Importing required libraries

In [1]:

```
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')
```

Importing Training and Testing dataset

In [2]:

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

1. Basic data checks

In [3]:

```
df_income_train.head()
```

Out[3]:

	Id	v2a1	hacdor	rooms	hacapo	v14a	refrig	v18q	v18q1	r4h1	...	SQBe
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	...	

5 rows × 143 columns

In [4]:

```
df_income_test.head()
```

Out[4]:

	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 [5]:

```
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: 25.4+ MB
```

In [6]:

```
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: 10.2+ MB
```

In [7]:

```
df_income_train.describe()
```

Out[7]:

	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

Identifying fields with their datatypes

In [8]:

```
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', 'r4h
2',
       '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')
```

Identify null values in train dataset

In [9]:

```
null_counts=df_income_train.isnull().sum()
```

In [10]:

```
null_counts[null_counts > 0]
```

Out[10]:

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

Observation :: All colums named for containing the null values are of float data type

2. Data Cleaning as few columns are mixed value and replacing null values with zero (0)

In [11]:

```
#creating dictionary mapping with 2 elements as YES and NO
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()
```

Out[11]:

	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

In [12]:

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

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

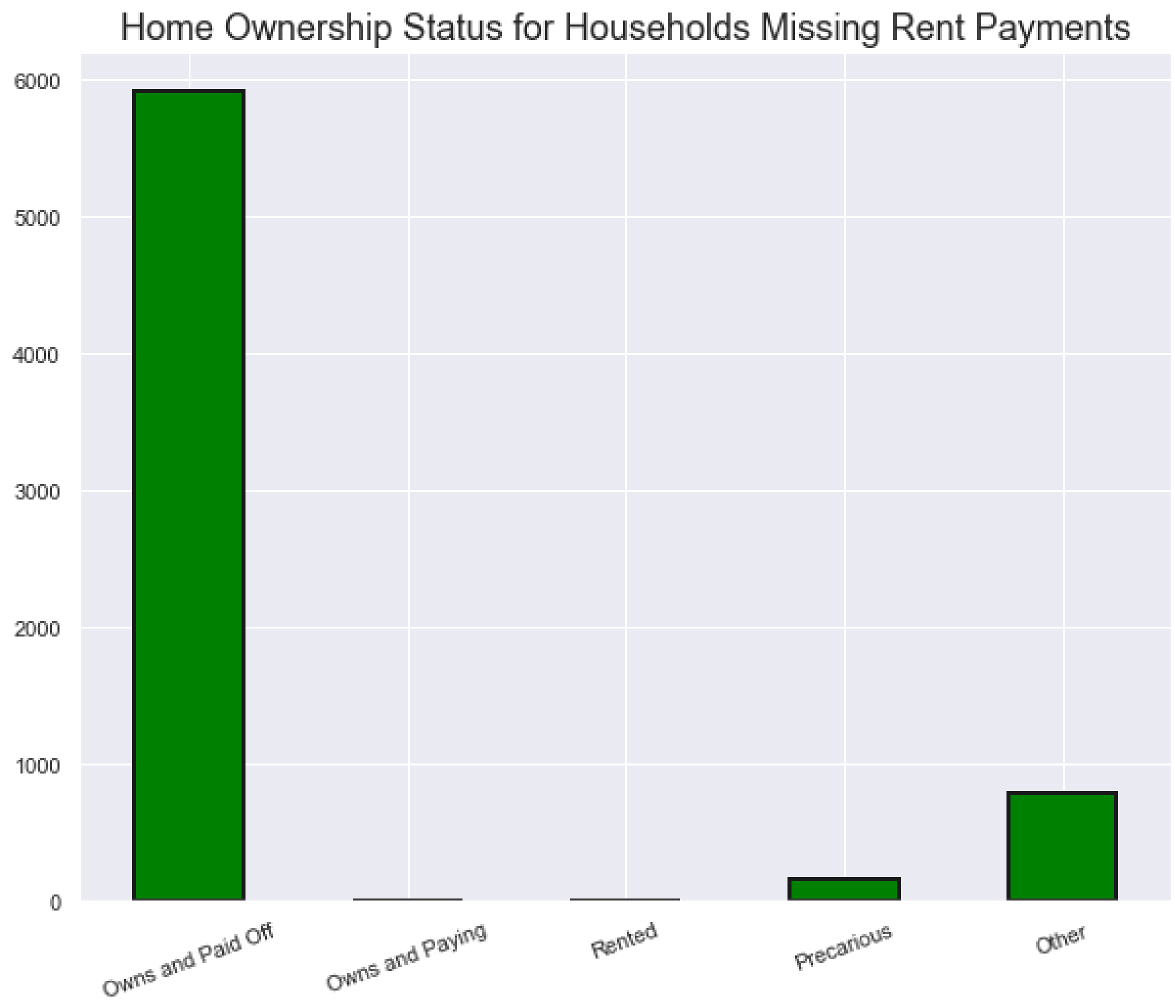
Out[12]:

	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

In [13]:

```
# 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
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);
```



In [14]:

```
#Looking at the above data it makes sense that when the house is fully paid, there will be
#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()
```

Out[14]:

```
v2a1    0
dtype: int64
```

In [15]:

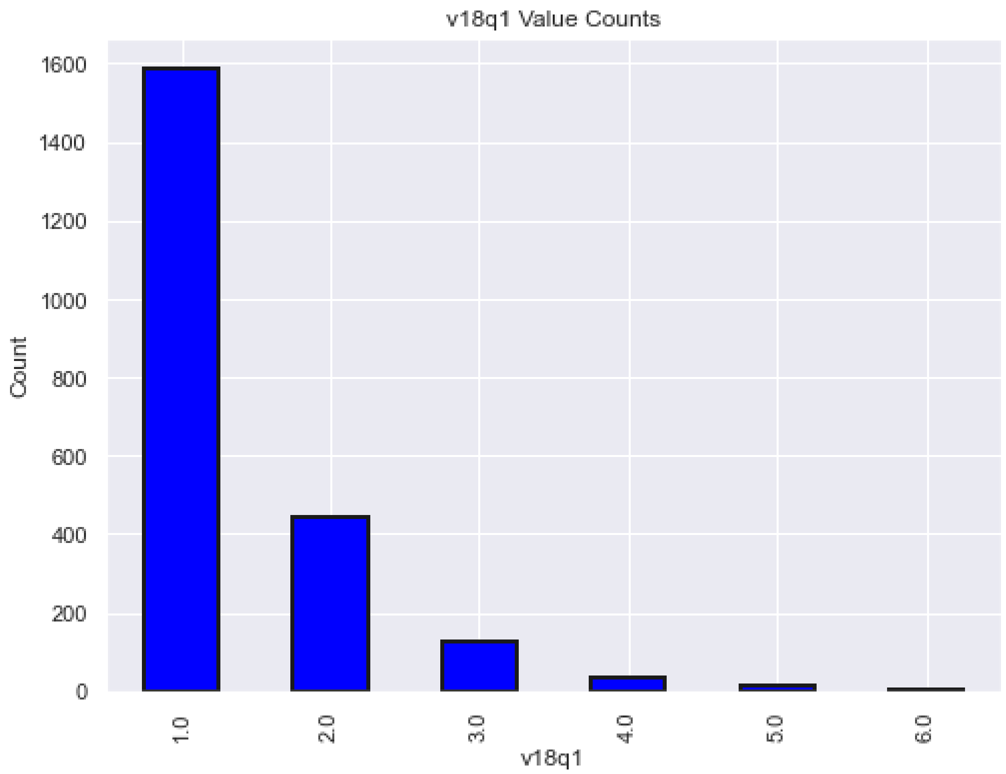
```
# Heads of household
heads = df_income_train.loc[df_income_train['parentesco1'] == 1].copy()
heads.groupby('v18q')['v18q1'].apply(lambda x: x.isnull().sum())
```

Out[15]:

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

In [16]:

```
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();
```



In [17]:

```
#Looking at the above data it makes sense that when owns a tablet column is 0, there will b
#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()
```

Out[17]:

```
v18q1    0
dtype: int64
```

In [18]:

```
# 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()
```

Out[18]:

```
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
```

In [19]:

```
#From the above , we see that when min age is 7 and max age is 17 for Years, then the 'behi
#Lets confirm
df_income_train.loc[df_income_train['rez_esc'].isnull()]['age'].describe()
```

Out[19]:

```
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
```

In [20]:

```
df_income_train.loc[(df_income_train['rez_esc'].isnull() & ((df_income_train['age'] > 7) &
```

Out[20]:

```
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
```

In [21]:

```
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 sch
#This explains why the member is behind in school.
```

Out[21]:

	Id	v2a1	hacdor	rooms	hacapo	v14a	refrig	v18q	v18q1	r4h1	...	SC
2514	ID_f012e4242	160000.0	0	6	0	1	1	1	1.0	0	...	

1 rows × 143 columns

In [22]:

```
#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()
```

Out[22]:

```
rez_esc    0
dtype: int64
```

In [23]:

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

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

Out[23]:

	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

In [24]:

```
#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()
```

Out[24]:

```
meaneduc    0
dtype: int64
```

In [25]:

```
#Lets look at SQBmeaned  (total nulls: 5) : square of the mean years of education of adults
# 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 escolar
#    head of household and gender, yes=1 and no=0
# edjefa, years of education of female head of household, based on the interaction of escol
#    head of household and gender, yes=1 and no=0
# instlevel1, =1 no level of education
# instlevel2, =1 incomplete primary
```

In [26]:

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

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

Out[26]:

	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

In [27]:

```
#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()
```

Out[27]:

```
SQBmeaned    0
dtype: int64
```

In [28]:

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

Out[28]:

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

In [29]:

```
# 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.'.f
```

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

In [30]:

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

Out[30]:

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

In [31]:

```
#Lets use Target value of the parent record (head of the household) and update rest. But be
# 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

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

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

In [32]:

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

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

In [33]:

```
#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_incom

    # 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.'.f
```

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

In [34]:

```
#Lets look at the dataset and plot head of household and Target
# 1 = extreme poverty, 2 = moderate poverty ,3 = vulnerable households, 4 = non vulnerable
target_counts = heads['Target'].value_counts().sort_index()
target_counts
```

Out[34]:

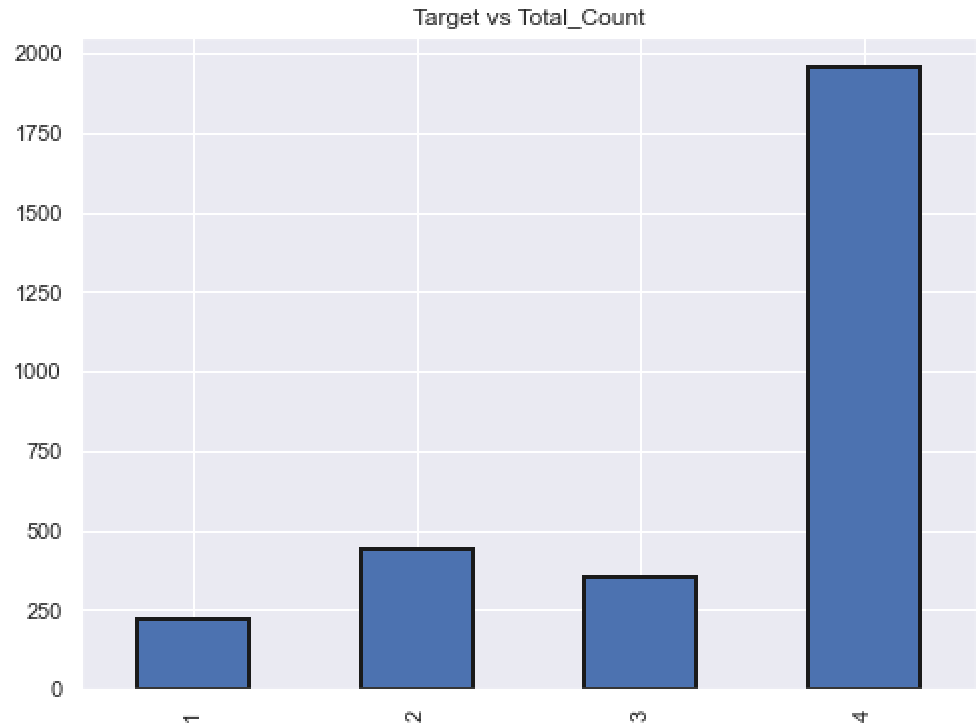
```
1     222
2     442
3     355
4    1954
Name: Target, dtype: int64
```

In [35]:

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

Out[35]:

```
<AxesSubplot:title={'center':'Target vs Total_Count'}>
```



In [36]:

```
#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)
```

In [37]:

```
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']
```

In [38]:

```
#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
```

Out[38]:

```
(2973, 98)
```

In [39]:

```
# 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
```

Out[39]:

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

In [40]:

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

Out[40]:

	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

In [41]:

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

In [42]:

```
# 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.
```

In [43]:

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

In [44]:

```
df_income_train.shape
```

Out[44]:

```
(9557, 131)
```

In [45]:

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

Out[45]:

```
(9557, 39)
```

In [46]:

```
# 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
```

Out[46]:

```
['female']
```

In [47]:

```
# 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)
```

In [48]:

```
df_income_train.shape
```

Out[48]:

```
(9557, 130)
```

In [49]:

```
#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
```

Out[49]:

```
(9557, 129)
```

In [50]:

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

In [51]:

```
df_income_train.shape
```

Out[51]:

```
(9557, 127)
```

Prediction using random forest classifier.

In [52]:

```
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,)
```

In [53]:

```
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,test_size=0.2,random_s
rmclassifier = RandomForestClassifier()
```

In [54]:

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

Out[54]:

```
RandomForestClassifier()
```

In [55]:

```
RandomForestClassifier(bootstrap=True, class_weight=None, criterion='gini',
                       max_depth=None, max_features='auto', max_leaf_nodes=None,
                       min_impurity_decrease=0.0, min_impurity_split=None,
                       min_samples_leaf=1, min_samples_split=2,
                       min_weight_fraction_leaf=0.0, n_estimators=10,
                       n_jobs=None, oob_score=False, random_state=None,
                       verbose=0, warm_start=False)
```

Out[55]:

```
RandomForestClassifier(n_estimators=10)
```

In [56]:

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

In [57]:

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

```
0.9476987447698745
[[ 135    0    0   22]
 [   1  283    1   32]
 [   0    1  191   41]
 [   0    1    1 1203]]
              precision    recall  f1-score   support

           1       0.99      0.86      0.92       157
           2       0.99      0.89      0.94       317
           3       0.99      0.82      0.90       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
```

In [58]:

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

In [59]:

```
y_predict_testdata
```

Out[59]:

```
array([4, 4, 4, ..., 4, 4, 4], dtype=int64)
```

Check the accuracy using random forest with cross validation

In [60]:

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

In [61]:

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

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

In [62]:

```
# Checking the score using 100 trees

um_trees= 100

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

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

In [63]:

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

Out[63]:

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

In [64]:

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

Out[64]:

```
array([4, 4, 4, ..., 4, 4, 4], dtype=int64)
```

In [65]:

```
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_importance
plt.xlabel('Importance')
```

Out[65]:

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