Exploratory Data Analysis

September 28, 2022

[1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
import warnings
warnings.filterwarnings('ignore')
```

[4]:
```
data=pd.read_csv('Travel.csv')
```

[14]:
```
data.head()
```

[14]:
```
   CustomerID  ProdTaken   Age    TypeofContact  CityTier  DurationOfPitch  \
0      200000          1  41.0     Self Enquiry         3              6.0
1      200001          0  49.0  Company Invited         1             14.0
2      200002          1  37.0     Self Enquiry         1              8.0
3      200003          0  33.0  Company Invited         1              9.0
4      200004          0   NaN     Self Enquiry         1              8.0

       Occupation  Gender  NumberOfPersonVisiting  NumberOfFollowups  \
0        Salaried  Female                       3                3.0
1        Salaried    Male                       3                4.0
2     Free Lancer    Male                       3                4.0
3        Salaried  Female                       2                3.0
4  Small Business    Male                       2                3.0

  ProductPitched  PreferredPropertyStar MaritalStatus  NumberOfTrips  \
0         Deluxe                    3.0        Single            1.0
1         Deluxe                    4.0      Divorced            2.0
2          Basic                    3.0        Single            7.0
3          Basic                    3.0      Divorced            2.0
4          Basic                    4.0      Divorced            1.0

   Passport  PitchSatisfactionScore  OwnCar  NumberOfChildrenVisiting  \
0         1                       2       1                       0.0
1         0                       3       1                       2.0
2         1                       3       0                       0.0
```

```
3         1                       5       1                        1.0
4         0                       5       1                        0.0

  Designation  MonthlyIncome
0     Manager        20993.0
1     Manager        20130.0
2   Executive        17090.0
3   Executive        17909.0
4   Executive        18468.0
```

[15]:
```python
data.columns
```

[15]:
```
Index(['CustomerID', 'ProdTaken', 'Age', 'TypeofContact', 'CityTier',
       'DurationOfPitch', 'Occupation', 'Gender', 'NumberOfPersonVisiting',
       'NumberOfFollowups', 'ProductPitched', 'PreferredPropertyStar',
       'MaritalStatus', 'NumberOfTrips', 'Passport', 'PitchSatisfactionScore',
       'OwnCar', 'NumberOfChildrenVisiting', 'Designation', 'MonthlyIncome'],
      dtype='object')
```

[25]:
```python
data.shape # indicates the number of rows,columns
```

[25]:
```
(4888, 20)
```

[26]:
```python
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 4888 entries, 0 to 4887
Data columns (total 20 columns):
 #   Column                   Non-Null Count  Dtype
---  ------                   --------------  -----
 0   CustomerID               4888 non-null   int64
 1   ProdTaken                4888 non-null   int64
 2   Age                      4662 non-null   float64
 3   TypeofContact            4863 non-null   object
 4   CityTier                 4888 non-null   int64
 5   DurationOfPitch          4637 non-null   float64
 6   Occupation               4888 non-null   object
 7   Gender                   4888 non-null   object
 8   NumberOfPersonVisiting   4888 non-null   int64
 9   NumberOfFollowups        4843 non-null   float64
 10  ProductPitched           4888 non-null   object
 11  PreferredPropertyStar    4862 non-null   float64
 12  MaritalStatus            4888 non-null   object
 13  NumberOfTrips            4748 non-null   float64
 14  Passport                 4888 non-null   int64
 15  PitchSatisfactionScore   4888 non-null   int64
 16  OwnCar                   4888 non-null   int64
```

```
 17   NumberOfChildrenVisiting  4822 non-null   float64
 18   Designation               4888 non-null   object
 19   MonthlyIncome             4655 non-null   float64
dtypes: float64(7), int64(7), object(6)
memory usage: 763.9+ KB
```

[36]:
```python
data.describe().T # Completely based on Integer or numerical features
```

[36]:
```
                          count          mean          std       min  \
CustomerID               4888.0  202443.500000  1411.188388  200000.0
ProdTaken                4888.0       0.188216     0.390925       0.0
Age                      4662.0      37.622265     9.316387      18.0
CityTier                 4888.0       1.654255     0.916583       1.0
DurationOfPitch          4637.0      15.490835     8.519643       5.0
NumberOfPersonVisiting   4888.0       2.905074     0.724891       1.0
NumberOfFollowups        4843.0       3.708445     1.002509       1.0
PreferredPropertyStar    4862.0       3.581037     0.798009       3.0
NumberOfTrips            4748.0       3.236521     1.849019       1.0
Passport                 4888.0       0.290917     0.454232       0.0
PitchSatisfactionScore   4888.0       3.078151     1.365792       1.0
OwnCar                   4888.0       0.620295     0.485363       0.0
NumberOfChildrenVisiting 4822.0       1.187267     0.857861       0.0
MonthlyIncome            4655.0   23619.853491  5380.698361    1000.0

                               25%       50%        75%       max
CustomerID               201221.75  202443.5  203665.25  204887.0
ProdTaken                     0.00       0.0       0.00       1.0
Age                          31.00      36.0      44.00      61.0
CityTier                      1.00       1.0       3.00       3.0
DurationOfPitch               9.00      13.0      20.00     127.0
NumberOfPersonVisiting        2.00       3.0       3.00       5.0
NumberOfFollowups             3.00       4.0       4.00       6.0
PreferredPropertyStar         3.00       3.0       4.00       5.0
NumberOfTrips                 2.00       3.0       4.00      22.0
Passport                      0.00       0.0       1.00       1.0
PitchSatisfactionScore        2.00       3.0       4.00       5.0
OwnCar                        0.00       1.0       1.00       1.0
NumberOfChildrenVisiting      1.00       1.0       2.00       3.0
MonthlyIncome             20346.00   22347.0   25571.00   98678.0
```

[20]:
```python
# Missing Values
data.isnull().sum()
```

[20]:
```
CustomerID                    0
ProdTaken                     0
Age                         226
TypeofContact                25
```

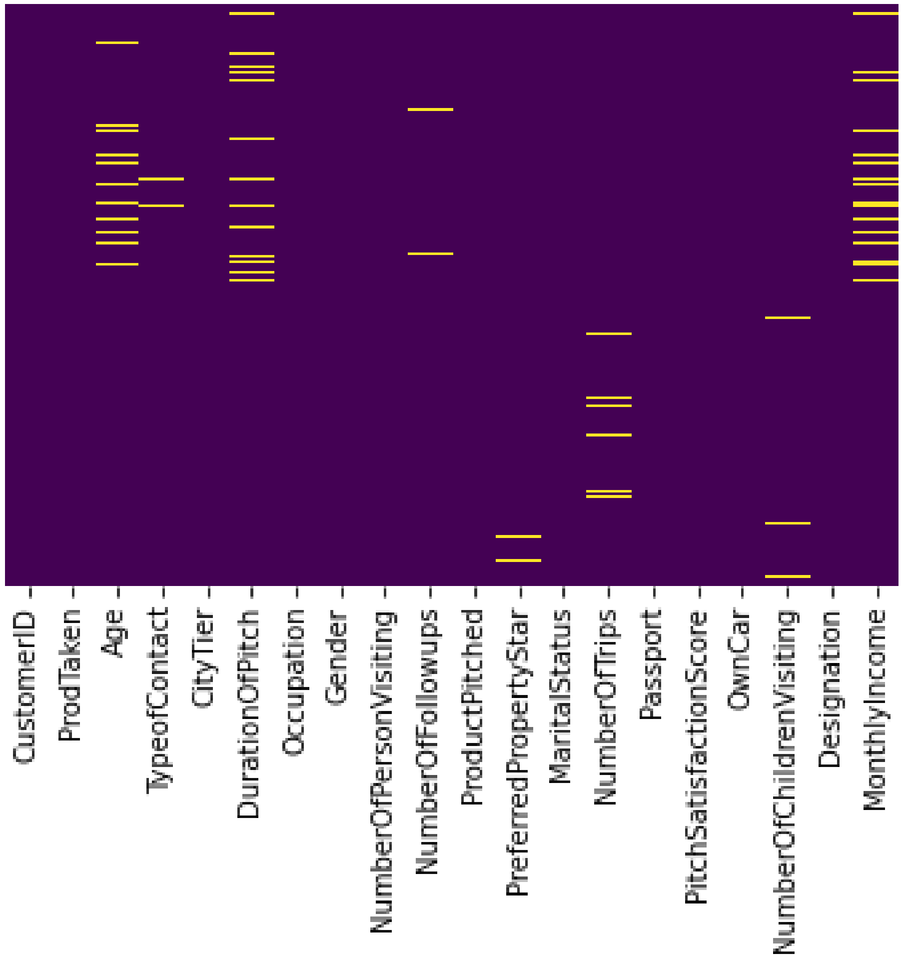
```
CityTier                      0
DurationOfPitch             251
Occupation                    0
Gender                        0
NumberOfPersonVisiting        0
NumberOfFollowups            45
ProductPitched                0
PreferredPropertyStar        26
MaritalStatus                 0
NumberOfTrips               140
Passport                      0
PitchSatisfactionScore        0
OwnCar                        0
NumberOfChildrenVisiting     66
Designation                   0
MonthlyIncome               233
dtype: int64
```

[22]:
```
[features for features in data.columns if data[features].isnull().sum()>0]
```

[22]:
```
['Age',
 'TypeofContact',
 'DurationOfPitch',
 'NumberOfFollowups',
 'PreferredPropertyStar',
 'NumberOfTrips',
 'NumberOfChildrenVisiting',
 'MonthlyIncome']
```

[28]:
```
sns.heatmap(data.isnull(),yticklabels=False,cbar=False,cmap="viridis") #␣
 ↪Graphically indicates the missing values
```

[28]:
```
<AxesSubplot:>
```



[31]:
```
cat_col=[fea for fea in data.columns if data[fea].dtype =='O'] #segregating␣
↪categorical and numerical variables
cat_col
```

[31]:
```
['TypeofContact',
 'Occupation',
 'Gender',
 'ProductPitched',
 'MaritalStatus',
 'Designation']
```

[32]:
```
num_col=[fea for fea in data.columns if data[fea].dtype !='O']#segregating␣
↪categorical and numerical variables
num_col
```

[32]:
```
['CustomerID',
 'ProdTaken',
 'Age',
 'CityTier',
 'DurationOfPitch',
 'NumberOfPersonVisiting',
 'NumberOfFollowups',
 'PreferredPropertyStar',
 'NumberOfTrips',
 'Passport',
 'PitchSatisfactionScore',
 'OwnCar',
 'NumberOfChildrenVisiting',
 'MonthlyIncome']
```

[33]:
```
data[cat_col]
```

[33]:
```
        TypeofContact      Occupation  Gender ProductPitched MaritalStatus  \
0        Self Enquiry        Salaried  Female         Deluxe        Single
1     Company Invited        Salaried    Male         Deluxe      Divorced
2        Self Enquiry     Free Lancer    Male          Basic        Single
3     Company Invited        Salaried  Female          Basic      Divorced
4        Self Enquiry  Small Business    Male          Basic      Divorced
…                 …               …       …              …             …
4883     Self Enquiry  Small Business    Male         Deluxe     Unmarried
4884  Company Invited        Salaried    Male          Basic        Single
4885     Self Enquiry        Salaried  Female       Standard       Married
4886     Self Enquiry  Small Business    Male          Basic        Single
4887     Self Enquiry        Salaried    Male          Basic     Unmarried

         Designation
0            Manager
1            Manager
2          Executive
3          Executive
4          Executive
…                  …
4883         Manager
4884       Executive
4885  Senior Manager
4886       Executive
4887       Executive

[4888 rows x 6 columns]
```

[34]:
```
data[num_col]
```

[34]:
```
      CustomerID  ProdTaken   Age  CityTier  DurationOfPitch  \
0         200000          1  41.0         3              6.0
1         200001          0  49.0         1             14.0
2         200002          1  37.0         1              8.0
3         200003          0  33.0         1              9.0
4         200004          0   NaN         1              8.0
…            …          …    …    …          …
4883      204883          1  49.0         3              9.0
4884      204884          1  28.0         1             31.0
4885      204885          1  52.0         3             17.0
4886      204886          1  19.0         3             16.0
4887      204887          1  36.0         1             14.0

      NumberOfPersonVisiting  NumberOfFollowups  PreferredPropertyStar  \
0                          3                3.0                    3.0
1                          3                4.0                    4.0
2                          3                4.0                    3.0
3                          2                3.0                    3.0
4                          2                3.0                    4.0
…                       …                …                    …
4883                       3                5.0                    4.0
4884                       4                5.0                    3.0
4885                       4                4.0                    4.0
4886                       3                4.0                    3.0
4887                       4                4.0                    4.0

      NumberOfTrips  Passport  PitchSatisfactionScore  OwnCar  \
0               1.0         1                       2       1
1               2.0         0                       3       1
2               7.0         1                       3       0
3               2.0         1                       5       1
4               1.0         0                       5       1
…             …        …                     …     …
4883            2.0         1                       1       1
4884            3.0         1                       3       1
4885            7.0         0                       1       1
4886            3.0         0                       5       0
4887            3.0         1                       3       1

      NumberOfChildrenVisiting  MonthlyIncome
0                          0.0        20993.0
1                          2.0        20130.0
2                          0.0        17090.0
3                          1.0        17909.0
4                          0.0        18468.0
…                        …            …
4883                       1.0        26576.0
```

```
4884                          2.0         21212.0
4885                          3.0         31820.0
4886                          2.0         20289.0
4887                          2.0         24041.0

[4888 rows x 14 columns]
```

[47]:
```
numeric_data_1=data[num_col]
numeric_data_1
```

[47]:
```
      CustomerID  ProdTaken   Age  CityTier  DurationOfPitch  \
0         200000          1  41.0         3              6.0
1         200001          0  49.0         1             14.0
2         200002          1  37.0         1              8.0
3         200003          0  33.0         1              9.0
4         200004          0   NaN         1              8.0
…            …          …    …          …              …
4883      204883          1  49.0         3              9.0
4884      204884          1  28.0         1             31.0
4885      204885          1  52.0         3             17.0
4886      204886          1  19.0         3             16.0
4887      204887          1  36.0         1             14.0

      NumberOfPersonVisiting  NumberOfFollowups  PreferredPropertyStar  \
0                          3                3.0                    3.0
1                          3                4.0                    4.0
2                          3                4.0                    3.0
3                          2                3.0                    3.0
4                          2                3.0                    4.0
…                        …                  …                      …
4883                       3                5.0                    4.0
4884                       4                5.0                    3.0
4885                       4                4.0                    4.0
4886                       3                4.0                    3.0
4887                       4                4.0                    4.0

      NumberOfTrips  Passport  PitchSatisfactionScore  OwnCar  \
0               1.0         1                       2       1
1               2.0         0                       3       1
2               7.0         1                       3       0
3               2.0         1                       5       1
4               1.0         0                       5       1
…               …         …                       …     …
4883            2.0         1                       1       1
4884            3.0         1                       3       1
4885            7.0         0                       1       1
4886            3.0         0                       5       0
```

```
4887             3.0          1                      3       1

      NumberOfChildrenVisiting  MonthlyIncome
0                          0.0        20993.0
1                          2.0        20130.0
2                          0.0        17090.0
3                          1.0        17909.0
4                          0.0        18468.0
…                         …            …
4883                       1.0        26576.0
4884                       2.0        21212.0
4885                       3.0        31820.0
4886                       2.0        20289.0
4887                       2.0        24041.0

[4888 rows x 14 columns]
```

[48]:
```python
numeric_data_1 = numeric_data_1.drop('CustomerID',axis=1) # dropping Customer ID
```

[49]:
```python
numeric_data_1.describe().T
```

[49]:
```
                          count          mean          std     min      25%  \
ProdTaken                4888.0      0.188216     0.390925     0.0      0.0
Age                      4662.0     37.622265     9.316387    18.0     31.0
CityTier                 4888.0      1.654255     0.916583     1.0      1.0
DurationOfPitch          4637.0     15.490835     8.519643     5.0      9.0
NumberOfPersonVisiting   4888.0      2.905074     0.724891     1.0      2.0
NumberOfFollowups        4843.0      3.708445     1.002509     1.0      3.0
PreferredPropertyStar    4862.0      3.581037     0.798009     3.0      3.0
NumberOfTrips            4748.0      3.236521     1.849019     1.0      2.0
Passport                 4888.0      0.290917     0.454232     0.0      0.0
PitchSatisfactionScore   4888.0      3.078151     1.365792     1.0      2.0
OwnCar                   4888.0      0.620295     0.485363     0.0      0.0
NumberOfChildrenVisiting 4822.0      1.187267     0.857861     0.0      1.0
MonthlyIncome            4655.0  23619.853491  5380.698361  1000.0  20346.0

                             50%      75%      max
ProdTaken                    0.0      0.0      1.0
Age                         36.0     44.0     61.0
CityTier                     1.0      3.0      3.0
DurationOfPitch             13.0     20.0    127.0
NumberOfPersonVisiting       3.0      3.0      5.0
NumberOfFollowups            4.0      4.0      6.0
PreferredPropertyStar        3.0      4.0      5.0
NumberOfTrips                3.0      4.0     22.0
Passport                     0.0      1.0      1.0
PitchSatisfactionScore       3.0      4.0      5.0
```

```
OwnCar                         1.0      1.0      1.0
NumberOfChildrenVisiting       1.0      2.0      3.0
MonthlyIncome              22347.0  25571.0  98678.0
```

[55]:
```python
numeric_data_1.corr() # checking correlation matrix
```

[55]:
```
                          ProdTaken       Age  CityTier  DurationOfPitch  \
ProdTaken                  1.000000 -0.147254  0.086852         0.078257
Age                       -0.147254  1.000000 -0.015625        -0.012063
CityTier                   0.086852 -0.015625  1.000000         0.022703
DurationOfPitch            0.078257 -0.012063  0.022703         1.000000
NumberOfPersonVisiting     0.009627  0.011621 -0.001671         0.065141
NumberOfFollowups          0.112171 -0.002577  0.023652         0.009434
PreferredPropertyStar      0.099577 -0.010474 -0.009164        -0.006637
NumberOfTrips              0.018898  0.184905 -0.029709         0.009715
Passport                   0.260844  0.033399  0.001793         0.033034
PitchSatisfactionScore     0.051394  0.018510 -0.042160        -0.002880
OwnCar                    -0.011508  0.048654  0.003817        -0.001626
NumberOfChildrenVisiting   0.007421  0.007370  0.000672         0.031408
MonthlyIncome             -0.130585  0.464869  0.051817        -0.006252

                          NumberOfPersonVisiting  NumberOfFollowups  \
ProdTaken                               0.009627           0.112171
Age                                     0.011621          -0.002577
CityTier                               -0.001671           0.023652
DurationOfPitch                         0.065141           0.009434
NumberOfPersonVisiting                  1.000000           0.328569
NumberOfFollowups                       0.328569           1.000000
PreferredPropertyStar                   0.033867          -0.024176
NumberOfTrips                           0.195223           0.139517
Passport                                0.011177           0.004970
PitchSatisfactionScore                 -0.019581           0.004054
OwnCar                                  0.010362           0.012112
NumberOfChildrenVisiting                0.610621           0.286425
MonthlyIncome                           0.195134           0.176503

                          PreferredPropertyStar  NumberOfTrips  Passport  \
ProdTaken                              0.099577       0.018898  0.260844
Age                                   -0.010474       0.184905  0.033399
CityTier                              -0.009164      -0.029709  0.001793
DurationOfPitch                       -0.006637       0.009715  0.033034
NumberOfPersonVisiting                 0.033867       0.195223  0.011177
NumberOfFollowups                     -0.024176       0.139517  0.004970
PreferredPropertyStar                  1.000000       0.012115  0.001040
NumberOfTrips                          0.012115       1.000000  0.012949
Passport                               0.001040       0.012949  1.000000
PitchSatisfactionScore                -0.022701      -0.004378  0.002926
```

```
OwnCar                             0.015742      -0.011825 -0.022330
NumberOfChildrenVisiting           0.035798       0.168795  0.020264
MonthlyIncome                      0.014289       0.139105  0.002545

                          PitchSatisfactionScore    OwnCar  \
ProdTaken                               0.051394 -0.011508
Age                                     0.018510  0.048654
CityTier                               -0.042160  0.003817
DurationOfPitch                        -0.002880 -0.001626
NumberOfPersonVisiting                 -0.019581  0.010362
NumberOfFollowups                       0.004054  0.012112
PreferredPropertyStar                  -0.022701  0.015742
NumberOfTrips                          -0.004378 -0.011825
Passport                                0.002926 -0.022330
PitchSatisfactionScore                  1.000000  0.068850
OwnCar                                  0.068850  1.000000
NumberOfChildrenVisiting                0.000878  0.026572
MonthlyIncome                           0.030421  0.080262

                          NumberOfChildrenVisiting  MonthlyIncome
ProdTaken                                 0.007421      -0.130585
Age                                       0.007370       0.464869
CityTier                                  0.000672       0.051817
DurationOfPitch                           0.031408      -0.006252
NumberOfPersonVisiting                    0.610621       0.195134
NumberOfFollowups                         0.286425       0.176503
PreferredPropertyStar                     0.035798       0.014289
NumberOfTrips                             0.168795       0.139105
Passport                                  0.020264       0.002545
PitchSatisfactionScore                    0.000878       0.030421
OwnCar                                    0.026572       0.080262
NumberOfChildrenVisiting                  1.000000       0.201643
MonthlyIncome                             0.201643       1.000000
```

[56]:

```
numeric_data_1.cov() # checking covariance matrix
```

[56]:

```
                          ProdTaken          Age   CityTier  \
ProdTaken                  0.152822    -0.535959   0.031120
Age                       -0.535959    86.795067  -0.134168
CityTier                   0.031120    -0.134168   0.840125
DurationOfPitch            0.260897    -0.944440   0.176544
NumberOfPersonVisiting     0.002728     0.078126  -0.001110
NumberOfFollowups          0.043969    -0.024058   0.021716
PreferredPropertyStar      0.031050    -0.077447  -0.006707
NumberOfTrips              0.013743     3.158372  -0.050474
Passport                   0.046318     0.141269   0.000747
PitchSatisfactionScore     0.027440     0.235235  -0.052778
```

```
OwnCar                       -0.002184      0.220050    0.001698
NumberOfChildrenVisiting      0.002494      0.058470    0.000529
MonthlyIncome              -276.097744  23365.183349  255.945958

                          DurationOfPitch  NumberOfPersonVisiting  \
ProdTaken                        0.260897                0.002728
Age                             -0.944440                0.078126
CityTier                         0.176544               -0.001110
DurationOfPitch                 72.584310                0.401434
NumberOfPersonVisiting           0.401434                0.525466
NumberOfFollowups                0.080699                0.238479
PreferredPropertyStar           -0.045149                0.019575
NumberOfTrips                    0.154174                0.261809
Passport                         0.128118                0.003680
PitchSatisfactionScore          -0.033569               -0.019386
OwnCar                          -0.006731                0.003646
NumberOfChildrenVisiting         0.229346                0.380176
MonthlyIncome                 -289.182796              756.518793

                          NumberOfFollowups  PreferredPropertyStar  \
ProdTaken                          0.043969               0.031050
Age                               -0.024058              -0.077447
CityTier                           0.021716              -0.006707
DurationOfPitch                    0.080699              -0.045149
NumberOfPersonVisiting             0.238479               0.019575
NumberOfFollowups                  1.005024              -0.019309
PreferredPropertyStar             -0.019309               0.636818
NumberOfTrips                      0.259783               0.017840
Passport                           0.002265               0.000377
PitchSatisfactionScore             0.005550              -0.024736
OwnCar                             0.005894               0.006102
NumberOfChildrenVisiting           0.246696               0.024441
MonthlyIncome                    958.027680              58.848919

                          NumberOfTrips  Passport  PitchSatisfactionScore  \
ProdTaken                      0.013743  0.046318                0.027440
Age                            3.158372  0.141269                0.235235
CityTier                      -0.050474  0.000747               -0.052778
DurationOfPitch                0.154174  0.128118               -0.033569
NumberOfPersonVisiting         0.261809  0.003680               -0.019386
NumberOfFollowups              0.259783  0.002265                0.005550
PreferredPropertyStar          0.017840  0.000377               -0.024736
NumberOfTrips                  3.418872  0.010882               -0.011035
Passport                       0.010882  0.206326                0.001815
PitchSatisfactionScore        -0.011035  0.001815                1.865387
OwnCar                        -0.010622 -0.004923                0.045641
NumberOfChildrenVisiting       0.267269  0.007898                0.001029
```

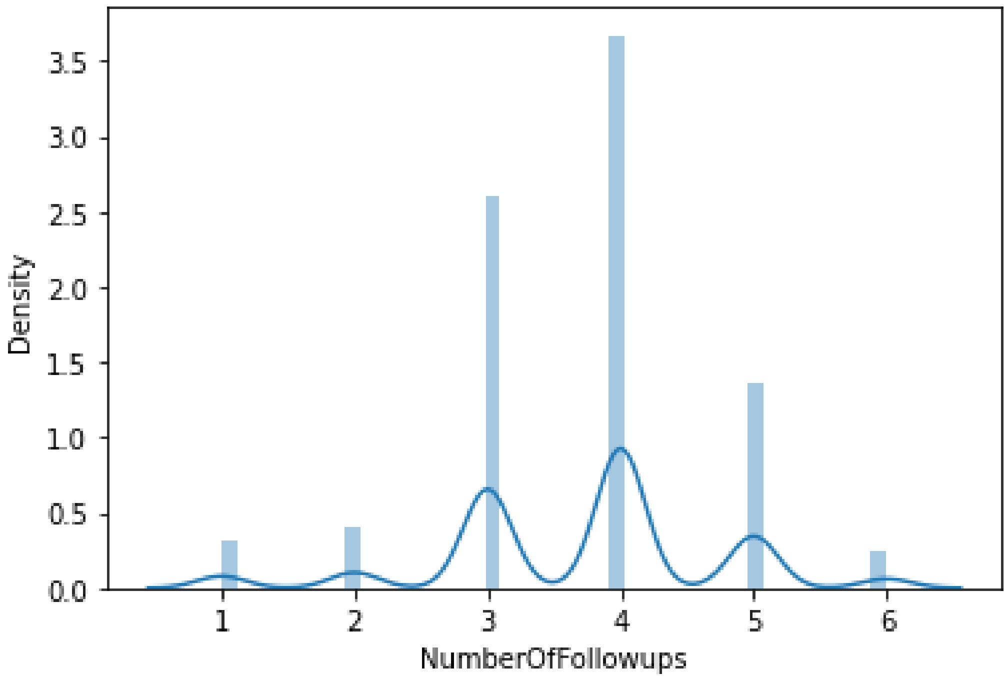
```
MonthlyIncome              1265.226486  6.230027            223.667867

                             OwnCar  NumberOfChildrenVisiting  MonthlyIncome
ProdTaken                 -0.002184                  0.002494  -2.760977e+02
Age                        0.220050                  0.058470   2.336518e+04
CityTier                   0.001698                  0.000529   2.559460e+02
DurationOfPitch           -0.006731                  0.229346  -2.891828e+02
NumberOfPersonVisiting     0.003646                  0.380176   7.565188e+02
NumberOfFollowups          0.005894                  0.246696   9.580277e+02
PreferredPropertyStar      0.006102                  0.024441   5.884892e+01
NumberOfTrips             -0.010622                  0.267269   1.265226e+03
Passport                  -0.004923                  0.007898   6.230027e+00
PitchSatisfactionScore     0.045641                  0.001029   2.236679e+02
OwnCar                     0.235577                  0.011073   2.095549e+02
NumberOfChildrenVisiting   0.011073                  0.735926   9.048496e+02
MonthlyIncome            209.554880                904.849579   2.895191e+07
```

[57]:
```python
numeric_data_1.skew()
```

[57]:
```
ProdTaken                   1.595763
Age                         0.382989
CityTier                    0.736531
DurationOfPitch             1.752037
NumberOfPersonVisiting      0.029817
NumberOfFollowups          -0.372719
PreferredPropertyStar       0.895545
NumberOfTrips               1.453884
Passport                    0.920980
PitchSatisfactionScore     -0.127726
OwnCar                     -0.495892
NumberOfChildrenVisiting    0.272199
MonthlyIncome               1.949160
dtype: float64
```

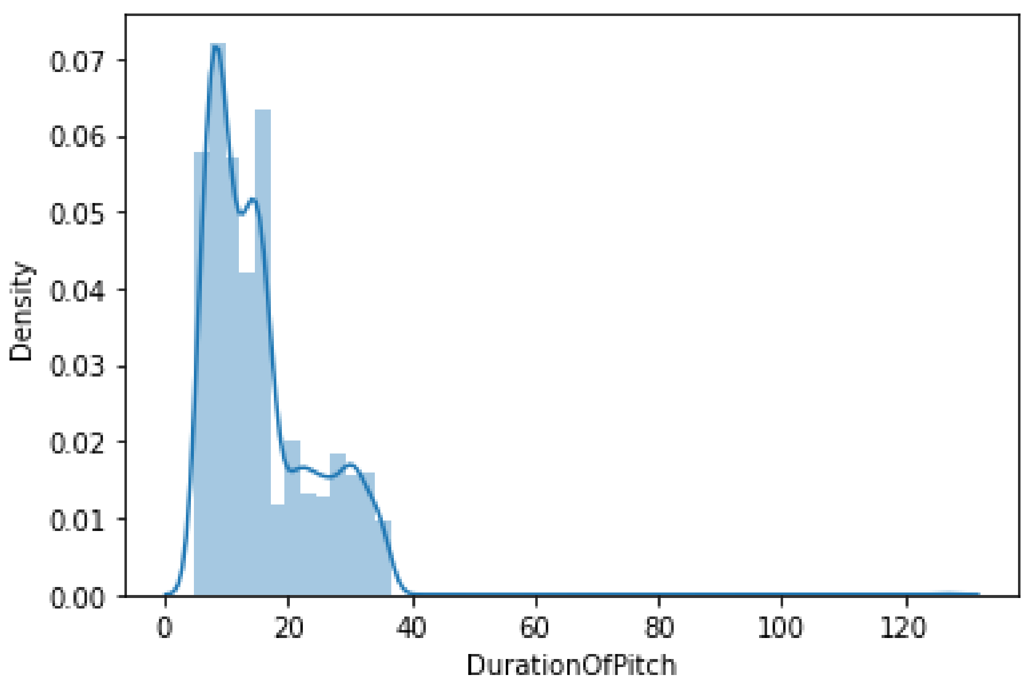
[62]:
```python
sns.distplot(numeric_data_1['NumberOfFollowups']) # Plotting distribution of␣
↪NumberOfFollowups feature
```

[62]:
```
<AxesSubplot:xlabel='NumberOfFollowups', ylabel='Density'>
```



[69]:
```
sns.distplot(numeric_data_1['DurationOfPitch']) # Plotting distribution of␣
 ↪DurationOfPitch feature
# Inference is that this feature is not nornaly distributed.
```

[69]: <AxesSubplot:xlabel='DurationOfPitch', ylabel='Density'>



[73]:
```
cat_df=data[cat_col].groupby('Gender').mean()
cat_df
```

[73]:
```
Empty DataFrame
Columns: []
Index: [Fe Male, Female, Male]
```

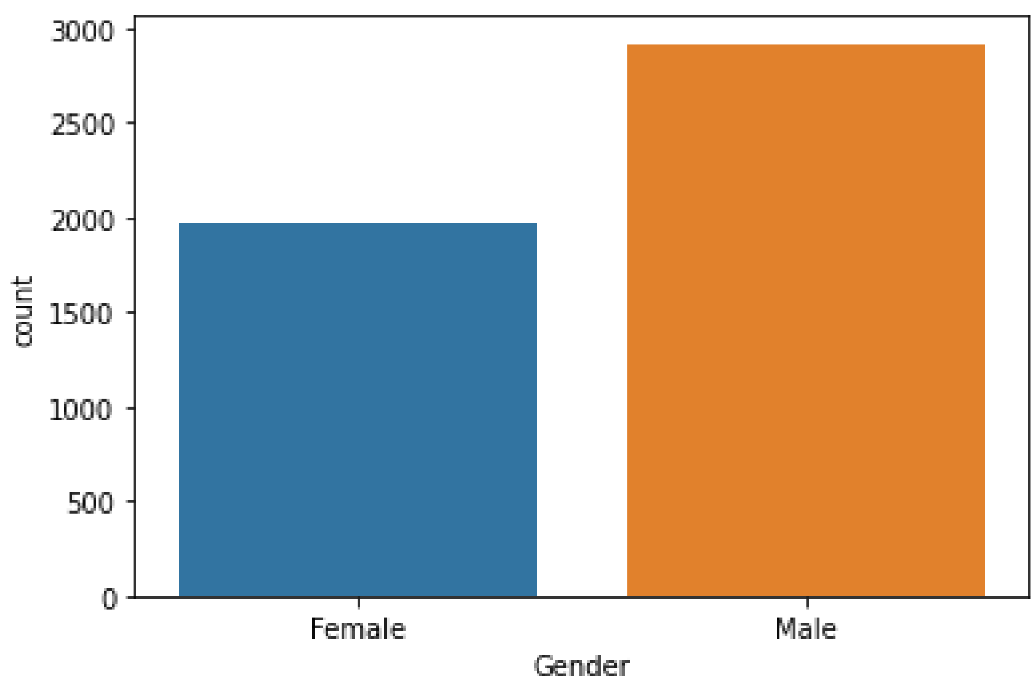
[75]:
```
cat_df=data[cat_col].groupby('Gender').mean()
cat_df
```

[75]:
```
Empty DataFrame
Columns: []
Index: [Fe Male, Female, Male]
```

[85]:
```
a=data[cat_col]['Gender'] = data[cat_col]['Gender'].replace({'Fe Male':
↪'Female'}) # Replacing "Fe Male by Female"
```

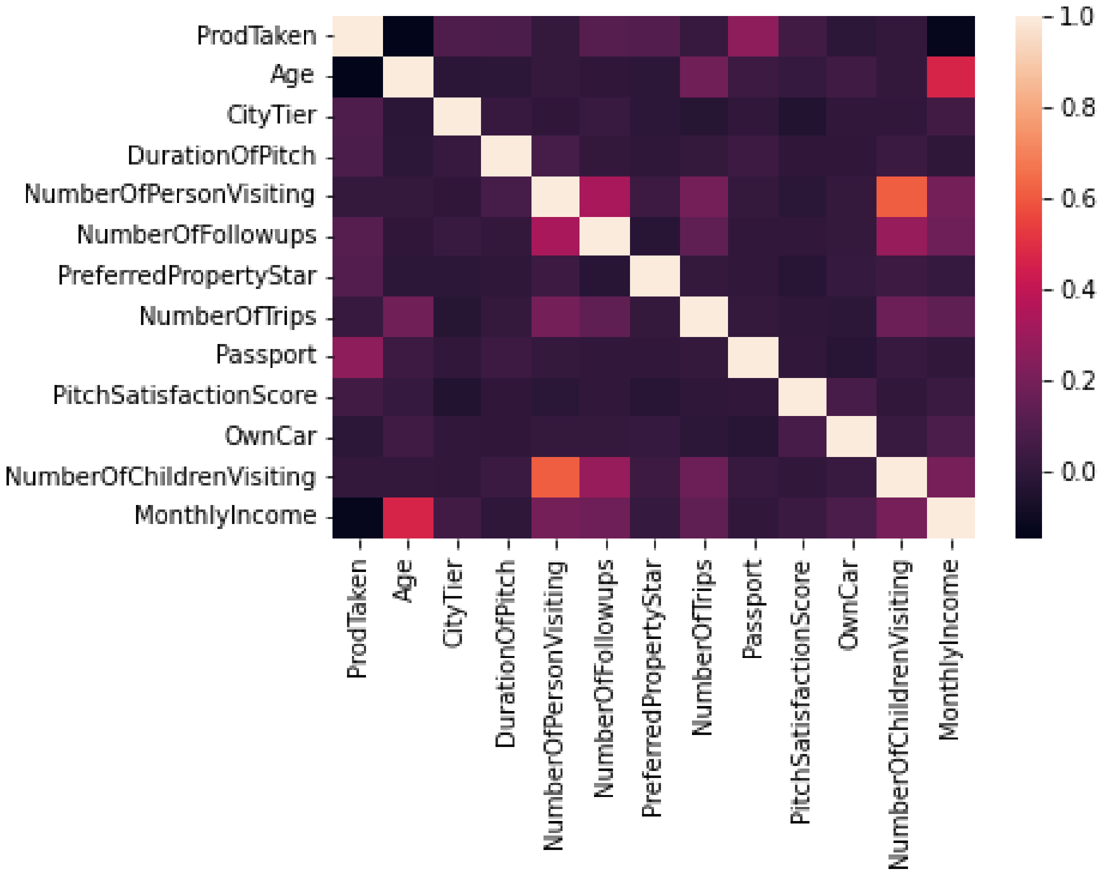
[87]:
```
sns.countplot(x=a)
```

[87]:
```
<AxesSubplot:xlabel='Gender', ylabel='count'>
```



[88]:
```
sns.heatmap(numeric_data_1.corr()) # drawing the correlation heatmap for␣
↪numerical features
```

[88]: <AxesSubplot:>



Encoding Categorical Variables

September 28, 2022

[53]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
import warnings
warnings.filterwarnings('ignore')
```

[54]:
```
data=pd.read_csv('Travel.csv')
```

[55]:
```
cat_col=[fea for fea in data.columns if data[fea].dtype =='O'] #segregating␣
 ↪categorical and numerical variables
cat_col
```

[55]:
```
['TypeofContact',
 'Occupation',
 'Gender',
 'ProductPitched',
 'MaritalStatus',
 'Designation']
```

[56]:
```
X=data[cat_col]
X
```

[56]:
```
        TypeofContact      Occupation  Gender ProductPitched MaritalStatus  \
0        Self Enquiry        Salaried  Female         Deluxe        Single
1     Company Invited        Salaried    Male         Deluxe      Divorced
2        Self Enquiry     Free Lancer    Male          Basic        Single
3     Company Invited        Salaried  Female          Basic      Divorced
4        Self Enquiry  Small Business    Male          Basic      Divorced
…                 …               …     …              …             …
4883     Self Enquiry  Small Business    Male         Deluxe     Unmarried
4884  Company Invited        Salaried    Male          Basic        Single
4885     Self Enquiry        Salaried  Female       Standard       Married
4886     Self Enquiry  Small Business    Male          Basic        Single
4887     Self Enquiry        Salaried    Male          Basic     Unmarried
```

```
         Designation
0            Manager
1            Manager
2          Executive
3          Executive
4          Executive
…                  …
4883         Manager
4884       Executive
4885  Senior Manager
4886       Executive
4887       Executive

[4888 rows x 6 columns]
```

[57]:
```
X.isnull().sum()
```

[57]:
```
TypeofContact     25
Occupation         0
Gender             0
ProductPitched     0
MaritalStatus      0
Designation        0
dtype: int64
```

[58]:
```
# Replacing Null values in "TypeofContact" feature by Mode
X=X.fillna(X.mode().iloc[0])
```

[59]:
```
X.isnull().sum()
```

[59]:
```
TypeofContact     0
Occupation        0
Gender            0
ProductPitched    0
MaritalStatus     0
Designation       0
dtype: int64
```

Method 1: Creating Binary variables through One Hot Encoding

[67]:
```
# Using Pandas
X_encoded=pd.get_dummies(X,drop_first=True)# drop_first =True implies that␣
↪dropping the first binary variable
```

[61]:
```
# Using Sklearn
from sklearn.preprocessing import OneHotEncoder
encoder=OneHotEncoder(categories='auto',drop='first',sparse=False)
```

```
X_encoded=encoder.fit(X)
X_encoded
```

[61]:
```
OneHotEncoder(drop='first', sparse=False)
```

[62]:
```
X_transformed=encoder.transform(X)
X_transformed
```

[62]:
```
array([[1., 0., 1., …, 1., 0., 0.],
       [0., 0., 1., …, 1., 0., 0.],
       [1., 0., 0., …, 0., 0., 0.],
       …,
       [1., 0., 1., …, 0., 1., 0.],
       [1., 0., 0., …, 0., 0., 0.],
       [1., 0., 1., …, 0., 0., 0.]])
```

Method 2: Repalcing Categories with Ordinal Numbers

[63]:
```
# Using sklearn
from sklearn.preprocessing import OrdinalEncoder
enc = OrdinalEncoder()
enc.fit(X)
X_trans=enc.transform(X)
X_trans
```

[63]:
```
array([[1., 2., 1., 1., 2., 2.],
       [0., 2., 2., 1., 0., 2.],
       [1., 0., 2., 0., 2., 1.],
       …,
       [1., 2., 1., 3., 1., 3.],
       [1., 3., 2., 0., 2., 1.],
       [1., 2., 2., 0., 3., 1.]])
```

Method 3: Label Encoding

[64]:
```
from sklearn.preprocessing import LabelEncoder
le = LabelEncoder()
le.fit(X['TypeofContact'])
```

[64]:
```
LabelEncoder()
```

[65]:
```
list(le.classes_)
```

[65]:
```
['Company Invited', 'Self Enquiry']
```

[66]:
```
le.transform(X['TypeofContact'])
```

[66]:
```
array([1, 0, 1, …, 1, 1, 1])
```

Handling_Missing_Values

September 28, 2022

[130]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
import warnings
warnings.filterwarnings('ignore')
```

[131]:
```
data=pd.read_csv('Travel.csv')
```

[132]:
```
num_col=[fea for fea in data.columns if (data[fea].dtype !='O' and data[fea].
↪dtype !=int)]#segregating categorical and numerical variables
num_col
```

[132]:
```
['Age',
 'DurationOfPitch',
 'NumberOfFollowups',
 'PreferredPropertyStar',
 'NumberOfTrips',
 'NumberOfChildrenVisiting',
 'MonthlyIncome']
```

[133]:
```
data[num_col].isnull().mean()
```

[133]:
```
Age                         0.046236
DurationOfPitch             0.051350
NumberOfFollowups           0.009206
PreferredPropertyStar       0.005319
NumberOfTrips               0.028642
NumberOfChildrenVisiting    0.013502
MonthlyIncome               0.047668
dtype: float64
```

Method 1: Performing Mean Imputation

[134]:
```
# Method 1: Performing Mean Imputation

for var in num_col:
```

```
    value=data[var].mean()
    data[var]=data[var].fillna(value)
```

[135]:
```
data[num_col].isnull().mean() # Checking after imputation
```

[135]:
```
Age                          0.0
DurationOfPitch              0.0
NumberOfFollowups            0.0
PreferredPropertyStar        0.0
NumberOfTrips                0.0
NumberOfChildrenVisiting     0.0
MonthlyIncome                0.0
dtype: float64
```

Method 2: Imputing Missing Values by mean using scikit-learn

[136]:
```
# Method 2: Imputing Missing Values by mean using scikit-learn
import sklearn
from sklearn.impute import SimpleImputer
imputer= SimpleImputer(strategy='mean')
```

[137]:
```
data=pd.read_csv('Travel.csv')
num_col=[fea for fea in data.columns if (data[fea].dtype !='O' and data[fea].
 ↪dtype !=int)]
#segregating categorical and numerical variables
X=data[num_col]
```

[138]:
```
imputer.fit(X) # fitting SimpleImputer to the datafrane X
```

[138]:
```
SimpleImputer()
```

[139]:
```
X
```

[139]:
```
       Age  DurationOfPitch  NumberOfFollowups  PreferredPropertyStar  \
0     41.0              6.0                3.0                    3.0
1     49.0             14.0                4.0                    4.0
2     37.0              8.0                4.0                    3.0
3     33.0              9.0                3.0                    3.0
4      NaN              8.0                3.0                    4.0
…     …               …                 …                     …
4883  49.0              9.0                5.0                    4.0
4884  28.0             31.0                5.0                    3.0
4885  52.0             17.0                4.0                    4.0
4886  19.0             16.0                4.0                    3.0
4887  36.0             14.0                4.0                    4.0

      NumberOfTrips  NumberOfChildrenVisiting  MonthlyIncome
```

```
0               1.0                       0.0        20993.0
1               2.0                       2.0        20130.0
2               7.0                       0.0        17090.0
3               2.0                       1.0        17909.0
4               1.0                       0.0        18468.0
…             …                       …            …
4883            2.0                       1.0        26576.0
4884            3.0                       2.0        21212.0
4885            7.0                       3.0        31820.0
4886            3.0                       2.0        20289.0
4887            3.0                       2.0        24041.0

[4888 rows x 7 columns]
```

[140]:
```python
X=imputer.transform(X)
X
```

[140]:
```
array([[4.1000e+01, 6.0000e+00, 3.0000e+00, …, 1.0000e+00, 0.0000e+00,
        2.0993e+04],
       [4.9000e+01, 1.4000e+01, 4.0000e+00, …, 2.0000e+00, 2.0000e+00,
        2.0130e+04],
       [3.7000e+01, 8.0000e+00, 4.0000e+00, …, 7.0000e+00, 0.0000e+00,
        1.7090e+04],
       …,
       [5.2000e+01, 1.7000e+01, 4.0000e+00, …, 7.0000e+00, 3.0000e+00,
        3.1820e+04],
       [1.9000e+01, 1.6000e+01, 4.0000e+00, …, 3.0000e+00, 2.0000e+00,
        2.0289e+04],
       [3.6000e+01, 1.4000e+01, 4.0000e+00, …, 3.0000e+00, 2.0000e+00,
        2.4041e+04]])
```

[143]:
```python
result=pd.DataFrame(X,columns=['Age',
 'DurationOfPitch',
 'NumberOfFollowups',
 'PreferredPropertyStar',
 'NumberOfTrips',
 'NumberOfChildrenVisiting',
 'MonthlyIncome'])
result # dataframe after mean imputation by sklearn's simple Imputer
```

[143]:
```
            Age  DurationOfPitch  NumberOfFollowups  PreferredPropertyStar  \
0     41.000000              6.0                3.0                    3.0
1     49.000000             14.0                4.0                    4.0
2     37.000000              8.0                4.0                    3.0
3     33.000000              9.0                3.0                    3.0
4     37.622265              8.0                3.0                    4.0
…           …               …                 …                     …
```

```
4883  49.000000            9.0                5.0                     4.0
4884  28.000000           31.0                5.0                     3.0
4885  52.000000           17.0                4.0                     4.0
4886  19.000000           16.0                4.0                     3.0
4887  36.000000           14.0                4.0                     4.0

      NumberOfTrips  NumberOfChildrenVisiting  MonthlyIncome
0               1.0                       0.0        20993.0
1               2.0                       2.0        20130.0
2               7.0                       0.0        17090.0
3               2.0                       1.0        17909.0
4               1.0                       0.0        18468.0
…             …                       …            …
4883            2.0                       1.0        26576.0
4884            3.0                       2.0        21212.0
4885            7.0                       3.0        31820.0
4886            3.0                       2.0        20289.0
4887            3.0                       2.0        24041.0

[4888 rows x 7 columns]
```

[144]:
```python
result.isnull().mean() # Checking after imputation
```

[144]:
```
Age                         0.0
DurationOfPitch             0.0
NumberOfFollowups           0.0
PreferredPropertyStar       0.0
NumberOfTrips               0.0
NumberOfChildrenVisiting    0.0
MonthlyIncome               0.0
dtype: float64
```

[145]:
```python
# The above imputations are applicable for median imputation also.
```

Method 3: Replacing missing values in categorical features by the feature's mode.

[146]:
```python
data=pd.read_csv('Travel.csv')
```

[147]:
```python
cat_col=[fea for fea in data.columns if data[fea].dtype =='O'] #segregating␣
 ↪categorical and numerical variables
cat_col
```

[147]:
```
['TypeofContact',
 'Occupation',
 'Gender',
 'ProductPitched',
 'MaritalStatus',
```

'Designation']

[149]:
```
X=data[cat_col]
X
```

[149]:
```
           TypeofContact      Occupation  Gender ProductPitched MaritalStatus  \
0           Self Enquiry        Salaried  Female         Deluxe        Single
1        Company Invited        Salaried    Male         Deluxe      Divorced
2           Self Enquiry     Free Lancer    Male          Basic        Single
3        Company Invited        Salaried  Female          Basic      Divorced
4           Self Enquiry  Small Business    Male          Basic      Divorced
…                    …               …       …              …             …
4883        Self Enquiry  Small Business    Male         Deluxe     Unmarried
4884     Company Invited        Salaried    Male          Basic        Single
4885        Self Enquiry        Salaried  Female       Standard       Married
4886        Self Enquiry  Small Business    Male          Basic        Single
4887        Self Enquiry        Salaried    Male          Basic     Unmarried

         Designation
0            Manager
1            Manager
2          Executive
3          Executive
4          Executive
…                …
4883         Manager
4884       Executive
4885  Senior Manager
4886       Executive
4887       Executive

[4888 rows x 6 columns]
```

[150]:
```
X.isnull().mean()
```

[150]:
```
TypeofContact     0.005115
Occupation        0.000000
Gender            0.000000
ProductPitched    0.000000
MaritalStatus     0.000000
Designation       0.000000
dtype: float64
```

[151]:
```
# Only the first feature that is TypeofContact has missing values
```

[152]:
```
value=X['TypeofContact'].mode()[0]
X['TypeofContact']=X['TypeofContact'].fillna(value)
```

```
X
```

[152]:
```
        TypeofContact      Occupation  Gender ProductPitched MaritalStatus  \
0        Self Enquiry        Salaried  Female         Deluxe        Single
1     Company Invited        Salaried    Male         Deluxe      Divorced
2        Self Enquiry     Free Lancer    Male          Basic        Single
3     Company Invited        Salaried  Female          Basic      Divorced
4        Self Enquiry  Small Business    Male          Basic      Divorced
…                 …             …     …            …            …
4883     Self Enquiry  Small Business    Male         Deluxe     Unmarried
4884  Company Invited        Salaried    Male          Basic        Single
4885     Self Enquiry        Salaried  Female       Standard       Married
4886     Self Enquiry  Small Business    Male          Basic        Single
4887     Self Enquiry        Salaried    Male          Basic     Unmarried

         Designation
0            Manager
1            Manager
2          Executive
3          Executive
4          Executive
…                …
4883         Manager
4884       Executive
4885  Senior Manager
4886       Executive
4887       Executive

[4888 rows x 6 columns]
```

[153]:
```
X.isnull().mean() # Checking after imputation, null values of 'TypeofContact'␣
↪feature is zero.
```

[153]:
```
TypeofContact     0.0
Occupation        0.0
Gender            0.0
ProductPitched    0.0
MaritalStatus     0.0
Designation       0.0
dtype: float64
```

Imputing using sklearn

[154]:
```
#Imputing using sklearn
X_1=data[cat_col]

imputer_1=SimpleImputer(strategy='most_frequent')
```

```
X_1.isnull().mean()
```

[154]:
```
TypeofContact     0.005115
Occupation        0.000000
Gender            0.000000
ProductPitched    0.000000
MaritalStatus     0.000000
Designation       0.000000
dtype: float64
```

[155]:
```
imputer_1.fit(X_1)
X_1=imputer_1.transform(X_1)
X_1
```

[155]:
```
array([['Self Enquiry', 'Salaried', 'Female', 'Deluxe', 'Single',
        'Manager'],
       ['Company Invited', 'Salaried', 'Male', 'Deluxe', 'Divorced',
        'Manager'],
       ['Self Enquiry', 'Free Lancer', 'Male', 'Basic', 'Single',
        'Executive'],
       …,
       ['Self Enquiry', 'Salaried', 'Female', 'Standard', 'Married',
        'Senior Manager'],
       ['Self Enquiry', 'Small Business', 'Male', 'Basic', 'Single',
        'Executive'],
       ['Self Enquiry', 'Salaried', 'Male', 'Basic', 'Unmarried',
        'Executive']], dtype=object)
```

[156]:
```
result_1=pd.DataFrame(X_1,columns=['TypeofContact',# converting back to
 ↪DataFrame from Numpy Array
 'Occupation',
 'Gender',
 'ProductPitched',
 'MaritalStatus',
 'Designation'])
result_1
```

[156]:
```
        TypeofContact      Occupation  Gender ProductPitched MaritalStatus  \
0        Self Enquiry        Salaried  Female         Deluxe        Single
1     Company Invited        Salaried    Male         Deluxe      Divorced
2        Self Enquiry     Free Lancer    Male          Basic        Single
3     Company Invited        Salaried  Female          Basic      Divorced
4        Self Enquiry  Small Business    Male          Basic      Divorced
…                 …             …     …              …             …
4883     Self Enquiry  Small Business    Male         Deluxe     Unmarried
4884  Company Invited        Salaried    Male          Basic        Single
4885     Self Enquiry        Salaried  Female       Standard       Married
```

```
4886     Self Enquiry  Small Business    Male           Basic         Single
4887     Self Enquiry        Salaried    Male           Basic      Unmarried

         Designation
0            Manager
1            Manager
2          Executive
3          Executive
4          Executive
…                …
4883         Manager
4884       Executive
4885  Senior Manager
4886       Executive
4887       Executive

[4888 rows x 6 columns]
```

[157]:
```python
result_1.isnull().mean() # Checking after imputation
```

[157]:
```
TypeofContact     0.0
Occupation        0.0
Gender            0.0
ProductPitched    0.0
MaritalStatus     0.0
Designation       0.0
dtype: float64
```

Method 4:Replacing Missing Values with an arbitary number

[158]:
```python
data=pd.read_csv('Travel.csv')
num_col=[fea for fea in data.columns if (data[fea].dtype !='O' and data[fea].
 ↪dtype !=int)]
#segregating categorical and numerical variables
X=data[num_col]
```

[159]:
```python
X.max()
```

[159]:
```
Age                            61.0
DurationOfPitch               127.0
NumberOfFollowups               6.0
PreferredPropertyStar           5.0
NumberOfTrips                  22.0
NumberOfChildrenVisiting        3.0
MonthlyIncome               98678.0
dtype: float64
```

[160]:
```
X.isnull().sum()
```

[160]:
```
Age                         226
DurationOfPitch             251
NumberOfFollowups            45
PreferredPropertyStar        26
NumberOfTrips               140
NumberOfChildrenVisiting     66
MonthlyIncome               233
dtype: int64
```

[161]:
```
X['Age'].fillna(70,inplace=True) # Replacing by Null values by an arbitary␣
 ↪number 70 for Age feature because it is greater than
# the max value of Age
```

[162]:
```
X.isnull().sum() # Checking after imputation
```

[162]:
```
Age                           0
DurationOfPitch             251
NumberOfFollowups            45
PreferredPropertyStar        26
NumberOfTrips               140
NumberOfChildrenVisiting     66
MonthlyIncome               233
dtype: int64
```

[163]:
```
# Using sklearn
imputer=SimpleImputer(strategy='constant',fill_value=70)
data=pd.read_csv('Travel.csv')
X_1=data['Age'].to_numpy() # Converting to Numpy array
X_1=X_1.reshape(-1, 1)
```

[164]:
```
imputer.fit(X_1)
```

[164]:
```
SimpleImputer(fill_value=70, strategy='constant')
```

[165]:
```
X_1=imputer.transform(X_1)
```

[166]:
```
result_1=pd.DataFrame(X_1,columns=['Age'])# converting back to DataFrame from␣
 ↪Numpy Array

result_1.isnull().sum() # checking after Imputation
```

[166]:
```
Age    0
dtype: int64
```

[168]:
```
result_1
```

[168]:
```
        Age
0      41.0
1      49.0
2      37.0
3      33.0
4      70.0
…       …
4883   49.0
4884   28.0
4885   52.0
4886   19.0
4887   36.0

[4888 rows x 1 columns]
```

Method 5: Replacing Missing Values in Categorical Variables

[169]:
```python
data=pd.read_csv('Travel.csv')
X=data[cat_col] # We would replace missing values with a string "Missing"
X.isnull().sum()
```

[169]:
```
TypeofContact     25
Occupation         0
Gender             0
ProductPitched     0
MaritalStatus      0
Designation        0
dtype: int64
```

[170]:
```python
for var in cat_col:
    X[var].fillna('Missing',inplace=True)
```

[171]:
```python
X.isnull().sum() # Checking after Imputation
```

[171]:
```
TypeofContact     0
Occupation        0
Gender            0
ProductPitched    0
MaritalStatus     0
Designation       0
dtype: int64
```

[172]:
```python
# Using sklearn
imputer=SimpleImputer(strategy='constant',fill_value='Missing')
data=pd.read_csv('Travel.csv')
X=data[cat_col]
imputer.fit(X)
```

[172]:
```
SimpleImputer(fill_value='Missing', strategy='constant')
```

[173]:
```
X=imputer.transform(X)
```

[174]:
```
X
```

[174]:
```
array([['Self Enquiry', 'Salaried', 'Female', 'Deluxe', 'Single',
        'Manager'],
       ['Company Invited', 'Salaried', 'Male', 'Deluxe', 'Divorced',
        'Manager'],
       ['Self Enquiry', 'Free Lancer', 'Male', 'Basic', 'Single',
        'Executive'],
       …,
       ['Self Enquiry', 'Salaried', 'Female', 'Standard', 'Married',
        'Senior Manager'],
       ['Self Enquiry', 'Small Business', 'Male', 'Basic', 'Single',
        'Executive'],
       ['Self Enquiry', 'Salaried', 'Male', 'Basic', 'Unmarried',
        'Executive']], dtype=object)
```

[175]:
```
result_1=pd.DataFrame(X)# converting back to DataFrame from Numpy Array

result_1.isnull().sum() # Checking after Imputation
```

[175]:
```
0    0
1    0
2    0
3    0
4    0
5    0
dtype: int64
```

Method 6:

Replacing missing values with a value at the end of the distribution

Replacing missing values with a value at the end of the distribution, is equivalent to replacing with an arbitary value manually. But in this case we do it by automatically selecting as those at the very end of the variable distribution. As per the IQR proximity rule,missing values are replaced with q3+1.5(IQR) at the right tail or by q1-1.5(IQR) at the left tail.

[176]:
```
X=data[num_col]
X.isnull().sum()
```

[176]:
```
Age                           226
DurationOfPitch               251
NumberOfFollowups              45
PreferredPropertyStar          26
```

```
NumberOfTrips                140
NumberOfChildrenVisiting      66
MonthlyIncome                233
dtype: int64
```

[177]:
```
for var in num_col:
    IQR =X[var].quantile(0.75)-X[var].quantile(0.25)
    value=X[var].quantile(0.75)+(1.5*IQR)
    X[var]=X[var].fillna(value)
```

[178]:
```
X
```

[178]:
```
       Age  DurationOfPitch  NumberOfFollowups  PreferredPropertyStar  \
0     41.0              6.0                3.0                    3.0
1     49.0             14.0                4.0                    4.0
2     37.0              8.0                4.0                    3.0
3     33.0              9.0                3.0                    3.0
4     63.5              8.0                3.0                    4.0
…      …               …                  …                      …
4883  49.0              9.0                5.0                    4.0
4884  28.0             31.0                5.0                    3.0
4885  52.0             17.0                4.0                    4.0
4886  19.0             16.0                4.0                    3.0
4887  36.0             14.0                4.0                    4.0

      NumberOfTrips  NumberOfChildrenVisiting  MonthlyIncome
0               1.0                       0.0        20993.0
1               2.0                       2.0        20130.0
2               7.0                       0.0        17090.0
3               2.0                       1.0        17909.0
4               1.0                       0.0        18468.0
…               …                         …             …
4883            2.0                       1.0        26576.0
4884            3.0                       2.0        21212.0
4885            7.0                       3.0        31820.0
4886            3.0                       2.0        20289.0
4887            3.0                       2.0        24041.0

[4888 rows x 7 columns]
```

[179]:
```
X.isnull().sum()# Checking after imputation
```

[179]:
```
Age                         0
DurationOfPitch             0
NumberOfFollowups           0
PreferredPropertyStar       0
NumberOfTrips               0
```

```
NumberOfChildrenVisiting    0
MonthlyIncome               0
dtype: int64
```

[180]:
```
# Doing the same with feature Engine
X=data[num_col]

import feature_engine
from feature_engine.imputation import EndTailImputer
```

[181]:
```
# set up the imputer
tail_imputer = EndTailImputer(imputation_method='gaussian',
                          tail='right',
                          fold=3,
                          variables=num_col)
# fit the imputer
tail_imputer.fit(X)
```

[181]:
```
EndTailImputer(variables=['Age', 'DurationOfPitch', 'NumberOfFollowups',
                          'PreferredPropertyStar', 'NumberOfTrips',
                          'NumberOfChildrenVisiting', 'MonthlyIncome'])
```

[183]:
```
X=tail_imputer.transform(X)
X
```

[183]:
```
            Age  DurationOfPitch  NumberOfFollowups  PreferredPropertyStar  \
0     41.000000              6.0                3.0                    3.0
1     49.000000             14.0                4.0                    4.0
2     37.000000              8.0                4.0                    3.0
3     33.000000              9.0                3.0                    3.0
4     65.571426              8.0                3.0                    4.0
…           …                …                  …                      …
4883  49.000000              9.0                5.0                    4.0
4884  28.000000             31.0                5.0                    3.0
4885  52.000000             17.0                4.0                    4.0
4886  19.000000             16.0                4.0                    3.0
4887  36.000000             14.0                4.0                    4.0

      NumberOfTrips  NumberOfChildrenVisiting  MonthlyIncome
0               1.0                       0.0        20993.0
1               2.0                       2.0        20130.0
2               7.0                       0.0        17090.0
3               2.0                       1.0        17909.0
4               1.0                       0.0        18468.0
…                 …                         …              …
4883            2.0                       1.0        26576.0
4884            3.0                       2.0        21212.0
```

```
4885            7.0                         3.0         31820.0
4886            3.0                         2.0         20289.0
4887            3.0                         2.0         24041.0

[4888 rows x 7 columns]
```

Method 7: Multivariate Imputation by Chained Equations

Multivariate Imputation by Chained Equations is a multiple Imputation Technique that models each variable with missing values as a function of the remaining variables and uses that estimate for Impputation

A more sophisticated approach is to use the IterativeImputer class, which models each feature with missing values as a function of other features, and uses that estimate for imputation. It does so in an iterated round-robin fashion: at each step, a feature column is designated as output y and the other feature columns are treated as inputs X. A regressor is fit on (X, y) for known y. Then, the regressor is used to predict the missing values of y. This is done for each feature in an iterative fashion, and then is repeated for max_iter imputation rounds. The results of the final imputation round are returned.

[184]:
```
import numpy as np
from sklearn.experimental import enable_iterative_imputer
from sklearn.impute import IterativeImputer
```

[185]:
```
X=data[num_col]
X
```

[185]:
```
       Age  DurationOfPitch  NumberOfFollowups  PreferredPropertyStar  \
0     41.0              6.0                3.0                    3.0
1     49.0             14.0                4.0                    4.0
2     37.0              8.0                4.0                    3.0
3     33.0              9.0                3.0                    3.0
4      NaN              8.0                3.0                    4.0
…     …               …                  …                     …
4883  49.0              9.0                5.0                    4.0
4884  28.0             31.0                5.0                    3.0
4885  52.0             17.0                4.0                    4.0
4886  19.0             16.0                4.0                    3.0
4887  36.0             14.0                4.0                    4.0

      NumberOfTrips  NumberOfChildrenVisiting  MonthlyIncome
0               1.0                       0.0        20993.0
1               2.0                       2.0        20130.0
2               7.0                       0.0        17090.0
3               2.0                       1.0        17909.0
4               1.0                       0.0        18468.0
…             …                         …            …
4883            2.0                       1.0        26576.0
```

```
4884          3.0                     2.0       21212.0
4885          7.0                     3.0       31820.0
4886          3.0                     2.0       20289.0
4887          3.0                     2.0       24041.0

[4888 rows x 7 columns]
```

[186]:
```python
X.isnull().sum()
```

[186]:
```
Age                        226
DurationOfPitch            251
NumberOfFollowups           45
PreferredPropertyStar       26
NumberOfTrips              140
NumberOfChildrenVisiting    66
MonthlyIncome              233
dtype: int64
```

[187]:
```python
imp = IterativeImputer(max_iter=10,random_state=0)
```

[188]:
```python
imp.fit(X)
```

[188]:
```
IterativeImputer(random_state=0)
```

[189]:
```python
X=imp.transform(X)
X
```

[189]:
```
array([[4.1000e+01, 6.0000e+00, 3.0000e+00, …, 1.0000e+00, 0.0000e+00,
        2.0993e+04],
       [4.9000e+01, 1.4000e+01, 4.0000e+00, …, 2.0000e+00, 2.0000e+00,
        2.0130e+04],
       [3.7000e+01, 8.0000e+00, 4.0000e+00, …, 7.0000e+00, 0.0000e+00,
        1.7090e+04],
       …,
       [5.2000e+01, 1.7000e+01, 4.0000e+00, …, 7.0000e+00, 3.0000e+00,
        3.1820e+04],
       [1.9000e+01, 1.6000e+01, 4.0000e+00, …, 3.0000e+00, 2.0000e+00,
        2.0289e+04],
       [3.6000e+01, 1.4000e+01, 4.0000e+00, …, 3.0000e+00, 2.0000e+00,
        2.4041e+04]])
```

[190]:
```python
result_1=pd.DataFrame(X)# Converting back to a DataFrame
result_1.isnull().sum()
```

[190]:
```
0    0
1    0
2    0
```

```
3    0
4    0
5    0
6    0
dtype: int64
```

```
[ ]:
```

Handling_Outliers

September 28, 2022

[1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
import warnings
warnings.filterwarnings('ignore')
```

[2]:
```
data=pd.read_csv('Travel.csv')
```

[3]:
```
num_col=[fea for fea in data.columns if (data[fea].dtype !='O' and data[fea].
 ↪dtype !=int)]
#segregating categorical and numerical variables
num_col
```

[3]:
```
['Age',
 'DurationOfPitch',
 'NumberOfFollowups',
 'PreferredPropertyStar',
 'NumberOfTrips',
 'NumberOfChildrenVisiting',
 'MonthlyIncome']
```

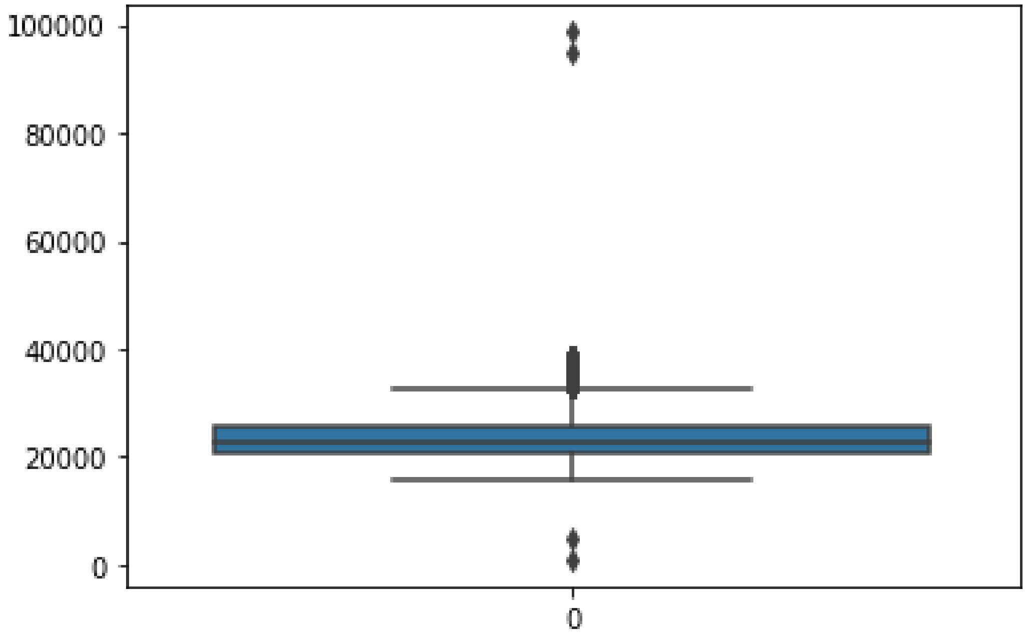
[4]:
```
X=data[num_col]
X['MonthlyIncome'].sum()
```

[4]:
```
109950418.0
```

[5]:
```
# Performing Mean Imputation

for var in num_col:
    value=X[var].mean()
    X[var]=X[var].fillna(value)
```

[6]:
```
sns.boxplot(X['MonthlyIncome']) # Taking Monthly Income as the variable
```

[6]:
```
<AxesSubplot:>
```



Method 1: Replacing Outliers in the dataset with threshold values or Winorization

[7]:
```
def find_boundaries(df,variable):

    IQR=df[variable].quantile(0.75)-df[variable].quantile(0.25)
    lower_boundary=df[variable].quantile(0.25)-(IQR*1.5)
    upper_boundary=df[variable].quantile(0.75)+(IQR*1.5)
    return upper_boundary,lower_boundary
```

[8]:
```
def replace_with_threshold(df,var):
    for variable in num_col:
        upper_boundary,lower_boundary=find_boundaries(df,variable)
        data.loc[data[variable]<lower_boundary,variable]=lower_boundary
        data.loc[data[variable]>upper_boundary,variable]=upper_boundary
```

[9]:
```
MonthlyIncome_upper_limit,MonthlyIncome_lower_limit=find_boundaries(X,'MonthlyIncome')
```

[10]:
```
MonthlyIncome_upper_limit,MonthlyIncome_lower_limit
```

[10]: (32834.375, 13075.375)

[11]:
```
replace_with_threshold(X,'MonthlyIncome')
```

[12]:
```
X['MonthlyIncome'].sum()
```

[12]: 115453843.86337271

Method 2: Trimming outliers from data set

Here we remove outliers completely

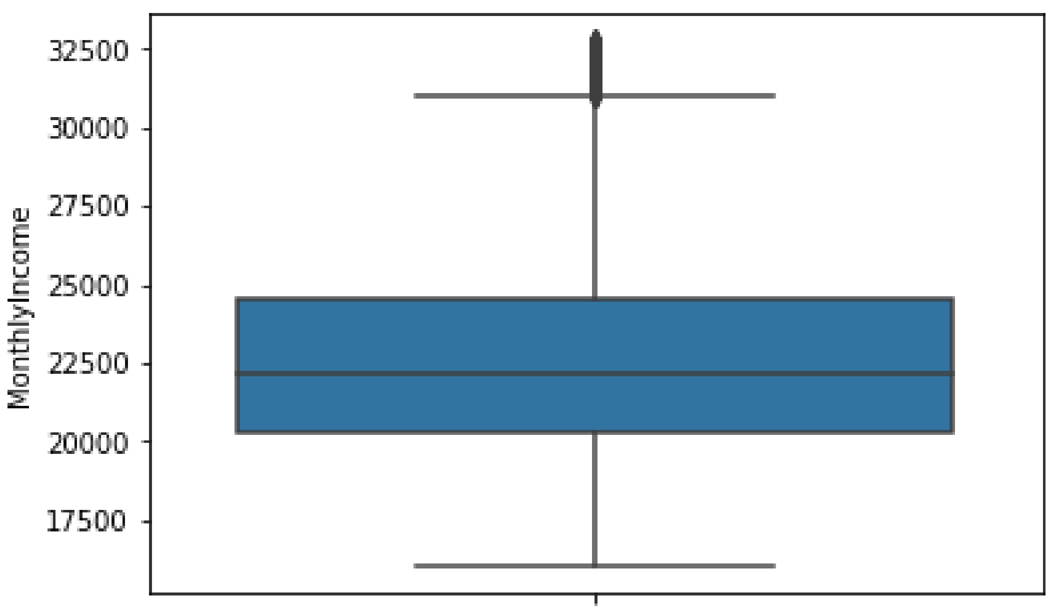
[14]:
```
outliers_MonthlyIncome = np.where(X['MonthlyIncome'] >␣
↪MonthlyIncome_upper_limit, True,
                           np.where(X['MonthlyIncome'] < MonthlyIncome_lower_limit,␣
↪True, False))
```

[27]:
```
X_trimmed = X.loc[~outliers_MonthlyIncome] # deleting Outliers

X.shape, X_trimmed.shape
```

[27]: ((4888, 7), (4513, 7))

[16]:
```
sns.boxplot(y=X_trimmed['MonthlyIncome'])
```

[16]: <AxesSubplot:ylabel='MonthlyIncome'>



Scaling

September 28, 2022

[4]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
import warnings
warnings.filterwarnings('ignore')
import sklearn
```

[5]:
```
data=pd.read_csv('Travel.csv')
```

[6]:
```
num_col=[fea for fea in data.columns if (data[fea].dtype !='O' and data[fea].
 ↪dtype !=int)]
#segregating categorical and numerical variables
num_col
```

[6]:
```
['Age',
 'DurationOfPitch',
 'NumberOfFollowups',
 'PreferredPropertyStar',
 'NumberOfTrips',
 'NumberOfChildrenVisiting',
 'MonthlyIncome']
```

[12]:
```
X=data[num_col]
```

Method 1: Standardizing Features

Standardization is the process of centering the variable at zero and standizing the variance to 1.To standardize the features we subtrsct the mean from each observation and then divide the result by standard deviation:

z=(x-mean(x))/std(x)

[11]:
```
# Performing Mean Imputation

for var in num_col:
    value=X[var].mean()
    X[var]=X[var].fillna(value)
```

[18]:
```
# using sklearn
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
scaler.fit(X)
X_scaled=scaler.transform(X)
X_scaled_final=pd.DataFrame(X_scaled)
X_scaled_final
```

[18]:

	0	1	2	3	4	5	6
0	3.712822e-01	-1.143871	-0.710021	-0.730127	-1.227404	-1.393568	-0.500322
1	1.250646e+00	-0.179681	0.292203	0.526467	-0.678603	0.953955	-0.664693
2	-6.839967e-02	-0.902823	0.292203	-0.730127	2.065400	-1.393568	-1.243704
3	-5.080815e-01	-0.782299	-0.710021	-0.730127	-0.678603	-0.219807	-1.087714
4	-7.810318e-16	-0.902823	-0.710021	0.526467	-1.227404	-1.393568	-0.981245
…	…	…	…	…	…	…	…
4883	1.250646e+00	-0.782299	1.294428	0.526467	-0.678603	-0.219807	0.563041
4884	-1.057684e+00	1.869222	1.294428	-0.730127	-0.129803	0.953955	-0.458610
4885	1.580407e+00	0.181890	0.292203	0.526467	2.065400	2.127717	1.561836
4886	-2.046968e+00	0.061367	0.292203	-0.730127	-0.129803	0.953955	-0.634409
4887	-1.783201e-01	-0.179681	0.292203	0.526467	-0.129803	0.953955	0.080213

[4888 rows x 7 columns]

Method 2: Performing mean normalization

In mean normaliztion ,we center the variable at zero and rescale the distribution to the value range. This procedure involves subtracting from the mean from each observation and then dividing the result by the difference between the minimum and maximum values.

x_scaled=(x-mean(x))/(max(x)-min(x))

The transformation results in a distribution centered around 0 ,with min and max values within the range of -1 to 1

[24]:
```
from sklearn.preprocessing import StandardScaler,RobustScaler
scaler_mean=StandardScaler(with_mean=True,with_std=False)# No division by␣
↪standard deviation
scaler_minmax=RobustScaler(with_centering=False,with_scaling=True,quantile_range=(0,100))
scaler_mean.fit(X)
scaler_minmax.fit(X)
X_scaled=scaler_minmax.transform(X)
X_scaled_final=pd.DataFrame(X_scaled)
X_scaled_final
```

[24]:

	0	1	2	3	4	5	6
0	0.953488	0.049180	0.6	1.5	0.047619	0.000000	0.214920
1	1.139535	0.114754	0.8	2.0	0.095238	0.666667	0.206085
2	0.860465	0.065574	0.8	1.5	0.333333	0.000000	0.174963
3	0.767442	0.073770	0.6	1.5	0.095238	0.333333	0.183347

```
4     0.874936  0.065574  0.6  2.0  0.047619  0.000000  0.189070
…          …         …   …   …         …         …         …
4883  1.139535  0.073770  1.0  2.0  0.095238  0.333333  0.272078
4884  0.651163  0.254098  1.0  1.5  0.142857  0.666667  0.217163
4885  1.209302  0.139344  0.8  2.0  0.333333  1.000000  0.325764
4886  0.441860  0.131148  0.8  1.5  0.142857  0.666667  0.207713
4887  0.837209  0.114754  0.8  2.0  0.142857  0.666667  0.246125

[4888 rows x 7 columns]
```

Method 3: Scaling to the maximum and minimum values

Scaling to the minimum and minimum values squeezes the values of the variables between 0 and 1.

xscaled=(x-min(x))/(max(x)-min(x))

[26]:
```
from sklearn.preprocessing import MinMaxScaler
scaler=MinMaxScaler()
scaler.fit(X)
X_scaled=scaler.transform(X)
X_scaled_final=pd.DataFrame(X_scaled)
X_scaled_final
```

[26]:
```
             0         1    2    3         4         5         6
0     0.534884  0.008197  0.4  0.0  0.000000  0.000000  0.204683
1     0.720930  0.073770  0.6  0.5  0.047619  0.666667  0.195848
2     0.441860  0.024590  0.6  0.0  0.285714  0.000000  0.164725
3     0.348837  0.032787  0.4  0.0  0.047619  0.333333  0.173110
4     0.456332  0.024590  0.4  0.5  0.000000  0.000000  0.178832
…          …         …   …   …         …         …         …
4883  0.720930  0.032787  0.8  0.5  0.047619  0.333333  0.261840
4884  0.232558  0.213115  0.8  0.0  0.095238  0.666667  0.206925
4885  0.790698  0.098361  0.6  0.5  0.285714  1.000000  0.315527
4886  0.023256  0.090164  0.6  0.0  0.095238  0.666667  0.197475
4887  0.418605  0.073770  0.6  0.5  0.095238  0.666667  0.235887

[4888 rows x 7 columns]
```

Method 4: Implementing Maximum absolute scaling

xscaled=x/max(x)

[ ]:
```
from sklearn.preprocessing import MaxAbsScaler
scaler=MaxAbsScaler()
scaler.fit(X)
X_scaled=scaler.transform(X)
X_scaled_final=pd.DataFrame(X_scaled)
X_scaled_final
```

Method 5: Scaling with median and Quantiles

xscaled= (x-median(x))/(q3(x)-q1(x))

[28]:
```
scaler=RobustScaler()
scaler.fit(X)
X_scaled=scaler.transform(X)
X_scaled_final=pd.DataFrame(X_scaled)
X_scaled_final
```

[28]:

	0	1	2	3	4	5	6
0	0.333333	-0.8	-1.0	0.0	-1.0	-1.0	-0.336454
1	1.000000	0.0	0.0	1.0	-0.5	1.0	-0.511159
2	0.000000	-0.6	0.0	0.0	2.0	-1.0	-1.126575
3	-0.333333	-0.5	-1.0	0.0	-0.5	0.0	-0.960777
4	0.051855	-0.6	-1.0	1.0	-1.0	-1.0	-0.847614
…	…	…	…	…	…	…	…
4883	1.000000	-0.5	1.0	1.0	-0.5	0.0	0.793765
4884	-0.750000	1.7	1.0	0.0	0.0	1.0	-0.292120
4885	1.250000	0.3	0.0	1.0	2.0	2.0	1.855357
4886	-1.500000	0.2	0.0	0.0	0.0	1.0	-0.478972
4887	-0.083333	0.0	0.0	1.0	0.0	1.0	0.280581

[4888 rows x 7 columns]

Method 6: Scaling to vector unit length

xscaled =x/norm

where norm may be either Manhattan distance or Euclidean Distance

[29]:
```
from sklearn.preprocessing import Normalizer
scaler=Normalizer(norm='l2')# l2 for Euclidean Distance
scaler.fit(X)
X_scaled=scaler.transform(X)
X_scaled_final=pd.DataFrame(X_scaled)
X_scaled_final
```

[29]:

	0	1	2	3	4	5	6
0	0.001953	0.000286	0.000143	0.000143	0.000048	0.000000	0.999998
1	0.002434	0.000695	0.000199	0.000199	0.000099	0.000099	0.999997
2	0.002165	0.000468	0.000234	0.000176	0.000410	0.000000	0.999997
3	0.001843	0.000503	0.000168	0.000168	0.000112	0.000056	0.999998
4	0.002037	0.000433	0.000162	0.000217	0.000054	0.000000	0.999998
…	…	…	…	…	…	…	…
4883	0.001844	0.000339	0.000188	0.000151	0.000075	0.000038	0.999998
4884	0.001320	0.001461	0.000236	0.000141	0.000141	0.000094	0.999998
4885	0.001634	0.000534	0.000126	0.000126	0.000220	0.000094	0.999998
4886	0.000936	0.000789	0.000197	0.000148	0.000148	0.000099	0.999999

```
4887  0.001497  0.000582  0.000166  0.000166  0.000125  0.000083  0.999999

[4888 rows x 7 columns]
```

Transforming Numerical Variables

September 28, 2022

[1]:
```python
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
import warnings
warnings.filterwarnings('ignore')
```

[2]:
```python
data=pd.read_csv('Travel.csv')
```

[7]:
```python
num_col=[fea for fea in data.columns if (data[fea].dtype !='O' and data[fea].
 ↪dtype !=int)]
#segregating categorical and numerical variables
num_col
```

[7]:
```
['Age',
 'DurationOfPitch',
 'NumberOfFollowups',
 'PreferredPropertyStar',
 'NumberOfTrips',
 'NumberOfChildrenVisiting',
 'MonthlyIncome']
```

[8]:
```python
cat_col=[fea for fea in data.columns if data[fea].dtype =='O'] #segregating␣
 ↪categorical and numerical variables
cat_col
```

[8]:
```
['TypeofContact',
 'Occupation',
 'Gender',
 'ProductPitched',
 'MaritalStatus',
 'Designation']
```

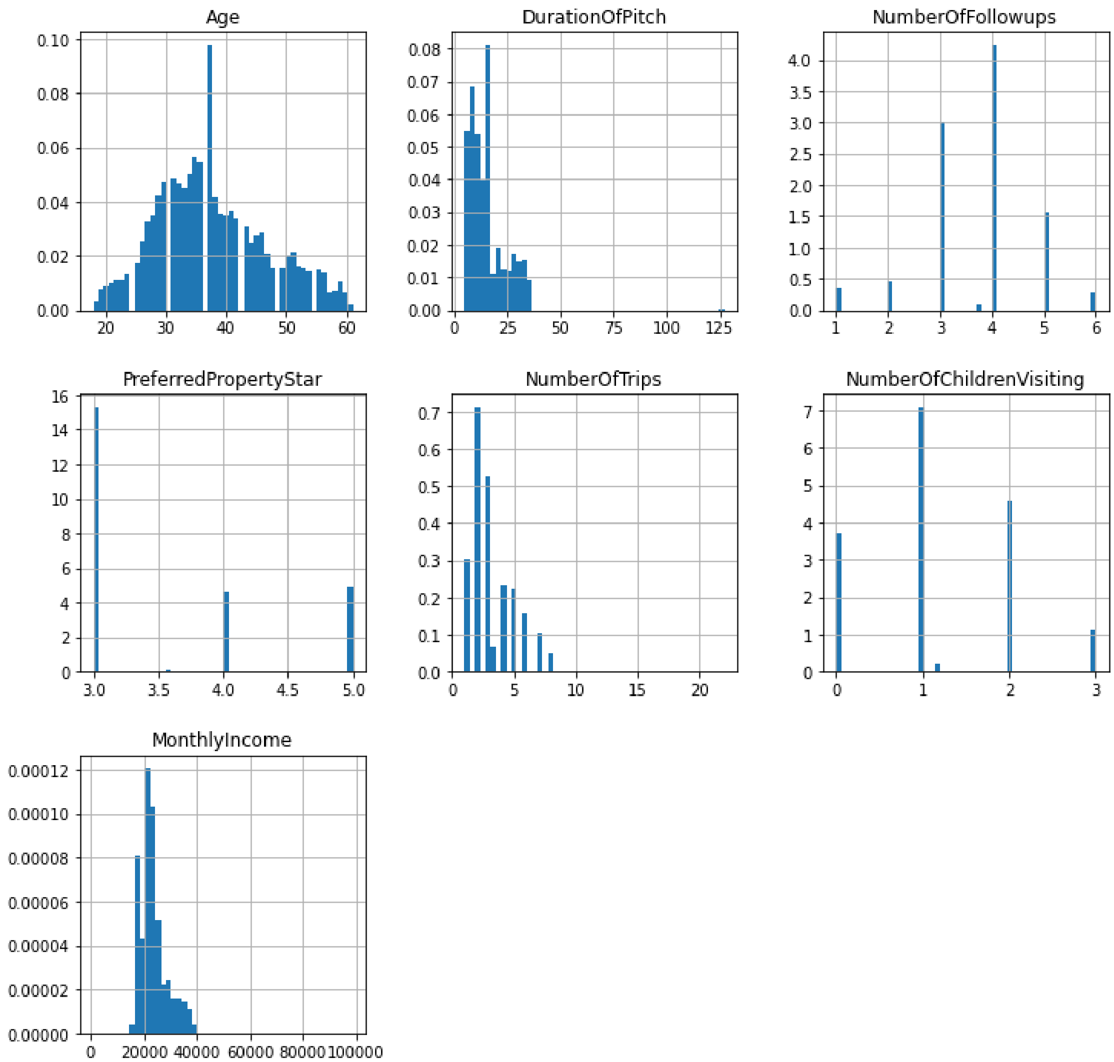
Method 1: Transforming Variables with the Logarithm:

Transforming Variables may improve the performance of Linear and Logistic regression machine learning models

[51]:
```python
#Using sklearn
import scipy.stats as stats
from sklearn.preprocessing import FunctionTransformer
X=data[num_col]
```

[52]:
```python
# Performing Mean Imputation
for var in num_col:
    value=X[var].mean()
    X[var]=X[var].fillna(value)
```

[53]:
```python
X.hist(bins=50,figsize=(12,12),density=True)
plt.show()
```



[54]:

```python
# creating a copy of the orginal dataframe using pandas copy()
X_tf=X.copy()
# Appling log transformation
X_tf=np.log(X_tf)
X_tf
```

[54]:

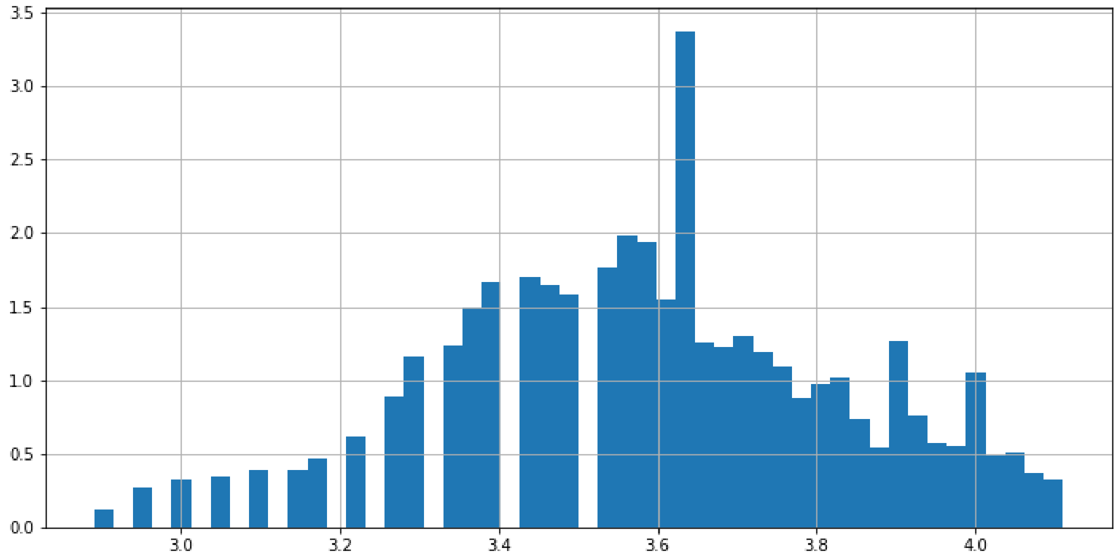
	Age	DurationOfPitch	NumberOfFollowups	PreferredPropertyStar
0	3.713572	1.791759	1.098612	1.098612
1	3.891820	2.639057	1.386294	1.386294
2	3.610918	2.079442	1.386294	1.098612
3	3.496508	2.197225	1.098612	1.098612
4	3.627596	2.079442	1.098612	1.386294
…	…	…	…	…
4883	3.891820	2.197225	1.609438	1.386294
4884	3.332205	3.433987	1.609438	1.098612
4885	3.951244	2.833213	1.386294	1.386294
4886	2.944439	2.772589	1.386294	1.098612
4887	3.583519	2.639057	1.386294	1.386294

	NumberOfTrips	NumberOfChildrenVisiting	MonthlyIncome
0	0.000000	-inf	9.951944
1	0.693147	0.693147	9.909967
2	1.945910	-inf	9.746249
3	0.693147	0.000000	9.793059
4	0.000000	-inf	9.823795
…	…	…	…
4883	0.693147	0.000000	10.187764
4884	1.098612	0.693147	9.962322
4885	1.945910	1.098612	10.367850
4886	1.098612	0.693147	9.917834
4887	1.098612	0.693147	10.087516

[4888 rows x 7 columns]

[55]:

```python
X_tf_1=X_tf['Age']
X_tf_1.hist(bins=50,figsize=(12,6),density=True)
plt.show()
```



[56]:
```python
#Using sklearn
transformer=FunctionTransformer(np.log)
```

[57]:
```python
data_tf=transformer.transform(X_tf)
```

[58]:
```python
data_tf=pd.DataFrame(data_tf)
```

[59]:
```python
data_tf
```

[59]:

	Age	DurationOfPitch	NumberOfFollowups	PreferredPropertyStar	\
0	1.311994	0.583198	0.094048	0.094048	
1	1.358877	0.970422	0.326634	0.326634	
2	1.283962	0.732099	0.326634	0.094048	
3	1.251765	0.787195	0.094048	0.094048	
4	1.288570	0.732099	0.094048	0.326634	
…	…	…	…	…	
4883	1.358877	0.787195	0.475885	0.326634	
4884	1.203634	1.233722	0.475885	0.094048	
4885	1.374030	1.041412	0.326634	0.326634	
4886	1.079918	1.019781	0.326634	0.094048	
4887	1.276345	0.970422	0.326634	0.326634	

	NumberOfTrips	NumberOfChildrenVisiting	MonthlyIncome
0	-inf	NaN	2.297768
1	-0.366513	-0.366513	2.293541
2	0.665730	NaN	2.276882
3	-0.366513	-inf	2.281674
4	-inf	NaN	2.284807

```
…           …                       …         …
4883  -0.366513                    -inf  2.321187
4884   0.094048               -0.366513  2.298810
4885   0.665730                0.094048  2.338710
4886   0.094048               -0.366513  2.294335
4887   0.094048               -0.366513  2.311299

[4888 rows x 7 columns]
```

Method 2: Transforming variables with reciprocal function

[63]:
```python
# Using Numpy
X_input=X['Age']
np.reciprocal(X_input)
```

[63]:
```
0       0.024390
1       0.020408
2       0.027027
3       0.030303
4       0.026580
          …
4883    0.020408
4884    0.035714
4885    0.019231
4886    0.052632
4887    0.027778
Name: Age, Length: 4888, dtype: float64
```

[67]:
```python
X_input=X['Age']
X_input
#Using sklearn
transformer=FunctionTransformer(np.reciprocal)
X_input=transformer.transform(X_input)
X_input
```

[67]:
```
0       0.024390
1       0.020408
2       0.027027
3       0.030303
4       0.026580
          …
4883    0.020408
4884    0.035714
4885    0.019231
4886    0.052632
4887    0.027778
Name: Age, Length: 4888, dtype: float64
```

Method 3: Transforming variables with square root and cube root

[73]:
```
#Using numpy
data=pd.read_csv('Travel.csv')
X=data[num_col]
X_tf=np.sqrt(X)
X_tf
```

[73]:

	Age	DurationOfPitch	NumberOfFollowups	PreferredPropertyStar	\
0	6.403124	2.449490	1.732051	1.732051	
1	7.000000	3.741657	2.000000	2.000000	
2	6.082763	2.828427	2.000000	1.732051	
3	5.744563	3.000000	1.732051	1.732051	
4	NaN	2.828427	1.732051	2.000000	
…	…	…	…	…	
4883	7.000000	3.000000	2.236068	2.000000	
4884	5.291503	5.567764	2.236068	1.732051	
4885	7.211103	4.123106	2.000000	2.000000	
4886	4.358899	4.000000	2.000000	1.732051	
4887	6.000000	3.741657	2.000000	2.000000	

	NumberOfTrips	NumberOfChildrenVisiting	MonthlyIncome
0	1.000000	0.000000	144.889613
1	1.414214	1.414214	141.880231
2	2.645751	0.000000	130.728727
3	1.414214	1.000000	133.824512
4	1.000000	0.000000	135.897020
…	…	…	…
4883	1.414214	1.000000	163.021471
4884	1.732051	1.414214	145.643400
4885	2.645751	1.732051	178.381613
4886	1.732051	1.414214	142.439461
4887	1.732051	1.414214	155.051604

[4888 rows x 7 columns]

[74]:
```
#using sklearn
data=pd.read_csv('Travel.csv')
X=data[num_col]
transformer=FunctionTransformer(np.sqrt)
X=transformer.transform(X)
X
```

[74]:

	Age	DurationOfPitch	NumberOfFollowups	PreferredPropertyStar	\
0	6.403124	2.449490	1.732051	1.732051	
1	7.000000	3.741657	2.000000	2.000000	
2	6.082763	2.828427	2.000000	1.732051	

```
3     5.744563          3.000000           1.732051               1.732051
4          NaN          2.828427           1.732051               2.000000
…        …               …                 …                      …
4883  7.000000          3.000000           2.236068               2.000000
4884  5.291503          5.567764           2.236068               1.732051
4885  7.211103          4.123106           2.000000               2.000000
4886  4.358899          4.000000           2.000000               1.732051
4887  6.000000          3.741657           2.000000               2.000000

      NumberOfTrips  NumberOfChildrenVisiting  MonthlyIncome
0          1.000000                  0.000000     144.889613
1          1.414214                  1.414214     141.880231
2          2.645751                  0.000000     130.728727
3          1.414214                  1.000000     133.824512
4          1.000000                  0.000000     135.897020
…               …                       …             …
4883       1.414214                  1.000000     163.021471
4884       1.732051                  1.414214     145.643400
4885       2.645751                  1.732051     178.381613
4886       1.732051                  1.414214     142.439461
4887       1.732051                  1.414214     155.051604

[4888 rows x 7 columns]
```

Method 4: Transforming variables with power transformations

[76]:
```
#using sklearn
data=pd.read_csv('Travel.csv')
X=data[num_col]
transformer=FunctionTransformer(lambda x: np.power(x,0.3))
X=transformer.transform(X)
X
```

[76]:
```
           Age  DurationOfPitch  NumberOfFollowups  PreferredPropertyStar  \
0     3.046738          1.711770           1.390389               1.390389
1     3.214096          2.207183           1.515717               1.515717
2     2.954340          1.866066           1.515717               1.390389
3     2.854659          1.933182           1.390389               1.390389
4          NaN          1.866066           1.390389               1.515717
…        …               …                 …                      …
4883  3.214096          1.933182           1.620657               1.515717
4884  2.717361          2.801615           1.620657               1.390389
4885  3.271907          2.339563           1.515717               1.515717
4886  2.418945          2.297397           1.515717               1.390389
4887  2.930156          2.207183           1.515717               1.515717

      NumberOfTrips  NumberOfChildrenVisiting  MonthlyIncome
```

```
0         1.000000              0.000000     19.798047
1         1.231144              1.231144     19.550287
2         1.792790              0.000000     18.613267
3         1.231144              1.000000     18.876497
4         1.000000              0.000000     19.051359
…            …                     …            …
4883      1.231144              1.000000     21.249410
4884      1.390389              1.231144     19.859782
4885      1.792790              1.390389     22.429007
4886      1.390389              1.231144     19.596486
4887      1.390389              1.231144     20.619862

[4888 rows x 7 columns]
```

Method 5: Transforming Numerical variables with Box-Cox transformations

[99]:
```python
#defined by (X**(lambda)-1)/X
#lambda is transformation parameter and X is the variable
data=pd.read_csv('Travel.csv')
X=data[num_col]
# Performing Mean Imputation
for var in num_col:
    value=X[var].mean()
    X[var]=X[var].fillna(value)
X_in=X['Age'].array.reshape(-1, 1)
from sklearn.preprocessing import PowerTransformer
#using sklearn
transformer=PowerTransformer(method='box-cox',standardize=False)
transformer.fit(X_in)
X_1=transformer.transform(X_in)
#X_in
```

Method 6: Transforming Numerical variables with Yeo-Johnson transformation

[102]:
```python
data=pd.read_csv('Travel.csv')
X=data[num_col]
# Performing Mean Imputation
for var in num_col:
    value=X[var].mean()
    X[var]=X[var].fillna(value)
X_in=X['Age'].array.reshape(-1, 1)
from sklearn.preprocessing import PowerTransformer
#using sklearn
transformer=PowerTransformer(method='yeo-johnson',standardize=False)
transformer.fit(X_in)
X_1=transformer.transform(X_in)

#X_in
```