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Date: 21\09\2022

## 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 | Tenure | Balance | NumOfProducts | HasCrCard | IsAc |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 1 | 15634602 | Hargrave | 619 | France | Female | 42 | 2 | 0.00 | 1 | 1 | |
| **1** | 2 | 15647311 | Hill | 608 | Spain | Female | 41 | 1 | 83807.86 | 1 | 0 | |
| **2** | 3 | 15619304 | Onio | 502 | France | Female | 42 | 8 | 159660.80 | 3 | 1 | |
| **3** | 4 | 15701354 | Boni | 699 | France | Female | 39 | 1 | 0.00 | 2 | 0 | |
| **4** | 5 | 15737888 | Mitchell | 850 | Spain | Female | 43 | 2 | 125510.82 | 1 | 1 | |

```
df.tail()
```

| | RowNumber | CustomerId | Surname | CreditScore | Geography | Gender | Age | Tenure | Balance | NumOfProducts | HasCrCard |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **9995** | 9996 | 15606229 | Obijiaku | 771 | France | Male | 39 | 5 | 0.00 | 2 | 1 |
| **9996** | 9997 | 15569892 | Johnstone | 516 | France | Male | 35 | 10 | 57369.61 | 1 | 1 |
| **9997** | 9998 | 15584532 | Liu | 709 | France | Female | 36 | 7 | 0.00 | 1 | 0 |
| **9998** | 9999 | 15682355 | Sabbatini | 772 | Germany | Male | 42 | 3 | 75075.31 | 2 | 1 |
| **9999** | 10000 | 15628319 | Walker | 792 | France | Female | 28 | 4 | 130142.79 | 1 | 1 |

## 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')
```

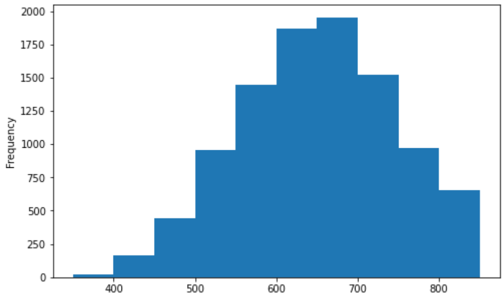
```
df.shape
```

```
(10000, 14)
```

```
credit = df['CreditScore']
```

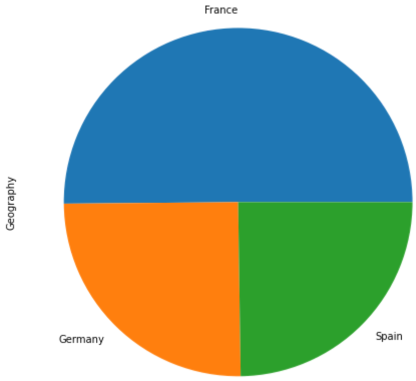
```
credit.plot(kind="hist",figsize=(8,5))
```

    <matplotlib.axes._subplots.AxesSubplot at 0x7fb33600e6d0>



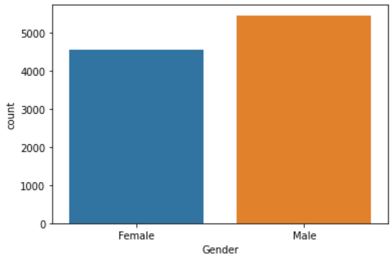

```
geo = df['Geography'].value_counts()
geo.plot(kind="pie",figsize=(10,8))
```

    <matplotlib.axes._subplots.AxesSubplot at 0x7fb335ac8790>



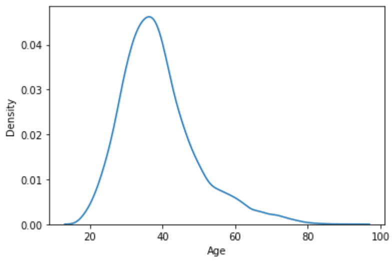

```
sns.countplot(df['Gender'])
```

    <matplotlib.axes._subplots.AxesSubplot at 0x7fb335aa3690>




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

    <matplotlib.axes._subplots.AxesSubplot at 0x7fb335a11590>

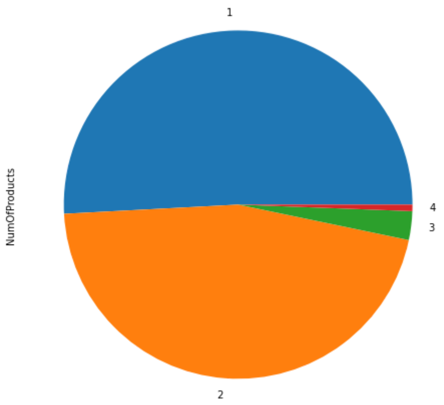



```
plt.figure(figsize=(10,8))
sns.countplot(df['Tenure'])
```

<matplotlib.axes._subplots.AxesSubplot at 0x7fb3359c67d0>

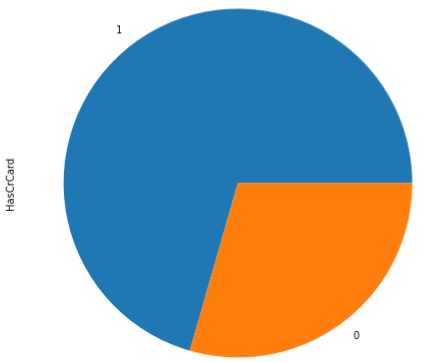

```
product = df['NumOfProducts'].value_counts()
product.plot(kind="pie",figsize=(10,8))
```

<matplotlib.axes._subplots.AxesSubplot at 0x7fb3359f6d10>



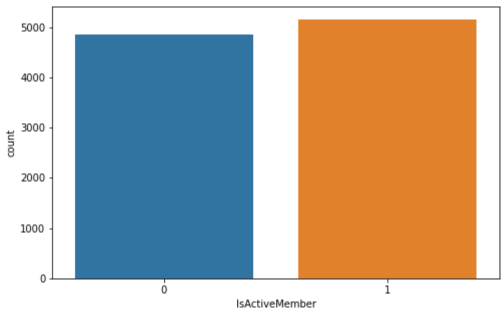

```
cr = df['HasCrCard'].value_counts()
cr.plot(kind="pie",figsize=(10,8))
```

<matplotlib.axes._subplots.AxesSubplot at 0x7fb3358fb910>



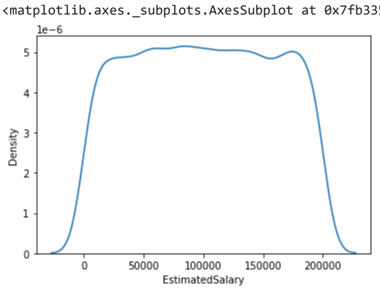

```
plt.figure(figsize=(8,5))
sns.countplot(df['IsActiveMember'])
```

<matplotlib.axes._subplots.AxesSubplot at 0x7fb33584cfd0>



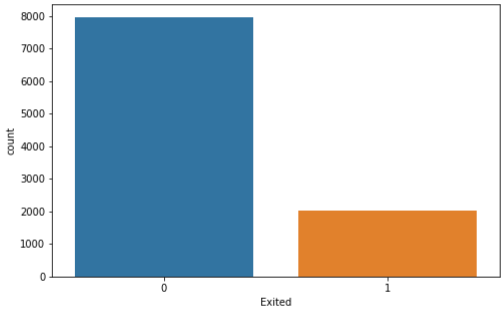

```
sns.distplot(df['EstimatedSalary'],hist=False)
```

<matplotlib.axes._subplots.AxesSubplot at 0x7fb33582f610>




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

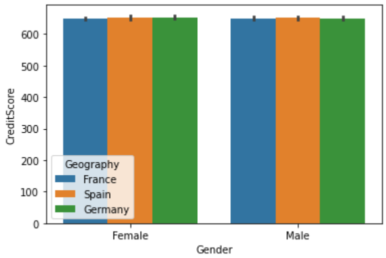
<matplotlib.axes._subplots.AxesSubplot at 0x7fb3357a49d0>




## 3 b) Bivariate analysis

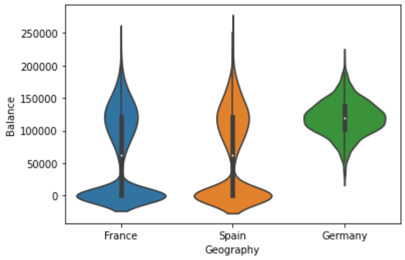
```
sns.barplot(x='Gender',y='CreditScore',hue='Geography',data=df)
```

<matplotlib.axes._subplots.AxesSubplot at 0x7fb3356d25d0>



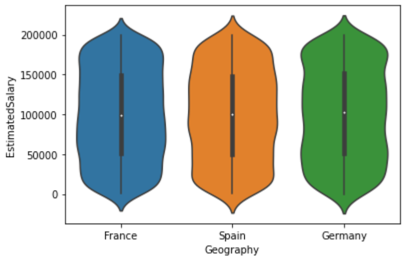

```
sns.violinplot(x='Geography',y='Balance',data=df)
```

<matplotlib.axes._subplots.AxesSubplot at 0x7fb33565d890>



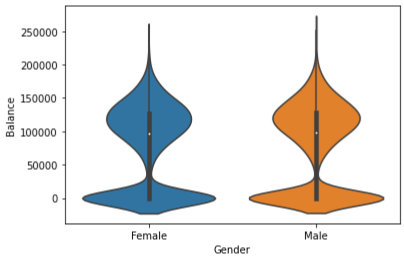

```
sns.violinplot(x='Geography',y='EstimatedSalary',data=df)
```

<matplotlib.axes._subplots.AxesSubplot at 0x7fb3355f5690>




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

<matplotlib.axes._subplots.AxesSubplot at 0x7fb335558990>

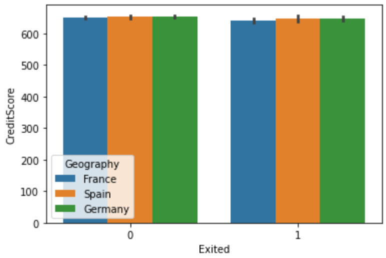



```
sns.barplot(x='Exited',y='CreditScore',hue='Gender',data=df)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fb3354d1c50>
```

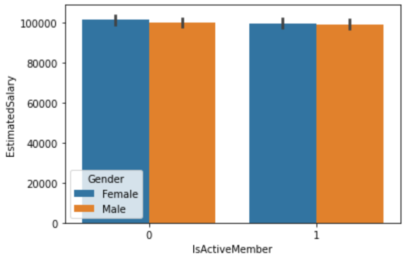
```
sns.barplot(x='Exited',y='CreditScore',hue='Geography',data=df)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fb33598c390>
```



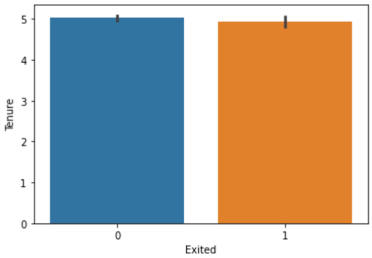

```
sns.barplot(x='IsActiveMember',y='EstimatedSalary',hue='Gender',data=df)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fb335645e90>
```




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

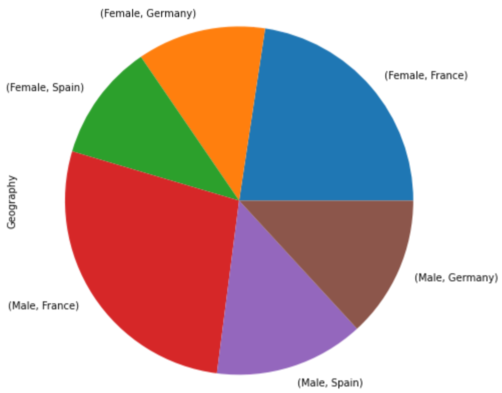
```
<matplotlib.axes._subplots.AxesSubplot at 0x7fb3353b5710>
```




## 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)
```

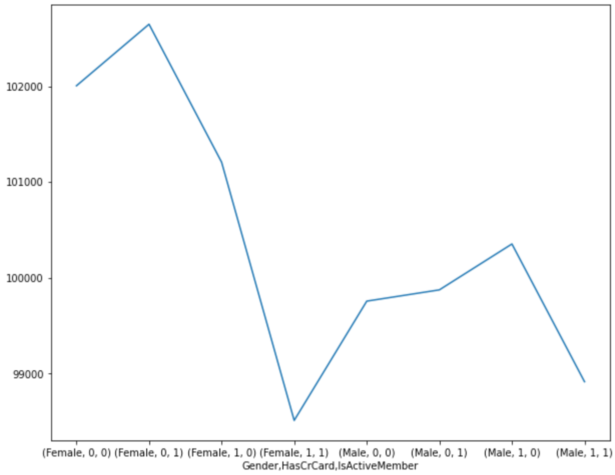
```
Gender
Female    39.238389
Male      38.658237
Name: Age, dtype: float64
```

```
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
```

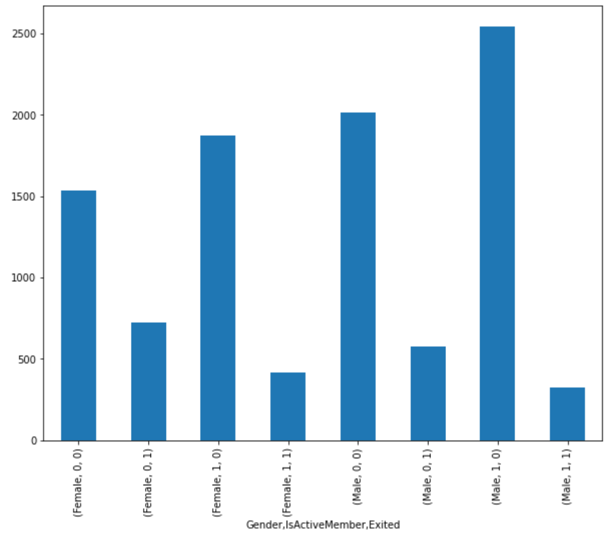
```
gp4 = df.groupby(['Gender','HasCrCard','IsActiveMember'])['EstimatedSalary'].mean()
gp4.plot(kind="line",figsize=(10,8))
print(gp4)
```

```
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% | 50% | 75% | max |
|---|---|---|---|---|---|---|---|---|
| **RowNumber** | 10000.0 | 5.000500e+03 | 2886.895680 | 1.00 | 2500.75 | 5.000500e+03 | 7.500250e+03 | 10000.00 |
| **CustomerId** | 10000.0 | 1.569094e+07 | 71936.186123 | 15565701.00 | 15628528.25 | 1.569074e+07 | 1.575323e+07 | 15815690.00 |
| **CreditScore** | 10000.0 | 6.505288e+02 | 96.653299 | 350.00 | 584.00 | 6.520000e+02 | 7.180000e+02 | 850.00 |
| **Age** | 10000.0 | 3.892180e+01 | 10.487806 | 18.00 | 32.00 | 3.700000e+01 | 4.400000e+01 | 92.00 |
| **Tenure** | 10000.0 | 5.012800e+00 | 2.892174 | 0.00 | 3.00 | 5.000000e+00 | 7.000000e+00 | 10.00 |
| **Balance** | 10000.0 | 7.648589e+04 | 62397.405202 | 0.00 | 0.00 | 9.719854e+04 | 1.276442e+05 | 250898.09 |
| **NumOfProducts** | 10000.0 | 1.530200e+00 | 0.581654 | 1.00 | 1.00 | 1.000000e+00 | 2.000000e+00 | 4.00 |
| **HasCrCard** | 10000.0 | 7.055000e-01 | 0.455840 | 0.00 | 0.00 | 1.000000e+00 | 1.000000e+00 | 1.00 |
| **IsActiveMember** | 10000.0 | 5.151000e-01 | 0.499797 | 0.00 | 0.00 | 1.000000e+00 | 1.000000e+00 | 1.00 |
| **EstimatedSalary** | 10000.0 | 1.000902e+05 | 57510.492818 | 11.58 | 51002.11 | 1.001939e+05 | 1.493882e+05 | 199992.48 |

## 5. Handling the missing values

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

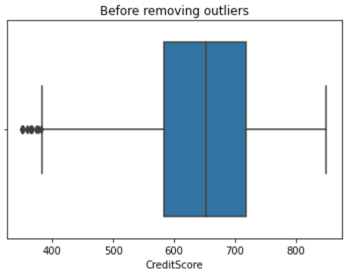
```
RowNumber          0
CustomerId         0
Surname            0
CreditScore        0
Geography          0
Gender             0
Age                0
Tenure             0
Balance            0
NumOfProducts      0
HasCrCard          0
IsActiveMember     0
EstimatedSalary    0
Exited             0
dtype: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

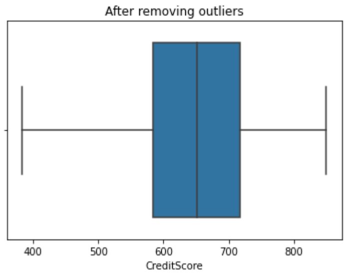
**There is no missing value in the dataset**

## 6. Finding outliers

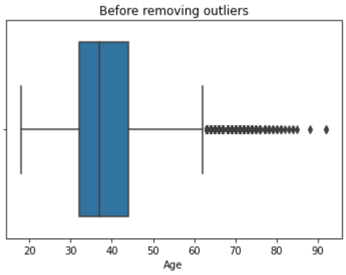
```
def replace_outliers(df, field_name):
    Q1 = np.percentile(df[field_name],25,interpolation='midpoint')
    Q3 = np.percentile(df[field_name],75,interpolation='midpoint')
    IQR = Q3-Q1
    maxi = Q3+1.5*IQR
    mini = Q1-1.5*IQR
    df[field_name]=df[field_name].mask(df[field_name]>maxi,maxi)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

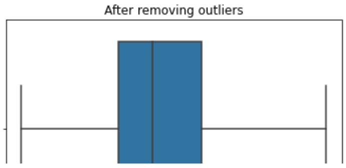
```
plt.title("Before removing outliers")
sns.boxplot(df['CreditScore'])
plt.show()
plt.title("After removing outliers")
replace_outliers(df, 'CreditScore')
sns.boxplot(df['CreditScore'])
plt.show()
```



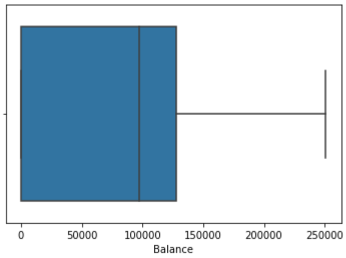

```
plt.title("Before removing outliers")
sns.boxplot(df['Age'])
plt.show()
plt.title("After removing outliers")
replace_outliers(df, 'Age')
sns.boxplot(df['Age'])
plt.show()
```



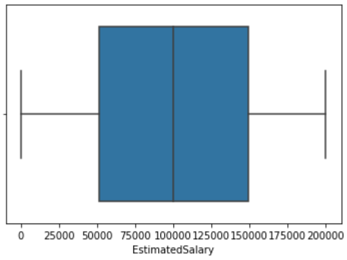

```
sns.boxplot(df['Balance'])
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fb33450fd10>
```




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

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fb3343ccd90>
```




**Outliers from Age and Credit Score columns are removed**

## 7. Check for categorical column and perform encoding.

[ ] ↳ *4 cells hidden*

# Removing unwanted columns and checking for feature importance

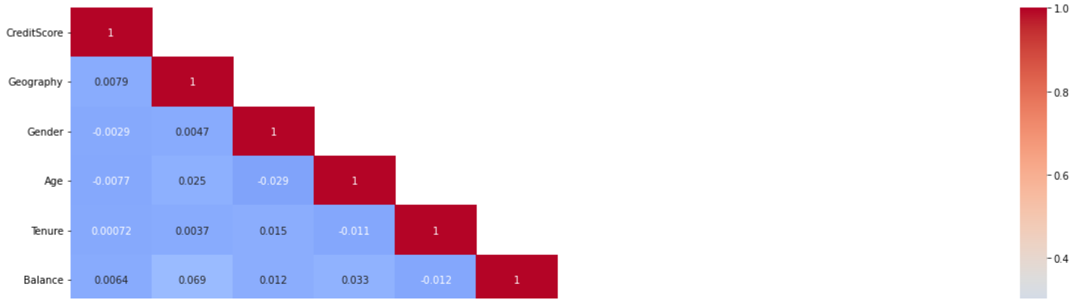
```
df = df.drop(['RowNumber','CustomerId','Surname'],axis=1)
```

```
df.head()
```

| | CreditScore | Geography | Gender | Age | Tenure | Balance | NumOfProducts | HasCrCard | IsActiveMember | EstimatedSalary | Ex: |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 619.0 | 0 | 0 | 42.0 | 2 | 0.00 | 1 | 1 | 1 | 101348.88 | |
| **1** | 608.0 | 2 | 0 | 41.0 | 1 | 83807.86 | 1 | 0 | 1 | 112542.58 | |
| **2** | 502.0 | 0 | 0 | 42.0 | 8 | 159660.80 | 3 | 1 | 0 | 113931.57 | |
| **3** | 699.0 | 0 | 0 | 39.0 | 1 | 0.00 | 2 | 0 | 0 | 93826.63 | |
| **4** | 850.0 | 2 | 0 | 43.0 | 2 | 125510.82 | 1 | 1 | 1 | 79084.10 | |

```
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 0x7fb3359c6610>
```




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 | IsActiveMember | EstimatedSalary |
|---|---|---|---|---|---|---|---|---|---|---|
| **0** | -0.326878 | 0 | 0 | 0.342615 | 2 | -1.225848 | 1 | 1 | 1 | 0.021886 |
| **1** | -0.440804 | 2 | 0 | 0.240011 | 1 | 0.117350 | 1 | 0 | 1 | 0.216534 |
| **2** | -1.538636 | 0 | 0 | 0.342615 | 8 | 1.333053 | 3 | 1 | 0 | 0.240687 |
| **3** | 0.501675 | 0 | 0 | 0.034803 | 1 | -1.225848 | 2 | 0 | 0 | -0.108918 |
| **4** | 2.065569 | 2 | 0 | 0.445219 | 2 | 0.785728 | 1 | 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,)
```