

## Assignment -2

|                     |   |
|---------------------|---|
| Project Name        | AI Based Discourse for Banking Industry |
| Student Name        | Ezhil Arasi N                           |
| Student Roll Number | 721919106027                            |
| Maximum Marks       | 2 Marks                                 |

### Question-1. Download dataset

#### Solution:

| RowNum | Customer | Surname   | CreditS | Geograph | Gender | Age | Tenure | Balance  | NumOfPro | HasCrCard | IsActiveM | Estimated | Exited |
|--------|----------|-----------|---------|----------|--------|-----|--------|----------|----------|-----------|-----------|-----------|--------|
| 1      | 15634602 | Hargrave  | 619     | France   | Female | 42  | 2      | 0        | 1        | 1         | 1         | 101348.9  | 1      |
| 2      | 15647311 | Hill      | 608     | Spain    | Female | 41  | 1      | 83807.86 | 1        | 0         | 1         | 112542.6  | 0      |
| 3      | 15619304 | Onio      | 502     | France   | Female | 42  | 8      | 159660.8 | 3        | 1         | 0         | 113931.6  | 1      |
| 4      | 15701354 | Boni      | 699     | France   | Female | 39  | 1      | 0        | 2        | 0         | 0         | 93826.63  | 0      |
| 5      | 15737888 | Mitchell  | 850     | Spain    | Female | 43  | 2      | 125510.8 | 1        | 1         | 1         | 79084.1   | 0      |
| 6      | 15574012 | Chu       | 645     | Spain    | Male   | 44  | 8      | 113755.8 | 2        | 1         | 0         | 149756.7  | 1      |
| 7      | 15592531 | Bartlett  | 822     | France   | Male   | 50  | 7      | 0        | 2        | 1         | 1         | 10062.8   | 0      |
| 8      | 15656148 | Obinna    | 376     | Germany  | Female | 29  | 4      | 115046.7 | 4        | 1         | 0         | 119346.9  | 1      |
| 9      | 15792365 | He        | 501     | France   | Male   | 44  | 4      | 142051.1 | 2        | 0         | 1         | 74940.5   | 0      |
| 10     | 15592389 | H?        | 684     | France   | Male   | 27  | 2      | 134603.9 | 1        | 1         | 1         | 71725.73  | 0      |
| 11     | 15767821 | Bearce    | 528     | France   | Male   | 31  | 6      | 102016.7 | 2        | 0         | 0         | 80181.12  | 0      |
| 12     | 15737173 | Andrews   | 497     | Spain    | Male   | 24  | 3      | 0        | 2        | 1         | 0         | 76390.01  | 0      |
| 13     | 15632264 | Kay       | 476     | France   | Female | 34  | 10     | 0        | 2        | 1         | 0         | 26260.98  | 0      |
| 14     | 15691483 | Chin      | 549     | France   | Female | 25  | 5      | 0        | 2        | 0         | 0         | 190857.8  | 0      |
| 15     | 15600882 | Scott     | 635     | Spain    | Female | 35  | 7      | 0        | 2        | 1         | 1         | 65951.65  | 0      |
| 16     | 15643966 | Goforth   | 616     | Germany  | Male   | 45  | 3      | 143129.4 | 2        | 0         | 1         | 64327.26  | 0      |
| 17     | 15737452 | Romeo     | 653     | Germany  | Male   | 58  | 1      | 132602.9 | 1        | 1         | 0         | 5097.67   | 1      |
| 18     | 15788218 | Henderso  | 549     | Spain    | Female | 24  | 9      | 0        | 2        | 1         | 1         | 14406.41  | 0      |
| 19     | 15661507 | Muldrow   | 587     | Spain    | Male   | 45  | 6      | 0        | 1        | 0         | 0         | 158684.8  | 0      |
| 20     | 15568982 | Hao       | 726     | France   | Female | 24  | 6      | 0        | 2        | 1         | 1         | 54724.03  | 0      |
| 21     | 15577657 | McDonald  | 732     | France   | Male   | 41  | 8      | 0        | 2        | 1         | 1         | 170886.2  | 0      |
| 22     | 15597945 | Dellucci  | 636     | Spain    | Female | 32  | 8      | 0        | 2        | 1         | 0         | 138555.5  | 0      |
| 23     | 15699309 | Gerasimo  | 510     | Spain    | Female | 38  | 4      | 0        | 1        | 1         | 0         | 118913.5  | 1      |
| 24     | 15725737 | Mosman    | 669     | France   | Male   | 46  | 3      | 0        | 2        | 0         | 1         | 8487.75   | 0      |
| 25     | 15625047 | Yen       | 846     | France   | Female | 38  | 5      | 0        | 1        | 1         | 1         | 187616.2  | 0      |
| 26     | 15738191 | Maclean   | 577     | France   | Male   | 25  | 3      | 0        | 2        | 0         | 1         | 124508.3  | 0      |
| 27     | 15736816 | Young     | 756     | Germany  | Male   | 36  | 2      | 136815.6 | 1        | 1         | 1         | 170042    | 0      |
| 28     | 15700772 | Nebechi   | 571     | France   | Male   | 44  | 9      | 0        | 2        | 0         | 0         | 38433.35  | 0      |
| 29     | 15728693 | McWilliam | 574     | Germany  | Female | 43  | 3      | 141349.4 | 1        | 1         | 1         | 100187.4  | 0      |
| 30     | 15656300 | Lucciano  | 411     | France   | Male   | 29  | 0      | 59697.17 | 2        | 1         | 1         | 53483.21  | 0      |
| 31     | 15589475 | Azikiwe   | 591     | Spain    | Female | 39  | 3      | 0        | 3        | 1         | 0         | 140469.4  | 1      |
| 32     | 15706552 | Odinakach | 533     | France   | Male   | 36  | 7      | 85311.7  | 1        | 0         | 1         | 156731.9  | 0      |
| 33     | 15750181 | Sandersor | 553     | Germany  | Male   | 41  | 9      | 110112.5 | 2        | 0         | 0         | 81898.81  | 0      |
| 34     | 15659428 | Maggard   | 520     | Spain    | Female | 42  | 6      | 0        | 2        | 1         | 1         | 34410.55  | 0      |
| 35     | 15732963 | Clements  | 722     | Spain    | Female | 29  | 9      | 0        | 2        | 1         | 1         | 142033.1  | 0      |
| 36     | 15794171 | Lombardo  | 475     | France   | Female | 45  | 0      | 134264   | 1        | 1         | 0         | 27822.99  | 1      |
| 37     | 15788448 | Watson    | 490     | Spain    | Male   | 31  | 3      | 145260.2 | 1        | 0         | 1         | 114066.8  | 0      |
| 38     | 15729599 | Lorenzo   | 804     | Spain    | Male   | 33  | 7      | 76548.6  | 1        | 0         | 1         | 98453.45  | 0      |
| 39     | 15717426 | Armstrong | 850     | France   | Male   | 36  | 7      | 0        | 1        | 1         | 1         | 40812.9   | 0      |
| 40     | 15585768 | Cameron   | 582     | Germany  | Male   | 41  | 6      | 70349.48 | 2        | 0         | 1         | 178074    | 0      |

### Question-2. Load the dataset

#### Solution:

```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
import sklearn
data = pd.read_csv(r'Churn_Modelling.csv')
df.head
```

```
<bound method NDFrame.head of
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
...
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  \
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
...
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
0         101348.88        1
1         112542.58        0
2         113931.57        1
3          93826.63        0
4          79084.10        0
...
9995          96270.64        0
9996         101699.77        0
9997          42085.58        1
9998          92888.52        1
9999          38190.78        0

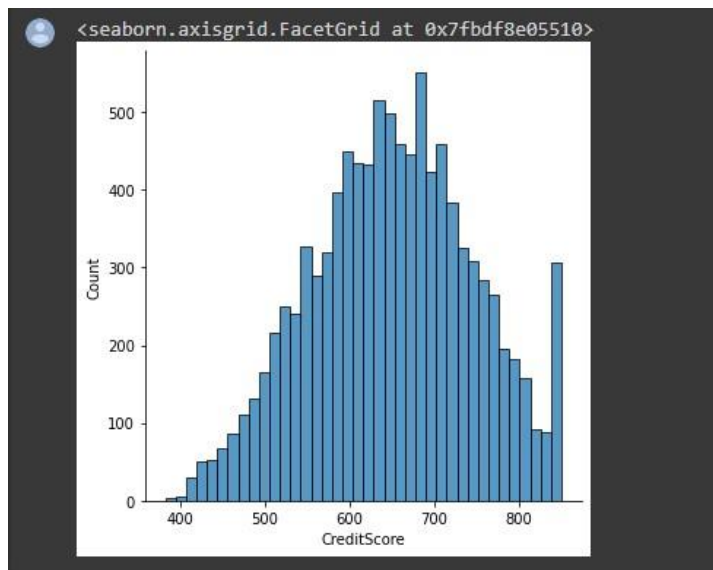
[10000 rows x 14 columns]>
```

**Question-3.** Perform Below Visualizations.

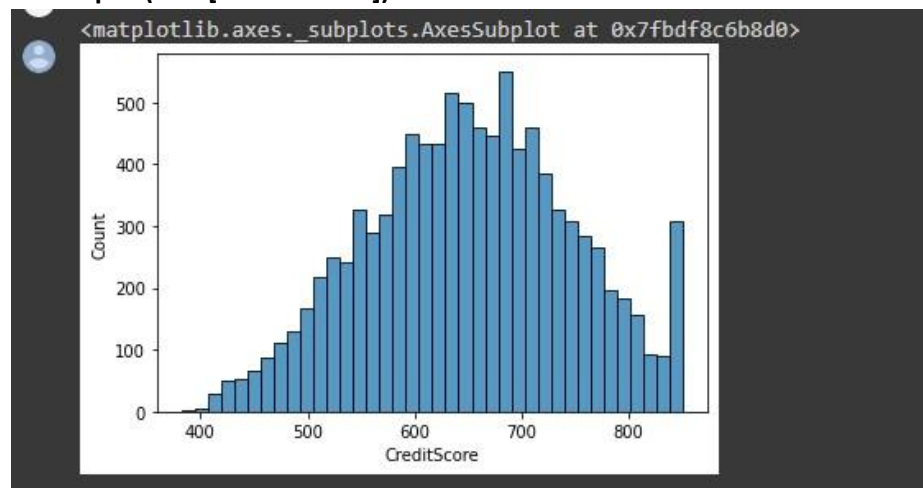
### 3.1 Univariate Analysis

**Solution:**

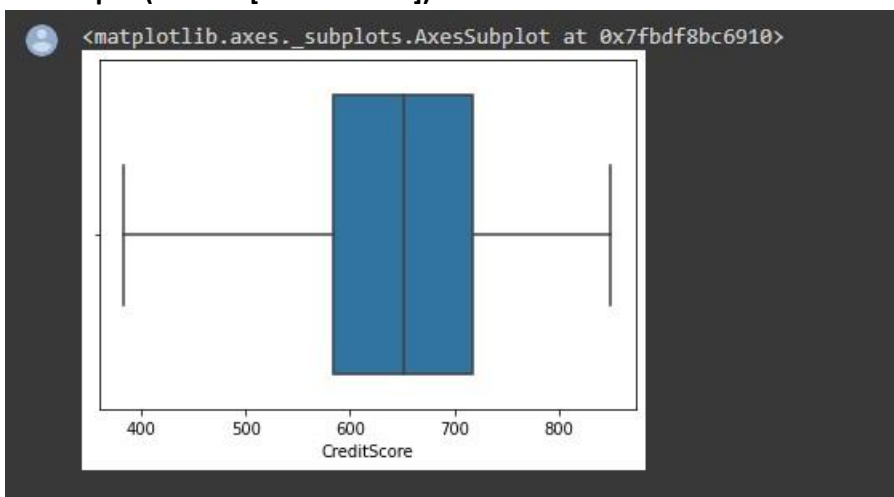
```
sns.displot(data['CreditScore'])
```



`sns.histplot(data['CreditScore'])`

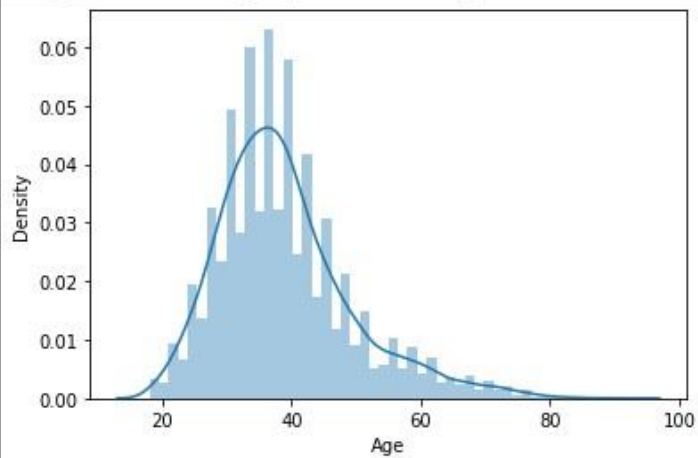


`sns.boxplot(x = data['CreditScore'])`



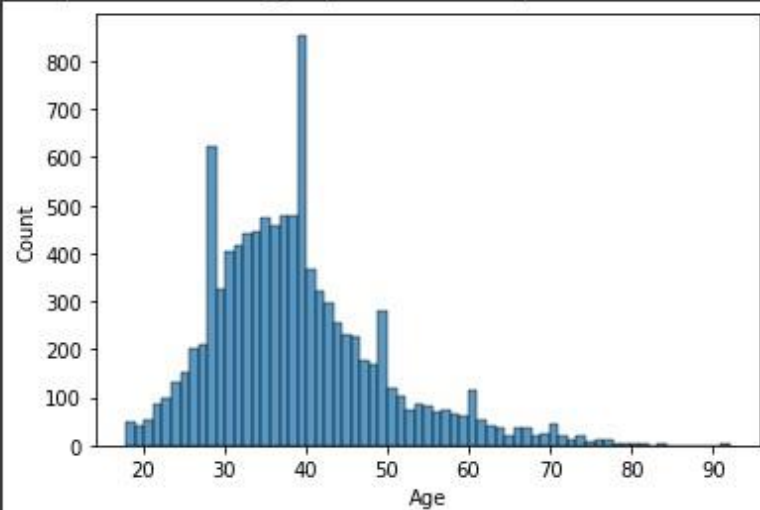
`sns.distplot(data['Age'])`

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fbe0d180550>
```



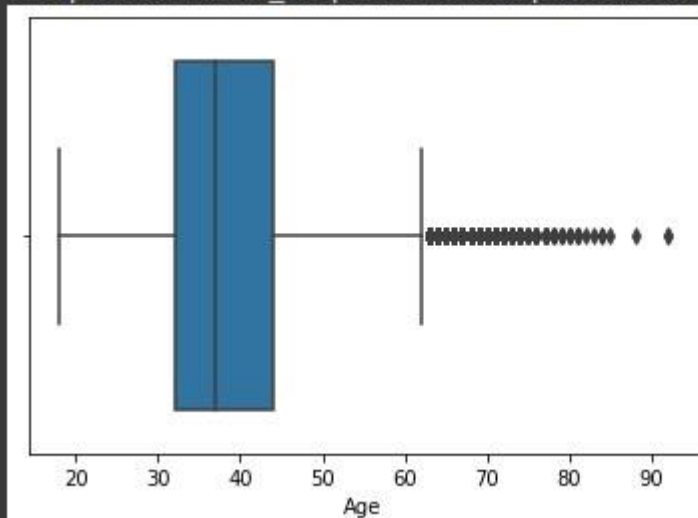
```
sns.histplot(data['Age'])
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fbe0d15f110>
```



```
sns.boxplot(data['Age'])
```

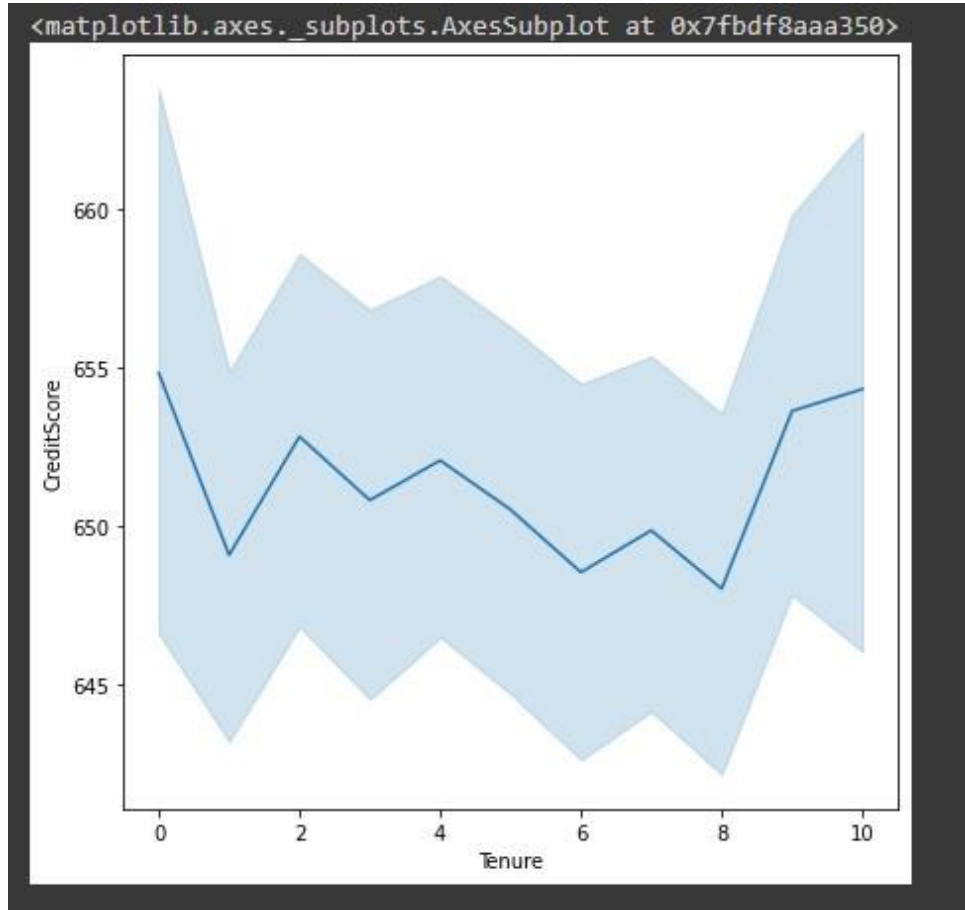
```
<matplotlib.axes._subplots.AxesSubplot at 0x7fbe0ca3c0d0>
```



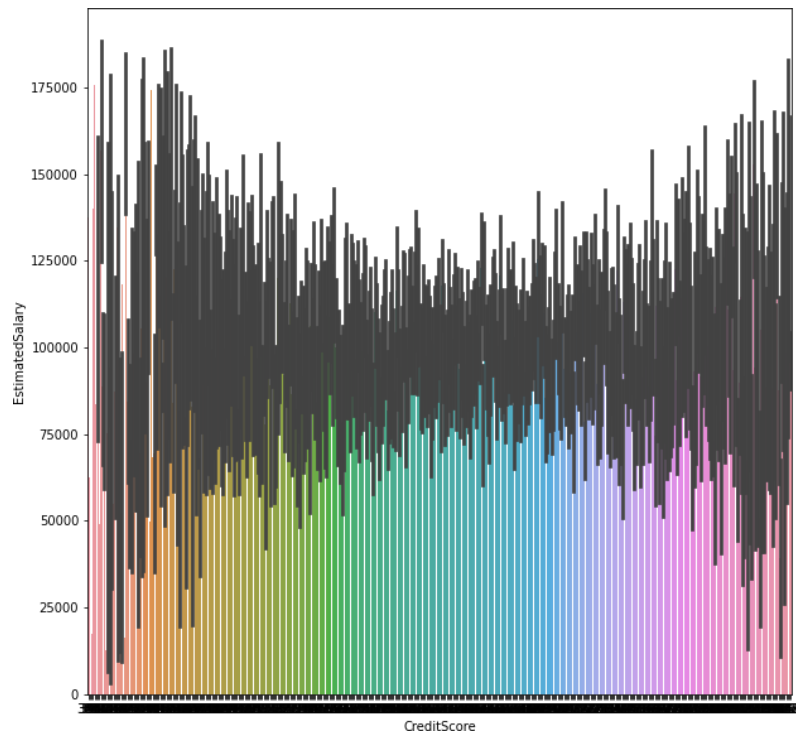
### 3.2 Bivariate Analysis

#### Solution:

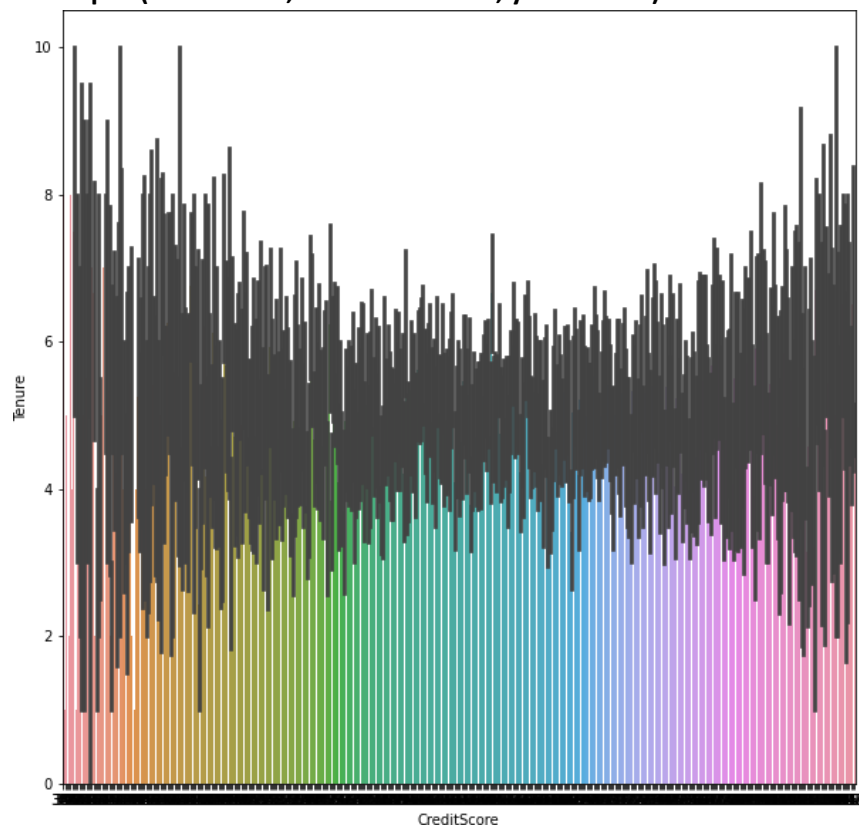
```
plt.figure(figsize=(7,7))  
sns.lineplot(data = data, x = 'Tenure', y = 'CreditScore')
```



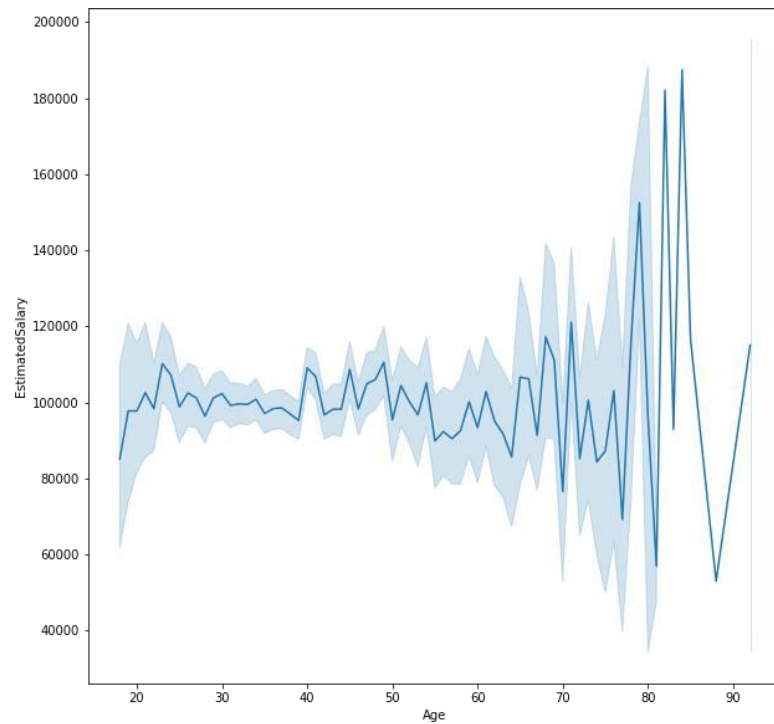
```
plt.figure(figsize=(10,10))  
sns.barplot(data = data, x = 'CreditScore', y = 'EstimatedSalary')
```



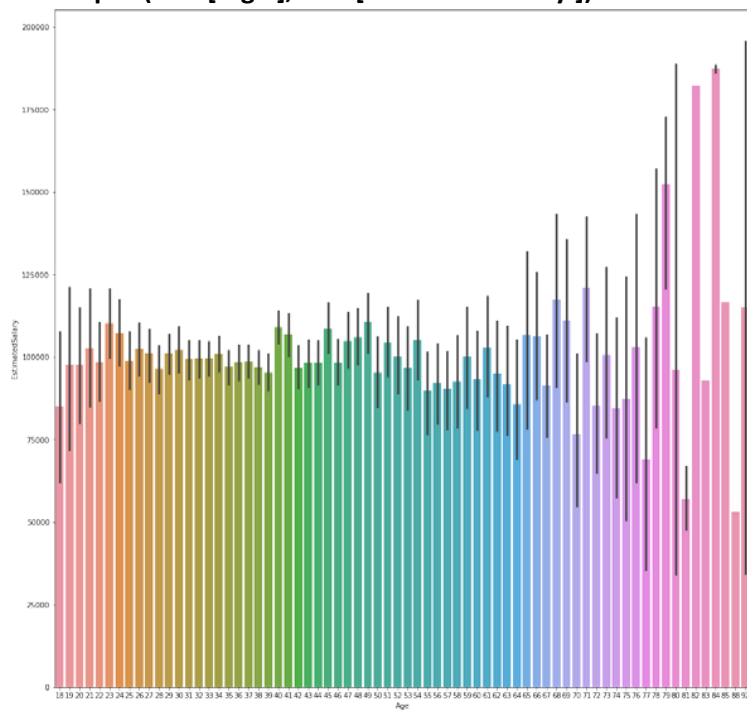
```
plt.figure(figsize=(10,10))
sns.barplot(data = data, x = 'CreditScore', y = 'Tenure')
```



```
plt.figure(figsize=(10,10))
sns.lineplot(data['Age'], data['EstimatedSalary'])
```

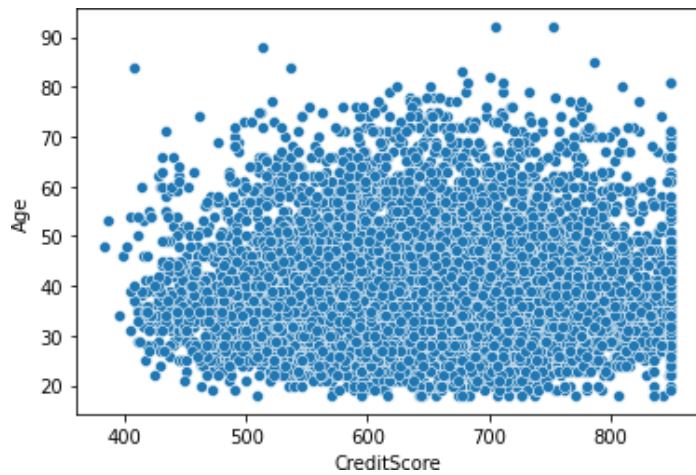


```
plt.figure(figsize=(17,17))
sns.barplot(data['Age'], data['EstimatedSalary'])
```



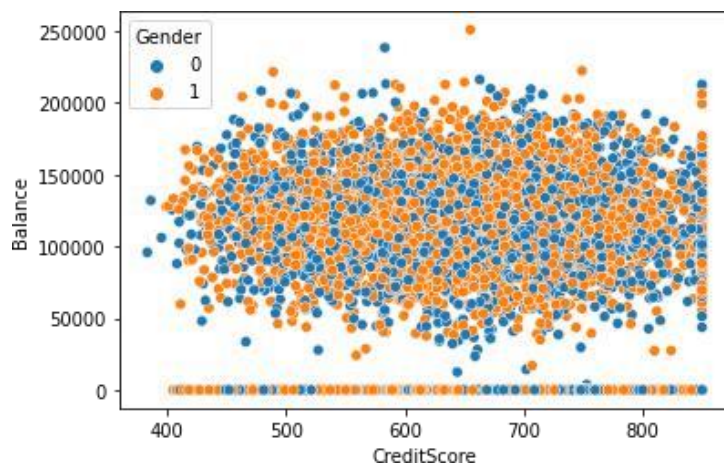
```
sns.scatterplot(data = data, x = 'CreditScore', y = 'Age')
```



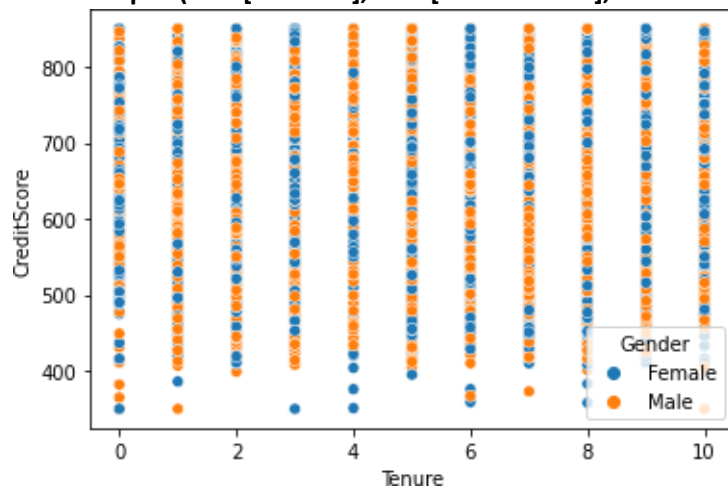


### 3.3 Multivariate Analysis

**Solution:** `sns.scatterplot(data = data, x = 'CreditScore', y = 'Balance', hue = 'Gender')`

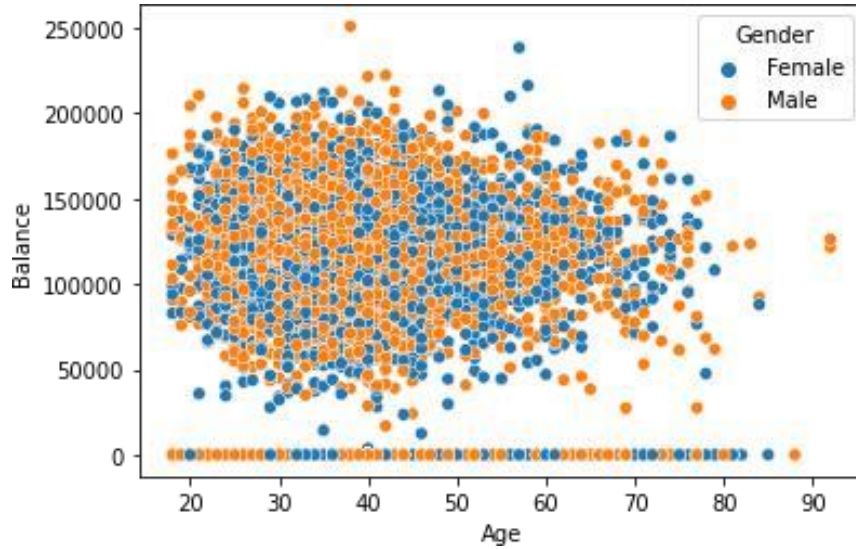


`sns.scatterplot(data['Tenure'], data['CreditScore'], hue = data['Gender'])`





`sns.scatterplot(data['Age'], data['Balance'], hue = data['Gender'])`



`sns.pairplot(data)`



**Question-4.** Perform descriptive statistics on the dataset.

### Solution:

**data.mean(numeric\_only = True)**

```
RowNumber      5.000500e+03
CustomerId     1.569094e+07
CreditScore    6.505288e+02
Age            3.892180e+01
Tenure         5.012800e+00
Balance        7.648589e+04
NumOfProducts  1.530200e+00
HasCrCard      7.055000e-01
IsActiveMember 5.151000e-01
EstimatedSalary 1.000902e+05
Exited         2.037000e-01
dtype: float64
```

**data.median(numeric\_only = True)**

```
RowNumber      5.000500e+03
CustomerId     1.569074e+07
CreditScore    6.520000e+02
Age            3.700000e+01
Tenure         5.000000e+00
Balance        9.719854e+04
NumOfProducts  1.000000e+00
HasCrCard      1.000000e+00
IsActiveMember 1.000000e+00
EstimatedSalary 1.001939e+05
Exited         0.000000e+00
dtype: float64
```

**data['CreditScore'].mode()**

```
0      850
dtype: int64
```

**data['EstimatedSalary'].mode()**

```
0      24924.92
dtype: float64
```

**data['HasCrCard'].unique()**

```
array([1, 0])
```

**data['Tenure'].unique()**

```
array([ 2,  1,  8,  7,  4,  6,  3, 10,  5,  9,  0])
```

**data.std(numeric\_only=True)**

```
RowNumber      2886.895680
CustomerId      71936.186123
CreditScore     96.653299
Age            10.487806
Tenure          2.892174
Balance        62397.405202
NumOfProducts   0.581654
HasCrCard       0.455840
IsActiveMember  0.499797
EstimatedSalary 57510.492818
Exited         0.402769
dtype: float64
```

**data.describe()**

|       | RowNumber   | CustomerId   | CreditScore  | Age          | Tenure       | Balance       | NumOfProducts | HasCrCard   | IsActiveMember | EstimatedSalary | Exited       |
|-------|-------------|--------------|--------------|--------------|--------------|---------------|---------------|-------------|----------------|-----------------|--------------|
| count | 10000.00000 | 1.000000e+04 | 10000.000000 | 10000.000000 | 10000.000000 | 10000.000000  | 10000.000000  | 10000.00000 | 10000.000000   | 10000.000000    | 10000.000000 |
| mean  | 5000.50000  | 1.569094e+07 | 650.528800   | 38.921800    | 5.012800     | 76485.889288  | 1.530200      | 0.70550     | 0.515100       | 100090.239881   | 0.203700     |
| std   | 2886.89568  | 7.193619e+04 | 96.653299    | 10.487806    | 2.892174     | 62397.405202  | 0.581654      | 0.45584     | 0.499797       | 57510.492818    | 0.402769     |
| min   | 1.00000     | 1.566570e+07 | 350.000000   | 18.000000    | 0.000000     | 0.000000      | 1.000000      | 0.00000     | 0.000000       | 11.580000       | 0.000000     |
| 25%   | 2500.75000  | 1.562853e+07 | 584.000000   | 32.000000    | 3.000000     | 0.000000      | 1.000000      | 0.00000     | 0.000000       | 51002.110000    | 0.000000     |
| 50%   | 5000.50000  | 1.569074e+07 | 652.000000   | 37.000000    | 5.000000     | 97198.540000  | 1.000000      | 1.00000     | 1.000000       | 100193.915000   | 0.000000     |
| 75%   | 7500.25000  | 1.575323e+07 | 718.000000   | 44.000000    | 7.000000     | 127644.240000 | 2.000000      | 1.00000     | 1.000000       | 149388.247500   | 0.000000     |
| max   | 10000.00000 | 1.581569e+07 | 850.000000   | 92.000000    | 10.000000    | 250898.090000 | 4.000000      | 1.00000     | 1.000000       | 199992.480000   | 1.000000     |

**data['Tenure'].value\_counts()**

```
2    1048
1    1035
7    1028
8    1025
5    1012
3    1009
4     989
9     984
6     967
10    490
0     413
Name: Tenure, dtype: int64
```

**Question-5.** Handle the Missing values.

**Solution:** `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

```

**data.isnull().sum()**

```

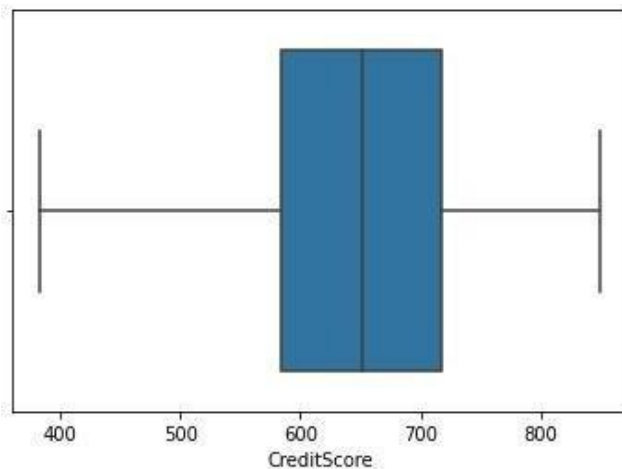
RowNumber      0
CustomerId     0
Surname        0
CreditScore    0
Geography      0
Gender         0
Age           0
Tenure        0
Balance       0
NumOfProducts 0
HasCrCard     0
IsActiveMember 0
EstimatedSalary 0
Exited        0
dtype: int64

```

**Question-6.** Find the outliers and replace the outliers

**Solution:**

**sns.boxplot(data['CreditScore'])    #Outlier detection - box plot**

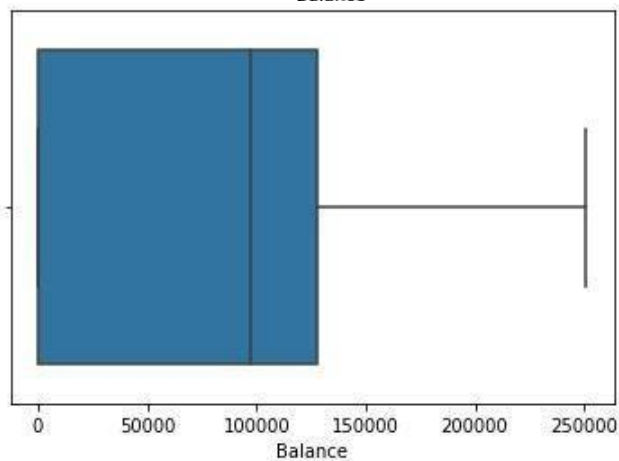
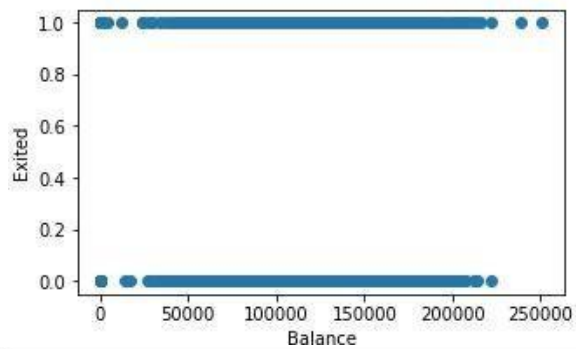


**fig, ax = plt.subplots(figsize = (5,3))    #Outlier detection - Scatter plot**  
**ax.scatter(data['Balance'], data['Exited'])**

```
# x-axis label
ax.set_xlabel('Balance')

# y-axis label ax.set_ylabel('Exited')
plt.show()
```

```
sns.boxplot(x=data['Balance'])
```



```
from scipy import stats      #Outlier detection – zscore
zscore = np.abs(stats.zscore(data['CreditScore']))
print(zscore)
print('No. of Outliers : ', np.shape(np.where(zscore>3)))
```

```
0      0.332952
1      0.447540
2      1.551761
3      0.500422
4      2.073415
...
9995   1.250458
9996   1.405920
9997   0.604594
9998   1.260876
9999   1.469219
Name: CreditScore, Length: 10000, dtype: float64
No. of Outliers : (1, 0)
```

```
q = data.quantile([0.75,0.25]) q
```

|      | RowNumber | CustomerId  | Surname | CreditScore | Geography | Gender | Age  | Tenure | Balance   | NumOfProducts | HasCrCard | IsActiveMember | EstimatedSalary | Exited |
|------|-----------|-------------|---------|-------------|-----------|--------|------|--------|-----------|---------------|-----------|----------------|-----------------|--------|
| 0.75 | 7500.25   | 15753233.75 | 2238.25 | 718.0       | 1.0       | 1.0    | 44.0 | 7.0    | 127644.24 | 2.0           | 1.0       | 1.0            | 149388.2475     | 0.0    |
| 0.25 | 2500.75   | 15628528.25 | 773.75  | 584.0       | 0.0       | 0.0    | 32.0 | 3.0    | 0.00      | 1.0           | 0.0       | 0.0            | 51002.1100      | 0.0    |

```
iqr = q.iloc[0] - q.iloc[1] iqr
```

```
RowNumber      4999.5000
CustomerId      124785.5000
Surname         1464.5000
CreditScore     134.0000
Geography       1.0000
Gender          1.0000
Age             12.0000
Tenure          4.0000
Balance         127644.2400
NumOfProducts   1.0000
HasCrCard       1.0000
IsActiveMember  1.0000
EstimatedSalary 98386.1375
Exited          0.0000
dtype: float64
```

```
u = q.iloc[0] + (1.5*iqr) u
```

```
RowNumber      1.499950e+04
CustomerId      1.594029e+07
Surname         4.435000e+03
CreditScore     9.190000e+02
Geography       2.500000e+00
Gender          2.500000e+00
Age             6.200000e+01
Tenure          1.300000e+01
Balance         3.191106e+05
NumOfProducts   3.500000e+00
HasCrCard       2.500000e+00
IsActiveMember  2.500000e+00
EstimatedSalary 2.969675e+05
Exited          0.000000e+00
dtype: float64
```

```
l = q.iloc[1] - (1.5*iqr)
```

```
l
```

```
RowNumber      -4.998500e+03
CustomerId      1.544147e+07
Surname        -1.423000e+03
CreditScore     3.830000e+02
Geography       -1.500000e+00
Gender          -1.500000e+00
Age             1.400000e+01
Tenure          -3.000000e+00
Balance         -1.914664e+05
NumOfProducts   -5.000000e-01
HasCrCard       -1.500000e+00
IsActiveMember  -1.500000e+00
EstimatedSalary -9.657710e+04
Exited          0.000000e+00
dtype: float64
```

```
Q1 = data['EstimatedSalary'].quantile(0.25) #Outlier detection - IQR
```



```

Q3 = data['EstimatedSalary'].quantile(0.75)
iqr = Q3 - Q1
print(iqr) upper=Q3
+ 1.5 * iqr lower=Q1
- 1.5 * iqr count =
np.size(np.where(d
ata['EstimatedSalar
y'] > upper)) count =
count +
np.size(np.where(d
ata['EstimatedSalar
y'] < lower))
print('No. of
outliers : ', count)

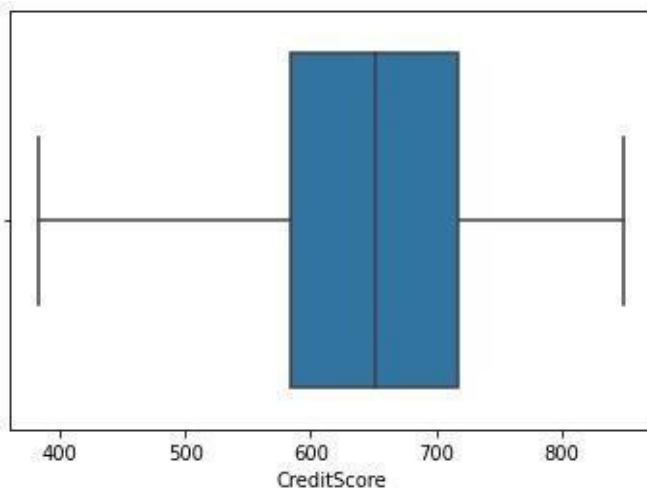
98386.1375
No. of outliers : 0

```

```

data['CreditScore'] = np.where(np.logical_or(data['CreditScore'] > 900, data['CreditScore'] < 383), 65
0, data['CreditScore']) sns.boxplot(data['CreditScore'])

```



```

upper = data.Age.mean() + (3 * data.Age.std()) #Outlier detection - 3 sigma lower
= data.Age.mean() - (3 * data.Age.std())
columns = data[ ( data['Age'] > upper ) | ( data['Age'] < lower )
] print('Upper range : ', upper) print('Lower range : ', lower)
print('No. of Outliers : ', len(columns))

Upper range : 70.38521935511383
Lower range : 7.458380644886169
No. of Outliers : 133

```

```

columns = ['EstimatedSalary', 'Age', 'Balance', 'NumOfProducts', 'Tenure', 'CreditScore'] #After
outlier removal

```



```

for i in columns:
    Q1 = data[i].quantile(0.25)
    Q3 = data[i].quantile(0.75)
    iqr = Q3 - Q1 upper=Q3 +
    1.5 * iqr lower=Q1 - 1.5 *
    iqr
    count = np.size(np.where(data[i] >upper))
    count = count + np.size(np.where(data[i] <lower)) print('No.
    of outliers in ', i, ' : ', count)
No. of outliers in EstimatedSalary : 0
No. of outliers in Age : 0
No. of outliers in Balance : 0
No. of outliers in NumOfProducts : 0
No. of outliers in Tenure : 0
No. of outliers in CreditScore : 0

```

**Question-7.** Check for Categorical columns and perform encoding

**Solution:**

```

from sklearn.preprocessing import LabelEncoder, OneHotEncoder
le = LabelEncoder() oneh = OneHotEncoder()
data['Surname'] = le.fit_transform(data['Surname']) data['Gender']
= le.fit_transform(data['Gender']) data['Geography'] =
le.fit_transform(data['Geography']) data.head()

```

| RowNumber | CustomerId | Surname  | CreditScore | Geography | Gender | Age | Tenure | Balance | NumOfProducts | HasCrCard | IsActiveMember | EstimatedSalary | Exited    |   |
|-----------|------------|----------|-------------|-----------|--------|-----|--------|---------|---------------|-----------|----------------|-----------------|-----------|---|
| 0         | 1          | 15634602 | 1115        | 619       | 0      | 0   | 42     | 2       | 0.00          | 1         | 1              | 1               | 101348.88 | 1 |
| 1         | 2          | 15647311 | 1177        | 608       | 2      | 0   | 41     | 1       | 83807.86      | 1         | 0              | 1               | 112542.58 | 0 |
| 2         | 3          | 15619304 | 2040        | 502       | 0      | 0   | 42     | 8       | 159660.80     | 3         | 1              | 0               | 113931.57 | 1 |
| 3         | 4          | 15701354 | 289         | 699       | 0      | 0   | 39     | 1       | 0.00          | 2         | 0              | 0               | 93826.63  | 0 |
| 4         | 5          | 15737888 | 1822        | 850       | 2      | 0   | 43     | 2       | 125510.82     | 1         | 1              | 1               | 79084.10  | 0 |

**Question-8.** Split the data into dependent and independent variables split the data in X and Y

**Solution:**

**x # independent values ( inputs)**

**x = data.iloc[:, 0:13]**

|      | RowNumber | CustomerId | Surname | CreditScore | Geography | Gender | Age | Tenure | Balance   | NumOfProducts | HasCrCard | IsActiveMember | EstimatedSalary |
|------|-----------|------------|---------|-------------|-----------|--------|-----|--------|-----------|---------------|-----------|----------------|-----------------|
| 0    | 1         | 15634602   | 1115    | 619         | 0         | 0      | 42  | 2      | 0.00      | 1             | 1         | 1              | 101348.88       |
| 1    | 2         | 15647311   | 1177    | 608         | 2         | 0      | 41  | 1      | 83807.86  | 1             | 0         | 1              | 112542.58       |
| 2    | 3         | 15619304   | 2040    | 502         | 0         | 0      | 42  | 8      | 159660.80 | 3             | 1         | 0              | 113931.57       |
| 3    | 4         | 15701354   | 289     | 699         | 0         | 0      | 39  | 1      | 0.00      | 2             | 0         | 0              | 93826.63        |
| 4    | 5         | 15737888   | 1822    | 850         | 2         | 0      | 43  | 2      | 125510.82 | 1             | 1         | 1              | 79084.10        |
| ...  | ...       | ...        | ...     | ...         | ...       | ...    | ... | ...    | ...       | ...           | ...       | ...            | ...             |
| 9995 | 9996      | 15606229   | 1999    | 771         | 0         | 1      | 39  | 5      | 0.00      | 2             | 1         | 0              | 96270.64        |
| 9996 | 9997      | 15569892   | 1336    | 516         | 0         | 1      | 35  | 10     | 57369.61  | 1             | 1         | 1              | 101699.77       |
| 9997 | 9998      | 15584532   | 1570    | 709         | 0         | 0      | 36  | 7      | 0.00      | 1             | 0         | 1              | 42085.58        |
| 9998 | 9999      | 15682355   | 2345    | 772         | 1         | 1      | 42  | 3      | 75075.31  | 2             | 1         | 0              | 92888.52        |
| 9999 | 10000     | 15628319   | 2751    | 792         | 0         | 0      | 28  | 4      | 130142.79 | 1             | 1         | 0              | 38190.78        |

10000 rows x 13 columns

**y # dependent values (output) y**

**= data['Exited']**

```
0      1
1      0
2      1
3      0
4      0
..
9995   0
9996   0
9997   1
9998   1
9999   0
Name: Exited, Length: 10000, dtype: int64
```

**Question-9.** Scale the independent variables

**Solution:**

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

```
array([[ -1.73187761, -0.78321342, -0.46418322, ...,  0.64609167,
         0.97024255,  0.02188649],
       [ -1.7315312 , -0.60653412, -0.3909112 , ..., -1.54776799,
         0.97024255,  0.21653375],
       [ -1.73118479, -0.99588476,  0.62898807, ...,  0.64609167,
        -1.03067011,  0.2406869 ],
       ...,
       [  1.73118479, -1.47928179,  0.07353887, ..., -1.54776799,
         0.97024255, -1.00864308],
       [  1.7315312 , -0.11935577,  0.98943914, ...,  0.64609167,
        -1.03067011, -0.12523071],
       [  1.73187761, -0.87055909,  1.4692527 , ...,  0.64609167,
        -1.03067011, -1.07636976]])
```

**Question-10.** Split x and y into Training and Testing

**Solution:**

```
from sklearn.model_selection import train_test_split
```

```
x_train, x_test, y_train, y_test = train_test_split(x_scaled, y, test_size = 0.3, random_state = 0)
```

**x\_train**

```
array([[ 0.92889885, -0.79703192, -1.47580983, ...,  0.64609167,
         0.97024255, -0.77021814],
       [ 1.39655257,  0.71431365, -1.58808148, ...,  0.64609167,
        -1.03067011, -1.39576675],
       [-0.4532777 ,  0.96344969, -0.24082173, ..., -1.54776799,
         0.97024255, -1.49965629],
       ...,
       [-0.60119484, -1.62052514, -0.36136603, ...,  0.64609167,
        -1.03067011,  1.41441489],
       [ 1.67853045, -0.37403866,  0.72589622, ...,  0.64609167,
         0.97024255,  0.84614739],
       [-0.78548505, -1.36411841,  1.3829808 , ...,  0.64609167,
        -1.03067011,  0.32630495]])
```

**x\_train.shape**

```
(7000, 13)
```

**x\_test**

```
array([[ 1.52229946, -1.04525042,  1.39834429, ...,  0.64609167,
         0.97024255,  1.61304597],
       [-1.42080128, -0.50381294, -0.78208925, ...,  0.64609167,
        -1.03067011,  0.49753166],
       [-0.90118604, -0.7932923 ,  0.41271742, ...,  0.64609167,
         0.97024255, -0.4235611 ],
       ...,
       [ 1.49216178, -0.14646448,  0.6868966 , ...,  0.64609167,
         0.97024255,  1.17045451],
       [ 1.1758893 , -1.29228727, -1.38481071, ...,  0.64609167,
         0.97024255, -0.50846777],
       [ 0.08088677, -1.38538833,  1.11707427, ...,  0.64609167,
         0.97024255, -1.15342685]])
```

**x\_test.shape**

```
(3000, 13)
```

**y\_train**

```
7681    1
9031    0
3691    0
202     1
5625    0
..
9225    0
4859    0
3264    0
9845    0
2732    1
Name: Exited, Length: 7000, dtype: int64
```

**y\_test**

```
9394    0
898     1
2398    0
5906    0
2343    0
..
4004    0
7375    0
9307    0
8394    0
5233    1
Name: Exited, Length: 3000, dtype: int64
```