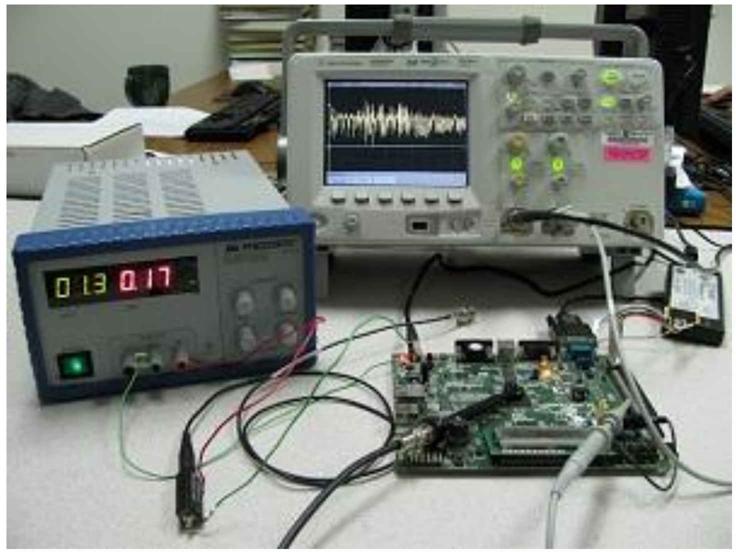
How to Certify the Leakage of a Chip?



François-Xavier Standaert

UCL Crypto Group, Belgium

CryptArchi, Fréjus, France, July 2013

Outline

- The Eurocrypt 2009 framework revisited
- New results towards information leakage bounds
- Security analyzes and time complexity

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How not to evaluate

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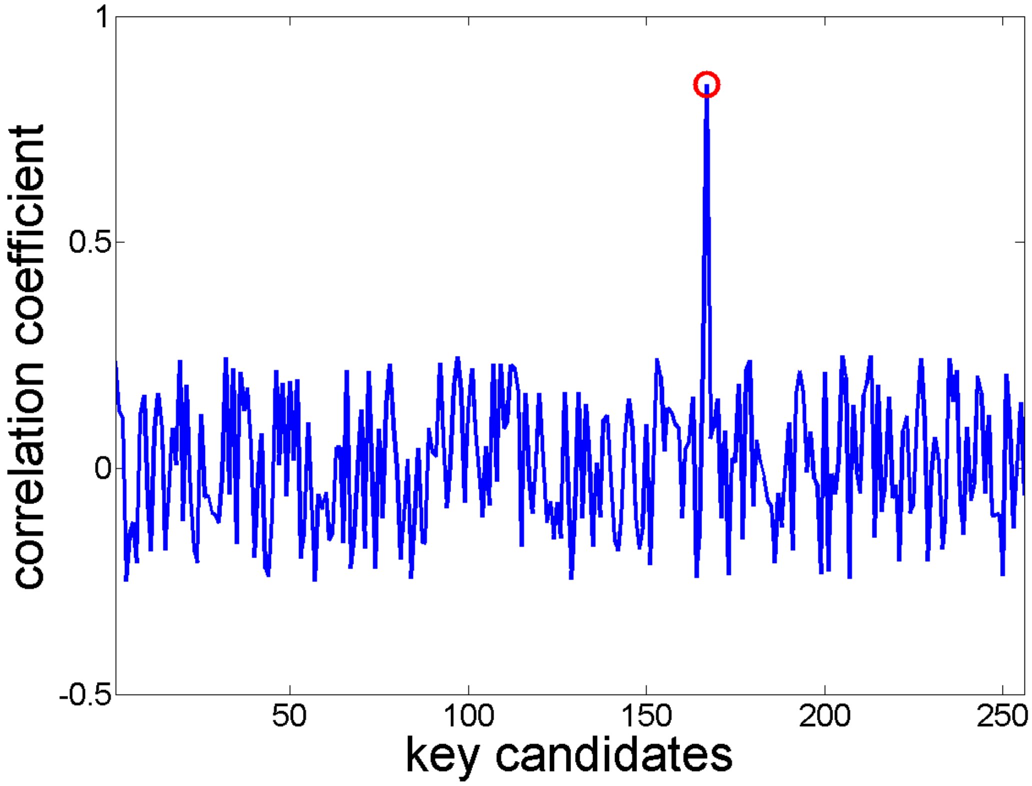

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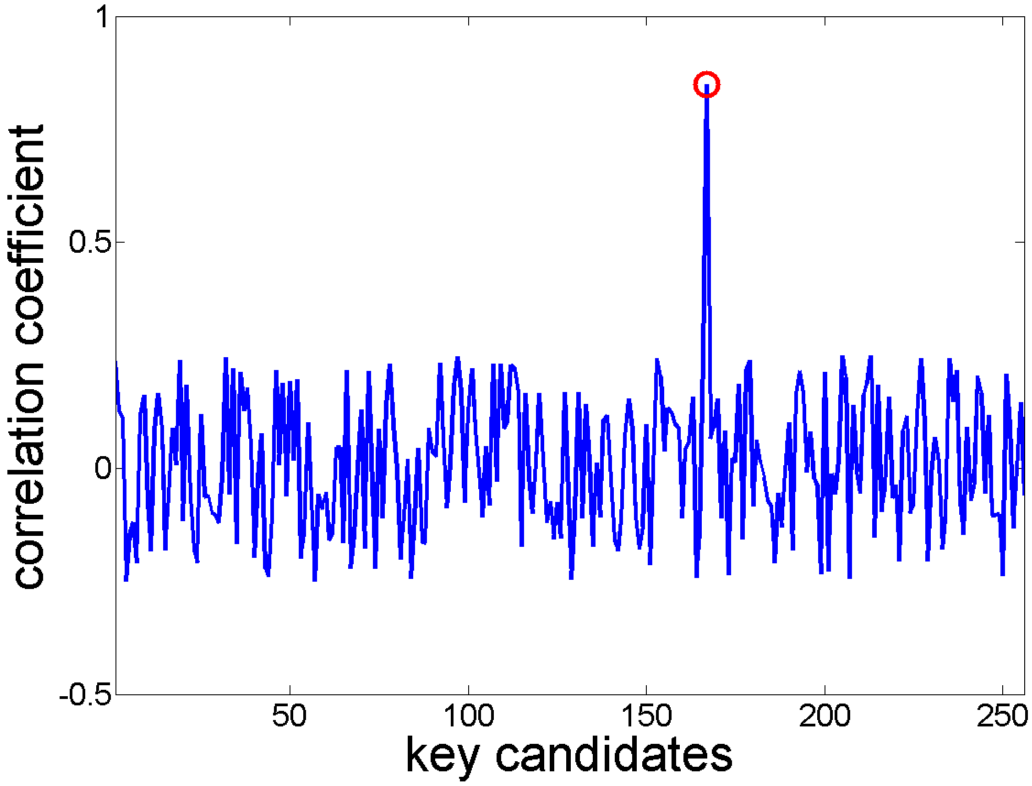
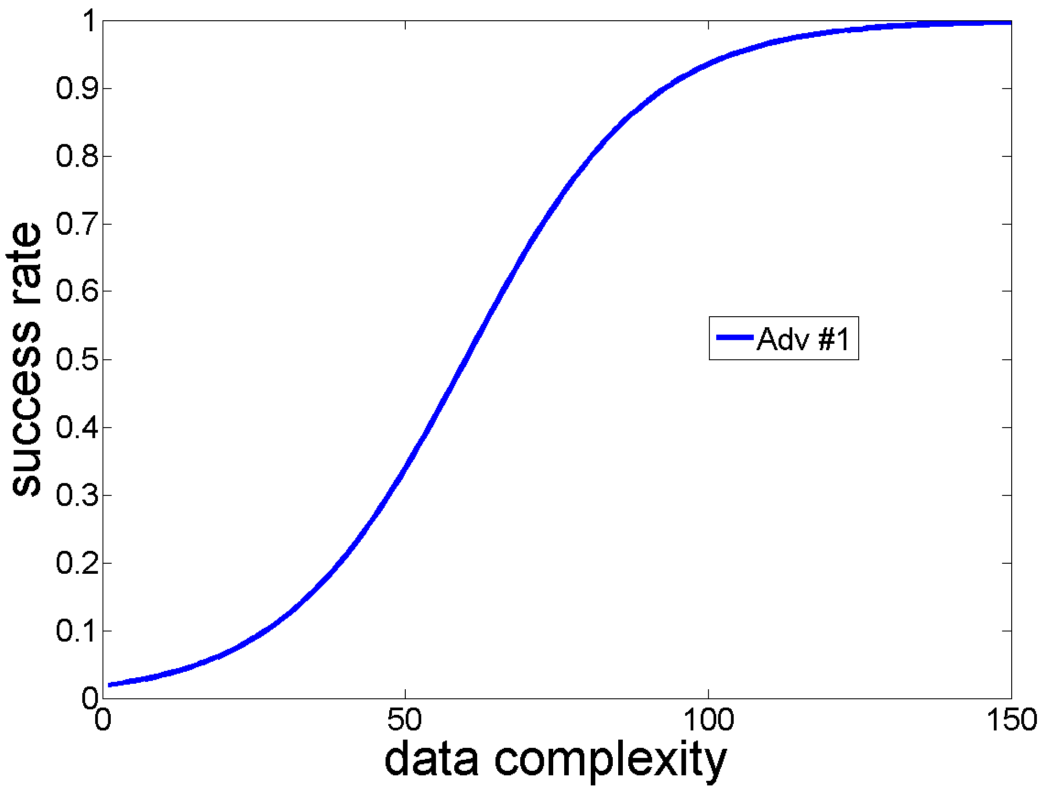


- First issue: no statistical confidence in evaluation

A first improvement

- Repeat the attack and estimate (e.g.) a success rate



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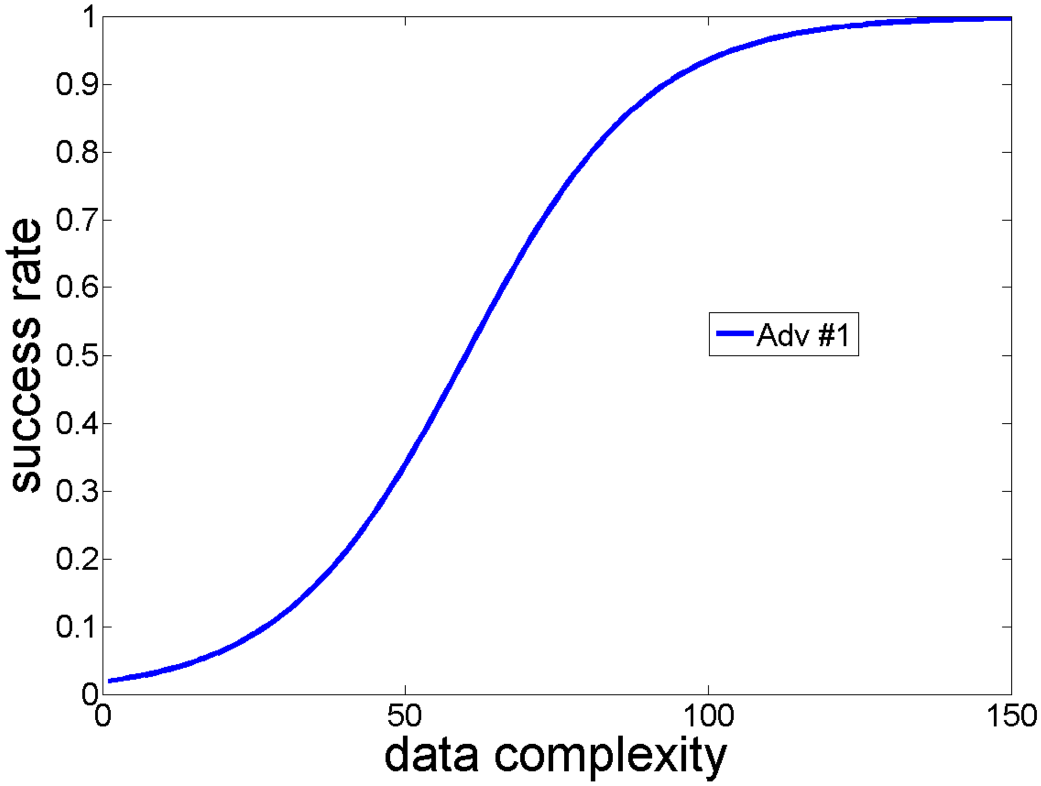

- Second issue: arbitrary adversary (maybe suboptimal)

A first improvement

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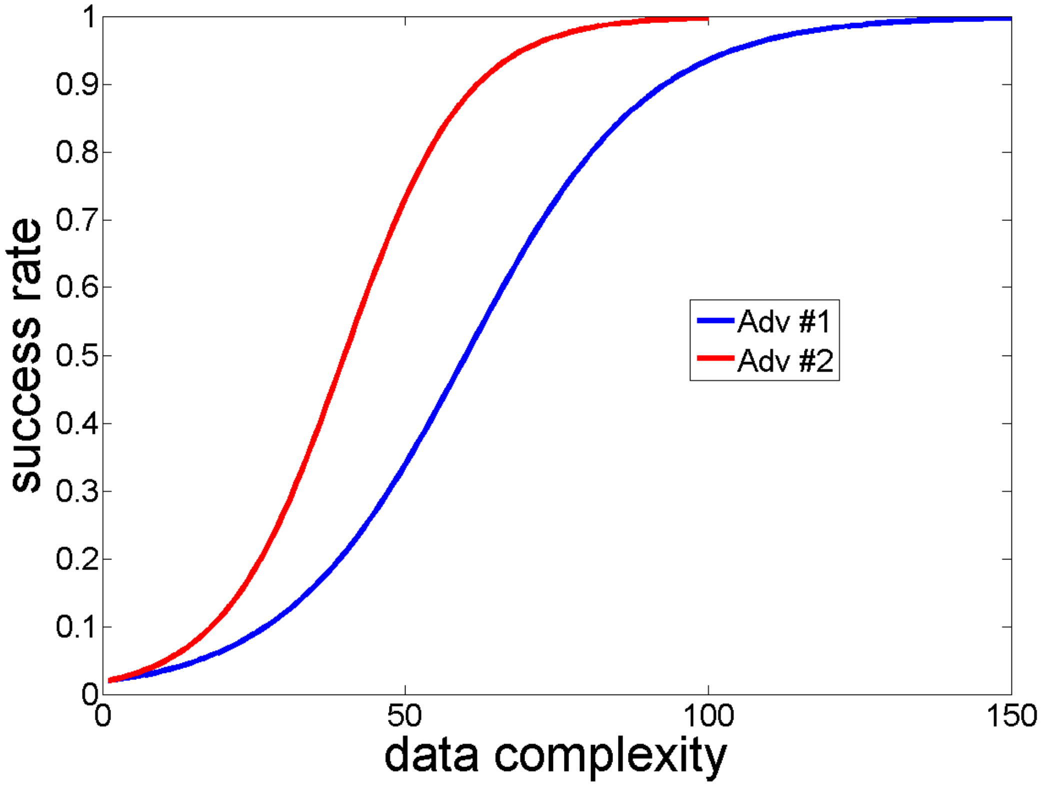
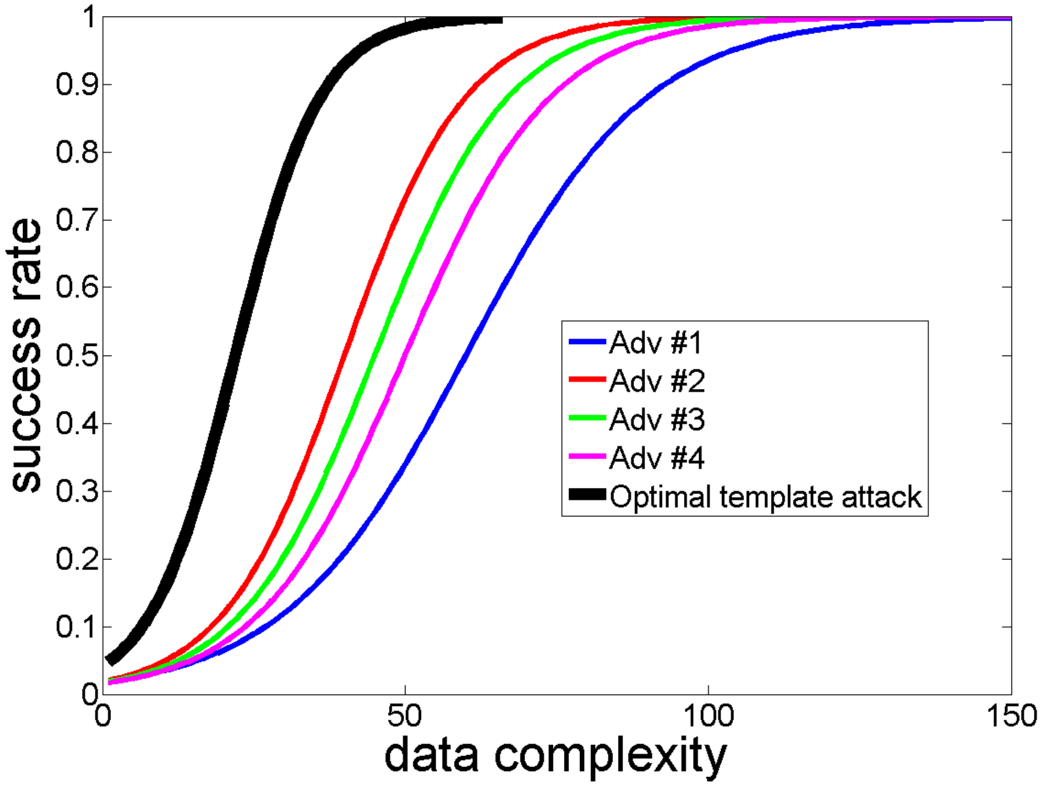


- A stronger adversary may invalidate the evaluation

A second improvement

- Apply an “optimal” template attack



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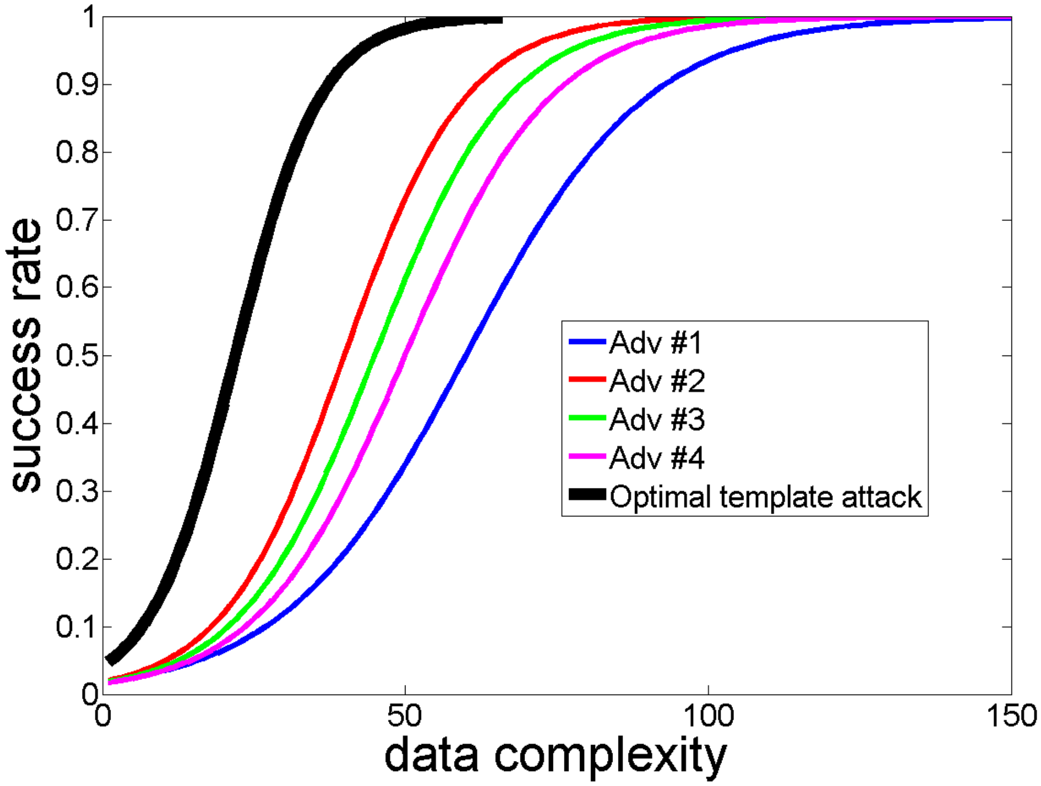
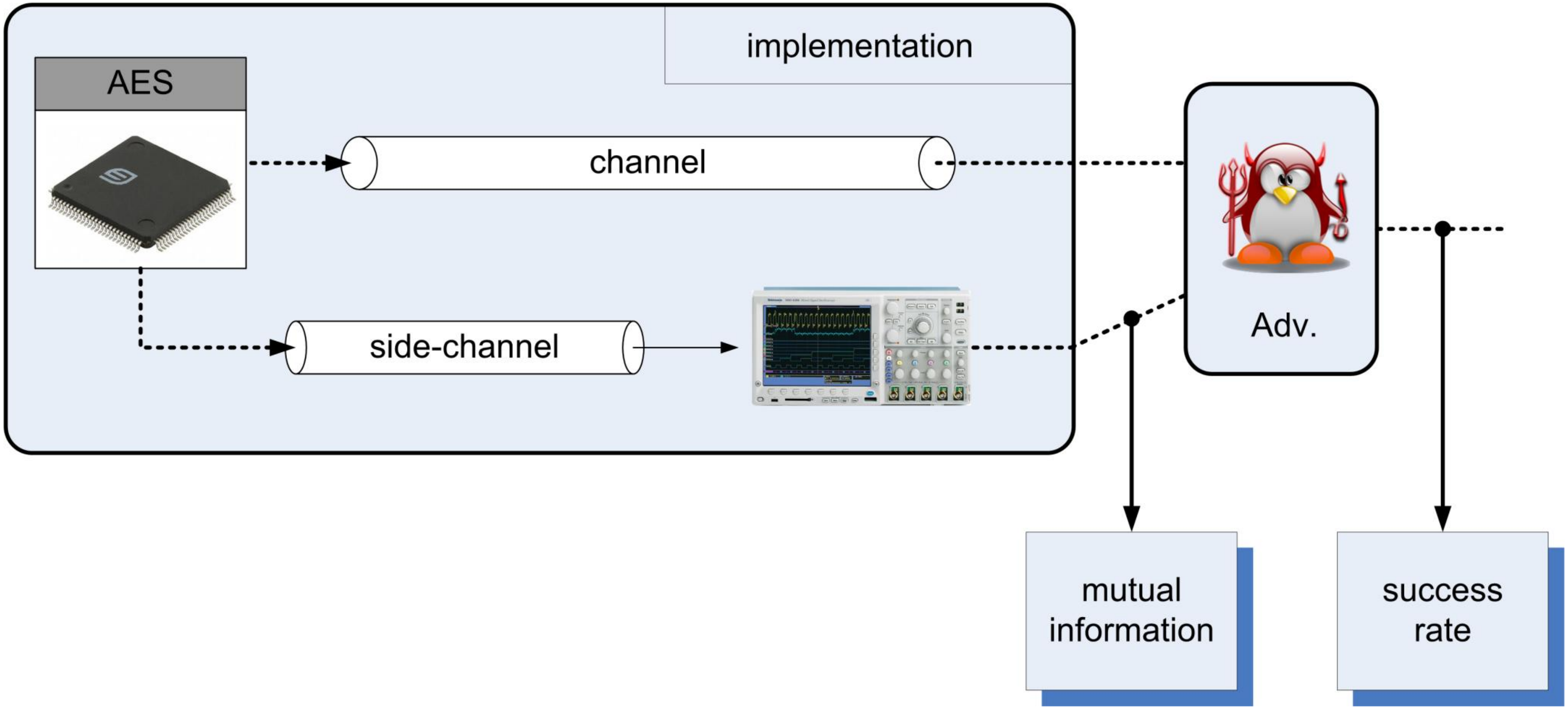


- Of course nobody know what is generally "optimal"!

Background: EC09 Framework [1]



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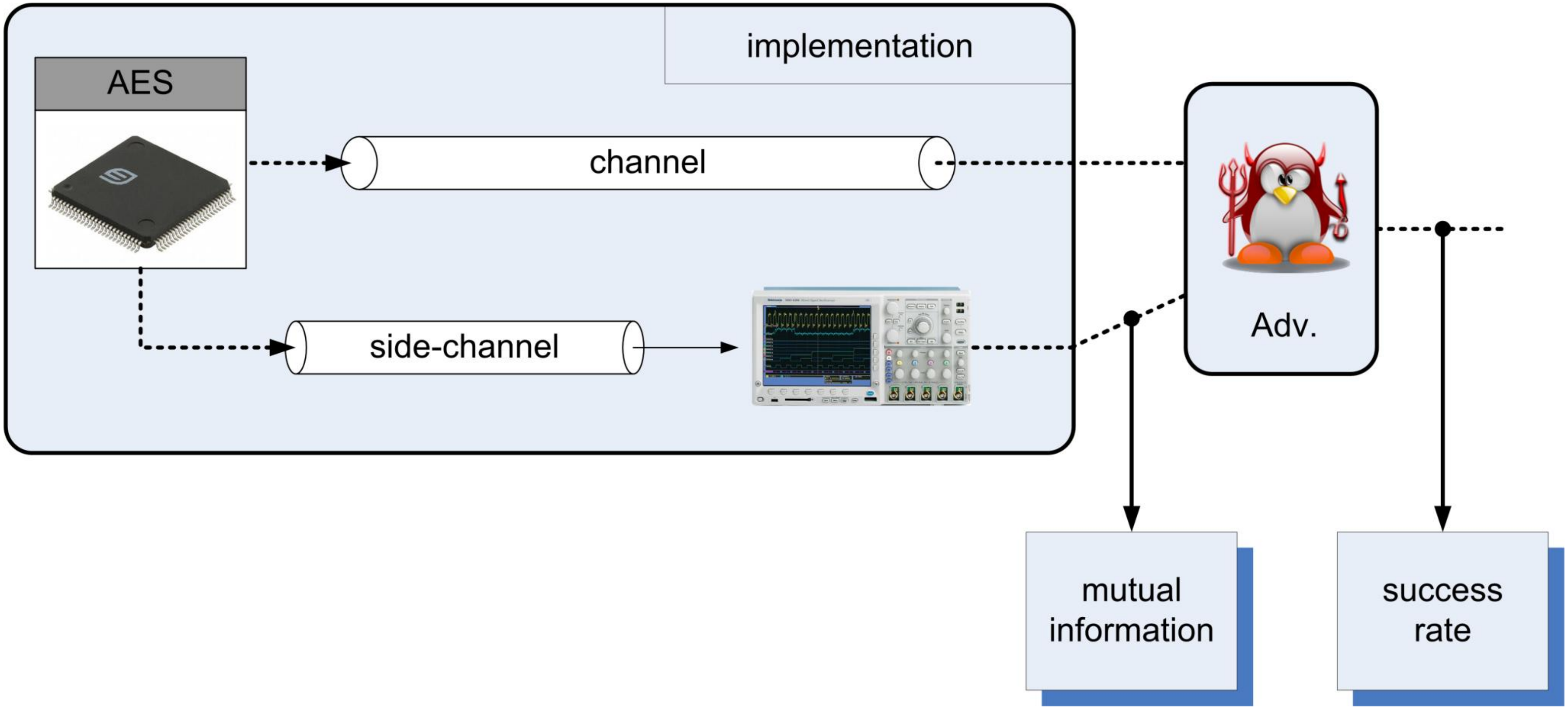

- More generally: evaluate implementations with IT metrics, evaluate adversaries with security metrics

Fair evaluation of side-channel leakage

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- Good news: side-channel attacks need a model
  - i.e. an estimation of the leakage distribution

Fair evaluation of side-channel leakage

- Leakage certification is first concerned with IT metrics (i.e. aims at estimating the information leakage independent of the adversary)
- *But estimating the mutual information between arbitrary distributions is notoriously hard!*
- Good news: side-channel attacks need a model
  - i.e. an estimation of the leakage distribution
- Main idea: estimate the mutual information from the “best available” profiled model (i.e. worst case)

- Information leakage on the secret key

$$\mathrm{H}[K] - \sum_{k} \mathrm{Pr}[k] \sum_{l} \mathrm{Pr}_{chip}\,[l|k]\ .\log_2 \widehat{\mathrm{Pr}}_{model}\,[k|l]$$

- where $\widehat{\mathrm{Pr}}_{model}\,[k|l]$ is obtained by profiling
- and $\mathrm{Pr}_{chip}\,[l|k]$ is obtained by sampling

In practice: two-step process

- *Step 1*: estimate the leakage model $\widehat{\Pr}_{model}\,[k|l]$
  - e.g. with Gaussian templates, linear regression, Gaussian mixtures, Kernel density estimation, …

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- Note: measurements to estimate the leakage model and the IT metric must be independent!

Example

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$$\Rightarrow \frac{1}{N}\sum_{i=1}^{N} \log_2 pi_1$$

Two cases can happen [2]

- Case #1 (ideal): perfect profiling phase
- i.e. $\widehat{\Pr}_{model}[k|l] = \Pr_{chip}[l|k]$

$$\widehat{\mathrm{MI}}(K;L) = \mathrm{H}[K] - \sum_{k} \Pr[k] \sum_{l} \Pr_{chip}[l|k] \,.\log_2 \Pr_{chip}[l|k]$$

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- Case #2 (actual): bounded profiling phase
- i.e. $\widehat{\Pr}_{model}[k|l] \neq \Pr_{chip}[l|k]$

$$\widehat{\mathrm{PI}}(K;L) = \mathrm{H}[K] - \sum_k \Pr[k] \sum_l \Pr_{chip}[l|k] \,.\log_2 \widehat{\Pr}_{model}[k|l]$$

Main theorem (informal)

- PI(K;L) is directly proportional to the success rate of an adversary using $\widehat{\Pr}_{model}[k|l]$ as template

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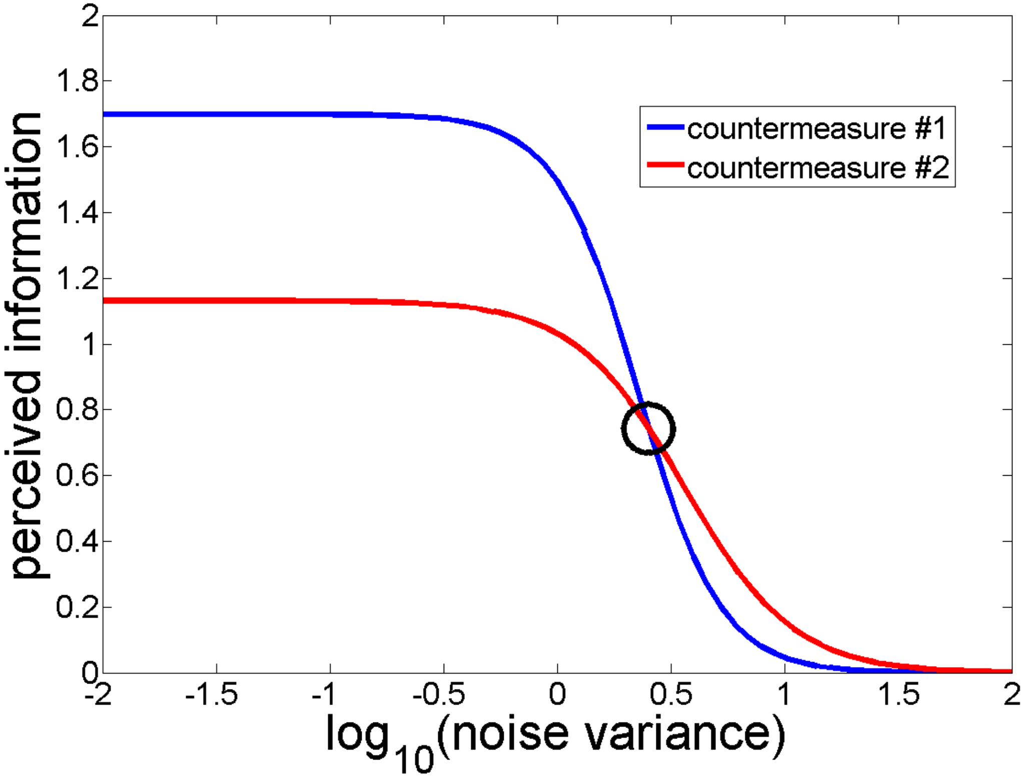
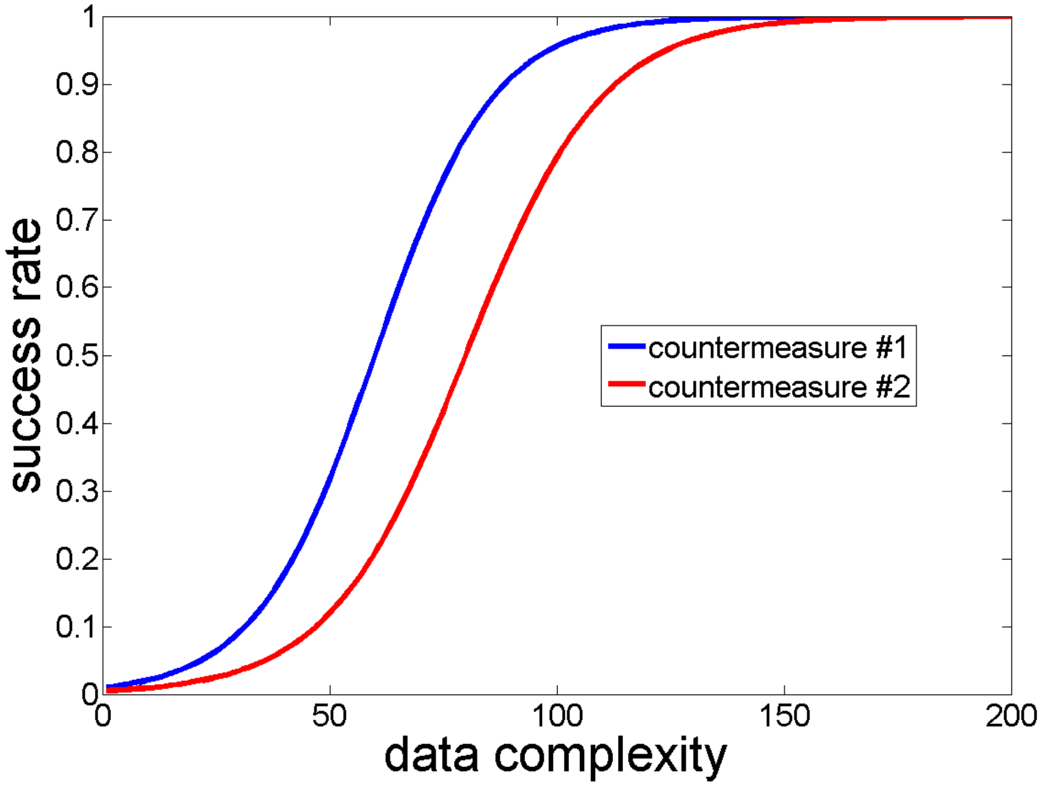
- e.g. PI(K;L) in function of the noise variance



As a result

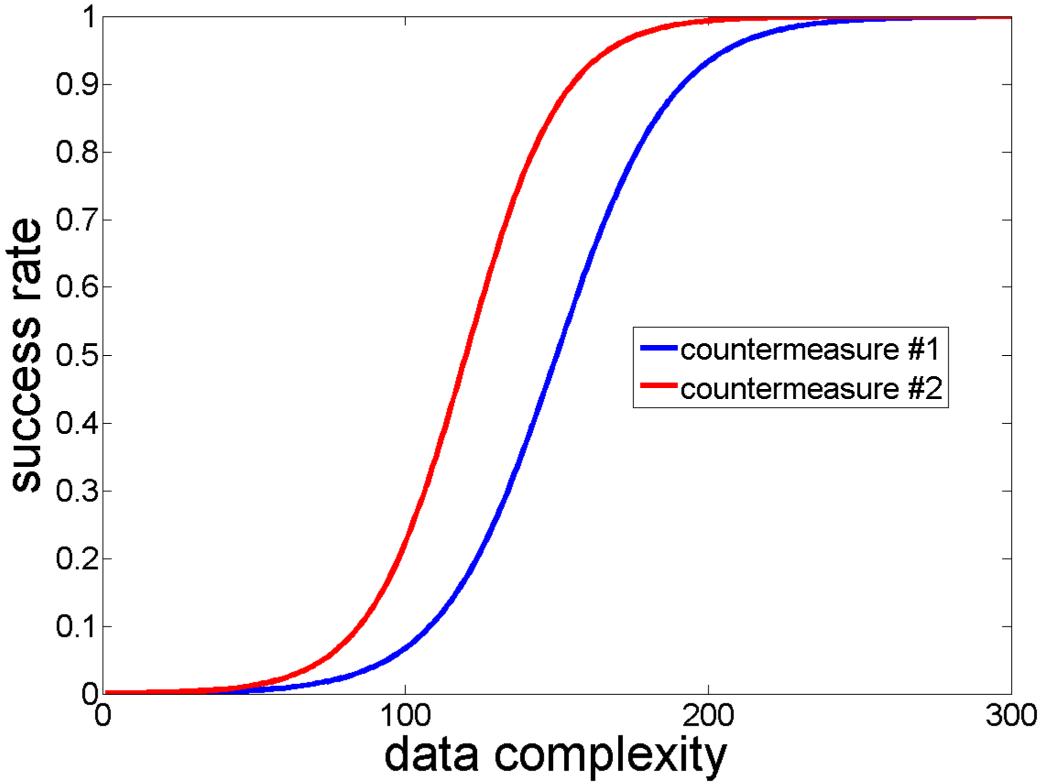
- Left of the intersection



- Countermeasure #2 more secure than first one

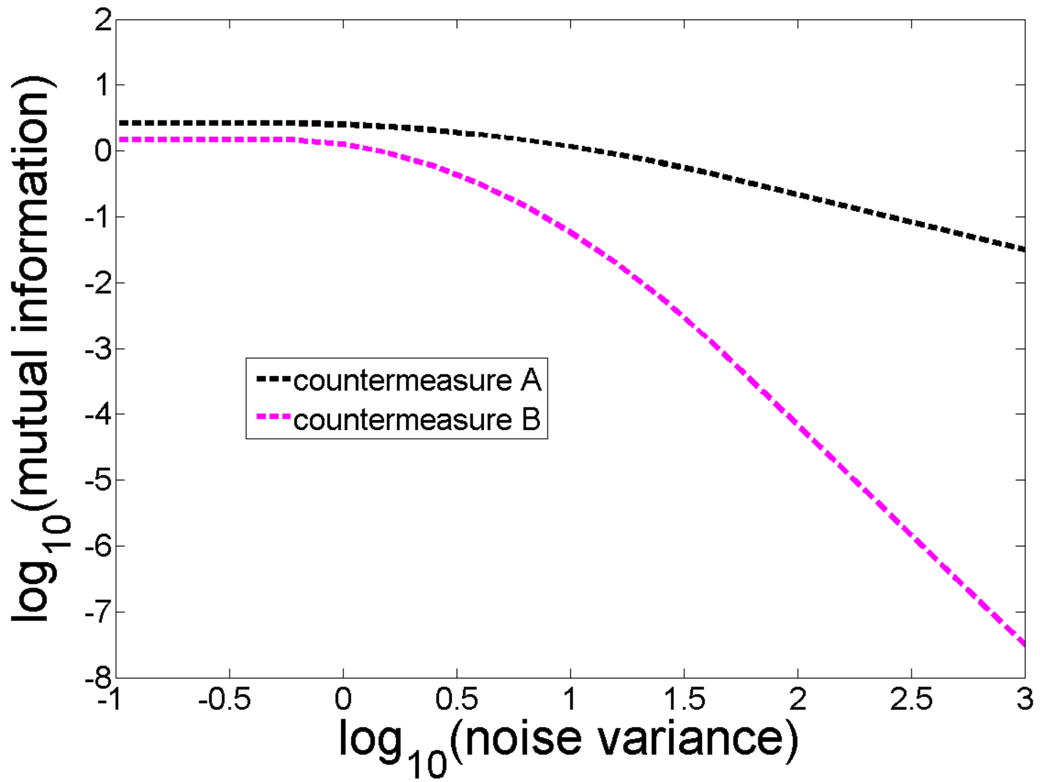
As a result

- Right of the intersection



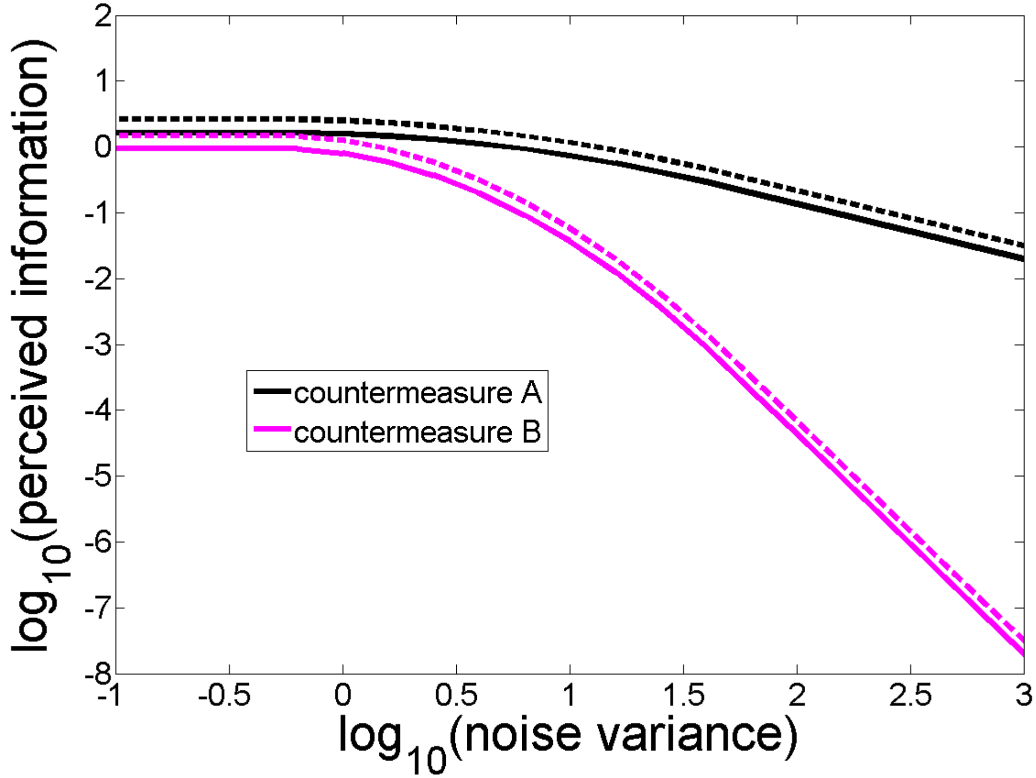
- Countermeasure #1 more secure than second one

- MI(K;L) measures the worst case data complexity

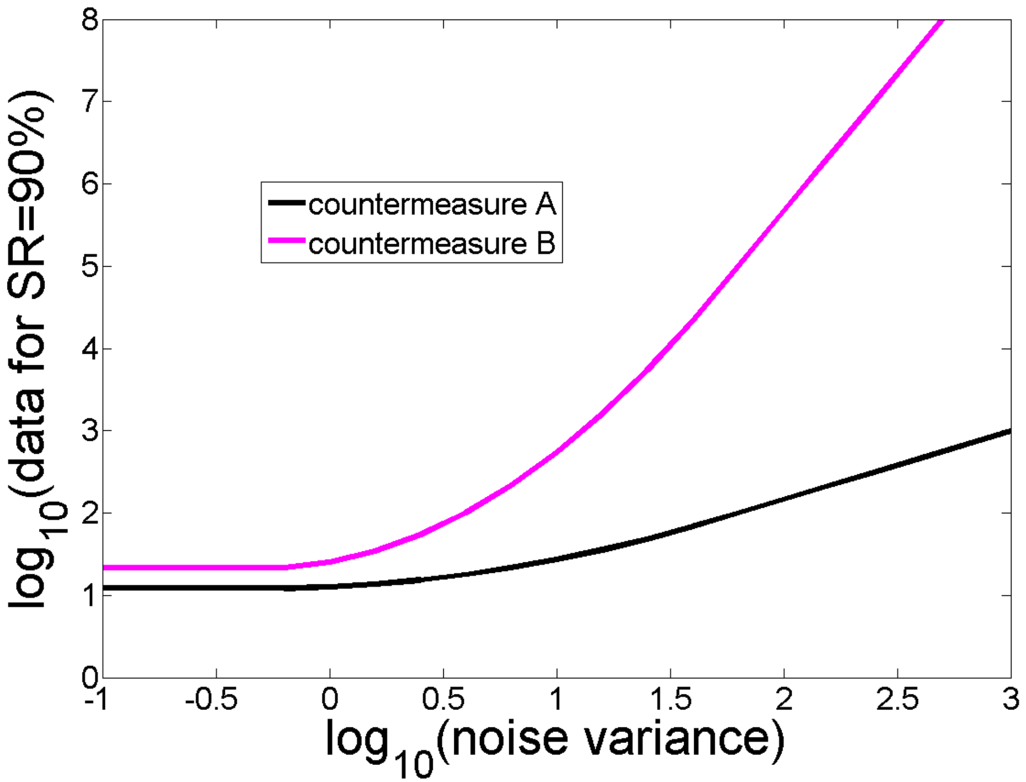


In other words

- PI(K;L) is the evaluator's best estimate



Relation with data complexity



- Theorem only proven in very specific cases
- But holds surprisingly well in real-world settings

Example: masking [3]

- Main idea: split the sensitive data in *r* shares

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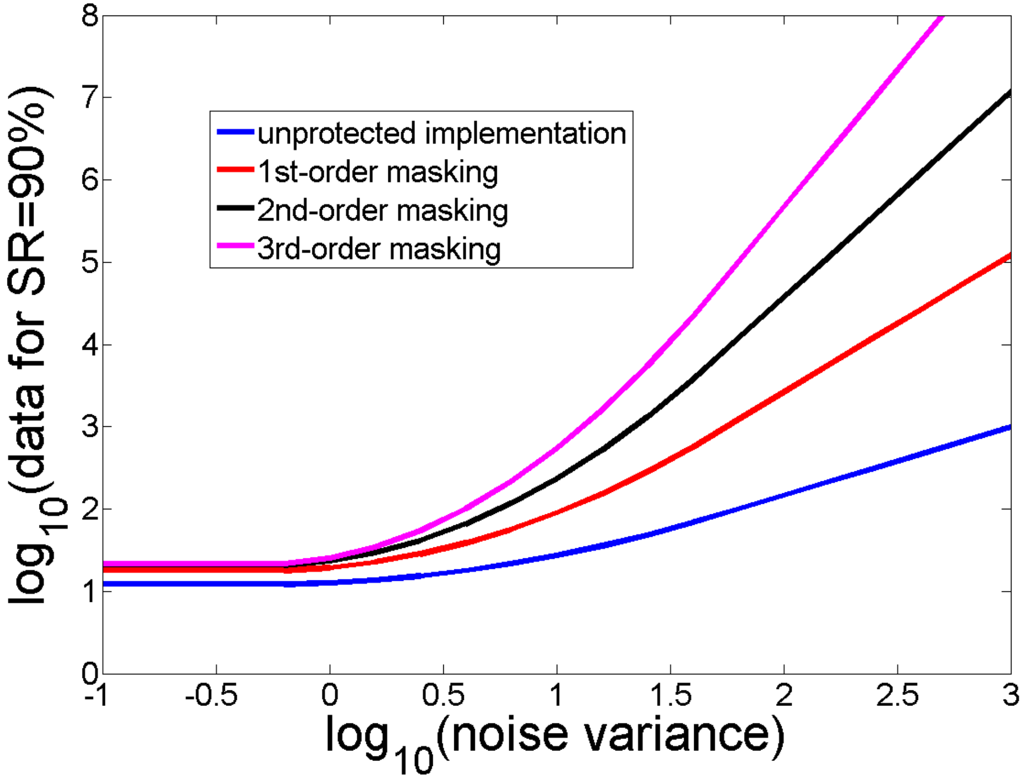
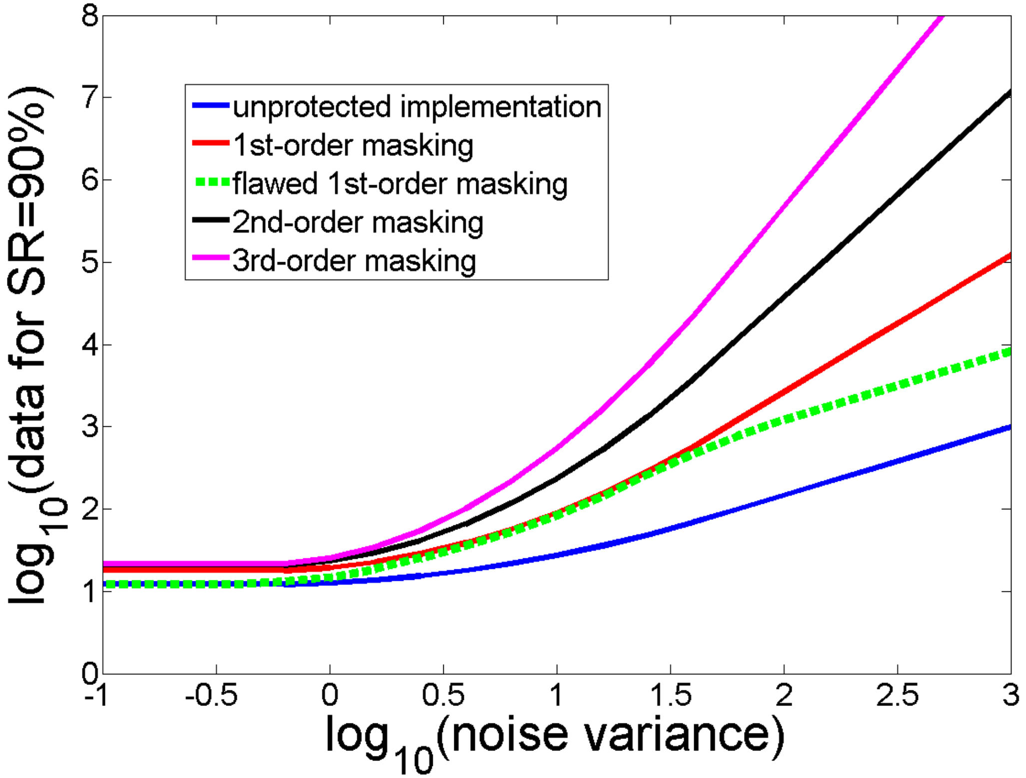
- If “perfect” implementation, the data complexity to break masking is proportional to $(\sigma_n^2)^r$
  - Perfect ≈ if the smallest-order key-dependent moment in the leakage distribution is *r*
  - Essentially depends on the hardware (e.g. glitches may make the implementation imperfect)

Information theoretic intuition



- Smallest-order key-dept. moment = curve slope

Information theoretic intuition



- Flaws due to physical defaults can be detected

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  - Critical point: PDF estimation problem

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- Implies to select good statistical tools
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- Tools are highly dependent on the contexts
  - So is the distance between MI and PI (and hence, the relevance of security evaluations)
- A few examples next…

Examples

	profiled attacks	non-profiled attacks
unprotected device, univariate leakage		
unprotected device, multivariate leakage		
dual-rail pre-charged implementation		
time randomizations		
masking		
combination of countermeasures		

- Different implementations and countermeasures
- Which cases are “easy to evaluate”?

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- Most distinguishers are asymtotically equivalent [4]
- … if provided with the same leakage model

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- PCA, LDA, … useful in the profiled case [5]
- Dimension reduction uneasy in non-profiled case

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- Same tools as for unprotected devices work well
- Non-linear leakage functions require profiling [6]

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- Uneasy to evaluate for both type of attacks
- Signal proc. can cancel countermeasures [7,8]

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- Becomes measurement intensive as r increases
- No solution is always optimal in non-profiled case

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- Specially hard if the design is unknown
- Large distance btw. profiled & non-profiled cases

Summarizing

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- IT curves capture most intuition regarding the data complexity of worst case side-channel attacks

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- Evaluator's goal: avoid "false sense of security"
  - PI(K;L) ≠ MI(K;L)
  - Significant differences may arise due to signal processing, bad assumptions on the leakage, …
  - Measurement setup also matters!

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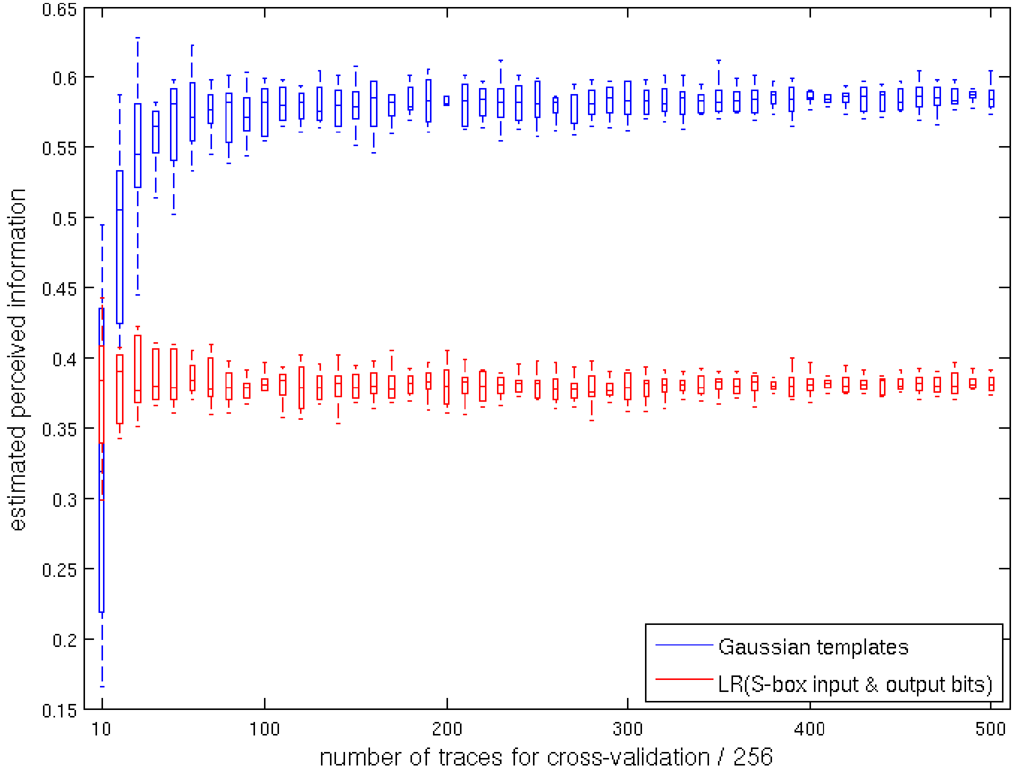
- Next: we show that indirect approaches allow answering the question quite rigorously

- Main idea: quantify *estimation* & *assumption* errors

1. Estimation errors => cross-validation

- Split traces in 10 (non-overlapping) sets, use 9/10th for profiling, 1/10th for estimating the PI
- Repeat 10 times to get average & spread



2. Assumption errors => distance sampling

- Fact: two multidimensional distributions $\mathcal{F}$ and $\mathcal{G}$ are equal if the variables X~$\mathcal{F}$ and Y~$\mathcal{G}$ generate identical distributions for the distance D(X,Y)

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- And the sampled distance

$$\hat{g}_N(d) = \Pr[l_1 - l_2 \leq d \mid l_1 \overset{N}{\Leftarrow} \widehat{\Pr}_{model}, l_2 \overset{N}{\Leftarrow} \Pr_{chip}]$$

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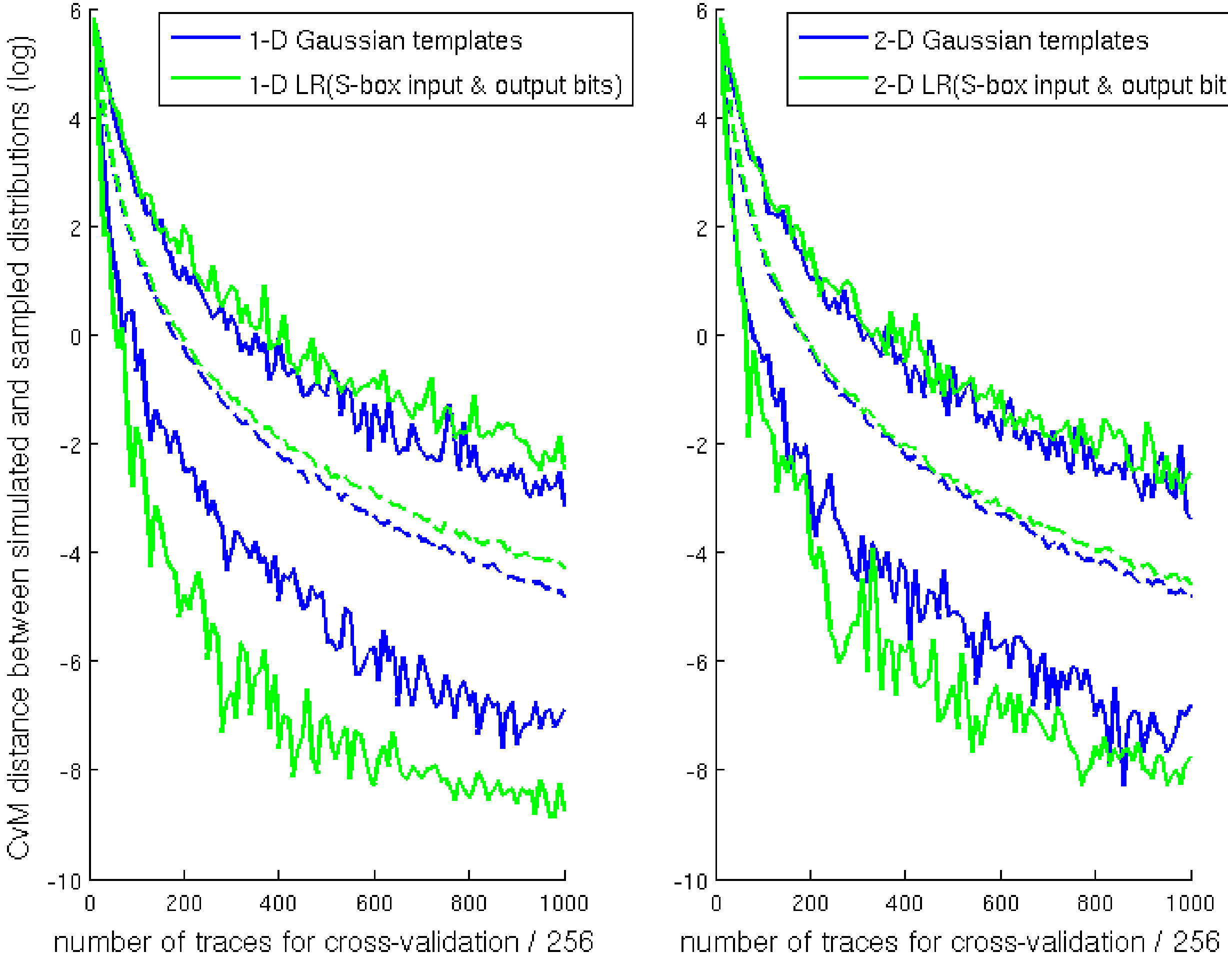
- And test their CvM divergence

$$\widehat{\mathrm{CvM}}\,(f_{sim}, \hat{g}_N) = \int [f_{sim}(x) - \hat{g}_N(x)]^2 dx$$

With cross-validation again, we obtain



- Any incorrect assumption => CvM saturates

3. Quantifying the information loss

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- Idea: try to detect when (i.e. for which # of traces in the cross-validation set) assumption errors become significant in front of estimation ones

How to?

- Compute a sampled simulated distance

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How to?

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$$\hat{f}_{sim,N}(d) = \Pr[l_1 - l_2 \leq d \mid l_1, l_2 \overset{N}{\Leftarrow} \widehat{\Pr}_{model}]$$

- Characterize the probability that a given divergence between f_{sim} and $\hat{f}_{sim,N}$ would be observed for a given number of traces *N*

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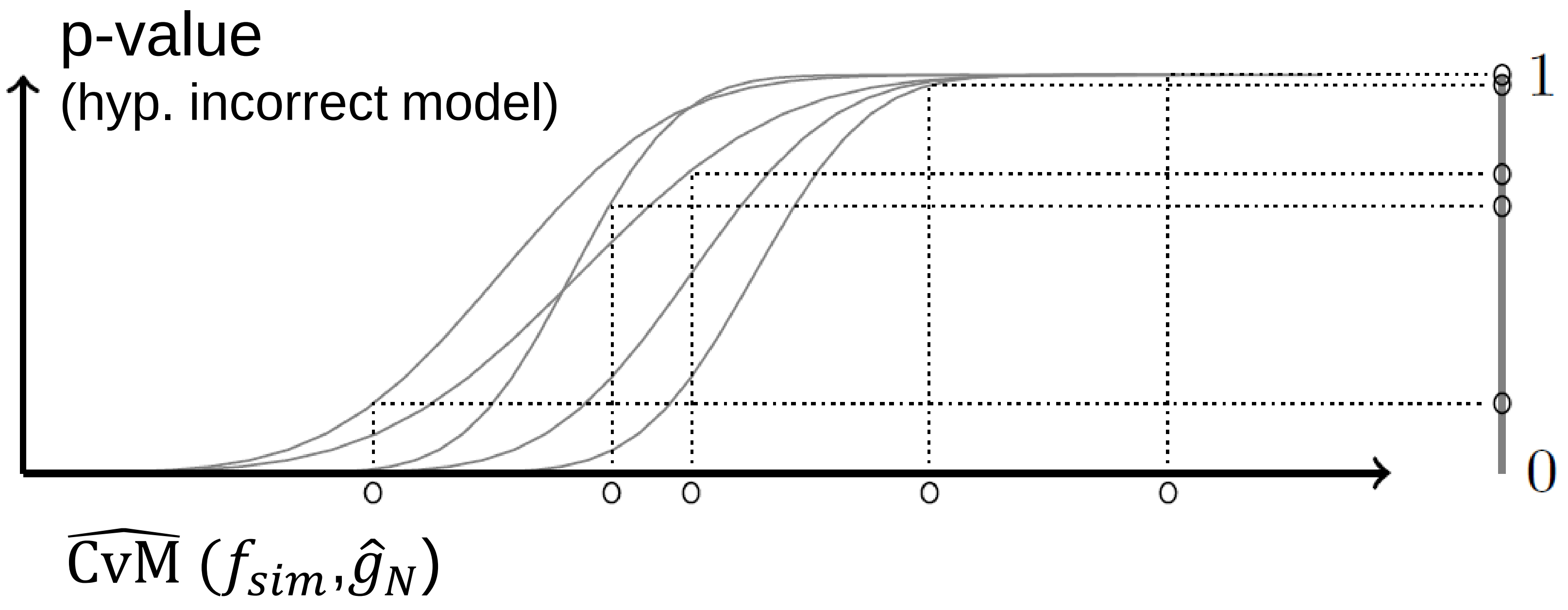
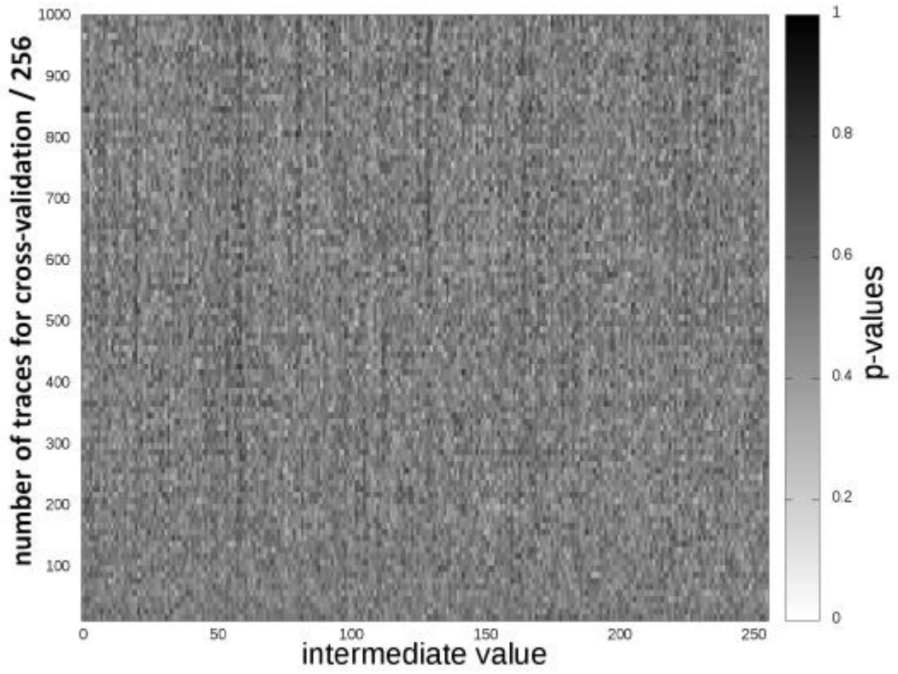
- Characterize the probability that a given divergence between f_{sim} and $\hat{f}_{sim,N}$ would be observed for a given number of traces *N*

- Look whether a given divergence between f_{sim} and $\hat{g}_N$ (the latter obtained during cross-validation again) can be due to estimation errors

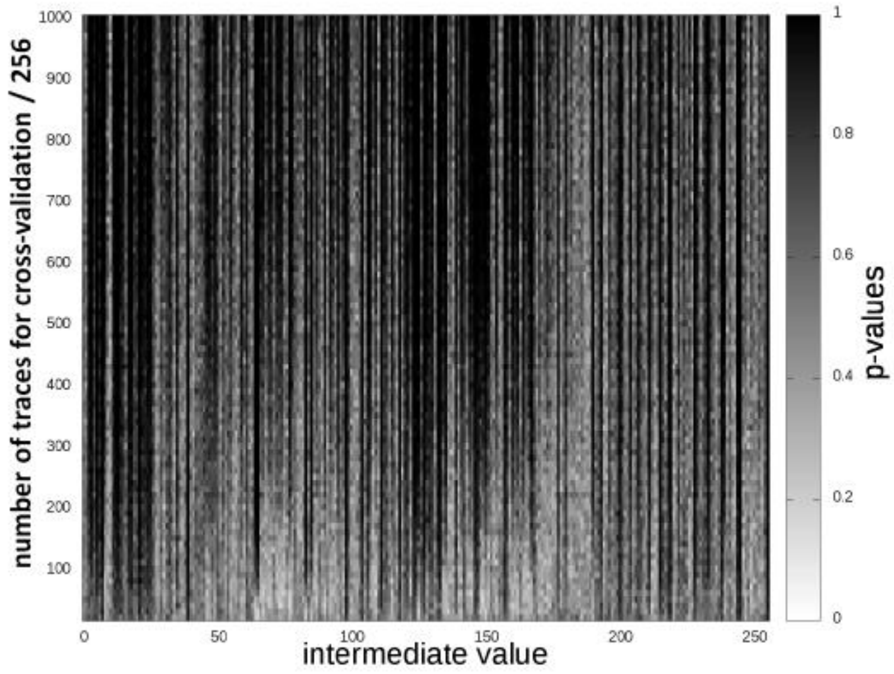
Illustration



Example



Gaussian templates



Stochastic model

Towards leakage bounds?

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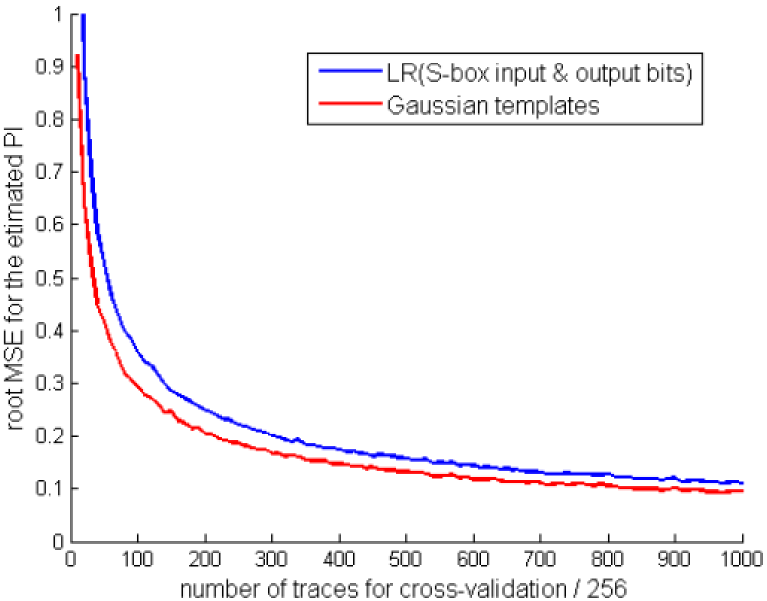
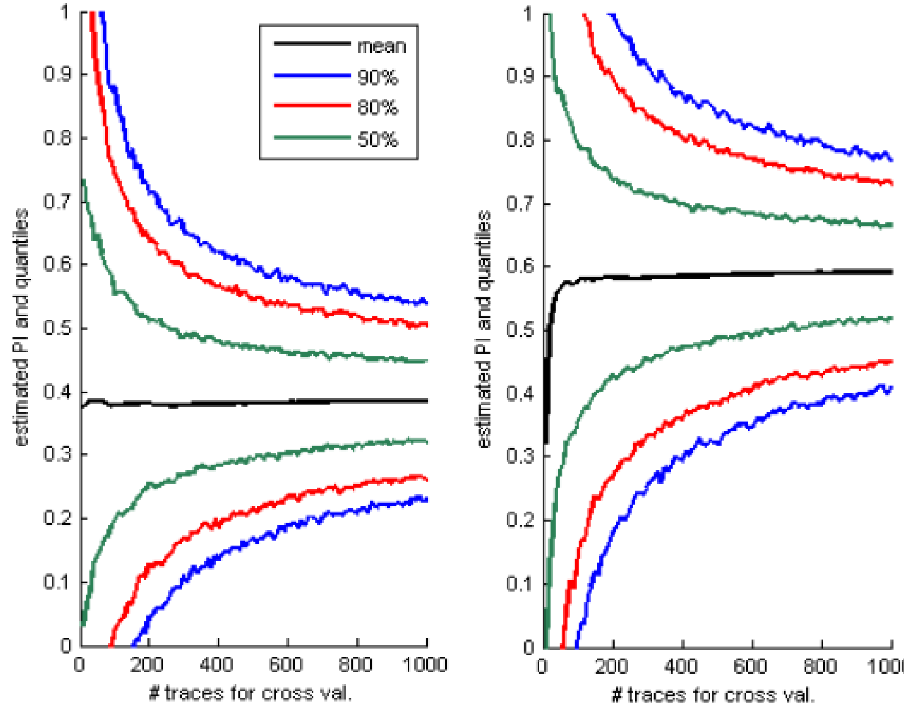
- Conjecture: For *N* such that the assumption errors are “not significant” in front of estimation errors, we can “bound” the information loss by quantifying the estimation error
  - (i.e. assumption errors that are detected for smaller *N*’s are inevitably larger)

Example





- Identified template attack with PI = 0.58

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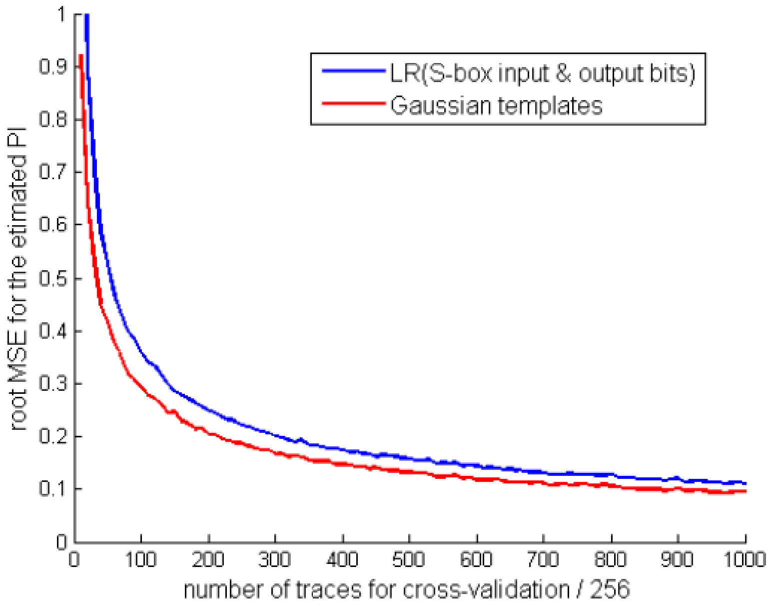
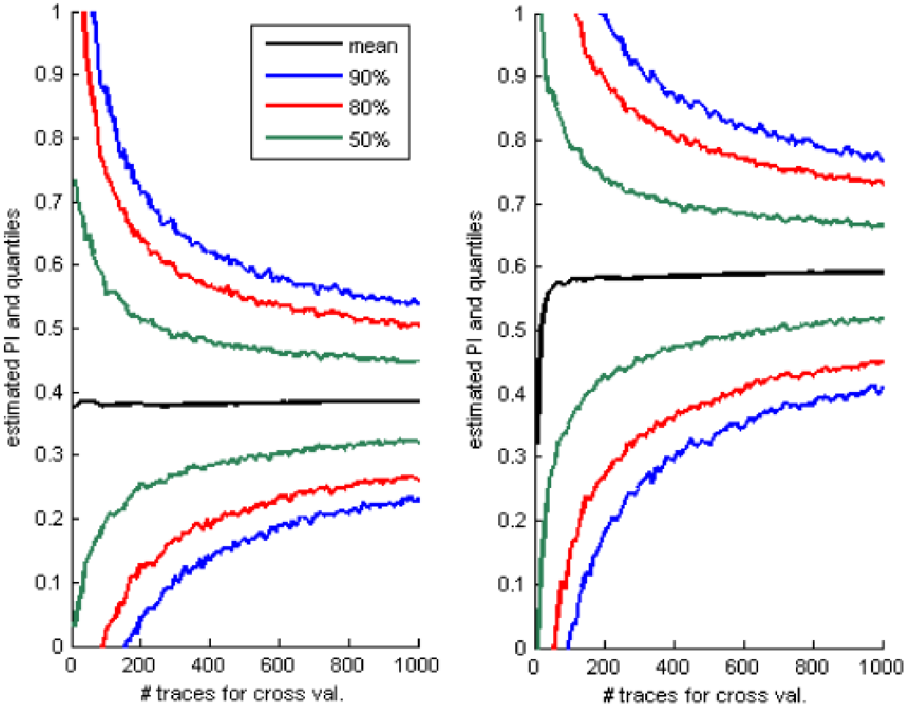
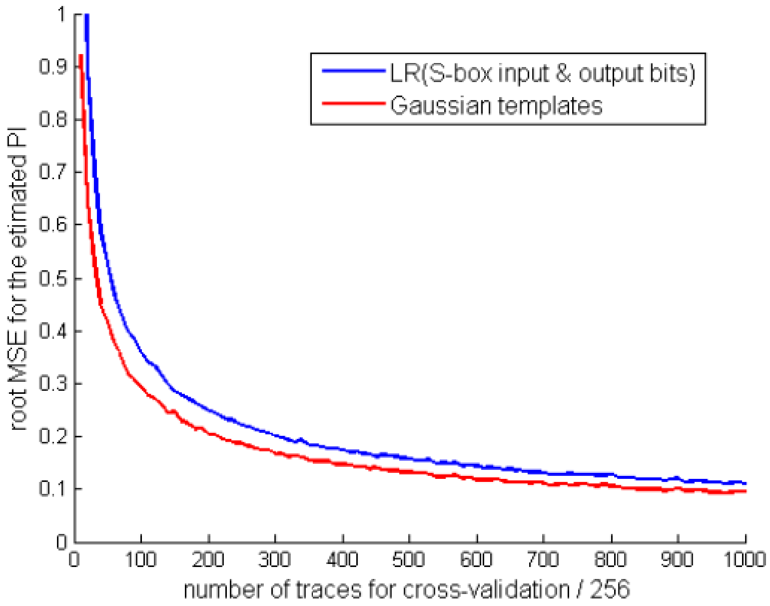
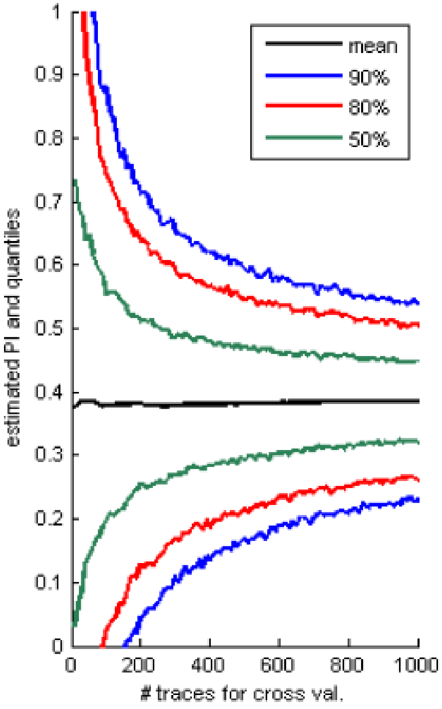
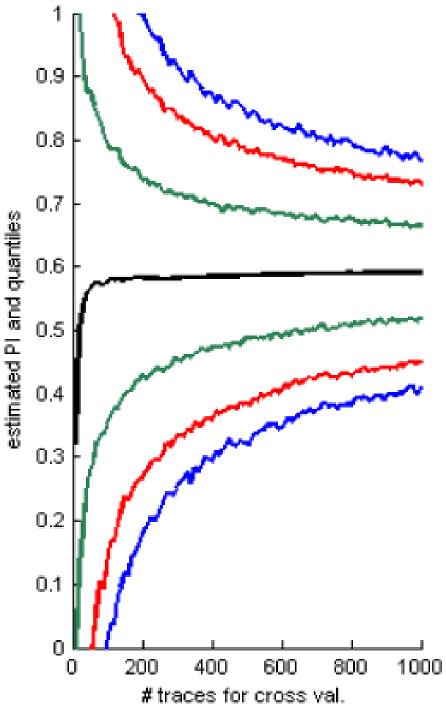




- Identified template attack with PI = 0.58
- No assumption errors for *N*=1000







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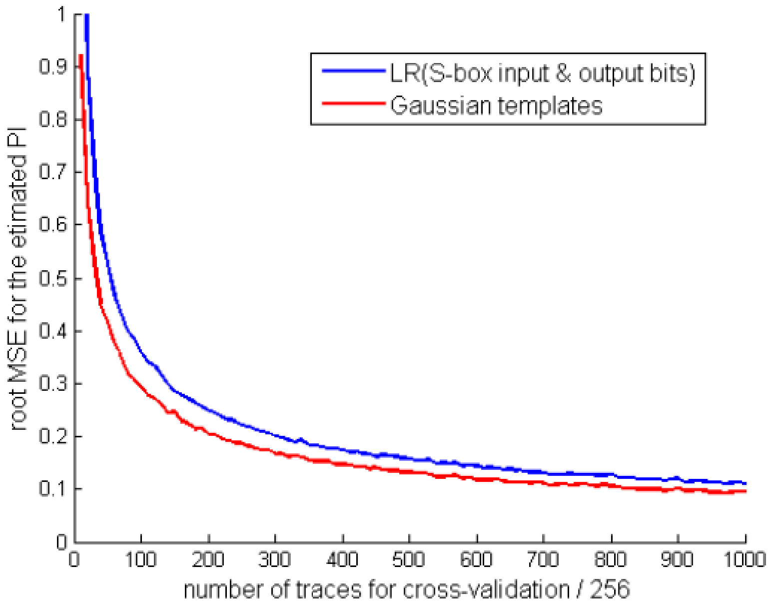
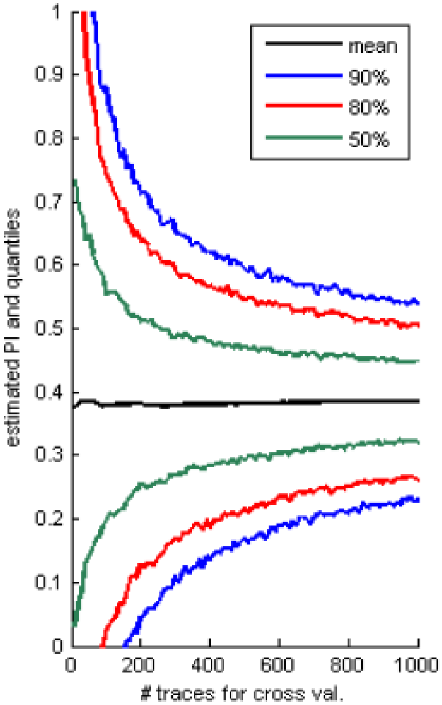
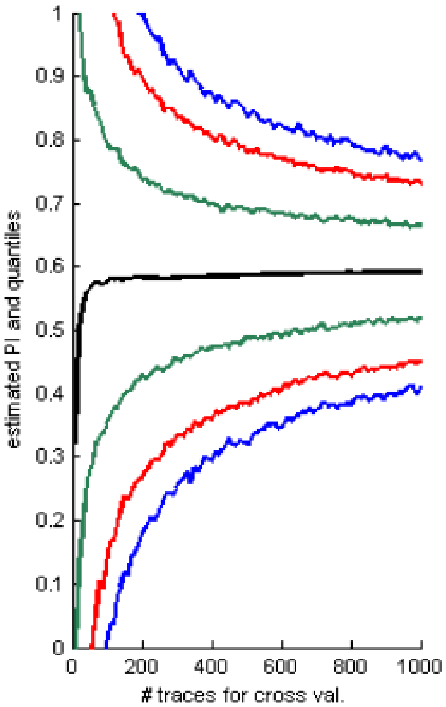
- Estimation error ~ 0.11 at this point

Example





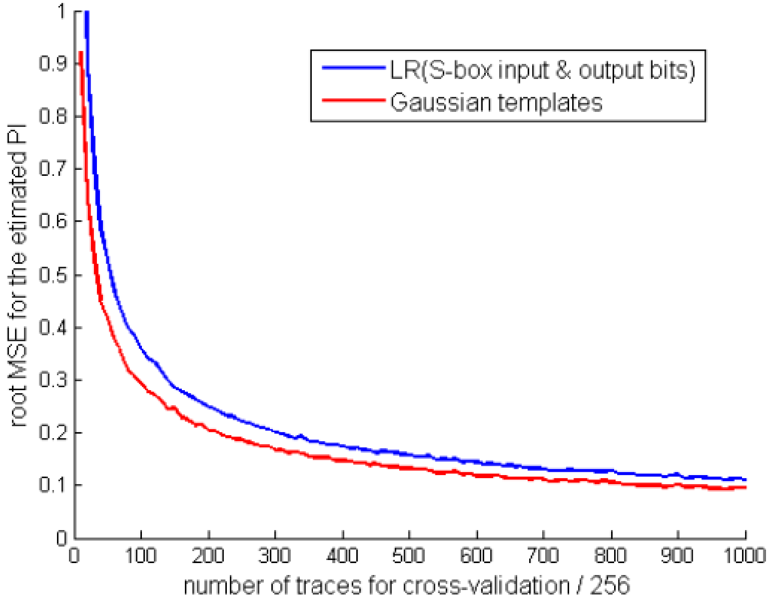


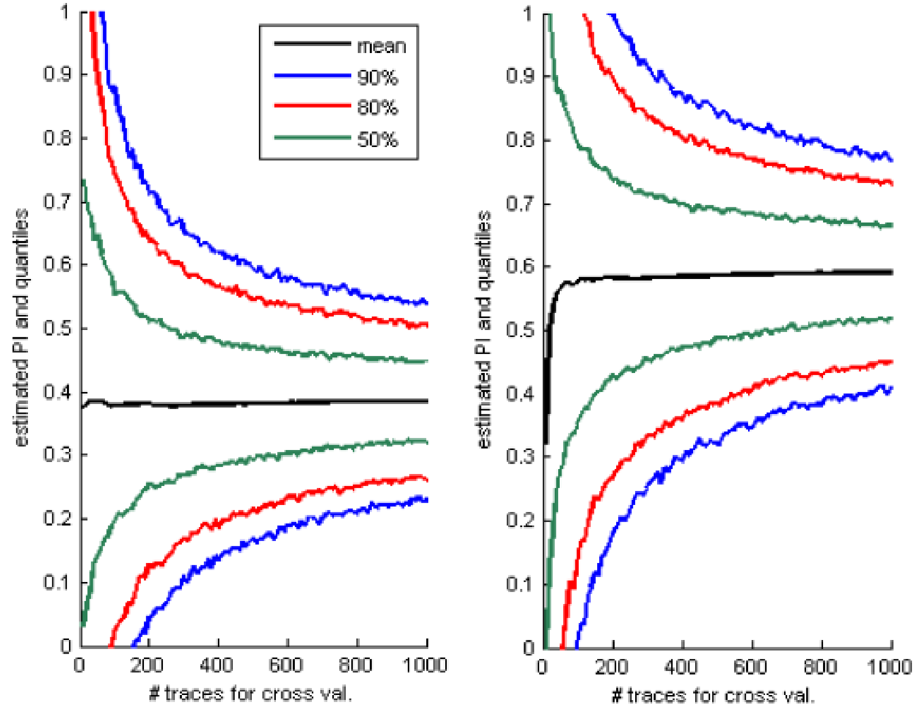
- Identified template attack with PI = 0.58
- No assumption errors for *N*=1000
- Estimation error ~ 0.11 at this point

=> With "low" confidence, no attack exist with PI>0.69

=> With "high" confidence, no attack exist with PI>0.80

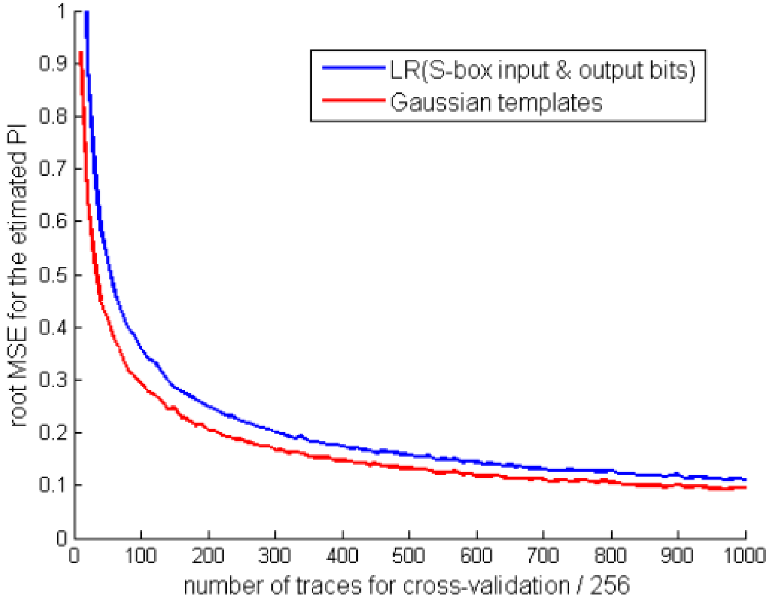
Example

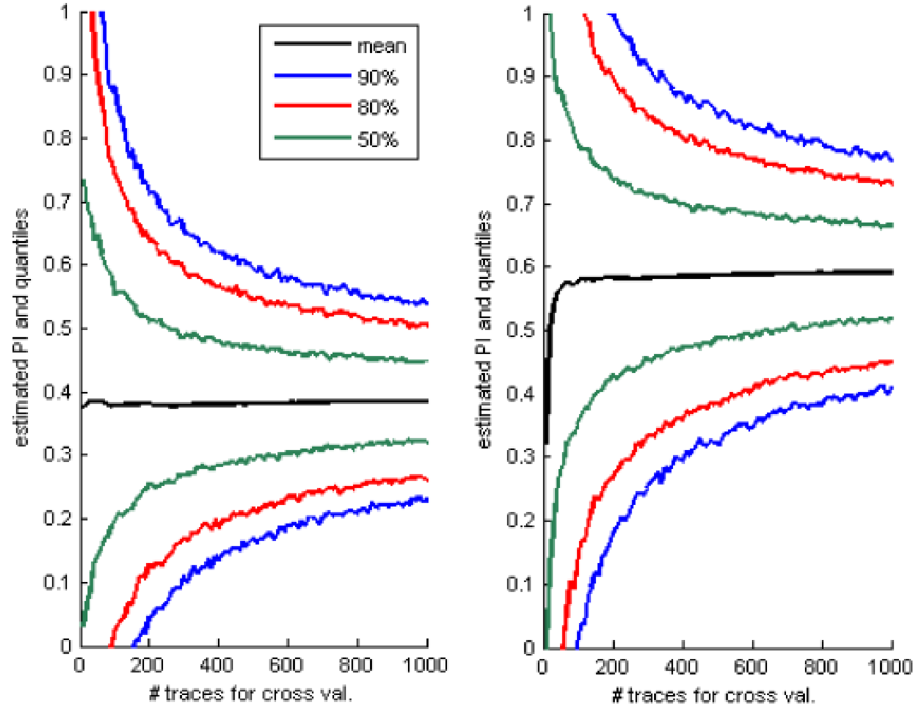




- Identified stochastic attack with PI = 0.38

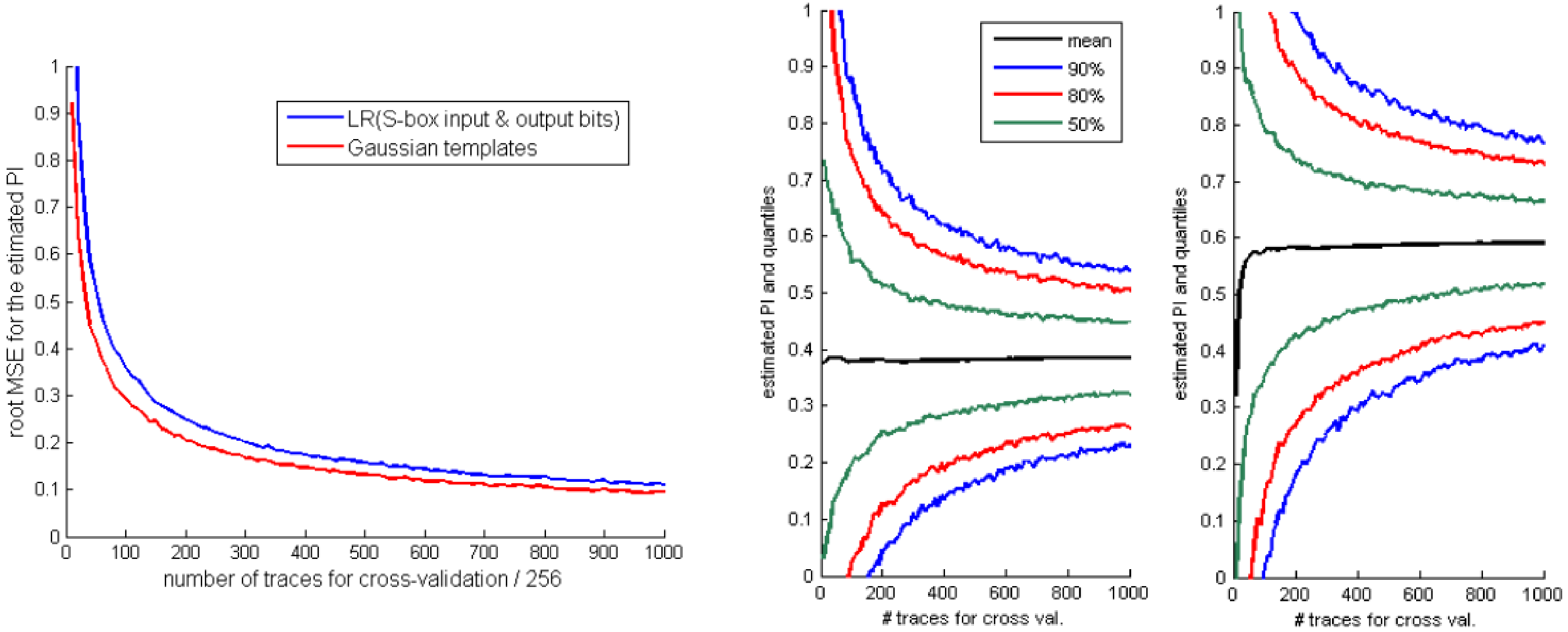
Example





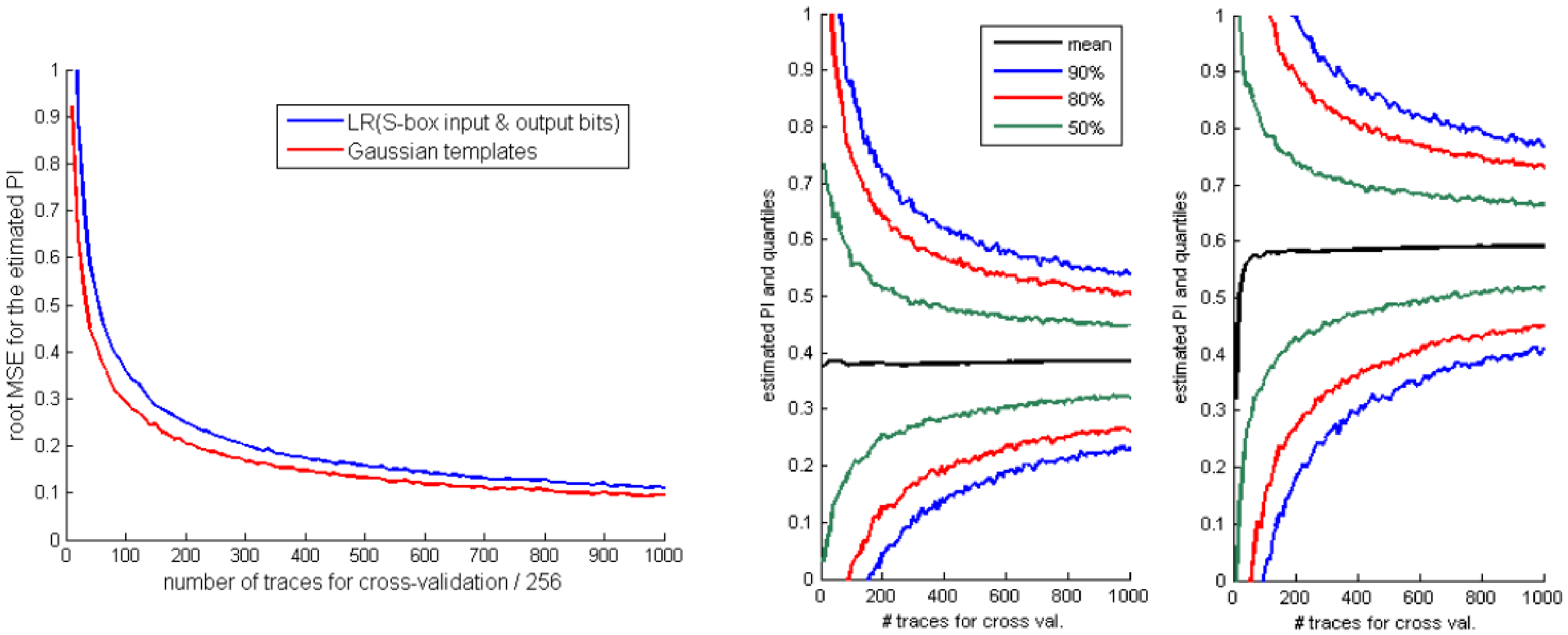
- Identified stochastic attack with PI = 0.38
- Assumption errors for N=100

Example



- Identified stochastic attack with PI = 0.38
- Assumption errors for N=100
- Estimation error ~ 0.29 at this point

Example

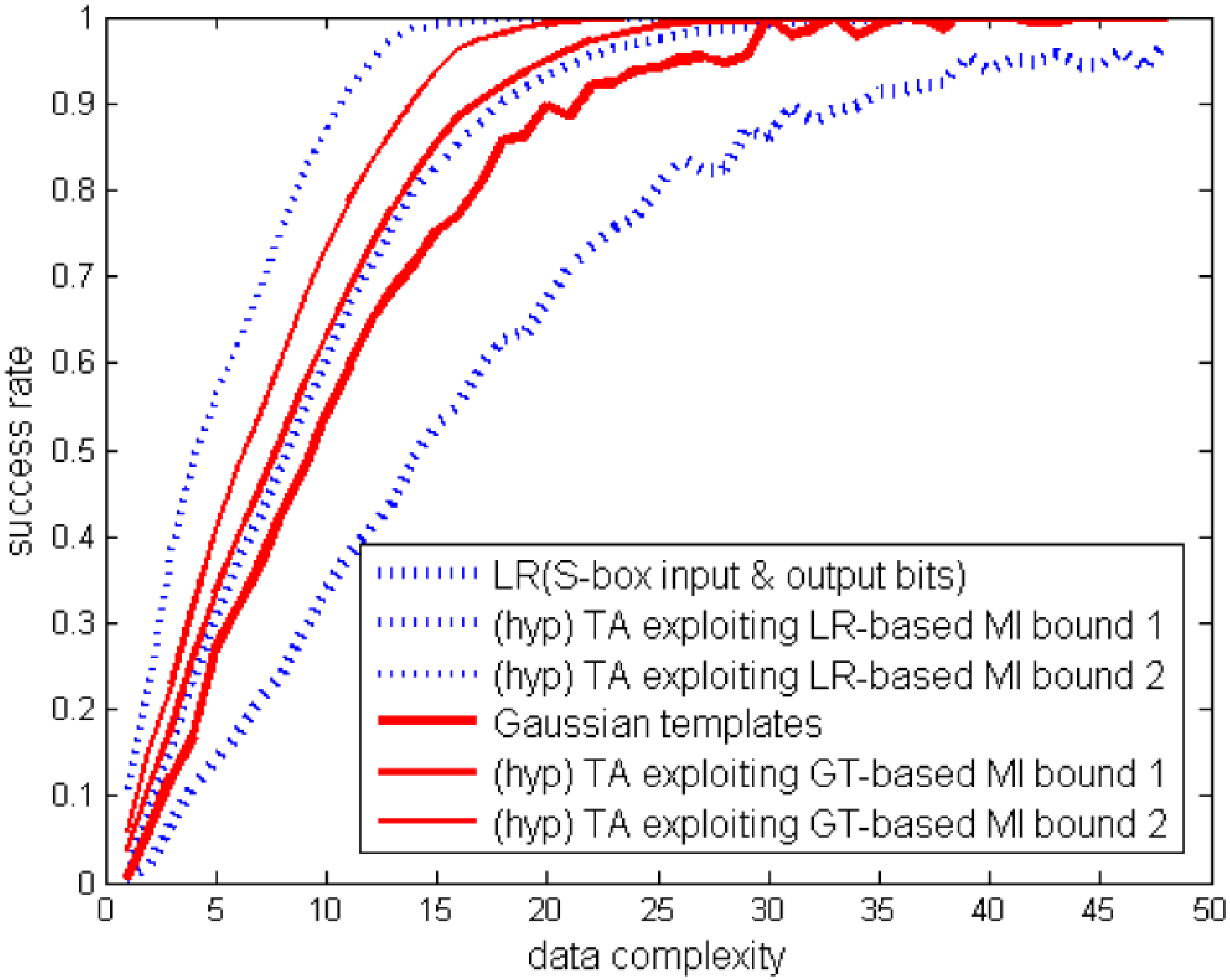


- Identified stochastic attack with PI = 0.38
- Assumption errors for *N*=100
- Estimation error ~ 0.29 at this point

=> With “low” confidence, no attack exist with PI>0.67

=> With “high” confidence, no attack exist with PI>0.96

Interpretation => success rates



Is that formally proven?

- No! (in fact there exist counterexamples)
- … but just as the PI <=> success rate connection

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    - (but corresponds to less relevant scenarios)

- Good news: can be tested in simulations (since we know the true MI values in these cases!)

Outline

- The Eurocrypt 2009 framework revisited
- New results towards information leakage bounds
- Security analyzes and time complexity

Security analyzes

- Note: previous discussion mainly relates to the data complexity of side-channel attacks
- Time/memory complexity also matters

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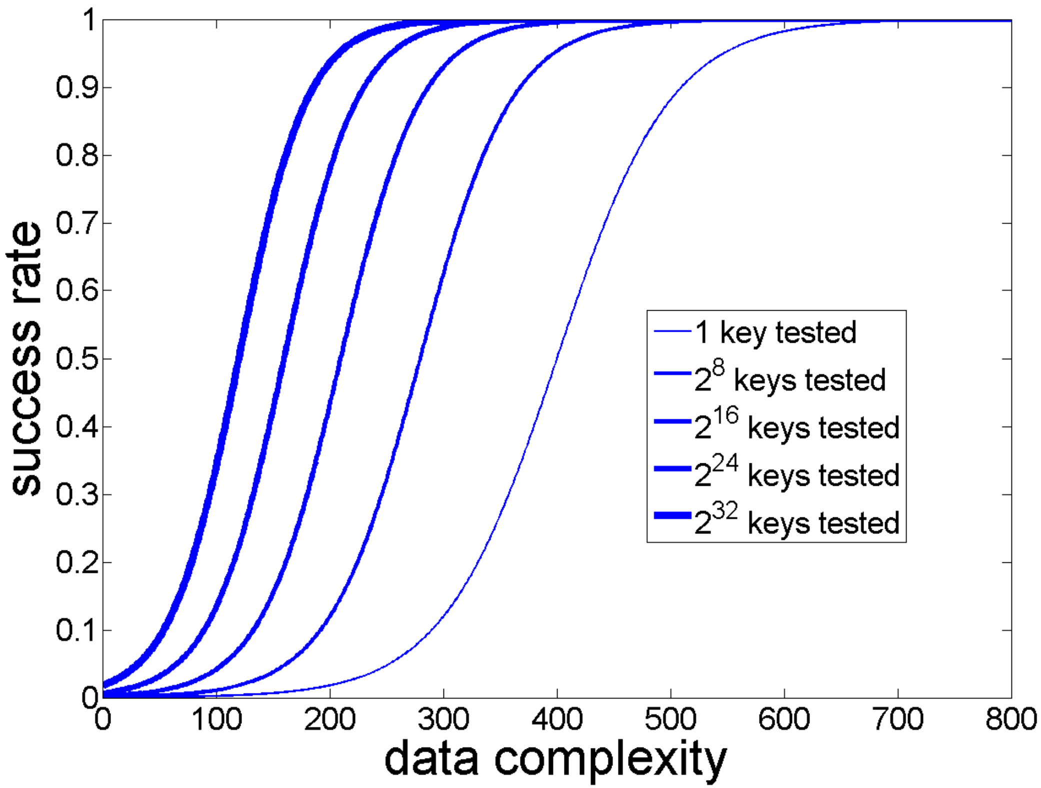
- Note: previous discussion mainly relates to the data complexity of side-channel attacks
- Time/memory complexity also matters

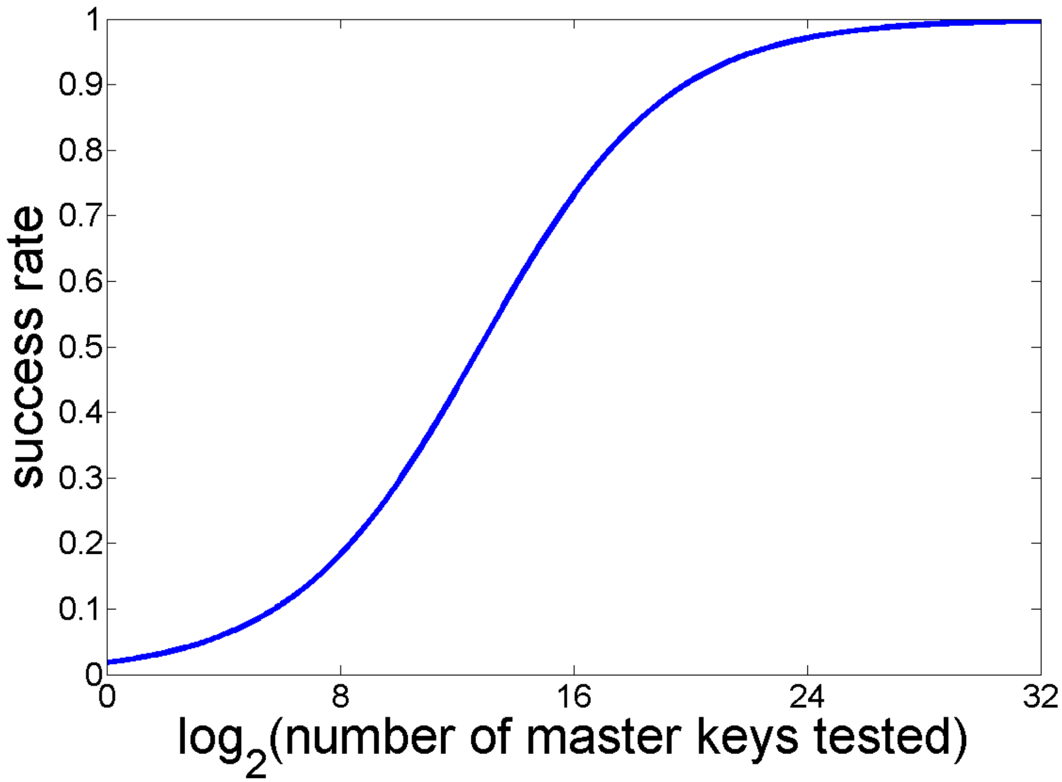
- In the context of “standard DPA”, the exploitation of computation is typically reflected by:
  - Key enumeration
  - Rank estimation

Key enumeration [9]



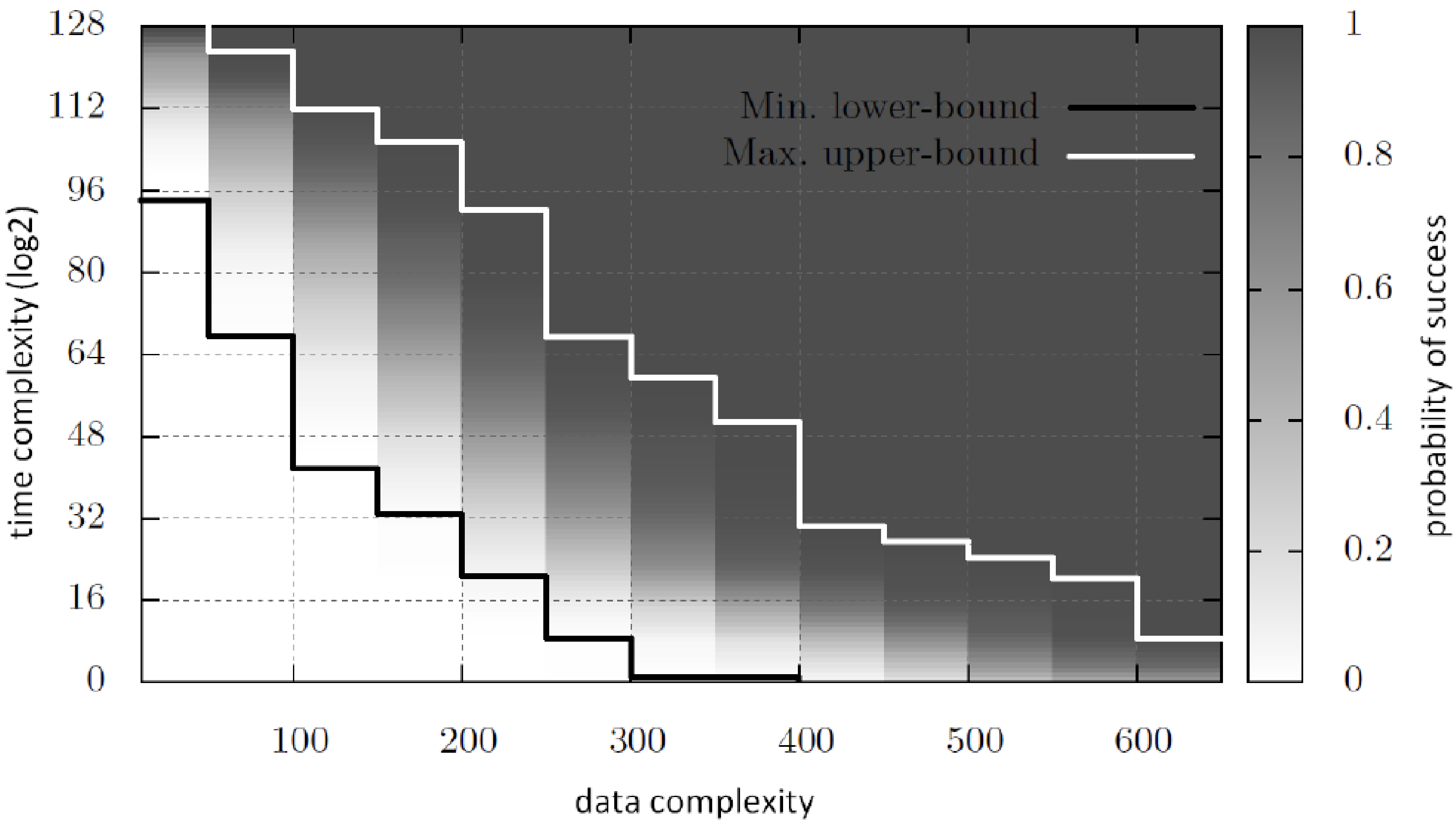
- Significant impact on the success rates!
- Very efficient attack tool (e.g. DPA contest)

Key enumeration [9]



- Missing data can always be traded for computations

Rank estimation [10]



- Evaluator's counterpart to key enumeration (the key must be known!) leading to complete security graphs

Conclusions

Main message:

- Possibility to “bound” the information leakage
- i.e. to know how far actual security evaluations computing the PI are from the true (unknown) MI
- Next: find meaningful examples/counterexamples

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- Possibility to “bound” the information leakage
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Cautionary note:
- Fair evaluations must consider both data and time
  - i.e. enumeration and rank estimation for DPA
  - But also algebraic side-channel attacks [11]

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THANKS

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