Project 3 - Income Qualification:

DESCRIPTION: Identify the level of income qualification needed for the families in Latin America.

```
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.
```

In [1]:

```
import pandas as pd
pd.set_option('display.max_rows', 150)
pd.set_option('display.max_columns', 150)

import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

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

In [2]:

```
train_data = pd.read_csv("D:/SimpliLearn-DataScience/2) Post Graduate Program in Data Scien
test_data = pd.read_csv("D:/SimpliLearn-DataScience/2) Post Graduate Program in Data Scienc
```

In [3]:

```
train_data.head()
```

Out[3]:

	Id	v2a1	hacdor	rooms	hacapo	v14a	refrig	v18q	v18q1	r4h1	r4h2	r4h
0	ID_279628684	190000.0	0	3	0	1	1	0	NaN	0	1	
1	ID_f29eb3ddd	135000.0	0	4	0	1	1	1	1.0	0	1	
2	ID_68de51c94	NaN	0	8	0	1	1	0	NaN	0	0	
3	ID_d671db89c	180000.0	0	5	0	1	1	1	1.0	0	2	
4	ID_d56d6f5f5	180000.0	0	5	0	1	1	1	1.0	0	2	

In [4]:

```
test_data.head()
```

Out[4]:

	Id	v2a1	hacdor	rooms	hacapo	v14a	refrig	v18q	v18q1	r4h1	r4h2	r4h
0	ID_2f6873615	NaN	0	5	0	1	1	0	NaN	1	1	
1	ID_1c78846d2	NaN	0	5	0	1	1	0	NaN	1	1	
2	ID_e5442cf6a	NaN	0	5	0	1	1	0	NaN	1	1	
3	ID_a8db26a79	NaN	0	14	0	1	1	1	1.0	0	1	
4	ID_a62966799	175000.0	0	4	0	1	1	1	1.0	0	0	

In [5]:

```
train_data.select_dtypes('object').columns
```

Out[5]:

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

In [6]:

```
for column in train_data.columns:
    if column not in test_data.columns:
        print("Output columns is: {}".format(column))
```

```
Output columns is: Target
```

In [7]:

```
train_data.Target.value_counts()
```

Out[7]:

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

Q1: Identify the output variable.

Answer: Target column contains output for dataset and has four levels - 1, 2, 3, 4

In [8]:

```
train_data.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
```

Q2: Understand the type of data.

Answer: There are 143 columns in dataset. The last column in dataset 'Target' has output i.e. income level. Remaining 142 columns will input variable for model (some input columns may be dropped during preprocessing/ feature selection).

```
- 8 columns are float64.
- 130 columns are int64.
- 5 columns are object.
```

Important columns in dataset

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

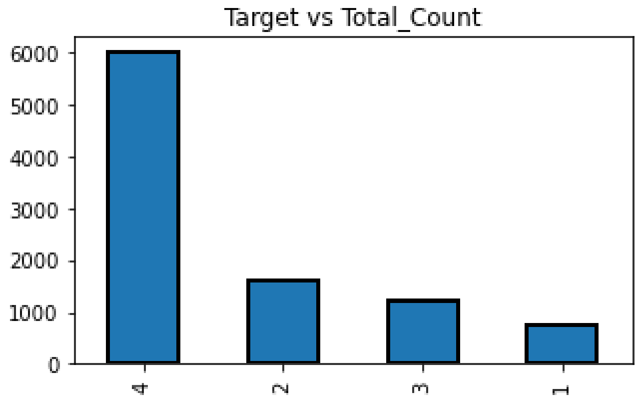
In [9]:

```
# List the columns for different datatypes:
print('Integer Type: ', list(train_data.select_dtypes(np.int64).columns))
print('Float Type: ', list(train_data.select_dtypes(np.float64).columns))
print('Object Type: ', list(train_data.select_dtypes(np.object).columns))
```

```
Integer Type:  ['hacdor', 'rooms', 'hacapo', 'v14a', 'refrig', 'v18q', 'r4h
1', 'r4h2', 'r4h3', 'r4m1', 'r4m2', 'r4m3', 'r4t1', 'r4t2', 'r4t3', 'tamho
g', 'tamviv', 'escolari', 'hhsize', 'paredblolad', 'paredzocalo', 'paredpre
b', 'pareddes', 'paredmad', 'paredzinc', 'paredfibras', 'paredother', 'pisom
oscer', 'pisocemento', 'pisoother', 'pisonatur', 'pisonotiene', 'pisomader
a', 'techozinc', 'techoentrepiso', 'techocane', 'techootro', 'cielorazo', 'a
bastaguadentro', 'abastaguafuera', 'abastaguano', 'public', 'planpri', 'noel
ec', 'coopele', 'sanitario1', 'sanitario2', 'sanitario3', 'sanitario5', 'san
itario6', 'energcocinar1', 'energcocinar2', 'energcocinar3', 'energcocinar
4', 'elimbasu1', 'elimbasu2', 'elimbasu3', 'elimbasu4', 'elimbasu5', 'elimba
su6', 'epared1', 'epared2', 'epared3', 'etecho1', 'etecho2', 'etecho3', 'evi
v1', 'eviv2', 'eviv3', 'dis', 'male', 'female', 'estadocivil1', 'estadocivil
2', 'estadocivil3', 'estadocivil4', 'estadocivil5', 'estadocivil6', 'estadoc
ivil7', 'parentesco1', 'parentesco2', 'parentesco3', 'parentesco4', 'parente
sco5', 'parentesco6', 'parentesco7', 'parentesco8', 'parentesco9', 'parentes
co10', 'parentesco11', 'parentesco12', 'hogar_nin', 'hogar_adul', 'hogar_may
or', 'hogar_total', 'instlevel1', 'instlevel2', 'instlevel3', 'instlevel4',
'instlevel5', 'instlevel6', 'instlevel7', 'instlevel8', 'instlevel9', 'bedro
oms', 'tipovivi1', 'tipovivi2', 'tipovivi3', 'tipovivi4', 'tipovivi5', 'comp
uter', 'television', 'mobilephone', 'qmobilephone', 'lugar1', 'lugar2', 'lug
ar3', 'lugar4', 'lugar5', 'lugar6', 'area1', 'area2', 'age', 'SQBescolari',
'SQBage', 'SQBhogar_total', 'SQBedjefe', 'SQBhogar_nin', 'agesq', 'Target']
Float Type:  ['v2a1', 'v18q1', 'rez_esc', 'meaneduc', 'overcrowding', 'SQBov
ercrowding', 'SQBdependency', 'SQBmeaned']
Object Type:  ['Id', 'idhogar', 'dependency', 'edjefe', 'edjefa']
```

In [10]:

```
train_data.Target.value_counts().plot.bar(figsize=(5,3), linewidth=2, edgecolor='k', title=
```



Q3: Check if there are any biases in your dataset.

Answer: Data bias in machine learning is a type of error in which certain elements of a dataset are more heavily weighted and/or represented than others. A biased dataset does not accurately represent a model's use case, resulting in skewed outcomes, low accuracy levels, and analytical errors.

From above plot of values in Target column, we can see that data is little biased.

In [11]:

```
train_data.nunique()
```

Out[11]:

```
Id              9557
v2a1             157
hacdor             2
rooms             11
hacapo             2
v14a               2
refrig             2
v18q               2
v18q1              6
r4h1               6
r4h2               9
r4h3               9
r4m1               6
r4m2               7
r4m3               9
r4t1               7
r4t2              11
r4t3              13
```

Column 'idhogar' in dataset contain household level information (household identity). There are 2988 household data in train file.

In [12]:

```
poverty_variance_within_household = train_data.groupby('idhogar')['Target'].nunique()
print(sum(poverty_variance_within_household>1))
#poverty_variance_within_household[list(poverty_variance_within_household>1)].index
```

85

In [13]:

```
# view data of household with different povert level among head/ members
train_data[train_data['idhogar'] == poverty_variance_within_household[
    list(poverty_variance_within_household>1)].index[0]][['idhogar', 'parentesco1', 'Target
```

Out[13]:

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

Q4: Check whether all members of the house have the same poverty level.

Answer: 85 housesholds out of total 2988 households in dataset have at least one member with income level different than other members of household.

In [14]:

```
idhogar_missing_head = []
grouped_head_info = train_data.groupby('idhogar')['parentesco1'].sum()

for i in range(len(grouped_head_info)):
    if grouped_head_info[i] == 0:
        idhogar_missing_head.append(grouped_head_info.index[i])

print(len(idhogar_missing_head))
# idhogar_missing_head
```

15

Q5: Check if there is a house without a family head.

Answer: 15 housesholds out of total 2988 households in dataset have no information about family head.

In order to set poverty level of the members and the head of the house within a family, first we will do it for households without head (all members should have the same poverty level), then we will set member's poverty level the same as its head's poverty level for those households in which head/ members have different poverty level.

In [15]:

```
# As found in previous section, 15 housesholds out of total 2988 households in dataset have
for value in idhogar_missing_head:
    k = train_data[train_data['idhogar']==value]['Target'].values
    if np.var(k) !=0:
        print('Members in household {} have different level of poverty'.format(value))
```

6(i) Members in each of these 15 households have same level of poverty. Now lets check data of households with family head.

In [16]:

```
for value in list(poverty_variance_within_household[list(poverty_variance_within_household>
    # find the poverty level of family head for each household
    head_poverty = int(train_data[(train_data['idhogar']==value) & (train_data['parentesco1

    # assign the correct level to each member of household
    train_data.loc[train_data['idhogar'] == value, 'Target'] = head_poverty

poverty_variance_within_household = train_data.groupby('idhogar')['Target'].nunique()
print(sum(poverty_variance_within_household>1))
```

```
0
```

6(ii) Now there is no household with head/ members having different poverty level.

Q6: Set poverty level of the members and the head of the house {same} within a family.

Answer: Done and verified in sr. no. 6(i) and 6(ii) as above.

In [17]:

```
train_data.isnull().sum()[train_data.isnull().sum()>0]
```

Out[17]:

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

In [18]:

```
train_data.isnull().sum().sum()
```

Out[18]:

```
22140
```

In [19]:

```
round(train_data.isnull().sum()[train_data.isnull().sum()>0]/len(train_data)*100,2)
```

Out[19]:

```
v2a1          71.78
v18q1         76.82
rez_esc       82.95
meaneduc       0.05
SQBmeaned      0.05
dtype: float64
```

Q7: Count how many null values are existing in columns.

Answer: Following 5 columns has null values mentioned against each column name:-

```
v2a1          6860
v18q1         7342
rez_esc       7928
meaneduc         5
SQBmeaned        5
```

Total null values in complete train dataset are: 22140

In [20]:

```
train_data.Target.isnull().sum()
```

Out[20]:

```
0
```

Q8: Remove null value rows of the target variable.

Answer: Target column does not have any null values.

Data Preprocessing and Feature Engineering before model building:

In [21]:

```
sr = train_data.isnull().sum()/len(train_data)*100
```

In [22]:

```
sr[sr>0]
```

Out[22]:

```
v2a1         71.779847
v18q1        76.823271
rez_esc      82.954902
meaneduc      0.052318
SQBmeaned     0.052318
dtype: float64
```

In [23]:

```
# lets us drop columns having more than 30% missing values
data1 = train_data.drop(list(sr[sr>30].index), axis=1)
```

In [24]:

```
sr1 = data1.isnull().sum()
sr1[sr1>0]
```

Out[24]:

```
meaneduc     5
SQBmeaned    5
dtype: int64
```

In [25]:

```
# we can drop rows having missing values as there are not many rows with missing values.
data1 = data1.dropna()
data1
```

Out[25]:

	Id	hacdor	rooms	hacapo	v14a	refrig	v18q	r4h1	r4h2	r4h3	r4m1	r4m2
0	ID_279628684	0	3	0	1	1	0	0	1	1	0	0
1	ID_f29eb3ddd	0	4	0	1	1	1	0	1	1	0	0
2	ID_68de51c94	0	8	0	1	1	0	0	0	0	0	1
3	ID_d671db89c	0	5	0	1	1	1	0	2	2	1	1
4	ID_d56d6f5f5	0	5	0	1	1	1	0	2	2	1	1
...	...	...	...	...	...	...	...	...	...	...	...	...
9552	ID_d45ae367d	0	6	0	1	1	0	0	2	2	1	2
9553	ID_c94744e07	0	6	0	1	1	0	0	2	2	1	2
9554	ID_85fc658f8	0	6	0	1	1	0	0	2	2	1	2
9555	ID_ced540c61	0	6	0	1	1	0	0	2	2	1	2
9556	ID_a38c64491	0	6	0	1	1	0	0	2	2	1	2

9552 rows × 140 columns

In [26]:

```
data1.describe(include='all')
```

Out[26]:

	Id	hacdor	rooms	hacapo	v14a	refrig	
count	9552	9552.000000	9552.000000	9552.000000	9552.000000	9552.000000	9552.0
unique	9552	NaN	NaN	NaN	NaN	NaN	
top	ID_fc6069d5e	NaN	NaN	NaN	NaN	NaN	
freq	1	NaN	NaN	NaN	NaN	NaN	
mean	NaN	0.038107	4.956554	0.023660	0.994765	0.957601	0.2
std	NaN	0.191465	1.467227	0.151995	0.072164	0.201509	0.4
min	NaN	0.000000	1.000000	0.000000	0.000000	0.000000	0.0
25%	NaN	0.000000	4.000000	0.000000	1.000000	1.000000	0.0
50%	NaN	0.000000	5.000000	0.000000	1.000000	1.000000	0.0
75%	NaN	0.000000	6.000000	0.000000	1.000000	1.000000	0.0
max	NaN	1.000000	11.000000	1.000000	1.000000	1.000000	1.0

In [27]:

```
data1.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 9552 entries, 0 to 9556
Columns: 140 entries, Id to Target
dtypes: float64(5), int64(130), object(5)
memory usage: 10.3+ MB
```

In [28]:

```
data1.select_dtypes('float64')
```

Out[28]:

	meaneduc	overcrowding	SQBovercrowding	SQBdependency	SQBmeaned
0	10.00	1.000000	1.000000	0.0000	100.0000
1	12.00	1.000000	1.000000	64.0000	144.0000
2	11.00	0.500000	0.250000	64.0000	121.0000
3	11.00	1.333333	1.777778	1.0000	121.0000
4	11.00	1.333333	1.777778	1.0000	121.0000
...	...	...	...	...	...
9552	8.25	1.250000	1.562500	0.0625	68.0625
9553	8.25	1.250000	1.562500	0.0625	68.0625
9554	8.25	1.250000	1.562500	0.0625	68.0625
9555	8.25	1.250000	1.562500	0.0625	68.0625
9556	8.25	1.250000	1.562500	0.0625	68.0625

9552 rows × 5 columns

In [29]:

```
data1.select_dtypes('int64')
```

Out[29]:

	hacdor	rooms	hacapo	v14a	refrig	v18q	r4h1	r4h2	r4h3	r4m1	r4m2	r4m3	r4t1
0	0	3	0	1	1	0	0	1	1	0	0	0	0
1	0	4	0	1	1	1	0	1	1	0	0	0	0
2	0	8	0	1	1	0	0	0	0	0	1	1	0
3	0	5	0	1	1	1	0	2	2	1	1	2	1
4	0	5	0	1	1	1	0	2	2	1	1	2	1
...	...	...	...	...	...	...	...	...	...	...	...	...	...
9552	0	6	0	1	1	0	0	2	2	1	2	3	1
9553	0	6	0	1	1	0	0	2	2	1	2	3	1
9554	0	6	0	1	1	0	0	2	2	1	2	3	1
9555	0	6	0	1	1	0	0	2	2	1	2	3	1
9556	0	6	0	1	1	0	0	2	2	1	2	3	1

9552 rows × 130 columns

In [30]:

```
data1.select_dtypes('object')
```

Out[30]:

	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

9552 rows × 5 columns

Feature Engineering

There is plenty more exploratory data analysis we can do, but first we should work on consolidating our data at a household level. We already have some of the information for each household, but for training, we will need all of the information summarized for each household. This means grouping the individuals in a house (groupby) and performing an aggregation (agg) of the individual variables.

Define Variable Categories in Dataset:

There are different categories of variables/ columns in dataset:

- Squared Variables: derived from squaring variables in the data
- Id variables: identifies the data and should not be used as features
- Household variables
    - Boolean: Yes or No (0 or 1)
    - Ordered Discrete: Integers with an ordering
    - Continuous numeric
- Individual Variables: these are characteristics of each individual rather than the household
    - Boolean: Yes or No (0 or 1)
    - Ordered Discrete: Integers with an ordering

(1) Squared Variables

First we will check correlation of the squared variables with their non-squared version of variables. Sometimes variables are squared or transformed as part of feature engineering because it can help linear models learn relationships that are non-linear. However, since we will be using more complex model, these squared features are superfluous. So we will drop highly correlated squared version of variables otherwise it will slowdown model training.

In [31]:

```
sqr_var = ['SQBescolari', 'SQBage', 'SQBhogar_total', 'SQBedjefe', 'SQBhogar_nin', 'SQBover
           'SQBmeaned', 'agesq']
```

In [32]:

```
sum(data1['SQBage'] == data1['agesq'])==len(data1)
```

Out[32]:

```
True
```

'SQBage' and 'agesq' contains exactly the same data so we can drop any one of them.

In [33]:

```
sqr_var = ['SQBescolari', 'SQBage', 'SQBhogar_total', 'SQBedjefe', 'SQBhogar_nin', 'SQBover
           'SQBmeaned']
```

Now let us check correlation between squared variables and original variables

In [34]:

```
nonsqr_var = ['escolari', 'age', 'hogar_total', 'edjefe', 'hogar_nin', 'overcrowding', 'dep
```

In [35]:

```
for i in range(len(sqr_var)):
    print(data1[[sqr_var[i], nonsqr_var[i]]].corr(),"\n")
```

```
             SQBescolari  escolari
SQBescolari     1.000000  0.943317
escolari        0.943317  1.000000

          SQBage       age
SQBage  1.000000  0.958078
age     0.958078  1.000000

                SQBhogar_total  hogar_total
SQBhogar_total        1.000000     0.950192
hogar_total           0.950192     1.000000

           SQBedjefe
SQBedjefe        1.0

              SQBhogar_nin  hogar_nin
SQBhogar_nin      1.000000   0.884172
hogar_nin         0.884172   1.000000

                 SQBovercrowding  overcrowding
SQBovercrowding         1.000000      0.945136
overcrowding            0.945136      1.000000

               SQBdependency
SQBdependency            1.0

           SQBmeaned  meaneduc
SQBmeaned   1.000000  0.948003
meaneduc    0.948003  1.000000
```

Since these squared variables are highly correlated with their corresponding original variables. lets drop these variables.

In [36]:

```
data1.drop(sqr_var,axis=1, inplace=True)
```

In [37]:

```
data1.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 9552 entries, 0 to 9556
Columns: 132 entries, Id to Target
dtypes: float64(2), int64(125), object(5)
memory usage: 9.7+ MB
```

(2) Id Variables:

These variables will be kept in the data as we would need them for identification later

In [38]:

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

(3) Household Variables:

In [39]:

```
# 2 columns under household categories already dropped since these columns has more more th

hh_var_boo = ['hacdor', 'hacapo', 'v14a', 'refrig', 'paredblolad', 'paredzocalo', 'paredpre
              'paredmad','paredzinc', 'paredfibras', 'paredother', 'pisomoscer', 'pisoother
              'pisomadera', 'techozinc', 'techoentrepiso', 'techocane', 'techootro', 'cielo
              'abastaguafuera', 'abastaguano', 'public', 'planpri', 'noelec', 'coopele', 's
              'sanitario3', 'sanitario5',  'sanitario6', 'energcocinar1', 'energcocinar2',
              'energcocinar4', 'elimbasu1', 'elimbasu2', 'elimbasu3', 'elimbasu4', 'elimbas
              'epared2', 'epared3', 'etecho1', 'etecho2', 'etecho3', 'eviv1', 'eviv2', 'evi
              'tipovivi3', 'tipovivi4', 'tipovivi5', 'computer', 'television', 'lugar1', 'l
              'lugar5', 'lugar6', 'area1', 'area2']

# hh_var_ordered = ['rooms', 'r4h1', 'r4h2', 'r4h3', 'r4m1','r4m2','r4m3', 'r4t1',  'r4t2',
#                  'tamviv','hhsize','hogar_nin', 'hogar_adul','hogar_mayor','hogar_total'
hh_var_ordered = ['rooms', 'r4h1', 'r4h2', 'r4h3', 'r4m1','r4m2','r4m3', 'r4t1',  'r4t2', '
                  'tamviv','hhsize','hogar_nin', 'hogar_adul','hogar_mayor','hogar_total',

# hh_var_cont = ['v2a1', 'dependency', 'edjefe', 'edjefa', 'meaneduc', 'overcrowding']
hh_var_cont = ['dependency', 'edjefe', 'edjefa', 'meaneduc', 'overcrowding']
```

In [40]:

```
head = data1.loc[data1['parentesco1'] == 1, :]
head = head[id_var + hh_var_boo + hh_var_cont + hh_var_ordered]
head.shape
```

Out[40]:

```
(2970, 96)
```

Highly Correlated Household Variables

Let's take a look at the correlations between all of the household variables. If there are any that are too highly correlated, then we will drop one of the pair of highly correlated variables.

The following code identifies any variables with a greater than 0.95 correlation.

In [41]:

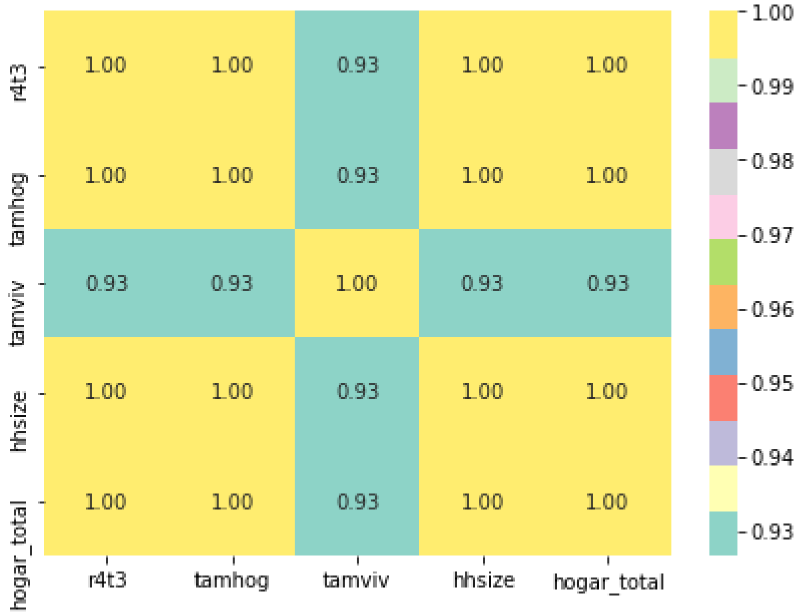
```
# Create correlation matrix
corr_matrix = head.corr()

# 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[41]:

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

In [42]:

```
# Lets plot the correlation
plt.figure(figsize=(7,5))
sns.heatmap(corr_matrix.loc[corr_matrix['tamhog'].abs() > 0.9, corr_matrix['tamhog'].abs()
            annot=True, cmap = plt.cm.Set3, fmt='.2f');
```



In [43]:

```
# Lets drop one from each pair of variables which are all highly correlated with one anothe
data1 = data1.drop(to_drop, axis= 1)
```

(4) Individual Level Variables

There are two types of individual level variables: Boolean (1 or 0 for True or False) and ordinal (discrete values with a meaningful ordering).

In [44]:

```
# WE have already dropped column 'rez_esc' from dataset because it had more than 30% null v

ind_var_boo = ['v18q', 'dis', 'male', 'female', 'estadocivil1', 'estadocivil2', 'estadocivi
               'estadocivil5', 'estadocivil6', 'estadocivil7', 'parentesco1', 'parentesco2'
               'parentesco4', 'parentesco5', 'parentesco6', 'parentesco7', 'parentesco8', '
               'parentesco11', 'parentesco12', 'instlevel1', 'instlevel2', 'instlevel3', 'i
               'instlevel6', 'instlevel7', 'instlevel8', 'instlevel9', 'mobilephone']

# ind_var_ordered = ['rez_esc', 'escolari', 'age']
ind_var_ordered = ['escolari', 'age']

ind = data1[id_var + ind_var_boo + ind_var_ordered]
ind.shape
```

Out[44]:

```
(9552, 38)
```

Highly Correlaetd Individual Variables

We can do the same process we did with the household level variables to identify any redundant individual variables. We'll focus on any variables that have an absolute magnitude of the correlation coefficient greater than 0.95.

In [45]:

```
#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[45]:

```
['female']
```

In [46]:

```
# 'Female' is simply the opposite of 'male'. Let's drop one of these two.
data1 = data1.drop('male', axis = 1)
```

Now let us check all 'object' type columns one by one

In [47]:

```
data1.select_dtypes('object')
```

Out[47]:

	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

9552 rows × 5 columns

Id - Not needed, since it is not useful in model building

idhogar - Not needed, since house level won't help in predicting anything.

In [48]:

```
data1 = data1.drop(['Id', 'idhogar'], axis=1)
data1.shape
```

Out[48]:

```
(9552, 124)
```

Now 3 columns are left with mixed (string and float/ integer) values:

- 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

In [49]:

```
# Custom function to convert object variables into numerical data.

def num_map(i):

    if i=='yes':
        return(float(1))
    elif i=='no':
        return(float(0))
    else:
        return(float(i))
```

In [50]:

```
data1['dependency']=data1['dependency'].apply(num_map)
data1['edjefe']=data1['edjefe'].apply(num_map)
data1['edjefa']=data1['edjefa'].apply(num_map)
```

In [51]:

```
data1.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 9552 entries, 0 to 9556
Columns: 124 entries, hacdor to Target
dtypes: float64(5), int64(119)
memory usage: 9.1 MB
```

In [52]:

```
X = data1.drop('Target', axis=1)
X
```

Out[52]:

	hacdor	rooms	hacapo	v14a	refrig	v18q	r4h1	r4h2	r4h3	r4m1	r4m2	r4m3	r4t1
0	0	3	0	1	1	0	0	1	1	0	0	0	0
1	0	4	0	1	1	1	0	1	1	0	0	0	0
2	0	8	0	1	1	0	0	0	0	0	1	1	0
3	0	5	0	1	1	1	0	2	2	1	1	2	1
4	0	5	0	1	1	1	0	2	2	1	1	2	1
...	...	...	...	...	...	...	...	...	...	...	...	...	...
9552	0	6	0	1	1	0	0	2	2	1	2	3	1
9553	0	6	0	1	1	0	0	2	2	1	2	3	1
9554	0	6	0	1	1	0	0	2	2	1	2	3	1
9555	0	6	0	1	1	0	0	2	2	1	2	3	1
9556	0	6	0	1	1	0	0	2	2	1	2	3	1

9552 rows × 123 columns

In [53]:

```
y = data1['Target']
y
```

Out[53]:

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

Creating Machine Learning model with Random Forest Classifier:

In [54]:

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

In [55]:

```
X_train, X_test, y_train, y_test = train_test_split(X, y)
print(X_train.shape, X_test.shape, y_train.shape, y_test.shape)
```

```
(7164, 123) (2388, 123) (7164,) (2388,)
```

In [56]:

```
RFC = RandomForestClassifier()
```

In [57]:

```
RFC.fit(X_train, y_train)
```

Out[57]:

```
RandomForestClassifier()
```

In [58]:

```
y_predict = RFC.predict(X_test)
```

In [59]:

```
RFC.score(X_train, y_train)   # testing accuracy on train data
```

Out[59]:

```
1.0
```

In [60]:

```
RFC.score(X_test, y_test)   # testing accuracy on test data
```

Out[60]:

```
0.9267169179229481
```

In [61]:

```
accuracy_score(y_test,y_predict)
```

Out[61]:

```
0.9267169179229481
```

In [62]:

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

```
[[ 160    4    1   27]
 [    2  335    1   52]
 [    4    3  206   76]
 [    0    5    0 1512]]
```

In [63]:

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

```
              precision    recall  f1-score   support

           1       0.96      0.83      0.89       192
           2       0.97      0.86      0.91       390
           3       0.99      0.71      0.83       289
           4       0.91      1.00      0.95      1517

    accuracy                           0.93      2388
   macro avg       0.96      0.85      0.90      2388
weighted avg       0.93      0.93      0.92      2388
```

Improving model performance using GridSearchCV:

In [64]:

```
from sklearn.model_selection import GridSearchCV

param_grid = {
    'n_estimators': [10,25,50,100],
    'max_depth': [None,1,5,10],
    'min_samples_leaf': [1,3,5]
}
```

In [65]:

```
gs = GridSearchCV(estimator=RFC, param_grid=param_grid, cv=3, verbose=1)
```

In [66]:

```
gs.fit(X,y)
#gs.fit(X_train,y_train)
```

```
Fitting 3 folds for each of 48 candidates, totalling 144 fits
```

Out[66]:

```
GridSearchCV(cv=3, estimator=RandomForestClassifier(),
             param_grid={'max_depth': [None, 1, 5, 10],
                         'min_samples_leaf': [1, 3, 5],
                         'n_estimators': [10, 25, 50, 100]},
             verbose=1)
```

In [67]:

```
gs.best_params_
```

Out[67]:

```
{'max_depth': 1, 'min_samples_leaf': 1, 'n_estimators': 10}
```

In [68]:

```
gs.best_score_
```

Out[68]:

```
0.628036013400335
```

In [69]:

```
gs_predictions = gs.predict(X_test)
```

In [70]:

```
from sklearn.metrics import accuracy_score
print('Accuracy Score:', accuracy_score(y_test,gs_predictions))
```

```
Accuracy Score: 0.6352596314907872
```

In [71]:

```
RFC.fit(X_train, y_train)
```

Out[71]:

```
RandomForestClassifier()
```

In [72]:

```
RFC.feature_importances_
```

Out[72]:

```
array([2.89557656e-03, 2.49236378e-02, 1.52018160e-03, 8.15530406e-04,
       4.64090886e-03, 1.29862250e-02, 1.33824915e-02, 1.91294727e-02,
       1.90855277e-02, 1.55539702e-02, 1.54402260e-02, 2.01423616e-02,
       2.11336882e-02, 2.08029037e-02, 1.89784321e-02, 1.91747766e-02,
       2.06843444e-02, 1.40096044e-02, 6.23387341e-03, 8.88973248e-03,
       7.57684287e-04, 7.06515200e-03, 7.25500803e-04, 8.39874844e-05,
       2.00458554e-04, 1.31749324e-02, 7.95515285e-03, 5.94757269e-06,
       8.88464018e-05, 1.12899251e-03, 4.57673860e-03, 1.65442194e-03,
       1.37455163e-03, 3.29513759e-04, 1.47353664e-05, 1.55468311e-02,
       2.59677466e-03, 2.45769809e-03, 4.40657959e-04, 5.83788467e-03,
       7.13093955e-05, 1.59024421e-04, 3.68734223e-04, 6.85091773e-03,
       6.91465260e-03, 1.61462594e-03, 2.78275635e-04, 3.26880637e-04,
       9.51699700e-03, 9.71950919e-03, 5.55104037e-03, 6.24984340e-03,
       2.28852096e-03, 5.52456210e-03, 3.49629027e-04, 0.00000000e+00,
       2.58188281e-05, 6.19188155e-03, 8.45142638e-03, 1.25078225e-02,
       7.72690508e-03, 7.97177235e-03, 1.17220313e-02, 6.28704890e-03,
       7.97586114e-03, 1.24334869e-02, 3.10889959e-03, 4.08679896e-03,
       1.70780062e-03, 3.94722315e-03, 4.34227414e-03, 1.30926529e-03,
       2.66190847e-03, 1.51781763e-03, 3.99636598e-03, 2.82332274e-03,
       2.30590432e-03, 3.37671736e-03, 8.41605542e-04, 1.79099116e-04,
       1.51718856e-03, 5.00665032e-04, 6.59432098e-05, 7.97056977e-04,
       2.09526476e-04, 5.26539500e-04, 2.78090344e-04, 3.09402811e-02,
       1.92912591e-02, 8.98736095e-03, 4.49206823e-02, 3.15836610e-02,
       2.13109149e-02, 7.29017645e-02, 2.86860735e-03, 3.93634886e-03,
       3.44392217e-03, 3.13334642e-03, 2.05560381e-03, 1.10476095e-03,
       5.97744015e-04, 4.14765986e-03, 5.32144411e-05, 1.73211866e-02,
       3.51860522e-02, 9.35313859e-03, 4.57808317e-03, 7.87048700e-03,
       1.86242708e-03, 6.79576877e-03, 3.15893552e-03, 9.47044314e-03,
       3.61554965e-03, 2.90231403e-02, 1.11616334e-02, 5.10675612e-03,
       7.32270752e-03, 5.99909687e-03, 7.71461462e-03, 4.62644852e-03,
       9.55259046e-03, 2.25874350e-02, 2.27978554e-02])
```

In [73]:

```
X_train.columns
```

Out[73]:

```
Index(['hacdor', 'rooms', 'hacapo', 'v14a', 'refrig', 'v18q', 'r4h1', 'r4h
2',
       'r4h3', 'r4m1',
       ...
       'qmobilephone', 'lugar1', 'lugar2', 'lugar3', 'lugar4', 'lugar5',
       'lugar6', 'area1', 'age', 'agesq'],
      dtype='object', length=123)
```

In [74]:

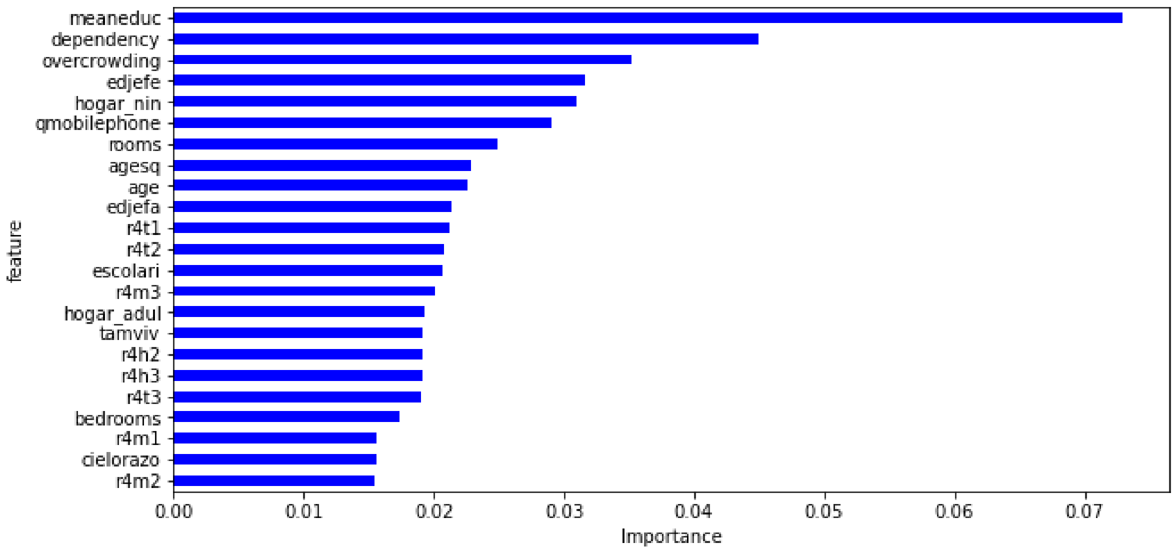
```
labels = list(X_train)
feature_importances = pd.DataFrame({'feature': labels, 'importance': RFC.feature_importance
feature_importances=feature_importances[feature_importances.importance>0.015]
feature_importances.head()
```

Out[74]:

	feature	importance
1	rooms	0.024924
7	r4h2	0.019129
8	r4h3	0.019086
9	r4m1	0.015554
10	r4m2	0.015440

In [75]:

```
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=(10, 5),color = feature_importance
plt.xlabel('Importance');
```



From the above plot we can observe that meaneduc, dependency and overcrowding has significant influence on the model.