



Improving Leakage Exploitability in Horizontal Side Channel Attacks through Anomaly Mitigation with Unsupervised Neural Networks

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Outline

- 1 Horizontal Attacks
- 2 Impact of anomalies on Pol selection
- 3 Anomalies mitigation
- 4 Results
- 5 Conclusion

Horizontal Attacks

Horizontal Attacks

- ▶ Single trace attack
- ▶ No profiling on open device possible, no leakage assessment.
- ▶ Usually on asymmetric implementations (RSA, ECC).
- ▶ Clustering approach:
 - 1 Divide trace into patterns
 - 2 Points of Interest (PoI) selection with univariate clustering
 - 3 Multidimensional clustering

Attack success highly relies on the quality of the trace.

Impact of anomalies on PoI selection

Anomalies in data

Outliers (interquartile range)

Distribution tails

$$x \notin [Q_1 - 1.5 \times IQR, Q_3 + 1.5 \times IQR]$$

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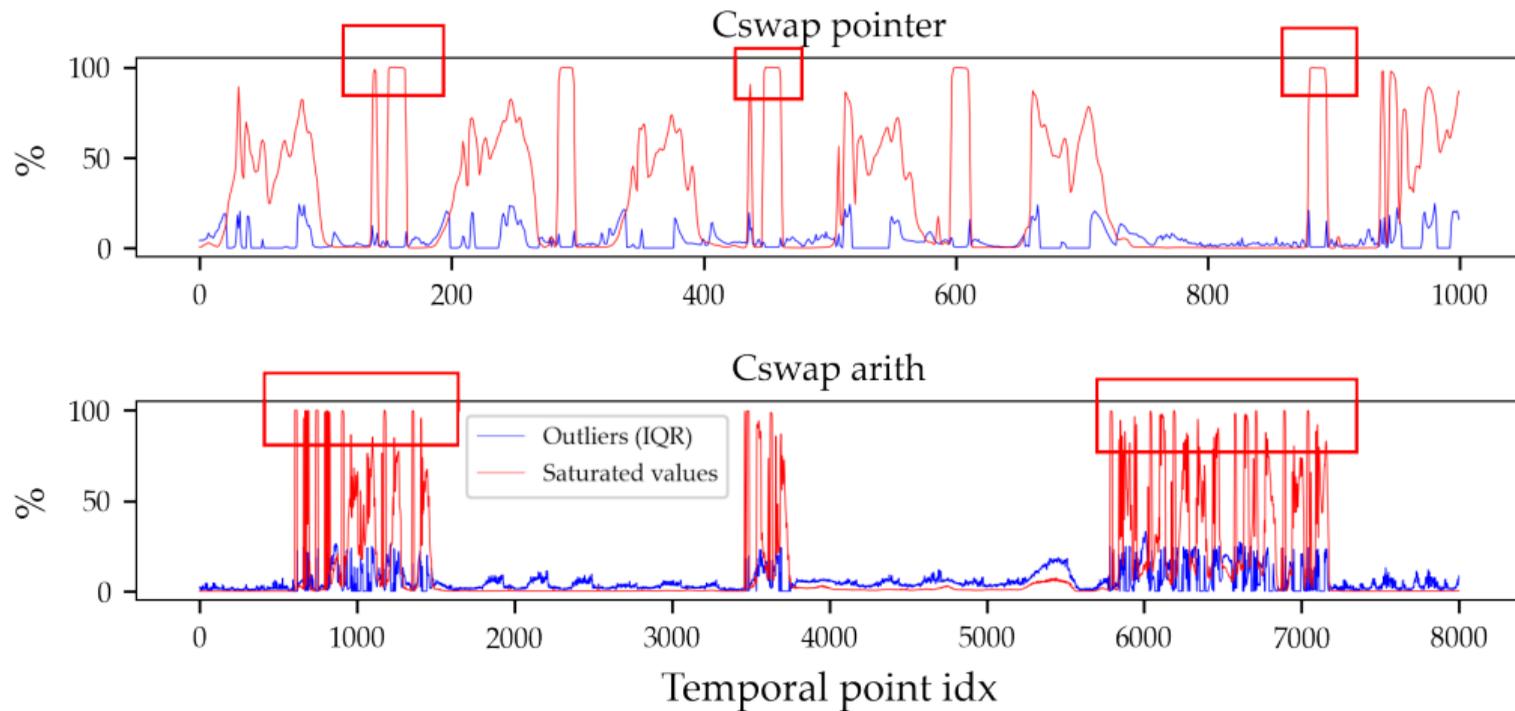
$$x \notin [Q_1 - 1.5 \times IQR, Q_3 + 1.5 \times IQR]$$

Saturated values

min/max values of digital sampling, for 8bit:

$$x = -128 \vee x = 127$$

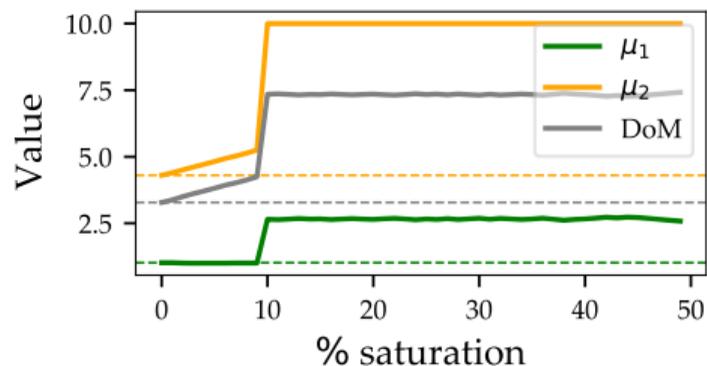
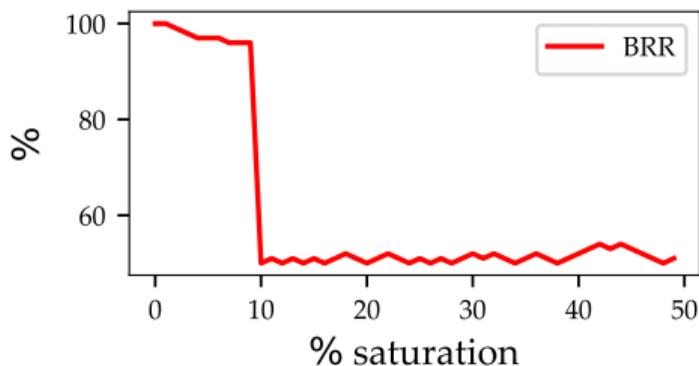
Anomalies in data



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

Impact of anomalies on Pol selection

- ▶ Clustering is **not robust** to anomalies in data
- ▶ Can cause centroids shift, singularities,...



Anomalies mitigation

Limits of simple mitigation

Mitigation by ablation

- ▶ Remove time points based on anomalies threshold
- ▶ Possibly losing 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

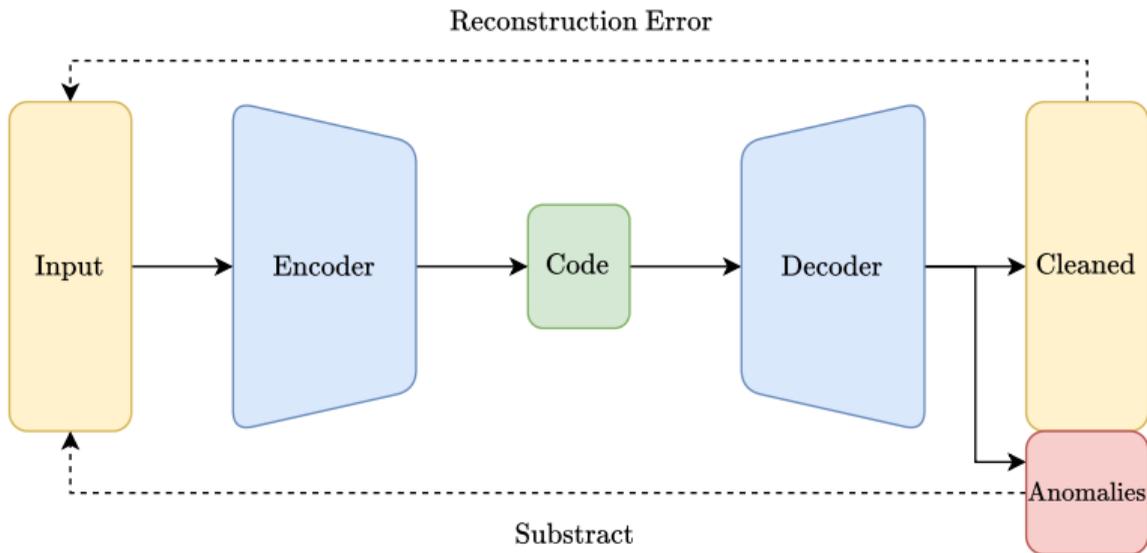
Contribution - Mitigation with neural networks

Consider alternative methods

- ▶ Able to be trained in an unsupervised manner
- ▶ Leakage/information conservation
- ▶ Two approaches:
 - ⋮ Robust auto-encoder
 - ⋮ CycleGAN

Robust auto-encoder unsupervised mitigation

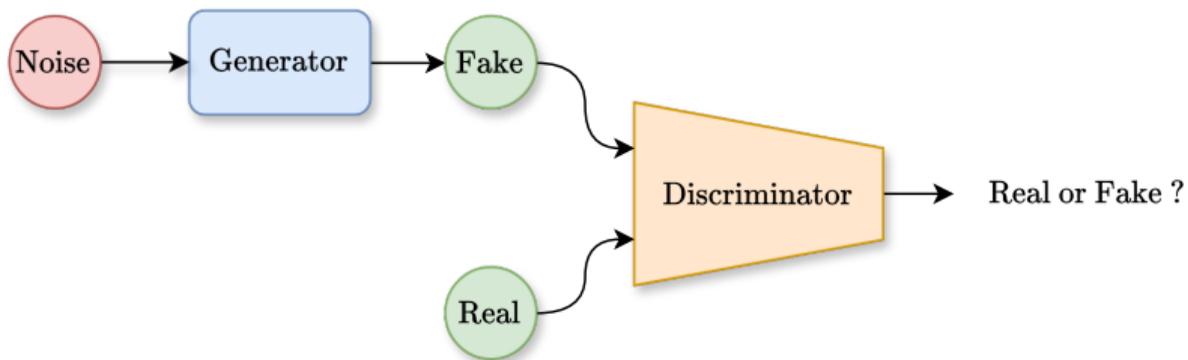
Decomposition of input data to **cleaned** and **anomalies** matrices.
Prior on the anomalies amount.



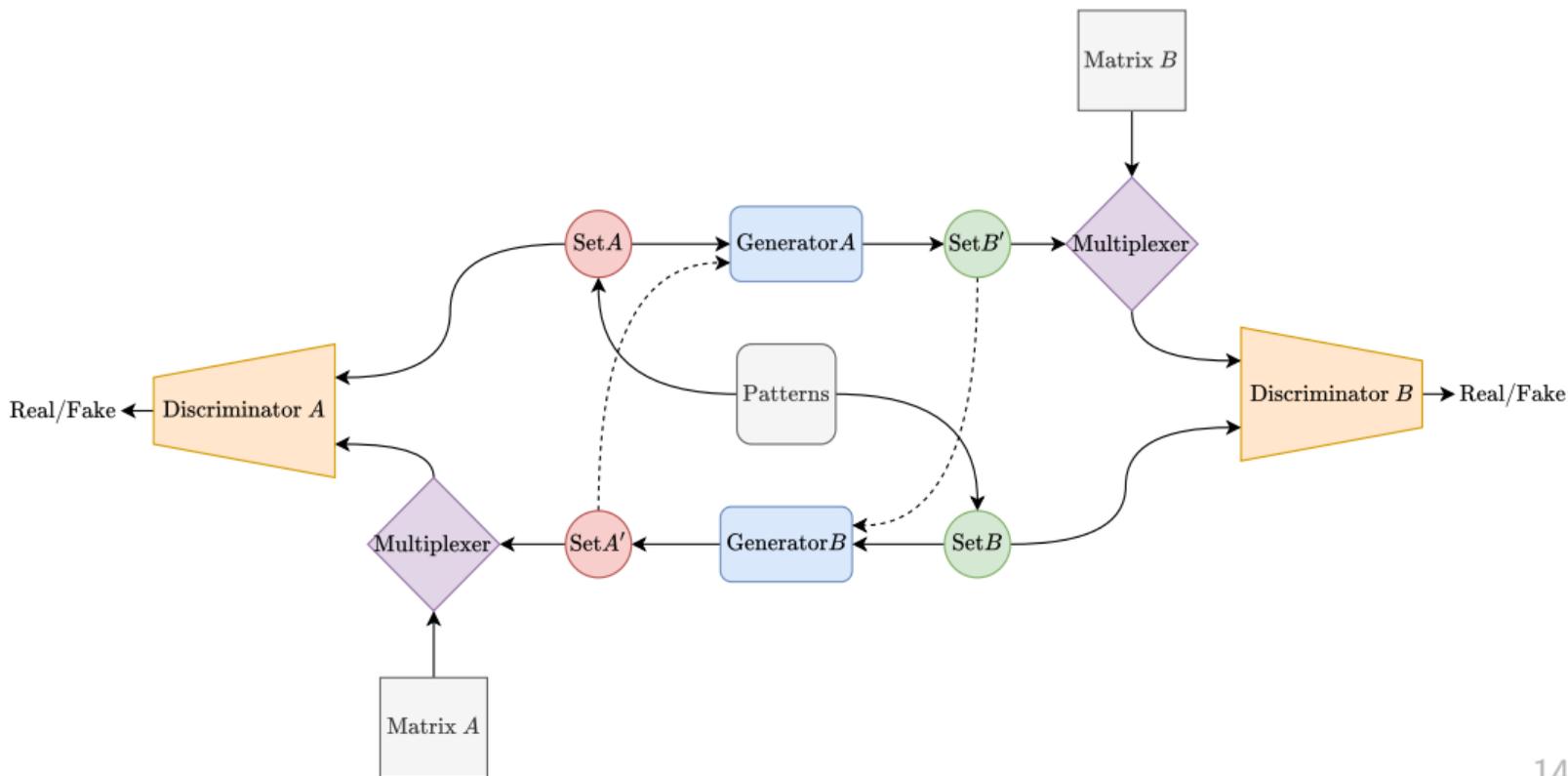
Limits

- ▶ RAE Generate new synthetic patterns
→ Can cause side effects on non anomalies points.
- ▶ RAE does not exploit the anomalies model.
→ Fully unsupervised

Generative Adversarial Networks



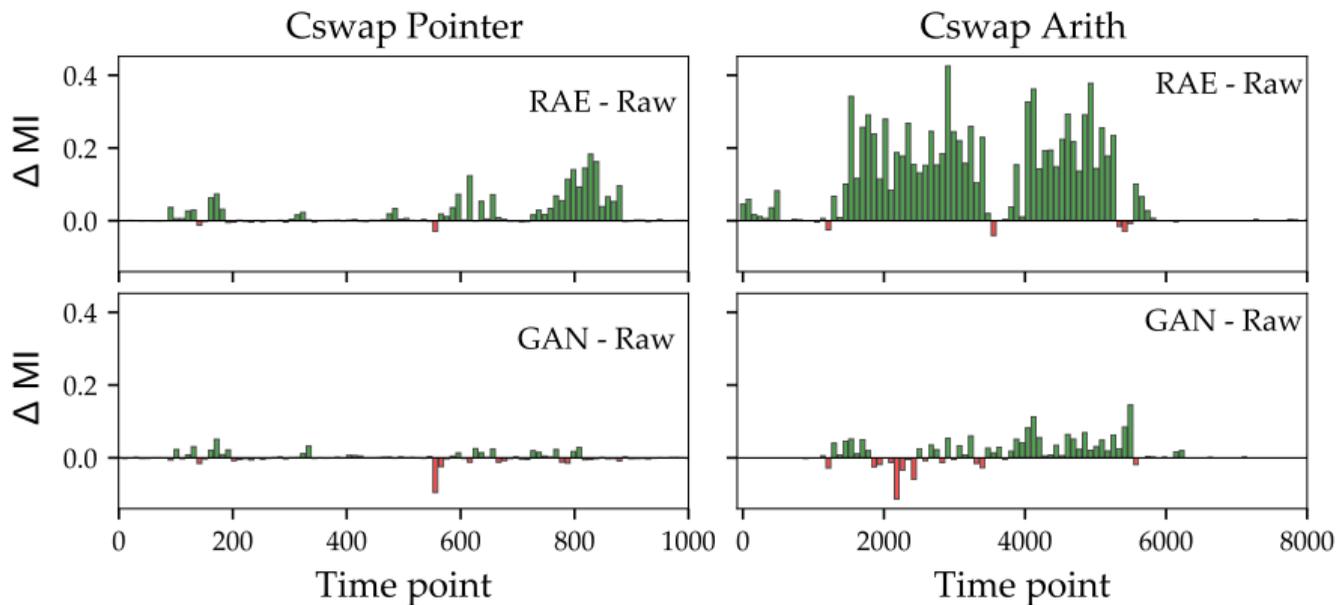
Multiplexer CycleGAN self-supervised mitigation



Results

Information conservation

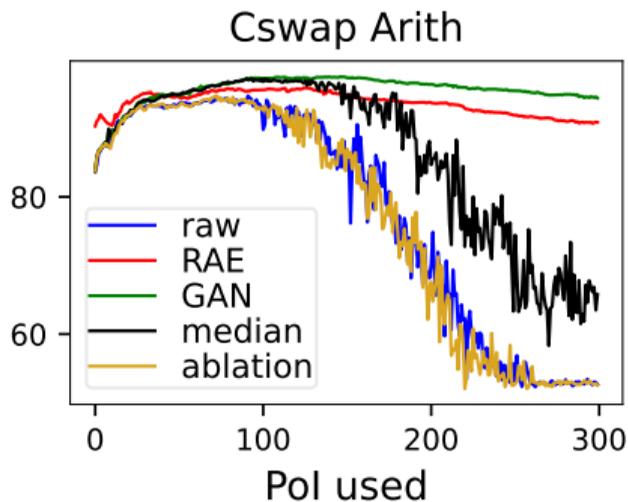
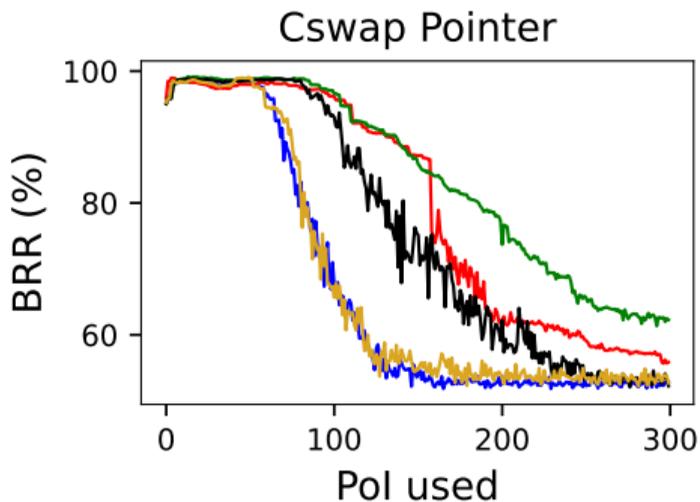
No change in the global MI. ¹



¹Estimated with MINE.

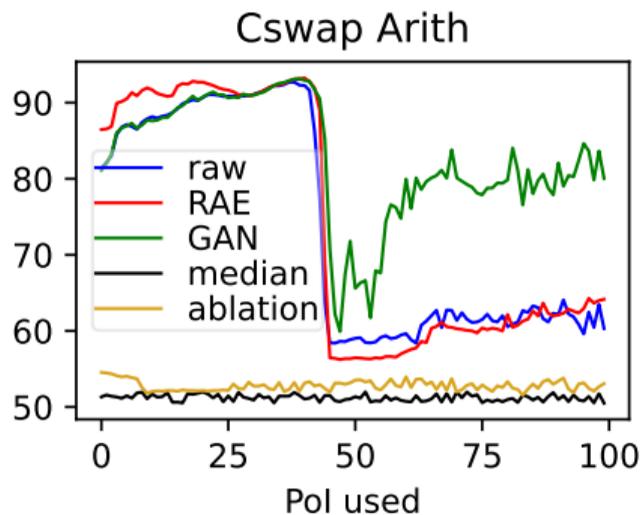
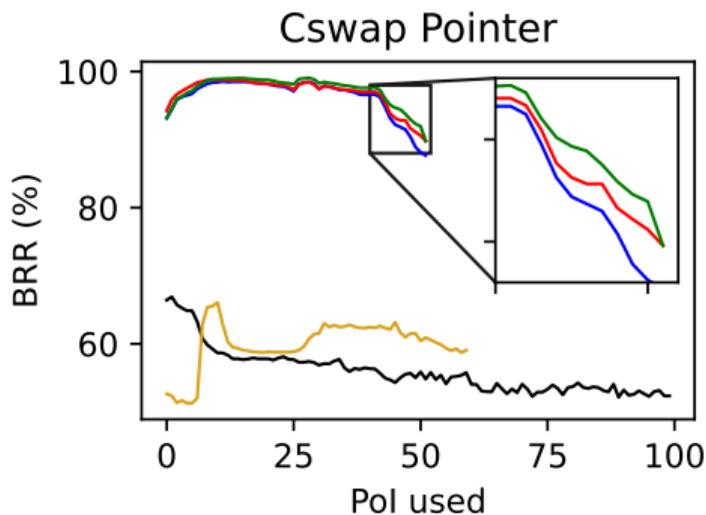
Supervised selection - upper bound

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



Unsupervised selection

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



Conclusion

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Future work

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

Thank you for your attention.

Do you have any question?

Bonus