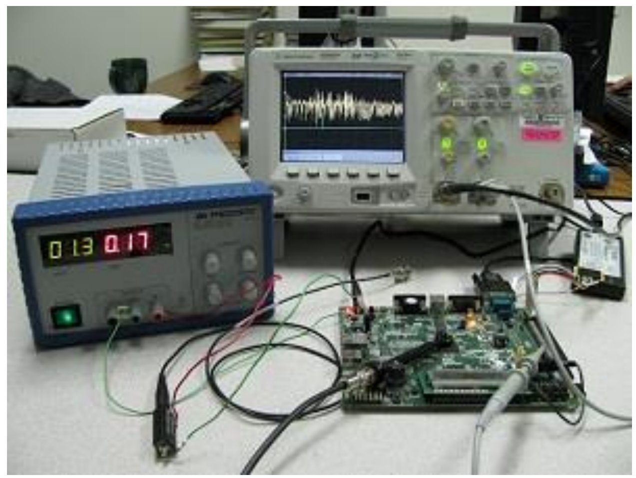
Towards Fair and Efficient Evaluations of Leaking Cryptographic Devices
(Overview of the ERC Project CRASH, part I)



François-Xavier Standaert

UCL Crypto Group, Belgium

SPACE, December 2016

Outline

- Introduction
  - Side-channel analysis (attack steps)
  - Heuristic vs. optimal separation
- Measurement & preprocessing
  - Filtering, leakage/POI detection, dimension. reduction
- Predictions & modeling
  - Profiled vs. non-profiled separation, leakage certification
- Exploitation
  - Soft Analytical Side-Channel Attacks
- Post-processing
  - Key enumeration, rank estimation
- Future trends
  - Security without obscurity
  - IT metrics & (tight) proofs

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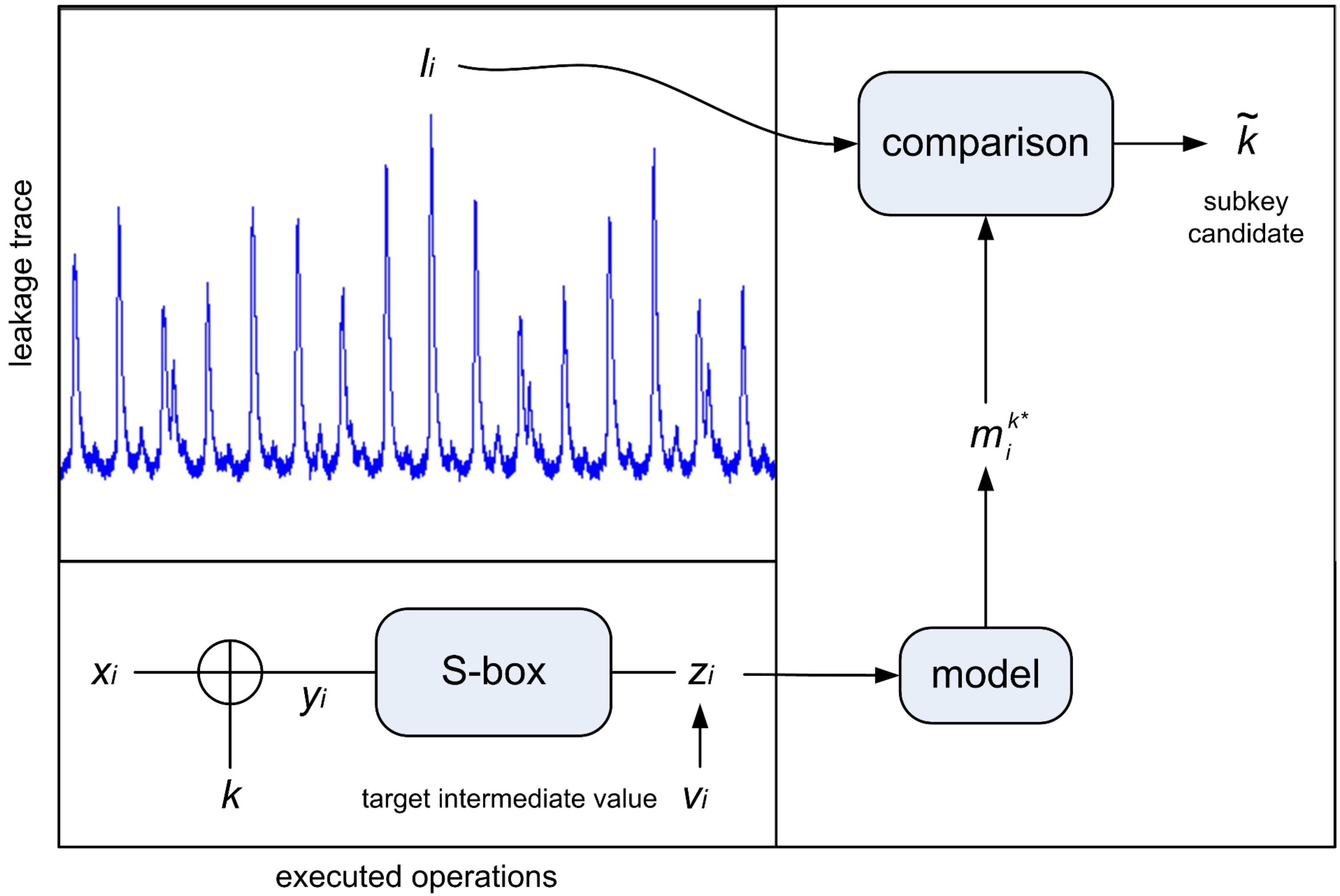
Standard DPA



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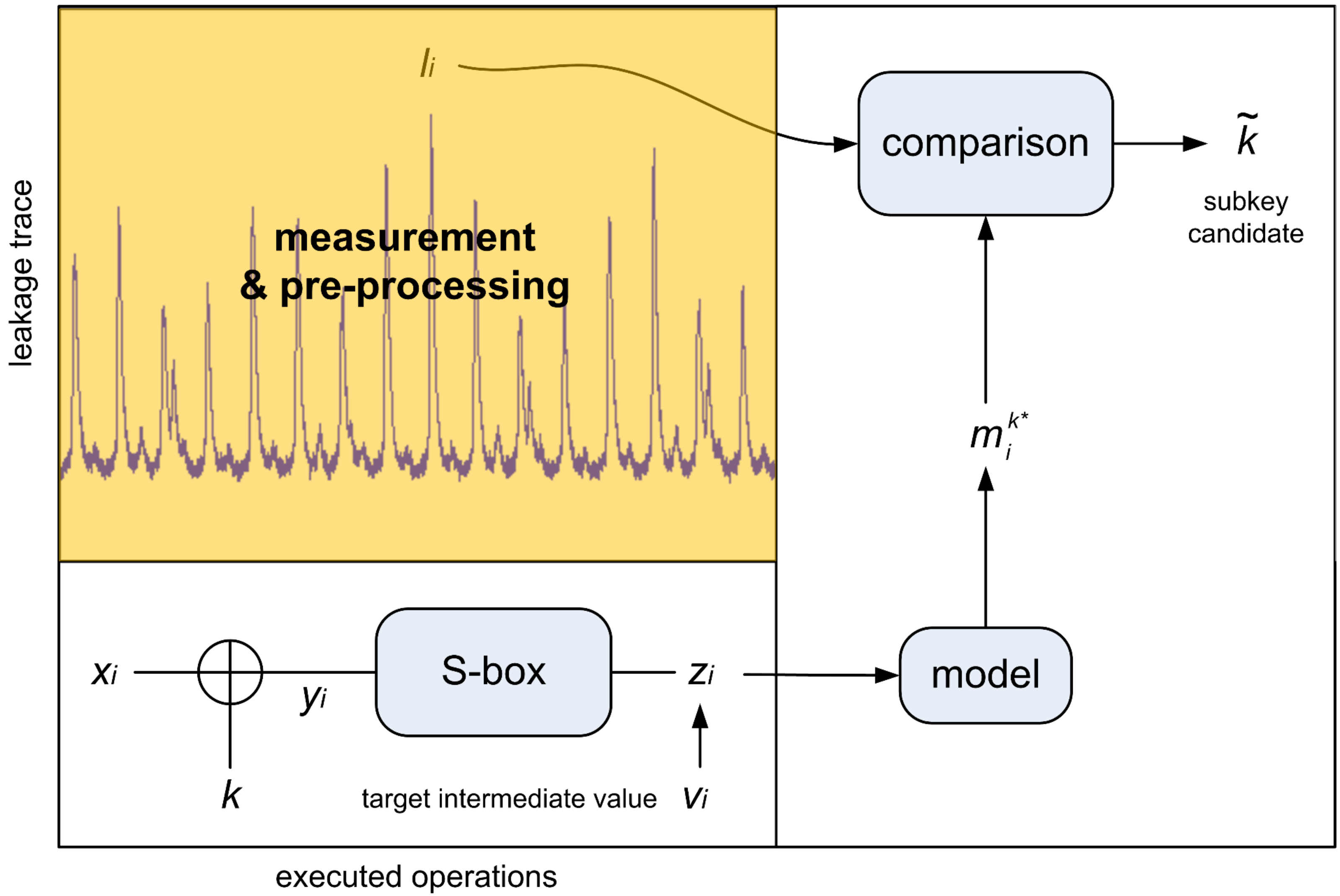

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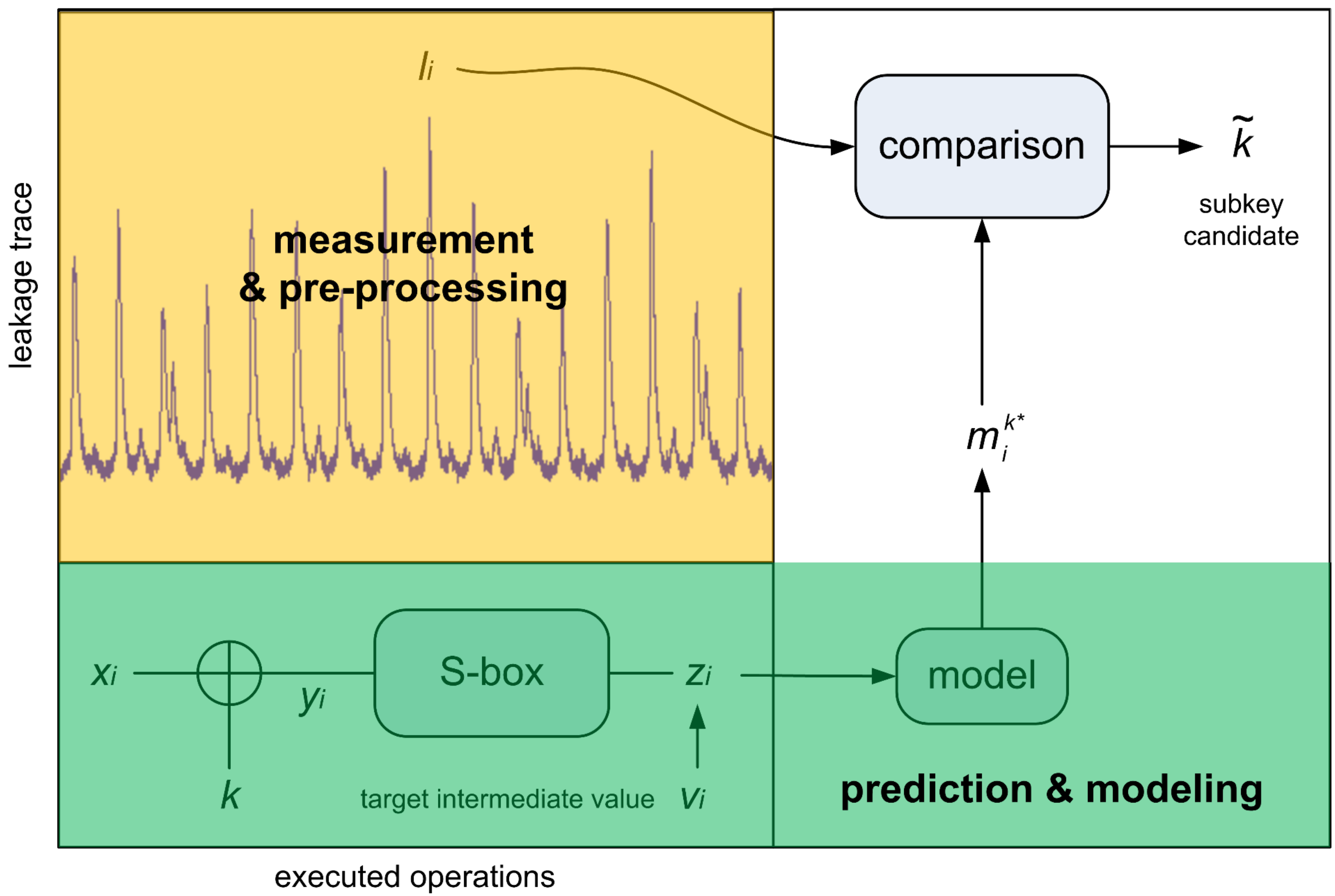

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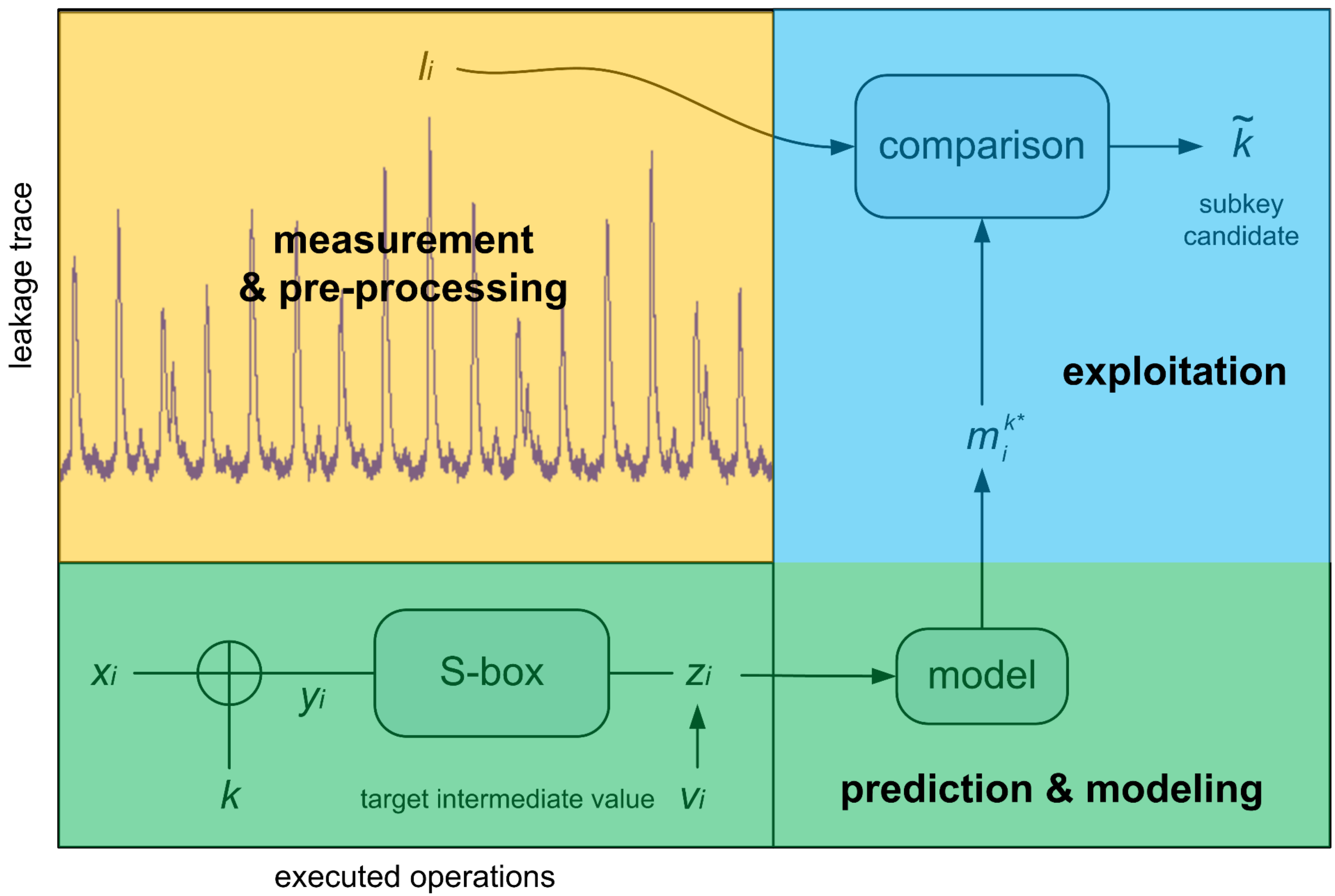

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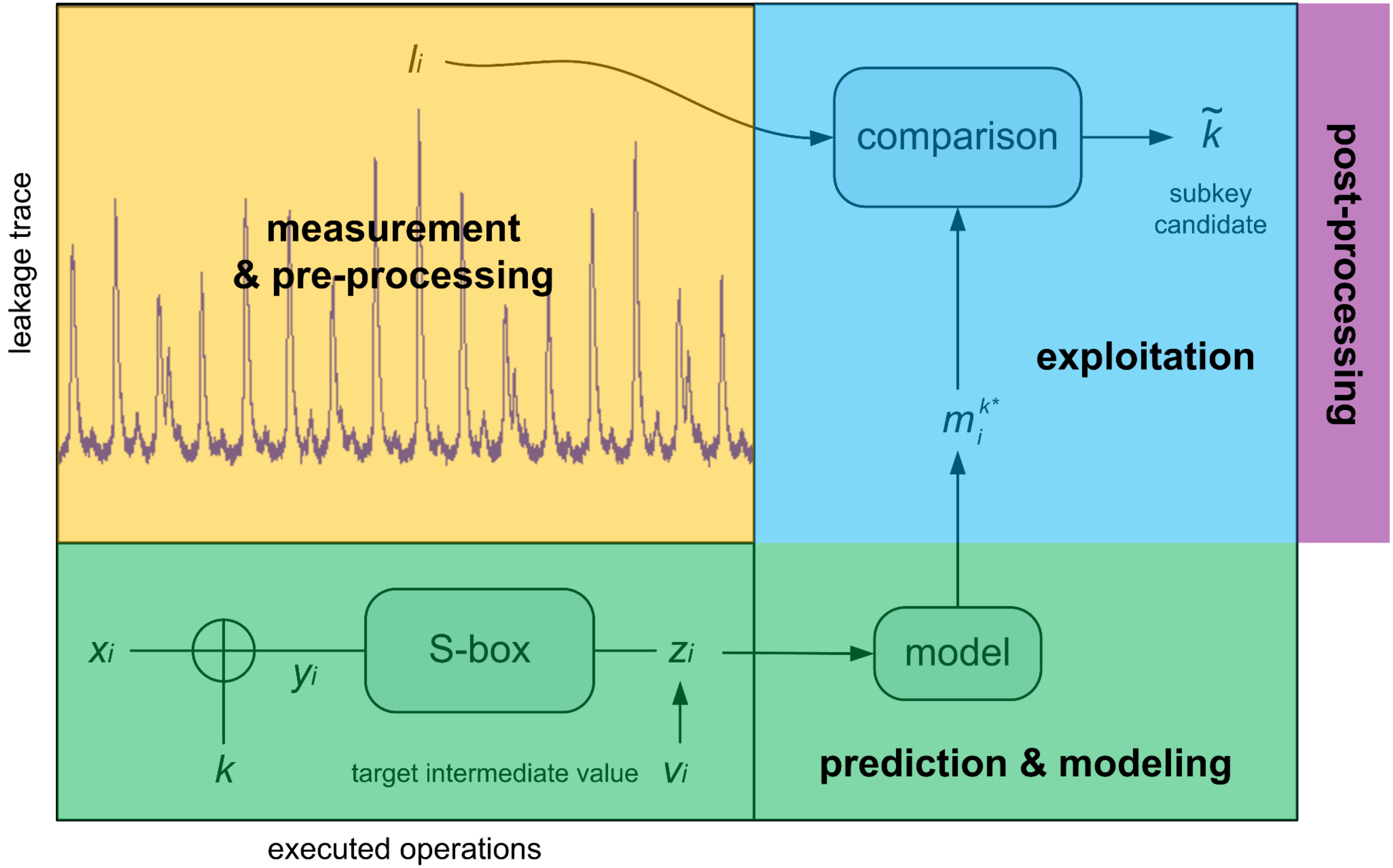

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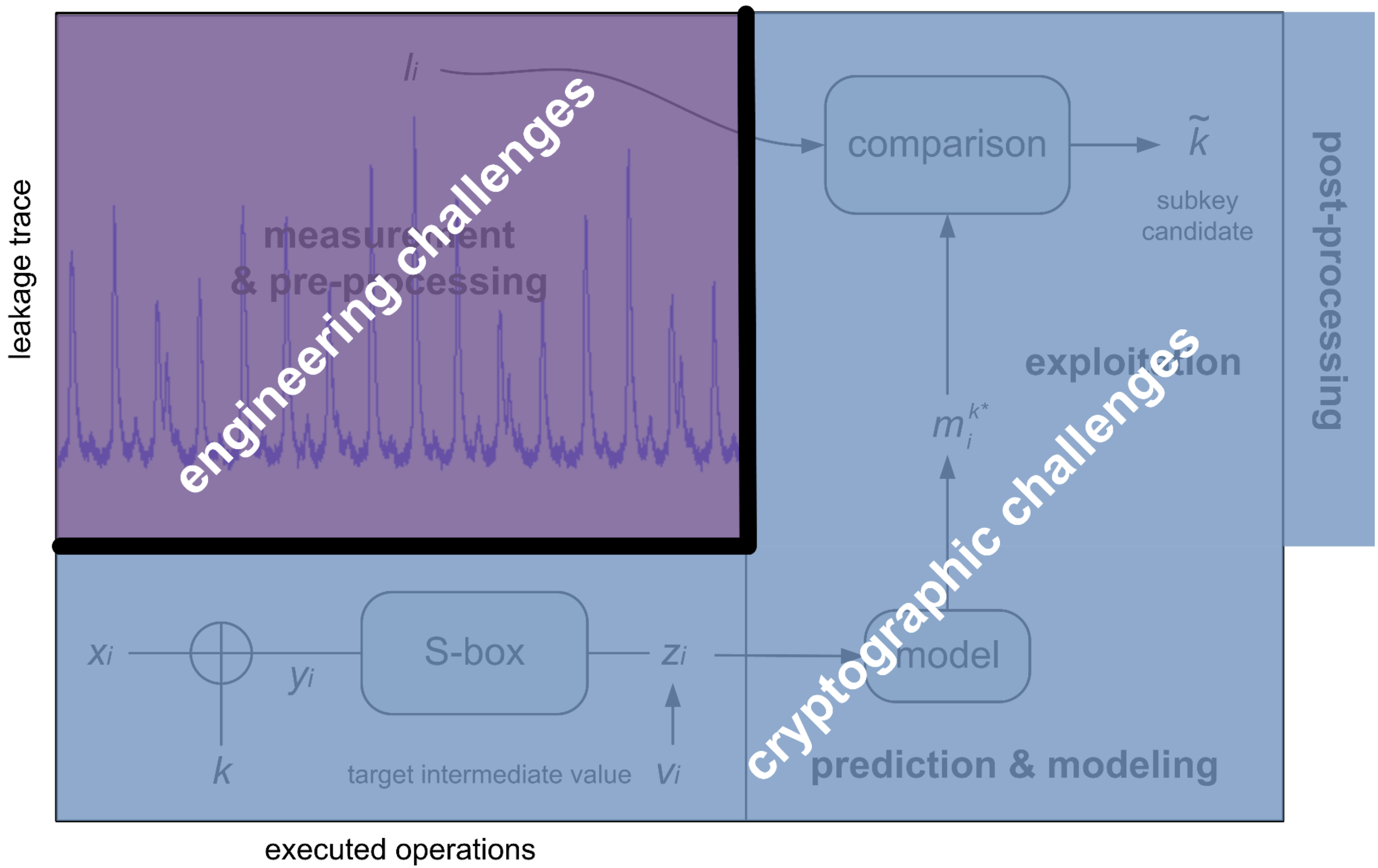

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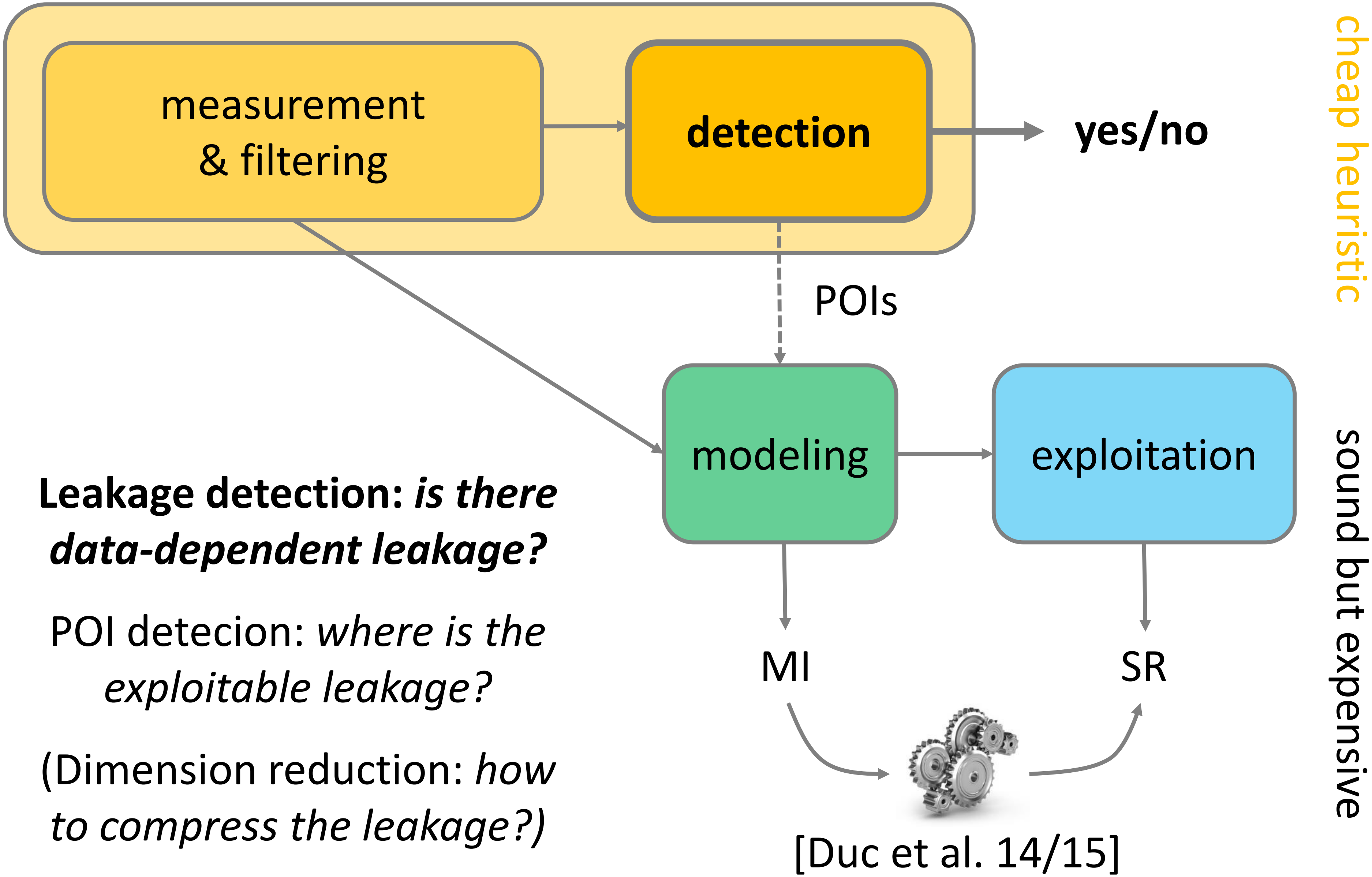
Side-channel attacks workflow



Leakage detection: *is there data-dependent leakage?*

POI detecion: *where is the exploitable leakage?*

(Dimension reduction: *how to compress the leakage?)*

Tool #1: CRI's "fixed vs. random" t-test

- AES Rijndael example
  - 128-bit key fixed
  - N_r traces with <u>random</u> plaintexts
  - N_f traces with a <u>fixed</u> plaintexts
  - Apply Student's t-test to the f&r classes:
  - $\Delta(t) = \left[\hat{\mu}_f(t) - \hat{\mu}_r(t)\right] / \left[\left(\hat{\sigma}_f^2\ (t)/N_f\right) + (\hat{\sigma}_r^2\ (t)/N_r)\right]$

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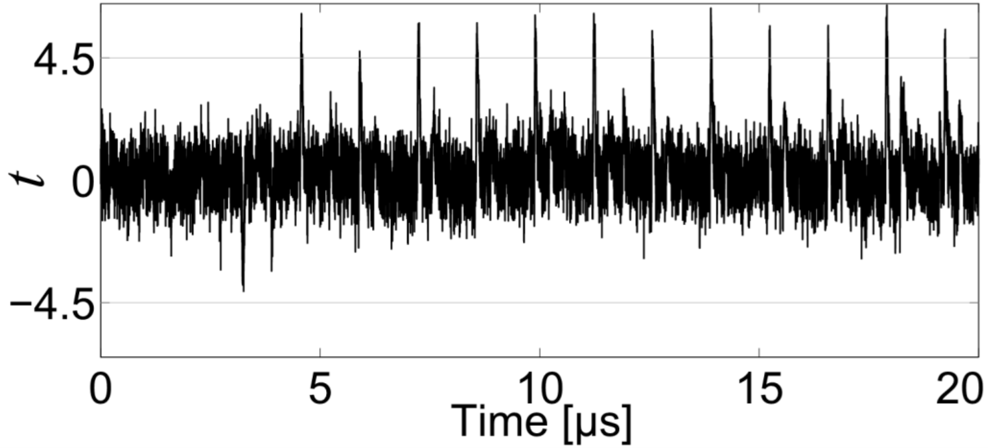
- Large t statistic: « some data dependency detected »



Tool #2: correlation-based detection

- ρ-test
  - 128-bit key fixed
  - *N* traces with random plaintexts
  - Targets an enumerable intermediate value *X*
  - Estimate Pearson's coefficient: $\hat{r}(t) = \hat{\rho}(L_X(t), \hat{model}_t(X))$

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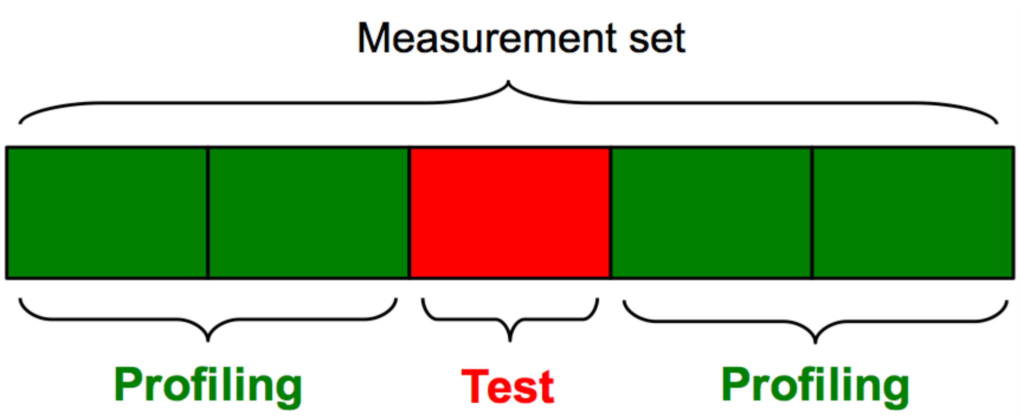

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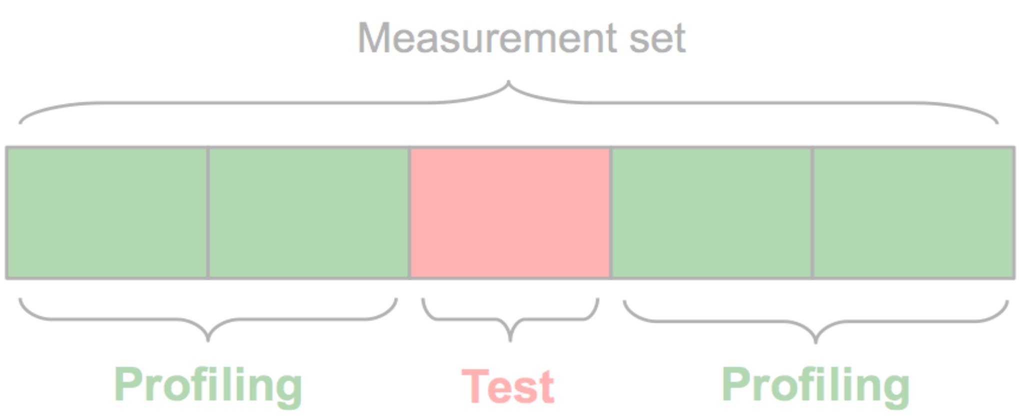
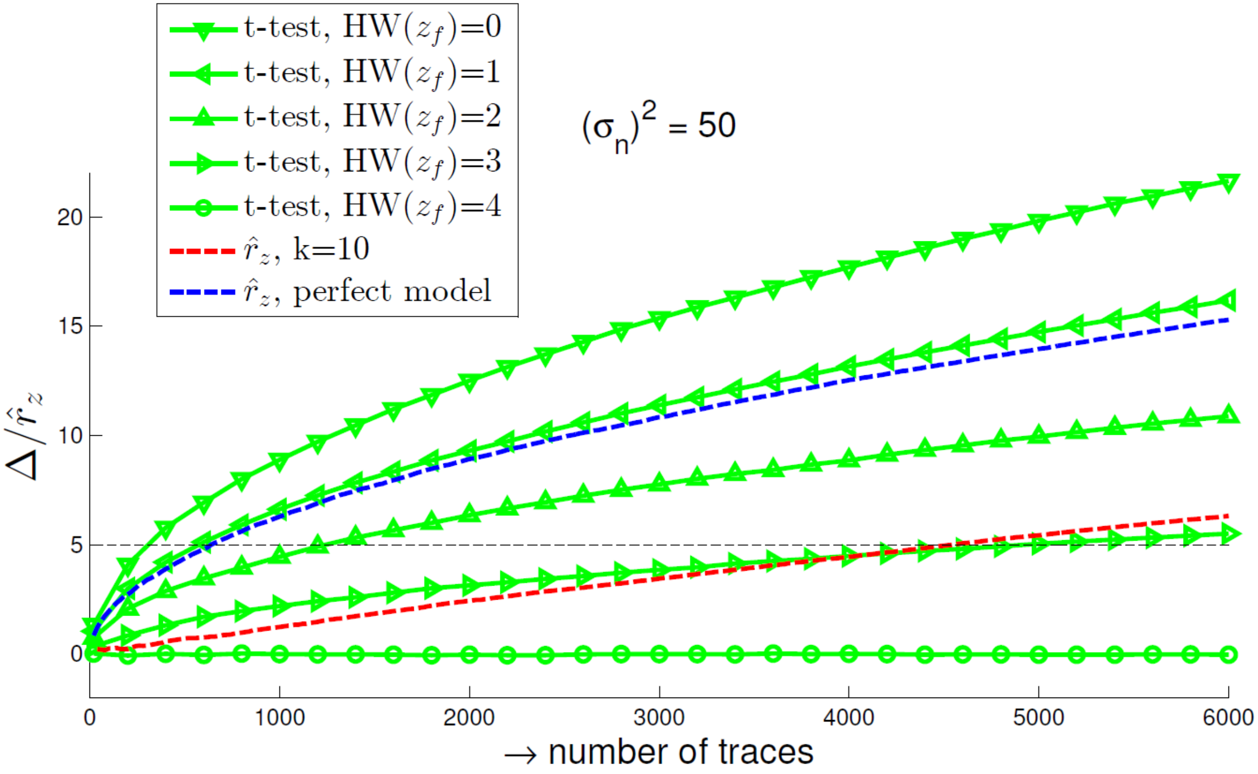


- Hypothesis test (Z transform): $\frac{1}{2} \times ln\left(\frac{1+\hat{r}(t)}{1-\hat{r}(t)}\right) \sim N\left(0, \frac{1}{\sqrt{N-3}}\right)$

Simulated experiments (8-bit noisy HW's)



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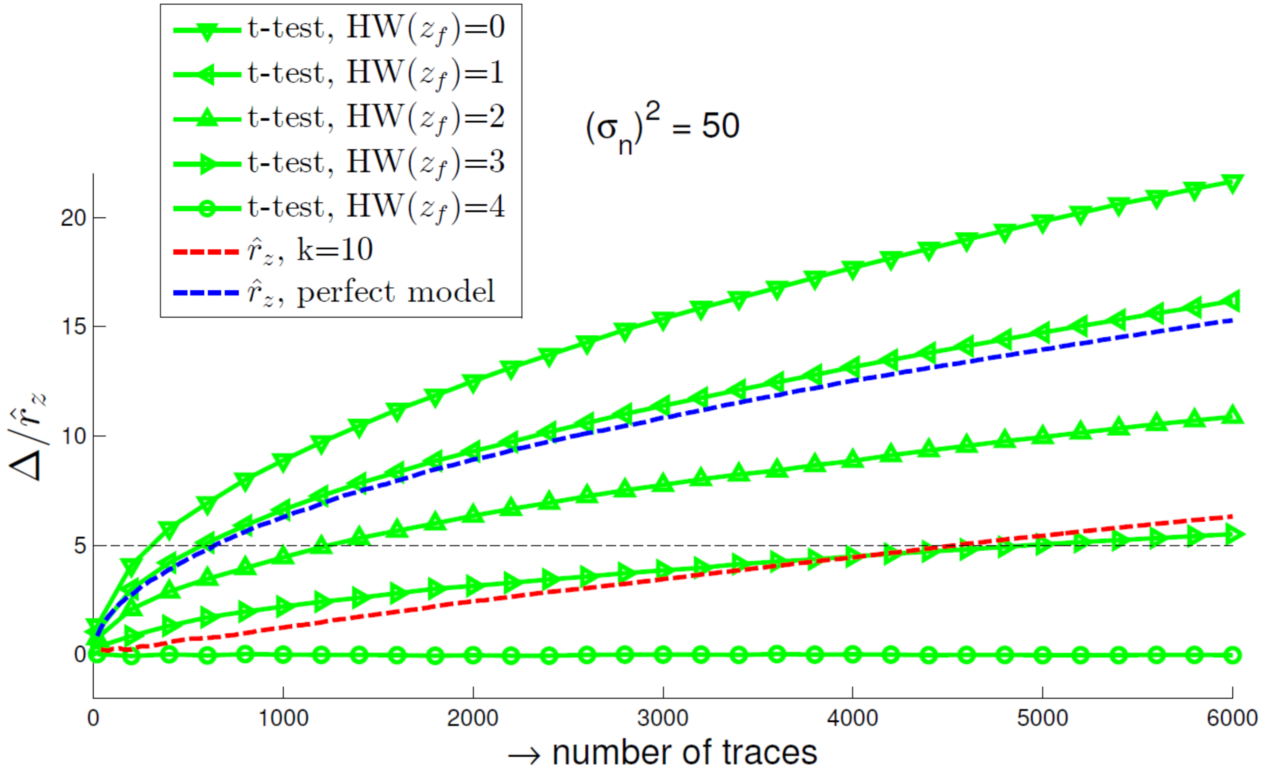

- CRI's t-test pro: sampling complexity!

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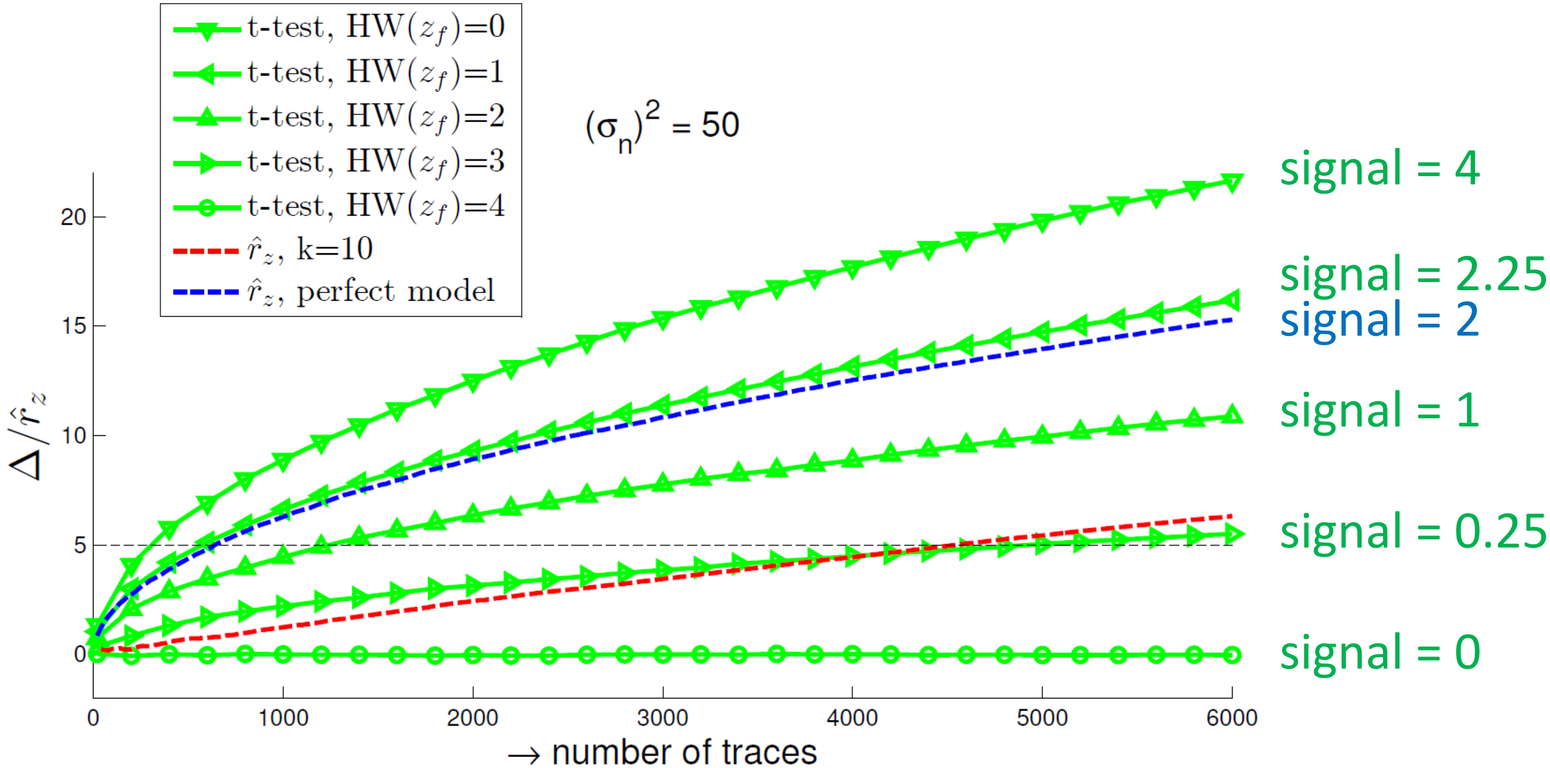

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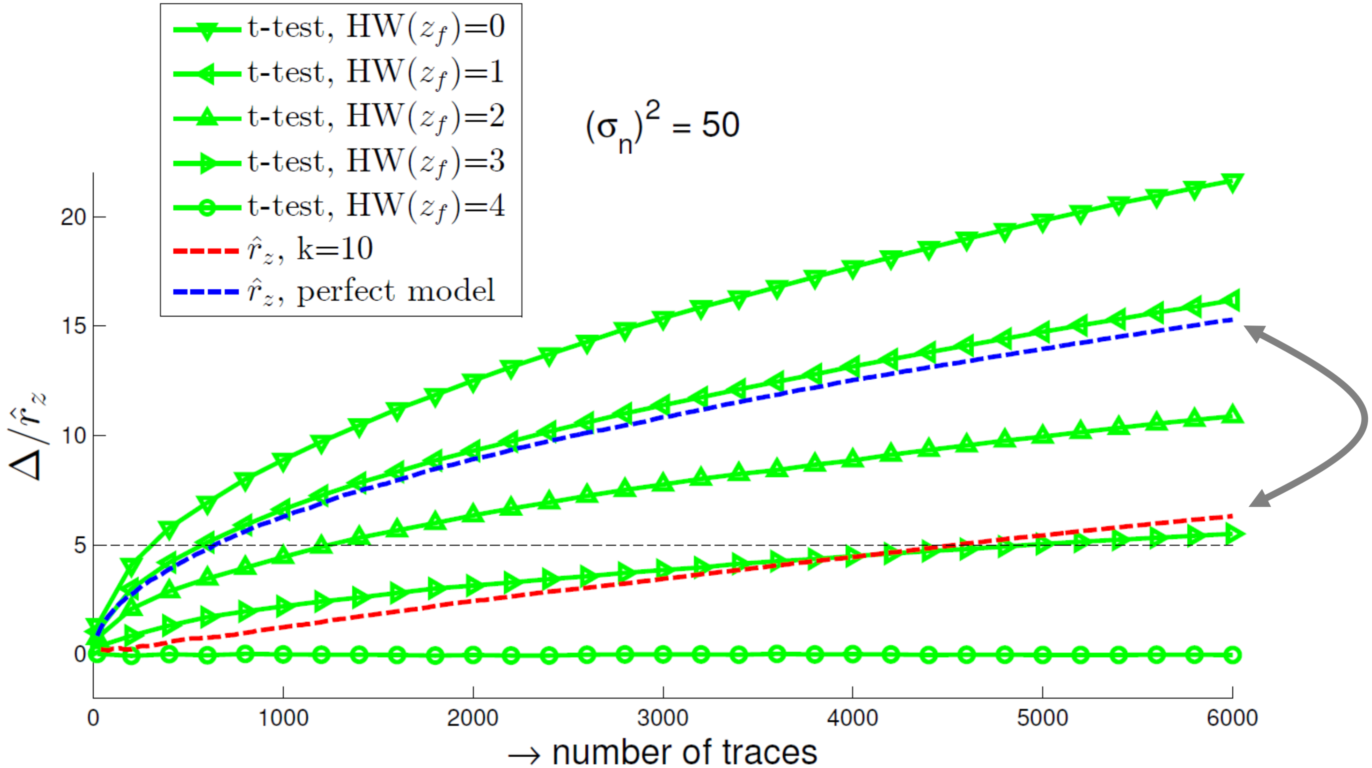
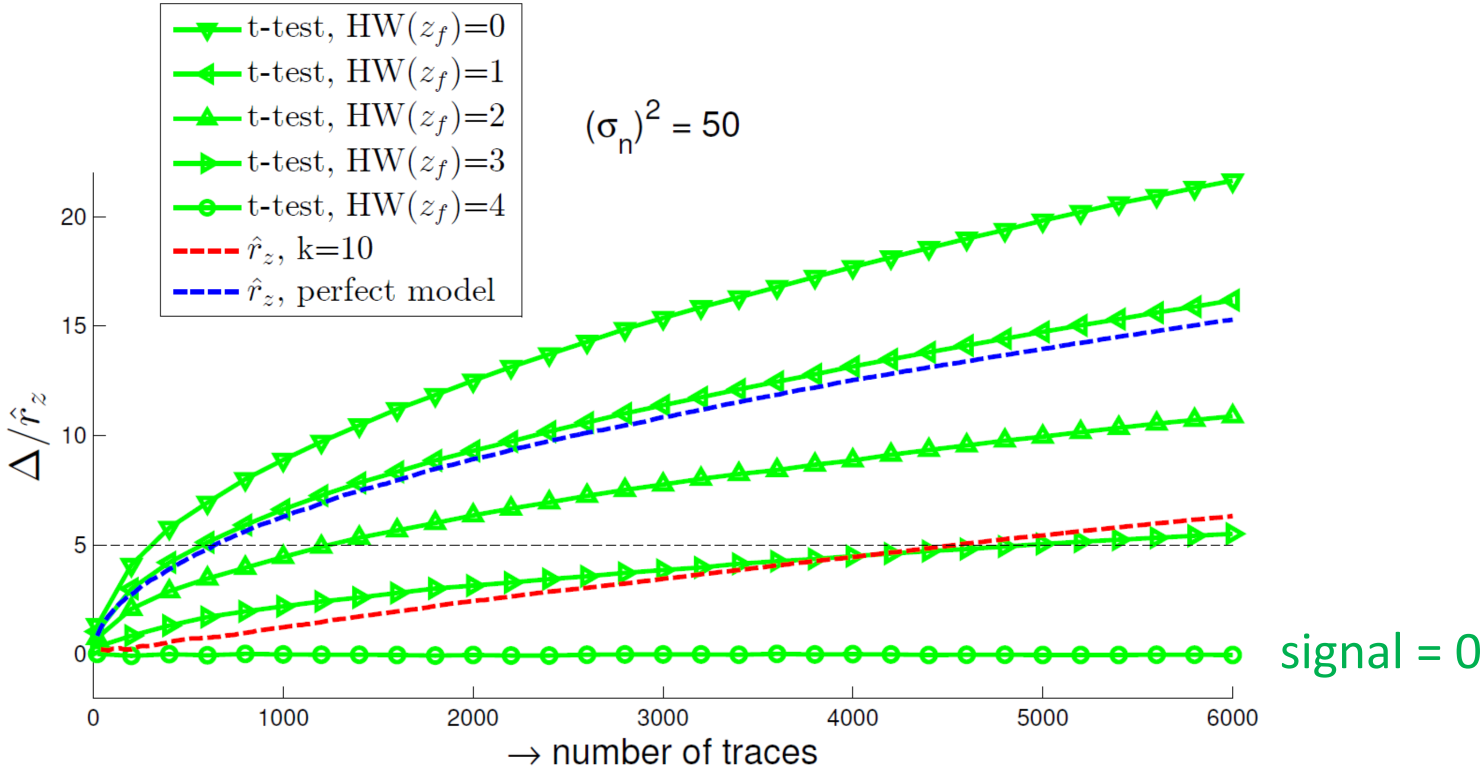
  - Better **signal** for well-chosen fixed classes



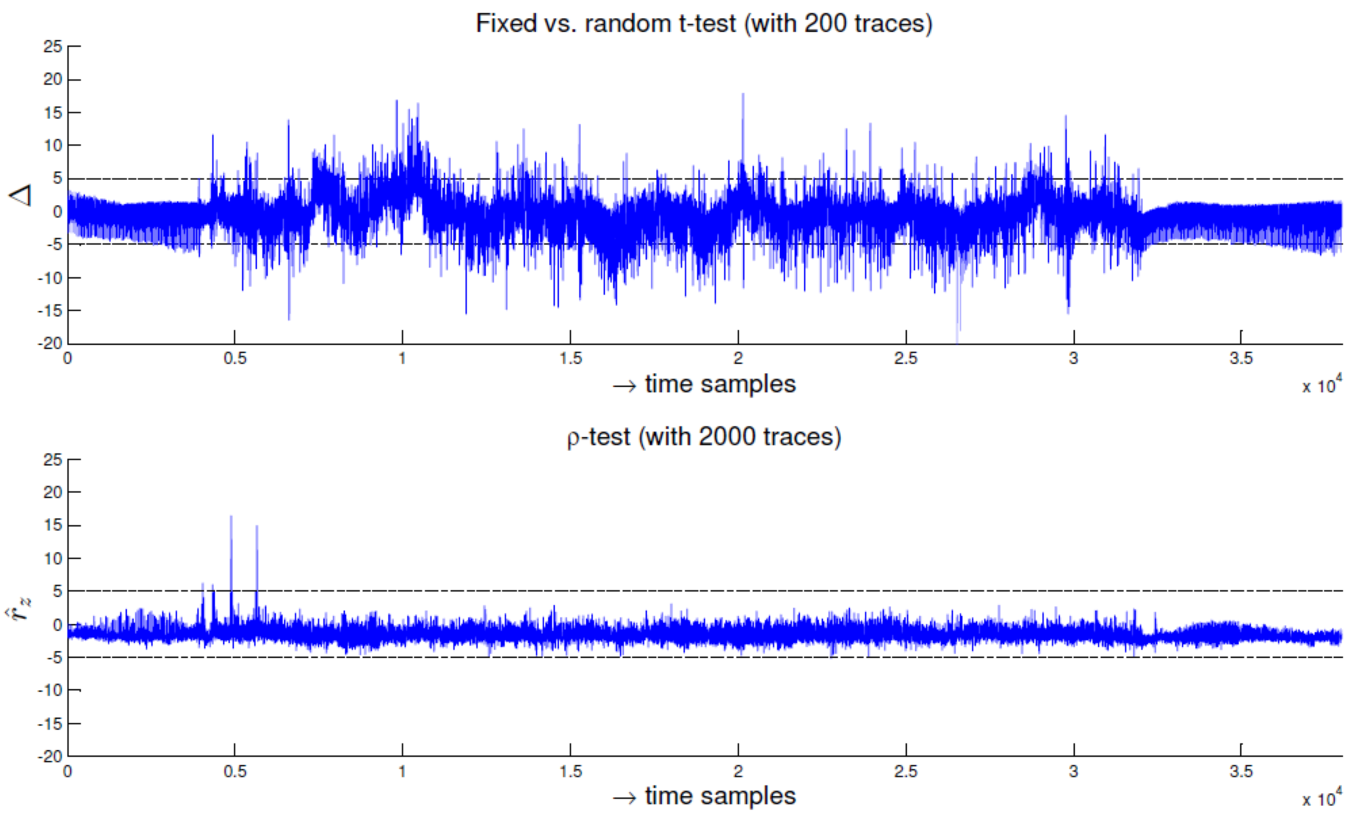
- CRI's t-test pro: sampling complexity!
  - Better **signal** for well-chosen fixed classes
  - Easier estimation (**2** classes vs. **256** classes)

Simulated experiments (8-bit noisy HW’s)



- CRI’s t-test con: possible false negative!
  - Possibly **no signal** for badly-chosen fixed classes

Real measurements (Atmel Atmega)



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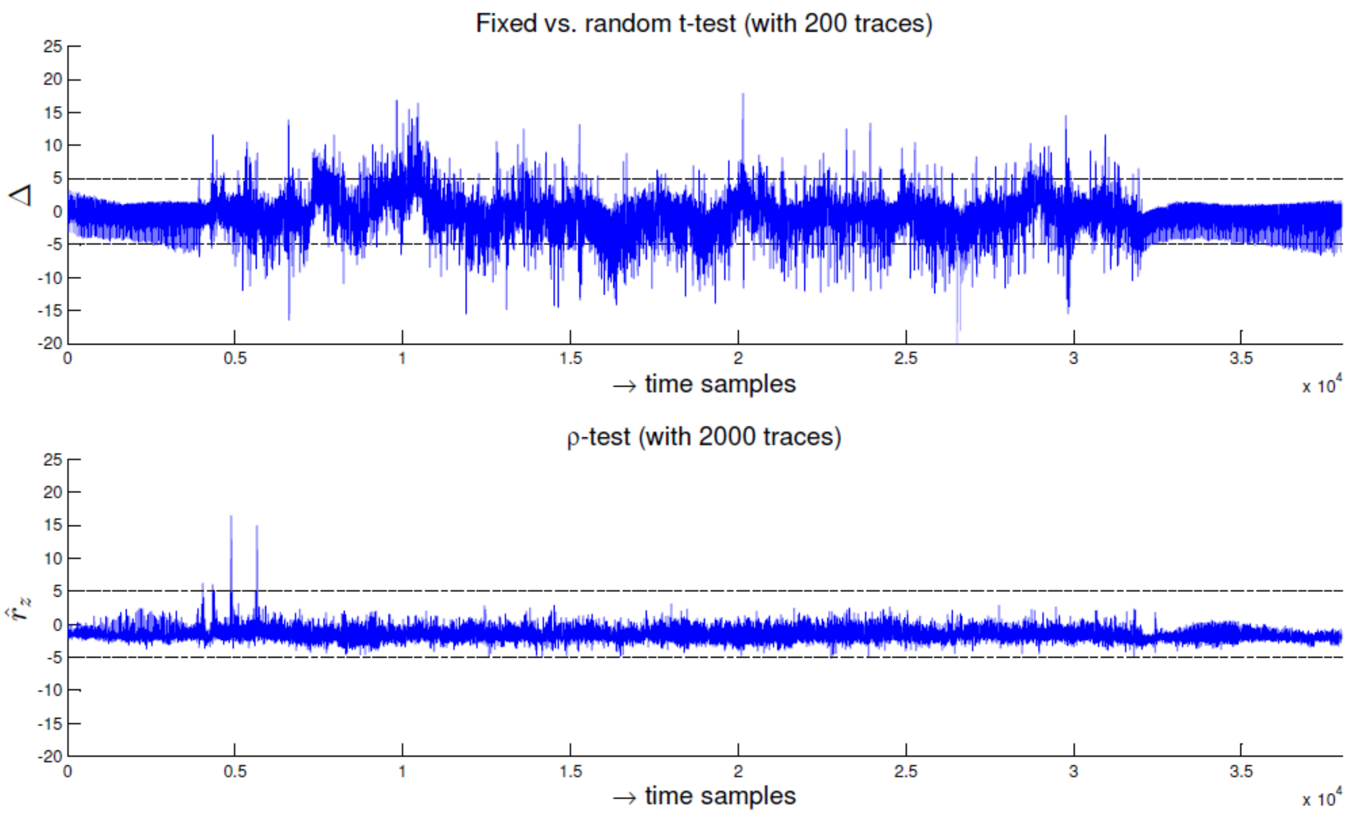

- t-test false negatives do not hurt (integrated over time)
- But there are many false positives (w.r.t. DPA)
- Only the value of ρ is connected with key recovery SR

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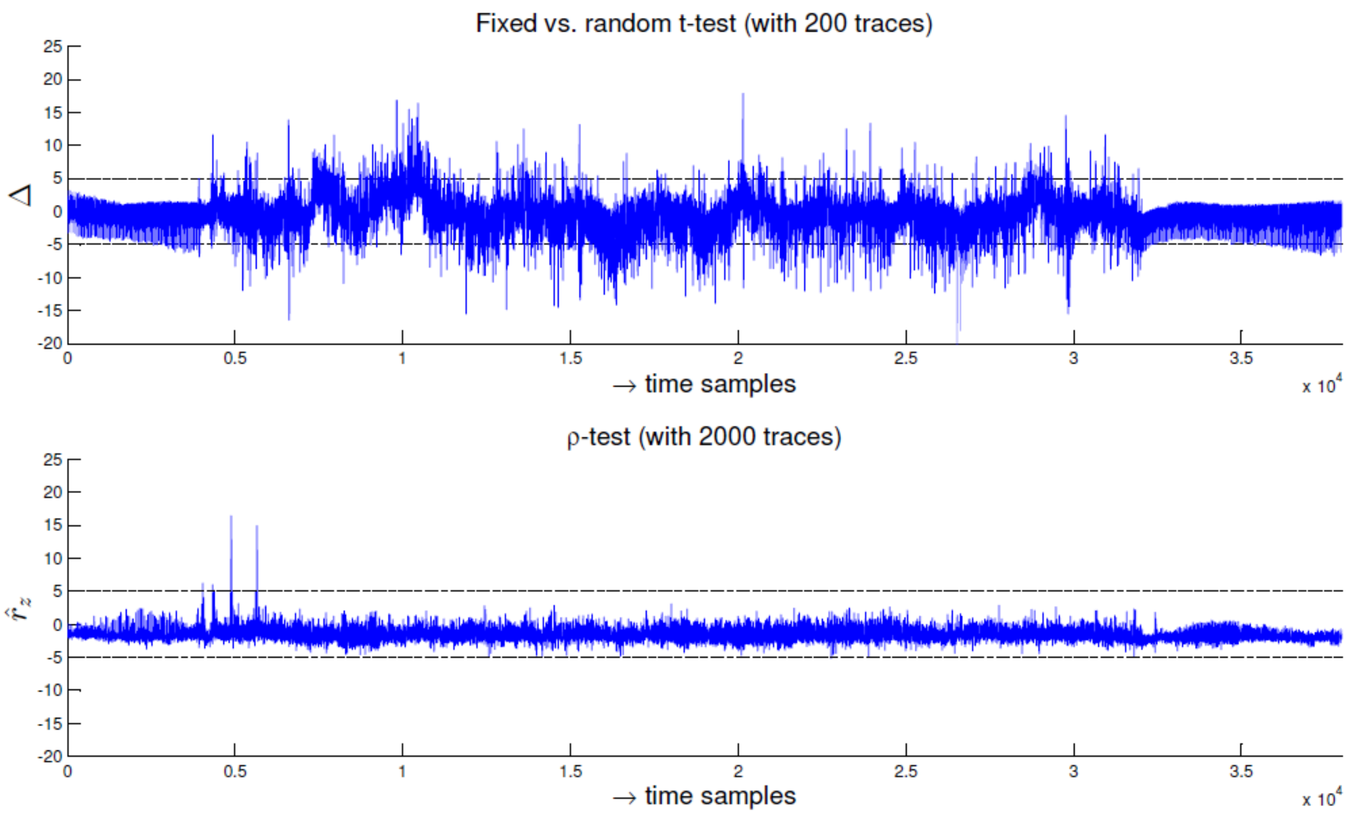

sampling complexity vs. informativeness tradeoff

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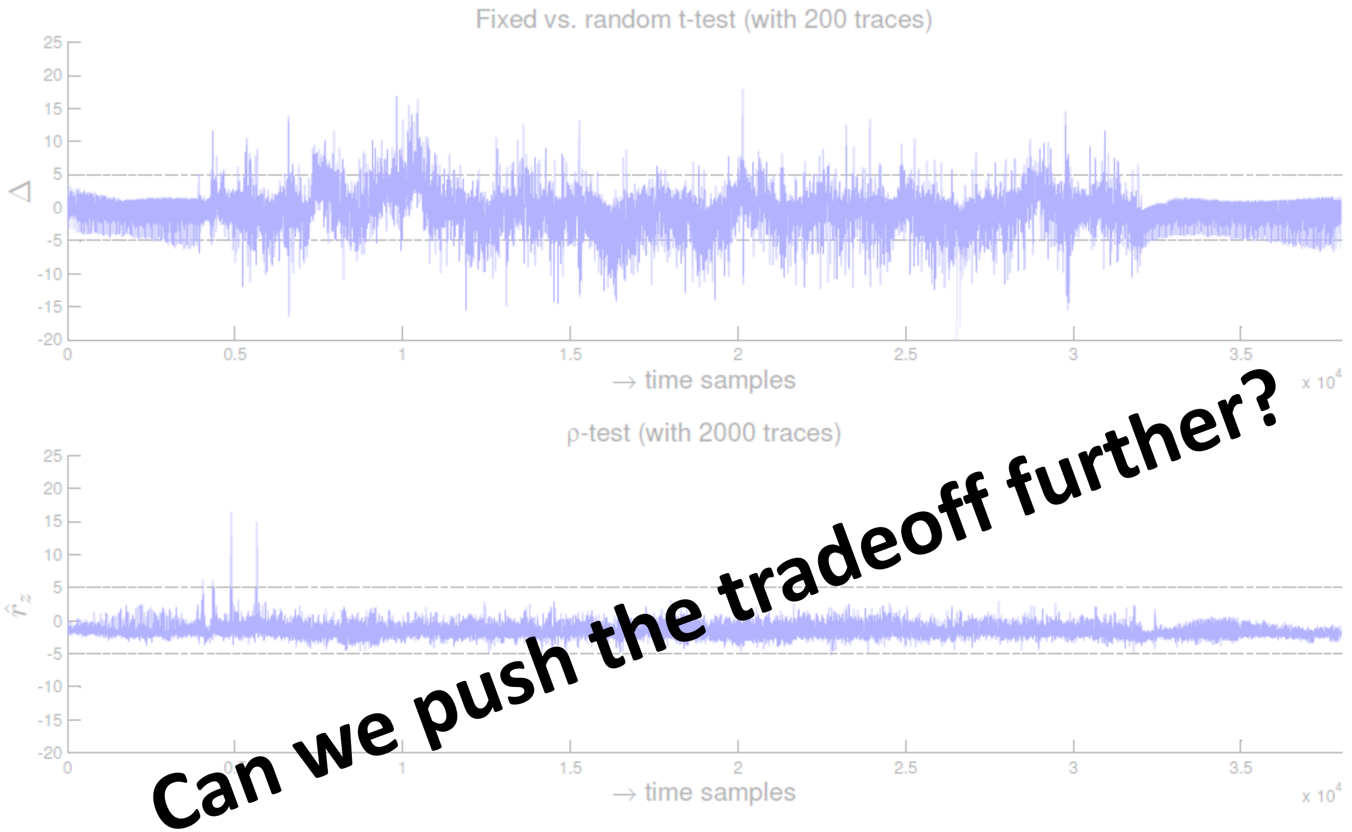

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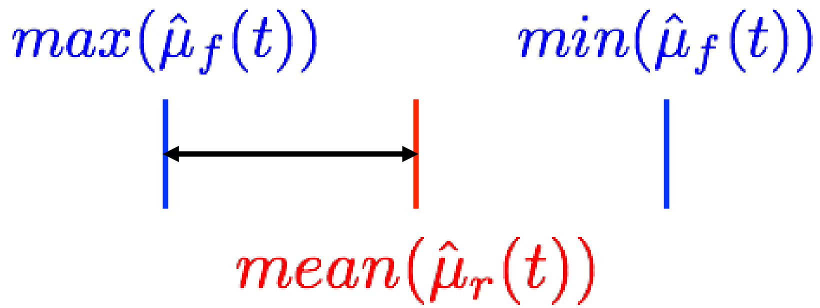
Fixed vs. fixed leakage detection test

- CRI's fixed vs. random test (e.g. HW leakages)
  - Maximum HW difference observed = 4
  - "Algorithmic noise" due to the random class



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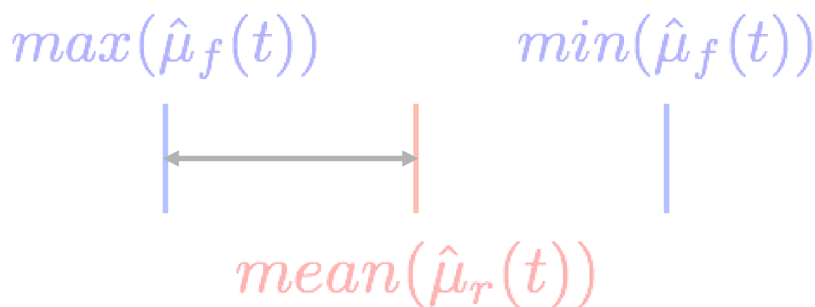
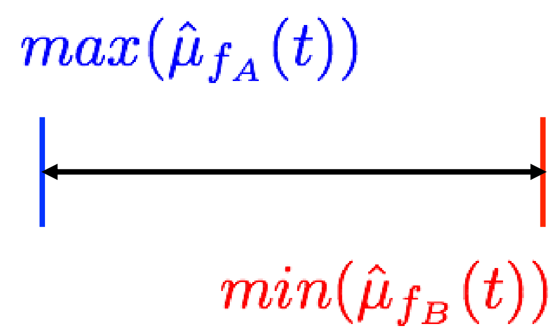


- Natural extension: *fixed vs. fixed test*
  - Maximum HW difference = 8
    - Average signal multiplied 2
  - No algorithmic noise!



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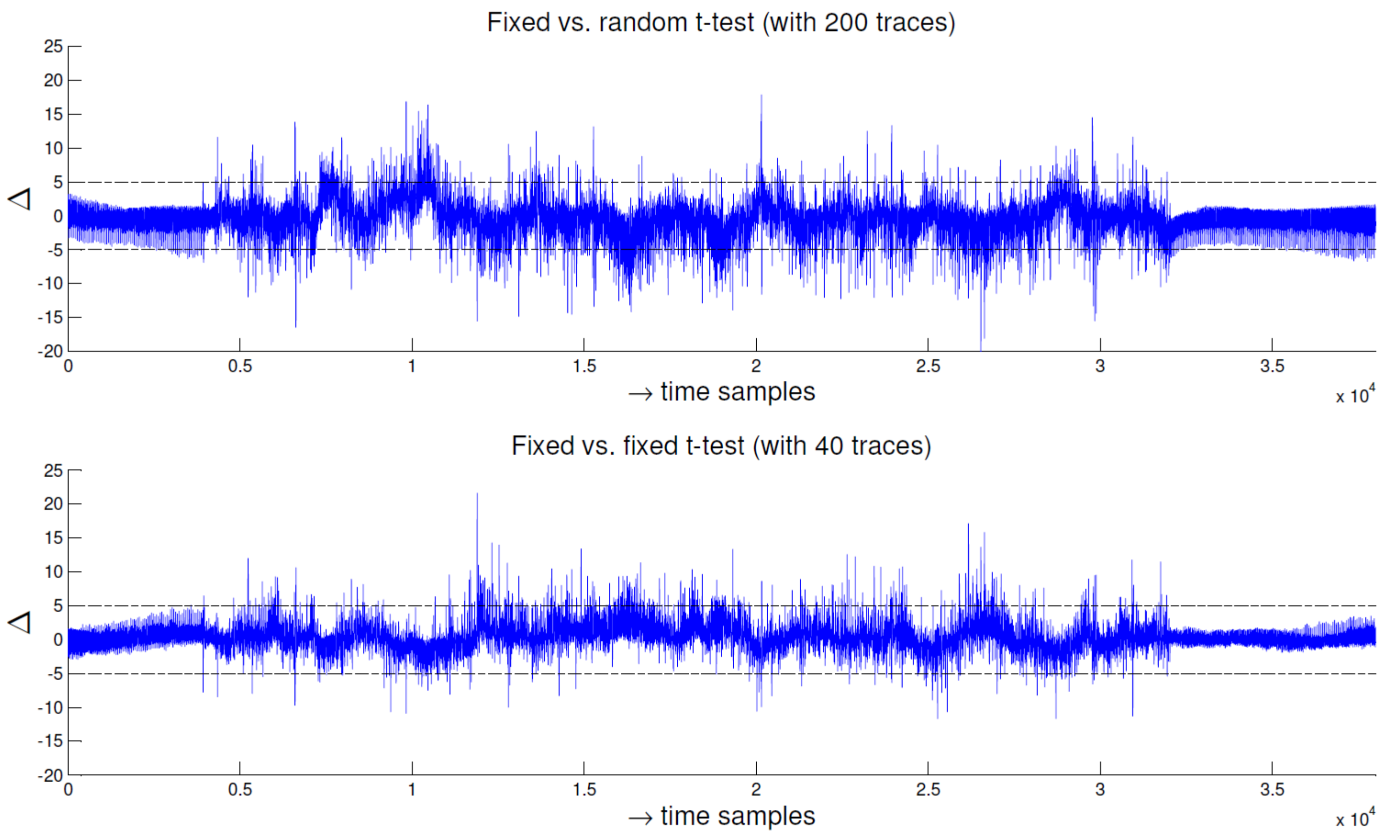
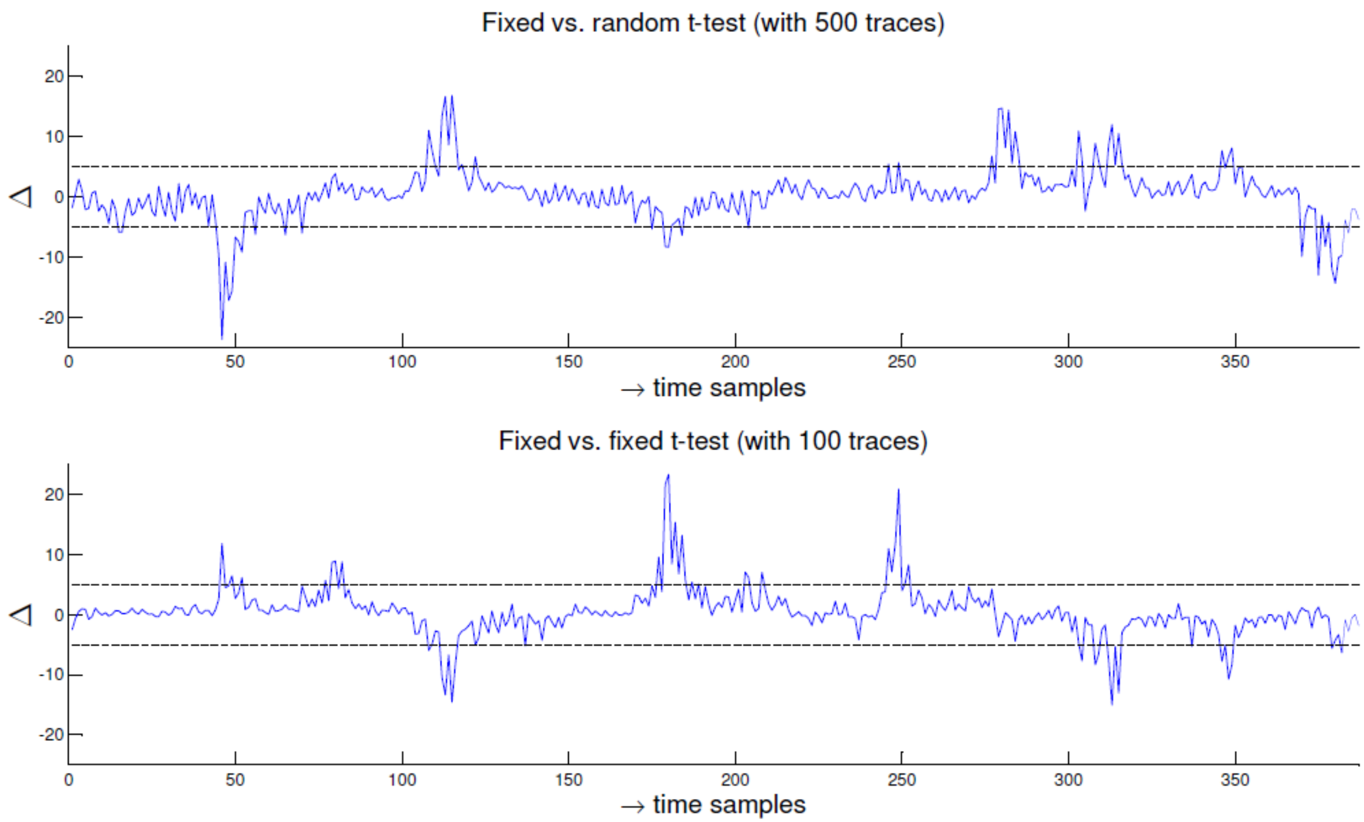


- Gain dominated by the increased signal
- Reduction of the sampling complexity by a factor ≈ 5

Real measurements (parallel AES in an FPGA)



- Gain dominated by the reduced noise
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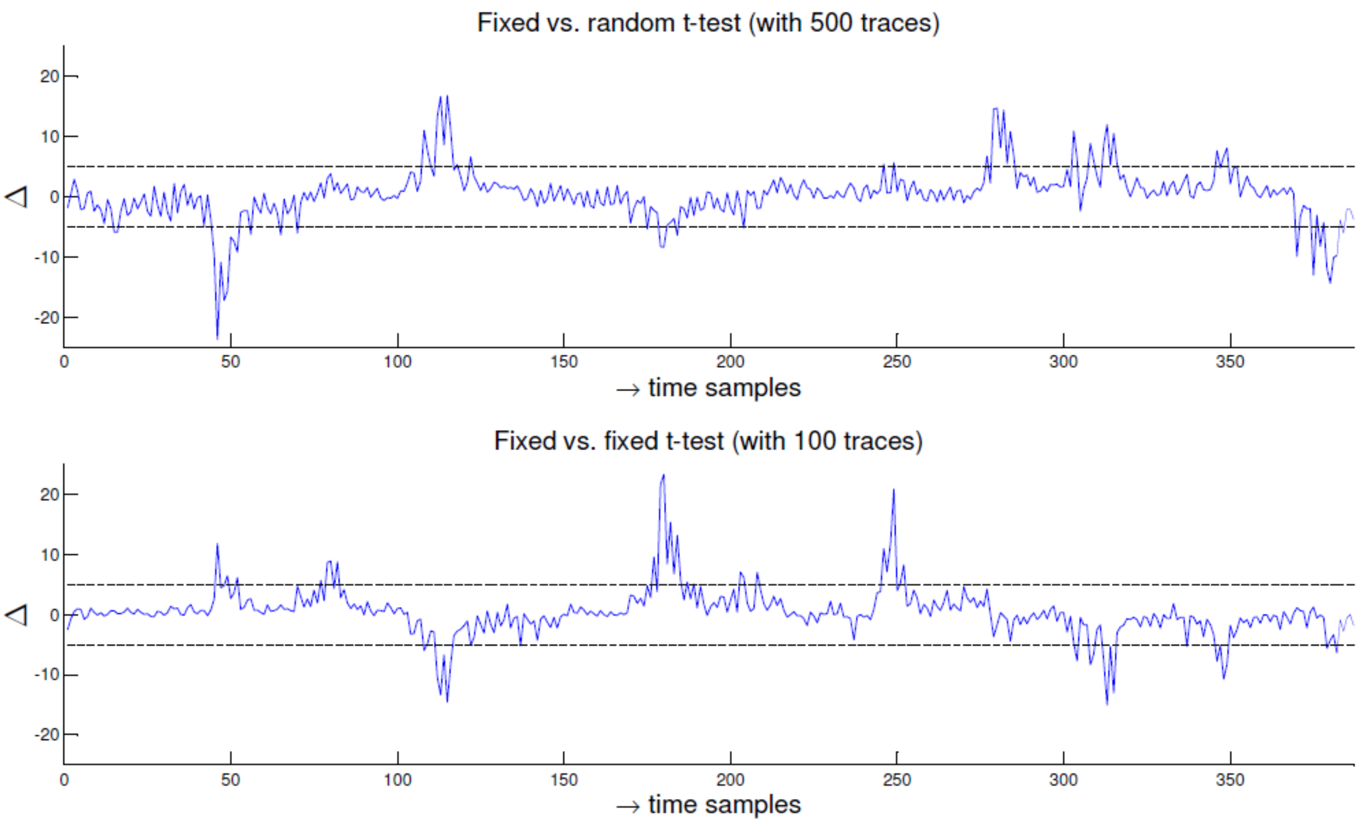

F vs. F better deal on average; similar risks of fasle positives & negatives

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Prediction and modeling

- General case: profiled DPA
  - Build "*templates*", i.e. $\hat{f}(l_i|k, x_i)$
    - e.g., Gaussian, regression-based
  - Which directly leads to $\widehat{\Pr}[k|l_i, x_i]$

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- "Simplified" case: non-profiled DPA
  - Just assumes some model
  - e.g., CPA with $m_i^{k^*} = \mathrm{HW}(z_i)$
  - e.g., DPA with $m_i^{k^*} = z_i[1]$
  - …

Separation result (I)

- Only profiled DPA is *guaranteed* to succeed!

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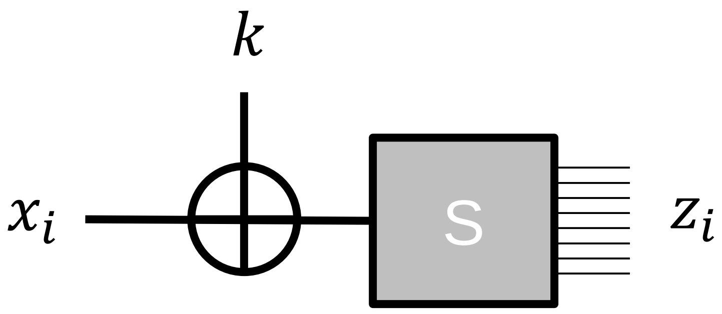
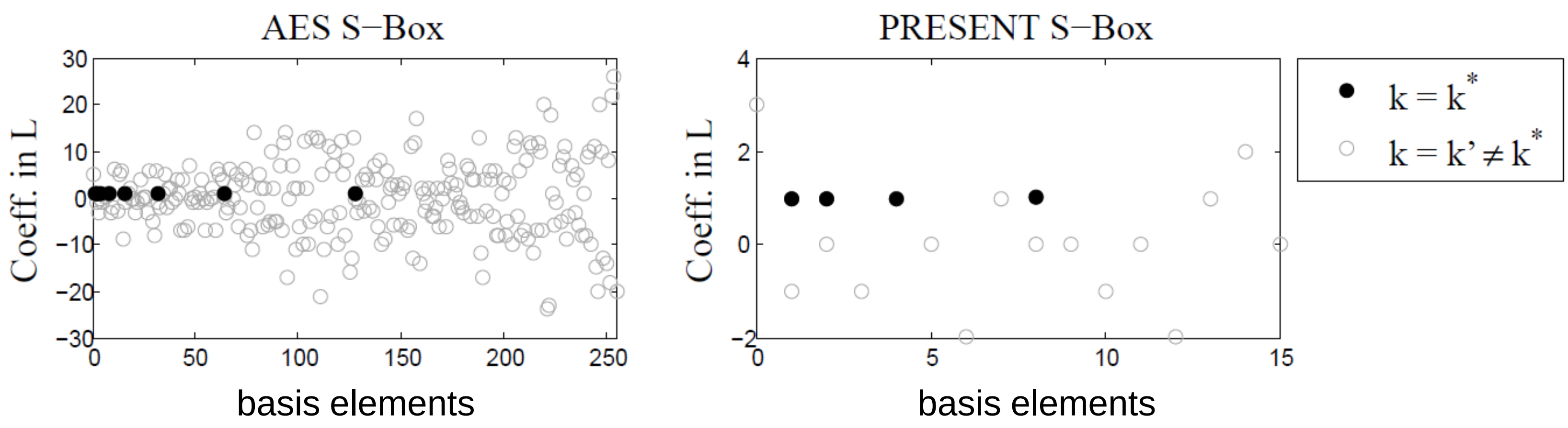


- Regression: $\mathrm{L}(z_i) \approx \mathrm{F}(z_i) + N_i$ with:
  - Linear basis (i.e., 8 bits)
  - Quadratic basis (i.e., add 28 products)
  - …
  - Full basis (i.e., 256 elements)

Separation result (II)

- e.g., if $\mathrm{L}(z_i) = \mathrm{HW}(z_i)$



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  - Even for incorrect key candidates!

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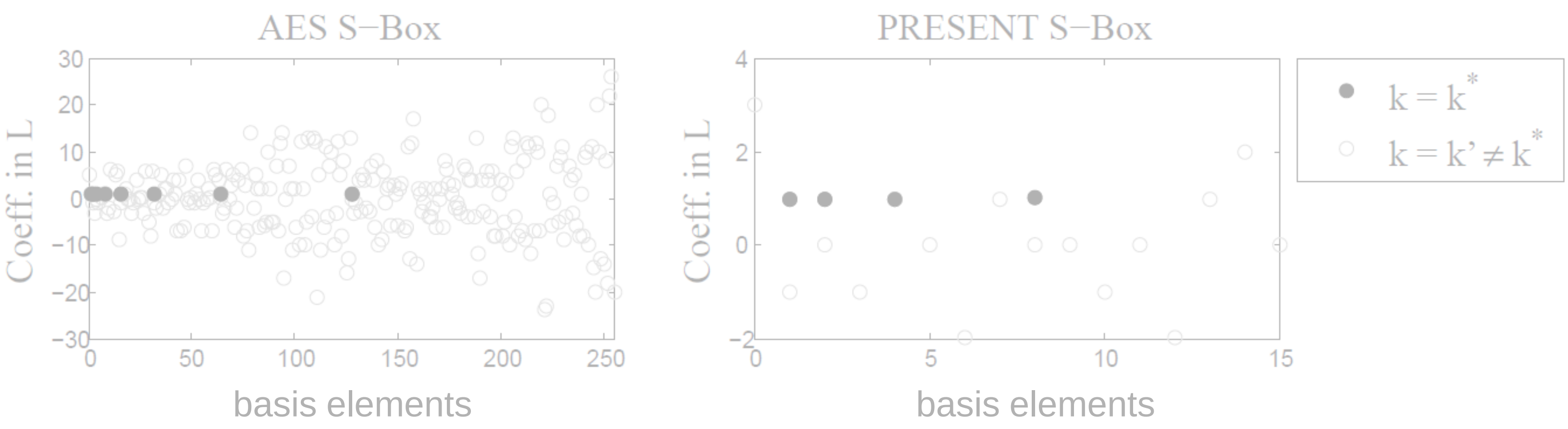

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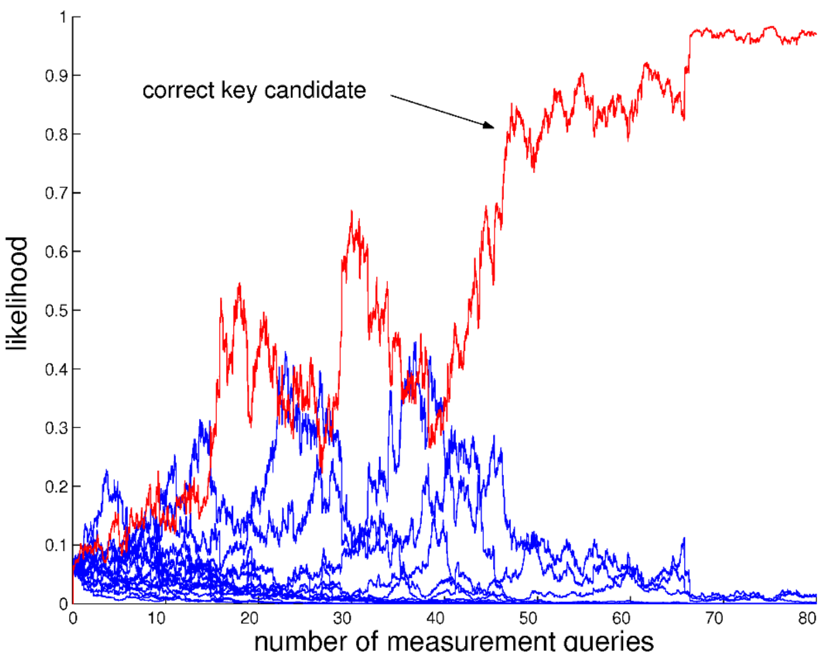
⇒ Non-profiled DPA needs a good assumption

- e.g., the model is linear, simple, …
- This, *in general*, is only provided by profiling

Illustration

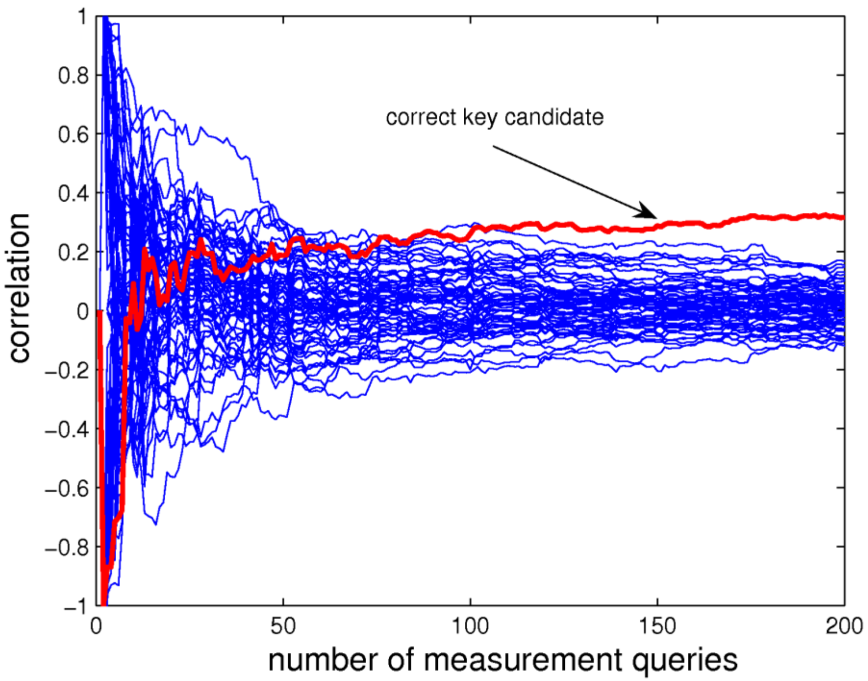
Gaussian templates



$$\tilde{k} = \underset{k^*}{\operatorname{argmax}} \prod_{i=1}^{q} \frac{1}{\sqrt{2 \cdot \pi} \cdot \sigma(L)} \cdot \exp\left(-\frac{1}{2} \cdot \left(\frac{l_i - m_i^{k^*}}{\sigma(L)}\right)^2\right)$$

- More efficient **(better model)**
- Outputs probabilities

CPA



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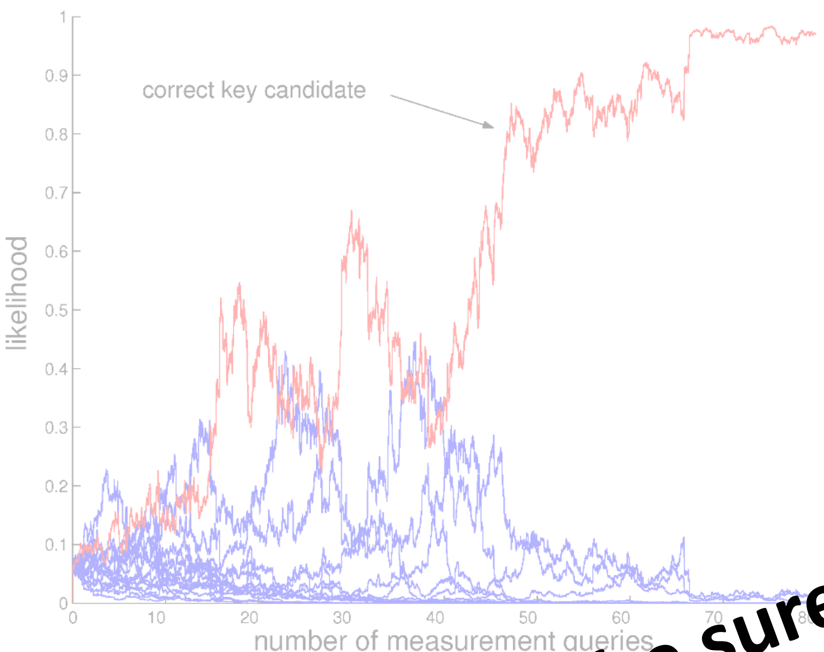

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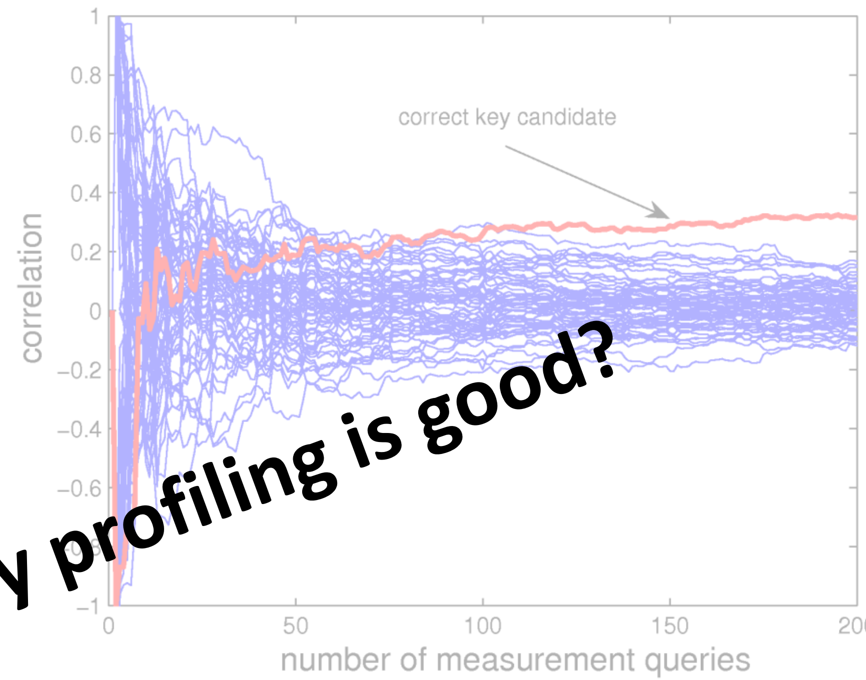

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How can I be sure my profiling is good?

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  - That could be reported in SR bounds [DFS15]

[DFS15] A Duc, S. Faust, F.-X. Standaert, *Making Masking Security Proofs Concrete […]*, EUROCRYPT 2015.

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- Problem: $\Pr_{chip}[l|k]$ is unknown

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Leakage certification [DSV14]

- Distinguish estimation & assumption errors
  - Recall estimation errors decrease with # meas.

[DSV14] F. Durvaux, F.-X. Standaert, N. Veyrat-Charvillon, *How to Certify the Leakage of a Chip*, EUROCRYPT 2014.

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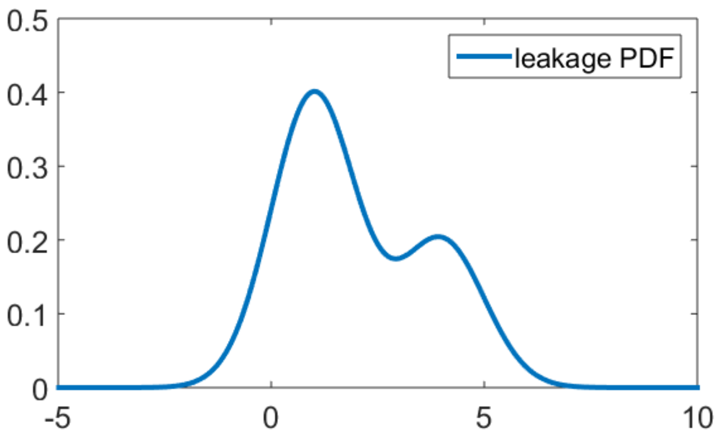

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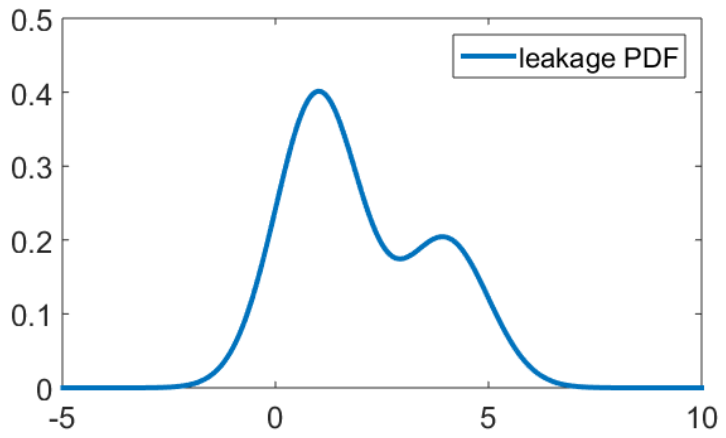
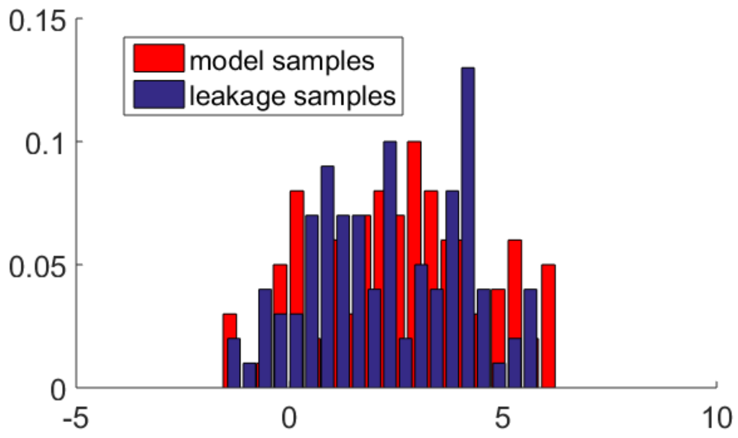
No samples





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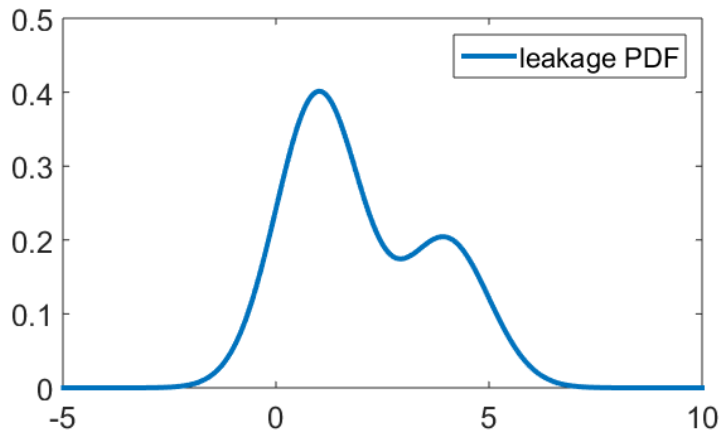
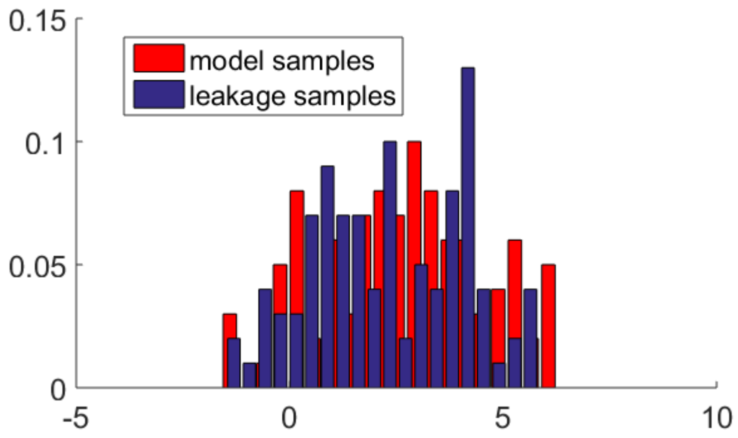
- Example:

estimation errors dominate





$\Rightarrow$ need to measure more

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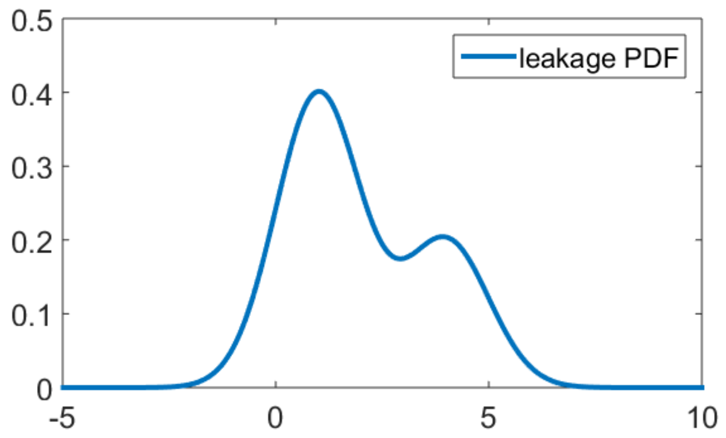
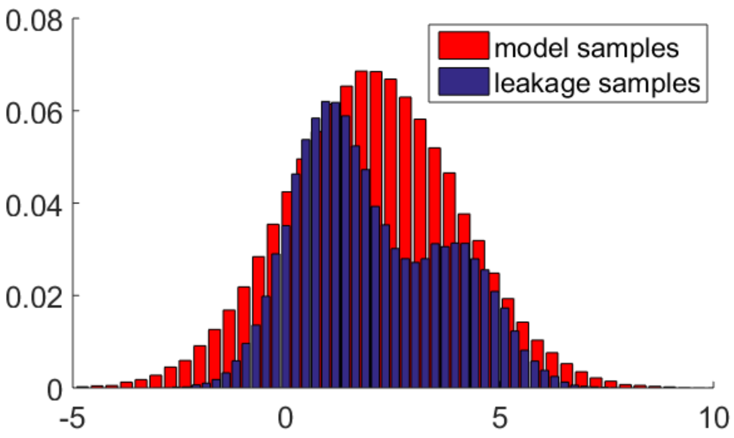


$N_1 > N_0$ samples



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Leakage certification [DSV14]

- Distinguish estimation & assumption errors
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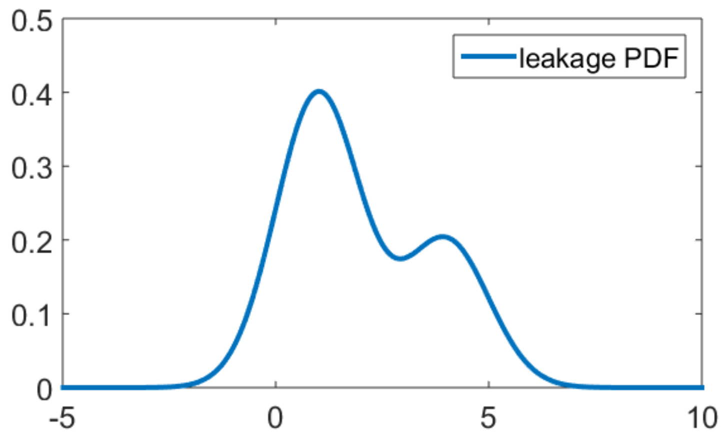
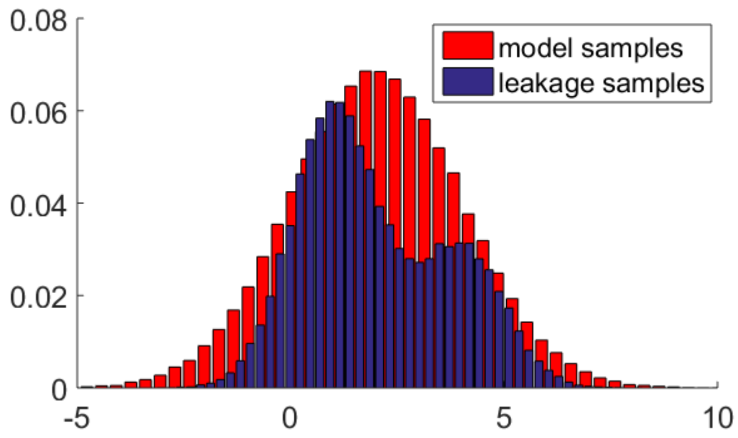
- Example:

assumption errors dominate





$\Rightarrow$ **need another model**

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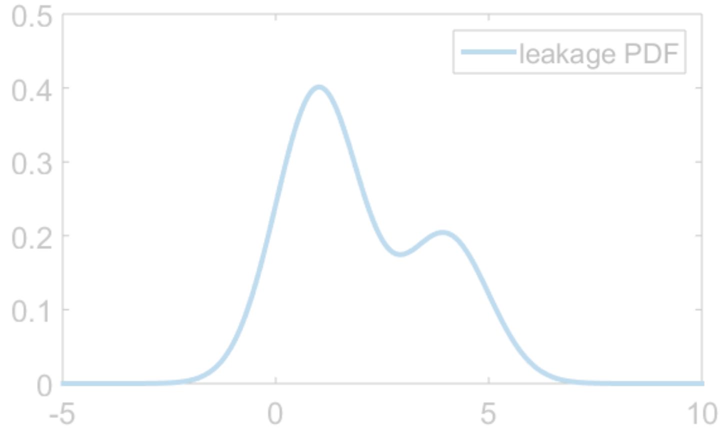

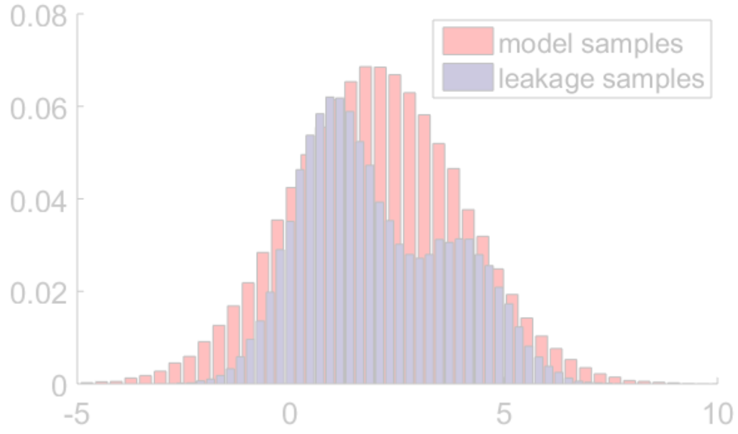

$\Rightarrow$ **need another model**

$\Rightarrow$ good enough model: *ass. err* << *est. err*. given *N*

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Leakage certification (II)

- Test the hypothesis that

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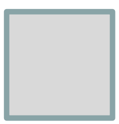
modeling samples


test samples

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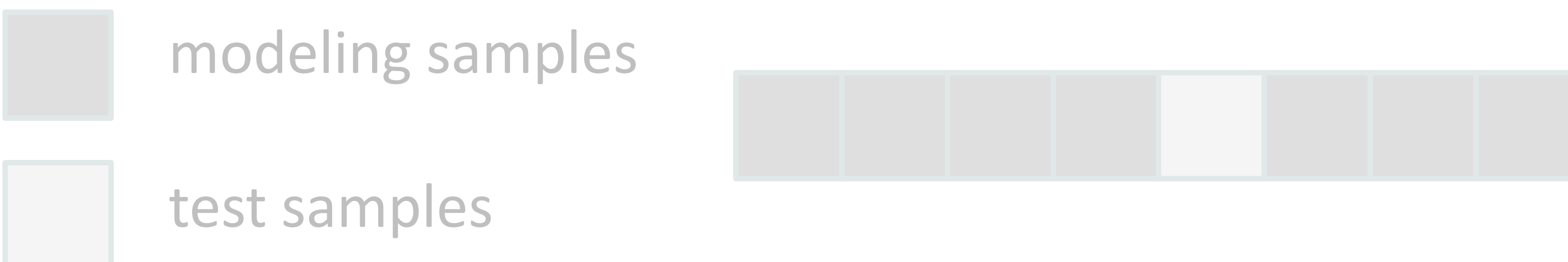

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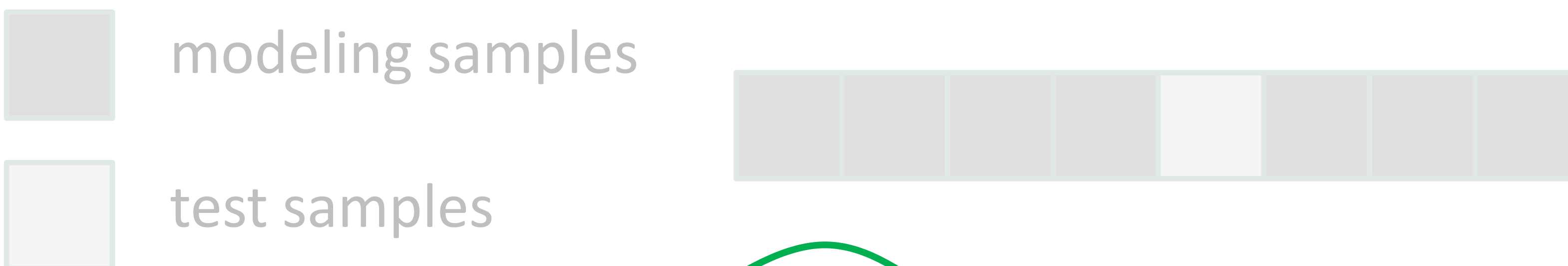

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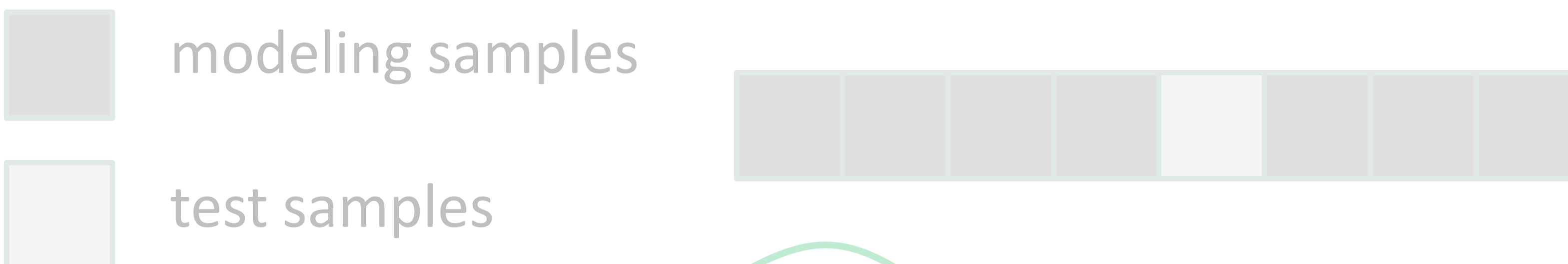

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- Main drawback: cost (of sampling distributions)

Towards easy certification

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- Compare moments (rather than distributions)

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$$\widehat{M}_d = \widetilde{M}_d$$

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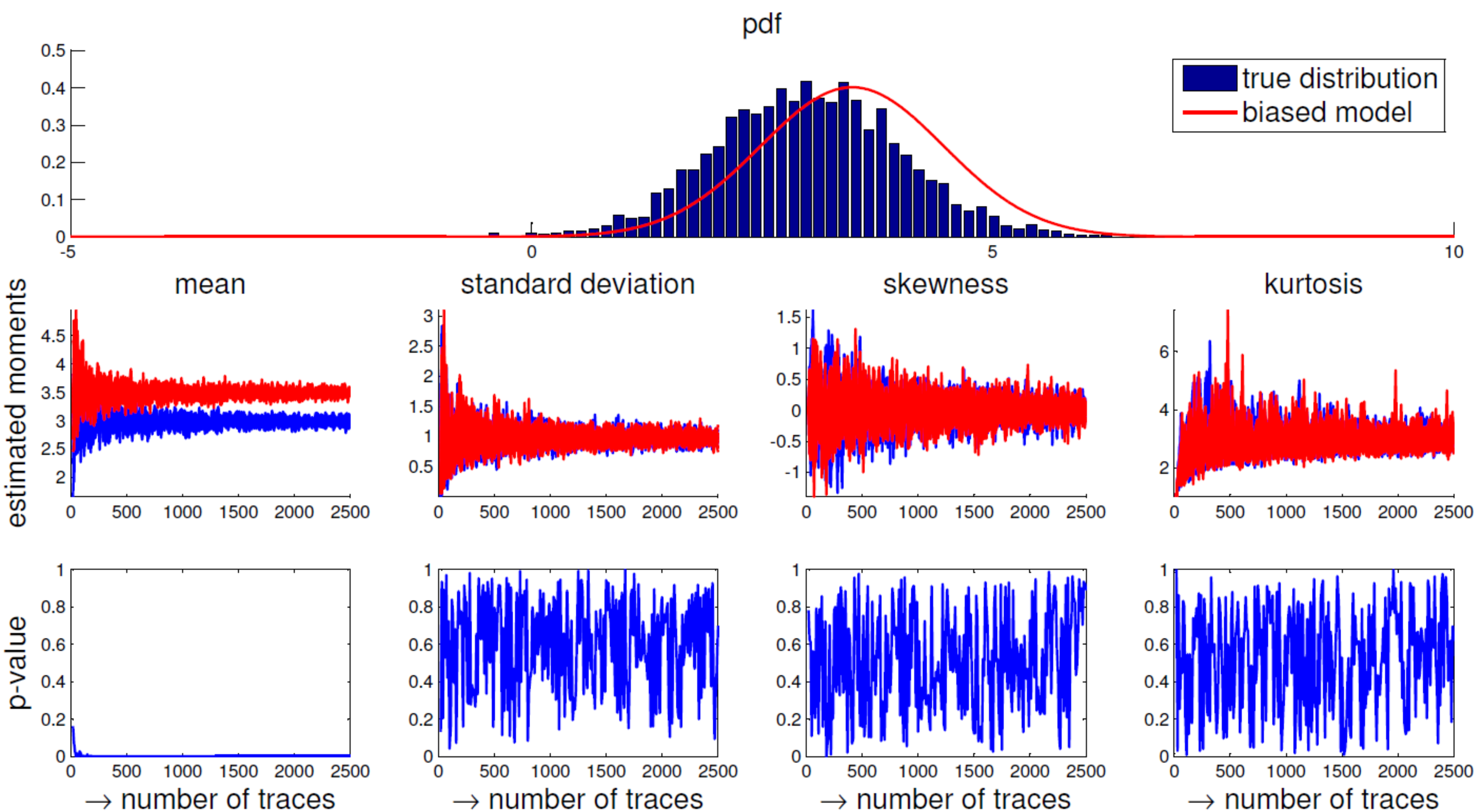
– Is it theoretically sound? No!

- But counterexamples are involved
- & SCA literature frequently does it
  - Leakage detection, HO attacks, …

Simulated examples



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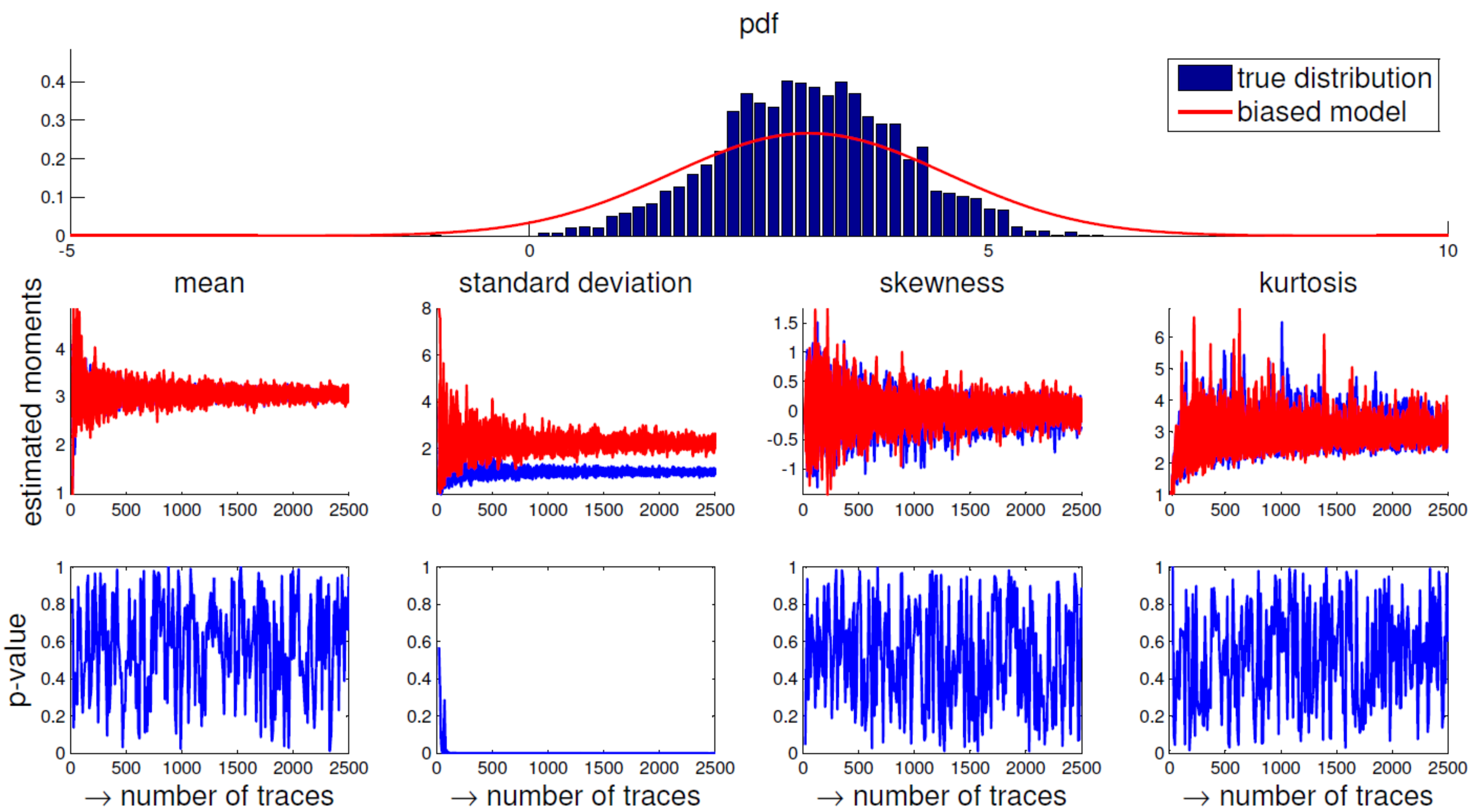

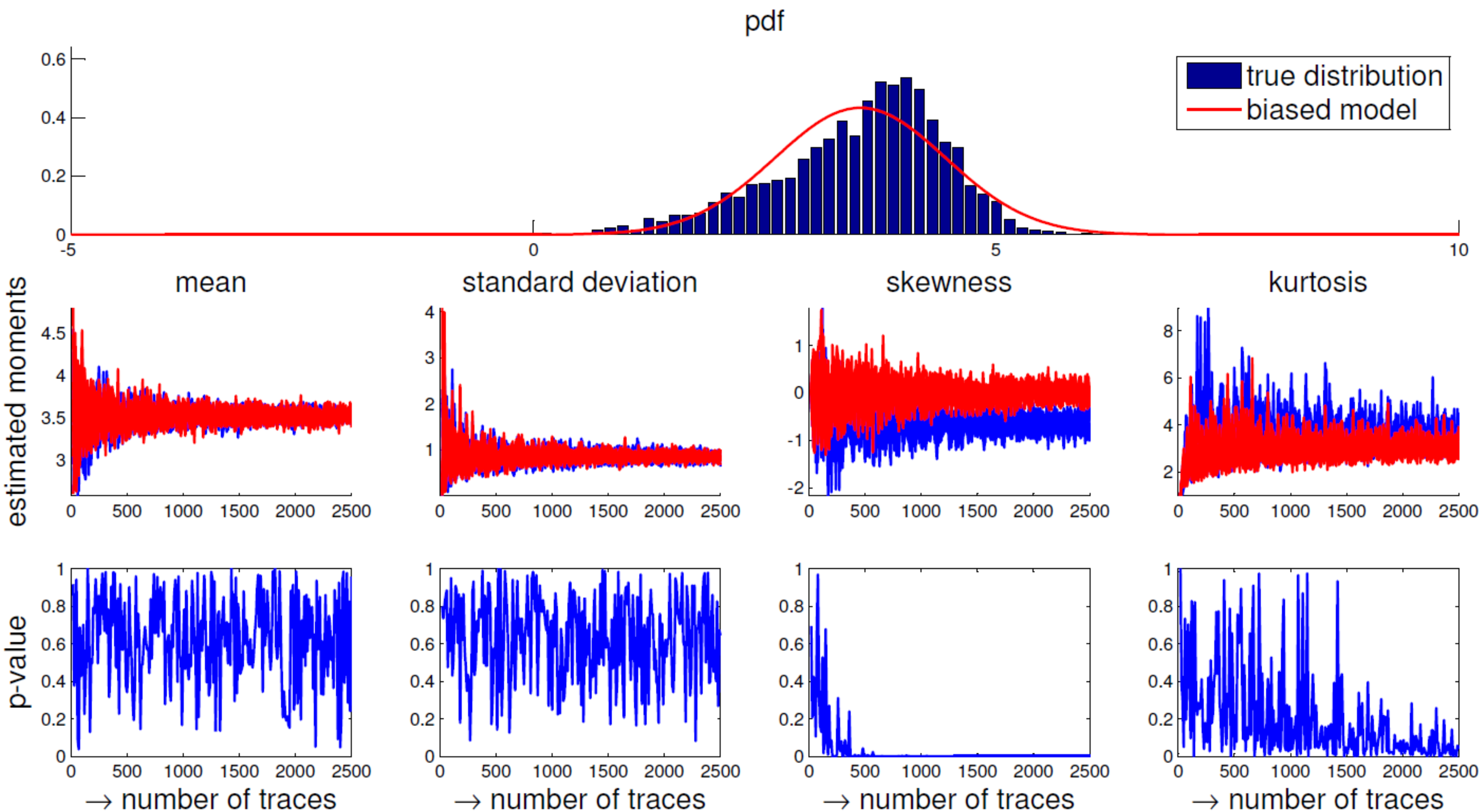
pdf
true distribution
biased model
mean
standard deviation
skewness
kurtosis
estimated moments
p-value
→ number of traces
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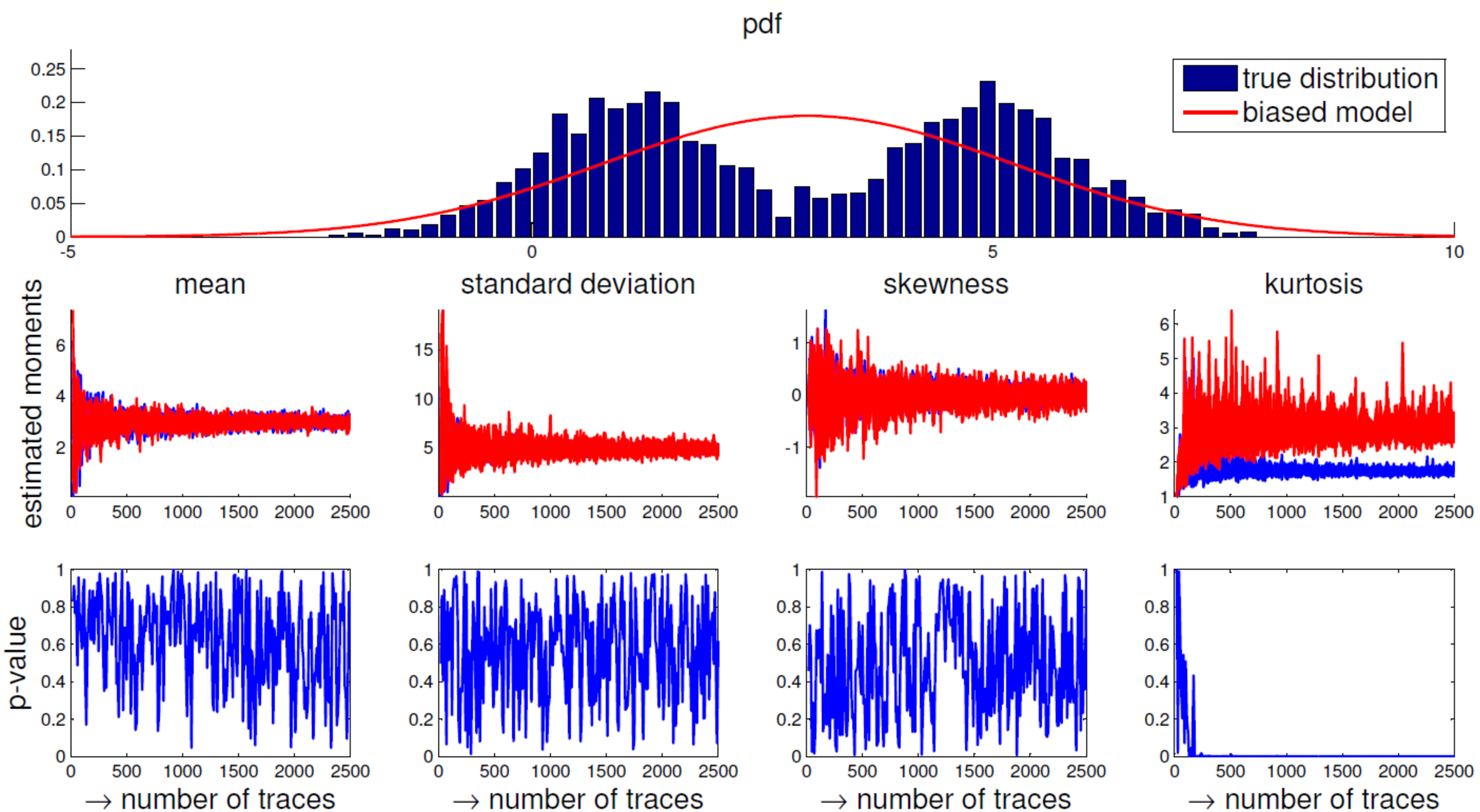

Software experiments

- Repeating the Eurocrypt 2014 case study

Software experiments

- Unprotected AES implementation, Atmel AVR

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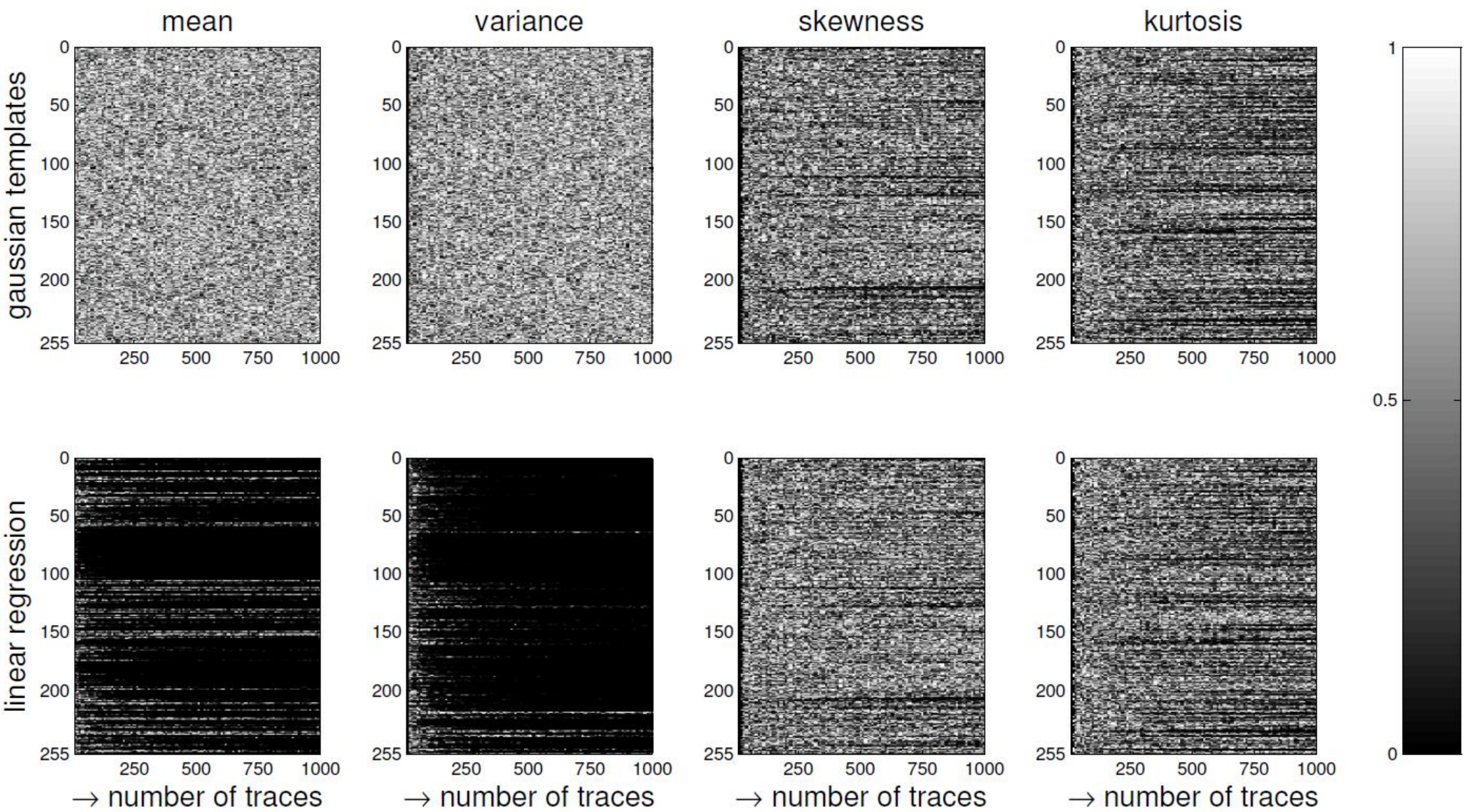

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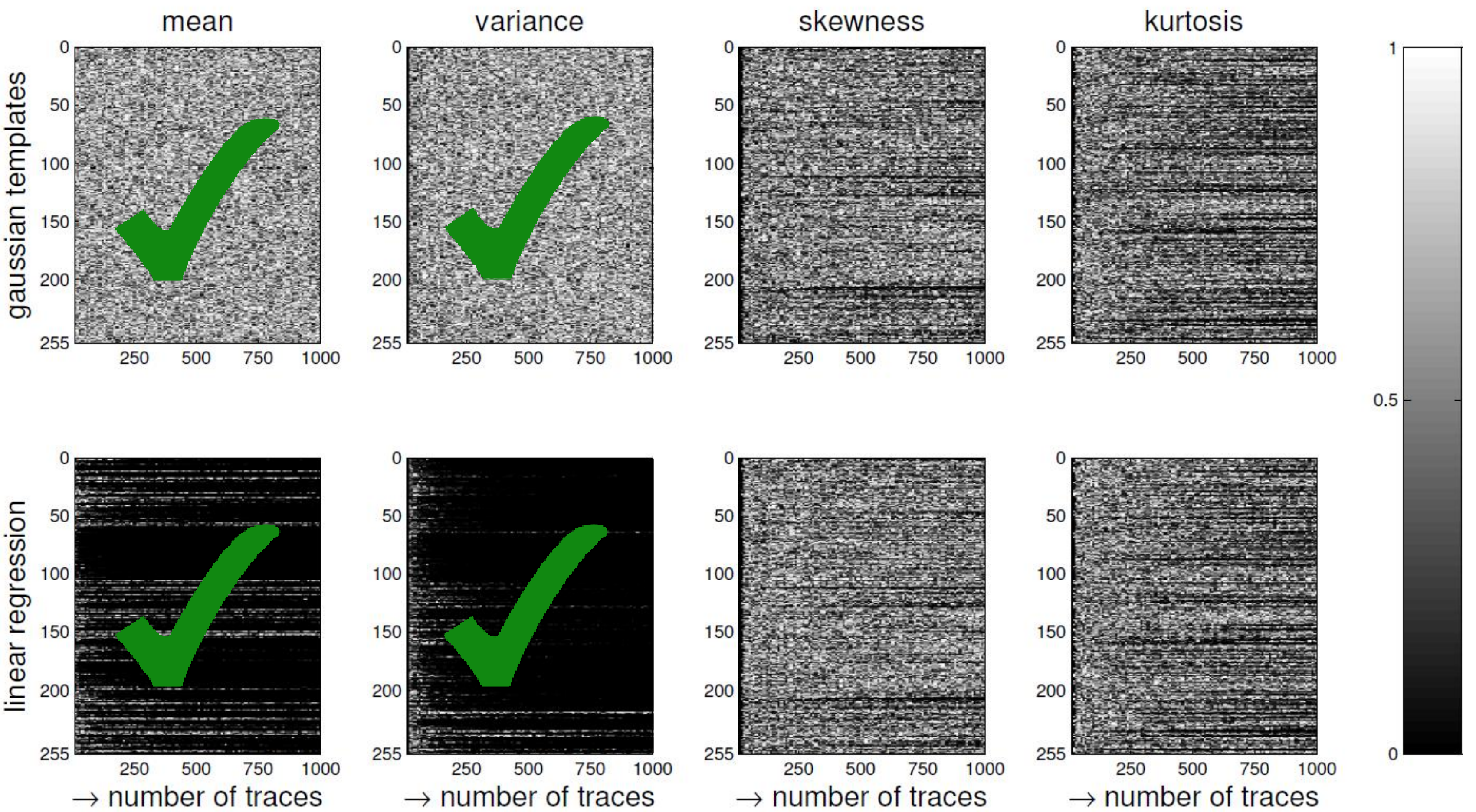

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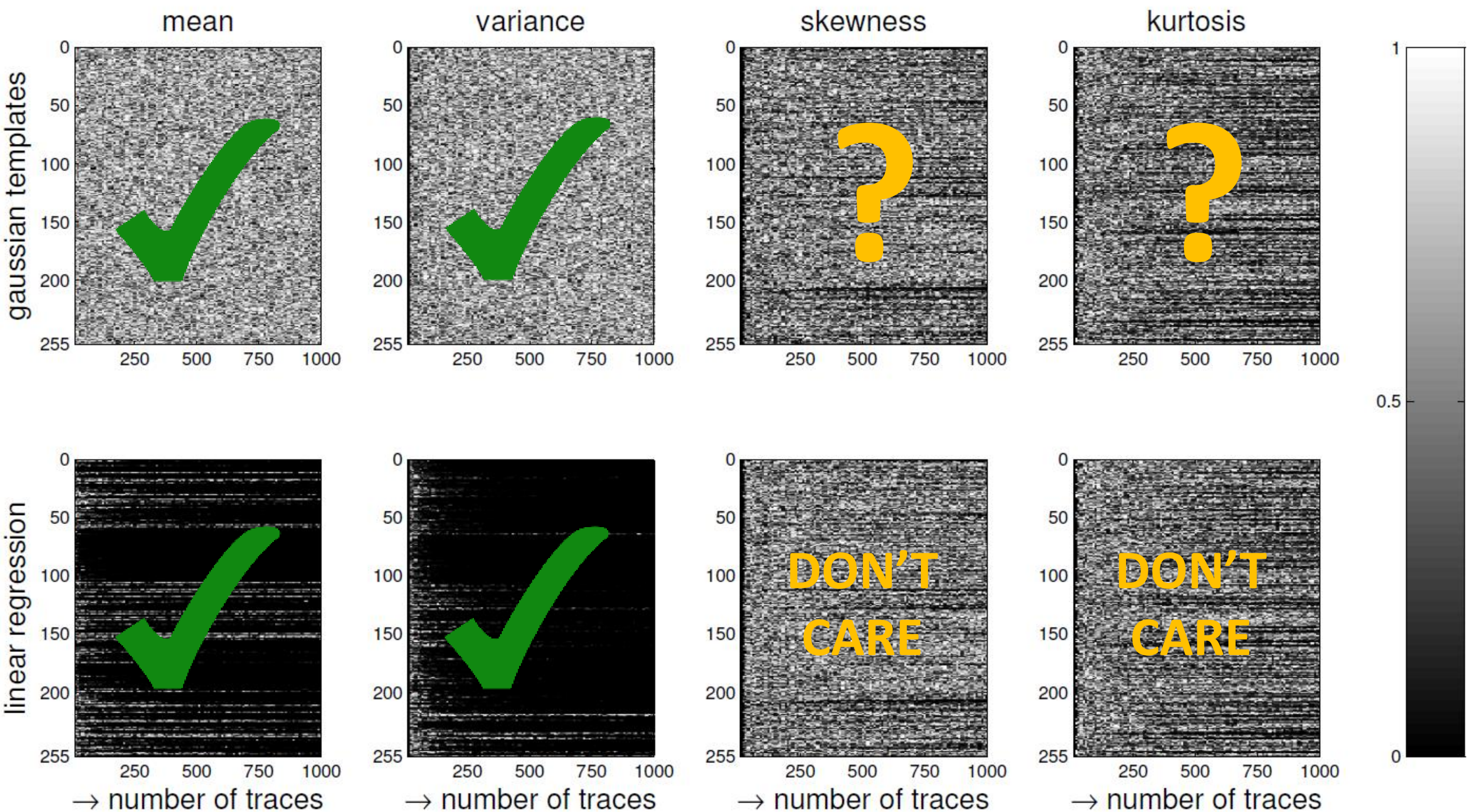

Software experiments (II)

- Eurocrypt 2014: no errors detected with up to 256x1000 measurements & Gaussian template
- CHES 2016: small errors in $\widetilde{M}_3$ and $\widetilde{M}_4$

$\Rightarrow$ *Is there an inconsistency in our results?*

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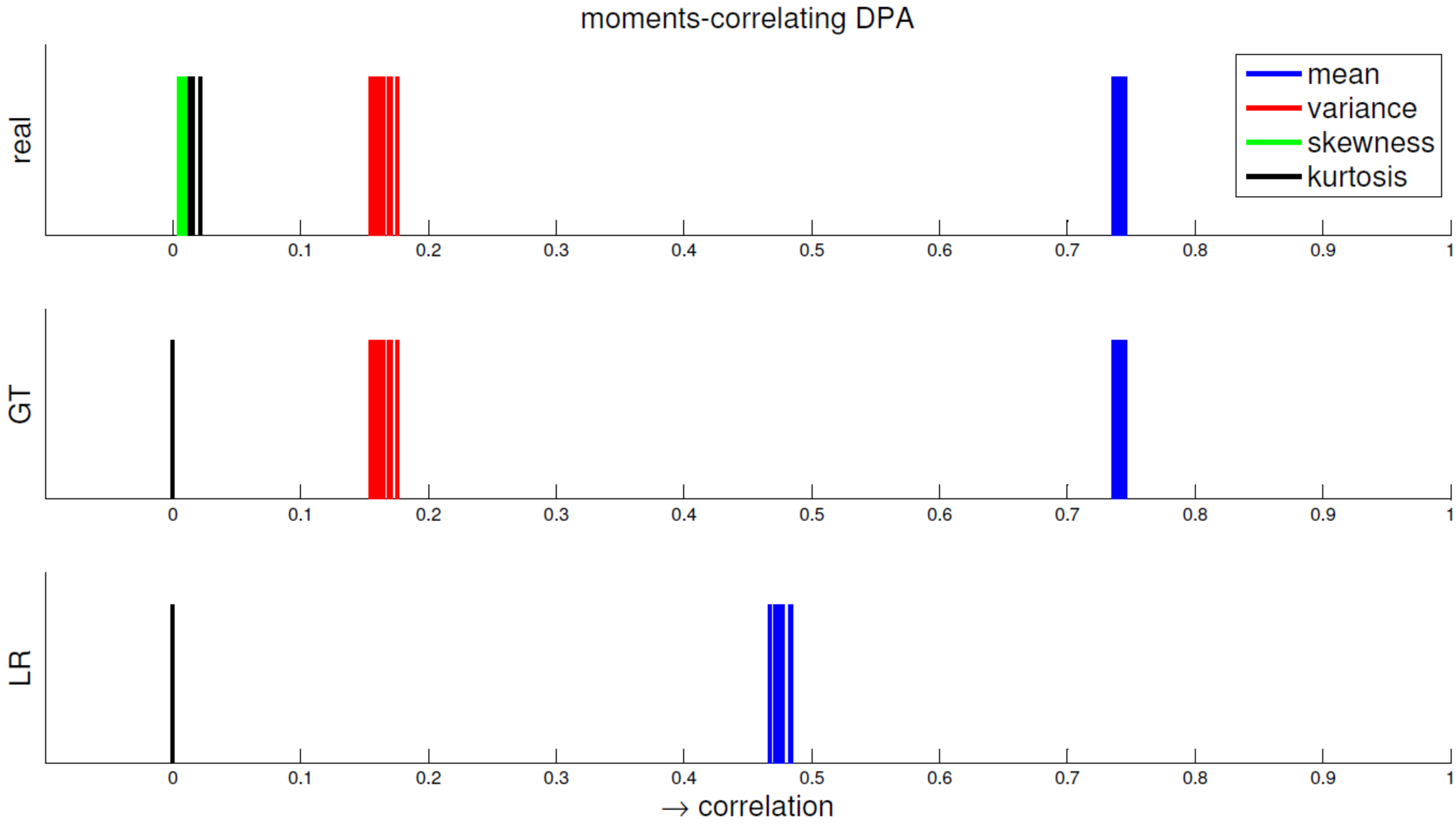
- Additional test: Moments-Correlating DPA [MS14]

$$\text{MPC-DPA}(d) = \hat{\rho}(\hat{M}_d, l^d)$$

- Metric intuition: $N_s = \frac{c}{\hat{\rho}(\hat{M}_d, l^d)^2}$

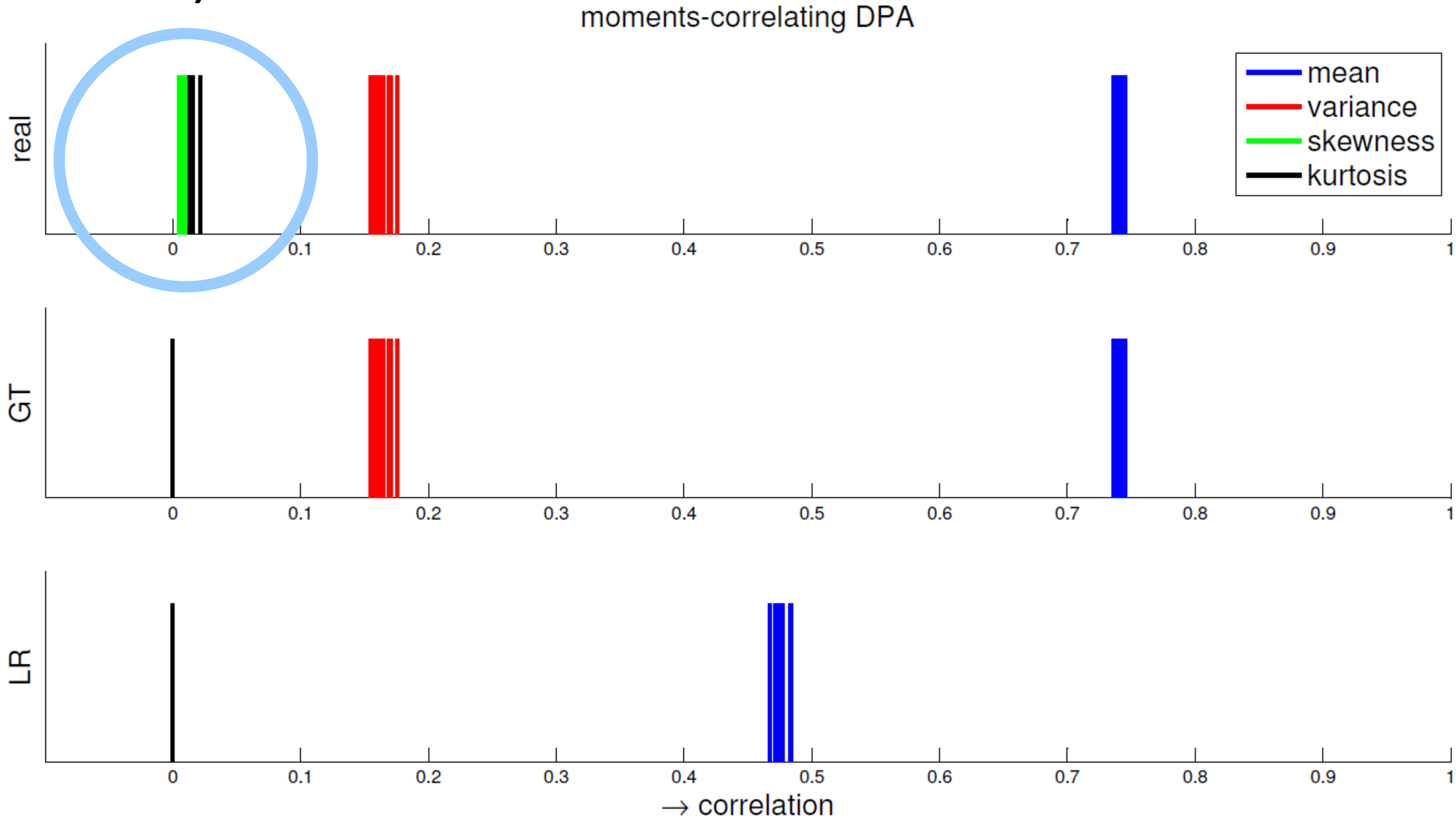
[MS14] A. Moradi, F.-X. Standaert, Moments-Correlating DPA, Theory of Implementations workshop, 2014.

Software experiments (III)



Software experiments (III)

little information in skewness/kurtosis



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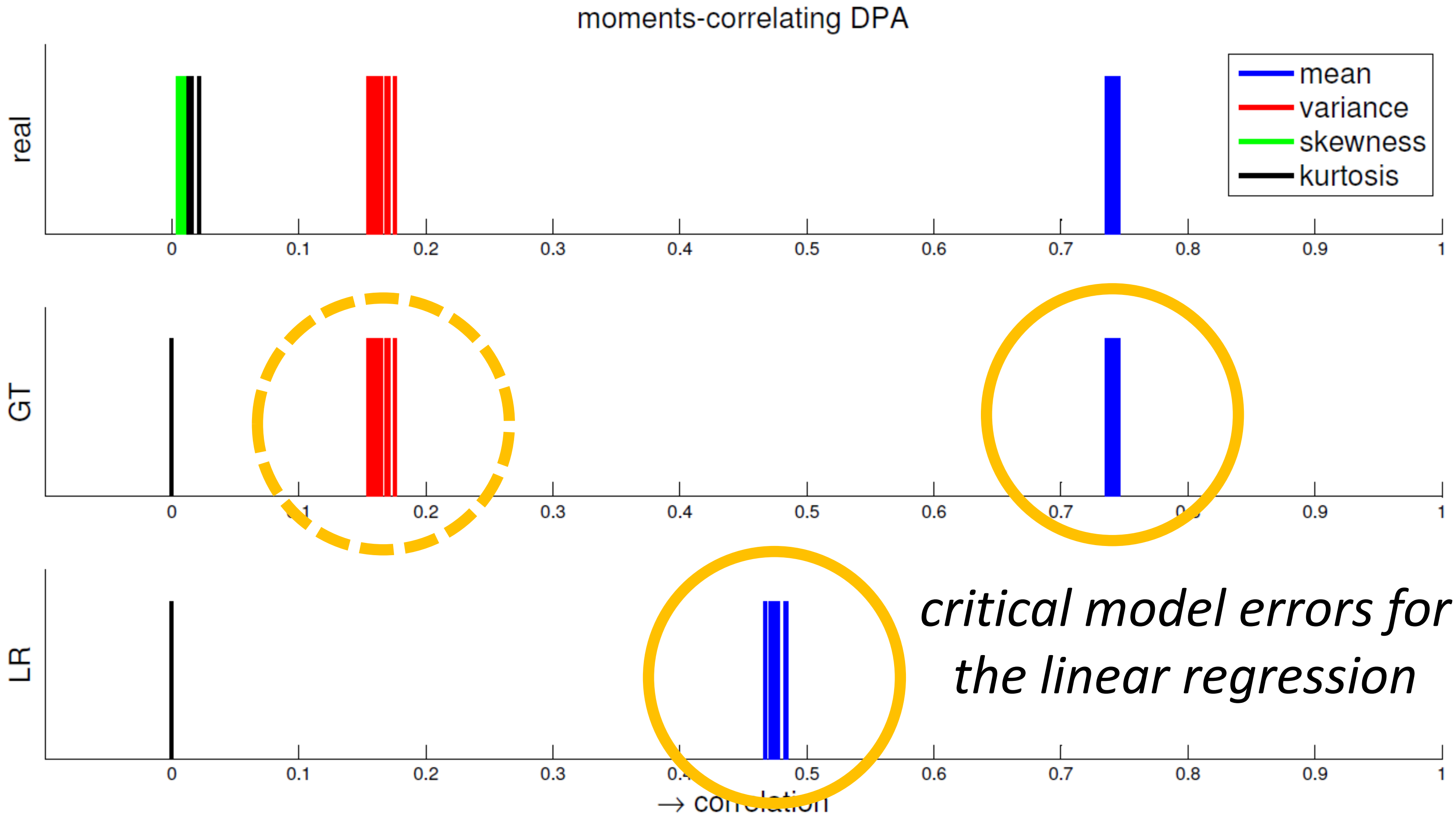
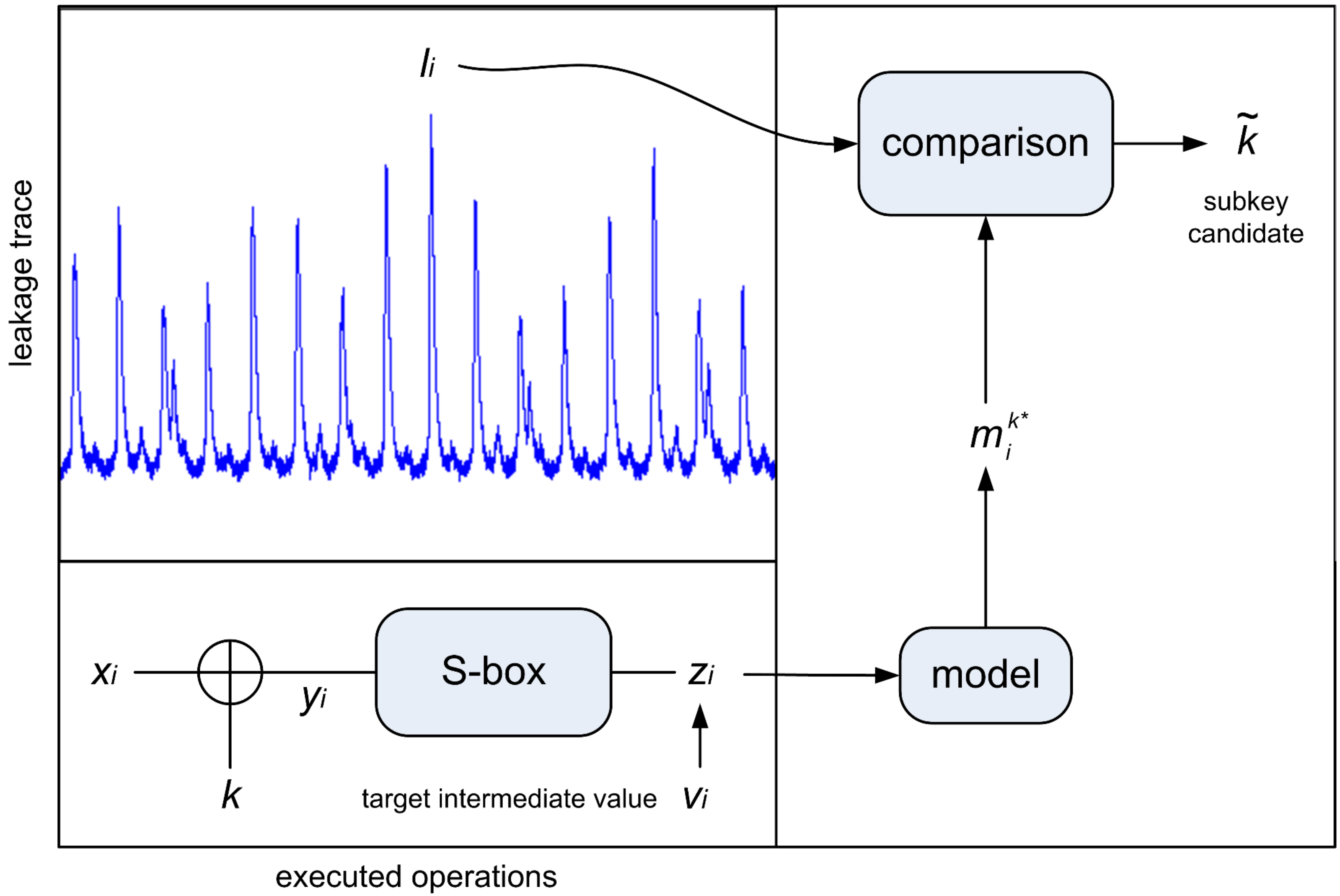


critical model errors for the linear regression

Outline

- Introduction
  - Side-channel analysis (attack steps)
  - Heuristic vs. optimal separation
- Measurement & preprocessing
  - Filtering, leakage/POI detection, dimension. reduction
- Predictions & modeling
  - Profiled vs. non-profiled separation, leakage certification
- Exploitation
  - Soft Analytical Side-Channel Attacks
- Post-processing
  - Key enumeration, rank estimation
- Future trends
  - Security without obscurity
  - IT metrics & (tight) proofs

Standard DPA



How to extract more information?

- More samples per intermediate value
  - Multivariate DPA
  - e.g., dimensionality reduction
    - Principal Component Analysis (PCA)
    - Linear Discriminant Analysis (LDA)
    - …

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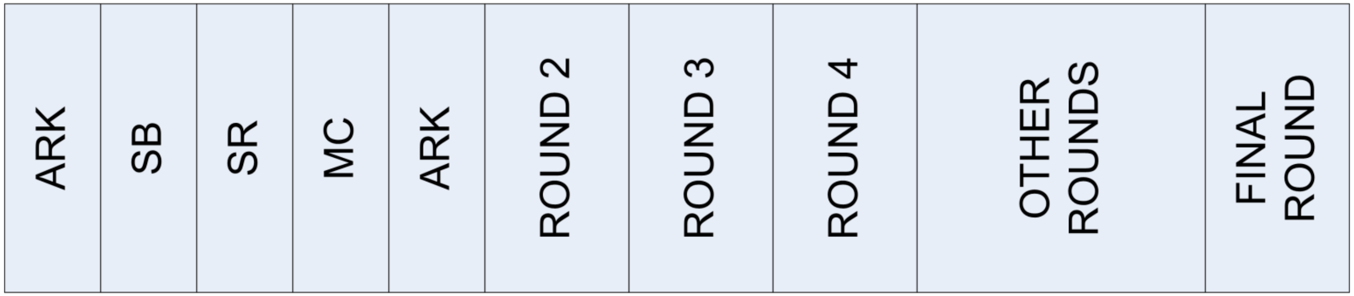

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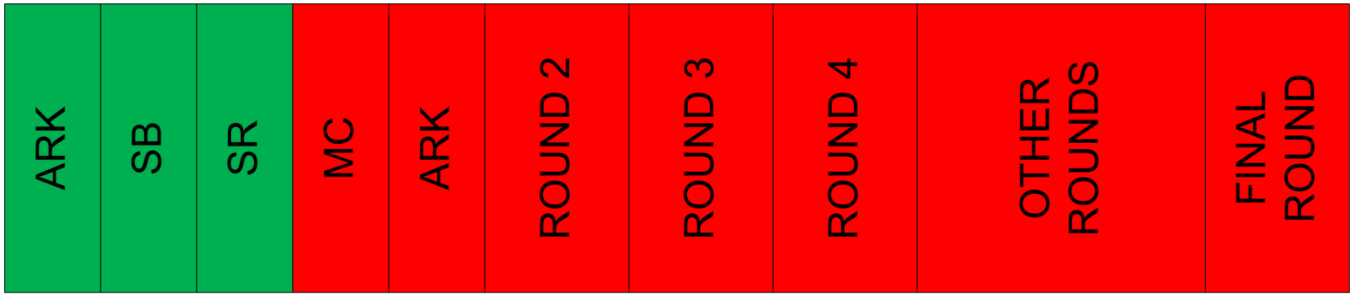

STANDARD
DPA

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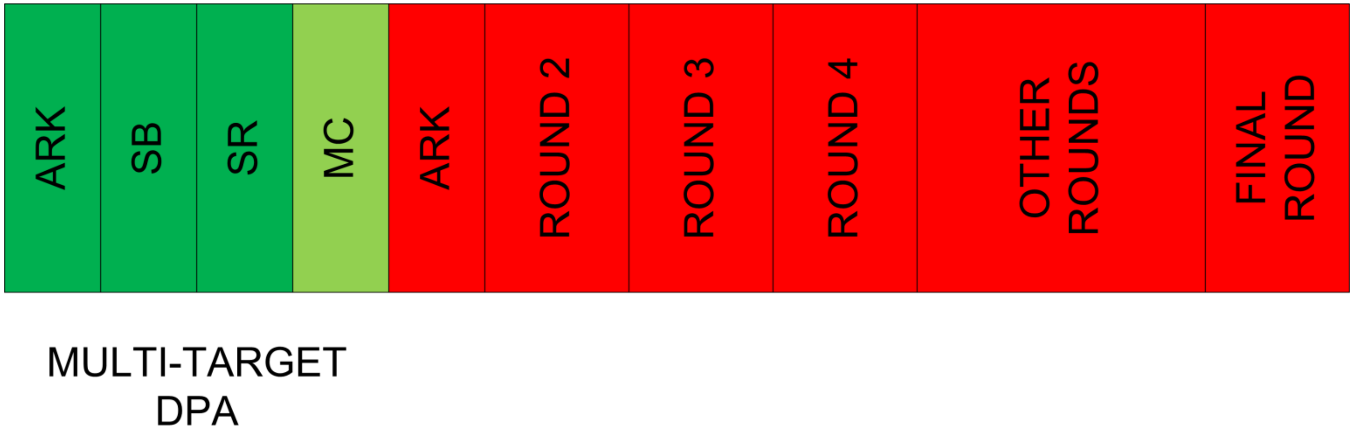

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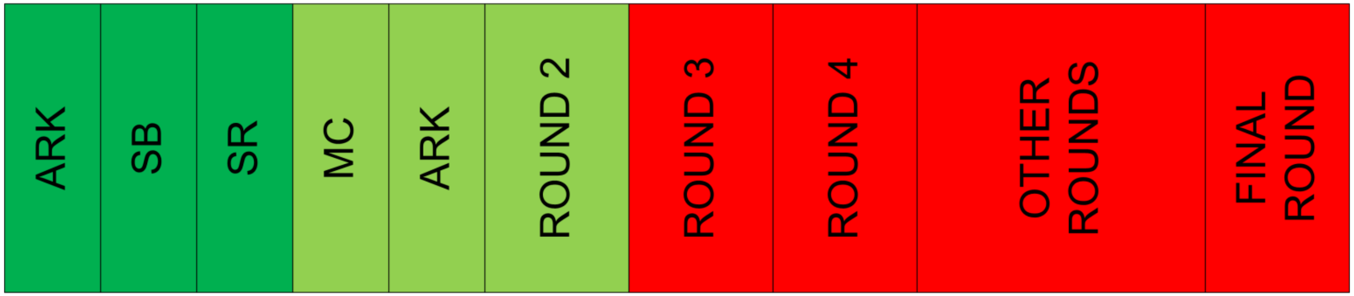

COLLISION ATTACKS

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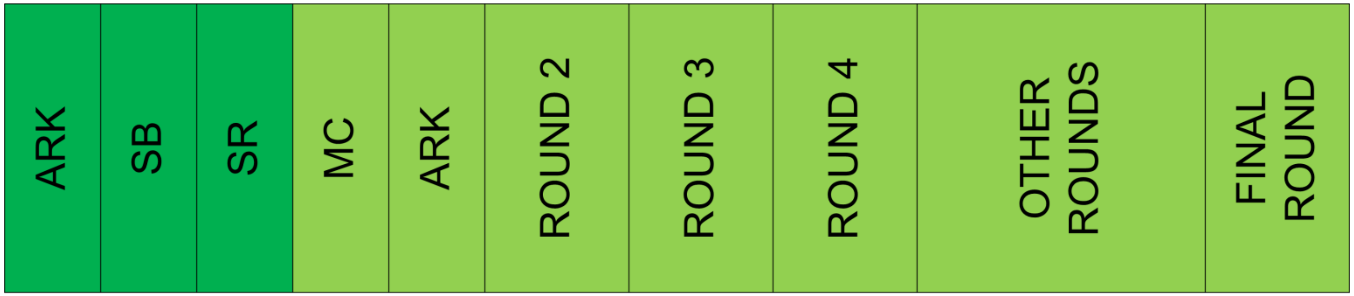

ALGEBRAIC SIDE-CHANNEL ATTACKS (ASCA)

ASCA limitations

- Cannot deal with measurement noise
  - Despite progresses, e.g., Tolerant ASCA
- Large (time and) memory complexities
  - Limited to a single plaintext, typically
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- ***Our contribution***: show this intuition is incorrect!

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- Representation of the algorithm/implementation

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    - A priori knowledge $f_i(x_i)=\Pr[x_i|L]$
      - ***Exactly the output of standard DPA!***
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- Edges carry two types of messages
  - Type *q* messages: from variables to factors
  - Type *r* messages: from factors to variables

SASCA (II): belief propagation

- Propagates the information (probabilities) through the factor graph via message passing

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$$q_{v_n \to f_m}(x_n) = \prod_{m' \in M \backslash m} r_{f_{m'} \to v_n}(x_n)$$

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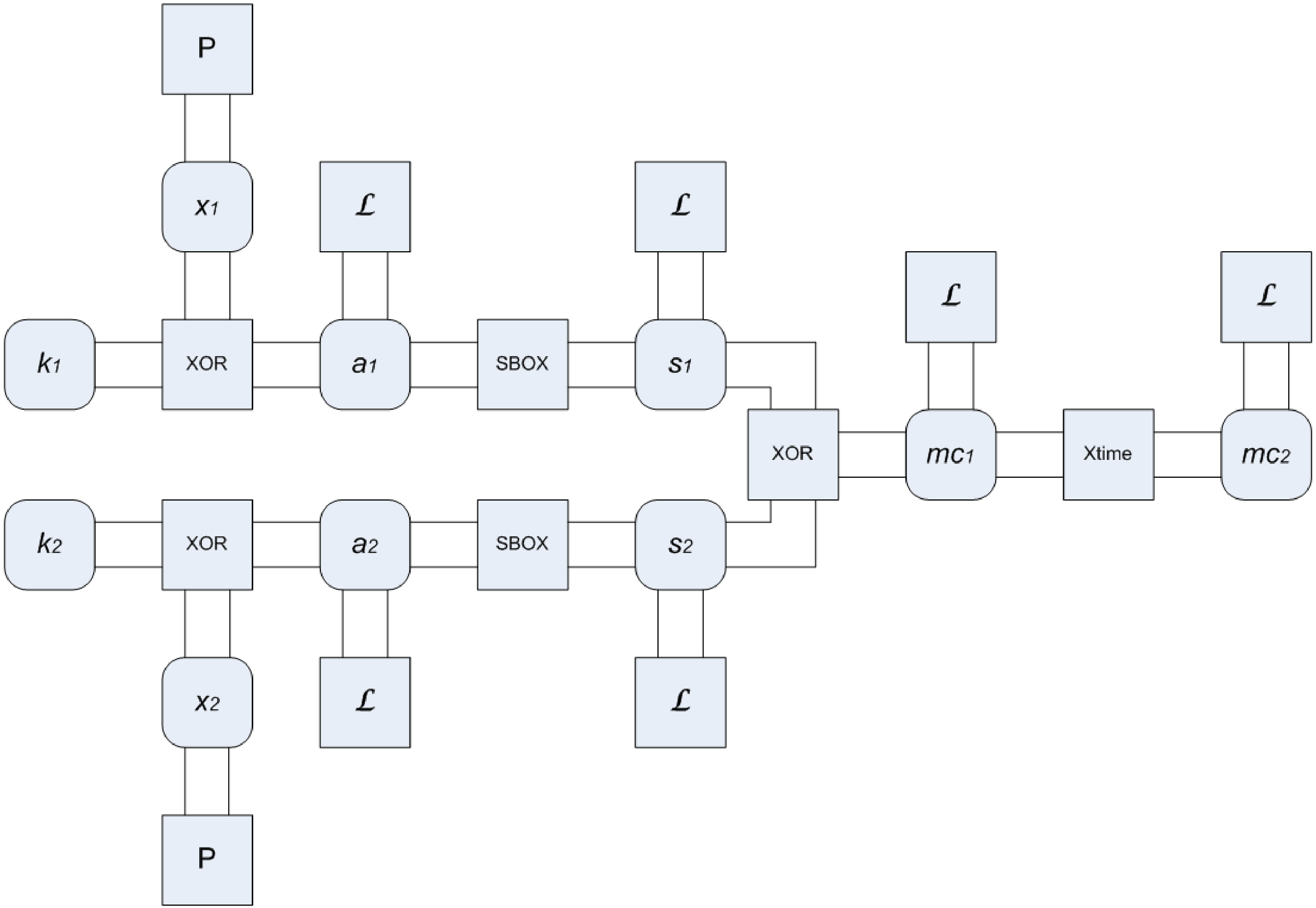
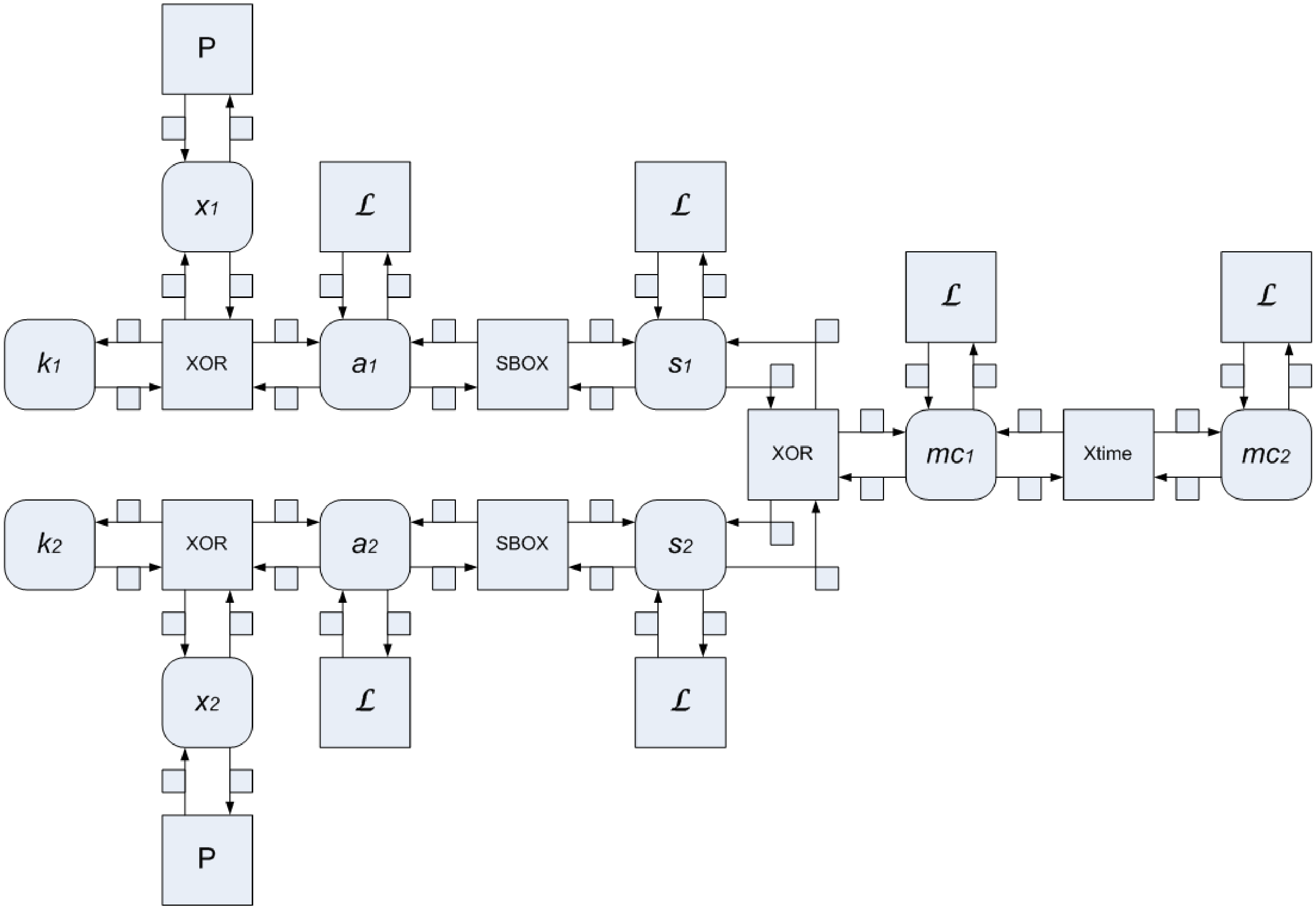
$$r_{f_m \to v_n}(x_n) = \sum_{x_m \neq x_n} f_m(x_m) \cdot \prod_{n' \in N \setminus n} q_{v_{n'} \to f_m}(x_{n'})$$

- ≈ weighted sum of products over all incoming messages excluding the target variable node

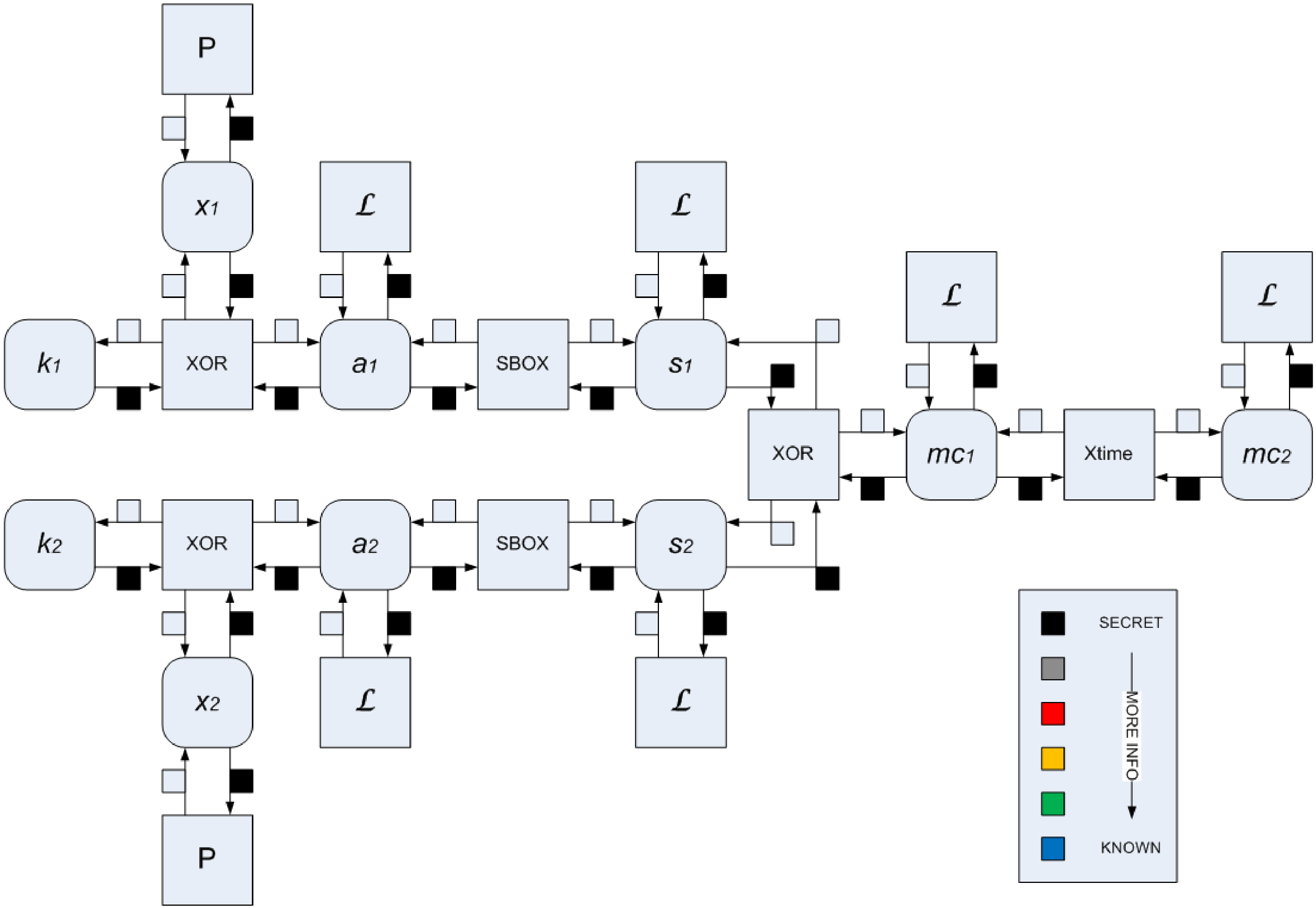
Example (I): factor graph



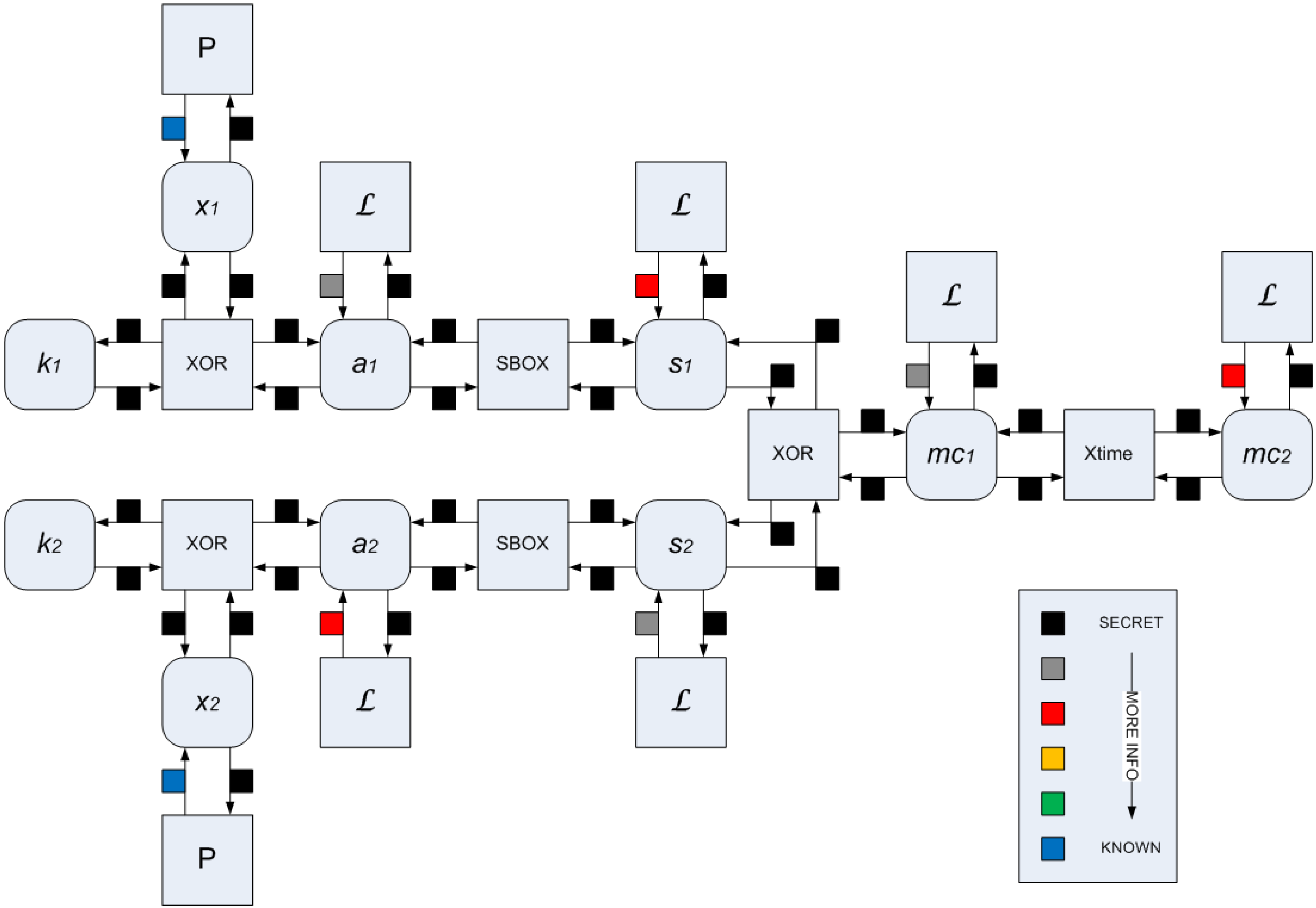
Example (II): adding the messages



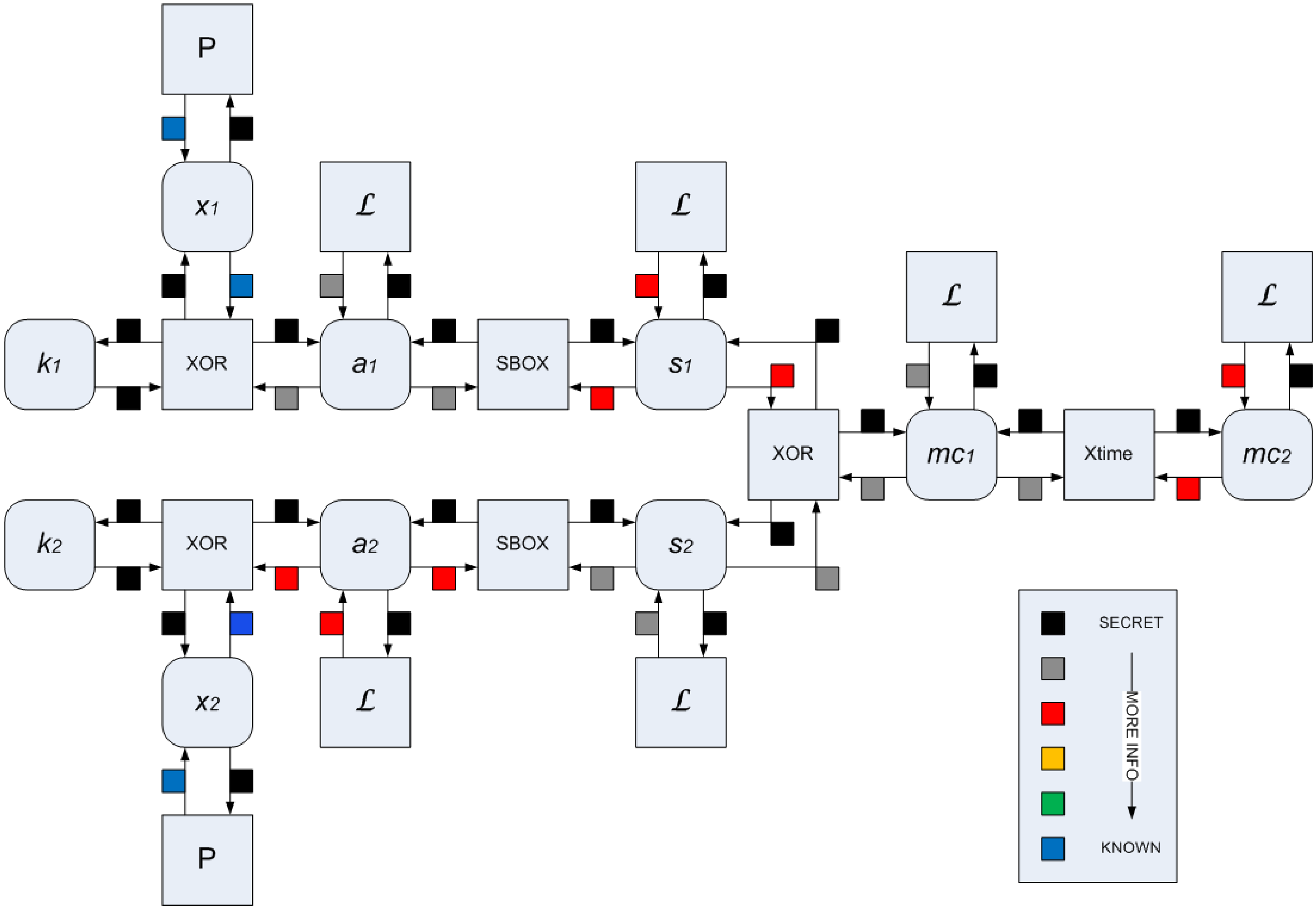
Example (III): initialize the *q*'s (v to f)



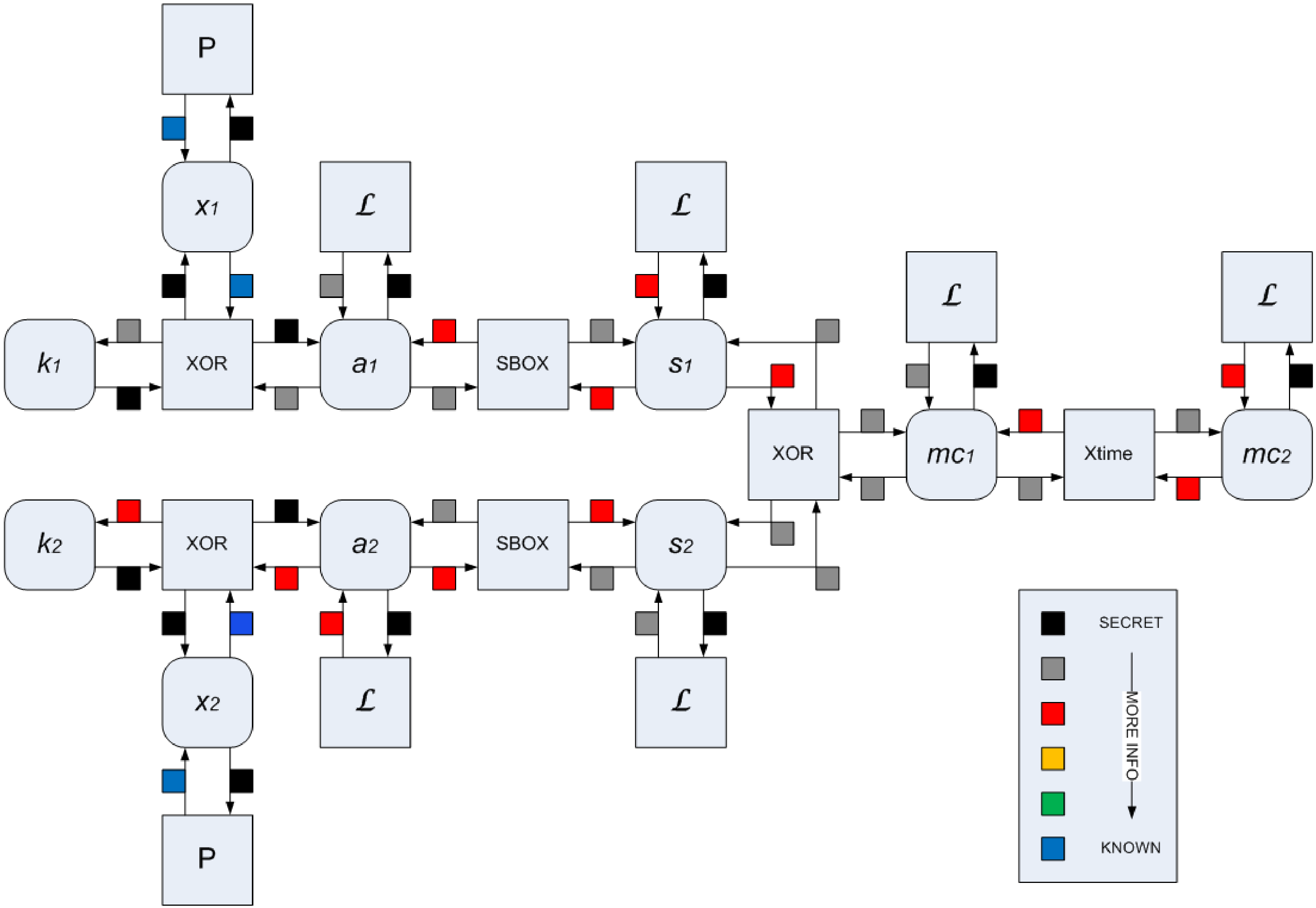
Example (IV): initialize the *r*’s (f to v)



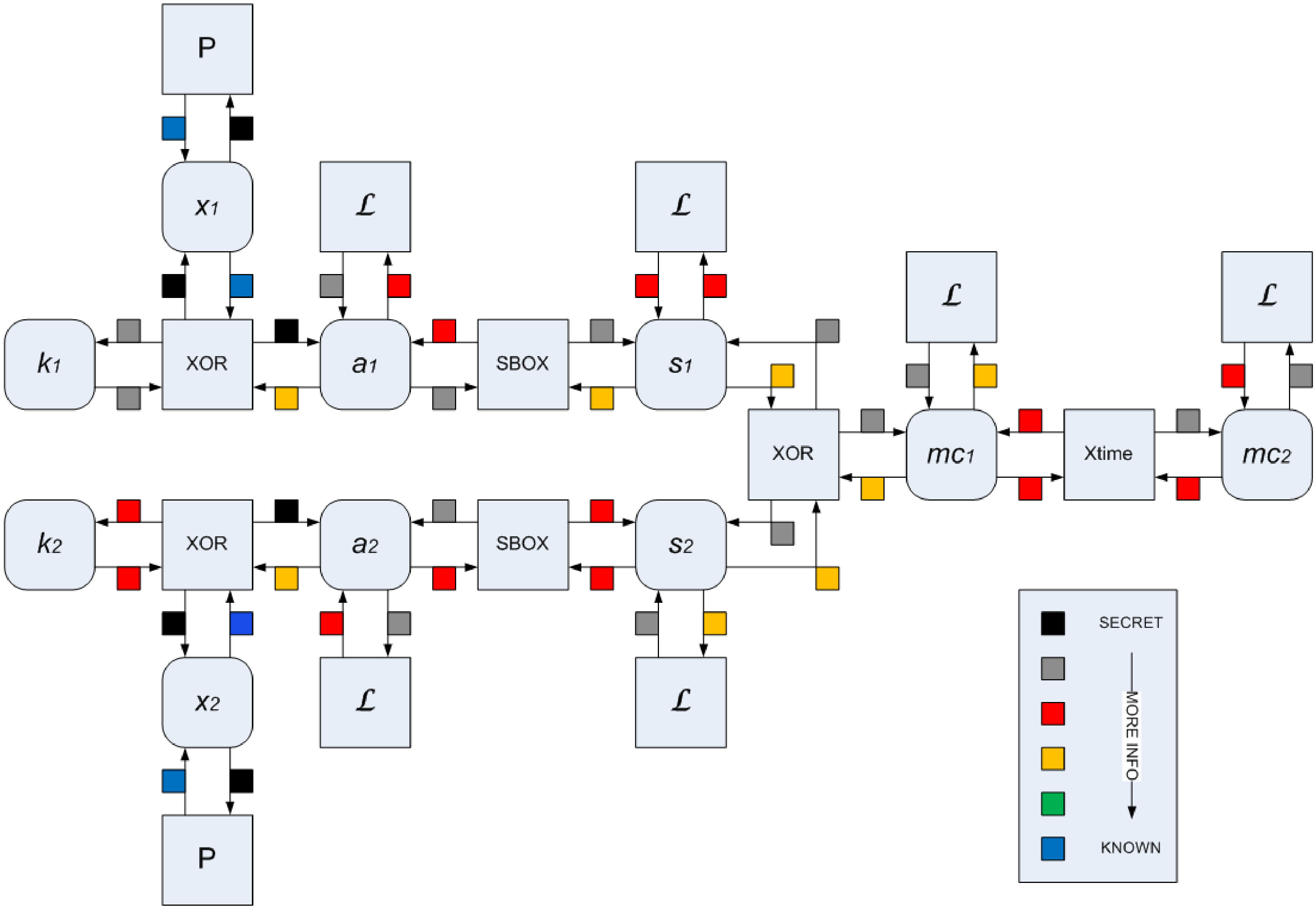
Example (V): update the *q*'s (v to f)



Example (VI): update the *r*'s (f to v)



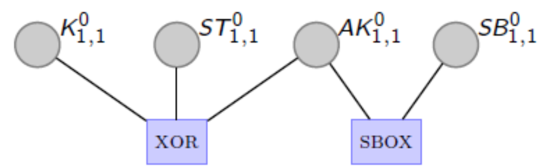
Example (VII): update the q's (v to f)

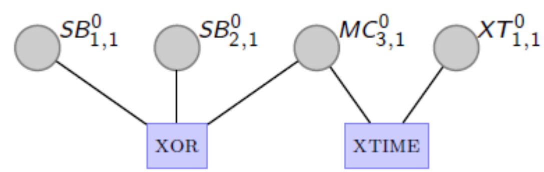


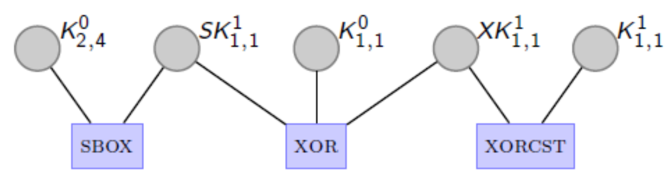
Experimental setting

- Good news: any knowledge can be exploited
- e.g. (open source) AES furious assembly code

ASM code	Graph description	Factor graph

`ld H1, Y+`
`eor ST11, H1`
`mov ZL, ST11`
`lpm ST11, Z`
	`*`
	`_Xor AK[1,1]_0 ST[1,1]_0 K[1,1]_0`
	`*`
	`_Sbox SB[1,1]_0 AK[1,1]_0`
		

`mov H3, ST11`
`eor H3, ST21`
`mov ZL, H3`
`lpm H3, Z`
	`*`
	`_Xor MC[3,1]_0 SB[1,1]_0 SB[2,1]_0`
	`*`
	`_Xtime XT[1,1]_0 MC[3,1]_0`
		

`mov ZL, ST24`
`lpm H3, Z`
`eor ST11, H3`
`eor ST11, H1`
	`*`
	`_Sbox SK[1,1]_1 K[2,4]_0`
	`_Xor XK[1,1]_1 SK[1,1]_1 K[1,1]_0`
	`_XorCst K[1,1]_1 XK[1,1]_1 0x1`
		

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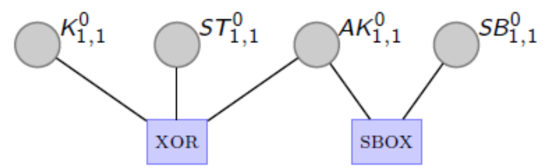
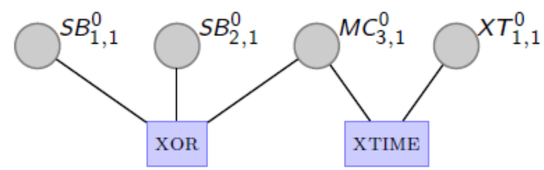
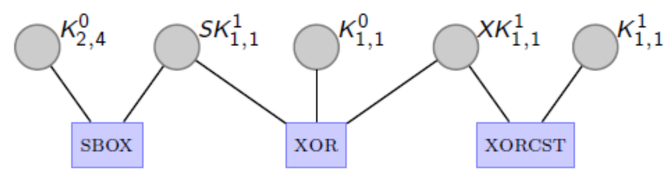
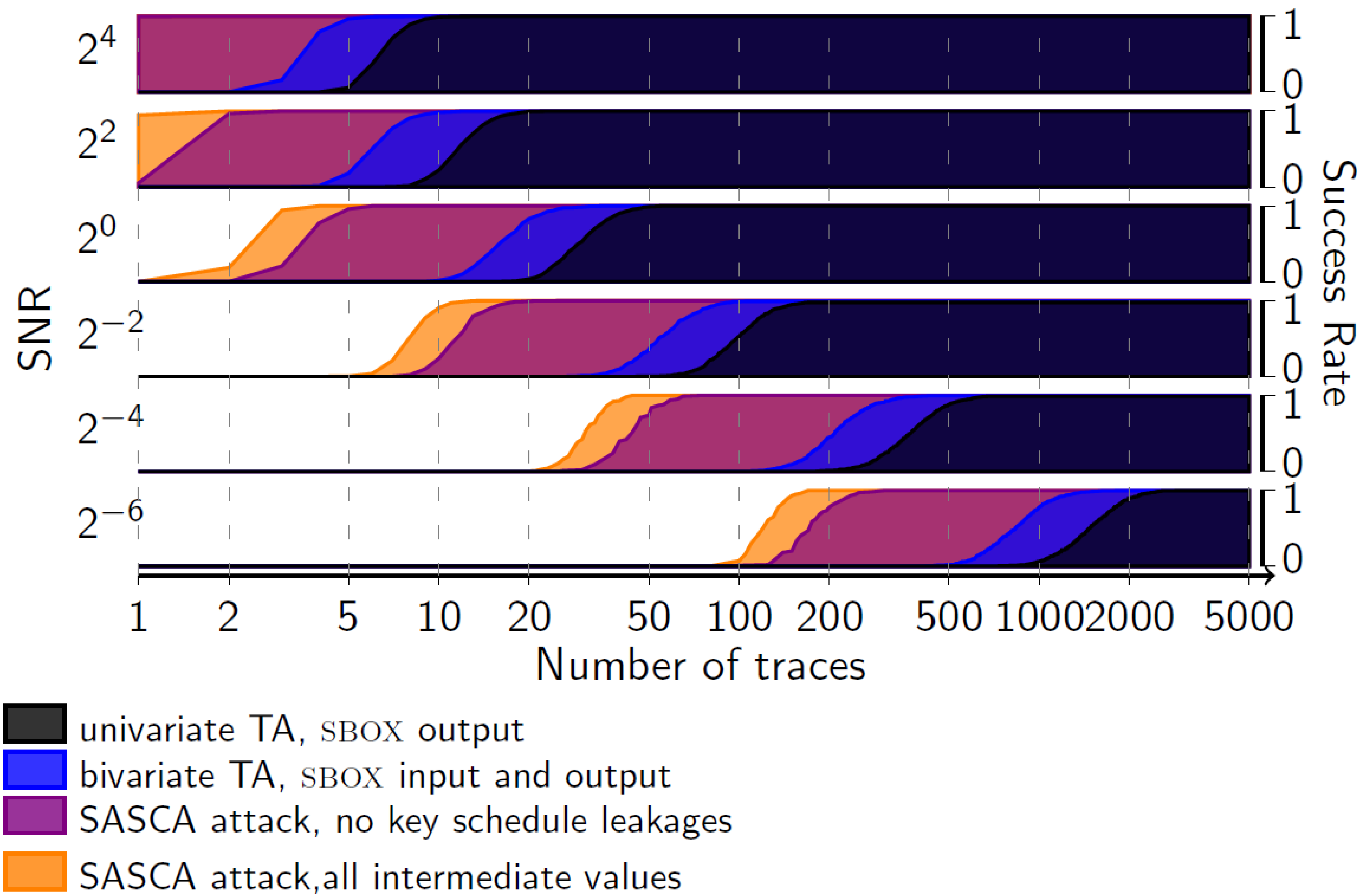
		

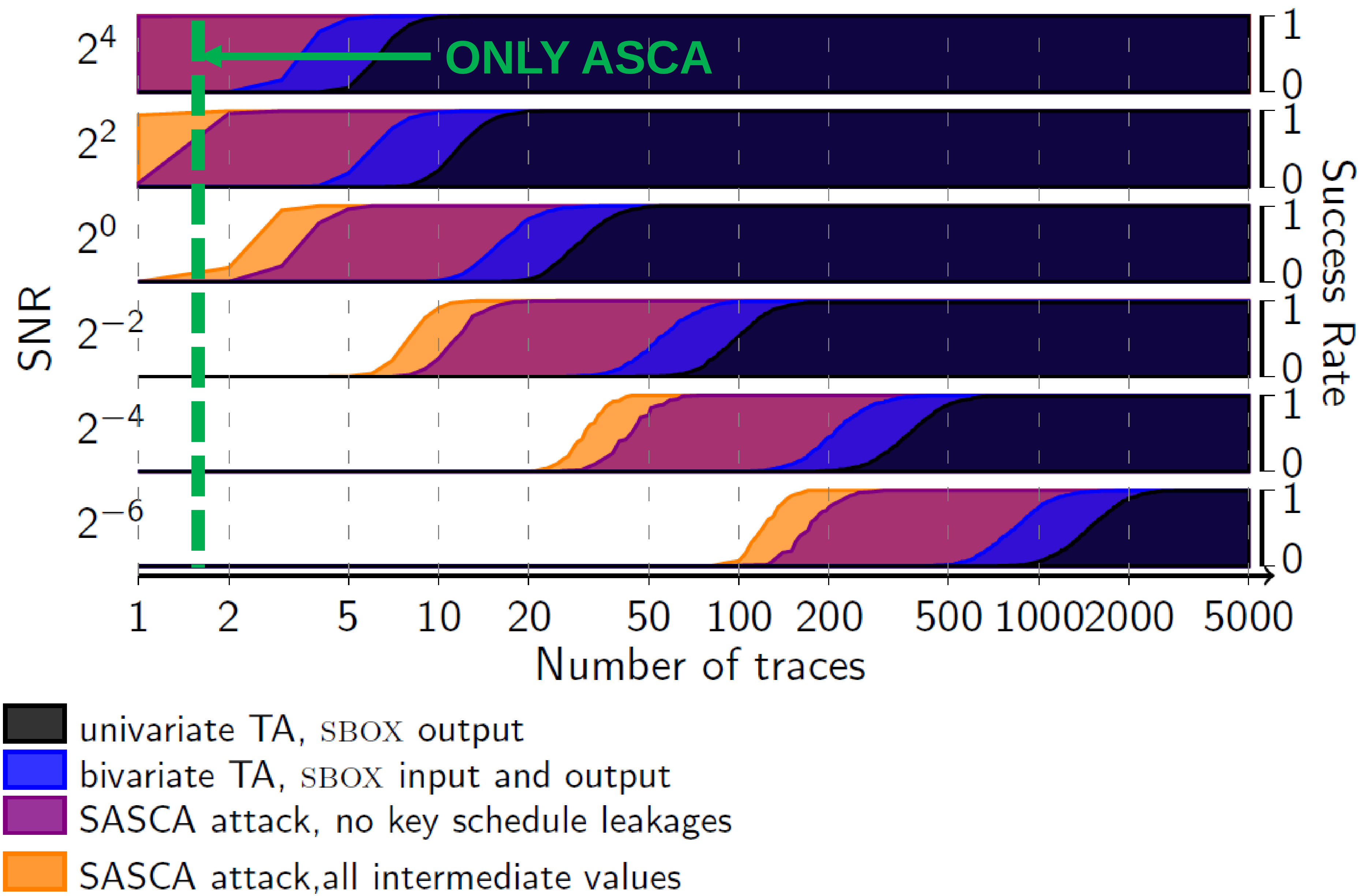
`mov H3, ST11`
`eor H3, ST21`
`mov ZL, H3`
`lpm H3, Z`
	`*`
	`_Xor MC[3,1]_0 SB[1,1]_0 SB[2,1]_0`
	`*`
	`_Xtime XT[1,1]_0 MC[3,1]_0`
		

`mov ZL, ST24`
`lpm H3, Z`
`eor ST11, H3`
`eor ST11, H1`
	`*`
	`_Sbox SK[1,1]_1 K[2,4]_0`
	`_Xor XK[1,1]_1 SK[1,1]_1 K[1,1]_0`
	`_XorCst K[1,1]_1 XK[1,1]_1 0x1`
		

- Simulated HW leakages with variable noise

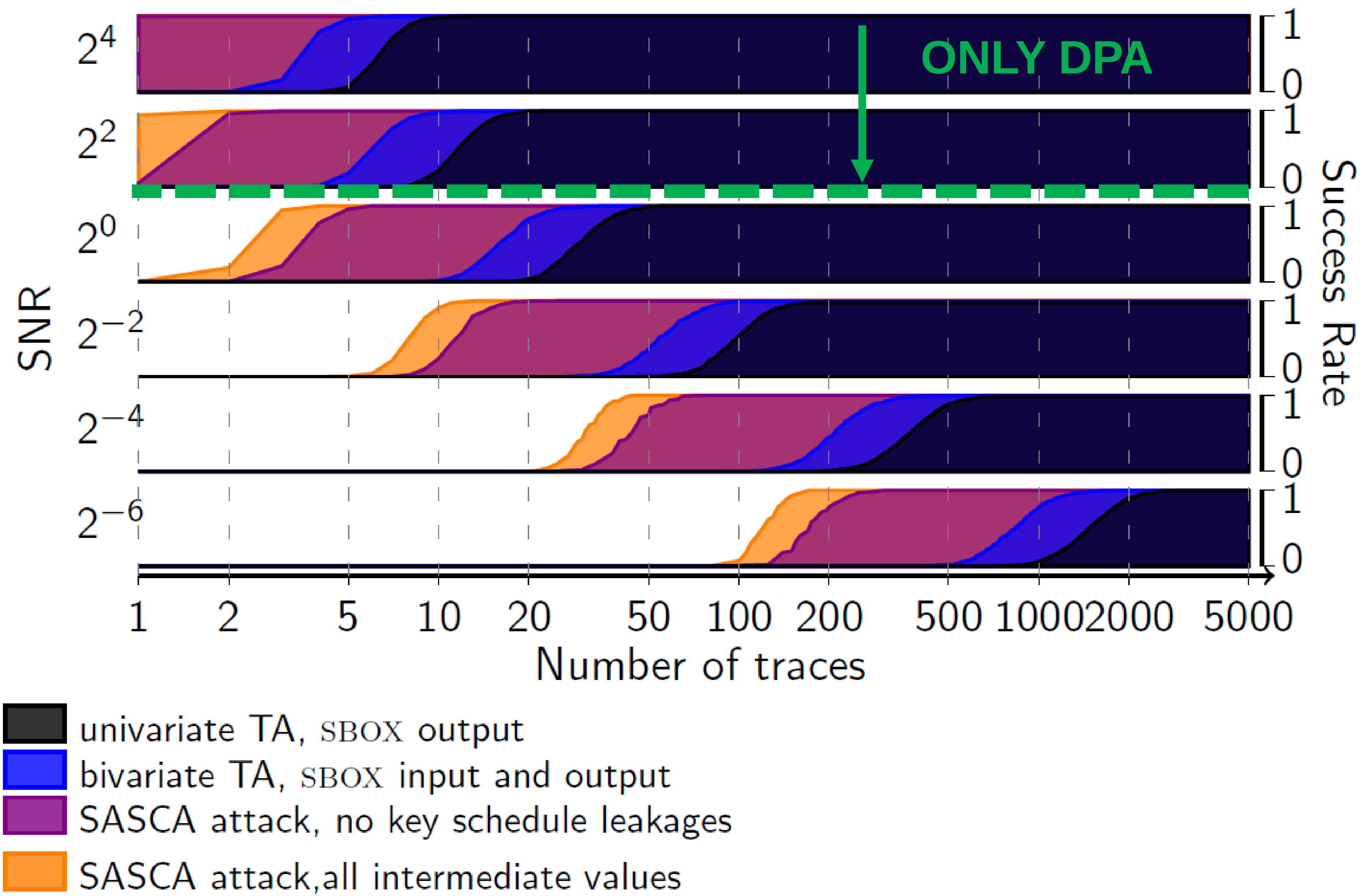
Experimental results





ONLY ASCA
SNR
2^4
2^2
2^0
2^{-2}
2^{-4}
2^{-6}
Success Rate
1
0
1 2 5 10 20 50 100 200 500 1000 2000 5000
Number of traces
univariate TA, SBOX output
bivariate TA, SBOX input and output
SASCA attack, no key schedule leakages
SASCA attack,all intermediate values

Experimental results



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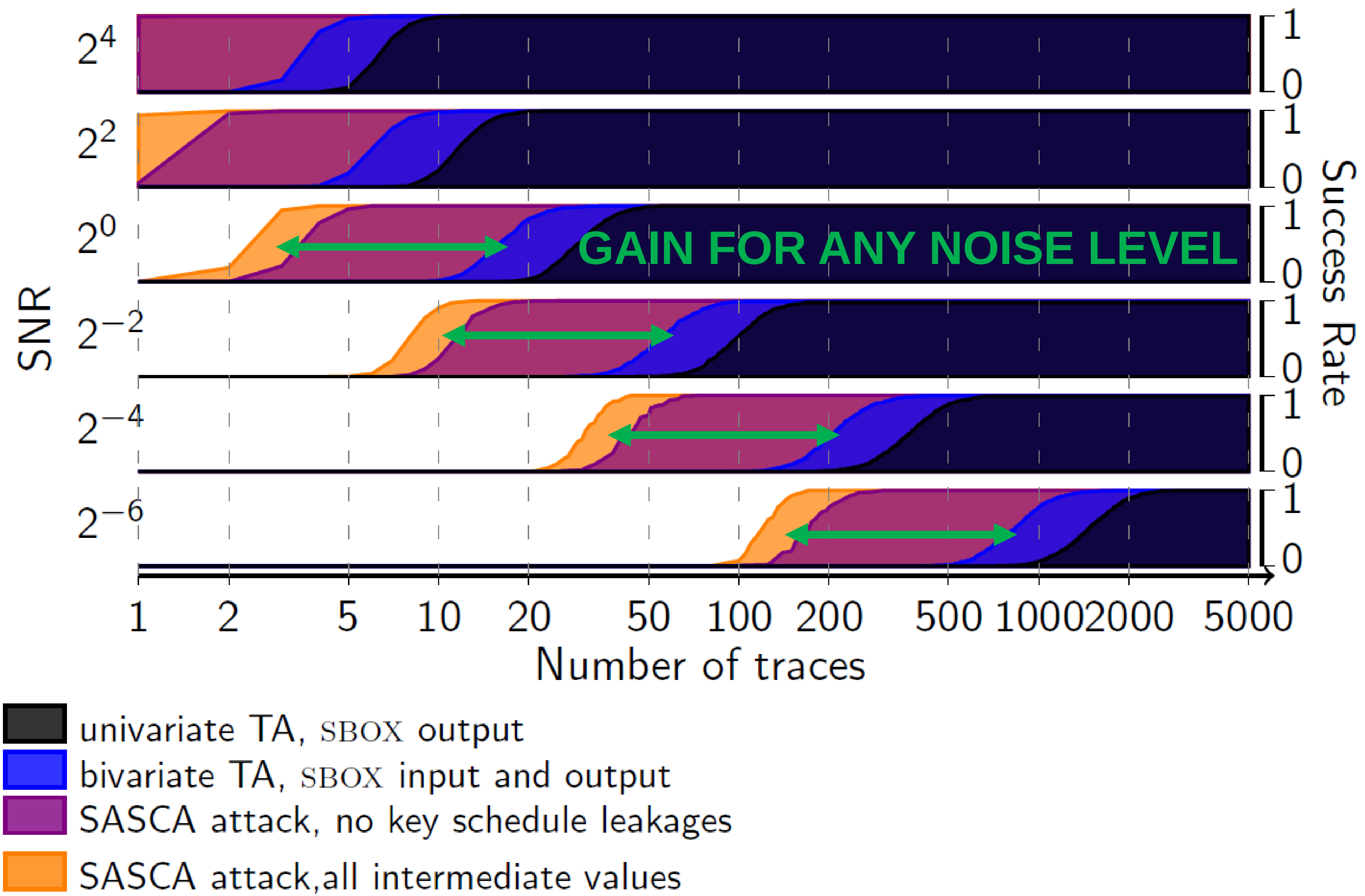

More results

- Also works in practice (Asiacrypt 2015)

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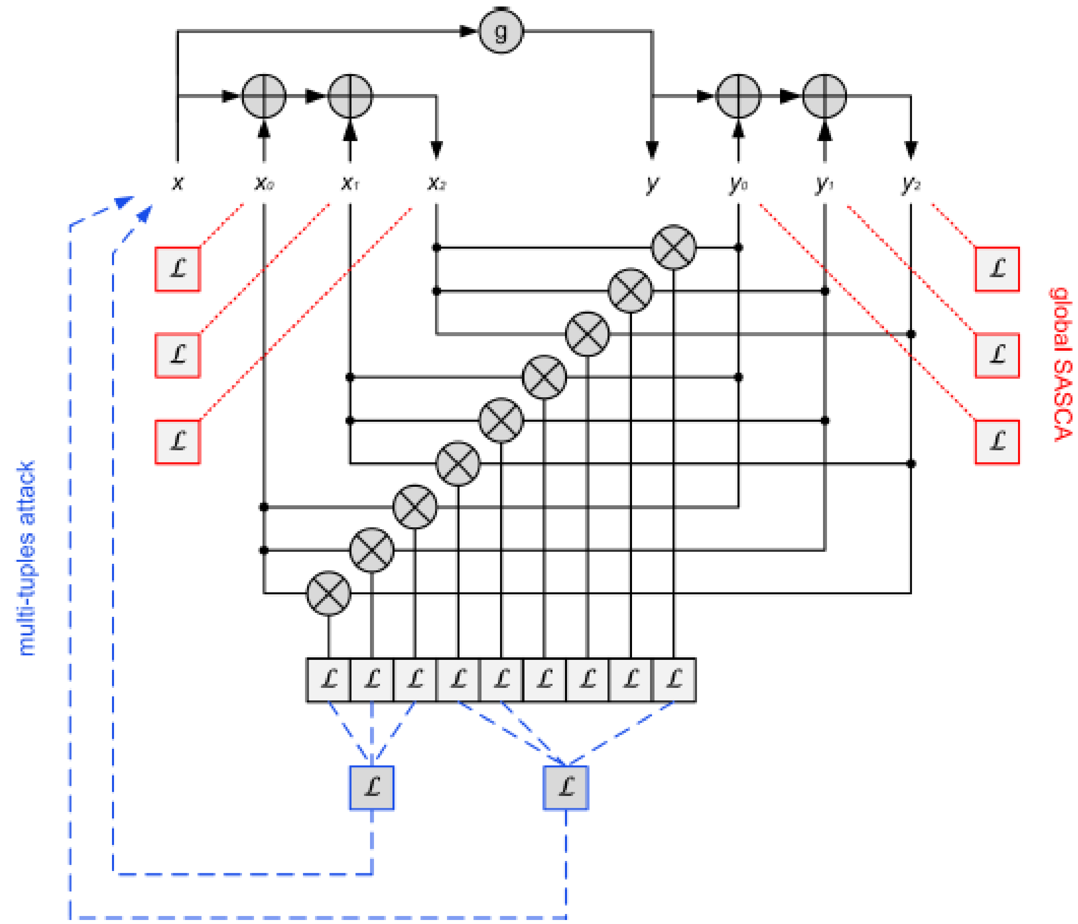
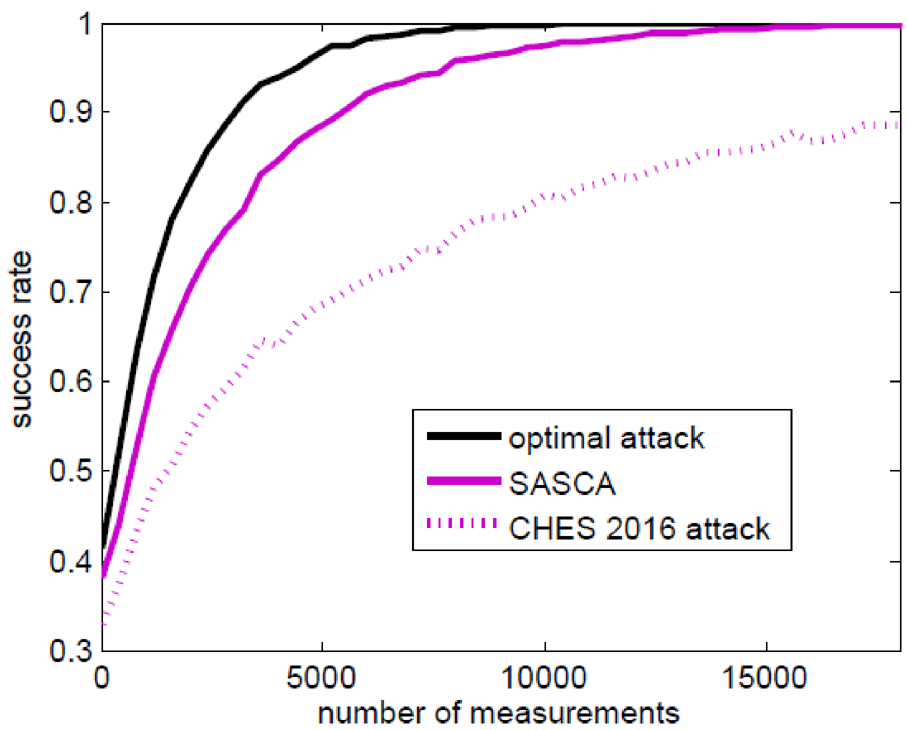


More results

- Also works in practice (Asiacrypt 2015)
- And against masked implementations
  - Improvement of the CHES 2016 horizontal attacks



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SCA possible outcomes

- Enough measurements ⇒ direct key recovery

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- Not enough measurements but enough computational power ⇒ key enumeration
- But what to do if it is not enough?
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    ⇒ Only possible for evaluators
- Note: only optimal with probabilities (to combine the information of ≠ S-boxes)

FSE 2015 rank estimation (I)

- Thanks to T-systems people (Glowacz, Schueth)

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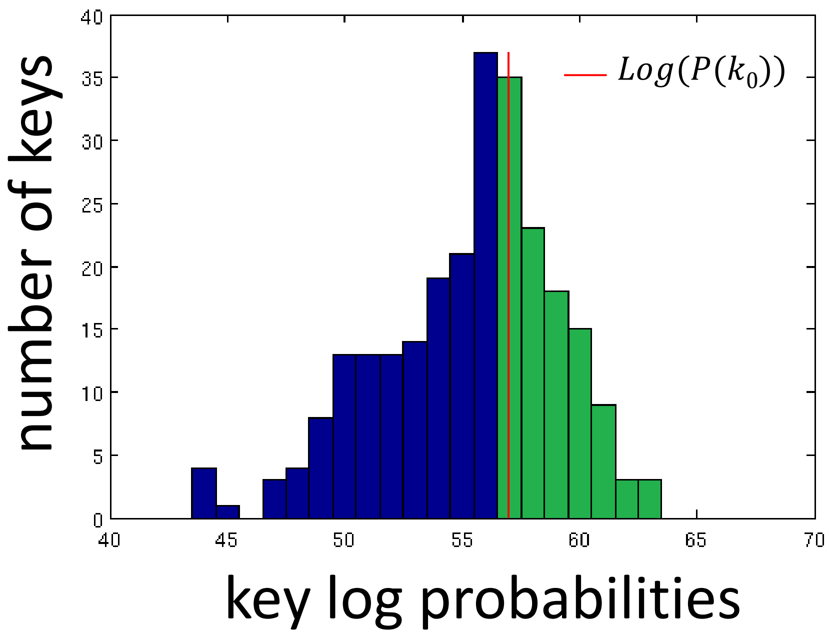
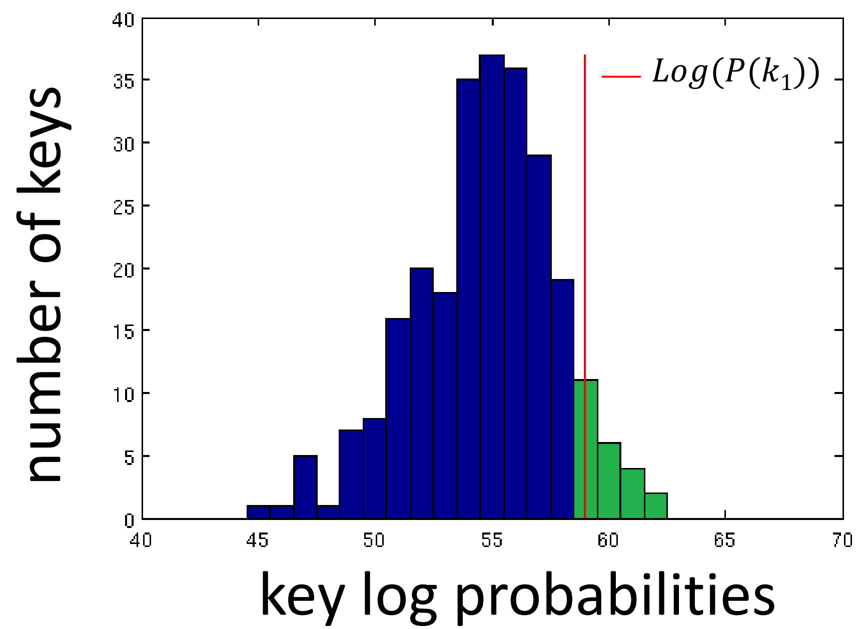
- Representation with histograms

S-box 0



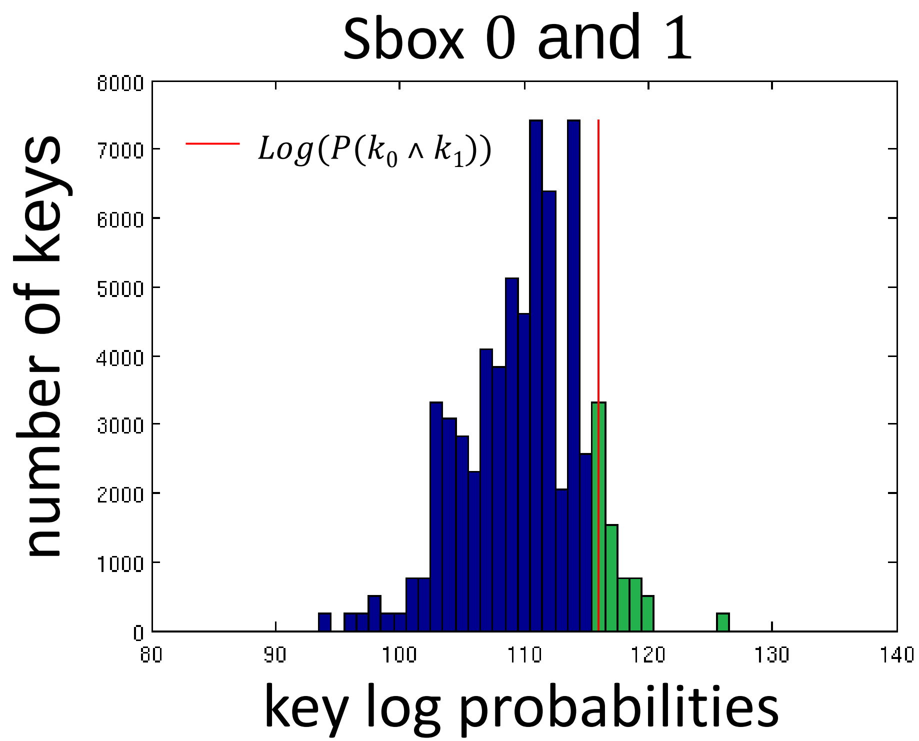
S-box 1



- The rank is the number of key in the green zone

FSE 2015 rank estimation (II)

- Combination with convolution



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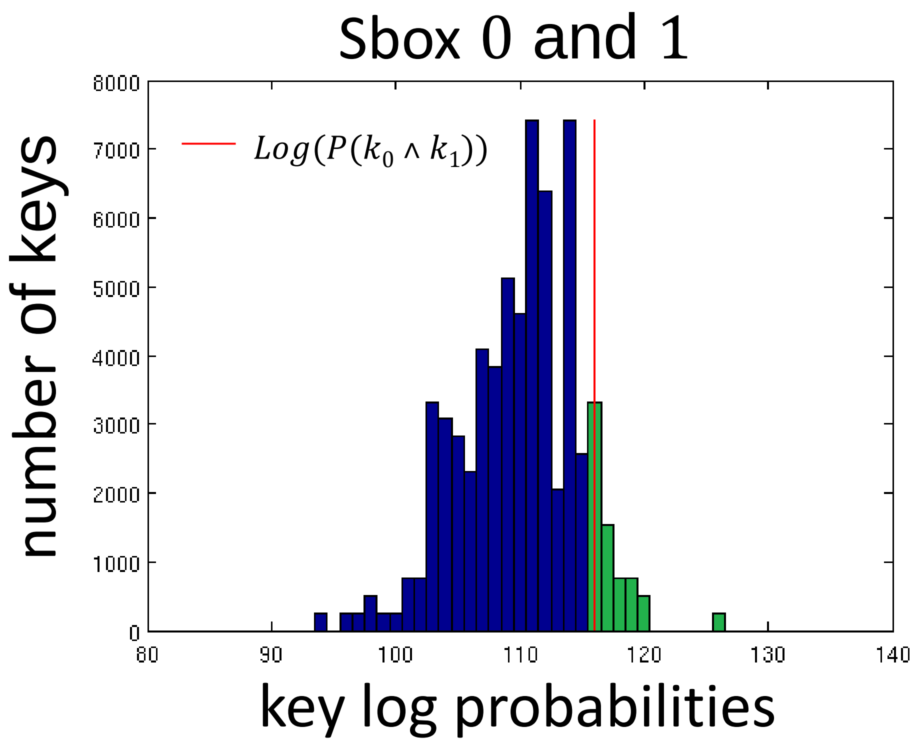

… and keep track of the error that depends on:

- The number of bins
- The number of conv.

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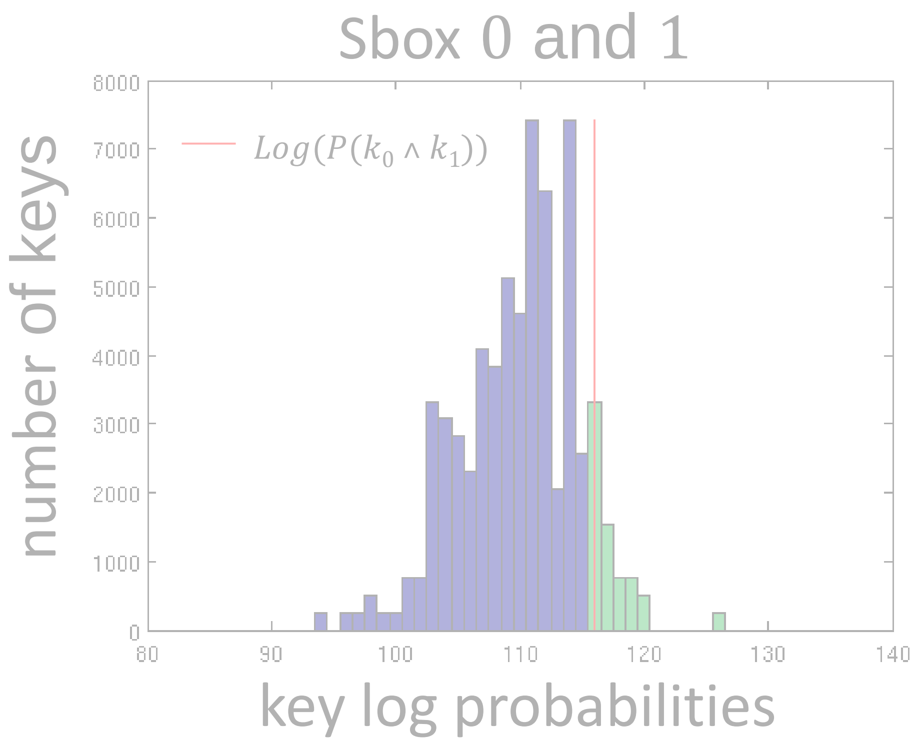


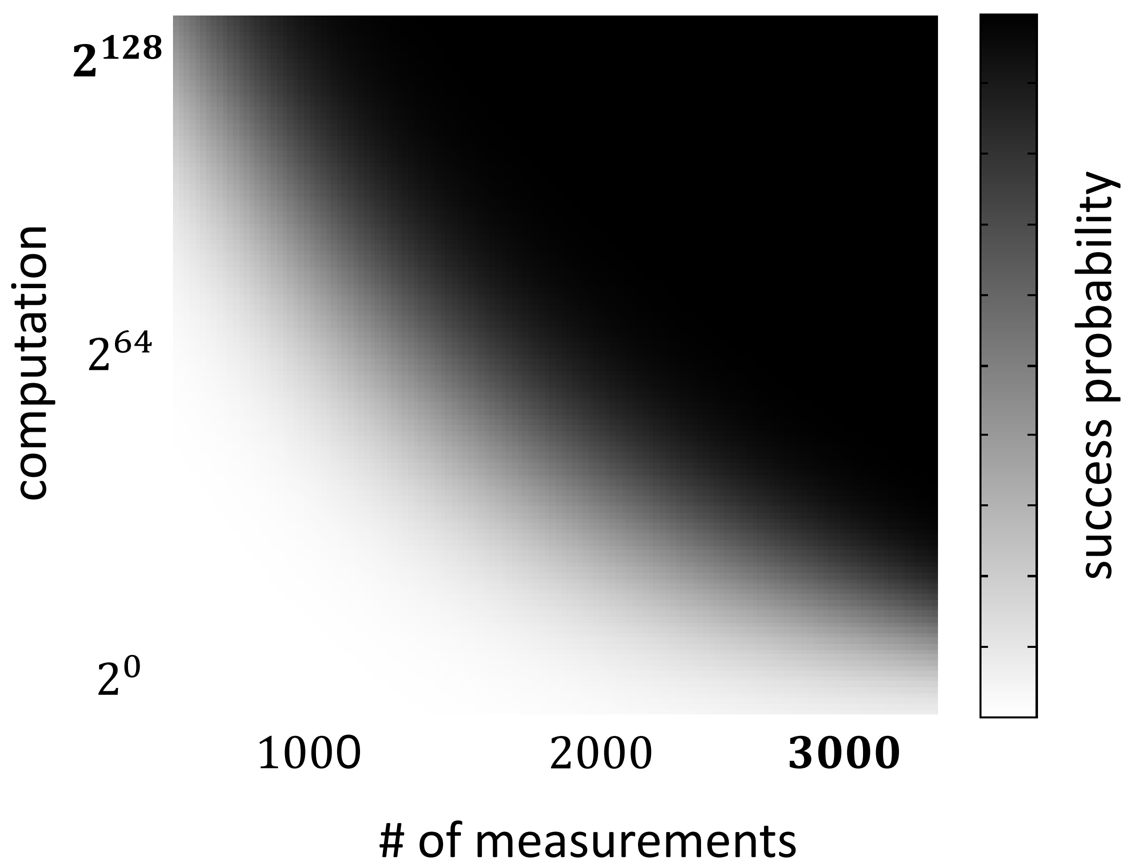
... and keep track of the error that depends on:

- The number of bins
- The number of conv.

- Just iterating this gives the key rank accurately
    - e.g., < 1 bits in < 1 sec. for a 128-bit key

Rank estimation result

- Security graph (IMO the sound outcome of an evaluation)



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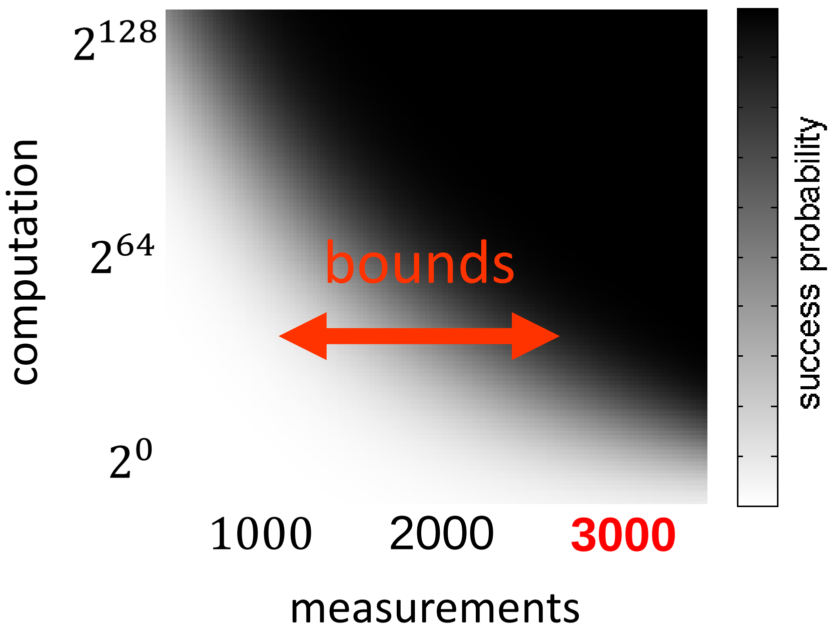
standard practice

attack-based evaluations



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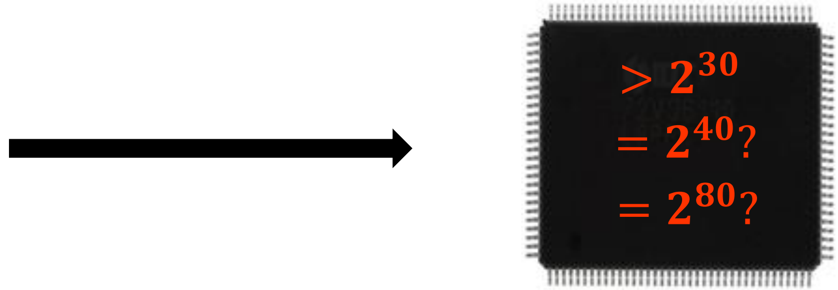

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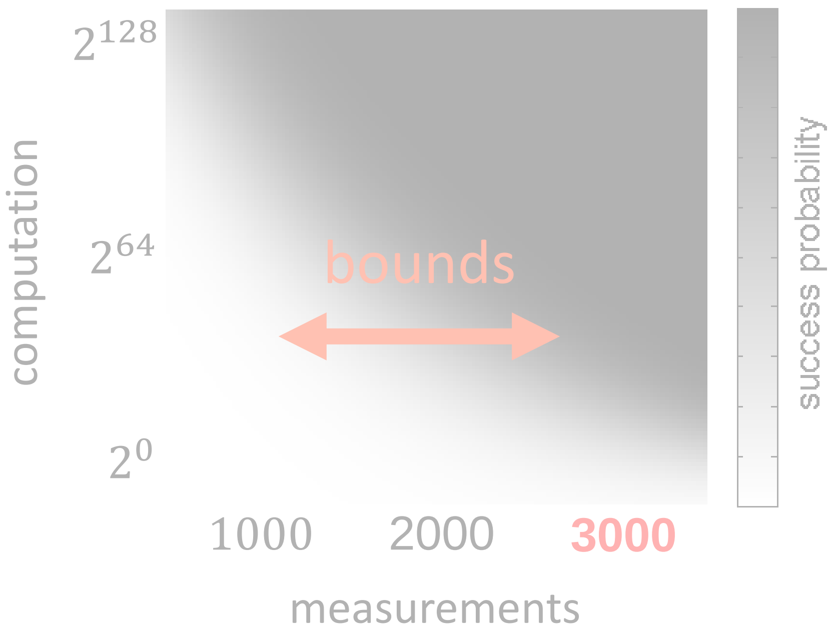
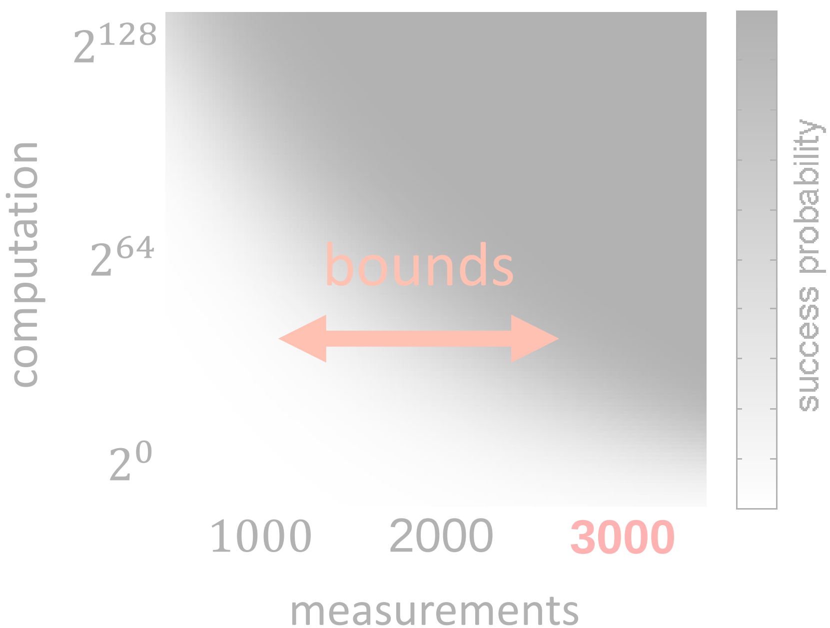


standard practice

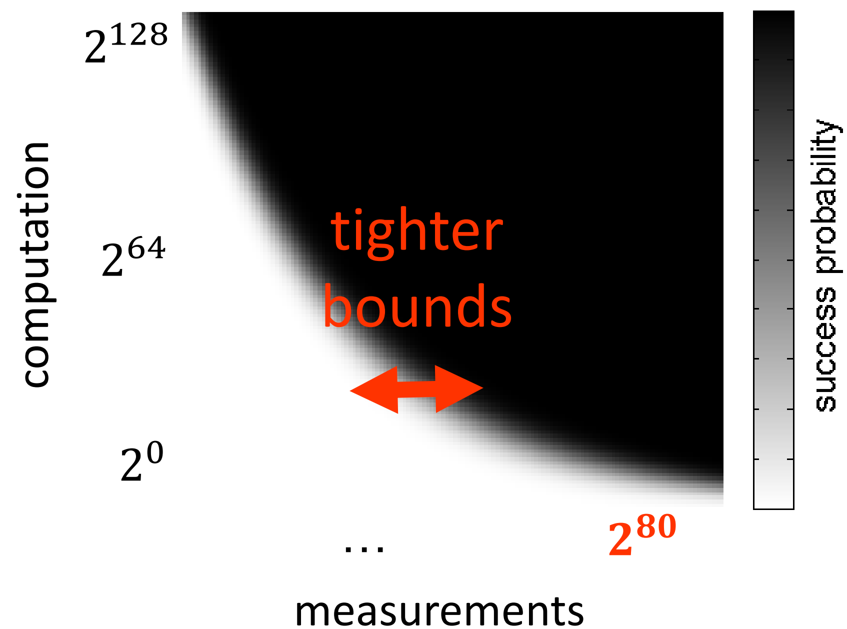
transparency

helps evaluations

attack-based evaluations



proof-based evaluations



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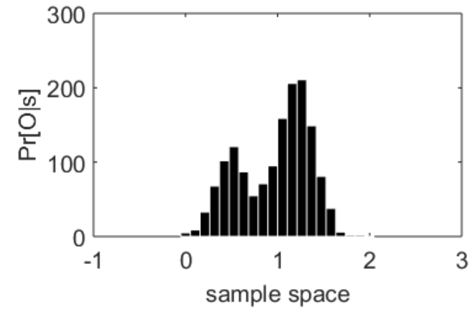
Mutual information

- Discrete observations:

$$\mathrm{MI}(S;O) = \mathrm{H}[S] + \sum_{s \in S} \Pr[s] \cdot \sum_{o \in O} \Pr[o|s] \cdot \log_2(\Pr[s|o])$$

- With: $\Pr[s|o] = \dfrac{\Pr[o|s]}{\sum_{s^*} \Pr[o|s^*]}$



Mutual information

- Continuous observations:

$$\mathrm{MI}(S;O) = \mathrm{H}[S] + \sum_{s \in S} \Pr[s] \cdot \int_{O} \mathrm{f}(o|s) \cdot \log_2(\Pr[s|o]) \, do$$

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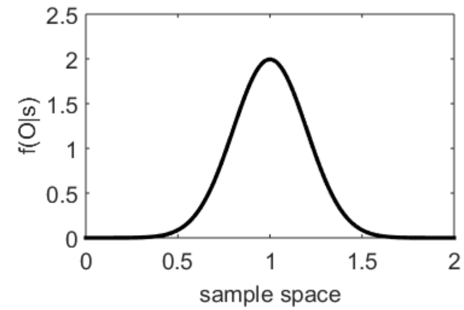

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- Intuition: average amount of information on S that is gained by observing a sample o

Main theorem (informal)

- Higher $\mathrm{MI}(S;O)$ asymptotically implies higher Bayesian classification success rate:

$$\mathrm{SR}(n) = \Pr_{O}\left[\ \operatorname*{argmax}_{s^*} \Pr[s^*|o_1]\cdot\Pr[s^*|o_2]\cdots\Pr[s^*|o_n] = s\ \right]$$

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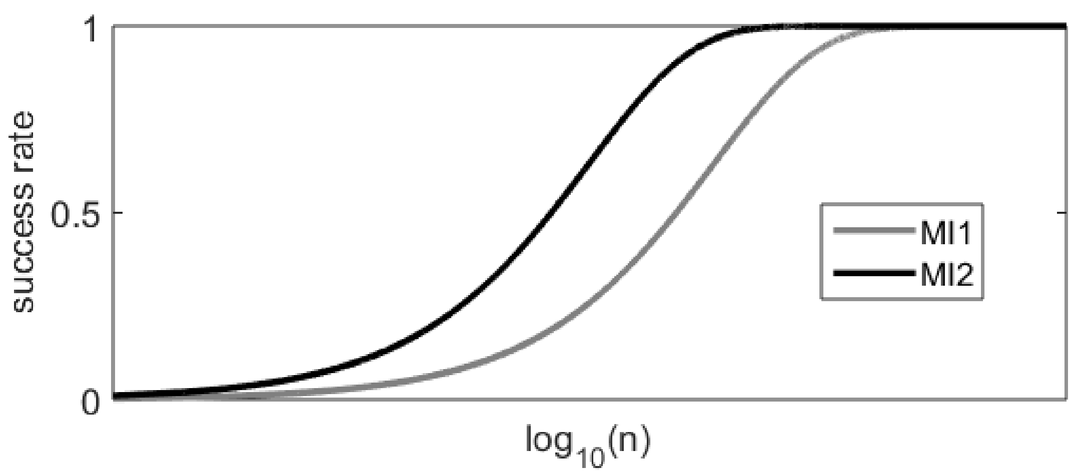
Example, with MI2 > MI1



- In practice, the true distributions $\mathrm{Pr}_{\mathrm{real}}[o|s]$ and $\mathrm{f}_{\mathrm{real}}(o|s)$ are generally unknown
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Concrete challenge

- In practice, the true distributions $\Pr_{\text{real}}[o|s]$ and $\mathrm{f}_{\text{real}}(o|s)$ are generally unknown
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$\Rightarrow$ *How to be sure that the model is good?*

- Exactly reflects this practical challenge
- For example in the continuous case:

$$\mathrm{PI}(S;O) = \mathrm{H}[S] + \sum_{s\in S} \mathrm{Pr}[s] \cdot \int_{O} \mathrm{f}_{\mathrm{real}}(o|s) \cdot \log_2\left(\mathrm{Pr}_{\mathrm{model}}[s|o]\right) do$$

The Perceived Information

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- Intuition: average amount of information on S that is gained by observing a sample o, biased by the model estimation/assumption errors
- $\mathrm{PI}(S;O)$ is a statistical distance between the real and modeled distributions (i.e., a measure of how well a model "explains" real observations)

How to estimate the PI?

- Say you have a set of $2m$ observations per s

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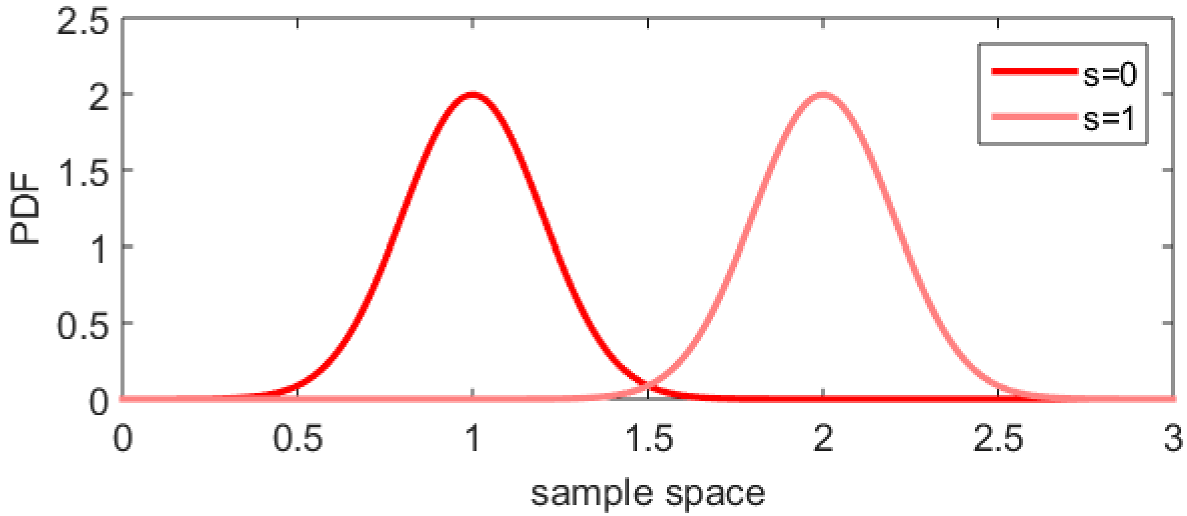

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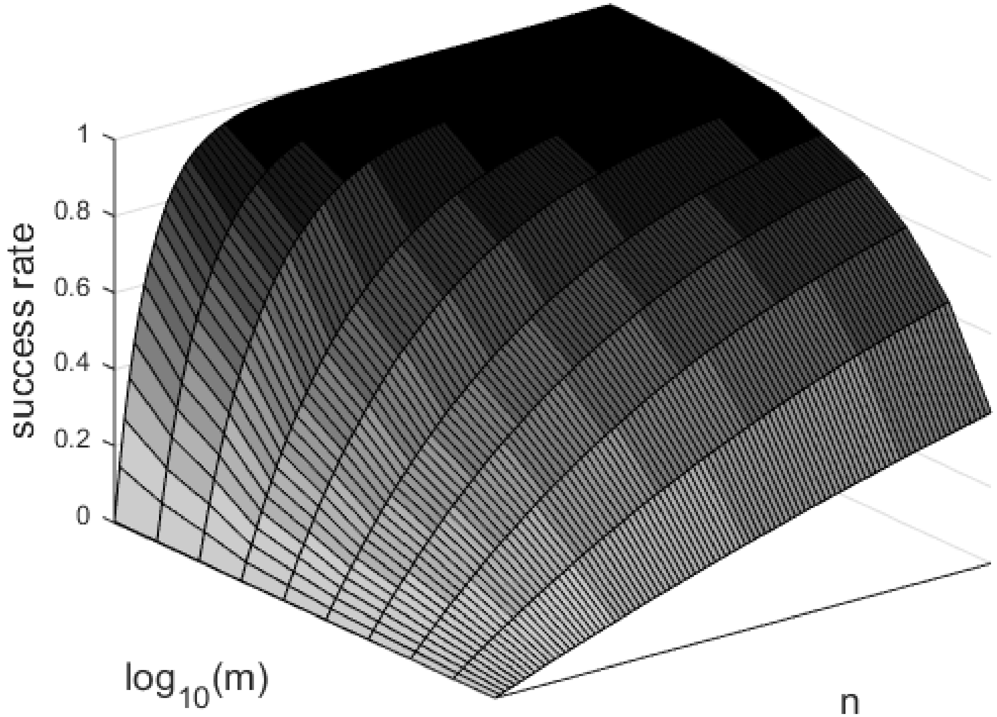
(*More efficient use of observations with cross-validation*)

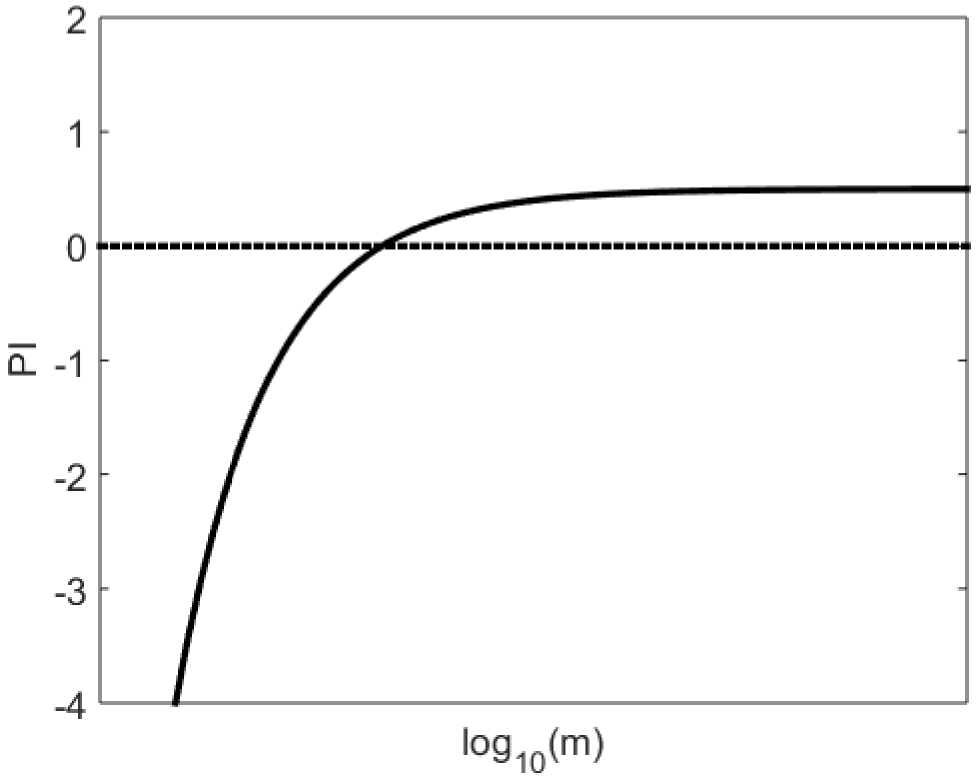
Efficiency gain (I)

- Directly estimating model *convergence* and *informativeness* based on the SR is expensive



Efficiency gain (II)

- The PI curve allows "getting rid of" the *n* axis
  ⇒ it is faster to estimate than the SR surface



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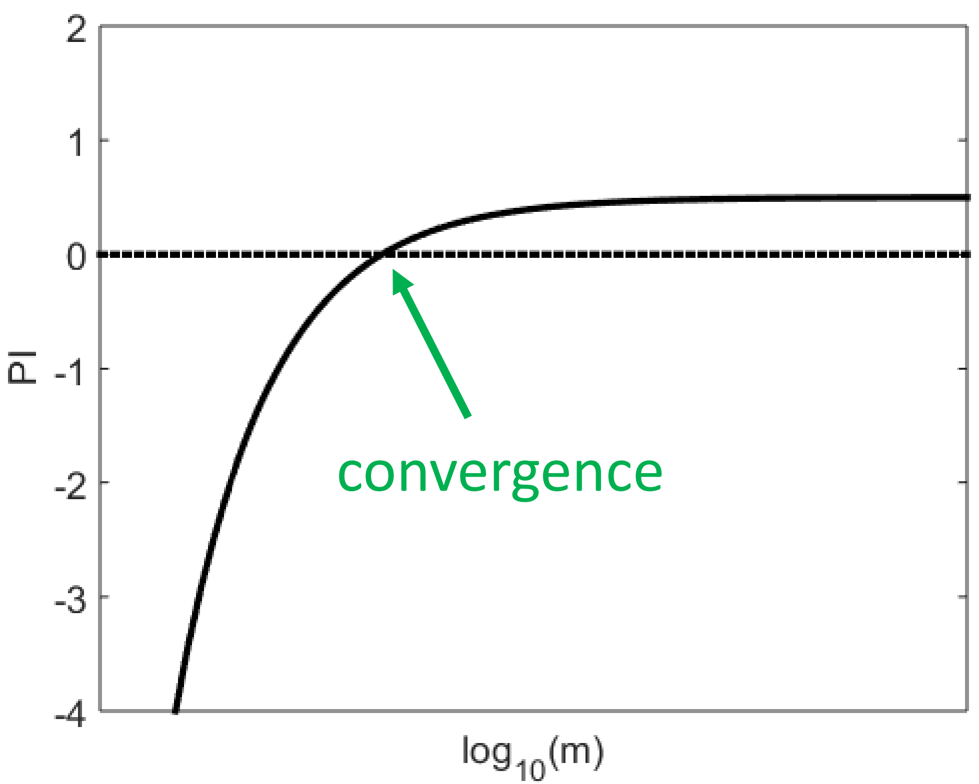

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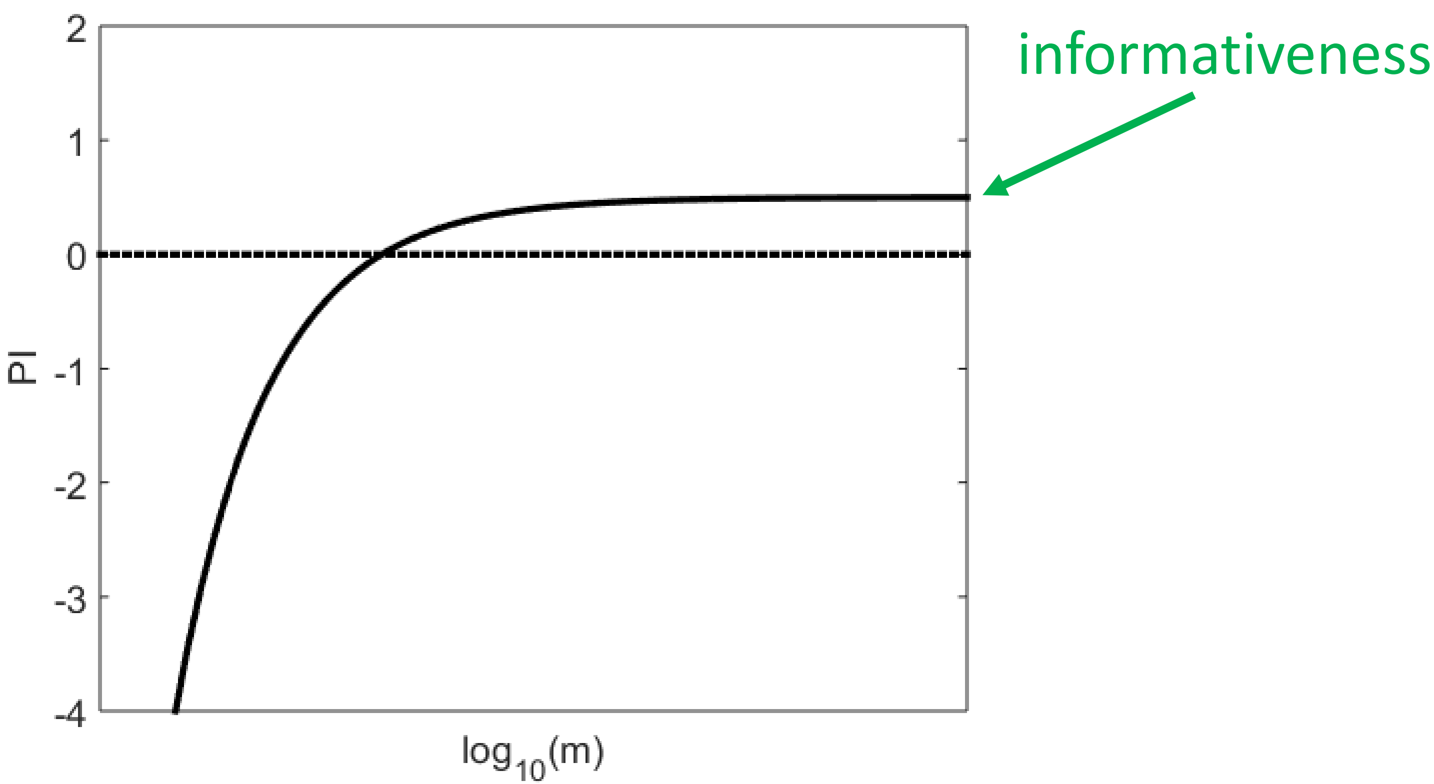
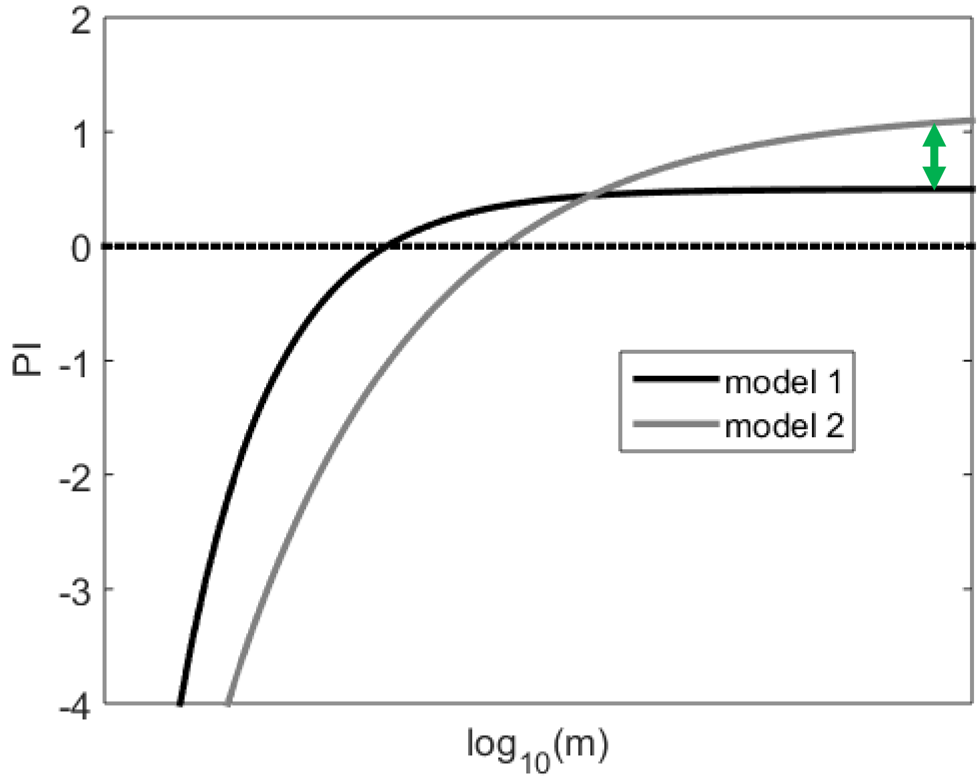


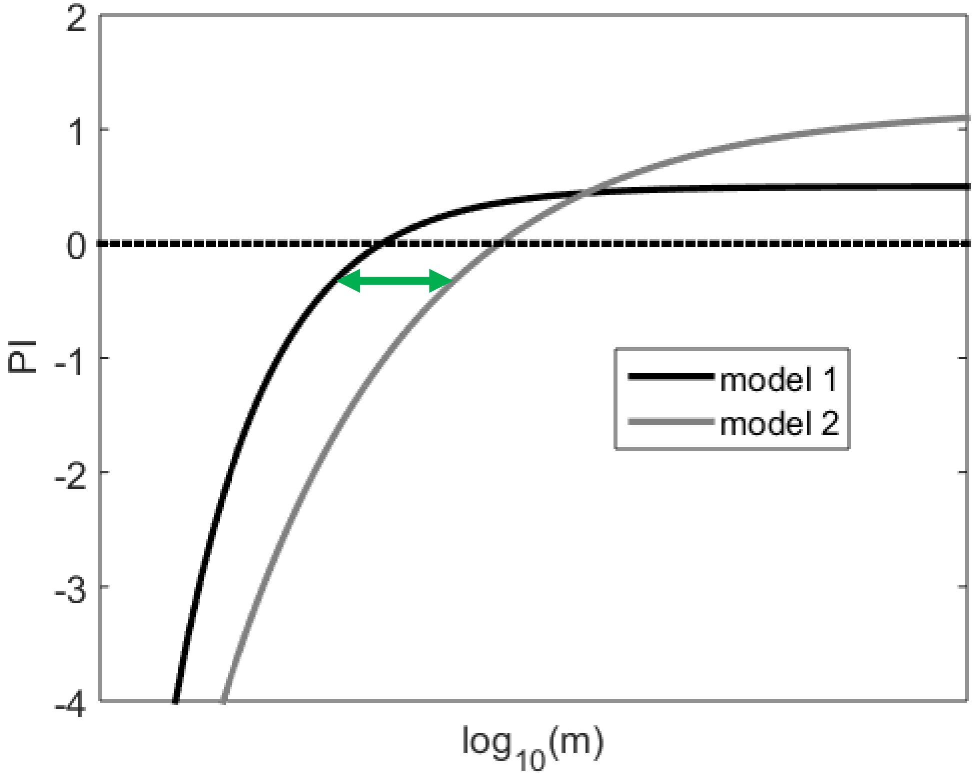
Interpretation (I)

- Allows sound & efficient comparison of models
  - e.g., model 2 more informative than model 1



Interpretation (I)

- Allows sound & efficient comparison of models
  - and model 1 converges faster than model 2



Interpretation (II)

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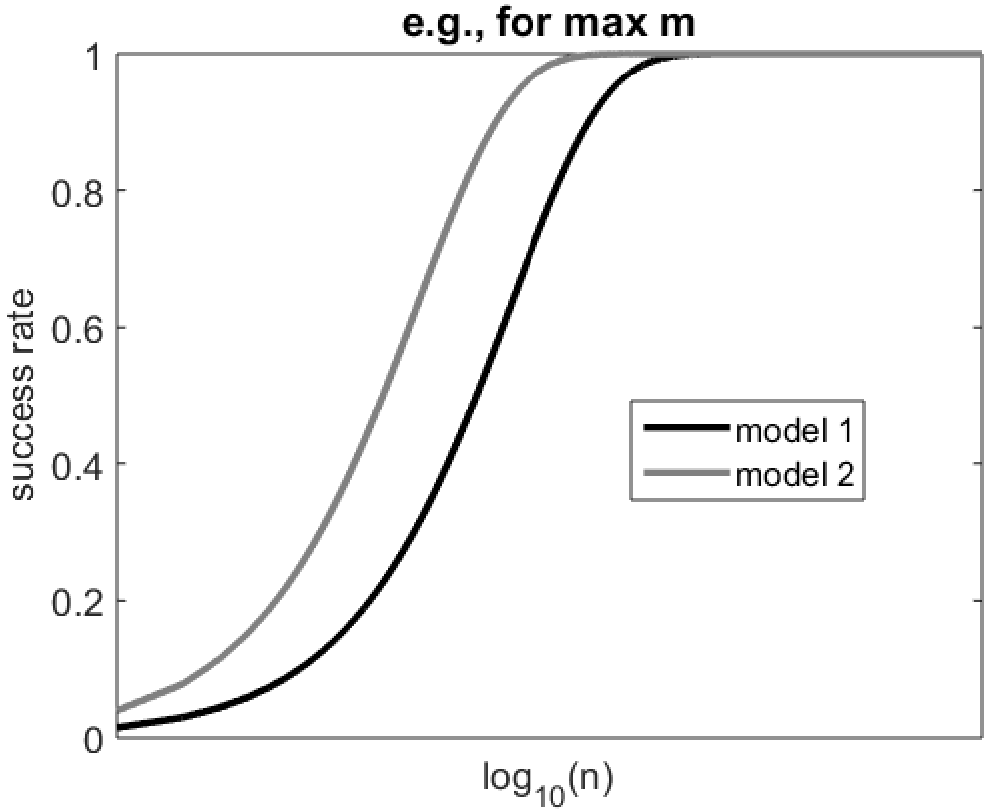

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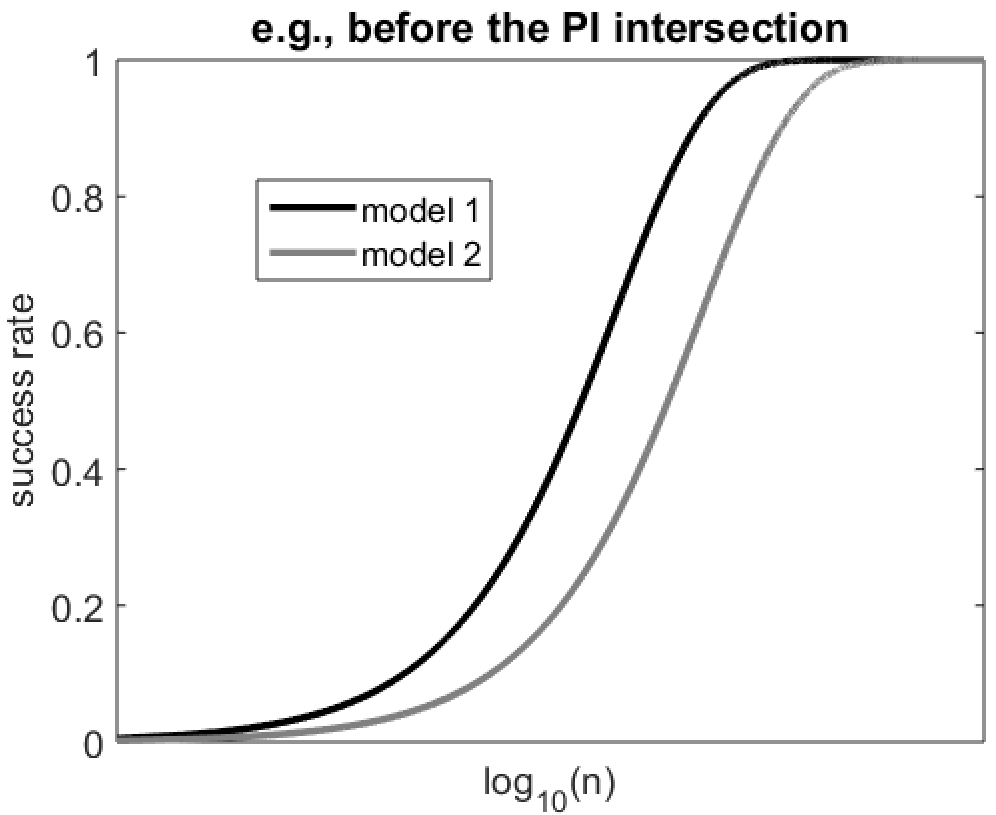
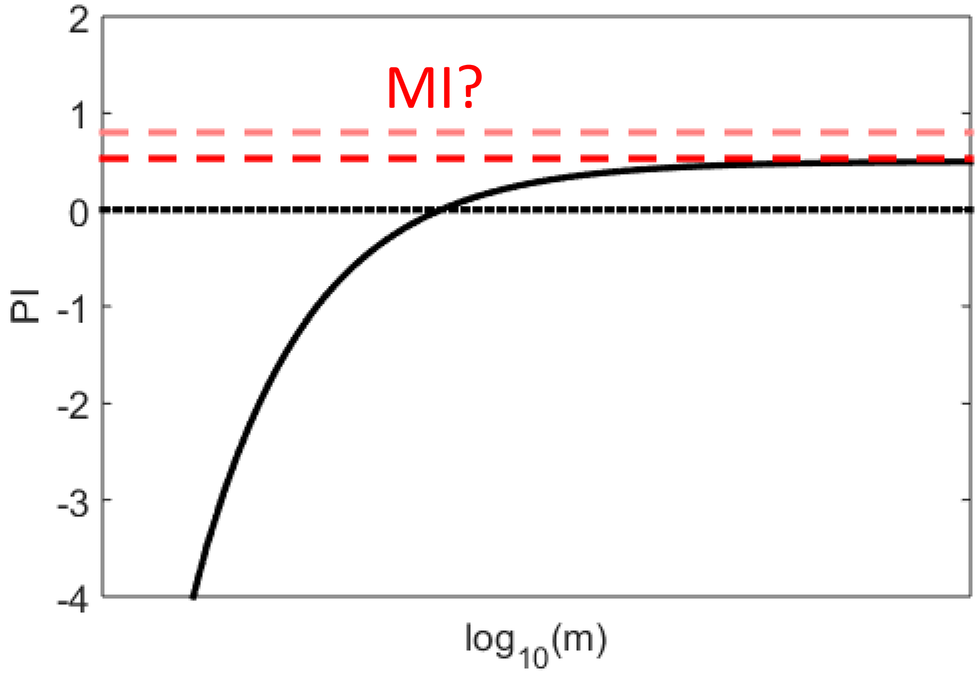


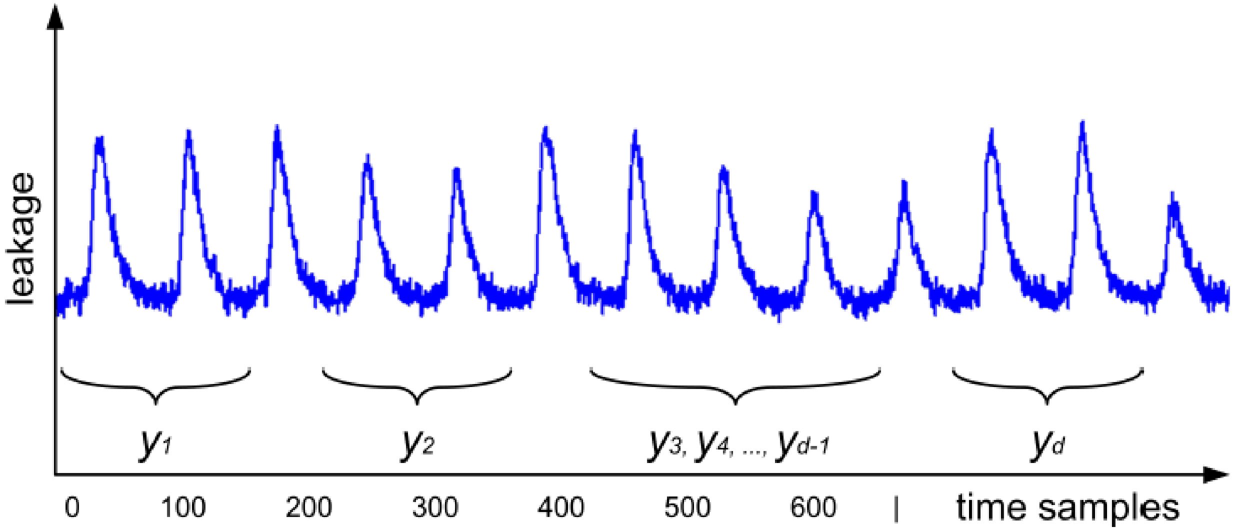
Optimality guarantees?

- Remaining question: how far are we from the MI?



- *Leakage certification* allows answering this!

- Let $z = S(x \oplus k) = S(y)$ be a leaking S-box
- Let $y = y_1 \oplus y_2 \oplus \cdots \oplus y_d$ be a sharing of y



- Perform computations on “shared” variables

More generally (II)

- Linear operations: $\mathrm{f(a)} = \mathrm{f}(a_1) \oplus \mathrm{f}(a_2) \oplus \cdots \oplus \mathrm{f}(a_d)$

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Yuval Ishai, Amit Sahai, David Wagner: *Private Circuits: Securing Hardware against Probing Attacks*. CRYPTO 2003: 463-481. Matthieu Rivain, Emmanuel Prouff*: Provably Secure Higher-Order Masking of AES*. CHES 2010: 413-427

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$$\begin{bmatrix} a_1 b_1 & a_1 b_2 & a_1 b_3 \\ a_2 b_1 & a_2 b_2 & a_2 b_3 \\ a_3 b_1 & a_3 b_2 & a_3 b_3 \end{bmatrix}$$

partial products

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partial products refreshing

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partial products refreshing compression

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partial products refreshing compression

$\Longrightarrow$ Quadratic overheads & randomness

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$\Rightarrow$ Quadratic overheads & randomness

$\Rightarrow$ Composable (from gadgets to circuits)

Yuval Ishai, Amit Sahai, David Wagner: *Private Circuits: Securing Hardware against Probing Attacks*. CRYPTO 2003: 463-481. Matthieu Rivain, Emmanuel Prouff*: Provably Secure Higher-Order Masking of AES*. CHES 2010: 413-427. Gilles Barthe, Sonia Belaïd, François Dupressoir, Pierre-Alain Fouque, Benjamin Grégoire, Pierre-Yves Strub, Rébecca Zucchini: *Strong Non-Interference and Type-Directed Higher-Order Masking*. ACM Conference on Computer and Communications Security 2016: 116-129

Main theorem (informal)

- Assume leakage variables $L_{Z_i} = \delta(Z_i) + N$ s.t.
  - $\mathrm{MI}(Z_i; L_{Z_i}) \leq \frac{c}{d}$ (why d? – or d^2 in proofs)
  - The leakages of the shares are independent
- For a masking scheme with *d* shares
- And an adversary using *m* measurements

- Then: $\mathrm{SR} \leq 1 - \left(1 - \mathrm{MI}(Z_i; L_{Z_i})^d\right)^m$

Alexandre Duc, Sebastian Faust, François-Xavier Standaert: Making Masking Security Proofs Concrete - Or How to Evaluate the Security of Any Leaking Device. EUROCRYPT (1) 2015: 401-429

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- For $m = 1$, $\mathrm{SR} \leq \mathrm{MI}(Z_i; L_{Z_i})^d \propto (\sigma_N^2)^d$
- (Intuitively ≈ "noisy" piling up lemma)

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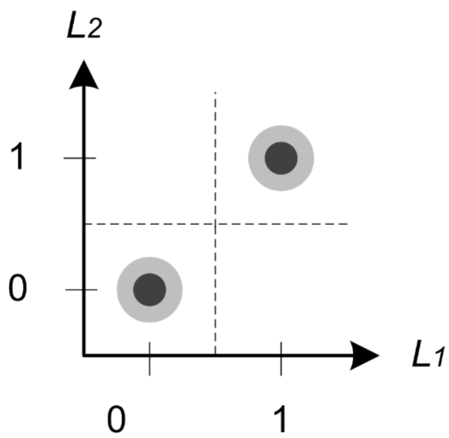
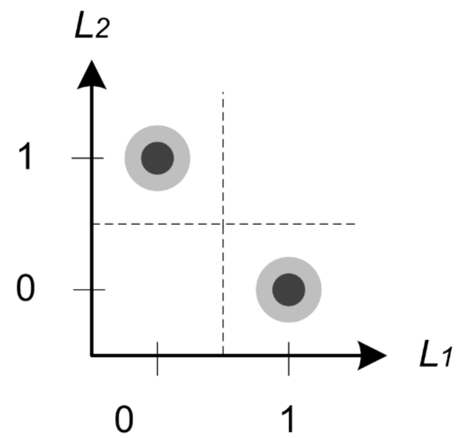
Statistical intuition

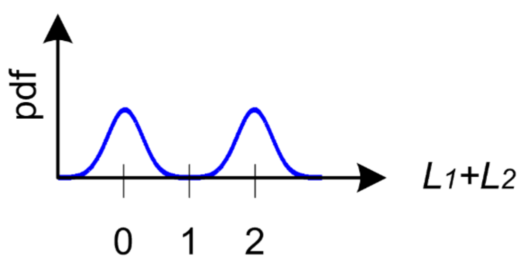
- 1-bit, 2-shares example



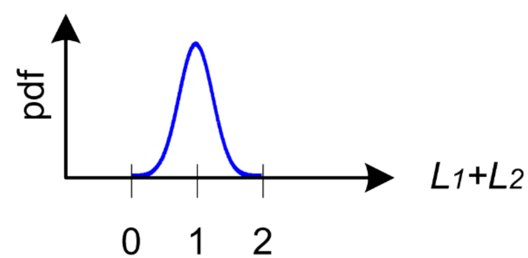
(a) $Z = 0$, serial.



(b) $Z = 1$, serial.



(c) $Z = 0$, parallel.

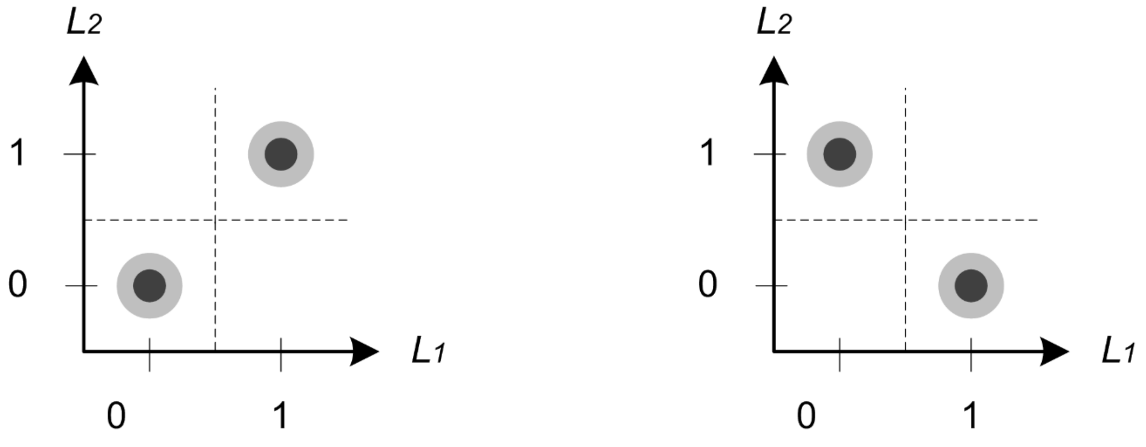


(d) $Z = 1$, parallel.

Statistical intuition

- 1-bit, 2-shares example

key-independent means



(a) Z = 0, serial.

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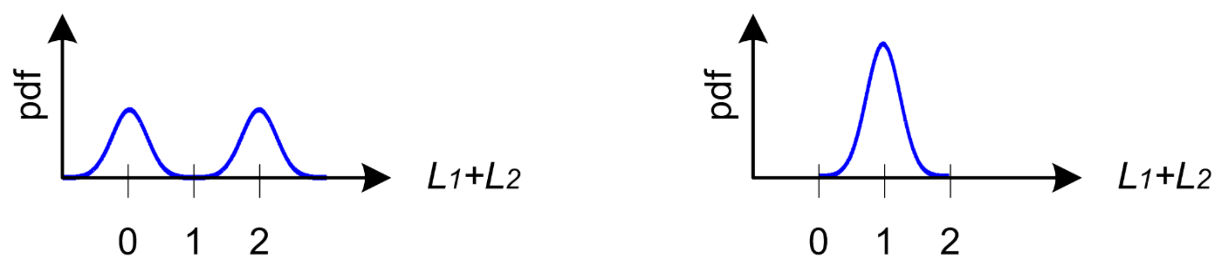
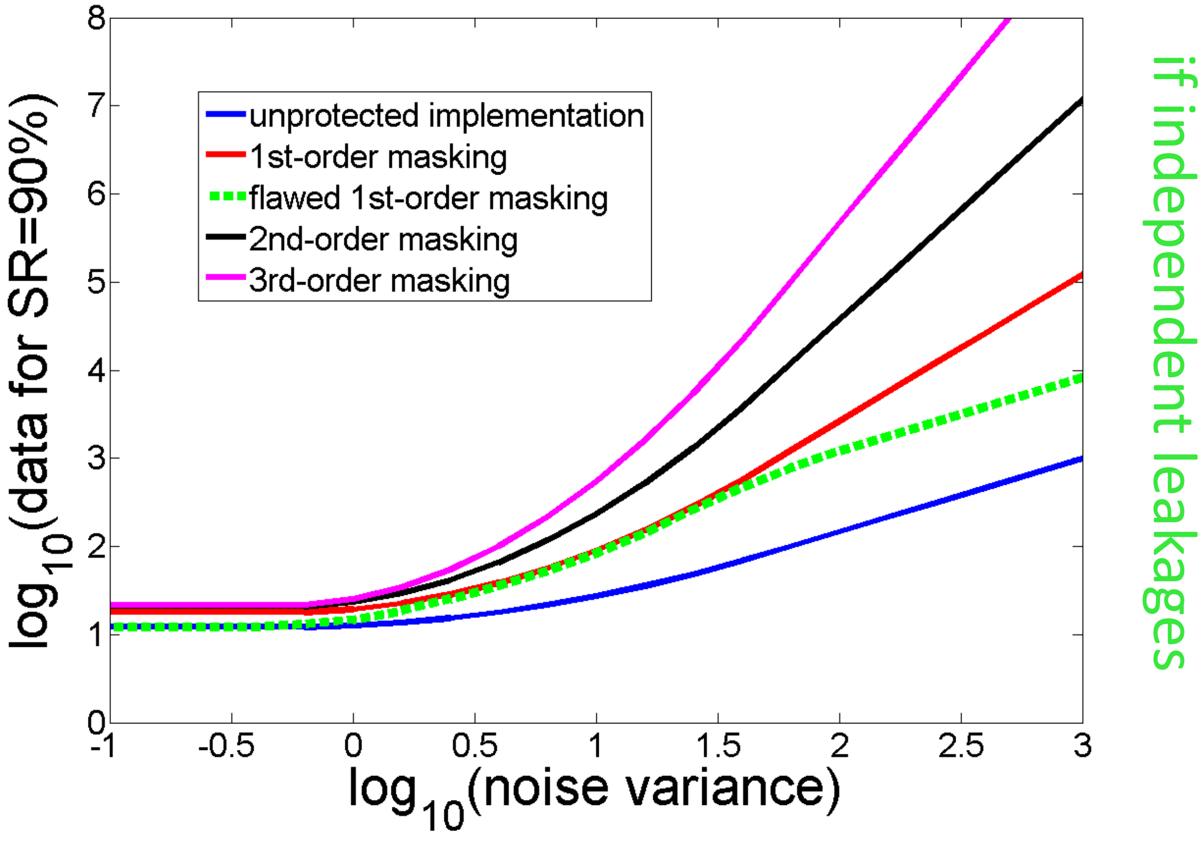


(c) Z = 0, parallel.

(d) Z = 1, parallel.

Information theoretic intuition

- Slope of the IT curves = d (i.e., security order)
  - e.g., for information leakage of an encoding



- As masking order increases, the # of *d*-tuples of informative samples increases (say by d)

⇒ the gap between "simple" attacks targeting one *d*-tuple and d ones increase by a factor d

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Beware of the *d(imensionality)*

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⇒ the gap between "simple" attacks targeting one d-tuple and d ones increase by a factor d

- If shares are re-used (allowing averaging before combination) this factor becomes d^d

⇒ It means security depends on efficiency (in cycles), e.g., parallelism reduces # of leaking tuples

- And that t-tests become irrelevant with large #dim.

Outline

- Introduction
  - Side-channel analysis (attack steps)
  - Heuristic vs. optimal separation
- Measurement & preprocessing
  - Filtering, leakage/POI detection, dimension. reduction
- Predictions & modeling
  - Profiled vs. non-profiled separation, leakage certification
- Exploitation
  - Soft Analytical Side-Channel Attacks
- Post-processing
  - Key enumeration, rank estimation
- Future trends
  - Security without obscurity
  - Exploiting (tight) proofs

Wrapping up!

Conclusions

- For some parts, verifiably fair (i.e., close to worst-case) security evaluations are possible
  - But measurements & preprocessing remain essentially based on engineering knowledge
  - & there remain challenges for highly multivariate and (very) high-order side-channel attacks

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- Transparency is needed for high security
  - e.g., HW with 2^{80} security should be open source

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  - But measurements & preprocessing remain essentially based on engineering knowledge
  - & there remain challenges for highly multivariate and (very) high-order side-channel attacks
- Transparency is needed for high security
  - e.g., HW with 2^{80} security should be open source
- First focus should be on understanding (adv.'s practicality comes only afterwards)
  - e.g., thing about linear cryptanalysis

Open problems

- Effective countermeasures against side-channel attacks always combine sound hardware assumptions & mathematical amplification

$\Rightarrow$ Empirically verifiable (falsifiable) assumptions
$\Rightarrow$ Systematic ways to deal with hardware defaults (or constructions that are less demanding)
$\Rightarrow$ Tight proofs in (reasonably) realistic models

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- We need both theoretical works to lay out foundations & experimental case studies

THANKS

http://perso.uclouvain.be/fstandae/

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