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Date: 21\09\2022

1.Download the dataset from the source

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
0	1	15634602	Hargrave	619	France	Female	42	2
1	2	15647311	Hill	608	Spain	Female	41	1
2	3	15619304	Onio	502	France	Female	42	8
3	4	15701354	Boni	699	France	Female	39	1
4	5	15737888	Mitchell	850	Spain	Female	43	2

```
df.tail()
```

	RowNumber	CustomerId	Surname	CreditScore	Geography	Gender	Age	Tenu
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	

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
```

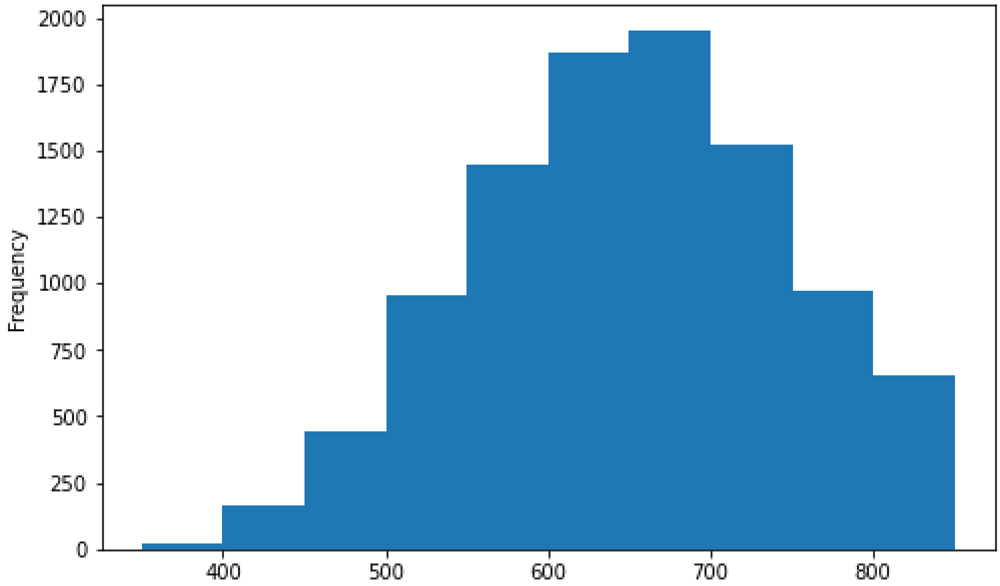
```
Index(['RowNumber', 'CustomerId', 'Surname', 'CreditScore', 'Geography',
       'Gender', 'Age', 'Tenure', 'Balance', 'NumOfProducts', 'HasCrCard',
       'IsActiveMember', 'EstimatedSalary', 'Exited'],
      dtype='object')
```

```
df.shape
```

```
(10000, 14)
```

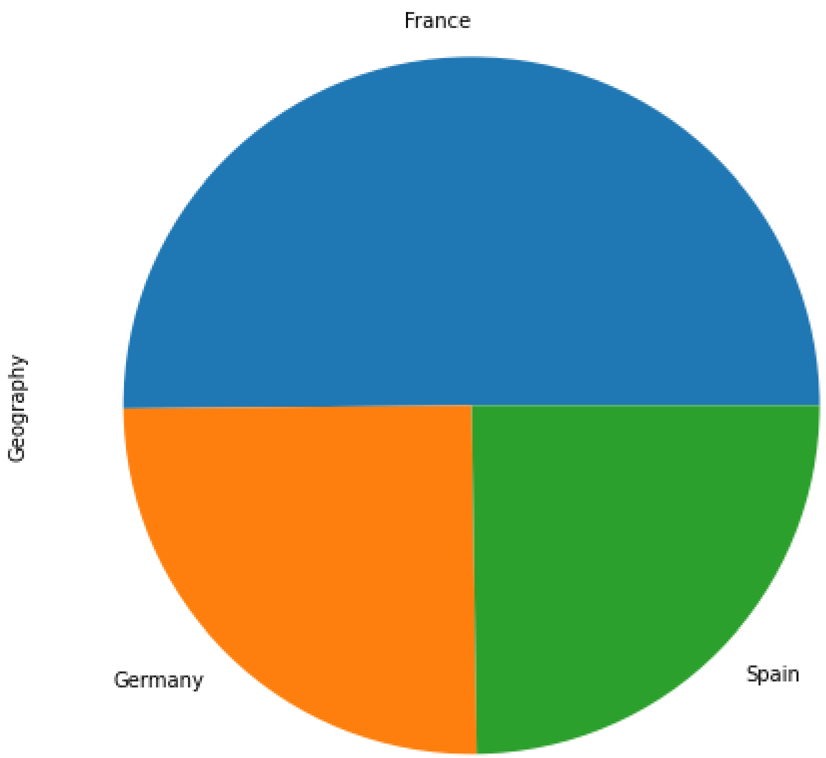
```
credit = df['CreditScore']
credit.plot(kind="hist",figsize=(8,5))
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f8f1c4c5d90>
```



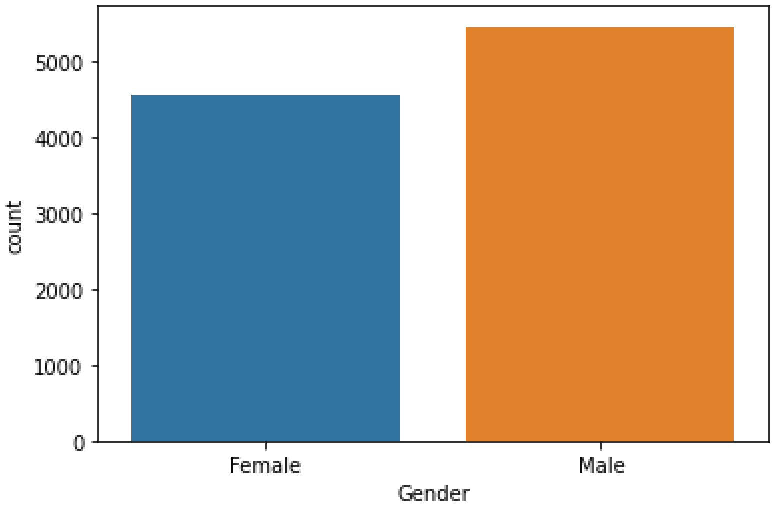

```
geo = df['Geography'].value_counts()
geo.plot(kind="pie",figsize=(10,8))
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f8f1ba4fb50>
```



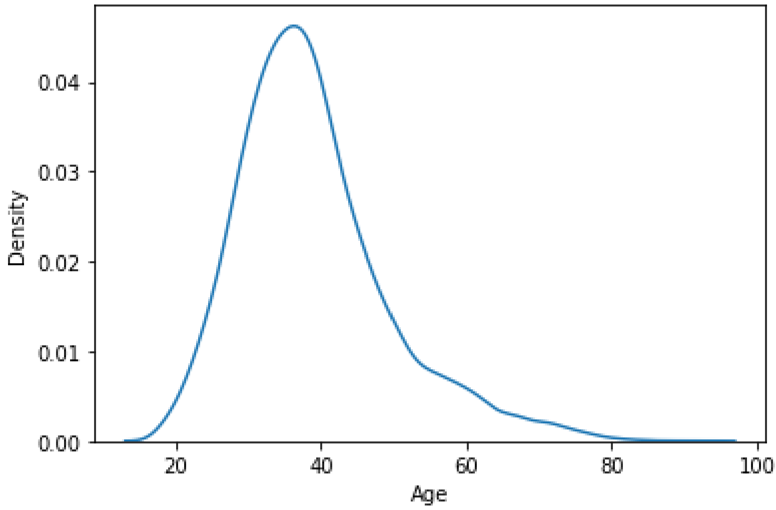
```
sns.countplot(df['Gender'])
```

<matplotlib.axes._subplots.AxesSubplot at 0x7f8f1b5614d0>



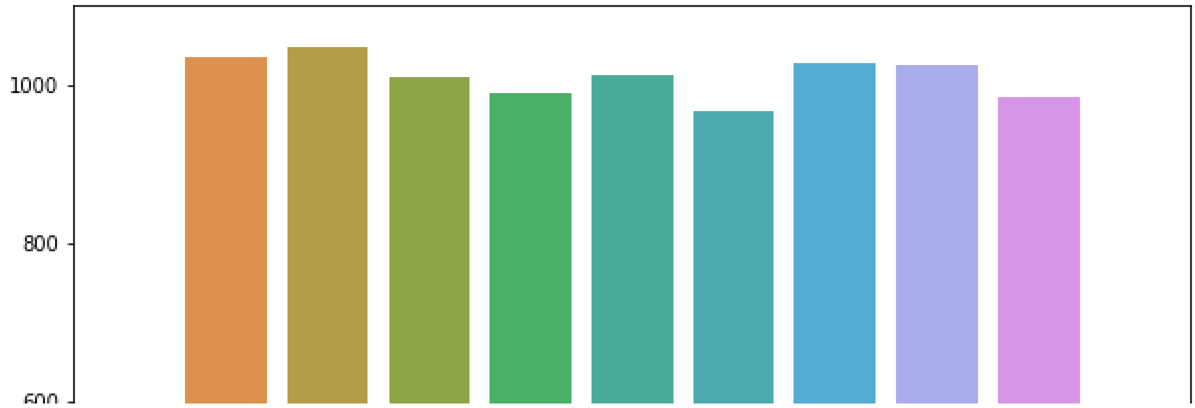

```
sns.distplot(df['Age'],hist=False)
```

<matplotlib.axes._subplots.AxesSubplot at 0x7f8f1b52cfd0>



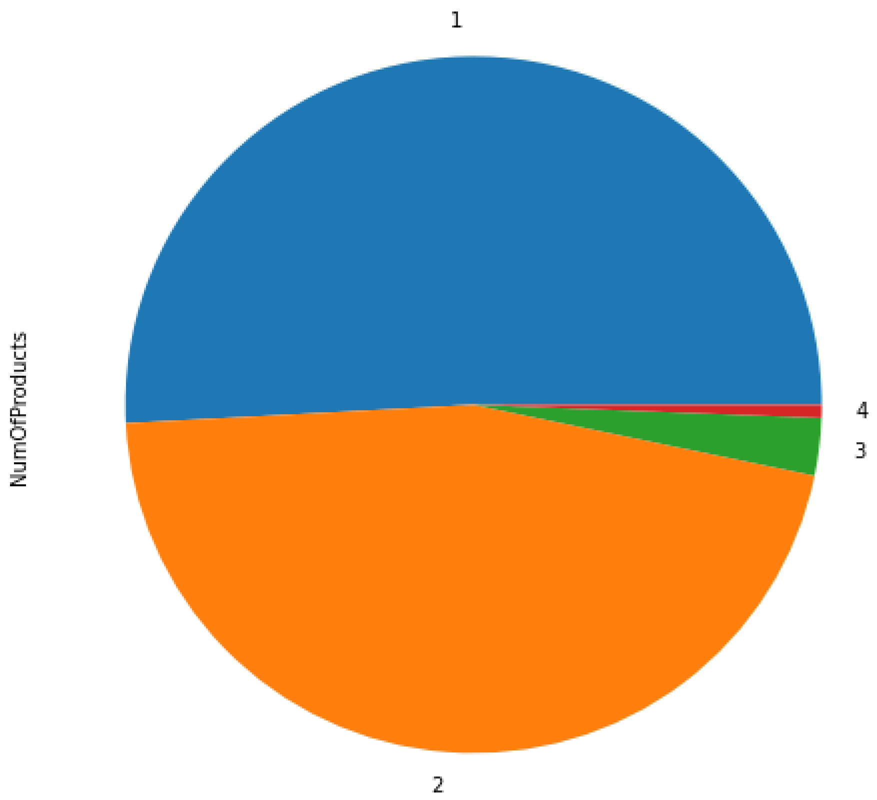

```
plt.figure(figsize=(10,8))
sns.countplot(df['Tenure'])
```

<matplotlib.axes._subplots.AxesSubplot at 0x7f8f1b4cfdd0>



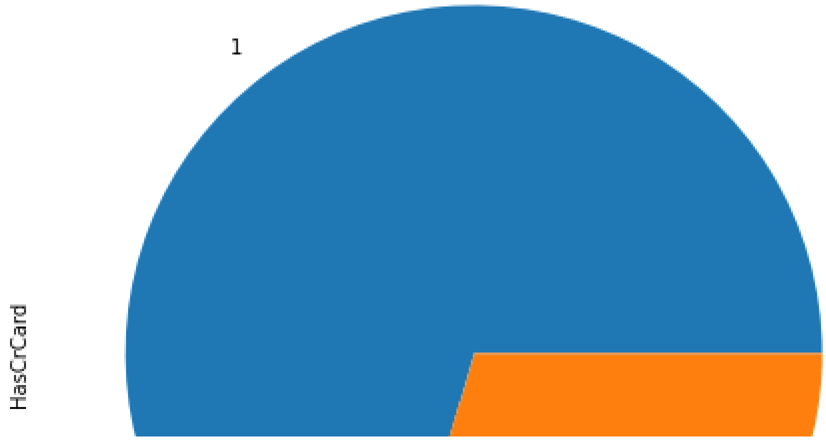

```
product = df['NumOfProducts'].value_counts()
product.plot(kind="pie",figsize=(10,8))
```

<matplotlib.axes._subplots.AxesSubplot at 0x7f8f1b54bbd0>



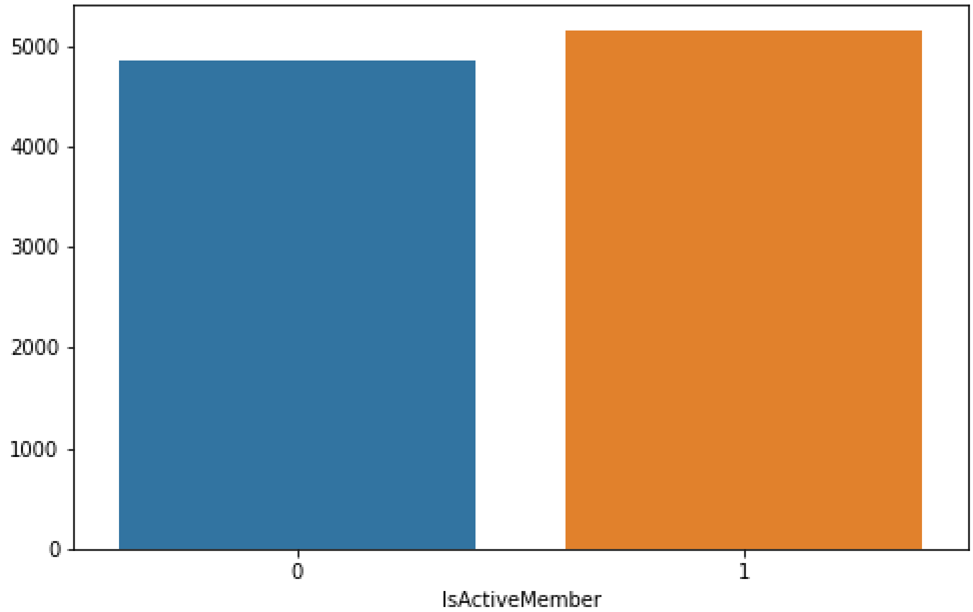

```
cr = df['HasCrCard'].value_counts()
cr.plot(kind="pie",figsize=(10,8))
```

<matplotlib.axes._subplots.AxesSubplot at 0x7f8f1b3bc850>




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

<matplotlib.axes._subplots.AxesSubplot at 0x7f8f1b36f6d0>

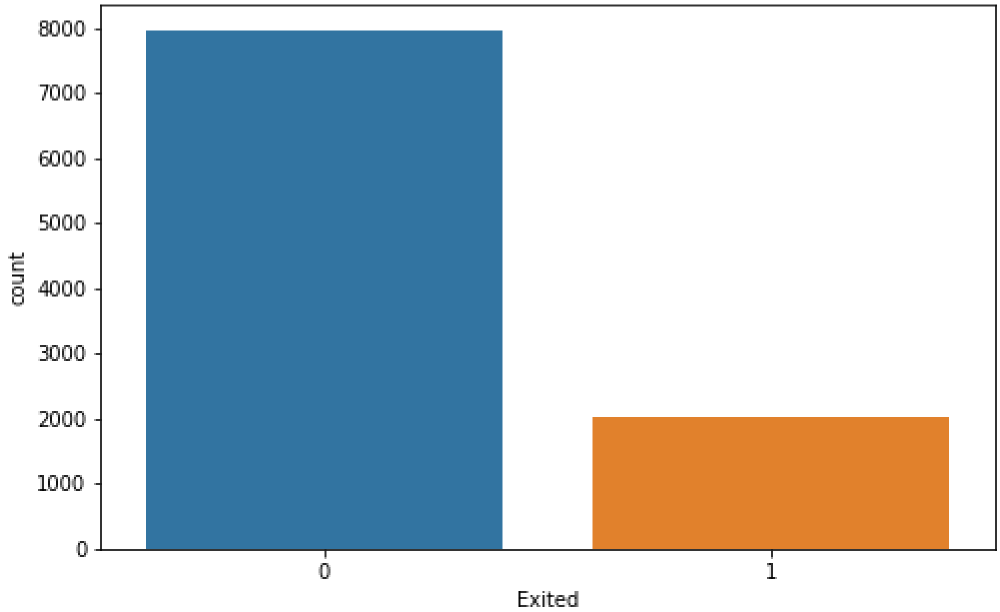



```
sns.distplot(df['EstimatedSalary'],hist=False)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f8f1b2e6110>
```

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

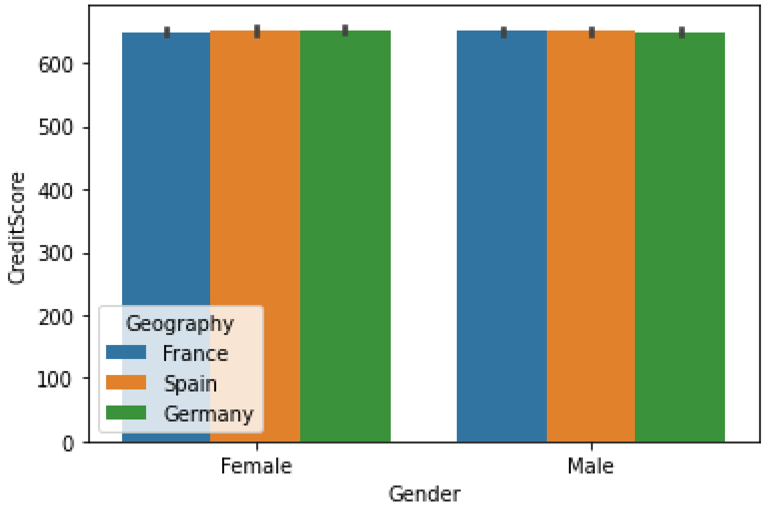
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f8f1b379b90>
```



3 b) Bivariate analysis

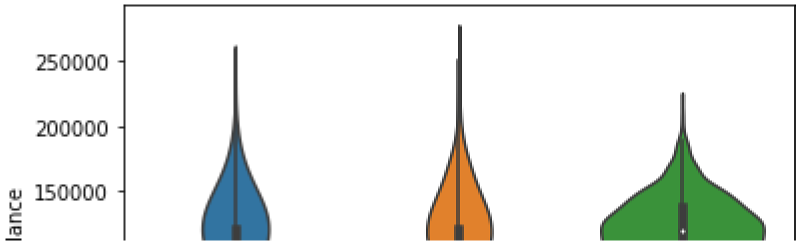
```
sns.barplot(x='Gender',y='CreditScore',hue='Geography',data=df)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f8f1b215410>
```



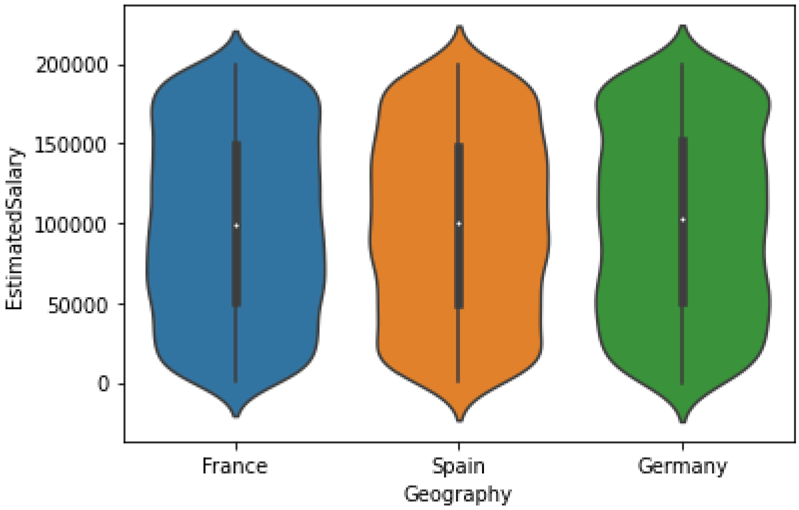

```
sns.violinplot(x='Geography',y='Balance',data=df)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f8f1b1bc2d0>
```



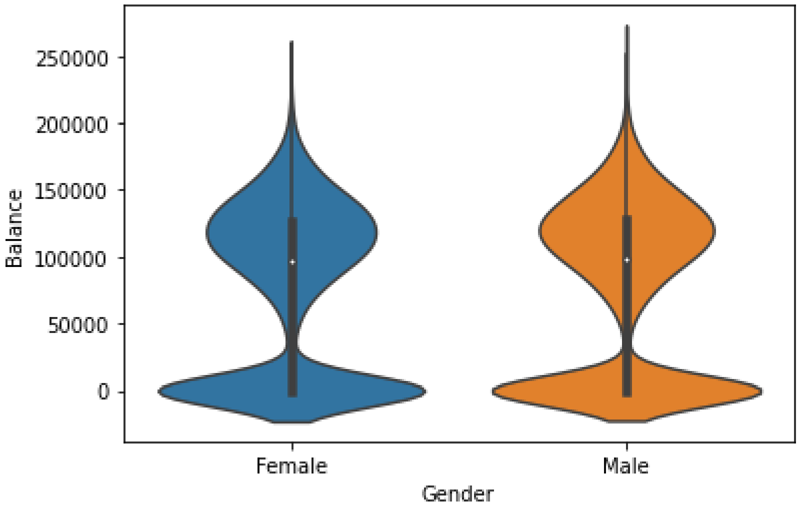

```
sns.violinplot(x='Geography',y='EstimatedSalary',data=df)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f8f1b0dcd90>
```



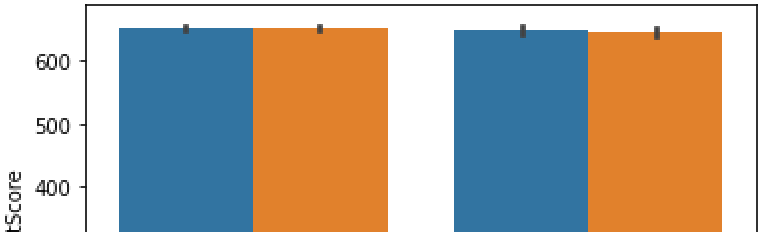

```
sns.violinplot(x='Gender',y='Balance',data=df)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f8f1b052850>
```



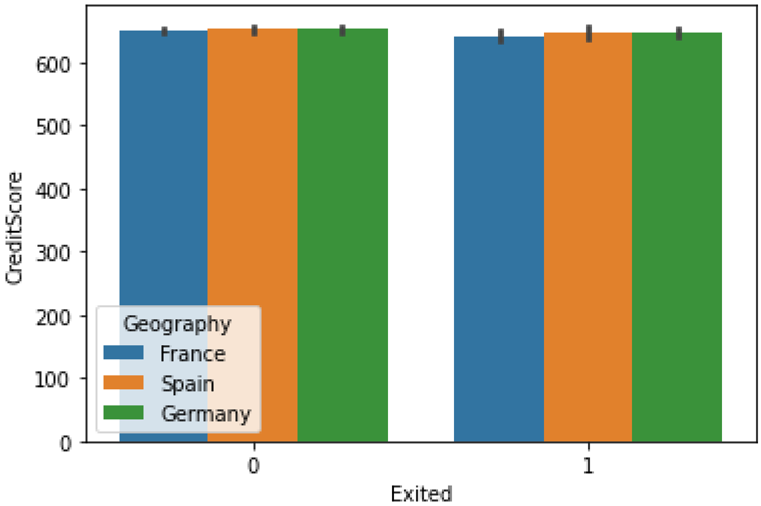

```
sns.barplot(x='Exited',y='CreditScore',hue='Gender',data=df)
```

<matplotlib.axes._subplots.AxesSubplot at 0x7f8f1b036d90>



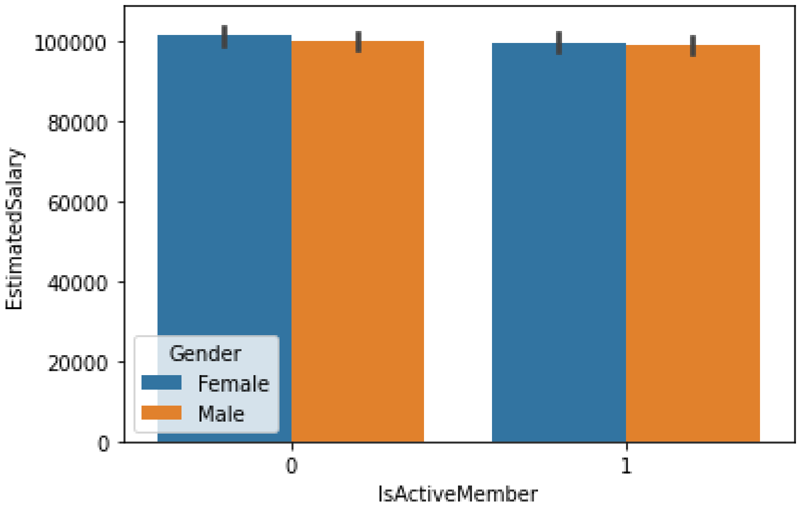

```
sns.barplot(x='Exited',y='CreditScore',hue='Geography',data=df)
```

<matplotlib.axes._subplots.AxesSubplot at 0x7f8f1afb8550>



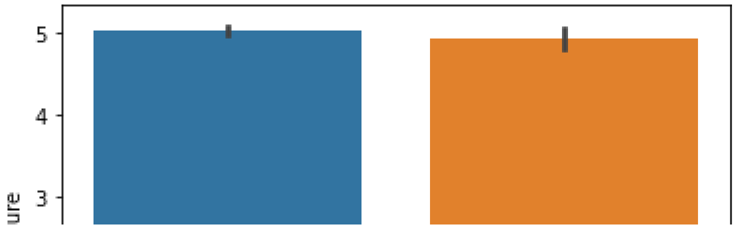

```
sns.barplot(x='IsActiveMember',y='EstimatedSalary',hue='Gender',data=df)
```

<matplotlib.axes._subplots.AxesSubplot at 0x7f8f1b3c8890>




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

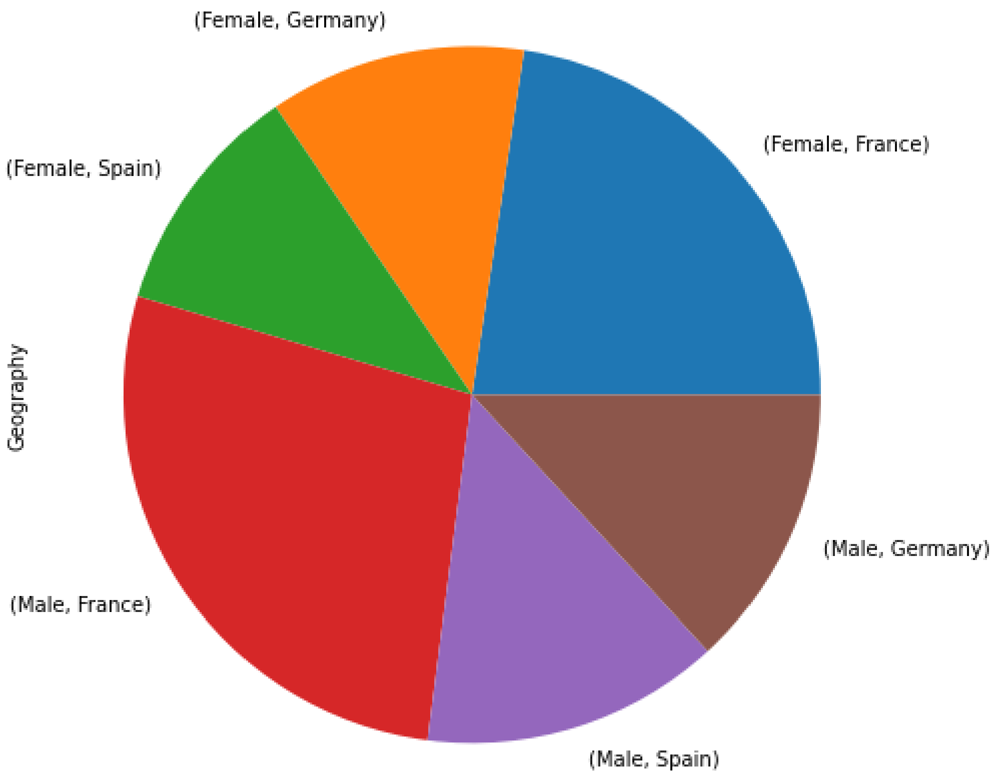
<matplotlib.axes._subplots.AxesSubplot at 0x7f8f1b220a90>



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)
```

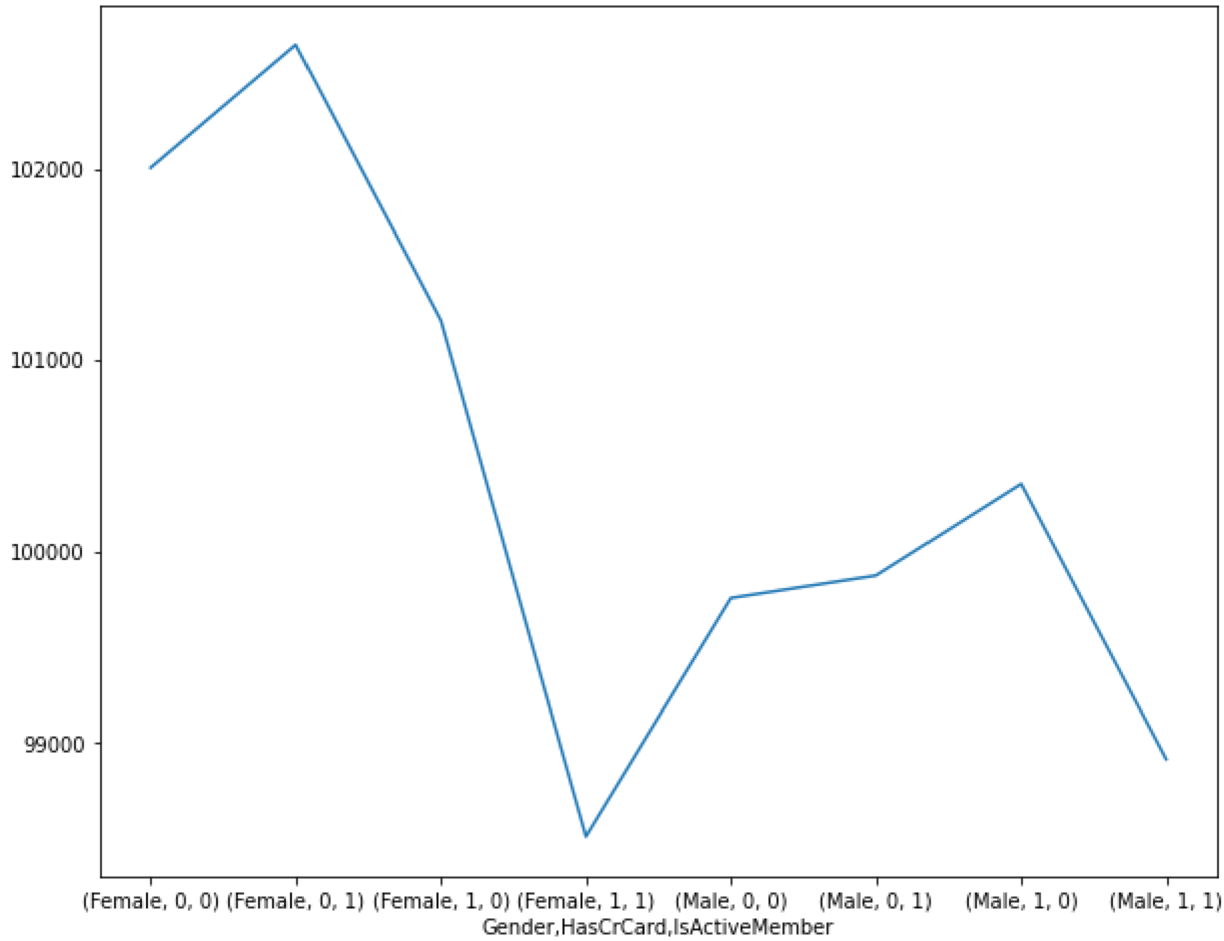
```
Gender
Female    39.238389
Male      38.658237
Name: Age, dtype: float64
```

```
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)
```

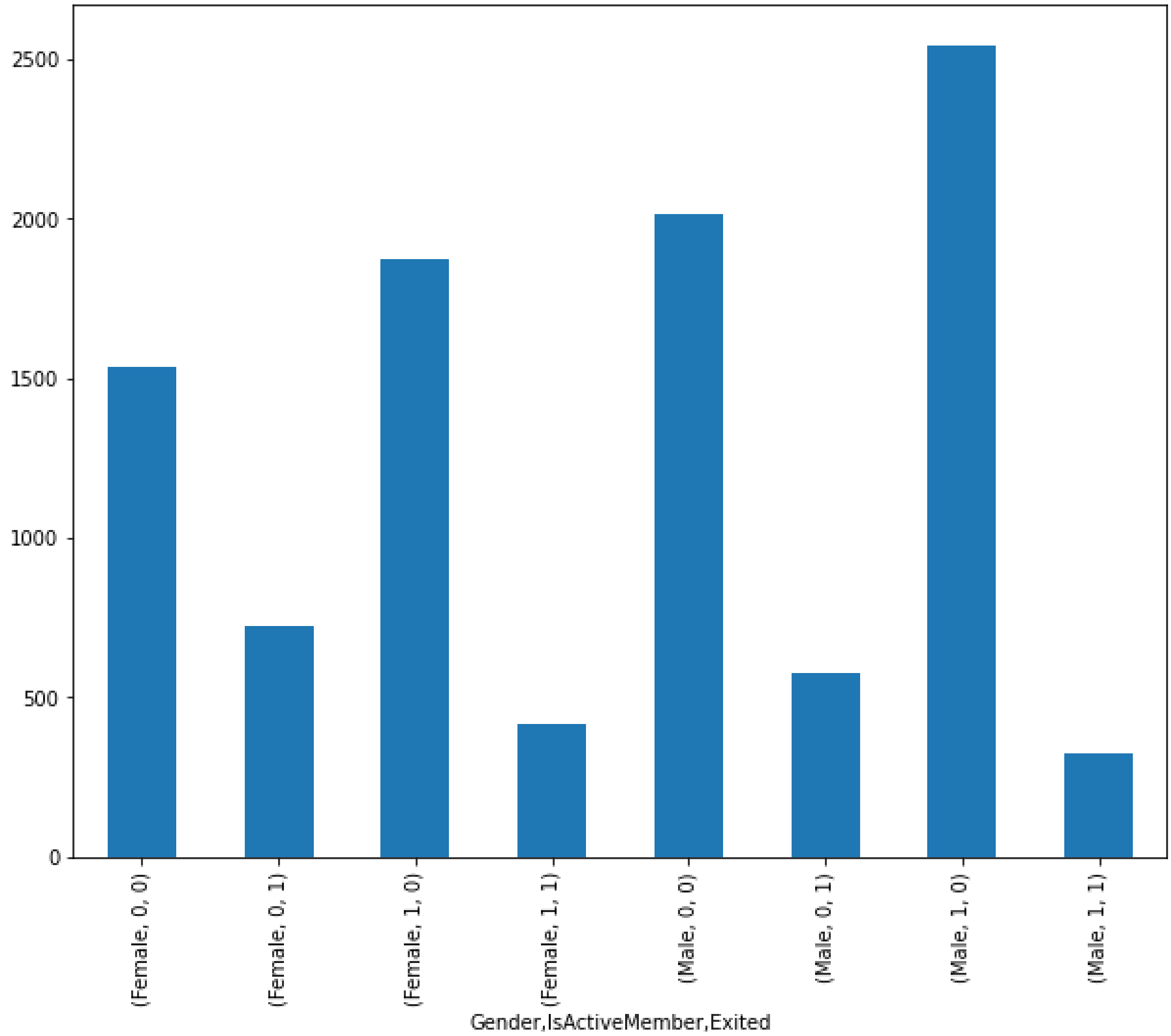
```
Gender  HasCrCard  IsActiveMember
Female  0          0                 102006.080352
                   1                 102648.996944
        1          0                 101208.014567
                   1                  98510.152300
Male    0          0                  99756.431151
                   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%	
RowNumber	10000.0	5.000500e+03	2886.895680	1.00	2500.75	5.000500
CustomerId	10000.0	1.569094e+07	71936.186123	15565701.00	15628528.25	1.569074
CreditScore	10000.0	6.505288e+02	96.653299	350.00	584.00	6.520000
Age	10000.0	3.892180e+01	10.487806	18.00	32.00	3.700000
Tenure	10000.0	5.012800e+00	2.892174	0.00	3.00	5.000000
Balance	10000.0	7.648589e+04	62397.405202	0.00	0.00	9.719854
NumOfProducts	10000.0	1.530200e+00	0.581654	1.00	1.00	1.000000
HasCrCard	10000.0	7.055000e-01	0.455840	0.00	0.00	1.000000
IsActiveMember	10000.0	5.151000e-01	0.499797	0.00	0.00	1.000000
EstimatedSalary	10000.0	1.000902e+05	57510.492818	11.58	51002.11	1.001939
Exited	10000.0	2.037000e-01	0.402769	0.00	0.00	0.000000

5. Handling the missing values

```
df.isnull().sum()
```

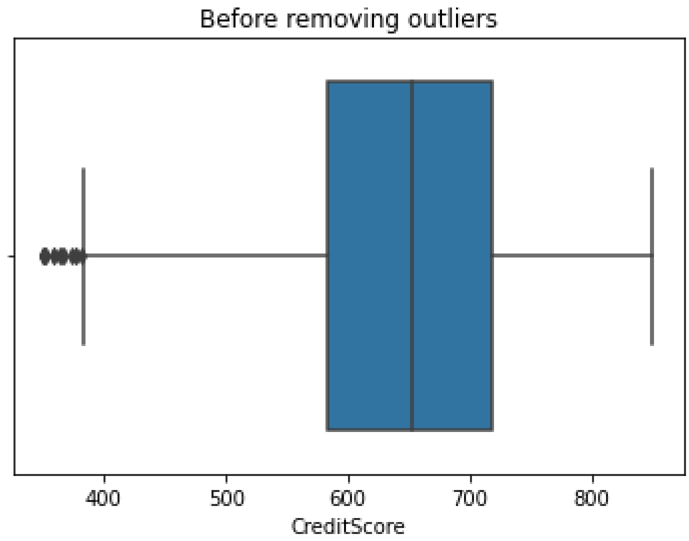
```
RowNumber          0
CustomerId         0
Surname            0
CreditScore        0
Geography          0
Gender             0
Age                0
Tenure             0
Balance            0
NumOfProducts      0
HasCrCard          0
IsActiveMember     0
EstimatedSalary    0
Exited             0
dtype: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

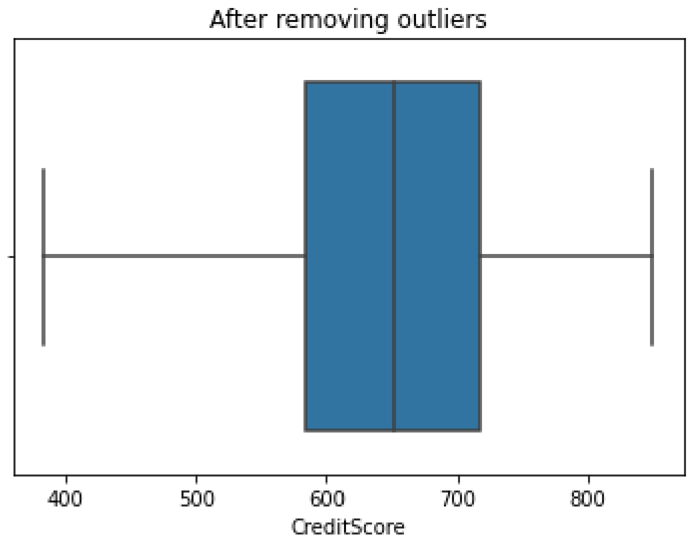
There is no missing value in the dataset

6.Finding outliers

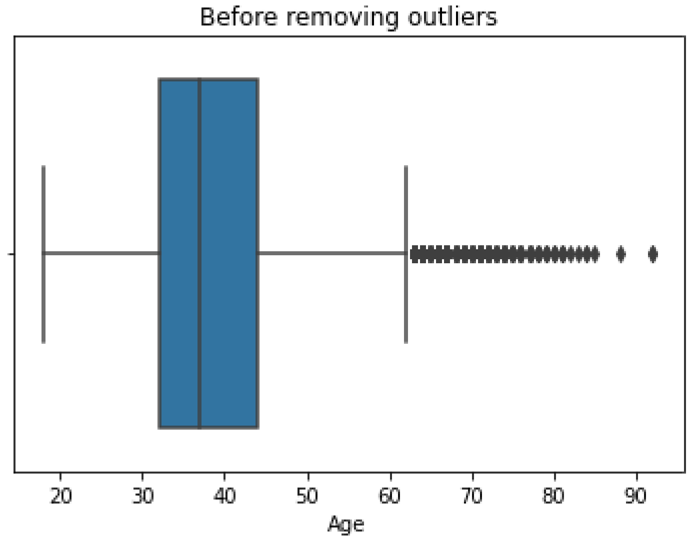
```
def replace_outliers(df, field_name):
    Q1 = np.percentile(df[field_name],25,interpolation='midpoint')
    Q3 = np.percentile(df[field_name],75,interpolation='midpoint')
    IQR = Q3-Q1
    maxi = Q3+1.5*IQR
    mini = Q1-1.5*IQR
    df[field_name]=df[field_name].mask(df[field_name]>maxi,maxi)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

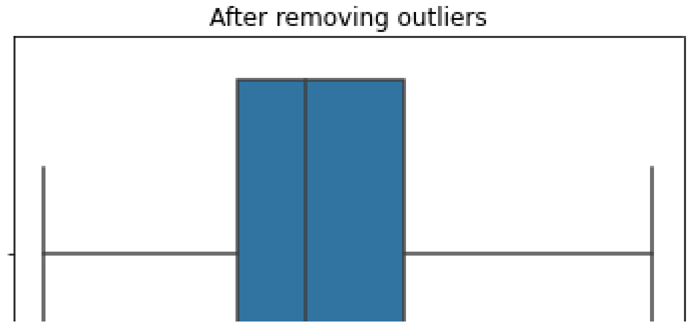
```
plt.title("Before removing outliers")
sns.boxplot(df['CreditScore'])
plt.show()
plt.title("After removing outliers")
replace_outliers(df, 'CreditScore')
sns.boxplot(df['CreditScore'])
plt.show()
```





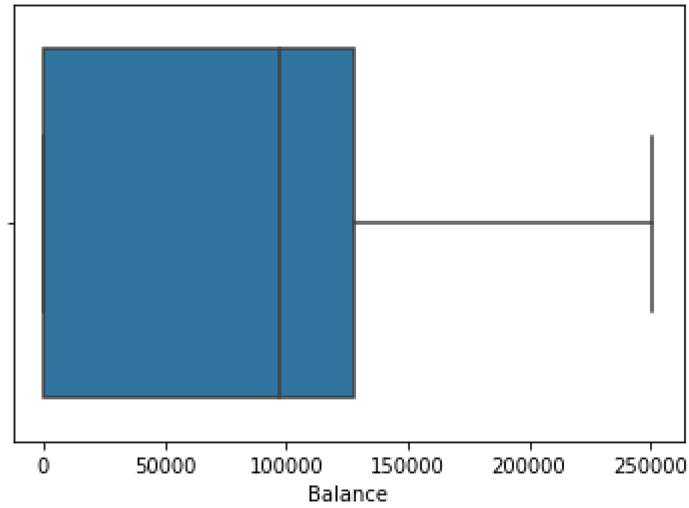

```
plt.title("Before removing outliers")
sns.boxplot(df['Age'])
plt.show()
plt.title("After removing outliers")
replace_outliers(df, 'Age')
sns.boxplot(df['Age'])
plt.show()
```





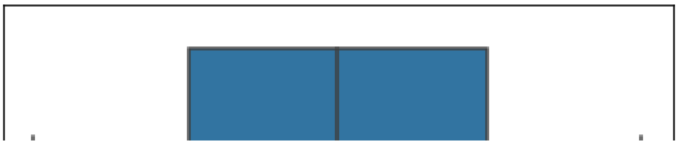

```
sns.boxplot(df['Balance'])
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f8f1ab8f310>
```




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

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f8f1aaf5f50>
```



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.head()
```

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

Only two columns(Gender and Geography) is label encoded

Removing unwanted columns and checking for feature importance

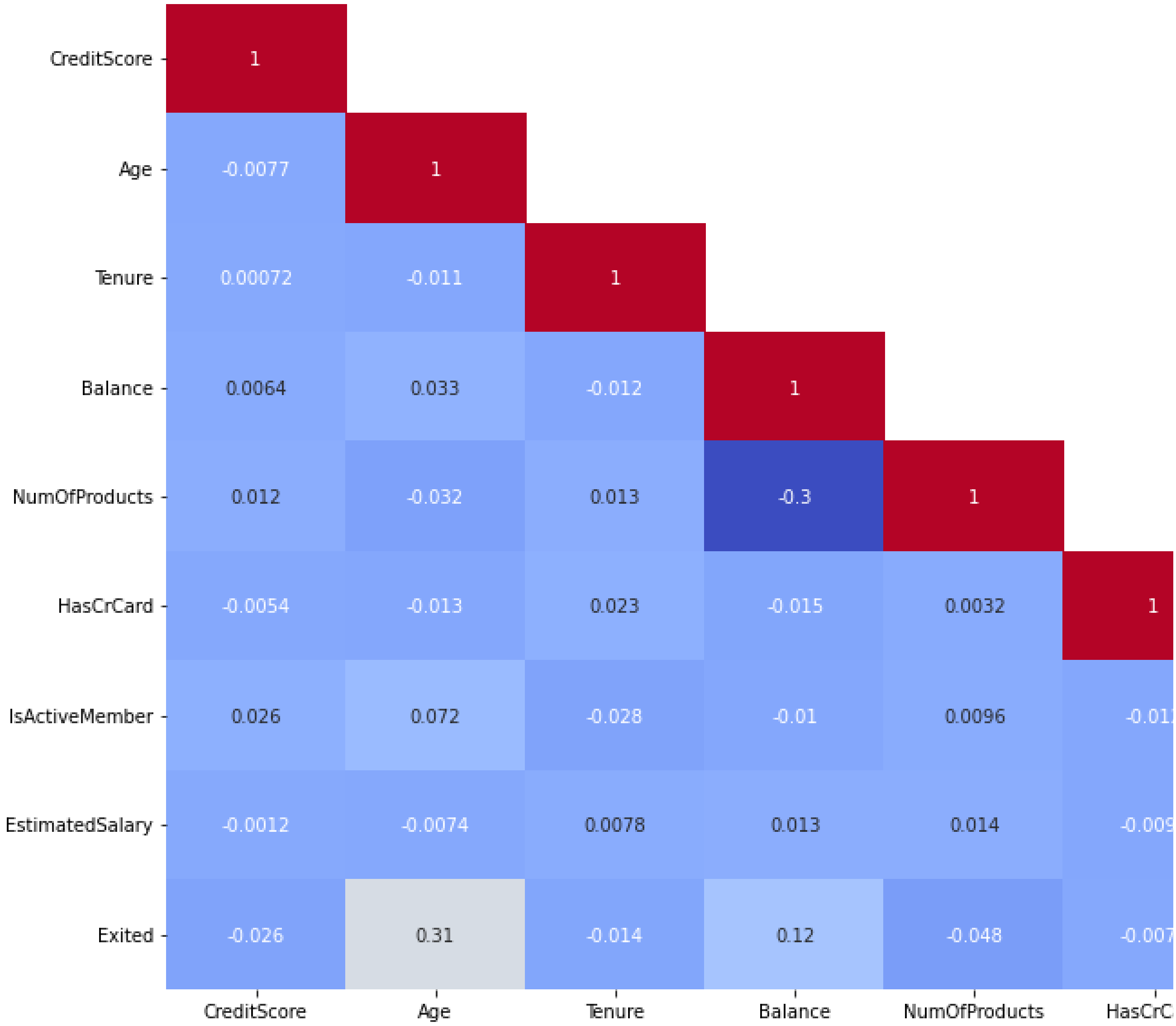
```
df = df.drop(['RowNumber','CustomerId','Surname'],axis=1)
```

```
df.head()
```

	CreditScore	Geography	Gender	Age	Tenure	Balance	NumOfProducts	HasCrC
0	619.0	France	Female	42.0	2	0.00	1	
1	608.0	Spain	Female	41.0	1	83807.86	1	
2	502.0	France	Female	42.0	8	159660.80	3	
3	699.0	France	Female	39.0	1	0.00	2	
4	850.0	Spain	Female	43.0	2	125510.82	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 0x7f8f1a34de10>
```



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	Ha:
0	-0.326878	France	Female	0.342615	2	-1.225848	1	
1	-0.440804	Spain	Female	0.240011	1	0.117350	1	
2	-1.538636	France	Female	0.342615	8	1.333053	3	
3	0.501675	France	Female	0.034803	1	-1.225848	2	
4	2.065569	Spain	Female	0.445219	2	0.785728	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_
```

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

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