Predict if a person has access to bank account or not.

Exemplary approach:

- Data cleaning & EDA
- missing value handling
- categorical reduction
- creating extra features (bining, scaling, etc)
- plotting evaluation scores

Machine learning: Supervised segmentation (classification)
Selected learners: [random forest, SVC, xgboost, lightGBM, deep learning]
Evaluation metric: mean absolute error

```
Start coding or generate with AI.
```

```
# libraries for data manipulation, visualization and data cleaning
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

```
Start coding or generate with AI.
```

data inspection

```
# load trainin and test data
train= pd.read_csv('data/Train.csv')
test= pd.read_csv('data/Test.csv')
```

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

```
Train set shape:  (23524, 13)
Test set shape:  (10086, 12)
```

```
# print first few rows
from pprint import pprint
def glimpse(data):
    print('[First rows]:\n')
    pprint(data.iloc[:, [1, 2, 3,4,  -1]].head())

    print('================================================================================')
    print('[Last rows]:\n')
    pprint(data.iloc[:, [1, 2, 3, -1]].tail(), indent=4)

    print('================================================================================')
    print('shape: ',data.shape)
```

```
glimpse(train)
```

```
[First rows]:

   year    uniqueid bank_account location_type                   job_type
0  2018  uniqueid_1          Yes         Rural              Self employed
1  2018  uniqueid_2           No         Rural       Government Dependent
2  2018  uniqueid_3          Yes         Urban              Self employed
3  2018  uniqueid_4           No         Rural  Formally employed Private
4  2018  uniqueid_5           No         Urban        Informally employed
==============================================================================
[Last rows]:

       year       uniqueid bank_account       job_type
23519  2018  uniqueid_2113           No   Other Income
23520  2018  uniqueid_2114           No   Other Income
23521  2018  uniqueid_2115           No   Other Income
23522  2018  uniqueid_2116           No  Self employed
23523  2018  uniqueid_2117           No      No Income
==============================================================================
shape:  (23524, 13)
```

```
glimpse(test)
```

```
[First rows]:

   year        uniqueid location_type cellphone_access  \
0  2018  uniqueid_6056         Urban              Yes
1  2018  uniqueid_6060         Urban              Yes
2  2018  uniqueid_6065         Rural               No
3  2018  uniqueid_6072         Rural               No
4  2018  uniqueid_6073         Urban               No

                       job_type
0  Formally employed Government
1     Formally employed Private
2          Remittance Dependent
3          Remittance Dependent
4          Remittance Dependent
==============================================================================
[Last rows]:

       year        uniqueid location_type       job_type
10081  2018  uniqueid_2998         Rural  Self employed
10082  2018  uniqueid_2999         Urban  Self employed
10083  2018  uniqueid_3000         Urban   Other Income
10084  2018  uniqueid_3001         Rural  Self employed
10085  2018  uniqueid_3002         Urban   Other Income
==============================================================================
shape:  (10086, 12)
```

```
# combine the training & testing set
all_data = pd.concat([train, test])
all_data0 = all_data.copy()
```

```
glimpse(all_data)
```

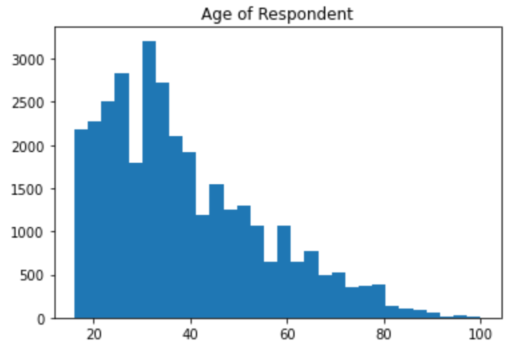
```
[First rows]:

   year    uniqueid bank_account location_type                    job_type
0  2018  uniqueid_1          Yes         Rural               Self employed
1  2018  uniqueid_2           No         Rural       Government Dependent
2  2018  uniqueid_3          Yes         Urban               Self employed
3  2018  uniqueid_4           No         Rural  Formally employed Private
4  2018  uniqueid_5           No         Urban        Informally employed
==============================================================================
[Last rows]:

       year        uniqueid bank_account       job_type
10081  2018  uniqueid_2998          NaN  Self employed
10082  2018  uniqueid_2999          NaN  Self employed
10083  2018  uniqueid_3000          NaN   Other Income
10084  2018  uniqueid_3001          NaN  Self employed
10085  2018  uniqueid_3002          NaN   Other Income
==============================================================================
shape:  (33610, 13)
```

```
all_data.info()
```

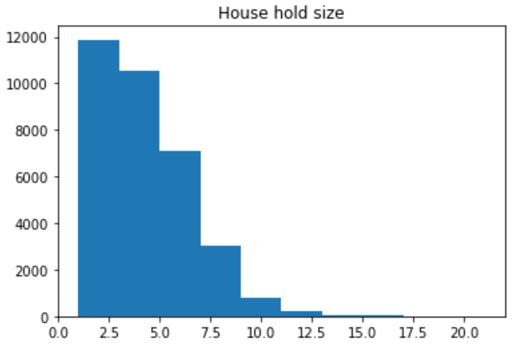
```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 33610 entries, 0 to 10085
Data columns (total 13 columns):
 #   Column                  Non-Null Count  Dtype
---  ------                  --------------  -----
 0   country                 33610 non-null  object
 1   year                    33610 non-null  int64
 2   uniqueid                33610 non-null  object
 3   bank_account            23524 non-null  object
 4   location_type           33610 non-null  object
 5   cellphone_access        33610 non-null  object
 6   household_size          33610 non-null  int64
 7   age_of_respondent       33610 non-null  int64
 8   gender_of_respondent    33610 non-null  object
 9   relationship_with_head  33610 non-null  object
 10  marital_status          33610 non-null  object
 11  education_level         33610 non-null  object
 12  job_type                33610 non-null  object
dtypes: int64(3), object(10)
memory usage: 3.6+ MB
```

Exploratory Data Analysis

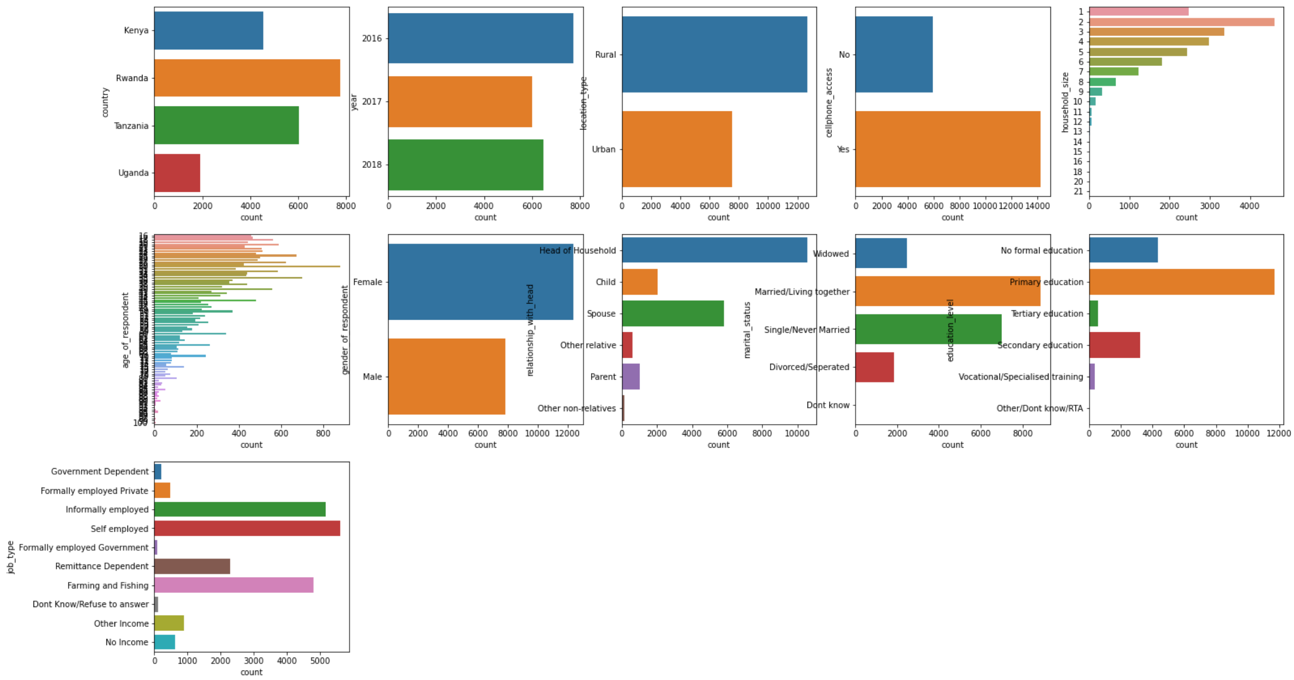
```
# age of respondent histogram plot
plt.title('Age of Respondent')
plt.hist(all_data['age_of_respondent'], bins=30);
```



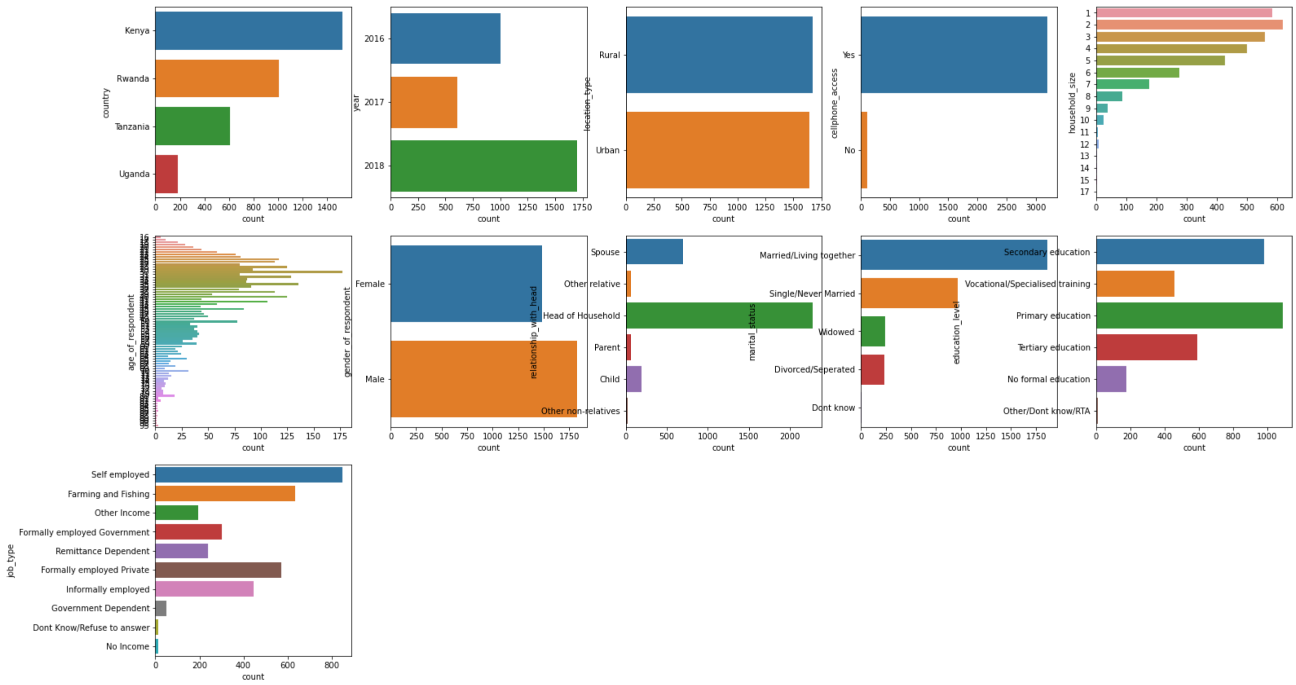

```
# household size histogram plot
plt.title('House hold size')
plt.hist(all_data['household_size'], bins=10);
```




```
# subseting the data to those who has bank account
# and those who do not have bank account.
negative = train[train['bank_account'] == 'No']; positive= train[train['bank_account'] == 'Yes']
ll= [     'country',
          'year',
          'location_type',
          'cellphone_access',
          'household_size',
          'age_of_respondent',
          'gender_of_respondent',
          'relationship_with_head',
          'marital_status',
          'education_level',
          'job_type']

plt.figure(figsize=(25, 25))
for index, col in enumerate(ll):
    plt.subplot(5, 5, index+1)
    sns.countplot(y= negative[col])
```




```
# categorical plot of target target that
# had bank account.
plt.figure(figsize=(25, 25))
for index, col in enumerate(ll):
    plt.subplot(5, 5, index+1)
    sns.countplot(y= positive[col])
```

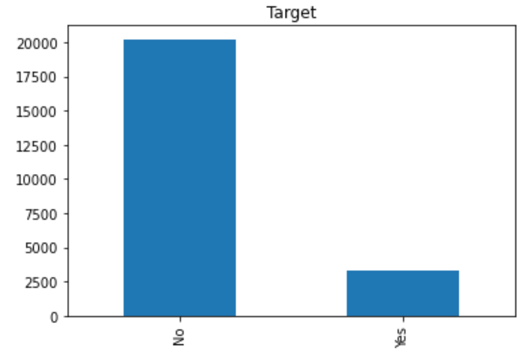



```
# number of uniques values in every column.
D = {}
for col in all_data.columns:
    D[col] = all_data[col].nunique()
print(pd.Series(D, name='Number of uniques'))
```

```
country                       4
year                          3
uniqueid                  12480
bank_account                  2
location_type                 2
cellphone_access              2
household_size               20
age_of_respondent            85
gender_of_respondent          2
relationship_with_head        6
marital_status                5
education_level               6
job_type                     10
Name: Number of uniques, dtype: int64
```

```
# target distribution for train set
train['bank_account'].value_counts().plot(kind='bar', title='Target')
print(train['bank_account'].value_counts(normalize=True))
```

```
No     0.859208
Yes    0.140792
Name: bank_account, dtype: float64
```



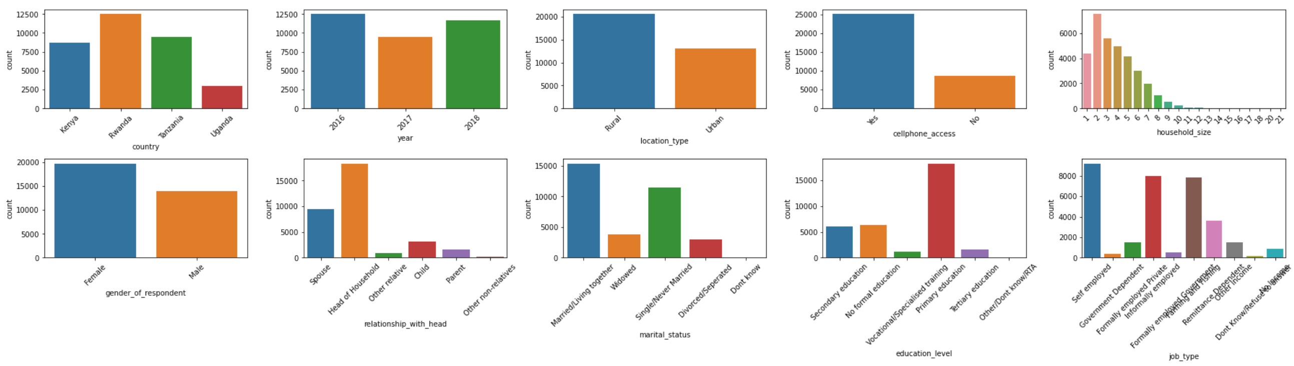

```
all_data.columns
```

```
Index(['country', 'year', 'uniqueid', 'bank_account', 'location_type',
       'cellphone_access', 'household_size', 'age_of_respondent',
       'gender_of_respondent', 'relationship_with_head', 'marital_status',
       'education_level', 'job_type'],
      dtype='object')
```

```
# categorical columns
col0= ['country', 'year',  'location_type',
       'cellphone_access', 'household_size',
       'gender_of_respondent', 'relationship_with_head', 'marital_status',
       'education_level', 'job_type']
len(col0)
```

```
10
```

```
# categorical plot of combine train and test data
plt.figure(figsize=(25, 7))
for index, col in enumerate(col0):
    plt.subplot(2, 5, index+1)
    plt.tight_layout()
    sns.countplot(x = all_data[col])
    plt.xticks(rotation=45)
```




```
Start coding or generate with AI.
```

```
# frequency distribution of some selected columns
```

```
all_data['relationship_with_head'].value_counts(normalize=True)
```

```
Head of Household      0.545016
Spouse                 0.278637
```

```
Child                  0.094942
Parent                 0.046147
Other relative         0.027551
Other non-relatives    0.007706
Name: relationship_with_head, dtype: float64
```

```
all_data['marital_status'].value_counts(normalize=True)
```

```
Married/Living together    0.458554
Single/Never Married       0.340077
Widowed                    0.113508
Divorced/Seperated         0.087593
Dont know                  0.000268
Name: marital_status, dtype: float64
```

```
all_data['job_type'].value_counts(normalize=True)
```

```
Self employed                   0.274026
Informally employed             0.237102
Farming and Fishing             0.232401
Remittance Dependent            0.108123
Other Income                    0.044719
Formally employed Private       0.044600
No Income                       0.026867
Formally employed Government    0.016453
Government Dependent            0.010324
Dont Know/Refuse to answer      0.005385
Name: job_type, dtype: float64
```

```
all_data['household_size'].describe([.15, .25, .5, .6, .75, .9, .95, 1])
```

```
count    33610.000000
mean         3.791877
std          2.223138
min          1.000000
15%          2.000000
25%          2.000000
50%          3.000000
60%          4.000000
75%          5.000000
90%          7.000000
95%          8.000000
100%        21.000000
max         21.000000
Name: household_size, dtype: float64
```

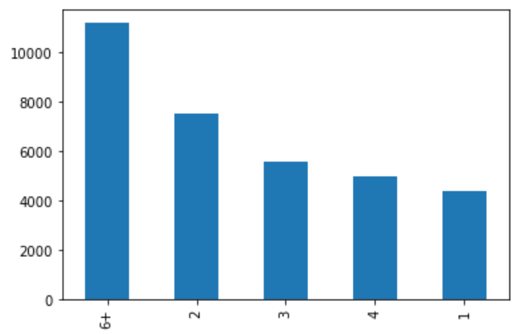
```
Start coding or generate with AI.
```

Bining

```
# create bins for household size
#[1-3, 4-6, 7-9, 10+]
all_data['household_size_bin']= np.where(all_data['household_size'].\
                                      between(5 ,np.inf, inclusive='both'), '6+', all_data['household_size'])
```

```
all_data['household_size_bin'].value_counts().plot(kind='bar')
```

<AxesSubplot:>




```
all_data['household_size_bin'].value_counts(normalize=True)
```

```
6+    0.333472
2     0.223178
3     0.165367
4     0.147754
```

```
1     0.130229
Name: household_size_bin, dtype: float64
```

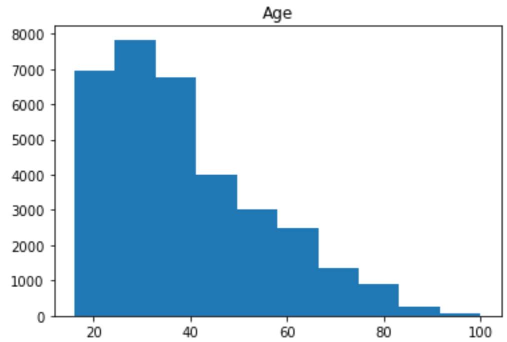
Start coding or generate with AI.

```
all_data['age_of_respondent'].describe([.15, .25, .5, .6, .75, .9, .95, 1])#histogram of "age of respondent"
```

```
count    33610.000000
mean        38.656114
std         16.447127
min         16.000000
15%         22.000000
25%         26.000000
50%         35.000000
60%         40.000000
75%         49.000000
90%         63.000000
95%         71.000000
100%       100.000000
max        100.000000
Name: age_of_respondent, dtype: float64
```

```
ax = all_data['age_of_respondent'].hist(grid=False)
ax.set_title('Age')
```

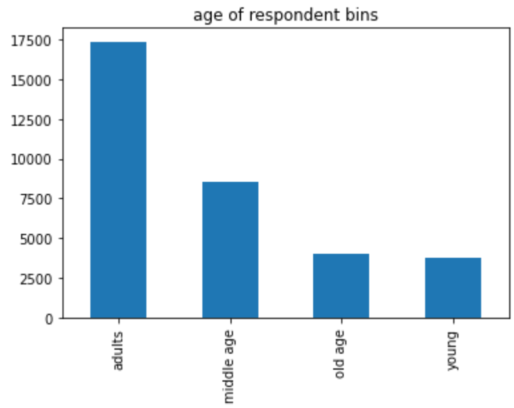
```
Text(0.5, 1.0, 'Age')
```




```
# creating age bins
all_data['age bins']= np.where(all_data['age_of_respondent'].between(15, 20), 'young', '')
all_data['age bins']= np.where(all_data['age_of_respondent'].between(21, 40), 'adults', all_data['age bins'])
all_data['age bins']= np.where(all_data['age_of_respondent'].between(41, 60), 'middle age', all_data['age bins'])
all_data['age bins']= np.where(all_data['age_of_respondent'].between(61, np.inf),
                                'old age', all_data['age bins'])
```

```
all_data['age bins'].value_counts().plot(kind='bar', title='age of respondent bins')
```

```
<AxesSubplot:title={'center':'age of respondent bins'}>
```

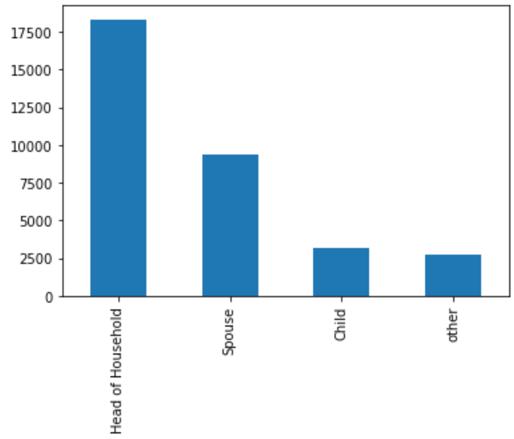


Start coding or generate with AI.

```
# relationship with head bins
all_data['relationship with head bin']=\
np.where(all_data['relationship_with_head'].isin(['Head of Household', 'Spouse', 'Child']),
                                              all_data['relationship_with_head'], 'other')
```

```
all_data['relationship with head bin'].value_counts().plot(kind='bar')
```

```
<AxesSubplot:>
```




```
Start coding or generate with AI.
```

```
all_data['marital_status'].unique()
```

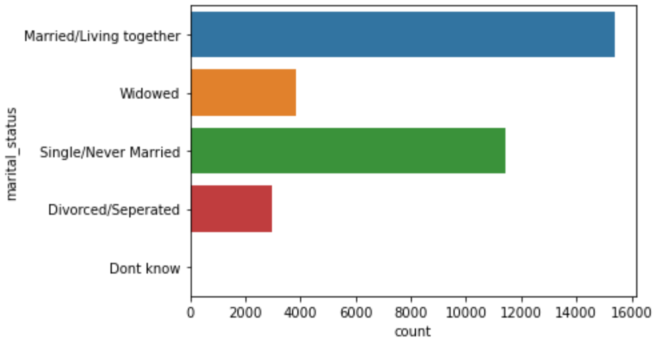
```
array(['Married/Living together', 'Widowed', 'Single/Never Married',
       'Divorced/Seperated', 'Dont know'], dtype=object)
```

```
all_data['marital_status'].value_counts()
```

```
Married/Living together    15412
Single/Never Married       11430
Widowed                     3815
Divorced/Seperated          2944
Dont know                      9
Name: marital_status, dtype: int64
```

```
sns.countplot(y = all_data['marital_status'])
```

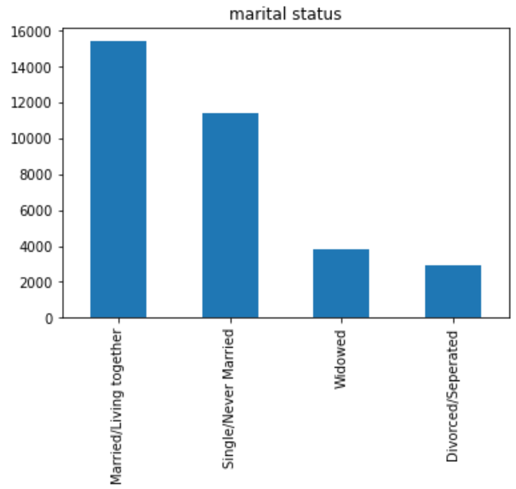
```
<AxesSubplot:xlabel='count', ylabel='marital_status'>
```




```
# reducing marital status categories
all_data['marital_status'].replace({'Dont know': 'Widowed'}, inplace=True)
```

```
all_data['marital_status'].value_counts().plot(kind='bar', title='marital status')
```

```
<AxesSubplot:title={'center':'marital status'}>
```



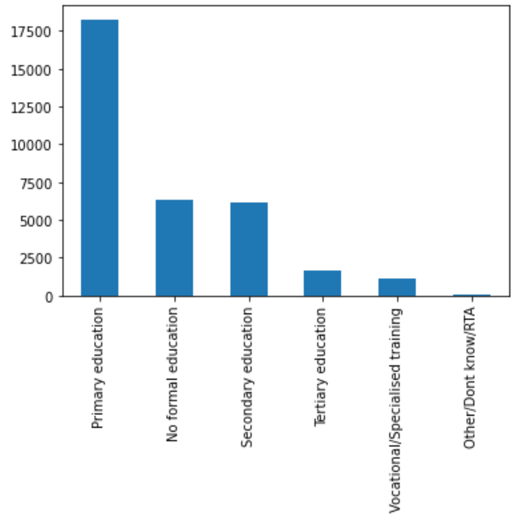

```
Start coding or generate with AI.
```

```
all_data['education_level'].value_counts(normalize=False) # count of "Education level"
```

```
Primary education                   18270
No formal education                  6351
Secondary education                  6125
Tertiary education                   1649
Vocational/Specialised training      1162
Other/Dont know/RTA                    53
Name: education_level, dtype: int64
```

```
all_data['education_level'].value_counts().plot(kind='bar') # plot of education level
```

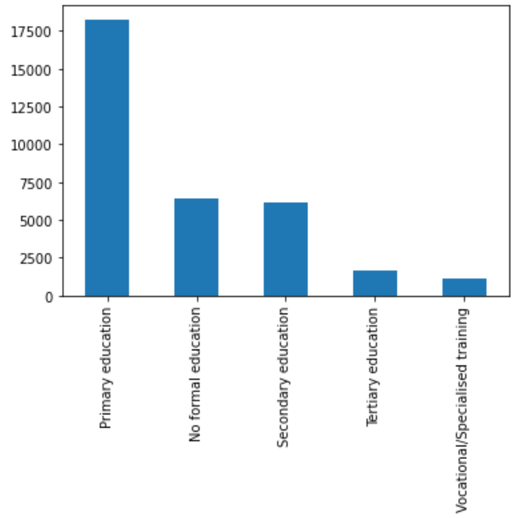
```
<AxesSubplot:>
```




```
all_data['education_level'].replace({'Other/Dont know/RTA': 'No formal education'}, inplace=True)
```

```
all_data['education_level'].value_counts().plot(kind='bar')
```

```
<AxesSubplot:>
```



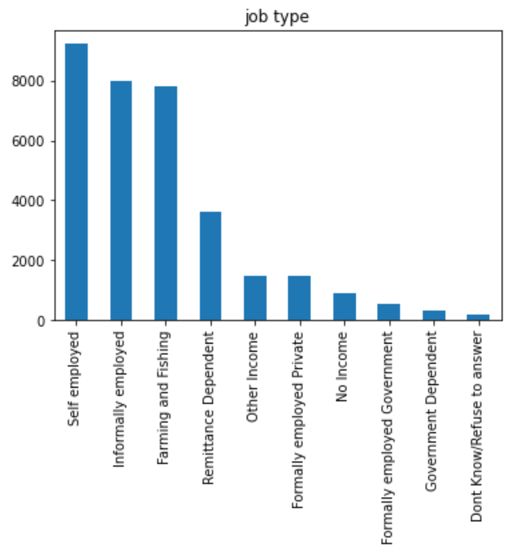

```
all_data['education_level'].value_counts(normalize=True)
```

```
Primary education                  0.543588
No formal education                0.190539
Secondary education                0.182237
Tertiary education                 0.049063
Vocational/Specialised training    0.034573
Name: education_level, dtype: float64
```

```
Start coding or generate with AI.
```

```
# reducing the categories of job type
all_data['job_type'].value_counts().plot(kind='bar', title='job type')
```

```
<AxesSubplot:title={'center':'job type'}>
```




```
all_data['job_type'].unique()
```

```
array(['Self employed', 'Government Dependent',
       'Formally employed Private', 'Informally employed',
       'Formally employed Government', 'Farming and Fishing',
       'Remittance Dependent', 'Other Income',
       'Dont Know/Refuse to answer', 'No Income'], dtype=object)
```

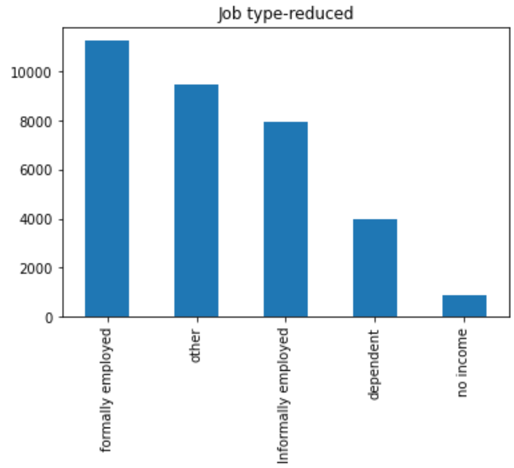
Unsupported Cell Type. Double-Click to inspect/edit the content.

```
all_data['job_type']= np.where(all_data['job_type'].isin(['Government Dependent', 'Remittance Dependent',
                                                        ]), 'dependent', all_data['job_type'])

all_data['job_type']= np.where(all_data['job_type'].\
                              isin(['Formally employed Private',
                                    'Formally employed Government',
                                    'Self employed']), 'formally employed',
                              all_data['job_type'])
```

```
all_data['job_type']= np.where(all_data['job_type'].isin(['Farming and Fishing','Other Income',
                                                          'Dont Know/Refuse to answer'
                                                        ]), 'other', all_data['job_type'])

all_data['job_type']= np.where(all_data['job_type'].isin(['No Income']), 'no income', all_data['job_type'])
```

```
all_data['job_type'].value_counts().plot(kind='bar', title='Job type-reduced')
```

```
<AxesSubplot:title={'center':'Job type-reduced'}>
```



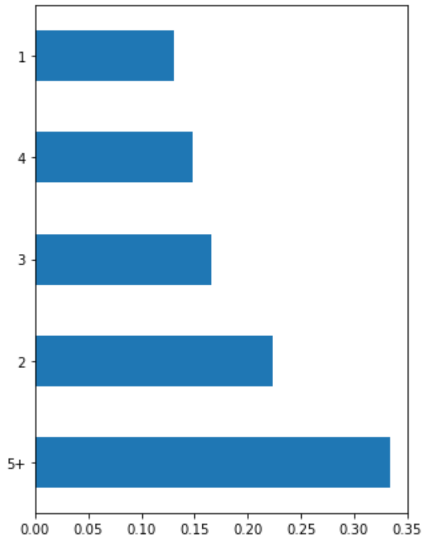

```
# reducing the age columns
all_data['age_of_respondent']=\
np.where(all_data['age_of_respondent'].between(50, np.inf), '50+', all_data['age_of_respondent'])
```

Start coding or generate with AI.

```
all_data['household_size']= \
np.where(all_data['household_size'].between(5, np.inf), '5+', all_data['household_size'])
```

```
all_data['household_size'].value_counts(normalize=True).plot(kind='barh', figsize=(5, 7))
```

```
<AxesSubplot:>
```




```
col1= ['country', 'year', 'location_type',
'cellphone_access', 'household_size', 'age_of_respondent',
'gender_of_respondent', 'relationship_with_head', 'marital_status',
'education_level', 'job_type', 'household_size_bin', 'age bins',
'relationship_with_head']

len(col1)
```

```
14
```

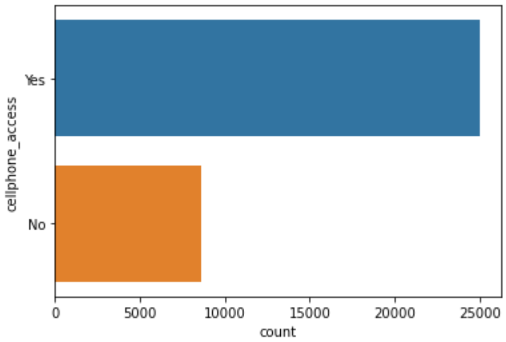
```
all_data[col1].info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 33610 entries, 0 to 10085
```

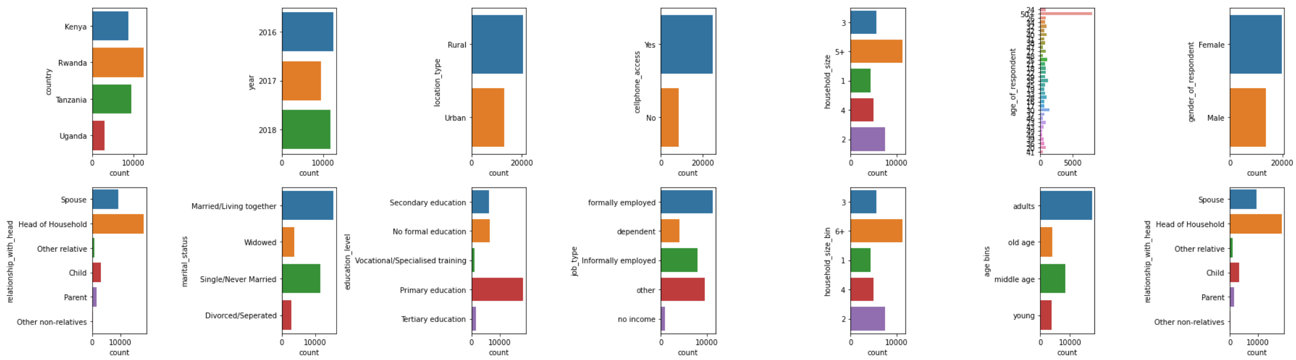
```
Data columns (total 14 columns):
 #   Column                  Non-Null Count  Dtype 
---  ------                  --------------  ----- 
 0   country                 33610 non-null  object
 1   year                    33610 non-null  int64 
 2   location_type           33610 non-null  object
 3   cellphone_access        33610 non-null  object
 4   household_size          33610 non-null  object
 5   age_of_respondent       33610 non-null  object
 6   gender_of_respondent    33610 non-null  object
 7   relationship_with_head  33610 non-null  object
 8   marital_status          33610 non-null  object
 9   education_level         33610 non-null  object
 10  job_type                33610 non-null  object
 11  household_size_bin      33610 non-null  object
 12  age bins                33610 non-null  object
 13  relationship_with_head  33610 non-null  object
dtypes: int64(1), object(13)
memory usage: 4.9+ MB
```

```
sns.countplot(y=all_data[col1[3]])
```

```
<AxesSubplot:xlabel='count', ylabel='cellphone_access'>
```




```
# visualizing current data
# after cleaning
plt.figure(figsize=(25, 7))
for index, col in enumerate(col1):
    plt.subplot(2, 7, index+1)
    plt.tight_layout()
    sns.countplot(y=all_data[col])
```




```
all_data.head()
```

	country	year	uniqueid	bank_account	location_type	cellphone_access	household_size	age_of_respondent	gender_c
0	Kenya	2018	uniqueid_1	Yes	Rural	Yes	3	24	
1	Kenya	2018	uniqueid_2	No	Rural	No	5+	50+	
2	Kenya	2018	uniqueid_3	Yes	Urban	Yes	5+	26	
3	Kenya	2018	uniqueid_4	No	Rural	Yes	5+	34	
4	Kenya	2018	uniqueid_5	No	Urban	No	5+	26	

```
all_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 33610 entries, 0 to 10085
Data columns (total 16 columns):
 #   Column                     Non-Null Count  Dtype
---  ------                     --------------  -----
 0   country                    33610 non-null  object
 1   year                       33610 non-null  int64
 2   uniqueid                   33610 non-null  object
 3   bank_account               23524 non-null  object
 4   location_type              33610 non-null  object
 5   cellphone_access           33610 non-null  object
 6   household_size             33610 non-null  object
 7   age_of_respondent          33610 non-null  object
 8   gender_of_respondent       33610 non-null  object
 9   relationship_with_head     33610 non-null  object
 10  marital_status             33610 non-null  object
 11  education_level            33610 non-null  object
 12  job_type                   33610 non-null  object
 13  household_size_bin         33610 non-null  object
 14  age bins                   33610 non-null  object
 15  relationship with head bin  33610 non-null  object
dtypes: int64(1), object(15)
memory usage: 5.4+ MB
```

```
all_data.shape
```

```
(33610, 16)
```

```
# drop columns that are not needed
all_data.drop(['uniqueid', ], axis=1, inplace=True)
```

```
# encode the target column
all_data['bank_account'].replace({'Yes':1, 'No': 0}, inplace=True)
```

```
all_data.isna().sum()
```

```
country                           0
year                              0
bank_account                  10086
location_type                     0
cellphone_access                  0
household_size                    0
age_of_respondent                 0
gender_of_respondent              0
relationship_with_head            0
marital_status                    0
education_level                   0
job_type                          0
household_size_bin                0
age bins                          0
relationship with head bin        0
dtype: int64
```

```
Start coding or generate with AI.
```

data spliting and model fiting

```
X= all_data[['country',
             'year',
             'location_type',
             'cellphone_access',
             'household_size',
             'age_of_respondent',
             'gender_of_respondent',
             'relationship_with_head',
             'marital_status',
             'education_level',
             'job_type',
             'household_size_bin',
             'age bins',
             'relationship with head bin',
             ]]

y = all_data['bank_account']
```

```
Start coding or generate with AI.
```

```
# libraries for model building & evaluation

from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
from lightgbm import LGBMClassifier
from sklearn.tree import DecisionTreeClassifier

from sklearn.model_selection import cross_val_score, KFold
from sklearn.metrics import auc, classification_report, f1_score, mean_absolute_error

from sklearn.compose import ColumnTransformer
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.preprocessing import OneHotEncoder, StandardScaler

from imblearn.over_sampling import RandomOverSampler, SMOTE
from imblearn.under_sampling import RandomUnderSampler
from imblearn.pipeline import Pipeline

# initialize the samplers, encoders and scalers
over= RandomOverSampler()
under = RandomUnderSampler()
smote= SMOTE()

ohe= OneHotEncoder()
```

```
Start coding or generate with AI.
```

```
from sklearn.model_selection import train_test_split
X_train, y_train = X.iloc[:23524, :], y.iloc[:23524] # train, validate and evaluate
X_test= X.iloc[23525:, :]# make model prediction.

#
X_train, X_val, y_train, y_val = train_test_split(X_train,
                                                      y_train,
                                                      stratify=y_train,
                                                      test_size=.019,
                                                      random_state=45)
print('train size: ', X_train.shape)
print('validation size: ', X_val.shape)
print('test size: ', X_test.shape)
```

```
train size:  (23077, 14)
validation size:  (447, 14)
test size:  (10085, 14)
```

```
cat_columns = list(X_train)

col_transformer = ColumnTransformer([('ohe', ohe, cat_columns),], remainder='passthrough')
model = Pipeline([('transformer', col_transformer), ('smote', smote), ('clf', RandomForestClassifier()) ])
```

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

```
preds= model.predict(X_val)
```

```
print(classification_report(y_val, preds))
print('mean absolute error::', mean_absolute_error(y_val, preds))
```

```
              precision    recall  f1-score   support

         0.0       0.91      0.93      0.92       384
         1.0       0.51      0.43      0.47        63

    accuracy                           0.86       447
   macro avg       0.71      0.68      0.69       447
weighted avg       0.85      0.86      0.86       447

mean absolute error:: 0.13870246085011187
```

```
# learners
light=LGBMClassifier()
tree= DecisionTreeClassifier()
logit= LogisticRegression(max_iter=1001)
forest= RandomForestClassifier()

clfs = [forest, tree, logit, light]
names= ['randomforest', 'decisiontree', 'logistic_regression', 'lgm']

MAE_SCORES=[]
for clf, name in zip(clfs, names):
    col_transformer = ColumnTransformer([('ohe', ohe, cat_columns), ],
                                    remainder='passthrough')
    pipe = Pipeline([('transformer', col_transformer), ('smote', smote), ('clf='+name, clf) ])
    pipe.fit(X_train, y_train)
    pred = pipe.predict(X_val)
    scores = mean_absolute_error(y_val, pred)
    MAE_SCORES.append(scores)


logs= pd.Series(MAE_SCORES, index=names)
```

```
logs
```

```
randomforest           0.154362
decisiontree           0.152125
logistic_regression    0.217002
lgm                    0.118568
dtype: float64
```

```
LGBMClassifier?
```

Unsupported Cell Type. Double-Click to inspect/edit the content.

```
# tuning LightGBM using bayesian method

import optuna
from optuna.samplers import TPESampler


def obj_fun(trial):

    num_leaves= trial.suggest_int('num_leaves', 30, 50)
    learning_rate= trial.suggest_uniform('learning_rate', 0.01, 0.1)

    clf = LGBMClassifier(
                    boosting_type = 'gbdt',
                    num_leaves=num_leaves,
                    learning_rate=learning_rate,
                    n_estimators= 200

                )



    cat_columns = list(X_train)
    ohe = OneHotEncoder()
    sc = StandardScaler()

    col_trans = ColumnTransformer([('encoder', ohe, cat_columns),])

    pipe= Pipeline(steps=[('column_transformer', col_trans),  ('over', over),
                      ('smote', smote),('clf', clf)])

    pipe.fit(X_train, y_train)
    pred = pipe.predict(X_val)
    score= mean_absolute_error(y_val, pred)
```

```python
        return score


    study= optuna.create_study(direction='minimize', sampler=TPESampler())
    study.optimize(obj_fun, n_trials=200)
    best_trail = study.best_trial.value
```

```
[I 2021-10-26 18:45:24,166] A new study created in memory with name: no-name-f836390a-a496-407f-a6d7-a5ebb29a65a5
[I 2021-10-26 18:45:25,009] Trial 0 finished with value: 0.21700223713646533 and parameters: {'num_leaves': 50,
[I 2021-10-26 18:45:25,713] Trial 1 finished with value: 0.18344519015659955 and parameters: {'num_leaves': 46,
[I 2021-10-26 18:45:26,649] Trial 2 finished with value: 0.2080536912751678 and parameters: {'num_leaves': 41,
[I 2021-10-26 18:45:27,241] Trial 3 finished with value: 0.2058165548098434 and parameters: {'num_leaves': 40,
[I 2021-10-26 18:45:27,886] Trial 4 finished with value: 0.19015659955257272 and parameters: {'num_leaves': 50,
[I 2021-10-26 18:45:28,848] Trial 5 finished with value: 0.21029082774049218 and parameters: {'num_leaves': 34,
[I 2021-10-26 18:45:29,506] Trial 6 finished with value: 0.21029082774049218 and parameters: {'num_leaves': 49,
[I 2021-10-26 18:45:30,194] Trial 7 finished with value: 0.19910514541387025 and parameters: {'num_leaves': 33,
[I 2021-10-26 18:45:30,858] Trial 8 finished with value: 0.19463087248322147 and parameters: {'num_leaves': 48,
[I 2021-10-26 18:45:31,533] Trial 9 finished with value: 0.19463087248322147 and parameters: {'num_leaves': 32,
[I 2021-10-26 18:45:32,200] Trial 10 finished with value: 0.1789709172259508 and parameters: {'num_leaves': 44,
[I 2021-10-26 18:45:32,850] Trial 11 finished with value: 0.19015659955257272 and parameters: {'num_leaves': 44,
[I 2021-10-26 18:45:33,452] Trial 12 finished with value: 0.19239373601789708 and parameters: {'num_leaves': 44,
[I 2021-10-26 18:45:34,121] Trial 13 finished with value: 0.203579418344519 and parameters: {'num_leaves': 45,
[I 2021-10-26 18:45:34,765] Trial 14 finished with value: 0.19463087248322147 and parameters: {'num_leaves': 38,
[I 2021-10-26 18:45:35,395] Trial 15 finished with value: 0.18568232662192394 and parameters: {'num_leaves': 46,
[I 2021-10-26 18:45:35,991] Trial 16 finished with value: 0.18568232662192394 and parameters: {'num_leaves': 41,
[I 2021-10-26 18:45:36,597] Trial 17 finished with value: 0.203579418344519 and parameters: {'num_leaves': 38,
[I 2021-10-26 18:45:37,201] Trial 18 finished with value: 0.19015659955257272 and parameters: {'num_leaves': 43,
[I 2021-10-26 18:45:37,880] Trial 19 finished with value: 0.19463087248322147 and parameters: {'num_leaves': 47,
[I 2021-10-26 18:45:38,742] Trial 20 finished with value: 0.19686800894854586 and parameters: {'num_leaves': 37,
[I 2021-10-26 18:45:39,410] Trial 21 finished with value: 0.19910514541387025 and parameters: {'num_leaves': 42,
[I 2021-10-26 18:45:40,018] Trial 22 finished with value: 0.19463087248322147 and parameters: {'num_leaves': 46,
[I 2021-10-26 18:45:40,608] Trial 23 finished with value: 0.18568232662192394 and parameters: {'num_leaves': 42,
[I 2021-10-26 18:45:41,144] Trial 24 finished with value: 0.19015659955257272 and parameters: {'num_leaves': 30,
[I 2021-10-26 18:45:41,716] Trial 25 finished with value: 0.2058165548098434 and parameters: {'num_leaves': 40,
[I 2021-10-26 18:45:42,622] Trial 26 finished with value: 0.19686800894854586 and parameters: {'num_leaves': 43,
[I 2021-10-26 18:45:43,474] Trial 27 finished with value: 0.19015659955257272 and parameters: {'num_leaves': 47,
[I 2021-10-26 18:45:44,100] Trial 28 finished with value: 0.19686800894854586 and parameters: {'num_leaves': 45,
[I 2021-10-26 18:45:44,794] Trial 29 finished with value: 0.19239373601789708 and parameters: {'num_leaves': 48,
[I 2021-10-26 18:45:45,441] Trial 30 finished with value: 0.2080536912751678 and parameters: {'num_leaves': 37,
[I 2021-10-26 18:45:46,060] Trial 31 finished with value: 0.19686800894854586 and parameters: {'num_leaves': 46,
[I 2021-10-26 18:45:46,667] Trial 32 finished with value: 0.18791946308724833 and parameters: {'num_leaves': 41,
[I 2021-10-26 18:45:47,258] Trial 33 finished with value: 0.18791946308724833 and parameters: {'num_leaves': 41,
[I 2021-10-26 18:45:47,854] Trial 34 finished with value: 0.19015659955257272 and parameters: {'num_leaves': 42,
[I 2021-10-26 18:45:48,469] Trial 35 finished with value: 0.18791946308724833 and parameters: {'num_leaves': 39,
[I 2021-10-26 18:45:49,102] Trial 36 finished with value: 0.19239373601789708 and parameters: {'num_leaves': 50,
[I 2021-10-26 18:45:49,687] Trial 37 finished with value: 0.174496644295302 and parameters: {'num_leaves': 43,
[I 2021-10-26 18:45:50,524] Trial 38 finished with value: 0.2058165548098434 and parameters: {'num_leaves': 44,
[I 2021-10-26 18:45:51,155] Trial 39 finished with value: 0.19910514541387025 and parameters: {'num_leaves': 49,
[I 2021-10-26 18:45:51,782] Trial 40 finished with value: 0.18120805369127516 and parameters: {'num_leaves': 43,
[I 2021-10-26 18:45:52,458] Trial 41 finished with value: 0.20134228187919462 and parameters: {'num_leaves': 43,
[I 2021-10-26 18:45:53,244] Trial 42 finished with value: 0.18344519015659955 and parameters: {'num_leaves': 46,
[I 2021-10-26 18:45:54,061] Trial 43 finished with value: 0.18791946308724833 and parameters: {'num_leaves': 45,
[I 2021-10-26 18:45:54,945] Trial 44 finished with value: 0.19463087248322147 and parameters: {'num_leaves': 47,
[I 2021-10-26 18:45:55,806] Trial 45 finished with value: 0.19686800894854586 and parameters: {'num_leaves': 44,
[I 2021-10-26 18:45:56,402] Trial 46 finished with value: 0.19463087248322147 and parameters: {'num_leaves': 45,
[I 2021-10-26 18:45:57,043] Trial 47 finished with value: 0.19015659955257272 and parameters: {'num_leaves': 48,
[I 2021-10-26 18:45:57,679] Trial 48 finished with value: 0.19015659955257272 and parameters: {'num_leaves': 43,
[I 2021-10-26 18:45:58,354] Trial 49 finished with value: 0.19463087248322147 and parameters: {'num_leaves': 46,
[I 2021-10-26 18:45:59,011] Trial 50 finished with value: 0.19015659955257272 and parameters: {'num_leaves': 49,
[I 2021-10-26 18:45:59,599] Trial 51 finished with value: 0.19015659955257272 and parameters: {'num_leaves': 42,
[I 2021-10-26 18:46:00,352] Trial 52 finished with value: 0.19239373601789708 and parameters: {'num_leaves': 40,
[I 2021-10-26 18:46:01,510] Trial 53 finished with value: 0.19463087248322147 and parameters: {'num_leaves': 44,
[I 2021-10-26 18:46:02,103] Trial 54 finished with value: 0.2058165548098434 and parameters: {'num_leaves': 42,
[I 2021-10-26 18:46:02,701] Trial 55 finished with value: 0.18568232662192394 and parameters: {'num_leaves': 43,
[I 2021-10-26 18:46:03,375] Trial 56 finished with value: 0.19910514541387025 and parameters: {'num_leaves': 39,
[I 2021-10-26 18:46:04,167] Trial 57 finished with value: 0.19239373601789708 and parameters: {'num_leaves': 45,
[I 2021-10-26 18:46:04,836] Trial 58 finished with value: 0.19910514541387025 and parameters: {'num_leaves': 43,
[I 2021-10-26 18:46:05,461] Trial 59 finished with value: 0.20134228187919462 and parameters: {'num_leaves': 47,
[I 2021-10-26 18:46:06,139] Trial 60 finished with value: 0.18568232662192394 and parameters: {'num_leaves': 44,
[I 2021-10-26 18:46:06,830] Trial 61 finished with value: 0.19910514541387025 and parameters: {'num_leaves': 44,
[I 2021-10-26 18:46:07,619] Trial 62 finished with value: 0.18568232662192394 and parameters: {'num_leaves': 46,
```