CSI NN

Reverse Engineering of Neural Network Architectures Through Electromagnetic Side Channel

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Machine Learning & Security

- Machine learning (ML) has wide applications across industries.
- Security is just one popular application for ML
- **US$ 35 Billion Industry by 2024**[1]
- Optimized ML model are Intellectual property
- Leaked models can leak information about sensitive training sets

1 https://www.marketwatch.com/press-release/artificial-intelligence-in-security-market-size-is-projected-to-be-around-us-35-billion-by-2024-2018-10-07

This Work ...

- Reverse Engineering

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- Reverse Engineering
- Through Side-Channel

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- Measured by Electromagnetic (EM) probes

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- Of Deep Neural Network (DNN) on embedded devices

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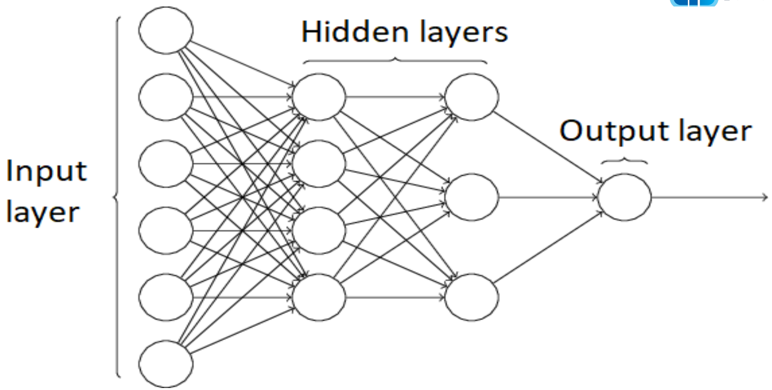

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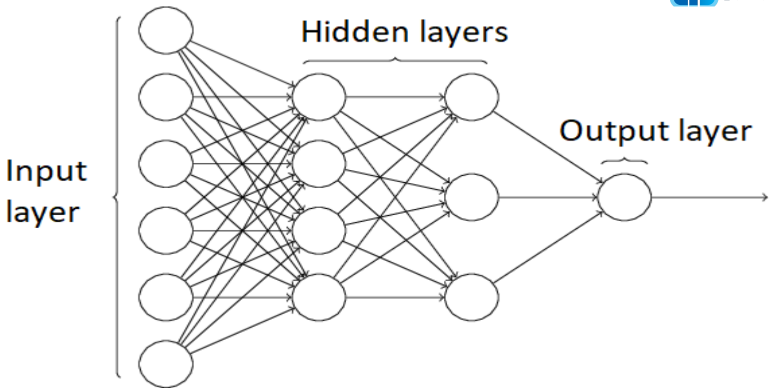

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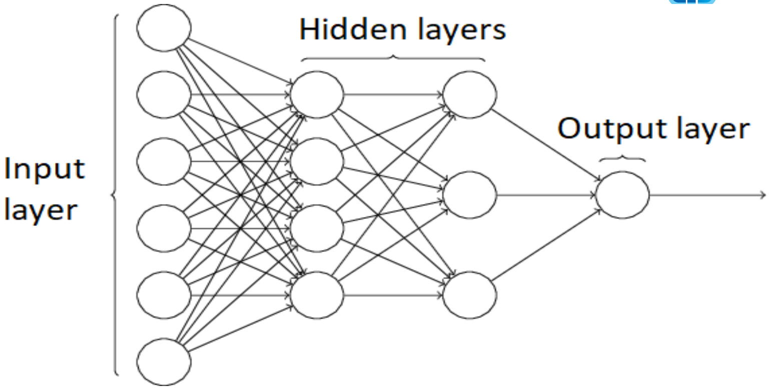

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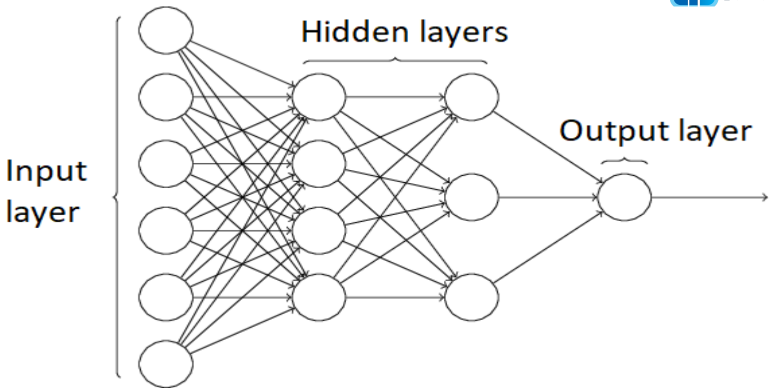

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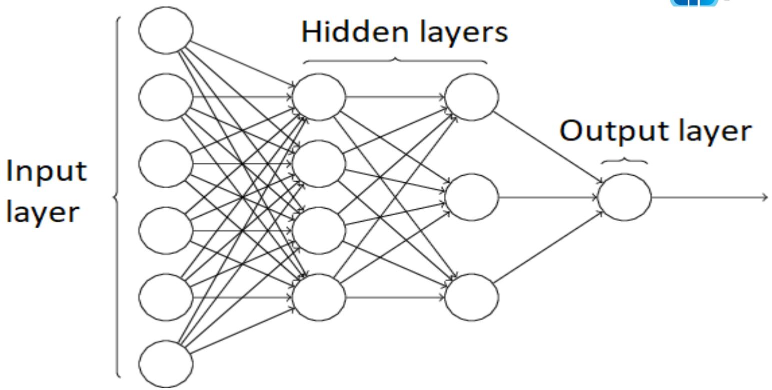

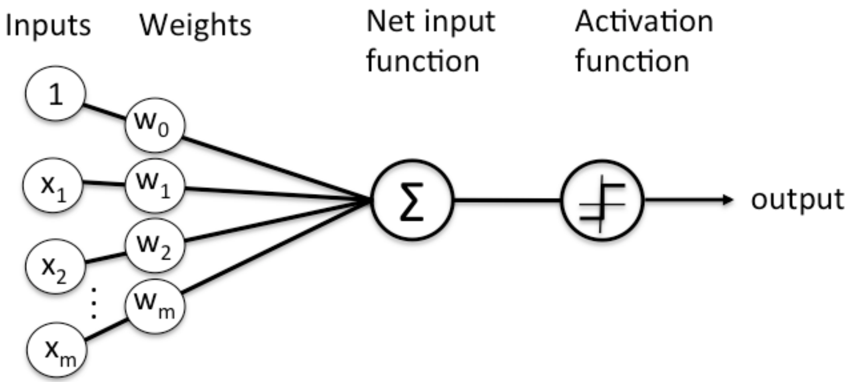

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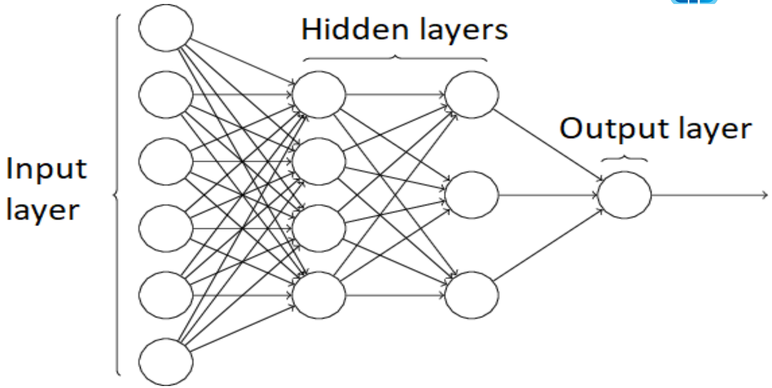

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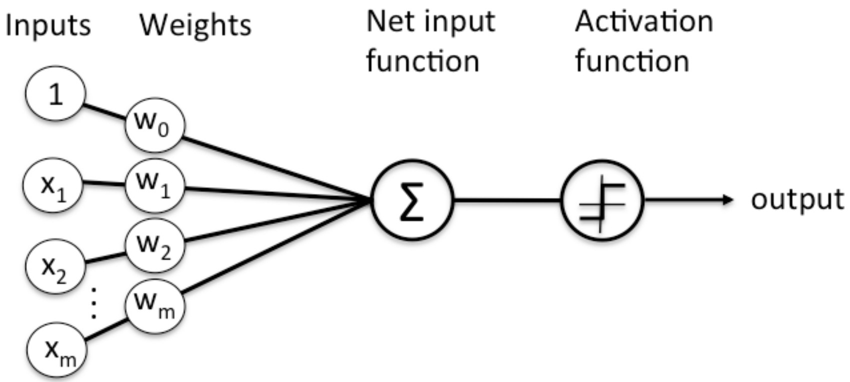

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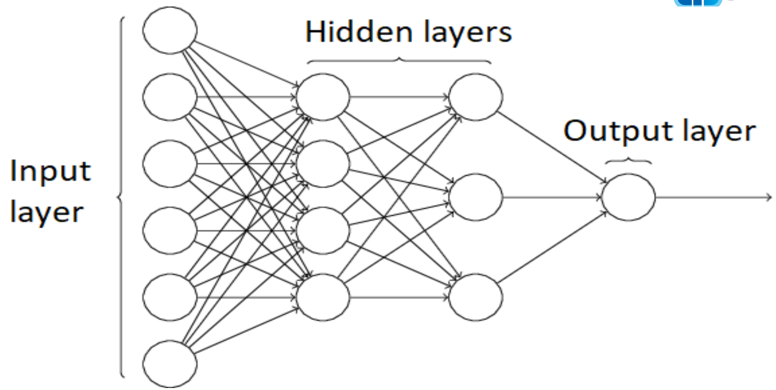

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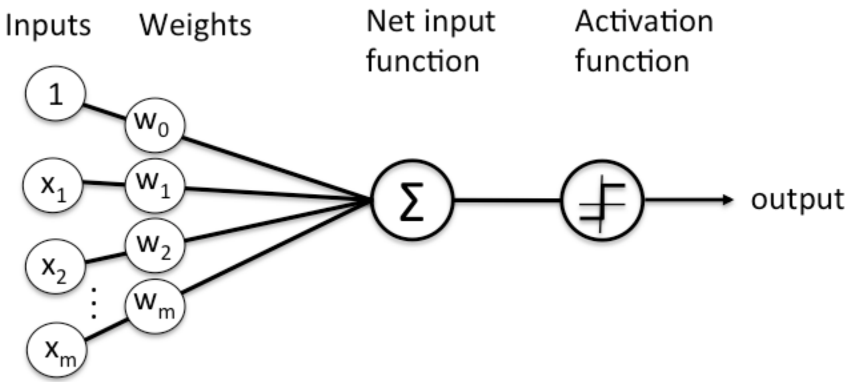
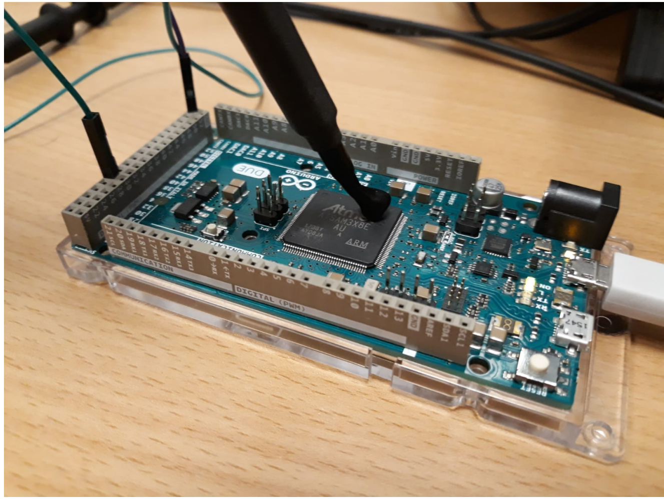
  - Activation function in each neuron
  - Input weights to each neuron

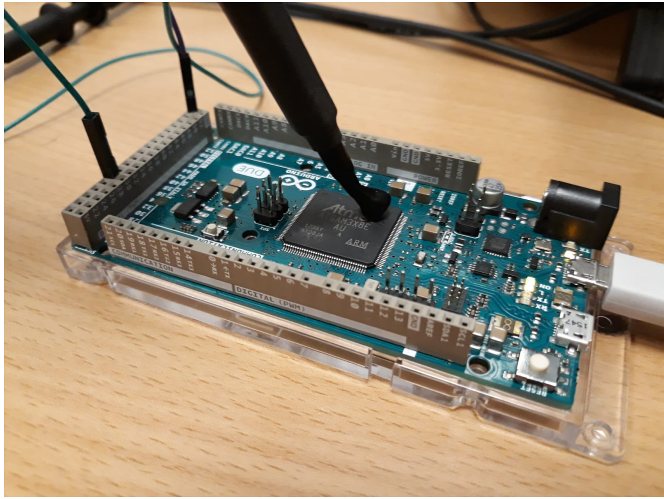


Electromagnetic (EM) SCA



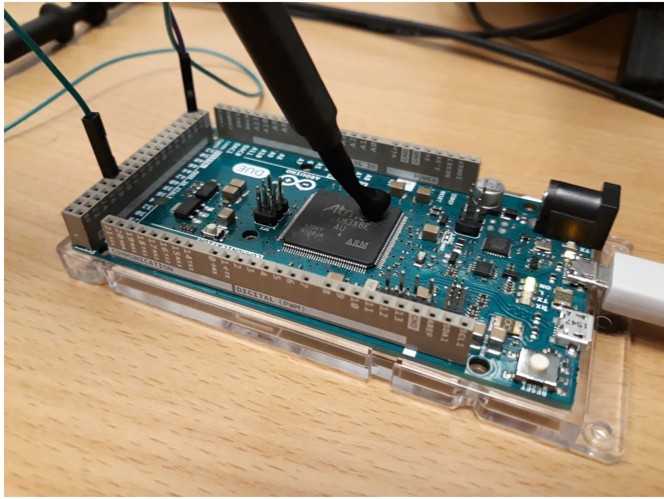
Electromagnetic (EM) SCA

- Non-invasive



Electromagnetic (EM) SCA

- Non-invasive
- Serious threat to pervasive computing



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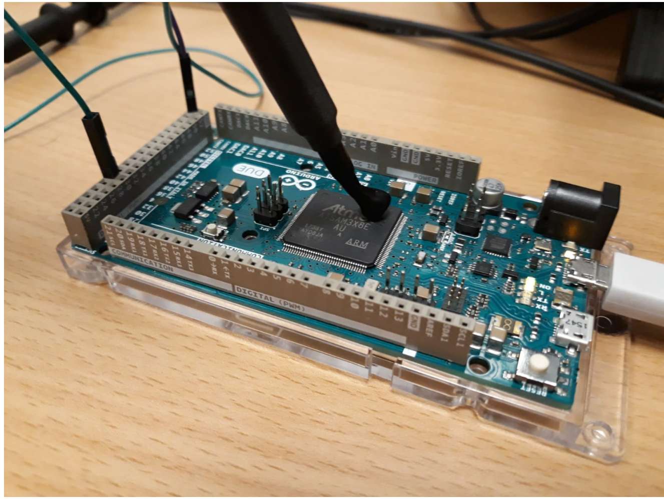
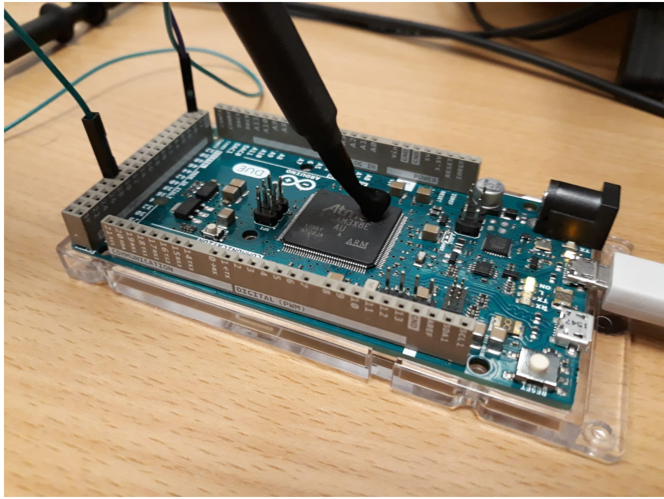
- Exploiting unintentional EM leakage



Electromagnetic (EM) SCA

- Non-invasive
- Serious threat to pervasive computing
- Exploiting unintentional EM leakage
- Powerful & practical
  - Keeloq
  - FPGA Bitstream encryption
  - Bitcoin wallets



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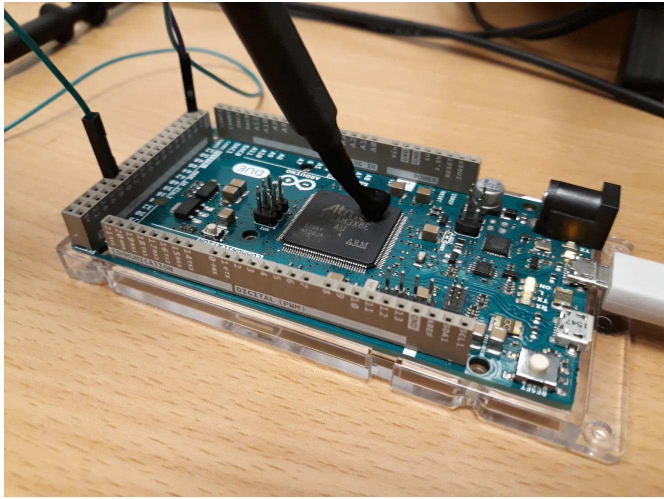

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- Serious threat to pervasive computing
- Exploiting unintentional EM leakage
- Powerful & practical
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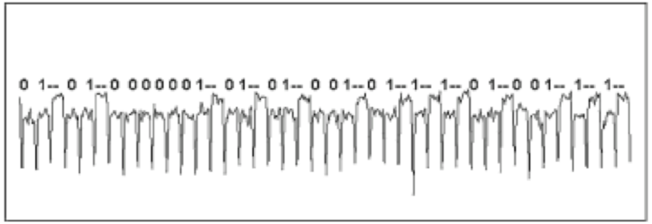
  - FPGA Bitstream encryption
  - Bitcoin wallets
- Applications beyond secret key recovery

Electromagnetic (EM) SCA

Simple EM Analysis (SEMA)

- Adversary learns secret information by visual inspection of (usually single) power/EM measurement
- Ex: observe square & multiply in exponentiation etc.



Differential EM Analysis (DEMA)

- Adversary extract secret information **statistically** from EM trace
- Target leakage from function f(x,k) of Secret **k,** input **x**
- EM leakage ➔ **L(f(x,k))**
- Correct key **k*** maximizes: ρ**(t, L(f(x,k)))**
- Most commonly used leakage model L is **Hamming Weight (HW)**
- A microcontroller leaks in **Hamming Weight** when sensitive data is loaded to pre-charged data bus

Source: https://anysilicon.com/side-channel-attacks-differential-power-analysis-dpa-simple-power-analysis-spa-works/

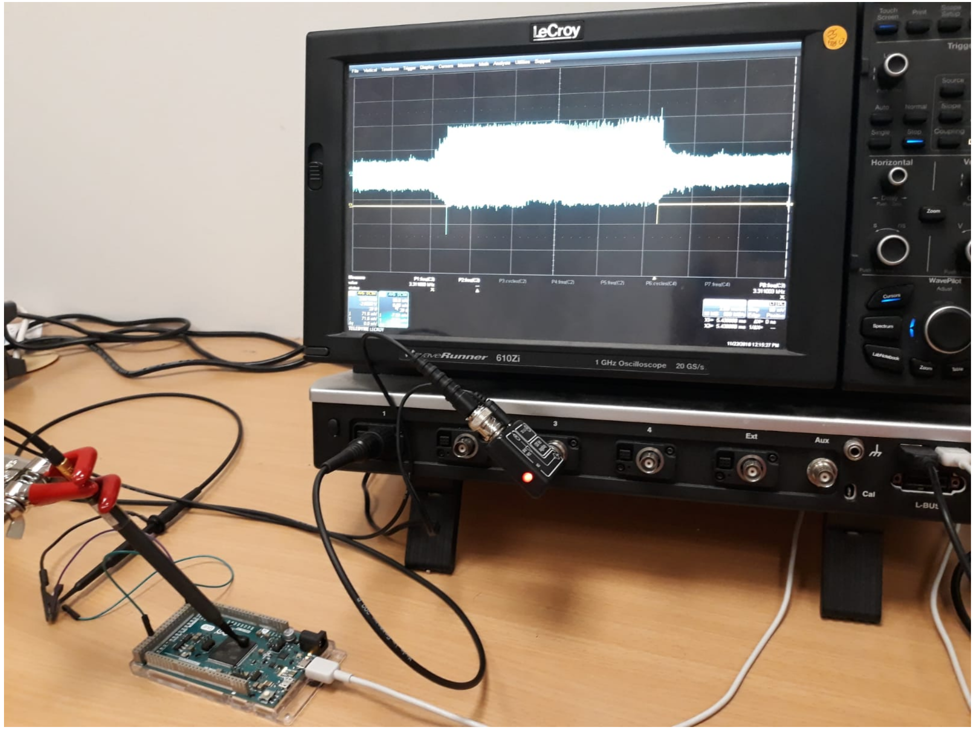
Adversary Model

- Recover the neural network architecture using only side-channel information
- Adversary does not know the architecture of the used network but can feed random/known inputs to the DNN and capture corresponding electromagnetic side-channel traces
- No assumption on the type of inputs; we work with real numbers
- **Assumption**: Implementation of the machine learning algorithm with no side-channel countermeasures

Experimental Setup

- Passive EM Measurement
- Near-field probe
- 30dB pre-amplifier for clear signal
- Measurements averaged for noise filtering
- For bigger networks, measurements are made sequentially for different layers
- Targets: ATMEGA AVR328P, ARM Cortex-M3

Experimental Setup



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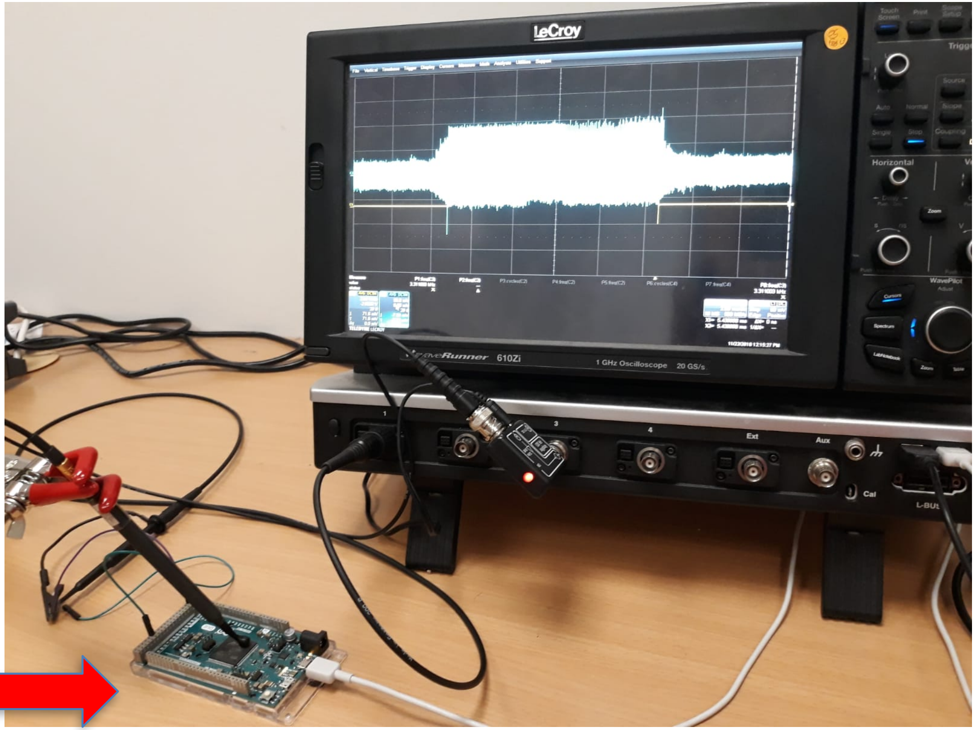

Target

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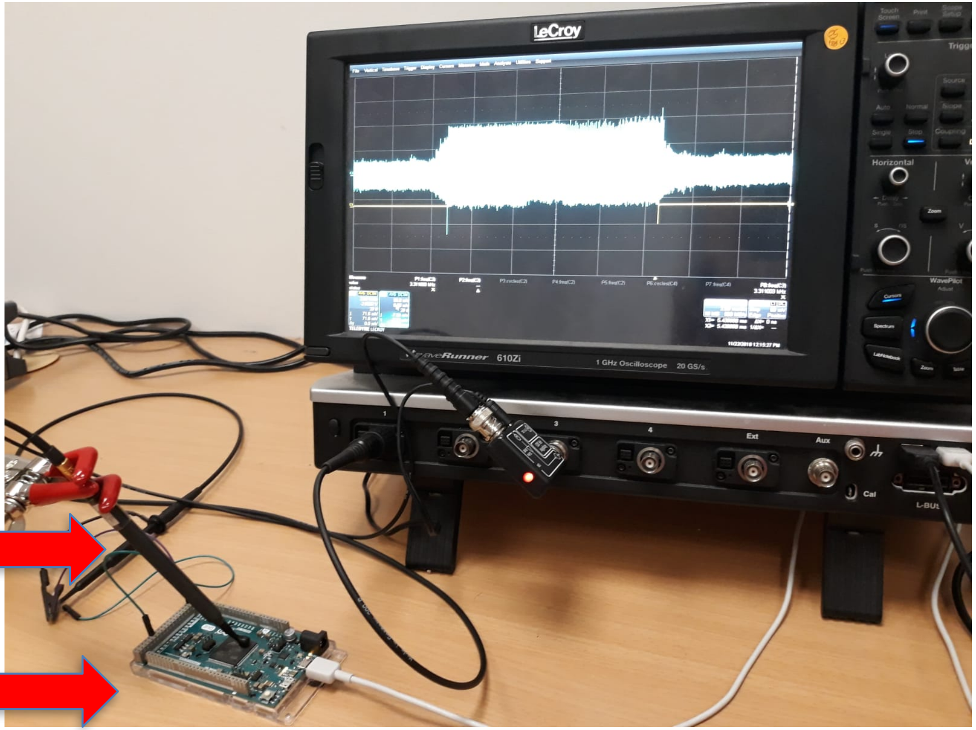

Probe

Target

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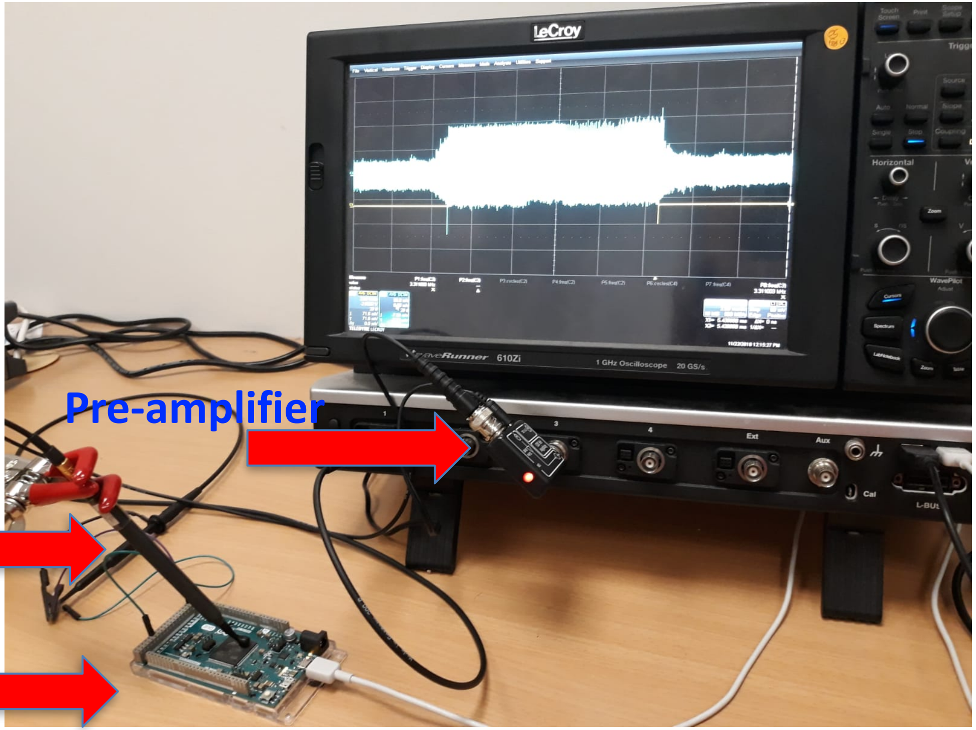

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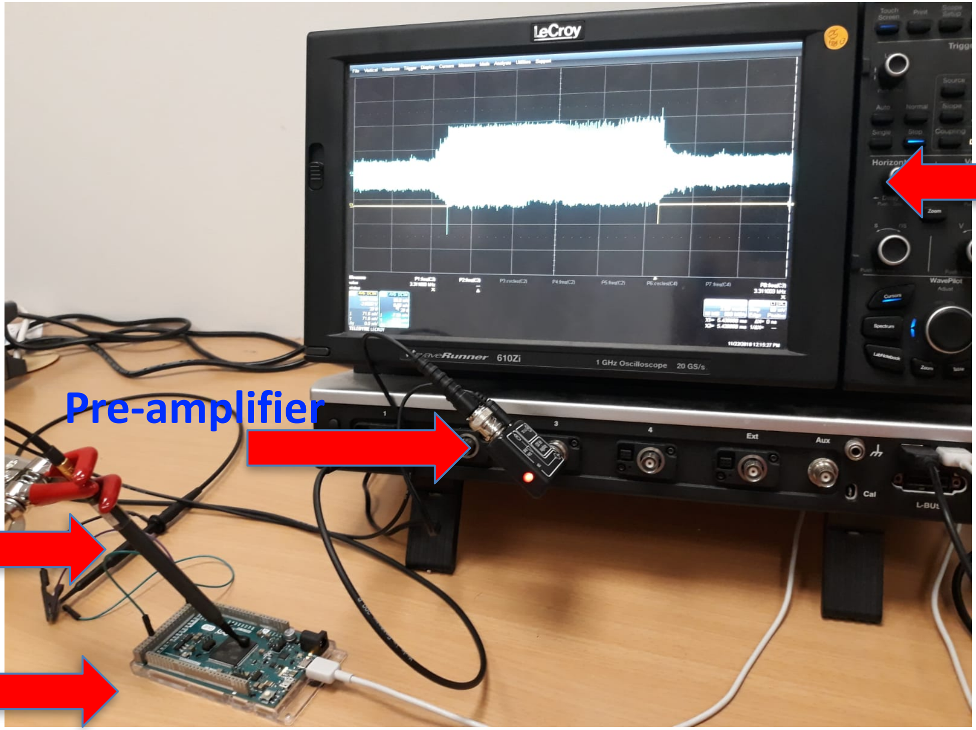


Pre-amplifier

Trace

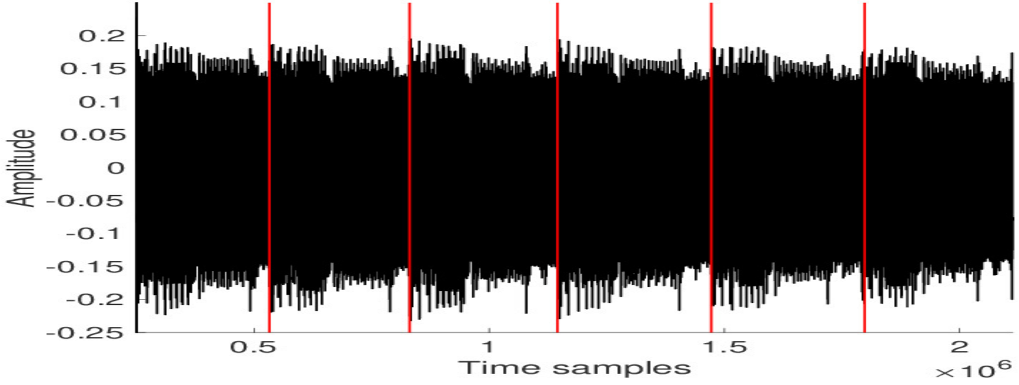
Probe

Target

Lets Start With Some Visual Inspection!!!!

Identifying Neurons

- **Simple EM Analysis**
- Hidden layer with 6 neurons = 6 repeating patterns
- Each neuron executes a series of multiplication, followed by activation
- Activation Function in this case = Sigmoid



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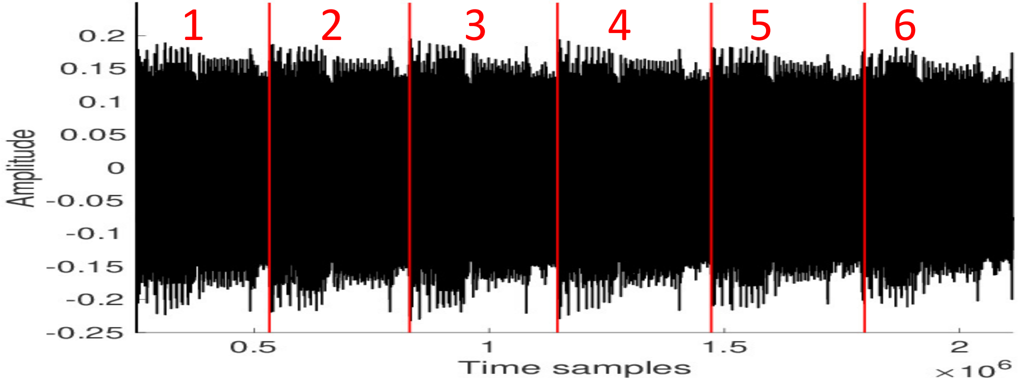
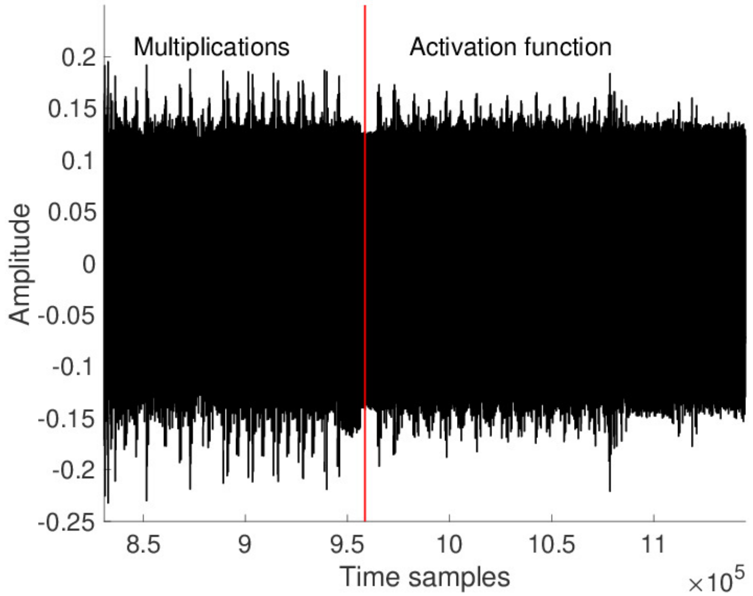


Recovering Activation Function

- **Timing Attack**
- Each activation function has distinct timing pattern
- Timing patterns can be pre-characterized for different NN libraries
- We measure **precise timing** of activation function using **EM measurement** on oscilloscope.



Timing Patterns of Various Activation Function

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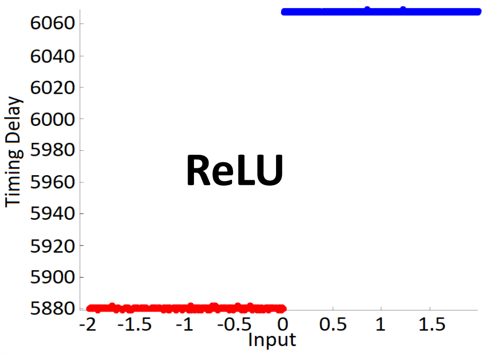

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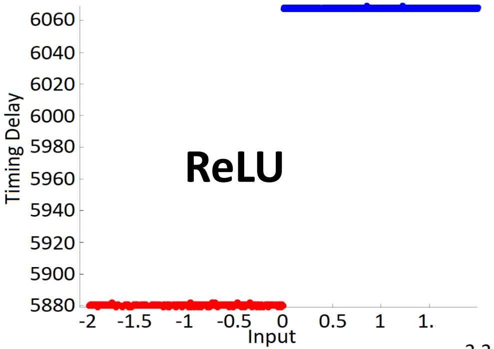

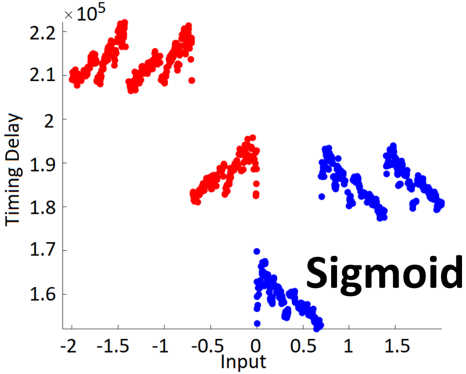

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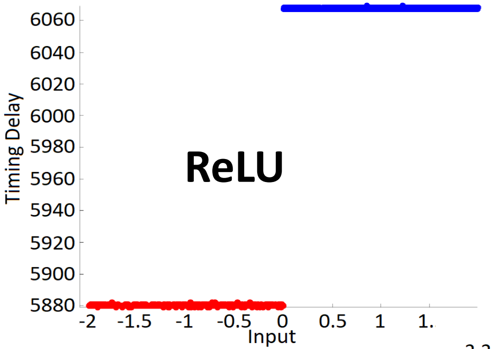

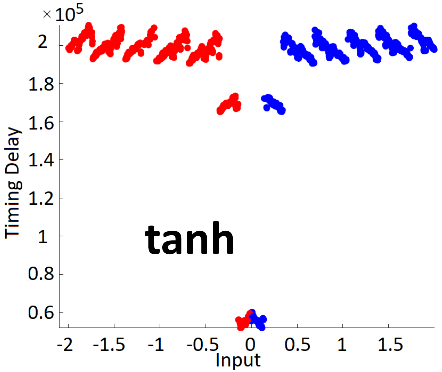

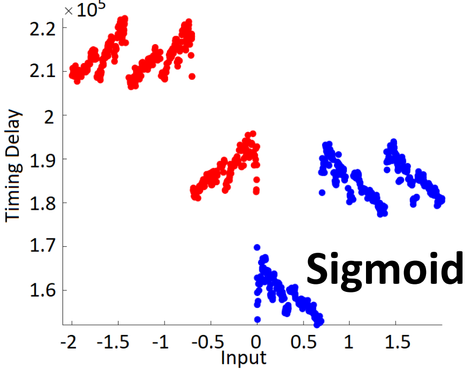

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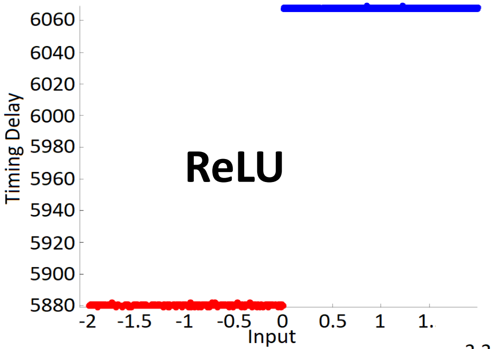
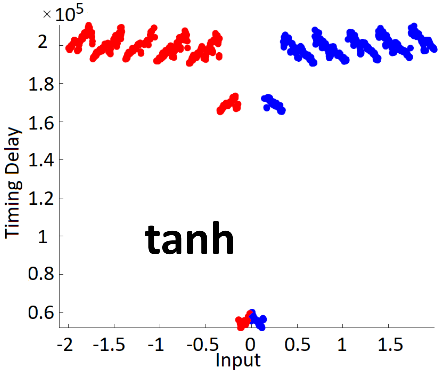
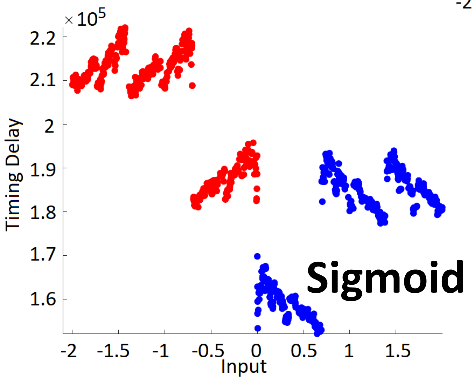
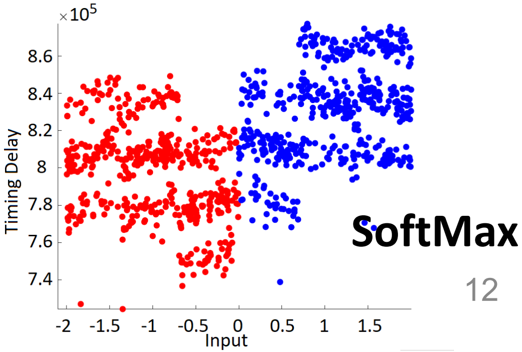
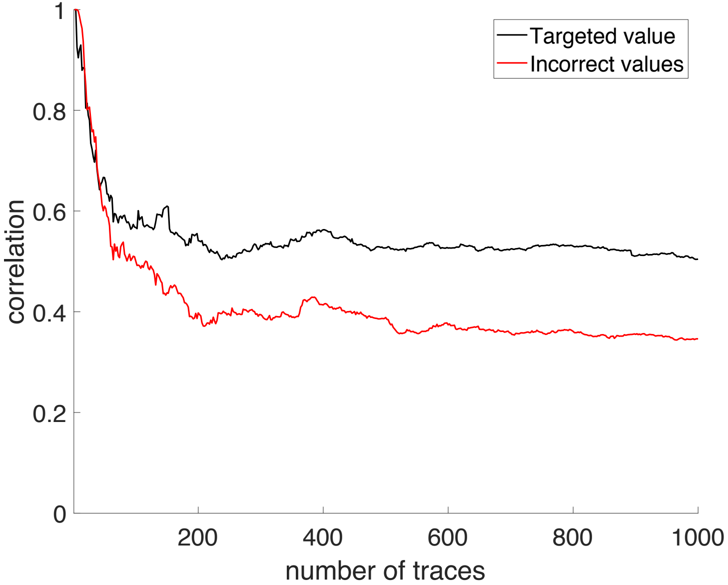




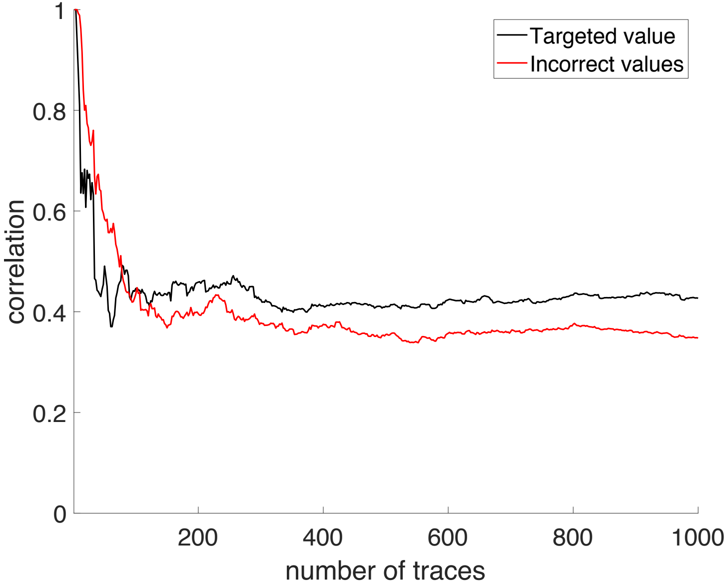




Recovering Weights

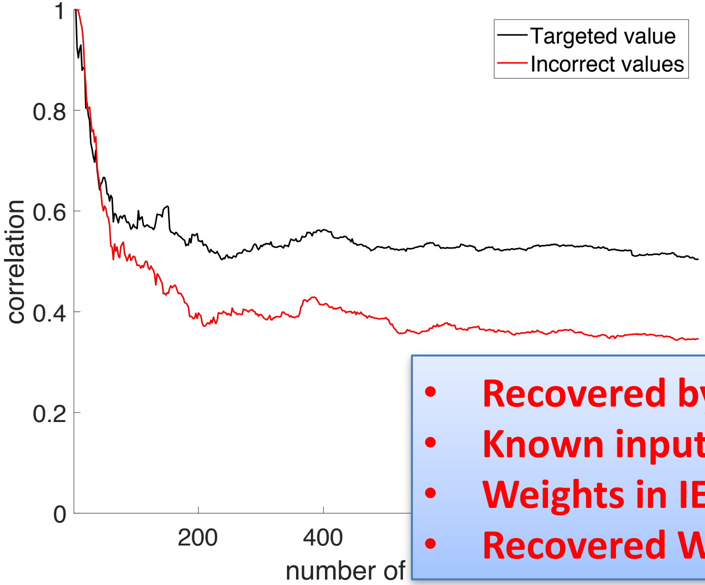


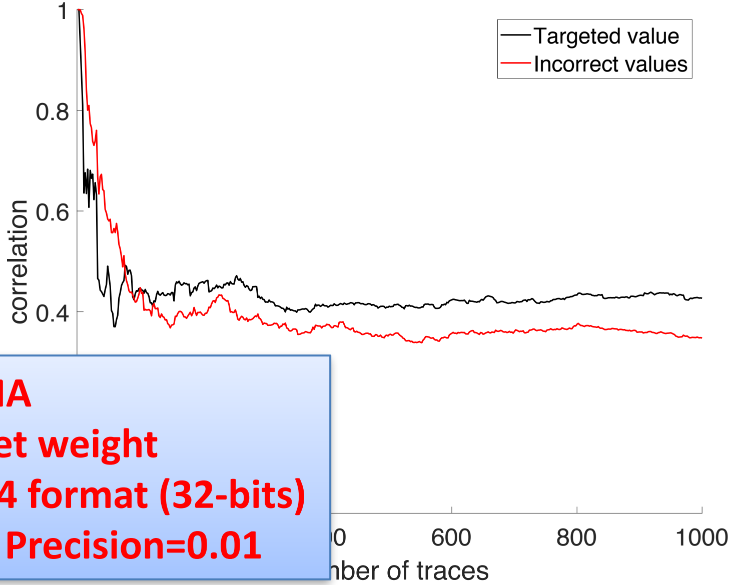
First byte recovery
(sign and 7-bit exponent)



Second byte recovery
(lsb exponent and mantissa)

Recovering Weights



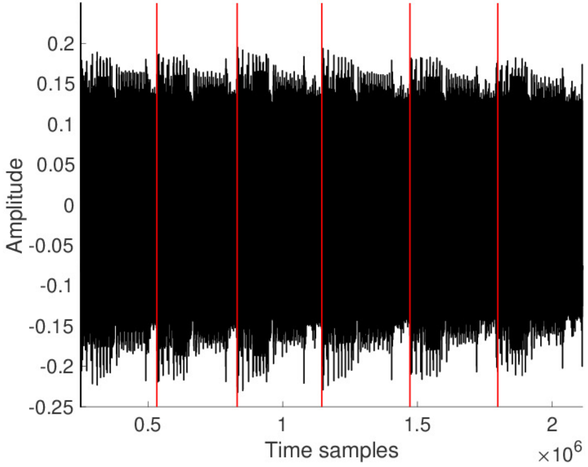


- **Recovered by DEMA**
- **Known input, secret weight**
- **Weights in IEEE 754 format (32-bits)**
- **Recovered Weight Precision=0.01**

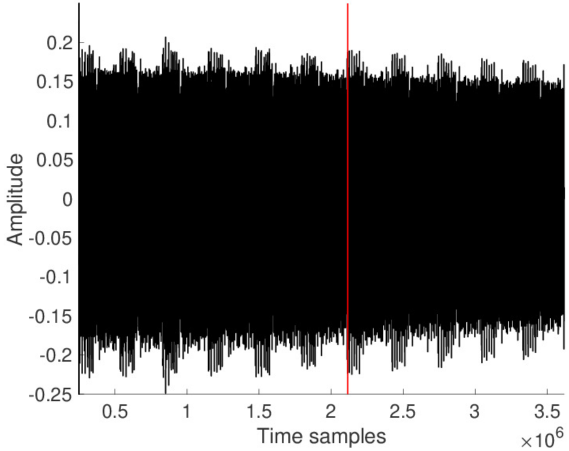
First byte recovery
(sign and 7-bit exponent)

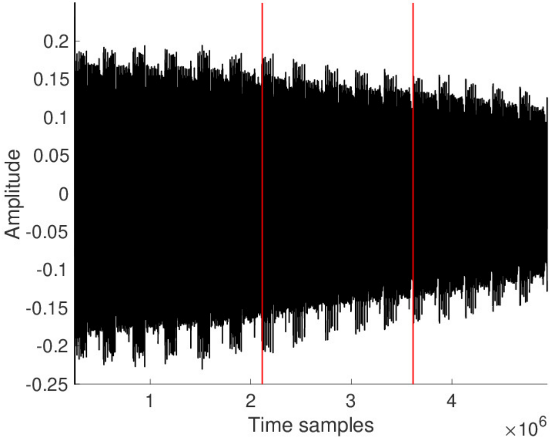
Second byte recovery
(lsb exponent and mantissa)

Recovering Number of Neurons & Layers



One hidden layer
6 neurons





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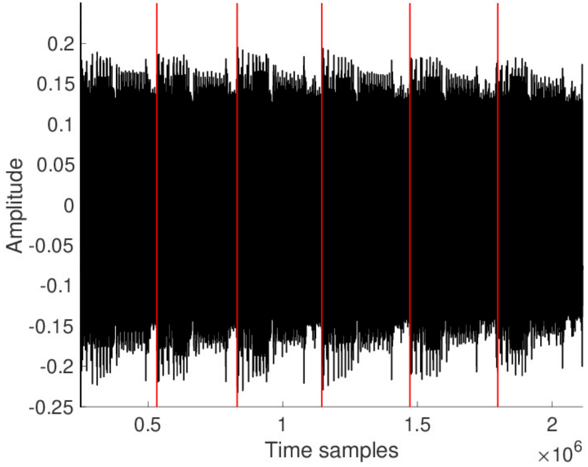
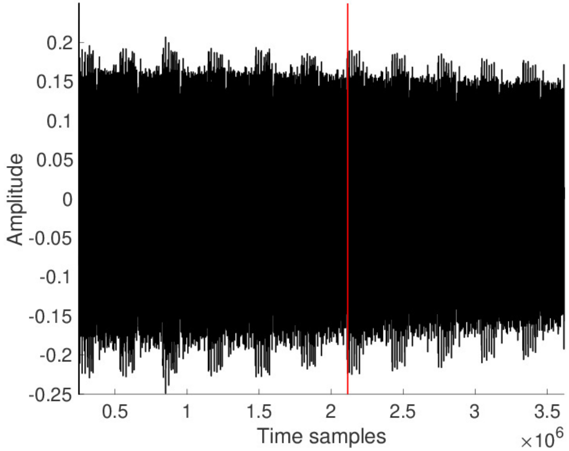
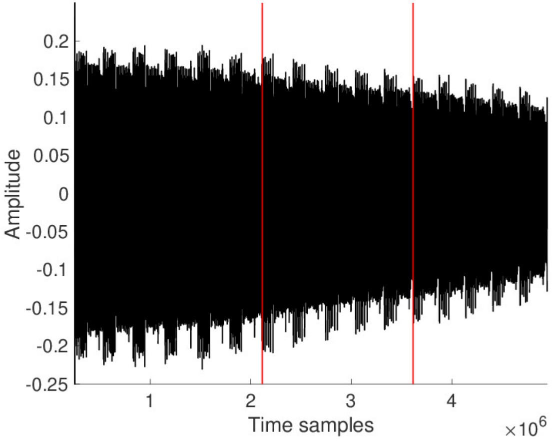


One hidden layer
6 neurons

Two hidden layer
(6,5) neurons

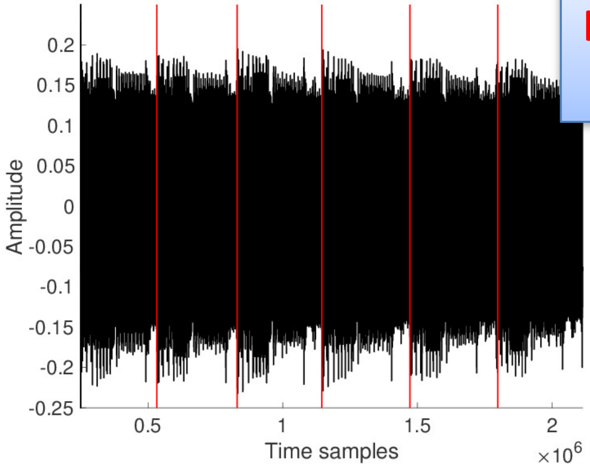




Three hidden layer
(6,5,5) neurons

Recovering Number of Neurons & Layers

DEMA on weights used to determine layer boundaries



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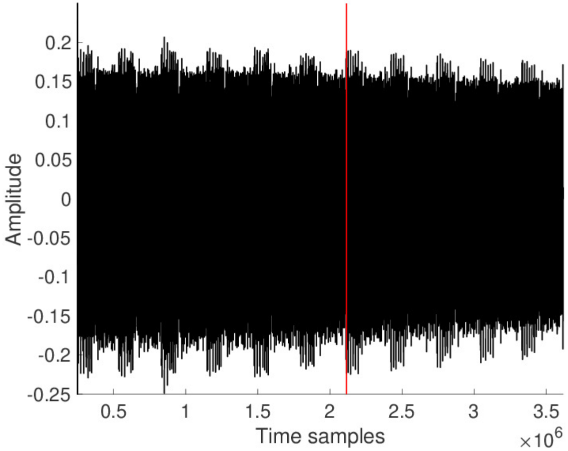

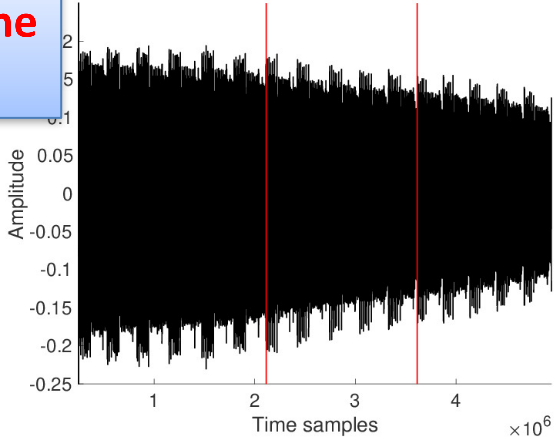

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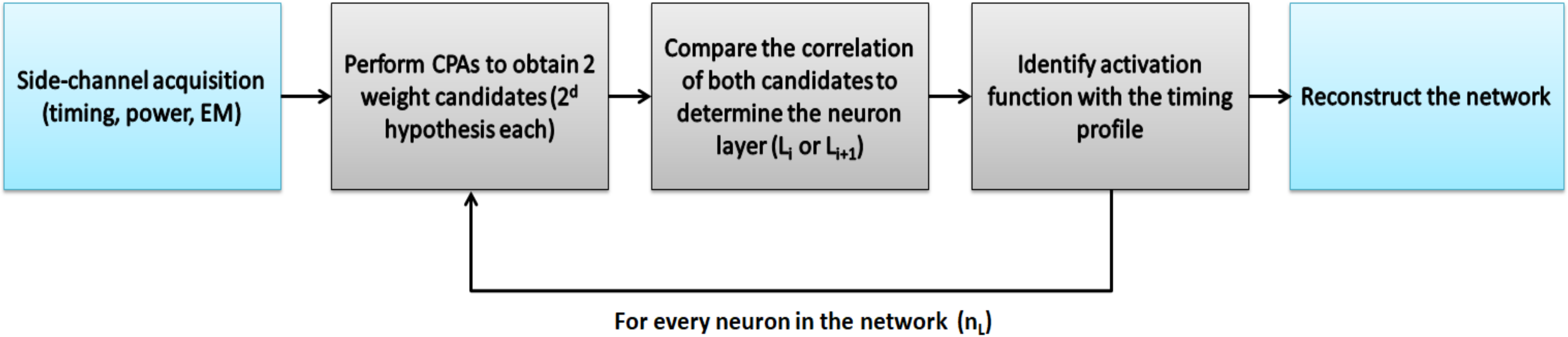
Full Network Recovery



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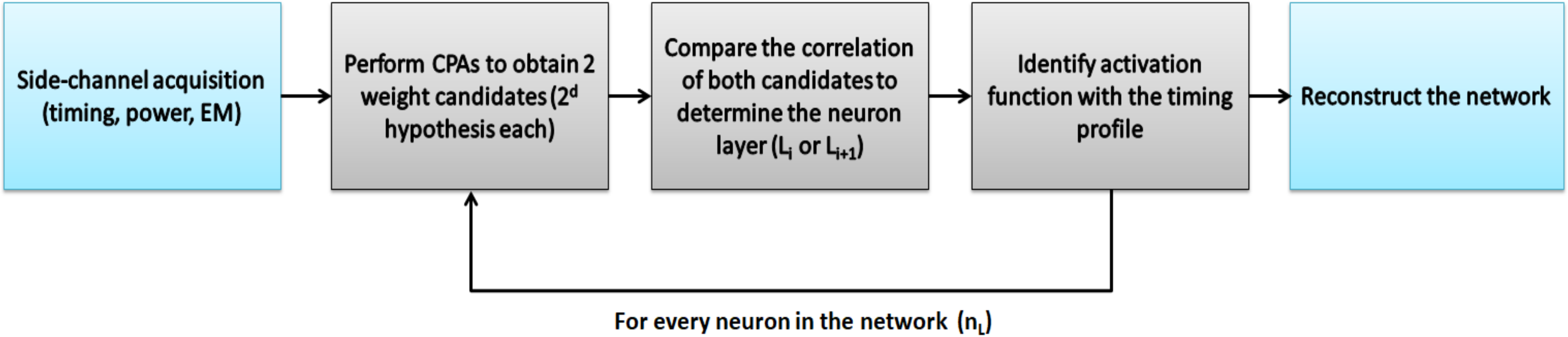
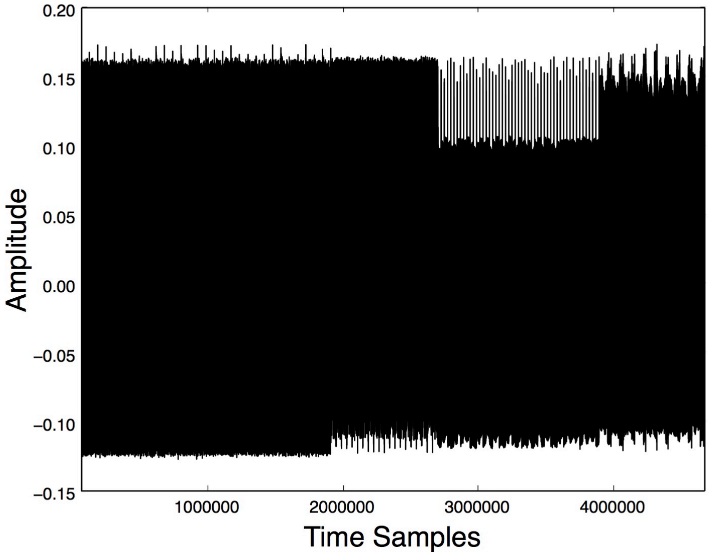
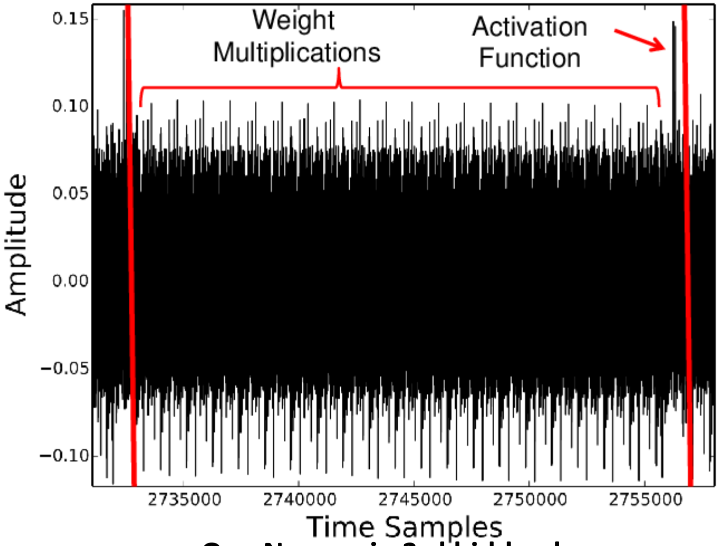


Recovery is performed layer by layer, neuron by neuron.
One neuron at a time, starting from input layer

Results on ARM Cortex-M3

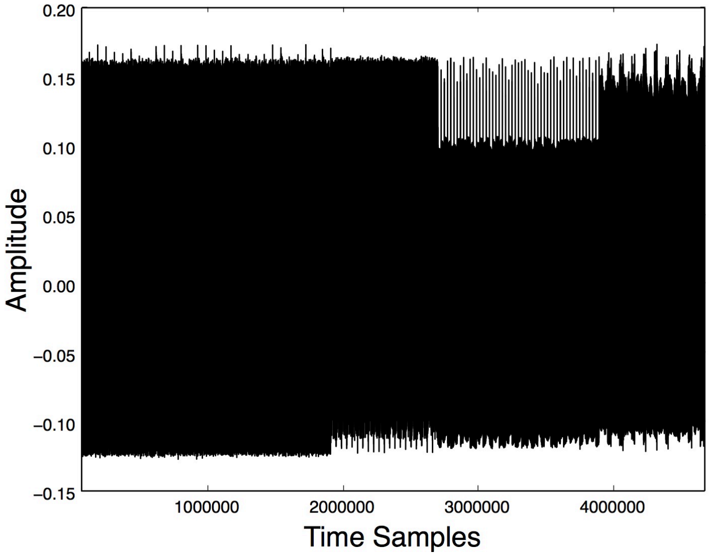


Four hidden layer
(50,30,20,50) neurons



One Neuron in 3rd hidden layer
20 multiplications, 1 ReLU

Results on ARM Cortex-M3



Four hidden layer
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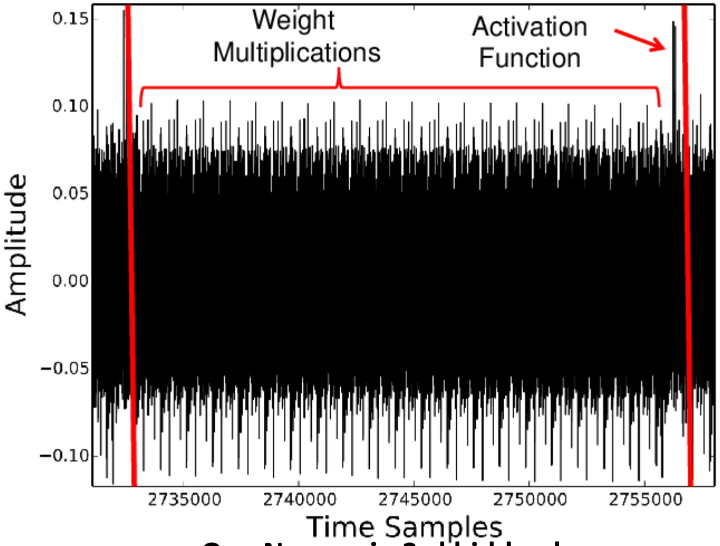
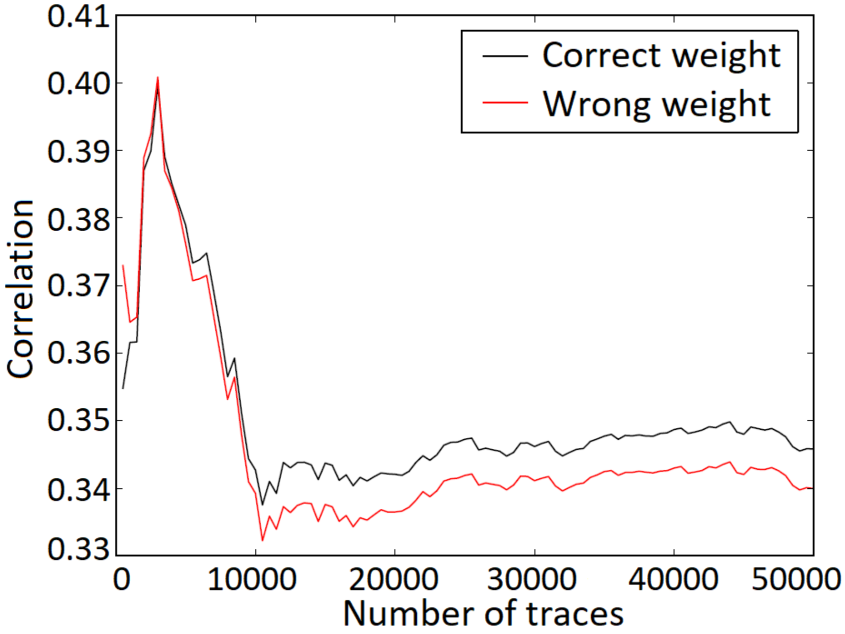


One Neuron in 3rd hidden layer
20 multiplications, 1 ReLU

With MNIST: Accuracy 98.16% (original) vs 98.15% (reverse engineered)
Average weight error: 0.0025.

Extension to CNN on ARM Cortex-M3

- CIFAR-10 dataset.
- Target the multiplication operation from the input with the weight, similar as in previous experiments.
- fixed-point arithmetic (8-bits).
- The original accuracy of the CNN equals 78.47% and the accuracy of the recovered CNN is 78.11%.



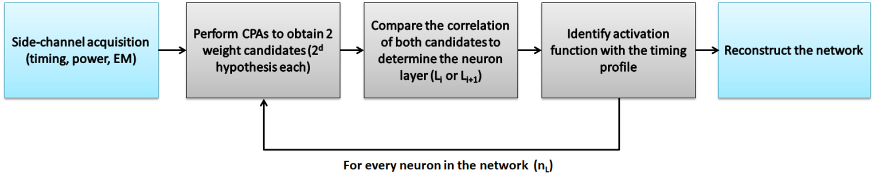
Conclusions

- With an appropriate combination of SEMA and DEMA techniques, all sensitive parameters of the network can be recovered.
- A serious threat to commercial NN IPs
- The attack methodology scales linearly with the size of the network.
- The proposed attacks are both generic in nature and more powerful than the previous works in this direction.
- Can be adapted for recovery of sensitive training/testing data
- SCA countermeasures (masking/hiding) would help but overhead will be too high for NN. Motivates research for optimised countermeasures.

Thank You !!!

Questions ???

Full Network Recovery



- The combination of previously developed individual techniques can thereafter result in full reverse engineering of the network.
- Recovery is performed layer by layer, neuron by neuron, one at a time.
- Complexity grows linearly with network size.
- The first step is to recover the weight w_{L0} of each connection from the input layer (L_0) and the first hidden layer (L_1).
- In order to determine the output of the sum of the multiplications, the number of neurons in the layer must be known.
- Using the same set of traces, timing patterns for different inputs to the activation function can be built.
- The same steps are repeated in the subsequent layers

Recovering Weights

- Correlation Power Analysis (CPA) i.e., a variant of DPA using the Pearson's correlation as a statistical test.
- CPA targets the multiplication $m = x \cdot w$ of a known input x with a secret weight w.
- Using the HW model, the adversary correlates the activity of the predicted output m for all hypothesis of the weight, with side-channel trace t
- The correct value of the weight w will result in a higher correlation standing out from all other wrong hypotheses w_*, given enough measurements.
- As data is represented in IEEE 754 format, each floating point number is 32 bits. 1 sign bit, 8 exponent bits and 23 mantissa bits
- Exact weight recovery is not required but only up to a precision (we choose 0.01)