income-qualification

March 25, 2023

[1]:
```
import os
os.chdir('E:\Datasets\Machine-Learning--Projects-master\Projects\Projects for␣
↪Submission\Project 2 - Income Qualification')
```

[2]:
```
import warnings
warnings.filterwarnings('ignore')
```

0.0.1 Problem Statement Scenario:

Many social programs have a hard time making sure the right people are given enough aid. It's tricky when a program focuses on the poorest segment of the population. This segment of 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.

[3]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
```

[4]:
```
train=pd.read_csv('train.csv')
test=pd.read_csv('test.csv')
```

Let us explore our dataset before moving further

[5]:
```
print('Shape of train dataset is {}'.format(train.shape))
print('Shape of test dataset is {}'.format(test.shape))
```

```
Shape of train dataset is (9557, 143)
Shape of test dataset is (23856, 142)
```

0.0.2 Let us identify our target variable

[6]:
```
for i in train.columns:
    if i not in test.columns:
        print("Our Target variable is {}".format(i))
```

```
Our Target variable is Target
```

0.0.3 Lets Understand the type of data.

[7]:
```
print(train.dtypes.value_counts())
```

```
int64      130
float64      8
object       5
dtype: int64
```

[8]:
```
print(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
None
```

We have mixed data types. Specified as below:

- float64 : 8 variables
- int64 : 130 vriables
- object :5 variables

[9]:
```
#lets explore each different types of datasets
for i in train.columns:
    a=train[i].dtype
    if a == 'object':
        print(i)
```

```
Id
idhogar
dependency
edjefe
edjefa
```

Below is Data dictionary for above object variables * 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

[10]:
```
# lets drop Id variable.

train.drop(['Id','idhogar'],axis=1,inplace=True)
```

[11]:
```
train['dependency'].value_counts()
```

[11]:
```
yes          2192
no           1747
.5           1497
2             730
1.5           713
.33333334     598
.66666669     487
8             378
.25           260
3             236
4             100
.75            98
.2             90
1.3333334      84
.40000001      84
2.5            77
5              24
3.5            18
1.25           18
.80000001      18
2.25           13
.71428573      12
1.2            11
1.75           11
.22222222      11
.83333331      11
.2857143        9
1.6666666       8
.60000002       8
6               7
.16666667       7
Name: dependency, dtype: int64
```

Lets Convert object variables into numerical data.

[12]:
```
def map(i):

    if i=='yes':
        return(float(1))
```

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

[13]:
```
train['dependency']=train['dependency'].apply(map)
```

[14]:
```
for i in train.columns:
    a=train[i].dtype
    if a == 'object':
        print(i)
```

```
edjefe
edjefa
```

[15]:
```
train.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 9557 entries, 0 to 9556
Columns: 141 entries, v2a1 to Target
dtypes: float64(9), int64(130), object(2)
memory usage: 10.3+ MB
```

[16]:
```
train['edjefe']=train['edjefe'].apply(map)
train['edjefa']=train['edjefa'].apply(map)
```

[17]:
```
train.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 9557 entries, 0 to 9556
Columns: 141 entries, v2a1 to Target
dtypes: float64(11), int64(130)
memory usage: 10.3 MB
```

Now all data is in numerical form

Lets identify variable with 0 varinace

[18]:
```
var_df=pd.DataFrame(np.var(train,0),columns=['variance'])
var_df.sort_values(by='variance').head(15)
print('Below are columns with variance 0.')
col=list((var_df[var_df['variance']==0]).index)
print(col)
```

```
Below are columns with variance 0.
['elimbasu5']
```

elimbasu5 : 1 if rubbish disposal mainly by throwing in river, creek or sea.

Interpretation :***From above it is shown that all values of elimbasu5 is same so there is no variablity in dataset therefor we will drop this variable***

0.0.4 Check if there are any biases in your dataset.

[19]:
```
contingency_tab=pd.crosstab(train['r4t3'],train['hogar_total'])
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:- 17022.072400560897
critical_value: 3.841458820694124
p-value: 0.0
Significance level:  0.05
Degree of Freedom:  1
chi-square statistic: 17022.072400560897
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
```

Therefore,variables ('r4t3','hogar_total') have relationship between them. For good result we can use any one of them.

[20]:
```
contingency_tab=pd.crosstab(train['tipovivi3'],train['v2a1'])
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:- 54.04781105990782
critical_value: 3.841458820694124
p-value: 1.9562129693895258e-13
Significance level:  0.05
Degree of Freedom:  1
chi-square statistic: 54.04781105990782
critical_value: 3.841458820694124
p-value: 1.9562129693895258e-13
Reject H0,There is a relationship between 2 categorical variables
```

```
Reject H0,There is a relationship between 2 categorical variables
```

Therefore,variables ('tipovivi3','v2a1') have relationship between them. For good result we can use any one of them.

[21]:
```python
contingency_tab=pd.crosstab(train['v18q'],train['v18q1'])
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:- 0
chi-square statistic:- 0.0
critical_value: nan
p-value: nan
Significance level:  0.05
Degree of Freedom:  0
chi-square statistic: 0.0
critical_value: nan
p-value: nan
Retain H0,There is no relationship between 2 categorical variables
```

```
Retain H0,There is no relationship between 2 categorical variables
```

Therefore,variables ('v18q','v18q1') have relationship between them. For good result we can use any one of them.

Conclusion : ***Therefore, there is bias in our dataset.***

[22]:
```
train.drop('r4t3',axis=1,inplace=True)
```

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

"parentesco1" =1 if household head

[23]:
```
train.parentesco1.value_counts()
```

[23]:
```
0    6584
1    2973
Name: parentesco1, dtype: int64
```

[24]:
```
pd.crosstab(train['edjefa'],train['edjefe'])
```

[24]:
```
edjefe   0.0   1.0   2.0   3.0   4.0   5.0   6.0   7.0   8.0   9.0  …  12.0  \
edjefa                                                              …
0.0      435   123   194   307   137   222  1845   234   257   486  …   113
1.0       69     0     0     0     0     0     0     0     0     0  …     0
2.0       84     0     0     0     0     0     0     0     0     0  …     0
3.0      152     0     0     0     0     0     0     0     0     0  …     0
4.0      136     0     0     0     0     0     0     0     0     0  …     0
5.0      176     0     0     0     0     0     0     0     0     0  …     0
6.0      947     0     0     0     0     0     0     0     0     0  …     0
7.0      179     0     0     0     0     0     0     0     0     0  …     0
8.0      217     0     0     0     0     0     0     0     0     0  …     0
9.0      237     0     0     0     0     0     0     0     0     0  …     0
10.0      96     0     0     0     0     0     0     0     0     0  …     0
11.0     399     0     0     0     0     0     0     0     0     0  …     0
12.0      72     0     0     0     0     0     0     0     0     0  …     0
13.0      52     0     0     0     0     0     0     0     0     0  …     0
14.0     120     0     0     0     0     0     0     0     0     0  …     0
15.0     188     0     0     0     0     0     0     0     0     0  …     0
16.0     113     0     0     0     0     0     0     0     0     0  …     0
17.0      76     0     0     0     0     0     0     0     0     0  …     0
18.0       3     0     0     0     0     0     0     0     0     0  …     0
19.0       4     0     0     0     0     0     0     0     0     0  …     0
20.0       2     0     0     0     0     0     0     0     0     0  …     0
21.0       5     0     0     0     0     0     0     0     0     0  …     0

edjefe  13.0  14.0  15.0  16.0  17.0  18.0  19.0  20.0  21.0
edjefa
0.0      103   208   285   134   202    19    14     7    43
```

```
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]
```

Interpretation : ***Above cross tab shows 0 male head and 0 female head which implies that there are 435 families with no family head.***

0.0.6 Count how many null values are existing in columns.

[25]:
```
train.isna().sum().value_counts()
```

[25]:
```
0       135
5         2
7928      1
6860      1
7342      1
dtype: int64
```

Lets Identify number of null values in Target variable

[26]:
```
train['Target'].isna().sum()
```

[26]:
```
0
```

Interpretation : **There are no null values in Target variable. Now lets proceed further and identify and fillna of other variable.**

[27]:
```
float_col=[]
for i in train.columns:
    a=train[i].dtype
    if a == 'float64':
        float_col.append(i)
print(float_col)
```

```
['v2a1', 'v18q1', 'rez_esc', 'dependency', 'edjefe', 'edjefa', 'meaneduc',
'overcrowding', 'SQBovercrowding', 'SQBdependency', 'SQBmeaned']
```

[28]:
```
train[float_col].isna().sum()
```

[28]:
```
v2a1               6860
v18q1              7342
rez_esc            7928
dependency            0
edjefe                0
edjefa                0
meaneduc              5
overcrowding          0
SQBovercrowding       0
SQBdependency         0
SQBmeaned             5
dtype: int64
```

[29]:
```
train['v18q1'].value_counts()
```

[29]:
```
1.0    1586
2.0     444
3.0     129
4.0      37
5.0      13
6.0       6
Name: v18q1, dtype: int64
```

[30]:
```
pd.crosstab(train['tipovivi1'],train['v2a1'])
```

[30]:
```
v2a1       0.0        12000.0    13000.0    14000.0    15000.0    16000.0    \
tipovivi1
0                 29          3          4          3          3          2

v2a1       17000.0    20000.0    23000.0    25000.0    …  570540.0   \
tipovivi1                                              …
0                  4         22          5         21  …         25

v2a1       600000.0   620000.0   684648.0   700000.0   770229.0   800000.0   \
tipovivi1
```

```
0                  11          3          3          7          3          4

v2a1       855810.0   1000000.0  2353477.0
tipovivi1
0                  11          7          2

[1 rows x 157 columns]
```

[31]:
```
pd.crosstab(train['v18q1'],train['v18q'])
```

[31]:
```
v18q      1
v18q1
1.0    1586
2.0     444
3.0     129
4.0      37
5.0      13
6.0       6
```

Interpretation and action : ***'v2a1', 'v18q1', 'rez_esc' have more than 50% null values, because for v18q1, there are families with their own house so they won't pay rent in that case it should be 0 and similar is for v18q1 there can be families with 0 tablets.***

Istead we can drop a column tipovivi3,v18q

- tipovivi3, =1 rented
- v18q, owns a tablet

as v2a1 alone can show both **as v18q1 alone can show that if respondent owns a tablet or not

[32]:
```
train['v2a1'].fillna(0,inplace=True)
train['v18q1'].fillna(0,inplace=True)
```

[33]:
```
train.drop(['tipovivi3', 'v18q','rez_esc','elimbasu5'],axis=1,inplace=True)
```

[34]:
```
train['meaneduc'].fillna(np.mean(train['meaneduc']),inplace=True)
train['SQBmeaned'].fillna(np.mean(train['SQBmeaned']),inplace=True)
print(train.isna().sum().value_counts())
```

```
0    136
dtype: int64
```

[35]:
```
int_col=[]
for i in train.columns:
    a=train[i].dtype
    if a == 'int64':
        int_col.append(i)
print(int_col)
```

```
['hacdor', 'rooms', 'hacapo', 'v14a', 'refrig', 'r4h1', 'r4h2', 'r4h3', 'r4m1',
'r4m2', 'r4m3', 'r4t1', 'r4t2', 'tamhog', 'tamviv', 'escolari', 'hhsize',
'paredblolad', 'paredzocalo', 'paredpreb', 'pareddes', 'paredmad', 'paredzinc',
'paredfibras', 'paredother', 'pisomoscer', 'pisocemento', 'pisoother',
'pisonatur', 'pisonotiene', 'pisomadera', 'techozinc', 'techoentrepiso',
'techocane', 'techootro', 'cielorazo', 'abastaguadentro', 'abastaguafuera',
'abastaguano', 'public', 'planpri', 'noelec', 'coopele', 'sanitario1',
'sanitario2', 'sanitario3', 'sanitario5', 'sanitario6', 'energcocinar1',
'energcocinar2', 'energcocinar3', 'energcocinar4', 'elimbasu1', 'elimbasu2',
'elimbasu3', 'elimbasu4', 'elimbasu6', 'epared1', 'epared2', 'epared3',
'etecho1', 'etecho2', 'etecho3', 'eviv1', 'eviv2', 'eviv3', 'dis', 'male',
'female', 'estadocivil1', 'estadocivil2', 'estadocivil3', 'estadocivil4',
'estadocivil5', 'estadocivil6', 'estadocivil7', 'parentesco1', 'parentesco2',
'parentesco3', 'parentesco4', 'parentesco5', 'parentesco6', 'parentesco7',
'parentesco8', 'parentesco9', 'parentesco10', 'parentesco11', 'parentesco12',
'hogar_nin', 'hogar_adul', 'hogar_mayor', 'hogar_total', 'instlevel1',
'instlevel2', 'instlevel3', 'instlevel4', 'instlevel5', 'instlevel6',
'instlevel7', 'instlevel8', 'instlevel9', 'bedrooms', 'tipovivi1', 'tipovivi2',
'tipovivi4', 'tipovivi5', 'computer', 'television', 'mobilephone',
'qmobilephone', 'lugar1', 'lugar2', 'lugar3', 'lugar4', 'lugar5', 'lugar6',
'area1', 'area2', 'age', 'SQBescolari', 'SQBage', 'SQBhogar_total', 'SQBedjefe',
'SQBhogar_nin', 'agesq', 'Target']
```

[36]:
```
train[int_col].isna().sum().value_counts()
```

[36]:
```
0    126
dtype: int64
```

Interpretation : ***Now there is no null value in our datset.***

[37]:
```
train.Target.value_counts()
```

[37]:
```
4    5996
2    1597
3    1209
1     755
Name: Target, dtype: int64
```

0.0.7 Set the poverty level of the members and the head of the house same in a family.

Now for people below poverty level can be people paying less rent and don't own a house. and it also depends on whether a house is in urban area or rural area.

[38]:
```
Poverty_level=train[train['v2a1'] !=0]
```

[39]:
```
Poverty_level.shape
```

[39]:
```
(2668, 136)
```

[40]:
```
poverty_level=Poverty_level.groupby('area1')['v2a1'].apply(np.median)
```

[41]:
```
poverty_level
```

[41]:
```
area1
0     80000.0
1    140000.0
Name: v2a1, dtype: float64
```

- For rural area level if people paying rent less than 8000 is under poverty level.
- For Urban area level if people paying rent less than 140000 is under poverty level.

[42]:
```
def povert(x):
    if x<8000:
        return('Below poverty level')

    elif x>140000:
        return('Above poverty level')
    elif x<140000:
        return('Below poverty level: Ur-ban ; Above poverty level : Rural ')
```

[43]:
```
c=Poverty_level['v2a1'].apply(povert)
```

[44]:
```
c.shape
```

[44]:
```
(2668,)
```

[45]:
```
pd.crosstab(c,Poverty_level['area1'])
```

[45]:

area1	0	1
v2a1		
Above poverty level	139	1103
Below poverty level: Ur-ban ; Above poverty lev…	306	1081

Interpretation : * ***There are total 1242 people above poverty level independent of area whether rural or Urban*** * ***Remaining 1111 people level depends on their area***

Rural :

Above poverty level= 445

Urban :

Above poverty level =1103

Below poverty level=1081

[46]:
```
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import train_test_split
```

[47]:
```
X_data=train.drop('Target',axis=1)
Y_data=train.Target
```

[48]:
```
X_data_col=X_data.columns
```

0.0.8 Applying Standard Scalling to dataset

[49]:
```
from sklearn.preprocessing import StandardScaler
SS=StandardScaler()
X_data_1=SS.fit_transform(X_data)
X_data_1=pd.DataFrame(X_data_1,columns=X_data_col)
```

0.0.9 Now we will proceed to model fitting

[50]:
```
X_train,X_test,Y_train,Y_test=train_test_split(X_data_1,Y_data,test_size=0.
↪25,stratify=Y_data,random_state=0)
```

Lets identify best parameters for our model using GridSearchCv

[51]:
```
from sklearn.pipeline import Pipeline
from sklearn.model_selection import GridSearchCV

rfc=RandomForestClassifier(random_state=0)
parameters={'n_estimators':[10,50,100,300],'max_depth':[3,5,10,15]}
grid=zip([rfc],[parameters])

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
    elif a.best_score_>best_.best_score_:
        best_=a


print ("Best CV Score",best_.best_score_)
print ("Model Parameters",best_.best_params_)
print("Best Estimator",best_.best_estimator_)
```

```
Best CV Score 0.8543323566345752
Model Parameters {'max_depth': 15, 'n_estimators': 100}
Best Estimator RandomForestClassifier(bootstrap=True, class_weight=None,
criterion='gini',
                       max_depth=15, max_features='auto', max_leaf_nodes=None,
                       min_impurity_decrease=0.0, min_impurity_split=None,
```

```
                              min_samples_leaf=1, min_samples_split=2,
                              min_weight_fraction_leaf=0.0, n_estimators=100,
                              n_jobs=None, oob_score=False, random_state=0, verbose=0,
                              warm_start=False)
```

[52]:
```
RFC=best_.best_estimator_
Model=RFC.fit(X_train,Y_train)
pred=Model.predict(X_test)
```

[53]:
```
print('Model Score of train data : {}'.format(Model.score(X_train,Y_train)))
print('Model Score of test data : {}'.format(Model.score(X_test,Y_test)))
```

```
Model Score of train data : 0.980326496442026
Model Score of test data : 0.8832635983263598
```

[54]:
```
Important_features=pd.DataFrame(Model.
 ↪feature_importances_,X_data_col,columns=['feature_importance'])
```

[55]:
```
Top50Features=Important_features.
 ↪sort_values(by='feature_importance',ascending=False).head(50).index
```

[56]:
```
Top50Features
```

[56]:
```
Index(['SQBmeaned', 'meaneduc', 'SQBdependency', 'dependency', 'overcrowding',
       'SQBovercrowding', 'qmobilephone', 'edjefe', 'SQBedjefe',
       'SQBhogar_nin', 'hogar_nin', 'cielorazo', 'r4t1', 'rooms', 'edjefa',
       'v2a1', 'agesq', 'r4h2', 'eviv3', 'age', 'SQBage', 'r4m3', 'r4t2',
       'hogar_adul', 'escolari', 'r4h3', 'epared3', 'r4m1', 'SQBescolari',
       'paredblolad', 'r4m2', 'bedrooms', 'tamviv', 'hhsize', 'tamhog',
       'v18q1', 'hogar_total', 'SQBhogar_total', 'pisomoscer', 'r4h1',
       'etecho3', 'lugar1', 'tipovivi1', 'energcocinar2', 'epared2',
       'energcocinar3', 'area1', 'area2', 'eviv2', 'television'],
      dtype='object')
```

[57]:
```
for i in Top50Features:
    if i not in X_data_col:
        print(i)
```

[58]:
```
X_data_Top50=X_data[Top50Features]
```

[59]:
```
X_train,X_test,Y_train,Y_test=train_test_split(X_data_Top50,Y_data,test_size=0.
 ↪25,stratify=Y_data,random_state=0)
```

[60]:
```
Model_1=RFC.fit(X_train,Y_train)
pred=Model_1.predict(X_test)
```

[61]:
```
from sklearn.metrics import confusion_matrix,f1_score,accuracy_score
```

[62]:
```
confusion_matrix(Y_test,pred)
```

[62]:
```
array([[ 144,   18,    0,   27],
       [   7,  317,    9,   66],
       [   1,   10,  214,   77],
       [   1,   10,    3, 1486]], dtype=int64)
```

[63]:
```
f1_score(Y_test,pred,average='weighted')
```

[63]:
```
0.900421392174492
```

[64]:
```
accuracy_score(Y_test,pred)
```

[64]:
```
0.90418410041841
```

0.0.10 Lets apply cleaning on test data and then find prediction for that.

[65]:
```
# lets drop Id variable.
test.drop('r4t3',axis=1,inplace=True)
test.drop(['Id','idhogar'],axis=1,inplace=True)
test['dependency']=test['dependency'].apply(map)
test['edjefe']=test['edjefe'].apply(map)
test['edjefa']=test['edjefa'].apply(map)
```

[66]:
```
test['v2a1'].fillna(0,inplace=True)
test['v18q1'].fillna(0,inplace=True)
```

[67]:
```
test.drop(['tipovivi3', 'v18q','rez_esc','elimbasu5'],axis=1,inplace=True)
```

[68]:
```
train['meaneduc'].fillna(np.mean(train['meaneduc']),inplace=True)
train['SQBmeaned'].fillna(np.mean(train['SQBmeaned']),inplace=True)
```

[69]:
```
test_data=test[Top50Features]
```

[70]:
```
test_data.isna().sum().value_counts()
```

[70]:
```
0     48
31     2
dtype: int64
```

[71]:
```
test_data.SQBmeaned.fillna(np.mean(test_data['SQBmeaned']),inplace=True)
```

[72]:
```
test_data.meaneduc.fillna(np.mean(test_data['meaneduc']),inplace=True)
```

[73]:
```
Test_data_1=SS.fit_transform(test_data)
X_data_1=pd.DataFrame(Test_data_1)
```

[74]:
```
test_prediction=Model_1.predict(test_data)
```

[75]:
```
test_prediction
```

[75]:
```
array([4, 4, 4, …, 2, 2, 4], dtype=int64)
```

Interpretation : ***Above is our prediction for test data.***

0.1 Conclusion :

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