Introduction to Deep Learning

Cristian Pachón García

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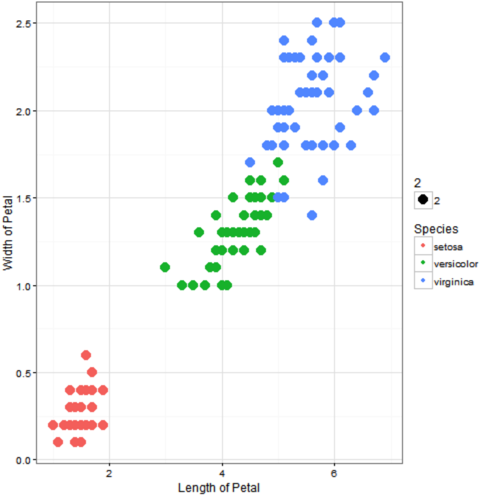
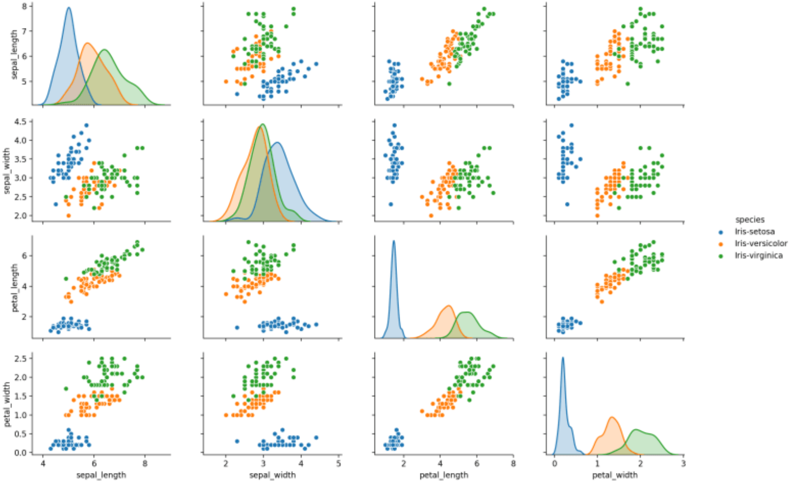
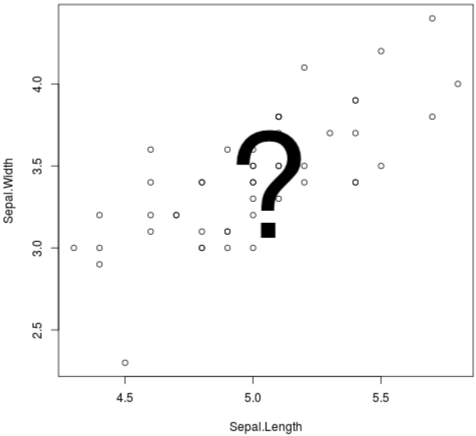
What is Machine Learning?

- Machine learning (ML) is the **scientific study** of **algorithms** and **statistical models** that computer systems use to perform a **specific task without using explicit instructions**, relying on patterns **learn from data**.
- The process of making the machine learn is called **the training process**.


2.5
2.0
1.5
1.0
0.5
0.0
Width of Petal
2
4
6
Length of Petal
2
2
Species
setosa
versicolor
virginica

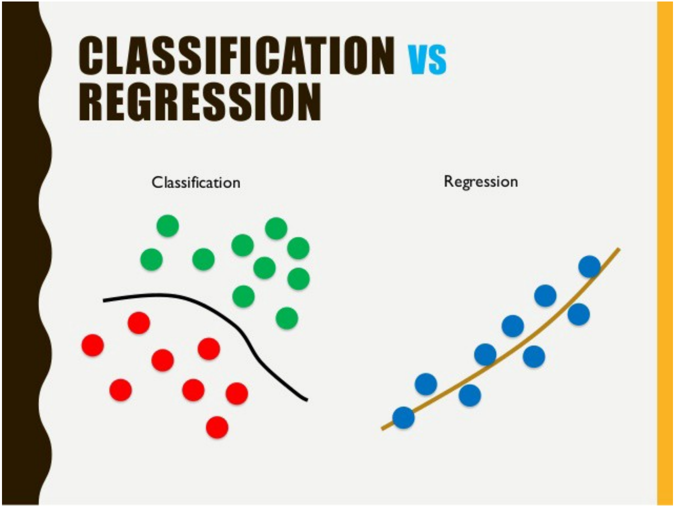

sepal_length
sepal_width
petal_length
petal_width
species
Iris-setosa
Iris-versicolor
Iris-virginica


Sepal.Width
Sepal.Length
2.5
3.0
3.5
4.0
4.5
5.0
5.5
?

ML algorithms can be classified into two different groups:

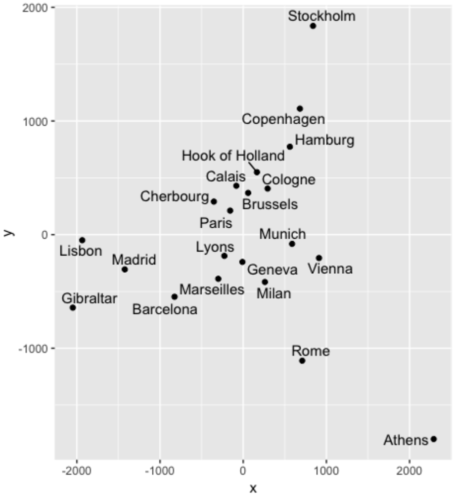
- Supervised learning.
- Unsupervised learning.

Supervised learning is the machine learning task of learning a function that **maps an input to an output**.



Unsupervised learning is the machine learning task that allows us to discover patterns from the data. Rather than prediction a variable (temperature, flower type, etc.) these algorithms are aimed to discover patterns in the data.

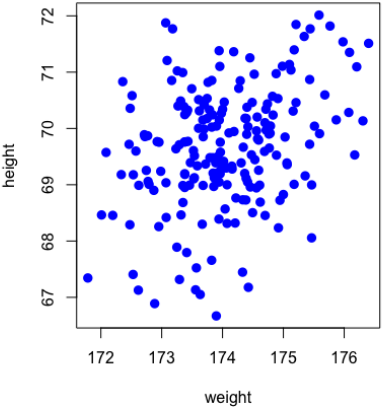
	Athens	Barcelona	Brussels	Calais	Cherbourg	$\cdots$
Athens	0	3313	2963	3175	3339	$\cdots$
Barcelona	3313	0	1318	1326	1294	$\cdots$
Brussels	2963	1318	0	204	583	$\cdots$
Calais	3175	1326	204	0	460	$\cdots$
Cherbourg	3339	1294	583	460	0	$\cdots$
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\ddots$


Stockholm
Copenhagen
Hamburg
Hook of Holland
Calais
Cologne
Cherbourg
Brussels
Paris
Munich
Lisbon
Lyons
Madrid
Geneva
Vienna
Marseilles
Milan
Gibraltar
Barcelona
Rome
Athens
2000
1000
0
-1000
-2000
y
x

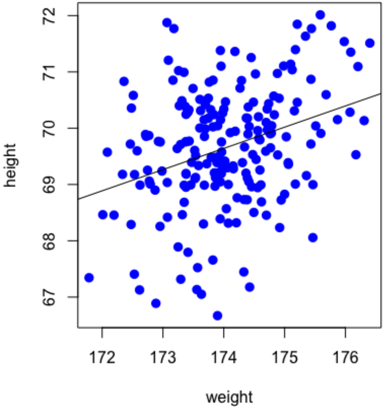
Linear regression

	height	weight
1	173.37	69.76
2	174.18	71.36
3	173.16	70.85
4	175.60	69.91
5	174.33	67.45
6	173.18	71.77
7	174.49	70.46
8	174.74	70.44
9	174.58	69.82
10	173.69	69.99
⋮	⋮	⋮
200	173.61	70.213

Is there any relationship between *height* and *weight*?



- We would like to find two coefficients (w and b) such that $weight = b + w * height$.
- In general, given two pairs of variables x and y, we would like to find two coefficients (w and b) such that $y = b + w * x$.
- w is known as the *weight* and b is known as the *bias*.



How can we find w and b such that $y = b + w * x$ is a "good approximation" to the data points?

More important question than *how* is: **why** do we know to know these parameters?

- If a system is modeled by an equation, it can help to predict what can happen under certain circumstances.

- Let's suppose $b = 4.057$ and $w = 0.3769$. It means

  $$y = 4.057 + 0.3769 * x.$$

  What would be the *weight* (y) of someone whose height (x) is 174 cm? $y = 4.057 + 0.3769 * 174 = 69.6376$ kg.

Loss function

- Previously, we asked the model to predict the *weight* of a persona whose height is 174 cm.
- The prediction was 69.6376 kg.
- **Notation:** when we use the model to predict, we use a special symbol for the results: $\hat{y}$.
- So, in the previous example: $\hat{y} = 69.6376$

How can we find w and b such that $y = b + w * x$ is a "good approximation" to the data points?

- We need a metric that tells what is "good" and what is "bad".
- We want a metric that is close to 0 when the model is correct.
- We want a metric that increases as long as the model is not correct.

Let's assume we have w and b. For instance, at random we choose $w = 0.2$ and $b = 3$:

	height(x)	weight(y)	prediction($\hat{y}$)	$error = (y - \hat{y})^2$
1	173.37	69.76	37.67	1029.39
2	174.18	71.36	37.84	1123.97
3	173.16	70.85	37.63	1103.53
⋮	⋮	⋮	⋮	⋮
200	173.6189	70.31279	37.72378	1062.0434

$$loss = MSE = \sqrt{\frac{1}{200}(1029.39 + 1123.97 + \cdots + 1062.0434)} = 31.86411$$

- In general, the formula for loss function (for regression problems) is the following one:

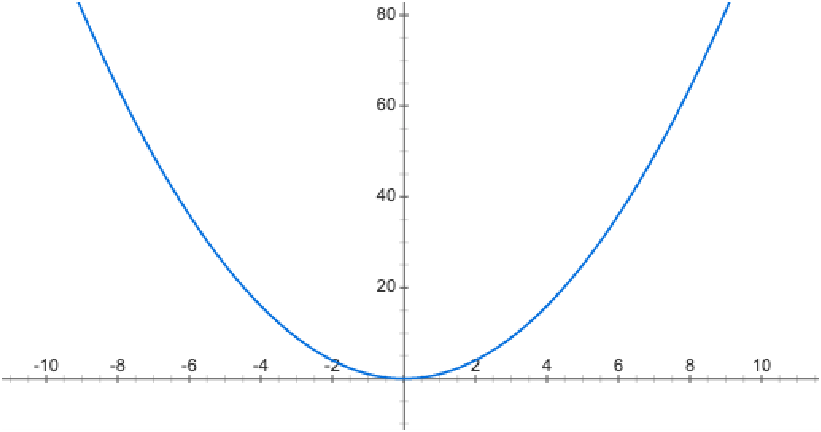
$$loss = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(y_i - (b + wx_i)\right)^2}.$$

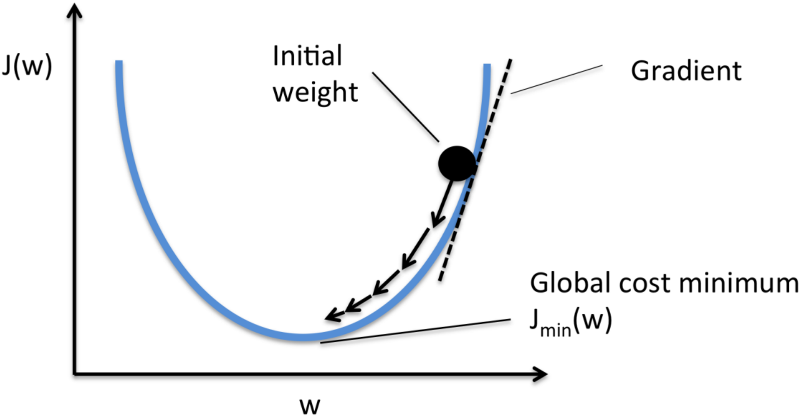
- Our goal is to find b and w such that the loss is minimum.
- How??? Choosing b and w randomly??? We will use **Gradient Descent** algorithm.

Gradient Descent

The idea is the following one:

- Given a function that depends on two paramenters $f(b, w)$, we want to find w^* and b^* such that $min\{f(b, w)\} = f(b^*, w^*)$.
- Gradient Descent (GD) allows us to find such parameter.
- GD works with more than two variables, i.e, let's supose we want to find the minimum value of a function that depends on n variables $f(z_1, z_2, \ldots, z_n)$, GD allows us to find $z_1^*, z_2^*, \ldots, z_n^*$ such that $min\{f(z_1, z2, \ldots, z_n)\} = f(z_1^*, z_2^*, \ldots, z_n^*)$.

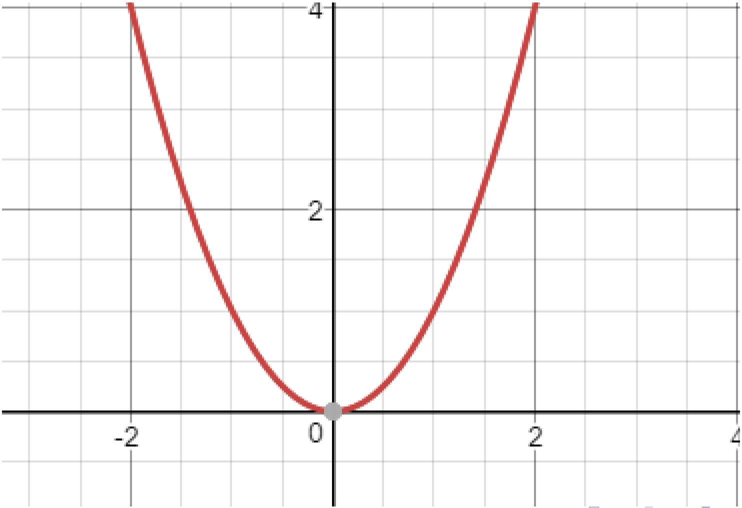

80
60
40
20
-10
-8
-6
-4
-2
2
4
6
8
10


J(w)
Initial weight
Gradient
Global cost minimum
$J_{min}(w)$
w

Algorithm 1: Gradient Descent algorithm

Result: Find w^* such that $min\{f(w)\} = f(w^*)$
$epsilon = 10^{-6}$;
$w_0 =$ (random) initial point;
$is\_minimum = FALSE$;
$learning\_rate = 0.1$;
$f_0 = f(w_0)$;
while *not is_minimum* **do**
  $derivative = f'(w_0)$;
  $w_1 = w_0 - learning\_rate \cdot derivative$;
  $f_1 = f(w_1)$;
  if $\mid f_1 - f_0 \mid < epsilon$ **then**
    $is\_minimum = TRUE$;
  end
  $w_0 = w_1$;
  $f_0 = f_1$;
end
return w_1

Given $f(w) = w^2$ and $w_0 = 1$, we want to apply GD algorithm to obtain the minimum. We expect to obtain, after some iterartions, $w^* = 0$ (or close to 0).



Remember that:

- $f(w) = w^2$.
- $derivative = f'(w) = 2w$.
- $w_1 = w_0 - learning\_rate \cdot derivative$.

We choose as learning rate a value of 0.01.

iteration	w_0	$f(w_0)$	derivative	w_1	$f(w_1)$	$\mid f(w_1) - f(w_0) \mid$
2	1.00	1.00	2.00	0.80	0.64	0.36
3	0.80	0.64	1.60	0.64	0.41	0.23
4	0.64	0.41	1.28	0.51	0.26	0.15
⋮	⋮	⋮	⋮	⋮	⋮	⋮
26	0.00	0.00	0.01	0.00	0.00	0.00
27	0.00	0.00	0.01	0.00	0.00	0.00

Back to our initial problem, we want w and b such that minimise

$$\sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(weight-(b+w\cdot height)\right)^2}.$$

- Applying GD we obtain $b = 4.0570$ and $w = 0.3769$.
- Loss function is 1.00795.
- Any other set of parameters would provide a loss function greater than 1.00795.

- GD is an algorithm that helps us find the optimal values for the parameters. That is why it is called *optimiser*.
- There are many *optimisers* algorithms:
    - Momentum
    - RMSprop
    - Adam
    - AdaMax
    - Adadelta
    - ...

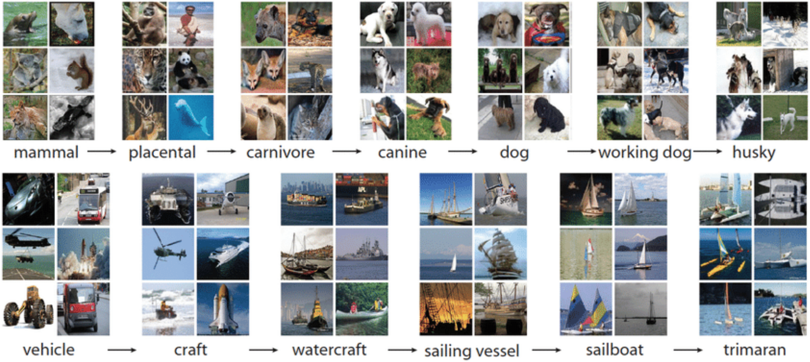
Introduction

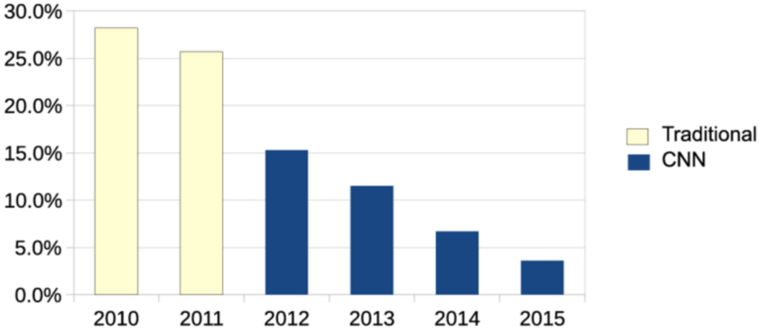
Why do we need *another* kind of models?

- Unfortunately real life is not linear. We need more *complex*/*flexible* models.
- Neural networks (Deep Learning models) are very flexible models. They are able to capture very non-linear patterns and model with a high precision.

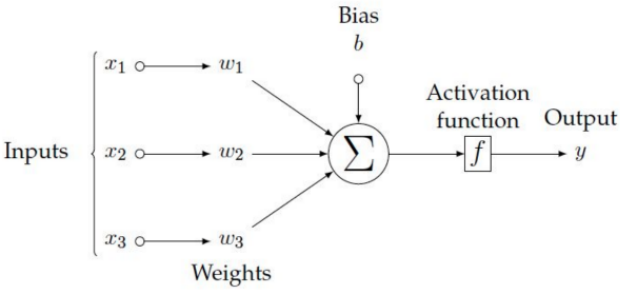
ImageNet problem

- The ImageNet project is a large visual database designed for use in visual object recognition software research.
- More than 14 million images have been hand-annotated.
- ImageNet contains more than 20.000 categories with a typical category, such as "balloon" or "strawberry", consisting of several hundred images.


mammal
placental
carnivore
canine
dog
working dog
husky
vehicle
craft
watercraft
sailing vessel
sailboat
trimaran

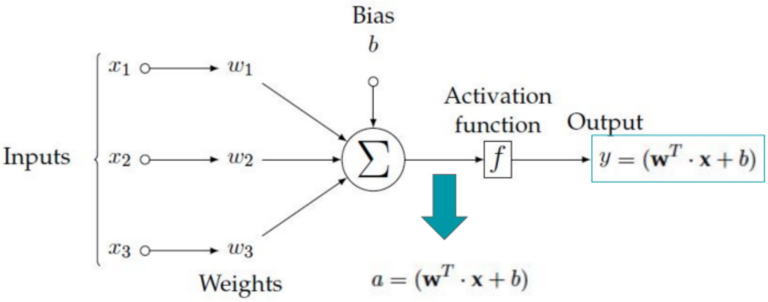

30.0%
25.0%
20.0%
15.0%
10.0%
5.0%
0.0%
2010
2011
2012
2013
2014
2015
Traditional
CNN

Single neuron model (perceptron)



- **Weights** and **bias** are the parameters that define the behaviour. They must be estimated during training.
- The **output** (y) is derived from a sum of the weighted inputs plus a bias term.
- The **activation** function **introduces non-linearities**.

Single neuron model: Linear Regression



Backpropagation

Rembember that GD formula is:

$$w = w - learning\_rate \cdot derivative.$$

We are going to use the following notation:

$$derivative = \frac{\partial L}{\partial w}.$$

Our goal is to find a way to calculate the derivative in an efficient way.

Thank You