Assignment Date: 21 September 2022

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Maximum Marks: 2 Marks

1.Download the dataset from the source here.

About the dataset:

This dataset is all about churn modelling of a credit company. It has the details about the end user who are using credit card and also it has some variables to depicit the churn of the customer.

RowNumber - Serial number of the rows
CustomerId - Unique identification of customer
Surname - Name of the customer
CreditScore - Cipil score of the customer
Geography - Location of the bank
Gender - Sex of the customer
Age - Age of the customer
Tenure - Repayment period for the credit amount
Balance - Current balance in thier creidt card
NumOfProducts - Products owned by the customer from the company
HasCrCard - Has credit card or not (0 - no , 1 - yes)
IsactiveMember - Is a active member or not
EstimatedSalary - Salary of the customer
Exited - Churn of the customer

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

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

2. Load the dataset

```
df = pd.read_csv("Churn_Modelling.csv")
df.head()
```

	RowNumber	CustomerId	Surname	CreditScore	Geography	Gender	Age	Tenure	Balan
0	1	15634602	Hargrave	619	France	Female	42	2	0.0
1	2	15647311	Hill	608	Spain	Female	41	1	83807.8
2	3	15619304	Onio	502	France	Female	42	8	159660.8
3	4	15701354	Boni	699	France	Female	39	1	0.0
4	5	15737888	Mitchell	850	Spain	Female	43	2	125510.8

```
df.tail()
```

	RowNumber	CustomerId	Surname	CreditScore	Geography	Gender	Age	Tenure	Ba
9995	9996	15606229	Obijiaku	771	France	Male	39	5	
9996	9997	15569892	Johnstone	516	France	Male	35	10	57
9997	9998	15584532	Liu	709	France	Female	36	7	
9998	9999	15682355	Sabbatini	772	Germany	Male	42	3	75
9999	10000	15628319	Walker	792	France	Female	28	4	130

3 a). Univariate analysis

```
#checking for categorical variables
category = df.select_dtypes(include=[np.object])
print("Categorical Variables: ",category.shape[1])

#checking for numerical variables
numerical = df.select_dtypes(include=[np.int64,np.float64])
print("Numerical Variables: ",numerical.shape[1])
```

```
Categorical Variables:  3
Numerical Variables:  11
```

```
df.columns
```

```
Index(['RowNumber', 'CustomerId', 'Surname', 'CreditScore', 'Geography',
       'Gender', 'Age', 'Tenure', 'Balance', 'NumOfProducts', 'HasCrCard',
```

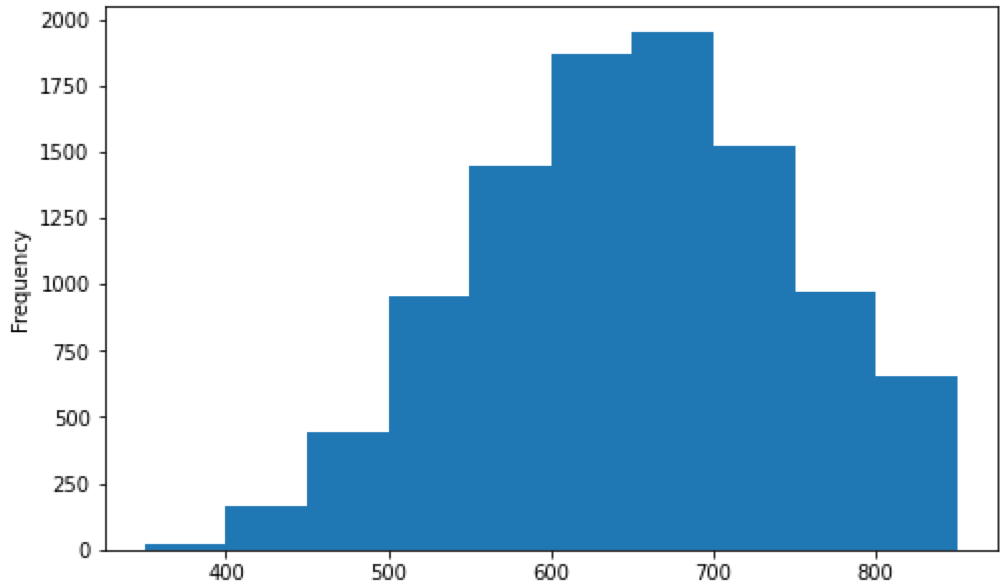
```
            'IsActiveMember', 'EstimatedSalary', 'Exited'],
           dtype='object')
```

```
df.shape
```

```
(10000, 14)
```

```
credit = df['CreditScore']
credit.plot(kind="hist",figsize=(8,5))
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fa6f232c310>
```

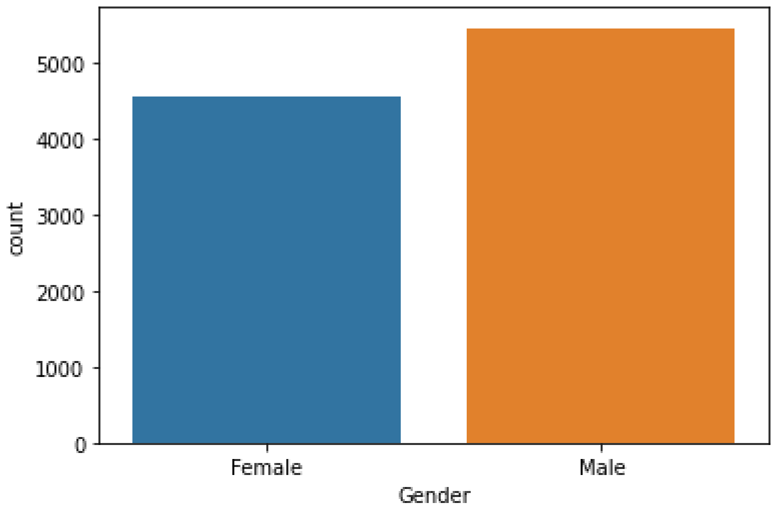



```
geo = df['Geography'].value_counts()
geo.plot(kind="pie",figsize=(10,8))
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fa6f1ddc190>
```

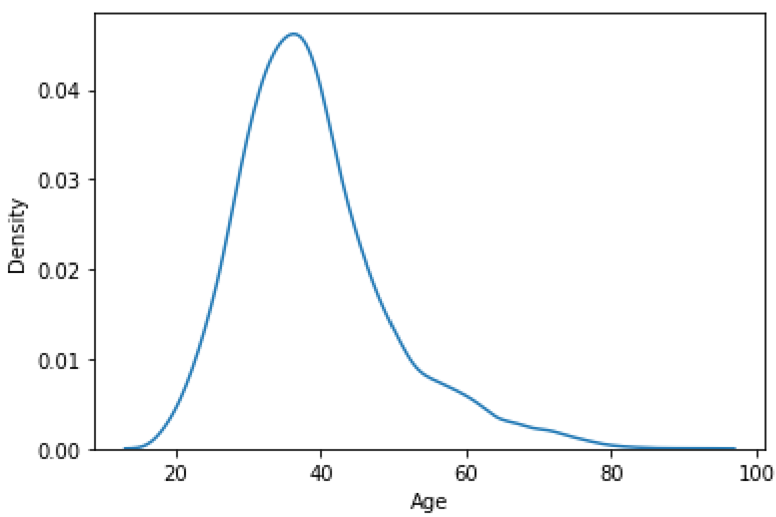

```
sns.countplot(df['Gender'])
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fa6f228a090>
```



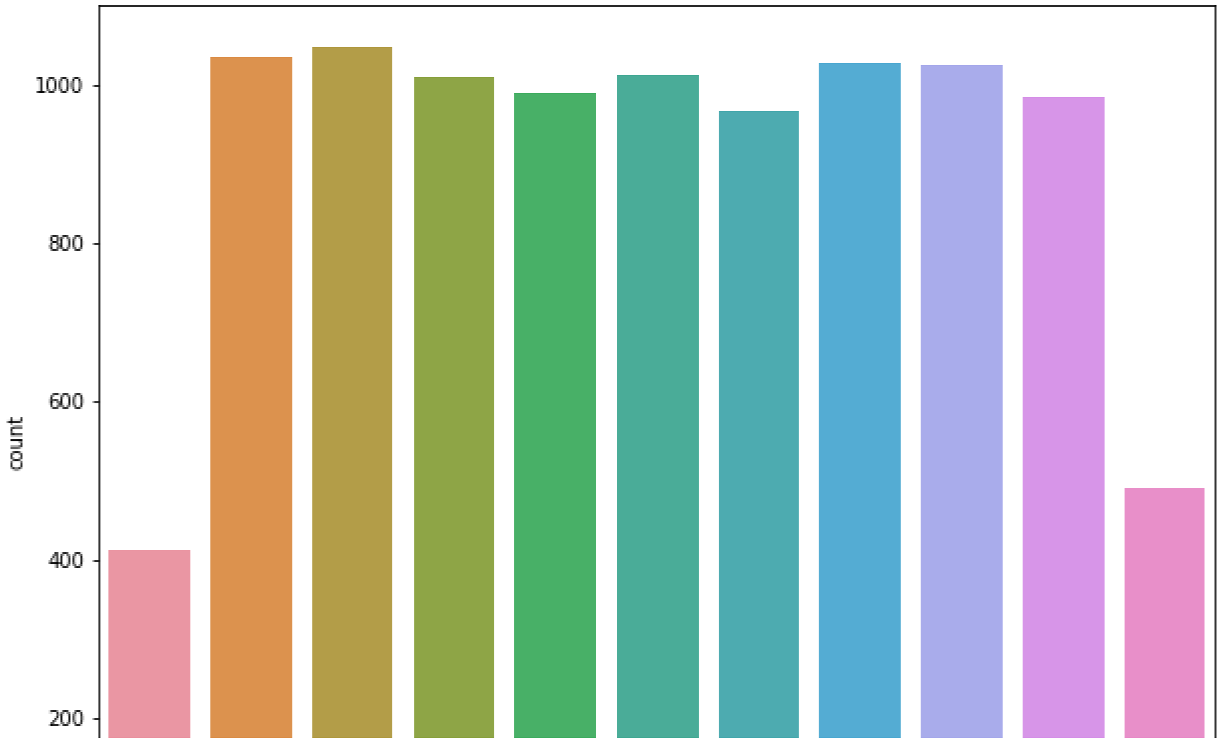

```
sns.distplot(df['Age'],hist=False)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fa6f1d8f310>
```



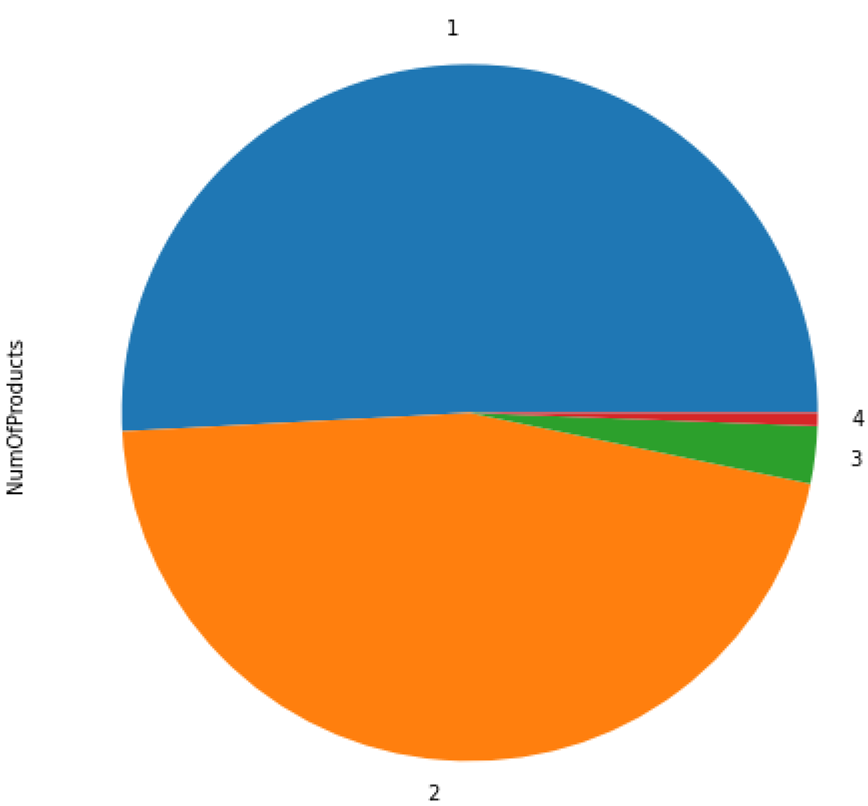

```
plt.figure(figsize=(10,8))
sns.countplot(df['Tenure'])
```

<matplotlib.axes._subplots.AxesSubplot at 0x7fa6f1d0e310>




```
product = df['NumOfProducts'].value_counts()
product.plot(kind="pie",figsize=(10,8))
```

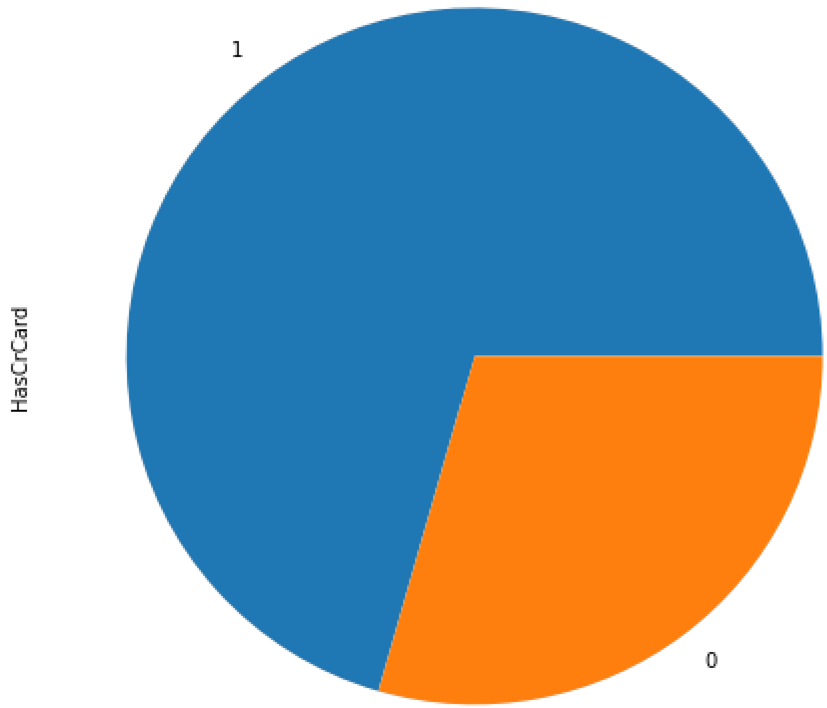
<matplotlib.axes._subplots.AxesSubplot at 0x7fa6f1c70d10>




```
cr = df['HasCrCard'].value_counts()
```

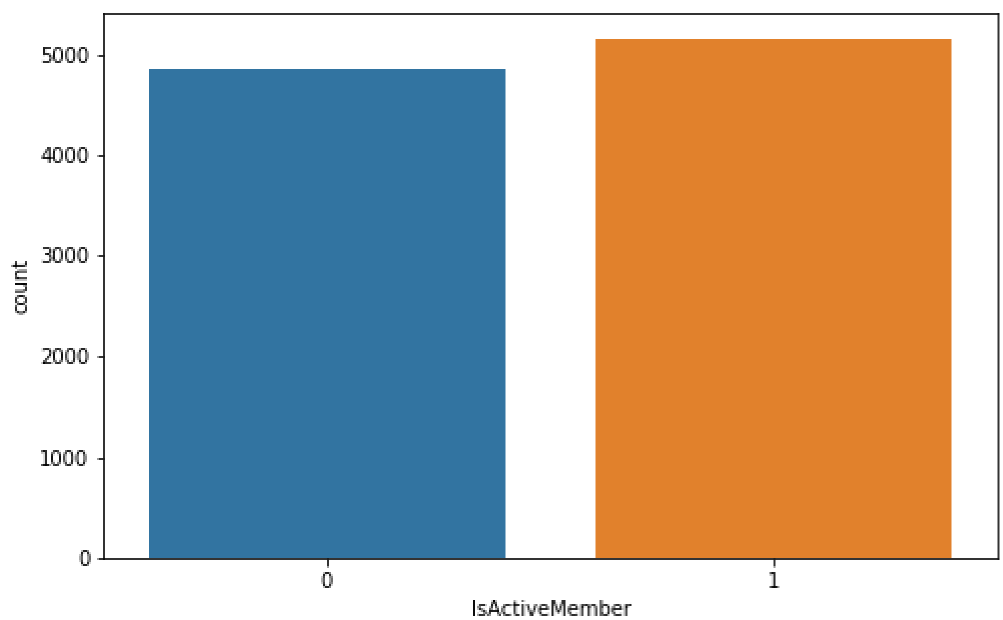
```
cr.plot(kind="pie",figsize=(10,8))
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fa6f1bd6b10>
```



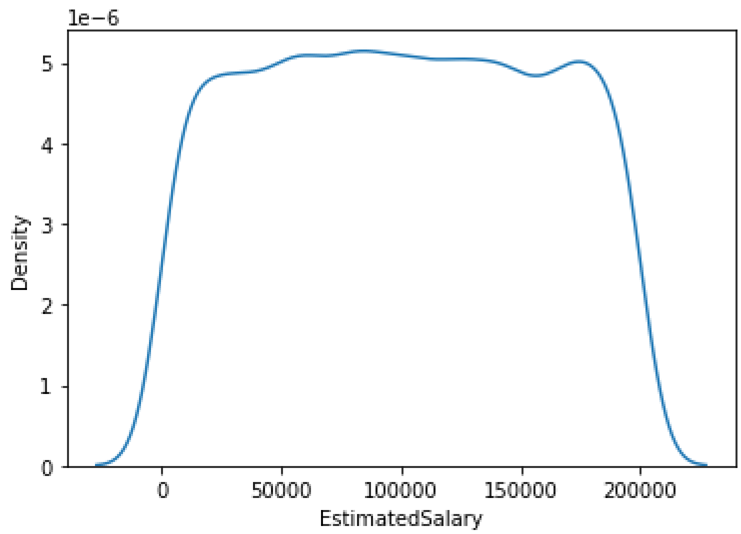

```
plt.figure(figsize=(8,5))
sns.countplot(df['IsActiveMember'])
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fa6f1b7e590>
```



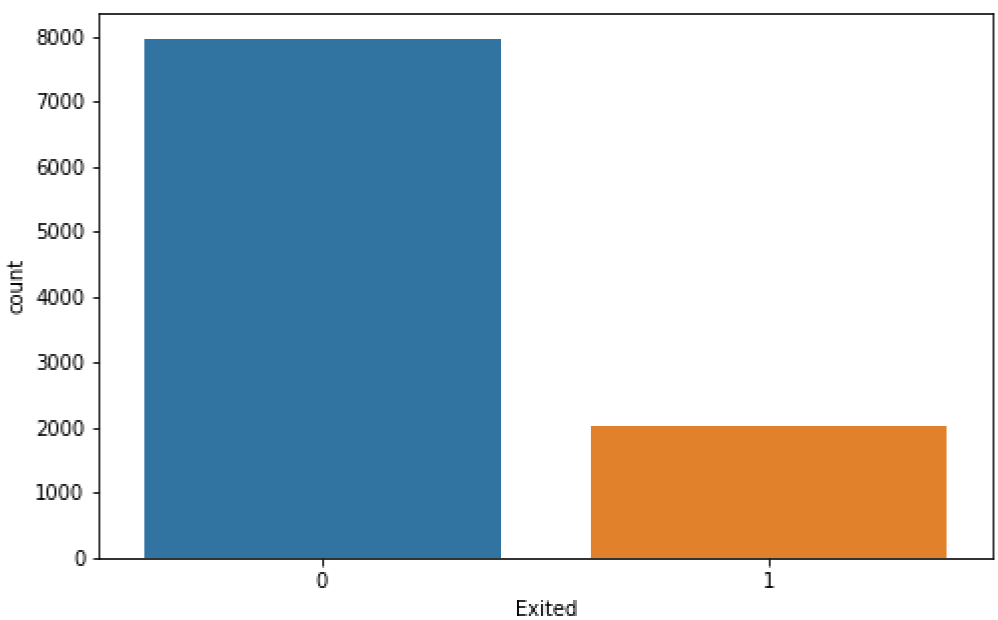

```
sns.distplot(df['EstimatedSalary'],hist=False)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fa6f1afe090>
```




```
plt.figure(figsize=(8,5))
sns.countplot(df['Exited'])
```

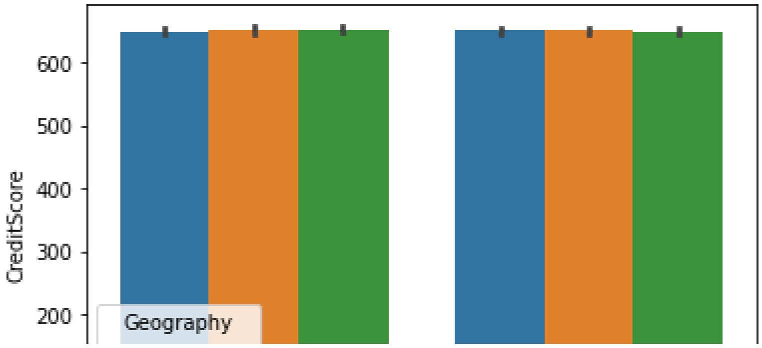
```
<matplotlib.axes._subplots.AxesSubplot at 0x7fa6f1a75210>
```



3 b). Bivariate analysis

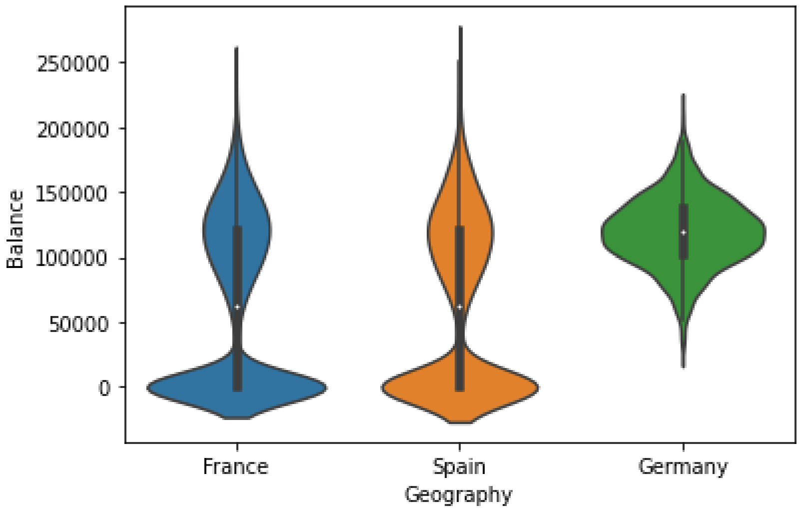
```
sns.barplot(x='Gender',y='CreditScore',hue='Geography',data=df)
```

<matplotlib.axes._subplots.AxesSubplot at 0x7fa6f1a33710>



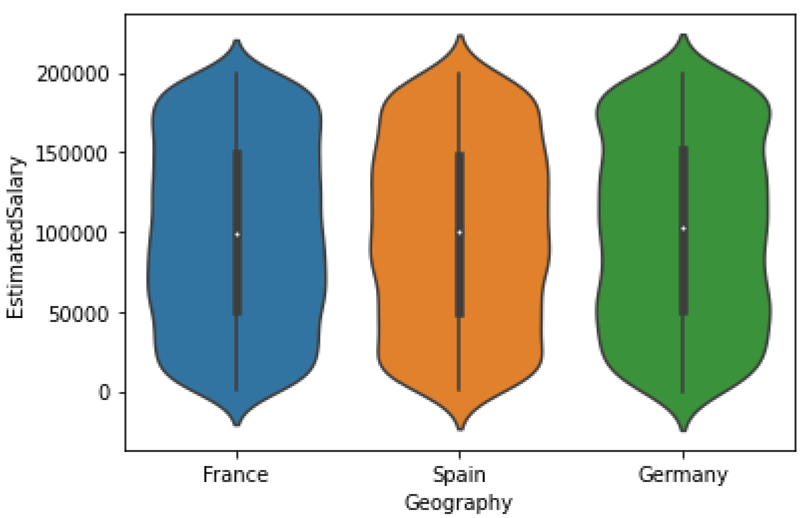

```
sns.violinplot(x='Geography',y='Balance',data=df)
```

<matplotlib.axes._subplots.AxesSubplot at 0x7fa6f1969ed0>



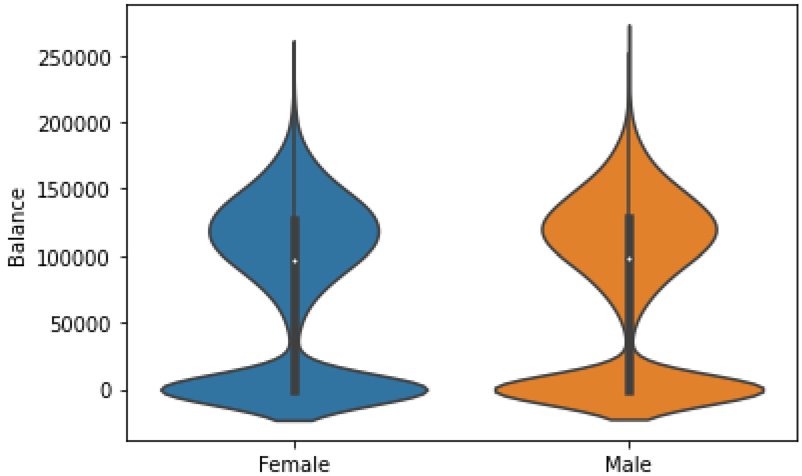

```
sns.violinplot(x='Geography',y='EstimatedSalary',data=df)
```

<matplotlib.axes._subplots.AxesSubplot at 0x7fa6f18f3450>



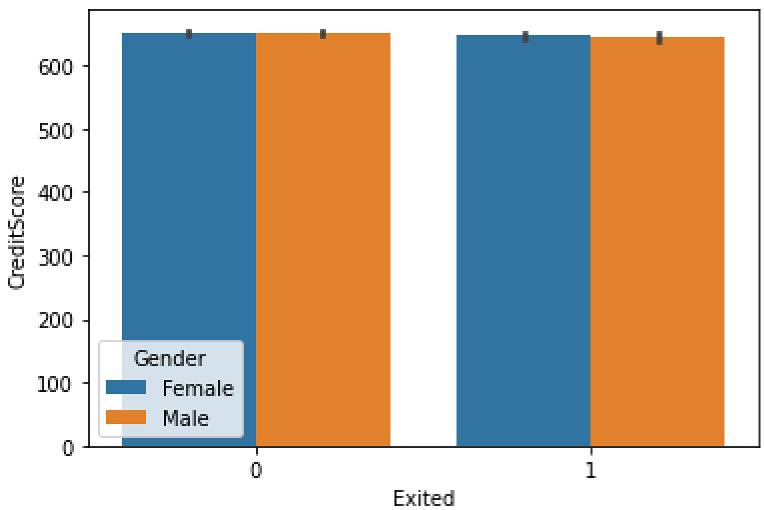

```
sns.violinplot(x='Gender',y='Balance',data=df)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fa6f186ce50>
```



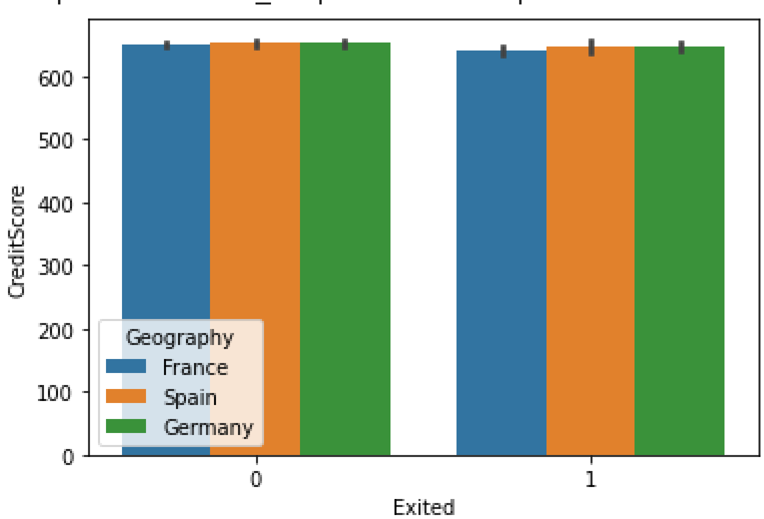

```
sns.barplot(x='Exited',y='CreditScore',hue='Gender',data=df)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fa6f1849d10>
```




```
sns.barplot(x='Exited',y='CreditScore',hue='Geography',data=df)
```

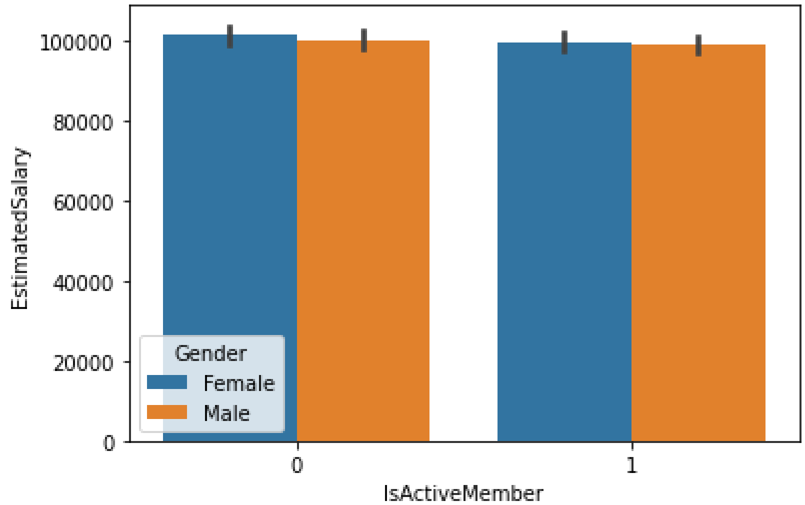
```
<matplotlib.axes._subplots.AxesSubplot at 0x7fa6f173e6d0>
```




```
sns.barplot(x='IsActiveMember',y='EstimatedSalary',hue='Gender',data=df)
```

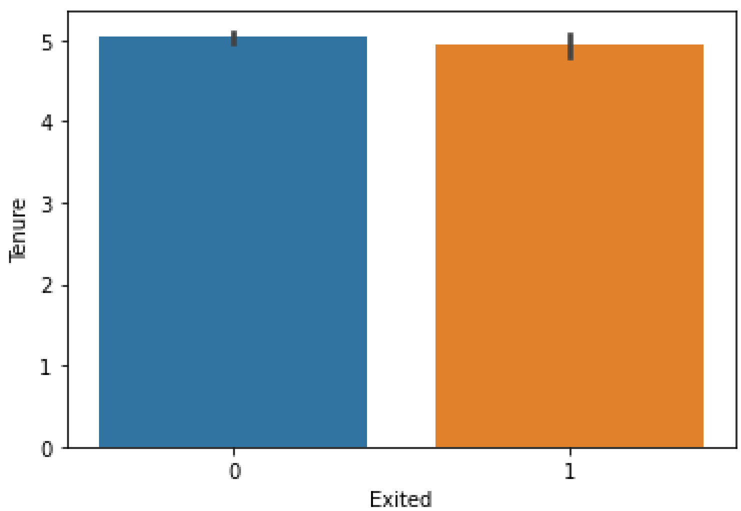
```
sns.barplot(x='IsActiveMember',y='EstimatedSalary',hue='Gender',data=df)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fa6f1a44390>
```




```
sns.barplot(x='Exited',y='Tenure',data=df)
```

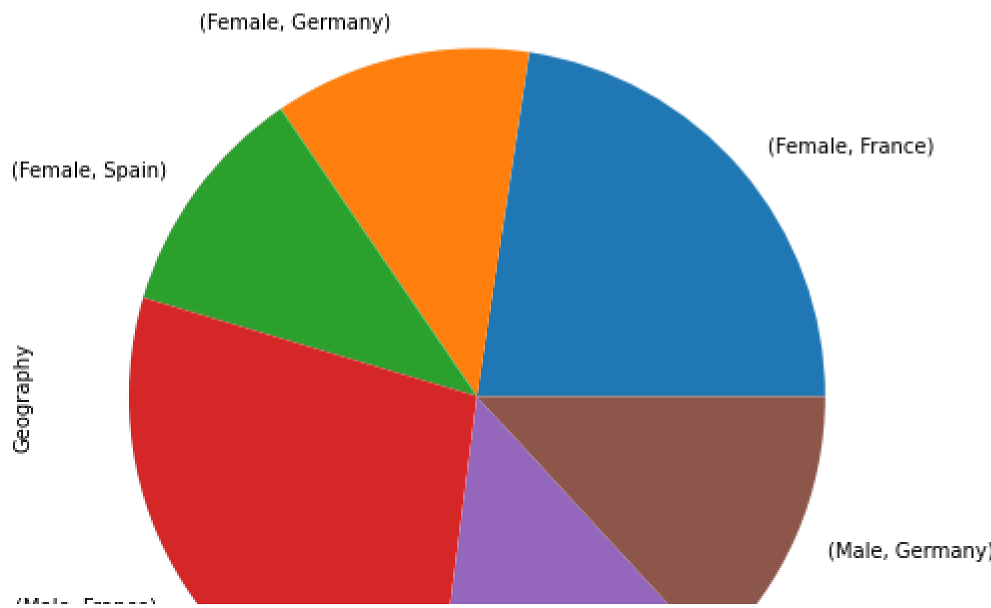
```
<matplotlib.axes._subplots.AxesSubplot at 0x7fa6f1a556d0>
```



3 c). Multivariate analysis

```
gp1 = df.groupby('Gender')['Geography'].value_counts()
gp1.plot(kind='pie',figsize=(10,8))
print(gp1)
```

```
Gender  Geography
Female  France       2261
        Germany      1193
        Spain        1089
Male    France       2753
        Spain        1388
        Germany      1316
Name: Geography, dtype: int64
```




```
gp2 = df.groupby('Gender')['Age'].mean()
print(gp2)
```

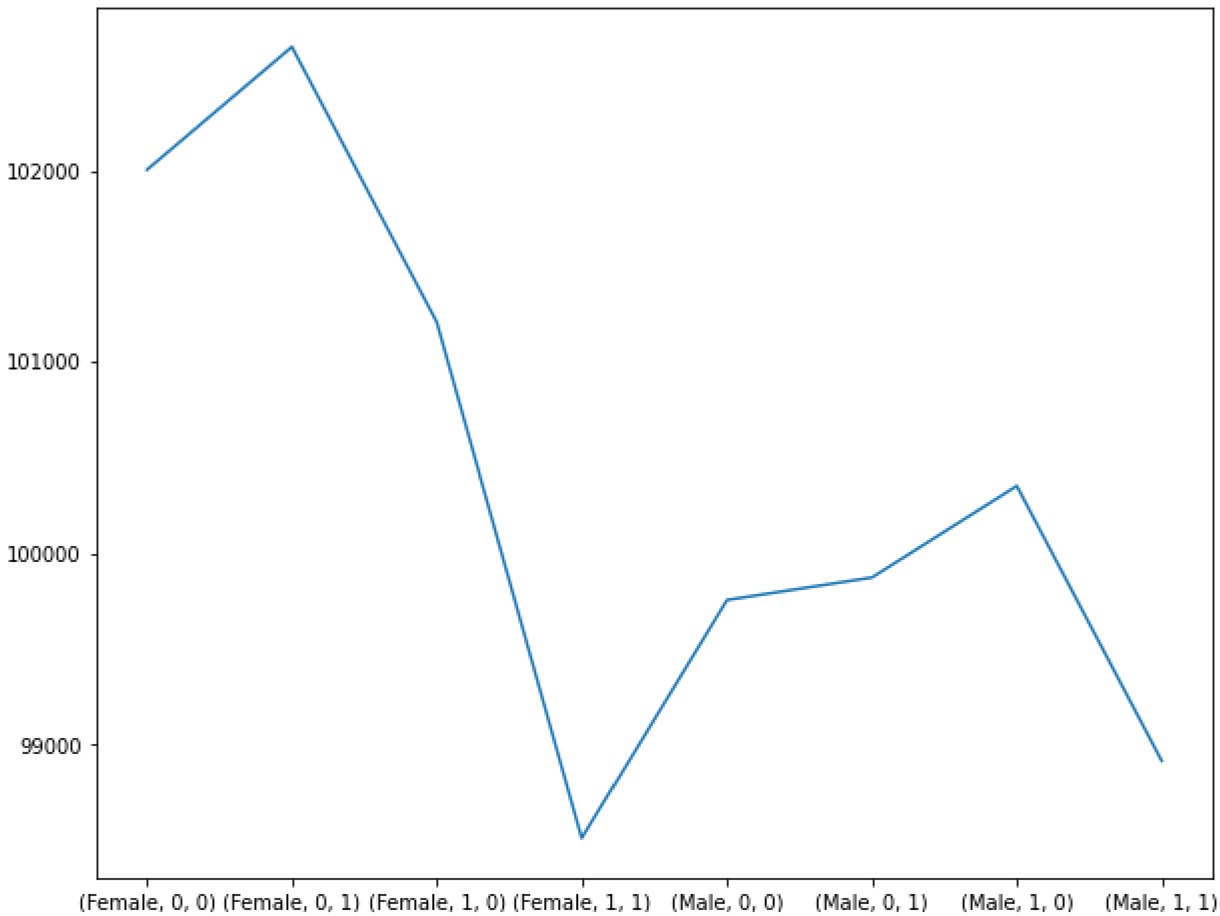
```
Gender
Female    39.238389
Male      38.658237
Name: Age, dtype: float64
```

```
gp3 = df.groupby(['Gender','Geography'])['Tenure'].mean()
print(gp3)
```

```
Gender  Geography
Female  France       4.950022
        Germany      4.965633
        Spain        5.000000
Male    France       5.049401
        Germany      5.050152
        Spain        5.057637
Name: Tenure, dtype: float64
```

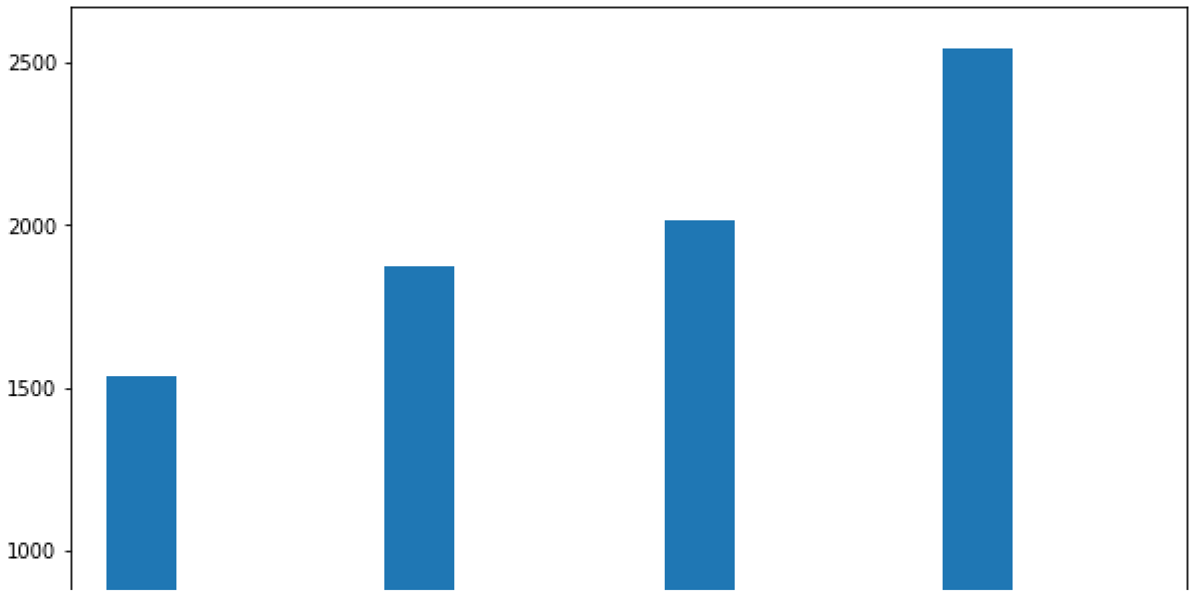
```
gp4 = df.groupby(['Gender','HasCrCard','IsActiveMember'])['EstimatedSalary'].mean()
gp4.plot(kind="line",figsize=(10,8))
print(gp4)
```

```
Gender  HasCrCard  IsActiveMember
Female  0          0                 102006.080352
                   1                 102648.996944
        1          0                 101208.014567
                   1                  98510.152300
Male    0          0                  99756.431151
                   1                  99873.931251
        1          0                 100353.378996
                   1                  98914.378703
Name: EstimatedSalary, dtype: float64
```




```
gp5 = df.groupby(['Gender','IsActiveMember'])['Exited'].value_counts()
gp5.plot(kind='bar',figsize=(10,8))
print(gp5)
```

```
Gender  IsActiveMember  Exited
Female  0               0         1534
                        1          725
        1               0         1870
                        1          414
Male    0               0         2013
                        1          577
        1               0         2546
                        1          321
Name: Exited, dtype: int64
```




```
gp6 = df.groupby('Exited')['Balance','EstimatedSalary'].mean()
print(gp6)
```

```
             Balance  EstimatedSalary
Exited
0       72745.296779     99738.391772
1       91108.539337    101465.677531
```

4. Descriptive statistics

```
df.describe().T
```

	count	mean	std	min	25%	50
RowNumber	10000.0	5.000500e+03	2886.895680	1.00	2500.75	5.000500e+0
CustomerId	10000.0	1.569094e+07	71936.186123	15565701.00	15628528.25	1.569074e+0
CreditScore	10000.0	6.505288e+02	96.653299	350.00	584.00	6.520000e+0
Age	10000.0	3.892180e+01	10.487806	18.00	32.00	3.700000e+0
Tenure	10000.0	5.012800e+00	2.892174	0.00	3.00	5.000000e+0

5. Handling the missing values

```
df.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
```

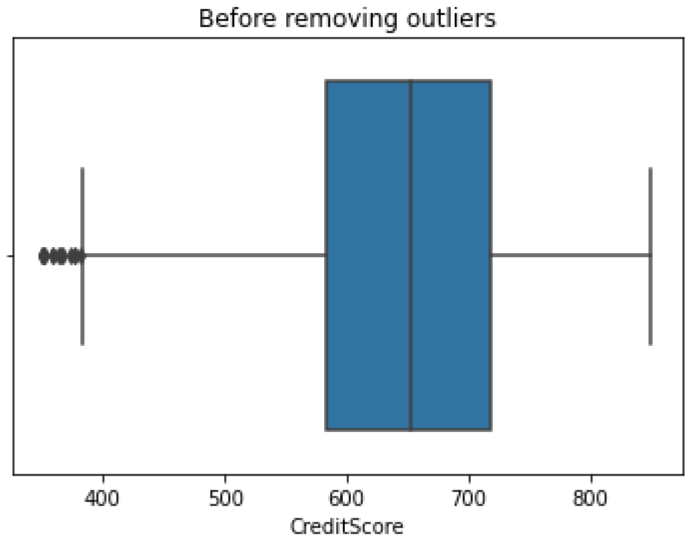
There is no missing value in the dataset

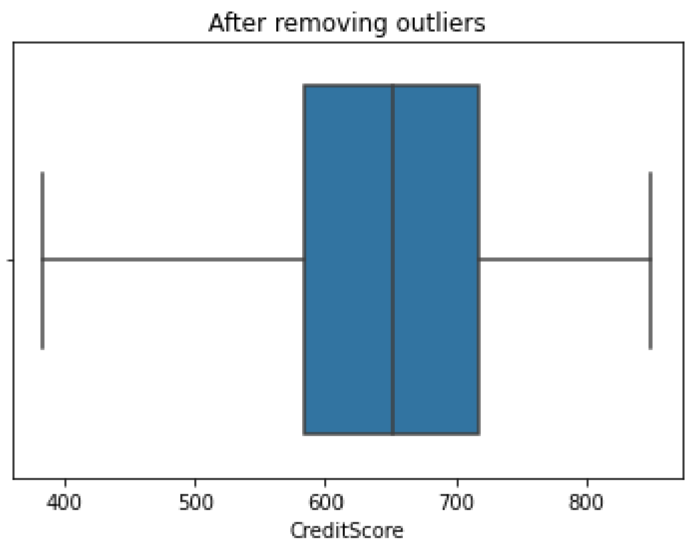
6. Finding outliers

```
def replace_outliers(df, field_name):
    Q1 = np.percentile(df[field_name],25,interpolation='midpoint')
    Q3 = np.percentile(df[field_name],75,interpolation='midpoint')
    IQR = Q3-Q1
    maxi = Q3+1.5*IQR
    mini = Q1-1.5*IQR
    df[field_name]=df[field_name].mask(df[field_name]>maxi,maxi)
    df[field_name]=df[field_name].mask(df[field_name]<mini,mini)
```

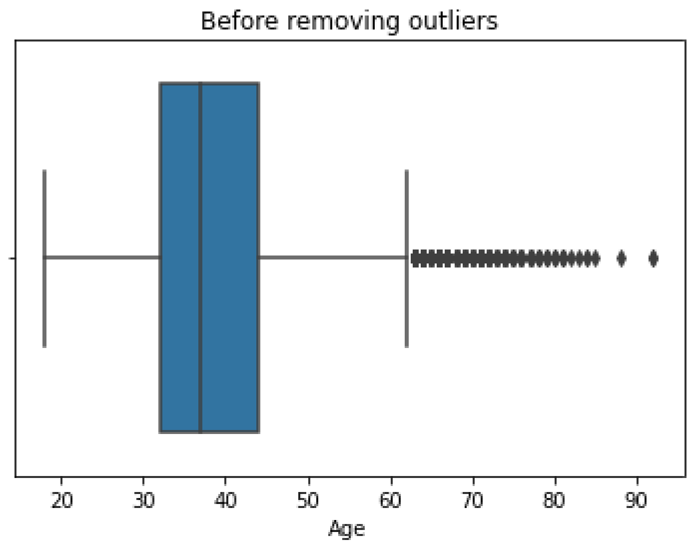
```
plt.title("Before removing outliers")
sns.boxplot(df['CreditScore'])
plt.show()
```

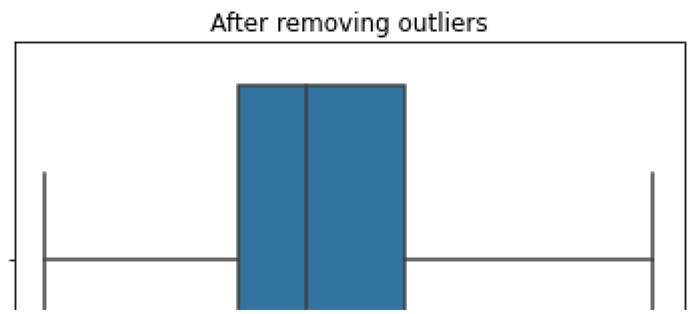
```
plt.show()
plt.title("After removing outliers")
replace_outliers(df, 'CreditScore')
sns.boxplot(df['CreditScore'])
plt.show()
```





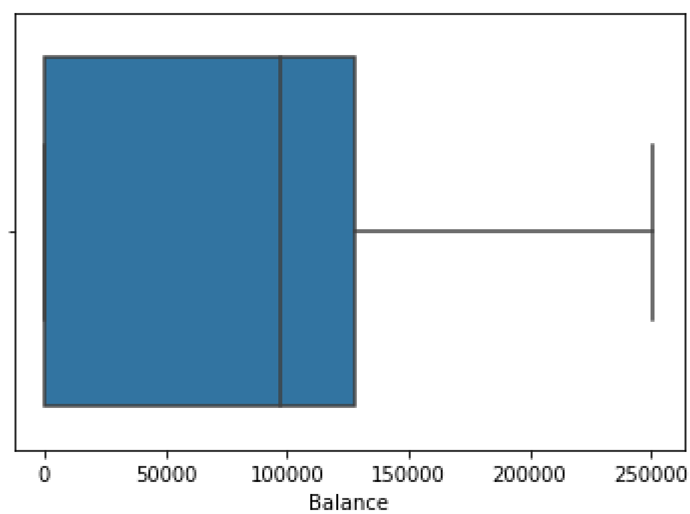

```
plt.title("Before removing outliers")
sns.boxplot(df['Age'])
plt.show()
plt.title("After removing outliers")
replace_outliers(df, 'Age')
sns.boxplot(df['Age'])
plt.show()
```





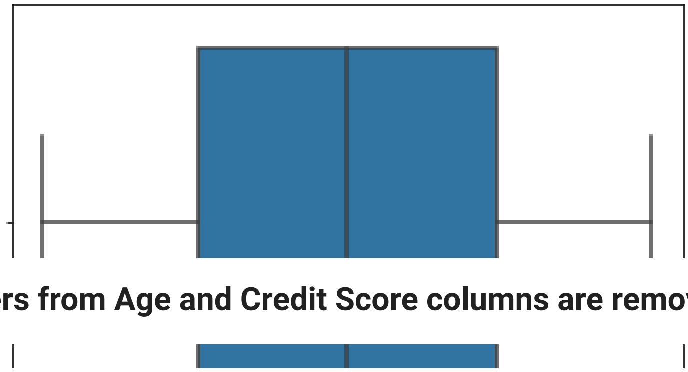

```
sns.boxplot(df['Balance'])
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fa6f07bb390>
```




```
sns.boxplot(df['EstimatedSalary'])
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fa6f071efd0>
```



Outliers from Age and Credit Score columns are removed

7. Check for categorical column and perform encoding.

```
from sklearn.preprocessing import LabelEncoder
le = LabelEncoder()
```

```
df['Gender'] = le.fit_transform(df['Gender'])
df['Geography'] = le.fit_transform(df['Geography'])
```

```
df.head()
```

	RowNumber	CustomerId	Surname	CreditScore	Geography	Gender	Age	Tenure	Balan
0	1	15634602	Hargrave	619.0	0	0	42.0	2	0.
1	2	15647311	Hill	608.0	2	0	41.0	1	83807.
2	3	15619304	Onio	502.0	0	0	42.0	8	159660.
3	4	15701354	Boni	699.0	0	0	39.0	1	0.
4	5	15737888	Mitchell	850.0	2	0	43.0	2	125510.

Only two columns(Gender and Geography) is label encoded

Removing unwanted columns and checking for feature importance

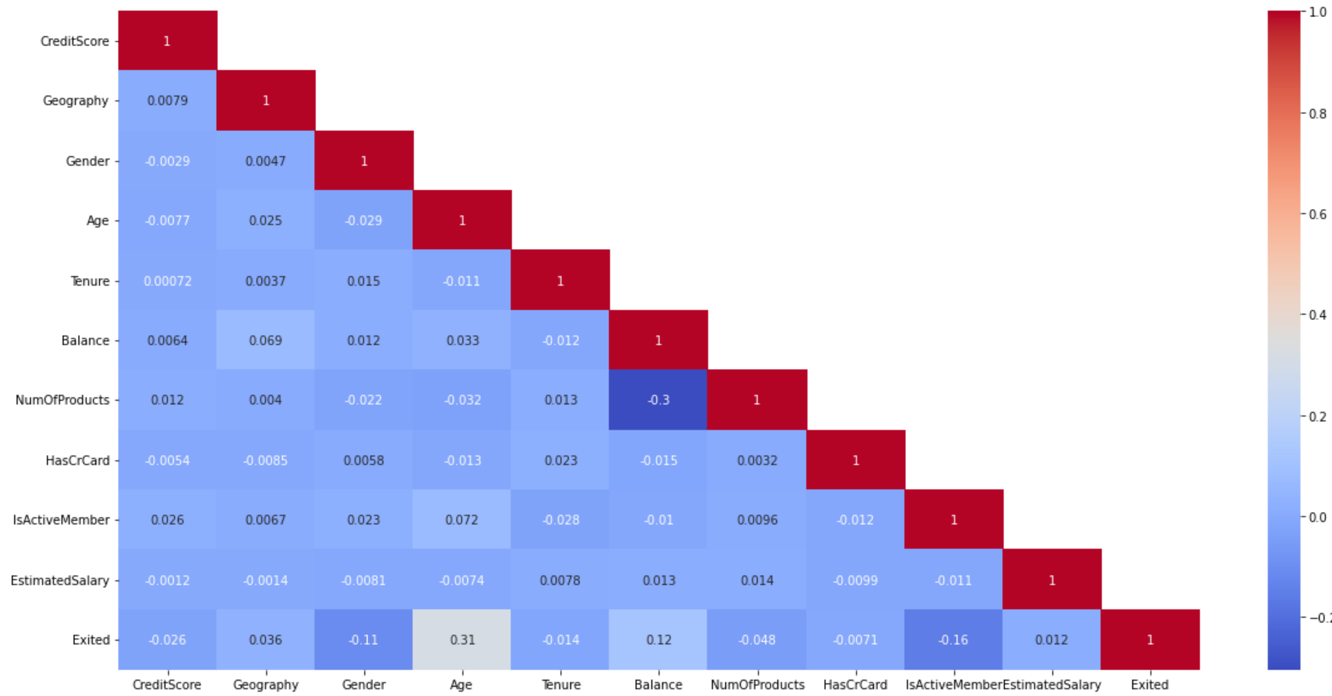
```
df = df.drop(['RowNumber','CustomerId','Surname'],axis=1)
```

```
df.head()
```

	CreditScore	Geography	Gender	Age	Tenure	Balance	NumOfProducts	HasCrCard	Is
0	619.0	0	0	42.0	2	0.00	1	1	
1	608.0	2	0	41.0	1	83807.86	1	0	
2	502.0	0	0	42.0	8	159660.80	3	1	
3	699.0	0	0	39.0	1	0.00	2	0	
4	850.0	2	0	43.0	2	125510.82	1	1	

```
plt.figure(figsize=(20,10))
df_lt = df.corr(method = "pearson")
df_lt1 = df_lt.where(np.tril(np.ones(df_lt.shape)).astype(np.bool))
sns.heatmap(df_lt1,annot=True,cmap="coolwarm")
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fa6efded450>
```



1. The Removed columns are nothing to do with model building.

2. Feature importance also checked using pearson correlation.

8. Data Splitting

```
target = df['Exited']
data = df.drop(['Exited'],axis=1)
```

```
print(data.shape)
print(target.shape)
```

```
(10000, 10)
(10000,)
```

9. Scaling the independent values

```
from sklearn.preprocessing import StandardScaler
se = StandardScaler()
```

```
data['CreditScore'] = se.fit_transform(pd.DataFrame(data['CreditScore']))
data['Age'] = se.fit_transform(pd.DataFrame(data['Age']))
data['Balance'] = se.fit_transform(pd.DataFrame(data['Balance']))
data['EstimatedSalary'] = se.fit_transform(pd.DataFrame(data['EstimatedSalary']))
```

```
data.head()
```

	CreditScore	Geography	Gender	Age	Tenure	Balance	NumOfProducts	HasCrCard
0	-0.326878	0	0	0.342615	2	-1.225848	1	1
1	-0.440804	2	0	0.240011	1	0.117350	1	0
2	-1.538636	0	0	0.342615	8	1.333053	3	1
3	0.501675	0	0	0.034803	1	-1.225848	2	0
4	2.065569	2	0	0.445219	2	0.785728	1	1

10. Train test split

```
from sklearn.model_selection import train_test_split
X_train,X_test,y_train,y_test = train_test_split(data,target,test_size=0.25,random_state=101)

print(X_train.shape)
print(X_test.shape)
print(y_train.shape)
print(y_test.shape)
```

```
(7500, 10)
(2500, 10)
(7500,)
(2500,)
```