Assignment -2

Data Visualization and Pre-processing in ipynb

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1.Download the dataset

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

2.Load the dataset

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

```
df.head()
```

```
   RowNumber  CustomerId   Surname  CreditScore Geography  Gender  Age  \
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

   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

   EstimatedSalary  Exited
0        101348.88       1
1        112542.58       0
2        113931.57       1
3         93826.63       0
4         79084.10       0
```

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000 entries, 0 to 9999
Data columns (total 14 columns):
 #   Column           Non-Null Count  Dtype
----  ---------------------------------------  --------
 0   RowNumber        10000 non-null  int64
 1   CustomerId       10000 non-null  int64
 2   Surname          10000 non-null  object
 3   CreditScore      10000 non-null  int64
```

```
 4   Geography        10000 non-null  object
 5   Gender           10000 non-null  object
 6   Age              10000 non-null  int64
 7   Tenure           10000 non-null  int64
 8   Balance          10000 non-null  float64
 9   NumOfProducts    10000 non-null  int64
 10  HasCrCard        10000 non-null  int64
 11  IsActiveMember   10000 non-null  int64
 12  EstimatedSalary  10000 non-null  float64
 13  Exited           10000 non-null  int64
dtypes: float64(2), int64(9), object(3)
memory usage: 1.1+ MB
```

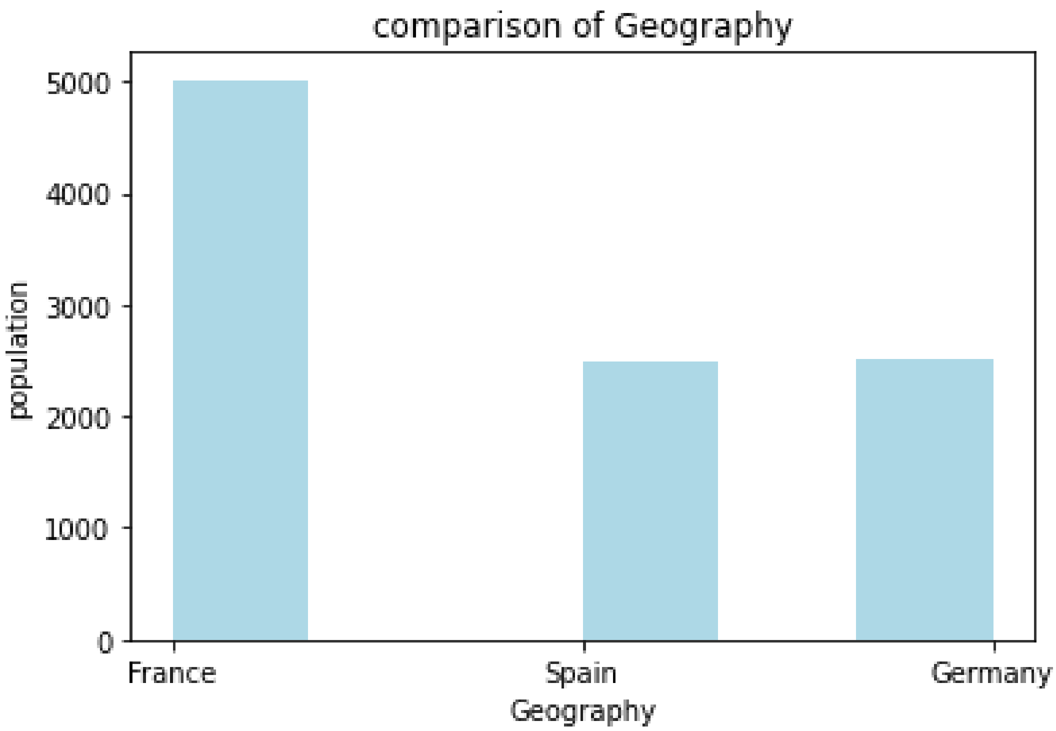
3. Perform Below Visualisations

Univariate Analysis

```
df['Geography'].value_counts()
```

```
France     5014
Germany    2509
Spain      2477
Name: Geography, dtype: int64
```

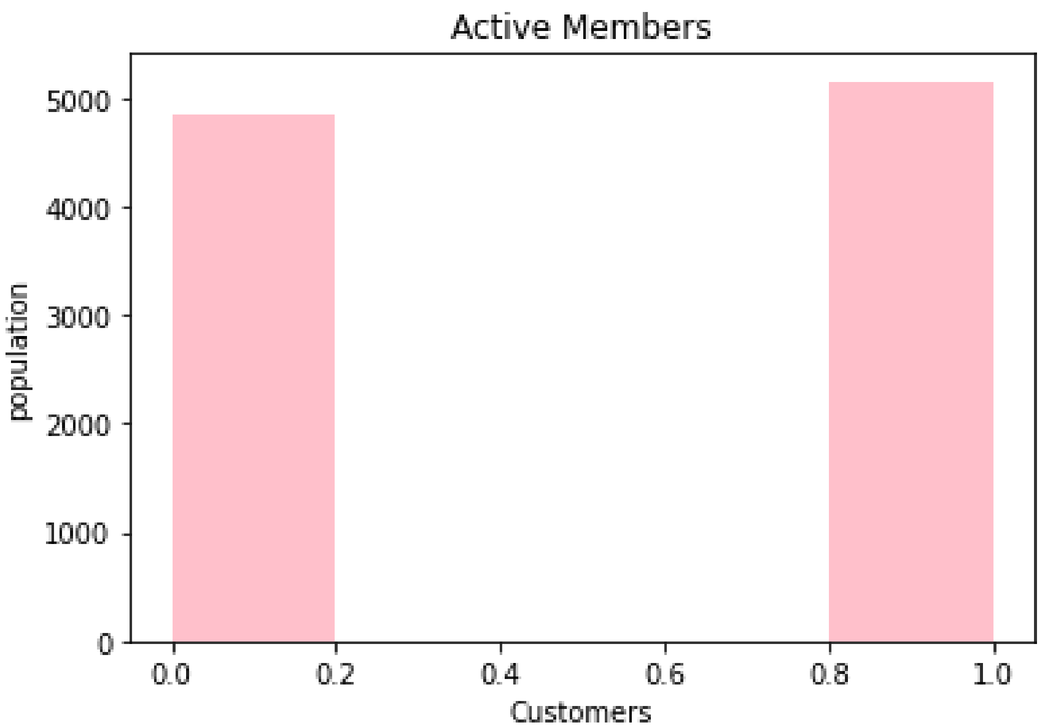
```
# comparison of geography

plt.hist(x = df.Geography, bins = 6, color = 'lightblue')
plt.title('comparison of Geography')
plt.xlabel('Geography')
plt.ylabel('population')
plt.show()
```



```
df['IsActiveMember'].value_counts()
```

```
1    5151
0    4849
Name: IsActiveMember, dtype: int64
```

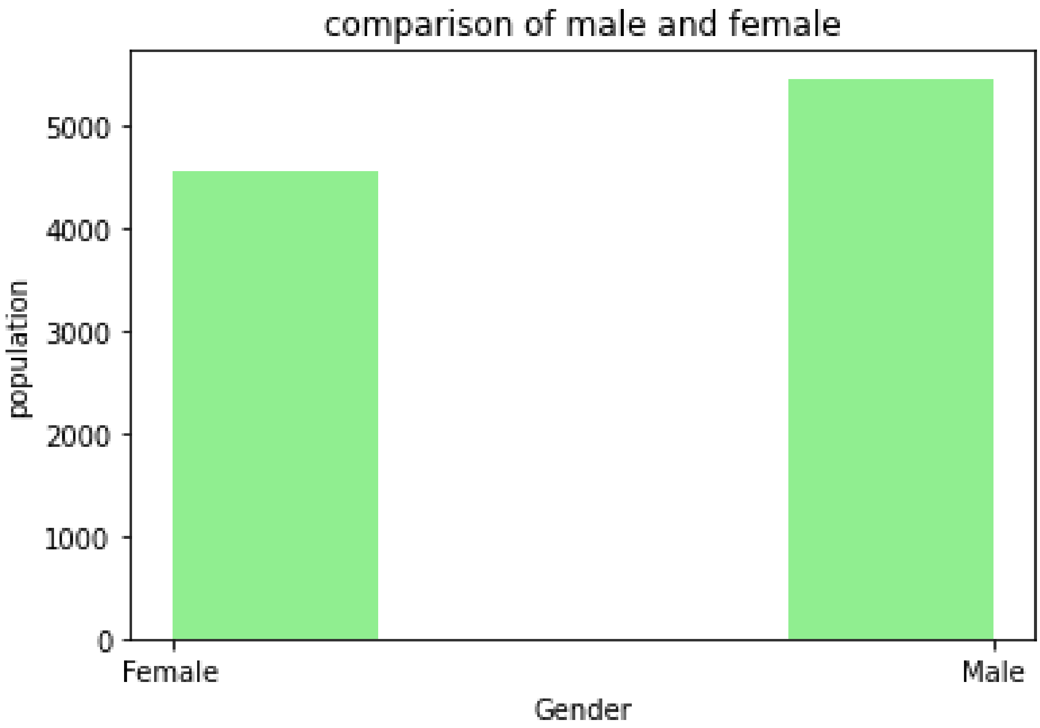
```
# How many active member does the bank have ?

plt.hist(x=df.IsActiveMember, bins=5, color='pink')
plt.title('Active Members')
plt.xlabel('Customers')
plt.ylabel('population')
plt.show()
```




```
df['Gender'].value_counts()
```

```
Male      5457
Female    4543
Name: Gender, dtype: int64
```

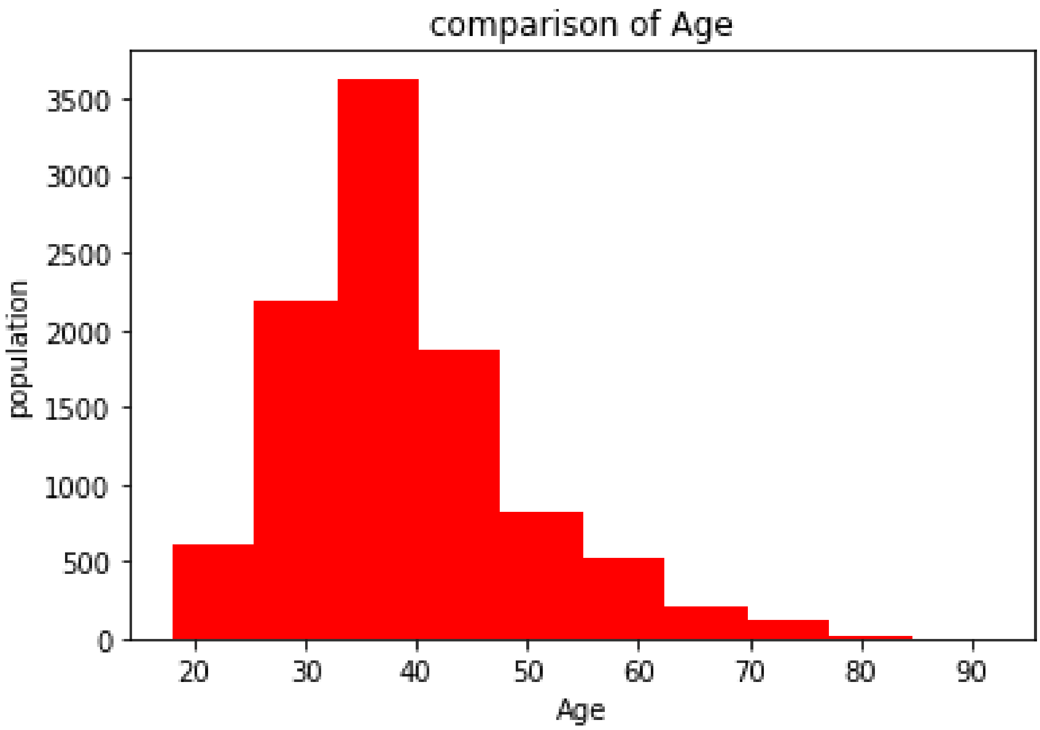
```
# Plotting the features of the dataset to see the correlation between them
plt.hist(x = df.Gender, bins = 4, color = 'lightgreen')
plt.title('comparison of male and female')
plt.xlabel('Gender')
plt.ylabel('population')
plt.show()
```




```
df['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
```

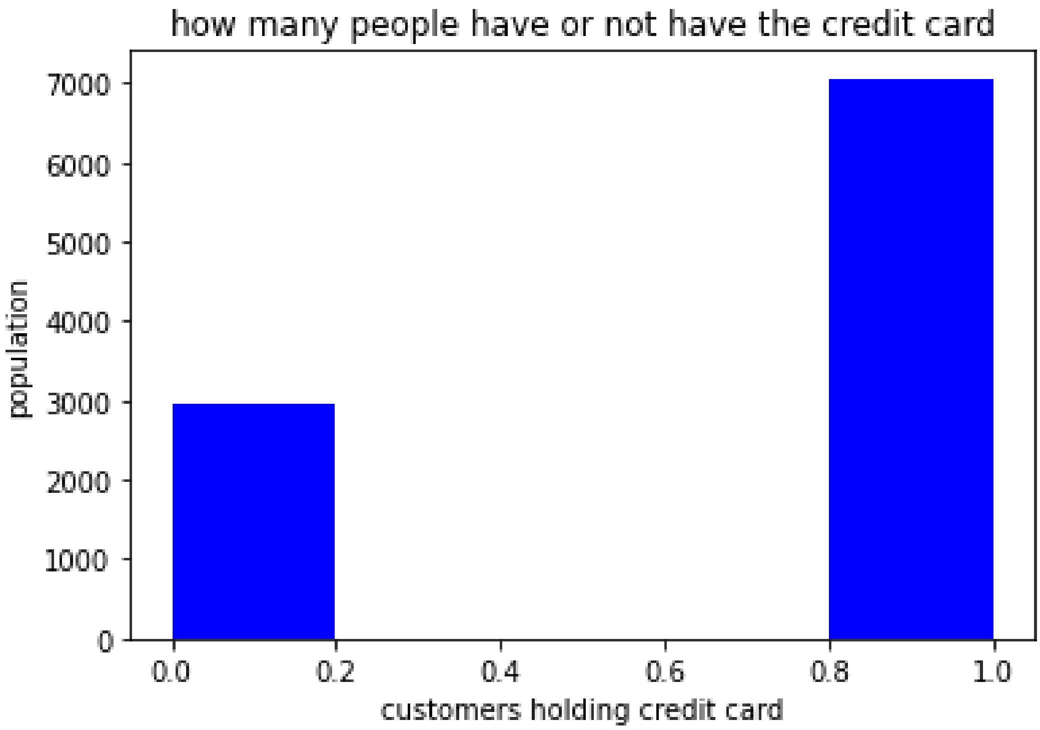
```
# comparison of age in the dataset

plt.hist(x = df.Age, bins = 10, color = 'red')
plt.title('comparison of Age')
plt.xlabel('Age')
plt.ylabel('population')
plt.show()
```




```
df['HasCrCard'].value_counts()
```

```
1    7055
0    2945
Name: HasCrCard, dtype: int64
```

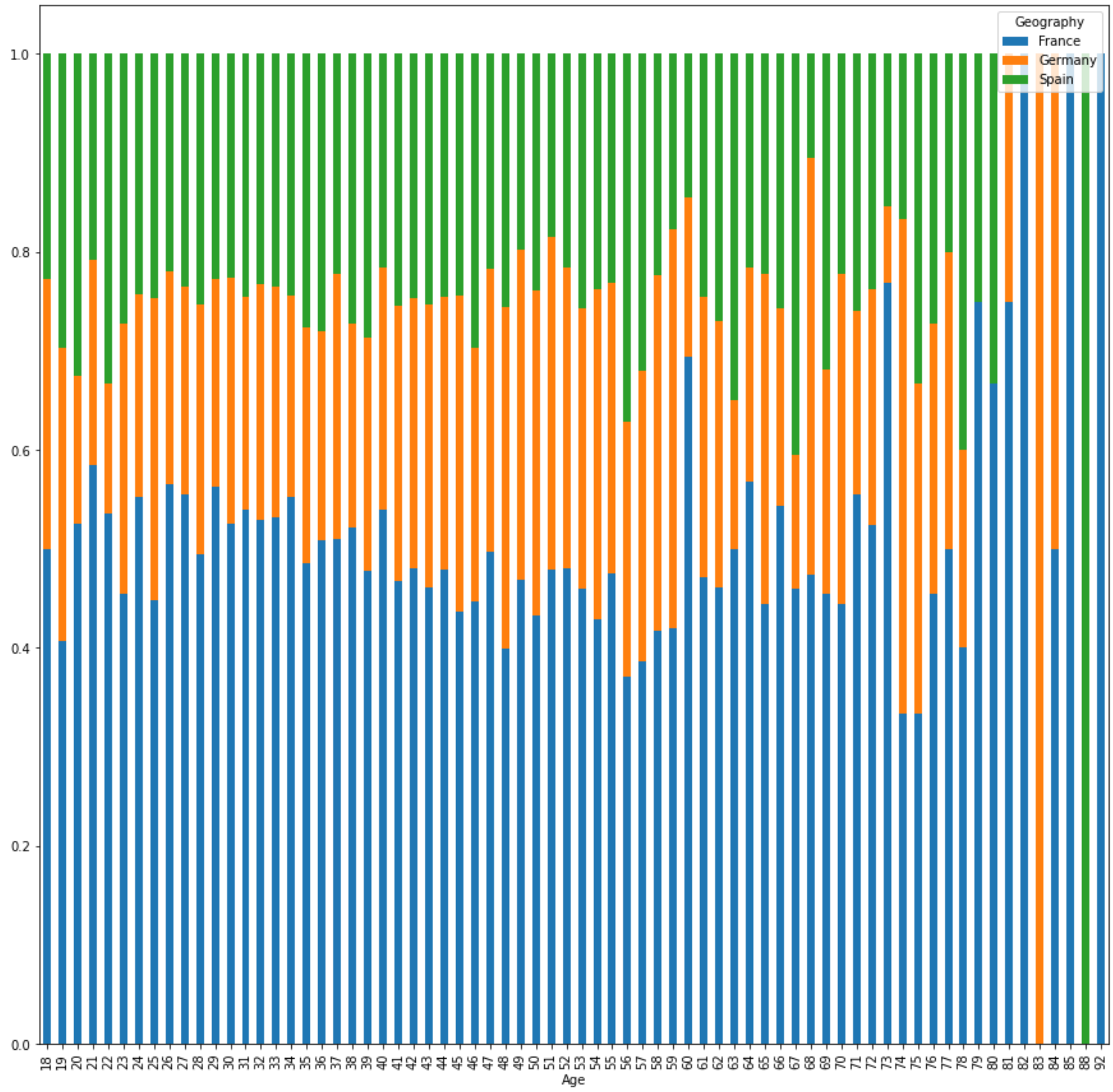
```
# comparison of how many customers hold the credit card

plt.hist(x = df.HasCrCard, bins = 5, color = 'blue')
plt.title('how many people have or not have the credit card')
plt.xlabel('customers holding credit card')
plt.ylabel('population')
plt.show()
```



Bi - Variate Analysis

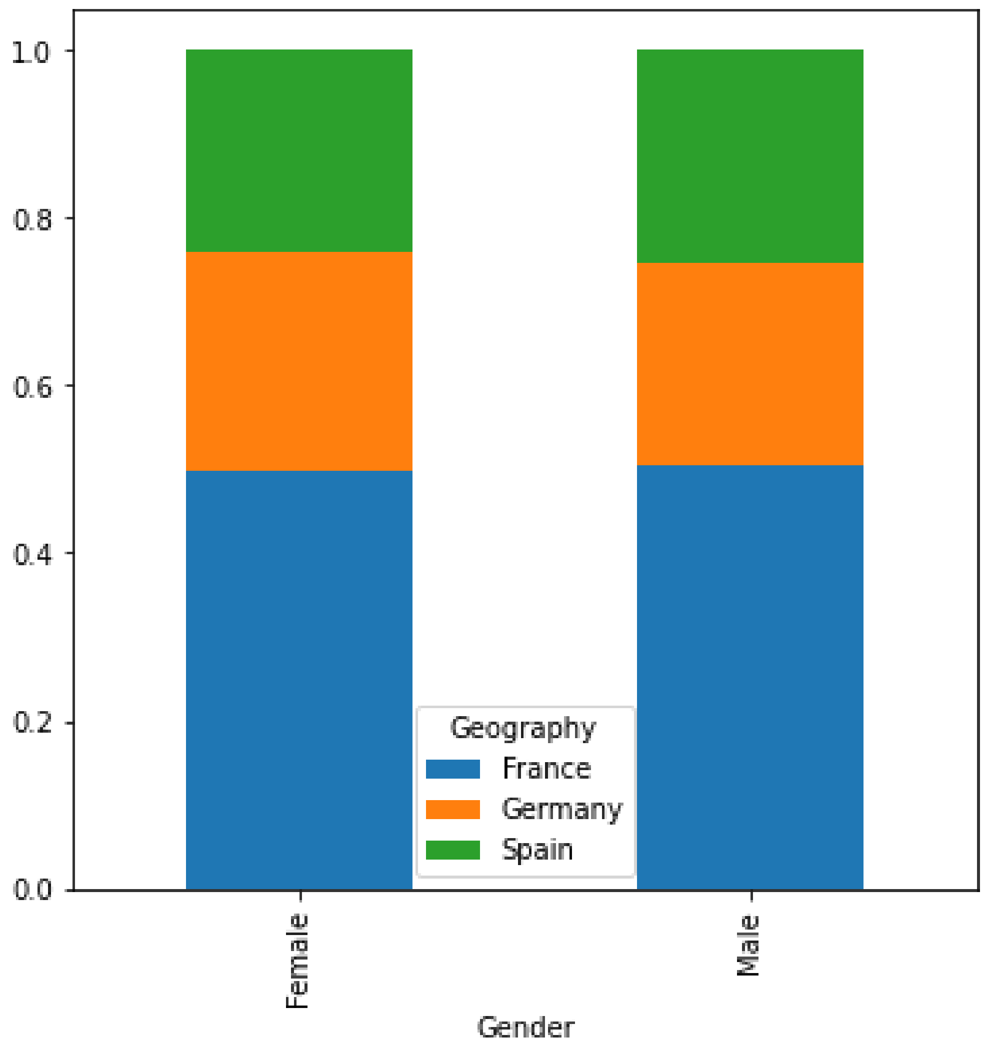
```
# comparing ages in different geographies

Age = pd.crosstab(df['Age'], df['Geography'])
Age.div(Age.sum(1).astype(float), axis = 0).plot(kind = 'bar', stacked =
True, figsize = (15,15))
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fa1a78a13d0>
```



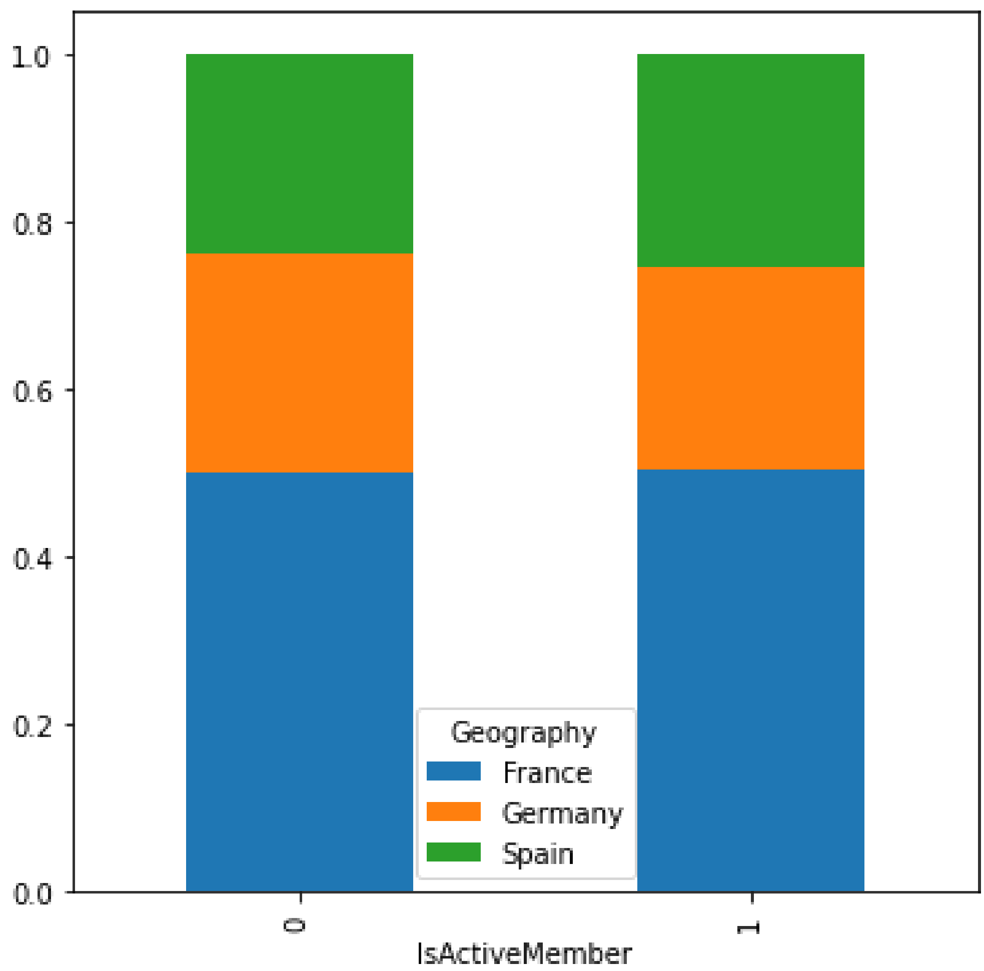

```
# comparison between Geography and Gender

Gender = pd.crosstab(df['Gender'],df['Geography'])
Gender.div(Gender.sum(1).astype(float), axis=0).plot(kind="bar",
stacked=True, figsize=(6, 6))
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fa1a6c48bd0>
```




```
# comparison of active member in differnt geographies

IsActiveMember = pd.crosstab(df['IsActiveMember'], df['Geography'])
IsActiveMember.div(IsActiveMember.sum(1).astype(float), axis =
0).plot(kind = 'bar',stacked = True, figsize= (6, 6))
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fa1a6c36810>
```

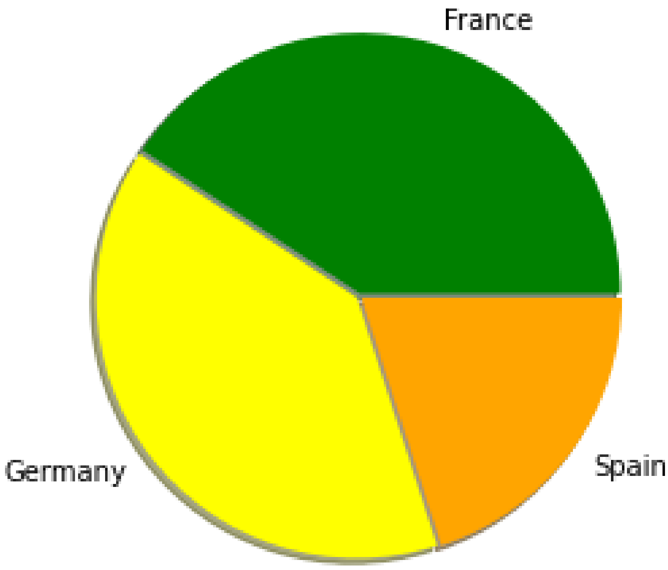



```
# calculating total balance in france, germany and spain

total_france = df.Balance[df.Geography == 'France'].sum()
total_germany = df.Balance[df.Geography == 'Germany'].sum()
total_spain = df.Balance[df.Geography == 'Spain'].sum()

print("Total Balance in France :",total_france)
print("Total Balance in Germany :",total_germany)
print("Total Balance in Spain :",total_spain)
```

```
Total Balance in France : 311332479.49
Total Balance in Germany : 300402861.38
Total Balance in Spain : 153123552.01
```

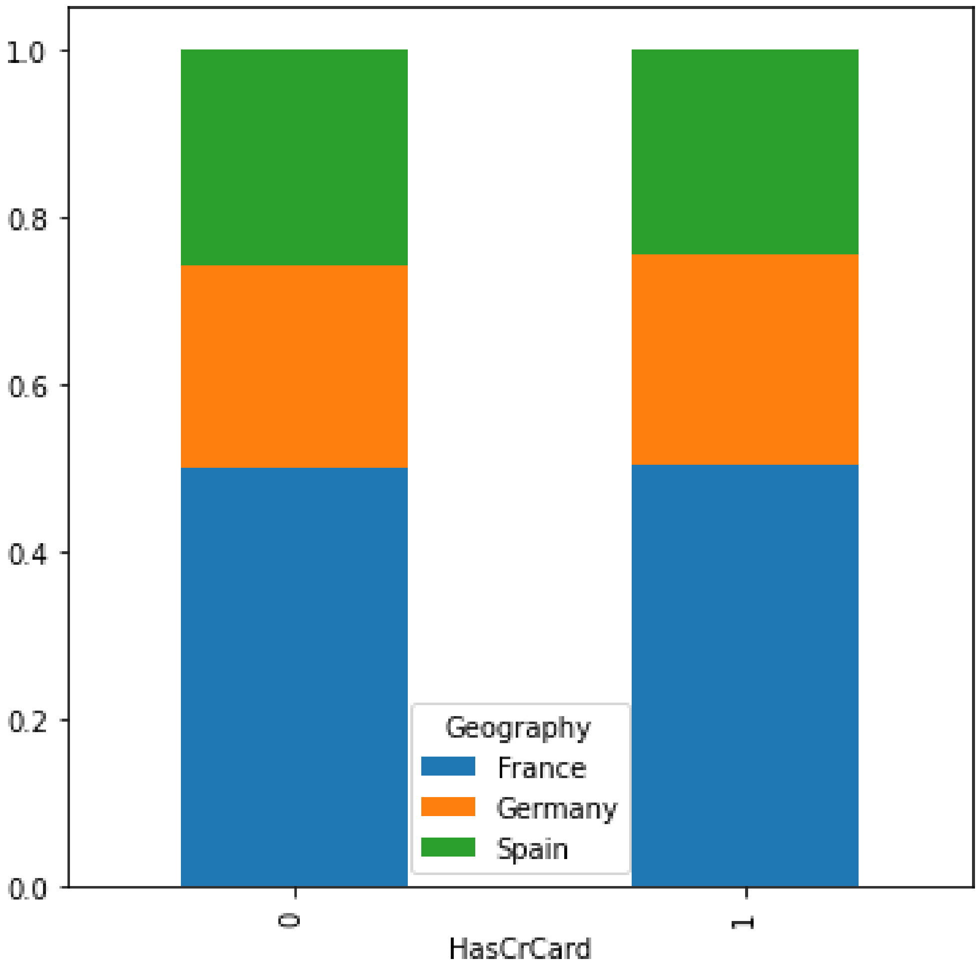
```
# plotting a pie chart

labels = 'France', 'Germany', 'Spain'
colors = ['green', 'yellow', 'orange']
sizes = [311, 300, 153]
explode = [ 0.01, 0.01, 0.01]

plt.pie(sizes, colors = colors, labels = labels, explode = explode, shadow
= True)
```

```
plt.axis('equal')
plt.show()
```




```
# comparison between geography and card holders

HasCrCard = pd.crosstab(df['HasCrCard'], df['Geography'])
HasCrCard.div(HasCrCard.sum(1).astype(float), axis = 0).plot(kind =
'bar',stacked = True,figsize = (6, 6))
```

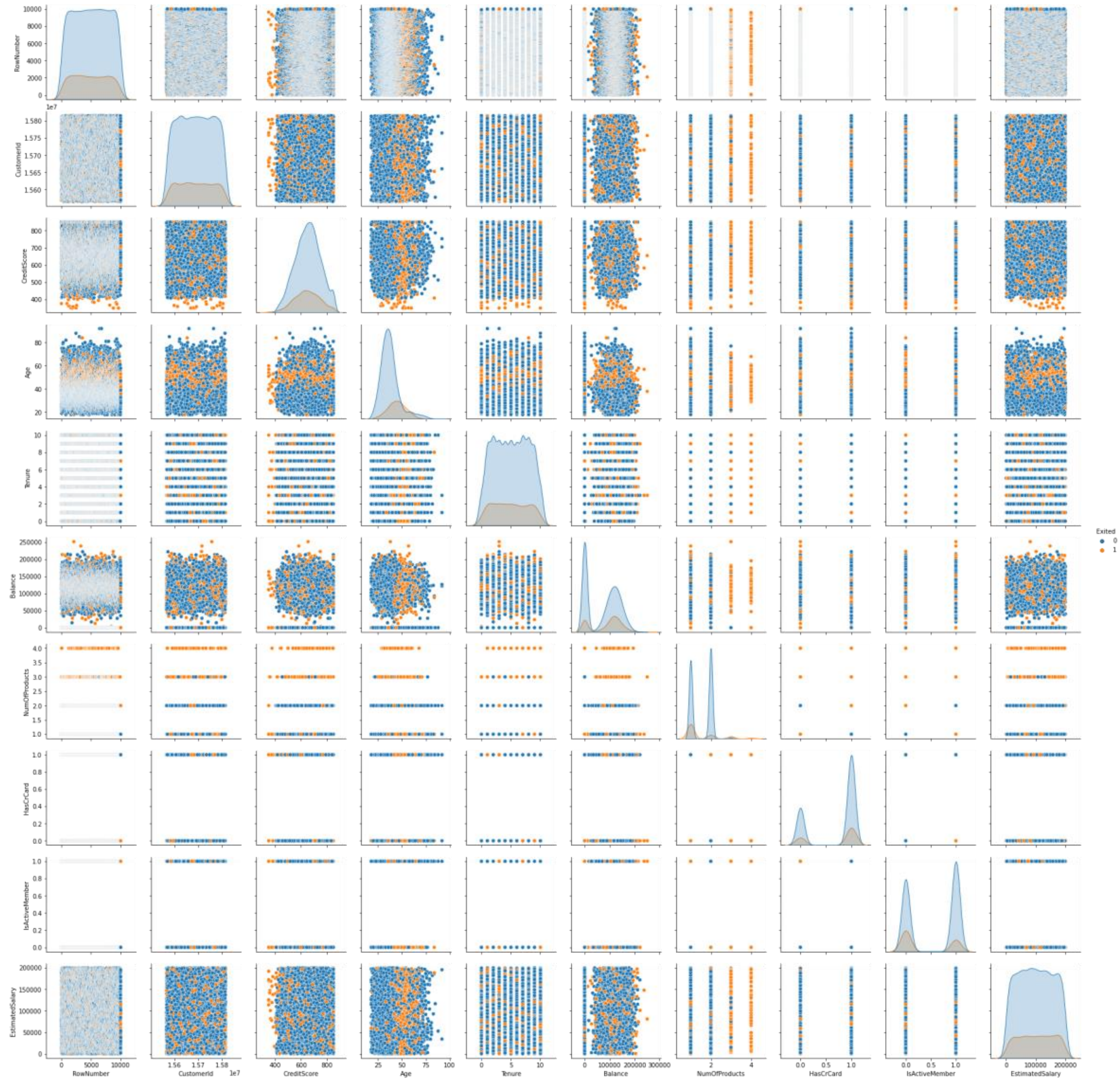
```
<matplotlib.axes._subplots.AxesSubplot at 0x7fa1a6b0c0d0>
```



Multi - Variate Analysis

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

```
<seaborn.axisgrid.PairGrid at 0x7fa1a1860550>
```



4. Perform descriptive statistics on the dataset

```
df.describe()
```

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

             Balance  NumOfProducts    HasCrCard  IsActiveMember  \
count   10000.000000   10000.000000  10000.00000    10000.000000
mean    76485.889288       1.530200      0.70550        0.515100
std     62397.405202       0.581654      0.45584        0.499797
min         0.000000       1.000000      0.00000        0.000000
25%         0.000000       1.000000      0.00000        0.000000
```

```
50%     97198.540000      1.000000      1.00000        1.000000
75%    127644.240000      2.000000      1.00000        1.000000
max    250898.090000      4.000000      1.00000        1.000000

       EstimatedSalary        Exited
count      10000.000000  10000.000000
mean      100090.239881      0.203700
std        57510.492818      0.402769
min           11.580000      0.000000
25%        51002.110000      0.000000
50%       100193.915000      0.000000
75%       149388.247500      0.000000
max       199992.480000      1.000000
```

5. Handle the Missing values

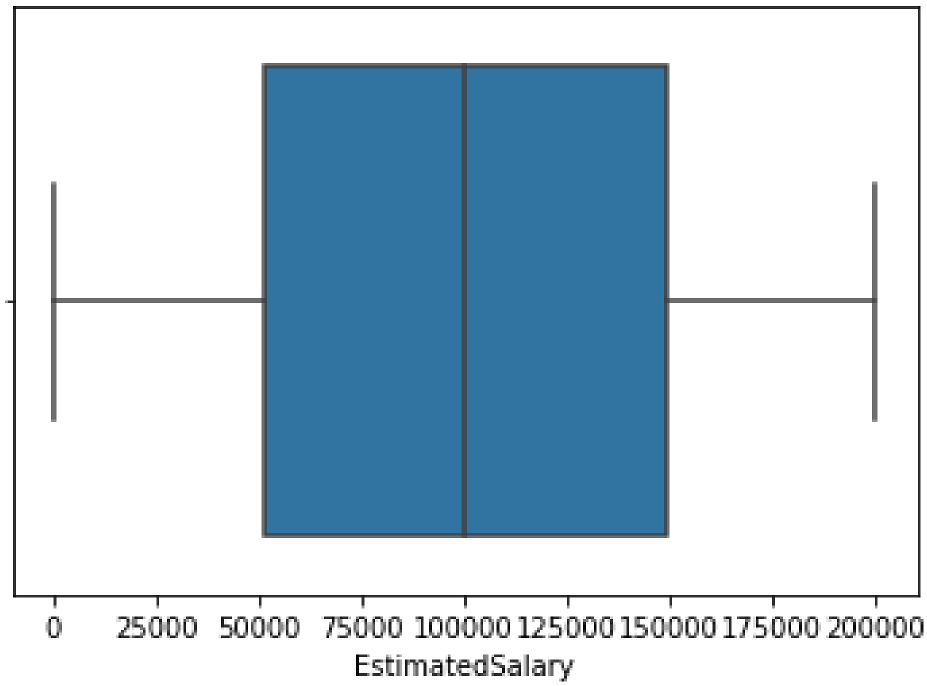
```
df.isnull().sum()
```

```
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
```

6. Find the outliers and replace the outliers

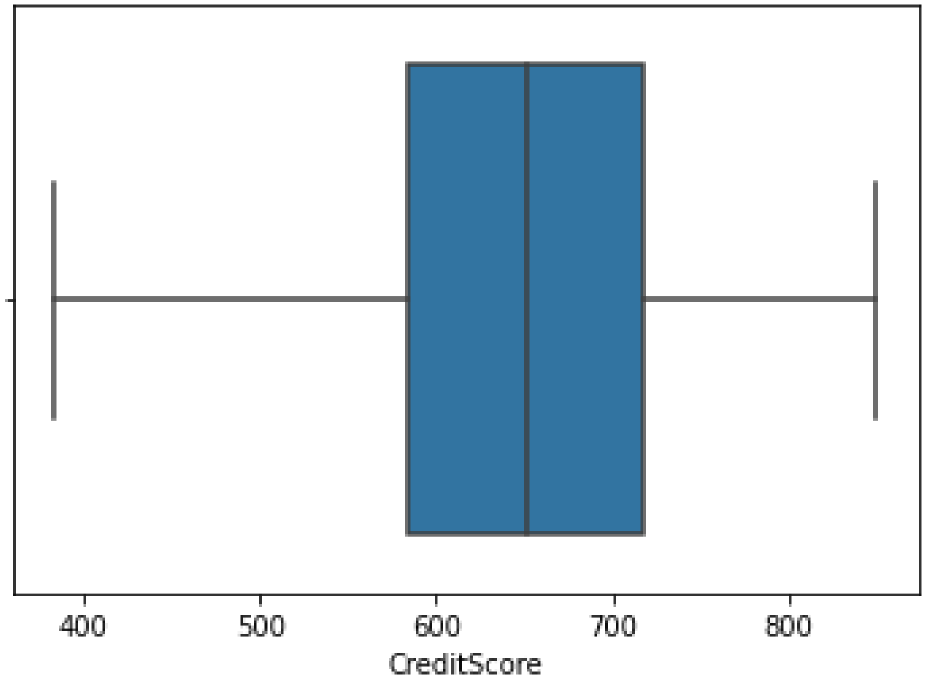
```
sns.boxplot(data = df, x = 'EstimatedSalary')
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fa19f13e510>
```



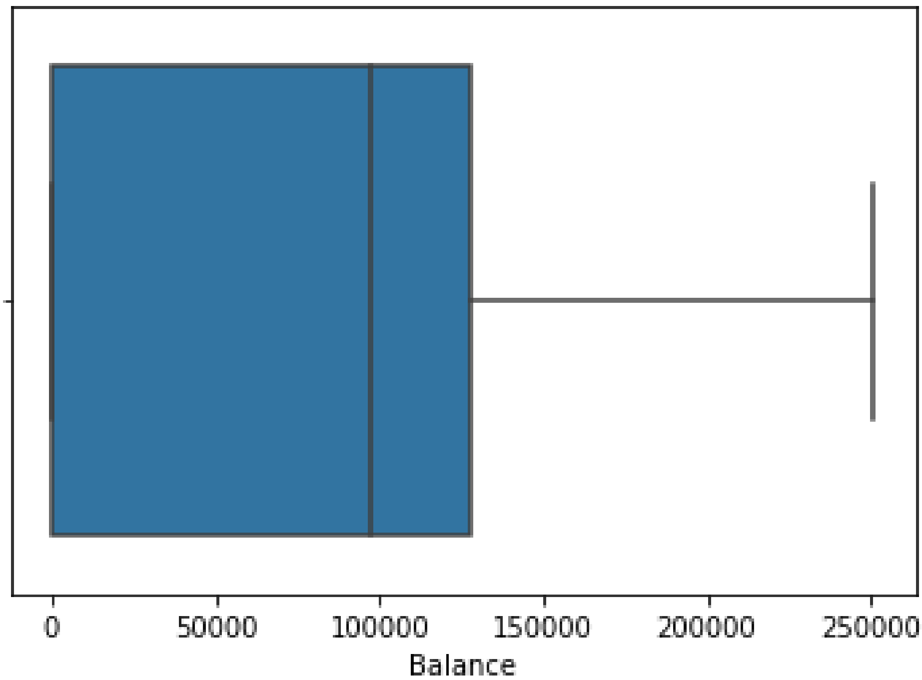

```
sns.boxplot(data = df, x = 'CreditScore')
```

<matplotlib.axes._subplots.AxesSubplot at 0x7fa19f0c2410>



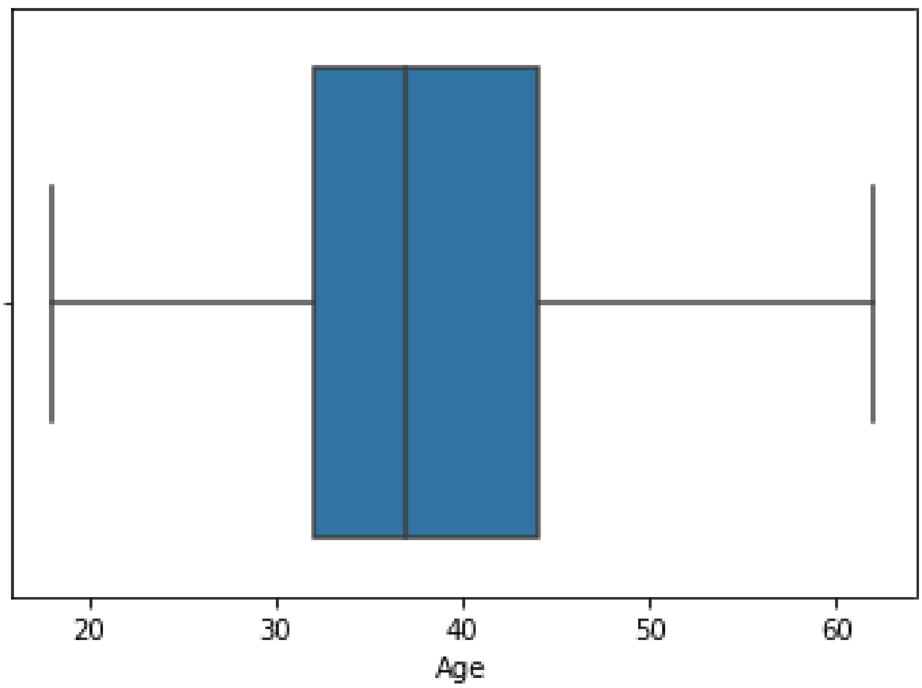

```
sns.boxplot(data = df, x = 'Balance')
```

<matplotlib.axes._subplots.AxesSubplot at 0x7fa19f03d1d0>



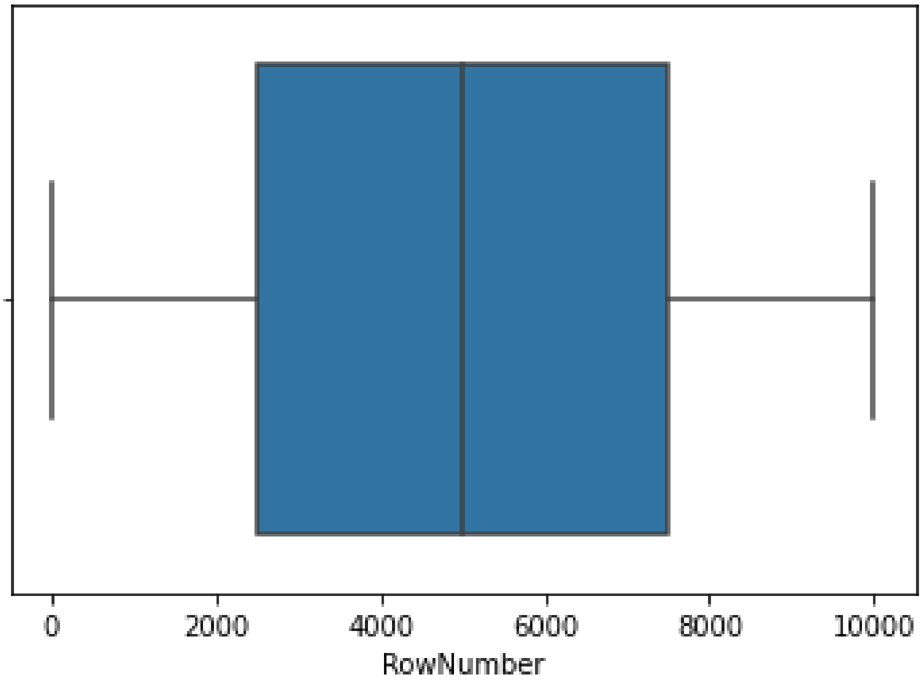

```
sns.boxplot(data = df, x ='Age')
```

<matplotlib.axes._subplots.AxesSubplot at 0x7fa19d74fb10>



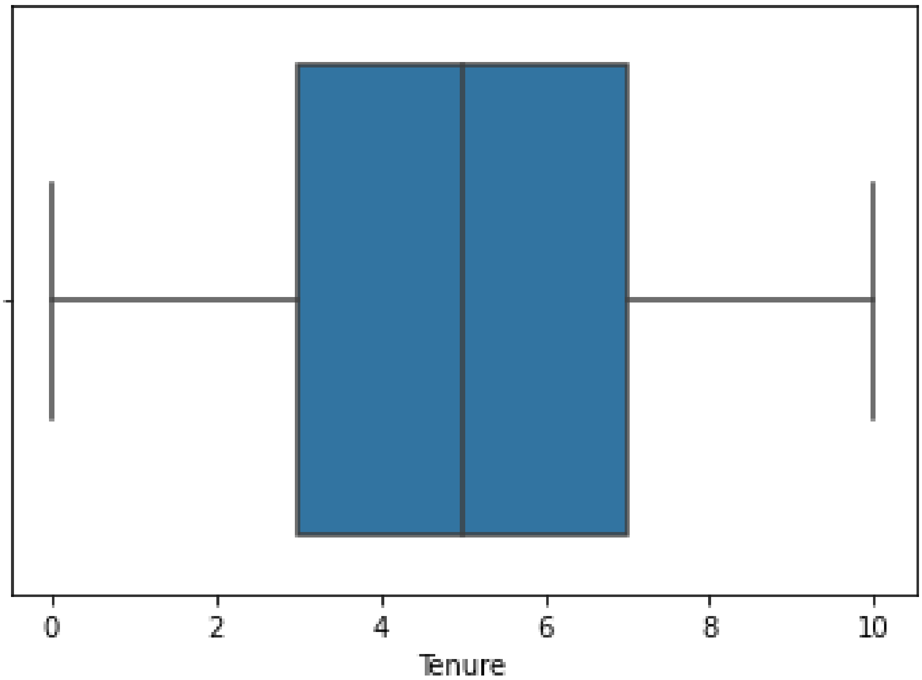

```
sns.boxplot(data = df, x = 'RowNumber')
```

<matplotlib.axes._subplots.AxesSubplot at 0x7fa19d7c2b90>




```
sns.boxplot(data = df, x = 'Tenure')
```

<matplotlib.axes._subplots.AxesSubplot at 0x7fa19be57c90>



7. Check for Categorical columns and perform encoding

```
x = pd.get_dummies(x)
```

```
x.head()
```

```
   RowNumber  CustomerId  CreditScore   Age  Tenure  Surname_Abazu  \
0        1.0  15634602.0        619.0  42.0     2.0              0
1        2.0  15647311.0        608.0  41.0     1.0              0
2        3.0  15619304.0        502.0  42.0     8.0              0
3        4.0  15701354.0        699.0  39.0     1.0              0
4        5.0  15737888.0        850.0  43.0     2.0              0

   Surname_Abbie Surname_Abbott  Surname_Abdullah  Surname_Abdulov  ...
\
0              0              0                 0                0  ...
1              0              0                 0                0  ...
2              0              0                 0                0  ...
3              0              0                 0                0  ...
4              0              0                 0                0  ...

   Surname_Zubarev   Surname_Zubareva  Surname_Zuev  Surname_Zuyev \
0                0                  0             0              0
1                0                  0             0              0
2                0                  0             0              0
3                0                  0             0              0
4                0                  0             0              0

   Surname_Zuyeva  Geography_France  Geography_Germany  Geography_Spain  \
0               0                 1                  0                0
1               0                 0                  0                1
2               0                 1                  0                0
3               0                 1                  0                0
4               0                 0                  0                1

   Gender_Female Gender_Male
0              1           0
1              1           0
2              1           0
3              1           0
4              1           0

[5 rows x 2942 columns]
```

8. Split the data into dependent and independent variables

```
# splitting the dataset into x(independent variables) and y(dependent
variables)

x = df.iloc[:,0:8]
y = df.iloc[:,8]

print(x.shape)
print(y.shape)

print(x.columns)
```

```
(10000, 8)
(10000,)
Index(['RowNumber', 'CustomerId', 'Surname', 'CreditScore', 'Geography',
       'Gender', 'Age', 'Tenure'],
      dtype='object')
```

9. Scale the independent variables

```
from sklearn.preprocessing import StandardScaler

sc = StandardScaler()
x_train = sc.fit_transform(x_train)
x_test = sc.fit_transform(x_test)

x_train = pd.DataFrame(x_train)
x_train.head()
```

```
         0         1         2         3         4         5    6       7
\
0 -0.702176 -1.343330 -0.736828  0.042283  0.008860 -0.016332   0.0
-0.0231
1 -1.485722  1.558330  1.025257 -0.674496  0.008860 -0.016332   0.0
-0.0231
2 -0.524522 -0.655156  0.808861 -0.469702  1.393293 -0.016332   0.0
-0.0231
3 -1.167396  1.200594  0.396677 -0.060114  0.008860 -0.016332   0.0
-0.0231
4 -1.451159  0.778798 -0.468908  1.373444  0.701077 -0.016332   0.0
-0.0231

     8    9   ...      2932  2933      2934      2935      2936      2937
\
0  0.0  0.0   ... -0.011548   0.0 -0.011548 -0.011548 -0.016332 -1.015588
1  0.0  0.0   ... -0.011548   0.0 -0.011548 -0.011548 -0.016332  0.984651
2  0.0  0.0   ... -0.011548   0.0 -0.011548 -0.011548 -0.016332 -1.015588
3  0.0  0.0   ... -0.011548   0.0 -0.011548 -0.011548 -0.016332 -1.015588
4  0.0  0.0   ... -0.011548   0.0 -0.011548 -0.011548 -0.016332  0.984651

       2938      2939      2940      2941
0  1.760216 -0.574682  1.087261 -1.087261
1 -0.568112 -0.574682  1.087261 -1.087261
2 -0.568112  1.740094  1.087261 -1.087261
3 -0.568112  1.740094 -0.919743  0.919743
4 -0.568112 -0.574682 -0.919743  0.919743

[5 rows x 2942 columns]
```

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 =
0.25, random_state = 0)

print(x_train.shape)
```

```
print(y_train.shape)
print(x_test.shape)
print(y_test.shape)
```

```
(7500, 2942)
(7500,)
(2500, 2942)
(2500,)
```