```
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
import seaborn as sns
import warnings
```

1.Download the dataset: Dataset 2.Load the dataset

```
data=pd.read_csv("Churn_Modelling.csv",encoding='ISO-8859-1')
data.head()
```

	RowNumber	CustomerId	Surname	CreditScore	Geography	Gender	Age	Tenure	Ba
0	1	15634602	Hargrave	619	France	Female	42	2	
1	2	15647311	Hill	608	Spain	Female	41	1	838
2	3	15619304	Onio	502	France	Female	42	8	1596
3	4	15701354	Boni	699	France	Female	39	1	
4	5	15737888	Mitchell	850	Spain	Female	43	2	1255

```
data.describe()
```

	RowNumber	CustomerId	CreditScore	Age	Tenure	Bala
count	10000.00000	1.000000e+04	10000.000000	10000.000000	10000.000000	10000.000
mean	5000.50000	1.569094e+07	650.528800	38.921800	5.012800	76485.889
std	2886.89568	7.193619e+04	96.653299	10.487806	2.892174	62397.405
min	1.00000	1.556570e+07	350.000000	18.000000	0.000000	0.000
25%	2500.75000	1.562853e+07	584.000000	32.000000	3.000000	0.000
50%	5000.50000	1.569074e+07	652.000000	37.000000	5.000000	97198.540
75%	7500.25000	1.575323e+07	718.000000	44.000000	7.000000	127644.240
max	10000.00000	1.581569e+07	850.000000	92.000000	10.000000	250898.090

```
data.dtypes
```

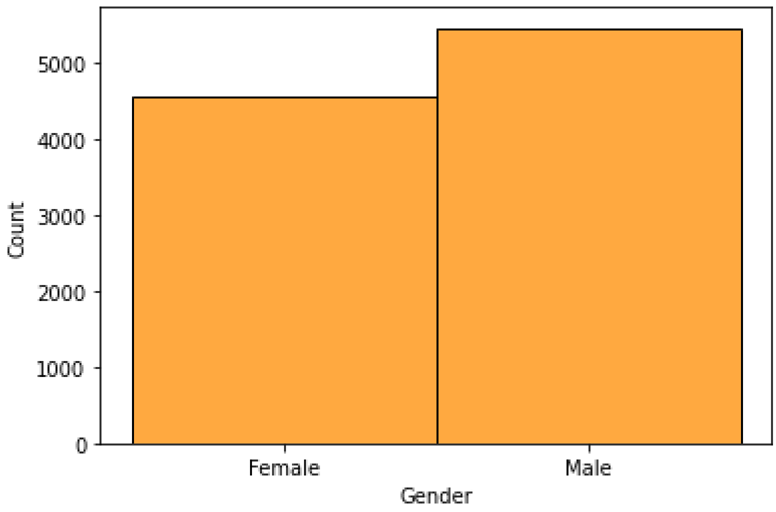
```
RowNumber            int64
CustomerId           int64
Surname             object
CreditScore          int64
Geography           object
Gender              object
Age                  int64
Tenure               int64
Balance            float64
```

```
NumOfProducts        int64
HasCrCard            int64
IsActiveMember       int64
EstimatedSalary    float64
Exited               int64
dtype: object
```

3.Perform Below Visualizations Univariate Analysis ,Bi - Variate Analysis,Multi - Variate Analysis
**

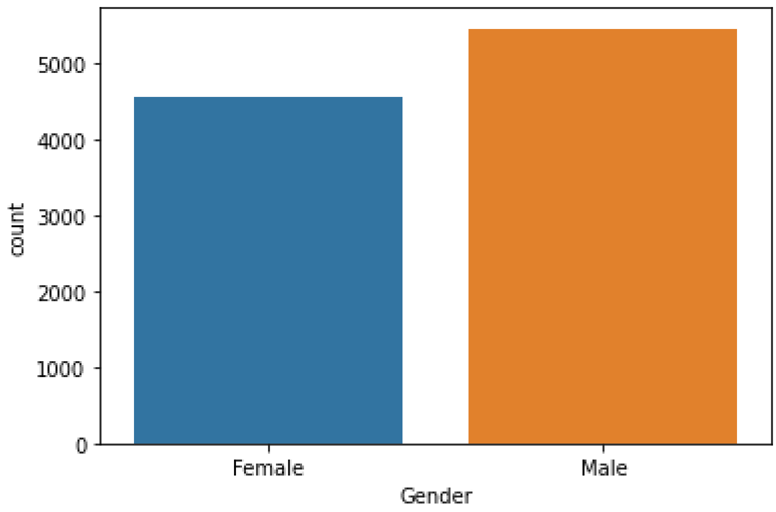
```
#univariate analysis "Histogram"
sns.histplot(data["Gender"],color='darkorange')
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f4e6e7e9e10>
```




```
#univariate analysis "Countlot"
sns.countplot(data['Gender'])
```

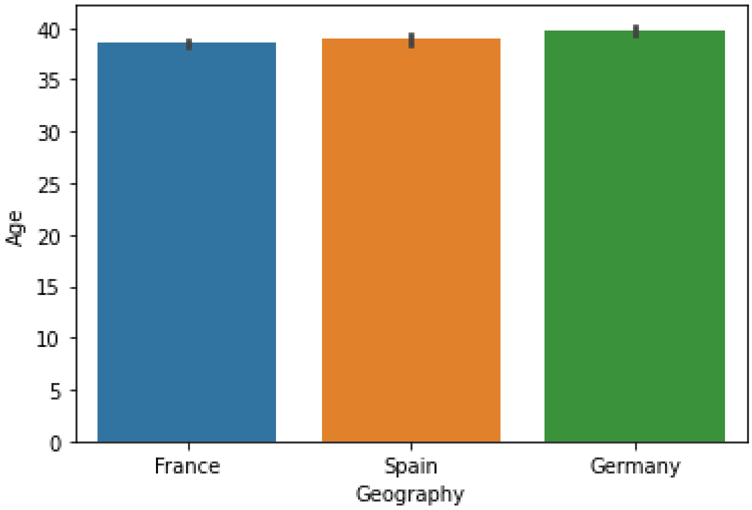
```
/usr/local/lib/python3.7/dist-packages/seaborn/_decorators.py:43: FutureWarning: Pass
  FutureWarning
<matplotlib.axes._subplots.AxesSubplot at 0x7f4e6e744090>
```



Double-click (or enter) to edit

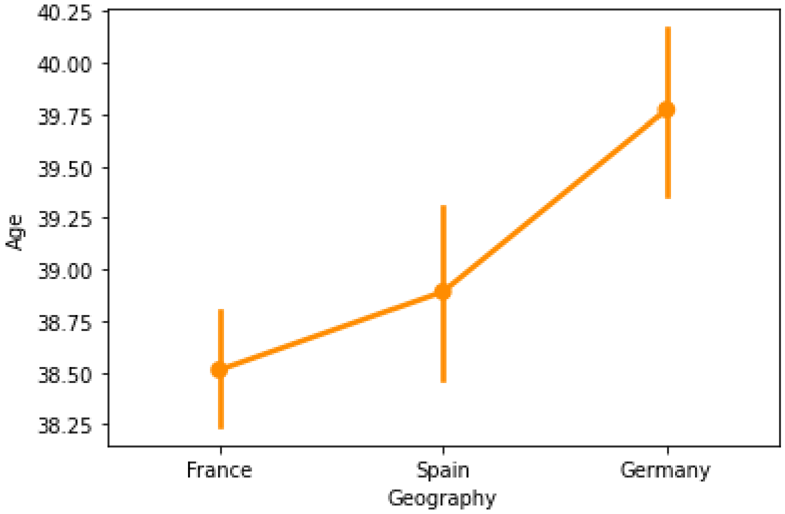
```
#bivariate analysis"Barplot"
sns.barplot(x='Geography',y='Age',data=data)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f4e6e256190>
```



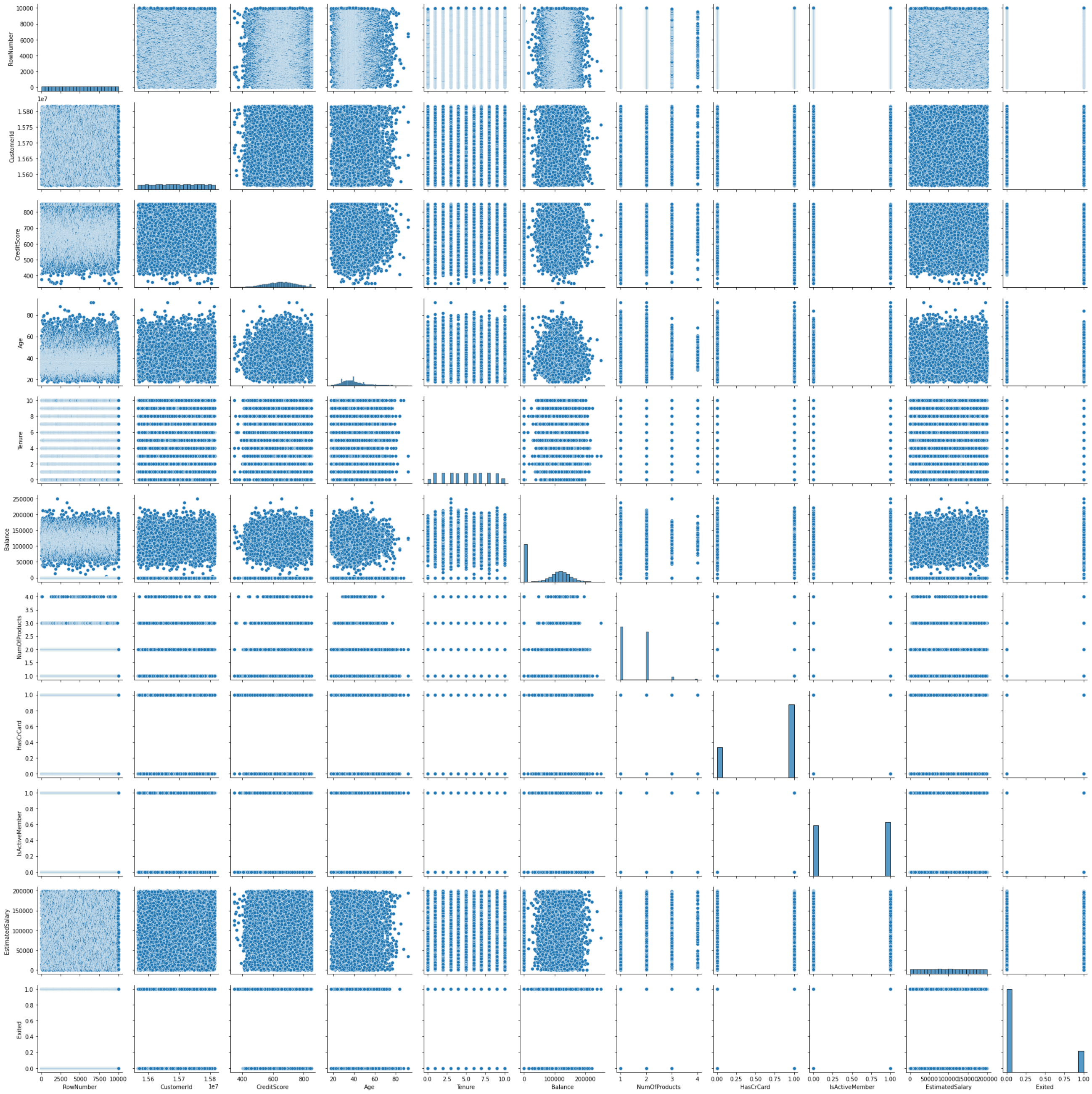

```
#bivariate analysis"Pointplot"
sns.pointplot(x='Geography',y='Age',data=data,color='darkorange')
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f4e6e17a390>
```




```
#Multivariate analysis"Pairplot"
sns.pairplot(data)
```

<seaborn.axisgrid.PairGrid at 0x7f4e65752690>



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

```
# Descriptive statistics of the data set accessed.
data.describe().T
```

	count	mean	std	min	25%	
RowNumber	10000.0	5.000500e+03	2886.895680	1.00	2500.75	5.00050
CustomerId	10000.0	1.569094e+07	71936.186123	15565701.00	15628528.25	1.56907
CreditScore	10000.0	6.505288e+02	96.653299	350.00	584.00	6.52000
Age	10000.0	3.892180e+01	10.487806	18.00	32.00	3.70000
Tenure	10000.0	5.012800e+00	2.892174	0.00	3.00	5.00000
Balance	10000.0	7.648589e+04	62397.405202	0.00	0.00	9.71985
NumOfProducts	10000.0	1.530200e+00	0.581654	1.00	1.00	1.00000
HasCrCard	10000.0	7.055000e-01	0.455840	0.00	0.00	1.00000
IsActiveMember	10000.0	5.151000e-01	0.499797	0.00	0.00	1.00000
EstimatedSalary	10000.0	1.000902e+05	57510.492818	11.58	51002.11	1.00193
Exited	10000.0	2.037000e-01	0.402769	0.00	0.00	0.00000

5.Handle the Missing values.

```
data.isnull().sum().sum()
```

```
0
```

This dataset does not contain any missing value.

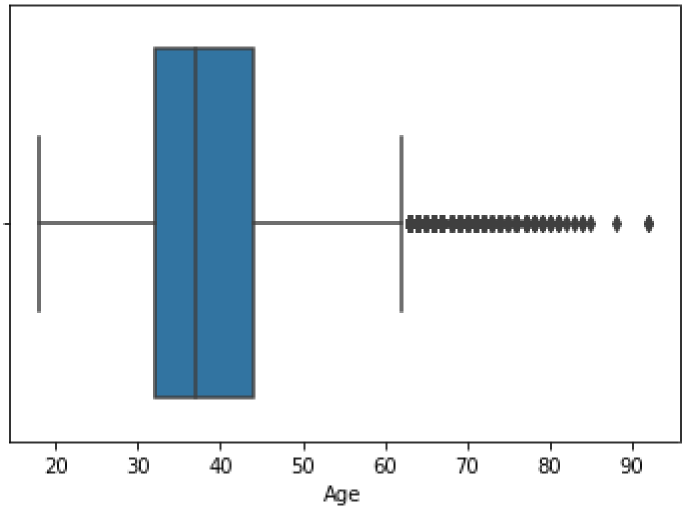
```
missing_values=data.isnull().sum()
missing_values[missing_values>0]/len(data)*100
```

```
Series([], dtype: float64)
```

6.Find the outliers and replace the outliers

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

```
/usr/local/lib/python3.7/dist-packages/seaborn/_decorators.py:43: FutureWarning: Pass
  FutureWarning
<matplotlib.axes._subplots.AxesSubplot at 0x7f4e6084d510>
```



7.Check for Categorical columns and perform encoding.

```
print(data['Gender'].unique())
print(data['Age'].unique())
```

```
['Female' 'Male']
[42 41 39 43 44 50 29 27 31 24 34 25 35 45 58 32 38 46 36 33 40 51 61 49
 37 19 66 56 26 21 55 75 22 30 28 65 48 52 57 73 47 54 72 20 67 79 62 53
 80 59 68 23 60 70 63 64 18 82 69 74 71 76 77 88 85 84 78 81 92 83]
```

```
data['Gender'].value_counts()
data['Age'].value_counts()
```

```
37    478
38    477
35    474
36    456
34    447
     ...
92      2
82      1
88      1
85      1
83      1
Name: Age, Length: 70, dtype: int64
```

```
one_hot_encoded_data = pd.get_dummies(data, columns = ['Age', 'Gender'])
print(one_hot_encoded_data)
```

```
      RowNumber  CustomerId    Surname  CreditScore Geography  Tenure  \
```

```
0            1    15634602   Hargrave         619    France       2
1            2    15647311       Hill         608     Spain       1
2            3    15619304       Onio         502    France       8
3            4    15701354       Boni         699    France       1
4            5    15737888   Mitchell         850     Spain       2
...        ...         ...        ...         ...       ...     ...
9995      9996    15606229   Obijiaku         771    France       5
9996      9997    15569892  Johnstone         516    France      10
9997      9998    15584532        Liu         709    France       7
9998      9999    15682355  Sabbatini         772   Germany       3
9999     10000    15628319     Walker         792    France       4

        Balance  NumOfProducts  HasCrCard  IsActiveMember  ...  Age_80  \
0          0.00              1          1               1  ...       0
1      83807.86              1          0               1  ...       0
2     159660.80              3          1               0  ...       0
3          0.00              2          0               0  ...       0
4     125510.82              1          1               1  ...       0
...         ...            ...        ...             ...  ...     ...
9995       0.00              2          1               0  ...       0
9996   57369.61              1          1               1  ...       0
9997       0.00              1          0               1  ...       0
9998   75075.31              2          1               0  ...       0
9999  130142.79              1          1               0  ...       0

      Age_81  Age_82  Age_83  Age_84  Age_85  Age_88  Age_92  Gender_Female  \
0          0       0       0       0       0       0       0              1
1          0       0       0       0       0       0       0              1
2          0       0       0       0       0       0       0              1
3          0       0       0       0       0       0       0              1
4          0       0       0       0       0       0       0              1
...      ...     ...     ...     ...     ...     ...     ...            ...
9995       0       0       0       0       0       0       0              0
9996       0       0       0       0       0       0       0              0
9997       0       0       0       0       0       0       0              1
9998       0       0       0       0       0       0       0              0
9999       0       0       0       0       0       0       0              1

      Gender_Male
0               0
1               0
2               0
3               0
4               0
...           ...
9995            1
9996            1
9997            0
9998            1
9999            0

[10000 rows x 84 columns]
```

8.Split the data into dependent and independent variables.

```
from sklearn.datasets import load_iris
```

```
from sklearn import preprocessing
data = load_iris()

# separate the independent and dependent variables
X_data = data.data
target = data.target
print("Dependent variable")
print(X_data)
print("Independent variable")
print(target)
```

```
Dependent variable
[[5.1 3.5 1.4 0.2]
 [4.9 3.  1.4 0.2]
 [4.7 3.2 1.3 0.2]
 [4.6 3.1 1.5 0.2]
 [5.  3.6 1.4 0.2]
 [5.4 3.9 1.7 0.4]
 [4.6 3.4 1.4 0.3]
 [5.  3.4 1.5 0.2]
 [4.4 2.9 1.4 0.2]
 [4.9 3.1 1.5 0.1]
 [5.4 3.7 1.5 0.2]
 [4.8 3.4 1.6 0.2]
 [4.8 3.  1.4 0.1]
 [4.3 3.  1.1 0.1]
 [5.8 4.  1.2 0.2]
 [5.7 4.4 1.5 0.4]
 [5.4 3.9 1.3 0.4]
 [5.1 3.5 1.4 0.3]
 [5.7 3.8 1.7 0.3]
 [5.1 3.8 1.5 0.3]
 [5.4 3.4 1.7 0.2]
 [5.1 3.7 1.5 0.4]
 [4.6 3.6 1.  0.2]
 [5.1 3.3 1.7 0.5]
 [4.8 3.4 1.9 0.2]
 [5.  3.  1.6 0.2]
 [5.  3.4 1.6 0.4]
 [5.2 3.5 1.5 0.2]
 [5.2 3.4 1.4 0.2]
 [4.7 3.2 1.6 0.2]
 [4.8 3.1 1.6 0.2]
 [5.4 3.4 1.5 0.4]
 [5.2 4.1 1.5 0.1]
 [5.5 4.2 1.4 0.2]
 [4.9 3.1 1.5 0.2]
 [5.  3.2 1.2 0.2]
 [5.5 3.5 1.3 0.2]
 [4.9 3.6 1.4 0.1]
 [4.4 3.  1.3 0.2]
 [5.1 3.4 1.5 0.2]
 [5.  3.5 1.3 0.3]
 [4.5 2.3 1.3 0.3]
 [4.4 3.2 1.3 0.2]
 [5.  3.5 1.6 0.6]
 [5.1 3.8 1.9 0.4]
 [4.8 3.  1.4 0.3]
 [5.1 3.8 1.6 0.2]
```

```
 [4.6 3.2 1.4 0.2]
 [5.3 3.7 1.5 0.2]
 [5.  3.3 1.4 0.2]
 [7.  3.2 4.7 1.4]
 [6.4 3.2 4.5 1.5]
 [6.9 3.1 4.9 1.5]
 [5.5 2.3 4.  1.3]
 [6.5 2.8 4.6 1.5]
 [5.7 2.8 4.5 1.3]
 [6.3 3.3 4.7 1.6]
```

9.Scale the independent variable**

```
# scale of independent variables
standard = preprocessing.scale(target)
print(standard)
```

```
[-1.22474487 -1.22474487 -1.22474487 -1.22474487 -1.22474487 -1.22474487
 -1.22474487 -1.22474487 -1.22474487 -1.22474487 -1.22474487 -1.22474487
 -1.22474487 -1.22474487 -1.22474487 -1.22474487 -1.22474487 -1.22474487
 -1.22474487 -1.22474487 -1.22474487 -1.22474487 -1.22474487 -1.22474487
 -1.22474487 -1.22474487 -1.22474487 -1.22474487 -1.22474487 -1.22474487
 -1.22474487 -1.22474487 -1.22474487 -1.22474487 -1.22474487 -1.22474487
 -1.22474487 -1.22474487 -1.22474487 -1.22474487 -1.22474487 -1.22474487
 -1.22474487 -1.22474487 -1.22474487 -1.22474487 -1.22474487 -1.22474487
 -1.22474487 -1.22474487  0.          0.          0.          0.
  0.          0.          0.          0.          0.          0.
  0.          0.          0.          0.          0.          0.
  0.          0.          0.          0.          0.          0.
  0.          0.          0.          0.          0.          0.
  0.          0.          0.          0.          0.          0.
  0.          0.          0.          0.          0.          0.
  0.          0.          0.          0.          0.          0.
  0.          0.          0.          0.          1.22474487  1.22474487
  1.22474487  1.22474487  1.22474487  1.22474487  1.22474487  1.22474487
  1.22474487  1.22474487  1.22474487  1.22474487  1.22474487  1.22474487
  1.22474487  1.22474487  1.22474487  1.22474487  1.22474487  1.22474487
  1.22474487  1.22474487  1.22474487  1.22474487  1.22474487  1.22474487
  1.22474487  1.22474487  1.22474487  1.22474487  1.22474487  1.22474487
  1.22474487  1.22474487  1.22474487  1.22474487  1.22474487  1.22474487
  1.22474487  1.22474487  1.22474487  1.22474487  1.22474487  1.22474487
  1.22474487  1.22474487  1.22474487  1.22474487  1.22474487  1.22474487]
```

10.Split the data into training and testing

```
import pandas as pd
from sklearn.linear_model import LinearRegression
from sklearn.model_selection import train_test_split
df = pd.read_csv('Churn_Modelling.csv')
X = df.iloc[:, :-1]
y = df.iloc[:, -1]
X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.05, random_state=0)
print(X_train, X_test, y_train, y_test)
```

```
      RowNumber  CustomerId          Surname  CreditScore Geography  Gender  \
799         800    15567367              Tao          601   Germany  Female   
1069       1070    15628674          Iadanza          844    France    Male   
8410       8411    15609913            Clark          743    France  Female   
9436       9437    15771000           Powell          684    France    Male   
5099       5100    15731555        Ross-Watt          595   Germany  Female   
...         ...         ...              ...          ...       ...     ...   
9225       9226    15584928  Ugochukwutubelum          594   Germany  Female   
4859       4860    15647111            White          794     Spain  Female   
3264       3265    15574372           Hoolan          738    France    Male   
9845       9846    15664035          Parsons          590     Spain  Female   
2732       2733    15592816         Udokamma          623   Germany  Female   

      Age  Tenure    Balance  NumOfProducts  HasCrCard  IsActiveMember  \
799    42       9  133636.16              1          0               1   
1069   40       7  113348.14              1          1               0   
8410   46       9       0.00              1          1               0   
9436   38       4       0.00              3          1               0   
5099   45       9  106000.12              1          0               0   
...   ...     ...        ...            ...        ...             ...   
9225   32       4  120074.97              2          1               1   
4859   22       4  114440.24              1          1               1   
3264   35       5  161274.05              2          1               0   
9845   38       9       0.00              2          1               1   
2732   48       1  108076.33              1          1               0   

      EstimatedSalary  
799         103315.74  
1069         31904.31  
8410        113436.08  
9436         75609.84  
5099        191448.96  
...               ...  
9225        162961.79  
4859        107753.07  
3264        181429.87  
9845        148750.16  
2732        118855.26  

[9500 rows x 13 columns]       RowNumber  CustomerId    Surname  CreditScore Geogr
9394       9395    15615753   Upchurch          597   Germany  Female   35   
898         899    15654700    Fallaci          523    France  Female   40   
2398       2399    15633877   Morrison          706     Spain  Female   42   
5906       5907    15745623    Worsnop          788    France    Male   32   
2343       2344    15765902     Gibson          706   Germany    Male   38   
...         ...         ...        ...          ...       ...     ...  ...   
8938       8939    15722409    Ritchie          693     Spain    Male   47   
9291       9292    15679804   Esquivel          636    France    Male   36   
491         492    15699005     Martin          710    France  Female   41   
2021       2022    15795519   Vasiliev          716   Germany  Female   18   
4299       4300    15711991  Chiawuotu          615    France    Male   30   

      Tenure    Balance  NumOfProducts  HasCrCard  IsActiveMember  \
9394       8  131101.04              1          1               1   
898        2  102967.41              1          1               0   
2398       8   95386.82              1          1               1   
5906       4  112079.58              1          0               0   
```