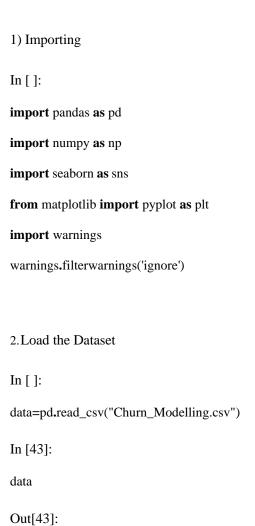
Assignment -II

Assignment date	24 September 2022
Student Name	K. Muhil
Student register number	820319106014
Maximum marks	2 marks



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9 9 9 5	9996	0.162 119	Obij iaku	771	Franc e	Ma le	3 9	5	0.00	2	1	0	96270.6 4	0
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9 9 9 7	9998	0.075 327	Liu	709	Franc e	Fe mal e	3 6	7	0.00	1	0	1	42085.5	1
9 9 9 8	9999	0.466 637	Sab bati ni	772	Germ	Ma le	4 2	3	7507 5.31	2	1	0	92888.5	1
9 9 9	10000	0.250 483	Wal ker	792	Franc e	Fe mal e	2 8	4	1301 42.7 9	1	1	0	38190.7 8	0

 $10000 \text{ rows} \times 14 \text{ columns}$

3. Visualizations	
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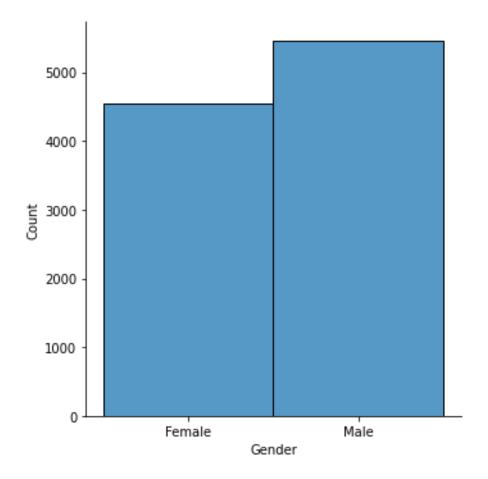
a) Univariate Analysis

In [44]:

sns.displot(data.Gender)

Out[44]:

<seaborn.axisgrid.FacetGrid at 0x7f80cb07c690>



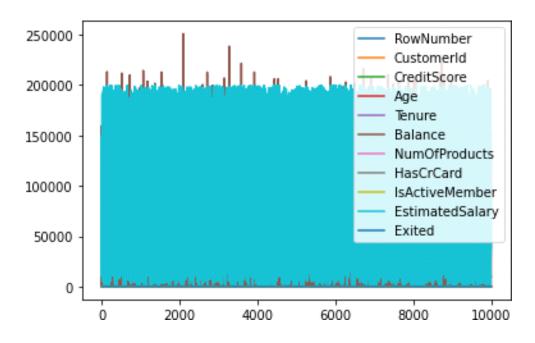
B) Bi-Variate Analysis

In [45]:

data.plot.line()

Out[45]:

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



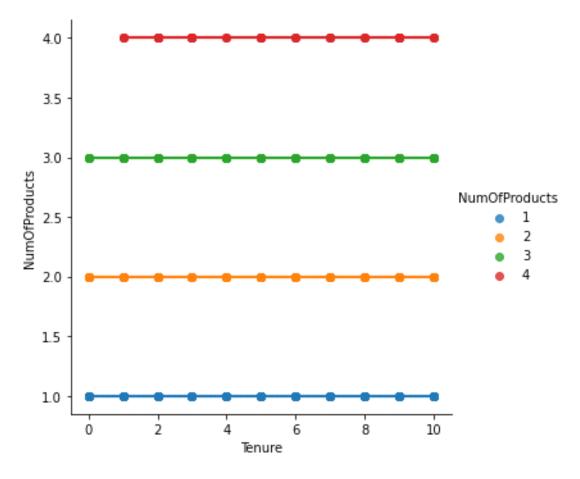
C) Multi - Variate Analysis

In [46]:

sns.Implot("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]:

	RowN umber	Custo merId	Credit Score	Age	Tenur e	Balanc e	NumOf Product s	HasC rCard	IsActive Member	Estimat edSalar y	Exited
co un t	10000. 00000	10000. 000000	10000. 000000	10000. 000000	10000. 000000	10000.0	10000.0	10000. 00000	10000.00	10000.00	10000. 000000
m ea	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	8800	900	00	89288	0	0		39881	00
st	2886.8	0.2877	96.653	6.4738	2.8921	62397.4	0.58165	0.4558	0.400707	57510.49	0.4027
d	9568	57	299	43	74	05202	4	4	0.499797	2818	69
mi	1.0000	0.0000	350.00	20.000	0.0000	0.00000	1.00000	0.0000	0.000000	11.58000	0.0000
n	0	00	0000	000	00	0	0	0		0	00
25	2500.7	0.2513	584.00	32.000	3.0000	0.00000	1.00000	0.0000	0.000000	51002.11	0.0000
%	5000	20	0000	000	00	0	0	0		0000	00
50	5000.5	0.5001	652.00	37.000	5.0000	97198.5	1.00000	1.0000	1.000000	100193.9	0.0000
%	0000	70	0000	000	00	40000	0	0		15000	00
75	7500.2	0.7501	718.00	40.000	7.0000	127644.	2.00000	1.0000	1.000000	149388.2	0.0000
%	5000	64	0000	000	00	240000	0	0		47500	00
m	10000.	1.0000	850.00	50.000	10.000	250898.	4.00000	1.0000	1.000000	199992.4	1.0000
ax	00000	00	0000	000	000	090000	0	0		80000	00
**		Missing v									

5) Handle the Missing values.

In []:

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

pd.isnull(data["Gender"])

Out[]:

- 0 False
- 1 False
- 2 False
- 3 False
- 4 False

•••

9995 False

9996 False

9997 False

9998 False

9999 False

Name: Gender, Length: 10000, dtype: bool

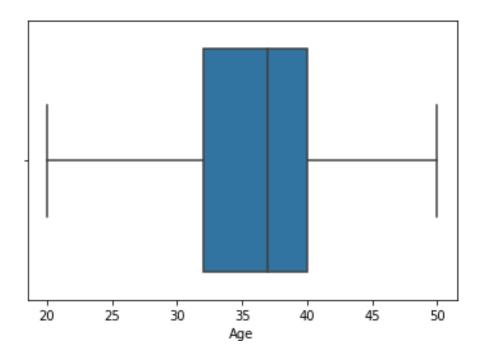
6) Find the outliers and replace the outliers

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]:

0 42

1 41

- 2 42
- 3 39
- 4 43

..

- 9995 39
- 9996 35
- 9997 36
- 9998 42
- 9999 28

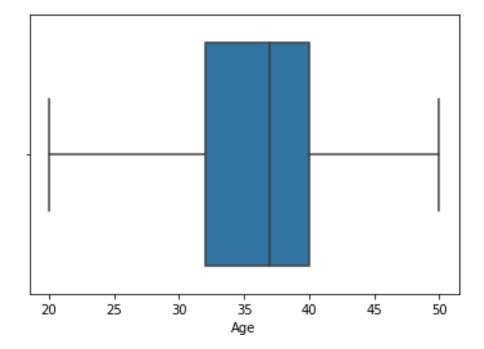
Name: Age, Length: 10000, dtype: int64

In [49]:

sns.boxplot(data['Age'])

Out[49]:

 $<\!matplotlib.axes._subplots. Axes Subplot\ at\ 0x7f80cb95fc10\!>$



In [34]: data['Age']=np.where(data['Age']<20,35,data['Age'])

data['Age']

Out[34]:
0 42

1 41

2 42

3 39

4 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]:

	Ro w Nu m be	C us to m er Id	S u r n a m	Cr ed itS co re	G eo gr ap hy	T e n u r e	B al a n ce	Nu mO fPr odu cts	H as Cr C ar	IsA ctiv eM em ber	G en de r_ 41	G en de r_ 42	G en de r_ 43	G en de r_ 44	G en de r_ 45	G en de r_ 46	G en de r_ 47	G en de r_ 48	G en de r_ 49	G en de r_ 50
0	1	0. 27	H ar	9	Fr	2	0.	1	1	1	0	1	0	0	0	0	0	0	0	0

		56	gr		ce		0													
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		0.					3													
		32	Н	60	Sp		8													
1	2	64	ill	8	ai	1	0	1	0	1	1	0	0	0	0	0	0	0	0	0
		54			n		7.													
							8													
							6													
							1													
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							5													
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		21					0.													
							8													
							0													
		0.																		
		54	В	69	Fr		0.													
3	4	26	0	9	an	1	0	2	0	0	0	0	0	0	0	0	0	0	0	0
		36	ni		ce		0													
		0.	M		a		1													
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4	5	87	с	0	ai	2	5	1	1	1	0	0	1	0	0	0	0	0	0	0
		78	h		n		5													
			el				1													
			h	0	n		5													

	1		0.							
			8							
			2							

 $5 \text{ rows} \times 45 \text{ columns}$

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]

[9999 15682355 'Sabbatini' ... 1 0 92888.52]
```

B) Split the data into Dependent variables.

[10000 15628319 'Walker' 1 0 38190.78]]

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]:

9999

0

2

0.00

print(data)

RowNumber	CustomerId	Surname	CreditScore	Geography	Gender A	oe \
Nownanioci	Customeria	Surname	Cicuiscoic	Ocography	Ochuci I	1 <u>2</u> 0 (

	8.1
0	1 0.275616 Hargrave 619 France Female 42
1	2 0.326454 Hill 608 Spain Female 41
2	3 0.214421 Onio 502 France Female 42
3	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

$Tenure \quad Balance \ NumOfProducts \ HasCrCard \ IsActiveMember \setminus$

1

792 France Female 28

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

10000 0.250483 Walker

1

```
EstimatedSalary Exited
101348.88 1
```

112542.58

0

1

0

1

[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
```

$$test_size = 0.5$$

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)