Credit EDA

```
# Importing all the necessary libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

NOTE - Please change the reading directory of the dataset in the below query as per your requirments

```
# Reading dataset from local

df=pd.read_csv(r"C:\Users\Samrat Sinha\Downloads\Credit EDA Case
Study-20190607T183139Z-001\Credit EDA Case Study\
application_data.csv")

# Determining the shape of the datset

df.shape

(307511, 122)

# Cleaning the missing data

# listing the null values columns having more than 30%

emptycol=df.isnull().sum()
emptycol=emptycol[emptycol.values>(0.3*len(emptycol))]
len(emptycol)

64
```

So, there are 64 columns having null values greater than 30% in the dataset

```
# Removing those 64 columns
emptycol = list(emptycol[emptycol.values>=0.3].index)
df.drop(labels=emptycol,axis=1,inplace=True)
print(len(emptycol))

64

# Checking the columns having less null percentage

df.isnull().sum()/len(df)*100

SK_ID_CURR                  0.000000
TARGET                      0.000000
NAME_CONTRACT_TYPE          0.000000
```

CODE_GENDER	0.000000
FLAG_OWN_CAR	0.000000
FLAG_OWN_REALTY	0.000000
CNT_CHILDREN	0.000000
AMT_INCOME_TOTAL	0.000000
AMT_CREDIT	0.000000
AMT_ANNUITY	0.003902
NAME_INCOME_TYPE	0.000000
NAME_EDUCATION_TYPE	0.000000
NAME_FAMILY_STATUS	0.000000
NAME_HOUSING_TYPE	0.000000
REGION_POPULATION_RELATIVE	0.000000
DAYS_BIRTH	0.000000
DAYS_EMPLOYED	0.000000
DAYS_REGISTRATION	0.000000
DAYS_ID_PUBLISH	0.000000
FLAG_MOBIL	0.000000
FLAG_EMP_PHONE	0.000000
FLAG_WORK_PHONE	0.000000
FLAG_CONT_MOBILE	0.000000
FLAG_PHONE	0.000000
FLAG_EMAIL	0.000000
CNT_FAM_MEMBERS	0.000650
REGION_RATING_CLIENT	0.000000
REGION_RATING_CLIENT_W_CITY	0.000000
WEEKDAY_APPR_PROCESS_START	0.000000
HOUR_APPR_PROCESS_START	0.000000
REG_REGION_NOT_LIVE_REGION	0.000000
REG_REGION_NOT_WORK_REGION	0.000000
LIVE_REGION_NOT_WORK_REGION	0.000000
REG_CITY_NOT_LIVE_CITY	0.000000
REG_CITY_NOT_WORK_CITY	0.000000
LIVE_CITY_NOT_WORK_CITY	0.000000
ORGANIZATION_TYPE	0.000000
DAYS_LAST_PHONE_CHANGE	0.000325
FLAG_DOCUMENT_2	0.000000
FLAG_DOCUMENT_3	0.000000
FLAG_DOCUMENT_4	0.000000
FLAG_DOCUMENT_5	0.000000
FLAG_DOCUMENT_6	0.000000
FLAG_DOCUMENT_7	0.000000
FLAG_DOCUMENT_8	0.000000
FLAG_DOCUMENT_9	0.000000
FLAG_DOCUMENT_10	0.000000
FLAG_DOCUMENT_11	0.000000
FLAG_DOCUMENT_12	0.000000
FLAG_DOCUMENT_13	0.000000
FLAG_DOCUMENT_14	0.000000
FLAG_DOCUMENT_15	0.000000

```
FLAG_DOCUMENT_16              0.000000
FLAG_DOCUMENT_17              0.000000
FLAG_DOCUMENT_18              0.000000
FLAG_DOCUMENT_19              0.000000
FLAG_DOCUMENT_20              0.000000
FLAG_DOCUMENT_21              0.000000
dtype: float64
```

So, 'AMT_ANNUITY' columns is having very few null values rows. Hence let's try to impute the missing values

Since this column is having an outlier which is very large it will be inappropriate to fill those missing values with mean, Hence Median comes to rescue for this and we will fill those missing banks with median value

```
# Filling missing values with median

values=df['AMT_ANNUITY'].median()

df.loc[df['AMT_ANNUITY'].isnull(),'AMT_ANNUITY']=values

# Searching for the column for null values

df.isnull().sum()

SK_ID_CURR                    0
TARGET                        0
NAME_CONTRACT_TYPE            0
CODE_GENDER                   0
FLAG_OWN_CAR                  0
FLAG_OWN_REALTY               0
CNT_CHILDREN                  0
AMT_INCOME_TOTAL              0
AMT_CREDIT                    0
AMT_ANNUITY                   0
NAME_INCOME_TYPE              0
NAME_EDUCATION_TYPE           0
NAME_FAMILY_STATUS            0
NAME_HOUSING_TYPE             0
REGION_POPULATION_RELATIVE    0
DAYS_BIRTH                    0
DAYS_EMPLOYED                 0
DAYS_REGISTRATION             0
DAYS_ID_PUBLISH               0
FLAG_MOBIL                    0
FLAG_EMP_PHONE                0
FLAG_WORK_PHONE               0
FLAG_CONT_MOBILE              0
FLAG_PHONE                    0
FLAG_EMAIL                    0
```

```
CNT_FAM_MEMBERS                 2
REGION_RATING_CLIENT            0
REGION_RATING_CLIENT_W_CITY     0
WEEKDAY_APPR_PROCESS_START      0
HOUR_APPR_PROCESS_START         0
REG_REGION_NOT_LIVE_REGION      0
REG_REGION_NOT_WORK_REGION      0
LIVE_REGION_NOT_WORK_REGION     0
REG_CITY_NOT_LIVE_CITY          0
REG_CITY_NOT_WORK_CITY          0
LIVE_CITY_NOT_WORK_CITY         0
ORGANIZATION_TYPE               0
DAYS_LAST_PHONE_CHANGE          1
FLAG_DOCUMENT_2                 0
FLAG_DOCUMENT_3                 0
FLAG_DOCUMENT_4                 0
FLAG_DOCUMENT_5                 0
FLAG_DOCUMENT_6                 0
FLAG_DOCUMENT_7                 0
FLAG_DOCUMENT_8                 0
FLAG_DOCUMENT_9                 0
FLAG_DOCUMENT_10                0
FLAG_DOCUMENT_11                0
FLAG_DOCUMENT_12                0
FLAG_DOCUMENT_13                0
FLAG_DOCUMENT_14                0
FLAG_DOCUMENT_15                0
FLAG_DOCUMENT_16                0
FLAG_DOCUMENT_17                0
FLAG_DOCUMENT_18                0
FLAG_DOCUMENT_19                0
FLAG_DOCUMENT_20                0
FLAG_DOCUMENT_21                0
dtype: int64
```

Now, all columns have been with zero null values

```
# Removing rows having null values greater than or equal to 30%

emptyrow=df.isnull().sum(axis=1)
emptyrow=list(emptyrow[emptyrow.values>=0.3*len(df)].index)
df.drop(labels=emptyrow,axis=0,inplace=True)
print(len(emptyrow))

0

# We will remove unwanted columns from this dataset

unwanted=['FLAG_MOBIL', 'FLAG_EMP_PHONE', 'FLAG_WORK_PHONE',
'FLAG_CONT_MOBILE',
```

```
       'FLAG_PHONE',
'FLAG_EMAIL','REGION_RATING_CLIENT','REGION_RATING_CLIENT_W_CITY','FLA
G_EMAIL','CNT_FAM_MEMBERS', 'REGION_RATING_CLIENT',
       'REGION_RATING_CLIENT_W_CITY','DAYS_LAST_PHONE_CHANGE',
'FLAG_DOCUMENT_2', 'FLAG_DOCUMENT_3','FLAG_DOCUMENT_4',
'FLAG_DOCUMENT_5', 'FLAG_DOCUMENT_6',
       'FLAG_DOCUMENT_7', 'FLAG_DOCUMENT_8',
'FLAG_DOCUMENT_9','FLAG_DOCUMENT_10', 'FLAG_DOCUMENT_11',
'FLAG_DOCUMENT_12',
       'FLAG_DOCUMENT_13', 'FLAG_DOCUMENT_14',
'FLAG_DOCUMENT_15','FLAG_DOCUMENT_16', 'FLAG_DOCUMENT_17',
'FLAG_DOCUMENT_18',
       'FLAG_DOCUMENT_19', 'FLAG_DOCUMENT_20', 'FLAG_DOCUMENT_21']

df.drop(labels=unwanted,axis=1,inplace=True)
```

There are some columns where the value is mentioned as 'XNA' which means 'Not Available'. So we have to find the number of rows and columns and implement suitable techniques on them to fill those missing values or to delete them.

```
# let's find these categorical columns having these 'XNA' values

# For Gender column

df[df['CODE_GENDER']=='XNA'].shape

(4, 28)

# For Organization column

df[df['ORGANIZATION_TYPE']=='XNA'].shape

(55374, 28)
```

So, there are 4 rows from Gender column and 55374 rows from Organization type column

```
# Describing the Gender column to check the number of females and
males

df['CODE_GENDER'].value_counts()

F      202448
M      105059
XNA         4
Name: CODE_GENDER, dtype: int64
```

Since, Female is having the majority and only 4 rows are having NA values, we can update those columns with Gender 'F' as there will be no impact on the dataset.

```
# Updating the column 'CODE_GENDER' with "F" for the dataset

df.loc[df['CODE_GENDER']=='XNA','CODE_GENDER']='F'
df['CODE_GENDER'].value_counts()
```

```
F    202452
M    105059
Name: CODE_GENDER, dtype: int64
```

```
# Describing the organization type column

df['ORGANIZATION_TYPE'].describe()
```

```
count                     307511
unique                        58
top       Business Entity Type 3
freq                       67992
Name: ORGANIZATION_TYPE, dtype: object
```

So, for column 'ORGANIZATION_TYPE', we have total count of 307511 rows of which 55374 rows are having 'XNA' values. Which means 18% of the column is having this values. Hence if we drop the rows of total 55374, will not have any major impact on our dataset.

```
# Hence, dropping the rows of total 55374 have 'XNA' values in the
organization type column

df=df.drop(df.loc[df['ORGANIZATION_TYPE']=='XNA'].index)
df[df['ORGANIZATION_TYPE']=='XNA'].shape
```

```
(0, 28)
```

```
# Casting all variable into numeric in the dataset

numeric_columns=['TARGET','CNT_CHILDREN','AMT_INCOME_TOTAL','AMT_CREDI
T','AMT_ANNUITY','REGION_POPULATION_RELATIVE','DAYS_BIRTH',

'DAYS_EMPLOYED','DAYS_REGISTRATION','DAYS_ID_PUBLISH','HOUR_APPR_PROCE
SS_START','LIVE_REGION_NOT_WORK_REGION', 'REG_CITY_NOT_LIVE_CITY',
       'REG_CITY_NOT_WORK_CITY', 'LIVE_CITY_NOT_WORK_CITY']

df[numeric_columns]=df[numeric_columns].apply(pd.to_numeric)
df.head(5)
```

```
   SK_ID_CURR  TARGET NAME_CONTRACT_TYPE CODE_GENDER FLAG_OWN_CAR  \
0      100002       1         Cash loans           M            N
1      100003       0         Cash loans           F            N
2      100004       0    Revolving loans           M            Y
3      100006       0         Cash loans           F            N
4      100007       0         Cash loans           M            N

  FLAG_OWN_REALTY  CNT_CHILDREN  AMT_INCOME_TOTAL  AMT_CREDIT
```

```
AMT_ANNUITY  \
0                Y              0          202500.0    406597.5
24700.5
1                N              0          270000.0   1293502.5
35698.5
2                Y              0           67500.0    135000.0
6750.0
3                Y              0          135000.0    312682.5
29686.5
4                Y              0          121500.0    513000.0
21865.5

   ... DAYS_ID_PUBLISH WEEKDAY_APPR_PROCESS_START
HOUR_APPR_PROCESS_START  \
0  ...           -2120                  WEDNESDAY
10
1  ...            -291                     MONDAY
11
2  ...           -2531                     MONDAY
9
3  ...           -2437                  WEDNESDAY
17
4  ...           -3458                   THURSDAY
11

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

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

   REG_CITY_NOT_WORK_CITY  LIVE_CITY_NOT_WORK_CITY
ORGANIZATION_TYPE
0                       0                        0  Business Entity
Type 3
1                       0                        0
School
2                       0                        0
Government
3                       0                        0  Business Entity
Type 3
4                       1                        1
```

```
Religion

[5 rows x 28 columns]
```

Derived Metrics

Now, Creating bins for continous variable categories column 'AMT_INCOME_TOTAL' and 'AMT_CREDIT'

```
# Creating bins for income amount

bins =
[0,25000,50000,75000,100000,125000,150000,175000,200000,225000,250000,
275000,300000,325000,350000,375000,400000,425000,450000,475000,500000,
10000000000]
slot = ['0-25000', '25000-50000','50000-75000','75000,100000','100000-
125000', '125000-150000', '150000-175000','175000-200000',
       '200000-225000','225000-250000','250000-275000','275000-
300000','300000-325000','325000-350000','350000-375000',
       '375000-400000','400000-425000','425000-450000','450000-
475000','475000-500000','500000 and above']

df['AMT_INCOME_RANGE']=pd.cut(df['AMT_INCOME_TOTAL'],bins,labels=slot)

# Creating bins for Credit amount

bins =
[0,150000,200000,250000,300000,350000,400000,450000,500000,550000,6000
00,650000,700000,750000,800000,850000,900000,1000000000]
slots = ['0-150000', '150000-200000','200000-250000', '250000-300000',
'300000-350000', '350000-400000','400000-450000',
        '450000-500000','500000-550000','550000-600000','600000-
650000','650000-700000','700000-750000','750000-800000',
        '800000-850000','850000-900000','900000 and above']

df['AMT_CREDIT_RANGE']=pd.cut(df['AMT_CREDIT'],bins=bins,labels=slots)

# Dividing the dataset into two dataset of  target=1(client with
payment difficulties) and target=0(all other)

target0_df=df.loc[df["TARGET"]==0]
target1_df=df.loc[df["TARGET"]==1]

# Calculating Imbalance percentage

# Since the majority is target0 and minority is target1

round(len(target0_df)/len(target1_df),2)
```

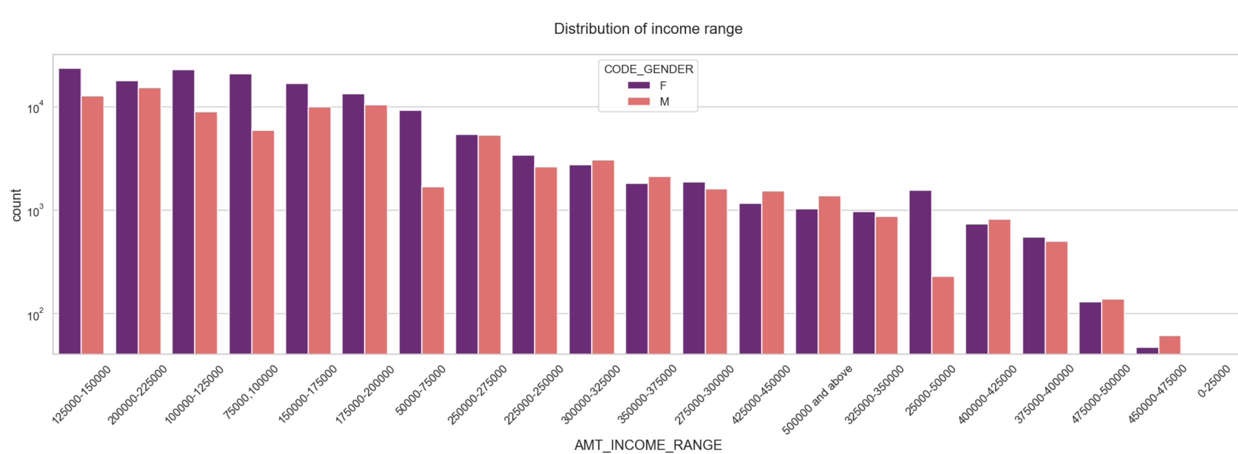
```
10.55
```

The Imbalance ratio is 10.55

Univariate analysis for categories

Now, doing Categorical Univariate Analysis in logarithmic scale for target=0(client with no payment difficulties)

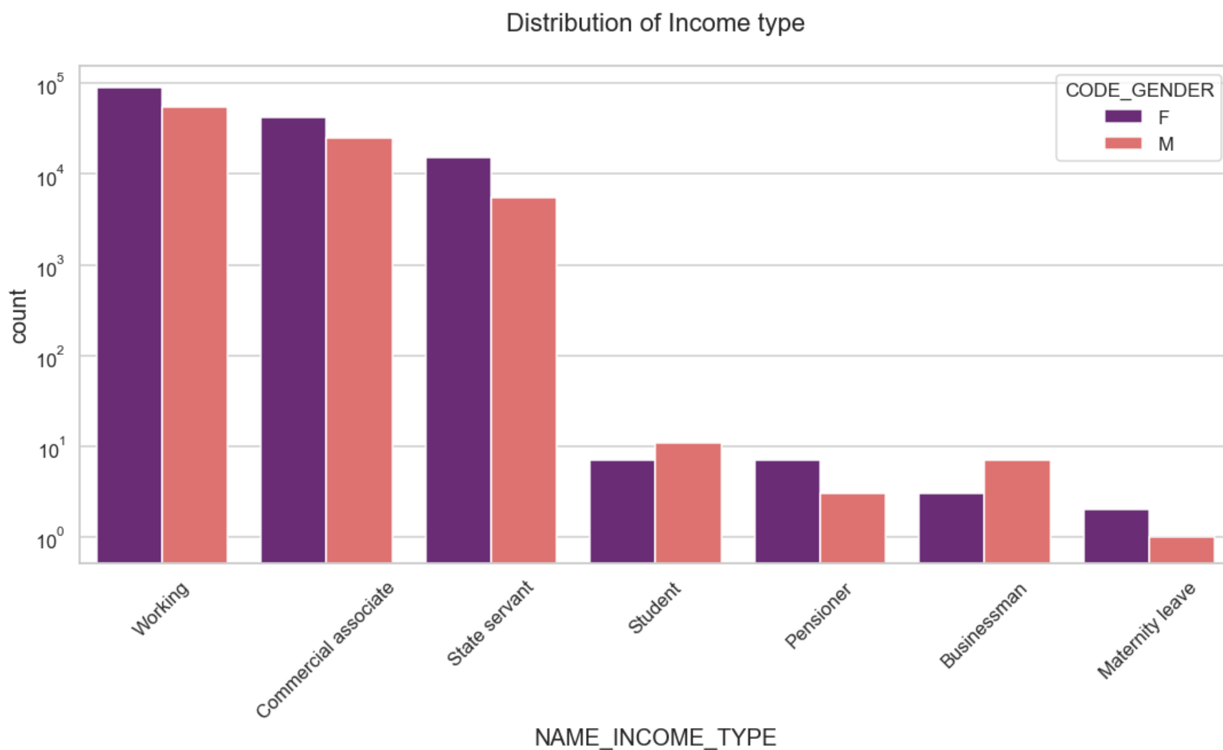
```
# Count plotting in logarithmic scale

def uniplot(df,col,title,hue =None):

    sns.set_style('whitegrid')
    sns.set_context('talk')
    plt.rcParams["axes.labelsize"] = 20
    plt.rcParams['axes.titlesize'] = 22
    plt.rcParams['axes.titlepad'] = 30


    temp = pd.Series(data = hue)
    fig, ax = plt.subplots()
    width = len(df[col].unique()) + 7 + 4*len(temp.unique())
    fig.set_size_inches(width , 8)
    plt.xticks(rotation=45)
    plt.yscale('log')
    plt.title(title)
    ax = sns.countplot(data = df, x= col,
order=df[col].value_counts().index,hue = hue,palette='magma')

    plt.show()

# PLotting for income range

uniplot(target0_df,col='AMT_INCOME_RANGE',title='Distribution of
income range',hue='CODE_GENDER')
```



Points to be concluded from the above graph.

1. Female counts are higher than male.
2. Income range from 100000 to 200000 is having more number of credits.
3. This graph show that females are more than male in having credits for that range.
4. Very less count for income range 400000 and above.

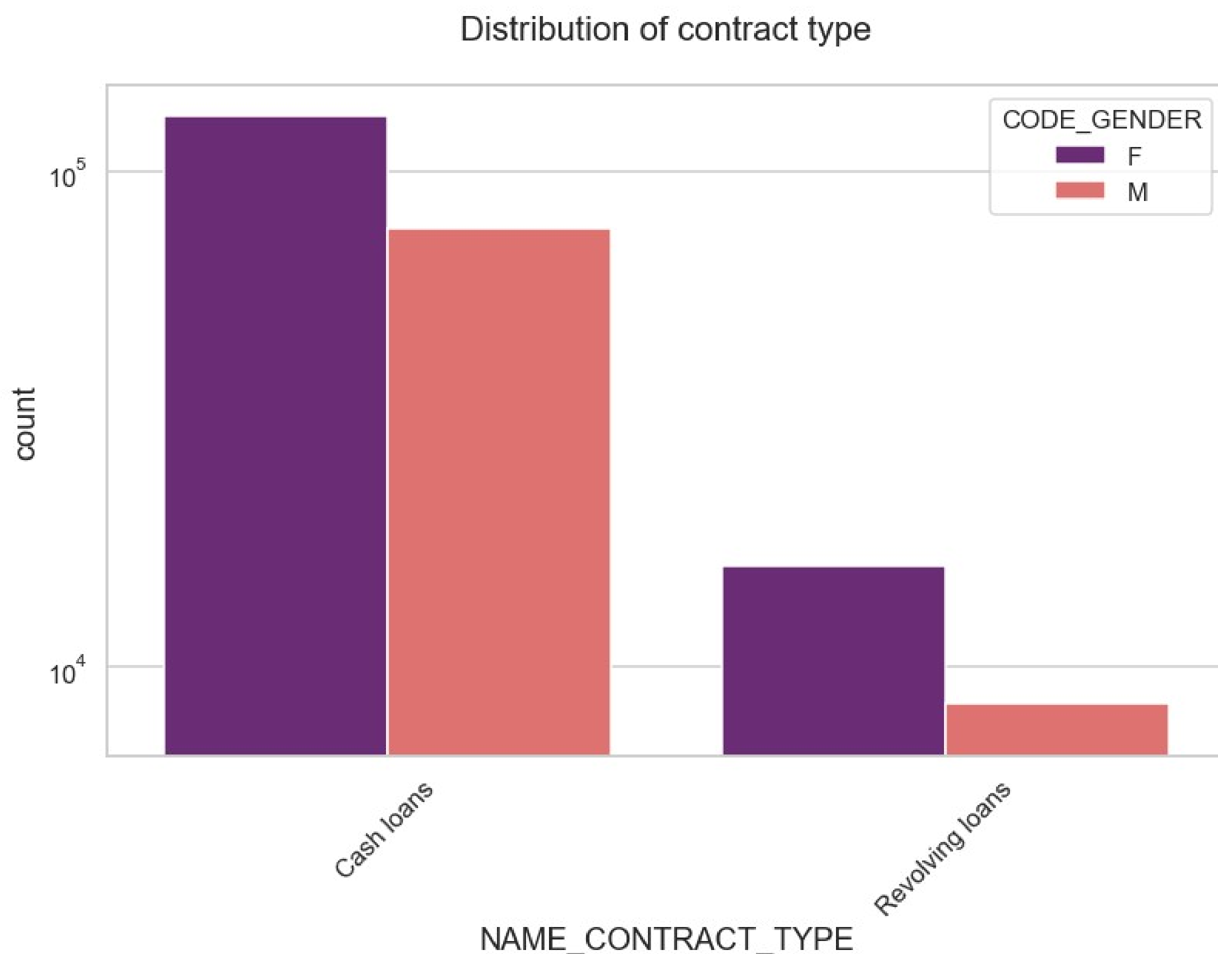
```
# Plotting for Income type

uniplot(target0_df,col='NAME_INCOME_TYPE',title='Distribution of
Income type',hue='CODE_GENDER')
```



Points to be concluded from the above graph.

1. For income type 'working', 'commercial associate', and 'State Servant' the number of credits are higher than others.
2. For this Females are having more number of credits than male.
3. Less number of credits for income type 'student' ,'pensioner', 'Businessman' and 'Maternity leave'.

```
# Plotting for Contract type

uniplot(target0_df,col='NAME_CONTRACT_TYPE',title='Distribution of
contract type',hue='CODE_GENDER')
```

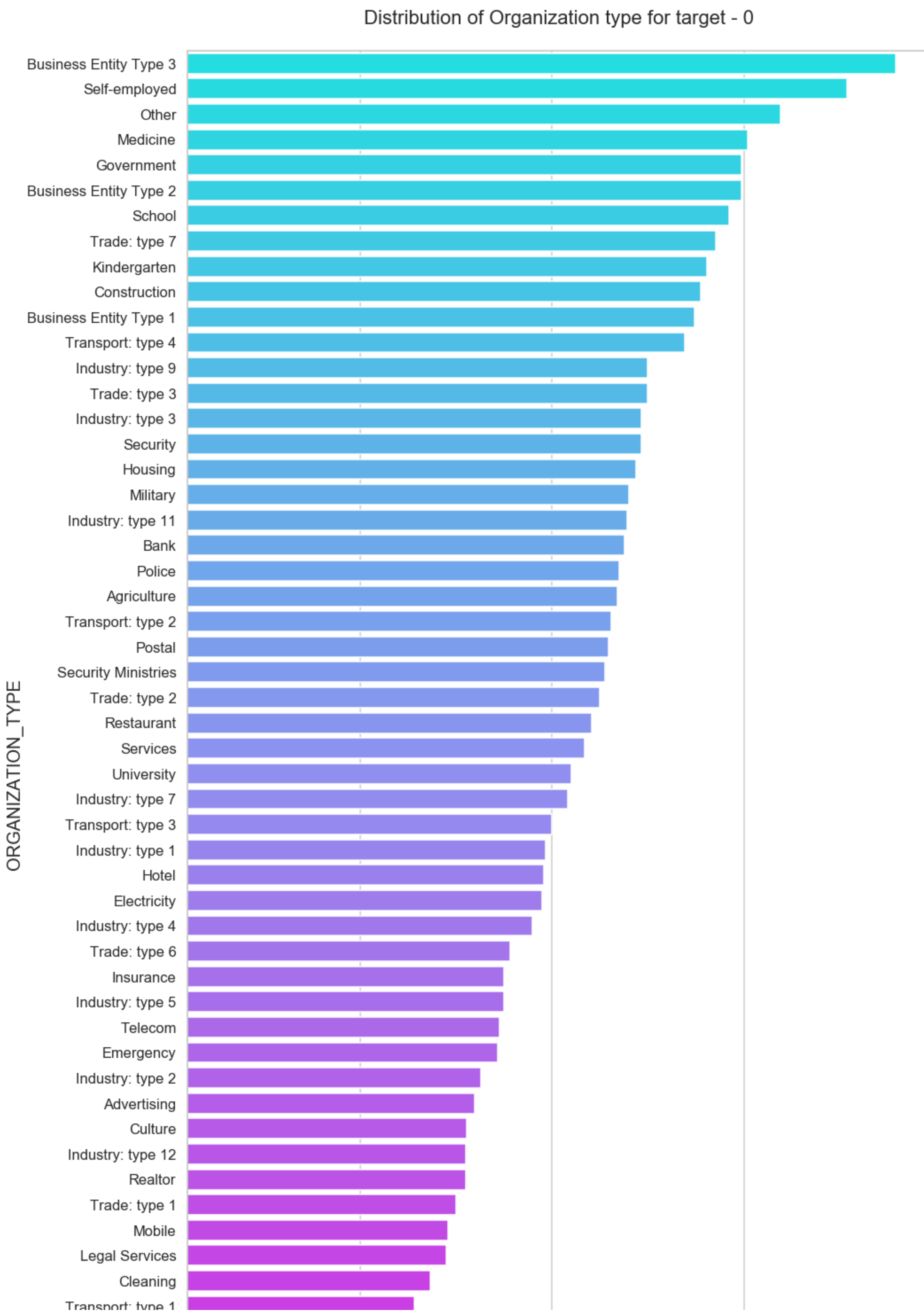


Points to be concluded from the above graph.

1. For contract type ‘cash loans’ is having higher number of credits than ‘Revolving loans’ contract type.
2. For this also Female is leading for applying credits.

```
# Plotting for Organization type in logarithmic scale

sns.set_style('whitegrid')
sns.set_context('talk')
plt.figure(figsize=(15,30))
plt.rcParams["axes.labelsize"] = 20
plt.rcParams['axes.titlesize'] = 22
plt.rcParams['axes.titlepad'] = 30

plt.title("Distribution of Organization type for target - 0")

plt.xticks(rotation=90)
plt.xscale('log')

sns.countplot(data=target0_df,y='ORGANIZATION_TYPE',order=target0_df['
ORGANIZATION_TYPE'].value_counts().index,palette='cool')
```

```
plt.show()
```



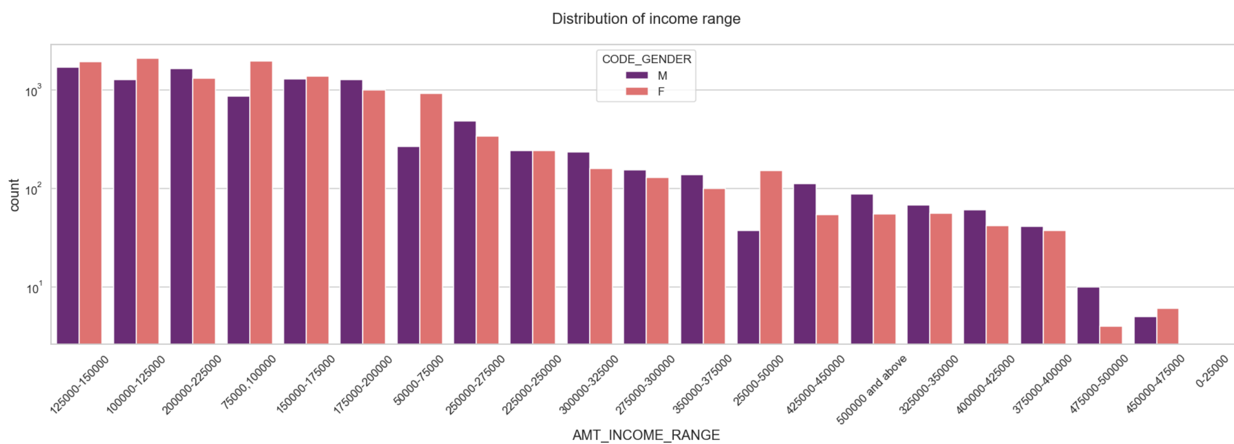
Distribution of Organization type for target - 0
ORGANIZATION_TYPE
Business Entity Type 3
Self-employed
Other
Medicine
Government
Business Entity Type 2
School
Trade: type 7
Kindergarten
Construction
Business Entity Type 1
Transport: type 4
Industry: type 9
Trade: type 3
Industry: type 3
Security
Housing
Military
Industry: type 11
Bank
Police
Agriculture
Transport: type 2
Postal
Security Ministries
Trade: type 2
Restaurant
Services
University
Industry: type 7
Transport: type 3
Industry: type 1
Hotel
Electricity
Industry: type 4
Trade: type 6
Insurance
Industry: type 5
Telecom
Emergency
Industry: type 2
Advertising
Culture
Industry: type 12
Realtor
Trade: type 1
Mobile
Legal Services
Cleaning

Points to be concluded from the above graph.

1. Clients which have applied for credits are from most of the organization type 'Business entity Type 3' , 'Self employed', 'Other' , 'Medicine' and 'Government'.
2. Less clients are from Industry type 8,type 6, type 10, religion and trade type 5, type 4.

Now, doing Categoroical Univariate Analysis in logarithmic scale for target=1(client with payment difficulties)

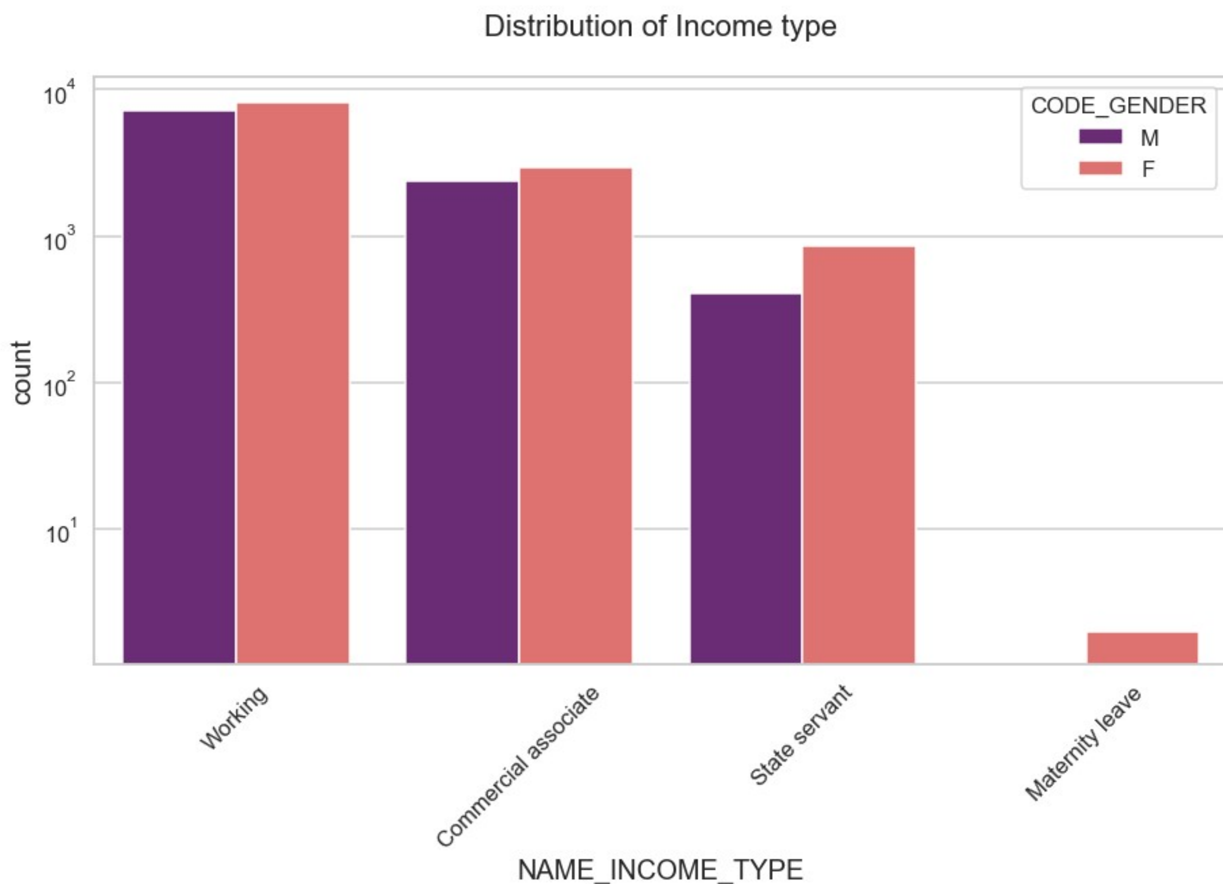
```
# PLotting for income range

uniplot(target1_df,col='AMT_INCOME_RANGE',title='Distribution of income range',hue='CODE_GENDER')
```



Points to be concluded from the above graph.

1. Male counts are higher than female.
2. Income range from 100000 to 200000 is having more number of credits.
3. This graph show that males are more than female in having credits for that range.
4. Very less count for income range 400000 and above.

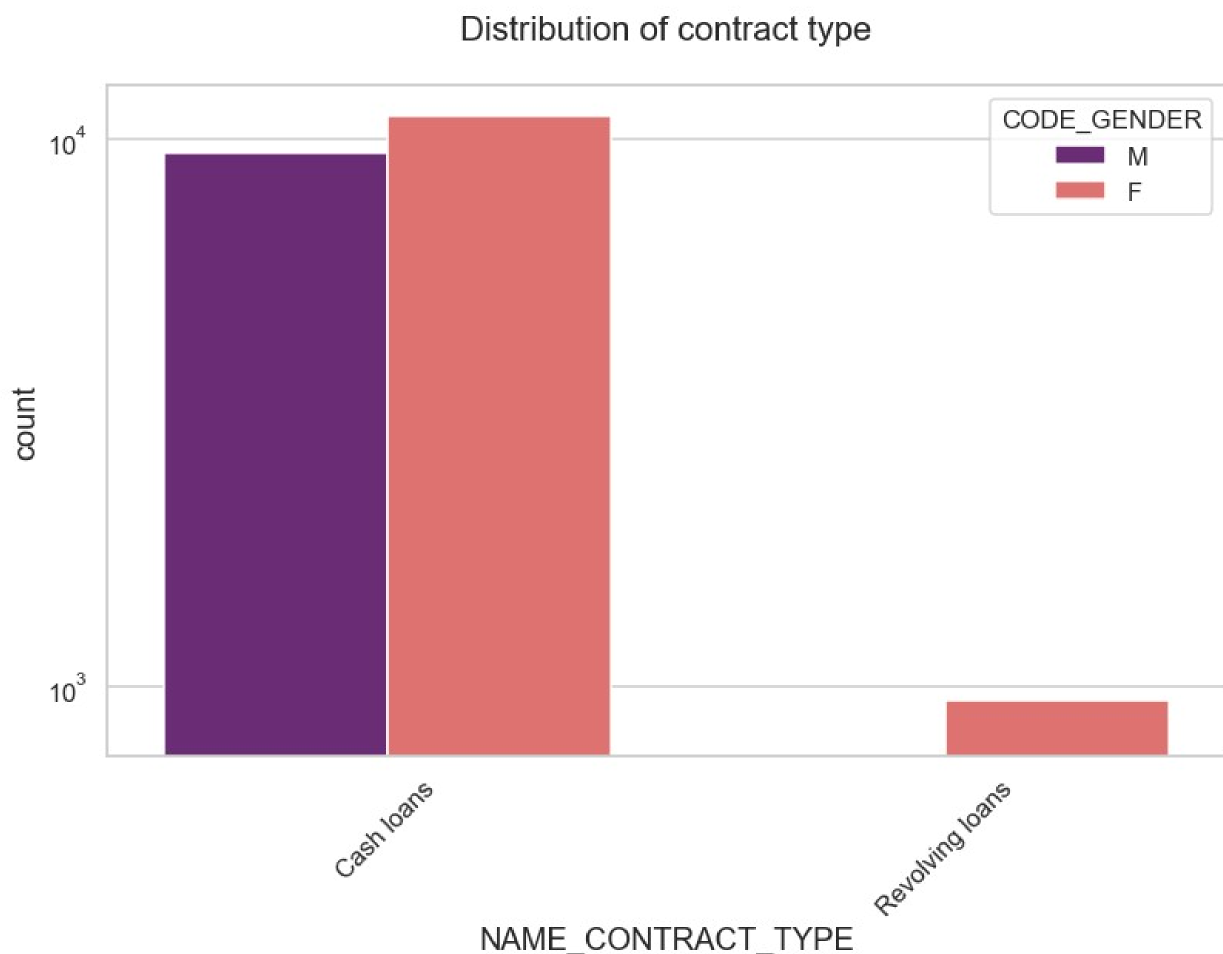
```
# Plotting for Income type

uniplot(target1_df,col='NAME_INCOME_TYPE',title='Distribution of Income type',hue='CODE_GENDER')
```



Points to be concluded from the above graph.

1. For income type 'working', 'commercial associate', and 'State Servant' the number of credits are higher than other i.e. 'Maternity leave.
2. For this Females are having more number of credits than male.
3. Less number of credits for income type 'Maternity leave'.
4. For type 1: There is no income type for 'student' , 'pensioner' and 'Businessman' which means they don't do any late payments.

```
# Plotting for Contract type

uniplot(target1_df,col='NAME_CONTRACT_TYPE',title='Distribution of contract type',hue='CODE_GENDER')
```

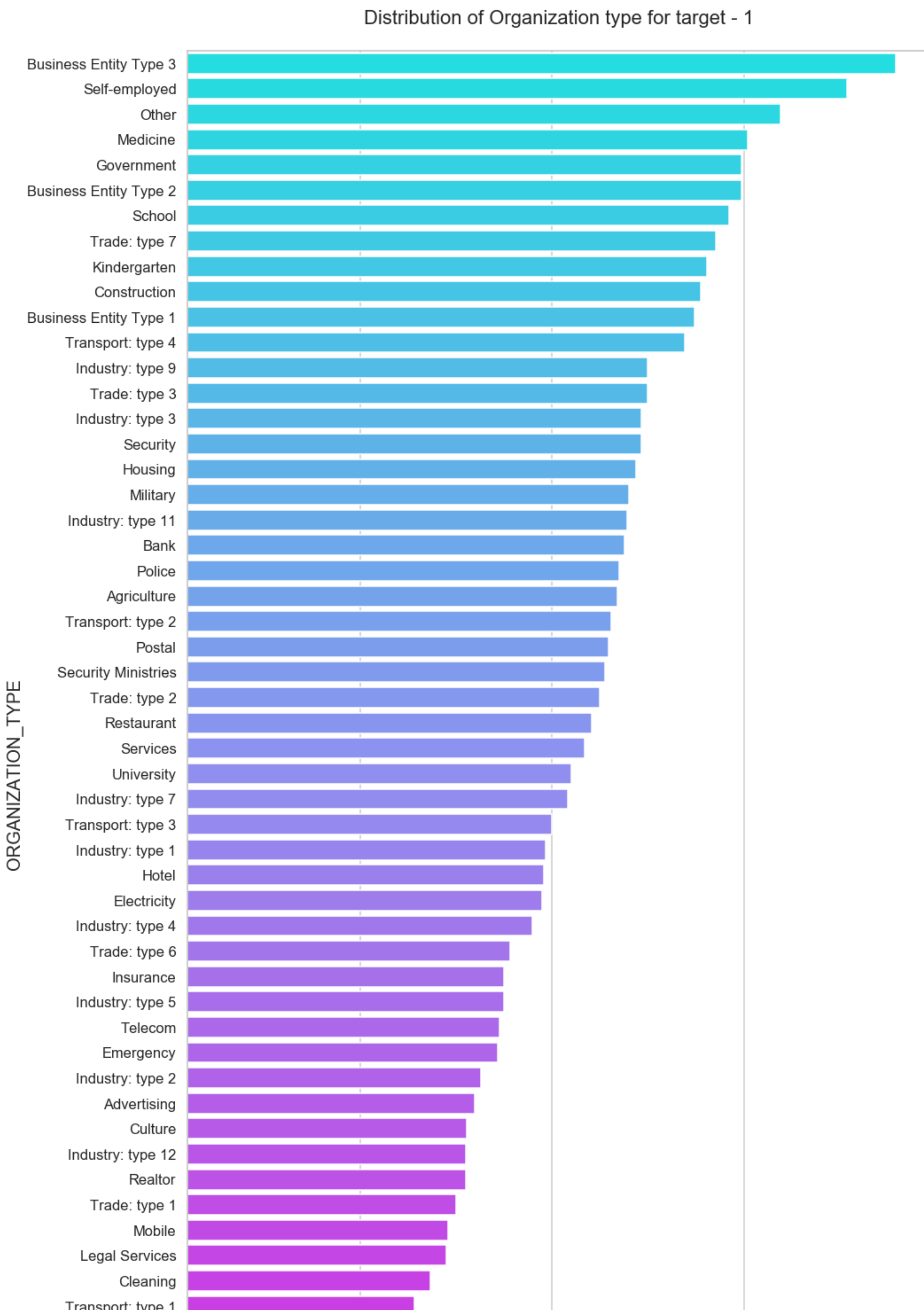


Points to be concluded from the above graph.

1. For contract type 'cash loans' is having higher number of credits than 'Revolving loans' contract type.
2. For this also Female is leading for applying credits.
3. For type 1 : there is only Female Revolving loans.

```
# Plotting for Organization type

sns.set_style('whitegrid')
sns.set_context('talk')
plt.figure(figsize=(15,30))
plt.rcParams["axes.labelsize"] = 20
plt.rcParams['axes.titlesize'] = 22
plt.rcParams['axes.titlepad'] = 30

plt.title("Distribution of Organization type for target - 1")

plt.xticks(rotation=90)
plt.xscale('log')

sns.countplot(data=target0_df,y='ORGANIZATION_TYPE',order=target0_df['
```

```
ORGANIZATION_TYPE'].value_counts().index,palette='cool')

plt.show()
```


Distribution of Organization type for target - 1
ORGANIZATION_TYPE
Business Entity Type 3
Self-employed
Other
Medicine
Government
Business Entity Type 2
School
Trade: type 7
Kindergarten
Construction
Business Entity Type 1
Transport: type 4
Industry: type 9
Trade: type 3
Industry: type 3
Security
Housing
Military
Industry: type 11
Bank
Police
Agriculture
Transport: type 2
Postal
Security Ministries
Trade: type 2
Restaurant
Services
University
Industry: type 7
Transport: type 3
Industry: type 1
Hotel
Electricity
Industry: type 4
Trade: type 6
Insurance
Industry: type 5
Telecom
Emergency
Industry: type 2
Advertising
Culture
Industry: type 12
Realtor
Trade: type 1
Mobile
Legal Services
Cleaning

Points to be concluded from the above graph.

1. Clients which have applied for credits are from most of the organization type 'Business entity Type 3' , 'Self employed' , 'Other' , 'Medicine' and 'Government'.
2. Less clients are from Industry type 8,type 6, type 10, religion and trade type 5, type 4.
3. Same as type 0 in distribution of organization type.

```
# Finding some correlation for numerical columns for both target 0 and
1

target0_corr=target0_df.iloc[0:,2:]
target1_corr=target1_df.iloc[0:,2:]

target0=target0_corr.corr(method='spearman')
target1=target1_corr.corr(method='spearman')

# Correlation for target 0

target0

                             CNT_CHILDREN  AMT_INCOME_TOTAL
AMT_CREDIT  \
CNT_CHILDREN                     1.000000         -0.021950   -
0.023652
AMT_INCOME_TOTAL                -0.021950          1.000000
0.403876
AMT_CREDIT                      -0.023652          0.403876
1.000000
AMT_ANNUITY                     -0.010795          0.472204
0.826689
REGION_POPULATION_RELATIVE      -0.030579          0.110074
0.060706
DAYS_BIRTH                       0.266534         -0.054666   -
0.169030
DAYS_EMPLOYED                    0.030948         -0.060868   -
0.104251
DAYS_REGISTRATION                0.155518          0.040559   -
0.015318
DAYS_ID_PUBLISH                 -0.119164         -0.036702   -
0.038197
HOUR_APPR_PROCESS_START         -0.030162          0.073503
0.036923
REG_REGION_NOT_LIVE_REGION      -0.022813          0.077634
0.015118
REG_REGION_NOT_WORK_REGION      -0.015475          0.159962
0.041693
LIVE_REGION_NOT_WORK_REGION     -0.005576          0.148281
0.045175
REG_CITY_NOT_LIVE_CITY           0.002344         -0.001023   -
0.040616
REG_CITY_NOT_WORK_CITY           0.007487         -0.013856   -
```

```
0.037000
LIVE_CITY_NOT_WORK_CITY          0.013295         -0.004758   -
0.011194

                             AMT_ANNUITY
REGION_POPULATION_RELATIVE  \
CNT_CHILDREN                   -0.010795                           -0.030579

AMT_INCOME_TOTAL                0.472204                            0.110074

AMT_CREDIT                      0.826689                            0.060706

AMT_ANNUITY                     1.000000                            0.064328

REGION_POPULATION_RELATIVE      0.064328                            1.000000

DAYS_BIRTH                     -0.100287                           -0.041663

DAYS_EMPLOYED                  -0.074643                            0.000900

DAYS_REGISTRATION               0.010712                           -0.042400

DAYS_ID_PUBLISH                -0.027354                           -0.010299

HOUR_APPR_PROCESS_START         0.032953                            0.133213

REG_REGION_NOT_LIVE_REGION      0.033435                           -0.025292

REG_REGION_NOT_WORK_REGION      0.070841                            0.032446

LIVE_REGION_NOT_WORK_REGION     0.069051                            0.056814

REG_CITY_NOT_LIVE_CITY         -0.019954                           -0.049779

REG_CITY_NOT_WORK_CITY         -0.024085                           -0.034808

LIVE_CITY_NOT_WORK_CITY        -0.008087                           -0.007332


                             DAYS_BIRTH  DAYS_EMPLOYED
DAYS_REGISTRATION  \
CNT_CHILDREN                   0.266534       0.030948
0.155518
AMT_INCOME_TOTAL              -0.054666      -0.060868
0.040559
AMT_CREDIT                    -0.169030      -0.104251           -
0.015318
AMT_ANNUITY                   -0.100287      -0.074643
0.010712
REGION_POPULATION_RELATIVE    -0.041663       0.000900           -
0.042400
```

```
DAYS_BIRTH                              1.000000        0.307787
0.265449
DAYS_EMPLOYED                           0.307787        1.000000
0.126708
DAYS_REGISTRATION                       0.265449        0.126708
1.000000
DAYS_ID_PUBLISH                         0.083331        0.106823
0.036788
HOUR_APPR_PROCESS_START                 0.051299        0.026444          -
0.029553
REG_REGION_NOT_LIVE_REGION              0.058627        0.065435
0.017715
REG_REGION_NOT_WORK_REGION              0.038104        0.086966
0.015092
LIVE_REGION_NOT_WORK_REGION             0.012789        0.063533
0.007716
REG_CITY_NOT_LIVE_CITY                  0.167477        0.118224
0.038064
REG_CITY_NOT_WORK_CITY                  0.111539        0.125954
0.047339
LIVE_CITY_NOT_WORK_CITY                 0.029007        0.069567
0.027231

                              DAYS_ID_PUBLISH  HOUR_APPR_PROCESS_START
\
CNT_CHILDREN                        -0.119164                -0.030162

AMT_INCOME_TOTAL                    -0.036702                 0.073503

AMT_CREDIT                          -0.038197                 0.036923

AMT_ANNUITY                         -0.027354                 0.032953

REGION_POPULATION_RELATIVE          -0.010299                 0.133213

DAYS_BIRTH                           0.083331                 0.051299

DAYS_EMPLOYED                        0.106823                 0.026444

DAYS_REGISTRATION                    0.036788                -0.029553

DAYS_ID_PUBLISH                      1.000000                 0.008538

HOUR_APPR_PROCESS_START              0.008538                 1.000000

REG_REGION_NOT_LIVE_REGION           0.027302                 0.051744

REG_REGION_NOT_WORK_REGION           0.020823                 0.067352

LIVE_REGION_NOT_WORK_REGION          0.008525                 0.053813
```

```
REG_CITY_NOT_LIVE_CITY                  0.054875                  0.011287
REG_CITY_NOT_WORK_CITY                  0.033427                 -0.005971
LIVE_CITY_NOT_WORK_CITY                 0.001476                 -0.010720

                             REG_REGION_NOT_LIVE_REGION  \
CNT_CHILDREN                                  -0.022813
AMT_INCOME_TOTAL                               0.077634
AMT_CREDIT                                     0.015118
AMT_ANNUITY                                    0.033435
REGION_POPULATION_RELATIVE                    -0.025292
DAYS_BIRTH                                     0.058627
DAYS_EMPLOYED                                  0.065435
DAYS_REGISTRATION                              0.017715
DAYS_ID_PUBLISH                                0.027302
HOUR_APPR_PROCESS_START                        0.051744
REG_REGION_NOT_LIVE_REGION                     1.000000
REG_REGION_NOT_WORK_REGION                     0.461596
LIVE_REGION_NOT_WORK_REGION                    0.090193
REG_CITY_NOT_LIVE_CITY                         0.342321
REG_CITY_NOT_WORK_CITY                         0.142429
LIVE_CITY_NOT_WORK_CITY                        0.003479

                             REG_REGION_NOT_WORK_REGION  \
CNT_CHILDREN                                  -0.015475
AMT_INCOME_TOTAL                               0.159962
AMT_CREDIT                                     0.041693
AMT_ANNUITY                                    0.070841
REGION_POPULATION_RELATIVE                     0.032446
DAYS_BIRTH                                     0.038104
DAYS_EMPLOYED                                  0.086966
DAYS_REGISTRATION                              0.015092
DAYS_ID_PUBLISH                                0.020823
HOUR_APPR_PROCESS_START                        0.067352
REG_REGION_NOT_LIVE_REGION                     0.461596
REG_REGION_NOT_WORK_REGION                     1.000000
LIVE_REGION_NOT_WORK_REGION                    0.860421
REG_CITY_NOT_LIVE_CITY                         0.148476
REG_CITY_NOT_WORK_CITY                         0.220372
LIVE_CITY_NOT_WORK_CITY                        0.178472

                             LIVE_REGION_NOT_WORK_REGION  \
CNT_CHILDREN                                   -0.005576
AMT_INCOME_TOTAL                                0.148281
AMT_CREDIT                                      0.045175
AMT_ANNUITY                                     0.069051
REGION_POPULATION_RELATIVE                      0.056814
DAYS_BIRTH                                      0.012789
```

```
DAYS_EMPLOYED                                               0.063533
DAYS_REGISTRATION                                           0.007716
DAYS_ID_PUBLISH                                             0.008525
HOUR_APPR_PROCESS_START                                     0.053813
REG_REGION_NOT_LIVE_REGION                                  0.090193
REG_REGION_NOT_WORK_REGION                                  0.860421
LIVE_REGION_NOT_WORK_REGION                                 1.000000
REG_CITY_NOT_LIVE_CITY                                      0.015010
REG_CITY_NOT_WORK_CITY                                      0.167753
LIVE_CITY_NOT_WORK_CITY                                     0.220865

                             REG_CITY_NOT_LIVE_CITY
REG_CITY_NOT_WORK_CITY  \
CNT_CHILDREN                                      0.002344
0.007487
AMT_INCOME_TOTAL                                 -0.001023                -
0.013856
AMT_CREDIT                                       -0.040616                -
0.037000
AMT_ANNUITY                                      -0.019954                -
0.024085
REGION_POPULATION_RELATIVE                       -0.049779                -
0.034808
DAYS_BIRTH                                        0.167477
0.111539
DAYS_EMPLOYED                                     0.118224
0.125954
DAYS_REGISTRATION                                 0.038064
0.047339
DAYS_ID_PUBLISH                                   0.054875
0.033427
HOUR_APPR_PROCESS_START                           0.011287                -
0.005971
REG_REGION_NOT_LIVE_REGION                        0.342321
0.142429
REG_REGION_NOT_WORK_REGION                        0.148476
0.220372
LIVE_REGION_NOT_WORK_REGION                       0.015010
0.167753
REG_CITY_NOT_LIVE_CITY                            1.000000
0.442640
REG_CITY_NOT_WORK_CITY                            0.442640
1.000000
LIVE_CITY_NOT_WORK_CITY                           0.011782
0.820828

                             LIVE_CITY_NOT_WORK_CITY
CNT_CHILDREN                                       0.013295
AMT_INCOME_TOTAL                                  -0.004758
```

```
AMT_CREDIT                                         -0.011194
AMT_ANNUITY                                        -0.008087
REGION_POPULATION_RELATIVE                         -0.007332
DAYS_BIRTH                                          0.029007
DAYS_EMPLOYED                                       0.069567
DAYS_REGISTRATION                                   0.027231
DAYS_ID_PUBLISH                                     0.001476
HOUR_APPR_PROCESS_START                            -0.010720
REG_REGION_NOT_LIVE_REGION                          0.003479
REG_REGION_NOT_WORK_REGION                          0.178472
LIVE_REGION_NOT_WORK_REGION                         0.220865
REG_CITY_NOT_LIVE_CITY                              0.011782
REG_CITY_NOT_WORK_CITY                              0.820828
LIVE_CITY_NOT_WORK_CITY                             1.000000

# Correlation for target 1

target1

                             CNT_CHILDREN  AMT_INCOME_TOTAL
AMT_CREDIT  \
CNT_CHILDREN                     1.000000         -0.039123
0.000427
AMT_INCOME_TOTAL                -0.039123          1.000000
0.364559
AMT_CREDIT                       0.000427          0.364559
1.000000
AMT_ANNUITY                      0.015133          0.428947
0.812093
REGION_POPULATION_RELATIVE      -0.029682          0.058005
0.043545
DAYS_BIRTH                       0.175025         -0.103026   -
0.200718
DAYS_EMPLOYED                    0.006823         -0.053798   -
0.107605
DAYS_REGISTRATION                0.110854          0.011378   -
0.021973
DAYS_ID_PUBLISH                 -0.091042         -0.051113   -
0.065143
HOUR_APPR_PROCESS_START         -0.040338          0.078779
0.024616
REG_REGION_NOT_LIVE_REGION      -0.035213          0.075615
0.015043
REG_REGION_NOT_WORK_REGION      -0.040853          0.156374
0.032536
LIVE_REGION_NOT_WORK_REGION     -0.027993          0.145982
0.034861
REG_CITY_NOT_LIVE_CITY          -0.016072         -0.003813   -
0.030974
REG_CITY_NOT_WORK_CITY          -0.005444         -0.006241   -
```

```
0.032882
LIVE_CITY_NOT_WORK_CITY          0.009557          0.004230   -
0.012465

                             AMT_ANNUITY
REGION_POPULATION_RELATIVE  \
CNT_CHILDREN                    0.015133                           -0.029682

AMT_INCOME_TOTAL                0.428947                            0.058005

AMT_CREDIT                      0.812093                            0.043545

AMT_ANNUITY                     1.000000                            0.028666

REGION_POPULATION_RELATIVE      0.028666                            1.000000

DAYS_BIRTH                     -0.100200                           -0.044444

DAYS_EMPLOYED                  -0.060193                           -0.015246

DAYS_REGISTRATION               0.019762                           -0.033490

DAYS_ID_PUBLISH                -0.044128                           -0.017779

HOUR_APPR_PROCESS_START         0.021129                            0.109400

REG_REGION_NOT_LIVE_REGION      0.029646                           -0.032702

REG_REGION_NOT_WORK_REGION      0.060363                           -0.008160

LIVE_REGION_NOT_WORK_REGION     0.059724                            0.012602

REG_CITY_NOT_LIVE_CITY         -0.011744                           -0.057239

REG_CITY_NOT_WORK_CITY         -0.015938                           -0.044761

LIVE_CITY_NOT_WORK_CITY        -0.003012                           -0.014753


                             DAYS_BIRTH  DAYS_EMPLOYED
DAYS_REGISTRATION  \
CNT_CHILDREN                   0.175025       0.006823
0.110854
AMT_INCOME_TOTAL              -0.103026      -0.053798
0.011378
AMT_CREDIT                    -0.200718      -0.107605           -
0.021973
AMT_ANNUITY                   -0.100200      -0.060193
0.019762
REGION_POPULATION_RELATIVE    -0.044444      -0.015246           -
0.033490
```

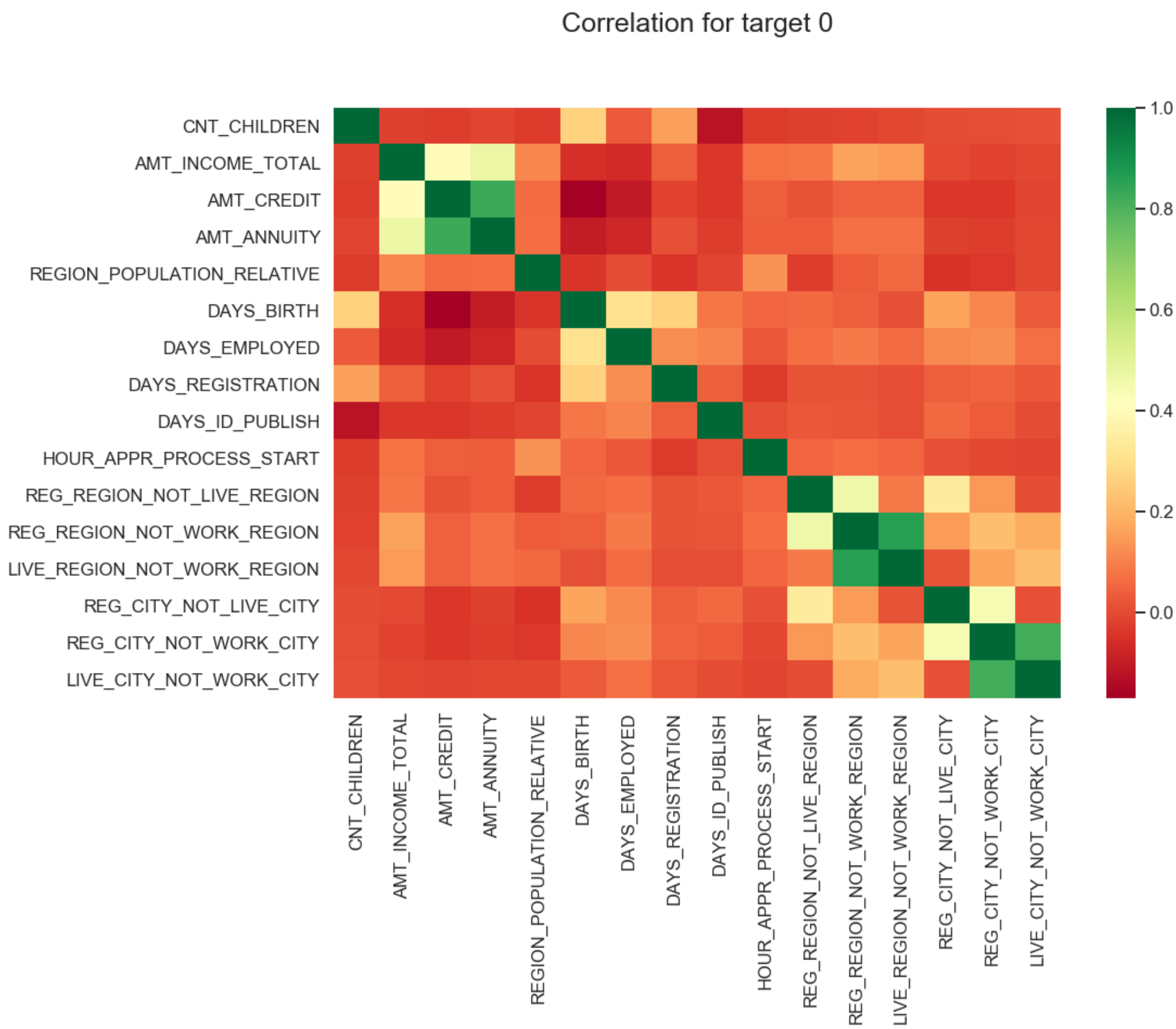
```
DAYS_BIRTH                       1.000000        0.256870
0.192350
DAYS_EMPLOYED                    0.256870        1.000000
0.086286
DAYS_REGISTRATION                0.192350        0.086286
1.000000
DAYS_ID_PUBLISH                  0.146246        0.104244
0.061563
HOUR_APPR_PROCESS_START          0.041994        0.010328           -
0.044753
REG_REGION_NOT_LIVE_REGION       0.046320        0.069566
0.006362
REG_REGION_NOT_WORK_REGION       0.022208        0.082264
0.000896
LIVE_REGION_NOT_WORK_REGION      0.000356        0.056081           -
0.001416
REG_CITY_NOT_LIVE_CITY           0.145884        0.118869
0.015831
REG_CITY_NOT_WORK_CITY           0.096181        0.139863
0.039204
LIVE_CITY_NOT_WORK_CITY          0.009633        0.069316
0.026105

                               DAYS_ID_PUBLISH  HOUR_APPR_PROCESS_START
\
CNT_CHILDREN                         -0.091042                -0.040338

AMT_INCOME_TOTAL                     -0.051113                 0.078779

AMT_CREDIT                           -0.065143                 0.024616

AMT_ANNUITY                          -0.044128                 0.021129

REGION_POPULATION_RELATIVE           -0.017779                 0.109400

DAYS_BIRTH                            0.146246                 0.041994

DAYS_EMPLOYED                         0.104244                 0.010328

DAYS_REGISTRATION                     0.061563                -0.044753

DAYS_ID_PUBLISH                       1.000000                 0.012709

HOUR_APPR_PROCESS_START               0.012709                 1.000000

REG_REGION_NOT_LIVE_REGION            0.024860                 0.050953

REG_REGION_NOT_WORK_REGION            0.013162                 0.063877

LIVE_REGION_NOT_WORK_REGION           0.002567                 0.050300
```

```
REG_CITY_NOT_LIVE_CITY              0.048184                  0.003947

REG_CITY_NOT_WORK_CITY              0.015838                  0.004775

LIVE_CITY_NOT_WORK_CITY            -0.015598                  0.002319


                             REG_REGION_NOT_LIVE_REGION  \
CNT_CHILDREN                                  -0.035213
AMT_INCOME_TOTAL                               0.075615
AMT_CREDIT                                     0.015043
AMT_ANNUITY                                    0.029646
REGION_POPULATION_RELATIVE                    -0.032702
DAYS_BIRTH                                     0.046320
DAYS_EMPLOYED                                  0.069566
DAYS_REGISTRATION                              0.006362
DAYS_ID_PUBLISH                                0.024860
HOUR_APPR_PROCESS_START                        0.050953
REG_REGION_NOT_LIVE_REGION                     1.000000
REG_REGION_NOT_WORK_REGION                     0.506747
LIVE_REGION_NOT_WORK_REGION                    0.068368
REG_CITY_NOT_LIVE_CITY                         0.322030
REG_CITY_NOT_WORK_CITY                         0.150968
LIVE_CITY_NOT_WORK_CITY                       -0.013946

                             REG_REGION_NOT_WORK_REGION  \
CNT_CHILDREN                                  -0.040853
AMT_INCOME_TOTAL                               0.156374
AMT_CREDIT                                     0.032536
AMT_ANNUITY                                    0.060363
REGION_POPULATION_RELATIVE                    -0.008160
DAYS_BIRTH                                     0.022208
DAYS_EMPLOYED                                  0.082264
DAYS_REGISTRATION                              0.000896
DAYS_ID_PUBLISH                                0.013162
HOUR_APPR_PROCESS_START                        0.063877
REG_REGION_NOT_LIVE_REGION                     0.506747
REG_REGION_NOT_WORK_REGION                     1.000000
LIVE_REGION_NOT_WORK_REGION                    0.846872
REG_CITY_NOT_LIVE_CITY                         0.141416
REG_CITY_NOT_WORK_CITY                         0.224370
LIVE_CITY_NOT_WORK_CITY                        0.181231

                             LIVE_REGION_NOT_WORK_REGION  \
CNT_CHILDREN                                   -0.027993
AMT_INCOME_TOTAL                                0.145982
AMT_CREDIT                                      0.034861
AMT_ANNUITY                                     0.059724
REGION_POPULATION_RELATIVE                      0.012602
DAYS_BIRTH                                      0.000356
```

```
DAYS_EMPLOYED                                              0.056081
DAYS_REGISTRATION                                         -0.001416
DAYS_ID_PUBLISH                                            0.002567
HOUR_APPR_PROCESS_START                                    0.050300
REG_REGION_NOT_LIVE_REGION                                 0.068368
REG_REGION_NOT_WORK_REGION                                 0.846872
LIVE_REGION_NOT_WORK_REGION                                1.000000
REG_CITY_NOT_LIVE_CITY                                    -0.006978
REG_CITY_NOT_WORK_CITY                                     0.167717
LIVE_CITY_NOT_WORK_CITY                                    0.233975

                             REG_CITY_NOT_LIVE_CITY
REG_CITY_NOT_WORK_CITY  \
CNT_CHILDREN                              -0.016072                -
0.005444
AMT_INCOME_TOTAL                          -0.003813                -
0.006241
AMT_CREDIT                                -0.030974                -
0.032882
AMT_ANNUITY                               -0.011744                -
0.015938
REGION_POPULATION_RELATIVE                -0.057239                -
0.044761
DAYS_BIRTH                                 0.145884
0.096181
DAYS_EMPLOYED                              0.118869
0.139863
DAYS_REGISTRATION                          0.015831
0.039204
DAYS_ID_PUBLISH                            0.048184
0.015838
HOUR_APPR_PROCESS_START                    0.003947
0.004775
REG_REGION_NOT_LIVE_REGION                 0.322030
0.150968
REG_REGION_NOT_WORK_REGION                 0.141416
0.224370
LIVE_REGION_NOT_WORK_REGION               -0.006978
0.167717
REG_CITY_NOT_LIVE_CITY                     1.000000
0.478266
REG_CITY_NOT_WORK_CITY                     0.478266
1.000000
LIVE_CITY_NOT_WORK_CITY                   -0.029432
0.768247

                             LIVE_CITY_NOT_WORK_CITY
CNT_CHILDREN                                0.009557
AMT_INCOME_TOTAL                            0.004230
```

```
AMT_CREDIT                                                    -0.012465
AMT_ANNUITY                                                   -0.003012
REGION_POPULATION_RELATIVE                                    -0.014753
DAYS_BIRTH                                                     0.009633
DAYS_EMPLOYED                                                  0.069316
DAYS_REGISTRATION                                              0.026105
DAYS_ID_PUBLISH                                               -0.015598
HOUR_APPR_PROCESS_START                                        0.002319
REG_REGION_NOT_LIVE_REGION                                    -0.013946
REG_REGION_NOT_WORK_REGION                                     0.181231
LIVE_REGION_NOT_WORK_REGION                                    0.233975
REG_CITY_NOT_LIVE_CITY                                        -0.029432
REG_CITY_NOT_WORK_CITY                                         0.768247
LIVE_CITY_NOT_WORK_CITY                                        1.000000
```

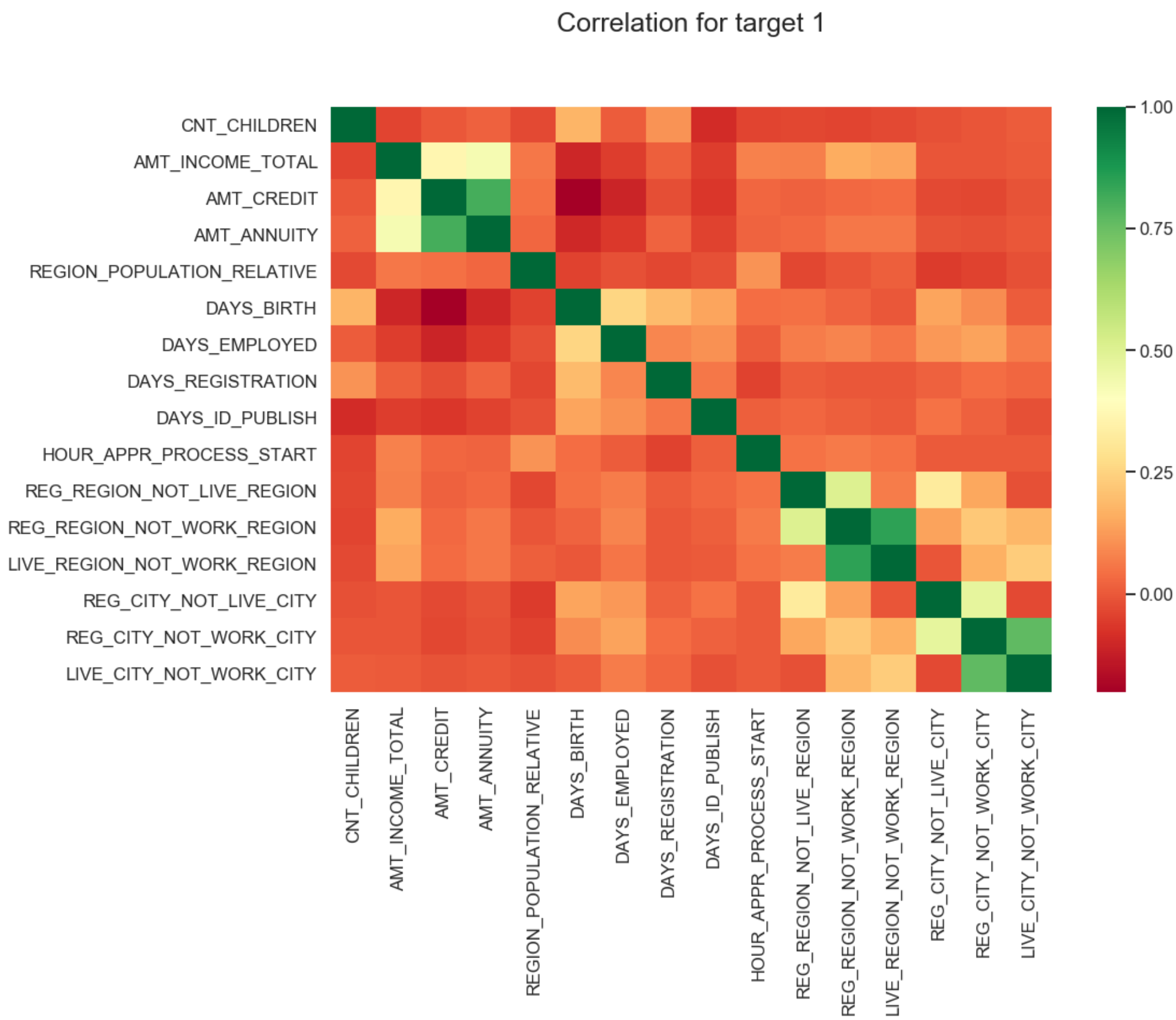
```
# Now, plotting the above correlation with heat map as it is the best
choice to visulaize

# figure size

def targets_corr(data,title):
    plt.figure(figsize=(15, 10))
    plt.rcParams['axes.titlesize'] = 25
    plt.rcParams['axes.titlepad'] = 70

# heatmap with a color map of choice


    sns.heatmap(data, cmap="RdYlGn",annot=False)

    plt.title(title)
    plt.yticks(rotation=0)
    plt.show()


# For Target 0

targets_corr(data=target0,title='Correlation for target 0')
```



As we can see from above correlation heatmap, There are number of observation we can point out

1. Credit amount is inversely proportional to the date of birth, which means Credit amount is higher for low age and vice-versa.
2. Credit amount is inversely proportional to the number of children client have, means Credit amount is higher for less children count client have and vice-versa.
3. Income amount is inversely proportional to the number of children client have, means more income for less children client have and vice-versa.
4. less children client have in densely populated area.
5. Credit amount is higher to densely populated area.
6. The income is also higher in densely populated area.

```
# For Target 1

targets_corr(data=target1,title='Correlation for target 1')
```



This heat map for Target 1 is also having quite a same observation just like Target 0. But for few points are different. They are listed below.

1. The client's permanent address does not match contact address are having less children and vice-versa
2. the client's permanent address does not match work address are having less children and vice-versa

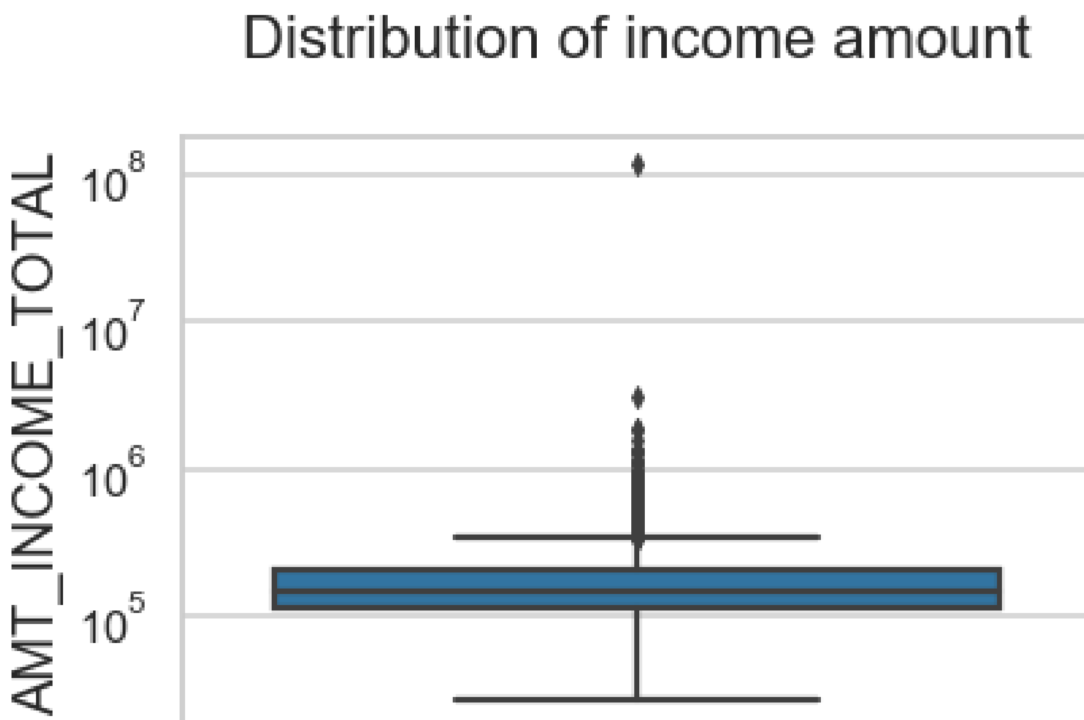
Univariate analysis for variables

```
# Box plotting for univariate variables analysis in logarithmic scale

def univariate_numerical(data,col,title):
    sns.set_style('whitegrid')
    sns.set_context('talk')
    plt.rcParams["axes.labelsize"] = 20
    plt.rcParams['axes.titlesize'] = 22
    plt.rcParams['axes.titlepad'] = 30
```

```
    plt.title(title)
    plt.yscale('log')
    sns.boxplot(data =target1_df, x=col,orient='v')
    plt.show()
```

For Target 0 - Finding any outliers

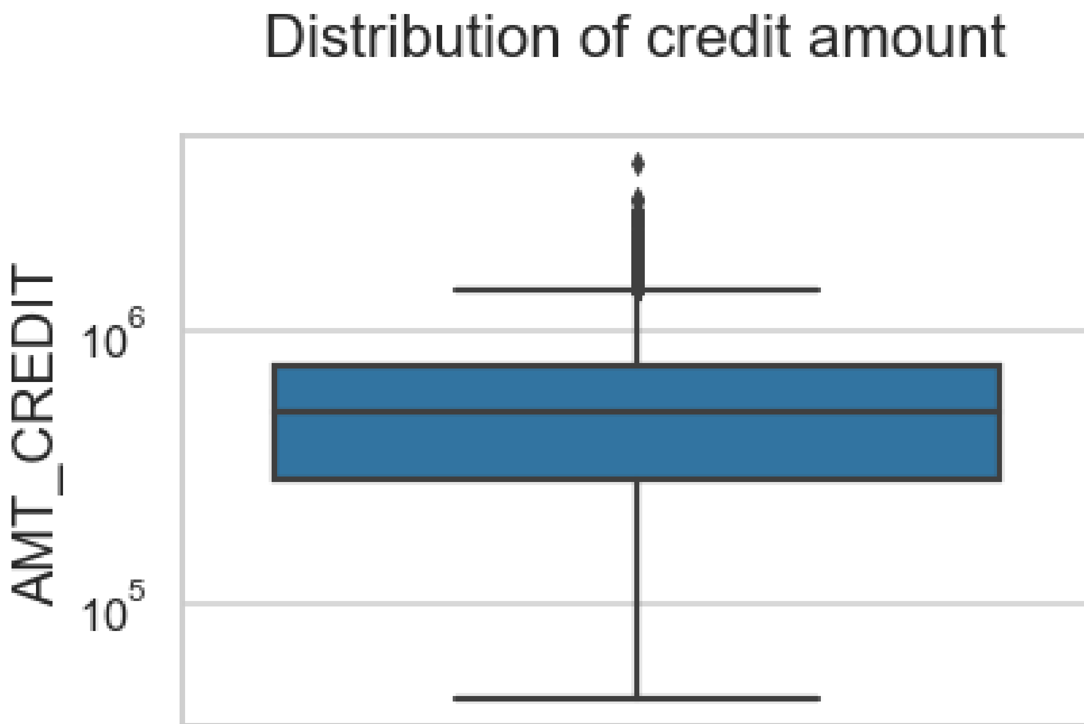
```
# Distribution of income amount

univariate_numerical(data=target0_df,col='AMT_INCOME_TOTAL',title='Dis
tribution of income amount')
```



Few points can be concluded from the graph above.

1. Some outliers are noticed in income amount.
2. The third quartiles is very slim for income amount.

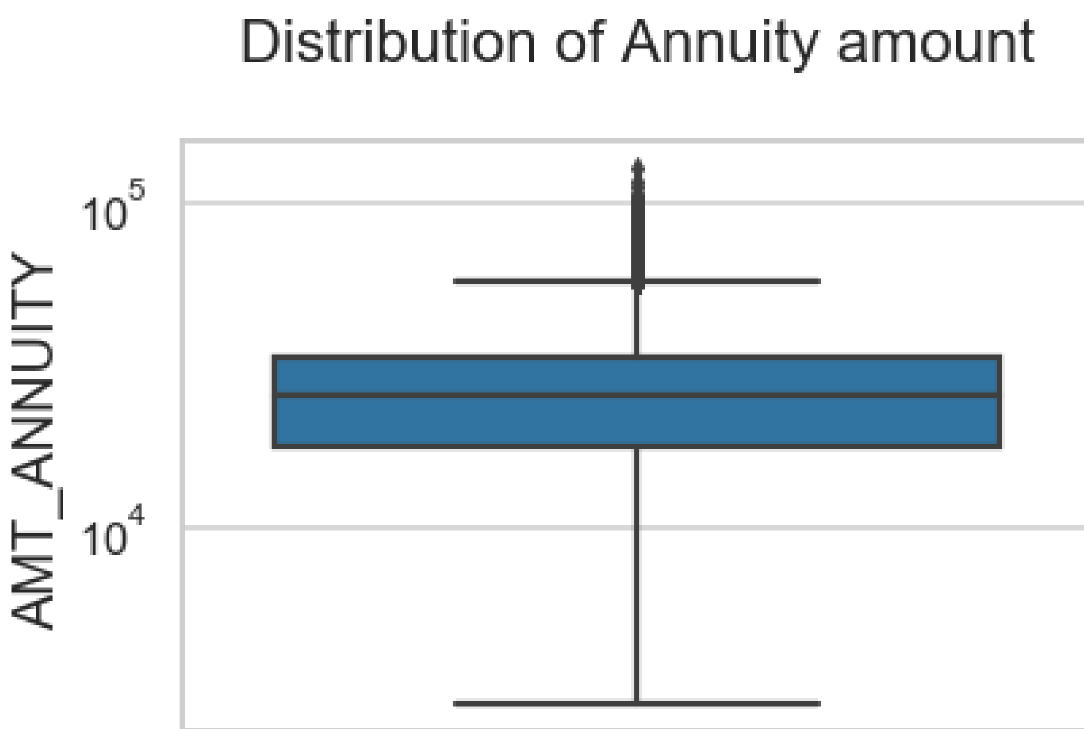
```
# Disrtibution of credit amount

univariate_numerical(data=target0_df,col='AMT_CREDIT',title='Distribut
ion of credit amount')
```



Few points can be concluded from the graph above.

1. Some outliers are noticed in credit amount.
2. The first quartile is bigger than third quartile for credit amount which means most of the credits of clients are present in the first quartile.

```
# Distribution of anuuity amount

univariate_numerical(data=target0_df,col='AMT_ANNUITY',title='Distribution of Annuity amount')
```

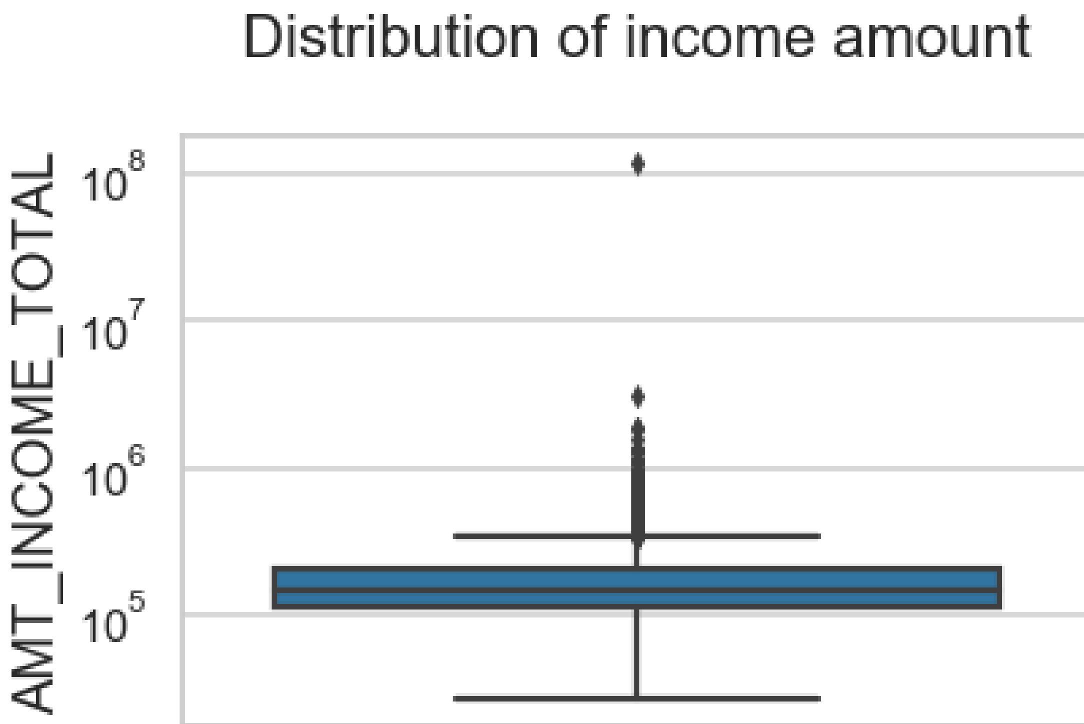


Few points can be concluded from the graph above.

1. Some outliers are noticed in annuity amount.
2. The first quartile is bigger than third quartile for annuity amount which means most of the annuity clients are from first quartile.

For Target 1 - Finding any outliers

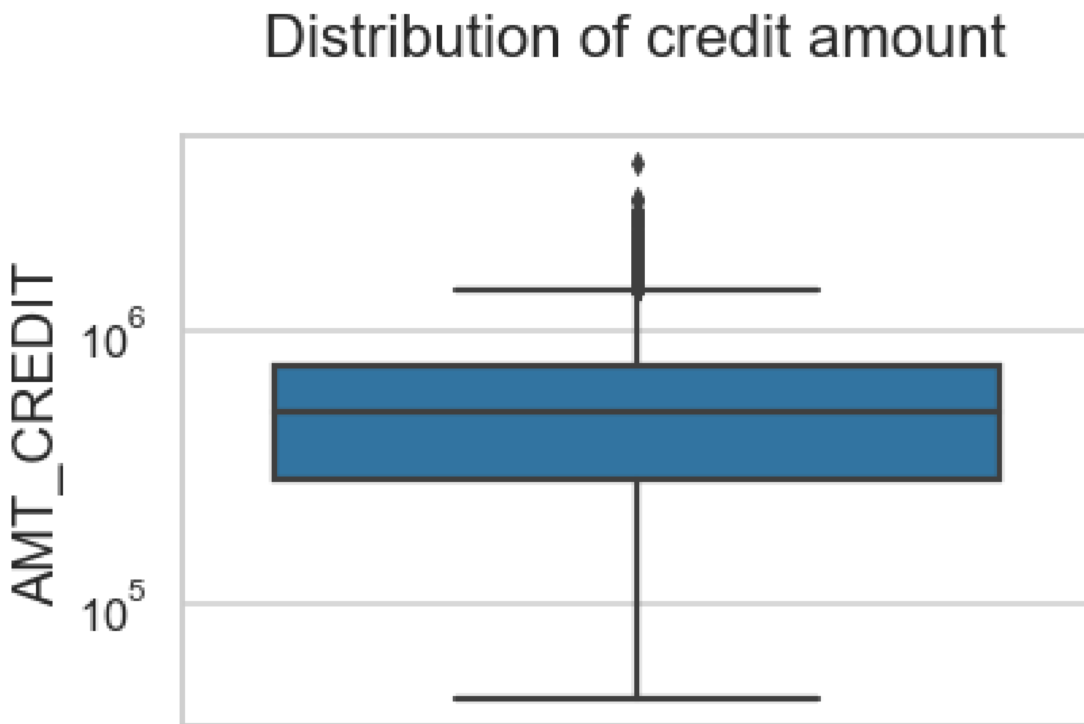
```
# Distribution of income amount

univariate_numerical(data=target1_df,col='AMT_INCOME_TOTAL',title='Distribution of income amount')
```



Few points can be concluded from the graph above.

1. Some outliers are noticed in income amount.
2. The third quartiles is very slim for income amount.
3. Most of the clients of income are present in first quartile.

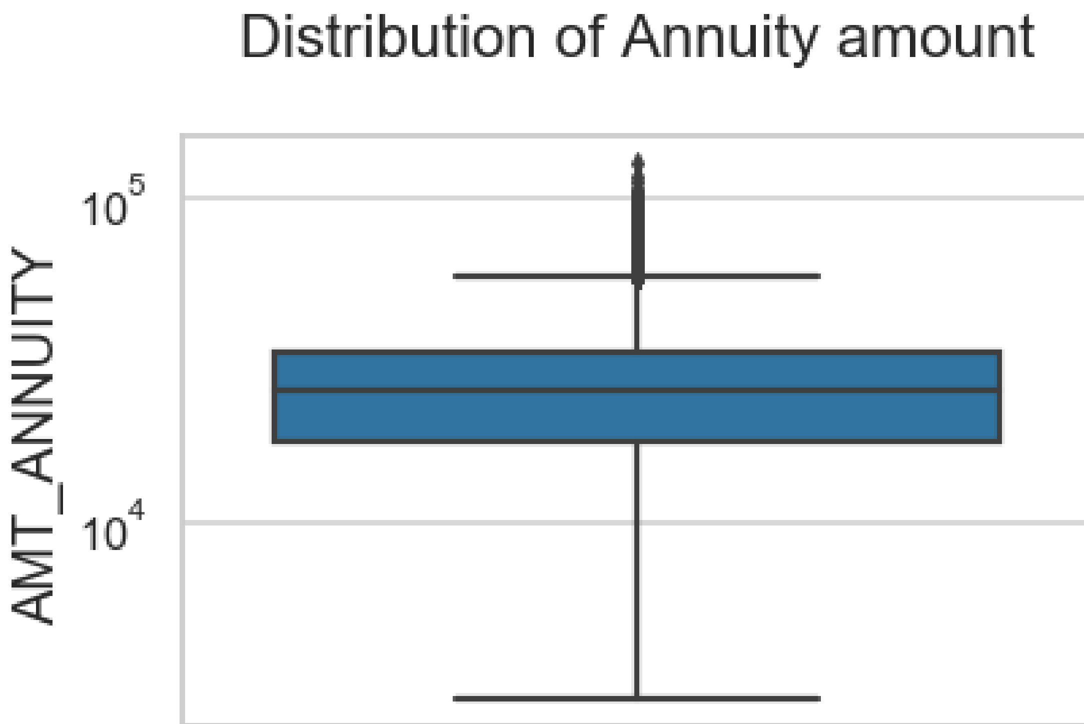
```
# Distribution of credit amount

univariate_numerical(data=target1_df,col='AMT_CREDIT',title='Distribut
ion of credit amount')
```



Few points can be concluded from the graph above.

1. Some outliers are noticed in credit amount.
2. The first quartile is bigger than third quartile for credit amount which means most of the credits of clients are present in the first quartile.

```
# Distribution of Annuity amount

univariate_numerical(data=target1_df,col='AMT_ANNUITY',title='Distribution of Annuity amount')
```



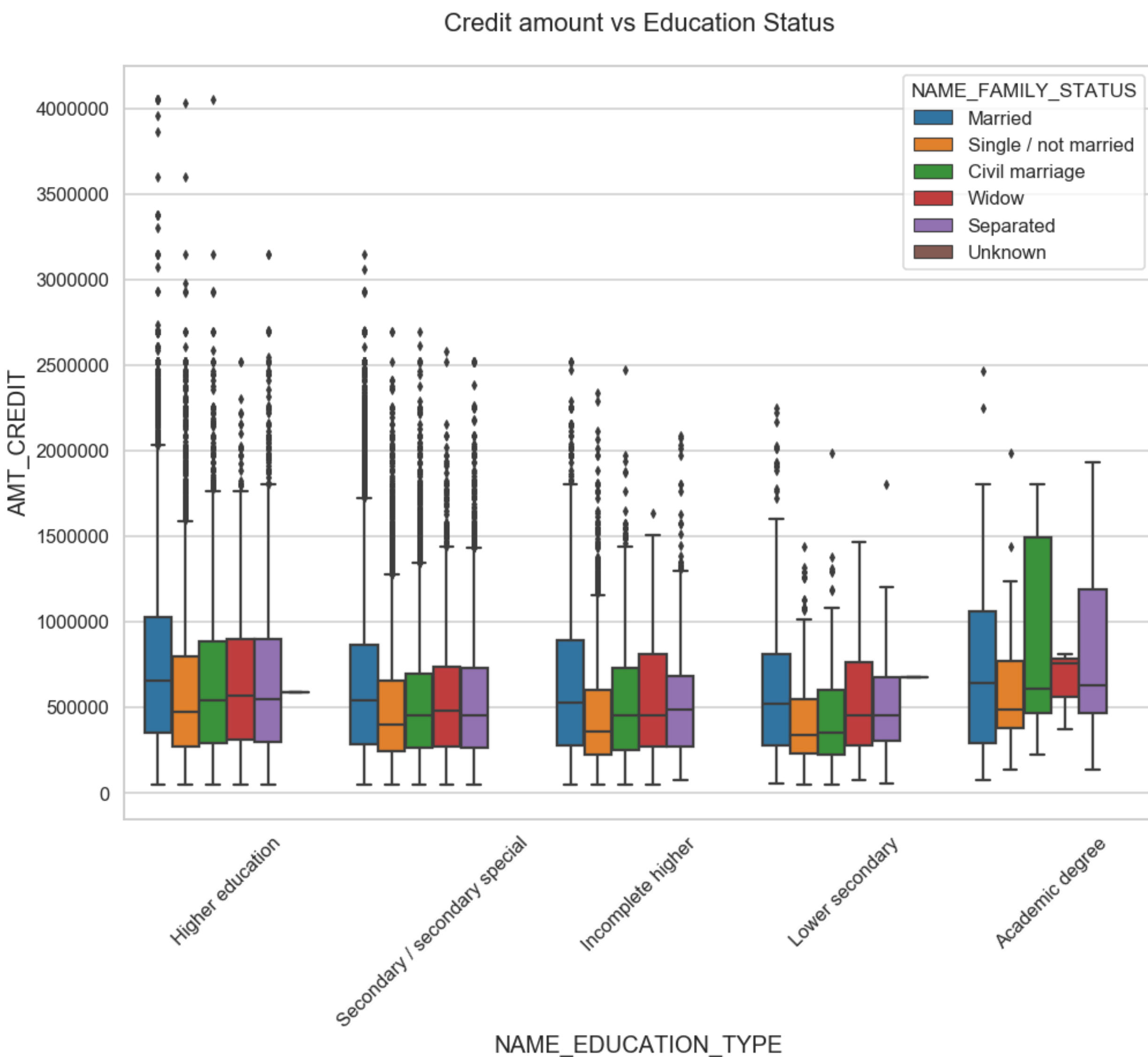
Few points can be concluded from the graph above.

1. Some outliers are noticed in annuity amount.
2. The first quartile is bigger than third quartile for annuity amount which means most of the annuity clients are from first quartile.

Bivariate analysis for numerical variables

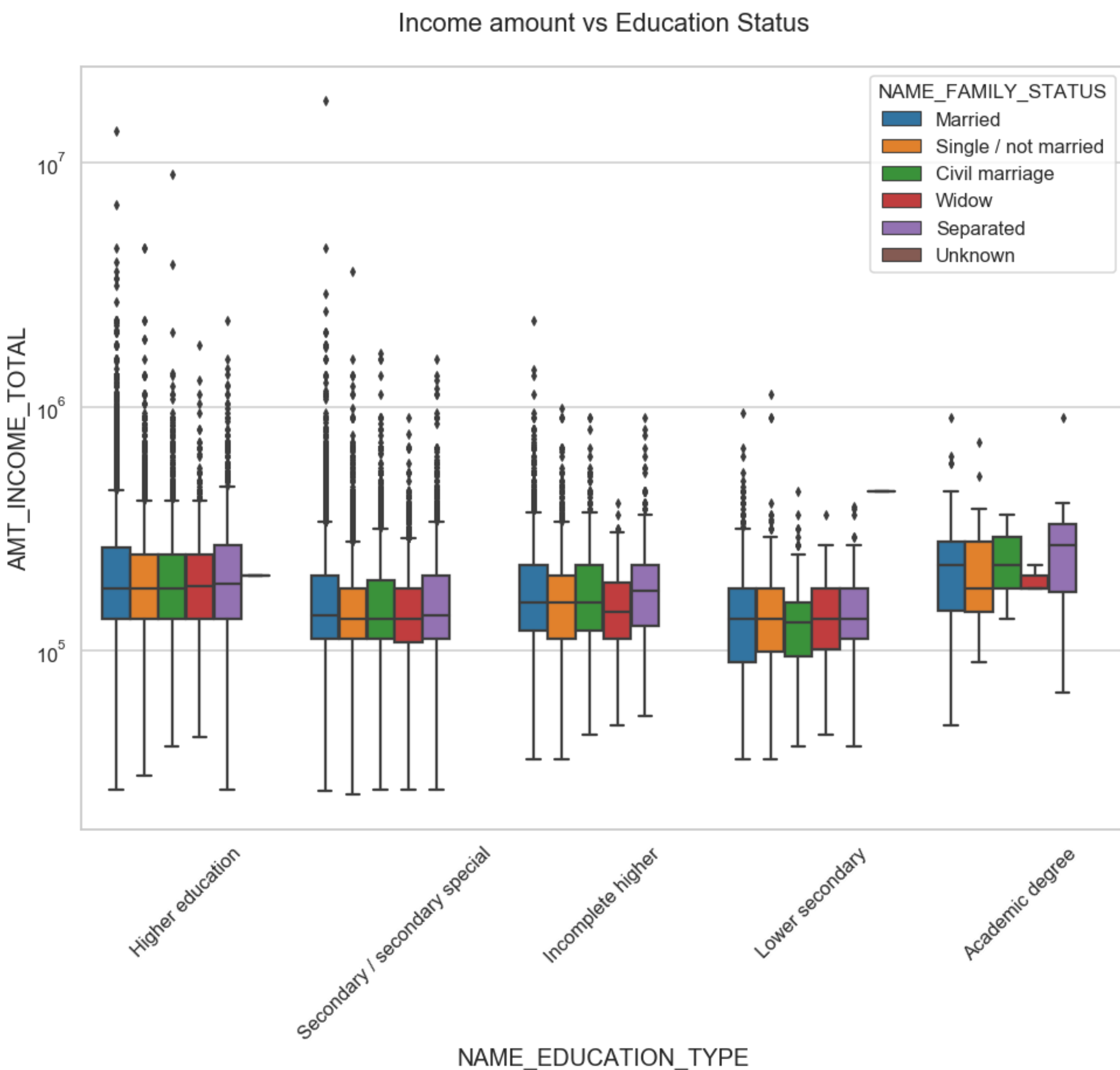
For Target 0

```
# Box plotting for Credit amount

plt.figure(figsize=(16,12))
plt.xticks(rotation=45)
sns.boxplot(data =target0_df, x='NAME_EDUCATION_TYPE',y='AMT_CREDIT',
hue ='NAME_FAMILY_STATUS',orient='v')
plt.title('Credit amount vs Education Status')
plt.show()
```



From the above box plot we can conclude that Family status of 'civil marriage', 'marriage' and 'separated' of Academic degree education are having higher number of credits than others. Also, higher education of family status of 'marriage', 'single' and 'civil marriage' are having more outliers. Civil marriage for Academic degree is having most of the credits in the third quartile.

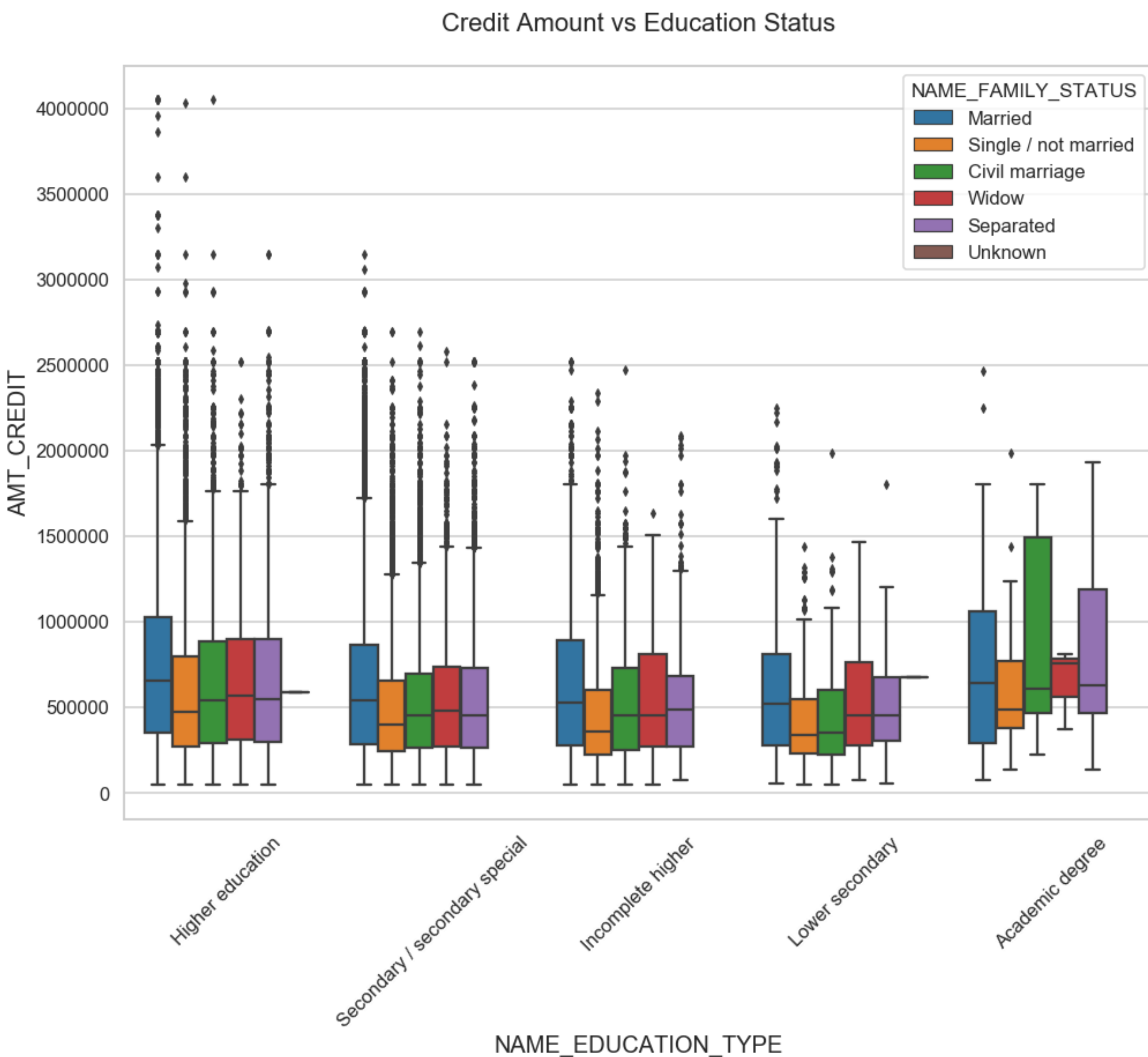
```
# Box plotting for Income amount in logarithmic scale

plt.figure(figsize=(16,12))
plt.xticks(rotation=45)
plt.yscale('log')
sns.boxplot(data =target0_df,
x='NAME_EDUCATION_TYPE',y='AMT_INCOME_TOTAL', hue
='NAME_FAMILY_STATUS',orient='v')
plt.title('Income amount vs Education Status')
plt.show()
```



From above boxplot for Education type 'Higher education' the income amount is mostly equal with family status. It does contain many outliers. Less outlier are having for Academic degree but there income amount is little higher that Higher education. Lower secondary of civil marriage family status are have less income amount than others.

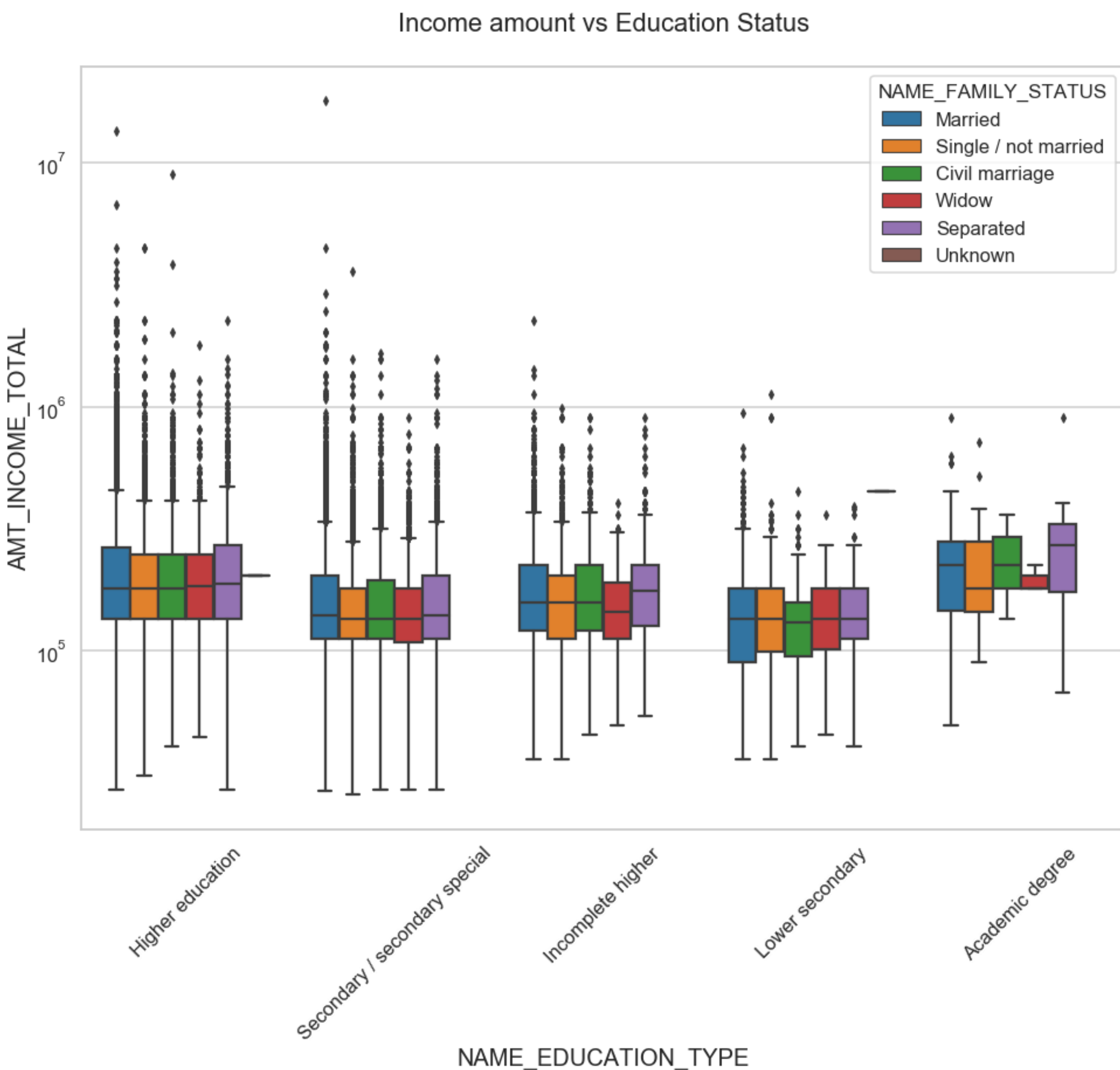
For Target 1

```
# Box plotting for credit amount

plt.figure(figsize=(16,12))
plt.xticks(rotation=45)
sns.boxplot(data =target0_df, x='NAME_EDUCATION_TYPE',y='AMT_CREDIT',
hue ='NAME_FAMILY_STATUS',orient='v')
plt.title('Credit Amount vs Education Status')
plt.show()
```



Quite similar with Target 0 From the above box plot we can say that Family status of 'civil marriage', 'marriage' and 'separated' of Academic degree education are having higher number of credits than others. Most of the outliers are from Education type 'Higher education' and 'Secondary'. Civil marriage for Academic degree is having most of the credits in the third quartile.

```
# Box plotting for Income amount in logarithmic scale

plt.figure(figsize=(16,12))
plt.xticks(rotation=45)
plt.yscale('log')
sns.boxplot(data =target0_df,
x='NAME_EDUCATION_TYPE',y='AMT_INCOME_TOTAL', hue
='NAME_FAMILY_STATUS',orient='v')
plt.title('Income amount vs Education Status')
plt.show()
```



Have some similarity with Target0, From above boxplot for Education type 'Higher education' the income amount is mostly equal with family status. Less outlier are having for Academic degree but there income amount is little higher that Higher education. Lower secondary are have less income amount than others.

NOTE - Please change the reading directory of the dataset in the below query as per your requirments

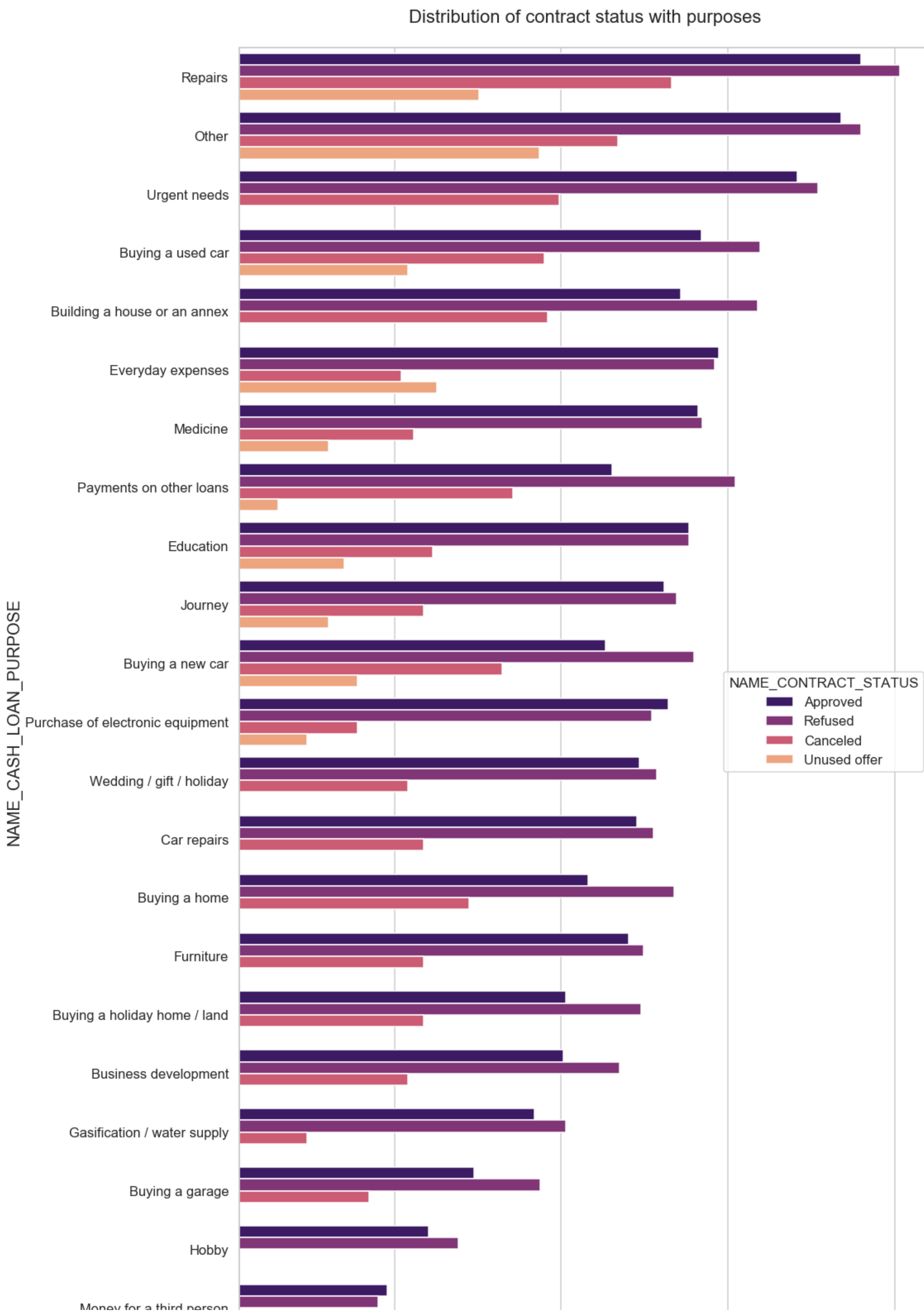
```
# Reading the dataset of previous application

df1=pd.read_csv(r"C:\Users\Samrat Sinha\Downloads\Credit EDA Case Study-20190607T183139Z-001\Credit EDA Case Study\previous_application.csv")
```

```
# Cleaning the missing data

# listing the null values columns having more than 30%

emptycol1=df1.isnull().sum()
emptycol1=emptycol1[emptycol1.values>(0.3*len(emptycol1))]
len(emptycol1)

15

# Removing those 15 columns

emptycol1 = list(emptycol1[emptycol1.values>=0.3].index)
df1.drop(labels=emptycol1,axis=1,inplace=True)

df1.shape

(1670214, 22)

# Removing the column values of 'XNA' and 'XAP'

df1=df1.drop(df1[df1['NAME_CASH_LOAN_PURPOSE']=='XNA'].index)
df1=df1.drop(df1[df1['NAME_CASH_LOAN_PURPOSE']=='XNA'].index)
df1=df1.drop(df1[df1['NAME_CASH_LOAN_PURPOSE']=='XAP'].index)

df1.shape

(69635, 22)

# Now merging the Application dataset with previous appliaction
dataset

new_df=pd.merge(left=df,right=df1,how='inner',on='SK_ID_CURR',suffixes
='_x')

# Renaming the column names after merging

new_df1 = new_df.rename({'NAME_CONTRACT_TYPE_' :
'NAME_CONTRACT_TYPE','AMT_CREDIT_':'AMT_CREDIT','AMT_ANNUITY_':'AMT_AN
NUITY',
                         'WEEKDAY_APPR_PROCESS_START_' :
'WEEKDAY_APPR_PROCESS_START',

'HOUR_APPR_PROCESS_START_':'HOUR_APPR_PROCESS_START','NAME_CONTRACT_TY
PEx':'NAME_CONTRACT_TYPE_PREV',

'AMT_CREDITx':'AMT_CREDIT_PREV','AMT_ANNUITYx':'AMT_ANNUITY_PREV',

'WEEKDAY_APPR_PROCESS_STARTx':'WEEKDAY_APPR_PROCESS_START_PREV',

'HOUR_APPR_PROCESS_STARTx':'HOUR_APPR_PROCESS_START_PREV'}, axis=1)
```

```
# Removing unwanted columns for analysis

new_df1.drop(['SK_ID_CURR','WEEKDAY_APPR_PROCESS_START',
'HOUR_APPR_PROCESS_START','REG_REGION_NOT_LIVE_REGION',

'REG_REGION_NOT_WORK_REGION','LIVE_REGION_NOT_WORK_REGION',
'REG_CITY_NOT_LIVE_CITY',
              'REG_CITY_NOT_WORK_CITY',
'LIVE_CITY_NOT_WORK_CITY','WEEKDAY_APPR_PROCESS_START_PREV',
              'HOUR_APPR_PROCESS_START_PREV',
'FLAG_LAST_APPL_PER_CONTRACT','NFLAG_LAST_APPL_IN_DAY'],axis=1,inplace
=True)
```

Performing univariate analysis

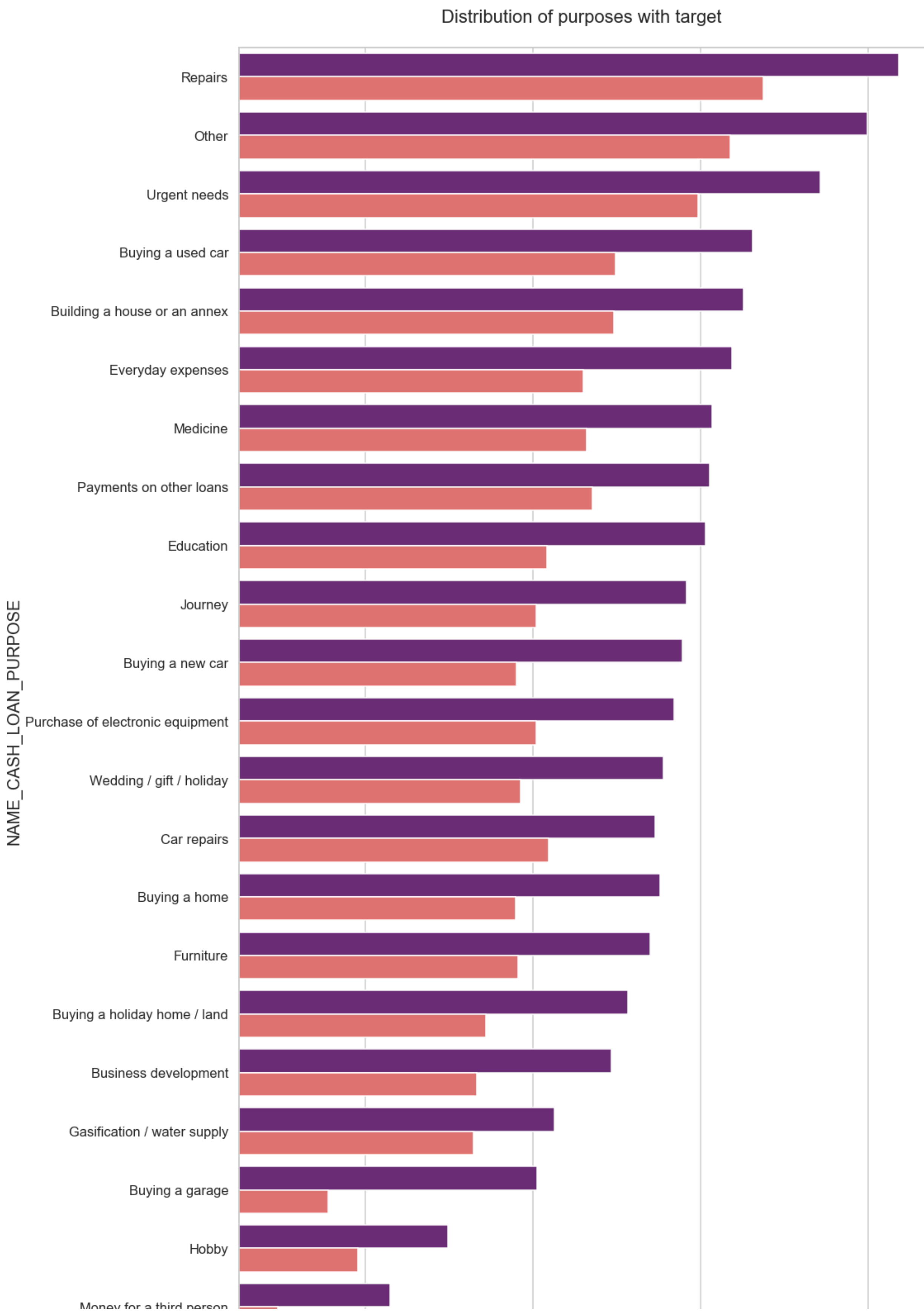
```
# Distribution of contract status in logarithmic scale

sns.set_style('whitegrid')
sns.set_context('talk')

plt.figure(figsize=(15,30))
plt.rcParams["axes.labelsize"] = 20
plt.rcParams['axes.titlesize'] = 22
plt.rcParams['axes.titlepad'] = 30
plt.xticks(rotation=90)
plt.xscale('log')
plt.title('Distribution of contract status with purposes')
ax = sns.countplot(data = new_df1, y= 'NAME_CASH_LOAN_PURPOSE',

order=new_df1['NAME_CASH_LOAN_PURPOSE'].value_counts().index,hue =
'NAME_CONTRACT_STATUS',palette='magma')
```


Distribution of contract status with purposes
NAME_CASH_LOAN_PURPOSE
Repairs
Other
Urgent needs
Buying a used car
Building a house or an annex
Everyday expenses
Medicine
Payments on other loans
Education
Journey
Buying a new car
Purchase of electronic equipment
Wedding / gift / holiday
Car repairs
Buying a home
Furniture
Buying a holiday home / land
Business development
Gasification / water supply
Buying a garage
Hobby
Money for a third person
NAME_CONTRACT_STATUS
Approved
Refused
Canceled
Unused offer

Points to be concluded from above plot:

1. Most rejection of loans came from purpose 'repairs'.
2. For education purposes we have equal number of approves and rejection
3. Payign other loans and buying a new car is having significant higher rejection than approves.

```
# Distribution of contract status

sns.set_style('whitegrid')
sns.set_context('talk')

plt.figure(figsize=(15,30))
plt.rcParams["axes.labelsize"] = 20
plt.rcParams['axes.titlesize'] = 22
plt.rcParams['axes.titlepad'] = 30
plt.xticks(rotation=90)
plt.xscale('log')
plt.title('Distribution of purposes with target ')
ax = sns.countplot(data = new_df1, y= 'NAME_CASH_LOAN_PURPOSE',

order=new_df1['NAME_CASH_LOAN_PURPOSE'].value_counts().index,hue =
'TARGET',palette='magma')
```



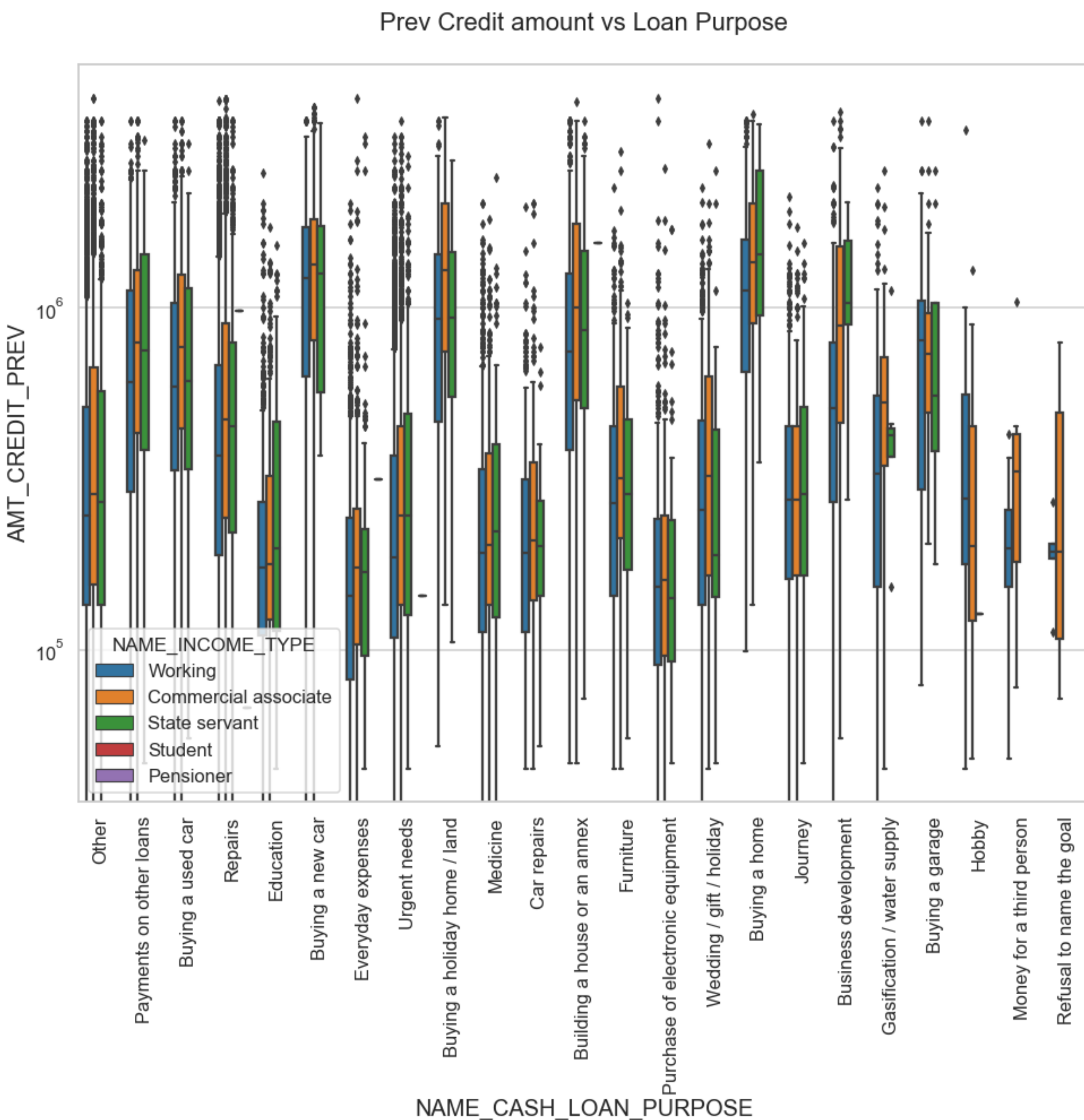
Distribution of purposes with target
NAME_CASH_LOAN_PURPOSE
Repairs
Other
Urgent needs
Buying a used car
Building a house or an annex
Everyday expenses
Medicine
Payments on other loans
Education
Journey
Buying a new car
Purchase of electronic equipment
Wedding / gift / holiday
Car repairs
Buying a home
Furniture
Buying a holiday home / land
Business development
Gasification / water supply
Buying a garage
Hobby

Few points we can conclude from abpve plot:

1. Loan purposes with 'Repairs' are facing more difficulites in payment on time.
2. There are few places where loan payment is significant higher than facing difficulties. They are 'Buying a garage', 'Business developemt', 'Buying land','Buying a new car' and 'Education' Hence we can focus on these purposes for which the client is having for minimal payment difficulties.

Performing bivariate analysis

```
# Box plotting for Credit amount in logarithmic scale

plt.figure(figsize=(16,12))
plt.xticks(rotation=90)
plt.yscale('log')
sns.boxplot(data =new_df1,
x='NAME_CASH_LOAN_PURPOSE',hue='NAME_INCOME_TYPE',y='AMT_CREDIT_PREV',
orient='v')
plt.title('Prev Credit amount vs Loan Purpose')
plt.show()
```

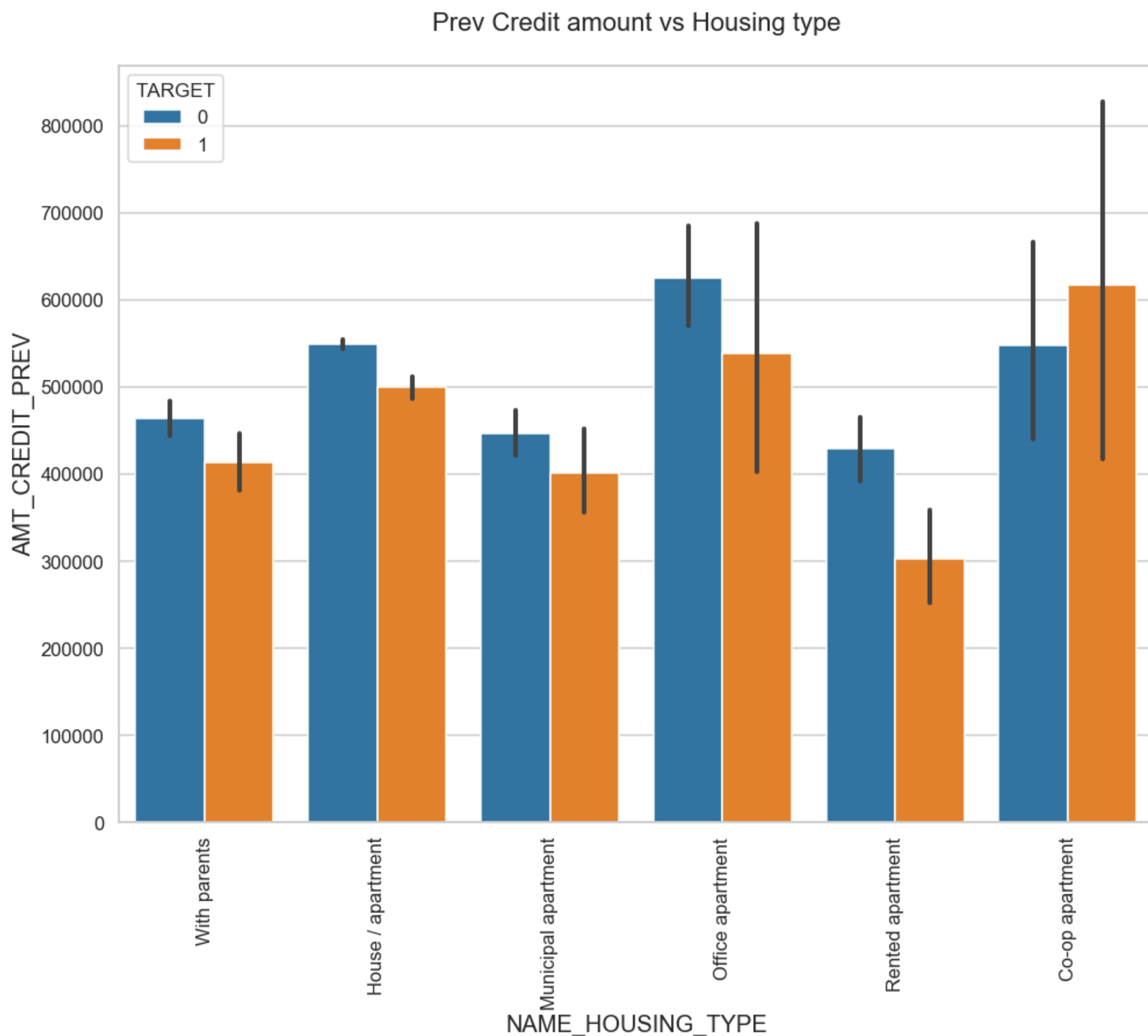


From the above we can conclude some points-

1. The credit amount of Loan purposes like 'Buying a home','Buying a land','Buying a new car' and'Building a house' is higher.
2. Income type of state servants have a significant amount of credit applied
3. Money for third person or a Hobby is having less credits applied for.

```
# Box plotting for Credit amount prev vs Housing type in logarithmic scale

plt.figure(figsize=(16,12))
plt.xticks(rotation=90)
```

```
sns.barplot(data =new_df1,
y='AMT_CREDIT_PREV',hue='TARGET',x='NAME_HOUSING_TYPE')
plt.title('Prev Credit amount vs Housing type')
plt.show()
```



Here for Housing type, office appartment is having higher credit of target 0 and co-op apartment is having higher credit of target 1. So, we can conclude that bank should avoid giving loans to the housing type of co-op apartment as they are having difficulties in payment. Bank can focus mostly on housing type with parents or House\appartment or miuncipal appartment for successful payments.

CONCLUSION

1. Banks should focus more on contract type ‘Student’ ,’pensioner’ and ‘Businessman’ with housing ‘type other than ‘Co-op apartment’ for successful payments.

2. Banks should focus less on income type ‘Working’ as they are having most number of unsuccessful payments.

3. Also with loan purpose ‘Repair’ is having higher number of unsuccessful payments on time.

4. Get as much as clients from housing type ‘With parents’ as they are having least number of unsuccessful payments.