

Introduction

[Méthode scientifique]

1st paradigm



Experimental science

2nd paradigm

$$i\hbar \frac{d}{dt} |\Psi(t)\rangle = \hat{H} |\Psi(t)\rangle$$

$$\nabla \times H = J + \frac{\partial D}{\partial t}$$

$$F = G \cdot \frac{m_1 \cdot m_2}{r^2}$$

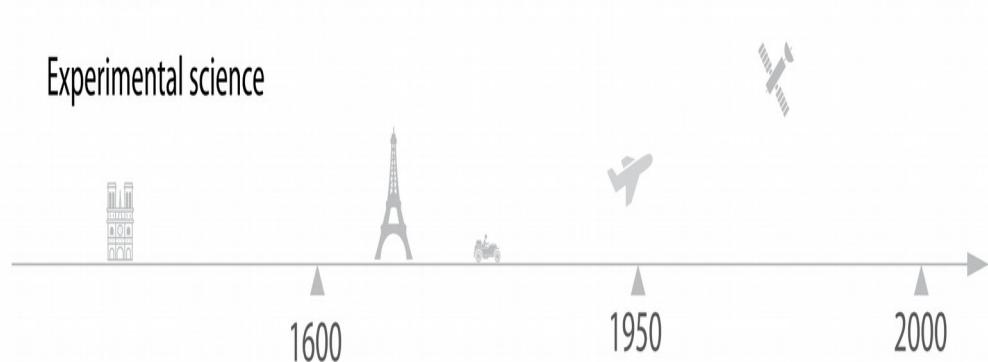
Theoretical science

3rd paradigm

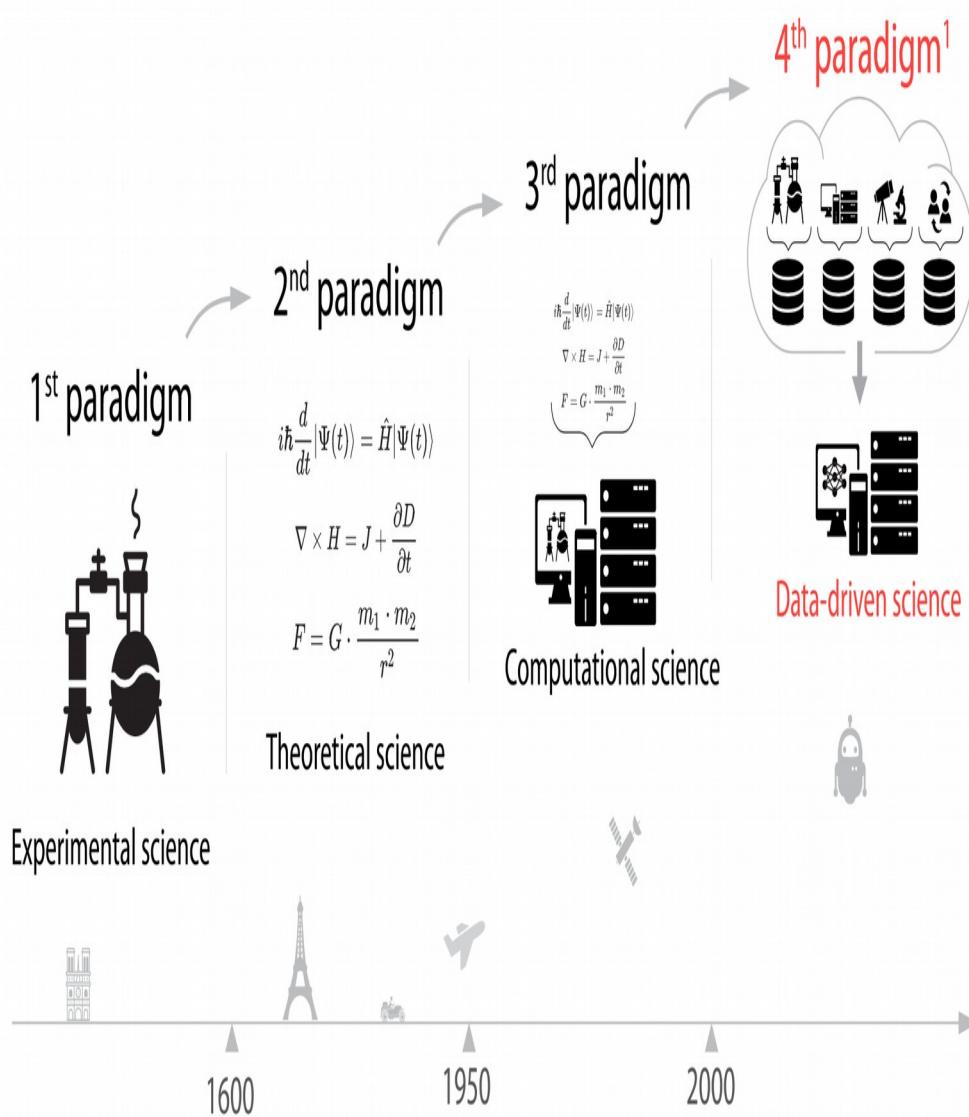
$$i\hbar \frac{d}{dt} |\Psi(t)\rangle = \hat{H} |\Psi(t)\rangle$$
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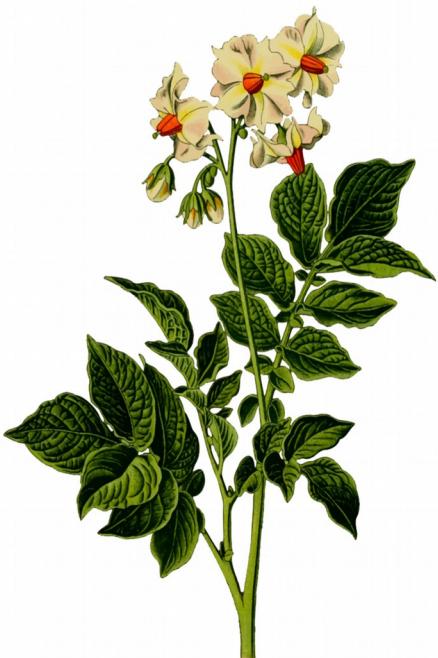
Computational science



[Méthode scientifique]



Intelligence, Intelligence artificielle ...Qu'est ce ?



[intelligence]

« Capacité de percevoir ou d'inférer l'information, et de la conserver comme une connaissance à appliquer à des comportements adaptatifs dans un environnement ou un contexte donné »

« Ability to perceive or infer information, and to retain it as knowledge to be applied towards adaptive behaviors within an environment or context »*

* Wikipedia - Illustration : [POTATO]



[intelligence]

« Ensemble des **fonctions mentales** ayant pour objet la connaissance **conceptuelle et rationnelle** »*

« *Set of mental functions aimed at conceptual and rational knowledge* »

* <https://www.larousse.fr>

The big Controversy

Modelling the brain :
« Penser s'apparente à un calcul massivement parallèle de **fonctions élémentaires**.
L'information est un **signal** avant d'être un **code** »¹

Connectionism

Modelling the brain
Modéliser le cerveau

Making a mind :
« Penser, c'est calculer des **symboles** qui ont à la fois une réalité matérielle et une valeur sémantique de représentation »¹
L'information est une donnée symbolique de **haut niveau**.

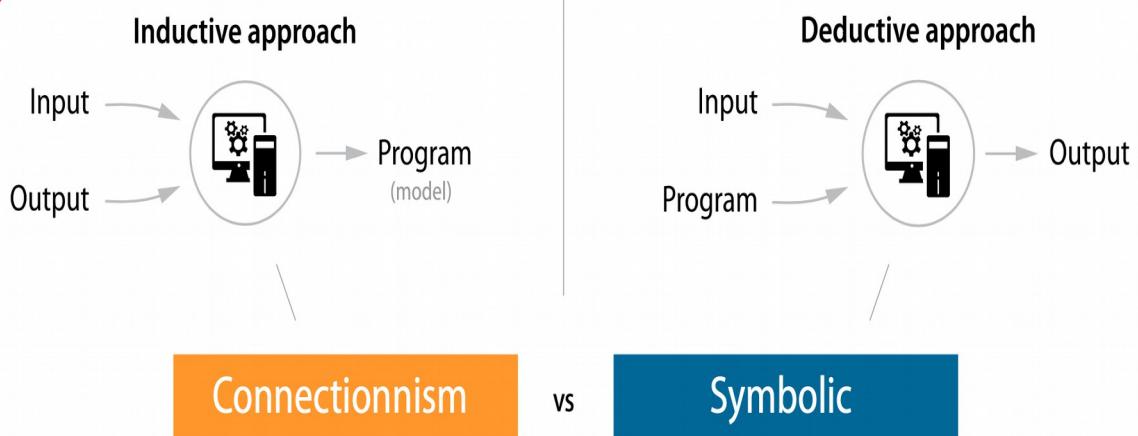
Symbolic

Making a mind
Forger une opinion

Tout [homme] est [mortel]
[Socrate] est un [homme]
Donc [Socrate] est [mortel]

¹ D Cardon, JP Cointet, A Mazieres, 2018 [LRDN]

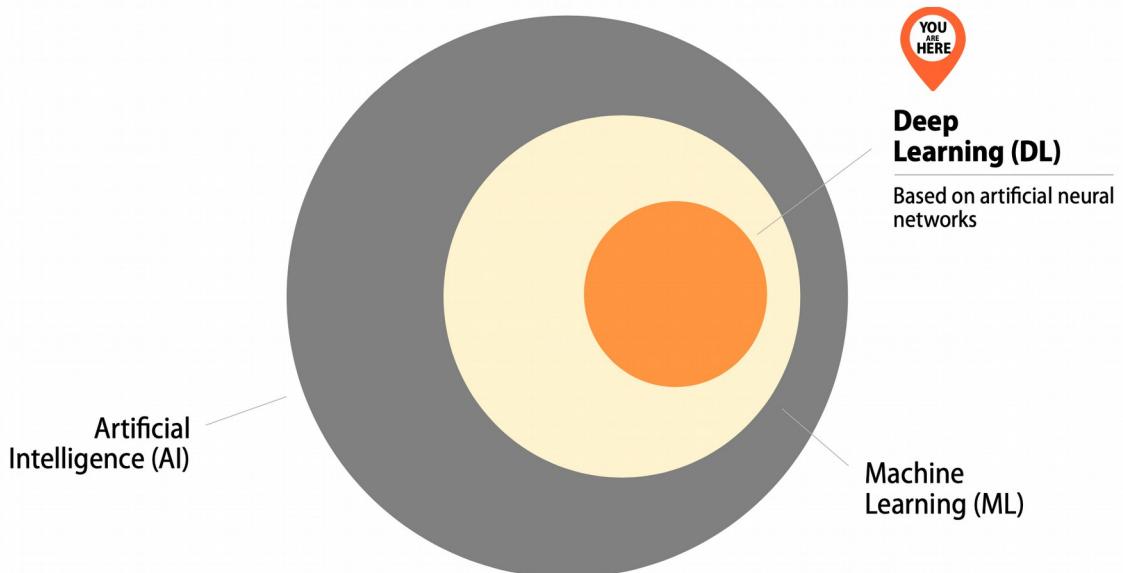
The big Controversy



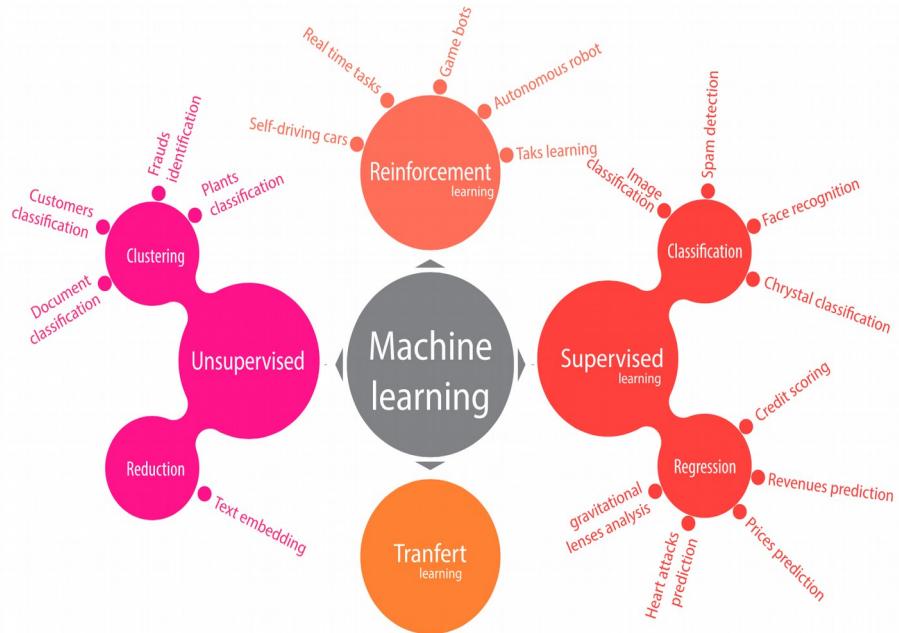
Facts ➤ Rules and laws
↓
Model

Expert
Rules and laws ➤ Special case

[*-learning]

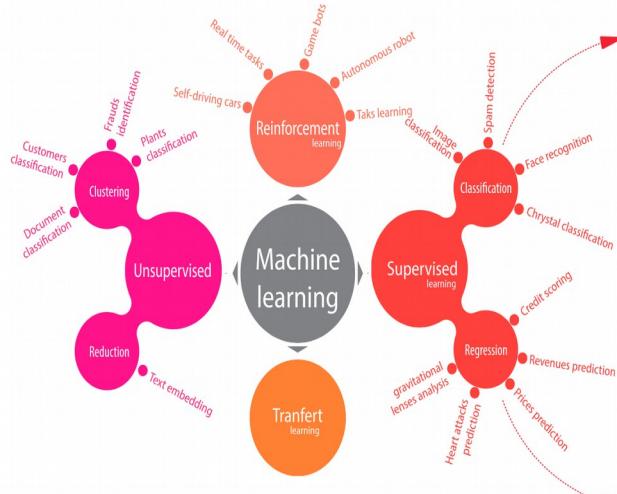


[*-learning]

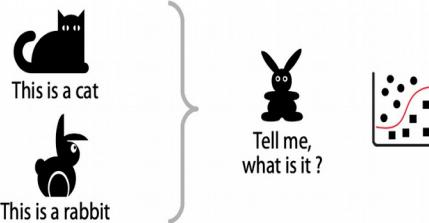


Supervised learning

Learning from examples

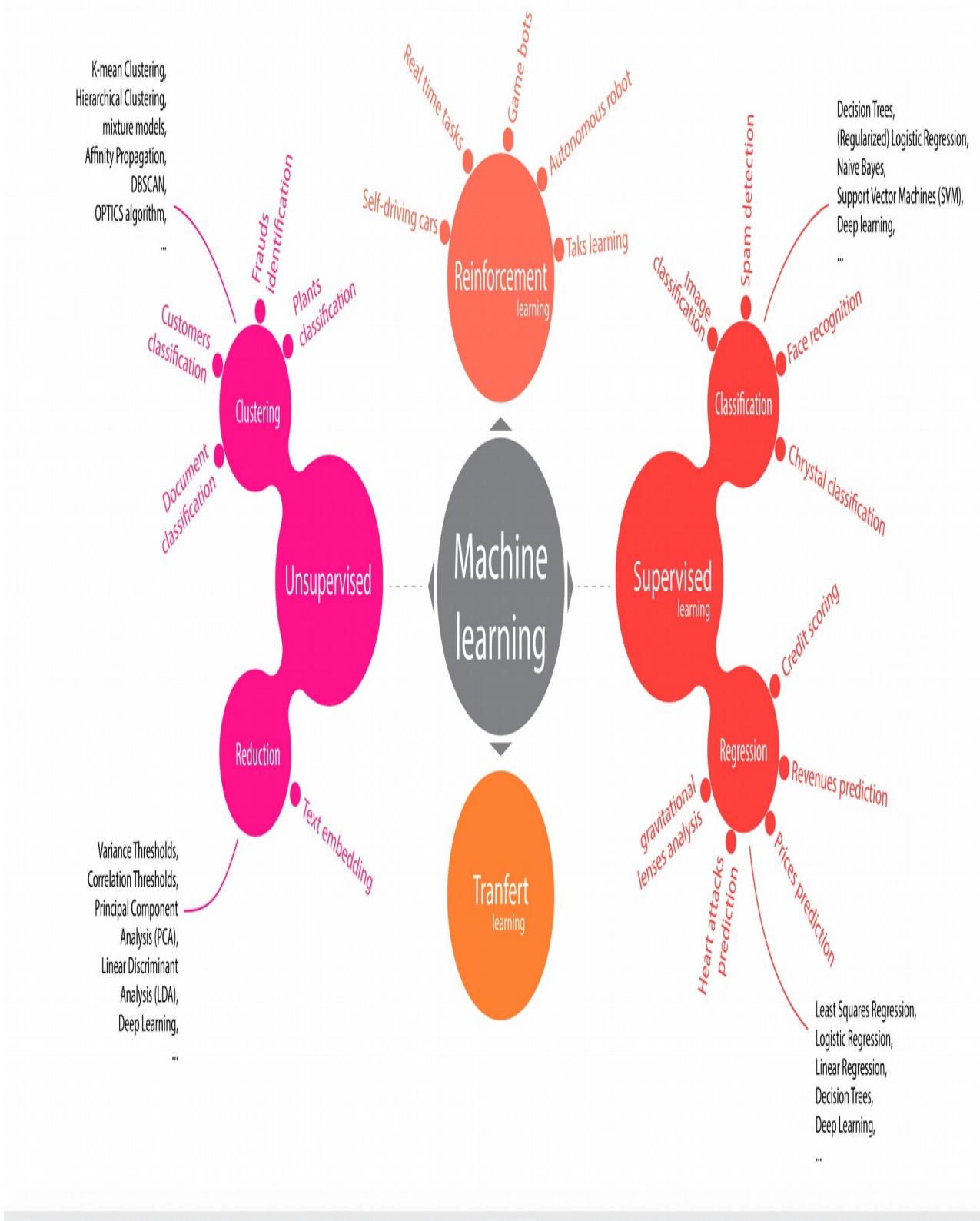


Classification :
Predict qualitative informations



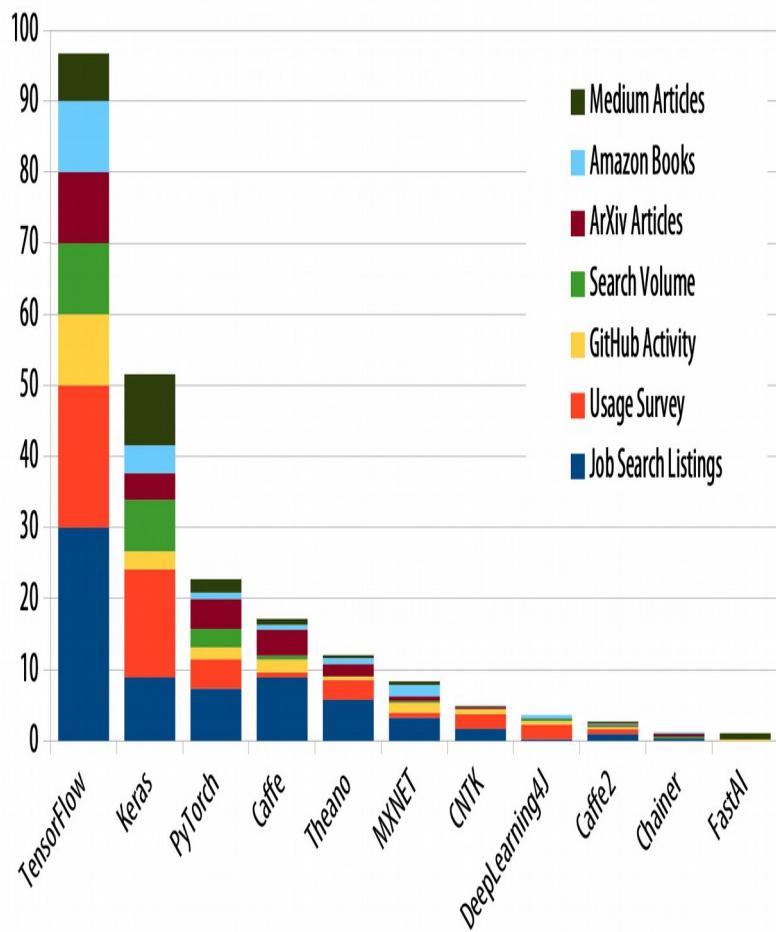
Regression :
Predict quantitative informations





A Python centered world

DL Framework Power Scores 2018



Most used DL framework
Supported by Google
Low level API – an hard way
Apache licence



By François Cholet (Google)
High level API
Part on TensorFlow since 2017
MIT licence



From Torch library
Supported by Facebook
BSD licence

Source : Jeff Hale, « Deep Learning Framework Power Scores 2018 » [DLPW]

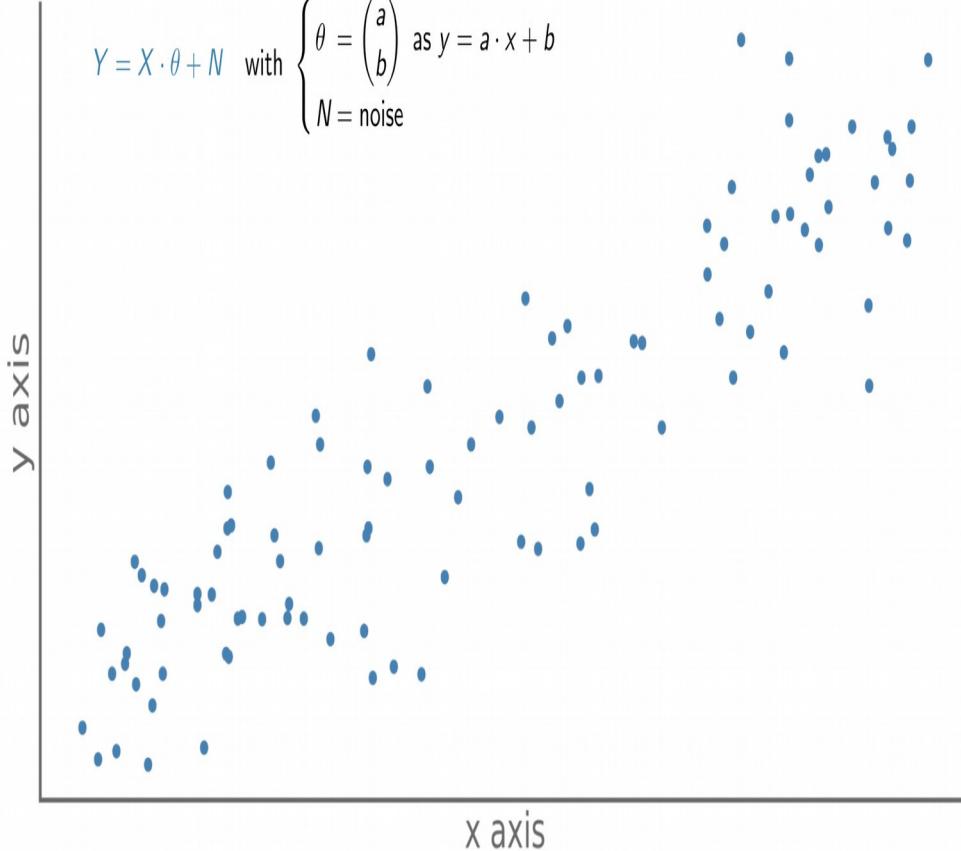
Introduction à l'apprentissage machine

L'exemple de la régression linéaire

Linear regression

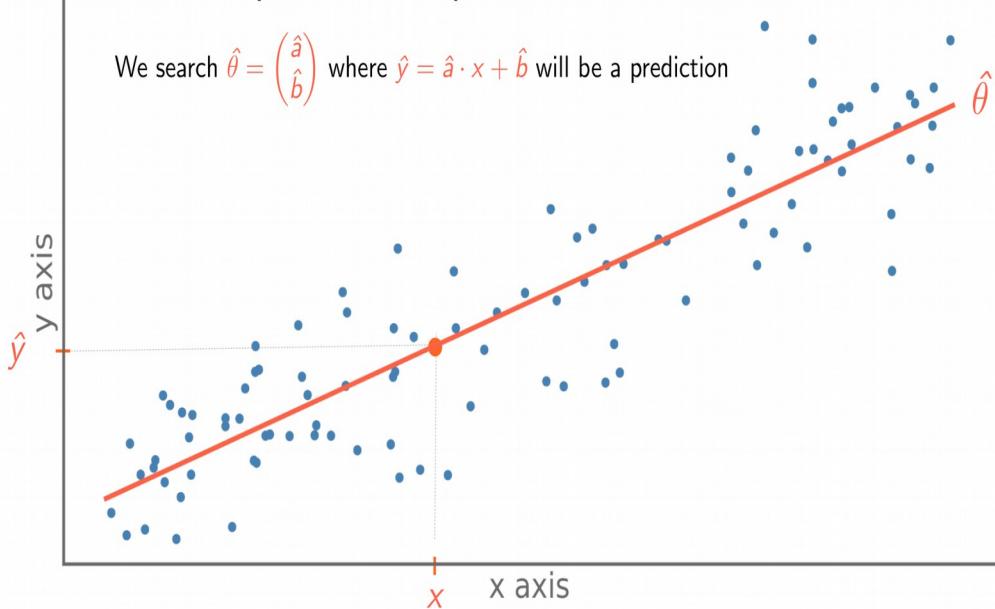
We have a phenomenon, for which we have observations

$$Y = X \cdot \theta + N \quad \text{with} \quad \begin{cases} \theta = \begin{pmatrix} a \\ b \end{pmatrix} \text{ as } y = a \cdot x + b \\ N = \text{noise} \end{cases}$$



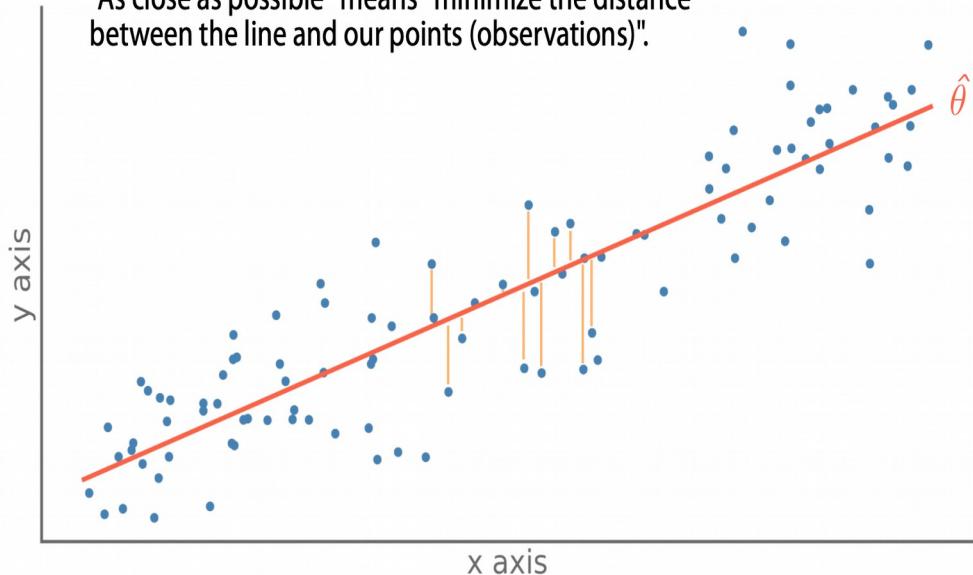
Linear regression

We are looking for a straight line that passes « as close as possible » to our points.



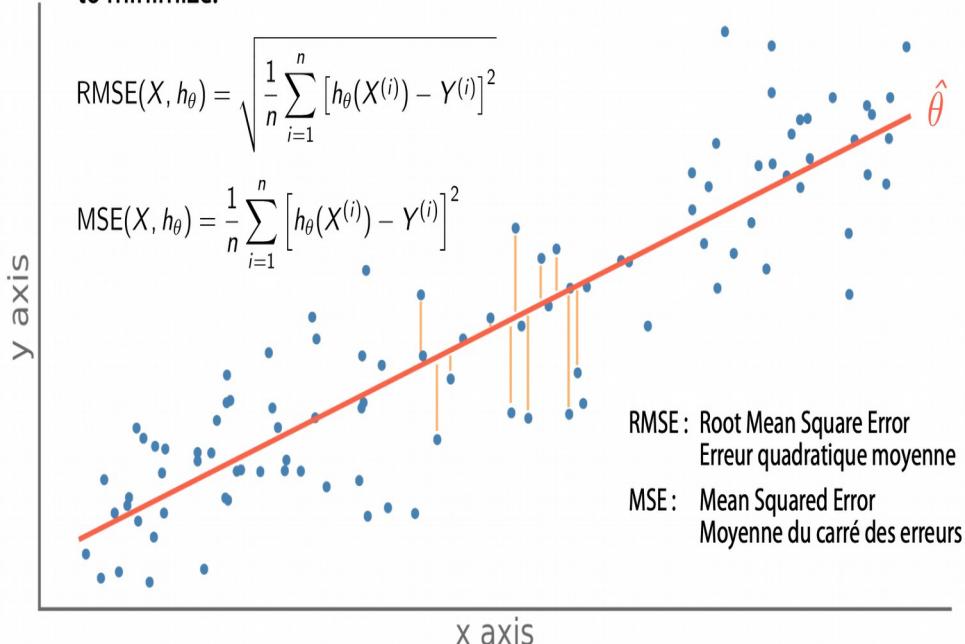
Linear regression

"As close as possible" means "minimize the distance between the line and our points (observations)".



Linear regression

For this, we will use an «loss function», which we will try to minimize.



Linear regression



Good news !
We have a direct solution !

$$\hat{\theta} = (X^{-T} \cdot X)^{-1} \cdot X^{-T} \cdot Y$$

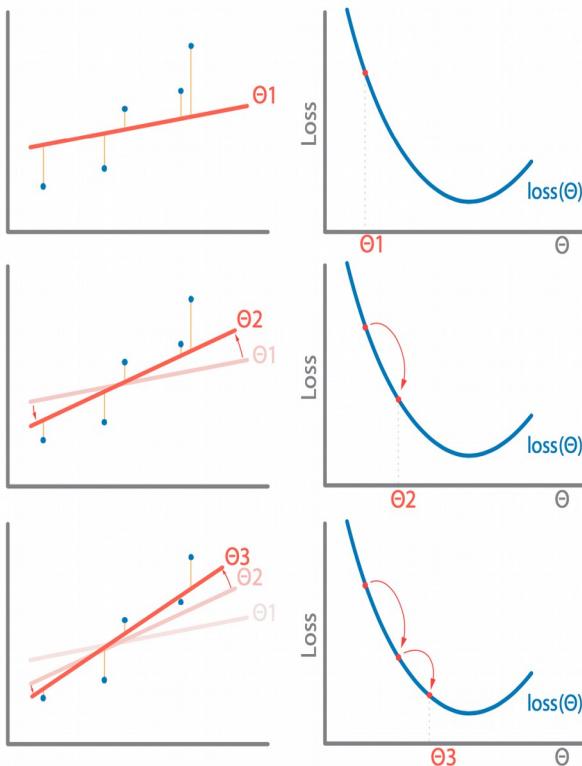
y axis

x axis



Bad news...
Complexity in n^3

Gradient descent



We will iteratively look for the best position of our line, by varying its parameters (Θ).



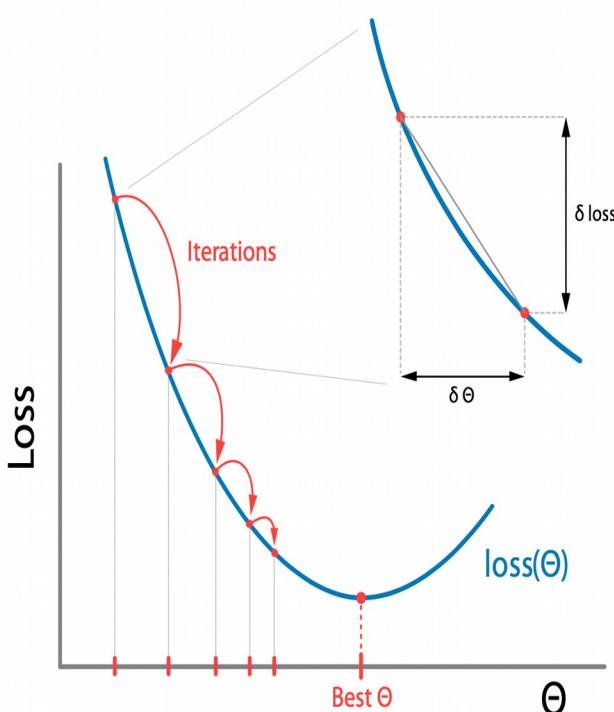
But how can we efficiently vary our parameters (Θ)?

Note : Loss functions could be :

$$\text{RMSE}(X, h_\theta) = \sqrt{\frac{1}{n} \sum_{i=1}^n [h_\theta(X^{(i)}) - Y^{(i)}]^2}$$

$$\text{MSE}(X, h_\theta) = \frac{1}{n} \sum_{i=1}^n [h_\theta(X^{(i)}) - Y^{(i)}]^2$$

Gradient descent



 By changing Θ from $\delta\Theta$
We improve $\text{loss}(\Theta)$ of δloss

The gradient is the slope we will follow to minimize our loss function.

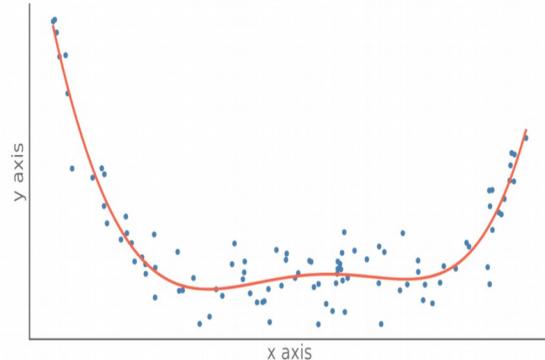
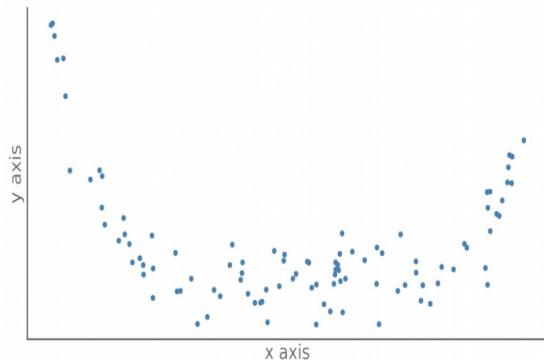
$$\text{gradient} = \frac{\delta \text{loss}}{\delta \theta}$$

One iterative solution is : $\theta \leftarrow \theta - \eta \cdot \frac{\delta \text{loss}}{\delta \theta}$

where η is the learning rate

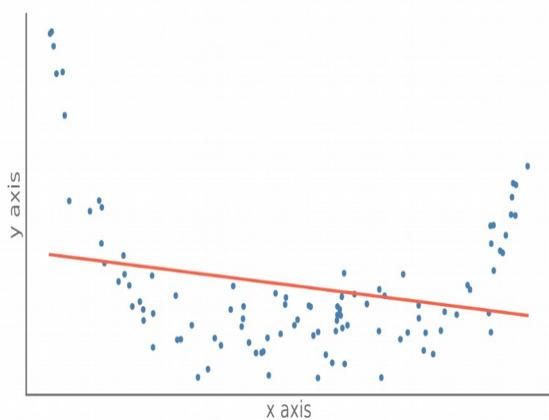
This process is called **gradient descent** and the function used to optimize the descent, **optimization function**

Polynomial regression

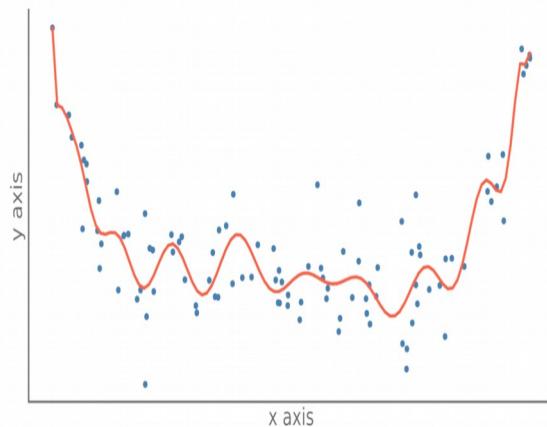


$$P_n(x) = a_0 + a_1 \cdot x + a_2 \cdot x^2 + \cdots + a_n \cdot x^n = \sum_{i=0}^n a_i \cdot x^n$$

Polynomial regression



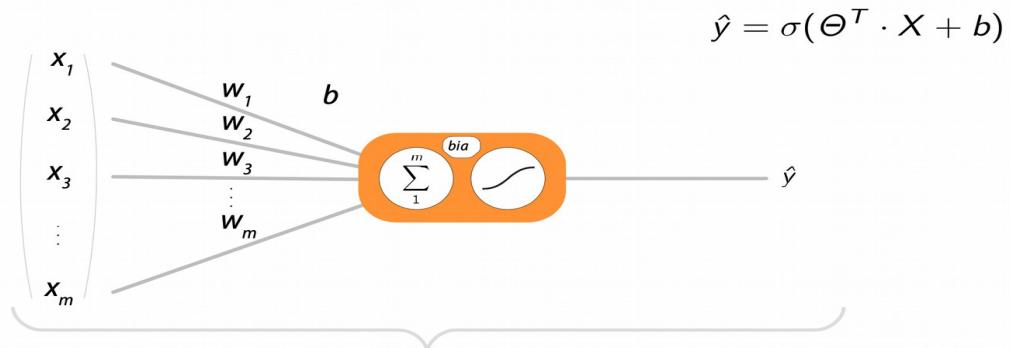
Underfitting



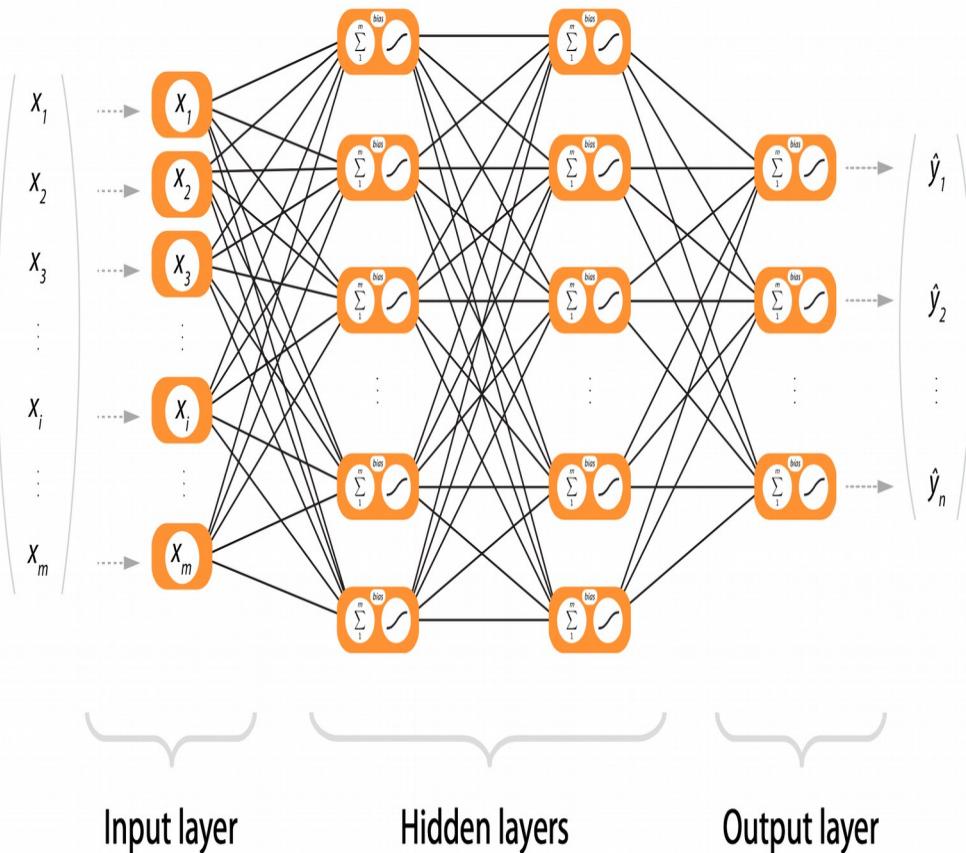
Overfitting

Architecture d'un réseau de neurone

Logistic regression

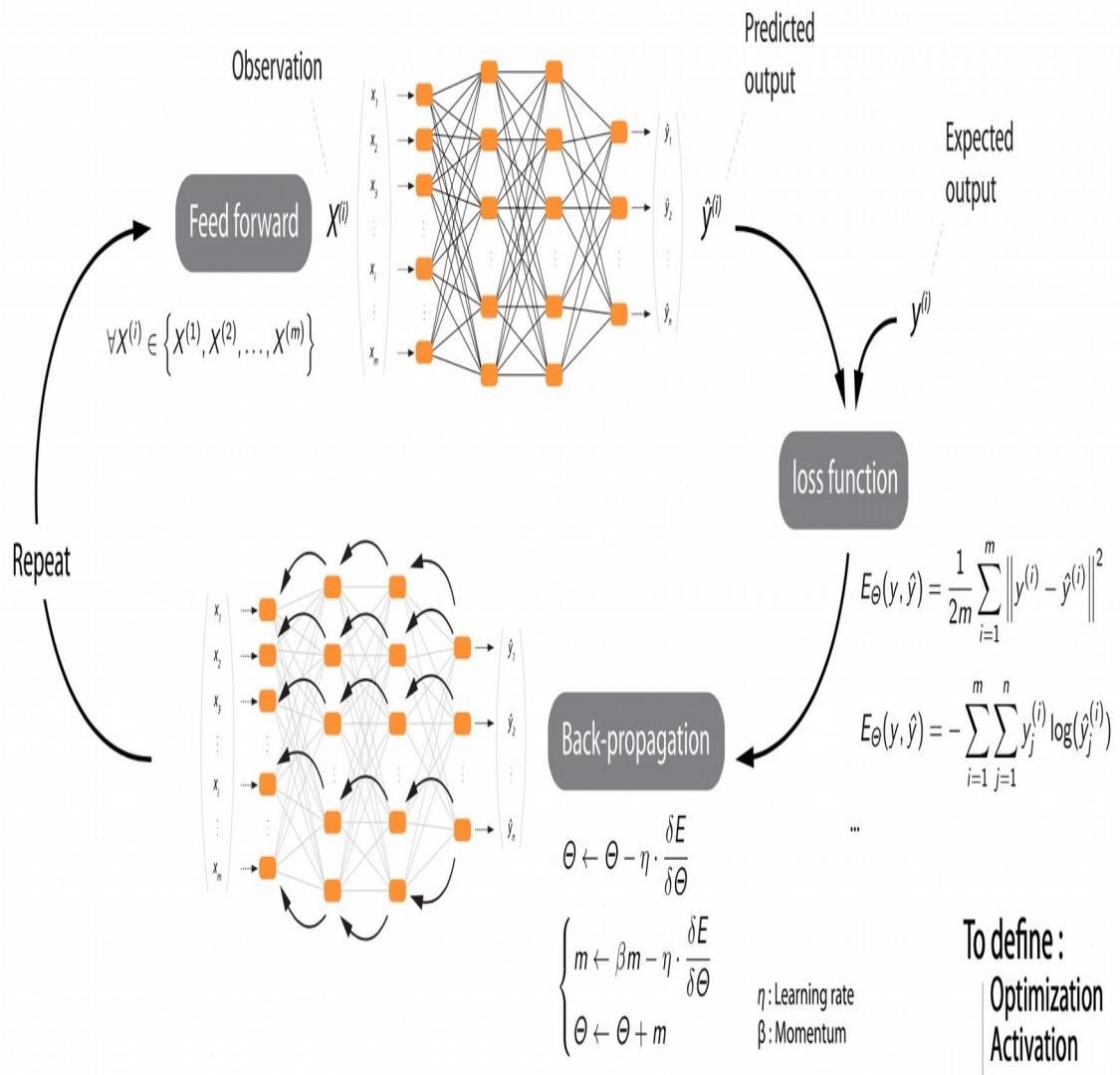


That's an « **artificial neuron** » !
So, we have a neural network of... 1 neuron !



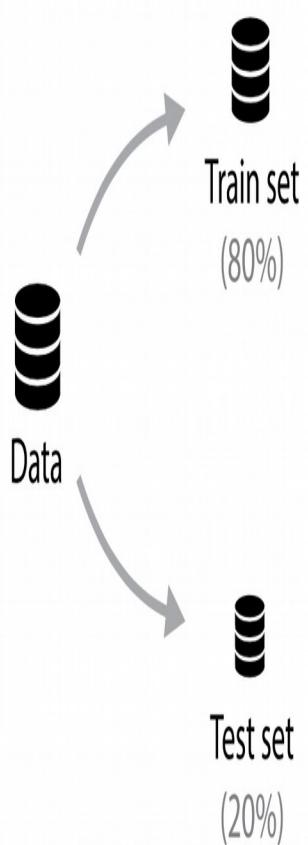
Apprentissage d'un réseau de neurone

Deep Neural Networks

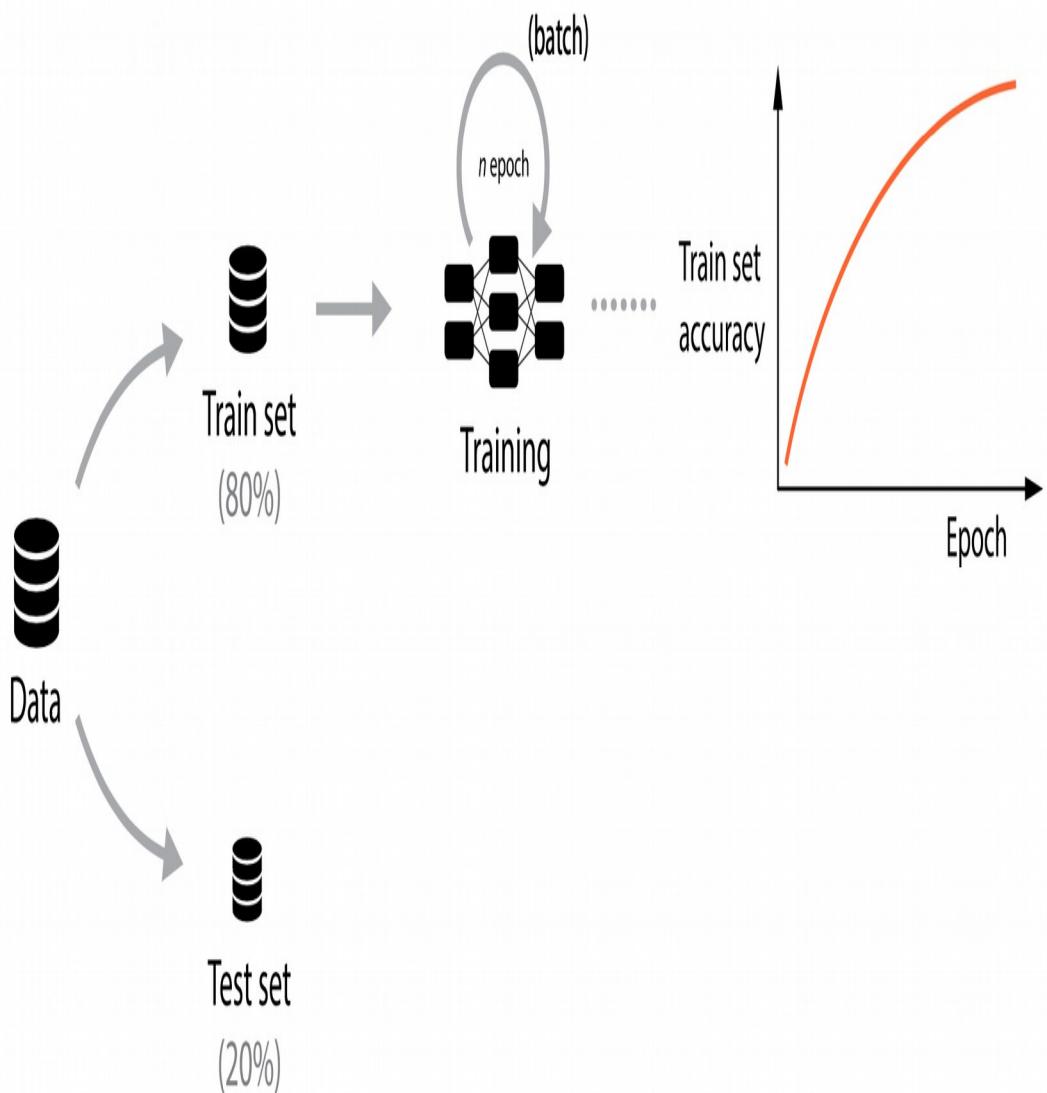


Back-propagation
Learning process

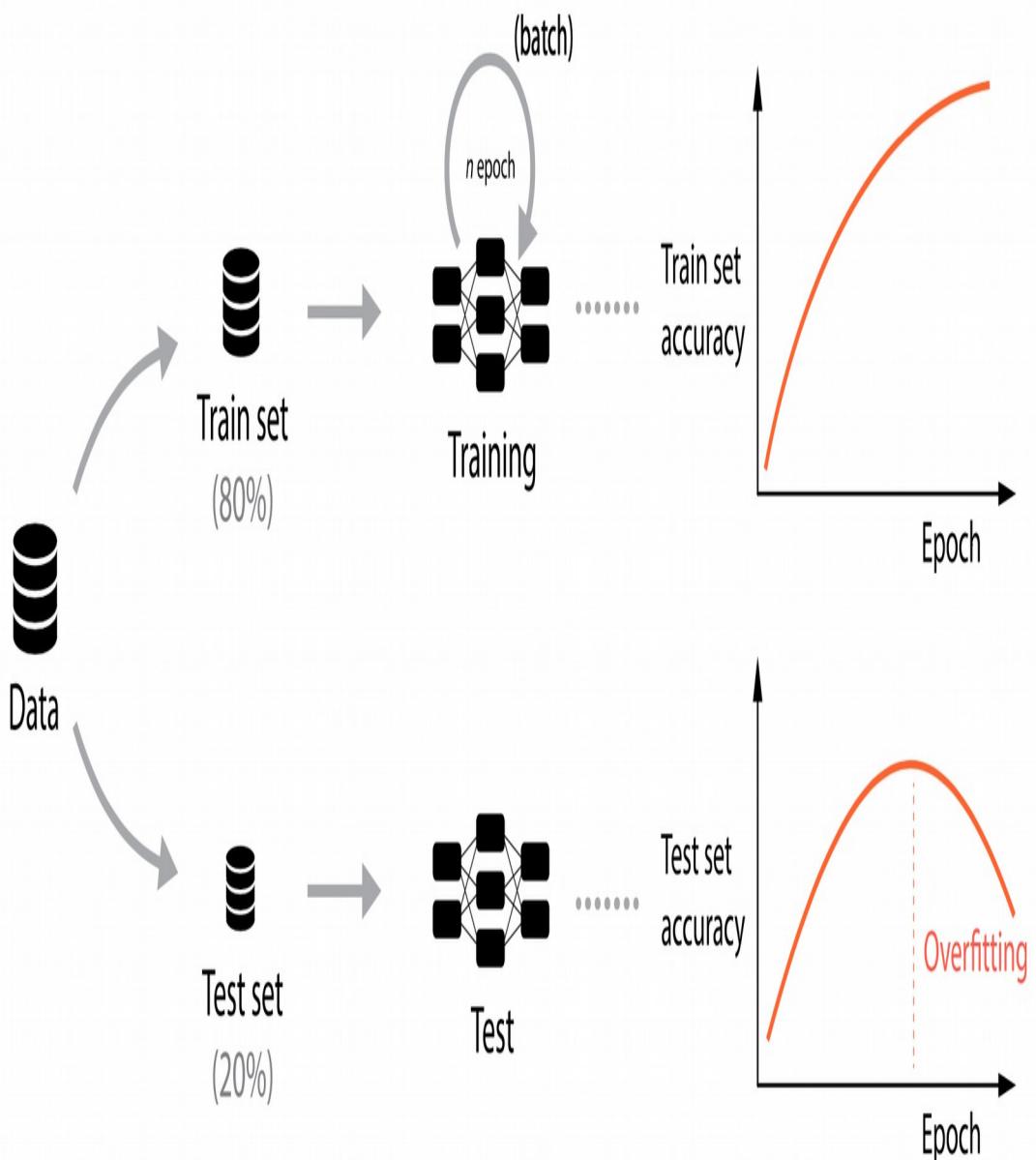
Training process - general



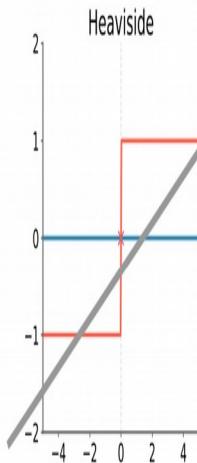
Training process - general



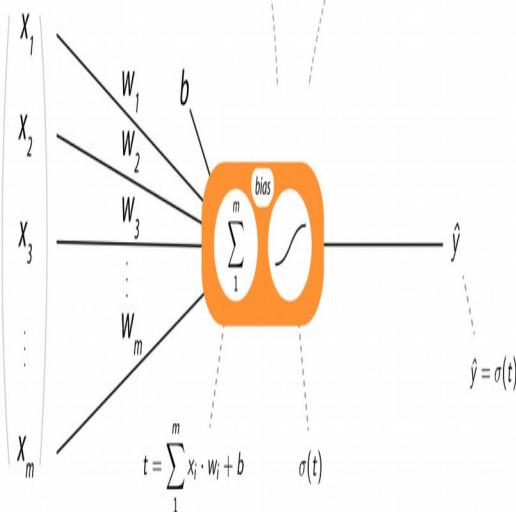
Training process - general



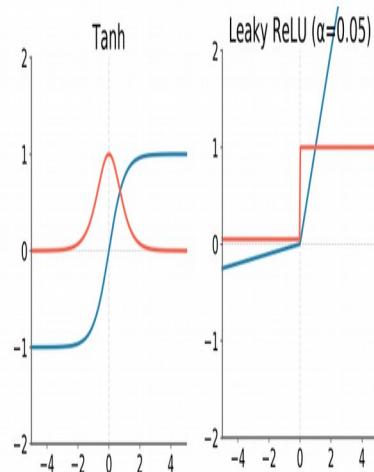
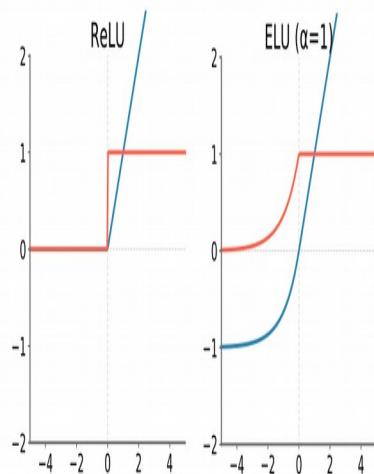
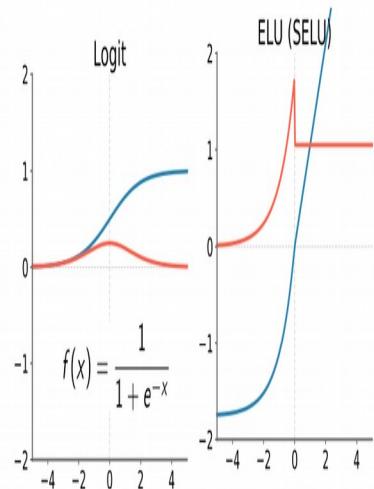
Deep Neural Networks



1958



Input	Bias / Weight	Activation function	Output
x	θ	$\sigma(t)$	\hat{y}

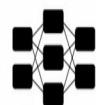


Etapes pour la mise en place d'un projet de machine Learning

Step 1 - Import and init



Step 4 - Build a model



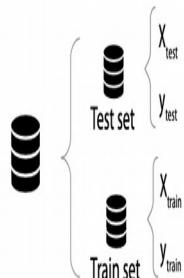
Step 2 - Retrieve data



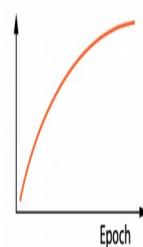
Step 5 - Train the model



Step 3 - Preparing the data



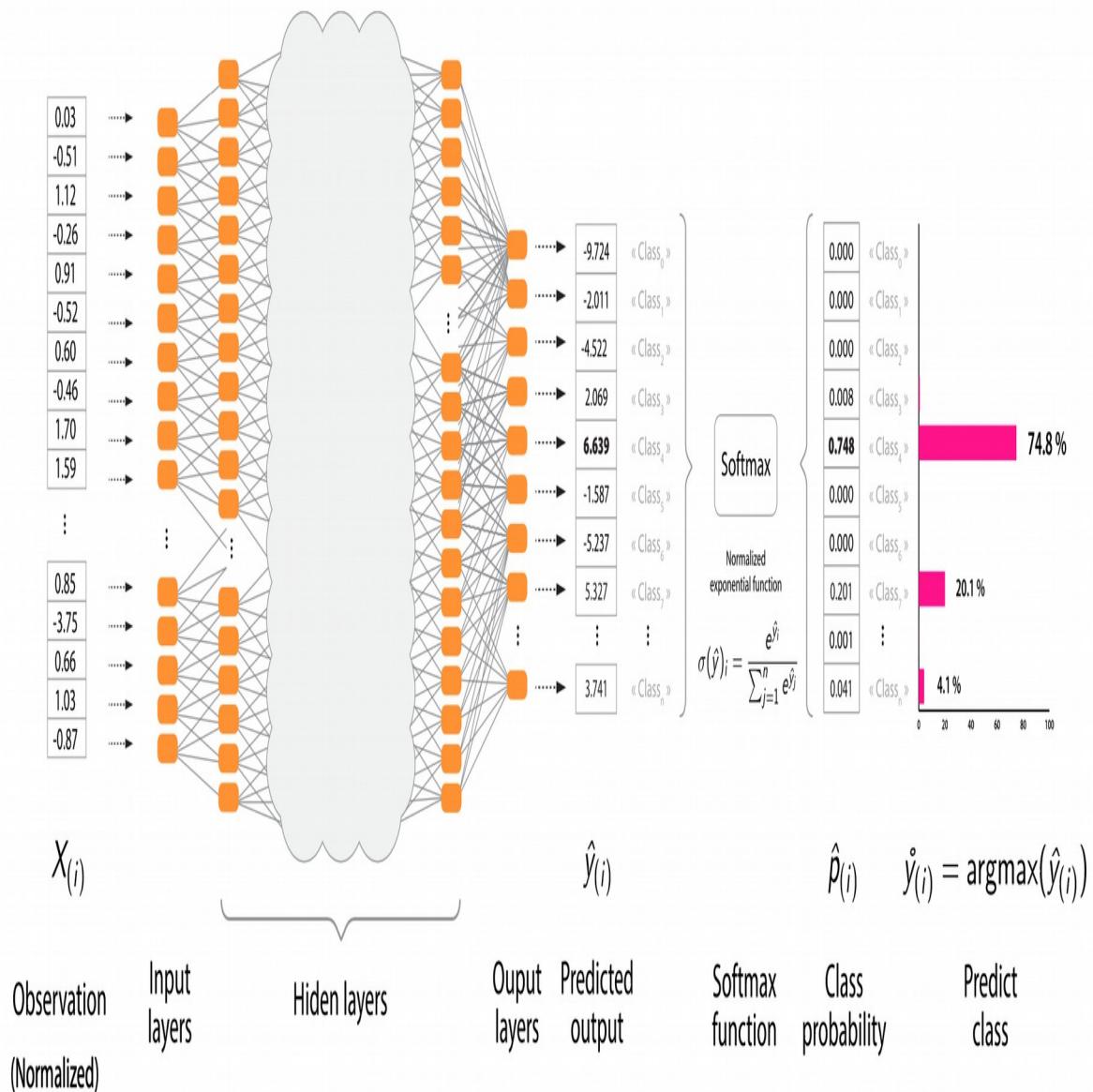
Step 6 - Evaluate



Regression
with a (DNN)
Notebook: [BHP1]



Classification with a DNN



Hold-out evaluation

Validation simple

