Assignment - 2

Data visualization and pre-prcessing.

```
from google.colab import drive
drive.mount('/content/drive')
```

2) load the dataset

```
import pandas as pd
df=pd.read_csv("Churn_Modelling.csv") # import dataset
print(df)
```

```
      RowNumber  CustomerId    Surname  CreditScore Geography  Gender
Age  \
0             1    15634602   Hargrave          619    France  Female
42
1             2    15647311       Hill          608     Spain  Female
41
2             3    15619304       Onio          502    France  Female
42
3             4    15701354       Boni          699    France  Female
39
4             5    15737888   Mitchell          850     Spain  Female
43
...         ...         ...        ...          ...       ...     ...
...
9995       9996    15606229   Obijiaku          771    France    Male
39
9996       9997    15569892  Johnstone          516    France    Male
35
9997       9998    15584532        Liu          709    France  Female
36
9998       9999    15682355  Sabbatini          772   Germany    Male
42
9999      10000    15628319     Walker          792    France  Female
28

      Tenure    Balance  NumOfProducts  HasCrCard  IsActiveMember  \
0          2       0.00              1          1               1
1          1   83807.86              1          0               1
2          8  159660.80              3          1               0
3          1       0.00              2          0               0
4          2  125510.82              1          1               1
...      ...        ...            ...        ...             ...
9995       5       0.00              2          1               0
9996      10   57369.61              1          1               1
9997       7       0.00              1          0               1
```

```
9998       3   75075.31              2          1               0
9999       4  130142.79              1          1               0

      EstimatedSalary  Exited
0           101348.88       1
1           112542.58       0
2           113931.57       1
3            93826.63       0
4            79084.10       0
...               ...     ...
9995         96270.64       0
9996        101699.77       0
9997         42085.58       1
9998         92888.52       1
9999         38190.78       0

[10000 rows x 14 columns]
```

3) Perform below visualization.

i) Univariate analysis.

a) summary statistics:

```
import pandas as pd
df=pd.read_csv("Churn_Modelling.csv")

#mean of CreditScore
M=df['CreditScore'].mean()

#median of CreditScore
Me=df['CreditScore'].median()

# standard deviation of CreditScore
std = df['CreditScore'].std()

print("mean value of CreditScore is {}".format(M))
print("median value of CreditScore is {}".format(Me))
print("Standard deviation of CreditScore is {}".format(std))
```

```
mean value of CreditScore is 650.5288
median value of CreditScore is 652.0
Standard deviation of CreditScore is 96.65329873613035
```

b) Frequncy Table:

```
import pandas as pd
df=pd.read_csv("Churn_Modelling.csv")

#frequency table for age
ft=df['Age'].value_counts()
```

```
print("Frequency table for Age is given below")
print("{}".format(ft))
```

```
Frequency table for Age is given below
37    478
38    477
35    474
36    456
34    447
     ...
92      2
82      1
88      1
85      1
83      1
Name: Age, Length: 70, dtype: int64
```

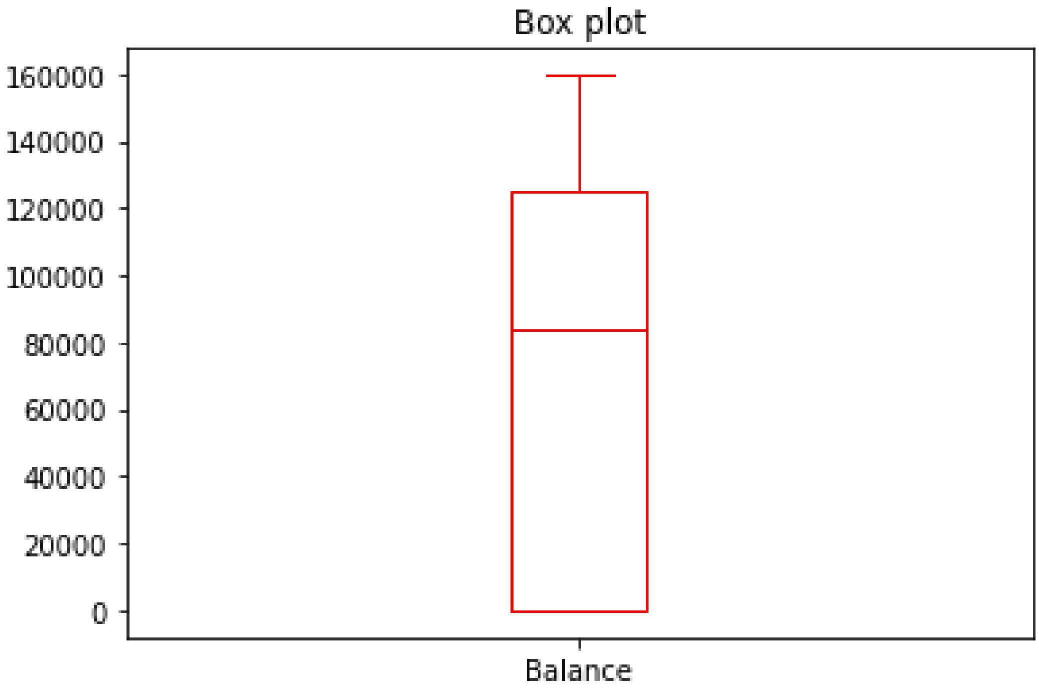
c) pie charts:

```
import matplotlib.pyplot as plt
dfs = df.head() # print first five table from top
print(dfs)

#box plot for Balance column

dfs.boxplot(column="Balance",grid=False,color="red")
plt.title('Box plot')
```

```
   RowNumber  CustomerId   Surname  CreditScore Geography  Gender  Age
\
0          1    15634602  Hargrave          619    France  Female   42

1          2    15647311      Hill          608     Spain  Female   41

2          3    15619304      Onio          502    France  Female   42

3          4    15701354      Boni          699    France  Female   39

4          5    15737888  Mitchell          850     Spain  Female   43


   Tenure    Balance  NumOfProducts  HasCrCard  IsActiveMember  \
0       2       0.00              1          1               1
1       1   83807.86              1          0               1
2       8  159660.80              3          1               0
3       1       0.00              2          0               0
4       2  125510.82              1          1               1

   EstimatedSalary  Exited
```

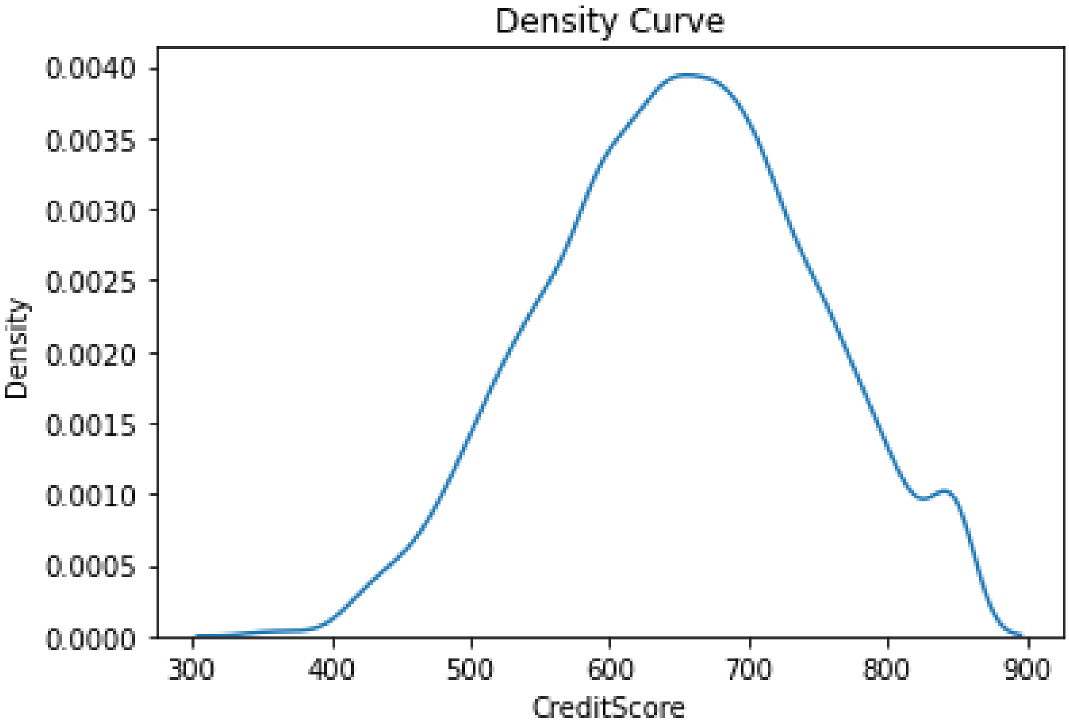
```
0        101348.88       1
1        112542.58       0
2        113931.57       1
3         93826.63       0
4         79084.10       0
```

```
Text(0.5, 1.0, 'Box plot')
```



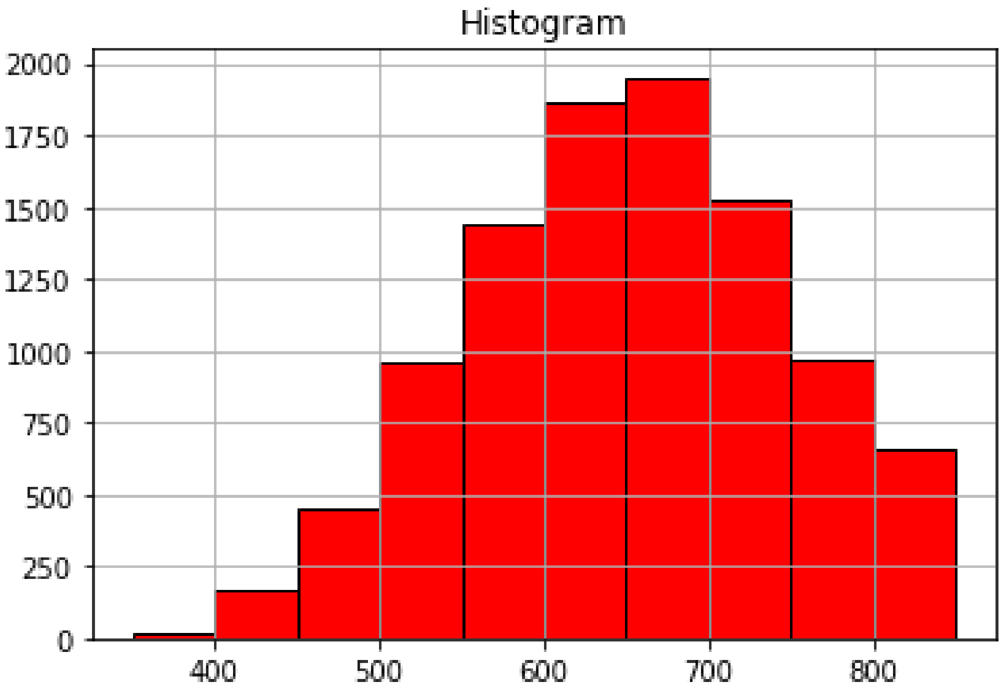
```
# Density curve

import seaborn as sns  #statistical data visualization

sns.kdeplot(df['CreditScore'])
plt.title('Density Curve')
```

```
Text(0.5, 1.0, 'Density Curve')
```



```
# Histogram for Credit Score

df.hist(column="CreditScore" ,grid=True, edgecolor ='black', color
='red')
plt.title('Histogram')
```

```
Text(0.5, 1.0, 'Histogram')
```

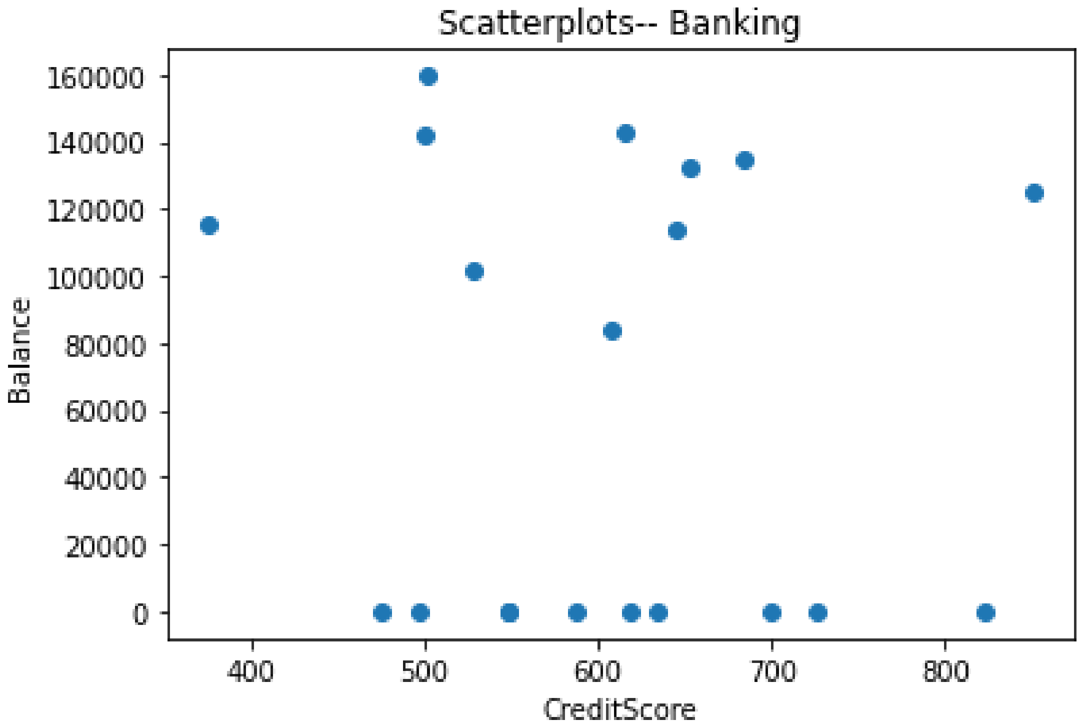


ii) Bi-variate analysis

a) scatterplots

```
import matplotlib.pyplot as plt # library for charts

dfs1 = df.head(20)
plt.scatter(dfs1.CreditScore,dfs1.Balance)
plt.title('Scatterplots-- Banking')
plt.xlabel("CreditScore")
plt.ylabel("Balance")
```

```
Text(0, 0.5, 'Balance')
```



b) Correlation co-efficient

```
df.corr()

                 RowNumber  CustomerId  CreditScore       Age
Tenure  \
RowNumber         1.000000    0.004202     0.005840  0.000783 -
0.006495
CustomerId        0.004202    1.000000     0.005308  0.009497 -
0.014883
CreditScore       0.005840    0.005308     1.000000 -0.003965
0.000842
Age               0.000783    0.009497    -0.003965  1.000000 -
0.009997
Tenure           -0.006495   -0.014883     0.000842 -0.009997
1.000000
Balance          -0.009067   -0.012419     0.006268  0.028308 -
0.012254
NumOfProducts     0.007246    0.016972     0.012238 -0.030680
0.013444
HasCrCard         0.000599   -0.014025    -0.005458 -0.011721
0.022583
IsActiveMember    0.012044    0.001665     0.025651  0.085472 -
0.028362
EstimatedSalary  -0.005988    0.015271    -0.001384 -0.007201
0.007784
Exited           -0.016571   -0.006248    -0.027094  0.285323 -
0.014001
```

```
                  Balance  NumOfProducts  HasCrCard  IsActiveMember  \
RowNumber       -0.009067       0.007246   0.000599        0.012044
CustomerId      -0.012419       0.016972  -0.014025        0.001665
CreditScore      0.006268       0.012238  -0.005458        0.025651
Age              0.028308      -0.030680  -0.011721        0.085472
Tenure          -0.012254       0.013444   0.022583       -0.028362
Balance          1.000000      -0.304180  -0.014858       -0.010084
NumOfProducts   -0.304180       1.000000   0.003183        0.009612
HasCrCard       -0.014858       0.003183   1.000000       -0.011866
IsActiveMember  -0.010084       0.009612  -0.011866        1.000000
EstimatedSalary  0.012797       0.014204  -0.009933       -0.011421
Exited           0.118533      -0.047820  -0.007138       -0.156128

                 EstimatedSalary    Exited
RowNumber              -0.005988 -0.016571
CustomerId              0.015271 -0.006248
CreditScore            -0.001384 -0.027094
Age                    -0.007201  0.285323
Tenure                  0.007784 -0.014001
Balance                 0.012797  0.118533
NumOfProducts           0.014204 -0.047820
HasCrCard              -0.009933 -0.007138
IsActiveMember         -0.011421 -0.156128
EstimatedSalary         1.000000  0.012097
Exited                  0.012097  1.000000
```

c) Simple linear regression:

```
import statsmodels.api as sm
# response variable
y = df['CreditScore']

# explanatory variable
x = df[['Balance']]

#add constant to predictor variables
x = sm.add_constant(x)

#fit linear regression model
model = sm.OLS(y, x).fit()

#view model summary
print(model.summary())
                            OLS Regression Results

======================================================================
========
Dep. Variable:            CreditScore   R-squared:
```

```
0.000
Model:                            OLS   Adj. R-squared:
-0.000
Method:                 Least Squares   F-statistic:
0.3929
Date:                Sat, 05 Nov 2022   Prob (F-statistic):
0.531
Time:                        09:42:36   Log-Likelihood:
-59900.
No. Observations:               10000   AIC:
1.198e+05
Df Residuals:                    9998   BIC:
1.198e+05
Df Model:                           1

Covariance Type:            nonrobust

======================================================================
========
                 coef    std err          t      P>|t|      [0.025
0.975]
----------------------------------------------------------------------
--------
const        649.7861      1.529    424.948      0.000     646.789
652.783
Balance      9.71e-06   1.55e-05      0.627      0.531   -2.07e-05
4.01e-05
======================================================================
========
Omnibus:                      132.594   Durbin-Watson:
2.014
Prob(Omnibus):                  0.000   Jarque-Bera (JB):
84.114
Skew:                          -0.072   Prob(JB):
5.43e-19
Kurtosis:                       2.574   Cond. No.
1.56e+05
======================================================================
========

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is
correctly specified.
[2] The condition number is large, 1.56e+05. This might indicate that
there are
strong multicollinearity or other numerical problems.

/usr/local/lib/python3.7/dist-packages/statsmodels/tsa/
tsatools.py:142: FutureWarning: In a future version of pandas all
arguments of concat except for the argument 'objs' will be keyword-
```

```
only
  x = pd.concat(x[::order], 1)
```

iii) Multi-variate Analysis

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

i. A Matrix Scatterplot

ii. A Scatterplot with the Data Points Labelled by their Group

iii. A Profile Plot

iv. Calculating Summary Statistics for Multivariate Data

v. Means and Variances Per Group

vi. Between-groups Variance and Within-groups Variance for a Variable

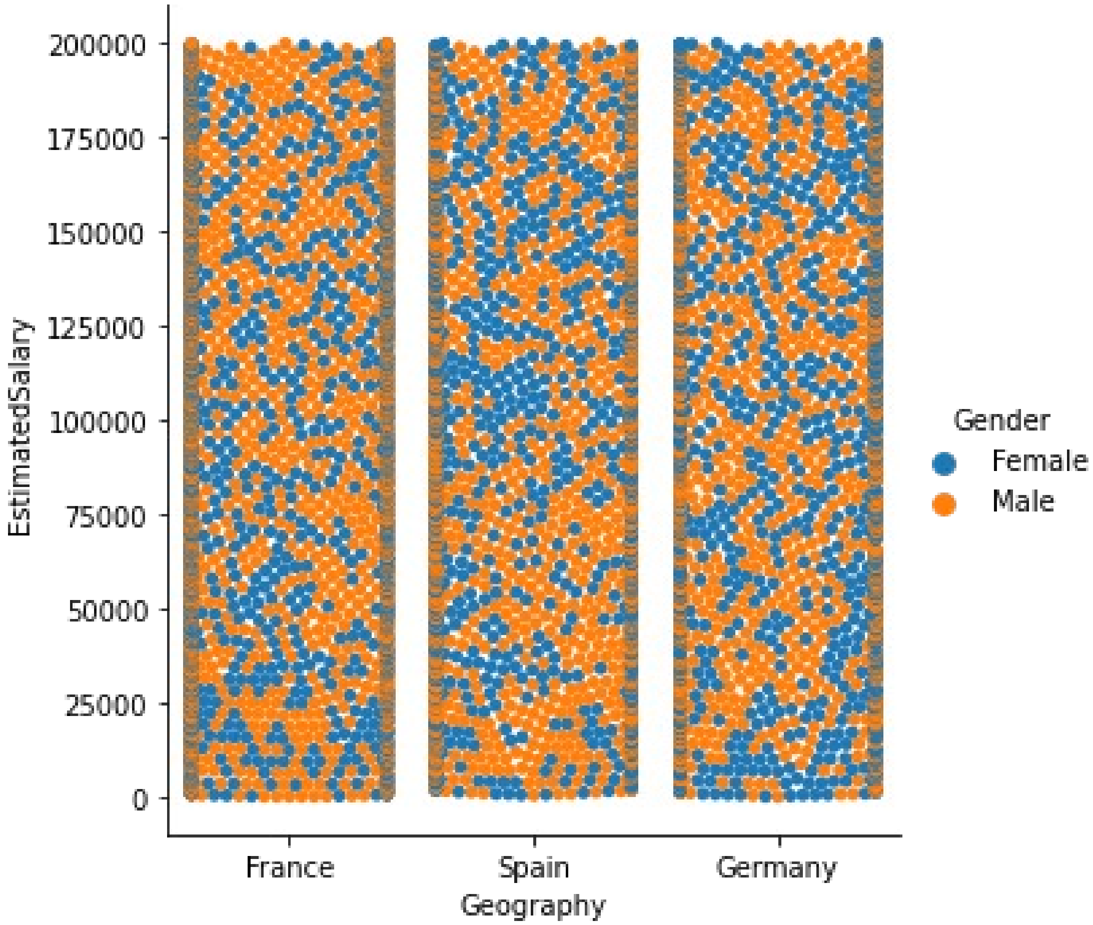
vii. Between-groups Covariance and Within-groups Covariance for Two Variables

viii. Calculating Correlations for Multivariate Data

ix. Standardising Variables

```
df=sns.catplot(x="Geography",y="EstimatedSalary",hue="Gender",kind="swarm",data=df)
print(df)
```

```
/usr/local/lib/python3.7/dist-packages/seaborn/categorical.py:1296: UserWarning: 80.8% of the points cannot be placed; you may want to decrease the size of the markers or use stripplot.
  warnings.warn(msg, UserWarning)
/usr/local/lib/python3.7/dist-packages/seaborn/categorical.py:1296: UserWarning: 62.1% of the points cannot be placed; you may want to decrease the size of the markers or use stripplot.
  warnings.warn(msg, UserWarning)
/usr/local/lib/python3.7/dist-packages/seaborn/categorical.py:1296: UserWarning: 62.5% of the points cannot be placed; you may want to decrease the size of the markers or use stripplot.
  warnings.warn(msg, UserWarning)

<seaborn.axisgrid.FacetGrid object at 0x7faf2d1c9990>
```



4) Perform descriptive statistics on the dataset.

```
#load data set into ld
ld= pd.read_csv("Churn_Modelling.csv")
five = ld.head() #for print first five rows

# information about used data set
ld.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
```

```
ld.describe() #description of the data in the Dataset
```

```
         RowNumber    CustomerId   CreditScore           Age 
Tenure  \
count  10000.00000  1.000000e+04  10000.000000  10000.000000 
10000.000000   
mean    5000.50000  1.569094e+07    650.528800     38.921800 
5.012800   
std     2886.89568  7.193619e+04     96.653299     10.487806 
2.892174   
min        1.00000  1.556570e+07    350.000000     18.000000 
0.000000   
25%     2500.75000  1.562853e+07    584.000000     32.000000 
3.000000   
50%     5000.50000  1.569074e+07    652.000000     37.000000 
5.000000   
75%     7500.25000  1.575323e+07    718.000000     44.000000 
7.000000   
max    10000.00000  1.581569e+07    850.000000     92.000000 
10.000000  

             Balance  NumOfProducts    HasCrCard  IsActiveMember  \
count   10000.000000   10000.000000  10000.00000    10000.000000   
mean    76485.889288       1.530200      0.70550        0.515100   
std     62397.405202       0.581654      0.45584        0.499797   
min         0.000000       1.000000      0.00000        0.000000   
25%         0.000000       1.000000      0.00000        0.000000   
50%     97198.540000       1.000000      1.00000        1.000000   
75%    127644.240000       2.000000      1.00000        1.000000   
max    250898.090000       4.000000      1.00000        1.000000   

       EstimatedSalary        Exited  
count     10000.000000  10000.000000  
mean     100090.239881      0.203700  
std       57510.492818      0.402769  
min          11.580000      0.000000  
25%       51002.110000      0.000000  
50%      100193.915000      0.000000  
75%      149388.247500      0.000000  
max      199992.480000      1.000000  
```

5) Handle the Missing values.

```
ld.isnull().any()
```

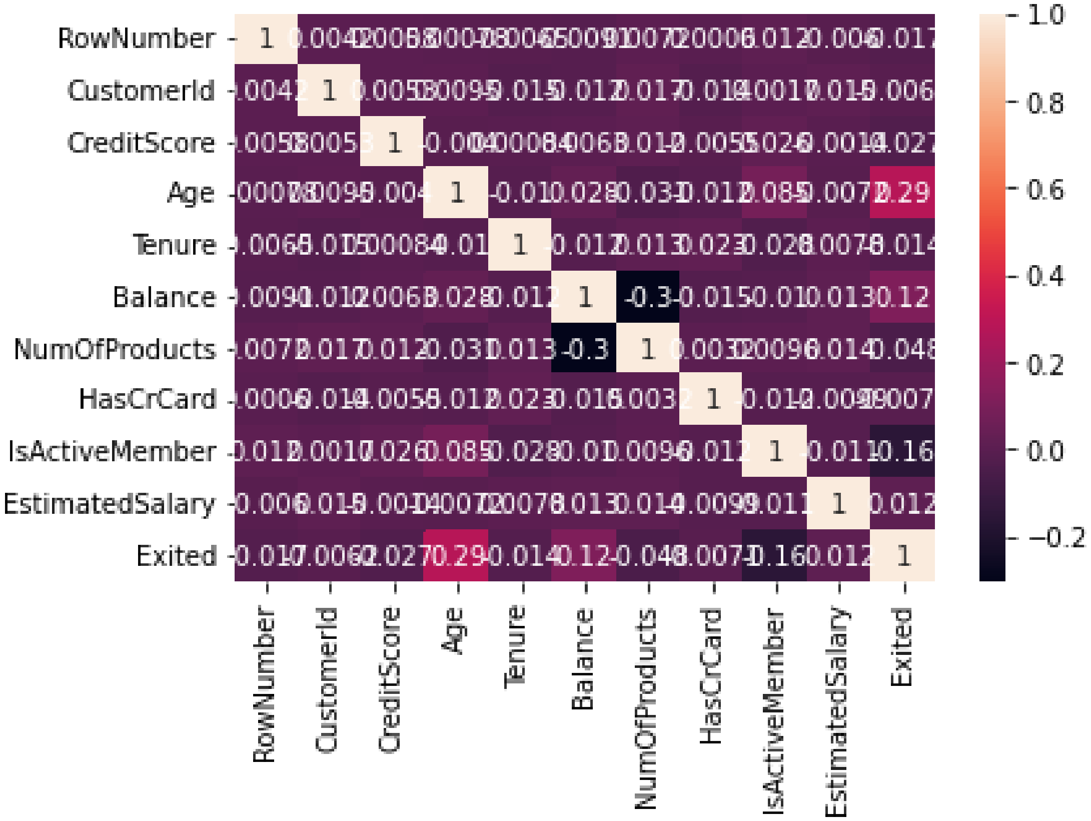
```
RowNumber          False
CustomerId         False
Surname            False
CreditScore        False
Geography          False
Gender             False
Age                False
Tenure             False
Balance            False
NumOfProducts      False
HasCrCard          False
IsActiveMember     False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

```
ld.isnull().sum()
```

```
RowNumber          0
CustomerId         0
Surname            0
CreditScore        0
Geography          0
Gender             0
Age                0
Tenure             0
Balance            0
NumOfProducts      0
HasCrCard          0
IsActiveMember     0
EstimatedSalary    0
Exited             0
dtype: int64
```

```
sns.heatmap(ld.corr(),annot=True) # heatmap -a plot of rectangular
data as a color-encoded matrix
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f77298ff610>
```

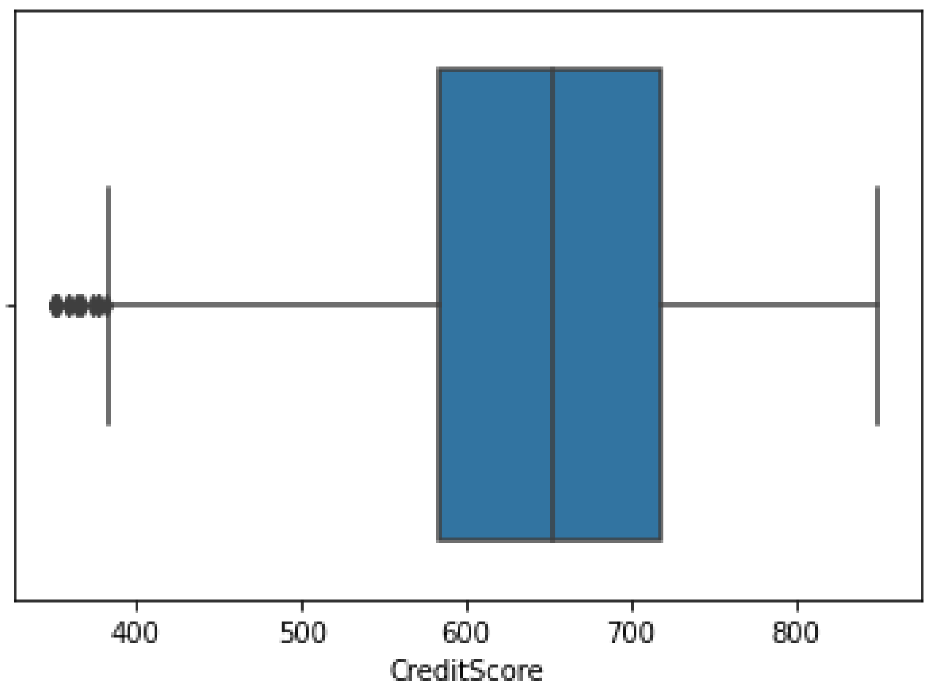


6) Find the outliers and replace the outliers

```
ld1= pd.read_csv("Churn_Modelling.csv")
sns.boxplot(ld1.CreditScore)
```

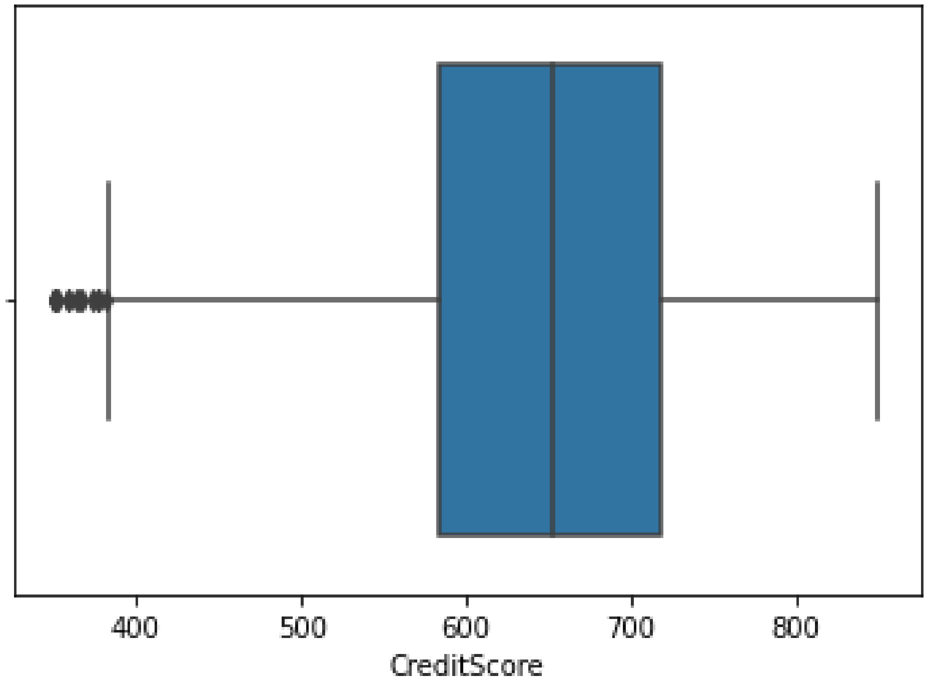
```
/usr/local/lib/python3.7/dist-packages/seaborn/_decorators.py:43:
FutureWarning: Pass the following variable as a keyword arg: x. From
version 0.12, the only valid positional argument will be `data`, and
passing other arguments without an explicit keyword will result in an
error or misinterpretation.
  FutureWarning
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f77295e0310>
```



```
#Use Mean Detection and Nearest Fill Methods - Outliers

Q1= ld1.CreditScore.quantile(0.25)
Q3=ld1.CreditScore.quantile(0.75)
IQR=Q3-Q1
upper_limit =Q3 + 1.5*IQR
lower_limit =Q1 - 1.5*IQR
ld1['CreditScore'] =
np.where(ld1['CreditScore']>upper_limit,30,ld1['CreditScore'])
sns.boxplot(ld1.CreditScore)
```

```
/usr/local/lib/python3.7/dist-packages/seaborn/_decorators.py:43:
FutureWarning: Pass the following variable as a keyword arg: x. From
version 0.12, the only valid positional argument will be `data`, and
passing other arguments without an explicit keyword will result in an
error or misinterpretation.
  FutureWarning

<matplotlib.axes._subplots.AxesSubplot at 0x7f7729615e90>
```



7) Check for Categorical columns and perform encoding.

```
ld1.head(5)
```

```
   RowNumber  CustomerId   Surname  CreditScore Geography  Gender  Age  
\
0          1    15634602  Hargrave          619    France  Female   42   

1          2    15647311      Hill          608     Spain  Female   41   

2          3    15619304      Onio          502    France  Female   42   

3          4    15701354      Boni          699    France  Female   39   

4          5    15737888  Mitchell          850     Spain  Female   43   


   Tenure    Balance  NumOfProducts  HasCrCard  IsActiveMember  \
0       2       0.00              1          1               1   
1       1   83807.86              1          0               1   
2       8  159660.80              3          1               0   
3       1       0.00              2          0               0   
4       2  125510.82              1          1               1   

   EstimatedSalary  Exited  
0        101348.88       1  
1        112542.58       0  
2        113931.57       1  
```

```
3         93826.63       0
4         79084.10       0
```

```
#label encoder
from sklearn.preprocessing import LabelEncoder
le=LabelEncoder()
ld1.Gender= le.fit_transform(ld1.Gender)
ld1.head(5)
```

```
   RowNumber  CustomerId   Surname  CreditScore Geography  Gender  Age
\
0          1    15634602  Hargrave          619    France       0   42

1          2    15647311      Hill          608     Spain       0   41

2          3    15619304      Onio          502    France       0   42

3          4    15701354      Boni          699    France       0   39

4          5    15737888  Mitchell          850     Spain       0   43


   Tenure    Balance  NumOfProducts  HasCrCard  IsActiveMember  \
0       2       0.00              1          1               1
1       1   83807.86              1          0               1
2       8  159660.80              3          1               0
3       1       0.00              2          0               0
4       2  125510.82              1          1               1

   EstimatedSalary  Exited
0        101348.88       1
1        112542.58       0
2        113931.57       1
3         93826.63       0
4         79084.10       0
```

```
#one hot encoding
ld1_main=pd.get_dummies(ld1,columns=['Geography'])
ld1_main.head()
```

```
   RowNumber  CustomerId   Surname  CreditScore  Gender  Age
Tenure  \
0          1    15634602  Hargrave          619       0   42       2

1          2    15647311      Hill          608       0   41       1

2          3    15619304      Onio          502       0   42       8

3          4    15701354      Boni          699       0   39       1
```

```
4          5    15737888  Mitchell          850       0   43       2


     Balance  NumOfProducts  HasCrCard  IsActiveMember  
EstimatedSalary  \
0       0.00              1          1               1       
101348.88   
1   83807.86              1          0               1       
112542.58   
2  159660.80              3          1               0       
113931.57   
3       0.00              2          0               0        
93826.63   
4  125510.82              1          1               1        
79084.10   

   Exited  Geography_France  Geography_Germany  Geography_Spain  
0       1                 1                  0                0  
1       0                 0                  0                1  
2       1                 1                  0                0  
3       0                 1                  0                0  
4       0                 0                  0                1  
```

8) Split the data into dependent and independent variables.

```
#Splitting the Dataset into the Independent Feature Matrix
df=pd.read_csv("Churn_Modelling.csv")
X = df.iloc[:, :-1].values
print(X)
```

```
[[1 15634602 'Hargrave' ... 1 1 101348.88]
 [2 15647311 'Hill' ... 0 1 112542.58]
 [3 15619304 'Onio' ... 1 0 113931.57]
 ...
 [9998 15584532 'Liu' ... 0 1 42085.58]
 [9999 15682355 'Sabbatini' ... 1 0 92888.52]
 [10000 15628319 'Walker' ... 1 0 38190.78]]
```

```
#Extracting the Dataset to Get the Dependent Vector
Y = df.iloc[:, -1].values
print(Y)
```

```
[1 0 1 ... 1 1 0]
```

9) Scale the independent

```
w = df.head()
q = w[['Age','Balance','EstimatedSalary']] #spliting the dataset into 
measureable values
q
```

```
   Age    Balance  EstimatedSalary
0   42       0.00        101348.88
1   41   83807.86        112542.58
2   42  159660.80        113931.57
3   39       0.00         93826.63
4   43  125510.82         79084.10
```

```
from sklearn.preprocessing import scale # library for scallling
from sklearn.preprocessing import MinMaxScaler
mm = MinMaxScaler()

x_scaled = mm.fit_transform(q)
x_scaled
```

```
array([[0.75      , 0.        , 0.63892099],
       [0.5       , 0.52491194, 0.96014087],
       [0.75      , 1.        , 1.        ],
       [0.        , 0.        , 0.42305883],
       [1.        , 0.78610918, 0.        ]])
```

```
from sklearn.preprocessing import StandardScaler
sc =  StandardScaler()
x_ss = sc.fit_transform(q)
x_ss
```

```
array([[ 0.44232587, -1.13763618,  0.09337626],
       [-0.29488391,  0.15434425,  0.96285595],
       [ 0.44232587,  1.32369179,  1.07074687],
       [-1.76930347, -1.13763618, -0.49092058],
       [ 1.17953565,  0.79723632, -1.6360585 ]])
```

```
from sklearn.preprocessing import scale
X_scaled=pd.DataFrame(scale(q),columns=q.columns)
X_scale=X_scaled.head()
X_scale
```

```
        Age   Balance  EstimatedSalary
0  0.442326 -1.137636         0.093376
1 -0.294884  0.154344         0.962856
2  0.442326  1.323692         1.070747
3 -1.769303 -1.137636        -0.490921
4  1.179536  0.797236        -1.636059
```

10) Split the data into training and testing

```
x= df[['Age','Balance','EstimatedSalary']]
x
```

```
      Age    Balance  EstimatedSalary
0      42       0.00        101348.88
1      41   83807.86        112542.58
2      42  159660.80        113931.57
```

```
3      39       0.00         93826.63
4      43  125510.82         79084.10
...   ...        ...              ...
9995   39       0.00         96270.64
9996   35   57369.61        101699.77
9997   36       0.00         42085.58
9998   42   75075.31         92888.52
9999   28  130142.79         38190.78

[10000 rows x 3 columns]
```

```
y = df['Balance']
y
```

```
0            0.00
1        83807.86
2       159660.80
3            0.00
4       125510.82
          ...
9995         0.00
9996     57369.61
9997         0.00
9998     75075.31
9999    130142.79
Name: Balance, Length: 10000, dtype: float64
```

```
#scaling
from sklearn.preprocessing import StandardScaler, MinMaxScaler
sc = StandardScaler()
x_scaled1 = sc.fit_transform(x)
x_scaled1
```

```
array([[ 0.29351742, -1.22584767,  0.02188649],
       [ 0.19816383,  0.11735002,  0.21653375],
       [ 0.29351742,  1.33305335,  0.2406869 ],
       ...,
       [-0.27860412, -1.22584767, -1.00864308],
       [ 0.29351742, -0.02260751, -0.12523071],
       [-1.04143285,  0.85996499, -1.07636976]])
```

```
#train and test data
from sklearn.model_selection import train_test_split
x_train, x_test, y_train, y_test = train_test_split(x_scaled1, y,
test_size = 0.3, random_state = 0)
```

```
x_train
```

```
array([[-0.56466489,  1.11721307, -0.77021814],
       [ 0.00745665, -1.22584767, -1.39576675],
       [ 3.53553951,  1.35419118, -1.49965629],
       ...,
       [-0.37395771,  1.35890908,  1.41441489],
       [-0.08789694, -1.22584767,  0.84614739],
       [ 0.86563897,  0.50630343,  0.32630495]])
```

```
x_test
```

```
array([[-0.37395771,  0.87532296,  1.61304597],
       [ 0.10281024,  0.42442221,  0.49753166],
       [ 0.29351742,  0.30292727, -0.4235611 ],
       ...,
       [ 0.10281024,  1.46672809,  1.17045451],
       [ 2.86806437,  1.25761599, -0.50846777],
       [ 0.96099256,  0.19777742, -1.15342685]])
```

```
x_test
```

```
array([[-0.37395771,  0.87532296,  1.61304597],
       [ 0.10281024,  0.42442221,  0.49753166],
       [ 0.29351742,  0.30292727, -0.4235611 ],
       ...,
       [ 0.10281024,  1.46672809,  1.17045451],
       [ 2.86806437,  1.25761599, -0.50846777],
       [ 0.96099256,  0.19777742, -1.15342685]])
```

```
x_test.shape
```

```
(3000, 3)
```

```
y_train
```

```
7681    146193.60
9031         0.00
3691    160979.68
202          0.00
5625    143262.04
          ...
9225    120074.97
4859    114440.24
3264    161274.05
9845         0.00
2732    108076.33
Name: Balance, Length: 7000, dtype: float64
```

```
y_test
```

```
9394    131101.04
898     102967.41
2398     95386.82
5906    112079.58
2343    163034.82
          ...
4004         0.00
```

```
7375     80926.02
9307    168001.34
8394    154953.94
5233     88826.07
Name: Balance, Length: 3000, dtype: float64
```