Café IA

Feedback on Machine Learning
[Reproducibility of trainings]

I2M / Groupe de Travail - IA / June 26, 2023

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Feedback on Machine Learning

Some points of interest

- [*If needed*...] Preliminaries: the historical way...
- Unsupervised / Supervised / Reinforcement learning
- Use a Virtual Python Environment (PVE) to work on ML...
- The repeatability of trainings: the key to compare trainings.

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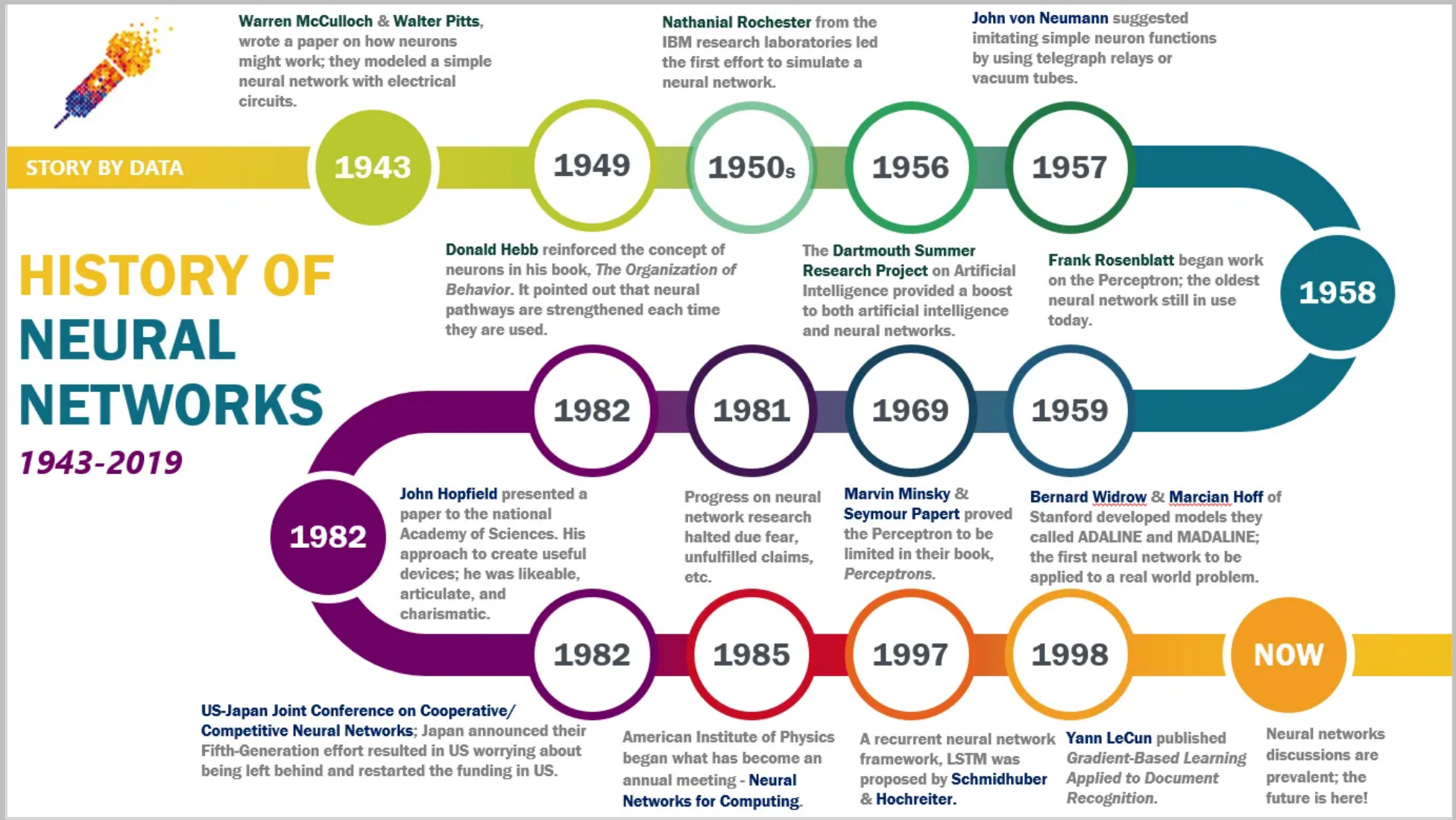
My profile

- I'm teaching Python programming (Scientific & Object Oriented)
- I started to get interested in ML in 2015
- I wrote several materials in ML : workshop, project & practical work for different shools (ENSAM, ENSEIRB, ENSPIMA, PPU...)

The historical way...

from: Kate Strachni: "Brief History of Neural Netowrks", medium.com



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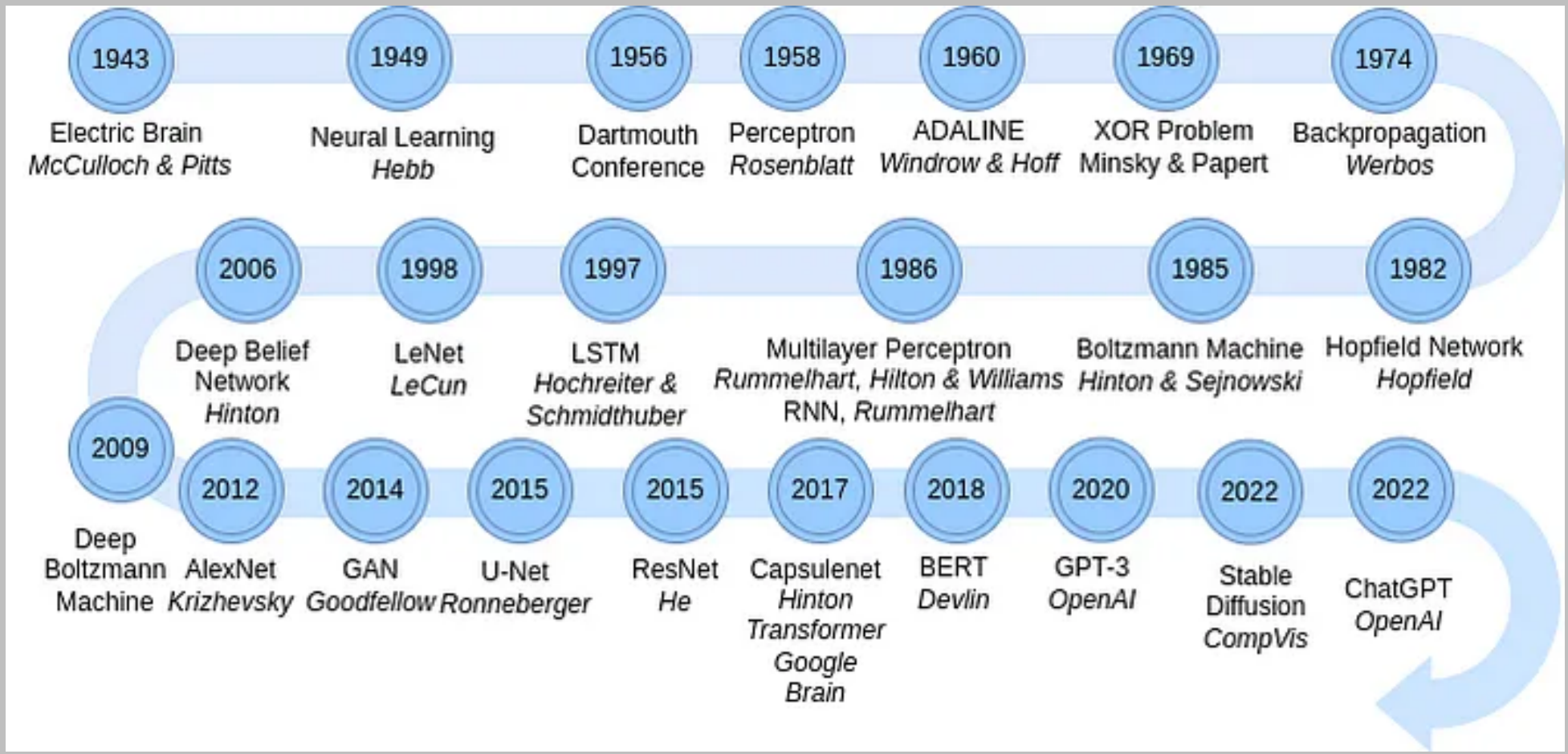

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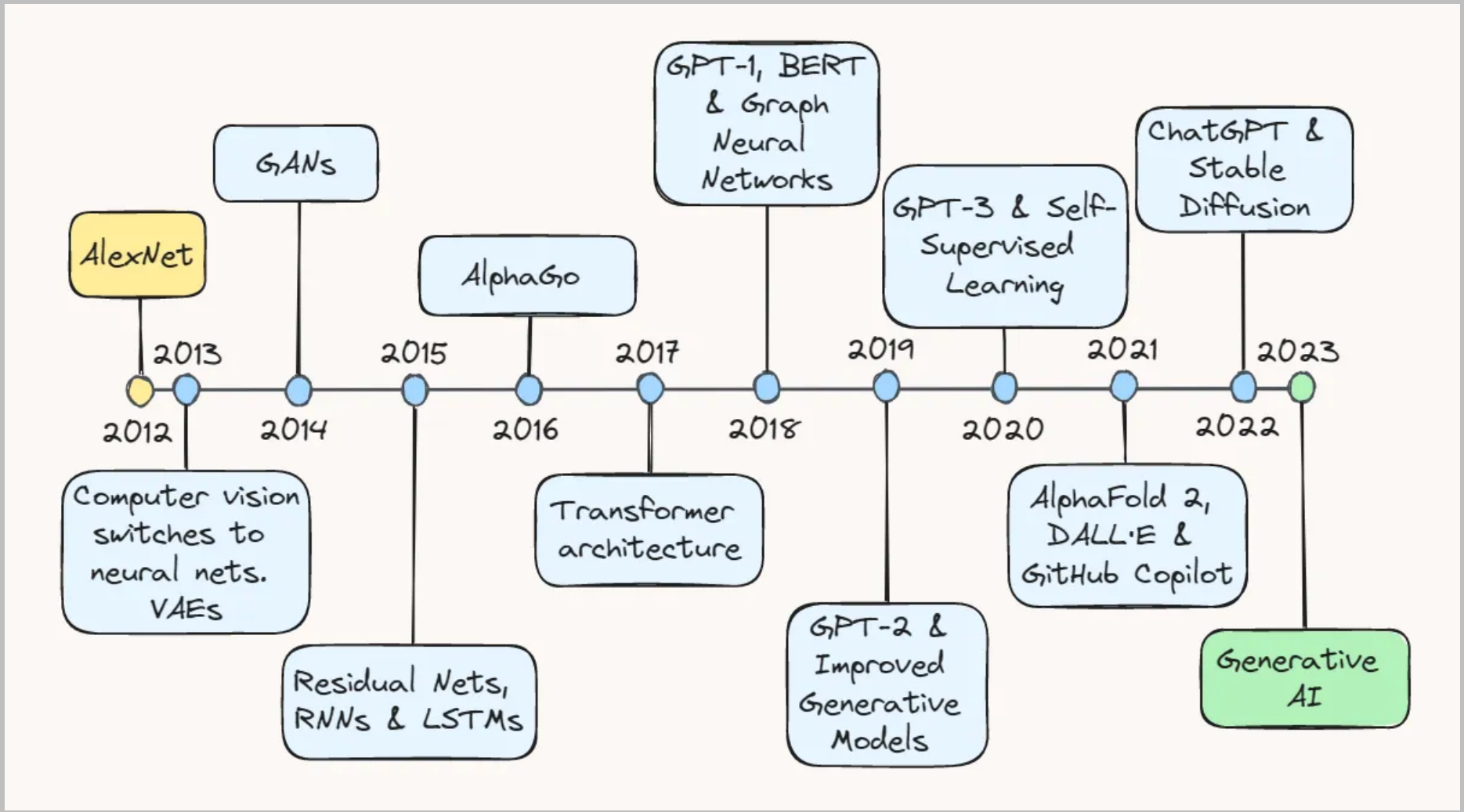

Artificial Intelligence ?

Historically[a] *badly chosen* term
Ambiguous current meaning
Many (contradictory) definitions depending on periods and authors...

[a] first used in 1956 by John McCarthy, researcher at Stanford during the Dartmouth conference

- *"...the science of making computers do things that require intelligence when done by humans."* Alan Turing, 1940
- *"the field of study that gives computers the ability to learn without being explicitly programmed."* Arthur Samuel, 1960
- *"A computer program is said to learn from experience E with respect to some class of tasks T and performance measure P, if its performance at tasks in T, as measured by P, improves with experience E."* Tom Mitchell, 1997
- Notion of *intelligent agent* or *rational agent*
  "...agent that acts in such a way as to reach the best solution or, in an uncertain environment, the best predictable solution."

  Stuart Russel, Peter Norvig, "Intelligence Artificielle" 2015

Artificial Intelligences ?

Strong AI

Weak AI

General AI

Narrow AI

Artificial Intelligences ?

Strong AI

- Build systems that think exactly the same way that people do.
- Try also to explain how humans think... Whe are not yet here.

Weak AI

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- Build systems that can behave like humans.
- The results will tell us nothing about how humans think.
- We already are there... We use it every day!
  (anti-spam, facial/voice recognition, language translation...)

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General AI

- AI systems designed for the ability to reason in general.

Narrow AI

- AI systems designed for specific tasks.

Branches of Machine Learning

Page from medium.com/machine-learning-for-humans/...

Machine learning ⊆ artificial intelligence

ARTIFICIAL INTELLIGENCE

Design an intelligent agent that perceives its environment and makes decisions to maximize chances of achieving its goal.
Subfields: vision, robotics, machine learning, natural language processing, planning, …

MACHINE LEARNING

Gives "computers the ability to learn without being explicitly programmed" (Arthur Samuel, 1959)

SUPERVISED LEARNING
Classification, regression

UNSUPERVISED LEARNING
Clustering, dimensionality reduction, recommendation

REINFORCEMENT LEARNING
Reward maximization

Machine Learning for Humans 🤖👶

Branches of Machine Learning

Supervised learning applications

labeled dataset is used to train algorithms to classify data:

- **Classification**
  - Images classification
  - Objects detection in images
  - Speech recognition...
- **Regression**
  - Predict a value...
- **Anomaly detection**
  - Spam detection
  - Manufacturing: finding known (learned) defects
  - Weather prediction
  - Diseases classification...

. . .

Branches of Machine Learning

Unsupervised learning application

Analyze and cluster **unlabeled datasets**:

- **Clustering** & **Grouping**
  - Data mining, web data grouping, news grouping...
  - Market segmentation
  - Astronomical data analysis...
- **Anomaly Detection**
  - Fraud detecion
  - Manufacturing: finding defects even new ones
  - Monitoring abnormal activity: failure, hacker, fraud...
  - Fake account on Internet...
- **Dimensionality reduction**
  - Compress data using fewer numbers...

. . .

Branches of Machine Learning

Reinforcement learning

An agent learns how to drive an environment by maximising a **reward**:

- **Control/command**
  - Controlling robots, drones, mecatronic systems
  - Factory optimization
  - Financial (stock) trading...
- **Decision making**
  - games (video games)
  - financial analysis...

. . .

Various approaches for ML algorithms

Supervised learning:

- Neural Networks
- Bayesian inference
- Random forest
- Decision Tree
- Support Vector Machine (SVM)
- K-Nearest Neighbor
- Linear regression
- Logistic regression...

Unsupervised learning:

- Neural Networks
- Principal Composant Analysis
- Singular Value Decomposition
- K-mean & Prob. clustering...

Reinforcement learning:

- Neural Networks(Q-learning, Actor-Critic, DDPG, PPO...)
- Monte Carlo
- SARSA

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The following deals only with **Artificial Neural Networks**.

Fields of ML

Computer Vision

- Image Classification
- Object Detection
- (Semantic) Segmentation
- Image Generation
  Les 10 Meilleurs Générateurs d'Images
- Pose Estimation
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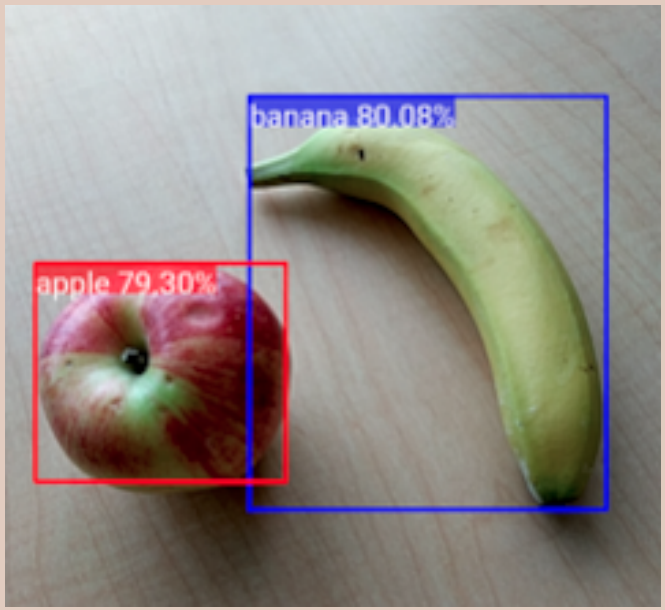

Image credit: Tensorflow

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Image credit: stylegan

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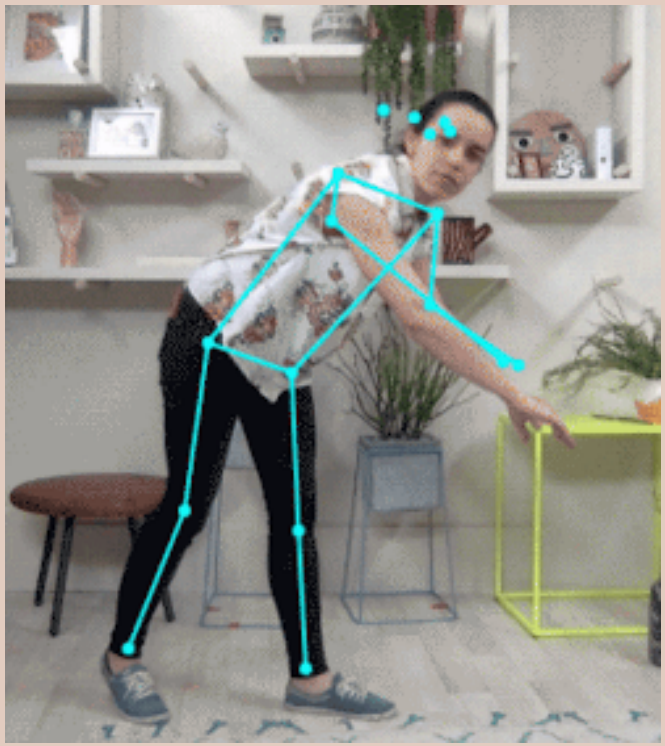

Image credit: Tensorflow-Pose Estimation

Fields of ML

Natural Language Processing: NLP

- Natural Language Understanding (NLU)
- Natural Language Generation (NLG)
- Speech recognition / Speech Synthesis (Text To Speech)
- Machine Translation
- Virtual agents and ChatBots
- Optical character recognition (OCR)
- ...

Neural Network Architectures

Common NN architectures:

- **Feed Forward**: the simplest NN made of successive layers of neurones, with *Feed Forward* and *Back Propagation* algorithms.
- **Convolutional** (CNN): Mostly used for analyzing and classifying images.
- **Recurrent** (RNN): Used to learn from time series, like the Long Short-Term Memory (LSTM) algorithm.
- **Transformers** : Recently used for Natural Language Processing and then for image classification.
- **Auto Encoder** (AEN): Dimensionality reduction, Feature extraction, Denoising of data/images, Imputing missing data.
- **Generative Adversarial** (GAN): to generate text, images, music...
- **Large Language Model** (LLM): read texte, sound, write books, images, speak, make music ...ChatGPT

[Graphical chart: from Saul Dobilas on Medium]

The need for PVE (Python Virtual Environment) to program NN training with Python

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Advantages

- Dedicated environment (disk tree) with fixed version of the Python interpreter and modules
- Easy to create and destroy if needed
- Each Python project can have its own PVE
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Disadvantages

- ? (just do it)

PVE: simple to create & use

with **conda**

- Download & install miniconda
- `conda create -n pyml python=3.8` ⇝ creates the `pyml` PVE
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 conda install and pip install can be conflicting...

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☺ No conflict with conda install

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the winning recipe

- Python Virtual Environment for every ML project
- Git repository (GitHub, GitLab...) for storing, sharing & versionning the project files
- requirement.txt to install the Python modules in the required version for each project
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Reproducibility of training

Where to find randomness in NN training

- **Random initialization of the weights** of the network before the training starts.
- Regularization, e.g. **dropout**, which involves randomly dropping nodes in the network while training.
- Optimization process like **stochastic gradient descent** or **Adam** also include randomness.
- Shuffling of data to build batches to train the NN
- and many others stages in ML algorithms where random genertaors are used...

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Practical work with tensorflow

- We will run a **Jupyter notebook** to illustrate the *Reproducibility of training* with **tensorflow**.
- See the PVE usage
- Create a simple *Feed Forward* dense network and train it to classify *hand written* images form the MNIST
- Explore where and how the question of the Reproducibility occurs... and how to solve it

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[1] *Artificial Intelligence: A Modern Approach (4th Edition)*, By Stuart Russell & Peter Norvig. Pearson, 2020. ISBN 978-0134610993. aima.cs.berkeley.edu

Intelligence artificielle – Une approche moderne – 4e éd., By Stuart Russell & Peter Norvig. Translated by L. Miclet, F. Popineau, & C. Cadet. Paris: Pearson Education France, 2021. ISBN 978-2326002210.

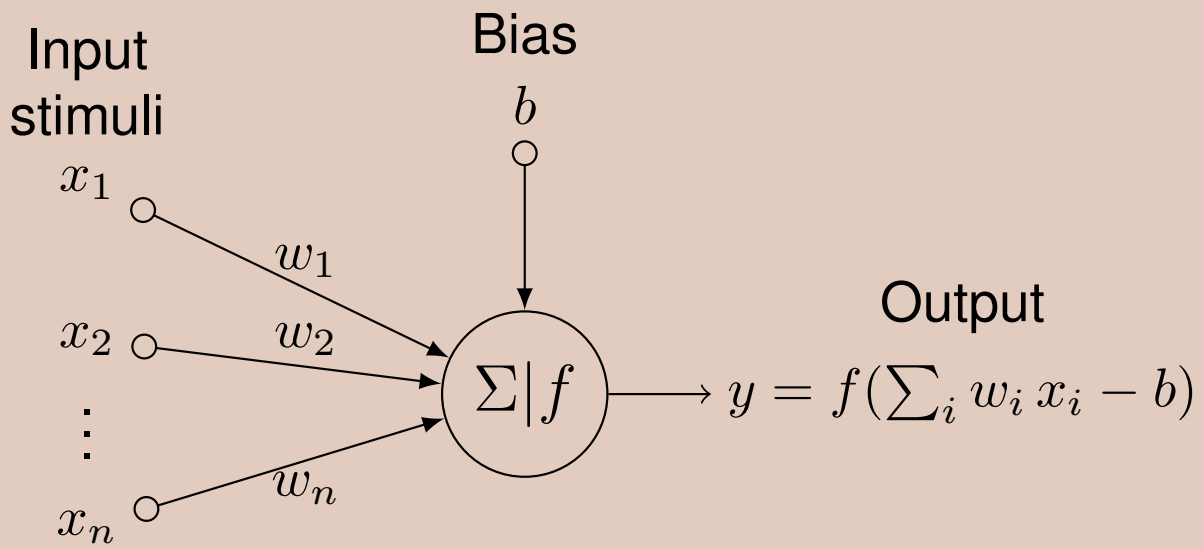
[2] *What is artificial intelligence (AI), and what is the difference between general AI and narrow AI?*, Kris Hammond, 2015
www.computerworld.com/article/2906336/what-is-artificial-intelligence.html

[3] *Stanford Encyclopedia of Philosophy*, plato.stanford.edu/entries/artificial-intelligence

[4] *Deep Learning.*, Goodfellow, Ian; Bengio, Yoshua; Courville, Aaron (2016), MIT Pres, ISBN 9780262035613

Artificial Neural Networks

The Artificial neuron model

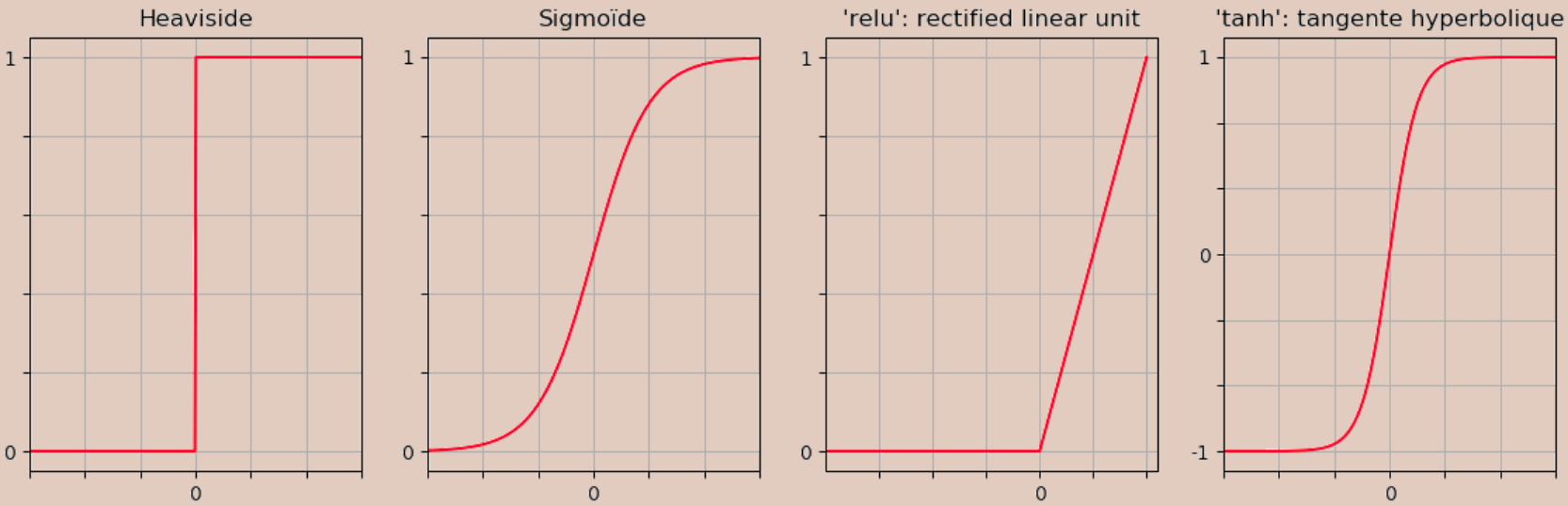


An **artificial neuron**:

- receives the input stimuli $(x_i)_{i=1..n}$ with **weights** (w_i)
- computes the **weighted sum** of the input $\sum_i w_i\, x_i - b$
- outputs its activation $f(\sum_i w_i\, x_i - b)$, computed with a non-linear **activation function** f .

Artificial Neural Networks

Common activation functions

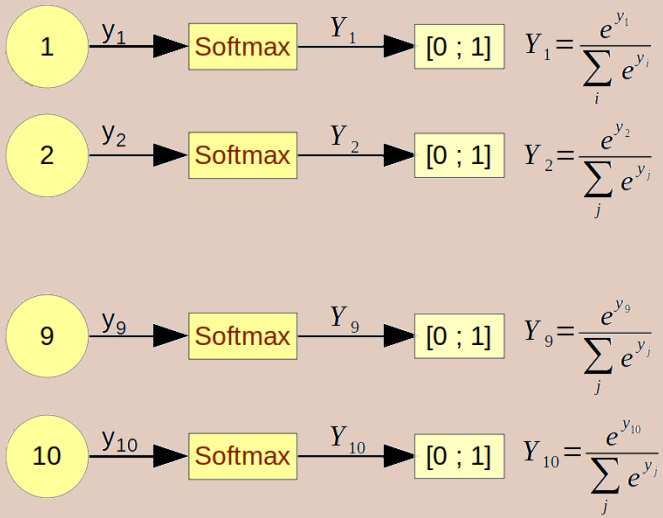


- Introduces a non-linear behavior.
- Sets the range of the neuron output: $[-1, 1]$, $[0, 1]$, $[0, \infty[$...
- The bias b sets the activation threshold of the neuron.

Réseau de neurones dense

- Dans les couches intermédiaires la fonction d'activation **relu** favorise l'apprentissage du réseau [1].
- La classification (dernière couche) utilise la fonction **softmax** :

Fonction d'activation *softmax*



- L'activation du neurone k est $Y_k = e^{y_k} / \sum_i e^{y_i}$ avec $y_k = \sum_i \omega_i x_i - b$ calculé par le neurone k.
- Les sorties des neurones s'interprètent comme des probabilités dans l'intervalle [0,1].

[1] évite le *vanishing gradient* qui apparaît dans l'algorithme de *back propagation*

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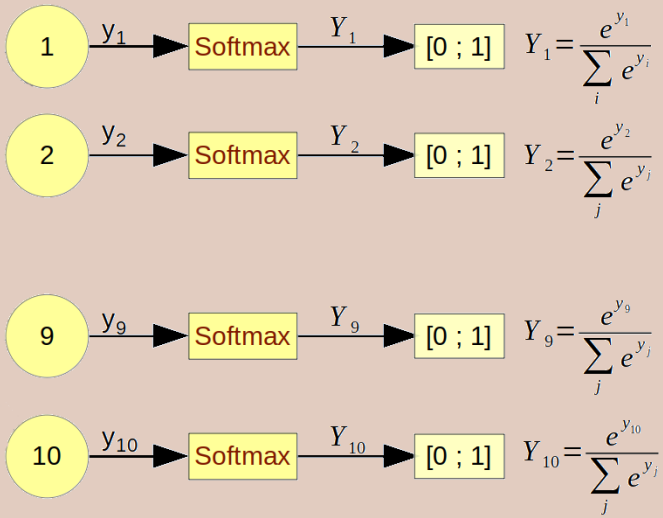

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Réponse du réseau $\rightsquigarrow$ label associé au neurone de plus grande probabilité.

[1] évite le *vanishing gradient* qui apparaît dans l'algorithme de *back propagation*

Réseau de neurones dense

Codage *One-hot* des labels

Mettre les labels des images au format de la sortie du réseau :

- Labels des images : **nombres entiers** de 0 à 9.
- Sortie du réseau : **vecteur de 10** `float` dans l'intervalle [0,1] calculés par les fonctions *softmax* des 10 neurones de sortie.
- Codage *one-hot* d'un ensemble ordonné $\mathfrak{L}$ de N labels :

  - chaque label est représenté par un vecteur à N composantes toutes nulles, sauf une (égale à 1),
  - le rang du 1 du vecteur associé à un label est le rang du label dans $\mathfrak{L}$.

Réseau de neurones dense

Codage *One-hot* des labels

Mettre les labels des images au format de la sortie du réseau :

- Labels des images : **nombres entiers** de 0 à 9.
- Sortie du réseau : **vecteur de 10** `float` dans l'intervalle [0,1] calculés par les fonctions *softmax* des 10 neurones de sortie.
- Codage *one-hot* d'un ensemble ordonné $\mathfrak{L}$ de N labels :

  bel est représenté par un vecteur à N composantes
  es, sauf une (égale à 1),
  1 du vecteur associé à un label est le rang du label

chiffre	vecteur *one-hot*
0	[1 0 0 0 0 0 0 0 0 0]
1	[0 1 0 0 0 0 0 0 0 0]
2	[0 0 1 0 0 0 0 0 0 0]
3	[0 0 0 1 0 0 0 0 0 0]
4	[0 0 0 0 1 0 0 0 0 0]
5	[0 0 0 0 0 1 0 0 0 0]
6	[0 0 0 0 0 0 1 0 0 0]
7	[0 0 0 0 0 0 0 1 0 0]
8	[0 0 0 0 0 0 0 0 1 0]
9	[0 0 0 0 0 0 0 0 0 1]

Le codage *one-hot* des labels '0' à '9' donne un vecteur à 10 composantes, comme celui calculé par le réseau de neurones.

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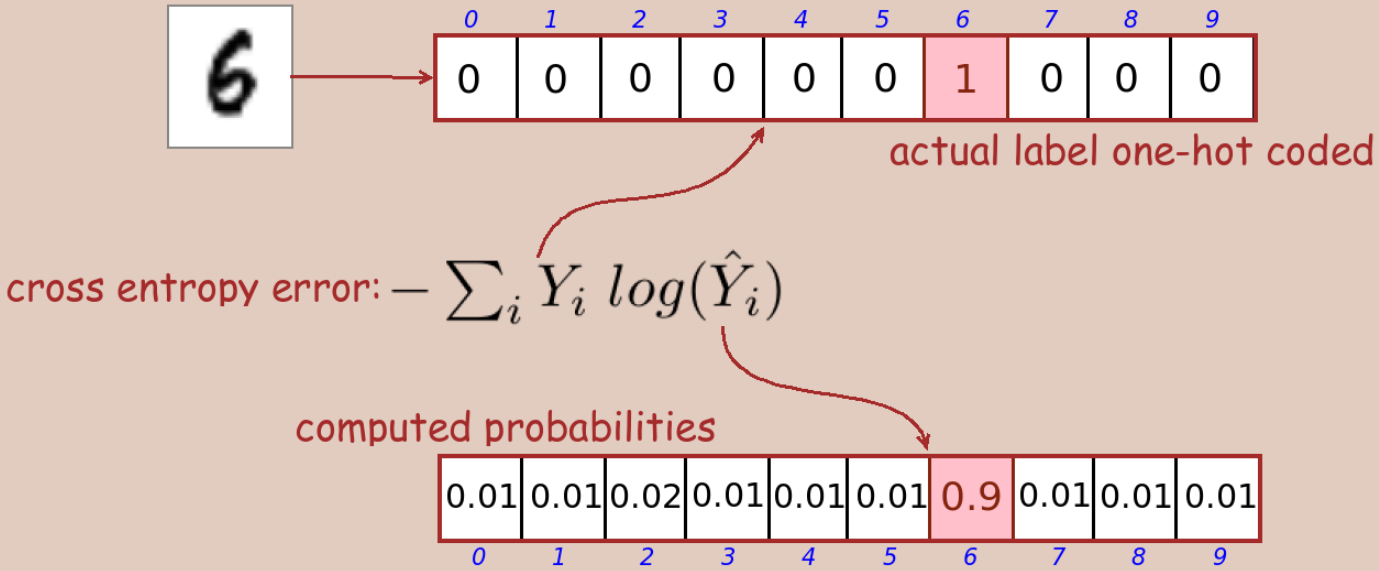
Fonction d'erreur : *Cross entropy error*

- L'image traitée par le réseau $\rightsquigarrow$ vecteur $\hat{Y}$ de 10 `float` à comparer au vecteur Y du codage *hot-one* du label de l'image.
- La fonction d'erreur (de perte) *cross entropy* est adaptée au codage *one-hot* : $e(Y, \hat{Y}) = -\sum_i Y_i \, log(\hat{Y}_i)$



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Optimisation et *Back Propagation*

- Pendant la phase d'apprentissage un algorithme d'optimisation calcule le gradient de la fonction d'erreur par rapport aux poids du réseau.

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- Exemples d'algorithme d'optimisation :
  - Descente de Gradient (*Gradient Descent (GD)*)
  - Descente de Gradient Stochastique (*Stochastic Gradient Descent (SGD)*)
  - *Adam* (version améliorée de descente de gradient)...

  Le module tf.keras.optimizers propose l'implémentation Python de plusieurs algorithmes d'optimisation.

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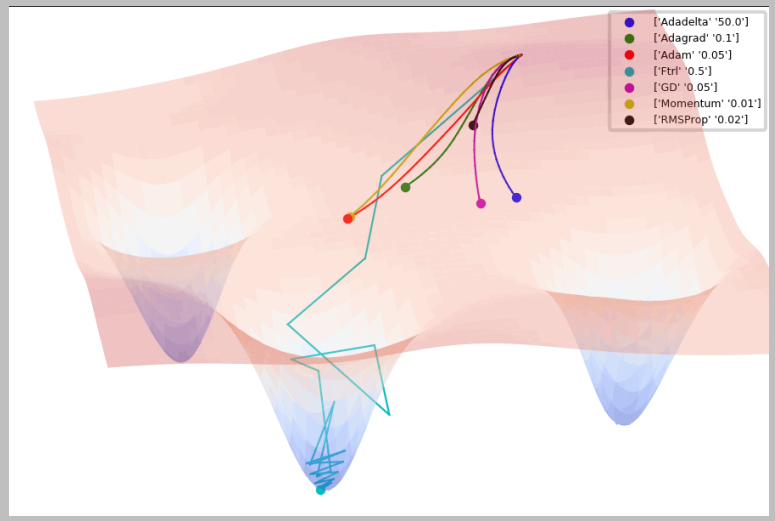
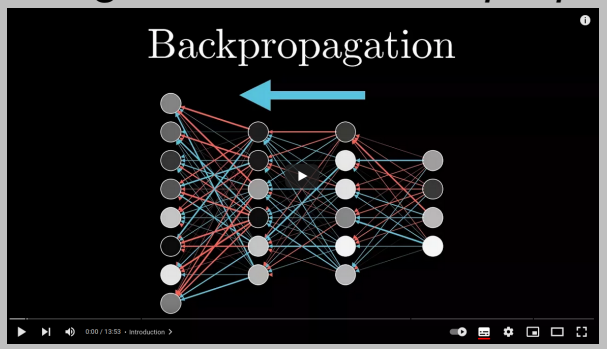
Visualisation des itérations d'algorithmes de descente de gradient pour une fonction de perte ultra-simple à seulement 2 variables :

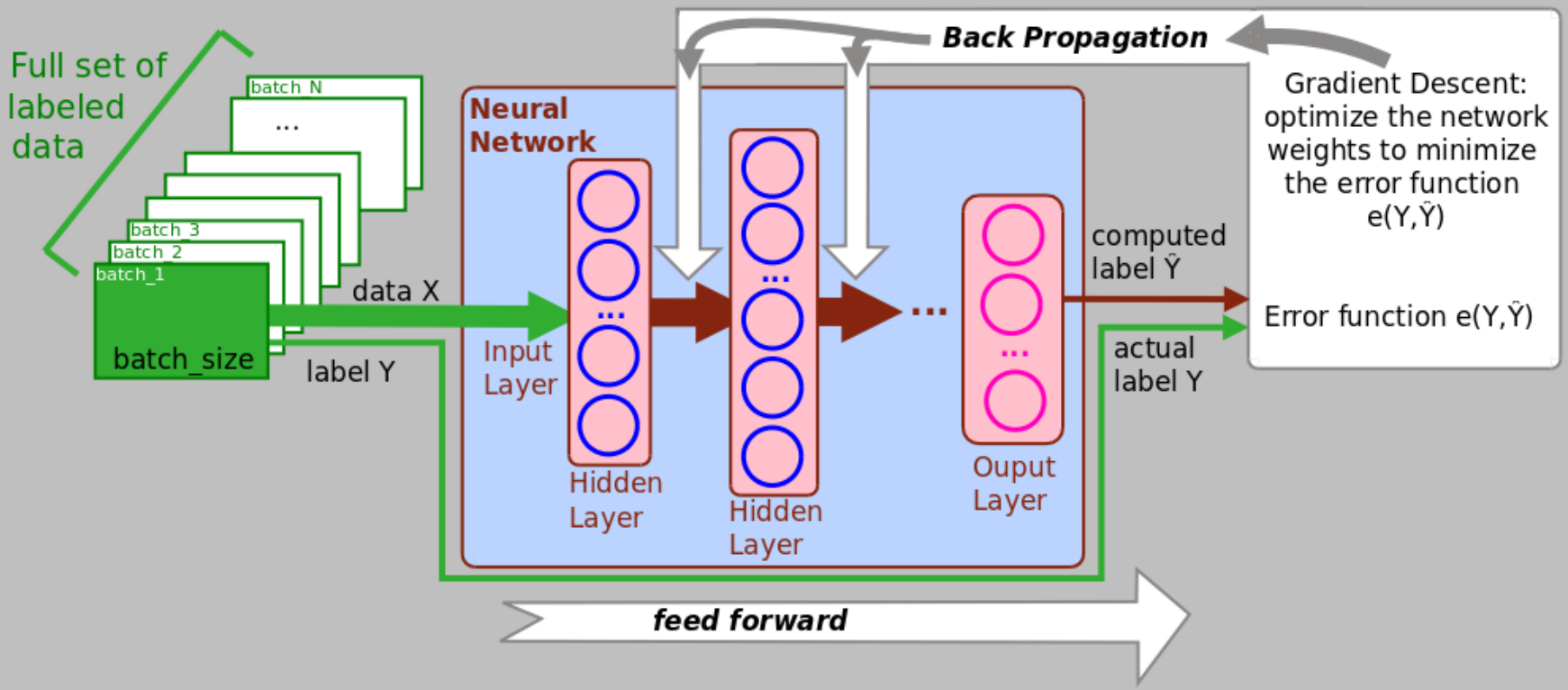


(source : github.com/Jaewan-Yun/optimizer-visualization)

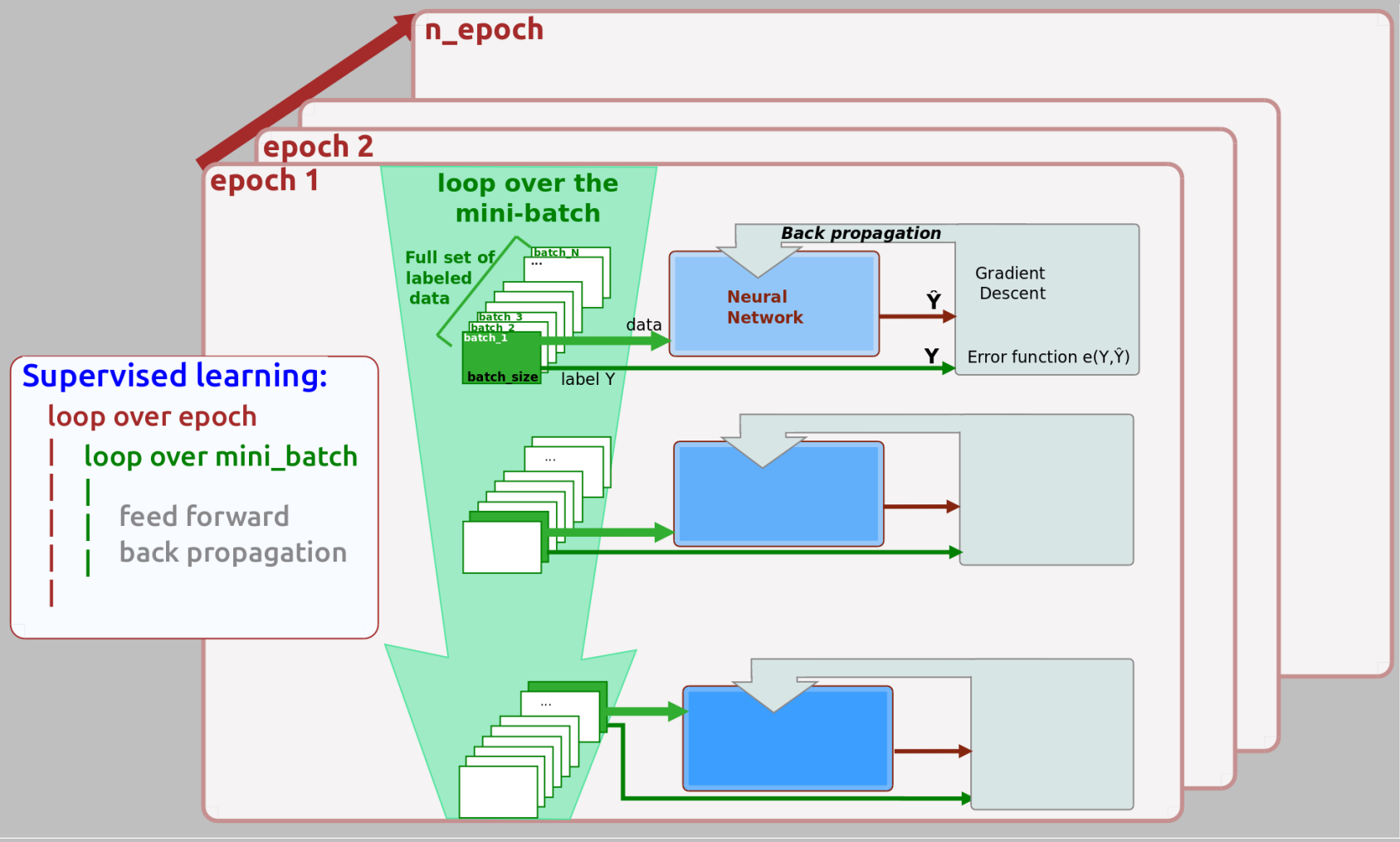
Vidéo d'explication de l'algorithme de *back propagation* :



Supervised learning : Feed Forward and Back Propagation



- Le jeu de données est découpé en (mini) **batches** de taille `batch_size`
- Après chaque *feed forward* l'algorithme de *Back Propagation* modifie les poids des neurones pour minimiser l'erreur e.



- L'entraînement avec le jeu de données est répété `n_epoch` fois,
- L'état du réseau à la fin de l'époque `n` sert d'état initial pour l'époque `n+1`.