Prestige_modeling

January 12, 2020

0.0.1 Contents -

Exploratory Data Analysis - Looking at Data - Plot and visualze Categorial Variables - Corelation and plot Neumerical variables - Missing Value Stats #### Phase 1 Modeling - Simple way of missing value Imputation - Model preperation - Random Forest - grid search, hyperparameter tuning and evaluation of best model by cross validation - XGboost - hyperparameter tuning,random search and evaluation of best model by cross validation - Conclusion from Phase 1 #### Phase 2 Modeling - Missing value imputation by KNN - Random Forest - XGboost - Is there any improvement ? #### Implementation on Test and Final Submission #### Conclusion and Future Work

0.0.2 Required Modules

[144]:
```
import numpy as np # linear algebra
import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
import sklearn.metrics as metrics
from xgboost import XGBClassifier
from xgboost import plot_importance
from time import time
import datetime
from scipy import stats
from sklearn.model_selection import KFold, StratifiedKFold,train_test_split
import gc
import json
from lightgbm import LGBMClassifier
import sklearn.metrics as metrics
from sklearn.metrics import roc_curve
from sklearn.metrics import roc_auc_score
from sklearn.model_selection import GridSearchCV,RandomizedSearchCV
from sklearn.impute import SimpleImputer
from fancyimpute import IterativeImputer
pd.set_option('display.max_columns', 1000)
```

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

Loading Data

[125]:
```
file_path="/Users/krishanubanerjee/Downloads/prestige_finance/Use"

train=pd.read_csv(file_path+"/application_train.csv")
test=pd.read_csv(file_path+"/application_test.csv")
```

0.0.3 1. Exploratory Data Analysis (EDA)

Looking at data

[4]:
```
train.shape
```

[4]:
```
(125000, 122)
```

[5]:
```
test.shape
```

[5]:
```
(48744, 121)
```

[6]:
```
train.head()
```

[6]:
```
   SK_ID_CURR  TARGET NAME_CONTRACT_TYPE CODE_GENDER FLAG_OWN_CAR  \
0      396902       0         Cash loans           F            Y
1      112096       0         Cash loans           F            N
2      285821       1         Cash loans           M            Y
3      376901       0         Cash loans           F            N
4      325138       0         Cash loans           F            Y

  FLAG_OWN_REALTY  CNT_CHILDREN  AMT_INCOME_TOTAL  AMT_CREDIT  AMT_ANNUITY  \
0               Y             0          121500.0    835380.0      40320.0
1               Y             0          202500.0    516069.0      26478.0
2               Y             1          180000.0    284400.0      22468.5
3               Y             0           90000.0    265536.0      13684.5
4               Y             0           94500.0    755190.0      30078.0

   AMT_GOODS_PRICE  NAME_TYPE_SUITE NAME_INCOME_TYPE  \
0         675000.0    Unaccompanied          Working
1         445500.0    Unaccompanied        Pensioner
2         225000.0  Spouse, partner          Working
3         180000.0    Unaccompanied          Working
4         675000.0    Unaccompanied        Pensioner

             NAME_EDUCATION_TYPE    NAME_FAMILY_STATUS  NAME_HOUSING_TYPE  \
```

```
0            Higher education           Separated  House / apartment
1  Secondary / secondary special            Widow  House / apartment
2  Secondary / secondary special          Married  House / apartment
3  Secondary / secondary special          Married  House / apartment
4  Secondary / secondary special  Single / not married  House / apartment

   REGION_POPULATION_RELATIVE  DAYS_BIRTH  DAYS_EMPLOYED  DAYS_REGISTRATION  \
0                    0.035792      -16647           -283             -611.0
1                    0.011657      -22237         365243              -34.0
2                    0.028663      -11399           -508            -1500.0
3                    0.031329      -20074           -221            -1264.0
4                    0.019689      -20691         365243            -2277.0

   DAYS_ID_PUBLISH  OWN_CAR_AGE  FLAG_MOBIL  FLAG_EMP_PHONE  FLAG_WORK_PHONE  \
0             -184         10.0           1               1                1
1            -4878          NaN           1               0                0
2             -920         16.0           1               1                0
3            -3559          NaN           1               1                0
4             -703         10.0           1               0                0

   FLAG_CONT_MOBILE  FLAG_PHONE  FLAG_EMAIL OCCUPATION_TYPE  CNT_FAM_MEMBERS  \
0                 1           0           0      Core staff              1.0
1                 1           0           0             NaN              1.0
2                 1           0           0        Laborers              3.0
3                 1           0           0  Medicine staff              2.0
4                 1           0           0             NaN              1.0

   REGION_RATING_CLIENT  REGION_RATING_CLIENT_W_CITY  \
0                     2                            2
1                     1                            1
2                     2                            2
3                     2                            2
4                     2                            2

  WEEKDAY_APPR_PROCESS_START  HOUR_APPR_PROCESS_START  \
0                     SUNDAY                       11
1                  WEDNESDAY                       10
2                     SUNDAY                       11
3                     FRIDAY                       10
4                   THURSDAY                       12

   REG_REGION_NOT_LIVE_REGION  REG_REGION_NOT_WORK_REGION  \
0                           0                           0
1                           0                           0
2                           0                           1
3                           0                           0
4                           0                           0
```

```
   LIVE_REGION_NOT_WORK_REGION  REG_CITY_NOT_LIVE_CITY  \
0                            0                       0
1                            0                       0
2                            1                       0
3                            0                       0
4                            0                       0

   REG_CITY_NOT_WORK_CITY  LIVE_CITY_NOT_WORK_CITY ORGANIZATION_TYPE  \
0                       0                        0        Restaurant
1                       0                        0               XNA
2                       1                        1      Construction
3                       0                        0      Kindergarten
4                       0                        0               XNA

   EXT_SOURCE_1  EXT_SOURCE_2  EXT_SOURCE_3  APARTMENTS_AVG  BASEMENTAREA_AVG  \
0      0.642816      0.606592      0.646330             NaN               NaN
1           NaN      0.172095      0.360613          0.1227            0.1213
2      0.446722      0.465626      0.106156             NaN               NaN
3           NaN      0.662464      0.266457          0.1320            0.0460
4           NaN      0.054296           NaN          0.0082            0.0216

   YEARS_BEGINEXPLUATATION_AVG  YEARS_BUILD_AVG  COMMONAREA_AVG  \
0                          NaN              NaN             NaN
1                       0.9762           0.6736          0.1901
2                          NaN              NaN             NaN
3                       0.9856           0.8028          0.0375
4                       0.9722              NaN             NaN

   ELEVATORS_AVG  ENTRANCES_AVG  FLOORSMAX_AVG  FLOORSMIN_AVG  LANDAREA_AVG  \
0            NaN            NaN            NaN            NaN           NaN
1           0.00         0.2069         0.1667         0.0417        0.0476
2            NaN            NaN            NaN            NaN           NaN
3           0.08         0.0345         0.6250         0.6667        0.0116
4           0.00         0.0345         0.0417            NaN        0.0038

   LIVINGAPARTMENTS_AVG  LIVINGAREA_AVG  NONLIVINGAPARTMENTS_AVG  \
0                   NaN             NaN                      NaN
1                0.1000          0.0941                   0.0000
2                   NaN             NaN                      NaN
3                0.1067          0.1327                   0.0039
4                   NaN          0.0095                      NaN

   NONLIVINGAREA_AVG  APARTMENTS_MODE  BASEMENTAREA_MODE  \
0                NaN              NaN                NaN
1             0.1375           0.1250             0.1259
2                NaN              NaN                NaN
```

```
3            0.0011           0.1345             0.0478
4            0.0000           0.0084             0.0225

   YEARS_BEGINEXPLUATATION_MODE  YEARS_BUILD_MODE  COMMONAREA_MODE  \
0                           NaN               NaN              NaN
1                        0.9762            0.6864           0.1918
2                           NaN               NaN              NaN
3                        0.9856            0.8105           0.0378
4                        0.9722               NaN              NaN

   ELEVATORS_MODE  ENTRANCES_MODE  FLOORSMAX_MODE  FLOORSMIN_MODE  \
0             NaN             NaN             NaN             NaN
1          0.0000          0.2069          0.1667          0.0417
2             NaN             NaN             NaN             NaN
3          0.0806          0.0345          0.6250          0.6667
4          0.0000          0.0345          0.0417             NaN

   LANDAREA_MODE  LIVINGAPARTMENTS_MODE  LIVINGAREA_MODE  \
0            NaN                    NaN              NaN
1         0.0487                 0.1093           0.0981
2            NaN                    NaN              NaN
3         0.0119                 0.1166           0.1382
4         0.0039                    NaN           0.0099

   NONLIVINGAPARTMENTS_MODE  NONLIVINGAREA_MODE  APARTMENTS_MEDI  \
0                       NaN                 NaN              NaN
1                    0.0000              0.1456           0.1239
2                       NaN                 NaN              NaN
3                    0.0039              0.0011           0.1332
4                       NaN              0.0000           0.0083

   BASEMENTAREA_MEDI  YEARS_BEGINEXPLUATATION_MEDI  YEARS_BUILD_MEDI  \
0                NaN                           NaN               NaN
1             0.1213                        0.9762            0.6780
2                NaN                           NaN               NaN
3             0.0460                        0.9856            0.8054
4             0.0216                        0.9722               NaN

   COMMONAREA_MEDI  ELEVATORS_MEDI  ENTRANCES_MEDI  FLOORSMAX_MEDI  \
0              NaN             NaN             NaN             NaN
1           0.1913            0.00          0.2069          0.1667
2              NaN             NaN             NaN             NaN
3           0.0377            0.08          0.0345          0.6250
4              NaN            0.00          0.0345          0.0417

   FLOORSMIN_MEDI  LANDAREA_MEDI  LIVINGAPARTMENTS_MEDI  LIVINGAREA_MEDI  \
0             NaN            NaN                    NaN              NaN
```

```
1          0.0417         0.0485                    0.1018           0.0958
2             NaN            NaN                       NaN              NaN
3          0.6667         0.0118                    0.1086           0.1351
4             NaN         0.0039                       NaN           0.0096

   NONLIVINGAPARTMENTS_MEDI  NONLIVINGAREA_MEDI     FONDKAPREMONT_MODE  \
0                       NaN                 NaN                    NaN
1                    0.0000              0.1404  reg oper spec account
2                       NaN                 NaN                    NaN
3                    0.0039              0.0011       reg oper account
4                       NaN              0.0000                    NaN

   HOUSETYPE_MODE  TOTALAREA_MODE WALLSMATERIAL_MODE EMERGENCYSTATE_MODE  \
0             NaN             NaN                NaN                 NaN
1  block of flats          0.1039       Stone, brick                  No
2             NaN             NaN                NaN                 NaN
3  block of flats          0.1251         Monolithic                  No
4  block of flats          0.0074       Stone, brick                  No

   OBS_30_CNT_SOCIAL_CIRCLE  DEF_30_CNT_SOCIAL_CIRCLE  \
0                       0.0                       0.0
1                       1.0                       1.0
2                       7.0                       0.0
3                       0.0                       0.0
4                       0.0                       0.0

   OBS_60_CNT_SOCIAL_CIRCLE  DEF_60_CNT_SOCIAL_CIRCLE  DAYS_LAST_PHONE_CHANGE  \
0                       0.0                       0.0                  -770.0
1                       1.0                       1.0                 -1069.0
2                       7.0                       0.0                  -933.0
3                       0.0                       0.0                 -1428.0
4                       0.0                       0.0                  -695.0

   FLAG_DOCUMENT_2  FLAG_DOCUMENT_3  FLAG_DOCUMENT_4  FLAG_DOCUMENT_5  \
0                0                1                0                0
1                0                1                0                0
2                0                1                0                0
3                0                1                0                0
4                0                1                0                0

   FLAG_DOCUMENT_6  FLAG_DOCUMENT_7  FLAG_DOCUMENT_8  FLAG_DOCUMENT_9  \
0                0                0                0                0
1                0                0                0                0
2                0                0                0                0
3                0                0                0                0
4                0                0                0                0
```

```
   FLAG_DOCUMENT_10  FLAG_DOCUMENT_11  FLAG_DOCUMENT_12  FLAG_DOCUMENT_13  \
0                 0                 0                 0                 0
1                 0                 0                 0                 0
2                 0                 0                 0                 0
3                 0                 0                 0                 0
4                 0                 0                 0                 0

   FLAG_DOCUMENT_14  FLAG_DOCUMENT_15  FLAG_DOCUMENT_16  FLAG_DOCUMENT_17  \
0                 0                 0                 0                 0
1                 0                 0                 0                 0
2                 0                 0                 0                 0
3                 0                 0                 0                 0
4                 0                 0                 0                 0

   FLAG_DOCUMENT_18  FLAG_DOCUMENT_19  FLAG_DOCUMENT_20  FLAG_DOCUMENT_21  \
0                 0                 0                 0                 0
1                 0                 0                 0                 0
2                 0                 0                 0                 0
3                 0                 0                 0                 0
4                 0                 0                 0                 0

   AMT_REQ_CREDIT_BUREAU_HOUR  AMT_REQ_CREDIT_BUREAU_DAY  \
0                         0.0                        0.0
1                         0.0                        0.0
2                         0.0                        0.0
3                         0.0                        0.0
4                         NaN                        NaN

   AMT_REQ_CREDIT_BUREAU_WEEK  AMT_REQ_CREDIT_BUREAU_MON  \
0                         0.0                        0.0
1                         0.0                        0.0
2                         0.0                        0.0
3                         0.0                        0.0
4                         NaN                        NaN

   AMT_REQ_CREDIT_BUREAU_QRT  AMT_REQ_CREDIT_BUREAU_YEAR
0                        0.0                         4.0
1                        0.0                         6.0
2                        0.0                         3.0
3                        1.0                         1.0
4                        NaN                         NaN
```

Is there any primary key ?

[231]:
```python
[list(train.columns)[i] for i in range(len(list(train.columns))) \
                     if train[list(train.columns)[i]].nunique()==train.shape[0]]
```

```
[231]: ['SK_ID_CURR']
```

Is it true for test also ?

```
[10]: [list(test.columns)[i] for i in range(len(list(test.columns))) \
                          if test[list(test.columns)[i]].nunique()==test.shape[0]]
```

```
[10]: ['SK_ID_CURR']
```

So we confirmed ,'SK_ID_CURR' is primary key and we will use this field for indexing in modeling

Let's see target

```
[11]: train['TARGET'].value_counts(normalize=True)
```

```
[11]: 0    0.918936
      1    0.081064
      Name: TARGET, dtype: float64
```

8% of TARGET in one class and 92% in other. That could be little challenging at the time of modeling

Let's separate numerical and categorical variables

```
[23]: numerical_features=[features[i] for i in range(len(features)) \
                          if ((train[features[i]].
       ↪dtypes=='float64')|(train[features[i]].dtypes=='int64')) and \
                                  features[i]!='TARGET']
```

```
[24]: categorical_features=[features[i] for i in range(len(features)) \
                          if (train[features[i]].dtypes!
       ↪='float64')&(train[features[i]].dtypes!='int64')]
```

Top5 numerical features corelated with TARGET

```
[84]: coeff=[]
      for num in numerical_features:
          coeff.append(np.corrcoef(train[num], train['TARGET'])[0][1])
      df_numercial_coeff_target=pd.
       ↪DataFrame(zip(numerical_features,coeff),columns=['feature','coefficient'])
      df_numercial_coeff_target.sort_values(by='coefficient',ascending=False).head(5)
```

```
[84]:                          feature  coefficient
      7                     DAYS_BIRTH     0.081524
      20  REGION_RATING_CLIENT_W_CITY     0.061044
      19         REGION_RATING_CLIENT     0.059906
      78       DAYS_LAST_PHONE_CHANGE     0.056998
```

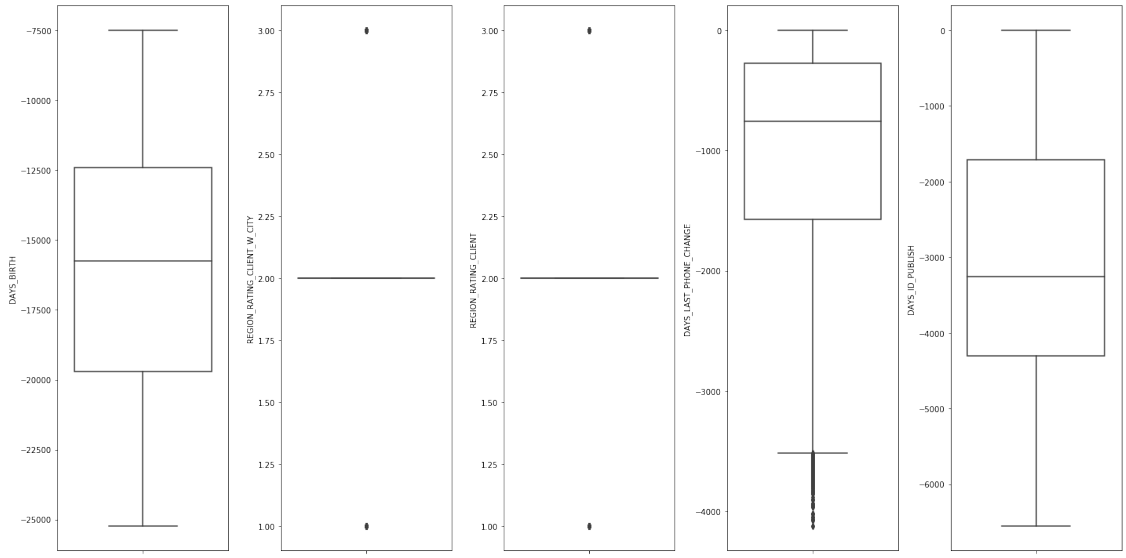
```
10             DAYS_ID_PUBLISH     0.053369
```

[85]:
```
def numeric_eda(df, hue=None):
    """Given dataframe, generate Distribution of of numeric data
    This function will give an idea of numerical data and can be extended for any
    numerical variables"""
    display(df.describe().T)
    columns = df.select_dtypes(include=np.number).columns
    figure = plt.figure(figsize=(20, 10))
    figure.add_subplot(1, len(columns), 1)
    for index, col in enumerate(columns):
        if index > 0:
            figure.add_subplot(1, len(columns), index + 1)
        sns.boxplot(y=col, data=df, boxprops={'facecolor': 'None'})
    figure.tight_layout()
    plt.show()
```

[86]:
```
numercial_coeff_target_col=list(df_numercial_coeff_target.
 ↪sort_values(by='coefficient',\
                                                          ascending=False).
 ↪head(5)['feature'])
numeric_eda(train[numercial_coeff_target_col])
```

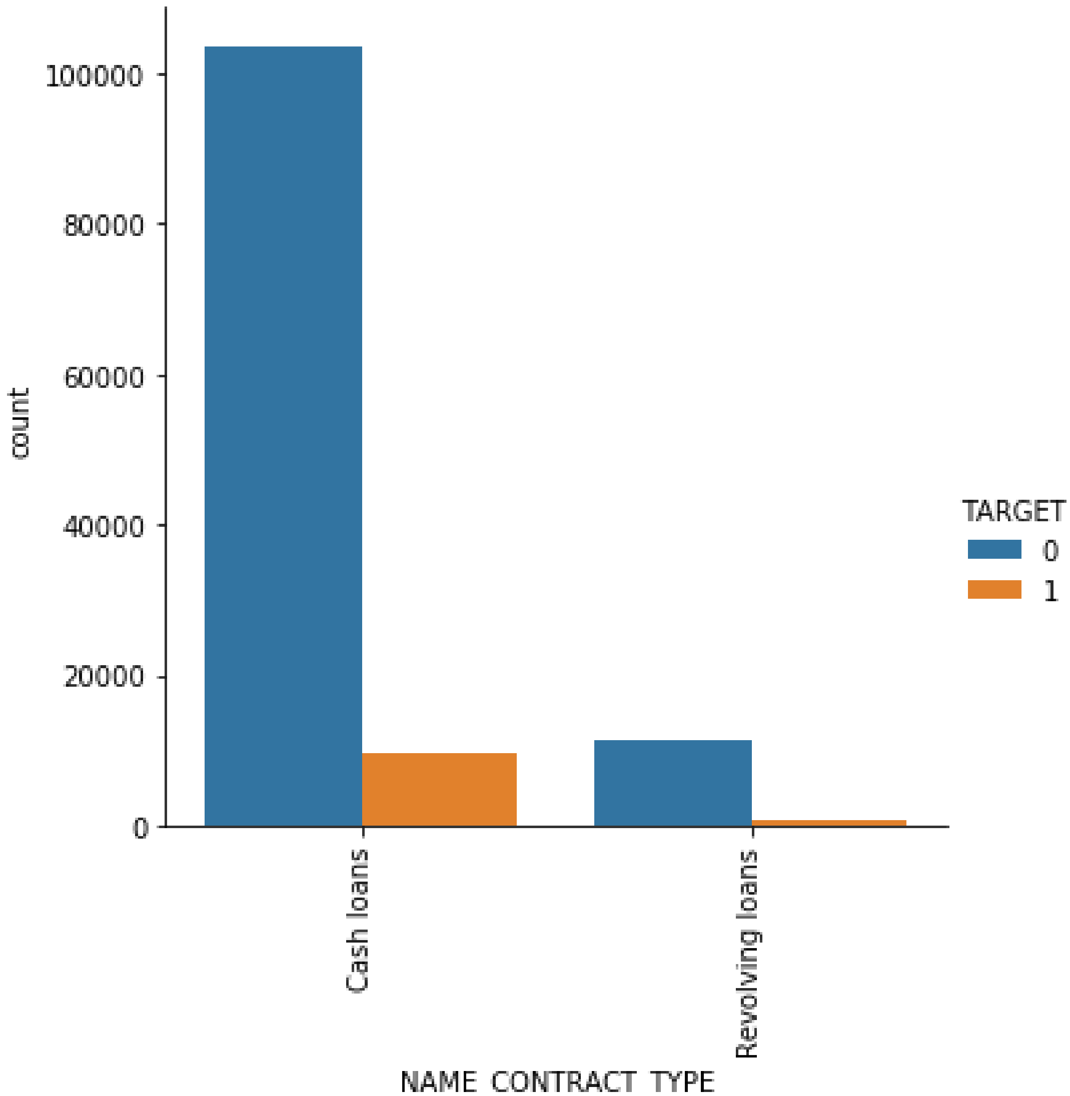
```
                              count          mean          std      min  \
DAYS_BIRTH                 125000.0 -16043.327896  4367.787586 -25229.0
REGION_RATING_CLIENT_W_CITY 125000.0      2.031768     0.503262      1.0
REGION_RATING_CLIENT       125000.0      2.052328     0.509721      1.0
DAYS_LAST_PHONE_CHANGE     125000.0   -965.803944   828.138874  -4121.0
DAYS_ID_PUBLISH            125000.0  -2995.506800  1512.924375  -6551.0

                                 25%      50%      75%     max
DAYS_BIRTH                 -19692.00 -15754.0 -12415.0 -7489.0
REGION_RATING_CLIENT_W_CITY      2.00      2.0      2.0     3.0
REGION_RATING_CLIENT             2.00      2.0      2.0     3.0
DAYS_LAST_PHONE_CHANGE       -1573.25   -760.0   -277.0     0.0
DAYS_ID_PUBLISH              -4304.00  -3260.0  -1713.0     0.0
```

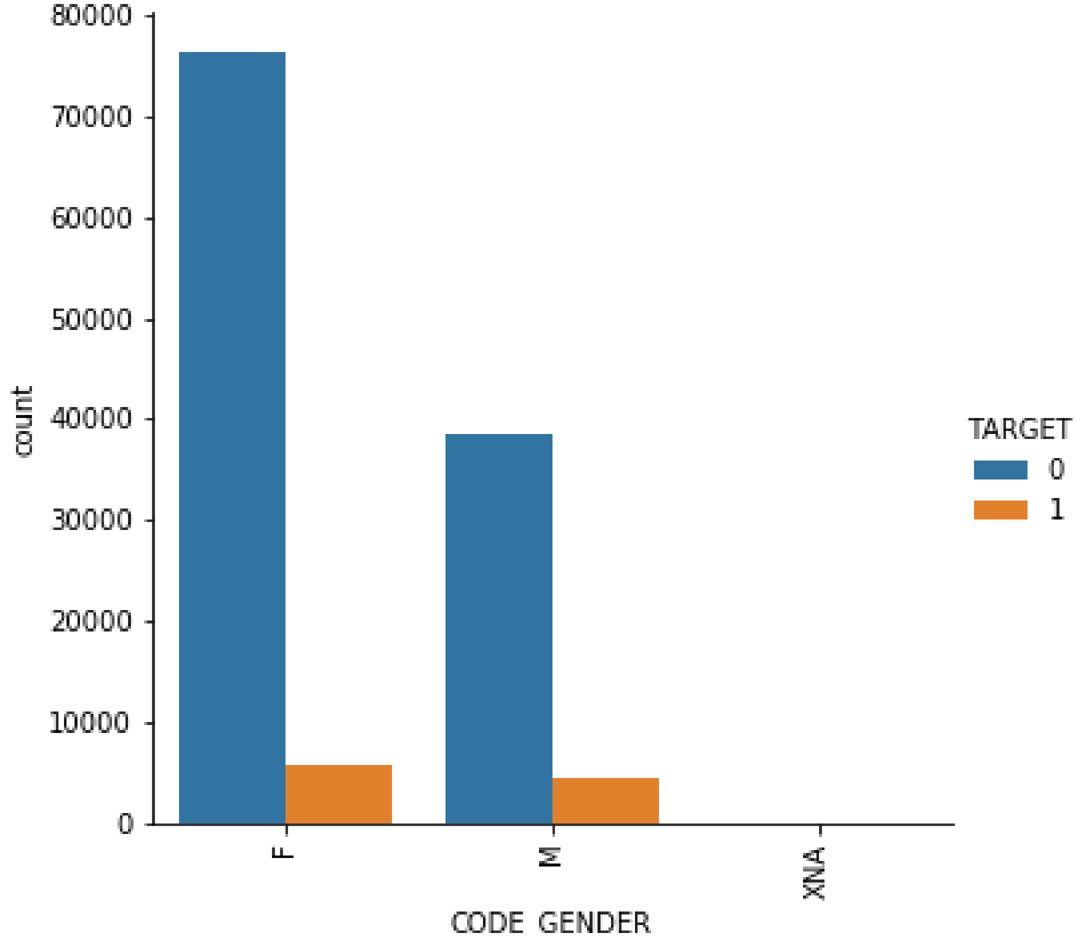


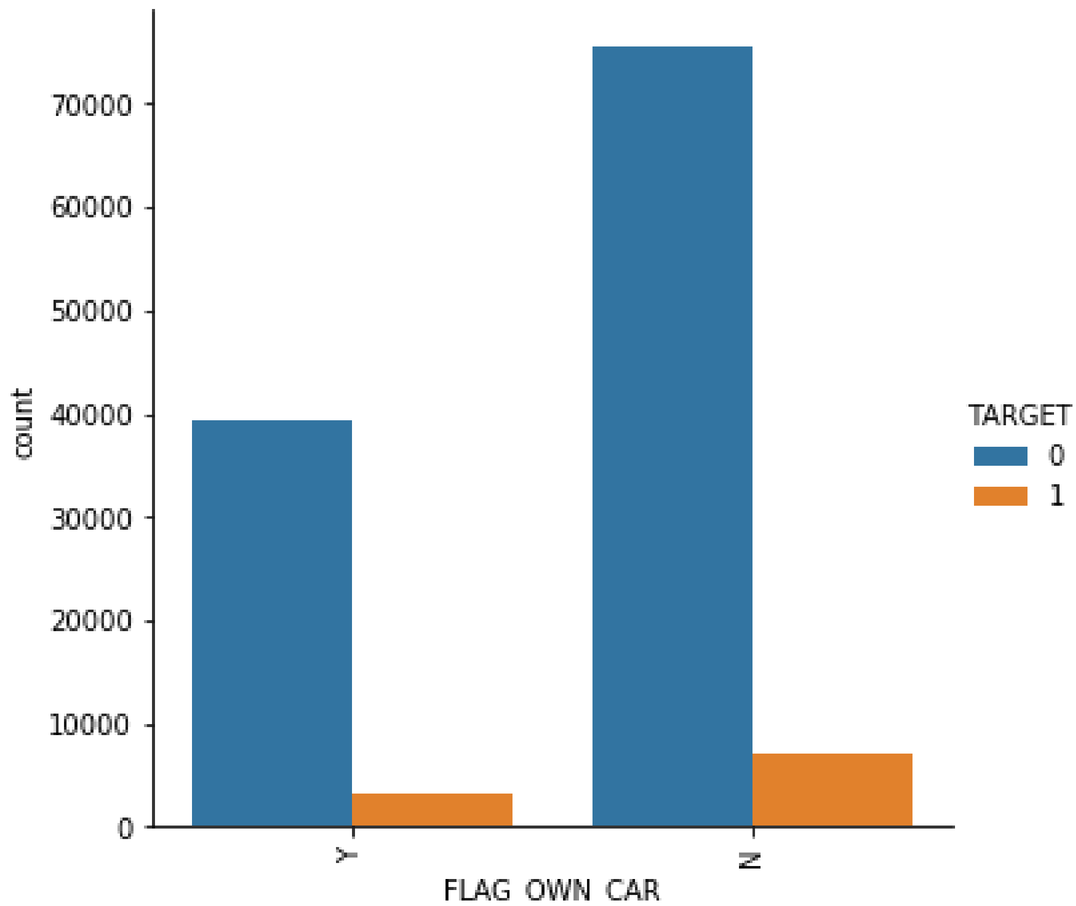
[87]:
```
def categorical_eda(df, hue=None):
    """Given dataframe, generate EDA of categorical data and relation with␣
↪TARGET"""
    # Plot count distribution of categorical data
    for col in list(categorical_features):
        fig = sns.catplot(x=col, kind="count", data=df, hue=hue)
        fig.set_xticklabels(rotation=90)
        plt.show()
```

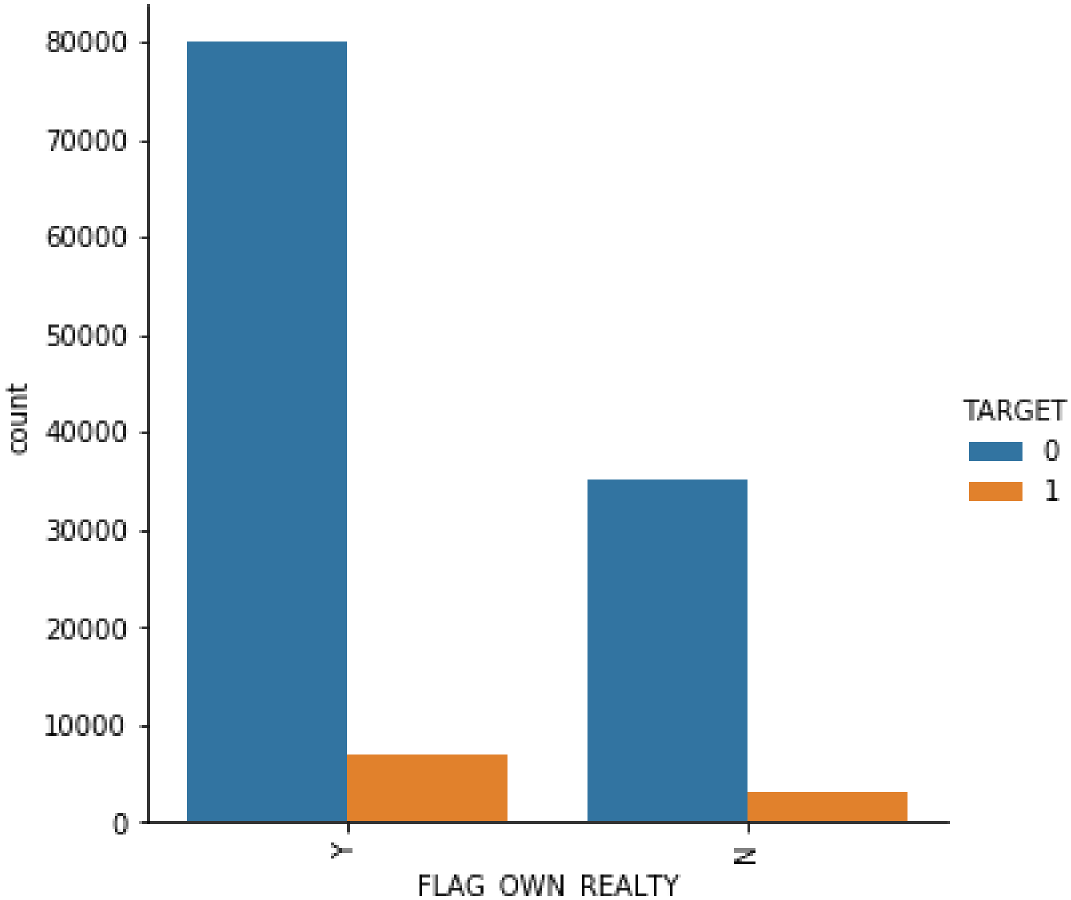
[88]:
```
categorical_eda(train,'TARGET')
```

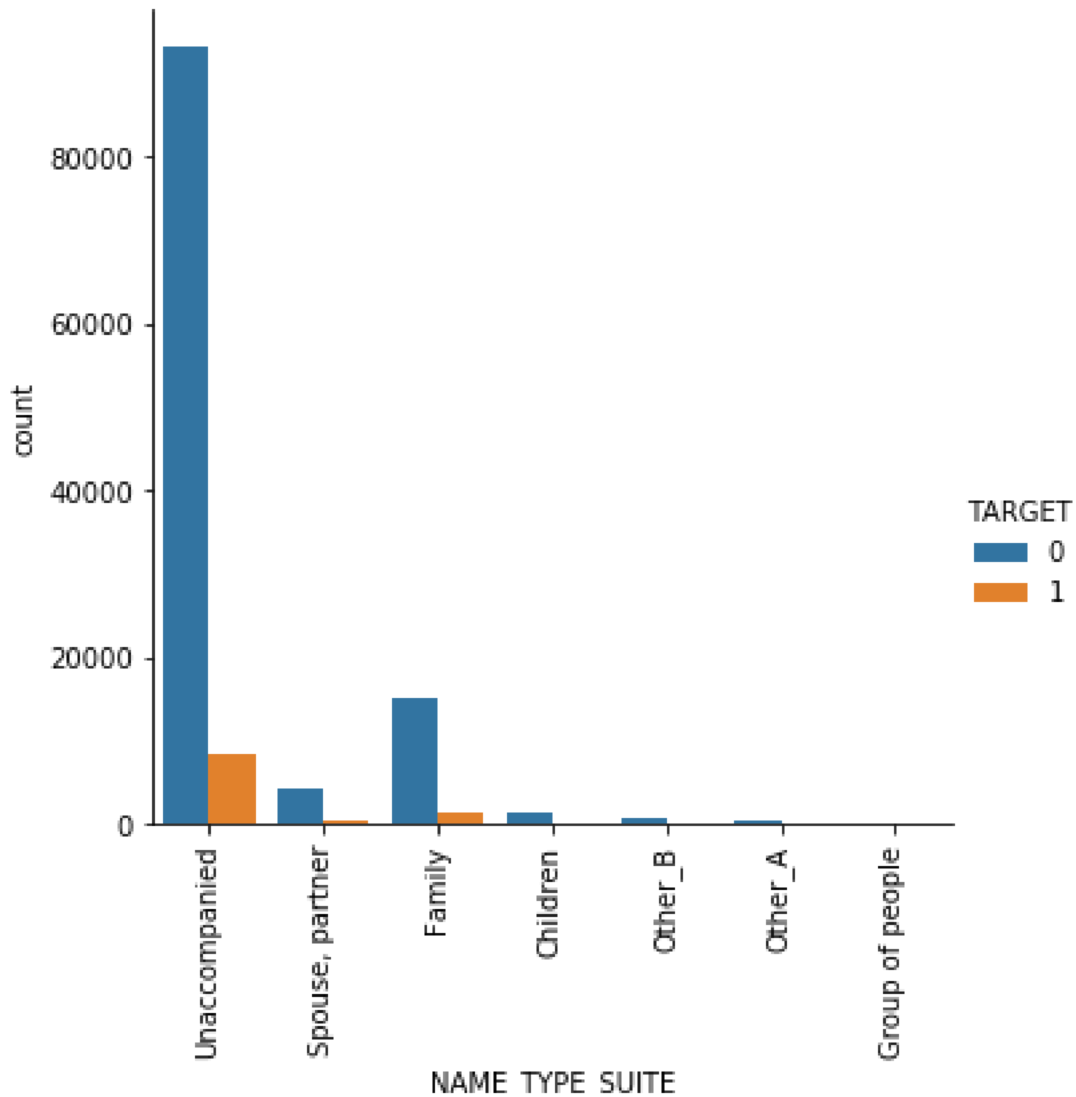


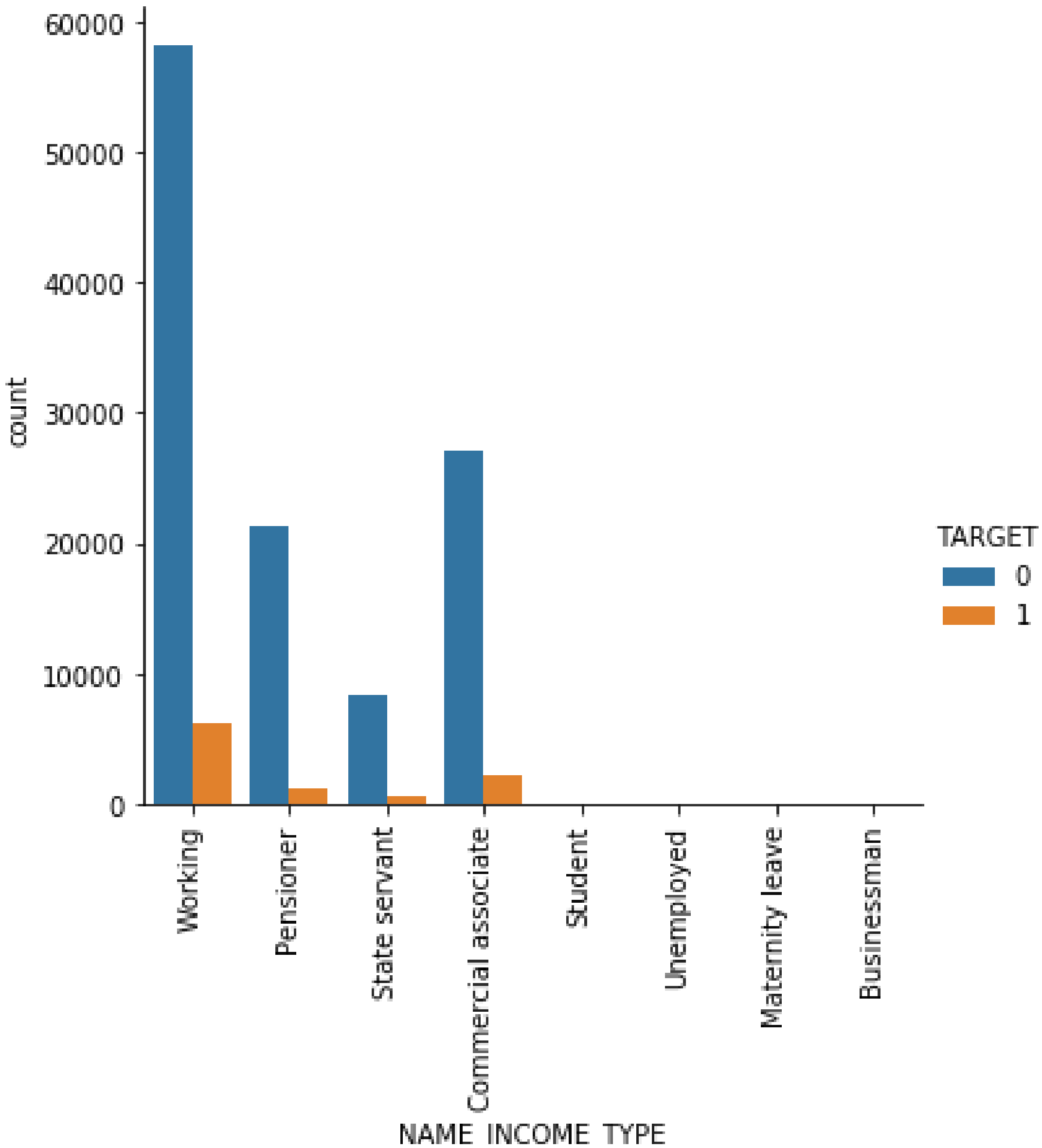
count
100000
80000
60000
40000
20000
0
TARGET
0
1
Cash loans
Revolving loans
NAME_CONTRACT_TYPE


80000
70000
60000
50000
40000
30000
20000
10000
0
count
F
M
XNA
CODE_GENDER
TARGET
0
1

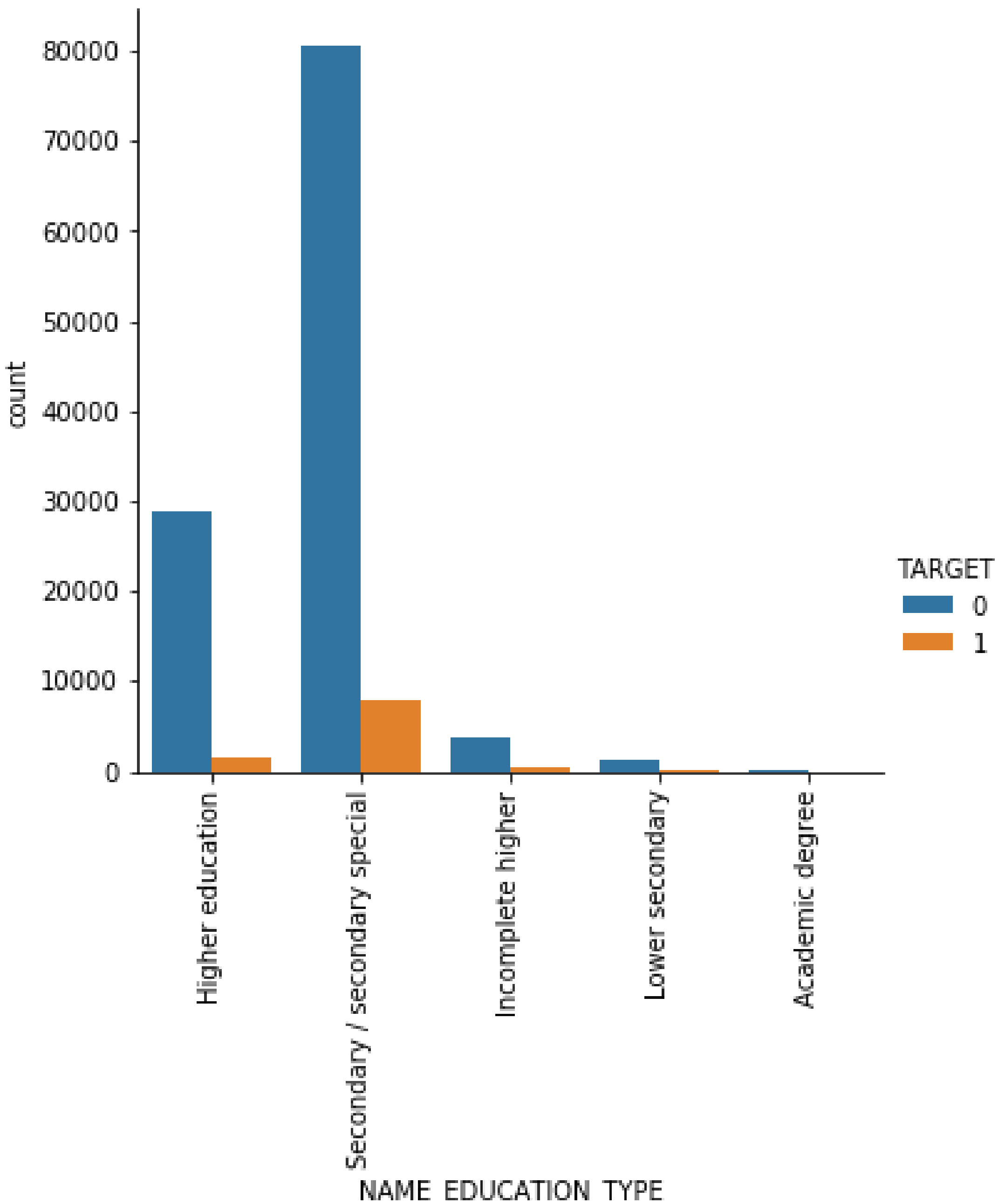

70000
60000
50000
40000
30000
20000
10000
0
count
TARGET
0
1
Y
N
FLAG_OWN_CAR


80000
70000
60000
50000
40000
30000
20000
10000
0
count
Y
N
FLAG_OWN_REALTY
TARGET
0
1

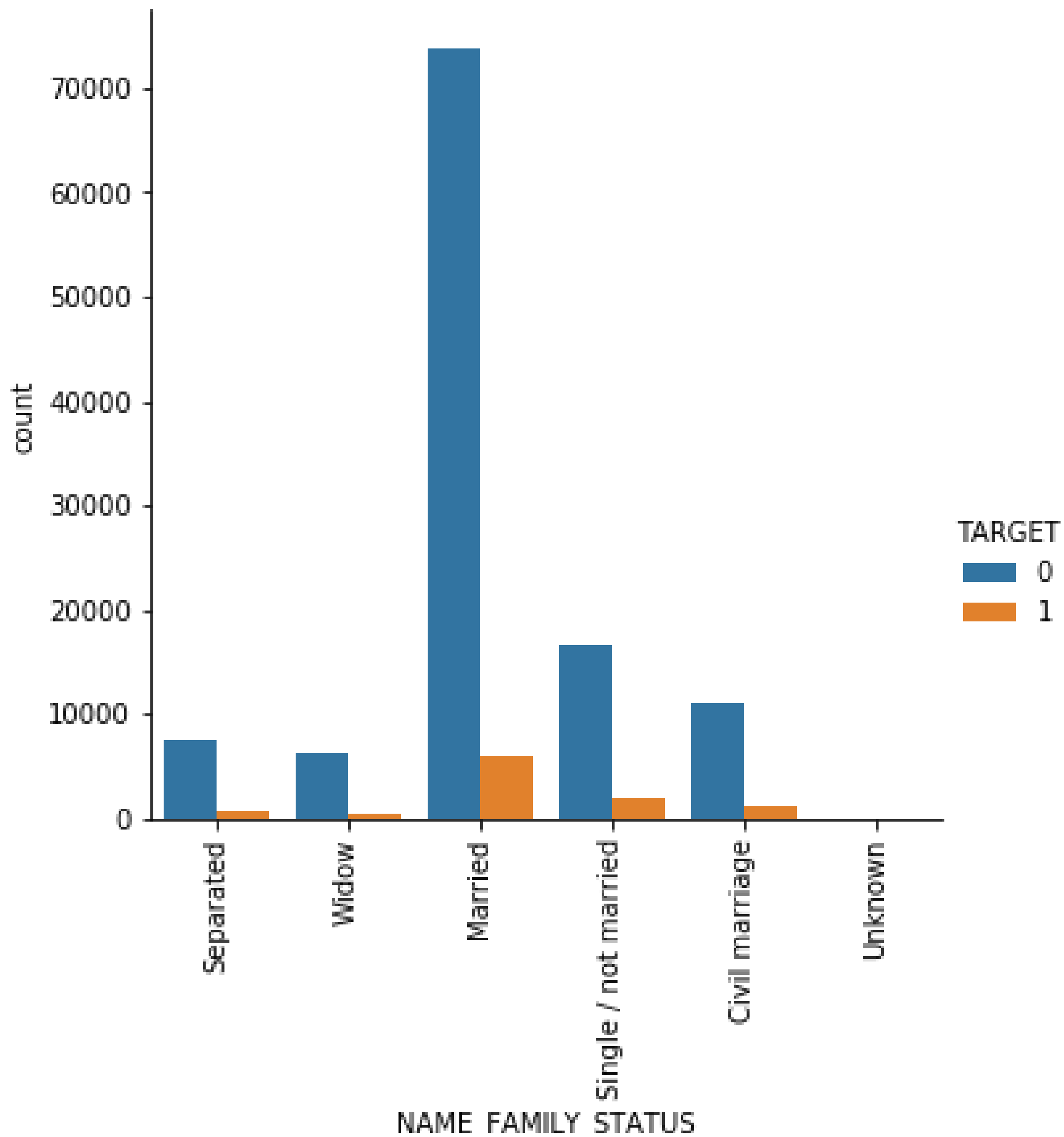

count
80000
60000
40000
20000
0
Unaccompanied
Spouse, partner
Family
Children
Other_B
Other_A
Group of people
NAME_TYPE_SUITE
TARGET
0
1



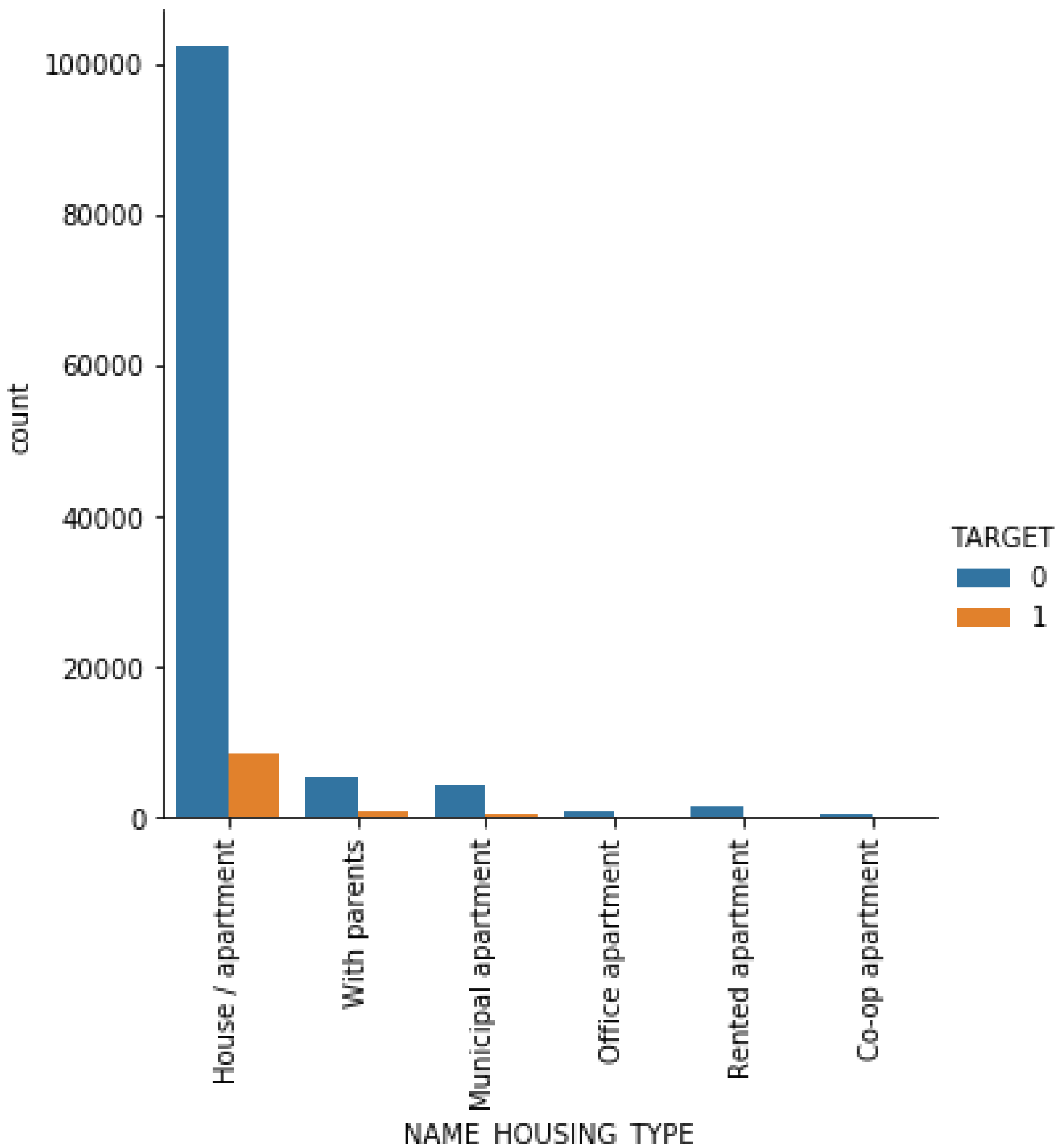
60000
50000
40000
30000
20000
10000
0
count
Working
Pensioner
State servant
Commercial associate
Student
Unemployed
Maternity leave
Businessman
NAME_INCOME_TYPE
TARGET
0
1



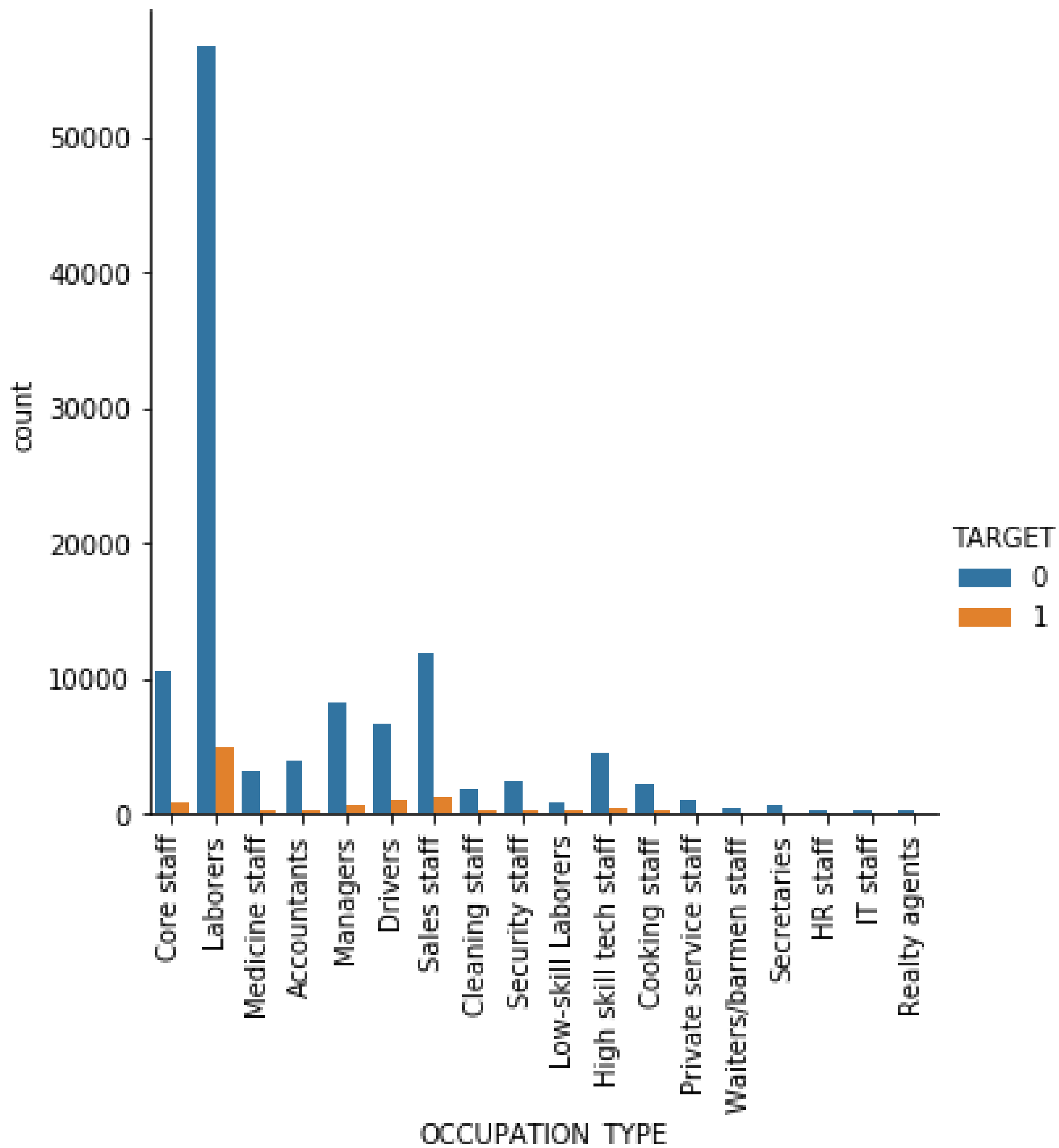
80000
70000
60000
50000
40000
30000
20000
10000
0
count
Higher education
Secondary / secondary special
Incomplete higher
Lower secondary
Academic degree
NAME_EDUCATION_TYPE
TARGET
0
1

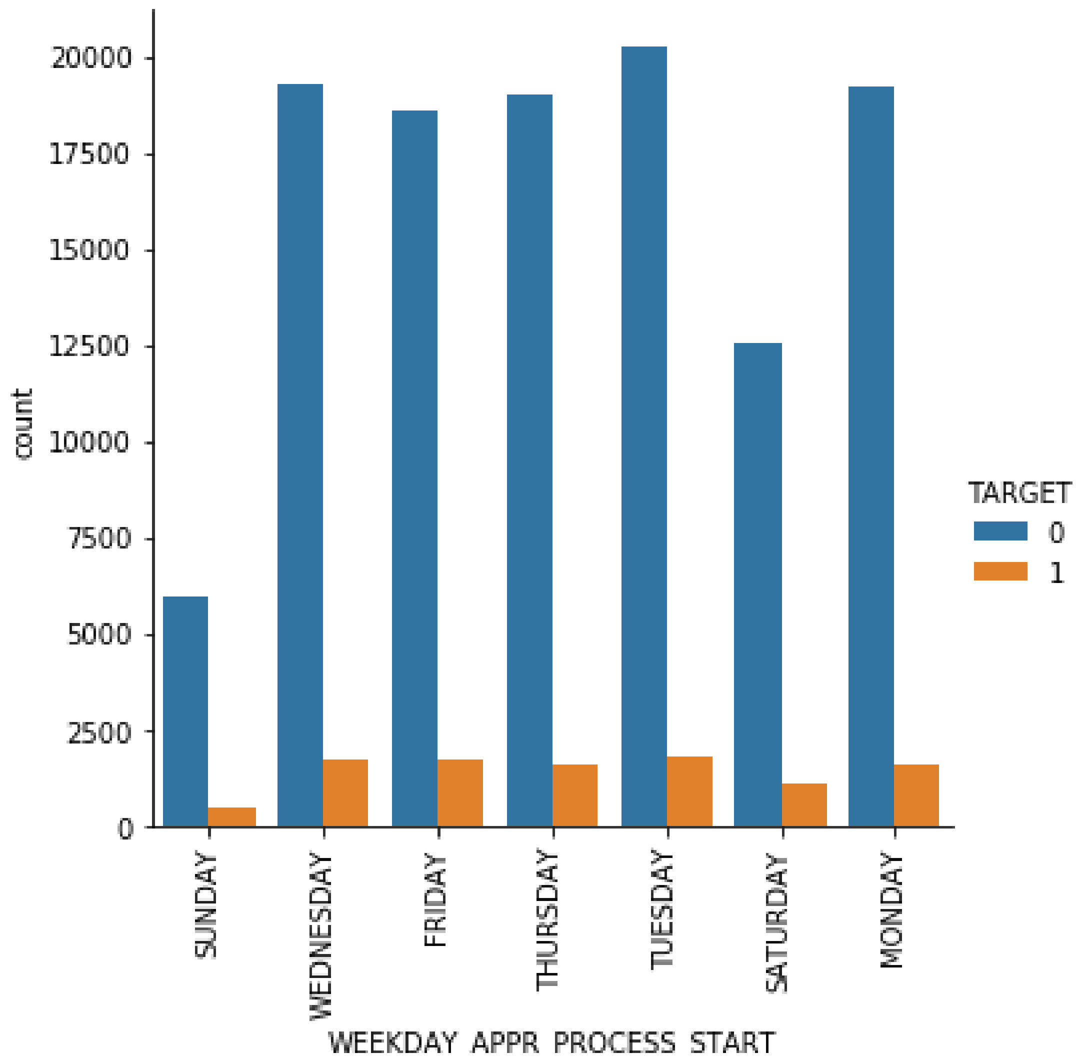


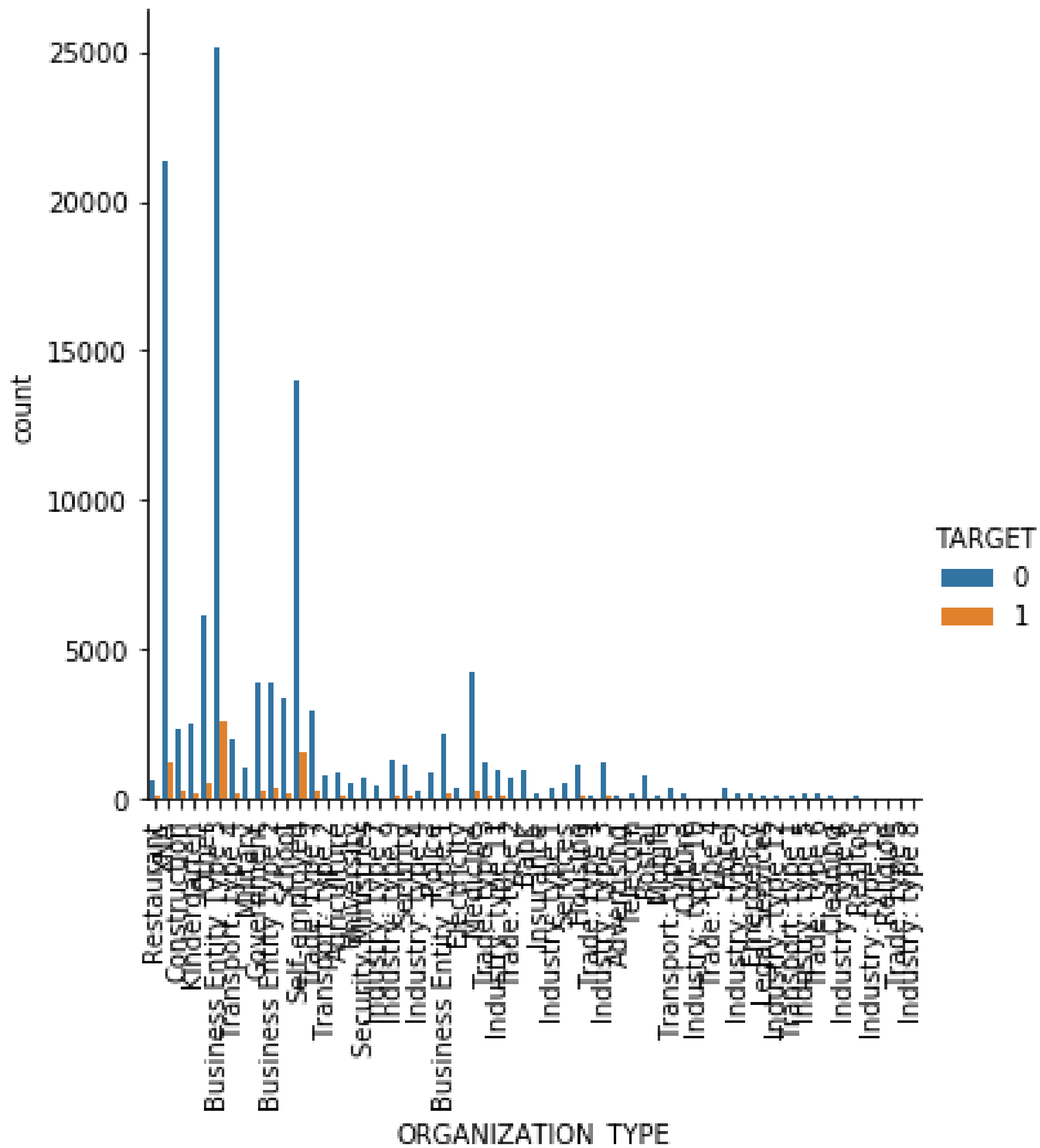
count
70000
60000
50000
40000
30000
20000
10000
0
Separated
Widow
Married
Single / not married
Civil marriage
Unknown
NAME_FAMILY_STATUS
TARGET
0
1



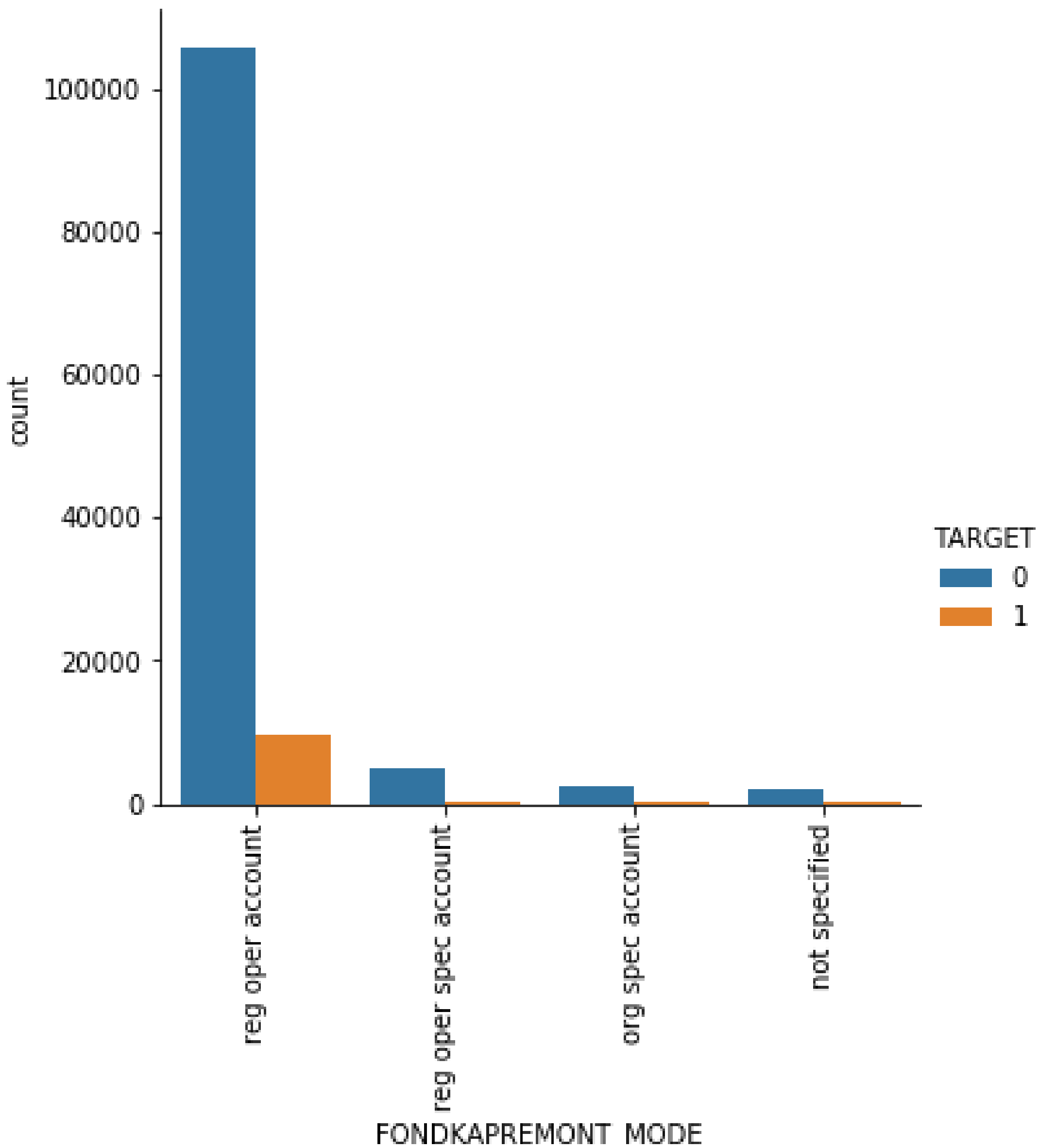
count
100000
80000
60000
40000
20000
0
TARGET
0
1
House / apartment
With parents
Municipal apartment
Office apartment
Rented apartment
Co-op apartment
NAME_HOUSING_TYPE

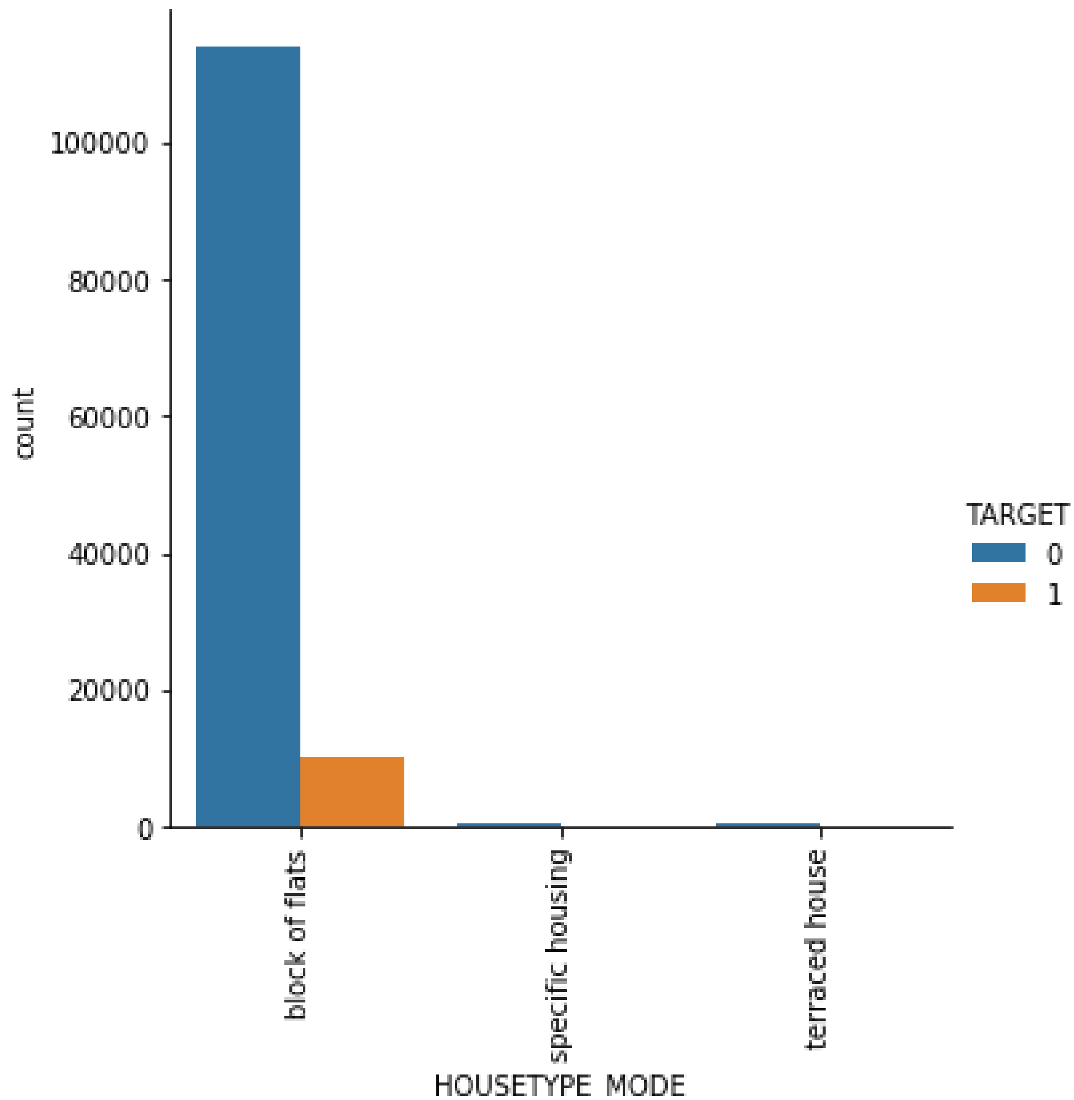

count
50000
40000
30000
20000
10000
0
TARGET
0
1
Core staff
Laborers
Medicine staff
Accountants
Managers
Drivers
Sales staff
Cleaning staff
Security staff
Low-skill Laborers
High skill tech staff
Cooking staff
Private service staff
Waiters/barmen staff
Secretaries
HR staff
IT staff
Realty agents
OCCUPATION_TYPE

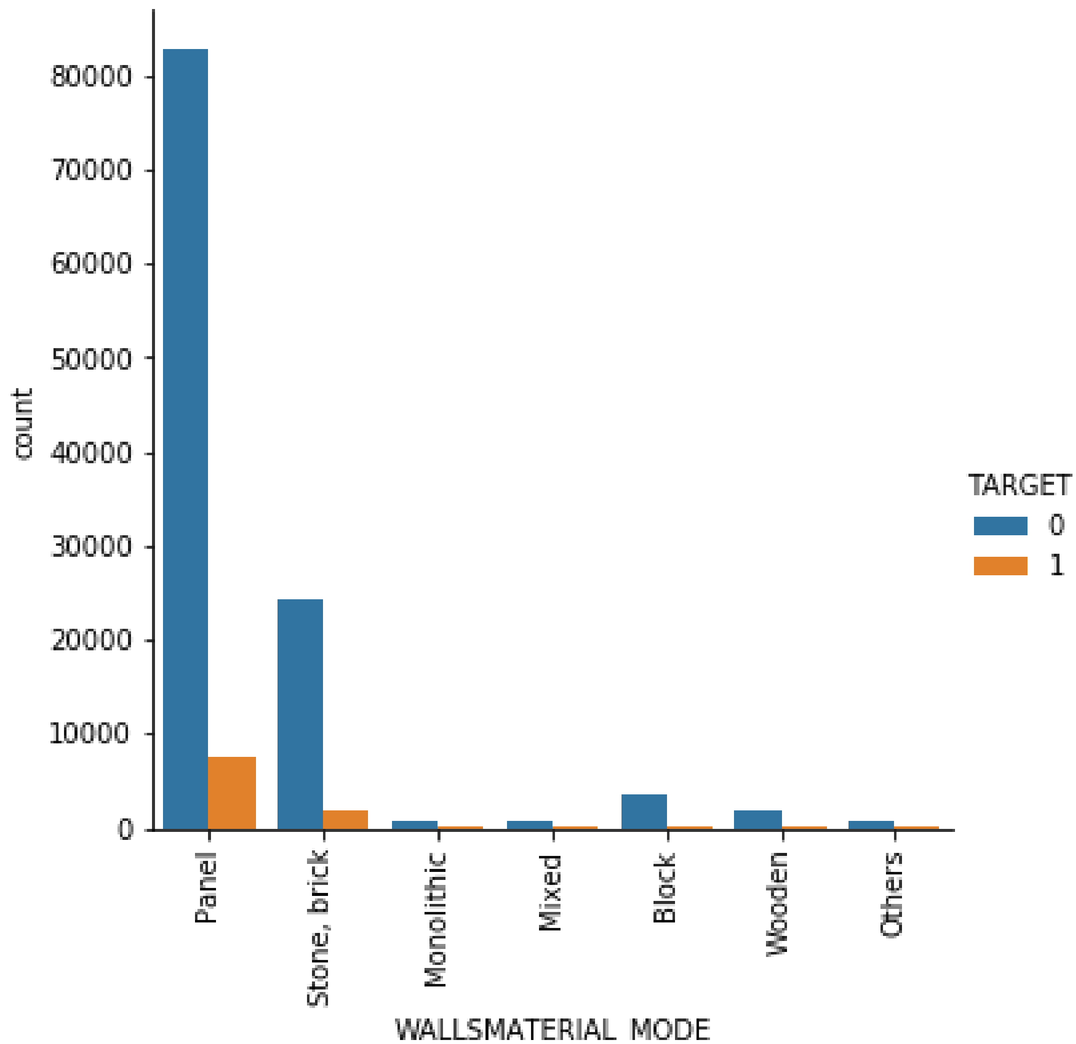

count
20000
17500
15000
12500
10000
7500
5000
2500
0
SUNDAY
WEDNESDAY
FRIDAY
THURSDAY
TUESDAY
SATURDAY
MONDAY
WEEKDAY_APPR_PROCESS_START
TARGET
0
1



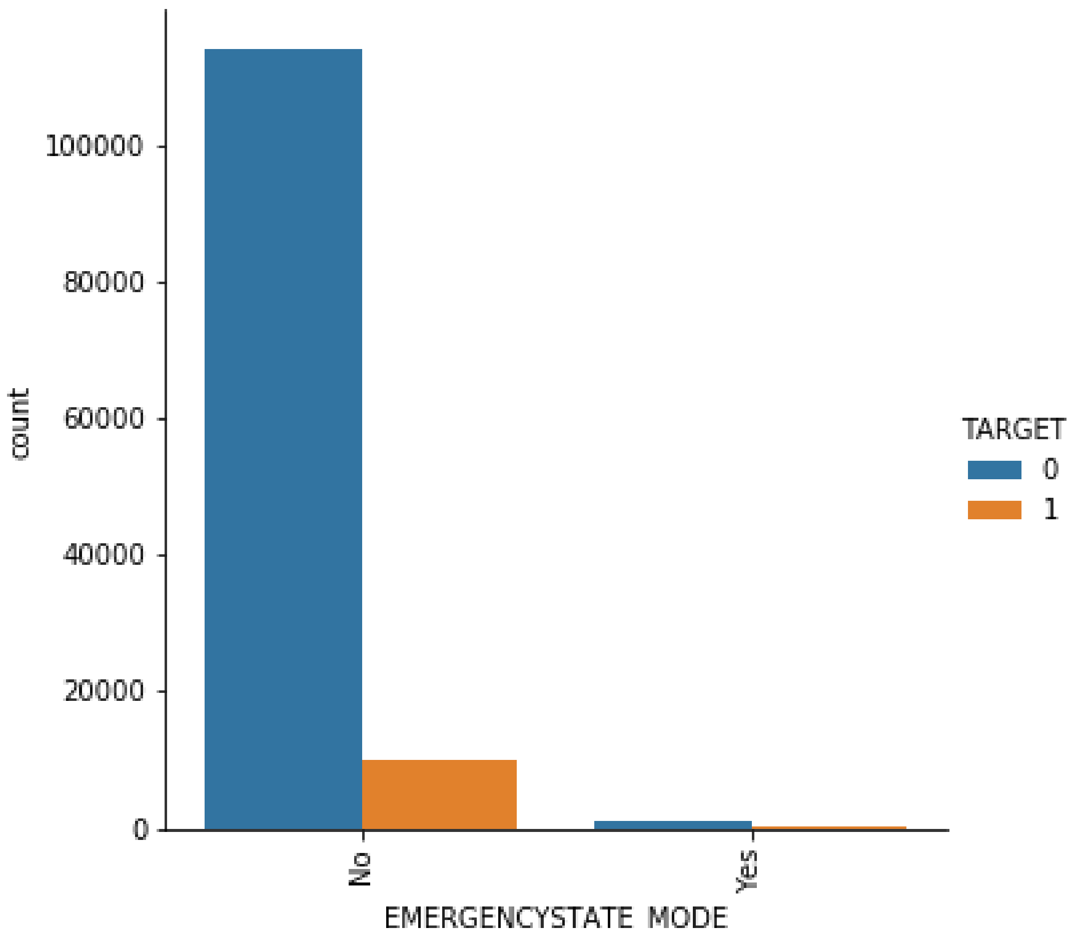
25000
20000
15000
10000
5000
0
count
ORGANIZATION_TYPE
TARGET
0
1


100000
80000
60000
40000
20000
0
count
TARGET
0
1
reg oper account
reg oper spec account
org spec account
not specified
FONDKAPREMONT_MODE


count
100000
80000
60000
40000
20000
0
block of flats
specific housing
terraced house
HOUSETYPE_MODE
TARGET
0
1



80000
70000
60000
50000
40000
30000
20000
10000
0
count
TARGET
0
1
Panel
Stone, brick
Monolithic
Mixed
Block
Wooden
Others
WALLSMATERIAL_MODE



Missing Value

[92]:
```
features=list(train.columns)
columns_to_drop=[]
for column in features:
    missing_prcntg=round(train[column].isnull().sum()/len(train),2)
    if missing_prcntg >= .6 :
        print (column+' - '+str(missing_prcntg))
        columns_to_drop.append(str(column))
print(len(columns_to_drop))
```

```
OWN_CAR_AGE - 0.66
YEARS_BUILD_AVG - 0.66
COMMONAREA_AVG - 0.7
FLOORSMIN_AVG - 0.68
LIVINGAPARTMENTS_AVG - 0.68
NONLIVINGAPARTMENTS_AVG - 0.69
YEARS_BUILD_MODE - 0.66
```

```
COMMONAREA_MODE - 0.7
FLOORSMIN_MODE - 0.68
LIVINGAPARTMENTS_MODE - 0.68
NONLIVINGAPARTMENTS_MODE - 0.69
YEARS_BUILD_MEDI - 0.66
COMMONAREA_MEDI - 0.7
FLOORSMIN_MEDI - 0.68
LIVINGAPARTMENTS_MEDI - 0.68
NONLIVINGAPARTMENTS_MEDI - 0.69
16
```

What we can observe from EDA For 16 columns missing value percentage is more than 60% If we change to 50% then we can see for 41 columns. Missing value percentage is very high Among the neumerical variables , DAYS_BIRTH is showing the highest corelation with TARGET. This distribution is also normal REGION_RATING_CLIENT_W_CITY and REGION_RATING_CLIENT -these two fields are showing good correlation with target. But their distribution is very unusual and need more data analysis for this fields DAYS_LAST_PHONE_CHANGE is right skewed distribution and that is expected For better understanding of numerical variables, more analysis required For all categorical variables, we can see more TARGET 0 than 1 and it is expected as ratio of TARGET 0 to TARGET 1 is 92:8 Some iteresting observations- for example, CODE_GENDER ratio of TARGET 1 to 0, is more for 'M' than 'W'. For NAME_EDUCATION_TYPE , 'Secondary' has more TARGET 1 to 0 ratio than other categories for NAME_TYPE_SUITE, 'Unaccompanied' has more TARGET 1 to 0 ratio In general, some interesting observation, we can find from EDA but more in depth EDA required for better understanding of the data

0.0.4 Phase 1 Modeling

Missing Value Imputation

First of all, we will drop features more than 60% null value

[93]:
```
numerical_features=list(set(numerical_features)-set(columns_to_drop))
```

Neumerical features missing values will be replaced by mean of that column

[94]:
```
train[numerical_features]=train[numerical_features].
↪fillna(train[numerical_features].mean())
```

[95]:
```
test[numerical_features]=test[numerical_features].
↪fillna(test[numerical_features].mean())
```

Categorical Features missing values will be replaced by most frequest observation

[96]:
```
categorical_features=list(set(categorical_features)-set(columns_to_drop))
```

[98]:
```
imp_mean = SimpleImputer( strategy='most_frequent')
imp_mean.fit(train[categorical_features])
train[categorical_features] = imp_mean.transform(train[categorical_features])
imp_mean.fit(test[categorical_features])
test[categorical_features] = imp_mean.transform(test[categorical_features])
```

[99]:
```
reduce_train=train[list(set(features)-set(columns_to_drop))]
reduce_train=pd.get_dummies(reduce_train)
reduce_train.shape
```

[99]: (125000, 230)

[100]:
```
reduce_test=test[list(set(features)-set(columns_to_drop)-{'TARGET'})]
reduce_test=pd.get_dummies(reduce_test)
reduce_test.shape
```

[100]: (48744, 226)

There are some features in train but not in test. We will drop any feature if not in test

[101]:
```
features=list(set(reduce_test.columns)|{'TARGET'})
reduce_train=reduce_train[features]
reduce_train.shape
```

[101]: (125000, 227)

Is there any useless feature ?

[102]:
```
[features[i] for i in range(len(features)) if reduce_train[features[i]].
 ↪mean()==0]
```

[102]: []

If two numerical features have corelation coefficient > .99 we will drop one of them

[118]:
```
to_reduce=[]
for feat_a in numerical_features:
    for feat_b in numerical_features:
        if feat_a != feat_b and feat_a not in to_reduce and feat_b not in␣
 ↪to_reduce:
            c = np.corrcoef(train[feat_a], train[feat_b])[0][1]
            if c > 0.99:
                to_reduce.append(feat_b)
```

[119]:
```
to_reduce
```

[119]: []

Check if any missing value exist

```
[104]: [list(reduce_train.columns)[i] for i in range(len(reduce_train.columns)) if \
            reduce_train[list(reduce_train.columns)[0]].isnull().values.any()==True]
```

[104]: []

```
[105]: [list(reduce_test.columns)[i] for i in range(len(reduce_test.columns)) if \
             reduce_test[list(reduce_test.columns)[0]].isnull().values.any()==True]
```

[105]: []

0.0.5 Model preparation

```
[106]: reduce_train=reduce_train.set_index(['SK_ID_CURR'])
reduce_test=reduce_test.set_index(['SK_ID_CURR'])
```

For final evaluation of different models , seperating 10% of data

```
[107]: indices=reduce_train.index.values
labels = np.array(reduce_train['TARGET'])
model_features= reduce_train.drop('TARGET', axis = 1)
model_features = np.array(model_features)
train_features, eval_features, train_labels, eval_labels,idx_train,idx_eval = \
            train_test_split(model_features, labels,indices, test_size = 0.1,␣
 ↪random_state = 42)
```

Base Model - Logistic regression

```
[108]: clf = LogisticRegression(random_state=0).fit(train_features, train_labels)
```

Let's define two functions for getting different metrices for score and error analysis later

```
[109]: def get_roc_curve_auc(model,features,labels):
    """ This function will take model, features and prediction labels and
    produce ROC curve with AUC value for train,eval data sets"""
    probs = model.predict_proba(features)
    preds = probs[:,1]
    fpr, tpr, threshold = metrics.roc_curve(labels, preds)
    roc_auc = metrics.auc(fpr, tpr)

    plt.title('Receiver Operating Characteristic')
```

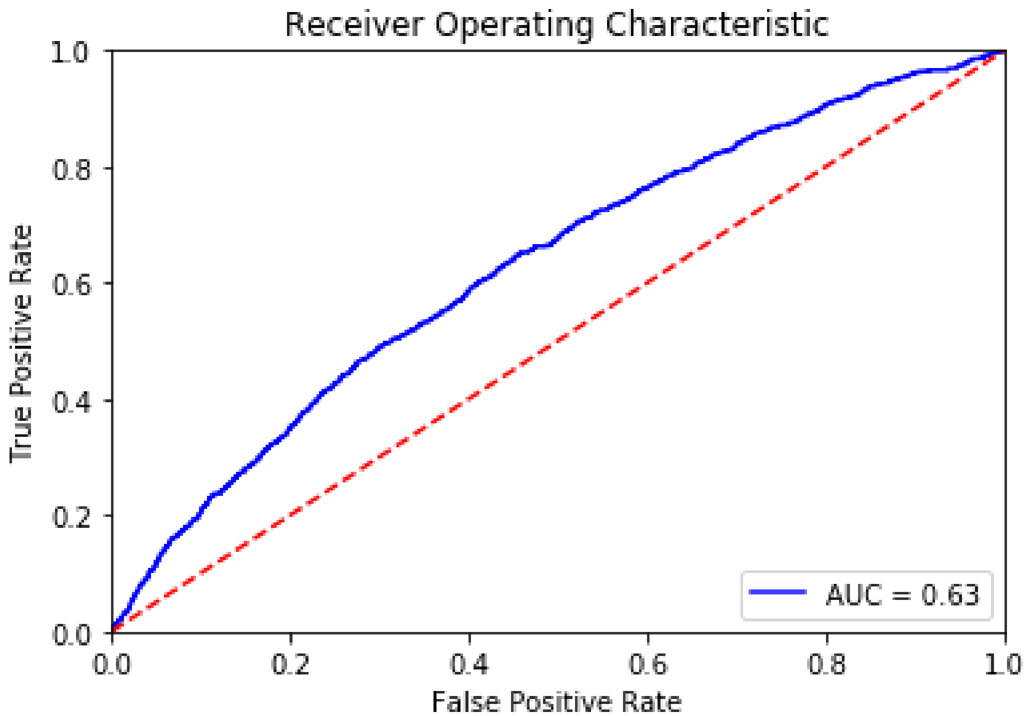
```
    plt.plot(fpr, tpr, 'b', label = 'AUC = %0.2f' % roc_auc)
    plt.legend(loc = 'lower right')
    plt.plot([0, 1], [0, 1],'r--')
    plt.xlim([0, 1])
    plt.ylim([0, 1])
    plt.ylabel('True Positive Rate')
    plt.xlabel('False Positive Rate')
    plt.show()
```

[110]:
```
def get_accuracy_for_target1_for_thresold(model,features,labels,thresold):
    """ Purpose of this function is to check accuracy when TARGET 1 with
        overall accuracy,FP,FN for given thresold also to see data for error␣
 ↪analysis
        input - model (random forest,xgboost etc.)
        features and labels (train,eval,test etc) and thresold
        output- accuracy for target 1,overall accuracy,FP,FN"""
    df_ana=pd.DataFrame(list(zip(model.predict_proba(features)[:,0],\
                    model.predict_proba(features)[:,1],labels)),\
                    columns=['prob_0','prob_1','true'])
    # check accuracy when true label=1
    df_ana_1=df_ana[df_ana['true']==1]
    df_ana_1['prob_1_thrshold']=np.where(df_ana_1['prob_1']>thresold,1,0)
    print('accuracy for target=1 :  '+ str(df_ana_1['prob_1_thrshold'].sum()/
 ↪df_ana_1.shape[0]))

    df_ana['prob_1_thrshold']=np.where(df_ana['prob_1']>thresold,1,0)

    print('accuracy  : '+str(df_ana[df_ana['prob_1_thrshold']==\
                                      df_ana['true']].shape[0]/df_ana.shape[0]))
   print('FP : '+str(df_ana[(df_ana['prob_1_thrshold']==1)&(df_ana['true']==0)]\
                                          .shape[0]/df_ana.shape[0]))
   print('FN : '+str(df_ana[(df_ana['prob_1_thrshold']==0)&(df_ana['true']==1)]\
                    .shape[0]/df_ana.shape[0]))
```

[111]:
```
get_roc_curve_auc(clf,eval_features,eval_labels)
```



[113]:
```
get_accuracy_for_target1_for_thresold(clf,train_features,train_labels,.1)
```

```
accuracy for target=1 :  0.45766041030117854
accuracy  : 0.6938044444444444
FP : 0.2620177777777778
FN : 0.0441777777777778
```

[112]:
```
get_accuracy_for_target1_for_thresold(clf,eval_features,eval_labels,.1)
```

```
accuracy for target=1 :  0.4716202270381837
accuracy  : 0.69448
FP : 0.26456
FN : 0.04096
```

Conclusion from base model Base model accuracy apparently not too bad . But we have 90% TARGET 0, that means without doing any modeling if we put 0 for all target still overall accuracy will be 90%. That is why we are interested to know accuracy for TARGET 1. We can see here FP is really high if we lower thresold to .1. Good part is that not much difference in traing and evaluation performance,i.e. not much overfitting Let's try some ensemble methods

Random Forest

We will run extensive grid search for pypermeter tuning to get best Random Forest(RF) model

All models will be cross validated (CV)

In the code below, I ran 36 models (total 180) including CV took around 1 hr in local machine

[255]:
```
%%time
forest = RandomForestClassifier()
n_estimators = [50,200,500]
max_depth = [3,5,10]
min_samples_split = [2,5]
min_samples_leaf = [1,3]

hyperF = dict(n_estimators = n_estimators, max_depth = max_depth,
              min_samples_split = min_samples_split,
             min_samples_leaf = min_samples_leaf)

gridF = GridSearchCV(forest, hyperF, cv = 5, verbose = 1, n_jobs = -1)
bestF = gridF.fit(train_features, train_labels)
print(bestF.best_params_)
```

```
Fitting 5 folds for each of 36 candidates, totalling 180 fits
```

```
[Parallel(n_jobs=-1)]: Using backend LokyBackend with 4 concurrent workers.
[Parallel(n_jobs=-1)]: Done  42 tasks      | elapsed:  7.5min
[Parallel(n_jobs=-1)]: Done 180 out of 180 | elapsed: 56.5min finished
```

```
{'max_depth': 3, 'min_samples_leaf': 1, 'min_samples_split': 2, 'n_estimators':
50}
CPU times: user 5.68 s, sys: 466 ms, total: 6.15 s
Wall time: 56min 36s
```

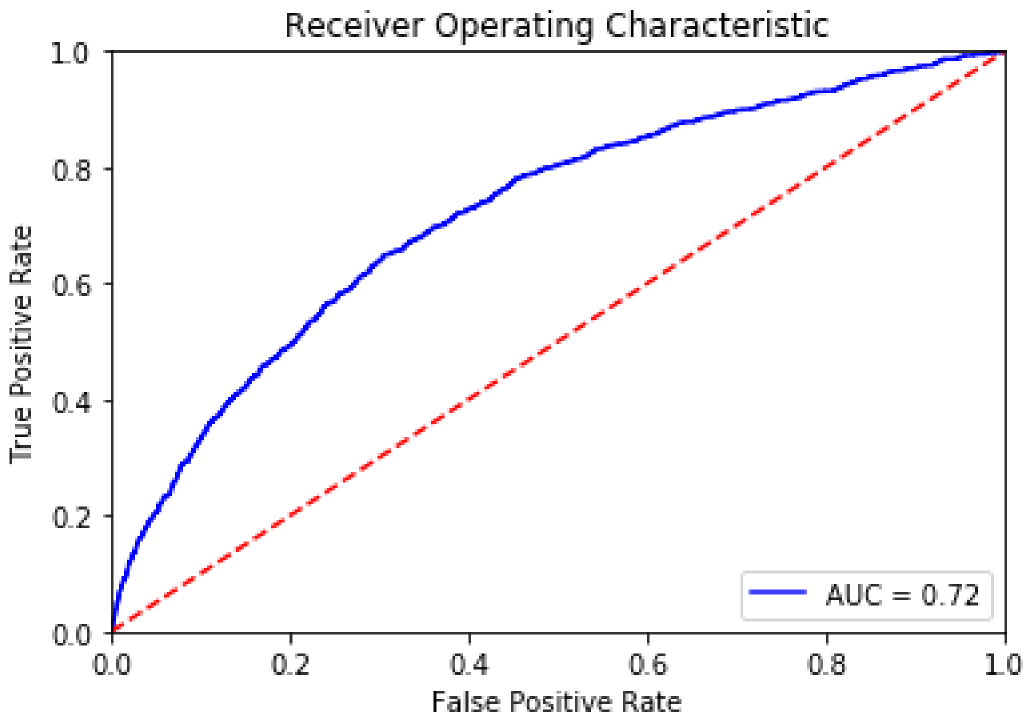
[256]:
```
bestF.best_params_
```

[256]:
```
{'max_depth': 3,
 'min_samples_leaf': 1,
 'min_samples_split': 2,
 'n_estimators': 50}
```

Best RF model and check performance in evaluation data set

[114]:
```
rf_model = RandomForestClassifier(random_state = 1,
                                  n_estimators=50,
                                  max_depth = 3,
                                  min_samples_split = 2,
                                  min_samples_leaf = 1)
```

```
rf_model.fit(train_features, train_labels)
get_roc_curve_auc(rf_model,eval_features,eval_labels)
```




```
[121]: print(get_accuracy_for_target1_for_thresold(rf_model,train_features,train_labels,.
        ↪1))
       print(get_accuracy_for_target1_for_thresold(rf_model,eval_features,eval_labels,.
        ↪1))
```

```
accuracy for target=1 :  0.39426014840680923
accuracy  : 0.8307377777777778
FP : 0.11992
FN : 0.049342222222222225
None
accuracy for target=1 :  0.3993808049535604
accuracy  : 0.82968
FP : 0.12376
FN : 0.04656
None
```

Conclusion from RF RF has significant improvement over Base model(Logistic Regression). AUC is now .72 instead of .63 But for lower thresold .1 we can see accuracy for target=1 is 40% which is not good <br. Another observation, the best model found has maximum depth 3 and number of estimators 50 which is not usual But FP has lowered and not overfitting

0.0.6 xgboost

Now Extensive random search for XGBoost. As XGBoost is very expensive instead of grid search we are doing random search

Total running time is 2 hrs 20 min in local machine

[287]:
```
params = {
        'min_child_weight': [1, 5, 10],
        'gamma': [0.5, 1, 1.5, 2, 5],
        'subsample': [0.6, 0.8, 1.0],
        'colsample_bytree': [0.6, 0.8, 1.0],
        'max_depth': [3, 4, 5]
        }
```

[288]:
```
xgb = XGBClassifier(learning_rate=0.01, n_estimators=600, objective='binary:
 ↪logistic',silent=True, nthread=1)
```

[289]:
```
%%time
folds = 5
param_comb = 5

Y = train_labels
X = train_features

skf = StratifiedKFold(n_splits=folds, shuffle = True, random_state = 1001)
random_search = RandomizedSearchCV(xgb, param_distributions=params, \
                    n_iter=param_comb, scoring='roc_auc', n_jobs=4, cv=skf.
 ↪split(X,Y), verbose=3, random_state=1001 )
random_search.fit(X, Y)
```

```
Fitting 5 folds for each of 5 candidates, totalling 25 fits

[Parallel(n_jobs=4)]: Using backend LokyBackend with 4 concurrent workers.
[Parallel(n_jobs=4)]: Done  25 out of  25 | elapsed: 126.0min finished

CPU times: user 13min 36s, sys: 2.67 s, total: 13min 39s
Wall time: 2h 19min 40s
```

[289]:
```
RandomizedSearchCV(cv=<generator object _BaseKFold.split at 0x118b3e7d0>,
                   error_score='raise-deprecating',
                   estimator=XGBClassifier(base_score=0.5, booster='gbtree',
                                           colsample_bylevel=1,
                                           colsample_bynode=1,
                                           colsample_bytree=1, gamma=0,
                                           learning_rate=0.01, max_delta_step=0,
                                           max_depth=3, min_child_weight=1,
                                           missing=None, n_estimators=600,
```

```
                                    n_jobs=1, nthread=1,
                                    objective='…
                                    reg_lambda=1, scale_pos_weight=1,
                                    seed=None, silent=True, subsample=1,
                                    verbosity=1),
                   iid='warn', n_iter=5, n_jobs=4,
                   param_distributions={'colsample_bytree': [0.6, 0.8, 1.0],
                                        'gamma': [0.5, 1, 1.5, 2, 5],
                                        'max_depth': [3, 4, 5],
                                        'min_child_weight': [1, 5, 10],
                                        'subsample': [0.6, 0.8, 1.0]},
                   pre_dispatch='2*n_jobs', random_state=1001, refit=True,
                   return_train_score=False, scoring='roc_auc', verbose=3)
```

[291]:
```
print('\n Best estimator:')
print(random_search.best_estimator_)
print('\n Best normalized gini score for %d-fold search with %d parameter␣
 ↪combinations:' % (folds, param_comb))
print(random_search.best_score_ * 2 - 1)
print('\n Best hyperparameters:')
print(random_search.best_params_)
```

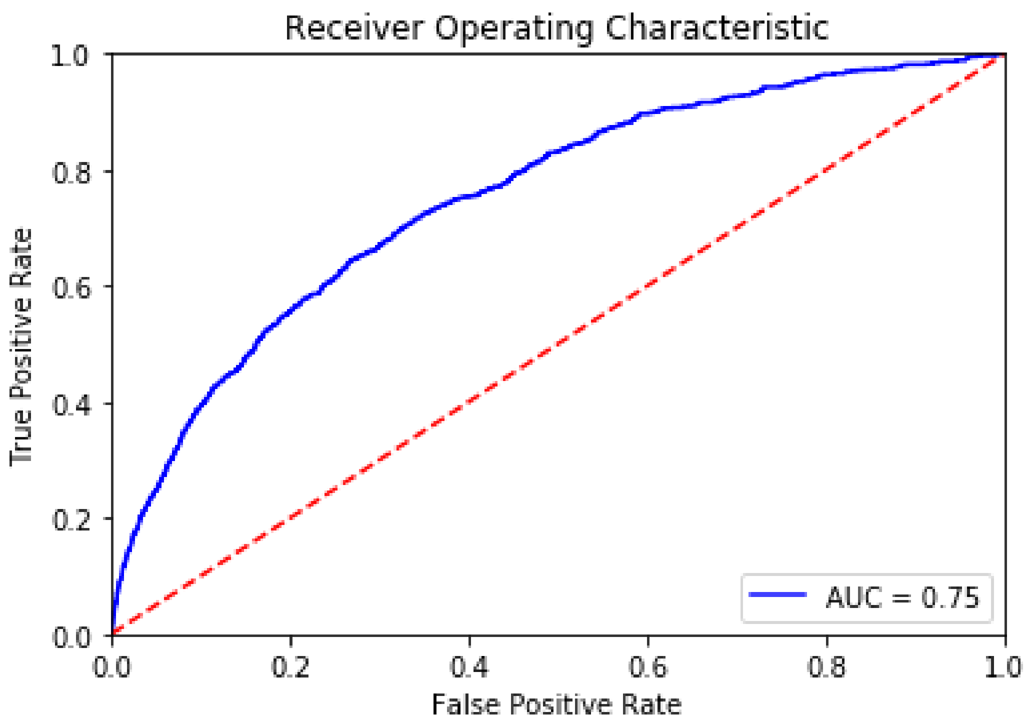
```
 Best estimator:
XGBClassifier(base_score=0.5, booster='gbtree', colsample_bylevel=1,
              colsample_bynode=1, colsample_bytree=0.8, gamma=1.5,
              learning_rate=0.01, max_delta_step=0, max_depth=5,
              min_child_weight=1, missing=None, n_estimators=600, n_jobs=1,
              nthread=1, objective='binary:logistic', random_state=0,
              reg_alpha=0, reg_lambda=1, scale_pos_weight=1, seed=None,
              silent=True, subsample=0.6, verbosity=1)

 Best normalized gini score for 5-fold search with 5 parameter combinations:
0.4995718372005442

 Best hyperparameters:
{'subsample': 0.6, 'min_child_weight': 1, 'max_depth': 5, 'gamma': 1.5,
'colsample_bytree': 0.8}
```

[123]:
```
%%time
xgb_model= XGBClassifier(base_score=0.5, booster='gbtree', colsample_bylevel=1,
              colsample_bynode=1, colsample_bytree=0.8, gamma=1.5,
              learning_rate=0.01, max_delta_step=0, max_depth=5,
              min_child_weight=1, missing=None, n_estimators=600, n_jobs=1,
              nthread=1, objective='binary:logistic', random_state=0,
              reg_alpha=0, reg_lambda=1, scale_pos_weight=1, seed=None,
              silent=True, subsample=0.6, verbosity=1)
```

```
xgb_model.fit(train_features,train_labels)
get_roc_curve_auc(xgb_model,eval_features,eval_labels)
```




```
CPU times: user 13min 51s, sys: 2.3 s, total: 13min 54s
Wall time: 13min 57s
```

[124]:
```
print(get_accuracy_for_target1_for_thresold(xgb_model,train_features,train_labels,.
  ↪1))
print(get_accuracy_for_target1_for_thresold(xgb_model,eval_features,eval_labels,.
  ↪1))
```

```
accuracy for target=1 :  0.6457878655608904
accuracy  : 0.7592888888888889
FP : 0.21185777777777778
FN : 0.028853333333333335
None
accuracy for target=1 :  0.5954592363261094
accuracy  : 0.7524
FP : 0.21624
FN : 0.03136
None
```

Conclusion from Phase 1 Starting from AUC .62 at Base model, RF and finally XGBoost showing significant development to AUC .75 But still model is not doing very good job in capturing TARGET 1 When we are getting better accuracy for TARGET 1, FP is also getting high or vice -versa Too much missing value could be a problem, let's try better method for missing value imputation

0.0.7 Phase 2

Approach This time we will use Multivariate Imputation of Chained Equation (MICE) for numerical variable For categorical variables (much less than numerical variables in this data set), we stay with same method as before

[126]:
```
features=list(train.columns)
numerical_features=[features[i] for i in range(len(features)) \
                     if ((train[features[i]].
↪dtypes=='float64')|(train[features[i]].dtypes=='int64')) and \
                            features[i]!='TARGET']
```

[127]:
```
%%time
MICE_imputer = IterativeImputer()
train_MICE = train[numerical_features].copy(deep=True)
train_MICE.iloc[:, :] = MICE_imputer.fit_transform(train_MICE)
```

```
CPU times: user 5min 33s, sys: 18.9 s, total: 5min 52s
Wall time: 2min 59s
```

[128]:
```
%%time
test_MICE = test[numerical_features].copy(deep=True)
test_MICE.iloc[:, :] = MICE_imputer.fit_transform(test_MICE)
```

```
CPU times: user 2min 14s, sys: 9.94 s, total: 2min 24s
Wall time: 1min 4s
```

[129]:
```
imp_mean = SimpleImputer( strategy='most_frequent')
imp_mean.fit(train[categorical_features])
train[categorical_features] = imp_mean.transform(train[categorical_features])
imp_mean.fit(test[categorical_features])
test[categorical_features] = imp_mean.transform(test[categorical_features])
```

[130]:
```
reduce_train=pd.
↪concat([train_MICE,train[list(set(categorical_features)|{'TARGET'})]],axis=1)
```

[131]:
```
reduce_test=pd.concat([test_MICE,test[categorical_features]],axis=1)
```

[132]:
```
print(reduce_train.shape)
print(reduce_test.shape)
```

```
(125000, 122)
(48744, 121)
```

[133]:
```
reduce_train=pd.get_dummies(reduce_train)
reduce_test=pd.get_dummies(reduce_test)
```

[134]:
```
reduce_train=reduce_train[list(set(list(reduce_test.columns))|{'TARGET'})]
```

[191]:
```
reduce_train.shape
```

[191]:
```
(125000, 243)
```

[192]:
```
reduce_test.shape
```

[192]:
```
(48744, 242)
```

[281]:
```
to_exclude=[]
test_features=list(reduce_test.columns)
for i in range(len(test_features)):
    adjust_factor=reduce_train[test_features[i]].mean()/
 ↪reduce_test[test_features[i]].mean()
    if (adjust_factor > 10) or (adjust_factor < .1) :
        to_exclude.append(test_features[i])
    else:
        reduce_test[test_features[i]] *=adjust_factor
```

[284]:
```
test_features=list(set(test_features)-set(to_exclude))
```

[284]:
```
227
```

[285]:
```
reduce_train=reduce_train[list(set(test_features)|{'TARGET'})]
reduce_train.shape
```

[285]:
```
(125000, 228)
```

[286]:
```
reduce_test=reduce_test[test_features]
reduce_test.shape
```

[286]:
```
(48744, 227)
```

Checking if everything is right

[135]:
```
set(list(reduce_train.columns))-set(list(reduce_test.columns))
```

[135]:
```
{'TARGET'}
```

[136]:
```
[list(reduce_train.columns)[i] for i in range(len(reduce_train.columns)) if \
        reduce_train[list(reduce_train.columns)[i]].isnull().values.any()==True]
```

[136]: []

[137]:
```
[list(reduce_test.columns)[i] for i in range(len(reduce_test.columns)) if \
         reduce_test[list(reduce_test.columns)[i]].isnull().values.any()==True]
```

[137]: []

Model preperation as before

[291]:
```
reduce_train=reduce_train.set_index(['SK_ID_CURR'])
reduce_test=reduce_test.set_index(['SK_ID_CURR'])
indices=reduce_train.index.values
labels = np.array(reduce_train['TARGET'])
model_features= reduce_train.drop('TARGET', axis = 1)
model_features = np.array(model_features)
train_features, eval_features, train_labels, eval_labels,idx_train,idx_eval = \
            train_test_split(model_features, labels,indices, test_size = 0.1,␣
 ↪random_state = 42)
```

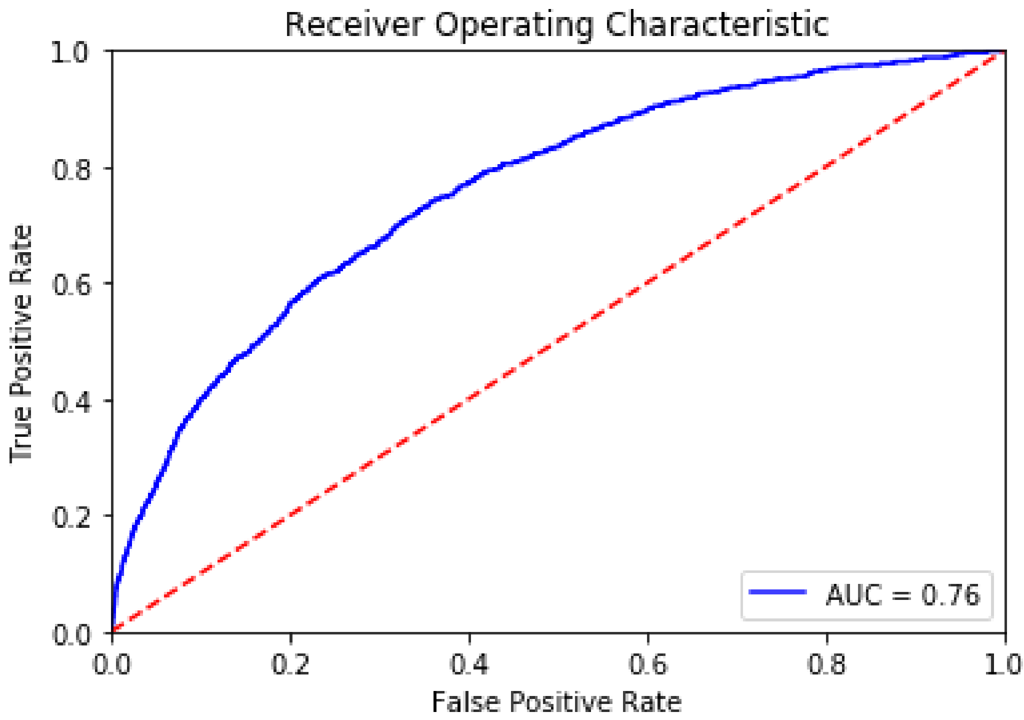
Best XGB model from Phase 1

[292]:
```
%%time
xgb_model = XGBClassifier(base_score=0.5, booster='gbtree', colsample_bylevel=1,
              colsample_bynode=1, colsample_bytree=0.8, gamma=1.5,
              learning_rate=0.02, max_delta_step=0, max_depth=5,
              min_child_weight=1, missing=None, n_estimators=600, n_jobs=1,
              nthread=1, objective='binary:logistic', random_state=0,
              reg_alpha=0, reg_lambda=1, scale_pos_weight=1, seed=None,
              silent=True, subsample=0.6, verbosity=1)
xgb_model.fit(train_features, train_labels)
```

```
CPU times: user 17min 6s, sys: 9.63 s, total: 17min 16s
Wall time: 21min 50s
```

[292]:
```
XGBClassifier(base_score=0.5, booster='gbtree', colsample_bylevel=1,
              colsample_bynode=1, colsample_bytree=0.8, gamma=1.5,
              learning_rate=0.02, max_delta_step=0, max_depth=5,
              min_child_weight=1, missing=None, n_estimators=600, n_jobs=1,
              nthread=1, objective='binary:logistic', random_state=0,
              reg_alpha=0, reg_lambda=1, scale_pos_weight=1, seed=None,
              silent=True, subsample=0.6, verbosity=1)
```

[309]:
```
get_roc_curve_auc(xgb_model,eval_features,eval_labels)
```



[294]:
```
get_accuracy_for_target1_for_thresold(xgb_model,eval_features,eval_labels,0.1)
```

```
accuracy for target=1 :  0.6037151702786377
accuracy  : 0.75664
FP : 0.21264
FN : 0.03072
```

[295]:
```
df_top_feature_importance=pd.DataFrame(zip(reduce_train.columns,xgb_model.
 ↪feature_importances_),\
                                       columns=['features','importance'])
df_top_feature_importance.sort_values(by='importance',ascending=False).head(10)
```

[295]:

	features	importance
39	EXT_SOURCE_3	0.024586
36	EXT_SOURCE_2	0.016910
221	ORGANIZATION_TYPE_Transport: type 1	0.011316
193	NAME_HOUSING_TYPE_House / apartment	0.010489
205	WALLSMATERIAL_MODE_Monolithic	0.009039
80	FLAG_DOCUMENT_3	0.008515
96	CODE_GENDER_F	0.008435
30	FLAG_OWN_CAR_N	0.008430
23	NAME_INCOME_TYPE_Working	0.008294
46	CODE_GENDER_M	0.008160

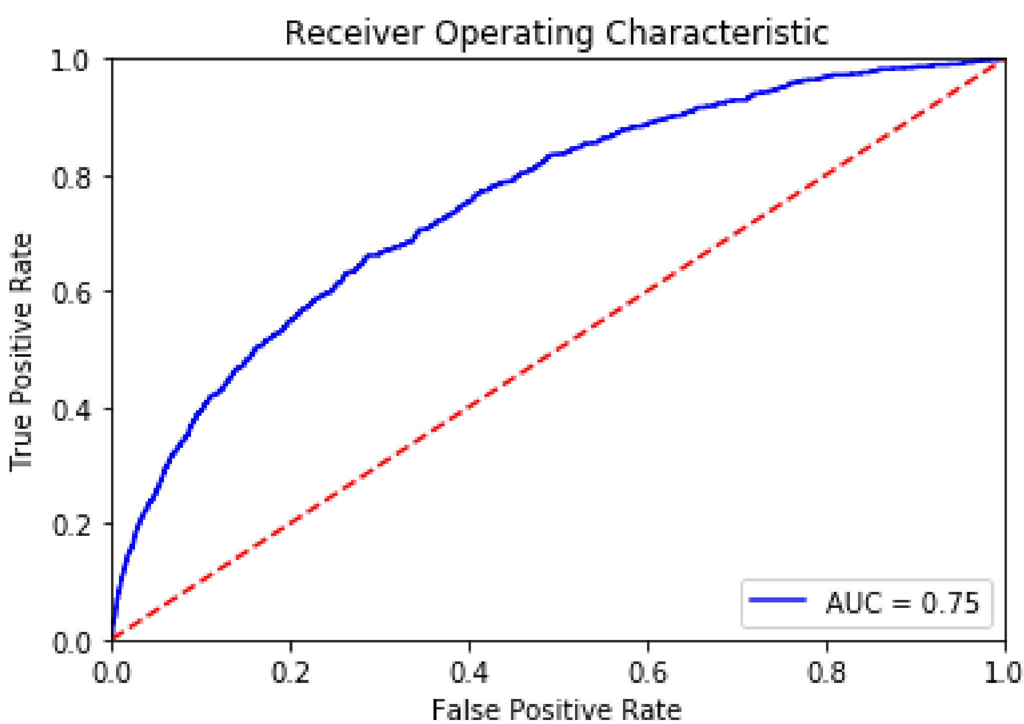
As we have noticed that best xgb_model at max depth 6, let's try max depth 8

[70]:
```
%%time
xgb_model_dpth8 = XGBClassifier(base_score=0.5, booster='gbtree',␣
↪colsample_bylevel=1,
                    colsample_bynode=1, colsample_bytree=0.8, gamma=1.5,
                    learning_rate=0.02, max_delta_step=0, max_depth=8,
                    min_child_weight=1, missing=None, n_estimators=600, n_jobs=1,
                    nthread=1, objective='binary:logistic', random_state=0,
                    reg_alpha=0, reg_lambda=1, scale_pos_weight=1, seed=None,
                    silent=True, subsample=0.6, verbosity=1)
xgb_model_dpth8.fit(train_features, train_labels)
```

```
CPU times: user 24min 46s, sys: 4.5 s, total: 24min 51s
Wall time: 24min 58s
```

[70]:
```
XGBClassifier(base_score=0.5, booster='gbtree', colsample_bylevel=1,
              colsample_bynode=1, colsample_bytree=0.8, gamma=1.5,
              learning_rate=0.02, max_delta_step=0, max_depth=8,
              min_child_weight=1, missing=None, n_estimators=600, n_jobs=1,
              nthread=1, objective='binary:logistic', random_state=0,
              reg_alpha=0, reg_lambda=1, scale_pos_weight=1, seed=None,
              silent=True, subsample=0.6, verbosity=1)
```

[77]:
```
get_roc_curve_auc(xgb_model_dpth8,eval_features,eval_labels)
```



[79]:
```
print(get_accuracy_for_target1_for_thresold(xgb_model_dpth8,eval_features,eval_labels,0.
    ↪1))
print(get_accuracy_for_target1_for_thresold(xgb_model_dpth8,eval_features,eval_labels,0.
    ↪15))
print(get_accuracy_for_target1_for_thresold(xgb_model_dpth8,eval_features,eval_labels,0.
    ↪2))
```

```
accuracy for target=1 :  0.5675954592363261
accuracy  : 0.76952
FP : 0.19696
FN : 0.03352
None
accuracy for target=1 :  0.41382868937048506
accuracy  : 0.85416
FP : 0.1004
FN : 0.04544
None
accuracy for target=1 :  0.29411764705882354
accuracy  : 0.88968
FP : 0.0556
FN : 0.05472
None
```

Conclusion from MICE with XGB After MICE and increasing depth for XGB, we don't see any significant development in model performance We can get 60% accuracy for TARGET 1 but in the cost of 20% FP.If we want to decrease FP we have to comprise in capturing TARGET 1

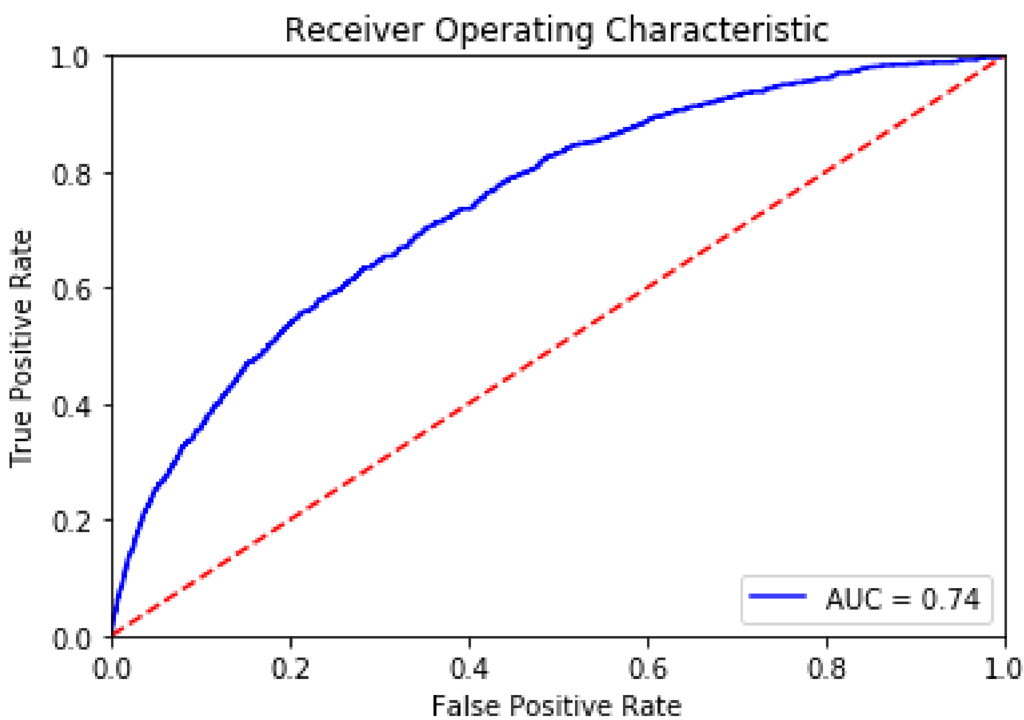
Let's try different approach - LightGBM For limited time we will not do extensive grid search

[229]:
```
X_train, X_valid, Y_train, Y_valid = train_test_split\
                                (train_features, train_labels, random_state=7,␣
    ↪test_size=0.2)
# model
lgb_model = LGBMClassifier(
        n_estimators=2000,
        learning_rate=0.1,
        num_leaves=100,
        colsample_bytree=.8,
        subsample=.9,
        max_depth=15,
        reg_alpha=.1,
        reg_lambda=.1,
        min_split_gain=.01,
        min_child_weight=2
```

```
    )

lgb_model.fit(X_train,Y_train,
            eval_set= [(X_train,Y_train),(X_valid,Y_valid)],
            eval_metric='auc', verbose=200, early_stopping_rounds=100
           )
get_roc_curve_auc(lgb_model,eval_features,eval_labels)
```

```
Training until validation scores don't improve for 100 rounds
Early stopping, best iteration is:
[41]	training's auc: 0.889748	training's binary_logloss: 0.201621
valid_1's auc: 0.744511 valid_1's binary_logloss: 0.250981
```



[267]:
```
print(get_accuracy_for_target1_for_thresold(lgb_model,eval_features,eval_labels,0.
↪1))
```

```
accuracy for target=1 :  0.56656346749226
accuracy  : 0.75664
FP : 0.20976
FN : 0.0336
None
```

Almost same story as XGB. Not much development As we are not getting much development after XGB model with max_depth=5, Final submission will be on this model

Implement on Test and Final Submission

[296]:
```
sample_submission=pd.read_csv(file_path+"/sample_submission.csv")
```

[300]:
```
sample_submission=sample_submission.drop(['TARGET'],axis=1)
```

[305]:
```
sample_submission.columns
```

[305]:
```
Index(['SK_ID_CURR'], dtype='object')
```

[302]:
```
test_indices=reduce_test.index.values
test_features = np.array(reduce_test)
```

[308]:
```
xgb_model.predict_proba
```

[308]:
```
<bound method XGBClassifier.predict_proba of XGBClassifier(base_score=0.5,
booster='gbtree', colsample_bylevel=1,
              colsample_bynode=1, colsample_bytree=0.8, gamma=1.5,
              learning_rate=0.02, max_delta_step=0, max_depth=5,
              min_child_weight=1, missing=None, n_estimators=600, n_jobs=1,
              nthread=1, objective='binary:logistic', random_state=0,
              reg_alpha=0, reg_lambda=1, scale_pos_weight=1, seed=None,
              silent=True, subsample=0.6, verbosity=1)>
```

[310]:
```
df_result=pd.DataFrame(list(zip(test_indices,xgb_model.
 ↪predict_proba(test_features)[:,0],\
                    xgb_model.predict_proba(test_features)[:,1])),\
                    columns=['SK_ID_CURR','prob_0','prob_1'])
df_result['TARGET']=np.where(df_result['prob_1']>.1,1,0)
```

[314]:
```
df_result[df_result['TARGET']==1].shape[0]/df_result.shape[0]
```

[314]:
```
0.3069916297390448
```

[315]:
```
df_result=df_result.drop(['prob_0','prob_1'],axis=1)
```

[316]:
```
sample_submission=pd.merge(sample_submission,df_result,on='SK_ID_CURR')
sample_submission.to_csv('sample_submission.csv', index=False)
```

0.0.8 Conclusion and Future work

In this project, dataset was not very balanced only 8% in one class and rest other class Missing value percentage was also high That suggests,if we make all prediction to zero still model accuracy will be 92% if the distribution in test is same as training set. For some practical cases, for example,fraud capturing TARGET 1 is important, This is why I created another measure for accuracy when TARGET at 1In this work, modeling was started with minimal EDA Primirily missing values were replaced by simple techniques. Base model came with .63 AUC score. AUC is improved to .75 after finding cv,hyperparameter tuning From feature importance point of view one variable EXT_SOURCE_3 is the highest 2% important all other parametrs contributing rest. For improvement of this model, in depth EDA is required to get better understanding of the data Missing value imputation technique, MICE did not work very well Dimension Reduction technique like PCA can be used in next phase Better feature engineering required More hyperparameter tuning and other modeling techniques need to explore Also stalking(ensembling or combining by some percentage) different models, can be useful

[ ]:

```

```