1. importing package import pandas as pd import seaborn as sns import seasoff as ship
import numpy as np
from matplotlib import pyplot as plt
%matplotlib inline

1. Loading dataset

df = pd.read_csv("Churn_Modelling.csv")

df							
Age 0 42 1 41 2 42 3	RowNumbe	er Custom	erId	Surname	CreditScore	Geography	Gender
	\	1 1563	4602	Hargrave	619	France	Female
		2 1564	7311	Hill	608	Spain	Female
		3 1561	9304	Onio	502	France	Female
		4 1570	1354	Boni	699	France	Female
39 4		5 1573	7888	Mitchell	850	Spain	Female
43 							
9995 39 9996	999	96 1560	6229	0bijiaku	771	France	Male
	999	97 1556	9892	Johnstone	516	France	Male
35 9997	999	98 1558	4532	Liu	709	France	Female
36 9998	999	99 1568	2355	Sabbatini	772	Germany	Male
42 9999	1000	00 1562	8319	Walker	792	France	Female
28							
0 1 2 3 4	Tenure 2 1 8 1 2	Balance 0.00 83807.86 159660.80 0.00 125510.82		OfProducts 1 1 3 2 1	HasCrCard 1 0 1 0 1	IsActiveMem	ber \ 1
9995 9996 9997 9998 9999	 5 10 7 3 4	0.00 57369.61 0.00 75075.31 130142.79		 2 1 1 2 1	1 1 0 1 1		 0 1 1 0 0

EstimatedSalary 101348.88 112542.58 113931.57 93826.63	Exited 1 0 1
/9084.10	0
96270.64	Θ
101699.77	0
42085.58	1
92888.52	1
38190.78	0
	101348.88 112542.58 113931.57 93826.63 79084.10 96270.64 101699.77 42085.58 92888.52

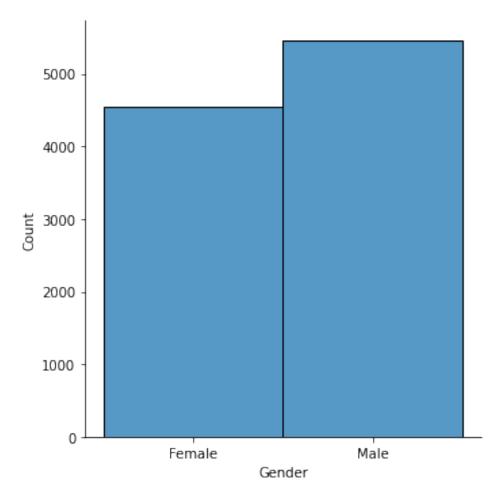
[10000 rows x 14 columns]

1. Visualizations

a) Univariate Analysis

sns.displot(df.Gender)

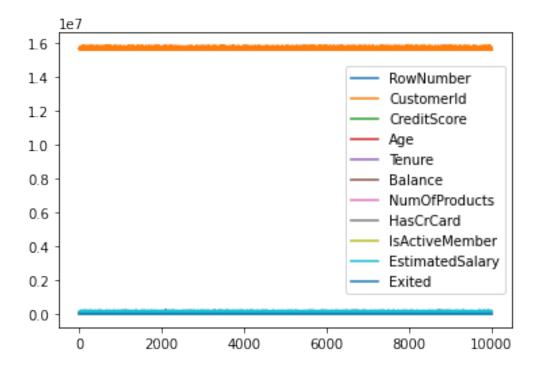
<seaborn.axisgrid.FacetGrid at 0x7f2935aae790>



b) Bi-Variate Analysis

df.plot.line()

<matplotlib.axes._subplots.AxesSubplot at 0x7f2932d2df50>

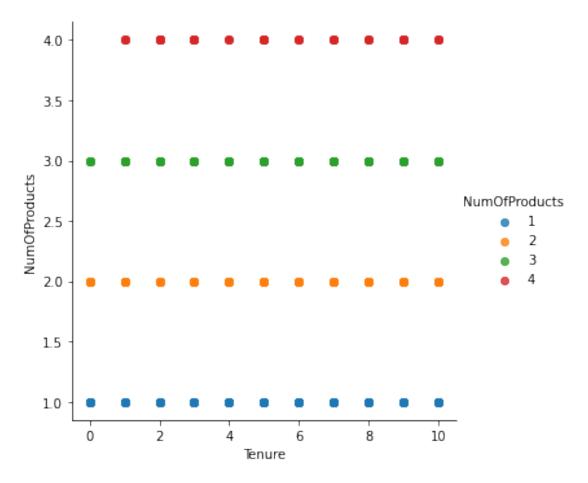


c) Multi - Variate Analysis

sns.lmplot("Tenure", "NumOfProducts", df, hue="NumOfProducts",
fit_reg=False);

/usr/local/lib/python3.7/dist-packages/seaborn/_decorators.py:43: FutureWarning: Pass the following variables as keyword args: x, y, data. 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



1. Perform descriptive statistics on the dataset. df.describe()

RowNumber	CustomerId	CreditScore	Age		
Tenure \			J		
count 10000.00000	1.000000e+04	10000.000000	10000.000000		
10000.000000					
mean 5000.50000	1.569094e+07	650.528800	38.921800		
5.012800					
std 2886.89568	7.193619e+04	96.653299	10.487806		
2.892174					
min 1.00000	1.556570e+07	350.000000	18.000000		
0.00000					
25% 2500.75000	1.562853e+07	584.000000	32.000000		
3.000000					
50% 5000.50000	1.569074e+07	652.000000	37.000000		
5.000000					
75% 7500.25000	1.575323e+07	718.000000	44.000000		
7.000000					
max 10000.00000	1.581569e+07	850.000000	92.000000		
10.000000					

```
10000.000000
                        10000.000000
                                       10000.00000
                                                       10000.000000
count
        76485.889288
                            1.530200
                                           0.70550
                                                           0.515100
mean
                                                           0.499797
std
        62397.405202
                            0.581654
                                           0.45584
            0.000000
                            1.000000
                                           0.00000
                                                           0.000000
min
25%
            0.000000
                            1.000000
                                           0.00000
                                                           0.000000
50%
        97198.540000
                            1.000000
                                           1.00000
                                                           1.000000
75%
       127644.240000
                                           1.00000
                            2.000000
                                                           1.000000
       250898.090000
                            4.000000
                                           1.00000
                                                           1.000000
max
       EstimatedSalarv
                                Exited
          10000.000000
                         10000.000000
count
         100090.239881
                             0.203700
mean
          57510.492818
                             0.402769
std
min
              11.580000
                             0.000000
          51002.110000
25%
                             0.000000
50%
         100193.915000
                             0.000000
75%
         149388.247500
                             0.000000
         199992.480000
                             1.000000
max
```

1. Handle the Missing values.

```
data = pd.read csv("Churn Modelling.csv")
pd.isnull(data["Gender"])
```

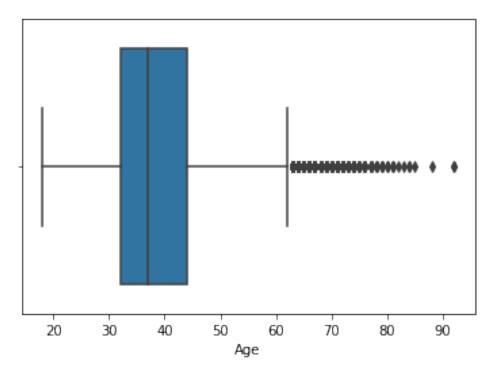
```
0
         False
1
         False
2
         False
3
         False
4
         False
         . . .
9995
         False
9996
         False
9997
         False
9998
         False
         False
9999
Name: Gender, Length: 10000, dtype: bool
```

Find the outliers and replace the outliers. sns.boxplot(df['Age'])

/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 0x7f2932b8c650>



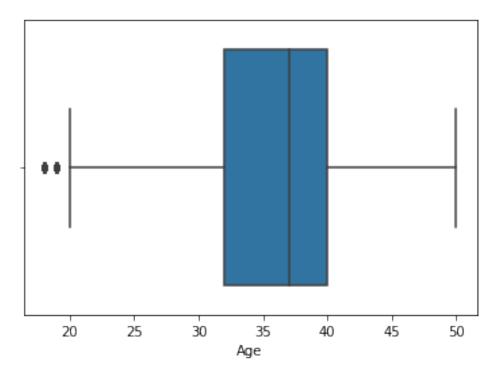
```
df['Age']=np.where(df['Age']>50,40,df['Age'])
df['Age']
0
        42
1
        41
2
        42
3
        39
        43
        39
9995
9996
        35
        36
9997
9998
        42
9999
        28
Name: Age, Length: 10000, dtype: int64
```

/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

sns.boxplot(df['Age'])

<matplotlib.axes._subplots.AxesSubplot at 0x7f2932a9a450>



```
df['Age']=np.where(df['Age']<20,35,df['Age'])</pre>
df['Age']
         42
0
1
        41
2
         42
3
         39
         43
         . .
39
9995
9996
         35
9997
         36
9998
         42
9999
         28
Name: Age, Length: 10000, dtype: int64
```

1. Check for Categorical columns and perform encoding.
pd.get_dummies(df, columns=["Gender", "Age"], prefix=["Age",
"Gender"]).head()

RowNumb Balance	ber	CustomerId	Surname	CreditScore	Geography	Tenure
0	` 1	15634602	Hargrave	619	France	2
0.00 1	2	15647311	Hill	608	Spain	1
83807.86	3	15619304	Onio	502	France	8
159660.80 3	4	15701354	Boni	699	France	1

```
0.00
                   15737888 Mitchell
                                                    850
                                                              Spain
                                                                            2
4
             5
125510.82
   NumOfProducts HasCrCard
                                                            Gender_41 Gender_42
                                 IsActiveMember
                                                     . . .
0
                                                                     0
                  1
                               1
                                                  1
                                                                                   1
                                                      . . .
                  1
                               0
                                                                                   0
1
                                                  1
                                                                     1
2
                  3
                               1
                                                  0
                                                                     0
                                                                                   1
3
                  2
                               0
                                                  0
                                                                                   0
                  1
                               1
                                                  1
4
                                                                     0
                                                                                   0
                                                      . . .
   Gender_43
                Gender_44
                              Gender_45
                                           Gender_46
                                                        Gender_47
                                                                     Gender 48
                                       0
0
             0
                          0
                                                    0
                                                                  0
             0
                          0
                                       0
                                                    0
                                                                  0
1
                                                                               0
2
                          0
                                                     0
             0
                                       0
                                                                  0
3
             0
                          0
                                       0
                                                     0
                                                                  0
                                                                               0
4
             1
                          0
                                       0
                                                                  0
                                                                               0
   Gender_49
                Gender_50
0
             0
             0
                          0
1
2
             0
                          0
3
             0
                          0
```

- [5 rows x 45 columns]
 - 1. Split the data into dependent and independent variables.
- a) Split the data into Independent variables.

```
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]]
```

b) Split the data into Dependent variables.

```
Y = df.iloc[:, -1].values
print(Y)
[1 \ 0 \ 1 \ \dots \ 1 \ 1 \ 0]
     Scale the independent variables
import pandas as pd
from sklearn.preprocessing import MinMaxScaler
scaler = MinMaxScaler()
df[["CustomerId"]] = scaler.fit transform(df[["CustomerId"]])
print(df)
      RowNumber CustomerId
                                  Surname CreditScore Geography
                                                                     Gender
Age
               1
                    0.275616
                                Hargrave
                                                    619
                                                            France
                                                                     Female
42
               2
1
                    0.326454
                                     Hill
                                                    608
                                                             Spain
                                                                     Female
41
               3
                    0.214421
2
                                     Onio
                                                    502
                                                            France
                                                                     Female
42
               4
                    0.542636
                                     Boni
                                                    699
                                                            France
                                                                    Female
3
39
               5
                     0.688778
                                Mitchell
4
                                                    850
                                                             Spain
                                                                     Female
43
. . .
                          . . .
                                                     . . .
                                                                . . .
                                                                        . . .
9995
                     0.162119
                                Obijiaku
            9996
                                                    771
                                                            France
                                                                       Male
39
                    0.016765
                               Johnstone
9996
            9997
                                                    516
                                                            France
                                                                       Male
35
9997
            9998
                    0.075327
                                      Liu
                                                    709
                                                            France
                                                                    Female
36
9998
            9999
                    0.466637
                               Sabbatini
                                                    772
                                                           Germany
                                                                       Male
42
9999
           10000
                    0.250483
                                   Walker
                                                    792
                                                            France Female
28
      Tenure
                 Balance
                           NumOfProducts HasCrCard
                                                       IsActiveMember
0
            2
                     0.00
                                        1
                                                    1
                                                                      1
            1
                83807.86
                                        1
                                                    0
                                                                      1
1
2
            8
               159660.80
                                        3
                                                    1
                                                                      0
3
                                        2
            1
                                                    0
                                                                      0
                    0.00
            2
4
               125510.82
                                        1
                                                    1
                                                                      1
            5
                                        2
9995
                    0.00
                                                    1
                                                                      0
9996
           10
                57369.61
                                        1
                                                    1
                                                                      1
                                        1
                                                                      1
9997
            7
                    0.00
                                                    0
            3
                75075.31
                                        2
                                                                      0
9998
                                                    1
```

1

1

0

9999

130142.79

```
EstimatedSalary
                         Exited
0
             101348.88
                               1
                               0
1
             112542.58
2
             113931.57
                               1
3
                               0
              93826.63
4
              79084.10
                               0
                             . . .
              96270.64
9995
                               0
9996
             101699.77
                               0
                               1
9997
              42085.58
9998
              92888.52
                               1
9999
              38190.78
                               0
[10000 \text{ rows } \times 14 \text{ columns}]
  1. Split the data into training and testing
from sklearn.model selection import train_test_split
train size=0.8
X = df.drop(columns = ['Tenure']).copy()
y = df['Tenure']
X train, X rem, y train, y rem = train test split(X,y, train size=0.8)
test size = 0.5
X_valid, X_test, y_valid, y_test = train_test_split(X_rem,y_rem,
test size=\overline{0.5})
print(X train.shape), print(y train.shape)
print(X_valid.shape), print(y_valid.shape)
print(X test.shape), print(y test.shape)
(8000, 13)
(8000,)
(1000, 13)
(1000,)
(1000, 13)
(1000,)
```

(None, None)