Assignment 2 :

Importing

In [1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

import warnings
warnings.filterwarnings("ignore")
```

Loading the dataset provided in the assignment folder

In [ ]:
```
df=pd.read_csv("Churn_Modelling.csv")
```

In [ ]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000 entries, 0 to 9999
Data columns (total 14 columns):
 #   Column           Non-Null Count  Dtype
---  ------           --------------  -----
 0   RowNumber        10000 non-null  int64
 1   CustomerId       10000 non-null  int64
 2   Surname          10000 non-null  object
 3   CreditScore      10000 non-null  int64
 4   Geography        10000 non-null  object
 5   Gender           10000 non-null  object
 6   Age              10000 non-null  int64
 7   Tenure           10000 non-null  int64
 8   Balance          10000 non-null  float64
 9   NumOfProducts    10000 non-null  int64
 10  HasCrCard        10000 non-null  int64
 11  IsActiveMember   10000 non-null  int64
 12  EstimatedSalary  10000 non-null  float64
 13  Exited           10000 non-null  int64
dtypes: float64(2), int64(9), object(3)
memory usage: 1.1+ MB
```

In [ ]:
```
df.describe()
```

Out[ ]:

	RowNumber	CustomerId	CreditScore	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	EstimatedSalary	Exited
count	10000.00000	1.000000e+04	10000.000000	10000.000000	10000.000000	10000.000000	10000.000000	10000.00000	10000.000000	10000.000000	10000.000000
mean	5000.50000	1.569094e+07	650.528800	38.921800	5.012800	76485.889288	1.530200	0.70550	0.515100	100090.239881	0.203700
std	2886.89568	7.193619e+04	96.653299	10.487806	2.892174	62397.405202	0.581654	0.45584	0.499797	57510.492818	0.402769
min	1.00000	1.556570e+07	350.000000	18.000000	0.000000	0.000000	1.000000	0.00000	0.000000	11.580000	0.000000
25%	2500.75000	1.562853e+07	584.000000	32.000000	3.000000	0.000000	1.000000	0.00000	0.000000	51002.110000	0.000000
50%	5000.50000	1.569074e+07	652.000000	37.000000	5.000000	97198.540000	1.000000	1.00000	1.000000	100193.915000	0.000000
75%	7500.25000	1.575323e+07	718.000000	44.000000	7.000000	127644.240000	2.000000	1.00000	1.000000	149388.247500	0.000000
max	10000.00000	1.581569e+07	850.000000	92.000000	10.000000	250898.090000	4.000000	1.00000	1.000000	199992.480000	1.000000

1. UNIVARIATE ANALYSIS

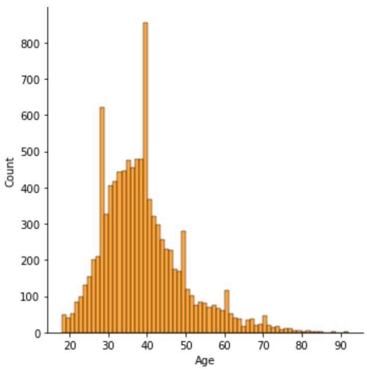
The term univariate analysis refers to the analysis of one variable. You can remember this because the prefix “uni” means “one.” There are three common ways to perform univariate analysis on one variable: 1. Summary statistics – Measures the center and spread of values.

# #

Histogram

In [ ]:
```
sns.displot(df["Age"], color='darkorange')
```

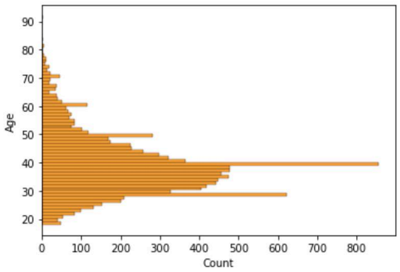
Out[ ]: <seaborn.axisgrid.FacetGrid at 0x7feaa047b460>



In Histogram, we can do it vertically too, by just changing the axis

In [ ]:
```
sns.histplot(y="Age",data=df,color='darkorange')
```

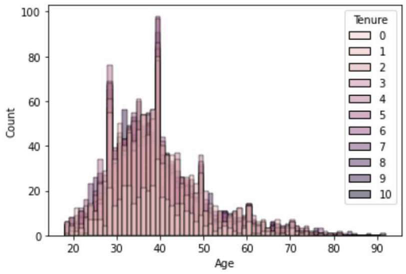
Out[ ]: <AxesSubplot:xlabel='Count', ylabel='Age'>



Now, we can also use Histogram for categorical variables

In [ ]:
```
sns.histplot(x='Age',data=df,hue=df['Tenure'])
```

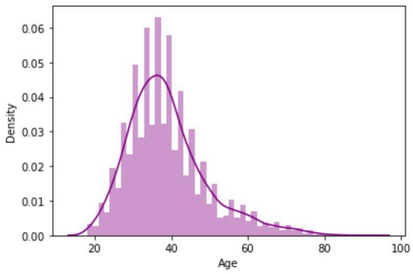
Out[ ]: <AxesSubplot:xlabel='Age', ylabel='Count'>



Distplot

In [ ]:
```
sns.distplot(df["Age"],color='purple')
```

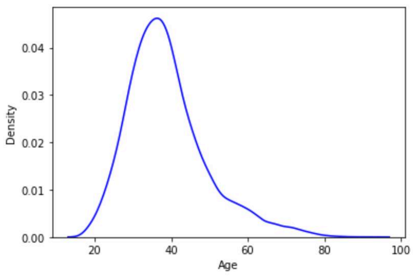
Out[ ]: <AxesSubplot:xlabel='Age', ylabel='Density'>



This is visualising displot alone

In [ ]:
```
sns.distplot(df["Age"],hist=False,color='blue')
```

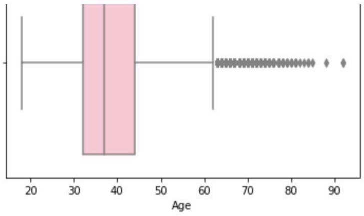
Out[ ]: <AxesSubplot:xlabel='Age', ylabel='Density'>



Boxplot

In [ ]:
```
sns.boxplot(df["Age"],color='pink')
```

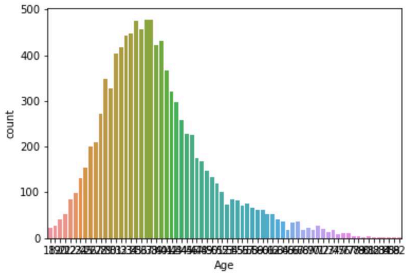
Out[ ]: <AxesSubplot:xlabel='Age'>



Countplot

In [ ]:
```
sns.countplot(df['Age'])
```

Out[ ]:
```
<AxesSubplot:xlabel='Age', ylabel='count'>
```



2. BIVARIATE ANALYSIS

# #

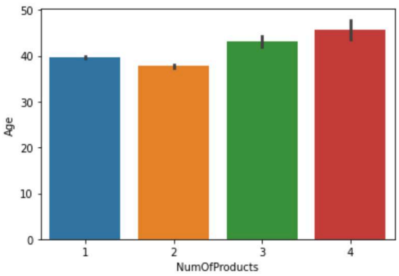
Image result for bivariate analysis in python It is a methodical statistical technique applied to a pair of variables (features/ attributes) of data to determine the empirical relationship between them. In order words, it is meant to determine any concurrent relations (usually over and above a simple correlation analysis).

# #

Barplot

In [ ]:
```
sns.barplot(df["NumOfProducts"],df["Age"])
```

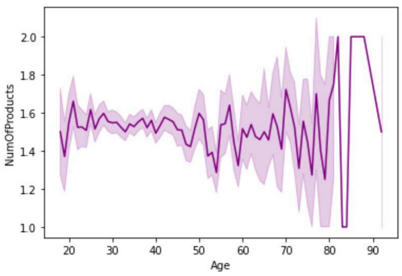
Out[ ]:
```
<AxesSubplot:xlabel='NumOfProducts', ylabel='Age'>
```



Linearplot

In [ ]:
```
sns.lineplot(df["Age"],df["NumOfProducts"], color='purple')
```

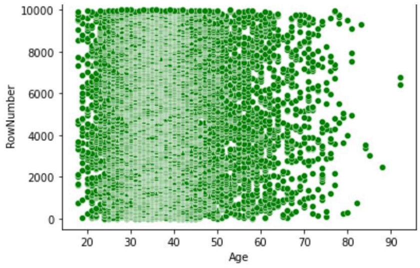
Out[ ]:
```
<AxesSubplot:xlabel='Age', ylabel='NumOfProducts'>
```



Scatterplot

In [ ]:
```
sns.scatterplot(x=df.Age,y=df.RowNumber,color='green')
```

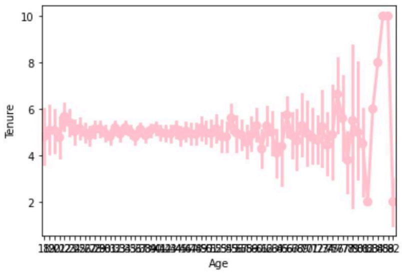
Out[ ]:
```
<AxesSubplot:xlabel='Age', ylabel='RowNumber'>
```



Pointplot

In [ ]:
```
sns.pointplot(x='Age',y='Tenure',data=df,color='pink')
```

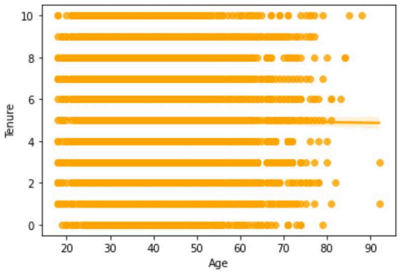
Out[ ]: <AxesSubplot:xlabel='Age', ylabel='Tenure'>



Regplot

In [ ]:
```
sns.regplot(df['Age'],df['Tenure'],color='orange')
```

Out[ ]: <AxesSubplot:xlabel='Age', ylabel='Tenure'>



3. MULTI - VARIATE ANALYSIS

# #

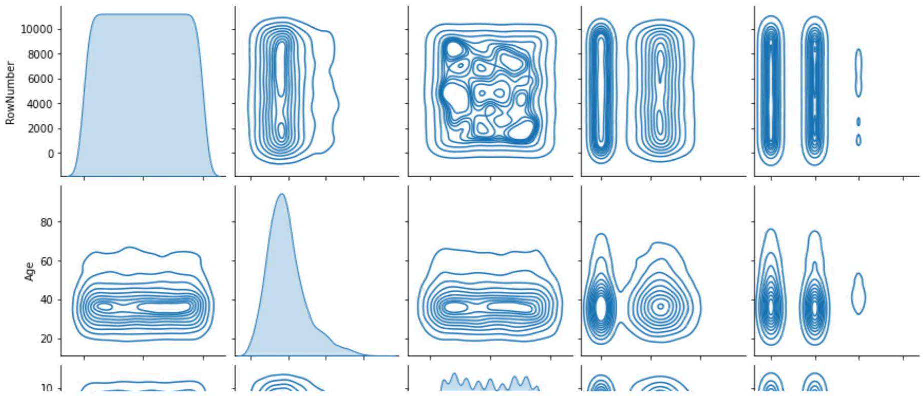
Multivariate analysis is based in observation and analysis of more than one statistical outcome variable at a time. In design and analysis, the technique is used to perform trade studies across multiple dimensions while taking into account the effects of all variables on the responses of interest.

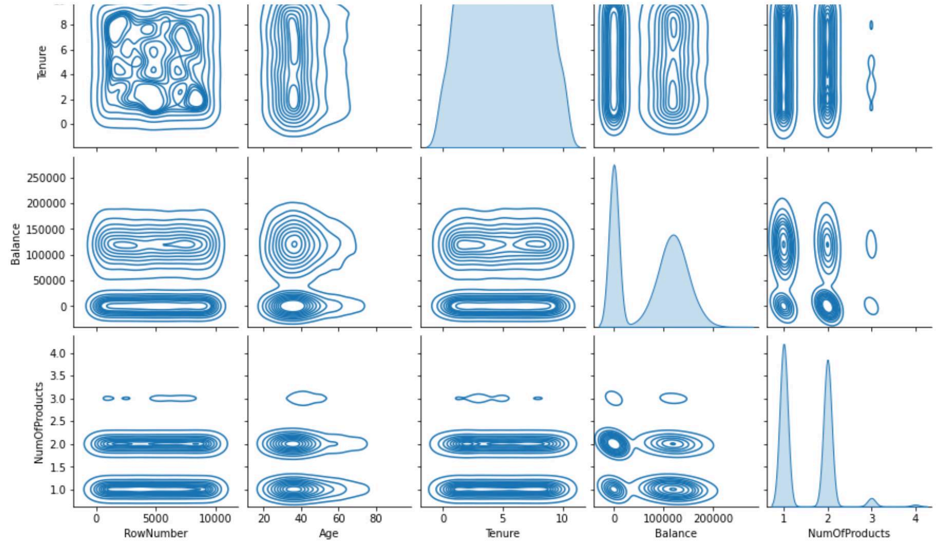
# #

Pairplot

In [ ]:
```
sns.pairplot(data=df[["RowNumber","Age","Tenure","Balance","NumOfProducts"]],kind="kde")
```

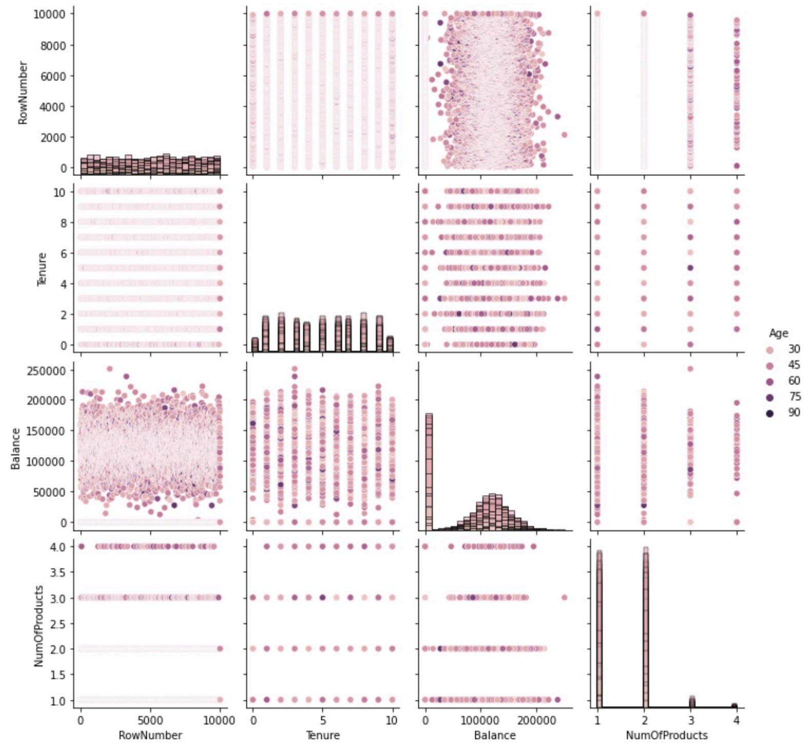
Out[ ]: <seaborn.axisgrid.PairGrid at 0x7feaa157b880>





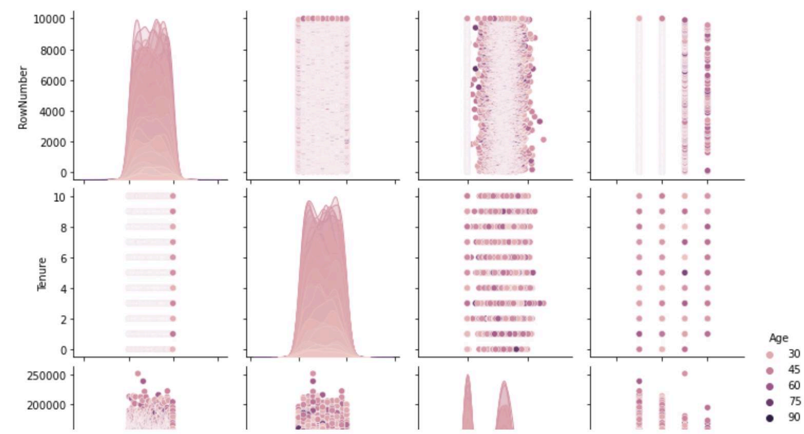
In [ ]:
```
sns.pairplot(data=df[["RowNumber","Age","Tenure","Balance","NumOfProducts"]], hue="Age", diag_kind="hist")
```

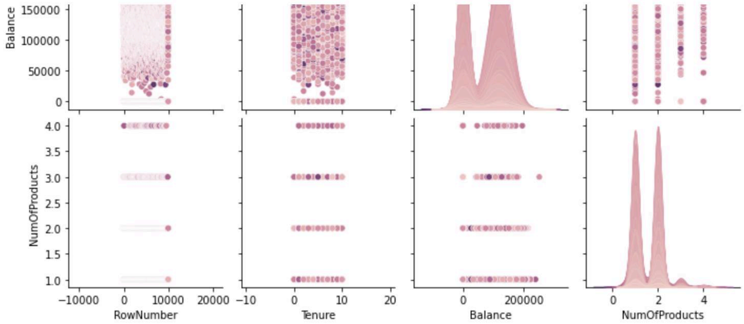
Out[ ]: <seaborn.axisgrid.PairGrid at 0x7fea64fb4700>



In [ ]:
```
sns.pairplot(data=df[["RowNumber","Age","Tenure","Balance","NumOfProducts"]], hue="Age")
```

Out[ ]: <seaborn.axisgrid.PairGrid at 0x7feaa1a66cd0>





4. Perform descriptive statistics on the dataset

#

Image result for descriptive statistics in python Python Descriptive Statistics process describes the basic features of data in a study. It delivers summaries on the sample and the measures and does not use the data to learn about the population it represents. Under descriptive statistics, fall two sets of properties- central tendency and dispersion.

#

In [ ]:

```
df.describe()
```

Out[ ]:

	RowNumber	CustomerId	CreditScore	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	EstimatedSalary	Exited
count	10000.00000	1.000000e+04	10000.000000	10000.000000	10000.000000	10000.000000	10000.000000	10000.00000	10000.000000	10000.000000	10000.000000
mean	5000.50000	1.569094e+07	650.528800	38.921800	5.012800	76485.889288	1.530200	0.70550	0.515100	100090.239881	0.203700
std	2886.89568	7.193619e+04	96.653299	10.487806	2.892174	62397.405202	0.581654	0.45584	0.499797	57510.492818	0.402769
min	1.00000	1.556570e+07	350.000000	18.000000	0.000000	0.000000	1.000000	0.00000	0.000000	11.580000	0.000000
25%	2500.75000	1.562853e+07	584.000000	32.000000	3.000000	0.000000	1.000000	0.00000	0.000000	51002.110000	0.000000
50%	5000.50000	1.569074e+07	652.000000	37.000000	5.000000	97198.540000	1.000000	1.00000	1.000000	100193.915000	0.000000
75%	7500.25000	1.575323e+07	718.000000	44.000000	7.000000	127644.240000	2.000000	1.00000	1.000000	149388.247500	0.000000
max	10000.00000	1.581569e+07	850.000000	92.000000	10.000000	250898.090000	4.000000	1.00000	1.000000	199992.480000	1.000000

5. Handle the Missing values.

In [ ]:

```
data=pd.DataFrame({"a":[1,2,np.nan],"b":[1,np.nan,np.nan],"c":[1,2,4]})
data
```

Out[ ]:

	a	b	c
0	1.0	1.0	1
1	2.0	NaN	2
2	NaN	NaN	4

In [ ]:

```
data.isnull().any()
```

Out[ ]:

```
a     True
b     True
c    False
dtype: bool
```

In [ ]:

```
data.isnull().sum()
```

Out[ ]:

```
a    1
b    2
c    0
dtype: int64
```

In [ ]:

```
data.fillna(value = "S")
```

Out[ ]:

	a	b	c
0	1.0	1.0	1
1	2.0	S	2
2	S	S	4

In [ ]:

```
data["a"].mean()
```

Out[ ]:

```
1.5
```

In [ ]:

```
data["a"].median()
```

Out[ ]:

```
1.5
```

6. Find the outliers and replace the outliers

#

For data that follows a normal distribution, the values that fall more than three standard deviations from the mean are typically considered outliers. Outliers can find their way into a dataset naturally through variability, or they can be the result of issues like human error, faulty equipment, or poor sampling.

#

In [ ]:
```
outlierss=df.quantile(q=(0.25,0.75))
```

In [ ]:
```
outlierss
```

Out[ ]:

	RowNumber	CustomerId	CreditScore	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	EstimatedSalary	Exited
0.25	2500.75	15628528.25	584.0	32.0	3.0	0.00	1.0	0.0	0.0	51002.1100	0.0
0.75	7500.25	15753233.75	718.0	44.0	7.0	127644.24	2.0	1.0	1.0	149388.2475	0.0

In [ ]:
```
aaa=qnt.loc[0.75]-qnt.loc[0.25]
```

In [ ]:
```
aaa
```

Out[ ]:
```
RowNumber            4999.5000
CustomerId         124705.5000
CreditScore           134.0000
Age                    12.0000
Tenure                  4.0000
Balance            127644.2400
NumOfProducts           1.0000
HasCrCard               1.0000
IsActiveMember          1.0000
EstimatedSalary     98386.1375
Exited                  0.0000
dtype: float64
```

In [ ]:
```
low = qnt.loc[0.25] - 1.5*aaa
```

In [ ]:
```
low
```

Out[ ]:
```
RowNumber         -4.998500e+03
CustomerId         1.544147e+07
CreditScore        3.830000e+02
Age                1.400000e+01
Tenure            -3.000000e+00
Balance           -1.914664e+05
NumOfProducts     -5.000000e-01
HasCrCard         -1.500000e+00
IsActiveMember    -1.500000e+00
EstimatedSalary   -9.657710e+04
Exited             0.000000e+00
dtype: float64
```

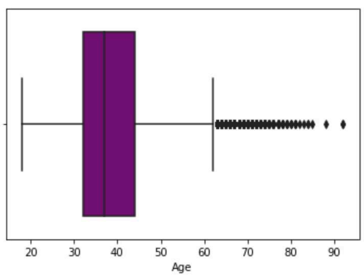
In [ ]:
```
high = qnt.loc[0.75] + 1.5 * aaa
```

In [ ]:
```
high
```

Out[ ]:
```
RowNumber          1.499950e+04
CustomerId         1.594029e+07
CreditScore        9.190000e+02
Age                6.200000e+01
Tenure             1.300000e+01
Balance            3.191106e+05
NumOfProducts      3.500000e+00
HasCrCard          2.500000e+00
IsActiveMember     2.500000e+00
EstimatedSalary    2.969675e+05
Exited             0.000000e+00
dtype: float64
```

In [ ]:
```
sns.boxplot(df["Age"],color='purple')
```

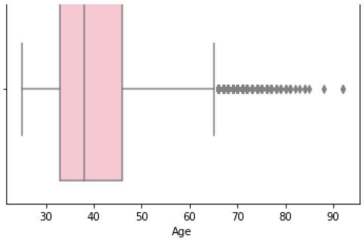
Out[ ]:
```
<AxesSubplot:xlabel='Age'>
```



In [ ]:
```
df["Age"]=np.where(df["Age"]<25,50,df["Age"])
```

In [ ]:
```
sns.boxplot(df["Age"],color='pink')
```

Out[ ]:
```
<AxesSubplot:xlabel='Age'>
```



7. Check for Categorical columns and perform encoding.

#

Categorical Columns : Categorical are a Pandas data type. A string variable consisting of only a few different values.

#

Encoding : For efficient storage of these strings, the sequence of code points is converted into a set of bytes. The process is known as encoding.

#

In [ ]:

```
df.head(4)
```

Out[ ]:

	RowNumber	CustomerId	Surname	CreditScore	Geography	Gender	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	EstimatedSalary	Exited
0	1	15634602	Hargrave	619	France	Female	42	2	0.00	1	1	1	101348.88	1
1	2	15647311	Hill	608	Spain	Female	41	1	83807.86	1	0	1	112542.58	0
2	3	15619304	Onio	502	France	Female	42	8	159660.80	3	1	0	113931.57	1
3	4	15701354	Boni	699	France	Female	39	1	0.00	2	0	0	93826.63	0

In [ ]:

```
df["Gender"].replace({"Female":0,"Male":1},inplace = True)
df["Geography"].replace({"France":1,"Spain":2,"Germany":3},inplace = True)
df["Gender"].replace({"Female":0,"Male":1},inplace = True)
df["Geography"].replace({"France":1,"Spain":2,"Germany":3},inplace = True)
```

In [ ]:

```
df.head(4)
```

Out[ ]:

	RowNumber	CustomerId	Surname	CreditScore	Geography	Gender	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	EstimatedSalary	Exited
0	1	15634602	Hargrave	619	1	0	42	2	0.00	1	1	1	101348.88	1
1	2	15647311	Hill	608	2	0	41	1	83807.86	1	0	1	112542.58	0
2	3	15619304	Onio	502	1	0	42	8	159660.80	3	1	0	113931.57	1
3	4	15701354	Boni	699	1	0	39	1	0.00	2	0	0	93826.63	0

8. Split the data into dependent and independent variables.

#

Dependent Variable : A dependent variable is a variable whose value depends on another variable.

#

Independent Variable : An Independent variable is a variable whose value never depends on another variable but the researcher.

#

In [ ]:

```
y = df["Surname"]
```

In [ ]:

```
x=df.drop(columns=["Surname"],axis=1)
```

In [ ]:

```
x.head()
```

Out[ ]:

	RowNumber	CustomerId	CreditScore	Geography	Gender	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	EstimatedSalary	Exited
0	1	15634602	619	1	0	42	2	0.00	1	1	1	101348.88	1
1	2	15647311	608	2	0	41	1	83807.86	1	0	1	112542.58	0
2	3	15619304	502	1	0	42	8	159660.80	3	1	0	113931.57	1
3	4	15701354	699	1	0	39	1	0.00	2	0	0	93826.63	0
4	5	15737888	850	2	0	43	2	125510.82	1	1	1	79084.10	0

9. Scale the independent variables

In [ ]:

```
names=x.columns
names
```

Out[ ]:
```
Index(['RowNumber', 'CustomerId', 'CreditScore', 'Geography', 'Gender', 'Age',
       'Tenure', 'Balance', 'NumOfProducts', 'HasCrCard', 'IsActiveMember',
       'EstimatedSalary', 'Exited'],
      dtype='object')
```

In [ ]:
```python
from sklearn.preprocessing import scale
```

In [ ]:
```python
X=scale(x)
```

In [ ]:
```python
X
```

Out[ ]:
```
array([[-1.73187761, -0.78321342, -0.32622142, ...,  0.97024255,
         0.02188649,  1.97716468],
       [-1.7315312 , -0.60653412, -0.44003595, ...,  0.97024255,
         0.21653375, -0.50577476],
       [-1.73118479, -0.99588476, -1.53679418, ..., -1.03067011,
         0.2406869 ,  1.97716468],
       ...,
       [ 1.73118479, -1.47928179,  0.60498839, ...,  0.97024255,
        -1.00864308,  1.97716468],
       [ 1.7315312 , -0.11935577,  1.25683526, ..., -1.03067011,
        -0.12523071,  1.97716468],
       [ 1.73187761, -0.87055909,  1.46377078, ..., -1.03067011,
        -1.07636976, -0.50577476]])
```

In [ ]:
```python
x = pd.DataFrame(X,columns = names )
x
```

Out[ ]:

	RowNumber	CustomerId	CreditScore	Geography	Gender	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	EstimatedSalary	Exited
0	-1.731878	-0.783213	-0.326221	-0.902587	-1.095988	0.179622	-1.041760	-1.225848	-0.911583	0.646092	0.970243	0.021886	1.977165
1	-1.731531	-0.606534	-0.440036	0.301665	-1.095988	0.080092	-1.387538	0.117350	-0.911583	-1.547768	0.970243	0.216534	-0.505775
2	-1.731185	-0.995885	-1.536794	-0.902587	-1.095988	0.179622	1.032908	1.333053	2.527057	0.646092	-1.030670	0.240687	1.977165
3	-1.730838	0.144767	0.501521	-0.902587	-1.095988	-0.118968	-1.387538	-1.225848	0.807737	-1.547768	-1.030670	-0.108918	-0.505775
4	-1.730492	0.652659	2.063884	0.301665	-1.095988	0.279152	-1.041760	0.785728	-0.911583	0.646092	0.970243	-0.365276	-0.505775
...	...	...	...	...	...	...	...	...	...	...	...	...	...
9995	1.730492	-1.177652	1.246488	-0.902587	0.912419	-0.118968	-0.004426	-1.225848	0.807737	0.646092	-1.030670	-0.066419	-0.505775
9996	1.730838	-1.682806	-1.391939	-0.902587	0.912419	-0.517088	1.724464	-0.306379	-0.911583	0.646092	0.970243	0.027988	-0.505775
9997	1.731185	-1.479282	0.604988	-0.902587	-1.095988	-0.417558	0.687130	-1.225848	-0.911583	-1.547768	0.970243	-1.008643	1.977165
9998	1.731531	-0.119356	1.256835	1.505917	0.912419	0.179622	-0.695982	-0.022608	0.807737	0.646092	-1.030670	-0.125231	1.977165
9999	1.731878	-0.870559	1.463771	-0.902587	-1.095988	-1.213798	-0.350204	0.859965	-0.911583	0.646092	-1.030670	-1.076370	-0.505775

10000 rows × 13 columns

10. Split the data into training and testing

# #

Train/Test is a method to measure the accuracy of your model. It is called Train/Test because you split the the data set into two sets: a training set and a testing set. 80% for training, and 20% for testing. You train the model using the training set.

# #

In [ ]:
```python
from sklearn.model_selection import train_test_split
```

In [ ]:
```python
x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.2,random_state=0)
```

In [ ]:
```python
x_train.head()
```

Out[ ]:

	RowNumber	CustomerId	CreditScore	Geography	Gender	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	EstimatedSalary	Exited
7389	0.827747	-0.195066	0.170424	0.301665	-1.095988	-0.616618	-0.004426	-1.225848	0.807737	0.646092	-1.030670	1.108382	-0.505775
9275	1.481077	0.810821	-2.312802	1.505917	0.912419	0.179622	-1.387538	-0.012892	-0.911583	0.646092	0.970243	-0.747592	-0.505775
2995	-0.694379	-1.507642	-1.195351	-0.902587	-1.095988	-1.114268	-1.041760	0.575076	-0.911583	0.646092	-1.030670	1.487464	-0.505775
5316	0.109639	1.243462	0.035916	0.301665	0.912419	-0.019438	-0.004426	0.467955	-0.911583	0.646092	-1.030670	1.278558	-0.505775
356	-1.608556	-1.100775	2.063884	0.301665	-1.095988	1.672571	1.032908	0.806010	0.807737	0.646092	0.970243	0.560069	-0.505775

In [ ]:
```python
x_train.shape,y_train.shape,x_test.shape,y_test.shape
```

Out[ ]:
```
((8000, 13), (8000,), (2000, 13), (2000,))
```

In [ ]: