Project 02: Income Qualification

Submitted By Mr. Vivek Gautam in October 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:

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

In [1]:

```
import numpy as np
import pandas as pd
from pandasql import sqldf
```

In [2]:

```
#pip install pandasql
```

In [3]:

```
#pip install sqlalchemy
#pip install pandasql
```

In [4]:

```
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
```

In [5]:

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

In [6]:

```
#Load the data
trainDf = pd.read_csv(r'D:\Data_Science_Data\Income_Qualification\train.csv')
```

In [7]:

```
trainDf
```

Out[7]:

	Id	v2a1	hacdor	rooms	hacapo	v14a	refrig	v18q	v18q1	r4h1	...	S
0	ID_279628684	190000.0	0	3	0	1	1	0	NaN	0	...	
1	ID_f29eb3ddd	135000.0	0	4	0	1	1	1	1.0	0	...	
2	ID_68de51c94	NaN	0	8	0	1	1	0	NaN	0	...	
3	ID_d671db89c	180000.0	0	5	0	1	1	1	1.0	0	...	
4	ID_d56d6f5f5	180000.0	0	5	0	1	1	1	1.0	0	...	
...	...	...	...	...	...	...	...	...	...	...	...	
9552	ID_d45ae367d	80000.0	0	6	0	1	1	0	NaN	0	...	
9553	ID_c94744e07	80000.0	0	6	0	1	1	0	NaN	0	...	
9554	ID_85fc658f8	80000.0	0	6	0	1	1	0	NaN	0	...	
9555	ID_ced540c61	80000.0	0	6	0	1	1	0	NaN	0	...	
9556	ID_a38c64491	80000.0	0	6	0	1	1	0	NaN	0	...	

9557 rows × 143 columns

In [8]:

```
trainDf.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
```

In [9]:

```
trainDf.describe()
```

Out[9]:

	v2a1	hacdor	rooms	hacapo	v14a	refrig	
count	2.697000e+03	9557.000000	9557.000000	9557.000000	9557.000000	9557.000000	9557.0(
mean	1.652316e+05	0.038087	4.955530	0.023648	0.994768	0.957623	0.2:
std	1.504571e+05	0.191417	1.468381	0.151957	0.072145	0.201459	0.42
min	0.000000e+00	0.000000	1.000000	0.000000	0.000000	0.000000	0.0(
25%	8.000000e+04	0.000000	4.000000	0.000000	1.000000	1.000000	0.0(
50%	1.300000e+05	0.000000	5.000000	0.000000	1.000000	1.000000	0.0(
75%	2.000000e+05	0.000000	6.000000	0.000000	1.000000	1.000000	0.0(
max	2.353477e+06	1.000000	11.000000	1.000000	1.000000	1.000000	1.0(

8 rows × 138 columns

2. Understand the type of data.

In [10]:

```
trainDf.dtypes
```

Out[10]:

```
Id                  object
v2a1               float64
hacdor               int64
rooms                int64
hacapo               int64
                    ...
SQBovercrowding    float64
SQBdependency      float64
SQBmeaned          float64
agesq                int64
Target               int64
Length: 143, dtype: object
```

In [11]:

```
trainDf.columns
```

Out[11]:

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

1. Identify the output variable

In [12]:

```
trainDf.Target.value_counts()
```

Out[12]:

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

In [13]:

```
trainDf.Target.value_counts() / trainDf.shape[0]*100
```

Out[13]:

```
4    62.739353
2    16.710265
3    12.650413
1     7.899969
Name: Target, dtype: float64
```

7. Count how many null values are existing in columns

In [14]:

```
# Total missing values in the DataFrame
sqldf('SELECT COUNT(*) FROM trainDf;')
```

Out[14]:

	COUNT(*)
0	9557

In [15]:

```
#sqldf('SELECT Target, COUNT(*) FROM trainDf GROUP BY Target;')
```

In [16]:

```
# Missing Values
trainDf.isnull().sum()
```

Out[16]:

```
Id                  0
v2a1             6860
hacdor              0
rooms               0
hacapo              0
                 ... 
SQBovercrowding     0
SQBdependency       0
SQBmeaned           5
agesq               0
Target              0
Length: 143, dtype: int64
```

In [17]:

```
trainDf_NaN = pd.DataFrame(data = trainDf.isnull().sum(), columns = ['CountOfNaN'])
print(trainDf_NaN)
```

```
                 CountOfNaN
Id                        0
v2a1                   6860
hacdor                    0
rooms                     0
hacapo                    0
...                     ...
SQBovercrowding           0
SQBdependency             0
SQBmeaned                 5
agesq                     0
Target                    0

[143 rows x 1 columns]
```

In [18]:

```
trainDf_NaN[trainDf_NaN['CountOfNaN'] != 0]
```

Out[18]:

	CountOfNaN
v2a1	6860
v18q1	7342
rez_esc	7928
meaneduc	5
SQBmeaned	5

There are five columns which have missing values

3. Check if there are any biases in your dataset.

3. Check if there are any biases in your dataset.

In [19]:

```
trainDf_NaN['% NaN'] = (trainDf_NaN['CountOfNaN'] / trainDf.shape[0]) * 100
trainDf_NaN[trainDf_NaN.sum(axis = 1) > 0]
```

Out[19]:

	CountOfNaN	% NaN
v2a1	6860	71.779847
v18q1	7342	76.823271
rez_esc	7928	82.954902
meaneduc	5	0.052318
SQBmeaned	5	0.052318

In [20]:

```
Missing_cols = trainDf.columns[trainDf.isnull().any()]
Missing_cols
```

Out[20]:

```
Index(['v2a1', 'v18q1', 'rez_esc', 'meaneduc', 'SQBmeaned'], dtype='object')
```

In [21]:

```
print('#of Missing Columns: {}'.format(len(Missing_cols)))
```

```
#of Missing Columns: 5
```

In [22]:

```
#pip install missingno
```

In [23]:

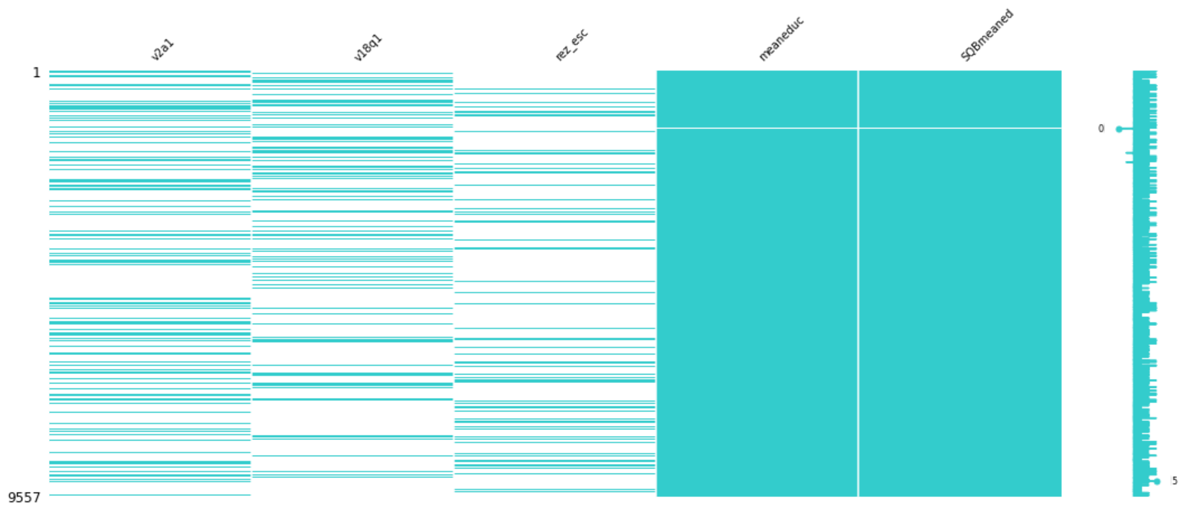
```
import missingno as msno
```

In [24]:

```
#Showing columns with missing values
msno.matrix(trainDf[Missing_cols], figsize = (18,7), fontsize = 10, color=(0.2,0.8,0.8))
```

Out[24]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x1b87e77e820>
```



Remove columns with missing values

In [25]:

```
trainDf.drop(Missing_cols, axis = 1, inplace = True)
```

In [26]:

```
trainDf.shape
```

Out[26]:

```
(9557, 138)
```

In [27]:

```
trainDf_dtypes = trainDf.dtypes.reset_index()
trainDf_dtypes.columns = ["col_names", "col_type"]
print(trainDf_dtypes)
```

```
           col_names col_type
0                 Id   object
1             hacdor    int64
2              rooms    int64
3             hacapo    int64
4               v14a    int64
..               ...      ...
133      SQBhogar_nin    int64
134  SQBovercrowding  float64
135     SQBdependency  float64
136            agesq    int64
137           Target    int64

[138 rows x 2 columns]
```

In [28]:

```
trainDf_dtypes.groupby("col_type").size()
```

Out[28]:

```
col_type
int64      130
float64      3
object       5
dtype: int64
```

In [29]:

```
trainDf.select_dtypes(include = ['object']).columns
```

Out[29]:

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

In [30]:

```
obj_cols = trainDf.select_dtypes(include = ['object']).columns
```

In [31]:

```
obj_df = trainDf[obj_cols]
```

In [32]:

```
obj_df.shape
```

Out[32]:

```
(9557, 5)
```

In [33]:

```
#df_obj.head()
trainDf[obj_cols]
```

Out[33]:

	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
...	...	...	...	...	...
9552	ID_d45ae367d	d6c086aa3	.25	9	no
9553	ID_c94744e07	d6c086aa3	.25	9	no
9554	ID_85fc658f8	d6c086aa3	.25	9	no
9555	ID_ced540c61	d6c086aa3	.25	9	no
9556	ID_a38c64491	d6c086aa3	.25	9	no

9557 rows × 5 columns

In [34]:

```
for col in obj_cols:
    print('Unique value in columns: {} = {}'.format(col, len(trainDf[col].unique())))
```

```
Unique value in columns: Id = 9557
Unique value in columns: idhogar = 2988
Unique value in columns: dependency = 31
Unique value in columns: edjefe = 22
Unique value in columns: edjefa = 22
```

In [35]:

```
#pip install pandas_profiling
#import pandas_profiling as pp
```

In [36]:

```
num_cols = trainDf.select_dtypes(exclude=['object']).columns
num_cols
```

Out[36]:

```
Index(['hacdor', 'rooms', 'hacapo', 'v14a', 'refrig', 'v18q', 'r4h1', 'r4h
2',
       'r4h3', 'r4m1',
       ...
       'age', 'SQBescolari', 'SQBage', 'SQBhogar_total', 'SQBedjefe',
       'SQBhogar_nin', 'SQBovercrowding', 'SQBdependency', 'agesq', 'Targe
t'],
      dtype='object', length=133)
```

In [37]:

```
num_df = trainDf[num_cols]
```

In [38]:

```
num_df.shape
```

Out[38]:

```
(9557, 133)
```

In [39]:

```
num_df.describe().T
```

Out[39]:

	count	mean	std	min	25%	50%	75%
hacdor	9557.0	0.038087	0.191417	0.00	0.000000	0.000000	0.000000
rooms	9557.0	4.955530	1.468381	1.00	4.000000	5.000000	6.000000
hacapo	9557.0	0.023648	0.151957	0.00	0.000000	0.000000	0.000000
v14a	9557.0	0.994768	0.072145	0.00	1.000000	1.000000	1.000000
refrig	9557.0	0.957623	0.201459	0.00	1.000000	1.000000	1.000000
...	...	...	...	...	...	...	...
SQBhogar_nin	9557.0	3.844826	6.946296	0.00	0.000000	1.000000	4.000000
SQBovercrowding	9557.0	3.249485	4.129547	0.04	1.000000	2.250000	4.000000
SQBdependency	9557.0	3.900409	12.511831	0.00	0.111111	0.444444	1.777778
agesq	9557.0	1643.774302	1741.197050	0.00	289.000000	961.000000	2601.000000
Target	9557.0	3.302292	1.009565	1.00	3.000000	4.000000	4.000000

133 rows × 8 columns

In [42]:

```
float_cols = trainDf.select_dtypes(include=['float64']).columns
```

In [45]:

```
trainDf[float_cols].describe().T
```

Out[45]:

	count	mean	std	min	25%	50%	75%	max
overcrowding	9557.0	1.605380	0.819946	0.20	1.000000	1.500000	2.000000	6.0
SQBovercrowding	9557.0	3.249485	4.129547	0.04	1.000000	2.250000	4.000000	36.0
SQBdependency	9557.0	3.900409	12.511831	0.00	0.111111	0.444444	1.777778	64.0

In [48]:

```
float_df = trainDf[float_cols]
float_df
```

Out[48]:

	overcrowding	SQBovercrowding	SQBdependency
0	1.000000	1.000000	0.0000
1	1.000000	1.000000	64.0000
2	0.500000	0.250000	64.0000
3	1.333333	1.777778	1.0000
4	1.333333	1.777778	1.0000
...	...	...	...
9552	1.250000	1.562500	0.0625
9553	1.250000	1.562500	0.0625
9554	1.250000	1.562500	0.0625
9555	1.250000	1.562500	0.0625
9556	1.250000	1.562500	0.0625

9557 rows × 3 columns

In [49]:

```
Q1 = float_df.quantile(0.25)
Q3 = float_df.quantile(0.75)
IQR = Q3 - Q1
print(IQR)
```

```
overcrowding       1.000000
SQBovercrowding    3.000000
SQBdependency      1.666667
dtype: float64
```

In [51]:

```
init = False

for col_name in list(float_df.columns):

    low = Q1[col_name] - 1.5 *IQR[col_name]
    high = Q3[col_name] + 1.5 *IQR[col_name]

    query_string = '{} <@low or {} > @high'.format(col_name, col_name)

    outlier_arr_loop = float_df.query(query_string).index

    if not init:
        outlier_arr = outlier_arr_loop
        init = True
    outlier_arr = outlier_arr.union(outlier_arr_loop)
```

In [52]:

```
len(outlier_arr)
```

Out[52]:

```
1527
```

In [53]:

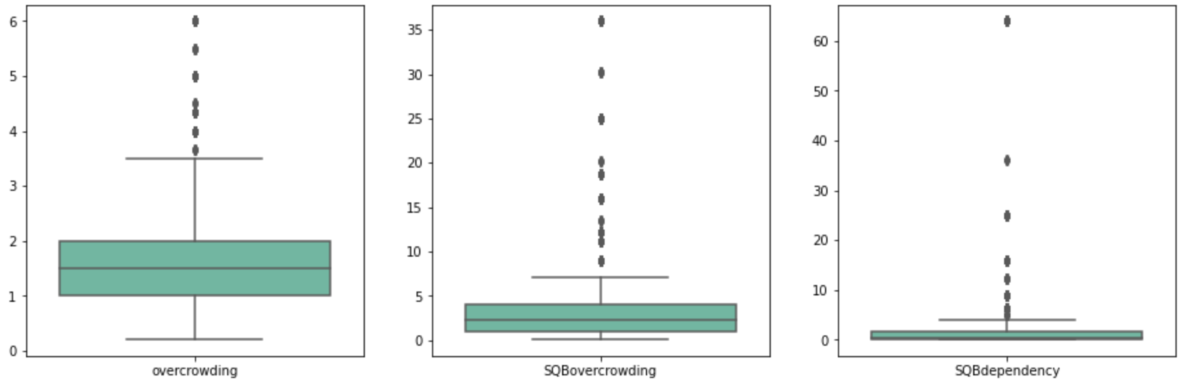
```
float_df.skew(axis=0)
```

Out[53]:

```
overcrowding       1.889641
SQBovercrowding    4.186951
SQBdependency      4.404052
dtype: float64
```

In [54]:

```
fig, (axes) = plt.subplots(nrows=1, ncols=3, figsize=(16, 5))
sns.boxplot(data=float_df[['overcrowding']], palette='Set2', ax=axes[0]);
sns.boxplot(data=float_df[['SQBovercrowding']] , palette='Set2', ax=axes[1]);
sns.boxplot(data=float_df[['SQBdependency']], palette='Set2', ax=axes[2]);
```

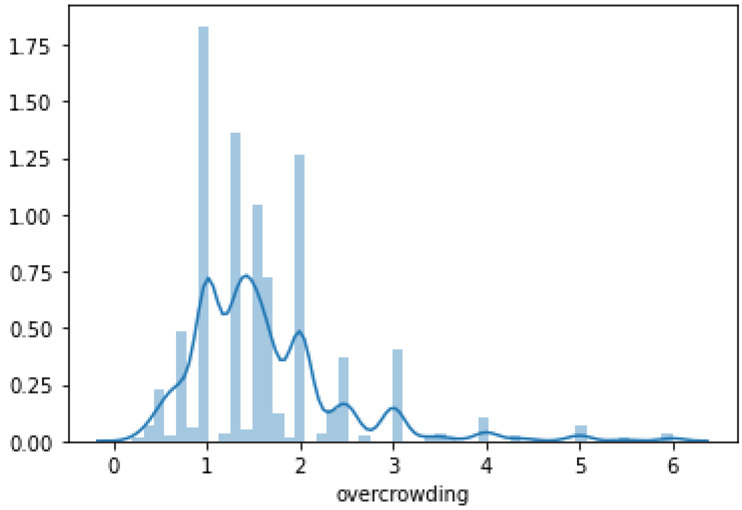


In [55]:

```
#overcrowding Distribution
sns.distplot(float_df.overcrowding)
```

Out[55]:

<matplotlib.axes._subplots.AxesSubplot at 0x1b800061250>

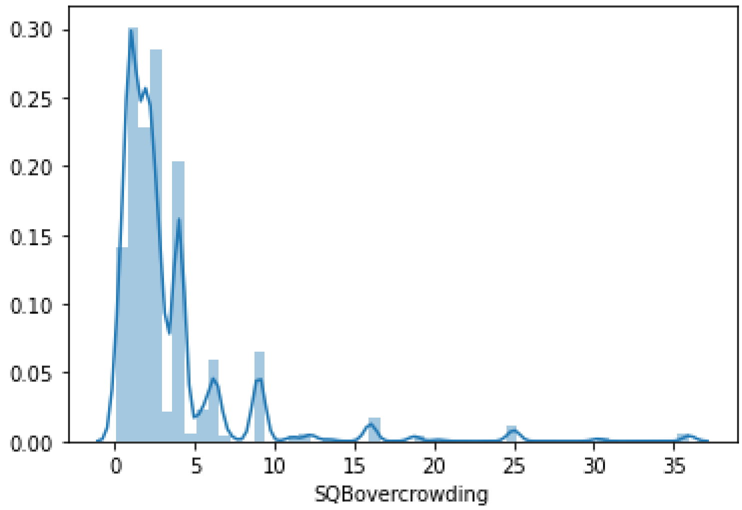


In [56]:

```
#SQBovercrowding Distribution
sns.distplot(float_df.SQBovercrowding)
```

Out[56]:

<matplotlib.axes._subplots.AxesSubplot at 0x1b8004ef1c0>

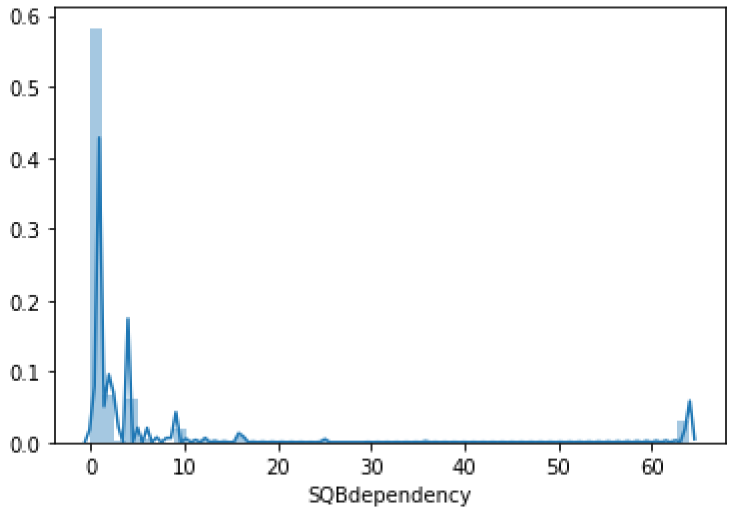


In [57]:

```
#SQBdependency Distribution
sns.distplot(float_df.SQBdependency)
```

Out[57]:

```
&lt;matplotlib.axes._subplots.AxesSubplot at 0x1b8000721c0&gt;
```



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

In [58]:

```
trainDf.shape
```

Out[58]:

```
(9557, 138)
```

In [59]:

```
#sqldf('SELECT COUNT(DISTINCT idhogar) FROM trainDf')
len(trainDf['idhogar'].unique())
```

Out[59]:

```
2988
```

In [60]:

```
sqldf('SELECT idhogar, Target FROM trainDf order by idhogar;')
```

Out[60]:

	idhogar	Target
0	001ff74ca	4
1	001ff74ca	4
2	003123ec2	2
3	003123ec2	2
4	003123ec2	2
...	...	...
9552	ffe90d46f	1
9553	fff7d6be1	4
9554	fff7d6be1	4
9555	fff7d6be1	4
9556	fff7d6be1	4

9557 rows × 2 columns

In [61]:

```
sqldf('SELECT idhogar, Target FROM trainDf order by idhogar;')
```

Out[61]:

	idhogar	Target
0	001ff74ca	4
1	001ff74ca	4
2	003123ec2	2
3	003123ec2	2
4	003123ec2	2
...	...	...
9552	ffe90d46f	1
9553	fff7d6be1	4
9554	fff7d6be1	4
9555	fff7d6be1	4
9556	fff7d6be1	4

9557 rows × 2 columns

In [62]:

```
trainDf.groupby(['idhogar','Target']).size().unstack()
```

Out[62]:

Target	1	2	3	4
idhogar				
001ff74ca	NaN	NaN	NaN	2.0
003123ec2	NaN	4.0	NaN	NaN
004616164	NaN	2.0	NaN	NaN
004983866	NaN	NaN	2.0	NaN
005905417	NaN	3.0	NaN	NaN
...	...	...	...	...
ff9343a35	NaN	NaN	NaN	4.0
ff9d5ab17	NaN	NaN	NaN	3.0
ffae4a097	NaN	NaN	NaN	2.0
ffe90d46f	4.0	NaN	NaN	NaN
fff7d6be1	NaN	NaN	NaN	4.0

2988 rows × 4 columns

In [63]:

```
trainDf.groupby(['idhogar','Target']).size().unstack().fillna(0).sample(10)
```

Out[63]:

Target	1	2	3	4
idhogar				
f86c4f7b1	0.0	0.0	4.0	0.0
2af7d54ce	0.0	0.0	0.0	2.0
3e27db2cd	0.0	0.0	0.0	3.0
597fd9997	0.0	0.0	0.0	1.0
5e9e3d554	0.0	0.0	0.0	3.0
d22d30c29	0.0	0.0	0.0	5.0
3fe2124d9	0.0	0.0	0.0	1.0
24559be8f	0.0	0.0	0.0	1.0
8ac40302b	0.0	0.0	0.0	4.0
05e1d4a10	0.0	3.0	0.0	0.0

In [64]:

```
df_family_level = trainDf.groupby(['idhogar','Target']).size().unstack().reset_index()
df_family_level.head()
```

Out[64]:

Target	idhogar	1	2	3	4
0	001ff74ca	NaN	NaN	NaN	2.0
1	003123ec2	NaN	4.0	NaN	NaN
2	004616164	NaN	2.0	NaN	NaN
3	004983866	NaN	NaN	2.0	NaN
4	005905417	NaN	3.0	NaN	NaN

In [65]:

```
df_family_level.columns
```

Out[65]:

```
Index(['idhogar', 1, 2, 3, 4], dtype='object', name='Target')
```

In [66]:

```
column_names = ['FamilyId', 'Level1', 'Level2', 'Level3', 'Level4']
df_family_level.columns = column_names
df_family_level.head()
```

Out[66]:

	FamilyId	Level1	Level2	Level3	Level4
0	001ff74ca	NaN	NaN	NaN	2.0
1	003123ec2	NaN	4.0	NaN	NaN
2	004616164	NaN	2.0	NaN	NaN
3	004983866	NaN	NaN	2.0	NaN
4	005905417	NaN	3.0	NaN	NaN

In [67]:

```
df_family_level.fillna(0, inplace = True)
```

In [68]:

```
df_family_level['Total_Levels'] = (df_family_level.Level1
                                   + df_family_level.Level2
                                   + df_family_level.Level3
                                   + df_family_level.Level4)
```

In [69]:

```
df_family_level.head()
```

Out[69]:

	FamilyId	Level1	Level2	Level3	Level4	Total_Levels
0	001ff74ca	0.0	0.0	0.0	2.0	2.0
1	003123ec2	0.0	4.0	0.0	0.0	4.0
2	004616164	0.0	2.0	0.0	0.0	2.0
3	004983866	0.0	0.0	2.0	0.0	2.0
4	005905417	0.0	3.0	0.0	0.0	3.0

In [70]:

```
poverty_level=trainDf.groupby('idhogar')['Target'].apply(lambda x: x.nunique() == 1)
print('{} Households have different Target value.'.format(sum(poverty_level == False)))
```

```
85 Households have different Target value.
```

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

In [71]:

```
trainDf.columns
```

Out[71]:

```
Index(['Id', 'hacdor', 'rooms', 'hacapo', 'v14a', 'refrig', 'v18q', 'r4h1',
       'r4h2', 'r4h3',
       ...
       'age', 'SQBescolari', 'SQBage', 'SQBhogar_total', 'SQBedjefe',
       'SQBhogar_nin', 'SQBovercrowding', 'SQBdependency', 'agesq', 'Targe
t'],
      dtype='object', length=138)
```

In [72]:

```
trainDf.parentesco1
```

Out[72]:

```
0       1
1       1
2       1
3       0
4       0
       ..
9552    1
9553    0
9554    0
9555    0
9556    0
Name: parentesco1, Length: 9557, dtype: int64
```

In [73]:

```
grouped = trainDf.groupby('idhogar')
grouped.apply(lambda x : x[x['parentesco1'] != 1]['parentesco1'])
```

Out[73]:

```
idhogar
001ff74ca  7471    0
003123ec2  8159    0
           8161    0
           8162    0
004616164  6473    0
                  ..
ffe90d46f  9350    0
           9351    0
fff7d6be1  5948    0
           5949    0
           5951    0
Name: parentesco1, Length: 6584, dtype: int64
```

In [74]:

```
trainDf.idhogar
```

Out[74]:

```
0       21eb7fcc1
1       0e5d7a658
2       2c7317ea8
3       2b58d945f
4       2b58d945f
          ...
9552    d6c086aa3
9553    d6c086aa3
9554    d6c086aa3
9555    d6c086aa3
9556    d6c086aa3
Name: idhogar, Length: 9557, dtype: object
```

In [75]:

```
sqldf('SELECT idhogar, parentesco1 FROM trainDf order by idhogar;')
```

Out[75]:

	idhogar	parentesco1
0	001ff74ca	0
1	001ff74ca	1
2	003123ec2	0
3	003123ec2	1
4	003123ec2	0
...	...	...
9552	ffe90d46f	0
9553	fff7d6be1	0
9554	fff7d6be1	0
9555	fff7d6be1	1
9556	fff7d6be1	0

9557 rows × 2 columns

In [76]:

```
sqldf('SELECT idhogar, COUNT(parentesco1) FROM trainDf GROUP BY idhogar HAVING COUNT(parent
```

Out[76]:

idhogar	COUNT(parentesco1)

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

In [80]:

```
#pl = sqldf('SELECT idhogar, Target FROM trainDf ORDER BY idhogar;')

pl = trainDf[['idhogar', 'Target']].sort_values(by='idhogar', ascending=True)
pl
```

Out[80]:

	idhogar	Target
7472	001ff74ca	4
7471	001ff74ca	4
8159	003123ec2	2
8160	003123ec2	2
8161	003123ec2	2
...	...	...
9351	ffe90d46f	1
5948	fff7d6be1	4
5949	fff7d6be1	4
5950	fff7d6be1	4
5951	fff7d6be1	4

9557 rows × 2 columns

In [81]:

```
pl.shape
```

Out[81]:

```
(9557, 2)
```

In [87]:

```
#a=pl.idhogar[0]
#for i in range(len(pl)) :

count = 0;

print('Family Id \t Poverty Level')

for i in range(5000):

    f1 = pl.idhogar[i]
    f2 = pl.idhogar[i+1]

    if (f1 == f2):
        t1=pl.Target[i]
        t2=pl.Target[i+1]

        if(t1 != t2):

            count = count + 1;
            pl.Target[i+1] = pl.Target[i]
            print(pl.idhogar[i],'\t', pl.Target[i+1])
print(count)
```

```
Family Id        Poverty Level
4b6077882        1
4b6077882        1
6833ac5dc        2
43b9c83e5        2
5c3f7725d        3
5c3f7725d        3
0f9494d3a        2
0f9494d3a        2
0f9494d3a        2
daafc1281        2
daafc1281        2
daafc1281        2
73d85d05d        2
bcaa2e2f5        4
44f219a16        3
efd3aec61        2
efd3aec61        2
3c6973219        4
0511912b6        4
f006348ed        3
f006348ed        3
f006348ed        3
a20ff33ba        2
5e9329fc6        3
e65d4b943        3
42ec8bef5        2
42ec8bef5        2
6bcf799cf        2
26b3a0f41        3
4dc11e11f        1
4dc11e11f        1
594d3eb27        2
594d3eb27        2
d9b1558b5        1
```

```
d9b1558b5        1
7ea6aca15        4
8bb6da3c1        2
8bb6da3c1        2
3df651058        1
811a35744        4
811a35744        4
2cb443214        2
42
```

In [89]:

```
pl
```

Out[89]:

	idhogar	Target
7472	001ff74ca	4
7471	001ff74ca	4
8159	003123ec2	2
8160	003123ec2	2
8161	003123ec2	2
...	...	...
9351	ffe90d46f	1
5948	fff7d6be1	4
5949	fff7d6be1	4
5950	fff7d6be1	4
5951	fff7d6be1	4

9557 rows × 2 columns

Now, poverty level of each member and the head of the house within a family is same.

8. Remove null value rows of the target variable.

In [90]:

```
trainDf['Target'].isnull().sum()
```

Out[90]:

```
0
```

In [ ]:

```

```

Null values are not present in target variable

9. Predict the accuracy using random forest classifier.

In [91]:

```
obj_df.columns
```

Out[91]:

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

In [92]:

```
obj_df.head()
```

Out[92]:

	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

In [93]:

```
obj_df.columns
```

Out[93]:

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

In [94]:

```
obj_df.head()
```

Out[94]:

	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

In [95]:

```
# Prepare DataFrame by Convertinjg Object columns into numeric columns using One Hot Encodi
obj_df_OHE = pd.DataFrame(pd.get_dummies(obj_df, columns=["idhogar", "dependency", "edjefe"
```

In [96]:

```
obj_df_OHE.head()
```

Out[96]:

	Id	idhogar_001ff74ca	idhogar_003123ec2	idhogar_004616164	idhogar_004983866
0	ID_279628684	0	0	0	0
1	ID_f29eb3ddd	0	0	0	0
2	ID_68de51c94	0	0	0	0
3	ID_d671db89c	0	0	0	0
4	ID_d56d6f5f5	0	0	0	0

5 rows × 3064 columns

In [97]:

```
obj_df_OHE.head().columns
```

Out[97]:

```
Index(['Id', 'idhogar_001ff74ca', 'idhogar_003123ec2', 'idhogar_004616164',
       'idhogar_004983866', 'idhogar_005905417', 'idhogar_006031de3',
       'idhogar_006555fe2', 'idhogar_00693f597', 'idhogar_006b64543',
       ...
       'edjefa_21', 'edjefa_3', 'edjefa_4', 'edjefa_5', 'edjefa_6', 'edjefa_
7',
       'edjefa_8', 'edjefa_9', 'edjefa_no', 'edjefa_yes'],
      dtype='object', length=3064)
```

In [98]:

```
# Prepare DataFrame by Convertinjg Object columns into numeric columns using One Hot Encodi
float_df_OHE = pd.DataFrame(pd.get_dummies(float_df.columns, columns=['overcrowding''SQBove
```

In [99]:

```
float_df_OHE.head()
```

Out[99]:

	SQBdependency	SQBovercrowding	overcrowding
0	0	0	1
1	0	1	0
2	1	0	0

In [101]:

```
# Drop object columns from Train DataFrame
#TrainDfDropObj = pd.DataFrame(trainDf.drop(["Id", "idhogar", "dependency", "edjefe", "edje
```

In [102]:

```
#TrainDfDrop.Id
```

In [103]:

```
#FinalTrainDf = pd.DataFrame(pd.concat([TrainDfDropObj, obj_df_OHE]))
FinalTrainDf = pd.DataFrame(pd.concat([obj_df_OHE, num_df]))
```

In [104]:

```
FinalTrainDf.shape
```

Out[104]:

```
(19114, 3197)
```

In [105]:

```
FinalTrainDf.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 19114 entries, 0 to 9556
Columns: 3197 entries, Id to Target
dtypes: float64(3196), object(1)
memory usage: 466.4+ MB
```

In [106]:

```
FinalTrainDf.select_dtypes(include = ['object']).columns
```

Out[106]:

```
Index(['Id'], dtype='object')
```

In [107]:

```
FinalTrainDf = FinalTrainDf.drop('Id', axis=1)
```

In [108]:

```
#FinalTrainDf.Id
```

In [109]:

```
FinalTrainDf.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 19114 entries, 0 to 9556
Columns: 3196 entries, idhogar_001ff74ca to Target
dtypes: float64(3196)
memory usage: 466.2 MB
```

In [110]:

```
# Missing Values
#FinalTrainDf.isnull().sum()
#FinalTrainDf.isna().sum()
FinalTrainDf_NaN = pd.DataFrame(data = FinalTrainDf.isnull().sum(), columns = ['CountOfNaN'
FinalTrainDf_NaN[FinalTrainDf_NaN['CountOfNaN'] != 0]
```

Out[110]:

	CountOfNaN
idhogar_001ff74ca	9557
idhogar_003123ec2	9557
idhogar_004616164	9557
idhogar_004983866	9557
idhogar_005905417	9557
...	...
SQBhogar_nin	9557
SQBovercrowding	9557
SQBdependency	9557
agesq	9557
Target	9557

3196 rows × 1 columns

In [111]:

```
FinalTrainDf.fillna(0, inplace = True)
FinalTrainDf.head()
```

Out[111]:

	idhogar_001ff74ca	idhogar_003123ec2	idhogar_004616164	idhogar_004983866	idhogar_00590
0	0.0	0.0	0.0	0.0	
1	0.0	0.0	0.0	0.0	
2	0.0	0.0	0.0	0.0	
3	0.0	0.0	0.0	0.0	
4	0.0	0.0	0.0	0.0	

5 rows × 3196 columns

In [112]:

```
#FinalTrainDf.isna().sum()
FinalTrainDf_NaN = pd.DataFrame(data = FinalTrainDf.isnull().sum(), columns = ['CountOfNaN'
FinalTrainDf_NaN[FinalTrainDf_NaN['CountOfNaN'] != 0]
```

Out[112]:

CountOfNaN

In [113]:

```
X = FinalTrainDf.drop('Target', axis=1)
y = FinalTrainDf['Target']
```

In [114]:

```
from sklearn.model_selection import train_test_split
X_train,X_test,y_train,y_test = train_test_split(X, y,test_size=0.3, random_state = 110)
#X_train,X_test,y_train,y_test = train_test_split(X, y,test_size=0.7, random_state = 11)
print(len(X_train))
print(len(X_test))
```

```
13379
5735
```

In [115]:

```
from sklearn.ensemble import RandomForestClassifier
rfc = RandomForestClassifier(n_estimators = 100, criterion = 'entropy')
rfc.fit(X_train, y_train)
```

Out[115]:

```
RandomForestClassifier(criterion='entropy')
```

In [116]:

```
from sklearn.metrics import classification_report, confusion_matrix, accuracy_score
```

In [117]:

```
predictions = rfc.predict(X_test)
print("---------- Test Accuracy ----------")
accuracy_test = accuracy_score(y_test, predictions)
print(accuracy_test)
print("\n---------- Confusion Matrix ----------")
conf_matrix = confusion_matrix(y_test, predictions)
print(conf_matrix)
print("\n---------- Classification Report ----------")
print(classification_report(y_test, predictions))
```

```
---------- Test Accuracy ----------
0.9150828247602442

---------- Confusion Matrix ----------
[[2853    0    0    0    0]
 [   0  134   19    0   79]
 [   0    4  304    3  170]
 [   0    0   18  156  189]
 [   0    0    4    1 1801]]

---------- Classification Report ----------
              precision    recall  f1-score   support

         0.0       1.00      1.00      1.00      2853
         1.0       0.97      0.58      0.72       232
         2.0       0.88      0.63      0.74       481
         3.0       0.97      0.43      0.60       363
         4.0       0.80      1.00      0.89      1806

    accuracy                           0.92      5735
   macro avg       0.93      0.73      0.79      5735
weighted avg       0.93      0.92      0.91      5735
```

Here, Accuracy on train data is 92 %

Apply the Model on Test Data

In [120]:

```
testDf = pd.read_csv(r'D:\Data_Science_Data\Income_Qualification\test.csv')
```

In [122]:

```
testDf.head()
```

Out[122]:

	Id	v2a1	hacdor	rooms	hacapo	v14a	refrig	v18q	v18q1	r4h1	...	age
0	ID_2f6873615	NaN	0	5	0	1	1	0	NaN	1	...	4
1	ID_1c78846d2	NaN	0	5	0	1	1	0	NaN	1	...	41
2	ID_e5442cf6a	NaN	0	5	0	1	1	0	NaN	1	...	41
3	ID_a8db26a79	NaN	0	14	0	1	1	1	1.0	0	...	59
4	ID_a62966799	175000.0	0	4	0	1	1	1	1.0	0	...	18

5 rows × 142 columns

In [123]:

```
testDf_NaN = pd.DataFrame(data = testDf.isnull().sum(), columns = ['CountOfNaN'])
print(testDf_NaN)
```

```
                 CountOfNaN
Id                        0
v2a1                  17403
hacdor                    0
rooms                     0
hacapo                    0
...                     ...
SQBhogar_nin              0
SQBovercrowding           0
SQBdependency             0
SQBmeaned                31
agesq                     0

[142 rows x 1 columns]
```

In [124]:

```
testDf_NaN['% NaN'] = (testDf_NaN['CountOfNaN'] / testDf.shape[0]) * 100
testDf_NaN[testDf_NaN.sum(axis = 1) > 0]
```

Out[124]:

	CountOfNaN	% NaN
v2a1	17403	72.950201
v18q1	18126	75.980885
rez_esc	19653	82.381791
meaneduc	31	0.129946
SQBmeaned	31	0.129946

In [125]:

```
Missing_cols_test = testDf.columns[testDf.isnull().any()]
Missing_cols_test
```

Out[125]:

```
Index(['v2a1', 'v18q1', 'rez_esc', 'meaneduc', 'SQBmeaned'], dtype='object')
```

In [126]:

```
testDf.drop(Missing_cols, axis = 1, inplace = True)
testDf.shape
```

Out[126]:

```
(23856, 137)
```

In [127]:

```
testDf.select_dtypes(include = ['object']).columns
```

Out[127]:

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

In [128]:

```
obj_cols_test = testDf.select_dtypes(include = ['object']).columns
```

In [129]:

```
obj_df_test = testDf[obj_cols_test]
```

In [130]:

```
for col in obj_cols_test:
    print('Unique value in columns: {} = {}'.format(col, len(testDf[col].unique())))
```

```
Unique value in columns: Id = 23856
Unique value in columns: idhogar = 7352
Unique value in columns: dependency = 35
Unique value in columns: edjefe = 22
Unique value in columns: edjefa = 22
```

In [131]:

```
from sklearn.preprocessing import LabelEncoder
lb_make = LabelEncoder()
```

In [132]:

```
testDf["idhogar_code"] = lb_make.fit_transform(testDf["idhogar"])
pd.unique(testDf[["idhogar", "idhogar_code"]].values.ravel())
```

Out[132]:

```
array(['72958b30c', 3230, '5b598fbc9', ..., 1659, 'd237404b6', 5963],
      dtype=object)
```

In [133]:

```
testDf["dependency_code"] = lb_make.fit_transform(testDf["dependency"])
pd.unique(testDf[["dependency", "dependency_code"]].values.ravel())
```

Out[133]:

```
array(['.5', 9, 'no', 33, '8', 32, 'yes', 34, '.25', 4, '2', 21,
       '.33333334', 6, '.375', 7, '.60000002', 10, '1.5', 19, '.2', 3,
       '.75', 12, '.66666669', 11, '3', 25, '.14285715', 1, '.40000001',
       8, '.80000001', 13, '1.6666666', 20, '.2857143', 5, '1.25', 17,
       '2.5', 24, '5', 29, '.85714287', 15, '1.3333334', 18, '.16666667',
       2, '4', 28, '.125', 0, '.83333331', 14, '2.3333333', 23, '7', 31,
       '1.2', 16, '3.5', 27, '2.25', 22, '3.3333333', 26, '6', 30],
      dtype=object)
```

In [134]:

```
testDf["edjefe_code"] = lb_make.fit_transform(testDf["edjefe"])
pd.unique(testDf[["edjefe", "edjefe_code"]].values.ravel())
```

Out[134]:

```
array(['no', 20, '16', 6, '10', 0, '6', 16, '11', 1, '8', 18, '13', 3,
       '14', 4, '5', 15, '3', 13, '9', 19, '17', 7, '15', 5, '7', 17,
       '21', 12, '4', 14, '12', 2, '2', 10, '20', 11, 'yes', 21, '19', 9,
       '18', 8], dtype=object)
```

In [135]:

```
testDf["edjefa_code"] = lb_make.fit_transform(testDf["edjefa"])
pd.unique(testDf[["edjefa", "edjefa_code"]].values.ravel())
```

Out[135]:

```
array(['17', 7, 'no', 20, '11', 1, '14', 4, '10', 0, '15', 5, '9', 19,
       '6', 16, '8', 18, '3', 13, '2', 10, '5', 15, '16', 6, '12', 2,
       'yes', 21, '7', 17, '13', 3, '21', 12, '4', 14, '19', 9, '18', 8,
       '20', 11], dtype=object)
```

In [136]:

```
#num_cols_test = testDf.select_dtypes(exclude=['object']).columns
#num_cols_test
```

In [137]:

```
#num_df_test = testDf[num_cols_test]
```

In [138]:

```
# Prepare DataFrame by Convertinjg Object columns into numeric columns using One Hot Encodi
# obj_df_OHE_test = pd.DataFrame(pd.get_dummies(obj_df_test, columns=["idhogar", "dependenc
# obj_df_OHE_test.head()
```

In [139]:

```
#num_drof_float_df = pd.DataFrame(num_df_test.drop(['SQBdependency', 'SQBovercrowding','ove
#TestDfDropObj = pd.DataFrame(testDf.drop(["Id", "idhogar", "dependency", "edjefe", "edjefa
#TestDfDropObj.head()
```

In [140]:

```
#obj_df_OHE_test.select_dtypes(include=['float64']).columns
```

In [141]:

```
#FinalTestDf = pd.DataFrame(pd.concat([TestDfDropObj, obj_df_OHE_test]))
#FinalTestDf = pd.DataFrame(pd.concat([TestDfDropObj, num_df_test]))
```

In [143]:

```
FinalTestDf.shape
```

```
---------------------------------------------------------------------------
NameError                                 Traceback (most recent call last)
<ipython-input-143-373aa887d663> in <module>
----> 1 FinalTestDf.shape

NameError: name 'FinalTestDf' is not defined
```

In [145]:

```
FinalTestDf.info()
```

```
---------------------------------------------------------------------------
NameError                                 Traceback (most recent call last)
<ipython-input-145-ff7f34d336e3> in <module>
----> 1 FinalTestDf.info()

NameError: name 'FinalTestDf' is not defined
```

In [146]:

```
FinalTestDf_NaN = pd.DataFrame(data = FinalTestDf.isnull().sum(), columns = ['CountOfNaN'])
FinalTestDf_NaN[FinalTestDf_NaN['CountOfNaN'] != 0]
```

```
---------------------------------------------------------------------------
NameError                                 Traceback (most recent call last)
<ipython-input-146-ce82a29d9b13> in <module>
----> 1 FinalTestDf_NaN = pd.DataFrame(data = FinalTestDf.isnull().sum(), co
lumns = ['CountOfNaN'])
      2 FinalTestDf_NaN[FinalTestDf_NaN['CountOfNaN'] != 0]

NameError: name 'FinalTestDf' is not defined
```

In [144]:

```
X = FinalTrainDf
```

In [147]:

```
predictions = rfc.predict(X_test)
print("---------- Test Accuracy ----------")
accuracy_test = accuracy_score(y_test, predictions)
print(accuracy_test)
print("\n---------- Confusion Matrix ----------")
conf_matrix = confusion_matrix(y_test, predictions)
print(conf_matrix)
print("\n---------- Classification Report ----------")
print(classification_report(y_test, predictions))
```

```
---------- Test Accuracy ----------
0.9150828247602442

---------- Confusion Matrix ----------
[[2853    0    0    0    0]
 [   0  134   19    0   79]
 [   0    4  304    3  170]
 [   0    0   18  156  189]
 [   0    0    4    1 1801]]

---------- Classification Report ----------
              precision    recall  f1-score   support

         0.0       1.00      1.00      1.00      2853
         1.0       0.97      0.58      0.72       232
         2.0       0.88      0.63      0.74       481
         3.0       0.97      0.43      0.60       363
         4.0       0.80      1.00      0.89      1806

    accuracy                           0.92      5735
   macro avg       0.93      0.73      0.79      5735
weighted avg       0.93      0.92      0.91      5735
```

Here, Accuracy on test data is 92 %

--- Thank You --

In [ ]:

```

```