Assignment – 2

Assignment Date	25 September 2022
Student Name	Rajarajeswari J
Student Roll Number	820419205044
Maximum Marks	2 Marks

1. Download the dataset: Dataset

2 . Load the Dataset

import pandas as pd import numpy as np
import matplotlib.pyplot as plt import
seaborn as sns
df =pd.read_csv("gdrive/My Drive/Churn_Modelling.csv") df.head()

OUTPUT:

```
   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
```

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

Mounted at /content/gdrive

#dropping row number columns as we already have index column by default dataset.drop(['RowNumber'], axis=1,inplace=True)

3 . Visualizations

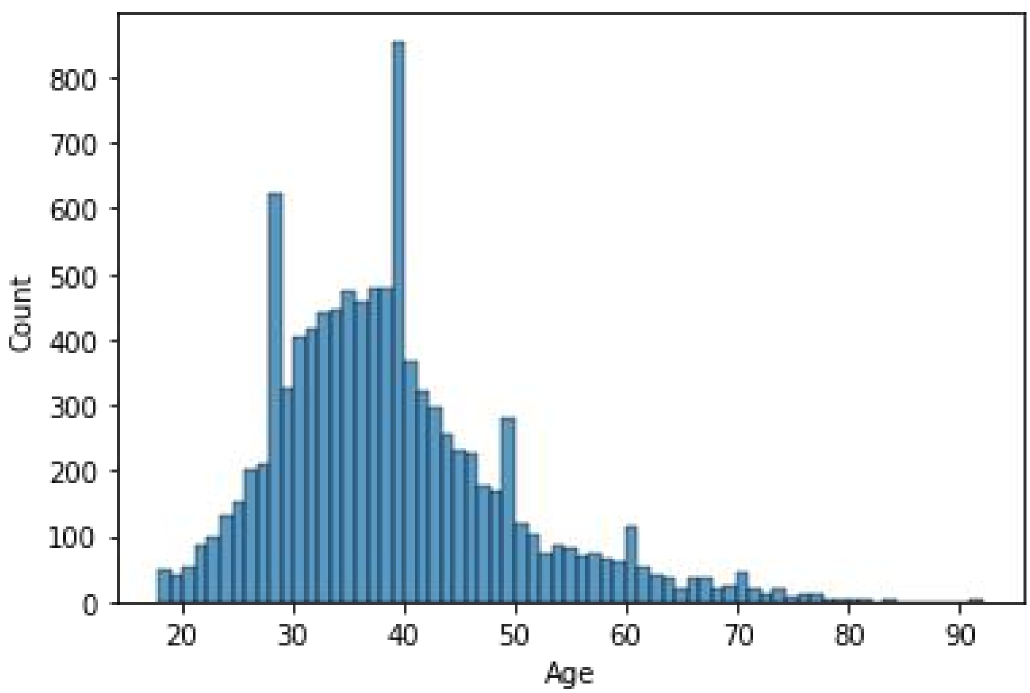
import matplotlib.pyplot as plt import
seaborn as sns

##**Univariate Analysis**

 # plt.scatter(churn.index,churn["Age"])
 # plt.show()

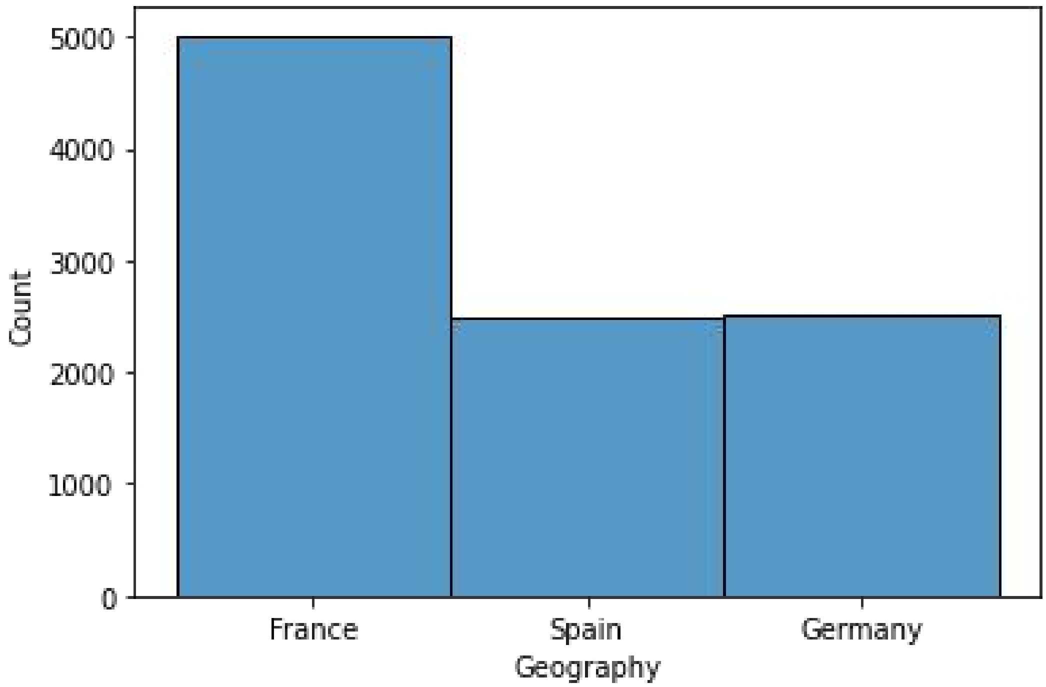
 # Age Histogram sns.histplot(x='Age',
data=dataset)

<matplotlib.axes._subplots.AxesSubplot at 0x7f76872b9410>



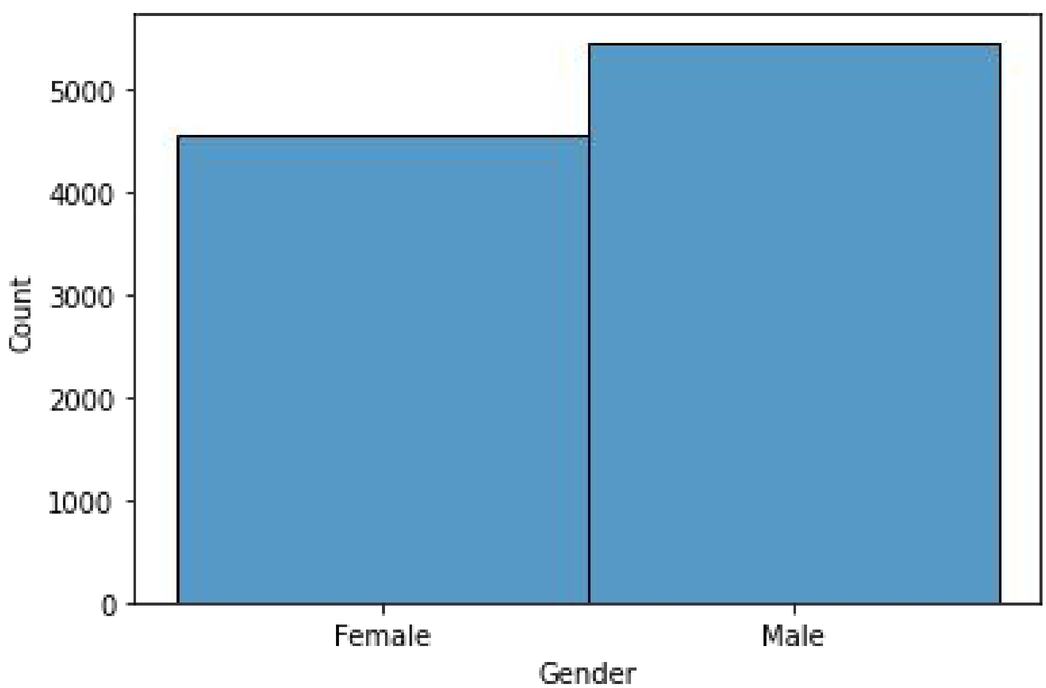
 # Geography Histogram sns.histplot(x='Geography',
data=dataset)

<matplotlib.axes._subplots.AxesSubplot at 0x7f76864b6390>



 # Geography Histogram sns.histplot(x='Gender', data=dataset)

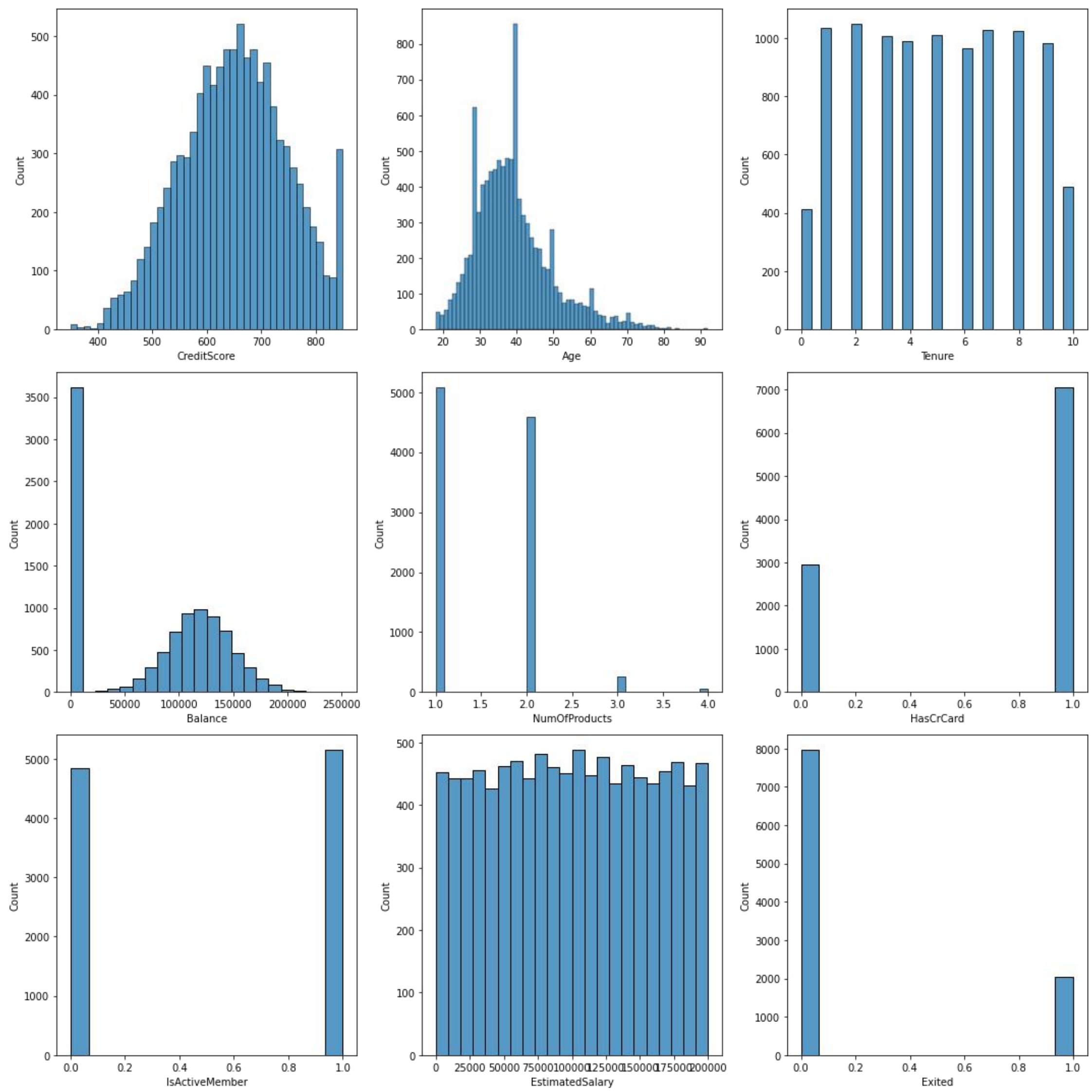
<matplotlib.axes._subplots.AxesSubplot at 0x7f7685fdee90>



cols = 3 rows = 3

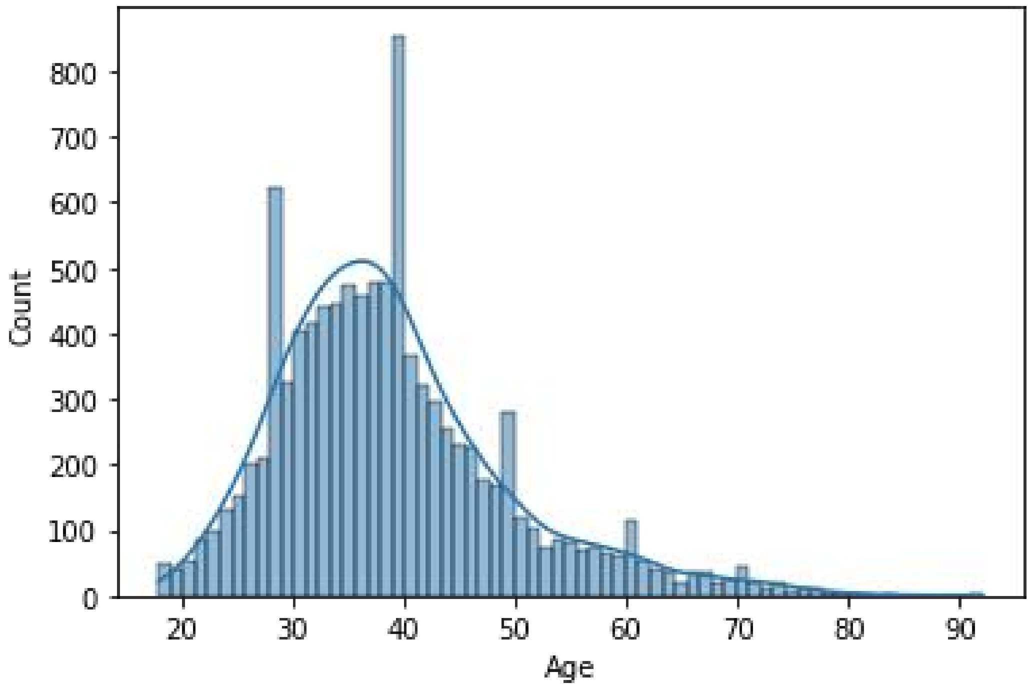
```
num_cols = dataset.select_dtypes(exclude='object').columns #exclude string based columns namely Surname, Geography, Gender print(num_cols)
fig = plt.figure(figsize=(cols*5, rows*5))
for i, col in enumerate(num_cols[1:]): #exclude Customer ID
    ax=fig.add_subplot(rows,cols,i+1)
    sns.histplot(x = dataset[col], ax = ax)

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

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



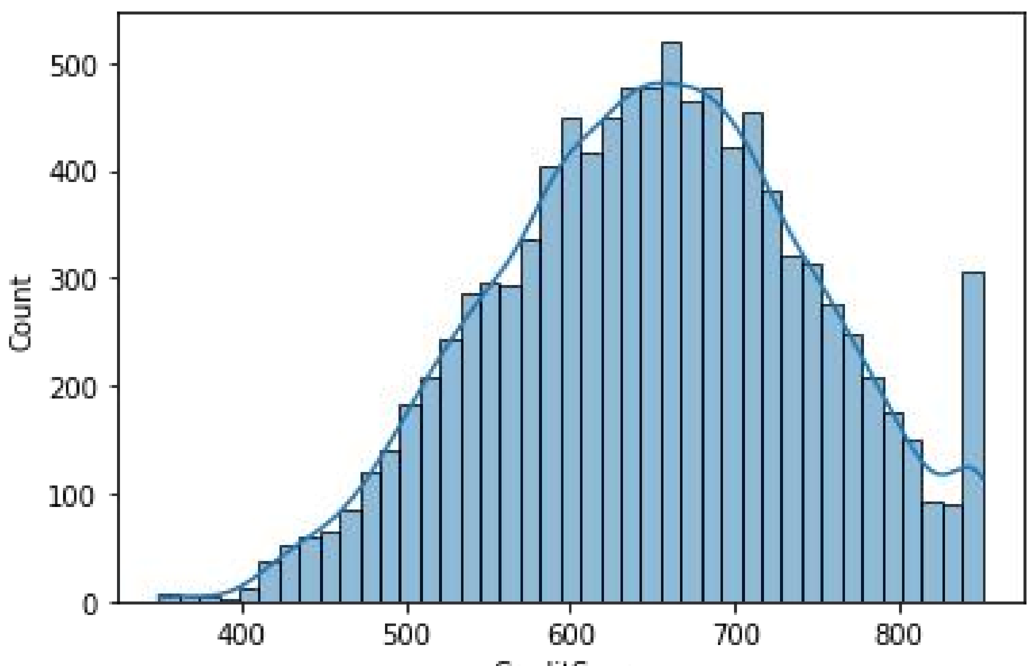

```
# sns.kdeplot(x='Age', data=churn, hue='Exited') sns.histplot(x='Age', data=dataset, kde=True)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f7685ba8290>
```



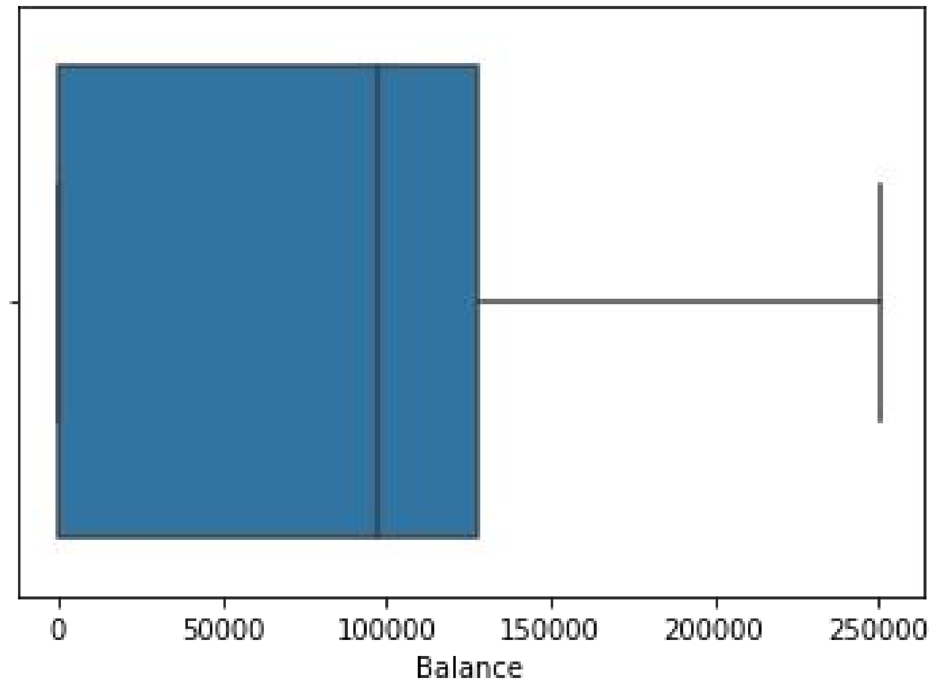
sns.kdeplot(x='Age', data=churn, hue='IsActiveMember') sns.histplot(x='CreditScore', data=dataset, kde=True)

<matplotlib.axes._subplots.AxesSubplot at 0x7f768597f2d0>



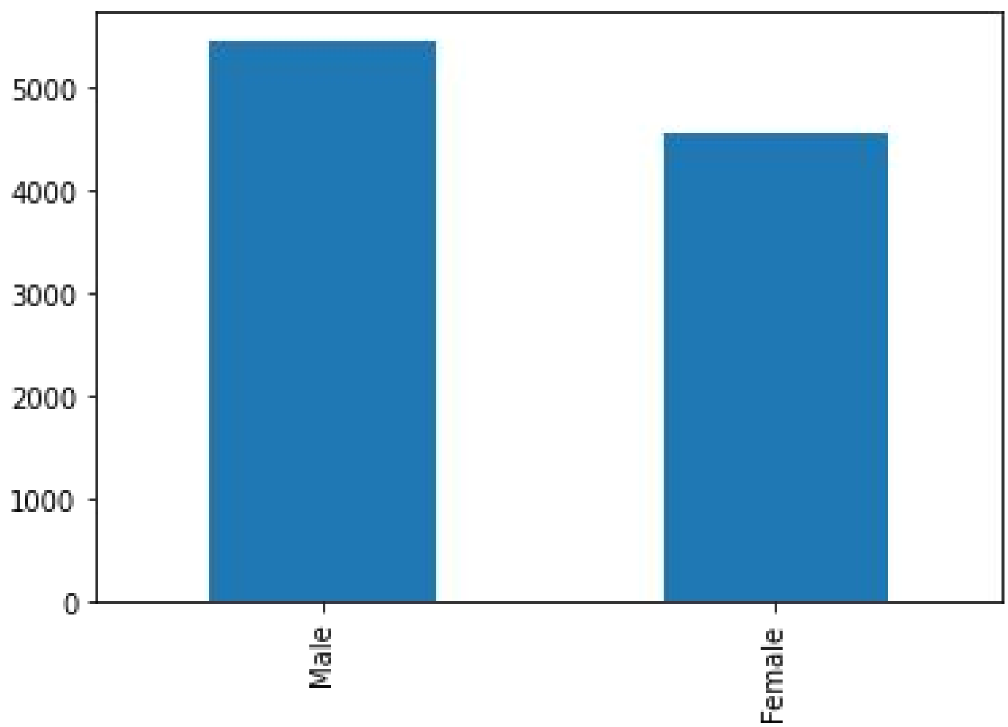
sns.boxplot(x=dataset['Balance'])

<matplotlib.axes._subplots.AxesSubplot at 0x7f7686032110>



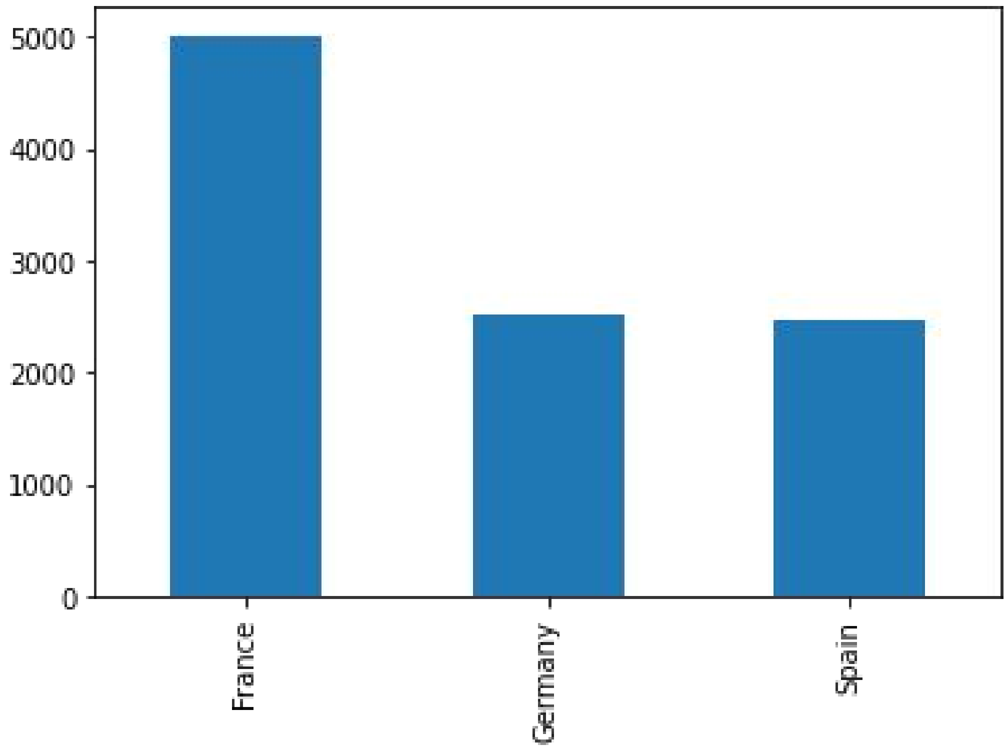
dataset['Gender'].value_counts().plot.bar()

<matplotlib.axes._subplots.AxesSubplot at 0x7f7682e1ea50>



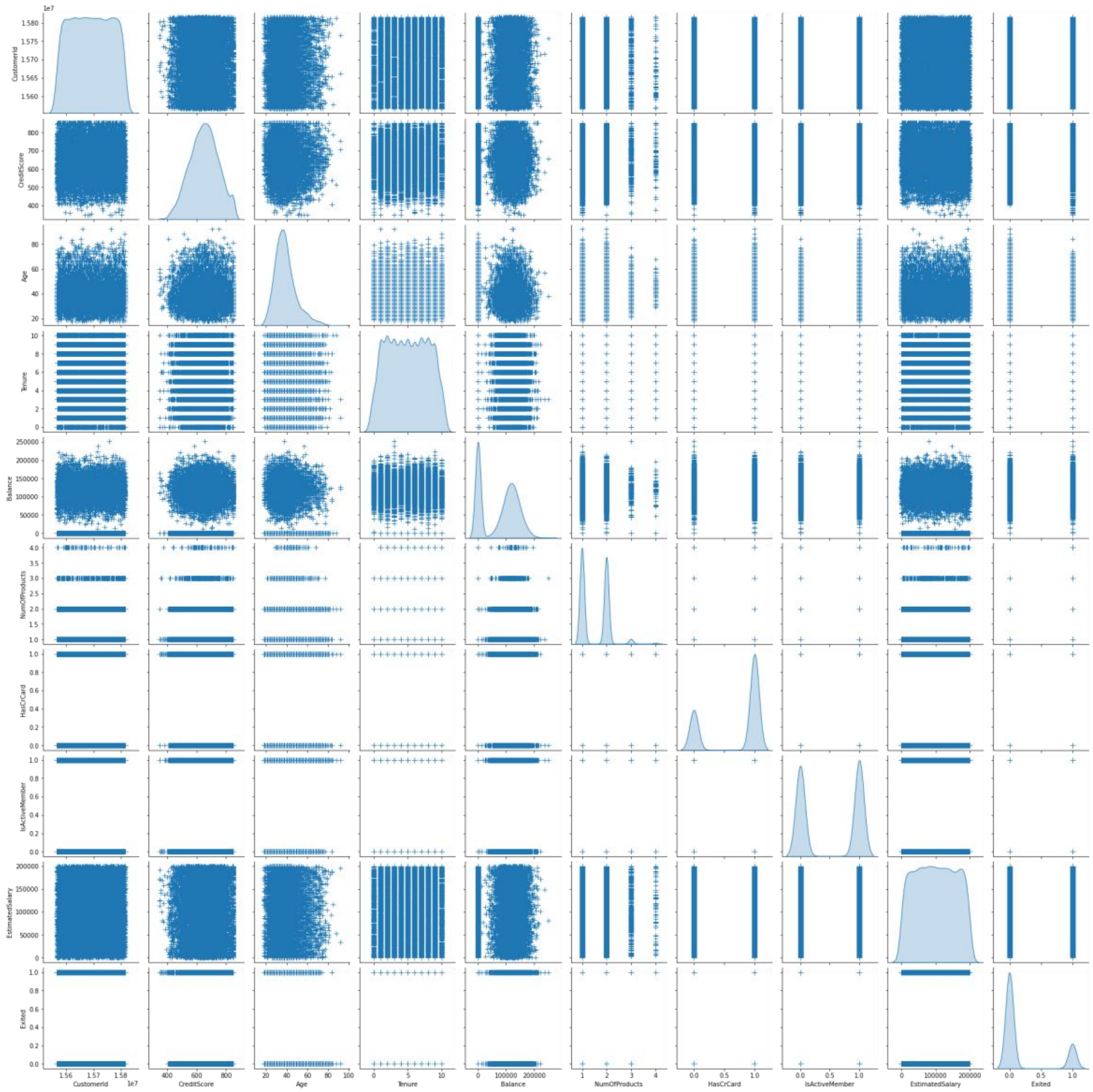
dataset['Geography'].value_counts().plot.bar()

<matplotlib.axes._subplots.AxesSubplot at 0x7f7683120d90>



##**Bi** - **Variate Analysis**

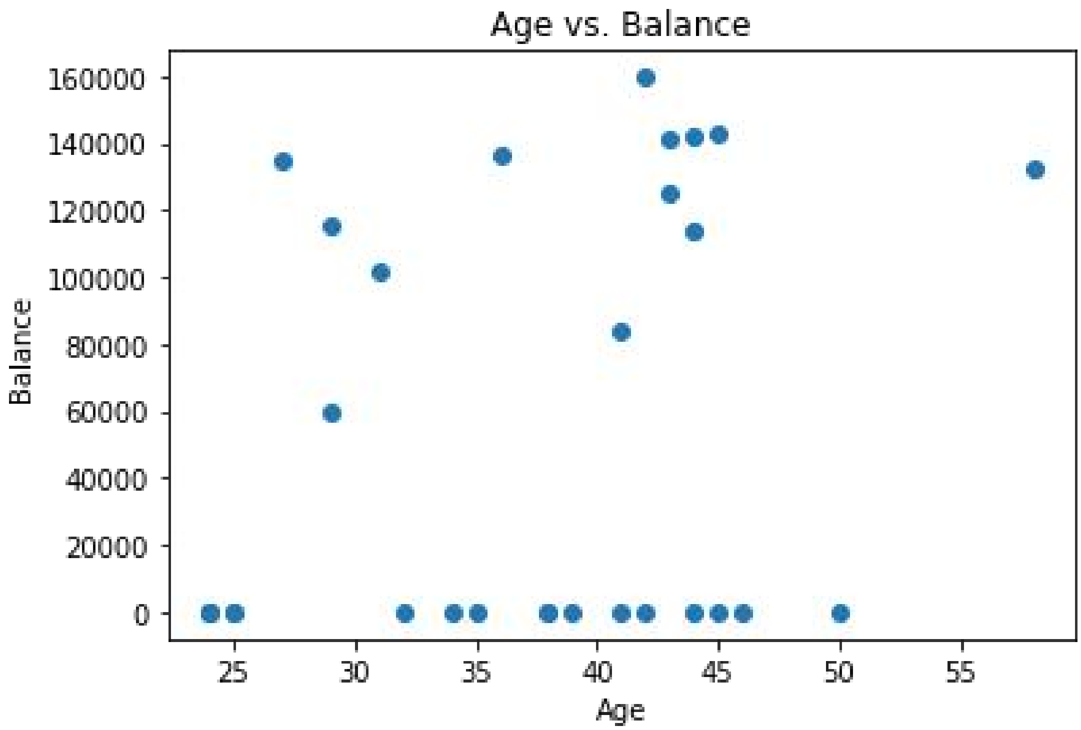
g = sns.pairplot(dataset, diag_kind="kde", markers="+", plot_kws=dict(s=50, edgecolor="b", linewidth=1), diag_kws=dict(shade=True))



import matplotlib.pyplot as plt

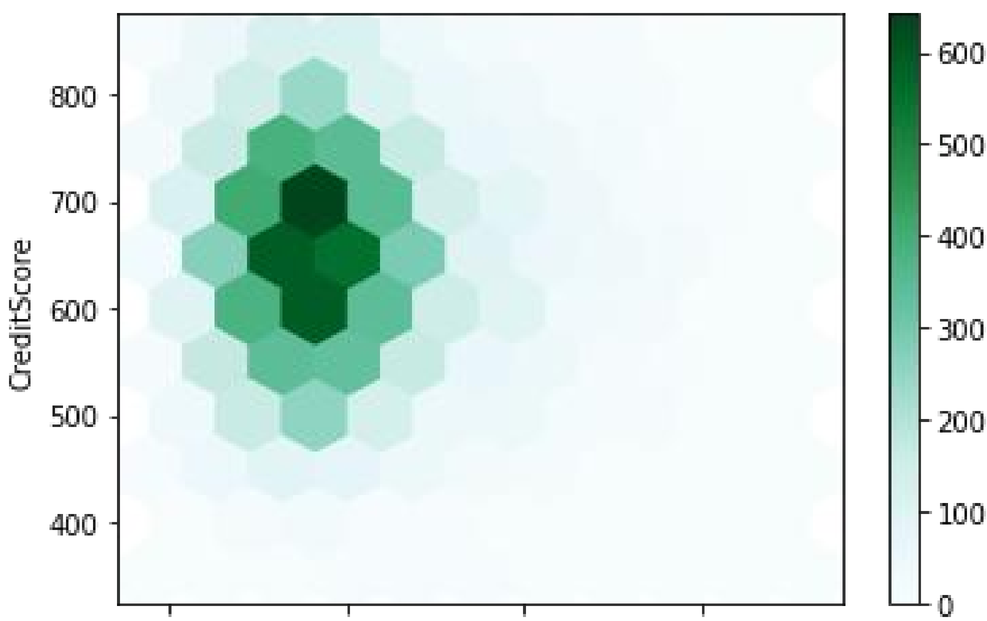
#create scatterplot of hours vs. score
plt.scatter(dataset.Age[:30], dataset.Balance[:30]) plt.title('Age vs. Balance') plt.xlabel('Age') plt.ylabel('Balance')

Text(0, 0.5, 'Balance')



dataset.plot.hexbin(x='Age', y='CreditScore', gridsize=10)

<matplotlib.axes._subplots.AxesSubplot at 0x7f7682d84690>



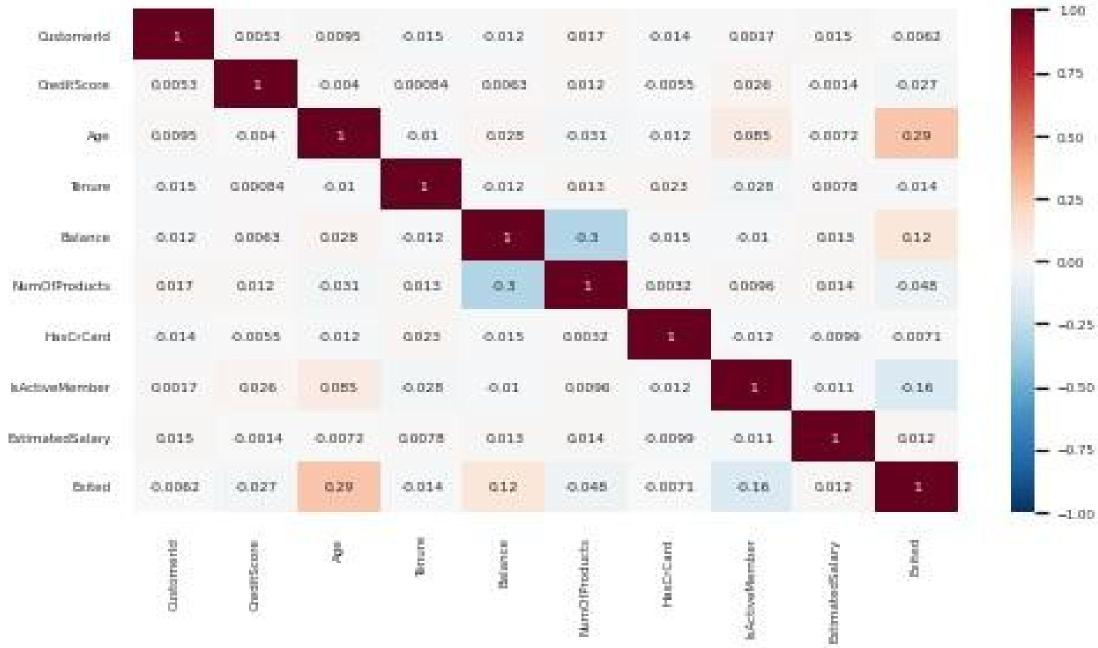
##**Multi-variate Analysis** dataset.corr()

```
             CustomerId  CreditScore       Age    Tenure   Balance  \
CustomerId     1.000000     0.005308  0.009497 -0.014883 -0.012419
```

```
CreditScore        0.005308     1.000000 -0.003965  0.000842  0.006268
Age                0.009497    -0.003965  1.000000 -0.009997  0.028308
Tenure            -0.014883     0.000842 -0.009997  1.000000 -0.012254
Balance           -0.012419     0.006268  0.028308 -0.012254  1.000000
NumOfProducts      0.016972     0.012238 -0.030680  0.013444 -0.304180
HasCrCard         -0.014025    -0.005458 -0.011721  0.022583 -0.014858
IsActiveMember     0.001665     0.025651  0.085472 -0.028362 -0.010084
EstimatedSalary    0.015271    -0.001384 -0.007201  0.007784  0.012797
Exited            -0.006248    -0.027094  0.285323 -0.014001  0.118533

       NumOfProducts  HasCrCard  IsActiveMember  EstimatedSalary  \
CustomerId             0.016972  -0.014025        0.001665
0.015271
CreditScore            0.012238  -0.005458        0.025651        -
0.001384
Age                   -0.030680  -0.011721        0.085472        -
0.007201
Tenure                 0.013444   0.022583       -0.028362
0.007784
Balance               -0.304180  -0.014858       -0.010084
0.012797
NumOfProducts          1.000000   0.003183        0.009612
0.014204
HasCrCard              0.003183   1.000000       -0.011866        -
0.009933
IsActiveMember         0.009612  -0.011866        1.000000        -
0.011421
EstimatedSalary        0.014204  -0.009933       -0.011421
1.000000    Exited                -0.047820  -0.007138       -0.156128
0.012097

                   Exited
CustomerId      -0.006248
CreditScore     -0.027094
Age              0.285323
Tenure          -0.014001
Balance          0.118533
NumOfProducts   -0.047820
HasCrCard       -0.007138
IsActiveMember  -0.156128
EstimatedSalary  0.012097
Exited           1.000000
```

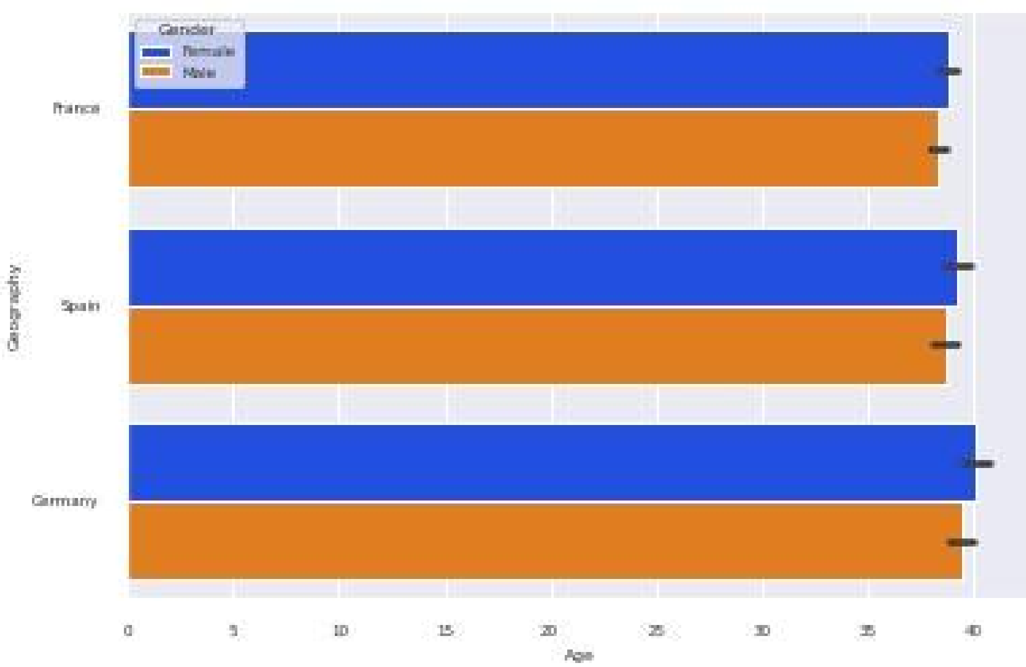
```
sns.set(font_scale=0.50) plt.figure(figsize=(8,4))
sns.heatmap(dataset.corr(),cmap='RdBu_r', annot=True, vmin=-1, vmax=1)
```

<matplotlib.axes._subplots.AxesSubplot at 0x7f7680979950>




```
#Three variables - Multivaraiate
sns.barplot(x='Age', y='Geography', data=dataset, palette='bright',hue='Gender')
```

<matplotlib.axes._subplots.AxesSubplot at 0x7f767ec905d0>



4 . Descriptive statistics import
statistics as st
dataset[['Age', 'Balance', 'EstimatedSalary']].mean()

Age 38.921800
Balance 76485.889288
EstimatedSalary 100090.239881

dtype: float64 dataset.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000 entries, 0 to 9999 Data
columns (total 13 columns):
 # Column Non-Null Count Dtype
--- ------ -------------- -----

```
0   CustomerId       10000 non-null  int64
1   Surname          10000 non-null  object
2   CreditScore      10000 non-null  int64
3   Geography        10000 non-null  object
4   Gender           10000 non-null  object
5   Age              10000 non-null  int64
6   Tenure           10000 non-null  int64
7   Balance          10000 non-null  float64
8   NumOfProducts    10000 non-null  int64
9   HasCrCard        10000 non-null  int64
10  IsActiveMember   10000 non-null  int64
11  EstimatedSalary  10000 non-null  float64  12  Exited
    10000 non-null  int64   dtypes: float64(2), int64(8), object(3)
    memory usage: 1015.8+ KB dataset.describe()

         CustomerId   CreditScore           Age        Tenure
Balance
\
count     1.000000e+04    10000.000000    10000.000000    10000.000000
10000.000000      mean     1.569094e+07      650.528800       38.921800
5.012800     76485.889288       std       7.193619e+04        96.653299
10.487806          2.892174     62397.405202      min      1.556570e+07
350.000000       18.000000         0.000000          0.000000      25%
1.562853e+07    584.000000     32.000000      3.000000       0.000000
50%    1.569074e+07    652.000000     37.000000      5.000000
97198.540000    75%    1.575323e+07    718.000000     44.000000
7.000000  127644.240000    max    1.581569e+07    850.000000
92.000000     10.000000  250898.090000
```

```
       NumOfProducts    HasCrCard  IsActiveMember  EstimatedSalary
\ count   10000.000000  10000.00000    10000.000000
10000.000000    mean        1.530200      0.70550        0.515100
100090.239881    std         0.581654      0.45584        0.499797
57510.492818    min         1.000000      0.00000        0.000000
11.580000    25%         1.000000      0.00000        0.000000
51002.110000
50%         1.000000      1.00000        1.000000    100193.915000
75%         2.000000      1.00000        1.000000    149388.247500
max         4.000000      1.00000        1.000000    199992.480000
```

Exited
count 10000.000000 mean
0.203700 std 0.402769
min 0.000000 25%
0.000000
50% 0.000000 75%
0.000000 max 1.000000
dataset['Age'].median()

37.0

standard_deviation = dataset['CreditScore'].std()

print(standard_deviation) 96.65329873613035

st.mode(dataset['Geography'])

{"type":"string"} st.median(dataset['Age'])

37.0 st.variance(dataset['CreditScore'])

9341.860156575658

5 . Handle Missing Values `dataset.isnull().sum()`

#no missing values

```
CustomerId        0
Surname           0
CreditScore       0
Geography         0
Gender            0
Age               0
Tenure            0
Balance           0
```

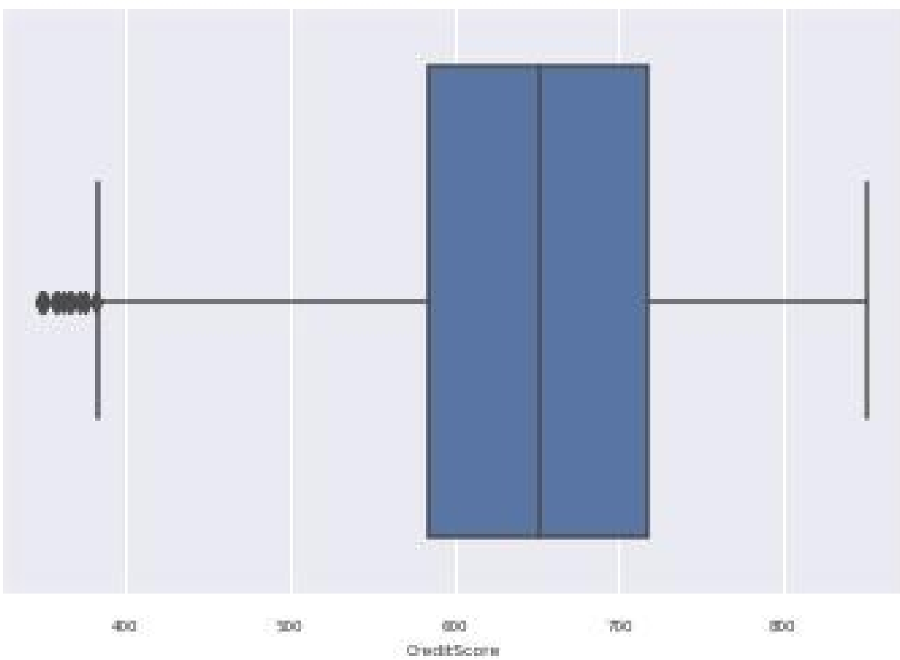
NumOfProducts 0
HasCrCard 0
IsActiveMember 0
EstimatedSalary 0
Exited 0 dtype: int64

6 . Find and replace outliers

Visualize Outliers sns.boxplot(dataset['CreditScore'],data=dataset)

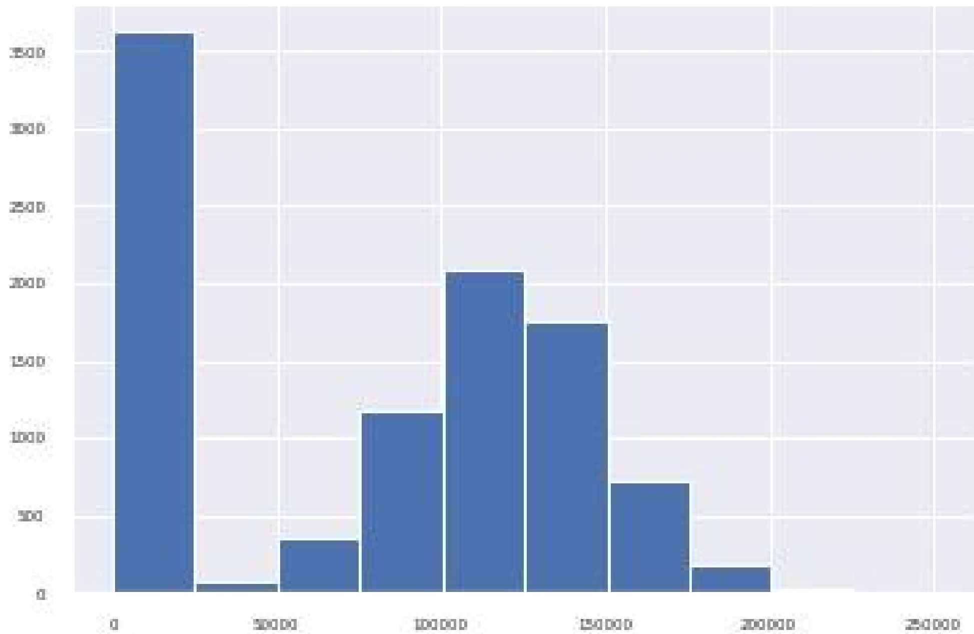
/usr/local/lib/python3.7/dist-packages/seaborn/_decorators.py:43:
FutureWarning: Pass the following variable as a keyword arg: x. From version 0.12, the only valid positional argument will be `data`, and passing other arguments without an explicit keyword will result in an error or misinterpretation. FutureWarning

<matplotlib.axes._subplots.AxesSubplot at 0x7f767ebd9d90>



dataset['Balance'].hist()

<matplotlib.axes._subplots.AxesSubplot at 0x7f767ebbefd0>




```
for col in num_cols[1:]:
  print('skewness value of ',col,dataset[col].skew())
```

#Skewness should be in the range of -1 to 1, any columns with skewness outside of that range would have outliers

```
skewness value of  CreditScore -0.07160660820092675
skewness value of  Age 1.0113202630234552 skewness
value of  Tenure 0.010991457977179042 skewness value of
Balance -0.14110871094154384 skewness value of
NumOfProducts 0.7455678882823168 skewness value of
HasCrCard -0.9018115952400578 skewness value of
IsActiveMember -0.06043662833499078 skewness value of
EstimatedSalary 0.0020853576615585162 skewness value of
Exited 1.4716106649378211
```

```
Q1=dataset['Age'].quantile(0.25)
Q3=dataset['Age'].quantile(0.75)
IQR=Q3-Q1
```

```
IQR
```

```
12.0
```

Removing Outliers

#Values above than the upper bound and below than the lower bound are considered outliers

```
upper = dataset['Age'] >= (Q3+1.5*IQR)
```

```
# print("Upper bound:",upper) print(np.where(upper))

lower = dataset['Age'] <= (Q1-1.5*IQR)
#   print("Lower   bound:",   lower)
print(np.where(lower))

(array([  58,   85,  104,  158,  181,  230,  234,  243,  252,  276,  310,
        364,  371,  385,  387,  399,  538,  559,  567,  602,  612,  617,
        658,  678,  696,  736,  766,  769,  807,  811,  823,  859,  884,
        888,  948,  952,  957,  963,  969,  997, 1009, 1039, 1040, 1055,
       1114, 1205, 1234, 1235, 1246, 1252, 1278, 1285, 1328, 1342, 1387,
       1407, 1410, 1433, 1439, 1457, 1519, 1543, 1607, 1614, 1642, 1790,
       1810, 1866, 1901, 1904, 1907, 1933, 1981, 1996, 2002, 2012, 2039,
       2053, 2078, 2094, 2108, 2154, 2159, 2164, 2244, 2274, 2433, 2458,
       2459, 2519, 2553, 2599, 2615, 2659, 2670, 2713, 2717, 2760, 2772,
       2778, 2791, 2855, 2877, 2901, 2908, 2925, 2926, 3008, 3033, 3054,
       3110, 3142, 3166, 3192, 3203, 3229, 3305, 3308, 3311, 3314, 3317,
       3346, 3366, 3368, 3378, 3382, 3384, 3387, 3396, 3403, 3434, 3462,
       3497, 3499, 3527, 3531, 3541, 3559, 3573, 3575, 3593, 3602, 3641,
       3646, 3647, 3651, 3690, 3691, 3702, 3719, 3728, 3733, 3761, 3813,
       3826, 3880, 3881, 3888, 3909, 3910, 3927, 3940, 3980, 3994, 4010,
       4025, 4048, 4051, 4095, 4142, 4147, 4157, 4162, 4170, 4241, 4244,
       4256, 4273, 4280, 4297, 4313, 4318, 4335, 4360, 4366, 4378, 4387,
       4396, 4435, 4438, 4463, 4490, 4501, 4506, 4559, 4563, 4590, 4595,
       4644, 4698, 4747, 4751, 4801, 4815, 4832, 4849, 4931, 4947, 4966,
       4992, 5000, 5020, 5038, 5068, 5132, 5136, 5148, 5159, 5197, 5223,
       5225, 5235, 5255, 5299, 5313, 5368, 5377, 5405, 5457, 5490, 5508,
       5514, 5576, 5577, 5581, 5655, 5660, 5664, 5671, 5698, 5777, 5783,
       5817, 5825, 5840, 5867, 5907, 5957, 5996, 6046, 6116, 6152, 6166,
       6167, 6173, 6212, 6230, 6278, 6289, 6315, 6357, 6366, 6373, 6375,
       6410, 6443, 6515, 6530, 6532, 6581, 6612, 6626, 6706, 6709, 6715,
       6721, 6759, 6763, 6812, 6899, 6970, 6997, 7008, 7057, 7058, 7063,
       7071, 7078, 7094, 7138, 7139, 7142, 7156, 7194, 7202, 7238, 7243,
       7272, 7302, 7362, 7375, 7392, 7499, 7514, 7523, 7526, 7548, 7552,
       7624, 7629, 7692, 7694, 7709, 7715, 7719, 7720, 7727, 7773, 7776,
       7784, 7788, 7802, 7813, 7851, 7894, 7898, 7933, 7956, 7995, 8019,
       8037, 8094, 8098, 8156, 8193, 8207, 8217, 8304, 8321, 8385, 8394,
       8444, 8458, 8467, 8469, 8478, 8488, 8562, 8568, 8577, 8602, 8674,
       8686, 8689, 8711, 8759, 8761, 8768, 8787, 8793, 8822, 8865, 8900,
       8917, 8930, 9018, 9062, 9080, 9112, 9116, 9162, 9223, 9279, 9292,
       9309, 9318, 9324, 9332, 9333, 9351, 9380, 9402, 9425, 9428, 9438,
       9472, 9490, 9506, 9555, 9557, 9582, 9587, 9589, 9593, 9646, 9671,
       9673, 9681, 9686, 9688, 9718, 9733, 9734, 9736, 9747, 9753, 9765,
       9832, 9879, 9894, 9936]),) (array([],
dtype=int64),)
```

```
#Removing outliers based off Age column

# IQR
Q1 = np.percentile(dataset['Age'], 25,
interpolation = 'midpoint')

Q3 = np.percentile(dataset['Age'], 75,
interpolation = 'midpoint')
IQR = Q3 - Q1

print("Old Shape: ", dataset.shape)

# Upper bound upper = np.where(dataset['Age'] >=
(Q3+1.5*IQR))
# Lower bound lower = np.where(dataset['Age'] <=
(Q1-1.5*IQR))

''' Removing the Outliers ''' dataset.drop(upper[0],
inplace = True) dataset.drop(lower[0], inplace =
True)

print("New Shape: ", dataset.shape)
```

```
Old Shape:  (10000, 13) New
Shape:  (9589, 13) dataset

      CustomerId    Surname  CreditScore Geography  Gender  Age  Tenure  \
0       15634602   Hargrave          619    France  Female   42       2
1       15647311       Hill          608     Spain  Female   41       1
2       15619304       Onio          502    France  Female   42       8
3       15701354       Boni          699    France  Female   39       1
4       15737888   Mitchell          850     Spain  Female   43       2
...          ...        ...          ...       ...     ...  ...     ...
9995    15606229   Obijiaku          771    France    Male   39       5
9996    15569892  Johnstone          516    France    Male   35      10
9997    15584532        Liu          709    France  Female   36       7
9998    15682355  Sabbatini          772   Germany    Male   42       3
        9999    15628319     Walker          792    France  Female   28
        4

        Balance  NumOfProducts  HasCrCard  IsActiveMember  EstimatedSalary  \
0          0.00              1          1               1        101348.88
1          83807.86              1          0               1
           112542.58
2          159660.80              3          1               0
           113931.57
3          0.00              2          0               0         93826.63
```

```
4           125510.82            1          1               1
            79084.10   ...        ...           ...        ...             .
            ..              ...
9995        0.00             2          1               0         96270.64
9996        57369.61            1          1               1
            101699.77
9997        0.00             1          0               1         42085.58
9998        75075.31            2          1               0
            92888.52
9999        130142.79            1          1               0
            38190.78         Exited
0           1
1           0
2           1
3           0
4           0  ...      ...
9995        0
9996        0
9997        1
9998        1
9999        0

[9589 rows x 13 columns]
```

```
for col in num_cols[1:]:
  print('skewness value of ',col,dataset[col].skew())

# Now we have reduced the Age column's skewness values within -1 to 1 range # We left the Exited column's skewness value as it is the dependent varaible
```

```
skewness value of  CreditScore -0.07274225895185718
skewness value of  Age 0.44721544739487257 skewness value
of  Tenure 0.008085830714996462 skewness value of
Balance -0.1409005824644143 skewness value of
NumOfProducts 0.7470530176747141 skewness value of
HasCrCard -0.9034483996482451 skewness value of
IsActiveMember -0.008552881368996219 skewness value of
EstimatedSalary -0.0025661797132480266 skewness value of
Exited 1.4798502461410206
```

7 . Check for Categorical columns and perform encoding

##Label encoding and One Hot encoding `dataset.reset_index(inplace=True)`

```
from sklearn.preprocessing import LabelEncoder from
sklearn.preprocessing import OneHotEncoder from
sklearn.compose import ColumnTransformer
```

```
categorical_feature_mask = dataset.dtypes==object categorical_cols =
dataset.columns[categorical_feature_mask].tolist()

categorical_cols=categorical_cols[1:] categorical_cols

['Geography', 'Gender']
le = LabelEncoder() dataset[categorical_cols] =
dataset[categorical_cols].apply(lambda col:
le.fit_transform(col)) dataset[categorical_cols].head(10)

   Geography  Gender
0          0       0
1          2       0
2          0       0
3          0       0
4          2       0
5          2       1
6          0       1
7          1       0
8          0       19          0       1

categorical_feature_mask

index              False CustomerId
False
Surname             True
CreditScore        False
Geography           True
Gender              True
Age                False
Tenure             False
Balance            False
NumOfProducts      False
HasCrCard          False
IsActiveMember     False
EstimatedSalary    False
Exited             False dtype:
bool

enc=OneHotEncoder()
enc_data=pd.DataFrame(enc.fit_transform(dataset[['Geography','Gender']]).toar
ray()) enc_data

        0    1    2    3    4
0     1.0  0.0  0.0  1.0  0.0
1     0.0  0.0  1.0  1.0  0.0
2     1.0  0.0  0.0  1.0  0.0
3     1.0  0.0  0.0  1.0  0.0
4     0.0  0.0  1.0  1.0  0.0...   ...  ...  ...  ...  ...
```

```
9584  1.0  0.0  0.0  0.0  1.0
9585  1.0  0.0  0.0  0.0  1.0
9586  1.0  0.0  0.0  1.0  0.0
9587  0.0  1.0  0.0  0.0  1.0
9588  1.0  0.0  0.0  1.0  0.0

[9589 rows x 5 columns]
```

```
#First three columns of enc_data is for Geography and the next two columns is for Gender, we can replace the already existing categorical columns with these encoded values

#Dropping already existing Geography and Gender columns
dataset.drop(['Geography'],       axis=1,inplace=True)
dataset.drop(['Gender'], axis=1,inplace=True)

dataset.insert(2, "Geography_France", enc_data.iloc[:,0], True)
dataset.insert(3, "Geography_Germany", enc_data.iloc[:,1], True)
dataset.insert(4, "Geography_Spain", enc_data.iloc[:,2], True)
dataset.insert(5, "Gender_Female", enc_data.iloc[:,3], True)
dataset.insert(6, "Gender_Male", enc_data.iloc[:,4], True) dataset
```

```
      index  CustomerId  Geography_France  Geography_Germany  Geography_Spain
\
0         0    15634602               1.0                0.0              0.0
1         1    15647311               0.0                0.0              1.0
2         2    15619304               1.0                0.0              0.0
3         3    15701354               1.0                0.0              0.0
4         4    15737888               0.0                0.0
          1.0    ...     ...         ...               ...               ...
                        ...
9584   9995    15606229               1.0                0.0              0.0
9585   9996    15569892               1.0                0.0              0.0
9586   9997    15584532               1.0                0.0              0.0
9587   9998    15682355               0.0                1.0              0.0
       9588   9999    15628319               1.0                0.0
       0.0

      Gender_Female  Gender_Male    Surname  CreditScore  Age  Tenure  \
0               1.0          0.0   Hargrave          619   42       2
1               1.0          0.0       Hill          608   41       1
2               1.0          0.0       Onio          502   42       8
3               1.0          0.0       Boni          699   39       1
4               1.0          0.0   Mitchell          850   43       2
...             ...          ...        ...          ...  ...     ...
9584            0.0          1.0   Obijiaku          771   39       5
9585            0.0          1.0  Johnstone          516   35      10
9586            1.0          0.0        Liu          709   36       7
```

```
9587            0.0         1.0  Sabbatini          772   42       3   9588
                1.0         0.0     Walker          792   28       4

        Balance  NumOfProducts  HasCrCard  IsActiveMember  EstimatedSalary  \
0          0.00              1          1               1        101348.88
1          83807.86              1          0               1
           112542.58
2          159660.80              3          1               0
           113931.57
3          0.00              2          0               0         93826.63
4          125510.82              1          1               1
           79084.10   ...         ...            ...        ...             .
           ..              ...
9584       0.00              2          1               0         96270.64
9585       57369.61              1          1               1
           101699.77
9586       0.00              1          0               1         42085.58
9587       75075.31              2          1               0
           92888.52   9588  130142.79             1          1
           0        38190.78

      Exited
0          1
1          0
2          1
3          0
4          0  ...      ...
9584       0
9585       0
9586       1
9587       1
9588       0

[9589 rows x 17 columns]
```

```
# We drop some irrelevant columns that does not contribute to prediction
dataset.drop(columns="CustomerId",axis=1,inplace=True)
dataset.drop(columns="Surname",axis=1,inplace=True)
dataset.drop(columns="index",axis=1,inplace=True) dataset
```

```
      Geography_France  Geography_Germany  Geography_Spain  Gender_Female  \
0                  1.0                0.0              0.0            1.0
1                  0.0                0.0              1.0            1.0
2                  1.0                0.0              0.0            1.0
3                  1.0                0.0              0.0            1.0
4                  0.0                0.0              1.0
                   1.0   ...                ...                ...
                             ...             ...
```

```
9584             1.0             0.0             0.0             0.0
9585             1.0             0.0             0.0             0.0
9586             1.0             0.0             0.0             1.0
9587             0.0             1.0             0.0             0.0
                 9588            1.0               0.0              0.0
                 1.0

     Gender_Male  CreditScore  Age  Tenure    Balance  NumOfProducts  \
0            0.0          619   42       2       0.00              1
1            0.0          608   41       1   83807.86              1
2            0.0          502   42       8  159660.80              3
3            0.0          699   39       1       0.00              2
4            0.0          850   43       2  125510.82
             1   ...           ...         ...  ...     ...        ...
                    ...
9584         1.0          771   39       5       0.00              2
9585         1.0          516   35      10   57369.61              1
9586         0.0          709   36       7       0.00              1
9587         1.0          772   42       3   75075.31              2   9588
             0.0          792   28       4  130142.79              1

     HasCrCard  IsActiveMember  EstimatedSalary  Exited
0            1               1        101348.88       1
1            0               1        112542.58       0
2            1               0        113931.57       1
3            0               0         93826.63       0
4            1               1         79084.10
             0  ...         ...             ...             ...     ...
9584         1               0         96270.64       0
9585         1               1        101699.77       0
9586         0               1         42085.58       1
9587         1               0         92888.52       1
9588         1               0         38190.78       0

[9589 rows x 14 columns]
```

8 . Split the data into dependent and independent variables

```
X= dataset.iloc[:,:-1].values #Indepedent variables y=
dataset.iloc[:,-1].values #Dependent varaibles

X

array([[1.0000000e+00, 0.0000000e+00, 0.0000000e+00, ..., 1.0000000e+00,
        1.0000000e+00, 1.0134888e+05],
       [0.0000000e+00, 0.0000000e+00, 1.0000000e+00, ..., 0.0000000e+00,
        1.0000000e+00, 1.1254258e+05],
```

```
       [1.0000000e+00, 0.0000000e+00, 0.0000000e+00, ..., 1.0000000e+00,
        0.0000000e+00, 1.1393157e+05],
       ...,
       [1.0000000e+00, 0.0000000e+00, 0.0000000e+00, ..., 0.0000000e+00,
        1.0000000e+00, 4.2085580e+04],
       [0.0000000e+00, 1.0000000e+00, 0.0000000e+00, ..., 1.0000000e+00,
        0.0000000e+00, 9.2888520e+04],
       [1.0000000e+00, 0.0000000e+00, 0.0000000e+00, ..., 1.0000000e+00,
        0.0000000e+00, 3.8190780e+04]]) y

array([1, 0, 1, ..., 1, 1, 0])
```

9 . Scale the independent variable

```
from sklearn.preprocessing import StandardScaler
scale= StandardScaler() X
= scale.fit_transform(X)
X

array([[ 0.99718823, -0.57955796, -0.57297497, ...,  0.64561166,
         0.99573337,  0.01997639],
       [-1.0028197 , -0.57955796,  1.74527693, ..., -1.54891873,
         0.99573337,  0.21465635],
       [ 0.99718823, -0.57955796, -0.57297497, ...,  0.64561166,
        -1.00428491,  0.23881355],
       ...,
       [ 0.99718823, -0.57955796, -0.57297497, ..., -1.54891873,
         0.99573337, -1.01072631],
       [-1.0028197 ,  1.72545295, -0.57297497, ...,  0.64561166,
        -1.00428491, -0.12716553],
       [ 0.99718823, -0.57955796, -0.57297497, ...,  0.64561166,
        -1.00428491, -1.07846436]])
```

10 . Split the data into training and testing

```
from sklearn.model_selection import train_test_split

# We use train_test_split function to split the data such that 25% is used
for testing while the remaining 75% is used for training
X_train, X_test, y_train, y_test = train_test_split(X,y ,
random_state=104,test_size=0.25, shuffle=True)

X_train

array([[ 0.99718823, -0.57955796, -0.57297497, ...,  0.64561166,
         0.99573337, -1.74019169],
       [-1.0028197 , -0.57955796,  1.74527693, ..., -1.54891873,
        -1.00428491, -1.39787901],
```

```
       [-1.0028197 ,  1.72545295, -0.57297497, ..., -1.54891873,
         0.99573337, -1.48817335],
       ...,
       [ 0.99718823, -0.57955796, -0.57297497, ...,  0.64561166,
        -1.00428491,  0.71481237],
       [ 0.99718823, -0.57955796, -0.57297497, ..., -1.54891873,
        -1.00428491,  0.60834563],
       [-1.0028197 ,  1.72545295, -0.57297497, ...,  0.64561166,
         0.99573337,  0.0525285 ]])
```

X_test

```
array([[-1.0028197 , -0.57955796,  1.74527693, ..., -1.54891873,
        -1.00428491, -0.90389608],
       [ 0.99718823, -0.57955796, -0.57297497, ...,  0.64561166,
         0.99573337, -0.54087223],
       [-1.0028197 , -0.57955796,  1.74527693, ...,  0.64561166,
         0.99573337, -1.02004733],
       ...,
       [ 0.99718823, -0.57955796, -0.57297497, ...,  0.64561166,
         0.99573337, -0.23978536],
       [ 0.99718823, -0.57955796, -0.57297497, ...,  0.64561166,
         0.99573337, -0.17457887],
       [ 0.99718823, -0.57955796, -0.57297497, ...,  0.64561166,
        -1.00428491, -0.0121091 ]])
```

y_train

```
array([0, 0, 0, ..., 0, 0, 0])
```

y_test

```
array([0, 1, 0, ..., 0, 0, 1])
```