Machine Learning: A General View

Dr. Víctor Uc Cetina

Facultad de Matemáticas
Universidad Autónoma de Yucatán

cetina@informatik.uni-hamburg.de
https://sites.google.com/view/victoruccetina

Content

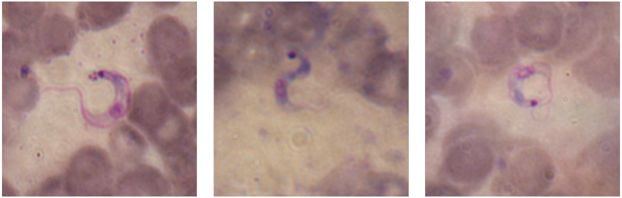
What is Machine Learning?

- 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.

Some Data	A Model	Decision Making
010101010100 010010101010 101000101010 100101001100 100101000111 0...	$y = f(x)$	*if y=a then do A* *else if y=b then do B* *else if y=c then do C* ...

What is Machine Learning?

- Example 1. 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.



What is Machine Learning?

- Example 2. 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.

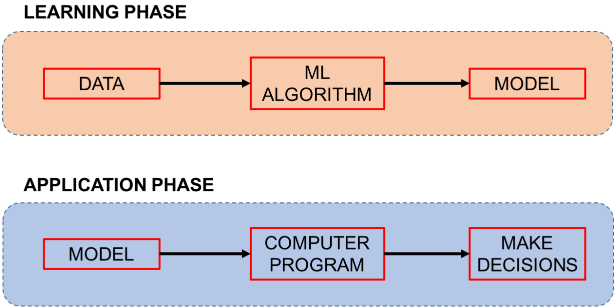
hola a todo el mundo - no me gusta decir adiós - hello people – adoro la comida - our world is wonderful - el planeta agua - ciencia ficción es ciencia - el algoritmo más rápido - la mesa es redonda - the door is black -
my chair is broken - el plato está limpio, esa escalera está muy inclinada - my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

What is Machine Learning?

- Example 3. 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.

What is Machine Learning?

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



What is Machine Learning?

- Based on the type of data available and the decisions needed, we can talk about three general kinds of machine learning algorithms:
  - Supervised Learning (SL)
  - Unsupervised Learning (UL)
  - Reinforcement Learning (RL)

What is Machine Learning?

- People involved in ML research and development comes from fields such as: Computer Science, Artificial Intelligence, Statistics, Neuroscience, Psychology, Robotics, Bioinformatics, etc.

About Learning Machine Learning

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1. Understanding the kind of machine learning problem (SL, UL, RL)

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2. Understanding the mathematics (basic statistics, probability, calculus, linear algebra)
3. Understanding the algorithms (data structures, complexity)
4. Coding (Matlab/Octave)
5. Experimenting (running programs and plotting graphs)

Important to know

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- You need to complete and deliver at least 5 exercises to have the right to write the final exam.

Part I - Supervised Learning

1. Linear regression

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Part II - Unsupervised Learning

1. Expectation-Maximization (EM) algorithm

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Part III - Reinforcement Learning

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- **Reinforcement Learning: An Introduction (second edition)**. Richard Sutton and Andrew Barto. The MIT Press. 2018.

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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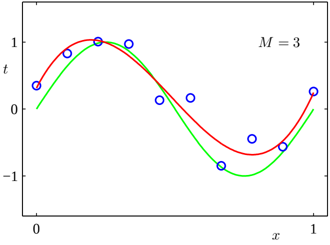

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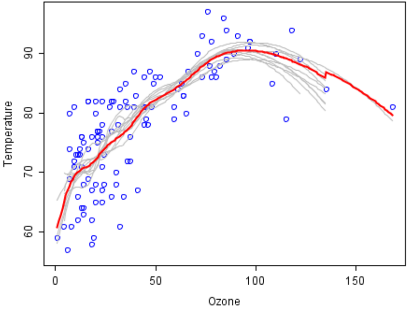

Classification

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  Example: $y = \frac{1}{1+e^{-(w_0+w_1x_1+w_2x_2)}}$

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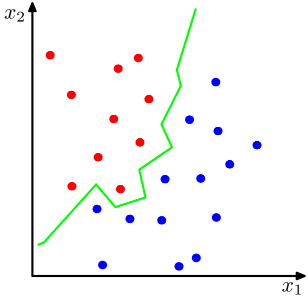

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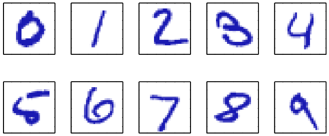

Clustering

The unsupervised learning problem is similar to the classification one, but the data is not labeled this means that we do not know the category of each example.

- In the clustering problem we have $C : X \to T$, $X \subseteq \mathbb{R}^d$, $T = \{t_1, t_2, \dots, t_n\}$, with unknown n. Example: $t = \arg\min_{t_i} \mathrm{distance}(t_i, x)$

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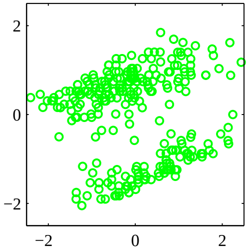

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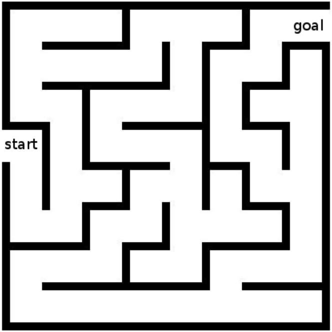
- The execution of the task can be seen as a sequence of actions $a_1, a_2, \ldots, a_n$.
- In order to learn the right sequence of actions the agent must interact with its environment selecting at each moment one action a_{t+1} as a function of the current environment state s_t. This is $a_{t+1} = F(s_t)$.

Reinforcement Learning

Markov decision process. $\text{MDP} = (S, A, T, R)$



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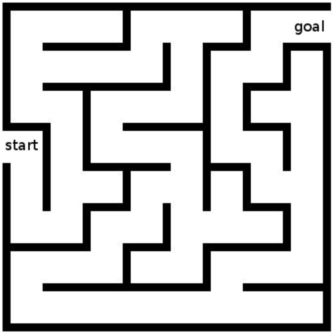

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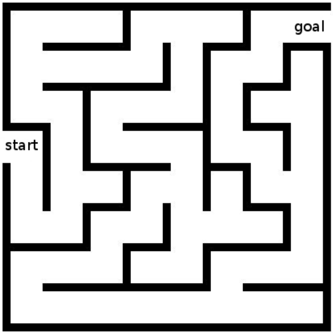

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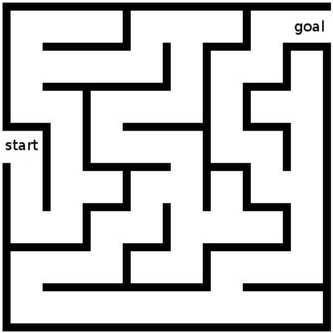

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  $T : S \times A \to S$

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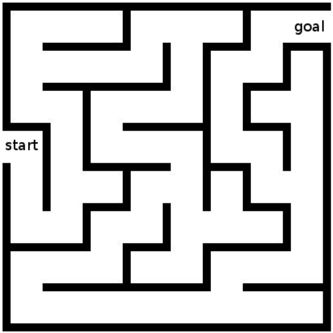

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- Set of actions $A(s) = \{a_1, a_2, \ldots\}$
- Transition function (dynamics of the environment) $T : S \times A \to S$
- Reward function $R : S \to \mathbb{R}$

Possible RL solution to the maze problem

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

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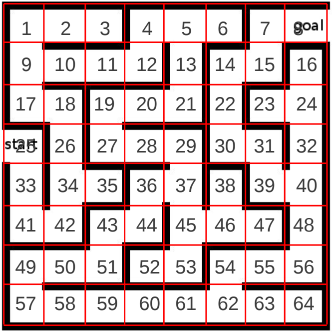

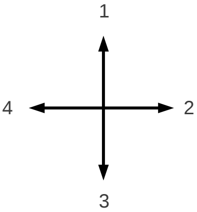

Reward Function:

$r = -1$ if state is not terminal

$r = 10$ if state is terminal

Function $V(s)$

S	$V(s)$
1	0
2	0
3	0
4	0
$\ldots$	$\ldots$
64	0

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S	$V(s)$
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2	-20
3	-5
4	-22
$\dots$	$\dots$
64	-24

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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        $s \leftarrow s'$
    Until s is terminal

Some videos

- Inverted pendulum
- Object handling

Thank you!

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