In [1]:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
plt.style.use('ggplot')
%matplotlib inline
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score,confusion_matrix,f1_score,classification_
```

In [2]:

```
data_train=pd.read_csv('train.csv')
data_test=pd.read_csv('test.csv')
```

In [3]:

```
print('Shape of train dataset is {}'.format(data_train.shape))
print('Shape of test dataset is {}'.format(data_test.shape))
```

```
Shape of train dataset is (9557, 143)
Shape of test dataset is (23856, 142)
```

Identify the output variable.

In [4]:

```
target_col = ""
for i in data_train.columns:
    if i not in data_test.columns:
        target_col = i
        print("Our output variable is {}".format(i))
        break
```

```
Our output variable is Target
```

Understand the type of data.

In [5]:

```
data_train.dtypes.value_counts()
```

Out[5]:

```
int64      130
float64      8
object       5
dtype: int64
```

In [6]:

```
data_train.select_dtypes(include='object')
```

Out[6]:

	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

Check if there are any biases in your dataset.

In [7]:

```
(data_train[target_col].value_counts() / data_train.shape[0]) * 100
```

Out[7]:

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

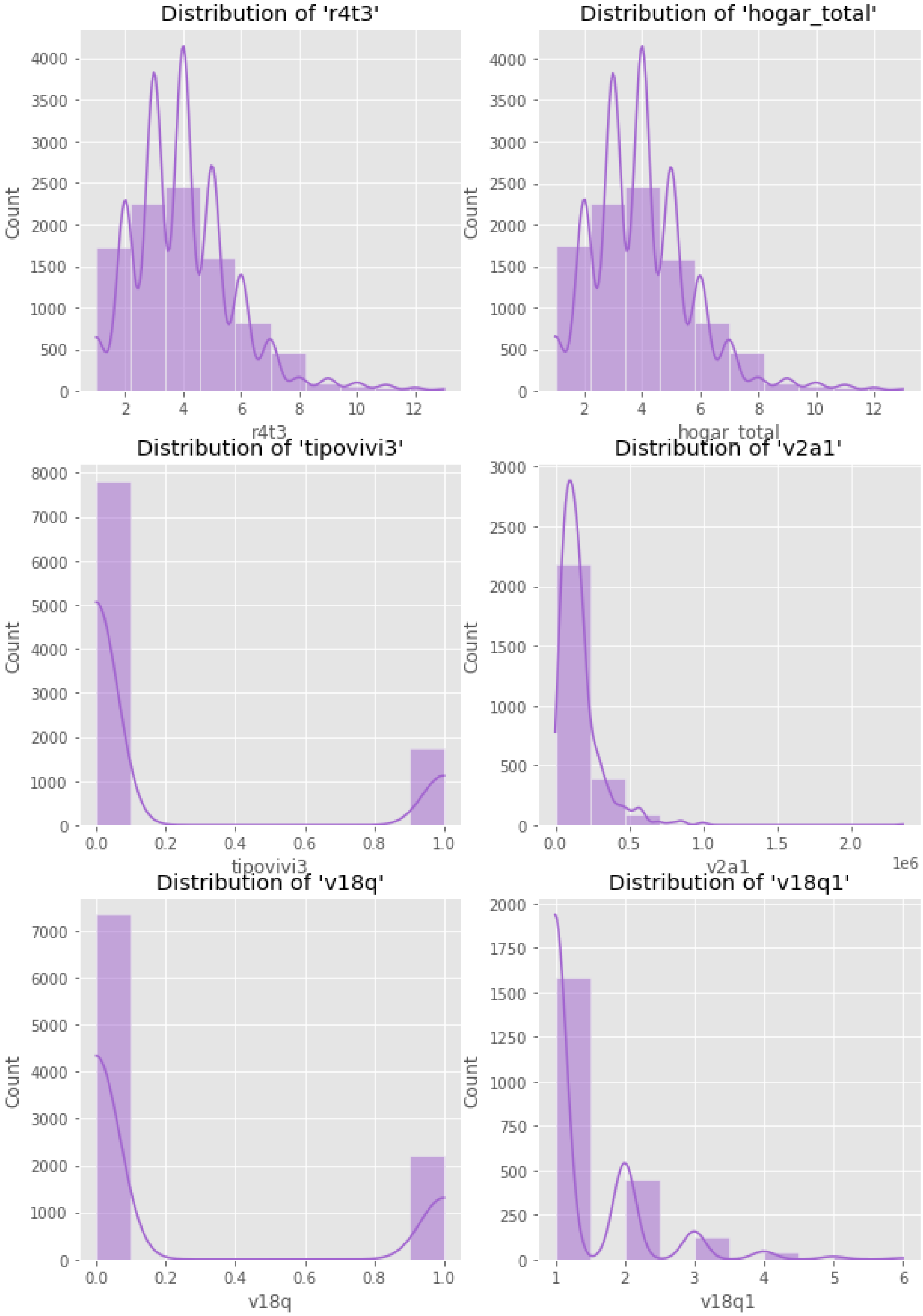
Above data shows that about 62% of people in training dataset fall under category `4` level of poverty

In [8]:

```
fig, axes = plt.subplots(3,2,figsize=(10,15))

sns.histplot(ax=axes[0,0], x=data_train['r4t3'],
            bins= 10, kde = True, cbar = True,
            color = '#A163CF').set(title = "Distribution of 'r4t3'")

sns.histplot(ax=axes[0,1], x=data_train['hogar_total'],
            bins = 10, kde = True, cbar = True,
            color = '#A163CF').set(title = "Distribution of 'hogar_total'")

sns.histplot(ax=axes[1,0], x=data_train['tipovivi3'],
            bins = 10, kde = True, cbar = True,
            color = '#A163CF').set(title= "Distribution of 'tipovivi3'")

sns.histplot(ax=axes[1,1], x=data_train['v2a1'],
            bins=10, kde=True,cbar = True,
            color = '#A163CF').set(title="Distribution of 'v2a1'")

sns.histplot(ax=axes[2,0],x=data_train['v18q'],
            bins=10, kde = True, cbar = True,
            color = '#A163CF').set(title="Distribution of 'v18q'")

sns.histplot(ax=axes[2,1],x=data_train['v18q1'],
            bins=10, kde = True, cbar = True,
            color = '#A163CF').set(title="Distribution of 'v18q1'")
```

Out[8]:

```
[Text(0.5, 1.0, "Distribution of 'v18q1'")]
```



Therefore,variables ('r4t3','hogar_total') have relationship between them. For good result we can use any one of them. Therefore,variables ('tipovivi3','v2a1') have relationship between them. For good result we can use any one of them. Therefore,variables ('v18q','v18q1') have relationship between them. For good result we can use any one of them. So,*Therefore, there is bias in our dataset.*

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

In [9]:

```
# Group By data wrt to family ID
family_group = data_train.groupby('idhogar')
```

In [10]:

```
# Get the count unique count of Target variable
unique_poverty_status = family_group[target_col].nunique()
# unique_poverty_status[unique_poverty_status > 1].index
any(unique_poverty_status > 1)
```

Out[10]:

```
True
```

In [11]:

```
sum(unique_poverty_status > 1), unique_poverty_status.shape[0]
```

Out[11]:

```
(85, 2988)
```

Above data shows that there are some families where members are of different poverty category within same family. Out of 2988 Families in dataset about 85 families have shown this behaviour

Check if there is a house without a family head.

In [12]:

```
num_head_in_family = family_group.parentesco1.sum()
any(num_head_in_family == 0)
```

Out[12]:

```
True
```

In [13]:

```
num_head_in_family[num_head_in_family == 0].shape[0], num_head_in_family.shape[0]
```

Out[13]:

```
(15, 2988)
```

Above data shows that out 2988 families about 15 families don't have family head in training dataset

Set the poverty level of the members and the head of the house same in a family.

In [14]:

```
def set_poverty_level_as_head(group):
    head_poverty_level = group[group.parentesco1 == 1].Target
    if not head_poverty_level.empty:
        group.Target = head_poverty_level.values[0]
    return group
```

In [15]:

```
# update training data
data_train = family_group.apply(set_poverty_level_as_head)
```

Count how many null values are existing in columns.

In [16]:

```
null_col_count = data_train.isnull().sum()
null_col_count[null_col_count != 0]
```

Out[16]:

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

Checking null of v2a1

In [17]:

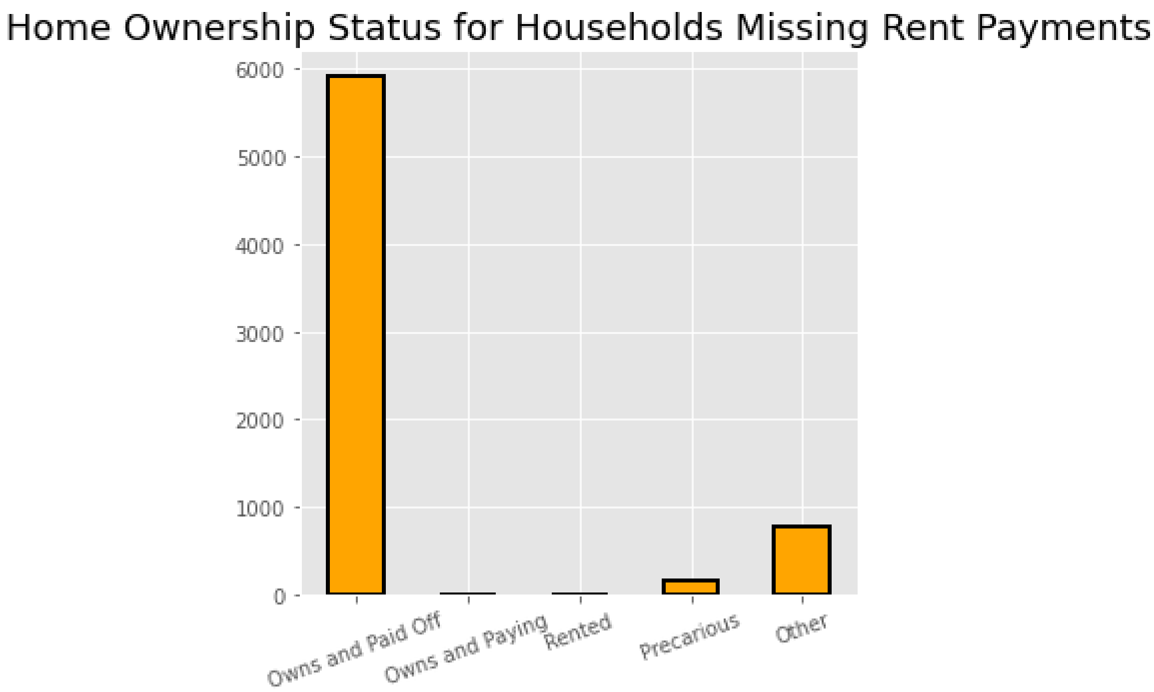
```
data = data_train[data_train['v2a1'].isnull()].head()

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

Out[17]:

	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 [18]:

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

# Plot of the home ownership variables for home missing rent payments
data_train.loc[data_train['v2a1'].isnull(), own_variables].sum().plot.bar(figsize =
                                                                        color = 'ora
                                                              edgecolor = 'k', linew
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 [19]:

```
data_train['v2a1'].fillna(0,inplace=True)
```

Looking at the above data it makes sense that when the house is fully paid, there will be no monthly rent payment. So, added 0 for all the null values.

Checking null values of v18q1

In [20]:

```
data_train['v18q1'].value_counts()
```

Out[20]:

```
1.0    1586
2.0     444
3.0     129
4.0      37
5.0      13
6.0       6
Name: v18q1, dtype: int64
```

In [21]:

```
data_train['v18q1'].isna().sum()
```

Out[21]:

```
7342
```

In [22]:

```
data_train['v18q'].value_counts()
```

Out[22]:

```
0    7342
1    2215
Name: v18q, dtype: int64
```

In [23]:

```
data_train['v18q1'].fillna(0,inplace=True)
```

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. So, added 0 for all the null values.

Checking for null values rez_esc

Lets look at rez_esc : Years behind in school

In [24]:

```
data_train[data_train['rez_esc'].notnull()]['age'].describe()
```

Out[24]:

```
count    1629.000000
mean       12.258441
std         3.218325
min         7.000000
25%         9.000000
50%        12.000000
75%        15.000000
max        17.000000
Name: age, dtype: float64
```

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.

In [25]:

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

Out[25]:

```
count    7928.000000
mean       38.833249
std        20.989486
min         0.000000
25%        24.000000
50%        38.000000
75%        54.000000
max        97.000000
Name: age, dtype: float64
```

In [26]:

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

Out[26]:

```
count     1.0
mean     10.0
std       NaN
min      10.0
25%      10.0
50%      10.0
75%      10.0
max      10.0
Name: age, dtype: float64
```

There is one value that has Null for the 'behind in school' column with age between 7 and 17

In [27]:

```
data_train[(data_train['age'] ==10) & data_train['rez_esc'].isnull()].head()
data_train[(data_train['Id'] =='ID_f012e4242')].head()
```

Out[27]:

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

1 rows × 143 columns

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.

In [28]:

```
for data in [data_train, data_test]:
    data['rez_esc'].fillna(value=0, inplace=True)
data_train[['rez_esc']].isnull().sum()
```

Out[28]:

```
rez_esc    0
dtype: int64
```

Checking for null values meaneduc

In [29]:

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

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

Out[29]:

	instlevel1	instlevel2
count	0.0	0.0
mean	NaN	NaN
std	NaN	NaN
min	NaN	NaN
25%	NaN	NaN
50%	NaN	NaN
75%	NaN	NaN
max	NaN	NaN

In [30]:

```
for data in [data_train, data_test]:
    data['meaneduc'].fillna(value=0, inplace=True)
data_train[['meaneduc']].isnull().sum()
```

Out[30]:

```
meaneduc    0
dtype: int64
```

Checking for null values SQBmeaned

In [31]:

```
for data in [data_train, data_test]:
    data['SQBmeaned'].fillna(value=0, inplace=True)
data_train[['SQBmeaned']].isnull().sum()
```

Out[31]:

```
SQBmeaned    0
dtype: int64
```

We find that SQBmeaned is null when no level of education is 0

Remove null value rows of the target variable.

In [32]:

```
data_train[target_col].isnull().sum()
```

Out[32]:

```
0
```

No Null values found in train data set for Target column

Predict the accuracy using random forest classifier. (Try other models too)

Data Processing

Categorise alpha numeric column

Dependency

In [33]:

```
# Dependency: # of members less than 19 or more than 64 / # of memebers b/w 19 and 6
data_train['dependency'].value_counts()
```

Out[33]:

```
yes           2192
no            1747
.5            1497
2              730
1.5            713
.33333334      598
.66666669      487
8              378
.25            260
3              236
4              100
.75             98
.2              90
.40000001       84
1.3333334       84
2.5             77
5               24
1.25            18
```

Since it is not clear if how much does a yes quantify to proceeding with assumption of 1 for `yes` and 0 for `no`

In [34]:

```
def map(i):

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

In [35]:

```
data_train['dependency']=data_train['dependency'].apply(map)
```

In [36]:

```
data_train.dependency.dtypes
```

Out[36]:

```
dtype('float64')
```

In [37]:

```
data_train['dependency'].isnull().sum()
```

Out[37]:

```
0
```

edjefe & edjefa

`edjefe` and `edjefa` features are not clear and wasn't able to find proper definiton so dropping them.

In [38]:

```
data_train = data_train.drop(columns = ['edjefe', 'edjefa'])
```

train & test split

In [39]:

```
X = data_train.drop(columns=[target_col])
```

In [40]:

```
y = data_train[[target_col]]
```

In [41]:

```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y,
                                                    random_state=42,
                                                    train_size=0.8)
```

In [42]:

```
X_train.shape
```

Out[42]:

```
(7645, 140)
```

In [43]:

```
X_test.shape
```

Out[43]:

```
(1912, 140)
```

EDA

Output variable distribution

In [44]:

```
target_counts=(y_train[target_col].value_counts() / y_train.shape[0]) * 100
target_counts
```

Out[44]:

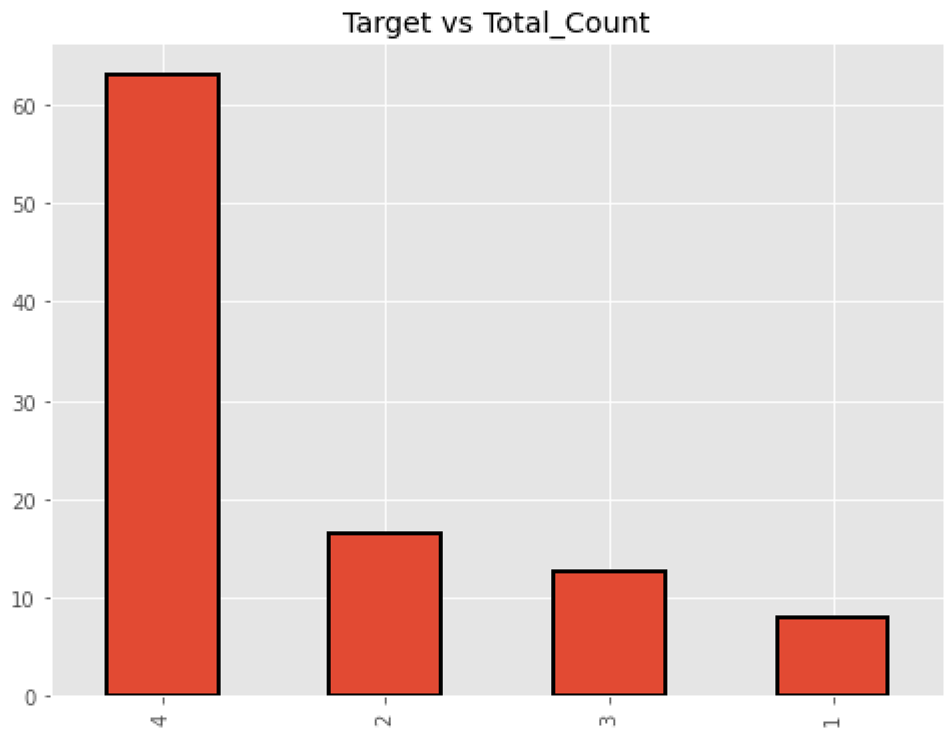
```
4    63.047744
2    16.429039
3    12.609549
1     7.913669
Name: Target, dtype: float64
```

In [45]:

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

Out[45]:

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



Output variable trends with raw data available

In [46]:

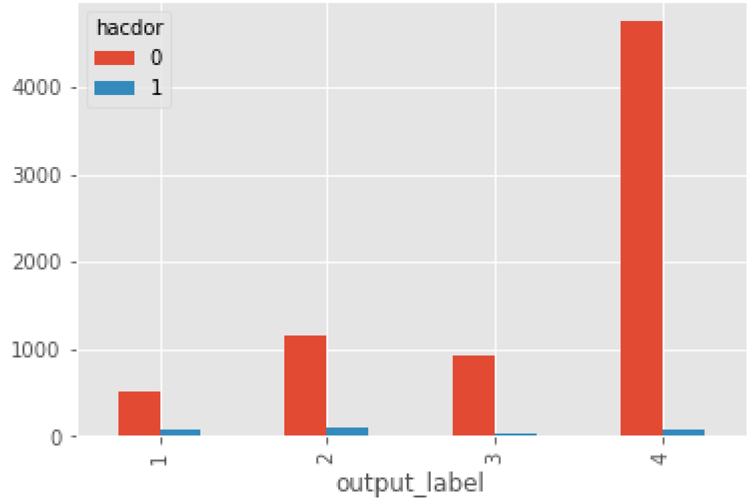
```
X_train['output_label'] = y_train.values
```

In [47]:

```
X_train.groupby(['output_label', 'hacdor']).Id.count().unstack().plot(kind='bar')
```

Out[47]:

```
<AxesSubplot:xlabel='output_label'>
```



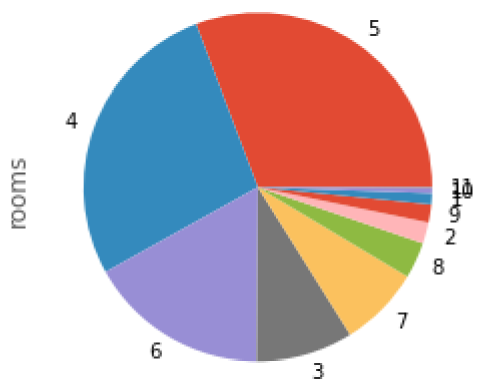
Hacdor doesn't seems to provide valuable insight about a person being in particular poverty category or not except for the fact that already biased data showing that if they don't have overcrouded bedroom they are likely to be in category `4` , will have to revisit about viability of this feature later

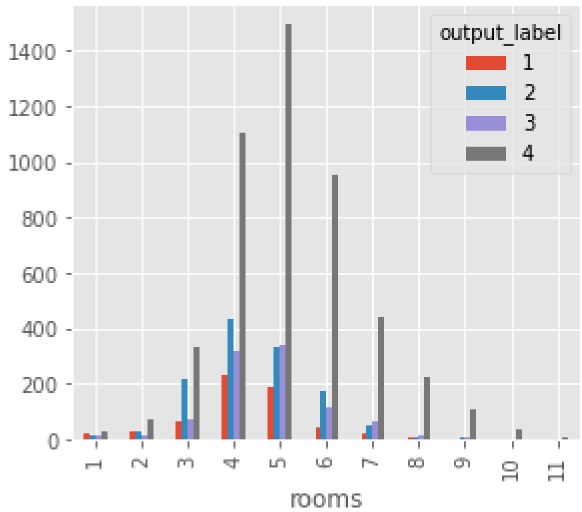
In [48]:

```
fig, axes = plt.subplots(nrows=1, ncols=2, figsize=(10, 4))
room_distribution = X_train['rooms'].value_counts()
room_count_x_output_label = X_train.groupby(['rooms', 'output_label']).Id.count().ur
room_distribution.plot(ax=axes[0], kind='pie')
room_count_x_output_label.plot(ax=axes[1], kind='bar')
```

Out[48]:

```
<AxesSubplot:xlabel='rooms'>
```





The graph above shows that most of the house holds have 5 rooms or 4 rooms per house of family covering more than 50% of data available in training set, however couldn't find a reliable pattern with output label

In [49]:

```
X_train.groupby(['output_label', 'v18q']).Id.count().unstack()
```

Out[49]:

v18q	0	1
output_label		
1	561	44
2	1162	94
3	851	113
4	3324	1496

Above matrix shows that it is more likely that if a person owns a tablet, he is more likely to be category 4 compared to other categories but this could still also be due to the bias in data from category 4

we can make gender column from `male` and `female` column

In [50]:

```
X_train[['male', 'female']].head(5)
```

Out[50]:

	male	female
9025	0	1
742	0	1
180	1	0
1115	0	1
9090	1	0

In [51]:

```
X_train['gender'] = np.where(X_train['female'], 1, 0)
```

In [52]:

```
X_train.groupby(['output_label', 'gender']).Id.count().unstack()
```

Out[52]:

gender	0	1
output_label		
1	264	341
2	600	656
3	454	510
4	2406	2414

The distribution of poverty marking seems to qually distributed across genders

Similarly we can reduce Zone column into single column

In [53]:

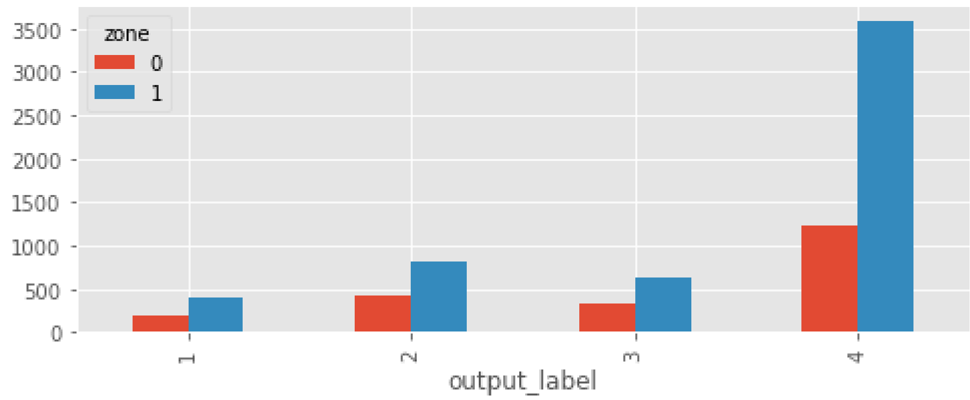
```
X_train['zone'] = np.where(X_train['area1'], 1, 0)
```

In [54]:

```
X_train.groupby(['output_label', 'zone']).Id.count().unstack().plot(kind='bar', figs
```

Out[54]:

<AxesSubplot:xlabel='output_label'>



Above graph shows a skewness of higher chance of people being in urban zone compared to rural and fall under category 4 however even for rural category 4 seems to be the prominent one.

Combining regions to get better perspective of distribution across region for poverty

In [55]:

```
X_train[['lugar1', 'lugar2', 'lugar3', 'lugar4', 'lugar5', 'lugar6']].head(3)
```

Out[55]:

	lugar1	lugar2	lugar3	lugar4	lugar5	lugar6
9025	0	0	0	0	0	1
742	1	0	0	0	0	0
180	1	0	0	0	0	0

In [56]:

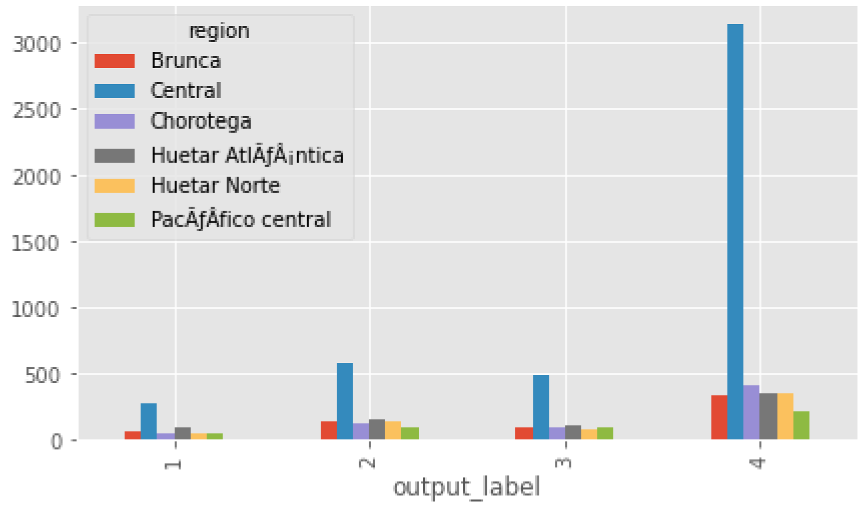
```
X_train['region'] = np.where(
        X_train['lugar1'] == 1, "Central",
        np.where(
            X_train['lugar2'] == 1, "Chorotega",
            np.where(
                X_train['lugar3'] == 1, "PacÃƒÂfico central",
                np.where(
                    X_train['lugar4'] == 1, "Brunca",
                    np.where(
                        X_train['lugar5'] == 1, "Huetar AtlÃƒÂ¡ntica",
                        "Huetar Norte"
                    )
                )
            )
        )
)
```

In [57]:

```
X_train.groupby(['output_label', 'region']).Id.count().unstack().plot(kind='bar', fi
```

Out[57]:

<AxesSubplot:xlabel='output_label'>



Above graph shows that majority of population is from central part and that too has a prominent category 4 population, this could also be due to inherit bias in data for category 4

In [58]:

```
region_map = {
    "Central": 0, "Chorotega": 1, "PacÃƒÂfico central": 2, "Brunca": 3, "Huetar AtlÃ
}
```

In [59]:

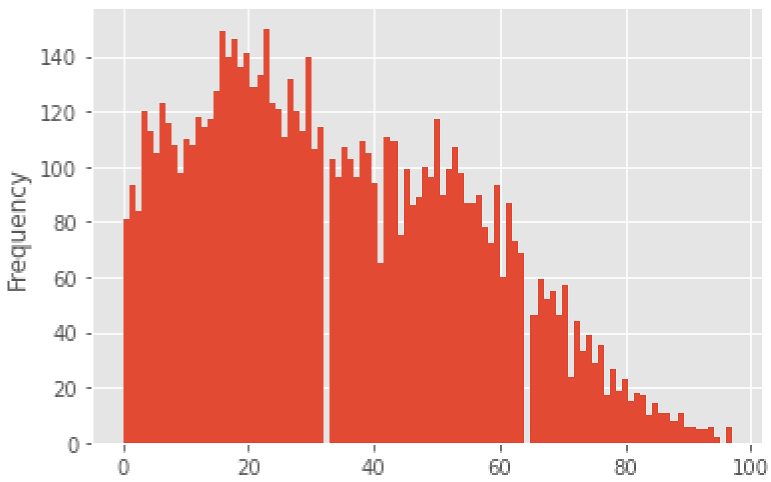
```
X_train['region'] = X_train['region'].map(region_map)
```

In [60]:

```
X_train['age'].plot(kind='hist', bins=100)
```

Out[60]:

```
<AxesSubplot:ylabel='Frequency'>
```

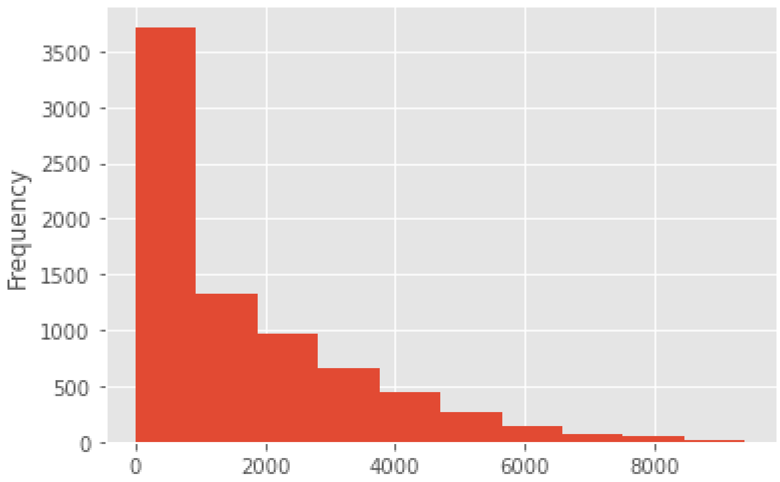


In [61]:

```
X_train['agesq'].plot(kind='hist')
```

Out[61]:

```
<AxesSubplot:ylabel='Frequency'>
```



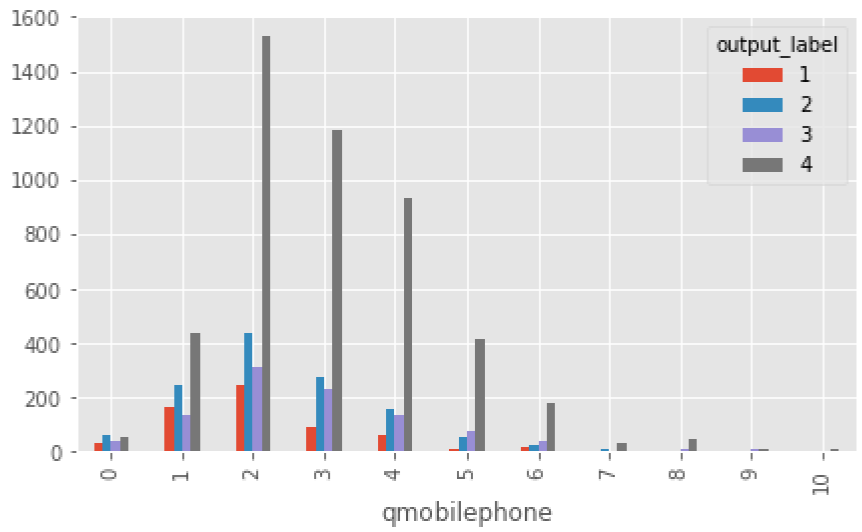
Age seems to be a right skewed distribution with majority of people being in age band of 15-30 years roughly.

In [62]:

```
X_train.groupby(['qmobilephone','output_label']).Id.count().unstack().plot(kind='bar
```

Out[62]:

```
<AxesSubplot:xlabel='qmobilephone'>
```



In [63]:

```
X_train['has_mobile_or_phone'] = np.where(X_train['qmobilephone'] == 0, 0, 1)
```

In [64]:

```
X_train.groupby(['has_mobile_or_phone', 'output_label']).Id.count().unstack()
```

Out[64]:

output_label	1	2	3	4
has_mobile_or_phone				
0	31	60	39	54
1	574	1196	925	4766

Couldn't find a valuable insight from a person being in poverty and having of mobile or phone

In [65]:

```
X_train[['tipovivi1', 'tipovivi2', 'tipovivi3', 'tipovivi4', 'tipovivi5']]
```

Out[65]:

	tipovivi1	tipovivi2	tipovivi3	tipovivi4	tipovivi5
9025	1	0	0	0	0
742	0	1	0	0	0
180	1	0	0	0	0
1115	0	0	1	0	0
9090	0	1	0	0	0
...	...	...	...	...	...
5734	0	1	0	0	0
5191	1	0	0	0	0
5390	0	0	0	0	1
860	0	0	1	0	0
7270	0	1	0	0	0

7645 rows × 5 columns

In [66]:

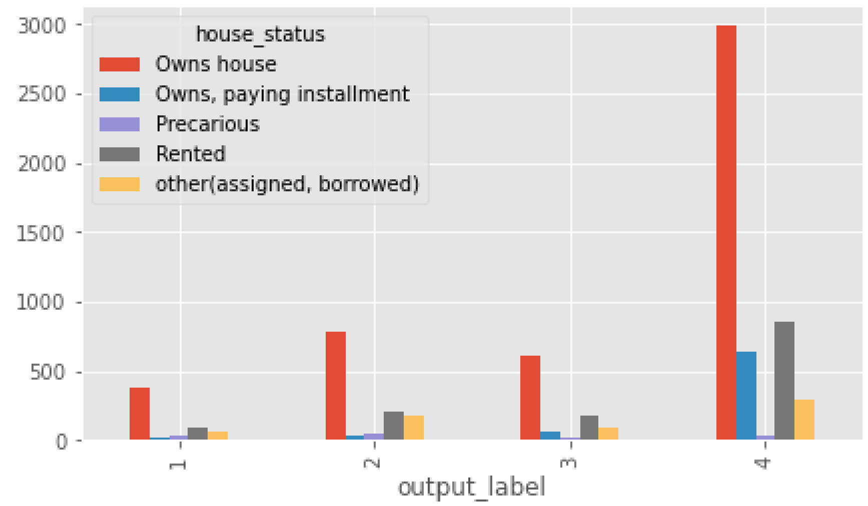
```
X_train['house_status'] = np.where(
        X_train['tipovivi1'] == 1, "Owns house",
        np.where(
            X_train['tipovivi2'] == 1, "Owns, paying installment",
            np.where(
                X_train['tipovivi3'] == 1, "Rented",
                np.where(
                    X_train['tipovivi4'] == 1, "Precarious",
                    "other(assigned, borrowed)"
                    )
                )
            )
        )
```

In [67]:

```
X_train.groupby(['output_label', 'house_status']).Id.count().unstack().plot(kind='ba
```

Out[67]:

```
<AxesSubplot:xlabel='output_label'>
```



House status shows an intresting insight that you are less likely to be in category 4 of target value if your house status is Precarious

In [68]:

```
map_house_status = {
    "Owns house": 0, "Owns, paying installment": 1, "Rented": 2, "Precarious": 3, "c
}
```

In [69]:

```
X_train['house_status'] = X_train['house_status'].map(map_house_status)
```

In [70]:

```
X_train = X_train.drop(columns = ['Id','idhogar','output_label'])
```

Feature Engineering

In [71]:

```
# Gender
X_test['gender'] = np.where(X_test['female'], 1, 0)
# Zone
X_test['zone'] = np.where(X_test['area1'], 1, 0)
#Has mobile or not
X_test['has_mobile_or_phone'] = np.where(X_test['qmobilephone'] == 0, 0, 1)
# Region
X_test['region'] = np.where(
        X_test['lugar1'] == 1, "Central",
        np.where(
            X_test['lugar2'] == 1, "Chorotega",
            np.where(
                X_test['lugar3'] == 1, "PacÃƒÂfico central",
                np.where(
                    X_test['lugar4'] == 1, "Brunca",
                    np.where(
                        X_test['lugar5'] == 1, "Huetar AtlÃƒÂ¡ntica",
                        "Huetar Norte"
                    )
                )
            )
        )
  )

# House Status
X_test['house_status'] = np.where(
        X_test['tipovivi1'] == 1, "Owns house",
        np.where(
            X_test['tipovivi2'] == 1, "Owns, paying installment",
            np.where(
                X_test['tipovivi3'] == 1, "Rented",
                np.where(
                    X_test['tipovivi4'] == 1, "Precarious",
                    "other(assigned, borrowed)"
                    )
                )
            )
        )
```

In [72]:

```
X_test['region'] = X_test['region'].map(region_map)
```

In [73]:

```
X_test['house_status'] = X_test['house_status'].map(map_house_status)
```

In [74]:

```
X_test = X_test.drop(columns = ['Id','idhogar'])
```

Models

RandomForest

In [75]:

```
model = RandomForestClassifier()
```

In [76]:

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

```
/var/folders/3c/lwghlsts08s19tyjdbv2ssd00000gn/T/ipykernel_93407/27213
49307.py:1: DataConversionWarning: A column-vector y was passed when a
1d array was expected. Please change the shape of y to (n_samples,), f
or example using ravel().
  model.fit(X_train,y_train)
```

Out[76]:

```
RandomForestClassifier()
```

In [77]:

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

```
/Users/saishruthicherukuri/opt/anaconda3/lib/python3.9/site-packages/s
klearn/base.py:493: FutureWarning: The feature names should match thos
e that were passed during fit. Starting version 1.2, an error will be
raised.
Feature names must be in the same order as they were in fit.

  warnings.warn(message, FutureWarning)
```

In [78]:

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

```
0.9288702928870293
[[ 144    3    0   22]
 [    5  258    0   39]
 [    2    4  195   56]
 [    0    4    1 1179]]
              precision    recall  f1-score   support

           1       0.95      0.85      0.90       169
           2       0.96      0.85      0.90       302
           3       0.99      0.76      0.86       257
           4       0.91      1.00      0.95      1184

    accuracy                           0.93      1912
   macro avg       0.95      0.87      0.90      1912
weighted avg       0.93      0.93      0.93      1912
```

Random Forest with K Folds

In [79]:

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

In [80]:

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

```
(9557, 140)
(9557,)
```

In [81]:

```
x_features = x_features.drop(columns = ['Id','idhogar'])
```

Checking the score using default 10 trees

In [82]:

```
seed=7
kfold=KFold(n_splits=5,random_state=seed,shuffle=True)
model=RandomForestClassifier(random_state=10,n_jobs = -1)
print(cross_val_score(model,x_features,y_features,cv=kfold,scoring='accuracy',error_
results=cross_val_score(model,x_features,y_features,cv=kfold,scoring='accuracy',erro
print(results.mean()*100)
```

```
[0.93410042 0.94142259 0.92935636 0.93040293 0.93092622]
93.32417035047041
```

Checking the score using 100 trees

In [83]:

```
num_trees= 100

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

```
[0.93410042 0.94142259 0.92935636 0.93040293 0.93092622]
93.32417035047041
```

In [84]:

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

Out[84]:

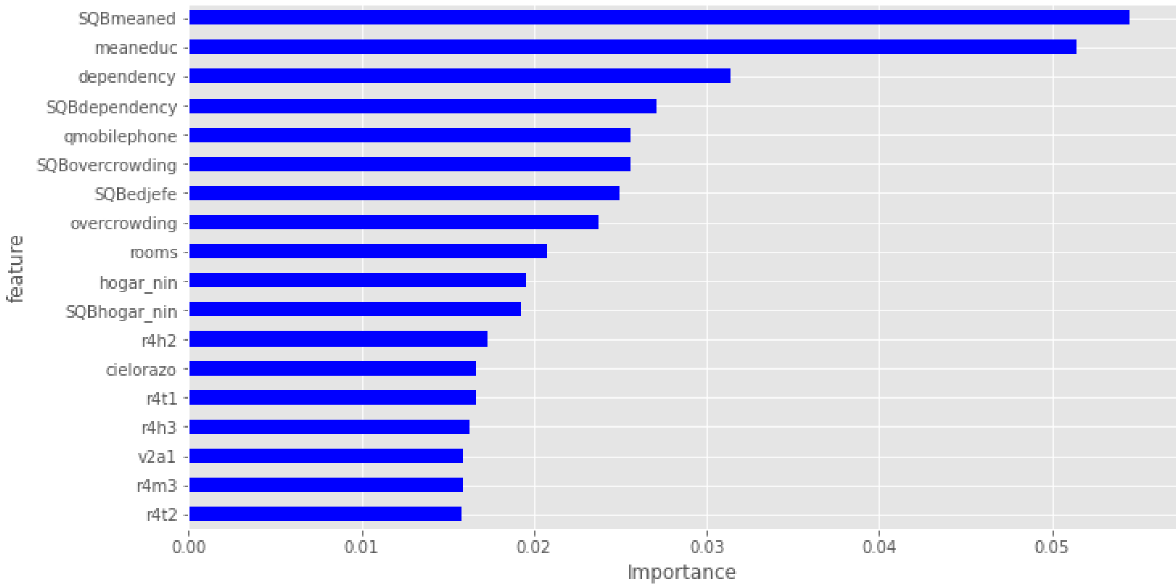
	feature	importance
0	v2a1	0.015878
2	rooms	0.020800
9	r4h2	0.017319
10	r4h3	0.016323
13	r4m3	0.015872

In [85]:

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

Out[85]:

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



In [86]:

```
feature_importances
```

Out[86]:

feature	importance	positive
r4t2	0.015845	True
r4m3	0.015872	True
v2a1	0.015878	True
r4h3	0.016323	True
r4t1	0.016652	True
cielorazo	0.016670	True
r4h2	0.017319	True
SQBhogar_nin	0.019292	True
hogar_nin	0.019557	True
rooms	0.020800	True
overcrowding	0.023703	True
SQBedjefe	0.024987	True
SQBovercrowding	0.025591	True
qmobilephone	0.025620	True
SQBdependency	0.027054	True
dependency	0.031348	True
meaneduc	0.051477	True
SQBmeaned	0.054520	True

In [87]:

```
for i in feature_importances:
    if i not in x_features:
        print(i)
```

```
importance
positive
```

In [88]:

```
X_data_Top_features= x_features[['r4t2','r4m3','v2a1','r4h3','r4t1','cielorazo','r4h
                                'SQBhogar_nin','hogar_nin','rooms','overcrowding','SQ
                                 'qmobilephone','SQBdependency','dependency','meanedu
```

In [89]:

```
X_train,X_test,Y_train,Y_test=train_test_split(X_data_Top_features,
                                               y_features,
                                               test_size=0.2,
                                               stratify=y_features,random_state=0)
```

In [90]:

```
X_data_Top_features.isnull().sum()
```

Out[90]:

```
r4t2              0
r4m3              0
v2a1              0
r4h3              0
r4t1              0
cielorazo         0
r4h2              0
r4t1              0
cielorazo         0
r4h2              0
SQBhogar_nin      0
hogar_nin         0
rooms             0
overcrowding      0
SQBedjefe         0
SQBovercrowding   0
qmobilephone      0
SQBdependency     0
dependency        0
meaneduc          0
SQBmeaned         0
dtype: int64
```

In [91]:

```
model = RandomForestClassifier()
model_final=model.fit(X_train,Y_train)
Y_pred=model_final.predict(X_test)
```

In [92]:

```
print(accuracy_score(Y_test,Y_pred))
print(confusion_matrix(Y_test,Y_pred))
print(classification_report(Y_test,Y_pred))
print(f1_score(Y_test,Y_pred,average='weighted'))
```

```
0.9633891213389121
[[ 144    0    0   11]
 [   6  292    3   11]
 [   1    3  228   12]
 [   2    7   14 1178]]
              precision    recall  f1-score   support

           1       0.94      0.93      0.94       155
           2       0.97      0.94      0.95       312
           3       0.93      0.93      0.93       244
           4       0.97      0.98      0.98      1201

    accuracy                           0.96      1912
   macro avg       0.95      0.95      0.95      1912
weighted avg       0.96      0.96      0.96      1912

0.9633129858012178
```

Test Data Cleaning and Prediction

In [93]:

```
# lets drop required variables.
data_test.drop(['Id','idhogar','edjefe','edjefa'],axis=1,inplace=True)
data_test['dependency']=data_test['dependency'].apply(map)
```

In [94]:

```
data_test['v2a1'].fillna(0,inplace=True)
data_test['v18q1'].fillna(0,inplace=True)
data_test['SQBmeaned'].fillna(0,inplace=True)
data_test['meaneduc'].fillna(0,inplace=True)
```

In [95]:

```
data_test.isna().sum().value_counts()
```

Out[95]:

```
0    138
dtype: int64
```

In [96]:

```
data_test=data_test[['r4t2','r4m3','v2a1','r4h3','r4t1','cielorazo','r4h2','r4t1','c
                               'SQBhogar_nin','hogar_nin','rooms','overcrowding','SQ
                                'qmobilephone','SQBdependency','dependency','meanedu
```

In [97]:

```
test_prediction=model_final.predict(data_test)
```

In [98]:

```
test_prediction
```

Out[98]:

```
array([4, 4, 4, ..., 2, 2, 2])
```

Using RandomForest Classifier we can predict test data with accuracy of 96%.

In [ ]:

```
```