Data Visualization and Pre-processing

Import libraries

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

Load dataset

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

```
Mounted at /content/drive
```

```
data = pd.read_csv('drive/My Drive/Churn_Modelling.csv')
```

```
data.head()
```

```
   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  
```

```
data.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
```

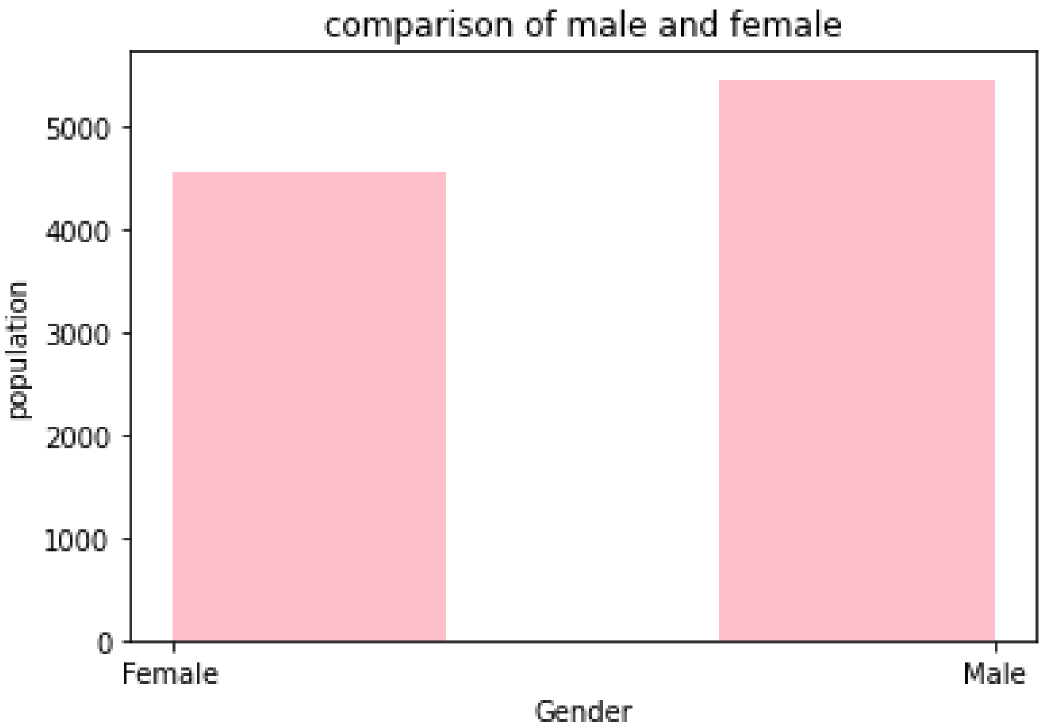
Visualisations

1. Univariate Analysis

```
data['Gender'].value_counts()
```

```
Male      5457
Female    4543
Name: Gender, dtype: int64
```

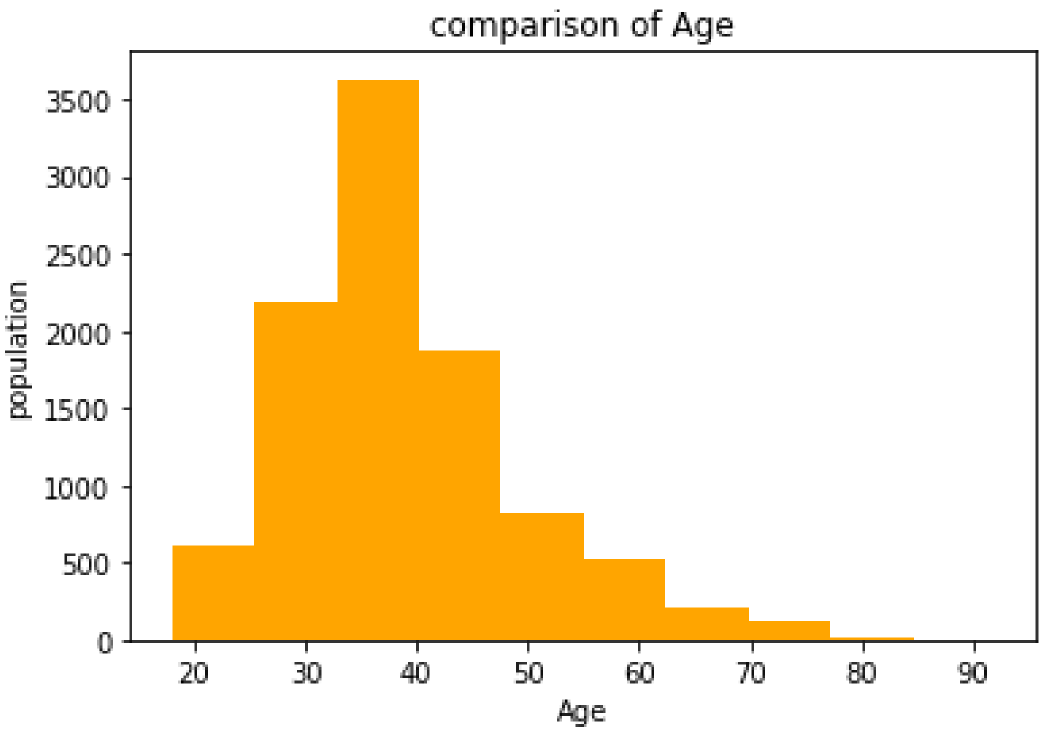
```
# Plotting the features of the dataset to see the correlation between them

plt.hist(x = data.Gender, bins = 3, color = 'pink')
plt.title('comparison of male and female')
plt.xlabel('Gender')
plt.ylabel('population')
plt.show()
```




```
data['Age'].value_counts()
```

```
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
```

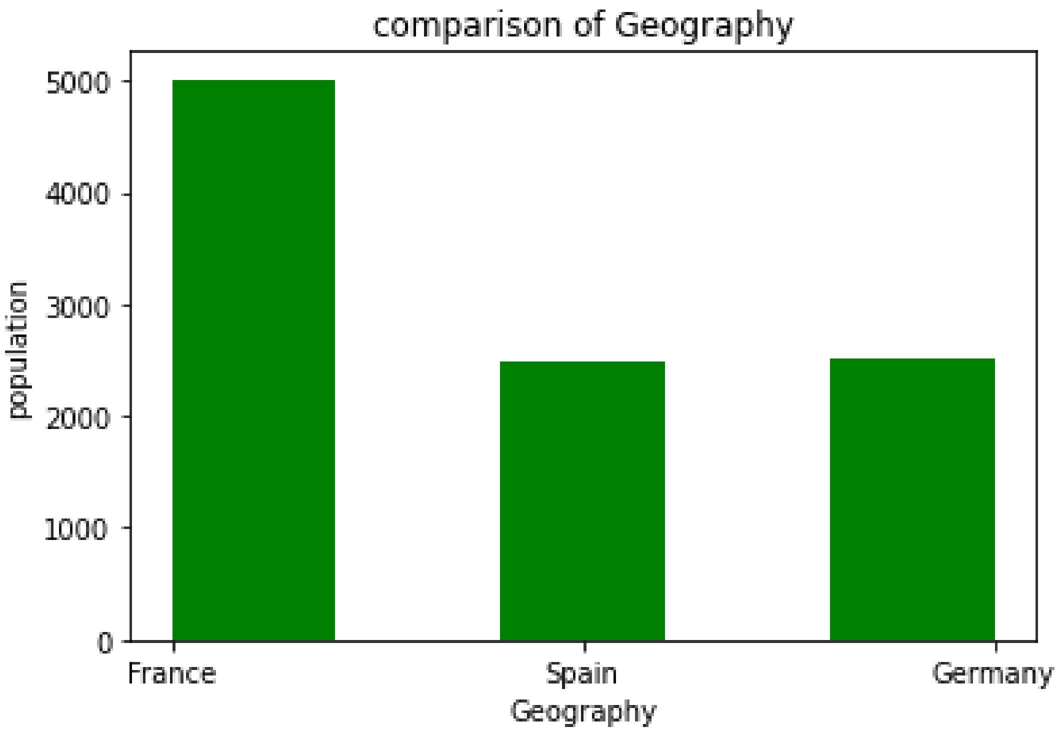
```
# comparison of age in the dataset

plt.hist(x = data.Age, bins = 10, color = 'orange')
plt.title('comparison of Age')
plt.xlabel('Age')
plt.ylabel('population')
plt.show()
```




```
data['Geography'].value_counts()
```

```
France     5014
Germany    2509
Spain      2477
Name: Geography, dtype: int64
```

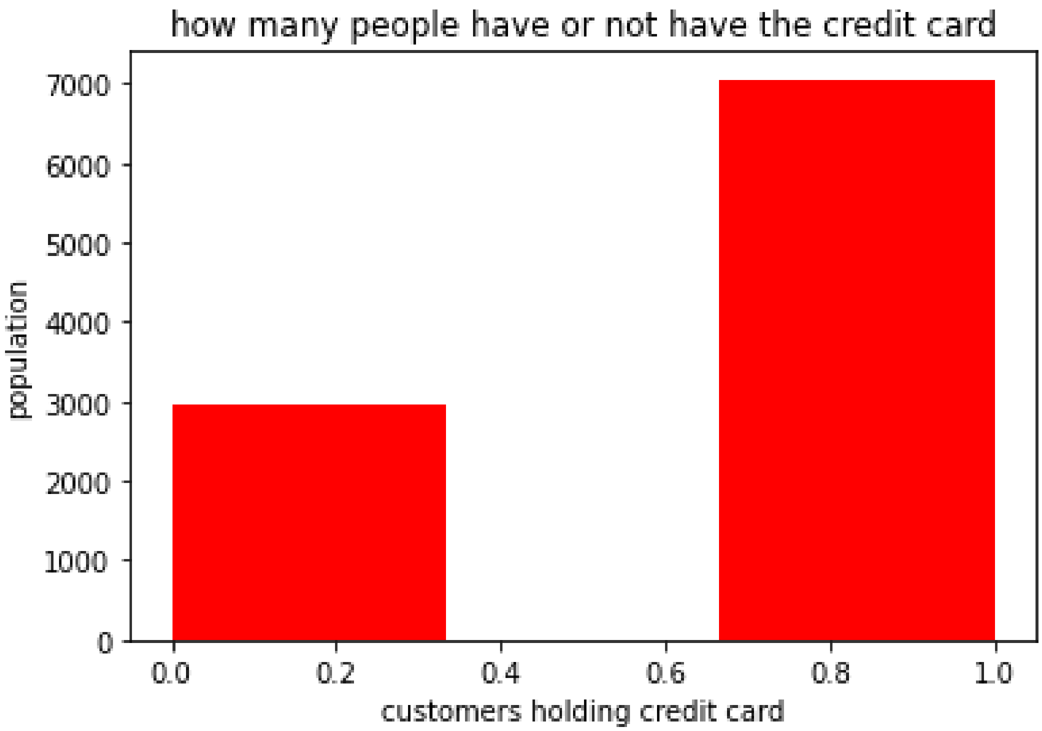
```
# comparison of geography

plt.hist(x = data.Geography, bins = 5, color = 'green')
plt.title('comparison of Geography')
plt.xlabel('Geography')
plt.ylabel('population')
plt.show()
```




```
data['HasCrCard'].value_counts()
```

```
1    7055
0    2945
Name: HasCrCard, dtype: int64
```

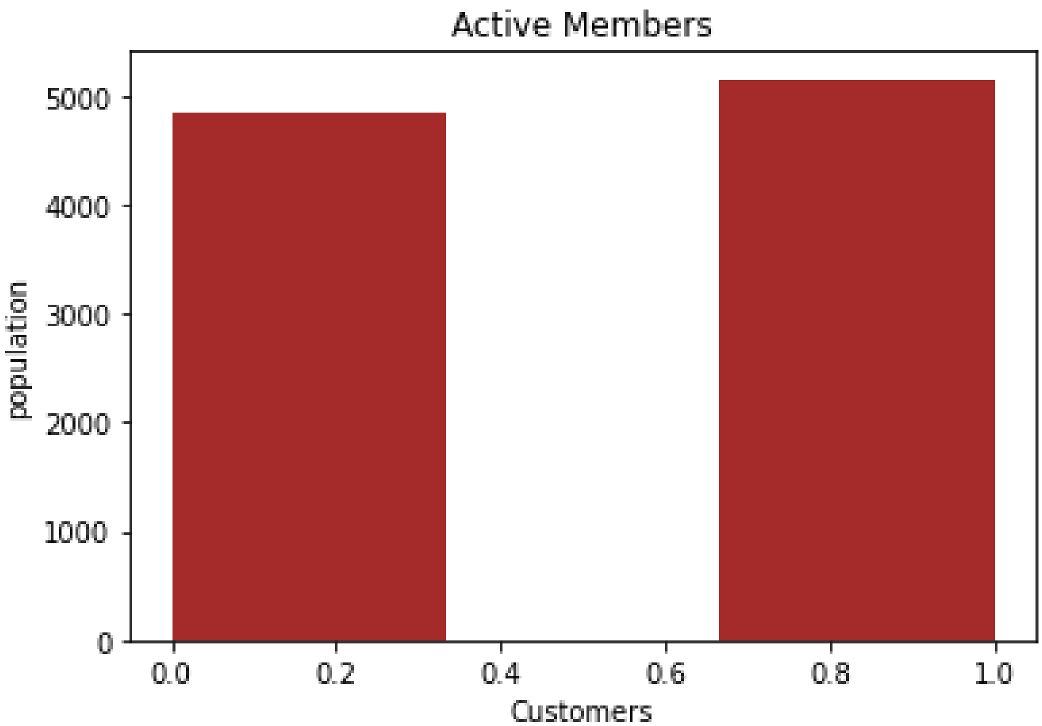
```
# comparision of how many customers hold the credit card

plt.hist(x = data.HasCrCard, bins = 3, color = 'red')
plt.title('how many people have or not have the credit card')
plt.xlabel('customers holding credit card')
plt.ylabel('population')
plt.show()
```




```
data['IsActiveMember'].value_counts()
```

```
1    5151
0    4849
Name: IsActiveMember, dtype: int64
```

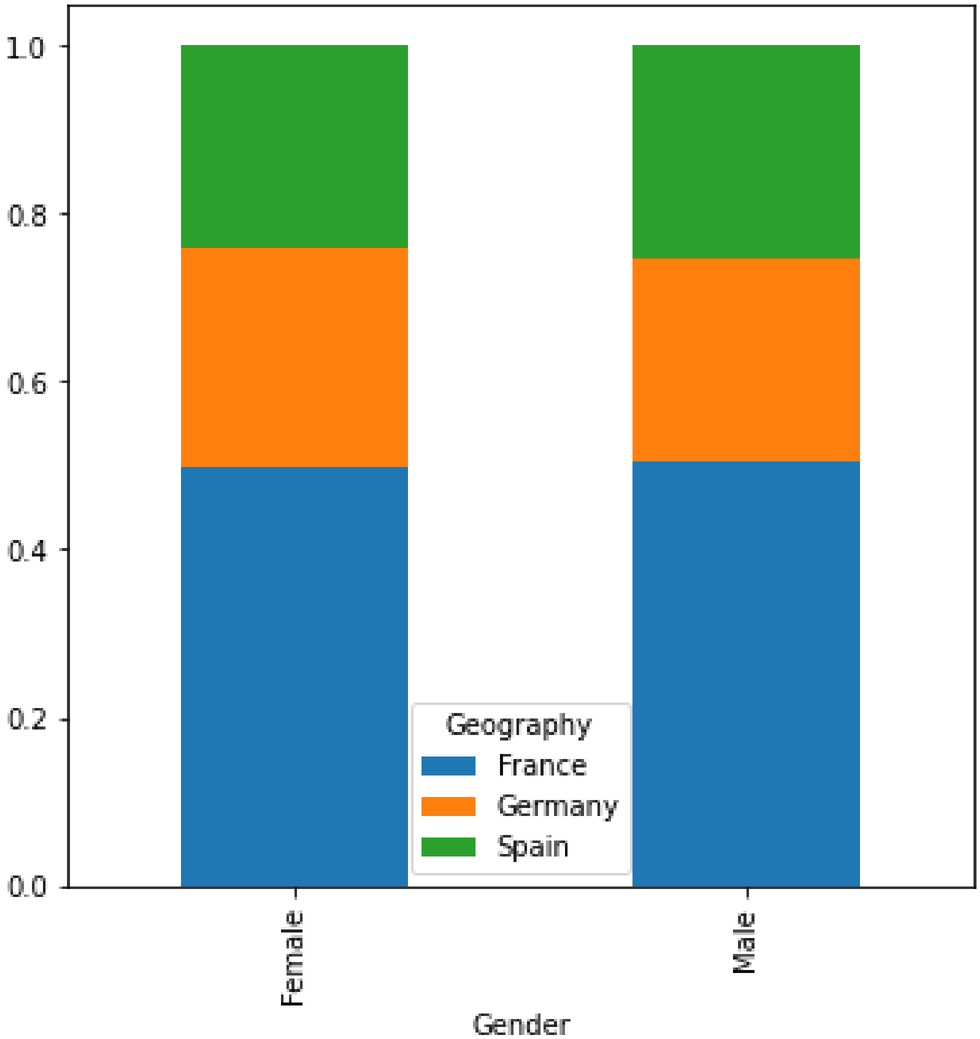
```
# How many active member does the bank have ?

plt.hist(x = data.IsActiveMember, bins = 3, color = 'brown')
plt.title('Active Members')
plt.xlabel('Customers')
plt.ylabel('population')
plt.show()
```



2. Bi - Variate Analysis

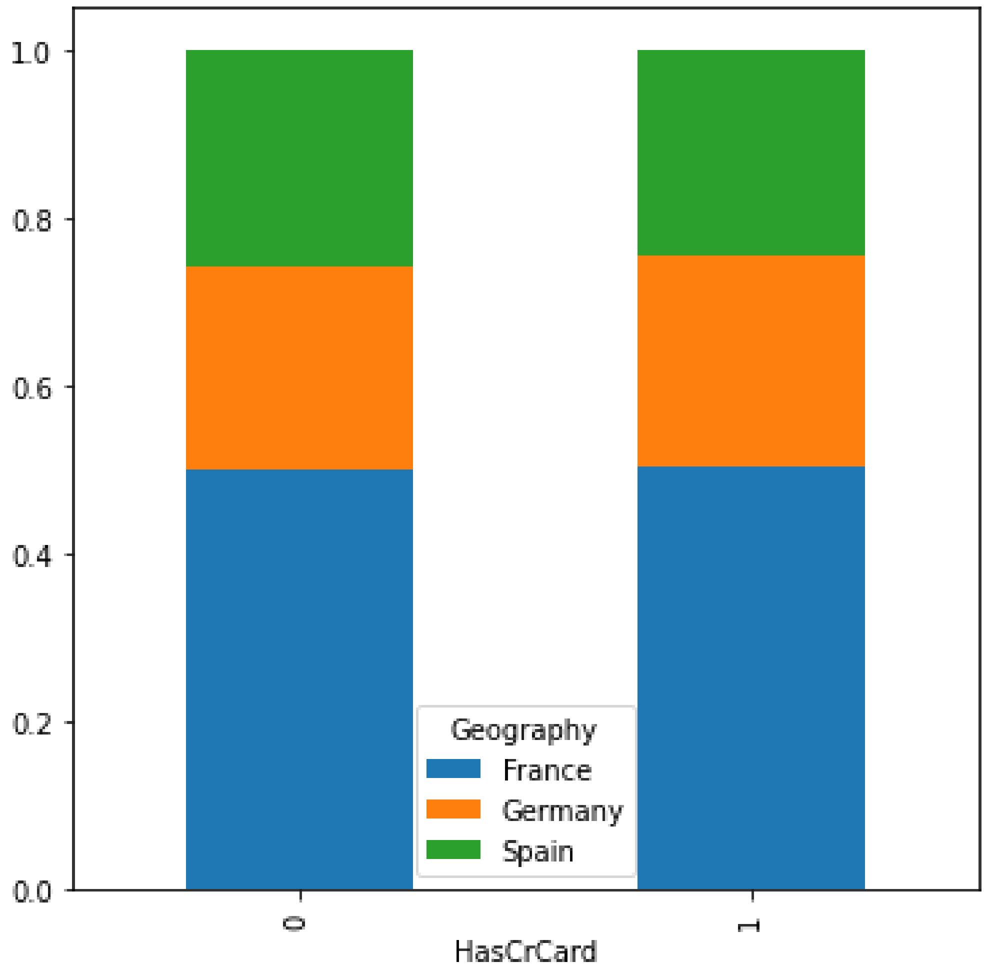
```
# comparison between Geography and Gender

Gender = pd.crosstab(data['Gender'],data['Geography'])
Gender.div(Gender.sum(1).astype(float), axis=0).plot(kind="bar",
stacked=True, figsize=(6, 6))
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f6a93dbbfd0>
```



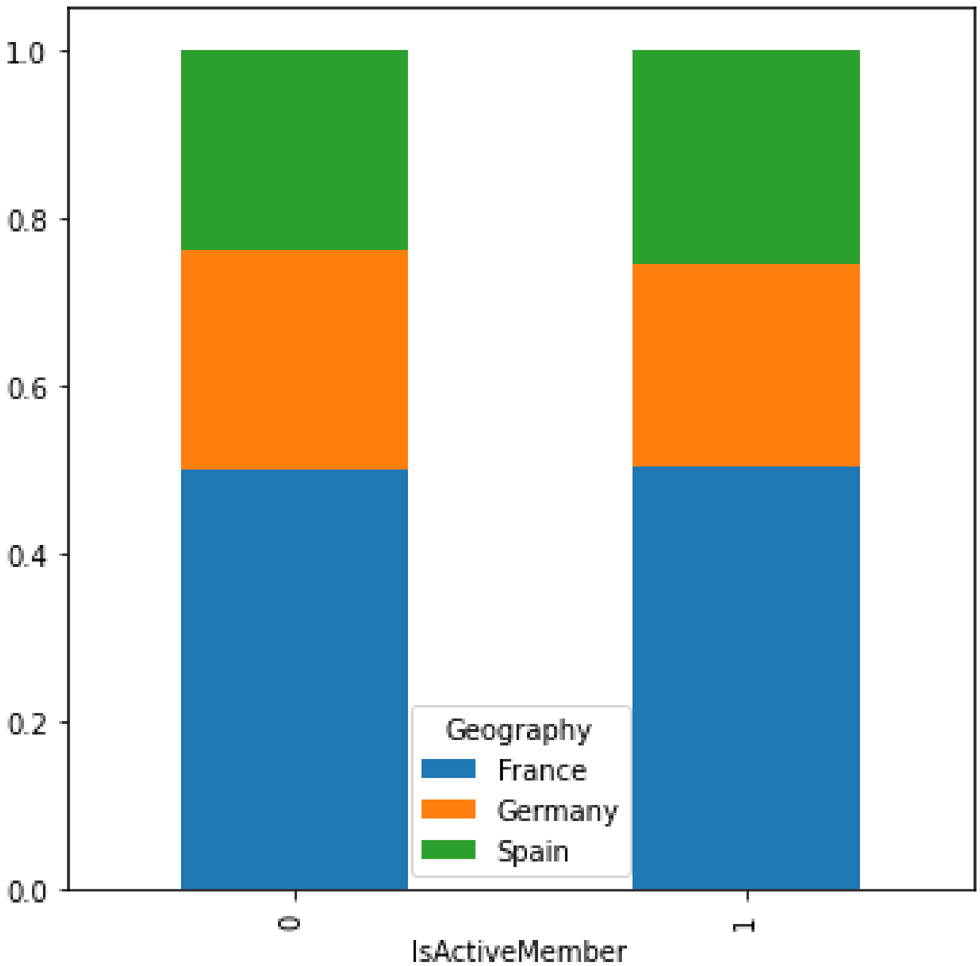

```
# comparison between geography and card holders

HasCrCard = pd.crosstab(data['HasCrCard'], data['Geography'])
HasCrCard.div(HasCrCard.sum(1).astype(float), axis = 0).plot(kind =
'bar',
                                                            stacked = True,figsize =
(6, 6))
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f6a93ced590>
```



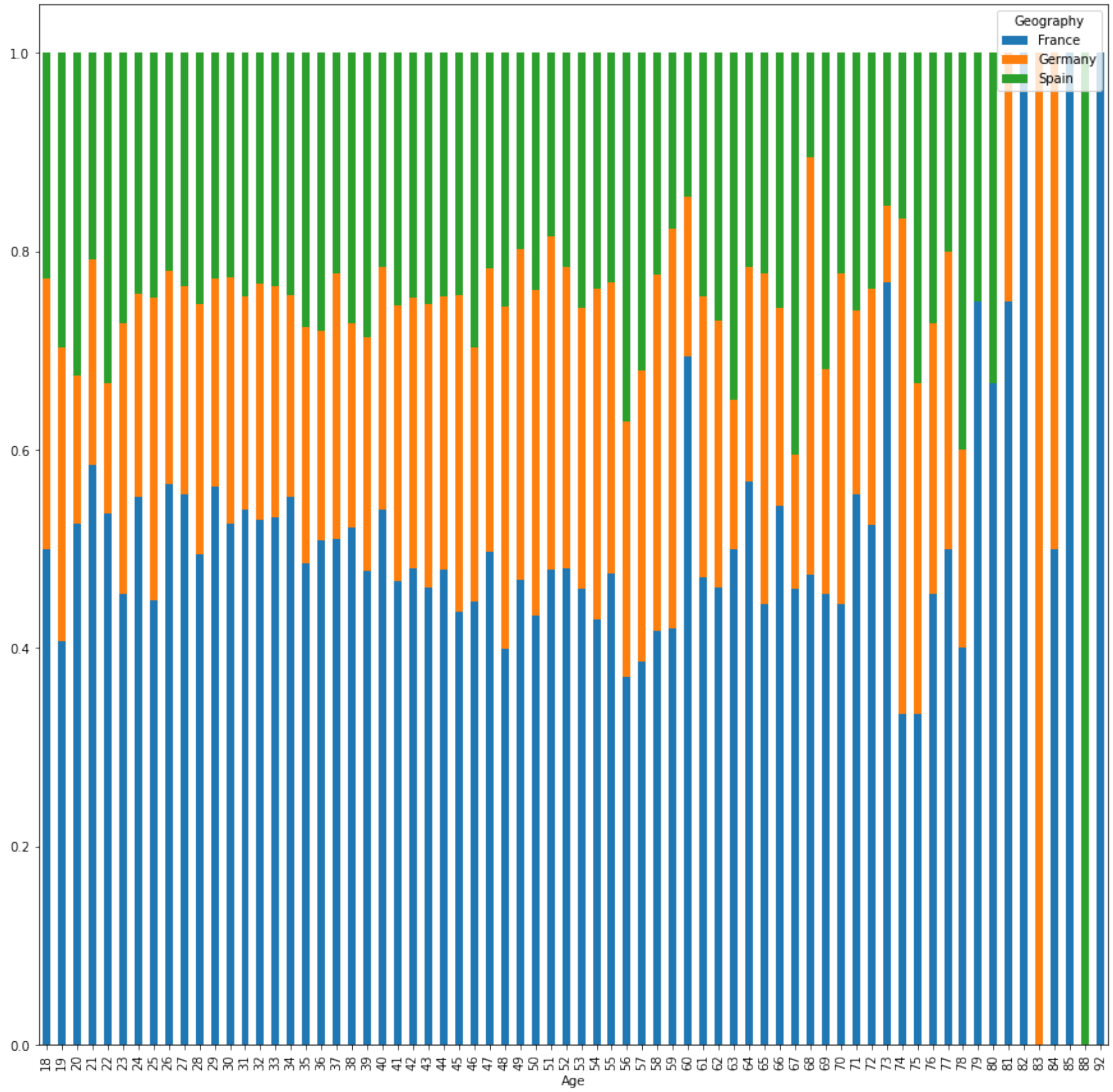

```
# comparison of active member in differnt geographies

IsActiveMember = pd.crosstab(data['IsActiveMember'],
data['Geography'])
IsActiveMember.div(IsActiveMember.sum(1).astype(float), axis =
0).plot(kind = 'bar',
                                                  stacked = True, figsize=
(6, 6))
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f6a93c7c950>
```




```
# comparing ages in different geographies

Age = pd.crosstab(data['Age'], data['Geography'])
Age.div(Age.sum(1).astype(float), axis = 0).plot(kind = 'bar',
                                                  stacked = True, figsize =
(15,15))
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f6a93bfea10>
```

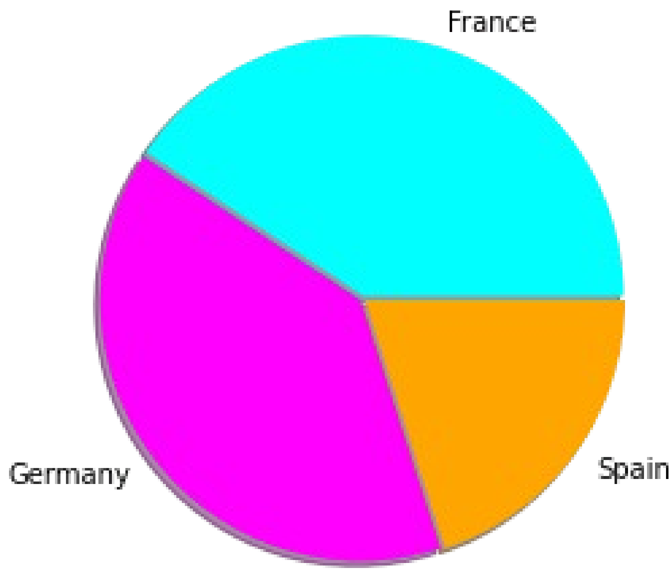



```
# calculating total balance in france, germany and spain

total_france = data.Balance[data.Geography == 'France'].sum()
total_germany = data.Balance[data.Geography == 'Germany'].sum()
total_spain = data.Balance[data.Geography == 'Spain'].sum()

print("Total Balance in France :",total_france)
print("Total Balance in Germany :",total_germany)
print("Total Balance in Spain :",total_spain)
```

```
Total Balance in France : 311332479.49
Total Balance in Germany : 300402861.38
Total Balance in Spain : 153123552.01
```

```
# plotting a pie chart

labels = 'France', 'Germany', 'Spain'
```

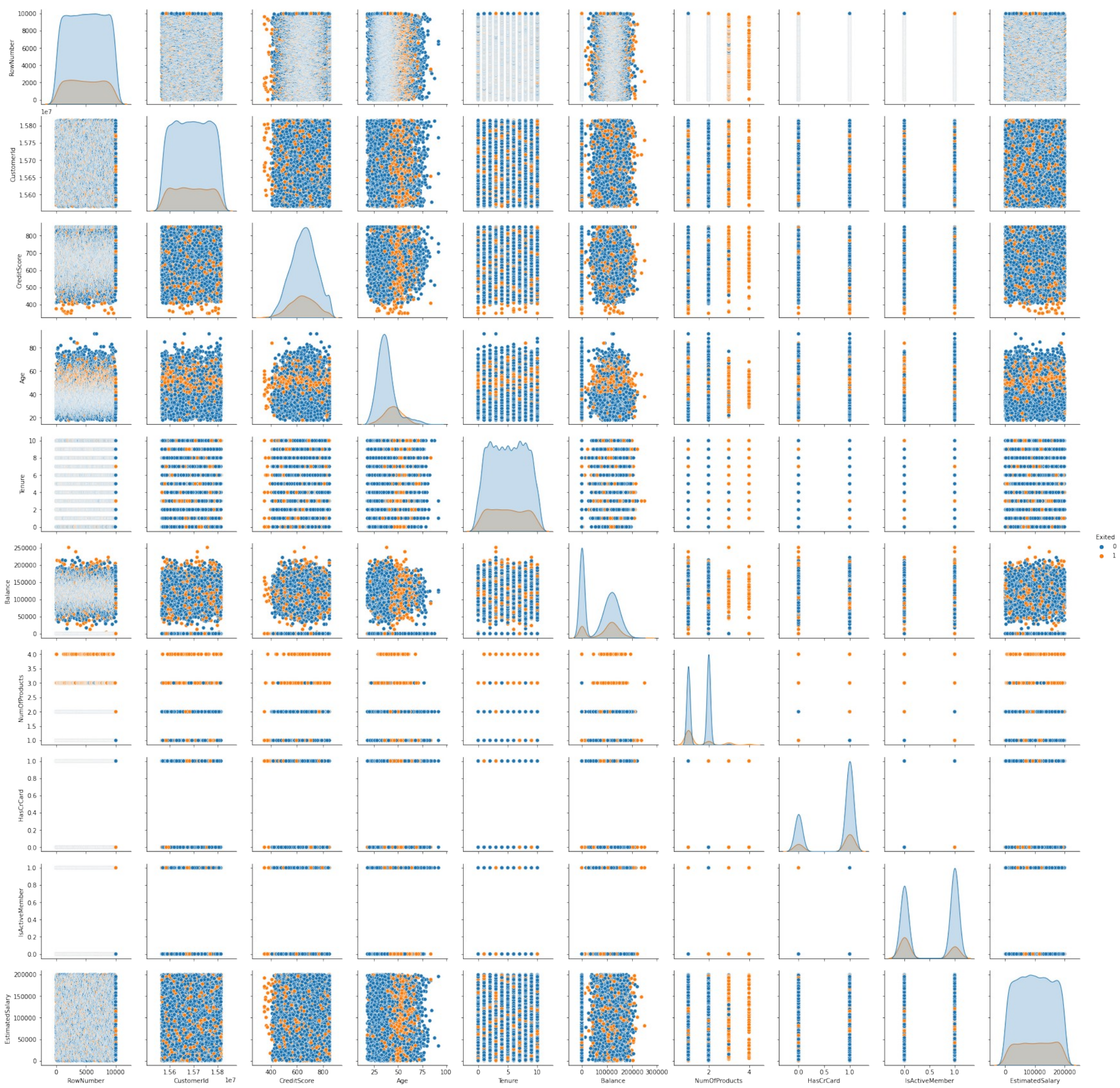
```
colors = ['cyan', 'magenta', 'orange']
sizes =  [311, 300, 153]
explode = [ 0.01, 0.01, 0.01]

plt.pie(sizes, colors = colors, labels = labels, explode = explode,
shadow = True)

plt.axis('equal')
plt.show()
```



3. Multi - Variate Analysis

```
sns.pairplot(data=data, hue='Exited')
```

```
<seaborn.axisgrid.PairGrid at 0x7f6a93ddd510>
```



Descriptive statistics

```
#Statistical analysis
data.describe()

         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
```

Handle the Missing values

```
#Missing Values
data.isnull().sum()
```

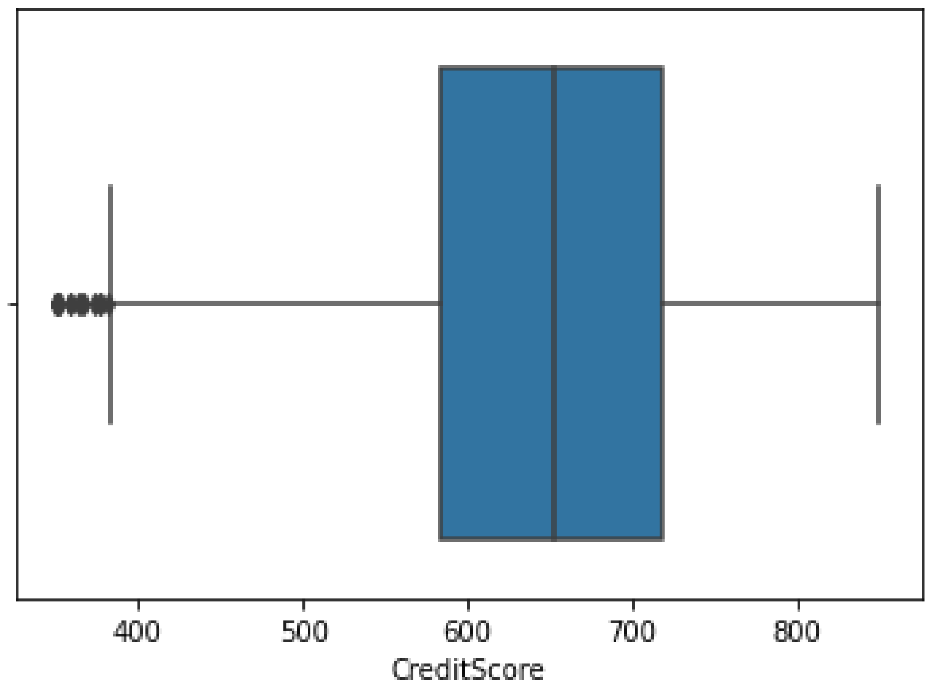
```
RowNumber          0
CustomerId         0
Surname            0
CreditScore        0
Geography          0
Gender             0
Age                0
Tenure             0
Balance            0
NumOfProducts      0
HasCrCard          0
IsActiveMember     0
EstimatedSalary    0
Exited             0
dtype: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

No missing values are found.

Find the outliers and replace the outliers

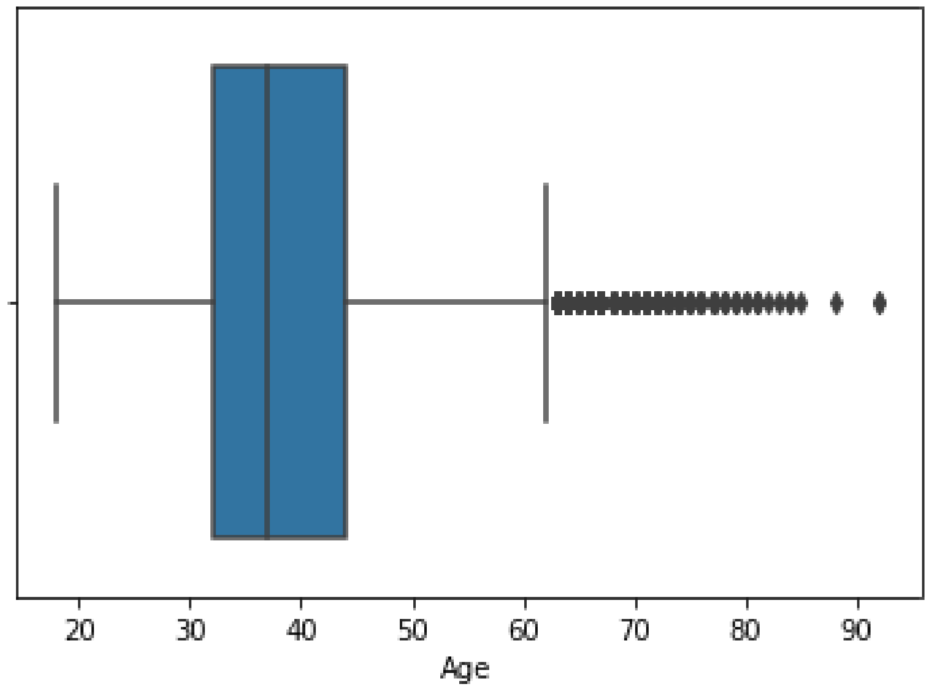
```
sns.boxplot(data = data, x = 'CreditScore')
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f6a8ecfe7d0>
```



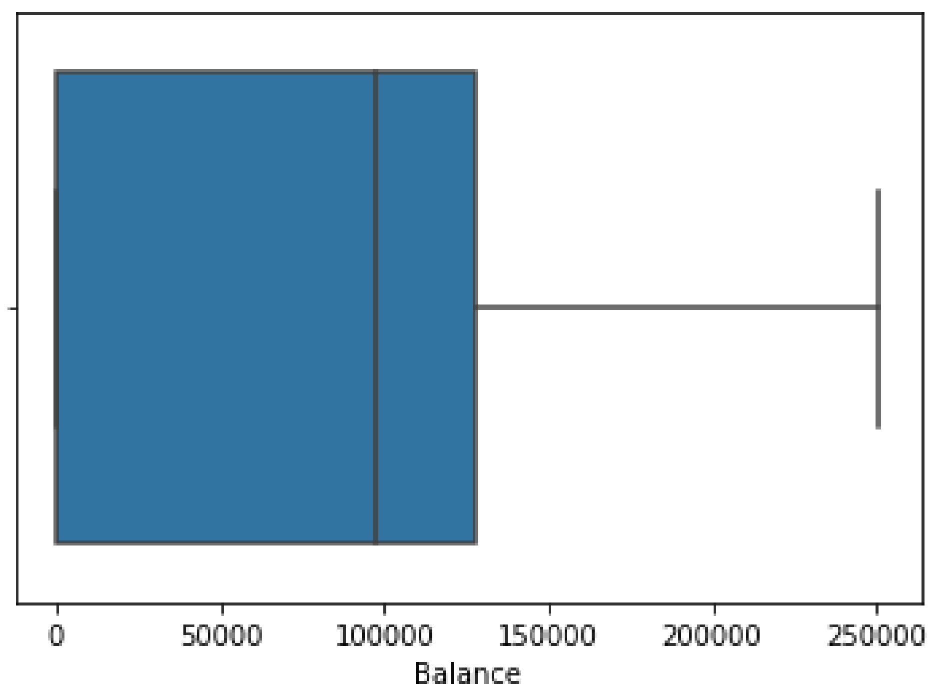

```
sns.boxplot(data = data, x = 'Age')
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f6a8e9a3f50>
```



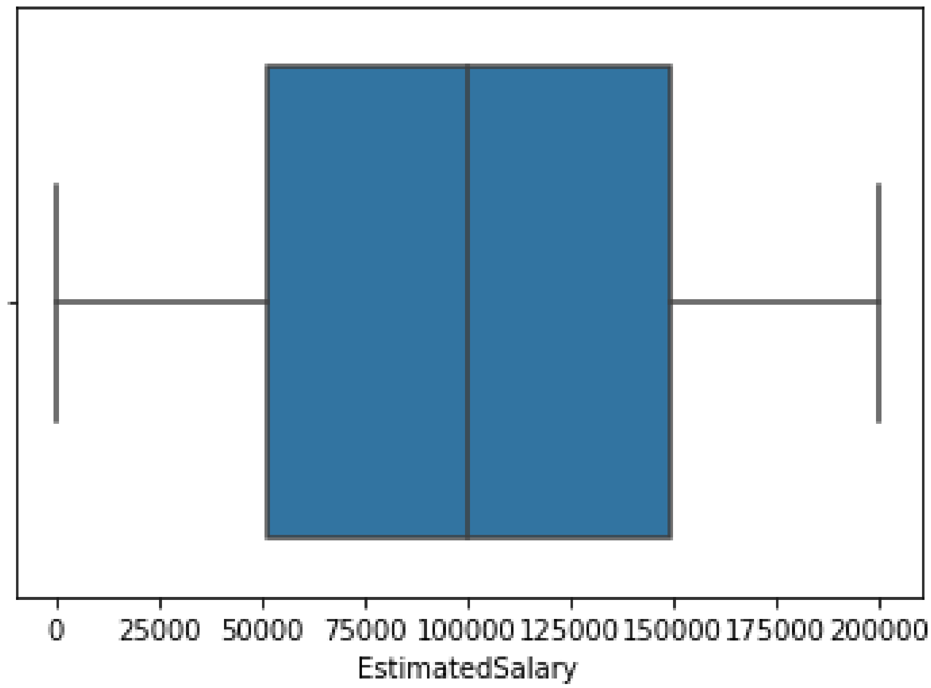

```
sns.boxplot(data = data, x = 'Balance')
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f6a8d0e0e90>
```




```
sns.boxplot(data = data, x = 'EstimatedSalary')
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f6a8d0e0c50>
```




```
for i in data:
    if data[i].dtype=='int64' or data[i].dtypes=='float64':
        q1=data[i].quantile(0.25)
        q3=data[i].quantile(0.75)
        iqr=q3-q1
        upper=q3+1.5*iqr
        lower=q1-1.5*iqr
        data[i]=np.where(data[i] >upper, upper, data[i])
        data[i]=np.where(data[i] <lower, lower, data[i])

data.describe()
```

```
         RowNumber    CustomerId   CreditScore           Age
Tenure  \
count  10000.00000  1.000000e+04  10000.000000  10000.000000
10000.000000
mean    5000.50000  1.569094e+07    650.561300     38.660800
5.012800
std     2886.89568  7.193619e+04     96.558702      9.746704
2.892174
min        1.00000  1.556570e+07    383.000000     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     62.000000
```

```
10.000000

             Balance  NumOfProducts    HasCrCard  IsActiveMember  \
count   10000.000000   10000.000000  10000.00000    10000.000000
mean    76485.889288       1.527200      0.70550        0.515100
std     62397.405202       0.570081      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       3.500000      1.00000        1.000000

       EstimatedSalary   Exited
count     10000.000000  10000.0
mean     100090.239881      0.0
std       57510.492818      0.0
min          11.580000      0.0
25%       51002.110000      0.0
50%      100193.915000      0.0
75%      149388.247500      0.0
max      199992.480000      0.0
```

Preprocessing

```
# Removing the unnecassary features from the dataset

data = data.drop(['CustomerId', 'Surname', 'RowNumber'], axis = 1)

print(data.columns)

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

data.shape

(10000, 11)
```

Split the data into dependent and independent variables

```
# splitting the dataset into x(independent variables) and y(dependent
variables)

x = data.iloc[:,0:10]
y = data.iloc[:,10]
```

```
print(x.shape)
print(y.shape)

print(x.columns)
```

```
(10000, 10)
(10000,)
Index(['CreditScore', 'Geography', 'Gender', 'Age', 'Tenure', 
'Balance',
       'NumOfProducts', 'HasCrCard', 'IsActiveMember', 
'EstimatedSalary'],
      dtype='object')
```

Check for Categorical columns and perform encoding

```
# Encoding Categorical variables into numerical variables
# One Hot Encoding

x = pd.get_dummies(x)

x.head()
```

```
   CreditScore   Age  Tenure    Balance  NumOfProducts  HasCrCard  \
0        619.0  42.0     2.0       0.00            1.0        1.0   
1        608.0  41.0     1.0   83807.86            1.0        0.0   
2        502.0  42.0     8.0  159660.80            3.0        1.0   
3        699.0  39.0     1.0       0.00            2.0        0.0   
4        850.0  43.0     2.0  125510.82            1.0        1.0   

   IsActiveMember  EstimatedSalary  Geography_France  
Geography_Germany  \
0             1.0        101348.88                 1                  
0   
1             1.0        112542.58                 0                  
0   
2             0.0        113931.57                 1                  
0   
3             0.0         93826.63                 1                  
0   
4             1.0         79084.10                 0                  
0   

   Geography_Spain  Gender_Female  Gender_Male  
0                0              1            0  
1                1              1            0  
2                0              1            0  
3                0              1            0  
4                1              1            0  
```

Split the data into training and testing

```
# splitting the data into training and testing set

from sklearn.model_selection import train_test_split
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size =
0.25, random_state = 0)

print(x_train.shape)
print(y_train.shape)
print(x_test.shape)
print(y_test.shape)
```

```
(7500, 13)
(7500,)
(2500, 13)
(2500,)
```

Scale the independent variables

```
# Feature Scaling
# Only on Independent Variable to convert them into values ranging
from -1 to +1

from sklearn.preprocessing import StandardScaler

sc = StandardScaler()
x_train = sc.fit_transform(x_train)
x_test = sc.fit_transform(x_test)

x_train = pd.DataFrame(x_train)
x_train.head()
```

```
         0         1         2         3         4         5         6
\
0 -0.736828  0.042283  0.008860  0.673160  2.583231 -1.553624 -
1.034460
1  1.025257 -0.674496  0.008860 -1.207724  0.822578  0.643657 -
1.034460
2  0.808861 -0.469702  1.393293 -0.356937  0.822578  0.643657
0.966688
3  0.396677 -0.060114  0.008860 -0.009356 -0.938076  0.643657
0.966688
4 -0.468908  1.373444  0.701077 -1.207724  0.822578  0.643657
0.966688

         7         8         9        10        11        12
0 -1.640810 -1.015588  1.760216 -0.574682  1.087261 -1.087261
1 -0.079272  0.984651 -0.568112 -0.574682  1.087261 -1.087261
2 -0.996840 -1.015588 -0.568112  1.740094  1.087261 -1.087261
```

3	-1.591746	-1.015588	-0.568112	1.740094	-0.919743	0.919743
4	1.283302	0.984651	-0.568112	-0.574682	-0.919743	0.919743