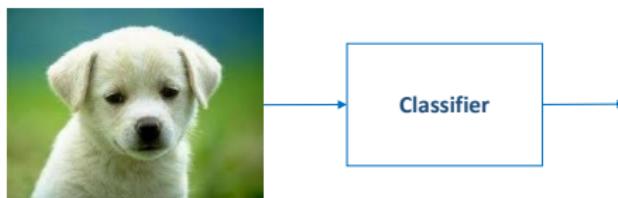
Classroom Side-Channel Attacks



Classification

Classification problem

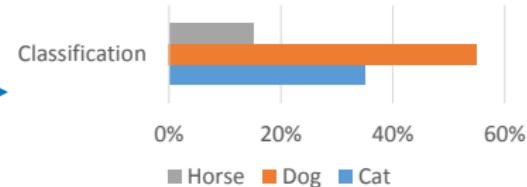
Assign to a datum \vec{X} (e.g. an image) a label Z among a set of possible labels
 $\mathcal{Z} = \{\text{Cat, Dog, Horse}\}$



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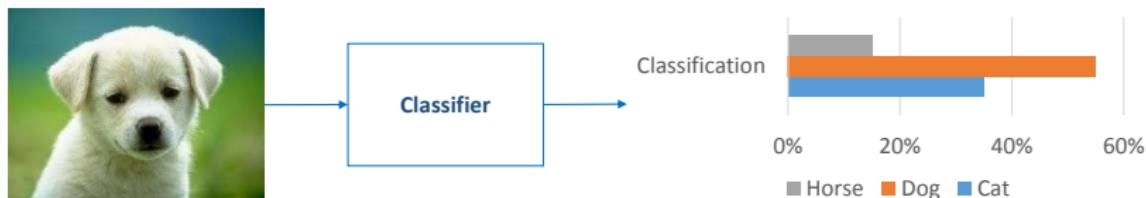
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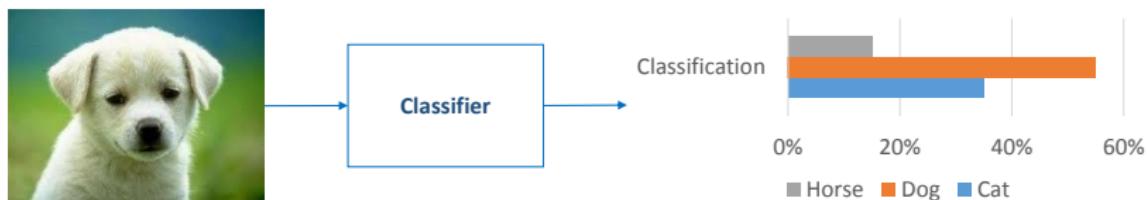
Advanced Attack as a Classification Problem



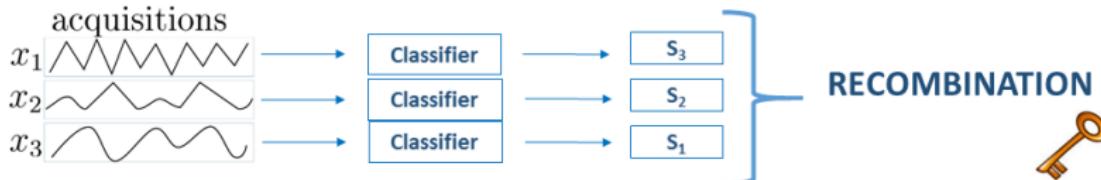
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Advanced Attack as Multiple Classification Problems

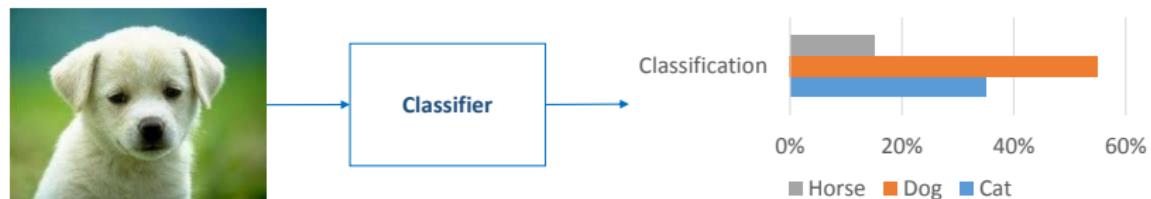


Classification

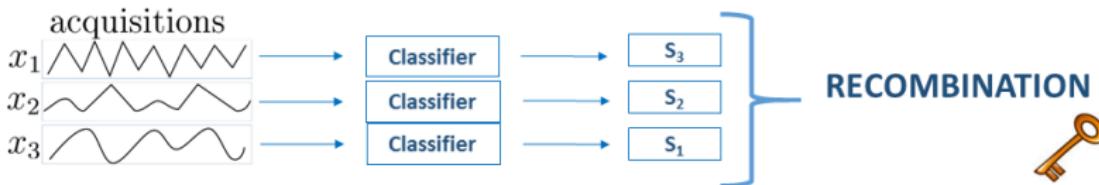
Machine Learning classifiers in Side-Channel literature:
SVM ([Hos+11; HZ12]), RF ([LBM14; LBM15])

Classification problem

Assign to a datum \vec{X} (e.g. an image) a label Z among a set of possible labels
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Advanced Attack as Multiple Classification Problems



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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 $Z = f(e, k)$ in $\mathcal{Z} = \{s_1, \dots, s_{|\mathcal{Z}|}\}$

Profiling attack scenario

- ▶ labelled traces $\mathcal{D}_{\text{train}} = (\vec{x}_i, e_i, k_i)_{i=1}^{N_t}$, 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)

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- ▶ 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

Profiling phase

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

Curse of dimensionality!

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 - ▶ Gaussian hypothesis (**Template Attack**) [CRR03]
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Profiling Attack

Profiling phase

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

Curse of dimensionality!

- ▶ mandatory dimensionality reduction $[D_{\text{train}} \longrightarrow \epsilon: \mathbb{R}^D \rightarrow \mathbb{R}^C]$
- ▶ estimate
 - ▶ $P_{\epsilon(\vec{X}) \mid Z=z} P_{\epsilon(\vec{X})} p_Z$ (generative model)
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Curse of dimensionality!

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- ▶ manage de-synchronization problem $[\mathcal{D}_{\text{train}} \longrightarrow \rho: \mathbb{R}^D \rightarrow \mathbb{R}^D]$
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- ▶ More generally, ameliorate the profiling attack strategy

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Dimensionality Reduction: State of the Art

Dimensionality Reduction

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

- ▶ Feature selection (Points of Interest selection)
- ▶ Feature extraction

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Feature selection

ϵ performs a sub-sampling

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

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Linear feature extraction

ϵ performs linear combinations

$$\epsilon(\vec{x}) = A\vec{x} \text{ with } A \in M_{\mathbb{R}}(C, D)$$

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

Dimensionality Reduction: State of the Art

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Contributions

- ▶ **Linear Dimensionality Reduction ([CARDIS 2015]):**
 - ▶ PCA, choice of components ELV
 - ▶ LDA in case of undersampling
- ▶ **Kernel Discriminant Analysis ([CARDIS 2016]):** application of an appropriate kernel trick to LDA, in order to manage masking countermeasure
- ▶ **Convolutional Neural Networks ([CHES 2017]):**
 - ▶ discriminative model by means of neural network classifiers
 - ▶ convolutional layers to manage desynchronization (a form of hiding)
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- ▶ **ASCAD public dataset** (submitted paper):
 - ▶ deep learning open comparison platform (implementation sources, side-channel traces, attack scripts)
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Dimensionality reduction in presence of masking

$(d - 1)$ th-order Sharing (or Masking)

Split each sensitive Z into shares M_1, \dots, M_d

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

Shares are handled at time samples

t_1, \dots, t_d (in general different if software countermeasure)

Indistinguishability of $p_{\vec{X} \mid Z=z}$ up to order $d - 1$

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$f(z) = \mathbb{E} [\vec{X}[t_1] \vec{X}[t_2] \dots \vec{X}[t_d] | Z = z]$ non-constant $\Rightarrow d$ th-order attack
 \Rightarrow extract features containing $\vec{X}[t_1] \vec{X}[t_2] \dots \vec{X}[t_d]$ (**Necessary condition**)

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

Feature selection

ϵ performs a sub-sampling

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

- ▶ Point-wise statistics -
- ▶ Exploit $\mathbb{E}[\vec{X}|Z = z]$ -

Linear feature extraction

ϵ performs linear combinations

$$\epsilon(\vec{x}) = A\vec{x} \text{ with } A \in M_{\mathbb{R}}(C, D)$$

- ▶ Principal Component Analysis (PCA) [Arc+06; BHW12]
- ▶ Linear Discriminant Analysis (LDA) [SA08; Bru+15]
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- ▶ Combine all time samples ✓
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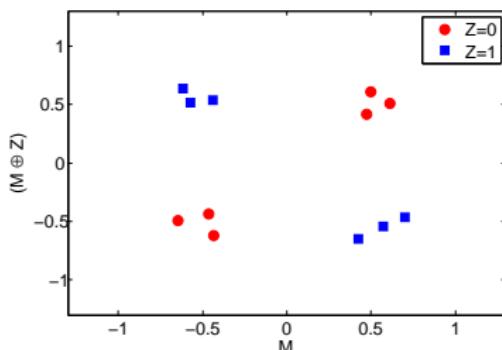
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Toy example: 2 time samples, 1-bit data

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

t_2 : $M \oplus Z + n$ (Boolean masking)

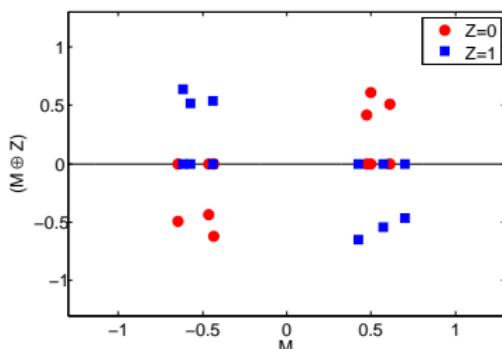
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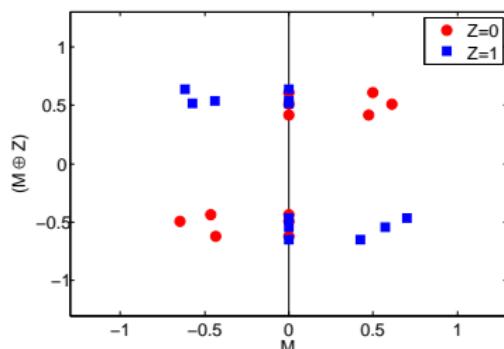
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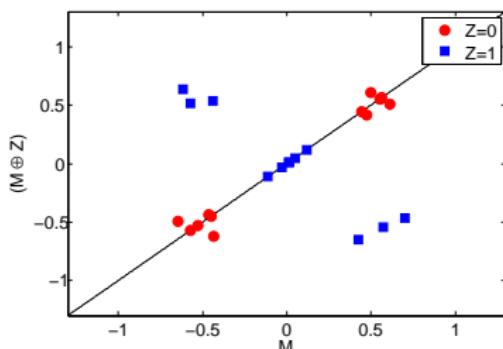
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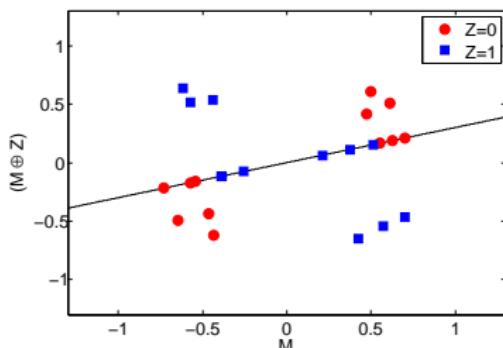
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Pols Research

A lacking literature

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

Kernel Discriminant Analysis starting point

Naive strategy: infer over all possible d -tuples

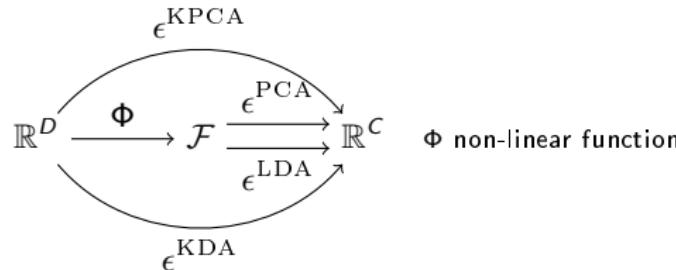
KDA: the purpose

Problem

All d th-degree monomials in the trace coordinates lie in:

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

⚠ Dimension increasing combinatorially with d and D



KDA

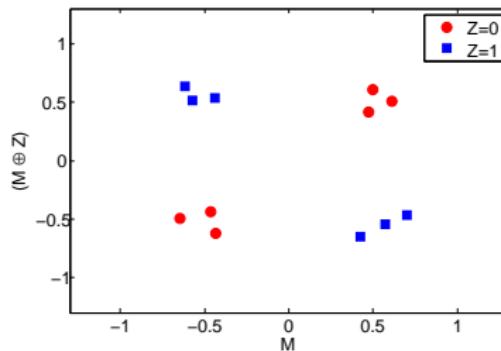
KDA allows performing LDA in \mathcal{F} , remaining in \mathbb{R}^D .

KDA: an intuition

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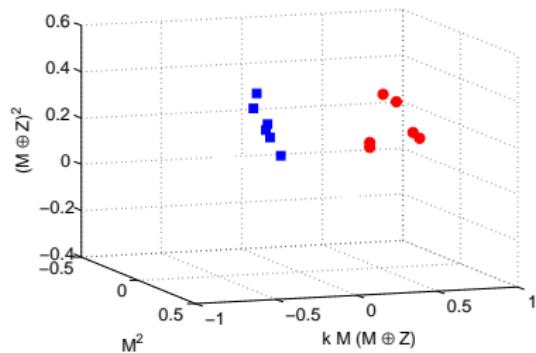
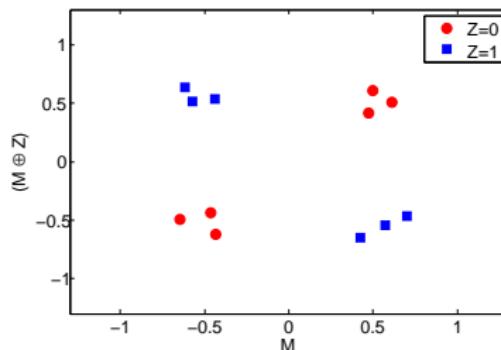


KDA: an intuition

Toy example: 2 time samples, 1-bit data

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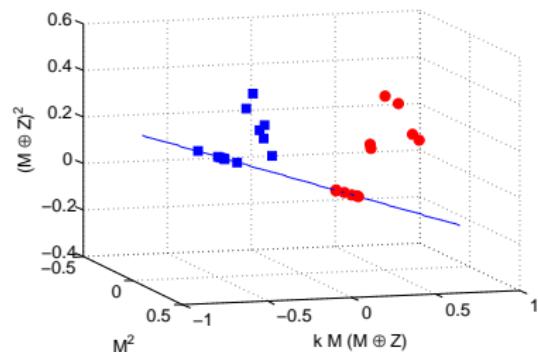
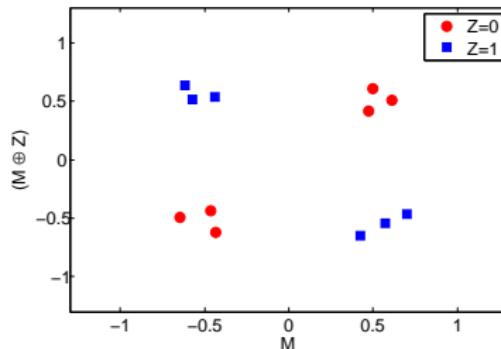
$$\Phi: \mathbb{R}^D \rightarrow \mathbb{R}^{\binom{D+d-1}{d}}$$
$$\Phi(t_1, t_2) = (t_1^2, t_2^2, k t_1 t_2)$$

KDA: an intuition

Toy example: 2 time samples, 1-bit data

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$$t_2: M \oplus Z + n \text{ (Boolean masking)}$$



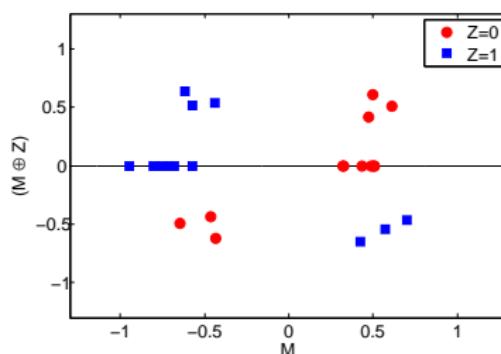
$\Phi \rightarrow \text{LDA}$

KDA: an intuition

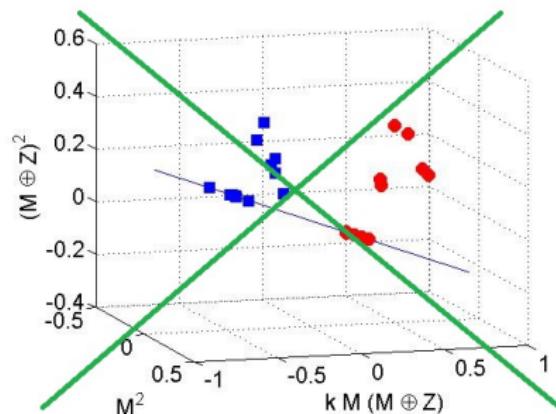
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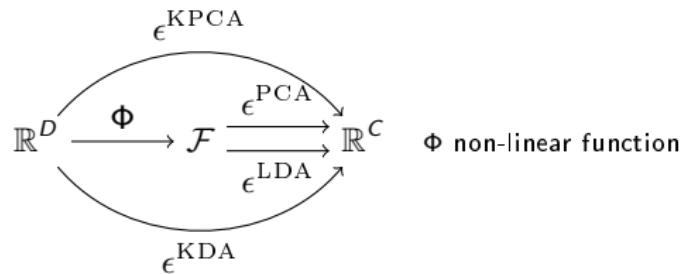
$$\mathbf{t}_2: M \oplus Z + n \text{ (Boolean masking)}$$



KDA
remains in \mathbb{R}^D



Kernel Function



Kernel Function

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

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

*d*th-degree Polynomial Kernel Function

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

KDA - the training

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

Between-class (inter-class) Covariance Matrix

LDA

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

KDA

$$\blacktriangleright \mathbf{M} = \sum_{z \in \mathcal{Z}} N_z (\vec{M}_s - \vec{M}_T)(\vec{M}_s - \vec{M}_T)^\top$$



¹ \vec{M}_s and \vec{M}_T are two N -sized column vectors whose entries are given by:

$$\vec{M}_z[j] = \frac{1}{N_z} \sum_{i:z_i=z}^{N_z} K(\mathbf{x}_j^{z_j}, \mathbf{x}_i^{z_i}), \quad \vec{M}_T[j] = \frac{1}{N} \sum_{i=1}^N K(\mathbf{x}_j^{z_j}, \mathbf{x}_i^{z_i}).$$

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

KDA - the training

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

Within-class (intra-class) Covariance Matrix

LDA

- $\mathbf{S}_B = \sum_{z \in \mathcal{Z}} N_z (\vec{\mu}_s - \vec{\bar{x}})(\vec{\mu}_s - \vec{\bar{x}})^T$
- $\mathbf{S}_W = \sum_{z \in \mathcal{Z}} \sum_{i=1}^{N_z} (\mathbf{x}_i^z - \vec{\mu}_s)(\mathbf{x}_i^z - \vec{\mu}_s)^T$

KDA

- $\mathbf{M} = \sum_{z \in \mathcal{Z}} N_z (\vec{M}_s - \vec{M}_T)(\vec{M}_s - \vec{M}_T)^T$ ¹
- $\mathbf{N} = \sum_{z \in \mathcal{Z}} \mathbf{K}_z (\mathbf{I} - \mathbf{I}_{N_z}) \mathbf{K}_z^T$ ²
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Eigenvector problem

Computational Complexity $O(D^3)$

LDA

- ▶ $\mathbf{S}_B = \sum_{z \in \mathcal{Z}} N_z (\vec{\mu}_s - \bar{\vec{x}})(\vec{\mu}_s - \bar{\vec{x}})^\top$
- ▶ $\mathbf{S}_W = \sum_{z \in \mathcal{Z}} \sum_{i=1}^{N_z} (\mathbf{x}_i^z - \vec{\mu}_s)(\mathbf{x}_i^z - \vec{\mu}_s)^\top$
- ▶ $\vec{\alpha}_i$ eigenvectors of $\mathbf{S}_W^{-1} \mathbf{S}_B$ $[D \times D]$

Computational Complexity $O(N^3)$

KDA

- ▶ $\mathbf{M} = \sum_{z \in \mathcal{Z}} N_z (\vec{M}_s - \vec{M}_T)(\vec{M}_s - \vec{M}_T)^\top$ ¹
- ▶ $\mathbf{N} = \sum_{z \in \mathcal{Z}} \mathbf{K}_z (\mathbf{I} - \mathbf{I}_{N_z}) \mathbf{K}_z^\top$ ²
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New trace projection

Computational Complexity $O(D^3)$

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- ▶ $\vec{\alpha}_i$ 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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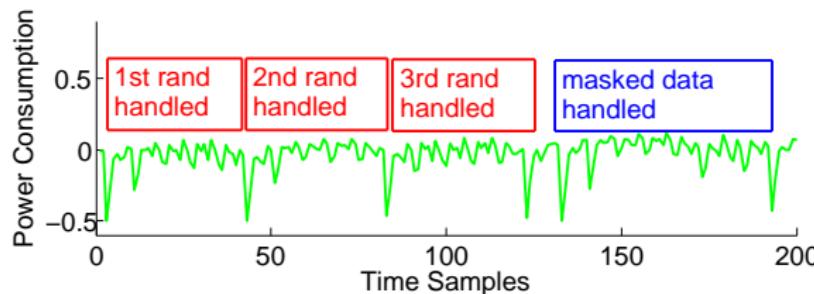
Experimental setup

Target device and acquisitions:

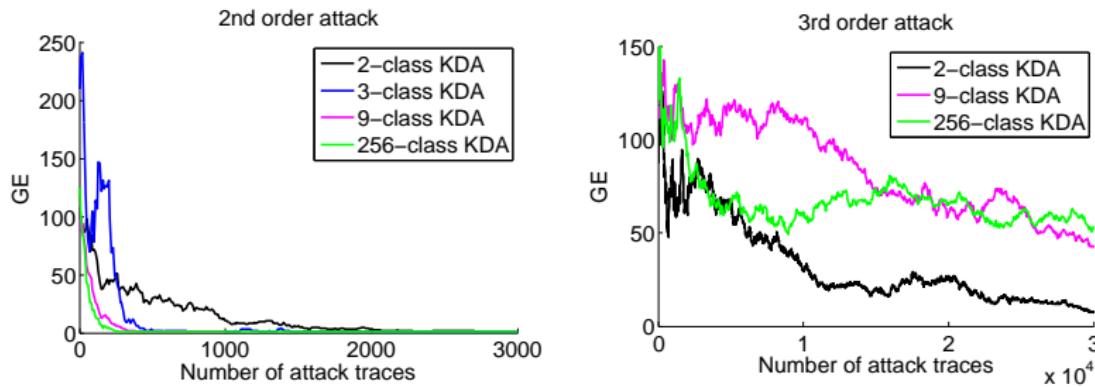
- ▶ 8-bit AVR microprocessor Atmega328P
- ▶ power-consumption acquired via the ChipWhisperer [OC14] platform
- ▶ $D = 200$, 4 clock-cycles are selected
- ▶ 9,000 KDA training traces

Sensitive variable: $Z = \text{Sbox}_{\text{AES}}(P \oplus K^*)$

One byte: 256 classes

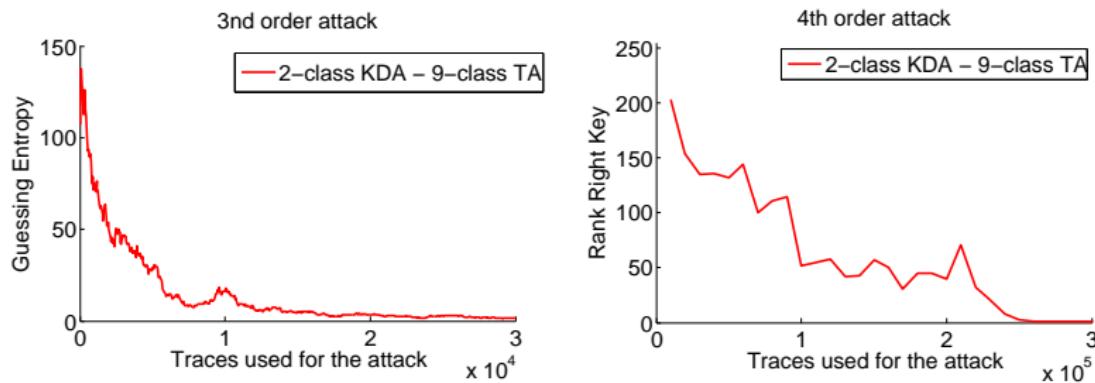


Second and third order



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

Third and Fourth Order



- $d = 2 \rightarrow \mathcal{F} = \mathbb{R}^{\binom{200+2-1}{2}} \Rightarrow 20,100$ implicit coefficients
- $d = 3 \rightarrow \mathcal{F} = \mathbb{R}^{\binom{200+3-1}{3}} \Rightarrow 1,353,400$ implicit coefficients
- $d = 4 \rightarrow \mathcal{F} = \mathbb{R}^{\binom{200+4-1}{4}} \Rightarrow 68,685,050$ 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 $[\epsilon_{\ell}^{\text{KDA}}(\vec{x}) = \sum_{i=1}^N \vec{\nu}_{\ell}[i] K(x_i^{z_i}, \vec{x})]$

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- ▶ Regularization hyper-parameter μ : $N = \sum_{z \in \mathcal{Z}} K_z(I - I_{N_z})K_z^T + \mu I$

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PP	✓	✗	✗

Limits and drawbacks

- ▶ Memory-based $[\epsilon_{\ell}^{\text{KDA}}(\vec{x}) = \sum_{i=1}^N \vec{\nu}_{\ell}[i] \mathbf{K}(\mathbf{x}_i^{z_i}, \mathbf{x})] + O(N^3)$ complexity → Non-scalability to big training set
- ▶ Regularization hyper-parameter μ : $\mathbf{N} = \sum_{z \in \mathcal{Z}} \mathbf{K}_z (\mathbf{I} - \mathbf{I}_{N_z}) \mathbf{K}_z^T + \mu \mathbf{I}$
- ▶ No localisation of Pols

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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
 - ▶ $P_{\epsilon(\rho(\vec{x}))} | Z=z$, $P_{\epsilon(\rho(\vec{x}))}$, p_Z (generative model)
 - ▶ Gaussian hypothesis (**Template Attack**) [CRR03]
 - ▶ $p_Z | \epsilon(\rho(\vec{x}))$ (discriminative model)

Many independent preprocessing steps and assumptions

Motivations

Profiling phase

DEEP LEARNING

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

Many independent preprocessing steps and assumptions
↔ integrated and agnostic approach

Multi-Layer Perceptron

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

Multi-Layer Perceptron (MLP)

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

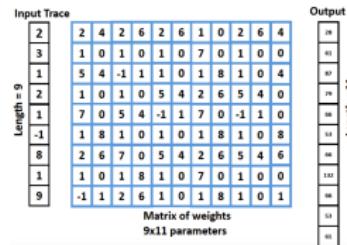
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λ_i linear functions (linear combinations of time samples) depending on some **trainable weights** W



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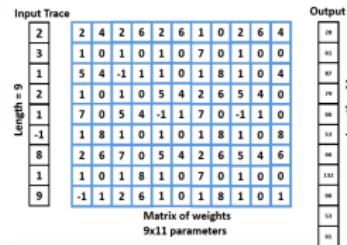
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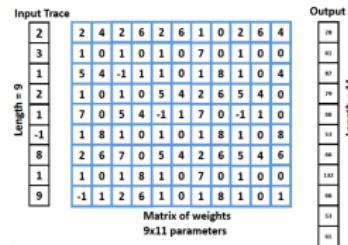
Multi-Layer Perceptron (MLP)

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

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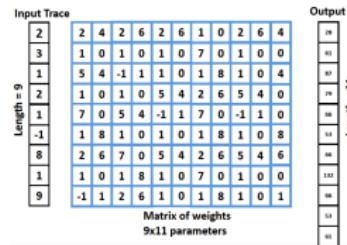
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Architecture hyper-parameters



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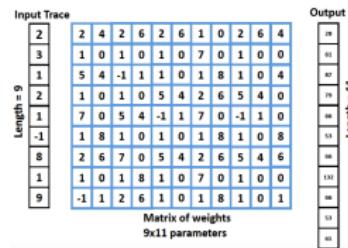
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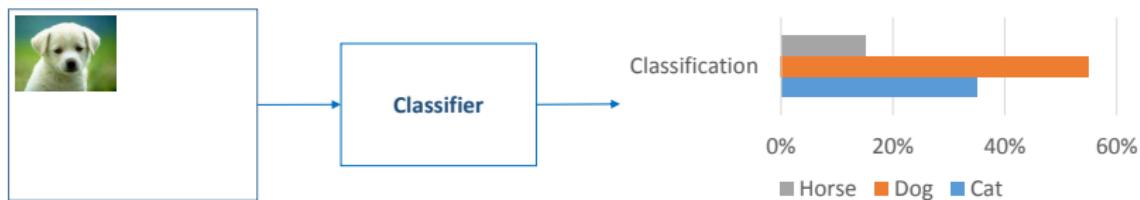
Architecture hyper-parameters

Universal approximation theorem



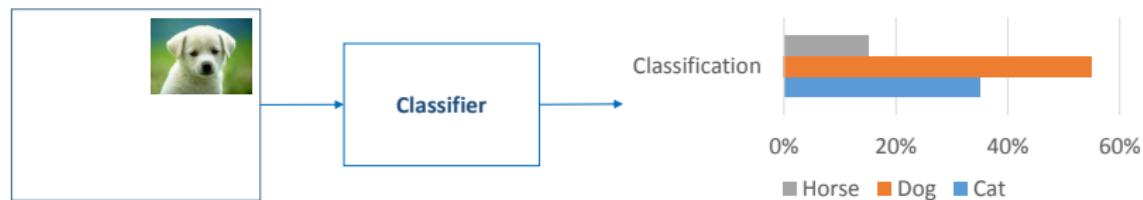
Convolutional Neural Networks

Translation-Invariance



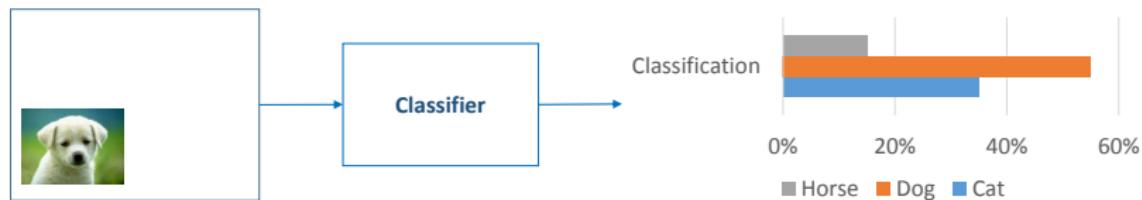
Convolutional Neural Networks

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Convolutional Neural Networks

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Convolutional Neural Networks

Translation-Invariance



Convolutional Layers

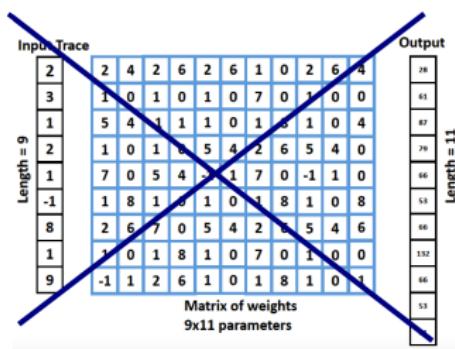
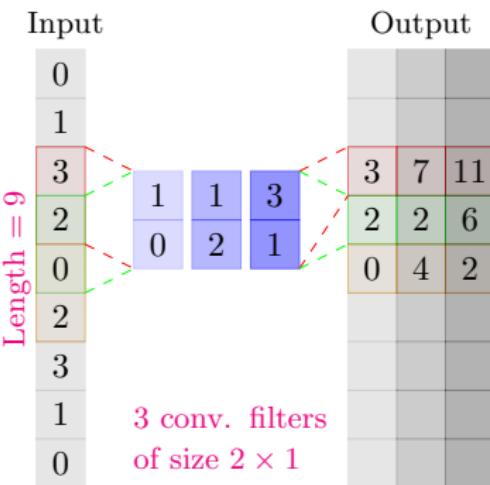


Figure: Linear layer in an MLP.



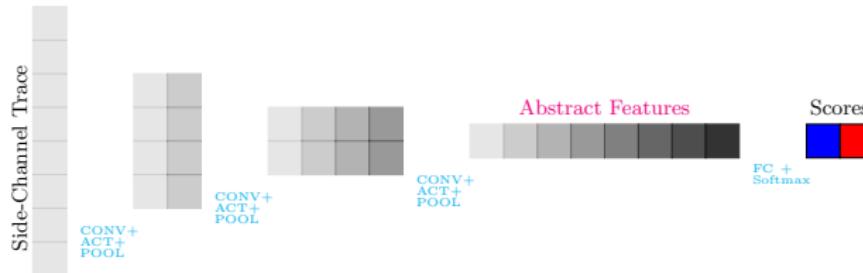
Depth = 1

Depth= 3

Figure: Convolutional layer in a CNN.

A kind of CNN architecture

Temporal Features



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

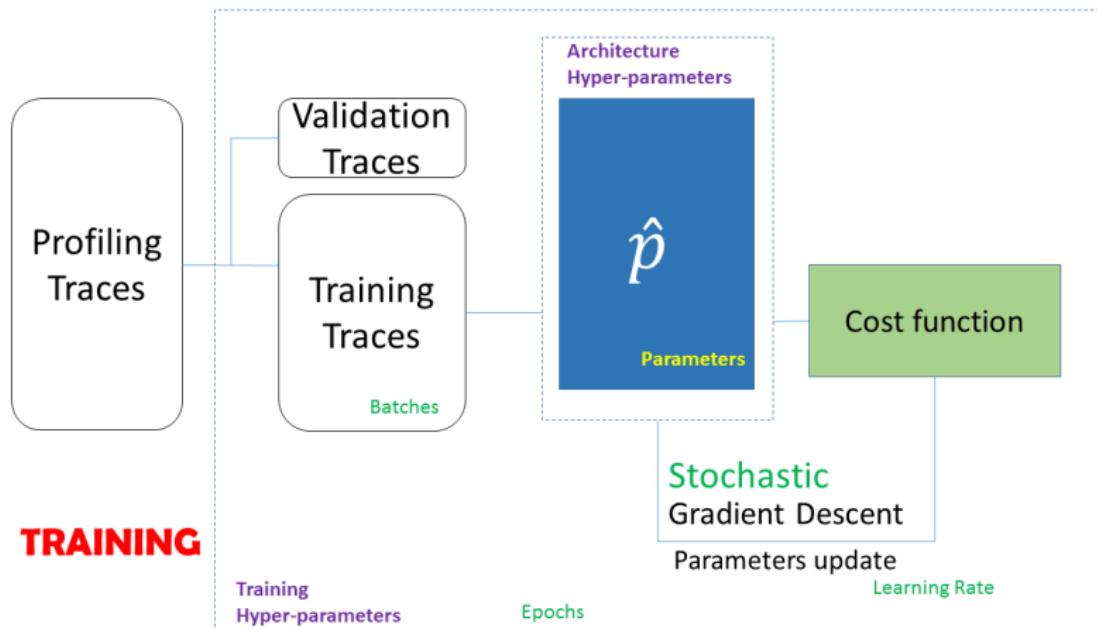
- ▶ Reduce temporal features to only one
- ▶ Maintain time complexity of each layer (one-half pooling when number of feature maps is doubled)

Model used in our experiments

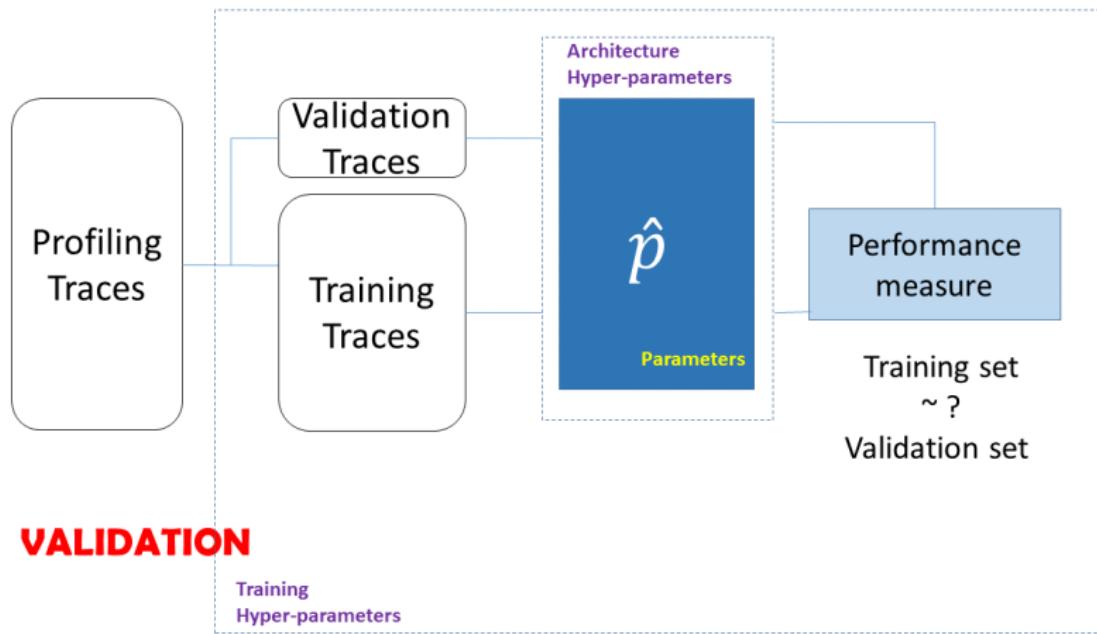
- ▶ 4 Conv + Pool layers
- ▶ tanh activations
- ▶ batch normalisation [IS15]
- ▶ 1 *fully connected layer* + softmax

Training and Validation

Training and Validation



Training and Validation

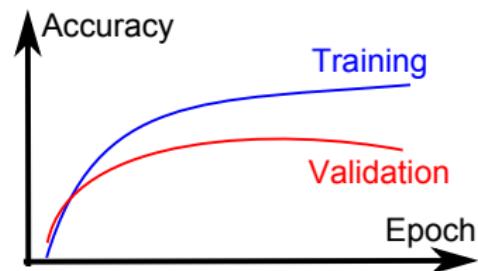


VALIDATION

Overfitting

Evaluate and compare training and validation accuracy

Learn by heart (**OVERRFITTING**)

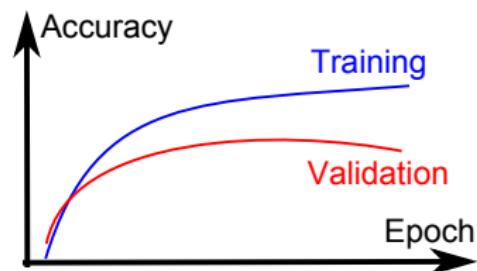
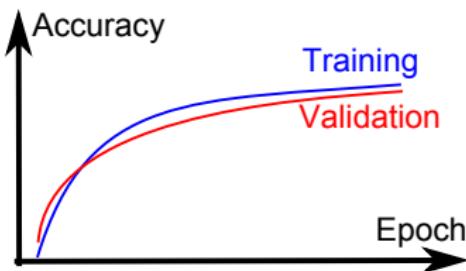


Overfitting

Evaluate and compare training and validation accuracy

Understand significant features

Learn by heart (**OVERFITTING**)



Overfitting

Evaluate and compare training and validation accuracy

Why?

Too complex model

Not enough training data

Solution?

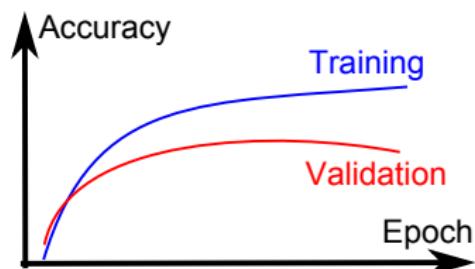
Reduce model capacity

Regularization

Dropout

Data augmentation

Learn by heart (**OVERTFITTING**)



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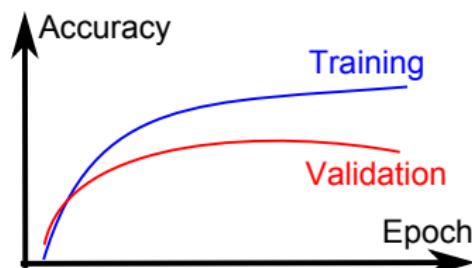
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Data Augmentation

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

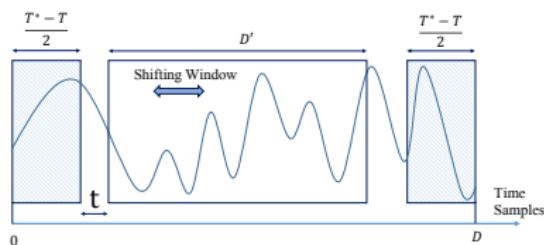


Figure: SH_T

ADD-REMOVE

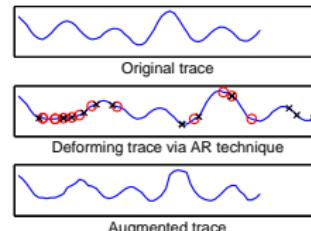


Figure: AR_R

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)

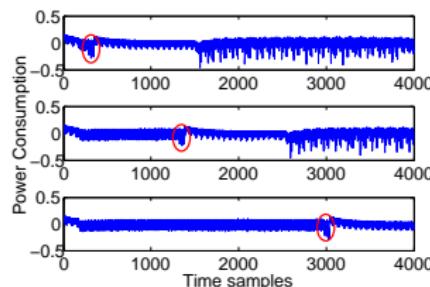
Keras 1.2.1 library with Tensorflow backend [Cho+15] (open source, today 2.2.4)

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Random delays



(a) One leaking operation

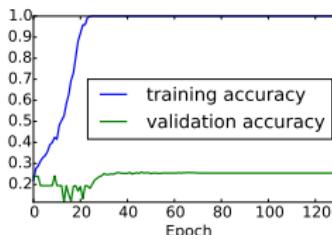
Setup

- ▶ Target Chip: Atmega328P
- ▶ Target Variable: $Z = \text{HW}(\text{Sbox}(P \oplus K))$
- ▶ 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

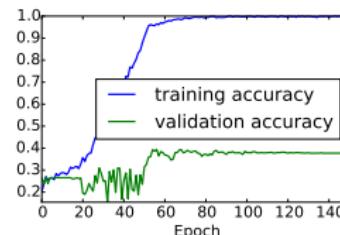
Random delays

Data augmentation vs overfitting

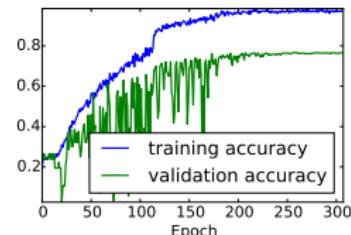
Training



SH_0



SH_{100}

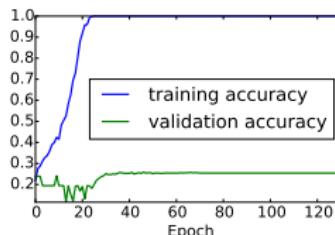


SH_{500}

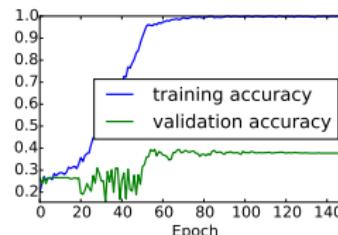
Random delays

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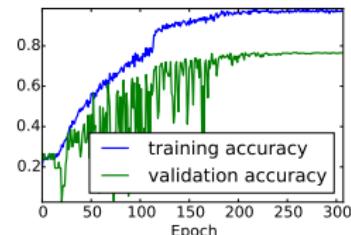
Training



SH_0



SH_{100}



SH_{500}

Attack

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

Table: N^* = number of attack traces to have GE = 1.

Conclusions about CNN

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- ▶ Effectiveness/efficiency of the CNN+Data Augmentation approach experimentally verified

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- ▶ In practical context, curse of dimensionality affects the potential optimality of profiling attacks
- ▶ In many domains Machine Learning solutions are used to tackle it
- ▶ Profiling attacks \approx classification task
- ▶ Generative model approach:
 - ▶ Classification-oriented techniques for dimensionality reduction
 - ▶ LDA and KDA generalization to tackle masking countermeasure
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- ▶ Advanced-attack-oriented machine learning task (instead of multiple classification)
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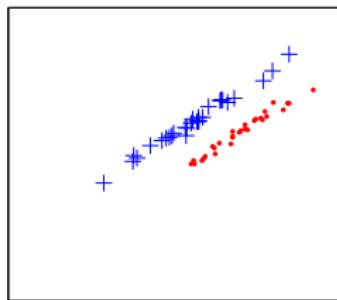
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References X

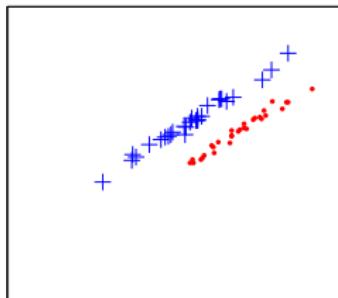
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LDA: an optimal binary linear classifier



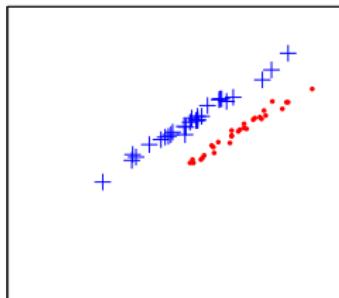
- ▶ Classify data \vec{x} into 2 classes $\mathcal{Z} = \{s_1, s_2\}$

LDA: an optimal binary linear classifier



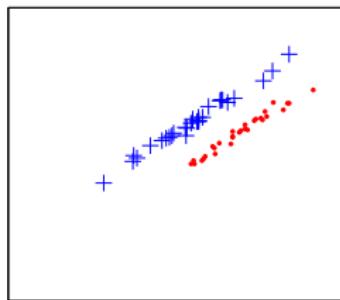
- ▶ Classify data \vec{x} into 2 classes $\mathcal{Z} = \{s_1, s_2\}$
- ▶ Generative model: $p_{\vec{X} | Z=s_j}(\vec{x})$, $p_Z(s_j)$ and $p_{\vec{X}}(\vec{x})$

LDA: an optimal binary linear classifier



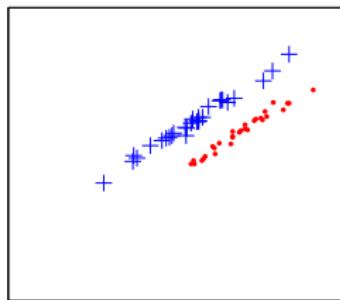
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- ▶ Generative model: $p_{\vec{X} | Z=s_j}(\vec{x})$, $p_Z(s_j)$ and $p_{\vec{X}}(\vec{x})$
- ▶ Posterior probabilities (via Bayes' theorem), then classify through the *log-likelihood ratio*: $a = \log \left[\frac{\Pr(s_1 | \vec{x})}{\Pr(s_2 | \vec{x})} \right]$
(boundary surface $a = 0$)

LDA: an optimal binary linear classifier



- ▶ Classify data \vec{x} into 2 classes $\mathcal{Z} = \{s_1, s_2\}$
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- ▶ Two assumptions about class-conditional densities:
 - ▶ Gaussian distributions with parameters μ_j, Σ_j
 - ▶ Homoscedasticity: $\Sigma_j = \Sigma$ for all j

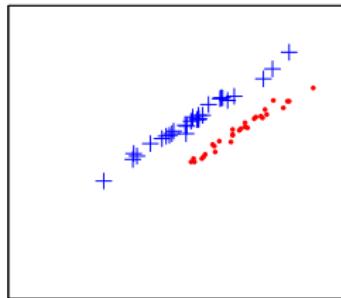
LDA: an optimal binary linear classifier



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 - ▶ Gaussian distributions with parameters μ_j, Σ_j
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- ▶ $\Rightarrow a = \vec{w}^T \vec{x} + w_0$ (linear decision boundary, \vec{w} and w_0 functions of Σ, μ_j)

LDA: an optimal binary linear classifier



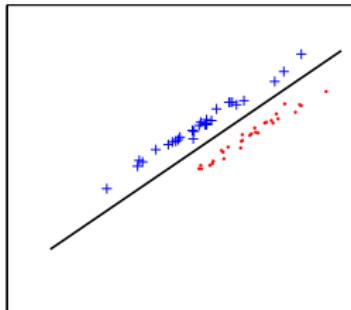
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Generalised linear discriminative model

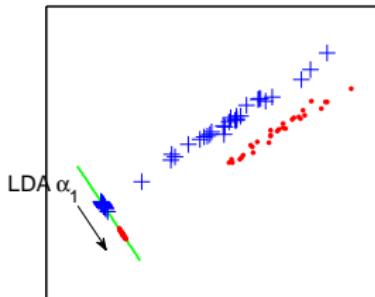
$$\Pr(s_1 | \vec{x}) = \sigma(\vec{w}^\top \vec{x} + w_0) \text{ , where } \sigma(a) = \frac{1}{1 + e^{-a}} \text{ logistic sigmoid} \quad (2)$$

LDA and Fisher Criterion



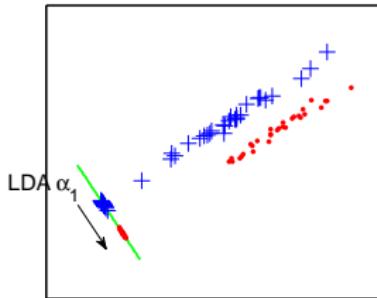
- ▶ LDA: linear decision boundary
 $a = \vec{w}^T \vec{x} + w_0$

LDA and Fisher Criterion



- ▶ LDA: linear decision boundary
 $a = \vec{w}^T \vec{x} + w_0$
- ▶ Equivalently, project data onto $\vec{w}^T \vec{x}$ (orthogonally to the decision boundary), than classify by a real threshold (optimally w_0).

LDA and Fisher Criterion

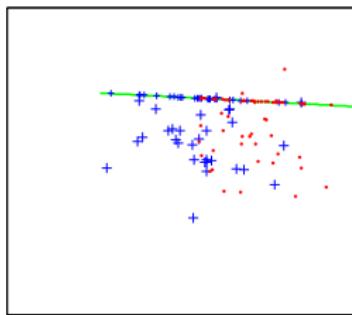


- ▶ LDA: linear decision boundary
 $a = \vec{w}^T \vec{x} + w_0$
- ▶ Equivalently, project data onto $\vec{w}^T \vec{x}$ (orthogonally to the decision boundary), than classify by a real threshold (optimally w_0).
- ▶ Two assumptions about class-conditional densities:
 - ▶ Gaussian distributions with parameters μ_j, Σ_j
 - ▶ Homoscedasticity: $\Sigma_j = \Sigma$ for all j

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
- ▶ continuation in the next slide: dimensionality reduction for template attack

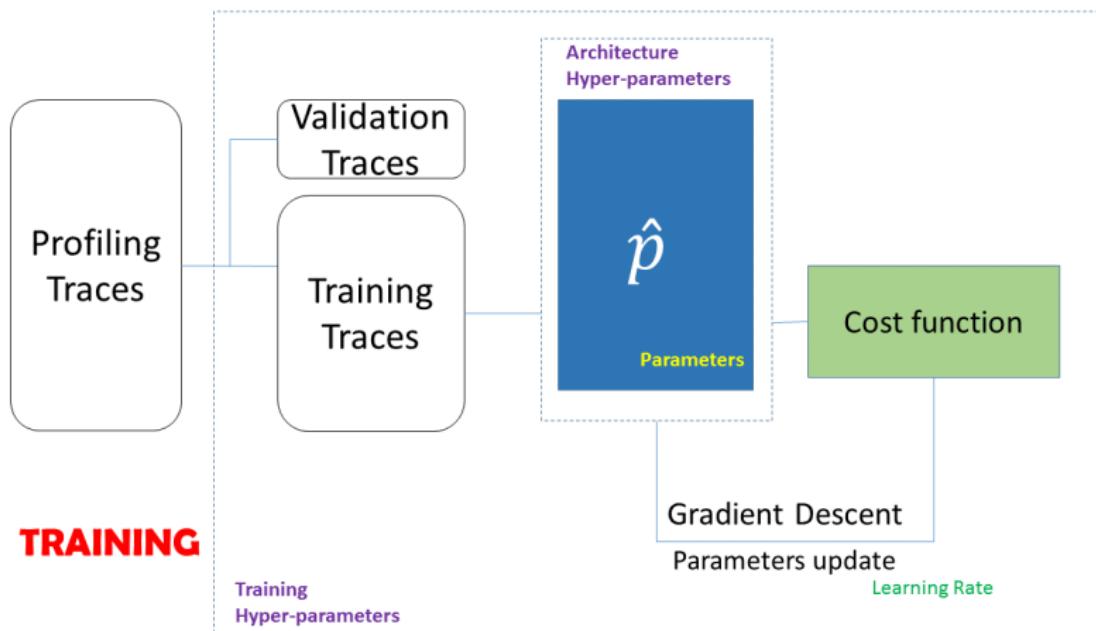
Linear separability



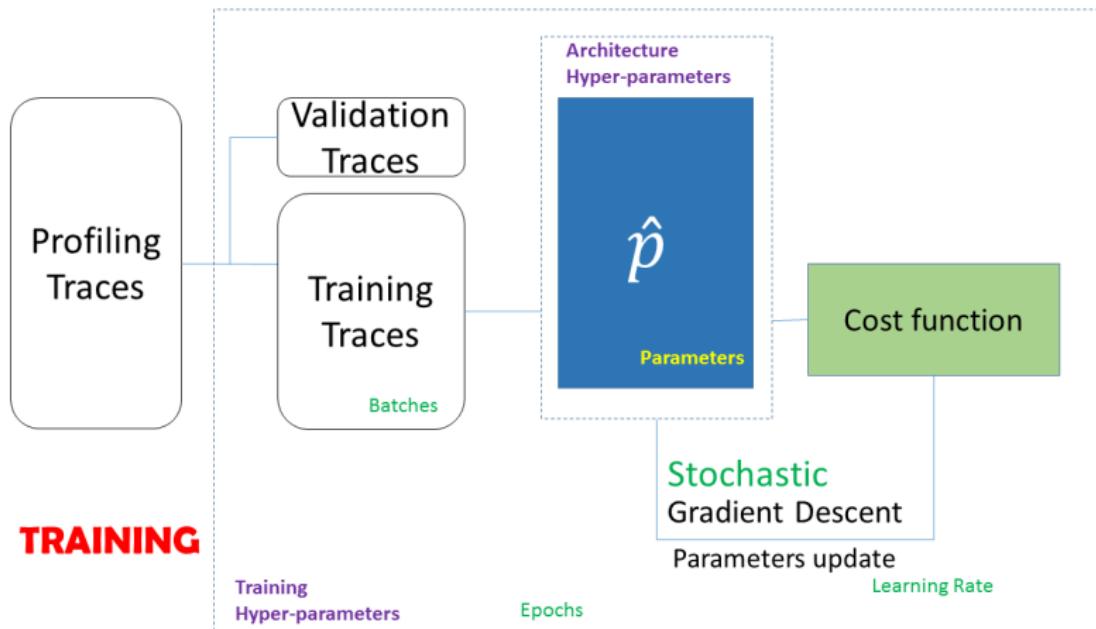
LDA: linear decision boundary $a = \vec{w}^\top \vec{x} + w_0$ ($\vec{w} = \Sigma^{-1}(\mu_1 - \mu_2)$)

What if $\mu_1 = \mu_2$?

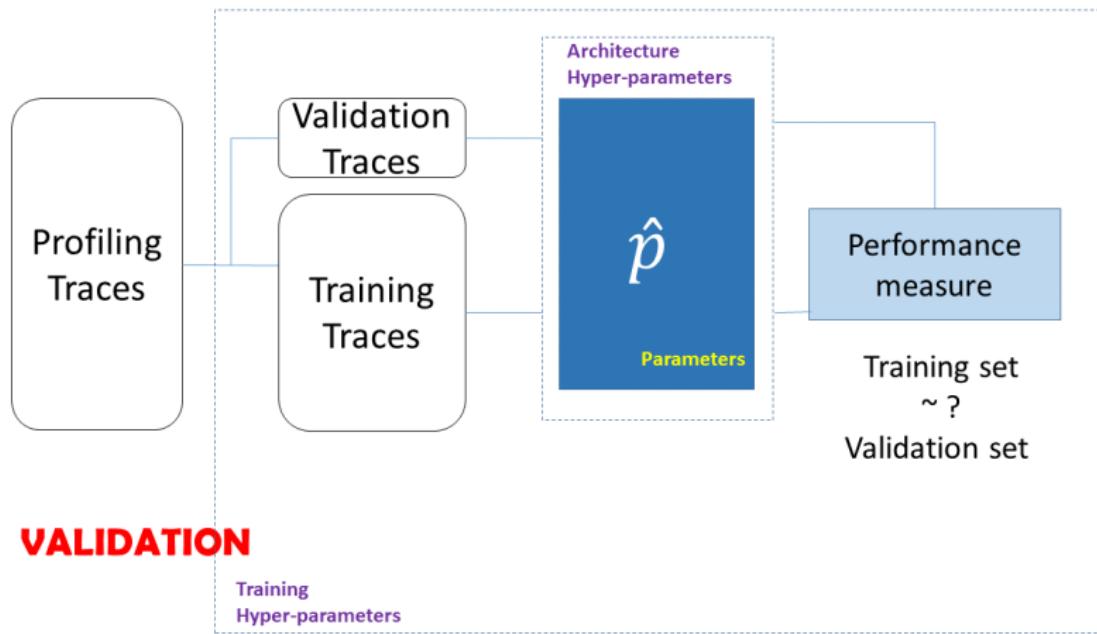
Training-Validation-Test



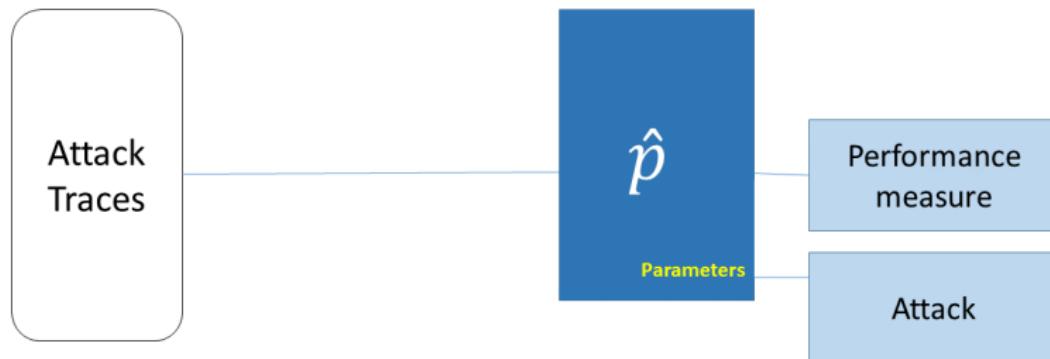
Training-Validation-Test



Training-Validation-Test

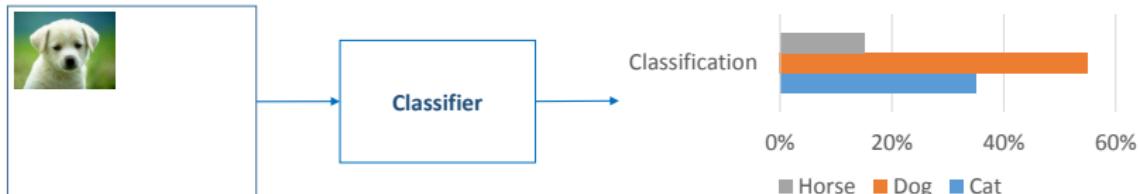


Training-Validation-Test

**TEST**

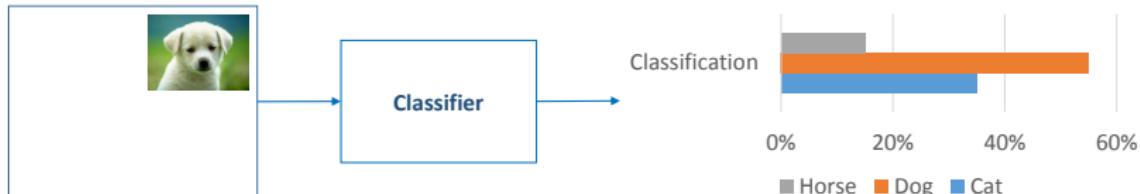
Convolutional Neural Networks

Translation-invariance



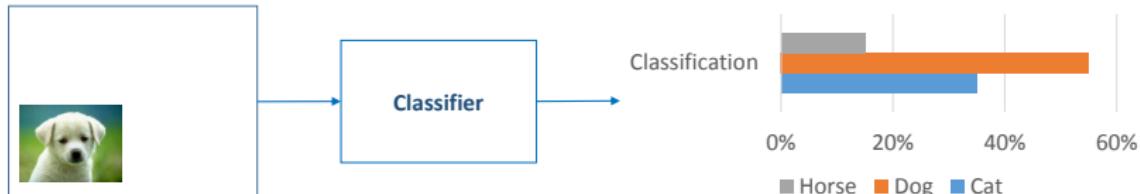
Convolutional Neural Networks

Translation-invariance



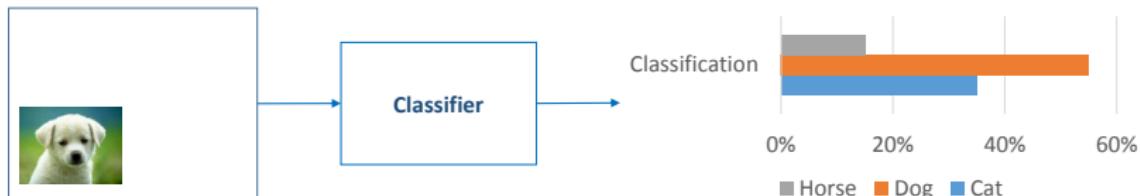
Convolutional Neural Networks

Translation-invariance



Convolutional Neural Networks

Translation-invariance



It is important to explicit the data 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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Convolutional Neural Networks

Translation-invariance



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Convolutional Neural Networks

Translation-invariance



It is important to explicit the data translation-invariance

Convolutional Neural Networks

Translation-invariance



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

Convolutional Neural Networks

Translation-invariance



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

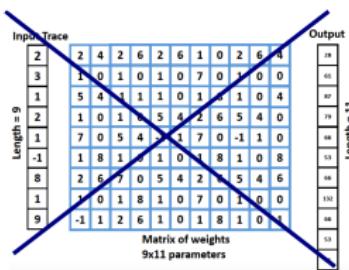


Figure: Linear layer of a CNN | 56/41

Convolutional Neural Networks

Translation-invariance



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

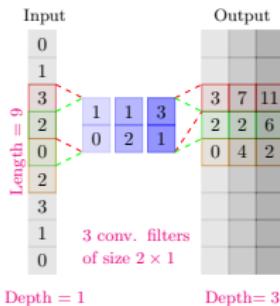


Figure: Linear layer in a ConvNet (*Convolutional*)

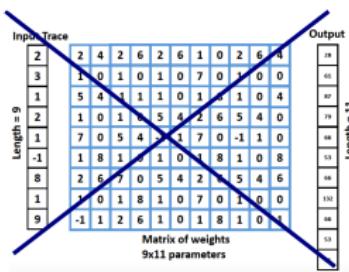


Figure: Linear layer 05/12/2018, Randomly Connected | 56 / 41

Convolutional Neural Networks

Translation-invariance



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

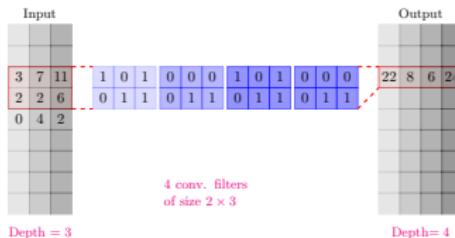


Figure: Linear layer in a ConvNet (*Convolutional Layer*)

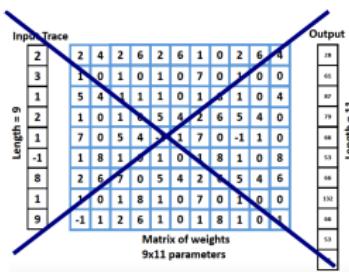


Figure: Linear layer in a ConvNet (*Matrix of weights*)

Convolutional Neural Networks

Translation-invariance



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

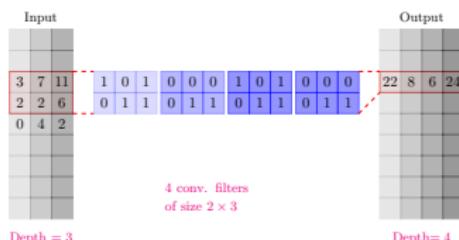


Figure: Linear layer in a ConvNet (*Convolutional Layer*)

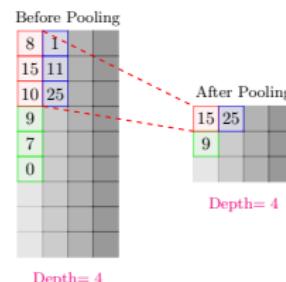


Figure: Max Pooling Layer

Cost function - Cross-entropy

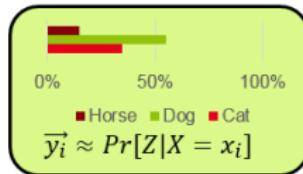
- ▶ batch of training data $(\vec{x}_i, z_i)_{i \in I}$, outputs of the current model $(\vec{y}_i)_{i \in I}$
- ▶ labels $z_i = s_j$ are *one-hot encoded*: $\vec{z}_i = \vec{s}_j = (0, \dots, 0, \underbrace{1}_j, 0, \dots, 0)$

Loss function

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

Maximum-*a-posteriori* or Cross-entropy

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



Cost function - Cross-entropy

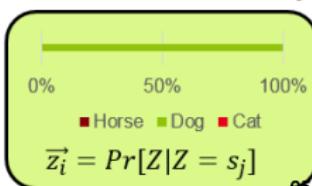
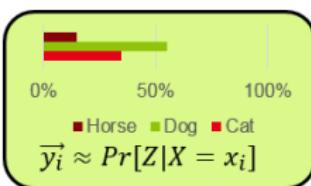
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Maximum-a-posteriori or Cross-entropy

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



Capacity-Overfitting-Regularization

Regression example

Performance metric: Mean Square Error (MSE)

MSE_train=44.228280, MSE_test=330.984916

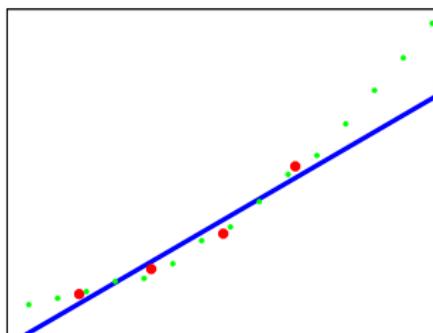


Figure: Linear regression → underfitting

Capacity-Overfitting-Regularization

Regression example

Performance metric: Mean Square Error (MSE)

MSE_train=44.228280, MSE_test=330.984916

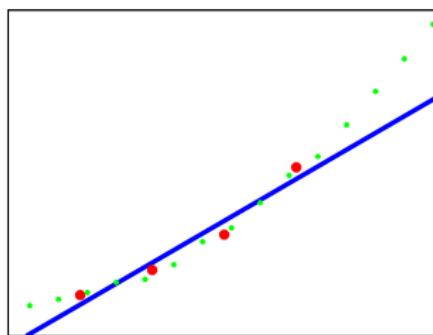


Figure: Linear regression → underfitting

MSE_train=2.243097, MSE_test=61.891672

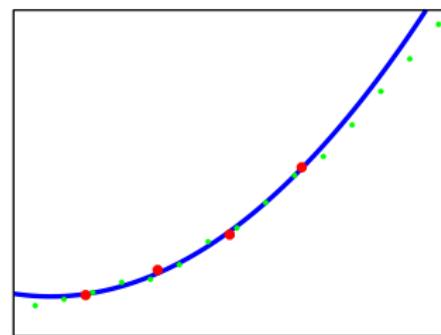


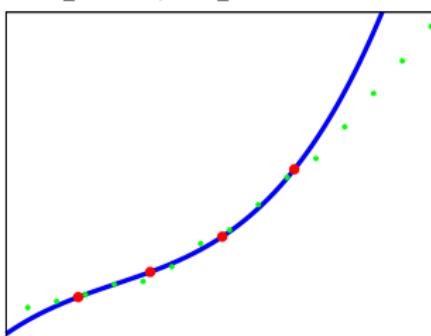
Figure: Quadratic regression → fits

Capacity-Overfitting-Regularization

Regression example

Performance metric: Mean Square Error (MSE)

MSE_train=0, MSE_test=970.081580



MSE_train=2.243097, MSE_test=61.891672

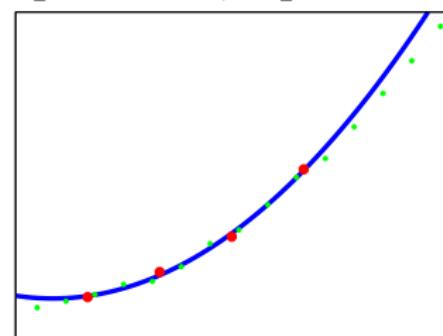


Figure: Cubic regression → overfitting

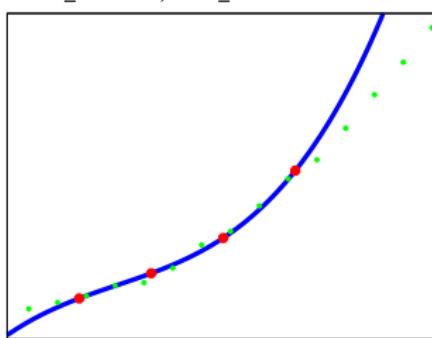
Figure: Quadratic regression → fits

Capacity-Overfitting-Regularization

Regression example

Performance metric: Mean Square Error (MSE)

MSE_train=0, MSE_test=970.081580



MSE_train=3.040333, MSE_test=58.377719

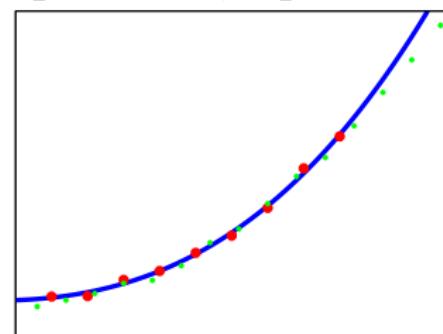


Figure: Cubic regression → overfitting

Figure: Cubic regression with more training data

Capacity-Overfitting-Regularization

Regression example

Performance metric: Mean Square Error (MSE)

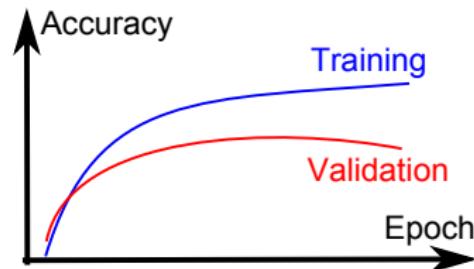
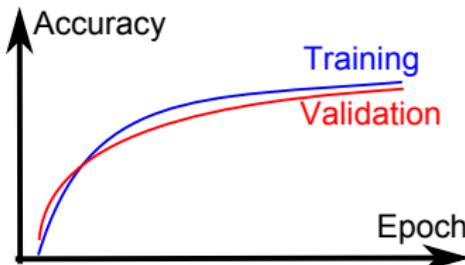
Classification via Neural Network

Performance measure: Accuracy (Classification rate)

Evaluate and compare training and validation accuracy

Understand significant features

Learn by heart (**OVERTFITTING**)



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

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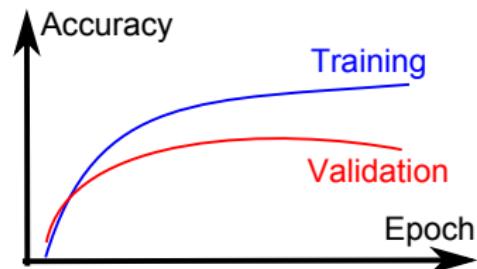
Why?

Too complex model

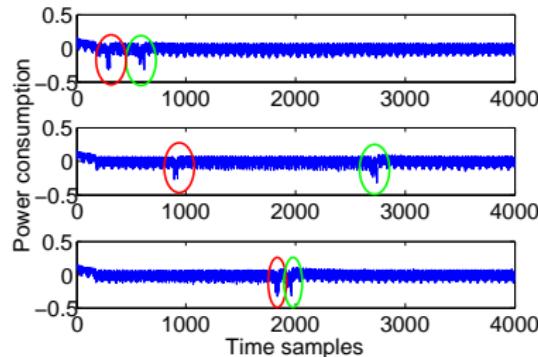
Not enough training data

Solution?

Data augmentation



Random Delays - Two Leaking Operations

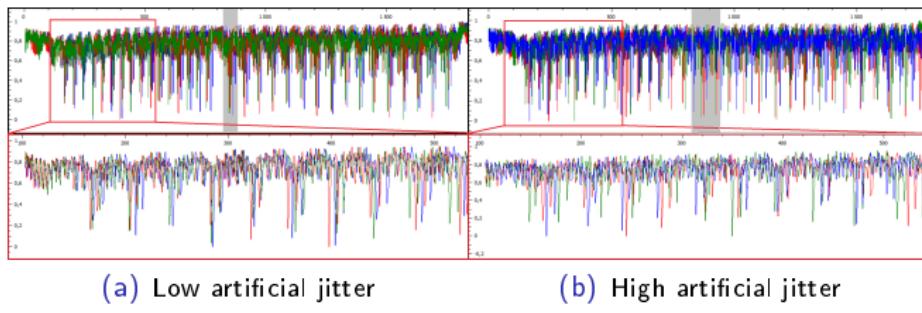


Two leaking operations

First operation - Test acc: 76.8%, $N^* = 7$

Second operation - Test acc: 82.5%, $N^* = 6$

Artificial Jitter



Target

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

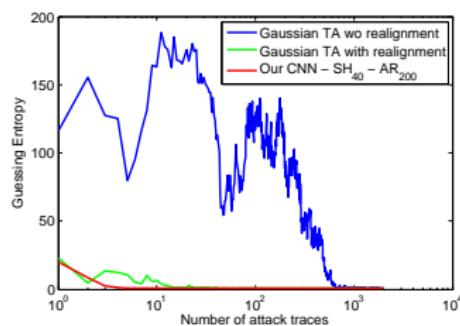
Artificial Jitter (2)

Low_jitter

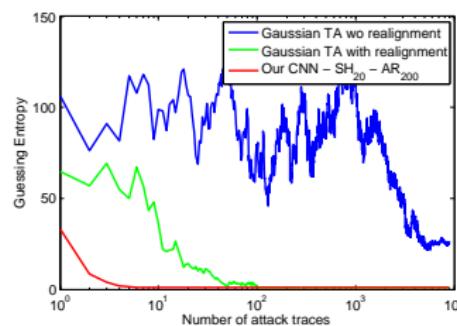
Acc	N^*	SH_0	SH_{20}	SH_{40}	
AR ₀		57.4%	14	82.5%	6
AR ₁₀₀		86.0%	6	87.0%	5
AR ₂₀₀		86.6%	6	85.7%	6

High_jitter

Acc	N^*	SH_0	SH_{20}	SH_{40}	
AR ₀		40.6%	35	51.1%	9
AR ₁₀₀		50.2%	15	72.4%	11
AR ₂₀₀		64.0%	11	75.5%	8



(c) Low Jitter



(d) High Jitter

Artificial Jitter

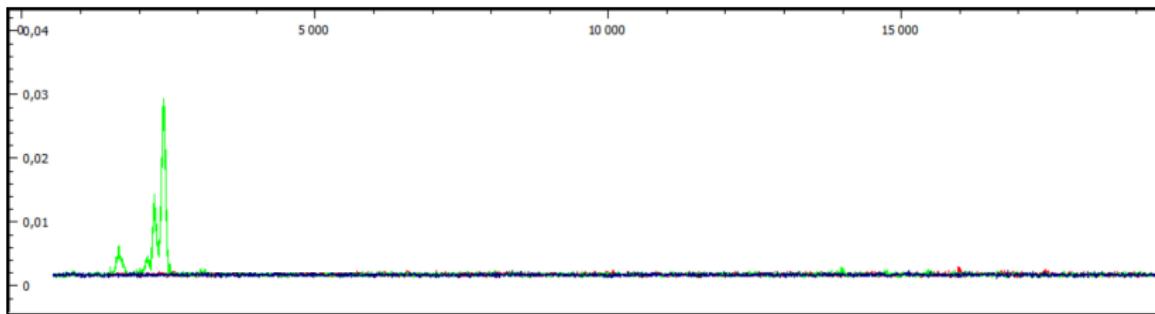
<i>DS_low_jitter</i>		SH ₀		SH ₂₀		SH ₄₀		SH ₂₀₀	
<i>a</i>	<i>b</i>								
<i>c</i>	<i>d</i>								
AR ₀	100.0%	68.7%	99.8%	86.1%	98.9%	84.1%			
	57.4%	14	82.5%	6	83.6%	6			
AR ₁₀₀	87.7%	88.2%	82.4%	88.4%	81.9%	89.6%			
	86.0%	6	87.0%	5	87.5%	6			
AR ₂₀₀	83.2%	88.6%	81.4%	86.9%	80.6%	88.9%			
	86.6%	6	85.7%	6	87.7%	5			
AR ₅₀₀							85.0%	88.6%	
							86.2%	5	
<i>DS_high_jitter</i>		SH ₀		SH ₂₀		SH ₄₀		SH ₂₀₀	
<i>a</i>	<i>b</i>								
<i>c</i>	<i>d</i>								
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: $Z = \text{Sbox}(P \oplus K)$
- ▶ 2,500 selected time samples
- ▶ 99,000 training traces

SNR first Sbox

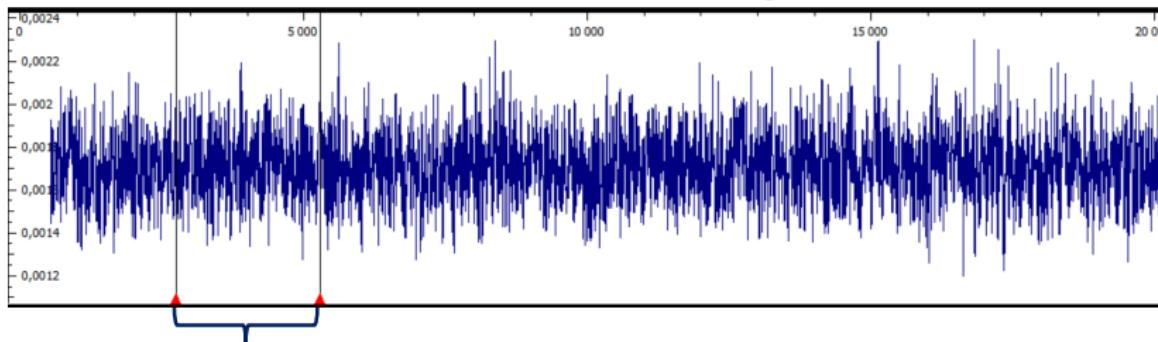


Real Jitter (1)

Target

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

SNR second Sbox without realignment



Entry region for CNN (2,500 pts)

Real Jitter (2)

		$SH_0 AR_0$	$SH_{10} AR_{100}$	$SH_{20} AR_{200}$		
Acc	N^*	1.2%	137	1.3%	89	1.8%
						54

Real Jitter (2)

		SH ₀ AR ₀	SH ₁₀ AR ₁₀₀	SH ₂₀ AR ₂₀₀
Acc	N*	1.2%	137	1.3%
			89	1.8% 54

