ML Project 2)Income Qualification

November 27, 2022

1 Income Qualification

1.0.1 DESCRIPTION

Identify the level of income qualification needed for the families in Latin America.

Problem Statement Scenario: Many social programs have a hard time ensuring that the right people are given enough aid. It's tricky when a program focuses on the poorest segment of the population. This segment of the population can't provide the necessary income and expense records to prove that they qualify.

In Latin America, a popular method called Proxy Means Test (PMT) uses an algorithm to verify income qualification. With PMT, agencies use a model that considers a family's observable household attributes like the material of their walls and ceiling or the assets found in their homes to classify them and predict their level of need.

While this is an improvement, accuracy remains a problem as the region's population grows and poverty declines.

The Inter-American Development Bank (IDB)believes that new methods beyond traditional econometrics, based on a dataset of Costa Rican household characteristics, might help improve PMT's performance.

Following actions should be performed:

1) Identify the output variable.
2) Understand the type of data.
3) Check if there are any biases in your dataset.
4) Check whether all members of the house have the same poverty level.
5) Check if there is a house without a family head.
6) Set poverty level of the members and the head of the house within a family.
7) Count how many null values are existing in columns.
8) Remove null value rows of the target variable.
9) Predict the accuracy using random forest classifier.
10) Check the accuracy using random forest with cross validation.

[ ]:

[71]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

from sklearn.preprocessing import LabelEncoder, StandardScaler
from sklearn.model_selection import train_test_split, cross_validate
from imblearn.over_sampling import SMOTE
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import classification_report, plot_confusion_matrix

import warnings
warnings.filterwarnings("ignore")
```

[ ]:

[72]:
```
income_train = pd.read_csv("train.csv")
```

[73]:
```
income_test = pd.read_csv("test.csv")
```

[ ]:

We will Work on Train and Test Data Simultaneously so that we can make same changes in Test Data that we do in Train Data.

[ ]:

1) Exploring Data:

[74]:
```
income_train.head()
```

[74]:
```
              Id      v2a1  hacdor  rooms  hacapo  v14a  refrig  v18q  v18q1  \
0  ID_279628684  190000.0       0      3       0     1       1     0    NaN
1  ID_f29eb3ddd  135000.0       0      4       0     1       1     1    1.0
2  ID_68de51c94       NaN       0      8       0     1       1     0    NaN
3  ID_d671db89c  180000.0       0      5       0     1       1     1    1.0
4  ID_d56d6f5f5  180000.0       0      5       0     1       1     1    1.0

   r4h1  …  SQBescolari  SQBage  SQBhogar_total  SQBedjefe  SQBhogar_nin  \
0     0  …          100    1849               1        100             0
1     0  …          144    4489               1        144             0
2     0  …          121    8464               1          0             0
3     0  …           81     289              16        121             4
4     0  …          121    1369              16        121             4

   SQBovercrowding  SQBdependency  SQBmeaned  agesq  Target
0         1.000000            0.0      100.0   1849       4
```

```
1         1.000000            64.0       144.0   4489       4
2         0.250000            64.0       121.0   8464       4
3         1.777778             1.0       121.0    289       4
4         1.777778             1.0       121.0   1369       4

[5 rows x 143 columns]
```

[75]:
```
income_test.head()
```

[75]:
```
             Id      v2a1  hacdor  rooms  hacapo  v14a  refrig  v18q  v18q1  \
0  ID_2f6873615       NaN       0      5       0     1       1     0    NaN
1  ID_1c78846d2       NaN       0      5       0     1       1     0    NaN
2  ID_e5442cf6a       NaN       0      5       0     1       1     0    NaN
3  ID_a8db26a79       NaN       0     14       0     1       1     1    1.0
4  ID_a62966799  175000.0       0      4       0     1       1     1    1.0

   r4h1  …  age  SQBescolari  SQBage  SQBhogar_total  SQBedjefe  \
0     1  …    4            0      16               9          0
1     1  …   41          256    1681               9          0
2     1  …   41          289    1681               9          0
3     0  …   59          256    3481               1        256
4     0  …   18          121     324               1          0

   SQBhogar_nin  SQBovercrowding  SQBdependency  SQBmeaned  agesq
0             1             2.25           0.25     272.25     16
1             1             2.25           0.25     272.25   1681
2             1             2.25           0.25     272.25   1681
3             0             1.00           0.00     256.00   3481
4             1             0.25          64.00        NaN    324

[5 rows x 142 columns]
```

[ ]:
```

```

[76]:
```
income_train.columns
```

[76]:
```
Index(['Id', 'v2a1', 'hacdor', 'rooms', 'hacapo', 'v14a', 'refrig', 'v18q',
       'v18q1', 'r4h1',
       …
       'SQBescolari', 'SQBage', 'SQBhogar_total', 'SQBedjefe', 'SQBhogar_nin',
       'SQBovercrowding', 'SQBdependency', 'SQBmeaned', 'agesq', 'Target'],
      dtype='object', length=143)
```

[77]:
```
income_test.columns
```

[77]:
```
Index(['Id', 'v2a1', 'hacdor', 'rooms', 'hacapo', 'v14a', 'refrig', 'v18q',
       'v18q1', 'r4h1',
```

```
 …
 'age', 'SQBescolari', 'SQBage', 'SQBhogar_total', 'SQBedjefe',
 'SQBhogar_nin', 'SQBovercrowding', 'SQBdependency', 'SQBmeaned',
 'agesq'],
dtype='object', length=142)
```

[ ]:

[78]:
```
income_train.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 9557 entries, 0 to 9556
Columns: 143 entries, Id to Target
dtypes: float64(8), int64(130), object(5)
memory usage: 10.4+ MB
```

[79]:
```
income_test.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 23856 entries, 0 to 23855
Columns: 142 entries, Id to agesq
dtypes: float64(8), int64(129), object(5)
memory usage: 25.8+ MB
```

[ ]:

[80]:
```
income_train.describe()
```

[80]:

	v2a1	hacdor	rooms	hacapo	v14a	\
count	2.697000e+03	9557.000000	9557.000000	9557.000000	9557.000000	
mean	1.652316e+05	0.038087	4.955530	0.023648	0.994768	
std	1.504571e+05	0.191417	1.468381	0.151957	0.072145	
min	0.000000e+00	0.000000	1.000000	0.000000	0.000000	
25%	8.000000e+04	0.000000	4.000000	0.000000	1.000000	
50%	1.300000e+05	0.000000	5.000000	0.000000	1.000000	
75%	2.000000e+05	0.000000	6.000000	0.000000	1.000000	
max	2.353477e+06	1.000000	11.000000	1.000000	1.000000	

	refrig	v18q	v18q1	r4h1	r4h2	…	\
count	9557.000000	9557.000000	2215.000000	9557.000000	9557.000000	…	
mean	0.957623	0.231767	1.404063	0.385895	1.559171	…	
std	0.201459	0.421983	0.763131	0.680779	1.036574	…	
min	0.000000	0.000000	1.000000	0.000000	0.000000	…	
25%	1.000000	0.000000	1.000000	0.000000	1.000000	…	
50%	1.000000	0.000000	1.000000	0.000000	1.000000	…	
75%	1.000000	0.000000	2.000000	1.000000	2.000000	…	
max	1.000000	1.000000	6.000000	5.000000	8.000000	…	

```
       SQBescolari       SQBage  SQBhogar_total    SQBedjefe  SQBhogar_nin  \
count  9557.000000  9557.000000     9557.000000  9557.000000   9557.000000
mean     74.222769  1643.774302       19.132887    53.500262      3.844826
std      76.777549  1741.197050       18.751395    78.445804      6.946296
min       0.000000     0.000000        1.000000     0.000000      0.000000
25%      16.000000   289.000000        9.000000     0.000000      0.000000
50%      36.000000   961.000000       16.000000    36.000000      1.000000
75%     121.000000  2601.000000       25.000000    81.000000      4.000000
max     441.000000  9409.000000      169.000000   441.000000     81.000000

       SQBovercrowding  SQBdependency    SQBmeaned        agesq       Target
count      9557.000000    9557.000000  9552.000000  9557.000000  9557.000000
mean          3.249485       3.900409   102.588867  1643.774302     3.302292
std           4.129547      12.511831    93.516890  1741.197050     1.009565
min           0.040000       0.000000     0.000000     0.000000     1.000000
25%           1.000000       0.111111    36.000000   289.000000     3.000000
50%           2.250000       0.444444    81.000000   961.000000     4.000000
75%           4.000000       1.777778   134.560010  2601.000000     4.000000
max          36.000000      64.000000  1369.000000  9409.000000     4.000000

[8 rows x 138 columns]
```

[81]:
```
income_test.describe()
```

[81]:
```
               v2a1        hacdor         rooms        hacapo          v14a  \
count  6.453000e+03  23856.000000  23856.000000  23856.000000  23856.000000
mean   1.748726e+05      0.050679      4.955776      0.028421      0.992748
std    1.567887e+05      0.219346      1.539753      0.166174      0.084850
min    0.000000e+00      0.000000      1.000000      0.000000      0.000000
25%    8.000000e+04      0.000000      4.000000      0.000000      1.000000
50%    1.400000e+05      0.000000      5.000000      0.000000      1.000000
75%    2.200000e+05      0.000000      6.000000      0.000000      1.000000
max    2.852700e+06      1.000000     15.000000      1.000000      1.000000

             refrig          v18q        v18q1          r4h1          r4h2  \
count  23856.000000  23856.000000  5730.000000  23856.000000  23856.000000
mean       0.961603      0.240191     1.348517      0.416541      1.563967
std        0.192157      0.427208     0.694216      0.713255      0.990171
min        0.000000      0.000000     1.000000      0.000000      0.000000
25%        1.000000      0.000000     1.000000      0.000000      1.000000
50%        1.000000      0.000000     1.000000      0.000000      1.000000
75%        1.000000      0.000000     1.750000      1.000000      2.000000
max        1.000000      1.000000     6.000000      6.000000      7.000000

       …           age  SQBescolari        SQBage  SQBhogar_total  \
count  …  23856.000000  23856.00000  23856.000000    23856.000000
mean   …     34.454183     74.44974   1657.798080       19.113389
```

```
std     …     21.696245     76.99701   1753.603406      17.314597
min     …      0.000000      0.00000      0.000000       1.000000
25%     …     16.000000     16.00000    256.000000       9.000000
50%     …     32.000000     36.00000   1024.000000      16.000000
75%     …     51.000000    121.00000   2601.000000      25.000000
max     …     97.000000    441.00000   9409.000000     169.000000

          SQBedjefe  SQBhogar_nin  SQBovercrowding  SQBdependency  \
count  23856.000000  23856.000000     23856.000000   23856.000000
mean      54.087232      3.885480         3.564751       4.171669
std       77.312255      6.878967         6.668757      13.105989
min        0.000000      0.000000         0.020408       0.000000
25%        0.000000      0.000000         1.000000       0.111111
50%       36.000000      1.000000         2.250000       0.444444
75%       81.000000      4.000000         4.000000       1.777778
max      441.000000    100.000000       169.000000      64.000000

          SQBmeaned        agesq
count  23825.000000  23856.000000
mean     100.509220   1657.798080
std       89.211063   1753.603406
min        0.000000      0.000000
25%       36.000000    256.000000
50%       75.111115   1024.000000
75%      132.250000   2601.000000
max     1296.000000   9409.000000

[8 rows x 137 columns]
```

[ ]:

```

```

2) Identify the output variable:

[82]:

```python
# Comparing Columns from Train and Test Data Frame. Whichever Column is Not␣
↪Present in Test Data is our Target Variable.
```

[83]:

```python
temp1 = income_train.columns.tolist()
```

[84]:

```python
temp2 = income_test.columns.tolist()
```

[85]:

```python
not_matching_colum = []

for i in temp1:
    if i not in temp2:
        not_matching_colum.append(i)
```

[86]:

```python
not_matching_colum
```

[86]: ['Target']

```
[87]: # So, "Target" Column in Train Data Frame is Our Target/Output Variable.
```

```
[88]: income_train["Target"].dtypes
```

[88]: dtype('int64')

```
[89]: income_train["Target"].unique()
```

[89]: array([4, 2, 3, 1], dtype=int64)

```
[90]: # So, "Target" is Categorical Variable.
```

```
[91]: income_train["Target"].value_counts()
```

```
[91]: 4    5996
      2    1597
      3    1209
      1     755
      Name: Target, dtype: int64
```

```
[ ]:
```

3) Understand the type of data:

```
[92]: income_train.dtypes
```

```
[92]: Id                    object
      v2a1                 float64
      hacdor                 int64
      rooms                  int64
      hacapo                 int64
                            …
      SQBovercrowding      float64
      SQBdependency        float64
      SQBmeaned            float64
      agesq                  int64
      Target                 int64
      Length: 143, dtype: object
```

```
[93]: income_test.dtypes
```

```
[93]: Id                    object
      v2a1                 float64
      hacdor                 int64
      rooms                  int64
      hacapo                 int64
                            …
```

```
SQBhogar_nin          int64
SQBovercrowding     float64
SQBdependency       float64
SQBmeaned           float64
agesq                 int64
Length: 142, dtype: object
```

[94]:
```
income_train.dtypes.value_counts()
```

[94]:
```
int64      130
float64      8
object       5
dtype: int64
```

[95]:
```
income_test.dtypes.value_counts()
```

[95]:
```
int64      129
float64      8
object       5
dtype: int64
```

[ ]:
```

```

[96]:
```
# Let's Explore "Object" Data Type First
```

[97]:
```
income_train.select_dtypes("object").columns
```

[97]:
```
Index(['Id', 'idhogar', 'dependency', 'edjefe', 'edjefa'], dtype='object')
```

[98]:
```
income_train["Id"].nunique()
```

[98]:
```
9557
```

[99]:
```
income_test["Id"].nunique()
```

[99]:
```
23856
```

[100]:
```
income_train.shape
```

[100]:
```
(9557, 143)
```

[101]:
```
income_test.shape
```

[101]:
```
(23856, 142)
```

[102]:
```
# Since ID is an Unique Number, We can make it an index.
```

[103]:
```
income_train = income_train.set_index("Id")
```

[104]:
```python
income_test = income_test.set_index("Id")
```

[105]:
```python
income_train.head()
```

[105]:
```
                   v2a1  hacdor  rooms  hacapo  v14a  refrig  v18q  v18q1  \
Id
ID_279628684  190000.0       0      3       0     1       1     0    NaN
ID_f29eb3ddd  135000.0       0      4       0     1       1     1    1.0
ID_68de51c94       NaN       0      8       0     1       1     0    NaN
ID_d671db89c  180000.0       0      5       0     1       1     1    1.0
ID_d56d6f5f5  180000.0       0      5       0     1       1     1    1.0

              r4h1  r4h2  …  SQBescolari  SQBage  SQBhogar_total  SQBedjefe  \
Id                        …
ID_279628684     0     1  …          100    1849               1        100
ID_f29eb3ddd     0     1  …          144    4489               1        144
ID_68de51c94     0     0  …          121    8464               1          0
ID_d671db89c     0     2  …           81     289              16        121
ID_d56d6f5f5     0     2  …          121    1369              16        121

              SQBhogar_nin  SQBovercrowding  SQBdependency  SQBmeaned  agesq  \
Id
ID_279628684             0         1.000000            0.0      100.0   1849
ID_f29eb3ddd             0         1.000000           64.0      144.0   4489
ID_68de51c94             0         0.250000           64.0      121.0   8464
ID_d671db89c             4         1.777778            1.0      121.0    289
ID_d56d6f5f5             4         1.777778            1.0      121.0   1369

              Target
Id
ID_279628684       4
ID_f29eb3ddd       4
ID_68de51c94       4
ID_d671db89c       4
ID_d56d6f5f5       4

[5 rows x 142 columns]
```

[106]:
```python
income_test.shape
```

[106]:
```
(23856, 141)
```

---

[107]:
```python
income_train["idhogar"].nunique()                                        #␣
↪idhogar: Household level identifier
```

[107]:
```
2988
```

[108]:
```
income_train["idhogar"].value_counts()
```

[108]:
```
fd8a6d014    13
ae6cf0558    12
0c7436de6    12
b7a0b59d7    11
4476ccd4c    11
             ..
9f6b2b309     1
75226a178     1
1637ac45b     1
0194d569d     1
21eb7fcc1     1
Name: idhogar, Length: 2988, dtype: int64
```

[109]:
```
income_test["idhogar"].nunique()
```

[109]: 7352

[110]:
```
income_test["idhogar"].value_counts()
```

[110]:
```
8e9159699    13
830539cad    13
9a906088e    13
ef31faf0f    12
7c6740850    11
             ..
c2975df37     1
25e1fff14     1
d6e3f9e9a     1
5a667591a     1
0df790c33     1
Name: idhogar, Length: 7352, dtype: int64
```

[111]:
```
# Applying Lable Encoder to Change Strings to Numbers.
```

[112]:
```
le = LabelEncoder()
```

[113]:
```
income_train["idhogar"] = le.fit_transform(income_train["idhogar"])
income_test["idhogar"] = le.fit_transform(income_test["idhogar"])
```

[114]:
```
income_train["idhogar"].value_counts()
```

[114]:
```
2946    13
2034    12
150     12
2132    11
816     11
```

```
        ..
1850     1
1379     1
275      1
18       1
401      1
Name: idhogar, Length: 2988, dtype: int64
```

[115]:
```
income_test["idhogar"].value_counts()
```

[115]:
```
4066    13
3739    13
4393    13
6859    12
3541    11
        ..
5493     1
1039     1
6118     1
2570     1
362      1
Name: idhogar, Length: 7352, dtype: int64
```

---

[116]:
```
income_train["dependency"].unique()                         # dependency :␣
 ↪Dependency rate, calculated = (number of members
                                                            # of the household␣
 ↪younger than 19 or older than 64)/(number of
                                                            # member of␣
 ↪household between 19 and 64)
```

[116]:
```
array(['no', '8', 'yes', '3', '.5', '.25', '2', '.66666669', '.33333334',
       '1.5', '.40000001', '.75', '1.25', '.2', '2.5', '1.2', '4',
       '1.3333334', '2.25', '.22222222', '5', '.83333331', '.80000001',
       '6', '3.5', '1.6666666', '.2857143', '1.75', '.71428573',
       '.16666667', '.60000002'], dtype=object)
```

[117]:
```
income_test["dependency"].unique()
```

[117]:
```
array(['.5', 'no', '8', 'yes', '.25', '2', '.33333334', '.375',
       '.60000002', '1.5', '.2', '.75', '.66666669', '3', '.14285715',
       '.40000001', '.80000001', '1.6666666', '.2857143', '1.25', '2.5',
       '5', '.85714287', '1.3333334', '.16666667', '4', '.125',
       '.83333331', '2.3333333', '7', '1.2', '3.5', '2.25', '3.3333333',
       '6'], dtype=object)
```

[118]:
```
# As we can See, There are Only Two Values in Column That are not Numbers.
# Let's Covert them to Numbers.
# Yes = 1, No = 0
```

[119]:
```
income_train["dependency"] = income_train["dependency"].replace({"yes" : 1,␣
↪"no" : 0})
income_test["dependency"] = income_test["dependency"].replace({"yes" : 1, "no" :
↪ 0})
```

[120]:
```
income_train["dependency"] = income_train["dependency"].astype("float")
```

[121]:
```
income_test["dependency"] = income_test["dependency"].astype("float")
```

[122]:
```
income_train["dependency"].unique()
```

[122]:
```
array([0.        , 8.        , 1.        , 3.        , 0.5       ,
       0.25      , 2.        , 0.66666669, 0.33333334, 1.5       ,
       0.40000001, 0.75      , 1.25      , 0.2       , 2.5       ,
       1.2       , 4.        , 1.3333334 , 2.25      , 0.22222222,
       5.        , 0.83333331, 0.80000001, 6.        , 3.5       ,
       1.6666666 , 0.2857143 , 1.75      , 0.71428573, 0.16666667,
       0.60000002])
```

[123]:
```
income_test["dependency"].unique()
```

[123]:
```
array([0.5       , 0.        , 8.        , 1.        , 0.25      ,
       2.        , 0.33333334, 0.375     , 0.60000002, 1.5       ,
       0.2       , 0.75      , 0.66666669, 3.        , 0.14285715,
       0.40000001, 0.80000001, 1.6666666 , 0.2857143 , 1.25      ,
       2.5       , 5.        , 0.85714287, 1.3333334 , 0.16666667,
       4.        , 0.125     , 0.83333331, 2.3333333 , 7.        ,
       1.2       , 3.5       , 2.25      , 3.3333333 , 6.        ])
```

---

[124]:
```
income_train["edjefe"].unique()
```

[124]:
```
array(['10', '12', 'no', '11', '9', '15', '4', '6', '8', '17', '7', '16',
       '14', '5', '21', '2', '19', 'yes', '3', '18', '13', '20'],
      dtype=object)
```

[125]:
```
income_test["edjefe"].unique()
```

[125]:
```
array(['no', '16', '10', '6', '11', '8', '13', '14', '5', '3', '9', '17',
       '15', '7', '21', '4', '12', '2', '20', 'yes', '19', '18'],
      dtype=object)
```

[126]:
```python
# As we can See, There are Only Two Values in Column That are not Numbers.
# Let's Covert them to Numbers.
# Yes = 1, No = 0
```

[127]:
```python
income_train["edjefe"] = income_train["edjefe"].replace({"yes" : 1, "no" : 0}).
↪astype("int64")
income_test["edjefe"] = income_test["edjefe"].replace({"yes" : 1, "no" : 0}).
↪astype("int64")
```

[128]:
```python
income_train["edjefe"].unique()
```

[128]:
```
array([10, 12,  0, 11,  9, 15,  4,  6,  8, 17,  7, 16, 14,  5, 21,  2, 19,
        1,  3, 18, 13, 20], dtype=int64)
```

[129]:
```python
income_test["edjefe"].unique()
```

[129]:
```
array([ 0, 16, 10,  6, 11,  8, 13, 14,  5,  3,  9, 17, 15,  7, 21,  4, 12,
        2, 20,  1, 19, 18], dtype=int64)
```

---

[130]:
```python
income_train["edjefa"].unique()
```

[130]:
```
array(['no', '11', '4', '10', '9', '15', '7', '14', '13', '8', '17', '6',
       '5', '3', '16', '19', 'yes', '21', '12', '2', '20', '18'],
      dtype=object)
```

[131]:
```python
income_test["edjefa"].unique()
```

[131]:
```
array(['17', 'no', '11', '14', '10', '15', '9', '6', '8', '3', '2', '5',
       '16', '12', 'yes', '7', '13', '21', '4', '19', '18', '20'],
      dtype=object)
```

[132]:
```python
# As we can See, There are Only Two Values in Column That are not Numbers.
# Let's Covert them to Numbers.
# Yes = 1, No = 0
```

[133]:
```python
income_train["edjefa"] = income_train["edjefa"].replace({"yes" : 1, "no" : 0}).
↪astype("int64")
income_test["edjefa"] = income_test["edjefa"].replace({"yes" : 1, "no" : 0}).
↪astype("int64")
```

[134]:
```python
income_train["edjefa"].unique()
```

[134]:
```
array([ 0, 11,  4, 10,  9, 15,  7, 14, 13,  8, 17,  6,  5,  3, 16, 19,  1,
       21, 12,  2, 20, 18], dtype=int64)
```

[135]:
```python
income_test["edjefa"].unique()
```

[135]: array([17, 0, 11, 14, 10, 15, 9, 6, 8, 3, 2, 5, 16, 12, 1, 7, 13,
       21, 4, 19, 18, 20], dtype=int64)

---

[136]:
```
income_train.dtypes.value_counts()
```

[136]:
```
int64      132
float64      9
int32        1
dtype: int64
```

[137]:
```
income_test.dtypes.value_counts()
```

[137]:
```
int64      131
float64      9
int32        1
dtype: int64
```

[ ]:
```

```

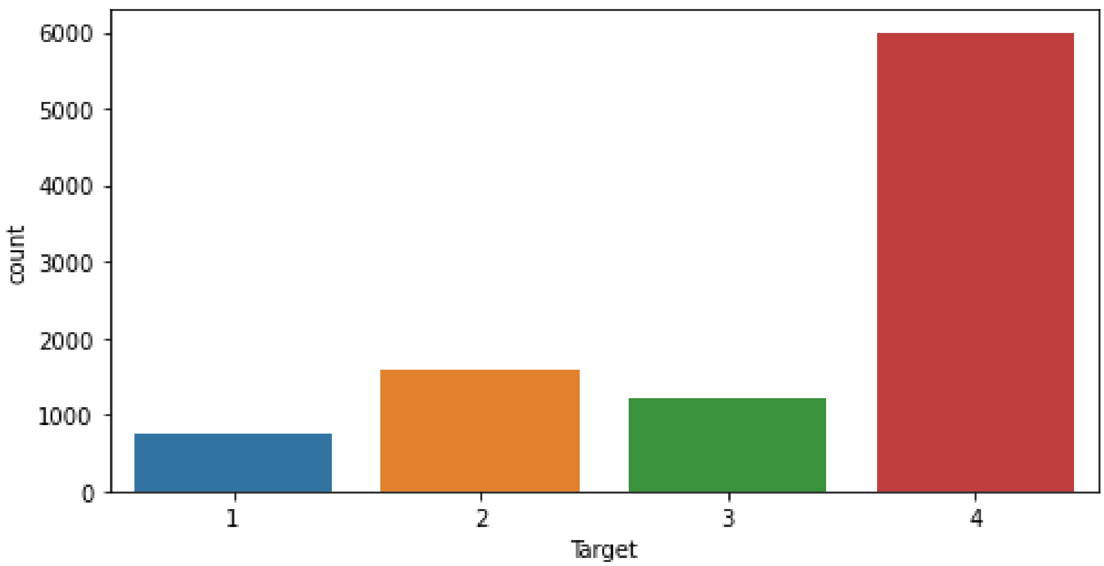
4) Check if there are any biases in your dataset:

[138]:
```
# Firstly, let's Check if Target Variable is Class Imbalanced or Not.
```

[139]:
```
income_train["Target"].value_counts()
```

[139]:
```
4    5996
2    1597
3    1209
1     755
Name: Target, dtype: int64
```

[140]:
```
plt.figure(figsize= (8,4))
sns.countplot(income_train["Target"])
plt.show()
```

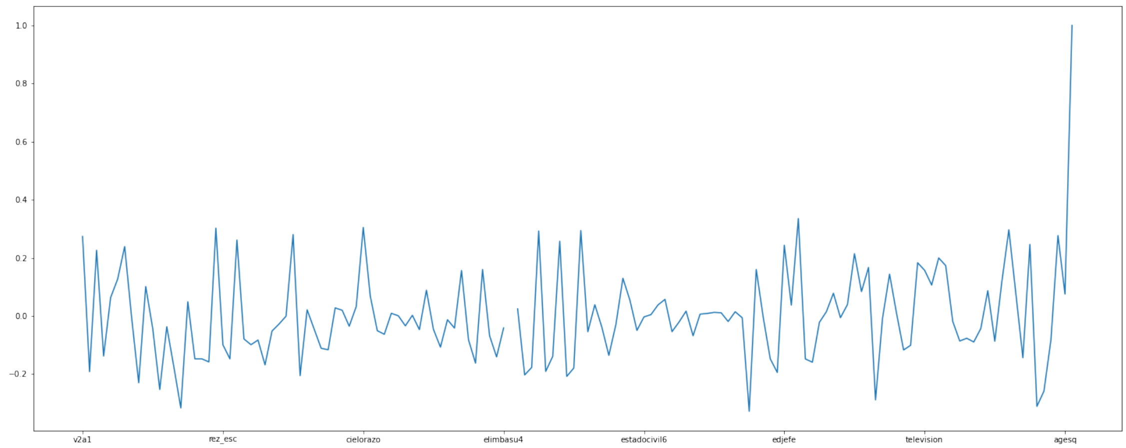


[141]:
```
# So, Our Dataset is Clearly Class Imbalanced.
```

---

[142]:
```
# Checking For Correlation of All Variables with Target Variable.
```

[143]:
```
plt.figure(figsize= (25,10))

income_train.corr()["Target"].plot()

plt.show()
```



[144]:
```
# As Seen from The Graph and Data above, None of the Variables Have Correlation␣
↪Greater Than 0.3 or less Than -0.3 To Target
# Variable. (Last Peek In Graph is Correlation of Target Variable With Itself,␣
↪which is Obviously 1.)

# So, Our Target Variable is Not Biased Towards any Independent Variable.
```

---

[145]:
```
# Checking For Correlation Between Independent Variables to Avoid␣
↪Multicolinearity.
```

[146]:
```
corr_matrix = income_train.drop("Target", axis= 1).corr().abs()
```

[147]:
```
corr_matrix
```

[147]:
```
                   v2a1    hacdor     rooms    hacapo      v14a    refrig  \
v2a1           1.000000  0.091732  0.443461  0.073509  0.033551  0.088970
hacdor         0.091732  1.000000  0.233369  0.652594  0.175011  0.101965
rooms          0.443461  0.233369  1.000000  0.213368  0.129183  0.130531
hacapo         0.073509  0.652594  0.213368  1.000000  0.150986  0.124506
v14a           0.033551  0.175011  0.129183  0.150986  1.000000  0.143143
…                   …         …         …         …         …         …
SQBhogar_nin   0.082246  0.388043  0.007952  0.367025  0.015193  0.108718
SQBovercrowding 0.191915  0.794699  0.355526  0.640096  0.174969  0.123054
SQBdependency  0.061352  0.005278  0.027575  0.014411  0.005712  0.034080
SQBmeaned      0.402561  0.099153  0.250061  0.103324  0.034711  0.117406
agesq          0.062343  0.102725  0.068288  0.075528  0.023831  0.025846

                   v18q    v18q1      r4h1      r4h2  …       age  \
v2a1           0.278364  0.302292  0.081900  0.002401  …  0.078897
hacdor         0.084680  0.049262  0.232508  0.059313  …  0.118168
rooms          0.254256  0.208919  0.066578  0.267627  …  0.077046
hacapo         0.067529  0.037414  0.226378  0.126645  …  0.087773
v14a           0.036396  0.011255  0.054769  0.018133  …  0.027193
…                   …         …         …         …  …       …
SQBhogar_nin   0.050562  0.092212  0.565494  0.124701  …  0.316034
SQBovercrowding 0.125936  0.062806  0.355660  0.144478  …  0.240636
SQBdependency  0.071504  0.033226  0.036977  0.157357  …  0.303847
SQBmeaned      0.302763  0.115522  0.083552  0.062217  …  0.085065
agesq          0.054670  0.031046  0.272690  0.054712  …  0.958090

               SQBescolari    SQBage  SQBhogar_total  SQBedjefe  \
v2a1              0.358305  0.062343        0.061309   0.364290
hacdor            0.109862  0.102725        0.350546   0.082229
rooms             0.233679  0.068288        0.221595   0.198890
hacapo            0.092703  0.075528        0.373720   0.071170
v14a              0.036483  0.023831        0.009100   0.018897
```

```
…                         …         …              …          …
SQBhogar_nin        0.181581  0.278921        0.733956   0.049536
SQBovercrowding     0.201253  0.218349        0.475192   0.106004
SQBdependency       0.049172  0.395814        0.104255   0.032319
SQBmeaned           0.510876  0.112386        0.067588   0.470993
agesq               0.051899  1.000000        0.238110   0.018314

                 SQBhogar_nin  SQBovercrowding  SQBdependency  SQBmeaned  \
v2a1                 0.082246         0.191915       0.061352   0.402561
hacdor               0.388043         0.794699       0.005278   0.099153
rooms                0.007952         0.355526       0.027575   0.250061
hacapo               0.367025         0.640096       0.014411   0.103324
v14a                 0.015193         0.174969       0.005712   0.034711
…                         …               …             …          …
SQBhogar_nin         1.000000         0.477876       0.049113   0.009591
SQBovercrowding      0.477876         1.000000       0.049525   0.150997
SQBdependency        0.049113         0.049525       1.000000   0.065129
SQBmeaned            0.009591         0.150997       0.065129   1.000000
agesq                0.278921         0.218349       0.395814   0.112386

                    agesq
v2a1             0.062343
hacdor           0.102725
rooms            0.068288
hacapo           0.075528
v14a             0.023831
…                     …
SQBhogar_nin     0.278921
SQBovercrowding  0.218349
SQBdependency    0.395814
SQBmeaned        0.112386
agesq            1.000000

[141 rows x 141 columns]
```

[148]:
```
# In this Correlation Matrix, Values above and Below Diagonal are Exactly Same.
# i.e. Coreelation of "v2a1" with "hacdor" is same as Correltion of "hacdor" with "v2a1".

# So, can use Either of the Upper or Traingle for Further Calculation.
```

[ ]:
```

```

https://numpy.org/doc/stable/reference/generated/numpy.triu.html

https://stackoverflow.com/questions/40690854/set-diagonal-triangle-in-pandas-dataframe-to-nan

https://numpy.org/doc/stable/reference/generated/numpy.where.html

[149]:
```
corr_matrix.shape
```

[149]:
```
(141, 141)
```

[150]:
```
np.ones(corr_matrix.shape)
```

[150]:
```
array([[1., 1., 1., …, 1., 1., 1.],
       [1., 1., 1., …, 1., 1., 1.],
       [1., 1., 1., …, 1., 1., 1.],
       …,
       [1., 1., 1., …, 1., 1., 1.],
       [1., 1., 1., …, 1., 1., 1.],
       [1., 1., 1., …, 1., 1., 1.]])
```

[151]:
```
np.triu(np.ones(corr_matrix.shape),k=1)
```

[151]:
```
array([[0., 1., 1., …, 1., 1., 1.],
       [0., 0., 1., …, 1., 1., 1.],
       [0., 0., 0., …, 1., 1., 1.],
       …,
       [0., 0., 0., …, 0., 1., 1.],
       [0., 0., 0., …, 0., 0., 1.],
       [0., 0., 0., …, 0., 0., 0.]])
```

[152]:
```
(np.triu(np.ones(corr_matrix.shape),k=1).astype(np.bool))
```

[152]:
```
array([[False,  True,  True, …,  True,  True,  True],
       [False, False,  True, …,  True,  True,  True],
       [False, False, False, …,  True,  True,  True],
       …,
       [False, False, False, …, False,  True,  True],
       [False, False, False, …, False, False,  True],
       [False, False, False, …, False, False, False]])
```

[153]:
```
corr_matrix.where(np.triu(np.ones(corr_matrix.shape),k=1).astype(np.bool))
```

[153]:

	v2a1	hacdor	rooms	hacapo	v14a	refrig	\
v2a1	NaN	0.091732	0.443461	0.073509	0.033551	0.088970	
hacdor	NaN	NaN	0.233369	0.652594	0.175011	0.101965	
rooms	NaN	NaN	NaN	0.213368	0.129183	0.130531	
hacapo	NaN	NaN	NaN	NaN	0.150986	0.124506	
v14a	NaN	NaN	NaN	NaN	NaN	0.143143	
…	…	…	…	…	…	…	
SQBhogar_nin	NaN	NaN	NaN	NaN	NaN	NaN	
SQBovercrowding	NaN	NaN	NaN	NaN	NaN	NaN	
SQBdependency	NaN	NaN	NaN	NaN	NaN	NaN	
SQBmeaned	NaN	NaN	NaN	NaN	NaN	NaN	
agesq	NaN	NaN	NaN	NaN	NaN	NaN	

```
                    v18q     v18q1      r4h1      r4h2  …       age  \
v2a1            0.278364  0.302292  0.081900  0.002401  …  0.078897
hacdor          0.084680  0.049262  0.232508  0.059313  …  0.118168
rooms           0.254256  0.208919  0.066578  0.267627  …  0.077046
hacapo          0.067529  0.037414  0.226378  0.126645  …  0.087773
v14a            0.036396  0.011255  0.054769  0.018133  …  0.027193
…                      …         …         …         …  …         …
SQBhogar_nin         NaN       NaN       NaN       NaN  …       NaN
SQBovercrowding      NaN       NaN       NaN       NaN  …       NaN
SQBdependency        NaN       NaN       NaN       NaN  …       NaN
SQBmeaned            NaN       NaN       NaN       NaN  …       NaN
agesq                NaN       NaN       NaN       NaN  …       NaN

                SQBescolari    SQBage  SQBhogar_total  SQBedjefe  \
v2a1               0.358305  0.062343        0.061309   0.364290
hacdor             0.109862  0.102725        0.350546   0.082229
rooms              0.233679  0.068288        0.221595   0.198890
hacapo             0.092703  0.075528        0.373720   0.071170
v14a               0.036483  0.023831        0.009100   0.018897
…                         …         …               …          …
SQBhogar_nin            NaN       NaN             NaN        NaN
SQBovercrowding         NaN       NaN             NaN        NaN
SQBdependency           NaN       NaN             NaN        NaN
SQBmeaned               NaN       NaN             NaN        NaN
agesq                   NaN       NaN             NaN        NaN

                SQBhogar_nin  SQBovercrowding  SQBdependency  SQBmeaned  \
v2a1                0.082246         0.191915       0.061352   0.402561
hacdor              0.388043         0.794699       0.005278   0.099153
rooms               0.007952         0.355526       0.027575   0.250061
hacapo              0.367025         0.640096       0.014411   0.103324
v14a                0.015193         0.174969       0.005712   0.034711
…                          …                …              …          …
SQBhogar_nin             NaN         0.477876       0.049113   0.009591
SQBovercrowding          NaN              NaN       0.049525   0.150997
SQBdependency            NaN              NaN            NaN   0.065129
SQBmeaned                NaN              NaN            NaN        NaN
agesq                    NaN              NaN            NaN        NaN

                   agesq
v2a1            0.062343
hacdor          0.102725
rooms           0.068288
hacapo          0.075528
v14a            0.023831
…                      …
```

```
SQBhogar_nin      0.278921
SQBovercrowding   0.218349
SQBdependency     0.395814
SQBmeaned         0.112386
agesq                  NaN

[141 rows x 141 columns]
```

[154]:
```python
Upper_Tri = corr_matrix.where(np.triu(np.ones(corr_matrix.shape),k=1).astype(np.
 ↪bool))
```

[155]:
```python
Upper_Tri
```

[155]:
```
                 v2a1    hacdor     rooms    hacapo      v14a    refrig  \
v2a1              NaN  0.091732  0.443461  0.073509  0.033551  0.088970
hacdor            NaN       NaN  0.233369  0.652594  0.175011  0.101965
rooms             NaN       NaN       NaN  0.213368  0.129183  0.130531
hacapo            NaN       NaN       NaN       NaN  0.150986  0.124506
v14a              NaN       NaN       NaN       NaN       NaN  0.143143
…                   …         …         …         …         …         …
SQBhogar_nin      NaN       NaN       NaN       NaN       NaN       NaN
SQBovercrowding   NaN       NaN       NaN       NaN       NaN       NaN
SQBdependency     NaN       NaN       NaN       NaN       NaN       NaN
SQBmeaned         NaN       NaN       NaN       NaN       NaN       NaN
agesq             NaN       NaN       NaN       NaN       NaN       NaN

                     v18q     v18q1      r4h1      r4h2  …       age  \
v2a1             0.278364  0.302292  0.081900  0.002401  …  0.078897
hacdor           0.084680  0.049262  0.232508  0.059313  …  0.118168
rooms            0.254256  0.208919  0.066578  0.267627  …  0.077046
hacapo           0.067529  0.037414  0.226378  0.126645  …  0.087773
v14a             0.036396  0.011255  0.054769  0.018133  …  0.027193
…                       …         …         …         …  …         …
SQBhogar_nin          NaN       NaN       NaN       NaN  …       NaN
SQBovercrowding       NaN       NaN       NaN       NaN  …       NaN
SQBdependency         NaN       NaN       NaN       NaN  …       NaN
SQBmeaned             NaN       NaN       NaN       NaN  …       NaN
agesq                 NaN       NaN       NaN       NaN  …       NaN

                 SQBescolari    SQBage  SQBhogar_total  SQBedjefe  \
v2a1                0.358305  0.062343        0.061309   0.364290
hacdor              0.109862  0.102725        0.350546   0.082229
rooms               0.233679  0.068288        0.221595   0.198890
hacapo              0.092703  0.075528        0.373720   0.071170
v14a                0.036483  0.023831        0.009100   0.018897
…                          …         …               …          …
SQBhogar_nin             NaN       NaN             NaN        NaN
```

```
SQBovercrowding          NaN       NaN             NaN         NaN
SQBdependency            NaN       NaN             NaN         NaN
SQBmeaned                NaN       NaN             NaN         NaN
agesq                    NaN       NaN             NaN         NaN

                 SQBhogar_nin  SQBovercrowding  SQBdependency  SQBmeaned  \
v2a1                 0.082246         0.191915       0.061352   0.402561
hacdor               0.388043         0.794699       0.005278   0.099153
rooms                0.007952         0.355526       0.027575   0.250061
hacapo               0.367025         0.640096       0.014411   0.103324
v14a                 0.015193         0.174969       0.005712   0.034711
…                         …                …             …         …
SQBhogar_nin              NaN         0.477876       0.049113   0.009591
SQBovercrowding           NaN              NaN       0.049525   0.150997
SQBdependency             NaN              NaN            NaN   0.065129
SQBmeaned                 NaN              NaN            NaN        NaN
agesq                     NaN              NaN            NaN        NaN

                    agesq
v2a1             0.062343
hacdor           0.102725
rooms            0.068288
hacapo           0.075528
v14a             0.023831
…                     …
SQBhogar_nin     0.278921
SQBovercrowding  0.218349
SQBdependency    0.395814
SQBmeaned        0.112386
agesq                 NaN

[141 rows x 141 columns]
```

[ ]:

[156]:
```python
# Now, we will Choose Colums which have Absolute Correlation Greater Than 0.
↪75(75%) and Drop them from Data
# to avoid Multicolinearity
```

[157]:
```python
Cols_to_drop = []

for i in Upper_Tri.columns:
    if any(Upper_Tri[i] > 0.75):
        Cols_to_drop.append(i)
```

[158]:
```python
Cols_to_drop
```

[158]: ['r4h3',
 'r4m3',
 'r4t1',
 'r4t2',
 'r4t3',
 'tamhog',
 'tamviv',
 'hhsize',
 'pisocemento',
 'techoentrepiso',
 'abastaguafuera',
 'coopele',
 'sanitario3',
 'energcocinar3',
 'elimbasu3',
 'epared3',
 'etecho3',
 'eviv3',
 'female',
 'hogar_nin',
 'hogar_adul',
 'hogar_total',
 'bedrooms',
 'area2',
 'SQBescolari',
 'SQBage',
 'SQBhogar_total',
 'SQBedjefe',
 'SQBhogar_nin',
 'SQBovercrowding',
 'SQBdependency',
 'SQBmeaned',
 'agesq']

[159]:
```
len(Cols_to_drop)
```

[159]: 33

[160]:
```
# We Will Drop This Columns From Both Train and Test Data.
```

[161]:
```
income_train = income_train.drop(Cols_to_drop, axis= 1)
income_test = income_test.drop(Cols_to_drop, axis= 1)
```

[162]:
```
income_train.shape
```

[162]: (9557, 109)

[163]:
```
income_test.shape
```

[163]: (23856, 108)

[ ]:
```

```

5) Check whether all members of the house have the same poverty level:

[164]:
```
# We will Group the Train Data Using "idhogar" Which is Unique for Each Family␣
↪and check the Variance in "Target" Varibale
# for them.
# If Variance of "Target" for Any "idhogar" is > 0, Members of That Family have␣
↪Different Poverty Level.
```

[165]:
```
temp = income_train.groupby("idhogar", as_index= False)["Target"].var().
↪sort_values("Target", ascending= False)
```

[166]:
```
temp
```

[166]:
```
      idhogar  Target
1079     1079     1.0
712       712     1.0
2205     2205     0.5
769       769     0.5
977       977     0.5
…        …      …
2957     2957     NaN
2960     2960     NaN
2970     2970     NaN
2975     2975     NaN
2977     2977     NaN

[2988 rows x 2 columns]
```

[167]:
```
# So, there are Some Families Having Members with Different Poverty Level.
# We will Store them in Differetnt Data Frame.
```

[168]:
```
diff_pov_level = temp[temp["Target"] > 0]
```

[169]:
```
diff_pov_level
```

[169]:
```
      idhogar    Target
1079     1079  1.000000
712       712  1.000000
2205     2205  0.500000
769       769  0.500000
977       977  0.500000
…        …         …
523       523  0.166667
836       836  0.166667
```

```
808        808  0.166667
2327      2327  0.166667
1222      1222  0.166667

[85 rows x 2 columns]
```

[170]:
```
# So, 85 Families are with Different Poverty Levels among Members.
```

[ ]:
```
```

6) Check if there is a house without a family head:

[171]:
```
income_train["parentesco1"].value_counts()
```

[171]:
```
0    6584
1    2973
Name: parentesco1, dtype: int64
```

[172]:
```
income_test["parentesco1"].value_counts()
```

[172]:
```
0    16522
1     7334
Name: parentesco1, dtype: int64
```

[173]:
```
# We will Group the Data Using "idhogar" Which is Unique for Each Family and␣
↪check the Sum of "parentesco1" Varibale for them.
# If Sum of "parentesco1" for Any "idhogar" is = 0, that House is Without a␣
↪Family Head.
```

[174]:
```
temp1 = income_train.groupby("idhogar", as_index= False)["parentesco1"].sum().
↪sort_values("parentesco1")
temp2 = income_test.groupby("idhogar", as_index= False)["parentesco1"].sum().
↪sort_values("parentesco1")
```

[175]:
```
temp1
```

[175]:

	idhogar	parentesco1
331	331	0
38	38	0
1143	1143	0
2027	2027	0
230	230	0
…	…	…
1001	1001	1
1002	1002	1
1003	1003	1
994	994	1
2987	2987	1

```
[2988 rows x 2 columns]
```

[176]:
```python
temp2
```

[176]:
```
      idhogar  parentesco1
689       689            0
6497     6497            0
6355     6355            0
2570     2570            0
6970     6970            0
…         …            …
2446     2446            1
2445     2445            1
2444     2444            1
2442     2442            1
7351     7351            1

[7352 rows x 2 columns]
```

[177]:
```python
# So, Both Training and Testing Data have Famlilies Without Family Head.
# We will Store them in Different Data Frame.
```

[178]:
```python
without_house_head = pd.concat([temp1, temp2])
```

[179]:
```python
without_house_head = without_house_head[without_house_head["parentesco1"] == 0]
```

[180]:
```python
without_house_head
```

[180]:
```
      idhogar  parentesco1
331       331            0
38         38            0
1143     1143            0
2027     2027            0
230       230            0
2807     2807            0
1268     1268            0
1613     1613            0
2251     2251            0
2068     2068            0
645       645            0
2241     2241            0
1867     1867            0
2453     2453            0
114       114            0
689       689            0
6497     6497            0
```

6355	6355	0
2570	2570	0
6970	6970	0
5935	5935	0
2907	2907	0
6525	6525	0
5021	5021	0
7252	7252	0
1287	1287	0
7092	7092	0
6099	6099	0
373	373	0
5155	5155	0
4154	4154	0
4483	4483	0
5852	5852	0

[181]:
```
# So, there are 33 Houses without a Family Head among Train and Test Data.
```

[ ]:
```

```

7) Set poverty level of the members and the head of the house within a family:

[182]:
```
temp1 = diff_pov_level["idhogar"].tolist()
temp2 = without_house_head["idhogar"].tolist()
```

[183]:
```
in_both_list = []

for i in temp1:
    if i in temp2:
        in_both_list.append(i)
```

[184]:
```
in_both_list
```

[184]: []

[185]:
```
# So, Families Without a Family Head have No Discrepencies in Poverty Level␣
↪among Membrers.

# For Families With Family Head, if Family Members have Different Poverty␣
↪Levels, we will Change it to Poverty Level of
# Family Head.
```

[186]:
```
for id in temp1:
    if income_train.groupby("idhogar").get_group(id)["Target"].var() > 0 :
        poverty_level = income_train[(income_train["idhogar"] == id) &␣
↪(income_train["parentesco1"] == 1)]["Target"]
```

```
        income_train.loc[income_train['idhogar']== id, 'Target'] =␣
↪float(poverty_level)
```

[187]:
```
# Let's Check If There are Any Families Left with Povert Level Discrepency␣
↪Amnong Members.
```

[188]:
```
income_train.groupby("idhogar", as_index= False)["Target"].var().
↪sort_values("Target", ascending= False)
```

[188]:
```
      idhogar  Target
0           0     0.0
1964     1964     0.0
1991     1991     0.0
1992     1992     0.0
1993     1993     0.0
…         …      …
2957     2957     NaN
2960     2960     NaN
2970     2970     NaN
2975     2975     NaN
2977     2977     NaN

[2988 rows x 2 columns]
```

[189]:
```
# So, Discepancies in Poverty Level among Members of Same Family is Settled.
```

[ ]:

8) Count how many null values are existing in columns:

[190]:
```
income_train.isnull().sum().sum()
```

[190]: 22135

[191]:
```
income_test.isnull().sum().sum()
```

[191]: 55213

---

[192]:
```
for i in income_train.columns:
    if income_train[i].isnull().sum() > 0:
        print(i, income_train[i].isnull().sum() / len(income_train) * 100)
```

```
v2a1 71.7798472323951
v18q1 76.82327090091033
rez_esc 82.95490216595167
meaneduc 0.05231767290990897
```

[193]:
```
for i in income_test.columns:
    if income_test[i].isnull().sum() > 0:
        print(i, income_test[i].isnull().sum() / len(income_test) * 100)
```

```
v2a1 72.95020120724345
v18q1 75.98088531187123
rez_esc 82.3817907444668
meaneduc 0.12994634473507713
```

[194]:
```
# So, Both Train and Test Data Frames have Missing Values in Same Variables.
# Let's Examine Each of These Variables and Try to Handle Missing Values.
```

---

[195]:
```
# "v2a1" : Monthly rent payment
```

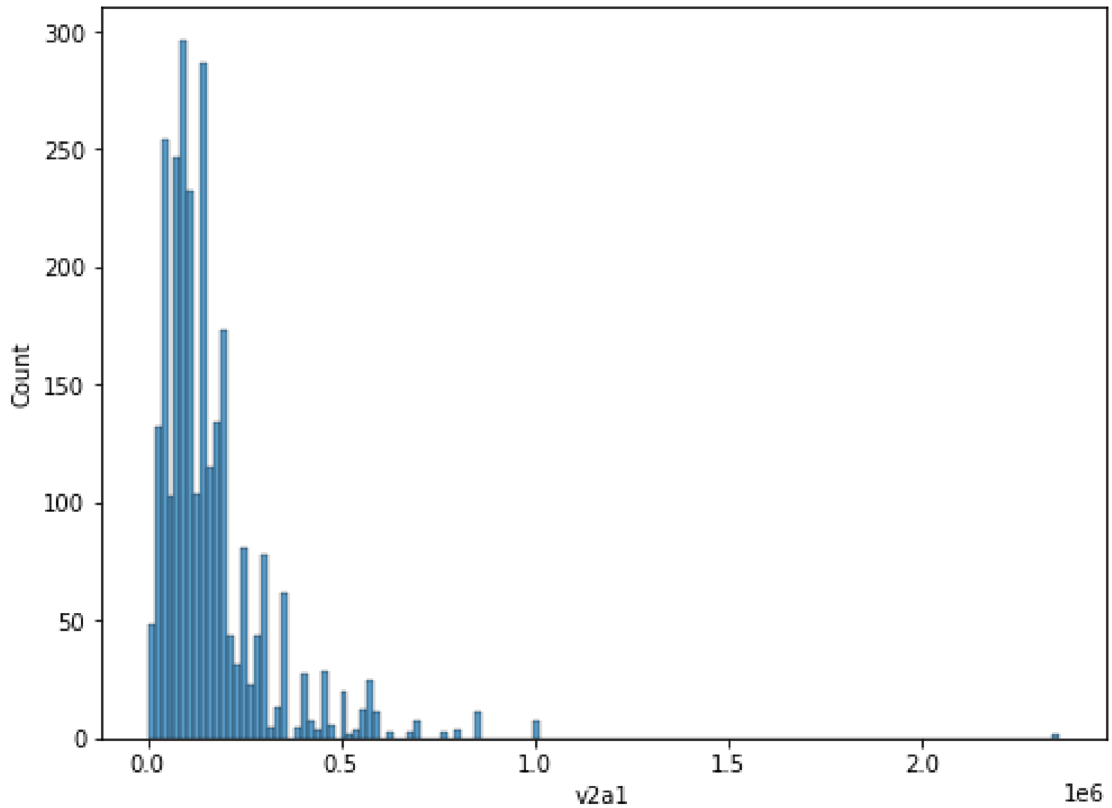
[196]:
```
# Monthly Rent Payment depends on Variables:
# tipovivi1 : =1 own and fully paid house
# tipovivi2 : =1 own, paying in installments
# tipovivi3 : =1 rented
# tipovivi4 : =1 precarious
# tipovivi5 : =1 other(assigned, borrowed)

# i.e. If House is Own and Fully Paid, and Monthly Rent Value is NaN, we can␣
↪replace that with 0.
```

[197]:
```
income_train[income_train["v2a1"].isnull() == True][["tipovivi1", "tipovivi2",␣
↪"tipovivi3", "tipovivi4", "tipovivi5"]].sum()
```

[197]:
```
tipovivi1    5911
tipovivi2       0
tipovivi3       0
tipovivi4     163
tipovivi5     786
dtype: int64
```

[198]:
```
# As we can See, Most of The NaN Values in "v2a1" belongs to the Houses that␣
↪are Owned and Fully Paid.
# For other two Variable, "tipovivi4" and "tipovivi5", we can fill Missing␣
↪Values of "v2a1" using either Mean or Median.
```

[199]:
```
plt.figure(figsize= (8,6))
sns.histplot(income_train["v2a1"])
plt.show()
```



[200]:
```
# The Distribution of "v2a1" is Skewed.
# So, we will Use Median of "v2a1" to fill Missing Values of Category␣
↪"tipovivi4" and "tipovivi5".
```

[201]:
```
income_train.loc[(income_train["tipovivi1"] ==1), "v2a1"] = 0
income_train.loc[(income_train["tipovivi4"] ==1), "v2a1"] =␣
↪income_train["v2a1"].median()
income_train.loc[(income_train["tipovivi5"] ==1), "v2a1"] =␣
↪income_train["v2a1"].median()
```

[202]:
```
income_train["v2a1"].isnull().sum()
```

[202]: 0

[ ]:

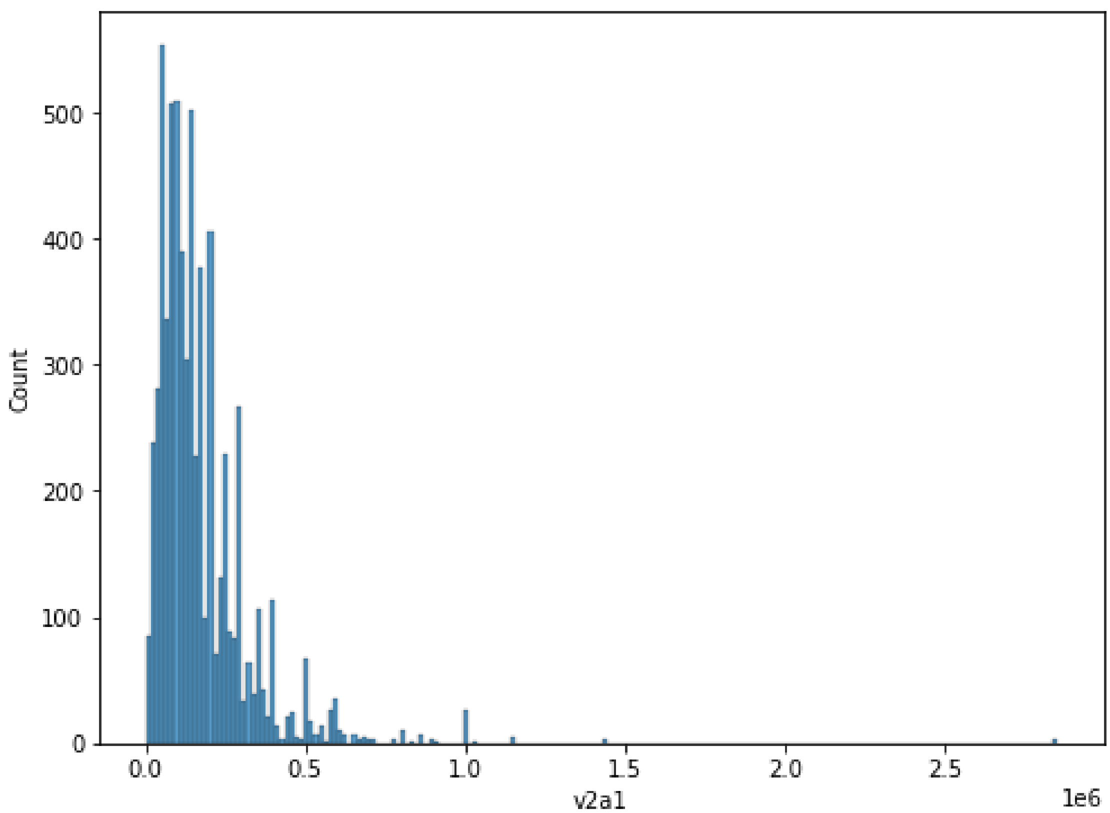
[203]:
```
# Doing Same Steps For Test Data
```

[204]:
```
income_test[income_test["v2a1"].isnull() == True][["tipovivi1", "tipovivi2",␣
↪"tipovivi3", "tipovivi4", "tipovivi5"]].sum()
```

[204]:
```
tipovivi1    14933
tipovivi2        0
tipovivi3        0
tipovivi4      434
tipovivi5     2036
dtype: int64
```

[205]:
```
# As we can See, Most of The NaN Values in "v2a1" belongs to the Houses that␣
↪are Owned and Fully Paid.
# For other two Variable, "tipovivi4" and "tipovivi5", we can fill Missing␣
↪Values of "v2a1" using either Mean or Median.
```

[206]:
```
plt.figure(figsize= (8,6))
sns.histplot(income_test["v2a1"])
plt.show()
```



[207]:
```
# The Distribution of "v2a1" is Skewed.
# So, we will Use Median of "v2a1" to fill Missing Values of Category␣
↪"tipovivi4" and "tipovivi5".
```

[208]:
```
income_test.loc[(income_test["tipovivi1"] ==1), "v2a1"] = 0
income_test.loc[(income_test["tipovivi4"] ==1), "v2a1"] = income_test["v2a1"].
↪median()
income_test.loc[(income_test["tipovivi5"] ==1), "v2a1"] = income_test["v2a1"].
↪median()
```

[209]:
```
income_test["v2a1"].isnull().sum()
```

[209]: 0

---

[210]:
```
# "v18q1" : number of tablets household owns
```

[211]:
```
# Number of Tablets Owned Depends on Variable:
# v18q : owns a tablet

# i.e. If Family Doesn't Own a Tablet, Number Tablets can be Set to 0 instead␣
↪of NaN.
```

[212]:
```
income_train[income_train["v18q1"].isnull() == True]["v18q"].sum()
```

[212]: 0

[213]:
```
# So, all the Missing Values in "v18q1" are for "v18q".
# i.e. Number of Tablets are NaN when Family Doesn't Own a Tablet.
# So, we can Replace all Missing Values in "v18q1" as 0.
```

[214]:
```
income_train["v18q1"] = income_train["v18q1"].fillna(0)
```

[215]:
```
income_train["v18q1"].isnull().sum()
```

[215]: 0

[ ]:
```

```

[216]:
```
# Doing Same Steps for Test Data
```

[217]:
```
income_test[income_test["v18q1"].isnull() == True]["v18q"].sum()
```

[217]: 0

[218]:
```
# So, all the Missing Values in "v18q1" are for "v18q".
# i.e. Number of Tablets are NaN when Family Doesn't Own a Tablet.
# So, we can Replace all Missing Values in "v18q1" as 0.
```

[219]:
```
income_test["v18q1"] = income_test["v18q1"].fillna(0)
```

[220]:
```
income_test["v18q1"].isnull().sum()
```

[220]: 0

---

[221]:
```
# "rez_esc" : Years behind in school
```

[222]:
```
# Years behind in school can be realted to the Variable:
# instlevel1 = 1 no level of education
# Age

# i.e. if Value of "rez_esc" is NaN for "instlevel1" = 1, we can fill it with 0.
# if Age<5 or Age>19, we can fill "rez_esc" with 0.
```

[223]:
```
income_train["rez_esc"].isnull().sum()
```

[223]: 7928

[224]:
```
income_train[income_train["rez_esc"].isnull() == True]["instlevel1"].sum()
```

[224]: 1183

[225]:
```
# 1183 records have NaN for Years Behind in School when They have No level of␣
↪Education.
```

[226]:
```
income_train.loc[(income_train["instlevel1"] == 1), "rez_esc"] = 0
```

[227]:
```
income_train.loc[(income_train["rez_esc"].isnull() == True) &␣
↪((income_train["age"] < 7) | (income_train["age"] > 19)),
                 "rez_esc"] = 0
```

[228]:
```
income_train["rez_esc"].isnull().sum()
```

[228]: 346

[229]:
```
# Filling this Missing Values with Mean of "rez_esc"
```

[230]:
```
income_train["rez_esc"] = income_train["rez_esc"].
↪fillna(income_train["rez_esc"].mean())
```

[231]:
```
income_train["rez_esc"].isnull().sum()
```

[231]: 0

[ ]:
```

```

[232]:
```
# Doing Same Steps for Test Data
```

[233]:
```
income_test["rez_esc"].isnull().sum()
```

[233]: 19653

```
[234]: income_test[income_test["rez_esc"].isnull() == True]["instlevel1"].sum()
```

[234]: 2863

```
[235]: # 2863 records have NaN for Years Behind in School when They have No level of␣
         ↪Education.
```

```
[236]: income_test.loc[(income_test["instlevel1"] == 1), "rez_esc"] = 0
```

```
[237]: income_test.loc[(income_test["rez_esc"].isnull() == True) &␣
         ↪((income_test["age"] < 7) | (income_test["age"] > 19)),
                          "rez_esc"] = 0
```

```
[238]: income_test["rez_esc"].isnull().sum()
```

[238]: 802

```
[239]: # Filling this Missing Values with Mean of "rez_esc"
```

```
[240]: income_test["rez_esc"] = income_test["rez_esc"].fillna(income_test["rez_esc"].
         ↪mean())
```

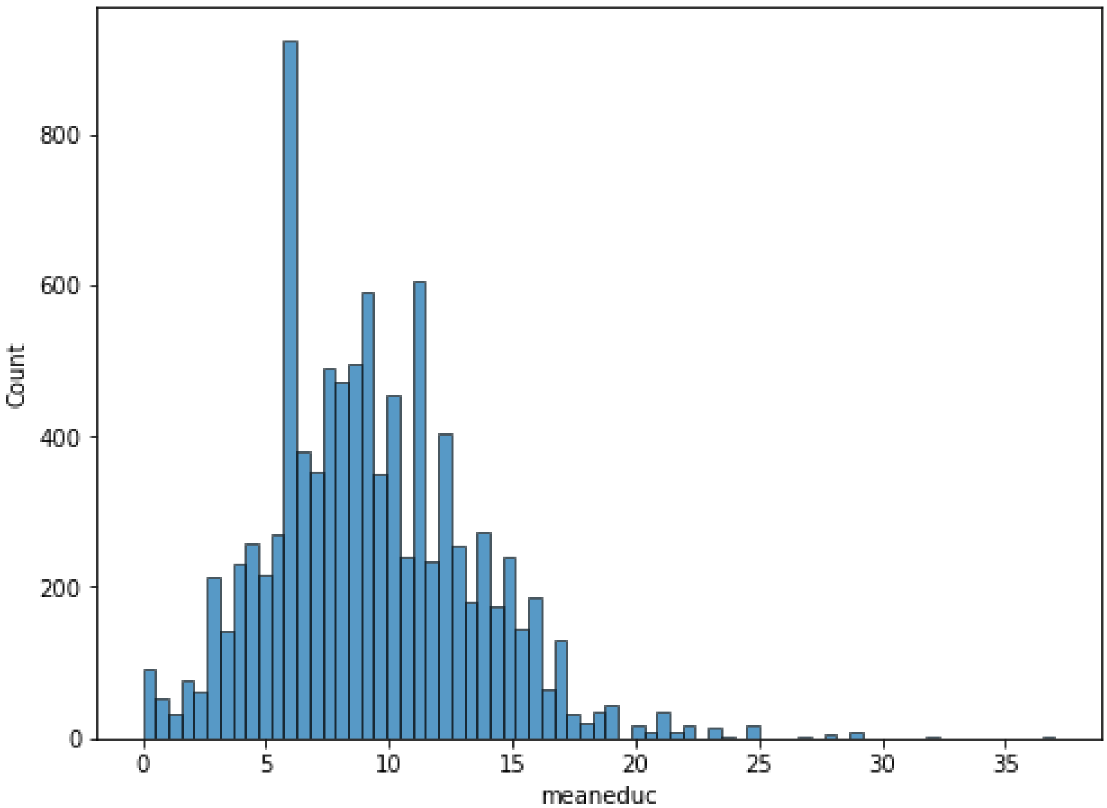
```
[241]: income_test["rez_esc"].isnull().sum()
```

[241]: 0

```
[242]: # meaneduc : average years of education for adults (18+)
```

```
[243]: # As there are Only 5% Values are Missing here, we can fill them with Mean or␣
         ↪Median of Variable.
```

```
[244]: plt.figure(figsize= (8,6))
       sns.histplot(income_train["meaneduc"])
       plt.show()
```



[245]:
```
income_train["meaneduc"].describe()
```

[245]:
```
count    9552.000000
mean        9.231523
std         4.167694
min         0.000000
25%         6.000000
50%         9.000000
75%        11.600000
max        37.000000
Name: meaneduc, dtype: float64
```

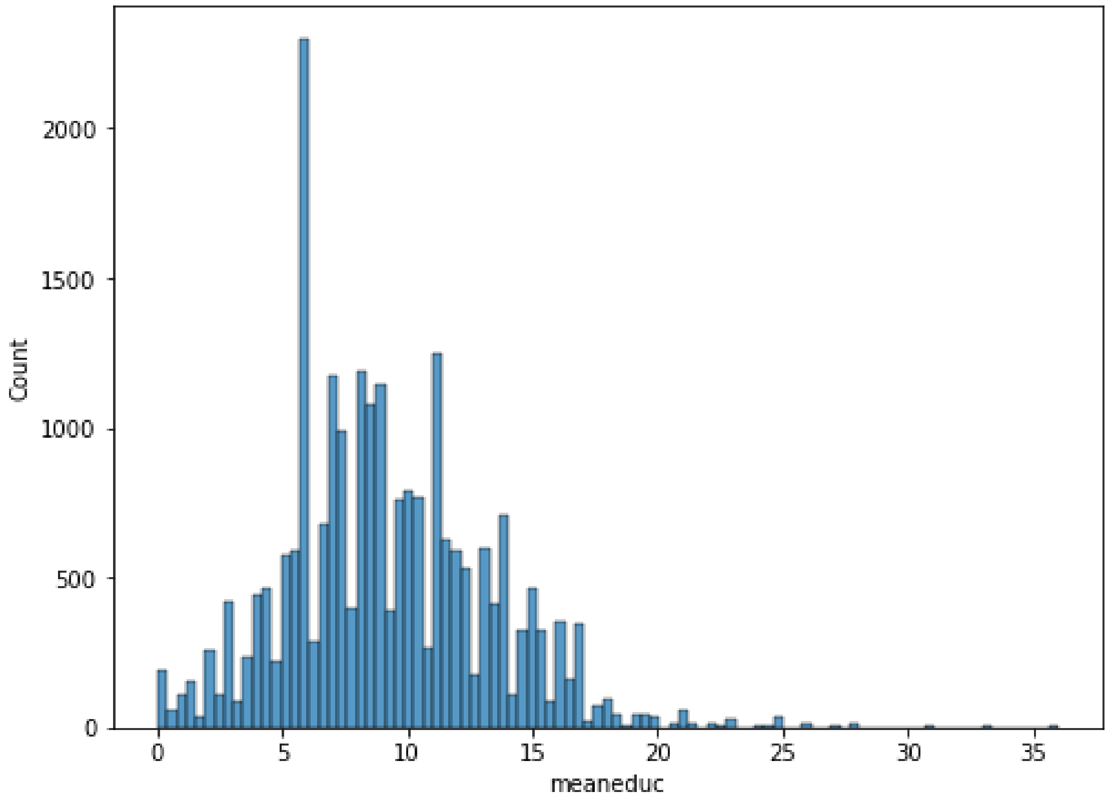
[246]:
```
# As Distribution is Mostly Normal except some Outliers, We will fill Missing␣
↪Values with Mean.
```

[247]:
```
income_train["meaneduc"] = income_train["meaneduc"].
↪fillna(income_train["meaneduc"].mean())
```

[ ]:
```

```

[248]:
```
# Doing Same Steps for Test Data
```

[249]:
```
plt.figure(figsize= (8,6))
sns.histplot(income_test["meaneduc"])
plt.show()
```



[250]:
```
income_test["meaneduc"].describe()
```

[250]:
```
count    23825.000000
mean         9.157474
std          4.080513
min          0.000000
25%          6.000000
50%          8.666667
75%         11.500000
max         36.000000
Name: meaneduc, dtype: float64
```

[251]:
```
# As Distribution is Mostly Normal except some Outliers, We will fill Missing␣
↪Values with Mean.
```

[252]:
```
income_test["meaneduc"] = income_test["meaneduc"].
↪fillna(income_test["meaneduc"].mean())
```

[253]:
```
income_train["meaneduc"].isna().sum()
```

[253]:
```
0
```

[254]:
```
income_test["meaneduc"].isna().sum()
```

[254]:
```
0
```

[ ]:
```

```

9) Remove null value rows of the target variable:

[255]:
```
income_train["Target"].isnull().sum()
```

[255]:
```
0
```

[256]:
```
# No Null Values in Target Variable.
```

[ ]:
```

```

10) Train Test Split:

[257]:
```
income_train.shape
```

[257]:
```
(9557, 109)
```

[258]:
```
# Features:

x= income_train.drop("Target", axis= 1)
```

[259]:
```
# Target:

y= income_train["Target"]
```

[ ]:
```

```

[260]:
```
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size= 0.2,␣
↪random_state= 42)
```

[261]:
```
print(x_train.shape)
print(x_test.shape)
print(y_train.shape)
print(y_test.shape)
```

```
(7645, 108)
(1912, 108)
(7645,)
(1912,)
```

[ ]:
```

```

11) Scalling:

[262]:
```
# We have to Scale Both Train and Test Data, as Test Data Needs to be in Same␣
↪Format as Train Data that was Used to Build
# The Model.
```

[263]:
```
sc = StandardScaler()
```

[ ]:
```

```

[264]:
```
# Scalling Train Data (x_train, x_test):
```

[265]:
```
temp = sc.fit_transform(x_train)
```

[266]:
```
x_train = pd.DataFrame(temp, index= x_train.index, columns= x_train.columns)
x_train.head()
```

[266]:
```
                 v2a1    hacdor     rooms   hacapo      v14a    refrig  \
Id
ID_cf18611af -0.436006 -0.201397 -0.654642 -0.15878  0.072524  0.210372
ID_759fc51f0  1.972360 -0.201397 -0.654642 -0.15878  0.072524  0.210372
ID_77e2d94b3 -0.436006 -0.201397  0.026090 -0.15878  0.072524  0.210372
ID_d83a6bf88  0.912679 -0.201397 -0.654642 -0.15878  0.072524  0.210372
ID_e6548451e  1.134249 -0.201397  0.706821 -0.15878  0.072524  0.210372

                 v18q     v18q1      r4h1      r4h2  …  mobilephone  \
Id                                                   …
ID_cf18611af -0.544245 -0.461845 -0.571774 -1.505326  …      0.15704
ID_759fc51f0 -0.544245 -0.461845 -0.571774 -0.543020  …      0.15704
ID_77e2d94b3  1.837409  0.974025 -0.571774  0.419286  …      0.15704
ID_d83a6bf88 -0.544245 -0.461845  0.885782 -0.543020  …      0.15704
ID_e6548451e -0.544245 -0.461845 -0.571774  1.381592  …      0.15704

             qmobilephone    lugar1    lugar2    lugar3    lugar4    lugar5  \
Id
ID_cf18611af      0.113060 -1.191667 -0.317727 -0.257387 -0.301232 -0.322693
ID_759fc51f0     -0.562210  0.839161 -0.317727 -0.257387 -0.301232 -0.322693
ID_77e2d94b3      0.788331  0.839161 -0.317727 -0.257387 -0.301232 -0.322693
ID_d83a6bf88      0.113060  0.839161 -0.317727 -0.257387 -0.301232 -0.322693
ID_e6548451e      0.788331 -1.191667 -0.317727 -0.257387 -0.301232 -0.322693

               lugar6     area1       age
Id
ID_cf18611af  3.348501  0.636250 -0.802546
ID_759fc51f0 -0.298641  0.636250 -0.201338
ID_77e2d94b3 -0.298641  0.636250 -0.663806
ID_d83a6bf88 -0.298641  0.636250  0.076142
ID_e6548451e  3.348501 -1.571709 -0.432572
```

```
[5 rows x 108 columns]
```

[ ]:

[267]:
```
temp = sc.transform(x_test)
x_test = pd.DataFrame(temp, index= x_test.index, columns= x_test.columns)
x_test.head()
```

[267]:
```
                  v2a1    hacdor     rooms   hacapo      v14a    refrig  \
Id
ID_17e173eb0 -0.436006 -0.201397 -0.654642 -0.15878  0.072524  0.210372
ID_38b872bd6 -0.436006 -0.201397 -0.654642 -0.15878  0.072524  0.210372
ID_39fd34f13 -0.436006 -0.201397 -0.654642 -0.15878  0.072524  0.210372
ID_90edd74c3 -0.436006 -0.201397  0.026090 -0.15878  0.072524  0.210372
ID_c35a5a413 -0.436006 -0.201397  0.026090 -0.15878  0.072524  0.210372

                  v18q     v18q1      r4h1      r4h2  …  mobilephone  \
Id                                                    …
ID_17e173eb0 -0.544245 -0.461845 -0.571774 -1.505326  …      0.15704
ID_38b872bd6 -0.544245 -0.461845 -0.571774  0.419286  …      0.15704
ID_39fd34f13 -0.544245 -0.461845  0.885782  0.419286  …      0.15704
ID_90edd74c3 -0.544245 -0.461845  0.885782 -0.543020  …      0.15704
ID_c35a5a413 -0.544245 -0.461845  0.885782 -0.543020  …      0.15704

              qmobilephone    lugar1    lugar2    lugar3    lugar4    lugar5  \
Id
ID_17e173eb0     -1.237481 -1.191667 -0.317727 -0.257387 -0.301232  3.098924
ID_38b872bd6     -0.562210 -1.191667 -0.317727 -0.257387  3.319705 -0.322693
ID_39fd34f13     -1.237481 -1.191667 -0.317727 -0.257387 -0.301232 -0.322693
ID_90edd74c3     -0.562210 -1.191667 -0.317727 -0.257387 -0.301232  3.098924
ID_c35a5a413     -0.562210 -1.191667 -0.317727 -0.257387  3.319705 -0.322693

                lugar6     area1       age
Id
ID_17e173eb0 -0.298641 -1.571709  1.186065
ID_38b872bd6 -0.298641 -1.571709 -0.571313
ID_39fd34f13  3.348501 -1.571709 -1.172521
ID_90edd74c3 -0.298641 -1.571709  0.446117
ID_c35a5a413 -0.298641 -1.571709 -1.126274

[5 rows x 108 columns]
```

[ ]:

[268]:
```
# Scalling Test Data (income_test):
```

[269]:
```
temp = sc.transform(income_test)
income_test = pd.DataFrame(temp, index= income_test.index, columns= income_test.
 ↪columns)
income_test.head()
```

[269]:
```
                  v2a1    hacdor     rooms   hacapo      v14a    refrig  \
Id
ID_2f6873615 -0.436006 -0.201397  0.026090 -0.15878  0.072524  0.210372
ID_1c78846d2 -0.436006 -0.201397  0.026090 -0.15878  0.072524  0.210372
ID_e5442cf6a -0.436006 -0.201397  0.026090 -0.15878  0.072524  0.210372
ID_a8db26a79 -0.436006 -0.201397  6.152677 -0.15878  0.072524  0.210372
ID_a62966799  1.249850 -0.201397 -0.654642 -0.15878  0.072524  0.210372

                  v18q     v18q1      r4h1      r4h2  …  mobilephone  \
Id                                                   …
ID_2f6873615 -0.544245 -0.461845  0.885782 -0.543020  …      0.15704
ID_1c78846d2 -0.544245 -0.461845  0.885782 -0.543020  …      0.15704
ID_e5442cf6a -0.544245 -0.461845  0.885782 -0.543020  …      0.15704
ID_a8db26a79  1.837409  0.974025 -0.571774 -0.543020  …      0.15704
ID_a62966799  1.837409  0.974025 -0.571774 -1.505326  …      0.15704

              qmobilephone    lugar1    lugar2    lugar3    lugar4    lugar5  \
Id
ID_2f6873615     -0.562210  0.839161 -0.317727 -0.257387 -0.301232 -0.322693
ID_1c78846d2     -0.562210  0.839161 -0.317727 -0.257387 -0.301232 -0.322693
ID_e5442cf6a     -0.562210  0.839161 -0.317727 -0.257387 -0.301232 -0.322693
ID_a8db26a79     -0.562210  0.839161 -0.317727 -0.257387 -0.301232 -0.322693
ID_a62966799     -1.237481  0.839161 -0.317727 -0.257387 -0.301232 -0.322693

                lugar6    area1       age
Id
ID_2f6873615 -0.298641  0.63625 -1.403755
ID_1c78846d2 -0.298641  0.63625  0.307376
ID_e5442cf6a -0.298641  0.63625  0.307376
ID_a8db26a79 -0.298641  0.63625  1.139818
ID_a62966799 -0.298641  0.63625 -0.756300

[5 rows x 108 columns]
```

[ ]:
```

```

12) Over Sampling:

[270]:
```
# As our Target Variable has Class Imbalance, We will Use Over Sampling to␣
 ↪Tackle that.
```

https://imbalanced-learn.org/stable/references/generated/imblearn.over_sampling.SMOTE.html

[271]:
```
sm = SMOTE()
```

[272]:
```
x_train_sm, y_train_sm = sm.fit_resample(x_train, y_train)
```

[273]:
```
print(x_train_sm.shape)
print(y_train_sm.shape)
```

```
(19280, 108)
(19280,)
```

[ ]:
```

```

13) Random Forest Classifier:

[274]:
```
RFC_Model = RandomForestClassifier(n_estimators= 100, n_jobs= -1)
```

[275]:
```
RFC_Model.fit(x_train_sm, y_train_sm)
```

[275]:
```
RandomForestClassifier(n_jobs=-1)
```

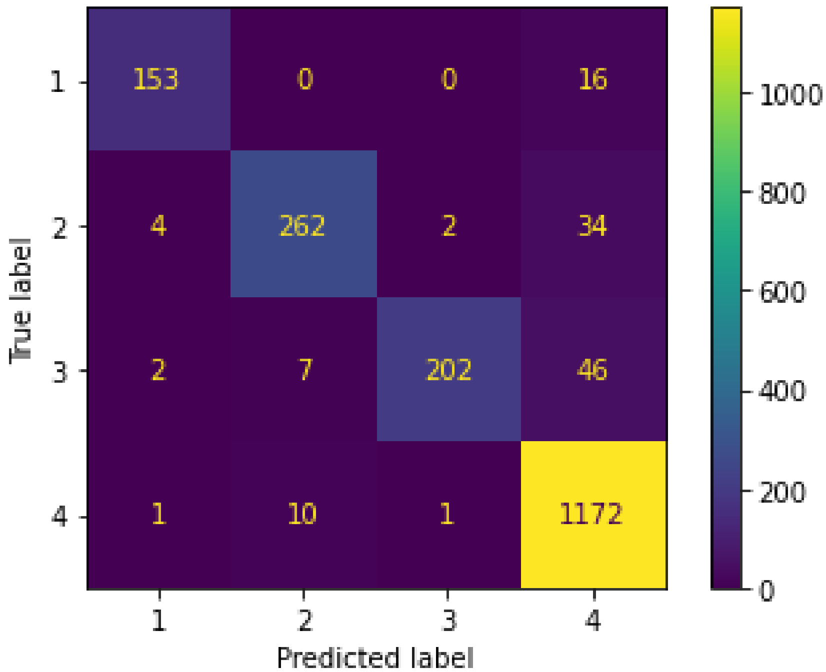
[276]:
```
pred = RFC_Model.predict(x_test)
```

[277]:
```
print(classification_report(y_test, pred))
```

```
              precision    recall  f1-score   support

           1       0.96      0.91      0.93       169
           2       0.94      0.87      0.90       302
           3       0.99      0.79      0.87       257
           4       0.92      0.99      0.96      1184

    accuracy                           0.94      1912
   macro avg       0.95      0.89      0.92      1912
weighted avg       0.94      0.94      0.93      1912
```

[278]:
```
plt.figure(figsize= (8,6))
plot_confusion_matrix(RFC_Model, x_test, y_test)
plt.show()
```

```
<Figure size 576x432 with 0 Axes>
```



[279]:

```
print(classification_report(y_test, pred))
```

```
              precision    recall  f1-score   support

           1       0.96      0.91      0.93       169
           2       0.94      0.87      0.90       302
           3       0.99      0.79      0.87       257
           4       0.92      0.99      0.96      1184

    accuracy                           0.94      1912
   macro avg       0.95      0.89      0.92      1912
weighted avg       0.94      0.94      0.93      1912
```

[ ]:

```

```

14) Check the accuracy using random forest with cross validation:

[280]:

```
# For Cross Validation, we will use full training data (not x_train and␣
↪y_train):

# For that, first we will have to Scale x and y as we did scalling only after␣
↪train test split.

# We will also need to Apply Oversampling on x and y after Scalling.
```

[281]:
```
x.head()
```

[281]:
```
                  v2a1  hacdor  rooms  hacapo  v14a  refrig  v18q  v18q1  \
Id
ID_279628684  190000.0       0      3       0     1       1     0    0.0
ID_f29eb3ddd  135000.0       0      4       0     1       1     1    1.0
ID_68de51c94       0.0       0      8       0     1       1     0    0.0
ID_d671db89c  180000.0       0      5       0     1       1     1    1.0
ID_d56d6f5f5  180000.0       0      5       0     1       1     1    1.0

              r4h1  r4h2  …  mobilephone  qmobilephone  lugar1  lugar2  \
Id                        …
ID_279628684     0     1  …            1             1       1       0
ID_f29eb3ddd     0     1  …            1             1       1       0
ID_68de51c94     0     0  …            0             0       1       0
ID_d671db89c     0     2  …            1             3       1       0
ID_d56d6f5f5     0     2  …            1             3       1       0

              lugar3  lugar4  lugar5  lugar6  area1  age
Id
ID_279628684       0       0       0       0      1   43
ID_f29eb3ddd       0       0       0       0      1   67
ID_68de51c94       0       0       0       0      1   92
ID_d671db89c       0       0       0       0      1   17
ID_d56d6f5f5       0       0       0       0      1   37

[5 rows x 108 columns]
```

[282]:
```
y.head()
```

[282]:
```
Id
ID_279628684    4
ID_f29eb3ddd    4
ID_68de51c94    4
ID_d671db89c    4
ID_d56d6f5f5    4
Name: Target, dtype: int64
```

[283]:
```
x.shape
```

[283]:
```
(9557, 108)
```

[284]:
```
y.shape
```

[284]:
```
(9557,)
```

[ ]:
```

```

[285]:
```
# Scalling x:
```

[286]:
```
sc1 = StandardScaler()
```

[287]:
```
temp = sc1.fit_transform(x)
x = pd.DataFrame(temp, index= x.index, columns= x.columns)
x.head()
```

[287]:
```
                   v2a1    hacdor     rooms    hacapo      v14a    refrig  \
Id
ID_279628684  1.313389 -0.198986 -1.331829 -0.155629  0.072521  0.210363
ID_f29eb3ddd  0.809548 -0.198986 -0.650771 -0.155629  0.072521  0.210363
ID_68de51c94 -0.427153 -0.198986  2.073460 -0.155629  0.072521  0.210363
ID_d671db89c  1.221781 -0.198986  0.030287 -0.155629  0.072521  0.210363
ID_d56d6f5f5  1.221781 -0.198986  0.030287 -0.155629  0.072521  0.210363

                   v18q     v18q1      r4h1      r4h2  …  mobilephone  \
Id                                                     …
ID_279628684 -0.549262 -0.466827 -0.566874 -0.539470  …     0.159120
ID_f29eb3ddd  1.820624  0.967727 -0.566874 -0.539470  …     0.159120
ID_68de51c94 -0.549262 -0.466827 -0.566874 -1.504237  …    -6.284565
ID_d671db89c  1.820624  0.967727 -0.566874  0.425297  …     0.159120
ID_d56d6f5f5  1.820624  0.967727 -0.566874  0.425297  …     0.159120

              qmobilephone    lugar1    lugar2    lugar3    lugar4    lugar5  \
Id
ID_279628684     -1.228106  0.837702 -0.319656 -0.257896 -0.300391 -0.321838
ID_f29eb3ddd     -1.228106  0.837702 -0.319656 -0.257896 -0.300391 -0.321838
ID_68de51c94     -1.902337  0.837702 -0.319656 -0.257896 -0.300391 -0.321838
ID_d671db89c      0.120356  0.837702 -0.319656 -0.257896 -0.300391 -0.321838
ID_d56d6f5f5      0.120356  0.837702 -0.319656 -0.257896 -0.300391 -0.321838

                 lugar6     area1       age
Id
ID_279628684 -0.296232  0.632039  0.402406
ID_f29eb3ddd -0.296232  0.632039  1.512945
ID_68de51c94 -0.296232  0.632039  2.669756
ID_d671db89c -0.296232  0.632039 -0.800678
ID_d56d6f5f5 -0.296232  0.632039  0.124771

[5 rows x 108 columns]
```

[ ]:
```

```

[288]:
```
# Applying SMOTE on x and y for Over Sampling:
```

[289]:
```
sm1 = SMOTE()
```

[290]:
```
x_sm, y_sm = sm1.fit_resample(x, y)
```

[291]:
```
print(x_sm.shape)
print(y_sm.shape)
```

```
(24016, 108)
(24016,)
```

[ ]:

[292]:
```
# Cross Validation On Random Forest Classifier:
```

[293]:
```
# Note: No need to perform Train Test Split for Cross Validation.
```

[294]:
```
cr_validate = cross_validate(RFC_Model, x_sm, y_sm, cv= 10)
```

[295]:
```
type(cr_validate)
```

[295]:
```
dict
```

[296]:
```
cr_validate.keys()
```

[296]:
```
dict_keys(['fit_time', 'score_time', 'test_score'])
```

[297]:
```
cr_validate
```

[297]:
```
{'fit_time': array([4.18234634, 1.86416841, 1.80156803, 1.83198905, 1.72789645,
        1.70344281, 1.7218492 , 1.6490531 , 1.62656355, 1.6830225 ]),
 'score_time': array([0.05090141, 0.04388213, 0.06224084, 0.06655192, 0.036901
,
        0.041888  , 0.04061532, 0.0594027 , 0.0502274 , 0.05304337]),
 'test_score': array([0.90840966, 0.93838468, 0.97085762, 0.96294754,
0.97918401,
        0.9683597 , 0.95210329, 0.9396085 , 0.91253644, 0.89046231])}
```

[298]:
```
# We have 10 Test Scores in result as we did 10 fold cross validation using␣
↪cv=10.

# So, we can simply take Average of all Test Scores to find Average Accuracy of␣
↪Cross Validation on Random Forest.
```

[299]:
```
cr_validate["test_score"].mean()
```

[299]:
```
0.9422853751264478
```

[300]:
```
# We are Getting 94.42% Accuracy, which is good unough to Use Model on New␣
↪Unseen Data (Test file Data) to make Predictions.
```

[ ]:

15) Making Predictions on Test Data:

[301]:
```
# As we have Maniputed The Original Test Data (Unseen Data), Let's Load it␣
↪Again.
```

[302]:
```
Unseen_Data = pd.read_csv("test.csv")
```

[303]:
```
Unseen_Data.head()
```

[303]:
```
             Id      v2a1  hacdor  rooms  hacapo  v14a  refrig  v18q  v18q1  \
0  ID_2f6873615       NaN       0      5       0     1       1     0    NaN
1  ID_1c78846d2       NaN       0      5       0     1       1     0    NaN
2  ID_e5442cf6a       NaN       0      5       0     1       1     0    NaN
3  ID_a8db26a79       NaN       0     14       0     1       1     1    1.0
4  ID_a62966799  175000.0       0      4       0     1       1     1    1.0

   r4h1  …  age  SQBescolari  SQBage  SQBhogar_total  SQBedjefe  \
0     1  …    4            0      16               9          0
1     1  …   41          256    1681               9          0
2     1  …   41          289    1681               9          0
3     0  …   59          256    3481               1        256
4     0  …   18          121     324               1          0

   SQBhogar_nin  SQBovercrowding  SQBdependency  SQBmeaned  agesq
0             1             2.25           0.25     272.25     16
1             1             2.25           0.25     272.25   1681
2             1             2.25           0.25     272.25   1681
3             0             1.00           0.00     256.00   3481
4             1             0.25          64.00        NaN    324

[5 rows x 142 columns]
```

[ ]:

[304]:
```
# Making Predictions on Test Data from "income_test" data frame which is in␣
↪same form as Training Data.
```

[305]:
```
income_test
```

[305]:
```
                  v2a1    hacdor     rooms    hacapo      v14a    refrig  \
Id
ID_2f6873615 -0.436006 -0.201397  0.026090 -0.158780  0.072524  0.210372
ID_1c78846d2 -0.436006 -0.201397  0.026090 -0.158780  0.072524  0.210372
ID_e5442cf6a -0.436006 -0.201397  0.026090 -0.158780  0.072524  0.210372
ID_a8db26a79 -0.436006 -0.201397  6.152677 -0.158780  0.072524  0.210372
ID_a62966799  1.249850 -0.201397 -0.654642 -0.158780  0.072524  0.210372
…                  …         …         …         …         …         …
ID_a065a7cad -0.436006  4.965316 -2.016106  6.298007  0.072524  0.210372
```

```
ID_1a7c6953b -0.436006 -0.201397 -1.335374 -0.158780  0.072524  0.210372
ID_07dbb4be2 -0.436006 -0.201397 -1.335374 -0.158780  0.072524  0.210372
ID_34d2ed046 -0.436006 -0.201397 -1.335374 -0.158780  0.072524  0.210372
ID_34754556f -0.436006 -0.201397 -1.335374 -0.158780  0.072524  0.210372

                 v18q     v18q1      r4h1      r4h2  …  mobilephone  \
Id                                                   …
ID_2f6873615 -0.544245 -0.461845  0.885782 -0.543020  …      0.15704
ID_1c78846d2 -0.544245 -0.461845  0.885782 -0.543020  …      0.15704
ID_e5442cf6a -0.544245 -0.461845  0.885782 -0.543020  …      0.15704
ID_a8db26a79  1.837409  0.974025 -0.571774 -0.543020  …      0.15704
ID_a62966799  1.837409  0.974025 -0.571774 -1.505326  …      0.15704
…                 …         …         …         …  …          …
ID_a065a7cad -0.544245 -0.461845 -0.571774  0.419286  …      0.15704
ID_1a7c6953b -0.544245 -0.461845 -0.571774 -0.543020  …      0.15704
ID_07dbb4be2 -0.544245 -0.461845 -0.571774 -0.543020  …      0.15704
ID_34d2ed046 -0.544245 -0.461845 -0.571774 -0.543020  …      0.15704
ID_34754556f -0.544245 -0.461845 -0.571774 -0.543020  …      0.15704

              qmobilephone    lugar1    lugar2    lugar3    lugar4    lugar5  \
Id
ID_2f6873615     -0.562210  0.839161 -0.317727 -0.257387 -0.301232 -0.322693
ID_1c78846d2     -0.562210  0.839161 -0.317727 -0.257387 -0.301232 -0.322693
ID_e5442cf6a     -0.562210  0.839161 -0.317727 -0.257387 -0.301232 -0.322693
ID_a8db26a79     -0.562210  0.839161 -0.317727 -0.257387 -0.301232 -0.322693
ID_a62966799     -1.237481  0.839161 -0.317727 -0.257387 -0.301232 -0.322693
…                      …         …         …         …         …         …
ID_a065a7cad     -1.237481 -1.191667 -0.317727 -0.257387 -0.301232 -0.322693
ID_1a7c6953b     -0.562210 -1.191667 -0.317727 -0.257387 -0.301232 -0.322693
ID_07dbb4be2     -0.562210 -1.191667 -0.317727 -0.257387 -0.301232 -0.322693
ID_34d2ed046     -0.562210 -1.191667 -0.317727 -0.257387 -0.301232 -0.322693
ID_34754556f     -0.562210 -1.191667 -0.317727 -0.257387 -0.301232 -0.322693

                lugar6     area1       age
Id
ID_2f6873615 -0.298641  0.636250 -1.403755
ID_1c78846d2 -0.298641  0.636250  0.307376
ID_e5442cf6a -0.298641  0.636250  0.307376
ID_a8db26a79 -0.298641  0.636250  1.139818
ID_a62966799 -0.298641  0.636250 -0.756300
…                 …         …         …
ID_a065a7cad  3.348501 -1.571709 -1.126274
ID_1a7c6953b  3.348501 -1.571709  0.908584
ID_07dbb4be2  3.348501 -1.571709 -1.033780
ID_34d2ed046  3.348501 -1.571709 -1.033780
ID_34754556f  3.348501 -1.571709  0.769844
```

```
[23856 rows x 108 columns]
```

[306]:
```
x_train_sm.shape
```

[306]:
```
(19280, 108)
```

[307]:
```
income_test.shape
```

[307]:
```
(23856, 108)
```

[308]:
```
test_pred = RFC_Model.predict(income_test)
```

[309]:
```
test_pred
```

[309]:
```
array([4, 4, 4, …, 4, 4, 2], dtype=int64)
```

[ ]:
```

```

[310]:
```
# Attaching Predictions as new column in original Unseen Data:
```

[311]:
```
Unseen_Data["Target"] = test_pred
```

[312]:
```
Unseen_Data.head()
```

[312]:
```
              Id      v2a1  hacdor  rooms  hacapo  v14a  refrig  v18q  v18q1  \
0  ID_2f6873615       NaN       0      5       0     1       1     0    NaN
1  ID_1c78846d2       NaN       0      5       0     1       1     0    NaN
2  ID_e5442cf6a       NaN       0      5       0     1       1     0    NaN
3  ID_a8db26a79       NaN       0     14       0     1       1     1    1.0
4  ID_a62966799  175000.0       0      4       0     1       1     1    1.0

   r4h1  …  SQBescolari  SQBage  SQBhogar_total  SQBedjefe  SQBhogar_nin  \
0     1  …            0      16               9          0             1
1     1  …          256    1681               9          0             1
2     1  …          289    1681               9          0             1
3     0  …          256    3481               1        256             0
4     0  …          121     324               1          0             1

   SQBovercrowding  SQBdependency  SQBmeaned  agesq  Target
0             2.25           0.25     272.25     16       4
1             2.25           0.25     272.25   1681       4
2             2.25           0.25     272.25   1681       4
3             1.00           0.00     256.00   3481       4
4             0.25          64.00        NaN    324       4

[5 rows x 143 columns]
```

[313]:
```
Unseen_Data["Target"].value_counts()
```

[313]:
```
4    18290
2     3672
1     1126
3      768
Name: Target, dtype: int64
```

[ ]:

1.0.2 16) Writing Data with Predictions in Excel File:

[315]:
```
Unseen_Data.to_excel("Test With Predictions.xlsx", index= False)
```