Deep Reinforcement Learning (DRL)

An introduction to using DRL in robotics

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November 2022

An introduction to using DRL in Robotics

An introduction to get familiarised with...

- Unsupervised / Supervised / Reinforcement learning.
- DRL Training & operating of Artificial Neural Networks
- Pytorch module for DRL training.
- Applications aof DRL to robotics.

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Ressources

- 2 hours of lecture and 1 $\times$ practical work Python session (4h) on **your laptop**
- Dedicated github repository with all the course material (PDF, notebooks...)

Practical Work: 1 × 4h

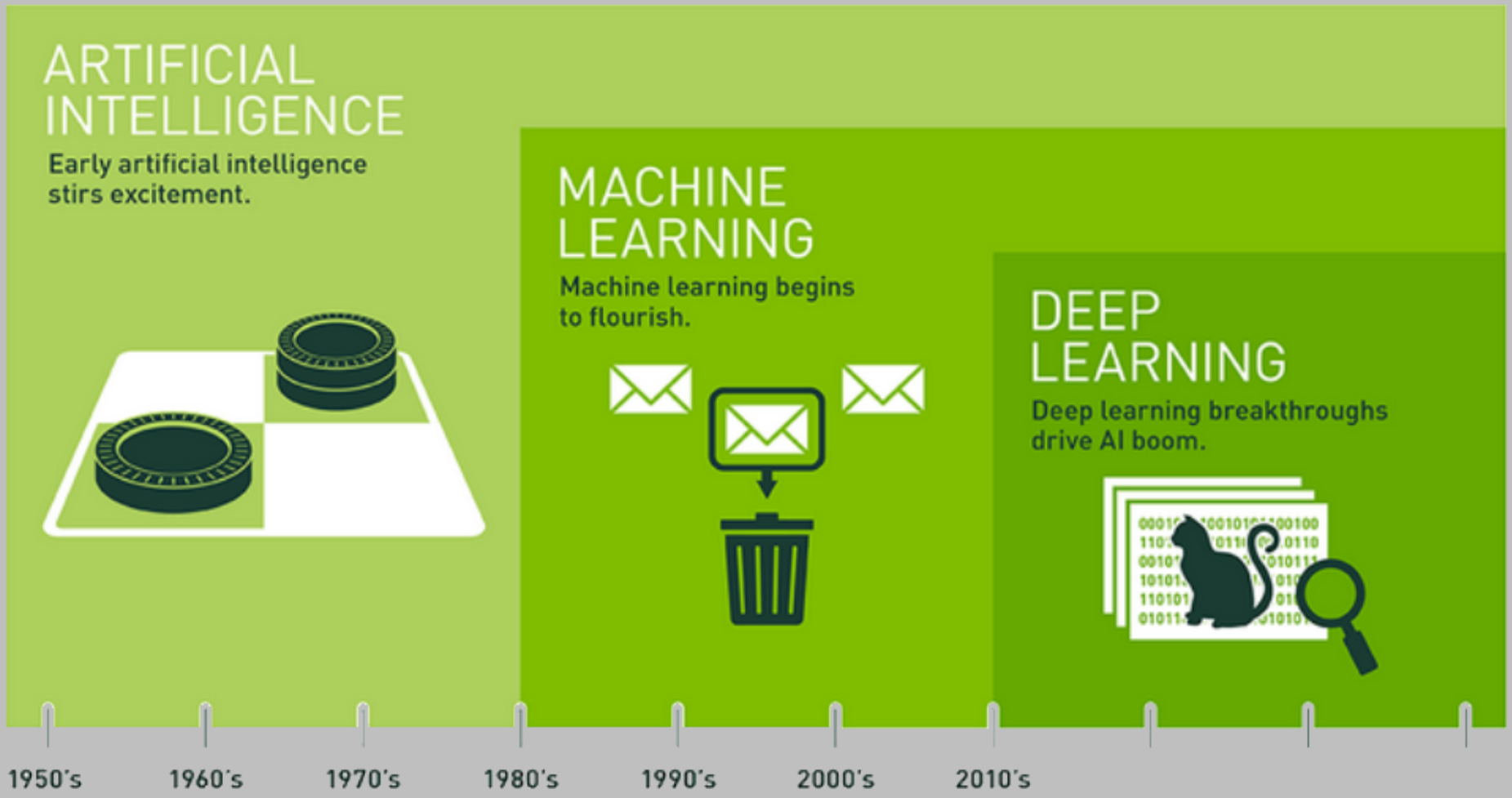
Optional : self training "Machine Learning"

- 3 *notebooks* `ML1_MNIST_en.ipynb`, `ML2_DNN_part1_en.ipynb` and `part2` target the skills:
  - load and pre-process MNIST images
  - build a **dense** neural network with tensorflow & keras
  - Train the network to recognize MNIST images
  - evaluate and operate the trained network.

DRL pactical work:

- Build the pybullet simulation of a 2 DOF robot arm based on its URDF description.
- train a PPO network to drive the displacement of the end effector of a 2 DOF robot arm.

The historical way...



(from : developer.nvidia.com/deep-learning)

Artificial Intelligence ?

Artificial Intelligence [1]: remains an ambiguous term with multiple definitions varying with time:

- *"...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

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

Artificial Intelligences ?

Qualifiers often encountered:

Strong AI

Weak AI

General AI

Narrow AI

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

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Weak AI

- 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.

Artificial Intelligence

already a reality:

- Runs in much of our present technology (smartphone apps...)
- Powered by rapid advances in data storage, computer processing power.
- Powered by **free dataset acces via Internet** and **code publishing as open source** environments.
- Rate of acceleration is already astounding.
- Will likeky shape our future more powerfully than any other innovation this century.

Machine Learning and AI

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
  - 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
  - DNA grouping
  - 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...
  - 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
- K-Nearest Neighbor
- Linear regression
- Logistic regression...

Unsupervised learning:

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

Reinforcement learning:

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

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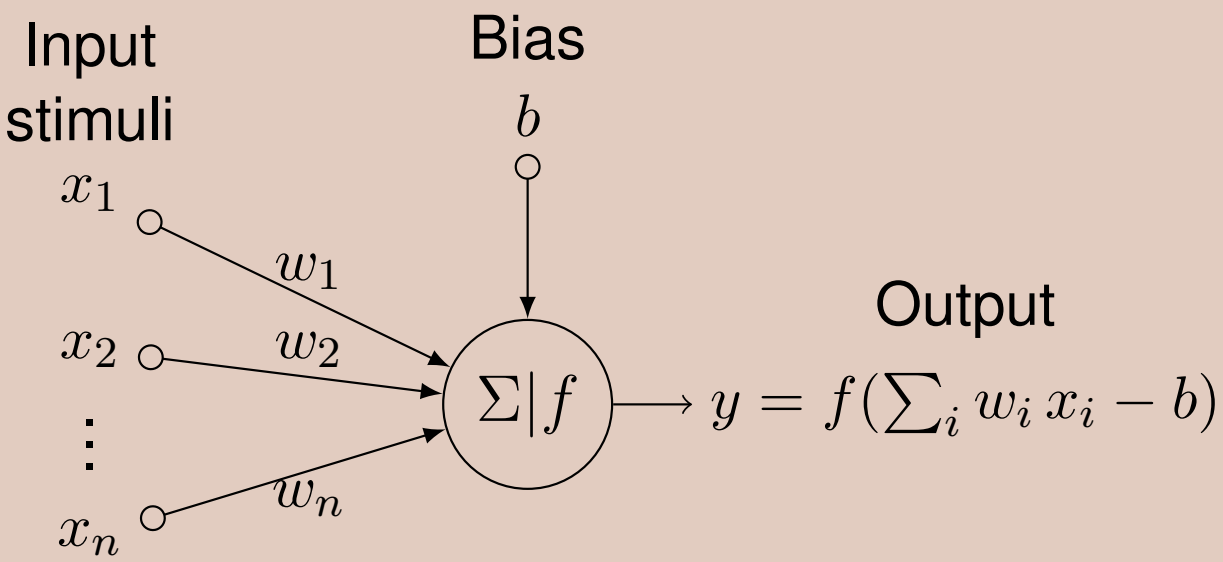
The following deals only with **Artificial Neural Networks**.

Artificial Neural Networks

The Artificial neuron model



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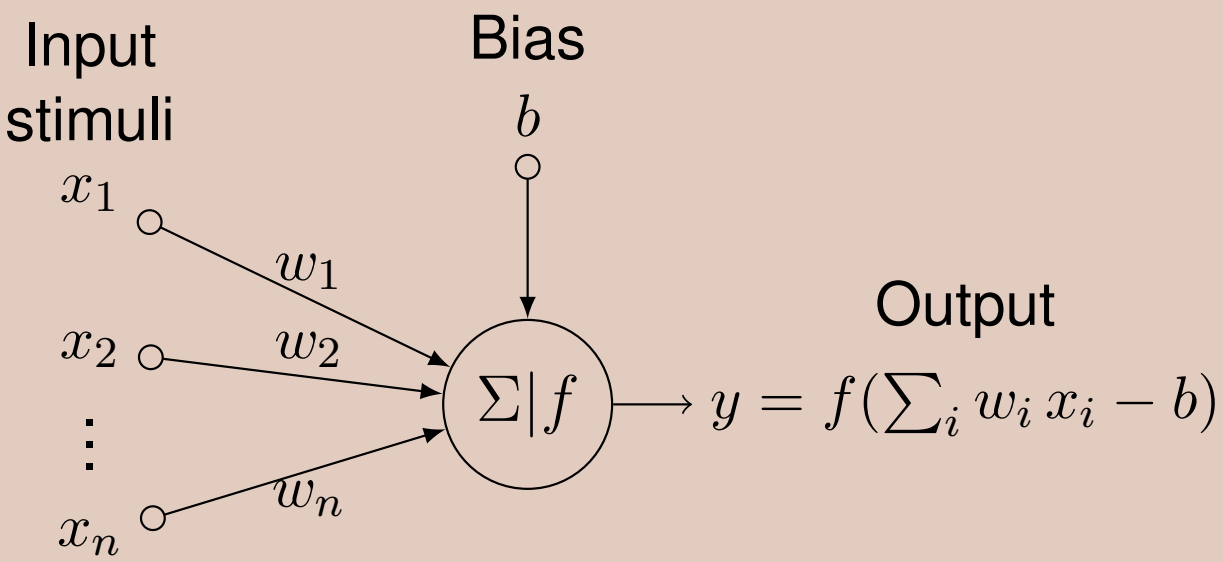

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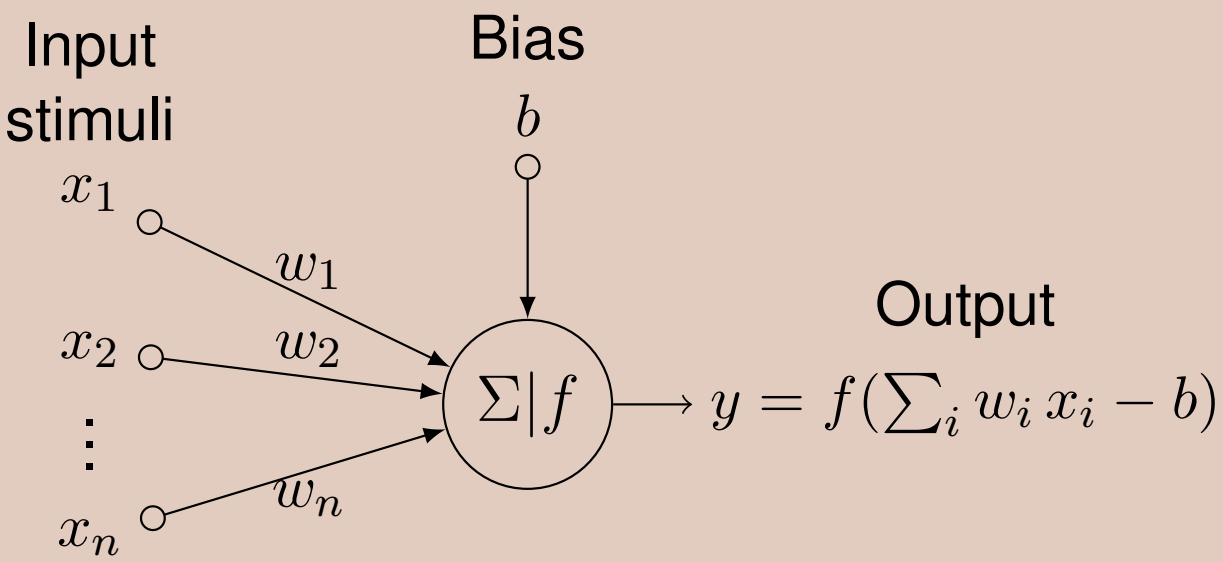

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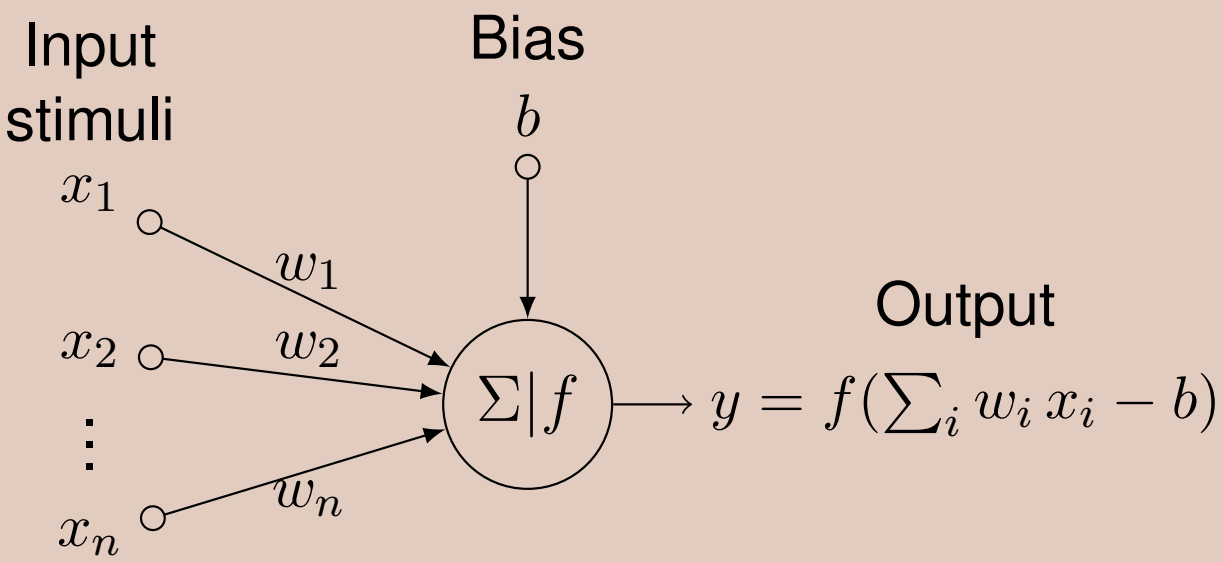

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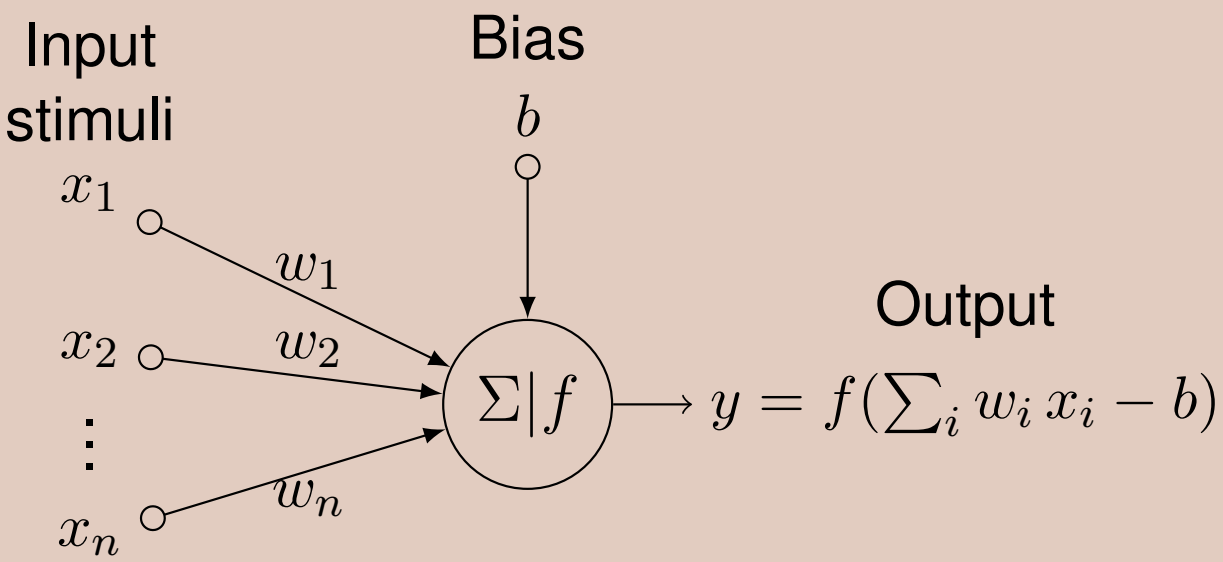

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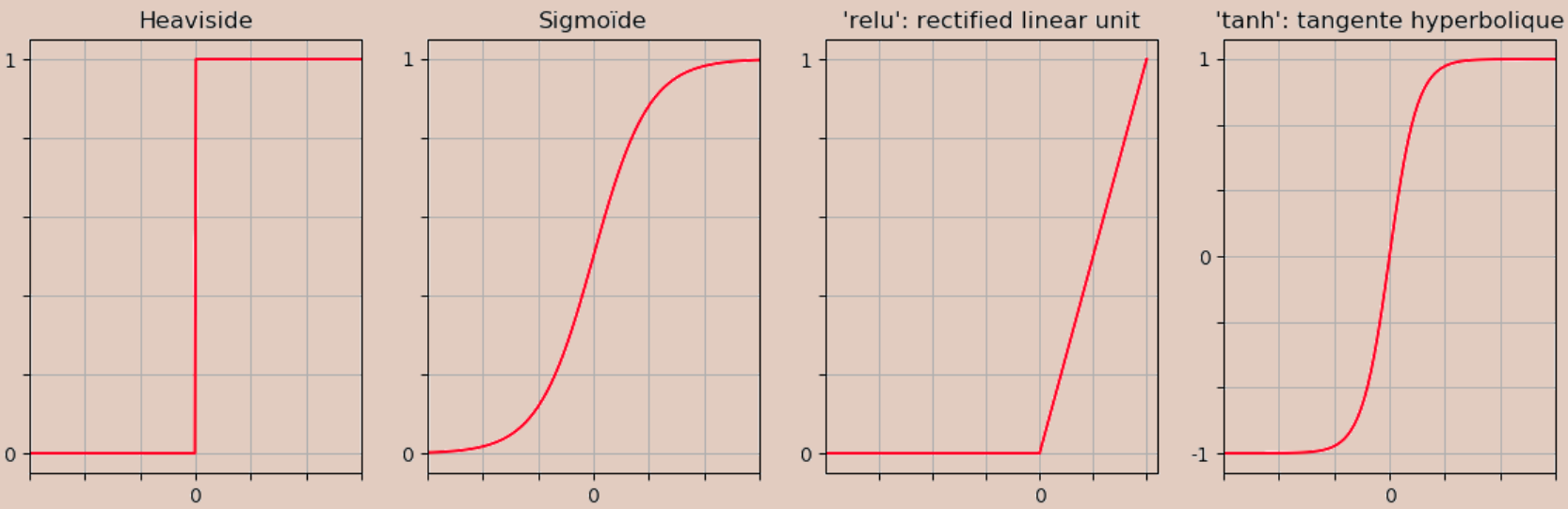
- receives the input stimuli $(x_i)_{i=1..n}$ with **weights** (w_i)
- computes the **weighted sum** of the input $\sum_i w_i\, x_i - b$
- outputs its activation $f(\sum_i w_i\, x_i - b)$, computed with a non-linear **activation function** f .

Artificial Neural Networks

Common activation functions



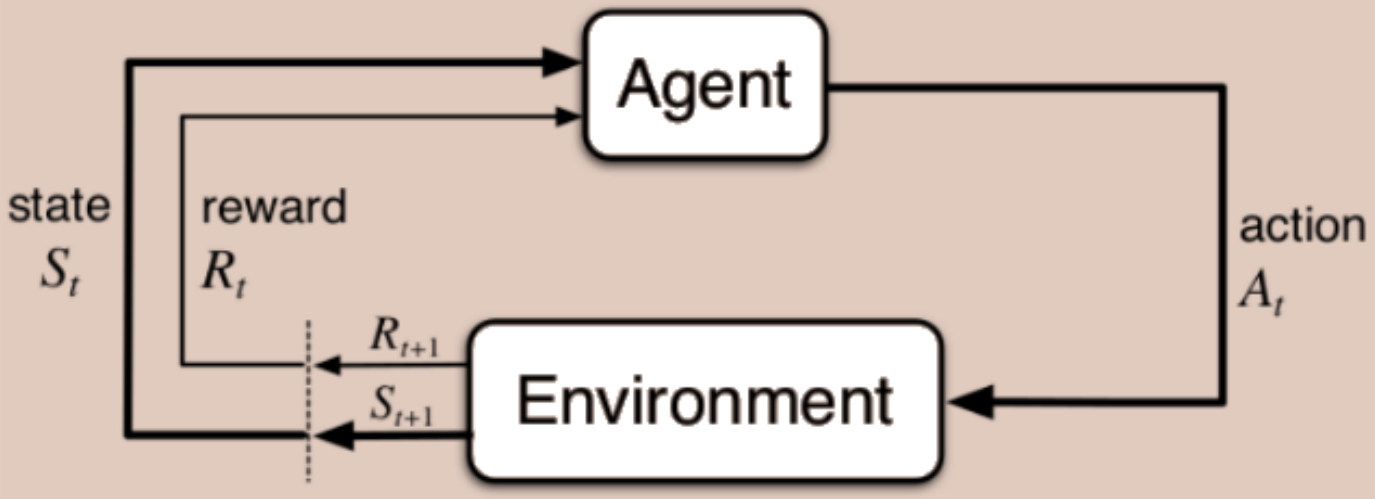
- Introduces a non-linear behavior.
- Sets the range of the neuron output: $[-1, 1]$, $[0, 1]$, $[0, \infty[$...
- The bias b sets the activation threshold of the neuron.

Neural Network Architectures

- **Dense** Sequential (DNN): 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** (Recursive) (RNN): Used to learn from time series.
- **Generative adversarial** (GANN): can generate images, text...

Reinforcement Learning

RL main ingredients



(Source: Reinforcement Learning: An Introduction by Richard S. Sutton and Andrew G. Barto)

The **agent** (the neural network) learns how to take the right **action** on the **environment** (the system to be controlled) in order to maximize its long-term **reward**.

RL ingredients: **Agent**

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  discrete: on/off, left/right...
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Discrete versus continuous action involves different algorithms for the learning stage

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- Decides wich **action** to be taken
- Action can be
  discrete: on/off, left/right...
  continuous: force/velocity applied....
- Goal: maximize the total reward it receives in the long run.

Discrete versus continuous action involves different algorithms for the learning stage

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The **Environment** is what the Agent wants to monitor:

RL ingredients: **reward** funtion

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RL ingredients: **reward** funtion

- Maps each (state, action) pair of the environment to a number indicating the intrinsic desirability of that state.
- The environment sends a **scalar value** as a **reward** to the in response to its action.

RL ingredients: **Policy**, **Value function**

- The **Policy** $\pi(a|s)$ is a probalistic mapping between action a and state s.
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- The **Value function** selects actions that bring states of the highest value over the long run.

Model-free versus Model-based DRL algorithms

Model-free

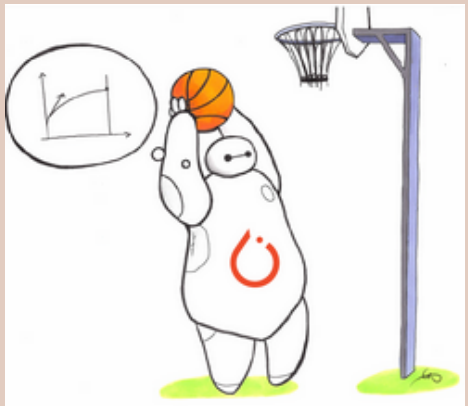
- No explicit representation of the environment
- Learning rely only on experiences using **trial and error**.
- Examples : Monte Carlo, SARSA, Q-learning, and Actor-Critic algorithms.
- Applies to car driving, robot control...

Model-based algorithms

- The agent has access to (or learns) a **model** of the environment.
- Applies to environment like Chess, Go...

RL reference sites

Stable-baseline3



A set of reliable implementations of reinforcement learning algorithms in **PyTorch**.

- github.com/DLR-RM/stable-baselines3
- docs:
  stable-baselines3.readthedocs.io
  spinningup.openai.com
- install:
  `pip install stable-baselines3`

A Taxonomy of RL Algorithms (Source: spinningup.openai.com)