

# TRAITEMENT D'IMAGES

Partie Introductive

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L'INSTITUT NATIONAL D'ENSEIGNEMENT SUPÉRIEUR POUR L'AGRICULTURE, L'ALIMENTATION ET L'ENVIRONNEMENT



0 - Préambule

I - Introduction

II - Définitions

III - Pré-traitement des images

IV - Segmentation image et contours

V - Hough et morphologie mathématique

VI – Analyse et Reconnaissance de formes

VII – Détection de mouvement

**VIII – Introduction au Deep Learning**

# VIII – Introduction au Deep Learning

## Systemes intelligents

Artificial Intelligence (AI ou IA)

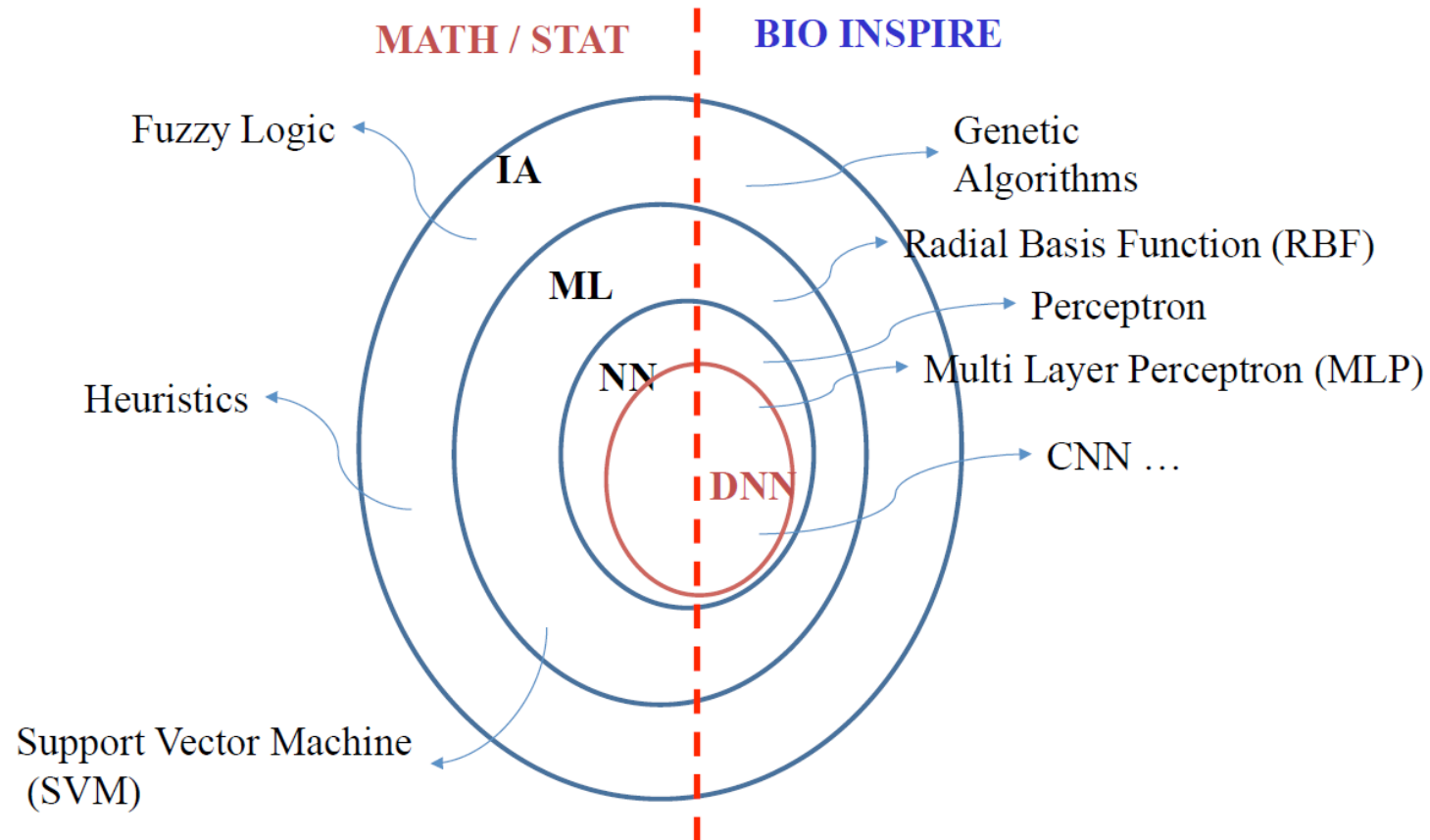
Machine Learning (ML)

Artificial Neural Network (ANN ou NN)

Deep Neural Network (DNN)

# VIII – Introduction au Deep Learning

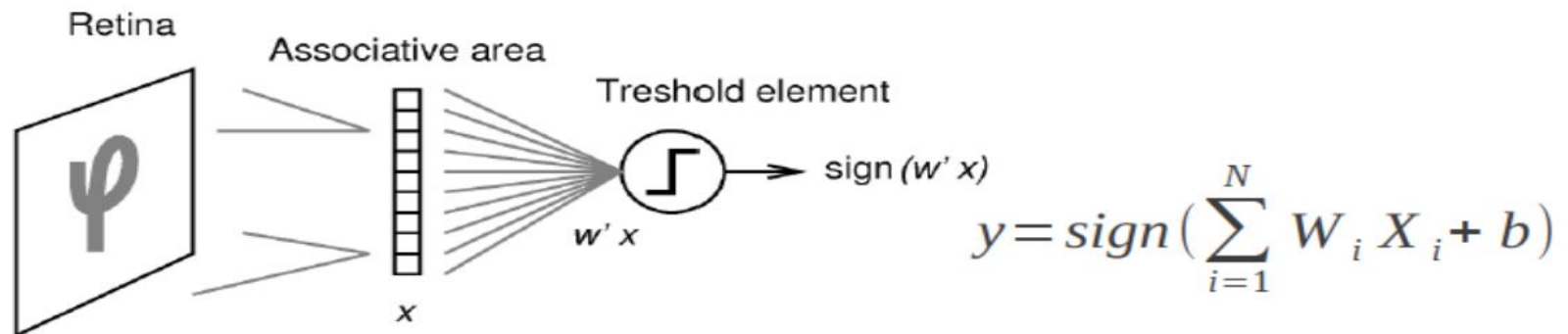
**IA > ML > ANN > DL**



# VIII – Introduction au Deep Learning

## Perceptron (Rosenblatt 1957)

- A simple simulated neuron with **adaptive** “synaptic weights”
  - ▶ Computes a weighted sum of inputs
  - ▶ Output is +1 if the weighted sum is above a threshold, -1 otherwise.



(cf Y.Lecun - Collège de France – 2016)

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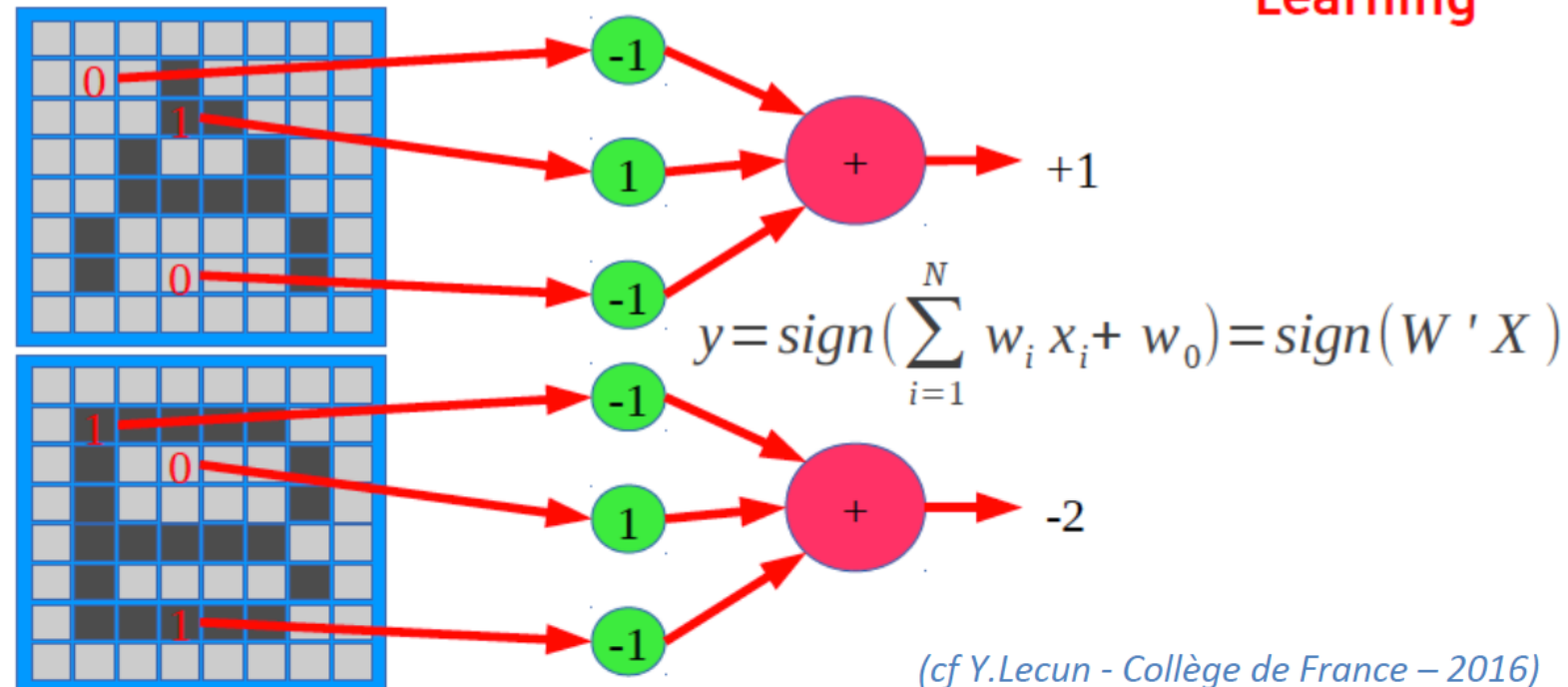
■ Example: classifying letters "A" from "B"

■ Learning: find the weight values that produce +1 for A and -1 for B

■ Training set:  $(X^1, Y^1), (X^2, Y^2), \dots, (X^P, Y^P)$

■ Example:  $(A, +1), (B, -1), (A, +1), (B, -1), (A, +1), (B, -1), \dots$

Supervised  
Learning

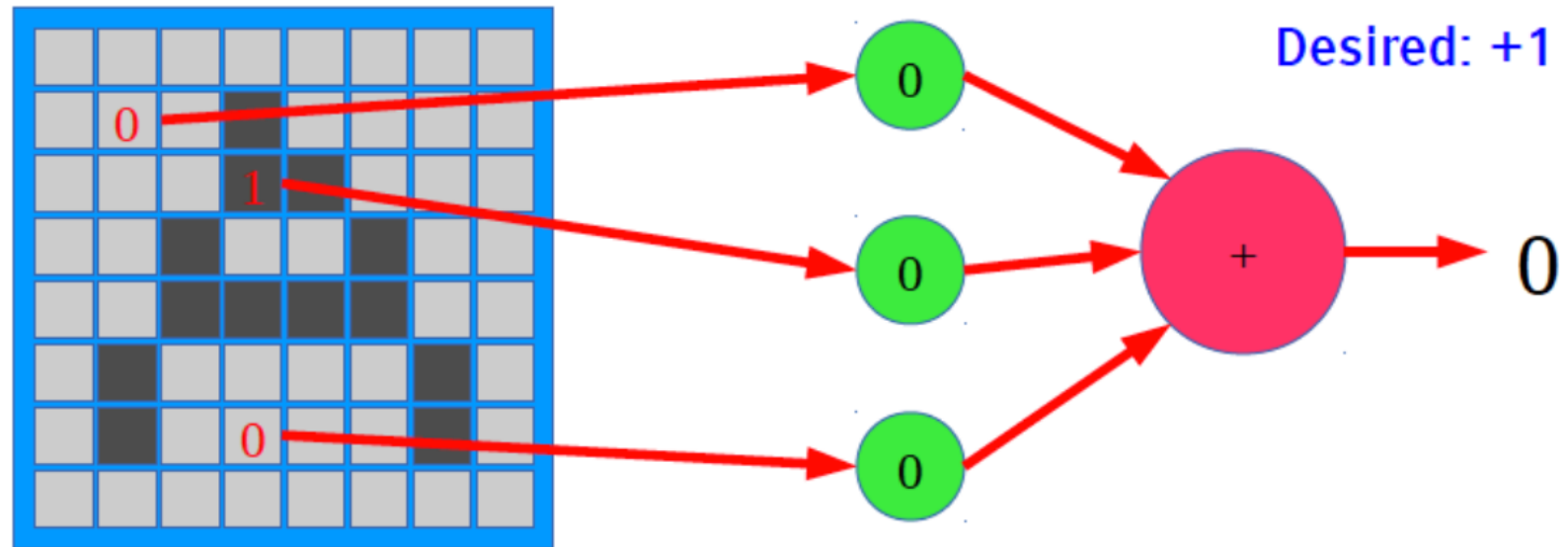


(cf Y.Lecun - Collège de France – 2016)

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- Learning: adjusting the weights so as to obtain the desired result
  - ▶ Initially, the weights are 0.

Apprentissage  
des poids  
synaptiques



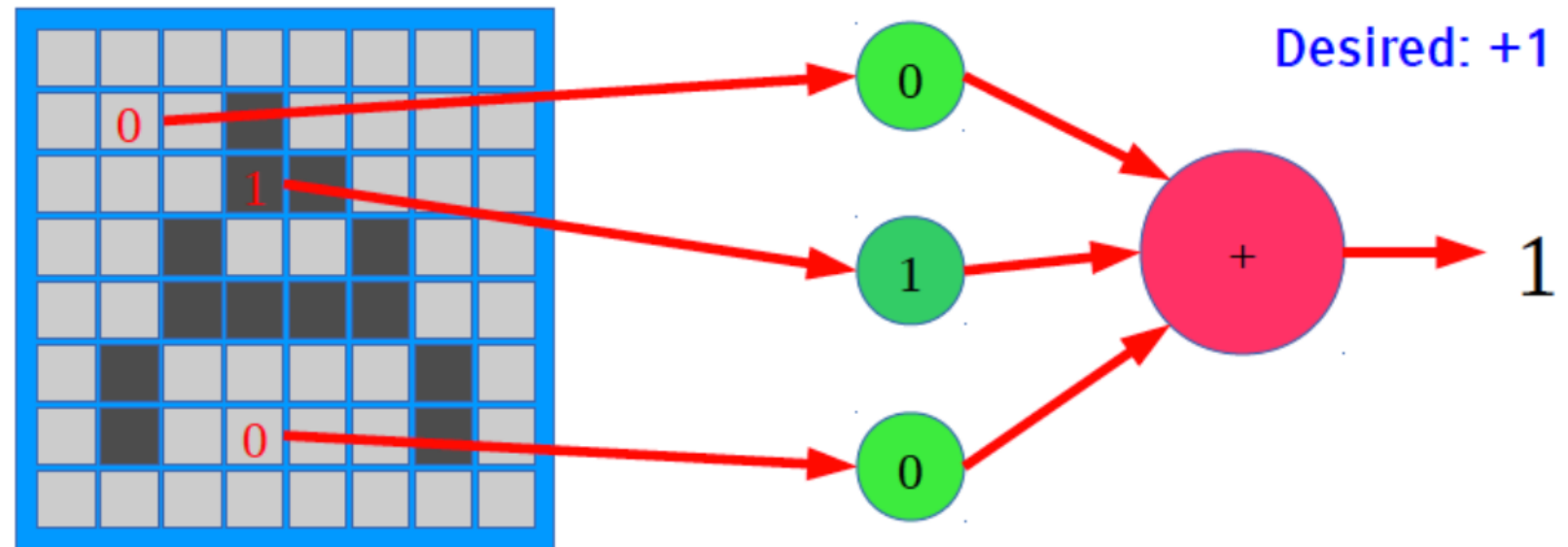
(cf Y.Lecun - Collège de France – 2016)

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■ Adjusting the weights when the the output is incorrect

► If the desired output is +1, add pixel values to the weights (Hebbian learning)

Apprentissage  
des poids  
synaptiques



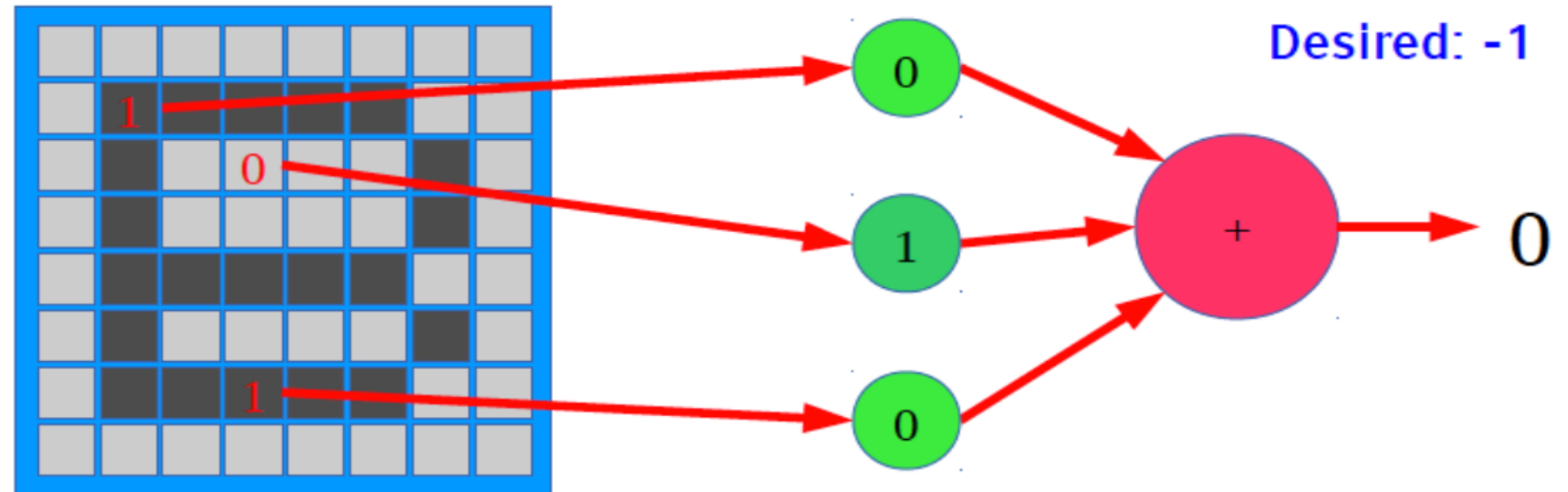
(cf Y.Lecun - Collège de France – 2016)



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- Adjusting the weights when the the output is incorrect
  - ▶ If the desired output is -1, subtract pixel values from the weights.

Apprentissage  
des poids  
synaptiques



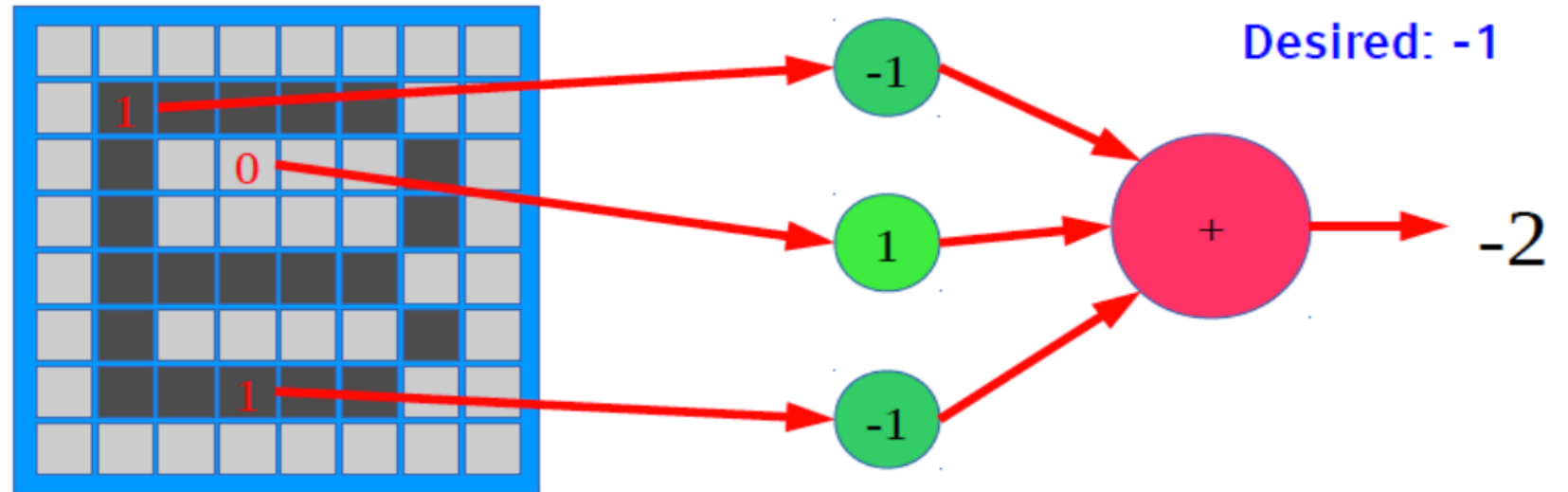
(cf Y.Lecun - Collège de France – 2016)

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■ Adjusting the weights when the the output is incorrect

► If the desired output is -1, subtract pixel values from the weights.

Apprentissage  
des poids  
synaptiques

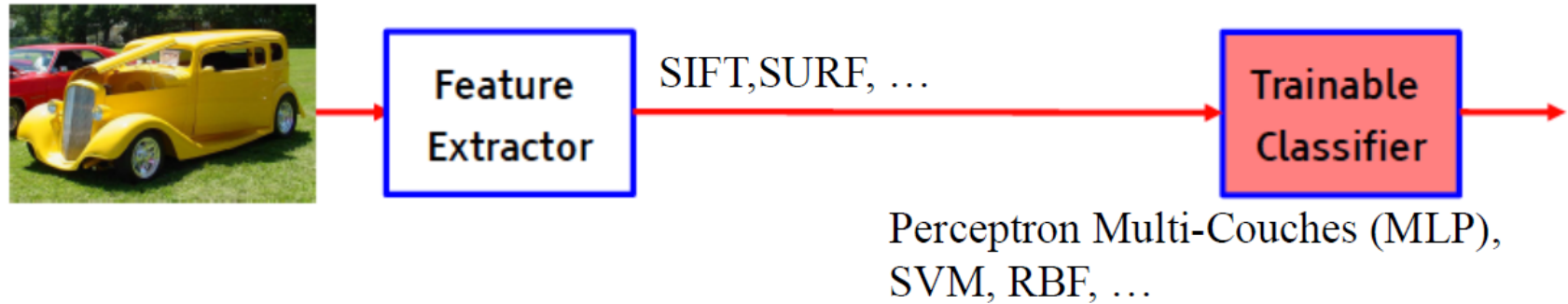


(cf Y.Lecun - Collège de France – 2016)

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## Modèles de vision artificielle

### Traditional Pattern Recognition: Fixed/Handcrafted Feature Extractor



### Deep Learning: Representations are hierarchical and trained



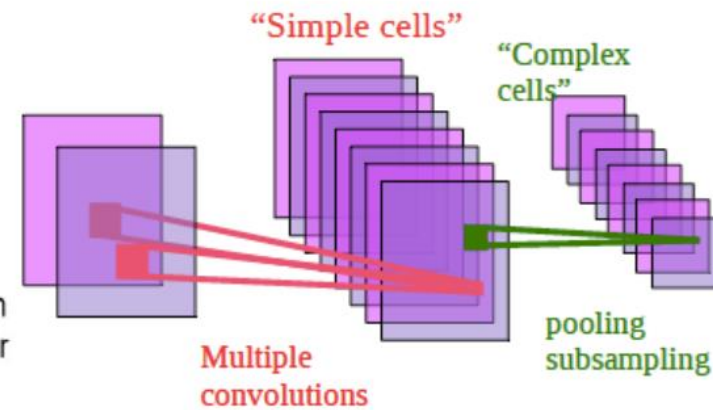
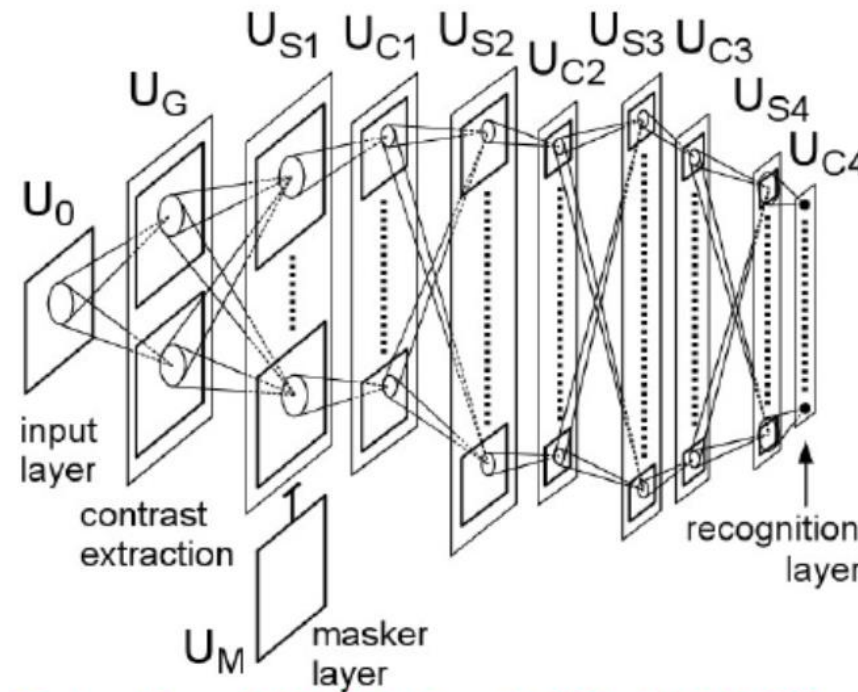
(cf Y.Lecun - Collège de France – 2016)

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L'apprentissage  
profond : >50 ans

■ [Hubel & Wiesel 1962]:

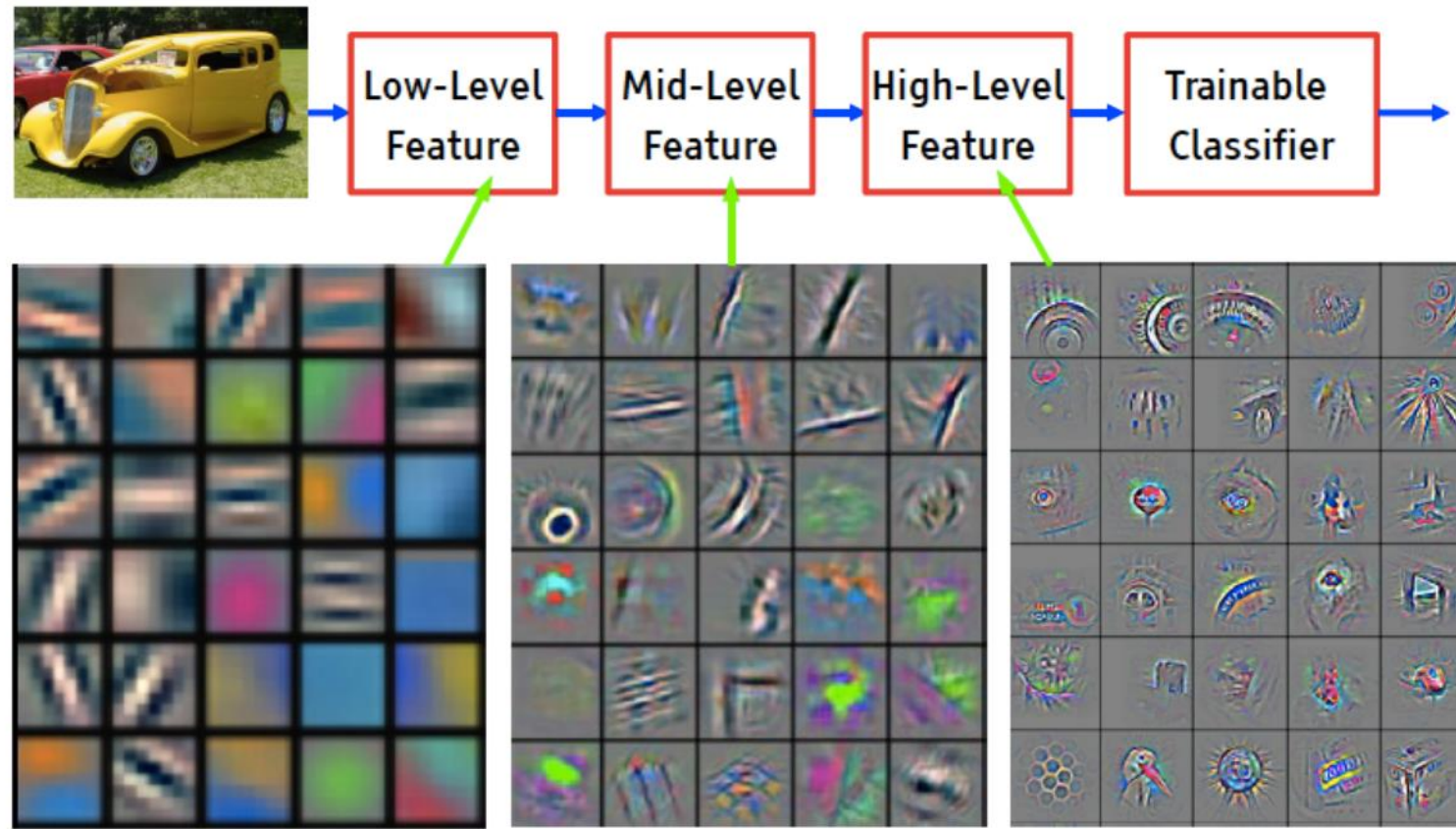
- ▶ **simple cells** detect local features
- ▶ **complex cells** “pool” the outputs of simple cells within a retinotopic neighborhood.



[Fukushima 1982][LeCun 1989, 1998],[Riesenhuber 1999].....

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■ It's deep if it has more than one stage of non-linear feature transformation



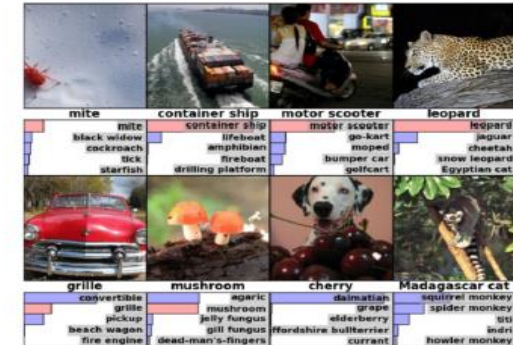
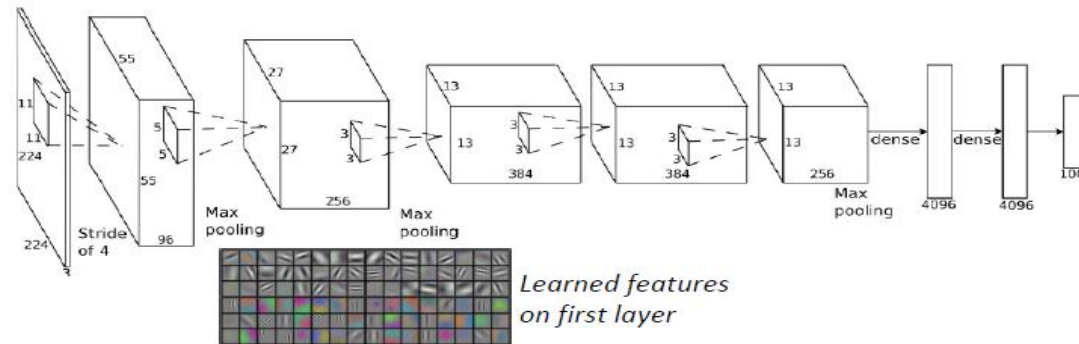
Feature visualization of convolutional net trained on ImageNet from [Zeiler & Fergus 2013]



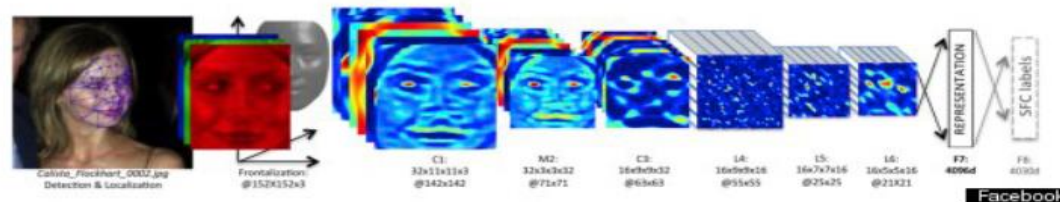
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## Modèles récents de DNN

- ImageNet classification (Hinton's team, hired by Google)
  - 1.2 million high res images, 1,000 different classes
  - Top-5 17% error rate (huge improvement)

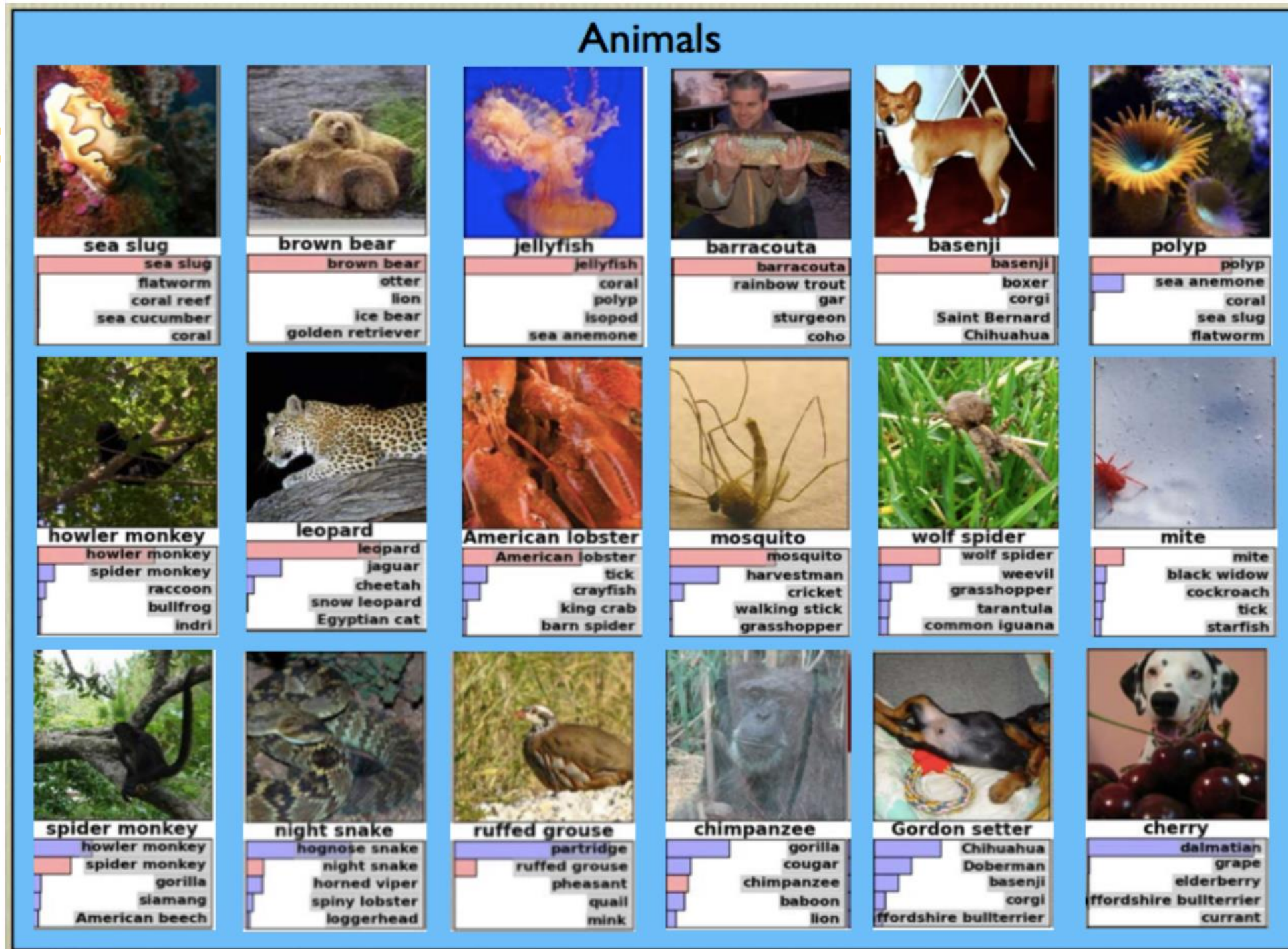


- Facebook's 'DeepFace' Program (labs head: Y. LeCun)
  - 4 million images, 4,000 identities
  - 97.25% accuracy, vs. 97.53% human performance



# VIII – Int







## Supervision par DNNs





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## Etat de l'art dans la reconnaissance

Database		# Images	# Classes	Best score
MNIST <i>Handwritten digits</i>		60,000 + 10,000	10	99.79% [3]
GTSRB <i>Traffic sign</i>		~ 50,000	43	99.46% [4]
CIFAR-10 <i>airplane, automobile, bird, cat, deer, dog, frog, horse, ship, truck</i>		50,000 + 10,000	10	91.2% [5]
Caltech-101		~ 50,000	101	86.5% [6]
ImageNet		~ 1,000,000	1,000	Top-5 83% [1]
DeepFace		~ 4,000,000	4,000	97.25% [2]

INCREASING COMPLEXITY

- State-of-the-art are Deep Neural Networks *every time*



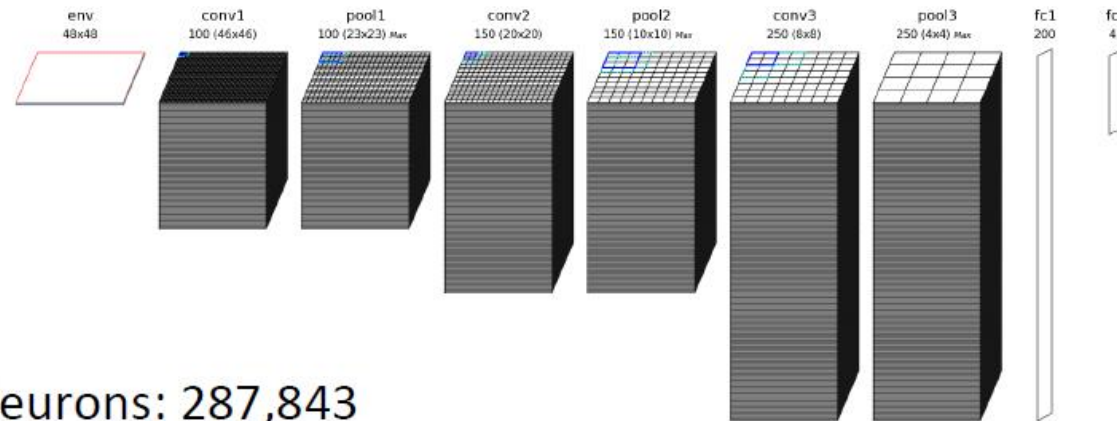
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The German Traffic Sign Recognition Benchmark (GTSRB)

43 traffic sign types  
> 50,000 images

Etat de l'art ex de  
CNNs



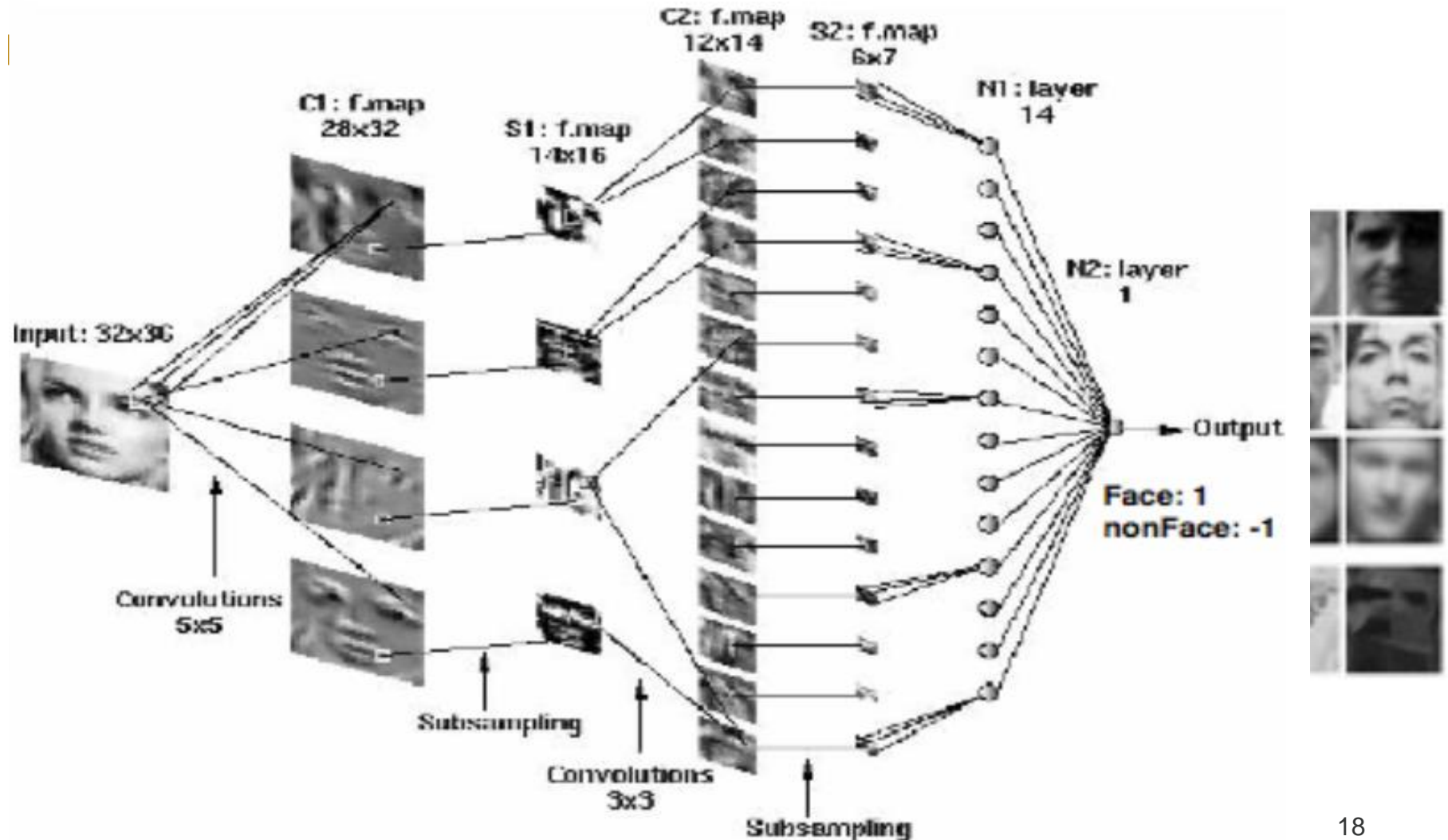
- Neurons: 287,843
- Synapses: 1,388,800
  - Total memory: 1.5MB (with 8 bits synapses)
- Connections: 124,121,800

[3] D. Cireşan, U. Meier, J. Masci, J. Schmidhuber, Multi-column deep neural network for traffic sign classification, Neural Networks (32), pp. 333-338, 2012

Near human recognition (> 98%) [3]

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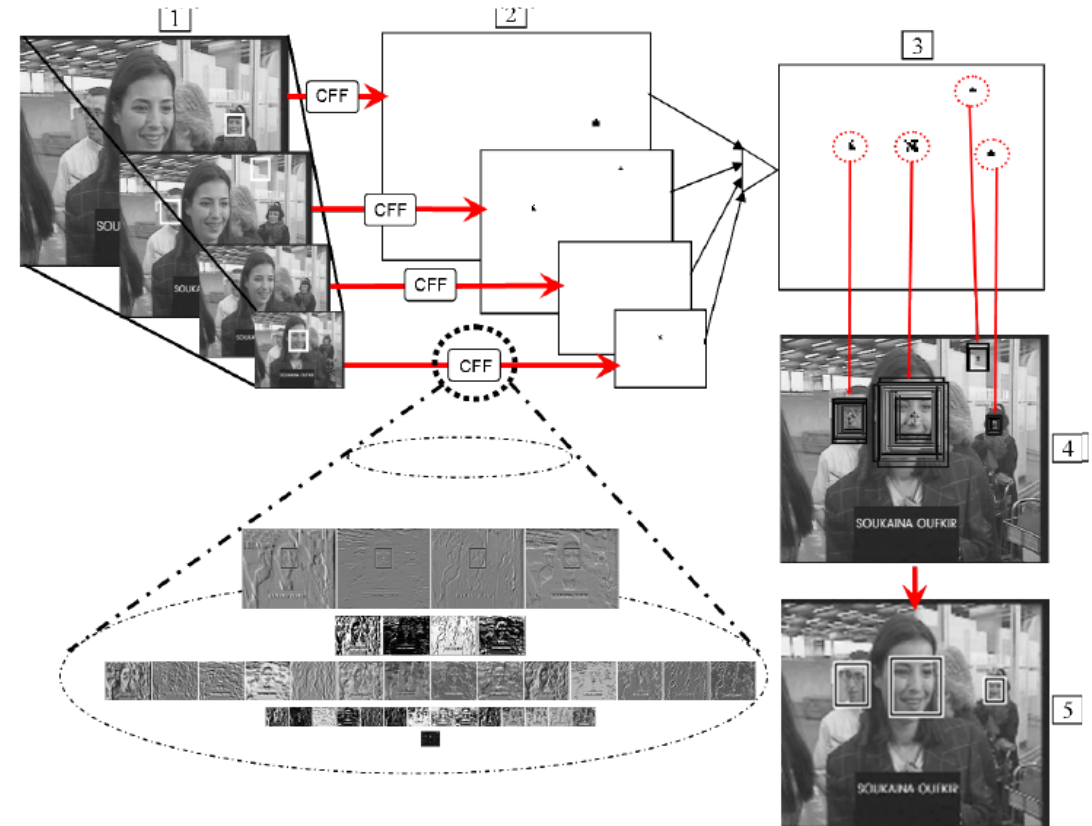
Adaptation des  
CNNs pour les  
visages



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## Système de détection CFF

- 1 Construire une **pyramide d'images** (facteur 1.2)
- 2 Appliquer **CFF** sur chaque image de la pyramide  
→ Positions des visages candidates
- 3 Projeter et fusionner les positions candidates dans l'image originale
- 4 Appliquer CFF autour des positions candidates (**position et échelle**)
- 5 Filtrer les résultats en fonction du «volume» des réponses positives (**ThrVol**)

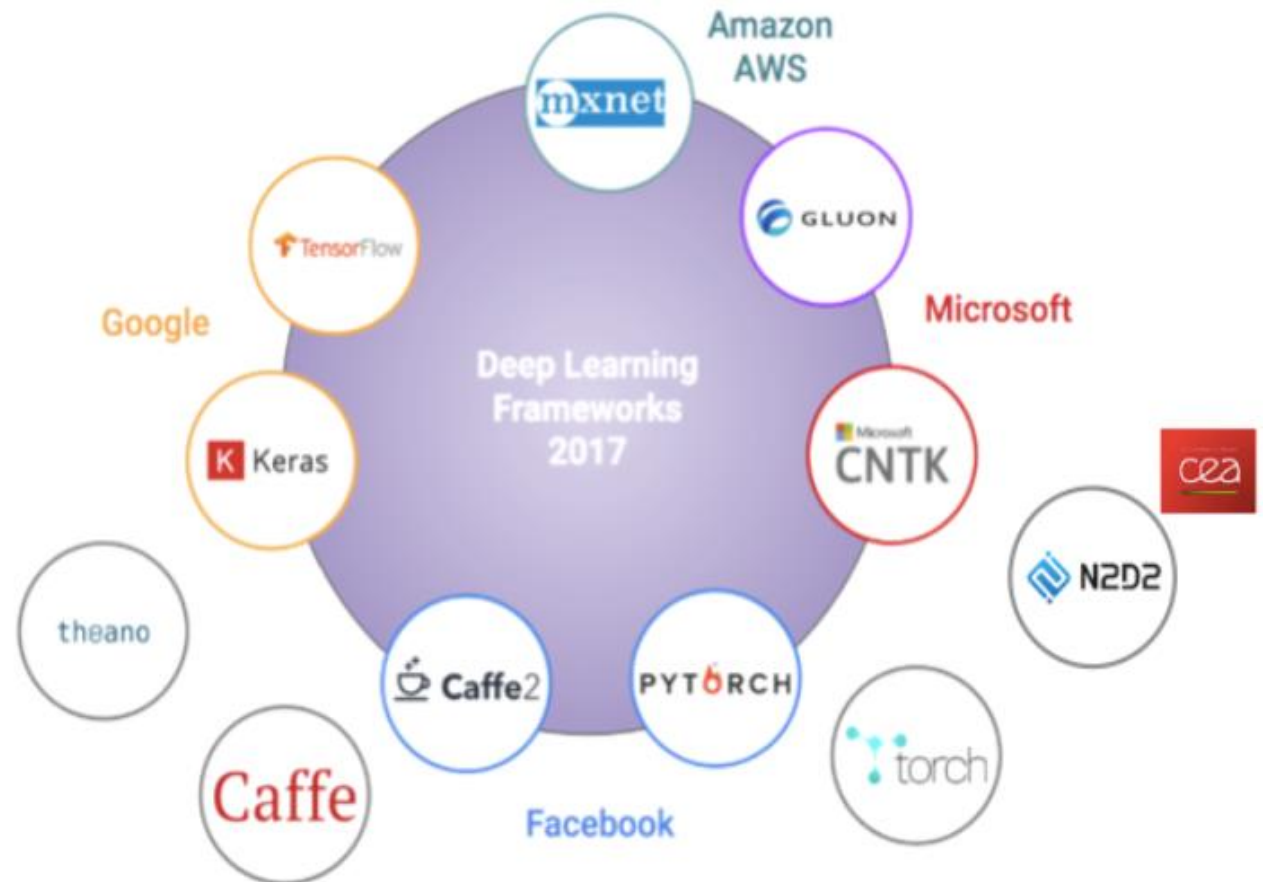


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## Frameworks pour développer des Deep Networks:

Numerous frameworks

- Most popular ones are open source
- Some are powered by “GAFAM”





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## Utilisation de Keras:

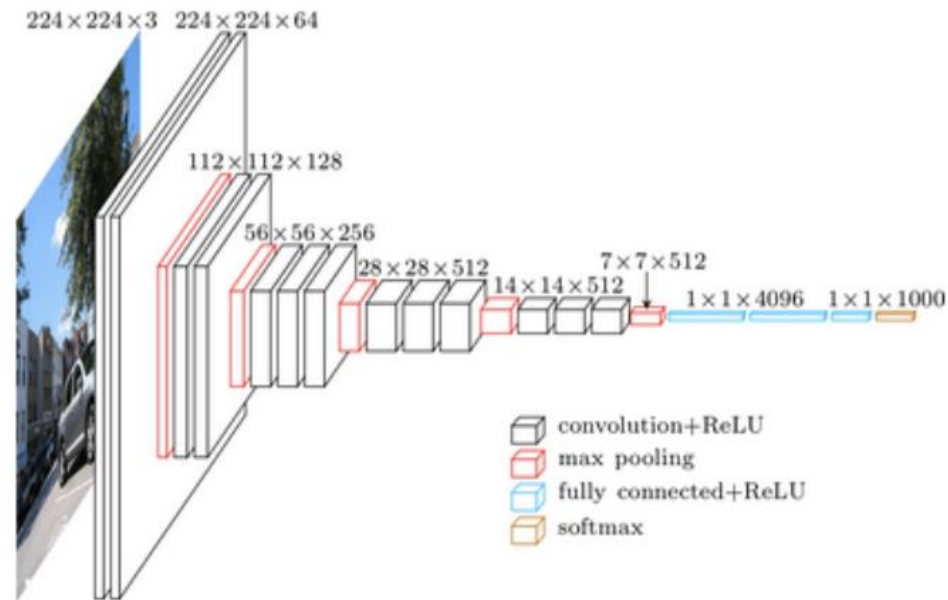
### Why use Keras...

- Keras prioritizes developer experience
- Keras has broad adoption in the industry and the research community
- Keras makes it easy to turn models into products
  - On iOS, via Apple's CoreML (Keras support officially provided by Apple).
  - On Android, via the TensorFlow Android runtime.
  - In the browser, via GPU-accelerated JavaScript runtimes such as Keras.js and WebDNN.
  - On Google Cloud, via TensorFlow-Serving.
  - In a Python webapp backend (such as a Flask app).
  - On the JVM, via DL4J model import provided by SkyMind.
  - On Raspberry Pi (direct Keras installation).

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## VGG-16

### Ex de Deep Network



Simonyan, Karen, and Zisserman. "Very deep convolutional networks for large-scale image recognition." (2014)