In [8]:

```
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')
```

In [11]:

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

In [12]:

```
print("Train:",train.shape)
print("Test:",test.shape)
```

```
Train: (9557, 143)
Test: (23856, 142)
```

In [13]:

```
train.head()
```

Out[13]:

	Id	v2a1	hacdor	rooms	hacapo	v14a	refrig	v18q	v18q1	r4h1	...	SQBescolari	SQBage	SQBhogar_total	SQBedjefe	SQBhogar_nin	SQBovercrowding	SQBdependency	SQBmeaned	agesq	Target
0	ID_279628684	190000.0	0	3	0	1	1	0	NaN	0	...	100	1849	1	100	0	1.000000	0.0	100.0	1849	4
1	ID_f29eb3ddd	135000.0	0	4	0	1	1	1	1.0	0	...	144	4489	1	144	0	1.000000	64.0	144.0	4489	4
2	ID_68de51c94	NaN	0	8	0	1	1	0	NaN	0	...	121	8464	1	0	0	0.250000	64.0	121.0	8464	4
3	ID_d671db89c	180000.0	0	5	0	1	1	1	1.0	0	...	81	289	16	121	4	1.777778	1.0	121.0	289	4
4	ID_d56d6f5f5	180000.0	0	5	0	1	1	1	1.0	0	...	121	1369	16	121	4	1.777778	1.0	121.0	1369	4

5 rows × 143 columns

In [14]:

```
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 [15]:

```
test.head()
```

Out[15]:

	Id	v2a1	hacdor	rooms	hacapo	v14a	refrig	v18q	v18q1	r4h1	...	age	SQBescolari	SQBage	SQBhogar_total	SQBedjefe	SQBhogar_nin	SQBovercrowding	SQBdependency	SQBmeaned	agesq
0	ID_2f6873615	NaN	0	5	0	1	1	0	NaN	1	...	4	0	16	9	0	1	2.25	0.25	272.25	16
1	ID_1c78846d2	NaN	0	5	0	1	1	0	NaN	1	...	41	256	1681	9	0	1	2.25	0.25	272.25	1681
2	ID_e5442cf6a	NaN	0	5	0	1	1	0	NaN	1	...	41	289	1681	9	0	1	2.25	0.25	272.25	1681
3	ID_a8db26a79	NaN	0	14	0	1	1	1	1.0	0	...	59	256	3481	1	256	0	1.00	0.00	256.00	3481
4	ID_a62966799	175000.0	0	4	0	1	1	1	1.0	0	...	18	121	324	1	0	1	0.25	64.00	NaN	324

5 rows × 142 columns

In [16]:

```
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
```

Looking at the train and test dataset we noticed that the following:

Train dataset: Rows: 9557 entries, 0 to 9556 Columns: 143 entries, Id to Target Column dtypes: float64(8), int64(130), object(5)

Test dataset: Rows: 23856 entries, 0 to 23855 Columns: 142 entries, Id to agesq dtypes: float64(8), int64(129), object(5)

The important piece of information here is that we don't have 'Target' feature in Test Dataset. There are 5 object type, 130(Train set)/ 129 (test set) integer type and 8 float type features. Lets look at those features next.

In [18]:

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

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


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


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

In [19]:

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

Out[19]:

	hacdor	rooms	hacapo	v14a	refrig	v18q	r4h1	r4h2	r4h3	r4m1	...	area1	area2	age	SQBescolari	SQBage	SQBhogar_total	SQBedjefe	SQBhogar_nin	agesq	Target
0	0	3	0	1	1	0	0	1	1	0	...	1	0	43	100	1849	1	100	0	1849	4
1	0	4	0	1	1	1	0	1	1	0	...	1	0	67	144	4489	1	144	0	4489	4
2	0	8	0	1	1	0	0	0	0	0	...	1	0	92	121	8464	1	0	0	8464	4
3	0	5	0	1	1	1	0	2	2	1	...	1	0	17	81	289	16	121	4	289	4
4	0	5	0	1	1	1	0	2	2	1	...	1	0	37	121	1369	16	121	4	1369	4

5 rows × 130 columns

In [20]:

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

Out[20]:

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

In [21]:

```
train.select_dtypes('float64').head()
```

Out[21]:

	v2a1	v18q1	rez_esc	meaneduc	overcrowding	SQBovercrowding	SQBdependency	SQBmeaned
0	190000.0	NaN	NaN	10.0	1.000000	1.000000	0.0	100.0
1	135000.0	1.0	NaN	12.0	1.000000	1.000000	64.0	144.0
2	NaN	NaN	NaN	11.0	0.500000	0.250000	64.0	121.0
3	180000.0	1.0	1.0	11.0	1.333333	1.777778	1.0	121.0
4	180000.0	1.0	NaN	11.0	1.333333	1.777778	1.0	121.0

In [22]:

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

Out[22]:

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

In [23]:

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

Out[23]:

	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 [24]:

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

Out[24]:

```
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 float type features. 3. For Object types v2a1 6860 v18q1 7342 rez_esc 7928 meaneduc 5 SQBmeaned 5

We also noticed that object type features dependency, edjefe, edjefa have mixed values.

Lets fix the data for features with null values and features with mixed values

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.

In [26]:

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

for df in [train,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)

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

Out[26]:

	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

In [27]:

```
# 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)"
```

In [28]:

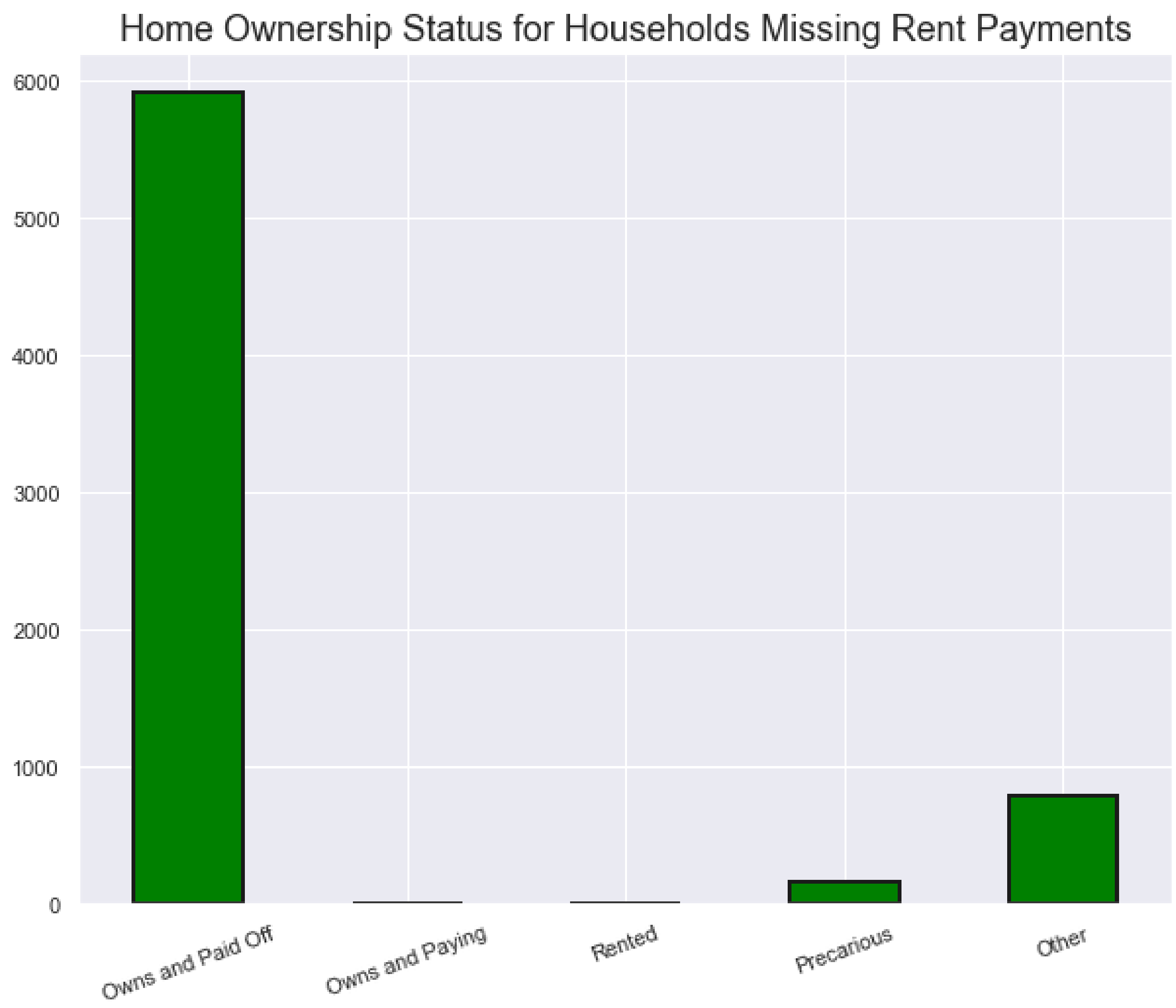
```
data = train[train['v2a1'].isnull()].head()

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

Out[28]:

	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 [29]:

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

# Plot of the home ownership variables for home missing rent payments
train.loc[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);
```



In [31]:

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

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

Out[31]:

```
v2a1    0
dtype: int64
```

In [32]:

```
# 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
```

In [33]:

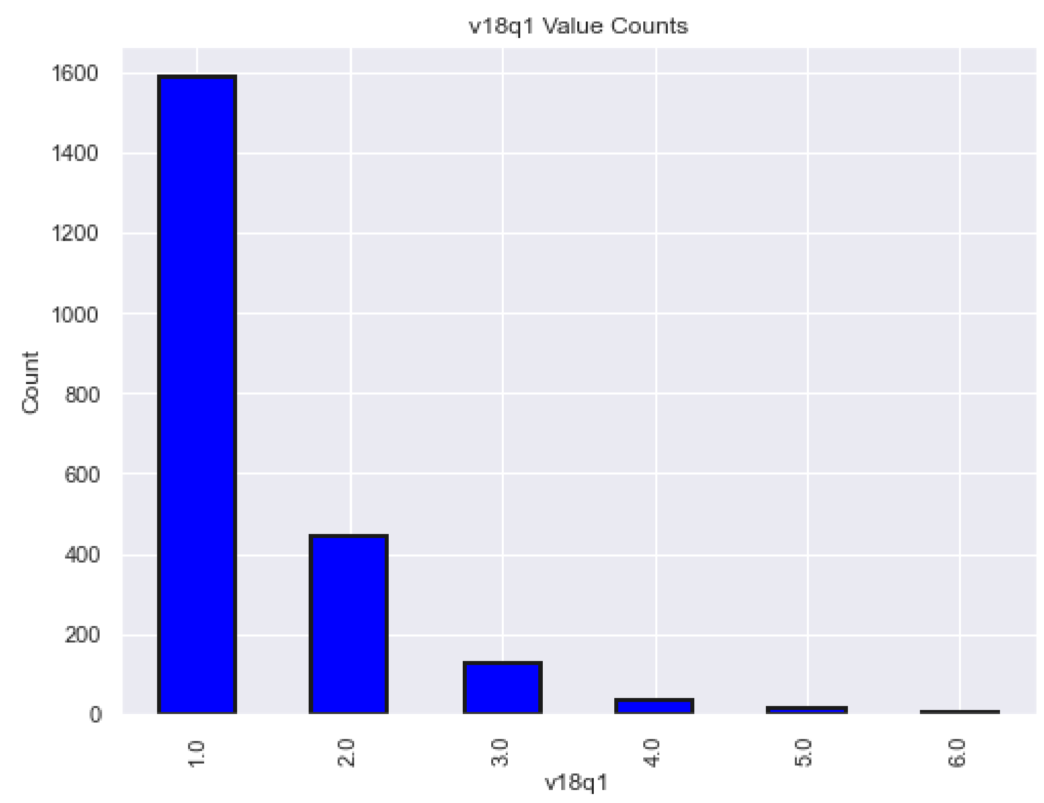
```
# Since this is a household variable, it only makes sense to look at it on a household level,
# so we'll only select the rows for the head of household.

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

Out[33]:

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

In [34]:

```
plt.figure(figsize = (8, 6))
col='v18q1'
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 [35]:

```
#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 [train, test]:
    df['v18q1'].fillna(value=0, inplace=True)

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

Out[35]:

```
v18q1    0
dtype: int64
```

In [36]:

```
# 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.
train[train['rez_esc'].notnull()]['age'].describe()
```

Out[36]:

```
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 [37]:

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

Out[37]:

```
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 [38]:

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

Out[38]:

```
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 [39]:

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

Out[39]:

	Id	v2a1	hacdor	rooms	hacapo	v14a	refrig	v18q	v18q1	r4h1	...	SQBescolari	SQBage	SQBhogar_total	SQBedjefe	SQBhogar_nin	SQBovercrowding	SQBdependency	SQBmeaned	agesq	Target
2514	ID_f012e4242	160000.0	0	6	0	1	1	1	1.0	0	...	0	100	9	121	1	2.25	0.25	182.25	100	4

1 rows × 143 columns

In [40]:

```
#from above we see that  the 'behind in school' column has null values
# Lets use the above to fix the data
for df in [train,test]:
    df['rez_esc'].fillna(value=0, inplace=True)
train[['rez_esc']].isnull().sum()
```

Out[40]:

```
rez_esc    0
dtype: int64
```

In [41]:

```
#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
```

In [42]:

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

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

Out[42]:

	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 [43]:

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

Out[43]:

```
meaneduc    0
dtype: int64
```

In [44]:

```
#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
```

In [45]:

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

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

Out[45]:

	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 [47]:

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

Out[47]:

```
SQBmeaned    0
dtype: int64
```

In [48]:

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

Out[48]:

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

Lets see if records belonging to same household has same target/score.

In [49]:

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

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

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

In [50]:

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

Out[50]:

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

	idhogar	parentesco1	Target
7655	0172ab1d9	0	2

In [51]:

```
#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 = train.groupby('idhogar')['parentesco1'].sum()

# Find households without a head
households_no_head = train.loc[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.
```

In [52]:

```
# 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.
```

In [54]:

```
#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(train[(train['idhogar'] == household) & (train['parentesco1'] == 1.0)]['Target'])

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


# Groupby the household and figure out the number of unique values
all_equal = 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.
```

In [55]:

```
#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
```

Out[55]:

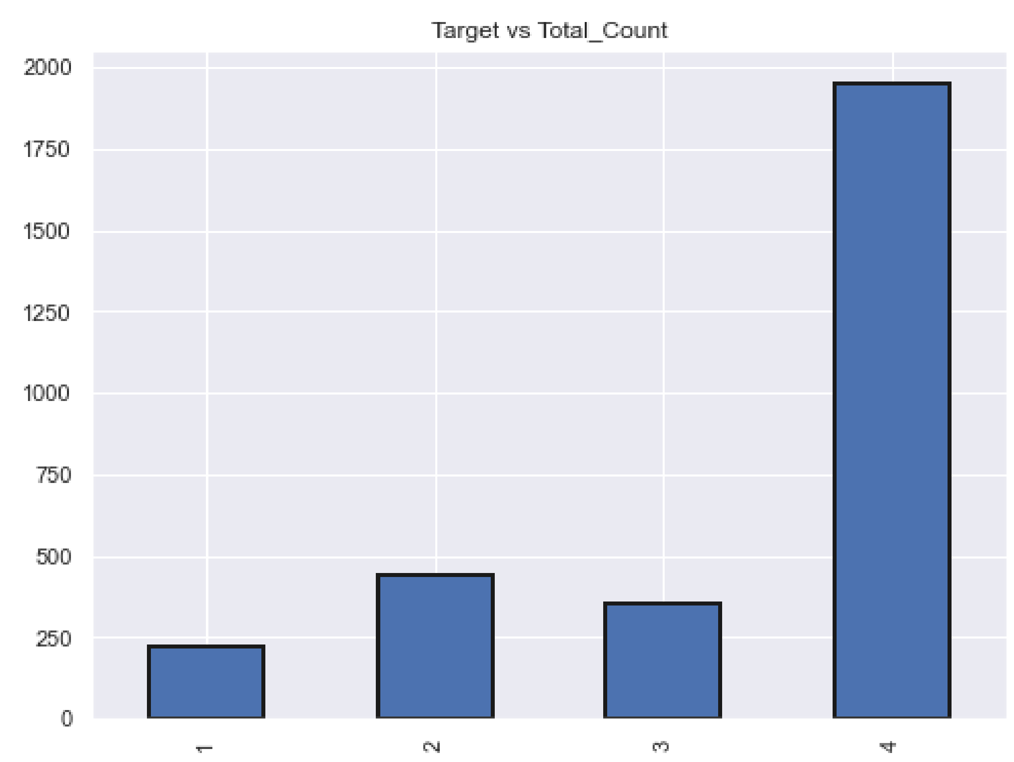
```
1     222
2     442
3     355
4    1954
Name: Target, dtype: int64
```

In [56]:

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

Out[56]:

```
<matplotlib.axes._subplots.AxesSubplot at 0xde88b0>
```



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

In [58]:

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


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

print(train.shape)
```

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

In [59]:

```
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 [60]:

```
#Check for redundant household variables
heads = train.loc[train['parentesco1'] == 1, :]
heads = heads[id_ + hh_bool + hh_cont + hh_ordered]
heads.shape
```

Out[60]:

```
(2973, 98)
```

In [61]:

```
# 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[61]:

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

In [62]:

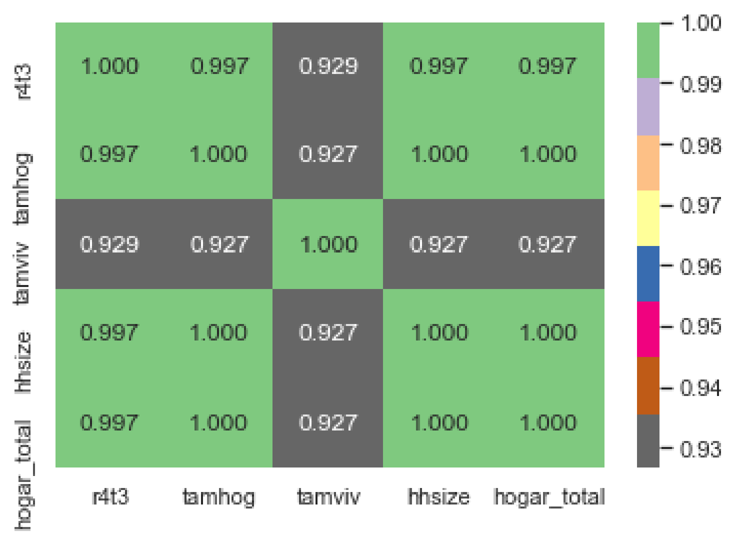
```
corr_matrix.loc[corr_matrix['tamhog'].abs() > 0.9, corr_matrix['tamhog'].abs() > 0.9]
```

Out[62]:

	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 [64]:

```
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');
```



In [65]:

```
# 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 [66]:

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

train.shape
```

Out[66]:

```
(9557, 131)
```

In [67]:

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

Out[67]:

```
(9557, 39)
```

In [68]:

```
# 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[68]:

```
['female']
```

['female']

In [76]:

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

train.shape
```

Out[76]:

```
(9557, 129)
```

In [77]:

```
#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 [train, test]:
    df.drop(columns = 'area2',inplace=True)

train.shape
```

Out[77]:

```
(9557, 128)
```

In [78]:

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

train.shape
```

Out[78]:

```
(9557, 126)
```

Predict the accuracy using random forest classifier.

In [80]:

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

```
(9557, 125)
(9557,)
```

In [81]:

```
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_state=1)
rmclassifier = RandomForestClassifier()
```

In [82]:

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

Out[82]:

```
RandomForestClassifier()
```

In [83]:

```
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[83]:

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

In [84]:

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

In [85]:

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

```
0.9518828451882845
[[ 134    0    0   23]
 [   2  289    0   26]
 [   0    1  194   38]
 [   0    1    1 1203]]
              precision    recall  f1-score   support

           1       0.99      0.85      0.91       157
           2       0.99      0.91      0.95       317
           3       0.99      0.83      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
```

In [87]:

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

In [88]:

```
y_predict_testdata
```

Out[88]:

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

Check the accuracy using random forest with cross validation.

In [89]:

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

Checking the score using default 10 trees

In [90]:

```
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)
```

```
[0.94717573 0.94665272 0.94400837 0.94348509 0.94819466]
94.59033146570505
```

Checking the score using 100 trees

In [92]:

```
num_trees= 100

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

```
[0.94717573 0.94665272 0.94400837 0.94348509 0.94819466]
94.59033146570505
```

In [95]:

```
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()
```

Out[95]:

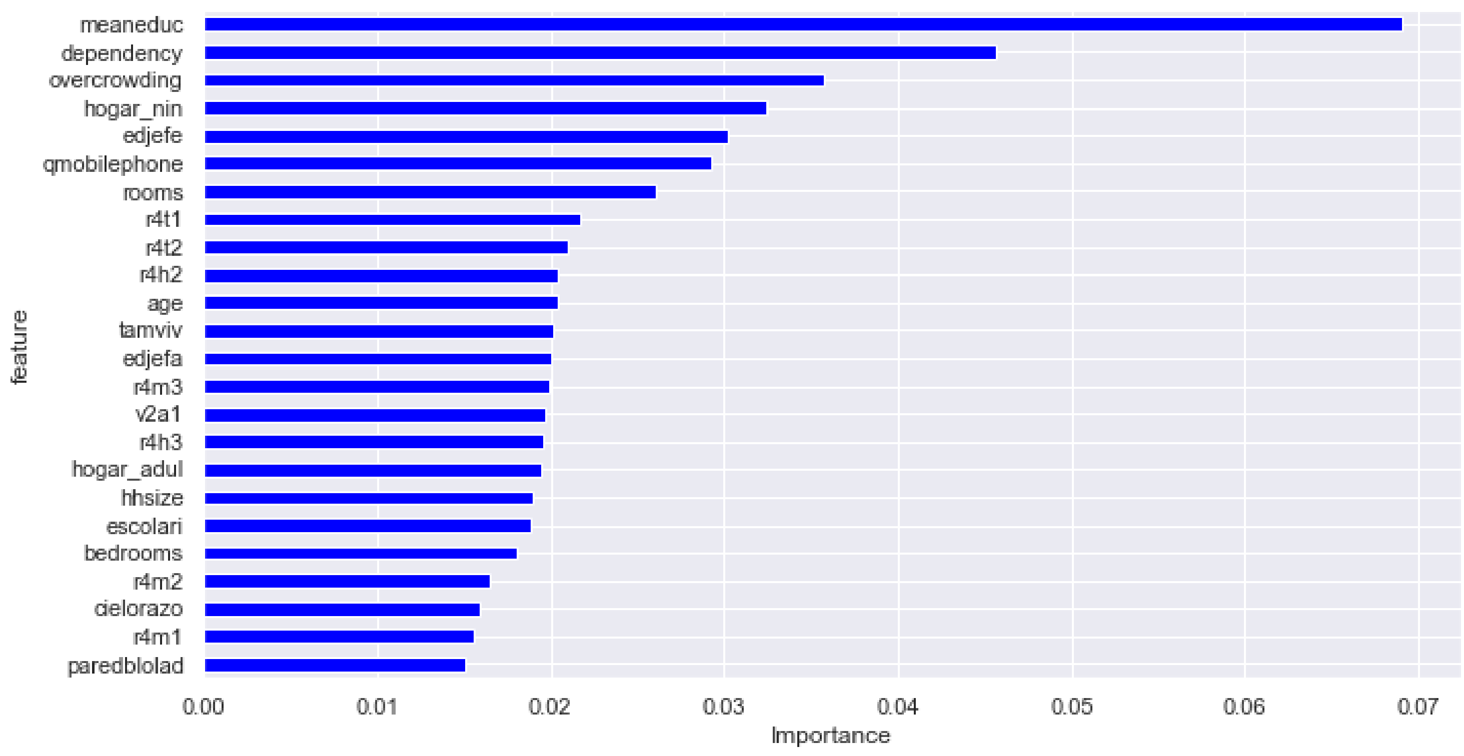
	feature	importance
0	v2a1	0.019724
2	rooms	0.026011
9	r4h2	0.020433
10	r4h3	0.019571
11	r4m1	0.015607

In [96]:

```
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')
```

Out[96]:

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



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

In [ ]: