Neural Networks: History and foundation

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Artificial and Natural Intelligence Toulouse Institute (ANITI)
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Course Intro

- Neural Networks
- Computer Vision
- NLP
- Audio

Course Intro

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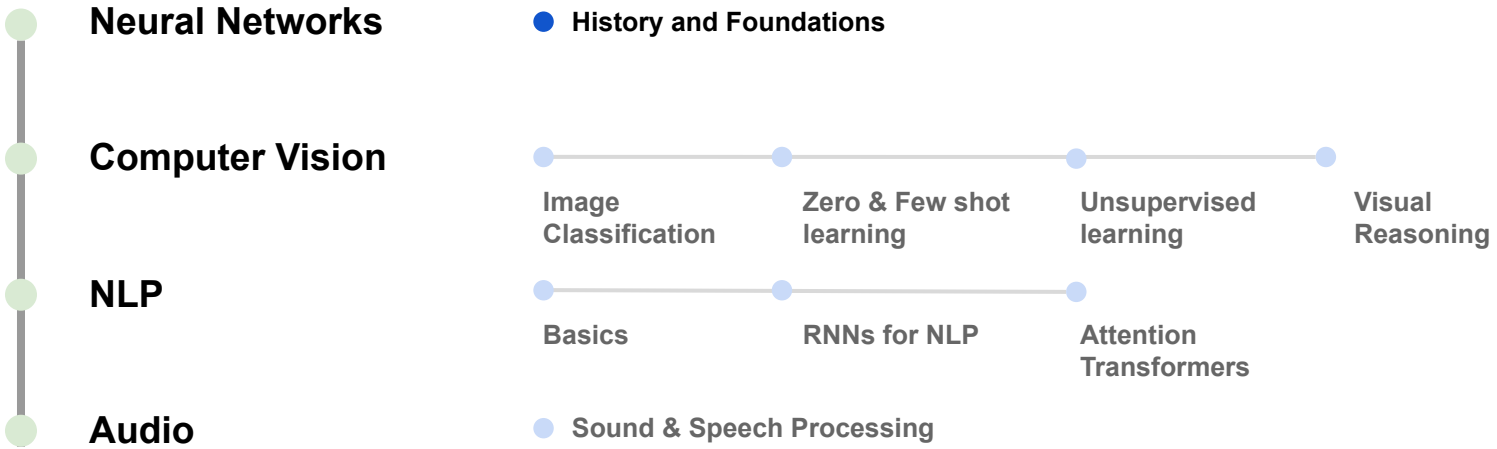
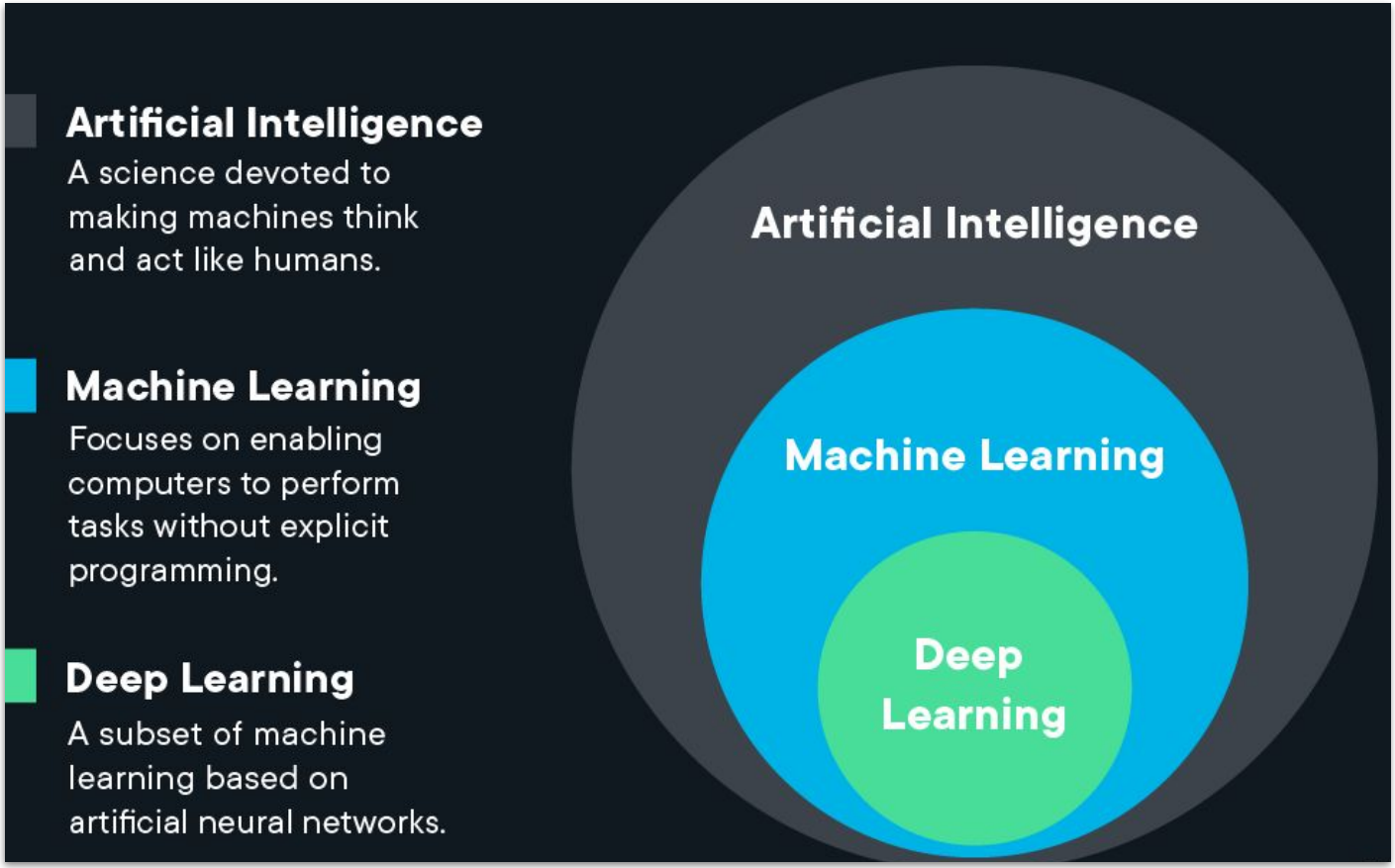
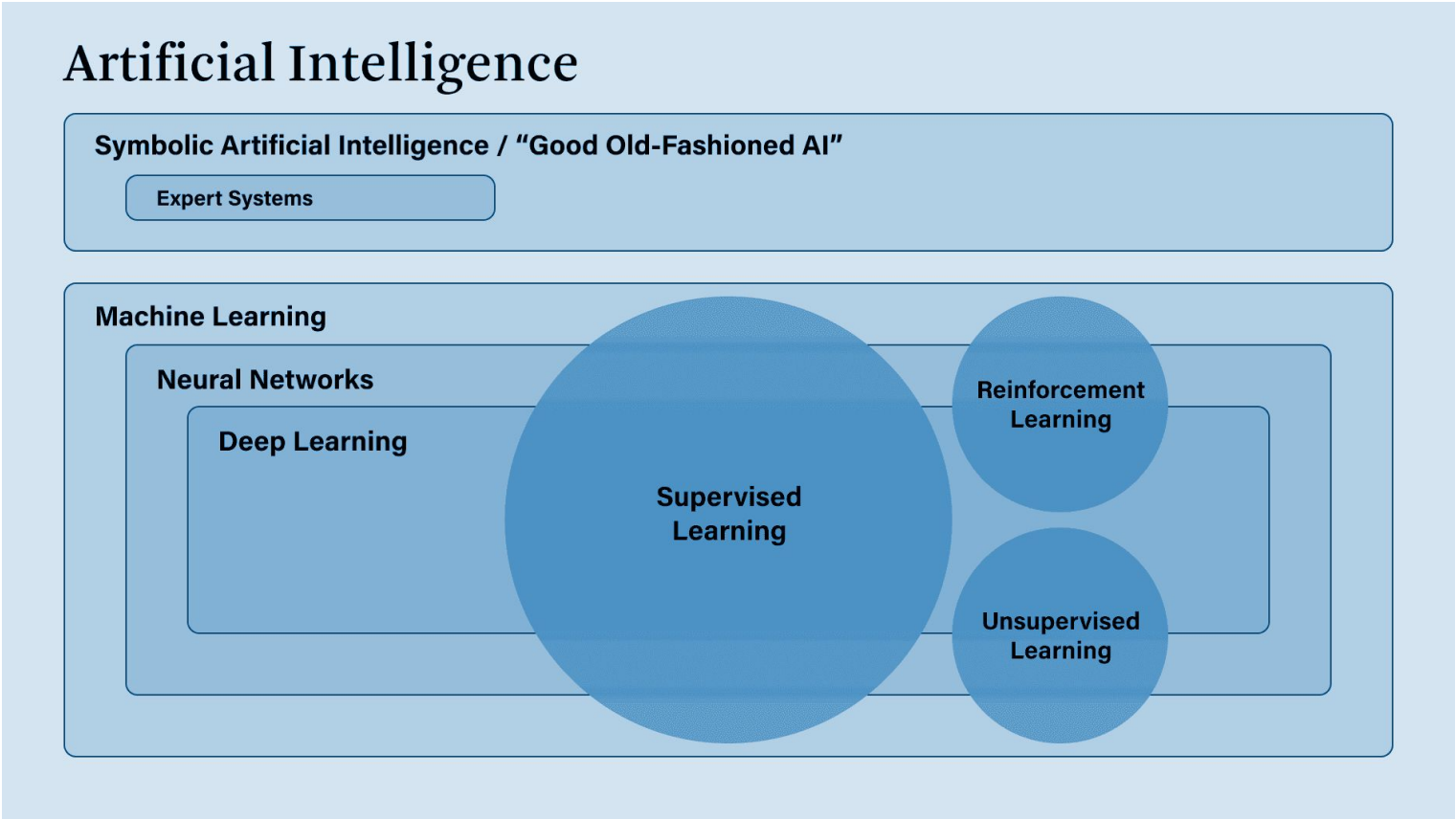


Introduction



Introduction



Introduction

THE PARTS

01 **Linear algebra / calculus**
Matrix operations, derivatives …

02 **Statistics / Probability**
Accuracy measurement tools, central tendency and variability.

03 **Optimization**
Learning algorithms (optimizers).

04 **Coding skills**
DL softwares (PyTorch, TensorFlow …). Data engineering.

Introduction

Neural networks milestones :

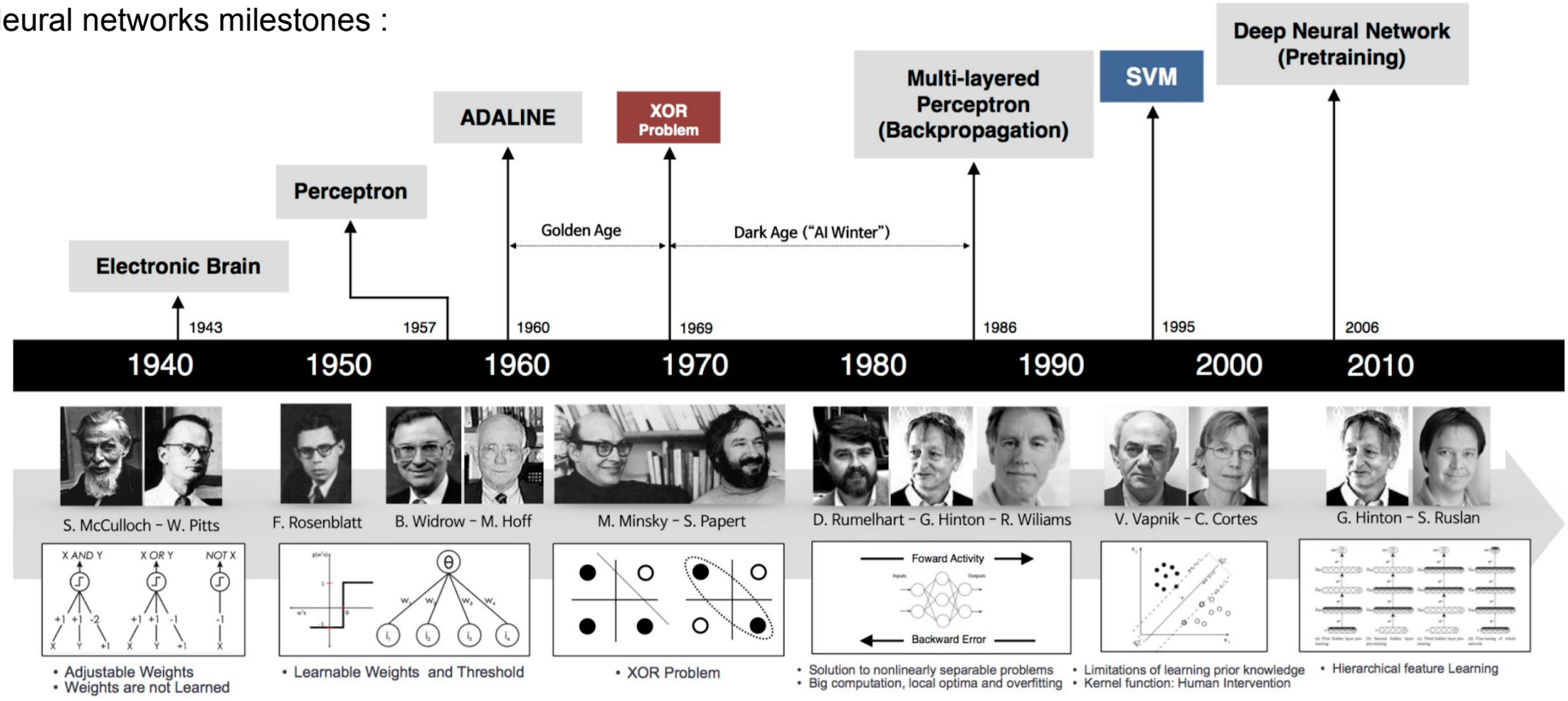
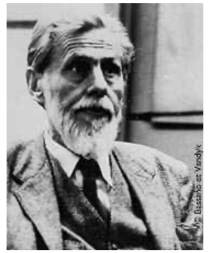


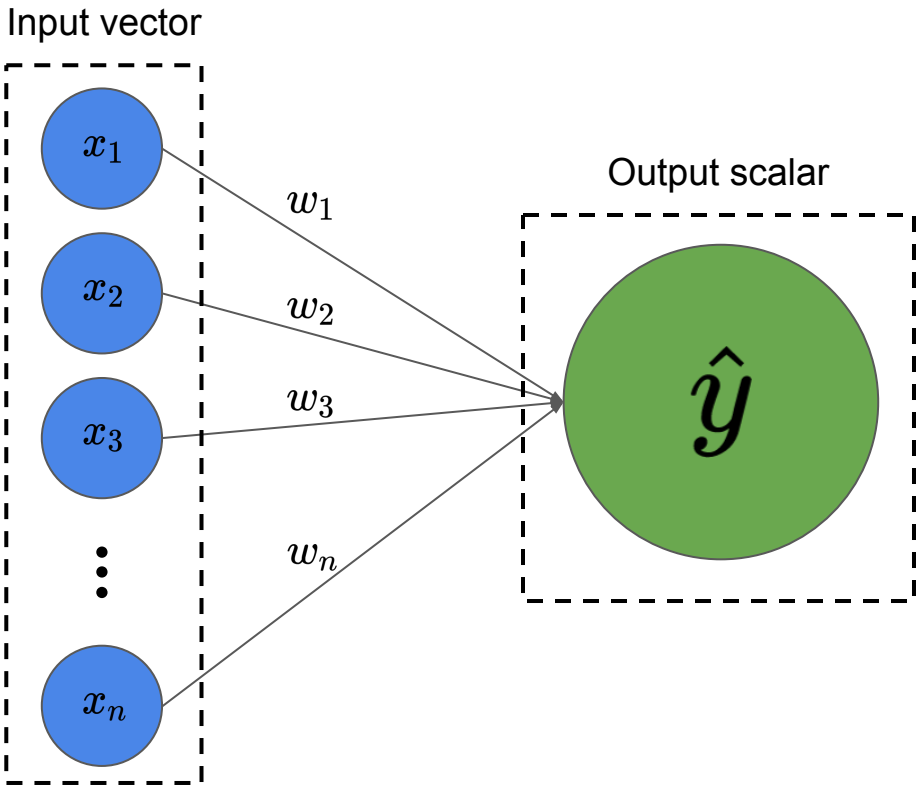
Image source: https://www.slideshare.net/deview/251-implementing-deep-learning-using-cu-dnn

Part 1 : Theory of Deep Learning

I- The Formal Neuron

Artificial neuron: McCulloch & Pitt's neuron model (1943)

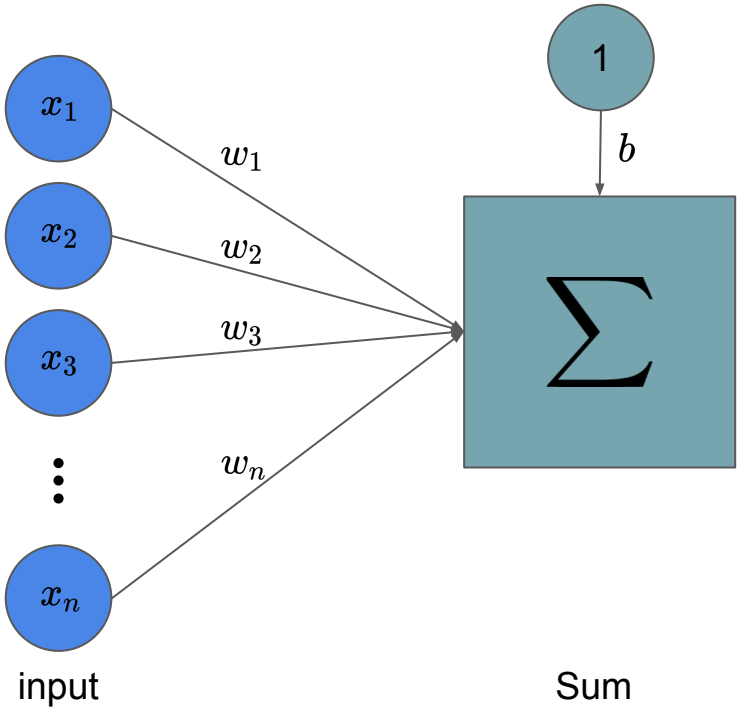




- Input : vector of size n
- Output : scalar
- Parameters w called **weights**

I- The Formal Neuron

- 1st step : Linear transformation : $s = \boldsymbol{w}^T \boldsymbol{x} + b$



Recall (Linear Algebra / Calculus)

Dot product

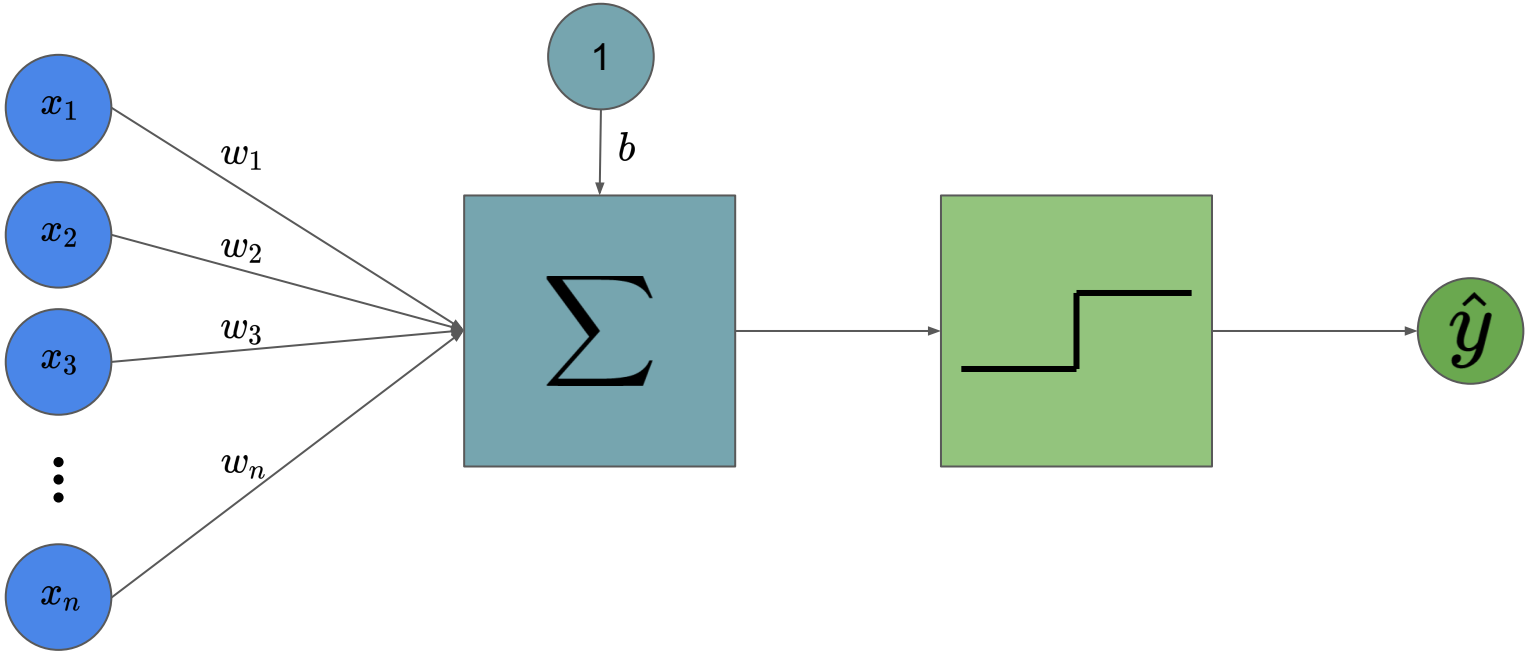
Two vectors : $\boldsymbol{x} = \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix} \qquad \boldsymbol{y} = \begin{bmatrix} y_1 \\ y_2 \\ y_3 \end{bmatrix}$

Transpose operator : $\boldsymbol{x}^T = \begin{bmatrix} x_1 & x_2 & x_3 \end{bmatrix}$

$$\boldsymbol{x}^T \boldsymbol{y} = \begin{bmatrix} x_1 & x_2 & x_3 \end{bmatrix} \begin{bmatrix} y_1 \\ y_2 \\ y_3 \end{bmatrix} = x_1 \times y_1 + x_2 \times y_2 + x_3 \times y_3 = \vec{\boldsymbol{x}} . \vec{\boldsymbol{y}}$$

I- The Formal Neuron

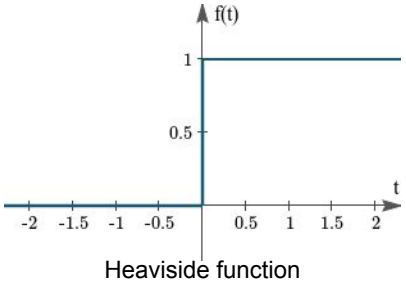
- 1st step : Linear transformation : $s = \boldsymbol{w}^T \boldsymbol{x} + b$
- 2nd step : Non-linear activation function : $\hat{y} = f(s)$



I- The Formal Neuron

Similarities with biological neurons:

- Choose f as Heaviside function : $H(z) = \begin{cases} 1 & \text{if } z \geq 0 \\ 0 & \text{otherwise} \end{cases}$



Heaviside function

- $\hat{y} = 1 \Leftrightarrow \mathbf{w}^{\mathrm{T}}\mathbf{x} \geq -\mathrm{b}$ activated
  $\hat{y} = 0 \Leftrightarrow \mathbf{w}^{\mathrm{T}}\mathbf{x} < -\mathrm{b}$ unactivated

- Biological neurons : produce output if input weighted by synaptic weight exceeds the threshold

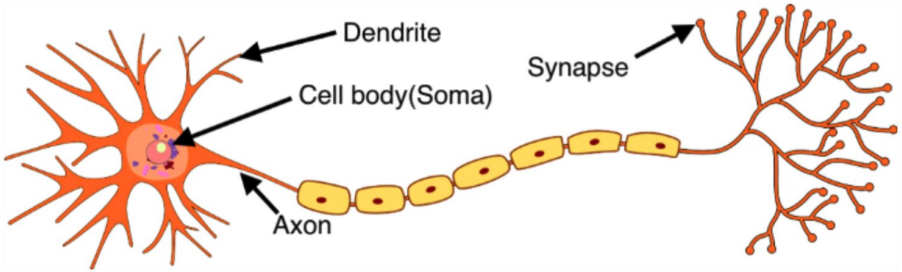
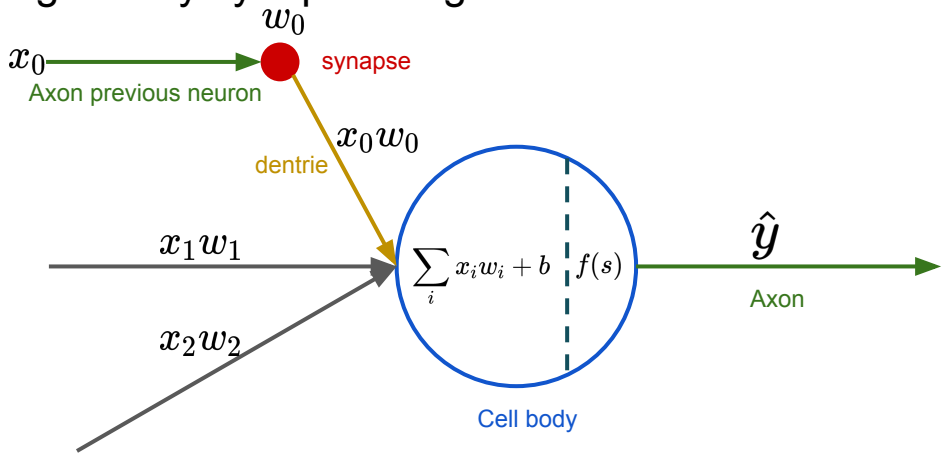


Image source: Wikimedia Commons



I- The Formal Neuron

- An artificial neuron could solve **linear** logical problems: AND, OR, NOT

AND

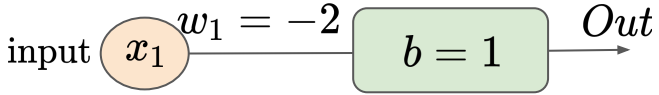
x_1	x_2	Out
0	0	0
0	1	0
1	0	0
1	1	1

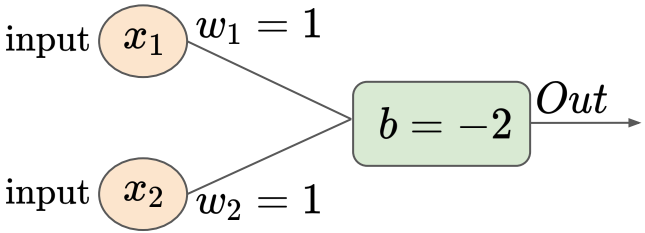
OR

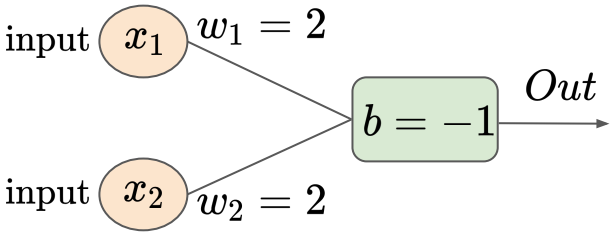
x_1	x_2	Out
0	0	0
0	1	1
1	0	1
1	1	1

NOT

x_1	Out
0	1
1	0

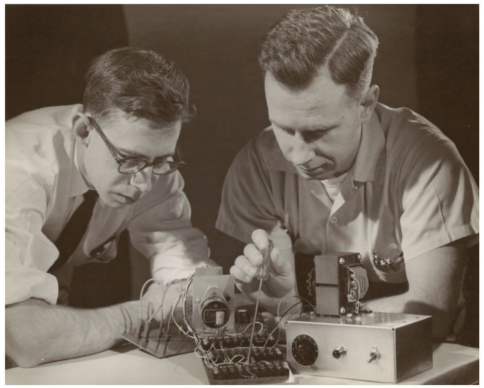




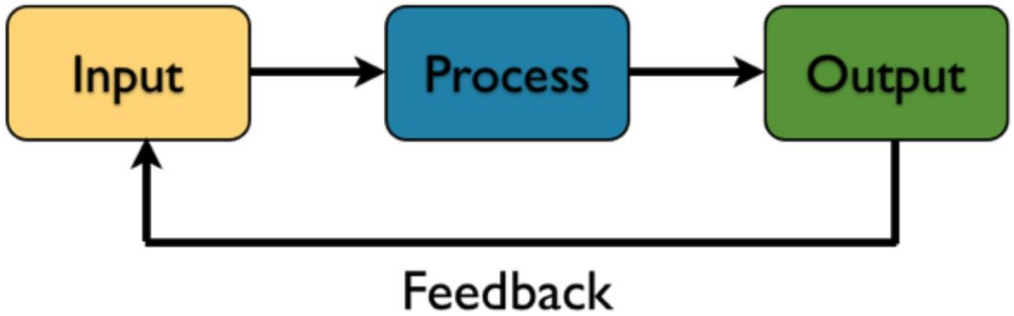


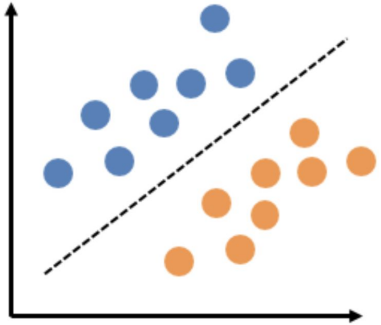
II- Perceptron: A learning algorithm for the neuron model

Rosenblatt, F. (1957). *The perceptron, a perceiving and recognizing automaton Project Para.*



- Automatic learning of weights
- Supervised learning of binary classifiers
- Could recognize letters and numbers





II- Perceptron: A learning algorithm for the neuron model

$$Let\ D = (\langle x_1, y_1 \rangle, \langle x_2, y_2 \rangle, \ldots, \langle x_n, y_n \rangle) \in (\mathbb{R}^m \times \{0, 1\})^n$$

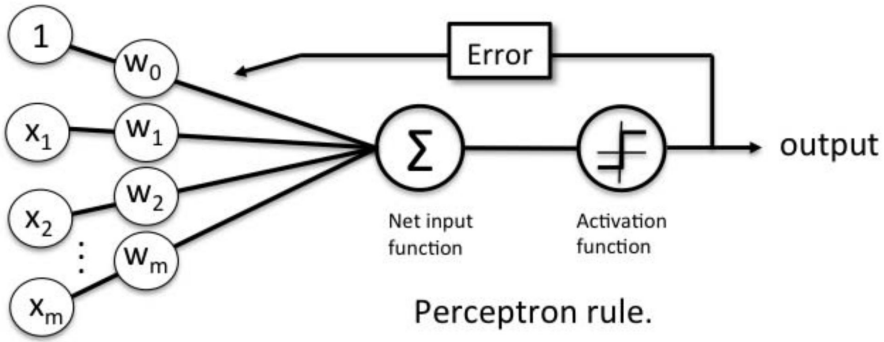
1. Initialise w_i *with random small values*
2. For every training epoch:

   For every sample $\langle x_i, y_i \rangle \in D$:

   (a) $\hat{y} := \sigma(x_i \times w)$ ← Compute output (prediction)

   (b) $err := (y_i - \hat{y}_i)$ ← Compute error

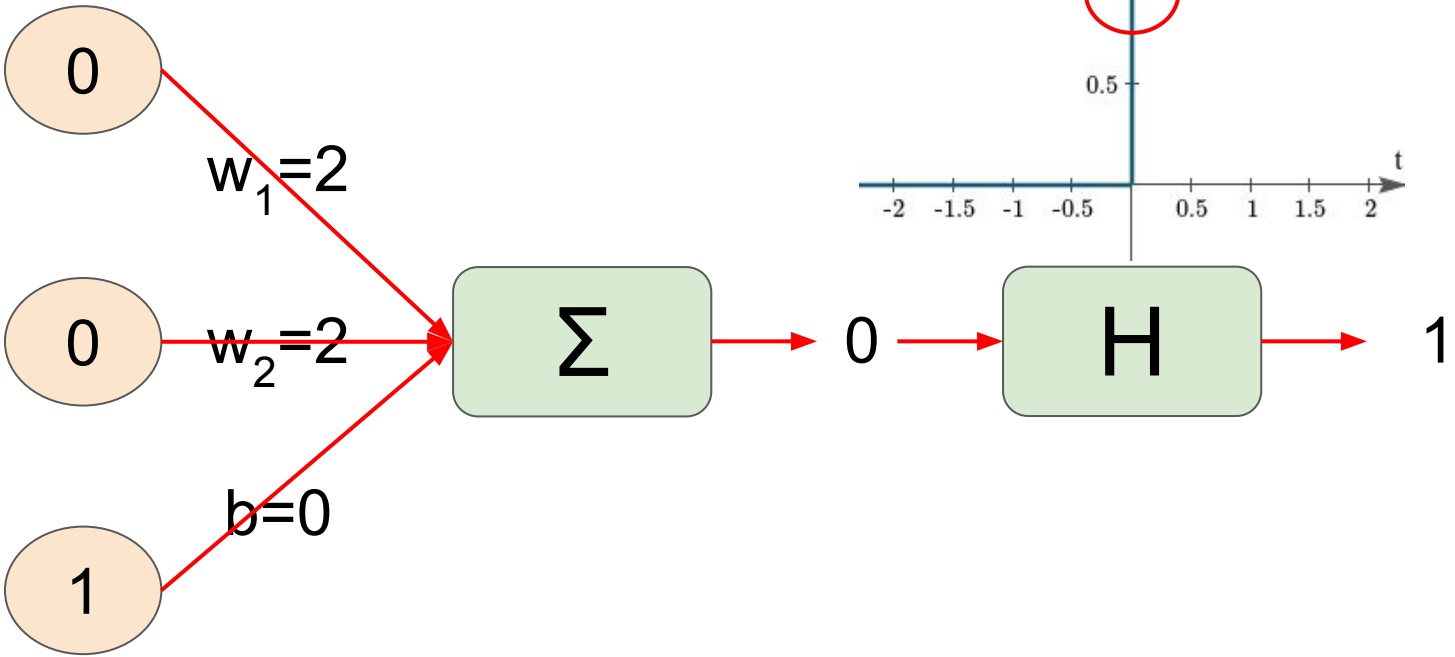
   (c) $w := w + err \times x_i$ ← Update parameters



Perceptron rule.

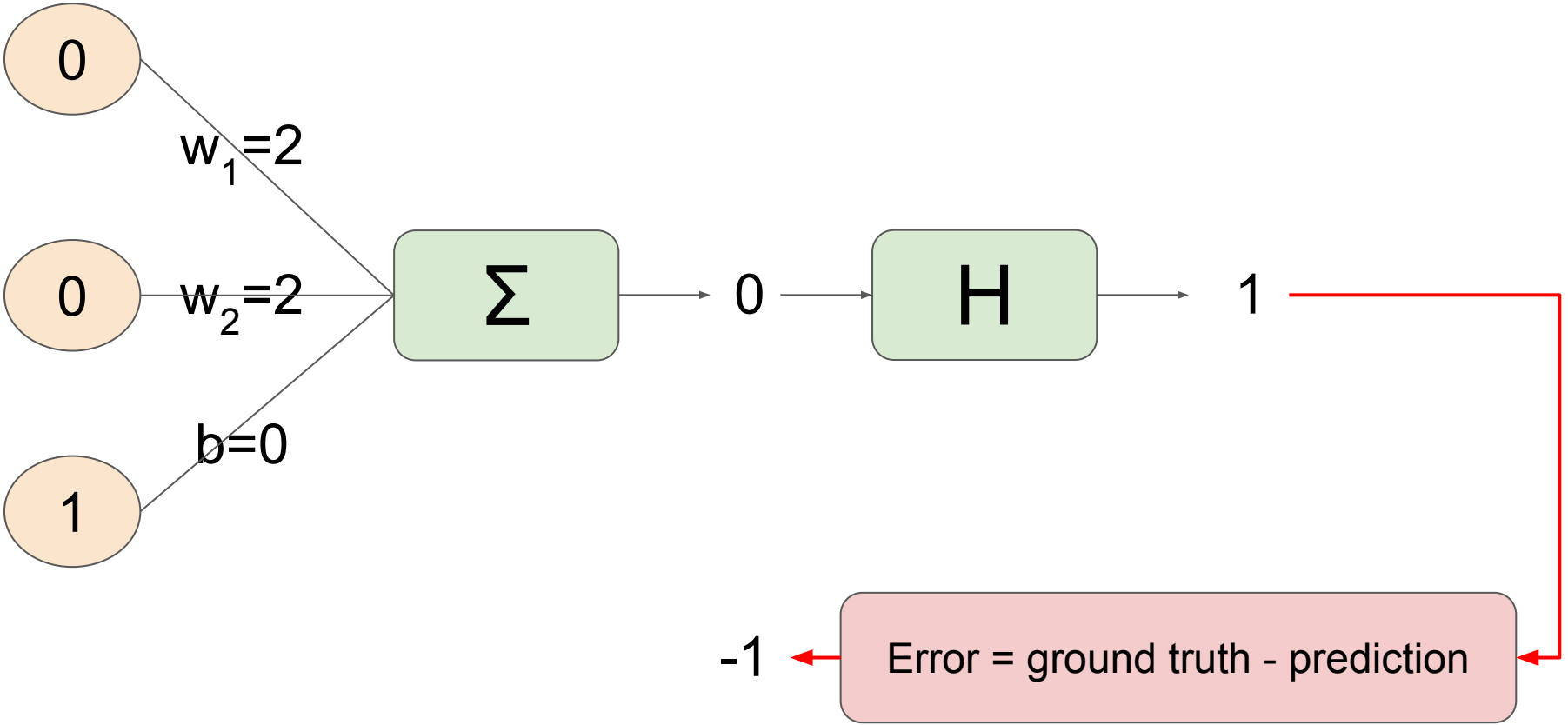
II- Perceptron: A learning algorithm for the neuron model

Learning OR gate : predict the value



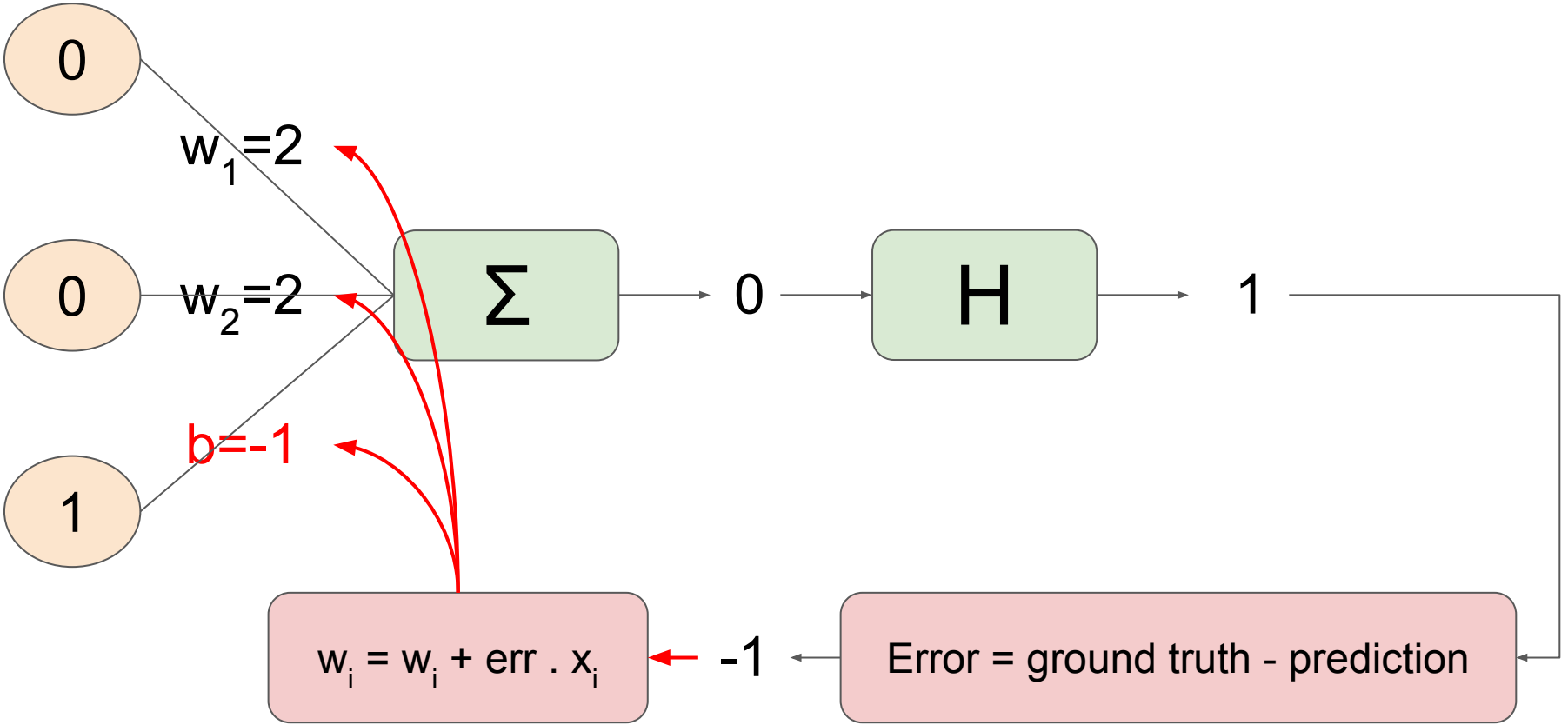
II- Perceptron: A learning algorithm for the neuron model

Learning OR gate : compute error



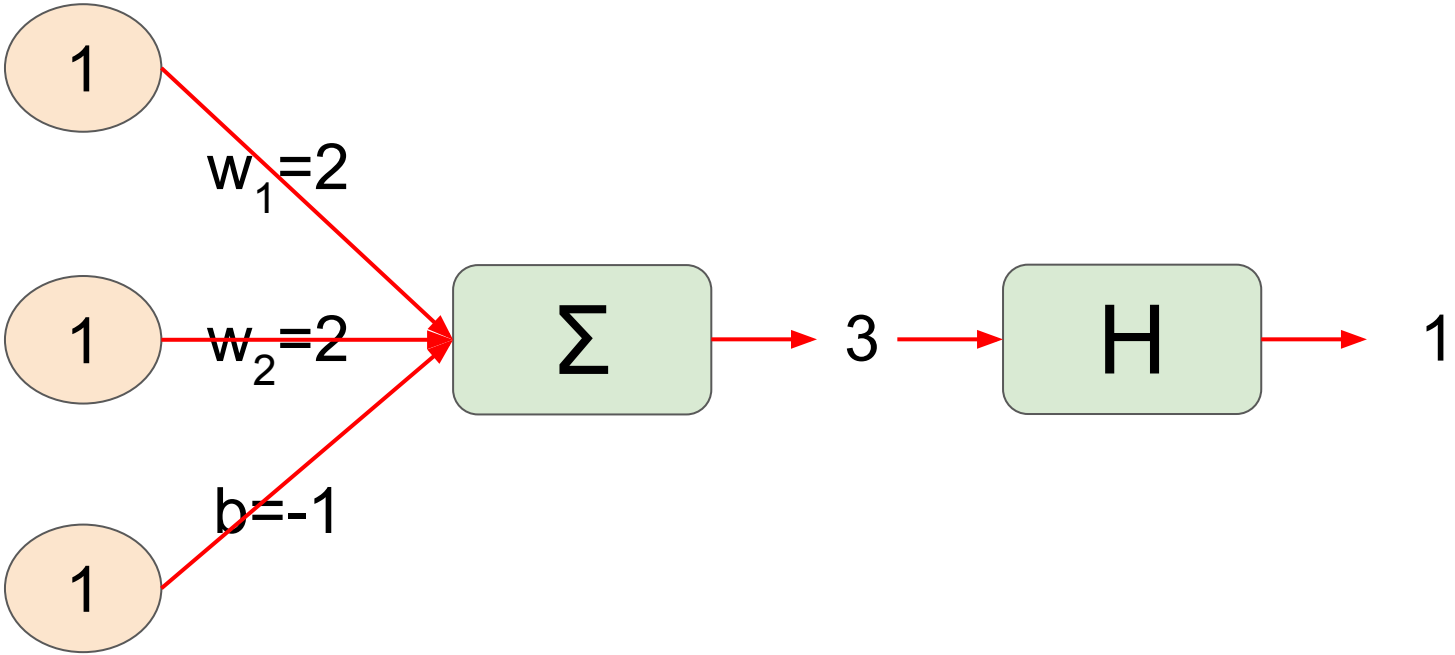
II- Perceptron: A learning algorithm for the neuron model

Learning OR gate : update weights



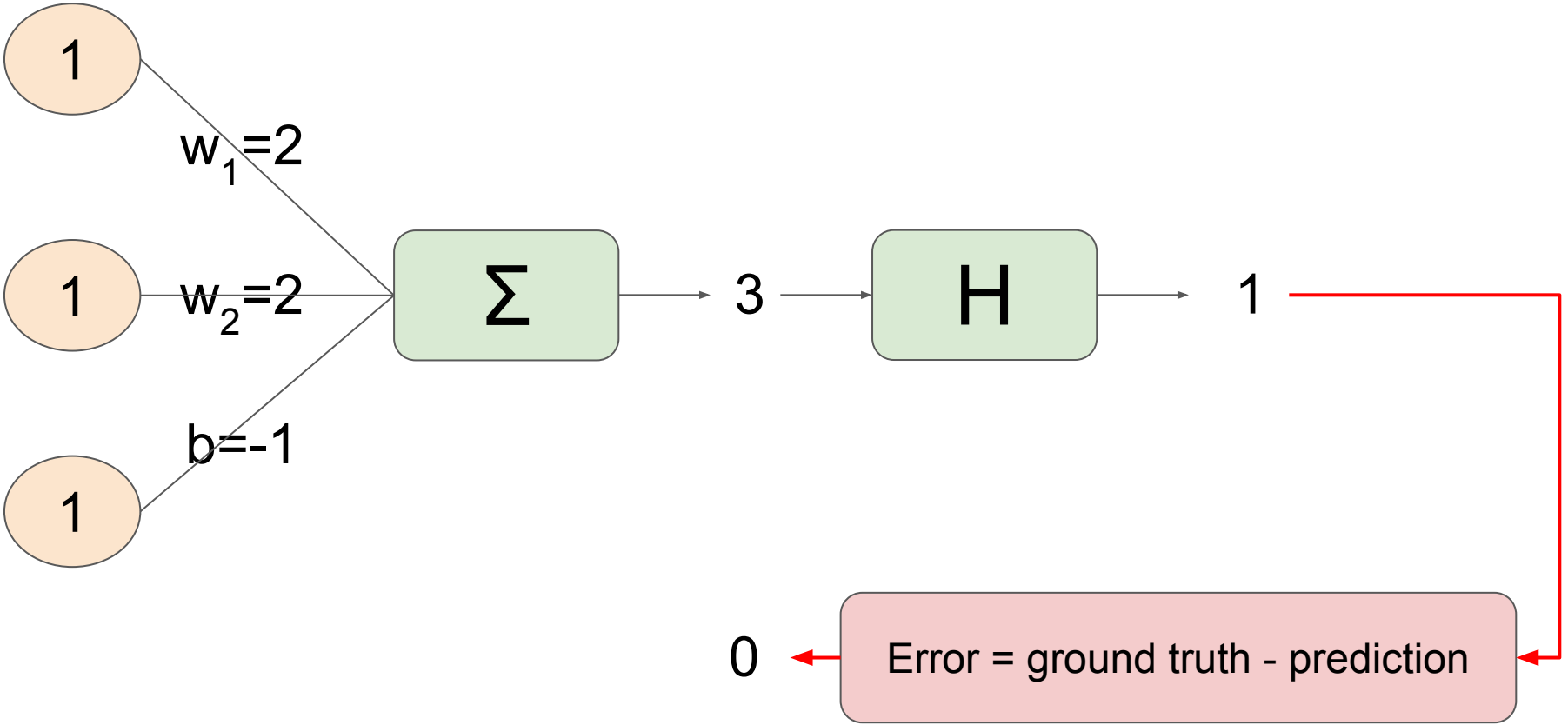
II- Perceptron: A learning algorithm for the neuron model

Learning OR gate : second pass



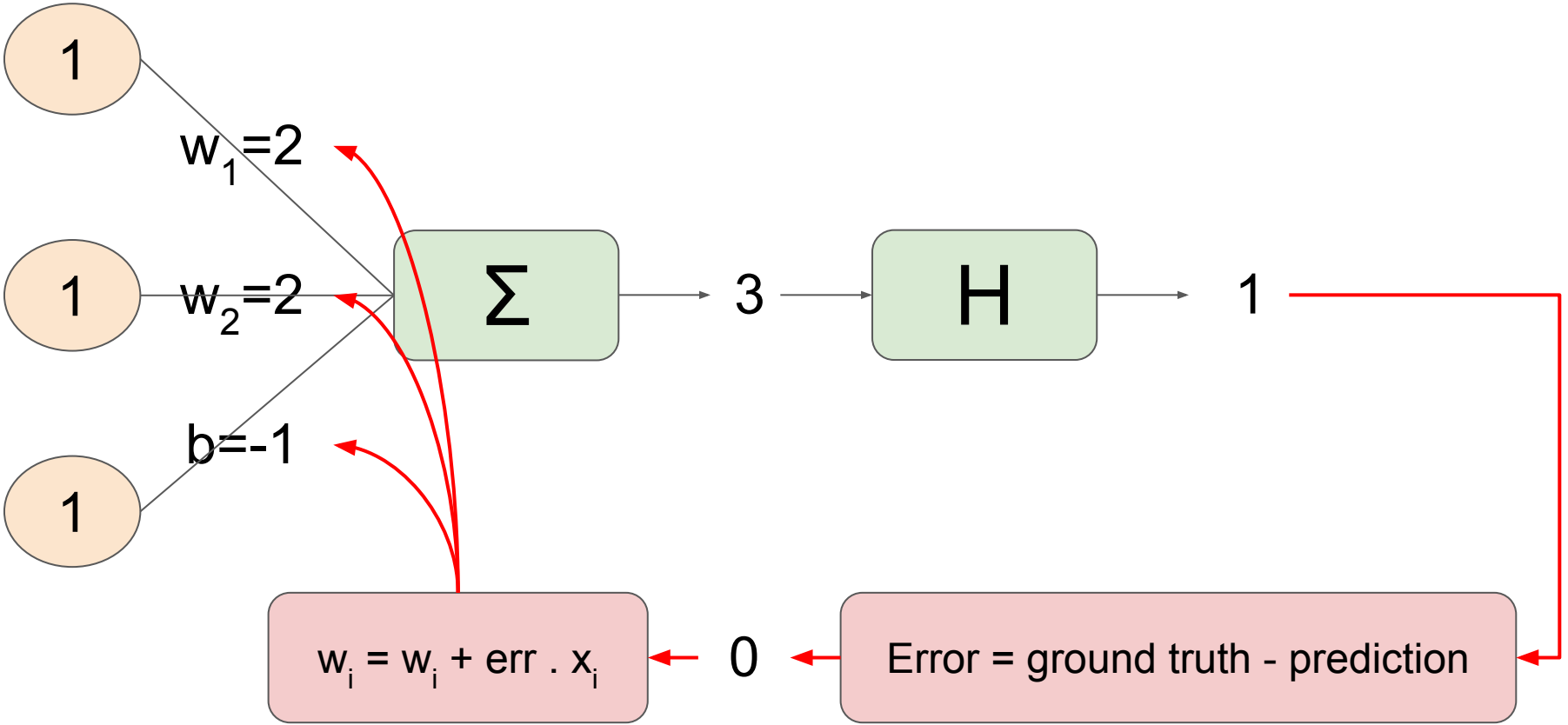
II- Perceptron: A learning algorithm for the neuron model

Learning OR gate : compute error



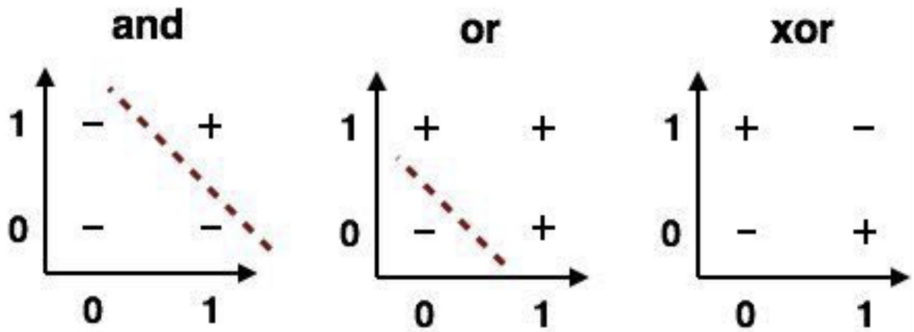
II- Perceptron: A learning algorithm for the neuron model

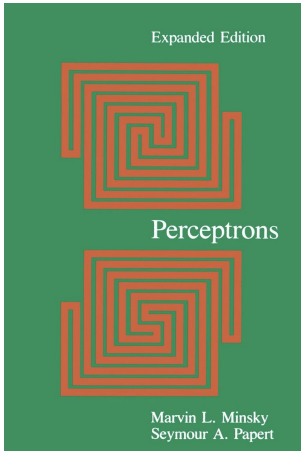
Learning OR gate : compute error



The first AI winter

Minsky and Papert (1969) show that the perceptron can't even solve the XOR problem



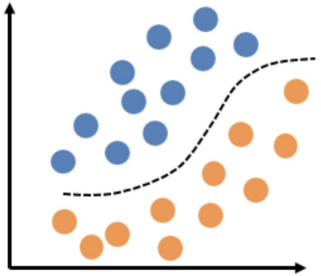


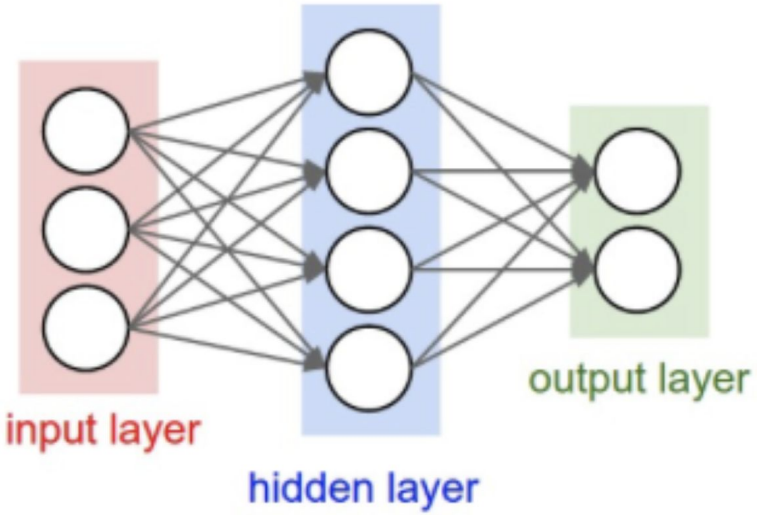
⇒ Kills research on neural nets for the next 15-20 years

III- Multilayer perceptrons (1980's)

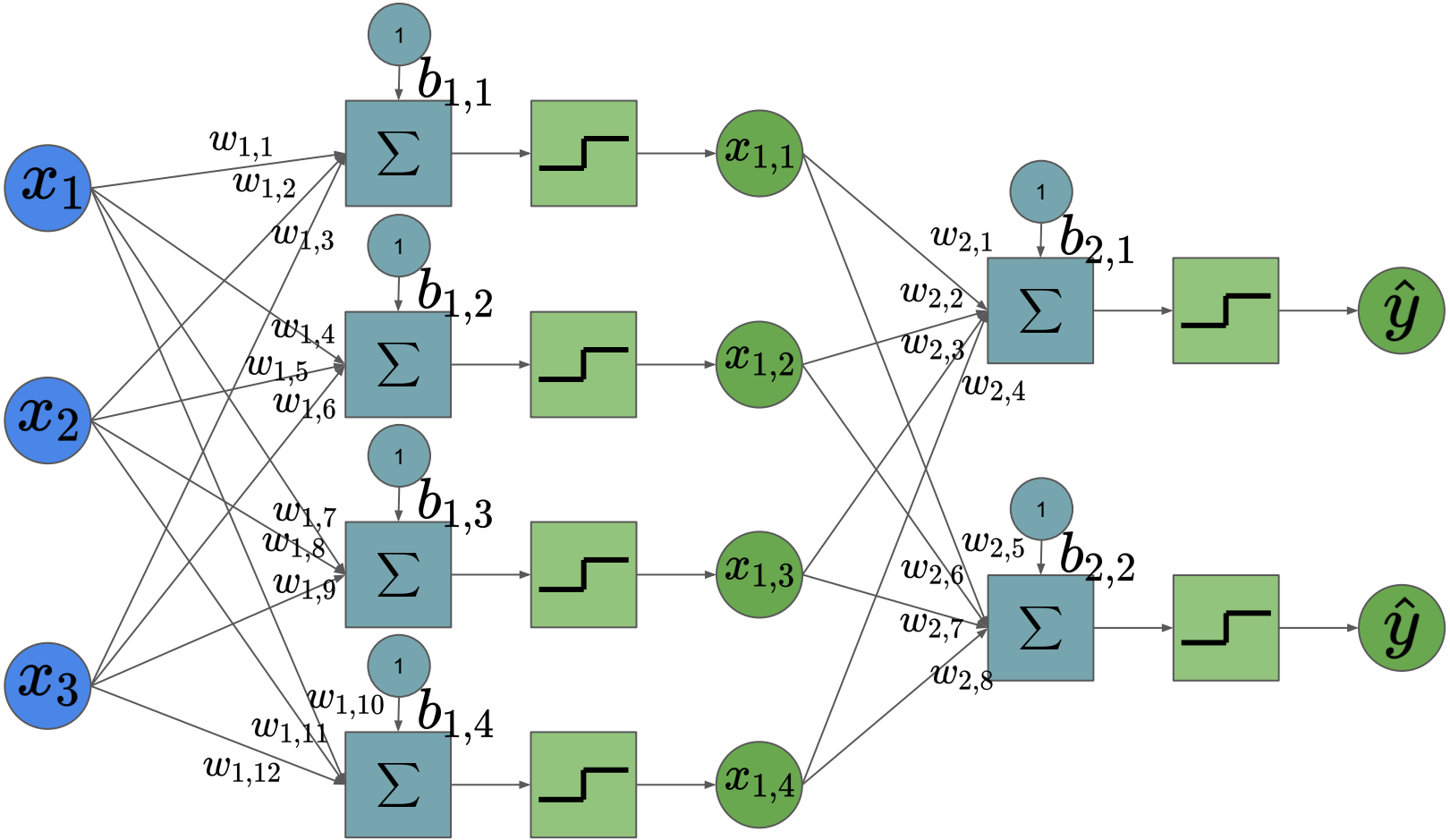
Solution to the XOR problem: **Multilayer perceptrons**

- Composed of: **input** layer, **hidden** layer(s) and an **output** layer.
- Each node (of hidden and output layers) is a neuron that uses a **nonlinear** activation function.
- It can distinguish data that is **not linearly** separable.





III- Multilayer perceptrons (1980's)



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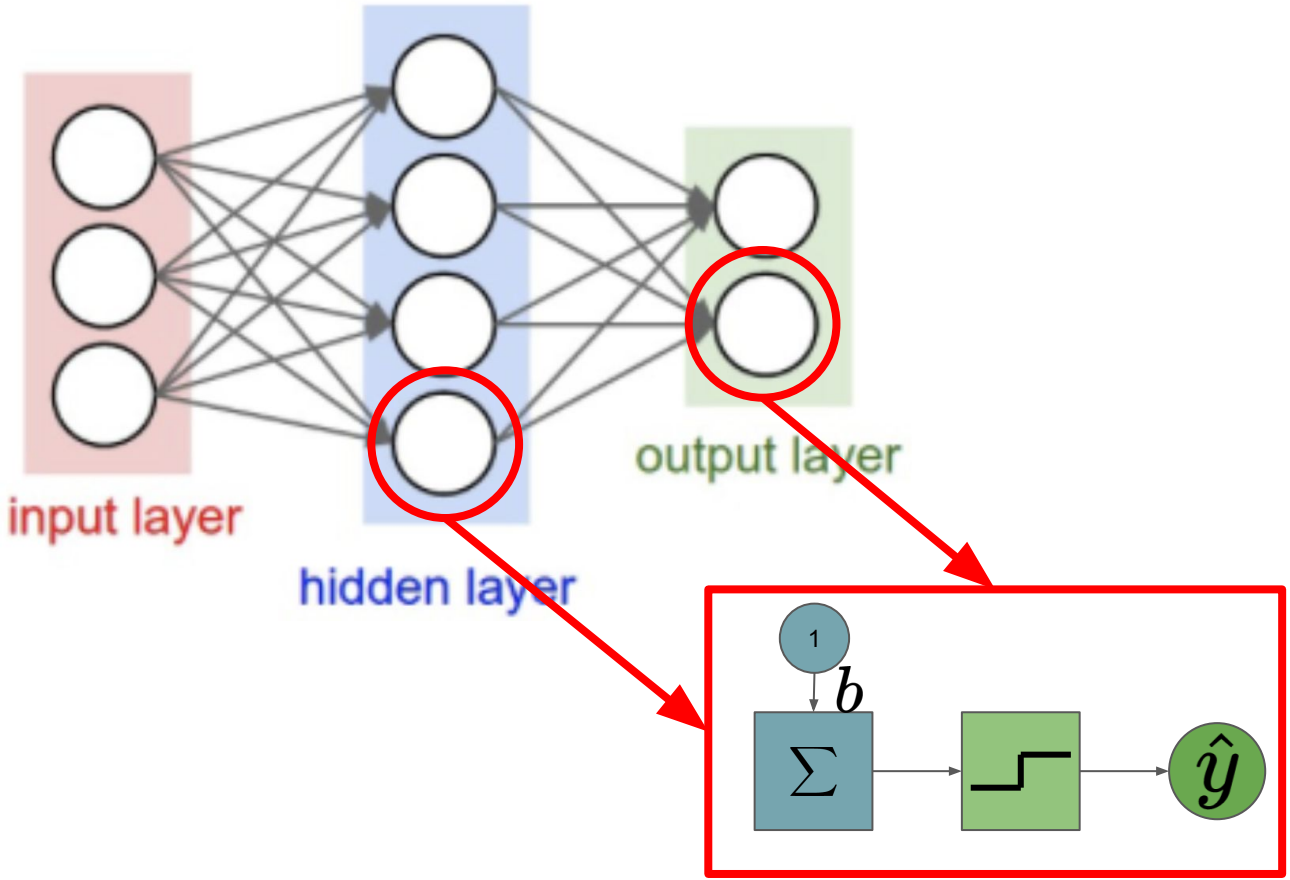


Recall (Linear Algebra / Calculus)

Matrix product :

$$\begin{bmatrix} a_1 & b_1 \\ c_1 & d_1 \end{bmatrix} \begin{bmatrix} a_2 & b_2 \\ c_2 & d_2 \end{bmatrix} = \begin{bmatrix} a_1 a_2 + b_1 c_2 & a_1 b_2 + b_1 d_2 \\ c_1 a_2 + d_1 c_2 & c_1 b_2 + d_1 d_2 \end{bmatrix}$$

1 neuron

$$\boldsymbol{w} = \begin{bmatrix} w_1 \\ w_2 \\ w_3 \\ w_{41} \end{bmatrix}$$

4 neurons

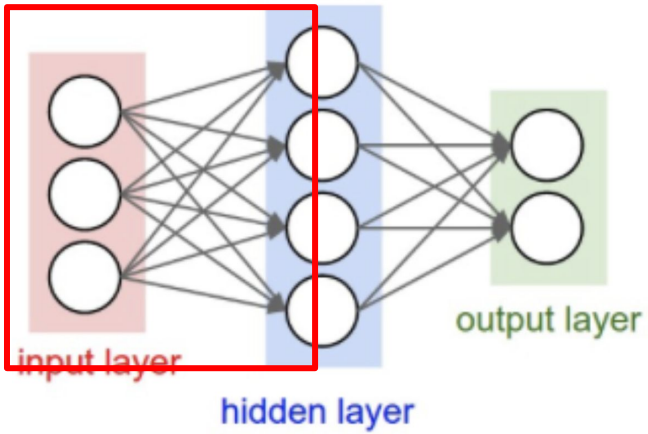
$$\boldsymbol{W} = \begin{bmatrix} w_{1,1} & w_{1,2} & w_{1,3} \\ w_{1,4} & w_{1,5} & w_{1,6} \\ w_{1,7} & w_{1,8} & w_{1,9} \\ w_{1,10} & w_{1,11} & w_{1,12} \end{bmatrix}$$

III- Multilayer perceptrons (1980's)

Mathematics behind a Multilayer perceptron :

1- Multiply the input by the weights $\boldsymbol{s} = \boldsymbol{W}\boldsymbol{x} + \boldsymbol{b}$

$$\boldsymbol{s} = \begin{bmatrix} w_{1,1} & w_{1,2} & w_{1,3} \\ w_{1,4} & w_{1,5} & w_{1,6} \\ w_{1,7} & w_{1,8} & w_{1,9} \\ w_{1,10} & w_{1,11} & w_{1,12} \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix} + \begin{bmatrix} b_1 \\ b_2 \\ b_3 \end{bmatrix} = \begin{bmatrix} w_{1,1}x_1 + w_{1,2}x_2 + w_{1,3}x_3 + b_1 \\ w_{1,4}x_1 + w_{1,5}x_2 + w_{1,6}x_3 + b_2 \\ w_{1,7}x_1 + w_{1,8}x_2 + w_{1,9}x_3 + b_3 \\ w_{1,10}x_1 + w_{1,11}x_2 + w_{1,12}x_3 + b_4 \end{bmatrix}$$

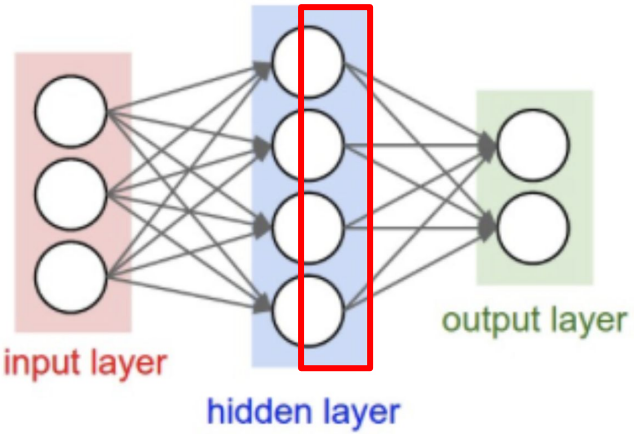


III- Multilayer perceptrons (1980's)

Mathematics behind a Multilayer perceptron :

1- Multiply the input by the weights $\boldsymbol{s} = \boldsymbol{W}\boldsymbol{x} + \boldsymbol{b}$

2- Apply non-linearity function $\begin{bmatrix} x_{11} \\ x_{12} \\ x_{13} \\ x_{14} \end{bmatrix} = f(\boldsymbol{s})$



III- Multilayer perceptrons (1980's)

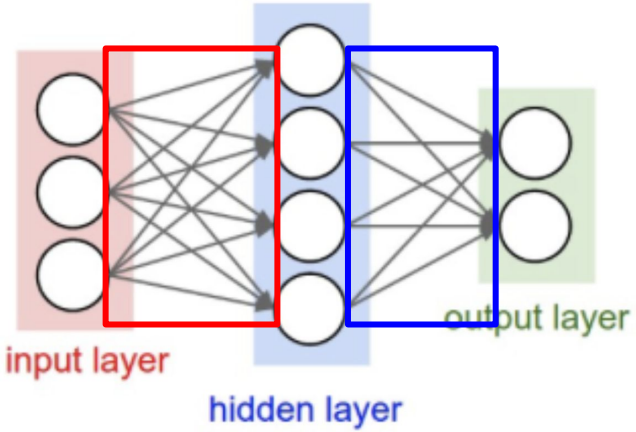
Mathematics behind a Multilayer perceptron :

1- Multiply the input by the weights $$\boldsymbol{s} = \boldsymbol{W}\boldsymbol{x} + \boldsymbol{b}$$

2- Apply non-linearity function $$\begin{bmatrix} x_{11} \\ x_{12} \\ x_{13} \\ x_{14} \end{bmatrix} = f(\boldsymbol{s})$$

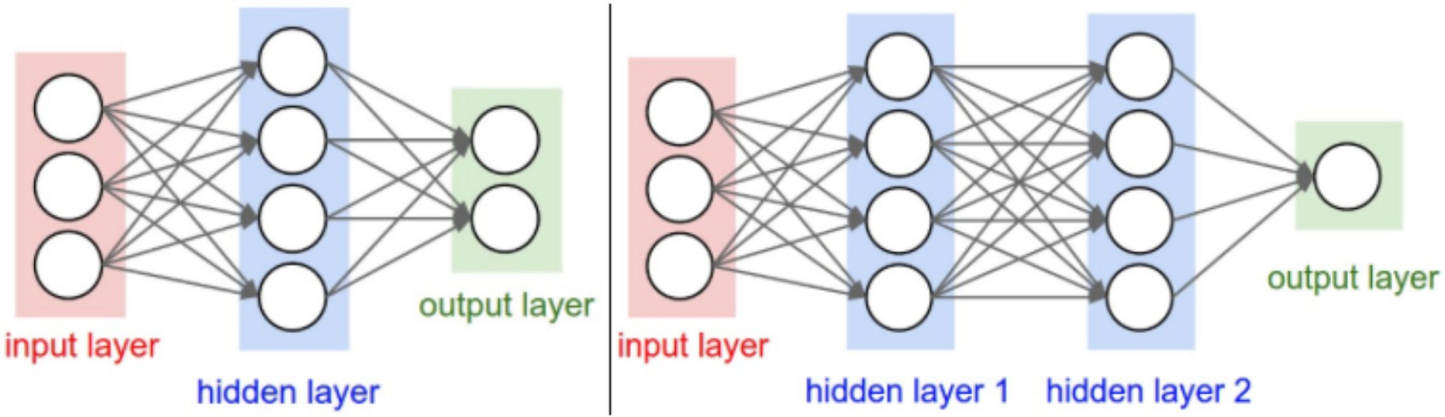
3- Do it for all the layers :

$$\hat{\boldsymbol{y}} = f(\boldsymbol{W_2} f(\boldsymbol{W_1}\boldsymbol{x_1} + \boldsymbol{b_1}) + \boldsymbol{b_2}$$



III- Multilayer perceptrons (1980's)

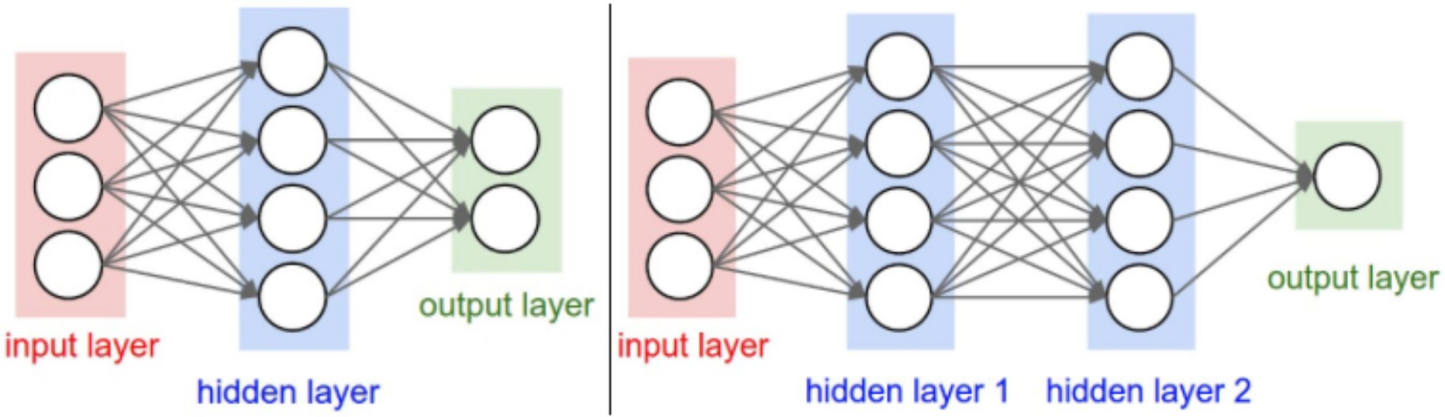
Can add more layers to increase capacity of the network



- <u>New problem:</u> MLPs are hard to train!

III- Multilayer perceptrons (1980's)

Can add more layers to increase capacity of the network



- New problem: MLPs are hard to train!

⇒ Solution: The **Backpropagation** algorithm

IV- Neural Network learning as optimization

Learning representations by back-propagating errors

David E. Rumelhart*, Geoffrey E. Hinton† & Ronald J. Williams*

* Institute for Cognitive Science, C-015, University of California, San Diego, La Jolla, California 92093, USA
† Department of Computer Science, Carnegie-Mellon University, Pittsburgh, Philadelphia 15213, USA

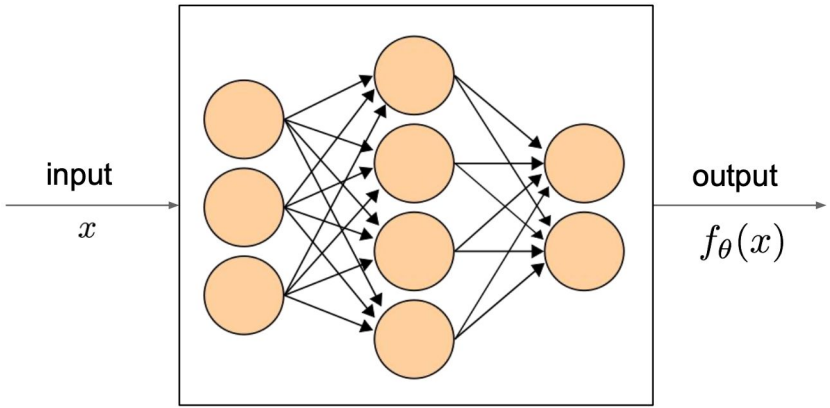
We describe a new learning procedure, back-propagation, for networks of neurone-like units. The procedure repeatedly adjusts the weights of the connections in the network so as to minimize a measure of the difference between the actual output vector of the net and the desired output vector. As a result of the weight adjustments, internal 'hidden' units which are not part of the input or output come to represent important features of the task domain, and the regularities in the task are captured by the interactions of these units. The ability to create useful new features distinguishes back-propagation from earlier, simpler methods such as the perceptron-convergence procedure[1].

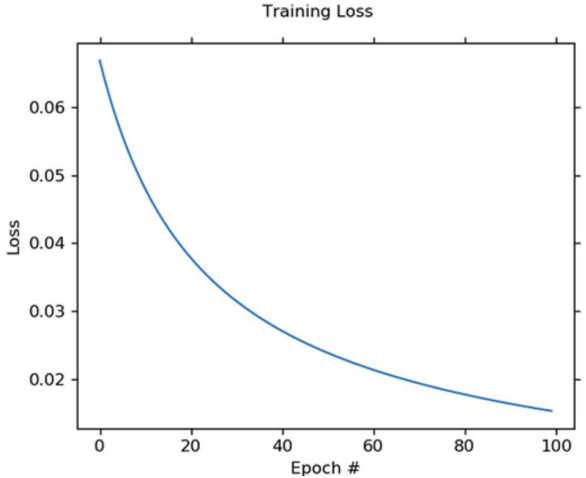
Rumelhart, Hinton, and Williams (1986) introduced Backpropagation to train MLPs

Principle: Computing the gradient of the cost function w.r.t the weights of the network

IV- Neural Network learning as optimization

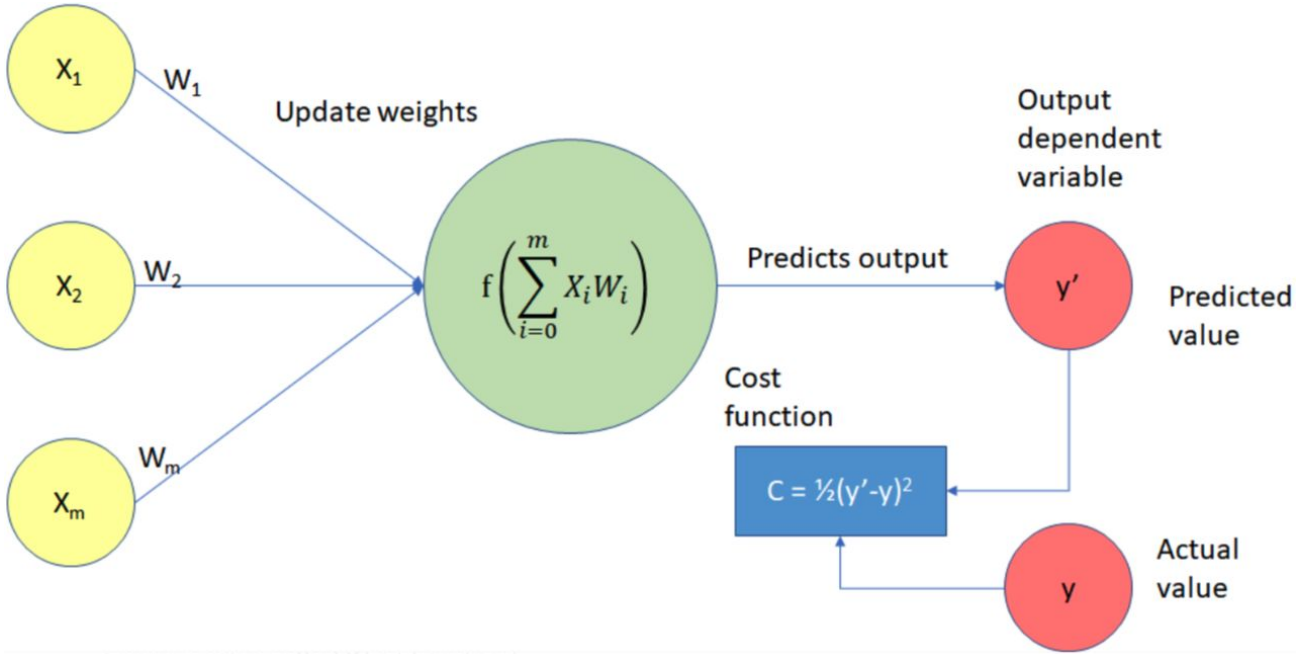
- Mapping a set of inputs to a set of outputs from training data
- Learning is cast as an **optimization** problem to make good enough predictions
- Training with **gradient descent**





IV.A - Cost functions (Statistics / Probability)

- A **cost function** is a measure of error between predictions and true values



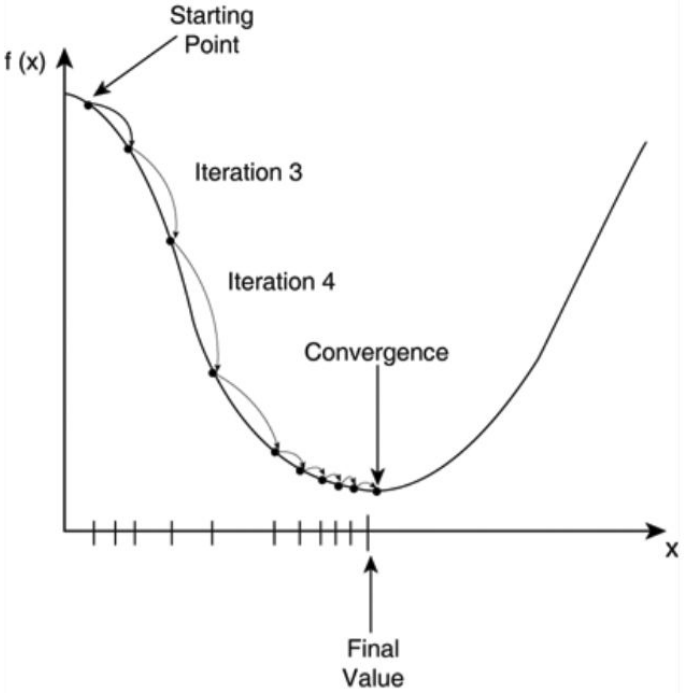
IV.A - Cost functions (Statistics / Probability)

- A **cost function** is a measure of error between predictions and true values
- Guides the training process to find a set of weights that minimizes its value

Some examples:

$$\text{MAE} = \underbrace{\frac{1}{n}}_{\text{test set}} \sum_{i=1}^{n} \underbrace{|y_i}_{\text{predicted vaue}} - \underbrace{\hat{y}_i|}_{\text{actual value}}$$

$$\text{MSE} = \underbrace{\frac{1}{n}}_{\text{test set}} \sum_{i=1}^{n} \underbrace{(y_i}_{\text{predicted vaue}} - \underbrace{\hat{y}_i)^2}_{\text{actual value}}$$



Recall Gradient (Optimization)

$$f'(x) = \lim_{h \to 0} \frac{f(x+h) - f(x)}{h}$$

The **derivative** shows the sensitivity of change of a function's output with respect to the input.
It can be seen as the slope of the function at a point.

In our case :

- The function is the error computed at the end of the Neural Network.
- We want to see how the error is impact by each parameter of the model →higher dimension than 1

Solution : use the **gradient**

Gradient of a function f at point a with $f : \mathbb{R}^3 \longrightarrow \mathbb{R}$

$$\nabla f(a) = \begin{bmatrix} \frac{\partial f}{\partial x}(a) \\ \frac{\partial f}{\partial y}(a) \\ \frac{\partial f}{\partial z}(a) \end{bmatrix}$$

Recall Gradient (Optimization)

Example :

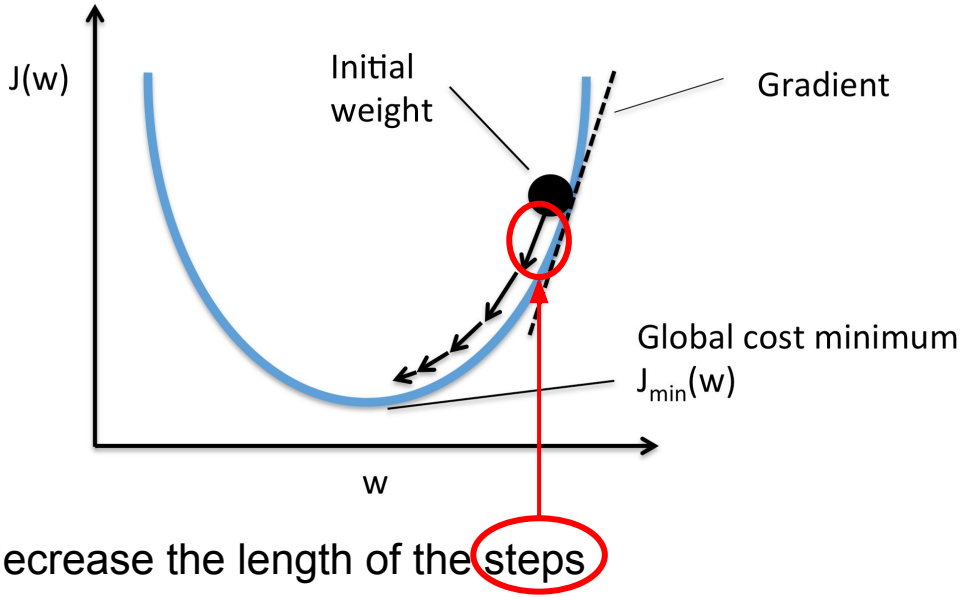
$$f(x,y,z) = x^2 + y * z \longrightarrow \nabla f = \begin{bmatrix} \frac{\partial f}{\partial x} \\ \frac{\partial f}{\partial y} \\ \frac{\partial f}{\partial z} \end{bmatrix} = \begin{bmatrix} 2x \\ z \\ y \end{bmatrix}$$

- We obtain the slope of the function f in each direction (x, y, z)
- The direction will be replaced by each parameter of the model (w and b)

IV.B- Gradient Descent (Optimization)

- Find the minimum of the cost function *C*
- The Negative gradient : $-\nabla C$ points in the direction where the function decreases most rapidly
- Calculate new weights: $W^+ = W - \eta \nabla C$

$$\begin{bmatrix} w_1^+ \\ w_2^+ \\ \vdots \\ w_n^+ \end{bmatrix} = \begin{bmatrix} w_1 \\ w_2 \\ \vdots \\ w_n \end{bmatrix} - \eta \begin{bmatrix} \frac{\partial C}{\partial w_1} \\ \frac{\partial C}{\partial w_2} \\ \vdots \\ \frac{\partial C}{\partial w_n} \end{bmatrix}$$



- η is called the learning rate : increase or decrease the length of the steps

IV.B- Gradient Descent (Optimization)

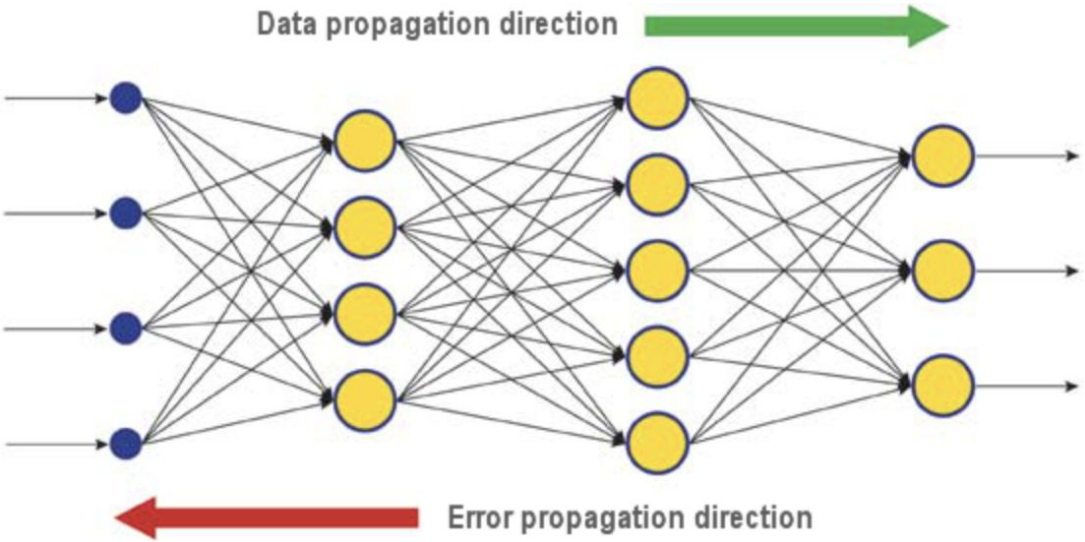
- Find the minimum of the cost function *C*
- The Negative gradient : $-\nabla C$ points in the direction where the function decreases most rapidly
- Calculate new weights: $W^+ = W - \eta \nabla C$

Gradient descent algorithm

$$\text{repeat until convergence } \{$$
$$\theta_j := \theta_j - \alpha \frac{\partial}{\partial \theta_j} J(\theta_0, \theta_1)$$
$$(\text{for } j = 1 \text{ and } j = 0)$$
$$\}$$

IV.C- Backpropagation (Optimization)

- **Minimization** through **gradient descent** requires computing the gradient
- **Backpropagation**: way to compute the gradient by applying the **chain rule**



Recall (Optimization)

Chain rule :

$$\frac{d}{dx}[f(g(x))] = f'(g(x))g'(x)$$

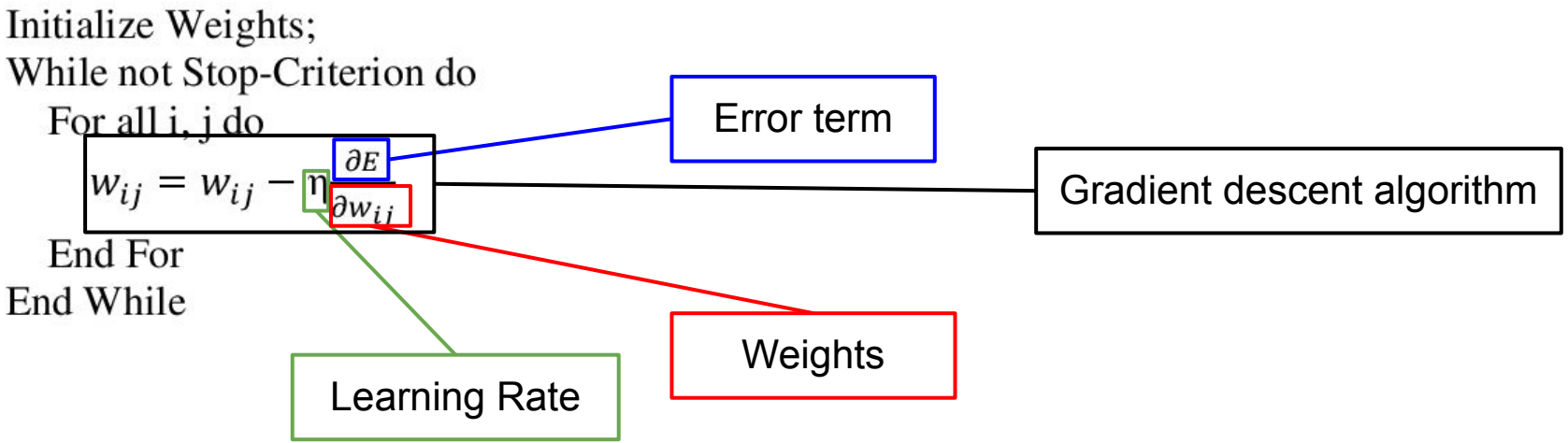
Example :

$$F(x) = f(g(x)) = \frac{1}{x^2}$$

$$F'(x) = f'(g(x))g'(x) = -\frac{1}{(x^2)^2} \cdot 2x = -\frac{2}{x^3}$$

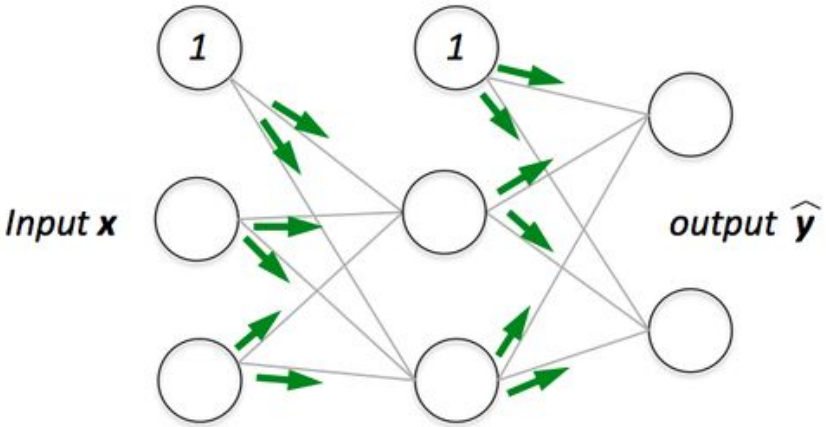
IV.C- Backpropagation (Optimization)

Backpropagation Algorithm :



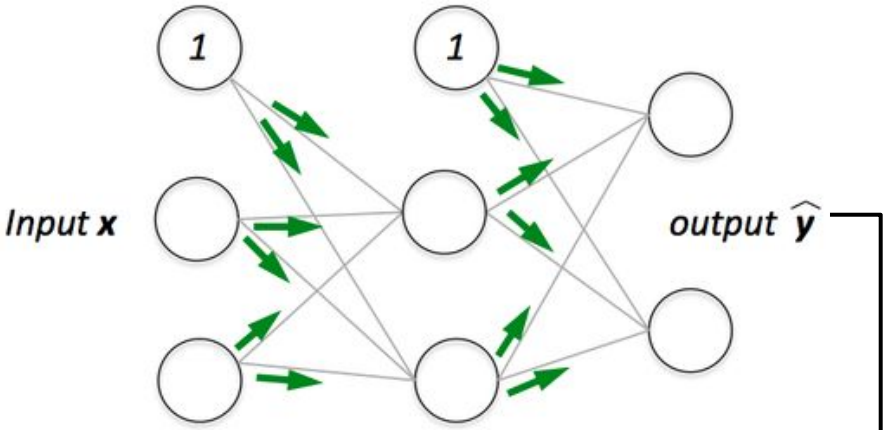
IV.C- Backpropagation (Optimization)

1) **Forward pass**: propagate data through the network to get predictions



IV.C- Backpropagation (Optimization)

1) **Forward pass**: propagate data through the network to get predictions
2) Calculate the total error with respect to the desired outputs



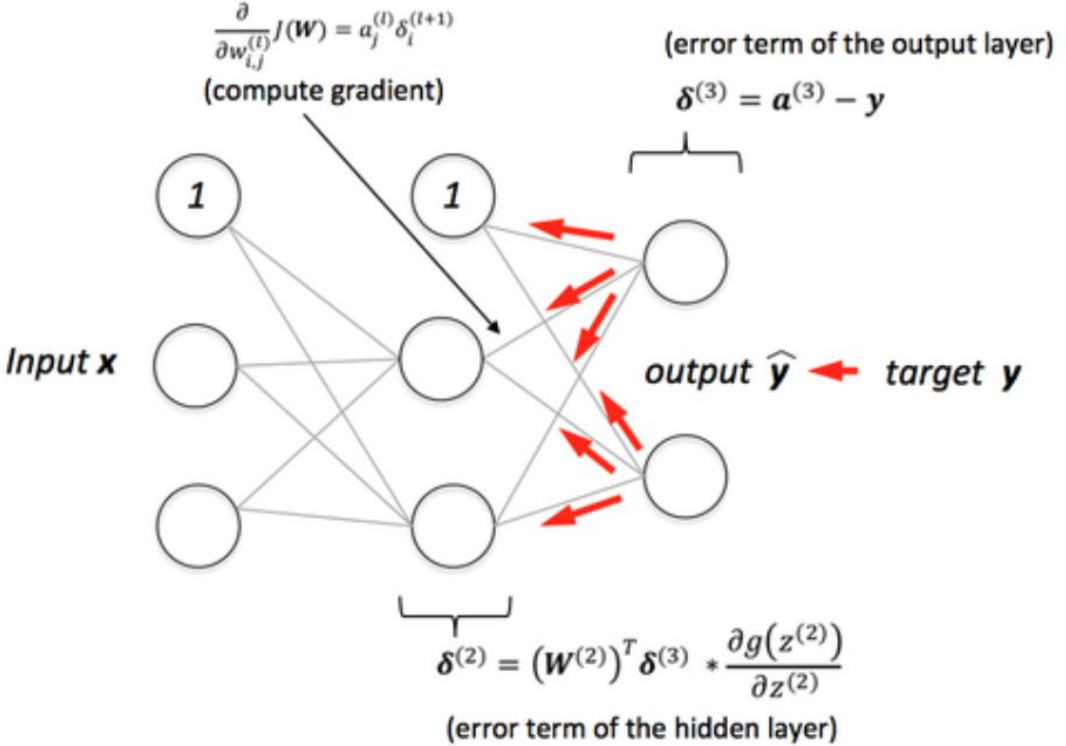
$$E = C(y, \hat{y})$$

IV.C- Backpropagation (Optimization)

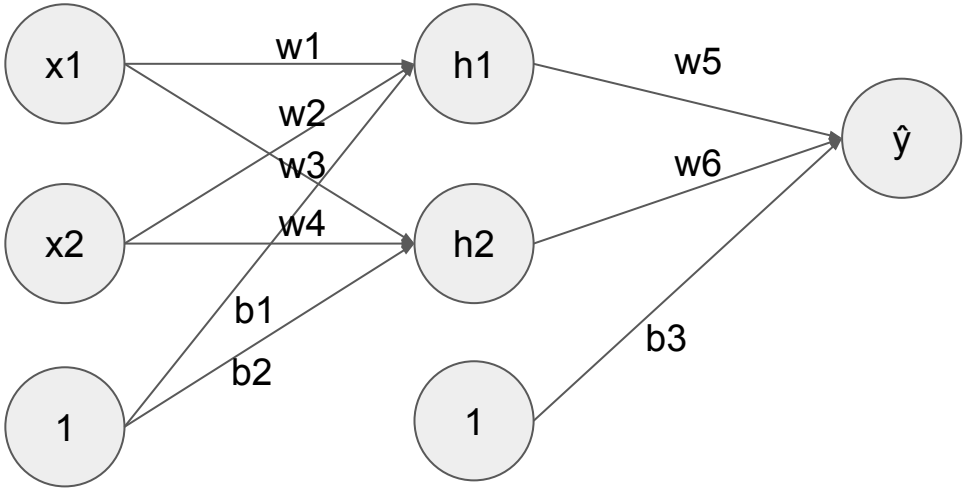
1) **Forward pass**: propagate data through the network to get predictions
2) Calculate the total error w.r.t desired outputs
3) **Backward pass**:

   a) Compute partial derivatives of the error w.r.t each weight $\frac{\mathrm{d}E}{\mathrm{d}w_{ij}}$ by applying the **chain rule**

   b) Update weights:
   $$w_i = w_i - \eta \frac{\mathrm{d}E}{\mathrm{d}w_{ij}}$$

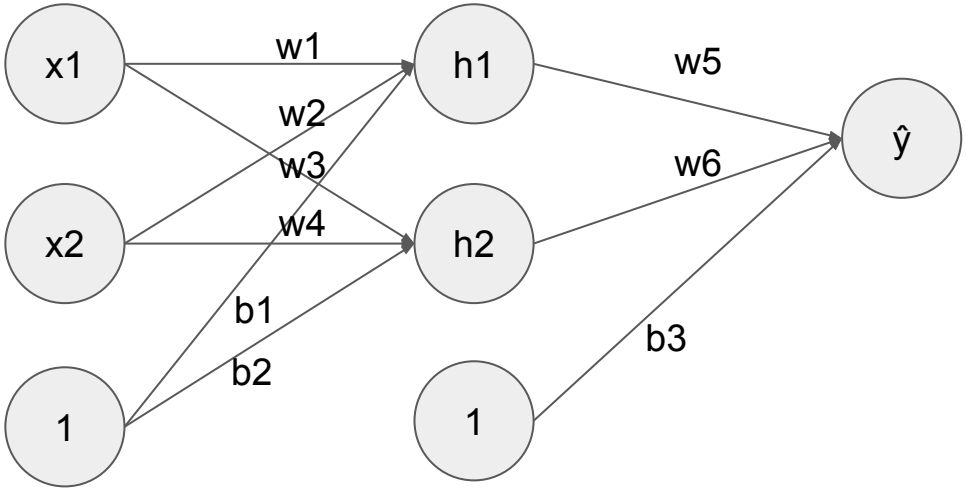


IV.C- Backpropagation (Optimization)



1- Compute error term : $E = (\hat{y} - y)^2$

IV.C- Backpropagation (Optimization)

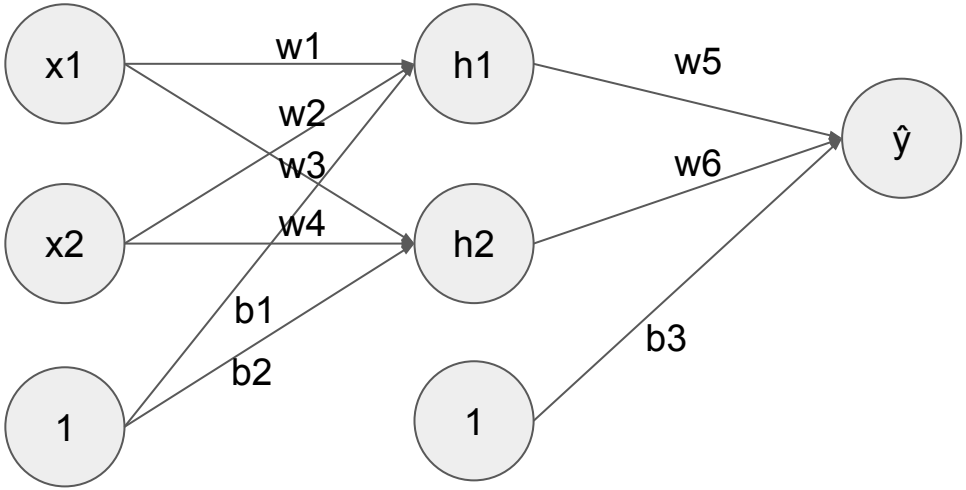


1- Compute error term : $E = (\hat{y} - y)^2$

2- Update weight : $w_5 = w_5 - \eta \frac{dE}{dw_5}$

Error term : $E = (f(w_5 f(w_1 x_1 + w_2 x_2 + b1) + w_6 f(w_3 x_1 + w_4 x_2 + b_2) + b_3) - y)^2$

IV.C- Backpropagation (Optimization)



1- Compute error term : $E = (\hat{y} - y)^2$

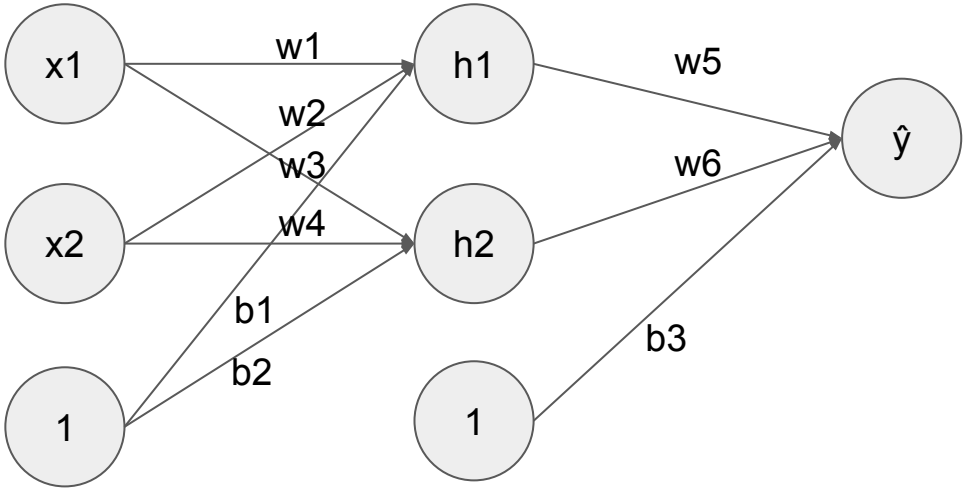
2- Update weight : $w_5 = w_5 - \eta \frac{dE}{dw_5}$

Error term : $E = (f(w_5 f(w_1 x_1 + w_2 x_2 + b1) + w_6 f(w_3 x_1 + w_4 x_2 + b_2) + b_3) - y)^2$

chain rule : $\frac{dE}{dw_5} = \frac{dE}{d\hat{y}} \cdot \frac{d\hat{y}}{ds} \cdot \frac{ds}{dw_5}$ with : $s = w_5 h_1 + w_6 h_2 + b_3$

$$\frac{dE}{dw_5} = 2(\hat{y} - y).\, f'(w_5 h_1 + w_6 h_2 + b_3).\, f(w_1 x_1 + w_2 x_2 + b_1)$$

IV.C- Backpropagation (Optimization)



1- Compute error term : $E = (\hat{y} - y)^2$

2- Update weight : $w_1 = w_1 - \eta \frac{dE}{dw_1}$

chain rule : $\frac{dE}{dw_1} = \frac{dE}{dh_1} \cdot \frac{dh_1}{ds_1} \cdot \frac{ds_1}{dw_1}$

$$\frac{dE}{dw_1} = \frac{dE}{d\hat{y}} \cdot \frac{d\hat{y}}{ds_3} \cdot \frac{ds_3}{dh_1} \cdot \frac{dh_1}{ds_1} \cdot \frac{ds_1}{dw_1}$$

$$\frac{dE}{dw_1} = 2(\hat{y} - y).\, f'(s_3).\, w_5 \cdot f'(s_1) \cdot x_1$$

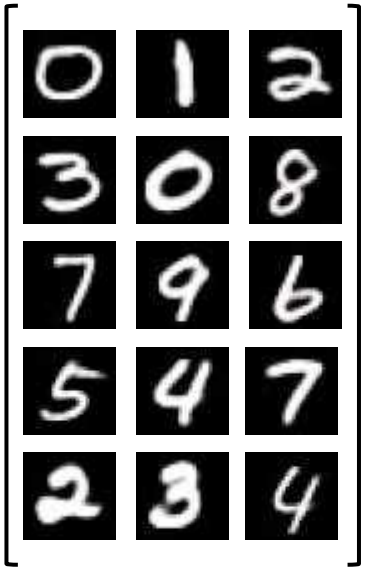
with : $s_3 = w_5 h_1 + w_6 h_2 + b_3$

$s_1 = w_1 x_1 + w_2 x_2 + b_1$

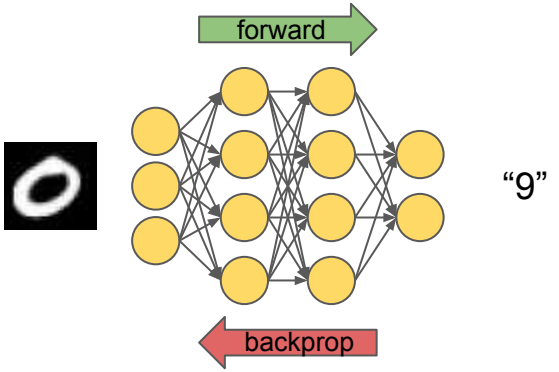
IV.D- Batches

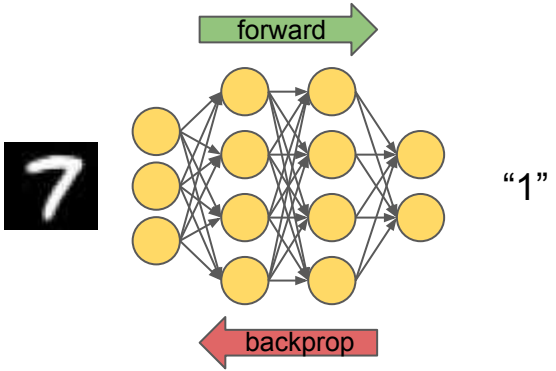
Compute Forward + Backprop for each data point : **Stochastic Gradient Descent**

- Bad idea

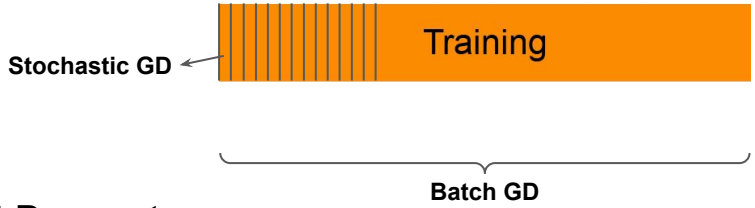


Dataset



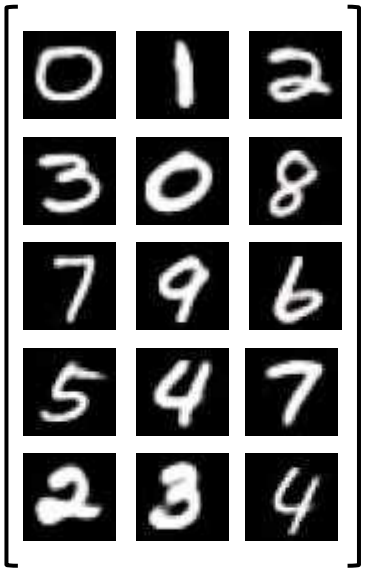


IV.D- Batches

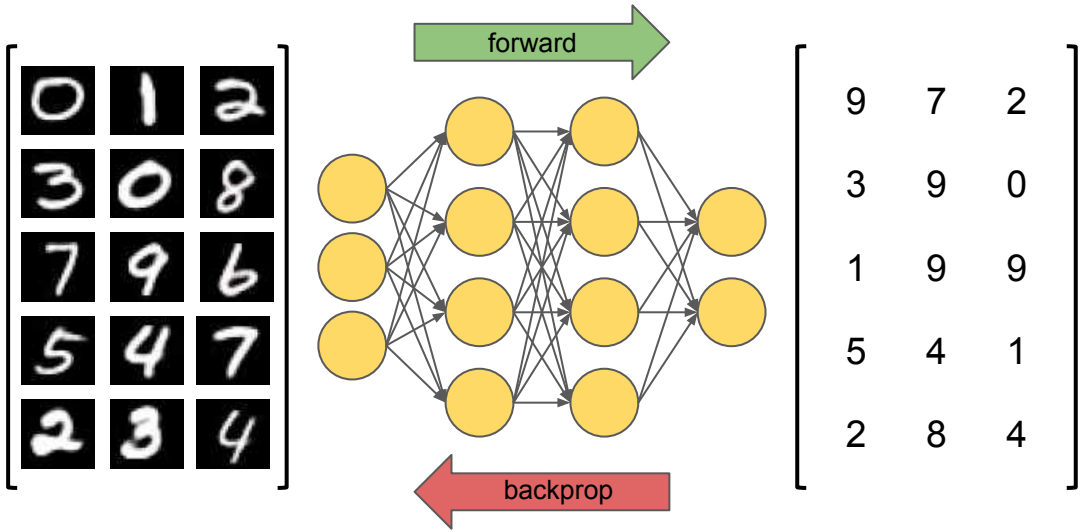


Compute Forward + Backprop for all dataset once : **Batch Gradient Descent**

- Not Feasible



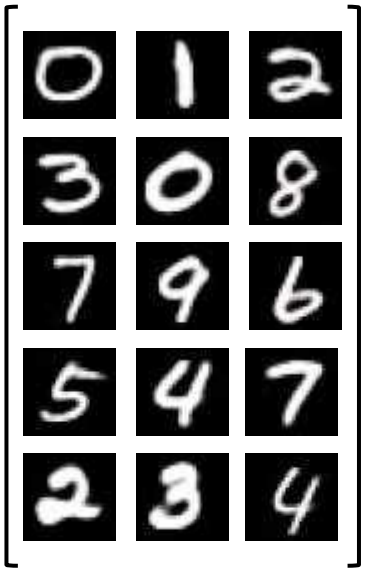
Dataset



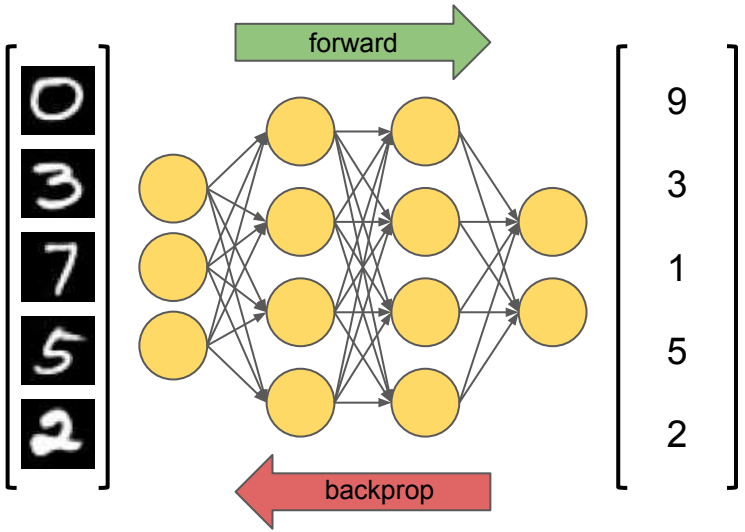
IV.D- Batches

Compute Forward + Backprop for a part (**Batch**) of the dataset : **Mini-Batch Gradient Descent**

- Good idea

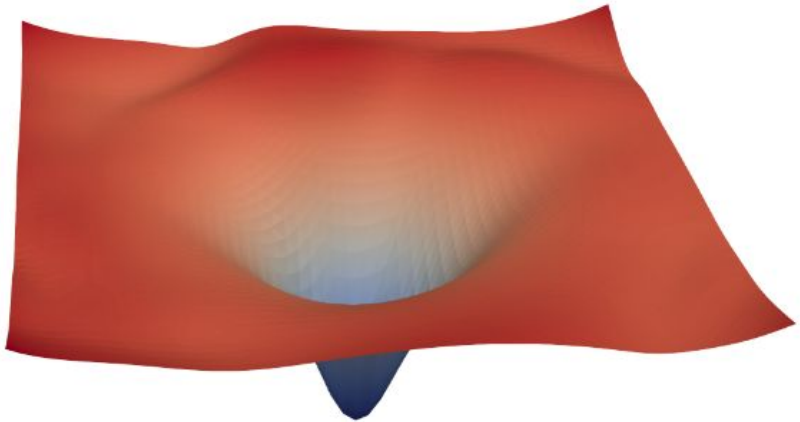


Dataset

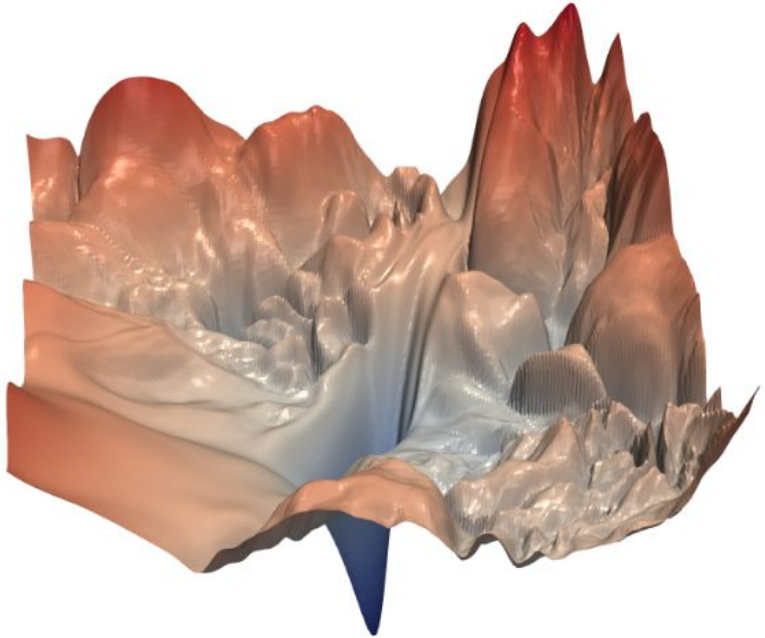


Training with Gradient descent and BP (Optimization)

Local VS global minimum



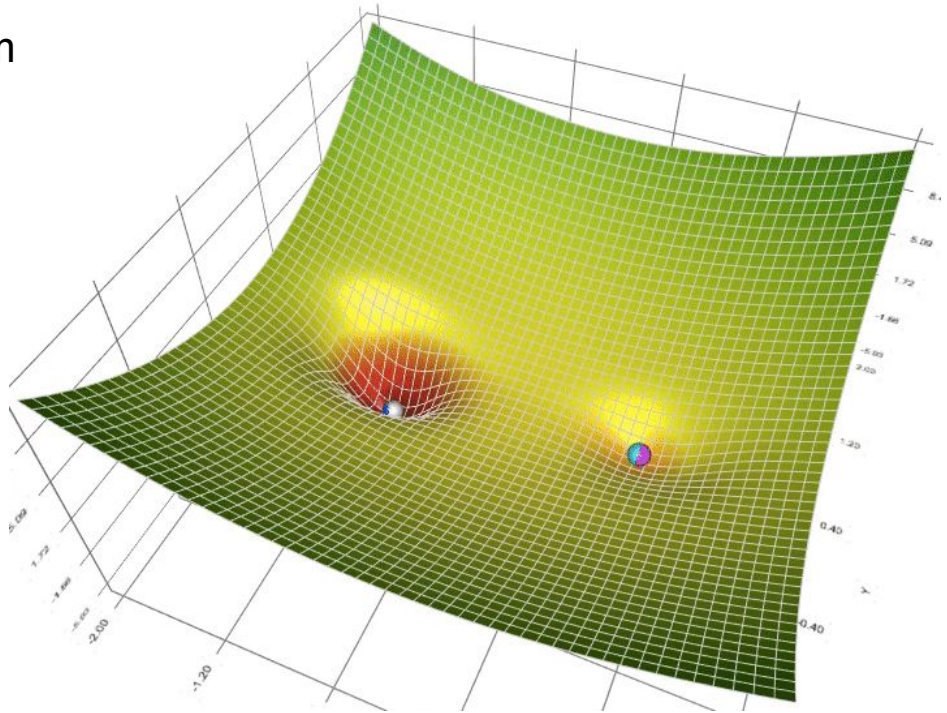
One global minimum



One global minimum & Multiple local minimum

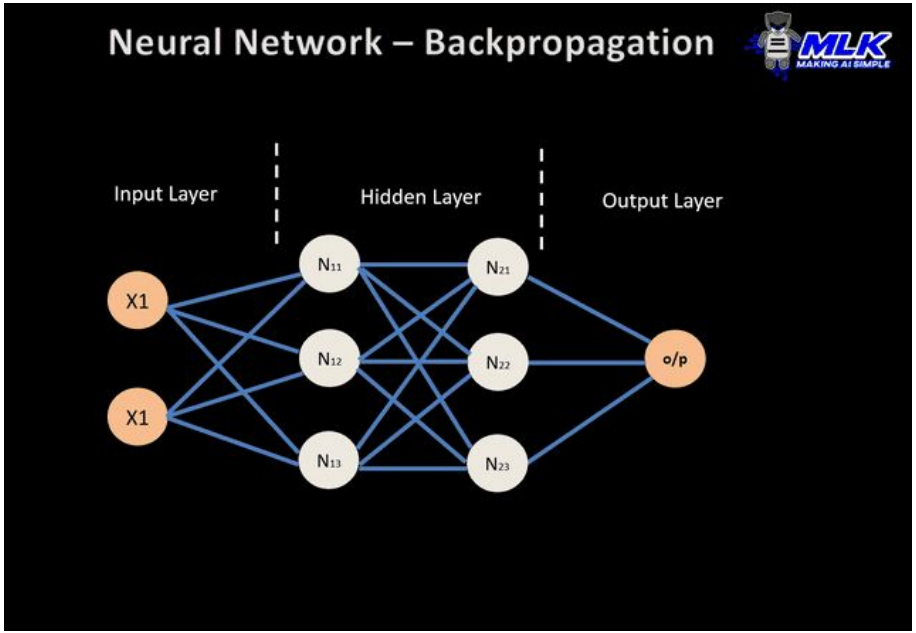
Training with Gradient descent and BP (Optimization)

Local VS global minimum



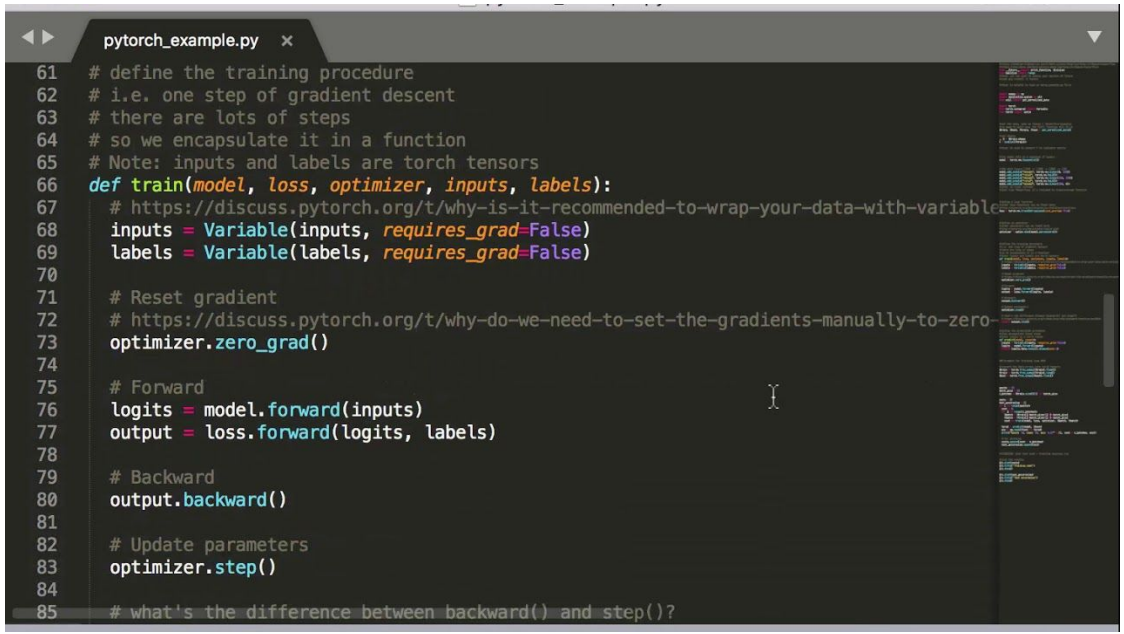
Depending on initialization the results can end up in a local or global minimum

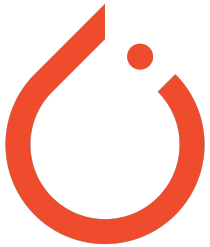
Training with Gradient descent and BP (Optimization)



Coding skills

Not so much





Some useful resources

http://neuralnetworksanddeeplearning.com/chap1.html

https://towardsdatascience.com/part-2-gradient-descent-and-backpropagation-bf90932c066a

https://towardsdatascience.com/a-concise-history-of-neural-networks-2070655d3fec#.ekc89166m

https://people.idsia.ch//~juergen/who-invented-backpropagation.html

Part 2 : Implementation of a Neural Network

Training a neural network

Data

Data Samples and Labels

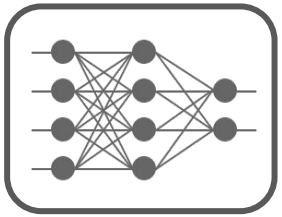
$\{(x_1, y_1), (x_2, y_2), ...\}$

Task

Input and output

$x_i \rightarrow y_i$

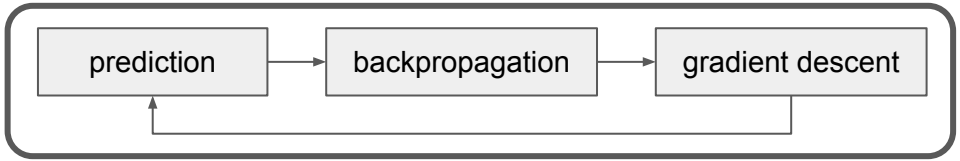
Architecture



Loss function

$loss = diff(prediction, label)$

Optimization



Training a neural network

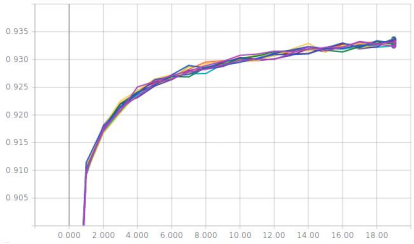
Data

Handwritten Digit Dataset

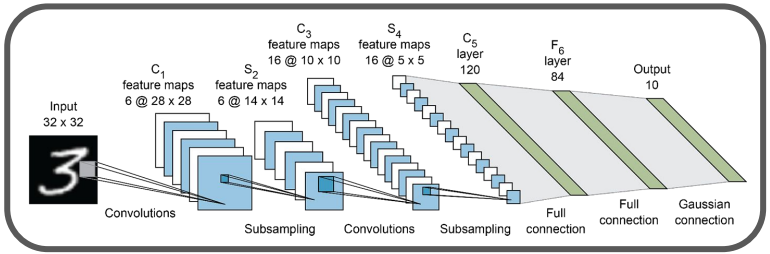
Task

0

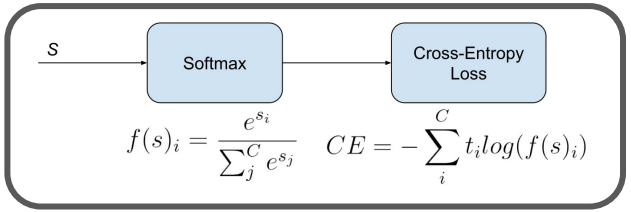
Digit Classification



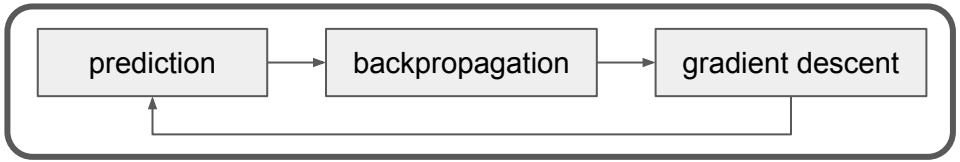
Architecture



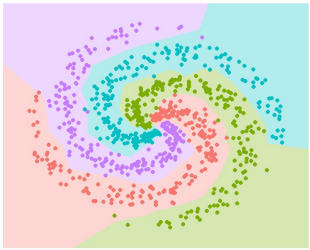
Loss function



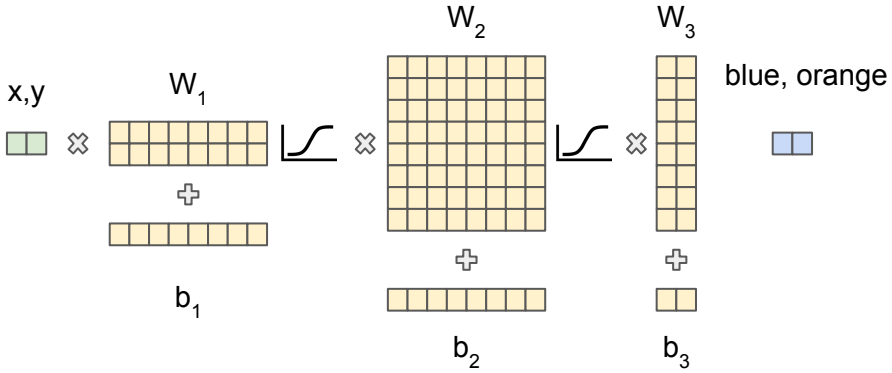
Optimization

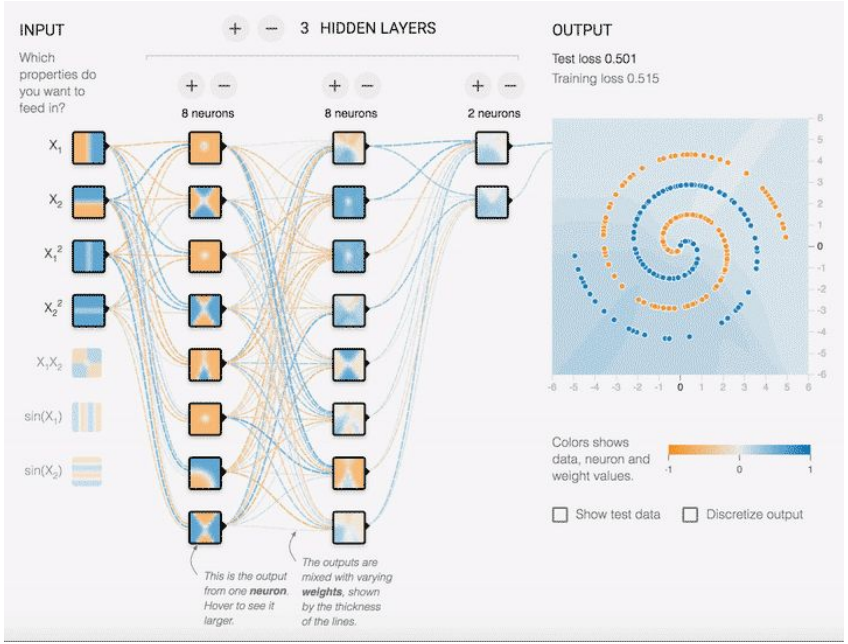


I- How to choose the architecture



Multi-layer perceptrons **MLPs** are <u>the standard solution</u> for data with simple structure (ex. tabular data).

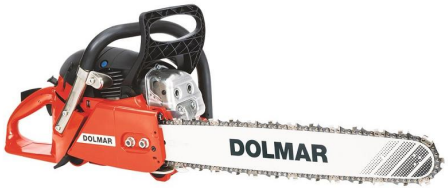


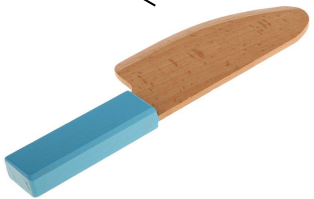


Source: playground.tensorflow.org

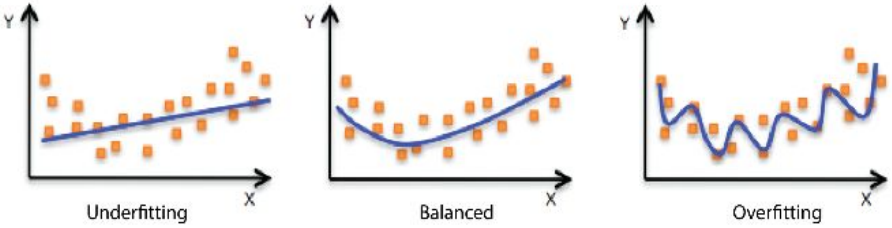
I- How to choose the architecture

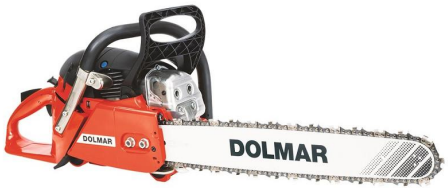
Tool ?





I- How to choose the architecture



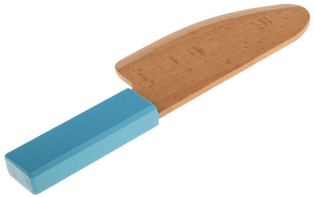


Model too complex :

- Overfitting →Very good at training but bad generalization
- Time and memory inefficient for training

Good model :

- Balanced →Good at training and generalize well
- Efficient time and memory for training



Model too simple :

- Underfitting →Bad on training and generalization
- Very efficient time and memory for training

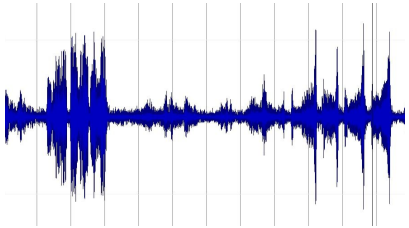
I- How to choose the architecture

Do MLPs work for all types of data ? Yes, but not efficiently

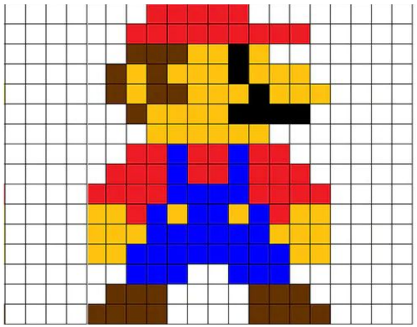
text

I am a student

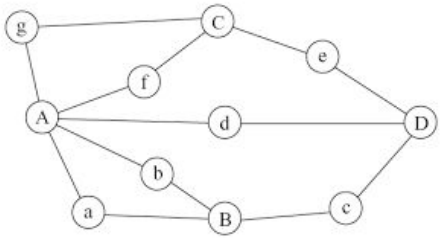
time sequences



images

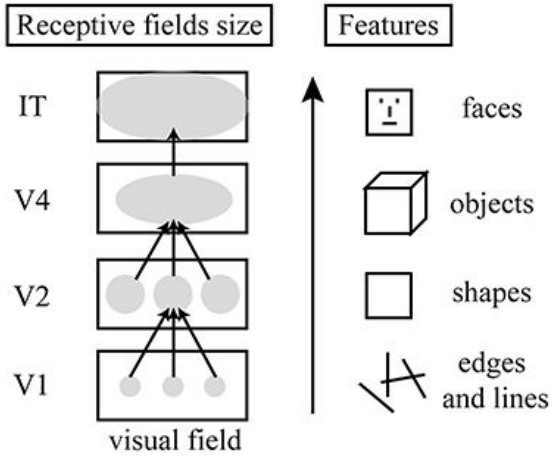


graphs



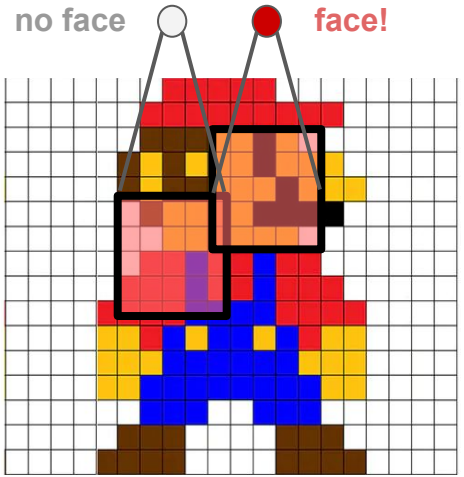
Inductive bias : an architectural assumption or constraint

I.A- Convolutional Neural Network (CNN)

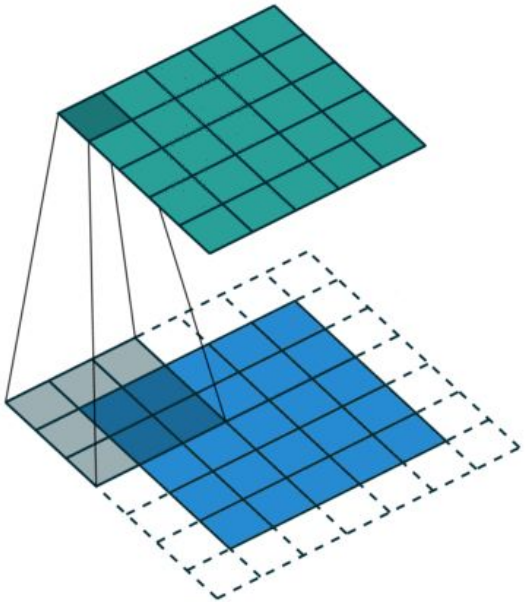


Local Connectivity

Hierarchical Processing

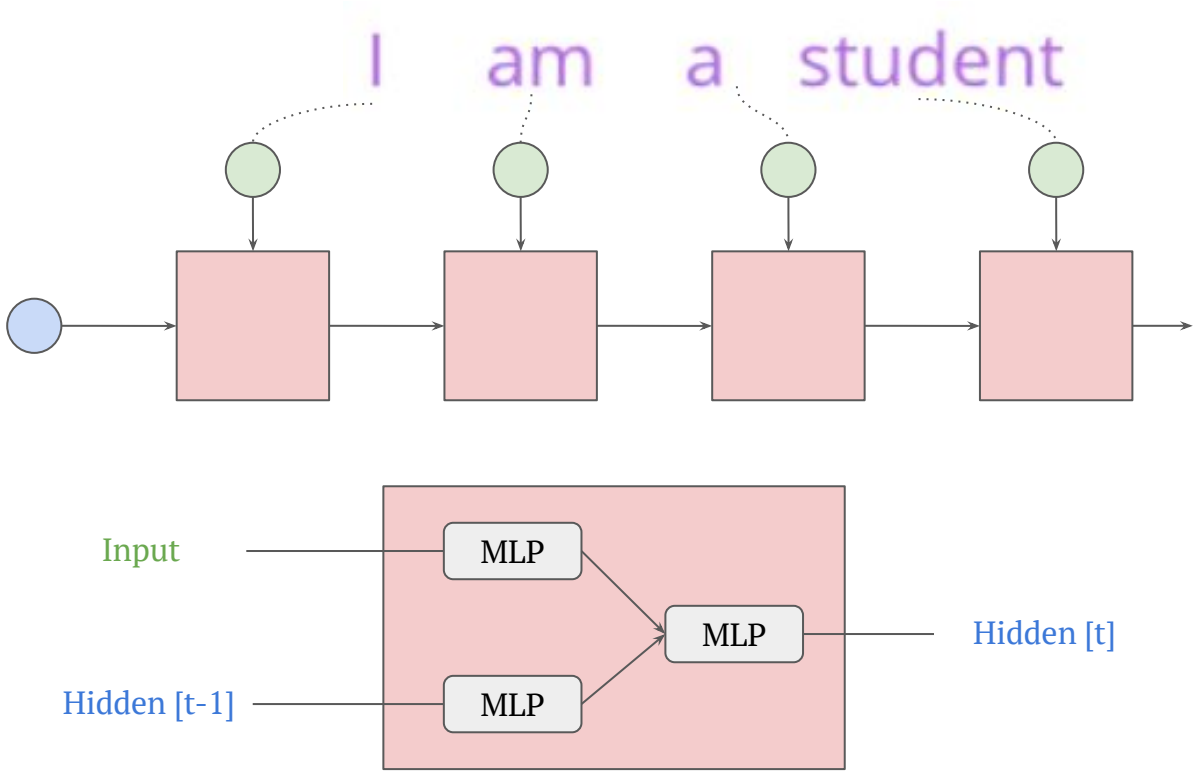


Weight sharing



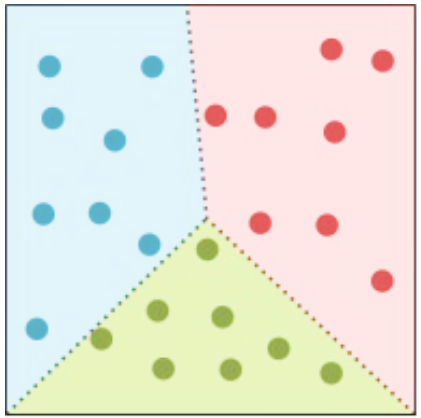
Convolution

I.B- Recurrent neural networks (RNN)



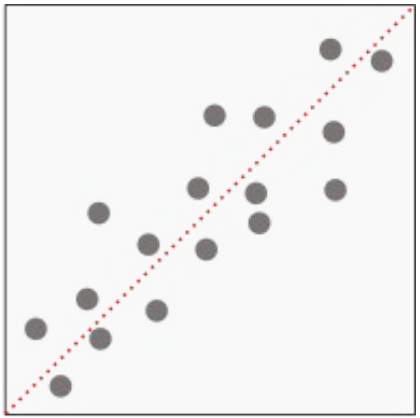
II- How to choose the loss

Two mains problems :



Classification

Cross Entropy
Hinge Loss



Regression

Mean Square Error
Mean Absolute Error

The choice of the **loss** is crucial !

What's important in the loss design?

- Adaptability to the problem
- Continuous and differentiable
- Numerically stable

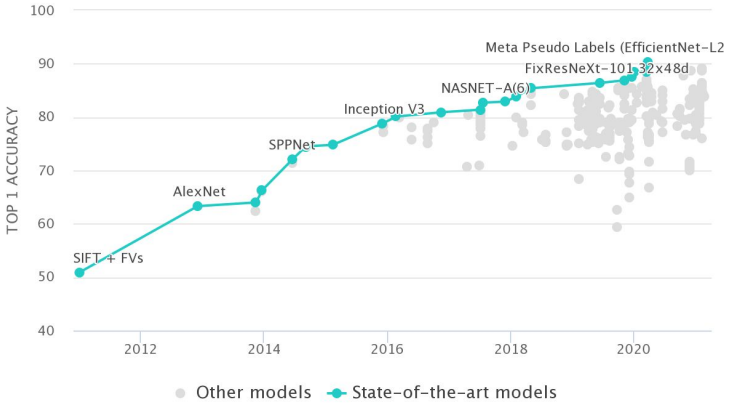
III - Training and Evaluation

Training: optimization of the model

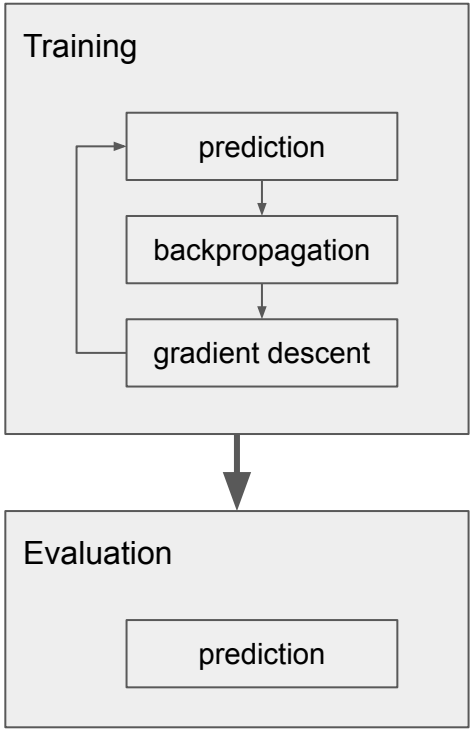
Evaluation: testing generalization

Metrics: Loss and accuracy

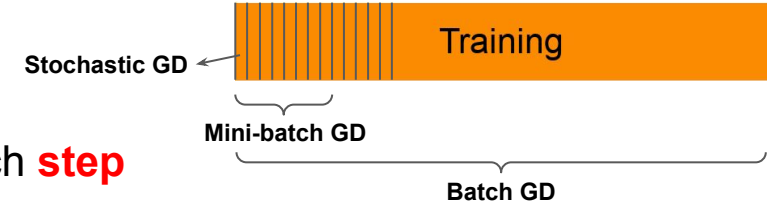
Models with the highest accuracy are state of the art (SOTA)



Imagenet Benchmark on paperswithcode.com

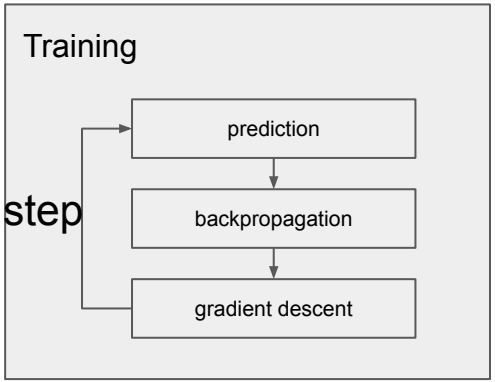


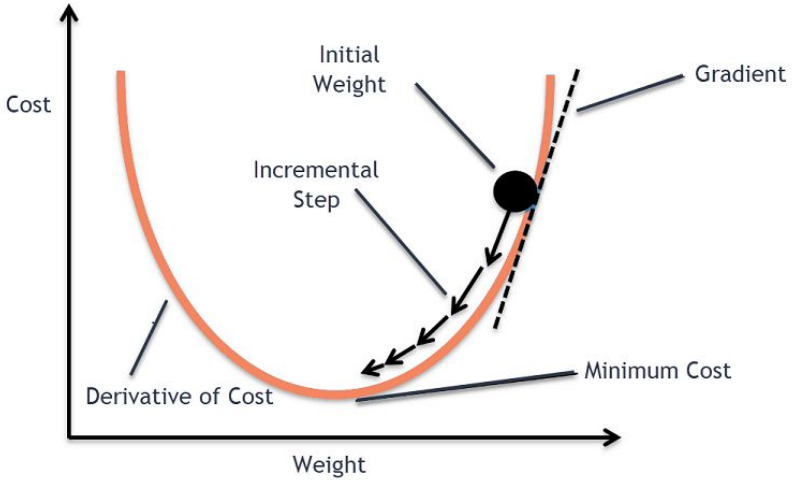
III - Training and Evaluation



SGD is compute on the **training set** at the end of each **step**

Epoch: one pass through the dataset

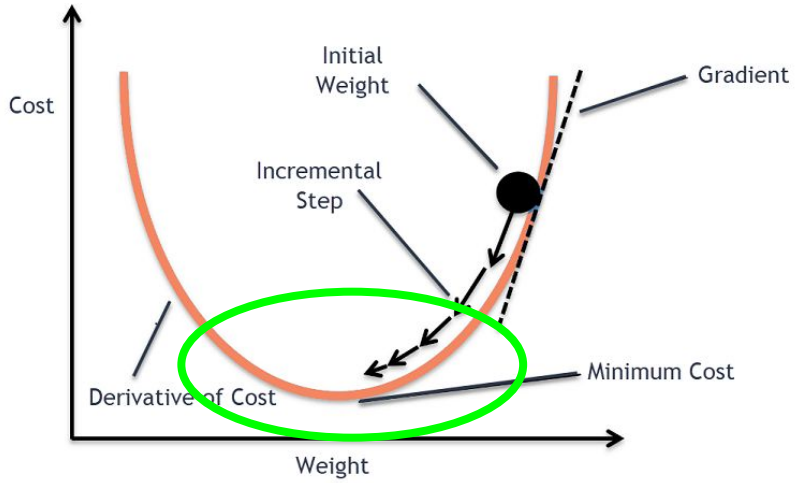




III - Training and Evaluation

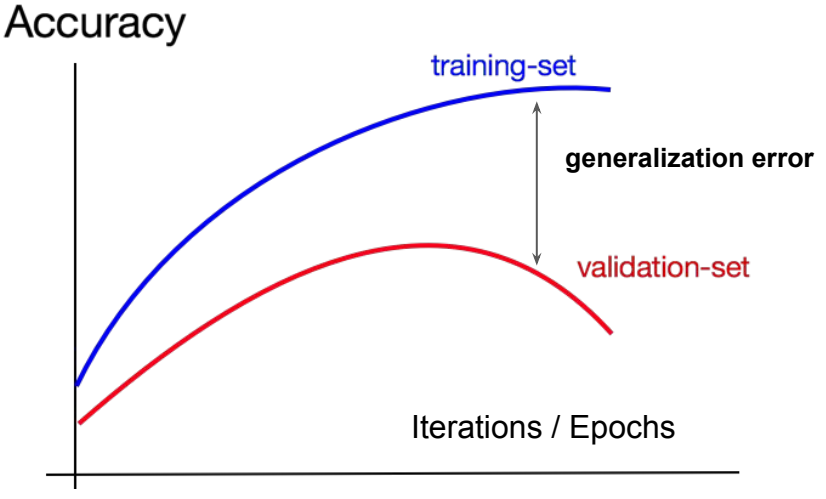
How do we know when to stop learning ?

When cost function reaches the minimum :
the model has **converged**

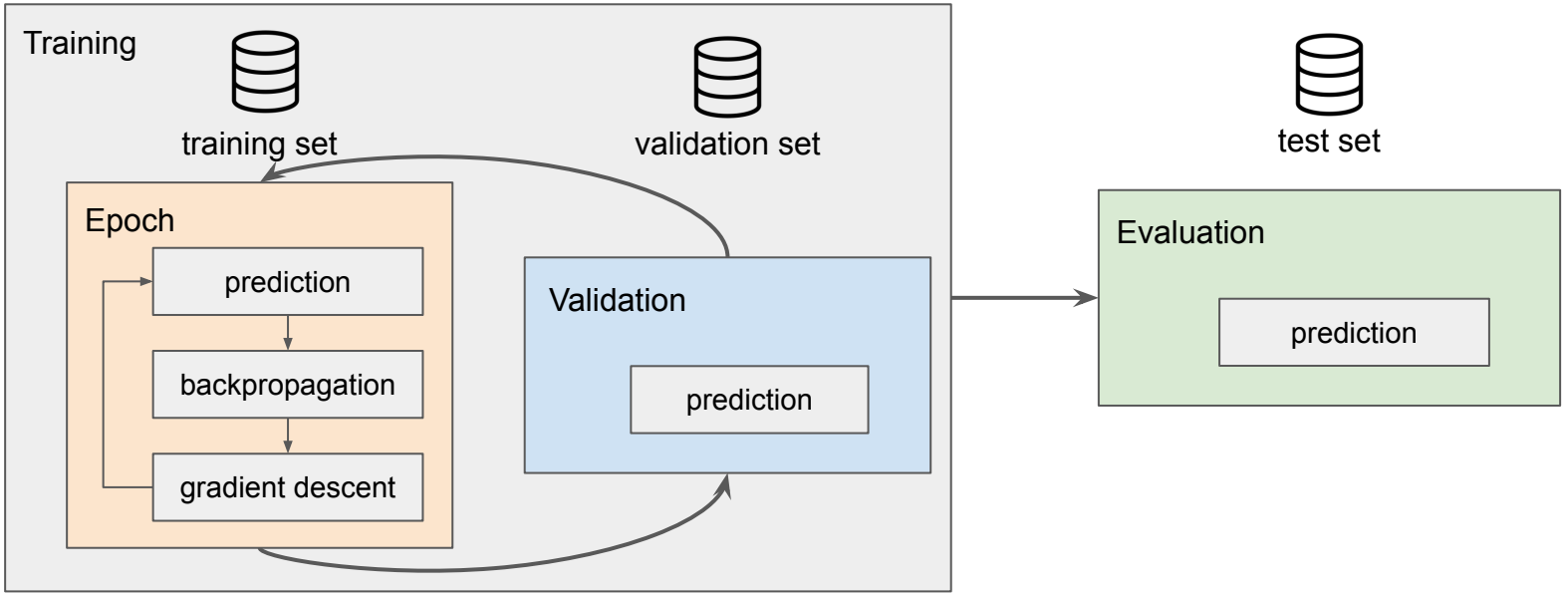


Model can **overfit** on training set

Stop the training when error on validation set reaches the minimum



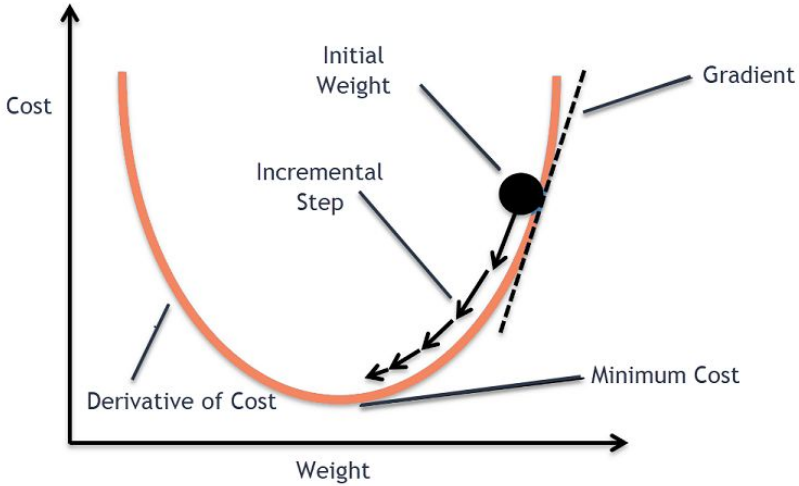
III - Training and Evaluation

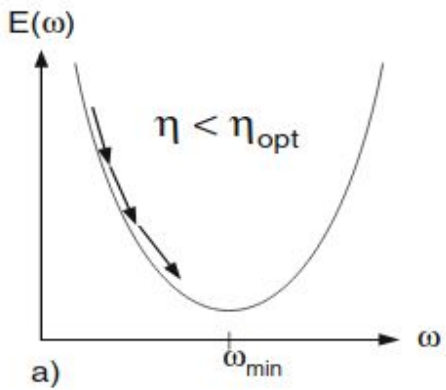


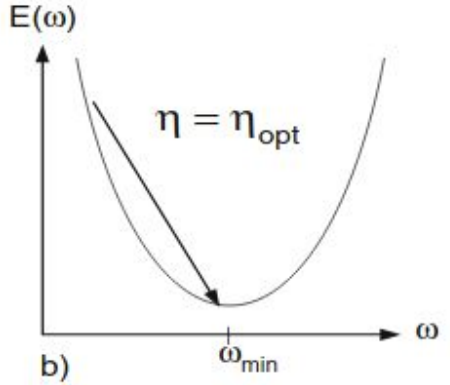
III - Training and Evaluation

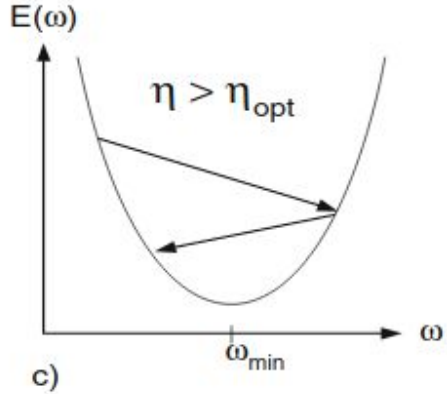
How to find the **learning rate** ? η

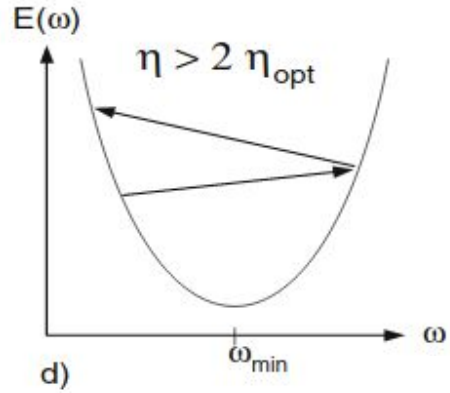
$$\theta \leftarrow \theta - \eta \frac{\partial \mathcal{L}}{\partial \theta}$$





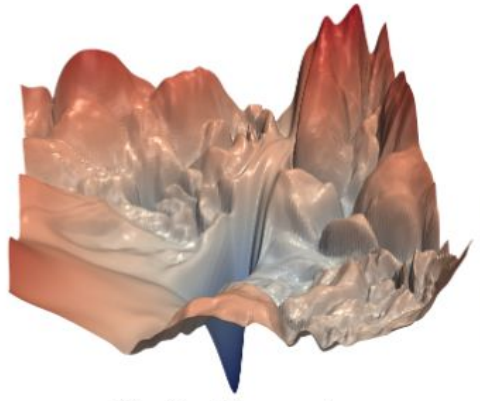






IV- Optimizers

$$\theta \leftarrow \theta - \eta \frac{\partial \mathcal{L}}{\partial \theta}$$



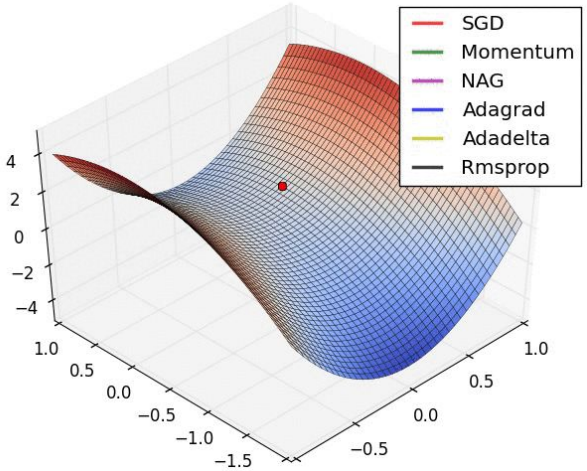
Loss landscapes are not easy to navigate for optimizers

Ideas:

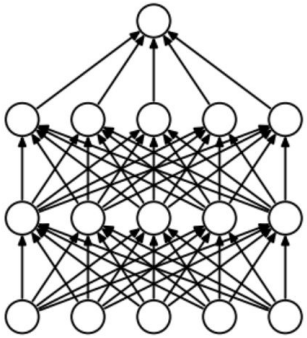
- Use the gradient history of previous timesteps to inform GD in future timesteps
- Adapt the learning rate to each parameter

This is a 2 parameter example!
Imagine millions

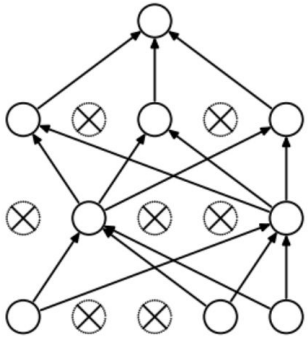
Adam optimizer is an extension of SGD which makes use of these two ideas. It is currently the most used optimizer in DL after SGD.



V- Regularization



(a) Standard Neural Net



(b) After applying dropout.

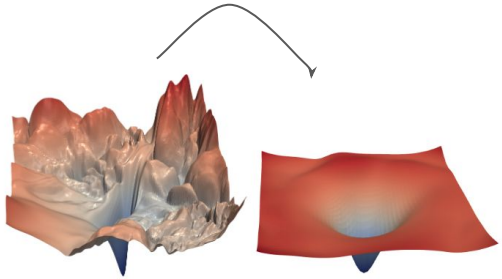
Additional constraints to reduce overfitting

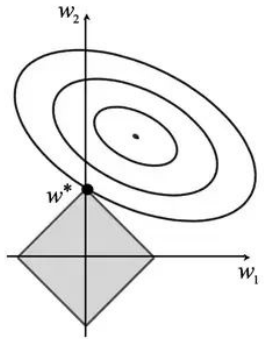
Dropout: stochastically dropping weights during inference

Early stopping: stopping the training as soon as the validation loss starts increasing

Weight penalties (weight decay): L1 norm (Lasso) / L2 norm (ridge). Terms added to the loss.

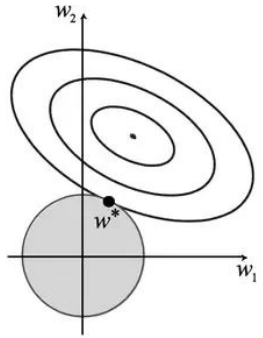
Data augmentations: artificially boosting the number of training samples





L1

Sparse weights



L2

Smaller weight values

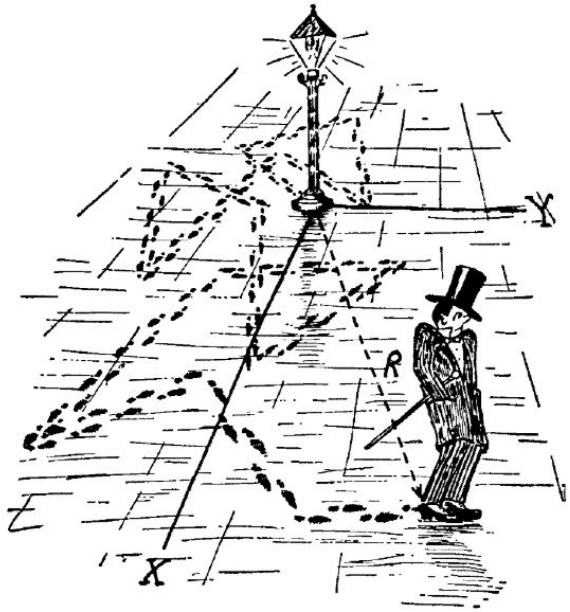
VI- Hyperparameters

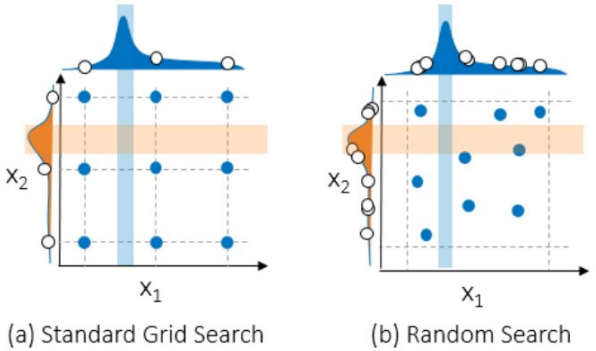
All parameters and settings that are set before training:

- Architectural choices: types and number of layers, size of each layer
- Losses/regularization: weights, additional constants
- Optimization: batch size, learning rate, iterations/epochs, schedule

Hyperparameter search. Another optimization problem ?

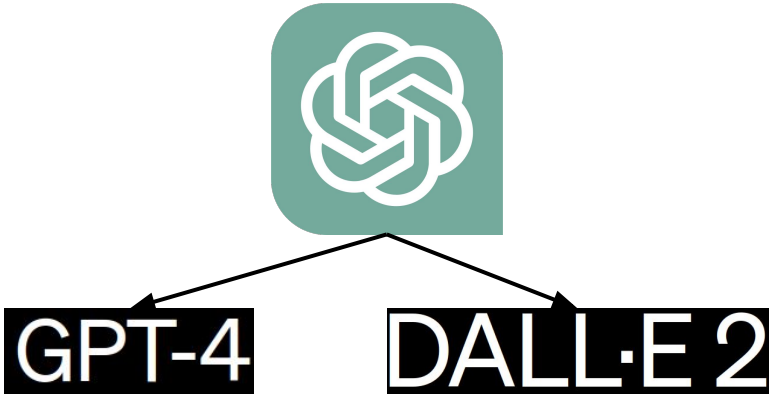
- Often done manually.
- When resources are available, large scale search is possible

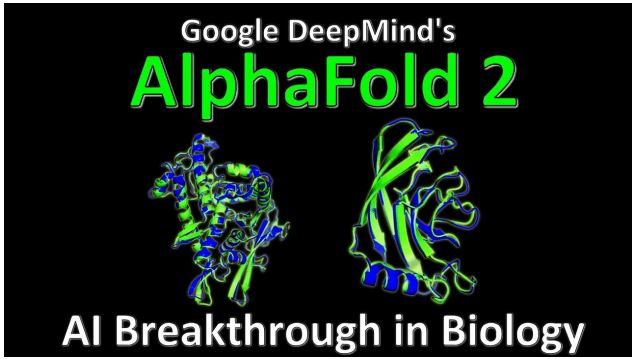




(a) Standard Grid Search (b) Random Search

Practical examples





Midjourney

Palm-E

Practical Work