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Date : 24/09/2022

Assignment 2

1.Download the dataset from the source /content/Churn_Modelling.csv

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	B
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

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

#check 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
```

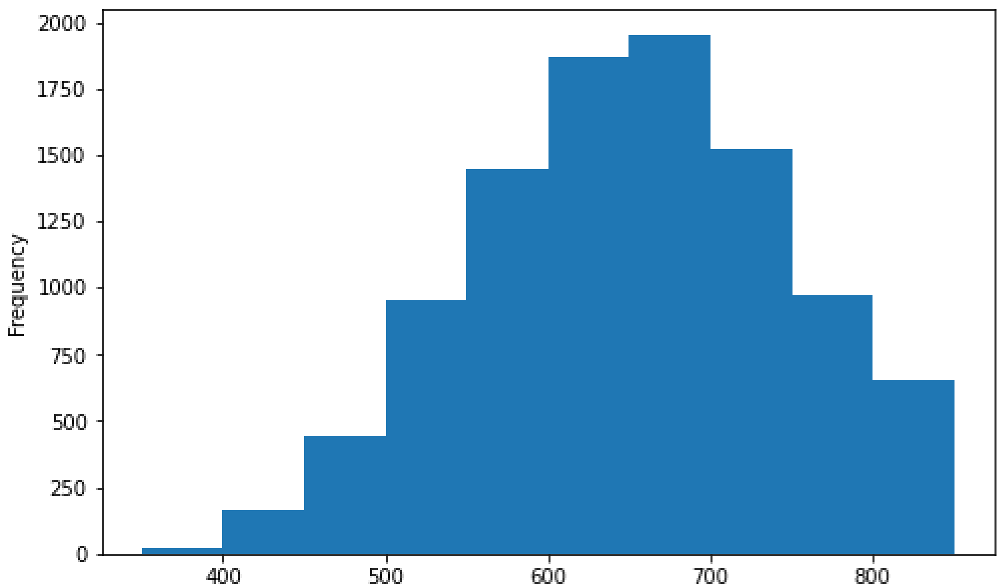
```
Index(['RowNumber', 'CustomerId', 'Surname', 'CreditScore', 'Geography',
       'Gender', 'Age', 'Tenure', 'Balance', 'NumOfProducts', 'HasCrCard',
       'IsActiveMember', 'EstimatedSalary', 'Exited'],
      dtype='object')
```

```
df.shape
```

```
(10000, 14)
```

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

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f706174f9d0>
```

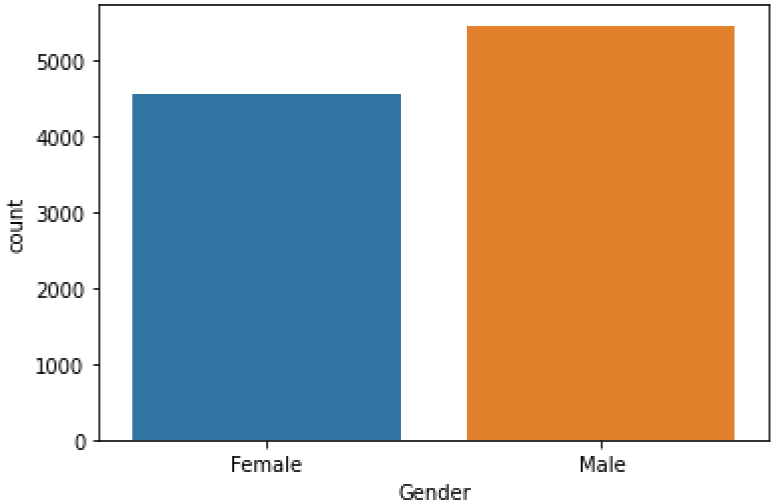



```
Geo = df['Geography'].value_counts()
Geo.plot(kind="pie",figsize=(10,8))
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f7061648c90>
```

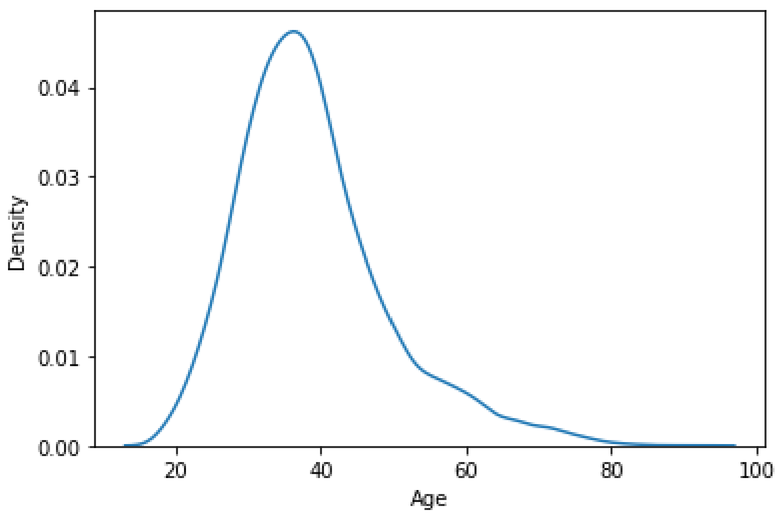
```
sns.countplot(df['Gender'])
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f70615c3150>
```



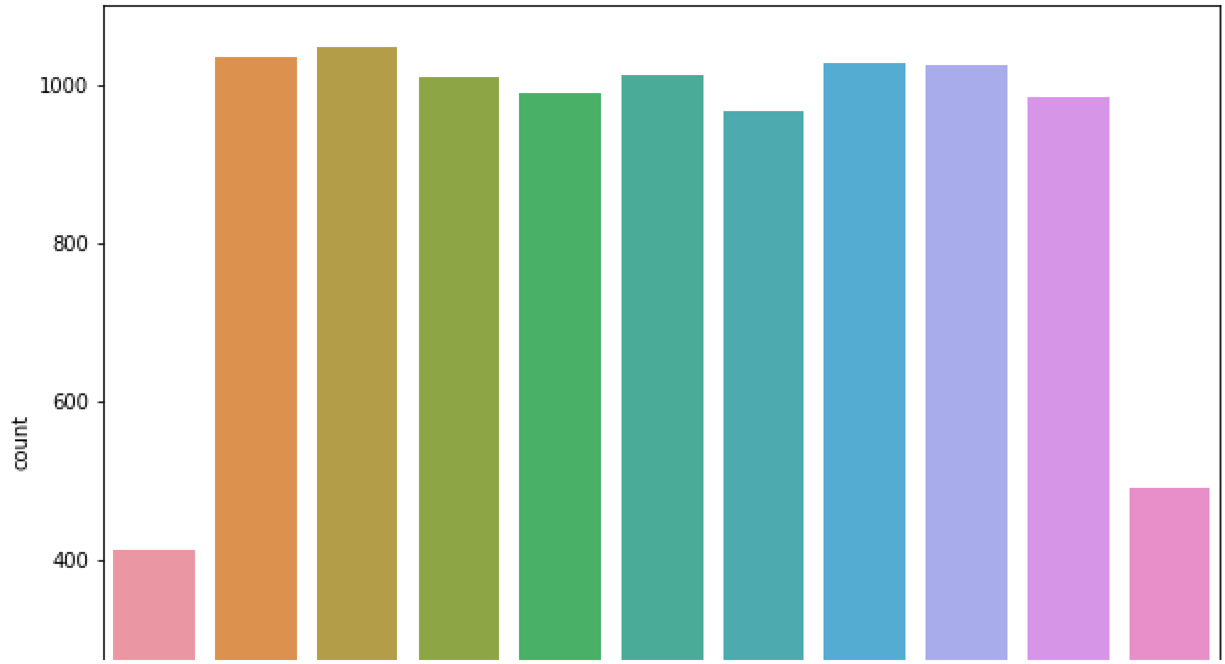
```
sns.distplot(df['Age'],hist=False)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f70615c3950>
```



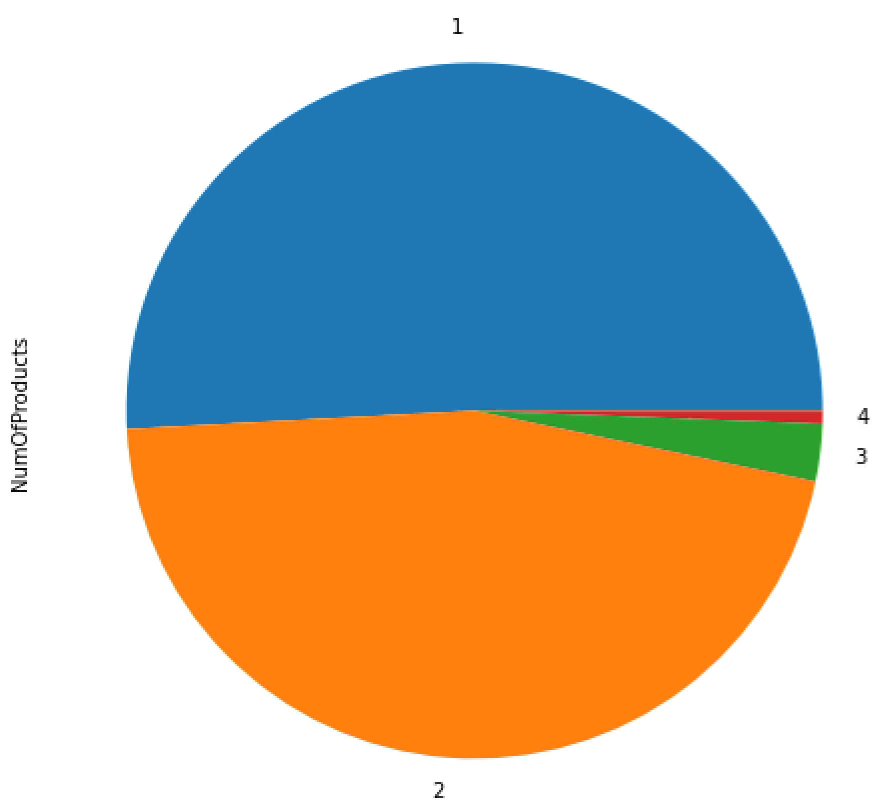

```
plt.figure(figsize=(10,8))
sns.countplot(df['Tenure'])
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f706174f0d0>
```



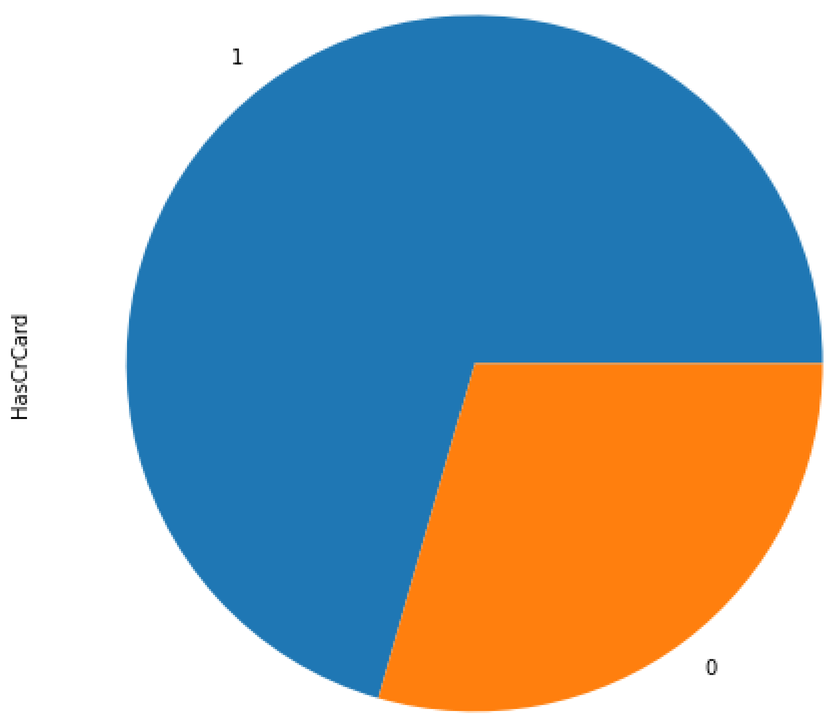

```
product = df['NumOfProducts'].value_counts()
product.plot(kind="pie",figsize=(10,8))
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f706149e390>
```



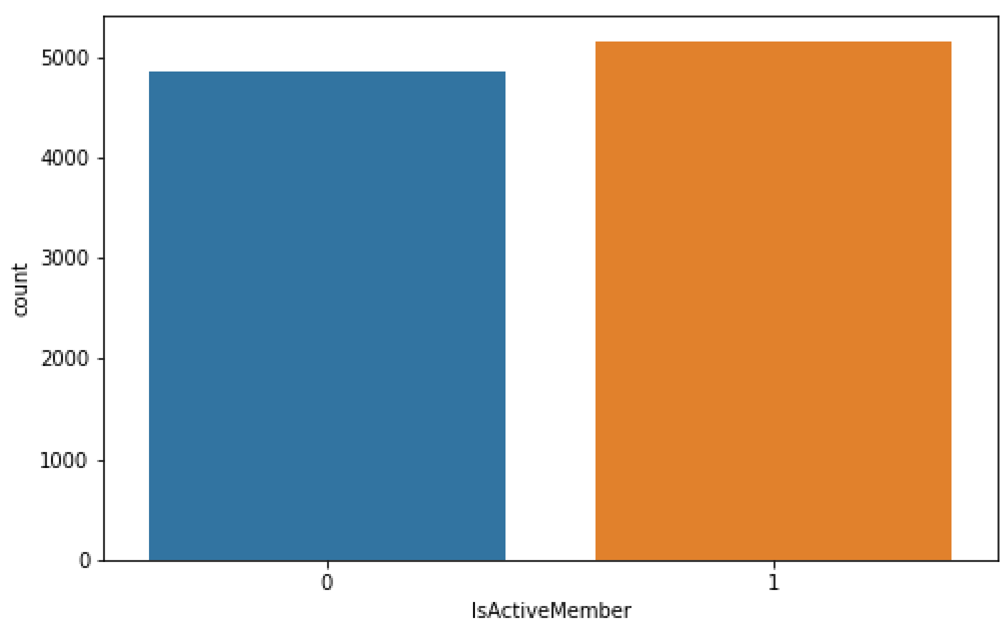

```
cr = df['HasCrCard'].value_counts()
cr.plot(kind="pie",figsize=(10,8))
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f70615109d0>
```



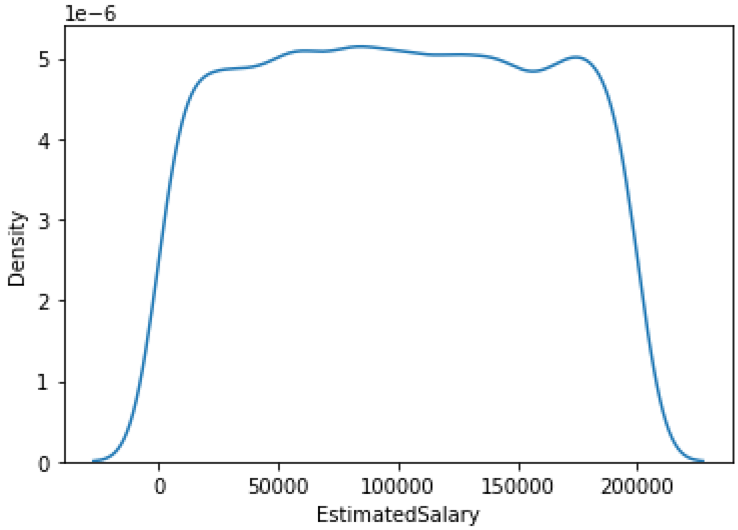

```
plt.figure(figsize=(8,5))
sns.countplot(df['IsActiveMember'])
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f70615608d0>
```



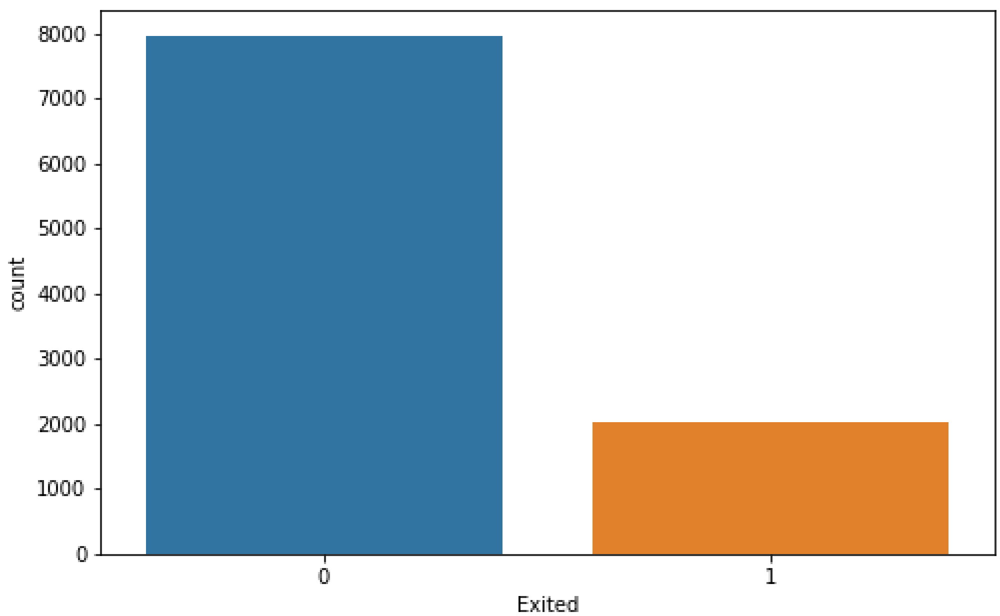

```
sns.distplot(df['EstimatedSalary'],hist=False)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f706148af50>
```




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

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f70612f7b10>
```



Inference:

1.There are 11 numerical variables and 3 categorical variables in the data.

2.It consist of 10000 rows and 14 columns. 3.The 700 is a normalized credit score,More than 500 people have credit score greater than 800.

4.France occupies 50% of customers, where as Germany and Spain shared equal.

5.Male Customers are dominated in the dataset.

6.Median age is around 40 to 45.

7.Two years tenure period for highest number of customer has thier .

8.Credit company has maximum customers, who uses single product.

9.Most of the customer has credit card.

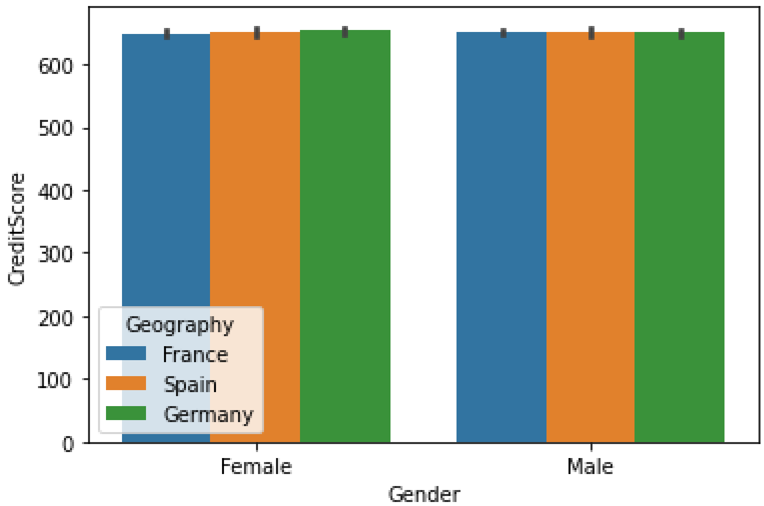
10.More than 40% of the population is not an active member.

11.The Churn is less compared to the satisfaction. Dataset is imbalanced.1.

3 b).Bivariate analysis

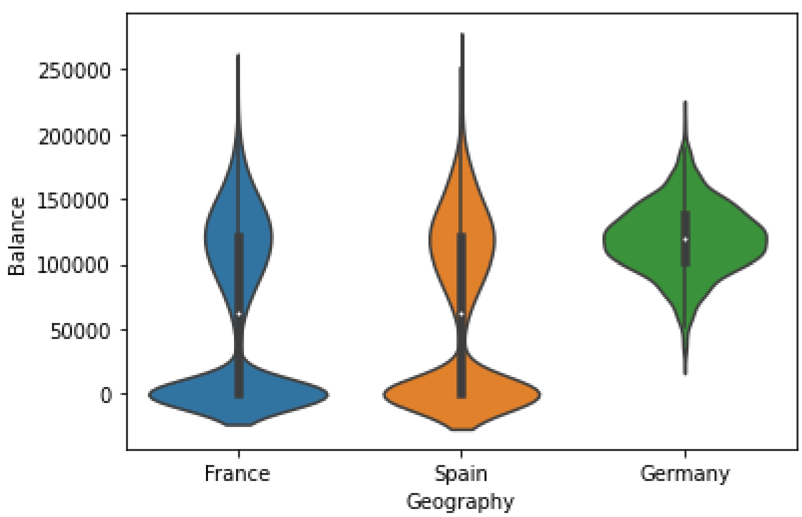
```
sns.barplot(x='Gender',y='CreditScore',hue='Geography',data=df)
```

<matplotlib.axes._subplots.AxesSubplot at 0x7f7061496350>



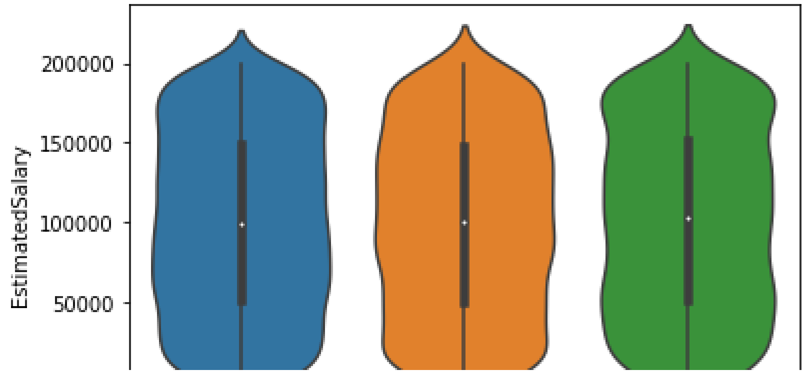

```
sns.violinplot(x='Geography',y='Balance',data=df)
```

<matplotlib.axes._subplots.AxesSubplot at 0x7f70611fbe90>



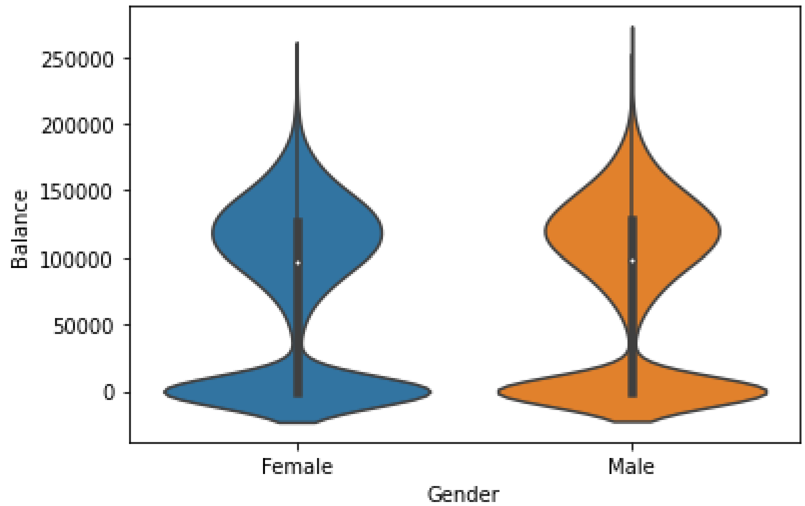

```
sns.violinplot(x='Geography',y='EstimatedSalary',data=df)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f706116bb90>
```



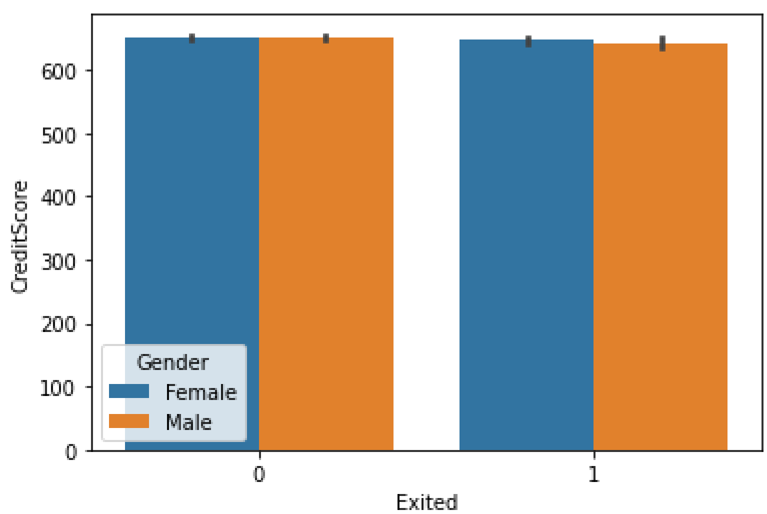

```
sns.violinplot(x='Gender',y='Balance',data=df)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f70610ef990>
```



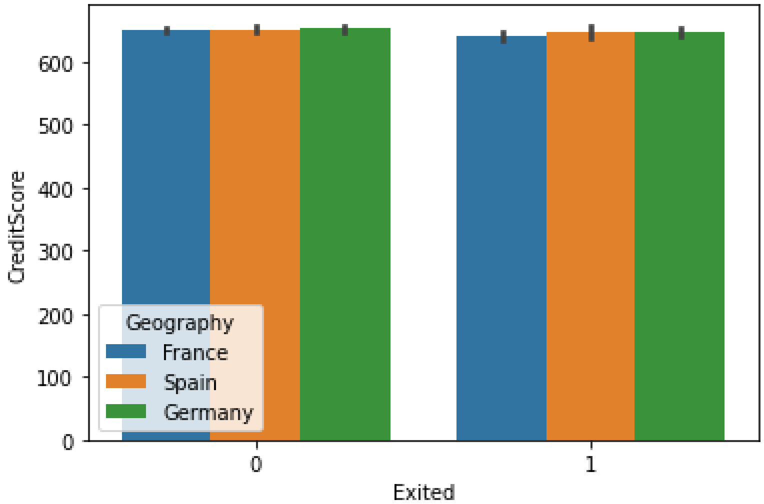

```
sns.barplot(x='Exited',y='CreditScore',hue='Gender',data=df)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f706106c6d0>
```



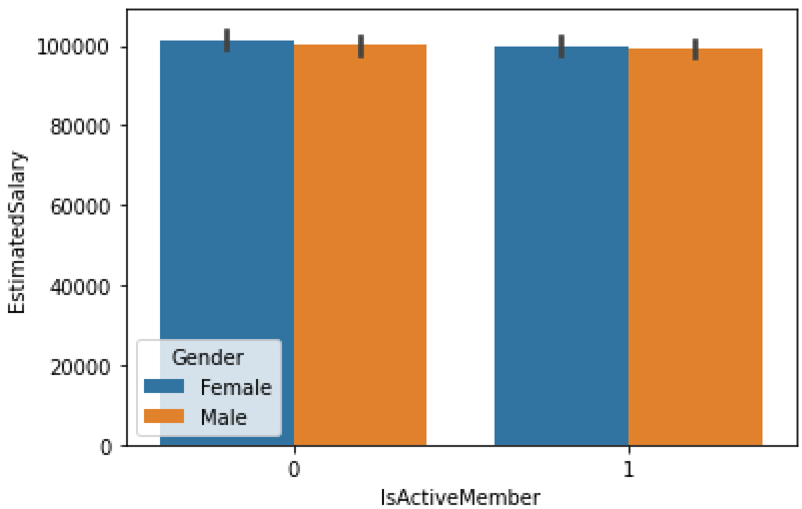

```
sns.barplot(x='Exited',y='CreditScore',hue='Geography',data=df)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f706105fa90>
```



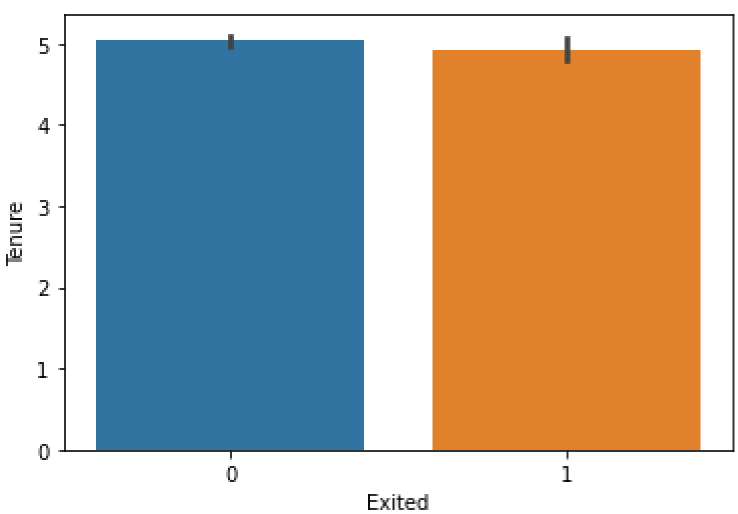

```
sns.barplot(x='IsActiveMember',y='EstimatedSalary',hue='Gender',data=df)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f7060f72750>
```




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

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f7060f5b910>
```



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.

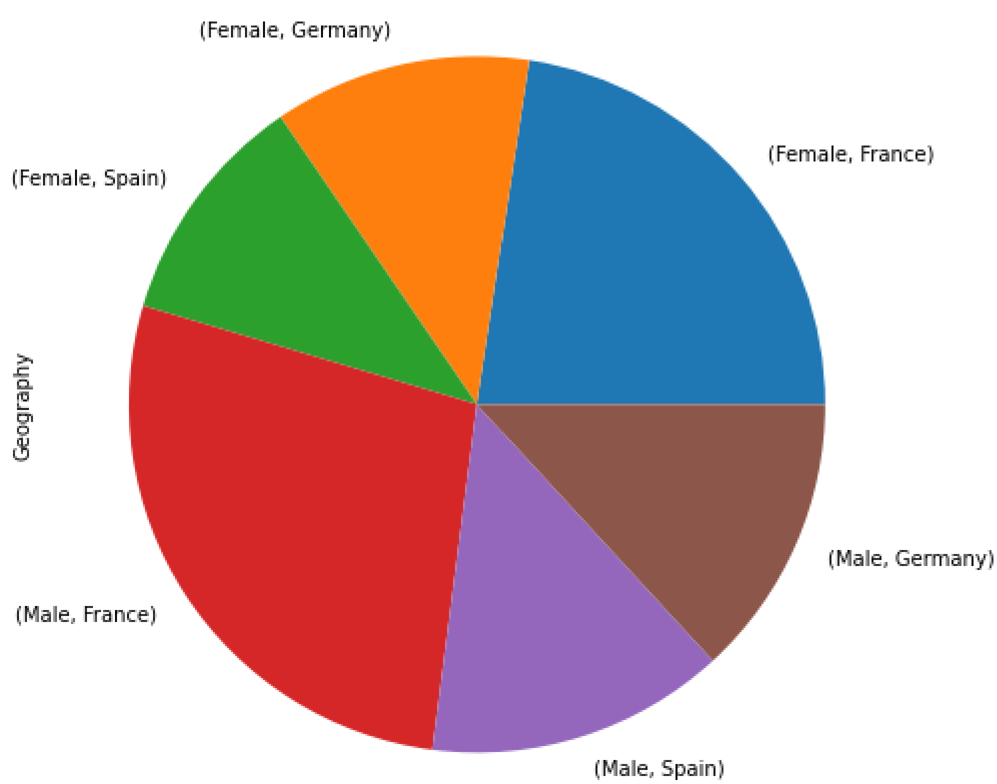
4.Credit score for churn is low. Churn in Germany is higher compared to other countries.

5.Exited people tenure period is around 6 years.

3 c). Multivariate analysis

```
group1 = df.groupby('Gender')['Geography'].value_counts()
group1.plot(kind='pie',figsize=(10,8))
print(group1)
```

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



```
group2 = df.groupby('Gender')['Age'].mean()
print(group2)
```

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

```
group3 = df.groupby(['Gender','Geography'])['Tenure'].mean()
print(group3)
```

```
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
```

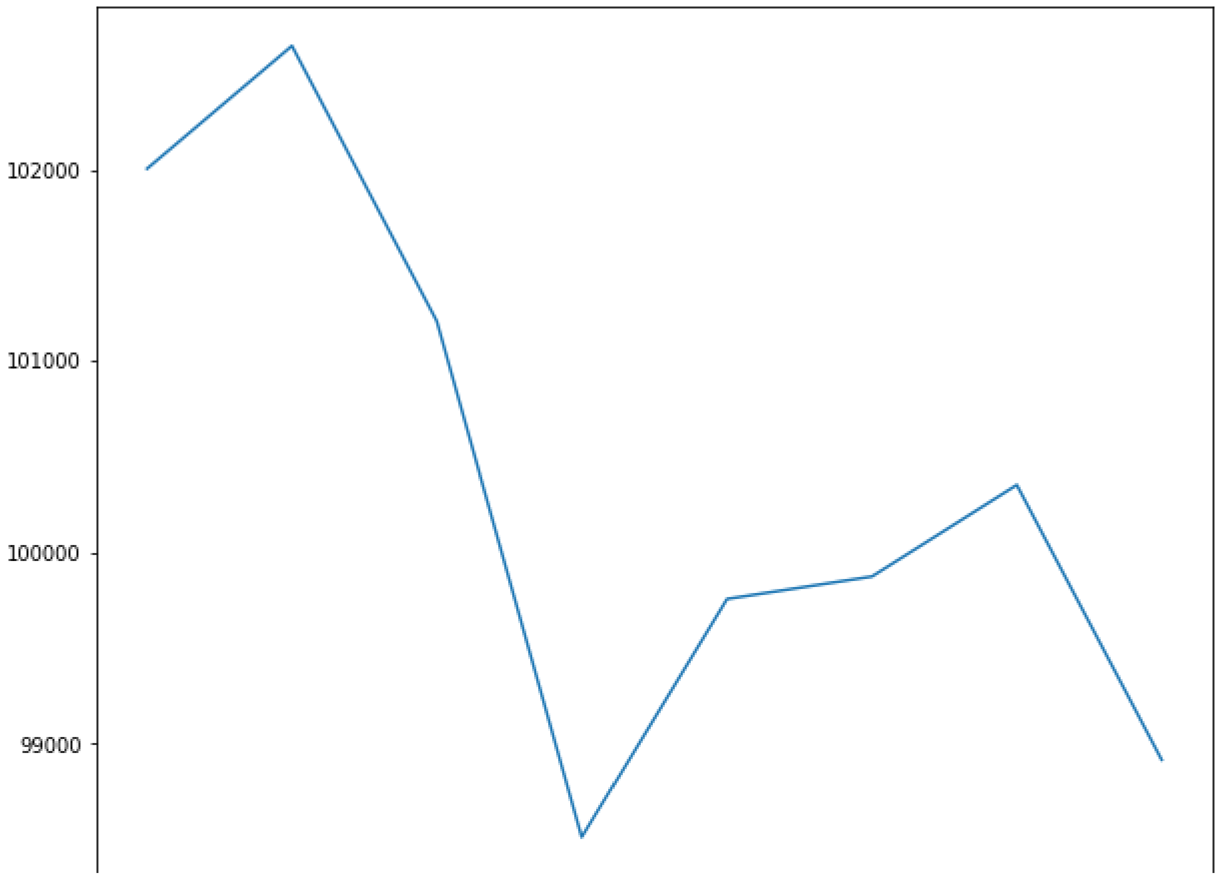
```
group4 = df.groupby('Geography')['HasCrCard','IsActiveMember'].value_counts()
group4.plot(kind="bar",figsize=(8,5))
print(group4)
```

```
---------------------------------------------------------------------------
AttributeError                            Traceback (most recent call last)
<ipython-input-217-eaf83aeebcb5> in <module>
----> 1 group4 = df.groupby('Geography')['HasCrCard','IsActiveMember'].value_counts()
      2 group4.plot(kind="bar",figsize=(8,5))
      3 print(group4)

/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'
```

SEARCH STACK OVERFLOW

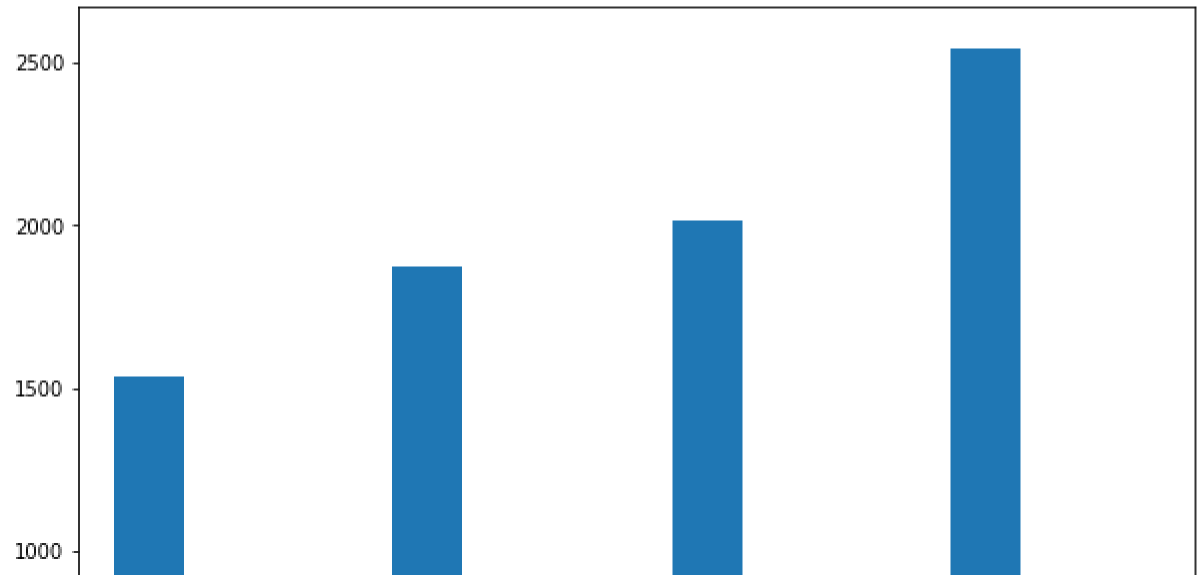
```
group5 = df.groupby(['Gender','HasCrCard','IsActiveMember'])['EstimatedSalary'].mean()
group5.plot(kind="line",figsize=(10,8))
print(group5)
```

```
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
```




```
group6 = df.groupby(['Gender','IsActiveMember'])['Exited'].value_counts()
group6.plot(kind='bar',figsize=(10,8))
print(group6)
```

```
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
```




```
group7 = df.groupby('Exited')['Balance','EstimatedSalary'].mean()
print(group7)
```

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


```
group8 = df.groupby('Gender')['Geography','Exited'].value_counts()
group8.plot(kind='bar',figsize=(10,8))
print(group8)
```

```
---------------------------------------------------------------------------
AttributeError                            Traceback (most recent call last)
<ipython-input-221-f2d3bc04e99f> in <module>
----> 1 group8 = df.groupby('Gender')['Geography','Exited'].value_counts()
```

Inference:

1.Female customers more than in the male customers in the Germany. 2.Average age of Male&Female is 38&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.Churn rate is high in the France.

4. Descriptive statistics

```
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	6.505613e+02	96.558702	383.00	584.00	6.520000e+(
Age	10000.0	3.866080e+01	9.746704	18.00	32.00	3.700000e+(
Tenure	10000.0	5.012800e+00	2.892174	0.00	3.00	5.000000e+(
Balance	10000.0	7.648589e+04	62397.405202	0.00	0.00	9.719854e+(
NumOfProducts	10000.0	1.530200e+00	0.581654	1.00	1.00	1.000000e+(
HasCrCard	10000.0	7.055000e-01	0.455840	0.00	0.00	1.000000e+(
IsActiveMember	10000.0	5.151000e-01	0.499797	0.00	0.00	1.000000e+(
EstimatedSalary	10000.0	1.000902e+05	57510.492818	11.58	51002.11	1.001939e+(
Exited	10000.0	2.037000e-01	0.402769	0.00	0.00	0.000000e+(

5. Handling the missing values

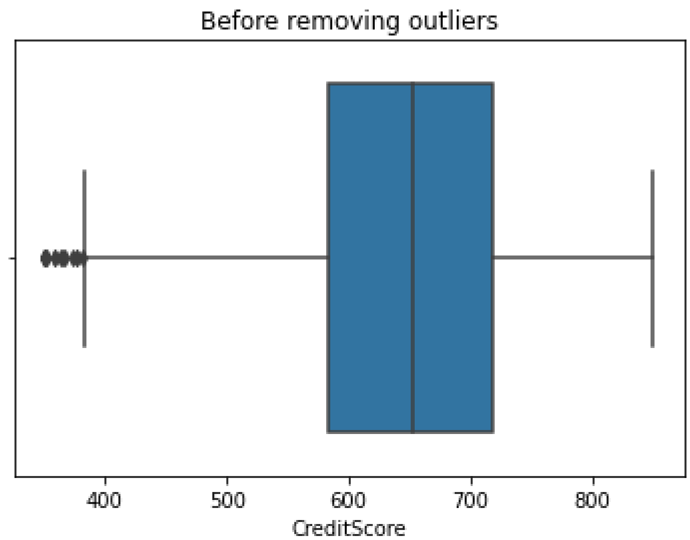
```
df.isnull().sum()
```

```
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
```

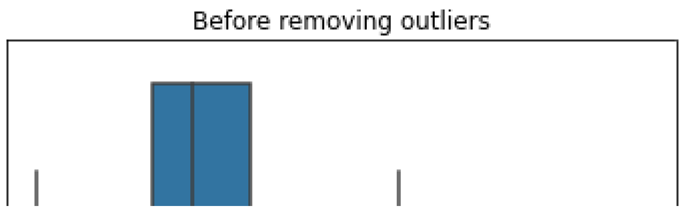
6. Finding outliers

```
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()
```

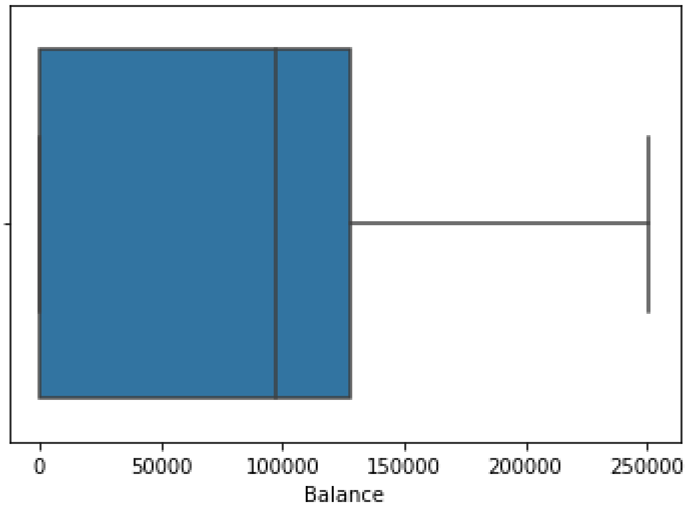



```
plt.title("Before removing outliers")
sns.boxplot(df['Age'])
plt.show()
plt.title("After removing outliers")
replace_outliers(df, 'Age')
sns.boxplot(df['Age'])
plt.show()
```



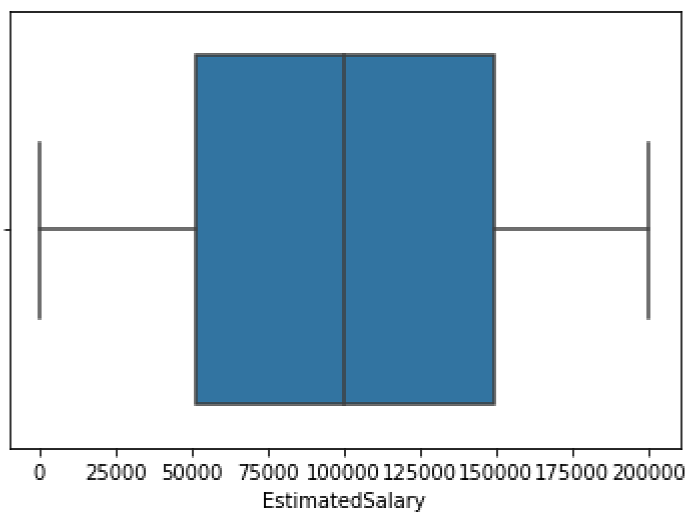

```
sns.boxplot(df['Balance'])
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f706148e210>
```



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

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f7060ce8810>
```



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	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

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()
```

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

```
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")
```

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. StandarScaler method used for scaling in this method.
2. The train and test split ratio is 15:5.
3. Basic algorithms are used to build ML models in the classification problem.