



Apprentissage automatique et applications

Matthieu Vilain

Stage L2 laboratoire ETIS

Tuteur : Pierre Andry

1951 – M.Minsky : premier réseau de neuron

1957 – F.Rosenblatt : Perceptron

1969 – Minsky & Papert : livre « Perceptrons »

Limites réseaux de neurones → AI winter

1986 – Rumrlhart & Hinton : backpropagation

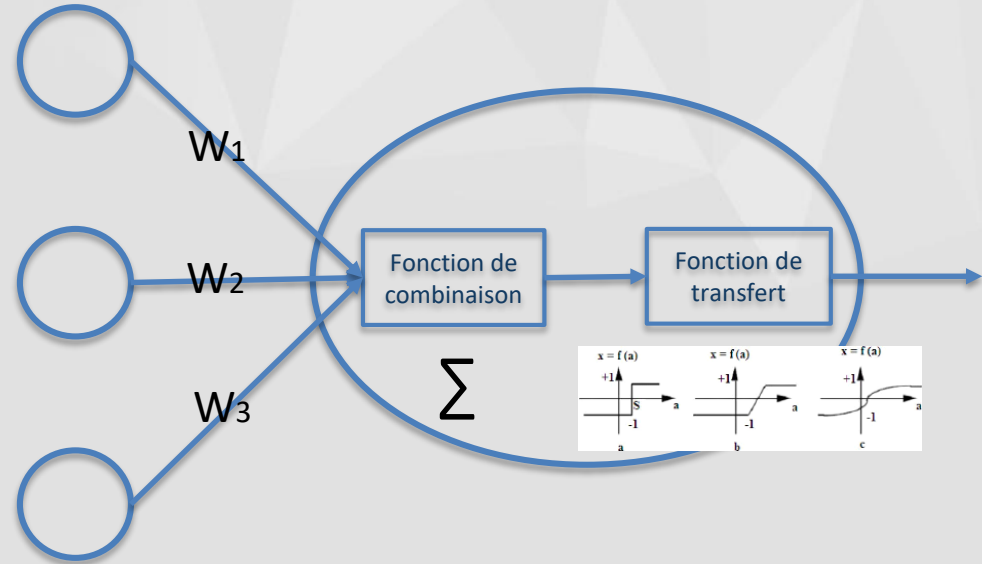
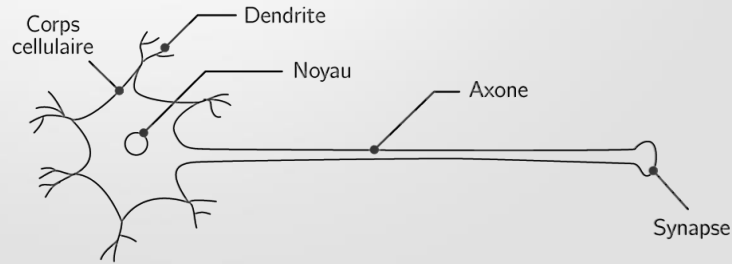
1989 – Watkins & Sutton : reinforcement learning

1997 – IBM : DeepBlue bat Kasparov aux échecs

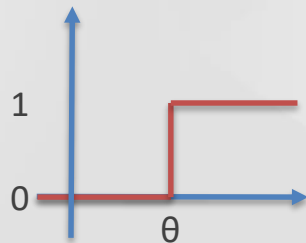
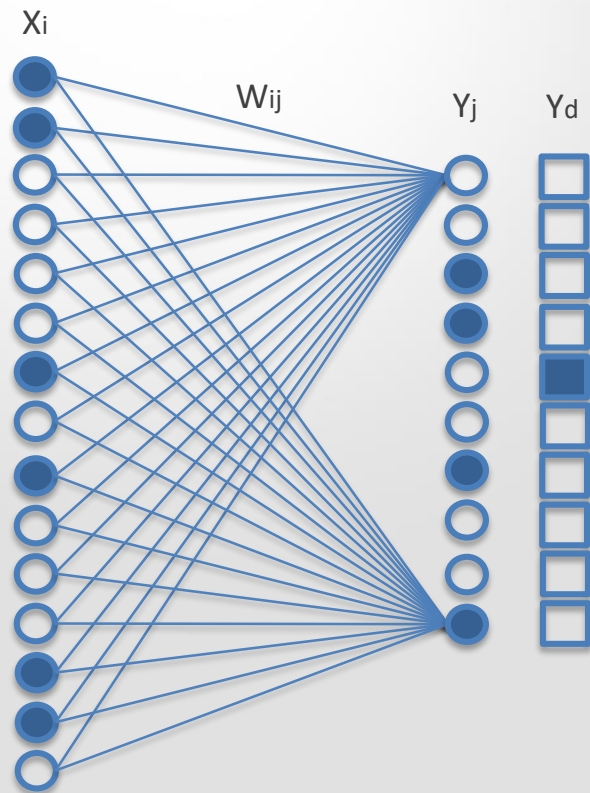
1998 – Y.LeCun : Deep learning

2016 – Google : AlphaGo bat Lee Sedol aux Go

Modélisation simpliste du fonctionnement d'un neurone biologique

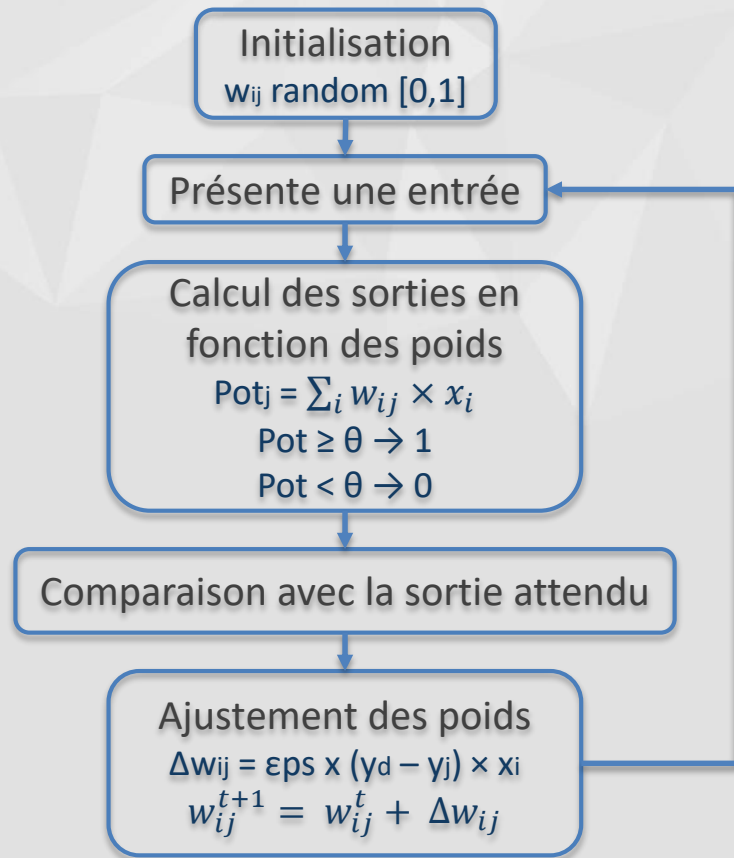


Fonctionnement perceptron simple

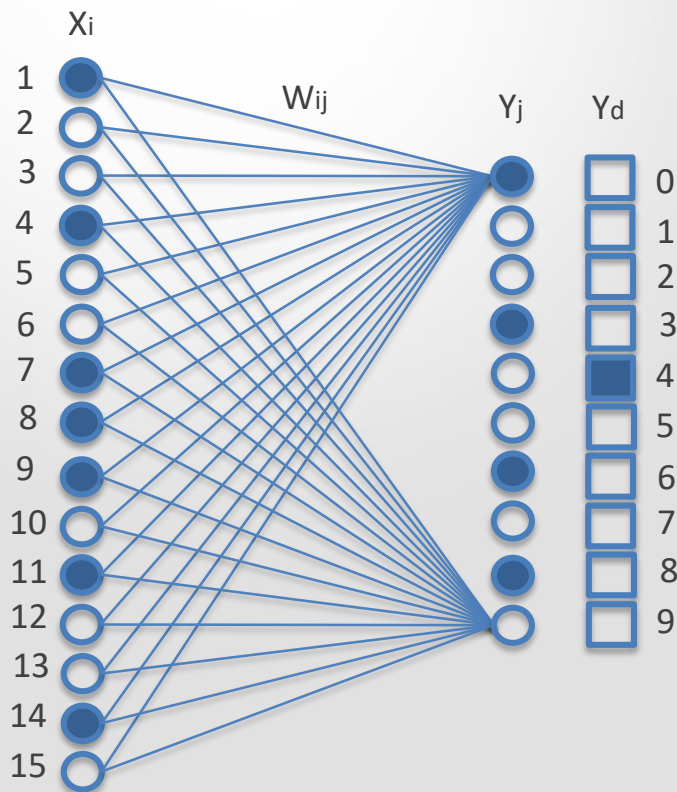


$$0 \leq \epsilon \leq 1$$

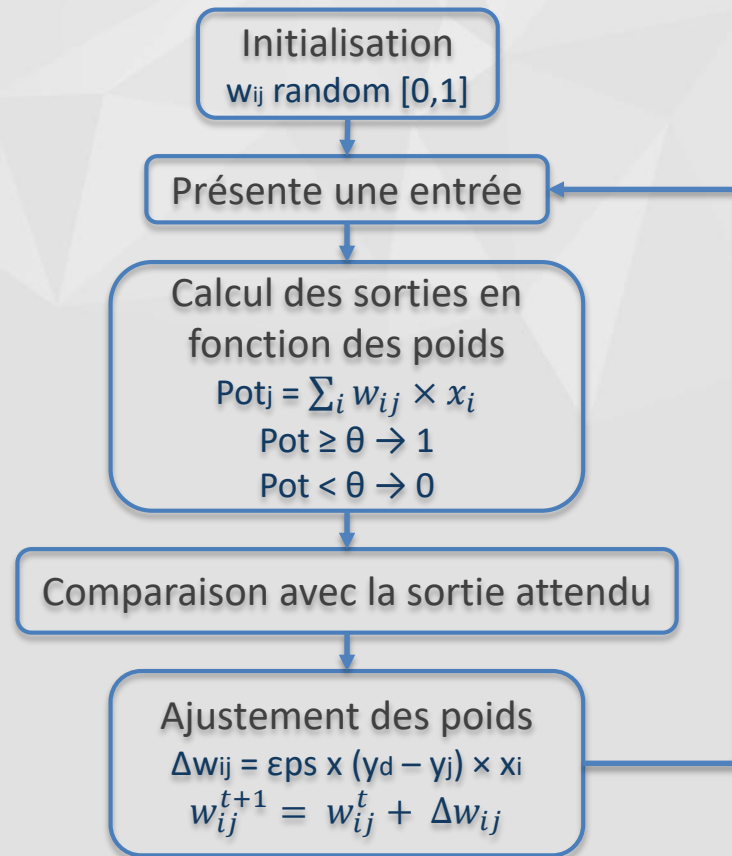
F.Rosenblatt 1957



Fonctionnement perceptron simple

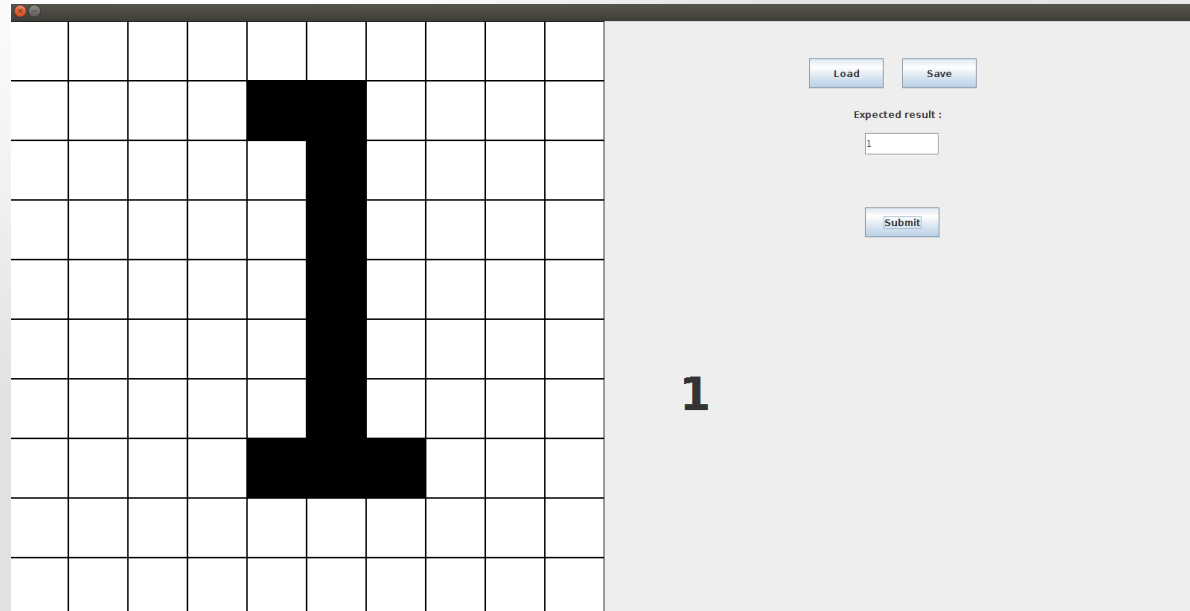


F.Rosenblatt 1957



Perceptron simple

Application

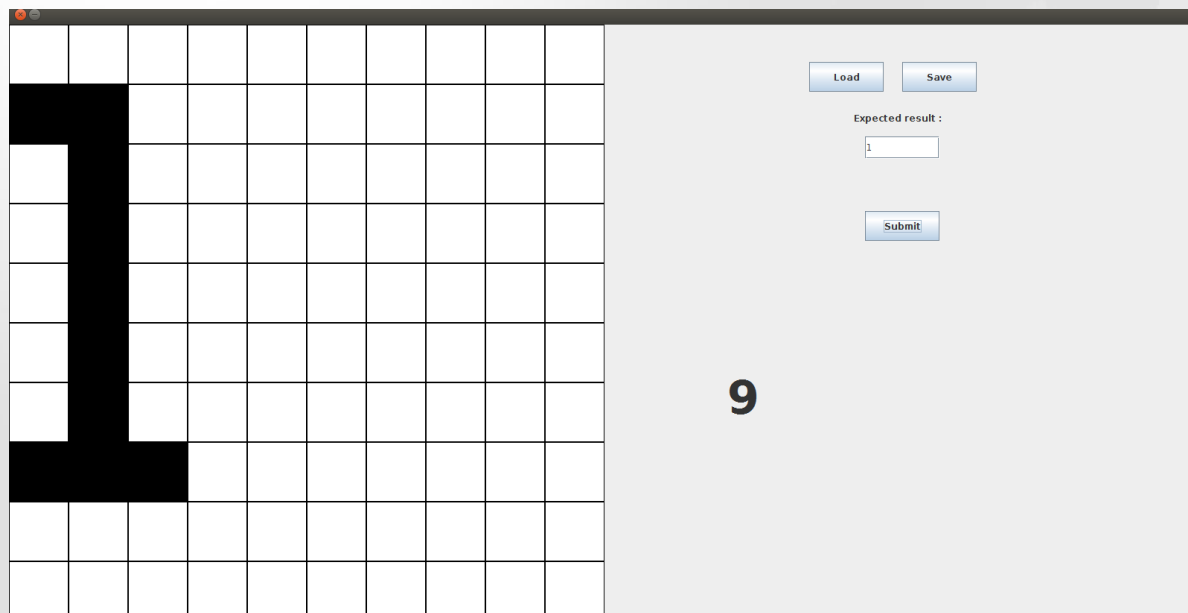


Rétine : 100 neurones

Sortie : 10 neurones

Limites

- Position dans la grille
- Temps d'apprentissage
- Non ergonomique

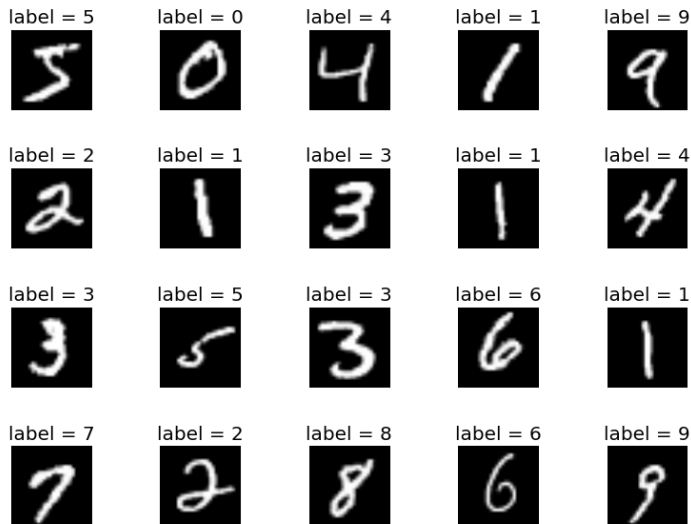


Rétine : 100 neurones

Sortie : 10 neurones

Limites

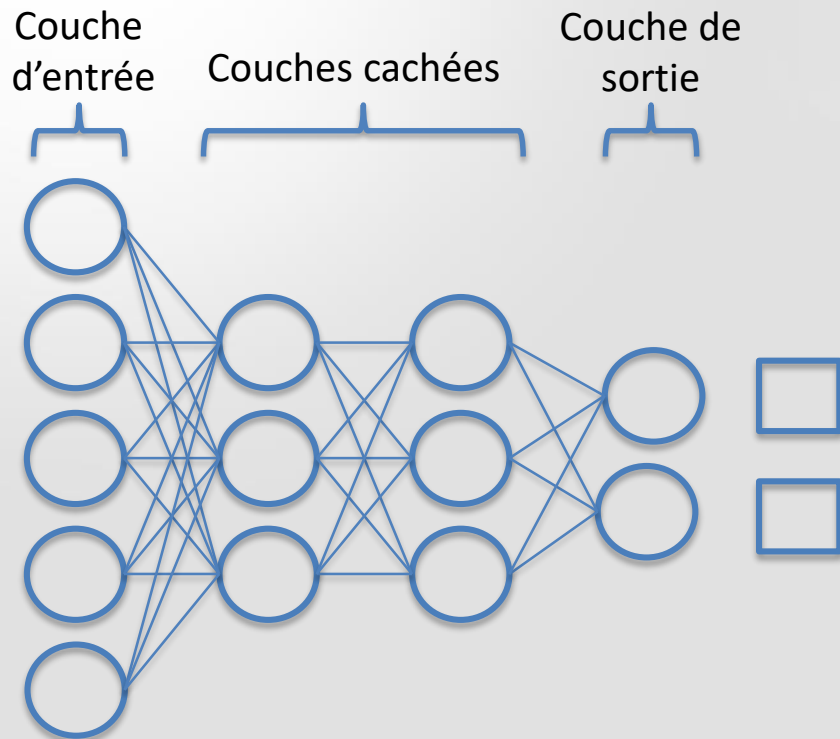
- Position dans la grille
- Temps d'apprentissage
- Non ergonomique



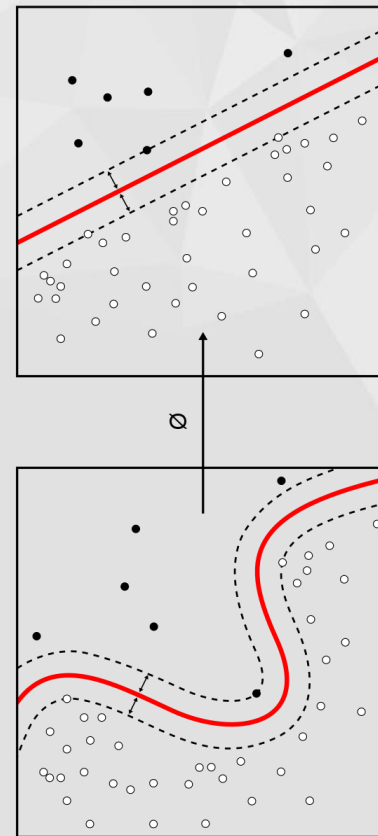
- Images 28x28
- Labélisées
- Base d'entraînement : 60 000 exemples
- Base de test : 10 000 exemples
 - 5000 normaux
 - 5000 bruités

Yann LeCun & Corinna Cortes & J.C. Burges

Fonctionnement perceptron multicouches



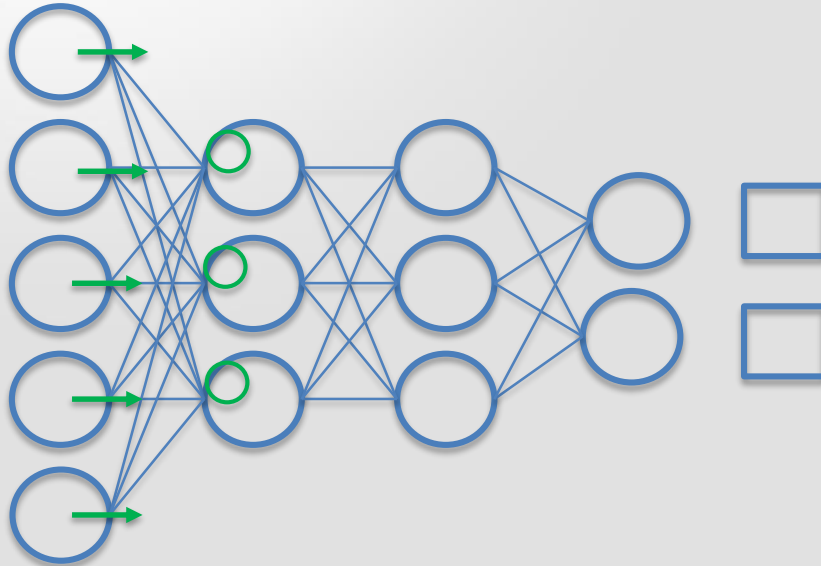
Rumelhart, Hinton, Williams 1986



Fonctionnement perceptron multicouches

Propagation de l'information

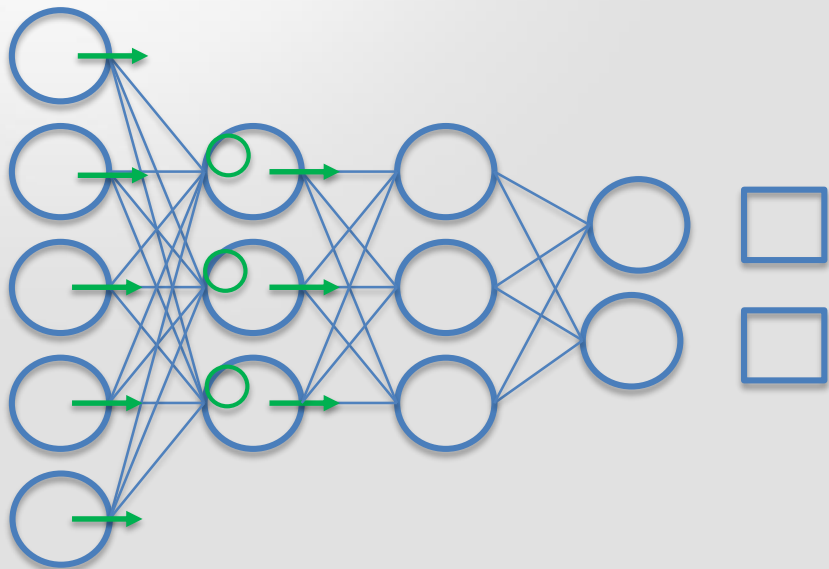
$$\text{Pot}_j = \sum_i w_{ij} \times x_i$$



Rumelhart, Hinton, Williams 1986

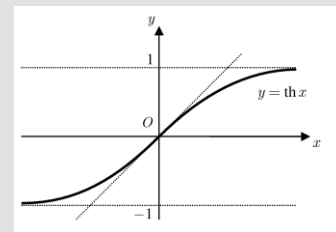
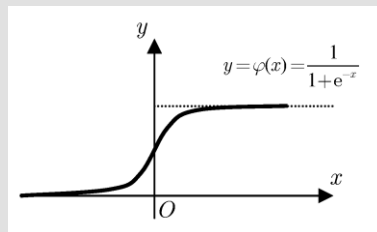
Fonctionnement perceptron multicouches

Propagation de l'information



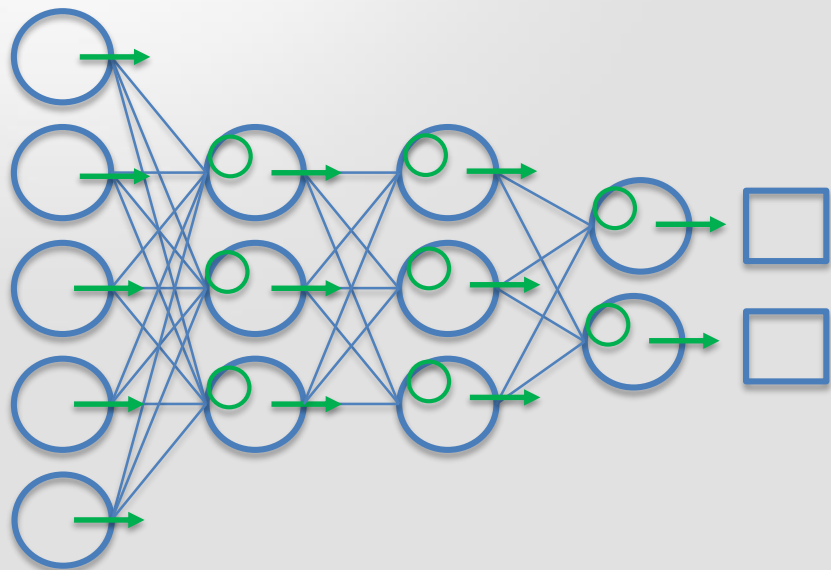
$$\text{Pot}_j = \sum_i w_{ij} \times x_i$$

$$\text{Signal}_{\text{out}} = \text{sigmoid}(\text{Pot})$$



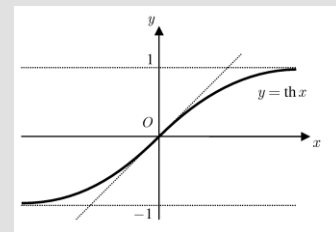
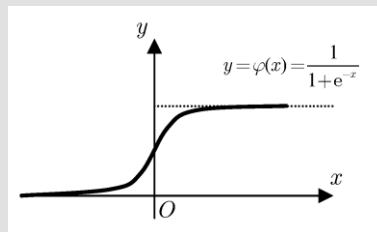
Rumelhart, Hinton, Williams 1986

Propagation de l'information



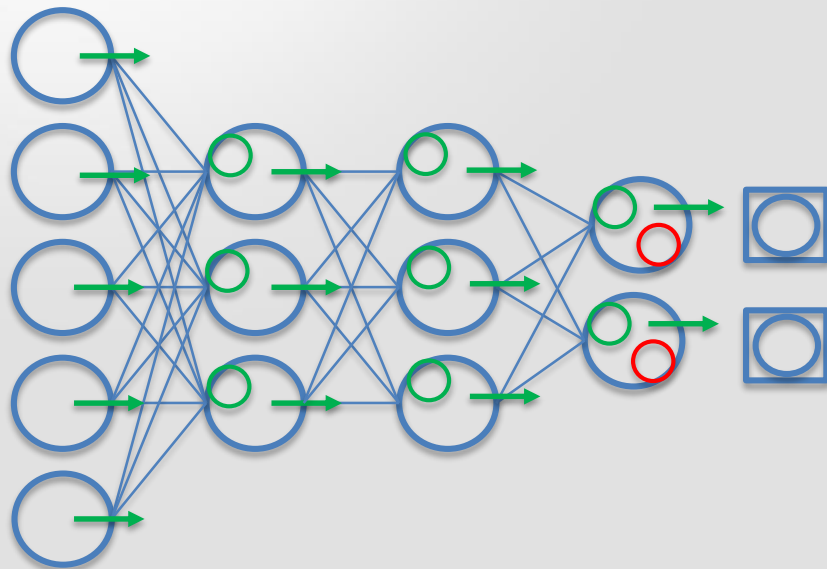
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Rumelhart, Hinton, Williams 1986

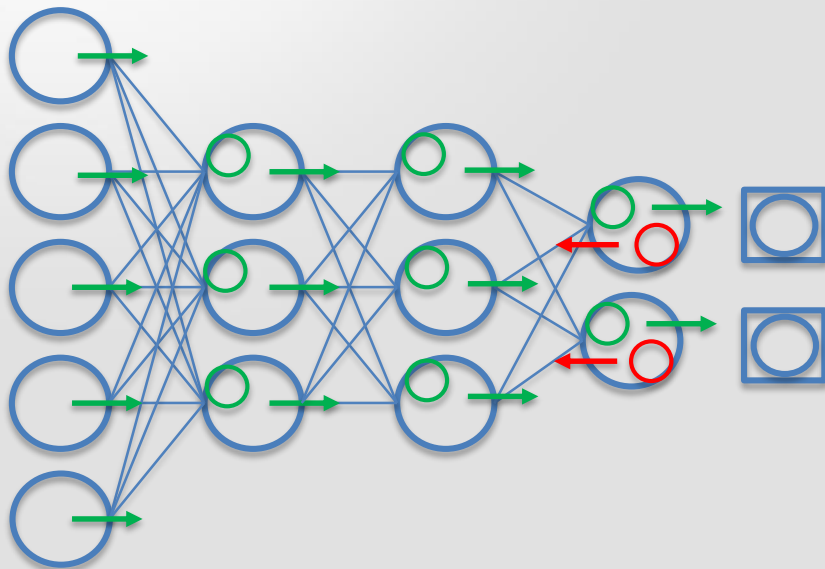
Calcul de l'erreur



$$E_i^{out} = \text{superviseur}_i^d - \text{sig}_i^{out}$$

Rumelhart, Hinton, Williams 1986

Calcul du signal d'erreur

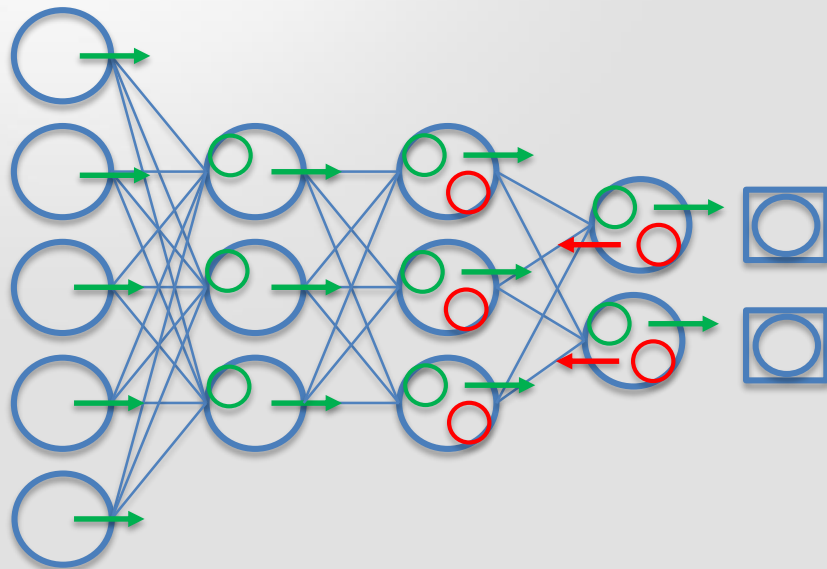


$$E_i^{out} = \text{superviseur}_i^d - \text{sig}_i^{out}$$

$$\delta^{out} = \text{sig}^{out} \odot (1 - \text{sig}^{out}) \odot E^{out}$$

Rumelhart, Hinton, Williams 1986

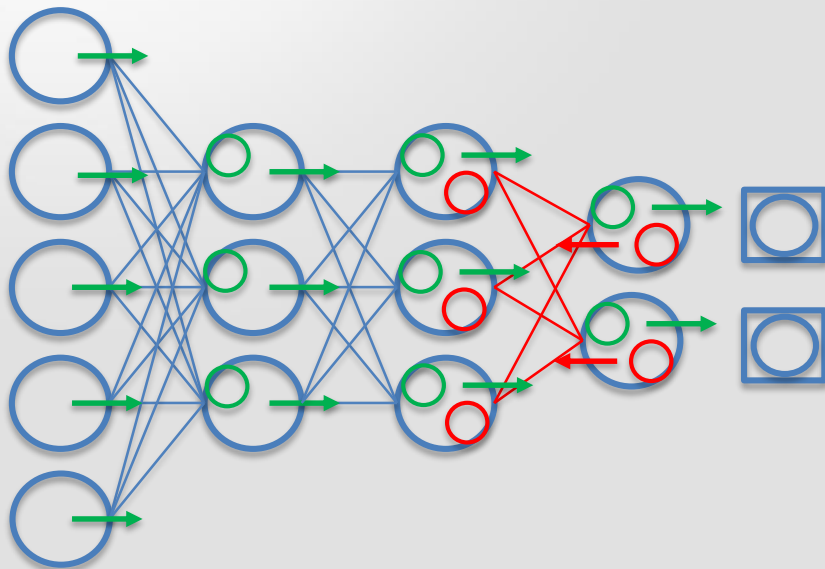
Propage signal d'erreur



$$E_i^n = \sum_j W_{ij} \times \delta_j^{n+1}$$

Rumelhart, Hinton, Williams 1986

Mise à jour des poids

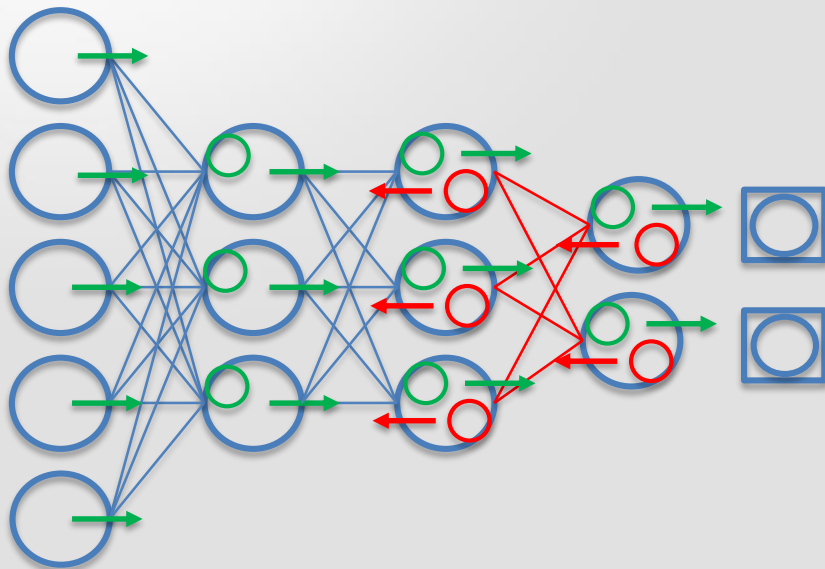


$$E_i^n = \sum_j W_{ij} \times \delta_j^{n+1}$$

$$W_{ij}^{t+1} = W_{ij}^t + \eta \times sig_i^n \times \delta_j^{n+1}$$

Rumelhart, Hinton, Williams 1986

Calcul du signal d'erreur



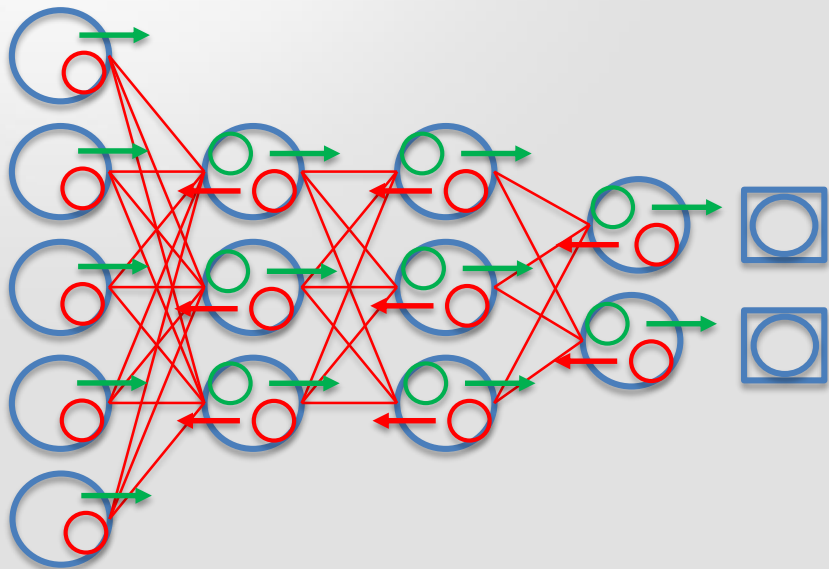
$$E_i^n = \sum_j W_{ij} \times \delta_j^{n+1}$$

$$W_{ij}^{t+1} = W_{ij}^t + \eta \times sig_i^n \times \delta_j^{n+1}$$

$$\delta^n = sig^n \odot (1 - sig^n) \odot E^n$$

Rumelhart, Hinton, Williams 1986

Propagation jusqu'au début



$$E_i^n = \sum_j W_{ij} \times \delta_j^{n+1}$$

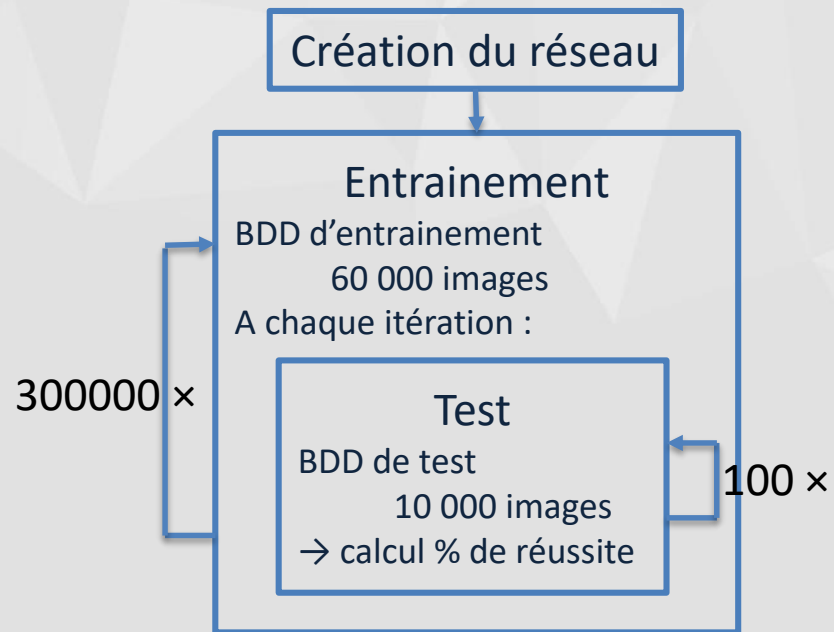
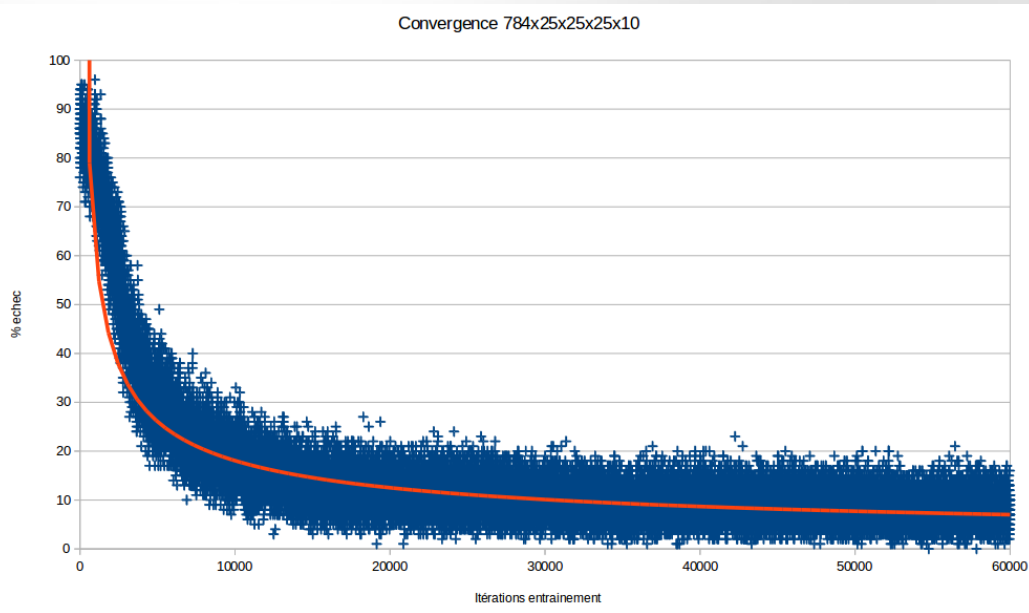
$$W_{ij}^{t+1} = W_{ij}^t + \eta \times sig_i^n \times \delta_j^{n+1}$$

$$\delta^n = sig^n \odot (1 - sig^n) \odot E^n$$

Rumelhart, Hinton, Williams 1986

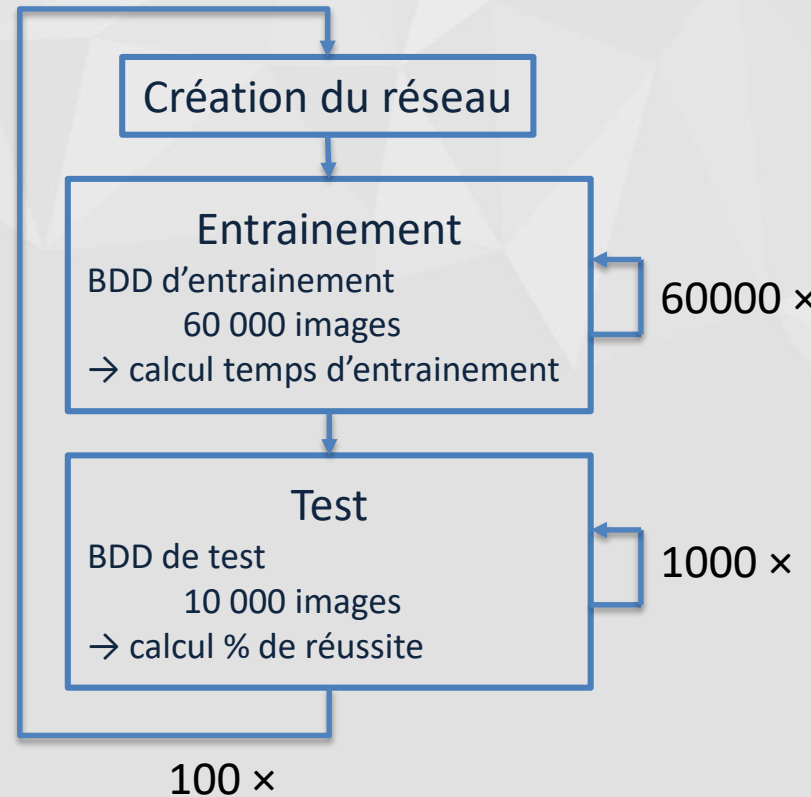
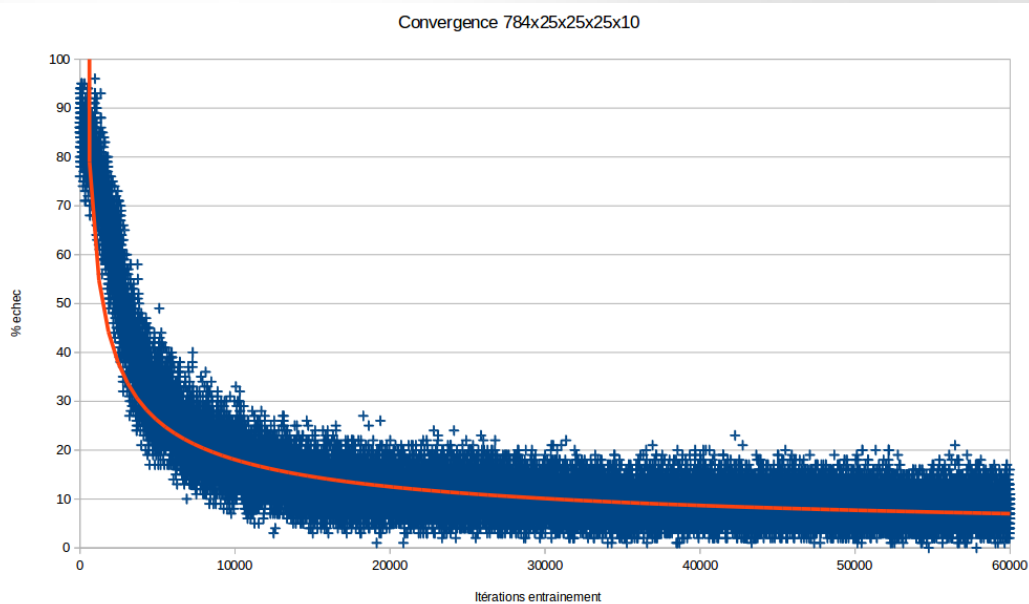
Perceptron multicouches

Résultats



Perceptron multicouches

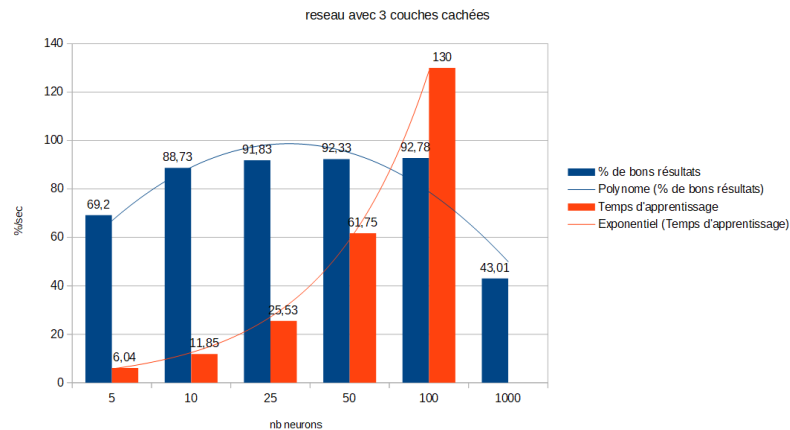
Résultats



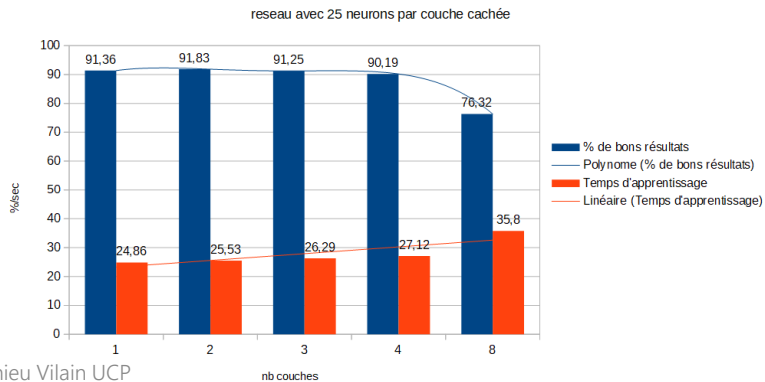
Perceptron multicouches

Optimisation

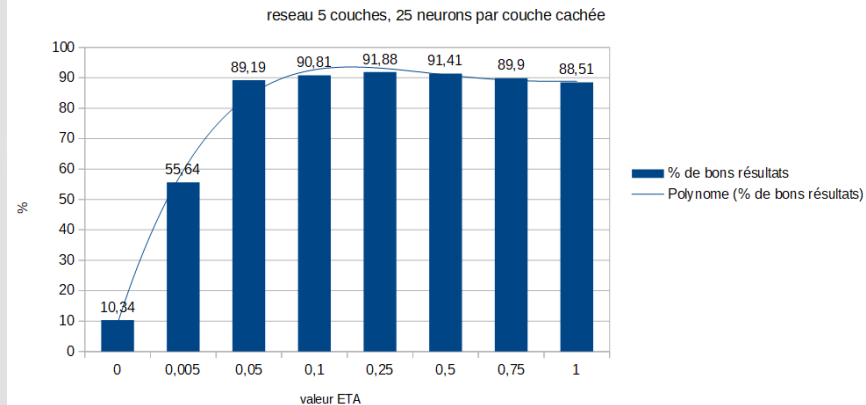
Performance en fonction du nombres de neurones dans les couches cachées



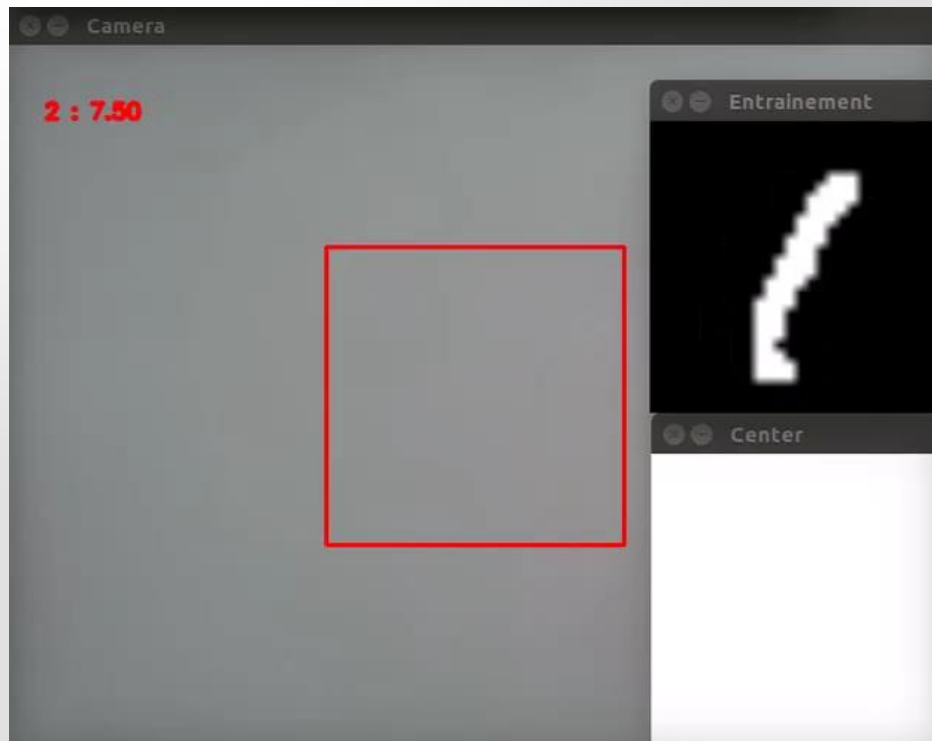
Performance en fonction du nombres de couches cachées



Performance en fonction de la valeur de ETA



150 000 – 200 000 training
95% de réussite
100 sec de training



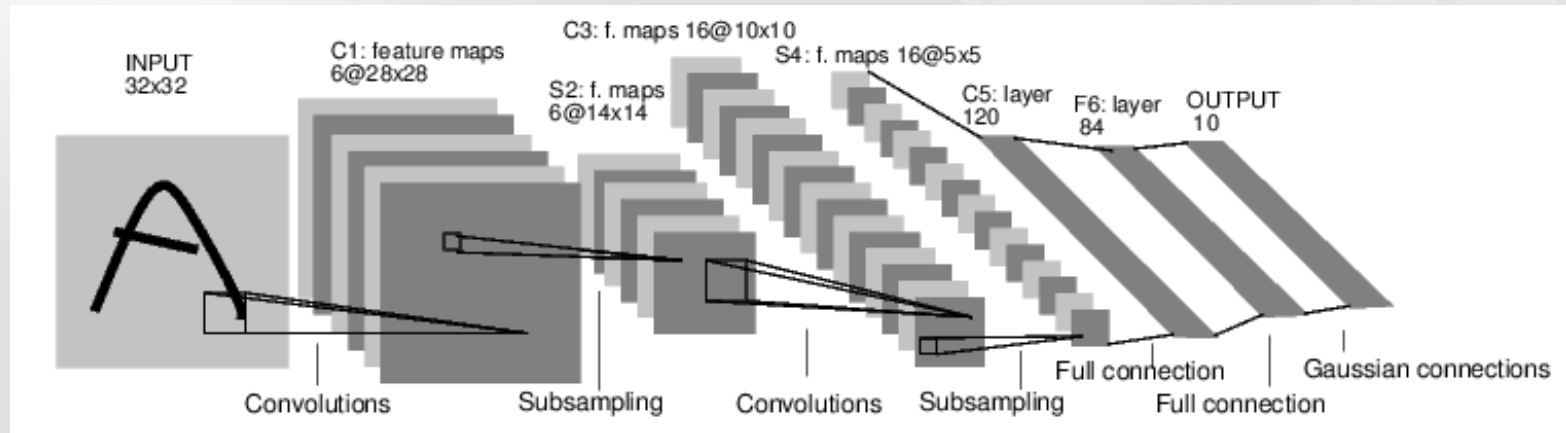
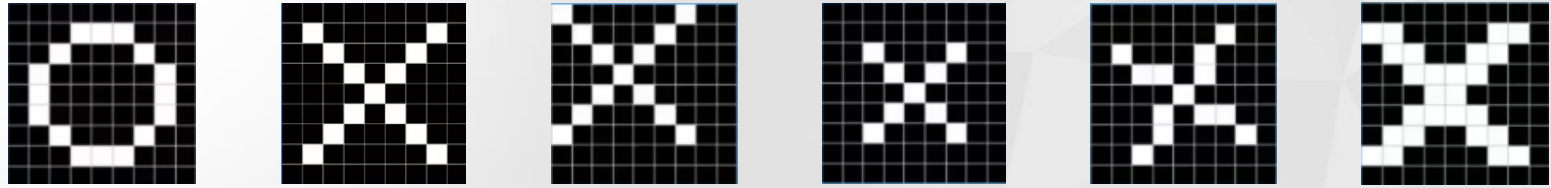
Problème

Non résistant aux :

- Translation
- Zoom
- Rotation
- Position
- Bruit

Réseau de neurones convolutif

Fonctionnement du CNN



Réseau de neurones convolutif
Yann LeCun 1998

Réseau de neurones convolutif

Couches de convolution

Filtres :

1	-1	-1
-1	1	-1
-1	-1	1

1	-1	1
-1	1	-1
1	-1	1

-1	-1	1
-1	1	-1
1	-1	-1

1	-1	-1
-1	1	-1
-1	-1	1

1	1	-1
1	1	1
-1	1	1

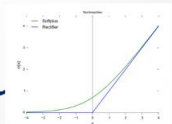
$$(1+1-1+1+1+1-1+1+1)/9 = .55$$

-1	-1	-1	-1	-1	-1	-1	-1	-1
-1	1	-1	-1	-1	-1	-1	1	-1
-1	-1	1	-1	-1	-1	1	-1	-1
-1	-1	-1	1	-1	1	-1	-1	-1
-1	-1	-1	-1	1	-1	-1	-1	-1
-1	-1	-1	1	-1	1	-1	-1	-1
-1	-1	1	-1	-1	-1	1	-1	-1
-1	1	-1	-1	-1	-1	-1	1	-1
-1	-1	-1	-1	-1	-1	-1	-1	-1

0.77	-0.11	0.11	0.33	0.55	-0.11	0.33
-0.11	1.00	-0.11	0.33	-0.11	0.11	-0.11
0.11	-0.11	1.00	-0.33	0.11	-0.11	0.55
0.33	0.33	-0.33	0.55	-0.33	0.33	0.33
0.55	-0.11	0.11	-0.33	1.00	-0.11	0.11
-0.11	0.11	-0.11	0.33	-0.11	1.00	-0.11
0.33	-0.11	0.55	0.33	0.11	-0.11	0.77

Réseau de neurones convolutif

Couches de normalisation



$$\log(\exp(x) + 1)$$
$$\max(0, x)$$

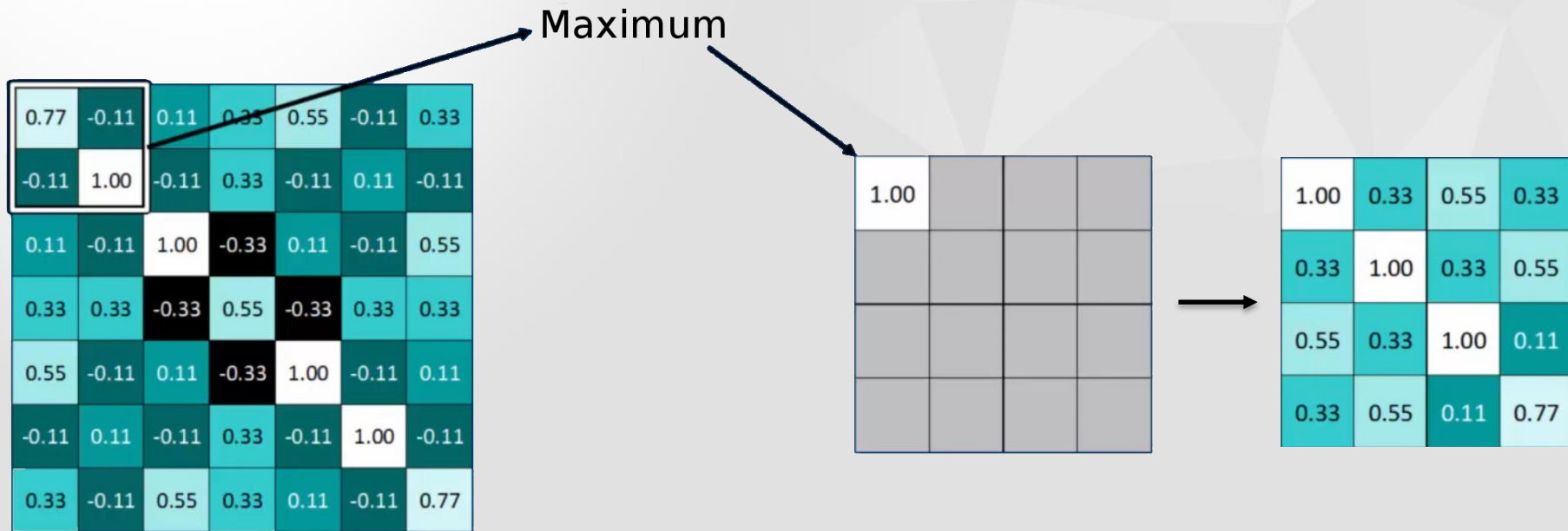
0.77	-0.11	0.11	0.33	0.55	-0.11	0.33
-0.11	1.00	-0.11	0.33	-0.11	0.11	-0.11
0.11	-0.11	1.00	-0.33	0.11	-0.11	0.55
0.33	0.33	-0.33	0.55	-0.33	0.33	0.33
0.55	-0.11	0.11	-0.33	1.00	-0.11	0.11
-0.11	0.11	-0.11	0.33	-0.11	1.00	-0.11
0.33	-0.11	0.55	0.33	0.11	-0.11	0.77

0.77						

0.77	0	0.11	0.33	0.55	0	0.33
0	1.00	0	0.33	0	0.11	0
0.11	0	1.00	0	0.11	0	0.55
0.33	0.33	0	0.55	0	0.33	0.33
0.55	0	0.11	0	1.00	0	0.11
0	0.11	0	0.33	0	1.00	0
0.33	0	0.55	0.33	0.11	0	0.77

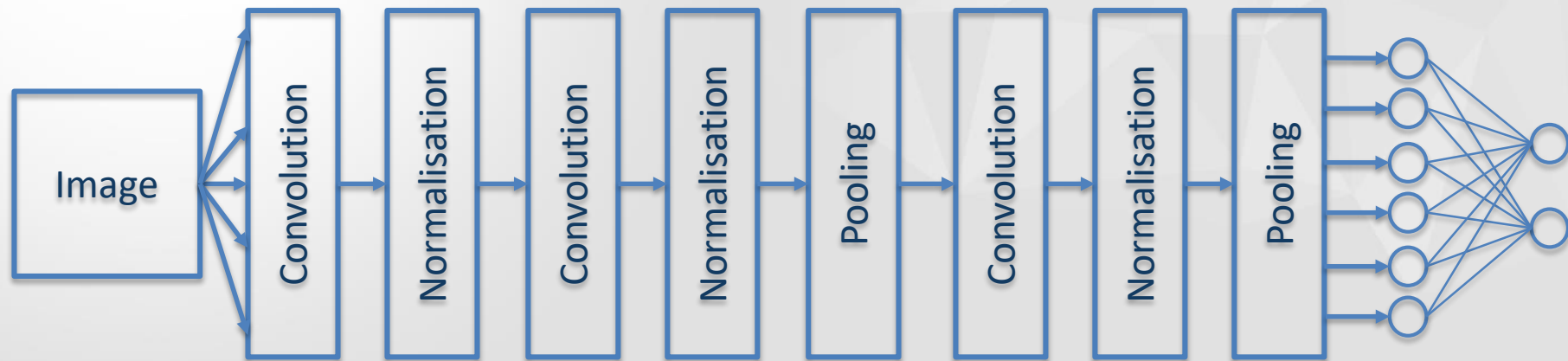
Réseau de neurones convolutif

Couches de pooling



Réseau de neurones convolutif

Organisation des couches

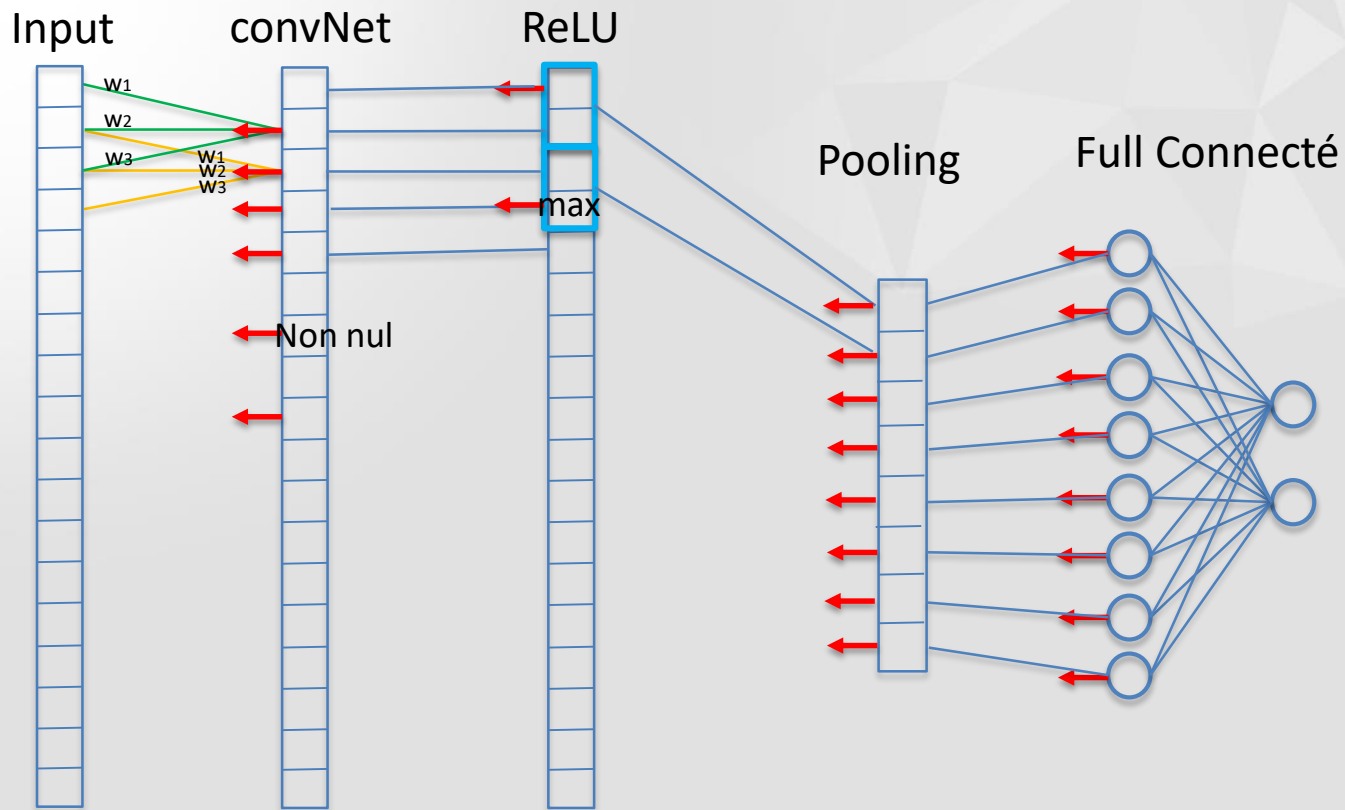


$$INPUT \rightarrow ((CONV \rightarrow ReLU) \times N \rightarrow POOL) \times M \rightarrow (FC \rightarrow RELU) \times K \rightarrow FC$$

Avec $0 \leq N \leq 3$, $M \geq 0$, $0 \leq K < 3$

Réseau de neurones convolutif

Backpropagation



LeNet-5

99,28% de réussite

26 minutes de training

20 000 training

CPU - 8 cœurs

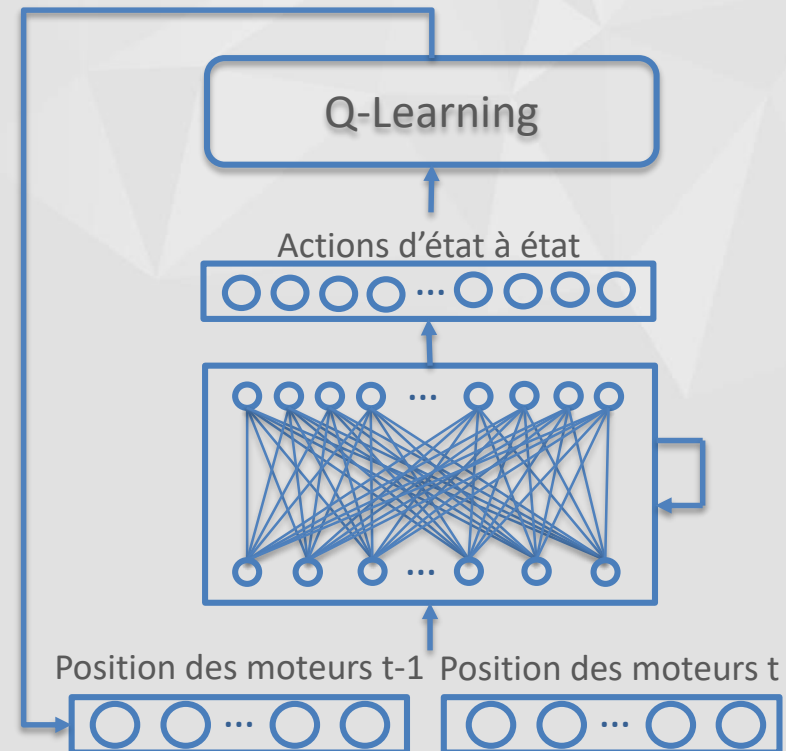
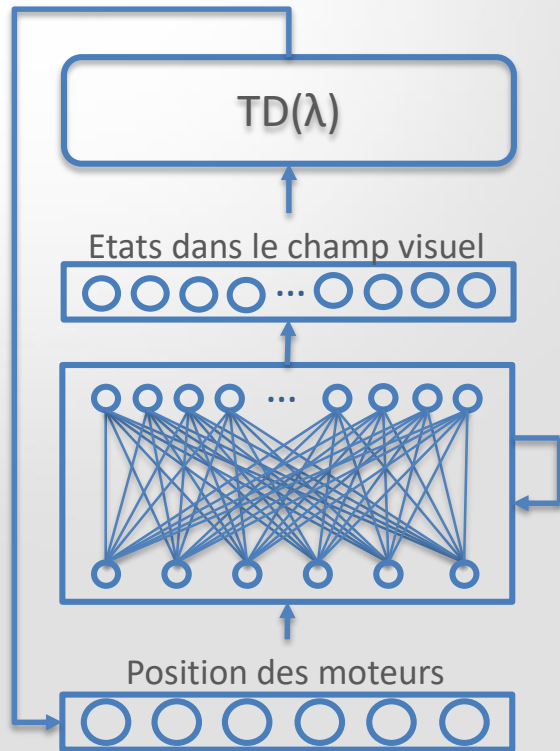




Apprendre à un bras robotique à
attraper des objets

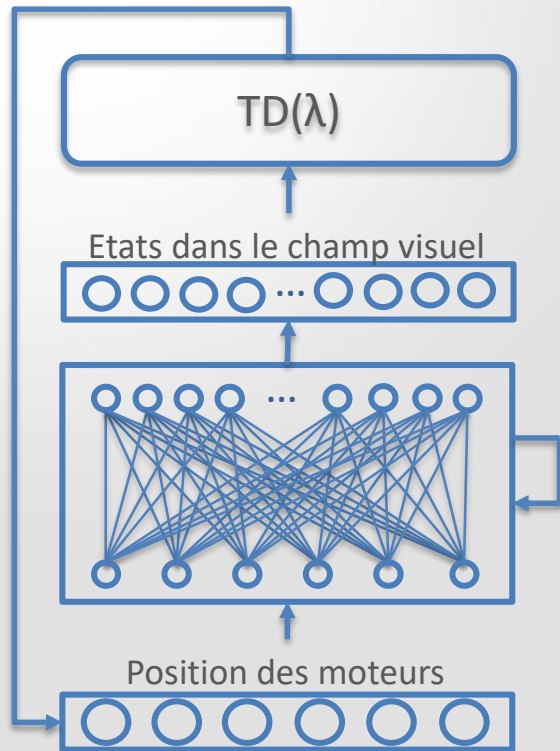
Réseau de neurones en robotique

Le model



Réseau de neurones en robotique

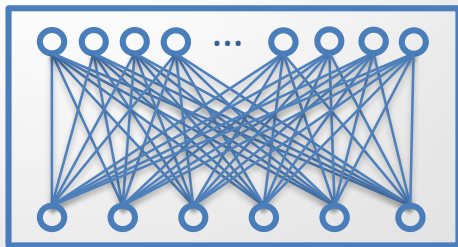
Le model



$$V(s_t) = V(s_t) + \alpha \times [R_{t+1} + \gamma V(s_{t+1}) - V(s_t)]$$

[0,0]	[0,1]	[0,2]	[0,3]	[0,4]	[0,5]	[0,6]	[0,7]	[0,8]	[0,9]
[1,0]	[1,1]	[1,2]	[1,3]	[1,4]	[1,5]	[1,6]	[1,7]	[1,8]	[1,9]
[2,0]	[2,1]	[2,2]	[2,3]	[2,4]	[2,5]	[2,6]	[2,7]	[2,8]	[2,9]
[3,0]	[3,1]	[3,2]	[3,3]	[3,4]	[3,5]	[3,6]	[3,7]	[3,8]	[3,9]
[4,0]	[4,1]	[4,2]	[4,3]	[4,4]	[4,5]	[4,6]	[4,7]	[4,8]	[4,9]
[5,0]	[5,1]	[5,2]	[5,3]	[5,4]	[5,5]	[5,6]	[5,7]	[5,8]	[5,9]
[6,0]	[6,1]	[6,2]	[6,3]	[6,4]	[6,5]	[6,6]	[6,7]	[6,8]	[6,9]
[7,0]	[7,1]	[7,2]	[7,3]	[7,4]	[7,5]	[7,6]	[7,7]	[7,8]	[7,9]
[8,0]	[8,1]	[8,2]	[8,3]	[8,4]	[8,5]	[8,6]	[8,7]	[8,8]	[8,9]
[9,0]	[9,1]	[9,2]	[9,3]	[9,4]	[9,5]	[9,6]	[9,7]	[9,8]	[9,9]

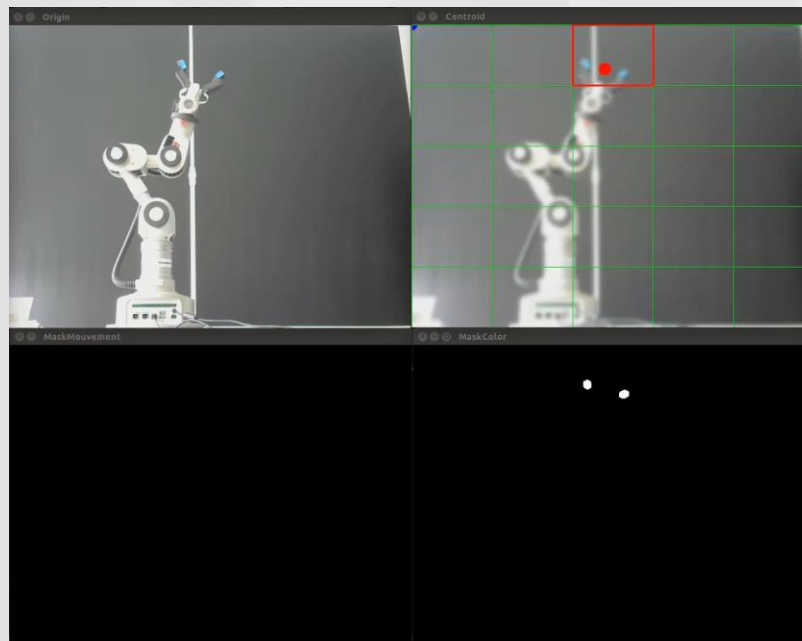
Réseau de neurones ✓



Renforcement TD ✗

$TD(\lambda)$

Traitement d'images ✓



Bilan du stage

- ✓ Appris énormément sur les réseaux de neurones
- ✓ Conforté dans mon choix d'orientation
- ✓ Plein de nouvelles idées de projets

Regret :

Pas avoir eu le temps de plus appliquer la théorie

Continuité du stage :

Projet de voiture autonome L3

Finir l'apprentissage sur le Katana