IN(1):
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

IN(2):

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

IN(6):

```
df
```

OP(6):

Out[6]:

	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
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
9995	9996	15606229	Obijiaku	771	France	Male	39	5	0.00	2	1	0	96270.64	0
9996	9997	15569892	Johnstone	516	France	Male	35	10	57369.61	1	1	1	101699.77	0
9997	9998	15584532	Liu	709	France	Female	36	7	0.00	1	0	1	42085.58	1
9998	9999	15682355	Sabbatini	772	Germany	Male	42	3	75075.31	2	1	0	92888.52	1
9999	10000	15628319	Walker	792	France	Female	28	4	130142.79	1	1	0	38190.78	0

10000 rows × 14 columns

IN(3):

```
df.head()
```

OP(3):

Out[3]:

	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(4):

```
df.shape
```

OP(4):

```
Out[4]: (10000, 14)
```

Univariate,Bivariate and MultiVariate Analysis

Univariate Analysis

IN[9]:

df_france=df.loc[df['Geography']=='France']

df_spain=df.loc[df['Geography']=='Spain']

df_germany=df.loc[df['Geography']=='Germany']

In [17]:

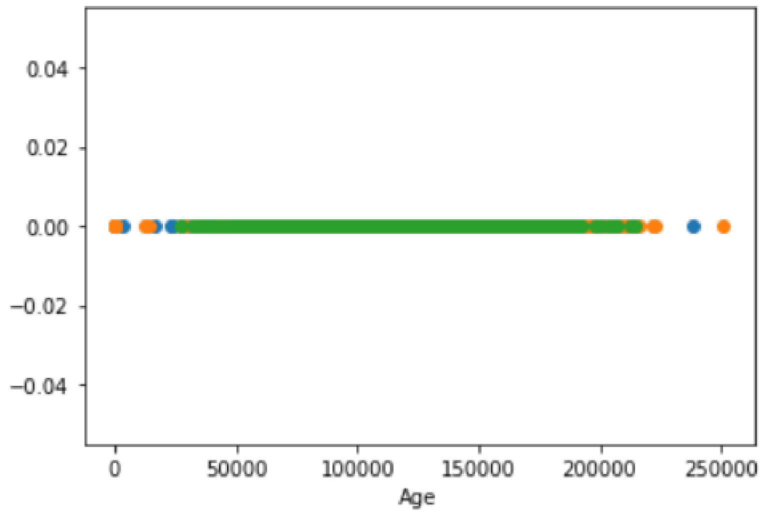
plt.plot(df_france['Balance'],np.zeros_like(df_france['Balance']),'o')

plt.plot(df_spain['Balance'],np.zeros_like(df_spain['Balance']),'o')

plt.plot(df_germany['Balance'],np.zeros_like(df_germany['Balance']),'o')

plt.xlabel('Age')

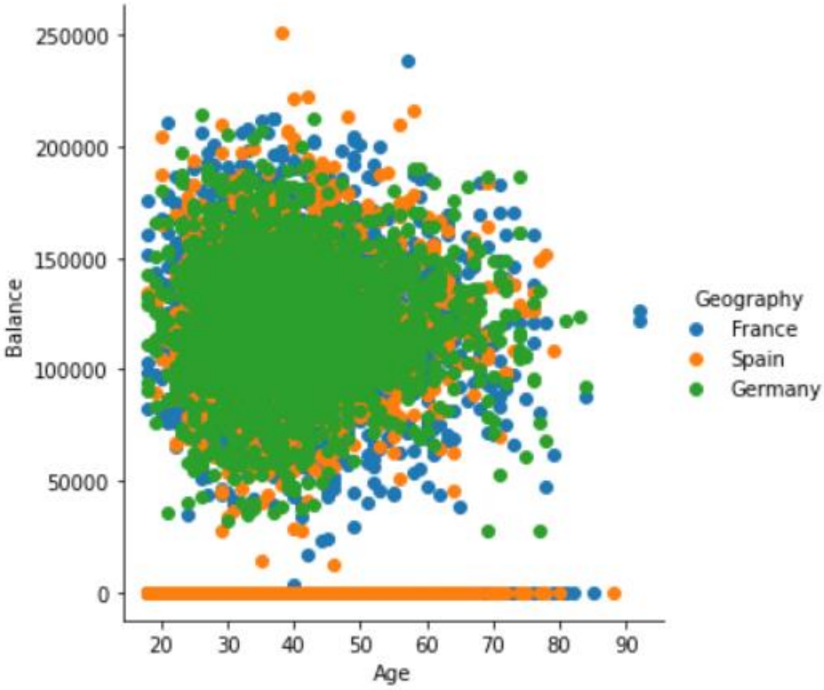
plt.show()



Bivariate Analysis

In [18]:

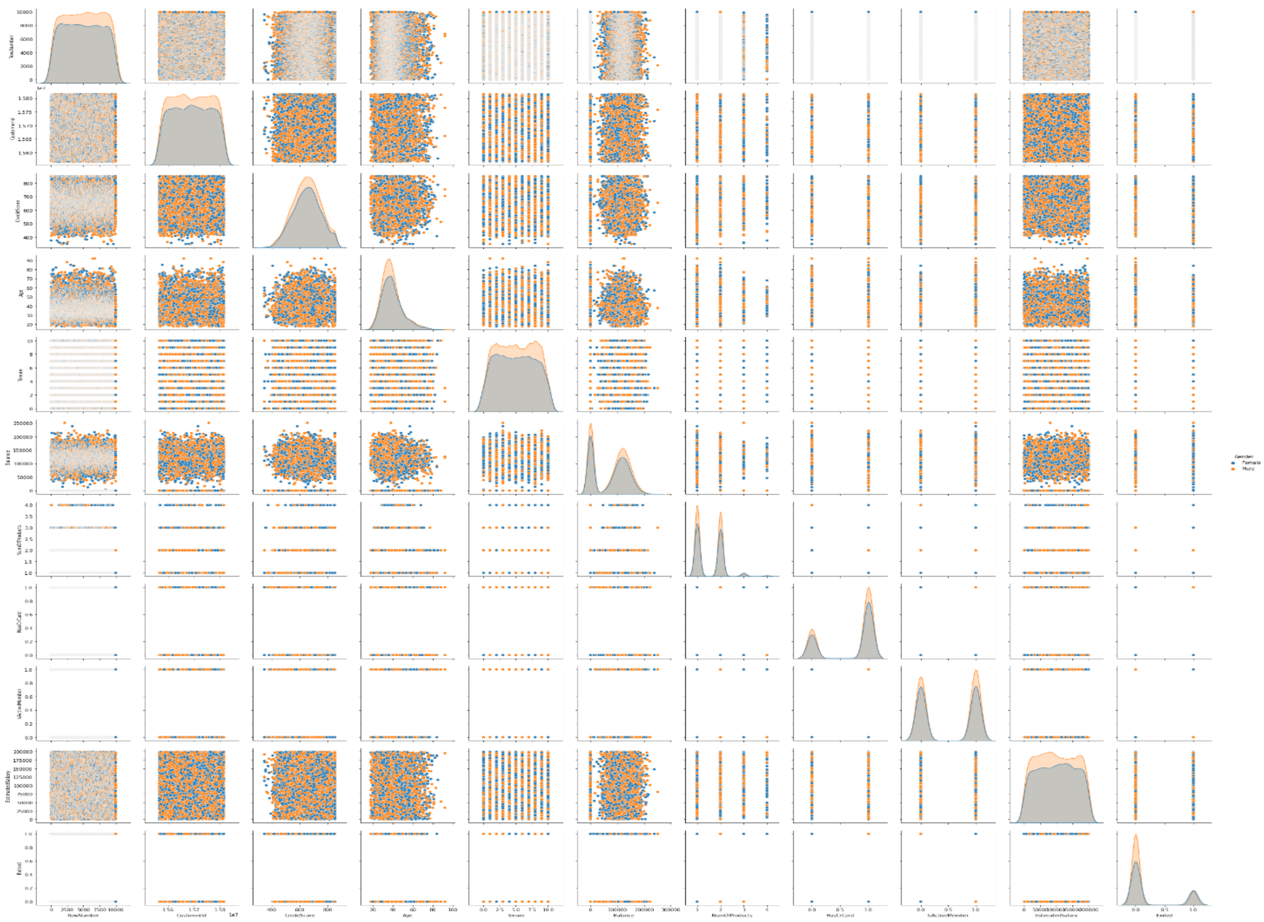
sns.FacetGrid(df,hue="Geography",size=5).map(plt.scatter,"Age","Balance").add_legend();
plt.show()



Multivariate Analysis

In [24]:

```
sns.pairplot(df,hue="Gender",size=3)
```



Descriptive Statistics

In [29]:
df.head()

Out[29]:

	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 [30]:

df.mean() # Get the mean of each column

```
Out[30]:  RowNumber          5.000500e+03
          CustomerId         1.569094e+07
          CreditScore        6.505288e+02
          Age                3.892180e+01
          Tenure             5.012800e+00
          Balance            7.648589e+04
          NumOfProducts      1.530200e+00
          HasCrCard          7.055000e-01
          IsActiveMember     5.151000e-01
          EstimatedSalary    1.000902e+05
          Exited             2.037000e-01
          dtype: float64
```

In [31]:

df.mean(axis=1)   # Get the mean of each row

```
Out[31]:  0       1.430602e+06
          1       1.440392e+06
          2       1.444860e+06
          3       1.435993e+06
          4       1.449399e+06
                      ...
          9995    1.428483e+06
          9996    1.430866e+06
          9997    1.421579e+06
          9998    1.441922e+06
          9999    1.437044e+06
          Length: 10000, dtype: float64
```

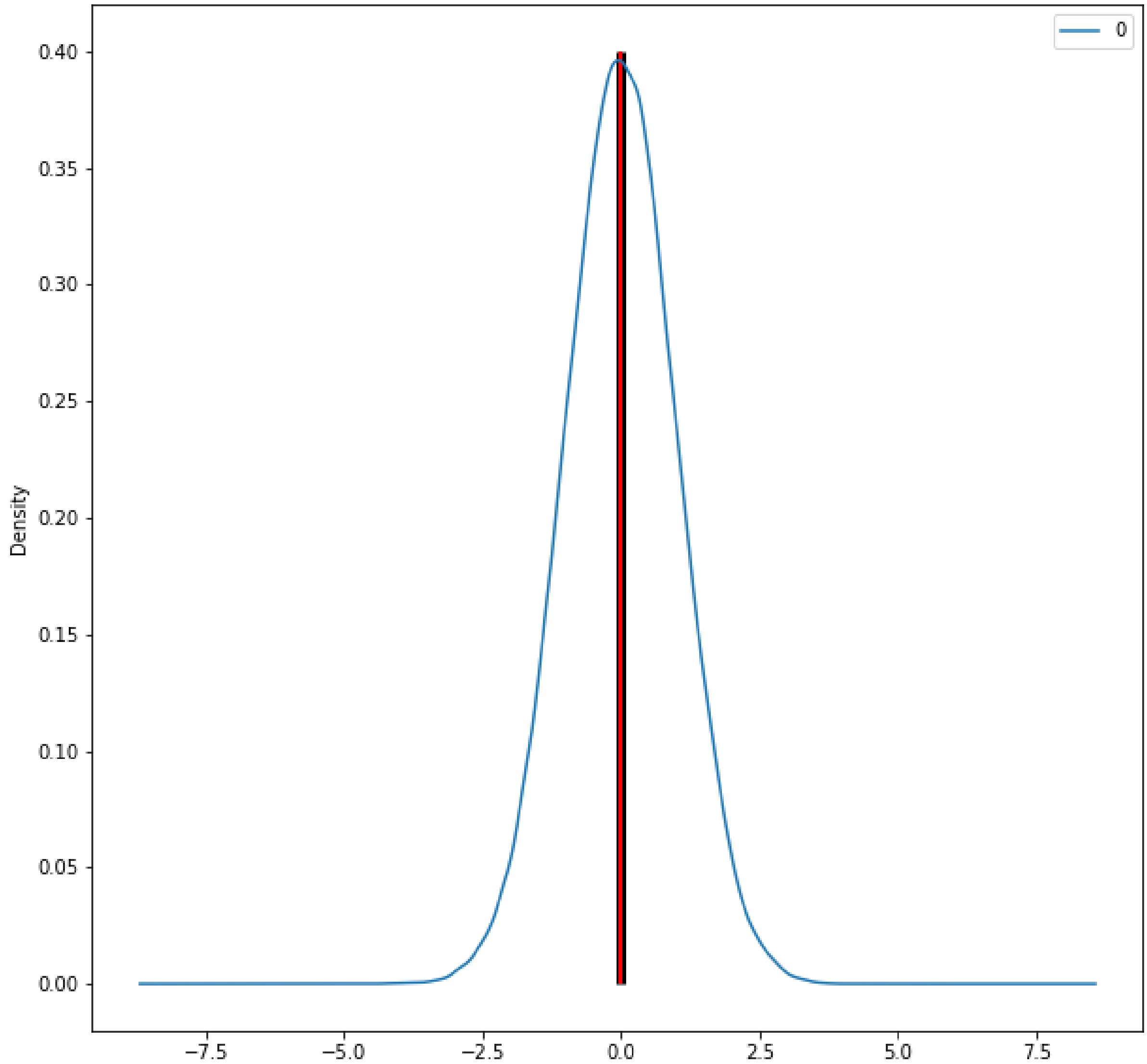
In [32]:

df.median()   # Get the median of each column

```
Out[32]:  RowNumber          5.000500e+03
          CustomerId         1.569074e+07
          CreditScore        6.520000e+02
          Age                3.700000e+01
          Tenure             5.000000e+00
          Balance            9.719854e+04
          NumOfProducts      1.000000e+00
          HasCrCard          1.000000e+00
          IsActiveMember     1.000000e+00
          EstimatedSalary    1.001939e+05
          Exited             0.000000e+00
          dtype: float64
```

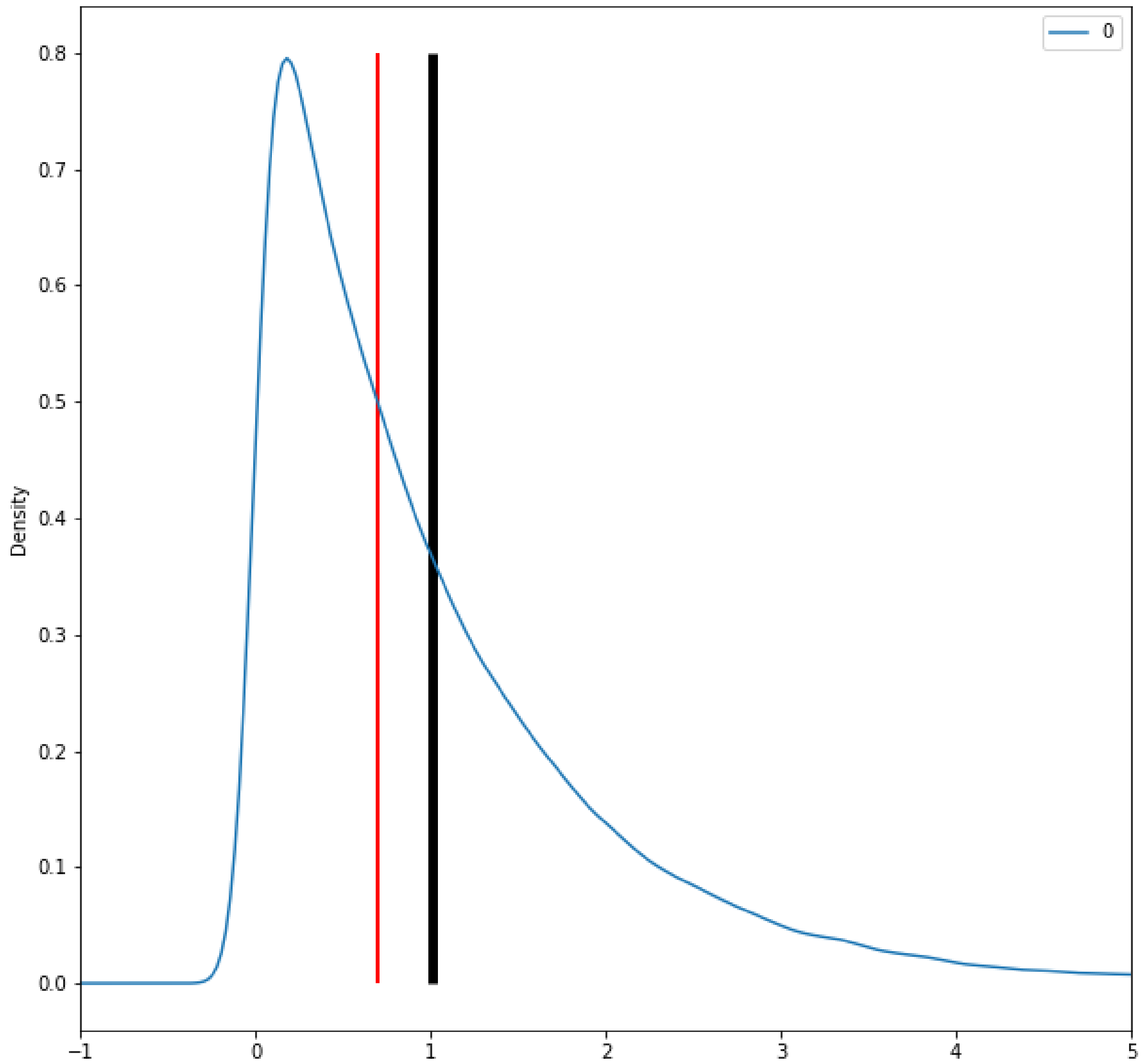
In [39]:

```
norm_data = pd.DataFrame(np.random.normal(size=100000))


norm_data.plot(kind="density",
            figsize=(10,10));
plt.vlines(norm_data.mean(),     # Plot black line at mean
         ymin=0,
         ymax=0.4,
         linewidth=5.0);


plt.vlines(norm_data.median(),   # Plot red line at median
         ymin=0,
         ymax=0.4,
         linewidth=2.0,
         color="red");
```



In [36]:

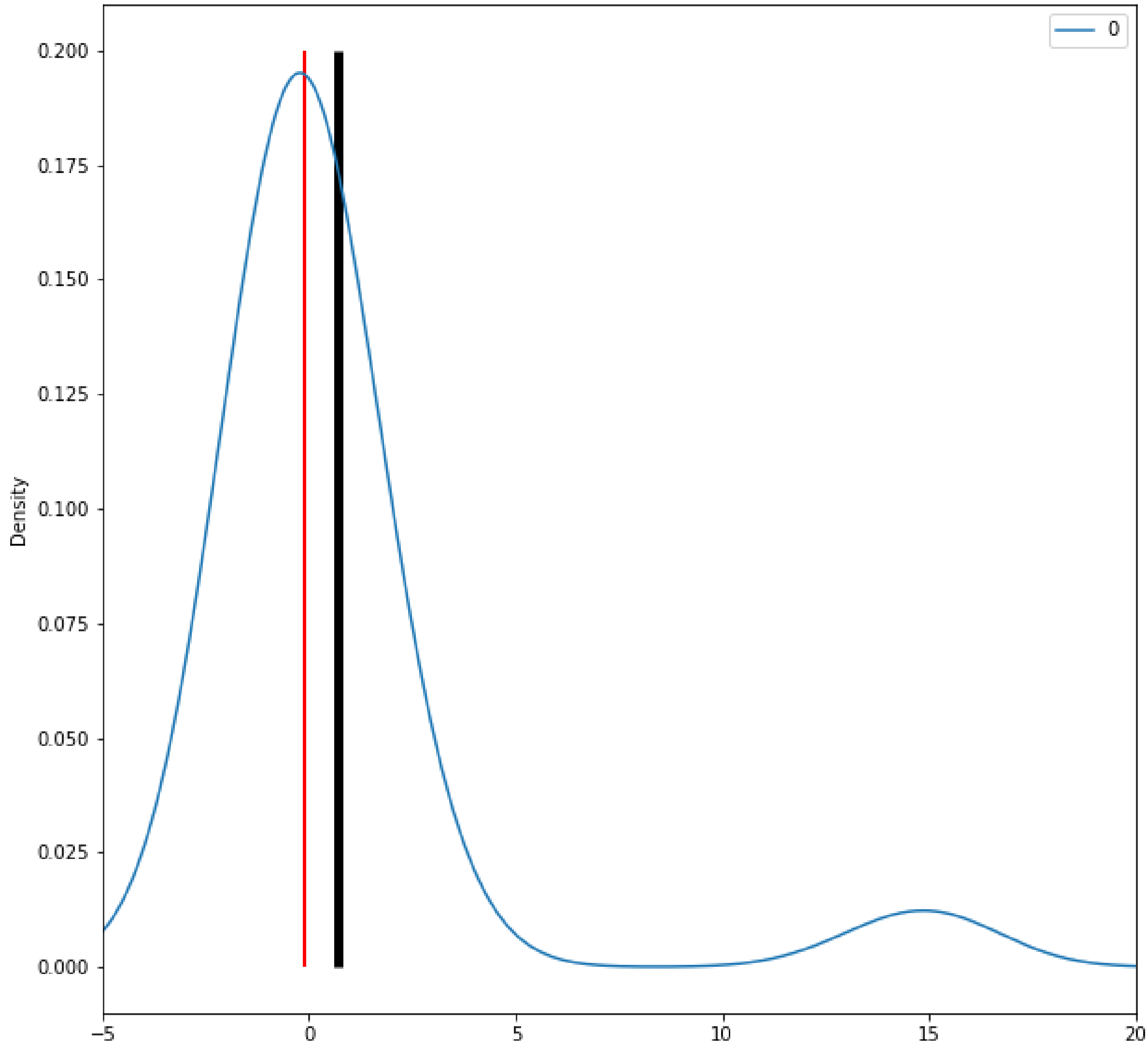
```
skewed_data = pd.DataFrame(np.random.exponential(size=100000))

skewed_data.plot(kind="density",
              figsize=(10,10),
              xlim=(-1,5));



plt.vlines(skewed_data.mean(),     # Plot black line at mean
           ymin=0,
           ymax=0.8,
           linewidth=5.0);

plt.vlines(skewed_data.median(),   # Plot red line at median
           ymin=0,
           ymax=0.8,
           linewidth=2.0,
           color="red");
```



In [40]:

```
norm_data = np.random.normal(size=50)

outliers = np.random.normal(15, size=3)

combined_data = pd.DataFrame(np.concatenate((norm_data, outliers), axis=0))


combined_data.plot(kind="density",

            figsize=(10,10),

            xlim=(-5,20));



plt.vlines(combined_data.mean(),     # Plot black line at mean

         ymin=0,

         ymax=0.2,

         linewidth=5.0);
```

```
plt.vlines(combined_data.median(),   # Plot red line at median
        ymin=0,
        ymax=0.2,
        linewidth=2.0,
        color="red");
```



In [42]:

```
df.mode()
```

Out[42]:

	RowNumber	CustomerId	Surname	CreditScore	Geography	Gender	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	EstimatedSalary	Exited
0	1	15565701	Smith	850.0	France	Male	37.0	2.0	0.0	1.0	1.0	1.0	24924.92	0.0
1	2	15565706	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
2	3	15565714	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
3	4	15565779	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
4	5	15565796	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
9995	9996	15815628	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
9996	9997	15815645	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
9997	9998	15815656	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
9998	9999	15815660	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
9999	10000	15815690	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN

10000 rows × 14 columns

Measures of Spread

In [43]:

```
max(df["Age"]) - min(df["Age"])
```

Out[43]:

```
74
```

In [45]:

```
five_num = [df["Age"].quantile(0),
        df["Age"].quantile(0.25),
        df["Age"].quantile(0.50),
        df["Age"].quantile(0.75),
        df["Age"].quantile(1)]

five_num
```

Out[45]:

```
[18.0, 32.0, 37.0, 44.0, 92.0]
```

In [46]:

```
df["Age"].describe()
```

Out[46]:

```
count    10000.000000
mean        38.921800
std         10.487806
min         18.000000
25%         32.000000
50%         37.000000
75%         44.000000
max         92.000000
Name: Age, dtype: float64
```

In [47]:

```
df["Age"].quantile(0.75) - df["Age"].quantile(0.25)
```

Out[47]: 12.0

In [49]:

df.boxplot(column="Age",

return_type='axes',

figsize=(8,8))

plt.text(x=0.74, y=22.25, s="3rd Quartile")

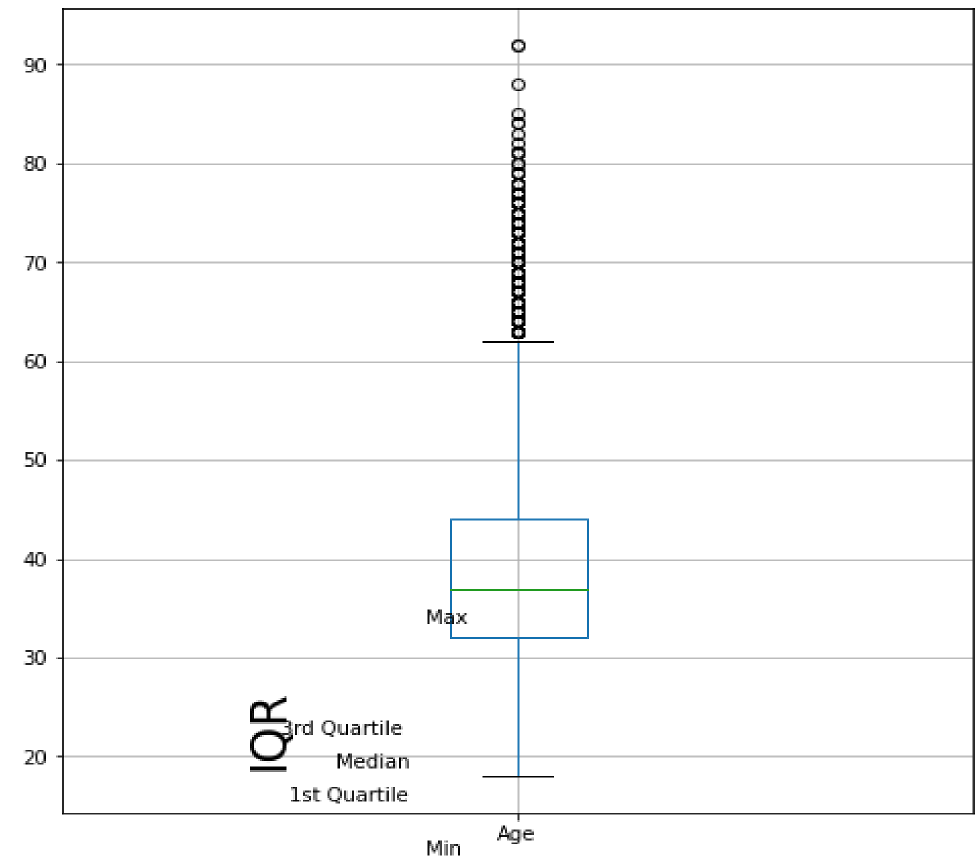
plt.text(x=0.8, y=18.75, s="Median")

plt.text(x=0.75, y=15.5, s="1st Quartile")

plt.text(x=0.9, y=10, s="Min")

plt.text(x=0.9, y=33.5, s="Max")

plt.text(x=0.7, y=19.5, s="IQR", rotation=90, size=25);



In [50]:

df["Age"].var()

Out[50]: 109.99408416841683

In [51]:

df["Age"].std()

Out[51]: 10.487806451704609

In [52]:

```
abs_median_devs = abs(df["Age"] - df["Age"].median())


abs_median_devs.median() * 1.4826
```

Out[52]: 8.8956

Skewness and Kurtosis

In [53]:

```
df["Age"].skew()  # Check skewness
```

Out[53]: 1.0113202630234552

In [54]:

```
df["Age"].kurt()  # Check kurtosis
```

Out[54]: 1.3953470615086956

In [55]:

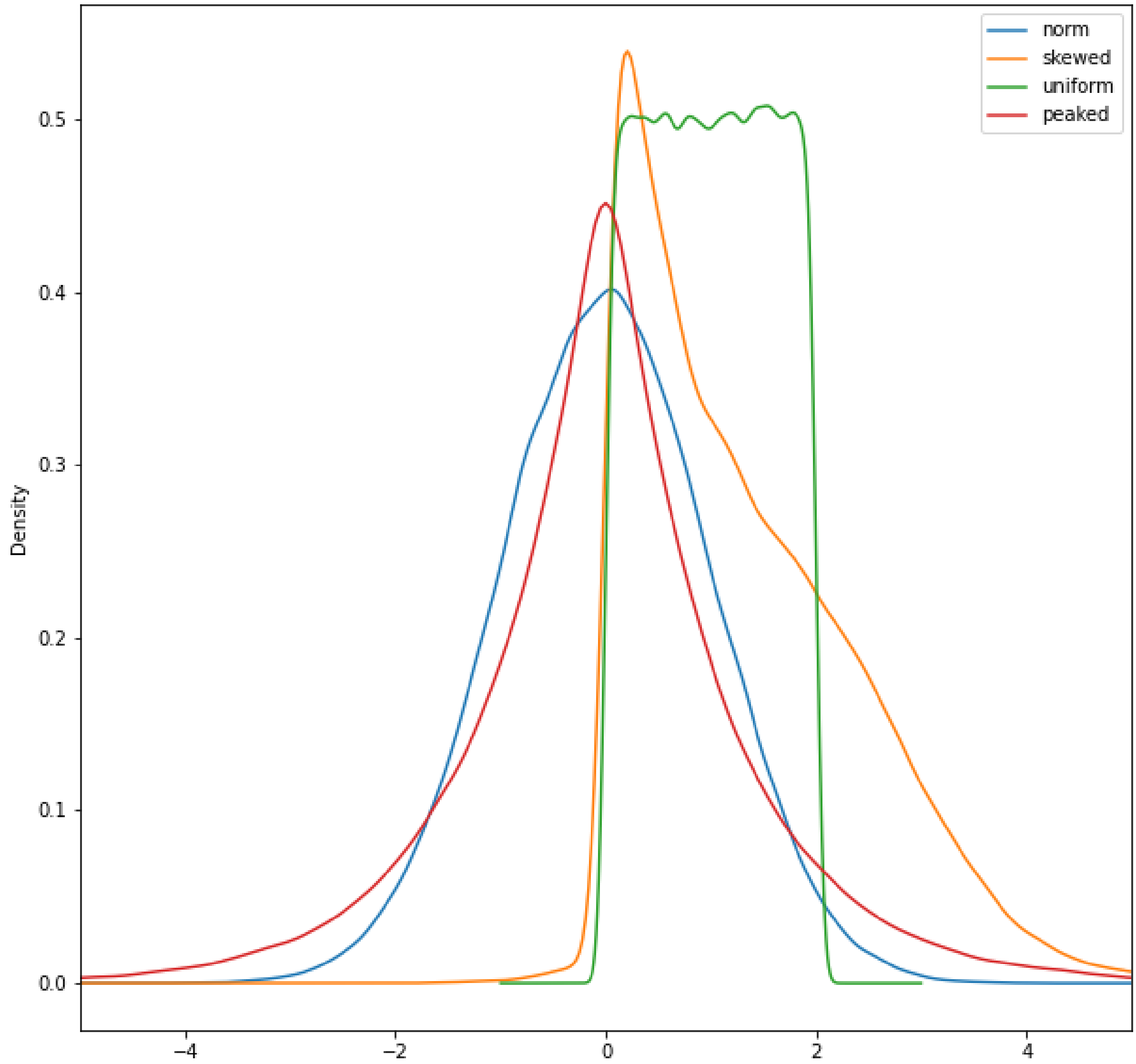
```
norm_data = np.random.normal(size=100000)
skewed_data = np.concatenate((np.random.normal(size=35000)+2,
                  np.random.exponential(size=65000)),
                  axis=0)
uniform_data = np.random.uniform(0,2, size=100000)
peaked_data = np.concatenate((np.random.exponential(size=50000),
                  np.random.exponential(size=50000)*(-1)),
                  axis=0)


data_df = pd.DataFrame({"norm":norm_data,
              "skewed":skewed_data,
              "uniform":uniform_data,
              "peaked":peaked_data})
```

In [56]:

data_df.plot(kind="density",

figsize=(10,10),

xlim=(-5,5));



In [57]:

data_df.skew()

```
Out[57]: norm       -0.007037
         skewed      1.002549
         uniform    -0.004434
         peaked      0.018058
         dtype: float64
```

In [58]:

data_df.kurt()

```
Out[58]: norm       -0.009914
         skewed      1.314497
         uniform    -1.201740
         peaked      2.971592
         dtype: float64
```

Handle the Missing values

In [83]:

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

Out[84]:

	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 [84]:

df.head()

Out[86]:

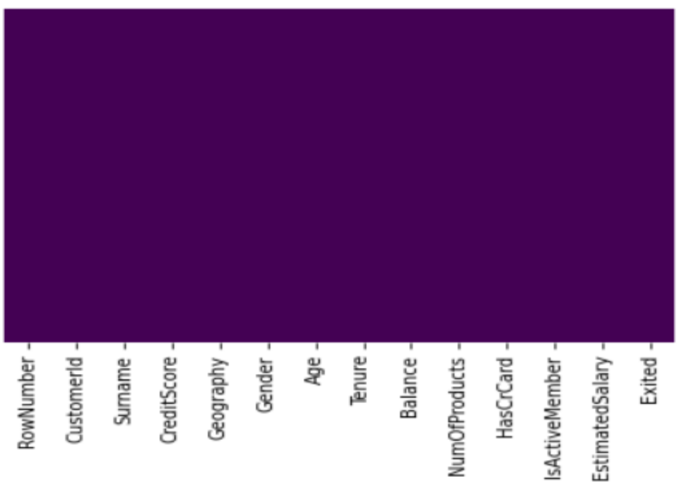
	RowNumber	CustomerId	Surname	CreditScore	Geography	Gender	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	EstimatedSalary	Exited
0	False	False	False	False	False	False	False	False	False	False	False	False	False	False
1	False	False	False	False	False	False	False	False	False	False	False	False	False	False
2	False	False	False	False	False	False	False	False	False	False	False	False	False	False
3	False	False	False	False	False	False	False	False	False	False	False	False	False	False
4	False	False	False	False	False	False	False	False	False	False	False	False	False	False
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
9995	False	False	False	False	False	False	False	False	False	False	False	False	False	False
9996	False	False	False	False	False	False	False	False	False	False	False	False	False	False
9997	False	False	False	False	False	False	False	False	False	False	False	False	False	False
9998	False	False	False	False	False	False	False	False	False	False	False	False	False	False
9999	False	False	False	False	False	False	False	False	False	False	False	False	False	False

10000 rows × 14 columns

In [86]:

df.isnull()

Out[89]: <matplotlib.axes._subplots.AxesSubplot at 0x7f9a987d8290>

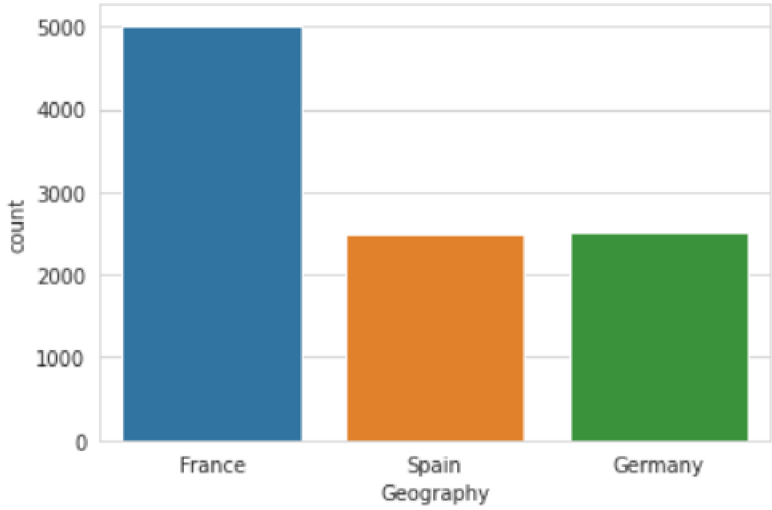


In [93]:

sns.set_style('whitegrid')

sns.countplot(x='Geography',data=df)

Out[93]: <matplotlib.axes._subplots.AxesSubplot at 0x7f9a92a88850>

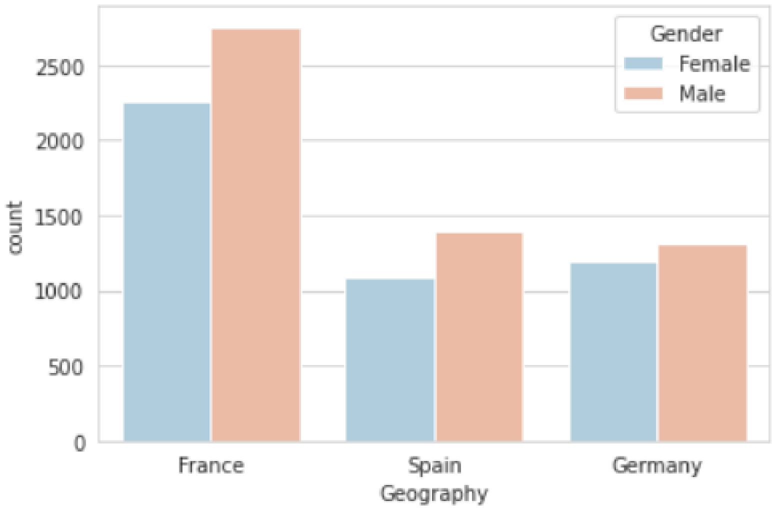


In [94]:

sns.set_style('whitegrid')

sns.countplot(x='Geography',hue='Gender',data=df,palette='RdBu_r')

Out[94]: <matplotlib.axes._subplots.AxesSubplot at 0x7f9a92ec10d0>

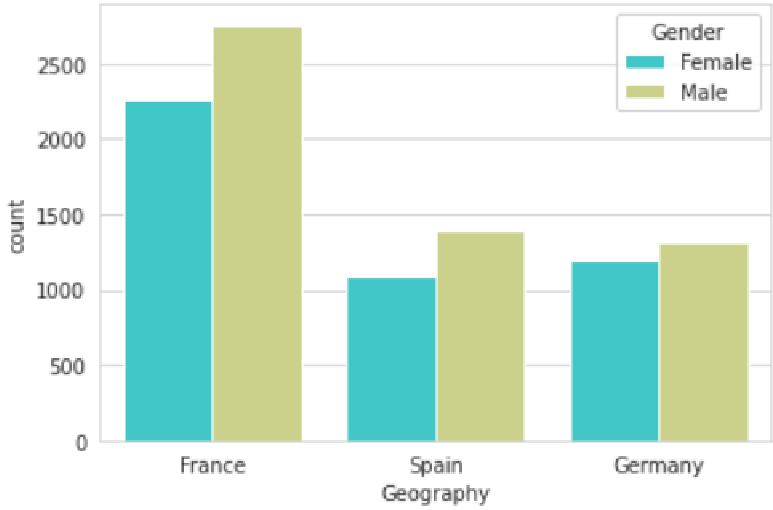


In [96]:

sns.set_style('whitegrid')

sns.countplot(x='Geography',hue='Gender',data=df,palette='rainbow')

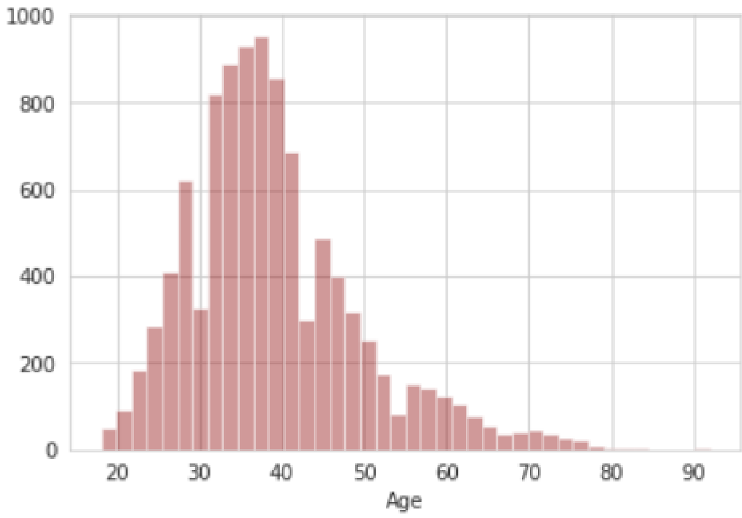
Out[96]: <matplotlib.axes._subplots.AxesSubplot at 0x7f9a92afac50>



In [97]:

sns.distplot(df['Age'].dropna(),kde=False,color='darkred',bins=40)

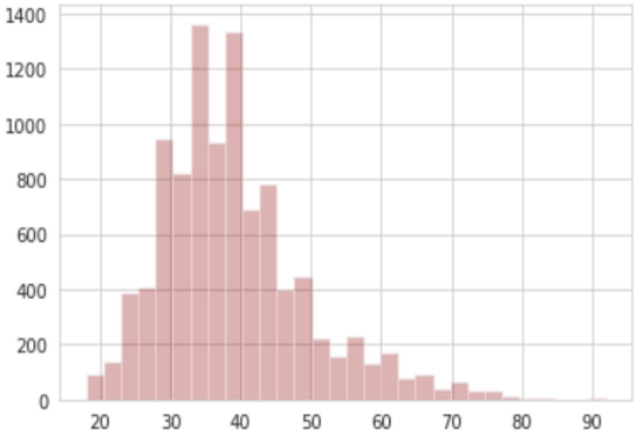
Out[97]: <matplotlib.axes._subplots.AxesSubplot at 0x7f9a98787590>



In [98]:

df['Age'].hist(bins=30,color='darkred',alpha=0.3)

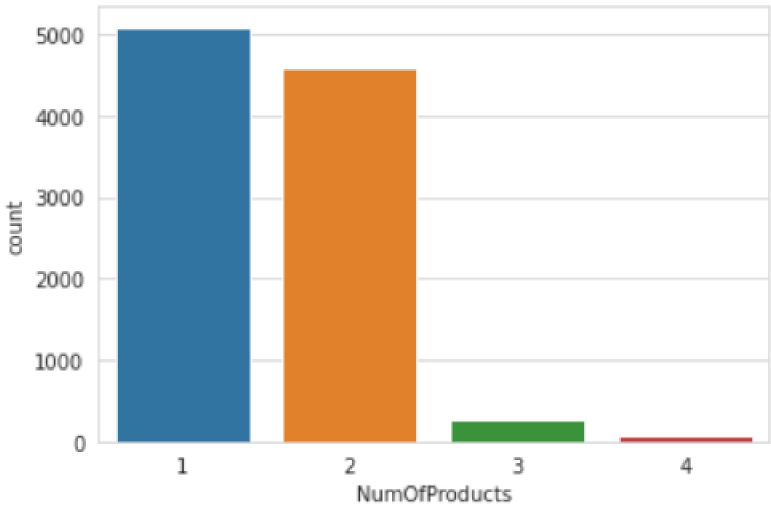
Out[98]: <matplotlib.axes._subplots.AxesSubplot at 0x7f9a92d64c10>



In [100]:

sns.countplot(x='NumOfProducts',data=df)

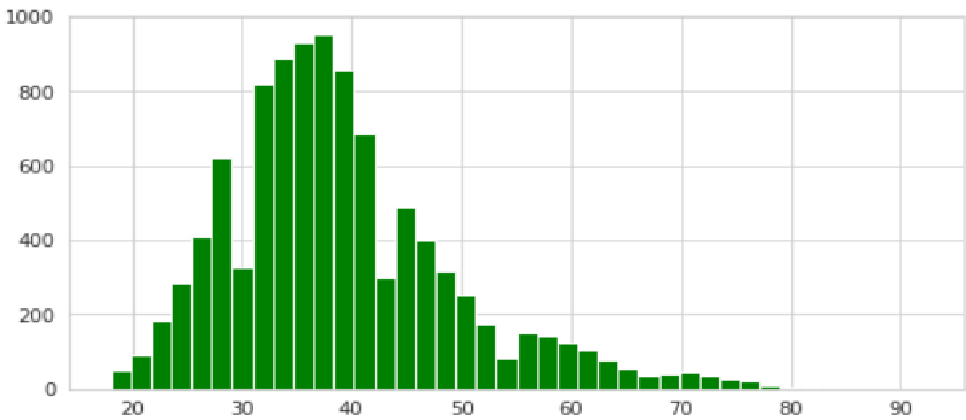
Out[100… <matplotlib.axes._subplots.AxesSubplot at 0x7f9a9306f790>



In [101]:

df['Age'].hist(color='green',bins=40,figsize=(8,4))

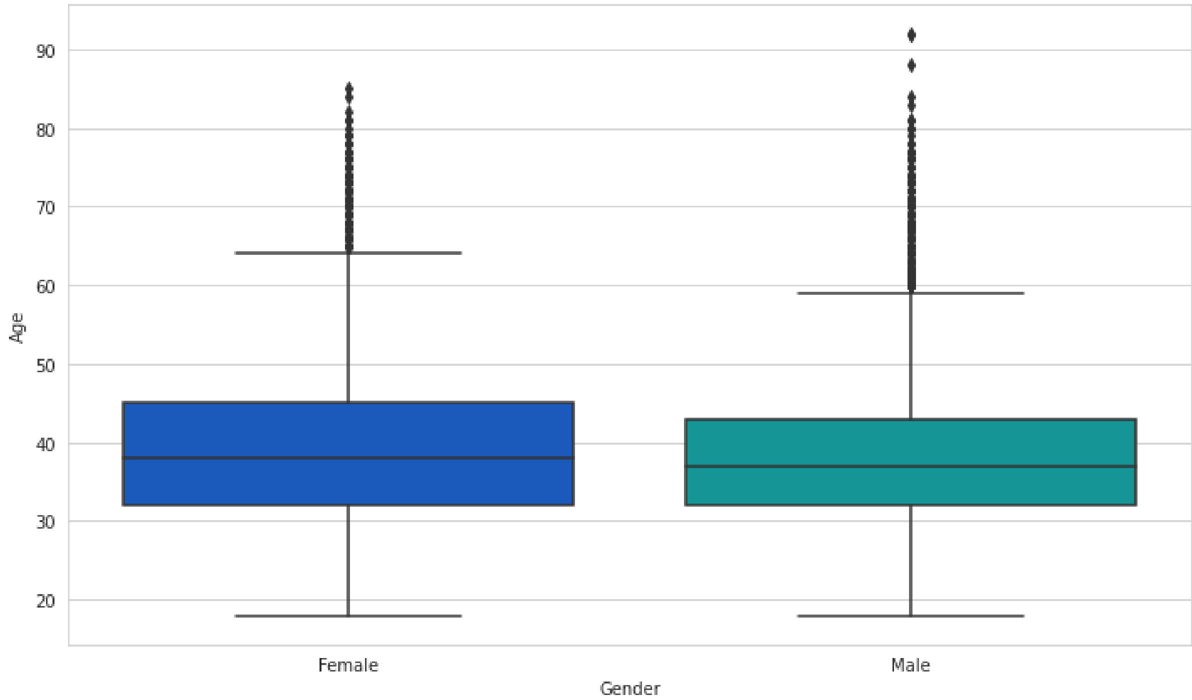
Out[101… <matplotlib.axes._subplots.AxesSubplot at 0x7f9a90f52d90>



Cufflinks for plots

In [102]:
```
import cufflinks as cf
cf.go_offline()
```
In [ ]:
```
df['Age'].iplot(kind='hist',bins=30,color='green')
```

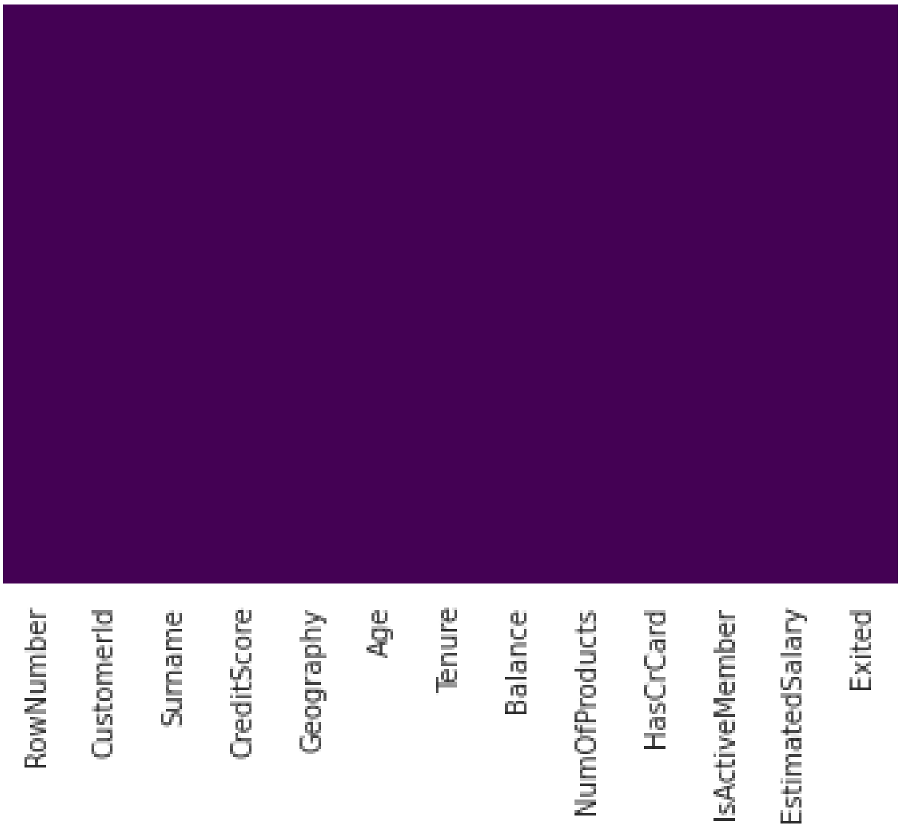
Data Cleaning

In [107]:
```
plt.figure(figsize=(12, 7))
sns.boxplot(x='Gender',y='Age',data=df,palette='winter')
```
Out[107]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f9a90f59450>
```


In [307]:
```
def impute_age(cols):
    Age = cols[0]
    Pclass = cols[1]

    if pd.isnull(Age):

        if Pclass == 1:
            return 37

        elif Pclass == 2:
            return 29

        else:
            return 24

    else:
        return Age
```
In [122]:
```
sns.heatmap(df.isnull(),yticklabels=False,cbar=False,cmap='viridis')
```

Out[122]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f9a8aa699d0>
```



In [112]:

```
df.drop('Gender',axis=1,inplace=True)
```

In [114]:

```
df.head()
```

Out[114]:

Out[114...	RowNumber	CustomerId	Surname	CreditScore	Geography	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	EstimatedSalary	Exited
0	1	15634602	Hargrave	619	France	42	2	0.00	1	1	1	101348.88	1
1	2	15647311	Hill	608	Spain	41	1	83807.86	1	0	1	112542.58	0
2	3	15619304	Onio	502	France	42	8	159660.80	3	1	0	113931.57	1
3	4	15701354	Boni	699	France	39	1	0.00	2	0	0	93826.63	0
4	5	15737888	Mitchell	850	Spain	43	2	125510.82	1	1	1	79084.10	0

Converting Categorical Features

In [116]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000 entries, 0 to 9999
Data columns (total 13 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   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(9), object(2)
memory usage: 1015.8+ KB
```

In [118]:
```
pd.get_dummies(df['Geography'],drop_first=True).head()
```

Out[118]:

Out[118...

	Germany	Spain
0	0	0
1	0	1
2	0	0
3	0	0
4	0	1

In [124]:
```
df.info
```

Out[124]:

```
<bound method DataFrame.info of       RowNumber  CustomerId    Surname  Cre
ditScore Geography  Age  Tenure  \
0             1    15634602   Hargrave          619    France   42       2
1             2    15647311       Hill          608     Spain   41       1
2             3    15619304       Onio          502    France   42       8
3             4    15701354       Boni          699    France   39       1
4             5    15737888   Mitchell          850     Spain   43       2
...         ...         ...        ...          ...       ...  ...     ...
9995       9996    15606229   Obijiaku          771    France   39       5
9996       9997    15569892  Johnstone          516    France   35      10
9997       9998    15584532        Liu          709    France   36       7
9998       9999    15682355  Sabbatini          772   Germany   42       3
9999      10000    15628319     Walker          792    France   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

[10000 rows x 13 columns]>
```

In [125]:

```
sex = pd.get_dummies(df['Age'],drop_first=True)
embark = pd.get_dummies(df['Balance'],drop_first=True)
```

In [127]:

```
df.drop(['Age','HasCrCard','Surname','CustomerId'],axis=1,inplace=True)
```

In [129]:

```
df.head()
```

Out[129]:

	RowNumber	CreditScore	Geography	Tenure	Balance	NumOfProducts	IsActiveMember	EstimatedSalary	Exited
0	1	619	France	2	0.00	1	1	101348.88	1
1	2	608	Spain	1	83807.86	1	1	112542.58	0
2	3	502	France	8	159660.80	3	0	113931.57	1
3	4	699	France	1	0.00	2	0	93826.63	0
4	5	850	Spain	2	125510.82	1	1	79084.10	0

In [130]:

```
train = pd.concat([df,sex,embark],axis=1)
```

In [131]:

```
train.head()
```

Out[131]:

	RowNumber	CreditScore	Geography	Tenure	Balance	NumOfProducts	IsActiveMember	EstimatedSalary	Exited	19	...	212692.97	212696.32	212778.2	213146.2	214
0	1	619	France	2	0.00	1	1	101348.88	1	0	...	0	0	0	0	
1	2	608	Spain	1	83807.86	1	1	112542.58	0	0	...	0	0	0	0	
2	3	502	France	8	159660.80	3	0	113931.57	1	0	...	0	0	0	0	
3	4	699	France	1	0.00	2	0	93826.63	0	0	...	0	0	0	0	
4	5	850	Spain	2	125510.82	1	1	79084.10	0	0	...	0	0	0	0	

5 rows × 6459 columns

Find the outliers and replace the outliers

In [147]:
```
dataset= [11,10,12,14,12,15,14,13,15,102,12,14,17,19,107,
10,13,12,14,12,108,12,11,14,13,15,10,15,12,10,14,13,15,10]
```

Detecting outlier using Z score

Using Z score

In [148]:
```
outliers=[]
def detect_outliers(data):

    threshold=3
    mean = np.mean(data)
    std =np.std(data)


    for i in data:
        z_score= (i - mean)/std
        if np.abs(z_score) > threshold:
            outliers.append(y)
    return outliers
```

In [151]:
```
outlier_pt=detect_outliers(dataset)
```

In [152]:
```
outlier_pt
```

Out[152]:
```
Out[152…  [0       101348.88
           1       112542.58
           2       113931.57
           3        93826.63
           4        79084.10
                      ...
           9995     96270.64
           9996    101699.77
           9997     42085.58
           9998     92888.52
           9999     38190.78
           Name: EstimatedSalary, Length: 10000, dtype: float64, 0       101348.88
           1       112542.58
           2       113931.57
           3        93826.63
           4        79084.10
                      ...
           9995     96270.64
           9996    101699.77
           9997     42085.58
           9998     92888.52
           9999     38190.78
           Name: EstimatedSalary, Length: 10000, dtype: float64, 0       101348.88
           1       112542.58
           2       113931.57
           3        93826.63
           4        79084.10
                      ...
           9995     96270.64
           9996    101699.77
           9997     42085.58
           9998     92888.52
           9999     38190.78
           Name: EstimatedSalary, Length: 10000, dtype: float64]
```

In [153]:
```
## Perform all the steps of IQR
sorted(dataset)
```
Out[153]:

Out[153…
```
[10,
 10,
 10,
 10,
 10,
 11,
 11,
 12,
 12,
 12,
 12,
 12,
 12,
 12,
 13,
 13,
 13,
 13,
 14,
 14,
 14,
 14,
 14,
 14,
 15,
 15,
 15,
 15,
 15,
 17,
 19,
 102,
 107,
 108]
```
In [155]:
```
quantile1, quantile3= np.percentile(dataset,[25,75])
```
In [156]:
```
print(quantile1,quantile3)
```
```
12.0 15.0
```
In [157]:
```
## Find the IQR

iqr_value=quantile3-quantile1
print(iqr_value)
```
```
3.0
```
In [159]:
```
## Find the lower bound value and the higher bound value

lower_bound_val = quantile1 -(1.5 * iqr_value)
upper_bound_val = quantile3 +(1.5 * iqr_value)
```

In [160]:
```
print(lower_bound_val,upper_bound_val)
```
```
7.5 19.5
```

Check for Categorical columns and perform encoding

In [161]:
```
df=pd.read_csv('/content/Churn_Modelling.csv')
```

In [162]:
```
df.head()
```

Out[162]:

Out[162...	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 [163]:
```
df_numeric = df[['RowNumber', 'CustomerId', 'CreditScore', 'Age', 'Tenure', 
'Balance',
'NumOfProducts','HasCrCard','IsActiveMember','EstimatedSalary','Exited']]
df_categorical = df[['Surname', 'Geography', 'Gender']]
```

In [164]:
```
df_numeric.head()
```

Out[164]:

Out[164...	RowNumber	CustomerId	CreditScore	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	EstimatedSalary	Exited
0	1	15634602	619	42	2	0.00	1	1	1	101348.88	1
1	2	15647311	608	41	1	83807.86	1	0	1	112542.58	0
2	3	15619304	502	42	8	159660.80	3	1	0	113931.57	1
3	4	15701354	699	39	1	0.00	2	0	0	93826.63	0
4	5	15737888	850	43	2	125510.82	1	1	1	79084.10	0

In [165]:
```
df_categorical.head()
```

Out[165]:

Out[165...	Surname	Geography	Gender
0	Hargrave	France	Female
1	Hill	Spain	Female
2	Onio	France	Female
3	Boni	France	Female
4	Mitchell	Spain	Female

In [166]:
```
print(df['Surname'].unique())
print(df['Geography'].unique())
print(df['Gender'].unique())
```
```
['Hargrave' 'Hill' 'Onio' ... 'Kashiwagi' 'Aldridge' 'Burbidge']
['France' 'Spain' 'Germany']
['Female' 'Male']
```

In [167]:
```
from sklearn.preprocessing import LabelEncoder

marry_encoder = LabelEncoder()
```
In [168]:
```
marry_encoder.fit(df_categorical['Gender'])
```
Out[168]:
```
LabelEncoder()
```
In [169]:
```
marry_values = marry_encoder.transform(df_categorical['Gender'])
```
In [170]:
```
print("Before Encoding:", list(df_categorical['Gender'][-10:]))
print("After Encoding:", marry_values[-10:])
print("The inverse from the encoding result:",
marry_encoder.inverse_transform(marry_values[-10:]))
```
```
Before Encoding: ['Male', 'Female', 'Male', 'Male', 'Female', 'Male', 'Male
', 'Female', 'Male', 'Female']
After Encoding: [1 0 1 1 0 1 1 0 1 0]
The inverse from the encoding result: ['Male' 'Female' 'Male' 'Male' 'Femal
e' 'Male' 'Male' 'Female' 'Male' 'Female']
```
In [171]:
```
residence_encoder = LabelEncoder()
residence_values =
residence_encoder.fit_transform(df_categorical['Geography'])

print("Before Encoding:", list(df_categorical['Geography'][:5]))
print("After Encoding:", residence_values[:5])
print("The inverse from the encoding result:",
residence_encoder.inverse_transform(residence_values[:5]))
```
```
Before Encoding: ['France', 'Spain', 'France', 'France', 'Spain']
After Encoding: [0 2 0 0 2]
The inverse from the encoding result: ['France' 'Spain' 'France' 'France' '
Spain']
```
In [172]:
```
from sklearn.preprocessing import OneHotEncoder

gender_encoder = OneHotEncoder()
```
In [174]:
```
from sklearn.preprocessing import OneHotEncoder
import numpy as np

gender_encoder = OneHotEncoder()
gender_reshaped = np.array(df_categorical['Gender']).reshape(-1, 1)
gender_values = gender_encoder.fit_transform(gender_reshaped)

print(df_categorical['Gender'][:5])
print()
print(gender_values.toarray()[:5])
print()
print(gender_encoder.inverse_transform(gender_values)[:5])
```
```
0    Female
1    Female
2    Female
3    Female
4    Female
Name: Gender, dtype: object
```

```
[[1. 0.]
 [1. 0.]
 [1. 0.]
 [1. 0.]
 [1. 0.]]

[['Female']
 ['Female']
 ['Female']
 ['Female']
 ['Female']]
```

In [175]:

```
smoke_encoder = OneHotEncoder()
smoke_reshaped = np.array(df_categorical['Surname']).reshape(-1, 1)
smoke_values = smoke_encoder.fit_transform(smoke_reshaped)

print(df_categorical['Surname'][:5])
print()
print(smoke_values.toarray()[:5])
print()
print(smoke_encoder.inverse_transform(smoke_values)[:5])
```

```
0    Hargrave
1        Hill
2        Onio
3        Boni
4    Mitchell
Name: Surname, dtype: object

[[0. 0. 0. ... 0. 0. 0.]
 [0. 0. 0. ... 0. 0. 0.]
 [0. 0. 0. ... 0. 0. 0.]
 [0. 0. 0. ... 0. 0. 0.]
 [0. 0. 0. ... 0. 0. 0.]]

[['Hargrave']
 ['Hill']
 ['Onio']
 ['Boni']
 ['Mitchell']]
```

In [176]:

```
work_encoder = OneHotEncoder()
work_reshaped = np.array(df_categorical['Geography']).reshape(-1, 1)
work_values = work_encoder.fit_transform(work_reshaped)

print(df_categorical['Geography'][:5])
print()
print(work_values.toarray()[:5])
print()
print(work_encoder.inverse_transform(work_values)[:5])
```

```
0    France
1     Spain
2    France
3    France
4     Spain
Name: Geography, dtype: object

[[1. 0. 0.]
 [0. 0. 1.]
 [1. 0. 0.]
 [1. 0. 0.]
```

```
 [0. 0. 1.]]

[['France']
 ['Spain']
 ['France']
 ['France']
 ['Spain']]
```

In [178]:

```
df_categorical_encoded = pd.get_dummies(df_categorical, drop_first=True)
df_categorical_encoded.head()
```

Out[178]:

	Surname_Abbie	Surname_Abbott	Surname_Abdullah	Surname_Abdulov	Surname_Abel	Surname_Abernathy	Surname_Abramov	Surname_Abramova	Surname_Abramov
0	0	0	0	0	0	0	0	0	0
1	0	0	0	0	0	0	0	0	0
2	0	0	0	0	0	0	0	0	0
3	0	0	0	0	0	0	0	0	0
4	0	0	0	0	0	0	0	0	0

5 rows × 2934 columns

In [179]:

```
df_new = pd.concat([df_numeric, df_categorical_encoded], axis=1)
df_new.head()
```

Out[179]:

	RowNumber	CustomerId	CreditScore	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	EstimatedSalary	...	Surname_Zotova	Surname_Zox	Surnam
0	1	15634602	619	42	2	0.00	1	1	1	101348.88	...	0	0	
1	2	15647311	608	41	1	83807.86	1	0	1	112542.58	...	0	0	
2	3	15619304	502	42	8	159660.80	3	1	0	113931.57	...	0	0	
3	4	15701354	699	39	1	0.00	2	0	0	93826.63	...	0	0	
4	5	15737888	850	43	2	125510.82	1	1	1	79084.10	...	0	0	

5 rows × 2945 columns

Split the data into dependent and independent variables.

In [180]:

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

In [182]:

```
print(df["Balance"].min())
print(df["Balance"].max())
print(df["Balance"].mean())
```

```
0.0
250898.09
76485.889288
```

In [183]:

```
print(df.count(0))
```

```
RowNumber          10000
CustomerId         10000
Surname            10000
CreditScore        10000
Geography          10000
Gender             10000
Age                10000
Tenure             10000
```

```
Balance            10000
NumOfProducts      10000
HasCrCard          10000
IsActiveMember     10000
EstimatedSalary    10000
Exited             10000
dtype: int64
```

In [184]:

```
print(df.shape)
```

```
(10000, 14)
```

In [185]:

```
print(df.size)
```

```
140000
```

In [187]:

```
X = df.iloc[:, :-1].values
print(X)
```

```
[[1 15634602 'Hargrave' ... 1 1 101348.88]
 [2 15647311 'Hill' ... 0 1 112542.58]
 [3 15619304 'Onio' ... 1 0 113931.57]
 ...
 [9998 15584532 'Liu' ... 0 1 42085.58]
 [9999 15682355 'Sabbatini' ... 1 0 92888.52]
 [10000 15628319 'Walker' ... 1 0 38190.78]]
```

In [271]:

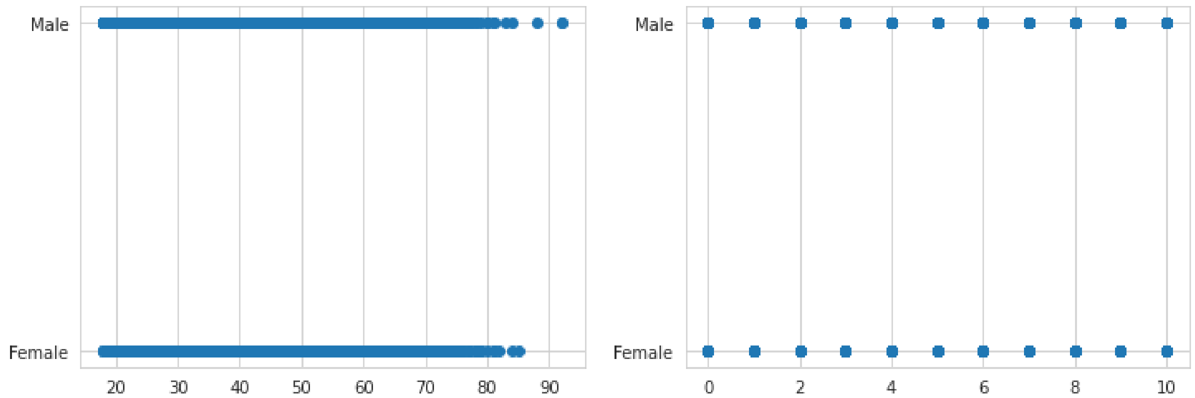
```
Y = df.iloc[:, -1].values
print(Y)
```

```
[1 0 1 ... 1 1 0]
```

Scale the independent variables

In [215]:

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

x = df[['Age', 'Tenure']].values
y = df['Gender'].values

fig, ax = plt.subplots(ncols=2, figsize=(12, 4))

ax[0].scatter(x[:,0], y)
ax[1].scatter(x[:,1], y)

plt.show()
```

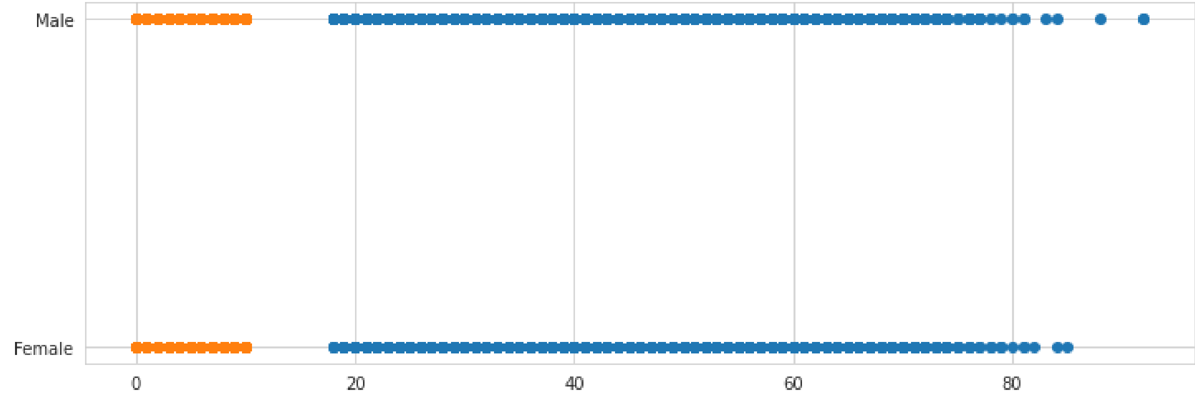


In [216]:

```
fig, ax = plt.subplots(figsize=(12, 4))

ax.scatter(x[:,0], y)
ax.scatter(x[:,1], y)
```

Out[216]:

```
<matplotlib.collections.PathCollection at 0x7f9a8a854ad0>
```

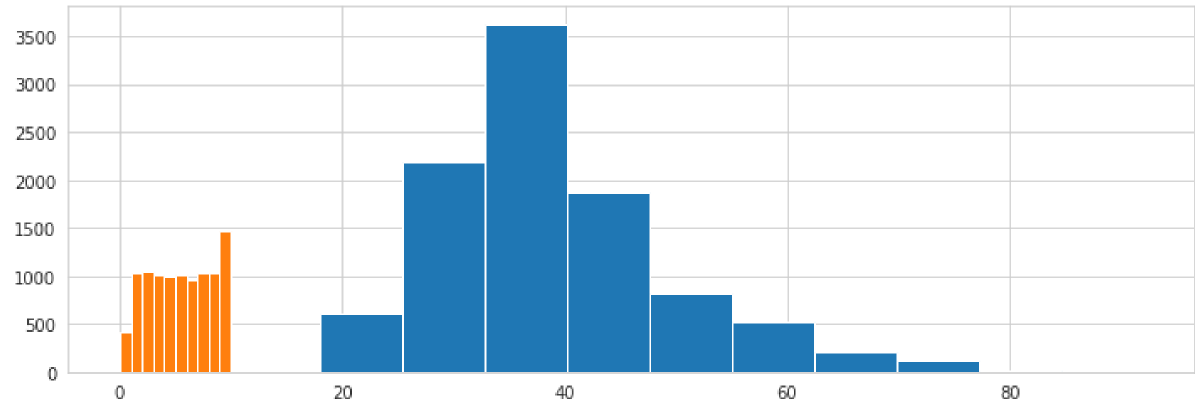


In [217]:

```
fig, ax = plt.subplots(figsize=(12, 4))

ax.hist(x[:,0])
ax.hist(x[:,1])
```

Out[217]:

```
(array([ 413., 1035., 1048., 1009.,  989., 1012.,  967., 1028., 1025.,
        1474.]),
 array([ 0.,  1.,  2.,  3.,  4.,  5.,  6.,  7.,  8.,  9., 10.]),
 <a list of 10 Patch objects>)
```



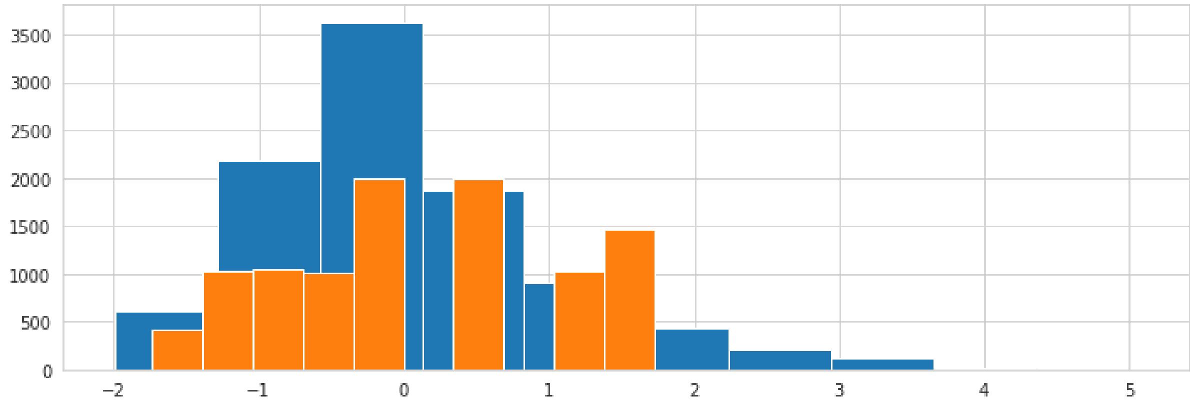
In [220]:

```
from sklearn.preprocessing import StandardScaler
from sklearn.preprocessing import MinMaxScaler
fig, ax = plt.subplots(figsize=(12, 4))

scaler = StandardScaler()
x_std = scaler.fit_transform(x)

ax.hist(x_std[:,0])
ax.hist(x_std[:,1])
```

Out[220]:

```
(array([ 413., 1035., 1048., 1009., 2001.,    0., 1995.,    0., 1025.,
        1474.]),
 array([-1.73331549, -1.38753759, -1.04175968, -0.69598177, -0.35020386,
        -0.00442596,  0.34135195,  0.68712986,  1.03290776,  1.37868567,
```

```
        1.72446358]),
 <a list of 10 Patch objects>)
```

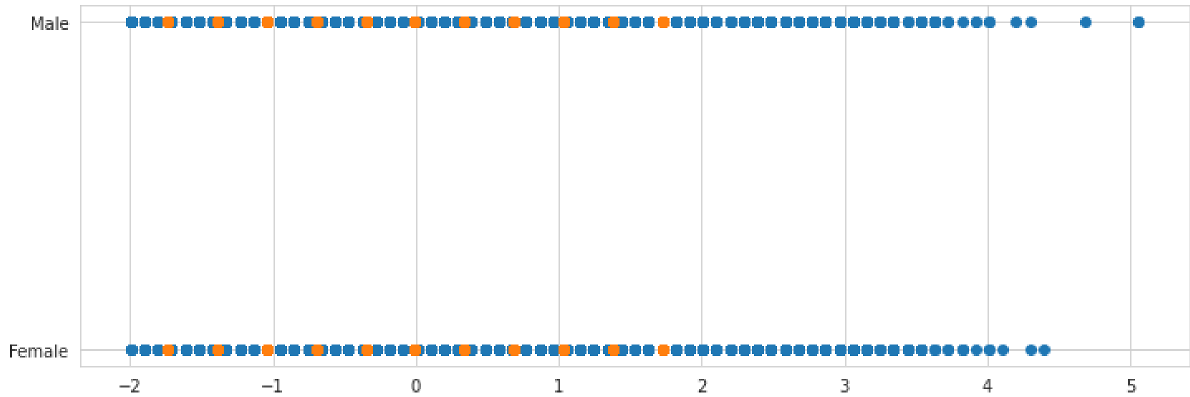


In [219]:

```
fig, ax = plt.subplots(figsize=(12, 4))

scaler = StandardScaler()
x_std = scaler.fit_transform(x)

ax.scatter(x_std[:,0], y)
ax.scatter(x_std[:,1], y)
```

Out[219]:

```
<matplotlib.collections.PathCollection at 0x7f9a8a2fde50>
```

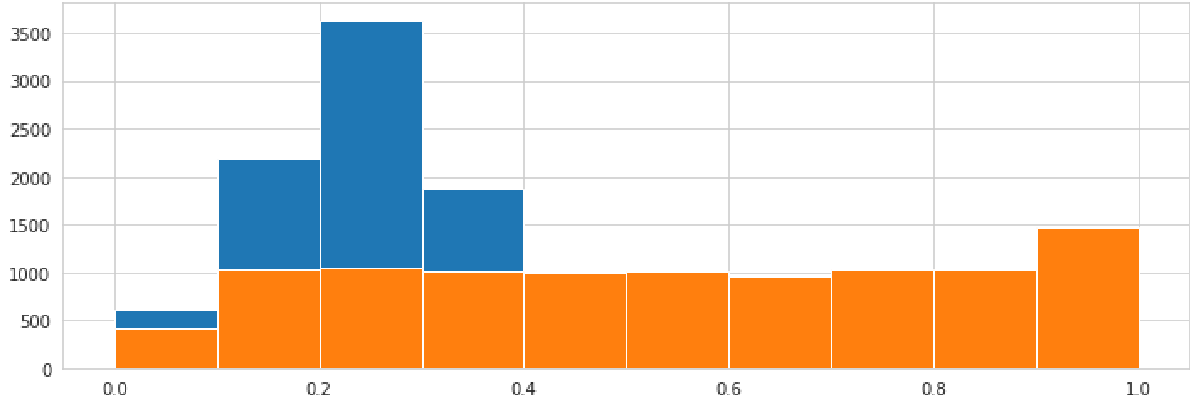


In [221]:

```
fig, ax = plt.subplots(figsize=(12, 4))

scaler = MinMaxScaler()
x_minmax = scaler.fit_transform(x)

ax.hist(x_minmax [:,0])
ax.hist(x_minmax [:,1])
```

Out[221]:

```
(array([ 413., 1035., 1048., 1009.,  989., 1012.,  967., 1028., 1025.,
        1474.]),
 array([0. , 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 1. ]),
 <a list of 10 Patch objects>)
```

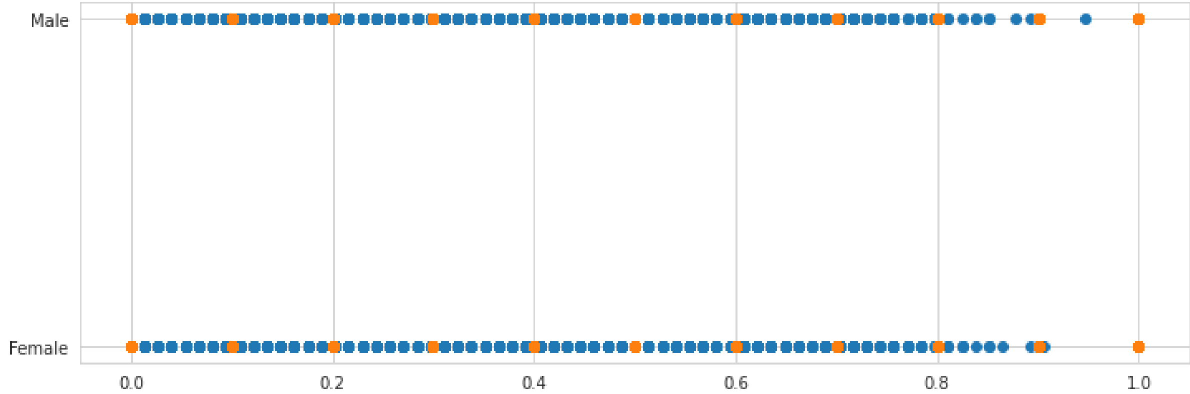


In [222]:

```
fig, ax = plt.subplots(figsize=(12, 4))

scaler = MinMaxScaler()
x_minmax = scaler.fit_transform(x)

ax.scatter(x_minmax [:,0], y)
ax.scatter(x_minmax [:,1], y)
```

Out[222]:

```
<matplotlib.collections.PathCollection at 0x7f9a8a0cae10>
```

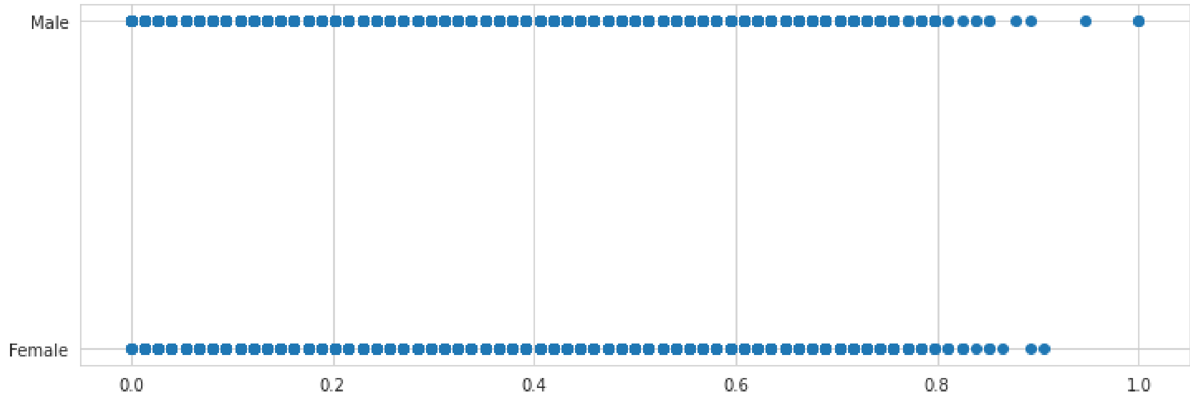


In [223]:

```
fig, ax = plt.subplots(figsize=(12, 4))

scaler = MinMaxScaler()
x_minmax = scaler.fit_transform(x)

ax.scatter(x_minmax [:,0], y)
```

Out[223]:

```
<matplotlib.collections.PathCollection at 0x7f9a8a0caf10>
```



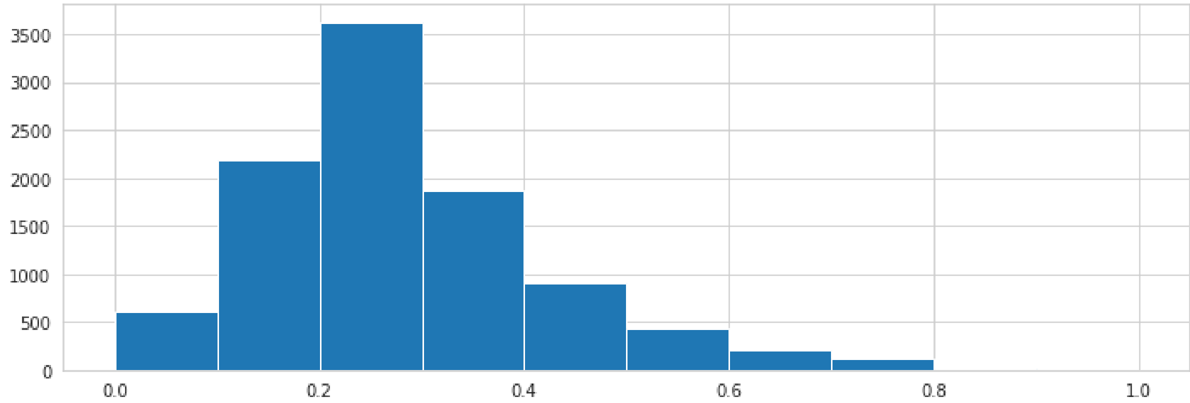
In [224]:

```
fig, ax = plt.subplots(figsize=(12, 4))
```

```
scaler = MinMaxScaler()
x_minmax = scaler.fit_transform(x)

ax.hist(x_minmax [:,0])
```

Out[224]:

```
(array([ 611., 2179., 3629., 1871.,  910.,  441.,  208.,  127.,   20.,
           4.]),
 array([0. , 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 1. ]),
 <a list of 10 Patch objects>)
```



In [227]:

```
from sklearn.model_selection import train_test_split
from sklearn.pipeline import Pipeline
from sklearn.linear_model import SGDRegressor
from sklearn.preprocessing import StandardScaler
from sklearn.preprocessing import MinMaxScaler
from sklearn.metrics import mean_absolute_error
import sklearn.metrics as metrics

import pandas as pd
import numpy as np
import matplotlib.pyplot as plt

# Import Data
df = pd.read_csv('/content/Churn_Modelling.csv')
x = df[['Age', 'Tenure']].values
y = df['Balance'].values

# Split into a training and testing set
X_train, X_test, Y_train, Y_test = train_test_split(x, y)

# Define the pipeline for scaling and model fitting
pipeline = Pipeline([
    ("MinMax Scaling", MinMaxScaler()),
    ("SGD Regression", SGDRegressor())
])

# Scale the data and fit the model
pipeline.fit(X_train, Y_train)

# Evaluate the model
Y_pred = pipeline.predict(X_test)
print('Mean Absolute Error: ', mean_absolute_error(Y_pred, Y_test))
print('Score', pipeline.score(X_test, Y_test))
```

```
Mean Absolute Error:  57120.533393590835
Score 0.0004207814312172653
```

Split the data into training and testing

In [267]:
```
dataset = pd.read_csv('/content/Churn_Modelling.csv')
print(dataset)
```

```
      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   
...         ...         ...        ...          ...       ...     ...  ...   
9995       9996    15606229   Obijiaku          771    France    Male   39   
9996       9997    15569892  Johnstone          516    France    Male   35   
9997       9998    15584532        Liu          709    France  Female   36   
9998       9999    15682355  Sabbatini          772   Germany    Male   42   
9999      10000    15628319     Walker          792    France  Female   28   

      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   
...      ...        ...            ...        ...             ...   
9995       5       0.00              2          1               0   
9996      10   57369.61              1          1               1   
9997       7       0.00              1          0               1   
9998       3   75075.31              2          1               0   
9999       4  130142.79              1          1               0   

      EstimatedSalary  Exited  
0           101348.88       1  
1           112542.58       0  
2           113931.57       1  
3            93826.63       0  
4            79084.10       0  
...               ...     ...  
9995         96270.64       0  
9996        101699.77       0  
9997         42085.58       1  
9998         92888.52       1  
9999         38190.78       0  

[10000 rows x 14 columns]
```

In [287]:
```
dataset.drop(["HasCrCard"],axis=1,inplace=True)
```

In [288]:
```
print(dataset.shape)#no. of rows and colume
print(dataset.head(10))
```

```
(10000, 7)
   CustomerId  CreditScore  Age  Tenure    Balance  IsActiveMember  \
0    15634602          619   42       2       0.00               1   
1    15647311          608   41       1   83807.86               1   
2    15619304          502   42       8  159660.80               0   
3    15701354          699   39       1       0.00               0   
4    15737888          850   43       2  125510.82               1   
```

```
5    15574012          645   44       8  113755.78                0
6    15592531          822   50       7       0.00                1
7    15656148          376   29       4  115046.74                0
8    15792365          501   44       4  142051.07                1
9    15592389          684   27       2  134603.88                1

   EstimatedSalary
0        101348.88
1        112542.58
2        113931.57
3         93826.63
4         79084.10
5        149756.71
6         10062.80
7        119346.88
8         74940.50
9         71725.73
```

In [289]:

```
X=dataset.iloc[:,:-1].values
X
```

Out[289]:

```
array([[1.5634602e+07, 6.1900000e+02, 4.2000000e+01, 2.0000000e+00,
        0.0000000e+00, 1.0000000e+00],
       [1.5647311e+07, 6.0800000e+02, 4.1000000e+01, 1.0000000e+00,
        8.3807860e+04, 1.0000000e+00],
       [1.5619304e+07, 5.0200000e+02, 4.2000000e+01, 8.0000000e+00,
        1.5966080e+05, 0.0000000e+00],
       ...,
       [1.5584532e+07, 7.0900000e+02, 3.6000000e+01, 7.0000000e+00,
        0.0000000e+00, 1.0000000e+00],
       [1.5682355e+07, 7.7200000e+02, 4.2000000e+01, 3.0000000e+00,
        7.5075310e+04, 0.0000000e+00],
       [1.5628319e+07, 7.9200000e+02, 2.8000000e+01, 4.0000000e+00,
        1.3014279e+05, 0.0000000e+00]])
```

In [290]:

```
Y=dataset.iloc[:,-1].values
Y
```

Out[290]:

```
array([101348.88, 112542.58, 113931.57, ...,  42085.58,  92888.52,
        38190.78])
```

In [291]:

```
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 )
```

In [306]:

```
from sklearn.preprocessing import StandardScaler
sc=StandardScaler()
X_train = sc.fit_transform(X_train)
X_test = sc.transform(X_test)
print(X_train)
```

```
[[-1.34333028 -0.73550706  0.01526571  0.00886037  0.67316003 -1.03446007]
 [ 1.55832963  1.02442719 -0.65260917  0.00886037 -1.20772417 -1.03446007]
 [-0.65515619  0.80829492 -0.46178778  1.39329338 -0.35693706  0.96668786]
 ...
 [-1.63542994  0.90092304 -0.36637708  0.00886037  1.36657199 -1.03446007]
 [-0.38540456 -0.62229491 -0.08014499  1.39329338 -1.20772417  0.96668786]
 [-1.37829524 -0.28265848  0.87396199 -1.37557264  0.51741687 -1.03446007]]
```

In [305]:

```
print(X_test)
```

```
[[-1.05852196 -0.55025082 -0.36637708  1.04718513  0.88494297  0.96668786]
 [-0.51554728 -1.31185979  0.11067641 -1.02946438  0.43586703 -1.03446007]
 [-0.8058485   0.57157862  0.3014978   1.04718513  0.31486378  0.96668786]
 ...
 [ 0.25326371  1.95070838  0.01526571 -1.37557264  0.30819395 -1.03446007]
 [-0.17836122  0.29369426 -0.08014499  0.70107688  0.55698791 -1.03446007]
 [ 0.40190663  0.870047   -0.74801987 -0.68335613  0.7006957  -1.03446007]]
```