Data Pre-Processing
and
Exploratory Data Analysis

Date : 31st May 2020 | Speaker : Ayon Roy

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Hello **Buddy!**

I am **Ayon Roy**

B.Tech CSE (2017-2021)

Data Science Intern @ **Lulu International Exchange**, Abu Dhabi

(**World's Leading Financial Services Company**)

Brought **Kaggle Days Meetup** Community in India for the 1st time

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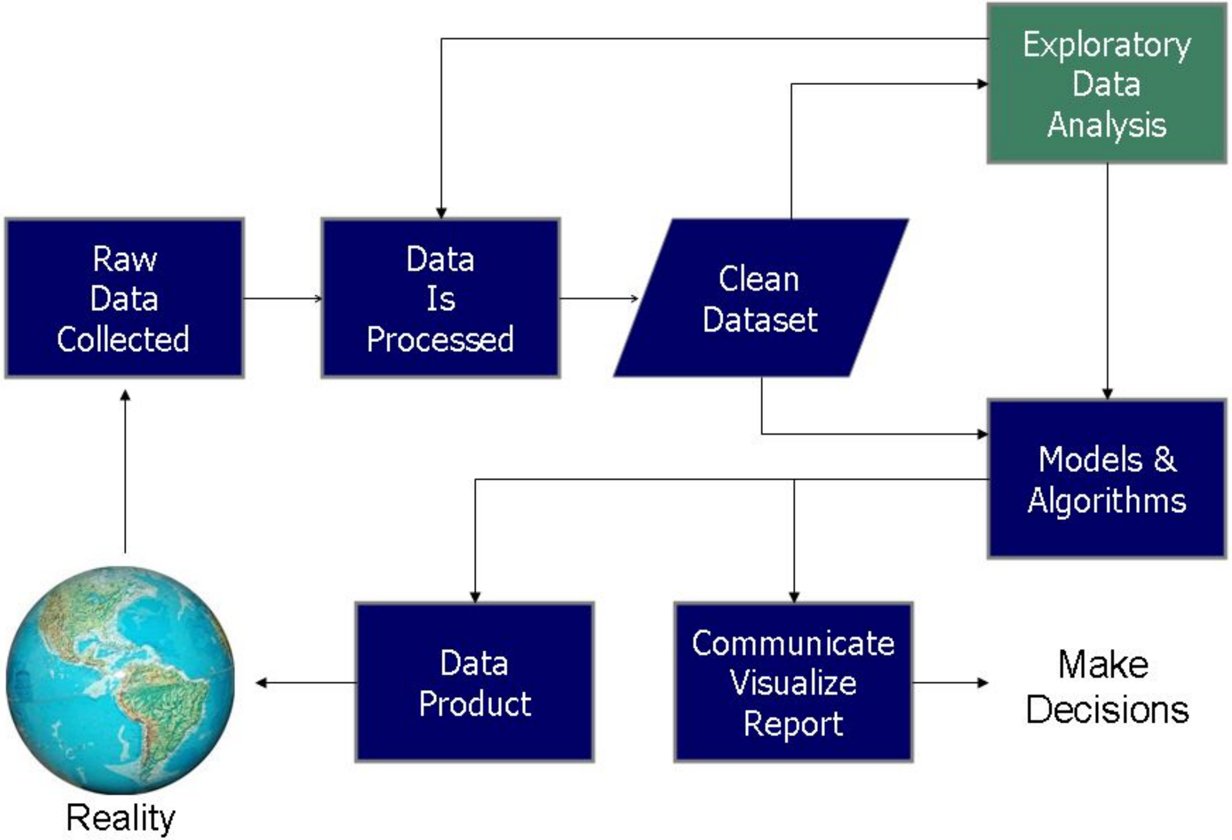
Agenda (31-5-2020)

- What is Data Pre-Processing (DPP) ?
- Why do we need it ?
- Major Steps in DPP
- What is Exploratory Data Analysis (EDA) ?
- Why do we need it ?
- What are the types of EDA ?
- A few EDA Approaches
- Major steps in EDA

LET'S GET STARTED!

Data Science Process



What is Data Pre-Processing ?

It is a technique that transforms raw data into an understandable format.

Why do we need it ?

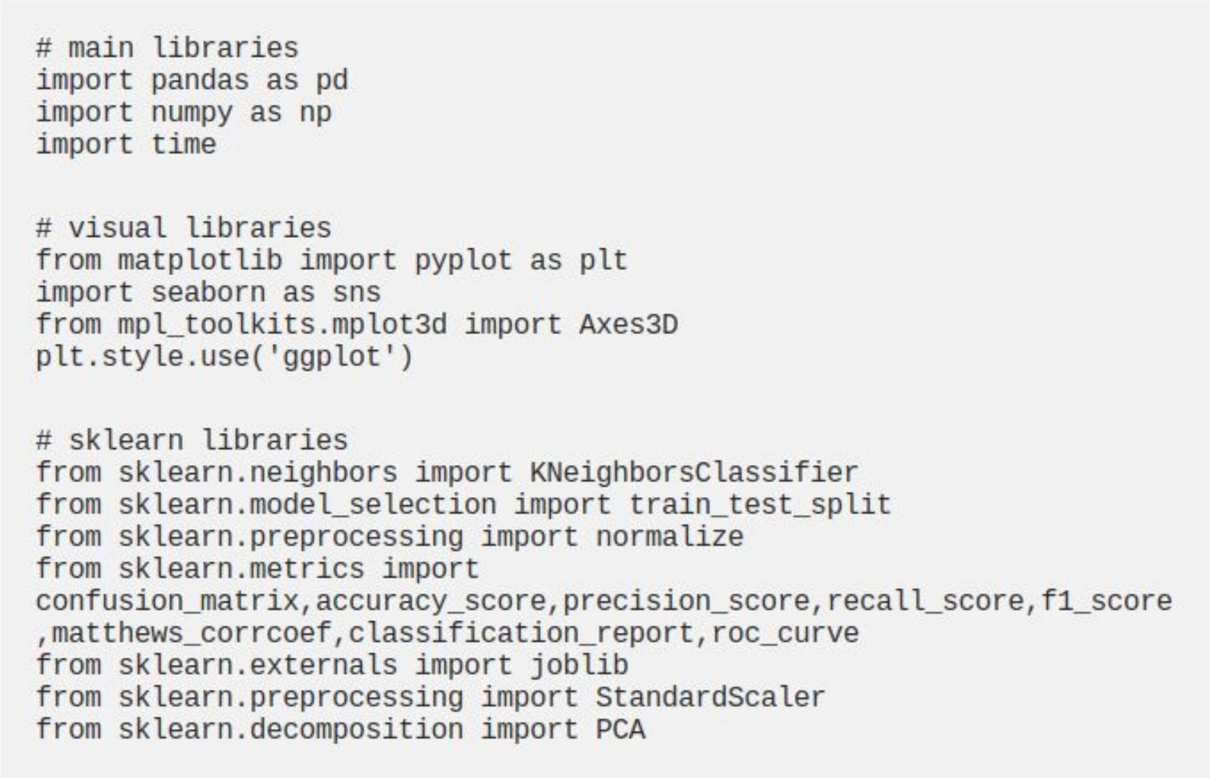
Raw data (Real world data) is always messy and that data cannot be sent through a model. That would cause certain errors.

So we need to preprocess data before sending through further analysis.

- CHANGE IS GOOD.
- YEAH, BUT IT'S NOT EASY.

Steps to be followed

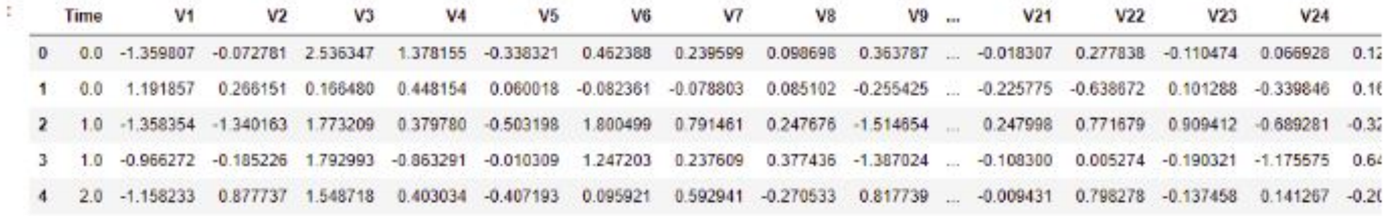
Get the data & Import the Libraries



```
# main libraries
import pandas as pd
import numpy as np
import time


# visual libraries
from matplotlib import pyplot as plt
import seaborn as sns
from mpl_toolkits.mplot3d import Axes3D
plt.style.use('ggplot')


# sklearn libraries
from sklearn.neighbors import KNeighborsClassifier
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import normalize
from sklearn.metrics import
confusion_matrix,accuracy_score,precision_score,recall_score,f1_score
,matthews_corrcoef,classification_report,roc_curve
from sklearn.externals import joblib
from sklearn.preprocessing import StandardScaler
from sklearn.decomposition import PCA
```

Read the data

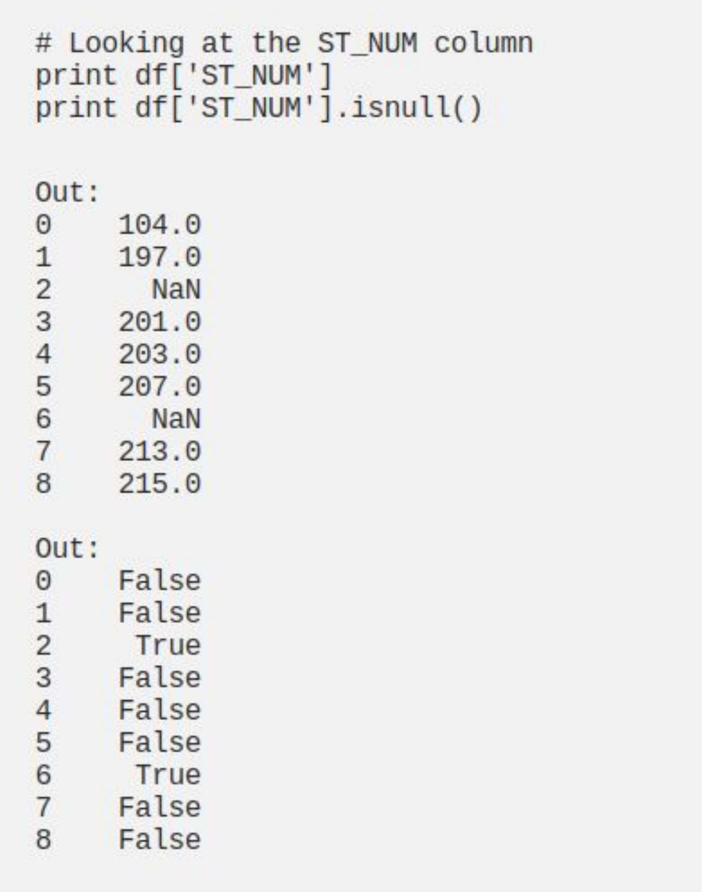
```
# Read the data in the CSV file using pandas
df = pd.read_csv('../input/creditcard.csv')
df.head()
```



	Time	V1	V2	V3	V4	V5	V6	V7	V8	V9	...	V21	V22	V23	V24	
0	0.0	-1.359807	-0.072781	2.536347	1.378155	-0.338321	0.462388	0.239599	0.098698	0.363787	...	-0.018307	0.277838	-0.110474	0.066928	0.12
1	0.0	1.191857	0.266151	0.166480	0.448154	0.060018	-0.082361	-0.078803	0.085102	-0.255425	...	-0.225775	-0.638672	0.101288	-0.339846	0.16
2	1.0	-1.358354	-1.340163	1.773209	0.379780	-0.503198	1.800499	0.791461	0.247676	-1.514654	...	0.247998	0.771679	0.909412	-0.689281	-0.32
3	1.0	-0.966272	-0.185226	1.792993	-0.863291	-0.010309	1.247203	0.237609	0.377436	-1.387024	...	-0.108300	0.005274	-0.190321	-1.175575	0.64
4	2.0	-1.158233	0.877737	1.548718	0.403034	-0.407193	0.095921	0.592941	-0.270533	0.817739	...	-0.009431	0.798278	-0.137458	0.141267	-0.20

Fig 1 : Dataset

Checking the Missing Values



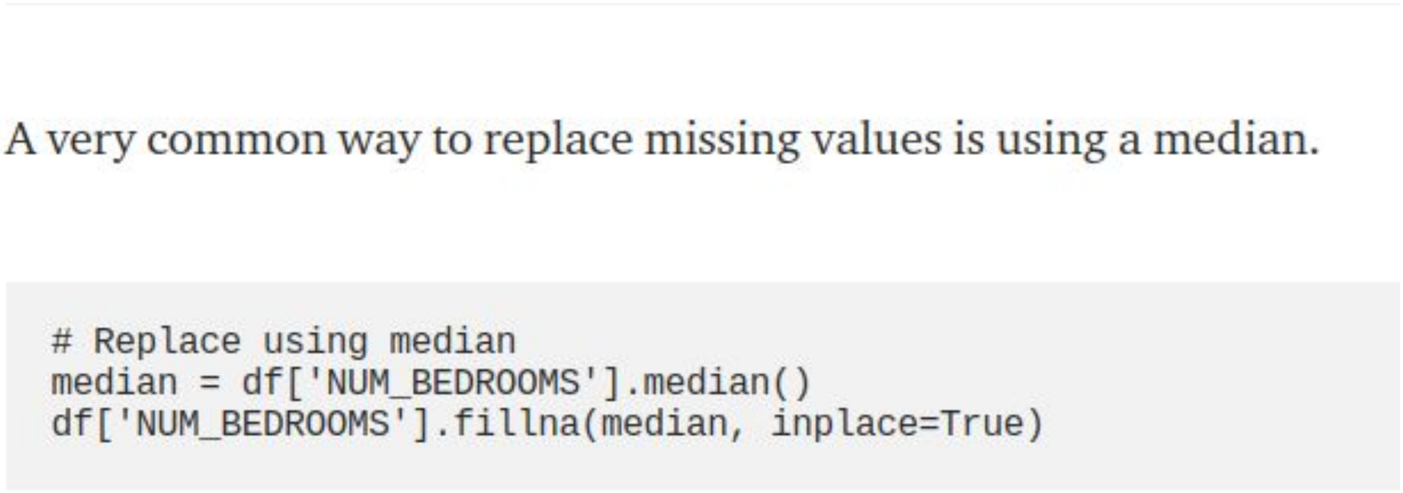
```
# Looking at the ST_NUM column
print df['ST_NUM']
print df['ST_NUM'].isnull()


Out:
0    104.0
1    197.0
2      NaN
3    201.0
4    203.0
5    207.0
6      NaN
7    213.0
8    215.0

Out:
0    False
1    False
2     True
3    False
4    False
5    False
6     True
7    False
8    False
```

Remove the Missing Values

Is it a Good idea ?

Can we do something for this ?

Replacing the Missing Values



A very common way to replace missing values is using a median.

```
# Replace using median
median = df['NUM_BEDROOMS'].median()
df['NUM_BEDROOMS'].fillna(median, inplace=True)
```

Exploring
Numerical Data & Categorical Data

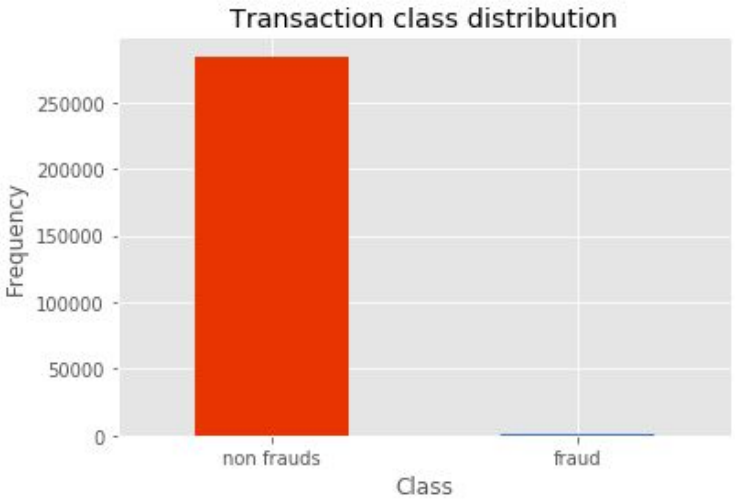


Fig 2 : Class vs Frequency

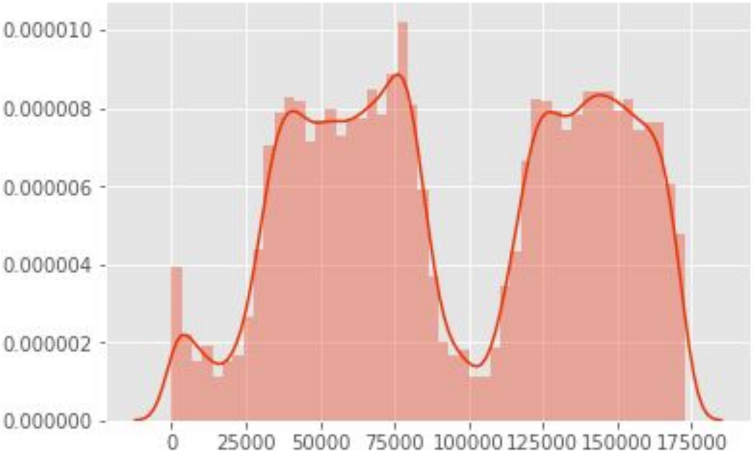


Fig 4 : Distribution of Time

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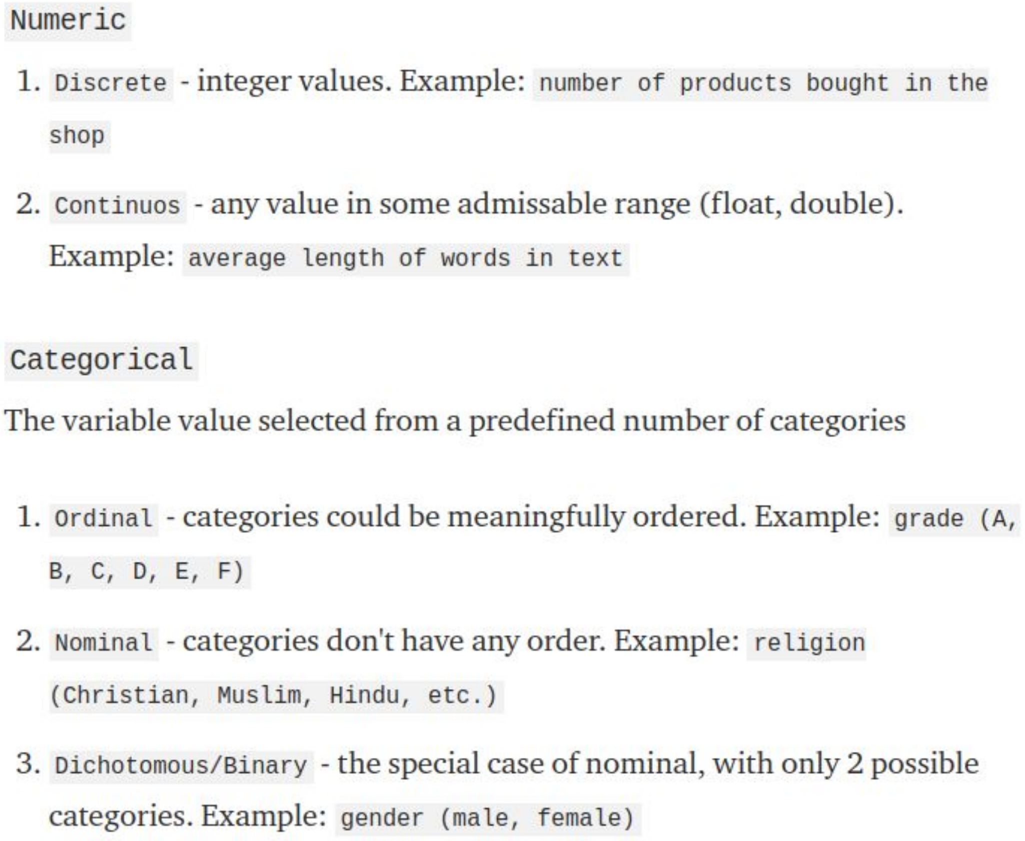
Numerical Data & Categorical Data



`Numeric`

1. `Discrete` - integer values. Example: `number of products bought in the shop`
2. `Continuos` - any value in some admissable range (float, double). Example: `average length of words in text`

`Categorical`

The variable value selected from a predefined number of categories

1. `Ordinal` - categories could be meaningfully ordered. Example: `grade (A, B, C, D, E, F)`
2. `Nominal` - categories don't have any order. Example: `religion (Christian, Muslim, Hindu, etc.)`
3. `Dichotomous/Binary` - the special case of nominal, with only 2 possible categories. Example: `gender (male, female)`

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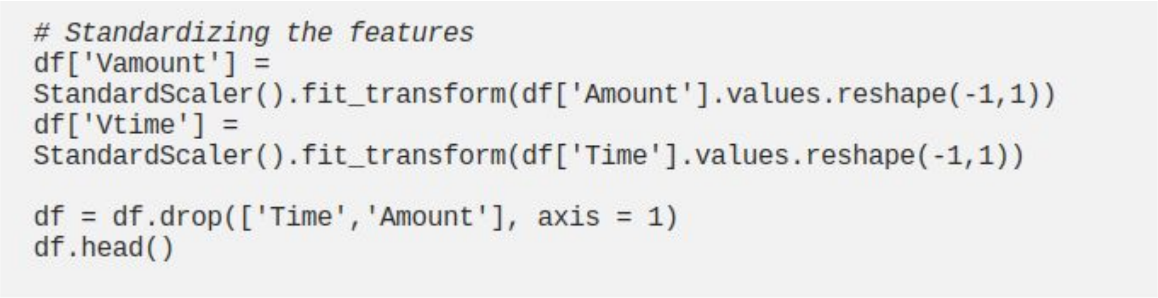
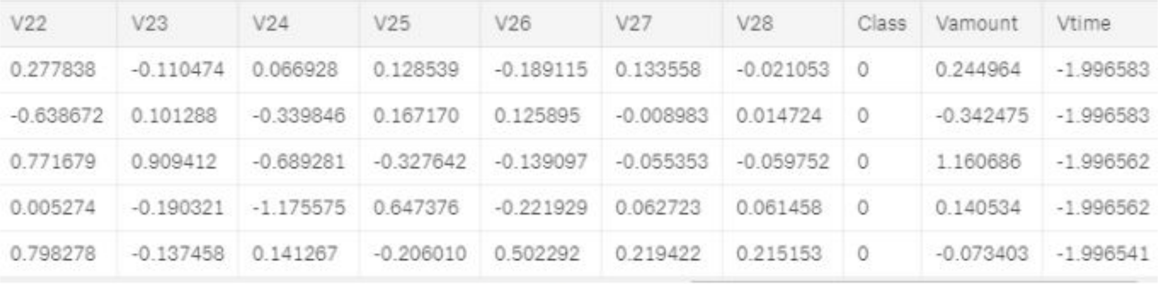
Standardizing the data



```
# Standardizing the features
df['Vamount'] =
StandardScaler().fit_transform(df['Amount'].values.reshape(-1,1))
df['Vtime'] =
StandardScaler().fit_transform(df['Time'].values.reshape(-1,1))

df = df.drop(['Time','Amount'], axis = 1)
df.head()
```

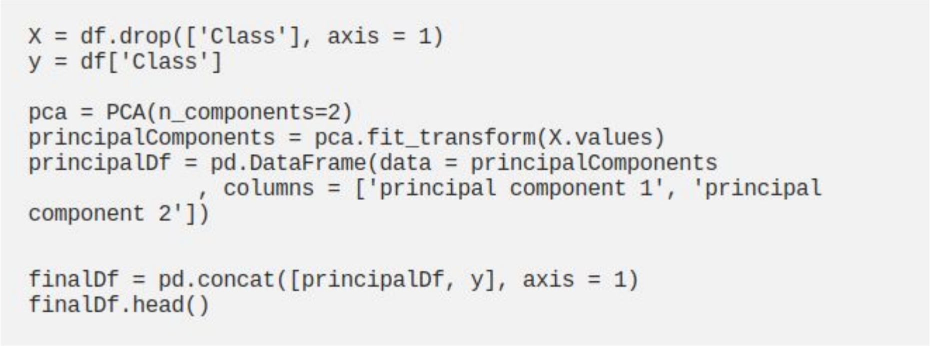


V22	V23	V24	V25	V26	V27	V28	Class	Vamount	Vtime
0.277838	-0.110474	0.066928	0.128539	-0.189115	0.133558	-0.021053	0	0.244964	-1.996583
-0.638672	0.101288	-0.339846	0.167170	0.125895	-0.008983	0.014724	0	-0.342475	-1.996583
0.771679	0.909412	-0.689281	-0.327642	-0.139097	-0.055353	-0.059752	0	1.160686	-1.996562
0.005274	-0.190321	-1.175575	0.647376	-0.221929	0.062723	0.061458	0	0.140534	-1.996562
0.798278	-0.137458	0.141267	-0.206010	0.502292	0.219422	0.215153	0	-0.073403	-1.996541

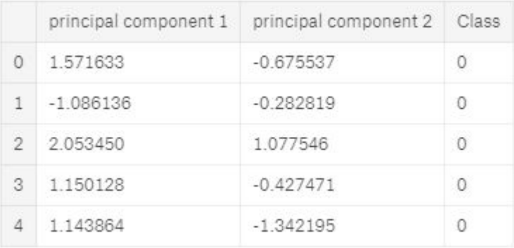
Fig 7 : Standardized dataset

Data Transformations (Like PCA)

PCA (Principal Component Analysis) mainly using to reduce the size of the feature space while retaining as much of the information as possible.



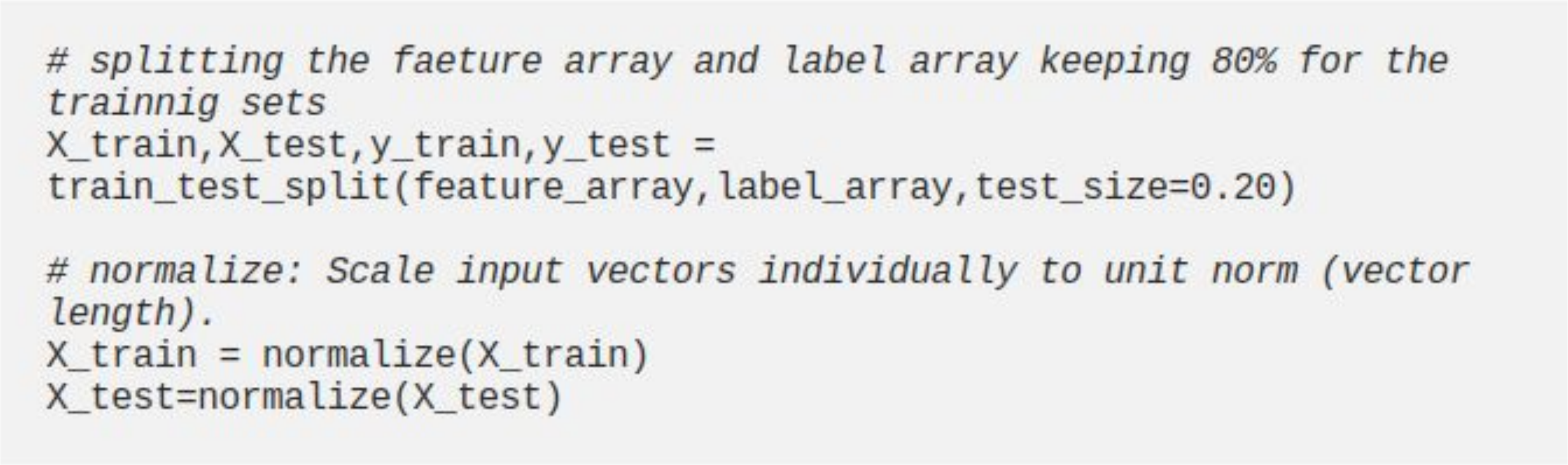
```
X = df.drop(['Class'], axis = 1)
y = df['Class']

pca = PCA(n_components=2)
principalComponents = pca.fit_transform(X.values)
principalDf = pd.DataFrame(data = principalComponents
             , columns = ['principal component 1', 'principal
component 2'])


finalDf = pd.concat([principalDf, y], axis = 1)
finalDf.head()
```



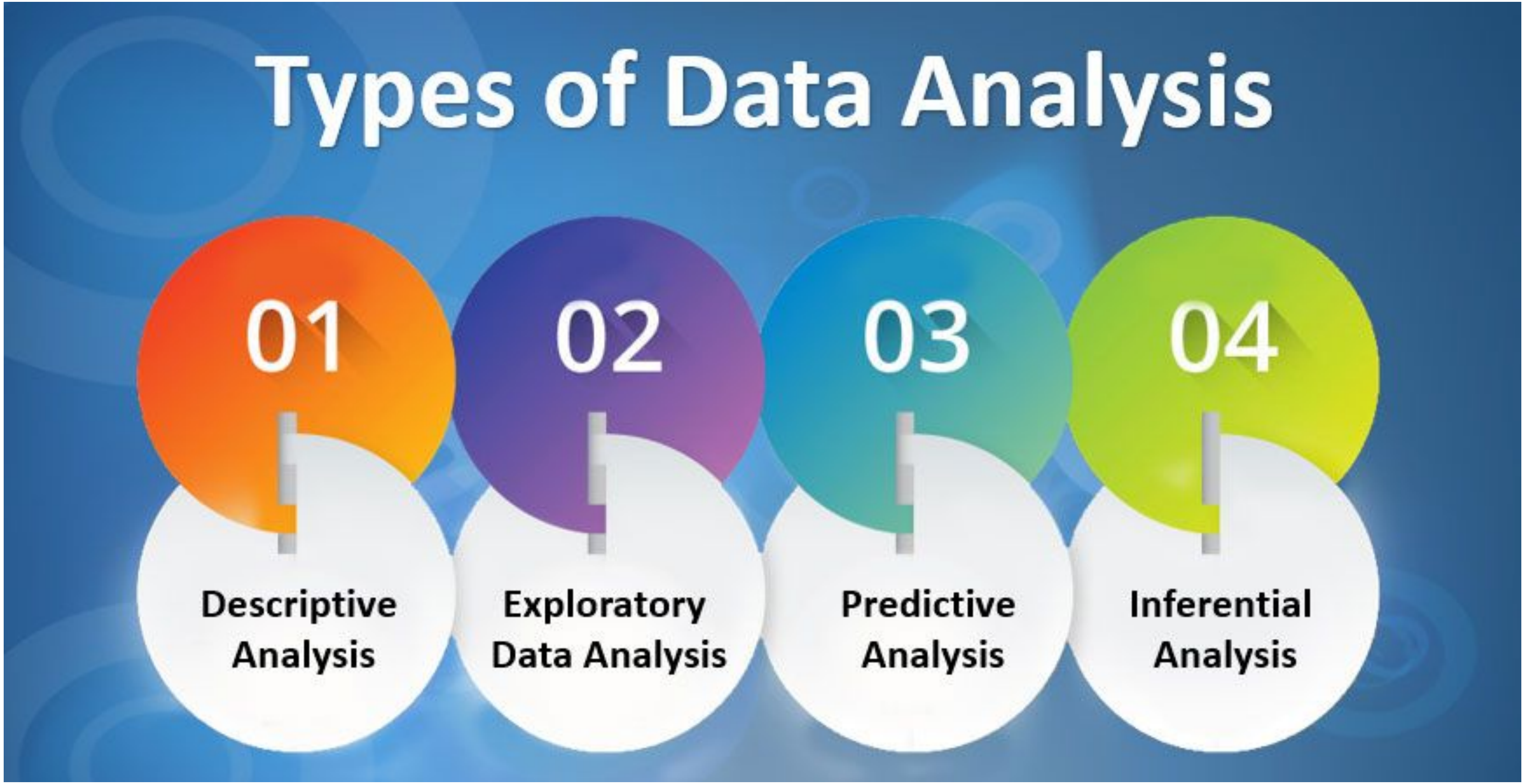
	principal component 1	principal component 2	Class
0	1.571633	-0.675537	0
1	-1.086136	-0.282819	0
2	2.053450	1.077546	0
3	1.150128	-0.427471	0
4	1.143864	-1.342195	0

Fig 8 : Dimensional reduction

Data Splitting



```
# splitting the faeture array and label array keeping 80% for the
trainnig sets
X_train,X_test,y_train,y_test =
train_test_split(feature_array,label_array,test_size=0.20)

# normalize: Scale input vectors individually to unit norm (vector
length).
X_train = normalize(X_train)
X_test=normalize(X_test)
```



Types of Data Analysis

- 01 Descriptive Analysis
- 02 Exploratory Data Analysis
- 03 Predictive Analysis
- 04 Inferential Analysis

OBJ

Exploratory Data Analysis

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What is Exploratory Data Analysis ?

A critical process of performing initial investigations on data so as to discover patterns,to spot anomalies,to test hypothesis and to check assumptions with the help of summary statistics and graphical representations.

Why do we need it ?

1. Detection of mistakes & missing data
2. Checking of assumptions
3. Preliminary selection of appropriate models
4. Determining relationships among the explanatory variables

With EDA, we can make sense of the data we have and then figure out what questions we want to ask and how to frame them

Types of Exploratory Data Analysis

Univariate Non-Graphical EDA

Concerned with understanding the underlying sample distribution and make observations about the population.

This also involves Outlier detection. We use the measures of central tendency like Mean, Median, Mode & measures of spread like Variance, Standard Deviation

Univariate Graphical EDA

Histograms are used to represent the frequency with bins chosen to depict the central tendency, spread, modality, shape and outliers.

Boxplots can also be used to present information about the central tendency, symmetry and skew, as well as outliers.

Multivariate Non-Graphical EDA

Used to show the relationship between two or more variables in the form of either cross-tabulation or statistics.

We can calculate covariance and/or correlation and assemble them into a matrix.

Multivariate Graphical EDA

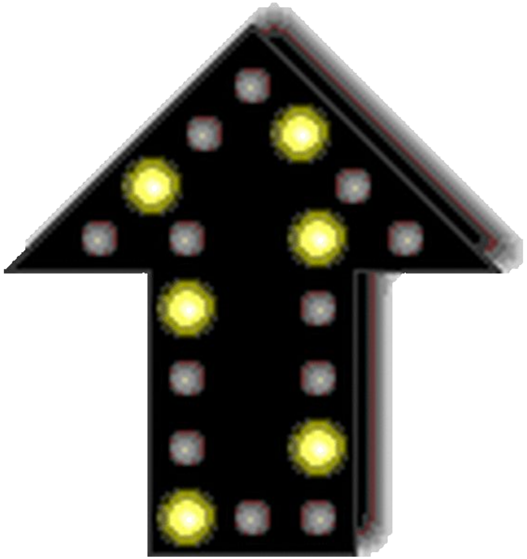
We use barplot with each group representing one level of one of the variables and each bar within a group representing the levels of the other variable.

We also use scatter plot which has one variable on the x-axis, one on the y-axis and a point for each case in your dataset. Typically, the explanatory variable goes on the X axis.

A few EDA Approaches

- Clustering and dimension reduction techniques, which help you to create graphical displays of high-dimensional data containing many variables;
- Univariate visualization of each field in the raw dataset, with summary statistics;
- Bivariate visualizations and summary statistics that allow you to assess the relationship between each variable in the dataset and the target variable you’re looking at;
- Multivariate visualizations, for mapping and understanding interactions between different fields in the data;
- K-Means Clustering (creating “centres” for each cluster, based on the nearest mean);
- Predictive models, e.g. linear regression.

Major Steps to be followed



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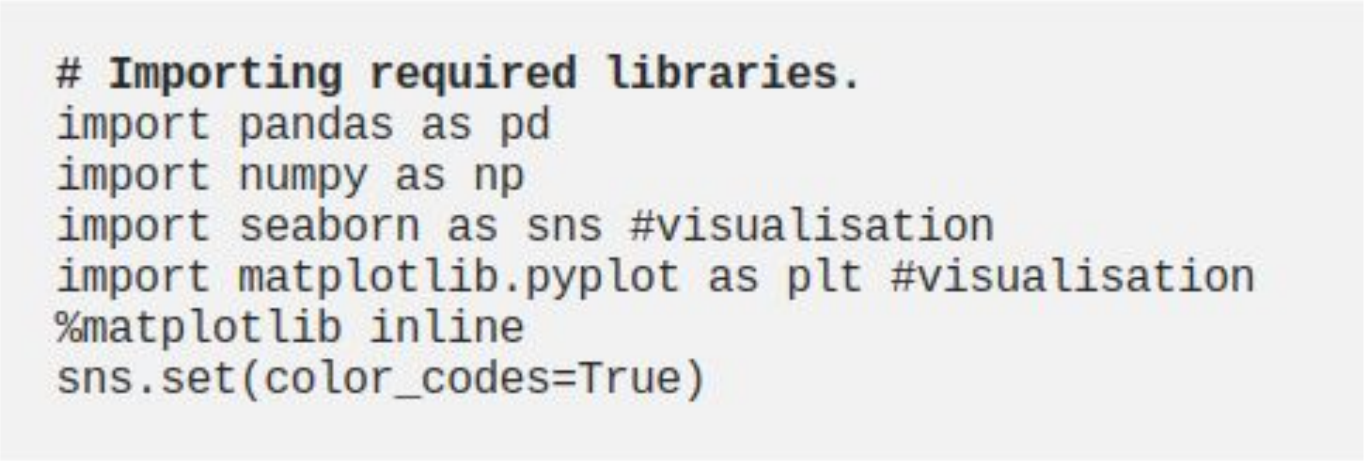
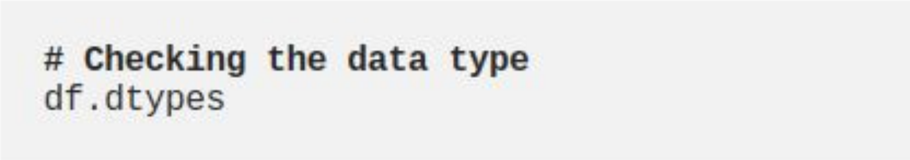
Import the Libraries

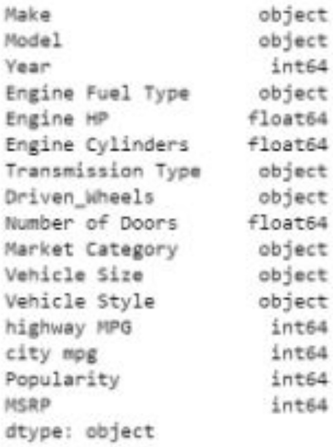


```
# Importing required libraries.
import pandas as pd
import numpy as np
import seaborn as sns #visualisation
import matplotlib.pyplot as plt #visualisation
%matplotlib inline
sns.set(color_codes=True)
```

Check the type of Data



```
# Checking the data type
df.dtypes
```



```
Make                  object
Model                 object
Year                   int64
Engine Fuel Type      object
Engine HP            float64
Engine Cylinders     float64
Transmission Type     object
Driven_Wheels         object
Number of Doors      float64
Market Category       object
Vehicle Size          object
Vehicle Style         object
highway MPG            int64
city mpg               int64
Popularity             int64
MSRP                   int64
dtype: object
```

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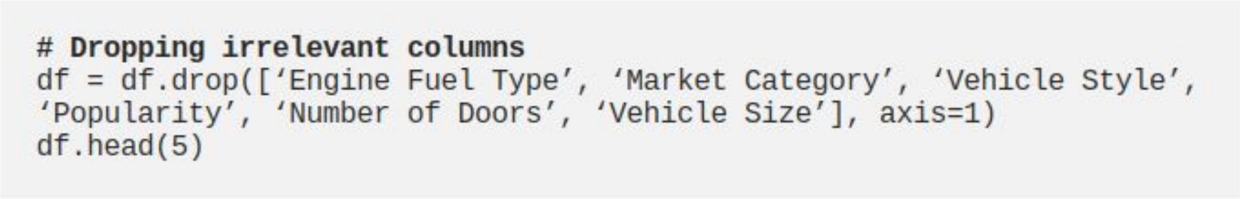
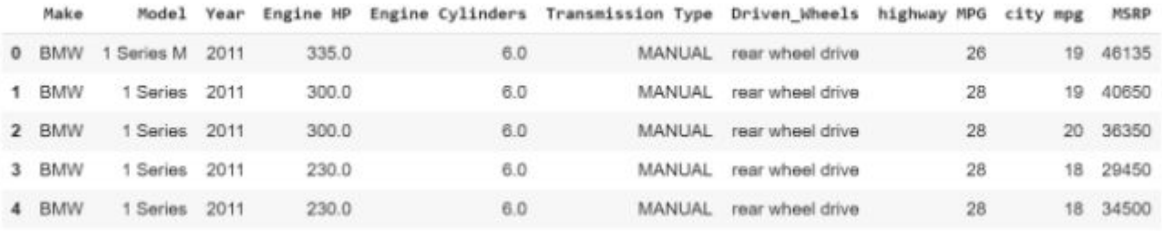
Dropping Irrelevant Columns



```
# Dropping irrelevant columns
df = df.drop([‘Engine Fuel Type’, ‘Market Category’, ‘Vehicle Style’,
‘Popularity’, ‘Number of Doors’, ‘Vehicle Size’], axis=1)
df.head(5)
```



	Make	Model	Year	Engine HP	Engine Cylinders	Transmission Type	Driven_Wheels	highway MPG	city mpg	MSRP
0	BMW	1 Series M	2011	335.0	6.0	MANUAL	rear wheel drive	26	19	46135
1	BMW	1 Series	2011	300.0	6.0	MANUAL	rear wheel drive	28	19	40650
2	BMW	1 Series	2011	300.0	6.0	MANUAL	rear wheel drive	28	20	36350
3	BMW	1 Series	2011	230.0	6.0	MANUAL	rear wheel drive	28	18	29450
4	BMW	1 Series	2011	230.0	6.0	MANUAL	rear wheel drive	28	18	34500

Dropping irrelevant columns.

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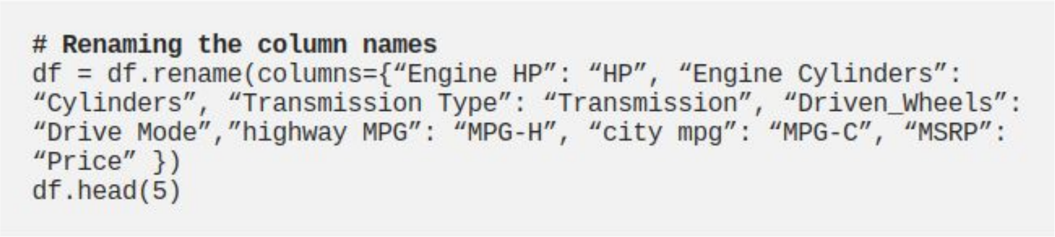
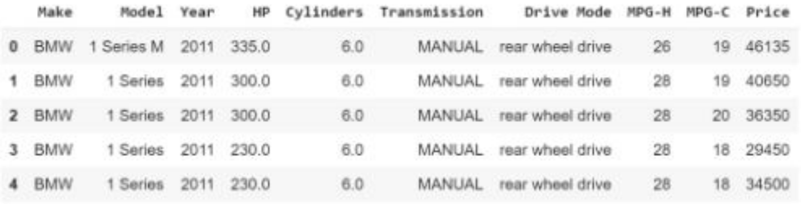
Renaming the Columns



```
# Renaming the column names
df = df.rename(columns={“Engine HP”: “HP”, “Engine Cylinders”:
“Cylinders”, “Transmission Type”: “Transmission”, “Driven_Wheels”:
“Drive Mode”,”highway MPG”: “MPG-H”, “city mpg”: “MPG-C”, “MSRP”:
“Price” })
df.head(5)
```



	Make	Model	Year	HP	Cylinders	Transmission	Drive Mode	MPG-H	MPG-C	Price
0	BMW	1 Series M	2011	335.0	6.0	MANUAL	rear wheel drive	26	19	46135
1	BMW	1 Series	2011	300.0	6.0	MANUAL	rear wheel drive	28	19	40650
2	BMW	1 Series	2011	300.0	6.0	MANUAL	rear wheel drive	28	20	36350
3	BMW	1 Series	2011	230.0	6.0	MANUAL	rear wheel drive	28	18	29450
4	BMW	1 Series	2011	230.0	6.0	MANUAL	rear wheel drive	28	18	34500

Renaming the column name.

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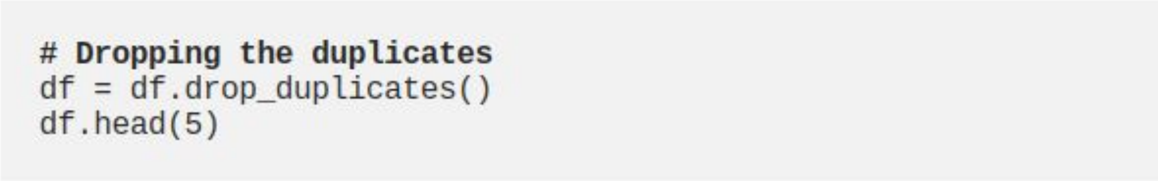
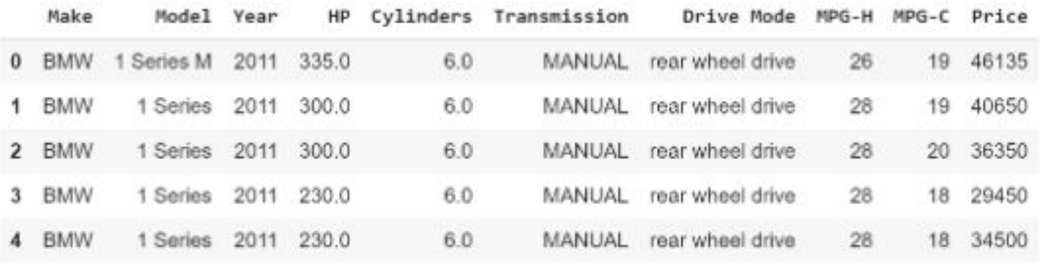
Removing the Duplicates



```
# Dropping the duplicates
df = df.drop_duplicates()
df.head(5)
```



	Make	Model	Year	HP	Cylinders	Transmission	Drive Mode	MPG-H	MPG-C	Price
0	BMW	1 Series M	2011	335.0	6.0	MANUAL	rear wheel drive	26	19	46135
1	BMW	1 Series	2011	300.0	6.0	MANUAL	rear wheel drive	28	19	40650
2	BMW	1 Series	2011	300.0	6.0	MANUAL	rear wheel drive	28	20	36350
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4	BMW	1 Series	2011	230.0	6.0	MANUAL	rear wheel drive	28	18	34500

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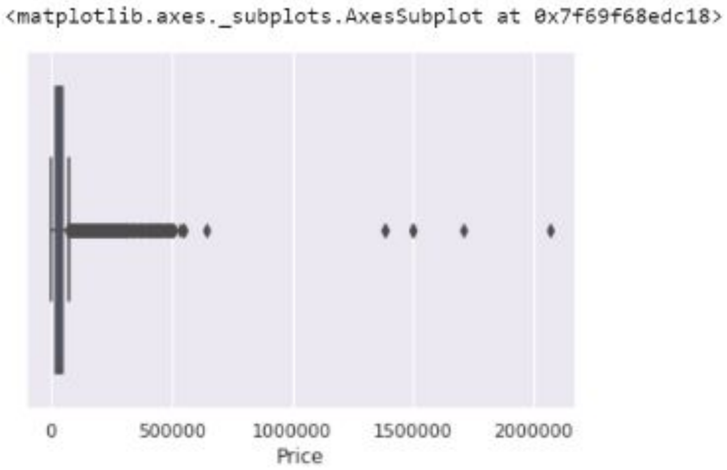
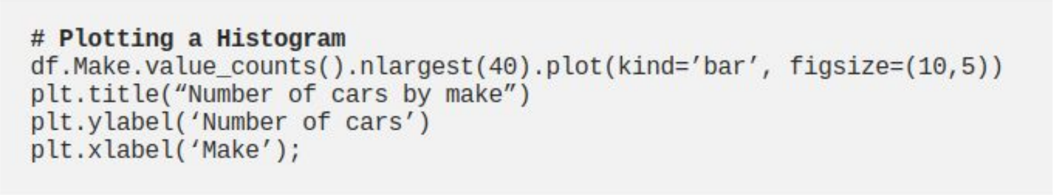
Detecting the Outliers

```
sns.boxplot(x=df['Price'])
```

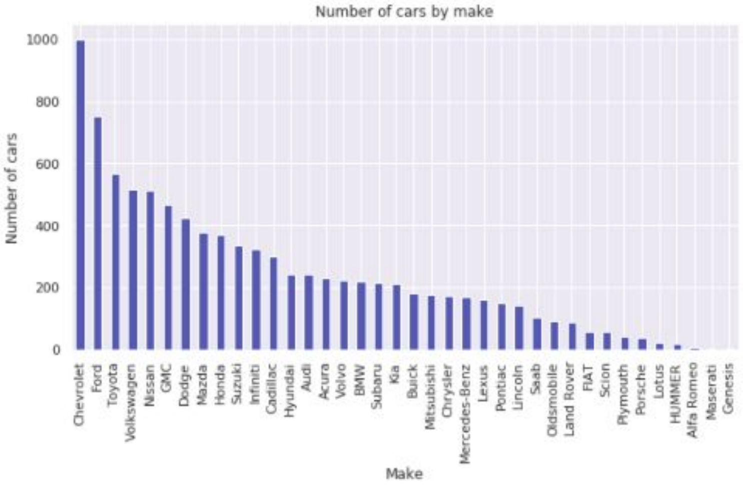


```
<matplotlib.axes._subplots.AxesSubplot at 0x7f69f68edc18>
```

Plotting different features

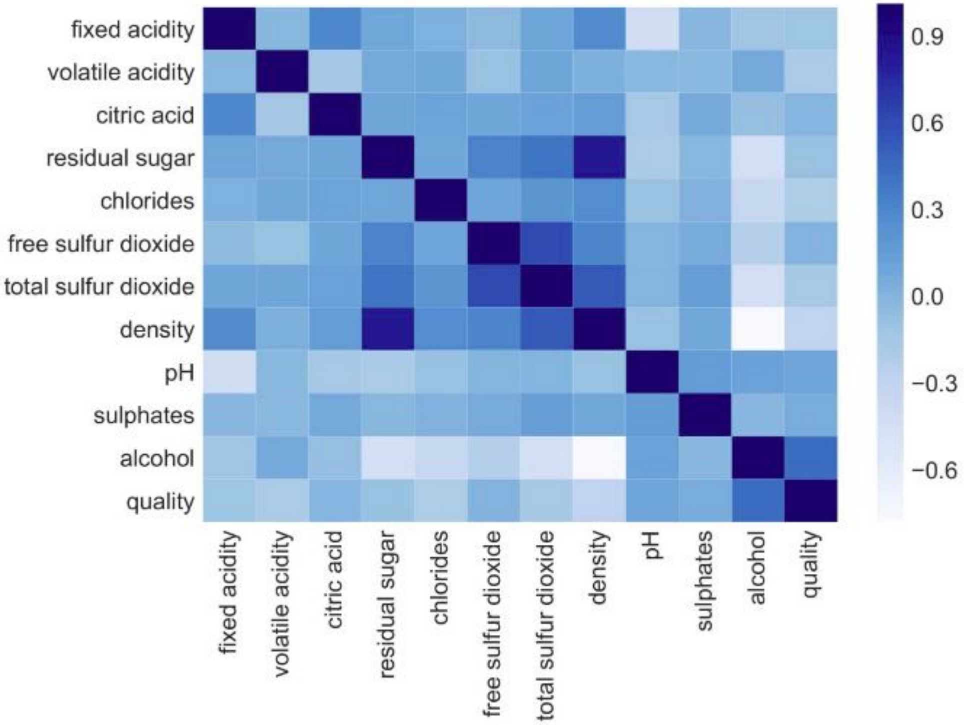


```
# Plotting a Histogram
df.Make.value_counts().nlargest(40).plot(kind='bar', figsize=(10,5))
plt.title("Number of cars by make")
plt.ylabel('Number of cars')
plt.xlabel('Make');
```



Histogram

Heatmaps



Heatmap

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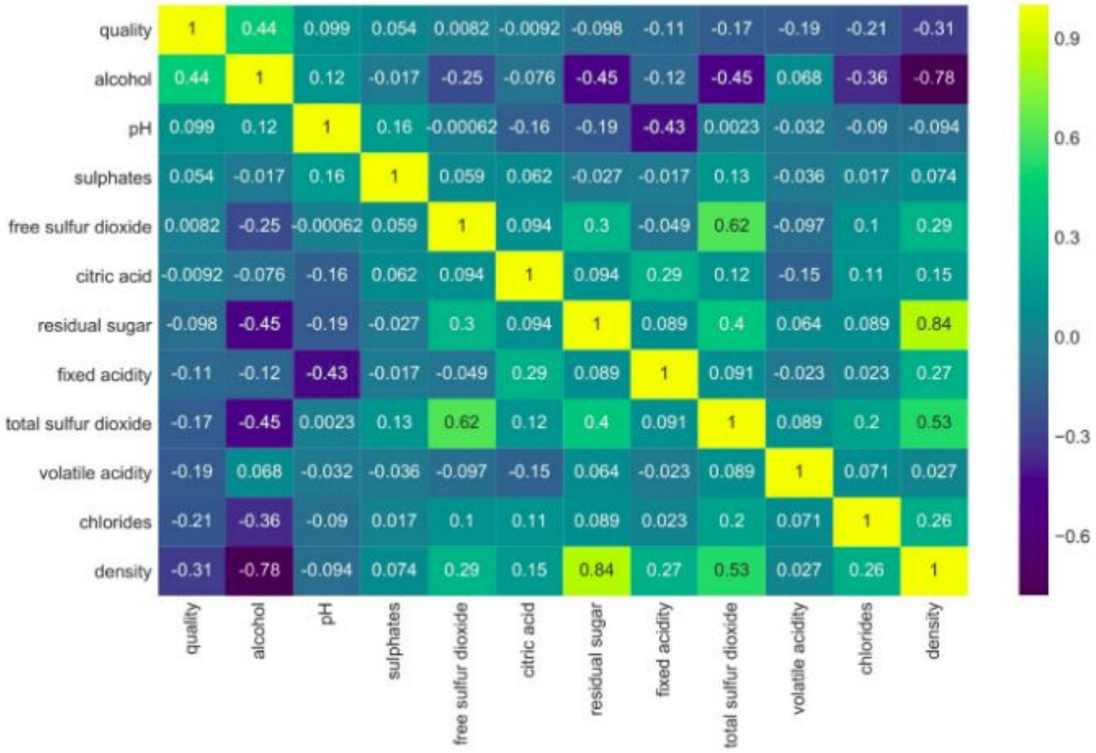
Correlation Matrix etc.



	quality	alcohol	pH	sulphates	free sulfur dioxide	citric acid	residual sugar	fixed acidity	total sulfur dioxide	volatile acidity	chlorides	density
quality	1	0.44	0.099	0.054	0.0082	-0.0092	-0.098	-0.11	-0.17	-0.19	-0.21	-0.31
alcohol	0.44	1	0.12	-0.017	-0.25	-0.076	-0.45	-0.12	-0.45	0.068	-0.36	-0.78
pH	0.099	0.12	1	0.16	-0.00062	-0.16	-0.19	-0.43	0.0023	-0.032	-0.09	-0.094
sulphates	0.054	-0.017	0.16	1	0.059	0.062	-0.027	-0.017	0.13	-0.036	0.017	0.074
free sulfur dioxide	0.0082	-0.25	-0.00062	0.059	1	0.094	0.3	-0.049	0.62	-0.097	0.1	0.29
citric acid	-0.0092	-0.076	-0.16	0.062	0.094	1	0.094	0.29	0.12	-0.15	0.11	0.15
residual sugar	-0.098	-0.45	-0.19	-0.027	0.3	0.094	1	0.089	0.4	0.064	0.089	0.84
fixed acidity	-0.11	-0.12	-0.43	-0.017	-0.049	0.29	0.089	1	0.091	-0.023	0.023	0.27
total sulfur dioxide	-0.17	-0.45	0.0023	0.13	0.62	0.12	0.4	0.091	1	0.089	0.2	0.53
volatile acidity	-0.19	0.068	-0.032	-0.036	-0.097	-0.15	0.064	-0.023	0.089	1	0.071	0.027
chlorides	-0.21	-0.36	-0.09	0.017	0.1	0.11	0.089	0.023	0.2	0.071	1	0.26
density	-0.31	-0.78	-0.094	0.074	0.29	0.15	0.84	0.27	0.53	0.027	0.26	1

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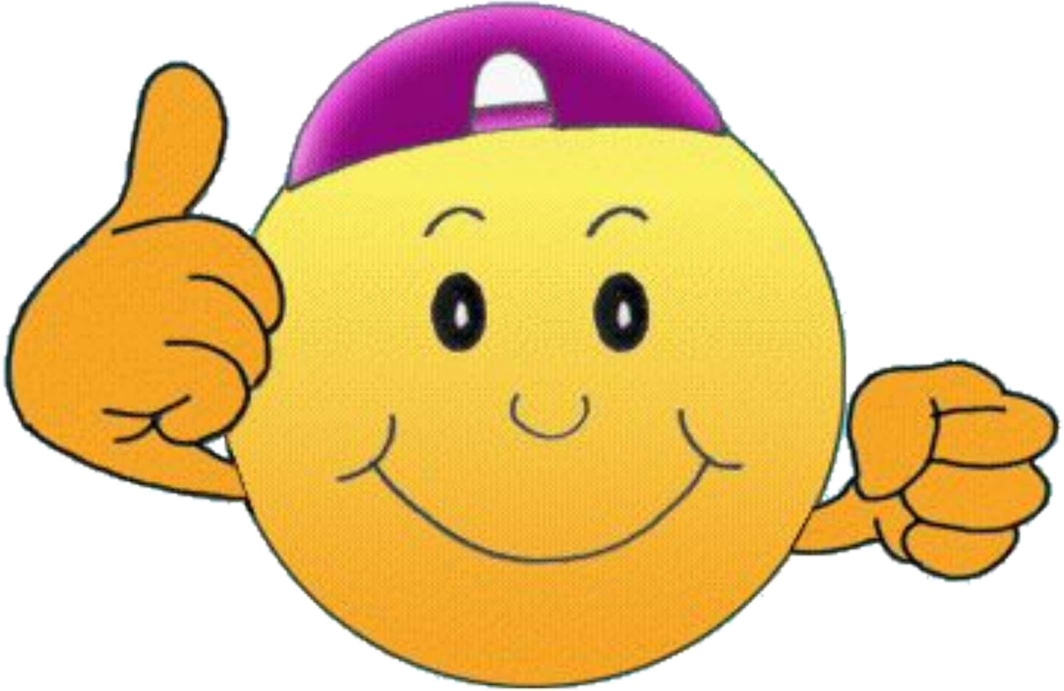
GO FOR IT !



GOOD LUCK !

Let me answer your Questions now.

Finally, it’s your time to speak.

Danke Scheon

Questions ? Any Feedbacks ? Did you like the talk?
Tell me about it.

If you think I can help you,
connect with me via

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