FROM RESEARCH TO INDUSTRY

Feature Extraction for Side-Channel Attacks

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Contents

Secure Component and Embedded Cryptography

A piece of hardware with security properties.
It usually embeds cryptography to provide security services (authentication, signature, secure messaging with terminals...)

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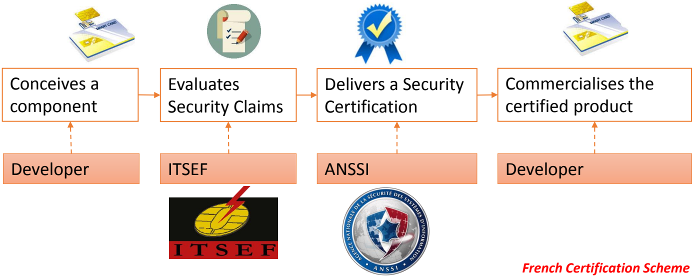
It usually embeds cryptography to provide security services (authentication, signature, secure messaging with terminals...)

- Sensitive applications: ID cards, credit cards, transport cards, health cards, SIM
- Pervasive aspect: several billion smartcards sold par year
- Hard to update
- Hostile environment

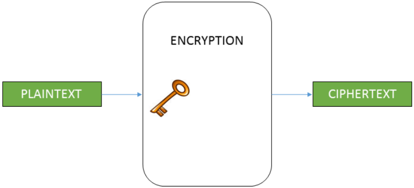
⇒ Requires protection against very high-level attacker

Security Certification



- Standardised Evaluation (*e.g.* ISO/IEC 15408 - Common Criteria)
- Assigns an Evaluation Assurance Level (EAL)
- The evaluator checks the Security Assurance Requirements (SAR), *e.g.* ADV, ALC, AVA, ...
- AVA: vulnerability assessment (penetration testing $\rightarrow$ attack potential rating)

Side-Channel Vulnerability of Embedded Cryptography



	Classical Cryptanalysis	Side-Channel Cryptanalysis
	Mathematical vulnerability	
	Black Box	

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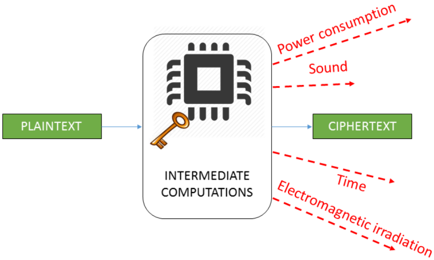

Classical Cryptanalysis	Side-Channel Cryptanalysis
Mathematical vulnerability	Physical vulnerability
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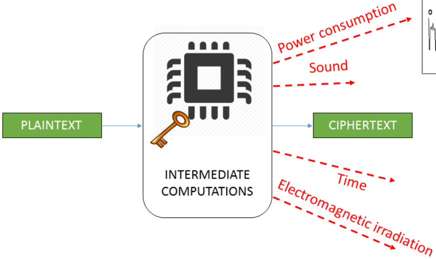

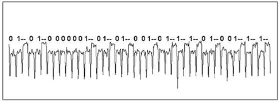

Source - Paul Kocher et al. “Introduction to differential power analysis”.

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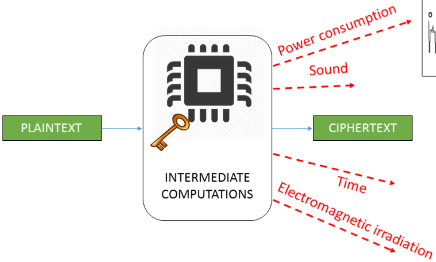

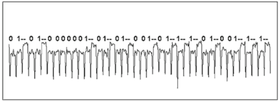

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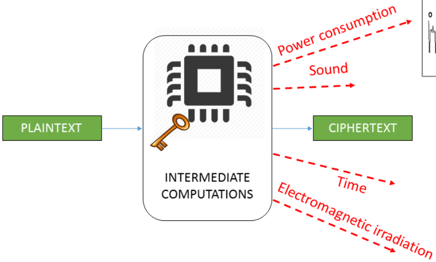

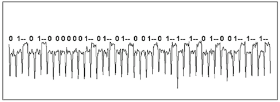

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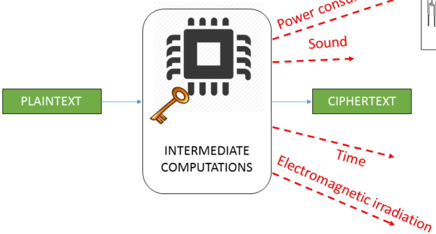

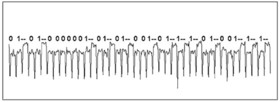

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Simple attack: only one plaintext

Classical Cryptanalysis	Side-Channel Cryptanalysis
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Formal attacker model	Attacker model?
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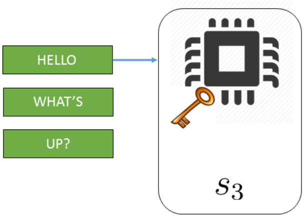
Advanced Side-Channel Attacks



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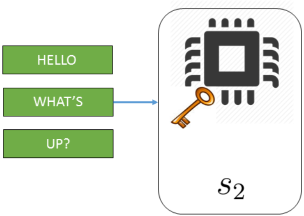

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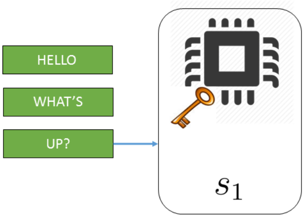

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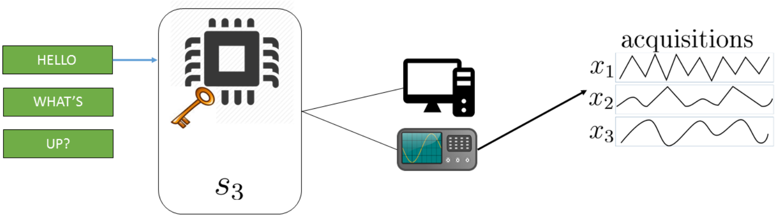

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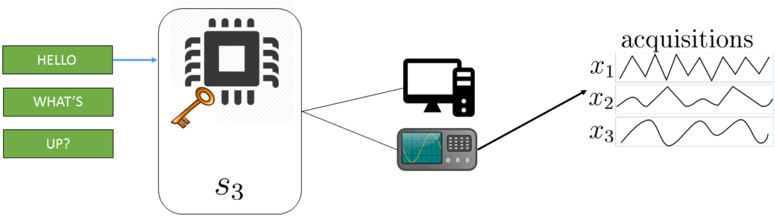

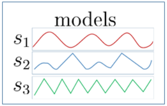

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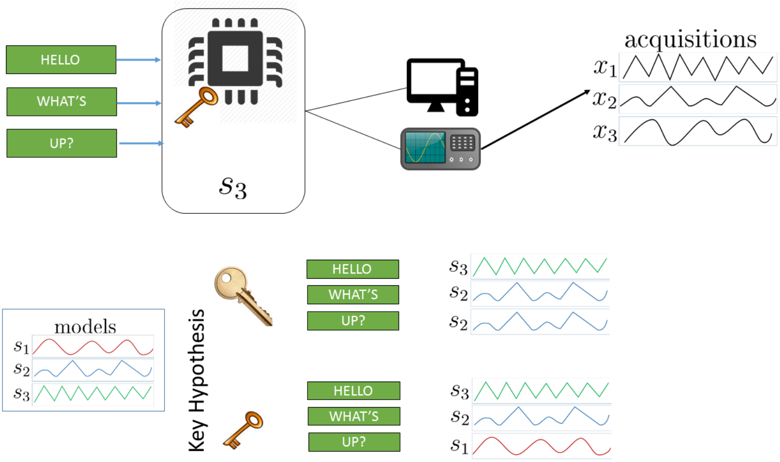

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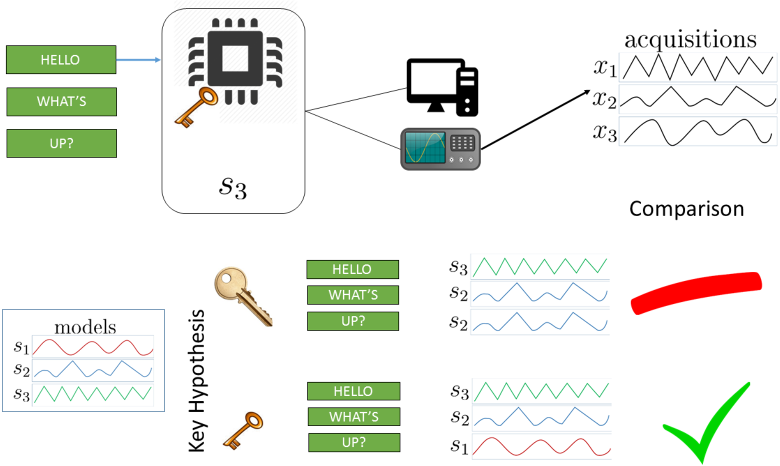
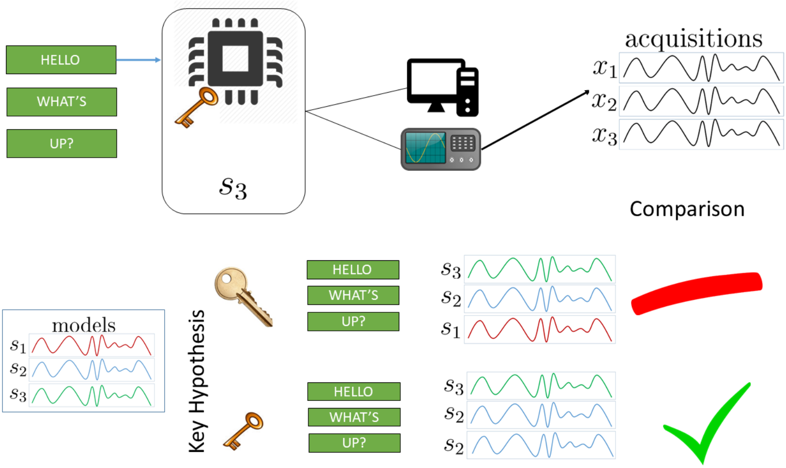
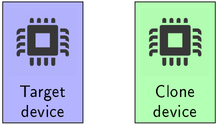


Advanced Side-Channel Attacks

Don't panic!



Profiling Attacks...Supervised Learning



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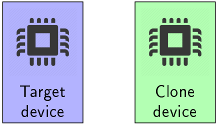

Machine Learning

Supervised Learning

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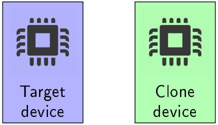
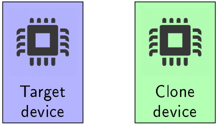


Machine Learning

"A computer program is said to learn from experience E with respect to some task T and performance measure P, if its performance on T, as measured by P, improves with experience E. "[TM97]

Supervised Learning

Profiling Attacks...Supervised Learning



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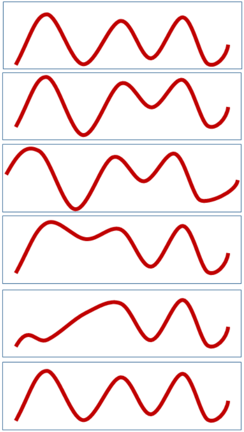
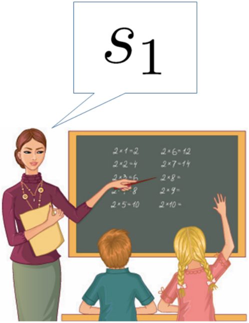
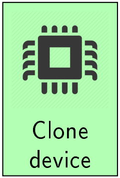
Supervised Learning

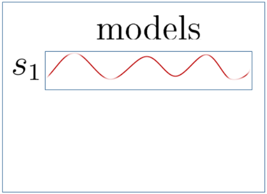
The *supervised* learning algorithms access to a dataset of examples, each associated in general to a *target* or *label*.

Classroom Side-Channel Attacks









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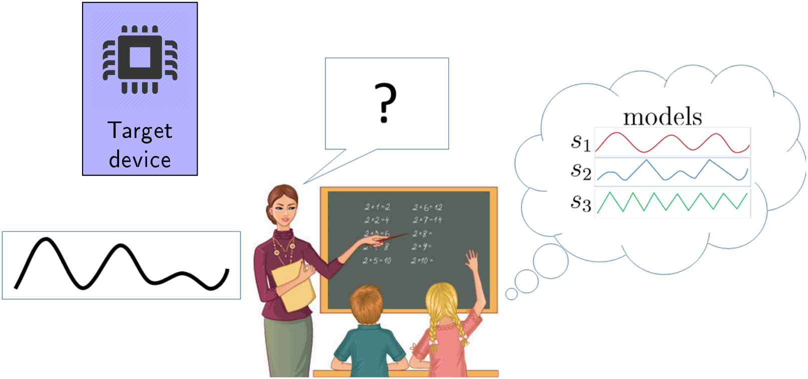
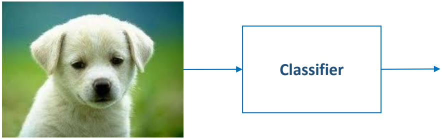


Classification

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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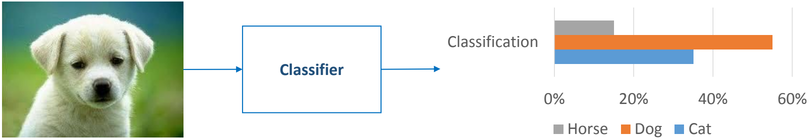

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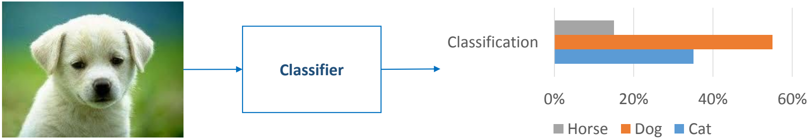

Simple Attack as a Classification Problem

Classification

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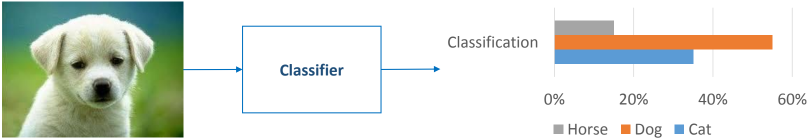

Advanced Attack as a Classification Problem

Classification

Classification problem

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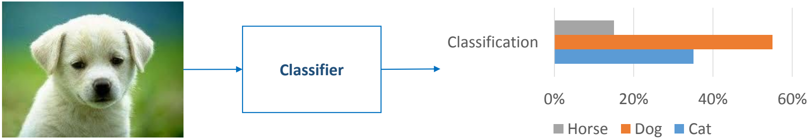
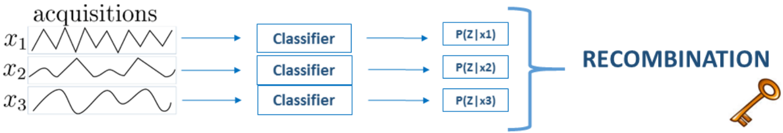


Advanced Attack as Multiple Classification Problems



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 $Z = f(\mathrm{plaintext}, \mathrm{key})$ in $\mathcal{Z} = \{s_1, \ldots, s_{|\mathcal{Z}|}\}$
- each label s_i identifies a *class*

Profiling attack scenario

- labelled traces $\mathcal{D}_{\mathbf{train}} = (\vec{x}_i, z_i)_{i=1}^{N}$, acquired under known Z, to characterise the signals
- attack traces $\mathcal{D}_{\mathbf{attack}} = (\vec{x}_i, p_i)_{i=1}^{N_a}$ acquired under known plaintext

Profiling Attack

Profiling phase

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

Attack phase

- Log-likelihood score for each key hypothesis k

$$d_k = \prod_{i=1}^{N_a} p_{\vec{X} \mid Z=f(p_i,k)}(\vec{x}_i)$$

Profiling Attack

Profiling phase

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

Attack phase

- Log-likelihood score for each key hypothesis k

$$d_k = \prod_{i=1}^{N_a} p_{\vec{X} \mid Z=f(p_i,k)}(\vec{x}_i)$$

- A-posteriori probability score for each key hypothesis k

$$p_{Z \mid \vec{X}=\vec{x}}(z) = \frac{p_{\vec{X} \mid Z=z}(\vec{x}) p_Z(z)}{p_{\vec{X}}(\vec{x})}$$ Bayes' theorem

$$d_k = \prod_{i=1}^{N_a} p_{Z \mid \vec{X}=\vec{x}_i}(f(k, e_i)) ,$$

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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Profiling Attack

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

Curse of dimensionality!

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Profiling Attack

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Profiling phase

- estimate
  - $p_{\vec{X} \mid Z=z}$, $p_{\vec{X}}$, p_Z (generative model)
    - Gaussian hypothesis (**Template Attack**) [CRR03]
    - Variants: *pooled* version [CK14], linear regression [SLP05]
  - $p_{Z \mid \vec{X}=\vec{x}}$ (discriminative model)

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Profiling Attack

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

Profiling phase

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

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

- manage de-synchronization problem $[\mathcal{D}_{\text{train}} \longrightarrow \rho\colon \mathbb{R}^D \to \mathbb{R}^D]$
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Objectives

Profiling phase

- manage de-synchronization problem [$\mathcal{D}_{\mathsf{train}} \longrightarrow \rho \colon \mathbb{R}^D \to \mathbb{R}^D$]
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Objectives

- Ameliorate the template attack routine by proposing efficient dimensionality reduction techniques

Objectives

Profiling phase

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  - $Z \mid \epsilon(\vec{X}) = \epsilon(\vec{x})$ (discriminative model)

Objectives

- Ameliorate the template attack routine by proposing efficient dimensionality reduction techniques
- Consider the presence of most-commonly-implemented SCA countermeasures (masking, hiding)

Objectives

Profiling phase

- manage de-synchronization problem [$\mathcal{D}_{\text{train}} \longrightarrow \rho \colon \mathbb{R}^D \to \mathbb{R}^D$]
- mandatory dimensionality reduction [$\mathcal{D}_{\text{train}} \longrightarrow \epsilon \colon \mathbb{R}^D \to \mathbb{R}^C$]
- estimate
  - $p_{\epsilon(\vec{X}) \mid Z=z}$, $p_{\epsilon(\vec{X})}$, p_Z (generative model)
    - Gaussian hypothesis [CRR03]
    - Variants: *pooled* version [CK14], linear regression [SLP05]
  - $Z \mid \epsilon(\vec{X}) = \epsilon(\vec{x})$ (discriminative model)

Objectives

- Ameliorate the template attack routine by proposing efficient dimensionality reduction techniques
- More generally, ameliorate the profiling attack strategy
- Consider the presence of most-commonly-implemented SCA countermeasures (masking, hiding)

Objectives

Profiling phase

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

DEEP LEARNING

- estimate
  - $p_{\epsilon(\vec{X}) \mid Z=z}$, $p_{\epsilon(\vec{X})}$, p_Z (generative model)
    - Gaussian hypothesis [CRR03]
    - Variants: *pooled* version [CK14], linear regression [SLP05]
  - $Z \mid \vec{X} = \vec{x}$ (discriminative model)

Objectives

- Ameliorate the template attack routine by proposing efficient dimensionality reduction techniques
- More generally, ameliorate the profiling attack strategy
- Consider the presence of most-commonly-implemented SCA countermeasures (masking, hiding)

Dimensionality Reduction: State of the Art

Dimensionality Reduction

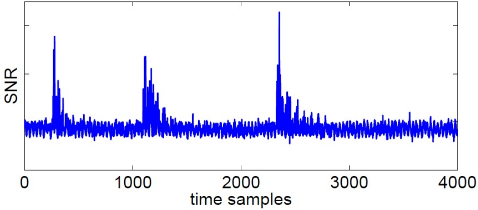
$$\epsilon : \mathbb{R}^D \to \mathbb{R}^C$$
$$\vec{x} \mapsto \epsilon(\vec{x})$$

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

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

$\epsilon(\vec{x}) = A\vec{x}$ 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]

Contributions

- **Linear Dimensionality Reduction**([CARDIS 2015]):
  - PCA, choise 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
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  - discriminative model by means of neural network classifiers
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Contents

Model-based SNR and Fisher's Criterion

Signal-to-Noise Ratio (SNR)

- Independent Noise Assumption: $\vec{X} = \varphi(Z) + \vec{B}$
- $\vec{\mu}_s = \hat{\mathbb{E}}[\vec{X} \mid Z = s] = \frac{1}{N_s} \sum_{i:\ z_i = s} \vec{x}_i$ sample mean per class ($\approx \varphi(Z)$)
- $\vec{\varrho}_s = \hat{\mathrm{Var}}(\vec{X} \mid Z = s) = \frac{1}{N_s - 1} \sum_{i:\ z_i = s} (\vec{x}_i - \vec{\mu}_s)^2$ sample variance per class ($\approx \mathrm{var}(\vec{B})$)
- $$\mathrm{SNR}(t) = \frac{\hat{\mathrm{Var}}(\vec{\mu}_Z(t))}{\hat{\mathbb{E}}[\vec{\varrho}_Z(t)]} \qquad \frac{\textit{variance inter-class}}{\textit{variance intra-class}}$$

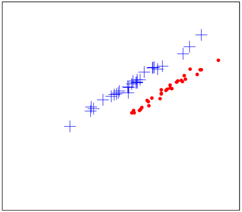
Fisher's Criterion for Linear Dimensionality Reduction

- $\mathbf{S_B} = \sum_{s \in \mathcal{Z}} N_s (\vec{\mu}_s - \bar{\vec{x}})(\vec{\mu}_s - \bar{\vec{x}})^{\intercal}$ (inter-class scatter matrix)
- $\mathbf{S_W} = \sum_{s \in \mathcal{Z}} \sum_{i=1:\ z_i = s} (\vec{x}_i - \vec{\mu}_s)(\vec{x}_i - \vec{\mu}_s)^{\intercal}$ (intra-class scatter matrix)
- Fisher's criterion

$$\hat{\vec{\alpha}} = \mathrm{argmax}_{\vec{\alpha}} \frac{\vec{\alpha}^{\intercal} \mathbf{S_B} \vec{\alpha}}{\vec{\alpha}^{\intercal} \mathbf{S_W} \vec{\alpha}} , \qquad (1)$$

$\epsilon(\vec{x}) = A\vec{x}$ where $A = [\vec{\alpha}_1, \dots, \vec{\alpha}_{|\mathcal{Z}|-1}]$ eigenvectors of $\mathbf{S_W}^{-1}\mathbf{S_B}$

LDA: an optimal binary linear classifier



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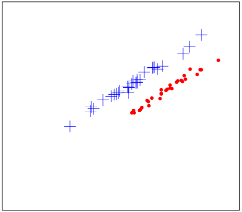

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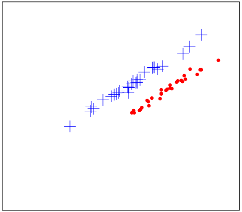

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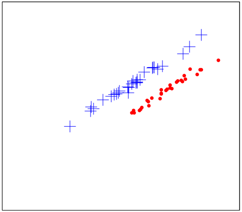

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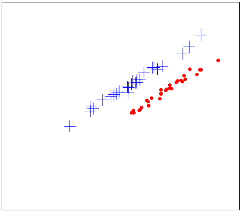

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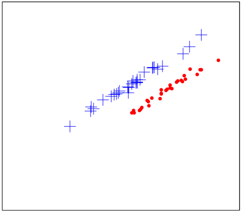

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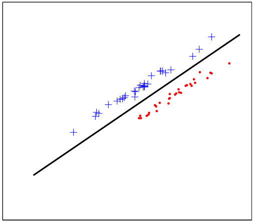
Generalised linear discriminative model

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

LDA and Fisher's Discriminant



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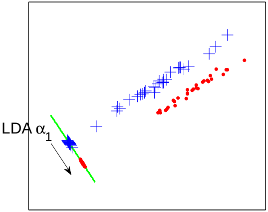

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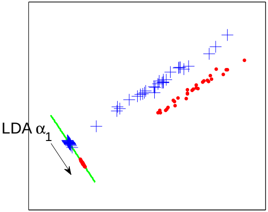

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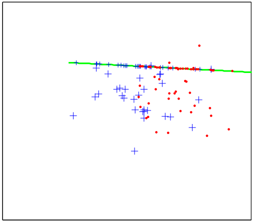
Fact, abuse and preference for the dimensionality reduction formulation

- 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



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What if $\mu_1 = \mu_2$?

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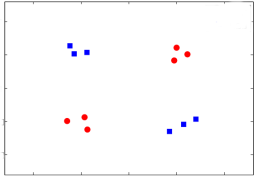

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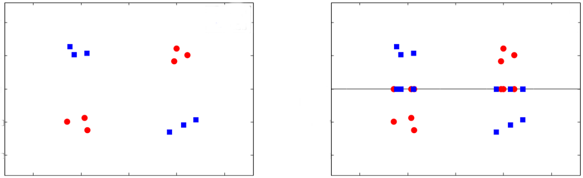

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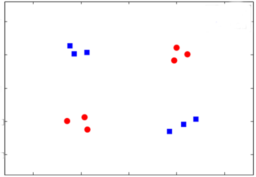

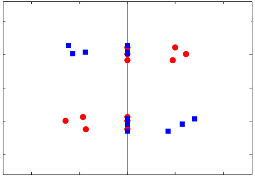

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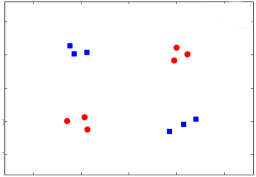

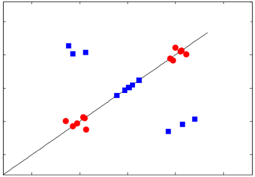

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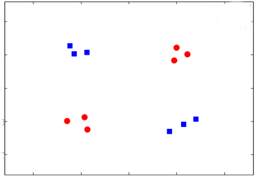

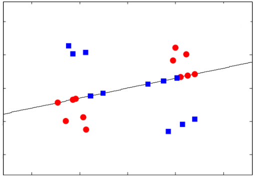

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Dimensionality reduction in presence of masking

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

Split each sensitive Z into shares $Z = M_1 \star \cdots \star M_d$
with $M_1, \ldots, M_{d-1}$ random shares (or masks)
and $M_d = Z \star M_1^{-1} \star \cdots \star M_{d-1}^{-1}$
Software implementations: shares are handled at different time samples

$$t_1, \ldots, t_d$$

$\Rightarrow$ each time sample is independent from Z.

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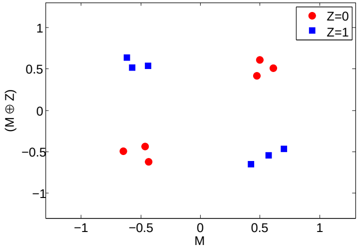

Toy example: 2 time samples, 1-bit data

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

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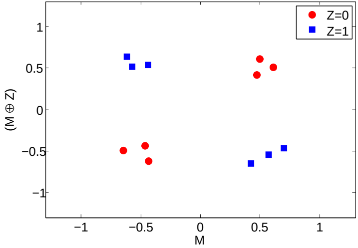

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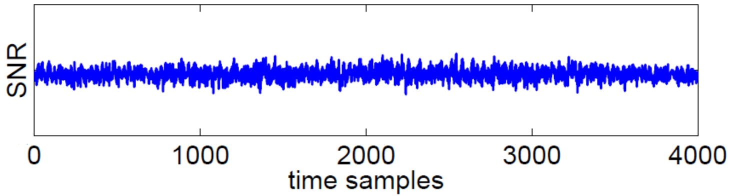

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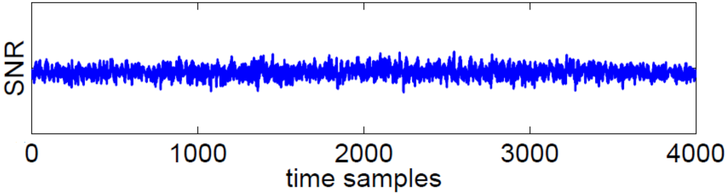

$\mathbb{E}[A\vec{X}|Z=z]$ is constant as well

Higher-Order Side-Channel Attacks

Exploit $f(z) = \mathbb{E}\left[\vec{X}[t_1]\vec{X}[t_2]\dots\vec{X}[t_d]|Z=z\right]$ non-constant.

Necessary condition

[Car+14] The statistic extracted from measurements must contain

$$\vec{X}[t_1]\vec{X}[t_2]\dots\vec{X}[t_d]$$

PoIs Research

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

A lacking literature

- many HO attacks papers assume the knowledge of $t_1, \ldots, t_d$
- PoI research exploiting the random shares knowledge (back to unprotected case using $M_1, \ldots, M_d$ instead of Z)
- naive strategy: infer over all possible d-tuples
- Hand selection via educated guess [Osw+06]

Generalizing extractors for higher-order context

- Selecting extractors $\longrightarrow$ Projection Pursuits [Dur+15]
- Projecting extractors $\longrightarrow$ Kernel Discriminant Analysis [CARDIS '16]

KDA: the purpose

Problem

Useful statistics lie in a high-dimensional *feature* space:

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

(all dth-degree monomials in the trace coordinates)

$$\begin{tikzcd}
\mathbb{R}^D \arrow[r, "\Phi"] \arrow[rr, bend left, "\epsilon^{\mathrm{KPCA}}"] \arrow[rr, bend right, "\epsilon^{\mathrm{KDA}}"'] & \mathcal{F} \arrow[r, shift left, "\epsilon^{\mathrm{PCA}}"] \arrow[r, shift right, "\epsilon^{\mathrm{LDA}}"'] & \mathbb{R}^C
\end{tikzcd}$$

Φ non-linear function

What KDA provides

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

KDA: an intuition

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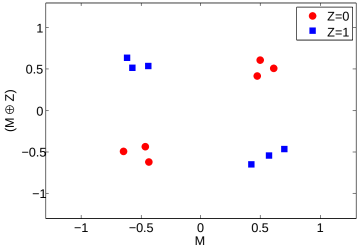

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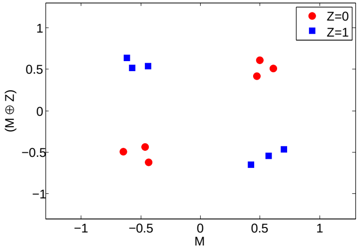

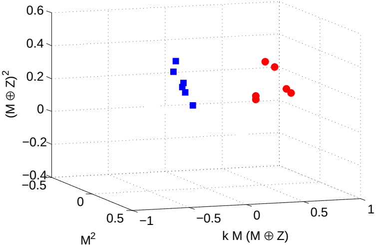

$$\Phi : \mathbb{R}^D \to \mathbb{R}^{\binom{D+d-1}{d}}$$

$$\Phi(t_1, t2) = (t_1^2, t_2^2, kt_1 t_2)$$

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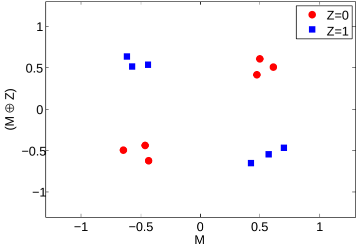

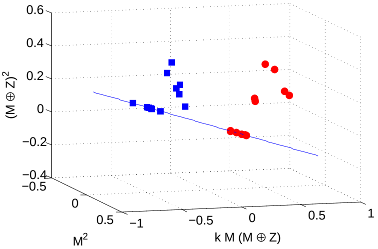

$\Phi \longrightarrow$ LDA

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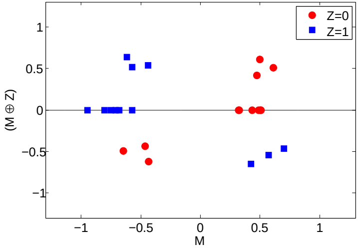

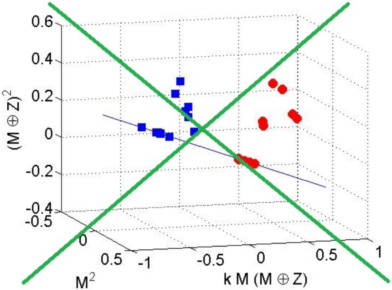

KDA
remains in $\mathbb{R}^D$

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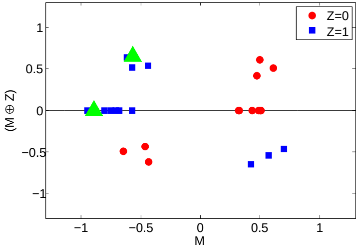

KDA procedure

- Training $\rightarrow \boldsymbol{\nu}_\ell$, C vectors of coefficients ($\ell = 1, \ldots, C$)

KDA: an intuition

Toy example: 2 time samples, 1-bit data

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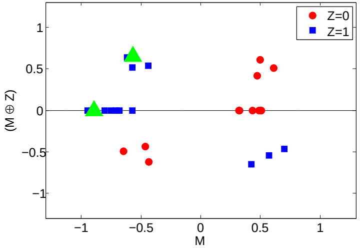

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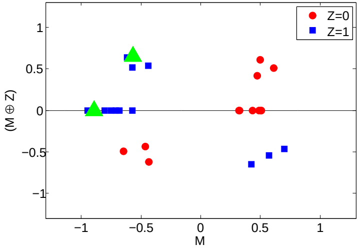

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- *Compare* the new trace with all training traces $K(\mathbf{x}_i^{z_i}, \mathbf{x})$, $K(\mathbf{x}_i^{z_i}, \mathbf{x})$
- *KDA projection*

$$\epsilon_\ell^{\mathrm{KDA}}(\vec{x}) = \sum_{i=1}^{N} \boldsymbol{\nu}_\ell[i] K(\mathbf{x}_i^{z_i}, \mathbf{x}) \ . \quad (3)$$

Kernel Function

Kernel Function

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

$$K(\mathbf{x}_i, \mathbf{x}_j) = \Phi(\mathbf{x}_i) \cdot \Phi(\mathbf{x}_j) \tag{4}$$

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

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Example: 2nd Degree Polynomial Kernel Function

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KDA - the training

Between-class (inter-class) Scatter Matrix

LDA

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

KDA

- $\mathbf{M} = \sum_{z \in \mathcal{Z}} N_z(\vec{M}_s - \vec{M}_T)(\vec{M}_s - \vec{M}_T)^\intercal$ [1]
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[1] $\vec{M}_s$ and $\vec{M}_T$ are two N-sized column vectors whose entries are given by:
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Within-class (inter-class) Scatter Matrix

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KDA - the training

Eigenvector problem

Computational Complexity $O(D^3)$

LDA

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

Computational Complexity $O(N^3)$

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KDA - the training

New trace projection

Computational Complexity $O(D^3)$

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Computational Complexity $O(N^3)$

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μ regularization parameter

Memory-based machine

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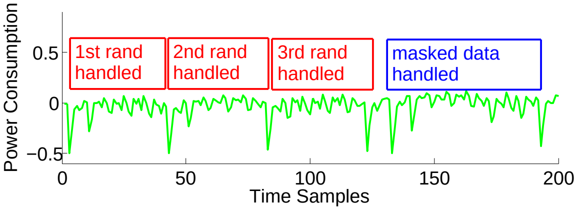
Experimental setup

Target device and acquisitions:

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

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



Efficiency/Accuracy trade-off

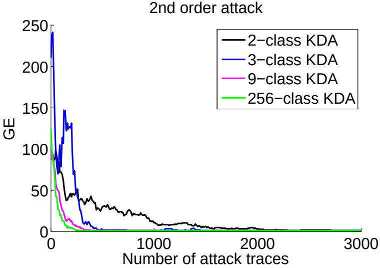
KDA training set size fixed ($\sim$ 9000 traces) to control efficiency

Adjust the number of classes to gain in accuracy

$Z = 0, \dots, 255$

Model	**number of classes**	**traces per class**
Value	256	35
HW	9	1000
HW $<, >, = 4$	3	3000
HW $\leq, > 4$	2	4500

Attack of second order



Implicit coefficients

$$\epsilon_\ell^{\mathrm{KDA}}(\mathbf{x}) = \sum_{i=1}^{N} \vec{\nu}_\ell[i] K(\mathbf{x}_i^{z_i}, \mathbf{x}) = \sum_{j=1}^{D}\sum_{k=1}^{D} [\ \underbrace{(\mathbf{x}[j]\mathbf{x}[k])}_{\text{multiplied time samples}} \ \underbrace{(\sum_{i=1}^{N} \boldsymbol{\nu}_\ell[i]\mathbf{x}_i[j]\mathbf{x}_i[k])]}_{\text{implicit coefficients}} \qquad (5)$$

$d = 2 \quad \longrightarrow \quad \binom{200+2-1}{2} = 20.100$ implicit coefficients

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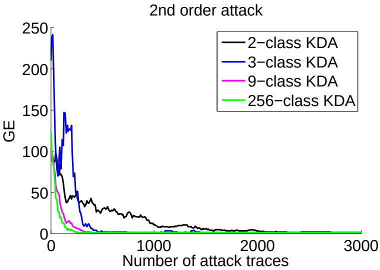

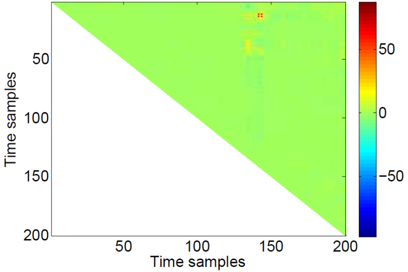

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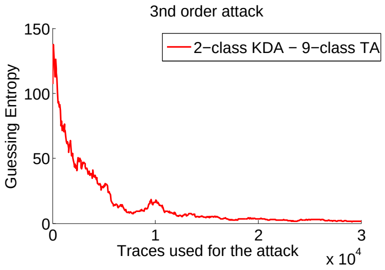
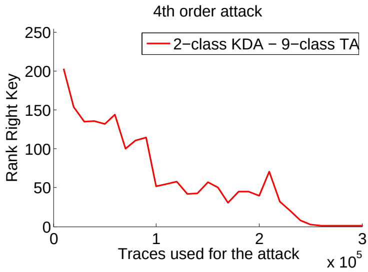
Third and Fourth Order

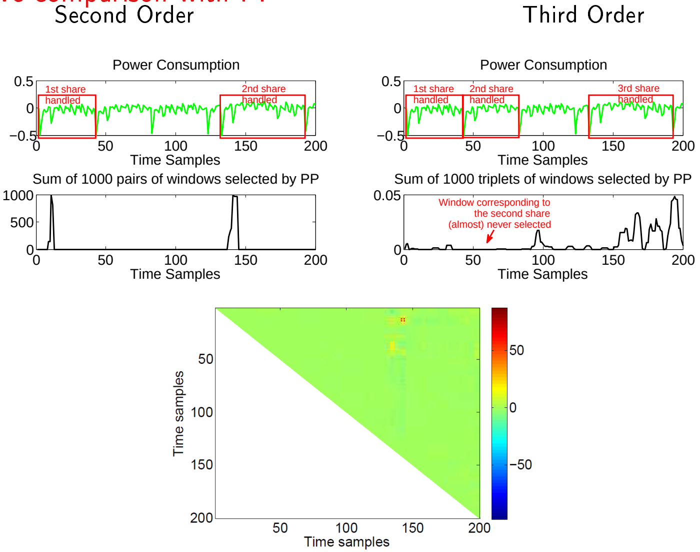




- $d = 3 \quad \longrightarrow \quad \binom{200+3-1}{3} = 1.353.400$ implicit coefficients
- $d = 4 \quad \longrightarrow \quad \binom{200+4-1}{4} = 68.685.050$ implicit coefficients

Same time of execution of the KDA algorithm!

Qualitative comparison with PP



Conclusions on KDA

Strong points

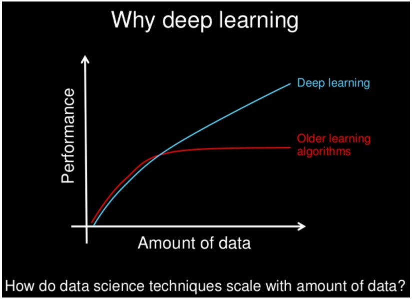
- KDA is suitable to attack $(d-1)$th-order masking
- Choice of the d-th degree polynomial kernel function
- KDA computational complexity is independent from the order d
- Tested and effective on a real case, positively compared to PP

Limits and drawbacks

- Memory-based + $O(N^3)$ complexity $\rightarrow$ Non-scalability to big training set $\rightarrow$ not suitable for highly-noisy higher-order masked signals
- Regularization hyper-parameter μ (and slow *validation*)

Contents

Motivations (1)



- not memory-based
- parallelizable computation(GPU optimizations)
- many hyper-parameters but faster validation

Motivations (2)

Profiling phase

- manage de-synchronization problem $[\mathcal{D}_{\text{train}} \longrightarrow \rho \colon \mathbb{R}^D \to \mathbb{R}^D]$
- mandatory dimensionality reduction $[\mathcal{D}_{\text{train}} \longrightarrow \epsilon \colon \mathbb{R}^D \to \mathbb{R}^C]$
- estimate
  - $p_{\epsilon(\rho(\vec{X}))\,|\,Z=z}$, $p_{\epsilon(\rho(\vec{X}))}$, p_Z (generative model)
    - Gaussian hypothesis [CRR03]
    - Variants: *pooled* version [CK14], linear regression [SLP05]
- $p_{Z\,|\,\epsilon(\rho(\vec{x}))}$ (discriminative model)

Many independent preprocessing steps and assumptions

Motivations (2)

Profiling phase

- manage de-synchronization problem $[\mathcal{D}_{\mathsf{train}} \longrightarrow \rho\colon \mathbb{R}^D \to \mathbb{R}^D]$
  DEEP LEARNING
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DEEP LEARNING

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

Multi-Layer Perceptron

Multi-Layer Perceptron (MLP)

$$F(\vec{x}, W) = s \circ \lambda_n \circ \sigma_{n-1} \circ \lambda_{n-1} \circ \cdots \circ \lambda_1(\vec{x}) = \vec{y} \approx \Pr[Z|\vec{X} = \vec{x}]$$

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- σ_i non-linear *activation* functions
- s normalizing *softmax* function

Multi-Layer Perceptron

Multi-Layer Perceptron (MLP)

$$F(\vec{x}, W) = s \circ \lambda_n \circ \sigma_{n-1} \circ \lambda_{n-1} \circ \cdots \circ \lambda_1(\vec{x}) = \vec{y} \approx \Pr[Z|\vec{X} = \vec{x}]$$

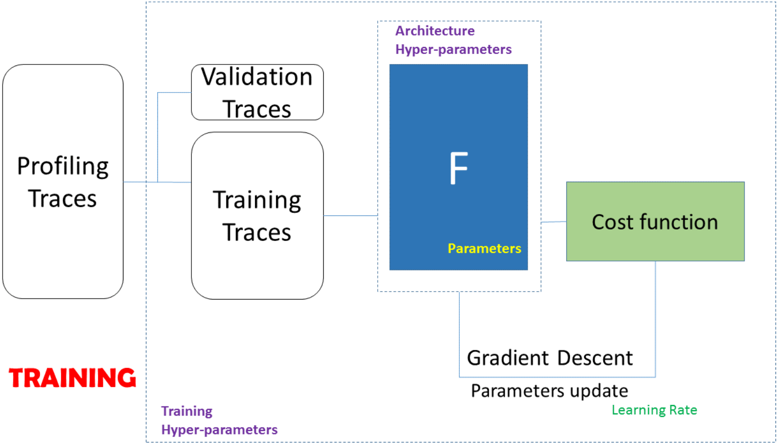
- λ_i linear functions (linear combinations of time samples) depending on some **trainable weights** W
- σ_i non-linear *activation* functions
- s normalizing *softmax* function

Softmax $\sim$ multi-class logistic sigmoid

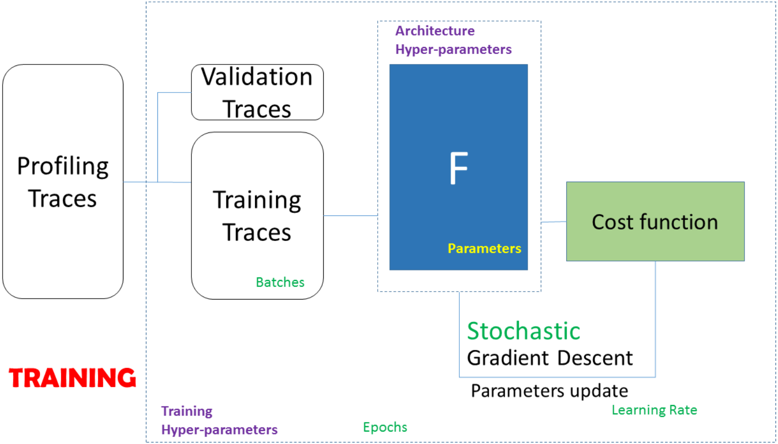
$$s(\mathbf{a})[k] = \frac{e^{\mathbf{a}[k]}}{\sum_{j=1}^{|\mathcal{Z}|} e^{\mathbf{a}[j]}} \ . \tag{6}$$

$$\Pr(s_j \mid \vec{x}) = \frac{\Pr(\vec{x} \mid s_j)\Pr(s_j)}{\Pr(\vec{x})} = \frac{\Pr(\vec{x} \mid s_j)\Pr(s_j)}{\sum_{k=1}^{|\mathcal{Z}|} \Pr(\vec{x} \mid s_k)\Pr(s_k)} = s(\mathbf{a})[j] \ , \tag{7}$$

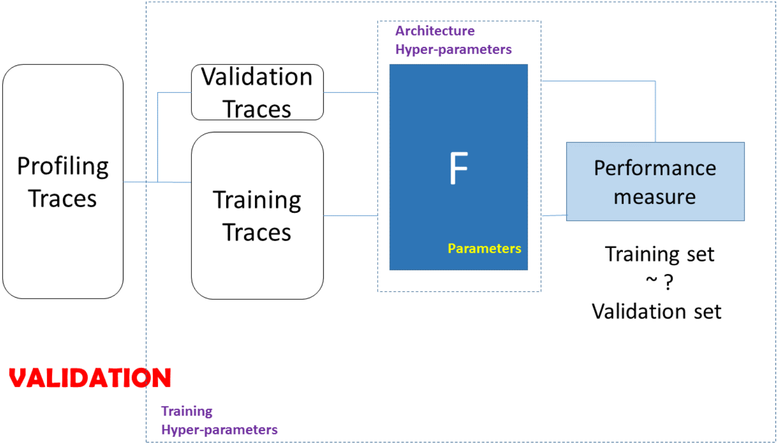
Training-Validation-Test



Training-Validation-Test



Training-Validation-Test



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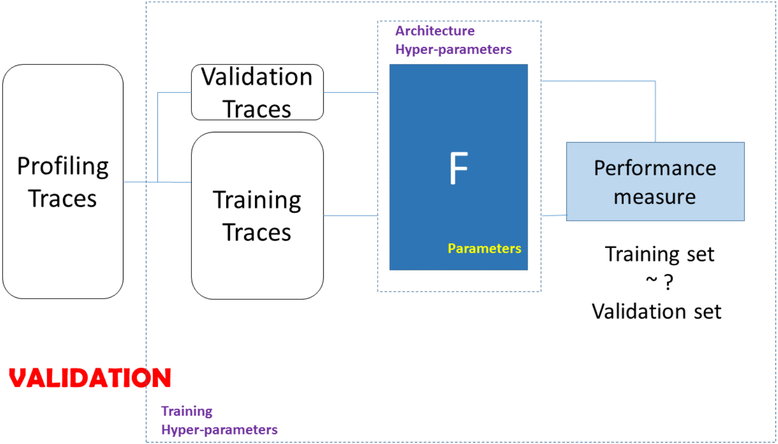


Cost function - Cross-entropy

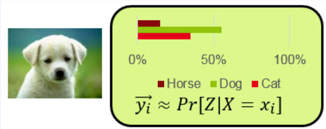
- batch of training data $(\vec{x}_i, z_i)_{i\in I}$, outputs of the current model $(\vec{y}_i)_{i\in I}$
- labels $z_i = s_j$ are *one-hot encoded*: $\vec{z}_i = \vec{s}_j = (0,\ldots,0,\underbrace{1}_{j},0,\ldots,0)$

Loss function

$$\mathcal{L} = -\frac{1}{|I|}\sum_{i\in I}\sum_{t=1}^{|\mathcal{Z}|}\vec{z}_i[t]\log\vec{y}_i[t] \tag{8}$$

Maximum-*a-posteriori* or Cross-entropy

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



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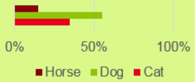
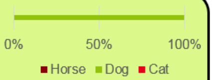
Maximum-*a-posteriori* or Cross-entropy

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



$\vec{y}_i \approx Pr[Z|X = x_i]$



$\vec{z}_i = Pr[Z|Z = s_j]$

Capacity-Overfitting-Regularization

Regression example

Performance metric: Mean Square Error (MSE)

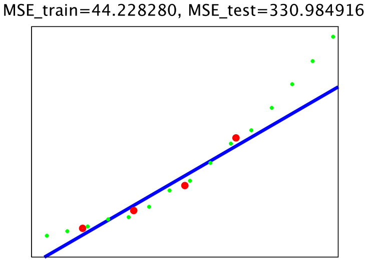


Figure: Linear regression → underfitting

Capacity-Overfitting-Regularization

Regression example

Performance metric: Mean Square Error (MSE)

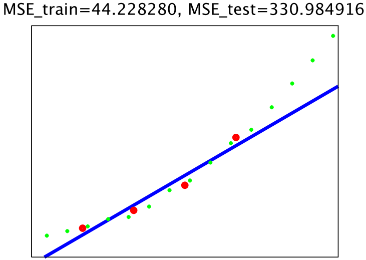


Figure: Linear regression → underfitting

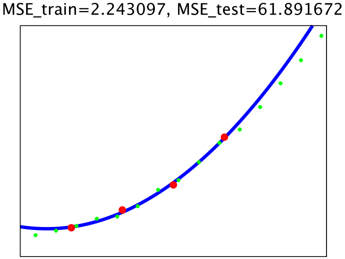


Figure: Linear regression → fits

Capacity-Overfitting-Regularization

Regression example

Performance metric: Mean Square Error (MSE)

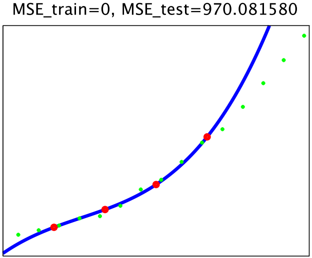


Figure: Cubic regression → overfitting

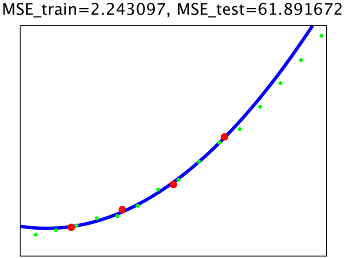


Figure: Linear regression → fits

Capacity-Overfitting-Regularization

Regression example

Performance metric: Mean Square Error (MSE)

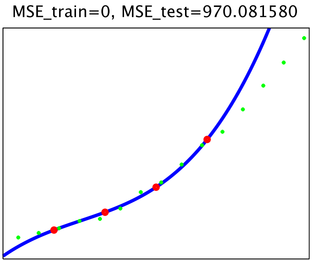


Figure: Cubic regression → overfitting

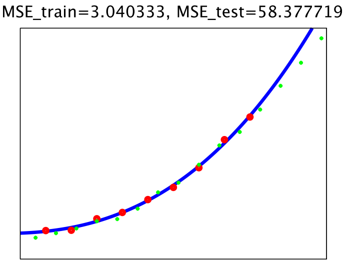


Figure: Cubic regression with more training data

Capacity-Overfitting-Regularization

Regression example

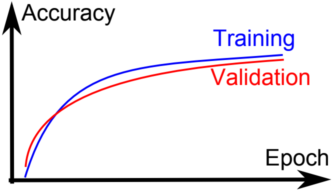
Performance metric: Mean Square Error (MSE)

Classification via Neural Network

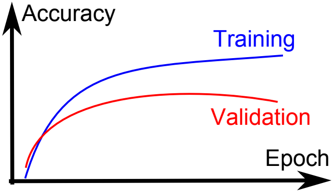
Performance measure: Accuracy (Classification rate)

Evaluate and compare training and validation accuracy

Understand significant features



Learn by heart (**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

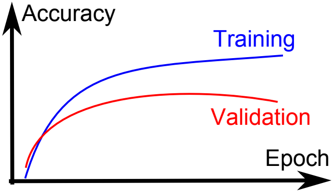
Learn by heart (**OVERFITTING**)

Why?

- Too complex model
- Not enough training data

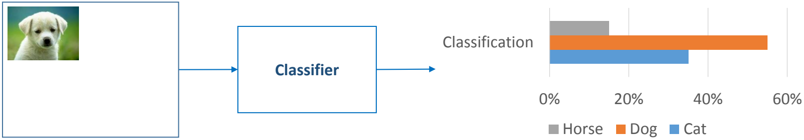
Solution?

- Data augmentation



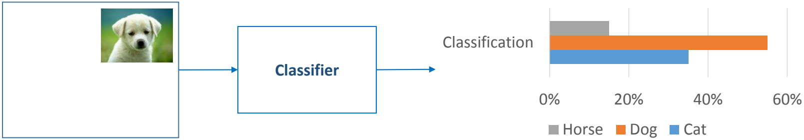
Convolutional Neural Networks

Translation-invariance



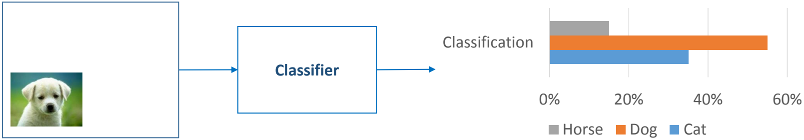
Convolutional Neural Networks

Translation-invariance



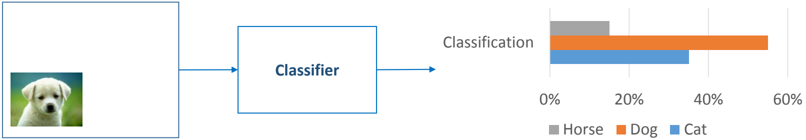
Convolutional Neural Networks

Translation-invariance



Convolutional Neural Networks

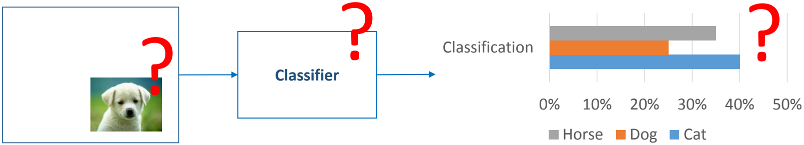
Translation-invariance



It is important to explicit the data translation-invariance

Convolutional Neural Networks

Translation-invariance



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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: share weights across space

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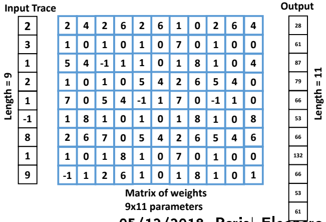
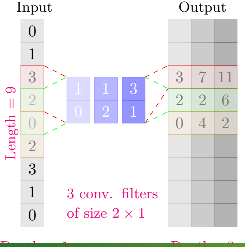
Convolutional Neural Networks: share weights across space

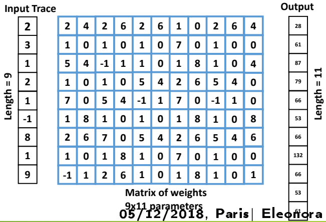


Convolutional Neural Networks

Translation-invariance

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





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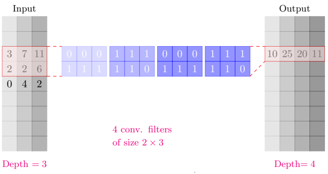

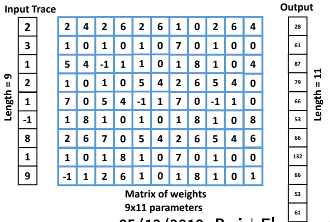

Figure: Linear layer in a ConvNet (*Convolutional*

Convolutional Neural Networks

Translation-invariance

It is important to explicit the data translation-invariance
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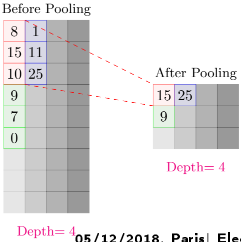
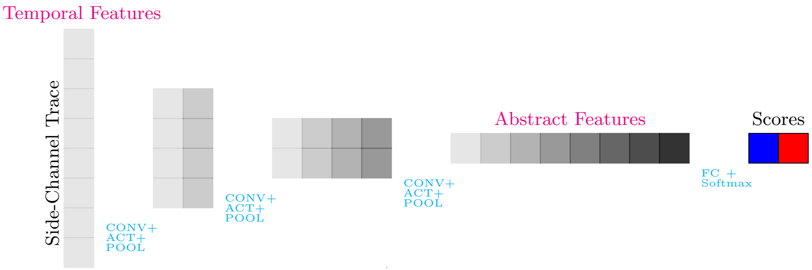


A kind of CNN architecture



VGG-like:

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

Model used in our experiments

$s \circ [\lambda]^1 \circ [\delta \circ [\sigma \circ \gamma]^1]^4$

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

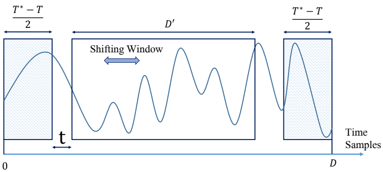


Figure: SH_T

ADD-REMOVE

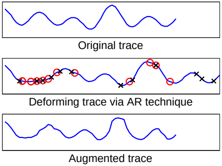


Figure: AR_R

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

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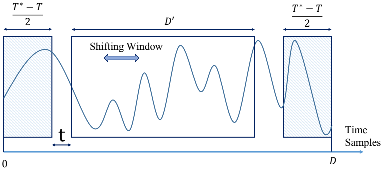


Figure: SH_T

ADD-REMOVE

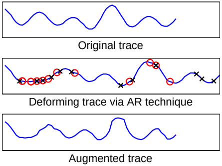


Figure: AR_R

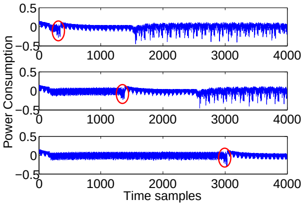
Parameter T: ♯ of possible positions $\longrightarrow$ new hyper-parameter
Parameter R: ♯ of added and removed points $\longrightarrow$ new hyper-parameter
Data Augmentation techniques are applied online during training phase

Experimental Results

- Random delays
- Artificial Jitter
- Real Jitter

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

Random delays



(a) One leaking operation

Setup

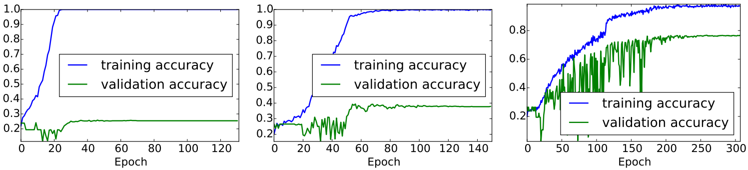
- Target Chip: Atmega328P
- Target Variable: $Z = \mathrm{HW}(\mathrm{Sbox}(P \oplus K))$
- Acquisition: through *ChipWhisperer*® platform, $\approx 4,000$ time samples
- Countermeasure: Random Delays - insertion of r *nop* operations, $r \in [0, 127]$ uniform random
- $1,000$ training traces

Random delays

Data augmentation vs overfitting

Metrics

- Test accuracy: classification accuracy over the attack traces
- $N^\star$: minimum number of attack traces to make *guessing entropy* of the right key permanently equal to one ($N^\star$ estimated over 10 independent attacks)



SH_0 SH_{100} SH_{500}

Random delays

Data augmentation vs overfitting

Metrics

- Test accuracy: classification accuracy over the attack traces
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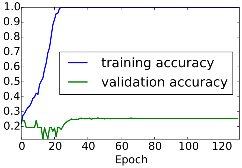
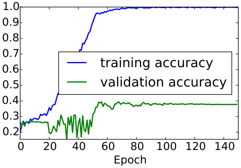
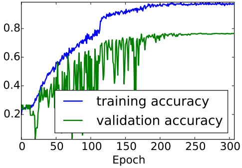


SH_0



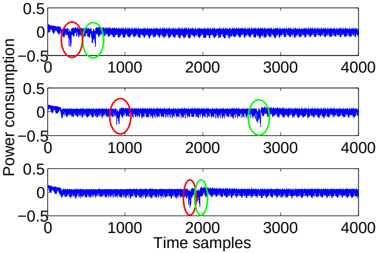
SH_{100}



SH_{500}

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

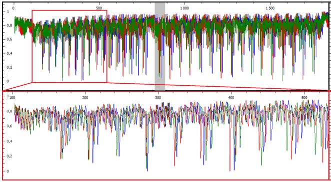
Random Delays - Two Leaking Operations



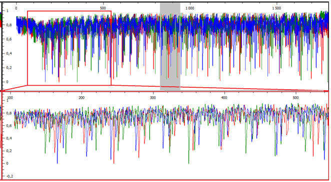
Two leaking operations

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

Artificial Jitter



(h) Low artificial jitter



(i) High artificial jitter

Target

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

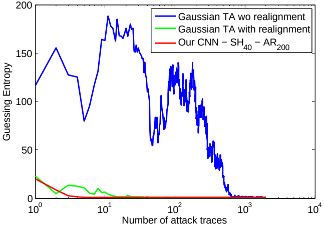
Artificial Jitter (2)

Low_jitter

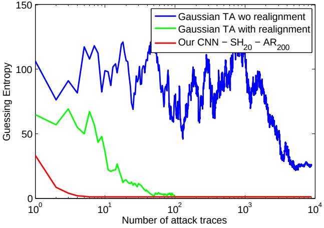
Acc	$N^{\star}$	SH_0		SH_{20}		SH_{40}	
AR_0		57.4%	14	82.5%	6	83.6%	6
AR_{100}		86.0%	6	87.0%	5	87.5%	6
AR_{200}		86.6%	6	85.7%	6	87.7%	5

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



(j) Low Jitter



(k) High Jitter

Artificial Jitter

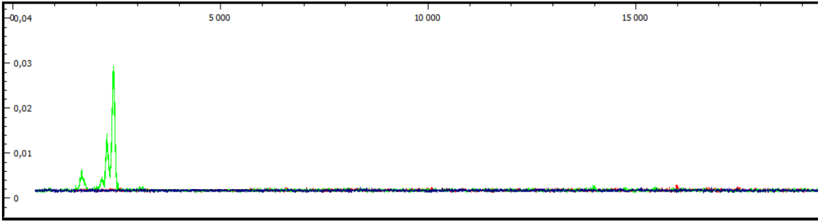
DS_low_jitter								
a b c d	SH_0		SH_{20}		SH_{40}		SH_{200}	
AR_0	100.0%	68.7%	99.8%	86.1%	98.9%	84.1%		
	57.4%	14	82.5%	6	83.6%	6		
AR_{100}	87.7%	88.2%	82.4%	88.4%	81.9%	89.6%		
	86.0%	6	87.0%	5	87.5%	6		
AR_{200}	83.2%	88.6%	81.4%	86.9%	80.6%	88.9%		
	86.6%	6	85.7%	6	87.7%	5		
AR_{500}							85.0%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

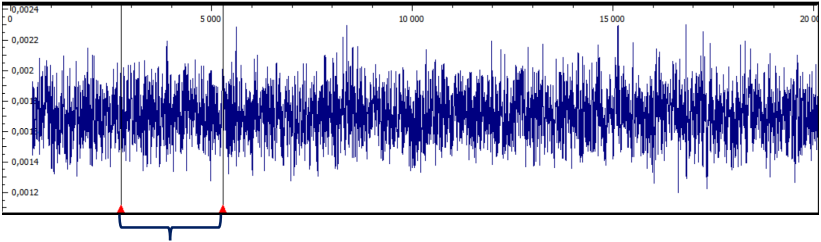


Real Jitter (1)

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 second Sbox without realignment



Entry region for CNN (2,500 pts)

Real Jitter (2)

		$\mathrm{SH}_{0}\mathrm{AR}_{0}$		$\mathrm{SH}_{10}\mathrm{AR}_{100}$		$\mathrm{SH}_{20}\mathrm{AR}_{200}$	
Acc	$N^{\star}$	1.2%	137	1.3%	89	1.8%	54

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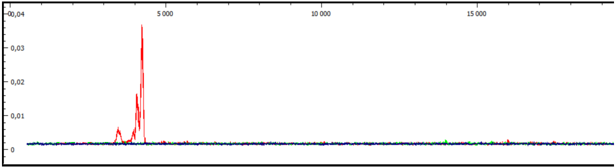
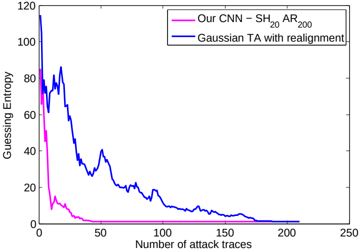
SNR second Sbox with realignment





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- From CNN to PoIs, visualizing techniques
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Thank You!

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