Income Qualification

July 18, 2020

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:

- 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
import seaborn as sns
sns.set()
```

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

[2]:
```python
df_income_train = pd.read_csv("train.csv")
```

[3]:
```python
df_income_test =  pd.read_csv("test.csv")
```

[4]:
```python
df_income_train.head()
```

[4]:
```
             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]
```

[5]:
```python
df_income_test.head()
```

[5]:
```
             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]
```

[6]:
```python
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
```

[7]:
```python
df_income_test.info()
```

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

1. Identify the output variable By looking at both the dataset we've found that we don't have 'target' column in the test dataset

- Understand the type of data

[8]:
```python
#List the columns for different datatypes:
print('Integer Type: '+df_income_train.select_dtypes(np.int64).columns)
```

```
Index(['Integer Type: hacdor', 'Integer Type: rooms', 'Integer Type: hacapo',
       'Integer Type: v14a', 'Integer Type: refrig', 'Integer Type: v18q',
       'Integer Type: r4h1', 'Integer Type: r4h2', 'Integer Type: r4h3',
       'Integer Type: r4m1',
       …
       'Integer Type: area1', 'Integer Type: area2', 'Integer Type: age',
       'Integer Type: SQBescolari', 'Integer Type: SQBage',
       'Integer Type: SQBhogar_total', 'Integer Type: SQBedjefe',
       'Integer Type: SQBhogar_nin', 'Integer Type: agesq',
       'Integer Type: Target'],
      dtype='object', length=130)
```

[9]:
```python
print('Float Type: '+df_income_train.select_dtypes(np.float64).columns)
```

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

[10]:
```
print('Object Type: '+df_income_train.select_dtypes(np.object).columns)
```

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

[11]:
```
df_income_train.select_dtypes('int64').head()
```

[11]:
```
   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]
```

[12]:
```
#Find columns with null values
null_counts=df_income_train.select_dtypes('int64').isnull().sum()
null_counts[null_counts > 0]
```

[12]:
```
Series([], dtype: int64)
```

[13]:
```
df_income_train.select_dtypes('float64').head()
```

[13]:
```
       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
```

[14]:
```python
#Find columns with null values
null_counts=df_income_train.select_dtypes('float64').isnull().sum()
null_counts[null_counts > 0]
```

[14]:
```
v2a1         6860
v18q1        7342
rez_esc      7928
meaneduc        5
SQBmeaned       5
dtype: int64
```

[15]:
```python
df_income_train.select_dtypes('object').head()
```

[15]:
```
             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
```

[16]:
```python
#Find columns with null values
null_counts=df_income_train.select_dtypes('object').isnull().sum()
null_counts[null_counts > 0]
```

[16]:
```
Series([], dtype: int64)
```

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 float types : v2a1 6860 v18q1 7342 rez_esc 7928 meaneduc 5 SQBmeaned 5

Also in object type features dependency, edjefe, edjefa have mixed values. Lets fix the data for features with null values and features with mixed values

Data cleansing - Check if there are any biases in your dataset Lets fix the column with mixed values. According to the documentation for these columns: 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

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

[17]:
```
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()
```

[17]:

	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

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

[18]:
```
# 1. Lets look at v2a1 (total nulls: 6860) : Monthly rent payment
# why the null values, Lets look at few rows with nulls in v2a1
# 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)"

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

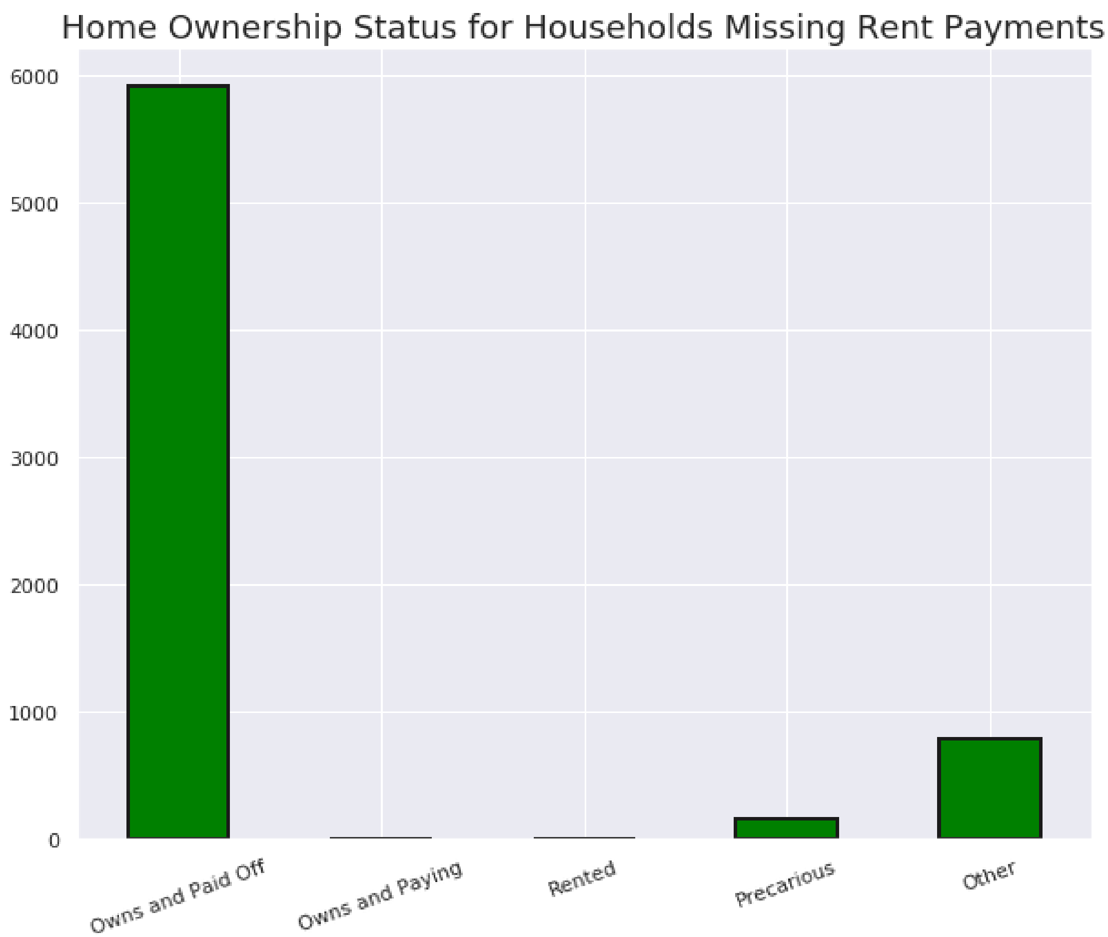
```
columns=['tipovivi1','tipovivi2','tipovivi3','tipovivi4','tipovivi5']
data[columns]
```

[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

[19]:

```
# 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);
```



[20]:
```
#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()
```

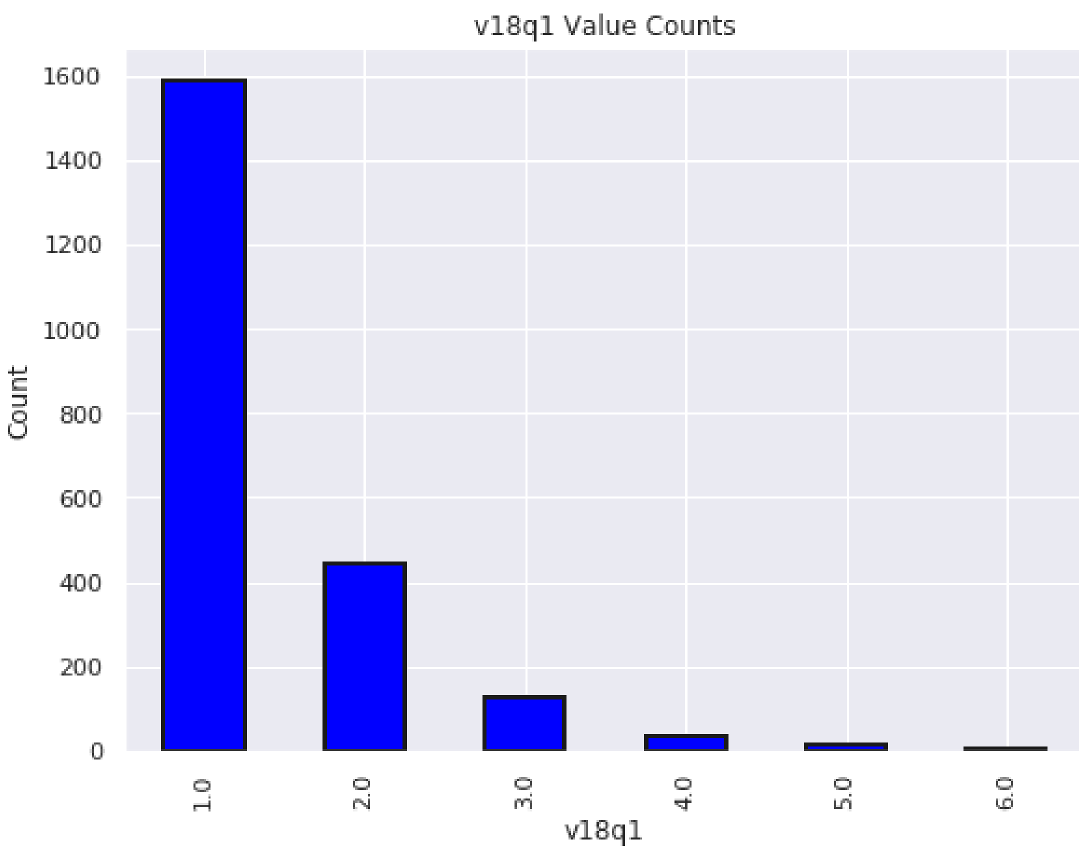
[20]:
```
v2a1    0
dtype: int64
```

[21]:
```
# 2. 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
heads = df_income_train.loc[df_income_train['parentesco1'] == 1].copy()
heads.groupby('v18q')['v18q1'].apply(lambda x: x.isnull().sum())
```

[21]:
```
v18q
0    2318
1       0
Name: v18q1, dtype: int64
```

[22]:
```
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();
```



[23]:
```python
#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()
```

[23]:
```
v18q1    0
dtype: int64
```

[24]:
```python
# 3. 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()
```

[24]:
```
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
```

[25]:
```python
#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()
```

[25]:
```
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
```

[26]:
```python
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
```

[26]:
```
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
```

[27]:
```
#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
df_income_train[(df_income_train['age'] ==10) & df_income_train['rez_esc'].
↪isnull()].head()
```

[27]:
```
                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]
```

[28]:
```
#behind in school.
df_income_train[(df_income_train['Id'] =='ID_f012e4242')].head()
```

[28]:
```
                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]
```

[29]:
```
#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()
```

[29]:
```
rez_esc    0
dtype: int64
```

[30]:
```
#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()
```

[30]:

	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

[31]:
```
#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()
```

[31]:
```
meaneduc    0
dtype: int64
```

[32]:
```
#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()
```

[32]:

	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

[33]:
```
#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()
```

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

[34]:
```
#Lets look at the overall data
null_counts = df_income_train.isnull().sum()
null_counts[null_counts > 0].sort_values(ascending=False)
```

[34]:
```
Series([], dtype: int64)
```

[35]:
```
#Target Data
# 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 have the same␣
↪target.'.format(len(not_equal)))
```

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

[36]:
```
#Lets check one household
df_income_train[df_income_train['idhogar'] == not_equal.index[0]][['idhogar',␣
↪'parentesco1', 'Target']]
```

[36]:

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

[37]:
```
#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[households_head == 0].index), :]

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

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

[38]:
```
# 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.
```

[39]:
```
#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.
```

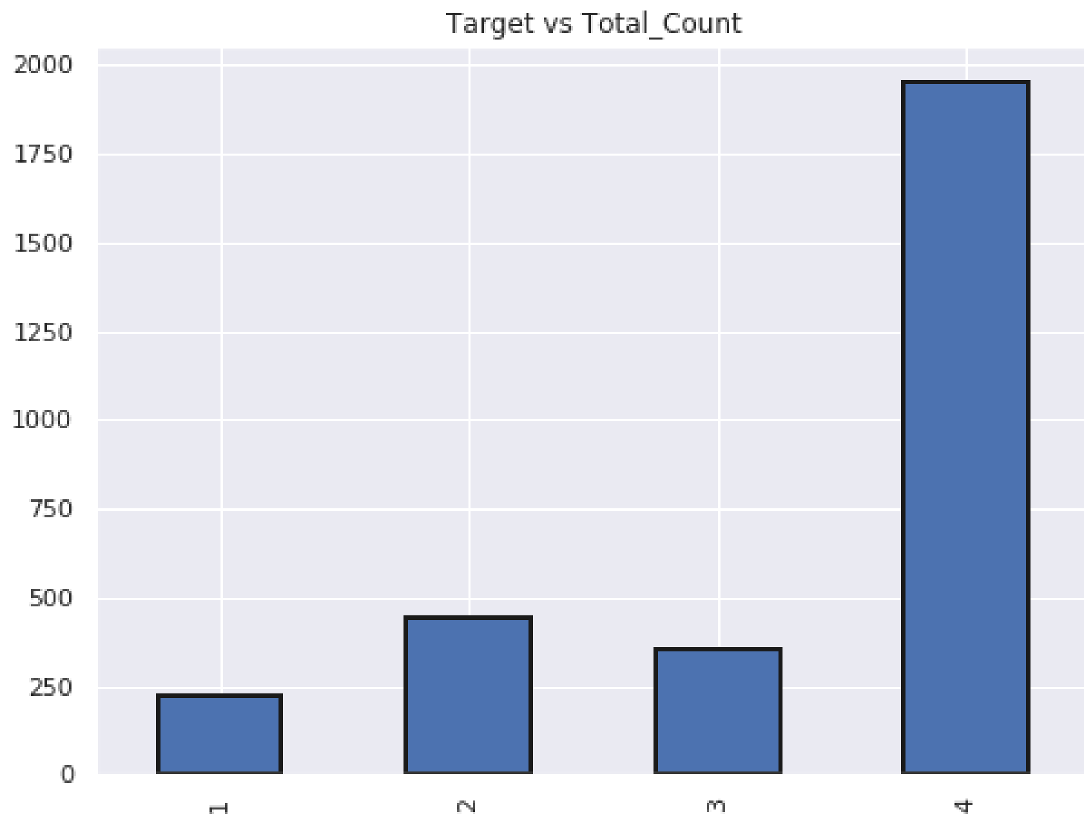
0.0.1 Checking Bias

[40]:
```
#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
```

[40]:
```
1     222
2     442
3     355
4    1954
Name: Target, dtype: int64
```

[41]:
```
target_counts.plot.bar(figsize = (8, 6),linewidth = 2,edgecolor =␣
 ↪'k',title="Target vs Total_Count")
```

[41]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7fef1df299d0>
```



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

[42]:
```
#Lets remove SQuared variables
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)
```

[43]:
```
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']
```

[44]:
```
#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
```

[44]: (2973, 98)

[45]:
```
# 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
```

[45]: ['coopele', 'area2', 'tamhog', 'hhsize', 'hogar_total']

[46]:
```
corr_matrix.loc[corr_matrix['tamhog'].abs() > 0.9, corr_matrix['tamhog'].abs()␣
 ↪> 0.9]
```

[46]:

	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

[47]:
```
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');
```

[48]:
```
# 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
```

[48]: (9557, 131)

[49]:
```
#Check for redundant Individual variables
ind = df_income_train[id_ + ind_bool + ind_ordered]
ind.shape
```

[49]: (9557, 39)

[50]:
```
# 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
```

[50]: ['female']

[51]:
```
# 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
```

[51]: (9557, 130)

```
[52]: #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
```

```
[52]: (9557, 129)
```

```
[53]: #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
```

```
[53]: (9557, 127)
```

0.0.2 Predict the accuracy using random forest classifier.

```
[54]: x_features=df_income_train.iloc[:,0:-1]
      y_features=df_income_train.iloc[:,-1]
      print(x_features.shape)
      print(y_features.shape)
```

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

```
[55]: 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
```

```
[56]: x_train,x_test,y_train,y_test=train_test_split(x_features,y_features,test_size=0.
       ↪2,random_state=1)
      rmclassifier = RandomForestClassifier()
```

```
[57]: rmclassifier.fit(x_train,y_train)
```

```
[57]: RandomForestClassifier(bootstrap=True, ccp_alpha=0.0, class_weight=None,
                             criterion='gini', max_depth=None, max_features='auto',
                             max_leaf_nodes=None, max_samples=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=None,
                         verbose=0, warm_start=False)
```

[58]:
```
y_predict = rmclassifier.predict(x_test)
```

[59]:
```
print(accuracy_score(y_test,y_predict))
```

```
0.9518828451882845
```

[60]:
```
print(confusion_matrix(y_test,y_predict))
```

```
[[ 133    1    0   23]
 [    0  288    1   28]
 [    0    1  196   36]
 [    0    1    1 1203]]
```

[61]:
```
print(classification_report(y_test,y_predict))
```

```
              precision    recall  f1-score   support

           1       1.00      0.85      0.92       157
           2       0.99      0.91      0.95       317
           3       0.99      0.84      0.91       233
           4       0.93      1.00      0.96      1205

    accuracy                           0.95      1912
   macro avg       0.98      0.90      0.93      1912
weighted avg       0.95      0.95      0.95      1912
```

[62]:
```
y_predict_testdata = rmclassifier.predict(df_income_test)
```

[63]:
```
y_predict_testdata
```

[63]:
```
array([4, 4, 4, …, 4, 4, 4])
```

0.0.3 Check the accuracy using random forest with cross validation

[64]:
```
from sklearn.model_selection import KFold,cross_val_score
```

[65]:
```
#Checking the score using default 10 trees
seed=7
kfold=KFold(n_splits=5,random_state=seed,shuffle=True)
```

[66]:
```
rmclassifier=RandomForestClassifier(random_state=10,n_jobs = -1)
print(cross_val_score(rmclassifier,x_features,y_features,cv=kfold,scoring='accuracy'))
```

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

[67]:
```
results=cross_val_score(rmclassifier,x_features,y_features,cv=kfold,scoring='accuracy')
print(results.mean()*100)
```

```
94.60081361157272
```

[68]:
```
#Checking the score using default 100 trees
rmclassifier=RandomForestClassifier(n_estimators=100, random_state=10,n_jobs =␣
↪-1)
print(cross_val_score(rmclassifier,x_features,y_features,cv=kfold,scoring='accuracy'))
```

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

[69]:
```
results=cross_val_score(rmclassifier,x_features,y_features,cv=kfold,scoring='accuracy')
print(results.mean()*100)
```

```
94.60081361157272
```

0.0.4 Looking at the accuracy score, RandomForestClassifier with cross validation has the highest accuracy score of 94.60%.

To get a better sense of what is going on inside the RandomForestClassifier model, lets visualize how our model uses the different features and which features have greater effect

[70]:
```
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()
```

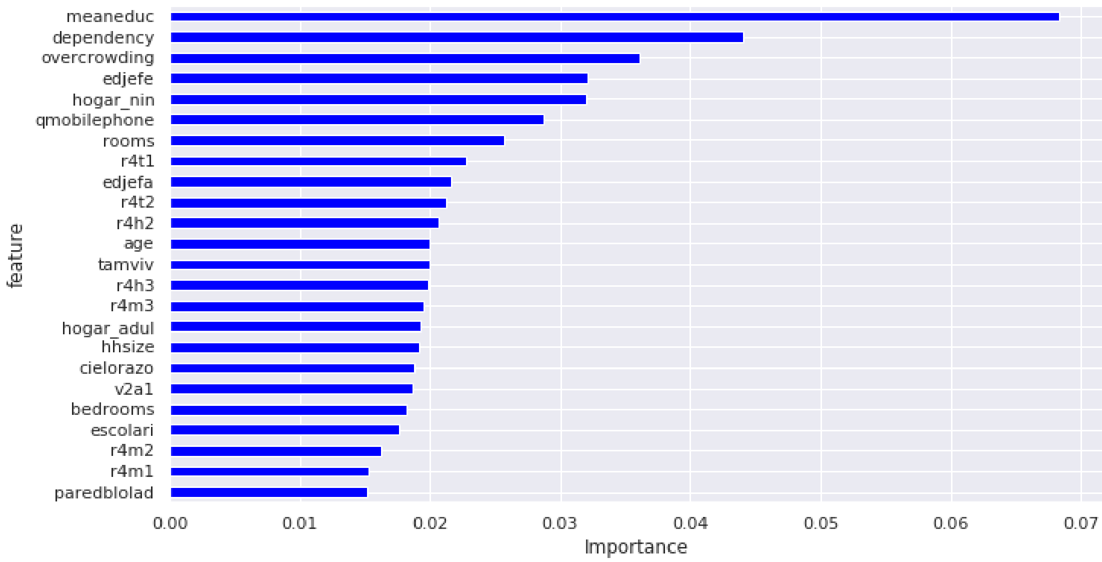
[70]:

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

[71]:
```
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')
```

[71]: Text(0.5,0,'Importance')



From the above figure, meaneduc,dependency,overcrowding has significant influence on the model

[ ]: