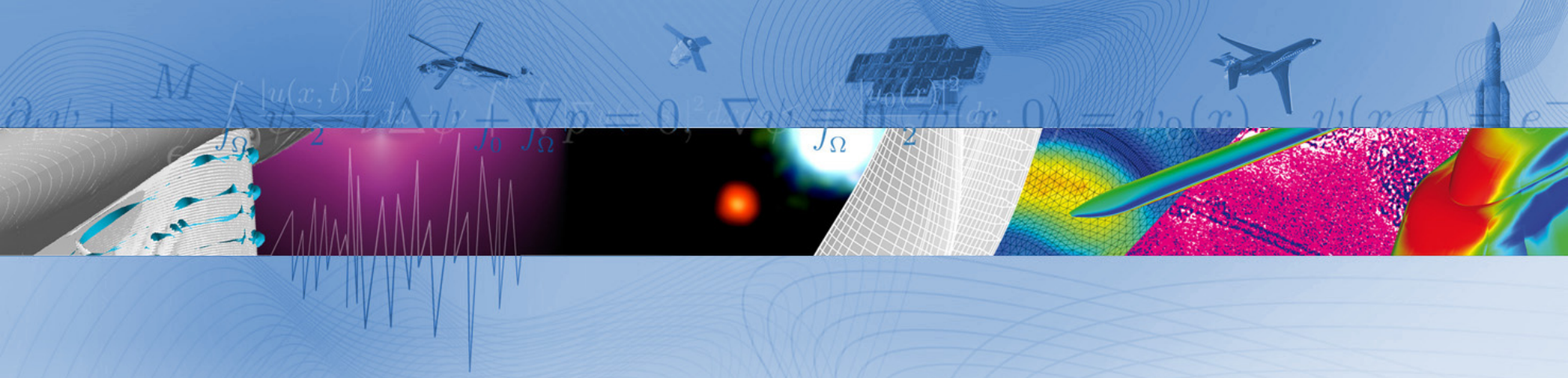

Machine Learning and Pattern Recognition

Deep Learning

Alexandre BOULCH

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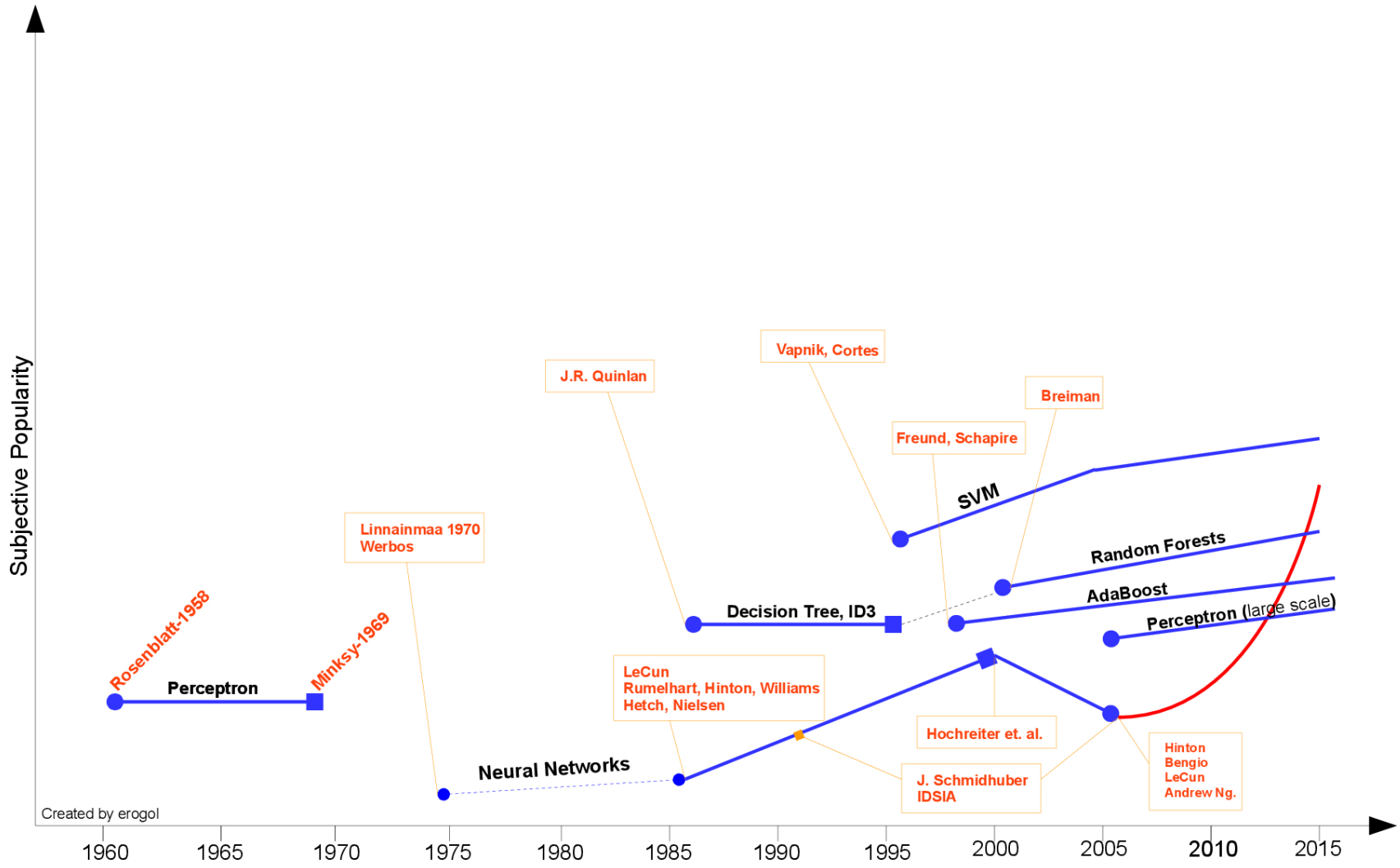
Introduction



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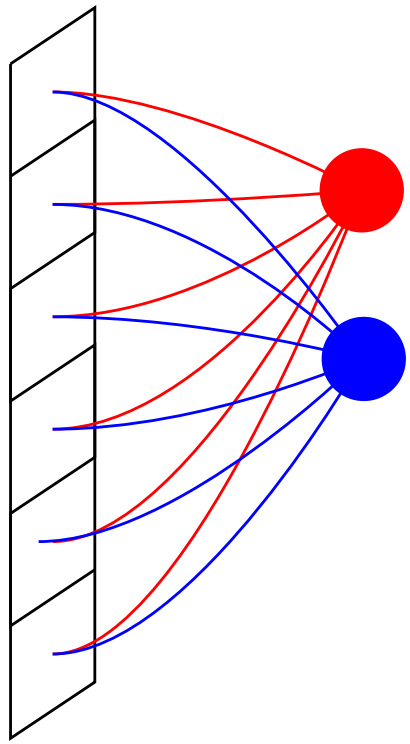
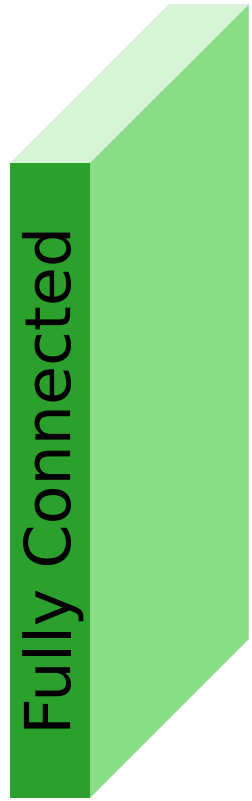
Fully connected

- Also called Linear layer or perceptron
- A neuron is connected to every input.
- High number of parameters ($|inputs| * |outputs|$)





Multi layer perceptron

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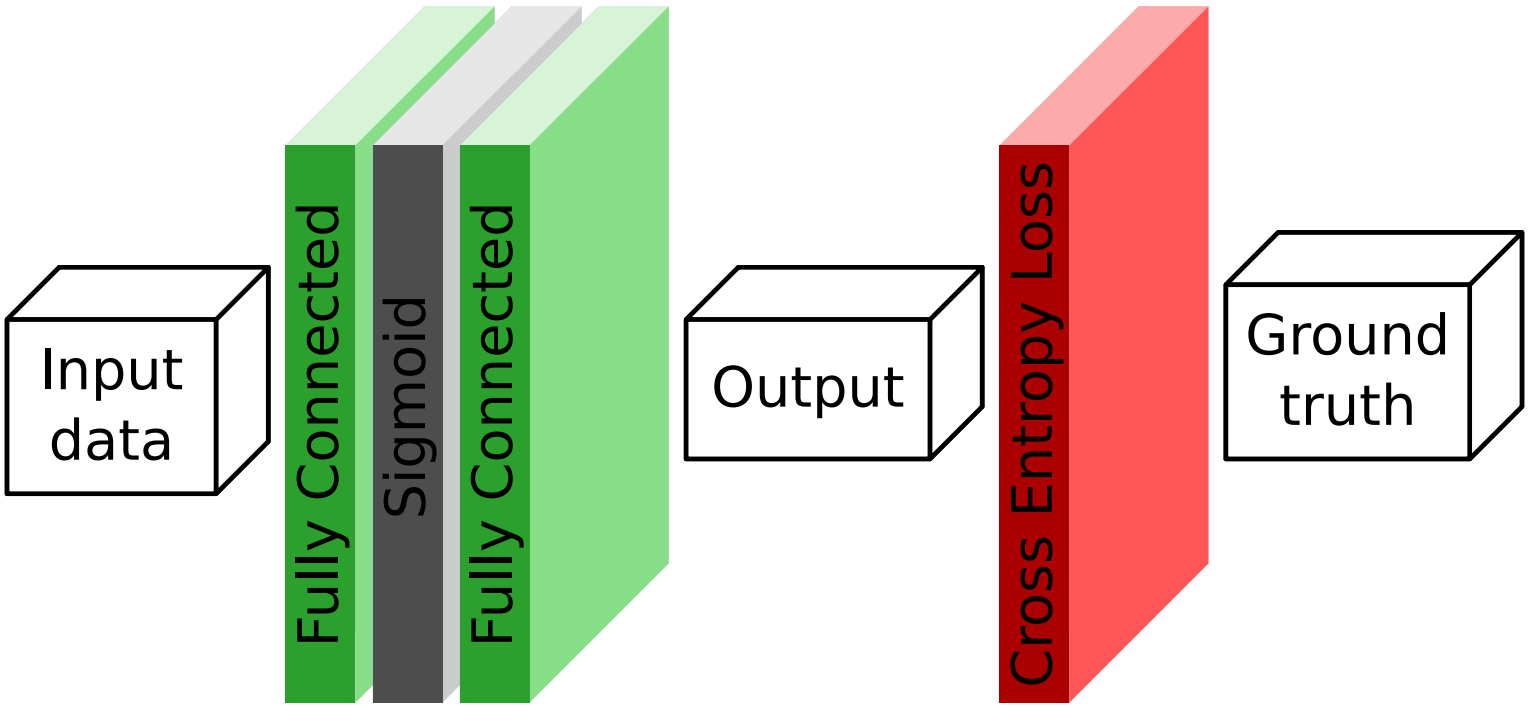
Multi Layer Perceptron

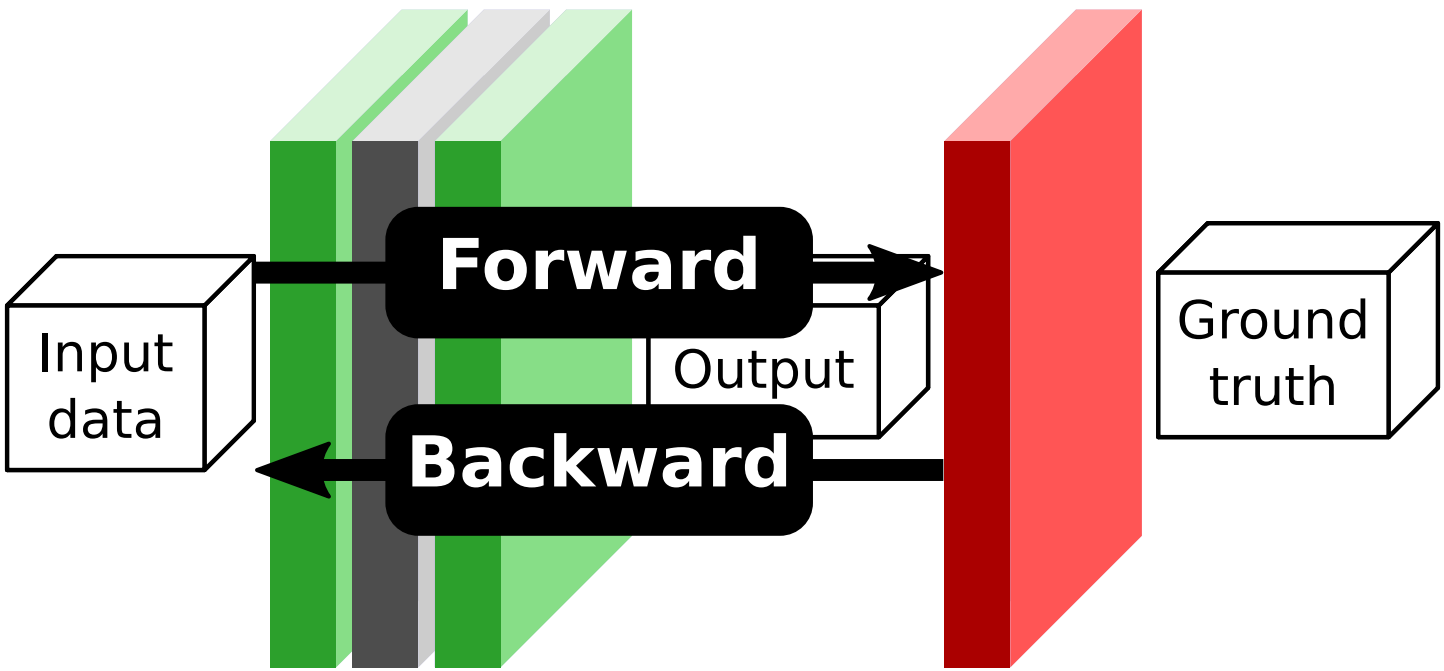
A stack of linear layers and activation functions (e.g. sigmoid).



Optimization

Forward-Backward algorithm

- **Forward**: iteratively compute the output of each layer from data to prediction
- **Backward**: iteratively compute the derivative of the parameters starting from the loss



Optimization

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Forward-Backward algorithm

- **Forward**: iteratively compute the output of each layer from data to prediction
- **Backward**: iteratively compute the derivative of the parameters starting from the loss

Chain rule

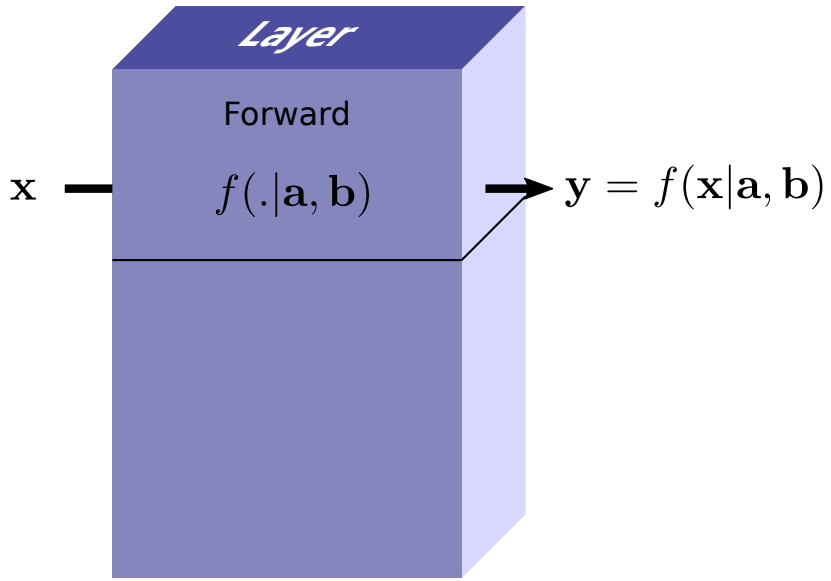
Easy differntiation is obtain by derivation of function composition:

$$\frac{\partial f(a = g(x, y, z), b, c)}{\partial x} = \frac{\partial g(x, y, z)}{\partial x} \frac{\partial f(a = g(x, y, z), b, c)}{\partial a}$$

Optimization: differentiation

Algorithm

- Forward pass



Optimization: differentiation

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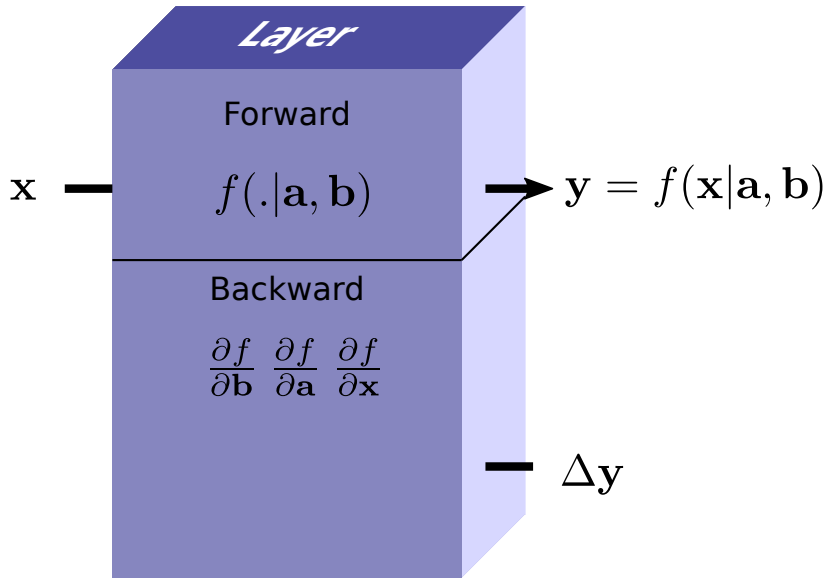
Algorithm

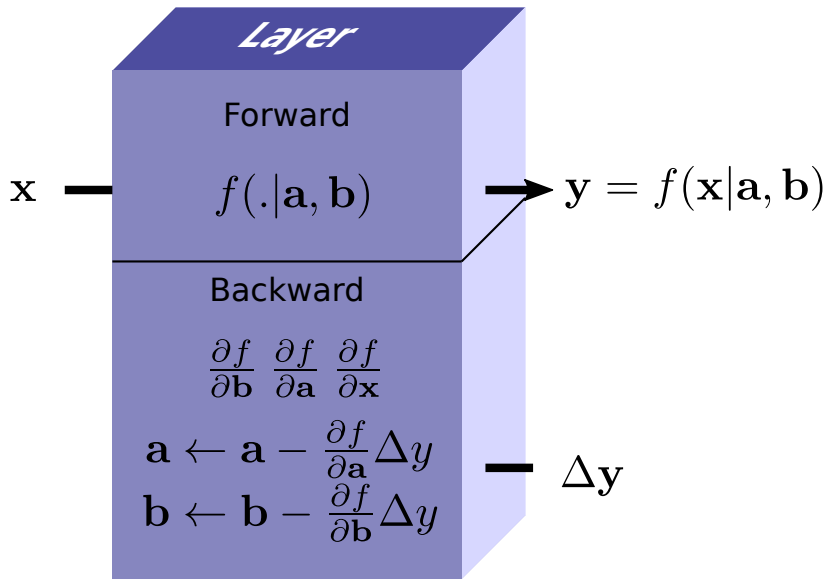
- Forward pass
- Get the output differential ($\Delta\mathbf{y}$)
- Compute partial derivatives for parameters and input



Optimization: differentiation

Algorithm

- Forward pass
- Get the output differential ($\Delta \mathbf{y}$)
- Compute partial derivatives for parameters and input
- Update the parameters



Optimization: differentiation

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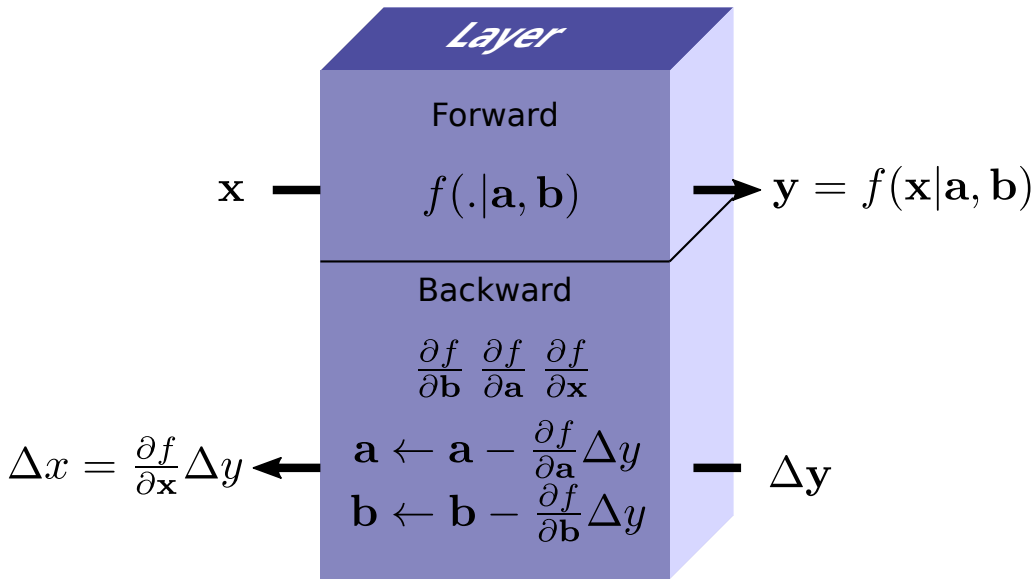
Algorithm

- Forward pass
- Get the output differential ($\Delta\mathbf{y}$)
- Compute partial derivatives for parameters and input
- Update the parameters
- Compute differential for input



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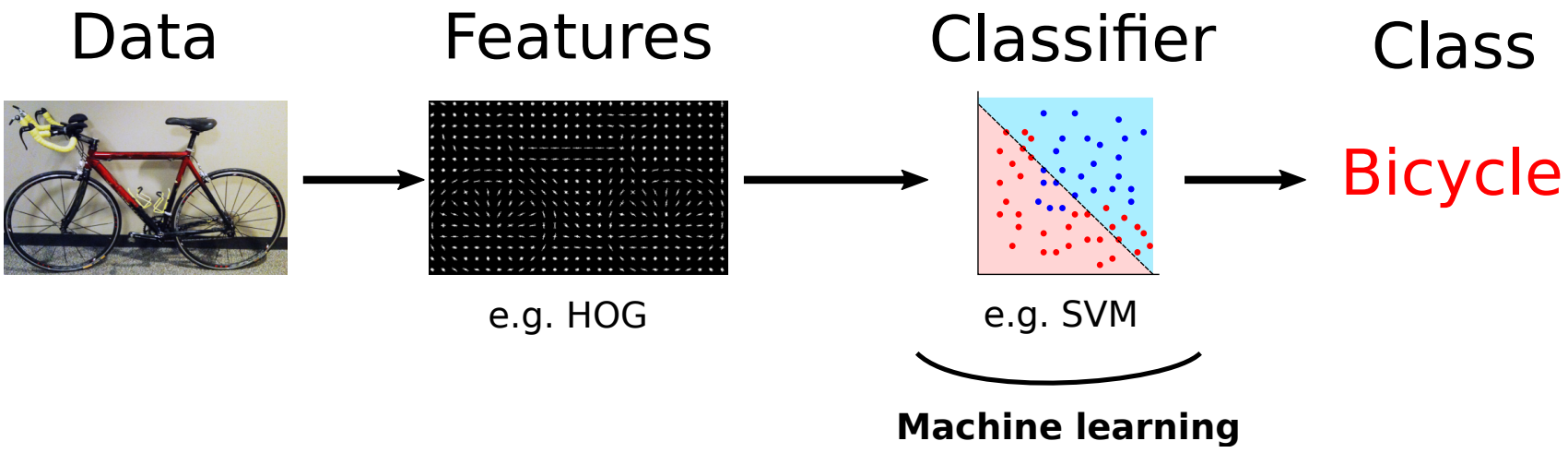
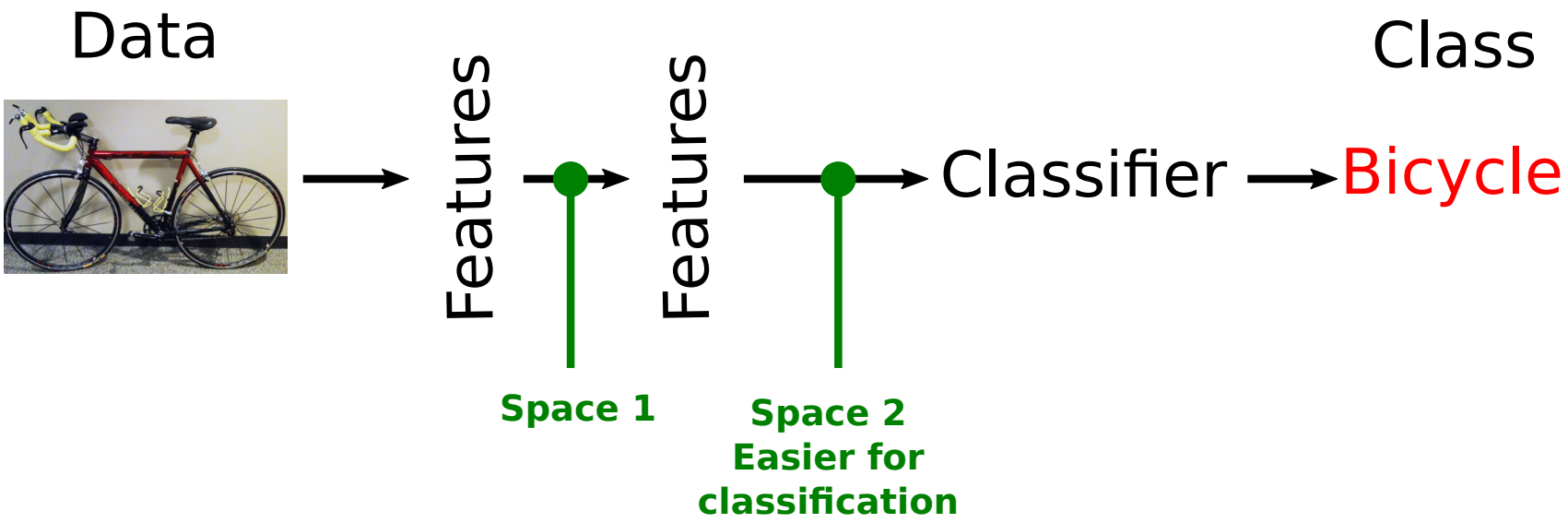
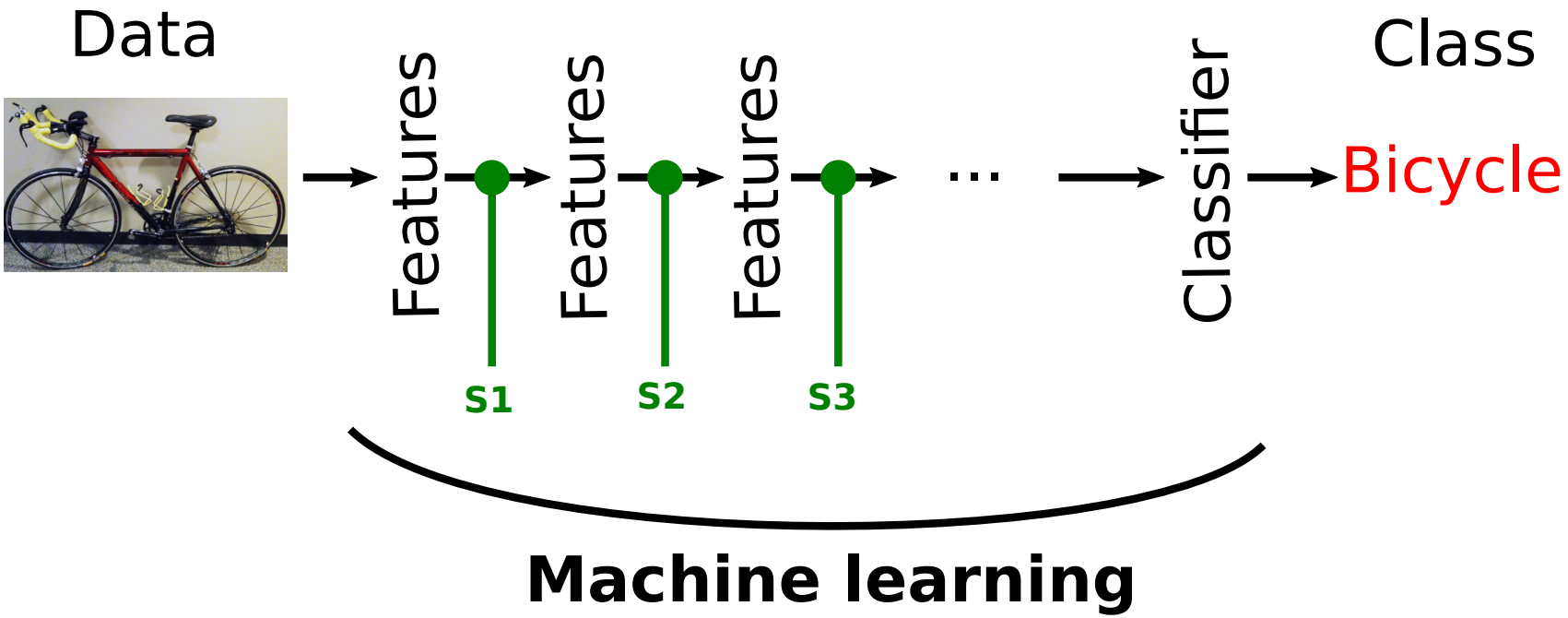
Deep learning concept



Deep learning concept



Deep learning concept



Concept

Deep learning is about learning representations.

Multi-layer perceptron

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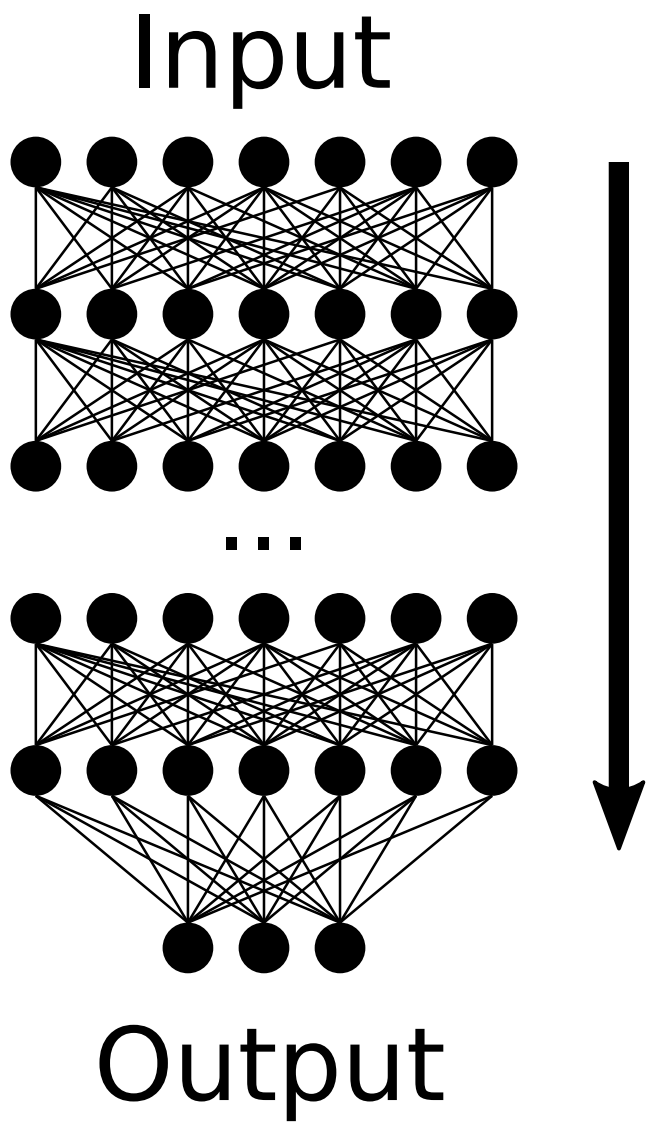
MLP becomes larger and deeper (before 1990)

- Difficult convergence
- Few data
- Very long training

$\longrightarrow$ Progessive loss of interest

SVM

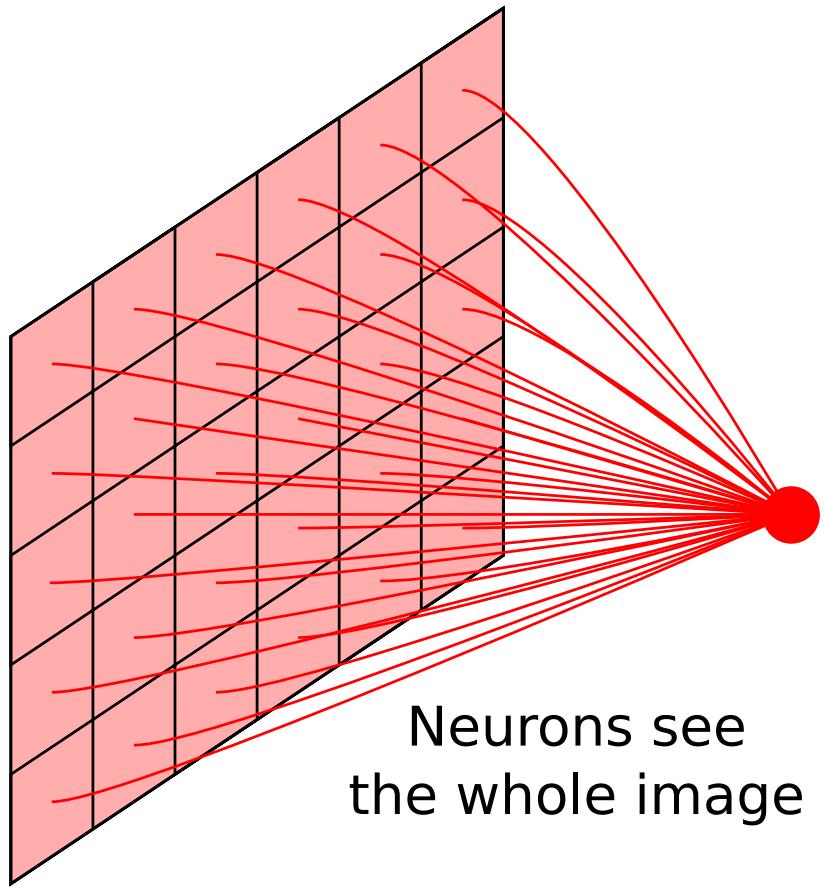
- Simpe to use
- Convergence proof
- Fast



Convolutions

Using a linear layer ?

- Lot of weights ! (at least one per pixel !)

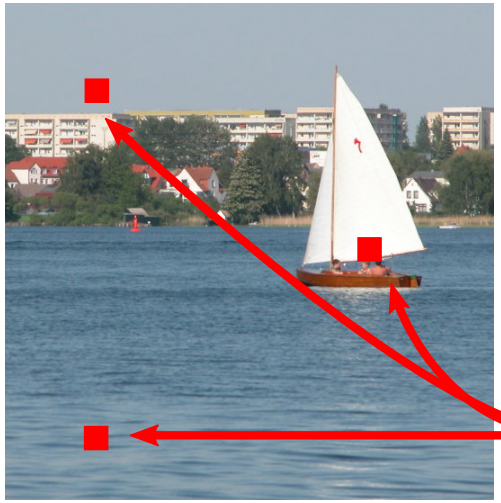


https://www.flickr.com/photos/nathelbiya/17050330

Convolutions

Using a linear layer ?

- Lot of weights ! (at least one per pixel !)
- Is it interesting to look at relations in the whole image ?



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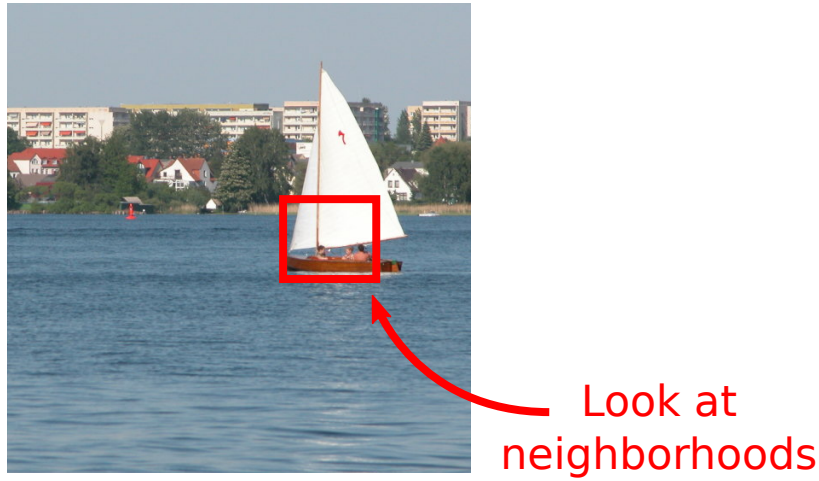
Convolutions

Idea ?

- Look at small neighborhoods (where the objects are)



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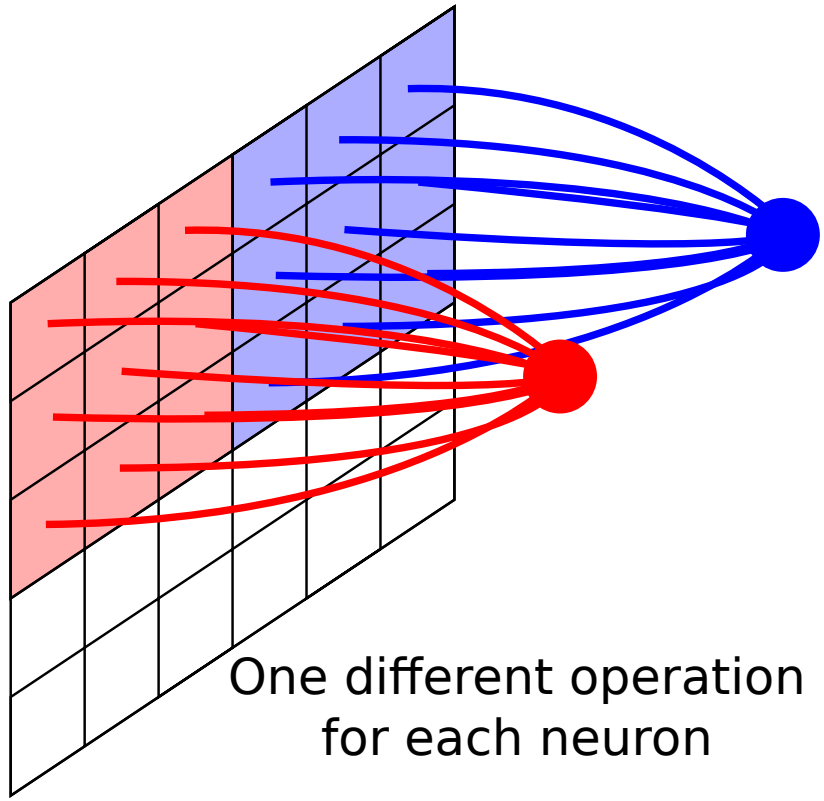
Convolutions

Idea ?

- Look at small neighborhoods (where the objects are)
- Create neurons that take a patch input



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Convolutions

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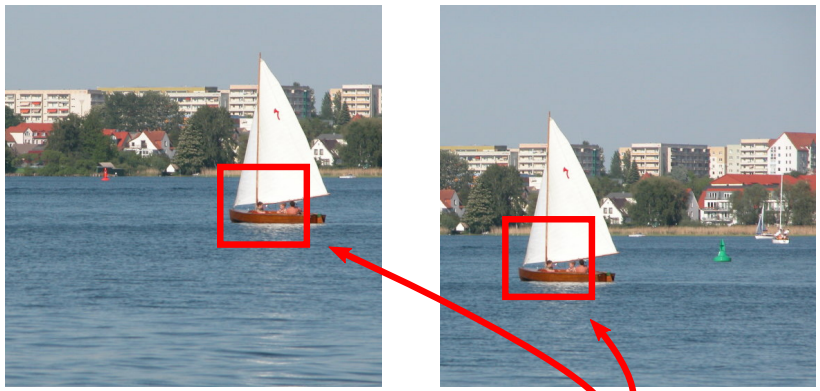
Problem ?

- Translation of the object must lead to same behaviour of the neurons



Same behaviour for the same pattern at different location

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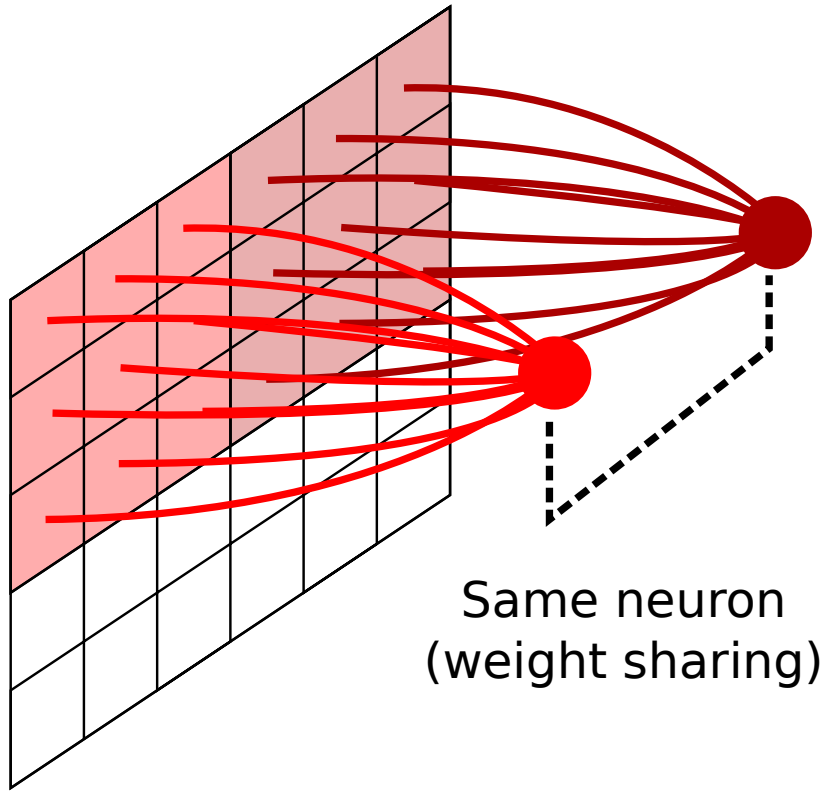
Convolutions

Problem ?

- Translation of the object must lead to same behaviour of the neurons

Solution ?

- Use the same neuron (i.e. all the neurons of the layer share weights)



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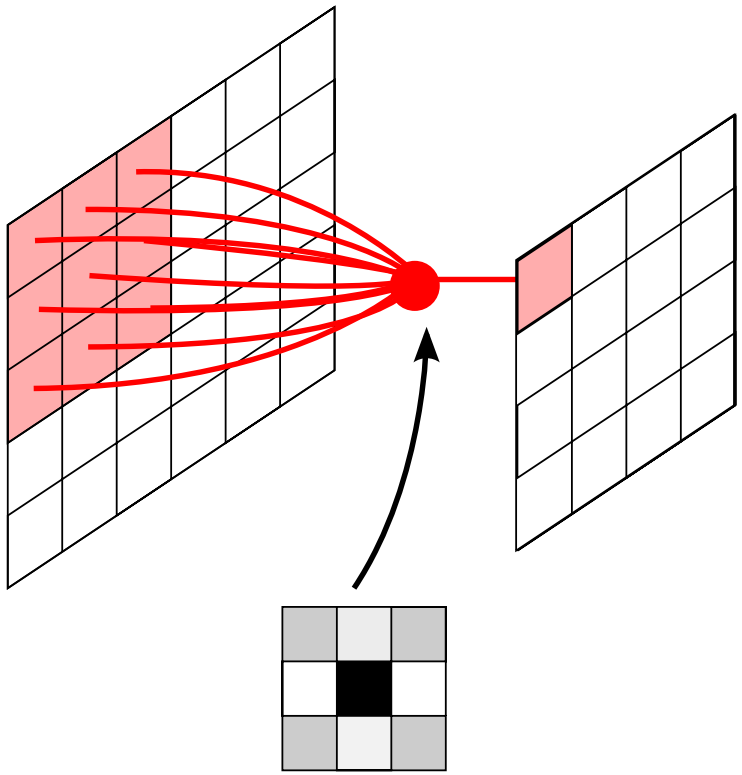
Convolutions



Forward

Let (i, j) be the coordinates in the input map.
(k, l) be the size of the patch (size of the kernel, usually $k = l$)
Then:

$$y_{i,j} = \sum_k \sum_l w_{k,l} x_{i+k,j+l} + b$$

Convolution

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Backward weight update

$$\frac{\partial y_{i,j}}{\partial w_{k,l}} = x_{i+k,j+l} \tag{1}$$

Let y be the output map and Δy be the gradient coming back:

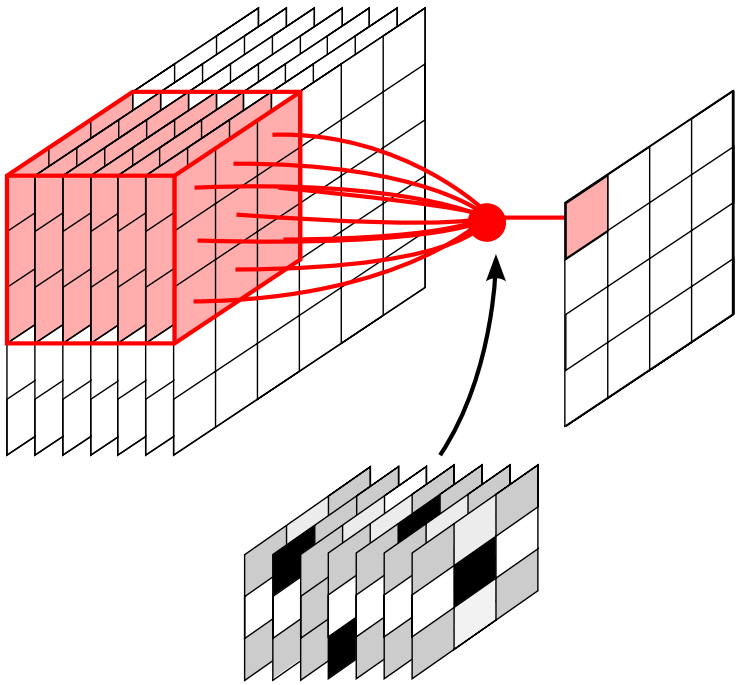
$$\frac{\partial y}{\partial w_{k,l}} = \sum_i \sum_j x_{i+k,j+l} \tag{2}$$

Finally, the update rule:

$$w_{k,l} \leftarrow w_{k,l} - \alpha \frac{\partial y}{\partial w_{k,l}} \Delta y \tag{3}$$

$$\leftarrow \sum_i \sum_j x_{i+k,j+l} \Delta y_{i,j} \tag{4}$$

Convolutions



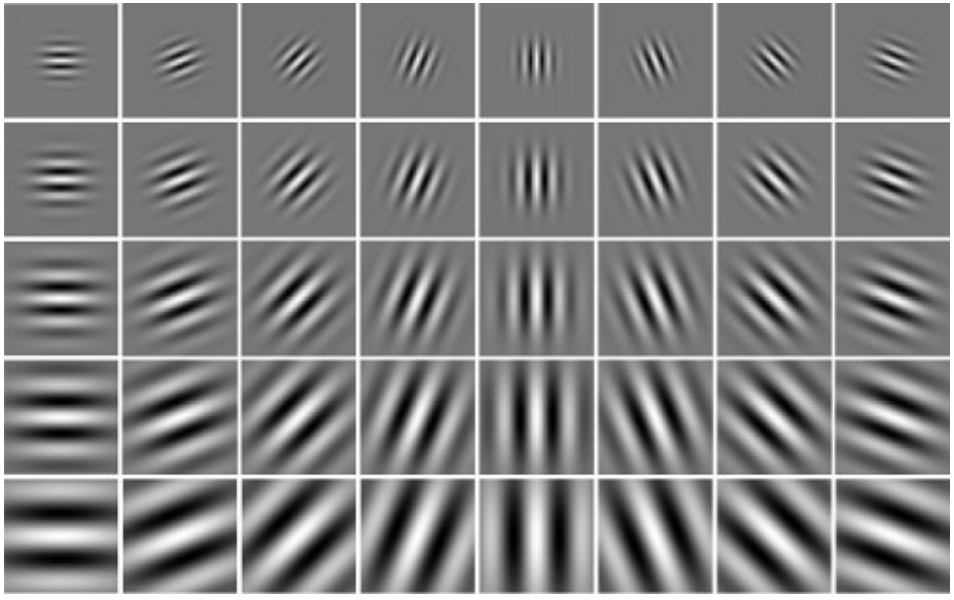
Forward

Same with term to term multiplication:

$$y_{i,j} = \sum_a \sum_b \mathbf{w}_{a,b} \mathbf{x}_{i+a,j+b}$$

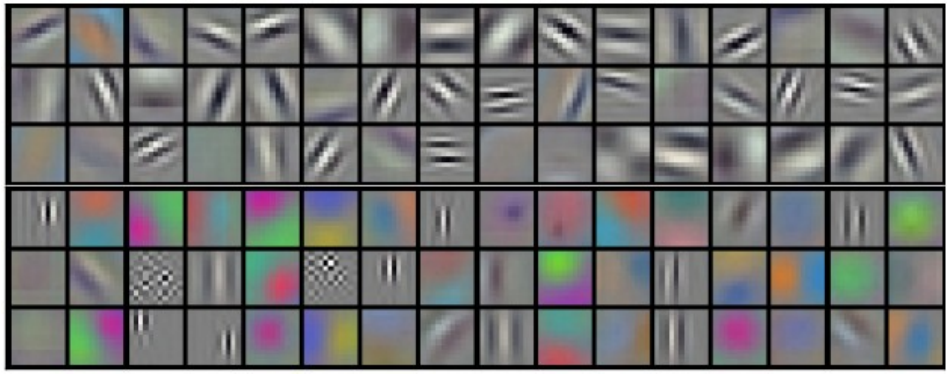
Convolution

What do convolutions learn ?



Gabor filters.

First layer of AlexNet.



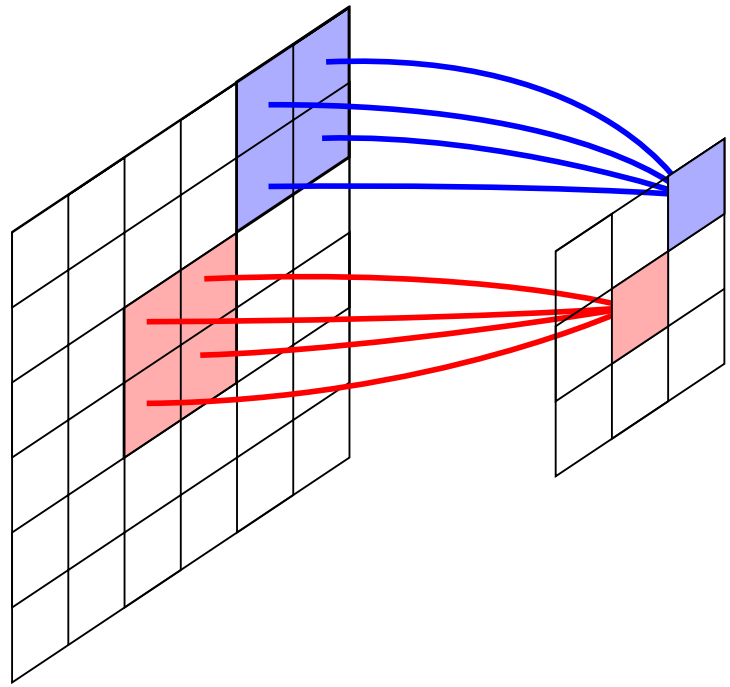
Dimension reduction

With the previous convolution, the output dimension is the same as the output dimension.
For classification: only one label, need for **dimension reduction**.

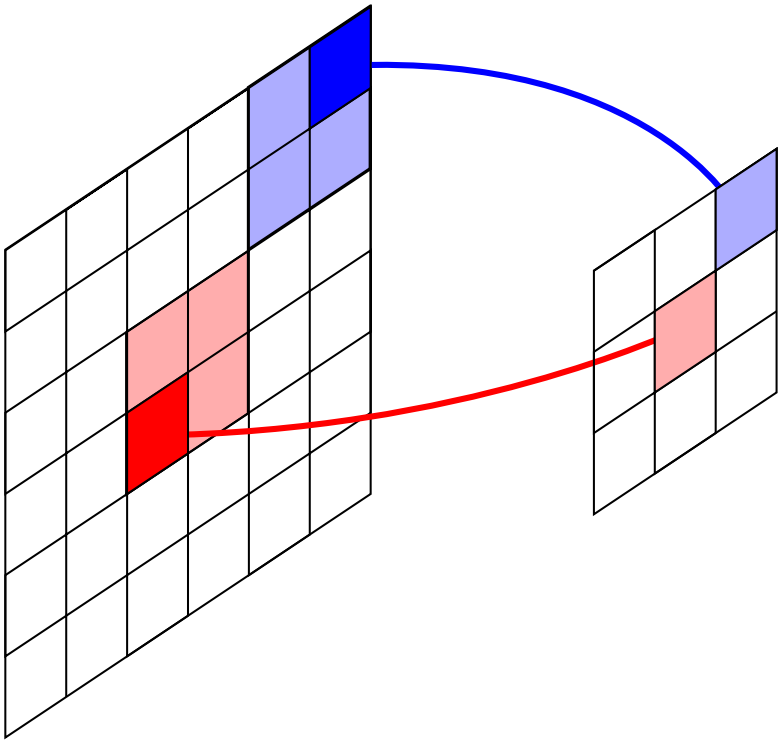
- convolution stride: do not look at all the pixels of the input (one every two, one every three...)
- **Max Pooling**

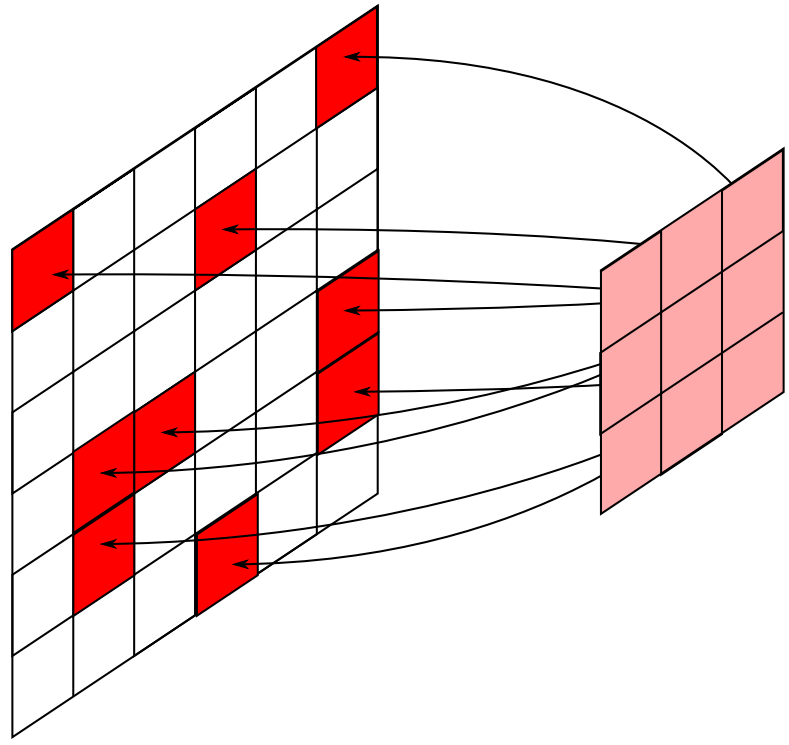
Max Pooling

- dimension reduction
- relative translation invariability



Max Pooling





Forward: max signal

Backward: Gradient transmission to max signal origin, zero otherwise

LeNet (1990)

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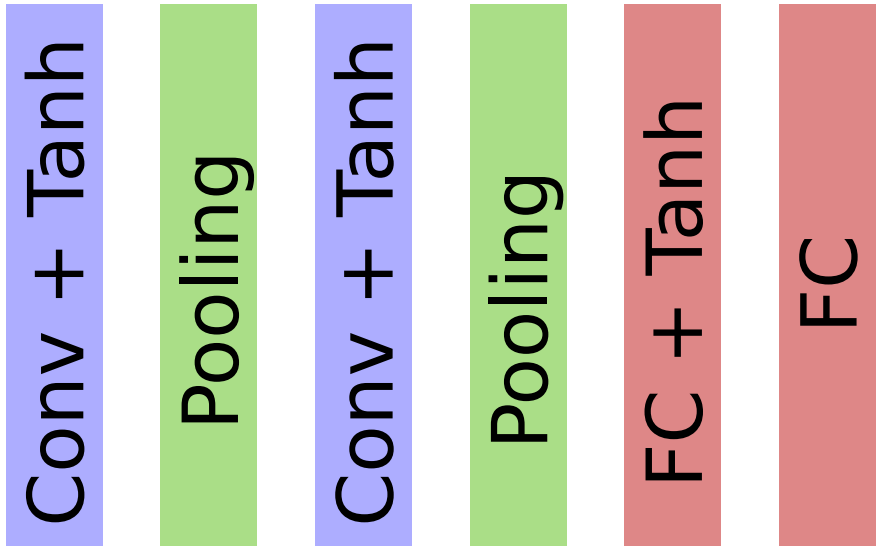
LeNet (1990)
Images 28x28



Very good results on digits recognition !

Issues

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Issues

- Learning speed
- Exploding or vanishing gradients
- Overfitting
- Local minima

Limitations

- Architecture
- Initialization
- Computing power
- Data
- Optimization

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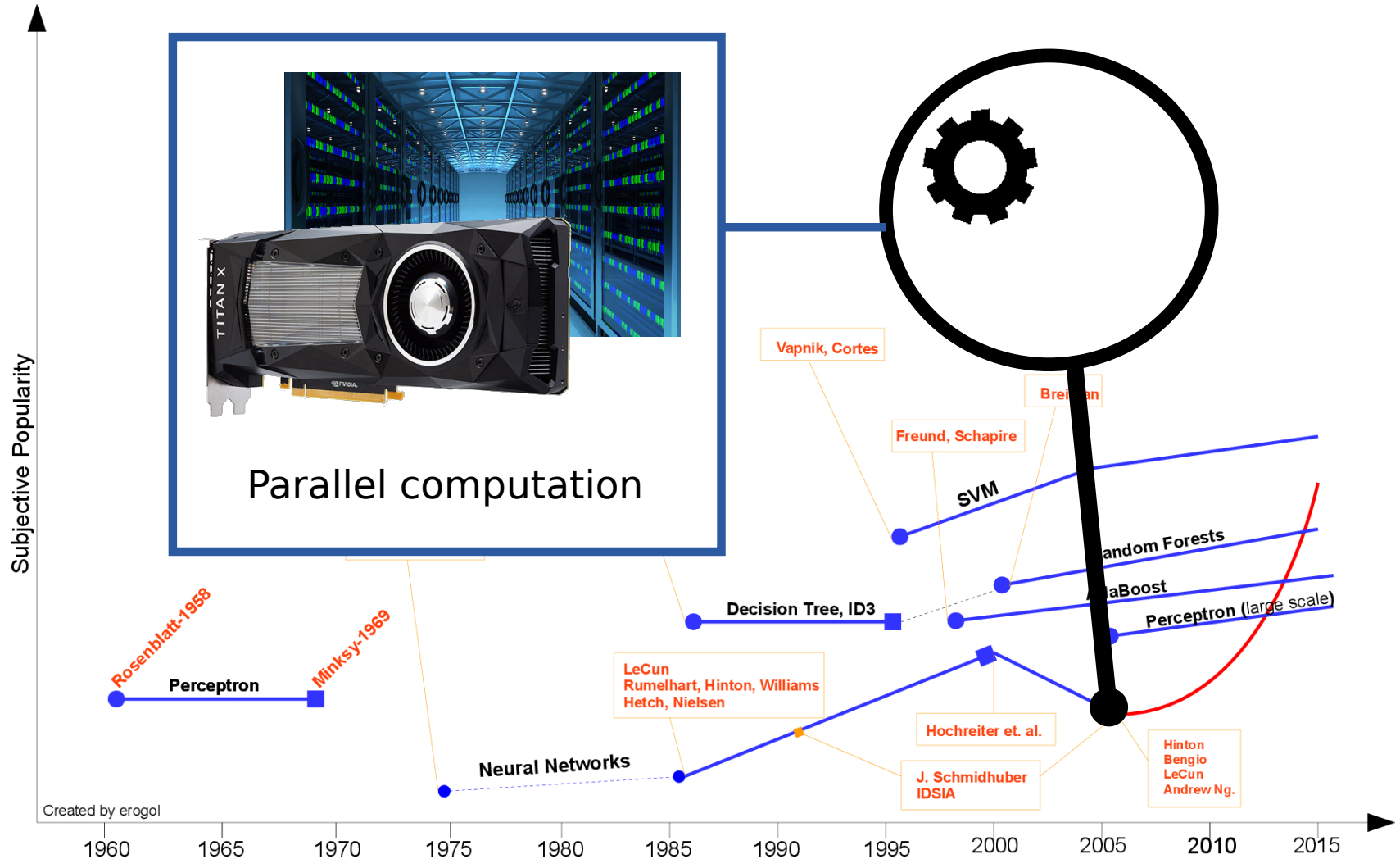
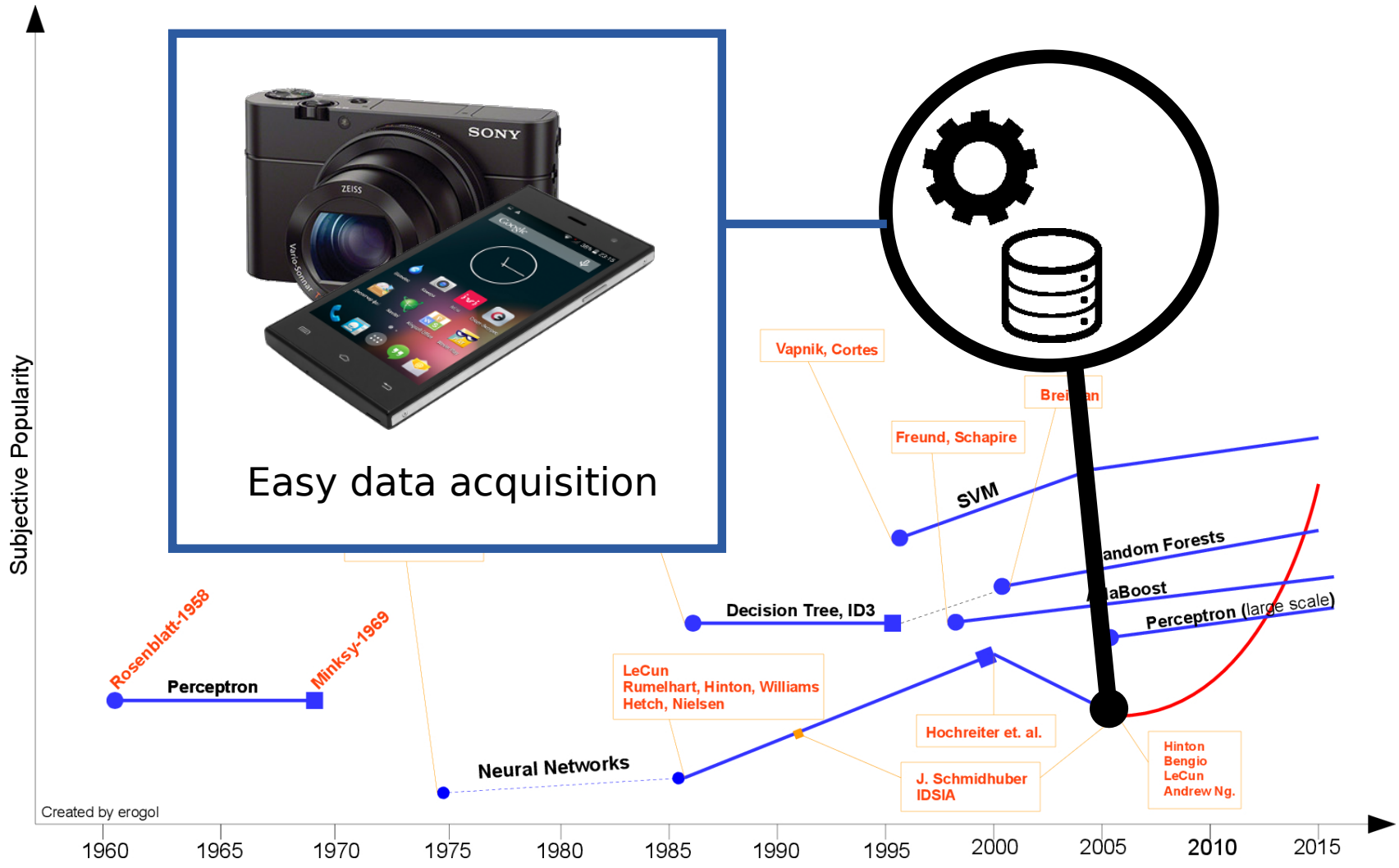
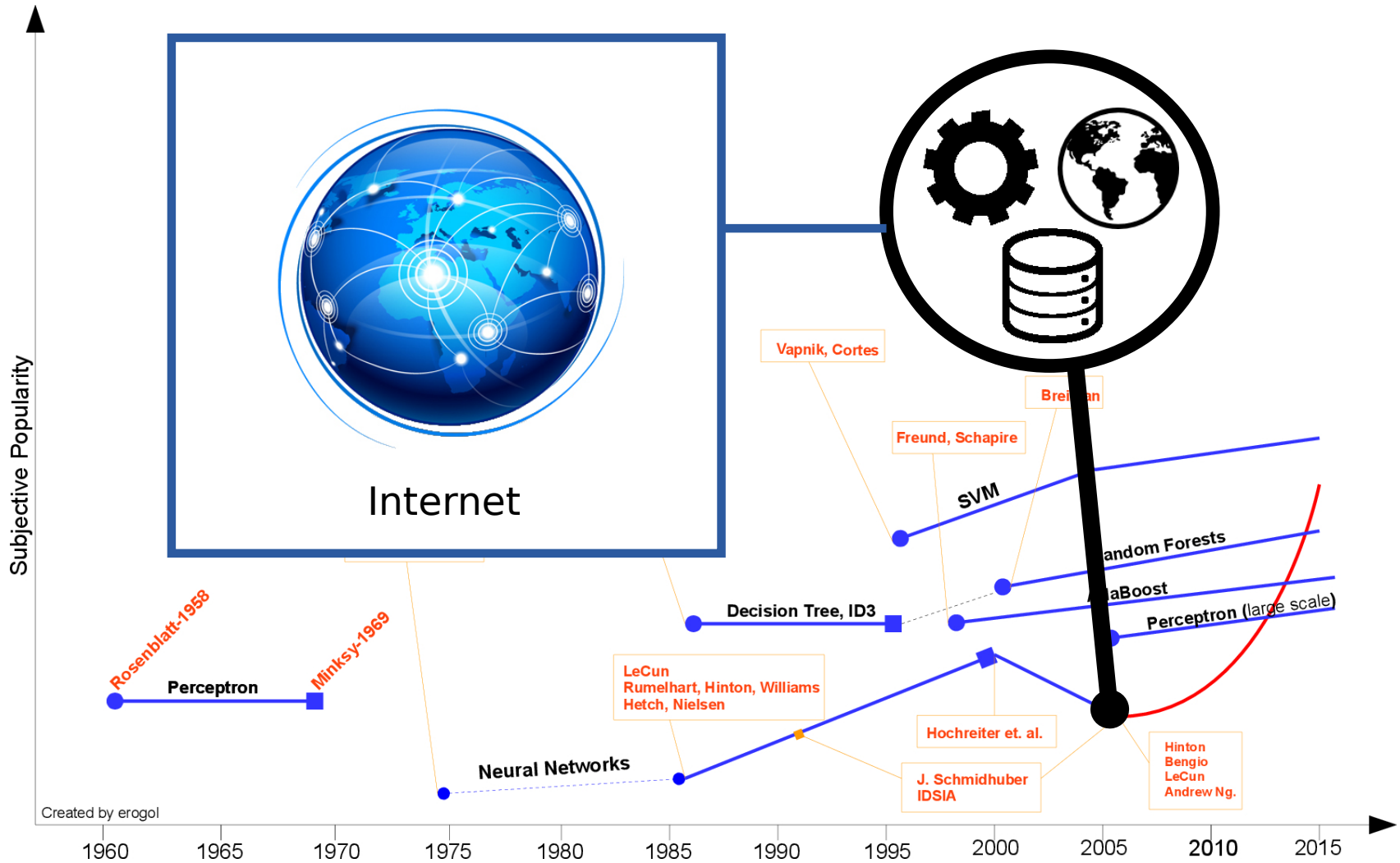
Massively data driven approaches



Massively data driven approaches



Massively data driven approaches



LeNet (1990)

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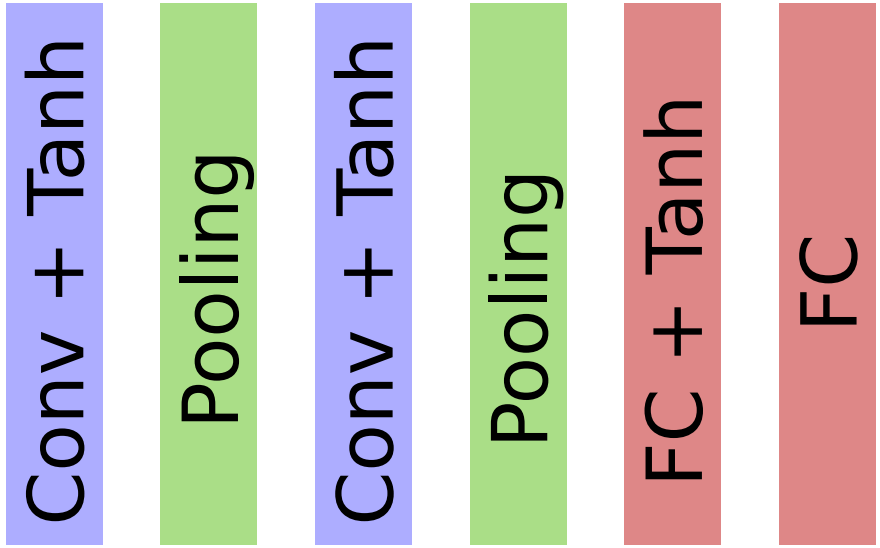
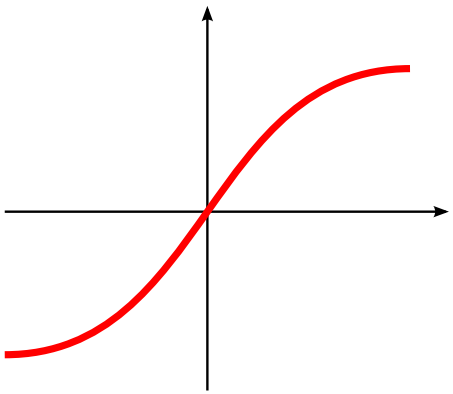
LeNet (1990)
Images 28x28

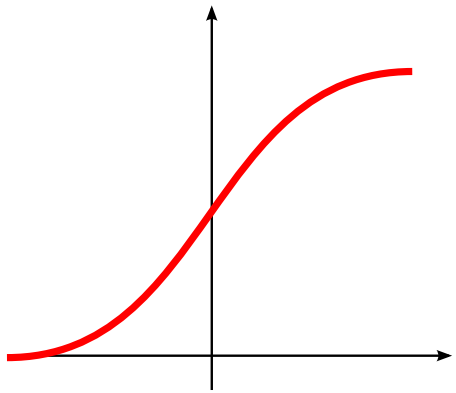


After each linear transformation (linear layer or convolution layer): a non linear layer (activation) otherwise **linear + linear = linear** (impossible to learn non linear decision).

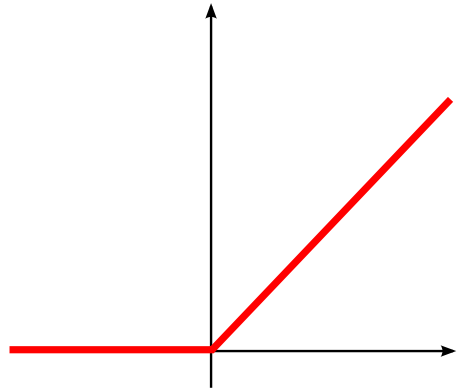
Activations



Tangente hypebolique



Sigmoïde

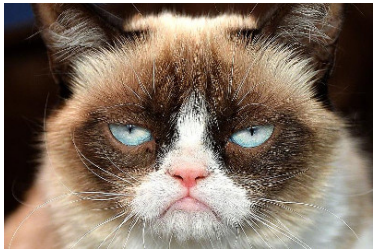


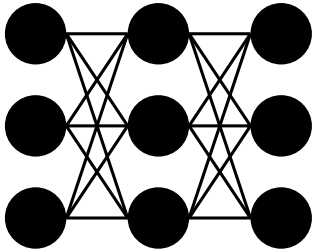
Rectified Linear Unit (ReLU)

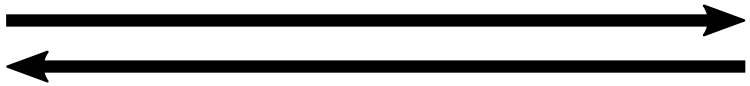
Rectified linear unit

1. Faster gradient computation
2. Similar convergence

Mini-batches

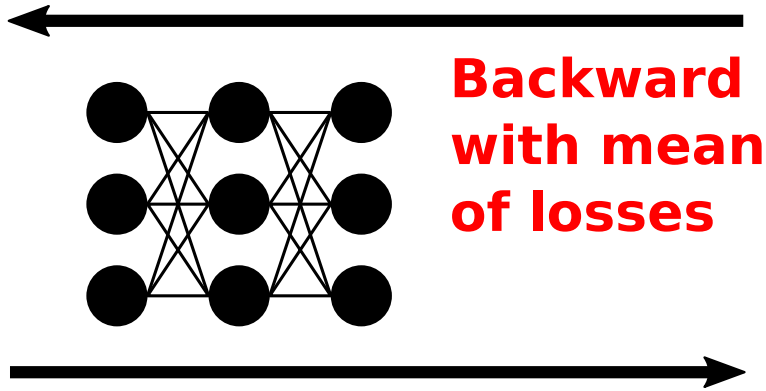






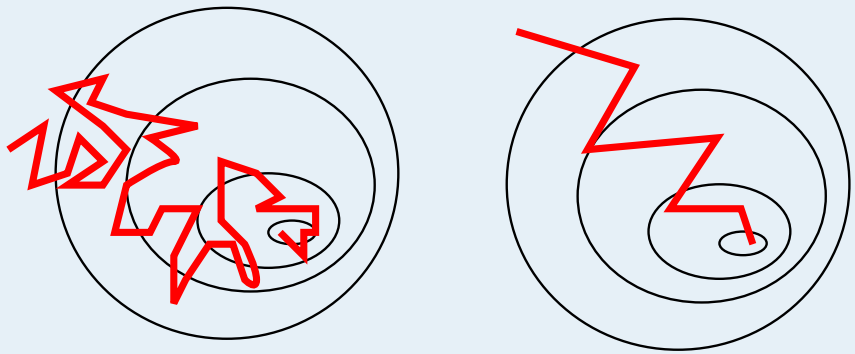
Loss image 1

Mini-batches



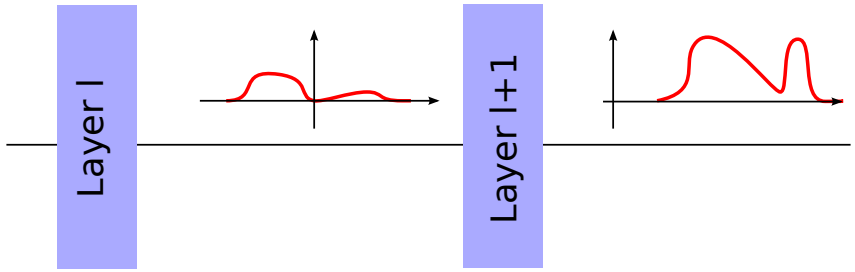
Loss image 1
Loss image 2
Loss image 3
Loss image 4
...

Gradient smoothing



Smoother gradient converges faster.

BatchNorm



Changes in the signal dynamic make the model more difficult to optimize: exponential or vanishing gradients.
Objective: control the signal distribution:

$$y^{l*} = \frac{y^l - \mu}{\sqrt{\sigma^2 + \epsilon}}\gamma + \beta \tag{5}$$

γ and β are learnt, μ and σ are computed (mean and standard deviation).
Learning is faster (iteration number) but slower (statistics computation).

Weight initialization

Weights have great influence on convergence speed. They are randomly initialized.

- too small weigths: vanishing signal
- to high: exploding signal

Objective

Conservation of signal properties.

$$Var(Y) = Var(X)$$

Weight initialization

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Xavier initialization

$X \in \mathbb{R}^n$, weights W and output $Y \in \mathbb{R}$

$$Y = W_1X_1 + W_2X_2 + \cdots + W_nX_n$$

X_i and W_i independent:

$$Var(W_iX_i) = E[X_i]^2 Var(W_i) + Var(X_i)Var(W_i) + Var(X_i)E[W_i]^2$$

$E[X_i] = 0$ and $E[W_i] = 0$:

$$Var(W_iX_i) = Var(X_i)Var(W_i)$$

finally $Var(Y) = nVar(X_i)Var(W_i)$ and we chose

$$Var(W_i) = \frac{1}{n}$$

Optimization - Stochastic Gradient Descent

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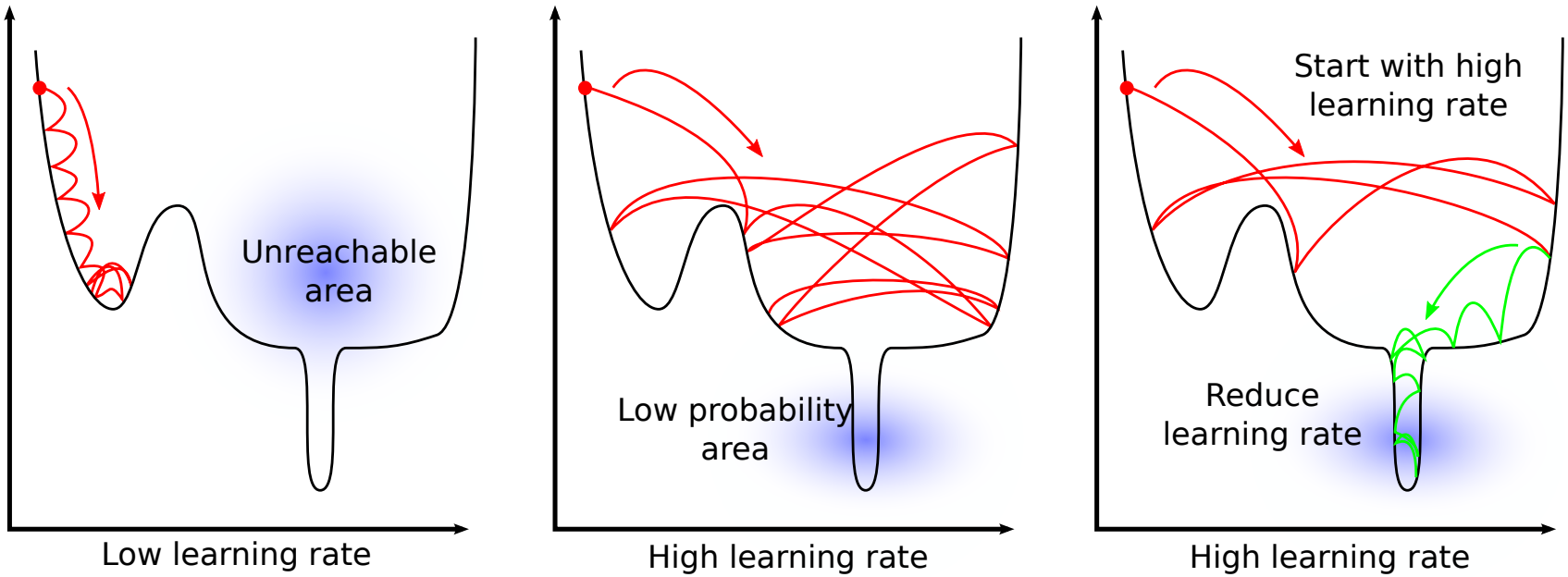
See neural network class

Update rule: $w_{t+1} = w_t + \alpha \Delta w$ (learning rate α)



Optimization - Stochastic Gradient Descent

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See neural network class

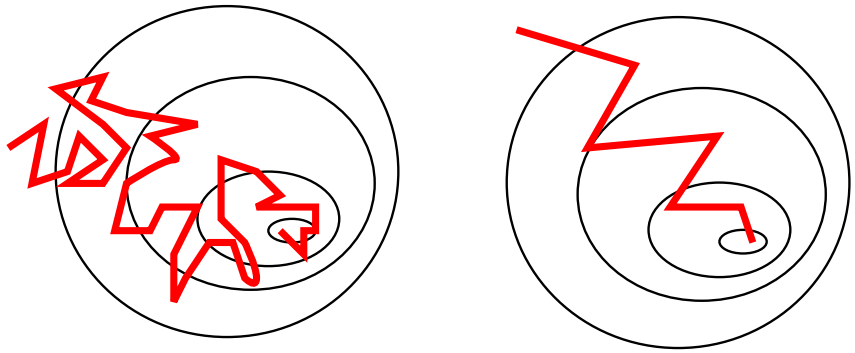
Update rule: $w_{t+1} = w_t + \alpha \Delta w$ (learning rate α)

Learning rate variation

- **Step decrease**
- Exponential decrease
- ...

Optimization - SGD with Momentum

Same idea as mini batch: smooth gradient in the good direction



Momentum

Use previous gradient to ponderate the direction of the new gradient.

$$\begin{aligned} v_t &= \gamma v_{t-1} + \alpha \Delta w \\ w_t &= w_{t-1} - v_t \end{aligned}$$

γ is the momentum.

Optimization - Adaptative methods

- **Adagrad**

$$w_{t+1,i} = w_{t,i} - \frac{\alpha}{\sqrt{G_{t,i} + \epsilon}} \Delta w_i$$

with $G_{t,i}$ sum of gradients of w_i

- **Adam (adaptive momentum estimation)**

$$\begin{aligned} m_t &= \frac{\beta_1}{1-\beta_1} m_{t-1} + \Delta w_t \\ v_t &= \frac{\beta_2}{1-\beta_2} v_{t-1} + \Delta w_t^2 \end{aligned}$$

$$w_{t+1} = w_t - \frac{\alpha}{\sqrt{v_t + \epsilon}} m_t$$

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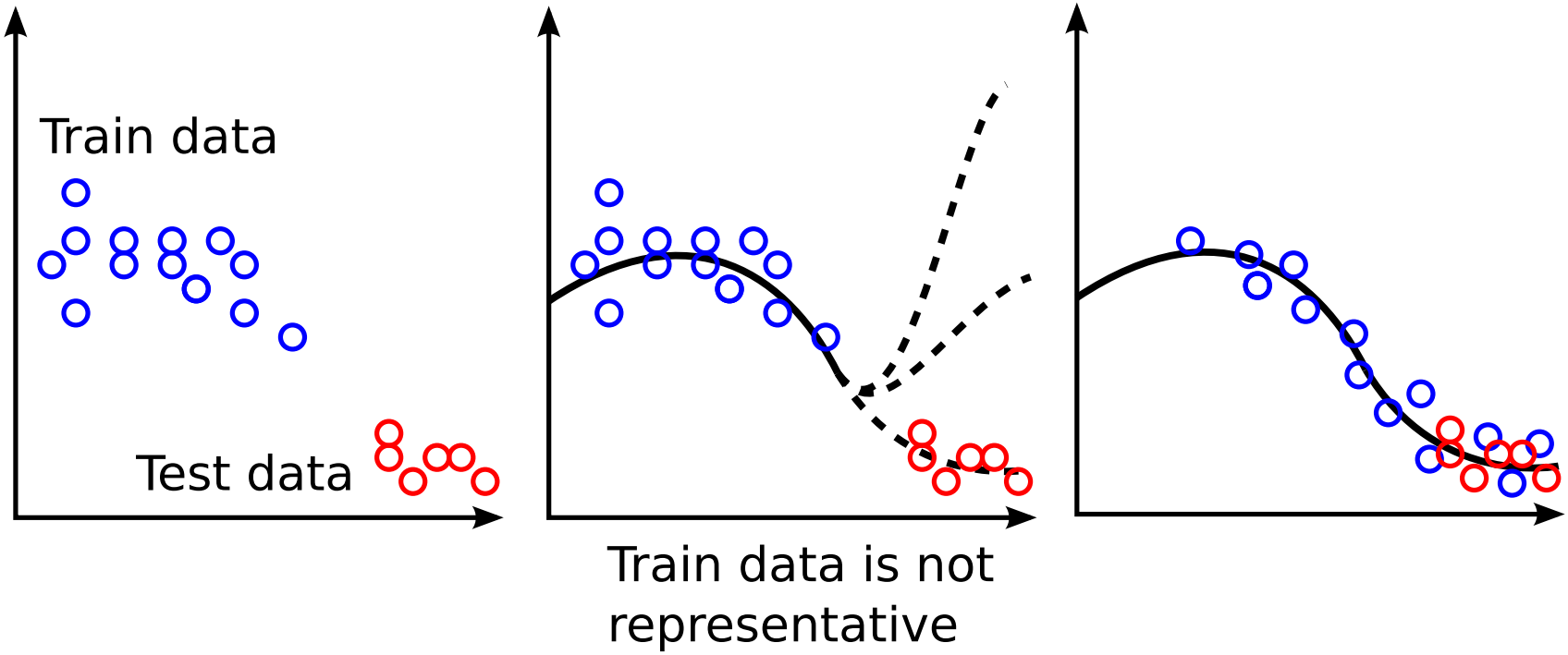
Data

- Representative
- Data augmentation
- Data normalization

Data

Train data must be representative of the problem



Data

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Data normalization

- Compute mean μ and standard deviation σ on the train set.
- Normalize input I (train and test):

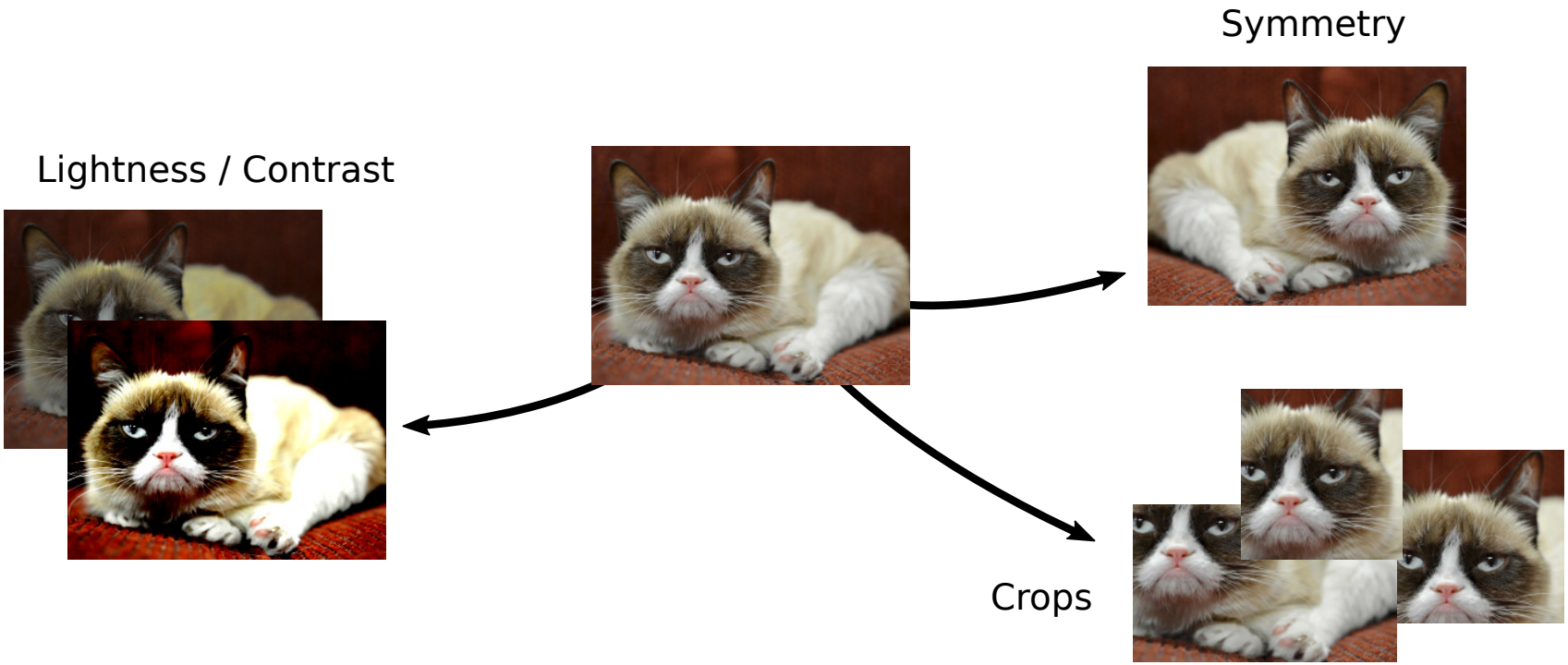
$$\hat{I} = \frac{I - \mu}{\sigma}$$

Data

Data augmentation

Random variations of input parameters (images: lightness, contrast ...)

- train on a more representative set
- avoid learning on unwanted features



Problems and partial solutions

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Problems

- Small amount of data
- Low computational power

Solutions ?

- Use classical approaches (Perceptron, SVM, . . .)

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Image classification - LeNet vs VGG

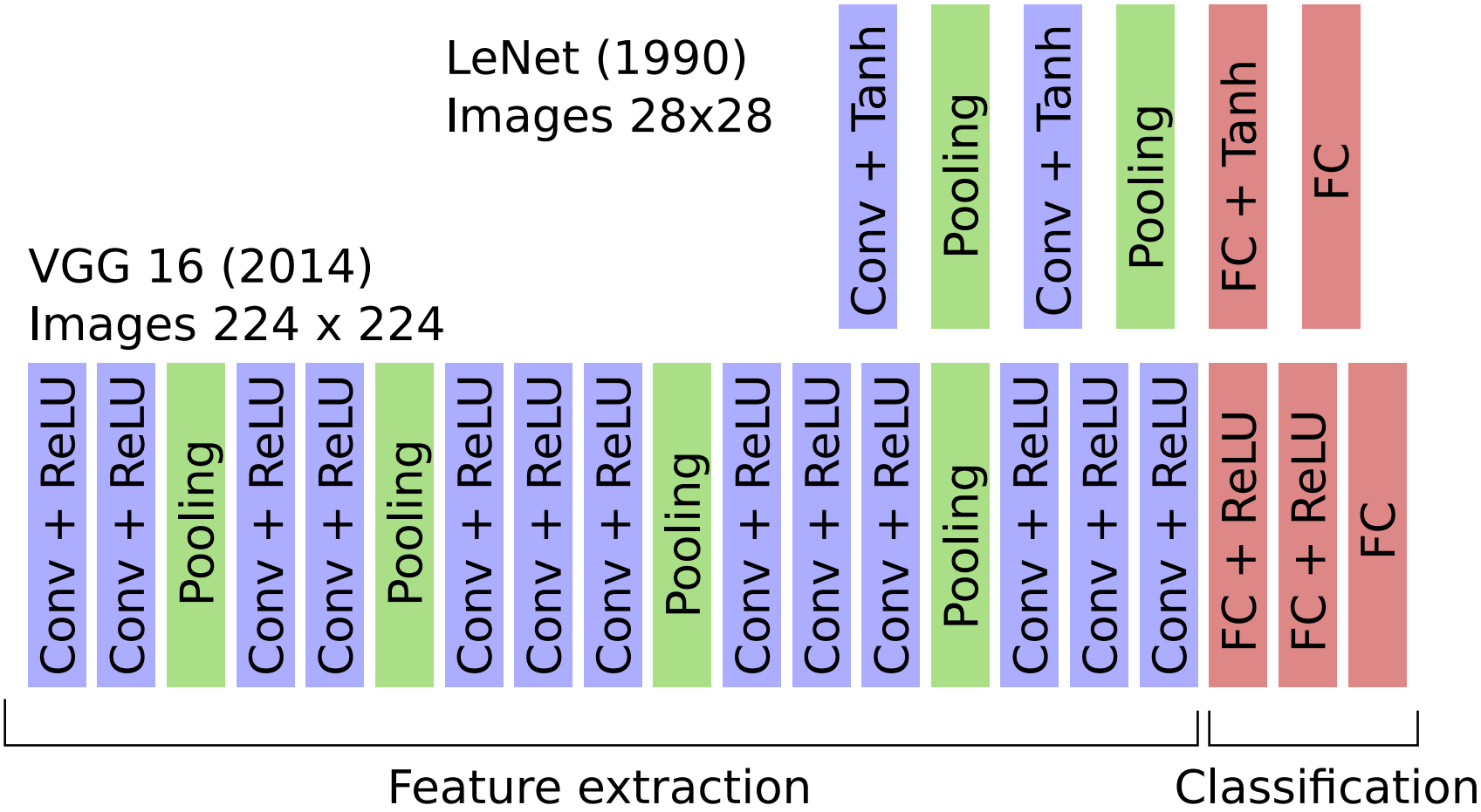
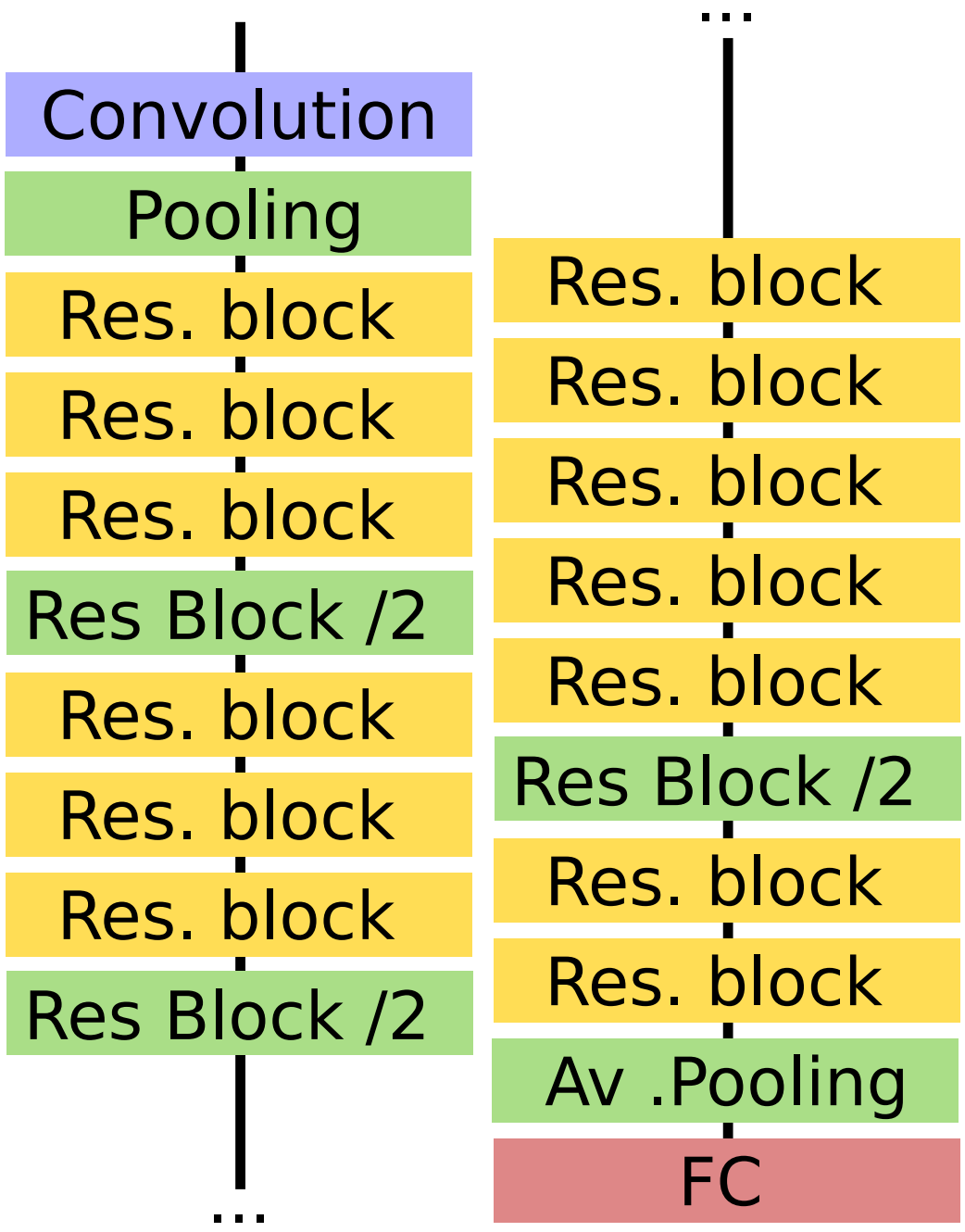
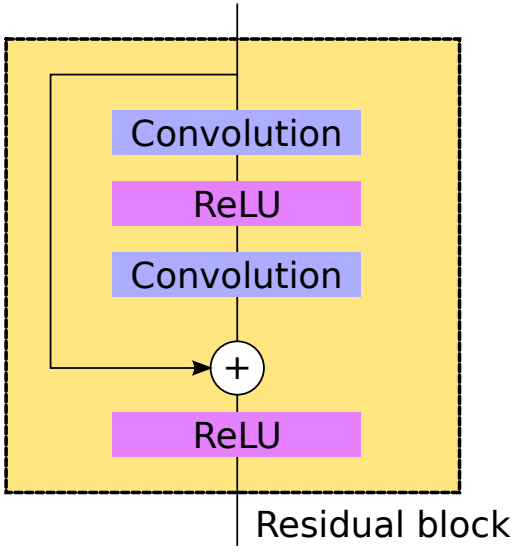


Image classification - ResNet





Semantic segmentation

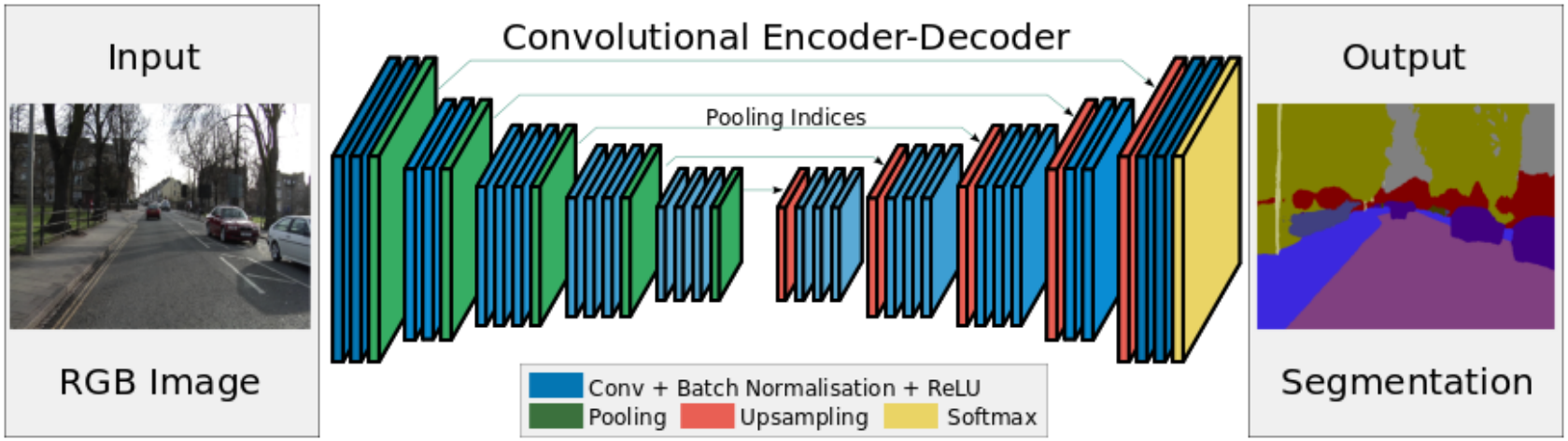
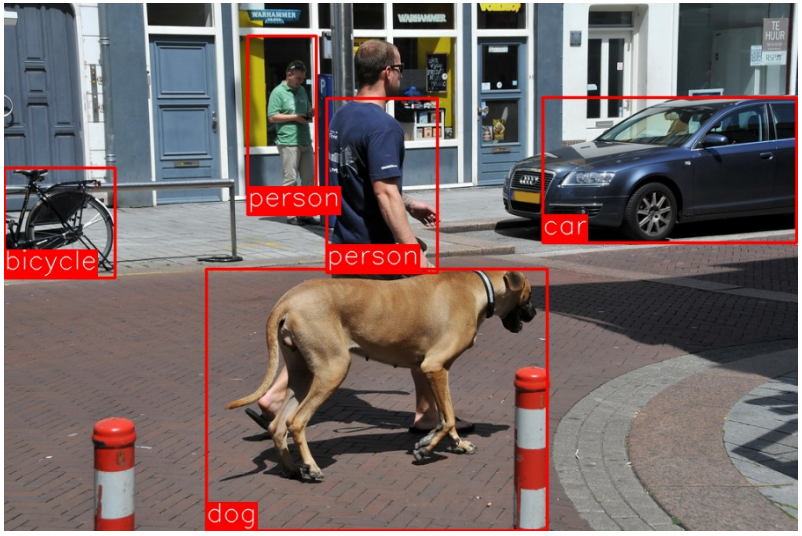
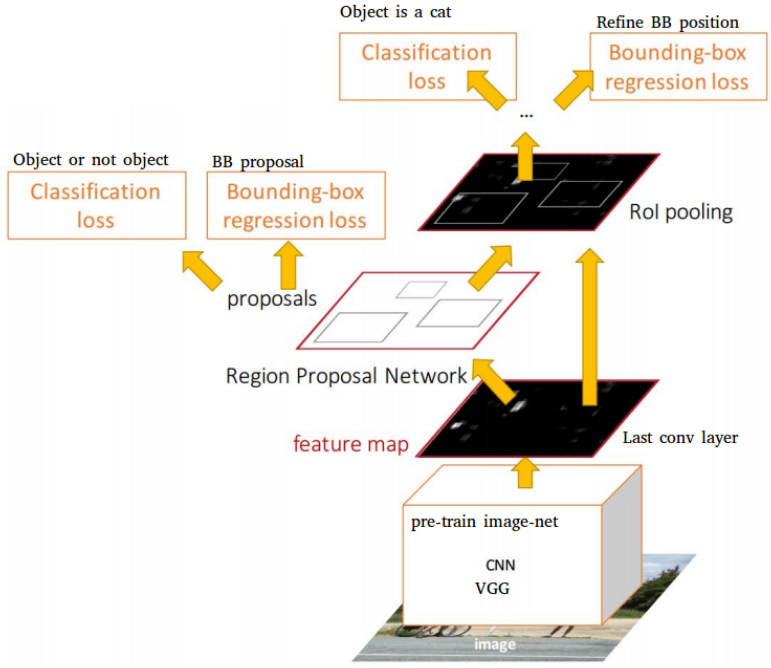


Image : http://mi.eng.cam.ac.uk/projects/segnet/

Detection


bicycle
person
person
car
dog


Object is a cat
Classification loss
Refine BB position
Bounding-box regression loss
...
Object or not object
Classification loss
BB proposal
Bounding-box regression loss
RoI pooling
proposals
Region Proposal Network
feature map
Last conv layer
pre-train image-net
CNN
VGG
image

Data generation

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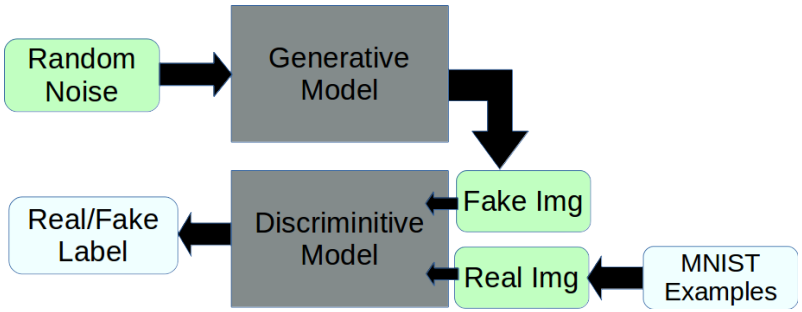
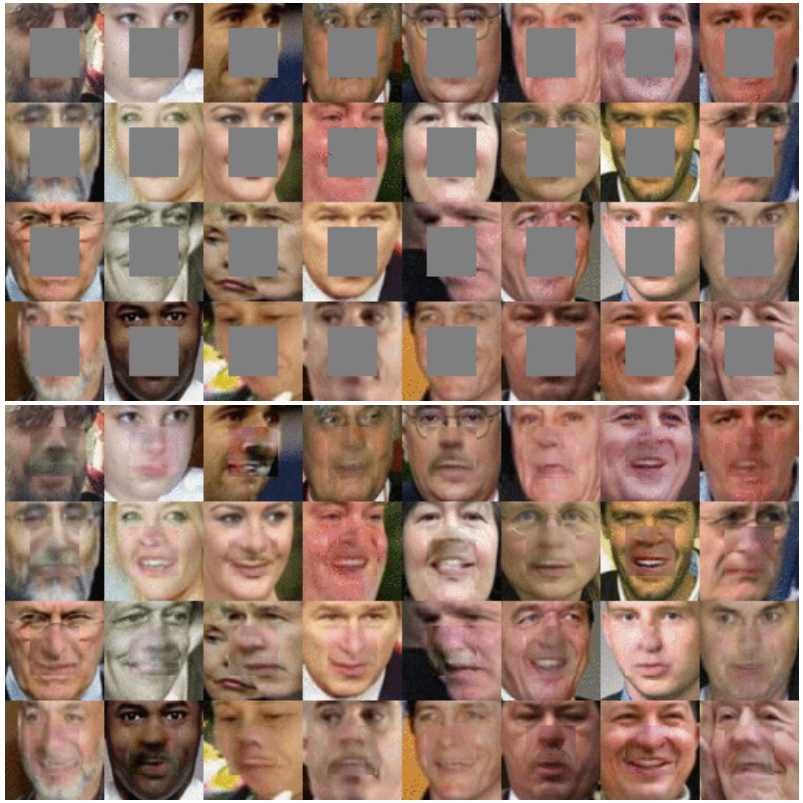
Generative Adversarial Networks

2 networks: one for data generation, one trying to discriminate real and generated data.

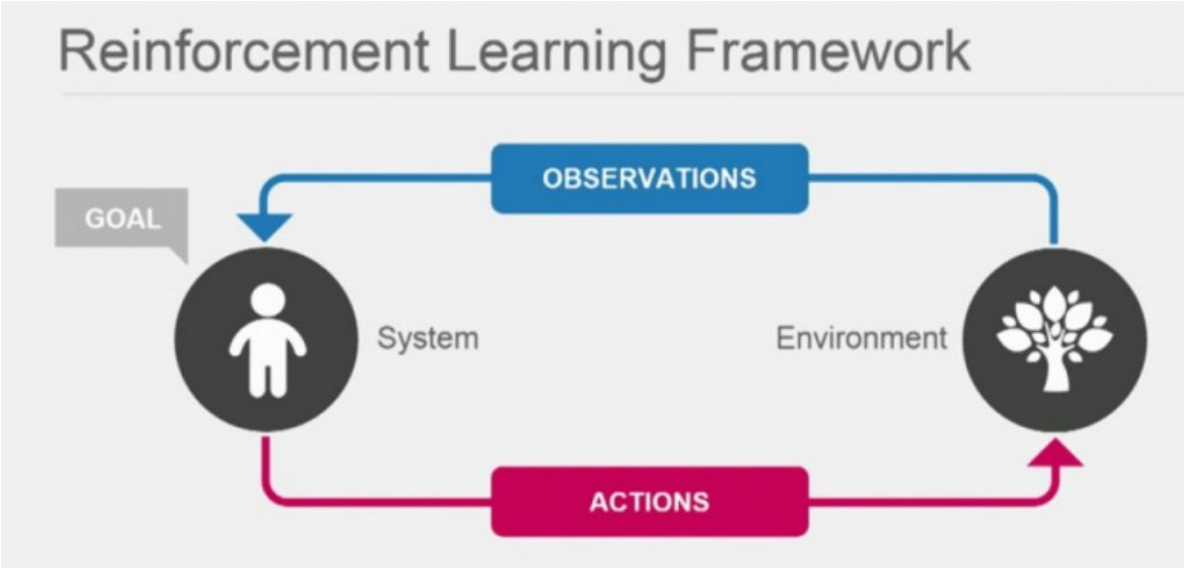




Reinforcement learning

Try and error learning

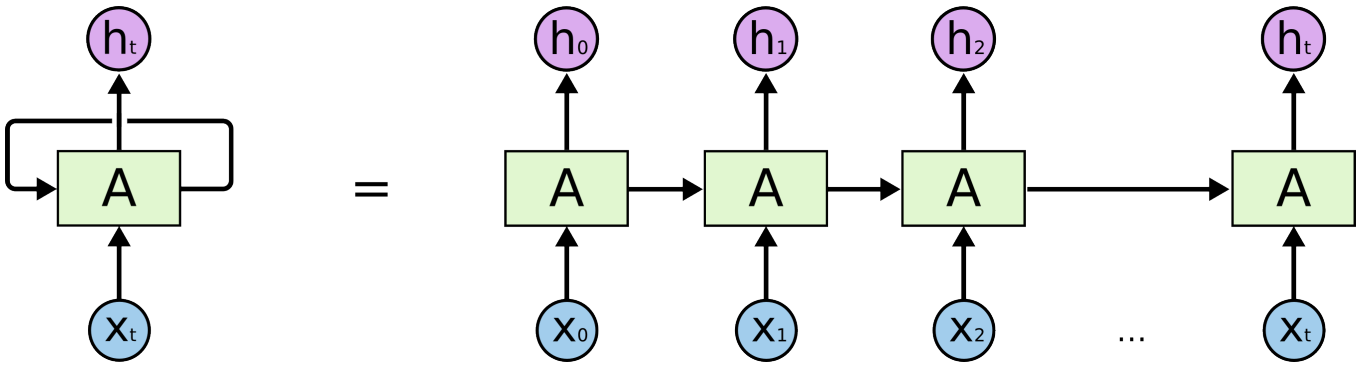
Reward and Penalty.



1

[1] Image http://visteon.bg/2017/03/02/machine-learning-algorithms-autonomous-cars/

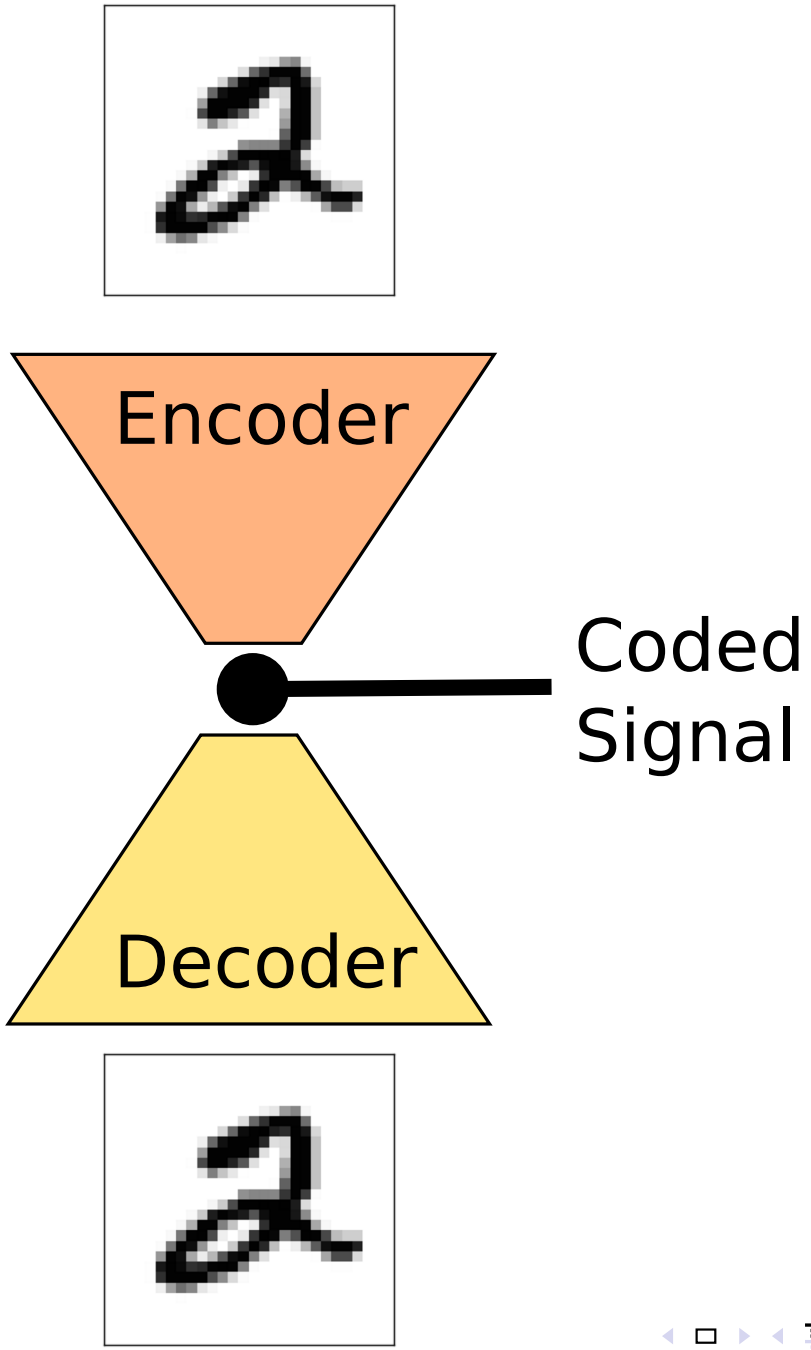
Recurrent neural networks



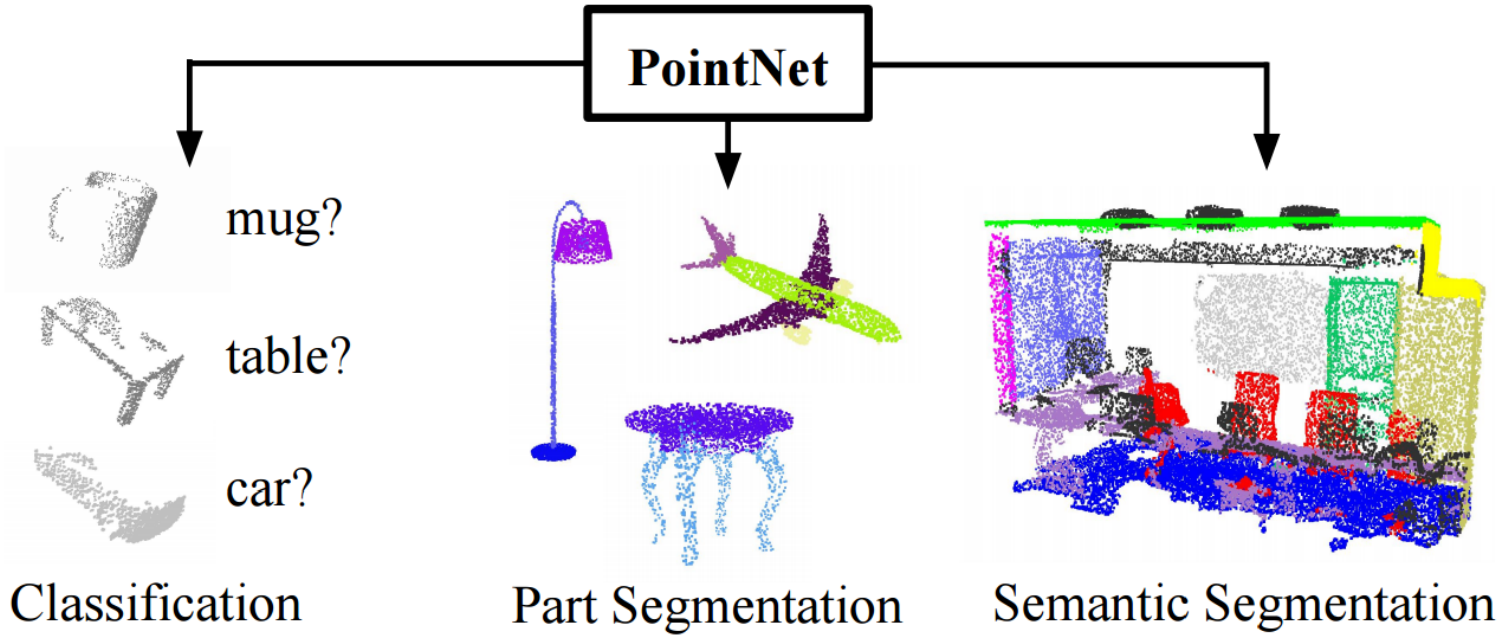
Dealing with sequences

Apply the same operation on each data and use a memroy to propagate information in time.

Autoencoders



3D data



- Use voxels (Similar to images)
- Take Snapshots of the point cloud (SnapNet)
- Deal directly with point clouds (PointNet, PointNet++ ...)

https://github.com/charlesq34/pointnet

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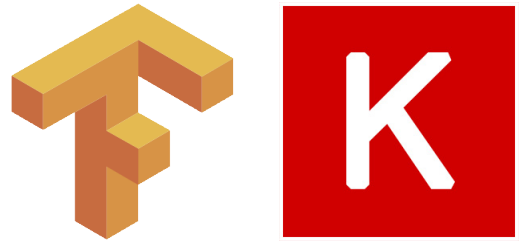
Frameworks

Torch



Tensorflow and Keras

Principaux frameworks Python

Pytorch and Tensorflow: CPU and GPU, good maintenance, tutorials.
Keras run on top of Tensorflow (and Theano, CNTK...). It provides a high level API.

Conclusion: some open problems

- Learn physics law ?
  (gravity...)

https://www.cos-mag.com/

Conclusion: some open problems

- Learn physics law ? (gravity...)
- Do it unsupervided ?

https://www.cos-mag.com/

Conclusion: some open problems

- Learn physics law ? (gravity...)
- Do it unsupervided ?
- Include physical knowledge in the machine learning ?

https://www.cos-mag.com/

Conclusion: some open problems

- Learn physics law ? (gravity...)
- Do it unsupervided ?
- Include physical knowledge in the machine learning ?
- Go from recognition to real reasoning ?

https://www.cos-mag.com/

Conclusion

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- Fast overview
- Few applications
- Practical work: create a CNN for image classification

Projects

Starting next week: projects.

- group of 2
- 3 subjects

For next week

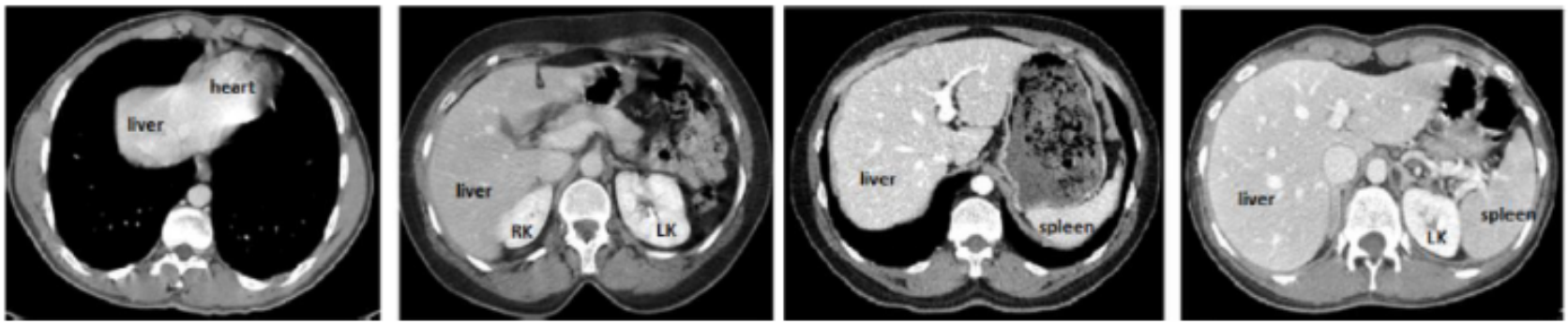
- form working pair
- choose subject

Project 1: dehazing

URL

https://competitions.codalab.org/competitions/21163

Project 2: medical images segmentation



URL `https://chaos.grand-challenge.org`

Project 3: trafic sign recognition

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- Classification
- 40+ classes
- 50000 images

URL `http://benchmark.ini.rub.de/?section=gtsrb&subsection=news`

Project Evaluation

Code (notebook) + **Report** (can be in the notebook)

Evaluation criteria

- Project execution (code)
- Justification of algorithmic choices
- Methodology
- Results analysis

Mid-course evaluation

Next class: **1h evaluation**

- All notes and course material
- **Exept for Neural networks and deep learning**
  $\longrightarrow$ knowledge and understanding test