Assignment -II

Name	B.BAVNA GRACE
Register Number	210519205012
Team Size	4
Team ID	PNT2022TMID25108

1) Importing

In [ ]:

```
import pandas as pd import
numpy as np import seaborn as
sns from matplotlib import
pyplot as plt import warnings
warnings.filterwarnings('ignore')
```

2.Load the Dataset

In [ ]:

```
data=pd.read_csv("Churn_Modelling.csv")
```

In [43]:

```
data
```

Out[43]:

	RowNum	CustomerId	Surname	CreditScore	Geography	Gend	Age	Tenu	Balance	NumOfProduc	HasCrCar	IsActiveMemb	EstimatedSalar	Exite
0	1	0.275616	Hargrave	619	France	Female	42	2	0.00	1	1	1	101348.88	1

1	2	0.326454	Hill	608	Spain	Female	41	1	83807.86	1	0	1	112542.58	0
2	3	0.214421	Onio	502	France	Female	42	8	159660.80	3	1	0	113931.57	1
3	4	0.542636	Bonci	699	France	Female	39	1	0.00	2	0	0	93826.63	0
4	5	0.688778	Mitchell	850	Spain	Female	43	2	125510.82	1	1	1	79084.10	0
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
9995	9996	0.162119	Obijiaku	771	France	Male	39	5	0.00	2	1	0	96270.64	0
9996	9997	0.016765	Johnston e	516	France	Male	35	10	573659.61	1	1	1	101699.77	0
9997	9998	0.075327	Liu	709	France	Female	36	7	0.00	1	0	1	42085.58	1

9998	9999	0.46637	Sabatini	772	Germany	Male	42	3	75075.31	2	1	0	92888.52	1
9999	10000	0.25048	Walker	792	France	Female	28	4	130142.79	1	1	0	38190.78	0

10000 rows × 14 columns

3.Visualizations

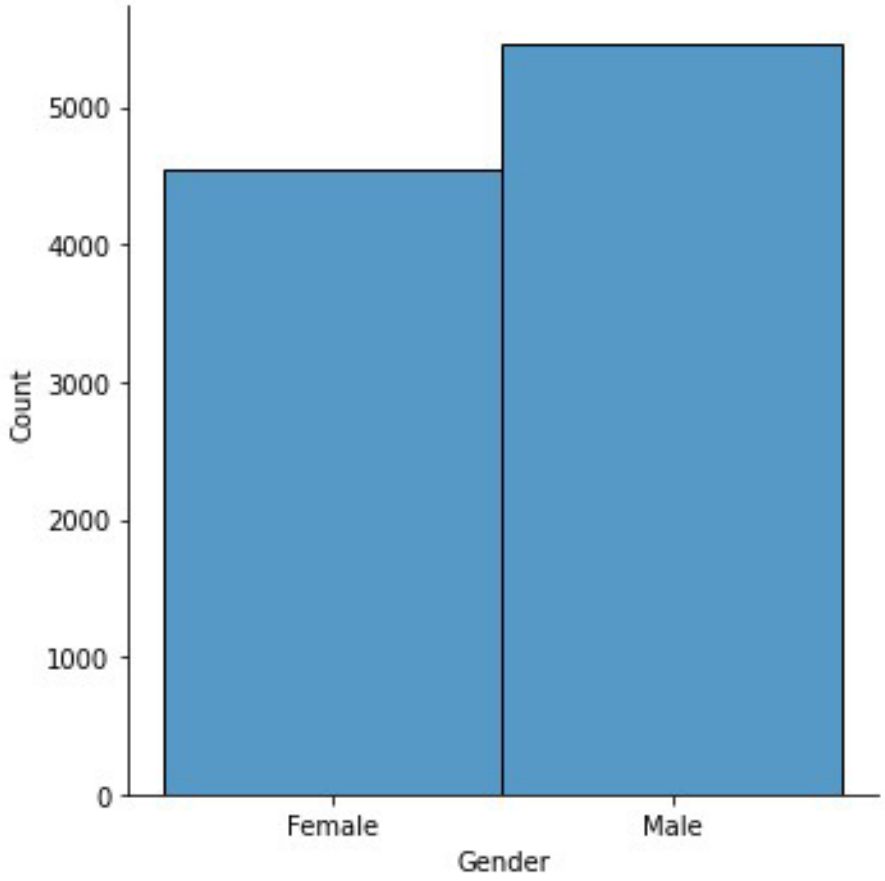
a) Univariate Analysis

In [44]:

```
sns.displot(data.Gender)
```

Out[44]:

```
<seaborn.axisgrid.FacetGrid at 0x7f80cb07c690>
```



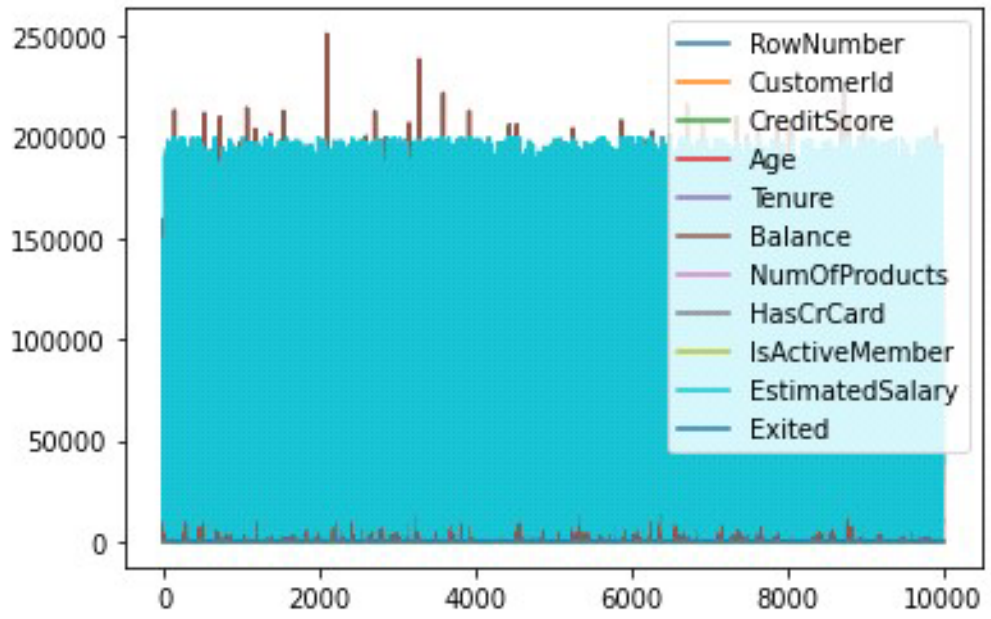
B)Bi-Variate Analysis

In [45]:

```
data.plot.line()
```

Out[45]:

<matplotlib.axes._subplots.AxesSubplot at 0x7f80cb9a8a50>



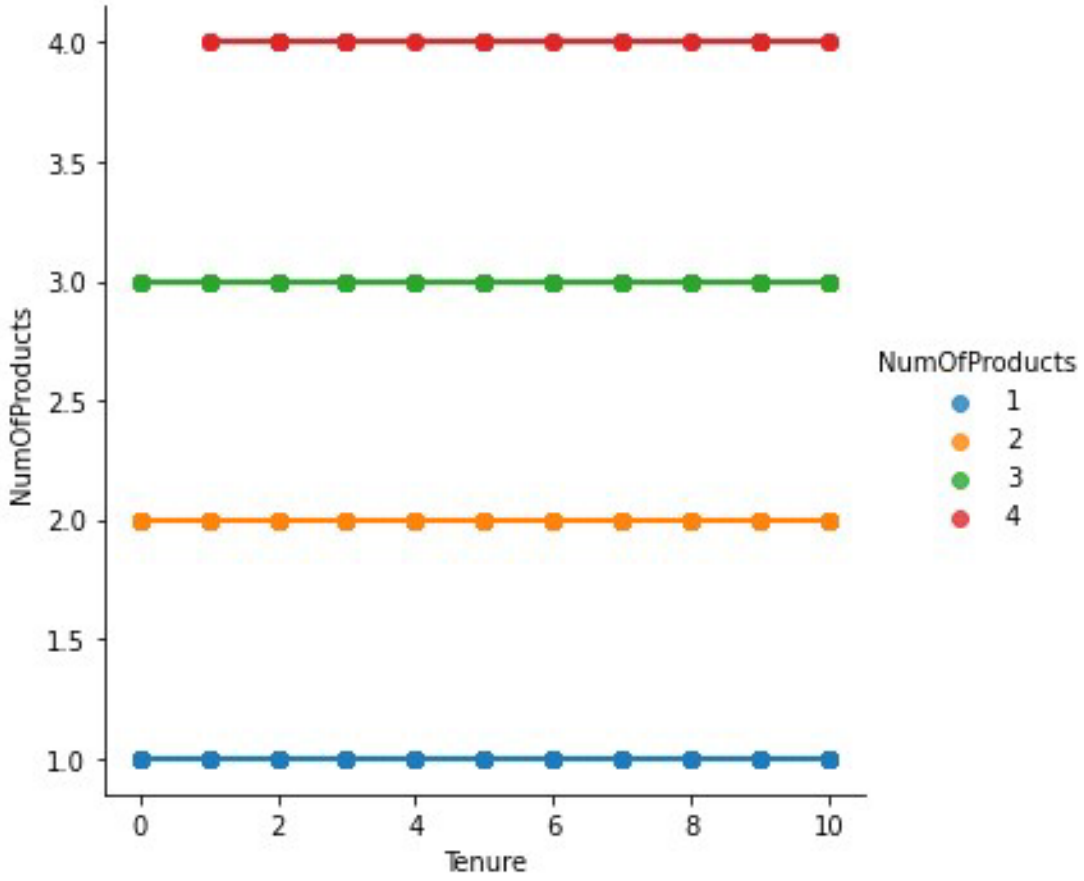
C)Multi - Variate Analysis

In [46]:

```
sns.lmplot("Tenure","NumOfProducts",data,hue="NumOfProducts")
```

Out[46]:

<seaborn.axisgrid.FacetGrid at 0x7f80cb95fe10>



4)Perform descriptive statistics on the dataset.

In [47]:
data.describe()
Out[47]:

	RowNumber	CustomerId	Credit Score	Age	Tenure	Balance	NumOf Products	HasCrCard	IsActive Member	EstimatedSalary	Exited
count	10000.00000	10000.000000	10000.000000	10000.000000	10000.000000	10000.000000	10000.000000	10000.00000	10000.0000	10000.0000	10000.000000
mean	5000.5	0.5009	650.52	36.533	5.0128	76485.8	1.53020	0.7055	0.515100	100090.2	0.2037
n	0000	80	880(	900	00	89288	0	0		39881	00

std	2886.89568	0.287757	96.6 53299	6.473843	2.892174	62397.405202	0.581654	0.455844	0.499797	57510.492818	0.402769
min	1.000000	0.000000	350000000C	20.000000	0.000000	0.000000	1.000000	0.000000	0.000000	11.580000	0.000000
25%	2500.75000	0.251320	584000000C	32.000000	3.000000	0.000000	1.000000	0.000000	0.000000	51002.110000	0.000000
50%	5000.50000	0.500170	652000000C	37.000000	5.000000	97198.540000	1.000000	1.000000	1.000000	100193.915000	0.000000
75%	7500.25000	0.750164	718000000C	40.000000	7.000000	127644.240000	2.000000	1.000000	1.000000	149388.247500	0.000000
max	10000.000000	1.000000	850000000C	50.000000	10.000000	250898.090000	4.000000	1.000000	1.000000	199992.480000	1.000000

5)Handle the Missing values.

In [ ]:

```
data = pd.read_csv("Churn_Modelling.csv")

pd.isnull(data["Gender"])
```

Out[ ]:

```
1       False
2       False
3       False
4       False
5       False
        ...
9995    False
9996    False
9997    False
9998    False
9999    False
```

Name: Gender, Length: 10000, dtype: bool

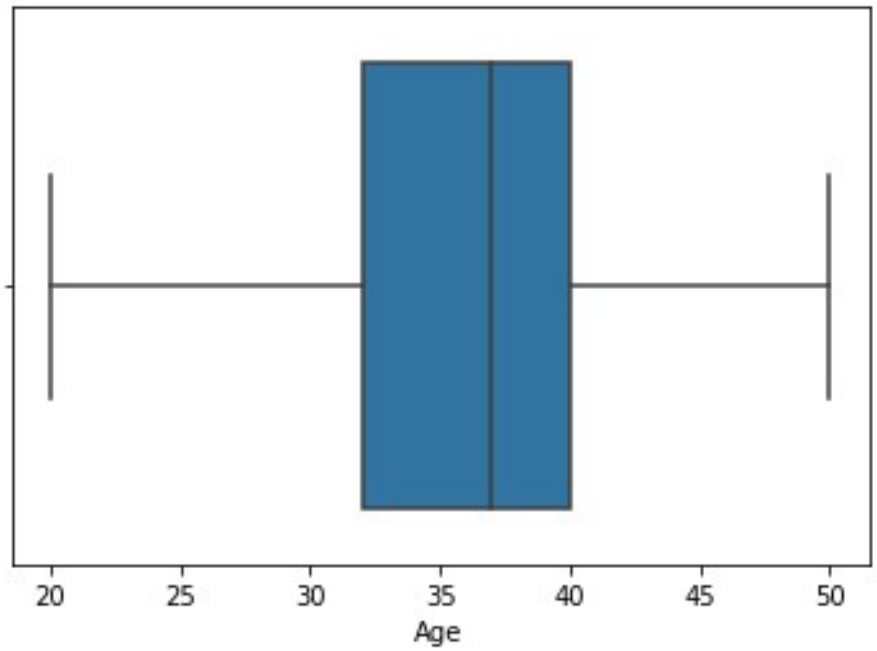
6)Find the outliers and replace the outliers

In [48]:

```
sns.boxplot(data['Age'])
```

Out[48]:

<matplotlib.axes._subplots.AxesSubplot at 0x7f80caeafc50>



In [28]:

```
data['Age']=np.where(data['Age']>50,40,data['Age'])
data['Age']
```

Out[28]:

```
1      42
2      41
3      42
4      39
5      43
      ..
9995   39
```

9996 35

9997 36

9998 42

9999 28

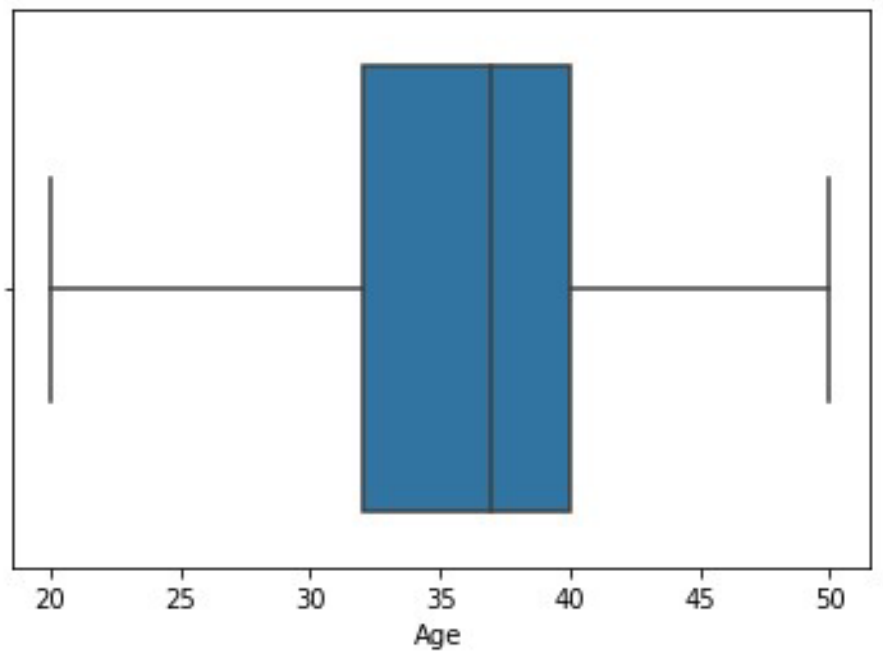
Name: Age, Length: 10000, dtype: int64

In [49]:

```
sns.boxplot(data['Age'])
```

Out[49]:

<matplotlib.axes._subplots.AxesSubplot at 0x7f80cb95fc10>



In [34]:

```
data['Age']=np.where(data['Age']<20,35,data['Age'])
data['Age']
```

Out[34]:

1 42

2 41

3 42

4 39

5 43

..

9995 39

9996 35

9997 36

9998 42

9999 28

Name: Age, Length: 10000, dtype: int64

7) Check for Categorical columns and perform encoding.

In [50]:

```
pd.get_dummies(data, columns=["Gender", "Age"], prefix=["Age",
"Gender"]).head()
```

Out[50]:

	Row Number	Customer Id	Surname	CreditScore	Geography	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	...	Gender_41	Gender_42	Gender_43	Gender_44	Gender_45	Gender_46	Gender_47	Gender_48	Gender_49	Gender_50
0	1	0.27	Har	619	France	2	0.00	1	1	1	...	0	1	0	0	0	0	0	0	0	0

		5616	grave		ce		0				.										

1	2	0.3264 54	Hill	608	Spain	1	838 07.86	1	0	1	..	1	0	0	0	0	0	0	0	0	0
2	3	0.2144 21	Onio	502	France	8	159660 .80	3	1	0	..	0	1	0	0	0	0	0	0	0	0
3	4	0.5426 36	Boni	699	France	1	0.00 0	2	0	0	..	0	0	0	0	0	0	0	0	0	0
4	5	0.6887 78	Mitchell	850	Spain	2	12551 1	1	1	1	..	0	0	1	0	0	0	0	0	0	0
							0.82														

5 rows × 45 columns

8) Split the data into dependent and independent

variables. A) Split the data into Independent

variables.

In [37]:

```
X = data.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]
[999915682355 'Sabbatini' ... 1 0 92888.52]  [10000
        15628319 'Walker' ... 1 0 38190.78]] B) Split the data
        into Dependent variables.
```

In [38]:

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

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

9) Scale the independent variables

In [39]:

```
import pandas as pd from
sklearn.preprocessing import MinMaxScaler
scaler = MinMaxScaler()

data[["CustomerId"]] = scaler.fit_transform(data[["CustomerId"]])
```

In [40]:

```
print(data)
```

```
    RowNumber  CustomerId   Surname  CreditScore Geography  Gender
Age  \
1           1  0.275616  Hargrave    619    France  Female   42
```

```
2          2  0.326454       Hill       608    Spain  Female   41
3          3  0.214421       Onio       502   France  Female   42
4          4  0.542636       Boni       699   France  Female   39 4       5  0.688778
           Mitchell            850    Spain  Female   43
...      ...       ...       ...          ...      ...    ... ...
9995    9996  0.162119  Obijiaku          771   France    Male   39
9996    9997  0.016765  Johnstone         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  \
1        2       0.00              1          1               1
2        1   83807.86              1          0               1
3        8  159660.80              3          1               0
4        1       0.00              2          0               0
5        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]

10)Split the data into training and testing

In [42]:

```
from sklearn.model_selection import train_test_split

train_size=0.8

X = data.drop(columns =

['Tenure']).copy() y = data['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=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,)

Out[42]:

(None, None)