

Improved Deep-Learning Side-Channel Attacks using Normalization Layers

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Good performance of neural networks in side-channel analysis

Improvement possible using **batch normalization** and **regularization**

No deep learning metric usable to evaluate networks for SCA

Proposition of a **metric** to tell how well a given architecture could perform

- 1 Batch Normalization
- 2 `train;val` : an SCA metric to evaluate performances
- 3 Regularization
- 4 Conclusion

1 Batch Normalization

2 `train;val` : an SCA metric to evaluate performances

3 Regularization

4 Conclusion

Batch Normalization

Goal

Standardize the data representation across all layers

Consequence

The network focuses on the relative differences of the values rather than on the numerical values

Values of the neurons

Neurons
 $(; 2)$


Batch Normalization

Values of the neurons

Neurons
 $(0; 1)$

Network architecture with Batch Normalization

Training on ASCAD desynchronized traces

Desync0: random shift between 0 and N applied to the 700 points of the traces

Desync0

Training on ASCAD desynchronized traces

Desync: random shift between 0 and N applied to the 700 points of the traces

Desync0

Desync50

Training on ASCAD desynchronized traces

Desync: random shift between 0 and N applied to the 700 points of the traces

Desync0

Desync50

Desync100

Evaluate the performance of a network

Training Acc. vs. Validation Acc.

Goal

Evaluate the networks during training

CNN_{best}

Training Acc. vs. Validation Acc.

Goal

Evaluate the networks during training

CNN_{best}

CNN_{on}

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The over fitting phenomena

Good estimation

Over fitting

Goal

Have a clear indication if the network is overfitting/underfitting and if the performance of the network can be improved

Notations

T_{train} = Set of traces the network used to train

T_{val} = Set of traces the network has never seen

$N_{\text{train}}(\text{model}) := \min_{n \in T_{\text{train}}} \{ \text{SR}_{\text{train}}^1(\text{model}(n)) = 90\% \}$

$N_{\text{val}}(\text{model}) := \min_{n \in T_{\text{val}}} \{ \text{SR}_{\text{val}}^1(\text{model}(n)) = 90\% \}$

Metric

$$\text{train;val}(\text{model}) = \frac{N_{\text{val}}(\text{model})}{N_{\text{train}}(\text{model})}$$

How to use the metric

Representation of train;att for CNN_{on}

- 1 Batch Normalization
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Regularization

Goal

Reduce $\text{train}_{\text{att}}$ even further using regularization

Means

Dropout with parameter D

L_2 -Norm regularization with parameter L_2

Regularization

Goal

Reduce $\text{train}_{\text{att}}$ even further using regularization

Means

Dropout with parameter D

L_2 -Norm regularization with parameter L_2

	Test (step = 0:1)		Choice for desync100	
	D	L_2	D	L_2
CONV1&2	[0; :::; 0:3]	[0; :::; 0:3]	0	0
CONV3	[0; :::; 0:8]	[0; :::; 0:3]	0:5	0:2
CONV4	[0; :::; 0:8]	[0; :::; 0:3]	0:6	0:3
CONV5	[0; :::; 0:8]	[0; :::; 0:3]	0:7	0:3
FC1	[0; :::; 0:8]	[0; :::; 0:3]	0	0:3
FC2	[0; :::; 0:3]	[0; :::; 0:3]	0	0

Architecture with regularization $\text{CNN}_{\text{bn+reg}}$

Results without regularization CNN_{bn}

Results with regularization $\text{CNN}_{\text{bn+reg}}$

Results with regularization $\text{CNN}_{\text{bn+reg}}$

Attack on desync100 using $g_{-2} = 0:1$ for CNN_{bn+reg}

Attack on desync100 using $g_{-2} = 0:2$ for CNN_{bn+reg}

Attack on desync100 using $g_{-2} = 0:3$ for CNN_{bn+reg}

Evolution of $N_{\text{train;att}}$ for different numbers of epochs

Best results on other desynchronizations

	N_{train}	N_{att}	$N_{\text{train;att}}$	FC1: L_2	Nb epochs
Desync0	104	272	168	0.1	125
Desync50	21	279	258	0.1	200
Desync100	76	395	319	0.3	175

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Conclusion

New metric to evaluate the possible improvement of an architecture

Normalization and regularization improve CNN performance in SCA

Given the amount of regularization needed to obtain those results, better architecture probably exists

Apply this technique to other networks

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Thank you for listening. Do you have questions ?



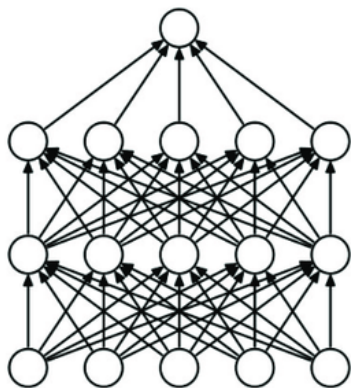
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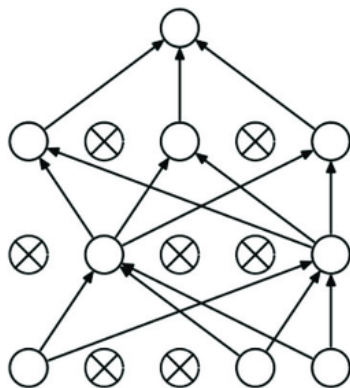


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Dropout example



(a) Standard Neural Network



(b) Neural Net with Dropout

Ref.: Roffo, Giorgio. (2017). Ranking to Learn and Learning to Rank: On the Role of Ranking in Pattern Recognition Applications.

Pooling example

Ref.: Max pooling in CNN.

Source: <http://cs231n.github.io/convolutional-networks/>