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2. Roll no:2k19ece017
3. Date:24.09.2022

Assignment 2

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  \
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
```

```
df.tail()
```

```
      RowNumber  CustomerId    Surname  CreditScore Geography  Gender
Age  \
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  \
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
9995         96270.64       0
9996        101699.77       0
9997         42085.58       1
9998         92888.52       1
9999         38190.78       0
```

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
```

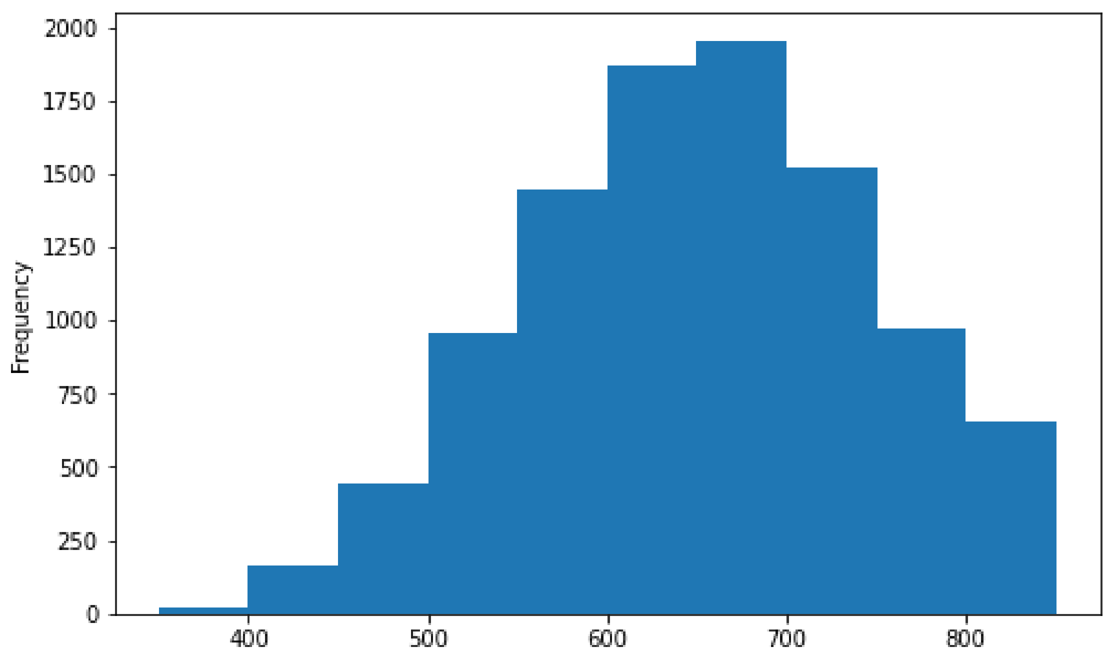
```
Index(['RowNumber', 'CustomerId', 'Surname', 'CreditScore',
'Geography',
       'Gender', 'Age', 'Tenure', 'Balance', 'NumOfProducts',
'HasCrCard',
       'IsActiveMember', 'EstimatedSalary', 'Exited'],
      dtype='object')
```

```
df.shape
```

```
(10000, 14)
```

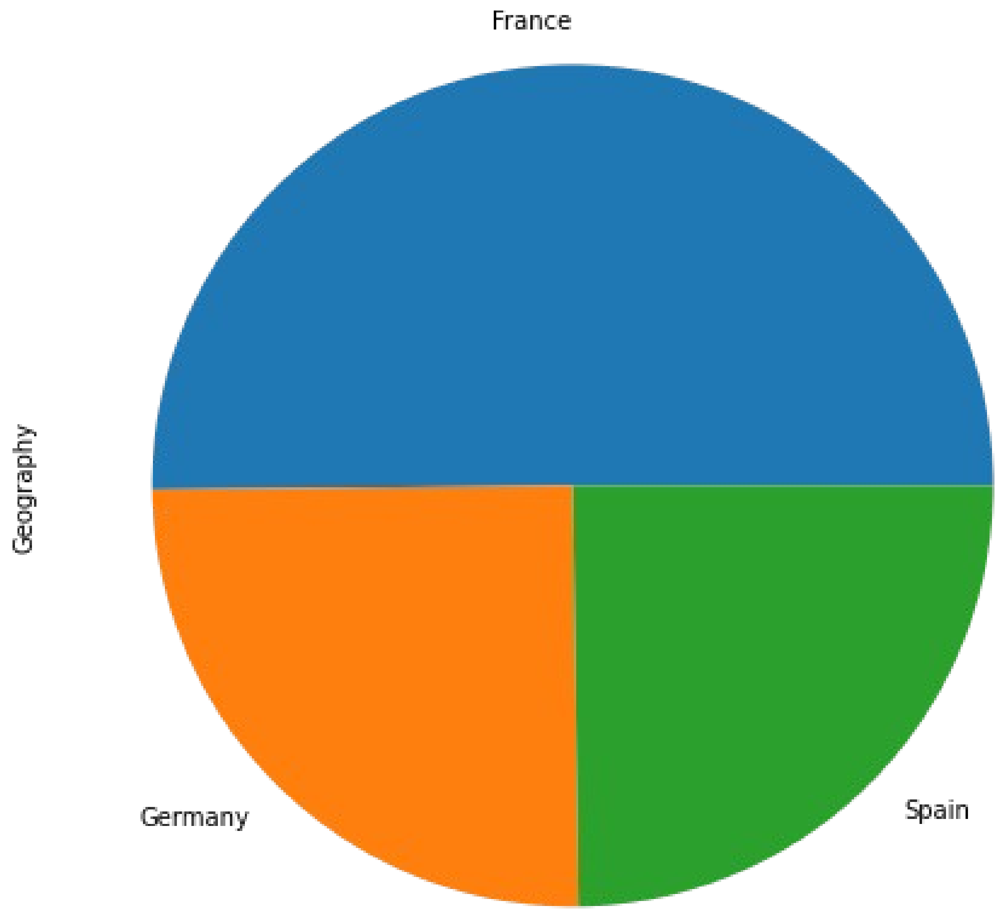
```
credit = df['CreditScore']
credit.plot(kind="hist",figsize=(8,5))
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fbbeac48910>
```



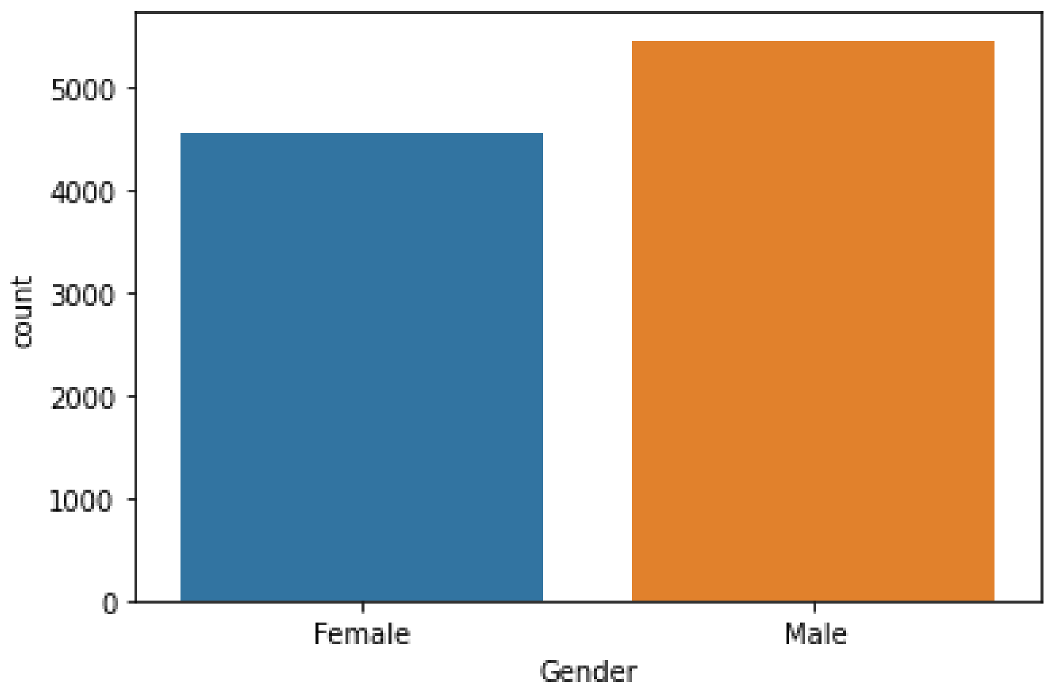

```
geo = df['Geography'].value_counts()
geo.plot(kind="pie",figsize=(10,8))
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fbbeb60f590>
```



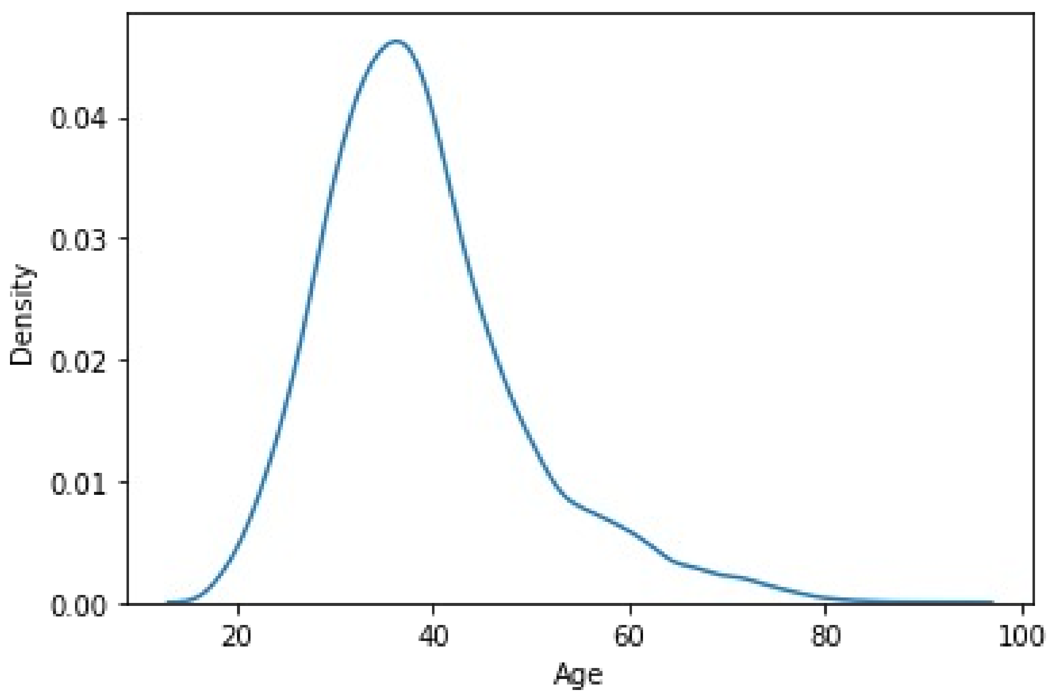

```
sns.countplot(df['Gender'])
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fbbea662390>
```



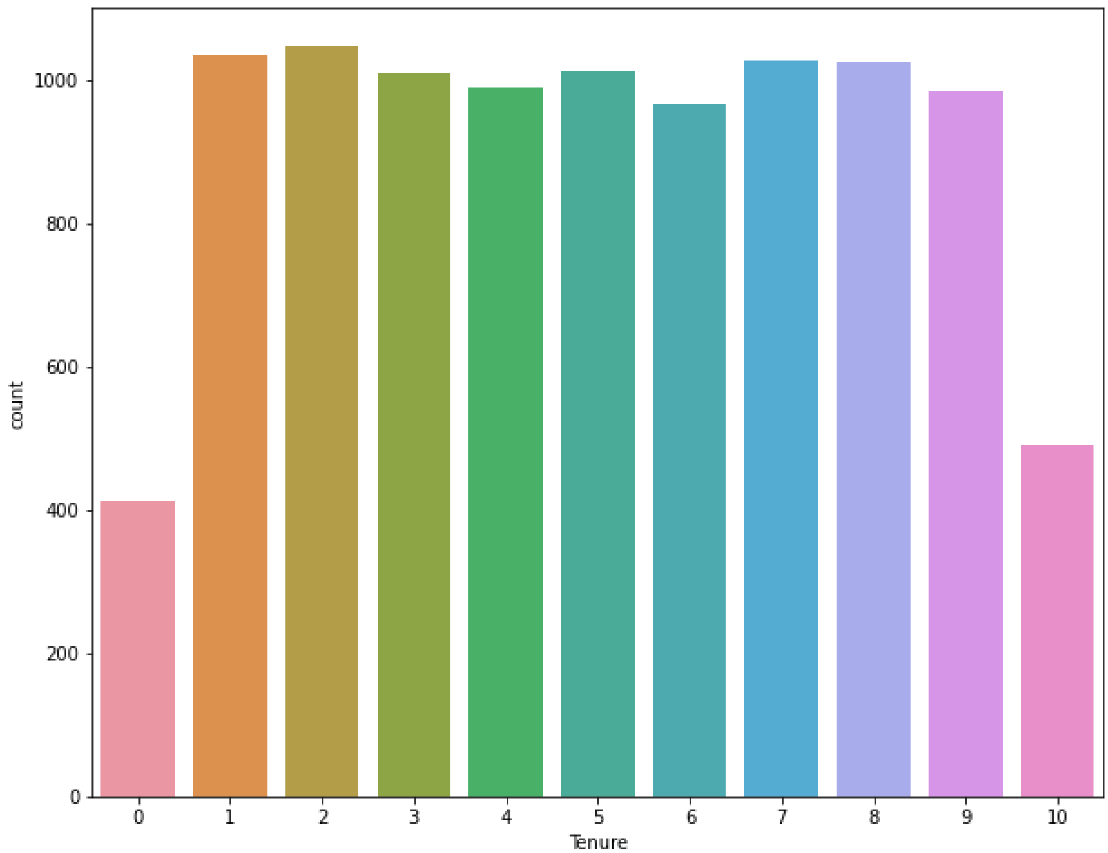

```
sns.distplot(df['Age'],hist=False)
```

<matplotlib.axes._subplots.AxesSubplot at 0x7fbbea632e90>



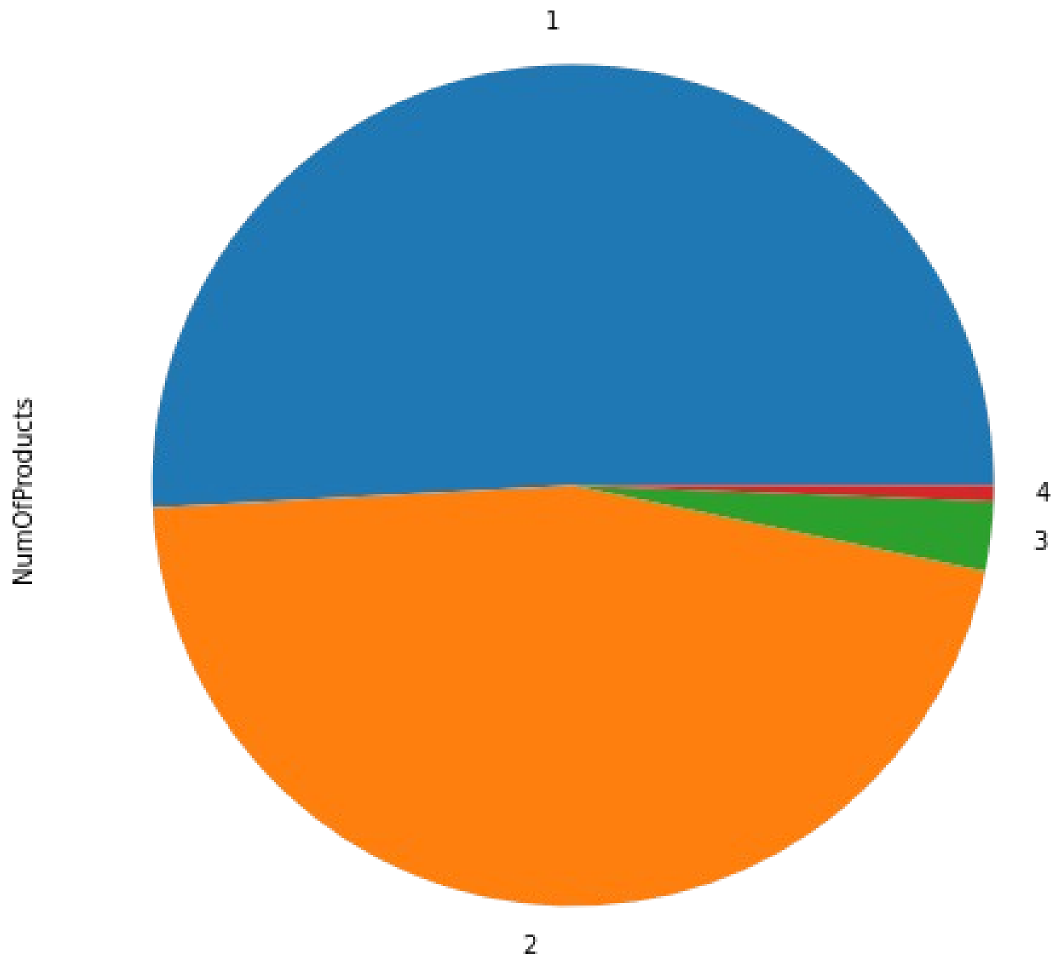

```
plt.figure(figsize=(10,8))
sns.countplot(df['Tenure'])
```

<matplotlib.axes._subplots.AxesSubplot at 0x7fbbea6098d0>



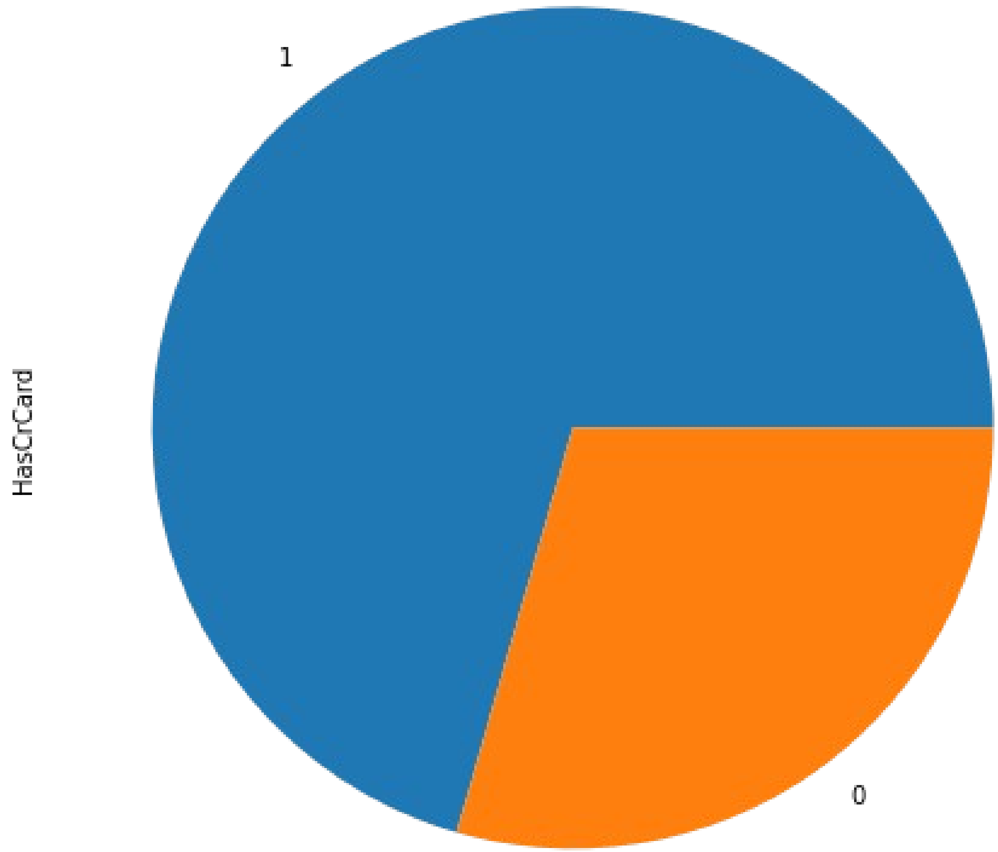

```
product = df['NumOfProducts'].value_counts()
product.plot(kind="pie",figsize=(10,8))
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fbbea4ede10>
```



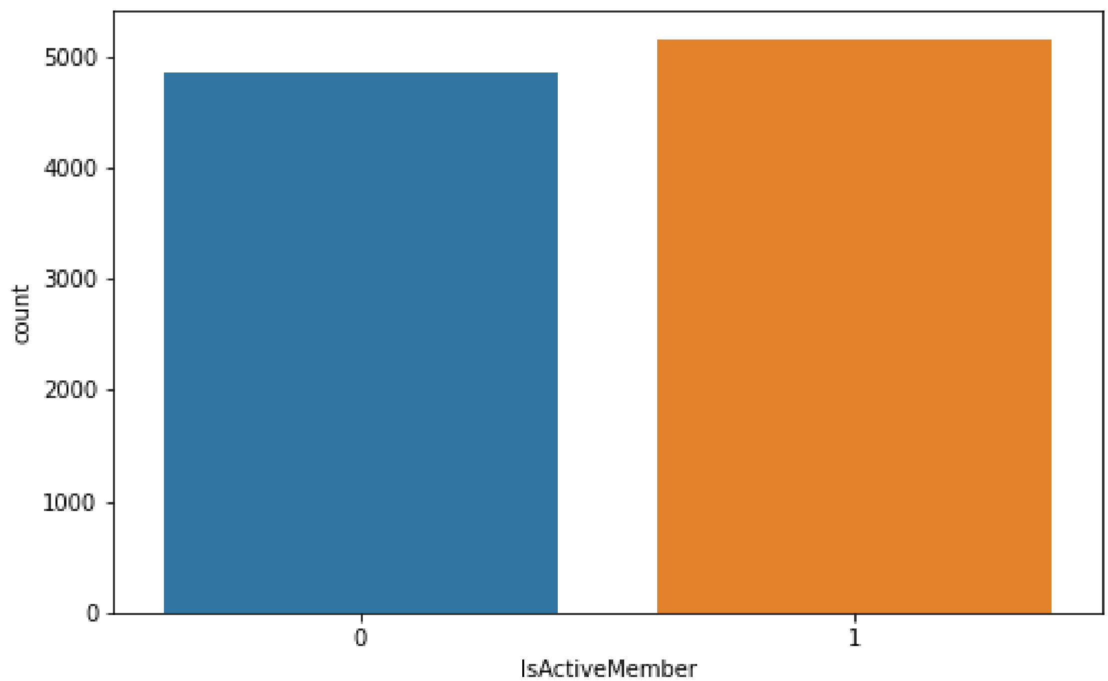

```
cr = df['HasCrCard'].value_counts()
cr.plot(kind="pie",figsize=(10,8))
```

<matplotlib.axes._subplots.AxesSubplot at 0x7fbbea4c8c50>



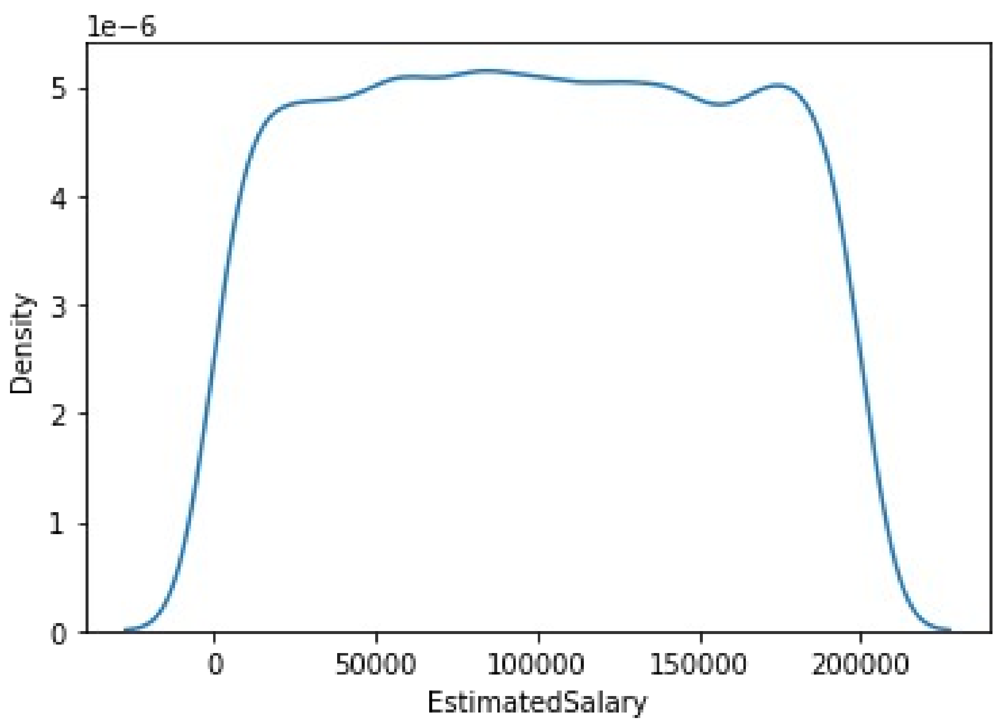

```
plt.figure(figsize=(8,5))
sns.countplot(df['IsActiveMember'])
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fbbea4bca10>
```



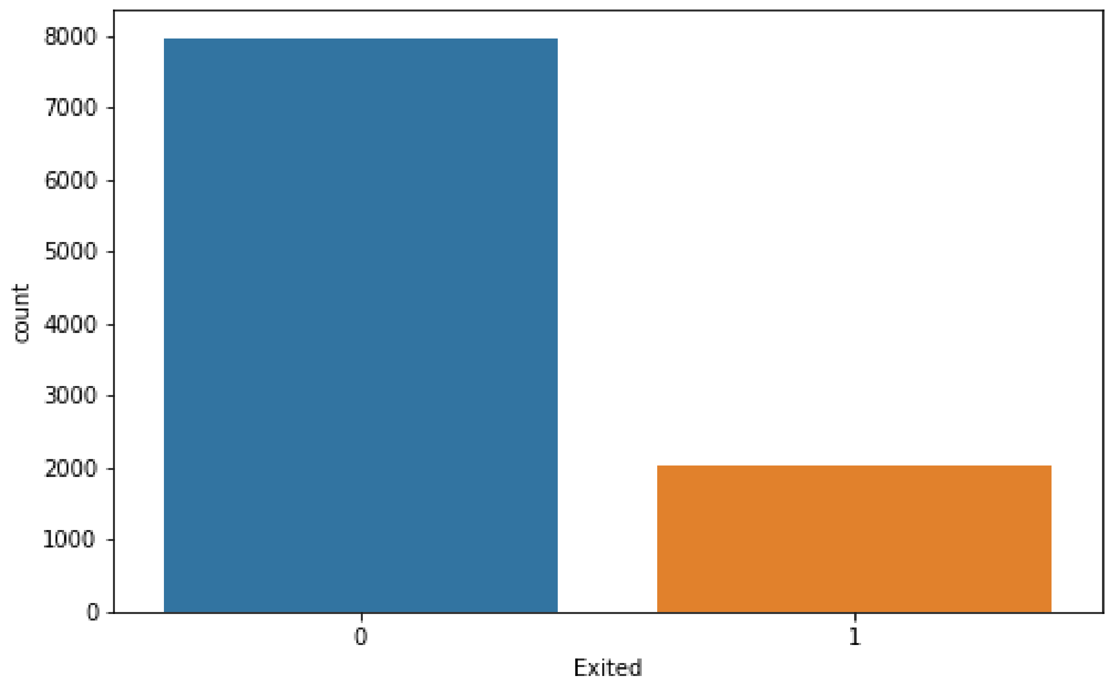

```
sns.distplot(df['EstimatedSalary'],hist=False)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fbbea3e3050>
```




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

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fbbea3b8f90>
```



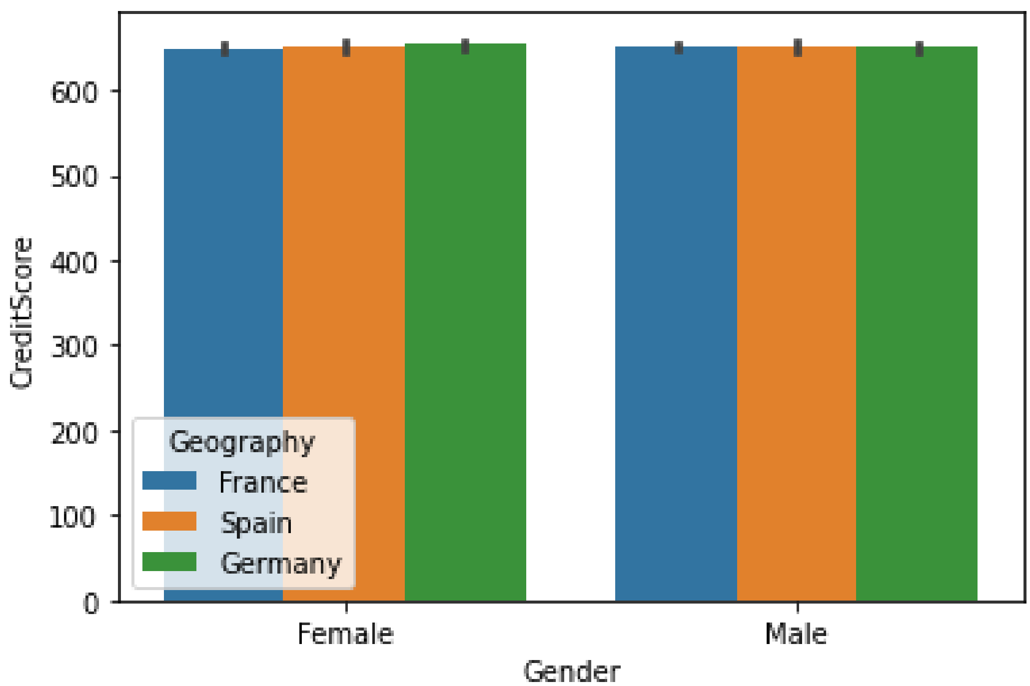
Inference:

1. The data has 11 numerical variables and 3 categorical variables.
2. It has 10000 rows and 14 columns
3. The normalized credit score is around 700, More than 500 people have credit score greater than 800.
4. France occupies 50% of customers, where as Germany and Spain shared equal.
5. Dataset is dominated by Male Customers.
6. Median age is around 40 to 45.
7. Highest number of customer has thier tenure period for 2 years.
8. Credit company has maximum customers, who uses single product.
9. Most of the customer has credit card.
10. More than 40% of the population is not an active member.
11. The Churn is less compared to the satisfaction. **Dataset is imbalanced.**

3 b). Bivariate analysis

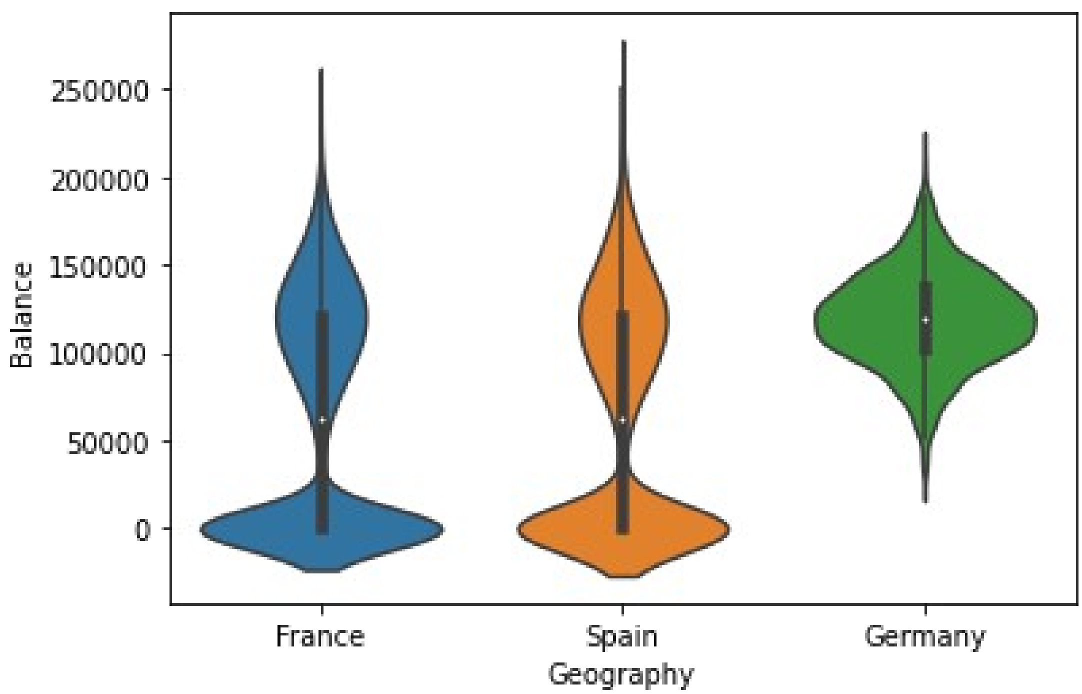
```
sns.barplot(x='Gender',y='CreditScore',hue='Geography',data=df)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fbbea33f490>
```



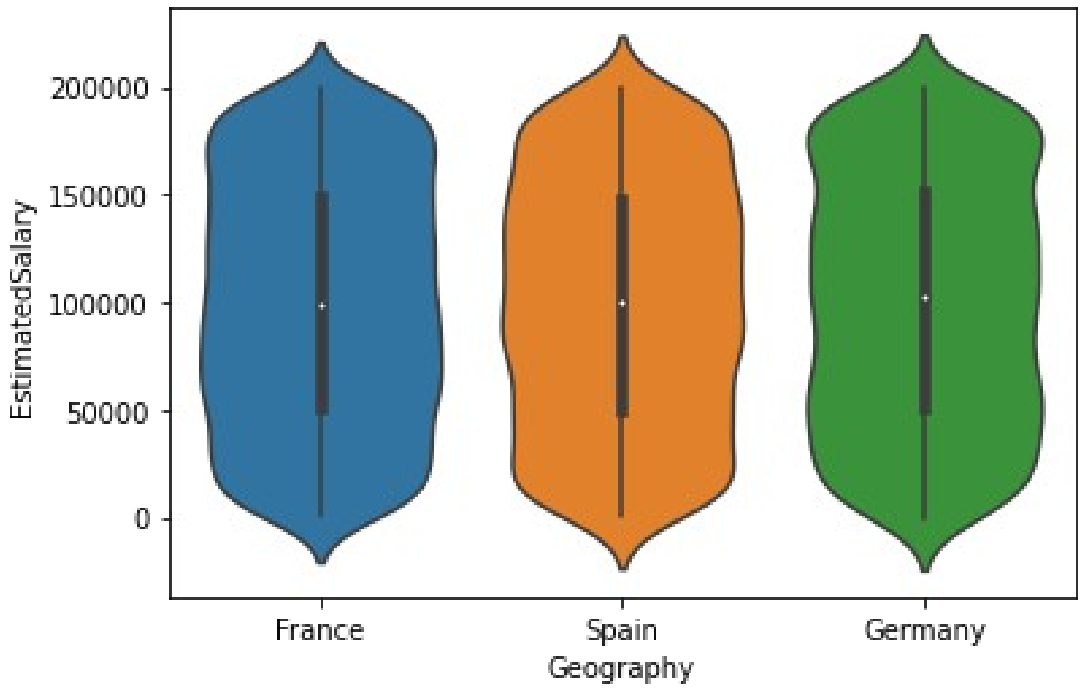

```
sns.violinplot(x='Geography',y='Balance',data=df)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fbbea2590d0>
```



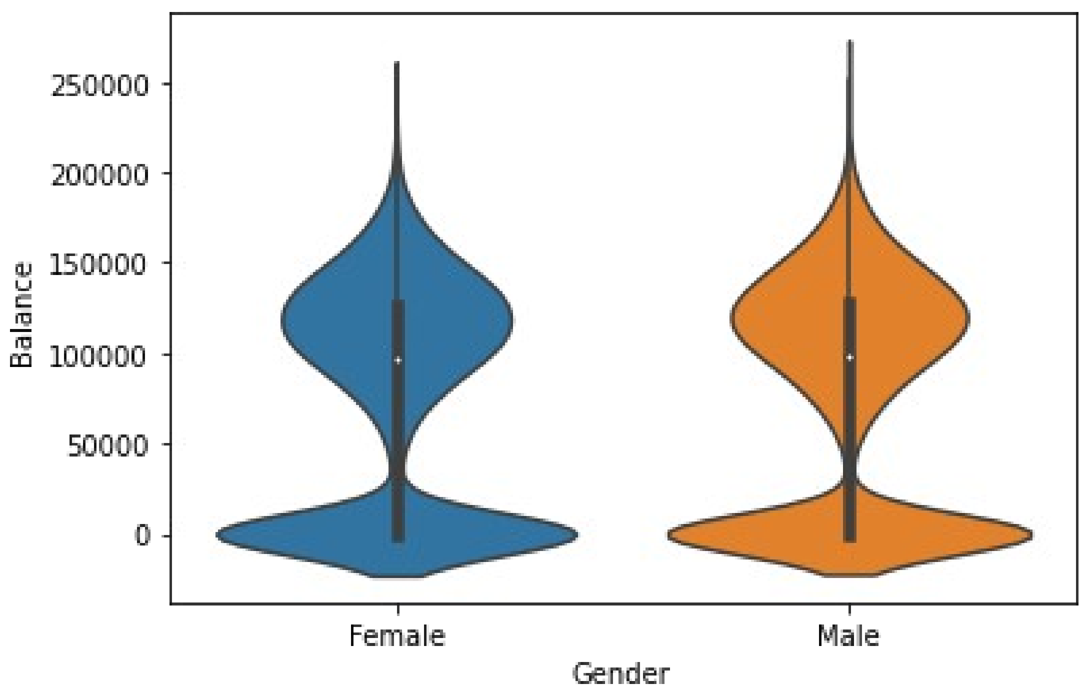

```
sns.violinplot(x='Geography',y='EstimatedSalary',data=df)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fbbea1eb1d0>
```



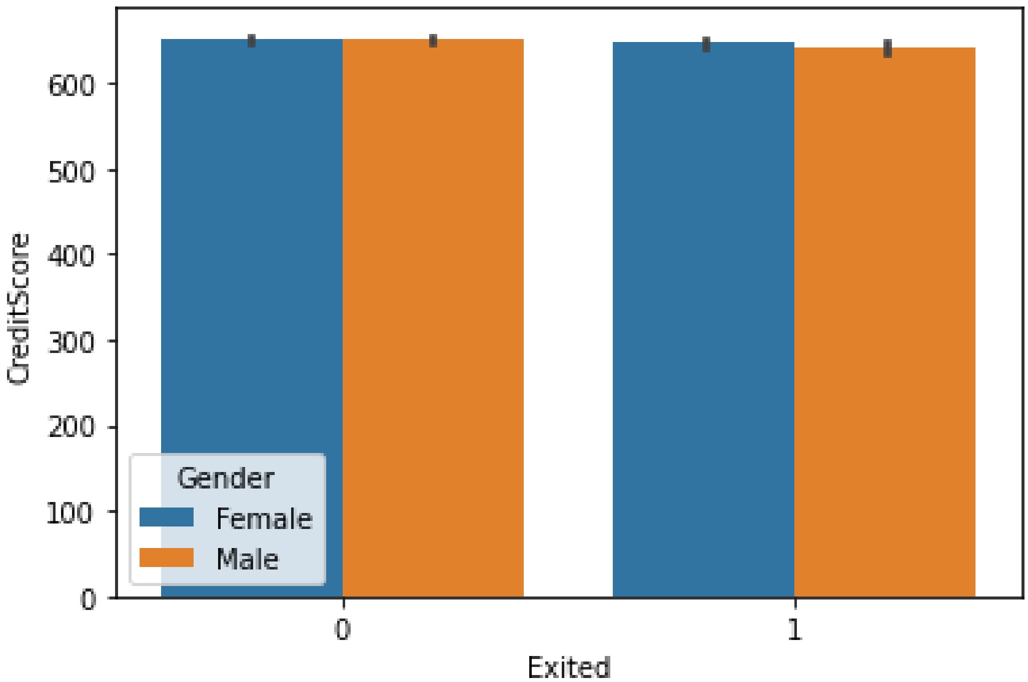

```
sns.violinplot(x='Gender',y='Balance',data=df)
```

<matplotlib.axes._subplots.AxesSubplot at 0x7fbbea14bcd0>



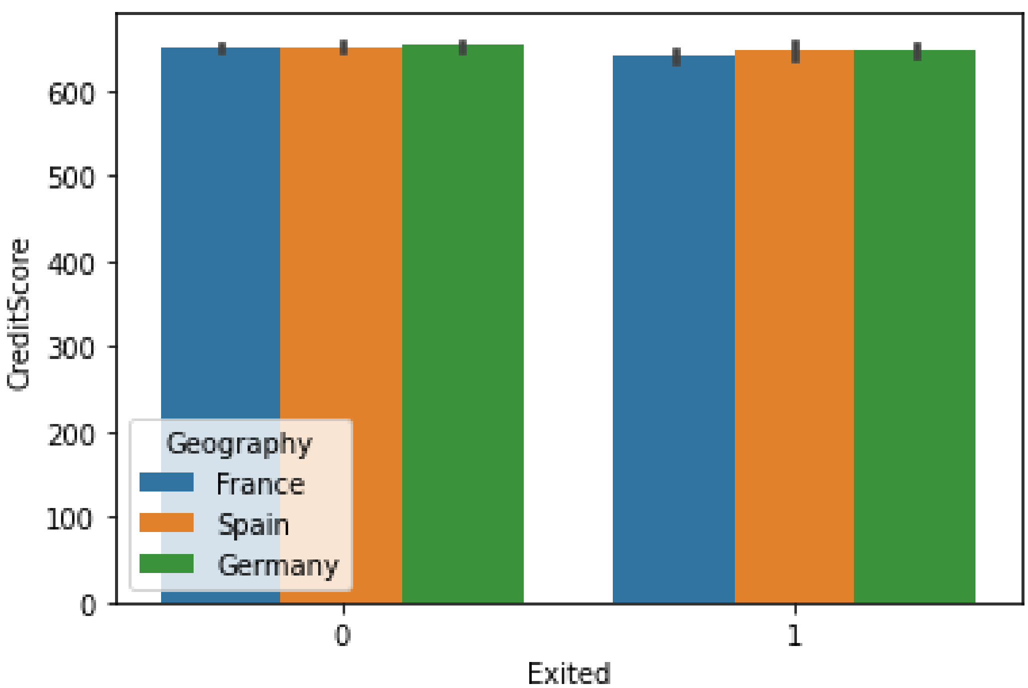

```
sns.barplot(x='Exited',y='CreditScore',hue='Gender',data=df)
```

<matplotlib.axes._subplots.AxesSubplot at 0x7fbbea149250>



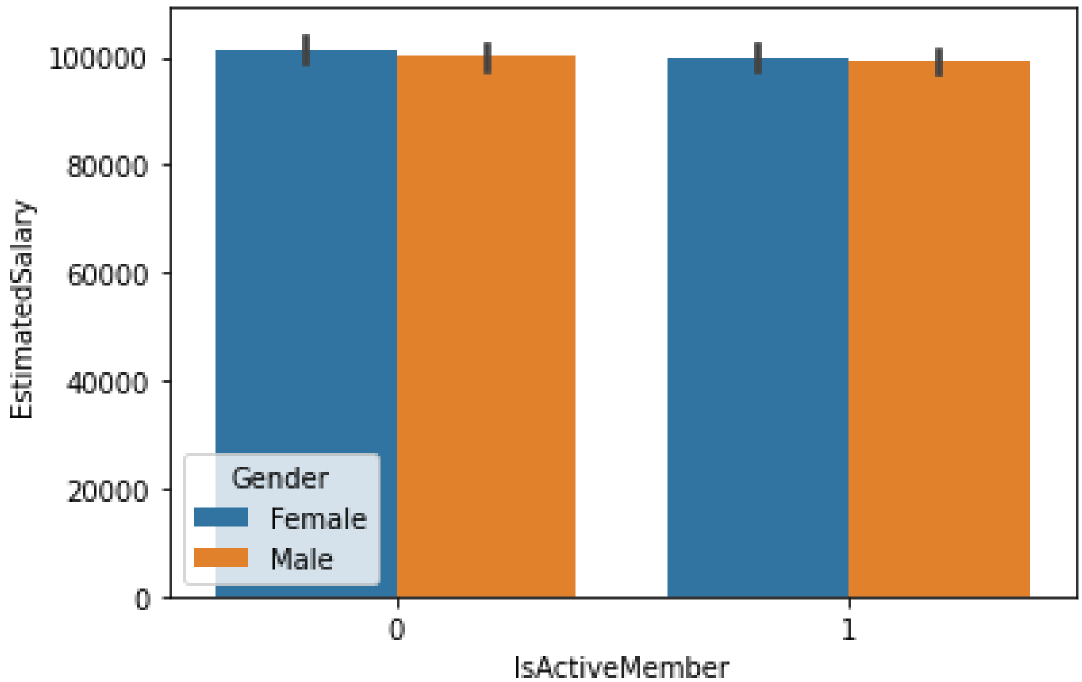

```
sns.barplot(x='Exited',y='CreditScore',hue='Geography',data=df)
```

<matplotlib.axes._subplots.AxesSubplot at 0x7fbbea451890>



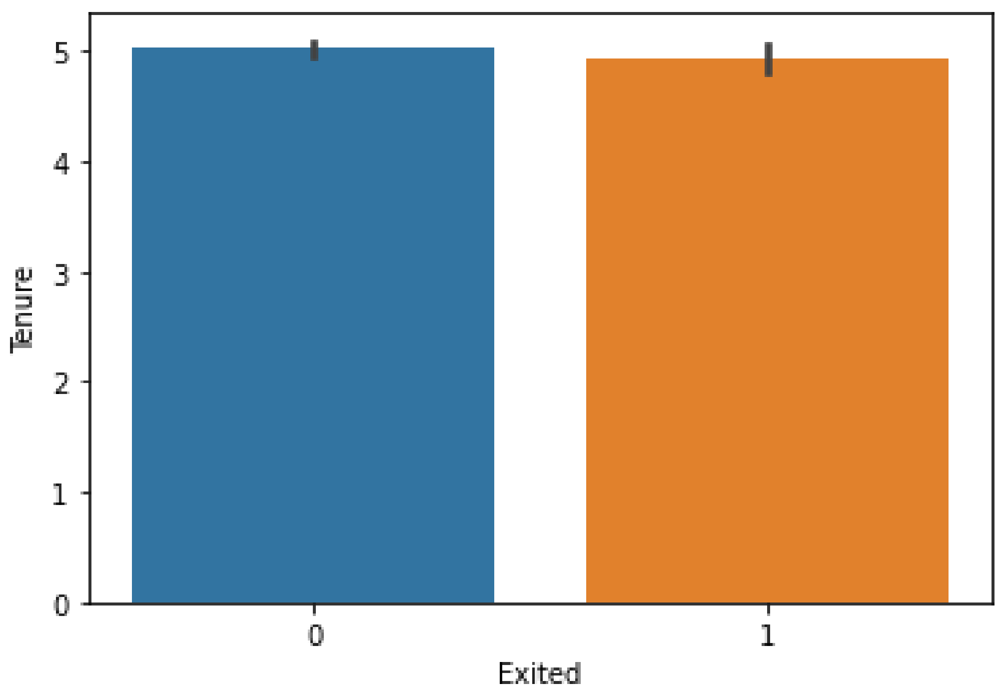

```
sns.barplot(x='IsActiveMember',y='EstimatedSalary',hue='Gender',data=d
f)
```

<matplotlib.axes._subplots.AxesSubplot at 0x7fbbea0ed610>




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

<matplotlib.axes._subplots.AxesSubplot at 0x7fbbe9fbc5d0>



Inference:

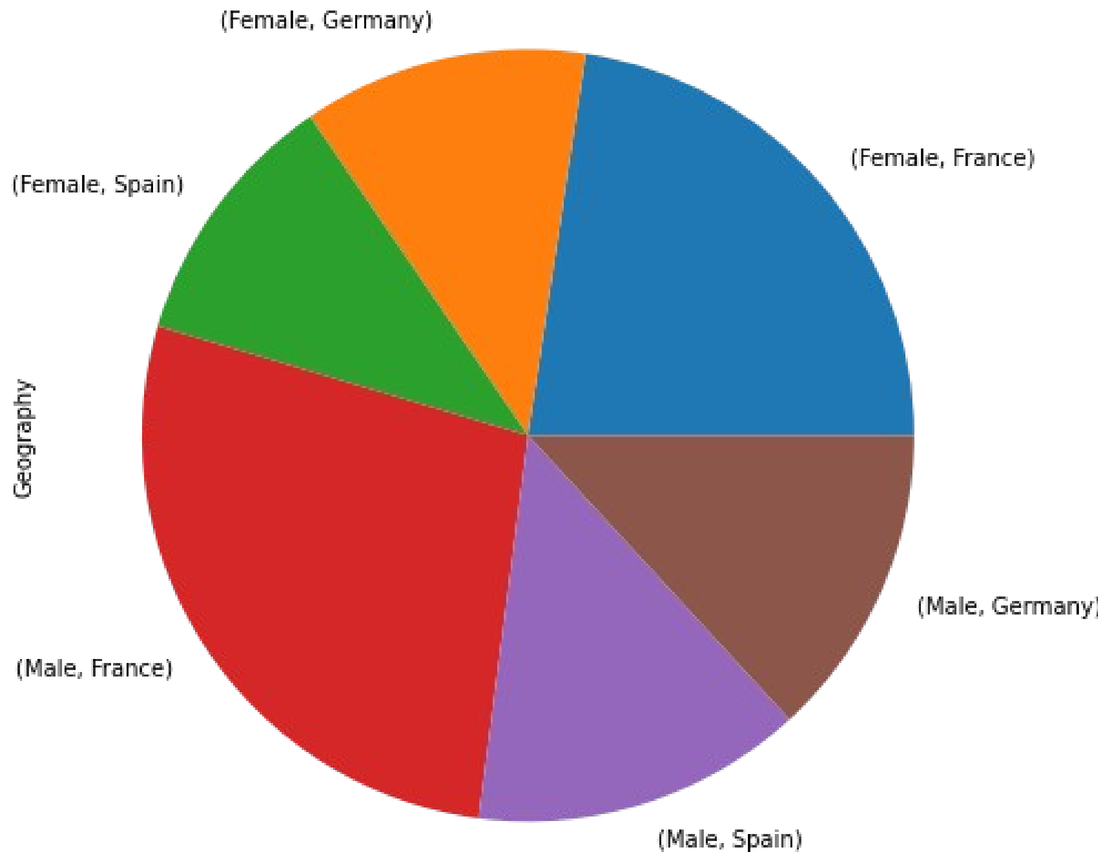
1. Credit score for Male is higher in Spain.

2. Average bank salary lies in the range of 100k to 150k.
3. Estimated salary is normalized and same for all country.
4. Credit score for churn is low.
5. Churn in Germany is higher compared to other countries.
6. Exited people tenure period is around 6 years.

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('Geography')
['HasCrCard','IsActiveMember'].value_counts()
gp4.plot(kind="bar",figsize=(8,5))
print(gp4)
```

```
----------------------------------------------------------------------
-----
AttributeError                           Traceback (most recent call
last)
<ipython-input-31-869056562afd> in <module>
----> 1 gp4 = df.groupby('Geography')
['HasCrCard','IsActiveMember'].value_counts()
      2 gp4.plot(kind="bar",figsize=(8,5))
      3 print(gp4)

/usr/local/lib/python3.7/dist-packages/pandas/core/groupby/groupby.py
in __getattr__(self, attr)
    910
    911         raise AttributeError(
--> 912             f"'{type(self).__name__}' object has no attribute
'{attr}'"
    913         )
    914

AttributeError: 'DataFrameGroupBy' object has no attribute
'value_counts'
```

```
gp5 = df.groupby(['Gender','HasCrCard','IsActiveMember'])
['EstimatedSalary'].mean()
gp5.plot(kind="line",figsize=(10,8))
print(gp5)

gp6 = df.groupby(['Gender','IsActiveMember'])['Exited'].value_counts()
gp6.plot(kind='bar',figsize=(10,8))
print(gp6)

gp7 = df.groupby('Exited')['Balance','EstimatedSalary'].mean()
print(gp7)

gp8 = df.groupby('Gender')['Geography','Exited'].value_counts()
gp8.plot(kind='bar',figsize=(10,8))
print (gp8)
```

Inference:

1. Germany has more female customers compared to male customers.
2. Average age of Male is 38, whereas average age of Female is 39.
3. Tenure period for both male and female is high in Spain.
4. It is observed that, those who have credit card are very active member in the company.

5. The estimated salary for a person who is not having credit card is high when compared to those having them.
6. Churn for inactive member is high compared to active member.
7. Those who churn has thier estimated salary very low.
8. France has the more churn rate.

4. Descriptive statistics

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

	count	mean	std	min	\
RowNumber	10000.0	5.000500e+03	2886.895680	1.00	
CustomerId	10000.0	1.569094e+07	71936.186123	15565701.00	
CreditScore	10000.0	6.505288e+02	96.653299	350.00	
Age	10000.0	3.892180e+01	10.487806	18.00	
Tenure	10000.0	5.012800e+00	2.892174	0.00	
Balance	10000.0	7.648589e+04	62397.405202	0.00	
NumOfProducts	10000.0	1.530200e+00	0.581654	1.00	
HasCrCard	10000.0	7.055000e-01	0.455840	0.00	
IsActiveMember	10000.0	5.151000e-01	0.499797	0.00	
EstimatedSalary	10000.0	1.000902e+05	57510.492818	11.58	
Exited	10000.0	2.037000e-01	0.402769	0.00	

	25%	50%	75%	max
RowNumber	2500.75	5.000500e+03	7.500250e+03	10000.00
CustomerId	15628528.25	1.569074e+07	1.575323e+07	15815690.00
CreditScore	584.00	6.520000e+02	7.180000e+02	850.00
Age	32.00	3.700000e+01	4.400000e+01	92.00
Tenure	3.00	5.000000e+00	7.000000e+00	10.00
Balance	0.00	9.719854e+04	1.276442e+05	250898.09
NumOfProducts	1.00	1.000000e+00	2.000000e+00	4.00
HasCrCard	0.00	1.000000e+00	1.000000e+00	1.00
IsActiveMember	0.00	1.000000e+00	1.000000e+00	1.00
EstimatedSalary	51002.11	1.001939e+05	1.493882e+05	199992.48
Exited	0.00	0.000000e+00	0.000000e+00	1.00

5. Handling the missing values

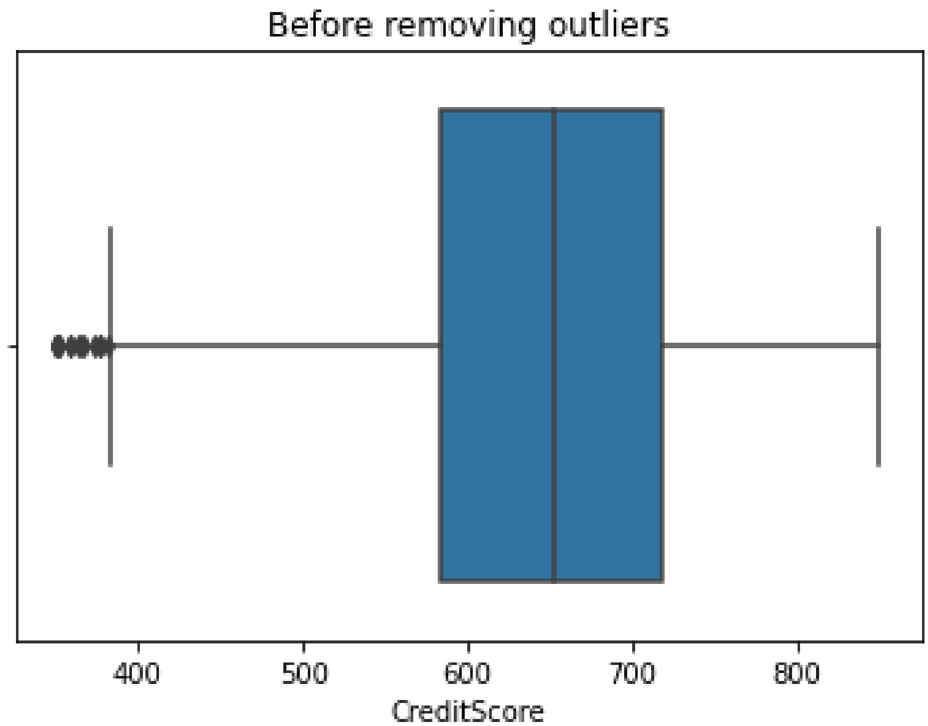
```
df.isnull().sum()
```

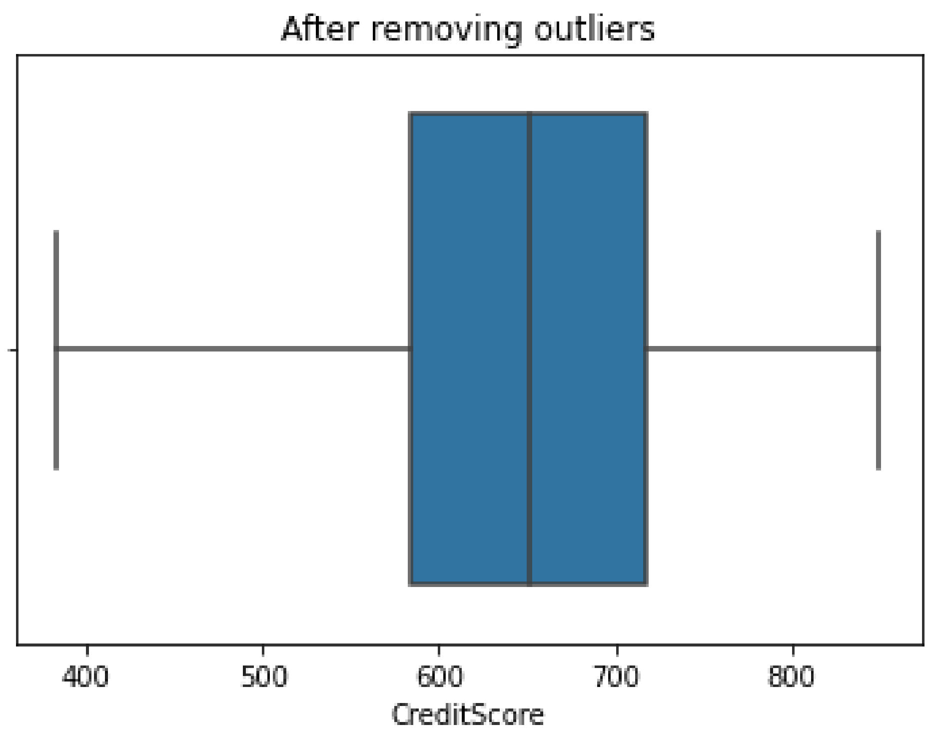
```
RowNumber          0
CustomerId         0
Surname            0
CreditScore        0
Geography          0
Gender             0
Age                0
Tenure             0
Balance            0
NumOfProducts      0
HasCrCard          0
IsActiveMember     0
EstimatedSalary    0
Exited             0
dtype: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

There is no missing value in the dataset

6. Finding outliers

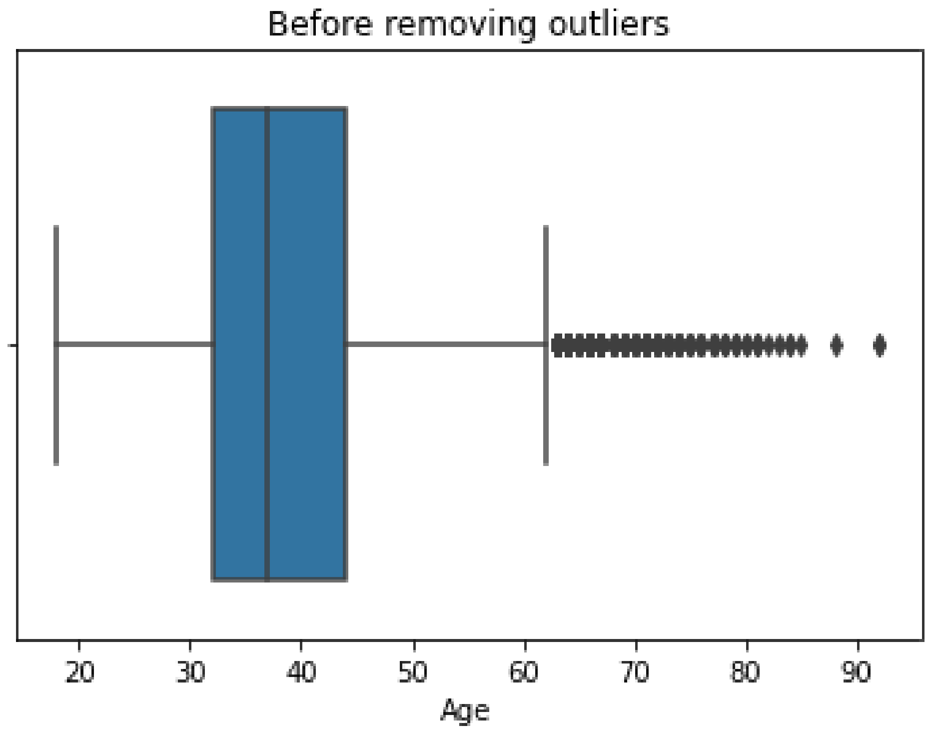
```
def replace_outliers(df, field_name):
    Q1 = np.percentile(df[field_name],25,interpolation='midpoint')
    Q3 = np.percentile(df[field_name],75,interpolation='midpoint')
    IQR = Q3-Q1
    maxi = Q3+1.5*IQR
    mini = Q1-1.5*IQR
    df[field_name]=df[field_name].mask(df[field_name]>maxi,maxi)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

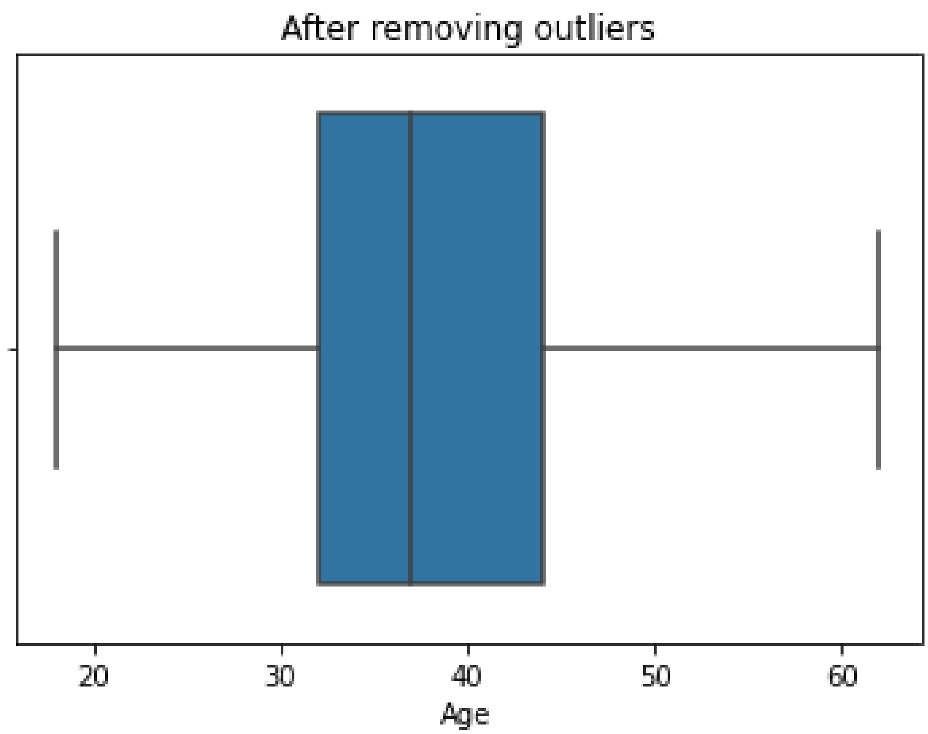





```
plt.title("Before removing outliers")
sns.boxplot(df['Age'])
plt.show()
plt.title("After removing outliers")
replace_outliers(df, 'Age')
```

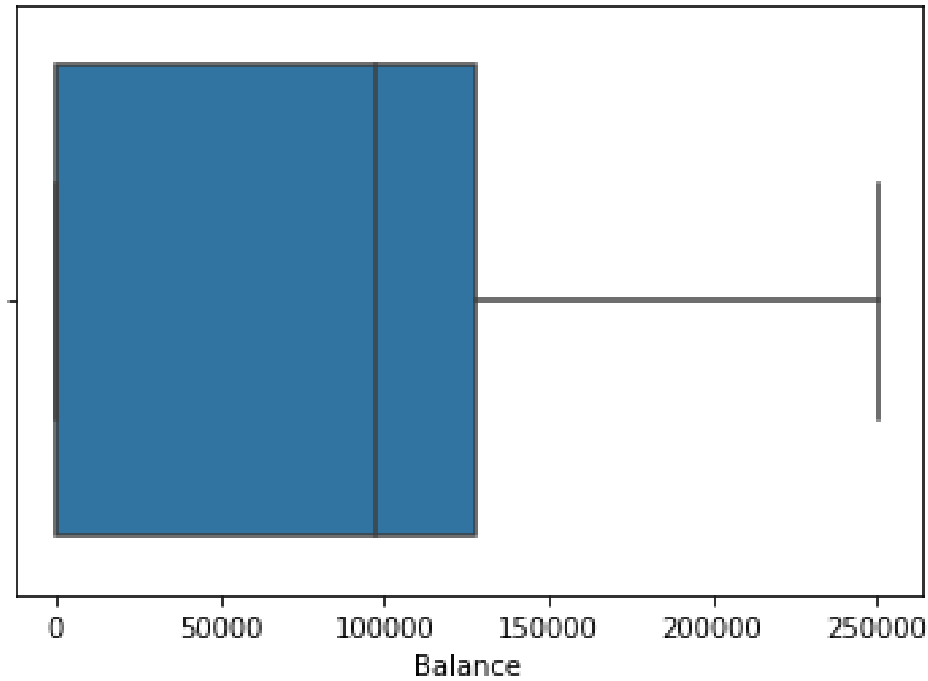
```
sns.boxplot(df['Age'])
plt.show()
```





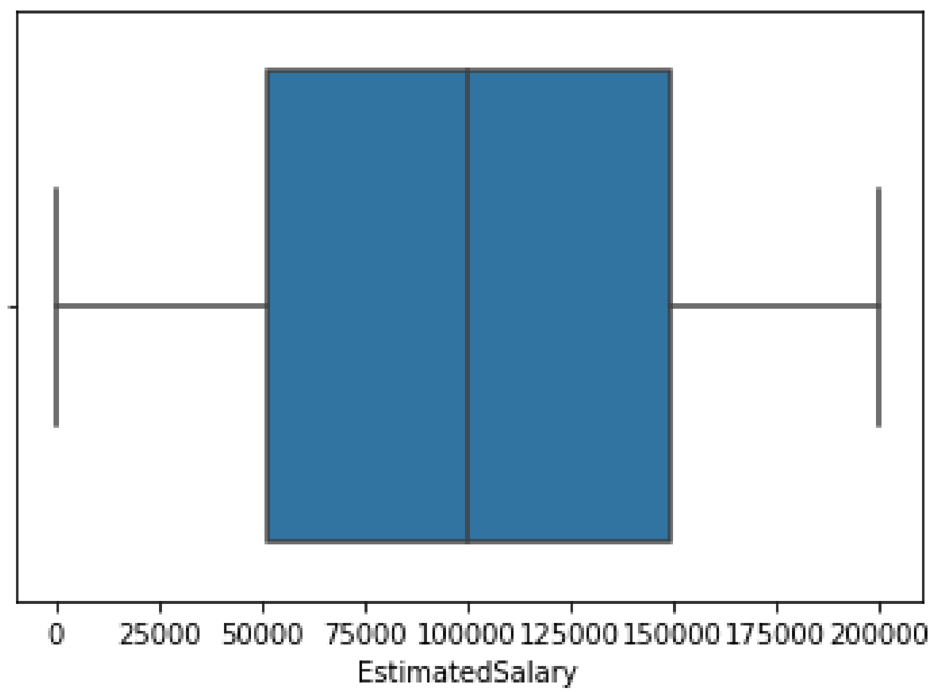

```
sns.boxplot(df['Balance'])
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fbbe9cc2990>
```




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

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fbbe9c32a50>
```



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  \
0          1    15634602  Hargrave        619.0          0       0
42.0
1          2    15647311      Hill        608.0          2       0
41.0
2          3    15619304      Onio        502.0          0       0
42.0
3          4    15701354      Boni        699.0          0       0
39.0
4          5    15737888  Mitchell        850.0          2       0
43.0

   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
```

Only two columns(Gender and Geography) is label encoded

Removing unwanted columns and checking for feature importance

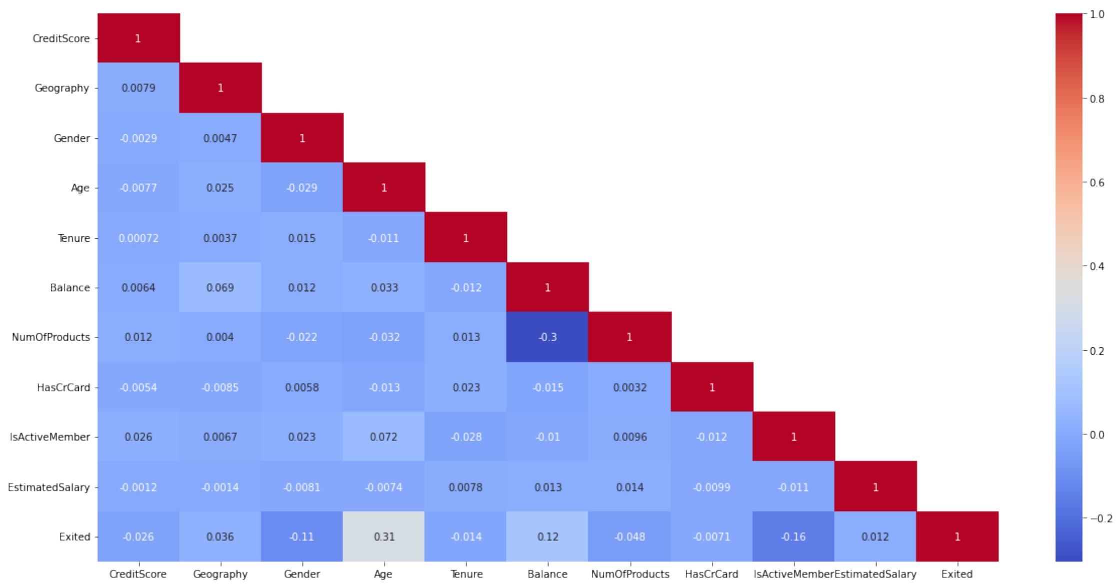
```
df = df.drop(['RowNumber','CustomerId','Surname'],axis=1)

df.head()
```

```
   CreditScore  Geography  Gender   Age  Tenure    Balance
NumOfProducts  \
0        619.0          0       0  42.0       2       0.00
1
1        608.0          2       0  41.0       1   83807.86
1
```

```
2        502.0          0       0  42.0       8  159660.80
3
3        699.0          0       0  39.0       1       0.00
2
4        850.0          2       0  43.0       2  125510.82
1

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

```
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 0x7fbbe94764d0>
```



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  \
0    -0.326878          0       0  0.342615       2 -1.225848  
1  
1    -0.440804          2       0  0.240011       1  0.117350  
1  
2    -1.538636          0       0  0.342615       8  1.333053  
3  
3     0.501675          0       0  0.034803       1 -1.225848  
2  
4     2.065569          2       0  0.445219       2  0.785728  
1  

   HasCrCard  IsActiveMember  EstimatedSalary  
0          1               1         0.021886  
1          0               1         0.216534  
2          1               0         0.240687  
3          0               0        -0.108918  
4          1               1        -0.365276  
```

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,)
```

Conclusion:

1. The model is scaled using StandarScaler method.
2. The train and test split ratio is 15:5.
3. As it is a classification problem, basic algorithms can be used to build ML models.