```
# import libraries

import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import GridSearchCV
from sklearn.metrics import accuracy_score

import warnings
warnings.filterwarnings('ignore')

IQ_train_df = pd.read_csv('train.csv')
IQ_train_df.head()
```

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

   r4h1  ...  SQBescolari  SQBage  SQBhogar_total  SQBedjefe
SQBhogar_nin  \
0     0  ...          100    1849               1        100
0
1     0  ...          144    4489               1        144
0
2     0  ...          121    8464               1          0
0
3     0  ...           81     289              16        121
4
4     0  ...          121    1369              16        121
4

   SQBovercrowding  SQBdependency  SQBmeaned  agesq  Target
0         1.000000            0.0      100.0   1849       4
1         1.000000           64.0      144.0   4489       4
2         0.250000           64.0      121.0   8464       4
3         1.777778            1.0      121.0    289       4
4         1.777778            1.0      121.0   1369       4
```

```
[5 rows x 143 columns]
```

```
IQ_train_df.shape
```

```
(9557, 143)
```

We have 9557 records with 143 columns.

### task 1: Identify the output variable

Target column is the output variable.

We can use y = IQ_train_df['target'] later.

### Task 2: Understand the type of data.

```
IQ_train_df.dtypes.value_counts()
```

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

There are 130 integer, 8 float and 5 object/string datatypes.

Lets find out the columns with datatype object.

```
IQ_train_df.columns[IQ_train_df.dtypes == 'object']
```

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

We can remove Id as it doesnt give any insights.

```
IQ_train_df.drop(['Id'], axis=1, inplace=True)
```

Lets check the object datatype data.

```
IQ_train_df[['idhogar', 'dependency', 'edjefe', 'edjefa']].head()
```

```
     idhogar dependency edjefe edjefa
0  21eb7fcc1         no     10     no
1  0e5d7a658          8     12     no
2  2c7317ea8          8     no     11
3  2b58d945f        yes     11     no
4  2b58d945f        yes     11     no
```

```
IQ_train_df['idhogar'].value_counts()
```

```
fd8a6d014    13
0c7436de6    12
ae6cf0558    12
b7a0b59d7    11
3fe29a56b    11
```

```
             ..
3659d839d     1
d2e45f8ad     1
7c1cfa65c     1
3a3346eff     1
980b28caa     1
Name: idhogar, Length: 2988, dtype: int64
```

```
IQ_train_df[IQ_train_df['idhogar'] == 'fd8a6d014'].head()
```

```
         v2a1  hacdor  rooms  hacapo  v14a  refrig  v18q  v18q1  r4h1
r4h2  \
2467  80000.0       1      4       1     1       1     0    NaN     5
2
2468  80000.0       1      4       1     1       1     0    NaN     5
2
2469  80000.0       1      4       1     1       1     0    NaN     5
2
2470  80000.0       1      4       1     1       1     0    NaN     5
2
2471  80000.0       1      4       1     1       1     0    NaN     5
2

      ...  SQBescolari  SQBage  SQBhogar_total  SQBedjefe
SQBhogar_nin  \
2467  ...           49     256             169          0
81
2468  ...            0       0             169          0
81
2469  ...            4      81             169          0
81
2470  ...            0      25             169          0
81
2471  ...           36     196             169          0
81

      SQBovercrowding  SQBdependency  SQBmeaned  agesq  Target
2467        18.777779         5.0625       16.0    256       1
2468        18.777779         5.0625       16.0      0       1
2469        18.777779         5.0625       16.0     81       1
2470        18.777779         5.0625       16.0     25       1
2471        18.777779         5.0625       16.0    196       1

[5 rows x 142 columns]
```

We have lots ofstring values representing house id.

```
IQ_train_df['dependency'].value_counts()
```

```
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
.80000001       18
1.25            18
3.5             18
2.25            13
.71428573       12
1.2             11
.22222222       11
.83333331       11
1.75            11
.2857143         9
.60000002        8
1.6666666        8
.16666667        7
6                7
Name: dependency, dtype: int64
```

There are few numeric values with two strings as yes and no. Here we can encode yes and no as 1 and 0 respectively.

```
IQ_train_df['edjefe'].value_counts()
```

```
no     3762
6      1845
11      751
9       486
3       307
15      285
8       257
7       234
5       222
14      208
17      202
2       194
4       137
16      134
yes     123
```

```
12      113
10      111
13      103
21       43
18       19
19       14
20        7
Name: edjefe, dtype: int64
```

```
IQ_train_df['edjefa'].value_counts()
```

```
no     6230
6       947
11      399
9       237
8       217
15      188
7       179
5       176
3       152
4       136
14      120
16      113
10       96
2        84
17       76
12       72
yes      69
13       52
21        5
19        4
18        3
20        2
Name: edjefa, dtype: int64
```

Similar to dependancy, we can encode for yes and no in the above two columns.

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

IQ_train_df['dependency'].replace(encode, inplace=True)
IQ_train_df['edjefe'].replace(encode, inplace=True)
IQ_train_df['edjefa'].replace(encode, inplace=True)
```

```
IQ_train_df['edjefa'].unique()
```

```
array([0, '11', '4', '10', '9', '15', '7', '14', '13', '8', '17', '6',
       '5', '3', '16', '19', 1, '21', '12', '2', '20', '18'],
dtype=object)
```

Now lets convert all the three columns to numeric as there is no yes and no values left.

```
IQ_train_df['dependency'] = pd.to_numeric(IQ_train_df['dependency'])
IQ_train_df['edjefe'] = pd.to_numeric(IQ_train_df['edjefe'])
IQ_train_df['edjefa'] = pd.to_numeric(IQ_train_df['edjefa'])
```

```
print(IQ_train_df['dependency'].dtype)
print(IQ_train_df['edjefe'].dtype)
print(IQ_train_df['edjefa'].dtype)
```

```
float64
int64
int64
```

### Task 3: Check if there are any biases in your dataset.

### Task 7: Count how many null values are existing in columns.

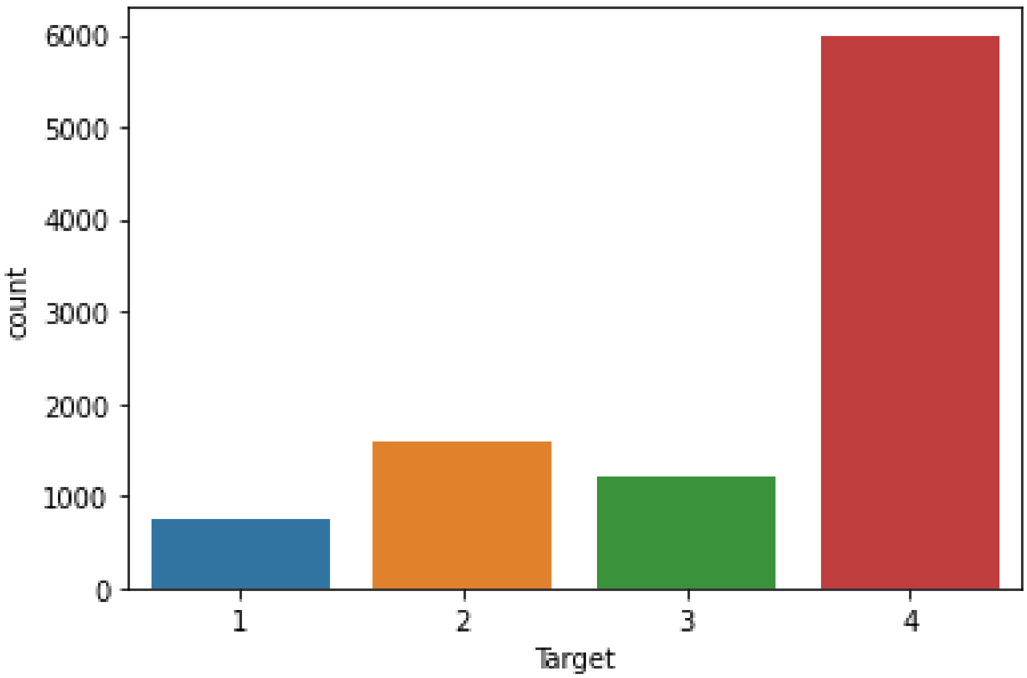
### Task 8: Remove null value rows of the target variable.

```
# Check Target column values
IQ_train_df['Target'].value_counts()
```

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

There are 4 poverty lavels (1,2,3,4). Its an imbalanced dataset as level 4 has more counts than others.

```
sns.countplot(IQ_train_df['Target'])
plt.show()
```




Lets do NaN check.

```
col_nan_counts = IQ_train_df.isna().sum()
col_nan_counts[col_nan_counts > 0]
```

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

Above 5 columns have NaN values. Total we have 9557 records. If few colums have large number of NaN values, its impossible to imput. We can drop those columns. For the columns with very less NaN values, we can do mean imputation.

```
IQ_train_df.drop(['v2a1', 'v18q1', 'rez_esc'], axis=1, inplace=True)
```

```
IQ_train_df['meaneduc'].fillna(IQ_train_df['meaneduc'].mean(),
inplace=True)
IQ_train_df['SQBmeaned'].fillna(IQ_train_df['SQBmeaned'].mean(),
inplace=True)
```

```
IQ_train_df.columns[IQ_train_df.isna().sum() > 0]
```

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

Now we got rid of NaN values.

Lets check for columns with constant values or zero variance.

```
IQ_train_df.drop('idhogar', axis=1).columns[IQ_train_df.var() == 0]
```

```
Index(['elimbasu5'], dtype='object')
```

```
IQ_train_df['elimbasu5'].nunique()
```

```
1
```

We can remove the 'elimbasu5' column as it has only constant value.

```
IQ_train_df.drop(['elimbasu5'], axis=1, inplace=True)
```

```
len(IQ_train_df.columns)
```

```
138
```

We have 137 columns including the target column. Its not possible to to EDA for each column and use boxplot to detect outliers.

We can select 20 columns with high corelation with target variable and do EDA for them only.

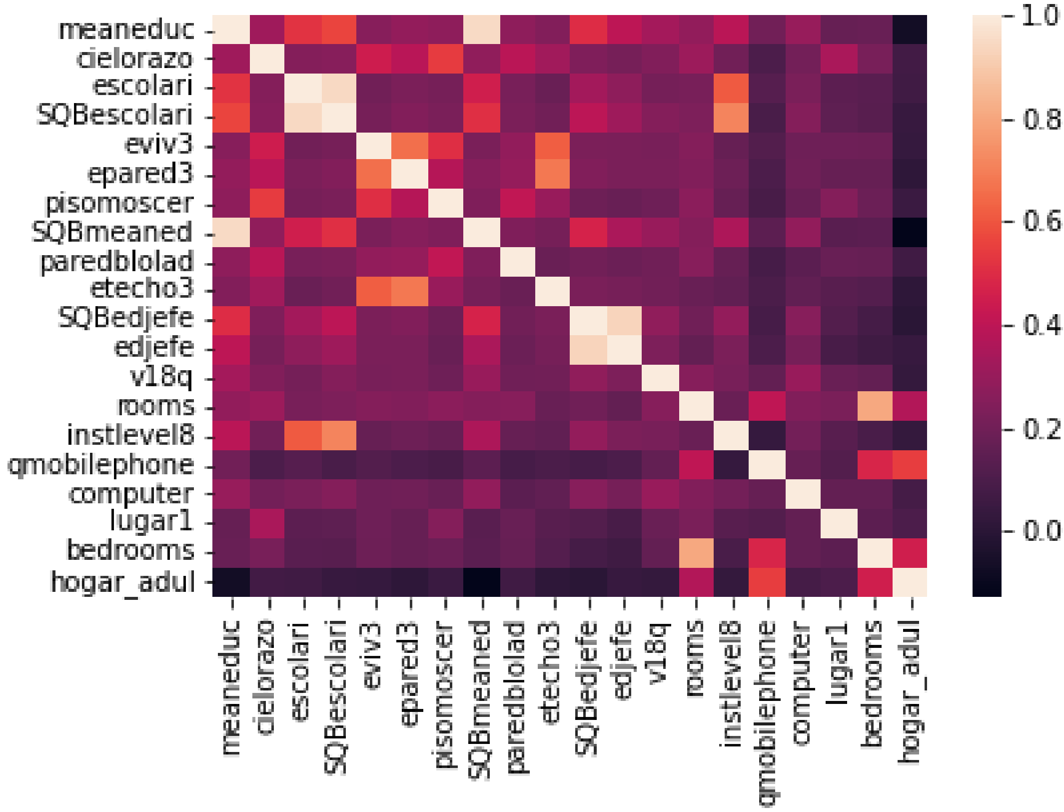
```
corr = IQ_train_df.corr()
```

```
corr_cols = corr['Target'].sort_values(ascending=False)[1:21].index
corr_cols
```

```
Index(['meaneduc', 'cielorazo', 'escolari', 'SQBescolari', 'eviv3',
'epared3',
       'pisomoscer', 'SQBmeaned', 'paredblolad', 'etecho3',
'SQBedjefe',
       'edjefe', 'v18q', 'rooms', 'instlevel8', 'qmobilephone',
'computer',
       'lugar1', 'bedrooms', 'hogar_adul'],
      dtype='object')
```

```
cols_corr = IQ_train_df[corr_cols].corr()
```

```
sns.heatmap(cols_corr)
plt.show()
```




We can see from the plot, multicolinearity is present in between few columns. So we can remove those.

```
# Delete cols with high correlation with selected columns.
def getColumnsToDelete(corr):
    cols_to_remove = set()
    for col in corr:
        if col not in cols_to_remove:
            delete_cols = corr[col][(corr[col] > 0.7) & (corr[col] <
1)].index.tolist()
            cols_to_remove.update(delete_cols)
    return cols_to_remove

cols_to_remove = getColumnsToDelete(cols_corr)

keep_cols = corr_cols[~corr_cols.isin(cols_to_remove)].tolist()
len(keep_cols)

16
```

We can do EDA with these 16 columns.

```
col_nuq = IQ_train_df[keep_cols].nunique()
col_nuq
```

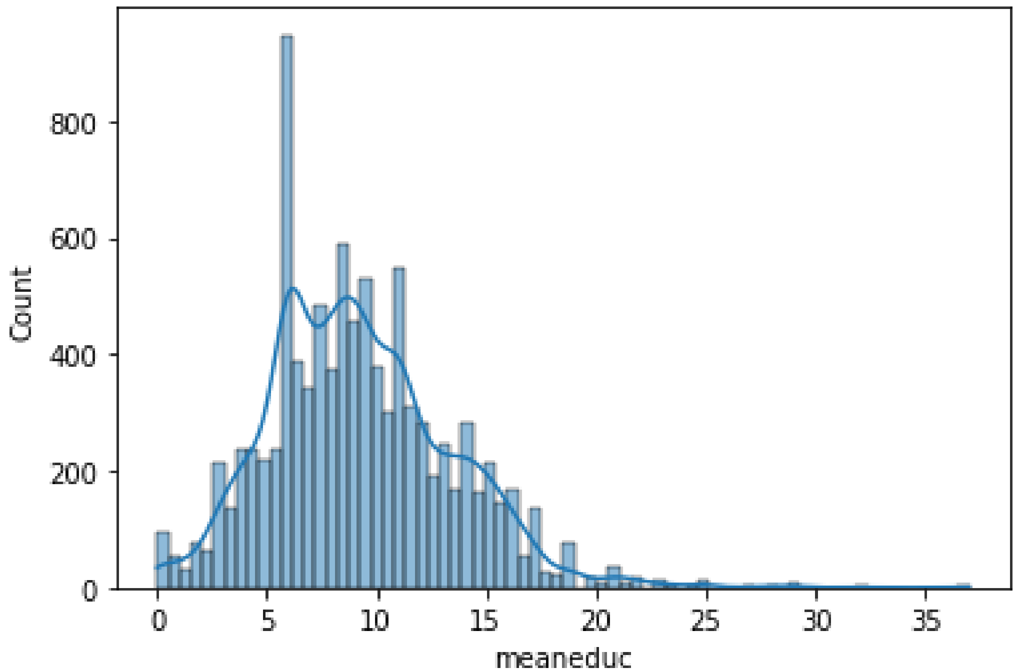
```
meaneduc        156
cielorazo         2
escolari         22
eviv3             2
epared3           2
pisomoscer        2
paredblolad       2
etecho3           2
SQBedjefe        22
v18q              2
rooms            11
instlevel8        2
qmobilephone     11
computer          2
lugar1            2
hogar_adul       10
dtype: int64
```

We have mostly integer values representing categorical values and float values representing continuous value.

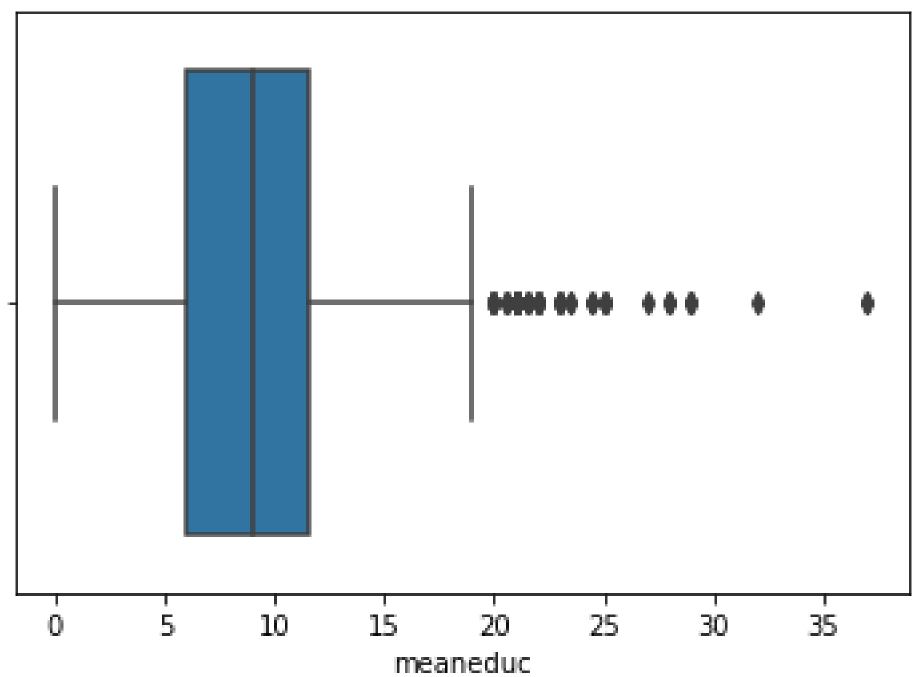
```python
def getHist(col):
    sns.histplot(IQ_train_df[col], kde=True)
    plt.show()

def getBox(col):
    sns.boxplot(IQ_train_df[col])
    plt.show()
```

Column: meaneduc EDA

```python
getHist('meaneduc')
```



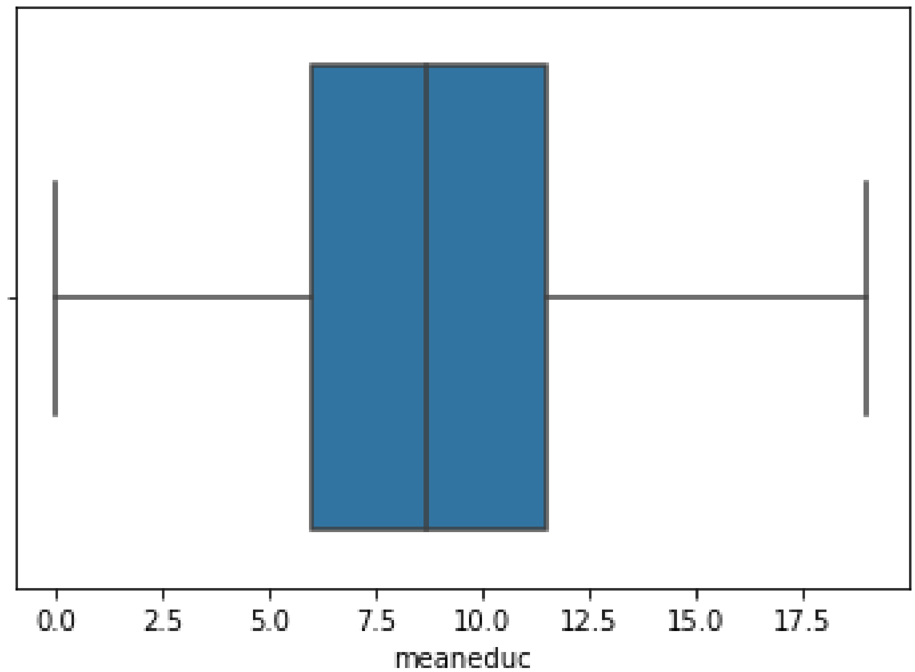

```
getBox('meaneduc')
```




There are lots of outliers. We can set limit as 19.

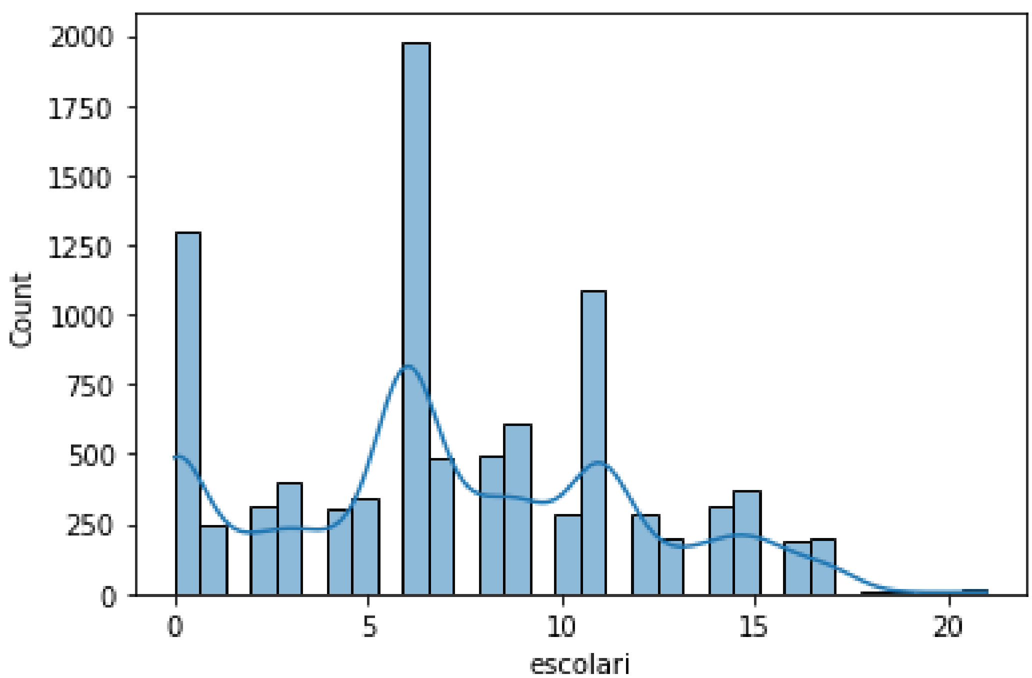
```
IQ_train_df = IQ_train_df[IQ_train_df['meaneduc'] <= 19]
```

```
getBox('meaneduc')
```

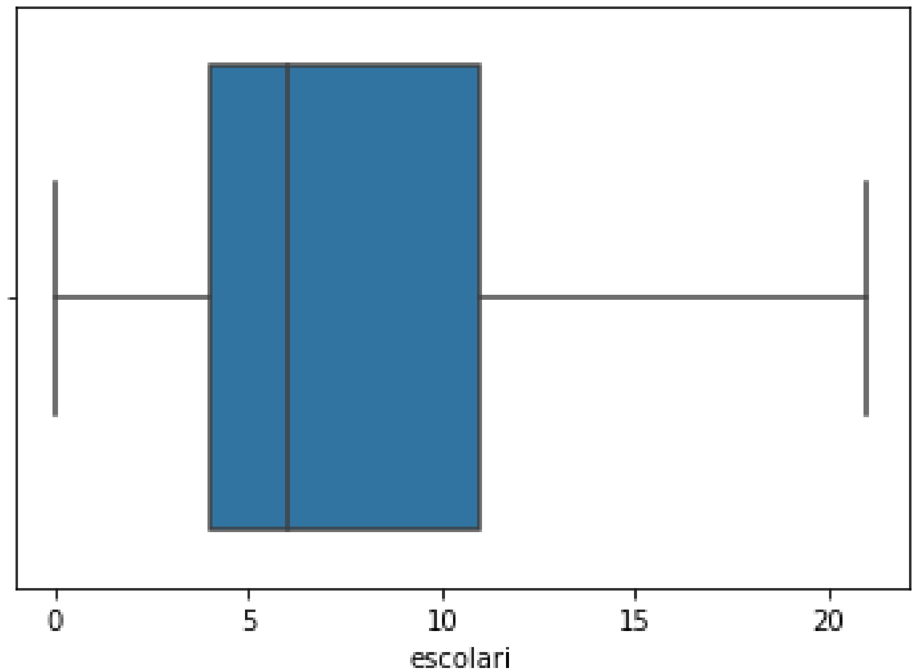



Column: escolari EDA

```
getHist('escolari')
```



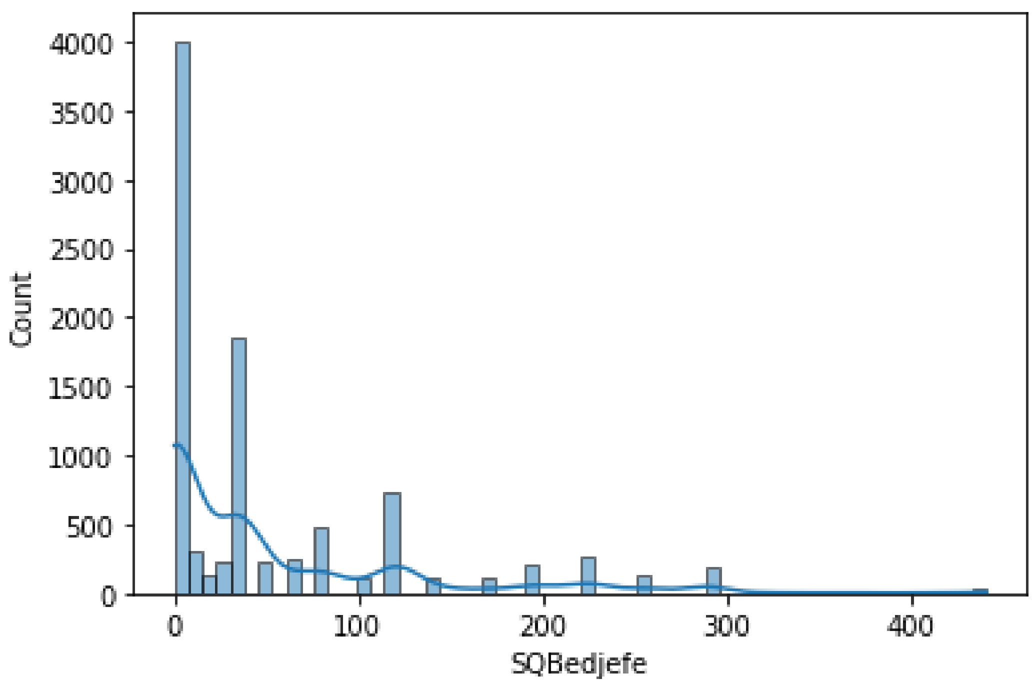

```
getBox('escolari')
```



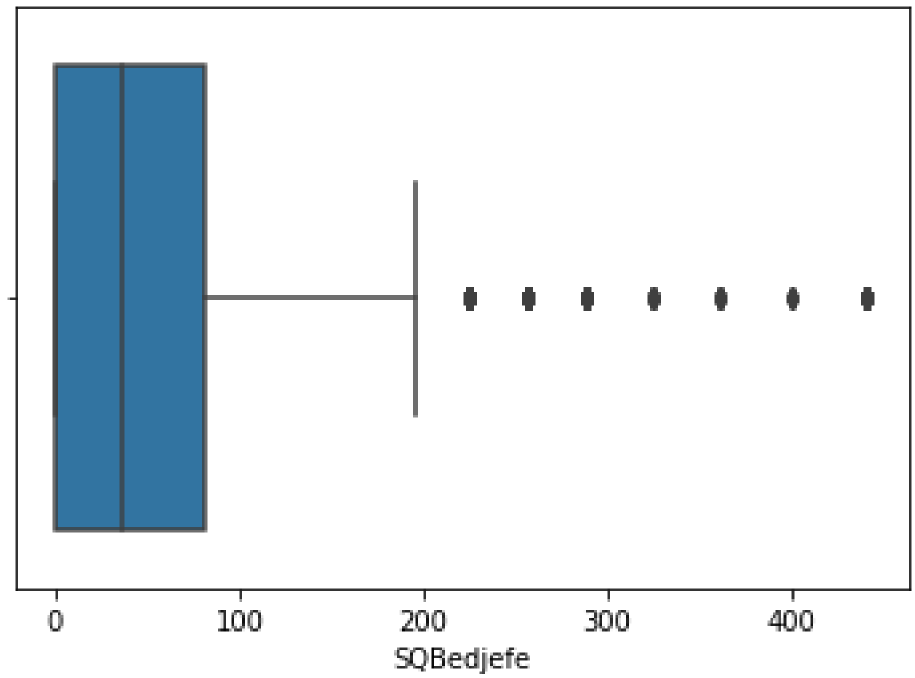

There is no outlier.

Column: SQBedjefe EDA

```
getHist('SQBedjefe')
```



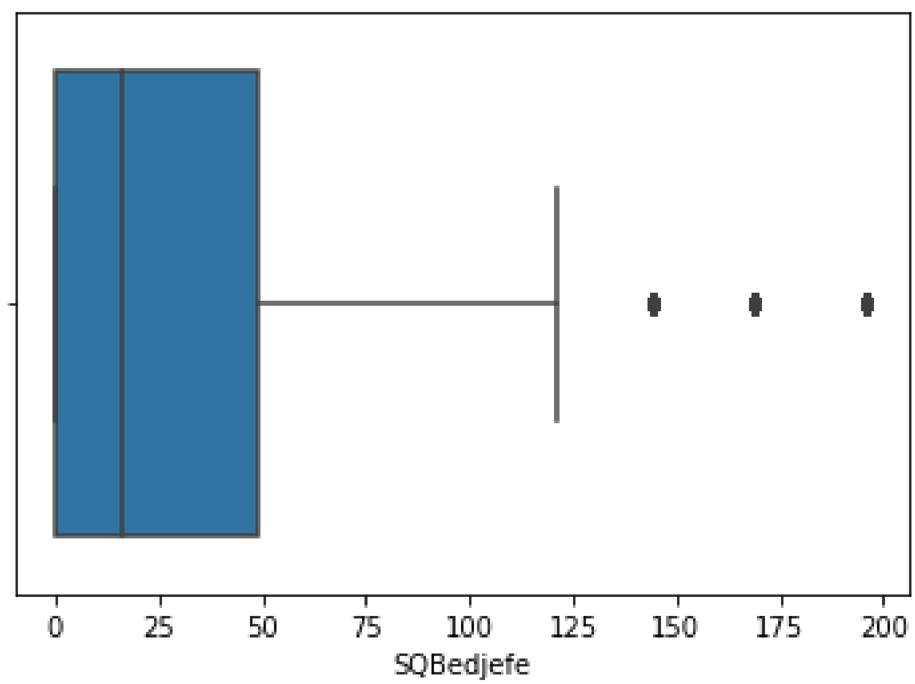

```
getBox('SQBedjefe')
```




There are few outliers. We can set limit as 200.

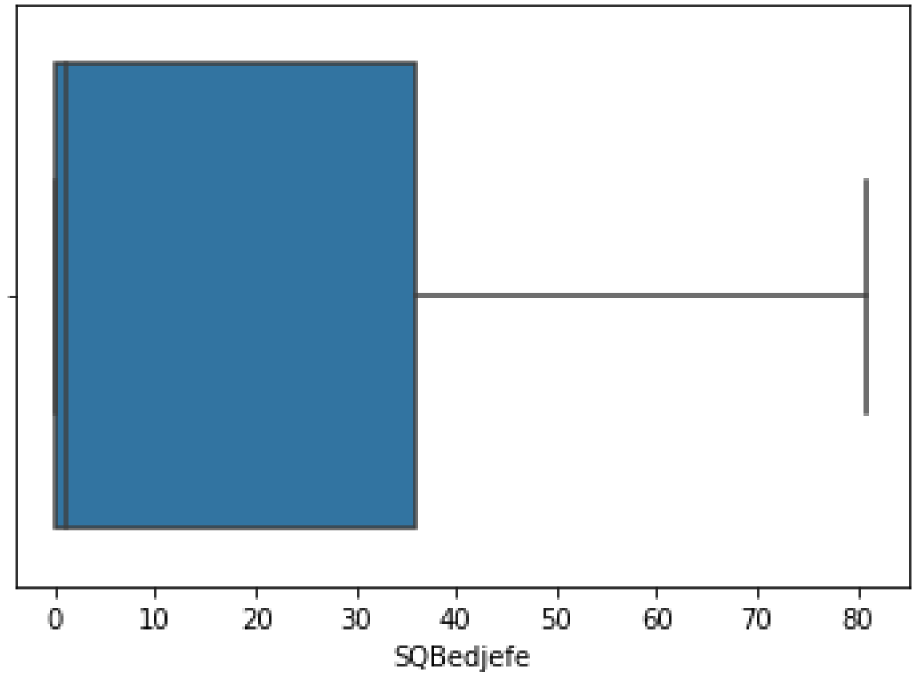
```
IQ_train_df = IQ_train_df[IQ_train_df['SQBedjefe'] <= 200]
```

```
getBox('SQBedjefe')
```



```
IQ_train_df = IQ_train_df[IQ_train_df['SQBedjefe'] <= 90]
```

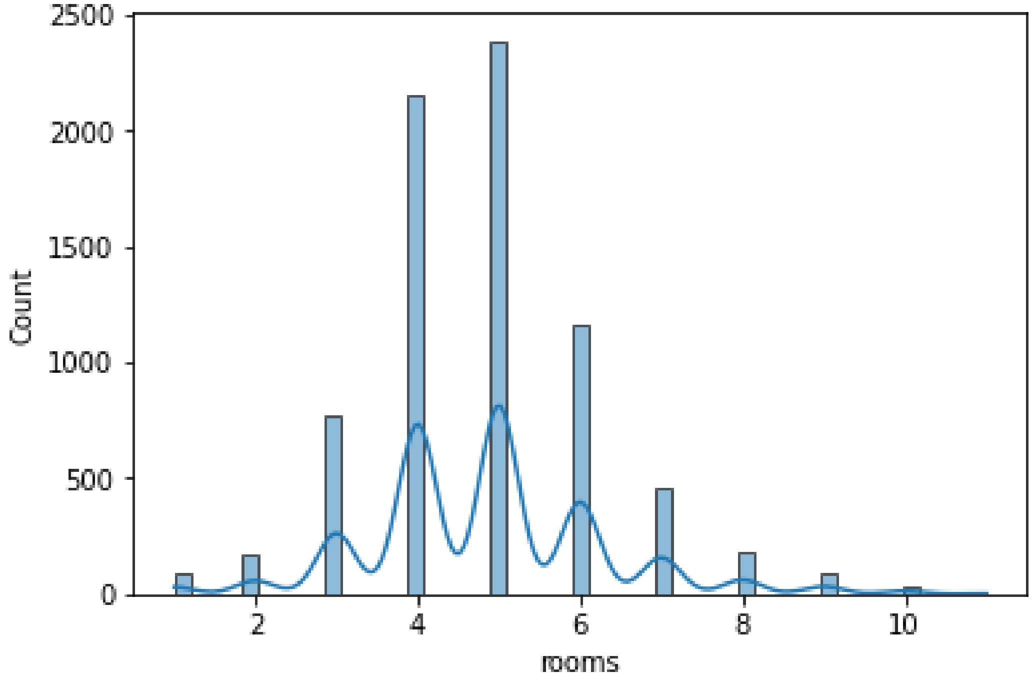
```
getBox('SQBedjefe')
```



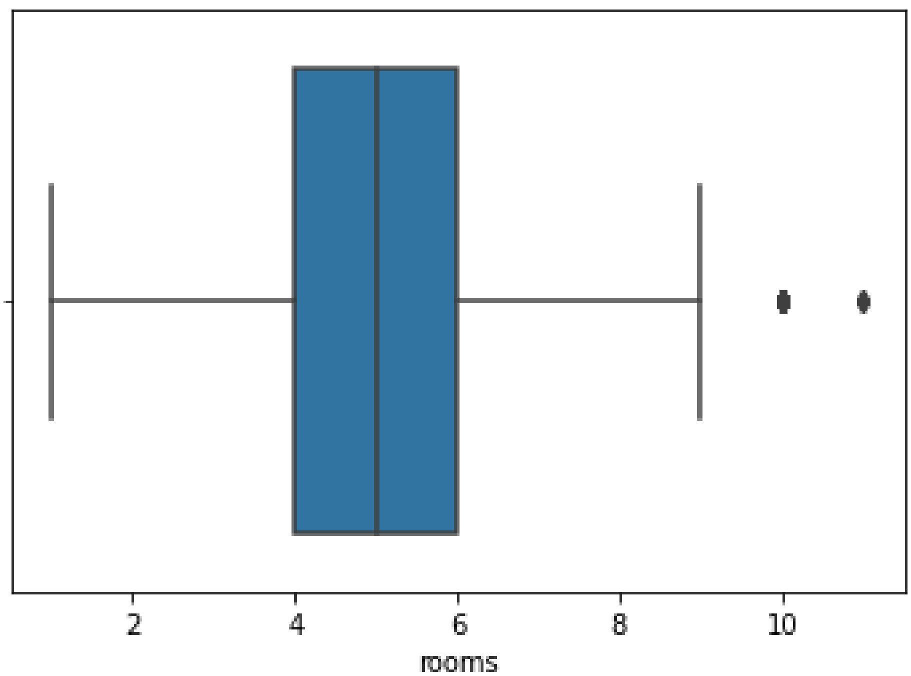

Outliers got removed by setting 90 as limit.

Column: rooms EDA

```
getHist('rooms')
```



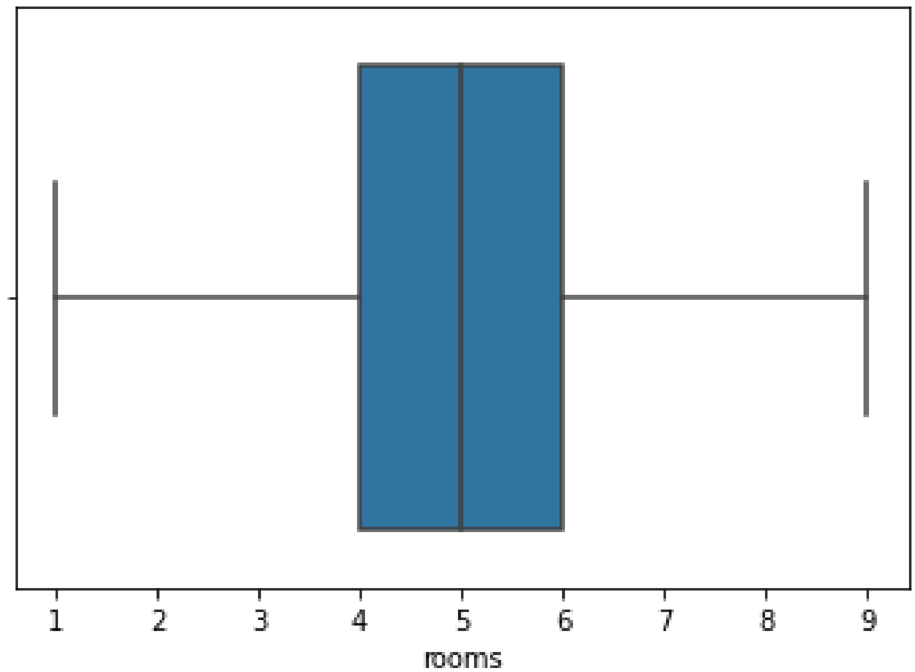

```
getBox('rooms')
```




There are two outliers. So we can set 9 as limit.

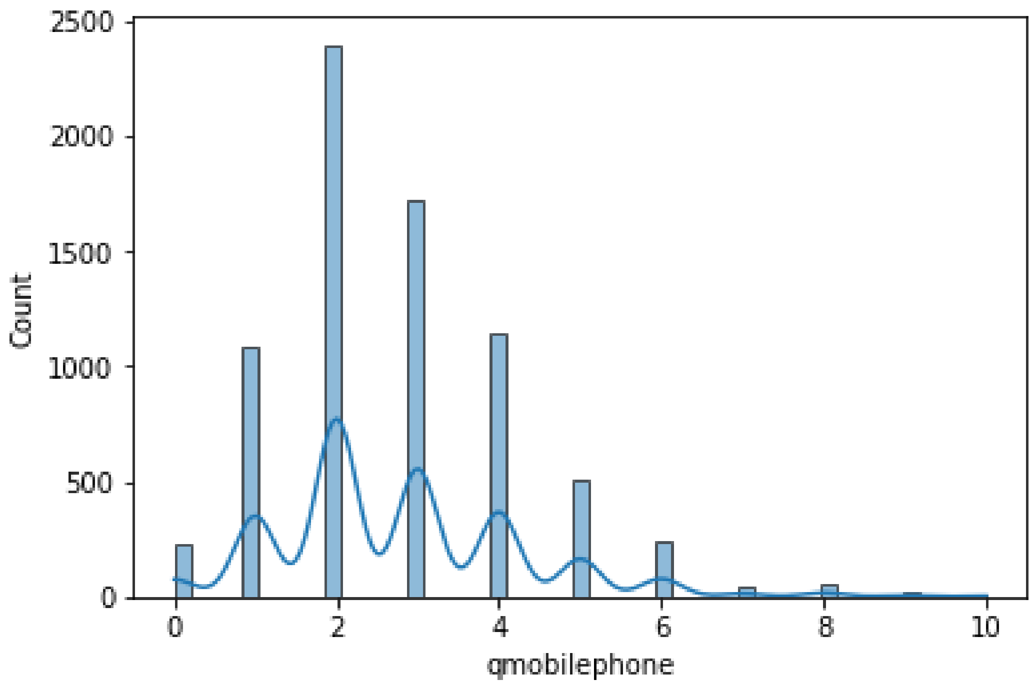
```
IQ_train_df = IQ_train_df[IQ_train_df['rooms'] <= 9]
```

```
getBox('rooms')
```

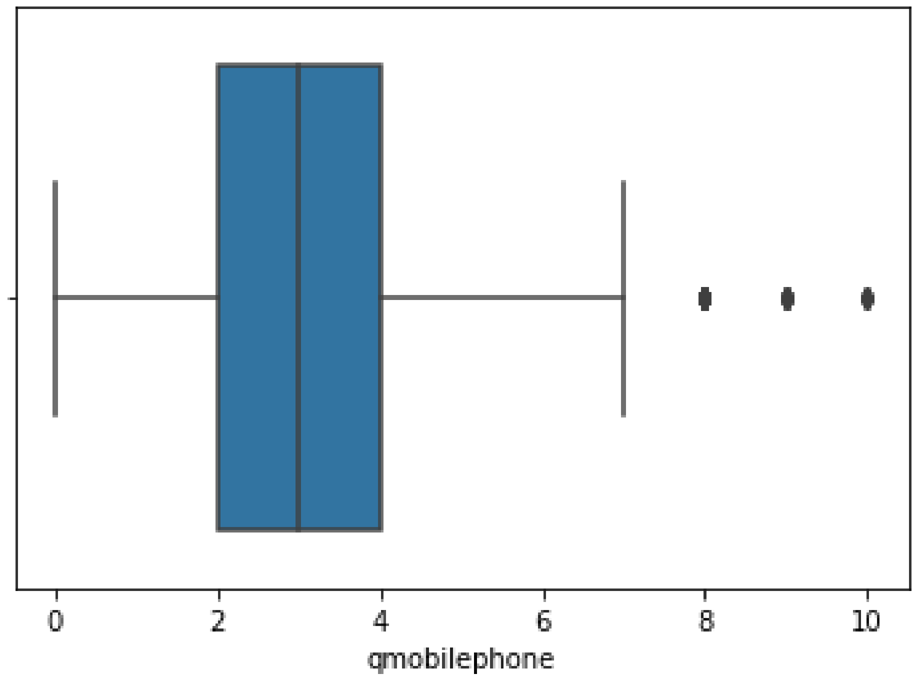



Column: qmobilephone EDA

```
getHist('qmobilephone')
```



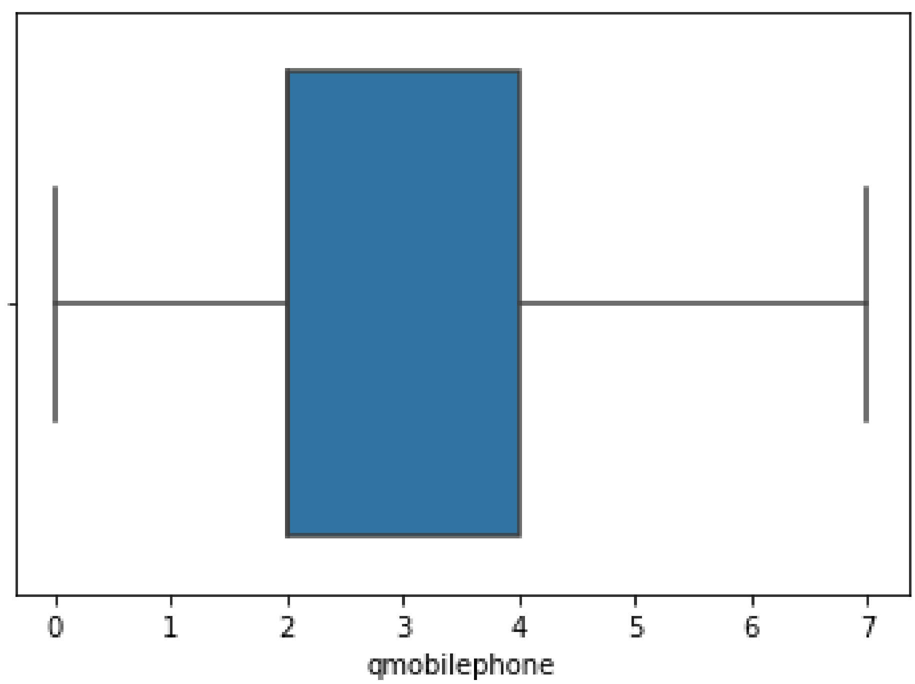

```
getBox('qmobilephone')
```




We can set 7 as limit here to remove the outliers.

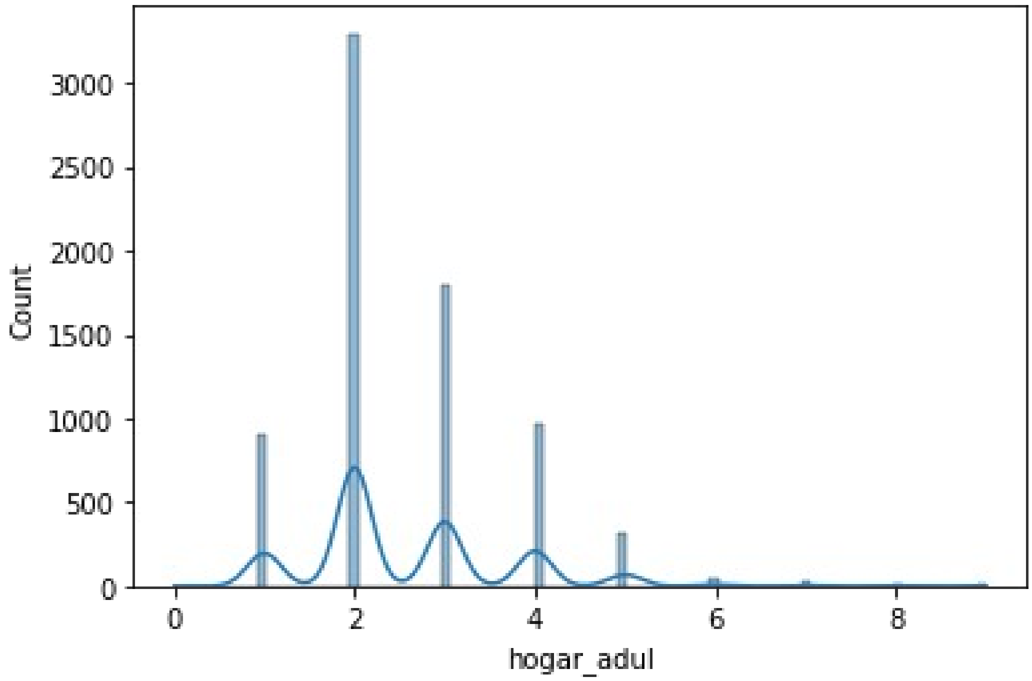
```
IQ_train_df = IQ_train_df[IQ_train_df['qmobilephone'] <= 7]
```

```
getBox('qmobilephone')
```

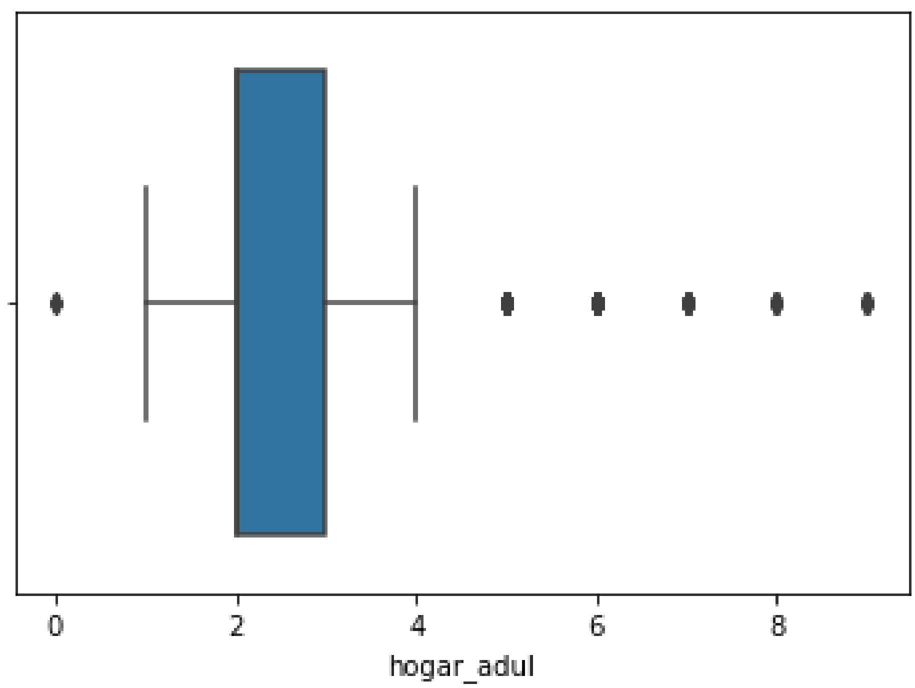



Column: hogar_adul EDA

```
getHist('hogar_adul')
```



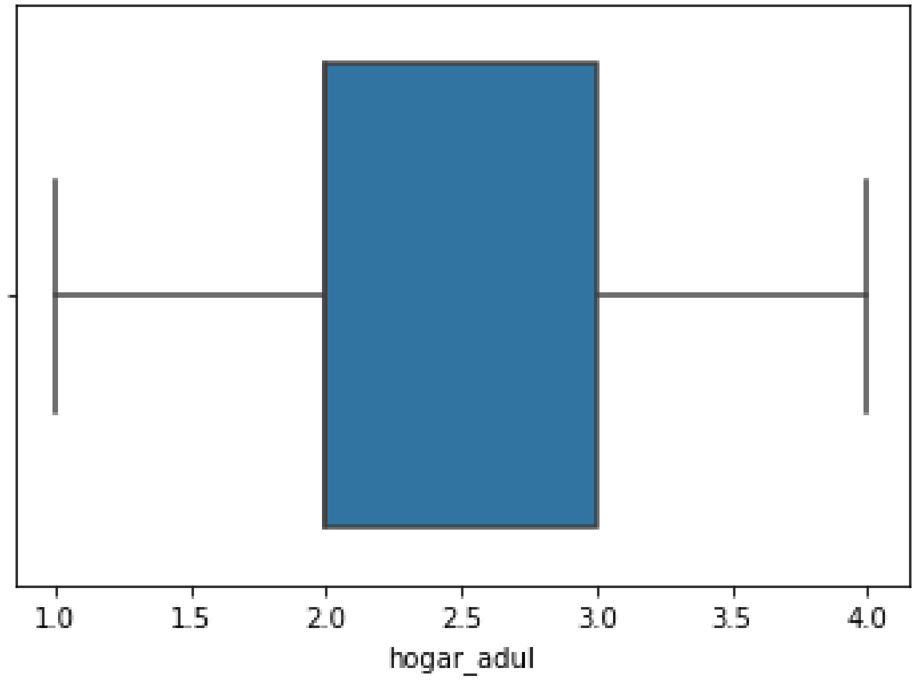

```
getBox('hogar_adul')
```



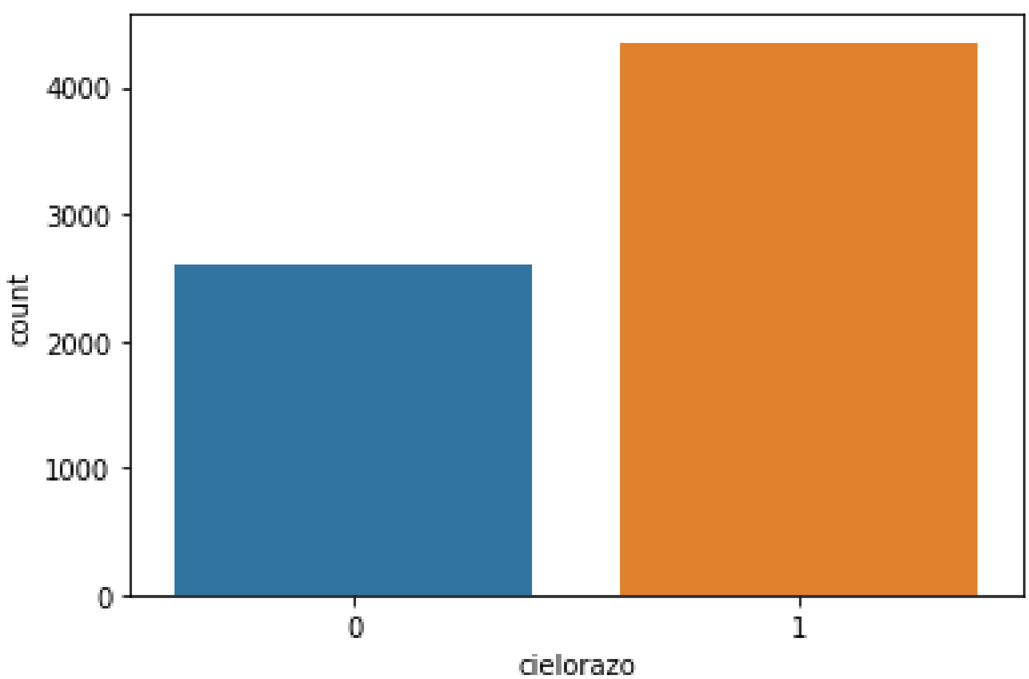

Here we need to set lower and upper limit as 1 and 4 respectively to get rid of outliers.

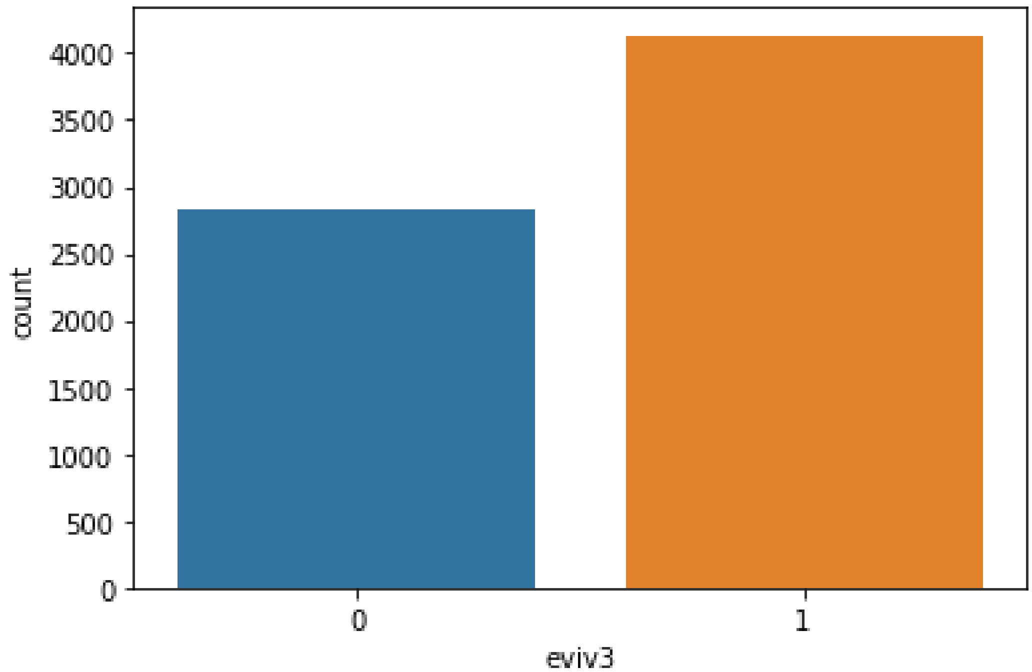
```
IQ_train_df = IQ_train_df[(IQ_train_df['hogar_adul'] >= 1) &
(IQ_train_df['hogar_adul'] <= 4)]
```

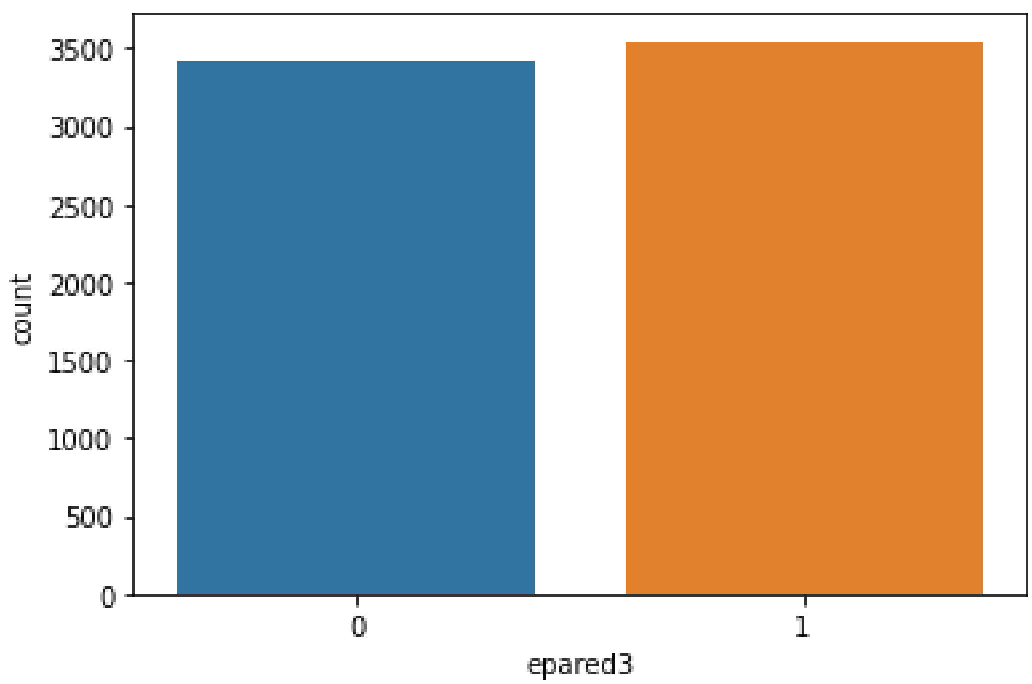
```
getBox('hogar_adul')
```

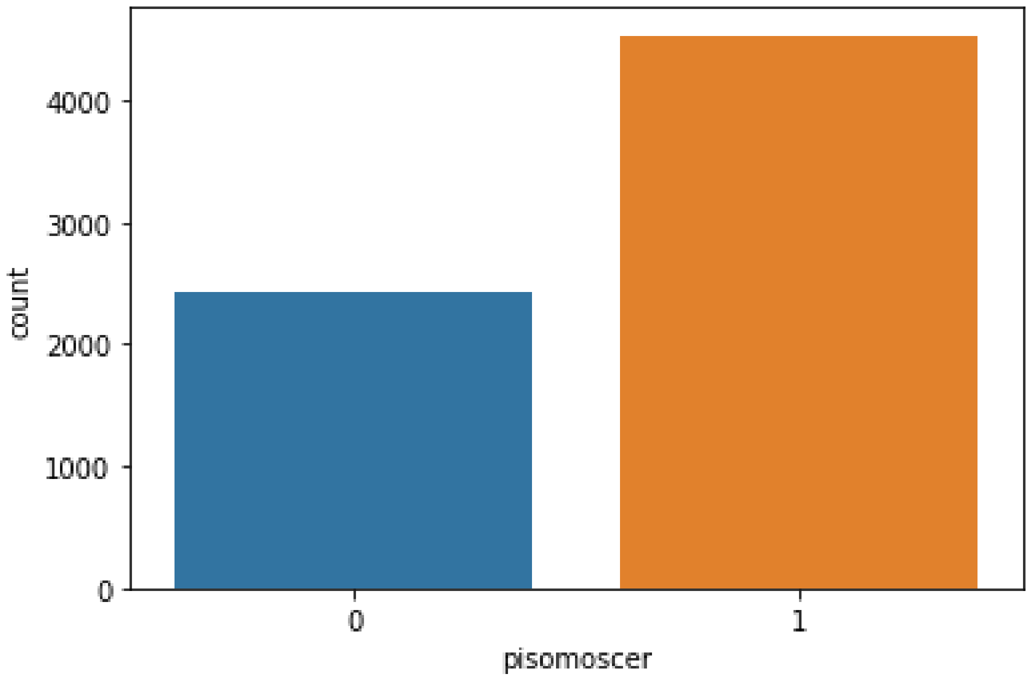



```
for index, val in zip(col_nuq.index, col_nuq):
    if val == 2:
        sns.countplot(IQ_train_df[index])
        plt.show()
```

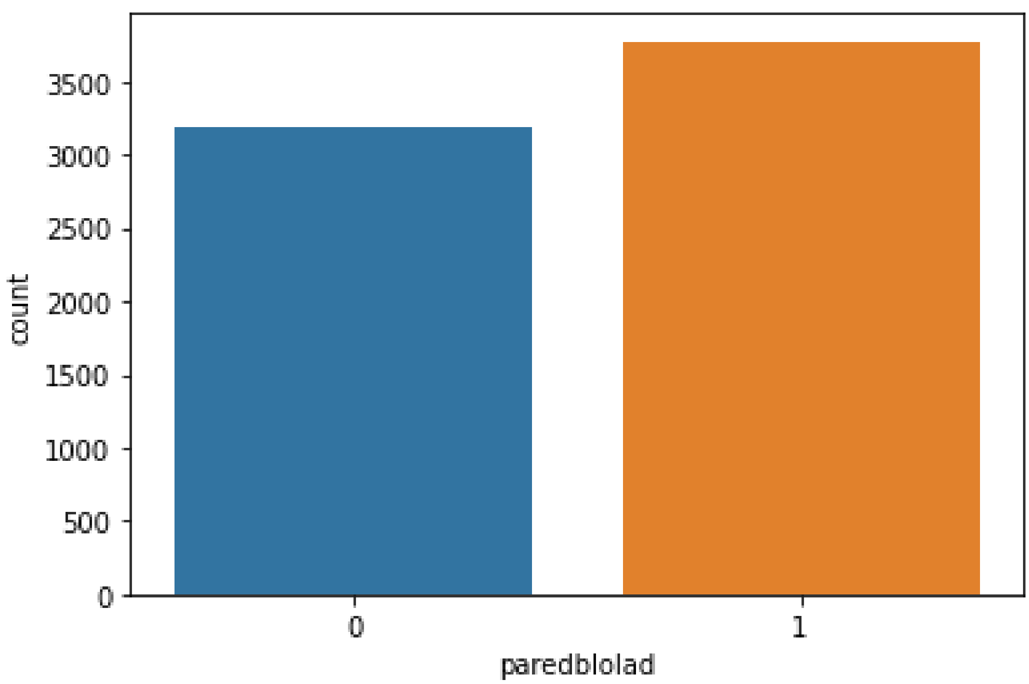



count
4000
3500
3000
2500
2000
1500
1000
500
0
0
1
eviv3

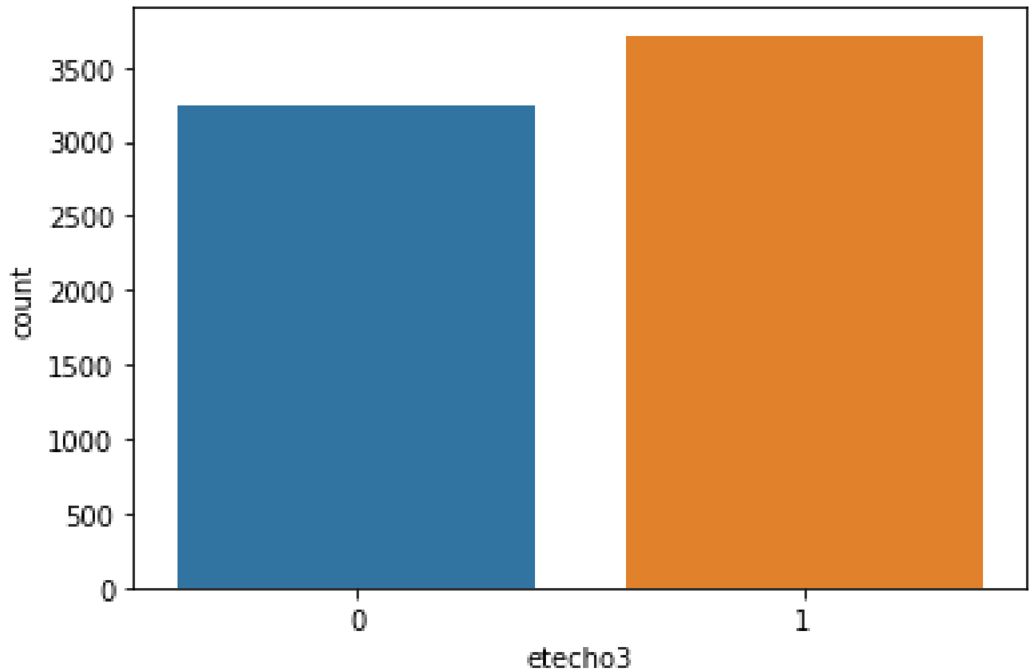

count
3500
3000
2500
2000
1500
1000
500
0
0
1
epared3

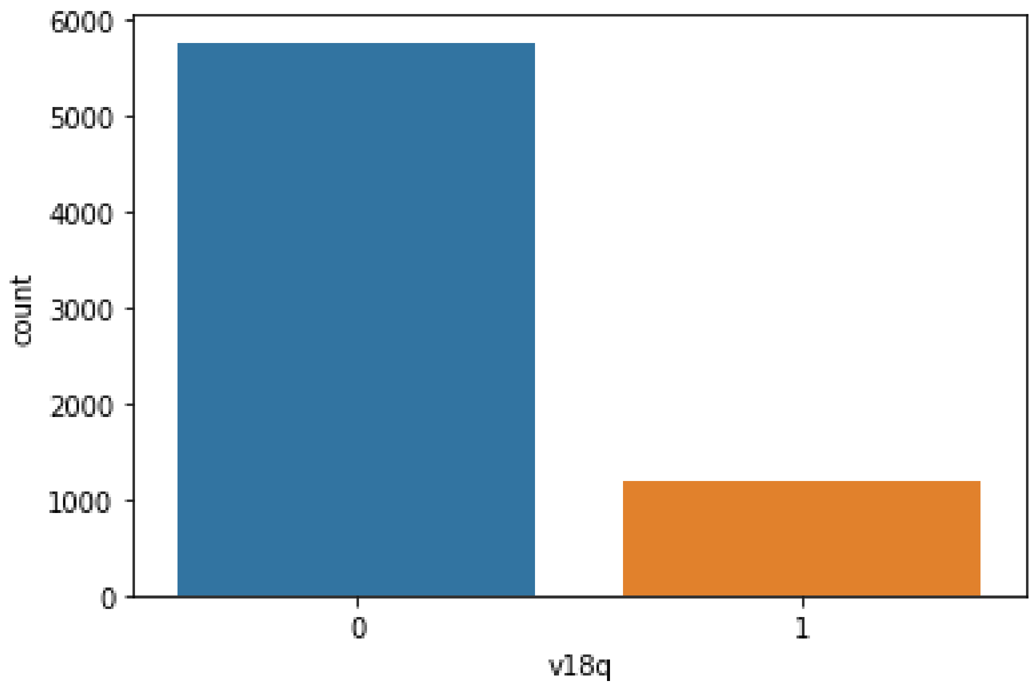


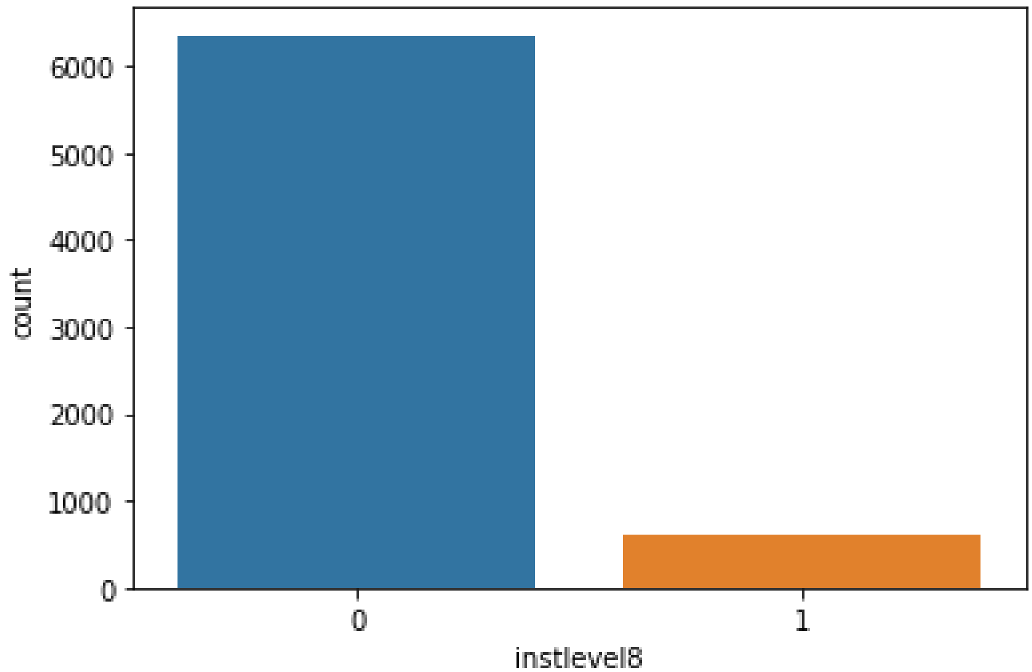
4000
3000
2000
1000
0
count
0
1
pisomoscer

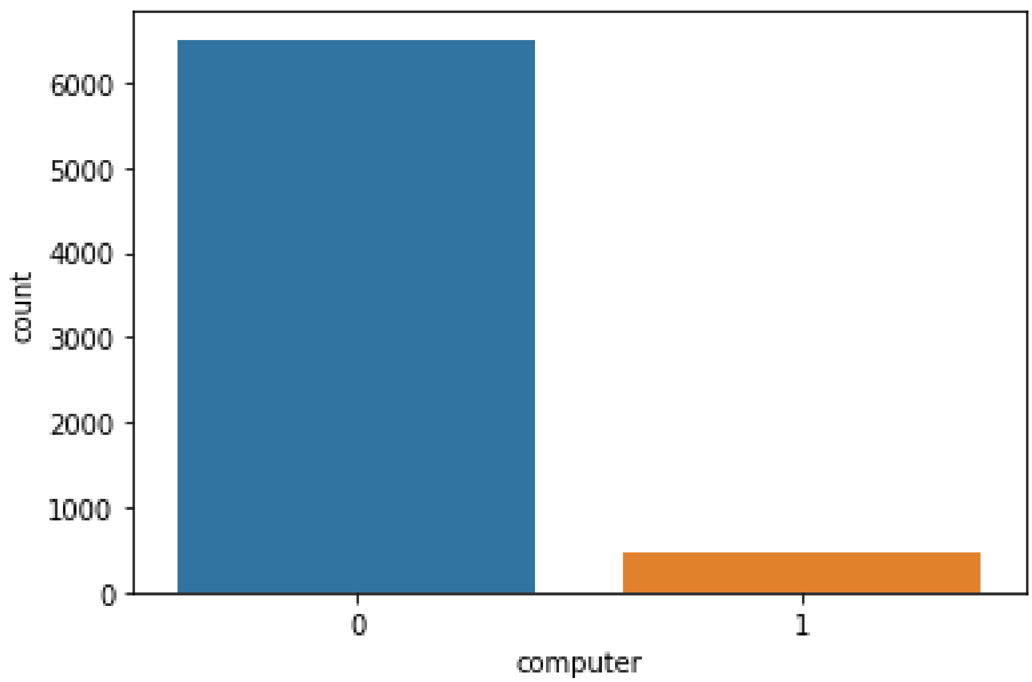
3500
3000
2500
2000
1500
1000
500
0
count
0
1
paredblolad


3500
3000
2500
2000
1500
1000
500
0
count
0
1
etecho3

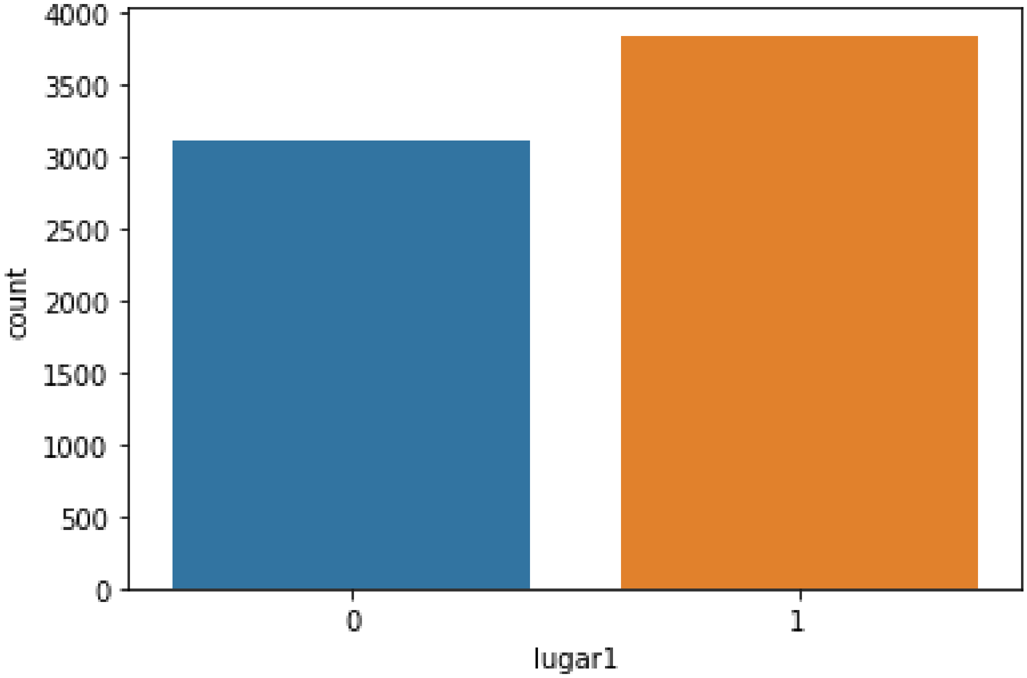

6000
5000
4000
3000
2000
1000
0
count
0
1
v18q



6000
5000
4000
3000
2000
1000
0
count
0
1
instlevel8

6000
5000
4000
3000
2000
1000
0
count
0
1
computer




We have reasonable values in the above columns, where for few columns, there are imbalance in its type. But its fine, we can keep it.

```
print('Final train data shape', IQ_train_df.shape)
```

```
Final train data shape (6963, 138)
```

Still we have enough records to train models.

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

```
per_house_uq_level = IQ_train_df.groupby('idhogar')
['Target'].nunique()
```

```
per_house_uq_level[per_house_uq_level == 1].size /
per_house_uq_level.size
```

```
0.9644602398933807
```

Only 96.44% household have all its members with same poverty level.

```
per_house_uq_level[per_house_uq_level > 1].size
```

```
80
```

There are 80 household like below which have different poverty level for each member.

```
per_house_uq_level[per_house_uq_level > 1][:1]
```

```
idhogar
0172ab1d9    2
Name: Target, dtype: int64
```

```
IQ_train_df[IQ_train_df['idhogar'] == '0172ab1d9']
```

```
      hacdor  rooms  hacapo  v14a  refrig  v18q  r4h1  r4h2  r4h3
r4m1  ...  \
7651       0      5       0     1       1     0     0     2     2
0  ...
7652       0      5       0     1       1     0     0     2     2
0  ...
7653       0      5       0     1       1     0     0     2     2
0  ...
7654       0      5       0     1       1     0     0     2     2
0  ...
7655       0      5       0     1       1     0     0     2     2
0  ...

      SQBescolari  SQBage  SQBhogar_total  SQBedjefe  SQBhogar_nin  \
7651           49     196              25         36             4
7652          100     289              25         36             4
7653           36    2601              25         36             4
7654           36    2304              25         36             4
7655          121     441              25         36             4

      SQBovercrowding  SQBdependency  SQBmeaned  agesq  Target
7651         2.777778       0.444444  58.777775    196       3
7652         2.777778       0.444444  58.777775    289       2
7653         2.777778       0.444444  58.777775   2601       3
7654         2.777778       0.444444  58.777775   2304       3
7655         2.777778       0.444444  58.777775    441       2

[5 rows x 138 columns]
```

For the household '0172ab1d9', members dont have same poverty level.

### Task 5: Check if there is a house without a family head.

```
houesehold_head = IQ_train_df.groupby('idhogar')['parentesco1'].sum()
houesehold_head[houesehold_head == 0].index
```

```
Index(['03c6bdf85', '09b195e7a', '1bc617b23', '374ca5a19',
'61c10e099',
       '6b1b2405f', '896fe6d3e', 'a0812ef17', 'ad687ad89',
'b1f4d89d7',
       'bfd5067c2', 'd363d9183', 'f2bfa75c4'],
      dtype='object', name='idhogar')
```

Above are the houses with no family head.

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

```
houseId_mismatch_level = per_house_uq_level[per_house_uq_level >
1].index.tolist()
len(houseId_mismatch_level)
```

```
80
```

There are 80 houses with different poverty level of each member. We need to update the level of each member same as the head i a house.

```
houseId_mismatch_level[0]
```

```
'0172ab1d9'
```

```
IQ_train_df[IQ_train_df['idhogar'] == '0172ab1d9']
```

```
      hacdor  rooms  hacapo  v14a  refrig  v18q  r4h1  r4h2  r4h3
r4m1  ...  \
7651       0      5       0     1       1     0     0     2     2
0  ...
7652       0      5       0     1       1     0     0     2     2
0  ...
7653       0      5       0     1       1     0     0     2     2
0  ...
7654       0      5       0     1       1     0     0     2     2
0  ...
7655       0      5       0     1       1     0     0     2     2
0  ...

      SQBescolari  SQBage  SQBhogar_total  SQBedjefe  SQBhogar_nin  \
7651           49     196              25         36             4
7652          100     289              25         36             4
7653           36    2601              25         36             4
7654           36    2304              25         36             4
7655          121     441              25         36             4

      SQBovercrowding  SQBdependency  SQBmeaned  agesq  Target
7651         2.777778       0.444444  58.777775    196       3
7652         2.777778       0.444444  58.777775    289       2
7653         2.777778       0.444444  58.777775   2601       3
7654         2.777778       0.444444  58.777775   2304       3
7655         2.777778       0.444444  58.777775    441       2

[5 rows x 138 columns]
```

```
for houseId in houseId_mismatch_level:
    head_level = IQ_train_df[(IQ_train_df['idhogar'] == '0172ab1d9') &
(IQ_train_df['parentesco1'] == 1)]['Target'].values[0]
    IQ_train_df.loc[IQ_train_df['idhogar'] == houseId, 'Target'] =
head_level
```

```
per_house_uq_level = IQ_train_df.groupby('idhogar')
['Target'].nunique()
per_house_uq_level[per_house_uq_level > 1].size
```

```
0
```

Now all the household have same poverty level.

### Task 9: Predict the accuracy using random forest classifier.

```
x = IQ_train_df.drop(['Target'], axis=1)
y = IQ_train_df['Target']

print(x.shape)
print(y.shape)
```

```
(6963, 137)
(6963,)
```

Now we dont need the houseId (idhogar), Lets delete that column too.

```
x.drop(['idhogar'], axis=1, inplace=True)

print(x.shape)
```

```
(6963, 136)
```

Before proceeding with the modeling, lets get rid of columns with high multi-colinearity.

```
colsToDelete = getColumnsToDelete(x.corr())
len(colsToDelete)
```

```
20
```

We can remove 20 columns.

```
x = x[x.columns[~x.columns.isin(colsToDelete)]]

print(x.shape)
```

```
(6963, 116)
```

```
# Do train test split

x_train, x_test, y_train, y_test = train_test_split(x, y)

print(x_train.shape)
print(x_test.shape)
print(y_train.shape)
print(y_test.shape)
```

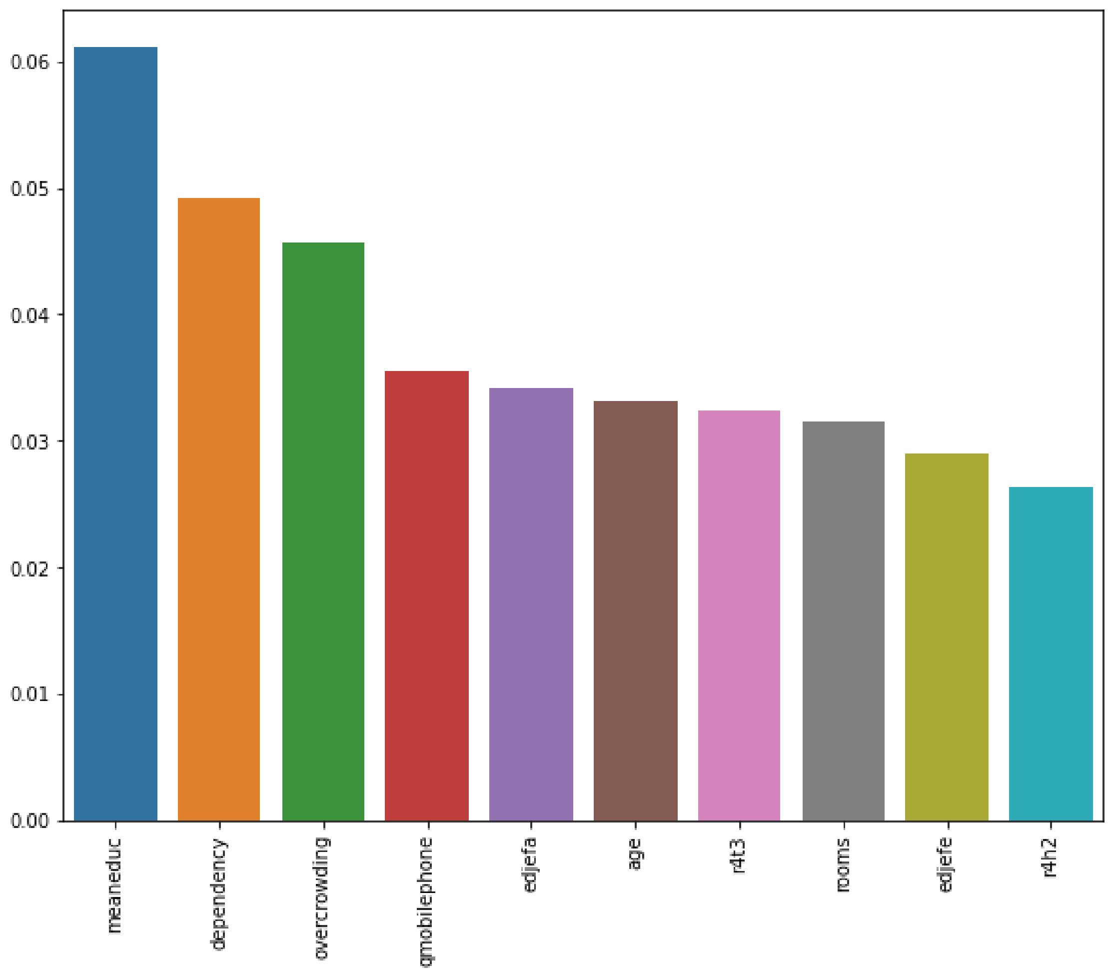
```
(5222, 116)
(1741, 116)
(5222,)
(1741,)
```

```
# Create a RandomForestClassifier oject
```

```
rfc = RandomForestClassifier(class_weight='balanced') # As we have
imbalanced dataset, we use class_weight

# Get accuracy
rfc.fit(x_train, y_train)
y_pred = rfc.predict(x_test)

print('Accuracy score for RandomForestClassifier: ',
accuracy_score(y_test, y_pred))
```

```
Accuracy score for RandomForestClassifier:  0.9310740953475014
```

```
cols_idx = rfc.feature_importances_.argsort()[::-1][:10]

important_features = x.columns[cols_idx]
importance_values = rfc.feature_importances_[cols_idx]

plt.figure(figsize=(10, 8))
sns.barplot(important_features, importance_values)
plt.xticks(rotation = 90)
plt.show()
```



### Task 10: Check the accuracy using random forest with cross validation.

Lets try out cross validation with GridSearchCV to find best parameter for RandomForestClassifier

```
params = {'n_estimators': [100, 150, 200], 'max_depth': [5, 10, 15],
'min_samples_split': [2, 4, 6]}

rfc_gscv = RandomForestClassifier(class_weight='balanced')
gscv = GridSearchCV(rfc_gscv, params, cv = 5, scoring='accuracy')

gscv.fit(x_train, y_train)
```

```
GridSearchCV(cv=5,
estimator=RandomForestClassifier(class_weight='balanced'),
             param_grid={'max_depth': [5, 10, 15],
                         'min_samples_split': [2, 4, 6],
                         'n_estimators': [100, 150, 200]},
             scoring='accuracy')
```

```
best_rfc = gscv.best_estimator_

best_rfc
```

```
RandomForestClassifier(class_weight='balanced', max_depth=15,
n_estimators=200)
```

```
gscv.best_params_
```

```
{'max_depth': 15, 'min_samples_split': 2, 'n_estimators': 200}
```

```
print('Accuracy with best classifier', gscv.best_score_)
```

```
Accuracy with best classifier 0.8923809785697262
```

Lets train the model and test it.

```
best_rfc.fit(x_train, y_train)
y_pred = best_rfc.predict(x_test)

print('Accuracy score for RandomForestClassifier: ',
accuracy_score(y_test, y_pred))
```

```
Accuracy score for RandomForestClassifier:  0.9247558874210224
```

Accuracy is almost the same.

Lets use the test dataset to predict.

```
IQ_test_df = pd.read_csv('test.csv')

IQ_test_df.head()
```

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

   r4h1  ...  age  SQBescolari  SQBage  SQBhogar_total  SQBedjefe  \
0     1  ...    4            0      16               9          0
1     1  ...   41          256    1681               9          0
2     1  ...   41          289    1681               9          0
3     0  ...   59          256    3481               1        256
4     0  ...   18          121     324               1          0

   SQBhogar_nin  SQBovercrowding  SQBdependency  SQBmeaned  agesq
0             1             2.25           0.25     272.25     16
1             1             2.25           0.25     272.25   1681
2             1             2.25           0.25     272.25   1681
3             0             1.00           0.00     256.00   3481
4             1             0.25          64.00        NaN    324

[5 rows x 142 columns]
```

```
# Drop columns
colsToDelete.update(['Id', 'idhogar', 'elimbasu5','v2a1', 'v18q1',
'rez_esc'])
IQ_test_df.drop(columns=colsToDelete, inplace=True, axis=1)

print(IQ_test_df.shape)
```

```
(23856, 116)
```

```
IQ_test_df['dependency'].replace(encode, inplace=True)
IQ_test_df['edjefe'].replace(encode, inplace=True)
IQ_test_df['edjefa'].replace(encode, inplace=True)

IQ_test_df['dependency'] = pd.to_numeric(IQ_test_df['dependency'])
IQ_test_df['edjefe'] = pd.to_numeric(IQ_test_df['edjefe'])
IQ_test_df['edjefa'] = pd.to_numeric(IQ_test_df['edjefa'])

IQ_test_df.dropna(inplace=True)
best_rfc.predict(IQ_test_df)
```

```
array([4, 4, 4, ..., 3, 3, 3])
```