Assignment -2

Assignment Date	21 September 2022
Student Name	BARANI K
Student Register Number	730419104009
Maximum Marks	2

In[1]:
```
import pandas as
pdimport numpyas np
import seabornas sns
import matplotlib.pyplotas plt
%matplotlibinline
importscipy.stats
#import statsmodels.api as sms
import statsmodels.formula.apias smf
from statsmodels.stats.stattoolsimport jarque_bera
```

In[2]:
```
data=pd.read_csv('Churn_Modelling.csv')
data
```

Out[2]:

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

10000 rows × 14 columns

Describe Function

In [7]:
```
data[['Age','Surname','Tenure','Balance']].describe()
```

Out[7]:

	Age	Tenure	Balance
count	10000.000000	10000.000000	10000.000000
mean	38.921800	5.012800	76485.889288

std	10.487806	2.892174	62397.405202
min	18.000000	0.000000	0.000000
25%	32.000000	3.000000	0.000000
50%	37.000000	5.000000	97198.540000
75%	44.000000	7.000000	127644.240000
max	92.000000	10.000000	250898.090000

Data Type

In [15]:
```
data.dtypes
```

Out[15]:
```
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
```

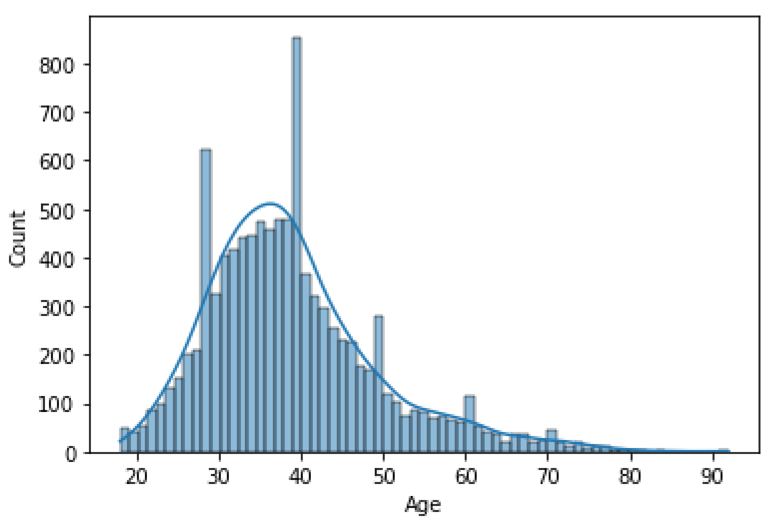
In [16]:
```
data.isnull().any()
```

Out[16]:
```
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
```

UNIVARIATE ANALYSIS

In [18]:
```
sns.histplot(data.Age,kde=True)
```

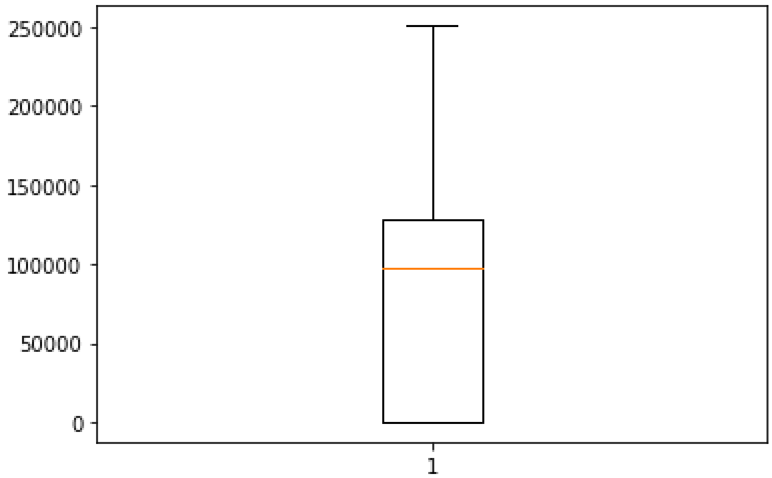
Out[18]:
```
<AxesSubplot:xlabel='Age', ylabel='Count'>
```



Loading [MathJax]/extensions/Safe.js

BIVARIATE ANALYSIS

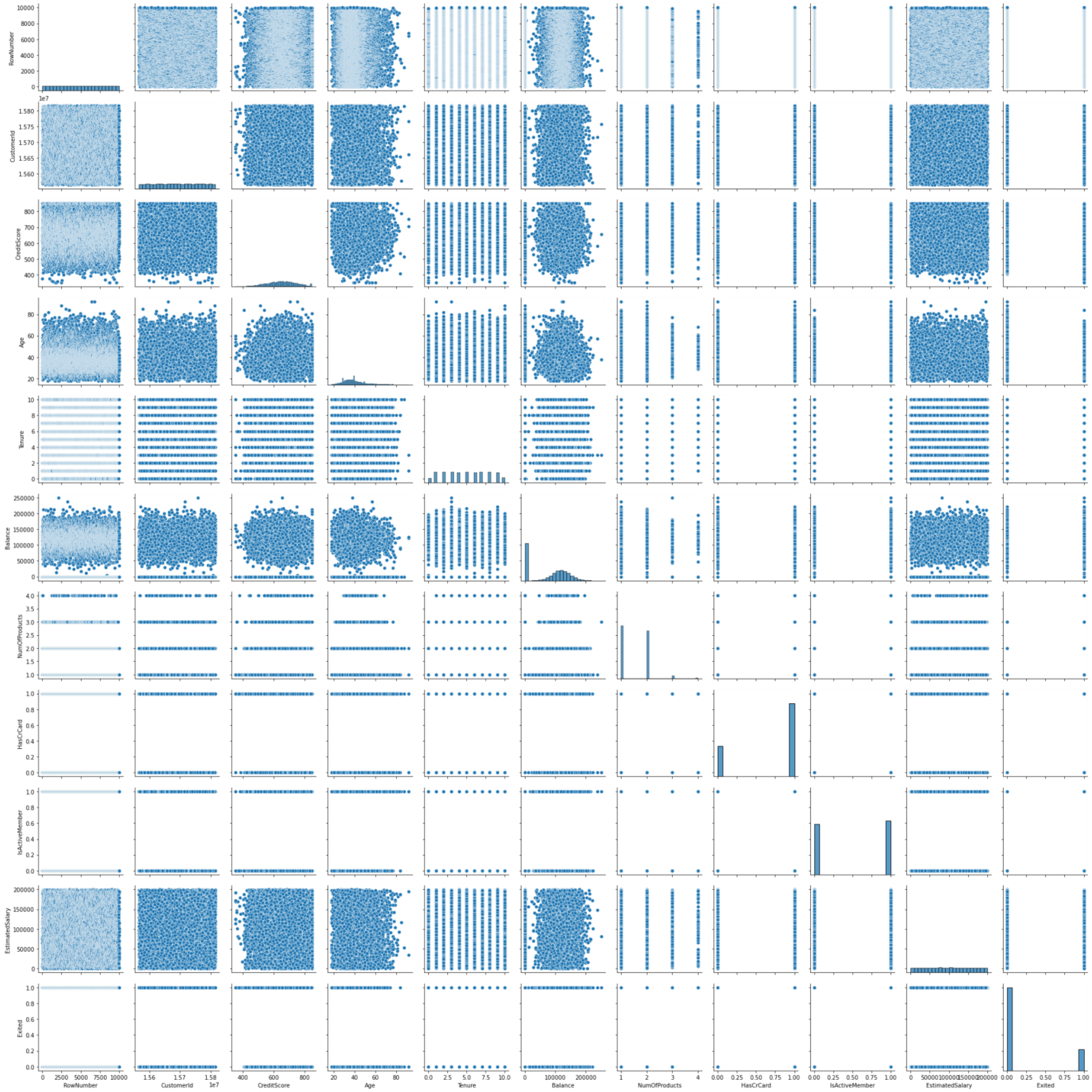
In [29]:
```
plt.boxplot(data.Balance)
plt.show()
```



MULTIVARIATE ANALYSIS

In [47]:
```
sns.pairplot(data)
```

Out[47]: <seaborn.axisgrid.PairGrid at 0x1cb8b759610>



Perform descriptive statistics on the dataset

In [3]:
```
data.describe(include='all')
```

Loading [MathJax]/extensions/Safe.js

Out[3]:

	RowNumber	CustomerId	Surname	CreditScore	Geography	Gender	Age	Tenure
count	10000.00000	1.000000e+04	10000	10000.000000	10000	10000	10000.000000	10000.000000
unique	NaN	NaN	2932	NaN	3	2	NaN	NaN
top	NaN	NaN	Smith	NaN	France	Male	NaN	NaN
freq	NaN	NaN	32	NaN	5014	5457	NaN	NaN
mean	5000.50000	1.569094e+07	NaN	650.528800	NaN	NaN	38.921800	5.012800
std	2886.89568	7.193619e+04	NaN	96.653299	NaN	NaN	10.487806	2.892174
min	1.00000	1.556570e+07	NaN	350.000000	NaN	NaN	18.000000	0.000000
25%	2500.75000	1.562853e+07	NaN	584.000000	NaN	NaN	32.000000	3.000000
50%	5000.50000	1.569074e+07	NaN	652.000000	NaN	NaN	37.000000	5.000000
75%	7500.25000	1.575323e+07	NaN	718.000000	NaN	NaN	44.000000	7.000000
max	10000.00000	1.581569e+07	NaN	850.000000	NaN	NaN	92.000000	10.000000

In [4]:

```
data.count()
```

Out[4]:

```
RowNumber          10000
CustomerId         10000
Surname            10000
CreditScore        10000
Geography          10000
Gender             10000
Age                10000
Tenure             10000
Balance            10000
NumOfProducts      10000
HasCrCard          10000
IsActiveMember     10000
EstimatedSalary    10000
Exited             10000
dtype: int64
```

Handle the Missing values.

Fill with Zeros for NAN values

In [7]:

```
a =data.fillna(0)
a
```

Out[7]:

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

10000 rows × 14 columns

Find the outliers and replace the outliers

In [8]:

```
a
```

Out[8]:

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

10000 rows × 14 columns

In [9]:

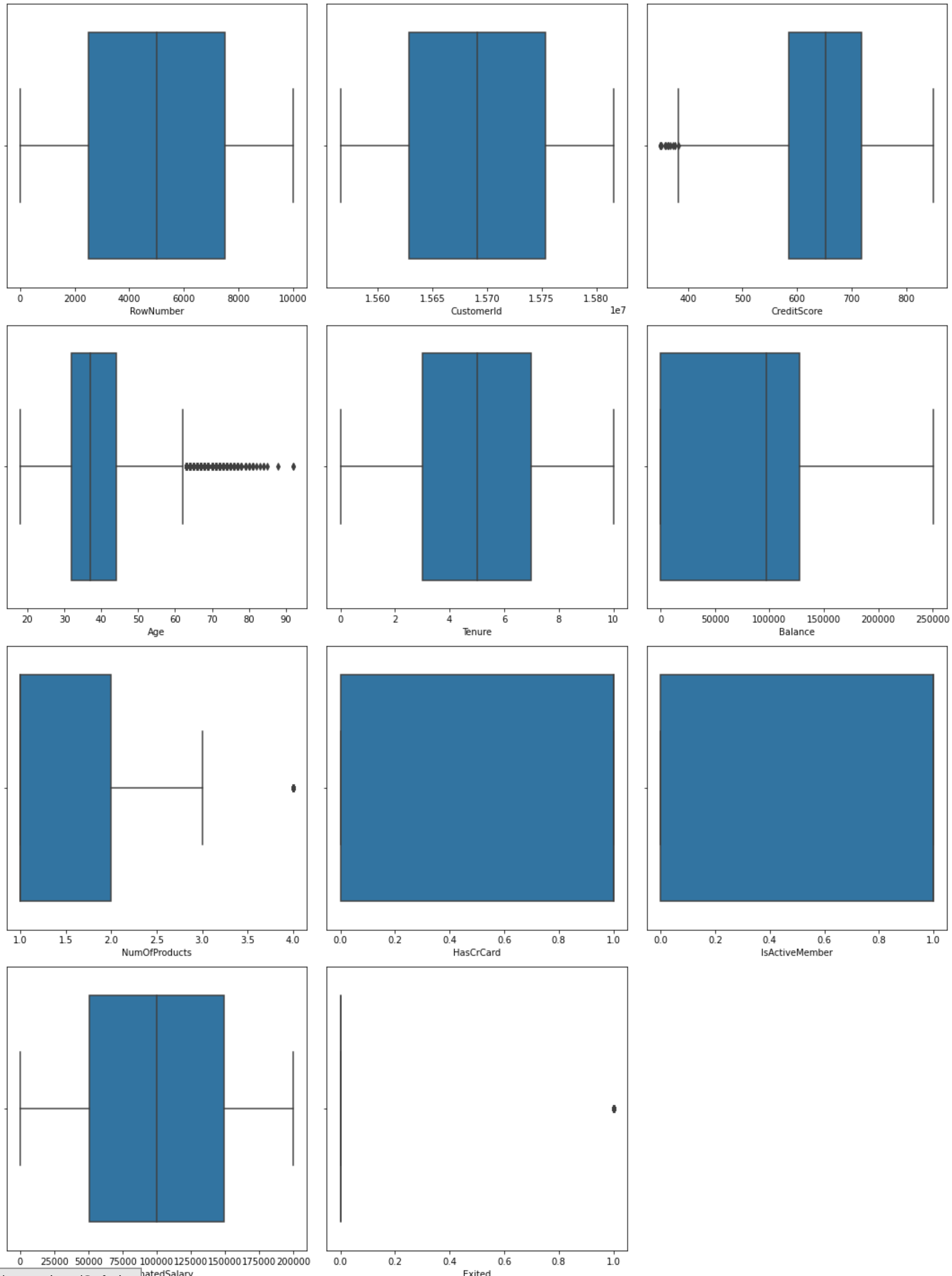
```
missing_values=data.isnull().sum()
missing_values[missing_values>0]/len(data)*100
```

Out[9]: Series([], dtype:float64)

In [13]:

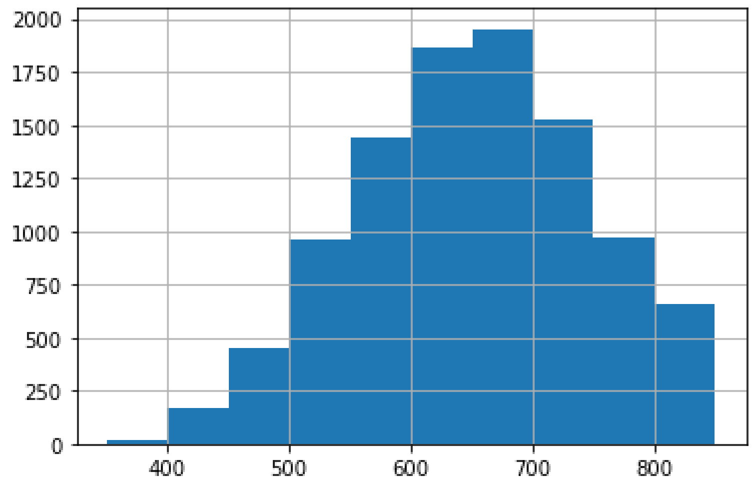
```
cols =3
rows =4
num_cols=data.select_dtypes(exclude='object').columns
fig = plt.figure( figsize=(cols*5, rows*5))
for i, col in enumerate(num_cols):
```

```
    ax=fig.add_subplot(rows,cols,i+1)

    sns.boxplot(x=data[col],ax=ax)

fig.tight_layout()
plt.show()
```



In [14]:
```python
data['CreditScore'].hist()
```

Out[14]: <AxesSubplot:>



In[15]:
```python
print('SkewnessvalueofAge:',data['Age'].skew())
Age_mean=data['Age'].mean()
print('Mean of Age is:',Age_mean)
Age_std= data['Age'].std()
print('Standard Deviation of Age is: ',Age_std)
low= Age_mean-(3 * Age_std)
high= Age_mean+ (3 * Age_std)
Age_outliers= data[(data['Age'] <low) | (data['Age'] >high)]
#print('OutliersofAgeis:\n',Age_outliers)
print('Outliers of Age is:')
Age_outliers.head()
```

```
Skewness value of Age: 1.0113202630234552
Mean of Age is:38.9218
Standard Deviation of Age is: 10.487806451704591
Outliers of Age is:
```

Out[15]:

	RowNumber	CustomerId	Surname	CreditScore	Geography	Gender	Age	Tenure	Balance	NumOfPro
85	86	15805254	Ndukaku	652	Spain	Female	75	10	0.00	
158	159	15589975	Maclean	646	France	Female	73	6	97259.25	
230	231	15808473	Ringrose	673	France	Male	72	1	0.00	
252	253	15793726	Matveyeva	681	France	Female	79	0	0.00	
310	311	15712287	Pokrovskii	652	France	Female	80	4	0.00	

Check for Categorical columns and perform encoding.

In [ ]:
```python
#data1=pd.read_csv('Churn_Modelling.csv')
#data1.head()
```

In [4]:
```python
import numpyas np #for numpy operations
import pandas as pd#for creating DataFrame using Pandas
# to split the dataset using sklearn
from sklearn.model_selectionimport train_test_split
# load titanic dataset
data1 = pd.read_csv('Churn_Modelling.csv',
```

Loading [MathJax]/extensions/Safe.js

```
 usecols=['Surname','Gender','Geography'])
data1.head()
```

Out[4]:

	Surname	Geography	Gender
0	Hargrave	France	Female
1	Hill	Spain	Female
2	Onio	France	Female
3	Boni	France	Female
4	Mitchell	Spain	Female

In [5]:
```
pd.get_dummies(data1)
```

Out[5]:

	Surname_Abazu	Surname_Abbie	Surname_Abbott	Surname_Abdullah	Surname_Abdulov	Surname_Abel
0	0	0	0	0	0	0
1	0	0	0	0	0	0
2	0	0	0	0	0	0
3	0	0	0	0	0	0
4	0	0	0	0	0	0
...	...	...	...	...	...	...
9995	0	0	0	0	0	0
9996	0	0	0	0	0	0
9997	0	0	0	0	0	0
9998	0	0	0	0	0	0
9999	0	0	0	0	0	0

10000 rows × 2937 columns

In [17]:
```
# Returns dictionary having key as category and values asnumber
deffind_category_mappings(data, variable):
 return {k: i for i, k inenumerate(data[variable].unique())}
# Returns the column after mapping with dictionary
definteger_encode(data,variable, ordinal_mapping):
 data[variable]=data[variable].map(ordinal_mapping)
for variable in ['Surname','Geography','Gender']:
 mappings=find_category_mappings(data1,variable)
 integer_encode(data1, variable, mappings)
data1.head()
```

Out[17]:

	Surname	Geography	Gender
0	0	0	0
1	1	1	0
2	2	0	0
3	3	0	0
4	4	1	0

Split the data into dependent and independent

variables.

Dependent Variable : A dependent variable is a variable whose value depends on another variable.

Independent Variable : An Independent variable is a variable whose value never depends on another variable.

In [6]:
```
print("TheMinimumvalueofDataset:\n",data1.min(numeric_only=True))
print("\n")
print("TheMaximumvalueofDataset:\n",data1.max(numeric_only=True))
print("\n")
print("TheMeanvalueofDataset:\n",data1.mean(numeric_only=True))
print("\n")


print(data1.count(0))
print(data1.shape)
print(data1.size)
```

```
The Minimum value ofDataset:
 Series([], dtype:float64)


The Maximum value ofDataset:
 Series([], dtype:float64)


The Mean value of Dataset:
 Series([], dtype:float64)


Surname      10000
Geography    10000
Gender       10000
dtype: int64
(10000, 3)
30000
```

In [7]:
```
y = data1["Surname"]
x=data1.drop(columns=["Surname"],axis=1)
x.head()
```

Out[7]:

	Geography	Gender
0	France	Female
1	Spain	Female
2	France	Female
3	France	Female
4	Spain	Female

Scale the independent variables

In [8]:
```
names=x.columnsnam
es
```

Out[8]: Index(['Geography', 'Gender'],dtype='object')

In [12]:
```
from sklearn.preprocessingimportscale
x=scale(x)
```

In [16]:
```
x
```

Out[16]:

	Geography	Gender
0	France	Female
1	Spain	Female
2	France	Female
3	France	Female
4	Spain	Female
...	...	...
9995	France	Male
9996	France	Male
9997	France	Female
9998	Germany	Male
9999	France	Female

10000 rows × 2 columns

Split the data into training and testing

The train-test split is used to estimate the performance of machine learning algorithms that are applicable for prediction-based Algorithms/Applications. By default, the Test set is split into 30 % of actual data and the training set is split into 70% of the actual data.

In [18]:
```
from sklearn.model_selectionimport train_test_split
```

In [19]:
```
x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.2,random_state=0)
```

In [20]:
```
x_train.head()
```

Out[20]:

	Geography	Gender
7389	Spain	Female
9275	Germany	Male
2995	France	Female
5316	Spain	Male
356	Spain	Female


```
,y_train.shape,x_test.shape,y_test.shape
```

```
Out[21]: ((8000, 2), (8000,), (2000, 2), (2000,))
```