



A Decade of Masking Security Proofs

Loïc Masure

WRACH, 23 Avril 2025, Roscoff



Agenda

Context: SCA & Security Evaluation

Masking

- Background & Intuitions

- Provably Secure Masking

Composition in the Random Probing Model

Tight Reduction

Conclusion

Content

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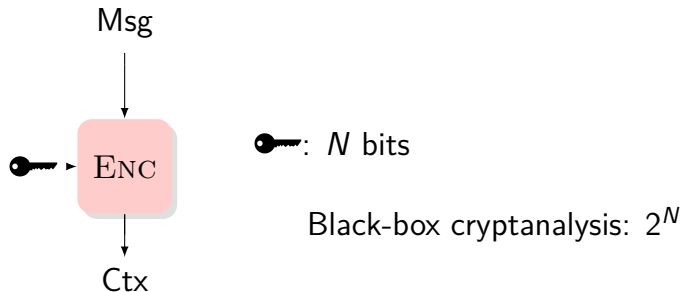
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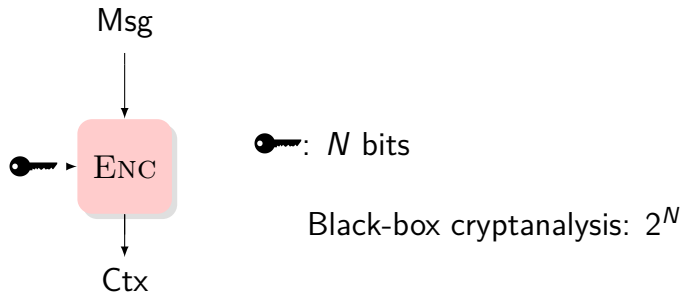
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Context : Side-Channel Analysis (SCA)



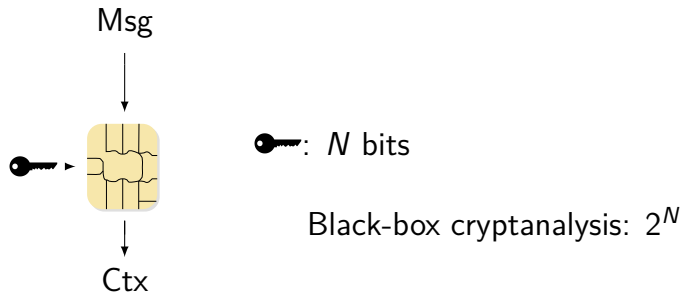
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“Cryptographic algorithms don’t run on paper,



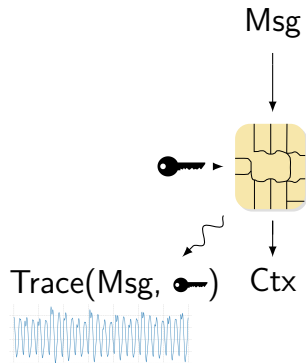
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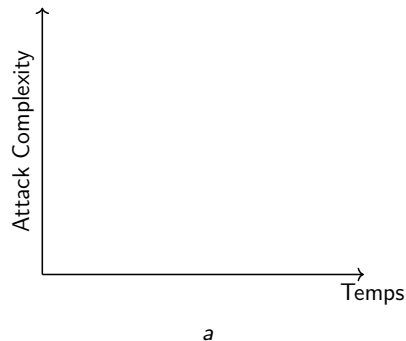
“Cryptographic algorithms don’t run on paper, they run on physical devices”



key: N bits

Black-box cryptanalysis: 2^N

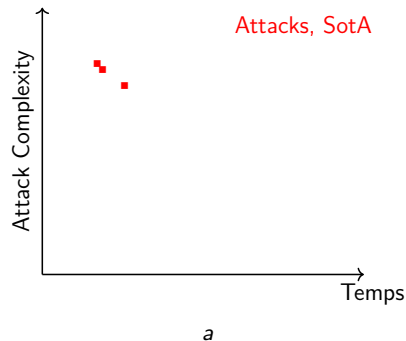
Evaluate Security against Side-Channel Attacks



Attack approach (industry):

^aShamelessly stolen to O. Bronchain

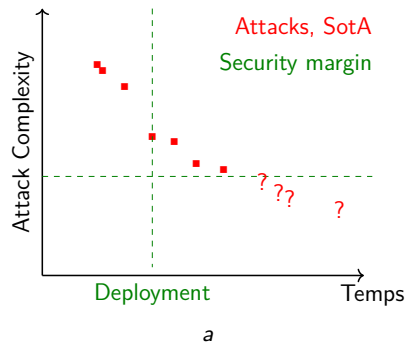
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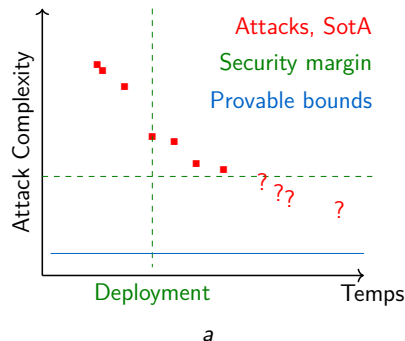
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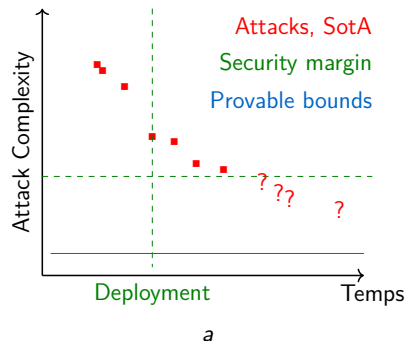
Approach by *proofs* (academia):

Rigorous approach ✓

Potentially conservative ✗

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Today's agenda: evaluation by proofs

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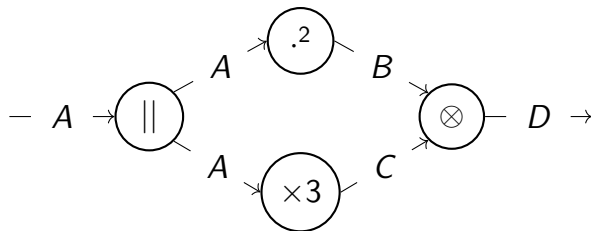
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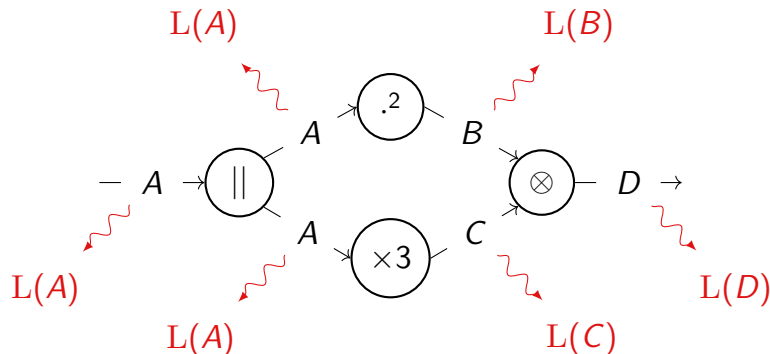
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Statement of the Problem

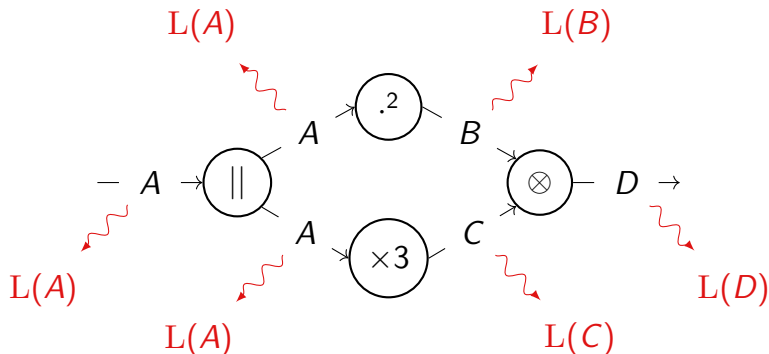


Statement of the Problem



For each wire X , a leakage function $L(X)$ is revealed to the adversary.

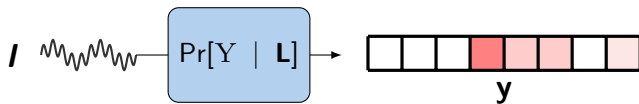
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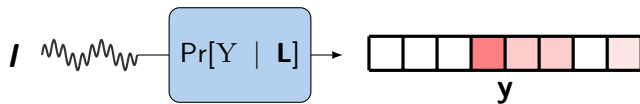
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How informative L about A ?

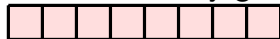
The Noisy Leakage Model



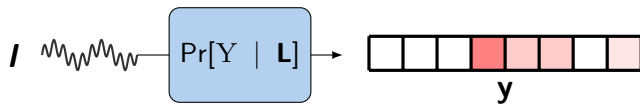
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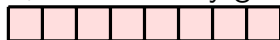
If, the adversary gets:



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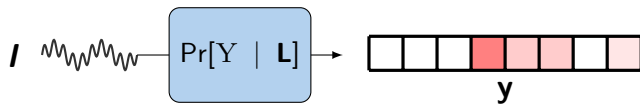
If, the adversary gets:



Very noisy leakage

Y indistinguishable from blind guess

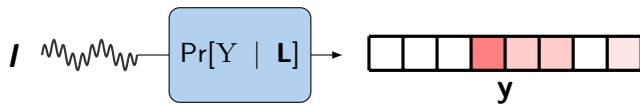
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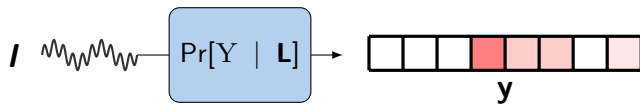


If, the adversary gets:



Low-noise leakage
Exact prediction for Y

The Noisy Leakage Model

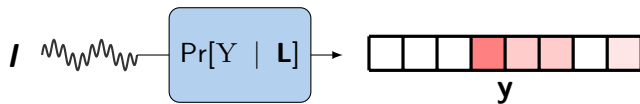


δ -NOISY ADVERSARY

Any intermediate computation Y leaks $L(Y)$ such that:

$$\text{SD}(Y; L) = \mathbb{E}_L \left[\text{TV} \left(\underbrace{\begin{array}{|c|c|c|c|c|c|c|c|} \hline \text{white} & \text{white} & \text{white} & \text{red} & \text{light red} & \text{light red} & \text{white} & \text{light red} \\ \hline \end{array}}_{\Pr[Y | L]}, \underbrace{\begin{array}{|c|c|c|c|c|c|c|c|} \hline \text{light red} & \text{light red} & \text{light red} & \text{light red} & \text{light red} & \text{light red} & \text{light red} & \text{light red} \\ \hline \end{array}}_{\Pr[Y]} \right) \right] \leq \delta$$

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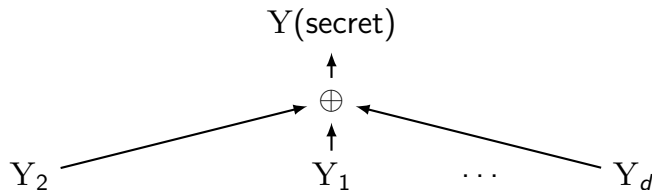
Main assumption: every observed leakage is δ -noisy

Masking: what is that ?

Masking, a.k.a. *MPC on silicon*:¹² secret sharing over a finite field $(\mathbb{F}, \oplus, \otimes)$
 $Y(\text{secret})$

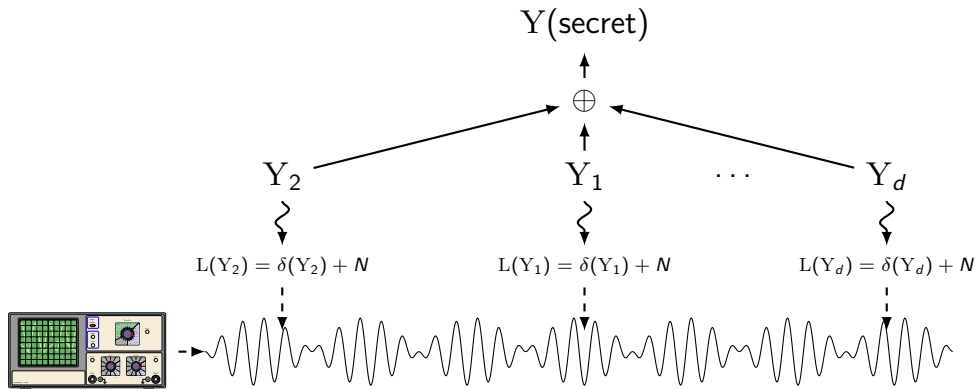
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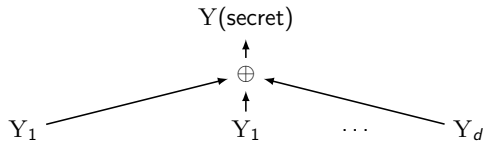
¹Chari et al., “Towards Sound Approaches to Counteract Power-Analysis Attacks”.

²Goubin and Patarin, “DES and Differential Power Analysis (The “Duplication” Method)”.

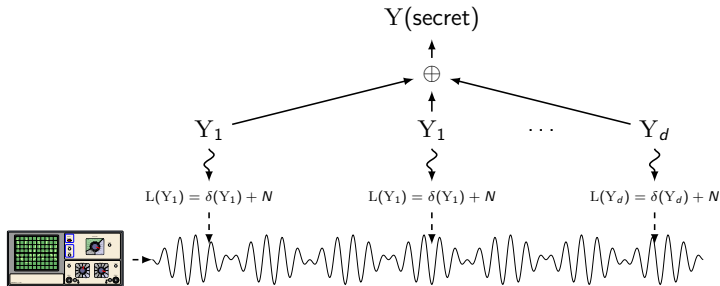
The Effect of Masking

Y(secret)

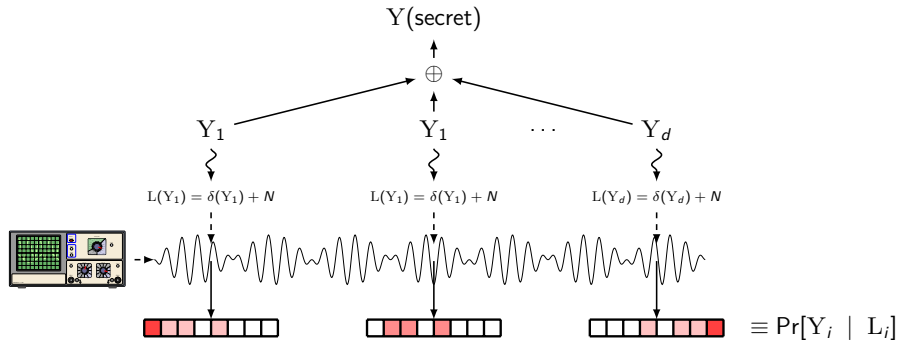
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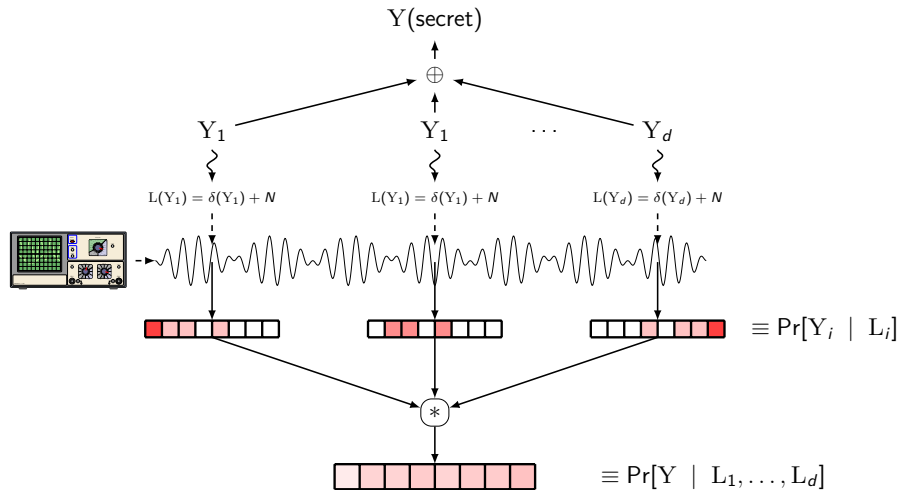
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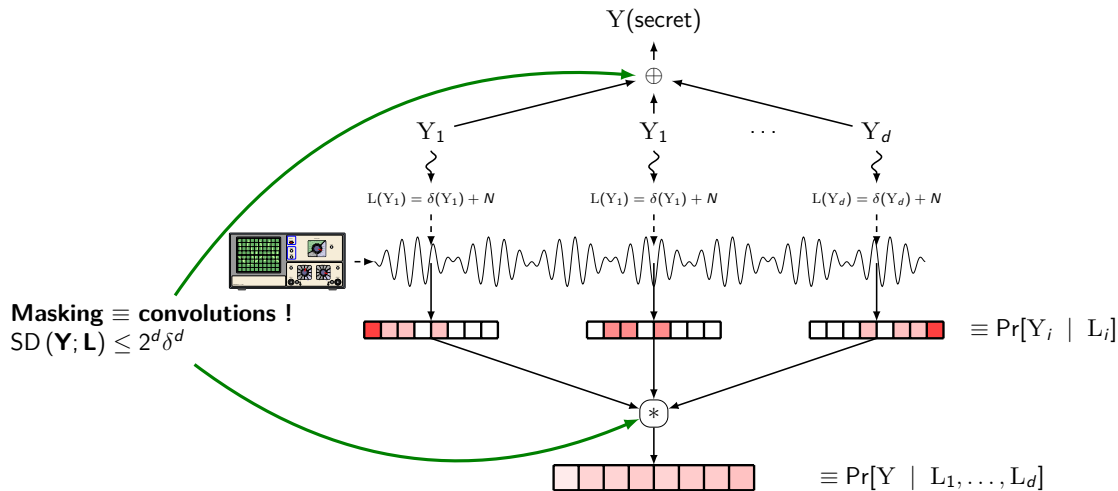
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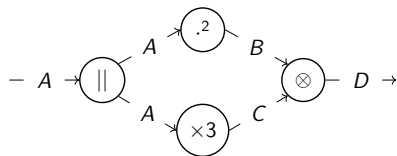
Idea to make a masked circuit

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Computing over Masked Secrets

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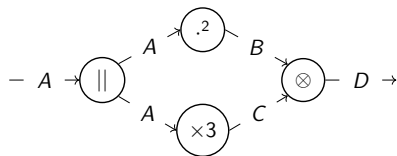
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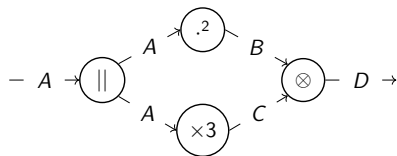
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→ Made of not, and gates³

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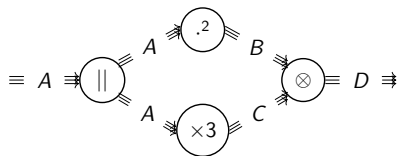
- View your algorithm as a circuit
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 - Made of $\oplus$, $\otimes$ gates ⁴

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Computing over Masked Secrets

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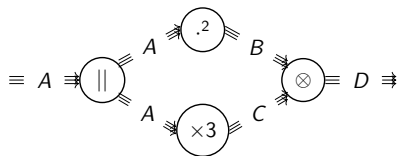
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- Replace each gate by a masked *gadget*

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Computing over Masked Secrets

Idea to make a masked circuit



- View your algorithm as a circuit
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- Replace each gate by a masked *gadget*
- Et voilà !**

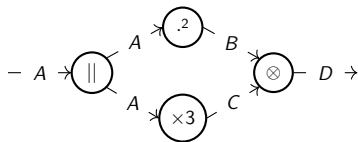
For now, let's assume the whole circuit to be *probing secure*: every subset of $d - 1$ wires is independent from the secret.

³Ishai, Sahai, and Wagner, "Private Circuits: Securing Hardware against Probing Attacks".

⁴Rivain and Prouff, "Provably Secure Higher-Order Masking of AES".

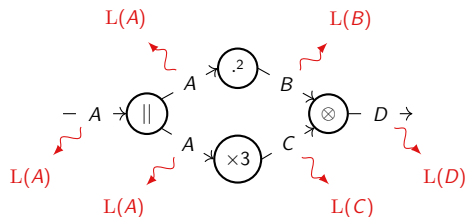
Security Proof for a Gadget

Consider a gadget with ℓ intermediate computations:



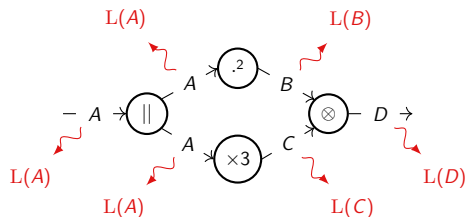
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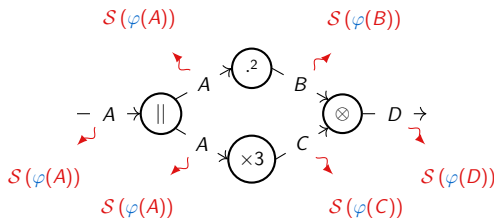


DATA-PROCESSING INEQUALITY

If for any x the leakage function $L(x)$

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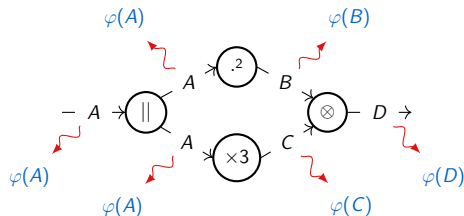


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DATA-PROCESSING INEQUALITY

If for any x the leakage function $L(x)$ may be expressed as $\mathcal{S}(\varphi(x))$, then:
 advantage from $L(x) \leq$ advantage from $\varphi(x)$

Reduction from Noisy Leakage to Random Probing

LEMMA (SIMULATABILITY BY RANDOM PROBING)

*The leakage function L can be simulated from a **random probing adversary**: $\varphi(x)$ reveals x with probability $\epsilon = 1 - \sum_l \min_x \Pr[L(x) = l] \leq \delta \cdot |\mathbb{F}|$.⁵*

Random probing model: easier to analyze for leakage from computations

⁵Duc, Dziembowski, and Faust, “Unifying Leakage Models: From Probing Attacks to Noisy Leakage”.

Security against a Random Probing Adversary

To succeed, at least d out of ℓ wires must be revealed to the adversary:

$$\Pr[\text{Adv. learns sth}] \leq \Pr[\text{At least } d \text{ wires revealed}]$$

⁶Boucheron, Lugosi, and Massart, *Concentration Inequalities: A Nonasymptotic Theory of Independence*, P.24, and Ex. 2.11.

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THEOREM (CHERNOFF CONCENTRATION INEQUALITY⁶)

If ℓ wires, each independently revealed with proba. ϵ :

$$\Pr[\text{At least } d \text{ wires revealed}] \leq \left(\frac{e \cdot \ell \cdot \epsilon}{d} \right)^d$$

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Putting all Together

In our context, $\ell \leq \mathcal{O}(d^2)$ (for $\otimes$ gadget), and $\epsilon \leq \delta \cdot |\mathbb{F}|$:

THEOREM (SECURITY BOUND)

For a single gadget with $\ell \leq \mathcal{O}(d^2)$ intermediate computations:

$$\text{SD}(k; \mathbf{L}) \leq (\mathcal{O}(d) \cdot \delta \cdot |\mathbb{F}|)^d$$

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For the whole circuit $\mathbb{C}$,

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Main Challenge

For the whole circuit $\mathbb{C}$,

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Main challenge: get rid of the three factors d , $|\mathbb{C}|$, and $|\mathbb{F}|$

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A few numbers:

$$d(2, 3, 4, \dots, 16) \ll |\mathbb{C}|(\approx 10^3, 10^5), |\mathbb{F}|(256, 2^{23}, 2^{50})$$

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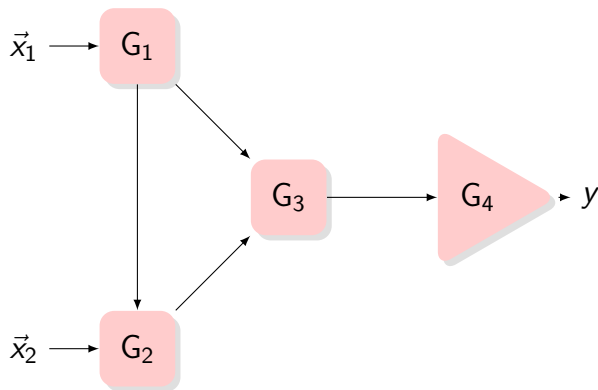


Figure: G_1 : SNI copy gadget, G_2 , G_3 : SNI gadgets, G_4 : Nlo gadget.

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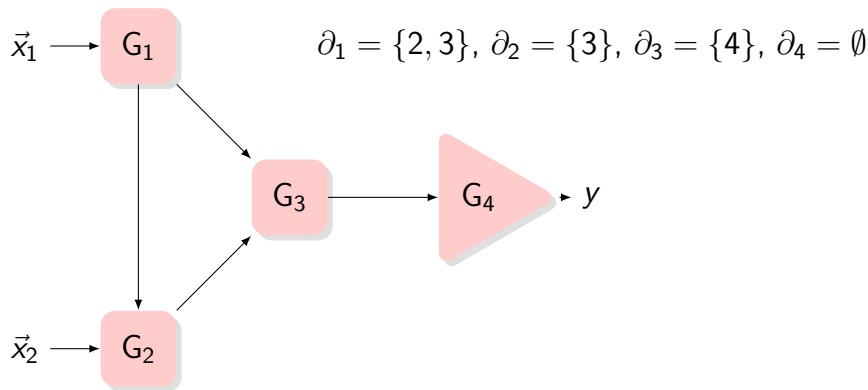


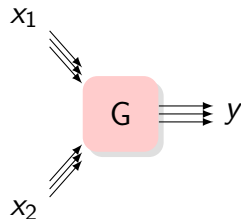
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∂_i : set of all subsequent gadgets linked to G_i

Strong Non-Interference⁸

DEFINITION (t -STRONG NON-INTERFERENCE)

A gadget G is t -SNI



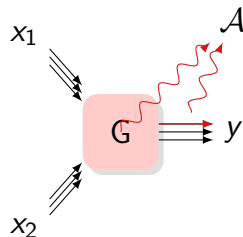
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Strong Non-Interference⁸

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A gadget G is t -SNI if any set W^G of internal probes and any set J^G of output probes such that $|W^G| + |J^G| \leq t$



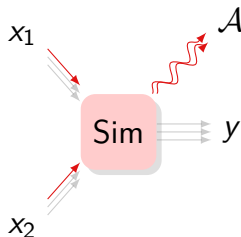
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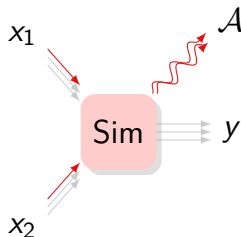
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- Composable : circ. SNI iff all gadgets SNI
- SNI $\implies$ probing security
- Extends to multiple outputs⁷

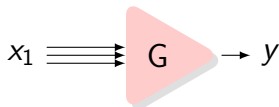
⁷Must be connected to different gadgets ✓

⁸Barthe et al., “Strong Non-Interference and Type-Directed Higher-Order Masking”.

Non-Interference with Public Outputs¹⁰

DEFINITION (t -NIO)

A gadget is t -NIO



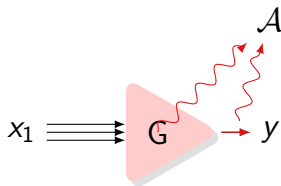
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A gadget is t -NIO if any set of $t_1 \leq t$ internal probes and the output



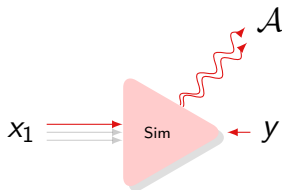
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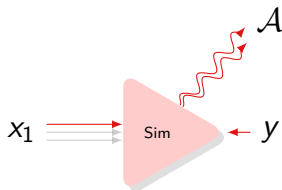
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- Output assumed to be public anyway
- Built from strong Refreshing⁹

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Composition Theorem

THEOREM

Assume: (1) Each output gadget $(d - 1)$ -NI;

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Assume: (1) Each output gadget $(d - 1)$ -NI; (2) Each internal gadget t_i -NI; (3) Each copy gadget connected to different gadgets; then, $\mathbb{C}$ is secure with proba $\geq 1 - \eta$ such that:

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Composition Theorem

THEOREM

Assume: (1) Each output gadget $(d - 1)$ -Nlo; (2) Each internal gadget t_i -SNl; (3) Each copy gadget connected to different gadgets; then, $\mathbb{C}$ is secure with proba $\geq 1 - \eta$ such that:

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COROLLARY

The d -share ISW compiler is $|\mathbb{C}| \cdot (\mathcal{O}(d) \cdot |\mathbb{F}| \cdot \delta)^d$ -noisy leakage secure

Proof Sketch

Apply SNI simulator gadget-wise, in reversed order, until complete or failure

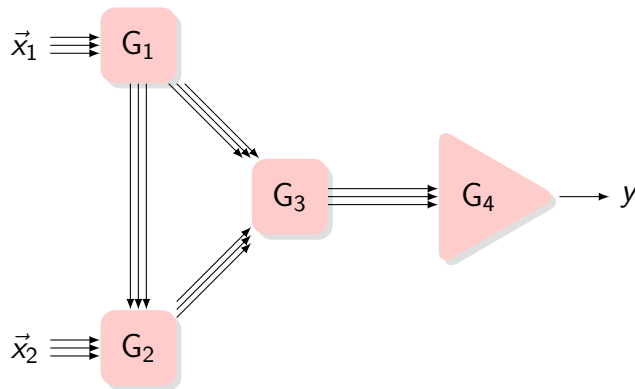


Figure: G_1 : SNI copy gadget, G_2, G_3 : SNI gadgets, G_4 : Nlo gadget. $\partial_1 = \{2, 3\}$, $\partial_2 = \{3\}$, $\partial_3 = \{4\}$, $\partial_4 = \emptyset$

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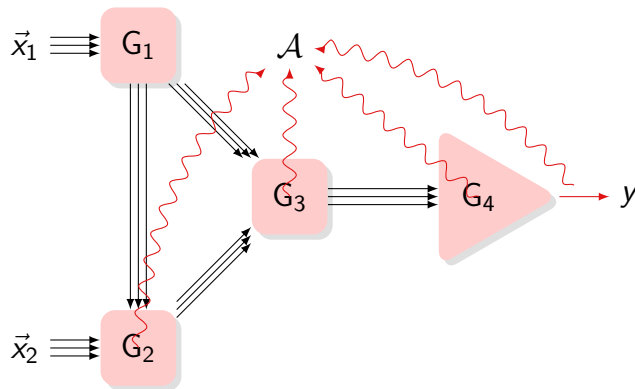


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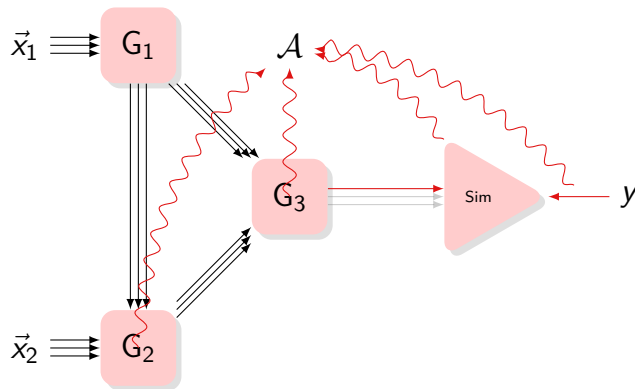


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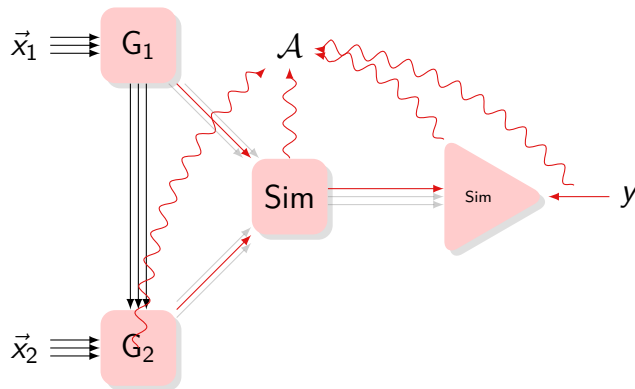


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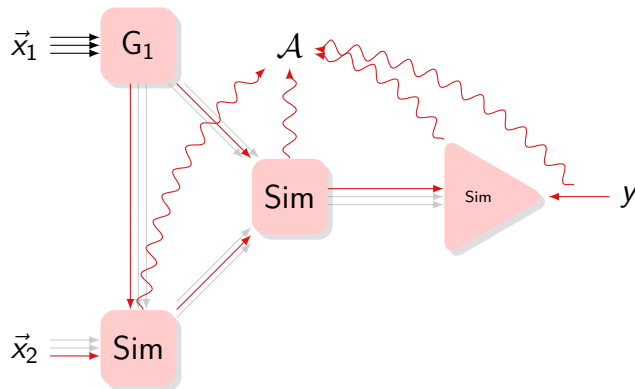


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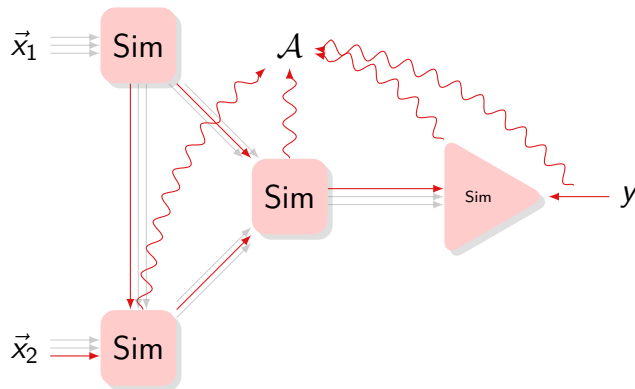


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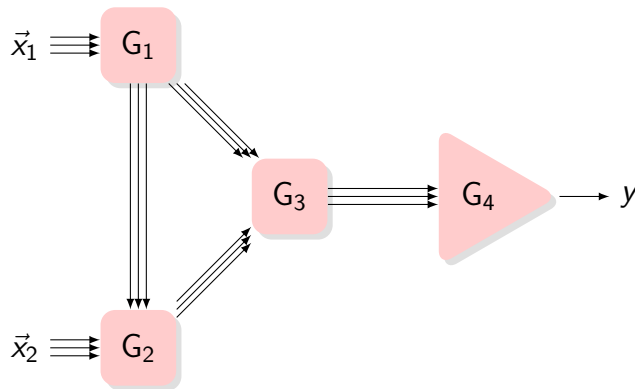


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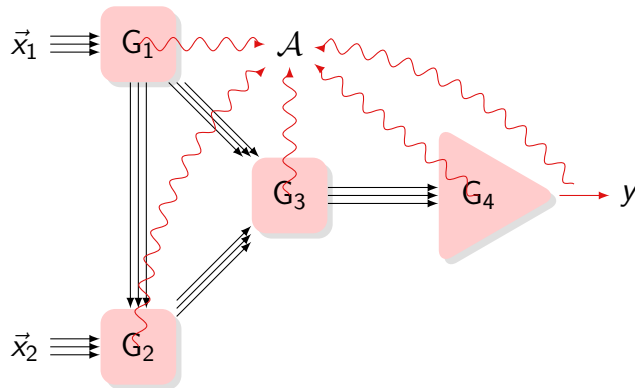


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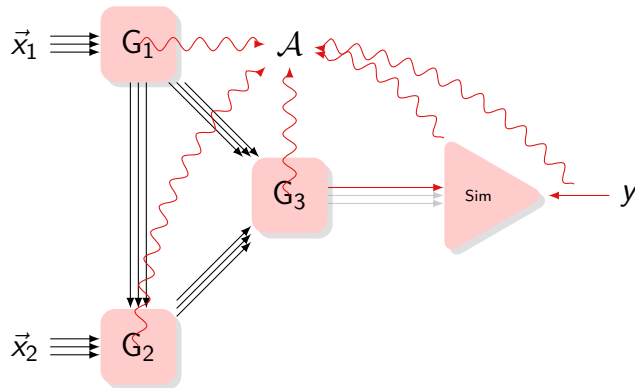


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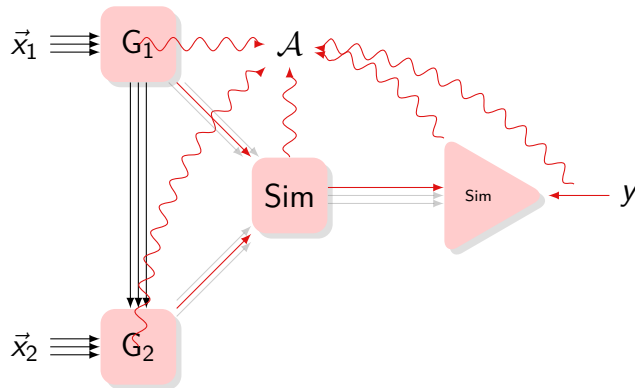


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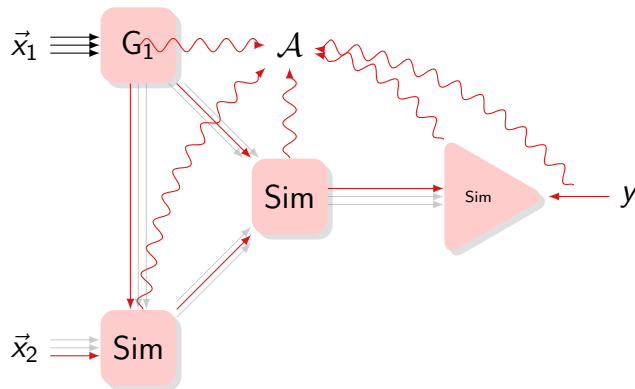


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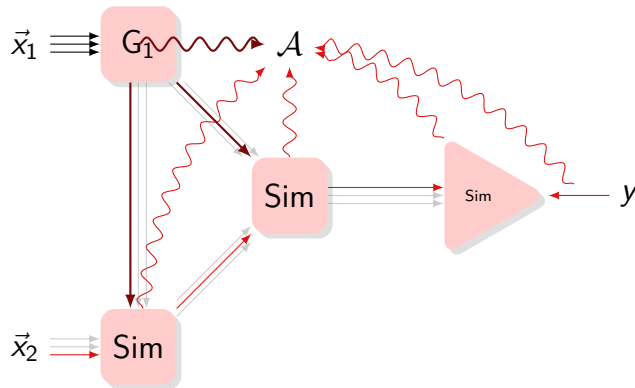


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Hence,

$$\Pr[\text{bad}_i] \leq \Pr \left[|W^{G_i}| + \sum_{j \in \partial_i} |W^{G_j}| \geq t_i \right]$$

Using the union bound:

$$\eta = \sum_{\substack{i=1 \\ G_i \text{ not output}}}^{|C|} \Pr[\text{bad}_i]$$

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Concluding the Proof

Using Chernoff:

$$\begin{aligned}\Pr\left[\left|W^{G_i}\right| + \sum_{j \in \partial_i} \left|W^{G_j}\right| > t_i\right] &= \Pr\left[\left|W^{G_i} \cup \left(\bigcup_{j \in \partial_i} W^{G_j}\right)\right| \geq t_i + 1\right] \\ &\leq \left(e \cdot \frac{|G_i| + \sum_{j \in \partial_i} |G_j|}{t_i + 1} \cdot \epsilon\right)^{t_i + 1}.\end{aligned}$$

Comparison with Previous Works

So far, trade-off was needed (see next talk):

→ Duc *et al.*:¹² $|C| \cdot (\mathcal{O}(d) \cdot |\mathbb{F}| \cdot \delta)^{d/2}$

→ Belaïd *et al.*:¹³ $|C| \cdot (\mathcal{O}(1) \cdot |\mathbb{F}| \cdot \delta)^{\approx d/3}$

→ Next talk: tighter and more generic way to compose

¹²Duc, Dziembowski, and Faust, “Unifying Leakage Models: From Probing Attacks to Noisy Leakage”.

¹³Taleb, “Secure and Verified Cryptographic Implementations in the Random Probing Model.
(Implémentations cryptographiques sûres et vérifiées dans le modèle random probing)”.

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Noisy-to-Random Reduction

LEMMA (SIMULATABILITY BY RANDOM PROBING¹⁴)

The leakage function L can be simulated from a *random probing adversary*:
 $\varphi(x)$ reveals x with probability $\epsilon = 1 - \sum_l \min_x \Pr[L(x) = l] \leq \delta \cdot |\mathbb{F}|$.

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Is it too much ?

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NL

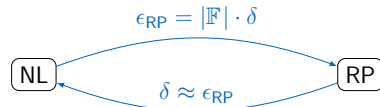
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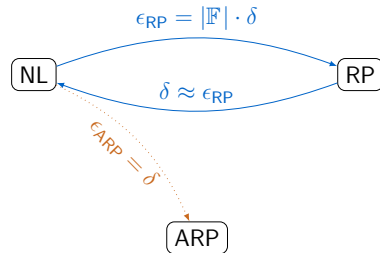
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Dependence

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- **ARP** (EC'24): $\varphi(x) = x$ with proba. ϵ_x



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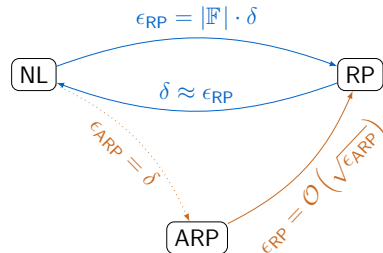
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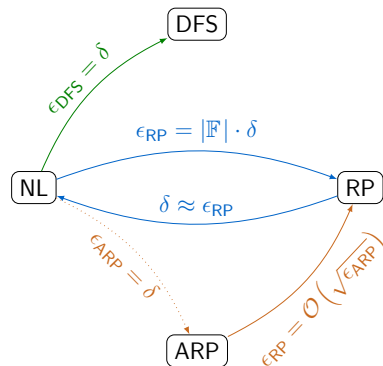
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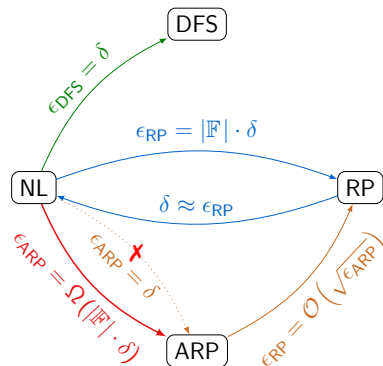
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Technical Results

THEOREM (ARP-SIMULABILITY)

L is simulable in the $\{\epsilon_x\}_x$ average random probing model iff¹⁵

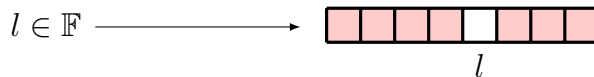
$$1 \leq \sum_l \min_{x': \epsilon_{x'} < 1} \left\{ \frac{\Pr[L(x') = l]}{1 - \epsilon_{x'}} \right\}$$

Remark: if ϵ_x constant, we get back the RP lemma

Proof: see appendix

¹⁵One needs at least one $\epsilon_x < 1$ for non-trivial simulation

The Catastrophic Channel, a.k.a., the *evil* function¹⁶



Equivalently:

$$\Pr[L(x) = l] = \begin{cases} 0 & \text{if } x = l, \\ \frac{1}{|\mathbb{F}|-1} & \text{otherwise} \end{cases}$$

Here, $\delta = \frac{1}{|\mathbb{F}|}$, but $\epsilon = \mathbb{E}_x[\epsilon_x] \geq \frac{1}{2}$

$$\text{Hence, } \frac{\epsilon}{\delta} \geq \Omega(|\mathbb{F}|) \quad \text{X}$$

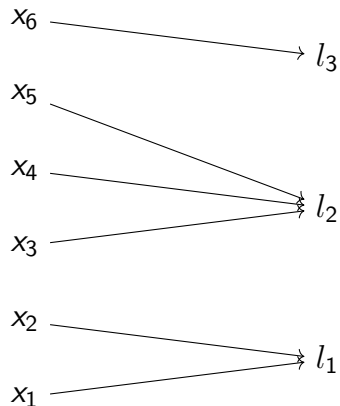
¹⁶Thus named by Gianluca Brian, as it appears as a worst-case in another of their works

Deterministic Leakage Functions

We can characterize the optimal simulator:

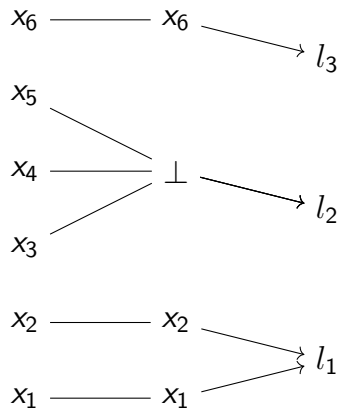
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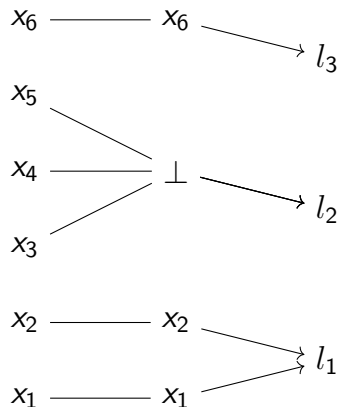
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$$\begin{aligned} \epsilon &= \mathbb{E}_x [\epsilon_x] = 1 - \frac{\max_l |\{x : L(x) = l\}|}{|\mathbb{F}|} \\ &\leq 1 - \frac{\mathbb{E}_l [|\{x : L(x) = l\}|]}{|\mathbb{F}|} \\ &= \delta \end{aligned}$$

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Join us in this line of research !

References I

-  Barthe, G. et al. “Masking the GLP Lattice-Based Signature Scheme at Any Order”. In: *J. Cryptol.* 37.1 (2024), p. 5. DOI: 10.1007/S00145-023-09485-Z. URL: <https://doi.org/10.1007/s00145-023-09485-z>.
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Reduction from Noisy Leakage to Random Probing (I)

Assume there exists such a simulator $\mathcal{S}$,

Reduction from Noisy Leakage to Random Probing (I)

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Constraints:

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Constraints:

- For all input x , $\Pr[\mathcal{S}(x)]$ should be a p.m.f.
- For the input $\perp$, $\Pr[\mathcal{S}(\perp)]$ should be a p.m.f.
- For any x, l , $\Pr[\mathcal{S}(\varphi(x)) = l] = \Pr[L(x) = l]$

Reduction from Noisy Leakage to Random Probing (II)

Let us start from the last constraint. For any x and any l :

$$\Pr[L(x) = l] = \Pr[\mathcal{S}(\varphi(x)) = l]$$

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Hence,

$$0 \leq \Pr[\mathcal{S}(\perp) = l] = \frac{\overbrace{\Pr[L(x) = l] - \epsilon \cdot \Pr[\mathcal{S}(x) = l]}^{\text{Should not depend on } X}}{1 - \epsilon}$$

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$$0 \leq \Pr[\mathcal{S}(x) = l] = \frac{\Pr[L(x) = l] - \pi(l)}{\epsilon} \quad (2)$$

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Hence,

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Is there any ϵ such that $\geq$ and $\leq$ are valid?

Reduction from Noisy Leakage to RP (III)

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Reduction from Noisy Leakage to RP (III)

Is there any ϵ such that $\geq$ and $\leq$ are valid? From (3), and (4), we get

$$0 \leq \pi(l) \leq \Pr[L(x) = l] \text{ for any } x$$

Reduction from Noisy Leakage to RP (III)

Is there any ϵ such that $\geq$ and $\leq$ are valid? From (3), and (4), we get

$$0 \leq \pi(l) \leq \Pr[L(x) = l] \text{ for any } x$$

In other words,

$$0 \leq \pi(l) \leq \min_x \Pr[L(x) = l]$$

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In other words,

$$0 \leq \pi(l) \leq \min_x \Pr[L(x) = l]$$

Furthermore, summing (3) over l , by definition of probability distributions,

$$\sum_l \pi(l) = \underbrace{\sum_l \Pr[L(x) = l]}_{=1} - \epsilon \cdot \underbrace{\sum_l \Pr[\mathcal{S}(x) = l]}_{=1}$$

Reduction from Noisy Leakage to RP (III)

Is there any ϵ such that $\geq$ and $\leq$ are valid? From (3), and (4), we get

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Reduction from Noisy Leakage to RP (III)

Is there any ϵ such that $\geq$ and $\leq$ are valid? From (3), and (4), we get

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Hence,

$$\epsilon = 1 - \sum_l \pi(l) \geq 1 - \sum_l \min_x \Pr[L(x) = l]$$

Reduction from Noisy Leakage to RP (III)

Is there any ϵ such that $\geq$ and $\leq$ are valid? From (3), and (4), we get

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Hence, to have the smallest ϵ ,

$$\epsilon = 1 - \sum_l \pi(l) = 1 - \sum_l \min_x \Pr[L(x) = l]$$

Reduction to Average Random Probing (I)

For any x and any l :

$$\Pr[L(x) = l] = \Pr[\mathcal{S}(\varphi(x)) = l]$$

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Hence, provided that $\epsilon_x < 1$,

$$0 \leq \Pr[\mathcal{S}(\perp) = l] = \frac{\overbrace{\Pr[L(x) = l] - \epsilon_x \cdot \Pr[\mathcal{S}(x) = l]}^{\text{Should not depend on } x}}{1 - \epsilon_x}$$

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Is there any ϵ such that $\geq$ and $\leq$ are valid? From (3), and (4), we get

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So (3) gives

$$\Pr[\mathcal{S}(\perp) = l] \leq \frac{\Pr[L(x) = l]}{1 - \epsilon_x} \text{ for any } x \text{ s.t. } \epsilon_x < 1$$

Reduction from Noisy Leakage to RP (III)

Is there any ϵ such that $\leq$ and $\geq$ are valid? From (3), and (4), we get

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So (3) gives

$$\Pr[\mathcal{S}(\perp) = l] \leq \frac{\Pr[L(x) = l]}{1 - \epsilon_x} \text{ for any } x \text{ s.t. } \epsilon_x < 1$$

In other words,

$$0 \leq \Pr[\mathcal{S}(\perp) = l] \leq \min_{x': \epsilon_{x'} < 1} \left\{ \frac{\Pr[L(x') = l]}{1 - \epsilon_{x'}} \right\}$$

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Is there any ϵ such that $\geq$ and $\leq$ are valid? From (3), and (4), we get

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In other words,

$$0 \leq \Pr[\mathcal{S}(\perp) = l] \leq \min_{x': \epsilon_{x'} < 1} \left\{ \frac{\Pr[L(x') = l]}{1 - \epsilon_{x'}} \right\}$$

And (3) also gives

$$0 \leq \pi(l, x) \leq (1 - \epsilon_x) \cdot \min_{x': \epsilon_{x'} < 1} \left\{ \frac{\Pr[L(x') = l]}{1 - \epsilon_{x'}} \right\}$$

Characterization of ARP-simulable Leakages

Furthermore, summing (3) over l , by definition of probability distributions,

$$\sum_l \pi(l, x) = \underbrace{\sum_l \Pr[L(x) = l]}_{=1} - \epsilon_x \cdot \underbrace{\sum_l \Pr[S(x) = l]}_{=1}$$

¹⁷One needs at least one $\epsilon_x < 1$ for non-trivial simulation

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Hence, the following result

THEOREM (ARP-SIMULABILITY)

L is simulable in the $\{\epsilon_x\}_x$ average random probing model iff¹⁷

$$1 \leq \sum_l \min_{x': \epsilon_{x'} < 1} \left\{ \frac{\Pr[L(x') = l]}{1 - \epsilon_{x'}} \right\}$$

¹⁷One needs at least one $\epsilon_x < 1$ for non-trivial simulation