# Machine Learning and Implementation Attacks

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# Outline

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# Where to use Machine Learning in Cryptology

- Machine learning is data driven approach.
- It seems more difficult to use such techniques for design.
- Additional benefit from using them in attacks: it is easy to validate the solution.

# Where to use Machine Learning - Classical Applications

- **Side-channel attacks**.
- **Fault injection**.
- Modeling attacks on PUFs.
- Detecting Hardware Trojans.
- Machine learning over encrypted data.

# Where to use Machine Learning - Exotic Applications

- Factoring numbers.
- Design of ciphers.

# Outline

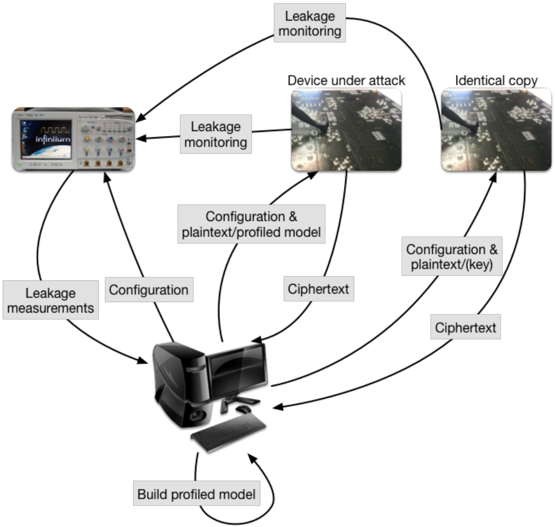
# Implementation Attacks and SCA

### Implementation attacks

Implementation attacks do not aim at the weaknesses of the algorithm, but on its implementation.

- **Side-channel attacks** (SCAs) – passive, non-invasive attacks.
- SCAs – one of the most powerful category of attacks on crypto devices.
- Profiled attacks – the most powerful among SCAs.
- Within profiling phase the adversary estimates leakage models for targeted intermediate computations, which are exploited to extract secret information in the actual attack phase.

# Profiled Attacks



# SCA and Profiling Attacks

Table: Overview of profiling side-channel attacks used in literature (up to March 2019 and limited to symmetric key crypto).

| Algorithm | Reference |
| --- | --- |
| Naive Bayes and its variants | [1, 2, 3, 4, 5, 6] |
| Random Forest | [2, 3, 4, 7, 8, 6, 9, 10, 11, 12, 13, 14] |
| Rotation Forest | [15, 4, 5, 16] |
| XGB | [5] |
| MultiBoost | [15] |
| Self-organizing maps | [9] |
| Support Vector Machines | [15, 4, 7, 8, 6, 17, 18, 9, 10, 11, 12, 19, 13, 20, 16] |
| Multivariate regression analysis | [21, 11, 12] |
| Multilayer Perceptron | [2, 3, 5, 7, 8, 6, 22, 23, 24, 25, 26, 27, 28] |
| Convolutional Neural Networks | [8, 5, 7, 29, 30, 22, 28] |
| Autoencoders | [8] |
| Recurrent Neural Networks | [8] |
| Template Attack and its variants | [1, 15, 4, 7, 8, 29, 30, 6, 17, 9, 10, 11, 12, 19, 13, 28, 16] |
| Stochastic attack | [11, 12, 7] |

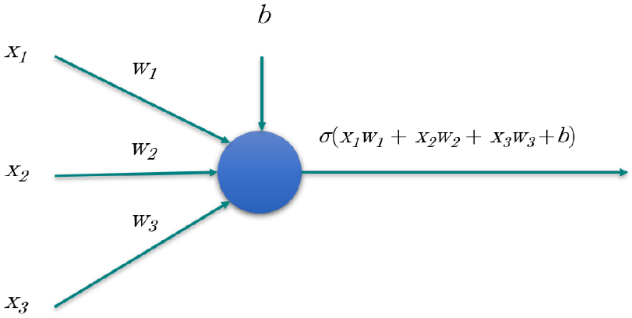
# Profiled Attacks

- Template Attack is the most powerful attack from the information theoretic point of view.
- Some machine learning techniques (supervised learning) also belong to the profiled attacks.
- Deep learning has been shown to be able to reach top performance even if the device is protected with countermeasures.

# Outline

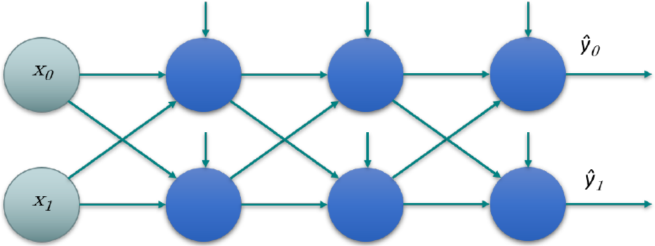
# Deep Learning

- Let us build a neural network.

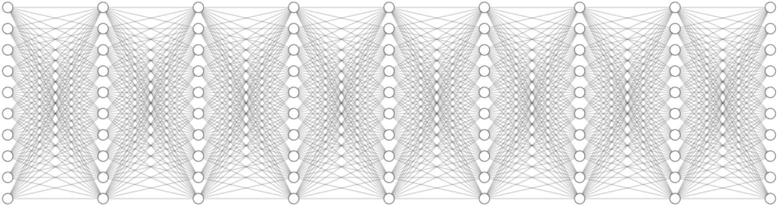


# Deep Learning

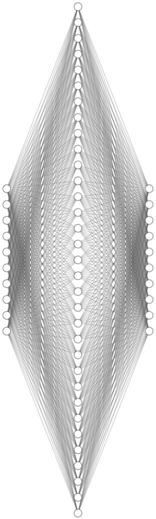
- Let us continue adding neurons.



# Multilayer Perceptron - "Many" Hidden Layers



# Multilayer Perceptron - One Hidden Layer



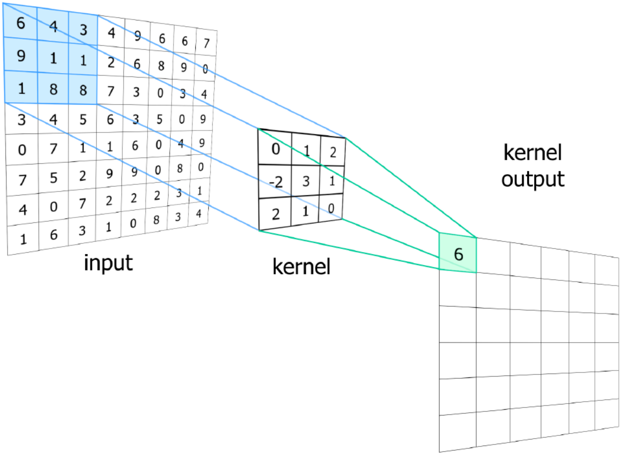
# Universal Approximation Theorem

- A feed-forward network with a single hidden layer containing a finite number of neurons can approximate continuous functions on compact subsets of $\mathbb{R}^n$.
- Given enough hidden units and enough data, multilayer perceptrons can approximate virtually any function to any desired accuracy.
- Valid results if and only if there is a sufficiently large number of training data in the series.

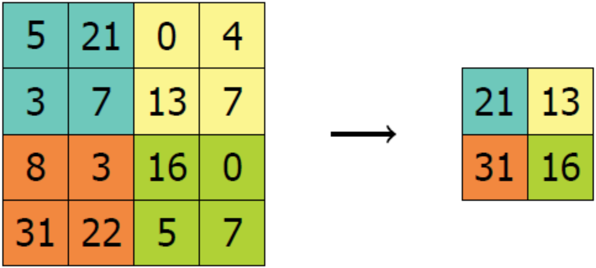
# Convolutional Neural Networks

- CNNs represent a type of neural networks which were first designed for 2-dimensional convolutions.
- They are primarily used for image classification but lately, they have proven to be powerful classifiers in other domains.
- From the operational perspective, CNNs are similar to ordinary neural networks: they consist of a number of layers where each layer is made up of neurons.
- CNNs use three main types of layers: convolutional layers, pooling layers, and fully-connected layers.

# Convolutional Neural Networks - Convolution Layer



# Convolutional Neural Networks - Pooling



# Design Principle - VGG Like CNN

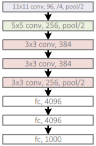
$$\mathtt{net} = \mathtt{fc}_{\theta,\mathtt{softmax}} \circ \prod_{p=1}^{P} \mathtt{fc}_{\theta^p,\mathtt{ReLU}} \circ \prod_{q=1}^{Q} \left(\mathtt{pool}_{\mathtt{Max}} \circ \prod_{r=1}^{R_q} \mathtt{conv}_{\phi^r,\mathtt{ReLU}}\right), \tag{1}$$

$$\mathtt{conv}_{\phi,\sigma}(X) = \sigma(\phi * X), \tag{2}$$

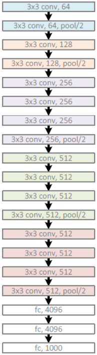
$$\mathtt{fc}_{\theta,\sigma}(x) = \sigma(\theta^\intercal x). \tag{3}$$

# Common Architectures

AlexNet, 8 layers
(ILSVRC 2012)




VGG, 19 layers
(ILSVRC 2014)




GoogleNet, 22 layers
(ILSVRC 2014)

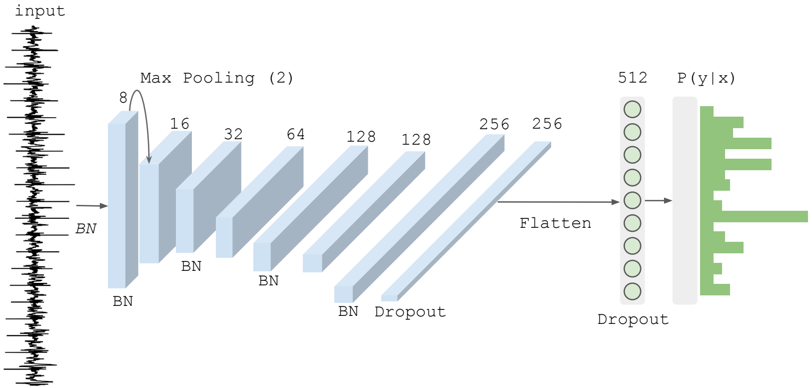
# More Complex Architectures

AlexNet, 8 layers
(ILSVRC 2012)

VGG, 19 layers
(ILSVRC 2014)

ResNet, 152 layers
(ILSVRC 2015)

# Convolutional Neural Network in SCA



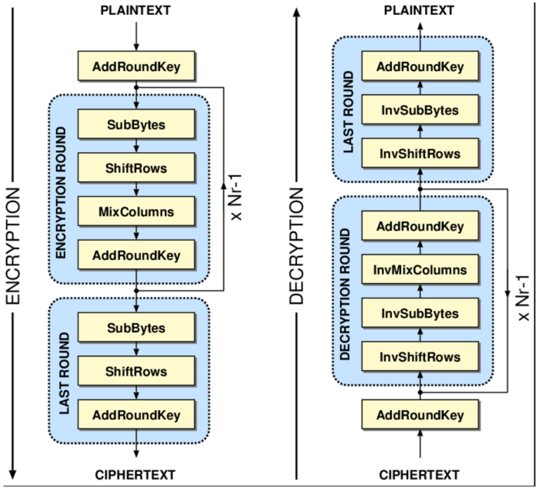
# Making the Architectures Even More Powerful

- To reduce the overfitting of the model, we introduce noise to the training phase.
- Since in our case, the input normalization is also learned during the training process via the BN layer, we added the noise tensor after the first BN.

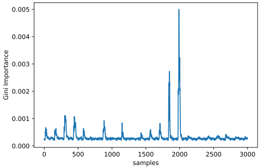
$$X^* = BN_0(X) + \Psi, \quad \Psi \sim \mathcal{N}(0, \alpha). \tag{4}$$

- The noise tensor follows the normal distribution.

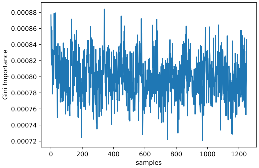
# AES


PLAINTEXT
AddRoundKey
ENCRYPTION ROUND
SubBytes
ShiftRows
MixColumns
AddRoundKey
x Nr-1
LAST ROUND
SubBytes
ShiftRows
AddRoundKey
CIPHERTEXT
ENCRYPTION
DECRYPTION
PLAINTEXT
LAST ROUND
AddRoundKey
InvSubBytes
InvShiftRows
DECRYPTION ROUND
AddRoundKey
InvMixColumns
InvSubBytes
InvShiftRows
x Nr-1
AddRoundKey
CIPHERTEXT

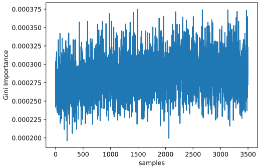
# Datasets



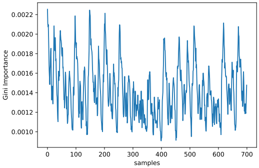

(a) DPAcontest v4 dataset




(b) AES_HD dataset

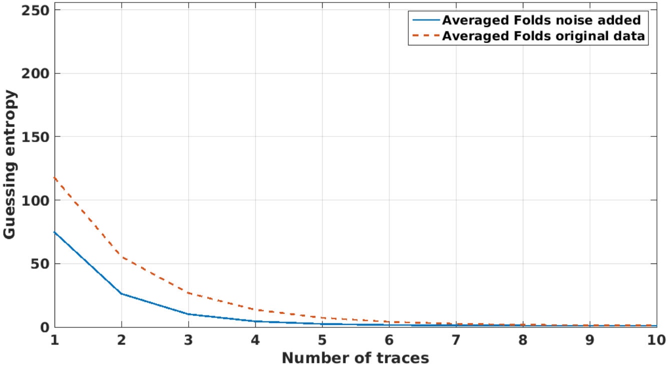



(c) Random Delay dataset



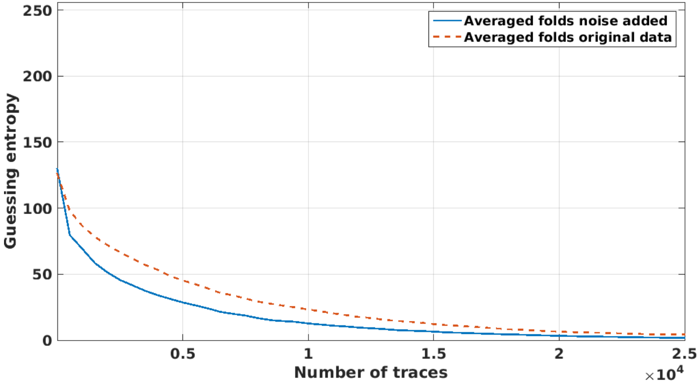

(d) ASCAD dataset

# Results DPAv4



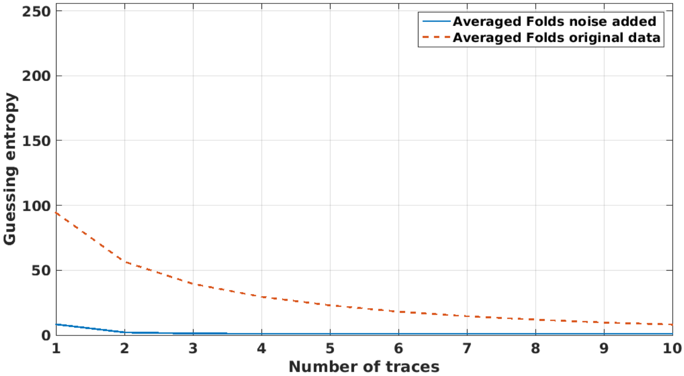

(e) RD network averaged

# Results AES_HD



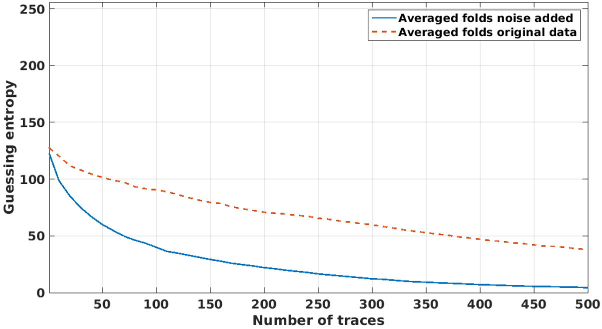

(f) ASCAD network averaged

# Results AES_RD




(g) RD network averaged

# Results ASCAD

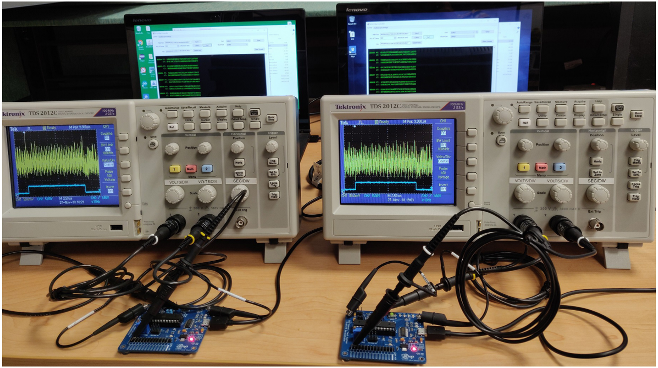



(h) ASCAD network averaged

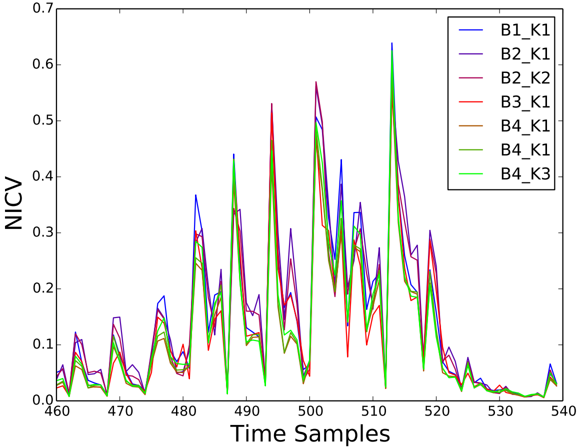
# Profiling Attacks and Portability

- There are two devices: one for training and the second one for attack.
- Two devices, different keys.
- Usually, we make our lives simpler and assume only one device and the same key.
- It is the same?

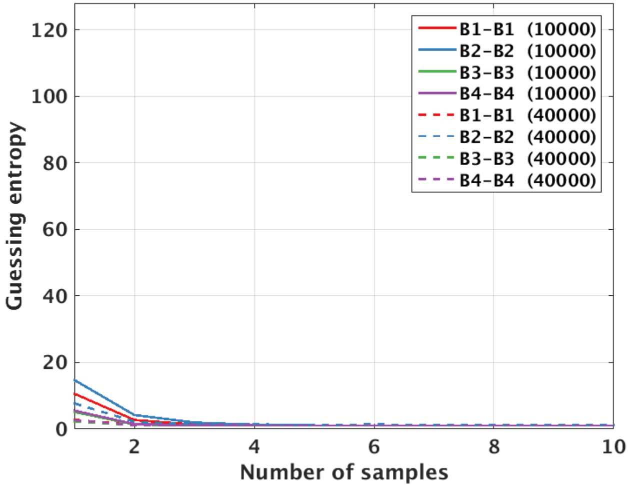
# Setup



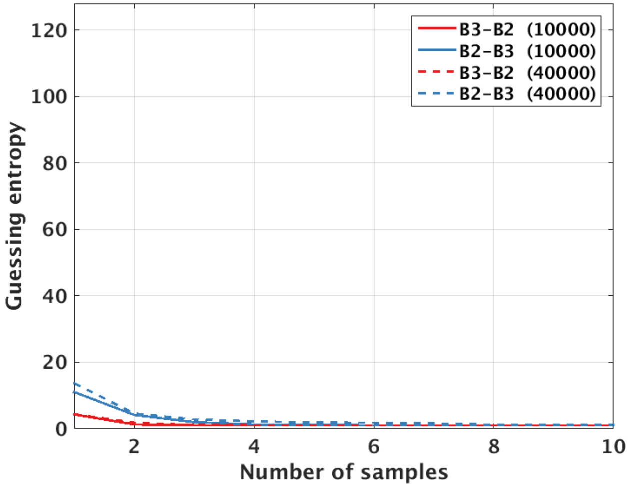
# NICV


NICV
Time Samples
0.0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
460
470
480
490
500
510
520
530
540
B1_K1
B2_K1
B2_K2
B3_K1
B4_K1
B4_K1
B4_K3

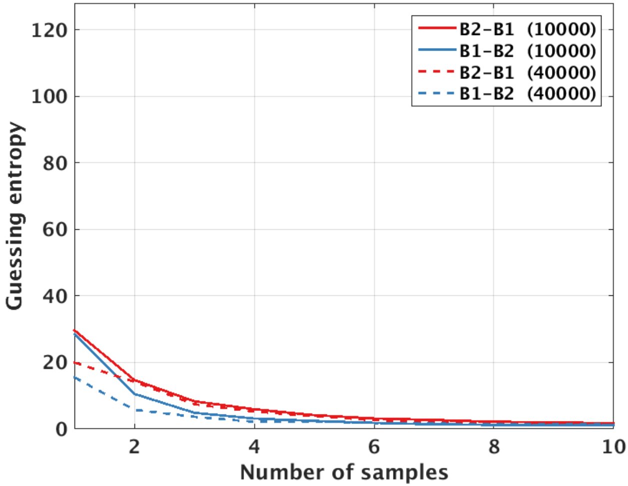
# Same Key and Device



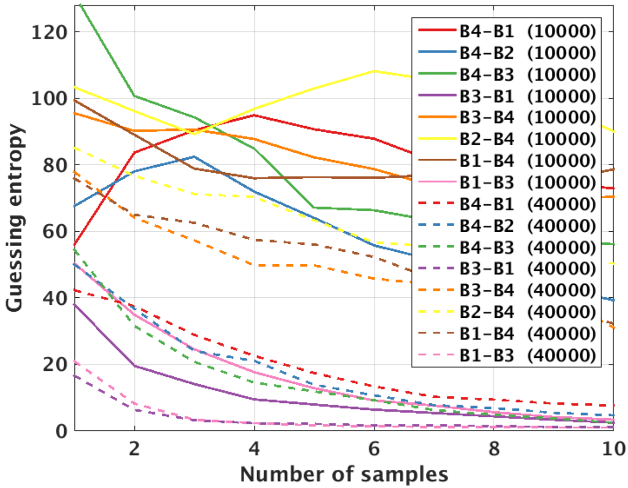
# Different key and Same Device



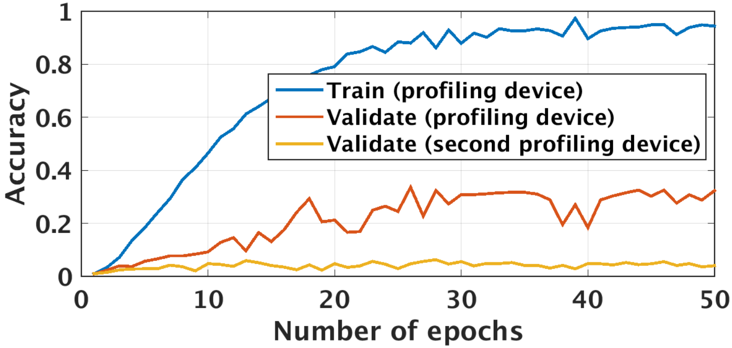
# Same Key and Different Device



# Different key and Device



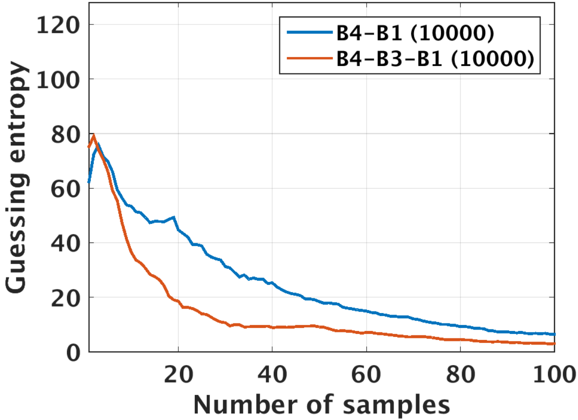
# Validation


Accuracy
1
0.8
0.6
0.4
0.2
0
Train (profiling device)
Validate (profiling device)
Validate (second profiling device)
0
10
20
30
40
50
Number of epochs

# Multiple Device Model

- Instead of validating on the same device as training, we need one more device!
- Separate devices for train, validation, attack.
- If we do not have a third device, we can use artificial noise.

# Multiple Device Model



# Problems and "Problems"

- Selection of machine learning techniques and hyper-parameter tuning.
- Portability.
- Lack of datasets.
- Reproducibility and explainability.
- Still no clear connection between machine learning and side-channel analysis metrics.
- Countermeasures.
- Academia vs. industry perspective.
- ...

# Introduction

- A fault injection (FI) attack is successful if after exposing the device to a specially crafted external interference, it shows an unexpected behavior exploitable by the attacker.
- Insertion of signals has to be precisely tuned for the fault injection to succeed.
- Finding the correct parameters for a successful FI can be considered as a search problem.
- The search space is typically too large to perform an exhaustive search.

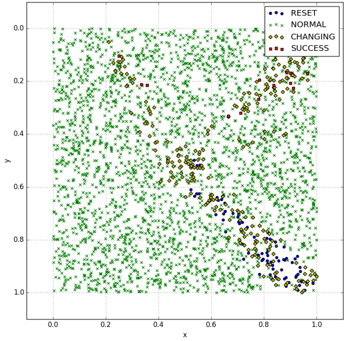
# Verdict classes

- FI testing equipment can output only verdict classes that correspond to successful measurements.
- Several possible classes for classifying a single measurement:
  1. NORMAL: smart card behaves as expected and the glitch is ignored
  2. RESET: smart card resets as a result of the glitch
  3. MUTE: smart card stops all communication as a result of the glitch
  4. INCONCLUSIVE: smart card responds in a way that cannot be classified in any other class
  5. SUCCESS: smart card response is a specific, predetermined value that does not happen under normal operation

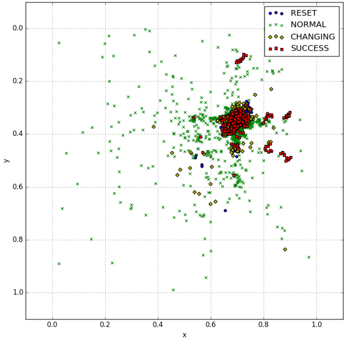
# Approaches

- Random search and exhaustive search.
- For voltage glitching and EMFI, we can use various heuristics, like genetic algorithms.
- Approaches as exhaustive search cannot work: would last 29 000 years.
- For laser FI, the situation is more complex as laser can easily break the target so we use deep learning.

# EMFI and Keccak

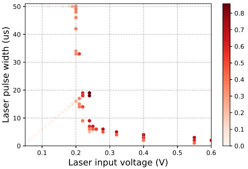



(i) Random search

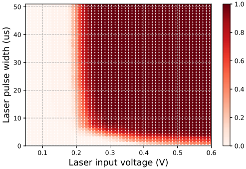



(j) GA and local search

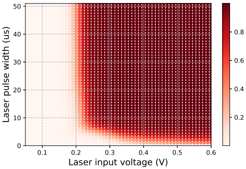
# LFI and DES




(k) Characterization

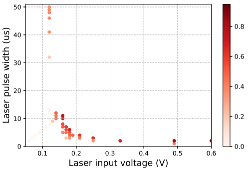



(l) Exhaustive search

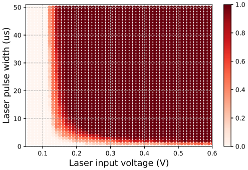



(m) Prediction with neural network

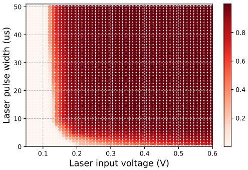
# LFI and AES




(n) Characterization




(o) Exhaustive search




(p) Prediction with neural network

# Outline

# Conclusions

- Machine learning (and even wider, artificial intelligence) play important role in cryptography.
- Currently, attacks perspective seem to be more developed.
- In implementation attacks, machine learning represents even the most powerful option.
- Still, our state-of-the-art techniques are usually much simpler than in other domains.
- There are some specific parts one does not encounter in other domains, but much of the knowledge is transferable.
- What do new attacks teach us about improving the countermeasures?

# Questions?

Thanks for your attention! Q?

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