

# Assignment-2

AssignmentDate	21 September2022
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StudentRegisterNumber	710119104019
MaximumMarks	2

```
In[1]: import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline
import scipy.stats
#import statsmodels.api as sm
import statsmodels.formula.api as smf
from statsmodels.stats.stattools import 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	Obijaku	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 x 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

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

# Data Type

Loading[MathJax]/extensions/Safe.js

```
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
```

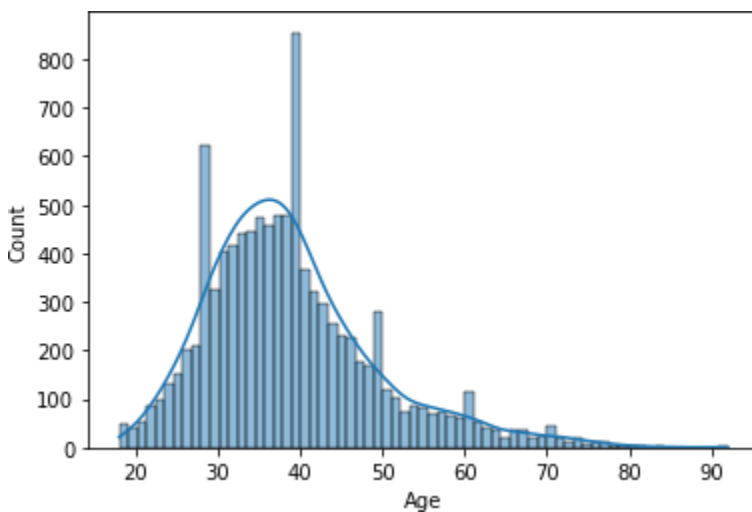
```
In[16]: data.isnull().any()
```

```
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

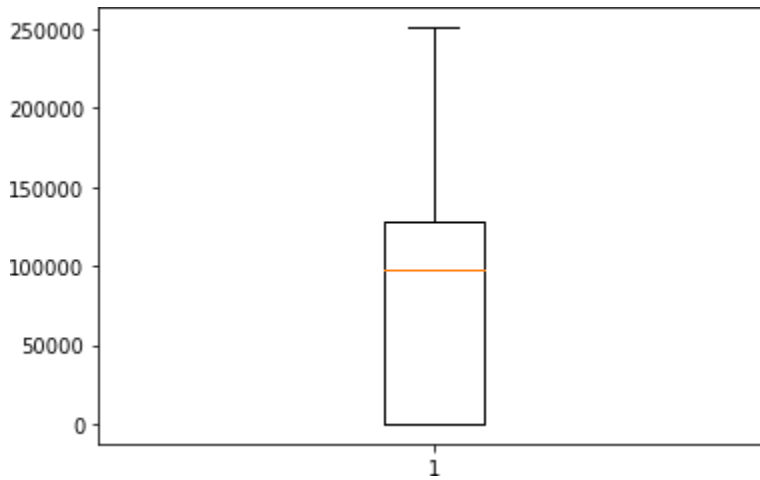
```
In[18]: sns.histplot(data.Age, kde=True)
```

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



# BIVARIATE ANALYSIS

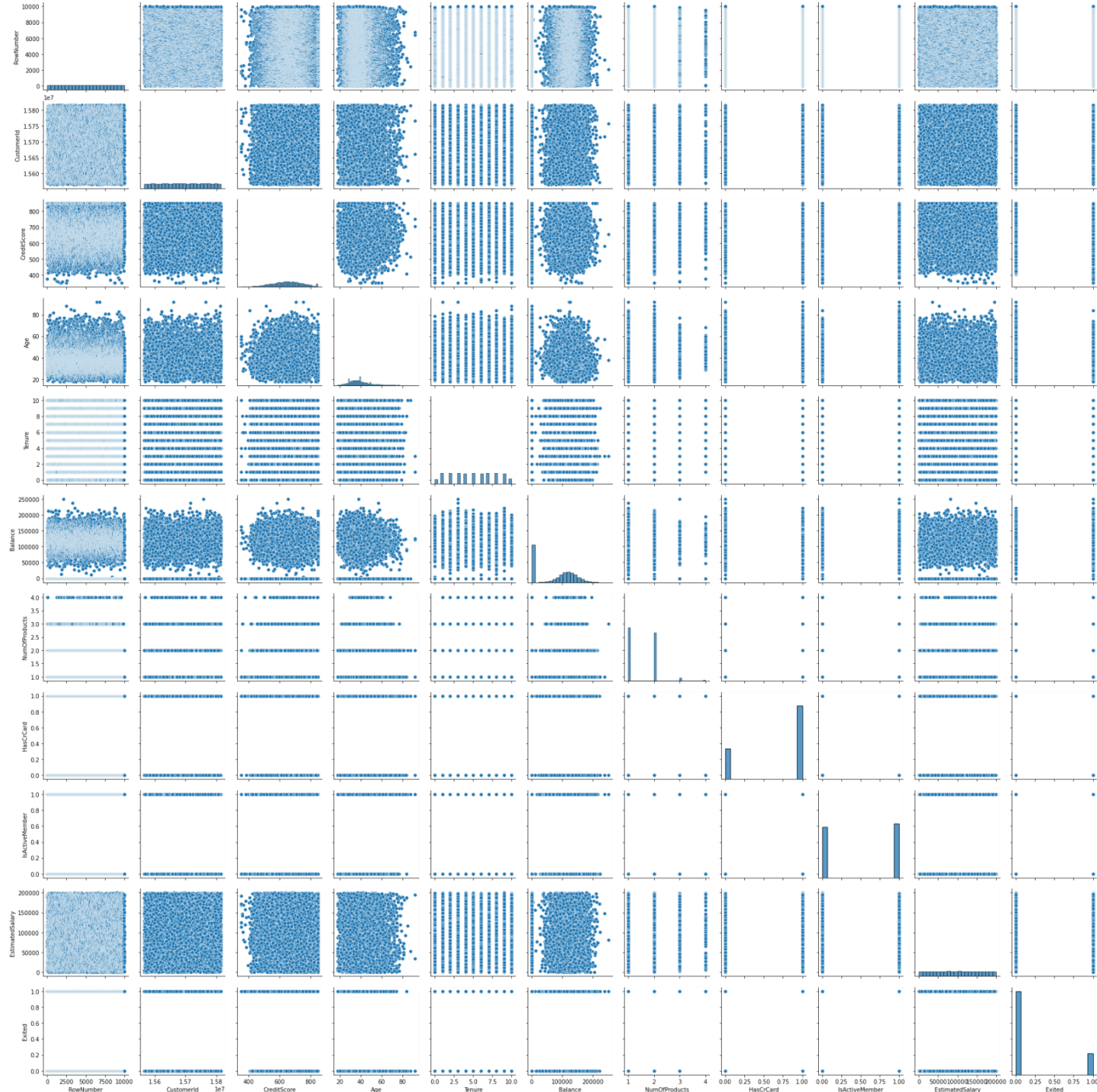
```
In[29]: plt.boxplot(data.Balance)
plt.show()
```



# MULTIVARIATE ANALYSIS

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

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



Performdescriptivestatisticson thedataset

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

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

CustomerId

Surname

CreditScore

Geography

Gender

Age

Tenure

Balance

NumOfProducts

HasCrCard

IsActiveMember

EstimatedSalary

Exited

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

10000rows x14 columns

# Findthe outliersand replacetheoutliers

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

10000rows x14 columns

In [9]:

missing\_values=data.isnull().sum()missing\_values[missing\_values>0]/len(data)\*100

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

In [13]:

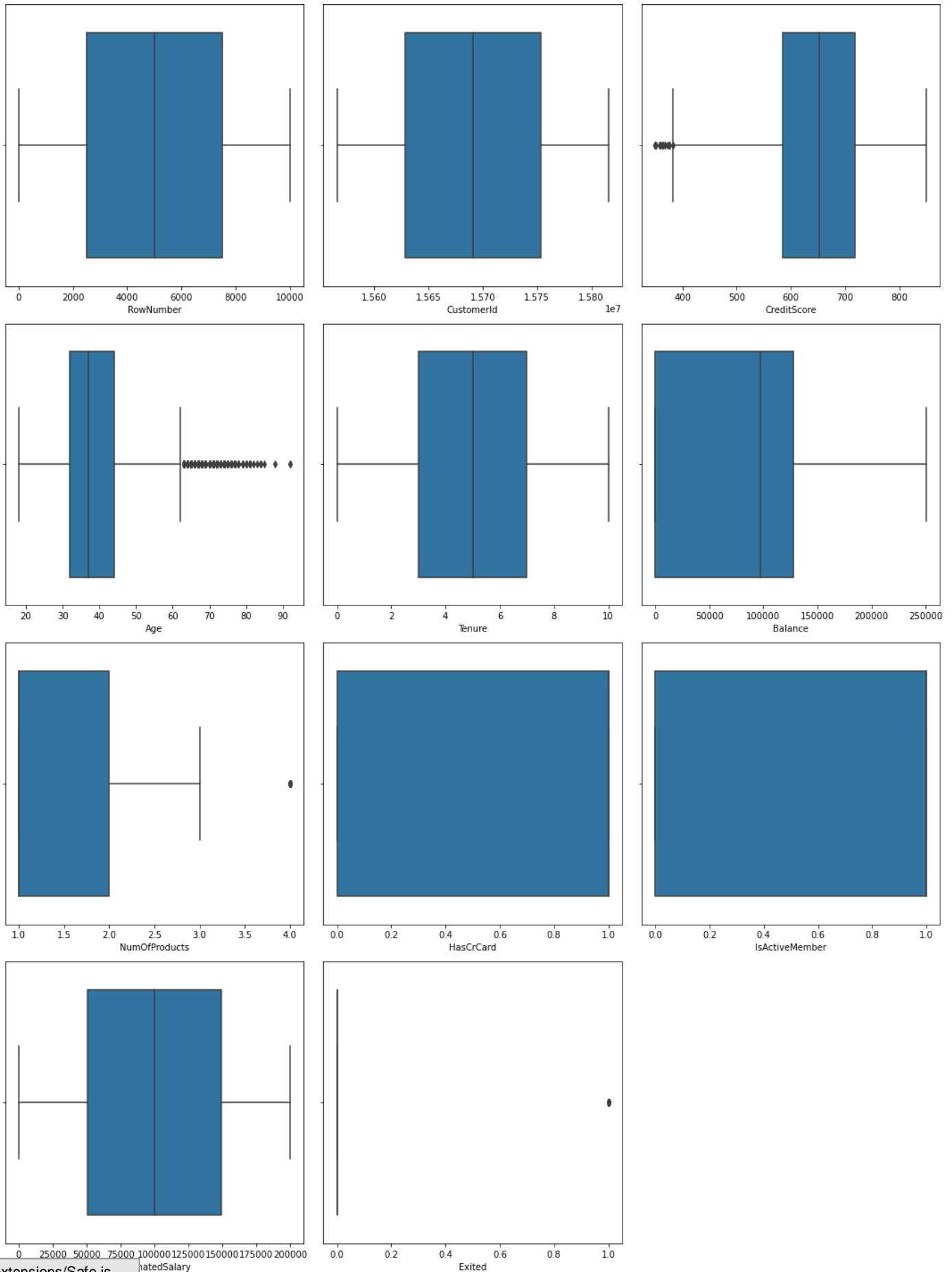
cols =3  
rows =4  
num\_cols=data.select\_dtypes(exclude='object').columns  
fig = plt.figure( figsize=(cols\*5, rows\*5))  
for i, col in enumerate(num\_cols):

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

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

```
fig.tight_layout()
```

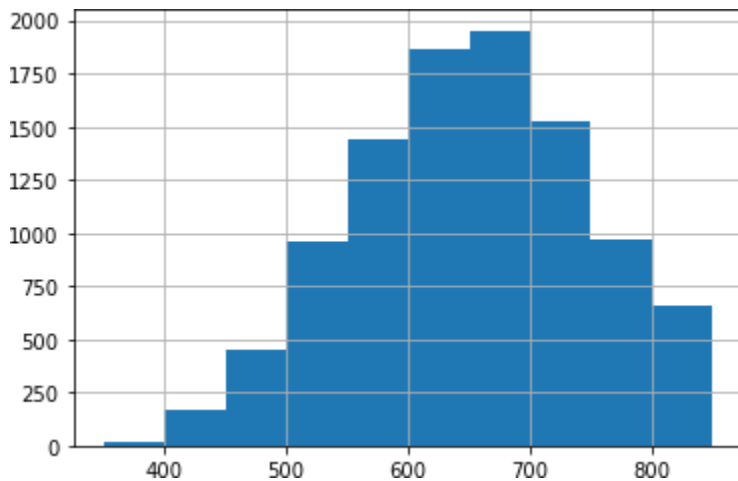
```
plt.show()
```





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

```
Out[14]: <AxesSubplot:>
```



```
In[15]:
```

```
print('SkewnessvalueofAge:',data['Age'].skew())Age
e_mean=data['Age'].mean()
print('MeanofAgeis:',Age_mean)Age
e_std=data['Age'].std()
print('StandardDeviationofAgeis:',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()
```

```
SkewnessvalueofAge:1.0113202630234552Mean
of Ageis:38.9218
StandardDeviationofAgeis:10.487806451704591Outl
iers ofAge 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	

## CheckforCategoricalcolumnsandperformen coding.

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

```
In [4]: importnumpyasnp#fornumpyoperations
import pandas as pd#for creating DataFrame using
Pandas#tosplit thedataset usingsklearn
from sklearn.model_selectionimport train_test_split
#loadtitanicdataset
data1= pd.read_csv('Churn_Modelling.csv',
```

```
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

10000rowsx2937columns

```
In[17]: #Returnsdictionaryhavingkeyascategoryandvaluesasnumber
def find_category_mappings(data,variable):
    return{k:ifori,kinenumerate(data[variable].unique())}# Returns
the column after mapping with
dictionarydef integer_encode(data,variable,ordinal_mapping):
    data[variable]=data[variable].map(ordinal_mapping)
for variable in ['Surname','Geography','Gender']:map
    pings=find_category_mappings(data1,variable)inte
    ger_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("The Minimum value of Dataset:\n", data1.min(numeric_only=True)) print("\n")
print("The Maximum value of Dataset:\n", data1.max(numeric_only=True)) print("\n")
print("The Mean value of Dataset:\n", data1.mean(numeric_only=True)) print("\n")

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

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

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

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

```
Surname      10000
Geography     10000
Genderdtype   10000
:int64
(10000, 3)
30000
```

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

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

```
[12]: fromsklearn.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

10000rows x2 columns

## Splitthedata intotrainingandtesting

The train-test split is used to estimate the performance of machine learning algorithms that are applicablefor prediction-based Algorithms/Applications. By default, the Test set is split into 30 % of actual data and thetrainingsetissplitinto70%oftheactual data.

```
In[18]: fromsklearn.model_selectionimporttrain_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

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