

## ASSIGNMENT 2

Assignment Date	21 /10/2022
Student Name	ANUVITHA G
Student Roll Number	61771921002
Maximum Marks	2 Marks

### Data Visualization and Pre-processing

Perform Below Tasks to complete the assignment: -

#### Tasks: -

1. Download the dataset: Dataset
2. Load the dataset.
3. Perform Below Visualizations.
  - Univariate Analysis
  - Bi - Variate Analysis
  - Multi - Variate Analysis
4. Perform descriptive statistics on the dataset.
5. Handle the Missing values.
6. Find the outliers and replace the outliers
7. Check for Categorical columns and perform encoding.
8. Split the data into dependent and independent variables.
9. Scale the independent variables
10. Split the data into training and testing

1.

### Downloading dataset

```
[ ] from google.colab import files
    uploaded = files.upload()
```

No file chosen      Upload widget is only available when the cell has been executed in the current browser session. Please rerun this cell to enable.  
Saving Churn\_Modelling.csv to Churn\_Modelling.csv

2.

### Loading dataset

```
import seaborn as sb
import pandas as pd
import matplotlib.pyplot as plt
churn=pd.read_csv("Churn_Modelling.csv")
churn.head()
```

	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
4	5	15737888	Mitchell	850	Spain	Female	43	2	125510.82	1	1	1	79084.10	0

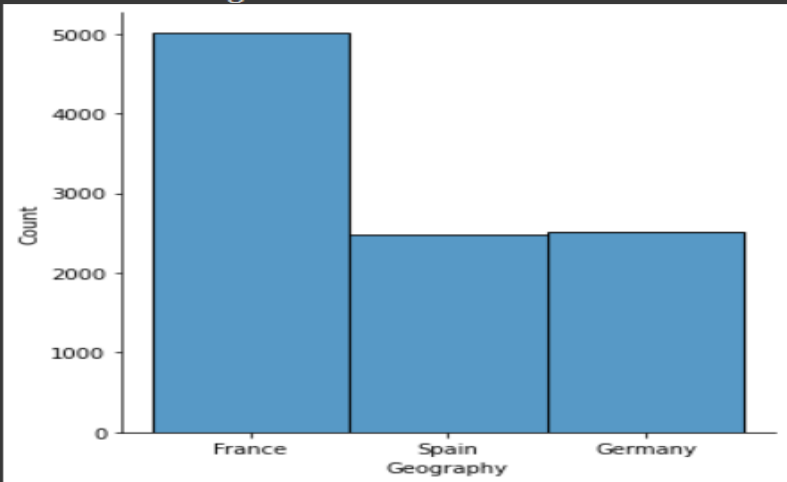
3.

## Visualization

### Univariate analysis

```
sb.displot(churn, x="Geography")
```

<seaborn.axisgrid.FacetGrid at 0x7f266d3fa3d0>

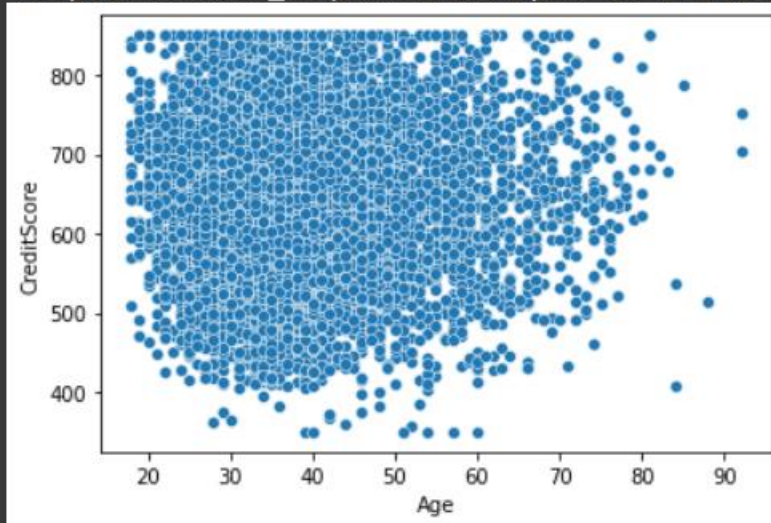


Geography	Count
France	5000
Spain	2500
Germany	2500

## Bivariate analysis

```
[ ] sb.scatterplot(data=churn, x="Age", y="CreditScore")
```

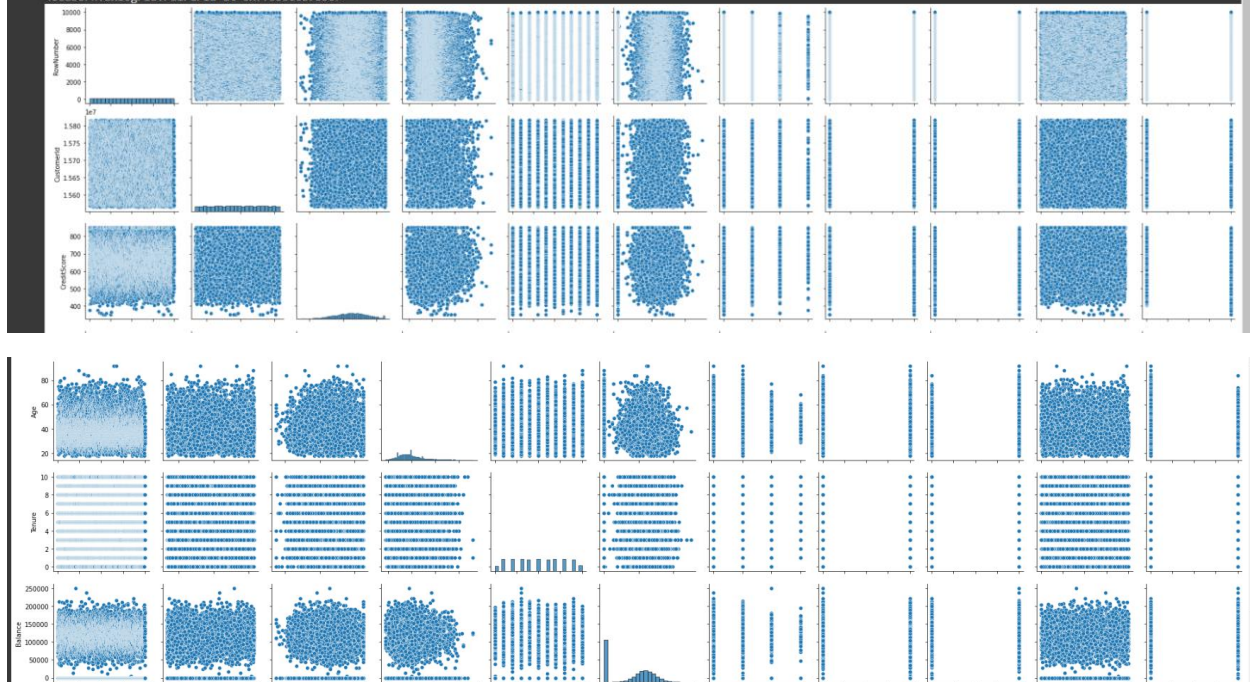
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f553e5f2150>
```

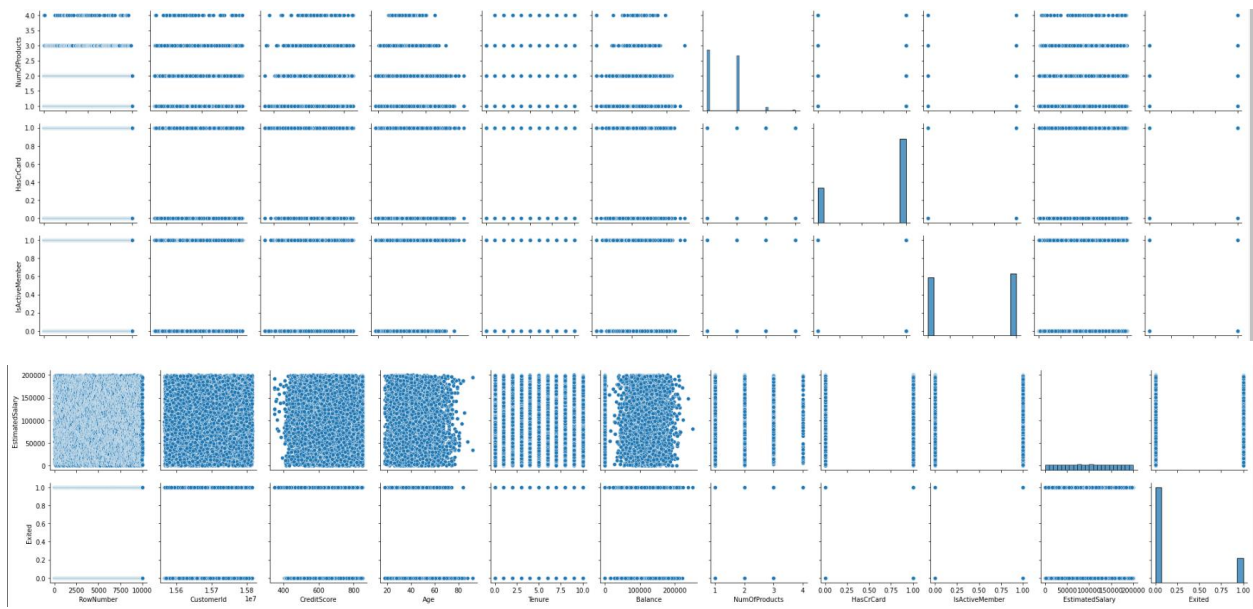


## Multivariate analysis

```
[ ] sb.pairplot(churn)
```

```
<seaborn.axisgrid.PairGrid at 0x7f553e0b7b50>
```





4.

### Descriptive statistics

`churn.describe()`

	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

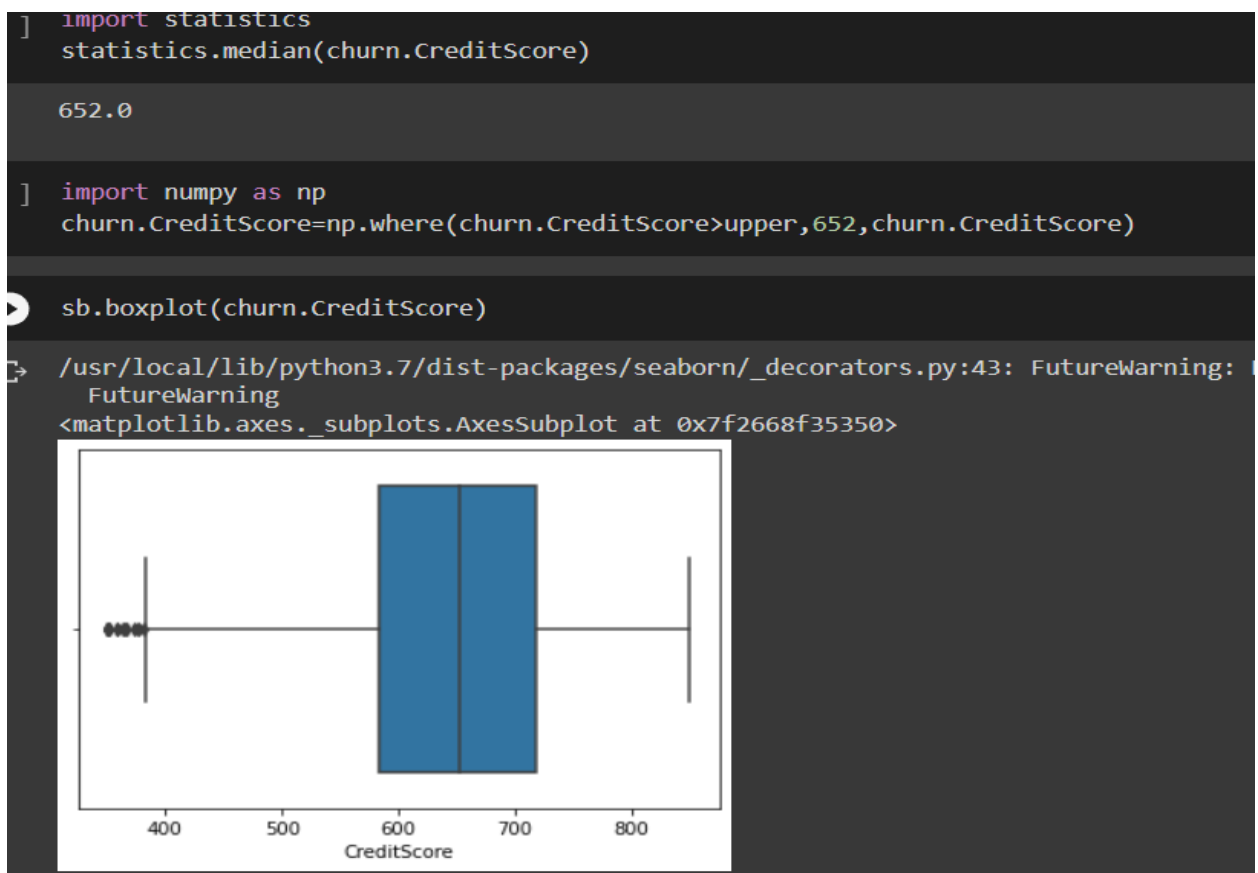
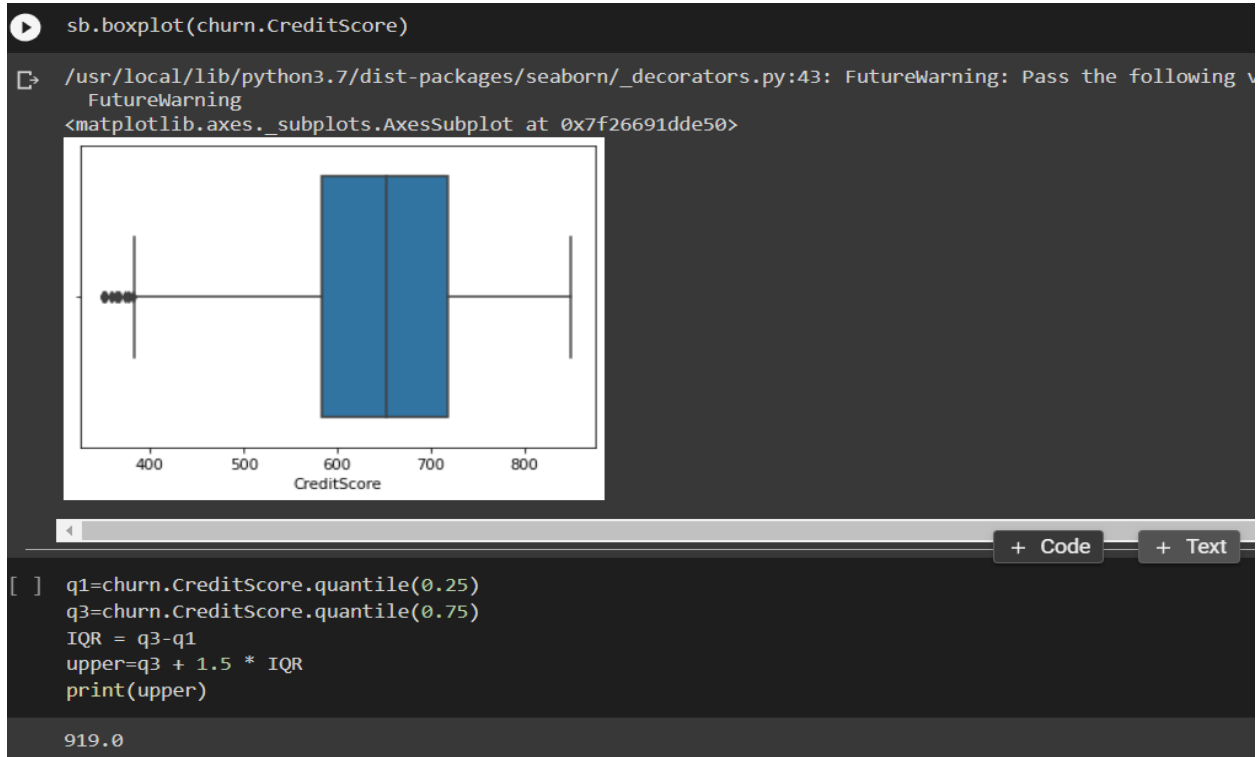
5.

### Handling missing value

`churn.isnull().any()`

RowNumber	False
CustomerId	False
Surname	False
CreditScore	False
Geography	False
Gender	False
Age	False
Tenure	False
Balance	False
NumOfProducts	False
HasCrCard	False
IsActiveMember	False
EstimatedSalary	False
Exited	False
dtype: bool	

6.



7.

## Check for Categorical columns and perform encoding.

### Checking for categorical column

```
[ ] churn.dtypes
```

```
RowNumber      int64
CustomerId      int64
Surname         object
CreditScore     int64
Geography       object
Gender          object
Age            int64
Tenure          int64
Balance         float64
NumOfProducts  int64
HasCrCard       int64
IsActiveMember  int64
EstimatedSalary float64
Exited          int64
dtype: object
```

```
obj = churn.select_dtypes(include=['object']).copy()
obj.head()
```

```
┌─┐  Surname  Geography  Gender
0  Hargrave    France  Female
1    Hill     Spain  Female
2    Onio     France  Female
3    Boni     France  Female
4  Mitchell    Spain  Female
```

### one hot encoding

```
df=pd.get_dummies(churn,columns=['Gender'])
df.head()
df2=pd.get_dummies(df,columns=['Geography'])
df2.head()
```

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

8.

## Splitting the data into dependent and independent variables

```
y=df2['Surname']
y
```

```
0      Hargrave
1        Hill
2        Onio
3        Boni
4      Mitchell
...
9995  Obijiaku
9996  Johnstone
9997      Liu
9998  Sabbatini
9999    Walker
Name: Surname, Length: 10000, dtype: object
```

```
X=df2.drop(columns=['Surname'],axis=1)
X.head()
```

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

+ Code

+ Text

9.

### Scaling the independent variables

```
[ ] from sklearn.preprocessing import scale
```

```
[ ] x_scaled=pd.DataFrame(scale(X),columns=X.columns)
x_scaled.head()
```

	RowNumber	CustomerId	CreditScore	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	EstimatedSalary	Exited	Gender_Female	Gender_Male	Geography_France
0	-1.731878	-0.783213	-0.326221	0.293517	-1.041760	-1.225848	-0.911583	0.646092	0.970243	0.021886	1.977165	1.095988	-1.095988	0.997204
1	-1.731531	-0.606534	-0.440036	0.198164	-1.387538	0.117350	-0.911583	-1.547768	0.970243	0.216534	-0.505775	1.095988	-1.095988	-1.002804
2	-1.731185	-0.995885	-1.536794	0.293517	1.032908	1.333053	2.527057	0.646092	-1.030670	0.240687	1.977165	1.095988	-1.095988	0.997204
3	-1.730838	0.144767	0.501521	0.007457	-1.387538	-1.225848	0.807737	-1.547768	-1.030670	-0.108918	-0.505775	1.095988	-1.095988	0.997204
4	-1.730492	0.652659	2.063884	0.388871	-1.041760	0.785728	-0.911583	0.646092	0.970243	-0.365276	-0.505775	1.095988	-1.095988	-1.002804

10.

### Splitting the data into training and testing

```
[ ] from sklearn.model_selection import train_test_split
X_train,X_test,y_train,y_test=train_test_split(x_scaled,y,test_size=0.2,random_state=0)
```

```
[ ] X_train.shape
```

(8000, 16)

```
[ ] X_test.shape
```

(2000, 16)

```
[ ] y_train.shape
```

(8000,)

```
[ ] y_test.shape
```

(2000,)