

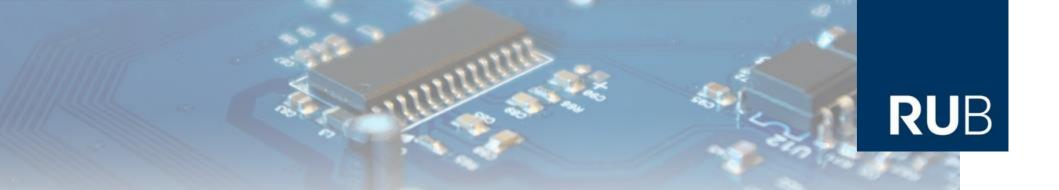
Improving Side-Channel Analysis with Optimal Pre-Processing

CARDIS 2012

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Ruhr-Universität Bochum



Improving Side-Channel Analysis with "Optimal" Pre-Processing

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Agenda



- Intro: SCA and (Linear) Transforms
- Theory: CPA and Linear Transforms
- Optimization: Linear Transforms
- Results: Practical Experiments
- Conclusion: Lessons Learned



Introduction: SCA and (Linear) Transforms

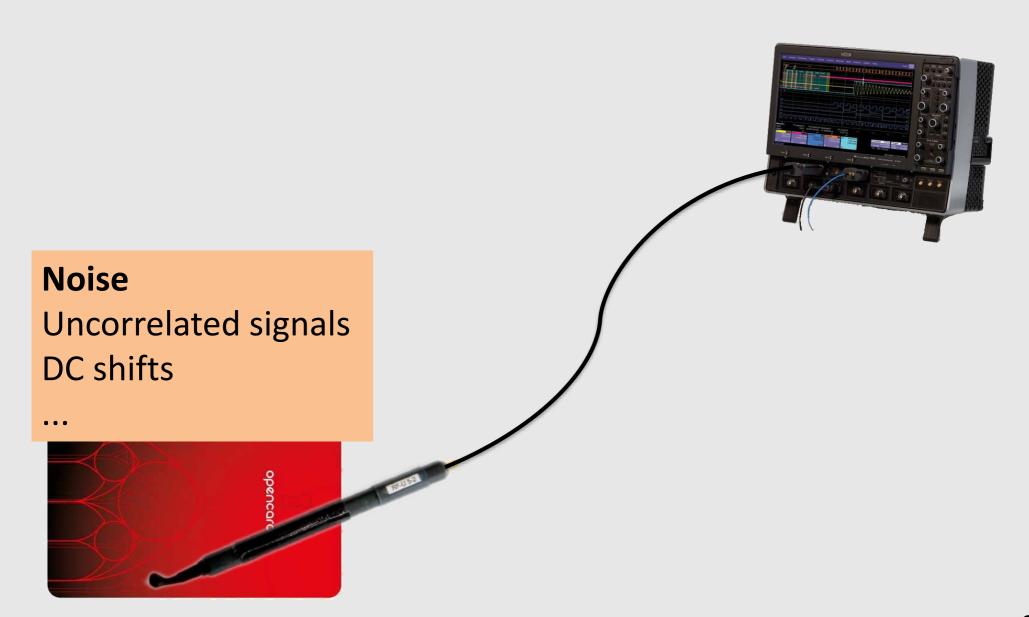


Side-Channel Analysis: Basic Setup



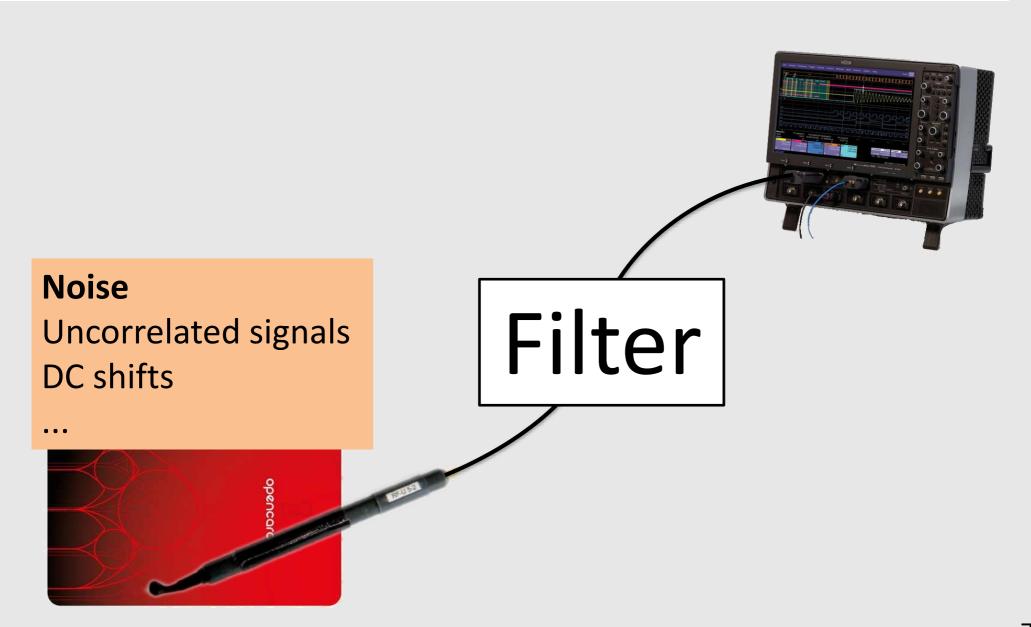


Side-Channel Analysis: Basic Setup





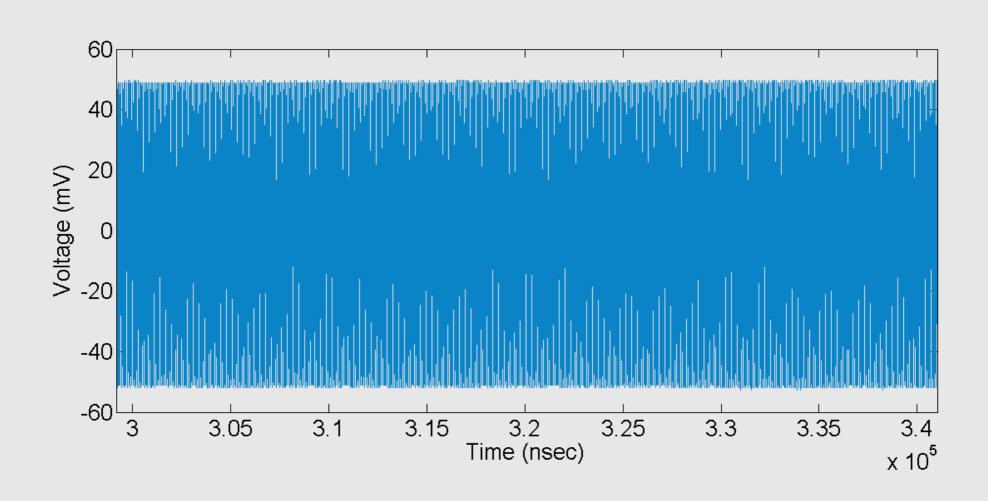
Side-Channel Analysis: Basic Setup



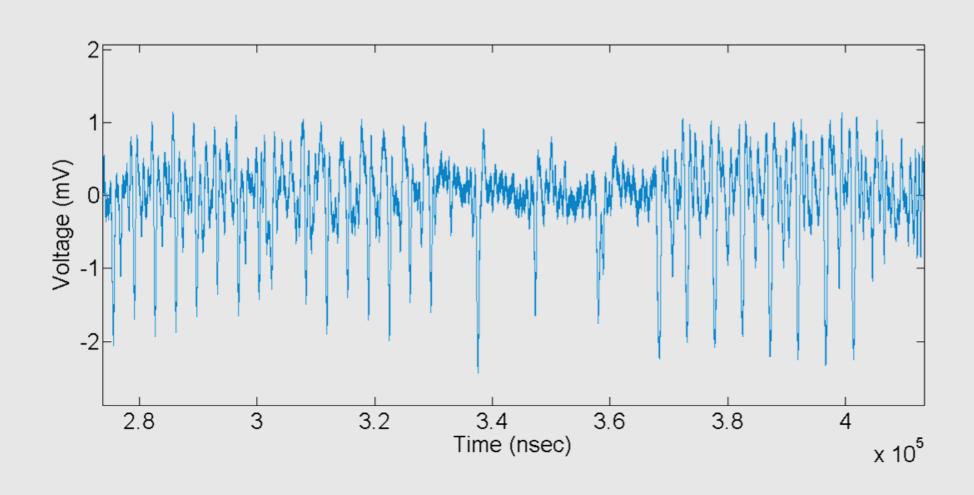
SCA and Filtering

- Pre-processing step more or less proposed together with DPA
- Our motivation: Practical experience
 - DESFire
 - many more examples

Practical Experience: DESFire



Practical Experience: DESFire



Problems



- Parameter selection is
 - Heuristic
 - Time consuming
 - Based on experience
- Can we do better?



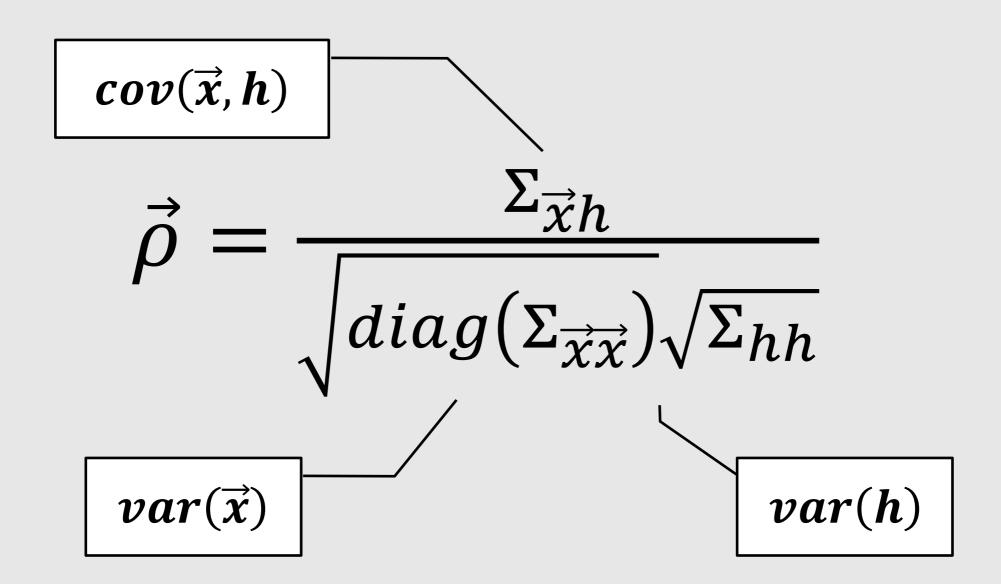
How does a linear filter affect the results of Correlation Power Analysis?



Correlation Power Analysis

- Correlation Power Analysis
- Most common distinguisher
- Trace vectors \vec{x}_i $0 \le i < N$
- (Key-dependent) prediction h_i

Matrix Notation



Linear Transform

Weighted sum of each trace

$$y_i = \vec{a}^T * \vec{x}_i$$

Can realize FIR filter

$$y(t) = \sum_{m} a(m) * x(t - m)$$

Linear Transforms

Usual approach:

- 1. Compute transform on each trace
- 2. Compute correlation

Our approach:

- 1. Compute correlation
- 2. Compute transform on result

Untransformed Correlation

$$\vec{\rho} = \frac{\Sigma_{\vec{x}h}}{\sqrt{diag(\Sigma_{\vec{x}\vec{x}})}\sqrt{\Sigma_{hh}}}$$

Transformed Correlation

$$\rho(\vec{a}) = \frac{\vec{a}^T * \Sigma_{\vec{x}h}}{\sqrt{\vec{a}^T * \Sigma_{\vec{x}x} * \vec{a}} \sqrt{\Sigma_{hh}}}$$

Intermezzo



Closed form:

Correlation after linear transform

- lacktriangle Needs covariance matrix $\Sigma_{ec{\chi}ec{\chi}}$
- Can include coefficients for h
- Can be combined with non-linear transforms (e.g. frequency domain)



How can we profit from this result?

Idea



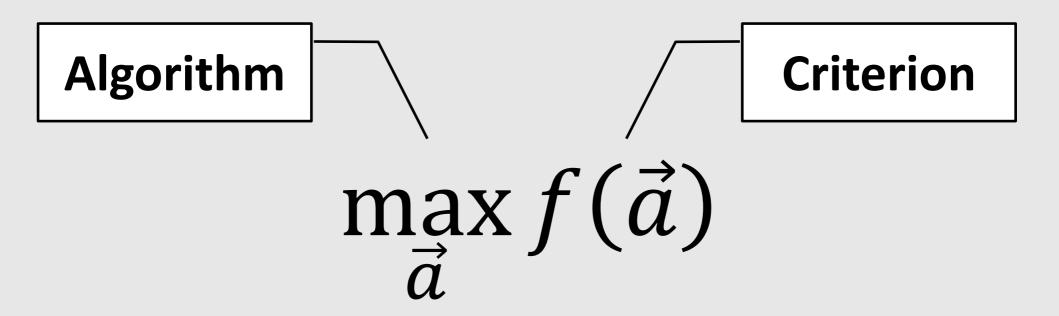
Usual approach:

Select coefficients manually (filter parameters, ...)

Our approach:

(Numerically) optimize coefficients

Numerical Optimization



Optimization Criterion

- Maximize "distinguishability" of correct key candidate
- Semi-profiled: Correct key known
- Efficient evaluation of f?



Optimization Criterion (1)

$$f(\vec{a}) = \frac{|\rho_{correct}(\vec{a})|}{mean(|\rho(\vec{a})|)}$$

Optimization Criterion (2)

$$\cdots = \frac{\left| \vec{a}^T * \Sigma_{\vec{x}h_{correct}} \right|}{\sum_{k} \left| \frac{1}{*} * \vec{a}^T * \Sigma_{\vec{x}h_k} \right|}$$

Algorithm

- f efficient to evaluate
- MATLAB optimization toolbox
- fminunc()
- Avoid overfitting: Better choices?

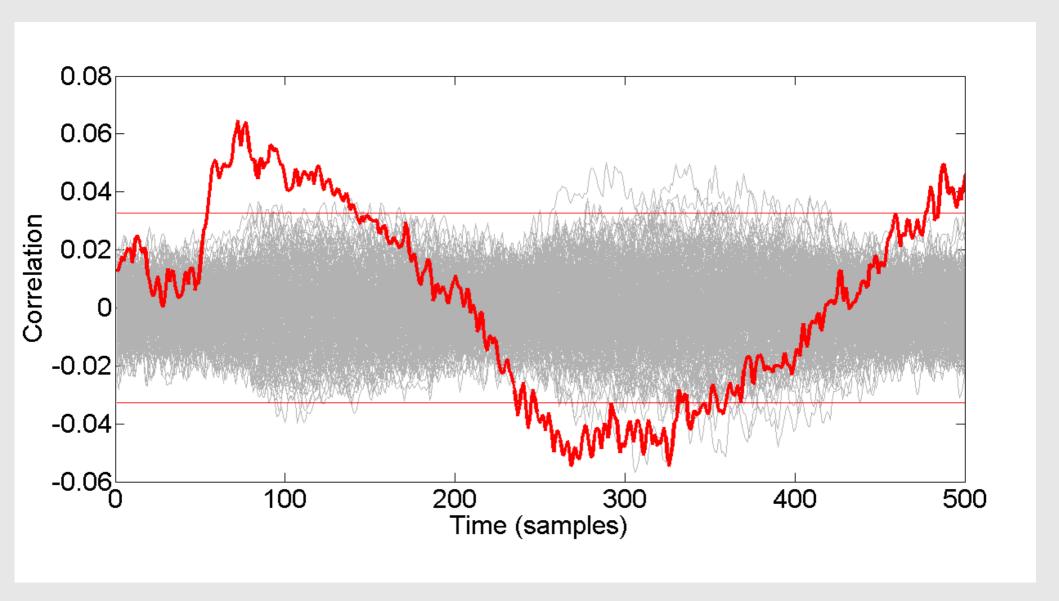


Does it work in practice?

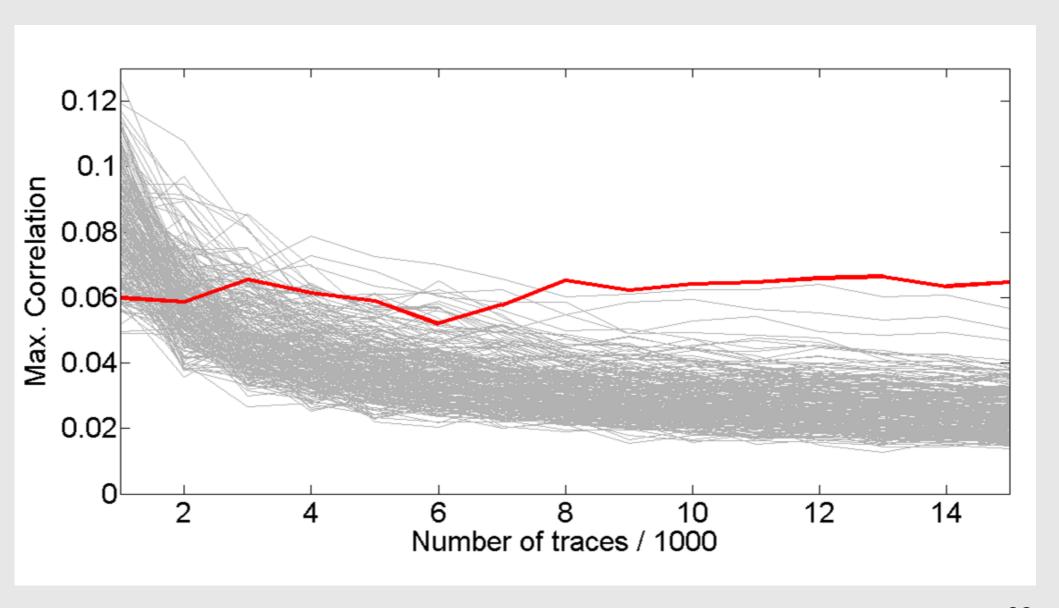
Practical Experiments

- Some simulations ...
- Then: DPA contest v2 traces
- AES on Sasebo G2
- Leakage characteristics known
- 15,000 traces

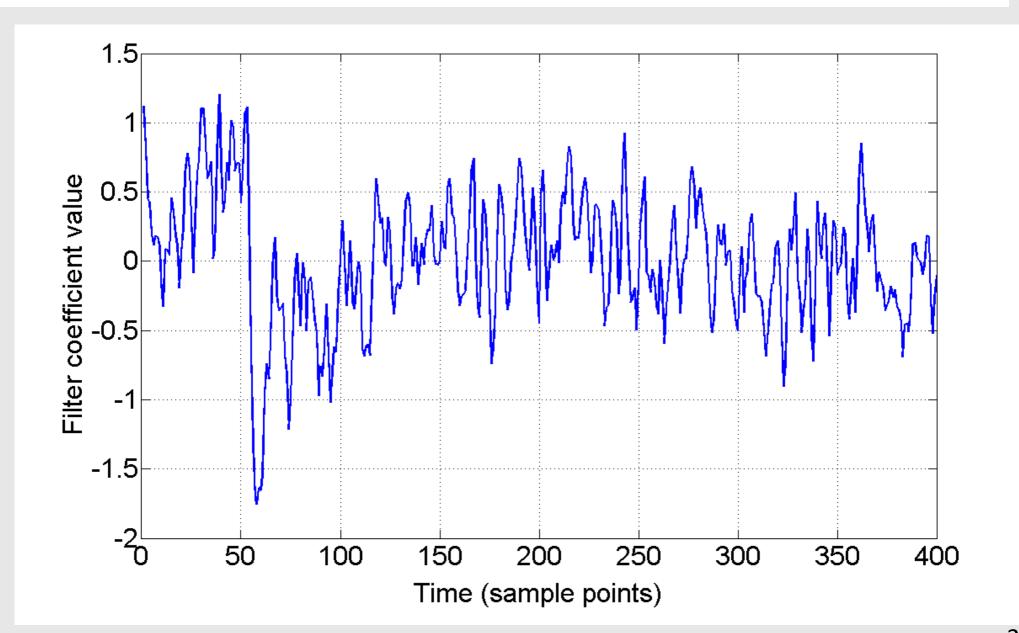
Untransformed Correlation (1)



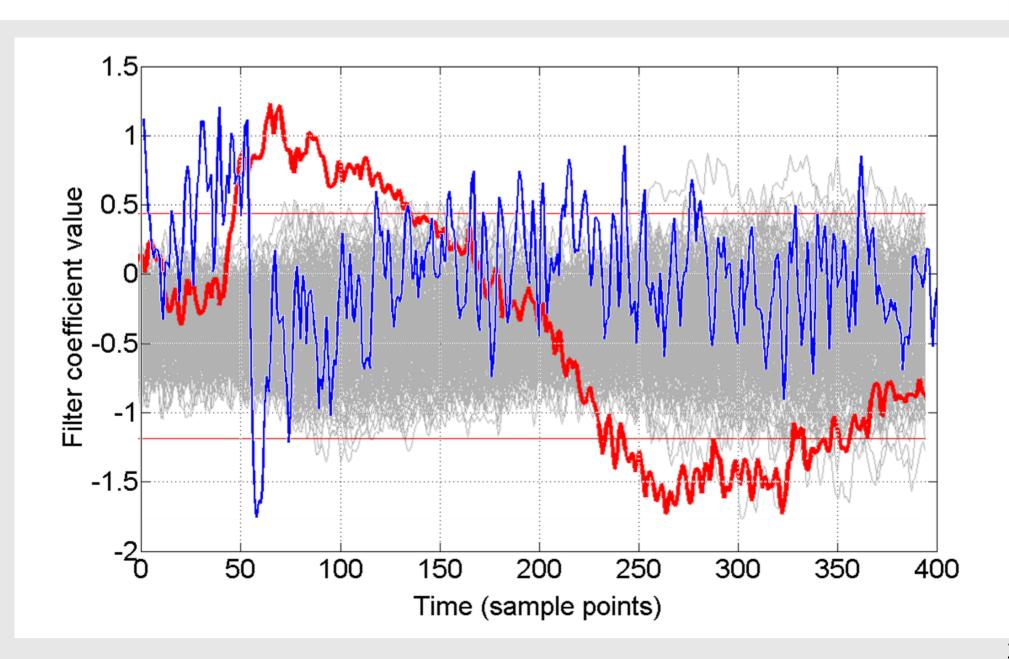
Untransformed Correlation (2)



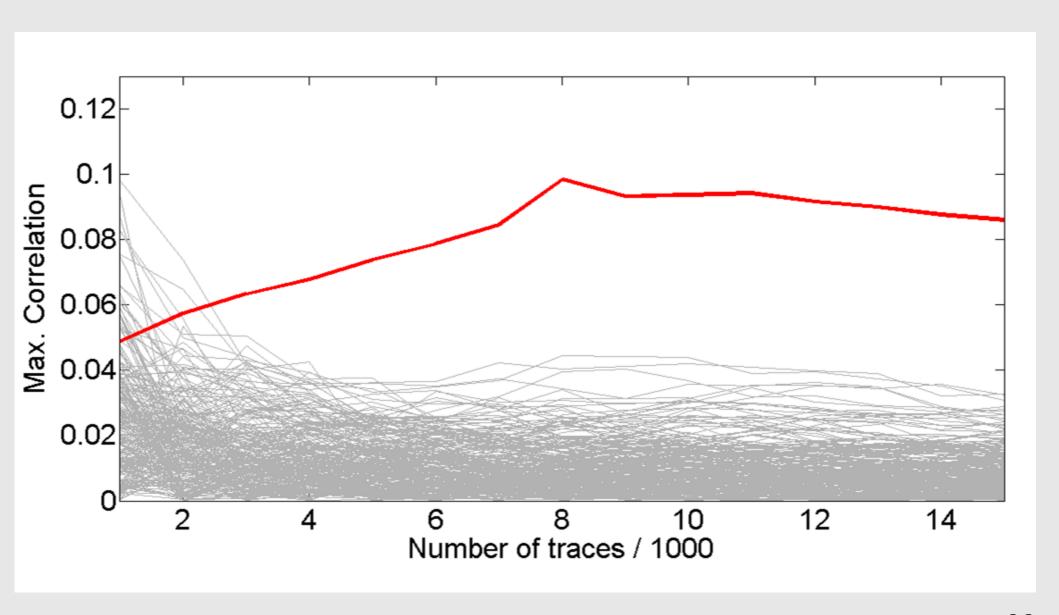
Optimized Transform (1)



Optimized Transform (2)



Transformed Correlation





Practical Experiments: Summary

- **■** From $0.064 \rightarrow 0.087$
- Better ratio correct vs. incorrect:
 1.83 vs. 2.9
- Not: Full DPA contest framework
- But: Results similar for all S-Boxes

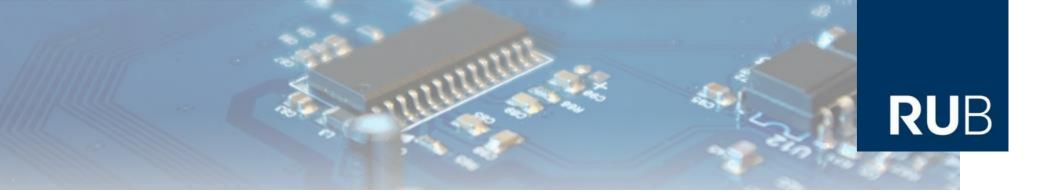


Conclusion: Lessons Learned

Lessons Learned



- More systematic way for selecting linear transforms for SCA
- More practical applications?
- Better criterion?
- Avoid overfitting?
- Analytical solutions?



Thanks! Questions?

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