Assignment 2 - authored by, R Lingeshwaran

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

Double-click (or enter) to edit

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

	RowNumber	CustomerId	Surname	CreditScore	Geography	Gender	Age	Tenure	Balar
0	1	15634602	Hargrave	619	France	Female	42	2	0.
1	2	15647311	Hill	608	Spain	Female	41	1	83807.
2	3	15619304	Onio	502	France	Female	42	8	159660.
3	4	15701354	Boni	699	France	Female	39	1	0.
4	5	15737888	Mitchell	850	Spain	Female	43	2	125510.

```
df.tail()
```

	RowNumber	CustomerId	Surname	CreditScore	Geography	Gender	Age	Tenure	E
9995	9996	15606229	Obijiaku	771	France	Male	39	5	
9996	9997	15569892	Johnstone	516	France	Male	35	10	5
9997	9998	15584532	Liu	709	France	Female	36	7	
9998	9999	15682355	Sabbatini	772	Germany	Male	42	3	7
9999	10000	15628319	Walker	792	France	Female	28	4	13

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',
```

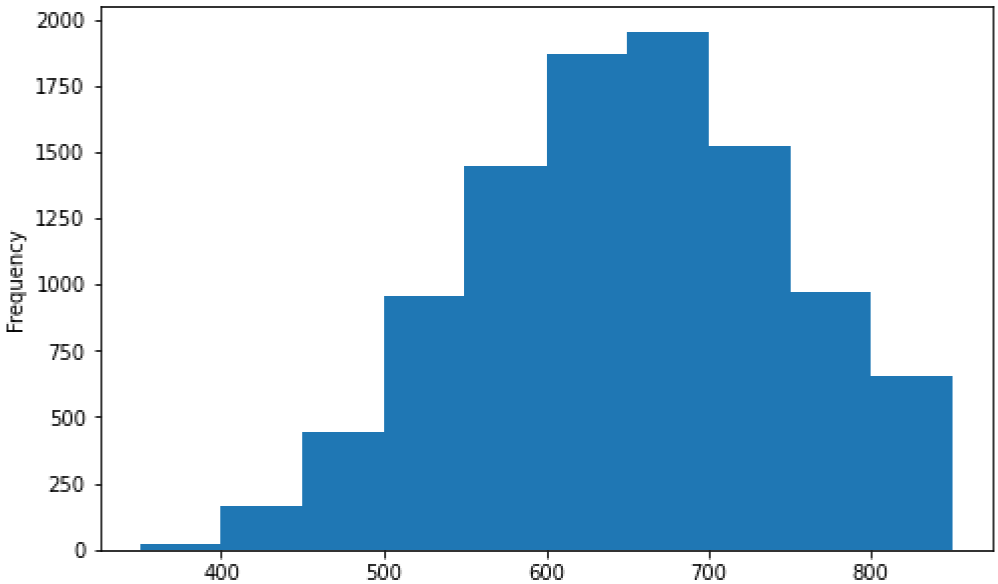
```
        'Gender', 'Age', 'Tenure', 'Balance', 'NumOfProducts', 'HasCrCard',
        'IsActiveMember', 'EstimatedSalary', 'Exited'],
       dtype='object')
```

```
df.shape
```

```
(10000, 14)
```

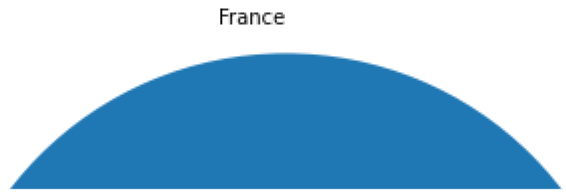
```
credit = df['CreditScore']
credit.plot(kind="hist",figsize=(8,5))
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f3728271c90>
```



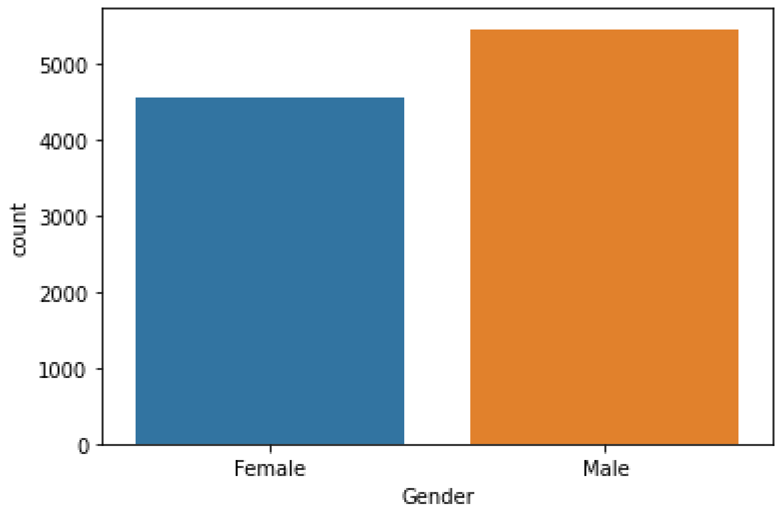

```
geo = df['Geography'].value_counts()
geo.plot(kind="pie",figsize=(10,8))
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f37282f3950>
```



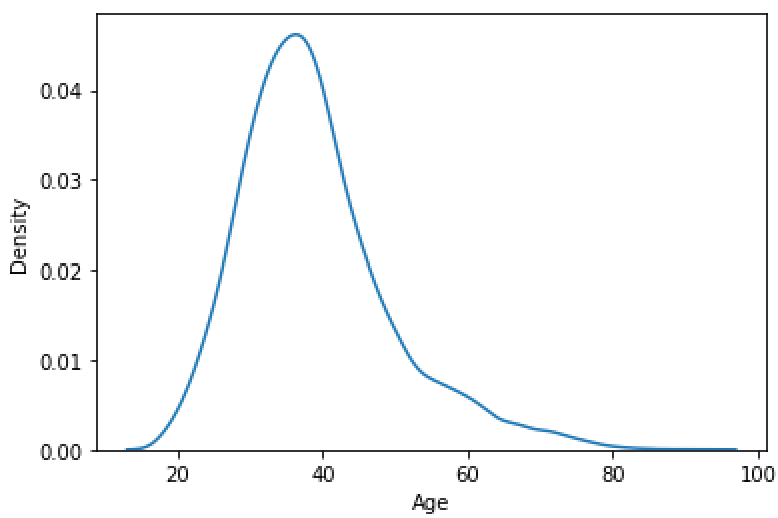

```
sns.countplot(df['Gender'])
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f372811c2d0>
```



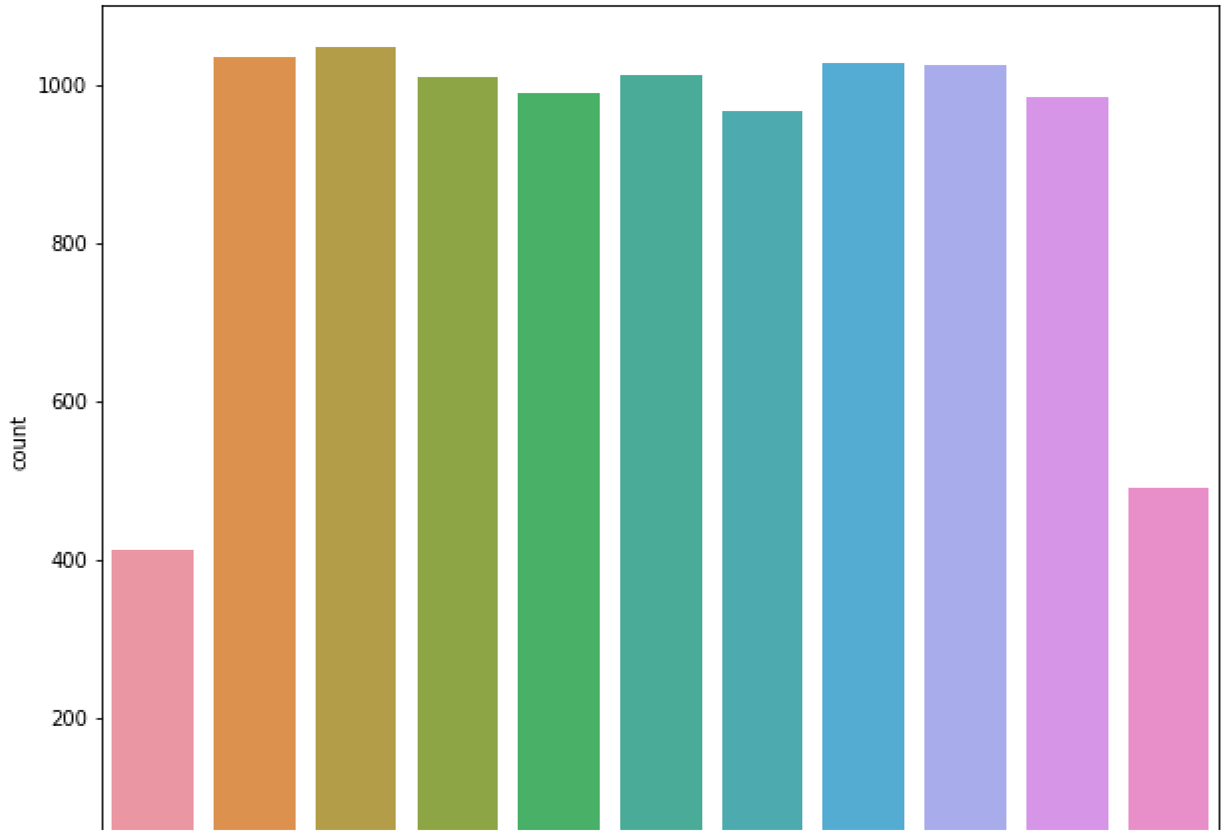

```
sns.distplot(df['Age'],hist=False)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f37280f5b10>
```




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

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f3728344e50>
```

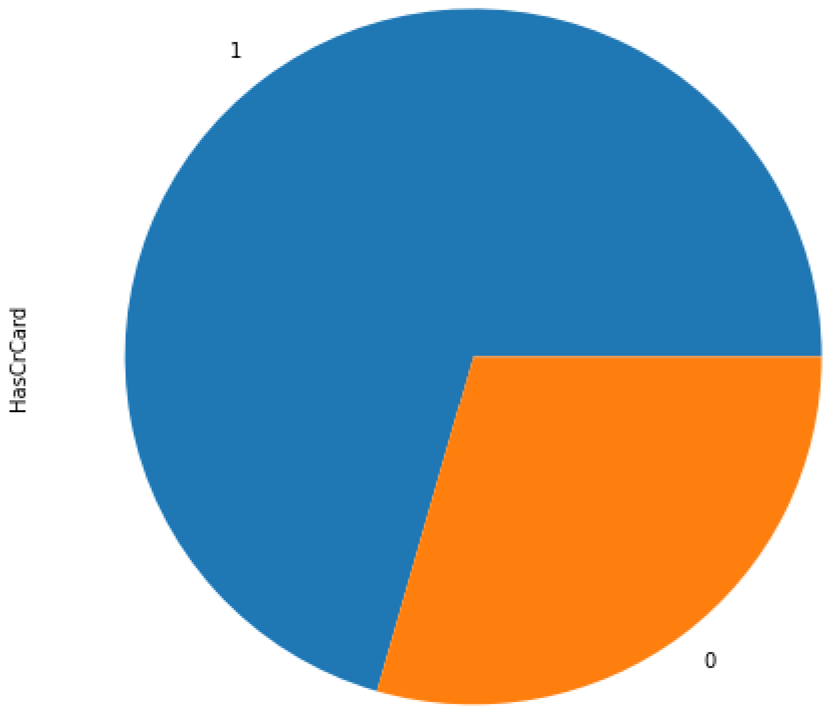



```
product = df['NumOfProducts'].value_counts()
product.plot(kind="pie",figsize=(10,8))
```

<matplotlib.axes._subplots.AxesSubplot at 0x7f37285b51d0>

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

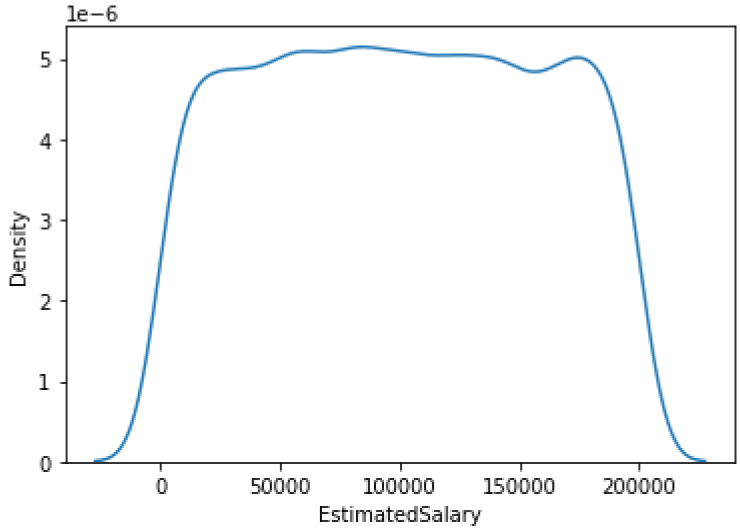
<matplotlib.axes._subplots.AxesSubplot at 0x7f37281c9150>




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

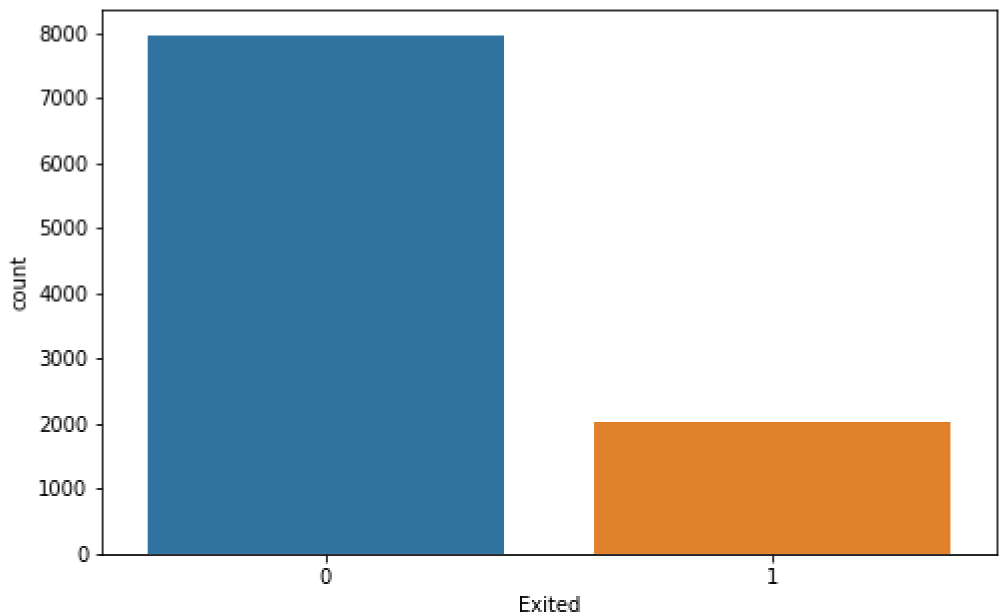
```
sns.distplot(df['EstimatedSalary'],hist=False)
```

<matplotlib.axes._subplots.AxesSubplot at 0x7f3727f419d0>




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

<matplotlib.axes._subplots.AxesSubplot at 0x7f3727fce350>



Inference:

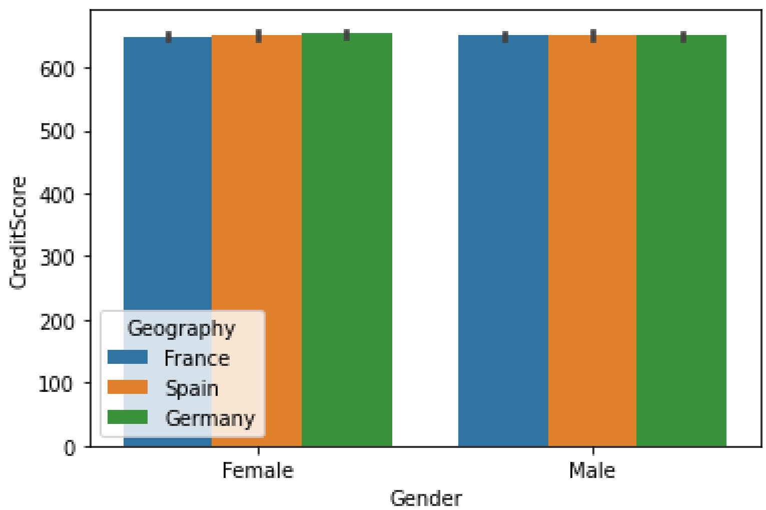
1. The data has 11 numerical variables and 3 categorical variables.
2. It has 10000 rows and 14 columns
3. The normalized credit score is around 700, More than 500 people have credit score greater than 800.

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 0x7f3727e11850>
```

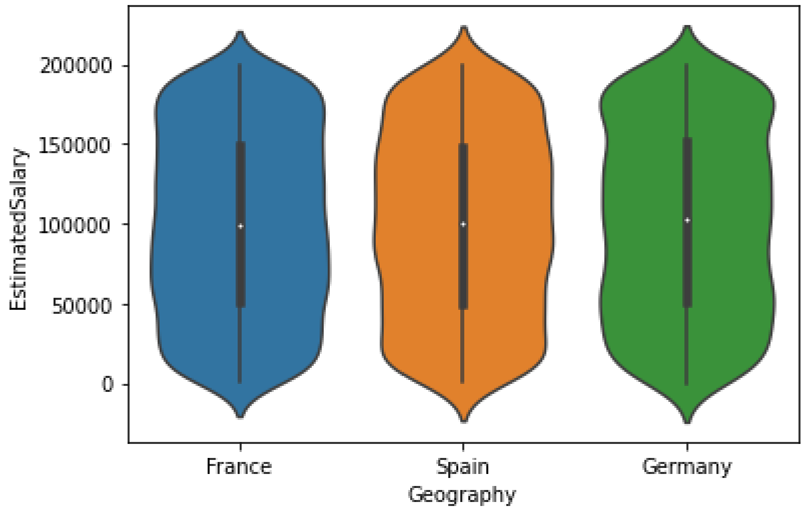



```
sns.violinplot(x='Geography',y='Balance',data=df)
```

<matplotlib.axes._subplots.AxesSubplot at 0x7f3727da9350>

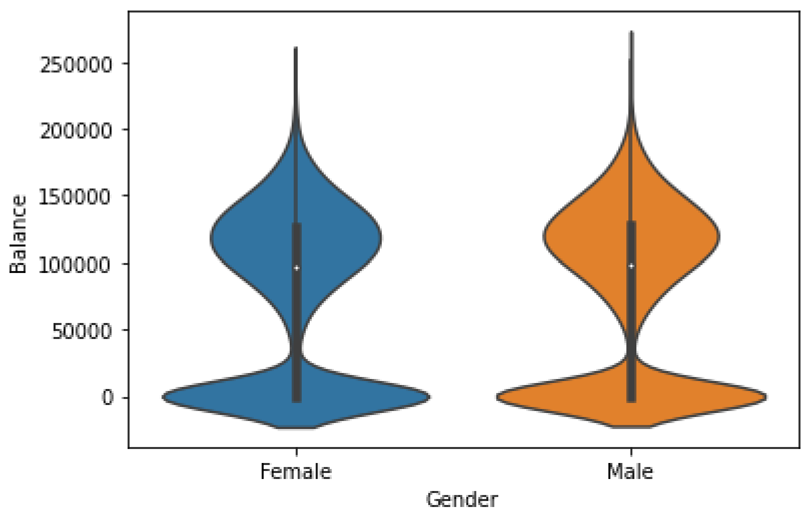
```
sns.violinplot(x='Geography',y='EstimatedSalary',data=df)
```

<matplotlib.axes._subplots.AxesSubplot at 0x7f3727d34650>




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

<matplotlib.axes._subplots.AxesSubplot at 0x7f3727ca9790>

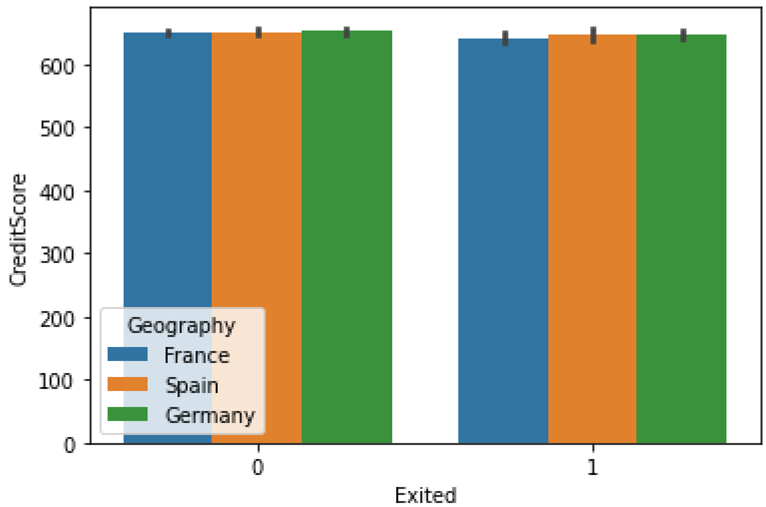



```
sns.barplot(x='Exited',y='CreditScore',hue='Gender',data=df)
```

<matplotlib.axes._subplots.AxesSubplot at 0x7f3727c33650>

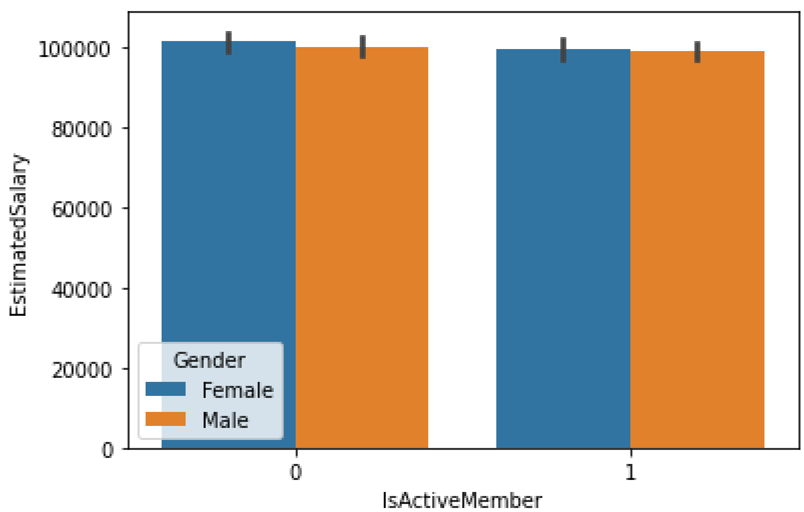

```
sns.barplot(x='Exited',y='CreditScore',hue='Geography',data=df)
```

<matplotlib.axes._subplots.AxesSubplot at 0x7f3727b9a1d0>



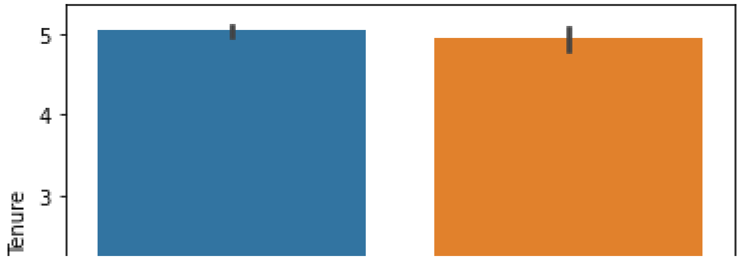

```
sns.barplot(x='IsActiveMember',y='EstimatedSalary',hue='Gender',data=df)
```

<matplotlib.axes._subplots.AxesSubplot at 0x7f3727b35410>




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

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f3727ab10d0>
```



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
```

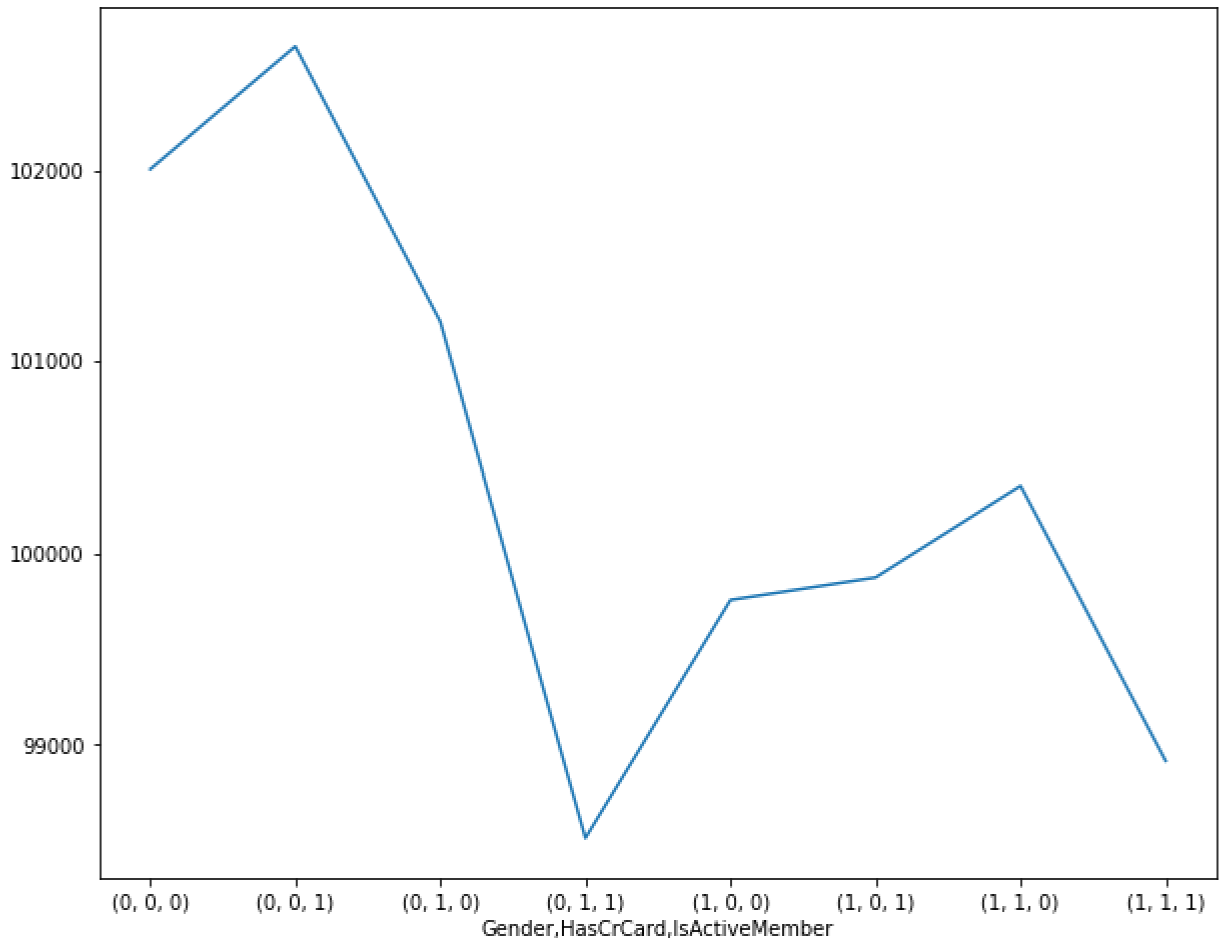
```
gp3 = df.groupby(['Gender','Geography'])['Tenure'].mean()
print(gp3)
```

```
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)
```

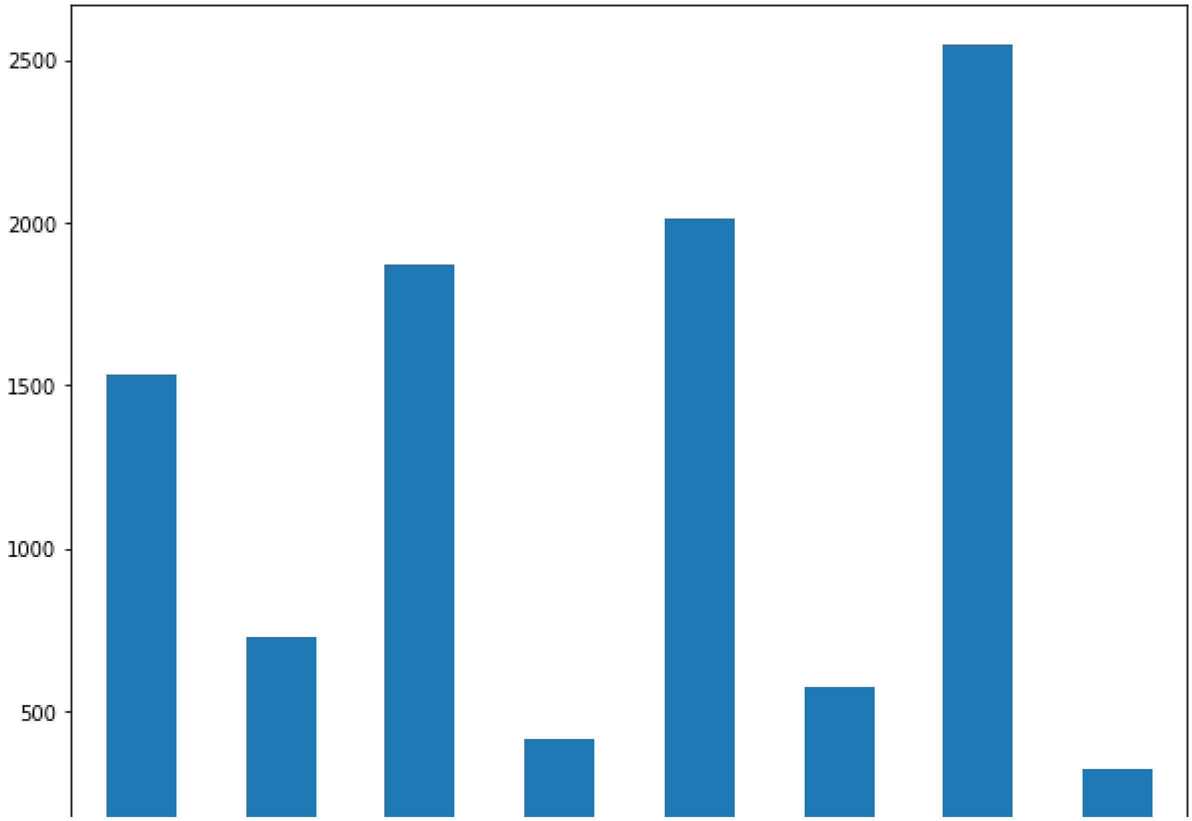
```
gp5 = df.groupby(['Gender','HasCrCard','IsActiveMember'])['EstimatedSalary'].mean()
gp5.plot(kind="line",figsize=(10,8))
print(gp5)
```

```
Gender  HasCrCard  IsActiveMember
0       0          0                 102006.080352
                   1                 102648.996944
        1          0                 101208.014567
                   1                  98510.152300
1       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
0       0               0         1534
                        1          725
        1               0         1870
                        1          414
1       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)
```

```
---------------------------------------------------------------------------
AttributeError                            Traceback (most recent call last)
<ipython-input-78-5748909a9cd0> in <module>
----> 1 gp8 = df.groupby('Gender')['Geography','Exited'].value_counts()
      2 gp8.plot(kind='bar',figsize=(10,8))
      3 print (gp8)

/usr/local/lib/python3.7/dist-packages/pandas/core/groupby/groupby.py in
__getattr__(self, attr)
    910
```

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

1. List item
2. List item

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

	count	mean	std	min	25%	5
RowNumber	10000.0	5.000500e+03	2886.895680	1.00	2500.75	5.000500e+
CustomerId	10000.0	1.569094e+07	71936.186123	15565701.00	15628528.25	1.569074e+
CreditScore	10000.0	6.505288e+02	96.653299	350.00	584.00	6.520000e+
Balance	10000.0	7.648589e+04	62397.405202	0.00	0.00	9.719854e+

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
```

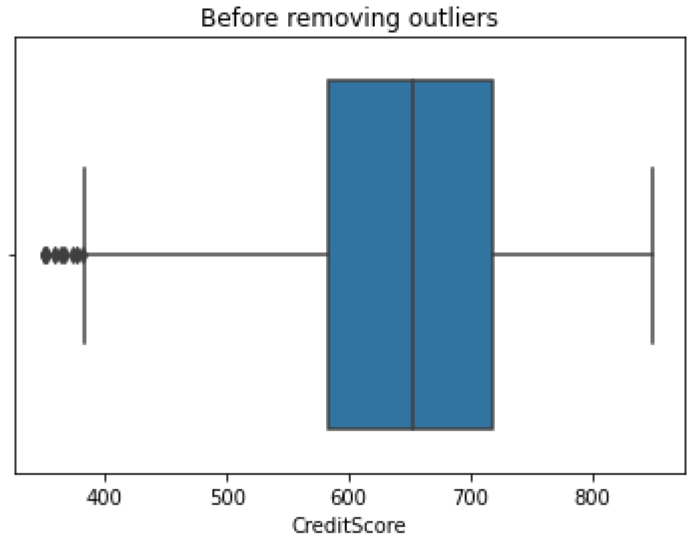
There is no missing value in the dataset

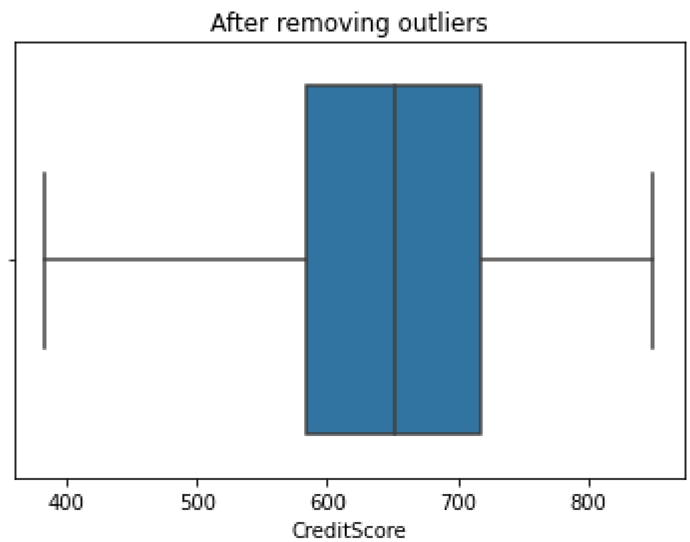
6. Finding outliers

```
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)
```

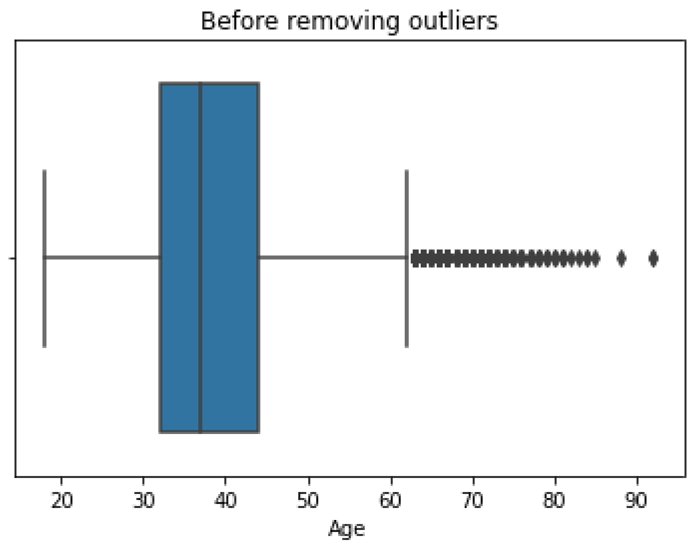
```
plt.title("Before removing outliers")
sns.boxplot(df['CreditScore'])
plt.show()
plt.title("After removing outliers")
replace_outliers(df, 'CreditScore')
```

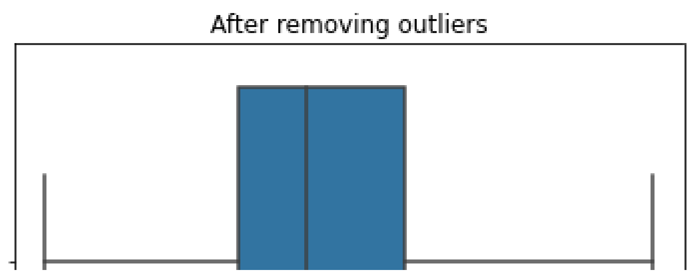
```
sns.boxplot(df['CreditScore'])
plt.show()
```





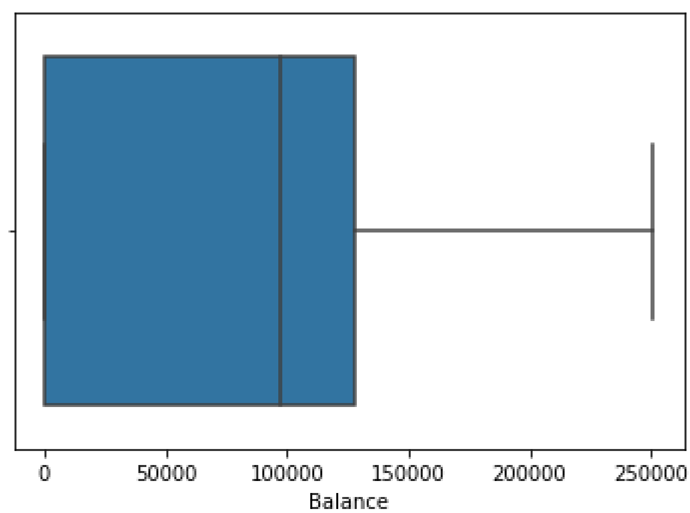

```
plt.title("Before removing outliers")
sns.boxplot(df['Age'])
plt.show()
plt.title("After removing outliers")
replace_outliers(df, 'Age')
sns.boxplot(df['Age'])
plt.show()
```





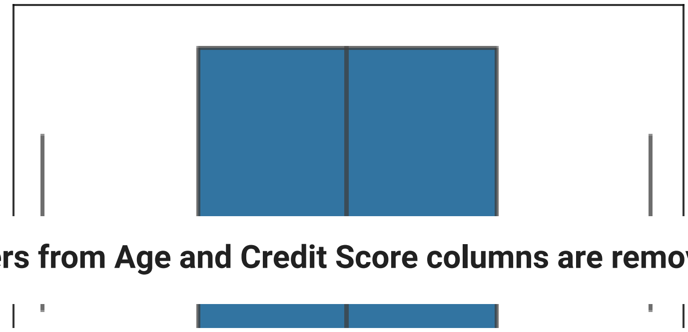

```
sns.boxplot(df['Balance'])
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f3727081c50>
```




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

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f3726f139d0>
```



Outliers from Age and Credit Score columns are removed

7. Check for categorical column and perform encoding.

EstimatedSalary

```
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	Bala
0	1	15634602	Hargrave	619.0	0	0	42.0	2	C
1	2	15647311	Hill	608.0	2	0	41.0	1	83807
2	3	15619304	Onio	502.0	0	0	42.0	8	15966C
3	4	15701354	Boni	699.0	0	0	39.0	1	C
4	5	15737888	Mitchell	850.0	2	0	43.0	2	12551C

Only two columns(Gender and Geography) is label encoded

Removing unwanted columns and checking for feature importance

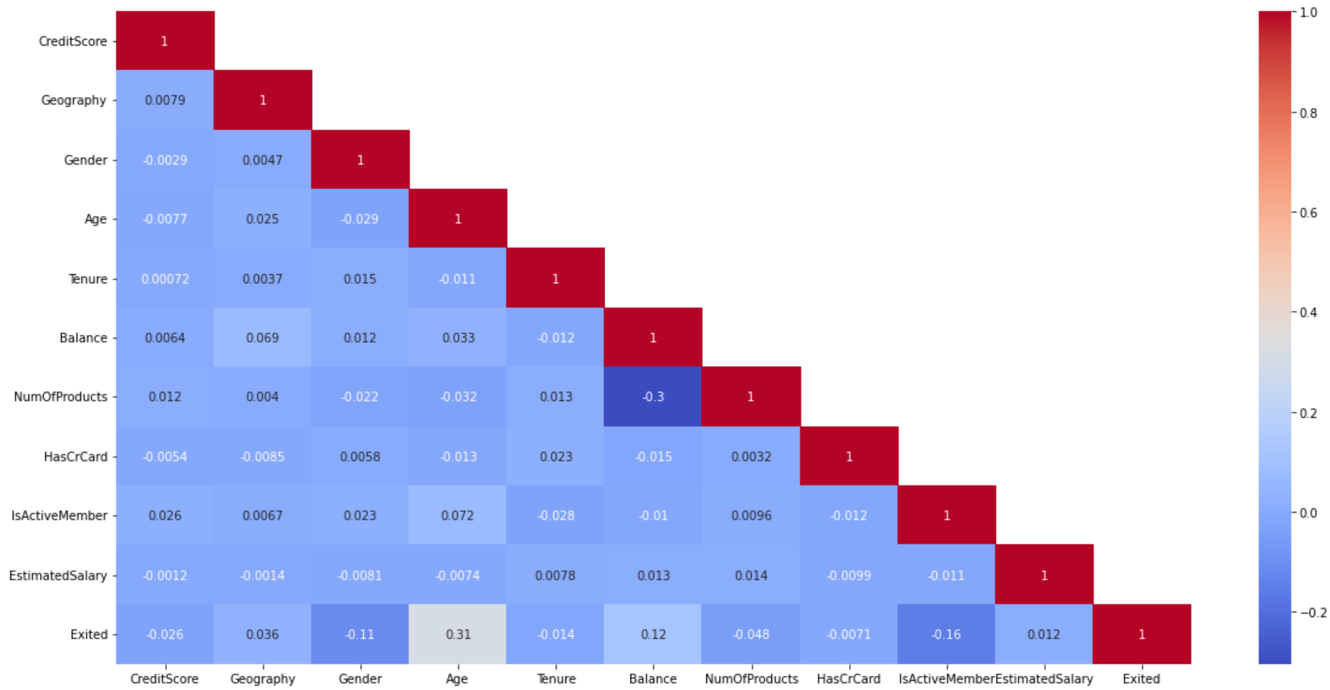
```
df = df.drop(['RowNumber','CustomerId','Surname'],axis=1)
```

```
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 0x7f372823fb90>
```



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,)
```

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.