Convolutional Neural Networks with Data Augmentation against Jitter-Based Countermeasures

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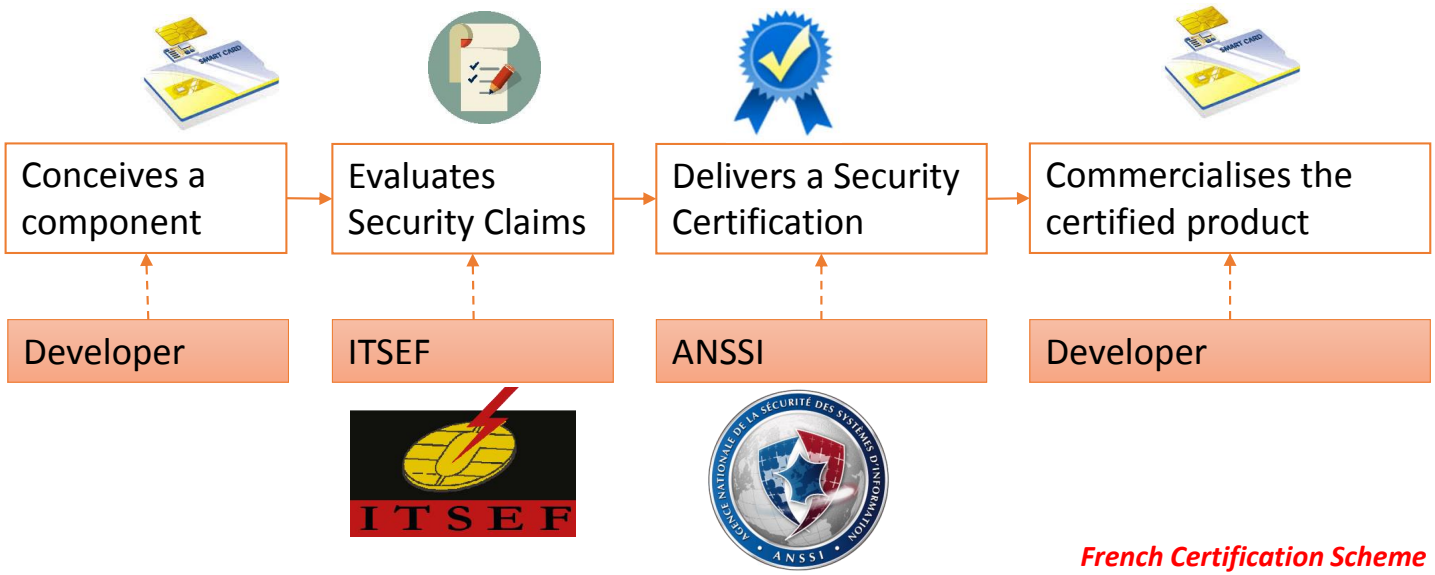
About the authors

Who we are



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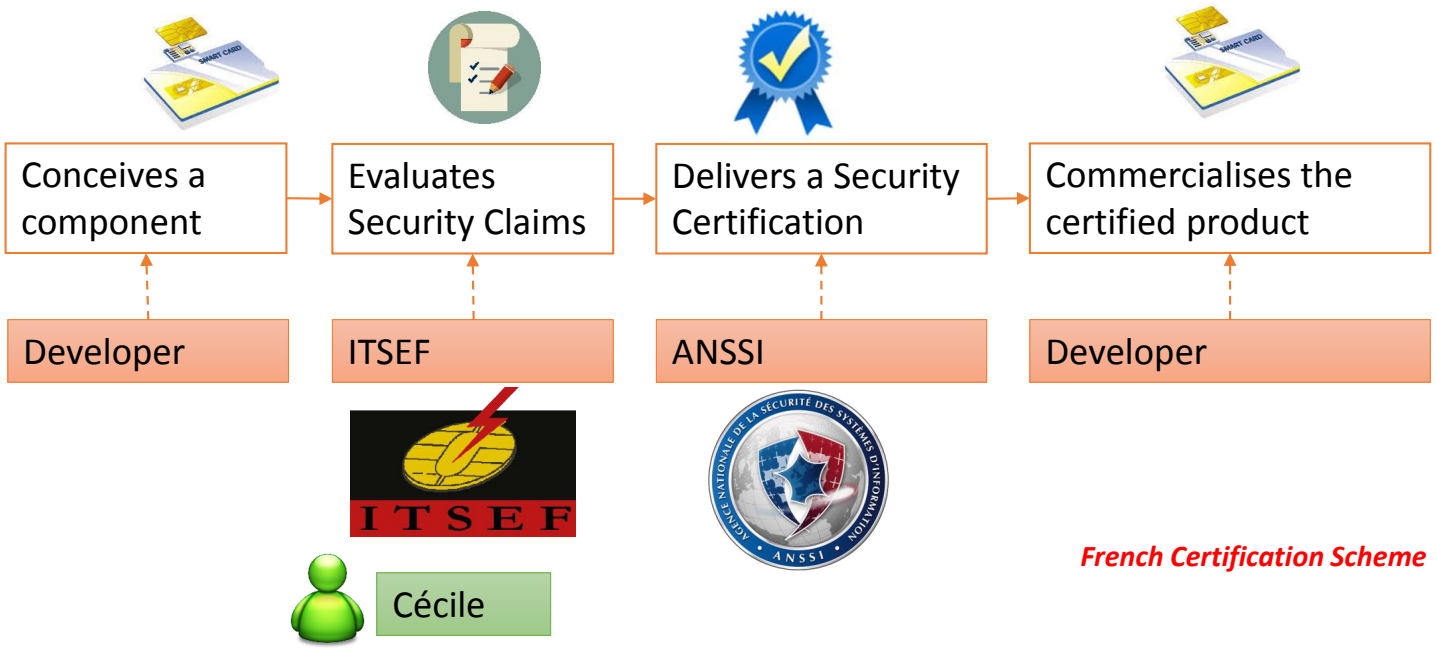

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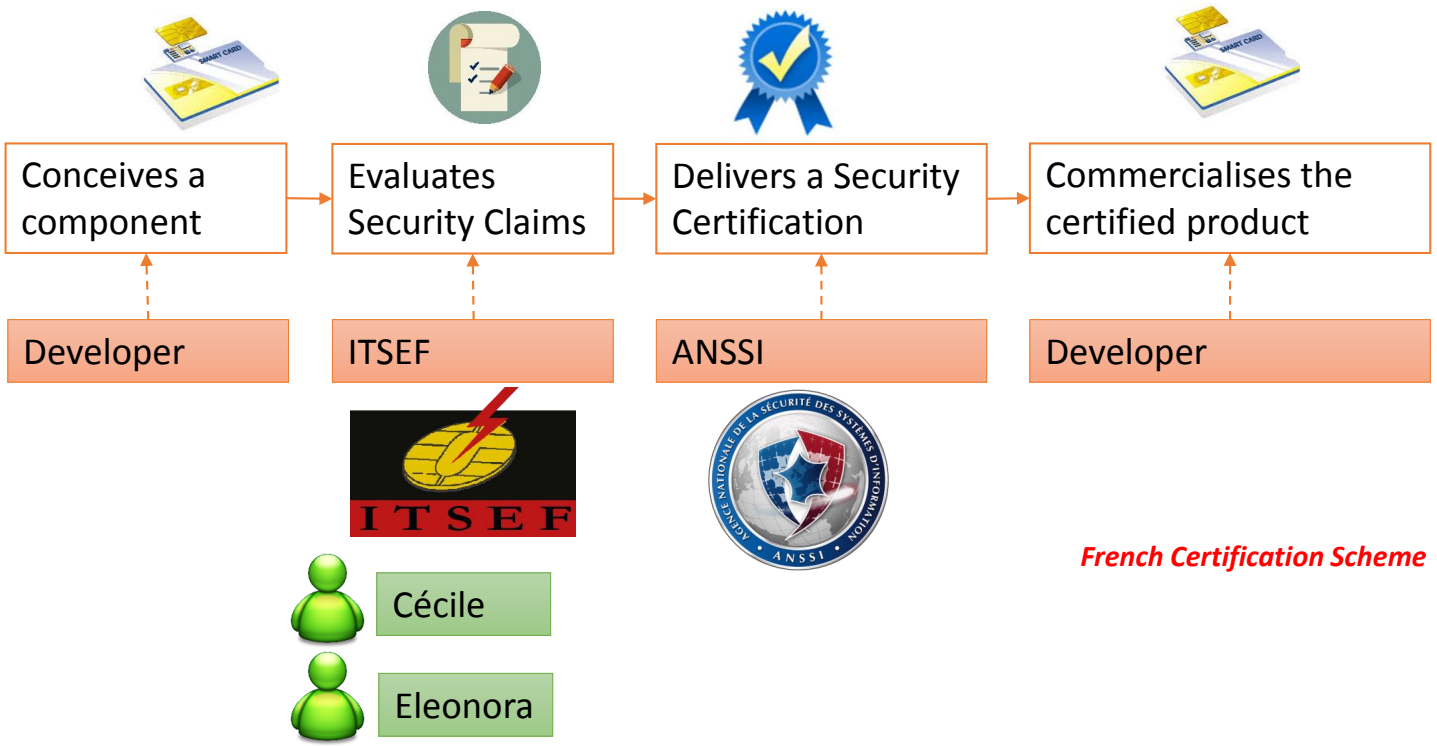

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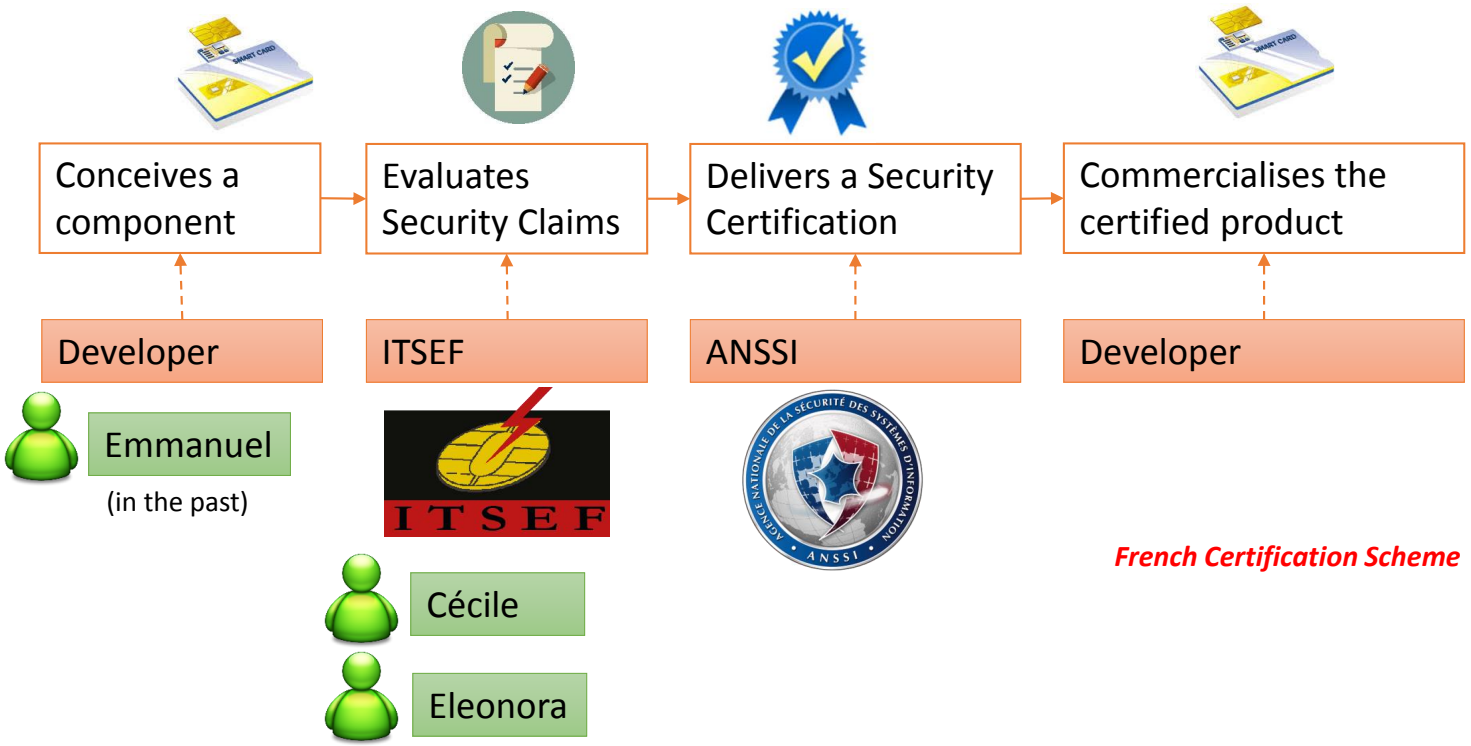

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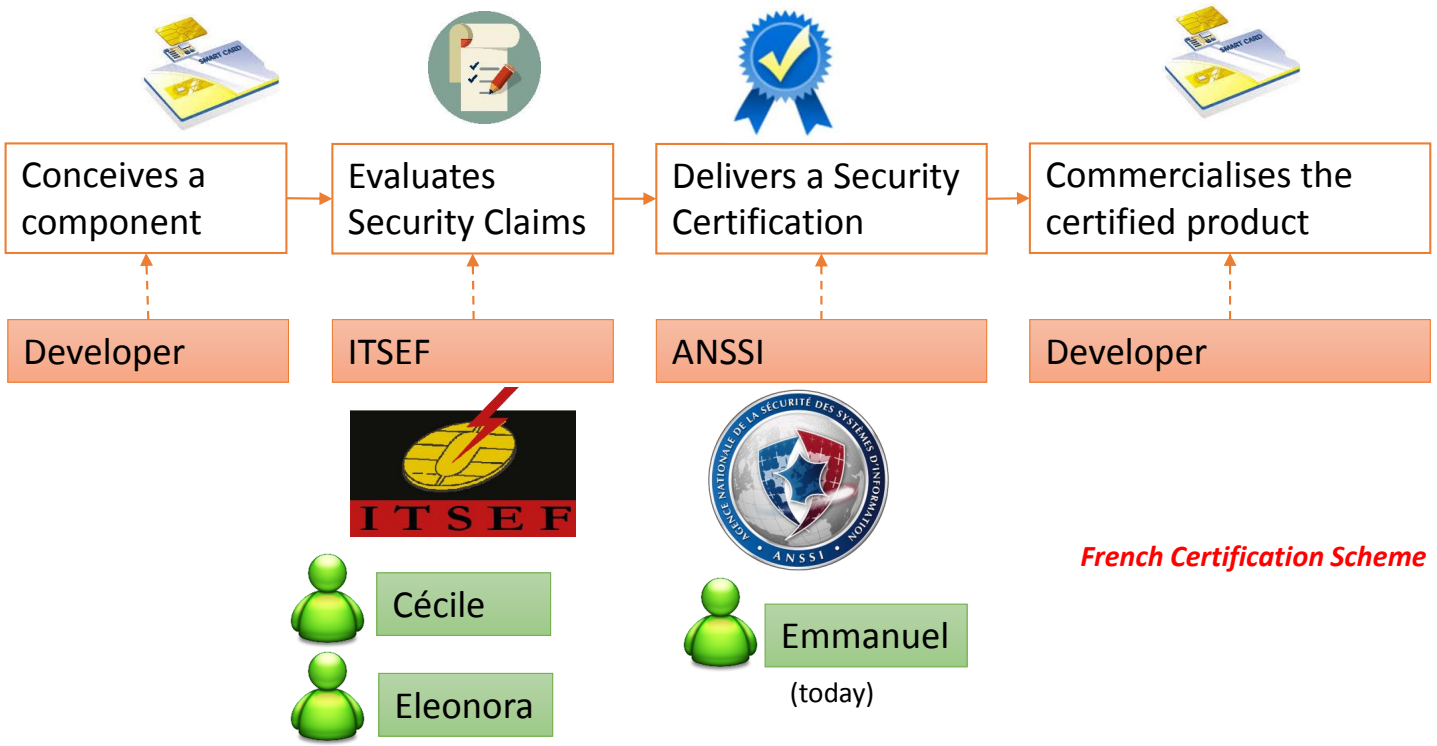

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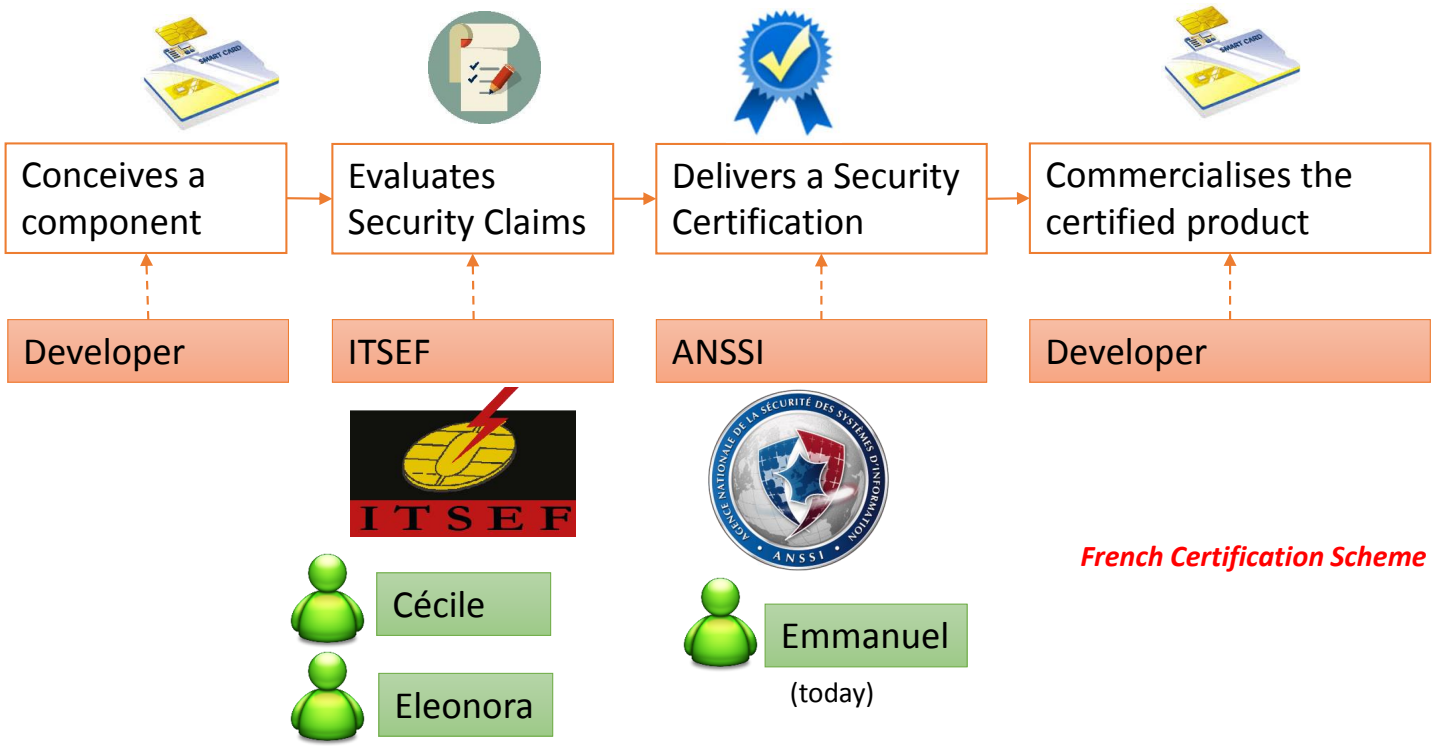

An evaluation point of view

- profiling attacks (worst-case security)
- practical aspects are concerned

Contents

Side Channel Attacks

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- Random Delays, Clock Jittering, ...
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Realignment

Mandatory realignment preprocessing

- not a wide literature
- in practice: evaluation labs home-made realignment techniques

Risks of realignment

An example

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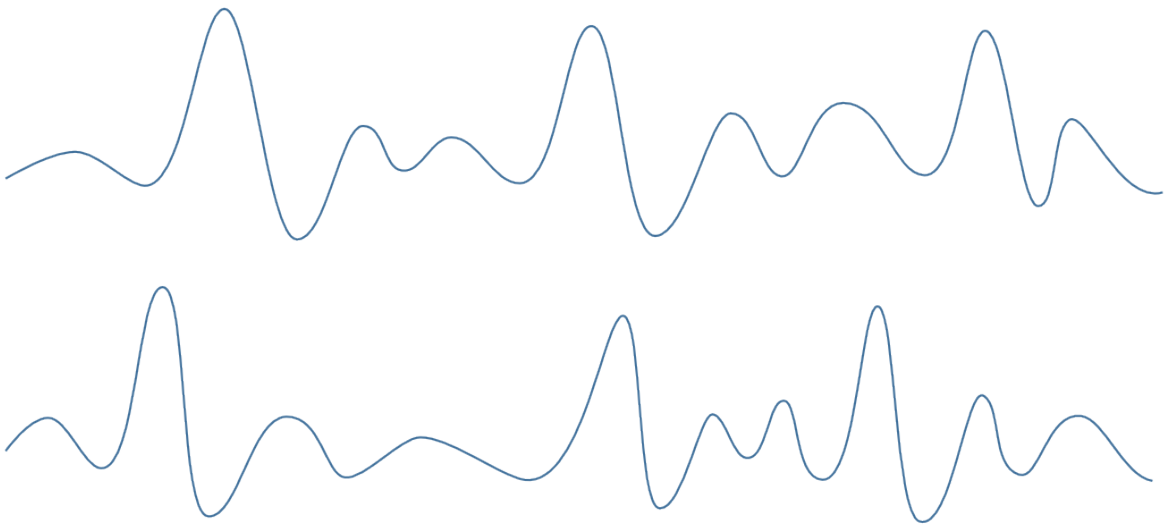

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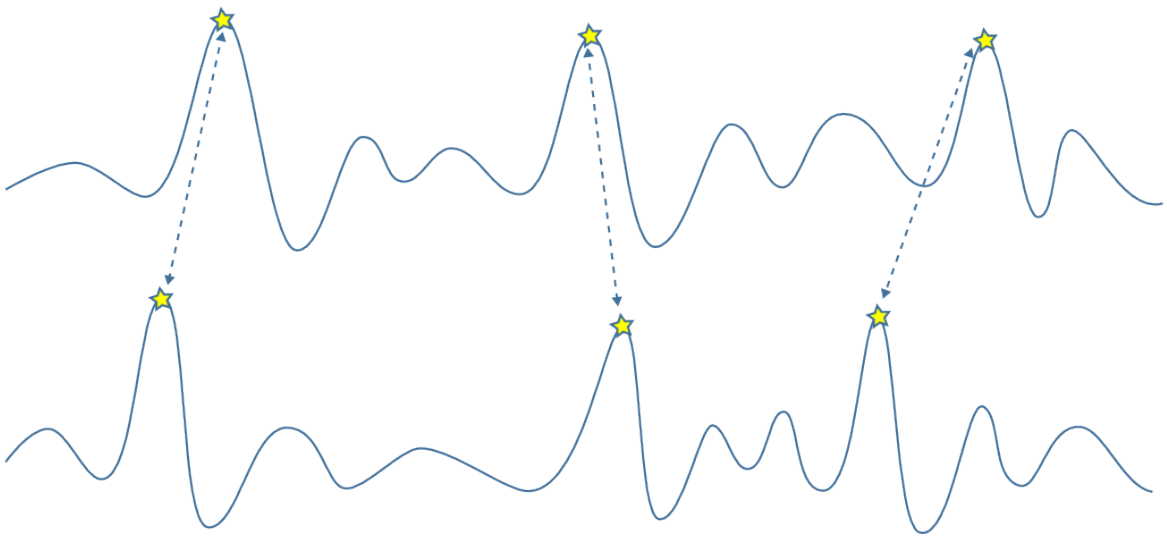

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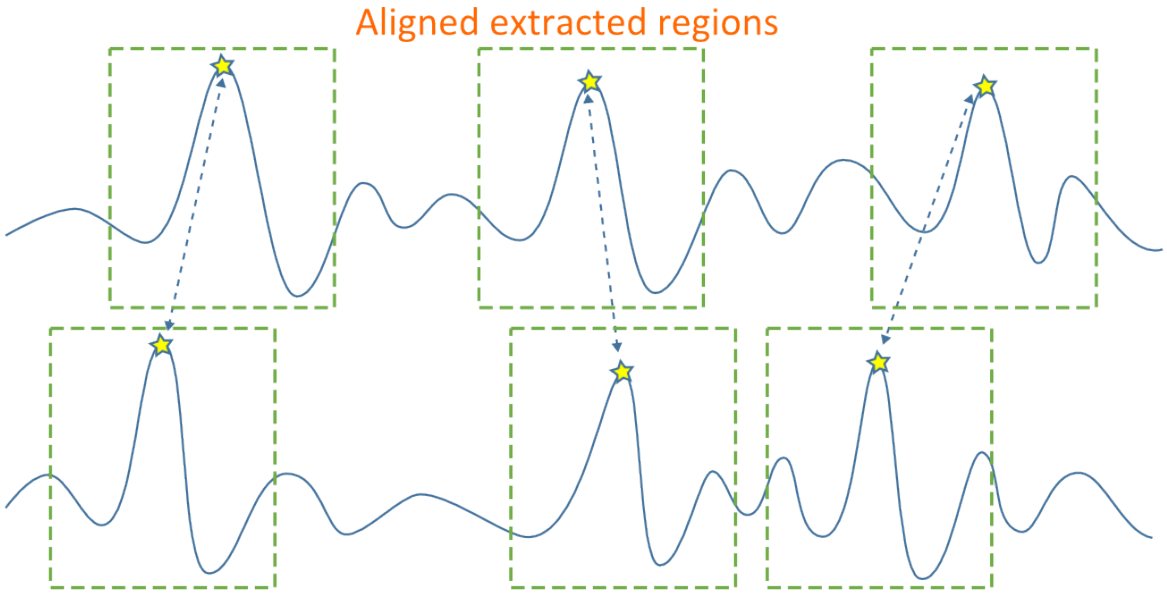

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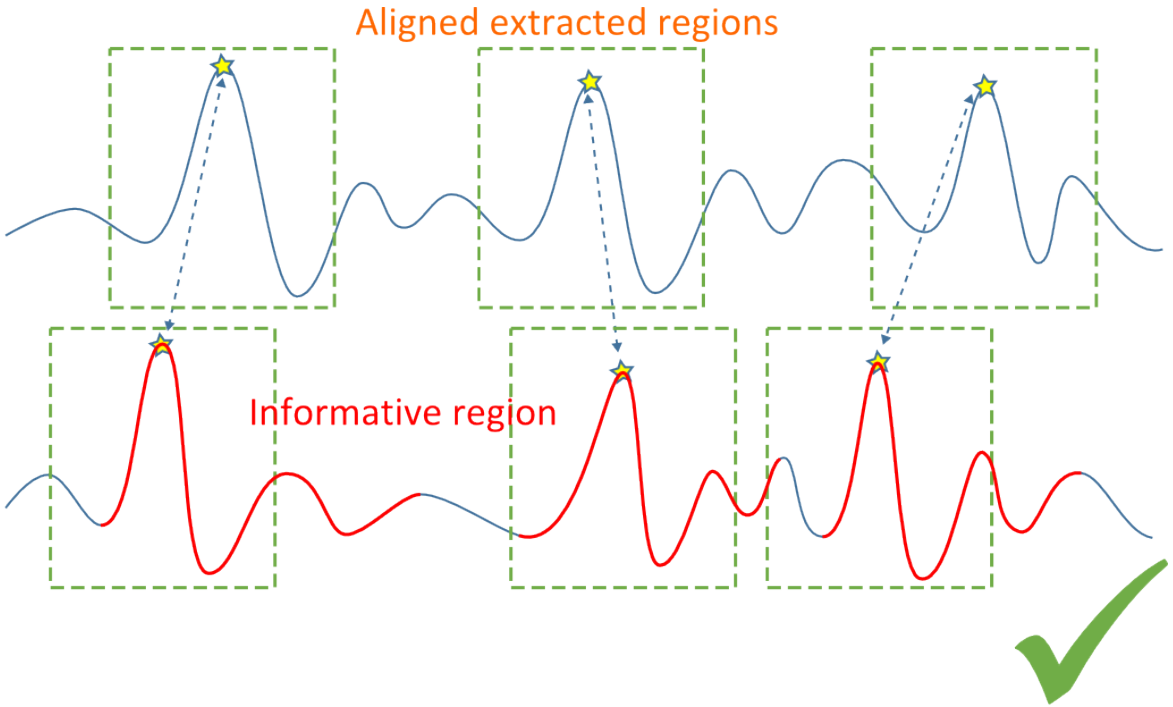

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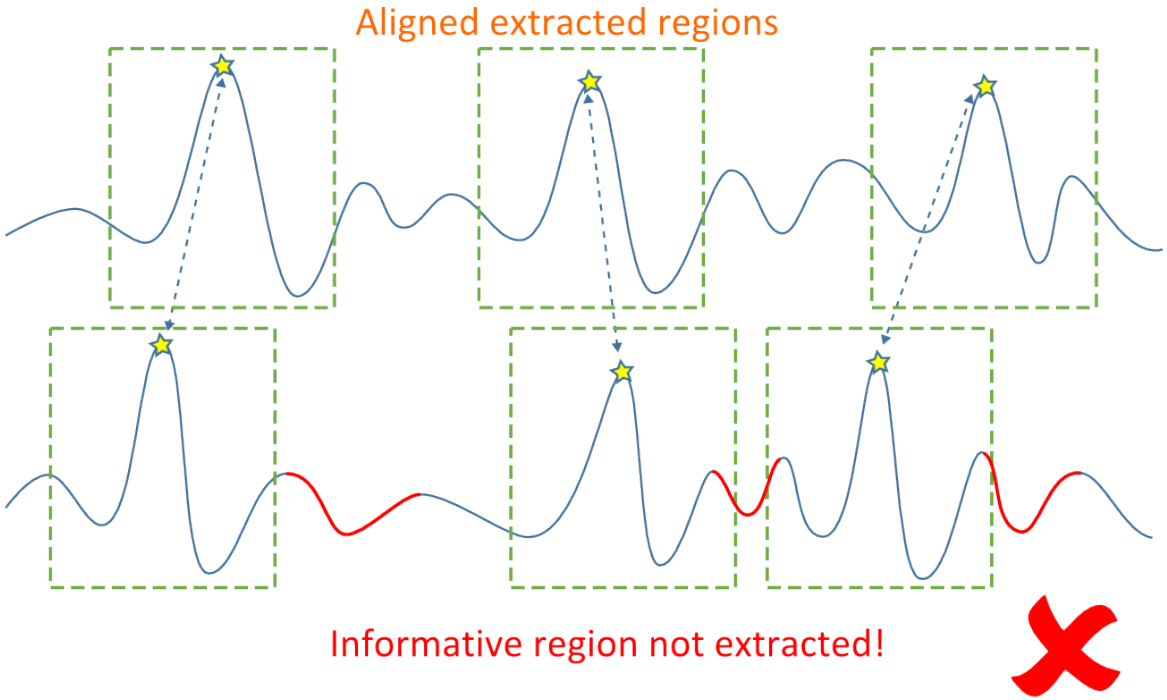

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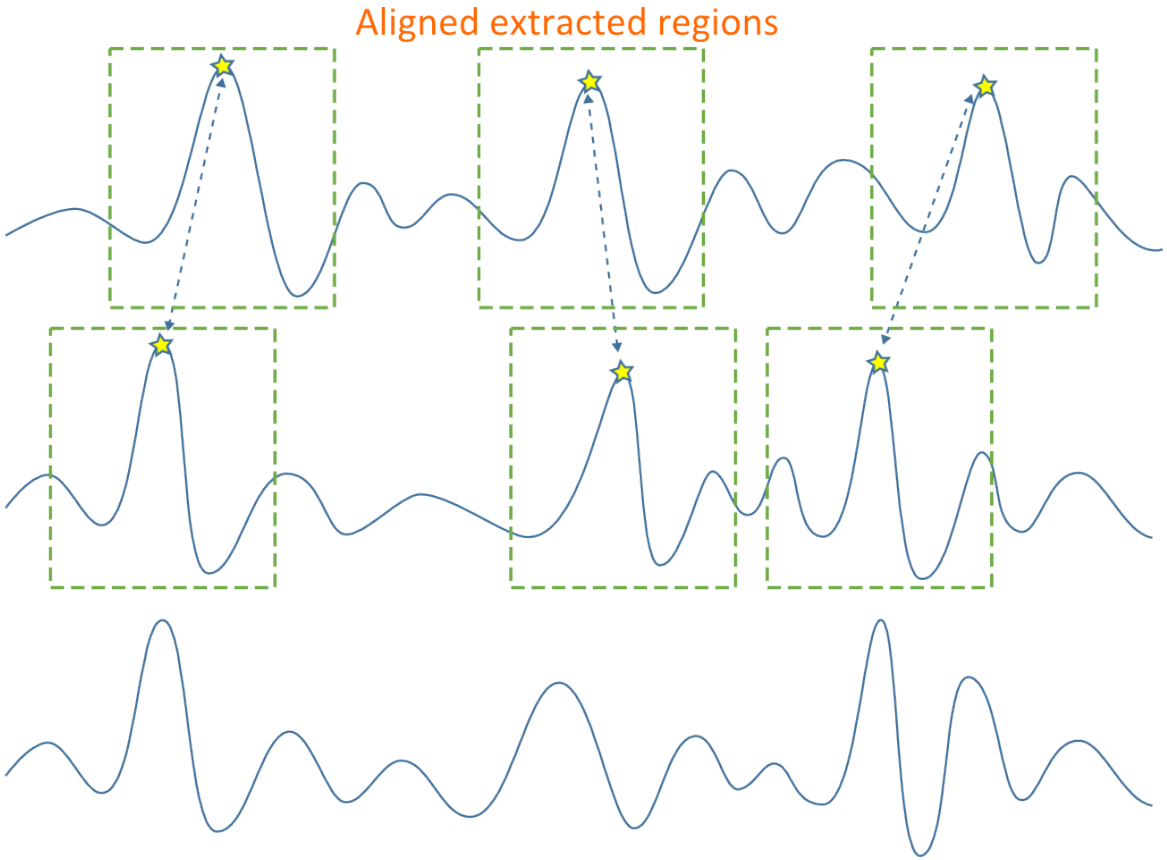

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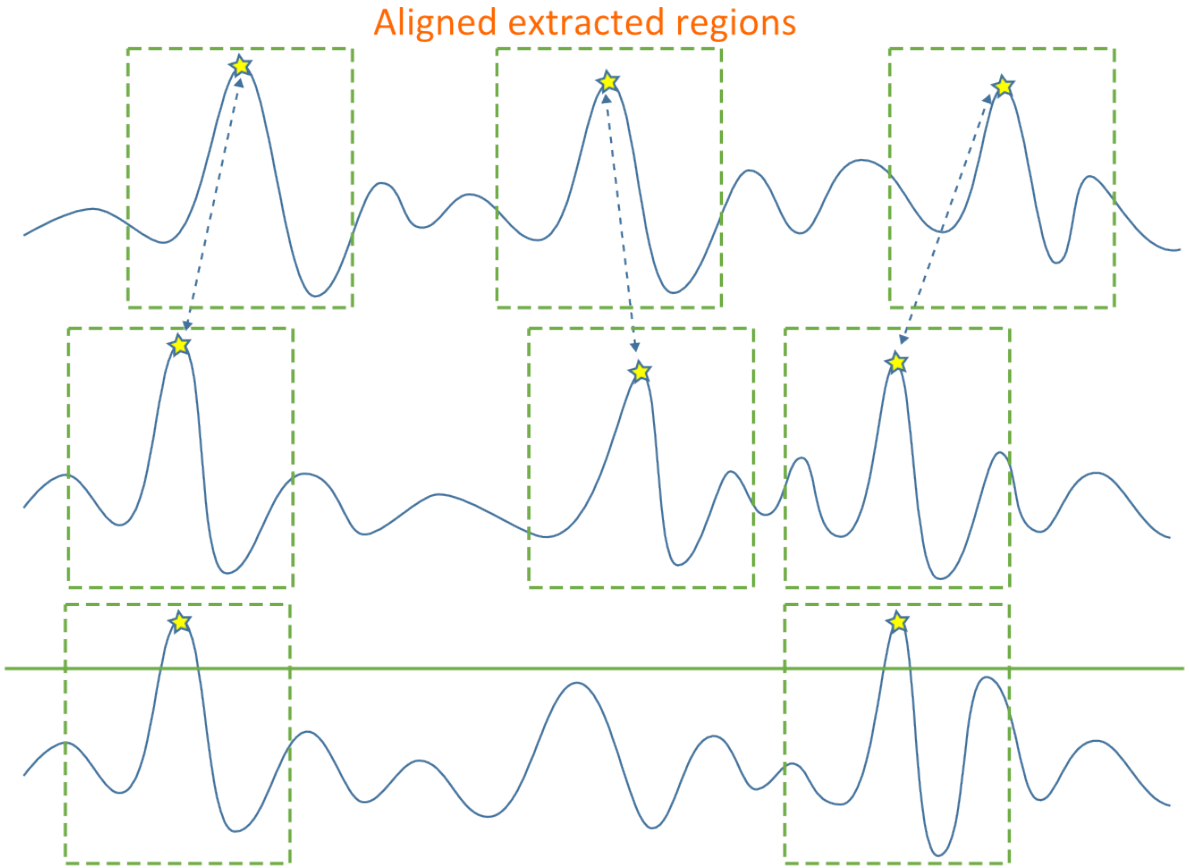

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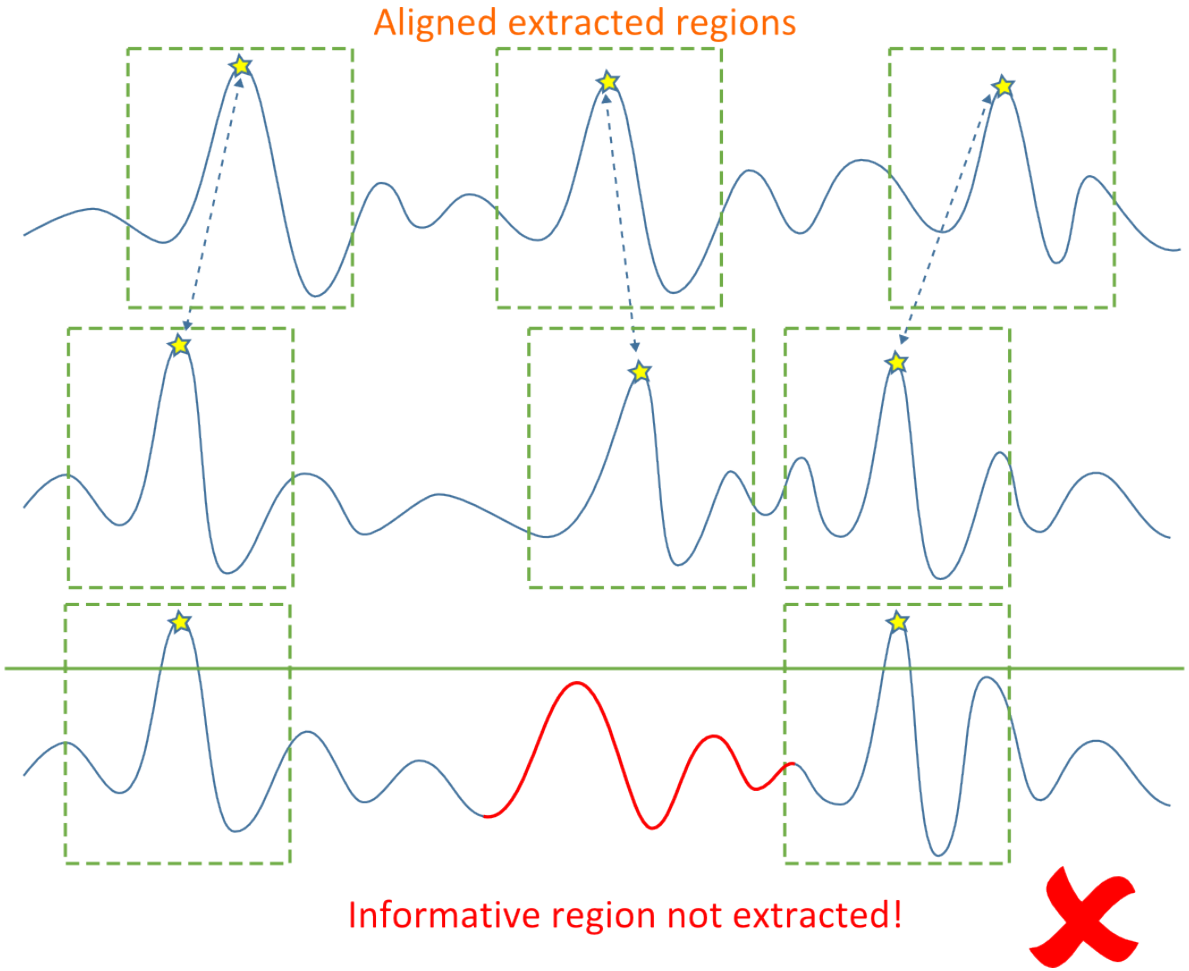

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No preprocessing ⇒ No risks of information loss

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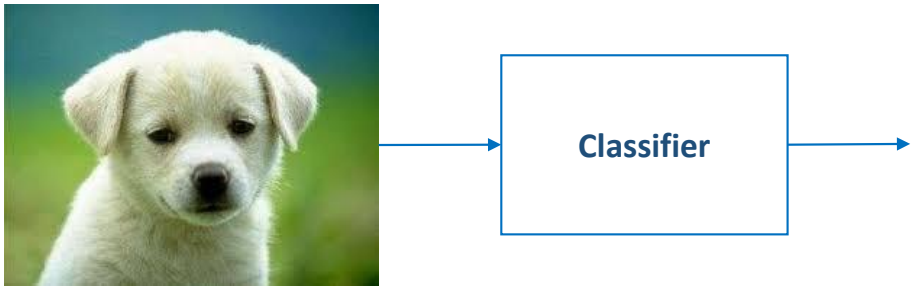

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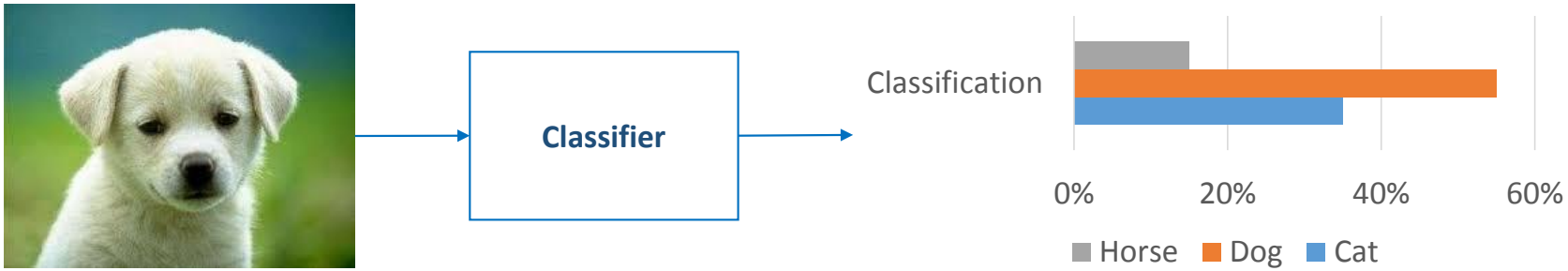

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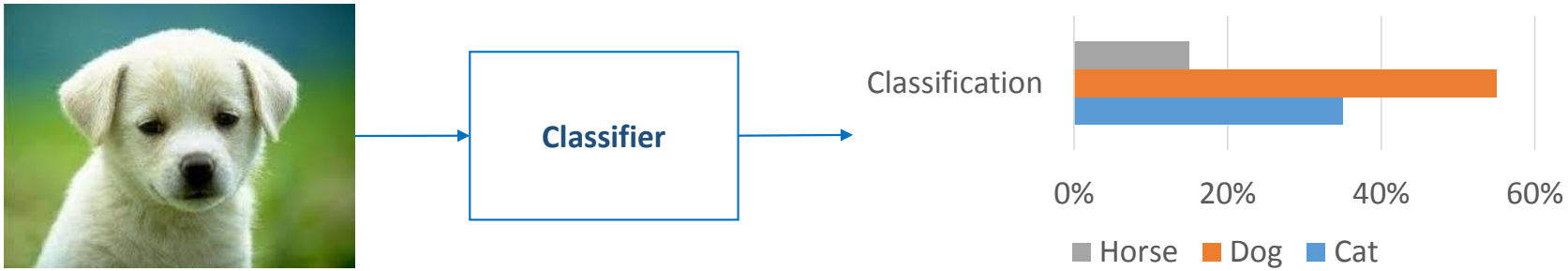

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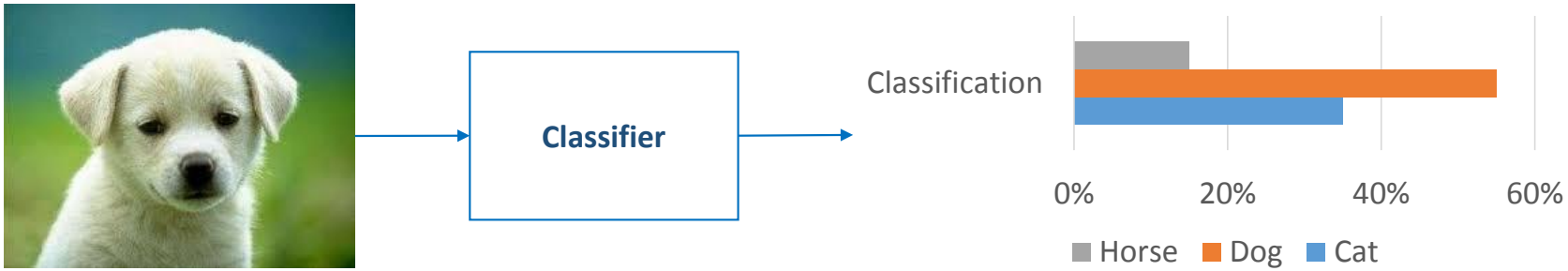

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SCA as a Classification Problem

Machine Learning Approach

Overview of Machine Learning Methodology

Human effort:

- choose a class of algorithms
- choose a model to fit + tune **hyper-parameters**

Automatic training:

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Convolutional Neural Networks

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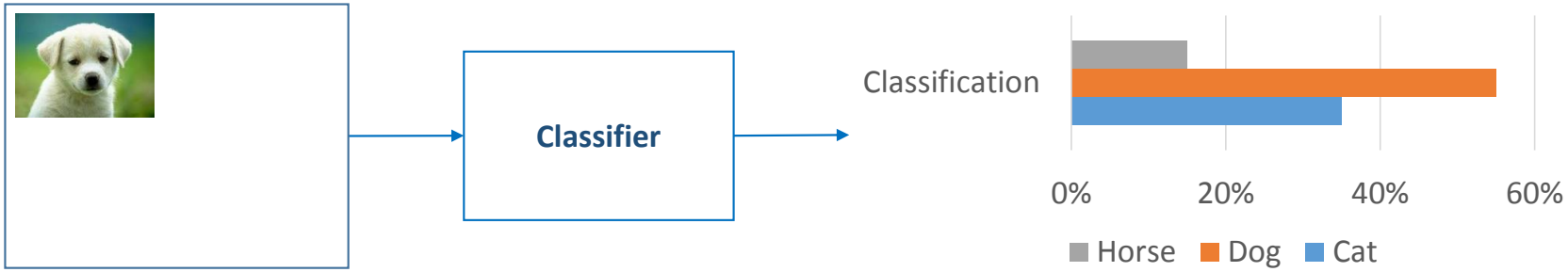

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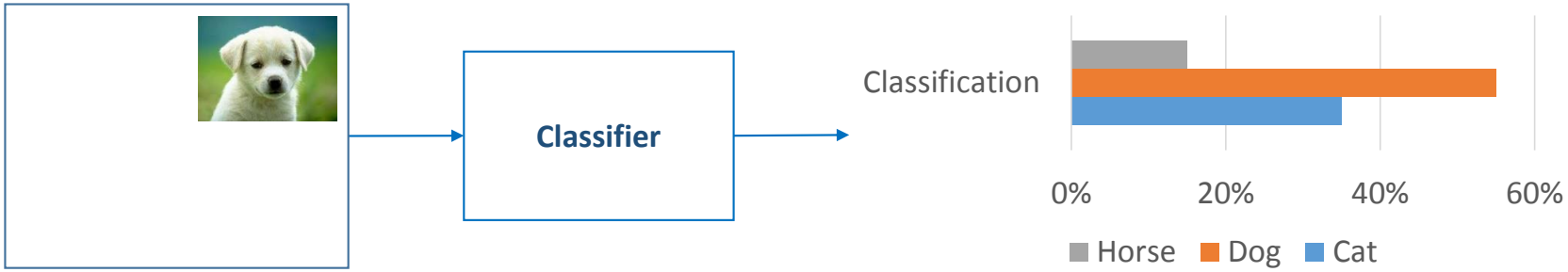

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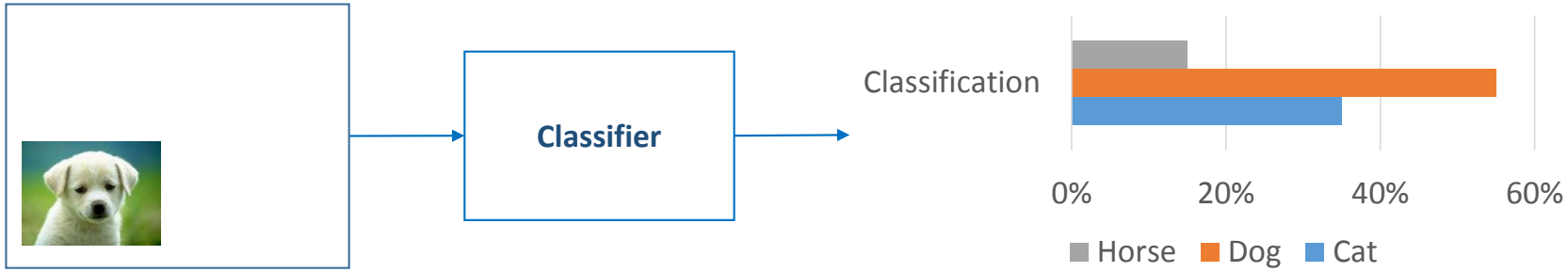

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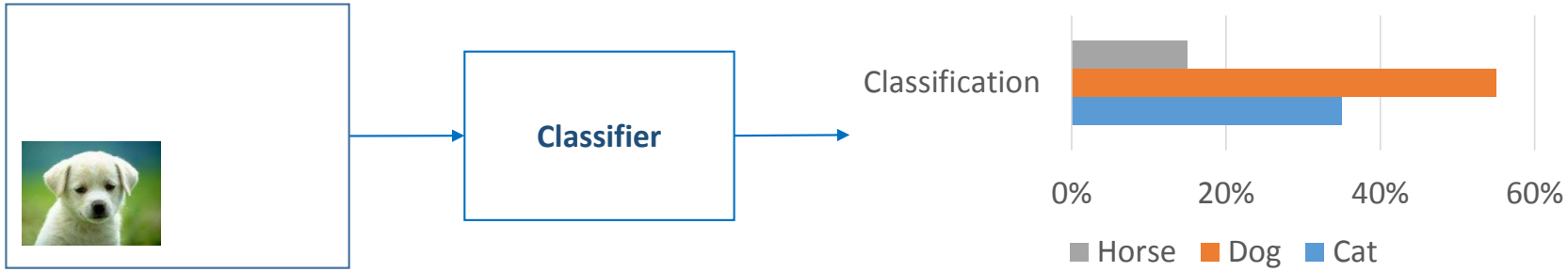

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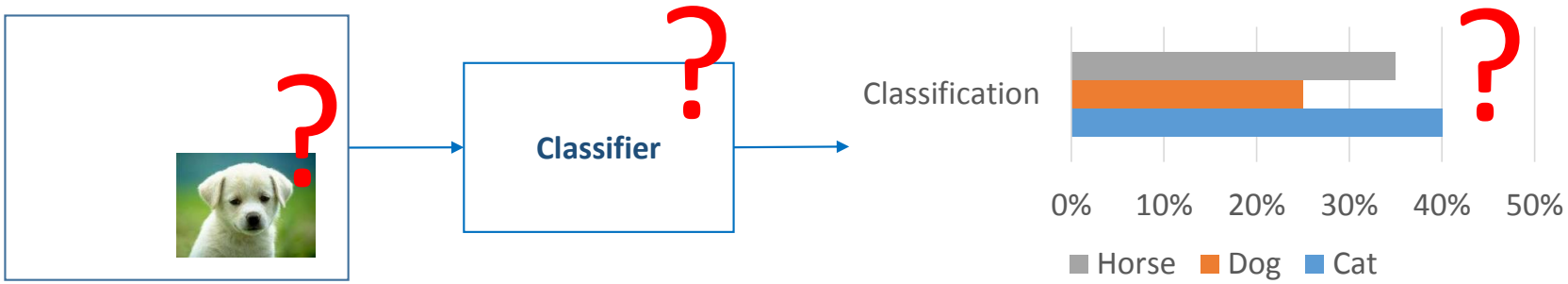

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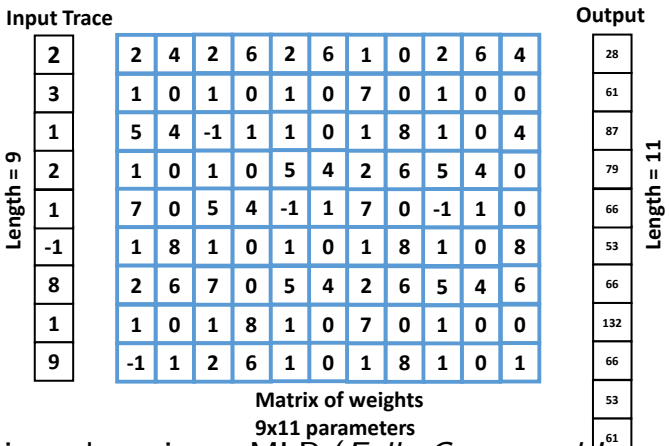

Linear layer in an MLP (*Fully Connected Layer*)

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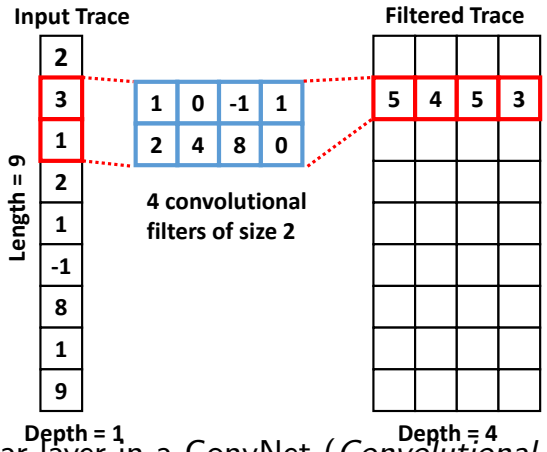
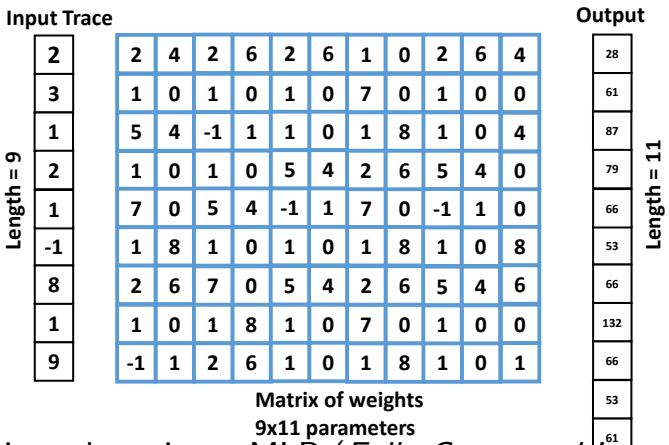
Convolutional Neural Networks: share weights across space



Linear layer in a ConvNet (*Convolutional Layer*)



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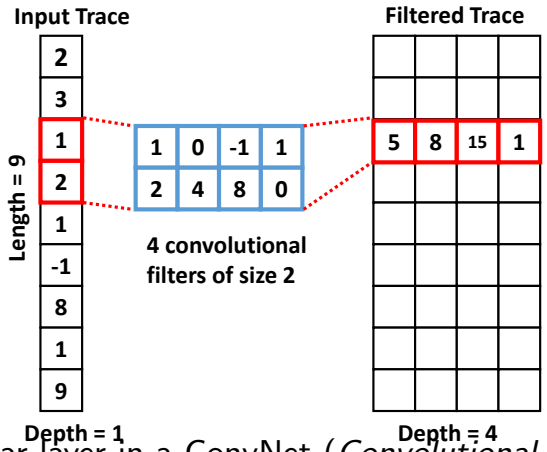

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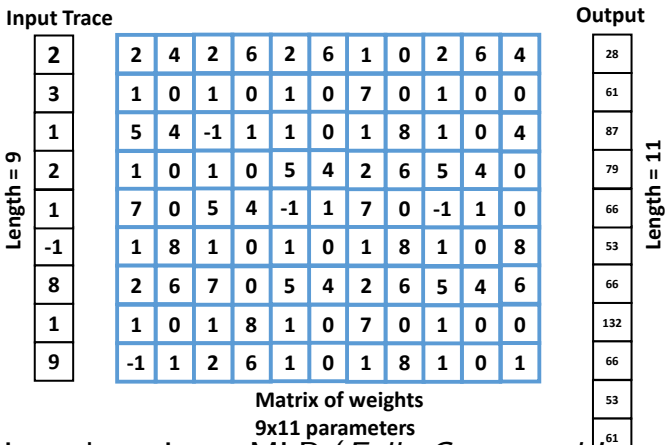

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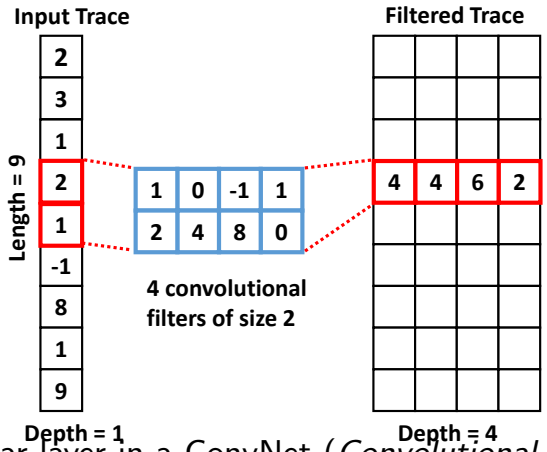

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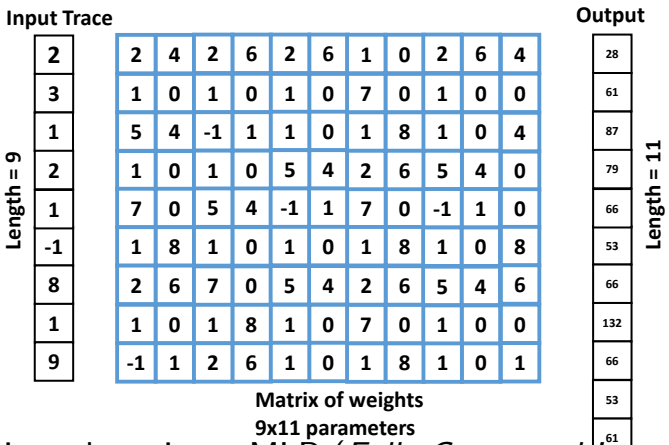

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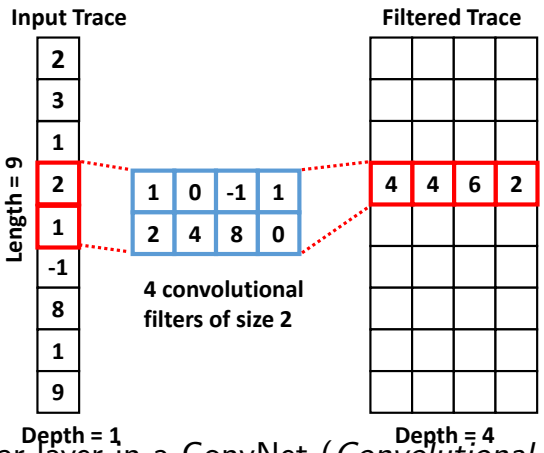

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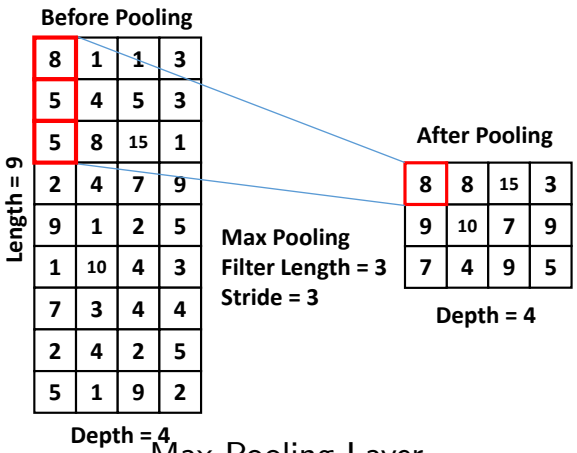
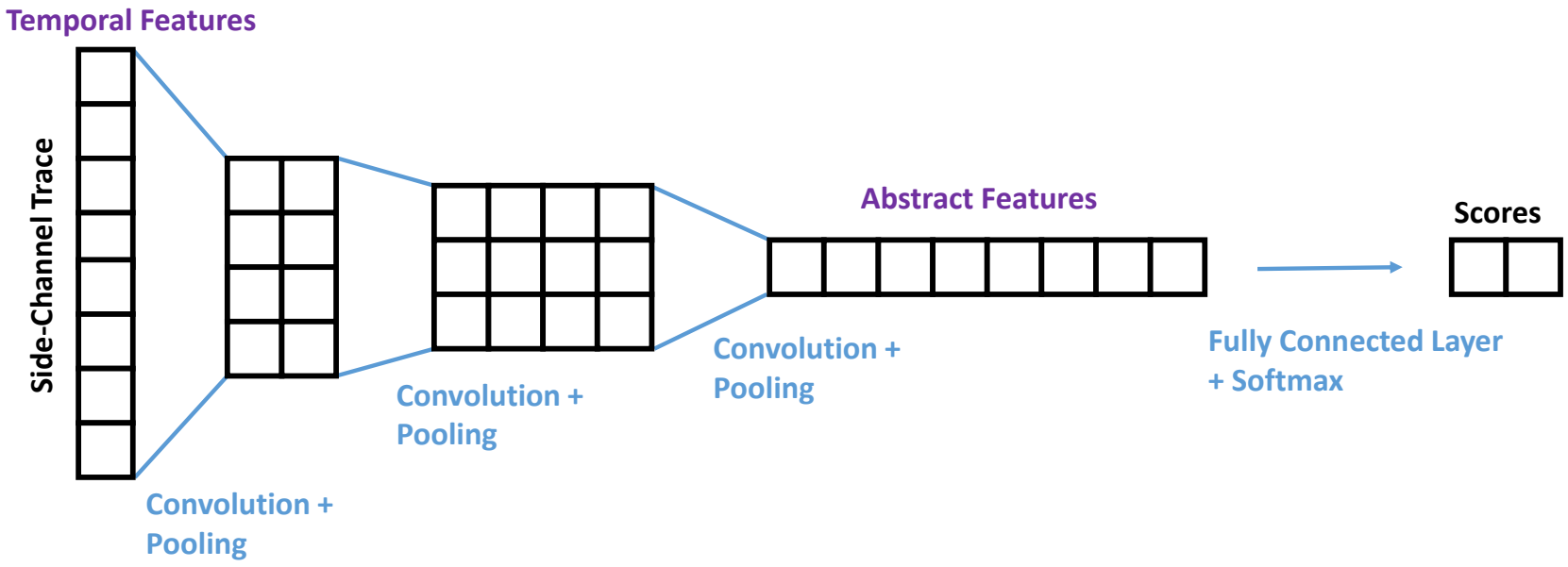


Max Pooling Layer

ConvNet typical architecture



Training and overfitting

Training

Profiling set $\rightarrow \begin{cases} \text{Training set} \\ \text{Validation set} \end{cases}$

Randomly partition training set into batches

Iterative algorithm over batches (one weights update per processed batch)

Epoch:= one pass over the entire training set

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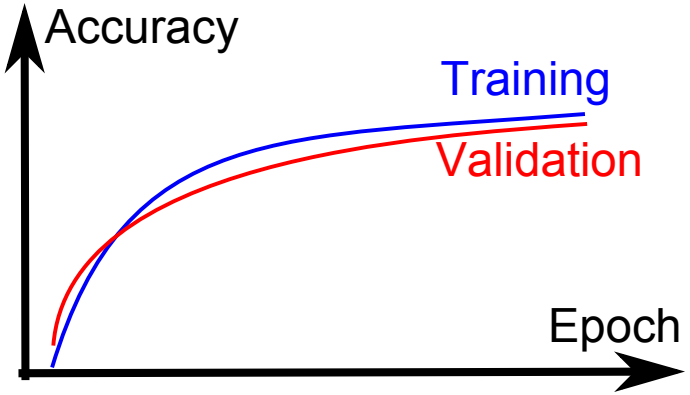
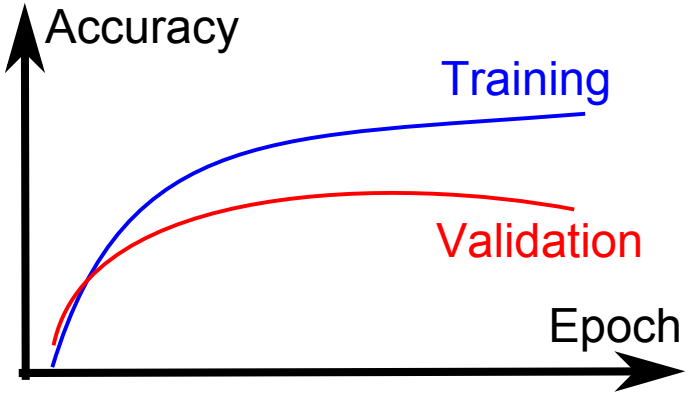
Evaluate and compare training and validation accuracy

Understand significant features



Learn by heart (**OVERFITTING**)



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Evaluate and compare training and validation accuracy

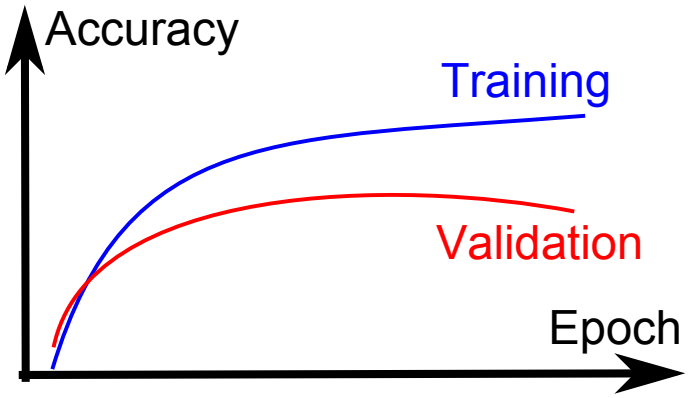
Why?

- Too complex model
- Not enough training data

Solution?

- Data augmentation

Learn by heart (**OVERFITTING**)



Contents

Data Augmentation

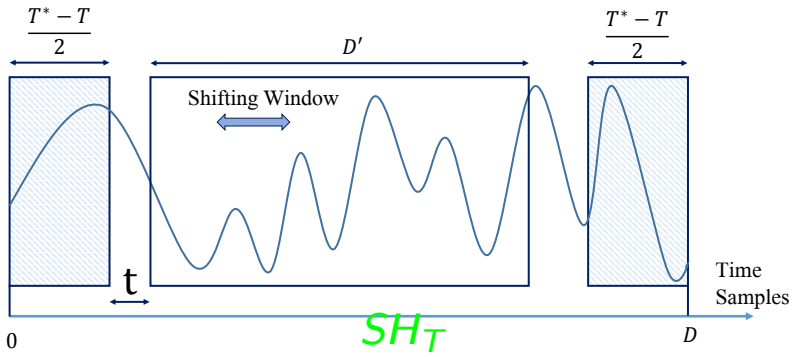
Data Augmentation

Artificially generate new training data by deforming those previously acquired,
Applying transformations that preserve the label **Z**

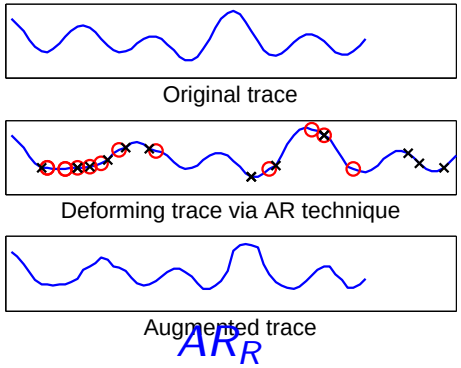
Countermeasure Emulation Idea

Emulate the effects of misaligning countermeasures to generate new traces

SHIFTING



ADD-REMOVE



Parameter T: ♯ of possible positions
Parameter R: ♯ of added and removed points
Data Augmentation techniques are applied online during training phase.

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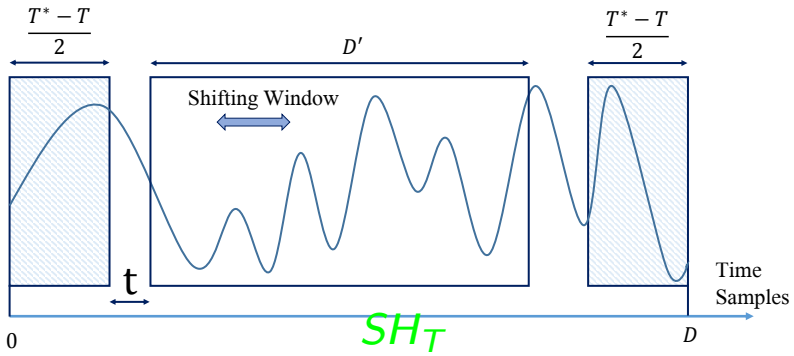

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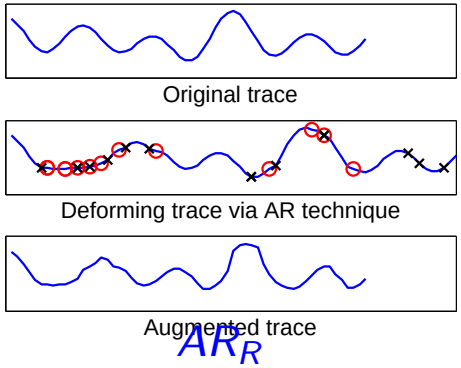

Parameter T: ♯ of possible positions ⟶ new hyper-parameter

Parameter R: ♯ of added and removed points ⟶ new hyper-parameter

Data Augmentation techniques are applied online during training phase.

Data Augmentation (2)

Quantitative example

A training set of $10,000$ traces of $1,000$ time samples

$$\Downarrow SH_{10}AR_5$$

A training set of $\approx 10^{31}$ traces of $9,990$ time samples

Contents

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- Random delays
- Artificial Jitter
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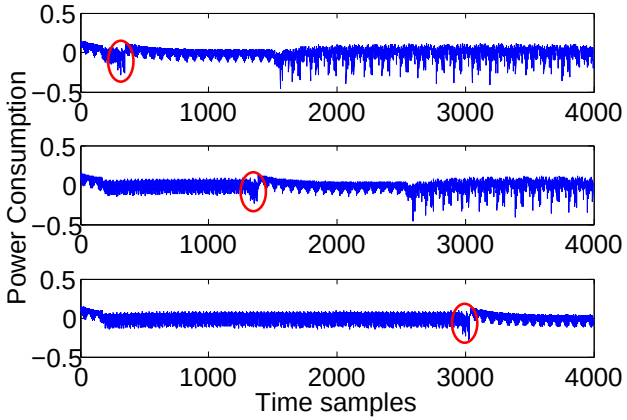
Random delays



One leaking operation

Setup

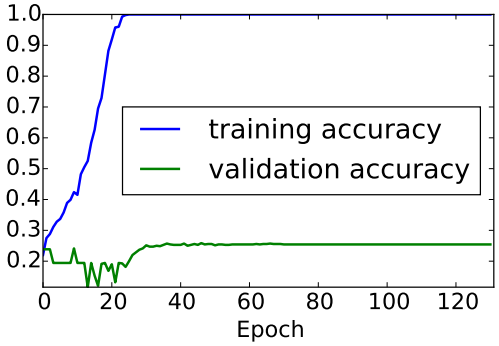
- Target Chip: Atmega328P
- Target Variable: $Z = \mathrm{HW}(\mathrm{Sbox}(P \oplus K))$
- Acquisition: through *ChipWhisperer*® platform, $\approx 4,000$ time samples
- Countermeasure: Random Delays - insertion of r *nop* operations, $r \in [0, 127]$ uniform random
- $1,000$ training traces

Random delays

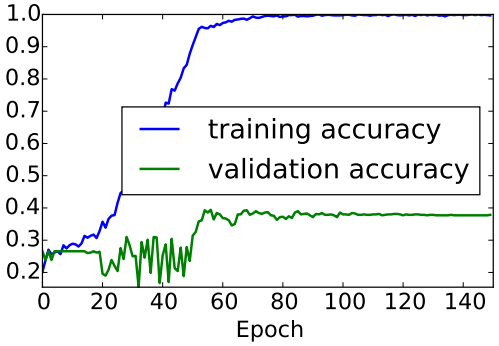
Data augmentation vs overfitting

Metrics

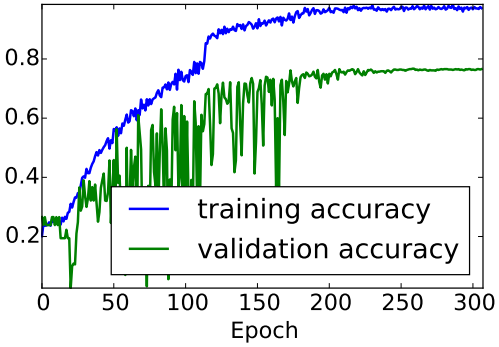
- Test accuracy: classification accuracy over the attack traces
- $N^\star$: minimum number of attack traces to make *guessing entropy* of the right key permanently equal to one ($N^\star$ estimated over 10 independent attacks)



SH_0



SH_{100}



SH_{500}

Random delays

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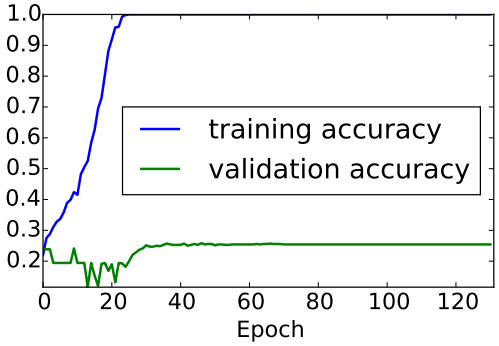
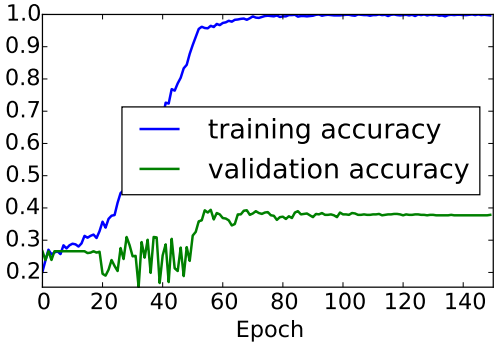
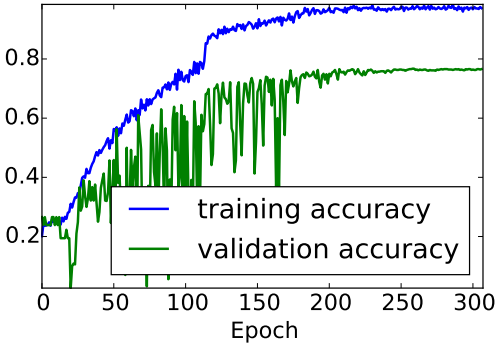


SH_0



SH_{100}



SH_{500}

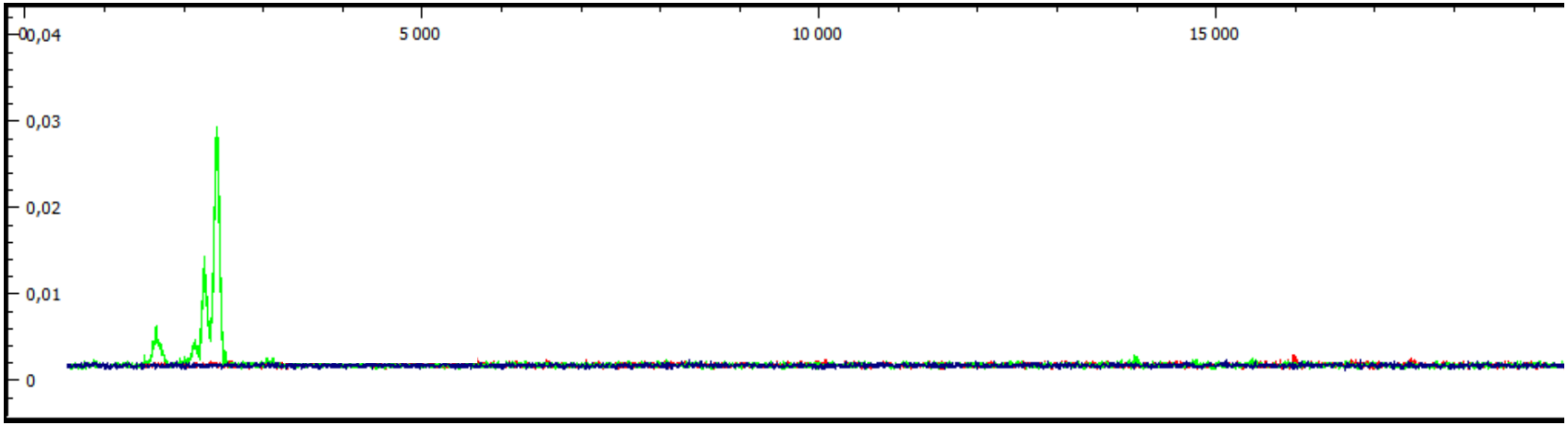
		SH_0		SH_{100}		SH_{500}	
Acc	$N^\star$	27.0%	$> 1,000$	31.8%	101	**78%**	**7**

Real Jitter (1)

Target

- AES hardware implementation
- strong jitter effect
- Target Variable: $Z = \mathrm{Sbox}(P \oplus K)$
- $2,500$ selected time samples
- $99,000$ training traces

SNR first Sbox



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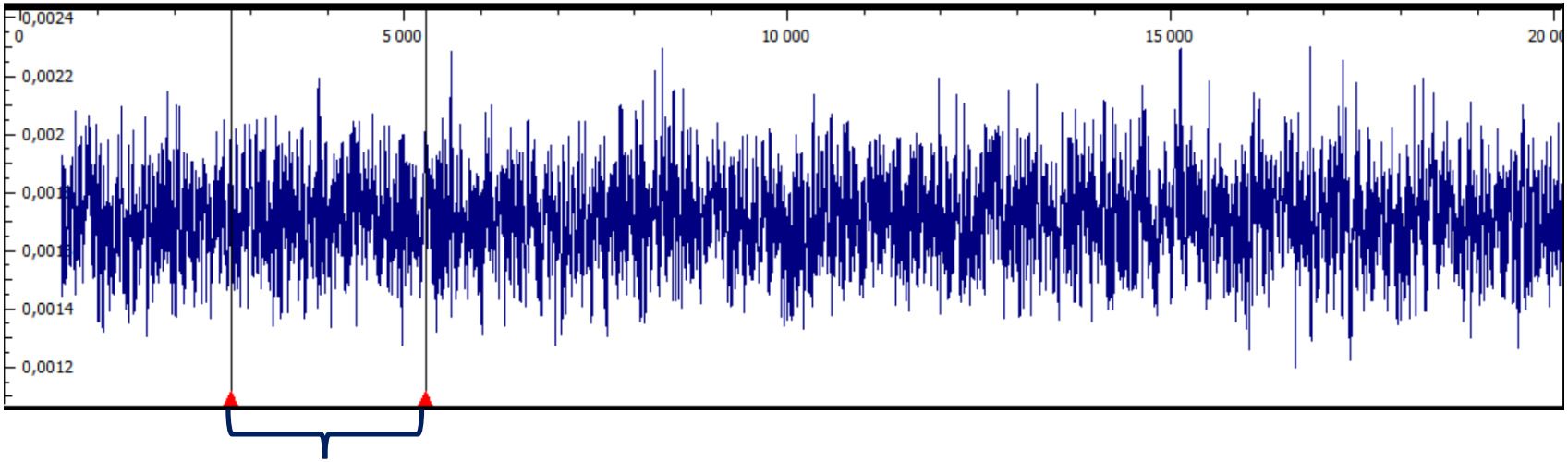
SNR second Sbox without realignment



Entry region for CNN (2,500 pts)

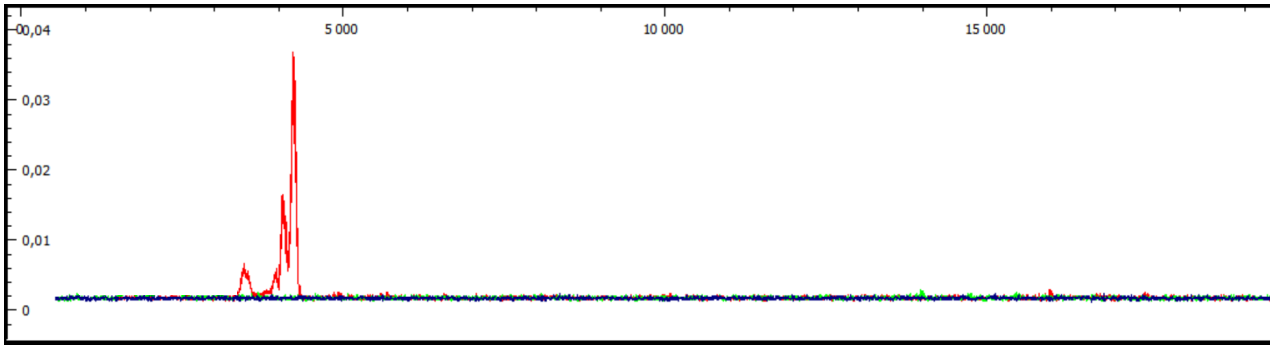
Real Jitter (2)

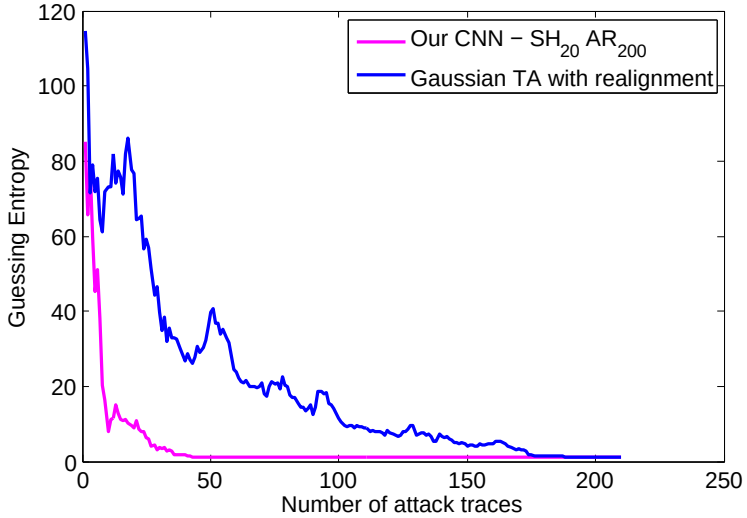
		SH_0AR_0		$SH_{10}AR_{100}$		$SH_{20}AR_{200}$	
Acc	$N^\star$	1.2%	137	1.3%	89	**1.8%**	**54**

Real Jitter (2)

		$SH_0 AR_0$		$SH_{10} AR_{100}$		$SH_{20} AR_{200}$	
Acc	$N^\star$	1.2%	137	1.3%	89	**1.8%**	**54**

SNR second Sbox with realignment





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Thank You!

Questions?

References I

[Ker] *Keras library*. https://keras.io/.

[KSH12] Alex Krizhevsky, Ilya Sutskever, and Geoffrey E Hinton. "ImageNet Classification with Deep Convolutional Neural Networks". In: *Advances in Neural Information Processing Systems 25*. Ed. by F. Pereira et al. Curran Associates, Inc., 2012, pp. 1097–1105. URL: http://papers.nips.cc/paper/4824-imagenet-classification-with-deep-convolutional-neural-networks.pdf.

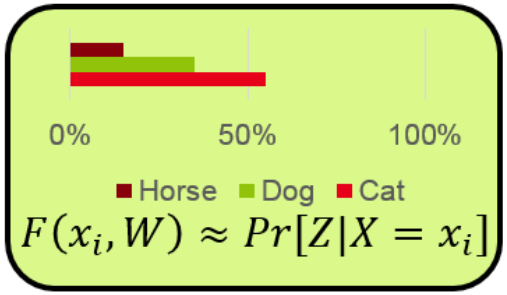
Cross-entropy Loss Function

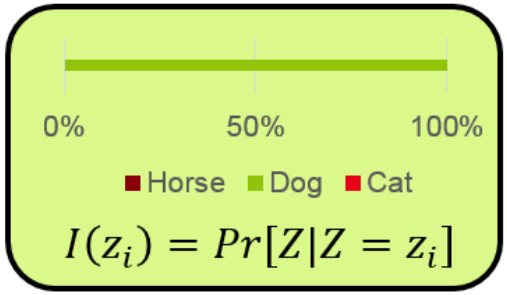
$$\mathrm{F(x,W)} = s \circ \lambda_n \circ \sigma_{n-1} \circ \lambda_{n-1} \circ \cdots \circ \lambda_1(x) = y \approx \Pr[Z|X = x]$$

- λ_i affine functions ($\lambda_i(x) = Ax + b$) depending on some parameters W (*weights*)
- σ_i non-linear functions *(activation functions)*
- s *softmax function* $s(x)[i] = \frac{e^{x[i]}}{\sum_j e^{x[j]}}$
- The weights W are *trained* on the basis of a *training set* $\{x_i, z_i\}_{i=1,..,N}$, by minimizing the *loss function*

$$L(W, x_i, z_i) = \frac{1}{N}\sum_{i=1}^{N} D(F(x_i, W), I(z_i))$$

where $I(z^i) = (0,0, \dots 0,1,0, \dots 0) = f_{Z|Z=z^i}$ (probability distribution of $Z|Z = z^i$)
and $D(f_X, f_Y) = -\sum_z \mathrm{f_Y(z)}\log(f_{X(z)})$ is the *cross-entropy* between two probability distributions f_X, f_Y (over the same probability space)





Cross-entropy measures dissimilarity between two probability distributions

Nowadays challenging image classification problems

Imagenet Large Scale Visual Recognition Challenge 2012 (ILSVRC 2012)

Classification and other tasks. 1000 categories.


Egyptian Cat



Tiger Cat

Convolutional Neural Networks (*AlexNet* [KSH12]) $\approx$ 84% of accuracy
Best of other submissions $\approx$ 74% of accuracy

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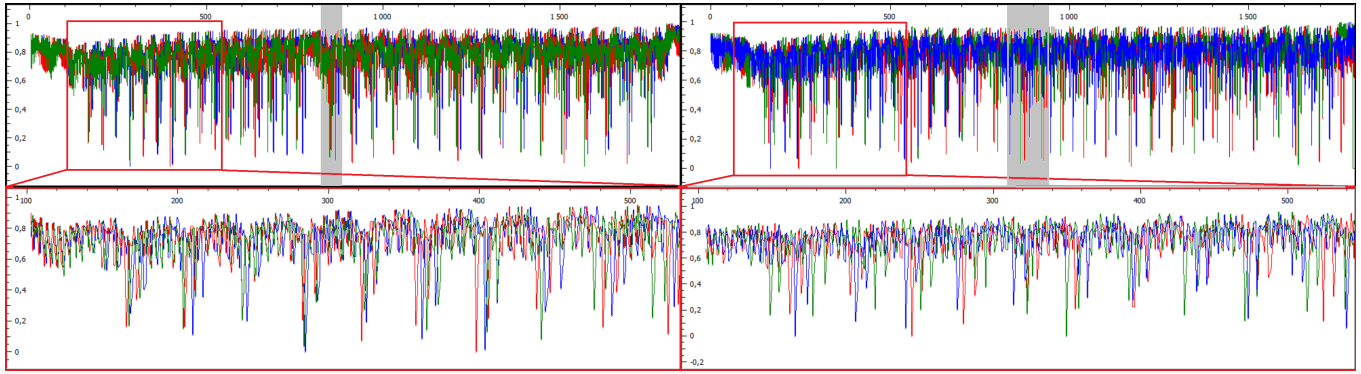
Today, CNNs are the most diffused and best performing technique in many domains (image recognition, video analysis, natural language processing,...)
It deals geometric deformation and de-synchronization (spacial or temporal)

Artificial Jitter



Low artificial jitter High artificial jitter

Target

- Target Variable: $Z = \mathrm{HW}(\mathrm{Sbox}(P \oplus K))$
- $\approx$ 2000 time samples
- Countermeasure: artificial signal treatment simulating clock jitter
- 10000 training traces

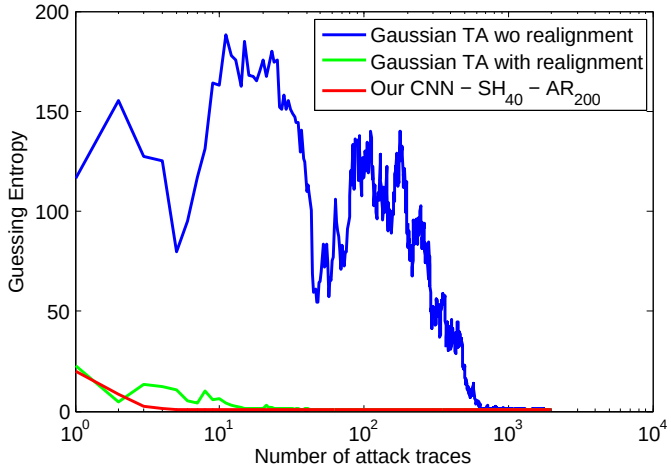
Artificial Jitter (2)

Low_jitter

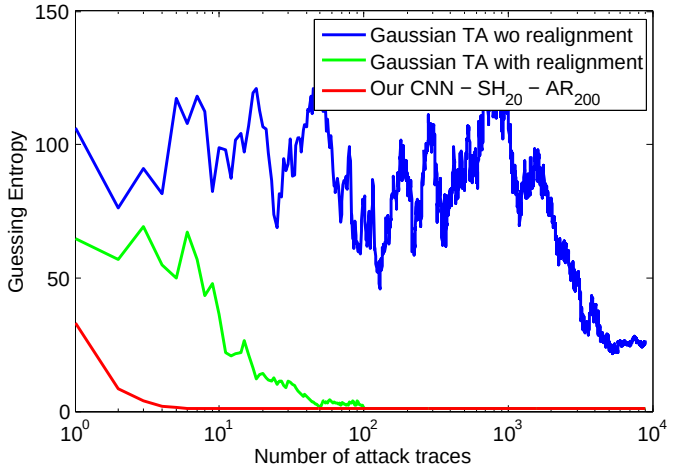
Acc	$N^\star$	SH_0		SH_{20}		SH_{40}	
AR_0		57.4%	14	82.5%	6	83.6%	6
AR_{100}		86.0%	6	87.0%	5	87.5%	6
AR_{200}		86.6%	6	85.7%	6	**87.7%**	**5**

High_jitter

Acc	$N^\star$	SH_0		SH_{20}		SH_{40}	
AR_0		40.6%	35	51.1%	9	62.4%	11
AR_{100}		50.2%	15	72.4%	11	73.5%	9
AR_{200}		64.0%	11	**75.5%**	**8**	74.4%	8

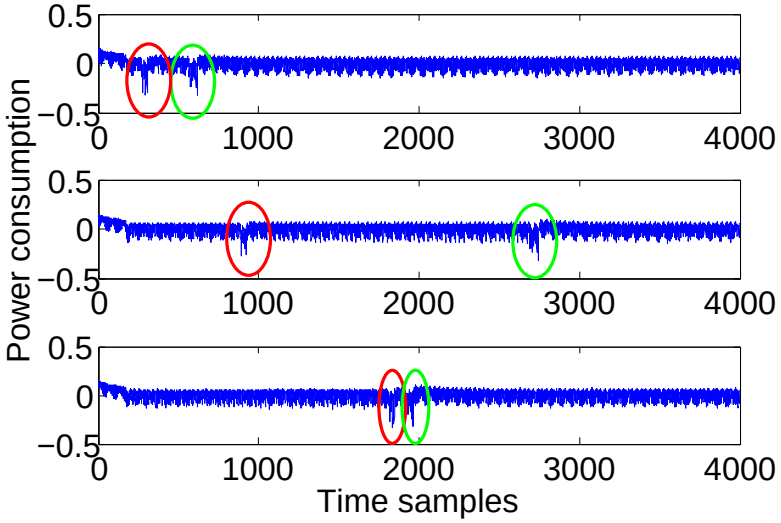


Low Jitter



High Jitter

Random Delays - Two Leaking Operations



Two leaking operations

First operation - Test acc: 76.8%, $N^\star = 7$
Second operation - Test acc: 82.5%, $N^\star = 6$

Artificial Jitter

DS_low_jitter									
a	*b*	SH_0		SH_{20}		SH_{40}		SH_{200}	
c	*d*								
AR_0		100.0%	68.7%	99.8%	86.1%	98.9%	84.1%		
		57.4%	14	82.5%	6	83.6%	6		
AR_{100}		87.7%	88.2%	82.4%	88.4%	81.9%	89.6%		
		86.0%	6	87.0%	5	87.5%	6		
AR_{200}		83.2%	88.6%	81.4%	86.9%	**80.6%**	**88.9%**		
		86.6%	6	85.7%	6	**87.7%**	**5**		
AR_{500}								85.0%	88.6%
								86.2%	5

DS_high_jitter									
a	*b*	SH_0		SH_{20}		SH_{40}		SH_{200}	
c	*d*								
AR_0		100%	45.0%	100%	60.0%	98.5%	67.6%		
		40.6%	35	51.1%	9	62.4%	11		
AR_{100}		90.4%	57.3%	76.6%	73.6%	78.5%	76.4%		
		50.2%	15	72.4%	11	73.5%	9		
AR_{200}		83.1%	67.7%	**82.0%**	**77.1%**	82.6%	77.0%		
		64.0%	11	**75.5%**	**8**	74.4%	8		
AR_{500}								83.6%	73.4%
								68.2%	11