# Assignment -2

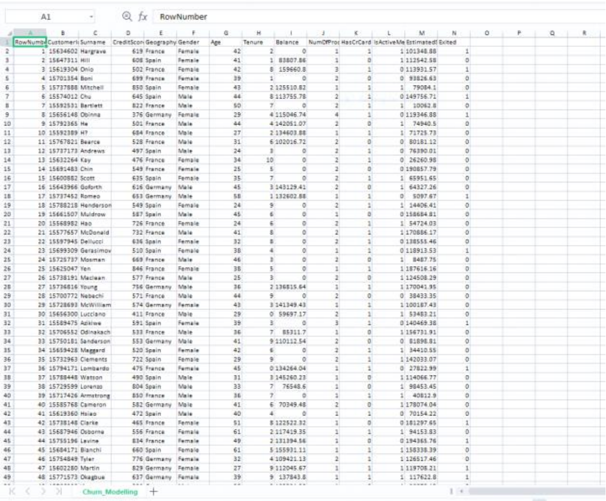
## Pre-processing data visualization

| | |
|---|---|
| Assignment Date | 28 September 2022 |
| Student Name | Priya V |
| Student Roll Number | 612419104017 |
| Maximum Marks | 2 Marks |

## Question-1:

Download the Dataset

**SOLUTION:**



A1 fx RowNumber

| | A | B | C | D | E | F | G | H | I | J | K | L | M | N |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | RowNumbe | CustomerI | Surname | CreditScor | Geography | Gender | Age | Tenure | Balance | NumOfProc | HasCrCard | IsActiveMe | Estimated | Exited |
| 2 | 1 | 15634602 | Hargrave | 619 | France | Female | 42 | 2 | 0 | 1 | 1 | 1 | 101348.88 | 1 |
| 3 | 2 | 15647311 | Hill | 608 | Spain | Female | 41 | 1 | 83807.86 | 1 | 0 | 1 | 112542.58 | 0 |
| 4 | 3 | 15619304 | Onio | 502 | France | Female | 42 | 8 | 159660.8 | 3 | 1 | 0 | 113931.57 | 1 |
| 5 | 4 | 15701354 | Boni | 699 | France | Female | 39 | 1 | 0 | 2 | 0 | 0 | 93826.63 | 0 |
| 6 | 5 | 15737888 | Mitchell | 850 | Spain | Female | 43 | 2 | 125510.82 | 1 | 1 | 1 | 79084.1 | 0 |
| 7 | 6 | 15574012 | Chu | 645 | Spain | Male | 44 | 8 | 113755.78 | 2 | 1 | 0 | 149756.71 | 1 |
| 8 | 7 | 15592531 | Bartlett | 822 | France | Male | 50 | 7 | 0 | 2 | 1 | 1 | 10062.8 | 0 |
| 9 | 8 | 15656148 | Obinna | 376 | Germany | Female | 29 | 4 | 115046.74 | 4 | 1 | 0 | 119346.88 | 1 |
| 10 | 9 | 15792365 | He | 501 | France | Male | 44 | 4 | 142051.07 | 2 | 0 | 1 | 74940.5 | 0 |
| 11 | 10 | 15592389 | H? | 684 | France | Male | 27 | 2 | 134603.88 | 1 | 1 | 1 | 71725.73 | 0 |
| 12 | 11 | 15767821 | Bearce | 528 | France | Male | 31 | 6 | 102016.72 | 2 | 0 | 0 | 80181.12 | 0 |
| 13 | 12 | 15737173 | Andrews | 497 | Spain | Male | 24 | 3 | 0 | 2 | 1 | 0 | 76390.01 | 0 |
| 14 | 13 | 15632264 | Kay | 476 | France | Female | 34 | 10 | 0 | 2 | 1 | 0 | 26260.98 | 0 |
| 15 | 14 | 15691483 | Chin | 549 | France | Female | 25 | 5 | 0 | 2 | 0 | 0 | 190857.79 | 0 |
| 16 | 15 | 15600882 | Scott | 635 | Spain | Female | 35 | 7 | 0 | 2 | 1 | 1 | 65951.65 | 0 |
| 17 | 16 | 15643966 | Goforth | 616 | Germany | Male | 45 | 3 | 143129.41 | 2 | 0 | 1 | 64327.26 | 0 |
| 18 | 17 | 15737452 | Romeo | 653 | Germany | Male | 58 | 1 | 132602.88 | 1 | 1 | 0 | 5097.67 | 1 |
| 19 | 18 | 15788218 | Henderson | 549 | Spain | Female | 24 | 9 | 0 | 2 | 1 | 1 | 14406.41 | 0 |
| 20 | 19 | 15661507 | Muldrow | 587 | Spain | Male | 45 | 6 | 0 | 1 | 0 | 0 | 158684.81 | 0 |
| 21 | 20 | 15568982 | Hao | 726 | France | Female | 24 | 6 | 0 | 2 | 1 | 1 | 54724.03 | 0 |
| 22 | 21 | 15577657 | McDonald | 732 | France | Male | 41 | 8 | 0 | 2 | 1 | 1 | 170886.17 | 0 |
| 23 | 22 | 15597945 | Dellucci | 636 | Spain | Female | 32 | 8 | 0 | 2 | 1 | 0 | 138555.46 | 0 |
| 24 | 23 | 15699309 | Gerasimov | 510 | Spain | Female | 38 | 4 | 0 | 1 | 1 | 0 | 118913.53 | 1 |
| 25 | 24 | 15725737 | Mosman | 669 | France | Male | 46 | 3 | 0 | 2 | 0 | 1 | 8487.75 | 0 |
| 26 | 25 | 15625047 | Yen | 846 | France | Female | 38 | 5 | 0 | 1 | 1 | 1 | 187616.16 | 0 |
| 27 | 26 | 15738191 | Maclean | 577 | France | Male | 25 | 3 | 0 | 2 | 0 | 1 | 124508.29 | 0 |
| 28 | 27 | 15736816 | Young | 756 | Germany | Male | 36 | 2 | 136815.64 | 1 | 1 | 1 | 170041.95 | 0 |
| 29 | 28 | 15700772 | Nebechi | 571 | France | Male | 44 | 9 | 0 | 2 | 0 | 0 | 38433.35 | 0 |
| 30 | 29 | 15728693 | McWilliam | 574 | Germany | Female | 43 | 3 | 141349.43 | 1 | 1 | 1 | 100187.43 | 0 |
| 31 | 30 | 15656300 | Lucciano | 411 | France | Male | 29 | 0 | 59697.17 | 2 | 1 | 1 | 53483.21 | 0 |
| 32 | 31 | 15589475 | Azikiwe | 591 | Spain | Female | 39 | 3 | 0 | 3 | 1 | 0 | 140469.38 | 1 |
| 33 | 32 | 15706552 | Odinakach | 533 | France | Male | 36 | 7 | 85311.7 | 1 | 0 | 1 | 156731.91 | 0 |
| 34 | 33 | 15750181 | Sanderson | 553 | Germany | Male | 41 | 9 | 110112.54 | 2 | 0 | 0 | 81898.81 | 0 |
| 35 | 34 | 15659428 | Maggard | 520 | Spain | Female | 42 | 6 | 0 | 2 | 1 | 1 | 34410.55 | 0 |
| 36 | 35 | 15732963 | Clements | 722 | Spain | Female | 29 | 9 | 0 | 2 | 1 | 1 | 142033.07 | 0 |
| 37 | 36 | 15794171 | Lombardo | 475 | France | Female | 45 | 0 | 134264.04 | 1 | 1 | 0 | 27822.99 | 1 |
| 38 | 37 | 15788448 | Watson | 490 | Spain | Male | 31 | 3 | 145260.23 | 1 | 0 | 1 | 114066.77 | 0 |
| 39 | 38 | 15729599 | Lorenzo | 804 | Spain | Male | 33 | 7 | 76548.6 | 1 | 0 | 1 | 98453.45 | 0 |
| 40 | 39 | 15717426 | Armstrong | 850 | France | Male | 36 | 7 | 0 | 1 | 1 | 1 | 40812.9 | 0 |
| 41 | 40 | 15585768 | Cameron | 582 | Germany | Male | 41 | 6 | 70349.48 | 2 | 0 | 1 | 178074.04 | 0 |
| 42 | 41 | 15619360 | Hsiao | 472 | Spain | Male | 40 | 4 | 0 | 1 | 1 | 0 | 70154.22 | 0 |
| 43 | 42 | 15738148 | Clarke | 465 | France | Female | 51 | 8 | 122522.32 | 1 | 0 | 0 | 181297.65 | 1 |
| 44 | 43 | 15687946 | Osborne | 556 | France | Female | 61 | 2 | 117419.35 | 1 | 1 | 1 | 94153.83 | 0 |
| 45 | 44 | 15755196 | Lavine | 834 | France | Female | 49 | 2 | 131394.56 | 1 | 0 | 0 | 194365.76 | 1 |
| 46 | 45 | 15684171 | Bianchi | 660 | Spain | Female | 61 | 5 | 155931.11 | 1 | 1 | 1 | 158338.39 | 0 |
| 47 | 46 | 15754849 | Tyler | 776 | Germany | Female | 32 | 4 | 109421.13 | 2 | 1 | 1 | 126517.46 | 0 |
| 48 | 47 | 15602280 | Martin | 829 | Germany | Female | 27 | 9 | 112045.67 | 1 | 1 | 1 | 119708.21 | 1 |
| 49 | 48 | 15771573 | Okagbue | 637 | Germany | Female | 39 | 9 | 137843.8 | 1 | 1 | 1 | 117622.8 | 1 |

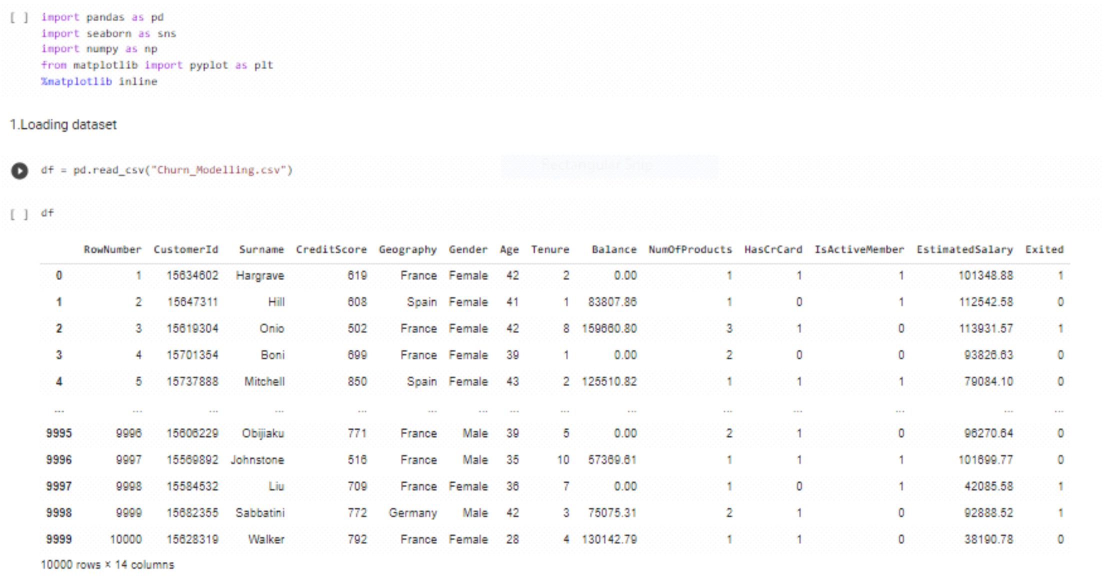
## Question-2:

Loading datase

**SOLUTION:**

```
import  pandas as pd

import seaborn as sns
import numpy as np

from matplotlib import pyplot as plt

%matplotlib inline
```

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



```
[ ] import pandas as pd
    import seaborn as sns
    import numpy as np
    from matplotlib import pyplot as plt
    %matplotlib inline
```

1.Loading dataset

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

```
[ ] df
```

| | 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

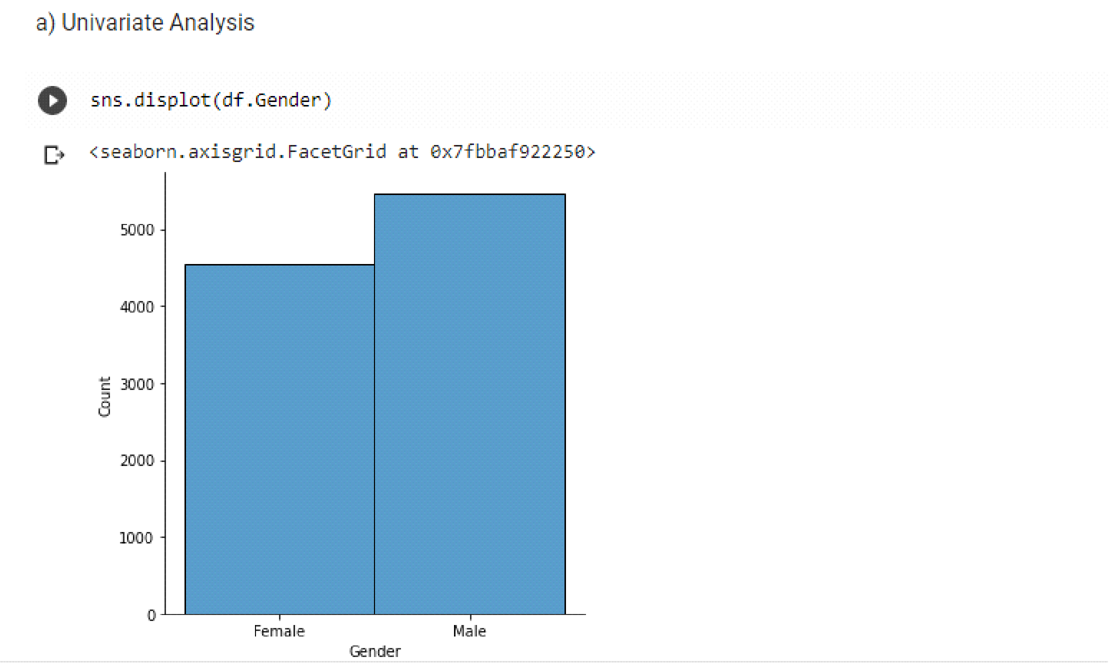
## Question-3:

### 1.Visualizations

### a) Univariate Analysis

**SOLUTION:**

```
sns.displot(df.Gender)
```



a) Univariate Analysis

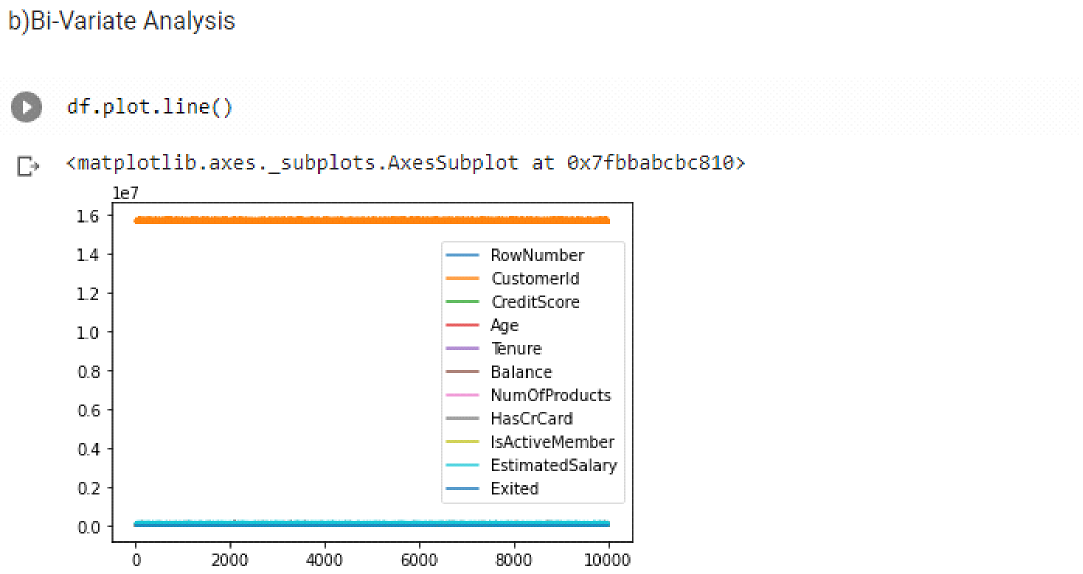
```
sns.displot(df.Gender)
```

```
<seaborn.axisgrid.FacetGrid at 0x7fbbaf922250>
```

## b) Bi-Variate Analysis

**SOLUTION:**

```
df.plot.line()
```



b)Bi-Variate Analysis

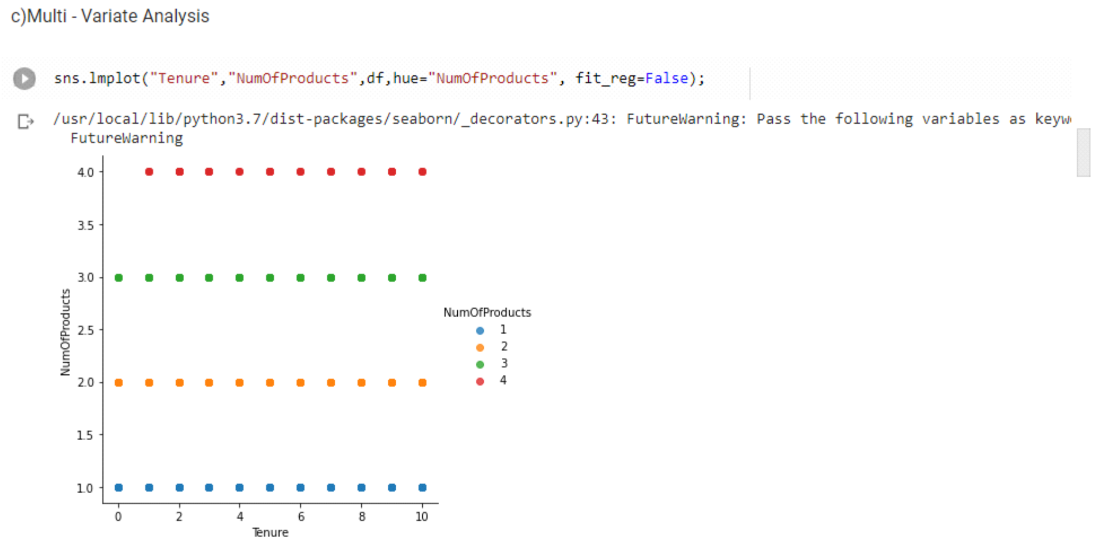
```
df.plot.line()
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fbbabcbc810>
```

## c) Multi - Variate Analysis

**SOLUTION:**

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



c)Multi - Variate Analysis

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

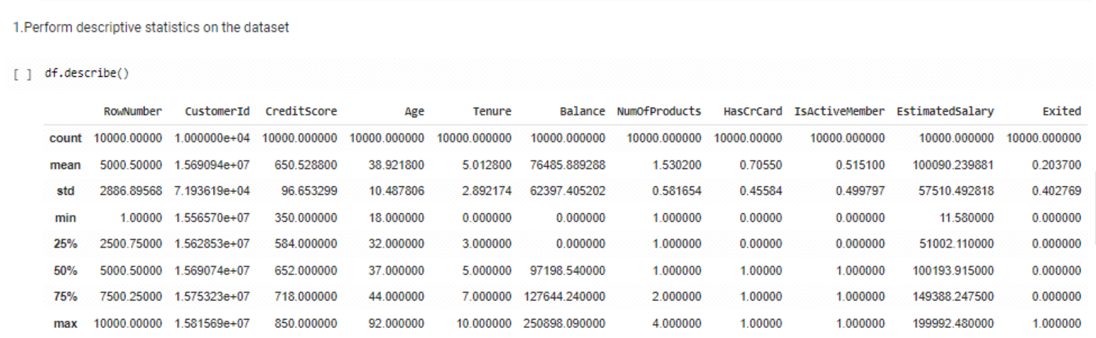
```
/usr/local/lib/python3.7/dist-packages/seaborn/_decorators.py:43: FutureWarning: Pass the following variables as keyw
  FutureWarning
```

## Question-4:

Perform descriptive statistics on the dataset.

### SOLUTION:

```
df.describe()
```



1.Perform descriptive statistics on the dataset

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

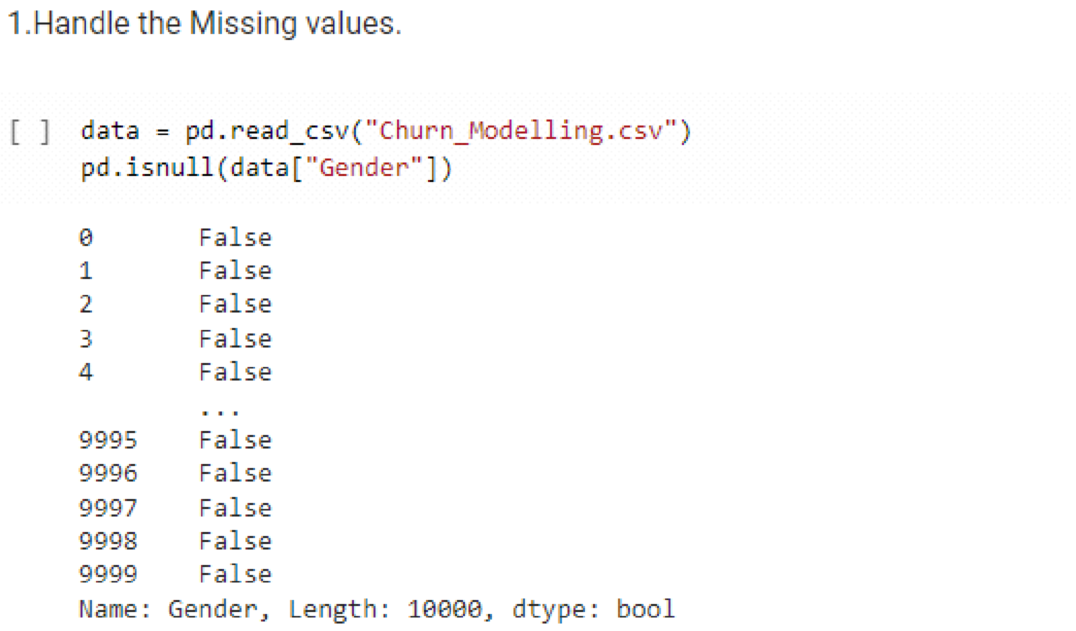
```
       RowNumber   CustomerId   CreditScore           Age        Tenure        Balance  NumOfProducts    HasCrCard  IsActiveMember  EstimatedSalary        Exited
count  10000.00000  1.000000e+04  10000.000000  10000.000000  10000.000000   10000.000000   10000.000000  10000.00000    10000.000000     10000.000000  10000.000000
mean    5000.50000  1.569094e+07    650.528800     38.921800      5.012800   76485.889288       1.530200      0.70550        0.515100    100090.239881      0.203700
std     2886.89568  7.193619e+04     96.653299     10.487806      2.892174   62397.405202       0.581654      0.45584        0.499797     57510.492818      0.402769
min        1.00000  1.556570e+07    350.000000     18.000000      0.000000       0.000000       1.000000      0.00000        0.000000        11.580000      0.000000
25%     2500.75000  1.562853e+07    584.000000     32.000000      3.000000       0.000000       1.000000      0.00000        0.000000     51002.110000      0.000000
50%     5000.50000  1.569074e+07    652.000000     37.000000      5.000000   97198.540000       1.000000      1.00000        1.000000    100193.915000      0.000000
75%     7500.25000  1.575323e+07    718.000000     44.000000      7.000000  127644.240000       2.000000      1.00000        1.000000    149388.247500      0.000000
max    10000.00000  1.581569e+07    850.000000     92.000000     10.000000  250898.090000       4.000000      1.00000        1.000000    199992.480000      1.000000
```

## Question-5:

Handle the Missing values.

**SOLUTION:**

```
data = pd.read_csv("Churn_Modelling.csv")
pd.isnull(data["Gender"])
```



1.Handle the Missing values.

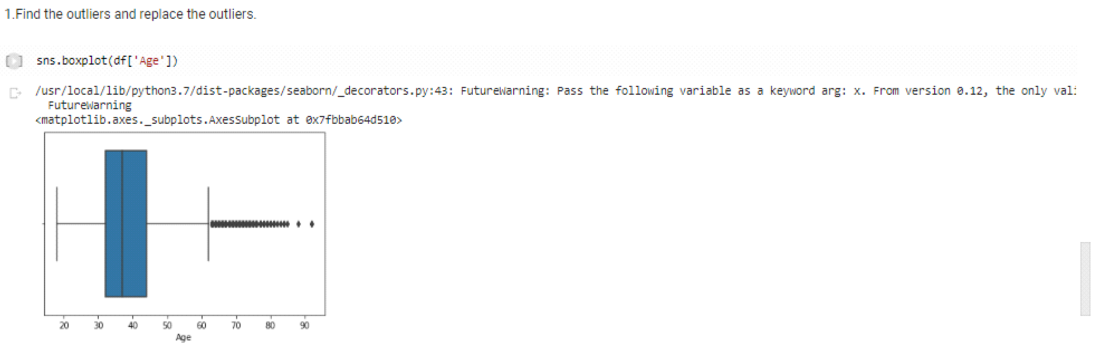
```
[ ]  data = pd.read_csv("Churn_Modelling.csv")
     pd.isnull(data["Gender"])

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

## Question-6:

Find the outliers and replace the outliers.

**SOLUTION:**

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



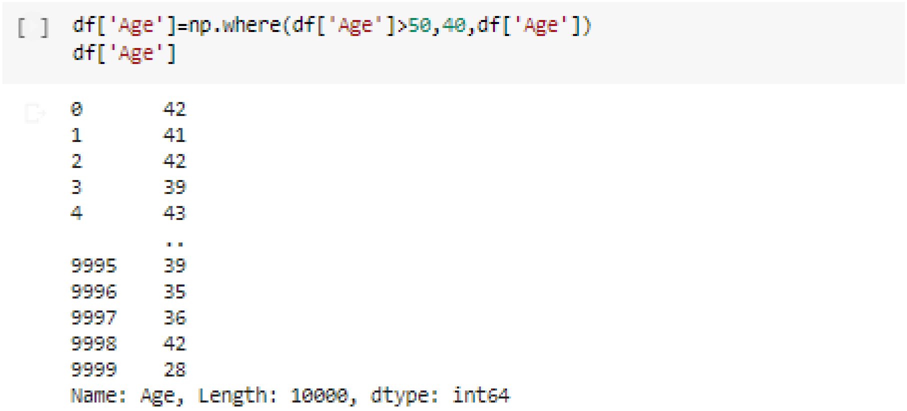
1.Find the outliers and replace the outliers.

```
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 val:
  FutureWarning
<matplotlib.axes._subplots.AxesSubplot at 0x7fbbab64d510>
```

## SOLUTION:

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



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

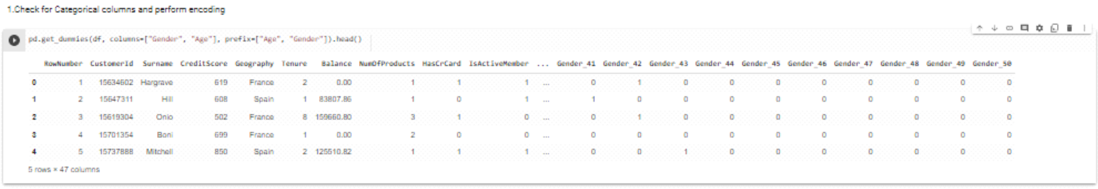
```
0       42
1       41
2       42
3       39
4       43
        ..
9995    39
9996    35
9997    36
9998    42
9999    28
Name: Age, Length: 10000, dtype: int64
```

## Question-7:

Check for Categorical columns and perform encoding.

## SOLUTION:

```
pd.get_dummies(df, columns=["Gender", "Age"], prefix=["Age", "Gender"])
.hea
```



1.Check for Categorical columns and perform encoding

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

| | RowNumber | CustomerId | 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 | 15634602 | Hargrave | 619 | France | 2 | 0.00 | 1 | 1 | 1 | ... | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| **1** | 2 | 15647311 | Hill | 608 | Spain | 1 | 83807.86 | 1 | 0 | 1 | ... | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| **2** | 3 | 15619304 | Onio | 502 | France | 8 | 159660.80 | 3 | 1 | 0 | ... | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| **3** | 4 | 15701354 | Boni | 699 | France | 1 | 0.00 | 2 | 0 | 0 | ... | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| **4** | 5 | 15737888 | Mitchell | 850 | Spain | 2 | 125510.82 | 1 | 1 | 1 | ... | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |

5 rows × 47 columns

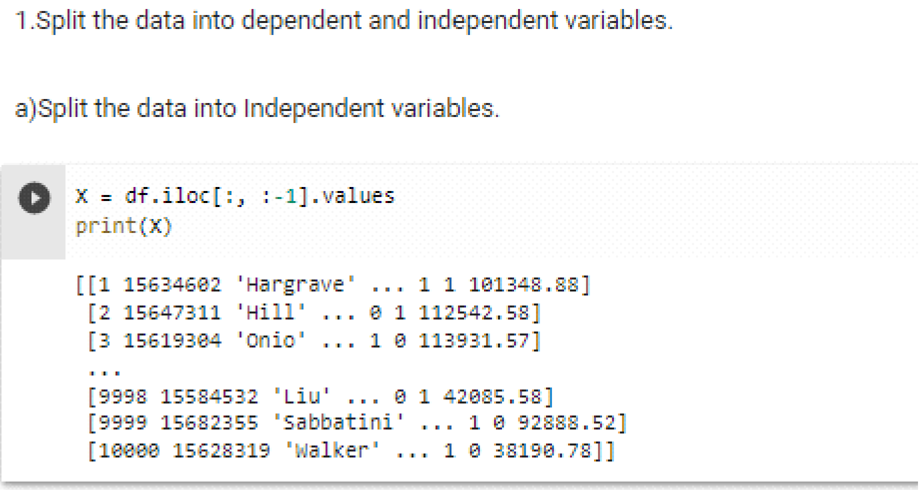
## Question-8:

. Split the data into dependent and independent variables.

(a) Split the data into Independent variables.

### SOLUTION:

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



1.Split the data into dependent and independent variables.

a)Split the data into Independent variables.

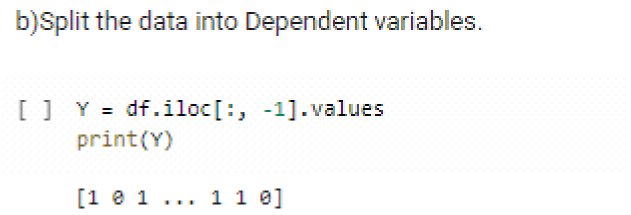
```
X = df.iloc[:, :-1].values
print(X)
```

```
[[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

**SOLUTION:**

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



b)Split the data into Dependent variables.

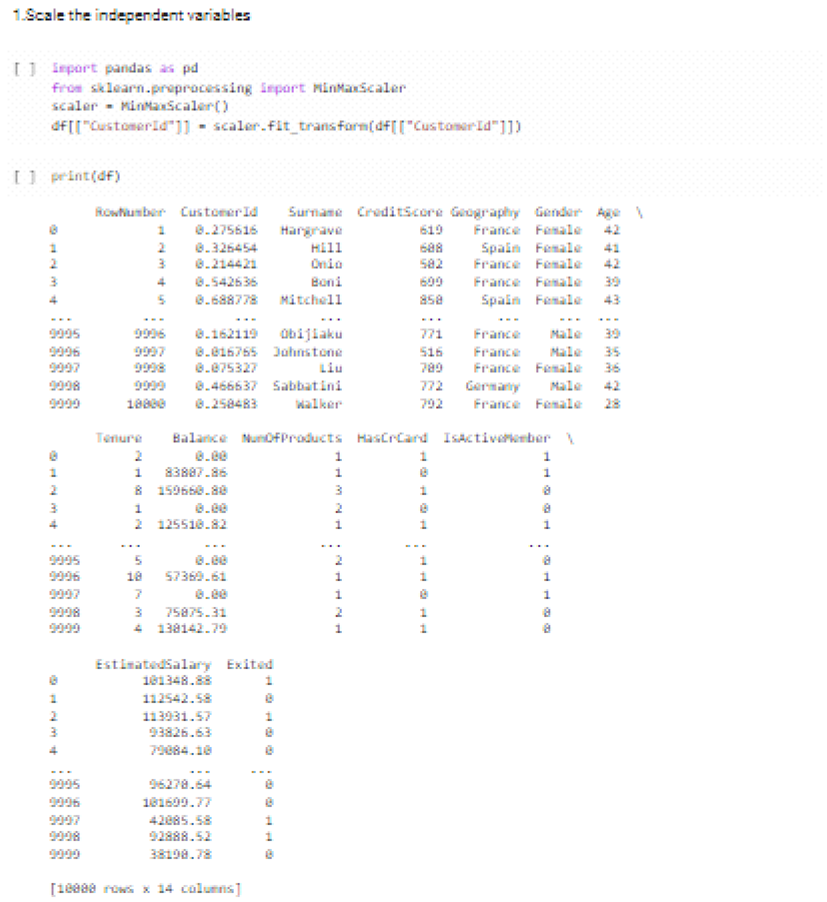
```
[ ]  Y = df.iloc[:, -1].values
     print(Y)

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

## Question-9:

Scale the independent variables

**SOLUTION:**

```
import pandas as pd
from sklearn.preprocessing import MinMaxScaler
scaler = MinMaxScaler()
df[["CustomerId"]] = scaler.fit_transform(df[["CustomerId"]])
print(df)
```



1.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  \
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   
9999      10000    0.250483     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]
```

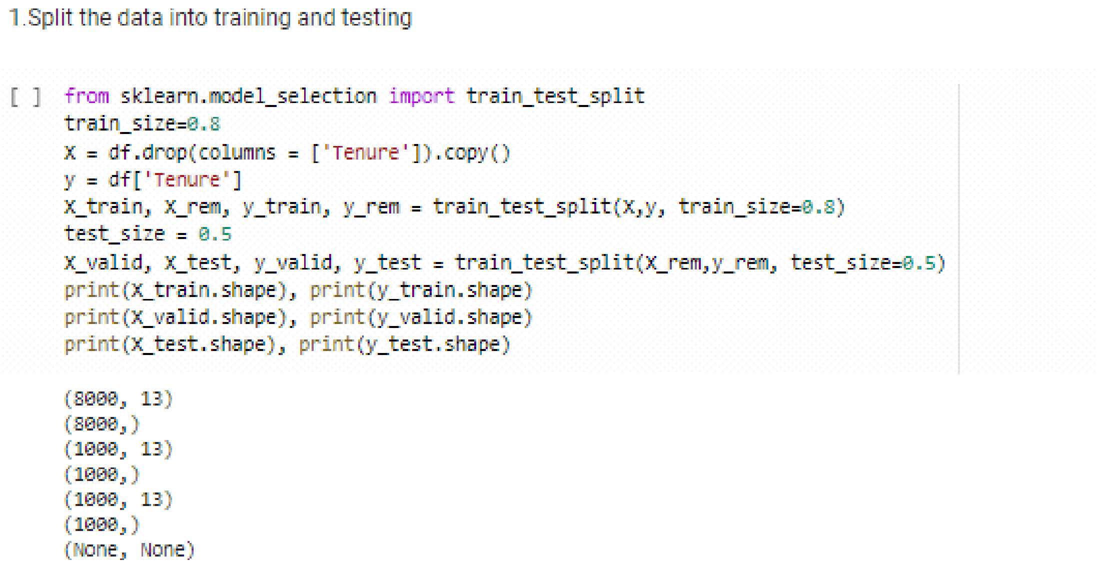
## Question-10:

Split the data into training and testing

### SOLUTION:

```
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_s
ize=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)
```



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=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)
```