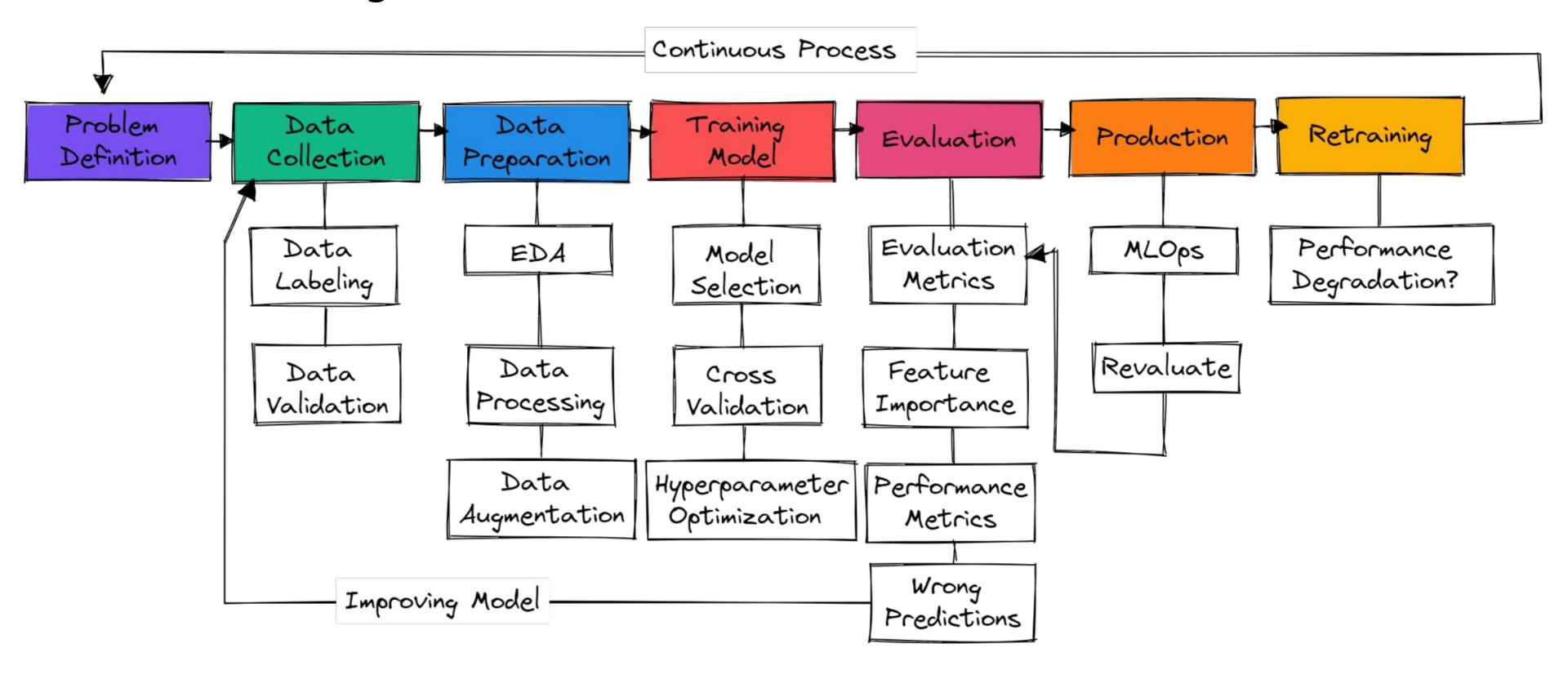


# Resumen ML

### ML Project



### Data Exploration

#### IMPORTANCE OF DATA EXPLORATION

WHEN PREPARING FOR DATA STORYTELLING



TO IDENTIFY ANY TRENDS, PATTERNS, OR CORRELATIONS



EXPLORING DATA
HELPS ENSURE
ACCURACY



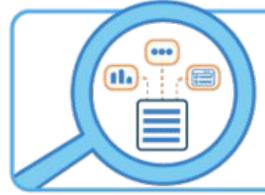
DATA EXPLORATION HELPS UNCOVER HIDDEN GEMS



HELPS YOU
UNDERSTAND THE ROLE
OF EACH VARIABLE



ALLOWS YOU TO IDENTIFY AND HANDLE ANY OUTLIERS



HELPS YOU
UNDERSTAND THE DATA
COLLECTION CONTEXT

### Types of Machine Learning – At a Glance

Supervised Learning

- Makes machine Learn explicitly
- Data with clearly defined output is given
- Direct feedback is given
- Predicts outcome/future
- Resolves classification and regression problems



Unsupervised Learning

- Machine understands the data (Identifies patterns/structures)
- Evaluation is qualitative or indirect
- Does not predict/find anything specific

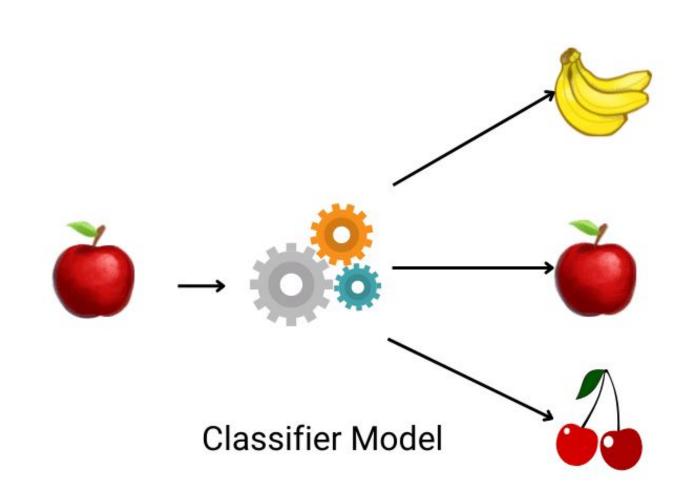


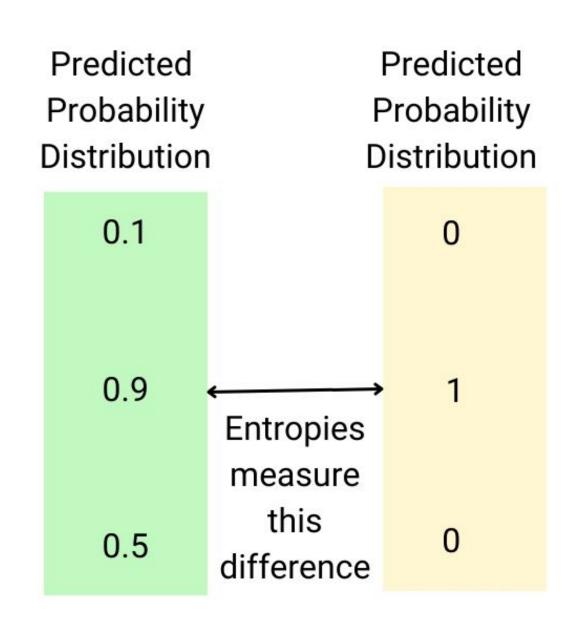
Reinforcement Learning

- An approach to Al
- Reward based learning
- Learning form +ve &
- +ve reinforcement
- Machine Learns how to act in a certain environment
- To maximize rewards



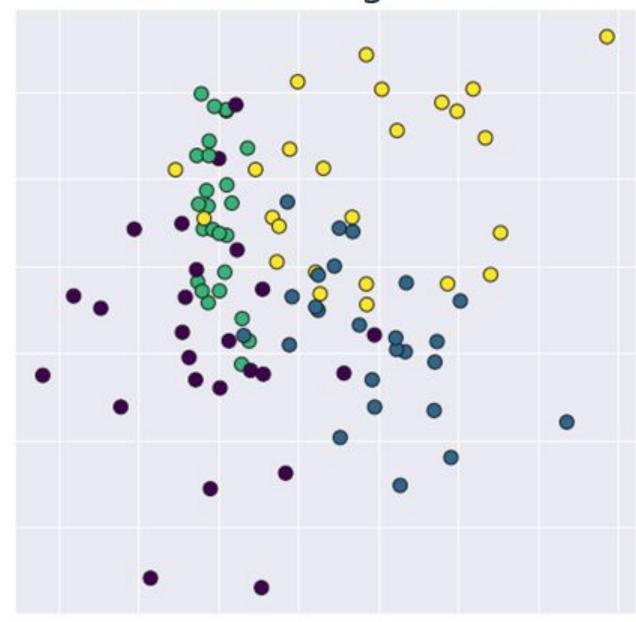
### Supervised-Classification





### Supervised-Multi Classification

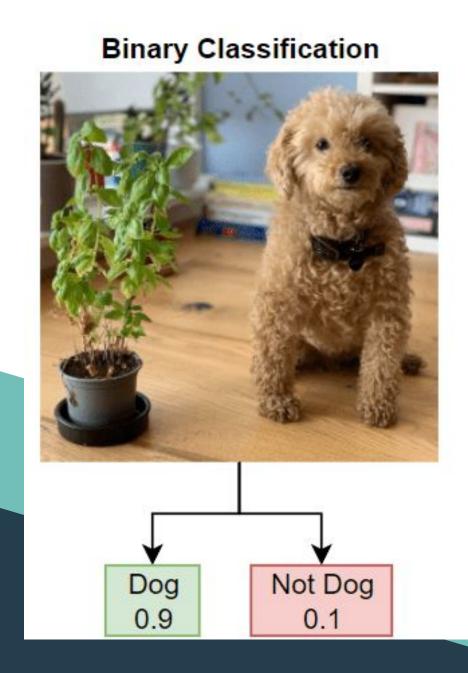
#### Dataset containing four classes

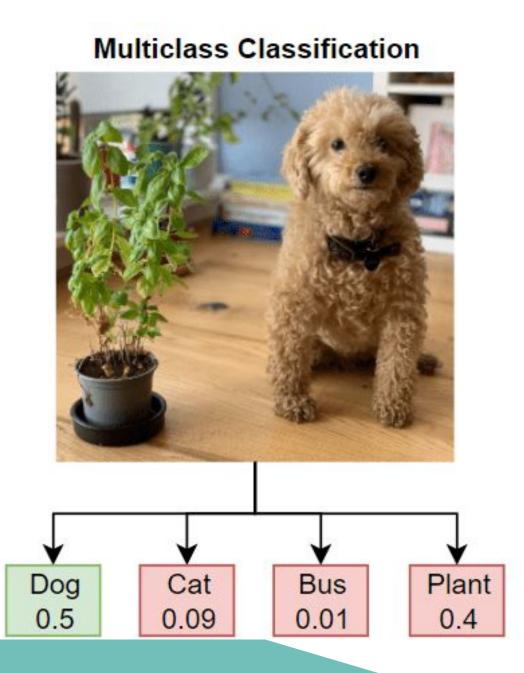


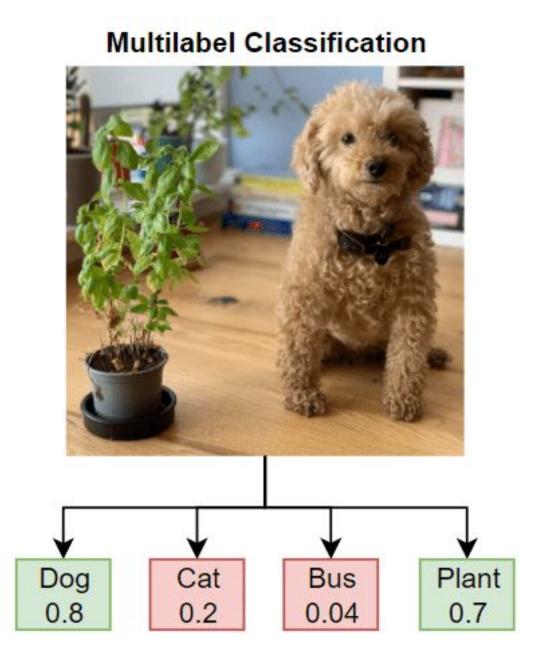


Train one binary model for **each class**, with remaining classes treated as aggregates. Also known as **One-vs-All**. Commonly used with logistic regression.

### Supervised-Classification

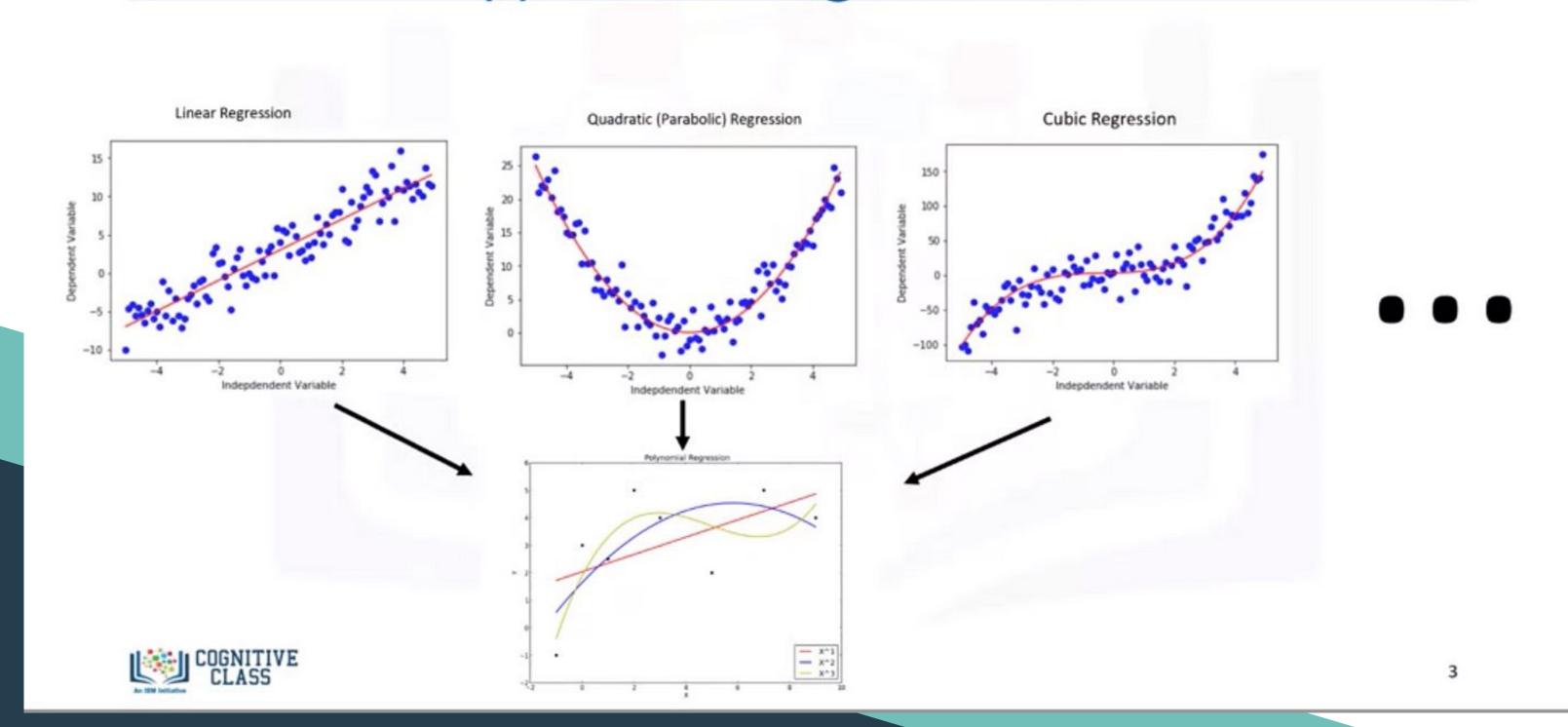






### Supervised-Regression

### Different types of regression



### Supervised-Metrics

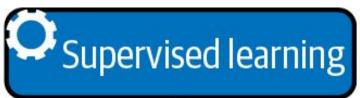
#### **Evaluation Metrics**

#### Classification

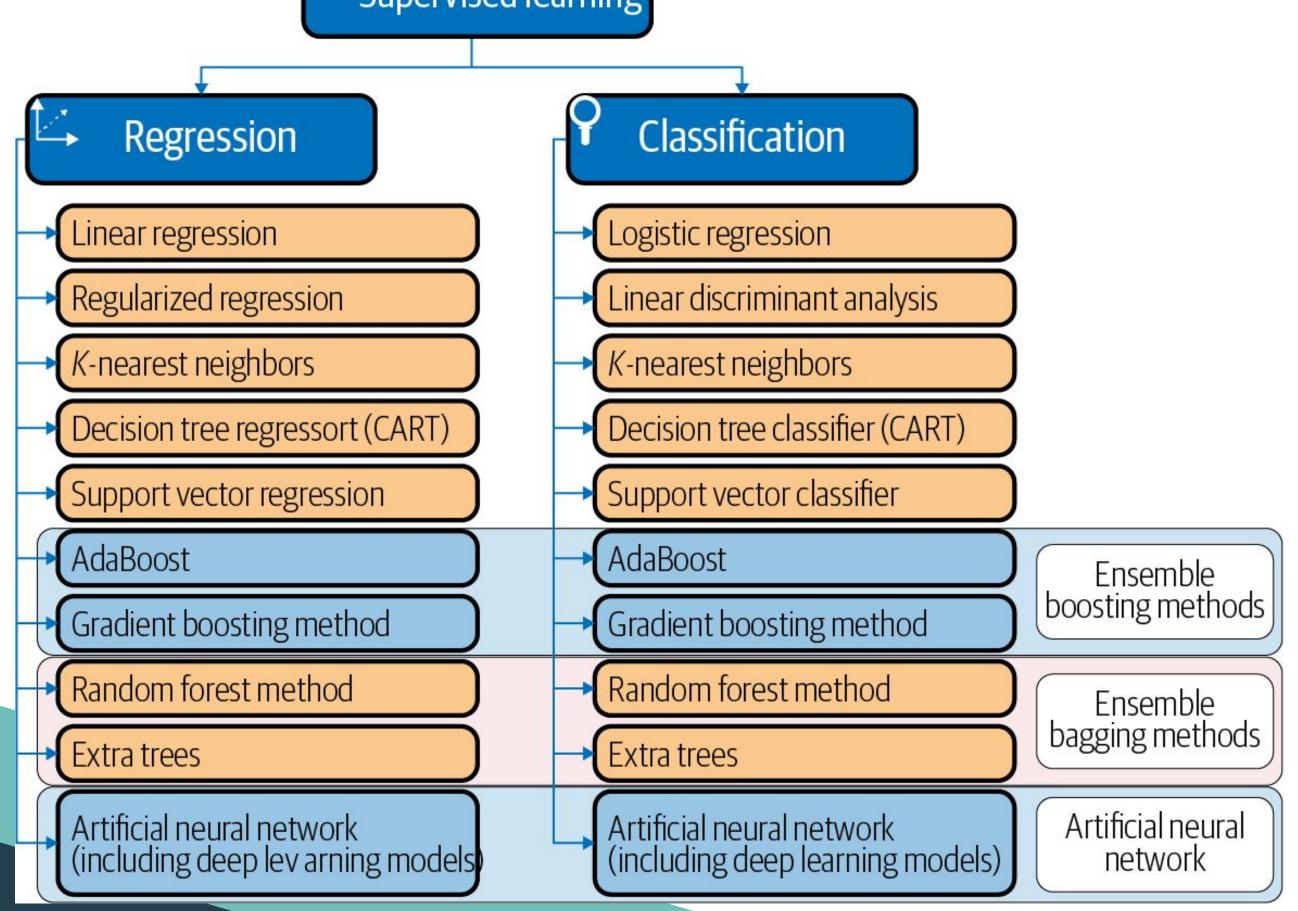
- Confusion
   Matrix
- Accuracy
- Precision and Recall
- F-score
- AUC-ROC
- Log Loss
- Gini Coefficient

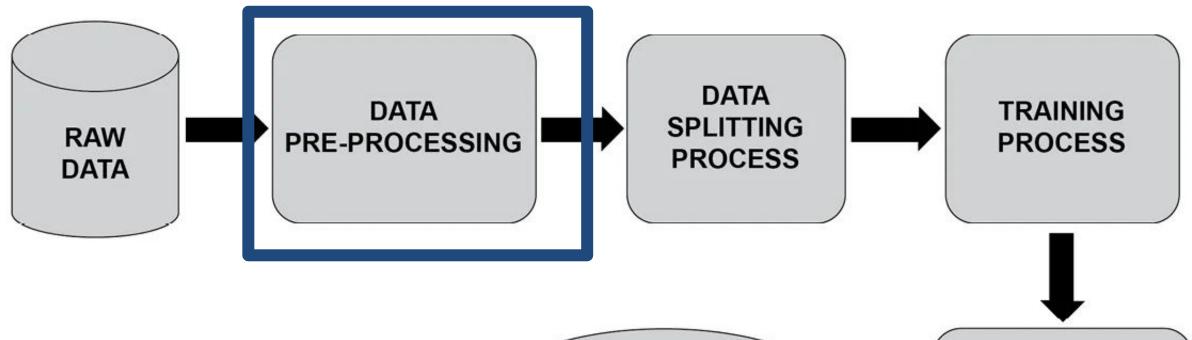
#### Regression

- MAE
- (mean abs. error)
- MSE
- (mean sq. error)
- RMSE
- (Root mean sq.error)
- RMSLE
- (Root mean sq.error
- log error)
- R<sup>2</sup> and Adjusted
   R<sup>2</sup>



# Supervised Models





#### Estas dos partes tiene mucho en

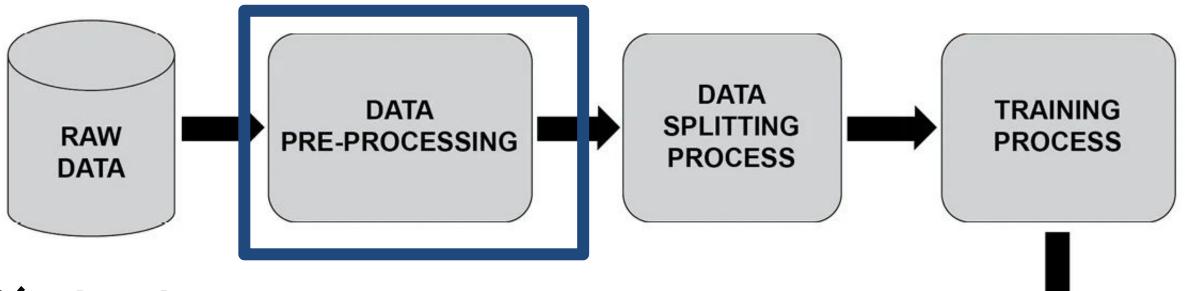
común. El preprocesamiento que hacemos al principio deberemos aplicarlo de la misma forma para cualquier set de datos del futuro (excepto casos muy particulares).

**EVALUATION VALIDATION PROCESS DATA DEPLOYMENT REAL DATA PROCESS** 

PREDICTION

RESULTS

Por eso intentamos usar pipelines y funciones que transforman los datos, para imitar todo este proceso.



#### Objetos de creación de columnas:

PolynomialFeatures

OneHotEncoder

PCA (reducción de dimensionalidad)

#### **Objetos normalizadores:**

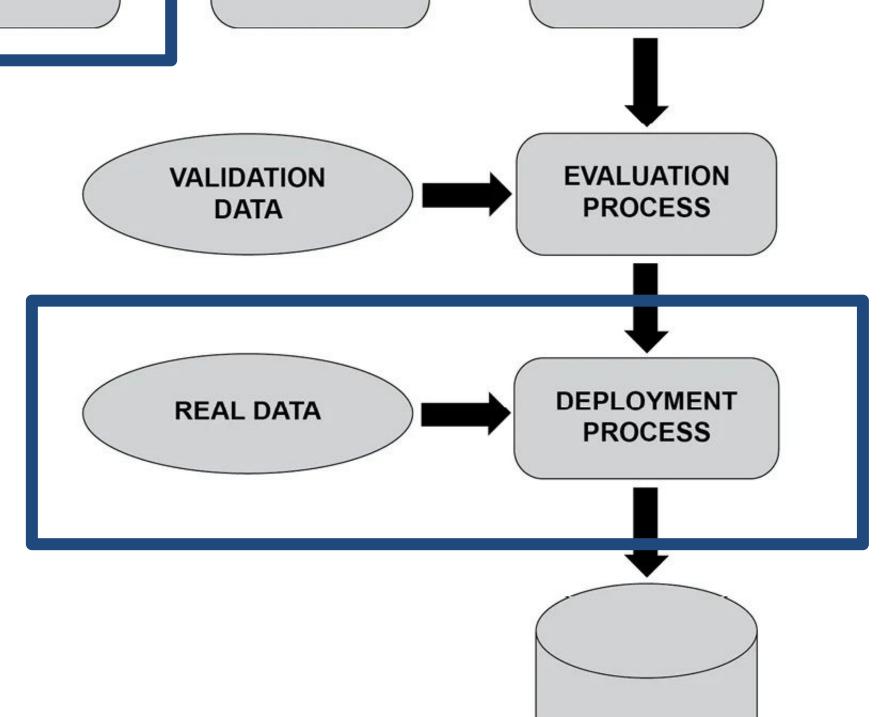
StandardScaler

MinMaxScaler

#### Objetos de imputación:

SimpleImputer

KNNImputer



**PREDICTION** 

RESULTS

#### Feature Selection

Subsetting the features

Ex: Using correlation with the dependent variable

#### Feature Extraction

Creating new features when we could **NOT** have used raw features

Ex: from images to RGB values.
Automatic methods such as PCA

#### Feature Engineering

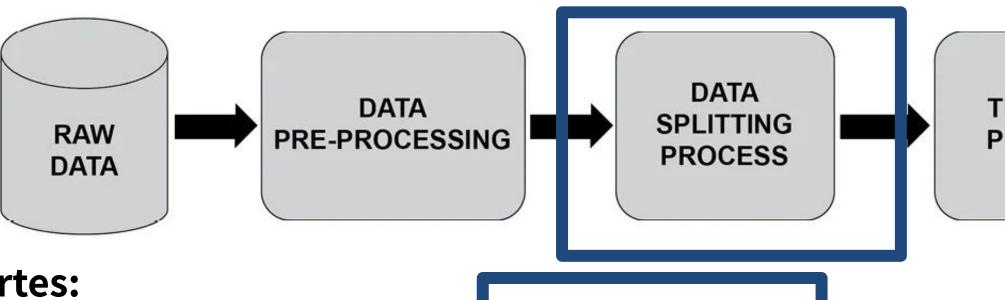
Creating new features when we could have used raw features

Ex: Creating a new dummy variable for working days

#### Feature Learning

Constructing features automatically

Ex: Supervised neural networks, Independent component analysis

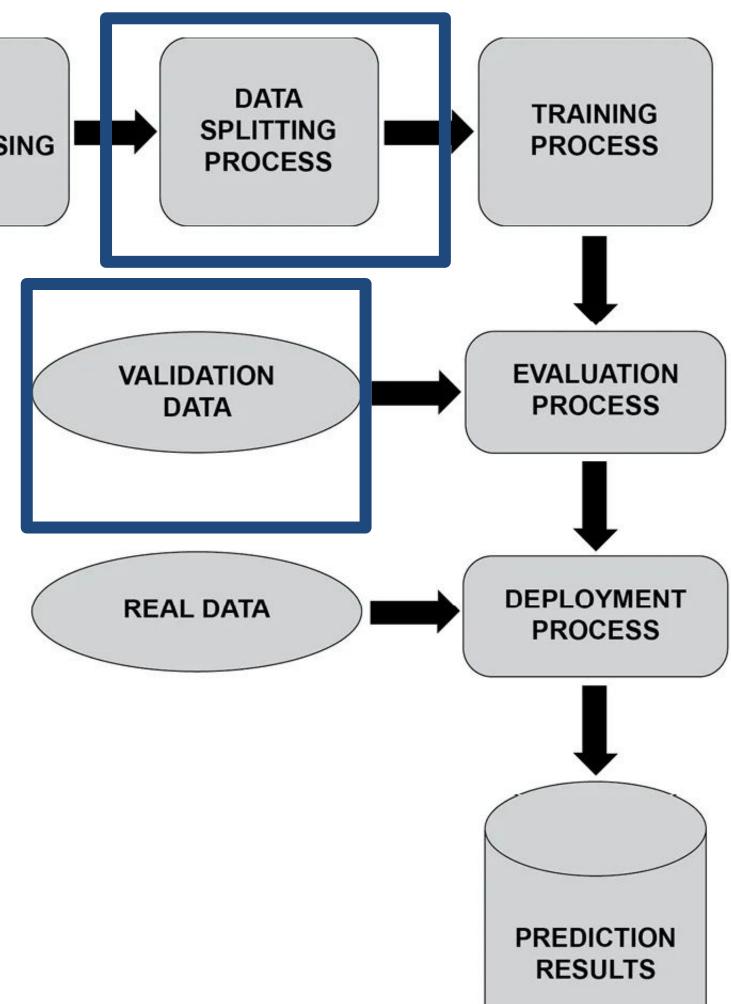


#### **Dividimos en 2 partes:**

¿Por que? Porque queremos tener la seguridad de que nuestro modelo sea estable.

**Train:** Set de datos con el que entrenaremos/buscaremos el modelo

**Test:** Set de datos donde veremos las métricas (También se puede llamar validation data aunque nosotros lo llamamos al rovés)



#### **Training process:**

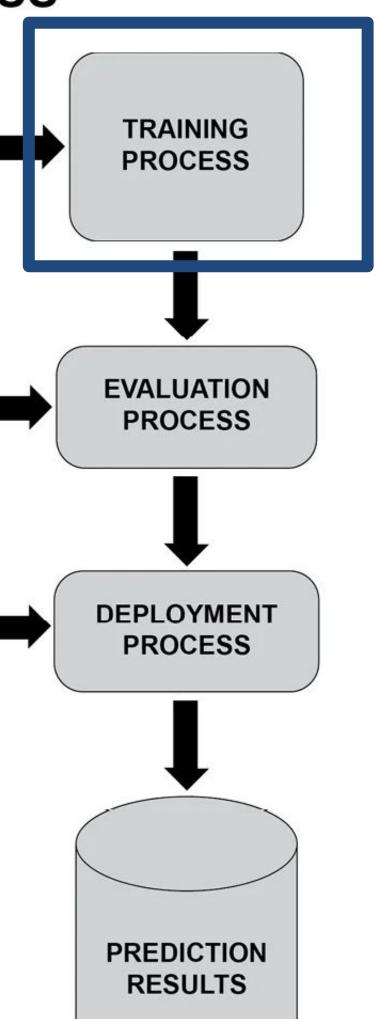
Aquí nosotros hacemos la elección de un tipo de modelo, dependiendo del tipo de problema. Asumimos que elegimos un XGBoost. Entrenamos un modelo a partir de enseñarles unas X y una Y asociadas.

Búsqueda de hiperparametros (get\_params y grid\_searchCV):

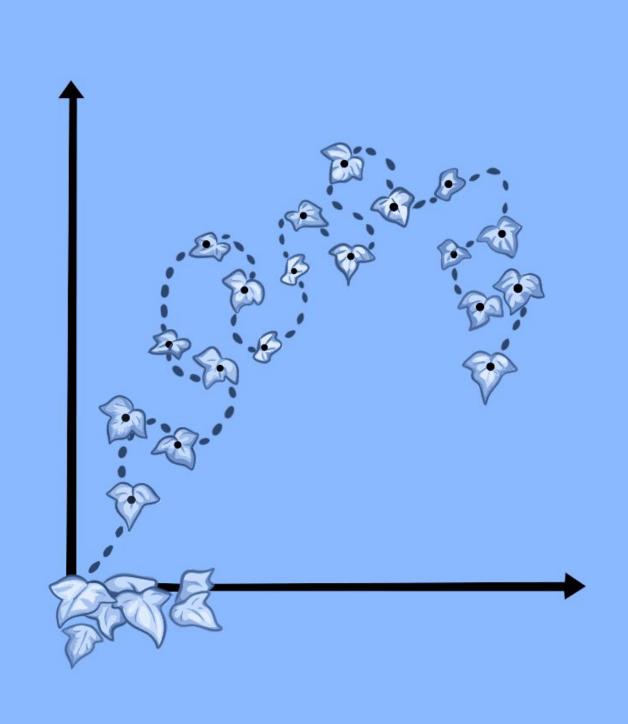
Definimos un conjunto de hiperparametros del modelo, como el max\_depth. Probaremos cada combinación de candidatos y elegiremos la mejor

#### Elegimos un método de validación (grid\_searchCV):

Cross-validation: En vez de tener una métrica de cada combinación tendremos K (5 normalmente, hacemos 5 modelos entrenando con 4 partes del train y testeando con 1 parte del train). Con estas K métricas elegimos el mejor modelo.



# Overfitting



### Overfitting

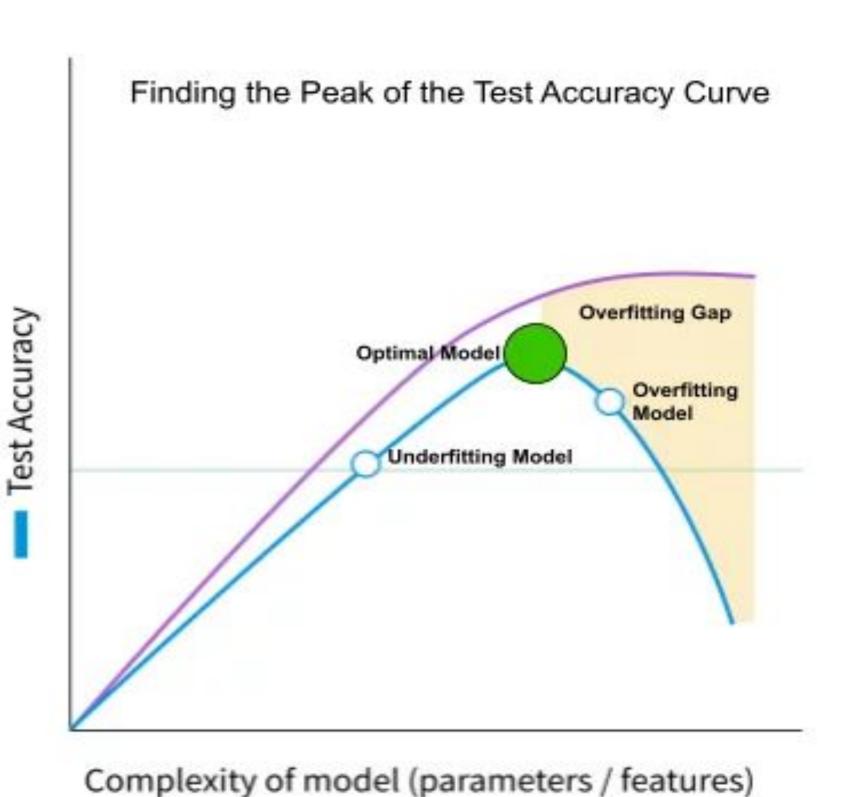
[ˈō-vər-ˈfi-tiŋ]

A modeling error in statistics that occurs when a function is too closely aligned to a limited set of data points.



### Overfitting

Train Accuracy

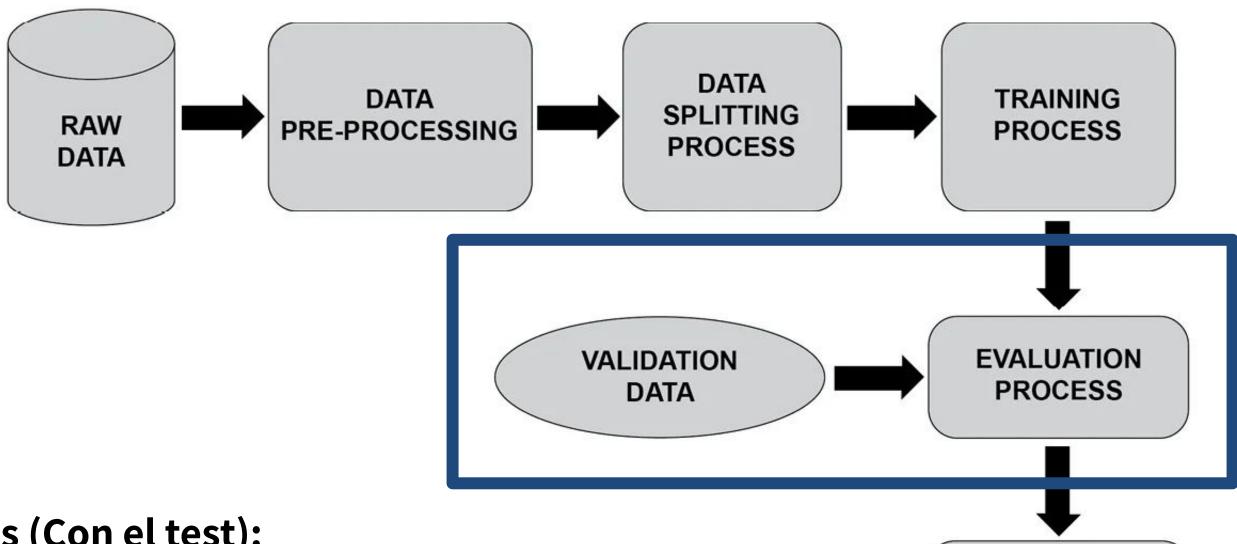


Appropriate capacity (Good fit) Overfitting Underfitting **Increase bias** Increase variance Validation data Generalization Training data Model capacity (ex. training iterations)

| Training loss | Validation loss | Situation    | Solution  |
|---------------|-----------------|--------------|---|
| High          | High            | Underfitting | Increase capacity                                       |
| Low           | High            | Overfitting  | Decrease capacity (shrink or regularization techniques) |
| Low           | Low             | Good fit     | Run test  |
| High          | Low             | Unlikely     | Debug   |

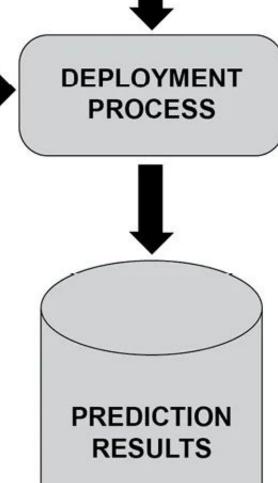
# Avoid Overfitting



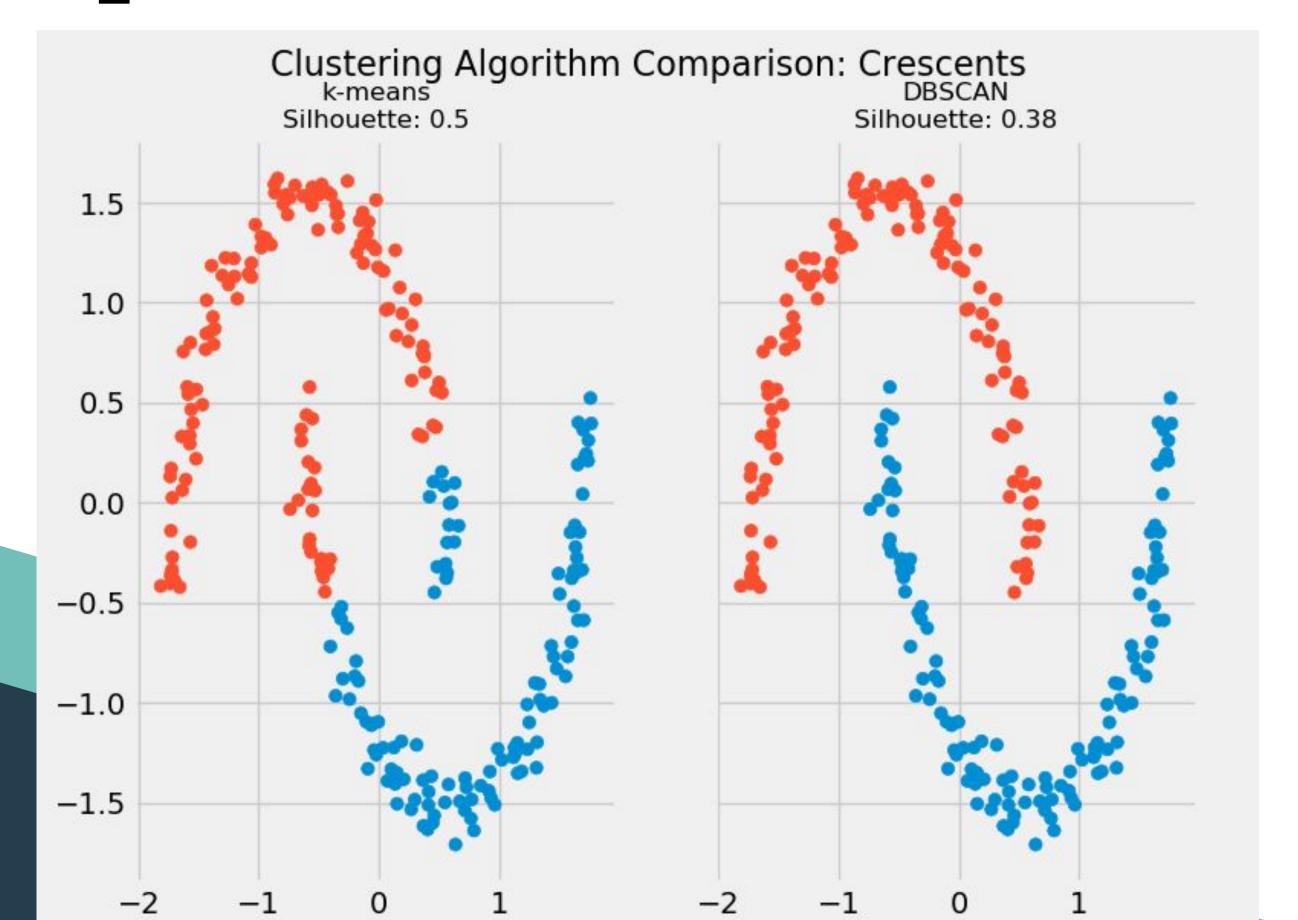


#### **Evaluation process (Con el test):**

Ya con la elección del modelo hecha automáticamente por el **grid\_searchCV**, utilizamos el mejor modelo (que ya está ajustado) para una última prueba con un conjunto de datos que no hemos utilizado todavía. Esta métrica será la referencia para saber si nuestro modelo es realmente estable.



### Unsupervised-Models



### Unsupervised-Models

