Importing Necessary Libraries

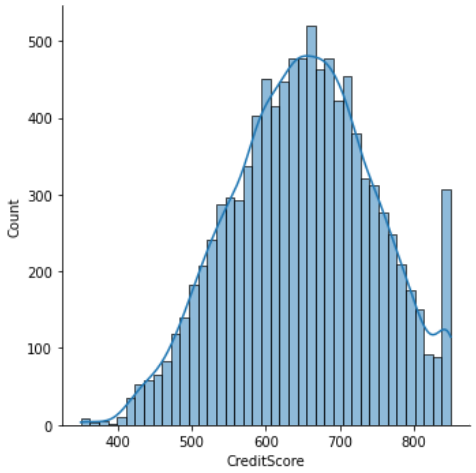
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.compose import ColumnTransformer

from sklearn.preprocessing import OneHotEncoder
from sklearn.preprocessing import StandardScaler
```

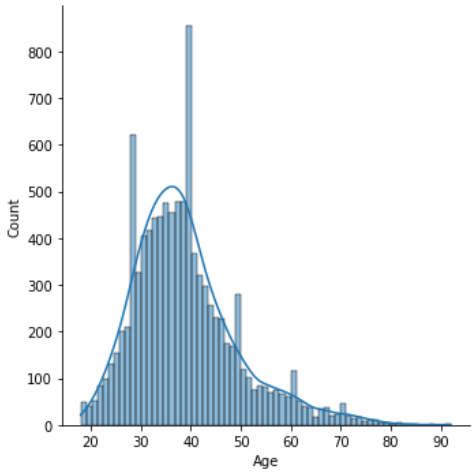
2. Load the dataset

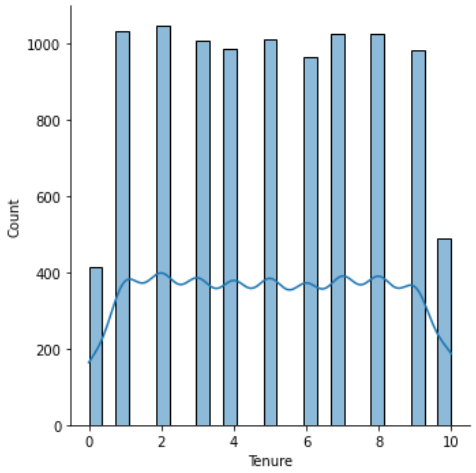
```
data = pd.read_csv('/content/Churn_Modelling.csv')
```

3. Perform Below Visualizations. UNIVARIATE ANALYSIS

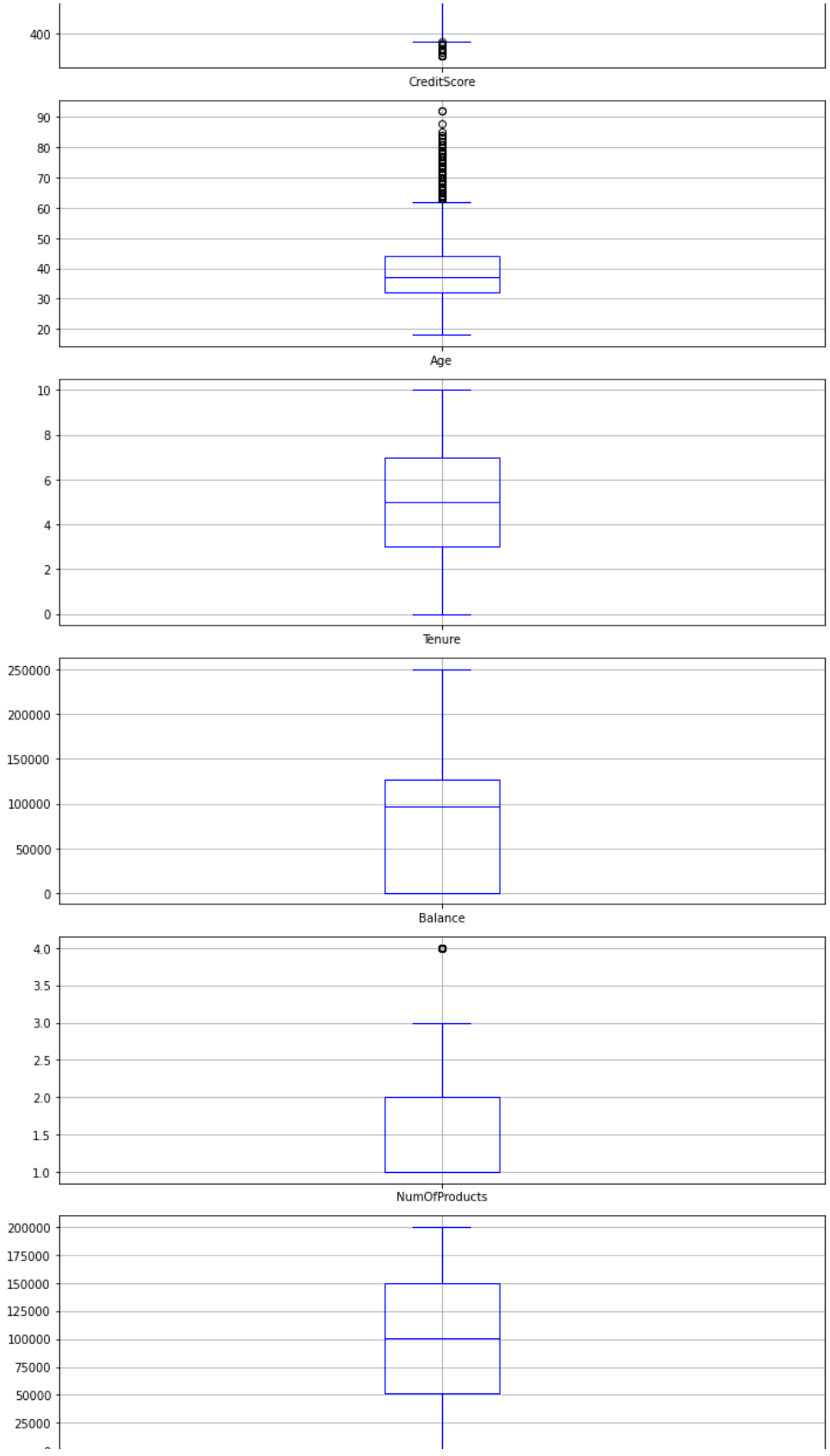
```
l=['CreditScore','Age', 'Tenure','Balance','NumOfProducts','EstimatedSalary']
for i in l:
    sns.displot(data=data[i],kde=True)
```



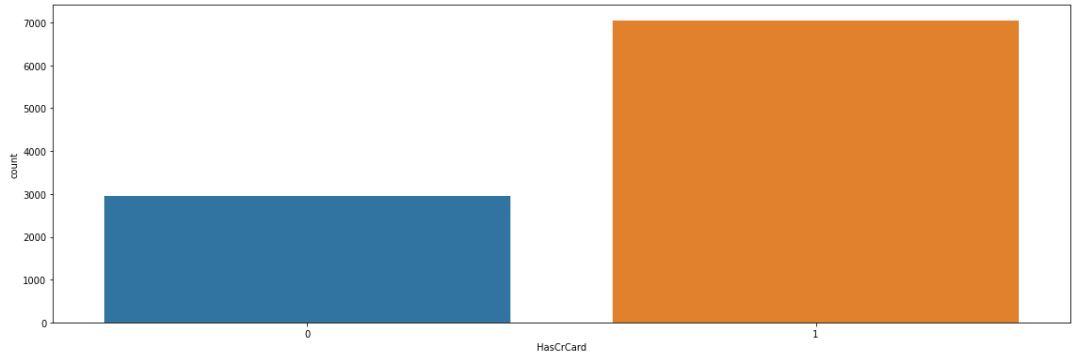



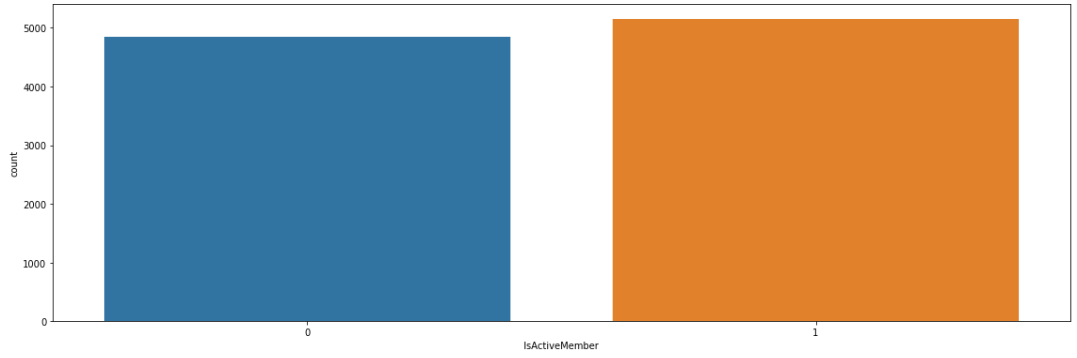



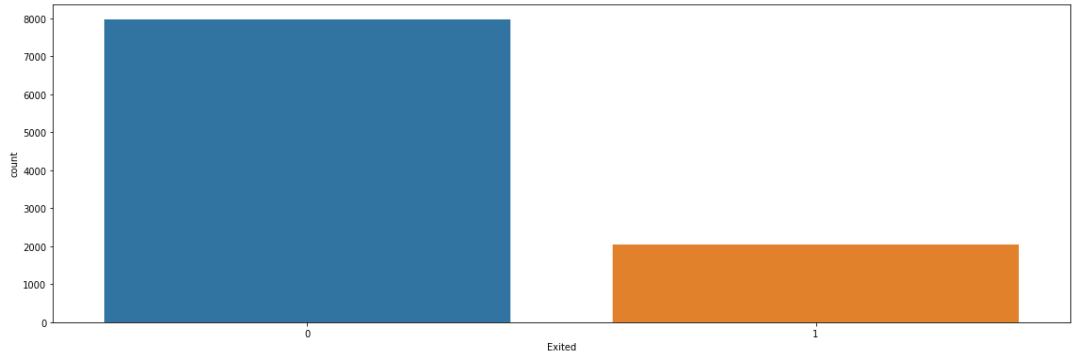

```
l=['CreditScore','Age', 'Tenure','Balance','NumOfProducts','EstimatedSalary']
fig, (ax1, ax2, ax3, ax4, ax5, ax6) = plt.subplots(nrows=6, ncols=1, figsize=(10,20))
data.boxplot(column=[l[0]],grid='False',color='blue',ax=ax1)
data.boxplot(column=[l[1]],grid='False',color='blue',ax = ax2)
data.boxplot(column=[l[2]],grid='False',color='blue',ax = ax3)
data.boxplot(column=[l[3]],grid='False',color='blue',ax = ax4)
data.boxplot(column=[l[4]],grid='False',color='blue',ax = ax5)
data.boxplot(column=[l[5]],grid='False',color='blue',ax = ax6)
plt.tight_layout()
```




```
import warnings
warnings.filterwarnings("ignore")
fig, (ax1, ax2, ax3) = plt.subplots(nrows=3, ncols=1, figsize=(16,16))
sns.countplot(data.HasCrCard,ax=ax1)
sns.countplot(data.IsActiveMember,ax=ax2)
sns.countplot(data.Exited,ax=ax3)
plt.tight_layout()
```

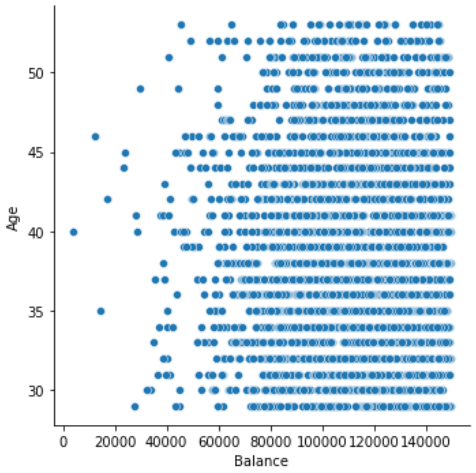


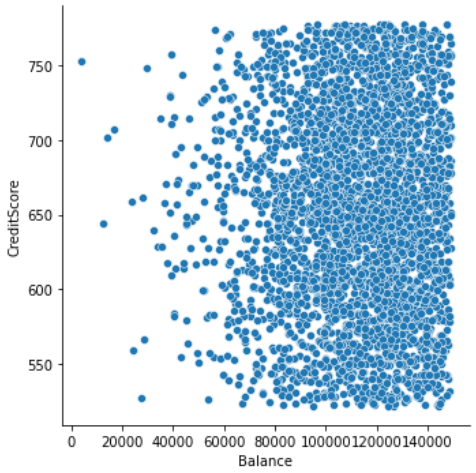




## BI - VARIATE ANALYSIS

```
for i in range(len(l)-1):
    for j in range(i+1,len(l)):
        sns.relplot(x = l[i],y = l[j],data = data)
```

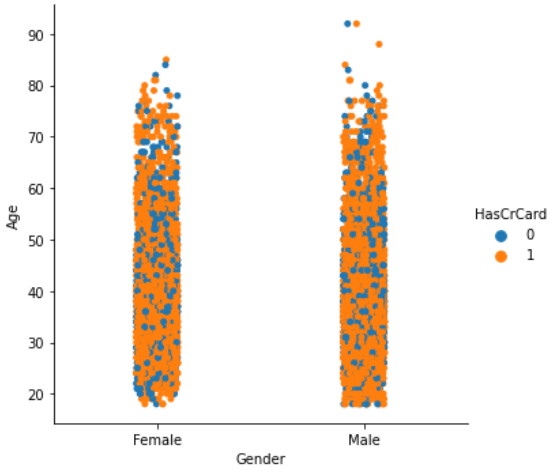



MULTI - VARIATE ANALYSIS

```
sns.catplot(x='Gender', y='Age', hue='HasCrCard', data=data)
```

```
<seaborn.axisgrid.FacetGrid at 0x7f086b124bd0>
```




```
sns.pairplot(data = data,hue='Exited')
```

```
<seaborn.axisgrid.PairGrid at 0x7f086b136e90>
```


4. Perform descriptive statistics on the dataset

```
data.head()
```

| | RowNumber | CustomerId | Surname | CreditScore | Geography | Gender | Age | Tenure | Balance | NumOfProduct |
|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 1 | 15634602 | Hargrave | 619 | France | Female | 42 | 2 | 0.00 | |
| **1** | 2 | 15647311 | Hill | 608 | Spain | Female | 41 | 1 | 83807.86 | |
| **2** | 3 | 15619304 | Onio | 502 | France | Female | 42 | 8 | 159660.80 | |
| **3** | 4 | 15701354 | Boni | 699 | France | Female | 39 | 1 | 0.00 | |
| **4** | 5 | 15737888 | Mitchell | 850 | Spain | Female | 43 | 2 | 125510.82 | |

```
data.describe()
```

| | RowNumber | CustomerId | CreditScore | Age | Tenure | Balance | NumOfProducts |
|---|---|---|---|---|---|---|---|
| **count** | 10000.00000 | 1.000000e+04 | 10000.000000 | 10000.000000 | 10000.000000 | 10000.000000 | 10000.000000 |
| **mean** | 5000.50000 | 1.569094e+07 | 650.528800 | 38.921800 | 5.012800 | 76485.889288 | 1.530200 |
| **std** | 2886.89568 | 7.193619e+04 | 96.653299 | 10.487806 | 2.892174 | 62397.405202 | 0.581654 |
| **min** | 1.00000 | 1.556570e+07 | 350.000000 | 18.000000 | 0.000000 | 0.000000 | 1.000000 |
| **25%** | 2500.75000 | 1.562853e+07 | 584.000000 | 32.000000 | 3.000000 | 0.000000 | 1.000000 |
| **50%** | 5000.50000 | 1.569074e+07 | 652.000000 | 37.000000 | 5.000000 | 97198.540000 | 1.000000 |

```
data.dtypes
```

```
RowNumber            int64
CustomerId           int64
Surname             object
CreditScore          int64
Geography           object
Gender              object
Age                  int64
Tenure               int64
Balance            float64
NumOfProducts        int64
HasCrCard            int64
IsActiveMember       int64
EstimatedSalary    float64
Exited               int64
dtype: object
```

```
data.skew()
```

```
RowNumber          0.000000
CustomerId         0.001149
CreditScore       -0.071607
Age                1.011320
Tenure             0.010991
Balance           -0.141109
NumOfProducts      0.745568
HasCrCard         -0.901812
IsActiveMember    -0.060437
EstimatedSalary    0.002085
Exited             1.471611
dtype: float64
```

5. Handle the Missing values.

```
data.isnull().any()
```

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

6. Find the outliers and replace the outliers

```
data['CreditScore'].describe()
```

```
count    10000.000000
mean       650.528800
std         96.653299
min        350.000000
25%        584.000000
50%        652.000000
75%        718.000000
max        850.000000
Name: CreditScore, dtype: float64
```

```
data['Age'].describe()
```

```
count    10000.000000
mean        38.921800
std         10.487806
min         18.000000
25%         32.000000
50%         37.000000
75%         44.000000
max         92.000000
Name: Age, dtype: float64
```

```
data['Balance'].describe()
```

```
count     10000.000000
mean      76485.889288
std       62397.405202
min           0.000000
25%           0.000000
50%       97198.540000
75%      127644.240000
max      250898.090000
Name: Balance, dtype: float64
```

```
l=['Balance','Age','CreditScore']
for i in l:
    percentile_least = data[i].quantile(0.1)
    percentile90 = data[i].quantile(0.9)
    data = data[(data[i]<percentile90)& (data[i]>percentile_least)]
data['CreditScore'].describe()
```

```
count    3354.000000
mean      651.885808
std        66.341508
min       522.000000
25%       601.000000
50%       652.000000
75%       705.000000
max       777.000000
Name: CreditScore, dtype: float64
```

```
data['Age'].describe()
```

```
count    3354.000000
mean       38.594812
std         6.171482
min        29.000000
25%        34.000000
50%        38.000000
75%        43.000000
max        53.000000
Name: Age, dtype: float64
```

```
data['Balance'].describe()
```

```
count      3354.000000
mean     111127.251270
std       23930.791436
min        3768.690000
25%       96579.825000
50%      113904.805000
75%      129621.140000
max      149238.970000
Name: Balance, dtype: float64
```

7. Check for Categorical columns and perform encoding.

```
from sklearn.preprocessing import LabelEncoder
encoder=LabelEncoder()
for i in data:
    if data[i].dtype=='object':
        data[i]=encoder.fit_transform(data[i])
data.head()
```

| | RowNumber | CustomerId | Surname | CreditScore | Geography | Gender | Age | Tenure | Balance | NumOfProduc |
|---|---|---|---|---|---|---|---|---|---|---|
| **1** | 2 | 15647311 | 645 | 608 | 2 | 0 | 41 | 1 | 83807.86 | |
| **5** | 6 | 15574012 | 302 | 645 | 2 | 1 | 44 | 8 | 113755.78 | |

8. Split the data into dependent and independent variables.

```
data.shape
(3354, 14)
x = data.iloc[:,:13]
y = data.iloc[:,13]
y.head()
```

```
1     0
5     1
10    0
15    0
26    0
Name: Exited, dtype: int64
```

```
x.head()
```

| | RowNumber | CustomerId | Surname | CreditScore | Geography | Gender | Age | Tenure | Balance | NumOfProduc |
|---|---|---|---|---|---|---|---|---|---|---|
| **1** | 2 | 15647311 | 645 | 608 | 2 | 0 | 41 | 1 | 83807.86 | |
| **5** | 6 | 15574012 | 302 | 645 | 2 | 1 | 44 | 8 | 113755.78 | |
| **10** | 11 | 15767821 | 109 | 528 | 0 | 1 | 31 | 6 | 102016.72 | |
| **15** | 16 | 15643966 | 561 | 616 | 1 | 1 | 45 | 3 | 143129.41 | |
| **26** | 27 | 15736816 | 1605 | 756 | 1 | 1 | 36 | 2 | 136815.64 | |

9. Scale the independent variables

```
from sklearn.preprocessing import StandardScaler
sc = StandardScaler()
x = sc.fit_transform(x)
```

10. Split the data into training and testing

```
from sklearn.model_selection import train_test_split
x_train,x_test,y_train,y_test = train_test_split(x,y,test_size=0.2, random_state=0)
x_train.shape
```

```
(2683, 13)
```

```
y_train.shape
```

```
(2683,)
```

```
x_test.shape
```

```
(671, 13)
```

```
y_test.shape
```

```
(671,)
```

Double-click (or enter) to edit