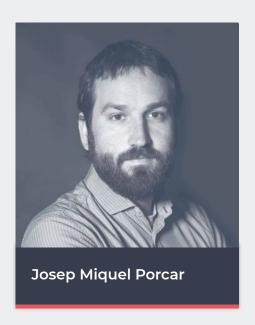


# Diseña tu primer modelo de machine learning

#### **NEOLAND**

#### **PONENTE**



Data Scientist, matemático y estadístico con varios años de experiencia en proyectos de investigación de Data Science.

Actualmente es **Head Teacher del Data Science Bootcamp de Barcelona en NEOLAND**.

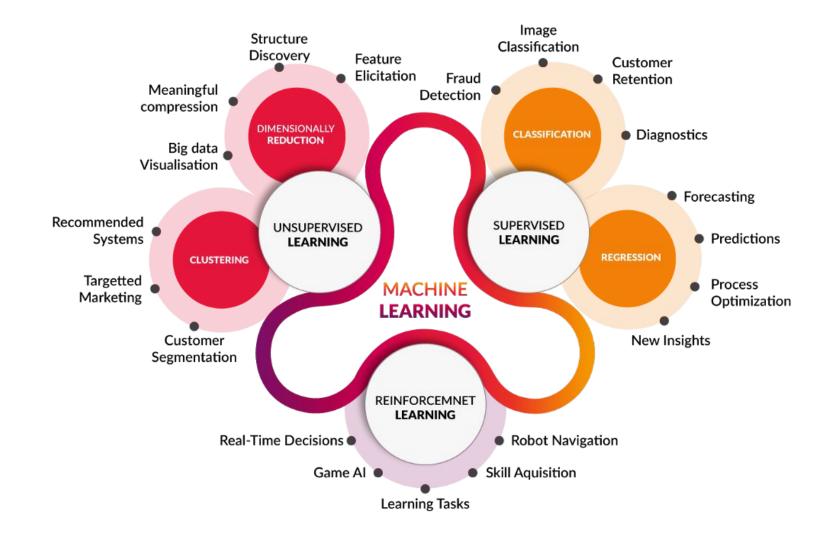
#### **DATA SCIENCE**

¿Qué veremos?

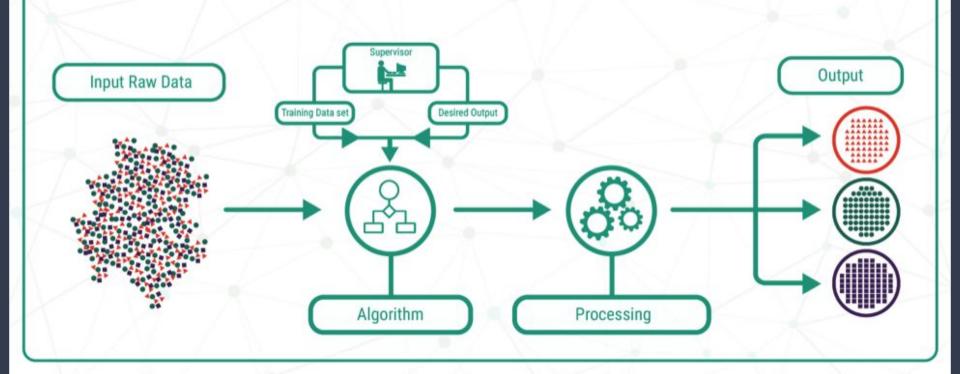
- 1. Statistical learning
- 2. Types of algorithms
- 3. Supervised learning
- 4. Linear Regression

- 5. Features types
- 6. Metrics
- 7. Polynomial regression
- 8. Validation

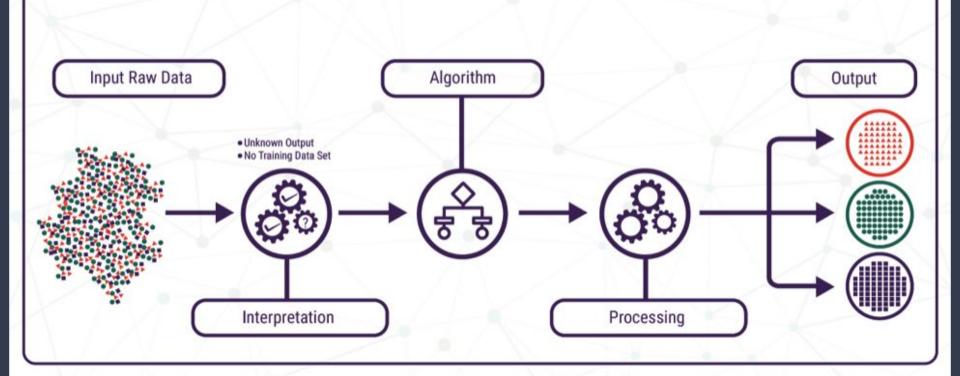
#### **BUSINESS UNDERSTANDING** 02 **DATA MINING DATA SCIENCE LIFECYCLE** 06 03 sudeep.co **DATA CLEANING PREDICTIVE** Fix the inconsistencies within the data and handle the missing values. **DATA EXPLORATION FEATURE ENGINEERING** Form hypotheses about your defined problem by visually analyzing the data.



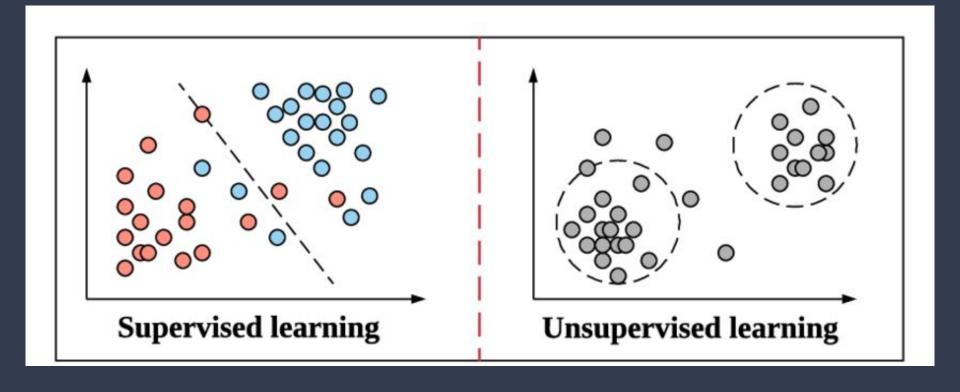
# SUPERVISED LEARNING



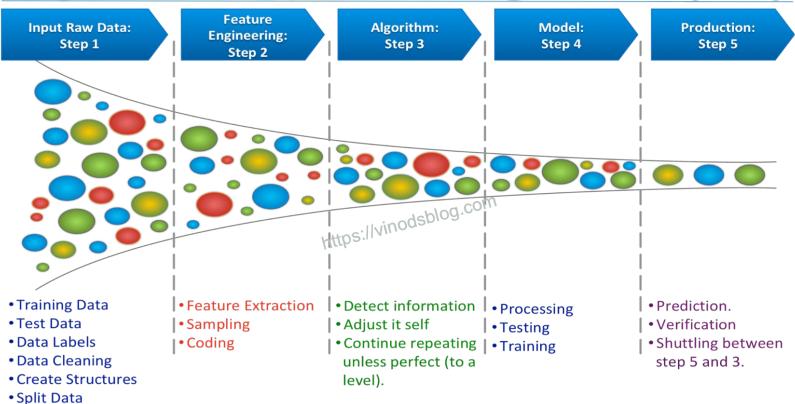
# UNSUPERVISED LEARNING

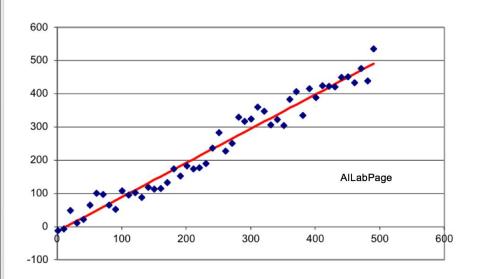


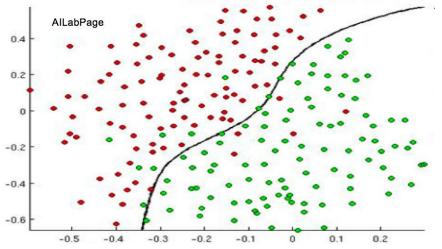
## Types of algorithms



#### Supervised Machine Learning Process (HLD)









#### Regression

The system attempts to predict a value for an input based on past data.

Example – 1. Temperature for tomorrow



#### Classification

In classification, predictions are made by classifying them into different categories. Example – 1. Type of cancer 2. Cancer Y/N

### Supervised learning

Supervised learning means learning from data:

- We have a quantitative outcome (regression) or categorical outcome (classification)
- We want to predict the *outcome* based on a set of *features* (supervised)
- We have a training set
- We build a prediction model for new unseen objects. The objective is to predict accurately

### Vocabulary

Outcome, target, response: Usually denoted by Y (quantitative) or G (qualitative)

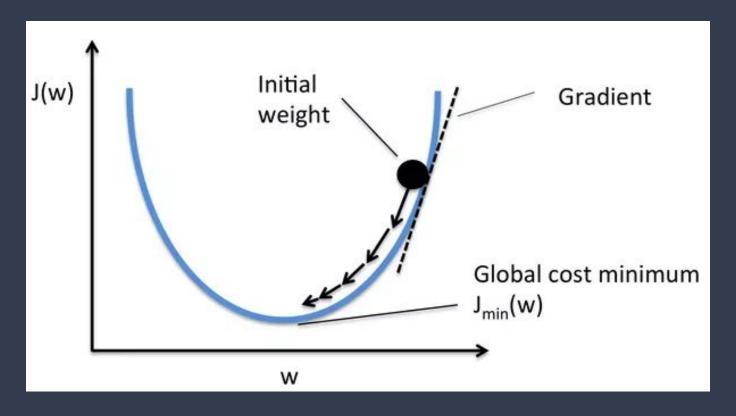
Features, columns, variables: Usually denoted by X (X is a vector of k features)

Training set: (x1, y1), ..., (xn, yn)

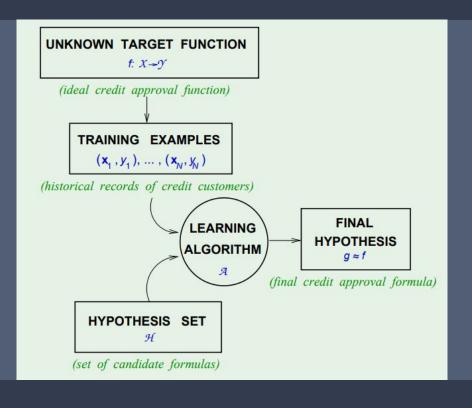
Objective: get a good prediction of Y called  $\hat{Y} = f(X)$ .

LOSS FUNCTION for penalizing errors (cost function)
Squared loss error (Y - f(X))^2

### Loss function



## Learning process



### Linear Regression

A linear regression model assumes that Y is linear in the inputs X:

$$f(X) = \beta_0 + \sum_{j=1}^p X_j \beta_j$$
  $Y = f(X) + \varepsilon$ 

$$Y = f(X) + \varepsilon$$

Basic assumptions on errors:  $\varepsilon \sim N(0, \sigma^2)$ 

$$\varepsilon \sim N(0, \sigma^2)$$

- Independent
- Mean zero
- Constant variance

## Predicting new data

Given a new set of features (X\_nuevo), we can predict the outcome as:

$$\hat{Y}_{nuevo} = \hat{\beta} X_{nuevo} = \hat{\beta}_0 + \hat{\beta}_1 X_{1,nuevo} + \dots + \hat{\beta}_p X_{p,nuevo}$$

# Features types in Linear regression

#### Quantitative - Continuous variables:

- Transformations: log, square root...
- Expansions: ^2, ^3, ...
- Interactions: X3 = X1\*X2

#### Qualitative - Categorical variables:

- Dummy coding of the levels. 1 variable with K categories -> K dummy variables

#### Metrics

$$R^2 = 1 - rac{\Sigma (y - \hat{y})^2}{\Sigma \left(y - ar{y}
ight)^2}$$

RMSE:

$$ext{RMSE} = \sqrt{rac{1}{n}\sum_{i=1}^n (y_i - \hat{y}_i)^2}$$

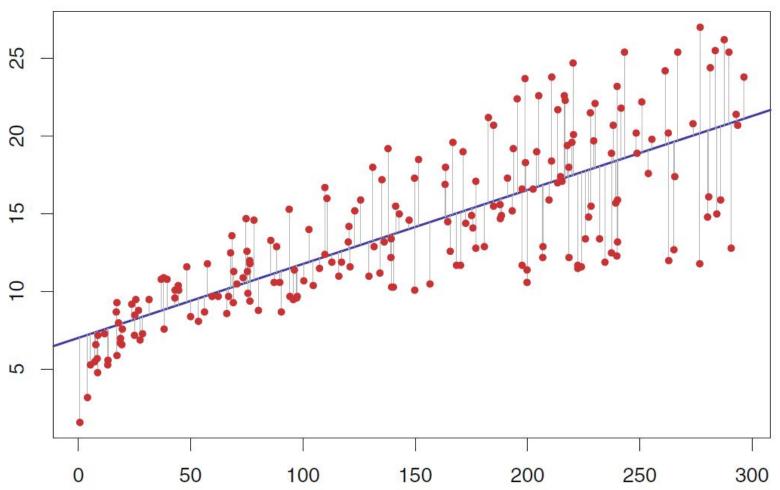
AIC:

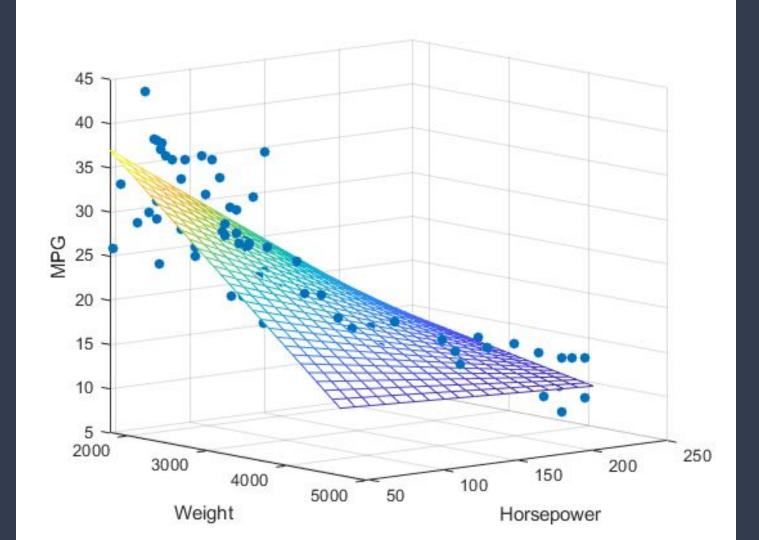
$$AIC = -2logL + 2q$$

BIC:

$$BIC = 2log(L) + qlog(N)$$

3. Linear Regression





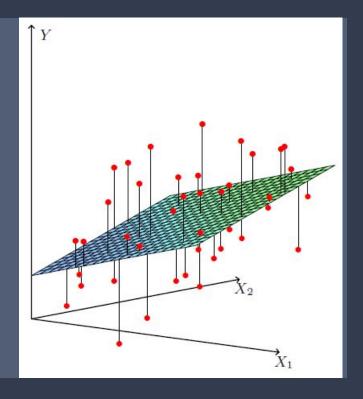
### Estimation: Least Squares in LR

$$RSS(\beta) = \sum_{i=1}^{N} (y_i - x_i^T \beta)^2.$$

$$RSS(\beta) = (y - X\beta)^T (y - X\beta)$$

$$\frac{\partial RSS}{\partial \beta} = -2X^T (y - X\beta)$$

$$\hat{\beta} = (X^T X)^{-1} X^T y,$$



## Interpreting estimators

$$\hat{Y} \,=\, \hat{\beta}_0 + \hat{\beta}_1 X_1 + \hat{\beta}_2 D_1 + \hat{\beta}_3 D_2$$

X1 is a continuous variable:

- sign
- size
- marginal effect

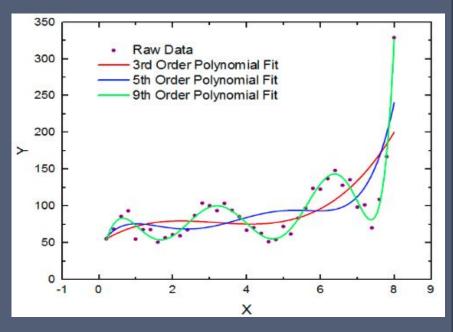
D1, D2 are the dummies of a categorical variable with 3 levels:

- reference category D3

### Polynomial regression

f(x) is a polynomial of order k:

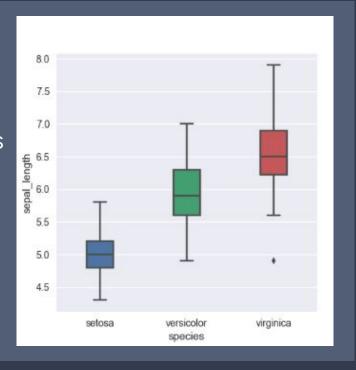
$$f(X) = \sum_{j=0}^{k} \beta_j X^j$$



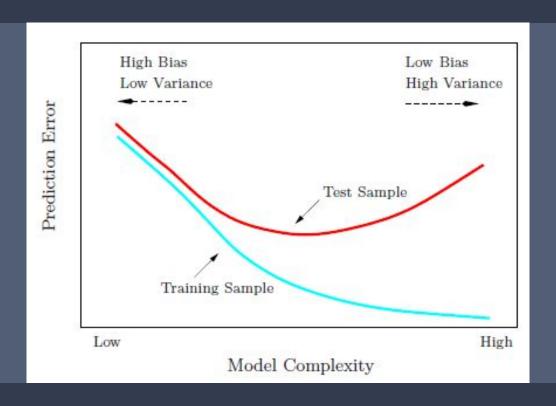
### **Outliers**

In words of Hawkins, 1980:

"An outlier is an observation which deviates so much from the other observations as to arouse suspicions that it was generated by a different mechanism"



### Validation





Conectar

Más...

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Ver todos los detalles



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