Introduction to Machine Learning

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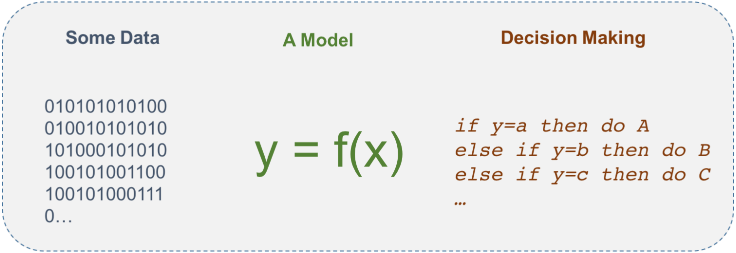
Content

What is Machine Learning?

- Machine learning (ML) refers to algorithms used to extract patterns from data and learn a mathematical model that could be used by a computer program to make intelligent decisions.



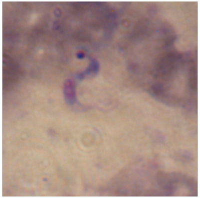
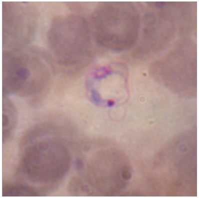
Supervised learning - Regression

- Given the characteristics and prices of several houses, develop a software for predicting the price of new houses.

Living area	Bedrooms	Price
560	2	37.000
1012	3	79.000
893	3	76.000
2196	4	130.000
⋮	⋮	⋮
936	3	72.000

Supervised learning - Classification

- Given a set of digital images of blood samples containing Chagas parasites, decide if a digital image of a new blood sample contains at least a Chagas parasite.

Unsupervised learning - Clustering

- Given a set of text phrases written in two different languages, decide if a new text phrase belongs to one of the languages existing in your set of phrases.

hola a todo el mundo - no me gusta decir adiós - hello people – adoro la comida - our world is wonderful - el planeta agua - ciencia ficción es ciencia - el algoritmo más rápido - la mesa es redonda - the door is black -
my chair is broken - el plato está limpio, esa escalera está muy inclinada - my mouse is wireless - an electronic book - a wide road is better, we were at home - …

Reinforcement learning - Control

- Given a history of the commands used to control a drone, decide which is the best command to perform in order to avoid a collision with the ground.

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- Supervised learning: **inputs and outputs**
- Unsupervised learning: **only inputs**
- Reinforcement learning: **states, actions, and rewards**

Fields of science getting involved in ML

Current machine learning developments come from fields such as:

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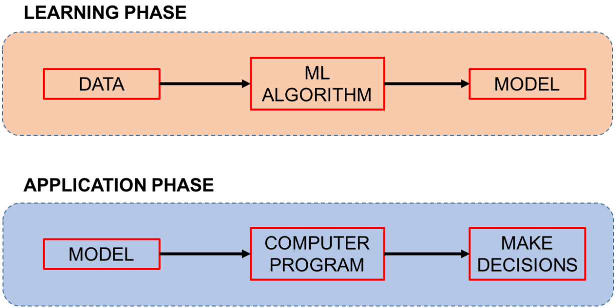
- Robotics

Practical aspects of machine learning

- Using machine learning algorithms usually involves at least two phases:



Learning machine learning

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4. Coding (Matlab/Octave/Python)

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3. Understanding the algorithms (data structures, complexity)
4. Coding (Matlab/Octave/Python)
5. Experimenting (running programs and plotting graphs)

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1. Linear regression

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Part II - Unsupervised Learning

1. Expectation-Maximization (EM) algorithm

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Regression

- In the regression problem we have $R : X \to Y$, $X \subseteq \mathbb{R}^d$, $Y \subseteq \mathbb{R}$. (Continuous) Example: $y = w_o + w_1 x + w_2 x^2 + w_3 x^3$

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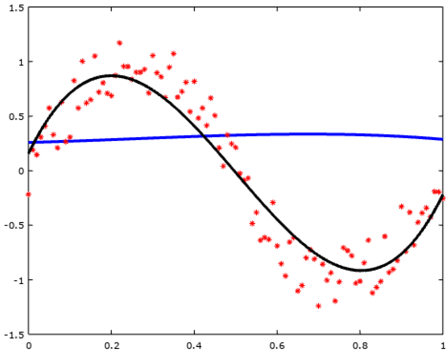

Classification

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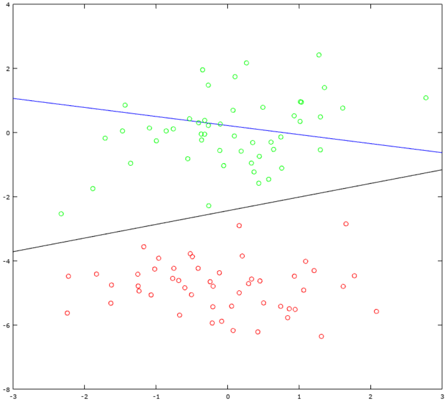

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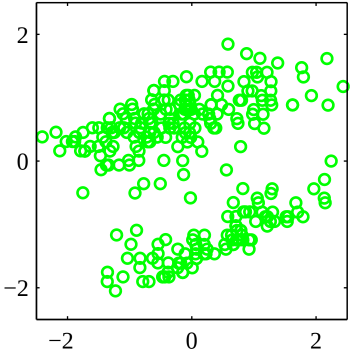
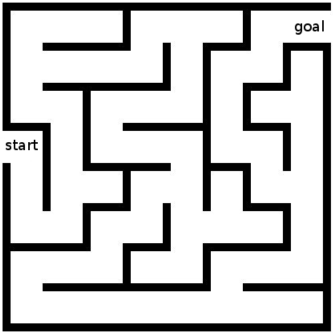


Reinforcement Learning

In reinforcement learning an agent (i.e. a robot) must learn to perform a task: a sequence of actions to go from one **start** state to one **goal** state.



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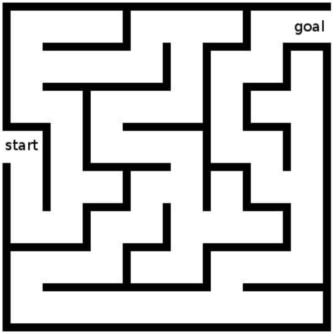

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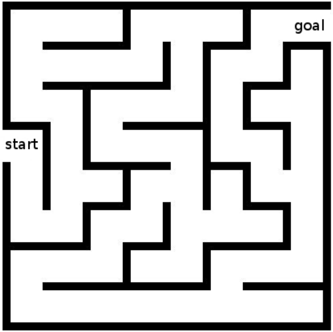

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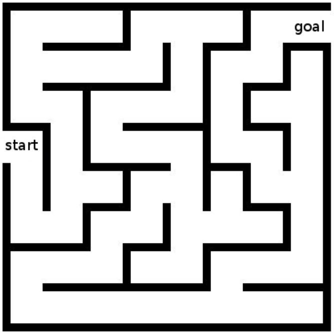

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- Transition function (dynamics of the environment)
  $T : S \times A \rightarrow S$

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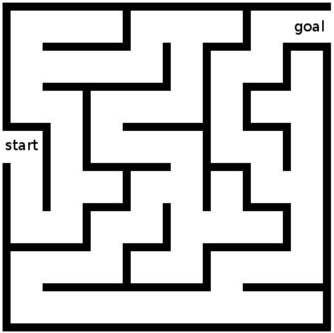

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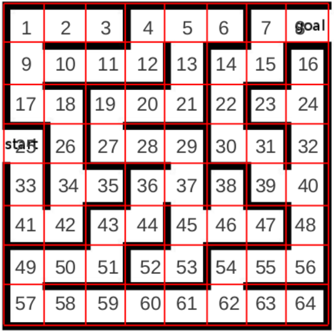
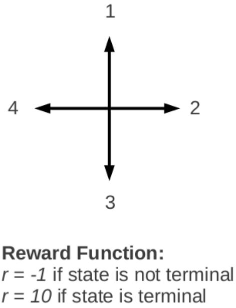
- Reward function
  $R : S \to \mathbb{R}$

Possible RL solution to the maze problem

We discretize states and actions: 64 states and 4 actions.





The agent interacts with the environment several times and the RL algorithm estimates a control function $a_{t+1} = \pi(s_t)$.

Function *Q(s,a)*

S	A	Q(s,a)
1	1	0
1	2	0
1	3	0
1	4	0
2	1	0
2	2	0
2	3	0
...	...	...
64	4	0

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...	...	...
64	4	0

S	A	Q(s,a)
1	1	-20
1	2	-23
1	3	-5
1	4	-22
2	1	-20
2	2	-5
2	3	-22
...	...	...
64	4	-24

Q-learning Algorithm

Initialize $Q(s, a)$ arbitrarily

Repeat (for each episode):

  Initialize s

  Repeat (for each step of episode):

    Choose a from s using policy derived from Q (ε-*greedy*)

    Take action a, observe r, s'

    $Q(s, a) \leftarrow Q(s, a) + \alpha\big[r + \gamma \max_{a'} Q(s', a') - Q(s, a)\big]$

    $s \leftarrow s'$

  Until s is terminal

Thank you!

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