Income Qualification

August 21, 2023

0.1 Problem Statement 2:

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:

Identify the output variable.

Understand the type of data.

Check if there are any biases in your dataset.

Check whether all members of the house have the same poverty level.

Check if there is a house without a family head.

Set poverty level of the members and the head of the house within a family.

Count how many null values are existing in columns.

Remove null value rows of the target variable.

Predict the accuracy using random forest classifier.

Check the accuracy using random forest with cross validation.

[1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline
```

```python
from sklearn import model_selection
```

[2]:
```python
Train_income= pd.read_csv('Train.csv')
Train_income.head()
```

[2]:
```
             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]
```

[3]:
```python
Test_income =pd.read_csv("Test.csv")
Test_income.head()
```

[3]:
```
             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]
```

0.1.1 let us find the shape, column,description of the train and test data

[4]:
```python
print("the train dataset is {}".format(Train_income.shape))
```

```
the train dataset is (9557, 143)
```

[5]:
```python
print("The test dataset is{}".format(Test_income.shape))
```

```
The test dataset is(23856, 142)
```

[6]:
```python
Train_income.columns
```

[6]:
```
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)
```

[7]:
```python
Test_income.columns
```

[7]:
```
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)
```

0.1.2 Identify the output variable.

[8]:
```python
Train_income.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
```

[9]:
```
for i in Train_income.columns:
    if i not in Test_income.columns:
        print("Our Target variable is {}".format(i))
```

```
Our Target variable is Target
```

0.2 Understand the type of data.

[10]:
```
Train_income.dtypes
```

[10]:
```
Id                    object
v2a1                 float64
hacdor                 int64
rooms                  int64
hacapo                 int64
                      …
SQBovercrowding      float64
SQBdependency        float64
SQBmeaned            float64
agesq                  int64
Target                 int64
Length: 143, dtype: object
```

we can see from above it is not clear how many datatypes. let us count the number of exaclty datatypes.

[11]:
```
Train_income.dtypes.value_counts()
```

[11]:
```
int64      130
float64      8
object       5
dtype: int64
```

From above we can see that total 130 columns are int64 types, 8 columns float64 types and 5 columns are string form. list these columns with different datatypes.

[12]:
```
print("Integer type:",Train_income.select_dtypes(np.int64).columns)

print('\n')

print('Float Type:', Train_income.select_dtypes(np.float64).columns)
print('\n')
print('Object Type:',Train_income.select_dtypes(np.object).columns)
```

```
Integer type: Index(['hacdor', 'rooms', 'hacapo', 'v14a', 'refrig', 'v18q',
'r4h1', 'r4h2',
       'r4h3', 'r4m1',
```

```
 …
 'area1', 'area2', 'age', 'SQBescolari', 'SQBage', 'SQBhogar_total',
 'SQBedjefe', 'SQBhogar_nin', 'agesq', 'Target'],
dtype='object', length=130)


Float Type: Index(['v2a1', 'v18q1', 'rez_esc', 'meaneduc', 'overcrowding',
       'SQBovercrowding', 'SQBdependency', 'SQBmeaned'],
      dtype='object')


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

```
/usr/local/lib/python3.7/site-packages/ipykernel_launcher.py:7:
DeprecationWarning: `np.object` is a deprecated alias for the builtin `object`.
To silence this warning, use `object` by itself. Doing this will not modify any
behavior and is safe.
Deprecated in NumPy 1.20; for more details and guidance:
https://numpy.org/devdocs/release/1.20.0-notes.html#deprecations
  import sys
```

in the above we can see the categorical data.
ID =unique ID.

idhogar= household level identifier.

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).

edjefe= years of education of male head of household, based on the interaction of escolari (years of education), head of household and gender, yes=1 and no=0.

edjefa= years of education of female head of household, based on the interaction of escolari (years of education), head of household and gender, yes=1 and no=0.

In the above column we can see that ID has no impact on income qualification and also with the idhogar, hence we will drop these columns

[13]:
```python
print("Before dropping the columns", Train_income.shape)
Train_income =Train_income.drop(['Id'], axis=1)
print("After dropping the columns", Train_income.shape)
```

```
Before dropping the columns (9557, 143)
After dropping the columns (9557, 142)
```

0.2.1 Count How Many Null Values re existing in Columns.

[14]:
```python
Train_income.isna().sum()
```

[14]:
```
v2a1                6860
hacdor                 0
rooms                  0
hacapo                 0
v14a                   0
                    …
SQBovercrowding        0
SQBdependency          0
SQBmeaned              5
agesq                  0
Target                 0
Length: 142, dtype: int64
```

lets split to get the null values according to int64, float64,object types.

[15]:
```
# check the null values in int64 type data.
null_counts =Train_income.select_dtypes('int64').isnull().sum()

null_counts[null_counts>0]
```

[15]:
```
Series([], dtype: int64)
```

[16]:
```
# check the null values in object datatypes.
null_counts =Train_income.select_dtypes('object').isnull().sum()
null_counts
```

[16]:
```
idhogar       0
dependency    0
edjefe        0
edjefa        0
dtype: int64
```

[17]:
```
# check the null values in float type data.
null_counts =Train_income.select_dtypes('float64').isnull().sum()
null_counts
```

[17]:
```
v2a1                6860
v18q1               7342
rez_esc             7928
meaneduc               5
overcrowding           0
SQBovercrowding        0
SQBdependency          0
SQBmeaned              5
dtype: int64
```

we have seen that v2a1,v18q1,rez_esc,meaneduc,SQBmeaned has null values.

v2a1= Monthly rent payment.

v18q1= number of tablets household owns.

rez_esc= Years behind in school.

meaneduc= average years of education for adults (18+).

SQBmeaned= square of the mean years of education of adults (>=18) in the household.

Lets fill with 0 value. Lets look at v2a1 (total nulls: 6860) : Monthly rent payment

why the null values, Lets look at few rows with nulls in v2a1:

0.2.2 Columns related to Monthly rent payment

tipovivi1, =1 own and fully paid house tipovivi2, "=1 own, paying in installments" tipovivi3, =1 rented tipovivi4, =1 precarious tipovivi5, "=1 other(assigned, borrowed)"

[18]:
```
data =Train_income[Train_income['v2a1'].isnull()].head()
column=['tipovivi1','tipovivi2','tipovivi3','tipovivi4','tipovivi5']
data[column]
```

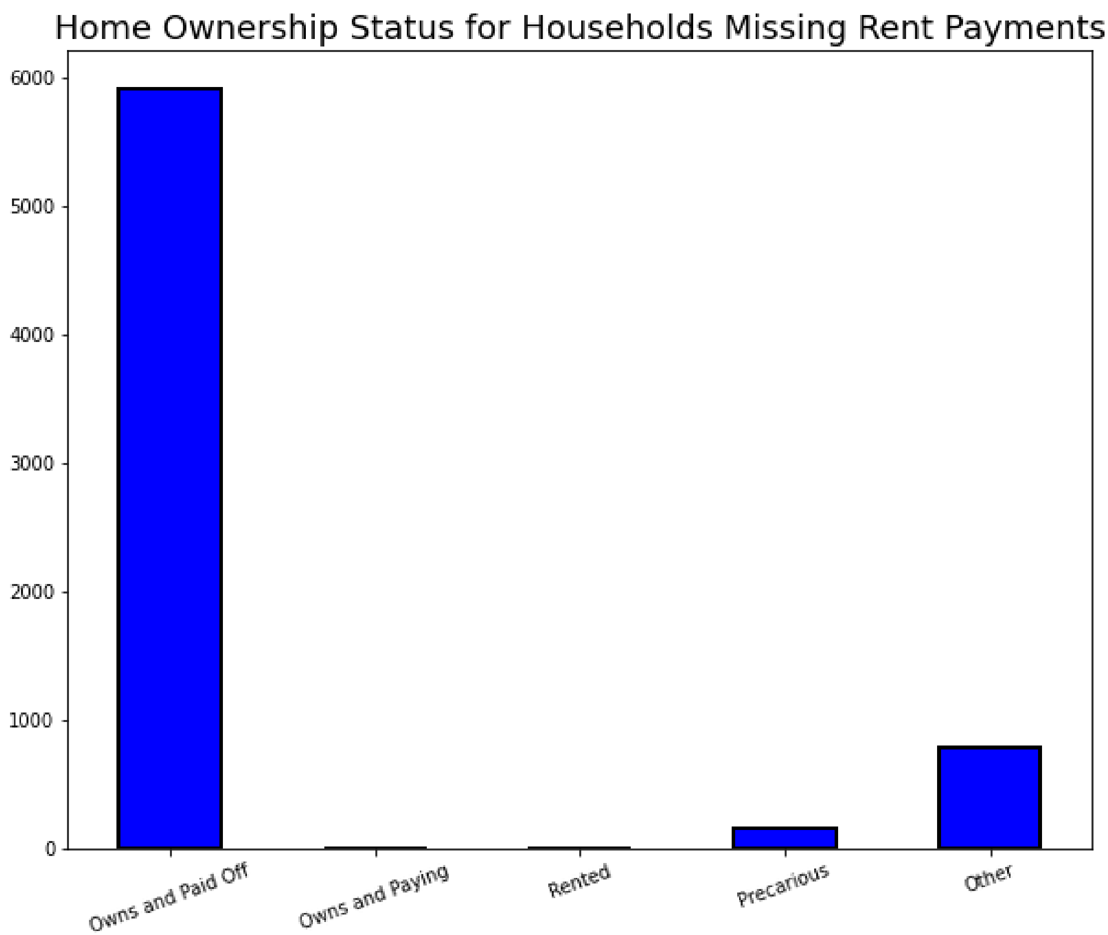
[18]:

	tipovivi1	tipovivi2	tipovivi3	tipovivi4	tipovivi5
2	1	0	0	0	0
13	1	0	0	0	0
14	1	0	0	0	0
26	1	0	0	0	0
32	1	0	0	0	0

0.3 let us plot the status for household that missing the payment (Nan Values)

[19]:
```
variable =[x for x in Train_income if x.startswith('tipo')]


# Plot of the home ownership variables for home missing rent payments
Train_income.loc[Train_income['v2a1'].isnull(),variable].sum().plot.
 ↪bar(figsize=(10,8),
                                                                              ␣
 ↪color='blue',edgecolor='k',linewidth=2);
plt.xticks([0, 1, 2, 3, 4],
           ['Owns and Paid Off', 'Owns and Paying', 'Rented', 'Precarious',␣
 ↪'Other'],
          rotation = 20)
plt.title('Home Ownership Status for Households Missing Rent Payments', size =␣
 ↪18);
```



we can clearly see that when the house is fully paid, there will be no monthly rent payment. Lets add 0 for all the null values. recheck the graph for any changes.

[20]:
```
for df in [Train_income, Test_income]:
    df['v2a1'].fillna(value=0, inplace= True)
```

[21]:
```
Train_income[['v2a1']].isnull().sum()
```

[21]:
```
v2a1    0
dtype: int64
```

[22]:
```
# test
Test_income[['v2a1']].isnull().sum()
```

[22]:
```
v2a1    0
dtype: int64
```

Lets look at v18q1 (total nulls: 7342) : number of tablets household owns why the null values,

Lets look at few rows with nulls in v18q1 Columns related to number of tablets household owns v18q, owns a tablet

Since this is a household variable, it only makes sense to look at it on a household level, so we'll only select the rows for the head of household.

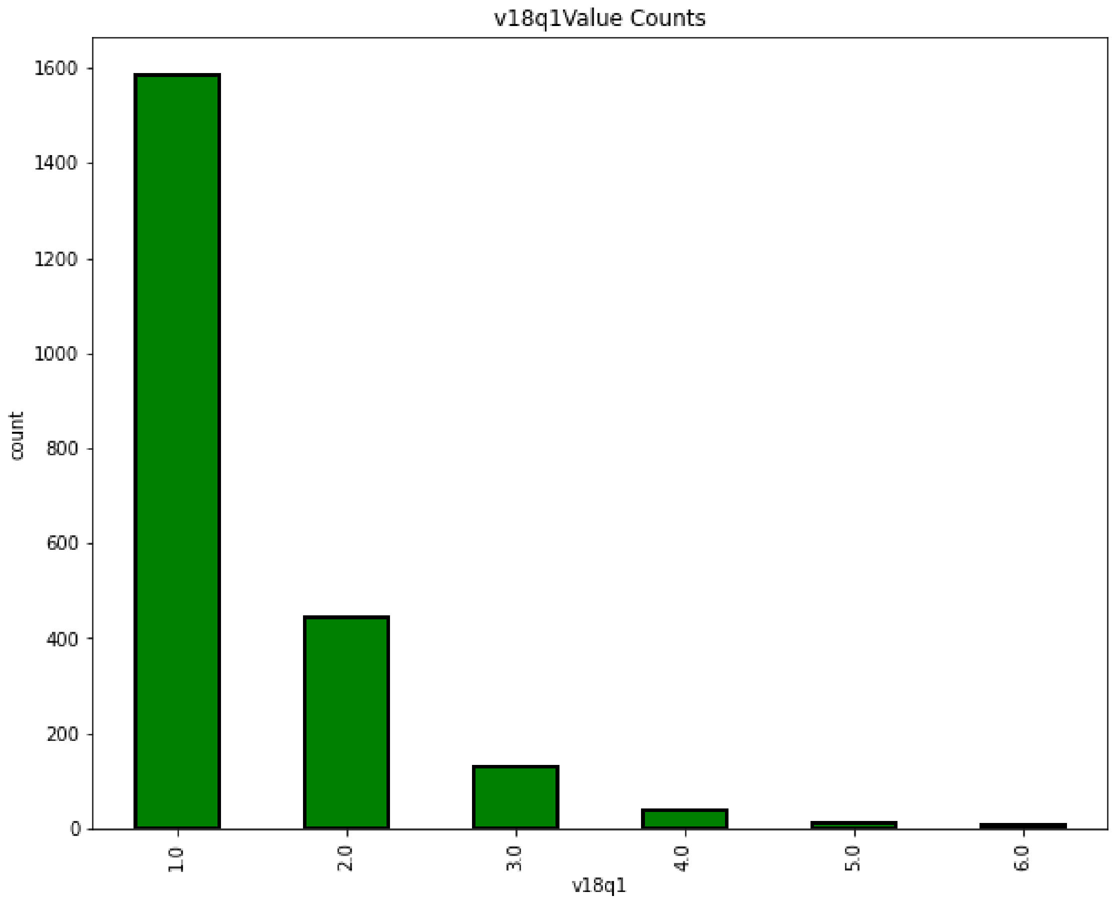
parentesco1, =1 if household head.

[23]:
```
head = Train_income.loc[Train_income['parentesco1']==1].copy()
```

[24]:
```
head.groupby('v18q1')['v18q'].apply(lambda x: x.isnull().sum())
```

[24]:
```
v18q1
1.0    0
2.0    0
3.0    0
4.0    0
5.0    0
6.0    0
Name: v18q, dtype: int64
```

[25]:
```
# lets plot the graph for more clear understanding
plt.figure(figsize=(10,8))
col='v18q1'
Train_income[col].value_counts().sort_index().plot.bar(color='green',
                                                        edgecolor='k',linewidth=2)
plt.xlabel('v18q1')
plt.ylabel('count')
plt.title(f'{col}Value Counts')
plt.show()
```



[26]:
```
# lets replace Nan values with   0.
for df in [Train_income, Test_income]:
    df['v18q1'].fillna(value=0, inplace= True)
```

[27]:
```
Train_income[['v18q1']].isnull().sum()
```

[27]:
```
v18q1    0
dtype: int64
```

[28]:
```
Test_income[['v18q1']].isnull().sum()
```

[28]:
```
v18q1    0
dtype: int64
```

1 lets do the same for rez_esc columns

Lets look at rez_esc (total nulls: 7928) : Years behind in school why the null values, Lets look at few rows with nulls in rez_esc Columns related to Years behind in school

age =Age in years

the strongest relation is between the columns age and rez_esc

[29]:
```
Train_income[Train_income['rez_esc'].notnull()]['age'].describe()
```

[29]:
```
count    1629.000000
mean       12.258441
std         3.218325
min         7.000000
25%         9.000000
50%        12.000000
75%        15.000000
max        17.000000
Name: age, dtype: float64
```

we can see that the minimum age is 7 years old and maximum age is 17, now we can rectify the null values and put zero values.

before filling the nan values lets find the age which is year behind the school

[30]:
```
Train_income.loc[(Train_income['rez_esc'].isnull()&
                  ((Train_income['age']>7)&(Train_income['age']<17)))]['age'].
 ↪describe()
```

[30]:
```
count     1.0
mean     10.0
std       NaN
min      10.0
25%      10.0
50%      10.0
75%      10.0
max      10.0
Name: age, dtype: float64
```

There is one value that has Null for the 'behind in school' column with age between 7 and 17 i.e year 10.

[31]:
```
Train_income[(Train_income['age']==10) &(Train_income['rez_esc'].isnull())].
 ↪head()
```

[31]:
```
          v2a1  hacdor  rooms  hacapo  v14a  refrig  v18q  v18q1  r4h1  r4h2  \
2514  160000.0       0      6       0     1       1     1    1.0     0     1
```

```
      …  SQBescolari  SQBage  SQBhogar_total  SQBedjefe  SQBhogar_nin  \
2514  …            0     100               9        121             1

      SQBovercrowding  SQBdependency  SQBmeaned  agesq  Target
2514             2.25           0.25     182.25    100       4

[1 rows x 142 columns]
```

lets fill with zero.

[32]:
```python
for df in [Train_income,Test_income]:
    df['rez_esc'].fillna(0, inplace =True)
```

[33]:
```python
Train_income[['rez_esc']].isnull().sum()
```

[33]:
```
rez_esc    0
dtype: int64
```

[34]:
```python
Test_income[['rez_esc']].isnull().sum()
```

[34]:
```
rez_esc    0
dtype: int64
```

2 Lets look at meaneduc (total nulls: 5) :

average years of education for adults (18+) why the null values, Lets look at few rows with nulls in meaneduc Columns related to average years of education for adults (18+)

edjefe, years of education of male head of household, based on the interaction of escolari (years of education), head of household and gender, yes=1 and no=0

edjefa, years of education of female head of household, based on the interaction of escolari (years of education), head of household and gender, yes=1 and no=0

instlevel1, =1 no level of education

instlevel2, =1 incomplete primary

[35]:
```python
data=Train_income[Train_income['meaneduc'].isnull()].head()
col=['edjefa','edjefe','instlevel1','instlevel2']
data[col][data[col]['instlevel1']>0].describe()
```

[35]:
```
       instlevel1  instlevel2
count         0.0         0.0
mean          NaN         NaN
std           NaN         NaN
min           NaN         NaN
```

```
25%            NaN          NaN
50%            NaN          NaN
75%            NaN          NaN
max            NaN          NaN
```

[36]:
```
for df in [Train_income,Test_income]:
    df['meaneduc'].fillna(np.mean (df['meaneduc']),inplace= True)
```

[37]:
```
Train_income[['meaneduc']].isnull().sum()
```

[37]:
```
meaneduc    0
dtype: int64
```

[38]:
```
Test_income[['meaneduc']].isnull().sum()
```

[38]:
```
meaneduc    0
dtype: int64
```

3 Lets look at SQBmeaned (total nulls: 5) :

square of the mean years of education of adults (>=18) in the household 142 why the null values, Lets look at few rows with nulls in SQBmeaned Columns related to average years of education for adults (18+) edjefe, years of education of male head of household, based on the interaction of escolari (years of education), head of household and gender, yes=1 and no=0 edjefa, years of education of female head of household, based on the interaction of escolari (years of education), head of household and gender, yes=1 and no=0 instlevel1, =1 no level of education instlevel2, =1 incomplete primary

[39]:
```
data = Train_income[Train_income['SQBmeaned'].isnull()].head()
col= ['edjefe','edjefa','instlevel1','instlevel2']
data[col][data[col]['instlevel1']>0].describe()
```

[39]:
```
       instlevel1  instlevel2
count         0.0         0.0
mean          NaN         NaN
std           NaN         NaN
min           NaN         NaN
25%           NaN         NaN
50%           NaN         NaN
75%           NaN         NaN
max           NaN         NaN
```

[40]:
```
for df in [Train_income,Test_income]:
    df['SQBmeaned'].fillna(np.mean(df['SQBmeaned']), inplace=True)
```

[41]:
```
Train_income['SQBmeaned'].isnull().sum()
```

[41]: 0

[42]:
```
Test_income['SQBmeaned'].isnull().sum()
```

[42]: 0

[43]:
```
null_count=Train_income.select_dtypes('float64').isnull().sum()
null_count.isna().sum()
```

[43]: 0

We finally sort the nan values for all the columns.

3.1 Check if there are any biases in your dataset.

[44]:
```
Train_income['dependency'].value_counts()
```

[44]:
```
yes           2192
no            1747
0.5           1497
2              730
1.5            713
0.33333334     598
0.66666669     487
8              378
0.25           260
3              236
4              100
0.75            98
0.2             90
0.40000001      84
1.3333334       84
2.5             77
5               24
1.25            18
0.80000001      18
3.5             18
2.25            13
0.71428573      12
1.75            11
1.2             11
0.22222222      11
0.83333331      11
0.2857143        9
```

```
0.60000002       8
1.6666666        8
6                7
0.16666667       7
Name: dependency, dtype: int64
```

we can see that in the above column bias datasets are avaliable, let us fix this mixed datasets.

[45]:
```python
Train_income['edjefe'].value_counts()
```

[45]:
```
no     3762
6      1845
11      751
9       486
3       307
15      285
8       257
7       234
5       222
14      208
17      202
2       194
4       137
16      134
yes     123
12      113
10      111
13      103
21       43
18       19
19       14
20        7
Name: edjefe, dtype: int64
```

[46]:
```python
Train_income['edjefa'].value_counts()
```

[46]:
```
no     6230
6       947
11      399
9       237
8       217
15      188
7       179
5       176
3       152
4       136
14      120
```

```
16       113
10        96
2         84
17        76
12        72
yes       69
13        52
21         5
19         4
18         3
20         2
Name: edjefa, dtype: int64
```

lets replace Yes nd NO with Binary 1 and 0 respectively.

[47]:
```
mapping={'yes':1,'no':0}

for df in [Train_income, Test_income]:
    df['dependency'] =df['dependency'].replace(mapping).astype(np.float64)
    df['edjefe'] =df['edjefe'].replace(mapping).astype(np.float64)
    df['edjefa'] =df['edjefa'].replace(mapping).astype(np.float64)

Train_income[['dependency','edjefe','edjefa']].describe()
```

[47]:

	dependency	edjefe	edjefa
count	9557.000000	9557.000000	9557.000000
mean	1.149550	5.096788	2.896830
std	1.605993	5.246513	4.612056
min	0.000000	0.000000	0.000000
25%	0.333333	0.000000	0.000000
50%	0.666667	6.000000	0.000000
75%	1.333333	9.000000	6.000000
max	8.000000	21.000000	21.000000

[48]:
```
def map(i):

    if i=='yes':
        return(float(1))
    elif i=='no':
        return(float(0))
    else:
        return(float(i))
```

[49]:
```
Train_income['dependency']=Train_income['dependency'].apply(map)
Train_income['edjefe'] =Train_income['edjefe'].apply(map)
Train_income['edjefa']=Train_income['edjefa'].apply(map)
```

[50]:
```
Train_income['dependency']
```

[50]:
```
0       0.00
1       8.00
2       8.00
3       1.00
4       1.00
        …
9552    0.25
9553    0.25
9554    0.25
9555    0.25
9556    0.25
Name: dependency, Length: 9557, dtype: float64
```

[51]:
```
Train_income.edjefe
```

[51]:
```
0       10.0
1       12.0
2        0.0
3       11.0
4       11.0
        …
9552     9.0
9553     9.0
9554     9.0
9555     9.0
9556     9.0
Name: edjefe, Length: 9557, dtype: float64
```

[52]:
```
Train_income.edjefa
```

[52]:
```
0        0.0
1        0.0
2       11.0
3        0.0
4        0.0
        …
9552     0.0
9553     0.0
9554     0.0
9555     0.0
9556     0.0
Name: edjefa, Length: 9557, dtype: float64
```

Similarly apply all for test data set :

[53]:
```
Test_income.dependency
```

[53]:
```
0        0.5
1        0.5
2        0.5
3        0.0
4        8.0
        …
23851    0.5
23852    1.0
23853    1.0
23854    1.0
23855    1.0
Name: dependency, Length: 23856, dtype: float64
```

[54]:
```
Test_income.edjefe
```

[54]:
```
0         0.0
1         0.0
2         0.0
3        16.0
4         0.0
         …
23851     5.0
23852     6.0
23853     6.0
23854     6.0
23855     6.0
Name: edjefe, Length: 23856, dtype: float64
```

[55]:
```
Test_income.edjefa
```

[55]:
```
0        17.0
1        17.0
2        17.0
3         0.0
4        11.0
         …
23851     0.0
23852     0.0
23853     0.0
23854     0.0
23855     0.0
Name: edjefa, Length: 23856, dtype: float64
```

3.2 Use the chi2_contingency to predict the accurate biases between the columns,

hence according to the data we have the region popultion grows and pverty declines consist of following linked columns: v2a1 =monnthly rent payment

```
v18q1 Columns related to number of tablets household owns v18q, owns a tablet
r4h3 = total males head in the household

r4h3 = total females head in the household.
r4t3 = total persons in household

tamhog =size of household
tamviv =number of persons living in household
rez_esc = years behind in school

hhsize = household size
parentesco1 = 1 household head

idhogar = household level identifier

hogar_total= total individual in the household.

edejefa = years of education of male head of the household

edefe= years of education of female head of household

meaneduc = average years of education for adults +18

instlelvel1 =  no level of education

instlevel2 = incomplete primary
tipoviv1 = own, and fully paid use

tipoviv2 =own . paying in installment

tipoviv3= 1 rented

tipoviv4= 1 precarious
 tipoviv5= 1 other (assigned borrowed)

    area1= 1 zon urban

    area2 = 2 zona rural

    age = age in years
```

[56]:
```
import scipy
from scipy.stats import chi2_contingency
```

[57]:
```
# find the biases between v2a1(Monthly rent payment) and tipovivi1(fully paid␣
↪owned house)
contingency_tab = pd.crosstab(Train_income['v2a1'],Train_income['tipovivi1'] )
contingency_tab
```

[57]:
```
tipovivi1    0     1
v2a1
0.0        978  5911
12000.0      3     0
13000.0      4     0
14000.0      3     0
15000.0      3     0
…          …     …
770229.0     3     0
800000.0     4     0
855810.0    11     0
1000000.0    7     0
2353477.0    2     0

[157 rows x 2 columns]
```

[58]:
```
observed_values =contingency_tab.values
b =chi2_contingency(contingency_tab)
expected_values=b[3]
no_of_rows =len(contingency_tab.iloc[0:2,0])
no_of_col =len(contingency_tab.iloc[0,0:2])
df= (no_of_rows-1)*(no_of_col-1)
print("Degree of Freedom:",df)
```

```
Degree of Freedom: 1
```

[59]:
```
from scipy.stats import chi2
chi_square =sum([(o-e)**2./e for o,e in zip(observed_values,expected_values)])
chi_square_statistic =chi_square[0]+chi_square[1]
print("Chi_square_statistics", chi_square_statistic)
```

```
Chi_square_statistics 6000.61165967958
```

[60]:
```
# check for the critical value
alpha=0.05
critical_value =chi2.ppf(q=1-alpha,df=df)
print("critical values:",critical_value)
```

```
critical values: 3.841458820694124
```

[61]:
```
# find the p value for prediction the bias hypothesis
p_value=1-chi2.cdf(x=chi_square_statistic,df=df)
print("p value",p_value)
print("significance level:",alpha)
print("degree of freedom",df)
print("chi-square statistics",chi_square_statistic)
print("critical value",critical_value)
print("P value",p_value)
if chi_square_statistic>=critical_value:
    print("Reject H0,There is a relationship between 2 categorical variables")
else:
    print("Retain H0,There is no relationship between 2 categorical variables")

if p_value<=alpha:
    print("Reject H0,There is a relationship between 2 categorical variables")
else:
    print("Retain H0,There is no relationship between 2 categorical variables")
```

```
p value 0.0
significance level: 0.05
degree of freedom 1
chi-square statistics 6000.61165967958
critical value 3.841458820694124
P value 0.0
Reject H0,There is a relationship between 2 categorical variables
Reject H0,There is a relationship between 2 categorical variables
```

[62]:
```
# lets find the relationship between monthly rent
#v2a1 and tipovivi3 ,tipovivi2,tipovivi4 and tipovivi5
contingency_tab=pd.crosstab(Train_income['v2a1'],Train_income['tipovivi5'])
Observed_Values=contingency_tab.values
import scipy.stats
b=scipy.stats.chi2_contingency(contingency_tab)
Expected_Values = b[3]
no_of_rows=len(contingency_tab.iloc[0:2,0])
no_of_columns=len(contingency_tab.iloc[0,0:2])
df=(no_of_rows-1)*(no_of_columns-1)
print("Degree of Freedom:-",df)
from scipy.stats import chi2
chi_square=sum([(o-e)**2./e for o,e in zip(Observed_Values,Expected_Values)])
chi_square_statistic=chi_square[0]+chi_square[1]
print("chi-square statistic:-",chi_square_statistic)
alpha=0.05
critical_value=chi2.ppf(q=1-alpha,df=df)
print('critical_value:',critical_value)
p_value=1-chi2.cdf(x=chi_square_statistic,df=df)
print('p-value:',p_value)
```

```
print('Significance level: ',alpha)
print('Degree of Freedom: ',df)
print('chi-square statistic:',chi_square_statistic)
print('critical_value:',critical_value)
print('p-value:',p_value)
if chi_square_statistic>=critical_value:
    print("Reject H0,There is a relationship between 2 categorical variables")
else:
    print("Retain H0,There is no relationship between 2 categorical variables")

if p_value<=alpha:
    print("Reject H0,There is a relationship between 2 categorical variables")
else:
    print("Retain H0,There is no relationship between 2 categorical variables")
```

```
Degree of Freedom:- 1
chi-square statistic:- 331.6841063892792
critical_value: 3.841458820694124
p-value: 0.0
Significance level:  0.05
Degree of Freedom:  1
chi-square statistic: 331.6841063892792
critical_value: 3.841458820694124
p-value: 0.0
Reject H0,There is a relationship between 2 categorical variables
Reject H0,There is a relationship between 2 categorical variables
```

we have seen that v2a1 and tipovivi1,tipovivi2,tipovivi3 has a relationship which shows that it has a biased datasets.

[63]:
```
 # lets find the relationship between parentesco1 = 1 household head,␣
 ↪hogar_total= total individual in the household,
#r4h3 = total males head in the household
#r4h3 = total females head in the household.
#r4t3 = total persons in household
#tamhog =size of household
#tamviv =number of persons living in household

contingency_tab=pd.crosstab(Train_income['r4t3'],Train_income['parentesco1'])
Observed_Values=contingency_tab.values
import scipy.stats
b=scipy.stats.chi2_contingency(contingency_tab)
Expected_Values = b[3]
no_of_rows=len(contingency_tab.iloc[0:2,0])
no_of_columns=len(contingency_tab.iloc[0,0:2])
df=(no_of_rows-1)*(no_of_columns-1)
print("Degree of Freedom:-",df)
from scipy.stats import chi2
```

```
chi_square=sum([(o-e)**2./e for o,e in zip(Observed_Values,Expected_Values)])
chi_square_statistic=chi_square[0]+chi_square[1]
print("chi-square statistic:-",chi_square_statistic)
alpha=0.05
critical_value=chi2.ppf(q=1-alpha,df=df)
print('critical_value:',critical_value)
p_value=1-chi2.cdf(x=chi_square_statistic,df=df)
print('p-value:',p_value)
print('Significance level: ',alpha)
print('Degree of Freedom: ',df)
print('chi-square statistic:',chi_square_statistic)
print('critical_value:',critical_value)
print('p-value:',p_value)
if chi_square_statistic>=critical_value:
    print("Reject H0,There is a relationship between 2 categorical variables")
else:
    print("Retain H0,There is no relationship between 2 categorical variables")

if p_value<=alpha:
    print("Reject H0,There is a relationship between 2 categorical variables")
else:
    print("Retain H0,There is no relationship between 2 categorical variables")
```

```
Degree of Freedom:- 1
chi-square statistic:- 1403.0430186768194
critical_value: 3.841458820694124
p-value: 0.0
Significance level:  0.05
Degree of Freedom:  1
chi-square statistic: 1403.0430186768194
critical_value: 3.841458820694124
p-value: 0.0
Reject H0,There is a relationship between 2 categorical variables
Reject H0,There is a relationship between 2 categorical variables
```

[64]:
```
# lets find the relationship between tablets column
#v18q1 Columns related to number of tablets household owns v18q, owns a tablet

contingency_tab=pd.crosstab(Train_income['v18q1'],Train_income['v18q'])
Observed_Values=contingency_tab.values
import scipy.stats
b=scipy.stats.chi2_contingency(contingency_tab)
Expected_Values = b[3]
no_of_rows=len(contingency_tab.iloc[0:2,0])
no_of_columns=len(contingency_tab.iloc[0,0:2])
df=(no_of_rows-1)*(no_of_columns-1)
print("Degree of Freedom:-",df)
```

```
from scipy.stats import chi2
chi_square=sum([(o-e)**2./e for o,e in zip(Observed_Values,Expected_Values)])
chi_square_statistic=chi_square[0]+chi_square[1]
print("chi-square statistic:-",chi_square_statistic)
alpha=0.05
critical_value=chi2.ppf(q=1-alpha,df=df)
print('critical_value:',critical_value)
p_value=1-chi2.cdf(x=chi_square_statistic,df=df)
print('p-value:',p_value)
print('Significance level: ',alpha)
print('Degree of Freedom: ',df)
print('chi-square statistic:',chi_square_statistic)
print('critical_value:',critical_value)
print('p-value:',p_value)
if chi_square_statistic>=critical_value:
    print("Reject H0,There is a relationship between 2 categorical variables")
else:
    print("Retain H0,There is no relationship between 2 categorical variables")

if p_value<=alpha:
    print("Reject H0,There is a relationship between 2 categorical variables")
else:
    print("Retain H0,There is no relationship between 2 categorical variables")
```

```
Degree of Freedom:- 1
chi-square statistic:- 9557.0
critical_value: 3.841458820694124
p-value: 0.0
Significance level:  0.05
Degree of Freedom:  1
chi-square statistic: 9557.0
critical_value: 3.841458820694124
p-value: 0.0
Reject H0,There is a relationship between 2 categorical variables
Reject H0,There is a relationship between 2 categorical variables
```

[65]:
```
# lets find the relationship between areas column
#area1= 1 zon urban ,area2 = 2 zona rural

contingency_tab=pd.crosstab(Train_income['area1'],Train_income['area2'])
Observed_Values=contingency_tab.values
import scipy.stats
b=scipy.stats.chi2_contingency(contingency_tab)
Expected_Values = b[3]
no_of_rows=len(contingency_tab.iloc[0:2,0])
no_of_columns=len(contingency_tab.iloc[0,0:2])
df=(no_of_rows-1)*(no_of_columns-1)
```

```
print("Degree of Freedom:-",df)
from scipy.stats import chi2
chi_square=sum([(o-e)**2./e for o,e in zip(Observed_Values,Expected_Values)])
chi_square_statistic=chi_square[0]+chi_square[1]
print("chi-square statistic:-",chi_square_statistic)
alpha=0.05
critical_value=chi2.ppf(q=1-alpha,df=df)
print('critical_value:',critical_value)
p_value=1-chi2.cdf(x=chi_square_statistic,df=df)
print('p-value:',p_value)
print('Significance level: ',alpha)
print('Degree of Freedom: ',df)
print('chi-square statistic:',chi_square_statistic)
print('critical_value:',critical_value)
print('p-value:',p_value)
if chi_square_statistic>=critical_value:
    print("Reject H0,There is a relationship between 2 categorical variables")
else:
    print("Retain H0,There is no relationship between 2 categorical variables")

if p_value<=alpha:
    print("Reject H0,There is a relationship between 2 categorical variables")
else:
    print("Retain H0,There is no relationship between 2 categorical variables")
```

```
Degree of Freedom:- 1
chi-square statistic:- 9557.0
critical_value: 3.841458820694124
p-value: 0.0
Significance level:  0.05
Degree of Freedom:  1
chi-square statistic: 9557.0
critical_value: 3.841458820694124
p-value: 0.0
Reject H0,There is a relationship between 2 categorical variables
Reject H0,There is a relationship between 2 categorical variables
```

[66]:
```
# lets find the relationship between years of education column
#edejefa = years of education of male head of the household
#edefe= years of education of female head of household
#rez_esc = years behind in school
#meaneduc = average years of education for adults +18
#instlevel1 =  no level of education
#instlevel2 = incomplete primary
#age = age in years

contingency_tab=pd.crosstab(Train_income['meaneduc'],Train_income['age'])
```

```python
Observed_Values=contingency_tab.values
import scipy.stats
b=scipy.stats.chi2_contingency(contingency_tab)
Expected_Values = b[3]
no_of_rows=len(contingency_tab.iloc[0:2,0])
no_of_columns=len(contingency_tab.iloc[0,0:2])
df=(no_of_rows-1)*(no_of_columns-1)
print("Degree of Freedom:-",df)
from scipy.stats import chi2
chi_square=sum([(o-e)**2./e for o,e in zip(Observed_Values,Expected_Values)])
chi_square_statistic=chi_square[0]+chi_square[1]
print("chi-square statistic:-",chi_square_statistic)
alpha=0.05
critical_value=chi2.ppf(q=1-alpha,df=df)
print('critical_value:',critical_value)
p_value=1-chi2.cdf(x=chi_square_statistic,df=df)
print('p-value:',p_value)
print('Significance level: ',alpha)
print('Degree of Freedom: ',df)
print('chi-square statistic:',chi_square_statistic)
print('critical_value:',critical_value)
print('p-value:',p_value)
if chi_square_statistic>=critical_value:
    print("Reject H0,There is a relationship between 2 categorical variables")
else:
    print("Retain H0,There is no relationship between 2 categorical variables")

if p_value<=alpha:
    print("Reject H0,There is a relationship between 2 categorical variables")
else:
    print("Retain H0,There is no relationship between 2 categorical variables")
```

```
Degree of Freedom:- 1
chi-square statistic:- 216.10450097295802
critical_value: 3.841458820694124
p-value: 0.0
Significance level:  0.05
Degree of Freedom:  1
chi-square statistic: 216.10450097295802
critical_value: 3.841458820694124
p-value: 0.0
Reject H0,There is a relationship between 2 categorical variables
Reject H0,There is a relationship between 2 categorical variables
```

from above we can see that there is a strong bias relatinship between the datasets, hence we will be required any one of the above for predicting the accuracy of model hence the columns we are choosing here to interprate the data accurately, are as follows: v2a1,v18q1,area1,edjefa,edjefe,age,meanedu,r4t3.

3.2.1 lets check the variance values.

[67]:
```
Train_income_var =Train_income.var()[Train_income.var()==0].index.values
Train_income_var
```

[67]:
```
array(['elimbasu5'], dtype=object)
```

[68]:
```
Train_income['elimbasu5'].var()
```

[68]:
```
0.0
```

we have seen that the variablity of elimbasu5 is zero as all values are same therefore we can drop the column for better prediction.

[69]:
```
Train_income.shape
```

[69]:
```
(9557, 142)
```

[70]:
```
Train_income =Train_income.drop('elimbasu5',axis=1)
Train_income.shape
```

[70]:
```
(9557, 141)
```

3.3 Check whether all the members of the house have the same poverty level.

The columns responsible for checking the members of the household have the same poverty level are:
tamhog =size of household tamviv =number of persons living in household hhsize = household size parentesco1 = 1 household head

idhogar = household level identifier

hogar_total= total individual in the household.

edejefa = years of education of male head of the household

edefe= years of education of female head of household

meaneduc = average years of education for adults +18

instlelvel1 = no level of education

instlevel2 = incomplete primary tipoviv2 =own . paying in installment

tipoviv3= 1 rented

area1= 1 zon urban

area2 = 2 zona rural Target

these are the columns that can help to predict the poverty level.

```python
[71]: all_value_equal =Train_income.groupby('idhogar')['Target'].apply(lambda x: x.
       ↪nunique()==1 )

      not_equal =all_value_equal[all_value_equal!=True]
      print('There are {} housholds where the family members do not have same poverty␣
       ↪level /target'.format(len(not_equal)))
```

```
There are 85 housholds where the family members do not have same poverty level
/target
```

3.4 Check if there is a house without a family head.

here we will be using parentesco1 and idhogar column

```python
[72]: household_head = Train_income.groupby('idhogar')['parentesco1'].sum().
       ↪value_counts()
      household_head.head()
```

```
[72]: 1    2973
      0      15
      Name: parentesco1, dtype: int64
```

```python
[73]: Train_income.parentesco1.value_counts()
```

```
[73]: 0    6584
      1    2973
      Name: parentesco1, dtype: int64
```

```python
[74]: pd.crosstab(Train_income['edjefe'],Train_income['edjefa'])
```

```
[74]: edjefa   0.0   1.0   2.0   3.0   4.0   5.0   6.0   7.0   8.0   9.0  …  12.0  \
      edjefe                                                             …
      0.0      435    69    84   152   136   176   947   179   217   237  …    72
      1.0      123     0     0     0     0     0     0     0     0     0  …     0
      2.0      194     0     0     0     0     0     0     0     0     0  …     0
      3.0      307     0     0     0     0     0     0     0     0     0  …     0
      4.0      137     0     0     0     0     0     0     0     0     0  …     0
      5.0      222     0     0     0     0     0     0     0     0     0  …     0
      6.0     1845     0     0     0     0     0     0     0     0     0  …     0
      7.0      234     0     0     0     0     0     0     0     0     0  …     0
      8.0      257     0     0     0     0     0     0     0     0     0  …     0
      9.0      486     0     0     0     0     0     0     0     0     0  …     0
      10.0     111     0     0     0     0     0     0     0     0     0  …     0
      11.0     751     0     0     0     0     0     0     0     0     0  …     0
      12.0     113     0     0     0     0     0     0     0     0     0  …     0
      13.0     103     0     0     0     0     0     0     0     0     0  …     0
      14.0     208     0     0     0     0     0     0     0     0     0  …     0
```

```
15.0      285    0    0    0    0    0    0    0    0    0  ...    0
16.0      134    0    0    0    0    0    0    0    0    0  ...    0
17.0      202    0    0    0    0    0    0    0    0    0  ...    0
18.0       19    0    0    0    0    0    0    0    0    0  ...    0
19.0       14    0    0    0    0    0    0    0    0    0  ...    0
20.0        7    0    0    0    0    0    0    0    0    0  ...    0
21.0       43    0    0    0    0    0    0    0    0    0  ...    0

edjefa  13.0  14.0  15.0  16.0  17.0  18.0  19.0  20.0  21.0
edjefe
0.0       52   120   188   113    76     3     4     2     5
1.0        0     0     0     0     0     0     0     0     0
2.0        0     0     0     0     0     0     0     0     0
3.0        0     0     0     0     0     0     0     0     0
4.0        0     0     0     0     0     0     0     0     0
5.0        0     0     0     0     0     0     0     0     0
6.0        0     0     0     0     0     0     0     0     0
7.0        0     0     0     0     0     0     0     0     0
8.0        0     0     0     0     0     0     0     0     0
9.0        0     0     0     0     0     0     0     0     0
10.0       0     0     0     0     0     0     0     0     0
11.0       0     0     0     0     0     0     0     0     0
12.0       0     0     0     0     0     0     0     0     0
13.0       0     0     0     0     0     0     0     0     0
14.0       0     0     0     0     0     0     0     0     0
15.0       0     0     0     0     0     0     0     0     0
16.0       0     0     0     0     0     0     0     0     0
17.0       0     0     0     0     0     0     0     0     0
18.0       0     0     0     0     0     0     0     0     0
19.0       0     0     0     0     0     0     0     0     0
20.0       0     0     0     0     0     0     0     0     0
21.0       0     0     0     0     0     0     0     0     0

[22 rows x 22 columns]
```

interpretion: there are 435 household without heads as 0 males head and 0 female head.

lets find by unique function.

3.5 Set poverty level of the members and the head of the house within a family.

[75]:
```python
# lets find the rows who does not own the house but pays rent

poverty_level =Train_income[Train_income['v2a1']!=0]
poverty_level.shape
```

[75]: (2668, 141)

[76]:
```
# let groupby the v2a1 monthly rent pyment with the area1 and area2
Poverty_level= poverty_level.groupby('area1')['v2a1'].apply(np.median)
Poverty_level
```

[76]:
```
area1
0     80000.0
1    140000.0
Name: v2a1, dtype: float64
```

[77]:
```
Poverty_level =poverty_level.groupby('area2')['v2a1'].apply(np.median)
```

[78]:
```
Poverty_level
```

[78]:
```
area2
0    140000.0
1     80000.0
Name: v2a1, dtype: float64
```

we have seen that both data has rural and urban house whose rental status is between 80000 to 140000 lets put a condition to verify the status of poverty level

[79]:
```
def povert(x):
    if x<80000:
        return('Below poverty level')
    elif x>140000:
        return('Above Poverty Level')
    elif x<140000:
        return('Below poverty leve:Urban;Above Poverty Level:Rural')
```

[80]:
```
c = poverty_level['v2a1'].apply(povert)
```

[81]:
```
c.shape
```

[81]:
```
(2668,)
```

[82]:
```
Poverty_crosstab=pd.crosstab(c,poverty_level['area1'])
Poverty_crosstab
```

[82]:
```
area1                                                 0     1
v2a1
Above Poverty Level                                 139  1103
Below poverty leve:Urban;Above Poverty Level:Rural   98   663
Below poverty level                                 208   418
```

Interpretation:

There are total 1242 people above poverty level independent of area whether rural or Urban

Remaining are the people level depends on their area Rural :

Above poverty level= 139+98+208=445

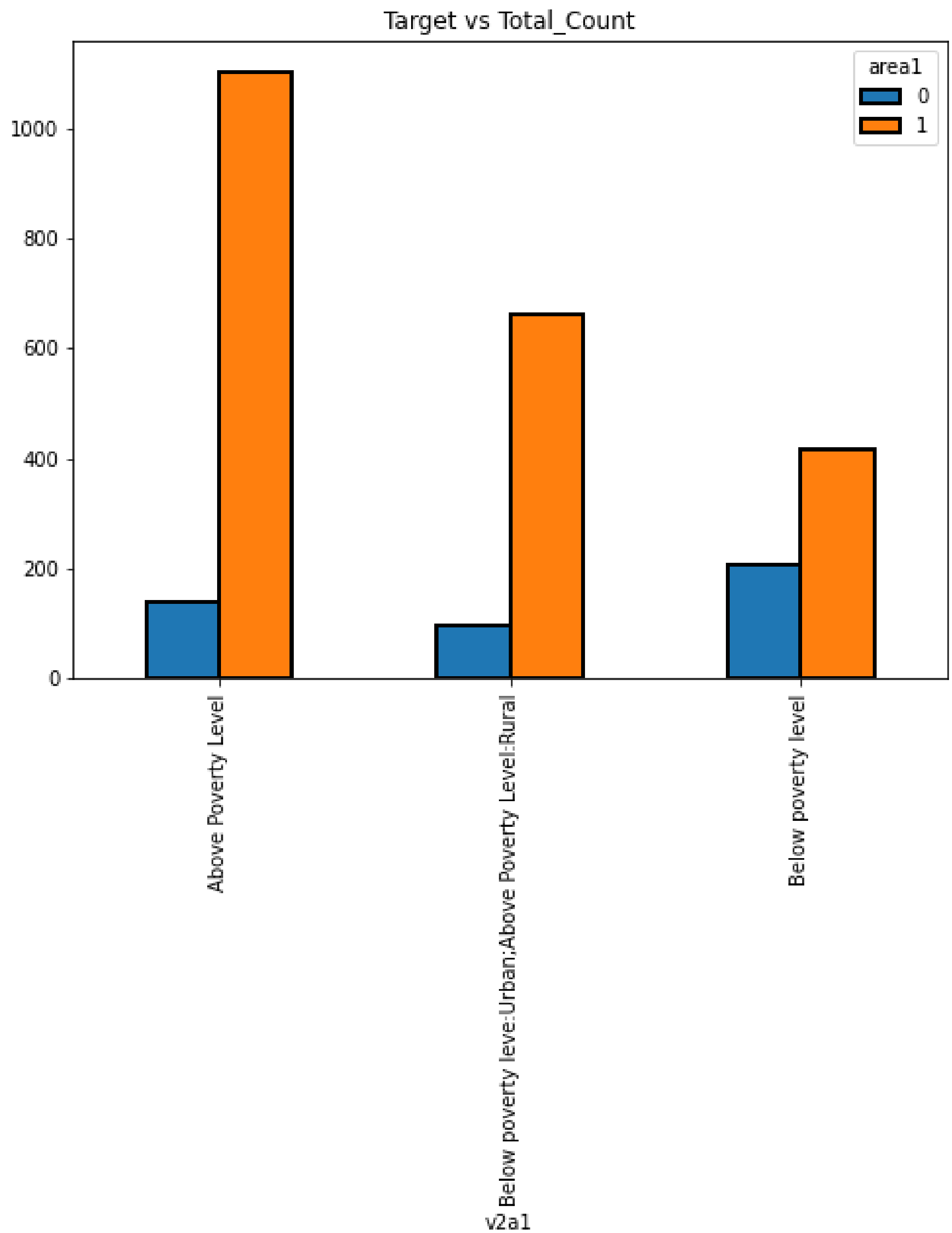
Urban :

Above poverty level =1103

Below poverty level= 663+418= 1081

[83]:
```
Poverty_crosstab.plot.bar(figsize = (8, 6),linewidth = 2,edgecolor =␣
↪'k',title="Target vs Total_Count")
```

[83]:
```
<AxesSubplot:title={'center':'Target vs Total_Count'}, xlabel='v2a1'>
```



Target vs Total_Count
area1
0
1
1000
800
600
400
200
0
Above Poverty Level
Below poverty leve:Urban;Above Poverty Level:Rural
Below poverty level
v2a1

4 Remove the null values rows of the target values

[84]:
```
Train_income['Target'].isna().sum()
```

[84]: 0

4.0.1 remove unwanted columns

[85]:
```
#lets remove the unwanted column and biased columns for better prediction.
null =Train_income.select_dtypes(np.int64).columns.sort_values()
null.value_counts()
```

[85]:
```
lugar5          1
parentesco2     1
escolari        1
pisonatur       1
parentesco6     1
               ..
pisoother       1
epared3         1
hogar_total     1
techocane       1
r4h2            1
Length: 129, dtype: int64
```

[86]:
```
#lets remove the unwanted column and biased columns for better prediction.
null =Train_income.select_dtypes(np.float64).columns
null.value_counts()
```

[86]:
```
SQBovercrowding    1
SQBmeaned          1
edjefa             1
overcrowding       1
SQBdependency      1
v18q1              1
meaneduc           1
edjefe             1
v2a1               1
rez_esc            1
dependency         1
dtype: int64
```

[87]:
```
#lets remove the unwanted column and biased columns for better prediction.
null =Train_income.select_dtypes(np.object).columns
null.value_counts()
```

```
/usr/local/lib/python3.7/site-packages/ipykernel_launcher.py:2:
DeprecationWarning: `np.object` is a deprecated alias for the builtin `object`.
To silence this warning, use `object` by itself. Doing this will not modify any
behavior and is safe.
Deprecated in NumPy 1.20; for more details and guidance:
https://numpy.org/devdocs/release/1.20.0-notes.html#deprecations
```

[87]:
```
idhogar    1
dtype: int64
```

5 lets drop the columns that is not affecting the prediction,

here we can see idhogar is the indetity of household, area2 has both data of urban and rural and similarly area1 and both are biased so we can use one of these. similarly we can drop tipovivi4,tipovivi5,hogar_total

[88]:
```
print("Before dropping the column",Train_income.shape)
col=['area2','tipovivi5','tipovivi4','hogar_total','idhogar']
Train_income= Train_income.drop(col,axis=1)
print("After dropping the columns",Train_income.shape)
```

```
Before dropping the column (9557, 141)
After dropping the columns (9557, 136)
```

[89]:
```
# Similarly we can do for Test_income dataset
print("Before dropping the column",Test_income.shape)
col=['Id','area2','tipovivi5','tipovivi4','hogar_total','idhogar']
Test_income= Test_income.drop(col,axis=1)
print("After dropping the columns",Test_income.shape)
```

```
Before dropping the column (23856, 142)
After dropping the columns (23856, 136)
```

[90]:
```
null_counts =Test_income.select_dtypes('int64').isnull().sum()

null_counts[null_counts>0]
```

[90]:
```
Series([], dtype: int64)
```

[91]:
```
null_counts =Test_income.select_dtypes('float64').isnull().sum()

null_counts[null_counts>0]
```

[91]:
```
Series([], dtype: int64)
```

[92]:
```
null_counts =Test_income.select_dtypes('object').isnull().sum()

null_counts[null_counts>0]
```

[92]:
```
Series([], dtype: float64)
```

All null values has been rectified in both train_income and test_income dataframe.

[ ]:
```

```

6 predict accuracy using random forest with cross validation

[93]:
```
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score
from sklearn.metrics import precision_score,f1_score,confusion_matrix
from sklearn.model_selection import train_test_split
from sklearn.model_selection import cross_val_score
```

[94]:
```
x = Train_income.drop('Target', axis=1)
y= Train_income.Target
```

[95]:
```
x.shape
```

[95]:
```
(9557, 135)
```

[96]:
```
x_data_col= x.columns
x_data_col
```

[96]:
```
Index(['v2a1', 'hacdor', 'rooms', 'hacapo', 'v14a', 'refrig', 'v18q', 'v18q1',
       'r4h1', 'r4h2',
       …
       'age', 'SQBescolari', 'SQBage', 'SQBhogar_total', 'SQBedjefe',
       'SQBhogar_nin', 'SQBovercrowding', 'SQBdependency', 'SQBmeaned',
       'agesq'],
      dtype='object', length=135)
```

[97]:
```
y.shape
```

[97]:
```
(9557,)
```

[98]:
```
from sklearn.preprocessing import StandardScaler
```

6.1 Apply the scaling process for better fit nd model prediction.

[99]:
```
scaler =StandardScaler()
```

[100]:
```
x= scaler.fit_transform(x)
x
```

[100]:
```
array([[ 1.31338864, -0.19898579, -1.33182893, …, -0.31175397,
        -0.02769211,  0.11787088],
       [ 0.8095477 , -0.19898579, -0.65077114, …,  4.8036723 ,
         0.4429589 ,  1.63414851],
       [-0.42715279, -0.19898579,  2.07346003, …,  4.8036723 ,
         0.19693678,  3.91718016],
       …,
       [ 0.30570676, -0.19898579,  0.71134445, …, -0.30675844,
        -0.36931521,  0.49177116],
       [ 0.30570676, -0.19898579,  0.71134445, …, -0.30675844,
        -0.36931521, -0.55583883],
       [ 0.30570676, -0.19898579,  0.71134445, …, -0.30675844,
        -0.36931521, -0.69081052]])
```

[101]:
```
x_data =pd.DataFrame(x,columns=x_data_col)
x_data.head()
```

[101]:
```
       v2a1    hacdor     rooms    hacapo      v14a    refrig      v18q  \
0  1.313389 -0.198986 -1.331829 -0.155629  0.072521  0.210363 -0.549262
1  0.809548 -0.198986 -0.650771 -0.155629  0.072521  0.210363  1.820624
2 -0.427153 -0.198986  2.073460 -0.155629  0.072521  0.210363 -0.549262
3  1.221781 -0.198986  0.030287 -0.155629  0.072521  0.210363  1.820624
4  1.221781 -0.198986  0.030287 -0.155629  0.072521  0.210363  1.820624

      v18q1     r4h1     r4h2  …       age  SQBescolari    SQBage  \
0 -0.466827 -0.566874 -0.539470  …  0.402406     0.335757  0.117871
1  0.967727 -0.566874 -0.539470  …  1.512945     0.908871  1.634149
2 -0.466827 -0.566874 -1.504237  …  2.669756     0.609289  3.917180
3  0.967727 -0.566874  0.425297  … -0.800678     0.088276 -0.778111
4  0.967727 -0.566874  0.425297  …  0.124771     0.609289 -0.157816

   SQBhogar_total  SQBedjefe  SQBhogar_nin  SQBovercrowding  SQBdependency  \
0       -0.967066   0.592794     -0.553536        -0.544758      -0.311754
1       -0.967066   1.153720     -0.553536        -0.544758       4.803672
2       -0.967066  -0.682039     -0.553536        -0.726385       4.803672
3       -0.167084   0.860508      0.022340        -0.356403      -0.231825
4       -0.167084   0.860508      0.022340        -0.356403      -0.231825

   SQBmeaned     agesq
0  -0.027692  0.117871
```

```
1   0.442959  1.634149
2   0.196937  3.917180
3   0.196937 -0.778111
4   0.196937 -0.157816

[5 rows x 135 columns]
```

7 Lets Apply model prediction to train set.

[102]:
```
x_train,x_test,y_train,y_test =train_test_split(x_data,y,test_size=0.
↪3,random_state=0)
```

[103]:
```
print("x_train shape:",x_train.shape)
print("y_train shape:",y_train.shape)
print("x_test shape:",x_test.shape)
print("y_test shape:",y_test.shape)
```

```
x_train shape: (6689, 135)
y_train shape: (6689,)
x_test shape: (2868, 135)
y_test shape: (2868,)
```

7.1 lets apply gridSerchCV to find the best parameters for prediction.

[104]:
```
from sklearn.pipeline import Pipeline
from sklearn.model_selection import GridSearchCV
```

[105]:
```
RFC =RandomForestClassifier(random_state=0)
parameter ={'n_estimators':[10,50,100,300], 'max_depth':[5,10,15,25]}
grid=zip([RFC],[parameter])
best_= None
for i,j in grid:
    a=GridSearchCV(i,param_grid=j,cv=3,n_jobs=1)
    a.fit(x_train,y_train)
    if best_ is None:
        best_=a
print("Best CV score",best_.best_score_)
print("Model Parameter",best_.best_params_)
print("Best Estimators",best_.best_estimator_)
```

```
Best CV score 0.8560328218664015
Model Parameter {'max_depth': 25, 'n_estimators': 300}
Best Estimators RandomForestClassifier(max_depth=25, n_estimators=300,
random_state=0)
```

[106]:
```
RFC_1 =best_.best_estimator_
Model= RFC_1.fit(x_train,y_train)
Model
```

[106]:
```
RandomForestClassifier(max_depth=25, n_estimators=300, random_state=0)
```

[107]:
```
y_pred= RFC_1.predict(x_test)
y_pred
```

[107]:
```
array([4, 4, 4, …, 4, 4, 2])
```

[108]:
```
# lets check the model score
print('Model score of the train data:{}'.format(Model.score(x_train,y_train)))
print("Model Score of the test data:{}".format(Model.score(x_test,y_test)))
```

```
Model score of the train data:1.0
Model Score of the test data:0.902370990237099
```

[109]:
```
Accuracy= accuracy_score(y_pred,y_test)
print("Accuracy",Accuracy)
```

```
Accuracy 0.902370990237099
```

[110]:
```
f_1_score= f1_score(y_pred,y_test,average='weighted')
print("f1Score",f_1_score)
```

```
f1Score 0.9063750271389078
```

[111]:
```
confusion_matrix=confusion_matrix(y_pred,y_test)
print("Confusion_Matrix",confusion_matrix)
```

```
Confusion_Matrix [[ 162    7    1    1]
 [  20  398   12    4]
 [   0    6  280    6]
 [  50   80   93 1748]]
```

[112]:
```
Important_features=pd.DataFrame(Model.
 ↪feature_importances_,x_data_col,columns=['feature_importance'])
Important_features.head()
```

[112]:

	feature_importance
v2a1	0.014516
hacdor	0.001949
rooms	0.018838
hacapo	0.001235
v14a	0.000720

[113]:
```python
Top50Features=Important_features.
↪sort_values(by='feature_importance',ascending=False).head(50).index
Top50Features
```

[113]:
```
Index(['SQBmeaned', 'meaneduc', 'SQBdependency', 'dependency', 'overcrowding',
       'SQBovercrowding', 'qmobilephone', 'edjefe', 'SQBedjefe',
       'SQBhogar_nin', 'hogar_nin', 'agesq', 'rooms', 'SQBage', 'age', 'r4t1',
       'edjefa', 'escolari', 'r4h2', 'r4t2', 'r4h3', 'r4m3', 'SQBescolari',
       'cielorazo', 'v2a1', 'hogar_adul', 'tamviv', 'bedrooms', 'r4m2',
       'eviv3', 'epared3', 'pisomoscer', 'r4t3', 'SQBhogar_total', 'hhsize',
       'r4m1', 'paredblolad', 'tamhog', 'r4h1', 'etecho3', 'v18q1', 'lugar1',
       'energcocinar2', 'energcocinar3', 'area1', 'television', 'v18q',
       'tipovivi1', 'paredpreb', 'epared2'],
      dtype='object')
```

[114]:
```python
for i in Top50Features:
    if i not in x_data_col:
        print(i)
```

[115]:
```python
X_data_Top50=x_data[Top50Features]
X_data_Top50
```

[115]:
```
      SQBmeaned  meaneduc  SQBdependency  dependency  overcrowding  \
0     -0.027692  0.184447      -0.311754   -0.715826     -0.738356
1      0.442959  0.664479       4.803672    4.265778     -0.738356
2      0.196937  0.424463       4.803672    4.265778     -1.348184
3      0.196937  0.424463      -0.231825   -0.093125     -0.331804
4      0.196937  0.424463      -0.231825   -0.093125     -0.331804
…           …         …             …          …            …
9552  -0.369315 -0.235581      -0.306758   -0.560150     -0.433442
9553  -0.369315 -0.235581      -0.306758   -0.560150     -0.433442
9554  -0.369315 -0.235581      -0.306758   -0.560150     -0.433442
9555  -0.369315 -0.235581      -0.306758   -0.560150     -0.433442
9556  -0.369315 -0.235581      -0.306758   -0.560150     -0.433442

      SQBovercrowding  qmobilephone    edjefe  SQBedjefe  SQBhogar_nin  …  \
0           -0.544758     -1.228106  0.934615   0.592794     -0.553536  …
1           -0.544758     -1.228106  1.315840   1.153720     -0.553536  …
2           -0.726385     -1.902337 -0.971513  -0.682039     -0.553536  …
3           -0.356403      0.120356  1.125228   0.860508      0.022340  …
4           -0.356403      0.120356  1.125228   0.860508      0.022340  …
…                 …             …         …          …             …  …
9552        -0.408537      0.120356  0.744002   0.350576     -0.409567  …
9553        -0.408537      0.120356  0.744002   0.350576     -0.409567  …
9554        -0.408537      0.120356  0.744002   0.350576     -0.409567  …
9555        -0.408537      0.120356  0.744002   0.350576     -0.409567  …
9556        -0.408537      0.120356  0.744002   0.350576     -0.409567  …
```

```
         v18q1    lugar1  energcocinar2  energcocinar3     area1  television  \
0    -0.466827  0.837702      -0.979390       1.086952  0.632039   -0.630742
1     0.967727  0.837702       1.021044      -0.920004  0.632039   -0.630742
2    -0.466827  0.837702       1.021044      -0.920004  0.632039   -0.630742
3     0.967727  0.837702       1.021044      -0.920004  0.632039   -0.630742
4     0.967727  0.837702       1.021044      -0.920004  0.632039   -0.630742
…          …         …              …              …         …           …
9552 -0.466827 -1.193742      -0.979390       1.086952 -1.582182    1.585435
9553 -0.466827 -1.193742      -0.979390       1.086952 -1.582182    1.585435
9554 -0.466827 -1.193742      -0.979390       1.086952 -1.582182    1.585435
9555 -0.466827 -1.193742      -0.979390       1.086952 -1.582182    1.585435
9556 -0.466827 -1.193742      -0.979390       1.086952 -1.582182    1.585435

          v18q  tipovivi1  paredpreb   epared2
0    -0.549262  -1.273275  -0.481219  1.433294
1     1.820624  -1.273275  -0.481219  1.433294
2    -0.549262   0.785376  -0.481219  1.433294
3     1.820624  -1.273275  -0.481219 -0.697694
4     1.820624  -1.273275  -0.481219 -0.697694
…          …          …          …         …
9552 -0.549262  -1.273275  -0.481219  1.433294
9553 -0.549262  -1.273275  -0.481219  1.433294
9554 -0.549262  -1.273275  -0.481219  1.433294
9555 -0.549262  -1.273275  -0.481219  1.433294
9556 -0.549262  -1.273275  -0.481219  1.433294

[9557 rows x 50 columns]
```

[116]:
```
X_train,X_test,Y_train,Y_test=train_test_split(X_data_Top50,y,test_size=0.
↪25,random_state=0)
```

[117]:
```
print('X train',X_train.shape)
print('Ytrain',Y_train.shape)
print('X test',X_test.shape)
print('Y test',Y_test.shape)
```

```
X train (7167, 50)
Ytrain (7167,)
X test (2390, 50)
Y test (2390,)
```

[118]:
```
Model_1=RFC_1.fit(X_train,Y_train)

Model_1
```

[118]:
```
RandomForestClassifier(max_depth=25, n_estimators=300, random_state=0)
```

[119]:
```
pred = RFC_1.predict(X_test)
pred
```

[119]: array([4, 4, 4, …, 4, 2, 1])

[120]:
```
f1_score(Y_test,pred,average='weighted')
```

[120]: 0.9199220786804884

[121]:
```
accuracy_score(Y_test,pred)
```

[121]: 0.9221757322175732

8 Check the accuracy using random forest with cross validation.

[122]:
```
from sklearn.model_selection import KFold,cross_val_score
```

[123]:
```
seed=7
kfold=KFold(n_splits=5,random_state=7,shuffle=True)
print(cross_val_score(RFC_1,x,y,cv=kfold,scoring='accuracy'))
result=cross_val_score(RFC_1,x,y,cv=kfold,scoring='accuracy')
print(result*100)
```

```
[0.92259414 0.92520921 0.91941392 0.91208791 0.92150706]
[92.25941423 92.5209205  91.94139194 91.20879121 92.15070644]
```

[124]:
```
Test_income.drop(['tipovivi3','rez_esc','elimbasu5'],axis=1,inplace=True)
```

[125]:
```
test_data=Test_income[Top50Features]
```

[126]:
```
Test_data_1=scaler.fit_transform(test_data)
X_data_1=pd.DataFrame(Test_data_1)
```

[127]:
```
test_prediction=Model_1.predict(test_data)
```

[128]:
```
test_prediction
```

[128]: array([4, 4, 4, …, 3, 3, 3])

9 Interpretation :

Above is our prediction for test data.

10 Conclusion :

Using RandomForest Classifier we can predict test_data with accuracy of 90%

accuracy using random forest with cross validation 92%..

```
[ ]:
```