Income Qualification

Course-end Project 2

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:

Core Data fields

Id - a unique identifier for each row. Target - the target is an ordinal variable indicating groups of income levels. 1 = extreme poverty 2 = moderate poverty 3 = vulnerable households 4 = non vulnerable households idhogar - this is a unique identifier for each household. This can be used to create household-wide features, etc. All rows in a given household will have a matching value for this identifier. parentesco1 - indicates if this person is the head of the household.

```python
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
sns.set()


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

```
from google.colab import files
uploaded=files.upload()
```

```
<IPython.core.display.HTML object>

Saving test.csv to test.csv
Saving train.csv to train (1).csv
```

Understand the Data

```
df_income_train = pd.read_csv("train.csv")
df_income_test =  pd.read_csv("test.csv")

df_income_train.head()
```

```
             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]
```

```
df_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
```

```
df_income_test.head()
```

```
             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]
```

NOTE

The important piece of information here is that we don’t have ‘Target’ feature in Test Dataset. There are 3 Types of the features: 5 object type 130(Train set)/ 129 (test set) integer type 8 float type

Lets analyze features:

```python
### List the columns for different datatypes:
print('Integer Type: ')
print(df_income_train.select_dtypes(np.int64).columns)
print('\n')
print('Float Type: ')
print(df_income_train.select_dtypes(np.float64).columns)
```

```
print('\n')
print('Object Type: ')
print(df_income_train.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')
```

```
df_income_train.select_dtypes('int64').head()
```

```
   hacdor  rooms  hacapo  v14a  refrig  v18q  r4h1  r4h2  r4h3
r4m1  ...  \
0       0      3       0     1       1     0     0     1     1
0  ...
1       0      4       0     1       1     1     0     1     1
0  ...
2       0      8       0     1       1     0     0     0     0
0  ...
3       0      5       0     1       1     1     0     2     2
1  ...
4       0      5       0     1       1     1     0     2     2
1  ...

   area1  area2  age  SQBescolari  SQBage  SQBhogar_total
SQBedjefe  \
0      1      0   43          100    1849               1        100

1      1      0   67          144    4489               1        144

2      1      0   92          121    8464               1          0

3      1      0   17           81     289              16        121
```

```
4      1      0   37          121    1369              16         121


   SQBhogar_nin  agesq  Target
0             0   1849       4
1             0   4489       4
2             0   8464       4
3             4    289       4
4             4   1369       4

[5 rows x 130 columns]
```

```python
#Find columns with null values
null_counts=df_income_train.select_dtypes('int64').isnull().sum()
null_counts[null_counts > 0]
```

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

```python
df_income_train.select_dtypes('float64').head()
```

```
       v2a1  v18q1  rez_esc  meaneduc  overcrowding
SQBovercrowding  \
0  190000.0    NaN      NaN      10.0      1.000000         1.000000

1  135000.0    1.0      NaN      12.0      1.000000         1.000000

2       NaN    NaN      NaN      11.0      0.500000         0.250000

3  180000.0    1.0      1.0      11.0      1.333333         1.777778

4  180000.0    1.0      NaN      11.0      1.333333         1.777778


   SQBdependency  SQBmeaned
0            0.0      100.0
1           64.0      144.0
2           64.0      121.0
3            1.0      121.0
4            1.0      121.0
```

```python
#Find columns with null values
null_counts=df_income_train.select_dtypes('float64').isnull().sum()
null_counts[null_counts > 0]
```

```
v2a1         6860
v18q1        7342
rez_esc      7928
meaneduc        5
SQBmeaned       5
dtype: int64
```

```
df_income_train.select_dtypes('object').head()
```

```
             Id    idhogar dependency edjefe edjefa
0  ID_279628684  21eb7fcc1         no     10     no
1  ID_f29eb3ddd  0e5d7a658          8     12     no
2  ID_68de51c94  2c7317ea8          8     no     11
3  ID_d671db89c  2b58d945f        yes     11     no
4  ID_d56d6f5f5  2b58d945f        yes     11     no
```

```
#Find columns with null values
null_counts=df_income_train.select_dtypes('object').isnull().sum()
null_counts[null_counts > 0]
```

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

NOTE

Looking at the different types of data and null values for each feature. We found the following:

1. No null values for Integer type features.
2. No null values for object type features.
3. For float64 types below featufres has null value
    a. v2a1 6860
    b. v18q1 7342
    c. rez_esc 7928
    d. meaneduc 5
    e. SQBmeaned 5

We also noticed that object type features dependency, edjefe, edjefa have mixed values. Lets fix the data for features with null values and features with mixed values

Data Cleaning

Let's fix first the column with mixed value:

ddependency, 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

For these three variables, it seems “yes” = 1 and “no” = 0. We can correct the variables using a mapping and convert to floats.

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

for df in [df_income_train, df_income_test]:
    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)

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

```
        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
```

NOTE

Lets fix the column with null values According to the documentation for these columns:

v2a1 (total nulls: 6860) : Monthly rent payment v18q1 (total nulls: 7342) : number of tablets household owns rez_esc (total nulls: 7928) : Years behind in school meaneduc (total nulls: 5) : average years of education for adults (18+) SQBmeaned (total nulls: 5) : square of the mean years of education of adults (>=18) in the household 142

Lets look at v2a1 (total nulls: 6860) : Monthly rent payment

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

1. Columns related to Monthly rent payment
2. tipovivi1, =1 own and fully paid house
3. tipovivi2, "=1 own, paying in installments"
4. tipovivi3, =1 rented
5. tipovivi4, =1 precarious
6. tipovivi5, "=1 other(assigned, borrowed)"

```
data = df_income_train[df_income_train['v2a1'].isnull()].head()

columns=['tipovivi1','tipovivi2','tipovivi3','tipovivi4','tipovivi5']
data[columns]
```

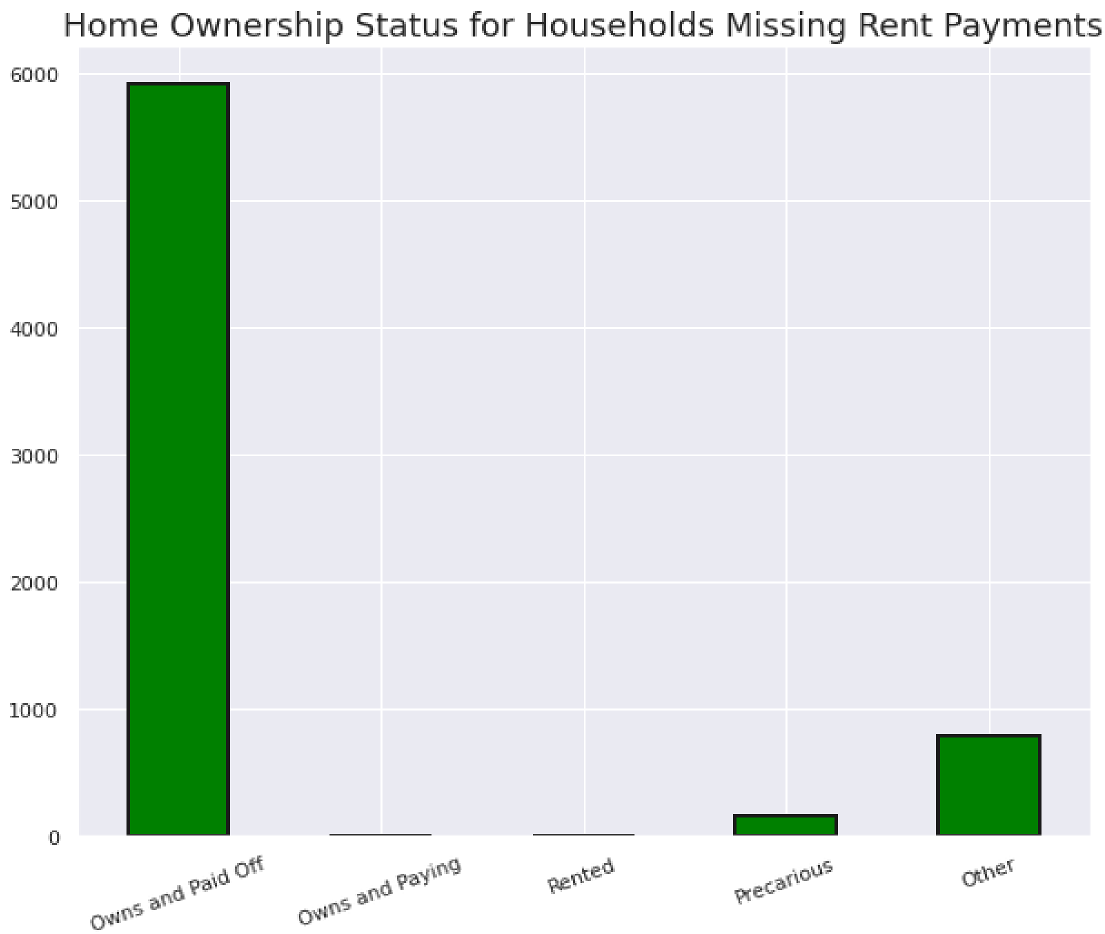
```
    tipovivi1  tipovivi2  tipovivi3  tipovivi4  tipovivi5
2           1          0          0          0          0
13          1          0          0          0          0
14          1          0          0          0          0
26          1          0          0          0          0
32    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

```
# Variables indicating home ownership
own_variables = [x for x in df_income_train if x.startswith('tipo')]


# Plot of the home ownership variables for home missing rent payments
df_income_train.loc[df_income_train['v2a1'].isnull(),
own_variables].sum().plot.bar(figsize = (10, 8),

color = 'green',

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);
```




```
#Looking at the above data it makes sense that when the house is fully
paid, there will be no monthly rent payment.
#Lets add 0 for all the null values.
for df in [df_income_train, df_income_test]:
```

```
    df['v2a1'].fillna(value=0, inplace=True)
```

```
df_income_train[['v2a1']].isnull().sum()
```

```
v2a1    0
dtype: int64
```

NOTE

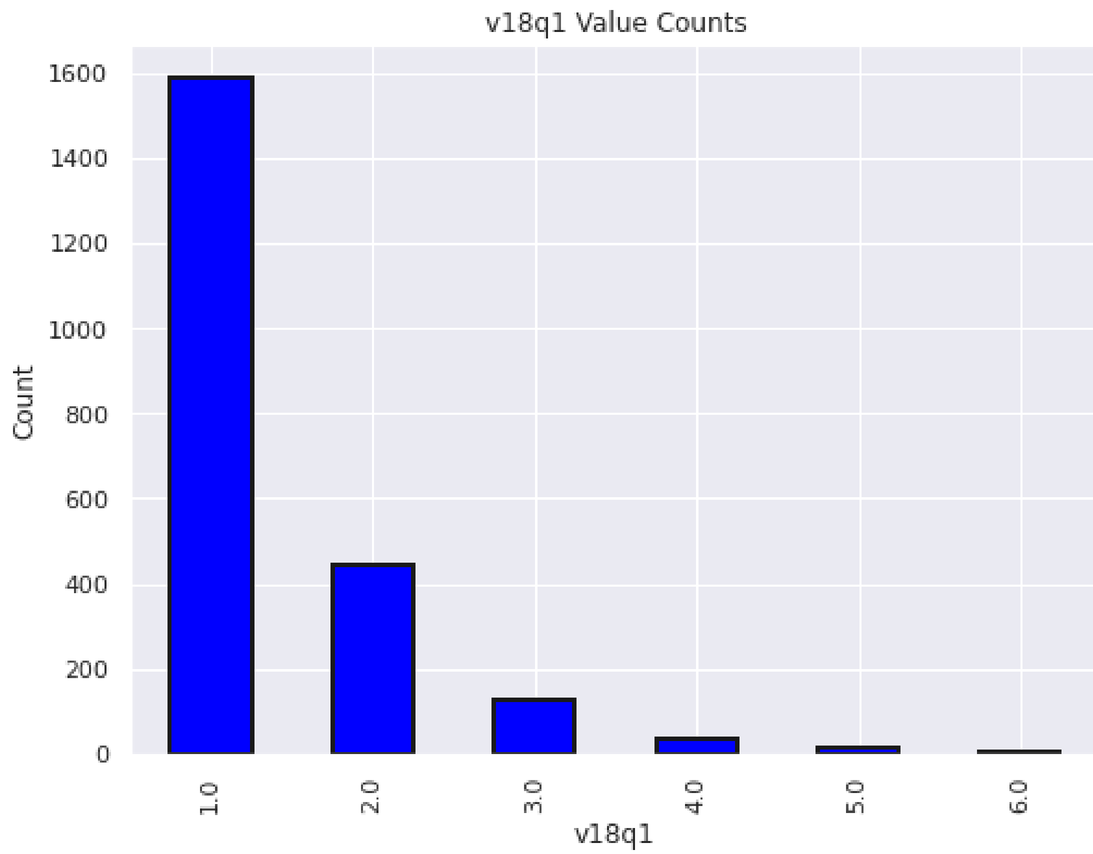
Lets look at v18q1 (total nulls: 7342) : number of tablets household owns why the null values, Lets look at few rows with nulls in v18q1 Columns related to number of tablets household owns v18q, owns a tablet

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.

```
# Heads of household### NOTE
heads = df_income_train.loc[df_income_train['parentesco1'] ==
1].copy()
heads.groupby('v18q')['v18q1'].apply(lambda x: x.isnull().sum())
```

```
v18q
0    2318
1       0
Name: v18q1, dtype: int64
```

```
plt.figure(figsize = (8, 6))
col='v18q1'
df_income_train[col].value_counts().sort_index().plot.bar(color =
'blue',
                                                             edgecolor = 'k',
                                                             linewidth = 2)
plt.xlabel(f'{col}'); plt.title(f'{col} Value Counts');
plt.ylabel('Count')
plt.show();
```



NOTE

Looking at the above data it makes sense that when owns a tablet column is 0, there will be no number of tablets household owns. Lets add 0 for all the null values.

```
for df in [df_income_train, df_income_test]:
    df['v18q1'].fillna(value=0, inplace=True)

df_income_train[['v18q1']].isnull().sum()
```

```
v18q1    0
dtype: int64
```

NOTE

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 in years

```
# Lets look at the data with not null values first.
df_income_train[df_income_train['rez_esc'].notnull()]
['age'].describe()
```

```
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
```

NOTE

From the above , we see that when min age is 7 and max age is 17 for Years, then the 'behind in school' column has a value. Lets confirm

```
df_income_train.loc[df_income_train['rez_esc'].isnull()]
['age'].describe()
```

```
count    7928.000000
mean       38.833249
std        20.989486
min         0.000000
25%        24.000000
50%        38.000000
75%        54.000000
max        97.000000
Name: age, dtype: float64
```

```
df_income_train.loc[(df_income_train['rez_esc'].isnull() &
                     ((df_income_train['age'] > 7) &
(df_income_train['age'] < 17)))]['age'].describe()
#There is one value that has Null for the 'behind in school' column
with age between 7 and 17
```

```
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
```

```
df_income_train[(df_income_train['age'] ==10) &
df_income_train['rez_esc'].isnull()].head()
df_income_train[(df_income_train['Id'] =='ID_f012e4242')].head()
#there is only one member in household for the member with age 10 and
who is 'behind in school'. This explains why the member is
#behind in school.
```

```
                Id      v2a1  hacdor  rooms  hacapo  v14a  refrig
v18q  \
2514  ID_f012e4242  160000.0       0      6       0     1       1
```

```
1

      v18q1  r4h1  ...  SQBescolari  SQBage  SQBhogar_total  SQBedjefe
\
2514    1.0     0  ...            0     100               9        121


      SQBhogar_nin  SQBovercrowding  SQBdependency  SQBmeaned  agesq
Target
2514             1             2.25           0.25     182.25    100
4

[1 rows x 143 columns]
```

```
#from above we see that  the 'behind in school' column has null values

# Lets use the above to fix the data
for df in [df_income_train, df_income_test]:
    df['rez_esc'].fillna(value=0, inplace=True)
df_income_train[['rez_esc']].isnull().sum()
```

```
rez_esc    0
dtype: int64
```

NOTE

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

```
data = df_income_train[df_income_train['meaneduc'].isnull()].head()

columns=['edjefe','edjefa','instlevel1','instlevel2']
data[columns][data[columns]['instlevel1']>0].describe()
```

```
       edjefe  edjefa  instlevel1  instlevel2
count     0.0     0.0         0.0         0.0
mean      NaN     NaN         NaN         NaN
std       NaN     NaN         NaN         NaN
min       NaN     NaN         NaN         NaN
25%       NaN     NaN         NaN         NaN
50%       NaN     NaN         NaN         NaN
75%       NaN     NaN         NaN         NaN
max       NaN     NaN         NaN         NaN
```

```
#from the above, we find that meaneduc is null when no level of
education is 0
#Lets fix the data
for df in [df_income_train, df_income_test]:
    df['meaneduc'].fillna(value=0, inplace=True)
df_income_train[['meaneduc']].isnull().sum()
```

```
meaneduc    0
dtype: int64
```

NOTE

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

```
data = df_income_train[df_income_train['SQBmeaned'].isnull()].head()

columns=['edjefe','edjefa','instlevel1','instlevel2']
data[columns][data[columns]['instlevel1']>0].describe()
```

	edjefe	edjefa	instlevel1	instlevel2
count	0.0	0.0	0.0	0.0
mean	NaN	NaN	NaN	NaN
std	NaN	NaN	NaN	NaN
min	NaN	NaN	NaN	NaN
25%	NaN	NaN	NaN	NaN
50%	NaN	NaN	NaN	NaN
75%	NaN	NaN	NaN	NaN
max	NaN	NaN	NaN	NaN

```
#from the above, we find that SQBmeaned is null when no level of
education is 0
#Lets fix the data
for df in [df_income_train, df_income_test]:
    df['SQBmeaned'].fillna(value=0, inplace=True)
df_income_train[['SQBmeaned']].isnull().sum()
```

```
SQBmeaned    0
dtype: int64
```

```
#Lets look at the overall data
null_counts = df_income_train.isnull().sum()
null_counts[null_counts > 0].sort_values(ascending=False)
```

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

```
# Groupby the household and figure out the number of unique values
all_equal = df_income_train.groupby('idhogar')['Target'].apply(lambda
x: x.nunique() == 1)

# Households where targets are not all equal
not_equal = all_equal[all_equal != True]
print('There are {} households where the family members do not all
have the same target.'.format(len(not_equal)))
```

```
There are 85 households where the family members do not all have the
same target.
```

```
#Lets check one household
df_income_train[df_income_train['idhogar'] == not_equal.index[0]]
[['idhogar', 'parentesco1', 'Target']]
```

```
        idhogar  parentesco1  Target
7651  0172ab1d9            0       3
7652  0172ab1d9            0       2
7653  0172ab1d9            0       3
7654  0172ab1d9            1       3
7655  0172ab1d9            0       2
```

```
#Lets use Target value of the parent record (head of the household)
and update rest. But before that lets check
# if all families has a head.

households_head = df_income_train.groupby('idhogar')
['parentesco1'].sum()

# Find households without a head
households_no_head =
df_income_train.loc[df_income_train['idhogar'].isin(households_head[ho
useholds_head == 0].index), :]

print('There are {} households without a
head.'.format(households_no_head['idhogar'].nunique()))
```

```
There are 15 households without a head.
```

```
# Find households without a head and where Target value are different
households_no_head_equal = households_no_head.groupby('idhogar')
['Target'].apply(lambda x: x.nunique() == 1)
print('{} Households with no head have different Target
value.'.format(sum(households_no_head_equal == False)))
```

```
0 Households with no head have different Target value.
```

```
#Lets fix the data
#Set poverty level of the members and the head of the house within a
family.
```

```
# Iterate through each household
for household in not_equal.index:
    # Find the correct label (for the head of household)
    true_target = int(df_income_train[(df_income_train['idhogar'] ==
household) & (df_income_train['parentesco1'] == 1.0)]['Target'])

    # Set the correct label for all members in the household
    df_income_train.loc[df_income_train['idhogar'] == household,
'Target'] = true_target


# Groupby the household and figure out the number of unique values
all_equal = df_income_train.groupby('idhogar')['Target'].apply(lambda
x: x.nunique() == 1)

# Households where targets are not all equal
not_equal = all_equal[all_equal != True]
print('There are {} households where the family members do not all
have the same target.'.format(len(not_equal)))
```

```
There are 0 households where the family members do not all have the
same target.
```

NOTE

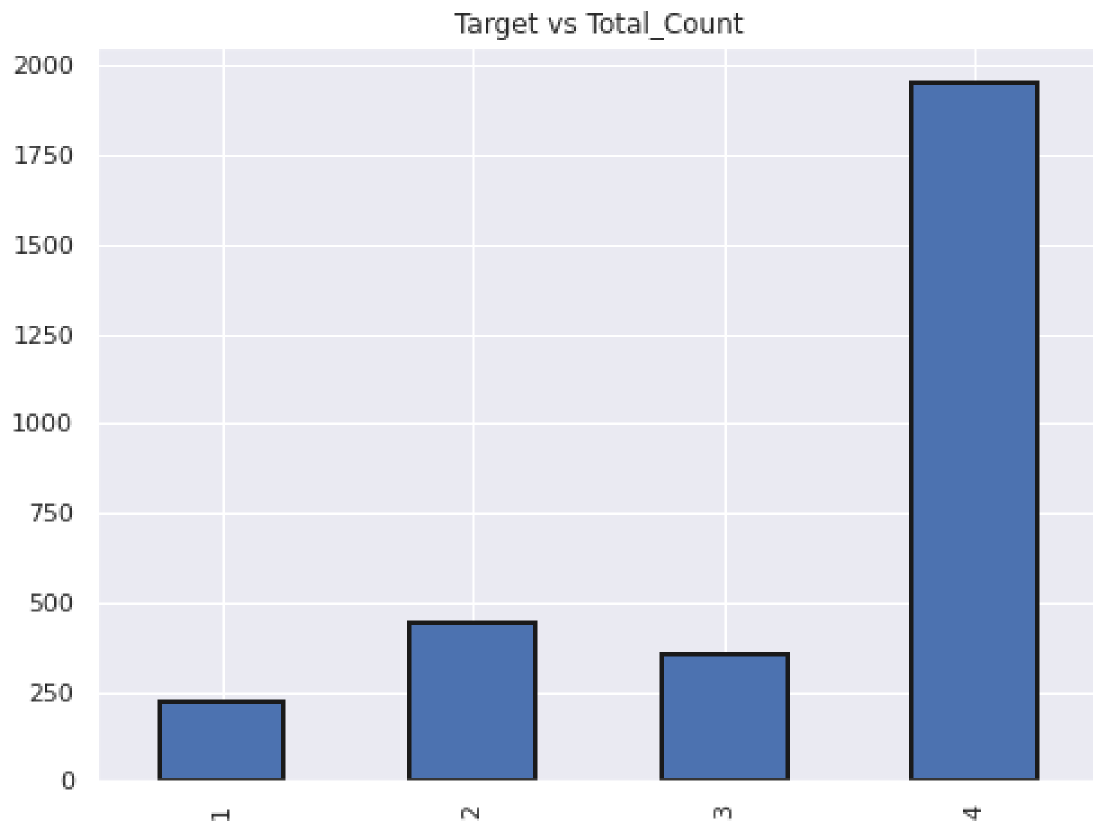
Lets look at the dataset and plot head of household and Target

```
# 1 = extreme poverty 2 = moderate poverty 3 = vulnerable households 4
= non vulnerable households
target_counts = heads['Target'].value_counts().sort_index()
target_counts
```

```
1     222
2     442
3     355
4    1954
Name: Target, dtype: int64
```

```
target_counts.plot.bar(figsize = (8, 6),linewidth = 2,edgecolor =
'k',title="Target vs Total_Count")
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f2b06ac6f10>
```



Note

extreme poverty is the smallest count in the train dataset. The dataset is biased.

Lets look at the Squared Variables ‘SQBescolari’ ‘SQBage’ ‘SQBhogar_total’ ‘SQBedjefe’ ‘SQBhogar_nin’ ‘SQBovercrowding’ ‘SQBdependency’ ‘SQBmeaned’ ‘agesq’

```
#Lets remove them
print(df_income_train.shape)
cols=['SQBescolari', 'SQBage', 'SQBhogar_total', 'SQBedjefe',
        'SQBhogar_nin', 'SQBovercrowding', 'SQBdependency',
'SQBmeaned', 'agesq']


for df in [df_income_train, df_income_test]:
    df.drop(columns = cols,inplace=True)

print(df_income_train.shape)
```

```
(9557, 143)
(9557, 134)
```

```
id_ = ['Id', 'idhogar', 'Target']
```

```
ind_bool = ['v18q', 'dis', 'male', 'female', 'estadocivil1',
'estadocivil2', 'estadocivil3',
            'estadocivil4', 'estadocivil5', 'estadocivil6',
'estadocivil7',
            'parentesco1', 'parentesco2',  'parentesco3',
'parentesco4', 'parentesco5',
            'parentesco6', 'parentesco7', 'parentesco8',
'parentesco9', 'parentesco10',
            'parentesco11', 'parentesco12', 'instlevel1',
'instlevel2', 'instlevel3',
            'instlevel4', 'instlevel5', 'instlevel6', 'instlevel7',
'instlevel8',
            'instlevel9', 'mobilephone']

ind_ordered = ['rez_esc', 'escolari', 'age']

hh_bool = ['hacdor', 'hacapo', 'v14a', 'refrig', 'paredblolad',
'paredzocalo',
           'paredpreb','pisocemento', 'pareddes', 'paredmad',
           'paredzinc', 'paredfibras', 'paredother', 'pisomoscer',
'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',
           'elimbasu5', 'elimbasu6', 'epared1', 'epared2', 'epared3',
           'etecho1', 'etecho2', 'etecho3', 'eviv1', 'eviv2', 'eviv3',

           'tipovivi1', 'tipovivi2', 'tipovivi3', 'tipovivi4',
'tipovivi5',
           'computer', 'television', 'lugar1', 'lugar2', 'lugar3',
           'lugar4', 'lugar5', 'lugar6', 'area1', 'area2']

hh_ordered = [ 'rooms', 'r4h1', 'r4h2', 'r4h3', 'r4m1','r4m2','r4m3',
'r4t1',  'r4t2',
              'r4t3', 'v18q1', 'tamhog','tamviv','hhsize','hogar_nin',
              'hogar_adul','hogar_mayor','hogar_total',  'bedrooms',
'qmobilephone']

hh_cont = ['v2a1', 'dependency', 'edjefe', 'edjefa', 'meaneduc',
'overcrowding']

#Check for redundant household variables
heads = df_income_train.loc[df_income_train['parentesco1'] == 1, :]
```

```
heads = heads[id_ + hh_bool + hh_cont + hh_ordered]
heads.shape
```

```
(2973, 98)
```

```
# Create correlation matrix
corr_matrix = heads.corr()

# Select upper triangle of correlation matrix
upper = corr_matrix.where(np.triu(np.ones(corr_matrix.shape),
k=1).astype(np.bool))

# Find index of feature columns with correlation greater than 0.95
to_drop = [column for column in upper.columns if
any(abs(upper[column]) > 0.95)]

to_drop
```

```
['coopele', 'area2', 'tamhog', 'hhsize', 'hogar_total']
```

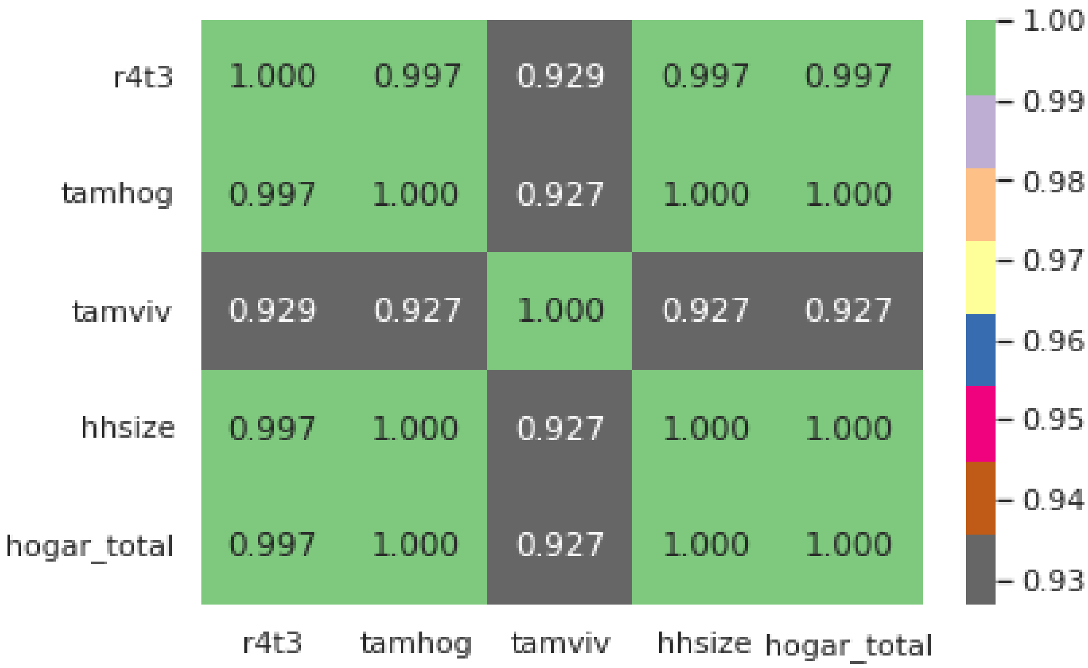
```
['coopele', 'area2', 'tamhog', 'hhsize', 'hogar_total']
```

```
['coopele', 'area2', 'tamhog', 'hhsize', 'hogar_total']
```

```
corr_matrix.loc[corr_matrix['tamhog'].abs() > 0.9,
corr_matrix['tamhog'].abs() > 0.9]
```

	r4t3	tamhog	tamviv	hhsize	hogar_total
r4t3	1.000000	0.996884	0.929237	0.996884	0.996884
tamhog	0.996884	1.000000	0.926667	1.000000	1.000000
tamviv	0.929237	0.926667	1.000000	0.926667	0.926667
hhsize	0.996884	1.000000	0.926667	1.000000	1.000000
hogar_total	0.996884	1.000000	0.926667	1.000000	1.000000

```
sns.heatmap(corr_matrix.loc[corr_matrix['tamhog'].abs() > 0.9,
corr_matrix['tamhog'].abs() > 0.9],
            annot=True, cmap = plt.cm.Accent_r, fmt='.3f');
```



Note

There are several variables here having to do with the size of the house: r4t3, Total persons in the household tamhog, size of the household tamviv, number of persons living in the household hhsize, household size hogar_total, # of total individuals in the household These variables are all highly correlated with one another.

```
cols=['tamhog', 'hogar_total', 'r4t3']
for df in [df_income_train, df_income_test]:
    df.drop(columns = cols,inplace=True)

df_income_train.shape
```

```
(9557, 131)
```

```
#Check for redundant Individual variables
ind = df_income_train[id_ + ind_bool + ind_ordered]
ind.shape
```

```
(9557, 39)
```

```
# Create correlation matrix
corr_matrix = ind.corr()

# Select upper triangle of correlation matrix
upper = corr_matrix.where(np.triu(np.ones(corr_matrix.shape),
k=1).astype(np.bool))
```

```
# Find index of feature columns with correlation greater than 0.95
to_drop = [column for column in upper.columns if
any(abs(upper[column]) > 0.95)]

to_drop
```

```
['female']
```

```
# This is simply the opposite of male! We can remove the male flag.
for df in [df_income_train, df_income_test]:
    df.drop(columns = 'male',inplace=True)

df_income_train.shape
```

```
(9557, 130)
```

```
#lets check area1 and area2 also
# area1, =1 zona urbana
# area2, =2 zona rural
#area2 redundant because we have a column indicating if the house is
in a urban zone

for df in [df_income_train, df_income_test]:
    df.drop(columns = 'area2',inplace=True)

df_income_train.shape
```

```
(9557, 129)
```

```
#Finally lets delete 'Id', 'idhogar'
cols=['Id','idhogar']
for df in [df_income_train, df_income_test]:
    df.drop(columns = cols,inplace=True)

df_income_train.shape
```

```
(9557, 127)
```

Predict the accuracy using random forest classifier.

```
df_income_train.iloc[:,0:-1]
```

```
          v2a1  hacdor  rooms  hacapo  v14a  refrig  v18q  v18q1  r4h1
r4h2  \
0     190000.0       0      3       0     1       1     0    0.0     0
1
1     135000.0       0      4       0     1       1     1    1.0     0
1
2          0.0       0      8       0     1       1     0    0.0     0
0
3     180000.0       0      5       0     1       1     1    1.0     0
```

```
2
4     180000.0       0      5       0     1       1     1    1.0     0
2
...        ...     ...    ...     ...   ...     ...   ...    ...   ...
...
9552   80000.0       0      6       0     1       1     0    0.0     0
2
9553   80000.0       0      6       0     1       1     0    0.0     0
2
9554   80000.0       0      6       0     1       1     0    0.0     0
2
9555   80000.0       0      6       0     1       1     0    0.0     0
2
9556   80000.0       0      6       0     1       1     0    0.0     0
2

      ...  mobilephone  qmobilephone  lugar1  lugar2  lugar3  lugar4
lugar5  \
0     ...            1             1       1       0       0       0
0
1     ...            1             1       1       0       0       0
0
2     ...            0             0       1       0       0       0
0
3     ...            1             3       1       0       0       0
0
4     ...            1             3       1       0       0       0
0
...   ...          ...           ...     ...     ...     ...     ...
...
9552  ...            1             3       0       0       0       0
0
9553  ...            1             3       0       0       0       0
0
9554  ...            1             3       0       0       0       0
0
9555  ...            1             3       0       0       0       0
0
9556  ...            1             3       0       0       0       0
0

      lugar6  area1  age
0          0      1   43
1          0      1   67
2          0      1   92
3          0      1   17
4          0      1   37
...      ...    ...  ...
9552       1      0   46
9553       1      0    2
```

```
9554       1      0   50
9555       1      0   26
9556       1      0   21

[9557 rows x 126 columns]
```

```
df_income_train.iloc[:,-1]
```

```
0       4
1       4
2       4
3       4
4       4
       ..
9552    2
9553    2
9554    2
9555    2
9556    2
Name: Target, Length: 9557, dtype: int64
```

```
x_features=df_income_train.iloc[:,0:-1] # feature without target
y_features=df_income_train.iloc[:,-1] # only target
print(x_features.shape)
print(y_features.shape)
```

```
(9557, 126)
(9557,)
```

```
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import train_test_split
from sklearn.metrics import
accuracy_score,confusion_matrix,f1_score,classification_report

x_train,x_test,y_train,y_test=train_test_split(x_features,y_features,t
est_size=0.2,random_state=1)
rmclassifier = RandomForestClassifier()
```

x_features, y_features: The first parameter is the dataset you're selecting to use. train_size: This parameter sets the size of the training dataset. There are three options: None, which is the default, Int, which requires the exact number of samples, and float, which ranges from 0.1 to 1.0. test_size: This parameter specifies the size of the testing dataset. The default state suits the training size. It will be set to 0.25 if the training size is set to default. random_state: The default mode performs a random split using np.random. Alternatively, you can add an integer using an exact number.

```
rmclassifier.fit(x_train,y_train)
```

```
RandomForestClassifier()
```

```
y_predict = rmclassifier.predict(x_test)
```

```
print(accuracy_score(y_test,y_predict))
print(confusion_matrix(y_test,y_predict))
print(classification_report(y_test,y_predict))
```

```
0.9492677824267782
[[ 135    0    0   22]
 [   1  288    0   28]
 [   0    1  189   43]
 [   0    1    1 1203]]
              precision    recall  f1-score   support

           1       0.99      0.86      0.92       157
           2       0.99      0.91      0.95       317
           3       0.99      0.81      0.89       233
           4       0.93      1.00      0.96      1205

    accuracy                           0.95      1912
   macro avg       0.98      0.89      0.93      1912
weighted avg       0.95      0.95      0.95      1912
```

```
y_predict_testdata = rmclassifier.predict(df_income_test)
```

```
y_predict_testdata
```

```
array([4, 4, 4, ..., 4, 4, 4])
```

Check the accuracy using random forest with cross validation.

```
from sklearn.model_selection import KFold,cross_val_score
```

```
seed=7
kfold=KFold(n_splits=5,random_state=seed,shuffle=True)

rmclassifier=RandomForestClassifier(random_state=10,n_jobs = -1)
print(cross_val_score(rmclassifier,x_features,y_features,cv=kfold,scor
ing='accuracy'))
results=cross_val_score(rmclassifier,x_features,y_features,cv=kfold,sc
oring='accuracy')
print(results.mean()*100)
```

```
[0.94246862 0.94979079 0.94557823 0.94243851 0.94976452]
94.60081361157272
```

```
num_trees= 100

rmclassifier=RandomForestClassifier(n_estimators=100,
random_state=10,n_jobs = -1)
print(cross_val_score(rmclassifier,x_features,y_features,cv=kfold,scor
ing='accuracy'))
results=cross_val_score(rmclassifier,x_features,y_features,cv=kfold,sc
```

```
oring='accuracy')
print(results.mean()*100)
```

```
[0.94246862 0.94979079 0.94557823 0.94243851 0.94976452]
94.60081361157272
```

```
rmclassifier.fit(x_features,y_features)
labels = list(x_features)
feature_importances = pd.DataFrame({'feature': labels, 'importance':
rmclassifier.feature_importances_})
feature_importances=feature_importances[feature_importances.importance
>0.015]
feature_importances.head()
```

	feature	importance
0	v2a1	0.018653
2	rooms	0.025719
9	r4h2	0.020706
10	r4h3	0.019808
11	r4m1	0.015271

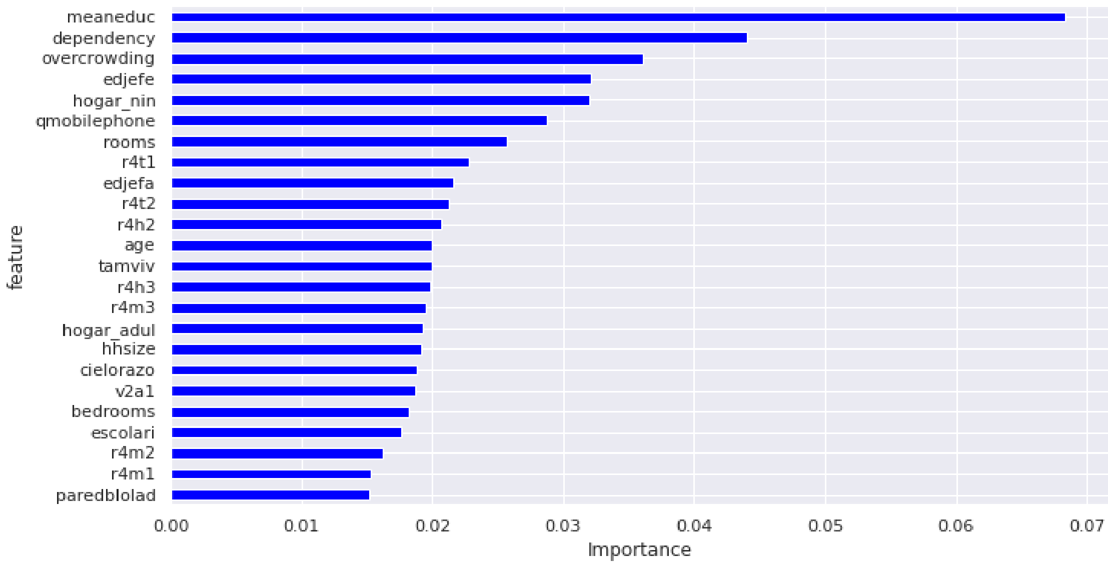
```
y_predict_testdata = rmclassifier.predict(df_income_test)
y_predict_testdata
```

```
array([4, 4, 4, ..., 4, 4, 4])
```

```
feature_importances.sort_values(by=['importance'], ascending=True,
inplace=True)
feature_importances['positive'] = feature_importances['importance'] >
0
feature_importances.set_index('feature',inplace=True)
feature_importances.head()
```

```
feature_importances.importance.plot(kind='barh', figsize=(11, 6),color
= feature_importances.positive.map({True: 'blue', False: 'red'}))
plt.xlabel('Importance')
```

```
Text(0.5, 0, 'Importance')
```



From the above figure, meaneduc,dependency,overcrowding has significant influence on the model. ----THE END ---

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