# Assignment -2

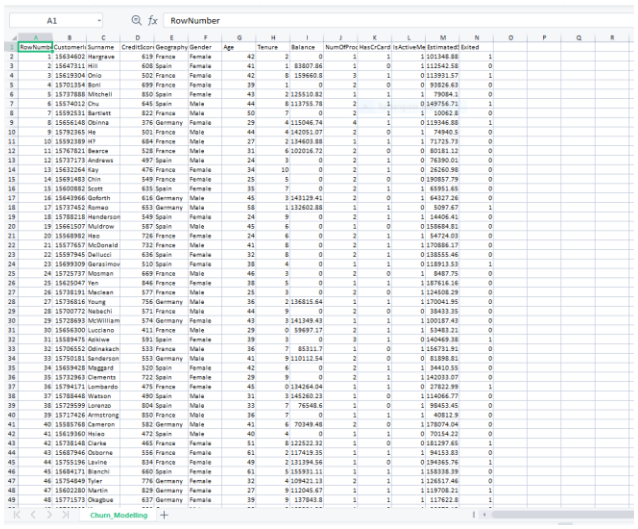
DATA VISUALISATION AND PRE-PROCESSING

| | |
|---|---|
| Assignment Date | 28 September 2022 |
| Student Name | Anitha A |
| Student Roll Number | 612419104004 |
| Maximum Marks | 2 Marks |

## Question-1:

Download the Dataset

## Solution:



A1 RowNumber

| | A | B | C | D | E | F | G | H | I | J | K | L | M | N |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | RowNumbe | Customerl | 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 |

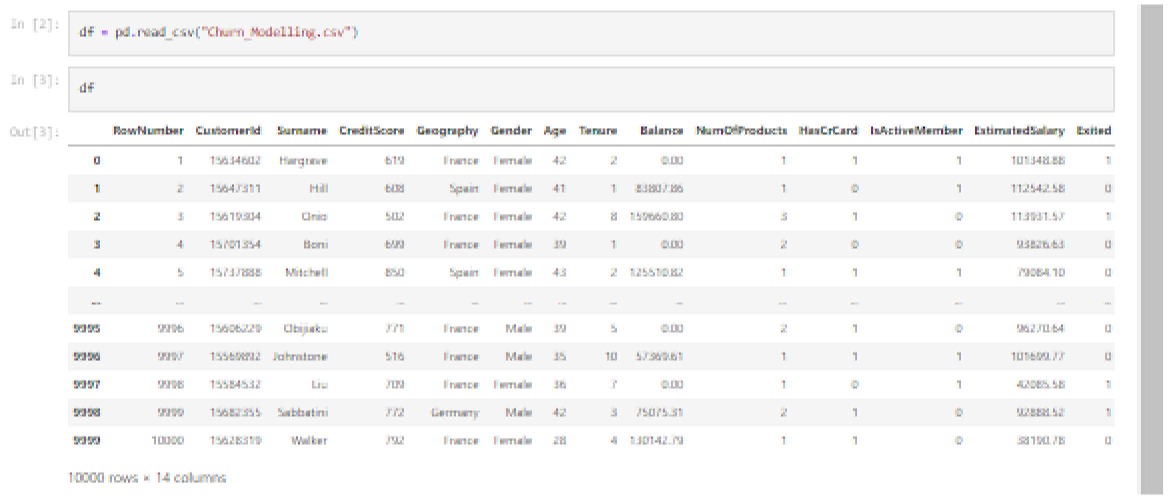
Churn_Modelling

## Question-2:

Loading dataset

## Solution:

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

df
```



```
In [2]: df = pd.read_csv("Churn_Modelling.csv")

In [3]: df

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 |
| **...** | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... |
| **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:**

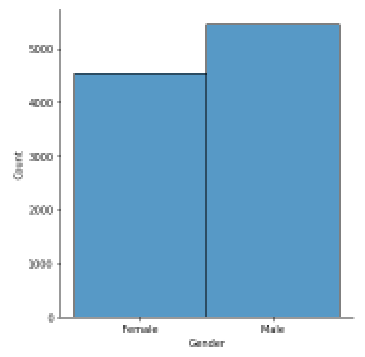
1.Visualizations

a) Univariate Analysis

**Solution:**

sns.displot(df.Gender)

```
In [4]: sns.displot(df.Gender)

Out[4]: <seaborn.axisgrid.FacetGrid at 0x7f2935aae790>
```

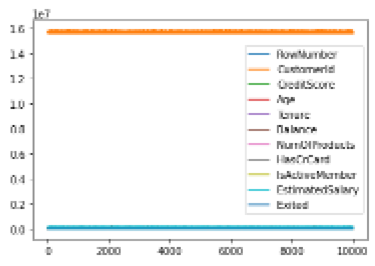


b) Bi - Variate Analysis

**Solution:**

df.plot.line()

```
In [5]: df.plot.line()
Out[5]: <matplotlib.axes._subplots.AxesSubplot at 0x7f2932d2df58>
```

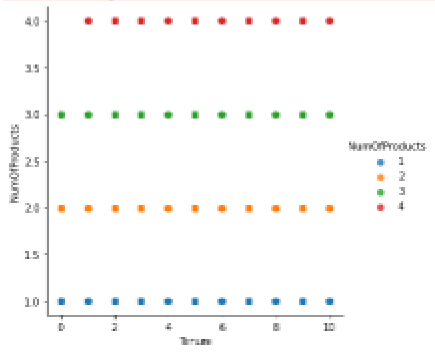


C)Multi - Variate Analysis

**Solution:**

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

```
In [6]: 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 v
ersion 0.12, the only valid positional argument will be `data`, and passing other arguments without an explicit keyword will result in an error o
r misinterpretation.
  FutureWarning
```

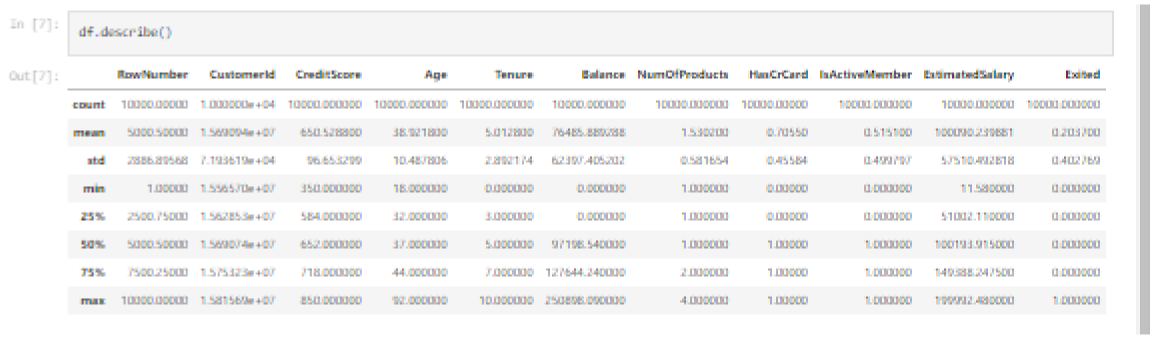


**Question-4:**

Perform descriptive statistics on the dataset.

**Solution:**

```
df.describe()
```



```
In [7]: df.describe()
```

Out[7]:

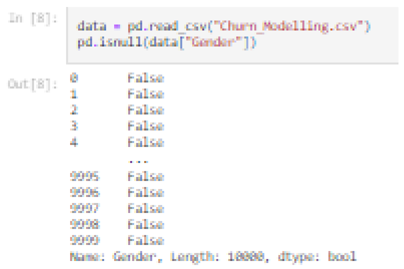
| | RowNumber | CustomerId | CreditScore | Age | Tenure | Balance | NumOfProducts | HasCrCard | IsActiveMember | EstimatedSalary | Exited |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **count** | 10000.00000 | 1.000000e+04 | 10000.000000 | 10000.000000 | 10000.000000 | 10000.000000 | 10000.000000 | 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"])
```



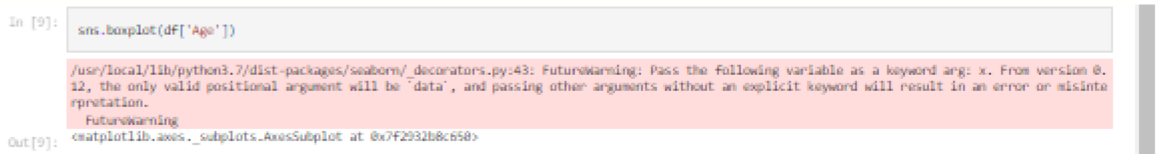
```
In [8]: data = pd.read_csv("Churn_Modelling.csv")
        pd.isnull(data["Gender"])

Out[8]: 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:

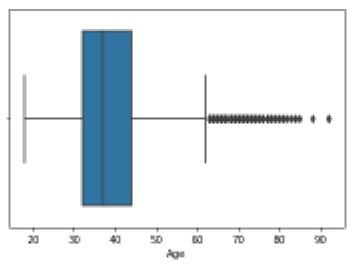
Find the outliers and replace the outliers.

## Solution:

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

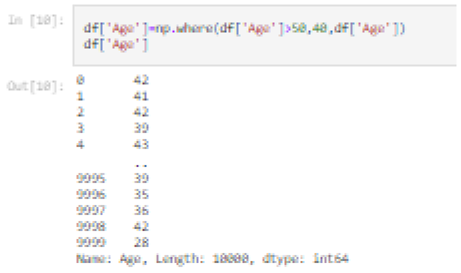


```
In [9]: sns.boxplot(df['Age'])

/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 misinte
rpretation.
  FutureWarning
Out[9]: <matplotlib.axes._subplots.AxesSubplot at 0x7f2932b8c650>
```



**Solution:**

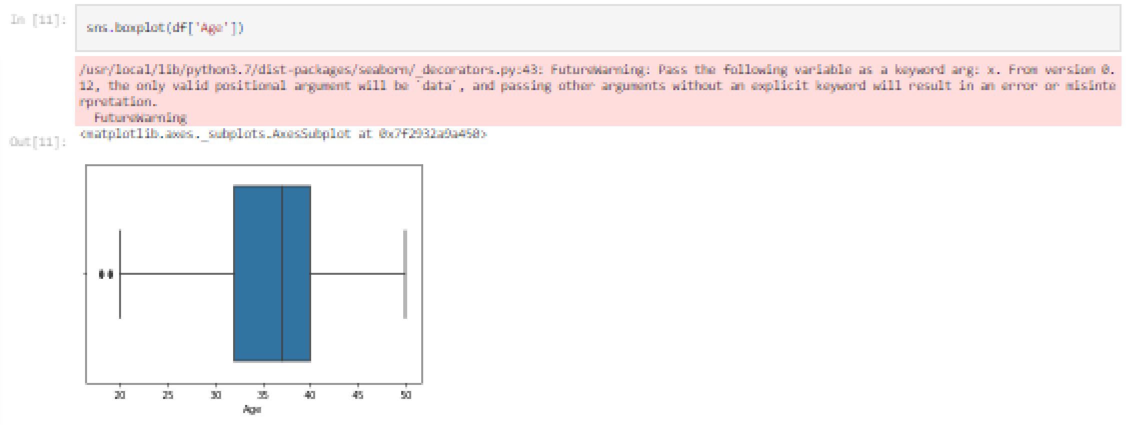
```
df['Age']=np.where(df['Age']>50,40,df['Age'])
df['Age']
```



```
In [10]:  df['Age']=np.where(df['Age']>50,40,df['Age'])
          df['Age']

Out[10]:  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
```

**Solution:**

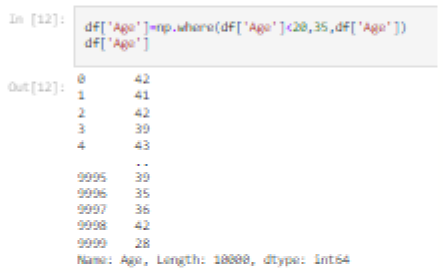
```
sns.boxplot(df['Age'])
```



```
In [11]:  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 misinte
rpretation.
  FutureWarning
Out[11]:  <matplotlib.axes._subplots.AxesSubplot at 0x7f2932a0a450>
```

**Solution:**

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



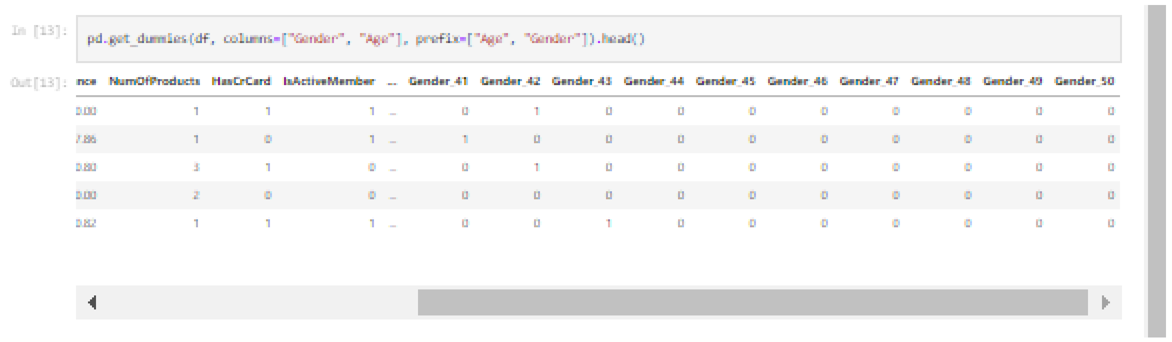
```
In [12]:  df['Age']=np.where(df['Age']<20,35,df['Age'])
          df['Age']

Out[12]:  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
```



```
In [13]: pd.get_dummies(df, columns=["Gender", "Age"], prefix=["Age", "Gender"]).head()
```

Out[13]:

| nce | NumOfProducts | HasCrCard | IsActiveMember | ... | Gender_41 | Gender_42 | Gender_43 | Gender_44 | Gender_45 | Gender_46 | Gender_47 | Gender_48 | Gender_49 | Gender_50 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 0.00 | 1 | 1 | 1 | ... | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 7.86 | 1 | 0 | 1 | ... | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 0.80 | 3 | 1 | 0 | ... | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 0.00 | 2 | 0 | 0 | ... | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 0.82 | 1 | 1 | 1 | ... | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |

**Question-8:**

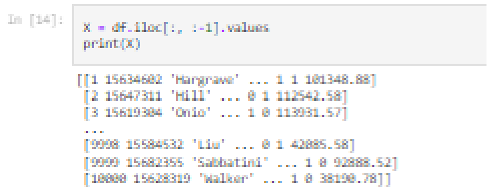
. Split the data into dependent and independent variables.

a)split the data into independent variables.

**Solution:**

X = df.iloc[:, :-1].value

sprint(X)



```
In [14]: X = df.iloc[:, :-1].values
         print(X)
```

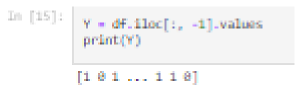
```
[[1 15634602 'Hargrave' ... 1 1 101348.88]
 [2 15647311 'Hill' ... 0 1 112542.58]
 [3 15619304 'Onio' ... 1 0 113931.57]
 ...
 [9998 15584532 'Liu' ... 0 1 42085.58]
 [9999 15682355 'Sabbatini' ... 1 0 92888.52]
 [10000 15628319 'Walker' ... 1 0 38190.78]]
```

b)split the data into dependent variables

**Solution:**

Y = df.iloc[:, -1].values

print(Y)



```
In [15]: Y = df.iloc[:, -1].values
         print(Y)
```

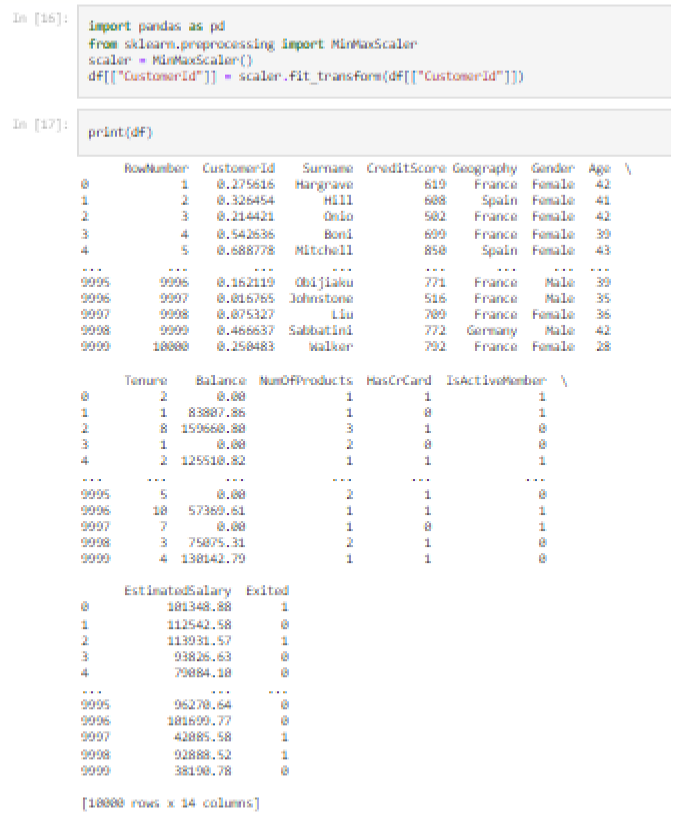
```
[1 0 1 ... 1 1 0]
```

**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"]])
```



```
In [16]: import pandas as pd
         from sklearn.preprocessing import MinMaxScaler
         scaler = MinMaxScaler()
         df[["CustomerId"]] = scaler.fit_transform(df[["CustomerId"]])

In [17]: 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_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)
```

In [18]:

```
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,)
```

Out[18]:

```
(None, None)
```