Assignment 2 - Sharan MV

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
```

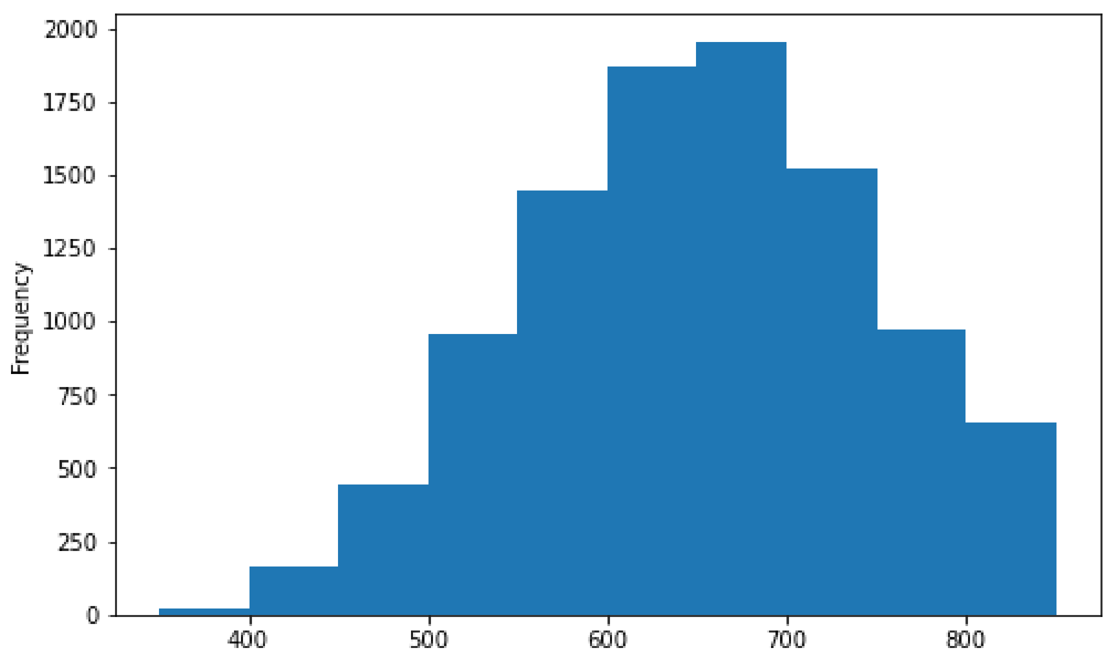
```
Index(['RowNumber', 'CustomerId', 'Surname', 'CreditScore',
'Geography',
       'Gender', 'Age', 'Tenure', 'Balance', 'NumOfProducts',
'HasCrCard',
       'IsActiveMember', 'EstimatedSalary', 'Exited'],
      dtype='object')
```

```
df.shape
```

```
(10000, 14)
```

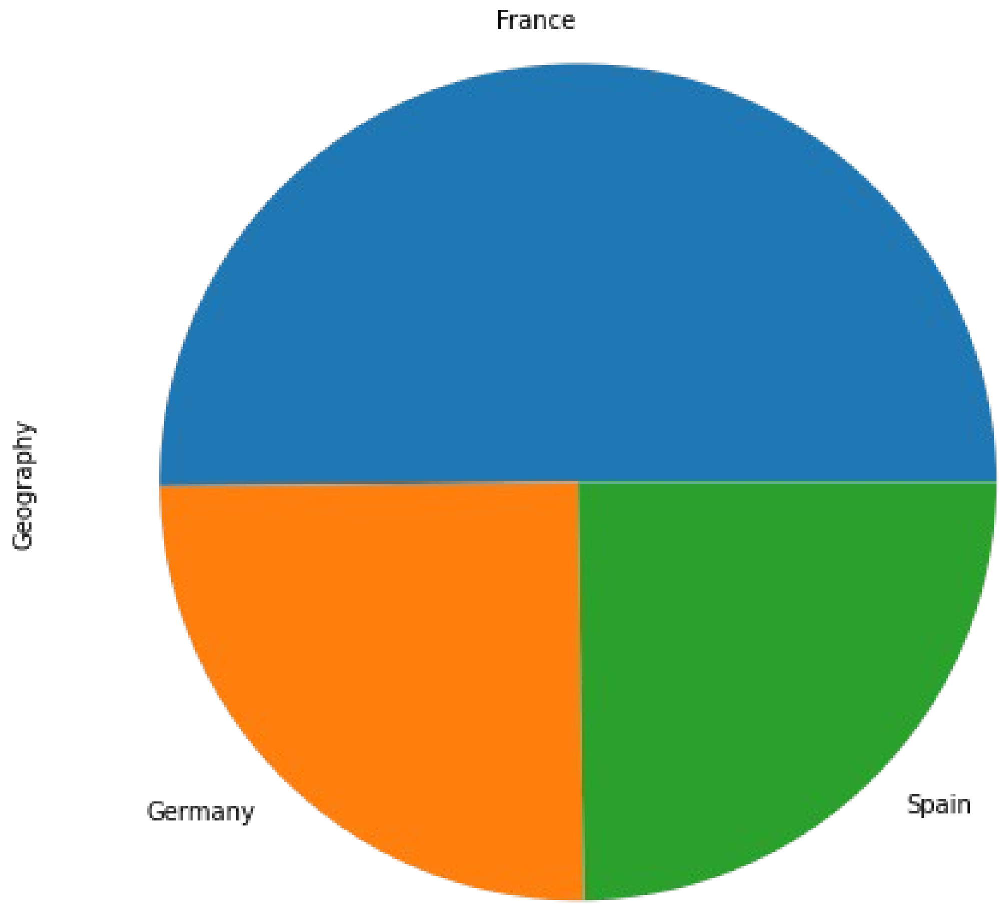
```
credit = df['CreditScore']
credit.plot(kind="hist",figsize=(8,5))
```

```
<AxesSubplot:ylabel='Frequency'>
```



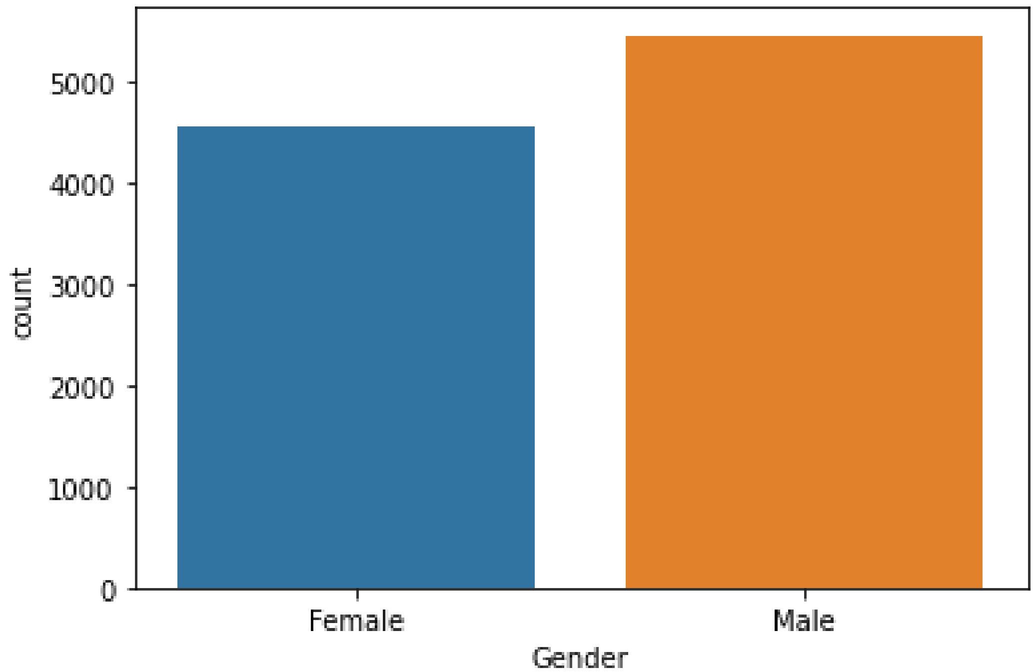

```
geo = df['Geography'].value_counts()
geo.plot(kind="pie",figsize=(10,8))
```

```
<AxesSubplot:ylabel='Geography'>
```



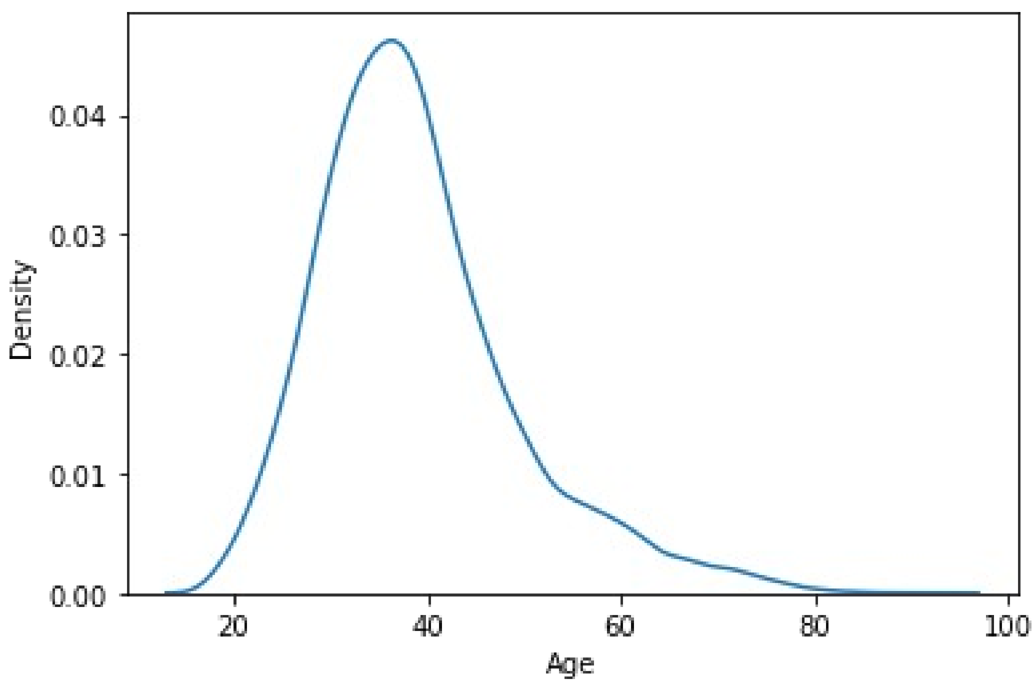

```
sns.countplot(df['Gender'])
```

<AxesSubplot:xlabel='Gender', ylabel='count'>



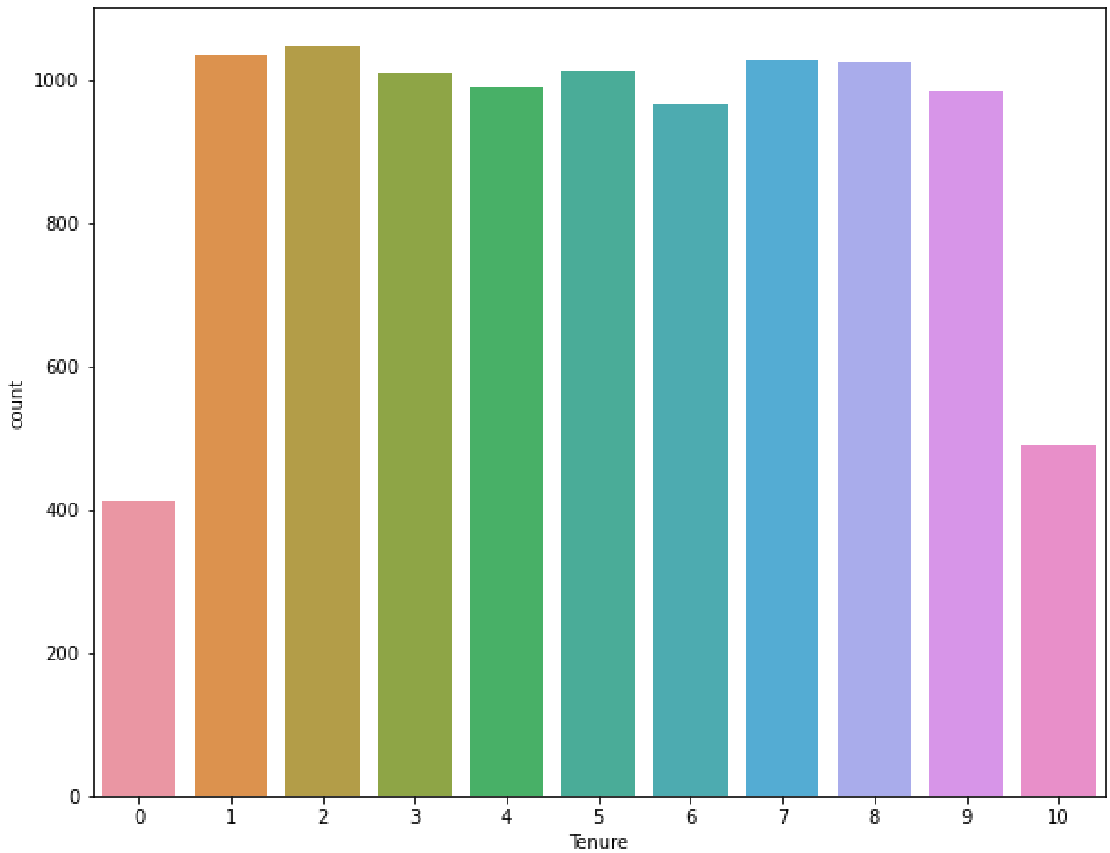

```
sns.distplot(df['Age'],hist=False)
```

```
<AxesSubplot:xlabel='Age', ylabel='Density'>
```



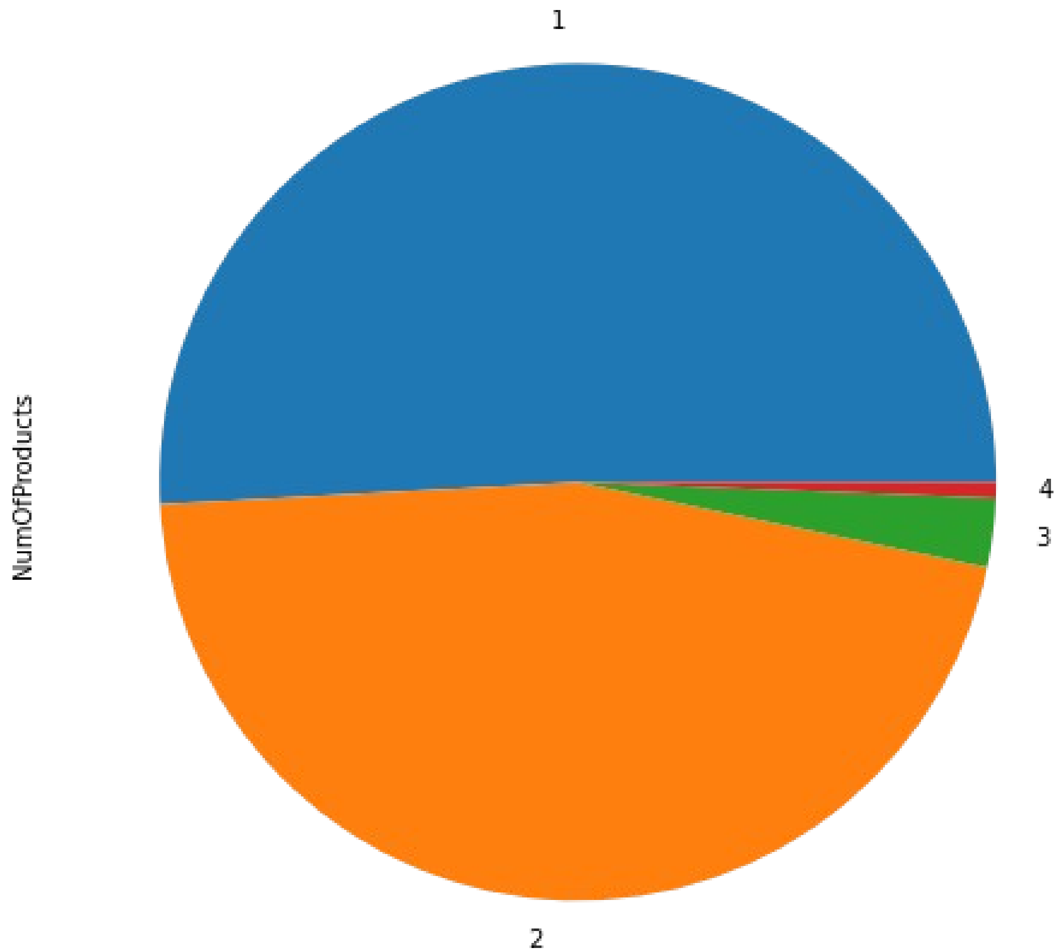

```
plt.figure(figsize=(10,8))
sns.countplot(df['Tenure'])
```

```
<AxesSubplot:xlabel='Tenure', ylabel='count'>
```



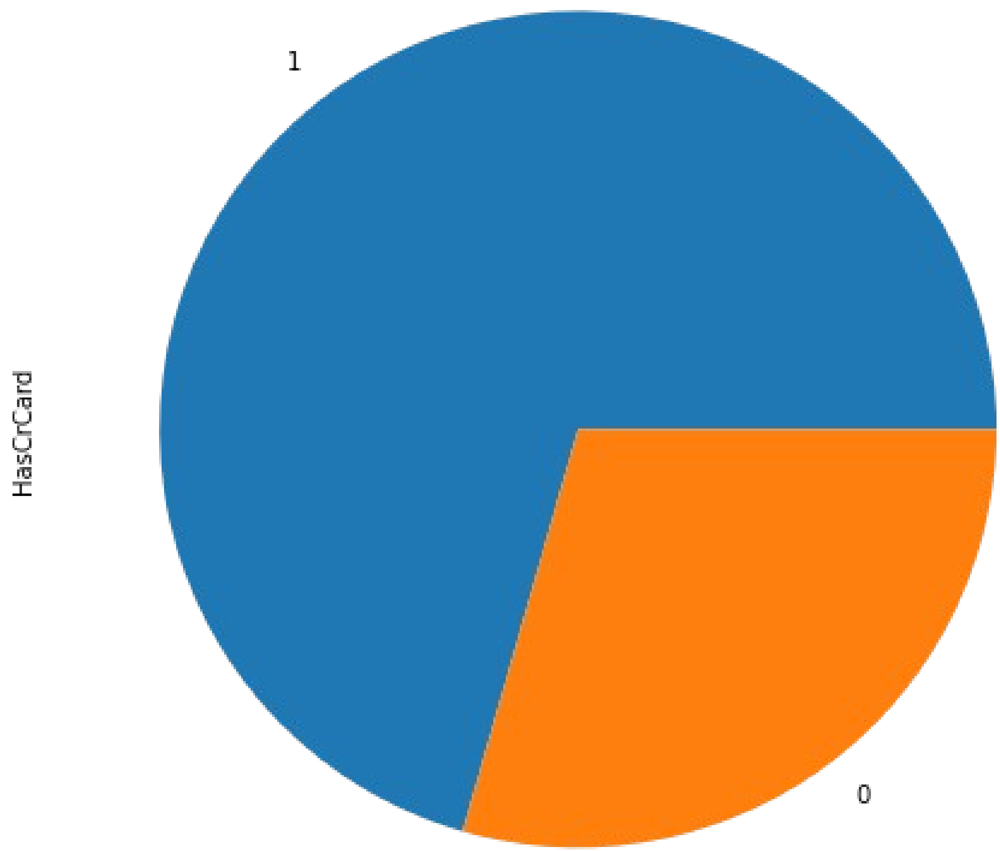

```
product = df['NumOfProducts'].value_counts()
product.plot(kind="pie",figsize=(10,8))
```

```
<AxesSubplot:ylabel='NumOfProducts'>
```



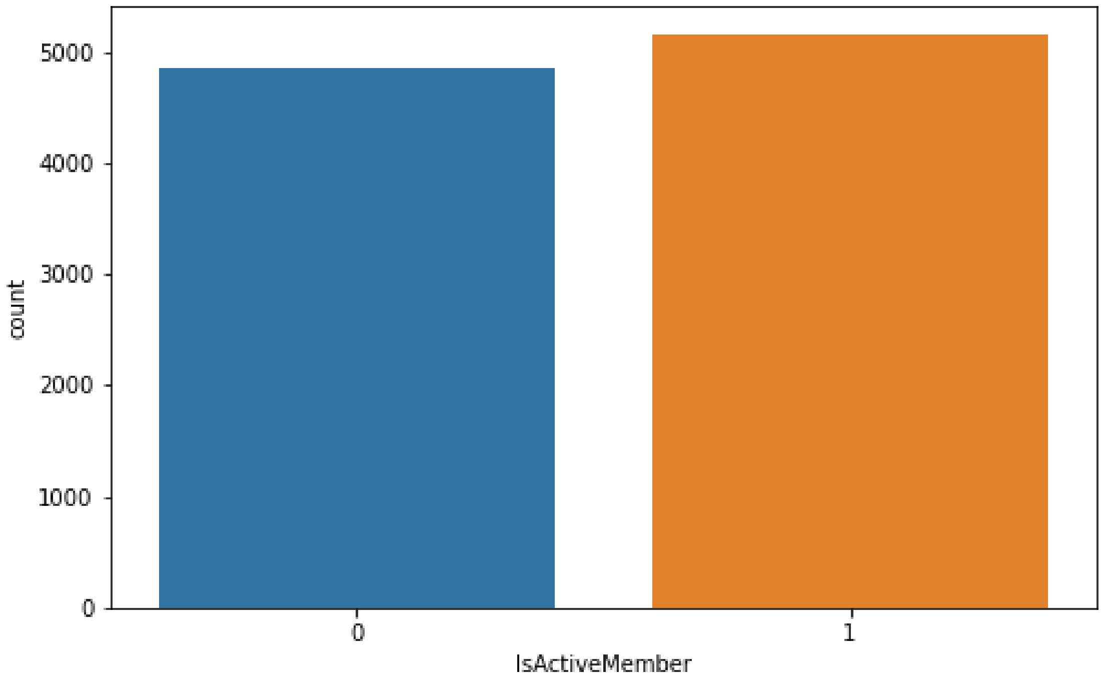

```
cr = df['HasCrCard'].value_counts()
cr.plot(kind="pie",figsize=(10,8))
```

<AxesSubplot:ylabel='HasCrCard'>



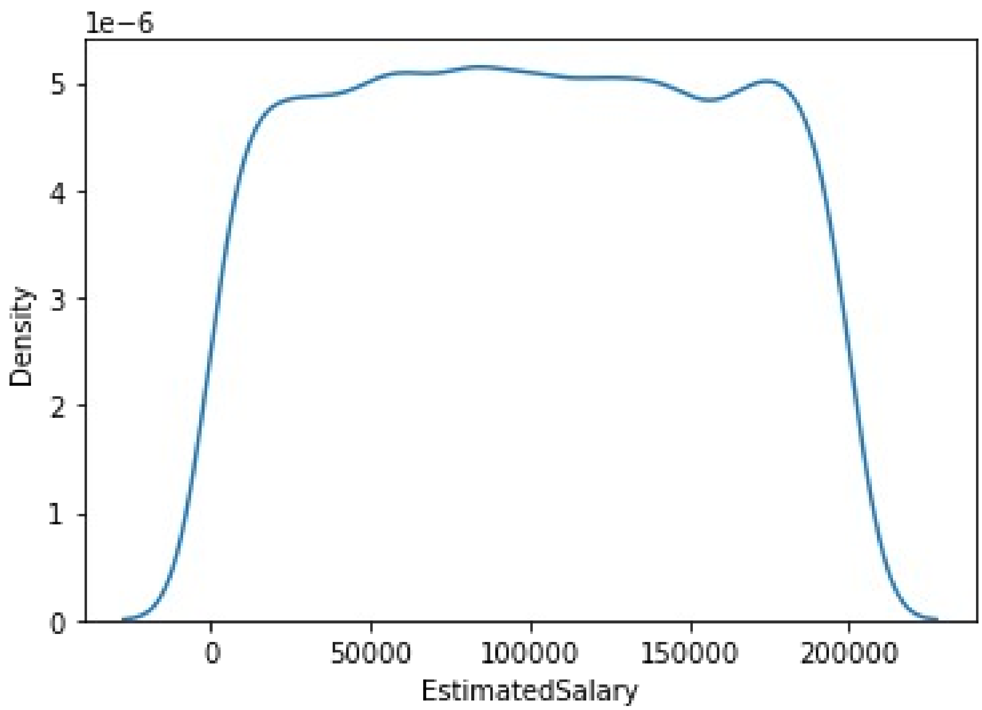

```
plt.figure(figsize=(8,5))
sns.countplot(df['IsActiveMember'])
```

```
<AxesSubplot:xlabel='IsActiveMember', ylabel='count'>
```



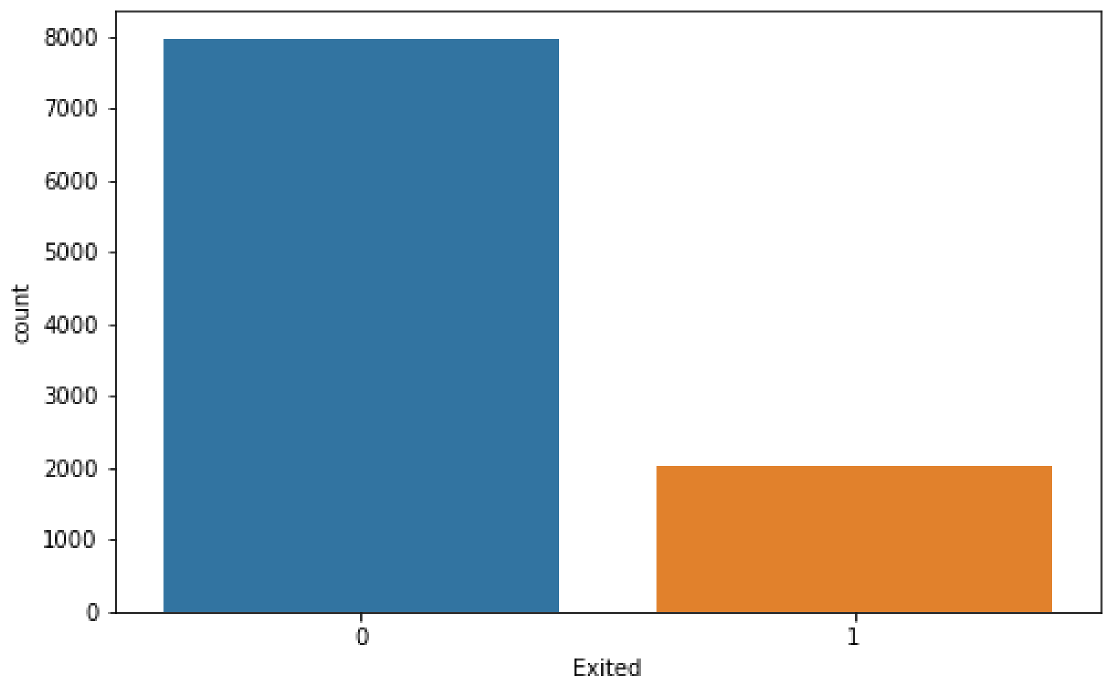

```
sns.distplot(df['EstimatedSalary'],hist=False)
```

```
<AxesSubplot:xlabel='EstimatedSalary', ylabel='Density'>
```




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

```
<AxesSubplot:xlabel='Exited', ylabel='count'>
```



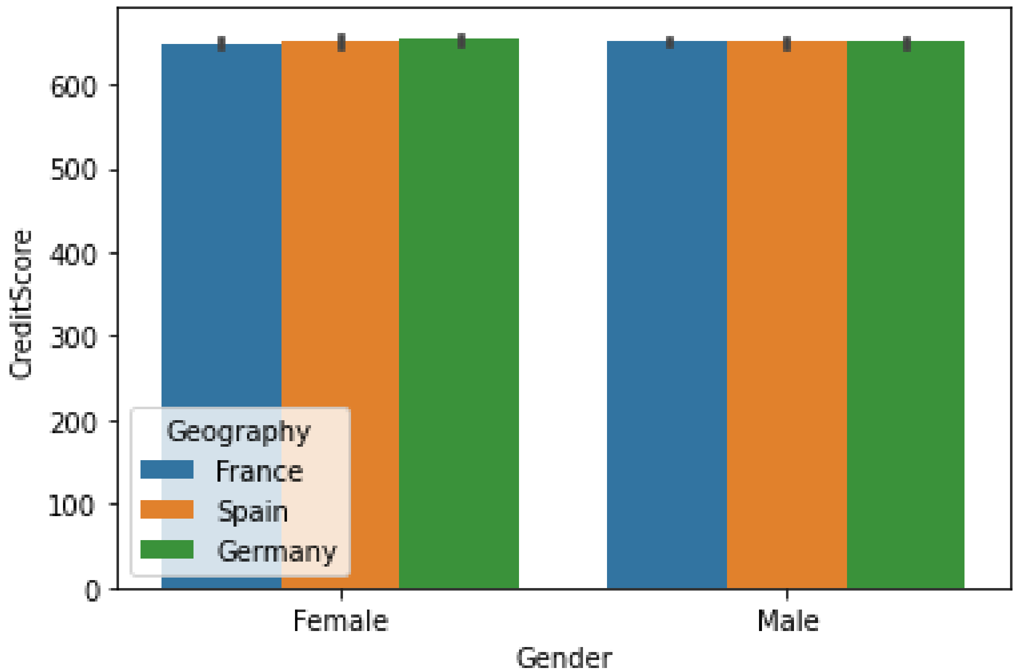
Inference:

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

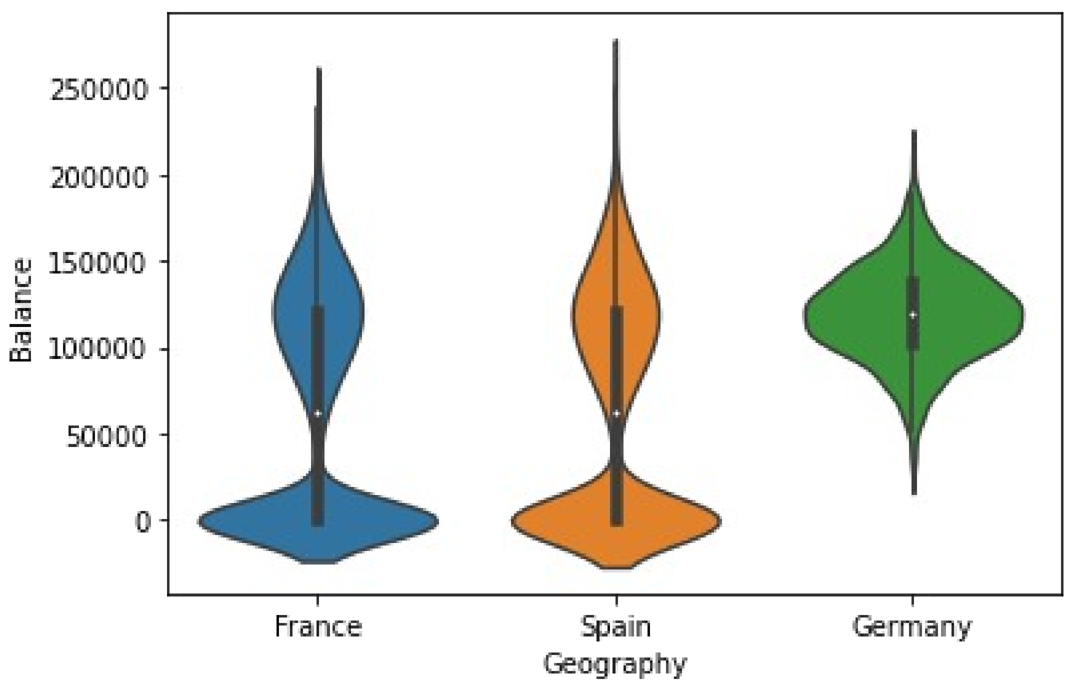
```
sns.barplot(x='Gender',y='CreditScore',hue='Geography',data=df)
```

```
<AxesSubplot:xlabel='Gender', ylabel='CreditScore'>
```



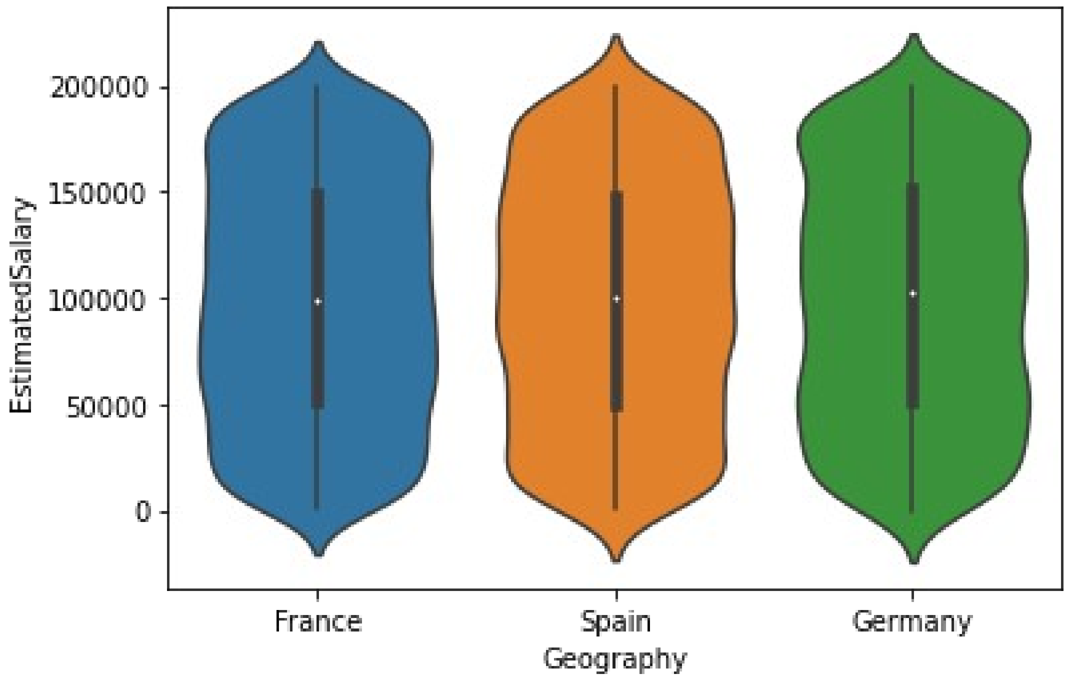

```
sns.violinplot(x='Geography',y='Balance',data=df)
```

<AxesSubplot:xlabel='Geography', ylabel='Balance'>



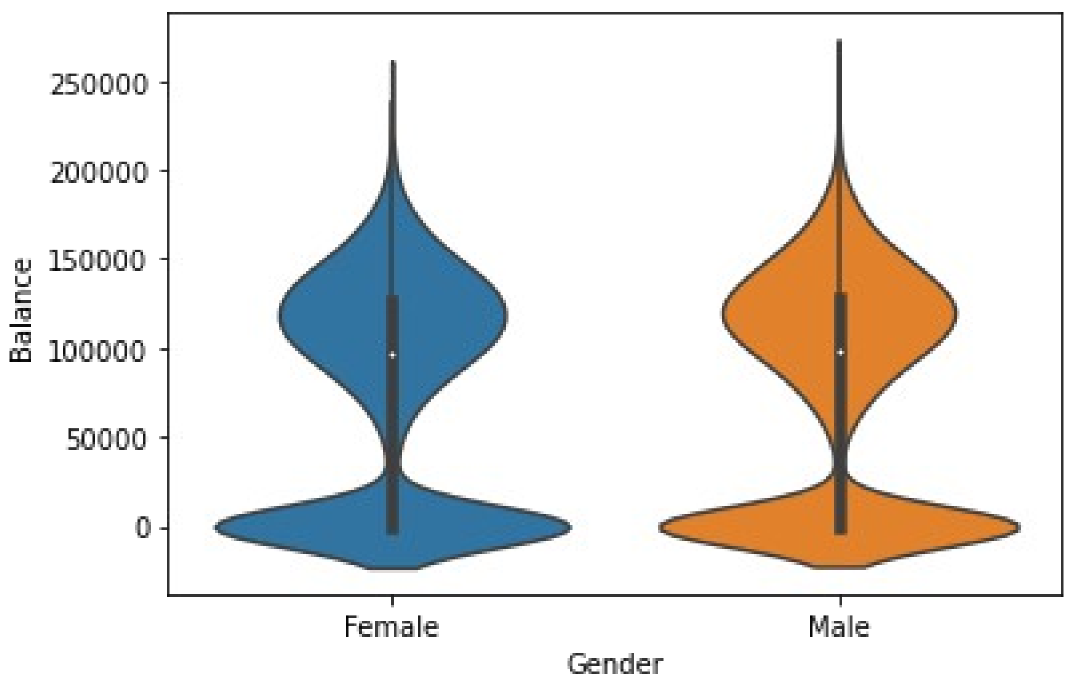

```
sns.violinplot(x='Geography',y='EstimatedSalary',data=df)
```

<AxesSubplot:xlabel='Geography', ylabel='EstimatedSalary'>



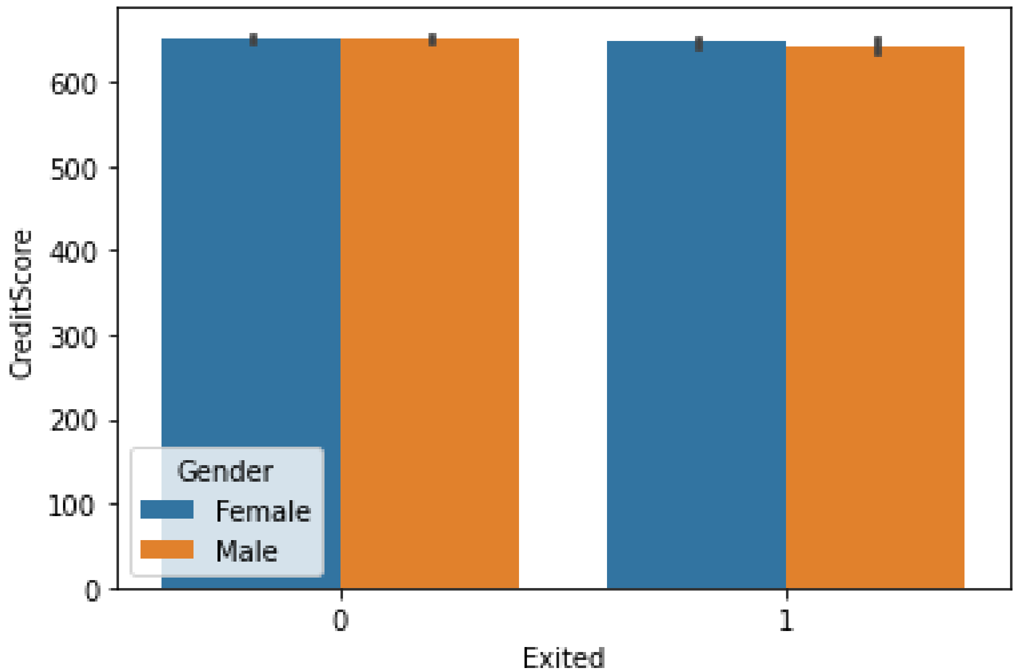

```
sns.violinplot(x='Gender',y='Balance',data=df)
```

<AxesSubplot:xlabel='Gender', ylabel='Balance'>



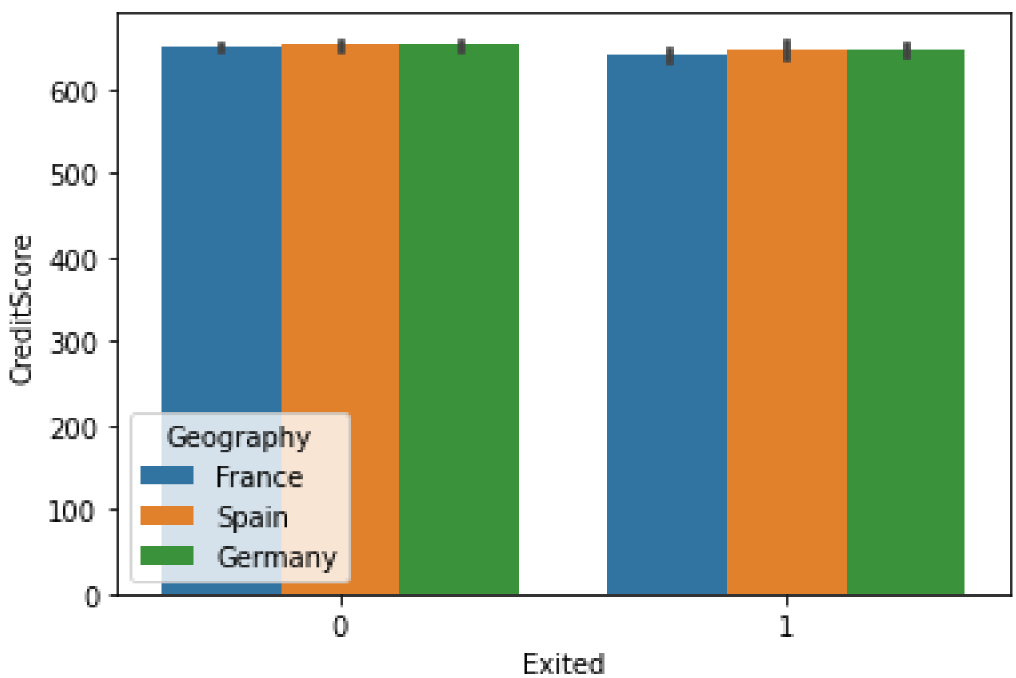

```
sns.barplot(x='Exited',y='CreditScore',hue='Gender',data=df)
```

<AxesSubplot:xlabel='Exited', ylabel='CreditScore'>



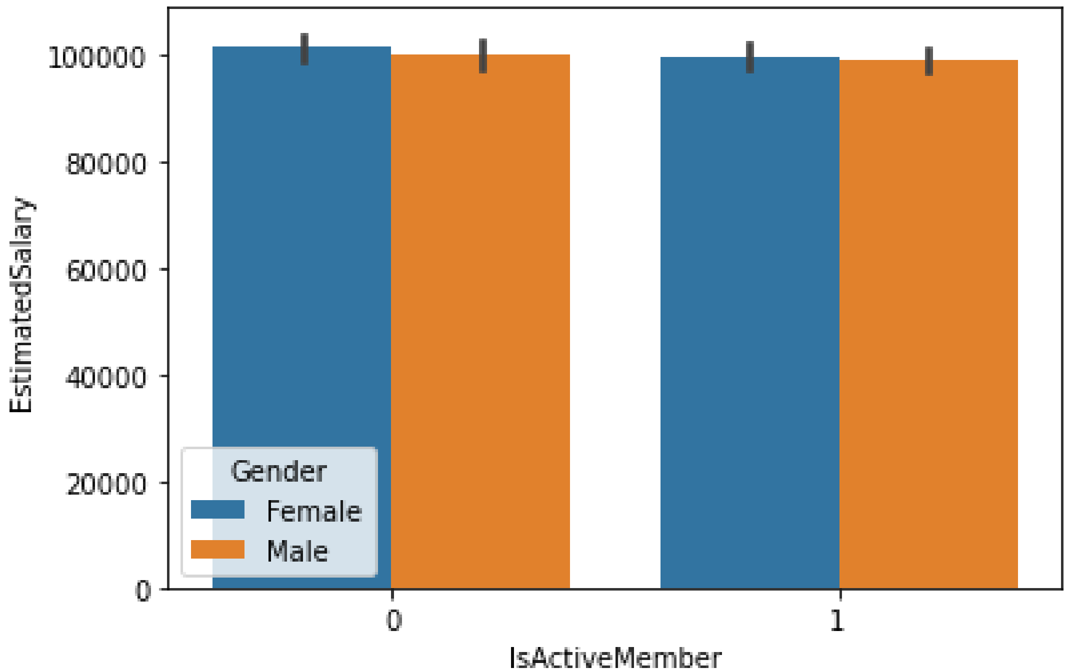

```
sns.barplot(x='Exited',y='CreditScore',hue='Geography',data=df)
```

```
<AxesSubplot:xlabel='Exited', ylabel='CreditScore'>
```



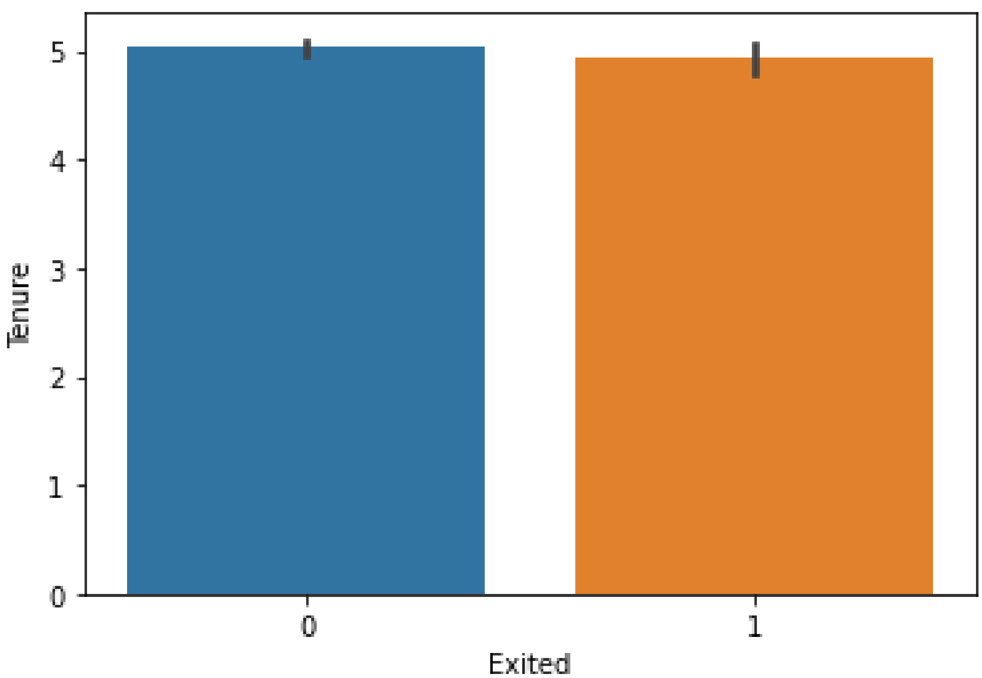

```
sns.barplot(x='IsActiveMember',y='EstimatedSalary',hue='Gender',data=d
f)
```

```
<AxesSubplot:xlabel='IsActiveMember', ylabel='EstimatedSalary'>
```




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

<AxesSubplot:xlabel='Exited', ylabel='Tenure'>



Inference:

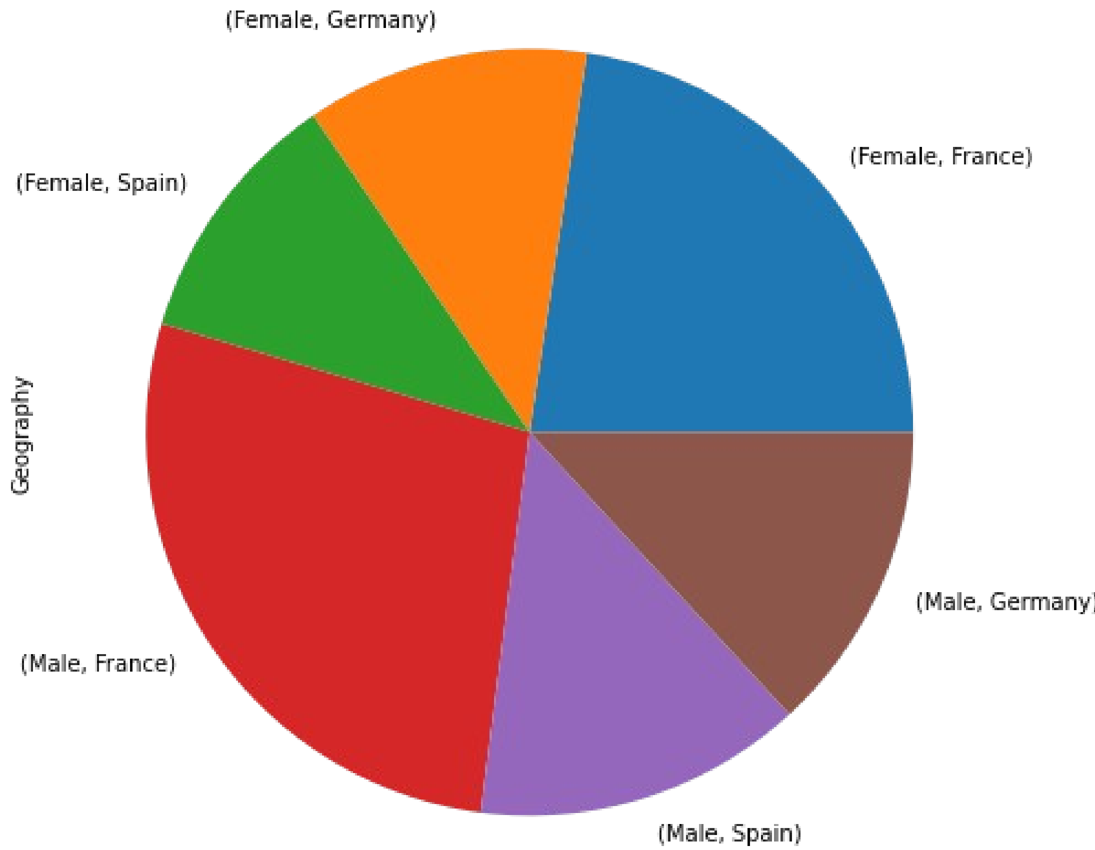
1. Credit score for Male is higher in Spain.

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)
```

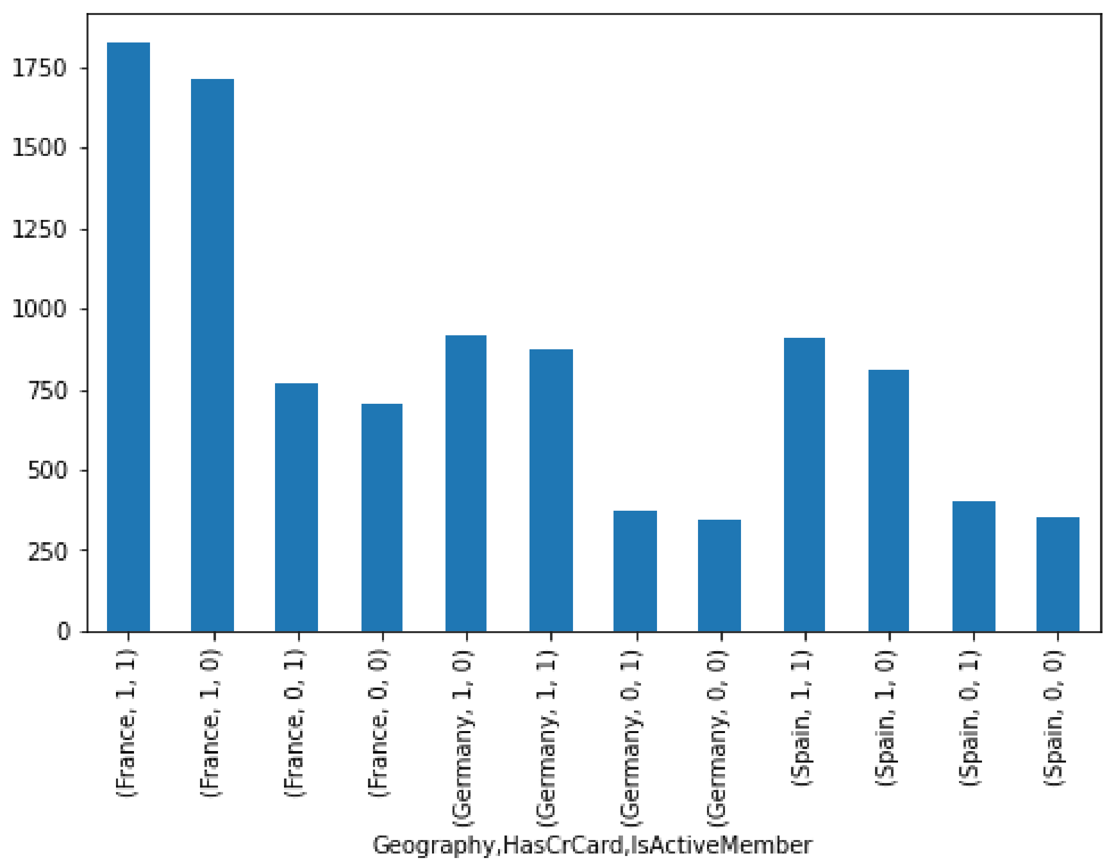
```
Gender
Female    39.238389
Male      38.658237
Name: Age, dtype: float64
```

```
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
```

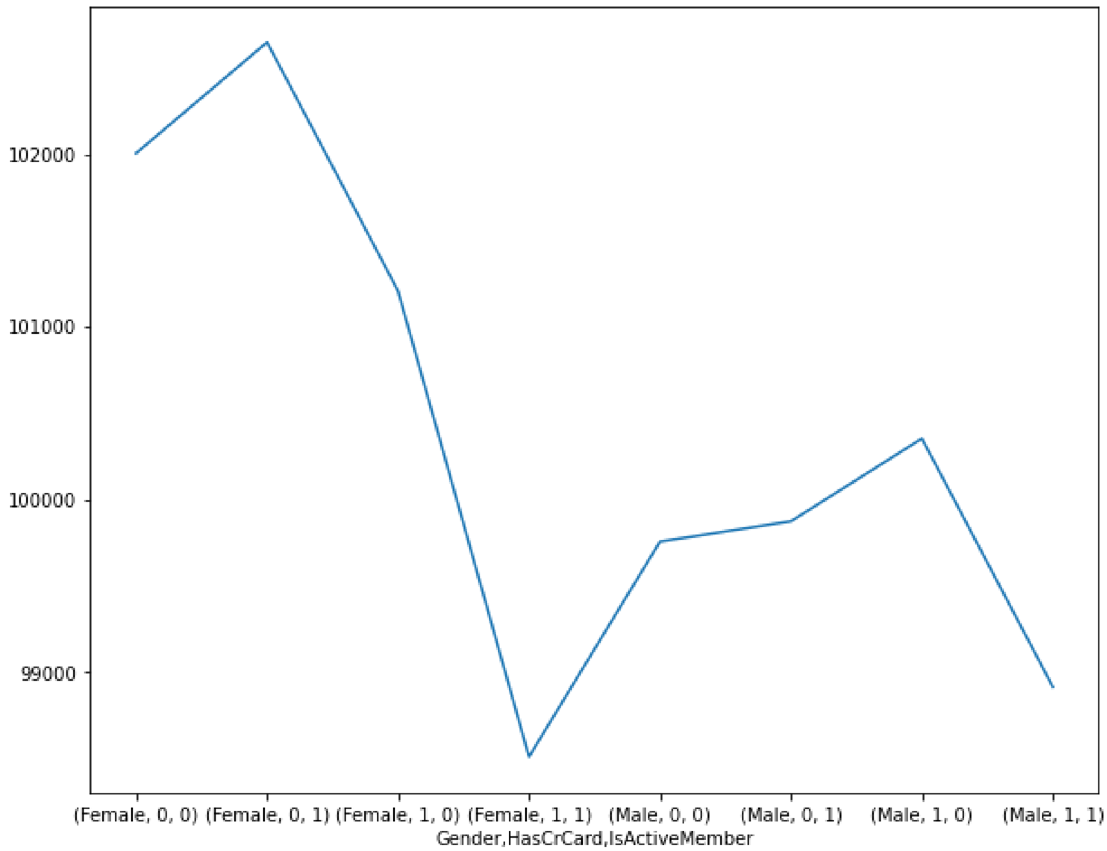
```
gp4 = df.groupby('Geography')
['HasCrCard','IsActiveMember'].value_counts()
gp4.plot(kind="bar",figsize=(8,5))
print(gp4)
```

```
Geography  HasCrCard  IsActiveMember
France     1          1                 1826
                      0                 1717
           0          1                  765
                      0                  706
Germany    1          0                  918
                      1                  873
           0          1                  375
                      0                  343
Spain      1          1                  908
                      0                  813
           0          1                  404
                      0                  352
dtype: int64
```




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

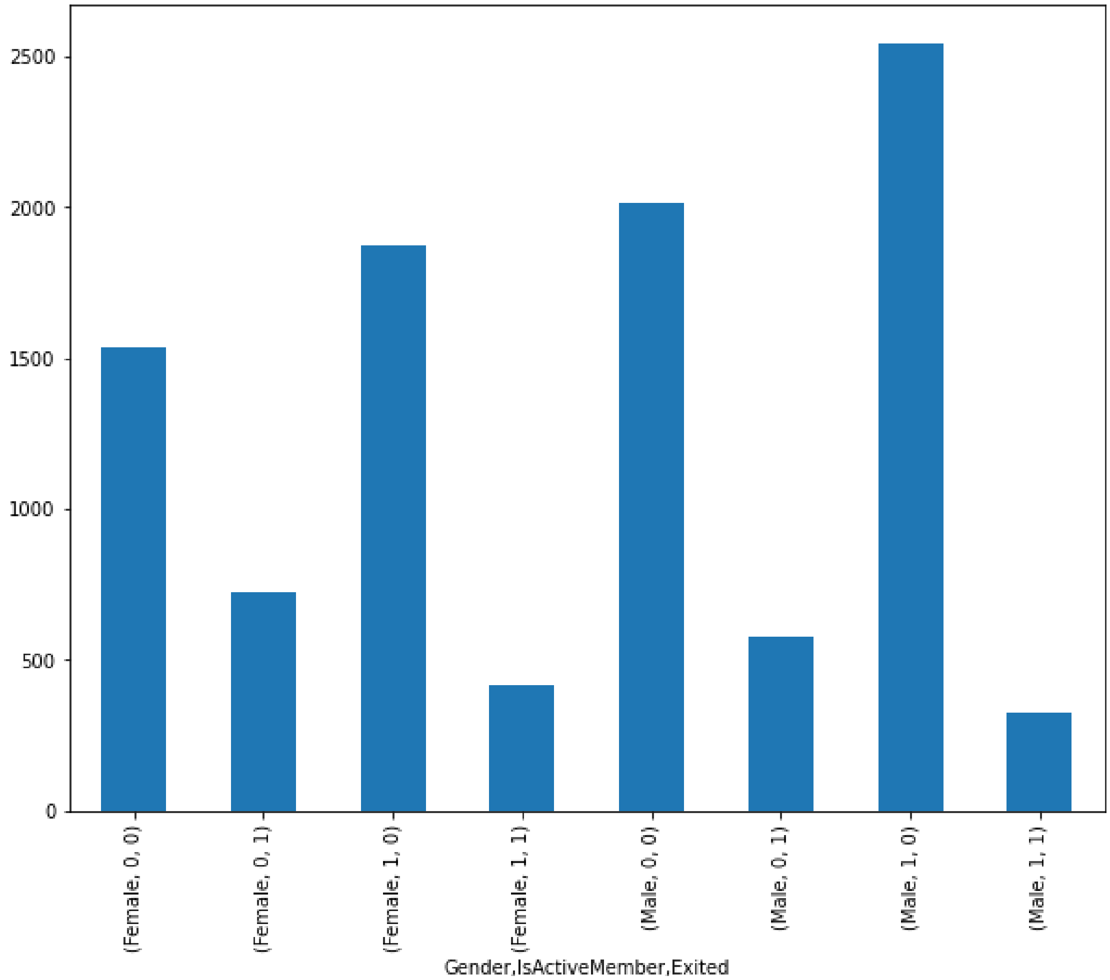
```
Gender  HasCrCard  IsActiveMember
Female  0          0                 102006.080352
                   1                 102648.996944
        1          0                 101208.014567
                   1                  98510.152300
Male    0          0                  99756.431151
       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




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

```
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
```



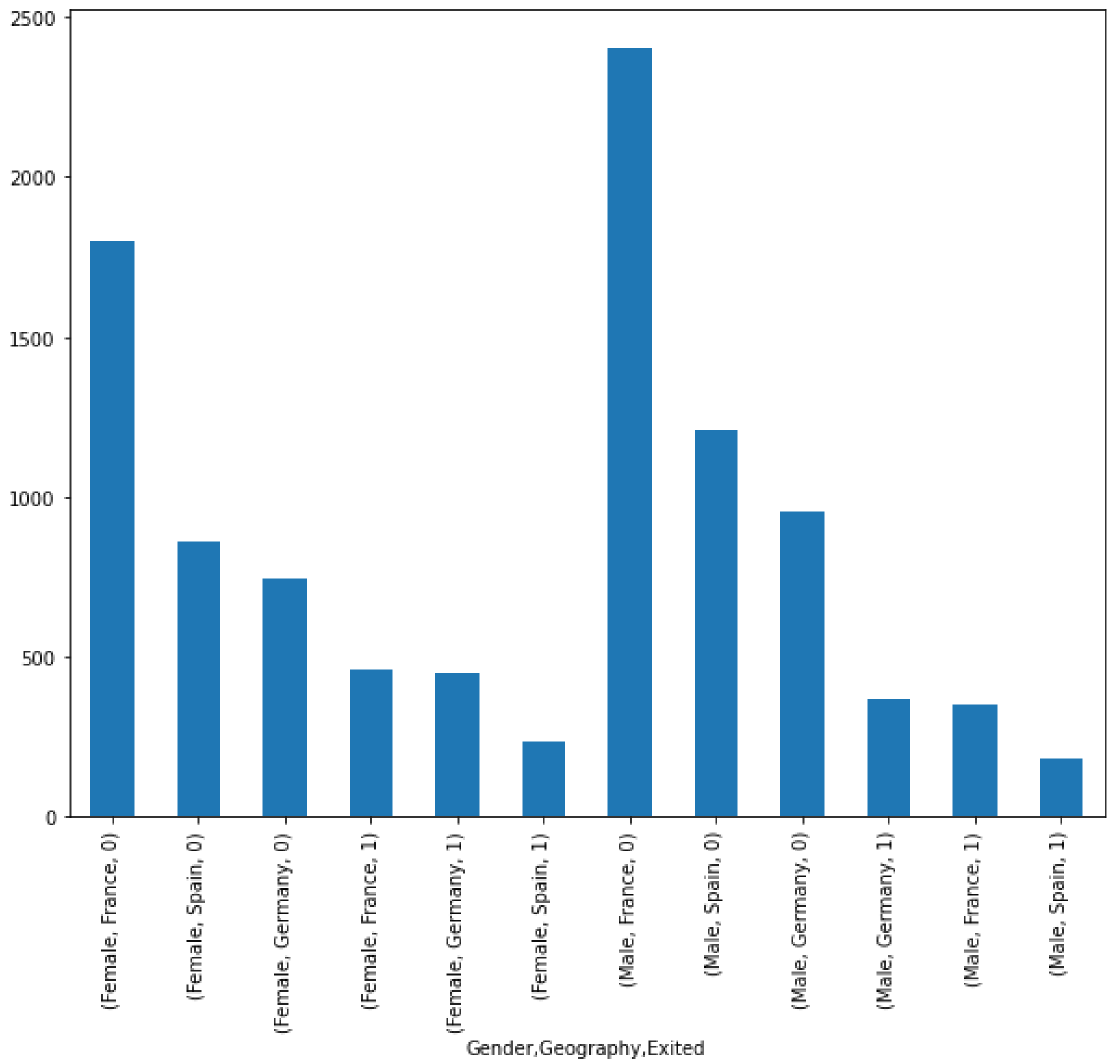

```
gp7 = df.groupby('Exited')['Balance','EstimatedSalary'].mean()
print(gp7)
```

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

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

```
Gender  Geography  Exited
Female  France     0         1801
        Spain      0          858
        Germany    0          745
        France     1          460
        Germany    1          448
```

```
        Spain      1          231
Male    France     0         2403
        Spain      0         1206
        Germany    0          950
                   1          366
        France     1          350
        Spain      1          182
dtype: int64
```



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

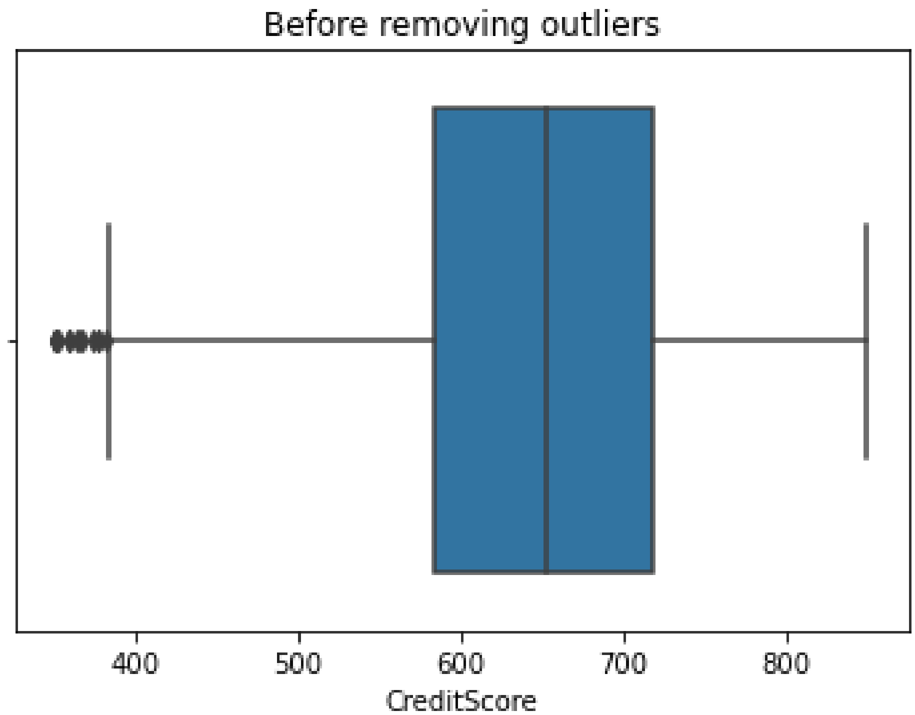
```
df.isnull().sum()
```

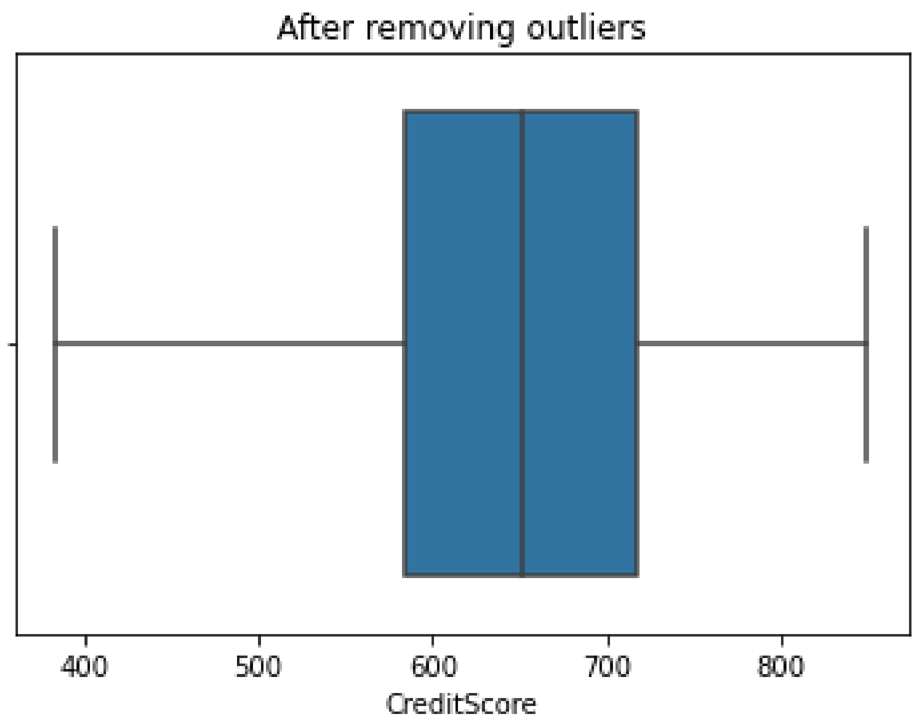
```
RowNumber          0
CustomerId         0
Surname            0
CreditScore        0
Geography          0
Gender             0
Age                0
Tenure             0
Balance            0
NumOfProducts      0
HasCrCard          0
IsActiveMember     0
EstimatedSalary    0
Exited             0
dtype: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

There is no missing value in the dataset

6. Finding outliers

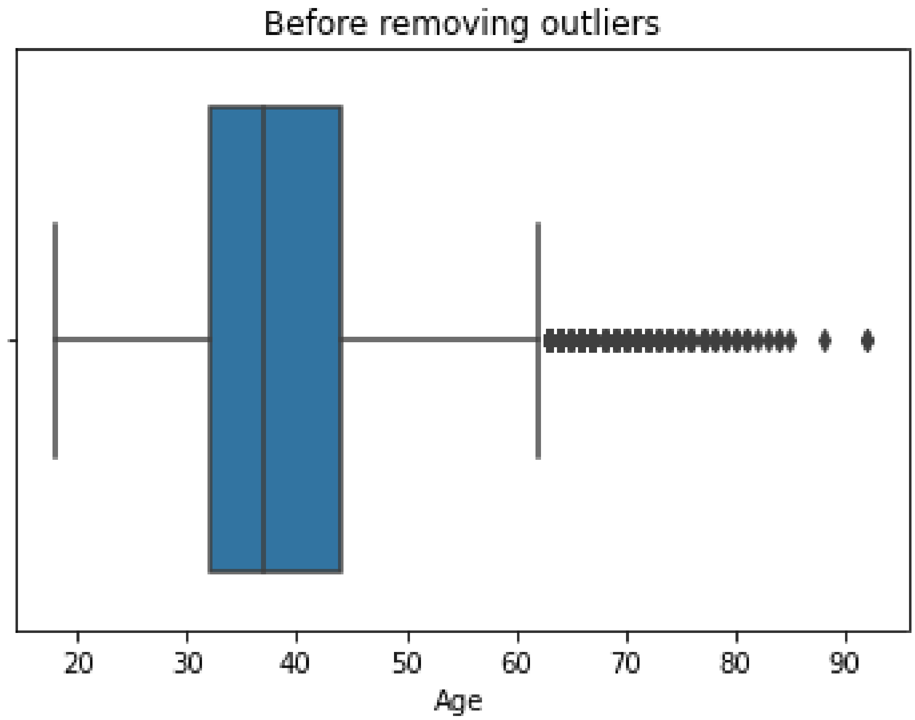
```
def replace_outliers(df, field_name):
    Q1 = np.percentile(df[field_name],25,interpolation='midpoint')
    Q3 = np.percentile(df[field_name],75,interpolation='midpoint')
    IQR = Q3-Q1
    maxi = Q3+1.5*IQR
    mini = Q1-1.5*IQR
    df[field_name]=df[field_name].mask(df[field_name]>maxi,maxi)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

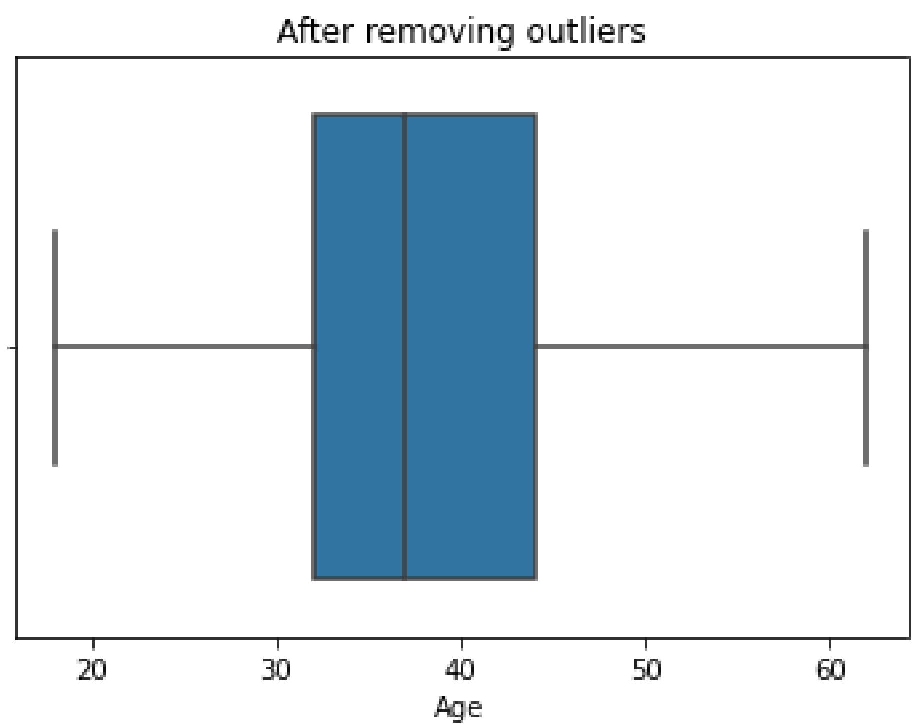





```
plt.title("Before removing outliers")
sns.boxplot(df['Age'])
plt.show()
plt.title("After removing outliers")
replace_outliers(df, 'Age')
```

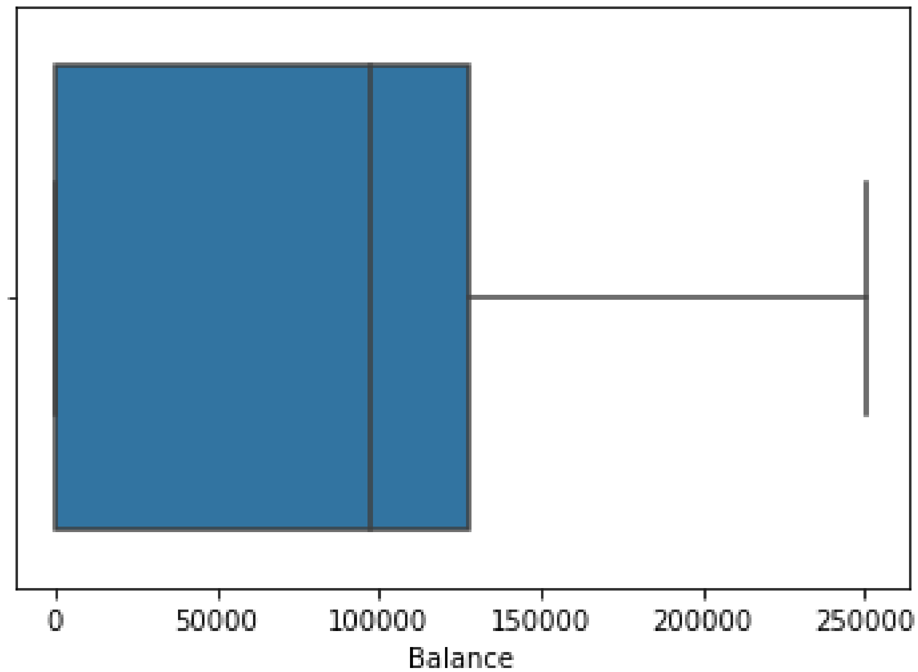
```
sns.boxplot(df['Age'])
plt.show()
```





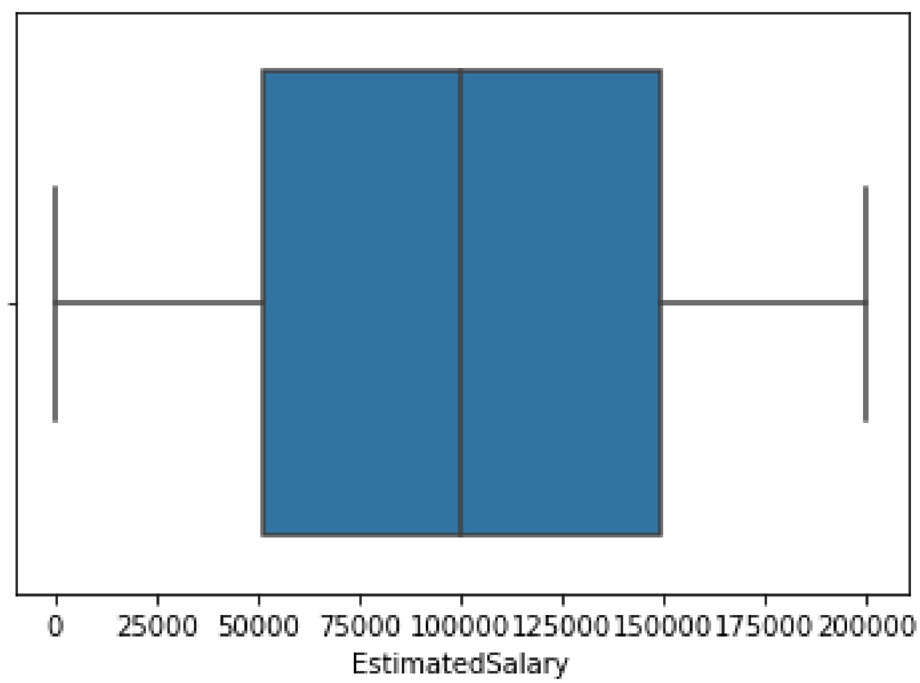

```
sns.boxplot(df['Balance'])
```

```
<AxesSubplot:xlabel='Balance'>
```




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

```
<AxesSubplot:xlabel='EstimatedSalary'>
```



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

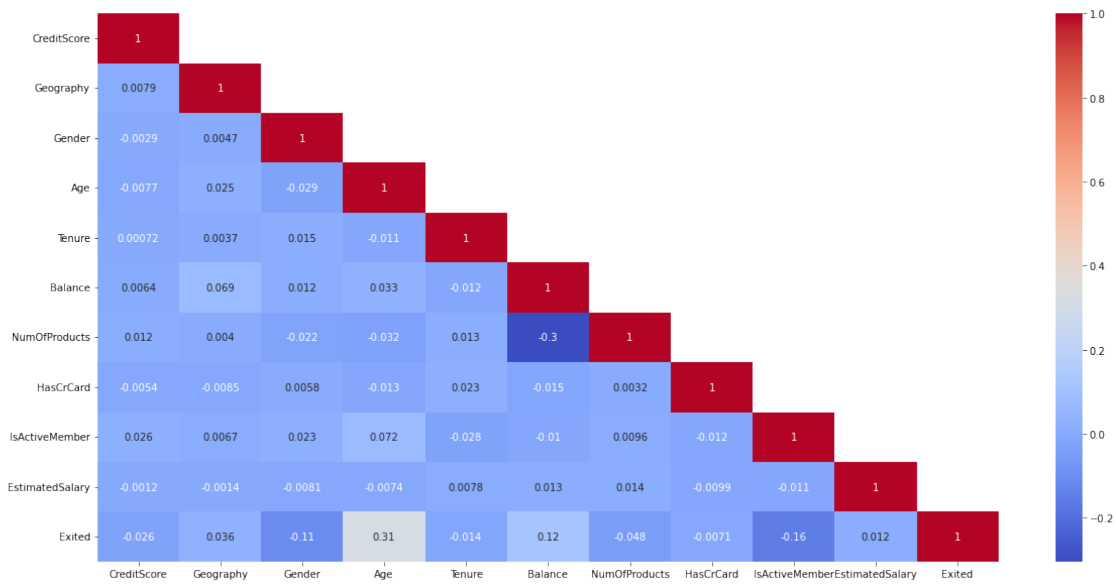
Removing unwanted columns and checking for feature importance

```
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")
```

```
<AxesSubplot:>
```



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.