Creachlab 23/05/2025

LIRMM

SERMA SAFETY & SECURITY

Anomalies Mitigation for Horizontal Side Channel Attacks with Unsupervised Neural Networks

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Outline

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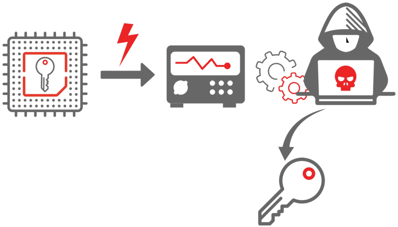
Horizontal Attacks

Side Channel Attacks

An attacker can recover sensitive information by listening on side-channels on a target device (Power, EM, timing, ...).



Several attacks:

- **Profiled**: Able to characterize the leakage before the attack (Templates, Deep Learning, ...)
- **Unprofiled**: Attack directly carried on target (SPA, DPA, ...).

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Horizontal Attacks

- Single trace attack
- No profiling on open device possible, no leakage assessment, black box
- Usually applied on asymmetric implementations (RSA, ECC, ...).
- Commonly used clustering approach:
  1. Divide trace into patterns, preprocessing steps (cutting, alignment, filtering, ...)
  2. **Points of Interest (PoI) selection with univariate clustering** or dimensionality reduction
  3. Multidimensional clustering

Attack success highly relies on the quality of the trace.

Impact of anomalies on PoI selection

Univariate anomalies model

Outliers (interquantile range)

Distribution tails

$$x \notin R = [Q_1 - \alpha\,\mathrm{IQR}, Q_3 + \alpha\,\mathrm{IQR}]$$
$$\mathrm{IQR} = Q_3 - Q_1$$

Saturated values

Min/max values of digital sampling vertical resolution, for 8bit:

$$x \in \xi(8) = \{-128, 127\}$$

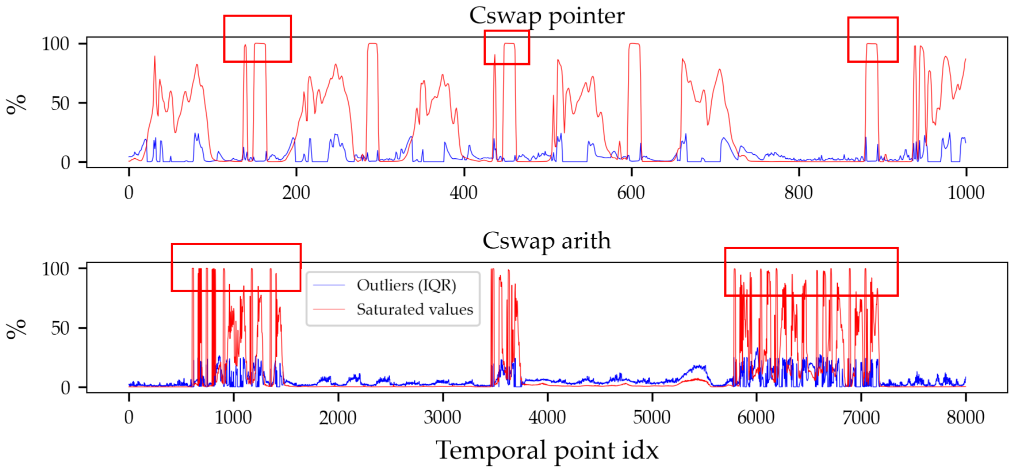
Considered Datasets

Cswap Pointer and Arith public datasets: ECC Scalar multiplication

- Arith dataset: Arithmetic swapping
- Pointer datset: Pointers swapping instead of values

We define the BRR as the percentage of correctly identified bits of the exponent scalar during the clustering process.

Anomalies in data



[1] Average anomalies Pointer:33.3%, Arith:16.5%

Impact of anomalies on PoI selection

Clustering is **not robust** to anomalies in data, can cause centroids shift, singularities,...

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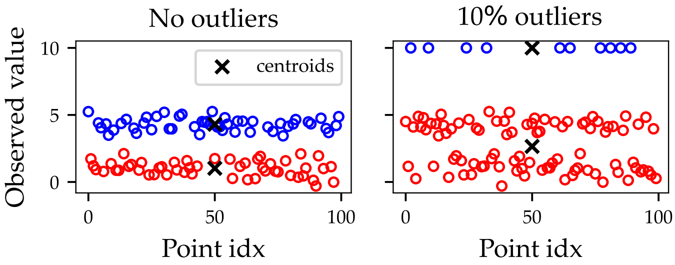

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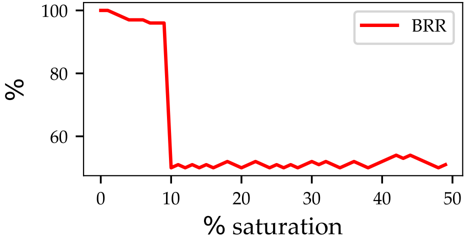

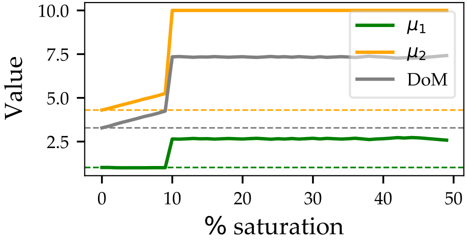

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[1]BRR: Bit Recovery Rate

Anomalies mitigation

Limits of simple mitigation

Mitigation by ablation

- Remove time points based on anomalies threshold
- Possibly loosing information about the leakage

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Mitigation by replacement

- Replace anomalies points with mean/median of non anomalies for each time point
- Decrease separability of mixture components

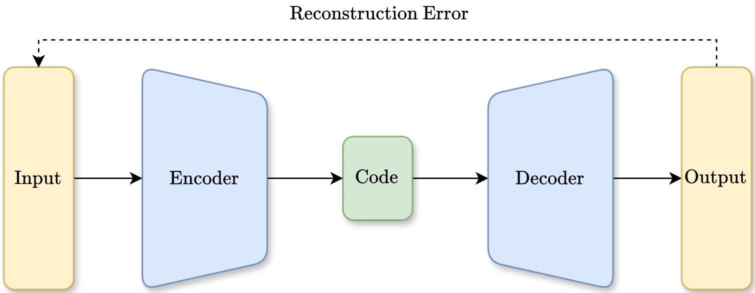
Contribution - Mitigation with neural networks

In this work, alternative methods are studied:

- Able to be trained in an unsupervised manner
- Leakage/information conservation
- Two approaches are considered:
  - Unsupervised mitigation: **Robust auto-encoder**
  - Selfsupervised mitigation: **Cycle generative adversarial networks**

Auto-encoder

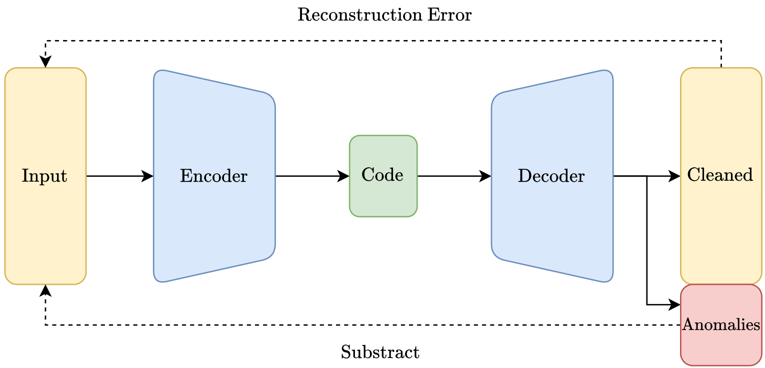
Built from a encoder/decoder $(\mathcal{E}_\phi, \mathcal{F}_\theta)$ network pair. Trained for input reconstruction.



$$\mathcal{L}(\theta, \phi) = ||\mathbf{X} - \mathcal{F}_\theta(\mathcal{E}_\phi(\mathbf{X}))||_2$$

Robust auto-encoder unsupervised mitigation

Decomposition of input data to **cleaned** and **anomalies** matrices.
Prior on the anomalies amount.



Robust auto-encoder unsupervised mitigation

The RAE aims at achieving the following decomposition:

$$\mathbf{X} = \mathbf{L} + \mathbf{S} \tag{1}$$

where:

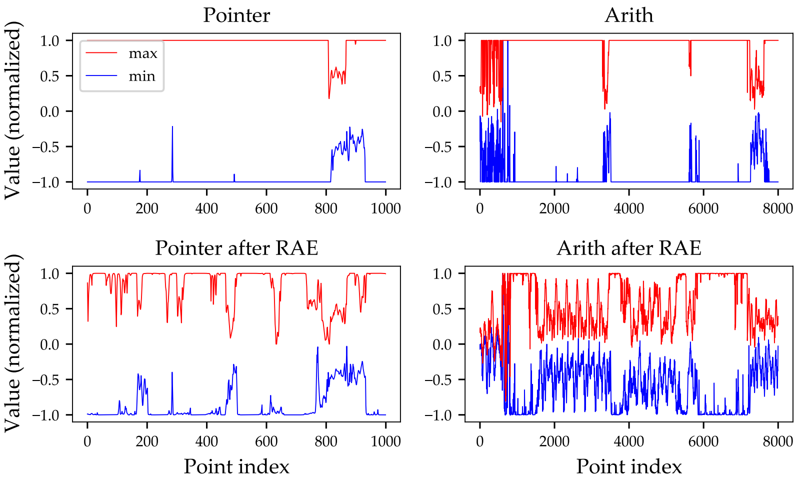
- $\mathbf{X}$: input patterns
- $\mathbf{L}$: cleaned patterns
- $\mathbf{S}$: extracted anomalies

The complete objective is given by:

$$\mathcal{L}(\theta, \phi) = ||\mathbf{L} - \mathcal{F}_\theta(\mathcal{E}_\phi(\mathbf{L}))||_2 + \tau||\mathbf{S}||_1 \tag{2}$$

Left term is optimized through gradient descent while right term is minized with a proximal operator.

Impact on patterns



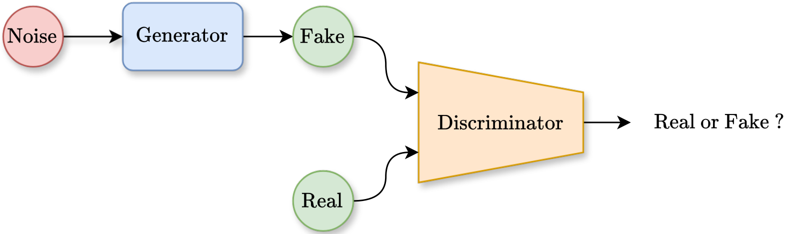
Limits of the RAE

While relevant, the RAE can suffer from some drawbacks:

- The RAE **generates new synthetic patterns**, this can cause **side effects on non anomalies points**.
- In addition, it does not exploit any anomalies model. It is fully unsupervised

An alternative method is proposed to to include the anomalies models, based on **generative adversarial networks**.

Generative Adversarial Networks



$$\min_G \max_D \mathcal{L}_{\mathsf{GAN}}(G, D, X, Z) = \mathbb{E}_{x\sim X} \log D(x) + \mathbb{E}_{z\sim Z} \log[1 - D(G(z))]$$

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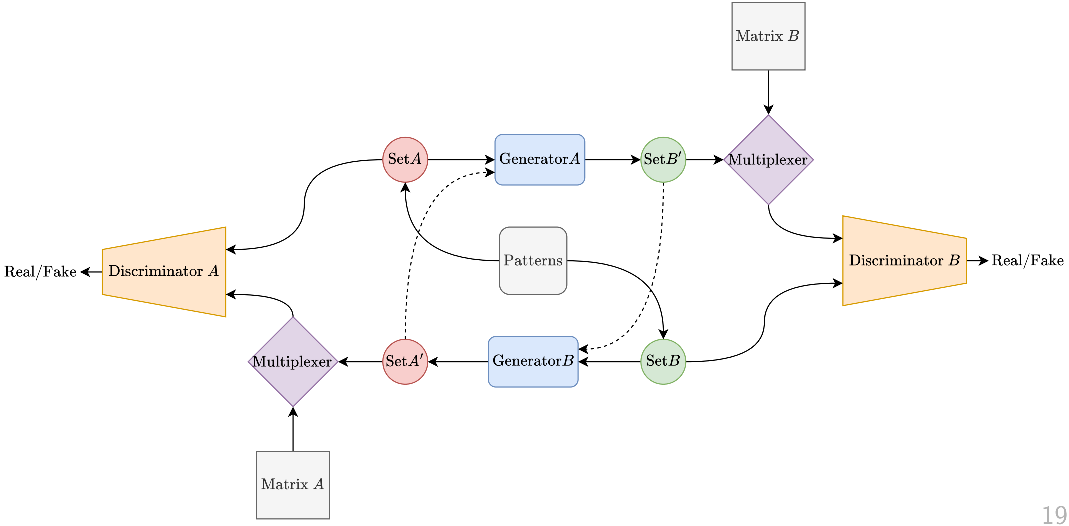
Multiplexer CycleGAN self-supervised mitigation



Multiplexer CycleGAN self-supervised mitigation

Complete loss is given by:

$$
\begin{aligned}
\mathcal{L}(G_A, G_B, D_A, D_B) &= \mathcal{L}_{\mathsf{GAN}}(G_A, D_B, A, B) \\
&+ \mathcal{L}_{\mathsf{GAN}}(G_B, D_A, B, A) \\
&+ \lambda \mathcal{L}_{\mathsf{cyc}}(G_A, G_B)
\end{aligned} \tag{3}
$$

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with consistency loss:

$$\begin{aligned}\mathcal{L}_{\mathsf{cyc}}(G_A, G_B) &= \mathbb{E}_{a\sim A}||G_B(G_A(a)) - a||_1 \\ &+ \mathbb{E}_{b\sim B}||G_A(G_B(b)) - b||_1\end{aligned} \tag{4}$$

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Aims at finding:

$$G_A^*, G_B^* = \operatorname*{argmin}_{G_A, G_B} \operatorname*{argmax}_{D_A, D_B} \mathcal{L}(G_A, G_B, D_A, D_B) \tag{5}$$

Multiplexer CycleGAN self-supervised mitigation

1. Build the anomalies matrix M such that:

$$m_{i,j} = \begin{cases} 1, & \text{if } x_{i,j} \in \xi(8) \vee x_{i,j} \notin R(x_{:,j}) \\ 0, & \text{otherwise} \end{cases} \tag{6}$$

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2. Split into A, B sets based on maximum Hamming distance:

$$\underset{i,j \in \{1,\ldots,n\}}{\operatorname{argmax}} \ \mathrm{HW}(m_{i,:} \oplus m_{j,:}), \quad i \neq j \tag{7}$$

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3. Train the model with gradient descent (previous slide).
4. Replace by generated values through multiplexers:

$$\begin{aligned} A'' &= \mathrm{mux}(A, G_B(B), M_A) = (M_A \wedge G_B(B)) \vee (\neg M_A \wedge A) \\ B'' &= \mathrm{mux}(B, G_A(A), M_B) = (M_B \wedge G_A(A)) \vee (\neg M_B \wedge B) \end{aligned} \tag{8}$$

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Benefits of proposed architecture

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- Selective correction that include the anomaly models.
- Only values marked as **anomalies** are generated, others are untouched.
- Multiplexers add training stability for GANs, reduce complexity.
- Sets matching on Hamming distance allows optimal correction.

Results

Mitigation results

	Cswap Pointer			Cswap Arith		
	Before	RAE	GAN	Before	RAE	GAN
Outliers (%)	4.32	5.36	**1.67**	5.15	4.73	**1.35**
Saturation (%)	30.27	**1.19**	10.22	12.88	**0.01**	5.19
Total (%)	33.39	**6.55**	11.85	16.54	**4.75**	6.49

Table: Percentage of outliers and extremes obtained on original patterns, after applying the RAE and the CycleGAN. Best results are highlighted in bold.

Impact on distributions

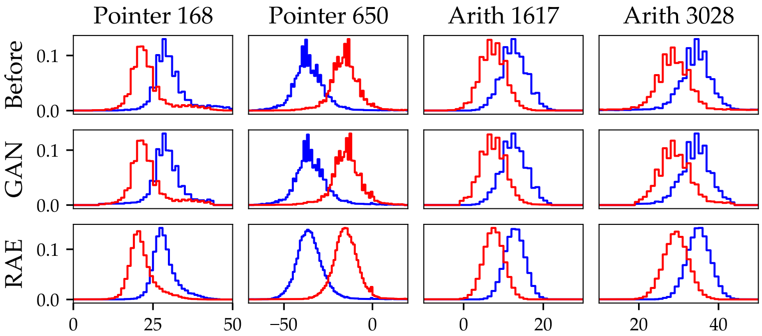
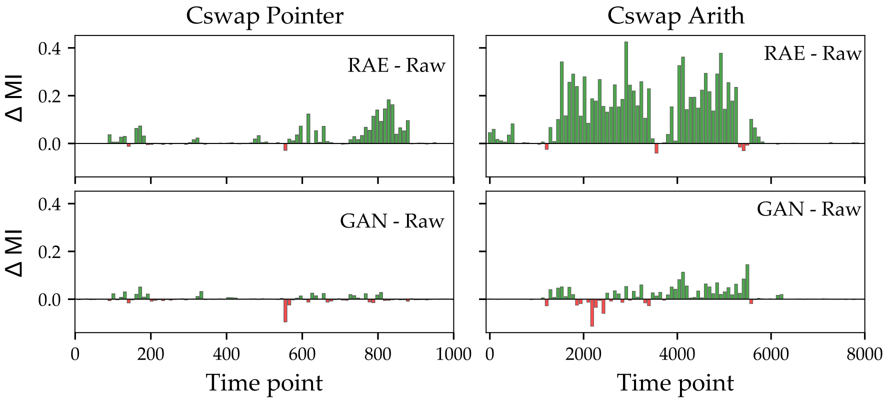


Figure: Empirical p.d.f of four samples before and after application of the RAE and CycleGAN to mitigate abnormal values. Blue p.d.f corresponds to class $c = 0$ (resp. red $c = 1$).

Information conservation

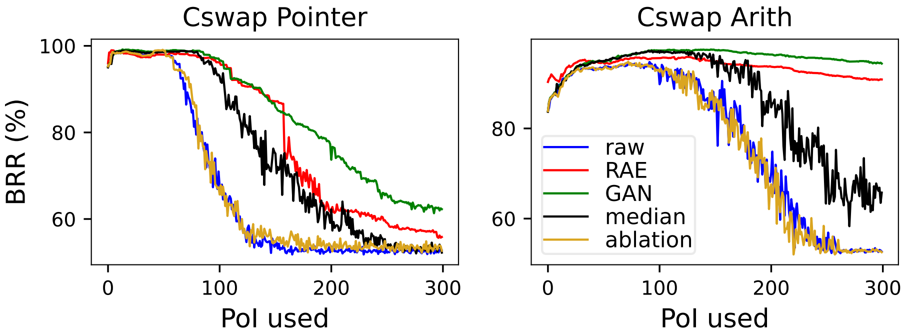
No change in the global MI. [1]



[1]Estimated with MINE.

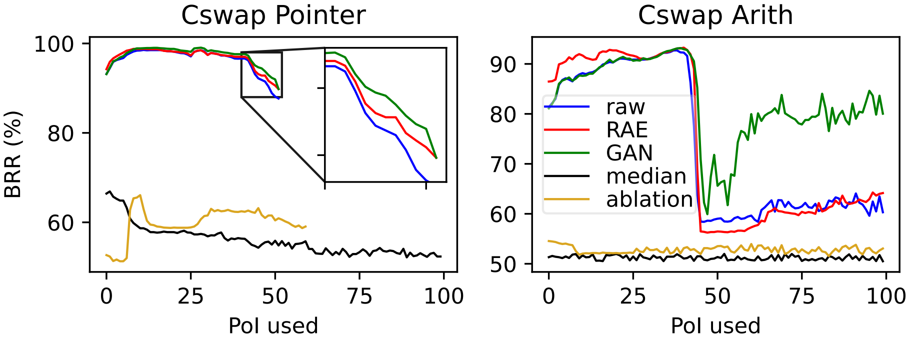
Supervised selection - upper bound

Select k PoI with highest t-values and apply multidimensional clustering.



Unsupervised selection

Multidimensional clustering on the best k PoI from Cler *et al.* 2023 unsupervised selection.



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- Architecture choice and parameters tuning can be hard in practice
- Attack success **still** depends on the exploitation method

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Future work

- Consider additional anomalies models
- Generalize on other targets/algorithms

Thank you for your attention

Do you have any questions ?

- Read the thesis: **hal.science/tel-04730413v1**
- Paper: **CASCADE 2025**, soon to be published (Springer)
- Contact: **g.cler@serma.com**

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