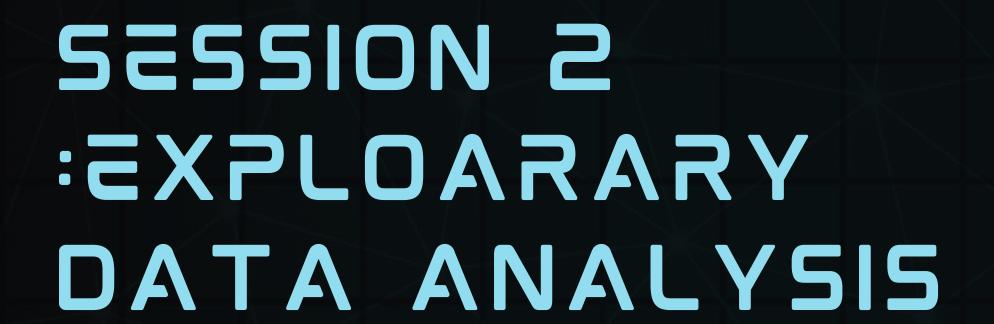
DATA C'EPT





PREPARED BY:
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CHAABANE

RECAP

Data

Features of a house: size, nbe of rooms,location...

Black Box

Generating a Rule

Y,

Price of the house

looking for patterns, relationship between variables...

Intuition behind machine Learning

BUT HOW?

EDA

investigate the data and summarize the key insights

FEATURE ENG

Creating features to help the model decide

STEPS

MODELLING

Defining ,Adapting and Tuning a Learning algorithm

EVALUATING

Evaluate the results and conclude

OUR STRATEGY:REVERSE LEARNING

We take a quick look at all the steps and then we organize sessions to dive deeper like: advanced missing values handling, Dealing with categorical features, TimeSeries, Dealing with imbalanced datasets, Regularization and confidence, cross-validation techniques....

EDA:

EDA is a process of performing some initial **investigations** on the dataset to discover the structure and the content of the given dataset.

It involves:

- Importing a dataset
- Understanding the big picture
- Preparation
- Understanding of variables
- Study of the relationships between variables
- Brainstorming

WHY PERFORMING EDA?

- An essential part in order to understand the problem
- It helps in Feature Selection
- It helps in Feature Engineering
- It helps in choosing the appropriate learning algorithm: for example if a feature is linearly highly correlated to the target ,linear regression will probably perform well.



LET'S TAKE AN EXAMPLE: THE WINE DATASET



OBJECTIVE:

Using chemical composition of wines in order to predict the quality of it.

LOADING THE DATASET

```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
df =pd.read_csv('https://archive.ics.uci.edu/ml/machine-learning-databases/wine-guality/winequality-red.csv',sep=';')
```

LET'S TAKE A LOOK HOW THE DATA LOOKS LIKE

df.head()												
	fixed acidity	volatile acidity	citric acid	residual sugar	chlorides	free sulfur dioxide	total sulfur dioxide	density	pH sulph	tes alco	hol q	quality
0	7.4	0.70	0.00	1.9	0.076	11.0	34.0	0.9978	3.51	0.56	9.4	5
1	7.8	0.88	0.00	2.6	0.098	25.0	67.0	0.9968	3.20	0.68	9.8	5
2	7.8	0.76	0.04	2.3	0.092	15.0	54.0	0.9970	3.26	0.65	9.8	5
3	11.2	0.28	0.56	1.9	0.075	17.0	60.0	0.9980	3.16	0.58	9.8	6
4	7.4	0.70	0.00	1.9	0.076	11.0	34.0	0.9978	3.51	0.56	9.4	5

SHAPE:

df.shape

(1599, 12)

number of rows(examples)

number of columns(features+target)

DESCRIPTIVE INFORMATION ABOUT THE DATASET:

86.	. di	OBC	TE	in the	m
-					

fixed acidity	volatile acidity	citric acid	residual sugar	chlorides	free sulfur dioxide	total sulfur dioxide	density	pli	sulphates	alcohol	quality
1599.000000	1599.000000	1599.000000	1599.000000	1599.000000	1599.000000	1599.000000	1599.000000	1599.000000	1599.000000	1599.000000	1599.000000
8.319637	0.527821	0.270976	2.538806	0.087467	15.874922	46.467792	0.996747	3.311113	0.658149	10.422983	5.636023
1.741096	0.179060	0.194801	1.409928	0.047065	10.460157	32.895324	0.001887	0.154386	0.169507	1.065668	0.807569
4.600000	0.120000	0.000000	0.900000	0.012000	1.000000	6.000000	0.990070	2.740000	0.330000	8.400000	3.000000
7.100000	0.390000	0.090000	1.900000	0.070000	7.000000	22.000000	0.995600	3.210000	0.550000	9.500000	5.000000
7.900000	0.520000	0.260000	2.200000	0.079000	14.000000	38.000000	0.996750	3.310000	0.620000	10.200000	6.000000
9.200000	0.640000	0.420000	2.600000	0.090000	21.000000	62.000000	0.997835	3.400000	0.730000	11.100000	6.000000
15.900000	1.580000	1.000000	15.500000	0.611000	72.000000	289.000000	1.003690	4.010000	2.000000	14.900000	8.000000
	1599.000000 8.319637 1.741096 4.600000 7.100000 7.900000 9.200000	1599.000000 1599.0000000 8.319637 0.527821 1.741096 0.179060 4.600000 0.120000 7.100000 0.390000 7.900000 0.520000 9.200000 0.640000	1599.000000 1599.000000 1599.0000000 8.319637 0.527821 0.270976 1.741096 0.179060 0.194801 4.600000 0.120000 0.0000000 7.100000 0.390000 0.090000 7.900000 0.520000 0.260000 9.200000 0.640000 0.420000	1599.000000 1599.000000 1599.000000 1599.000000 8.319637 0.527821 0.270976 2.538806 1.741096 0.179060 0.194801 1.409928 4.600000 0.120000 0.000000 0.900000 7.100000 0.390000 0.090000 1.900000 7.900000 0.520000 0.260000 2.200000 9.200000 0.640000 0.420000 2.600000	1599.000000 1599.000000 1599.000000 1599.000000 1599.000000 8.319637 0.527821 0.270976 2.538806 0.087467 1.741096 0.179060 0.194801 1.409928 0.047065 4.600000 0.120000 0.000000 0.900000 0.012000 7.100000 0.390000 0.090000 1.900000 0.070000 7.900000 0.520000 0.260000 2.200000 0.079000 9.200000 0.640000 0.420000 2.600000 0.090000	1599.000000 1599.000000 1599.000000 1599.000000 1599.000000 8.319637 0.527821 0.270976 2.538806 0.087467 15.874922 1.741096 0.179060 0.194801 1.409928 0.047065 10.460157 4.600000 0.120000 0.090000 0.900000 0.012000 1.000000 7.100000 0.390000 0.090000 1.900000 0.070000 7.000000 7.900000 0.520000 0.260000 2.200000 0.079000 14.000000 9.200000 0.640000 0.420000 2.600000 0.090000 21.000000	1599.000000 1599.00000 1599.000000 1599.00000 1599.00000 1599.00000 1599.00000 1599.00000 1599.00000 1599.00000 1599.00000 1599.00000 1599.0000 1599.	1599.000000 1599.000000 1599.000000 1599.000000 1599.000000 1599.000000 1599.000000 8.319637 0.527821 0.270976 2.538806 0.087467 15.874922 46.467792 0.996747 1.741096 0.179060 0.194801 1.409928 0.047065 10.460157 32.895324 0.001887 4.800000 0.120000 0.000000 0.900000 0.012000 1.000000 8.000000 0.990070 7.100000 0.390000 0.090000 0.070000 7.000000 22.000000 0.995800 7.900000 0.640000 0.420000 2.600000 0.090000 21.000000 62.000000 0.997835	1599,000000 1599,00000 1599,000000 1599,000000 1,000000 1,0000000 <th< th=""><th>1599.000000 1599.00000 1599.000000 1599.00000 1599.000000 1599.00000</th><th>1599,000000 10,00000 1599,000000 1599,000000 1599,000000 10,00000 1599,000000 1599,000000 10,00000 1599,000000 1599,000000 10,00000 1599,00000 1599,00000 10,00000 1599,00000 1599,00000 10,00000 1599,00000 1599,00000 10,00000 10,00000 1599,00000</th></th<>	1599.000000 1599.00000 1599.000000 1599.00000 1599.000000 1599.00000	1599,000000 10,00000 1599,000000 1599,000000 1599,000000 10,00000 1599,000000 1599,000000 10,00000 1599,000000 1599,000000 10,00000 1599,00000 1599,00000 10,00000 1599,00000 1599,00000 10,00000 1599,00000 1599,00000 10,00000 10,00000 1599,00000

LET'S DIVE DEEPER

- are there any useless or redundant variables?
- are there any duplicate columns,rows?
- does the nomenclature make sense?
- are there any new variables we want to create?

DROPPING DUPLICATES :

```
df.duplicated().sum()

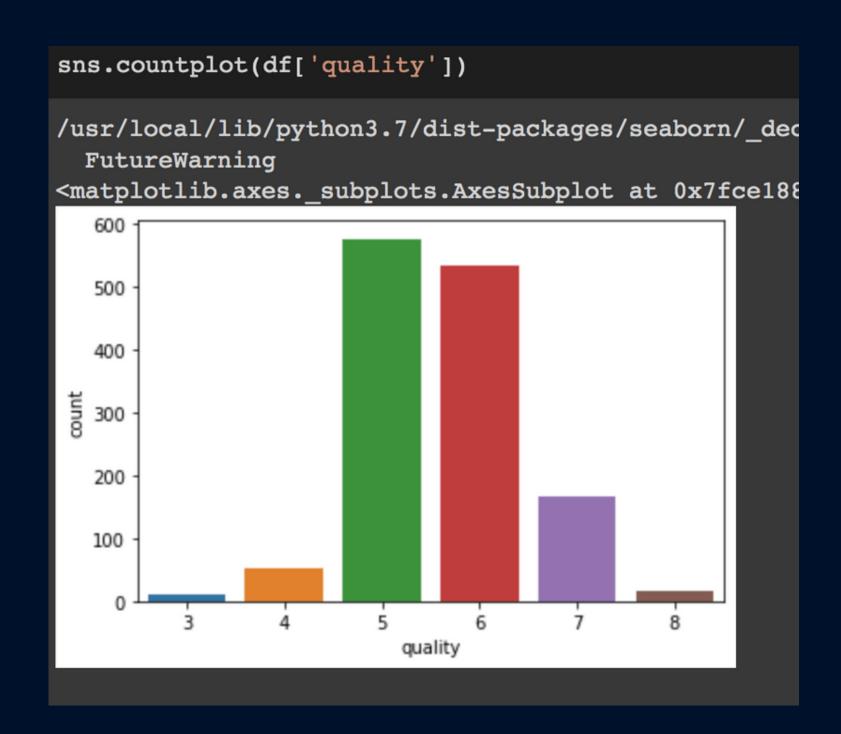
240

df=df.drop_duplicates()
```

DISTRIBUTION OF THE TARGET

We're dealing with a highly imbalanced datasets, Some classes are underrepresented.

We will learn how to deal with imbalanced Datasets in the upcoming sessions.



MISSING VALUES:

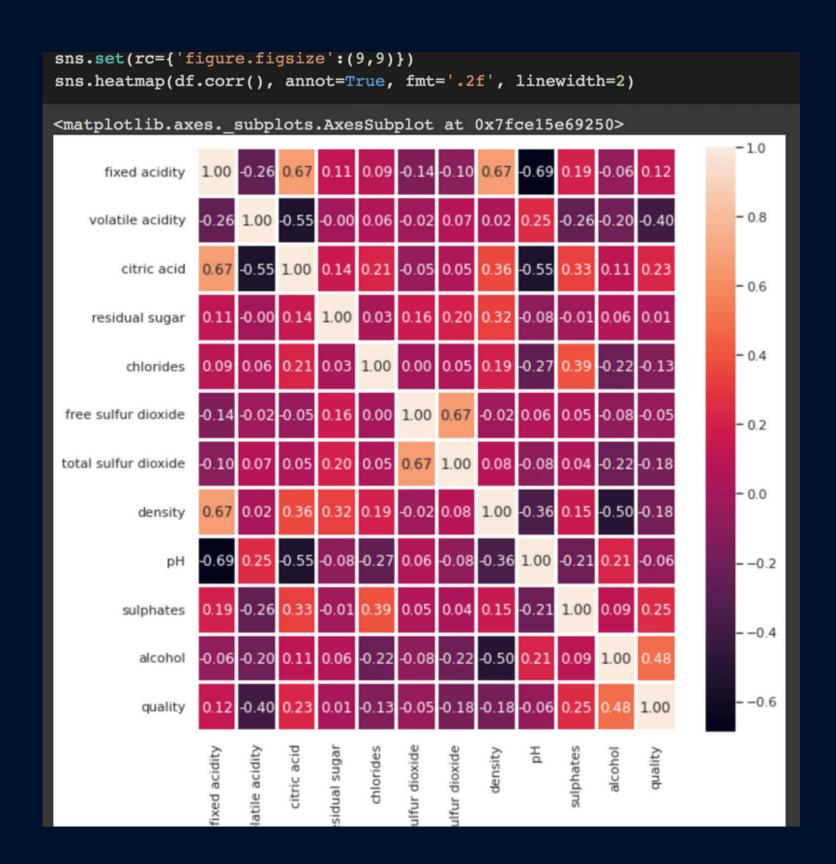
<pre>df.isna().sum()/df.shape[0]</pre>						
fixed acidity volatile acidity citric acid residual sugar chlorides free sulfur dioxide total sulfur dioxide density pH sulphates alcohol quality	0.0 0.0 0.0 0.0 0.0 0.0 0.0					
dtype: float64						

--->No missing values

CORRELATION BETWEEN FEATURES :

$$r = rac{\mathrm{Cov}(X,Y)}{\sigma_X \sigma_Y}$$

it refers to the degree to which a pair of variables are linearly related.

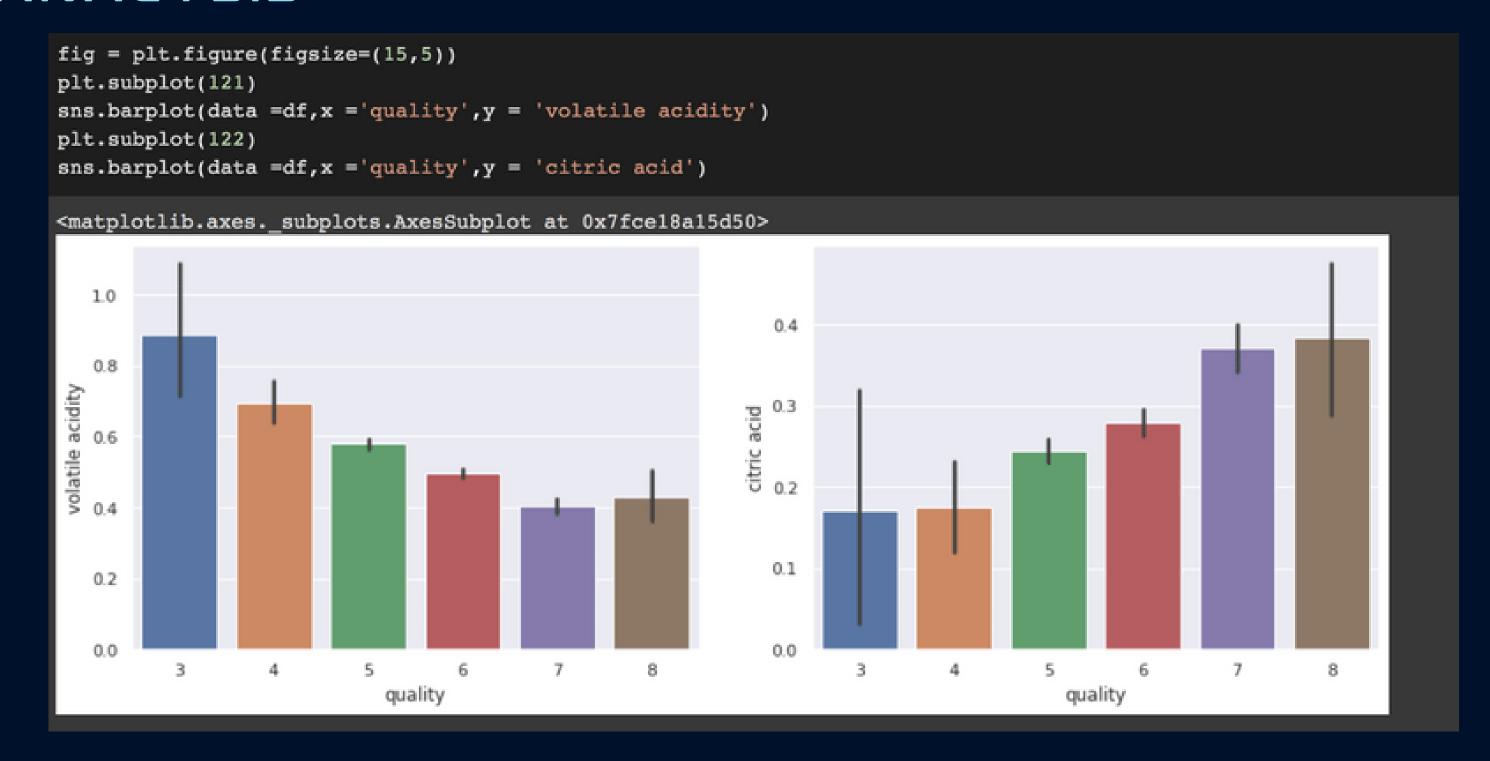


Quick Observation

- fixed acidity has high correlation(>0.6) with density and citric acid and a negative correlation(<-0.69) with pH.
- volatile acidity seems to have a negative effect on quality (-0.41).
- free sulfur dioxide is more if total sulfur dioxide is more and vice versa.
- alcohol is having influence on quality of wine.
- alcohol and density have a negative correlation(-0.49)
- pH,free and total sulfure dioxide, chlorides, residual sugar do not have high correlation on quality

Ps : This only reflects linear relationship between variables

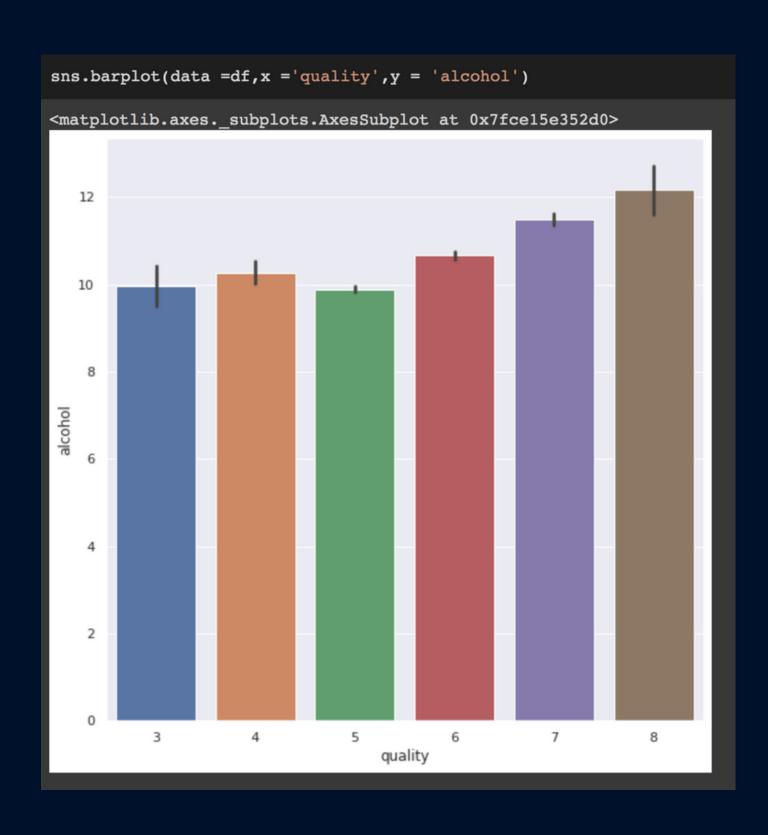
ANALYSIS:



Quick Observation

- It's very distinctive from the above visualtion that a wine is of top quality if it's volatile acidity is less.
- Top quality wines usually have high citric acid.

LET'S CHECK HOW QUALITY OF THE WINE IS AFFECTED BY ALCOHOL CONTENT:



So, Quality of the wine improves when we increase it's alcohol content.

THANK YOU FOR YOUR ATTENTION!