Data Visualization and Pre-processing

Import libraries

In [ ]:

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

Load dataset

In [ ]:

```
from google.colab import drive
drive.mount('/content/drive')
```

```
Mounted at /content/drive
```

In [ ]:

```
data = pd.read_csv('drive/My Drive/Churn_Modelling.csv')

data.head()
```

Out[ ]:

	RowNumber	CustomerId	Surname	CreditScore	Geography	Gender	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	EstimatedSalary	Exited
0	1	15634602	Hargrave	619	France	Female	42	2	0.00	1	1	1	101348.88	1
1	2	15647311	Hill	608	Spain	Female	41	1	83807.86	1	0	1	112542.58	0
2	3	15619304	Onio	502	France	Female	42	8	159660.80	3	1	0	113931.57	1
3	4	15701354	Boni	699	France	Female	39	1	0.00	2	0	0	93826.63	0
4	5	15737888	Mitchell	850	Spain	Female	43	2	125510.82	1	1	1	79084.10	0

In [ ]:

```
data.info()
```

```
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
```

Visualisations

1. Univariate Analysis

In [ ]:

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

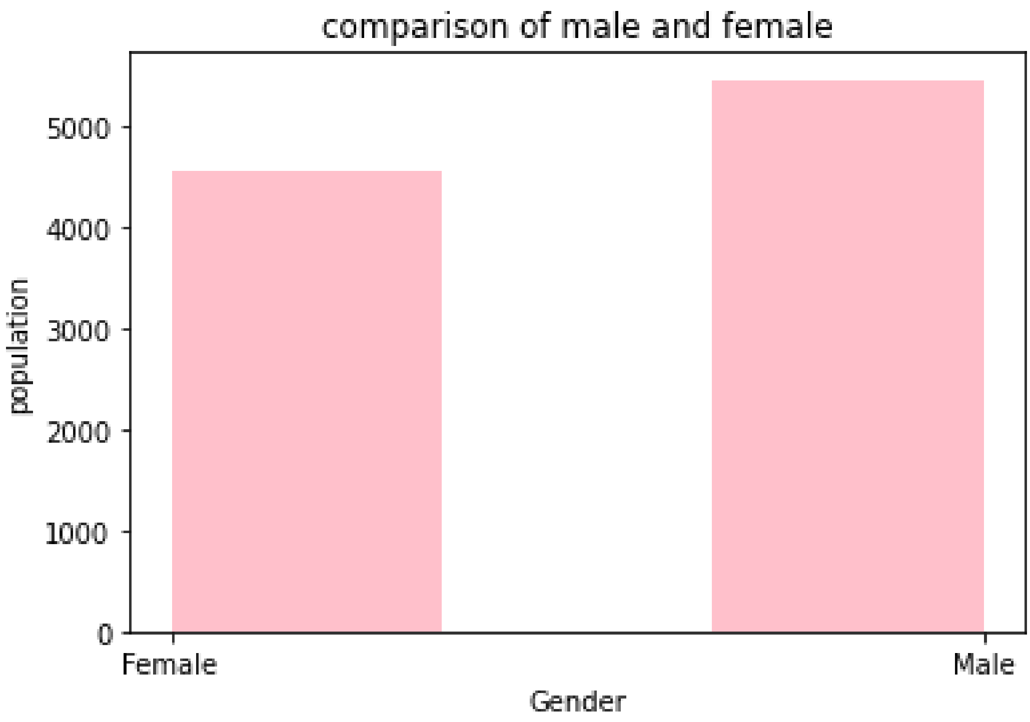
Out[ ]:

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

In [ ]:

```
# Plotting the features of the dataset to see the correlation between them

plt.hist(x = data.Gender, bins = 3, color = 'pink')
plt.title('comparison of male and female')
plt.xlabel('Gender')
plt.ylabel('population')
plt.show()
```



In [ ]:

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

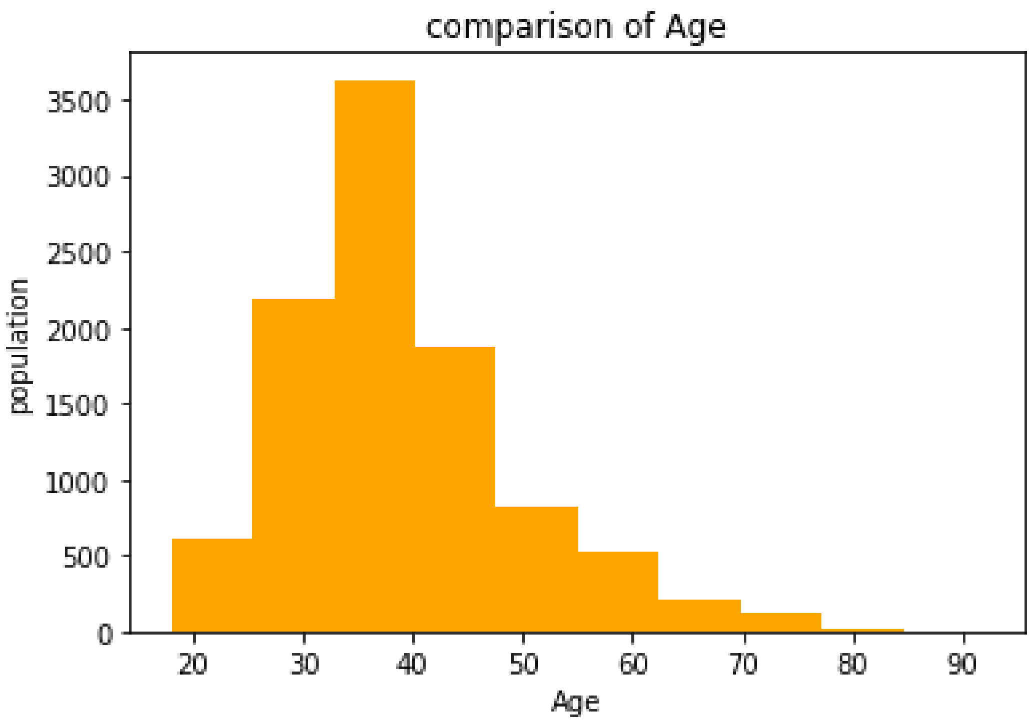
Out[ ]:

```
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
```

In [ ]:

```
# comparison of age in the dataset

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



In [ ]:

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

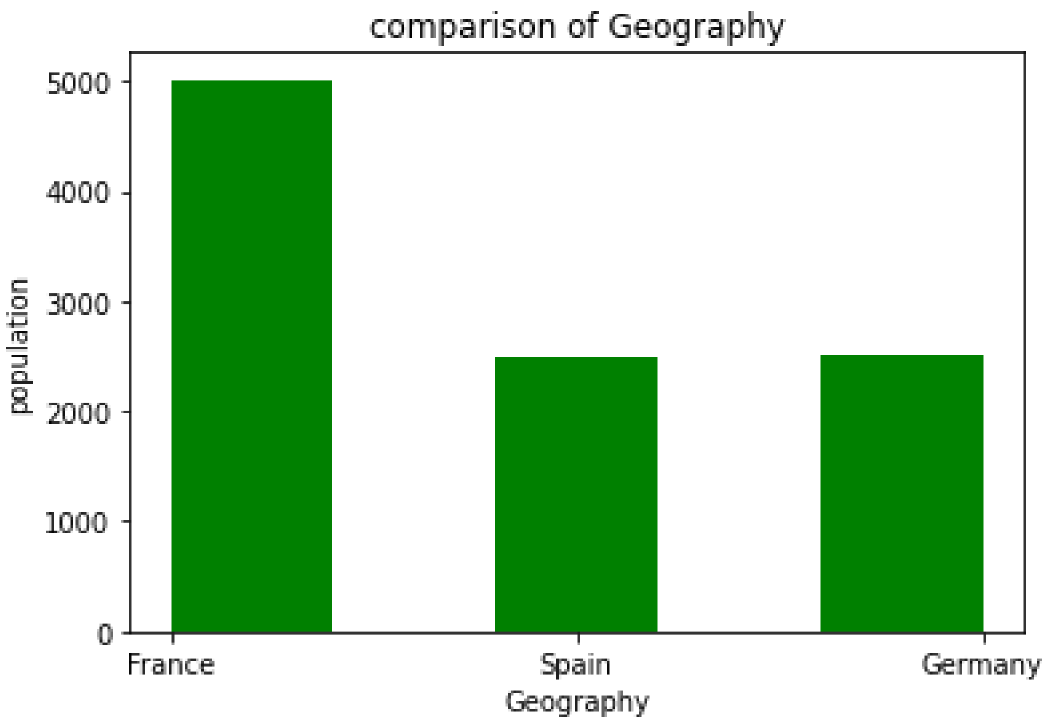
Out[ ]:

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

In [ ]:

```
# comparison of geography

plt.hist(x = data.Geography, bins = 5, color = 'green')
plt.title('comparison of Geography')
plt.xlabel('Geography')
plt.ylabel('population')
plt.show()
```



In [ ]:

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

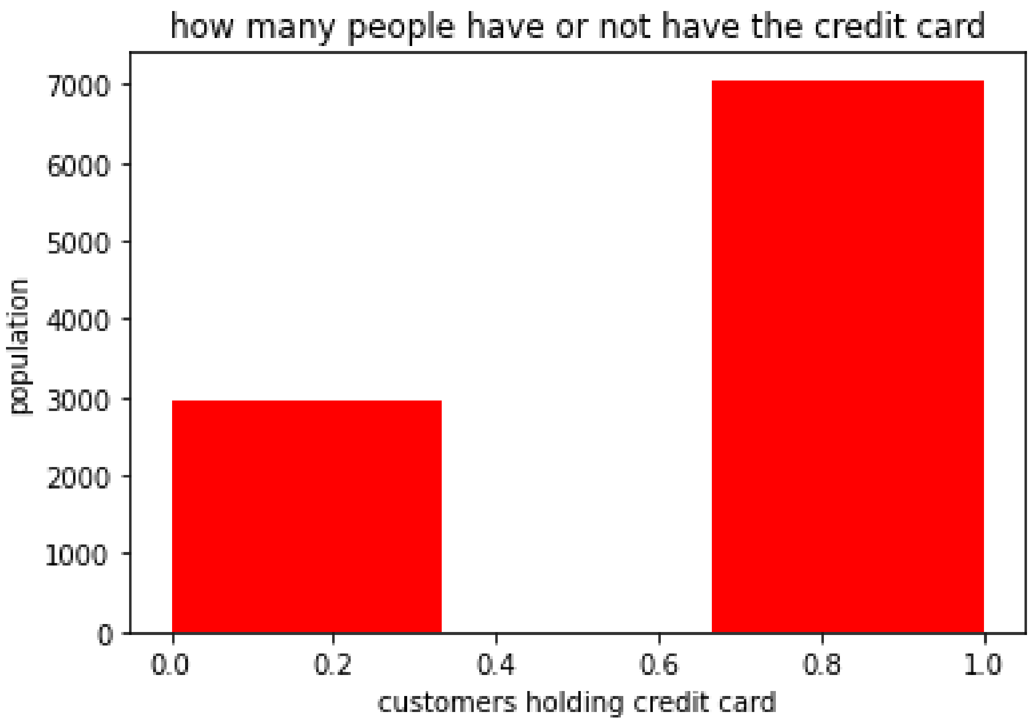
Out[ ]:

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

In [ ]:

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

plt.hist(x = data.HasCrCard, bins = 3, color = 'red')
plt.title('how many people have or not have the credit card')
plt.xlabel('customers holding credit card')
plt.ylabel('population')
plt.show()
```



In [ ]:

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

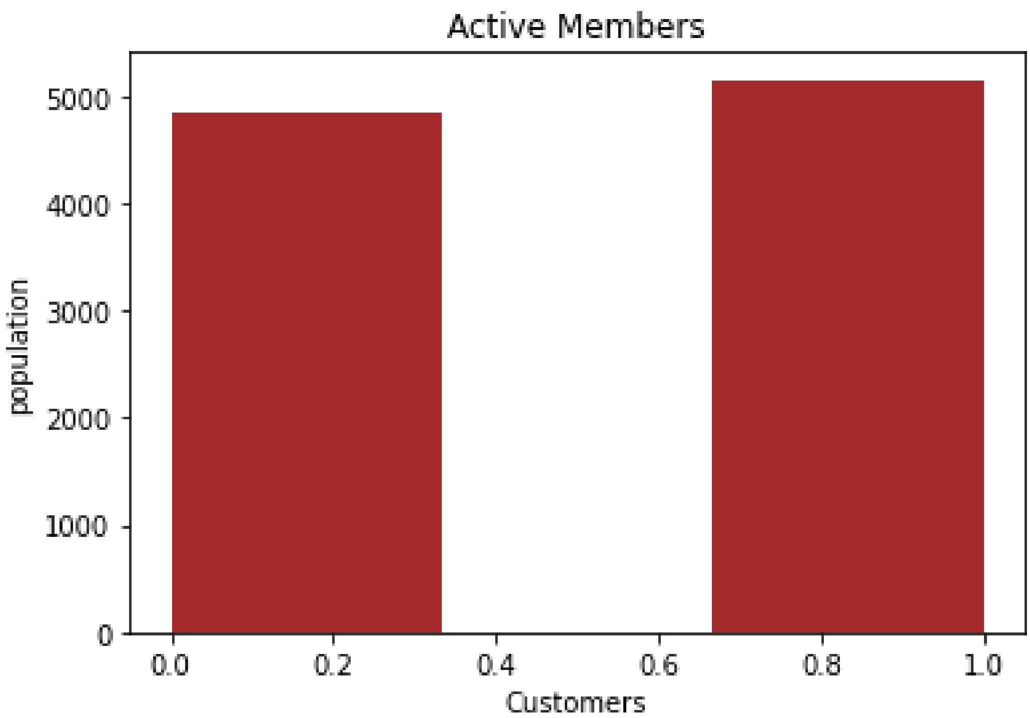
Out[ ]:

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

In [ ]:

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

plt.hist(x = data.IsActiveMember, bins = 3, color = 'brown')
plt.title('Active Members')
plt.xlabel('Customers')
plt.ylabel('population')
plt.show()
```



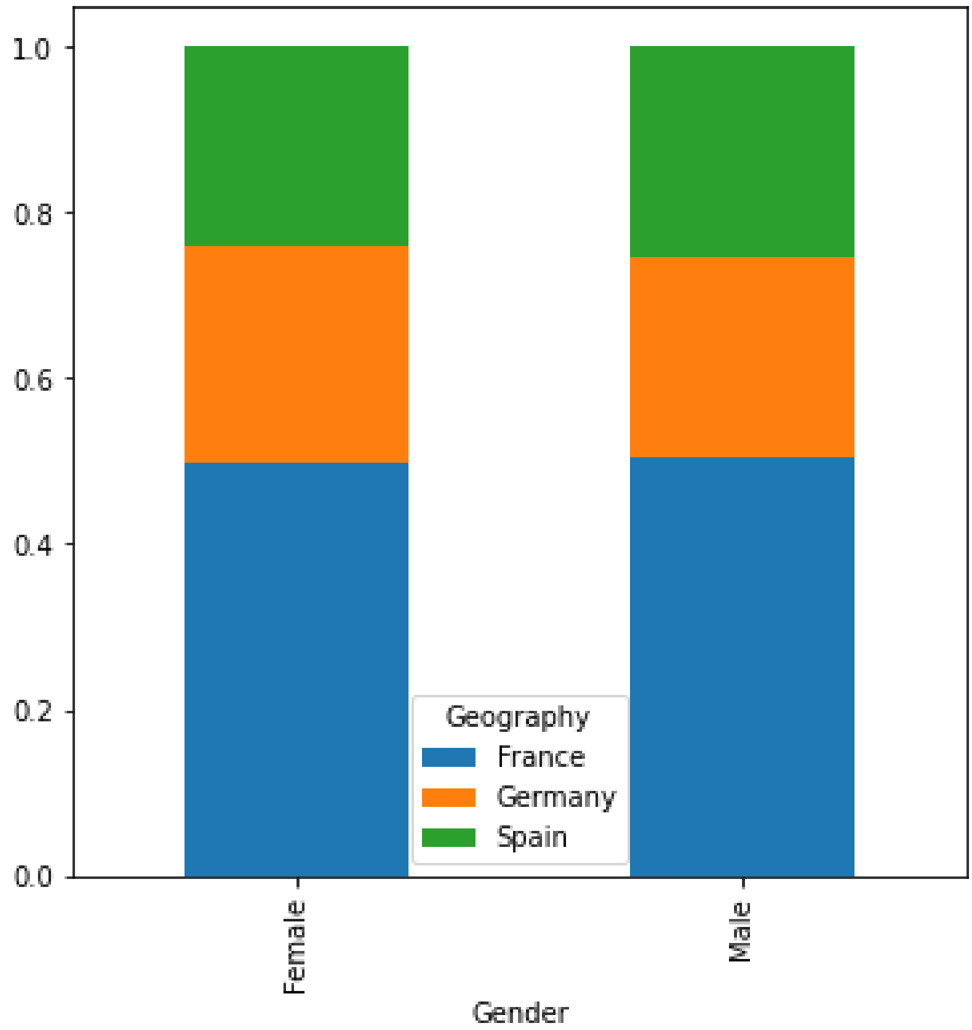
2. Bi - Variate Analysis

In [ ]:

```
# comparison between Geography and Gender

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

Out[ ]:

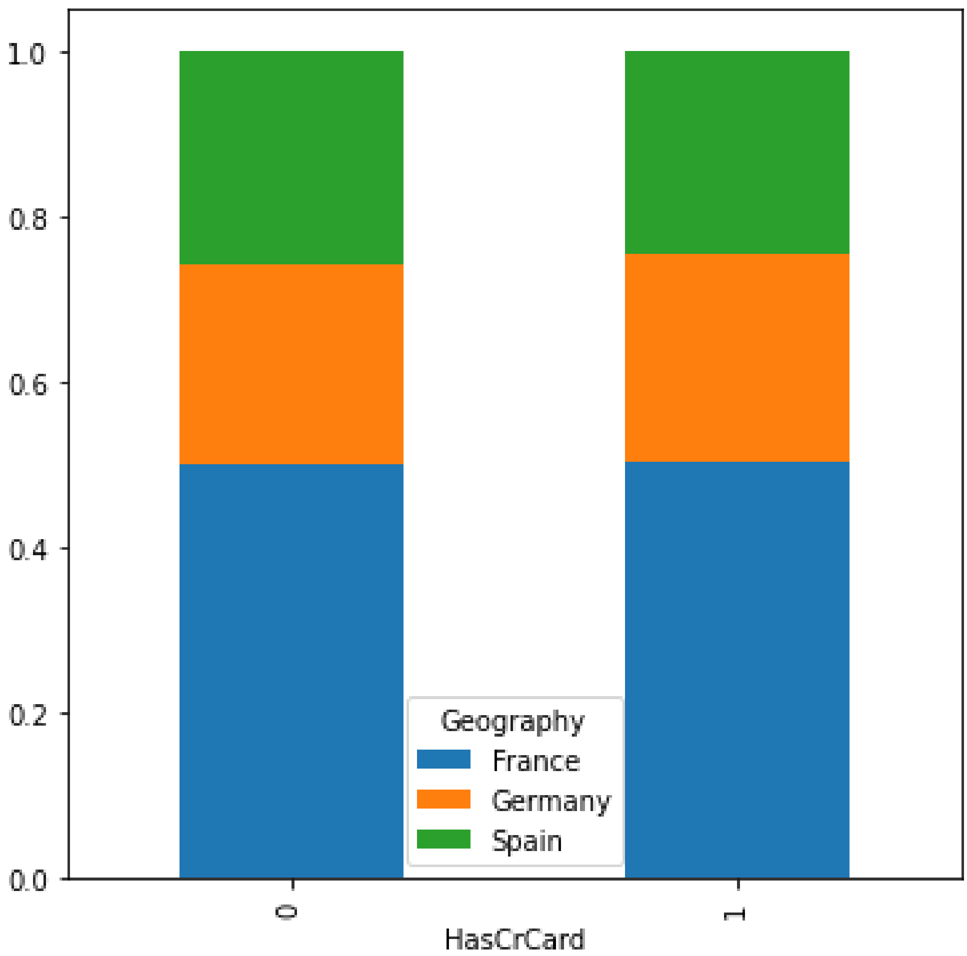


In [ ]:

```
# comparison between geography and card holders

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

Out[ ]:

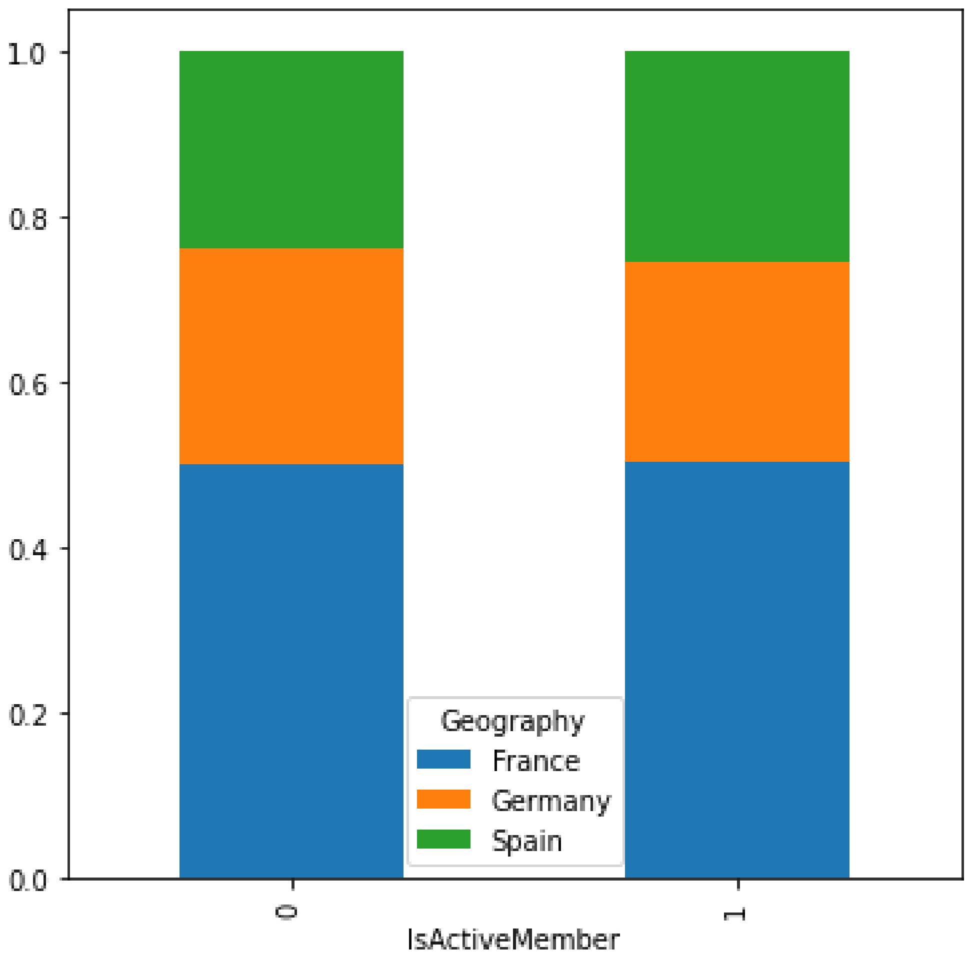


In [ ]:

```
# comparison of active member in diffrent geographies

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

Out[ ]:

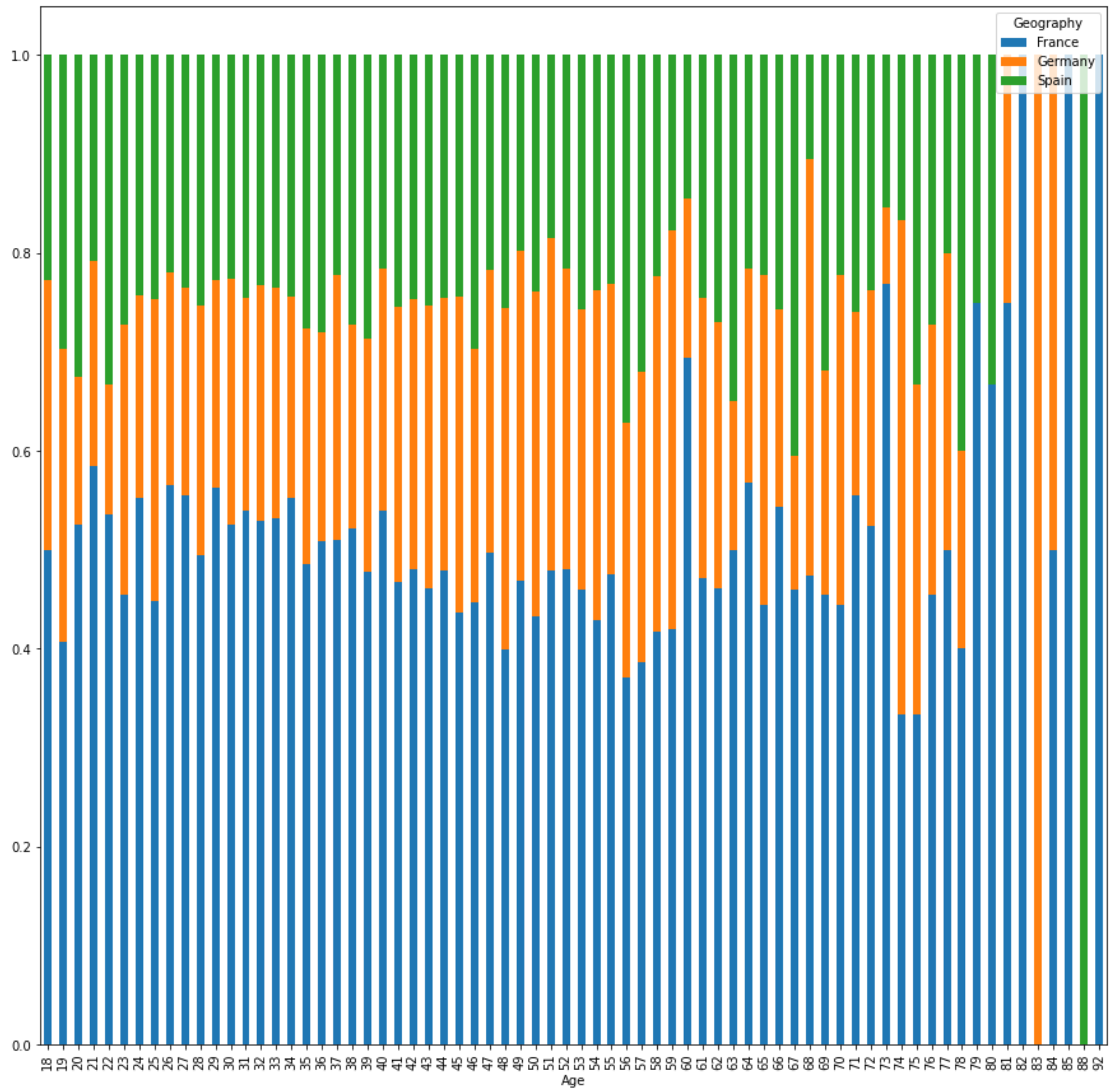


In [ ]:

```
# comparing ages in different geographies

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

Out[ ]:



In [ ]:

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

total_france = data.Balance[data.Geography == 'France'].sum()
total_germany = data.Balance[data.Geography == 'Germany'].sum()
total_spain = data.Balance[data.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
```

In [ ]:

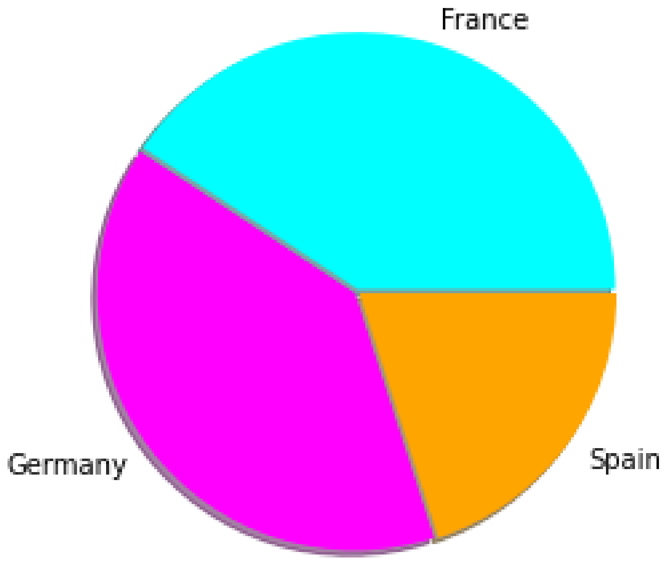
```
# plotting a pie chart

labels = 'France', 'Germany', 'Spain'
colors = ['cyan', 'magenta', '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()
```

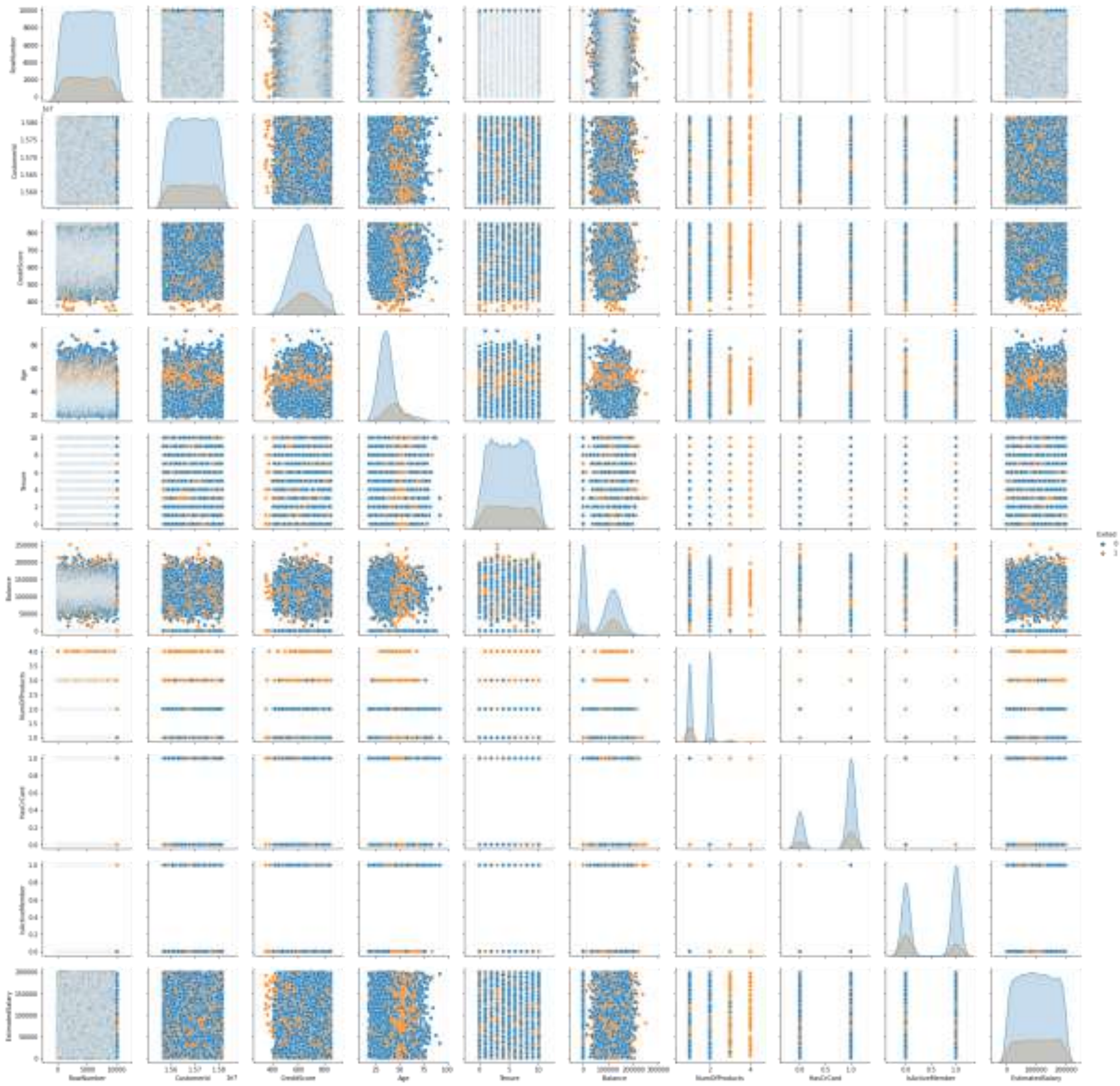


3. Multi - Variate Analysis

In [ ]:

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

Out[ ]:



Descriptive statistics

In [ ]:

```
#Statistical analysis
data.describe()
```

Out[ ]:

	RowNumber	CustomerId	CreditScore	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	EstimatedSalary	Exited
count	10000.00000	1.000000e+04	10000.000000	10000.000000	10000.000000	10000.000000	10000.000000	10000.00000	10000.000000	10000.000000	10000.000000

	RowNumber	CustomerId	CreditScore	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	EstimatedSalary	Exited
mean	5000.50000	1.569094e+07	650.528800	38.921800	5.012800	76485.889288	1.530200	0.70550	0.515100	100090.239881	0.203700
std	2886.89568	7.193619e+04	96.653299	10.487806	2.892174	62397.405202	0.581654	0.45584	0.499797	57510.492818	0.402769
min	1.00000	1.556570e+07	350.000000	18.000000	0.000000	0.000000	1.000000	0.00000	0.000000	11.580000	0.000000
25%	2500.75000	1.562853e+07	584.000000	32.000000	3.000000	0.000000	1.000000	0.00000	0.000000	51002.110000	0.000000
50%	5000.50000	1.569074e+07	652.000000	37.000000	5.000000	97198.540000	1.000000	1.00000	1.000000	100193.915000	0.000000
75%	7500.25000	1.575323e+07	718.000000	44.000000	7.000000	127644.240000	2.000000	1.00000	1.000000	149388.247500	0.000000
max	10000.00000	1.581569e+07	850.000000	92.000000	10.000000	250898.090000	4.000000	1.00000	1.000000	199992.480000	1.000000

Handle the Missing values

In [ ]:

```
#Missing Values
data.isnull().sum()
```

Out[ ]:

```
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
```

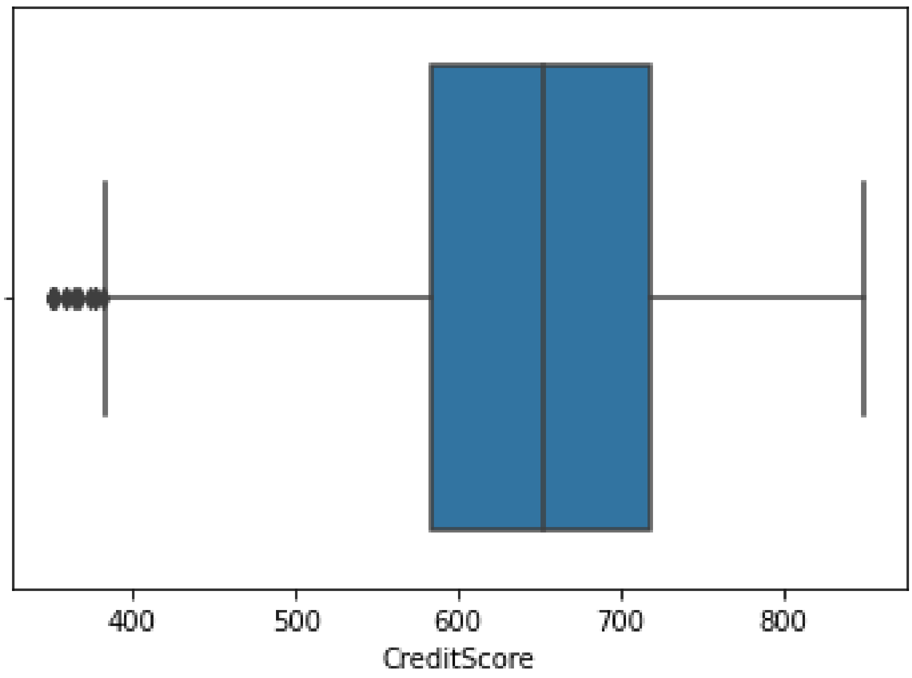
No missing values are found.

Find the outliers and replace the outliers

In [ ]:

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

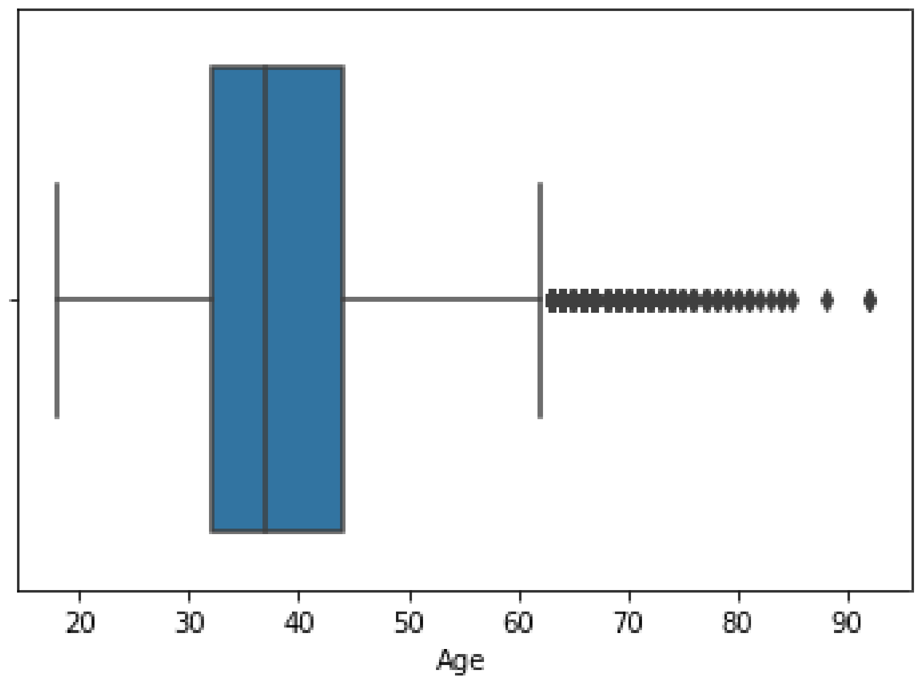
Out[ ]:



In [ ]:

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

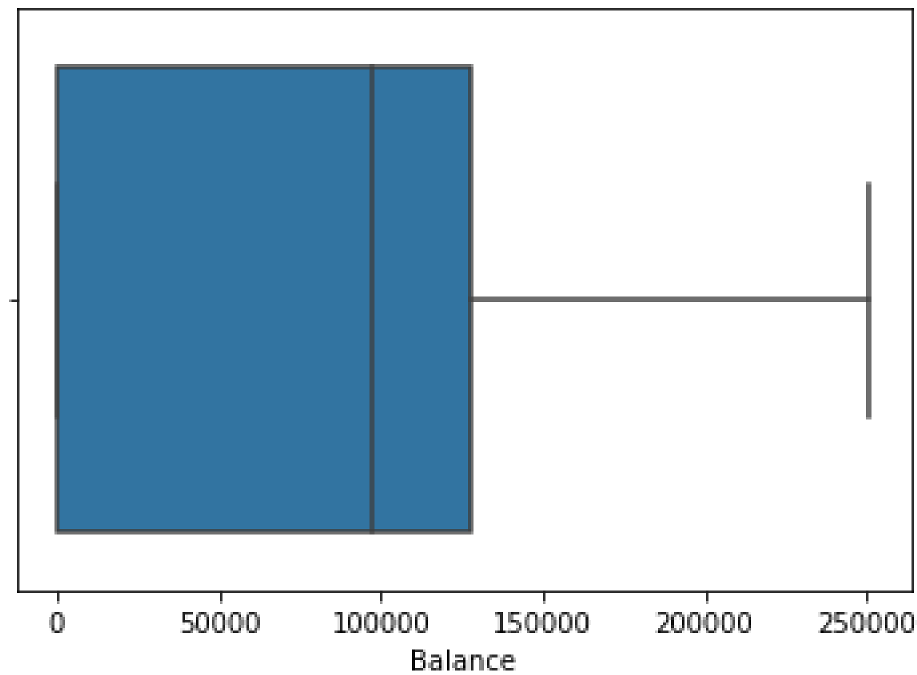
Out[ ]:



In [ ]:

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

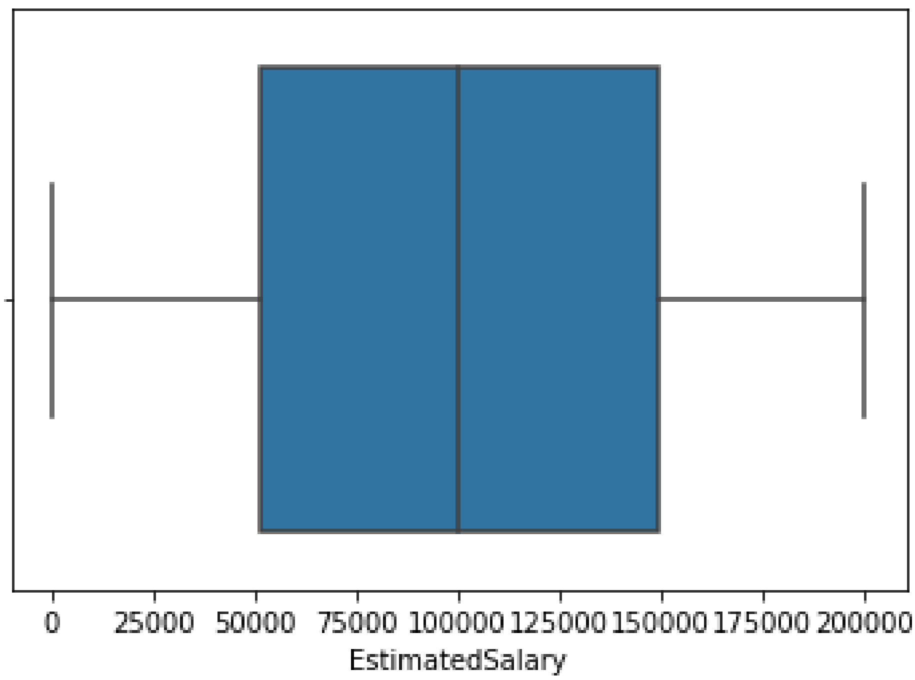
Out[ ]:



In [ ]:

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

Out[ ]:



In [ ]:

```
for i in data:
    if data[i].dtype=='int64' or data[i].dtypes=='float64':
        q1=data[i].quantile(0.25)
        q3=data[i].quantile(0.75)
        iqr=q3-q1
        upper=q3+1.5*iqr
        lower=q1-1.5*iqr
        data[i]=np.where(data[i] >upper, upper, data[i])
        data[i]=np.where(data[i] <lower, lower, data[i])
```

In [ ]:

```
data.describe()
```

Out[ ]:

	RowNumber	CustomerId	CreditScore	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	EstimatedSalary	Exited
count	10000.00000	1.000000e+04	10000.000000	10000.000000	10000.000000	10000.000000	10000.000000	10000.00000	10000.000000	10000.000000	10000.0
mean	5000.50000	1.569094e+07	650.561300	38.660800	5.012800	76485.889288	1.527200	0.70550	0.515100	100090.239881	0.0
std	2886.89568	7.193619e+04	96.558702	9.746704	2.892174	62397.405202	0.570081	0.45584	0.499797	57510.492818	0.0

	RowNumber	CustomerId	CreditScore	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	EstimatedSalary	Exited
min	1.00000	1.556570e+07	383.000000	18.000000	0.000000	0.000000	1.000000	0.00000	0.000000	11.580000	0.0
25%	2500.75000	1.562853e+07	584.000000	32.000000	3.000000	0.000000	1.000000	0.00000	0.000000	51002.110000	0.0
50%	5000.50000	1.569074e+07	652.000000	37.000000	5.000000	97198.540000	1.000000	1.00000	1.000000	100193.915000	0.0
75%	7500.25000	1.575323e+07	718.000000	44.000000	7.000000	127644.240000	2.000000	1.00000	1.000000	149388.247500	0.0
max	10000.00000	1.581569e+07	850.000000	62.000000	10.000000	250898.090000	3.500000	1.00000	1.000000	199992.480000	0.0

Preprocessing

In [ ]:

```
# Removing the unnecassary features from the dataset

data = data.drop(['CustomerId', 'Surname', 'RowNumber'], axis = 1)

print(data.columns)
```

```
Index(['CreditScore', 'Geography', 'Gender', 'Age', 'Tenure', 'Balance',
       'NumOfProducts', 'HasCrCard', 'IsActiveMember', 'EstimatedSalary',
       'Exited'],
      dtype='object')
```

In [ ]:

```
data.shape
```

Out[ ]:

```
(10000, 11)
```

Split the data into dependent and independent variables

In [ ]:

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

```
x = data.iloc[:,0:10]
y = data.iloc[:,10]

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

print(x.columns)
```

```
(10000, 10)
(10000,)
Index(['CreditScore', 'Geography', 'Gender', 'Age', 'Tenure', 'Balance',
       'NumOfProducts', 'HasCrCard', 'IsActiveMember', 'EstimatedSalary'],
      dtype='object')
```

Check for Categorical columns and perform encoding

In [ ]:

```
# Encoding Categorical variables into numerical variables
# One Hot Encoding

x = pd.get_dummies(x)

x.head()
```

Out[ ]:

	CreditScore	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	EstimatedSalary	Geography_France	Geography_Germany	Geography_Spain	Gender_Female	Gender_Male
0	619.0	42.0	2.0	0.00	1.0	1.0	1.0	101348.88	1	0	0	1	0
1	608.0	41.0	1.0	83807.86	1.0	0.0	1.0	112542.58	0	0	1	1	0
2	502.0	42.0	8.0	159660.80	3.0	1.0	0.0	113931.57	1	0	0	1	0
3	699.0	39.0	1.0	0.00	2.0	0.0	0.0	93826.63	1	0	0	1	0

	CreditScore	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	EstimatedSalary	Geography_France	Geography_Germany	Geography_Spain	Gender_Female	Gender_Male
4	850.0	43.0	2.0	125510.82	1.0	1.0	1.0	79084.10	0	0	1	1	0

Split the data into training and testing

In [ ]:

```
# splitting the data into training and testing set

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, 13)
(7500,)
(2500, 13)
(2500,)
```

Scale the independent variables

In [ ]:

```
# Feature Scaling
# Only on Independent Variable to convert them into values ranging from -1
to +1

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()
```

Out[ ]:

	0	1	2	3	4	5	6	7	8	9	10	11	12
0	-0.736828	0.042283	0.008860	0.673160	2.583231	-1.553624	-1.034460	-1.640810	-1.015588	1.760216	-0.574682	1.087261	-1.087261

	0	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**
1	1.025257	-0.674496	0.008860	-1.207724	0.822578	0.643657	-1.034460	-0.079272	0.984651	-0.568112	-0.574682	1.087261	-1.087261
2	0.808861	-0.469702	1.393293	-0.356937	0.822578	0.643657	0.966688	-0.996840	-1.015588	-0.568112	1.740094	1.087261	-1.087261
3	0.396677	-0.060114	0.008860	-0.009356	-0.938076	0.643657	0.966688	-1.591746	-1.015588	-0.568112	1.740094	-0.919743	0.919743
4	-0.468908	1.373444	0.701077	-1.207724	0.822578	0.643657	0.966688	1.283302	0.984651	-0.568112	-0.574682	-0.919743	0.919743