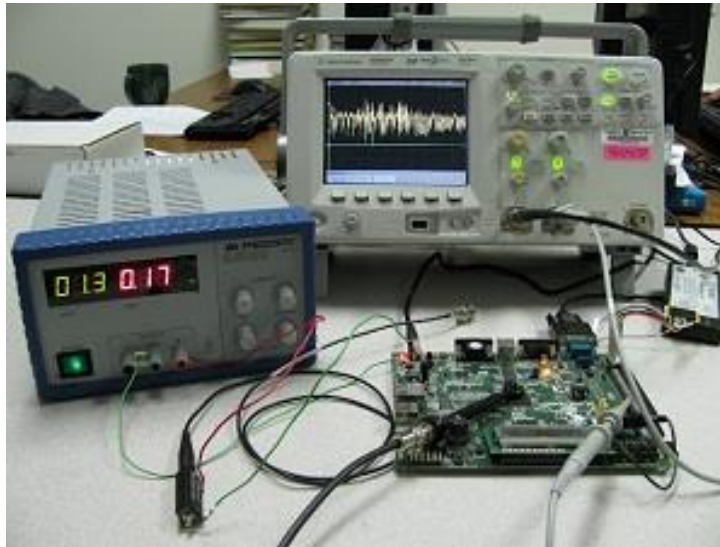


Introduction to Side-Channel Analysis



François-Xavier Standaert

UCL Crypto Group, Belgium

Summer school on real-world crypto, 2016

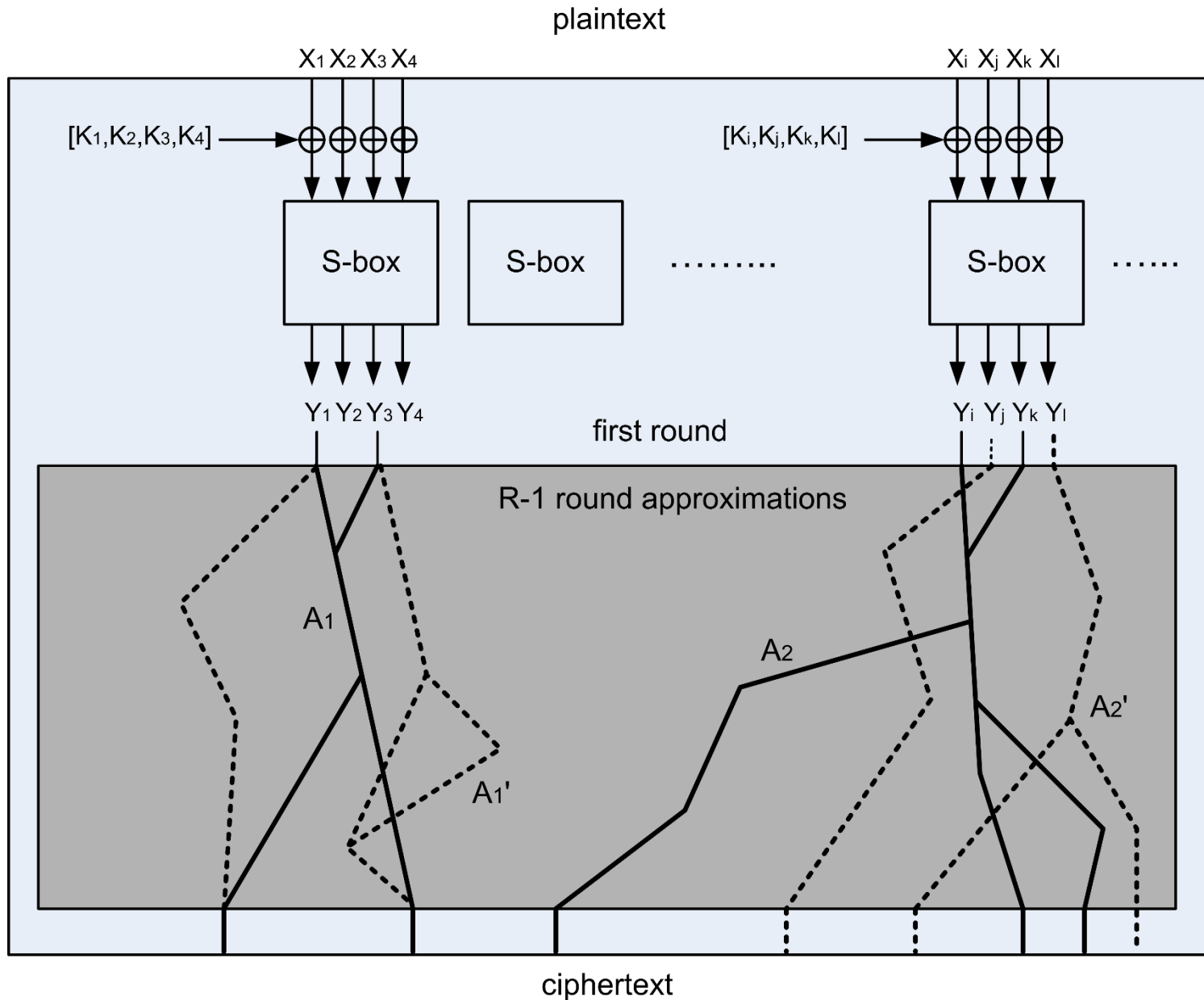
Outline

- Link with linear cryptanalysis
- Standard Differential Power Analysis
- Noise-based security (is not enough)
- *CPA vs Gaussian templates*
- Post-processing the traces
- Noise amplification (aka masking)
- Conclusions & advanced topics

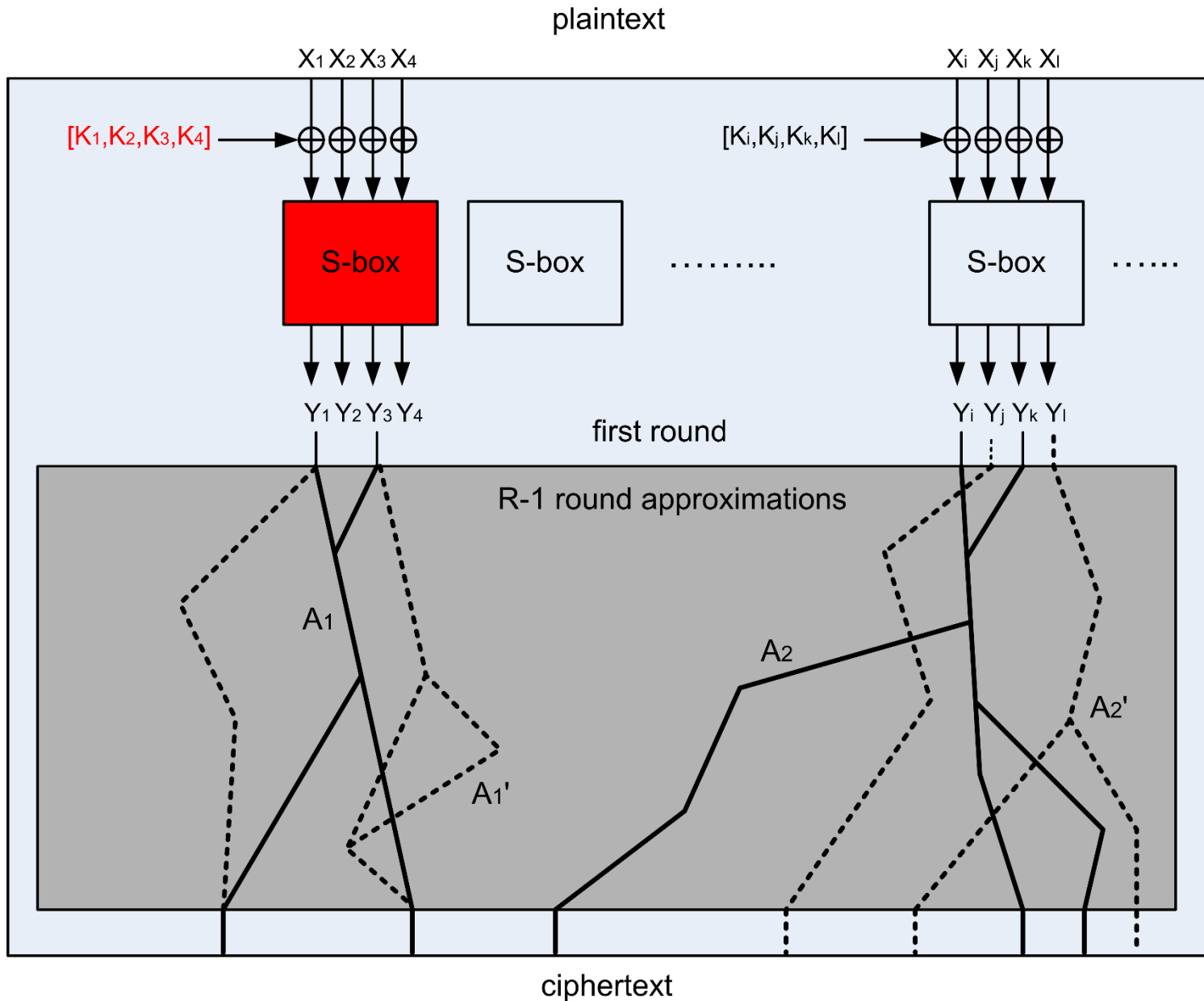
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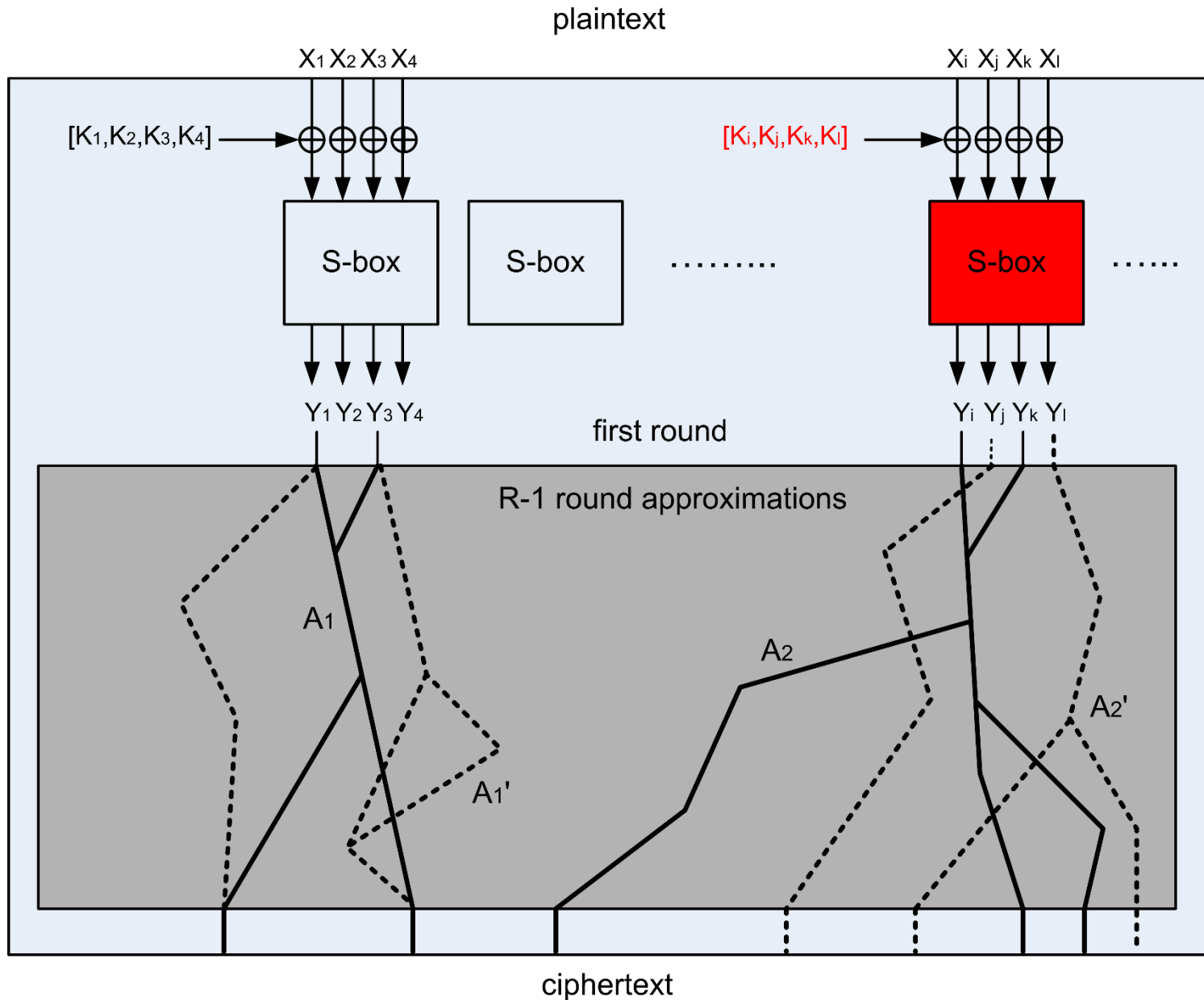
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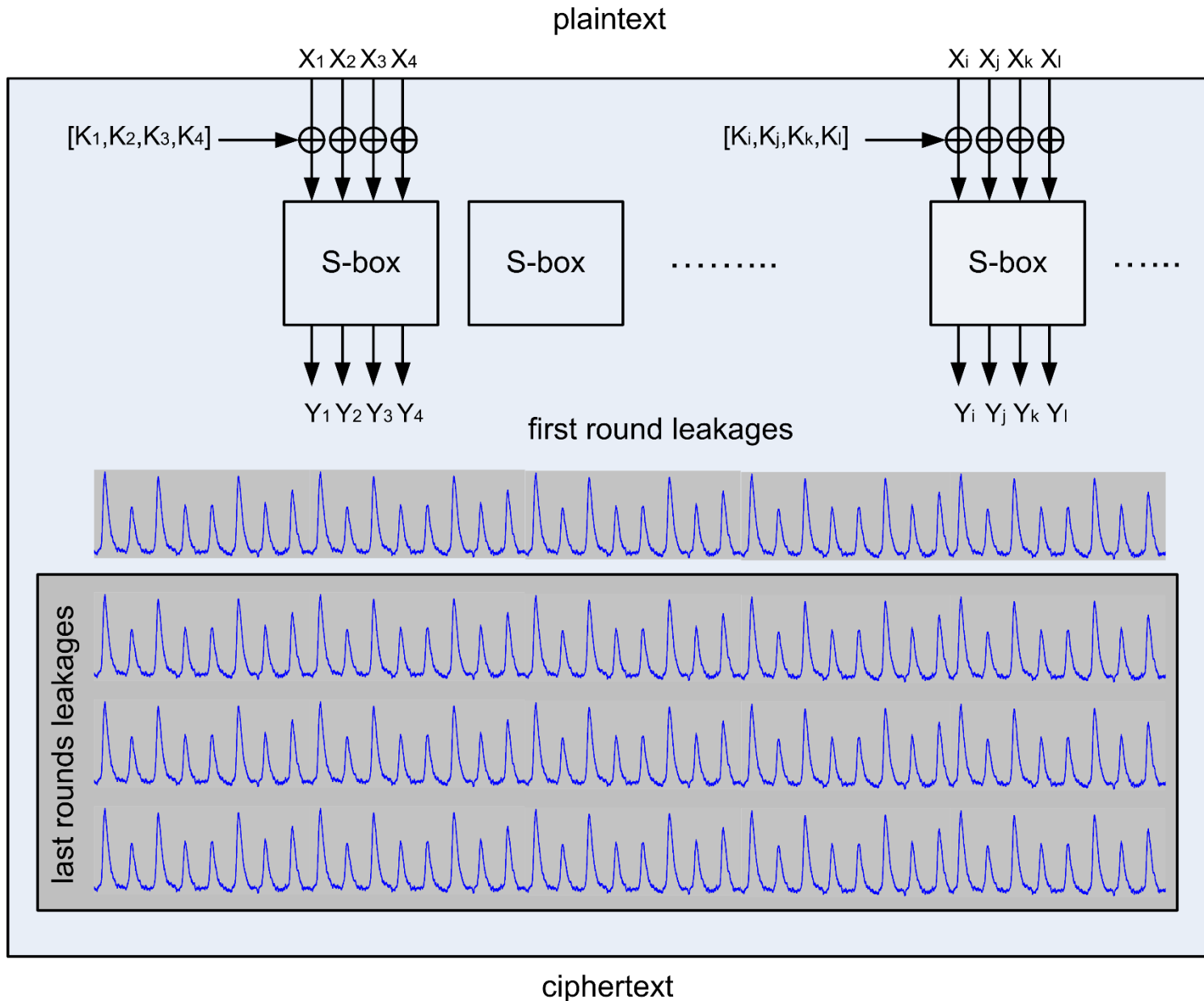


- Main characteristics
 - Divide-and-conquer attack
 - Data complexity $\propto \frac{1}{\varepsilon^2}$
 - $\varepsilon = 2^{n-1} \cdot \prod_{S=1}^n \varepsilon_S$ (n S-boxes in A , bias ε_S)
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\Rightarrow AES: $\varepsilon < 2^{-64}$ after a few of rounds



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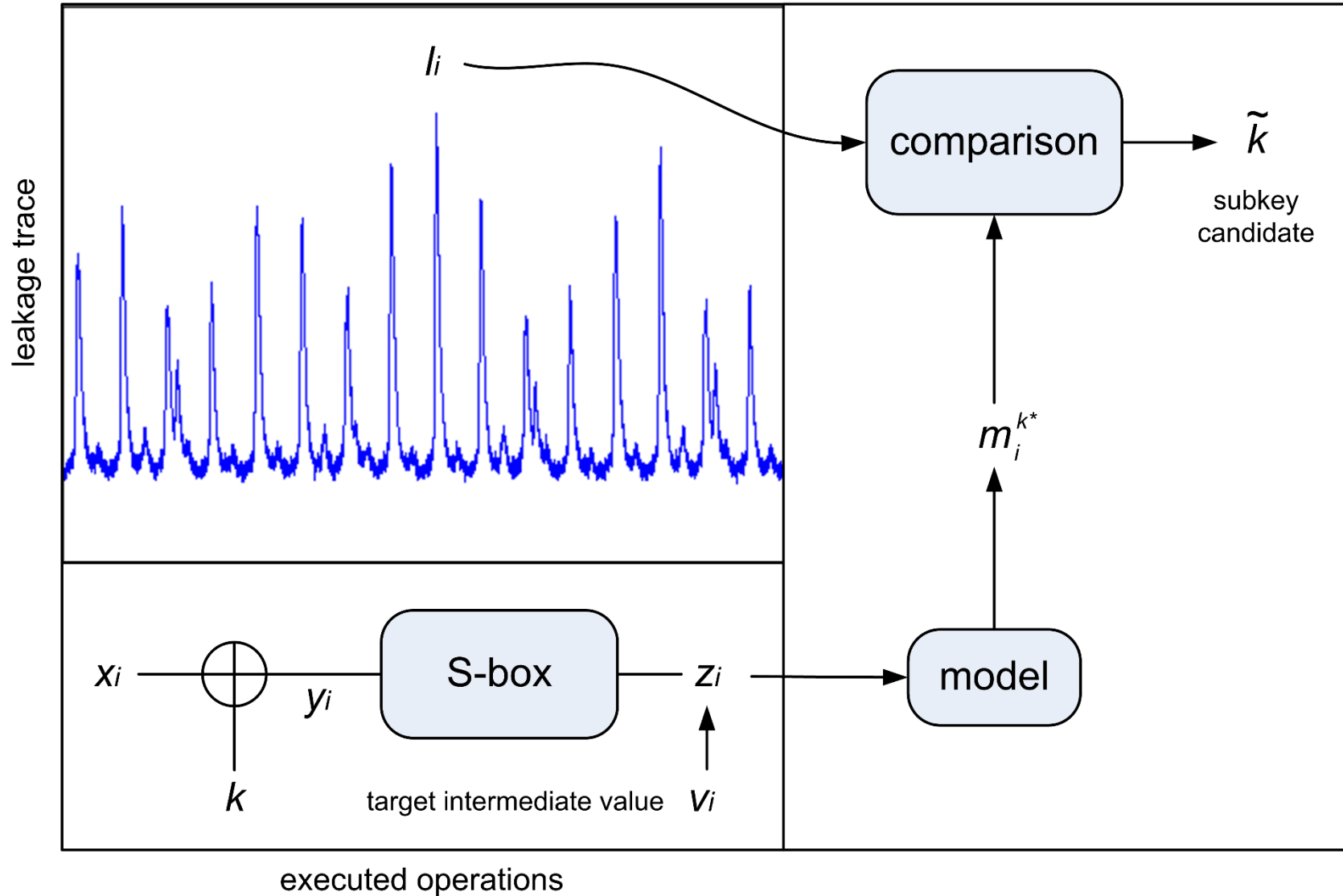
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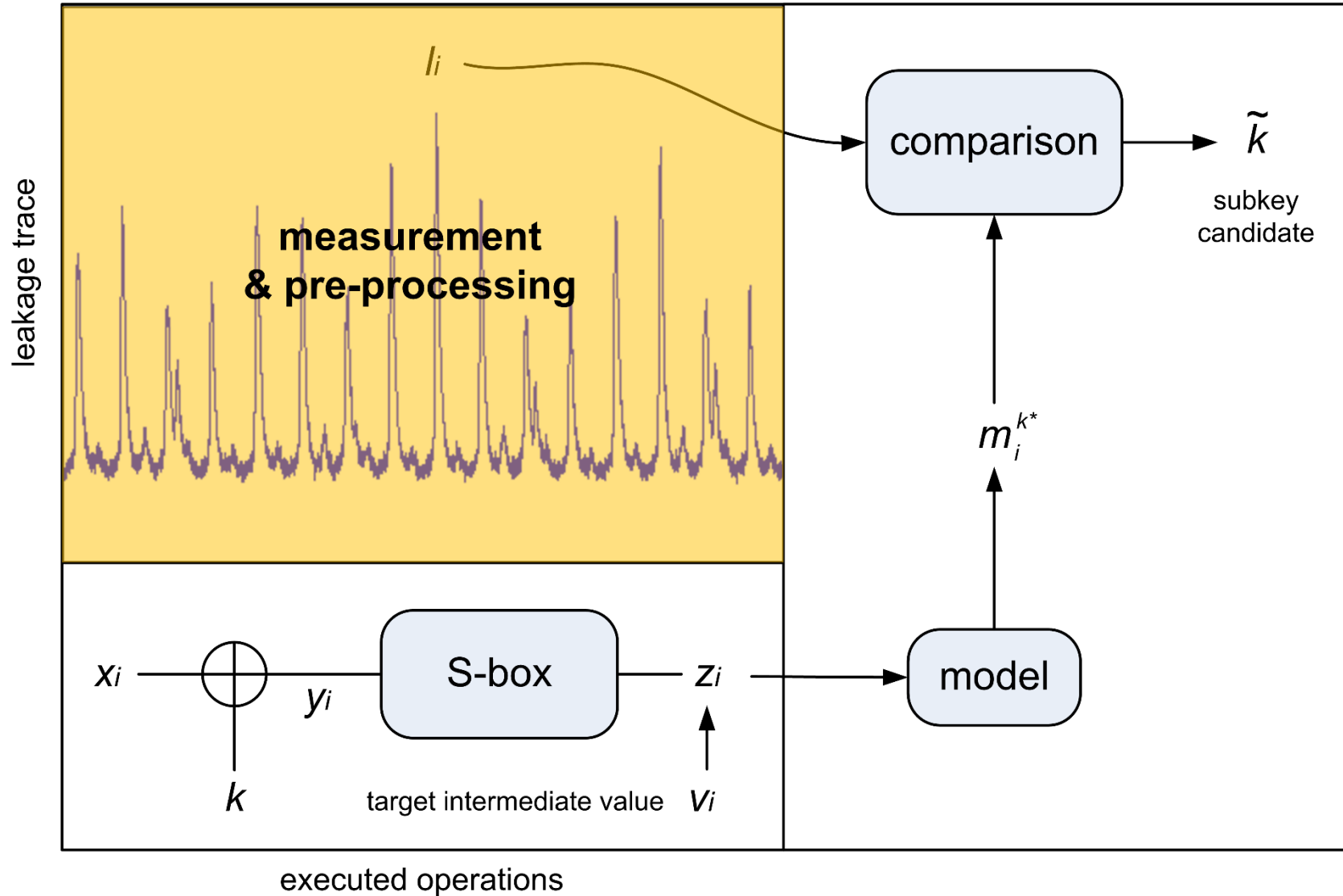
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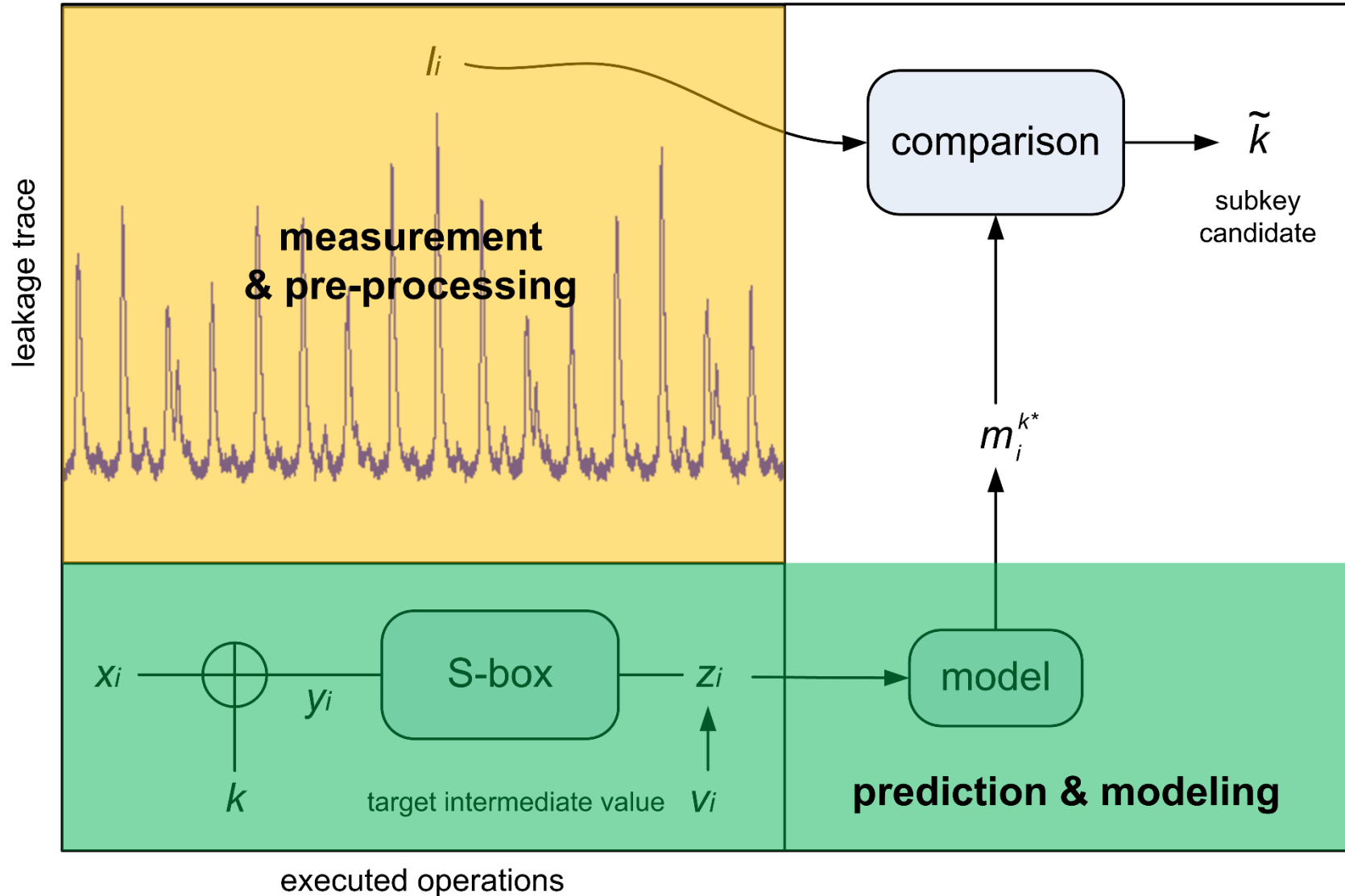
\Rightarrow Unprotected implem: $\text{MI}(K; L, X) > 0.01$

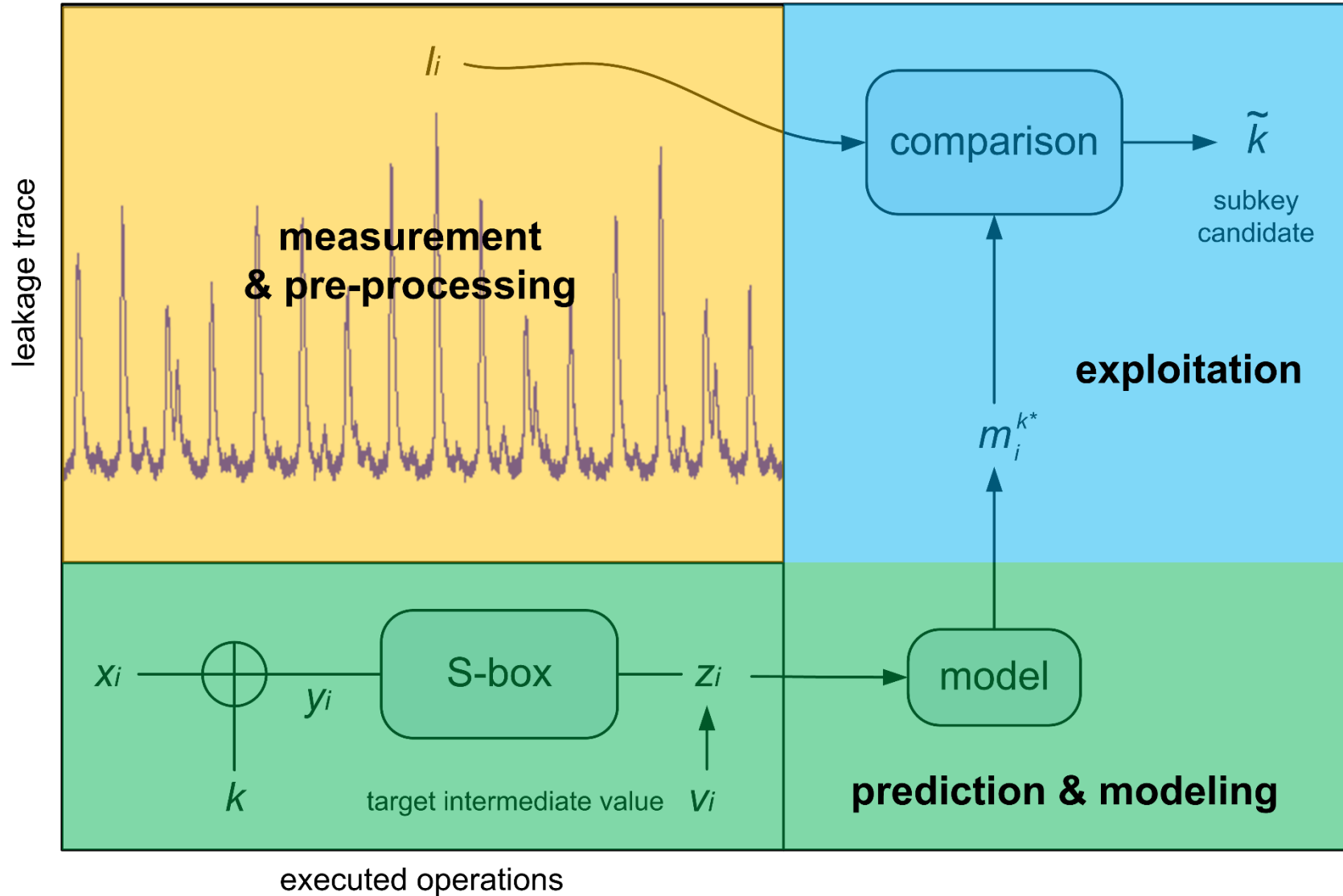
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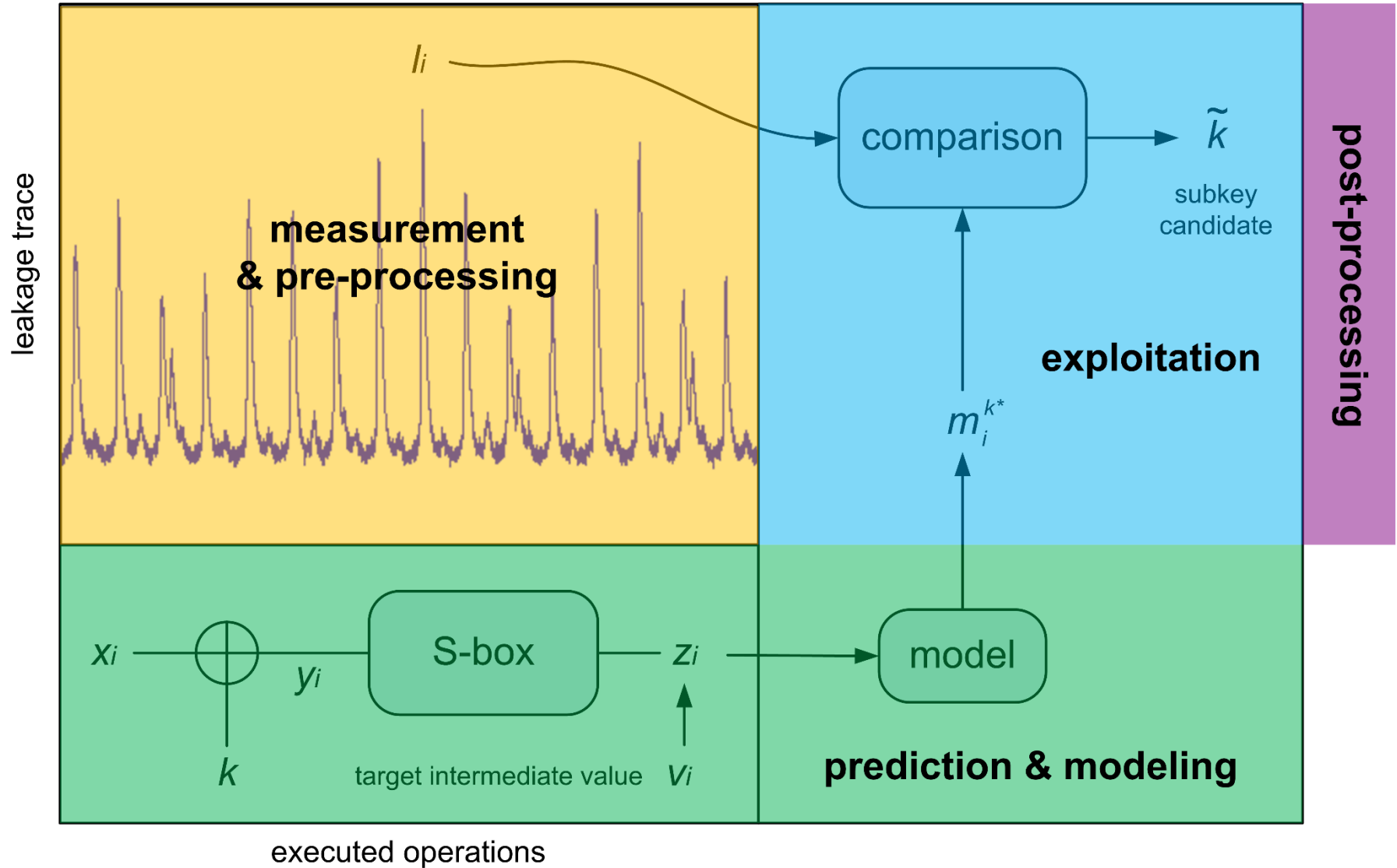
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- Noise reduction via good setups (!)
- Filtering, averaging (FFT, SSA, ...)
- Detection of Points-Of-Interest (POI)
- Dimensionality reduction (PCA, LDA,...)
- ...

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

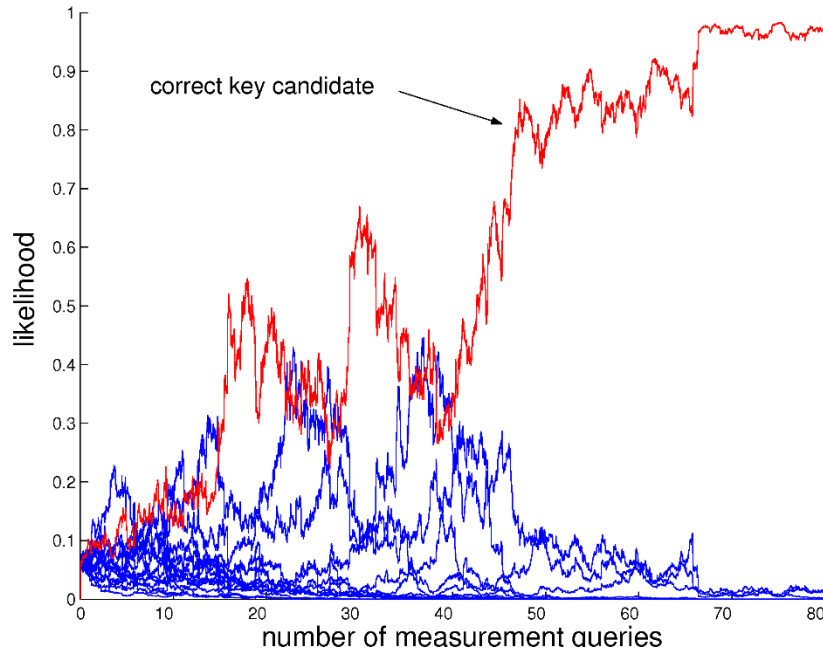
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- “Simplified” case: non-profiled DPA
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- Separation: only profiled DPA is guaranteed to succeed against any leaking device (!)

- Profiled case: maximum likelihood

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- Unprofiled case:
 - Difference-of-Means
 - Correlation (CPA)
 - « On-the-fly » regression
 - Mutual Information Analysis (MIA)
 - [...]

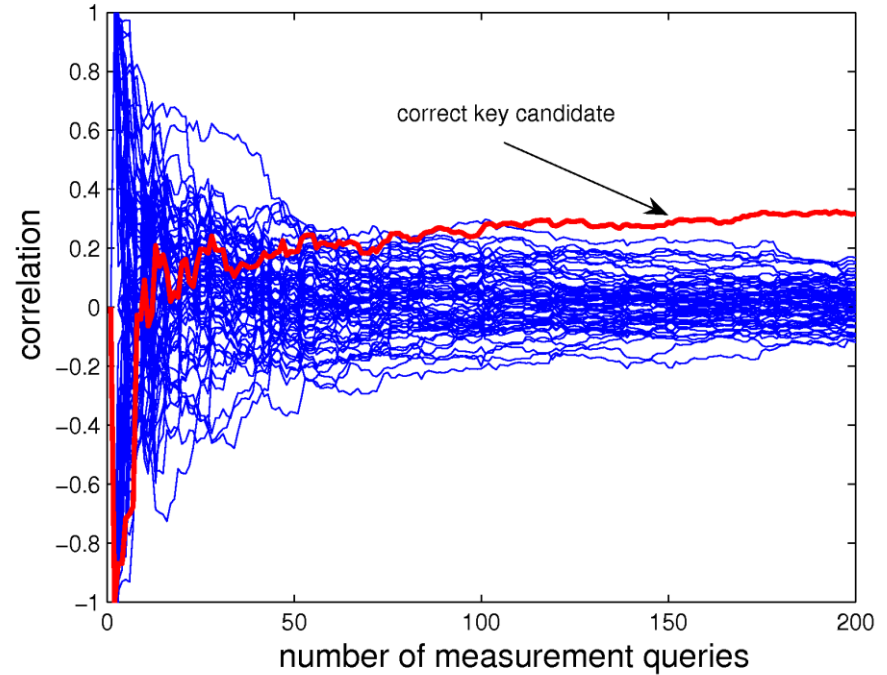
Gaussian templates



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

- More efficient (**why?**)
- Outputs probabilities

CPA



$$\tilde{k} = \operatorname{argmax}_{k^*} \frac{E(L \cdot M^{k^*}) - E(L) \cdot E(M^{k^*})}{\sigma(L) \cdot \sigma(M^{k^*})}$$

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- **Lemma 1.** The mutual information between two normally distributed random variables X, Y with means μ_X, μ_Y and variances σ_X^2, σ_Y^2 equals:

$$\text{MI}(X; Y) = -\frac{1}{2} \log_2(1 - \rho(X, Y)^2)$$

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- **Lemma 2.** In a CPA, the number of samples required to distinguish the correct key with model M_k from the other key candidates with models M_{k^*} is $\propto \frac{c}{\rho(M_k, L)^2}$ (with c a small constant depending on the SR & # of key candidates)

- **Lemma 3.** Let X, Y and L be three random variables s.t. $Y = X + N_1$ and $L = Y + N_2$ with N_1 and N_2 two additive noise variables. Then:

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- **Lemma 4.** The correlation coefficient between the sum of n independent and identically distributed random variables and the sum of the first $m < n$ of these equals $\sqrt{m/n}$

- FPGA implementation of the AES
- Adversary targeting the 1st byte of key
- Hamming weight leakage function/model
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- How does the attack data complexity scale
 - For a 32-bit architecture?
 - i.e. with 24 bits of « algorithmic noise »
 - For a 128-bit architecture?
 - i.e. with 120 bits of « algorithmic noise »

- Hint: $L = M + N = (M_P + M_U) + N$

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- Lemma 2: $\frac{c}{(\sqrt{8/8} \cdot \rho(M, L))^2} = 10$

- Data complexity for the 32-bit case:
- Data complexity for the 128-bit case:

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 - ($10 < \text{data complexity} < 40$ because of c)

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 - i.e. unprotected implementations
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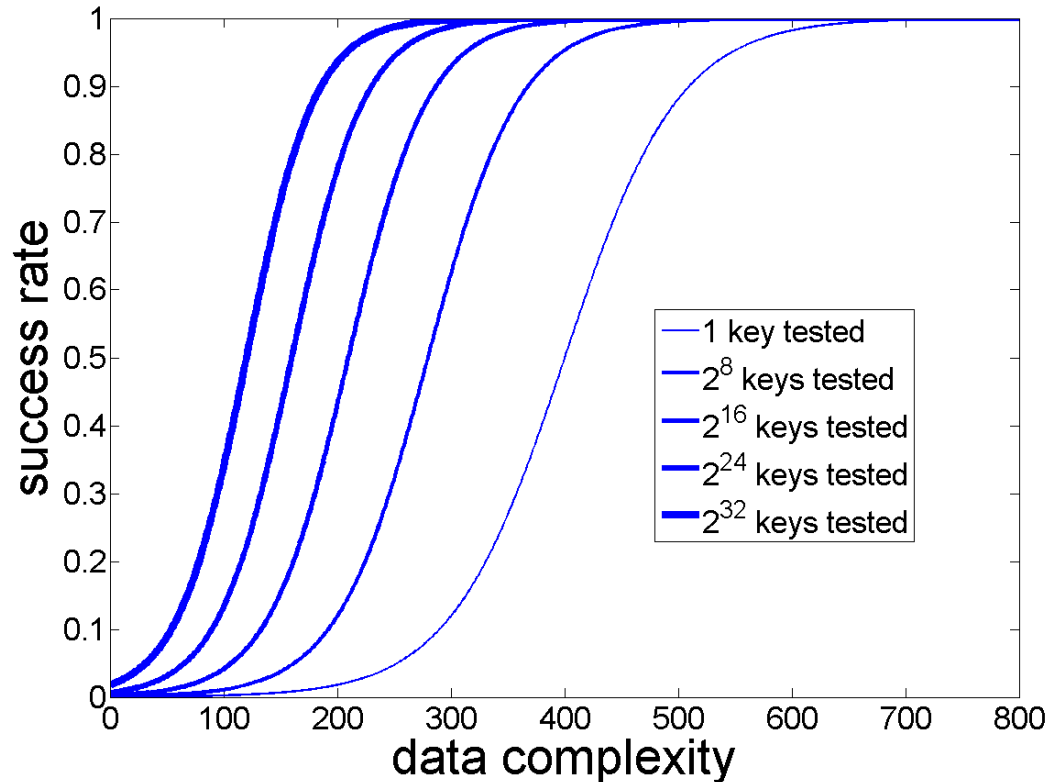
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⇒ Gaussian templates outperforms CPA because it (usually) exploits a better (profiled) **model**

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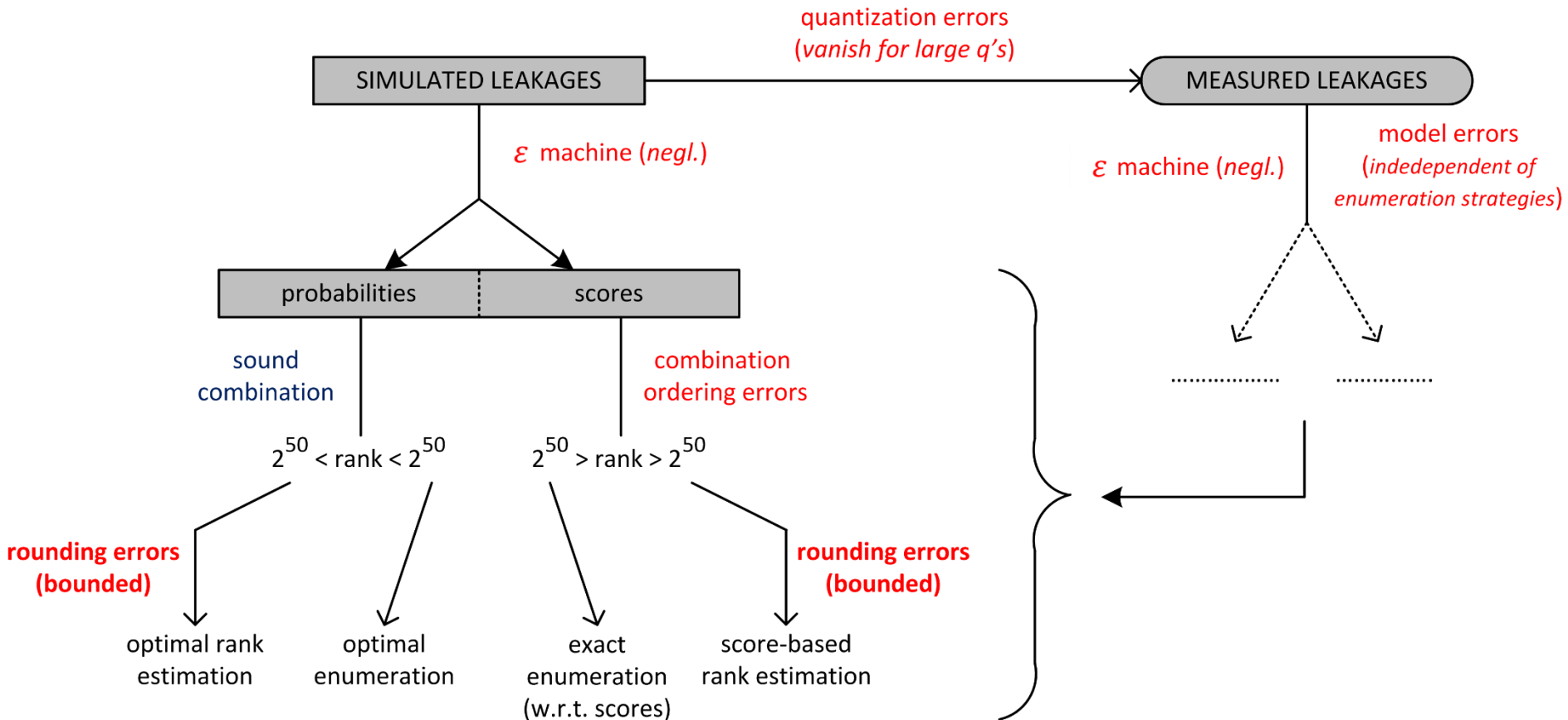
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- Key enumeration



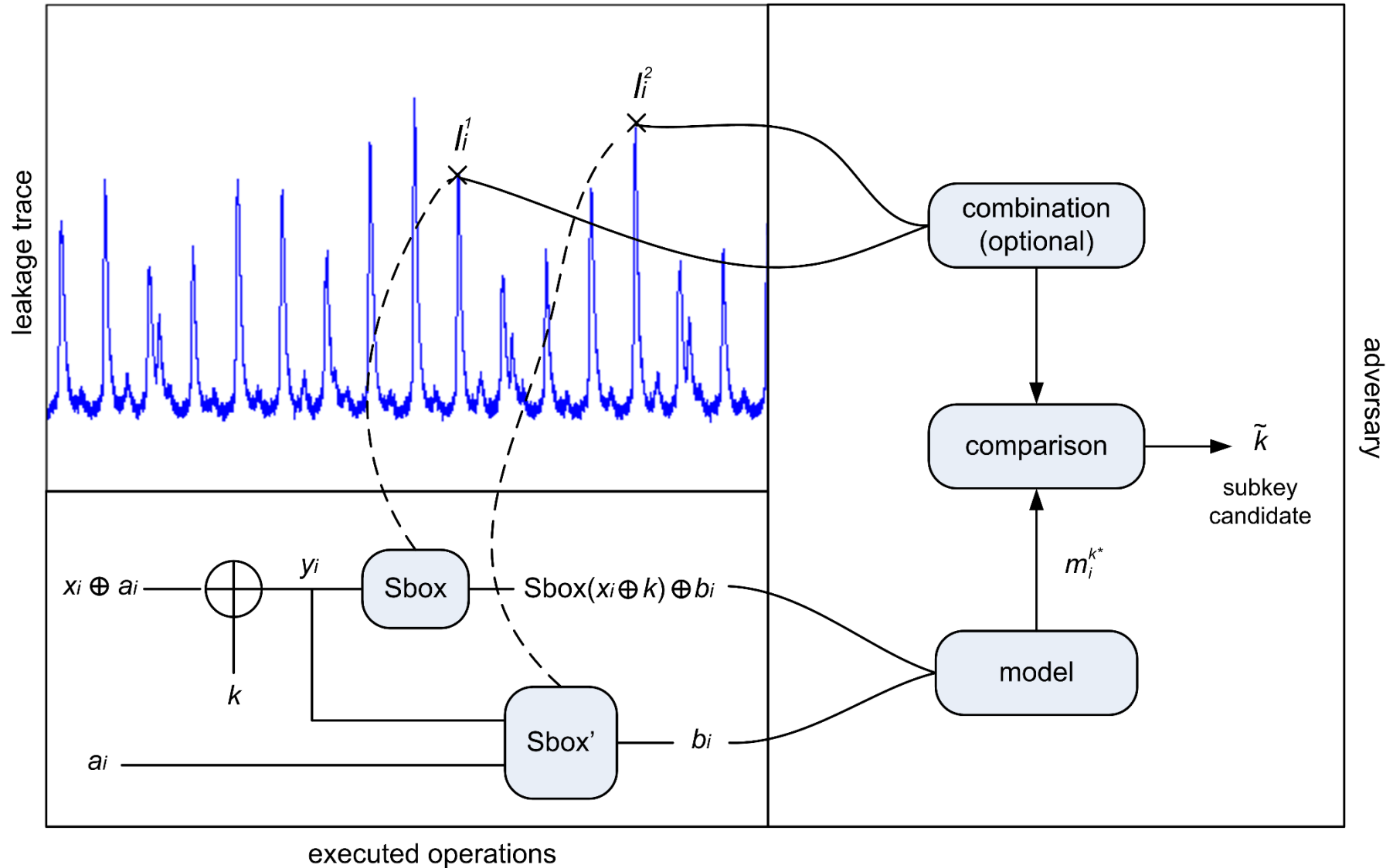
- & rank estimation if key is beyond enumeration

- Enumeration / rank estimation errors

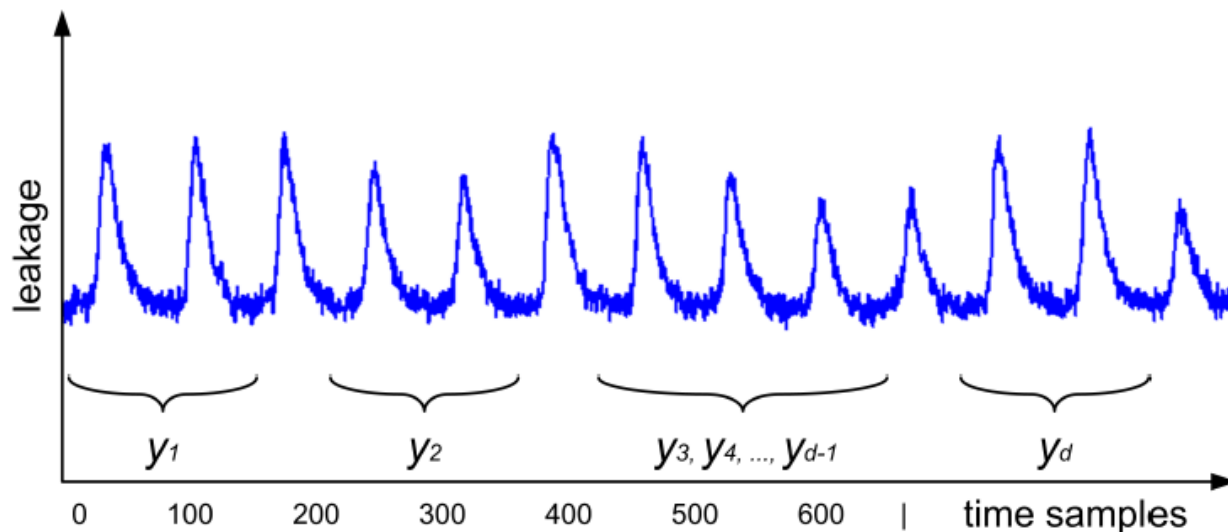


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- Let $z = S(x \oplus k) = S(y)$ be a leaking S-box
- Let $y = y_1 \oplus y_2 \oplus \dots \oplus y_d$ be a sharing of y



- Perform computations on “shared” variables

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

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partial products

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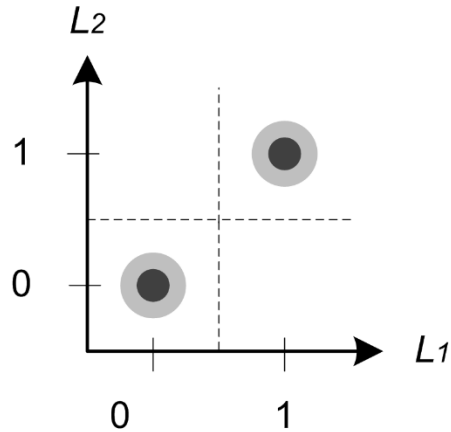
\Rightarrow Quadratic overheads & randomness

- Assume leakage variables $L_{Z_i} = \delta(Z_i) + N$ s.t.
 - $\text{MI}(Z_i; L_{Z_i}) \leq \frac{c}{d^2}$ (why d^2 ?)
 - The leakages of the shares are independent
- For a masking scheme with d shares
- And an adversary using m measurements
- Then: $\text{SR} \leq 1 - \left(1 - \text{MI}(Z_i; L_{Z_i})\right)^d)^m$

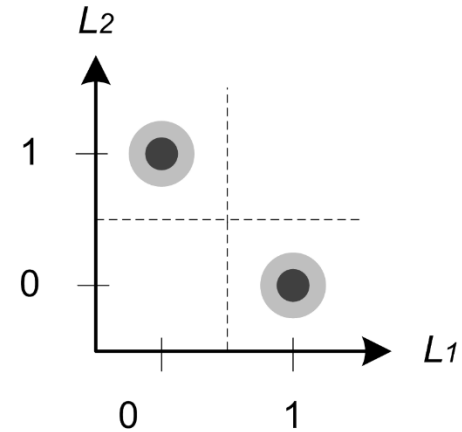
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- For $m = 1$, $\text{SR} \leq \text{MI}(Z_i; L_{Z_i})^d \propto (\sigma_N^2)^d$
- (Intuitively \approx “noisy” piling up lemma)

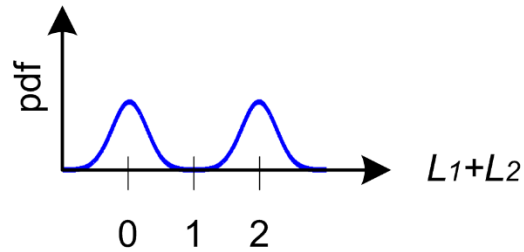
- 1-bit, 2-shares example



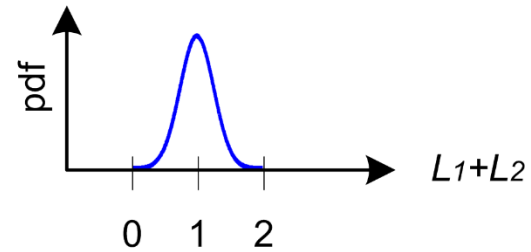
(a) $Z = 0$, serial.



(b) $Z = 1$, serial.



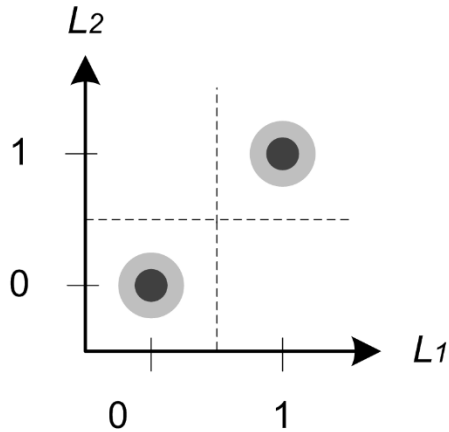
(c) $Z = 0$, parallel.



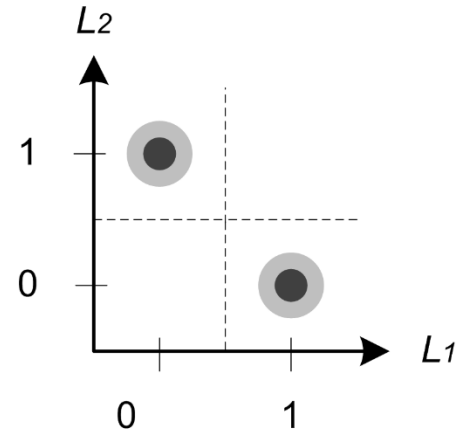
(d) $Z = 1$, parallel.

- 1-bit, 2-shares example

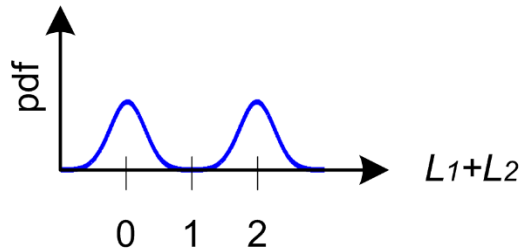
key-independent means



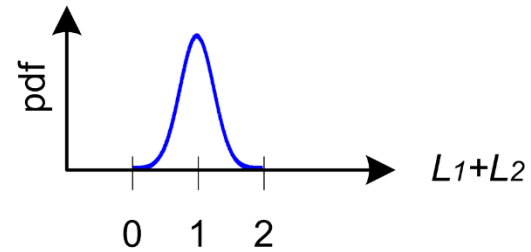
(a) $Z = 0$, serial.



(b) $Z = 1$, serial.

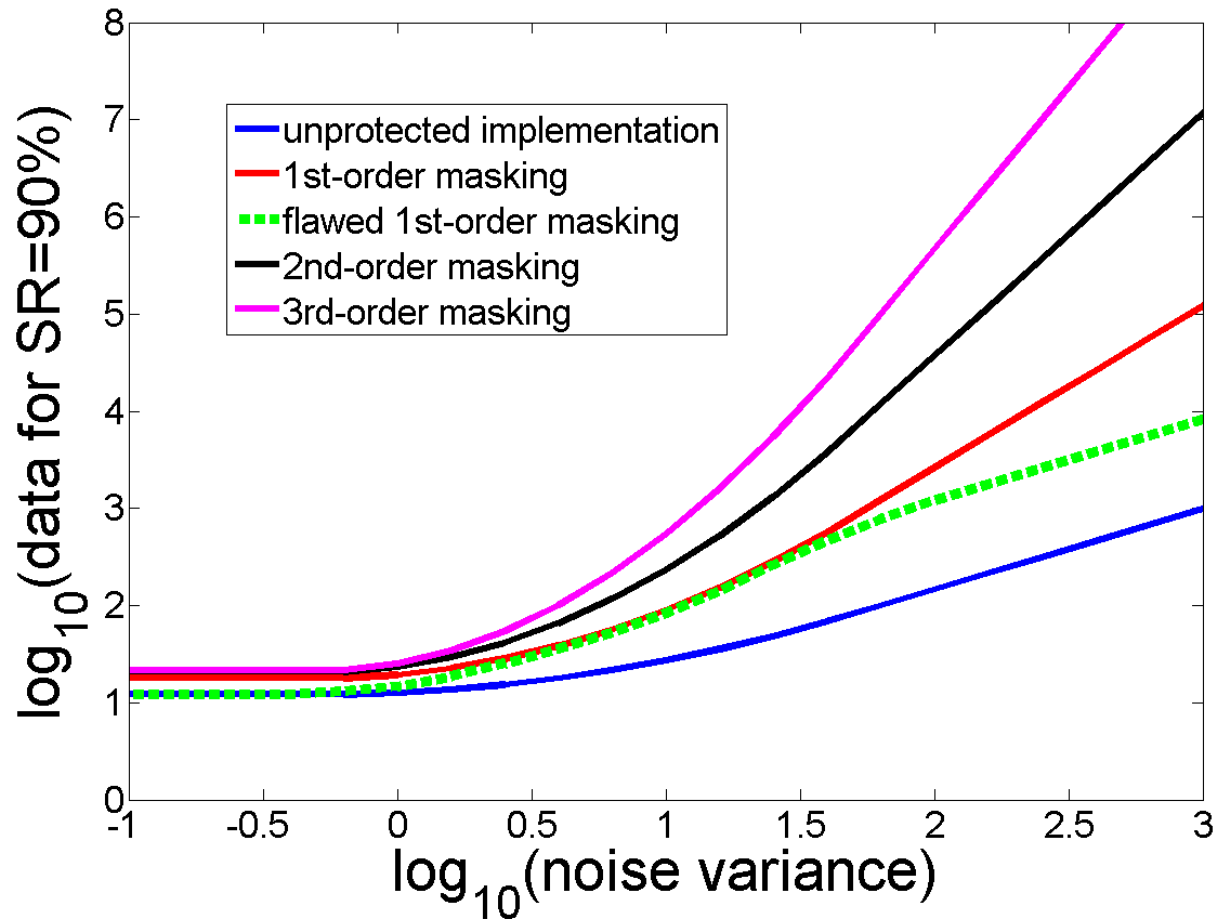


(c) $Z = 0$, parallel.



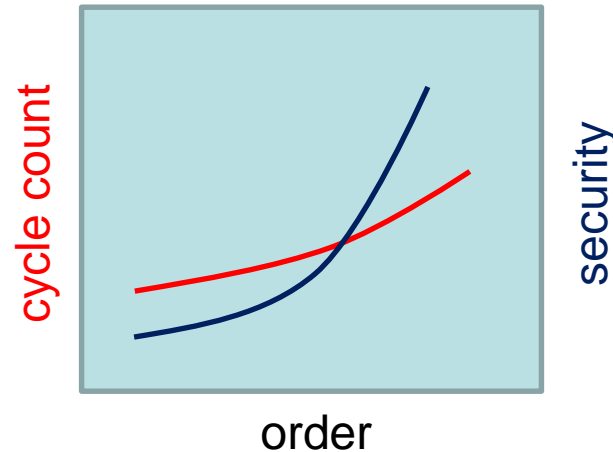
(d) $Z = 1$, parallel.

- Slope of the IT curves = d (if independent leaks)

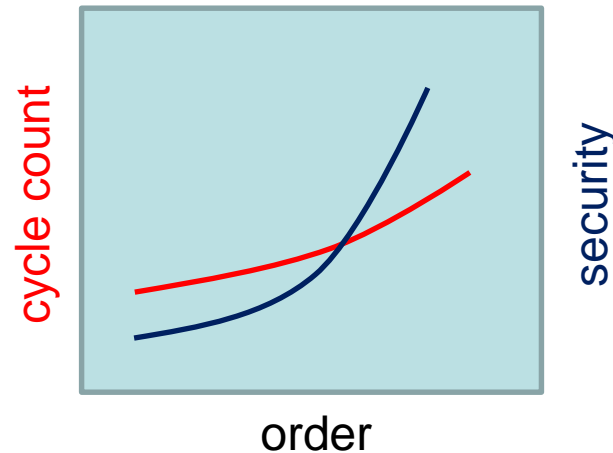


- Is masking an efficient countermeasure?
 - Security (data) is exponential in d
 - Cost is [...]

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- If the leakages are noisy and independent (!)

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- If the leakages are noisy and independent (!)
- How does the time complexity scale in d ?

- Is masking an efficient countermeasure?
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- If the leakages are noisy and independent (!)
- How does the time complexity scale in d ?
 - Depends on the implem. (e.g. serial or //)

Outline

- Link with linear cryptanalysis
- Standard Differential Power Analysis
- Noise-based security (is not enough)
- *CPA vs Gaussian templates*
- Post-processing the traces
- Noise amplification (aka masking)
- **Conclusions & advanced topics**

- Unprotected implementations are easy targets
 - Physical biases are usually large
- Noise is an ingredient – not the solution
- Noise amplification is possible (via masking)
 - But is hard to implement securely

- Unprotected implementations are easy targets
 - Physical biases are usually large
 - Noise is an ingredient – not the solution
 - Noise amplification is possible (via masking)
 - But is hard to implement securely
- More generally, efficient countermeasures against side-channel attacks always combine two ingredients: sound (*falsifiable*) hardware assumptions & mathematical amplification

- More elaborate/powerful attacks
 - Algebraic/analytical SCA
- Simpler/cheaper evaluations
 - Leakage detection
- Worst-case evaluations
 - Model certification
- Secure & efficient masking
 - Inner product masking
 - Threshold implementations (HW)
 - Formal verification (SW)
- Security by design (leakage-resilience)

THANKS

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

Related publications & further readings. Standard DPA (slide 5). Stefan Mangard, Elisabeth Oswald, François-Xavier Standaert: *One for all - all for one: unifying standard differential power analysis attacks*. IET Information Security 5(2): 100-110 (2011). **Pre-processing (slide 6).** Victor Lomné, Emmanuel Prouff, Thomas Roche: *Behind the Scene of Side Channel Attacks*. ASIACRYPT (1) 2013: 506-525. **Filtering.** Santos Merino Del Pozo, François-Xavier Standaert: *Blind Source Separation from Single Measurements Using Singular Spectrum Analysis*. CHES 2015: 42-59. **POI detection.** Oscar Reparaz, Benedikt Gierlichs, Ingrid Verbauwhede: *Selecting Time Samples for Multivariate DPA Attacks*. CHES 2012: 155-174. François Durvaux, François-Xavier Standaert, Nicolas Veyrat-Charvillon, Jean-Baptiste Mairy, Yves Deville: *Efficient Selection of Time Samples for Higher-Order DPA with Projection Pursuits*. 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François-Xavier Standaert, Eric Peeters, Gaël Rouvroy, Jean-Jacques Quisquater, *An Overview of Power Analysis Attacks Against Field Programmable Gate Arrays*, Proceedings of the IEEE, 94(2): 383-394 (2006). **Trading data for time (slide 14).** Luke Mather, Elisabeth Oswald, Carolyn Whitnall: *Multi-target DPA Attacks: Pushing DPA Beyond the Limits of a Desktop Computer*. ASIACRYPT (1) 2014: 243-261. **CPA vs. Gaussian templates (slide 15).** Stefan Mangard, Elisabeth Oswald, François-Xavier Standaert: *One for all - all for one: unifying standard differential power analysis attacks*. IET Information Security 5(2): 100-110 (2011). **Key enumeration/rank estimation (slide 16).** Nicolas Veyrat-Charvillon, Benoît Gérard, Mathieu Renaud, François-Xavier Standaert: *An Optimal Key Enumeration Algorithm and Its Application to Side-Channel Attacks*. Selected Areas in Cryptography 2012: 390-406. Nicolas Veyrat-Charvillon, Benoît Gérard, François-Xavier Standaert: *Security Evaluations Beyond Computing Power: How to Analyze Side-Channel Attacks you Cannot Mount?* EUROCRYPT 2013: 126-141. Cezary Glowacz, Vincent Grosso, Romain Poussier, Joachim Schüth, François-Xavier Standaert: *Simpler and More Efficient Rank Estimation for Side-Channel Security Assessment*. FSE 2015: 117-129. Daniel P. Martin, Jonathan F. O'Connell, Elisabeth Oswald, Martijn Stam: *Counting Keys in Parallel After a Side Channel Attack*. ASIACRYPT (2) 2015: 313-337. **Key enumeration/rank estimation errors (slide 17).** Romain Poussier, Vincent Grosso, François-Xavier Standaert: *Comparing Approaches to Rank Estimation for Side-Channel Security Evaluations*. CARDIS 2015: 125-142. **Masking (slides 19-20).** 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*. 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