Improved Deep-Learning Side-Channel Attacks using Normalization Layers

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Introduction

- **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

Content

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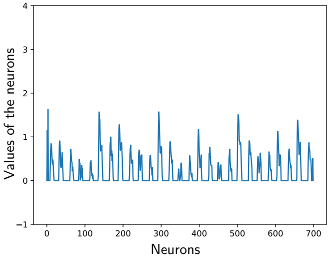
Batch Normalization

Goal

Standardize the data representation across all layers

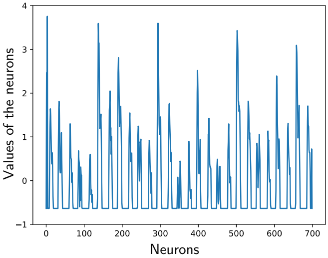
Consequence

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



(μ, σ^2)

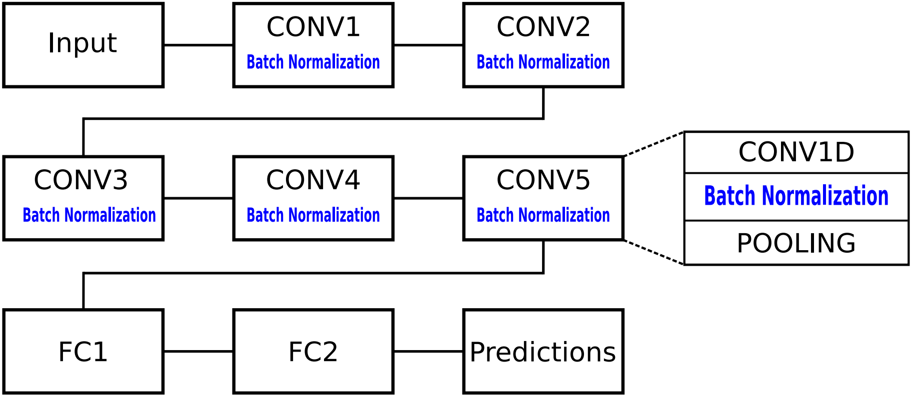
Batch Normalization



$(0, 1)$

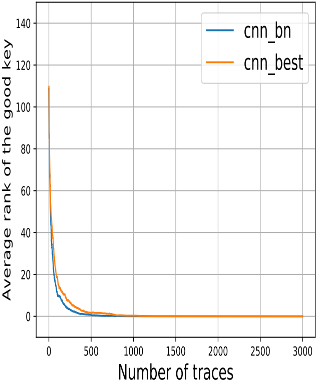
Updated architecture: CNN_{bn}

Network architecture with Batch Normalization



Training on ASCAD desynchronized traces

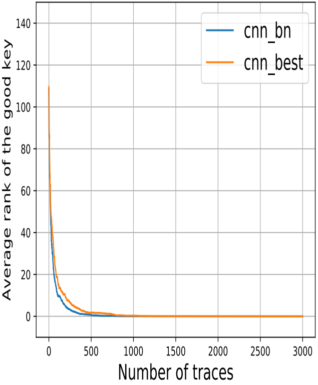
- Desync$N$: random shift between 0 and N applied to the 700 points of the traces



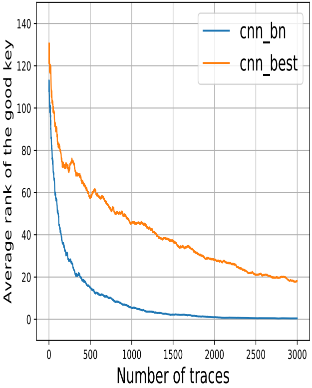
Desync0

Training on ASCAD desynchronized traces

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



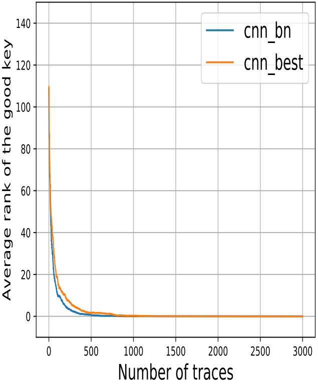
Desync0



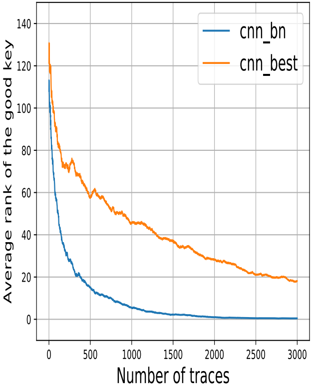
Desync50

Training on ASCAD desynchronized traces

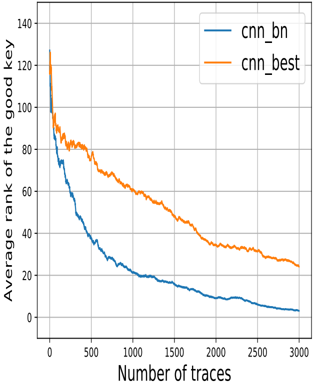
- Desync$N$: random shift between 0 and N applied to the 700 points of the traces



Desync0

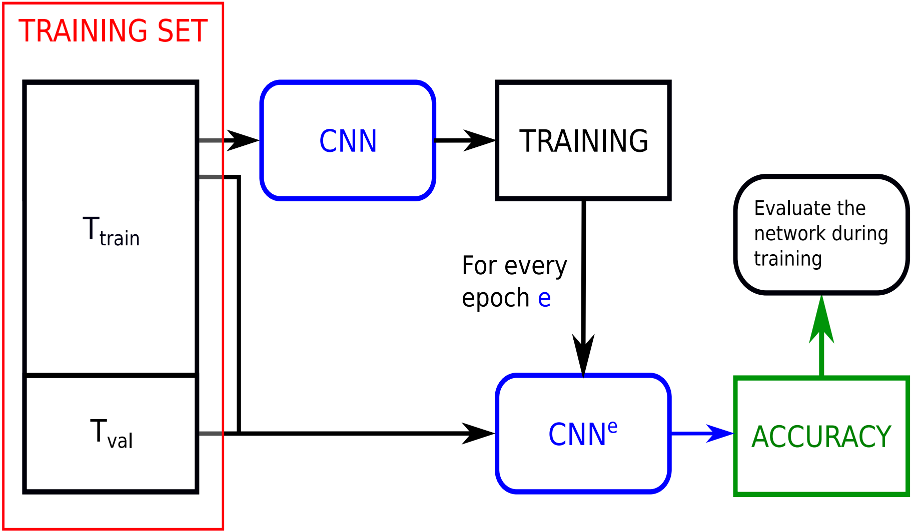


Desync50



Desync100

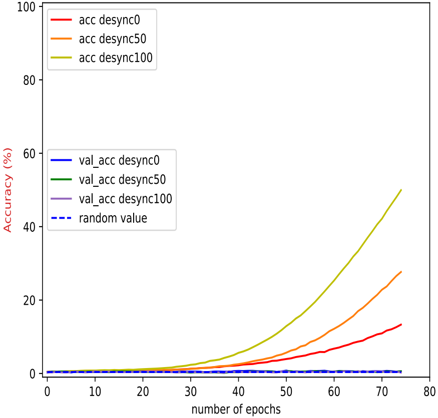
Evaluate the performance of a network



Training Acc. vs. Validation Acc.

Goal

Evaluate the networks during training

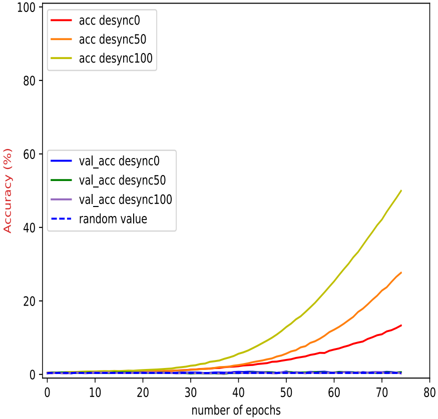


CNN_{best}

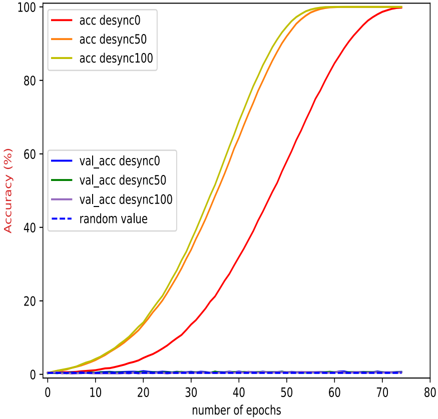
Training Acc. vs. Validation Acc.

Goal

Evaluate the networks during training



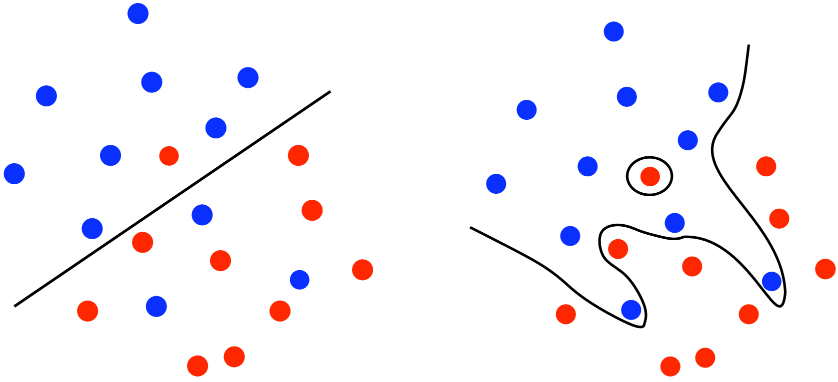
CNN_{best}



CNN_{bn}

Content

The overfitting phenomena



Good estimation

Overfitting

$\Delta_{train,val}$: evaluation of the generalization capacity

Goal

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

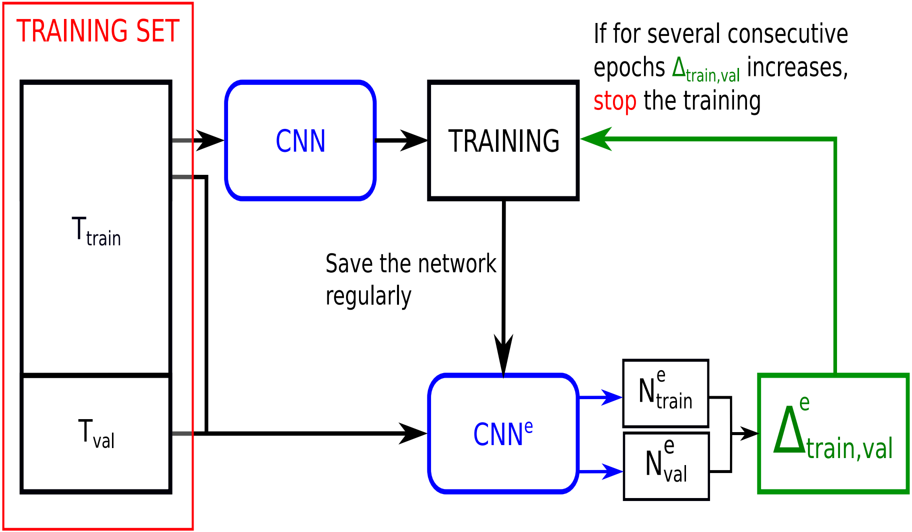
Notations

- T_{train} = Set of traces the network used to train
- T_{val} = Set of traces the network has never seen
- $N_{train}(model) := min\{n_{train} \mid \forall n \geq n_{train}, SR^1_{train}(model(n)) = 90\%\}$
- $N_{val}(model) := min\{n_{val} \mid \forall n \geq n_{val}, SR^1_{val}(model(n)) = 90\%\}$

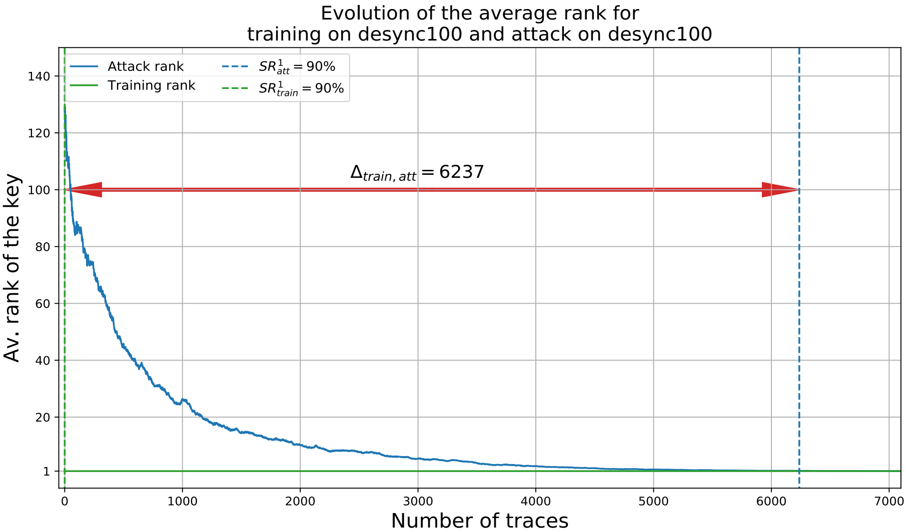
Metric

$$\Delta_{train,val}(model) = \mid N_{val}(model) - N_{train}(model) \mid$$

How to use the metric



Representation of $\Delta_{train,att}$ for CNN_{bn}



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Regularization

Goal

Reduce $\Delta_{train,att}$ even further using regularization

Means

- Dropout with parameter $\boldsymbol{\lambda_D}$
- L_2-Norm regularization with parameter $\boldsymbol{\lambda_{L_2}}$

Regularization

Goal

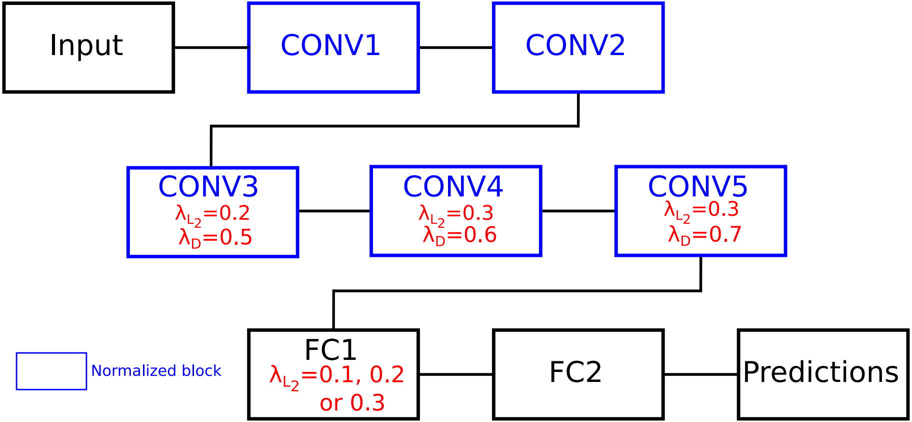
Reduce $\Delta_{train,att}$ even further using regularization

Means

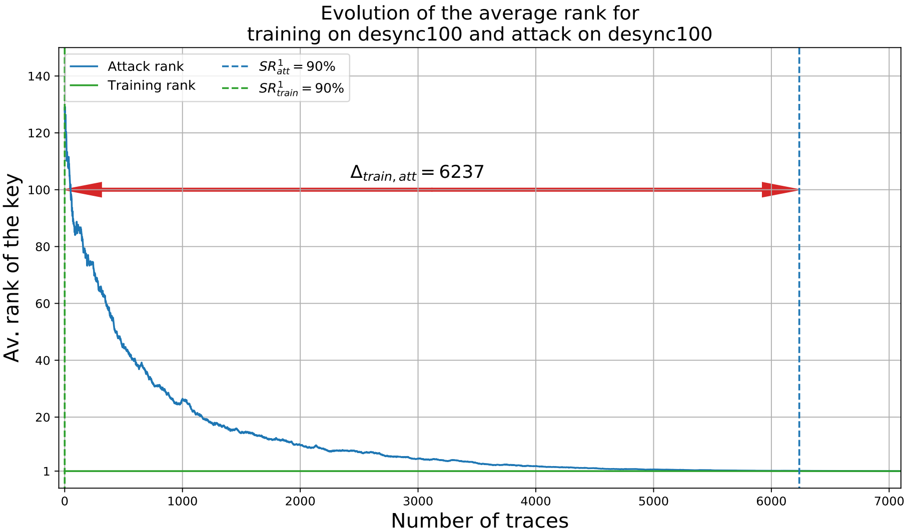
- Dropout with parameter $\boldsymbol{\lambda_D}$
- L_2-Norm regularization with parameter $\boldsymbol{\lambda_{L_2}}$

	Test ($step = 0.1$)		Choice for desync100	
	$\boldsymbol{\lambda_D}$	$\boldsymbol{\lambda_{L_2}}$	$\boldsymbol{\lambda_D}$	$\boldsymbol{\lambda_{L_2}}$
$CONV1\&2$	[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

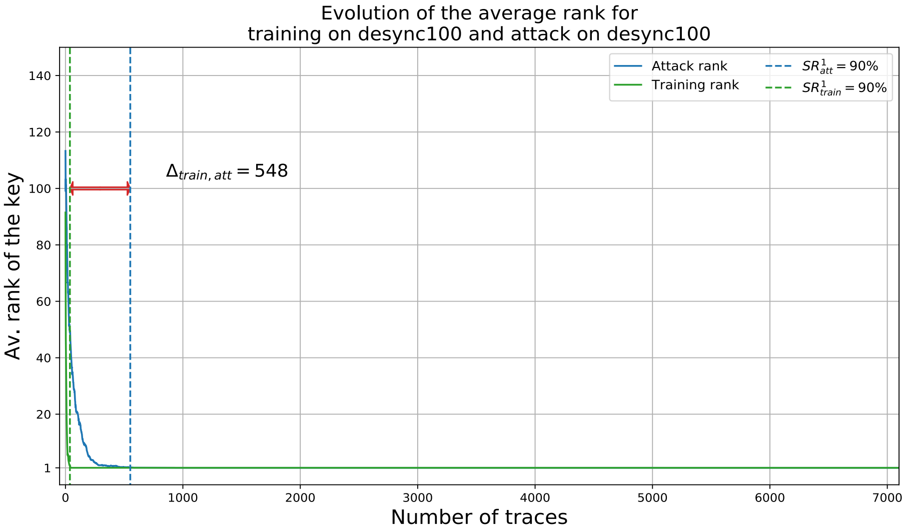
Architecture with regularization: CNN_{bn+reg}



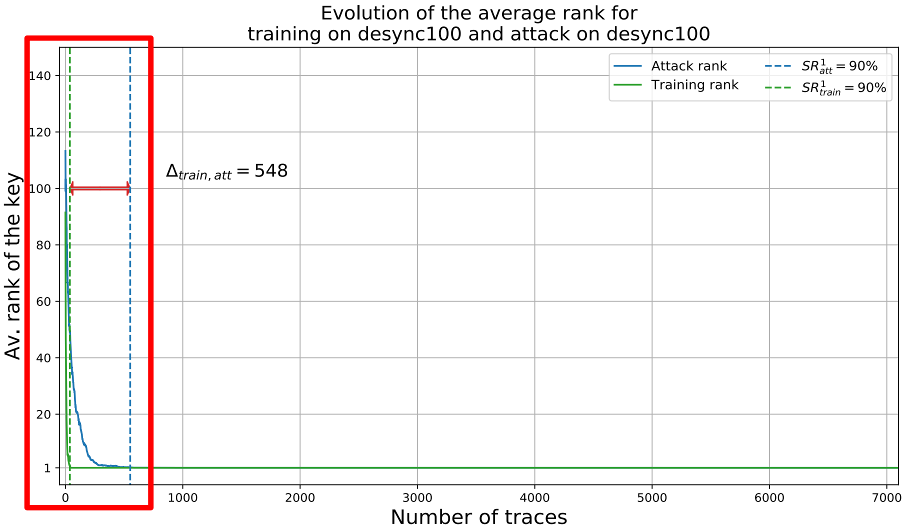
Results without regularization: CNN_{bn}



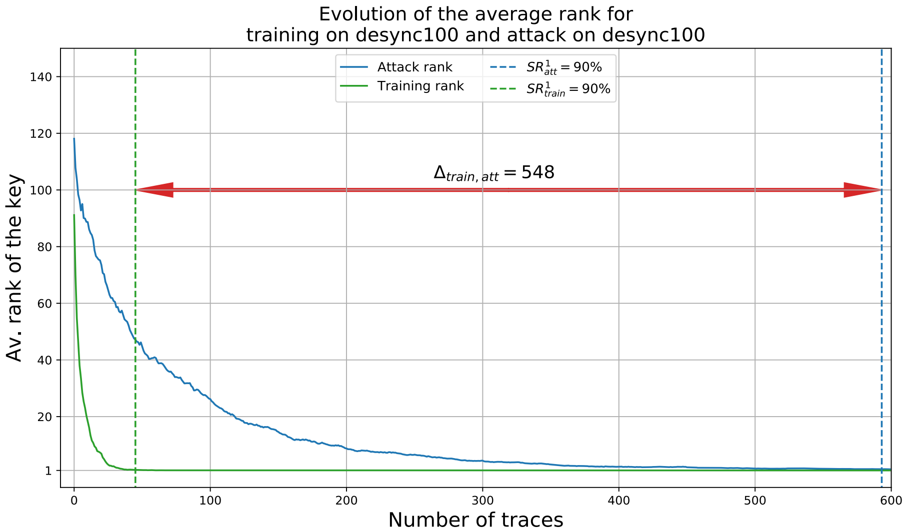
Results with regularization: CNN_{bn+reg}



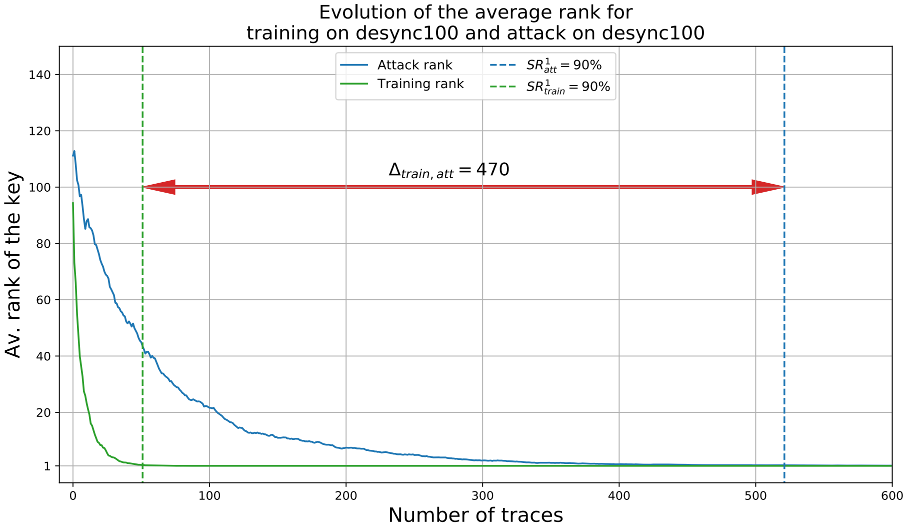
Results with regularization: CNN_{bn+reg}



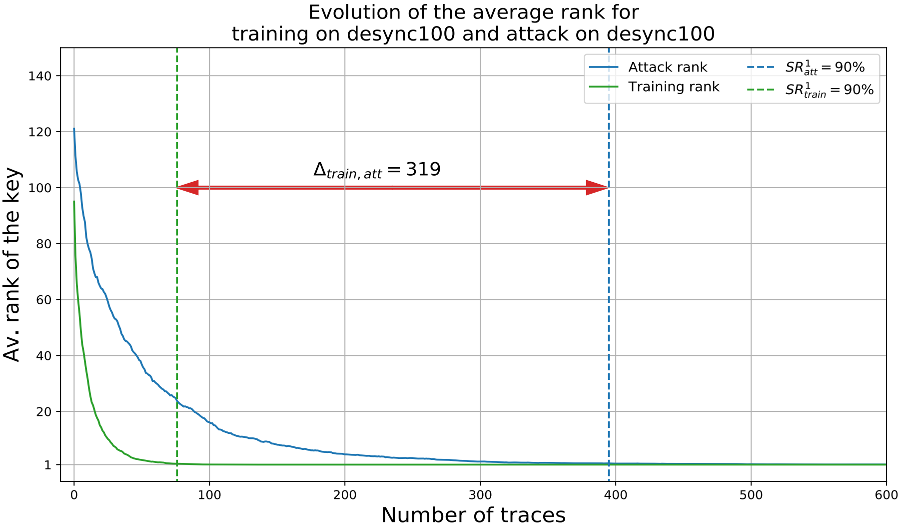
Attack on desync100 using $\lambda_{L_2} = 0.1$ for CNN_{bn+reg}



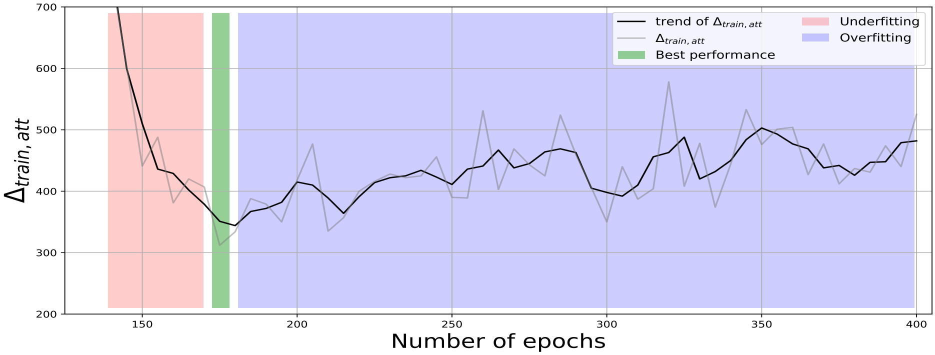
Attack on desync100 using $\lambda_{L_2} = 0.2$ for CNN_{bn+reg}



Attack on desync100 using $\lambda_{L_2} = 0.3$ for CNN_{bn+reg}



Evolution of $\Delta_{train,att}$ for different numbers of epochs



Best results on other desynchronizations

	N_{train}	N_{att}	$\Delta_{train,att}$	FC1: λ_{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, **a better architecture probably exists**
- Apply this technique to **other networks**

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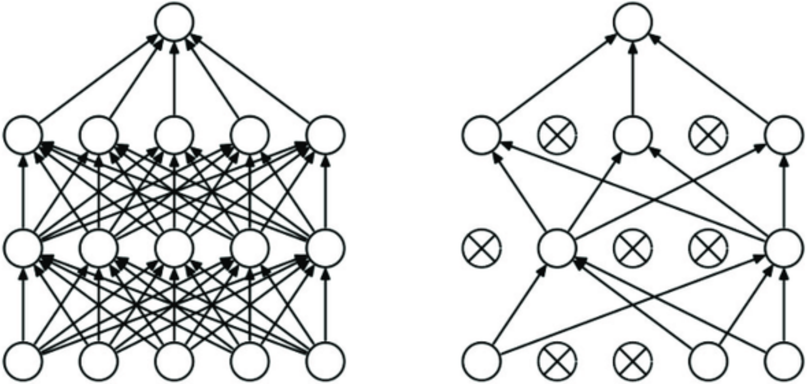
Thank you for listening. Do you have questions ?

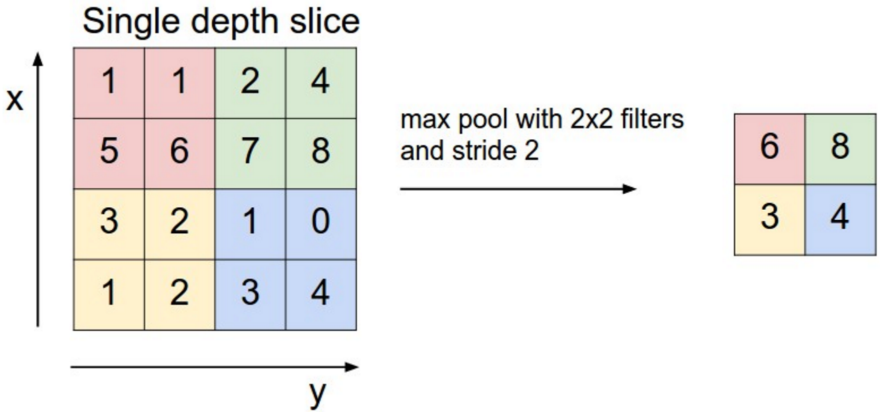
Dropout example



(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/