

Feature Extraction for Side-Channel Attacks

Eleonora Cagli

05/12/2018, Paris

*PhD Supervisor : Emmanuel Prouff
(ANSSI)*

*CEA Supervisor : Cécile Dumas
(CEA-Leti Grenoble)*

Contents

1. Context
2. State of the Art, Objectives, Contributions
3. Kernel Discriminant Analysis against Masking
 - 3.1 Kernel Discriminant Analysis
 - 3.2 Experimental Results
4. Deep Learning against Misalignment
 - 4.1 Data Augmentation
 - 4.2 Experimental Results
5. Conclusions

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...)

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...)



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

⇒ Requires protection against very high-level attacker

Security Certification



- ▶ Standardised Evaluation (e.g. ISO/IEC 15408 - Common Criteria)
- ▶ Many evaluation tasks
- ▶ AVA class: vulnerability assessment (penetration testing)

Side-Channel Vulnerability of Embedded Cryptography

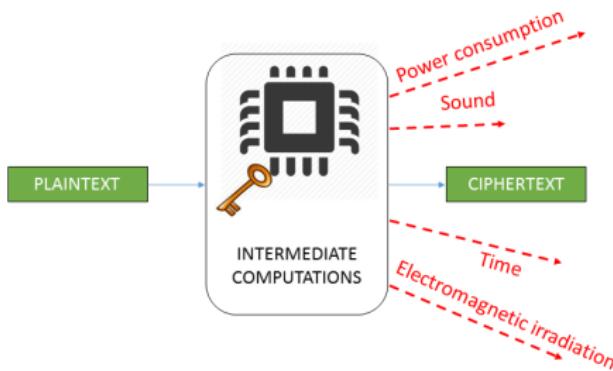


Classical Cryptanalysis

Mathematical vulnerability
Black Box

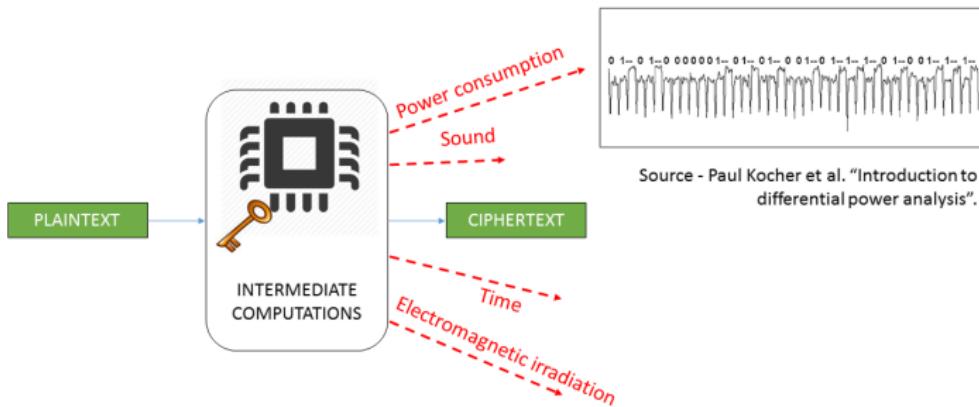
Side-Channel Cryptanalysis

Side-Channel Vulnerability of Embedded Cryptography



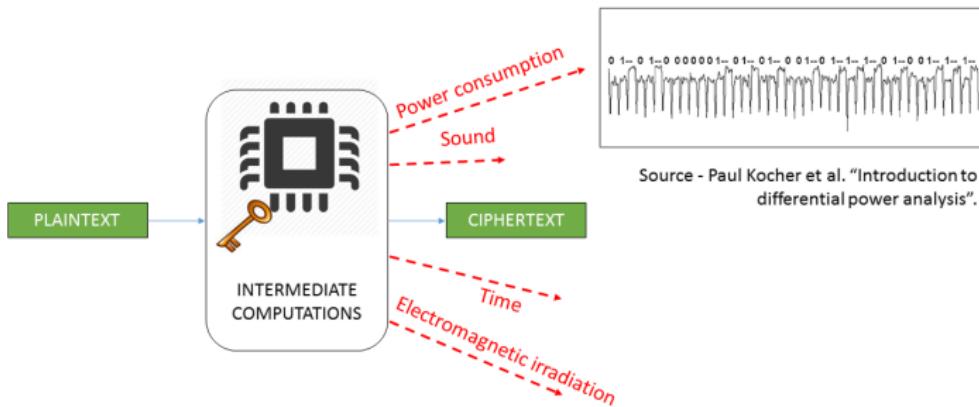
Classical Cryptanalysis	Side-Channel Cryptanalysis
Mathematical vulnerability Black Box	Physical vulnerability Grey Box / Divide-and-conquer

Side-Channel Vulnerability of Embedded Cryptography



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

Side-Channel Vulnerability of Embedded Cryptography



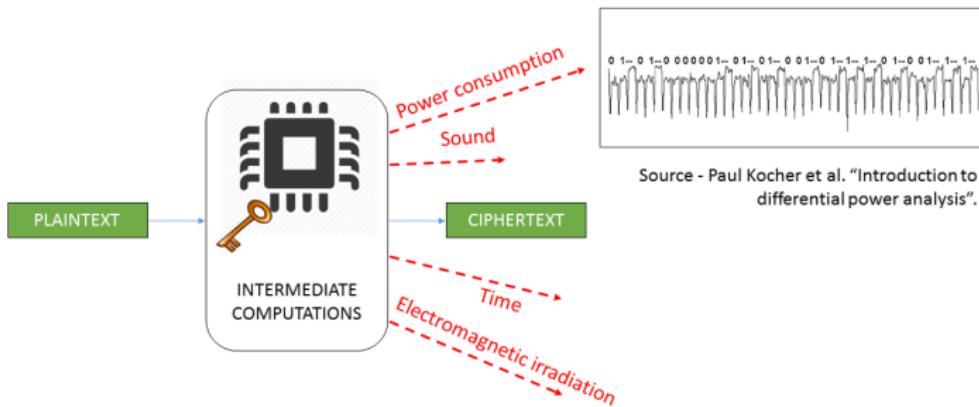
Classical Cryptanalysis

Mathematical vulnerability
Black Box

Side-Channel Cryptanalysis

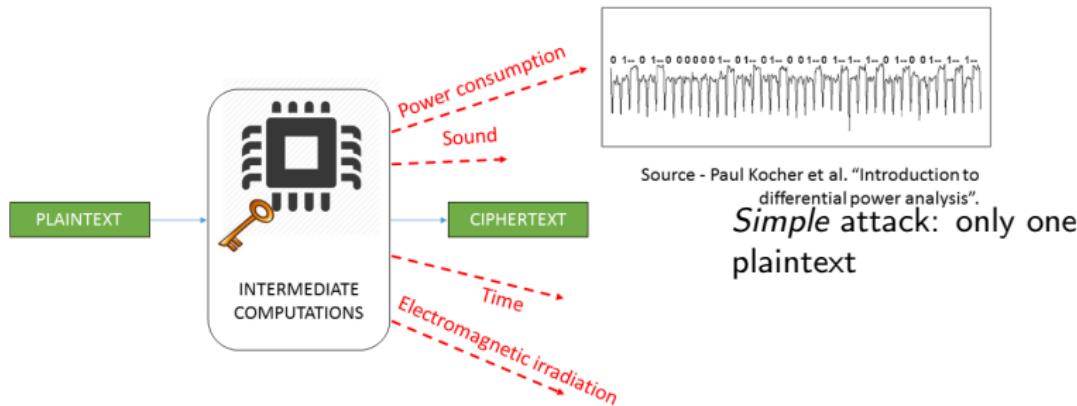
Physical vulnerability
Grey Box / Divide-and-conquer

Side-Channel Vulnerability of Embedded Cryptography



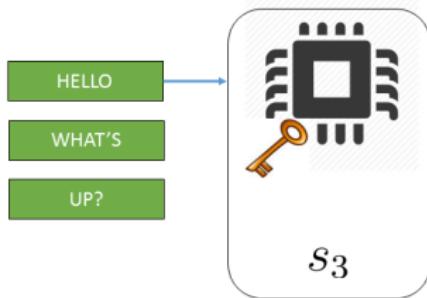
Classical Cryptanalysis	Side-Channel Cryptanalysis
Mathematical vulnerability Black Box	Physical vulnerability Grey Box / Divide-and-conquer

Side-Channel Vulnerability of Embedded Cryptography

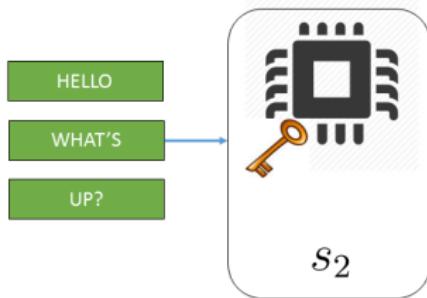


Classical Cryptanalysis	Side-Channel Cryptanalysis
Mathematical vulnerability Black Box	Physical vulnerability Grey Box / Divide-and-conquer

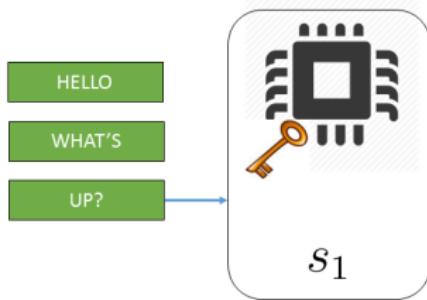
Advanced Side-Channel Attacks



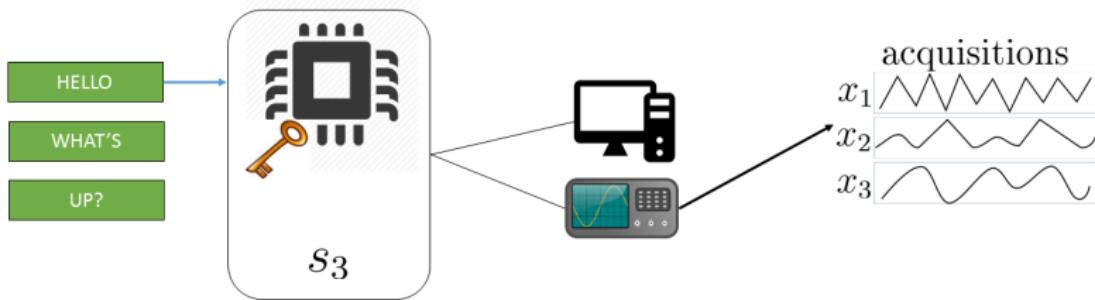
Advanced Side-Channel Attacks



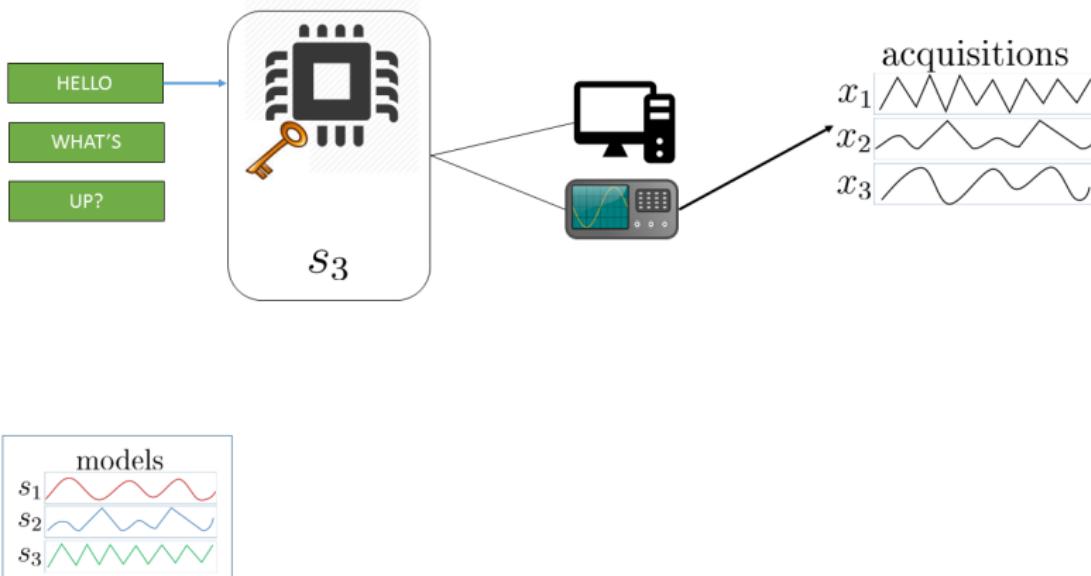
Advanced Side-Channel Attacks



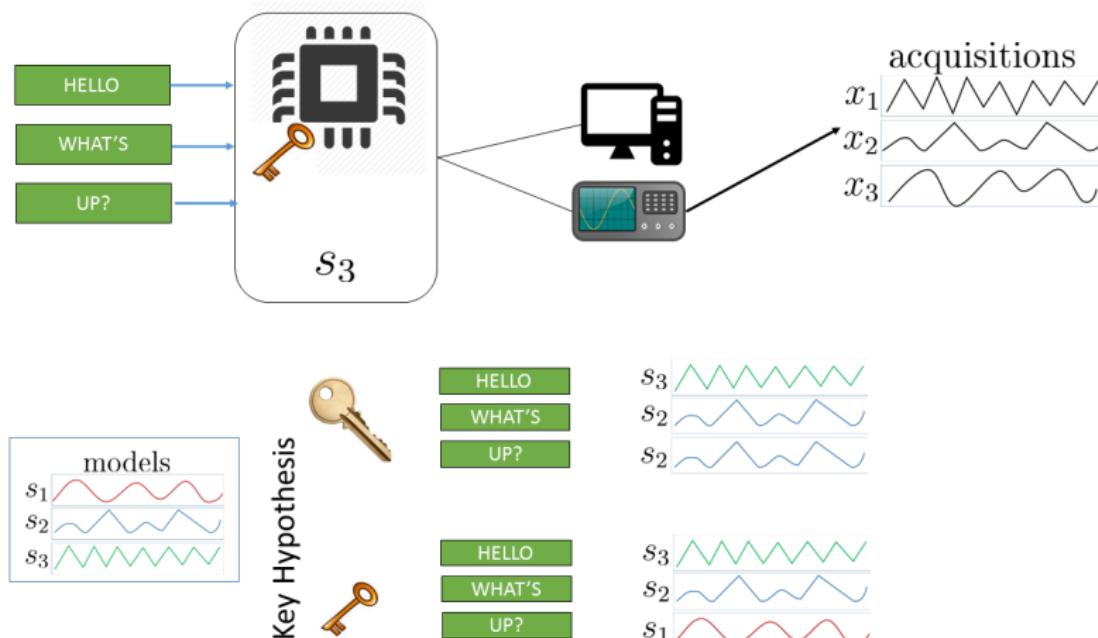
Advanced Side-Channel Attacks



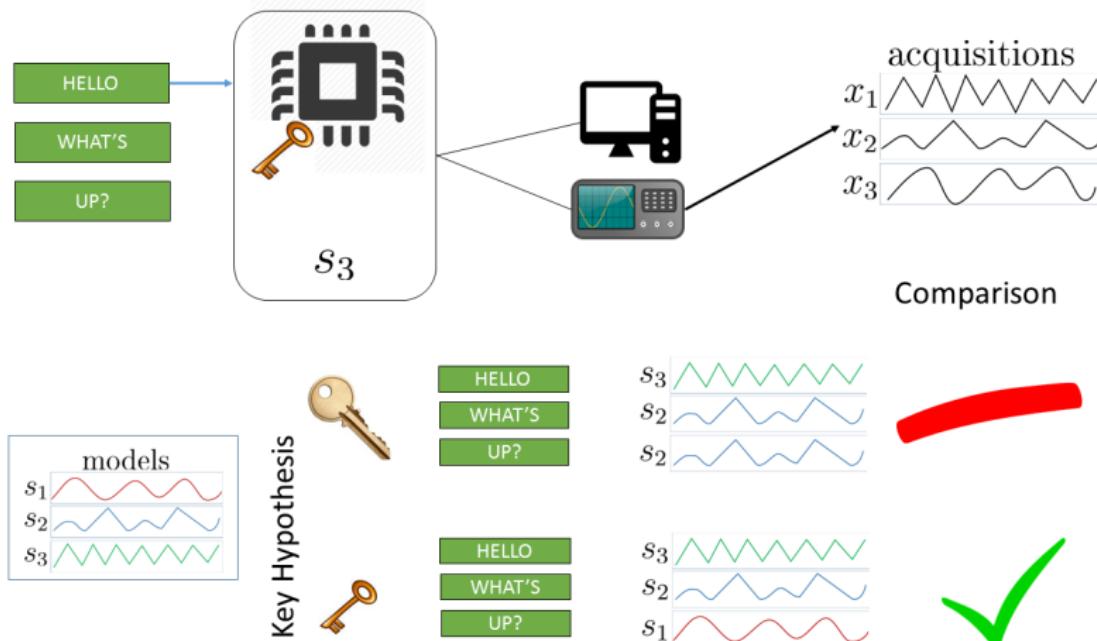
Advanced Side-Channel Attacks



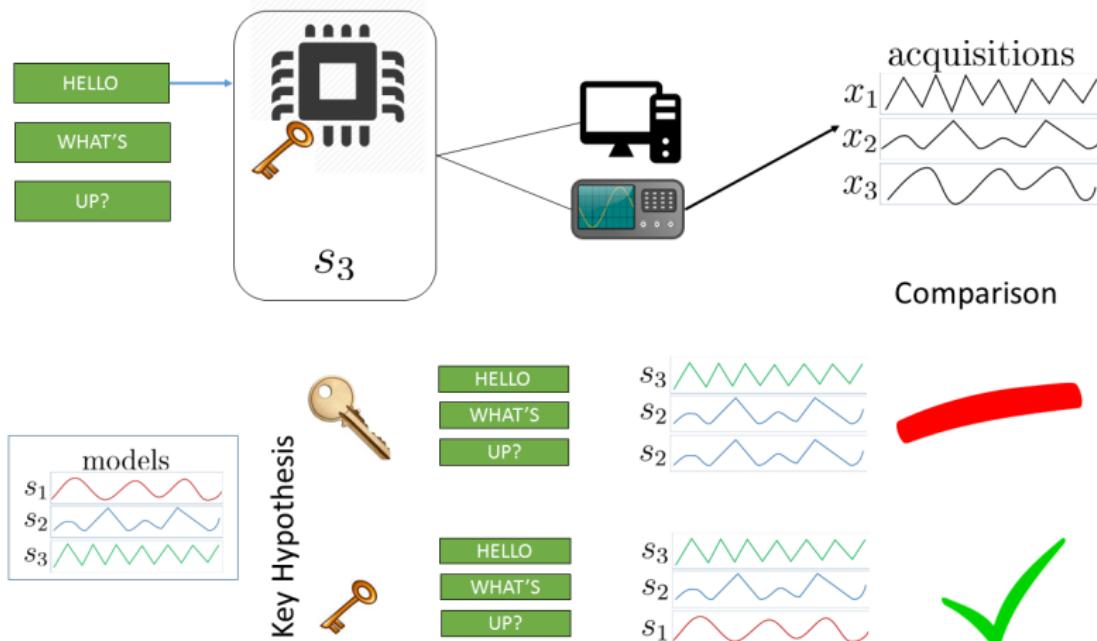
Advanced Side-Channel Attacks



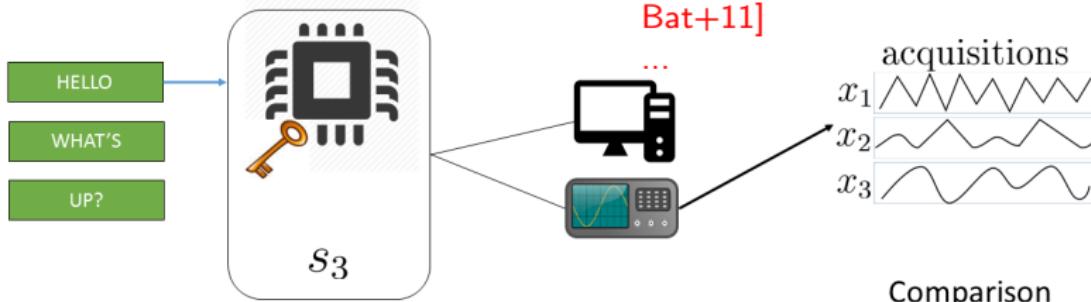
Advanced Side-Channel Attacks



Advanced Side-Channel Attacks

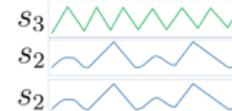
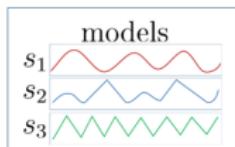


Advanced Side-Channel Attacks

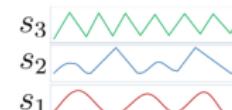


Non-profiling attacks

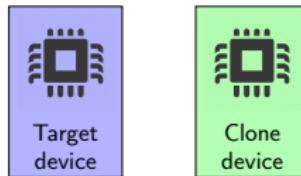
Profiling attacks ...



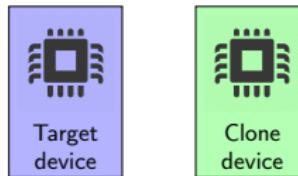
Comparison



Profiling Attacks...Supervised Learning



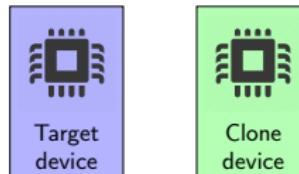
Profiling Attacks...Supervised Learning



Machine Learning

Supervised Learning

Profiling Attacks...Supervised Learning

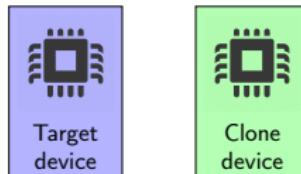


Machine Learning

"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



Machine Learning

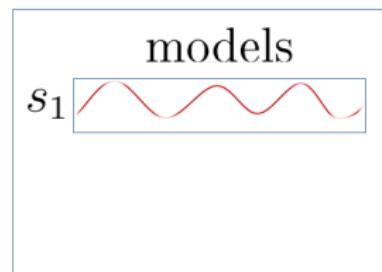
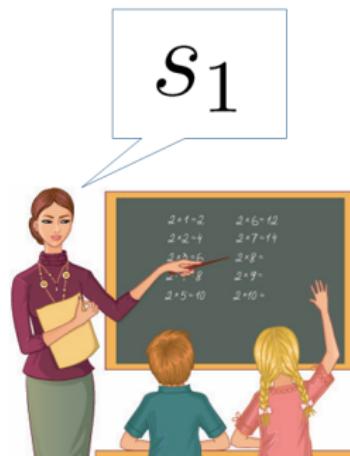
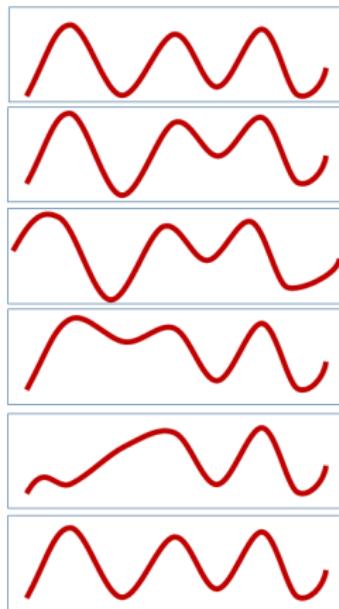
"A computer program is said to learn from experience E with respect to some task T and performance measure P, if its performance on T, as measured by P, improves with experience E. "[TM97]

Supervised Learning

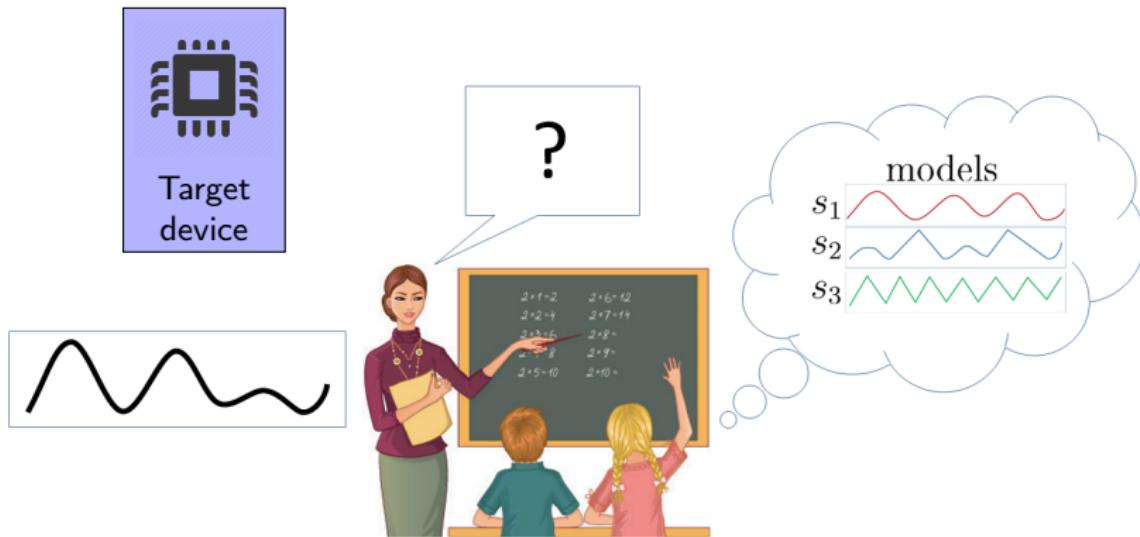
The *supervised* learning algorithms access to a dataset of examples, each associated in general to a *target* or *label*.



Classroom Side-Channel Attacks



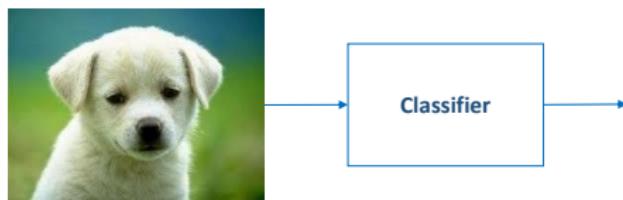
Classroom Side-Channel Attacks



Classification

Classification problem

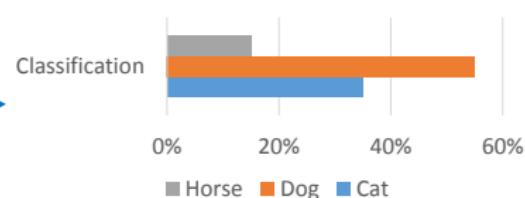
Assign to a datum \vec{X} (e.g. an image) a label Z among a set of possible labels
 $\mathcal{Z} = \{\text{Cat, Dog, Horse}\}$



Classification

Classification problem

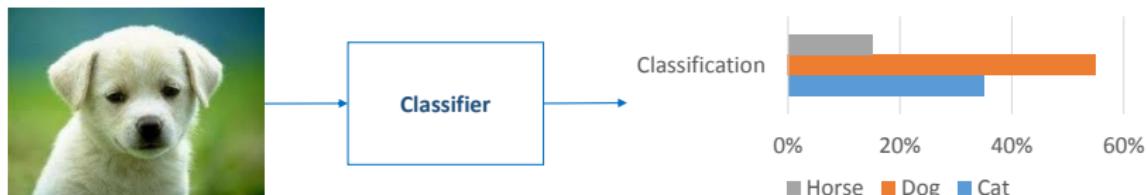
Assign to a datum \vec{X} (e.g. an image) a label Z among a set of possible labels
 $\mathcal{Z} = \{\text{Cat}, \text{Dog}, \text{Horse}\}$



Classification

Classification problem

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



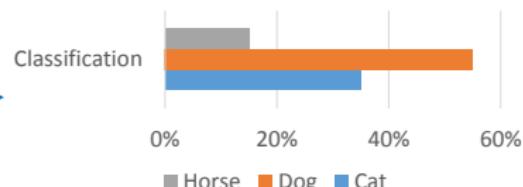
Advanced Attack as a Classification Problem



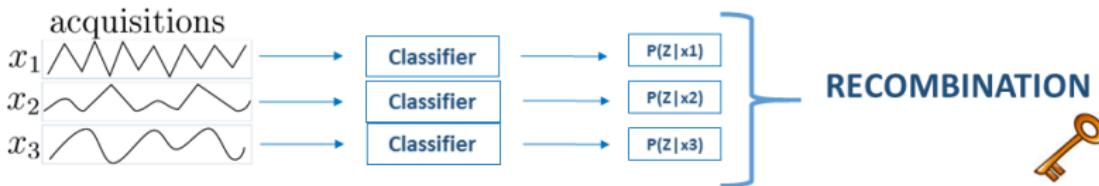
Classification

Classification problem

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



Advanced Attack as Multiple Classification Problems



Contents

1. Context
2. State of the Art, Objectives, Contributions
3. Kernel Discriminant Analysis against Masking
 - 3.1 Kernel Discriminant Analysis
 - 3.2 Experimental Results
4. Deep Learning against Misalignment
 - 4.1 Data Augmentation
 - 4.2 Experimental Results
5. Conclusions

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 $Z = f(\text{plaintext}, \text{key})$ in $\mathcal{Z} = \{s_1, \dots, s_{|\mathcal{Z}|}\}$

Profiling attack scenario

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

Profiling Attack

Profiling phase

- ▶ estimate
 - ▶ $p_{\vec{X}} | Z=z$

Attack phase

- ▶ Likelihood score for each key hypothesis k

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

Profiling Attack

Profiling phase

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

Attack phase

- ▶ 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

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

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

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)

Attack phase

- ▶ 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

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

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

Profiling Attack

Profiling phase

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

Curse of dimensionality!

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

Attack phase

- ▶ Likelihood score for each key hypothesis k

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

- ▶ A-posteriori probability score for each key hypothesis k

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

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

Profiling Attack

Profiling phase

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

Curse of dimensionality!

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

Attack phase

- ▶ Likelihood score for each key hypothesis k

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

- ▶ A-posteriori probability score for each key hypothesis k

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

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

Profiling Attack

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

Curse of dimensionality!

Profiling phase

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

Attack phase

- ▶ Likelihood score for each key hypothesis k

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

- ▶ A-posteriori probability score for each key hypothesis k

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

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

Profiling Attack

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

Curse of dimensionality!

Profiling phase

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

Attack phase

- ▶ Likelihood score for each key hypothesis k

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

- ▶ A-posteriori probability score for each key hypothesis k

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

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

Objectives

Profiling phase

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

Objectives

Objectives

Profiling phase

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

Objectives

Profiling phase

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

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

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

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

Feature selection

ϵ performs a sub-sampling

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

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

Feature selection

ϵ performs a sub-sampling

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

Linear feature extraction

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

- ▶ 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

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

Feature selection

ϵ performs a sub-sampling

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

Linear feature extraction

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

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

SNR, Fisher's criterion and LDA classifier

Feature selection - SNR

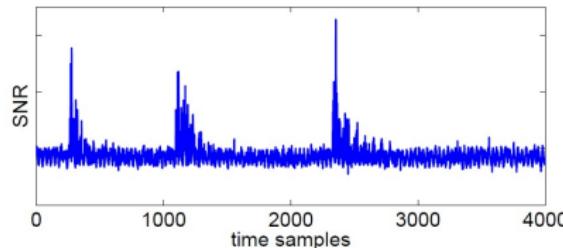


Figure: $SNR(t) = \frac{\text{variance inter-class}}{\text{variance intra-class}}$

SNR, Fisher's criterion and LDA classifier

Feature extraction - LDA

Feature selection - SNR

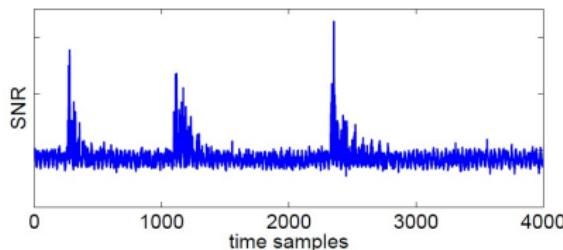


Figure: $SNR(t) = \frac{\text{variance inter-class}}{\text{variance intra-class}}$

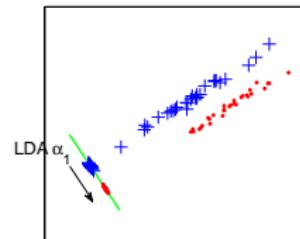


Figure: Fisher's Criterion: project into a subspace in which $\frac{\text{inter-class covariance matrix}}{\text{intra-class covariance matrix}}$ is maximised

SNR, Fisher's criterion and LDA classifier

Feature extraction - LDA

Feature selection - SNR

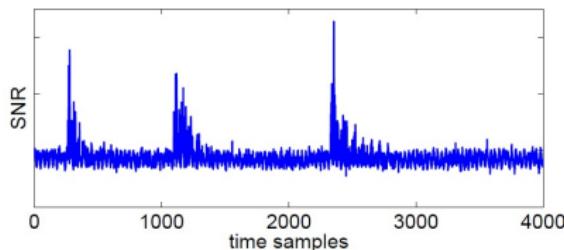


Figure: $SNR(t) = \frac{\text{variance inter-class}}{\text{variance intra-class}}$

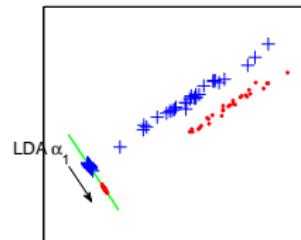


Figure: Fisher's Criterion: project into a subspace in which $\frac{\text{inter-class covariance matrix}}{\text{intra-class covariance matrix}}$ is maximised

LDA: optimal classifier under following hypothesis

- ▶ Gaussian distributions with parameters μ_j, Σ_j
- ▶ Homoscedasticity: $\Sigma_j = \Sigma$ for all j

Fisher's criterion \Leftrightarrow LDA

SNR, Fisher's criterion and LDA classifier

Feature extraction - LDA

Feature selection - SNR

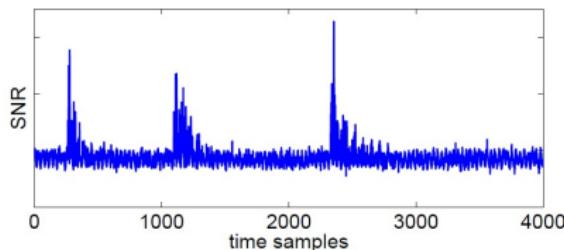


Figure: $SNR(t) = \frac{\text{variance inter-class}}{\text{variance intra-class}}$

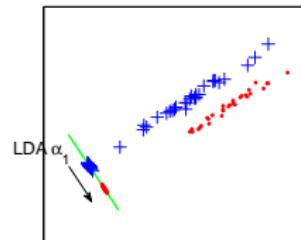


Figure: Fisher's Criterion: project into a subspace in which $\frac{\text{inter-class covariance matrix}}{\text{intra-class covariance matrix}}$ is maximised

LDA: optimal classifier under following hypothesis

- ▶ Gaussian distributions with parameters μ_j, Σ_j
- ▶ Homoscedasticity: $\Sigma_j = \Sigma$ for all j

Fisher's criterion \Leftrightarrow LDA

SNR and LDA most suitable selector and extractor for classification purposes

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)
 - ▶ Data Augmentation techniques to reduce overfitting

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)
 - ▶ Data Augmentation techniques to reduce overfitting

Contents

1. Context
2. State of the Art, Objectives, Contributions
3. Kernel Discriminant Analysis against Masking
 - 3.1 Kernel Discriminant Analysis
 - 3.2 Experimental Results
4. Deep Learning against Misalignment
 - 4.1 Data Augmentation
 - 4.2 Experimental Results
5. Conclusions

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, \dots, M_{d-1} random shares (or masks)
and $M_d = Z \star M_1^{-1} \star \cdots \star M_{d-1}^{-1}$
Shares are handled at time samples

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

Indistinguishability up to order $d - 1$

$$f(z) = \mathbb{E}[\vec{X}|Z = z] \text{ constant}$$

$$f(z) = \text{Cov}(\vec{X}|Z = z) \text{ constant}$$

...

$(d - 1)$ th statistical orders of $\vec{X}|Z = z$, all identical

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, \dots, M_{d-1} random shares (or masks)
and $M_d = Z \star M_1^{-1} \star \cdots \star M_{d-1}^{-1}$
Shares are handled at time samples

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

Indistinguishability up to order $d - 1$

$$f(z) = \mathbb{E}[\vec{X}|Z = z] \text{ constant}$$

$$f(z) = \text{Cov}(\vec{X}|Z = z) \text{ constant}$$

...

$(d - 1)$ th statistical orders of $\vec{X}|Z = z$, all identical

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

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, \dots, M_{d-1} random shares (or masks)
and $M_d = Z \star M_1^{-1} \star \cdots \star M_{d-1}^{-1}$
Shares are handled at time samples

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

Indistinguishability up to order $d - 1$

$$f(z) = \mathbb{E}[\vec{X}|Z = z] \text{ constant}$$

$$f(z) = \text{Cov}(\vec{X}|Z = z) \text{ constant}$$

...

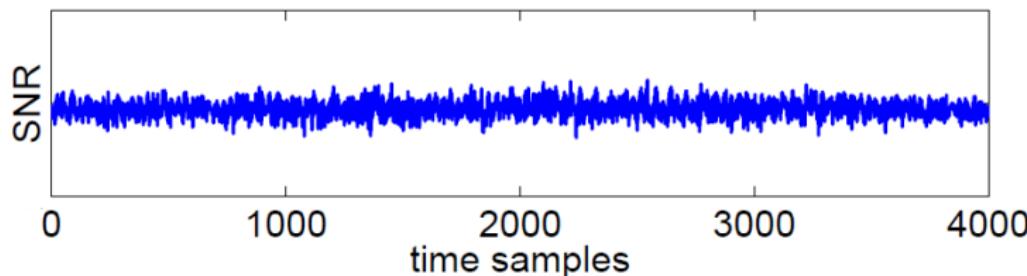
$(d - 1)$ th statistical orders of $\vec{X}|Z = z$, all identical

$f(z) = \mathbb{E} [\vec{X}[t_1]\vec{X}[t_2] \dots \vec{X}[t_d]|Z = z]$ 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**)

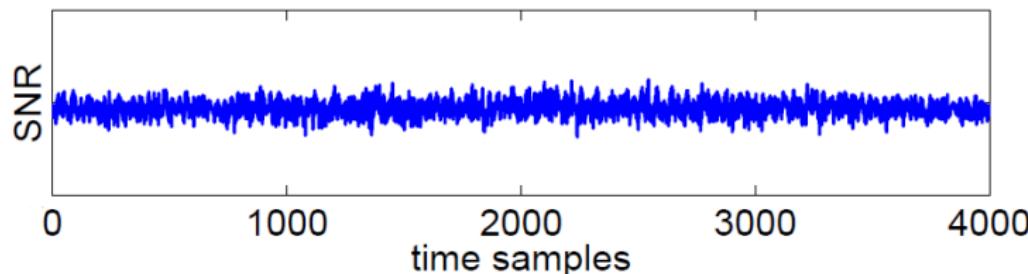
How to detect the d -tuple t_1, \dots, t_d ?

$f(z) = \mathbb{E}[\vec{X}|Z = z]$ is constant \Rightarrow Variance inter-class null! \Rightarrow SNR, SOD, t-statistic null!

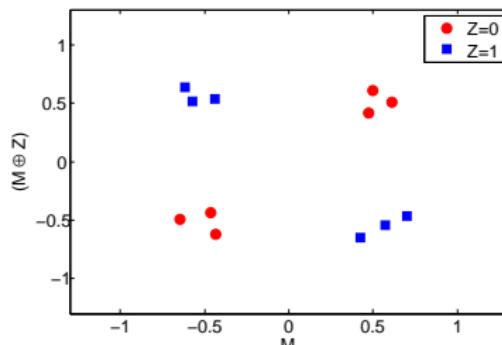


How to detect the d -tuple t_1, \dots, t_d ?

$f(z) = \mathbb{E}[\vec{X}|Z = z]$ is constant \Rightarrow Variance inter-class null! \Rightarrow SNR, SOD, t-statistic null!



$\mathbb{E}[A\vec{X}|Z = z]$ is constant as well \Rightarrow any projecting extraction is useless!



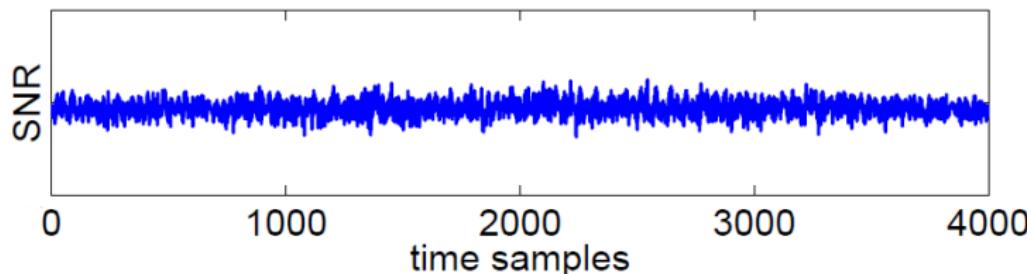
Toy example: 2 time samples, 1-bit data

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

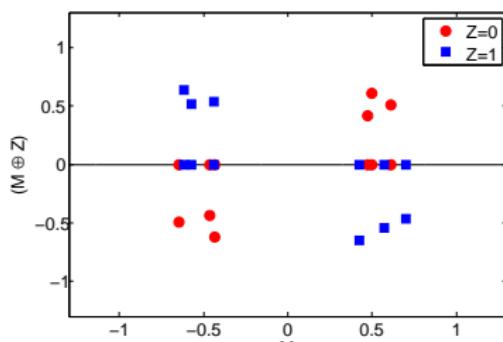
$t_2: M \oplus Z + n$ (Boolean masking)

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

$f(z) = \mathbb{E}[\vec{X}|Z = z]$ is constant \Rightarrow Variance inter-class null! \Rightarrow SNR, SOD, t-statistic null!



$\mathbb{E}[A\vec{X}|Z = z]$ is constant as well \Rightarrow any projecting extraction is useless!



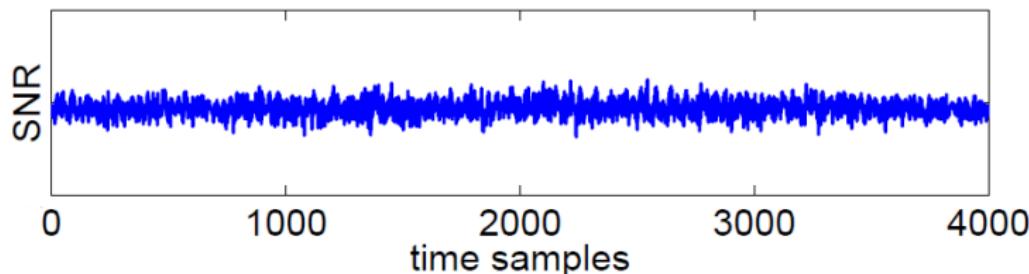
Toy example: 2 time samples, 1-bit data

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

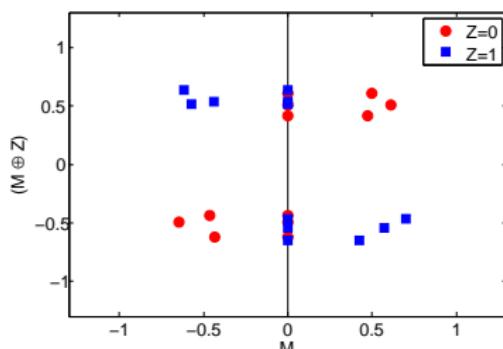
$t_2: M \oplus Z + n$ (Boolean masking)

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

$f(z) = \mathbb{E}[\vec{X}|Z = z]$ is constant \Rightarrow Variance inter-class null! \Rightarrow SNR, SOD, t-statistic null!



$\mathbb{E}[A\vec{X}|Z = z]$ is constant as well \Rightarrow any projecting extraction is useless!



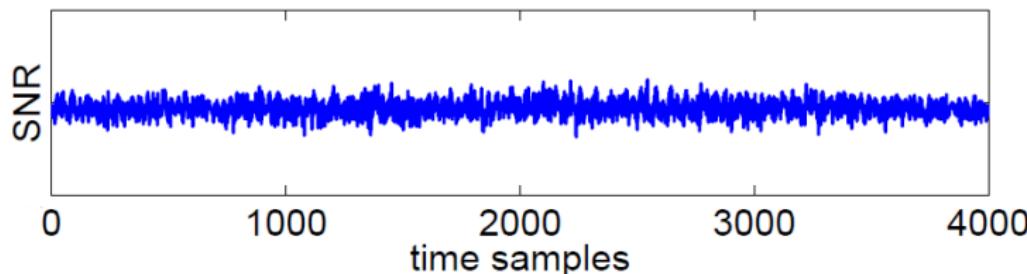
Toy example: 2 time samples, 1-bit data

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

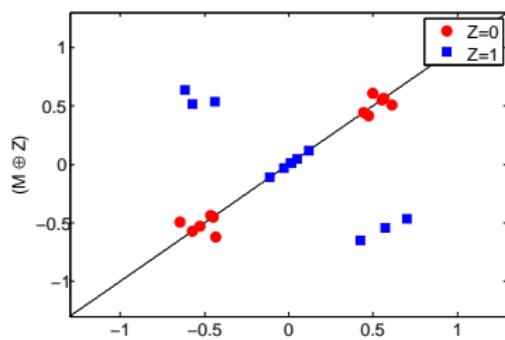
$t_2: M \oplus Z + n$ (Boolean masking)

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

$f(z) = \mathbb{E}[\vec{X}|Z = z]$ is constant \Rightarrow Variance inter-class null! \Rightarrow SNR, SOD, t-statistic null!



$\mathbb{E}[A\vec{X}|Z = z]$ is constant as well \Rightarrow any projecting extraction is useless!



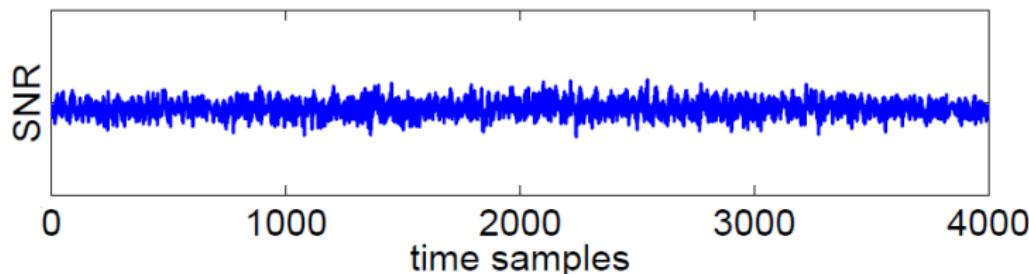
Toy example: 2 time samples, 1-bit data

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

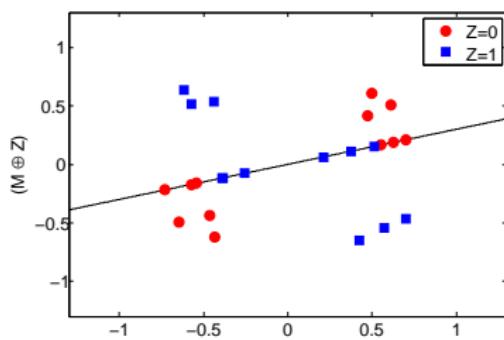
$t_2: M \oplus Z + n$ (Boolean masking)

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

$f(z) = \mathbb{E}[\vec{X}|Z = z]$ is constant \Rightarrow Variance inter-class null! \Rightarrow SNR, SOD, t-statistic null!



$\mathbb{E}[A\vec{X}|Z = z]$ is constant as well \Rightarrow any projecting extraction is useless!



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)

Pols Research

A lacking literature

- ▶ many HO attacks papers assume the knowledge of t_1, \dots, t_d
- ▶ Pol research exploiting the random shares knowledge (back to unprotected case using M_1, \dots, M_d instead of Z)
- ▶ 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

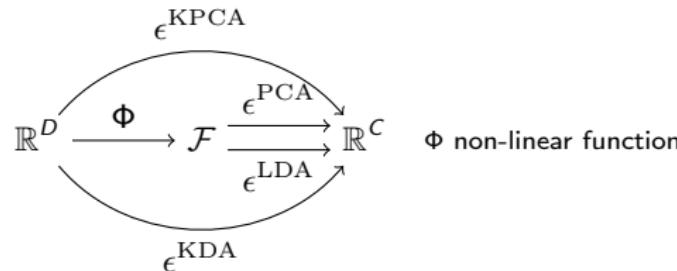
KDA: the purpose

Problem

Naive strategy: useful statistics lie in a high-dimensional *feature* space:

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

(all d th-degree monomials in the trace coordinates)



What KDA provides

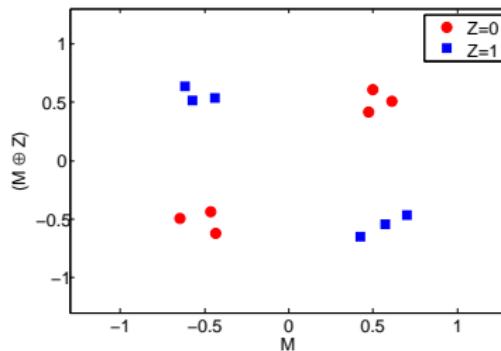
KDA allows performing LDA in \mathcal{F} , remaining in \mathbb{R}^D .

KDA: an intuition

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)

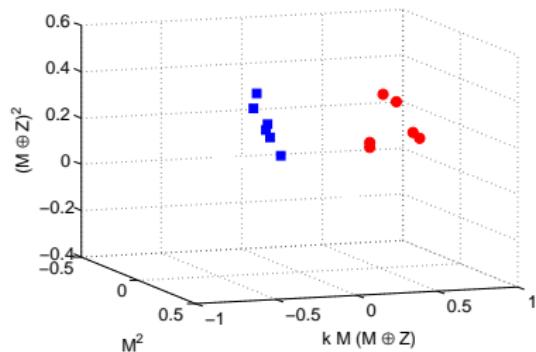
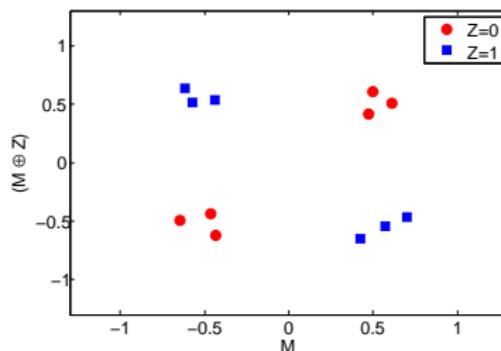


KDA: an intuition

Toy example: 2 time samples, 1-bit data

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

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



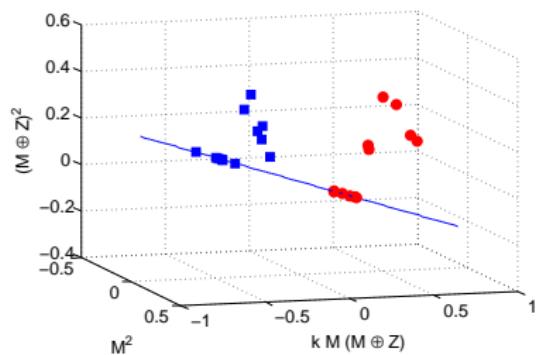
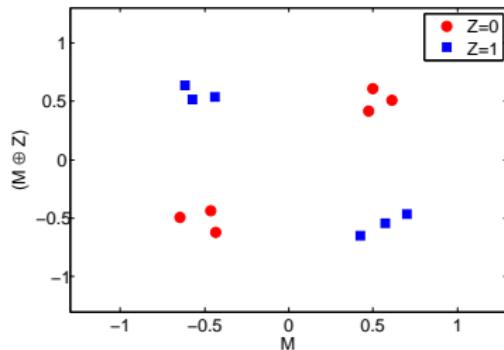
$$\Phi: \mathbb{R}^D \rightarrow \mathbb{R}^{\binom{D+d-1}{d}}$$
$$\Phi(t_1, t_2) = (t_1^2, t_2^2, kt_1 t_2)$$

KDA: an intuition

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)



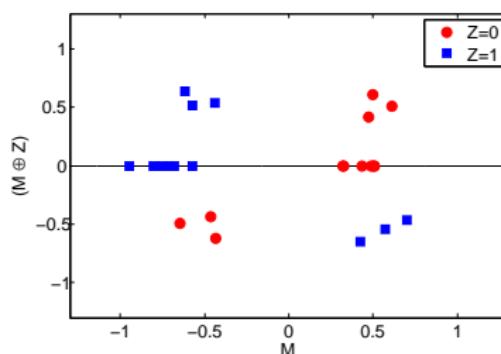
$\Phi \rightarrow \text{LDA}$

KDA: an intuition

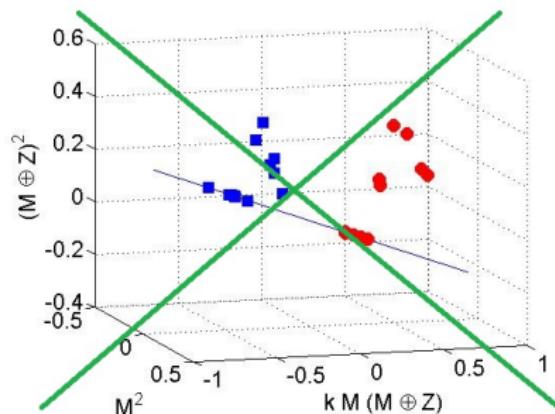
Toy example: 2 time samples, 1-bit data

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

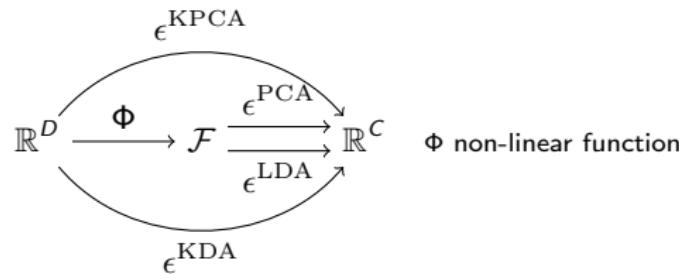
$$t_2: M \oplus Z + n \text{ (Boolean masking)}$$



KDA
remains in \mathbb{R}^D



Kernel Function



Kernel Function

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

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

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

Between-class (inter-class) Covariance Matrix

LDA

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

KDA

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



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

KDA - the training

Within-class (intra-class) Covariance Matrix

LDA

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

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
- ▶

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

KDA - the training

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
- ▶ $\vec{\nu}_i$ eigenvectors of $\mathbf{N}^{-1} \mathbf{M}$ $[N \times N]$
- ▶

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

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

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

KDA - the training

New trace projection

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 $\mathbf{S}_W^{-1} \mathbf{S}_B$ $[D \times D]$
- ▶ $\epsilon_\ell^{LDA}(\vec{x}) = \sum_{i=1}^D \vec{\alpha}_\ell[i] \vec{x}[i]$

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
- ▶ $\vec{\nu}_i$ eigenvectors of $\mathbf{N}^{-1} \mathbf{M}$ $[N \times N]$
- ▶ $\epsilon_\ell^{KDA}(\vec{x}) = \sum_{i=1}^N \vec{\nu}_\ell[i] K(\mathbf{x}_i^{z_i}, \mathbf{x})$

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

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

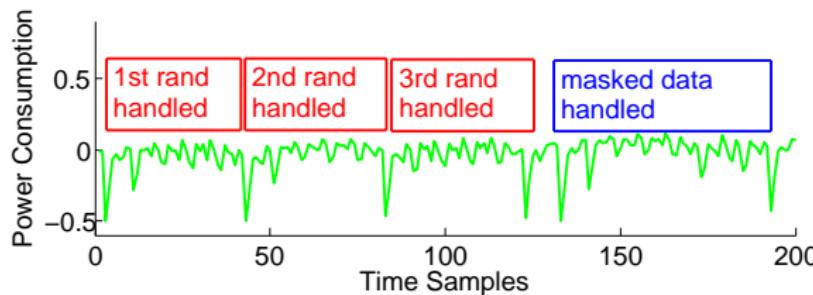
² \mathbf{I} is a $N_z \times N_z$ identity matrix, \mathbf{I}_{N_z} is a $N_z \times N_z$ matrix with all entries equal to $\frac{1}{N_z}$ and \mathbf{K}_z is the $N \times N_z$ sub-matrix of $\mathbf{K} = (K(\mathbf{x}_i^{z_i}, \mathbf{x}_j^{z_j}))_{i=1, \dots, N} \atop j=1, \dots, N$ storing only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

Experimental setup

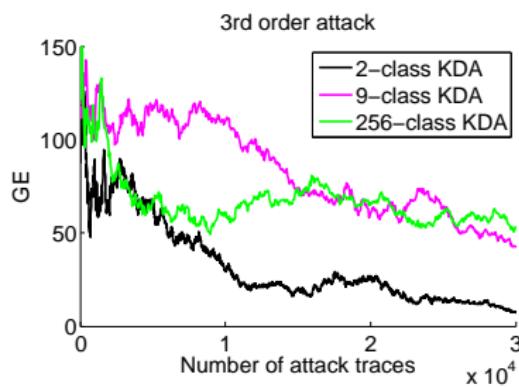
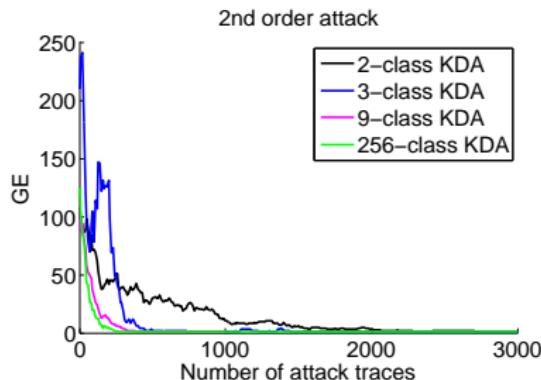
Target device and acquisitions:

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

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

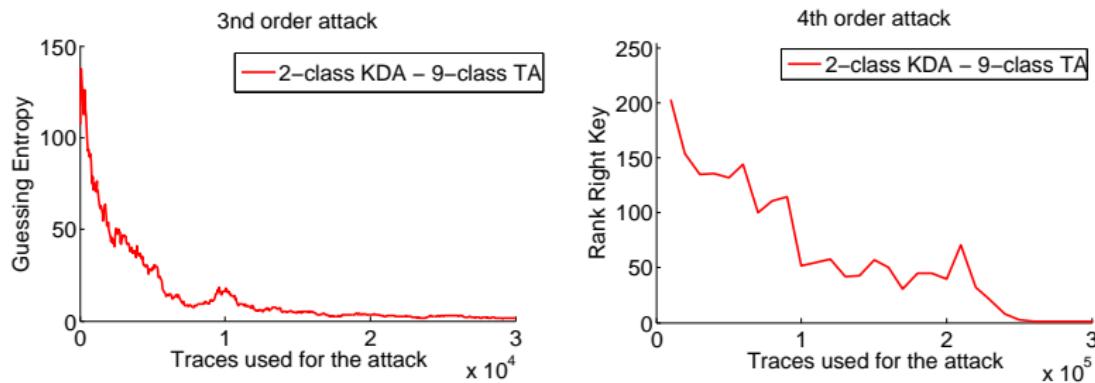


Second and third order



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

- ▶ Regularization hyper-parameter μ : $\mathbf{N} = \sum_{z \in \mathcal{Z}} \mathbf{K}_z (\mathbf{I} - \mathbf{I}_{N_z}) \mathbf{K}_z^T + \mu \mathbf{I}$
- ▶ Does not allow the localisation of Pol

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

- ▶ Regularization hyper-parameter μ : $\mathbf{N} = \sum_{z \in \mathcal{Z}} \mathbf{K}_z (\mathbf{I} - \mathbf{I}_{N_z}) \mathbf{K}_z^T + \mu \mathbf{I}$
- ▶ Does not allow the localisation of Pol
- ▶ Memory-based [$\epsilon_\ell^{\text{KDA}}(\vec{x}) = \sum_{i=1}^N \vec{\nu}_\ell[i] K(\mathbf{x}_i^{z_i}, \mathbf{x}))$]

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	✓	✗	✗

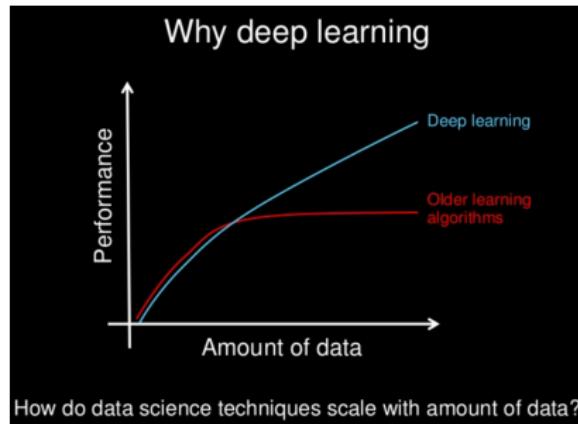
Limits and drawbacks

- ▶ Regularization hyper-parameter μ : $\mathbf{N} = \sum_{z \in \mathcal{Z}} \mathbf{K}_z (\mathbf{I} - \mathbf{I}_{N_z}) \mathbf{K}_z^T + \mu \mathbf{I}$
- ▶ Does not allow the localisation of Pol
- ▶ Memory-based $[\epsilon_\ell^{\text{KDA}}(\vec{x}) = \sum_{i=1}^N \vec{\nu}_\ell[i] \mathcal{K}(\mathbf{x}_i^{z_i}, \mathbf{x})] + O(N^3)$ complexity \rightarrow Non-scalability to big training set

Contents

1. Context
2. State of the Art, Objectives, Contributions
3. Kernel Discriminant Analysis against Masking
 - 3.1 Kernel Discriminant Analysis
 - 3.2 Experimental Results
4. Deep Learning against Misalignment
 - 4.1 Data Augmentation
 - 4.2 Experimental Results
5. Conclusions

Motivations (1)



How do data science techniques scale with amount of data?

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

Motivations (2)

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]
 - ▶ 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

DEEP LEARNING

- ▶ 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]
 - ▶ Variants: *pooled* version [CK14], linear regression [SLP05]
- ▶ $p_{Z | \vec{X}}$ (discriminative model)
by means of a neural network $F(\vec{X}) \approx p_{Z | \vec{X}}$

Many independent preprocessing steps and assumptions

Motivations (2)

Profiling phase

DEEP LEARNING

- ▶ 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]
 - ▶ Variants: *pooled* version [CK14], linear regression [SLP05]
 - ▶ $p_{Z | \vec{X}}$ (discriminative model)
by means of a neural network $F(\vec{X}) \approx p_{Z | \vec{X}}$

Many independent preprocessing steps and assumptions
↔ integrated and agnostic approach

Multi-Layer Perceptron

Multi-Layer Perceptron (MLP)

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

Multi-Layer Perceptron

Multi-Layer Perceptron (MLP)

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

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

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

Multi-Layer Perceptron

Multi-Layer Perceptron (MLP)

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

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

σ_i non-linear *activation* functions

$\textcolor{red}{s}$ normalizing *softmax* function

Multi-Layer Perceptron

Multi-Layer Perceptron (MLP)

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

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

σ_i non-linear *activation* functions

$\textcolor{red}{s}$ normalizing *softmax* function

Architecture hyper-parameters

Multi-Layer Perceptron

Multi-Layer Perceptron (MLP)

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

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

σ_i non-linear *activation* functions

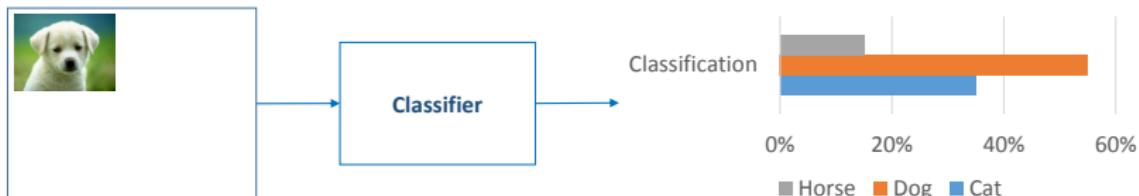
$\textcolor{red}{s}$ normalizing *softmax* function

Architecture hyper-parameters

Universal approximation theorem

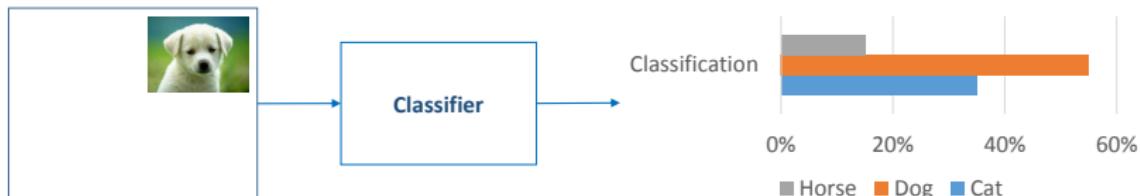
Convolutional Neural Networks

Translation-invariance



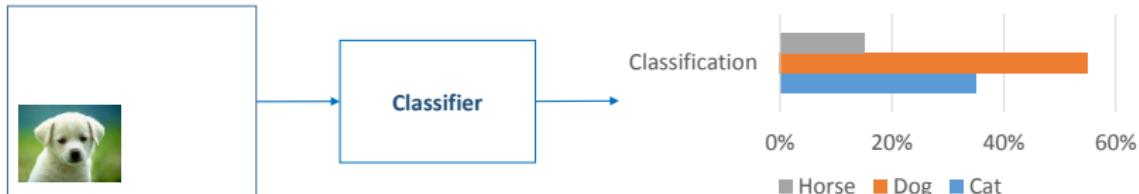
Convolutional Neural Networks

Translation-invariance



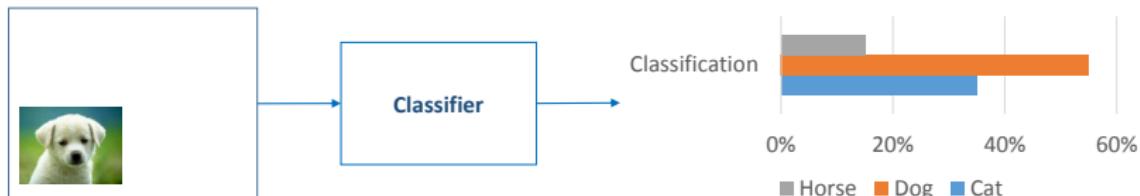
Convolutional Neural Networks

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



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



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

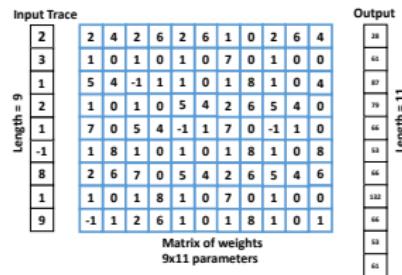


Figure: Linear layer in an MLP (*Fully Connected Layer*)

Convolutional Neural Networks

Translation-invariance



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

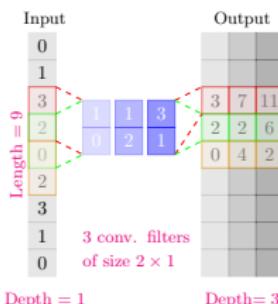


Figure: Linear layer in a ConvNet (*Convolutional Layer*)

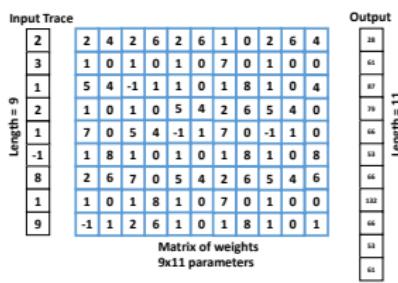


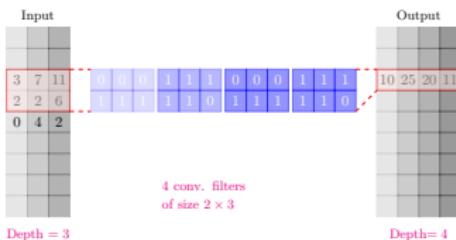
Figure: Linear layer in an MLP (Fully Connected Layer) 05/12/2018, Paris | Eleonora Cag

Convolutional Neural Networks

Translation-invariance



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



	Input Trace										Output										
	2	4	2	6	2	6	1	0	2	6	4	28	42	42	39	42	42	42	42	42	42
1	0	1	0	1	0	7	0	1	0	0	0	28	42	42	39	42	42	42	42	42	42
2	5	4	-1	1	1	0	1	8	1	0	4	28	42	42	39	42	42	42	42	42	42
3	1	0	1	0	5	4	2	6	5	4	0	28	42	42	39	42	42	42	42	42	42
4	7	0	5	4	-1	1	7	0	-1	1	0	28	42	42	39	42	42	42	42	42	42
5	1	8	1	0	1	0	1	8	1	0	8	28	42	42	39	42	42	42	42	42	42
6	2	6	7	0	5	4	2	6	5	4	6	28	42	42	39	42	42	42	42	42	42
7	1	0	1	8	1	0	7	0	1	0	0	28	42	42	39	42	42	42	42	42	42
8	-1	1	2	6	1	0	1	8	1	0	0	28	42	42	39	42	42	42	42	42	42
9																					

Length = 9

Length = 11

Matrix of weights 9x11 parameters

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

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

Convolutional Neural Networks

Translation-invariance



It is important to explicit the data translation-invariance

Convolutional Neural Networks: share weights across space

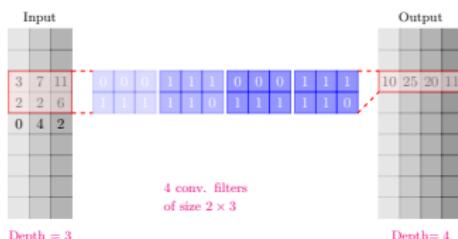


Figure: Linear layer in a ConvNet (*Convolutional Layer*)

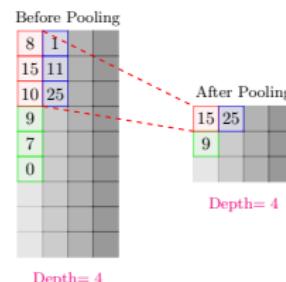
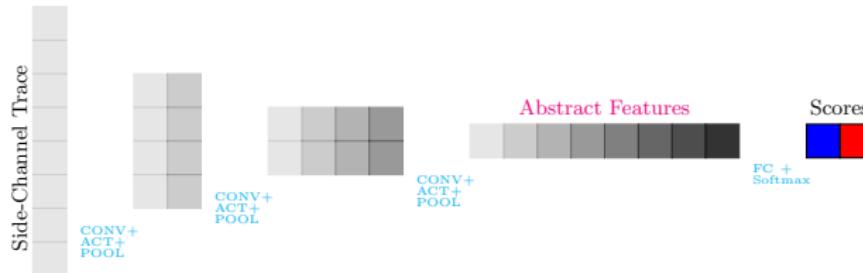


Figure: Max Pooling Layer

A kind of CNN architecture

Temporal Features



VGG-like [SZ14]:

- ▶ 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

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

Training and overfitting

Training

Profiling set → $\begin{cases} \text{Training set} \\ \text{Validation set} \end{cases}$

Randomly partition training set into batches

Iterative optimization algorithm over batches (cost function, stochastic gradient descent)

Epoch:= one pass over the entire training set

Training and overfitting

Training

Profiling set → $\begin{cases} \text{Training set} \\ \text{Validation set} \end{cases}$

Randomly partition training set into batches

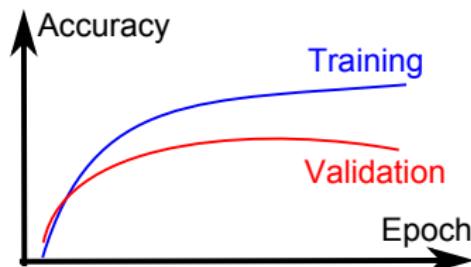
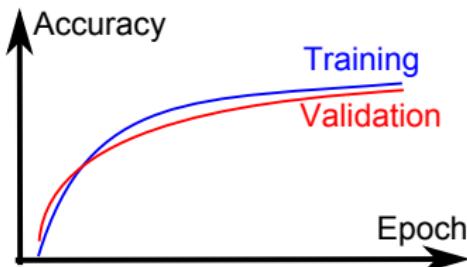
Iterative optimization algorithm over batches (cost function, stochastic gradient descent)

Epoch := one pass over the entire training set

Evaluate and compare training and validation accuracy

Understand significant features

Learn by heart (**OVERTFITTING**)



Training and overfitting

Training

Profiling set → $\begin{cases} \text{Training set} \\ \text{Validation set} \end{cases}$

Randomly partition training set into batches

Iterative optimization algorithm over batches (cost function, stochastic gradient descent)

Epoch := one pass over the entire training set

Evaluate and compare training and validation accuracy

Learn by heart (**OVERTFITTING**)

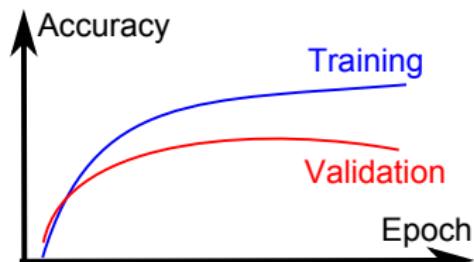
Why?

Too complex model

Not enough training data

Solution?

Data augmentation



Data Augmentation

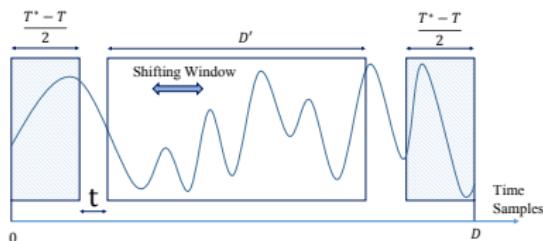
Data Augmentation

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



ADD-REMOVE

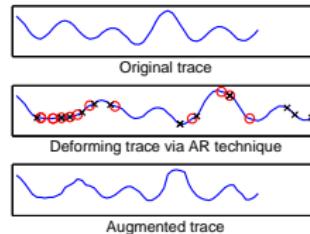


Figure: SH_T

Parameter T : # of possible positions

Parameter R : # of added and removed points

Data Augmentation techniques are applied online during training phase.

Figure: AR_R

Experimental Results

- ▶ Random delays
- ▶ Artificial Jitter
- ▶ Real Jitter

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

Experimental Results

- ▶ Random delays
- ▶ Artificial Jitter
- ▶ Real Jitter

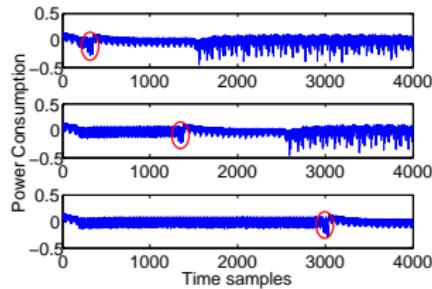
Keras 1.2.1 library with Tensorflow backend [Cho+15] (open source, today 2.2.4)

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

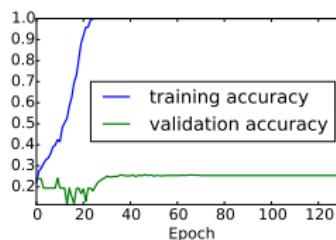
- ▶ Target Chip: Atmega328P
- ▶ Target Variable: $Z = \text{HW}(\text{Sbox}(P \oplus K))$
- ▶ Acquisition: through *ChipWhisperer®* platform, $\approx 4,000$ time samples
- ▶ Countermeasure: Random Delays - insertion of r *nop* operations,
 $r \in [0, 127]$ uniform random
- ▶ 1,000 training traces

Random delays

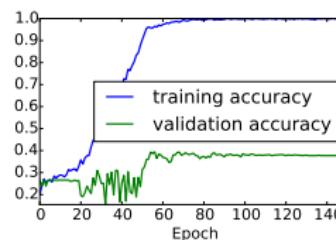
Data augmentation vs overfitting

Metrics

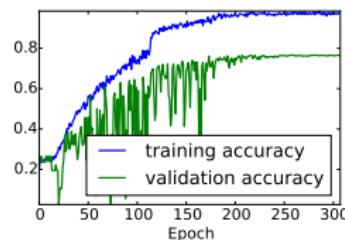
- ▶ Test accuracy: classification accuracy over the attack traces
- ▶ N^* : minimum number of attack traces to make *guessing entropy* of the right key permanently equal to one (N^* estimated over 10 independent attacks)



SH_0



SH_{100}



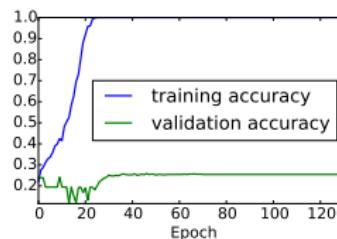
SH_{500}

Random delays

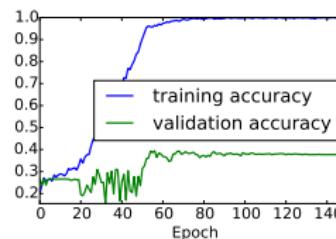
Data augmentation vs overfitting

Metrics

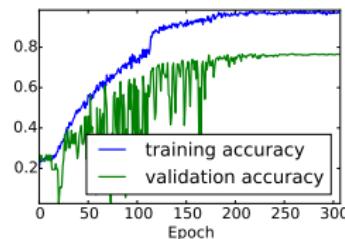
- ▶ Test accuracy: classification accuracy over the attack traces
- ▶ N^* : minimum number of attack traces to make *guessing entropy* of the right key permanently equal to one (N^* estimated over 10 independent attacks)



SH_0



SH_{100}



SH_{500}

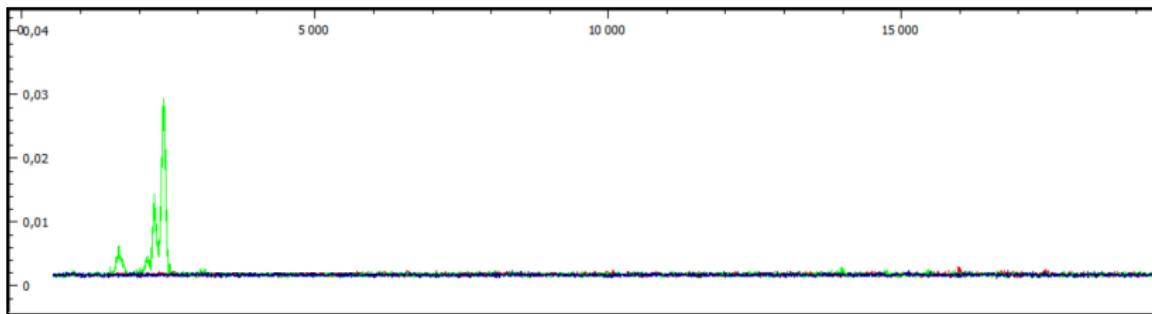
		SH_0		SH_{100}		SH_{500}	
Acc	N^*	27.0%	> 1,000	31.8%	101	78%	7

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

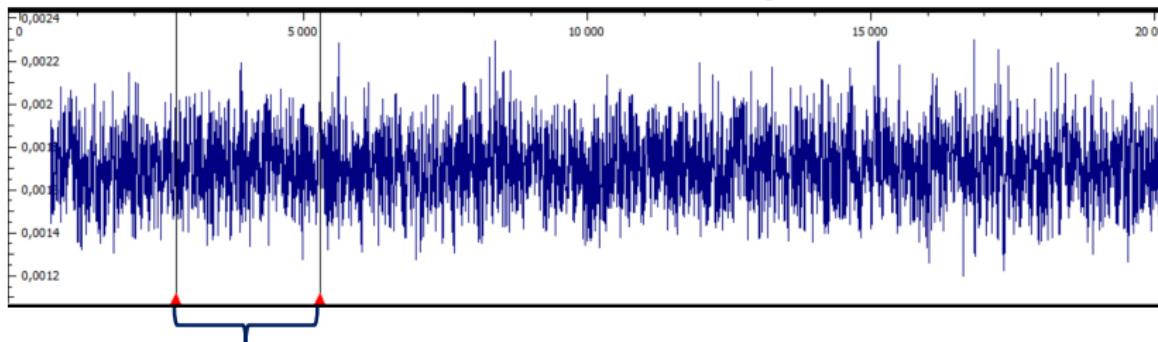


Real Jitter (1)

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



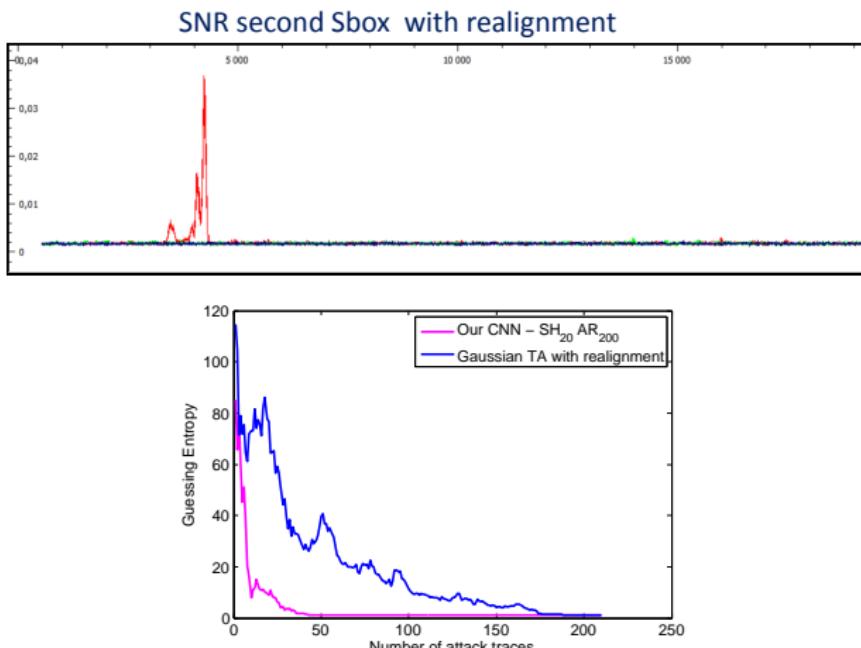
Entry region for CNN (2,500 pts)

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



Conclusions about CNN

- ▶ State-of-the-Art Template Attack routine separates resynchronization/dimensionality reduction from characterization

Conclusions about CNN

- ▶ State-of-the-Art Template Attack routine separates resynchronization/dimensionality reduction from characterization
- ▶ CNNs provide an integrated approach to directly construct a discriminative model from rough data

Conclusions about CNN

- ▶ State-of-the-Art Template Attack routine separates resynchronization/dimensionality reduction from characterization
- ▶ CNNs provide an integrated approach to directly construct a discriminative model from rough data
- ▶ CNN models may have high capacity and require plenty of data to be trained

Conclusions about CNN

- ▶ State-of-the-Art Template Attack routine separates resynchronization/dimensionality reduction from characterization
- ▶ CNNs provide an integrated approach to directly construct a discriminative model from rough data
- ▶ CNN models may have high capacity and require plenty of data to be trained
- ▶ Data Augmentation provides an answer to the lack of data

Conclusions about CNN

- ▶ State-of-the-Art Template Attack routine separates resynchronization/dimensionality reduction from characterization
- ▶ CNNs provide an integrated approach to directly construct a discriminative model from rough data
- ▶ CNN models may have high capacity and require plenty of data to be trained
- ▶ Data Augmentation provides an answer to the lack of data
- ▶ we proposed two Side-Channel-adapted Data Augmentation techniques (inspired by trace misalignment)

Conclusions about CNN

- ▶ State-of-the-Art Template Attack routine separates resynchronization/dimensionality reduction from characterization
- ▶ CNNs provide an integrated approach to directly construct a discriminative model from rough data
- ▶ CNN models may have high capacity and require plenty of data to be trained
- ▶ Data Augmentation provides an answer to the lack of data
- ▶ we proposed two Side-Channel-adapted Data Augmentation techniques (inspired by trace misalignment)
- ▶ we verified the effectiveness/efficiency of the CNN+Data Augmentation approach over different sets of misaligned data

Contents

1. Context
2. State of the Art, Objectives, Contributions
3. Kernel Discriminant Analysis against Masking
 - 3.1 Kernel Discriminant Analysis
 - 3.2 Experimental Results
4. Deep Learning against Misalignment
 - 4.1 Data Augmentation
 - 4.2 Experimental Results
5. Conclusions

Conclusions

- ▶ A wide part of Side-Channel litterature consider leakages localised in small and known portions of signal
- ▶ In practical contexte, curse of dimensionality affects the potential optimality of profiling attacks
- ▶ In many applicative 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
- ▶ Discriminative model approach:
 - ▶ Neural Networks, big data scalability
 - ▶ CNN to integrate resynchronization in a unique model construction process

Conclusions

- ▶ A wide part of Side-Channel litterature consider leakages localised in small and known portions of signal
- ▶ In practical contexte, curse of dimensionality affects the potential optimality of profiling attacks
- ▶ In many applicative 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
- ▶ Discriminative model approach:
 - ▶ Neural Networks, big data scalability
 - ▶ CNN to integrate resynchronization in a unique model construction process

Today and in the future

- ▶ ASCAD database and SCA/DL community
- ▶ From CNN to Pol, visualizing techniques
- ▶ Advanced-attack-oriented machine learning task (instead of multiple classification)
- ▶ Collision attacks \approx verification task (siamese network)

Conclusions

- ▶ A wide part of Side-Channel litterature consider leakages localised in small and known portions of signal
- ▶ In practical contexte, curse of dimensionality affects the potential optimality of profiling attacks
- ▶ In many applicative 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
- ▶ Discriminative model approach:
 - ▶ Neural Networks, big data scalability
 - ▶ CNN to integrate resynchronization in a unique model construction process

Today and in the future

- ▶ ASCAD database and SCA/DL community
- ▶ From CNN to Pol, visualizing techniques
- ▶ Advanced-attack-oriented machine learning task (instead of multiple classification)
- ▶ Collision attacks \approx verification task (siamese network)

References I

- [Arc+06] C. Archambeau et al. "Template Attacks in Principal Subspaces". English. In: *Cryptographic Hardware and Embedded Systems - CHES 2006*. Ed. by Louis Goubin and Mitsuru Matsui. Vol. 4249. Lecture Notes in Computer Science. Springer Berlin Heidelberg, 2006, pp. 1–14. ISBN: 978-3-540-46559-1. DOI: 10.1007/11894063_1. URL: http://dx.doi.org/10.1007/11894063_1.
- [BDP10] Martin Bär, Hermann Drexler, and Jürgen Pulkus. "Improved template attacks". In: *COSADE2010* (2010).
- [BHW12] Lejla Batina, Jip Hogenboom, and Jasper G.J. van Woudenberg. "Getting More from PCA: First Results of Using Principal Component Analysis for Extensive Power Analysis". English. In: *Topics in Cryptology CT-RSA 2012*. Ed. by Orr Dunkelman. Vol. 7178. Lecture Notes in Computer Science. Springer Berlin Heidelberg, 2012, pp. 383–397. ISBN: 978-3-642-27953-9. DOI: 10.1007/978-3-642-27954-6_24. URL: http://dx.doi.org/10.1007/978-3-642-27954-6_24.

References II

- [Bat+11] Lejla Batina et al. "Mutual information analysis: a comprehensive study". In: *Journal of Cryptology* 24.2 (2011), pp. 269–291.
- [Bha+14] Shivam Bhasin et al. "Side-channel leakage and trace compression using normalized inter-class variance". In: *Proceedings of the Third Workshop on Hardware and Architectural Support for Security and Privacy*. ACM. 2014, p. 7.
- [BCO04] Eric Brier, Christophe Clavier, and Francis Olivier. "Correlation power analysis with a leakage model". In: *International Workshop on Cryptographic Hardware and Embedded Systems*. Springer. 2004, pp. 16–29.
- [Bru+15] Nicolas Bruneau et al. "Less is more". In: *International Workshop on Cryptographic Hardware and Embedded Systems*. Springer. 2015, pp. 22–41.
- [Car+14] Claude Carlet et al. "Achieving side-channel high-order correlation immunity with leakage squeezing". In: *Journal of Cryptographic Engineering* 4.2 (2014), pp. 107–121.

References III

- [CRR03] Suresh Chari, JosyulaR. Rao, and Pankaj Rohatgi. "Template Attacks". English. In: *Cryptographic Hardware and Embedded Systems - CHES 2002*. Ed. by Burton S. Kaliski, Cetin K. Koc, and Christof Paar. Vol. 2523. Lecture Notes in Computer Science. Springer Berlin Heidelberg, 2003, pp. 13–28. ISBN: 978-3-540-00409-7. DOI: 10.1007/3-540-36400-5_3. URL: http://dx.doi.org/10.1007/3-540-36400-5_3.
- [Cho+15] François Chollet et al. *Keras*. <https://github.com/fchollet/keras>. 2015.
- [CK14] Omar Choudary and Markus G Kuhn. "Efficient template attacks". In: *Smart Card Research and Advanced Applications*. Springer, 2014, pp. 253–270.
- [Dur+15] François Durvaux et al. "Efficient selection of time samples for higher-order DPA with projection pursuits". In: *Constructive Side-Channel Analysis and Secure Design*. Springer, 2015, pp. 34–50.

References IV

- [GLRP06] Benedikt Gierlichs, Kerstin Lemke-Rust, and Christof Paar. "Templates vs. stochastic methods". In: *International Workshop on Cryptographic Hardware and Embedded Systems*. Springer. 2006, pp. 15–29.
- [Gie+08] Benedikt Gierlichs et al. "Mutual information analysis". In: *International Workshop on Cryptographic Hardware and Embedded Systems*. Springer. 2008, pp. 426–442.
- [KJJ99] Paul Kocher, Joshua Jaffe, and Benjamin Jun. "Differential power analysis". In: *Annual International Cryptology Conference*. Springer. 1999, pp. 388–397.
- [MOP08] Stefan Mangard, Elisabeth Oswald, and Thomas Popp. *Power analysis attacks: Revealing the secrets of smart cards*. Vol. 31. Springer Science & Business Media, 2008.

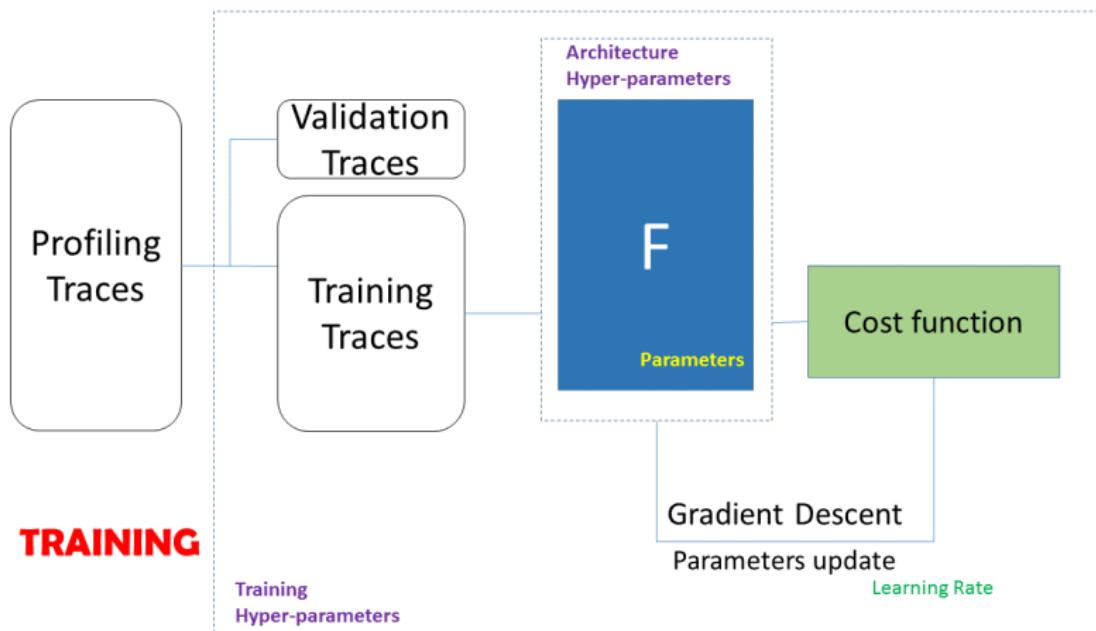
References V

- [OC14] Colin O'Flynn and Zhizhang David Chen. "ChipWhisperer: An open-source platform for hardware embedded security research". In: *Constructive Side-Channel Analysis and Secure Design*. Springer, 2014, pp. 243–260.
- [Osw+06] Elisabeth Oswald et al. "Practical Second-Order DPA Attacks for Masked Smart Card Implementations of Block Ciphers". English. In: *Topics in Cryptology CT-RSA 2006*. Ed. by David Pointcheval. Vol. 3860. Lecture Notes in Computer Science. Springer Berlin Heidelberg, 2006, pp. 192–207. ISBN: 978-3-540-31033-4. DOI: [10.1007/11605805_13](https://doi.org/10.1007/11605805_13). URL: http://dx.doi.org/10.1007/11605805_13.
- [SLP05] Werner Schindler, Kerstin Lemke, and Christof Paar. "A stochastic model for differential side channel cryptanalysis". In: *International Workshop on Cryptographic Hardware and Embedded Systems*. Springer. 2005, pp. 30–46.

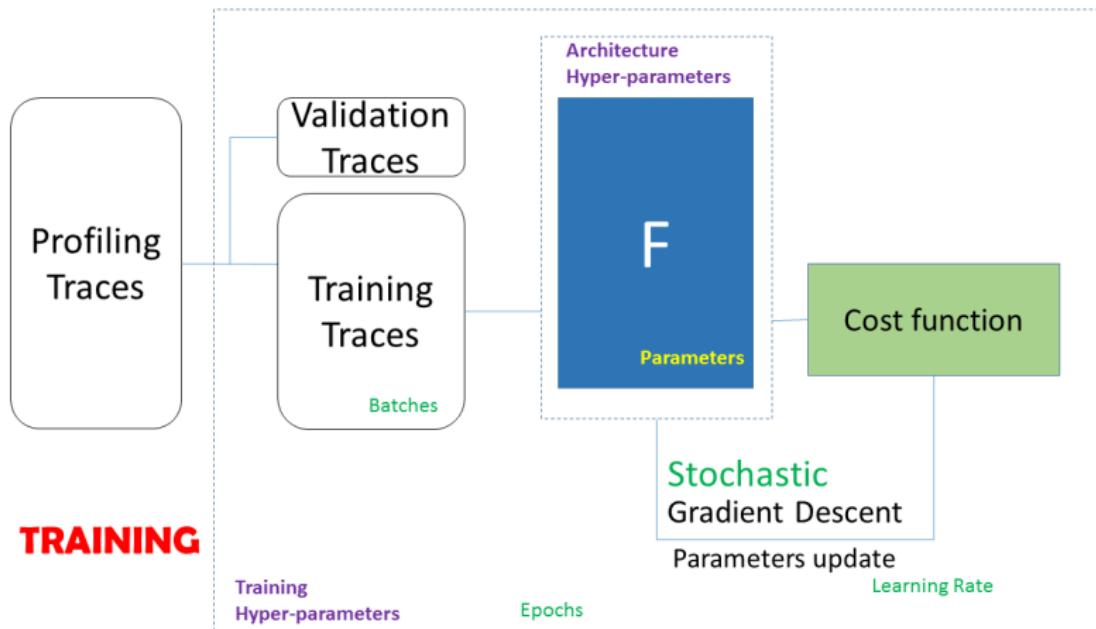
References VI

- [SZ14] Karen Simonyan and Andrew Zisserman. "Very deep convolutional networks for large-scale image recognition". In: *arXiv preprint arXiv:1409.1556* (2014).
- [SA08] François-Xavier Standaert and Cedric Archambeau. "Using Subspace-Based Template Attacks to Compare and Combine Power and Electromagnetic Information Leakages". English. In: *Cryptographic Hardware and Embedded Systems CHES 2008*. Ed. by Elisabeth Oswald and Pankaj Rohatgi. Vol. 5154. Lecture Notes in Computer Science. Springer Berlin Heidelberg, 2008, pp. 411–425. ISBN: 978-3-540-85052-6. DOI: 10.1007/978-3-540-85053-3_26. URL: http://dx.doi.org/10.1007/978-3-540-85053-3_26.
- [TM97] Mitchell T. M. *Machine Learning*. McGraw-Hill, New York, 1997.

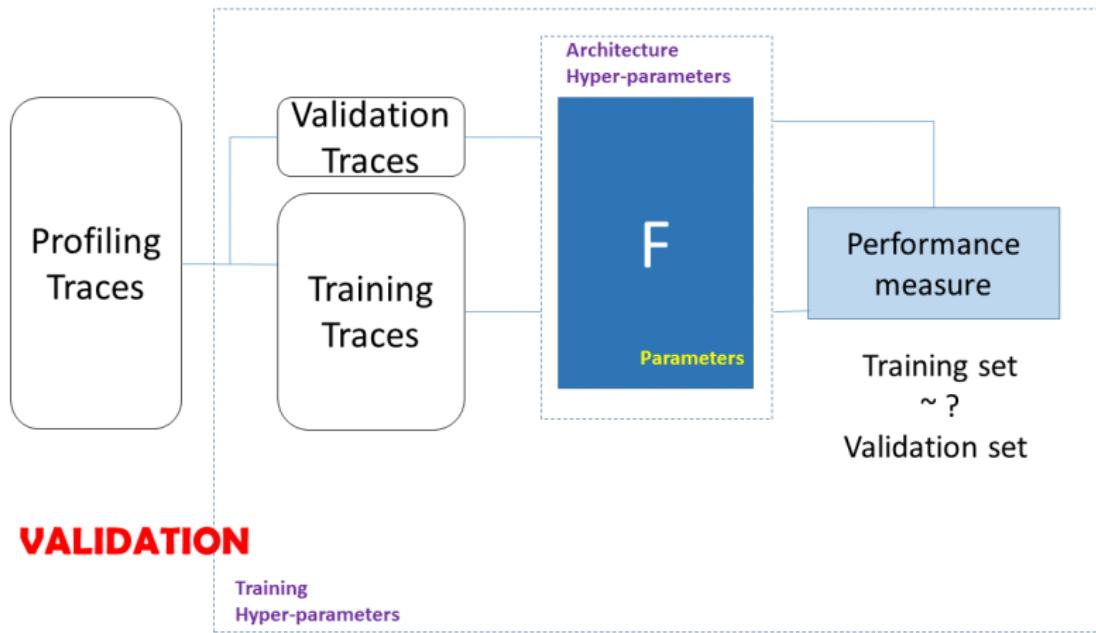
Training-Validation-Test



Training-Validation-Test



Training-Validation-Test



Training-Validation-Test

**TEST**

Cost function - Cross-entropy

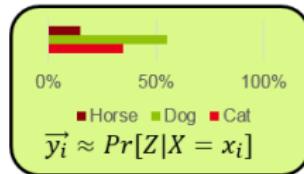
- ▶ batch of training data $(\vec{x}_i, z_i)_{i \in I}$, outputs of the current model $(\vec{y}_i)_{i \in I}$
- ▶ labels $z_i = s_j$ are *one-hot encoded*: $\vec{z}_i = \vec{s}_j = (0, \dots, 0, \underbrace{1}_j, 0, \dots, 0)$

Loss function

$$\mathcal{L} = -\frac{1}{|I|} \sum_{i \in I} \sum_{t=1}^{|Z|} \vec{z}_i[t] \log \vec{y}_i[t] \quad (2)$$

Maximum-a-posteriori or Cross-entropy

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



Cost function - Cross-entropy

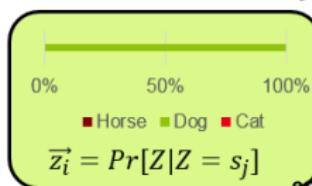
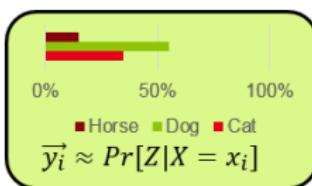
- ▶ batch of training data $(\vec{x}_i, z_i)_{i \in I}$, outputs of the current model $(\vec{y}_i)_{i \in I}$
- ▶ labels $z_i = s_j$ are *one-hot encoded*: $\vec{z}_i = \vec{s}_j = (0, \dots, 0, \underbrace{1}_{j}, 0, \dots, 0)$

Loss function

$$\mathcal{L} = -\frac{1}{|I|} \sum_{i \in I} \sum_{t=1}^{|Z|} \vec{z}_i[t] \log \vec{y}_i[t] \quad (2)$$

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

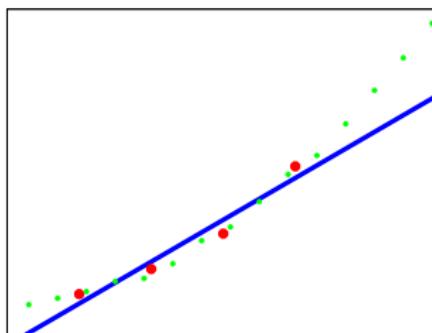


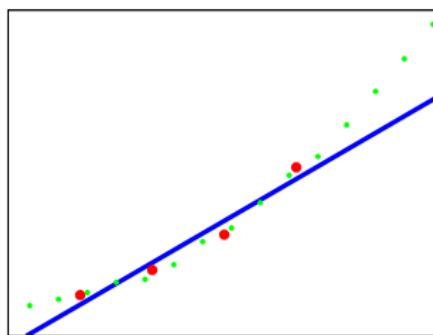
Figure: Linear regression → underfitting

Capacity-Overfitting-Regularization

Regression example

Performance metric: Mean Square Error (MSE)

MSE_train=44.228280, MSE_test=330.984916



MSE_train=2.243097, MSE_test=61.891672

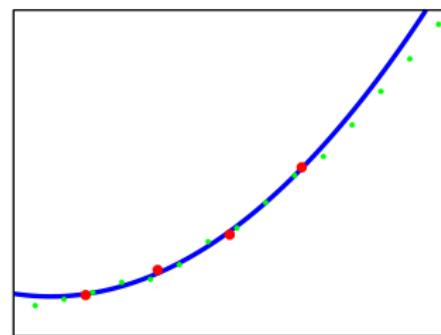


Figure: Linear regression → underfitting

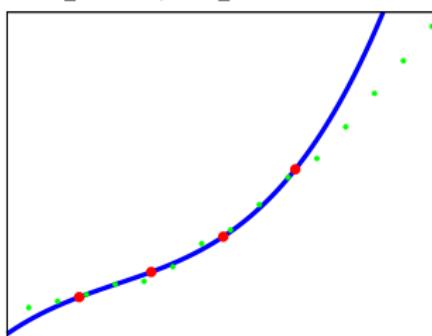
Figure: Quadratic regression → fits

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

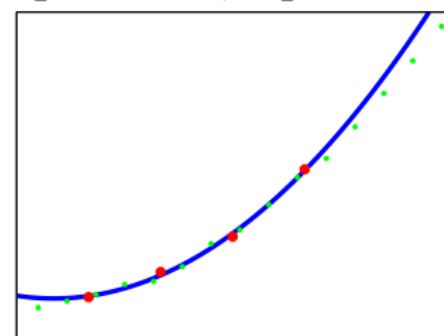


Figure: Cubic regression → overfitting

Figure: Quadratic regression → fits

Capacity-Overfitting-Regularization

Regression example

Performance metric: Mean Square Error (MSE)

MSE_train=0, MSE_test=970.081580

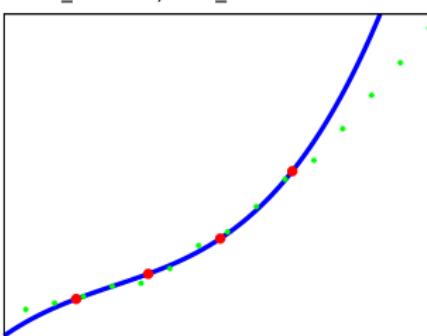


Figure: Cubic regression → overfitting

MSE_train=3.040333, MSE_test=58.377719

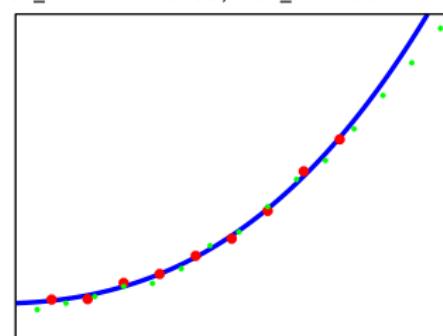


Figure: Cubic regression with more training data

Capacity-Overfitting-Regularization

Regression example

Performance metric: Mean Square Error (MSE)

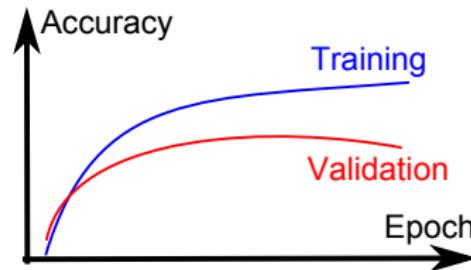
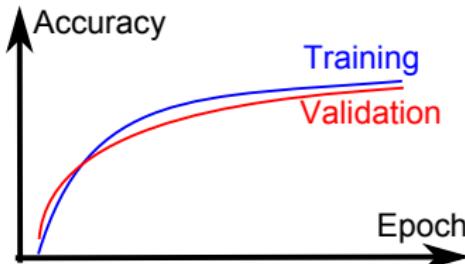
Classification via Neural Network

Performance measure: Accuracy (Classification rate)

Evaluate and compare training and validation accuracy

Understand significant features

Learn by heart (**OVERFITTING**)



Capacity-Overfitting-Regularization

Regression example

Performance metric: Mean Square Error (MSE)

Classification via Neural Network

Performance measure: Accuracy (Classification rate)

Evaluate and compare training and validation accuracy

Learn by heart (**OVERTFITTING**)

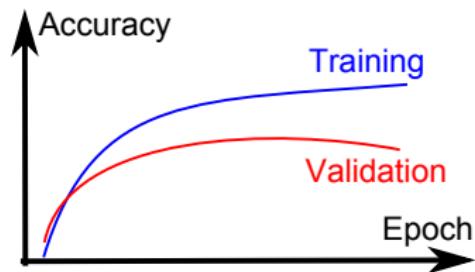
Why?

Too complex model

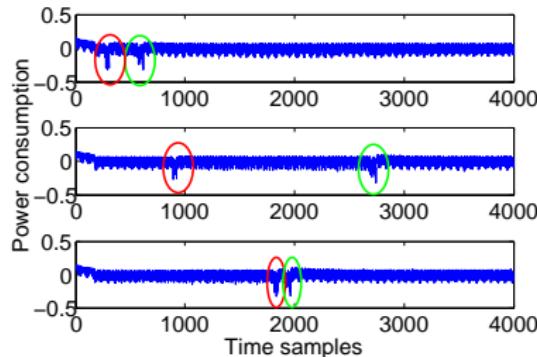
Not enough training data

Solution?

Data augmentation



Random Delays - Two Leaking Operations

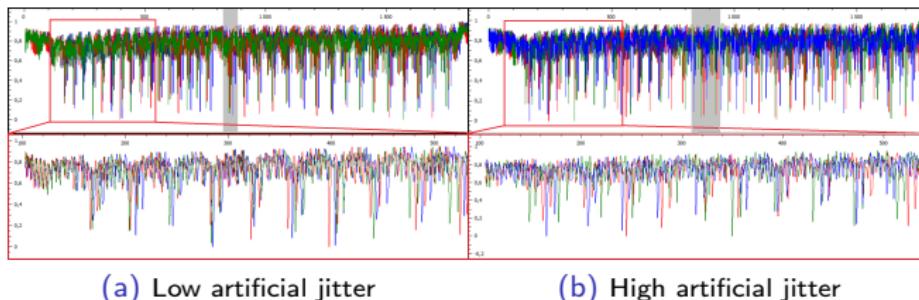


Two leaking operations

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

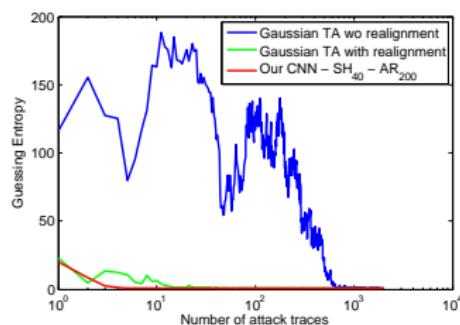
Artificial Jitter (2)

Low jitter

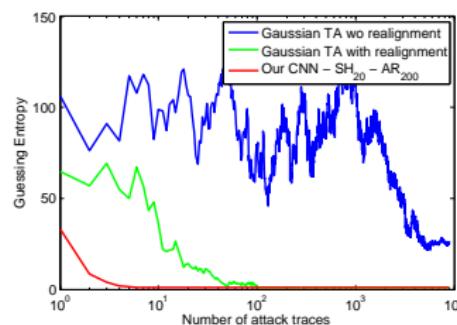
Acc	N^*	SH_0	SH_{20}	SH_{40}	
AR_0		57.4%	14	82.5%	6
AR_{100}		86.0%	6	87.0%	5
AR_{200}		86.6%	6	85.7%	6
				83.6%	6
				87.5%	6
				87.7%	5

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
				62.4%	11
				73.5%	9
				74.4%	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	