Assignment -2

Data Visualization and Pre-processing in ipynb

Assignment Date	21 October 2022
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Maximum Marks	2 Marks

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 GeographyGender  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-    int64
                            null
 1   CustomerId      10000  non-    int64
                            null
 2   Surname         10000  non-    objec
                            null    t
 3   CreditScore     10000  non-    int64
                            null
 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
```

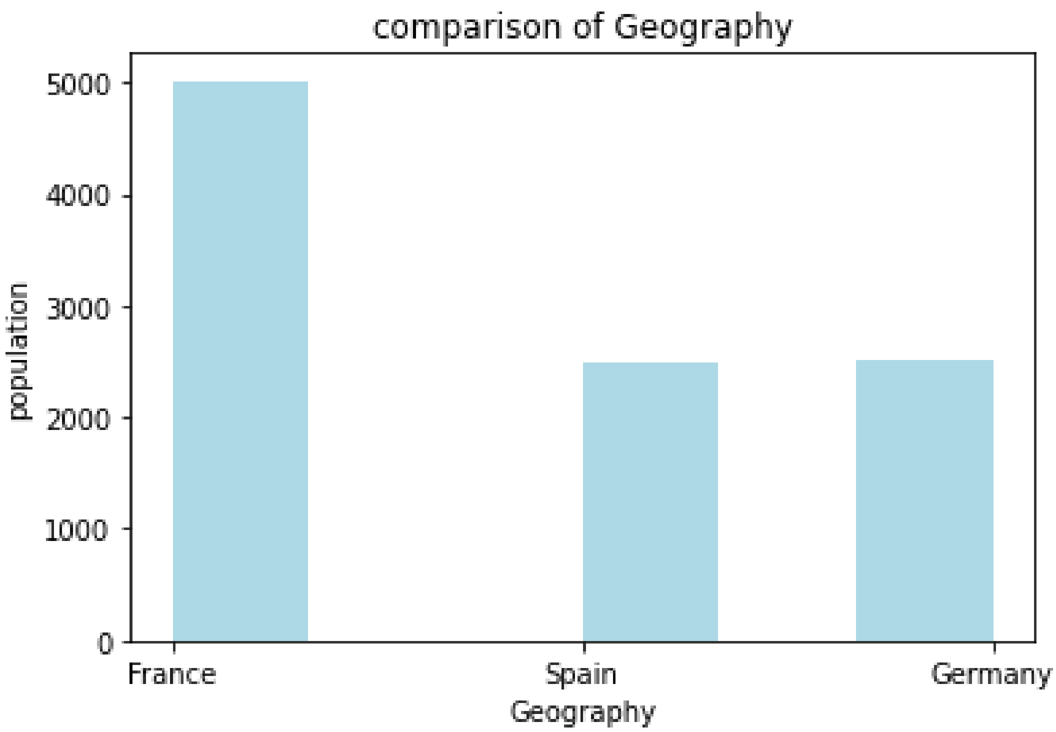
3. Perform Below Visualisations

Univariate Analysis

```
df['Geography'].value_count

s()
```

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

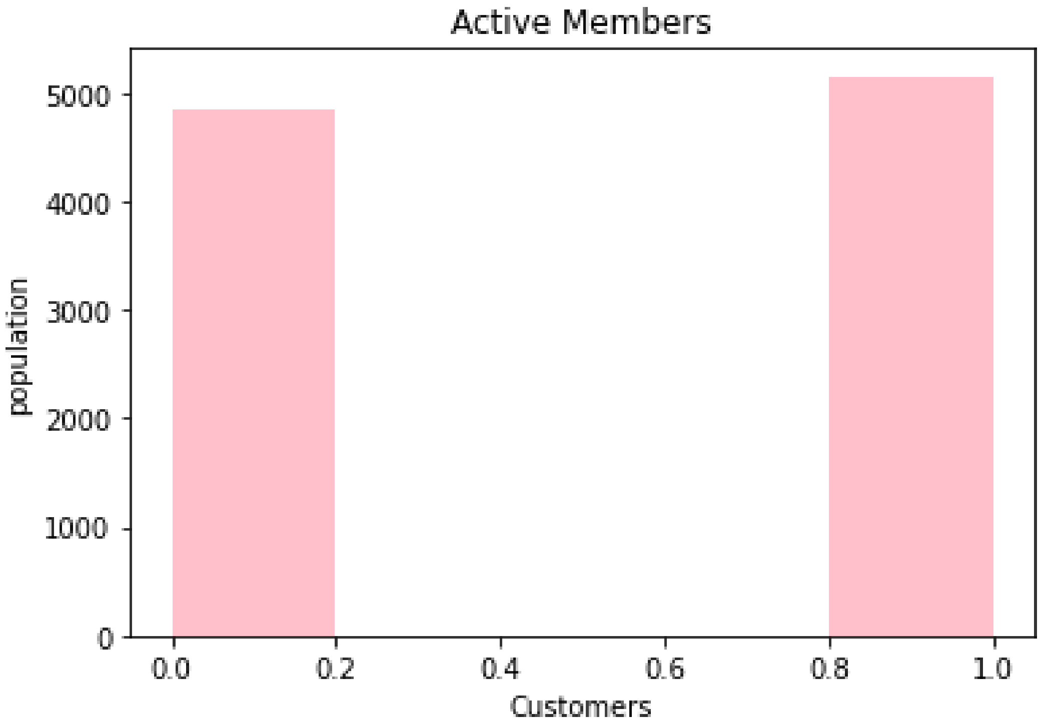
```
# comparison of geography

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()
```

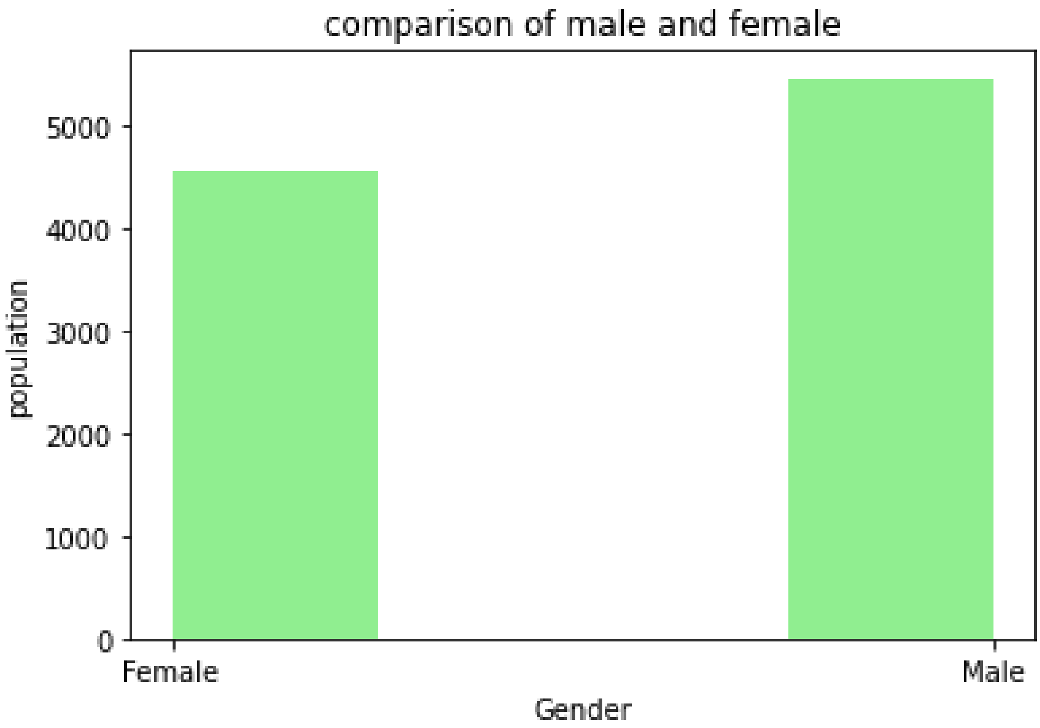
```
1    5151
0    4849
Name: IsActiveMember, dtype: int64
```

```
# 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_count
s() Male 5457
Female   4543
Name: Gender, dtype: int64
```

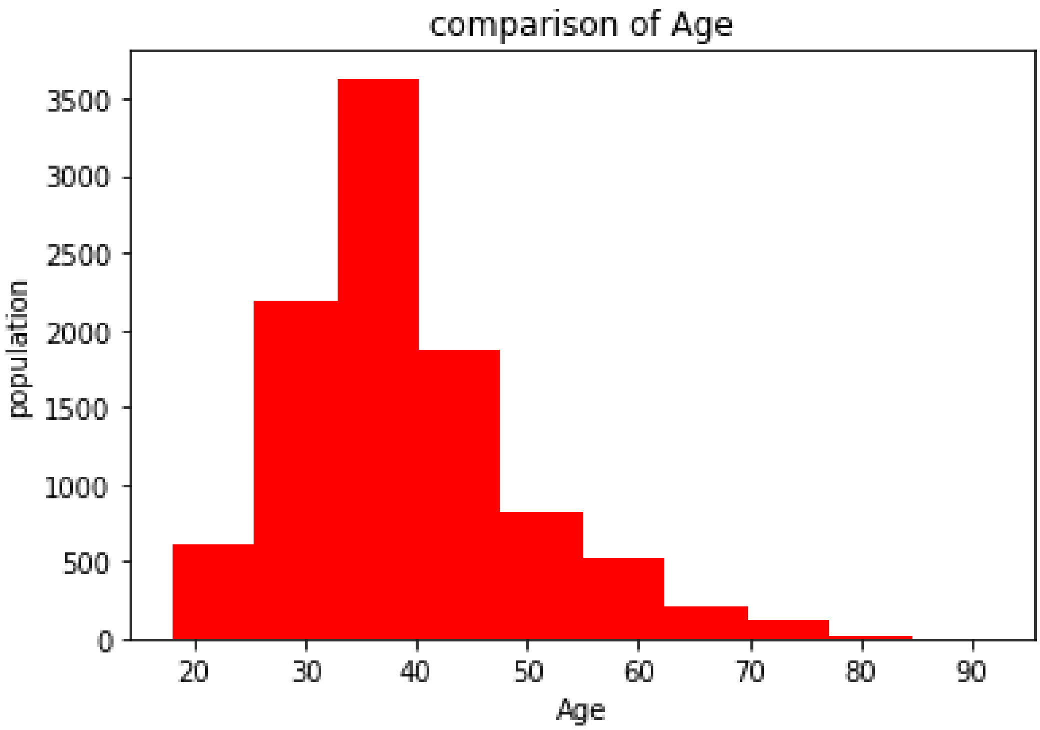
```
# Plotting the features of the dataset to see the correlation
between them plt.hist(x = df.Gender, bins = 4, color = 'lightgreen')
plt.title('comparison of male and female')
plt.xlabel('Gender')
plt.ylabel('population')
plt.show()
```




```
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
```

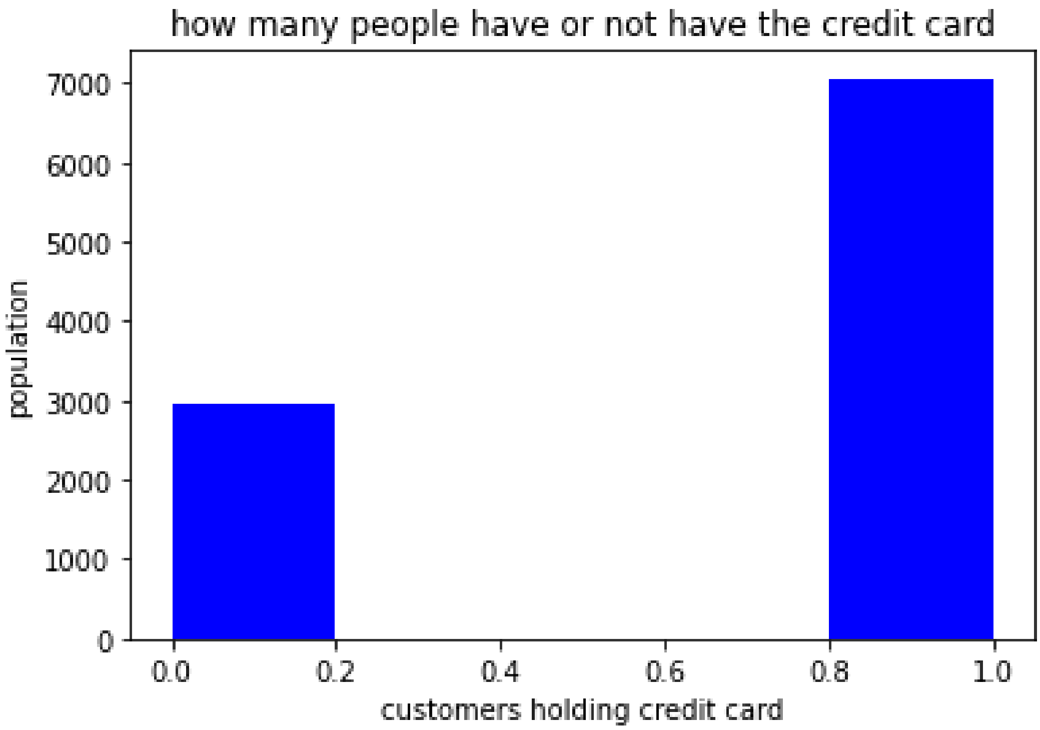
```
# comparison of age in the dataset

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
```

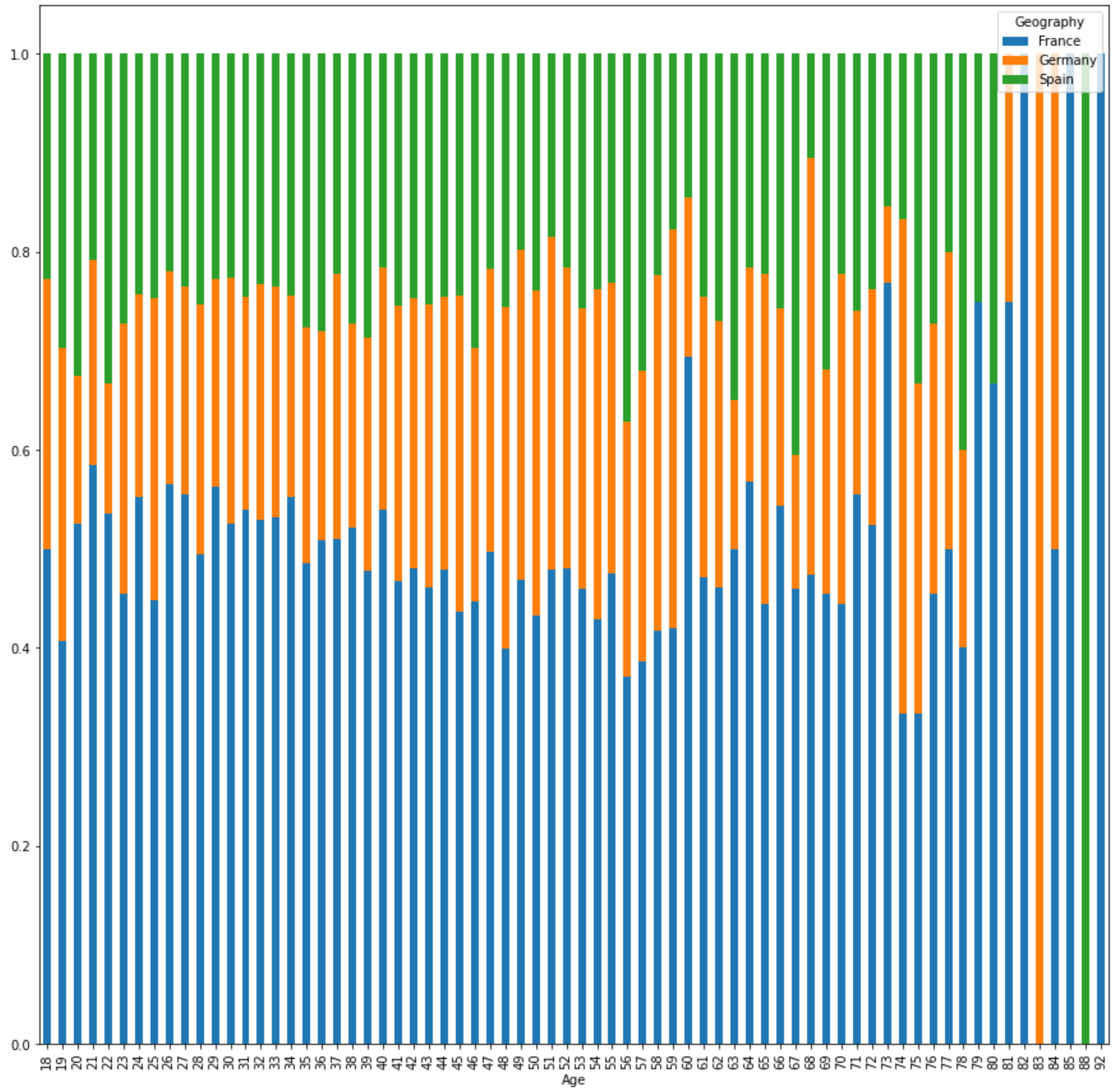
```
# comparison of how many customers hold the credit card

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

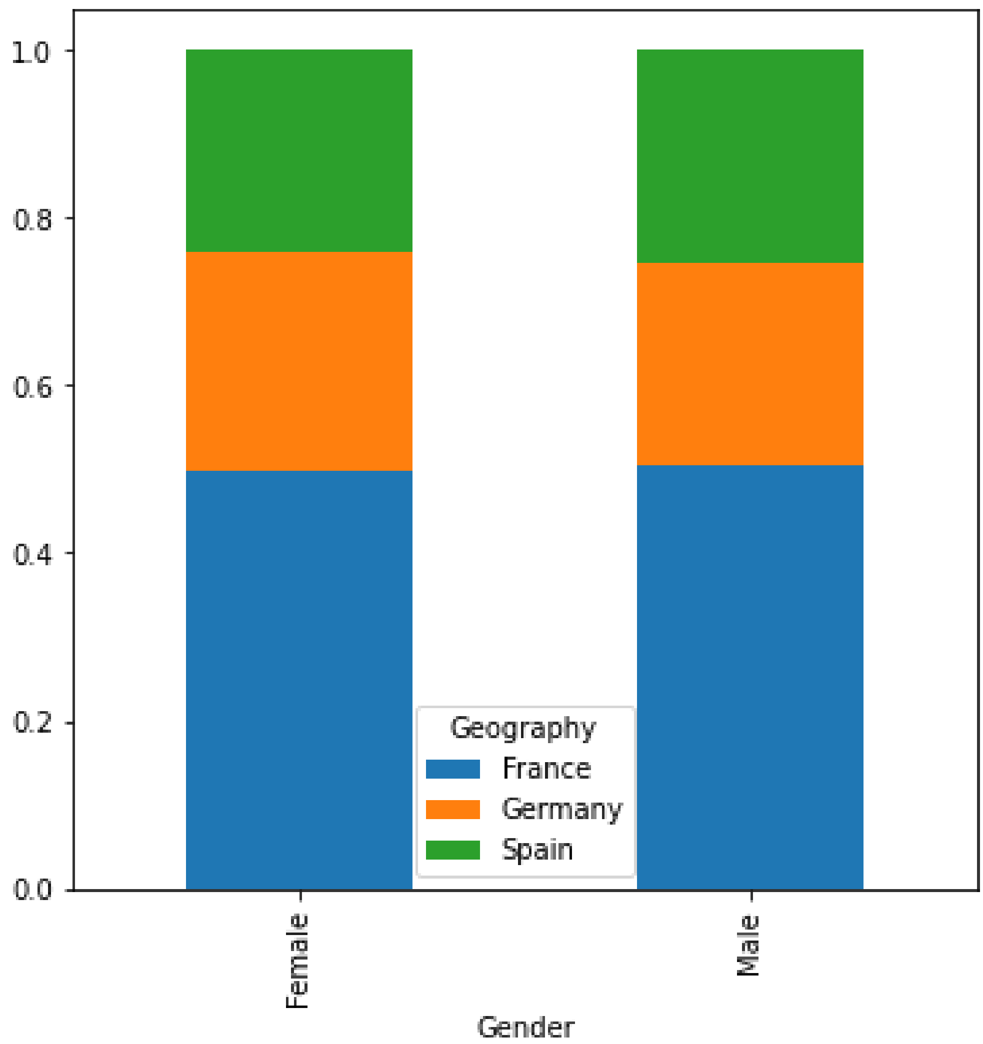
```
# comparing ages in different geographies

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>
```



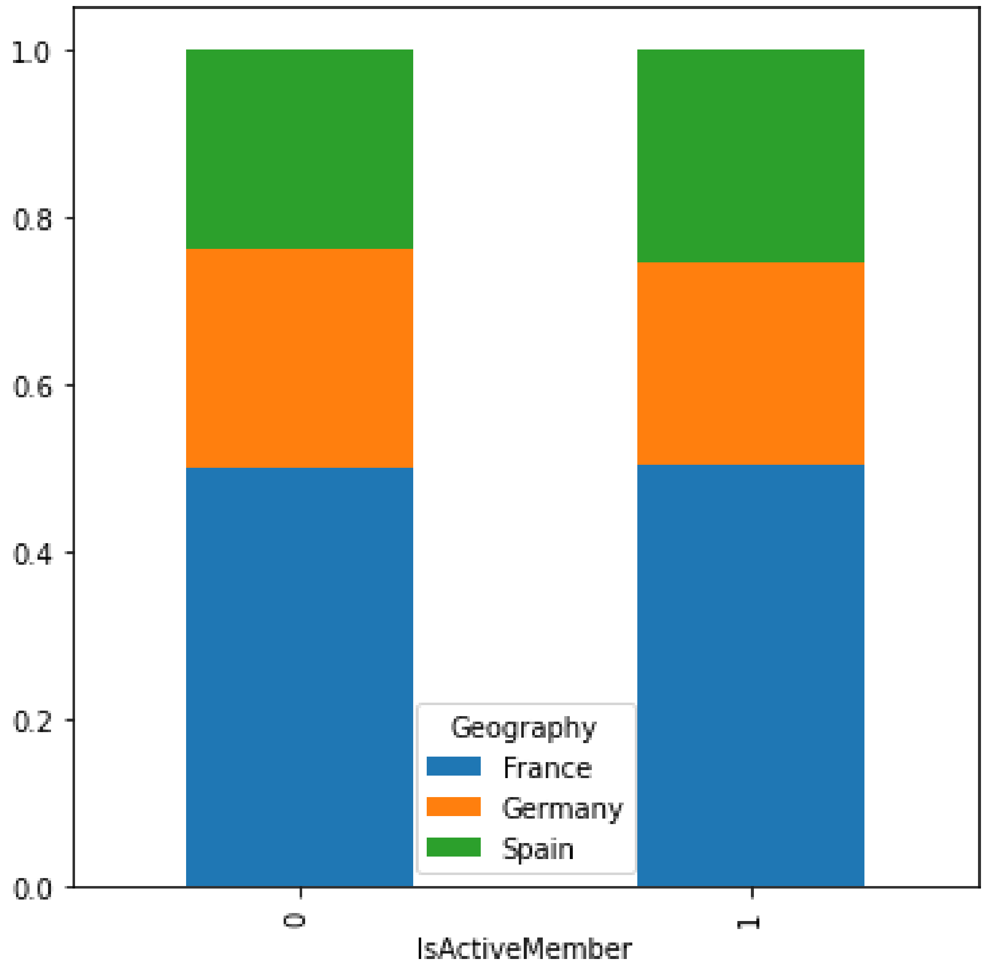

```
# comparison between Geography and Gender

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>
```



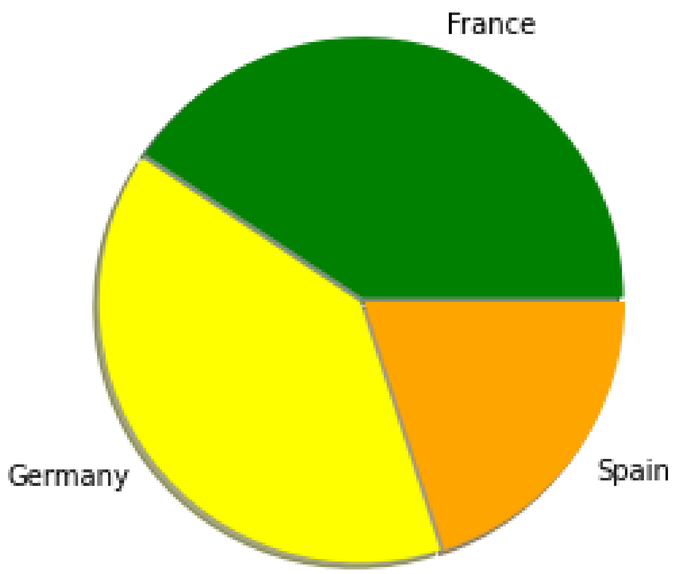

```
# comparison of active member in differnt geographies

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>
```



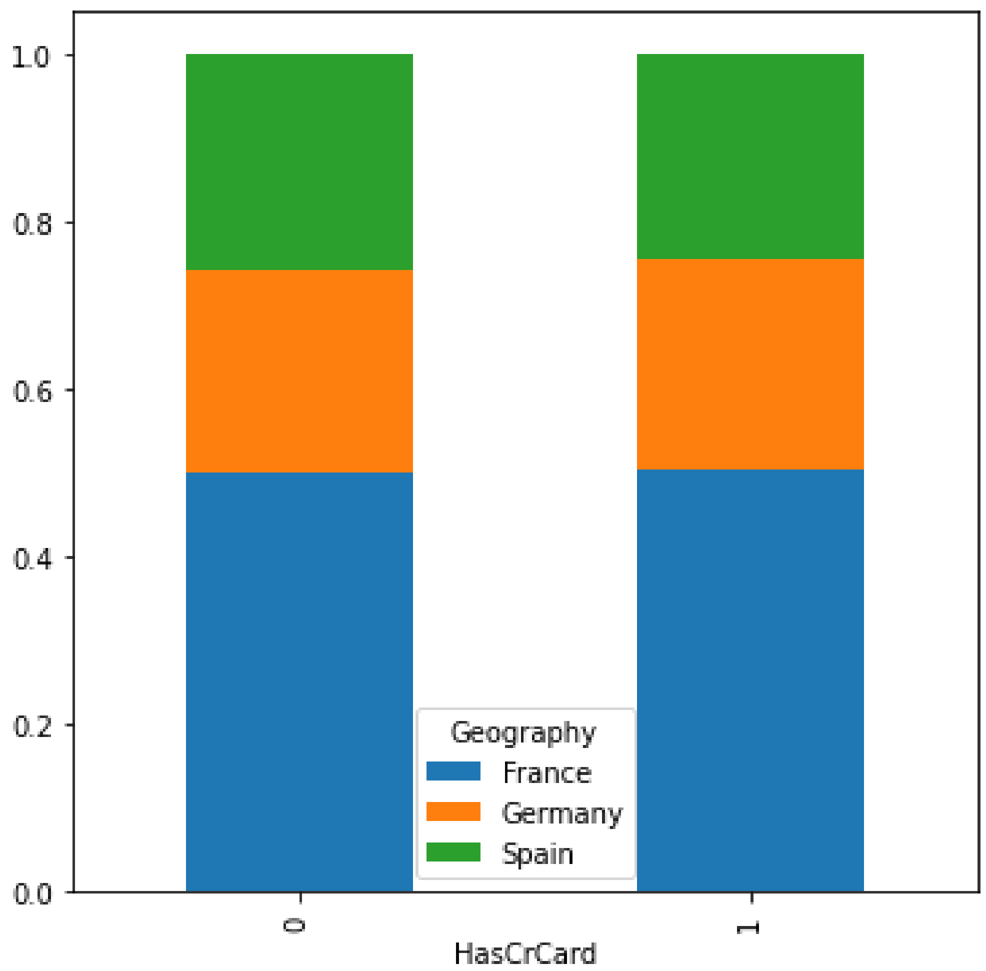

```
# calculating total balance in france, germany and spain

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))
```

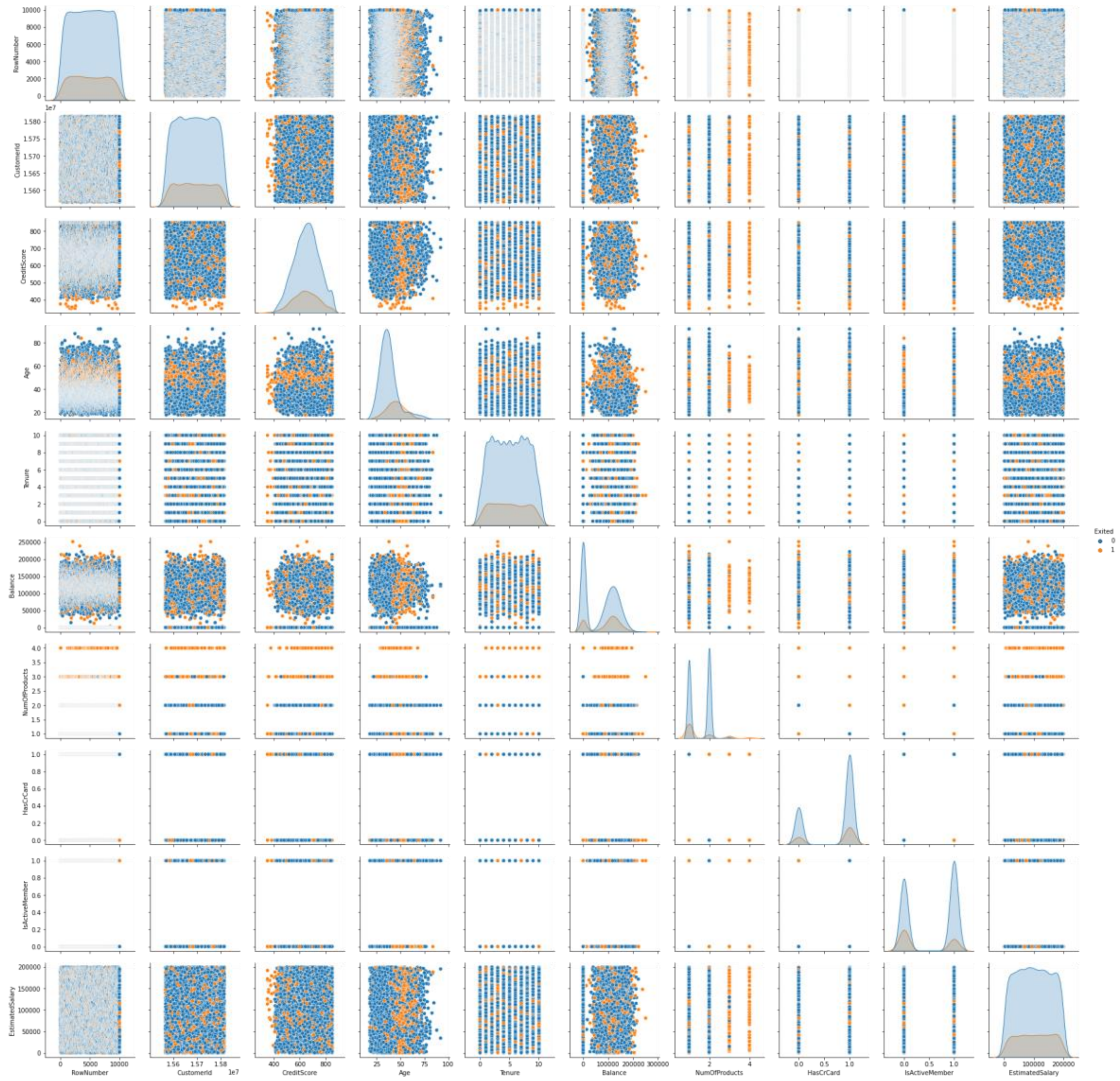
```
<matplotlib.axes._subplots.AxesSubplot at 0x7fa1a6b0c0d0>
```



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         Tenur
\                                                                    e
count  10000.00000 1.000000e+0  10000.000000 10000.00000   10000.00000
                             4                           0  0
mean    5000.50000 1.569094e+0    650.528800    38.921800      5.01280
                             7                                 0
std     2886.89568 7.193619e+0     96.653299    10.487806      2.89217
                             4                                 4
min        1.00000 1.556570e+0    350.000000    18.000000      0.00000
                             7                                 0
25%     2500.75000 1.562853e+0    584.000000    32.000000      3.00000
                             7                                 0
50%     5000.50000 1.569074e+0    652.000000    37.000000      5.00000
                             7                                 0
75%     7500.25000 1.575323e+0    718.000000    44.000000      7.00000
                             7                                 0
max    10000.00000 1.581569e+0    850.000000    92.000000     10.00000
                             7                                0

            Balance  NumOfProduct   HasCrCard  IsActiveMembe  \
                     s                         r
count  10000.000000   10000.00000 10000.00000    10000.00000
                      0                          0
```

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

       EstimatedSalar       Exited
       y
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

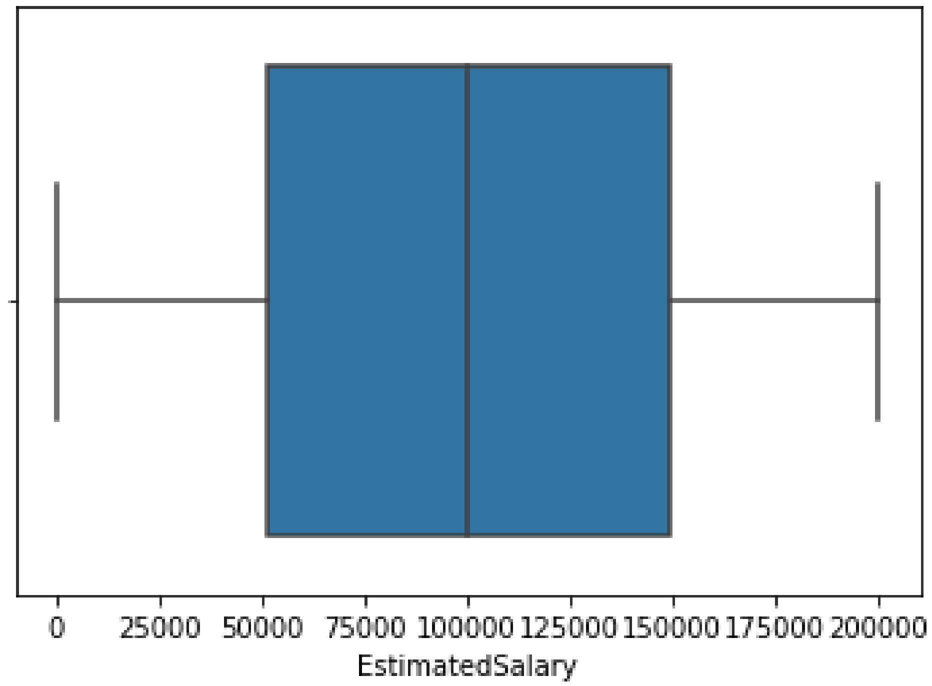
```
df.isnull().sum()
```

```
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

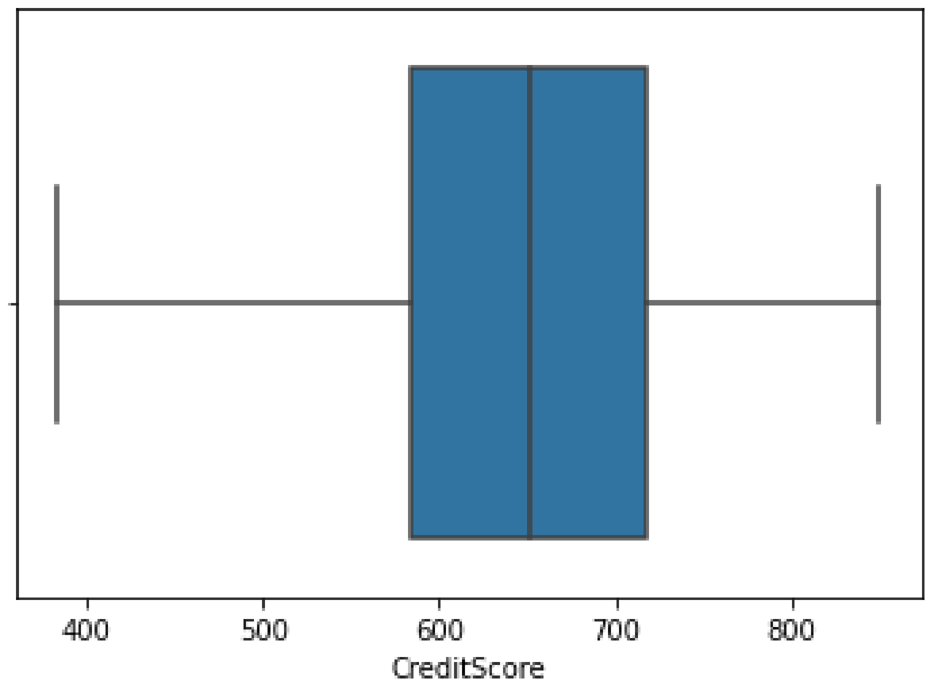
```
sns.boxplot(data = df, x = 'EstimatedSalary')
```

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



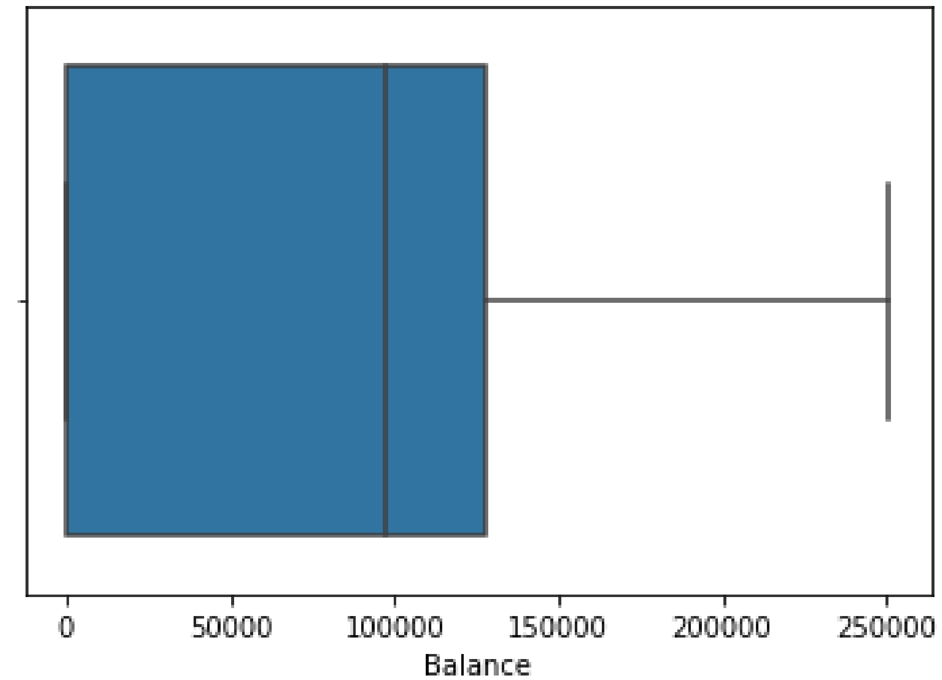

```
sns.boxplot(data = df, x = 'CreditScore')
```

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



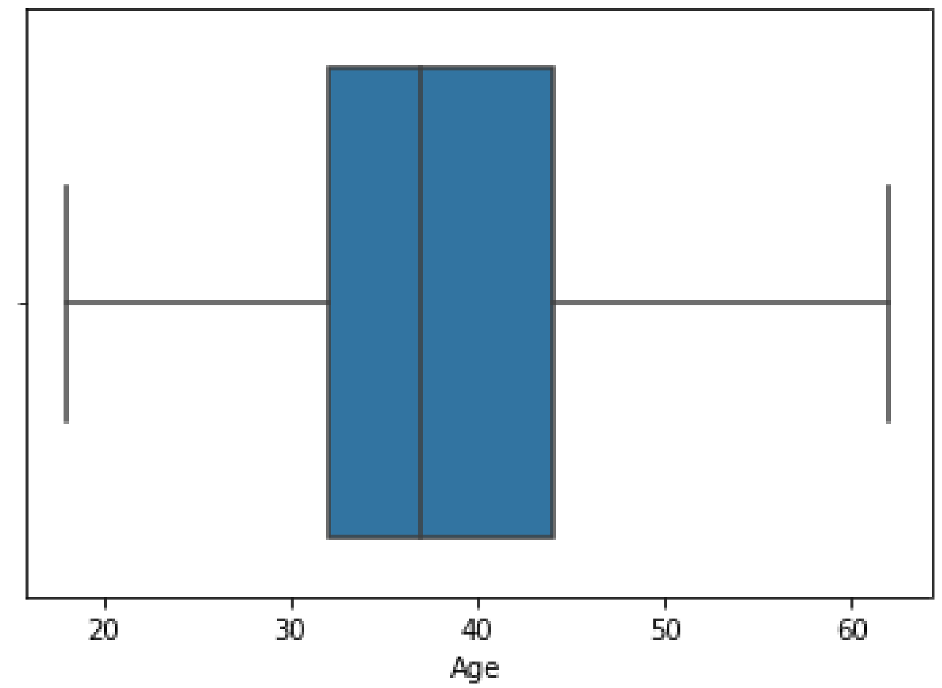

```
sns.boxplot(data = df, x = 'Balance')
```

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



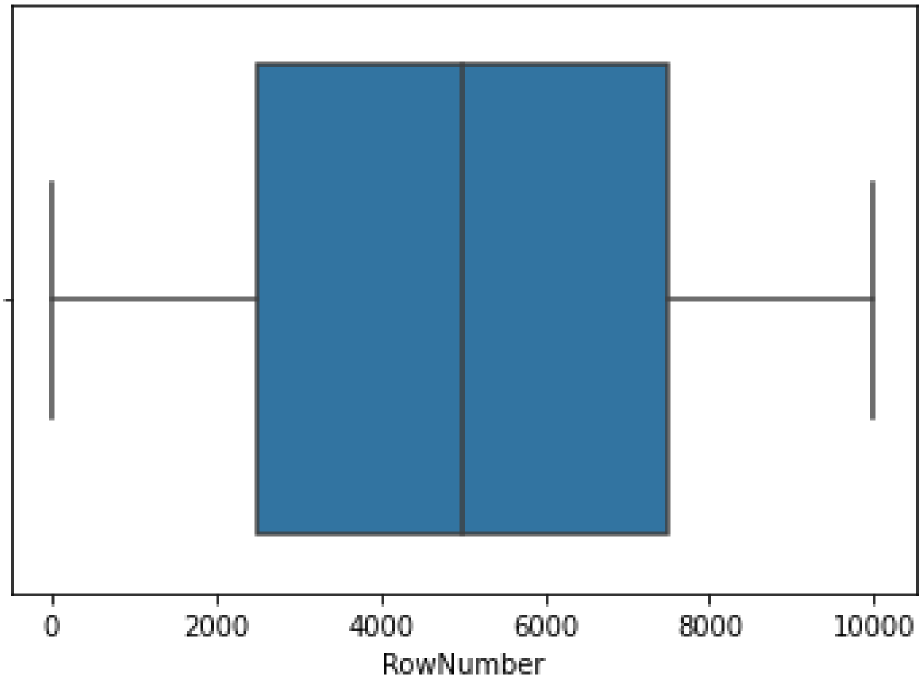

```
sns.boxplot(data = df, x = 'Age')
```

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



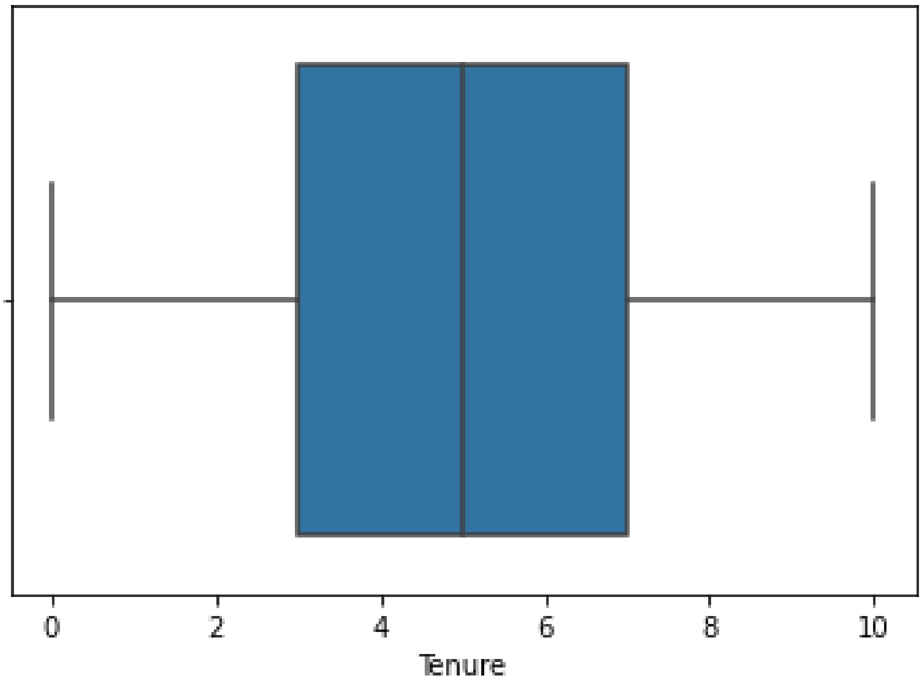

```
sns.boxplot(data = df, x = 'RowNumber')
```

```
<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 CreditScor   Age  Tenure  Surname_Abaz  \
                        e                         u
0        1.0  15634602.0       619.  42.0     2.0             0
                               0
1        2.0  15647311.0       608.  41.0     1.0             0
                               0
2        3.0  15619304.0       502.  42.0     8.0             0
                               0
3        4.0  15701354.0       699.  39.0     1.0             0
                               0
4        5.0  15737888.0       850.  43.0     2.0             0
                               0

   Surname_Abbie Surname_Abbot  Surname_Abdullah Surname_Abdul   ...
\                t                               ov
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_Zubar   Surname_Zubarev  Surname_Zuev Surname_Zuyev \
   ev              a
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_Zuyev   Geography_France Geography_German  Geography_Spain \
   a                                y
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 -         -         -         0.042283 0.00886  -0.016332  0.0
0.702176   1.343330 0.736828           0
-0.0231
1 -          1.55833  1.02525  -0.674496 0.00886  -0.016332  0.0
1.485722    0         7                  0
-0.0231
2 -         -          0.80886 -0.469702 1.39329  -0.016332  0.0
0.524522   0.655156  1                   3
-0.0231
3 -          1.20059  0.39667  -0.060114 0.00886  -0.016332  0.0
1.167396    4         7                  0
-0.0231
4 -          0.77879 -          1.373444 0.70107  -0.016332  0.0
1.451159    8       0.468908             7
-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 -         -         -          0.98465
                                  0.011548 0.011548 0.016332  1
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 -         -         -          0.98465
                                  0.011548 0.011548 0.016332  1

        2938      2939      2940      2941
           0         - 1.087261         -
   1.76021 0.574682           1.087261
           6
         1 -         - 1.087261         -
  0.568112 0.574682           1.087261
         2 - 1.740094 1.087261         -
  0.568112                    1.087261
         3 - 1.740094         - 0.919743
  0.568112          0.919743
```

```
       4 -          -          - 0.919743
  0.568112 0.574682 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,)
```