Trainity Assignment - 6

Bank Loan Case Study

```
#importing libraries
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
```

```
from google.colab import drive
drive.mount('/gdrive')

from google.colab import drive
drive.mount('/content/drive')
```

```
    Mounted at /gdrive
    Mounted at /content/drive
```

```
#import the data
data=pd.read_csv("/content/drive/MyDrive/Trainity Assignments/Trainity Assignment - 6/Dataset/application_data_cleaned.
```

Data Quality Check & Missing Values

Find the percentage of missing values of the columns

```
# function to get null value
def column_wise_null_percentage(df):
    output = round(df.isnull().sum()/len(df.index)*100,2)
    return output
```

```
# get missign values of all columns
NA_col = column_wise_null_percentage(data)
NA_col
```

```
    SK_ID_CURR                      0.00
    TARGET                          0.00
    NAME_CONTRACT_TYPE              0.00
    CODE_GENDER                     0.00
    FLAG_OWN_CAR                    0.00
    FLAG_OWN_REALTY                 0.00
    CNT_CHILDREN                    0.00
    AMT_INCOME_TOTAL                0.00
    AMT_CREDIT                      0.00
    AMT_ANNUITY                     0.01
    AMT_GOODS_PRICE                 0.08
    NAME_TYPE_SUITE                 0.40
    NAME_INCOME_TYPE                0.00
    NAME_EDUCATION_TYPE             0.00
    NAME_FAMILY_STATUS              0.00
    NAME_HOUSING_TYPE               0.00
    REGION_POPULATION_RELATIVE      0.00
    DAYS_BIRTH                      0.00
    DAYS_EMPLOYED                   0.00
    DAYS_REGISTRATION               0.00
    DAYS_ID_PUBLISH                 0.00
    OCCUPATION_TYPE                31.31
    CNT_FAM_MEMBERS                 0.00
    REGION_RATING_CLIENT            0.00
    REGION_RATING_CLIENT_W_CITY     0.00
    WEEKDAY_APPR_PROCESS_START      0.00
    HOUR_APPR_PROCESS_START         0.00
    REG_REGION_NOT_LIVE_REGION      0.00
    REG_REGION_NOT_WORK_REGION      0.00
    LIVE_REGION_NOT_WORK_REGION     0.00
    REG_CITY_NOT_LIVE_CITY          0.00
    REG_CITY_NOT_WORK_CITY          0.00
    LIVE_CITY_NOT_WORK_CITY         0.00
    ORGANIZATION_TYPE               0.00
    EXT_SOURCE_2                    0.23
    OBS_30_CNT_SOCIAL_CIRCLE        0.33
    DEF_30_CNT_SOCIAL_CIRCLE        0.33
```

```
OBS_60_CNT_SOCIAL_CIRCLE        0.33
DEF_60_CNT_SOCIAL_CIRCLE        0.33
DAYS_LAST_PHONE_CHANGE          0.00
AMT_REQ_CREDIT_BUREAU_HOUR     13.41
AMT_REQ_CREDIT_BUREAU_DAY      13.41
AMT_REQ_CREDIT_BUREAU_WEEK     13.41
AMT_REQ_CREDIT_BUREAU_MON      13.41
AMT_REQ_CREDIT_BUREAU_QRT      13.41
AMT_REQ_CREDIT_BUREAU_YEAR     13.41
dtype: float64
```

Since its EDA we will not replace but if one must replace the coloumns itll be my means of central tendency ie,mean ,median or mode

```
# Get columns having <15% null values
NA_col_15 = NA_col[NA_col<15]
print("Number of columns having null value less than 15% :", len(NA_col_15.index))
print(NA_col_15)
```

```
Number of columns having null value less than 15% : 45
SK_ID_CURR                      0.00
TARGET                          0.00
NAME_CONTRACT_TYPE              0.00
CODE_GENDER                     0.00
FLAG_OWN_CAR                    0.00
FLAG_OWN_REALTY                 0.00
CNT_CHILDREN                    0.00
AMT_INCOME_TOTAL                0.00
AMT_CREDIT                      0.00
AMT_ANNUITY                     0.01
AMT_GOODS_PRICE                 0.08
NAME_TYPE_SUITE                 0.40
NAME_INCOME_TYPE                0.00
NAME_EDUCATION_TYPE             0.00
NAME_FAMILY_STATUS              0.00
NAME_HOUSING_TYPE               0.00
REGION_POPULATION_RELATIVE      0.00
DAYS_BIRTH                      0.00
DAYS_EMPLOYED                   0.00
DAYS_REGISTRATION               0.00
DAYS_ID_PUBLISH                 0.00
CNT_FAM_MEMBERS                 0.00
REGION_RATING_CLIENT            0.00
REGION_RATING_CLIENT_W_CITY     0.00
WEEKDAY_APPR_PROCESS_START      0.00
HOUR_APPR_PROCESS_START         0.00
REG_REGION_NOT_LIVE_REGION      0.00
REG_REGION_NOT_WORK_REGION      0.00
LIVE_REGION_NOT_WORK_REGION     0.00
REG_CITY_NOT_LIVE_CITY          0.00
REG_CITY_NOT_WORK_CITY          0.00
LIVE_CITY_NOT_WORK_CITY         0.00
ORGANIZATION_TYPE               0.00
EXT_SOURCE_2                    0.23
OBS_30_CNT_SOCIAL_CIRCLE        0.33
DEF_30_CNT_SOCIAL_CIRCLE        0.33
OBS_60_CNT_SOCIAL_CIRCLE        0.33
DEF_60_CNT_SOCIAL_CIRCLE        0.33
DAYS_LAST_PHONE_CHANGE          0.00
AMT_REQ_CREDIT_BUREAU_HOUR     13.41
AMT_REQ_CREDIT_BUREAU_DAY      13.41
AMT_REQ_CREDIT_BUREAU_WEEK     13.41
AMT_REQ_CREDIT_BUREAU_MON      13.41
AMT_REQ_CREDIT_BUREAU_QRT      13.41
AMT_REQ_CREDIT_BUREAU_YEAR     13.41
dtype: float64
```

```
NA_col_15.index
```

```
Index(['SK_ID_CURR', 'TARGET', 'NAME_CONTRACT_TYPE', 'CODE_GENDER',
       'FLAG_OWN_CAR', 'FLAG_OWN_REALTY', 'CNT_CHILDREN', 'AMT_INCOME_TOTAL',
       'AMT_CREDIT', 'AMT_ANNUITY', 'AMT_GOODS_PRICE', 'NAME_TYPE_SUITE',
       'NAME_INCOME_TYPE', 'NAME_EDUCATION_TYPE', 'NAME_FAMILY_STATUS',
       'NAME_HOUSING_TYPE', 'REGION_POPULATION_RELATIVE', 'DAYS_BIRTH',
       'DAYS_EMPLOYED', 'DAYS_REGISTRATION', 'DAYS_ID_PUBLISH',
       'CNT_FAM_MEMBERS', 'REGION_RATING_CLIENT',
       'REGION_RATING_CLIENT_W_CITY', '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', 'ORGANIZATION_TYPE', 'EXT_SOURCE_2',
       'OBS_30_CNT_SOCIAL_CIRCLE', 'DEF_30_CNT_SOCIAL_CIRCLE',
       'OBS_60_CNT_SOCIAL_CIRCLE', 'DEF_60_CNT_SOCIAL_CIRCLE',
```

```
       'DAYS_LAST_PHONE_CHANGE', 'AMT_REQ_CREDIT_BUREAU_HOUR',
       'AMT_REQ_CREDIT_BUREAU_DAY', 'AMT_REQ_CREDIT_BUREAU_WEEK',
       'AMT_REQ_CREDIT_BUREAU_MON', 'AMT_REQ_CREDIT_BUREAU_QRT',
       'AMT_REQ_CREDIT_BUREAU_YEAR'],
      dtype='object')
```

```
# understand the insight of missing columns having <15% null values
data[NA_col_15.index].describe()
```

	SK_ID_CURR	TARGET	CNT_CHILDREN	AMT_INCOME_TOTAL	AMT_CREDIT	AMT_ANNUITY	AMT_GOODS_PRICE	REGION_
count	65535.000000	65535.000000	65535.000000	6.553500e+04	6.553500e+04	65530.000000	6.548200e+04	
mean	138007.241657	0.080537	0.419532	1.697612e+05	5.993438e+05	27071.782725	5.386308e+05	
std	21894.402583	0.272125	0.724485	4.667518e+05	4.026696e+05	14485.959968	3.699318e+05	
min	100002.000000	0.000000	0.000000	2.565000e+04	4.500000e+04	2052.000000	4.500000e+04	
25%	119110.500000	0.000000	0.000000	1.125000e+05	2.700000e+05	16456.500000	2.385000e+05	
50%	137975.000000	0.000000	0.000000	1.440000e+05	5.135310e+05	24903.000000	4.500000e+05	
75%	156904.500000	0.000000	1.000000	2.025000e+05	8.086500e+05	34587.000000	6.795000e+05	
max	176002.000000	1.000000	11.000000	1.170000e+08	4.050000e+06	258025.500000	4.050000e+06	

8 rows × 34 columns

```
# identify unique values in the colums having <15% null value
data[NA_col_15.index].nunique().sort_values(ascending=False)
```

```
SK_ID_CURR                      65535
EXT_SOURCE_2                    48549
DAYS_BIRTH                      16427
DAYS_REGISTRATION               13320
AMT_ANNUITY                      9566
DAYS_EMPLOYED                    8794
DAYS_ID_PUBLISH                  5856
AMT_CREDIT                       3709
DAYS_LAST_PHONE_CHANGE           3480
AMT_INCOME_TOTAL                  948
AMT_GOODS_PRICE                   555
REGION_POPULATION_RELATIVE         80
ORGANIZATION_TYPE                  58
OBS_30_CNT_SOCIAL_CIRCLE           29
OBS_60_CNT_SOCIAL_CIRCLE           28
HOUR_APPR_PROCESS_START            24
AMT_REQ_CREDIT_BUREAU_MON          20
AMT_REQ_CREDIT_BUREAU_YEAR         19
CNT_CHILDREN                       11
CNT_FAM_MEMBERS                    11
AMT_REQ_CREDIT_BUREAU_QRT           9
NAME_INCOME_TYPE                    8
AMT_REQ_CREDIT_BUREAU_WEEK          7
WEEKDAY_APPR_PROCESS_START          7
AMT_REQ_CREDIT_BUREAU_DAY           7
DEF_30_CNT_SOCIAL_CIRCLE            7
NAME_TYPE_SUITE                     7
NAME_HOUSING_TYPE                   6
DEF_60_CNT_SOCIAL_CIRCLE            6
NAME_FAMILY_STATUS                  6
NAME_EDUCATION_TYPE                 5
AMT_REQ_CREDIT_BUREAU_HOUR          4
CODE_GENDER                         3
REGION_RATING_CLIENT                3
REGION_RATING_CLIENT_W_CITY         3
FLAG_OWN_REALTY                     2
REG_CITY_NOT_WORK_CITY              2
FLAG_OWN_CAR                        2
REG_CITY_NOT_LIVE_CITY              2
LIVE_REGION_NOT_WORK_REGION         2
REG_REGION_NOT_WORK_REGION          2
REG_REGION_NOT_LIVE_REGION          2
NAME_CONTRACT_TYPE                  2
TARGET                              2
LIVE_CITY_NOT_WORK_CITY             2
dtype: int64
```

For analysis we selected 7 variables

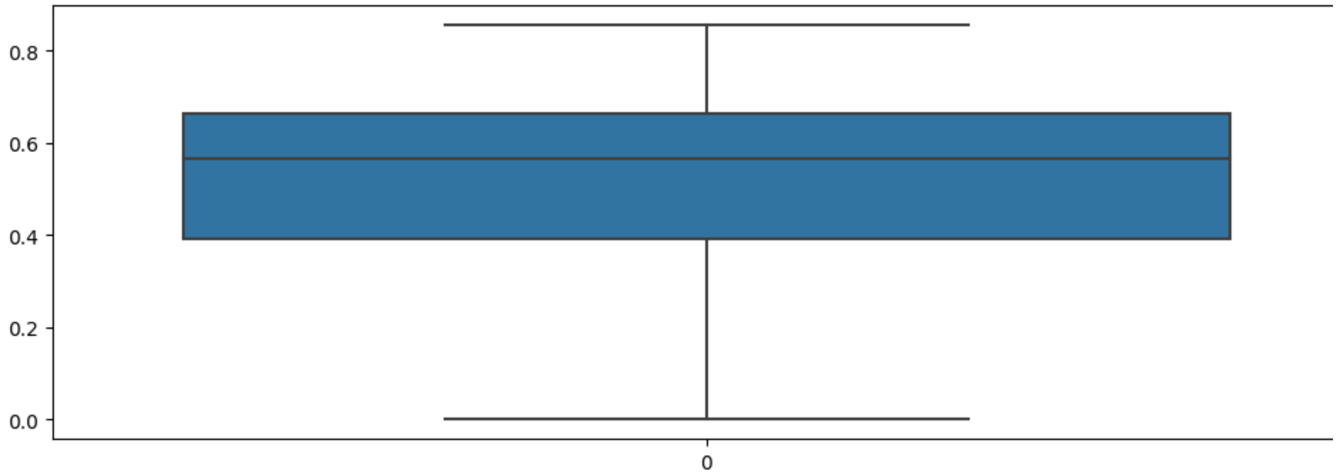
1)Continous variables:

'EXT_SOURCE_2', 'AMT_GOODS_PRICE'

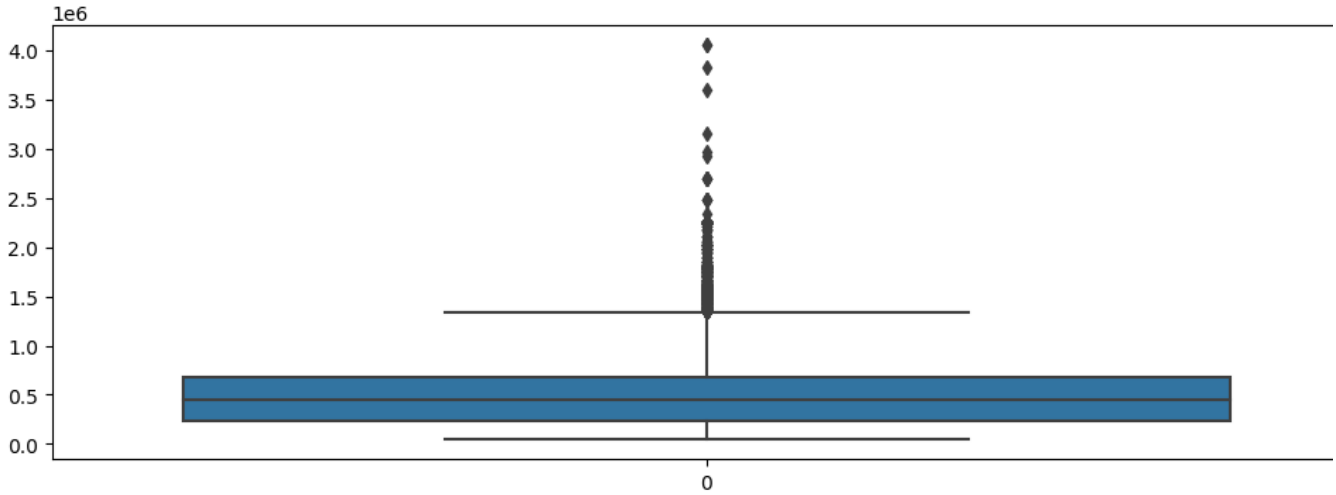
2)Categorial variables:

'OBS_30_CNT_SOCIAL_CIRCLE', 'OBS_60_CNT_SOCIAL_CIRCLE', 'DEF_60_CNT_SOCIAL_CIRCLE', 'DEF_30_CNT_SOCIAL_CIRCLE', 'NAME_TYPE_SUITE'

```
# Box plot for continuious variable
plt.figure(figsize=(12,4))
sns.boxplot(data['EXT_SOURCE_2'])
plt.show()
```




```
plt.figure(figsize=(12,4))
sns.boxplot(data['AMT_GOODS_PRICE'])
plt.show()
```



Inference from box plot:

for 'EXT_SOURCE_2' there is no outliers present. And there is no significant diffence observed between mean and median. However data look to be right skewed. So missing values can be imputed with median value: 0.565 for 'AMT_GOODS_PRICE' there is significant number of outlier present in the data. SO data should be imputed with median value: 450000

```
#For Categorical variables
# identify maximum frequency values
print('Maximum Frequncy categorical values are,')
print('NAME_TYPE_SUITE: ',data['NAME_TYPE_SUITE'].mode()[0])
print('OBS_30_CNT_SOCIAL_CIRCLE:', data['OBS_30_CNT_SOCIAL_CIRCLE'].mode()[0])
print('DEF_30_CNT_SOCIAL_CIRCLE:', data['DEF_30_CNT_SOCIAL_CIRCLE'].mode()[0])
print('OBS_60_CNT_SOCIAL_CIRCLE:', data['OBS_60_CNT_SOCIAL_CIRCLE'].mode()[0])
print('DEF_60_CNT_SOCIAL_CIRCLE:', data['DEF_60_CNT_SOCIAL_CIRCLE'].mode()[0])
```

```
Maximum Frequncy categorical values are,
NAME_TYPE_SUITE:  Unaccompanied
OBS_30_CNT_SOCIAL_CIRCLE: 0.0
DEF_30_CNT_SOCIAL_CIRCLE: 0.0
OBS_60_CNT_SOCIAL_CIRCLE: 0.0
DEF_60_CNT_SOCIAL_CIRCLE: 0.0
```

```
data.head()
```

E_CONTRACT_TYPE	CODE_GENDER	FLAG_OWN_CAR	FLAG_OWN_REALTY	CNT_CHILDREN	AMT_INCOME_TOTAL	AMT_CREDIT	AMT_ANNUITY
Cash loans	M	N	Y	0	202500.0	406597.5	24700.5
Cash loans	F	N	N	0	270000.0	1293502.5	35698.5
Revolving loans	M	Y	Y	0	67500.0	135000.0	6750.0
Cash loans	F	N	Y	0	135000.0	312682.5	29686.5
Cash loans	M	N	Y	0	121500.0	513000.0	21865.5

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.

```
# For Code Gender column

print('CODE_GENDER: ',data['CODE_GENDER'].unique())
print('No of values: ',data[data['CODE_GENDER']=='XNA'].shape[0])

XNA_count = data[data['CODE_GENDER']=='XNA'].shape[0]
per_XNA = round(XNA_count/len(data.index)*100,3)

print('% of XNA Values:',  per_XNA)

print('maximum frequency data :', data['CODE_GENDER'].describe().top)
```

```
CODE_GENDER:  ['M' 'F' 'XNA']
No of values:  2
% of XNA Values: 0.003
maximum frequency data : F
```

Since, Female is having the majority and only 2 rows are having XNA values, we can impute those with Gender 'F' as there will be no impact on the dataset. Also there will no impact if we drop those rows.

```
# Dropping the XNA value in column 'CODE_GENDER' with "F" for the dataset

data = data.drop(data.loc[data['CODE_GENDER']=='XNA'].index)
data[data['CODE_GENDER']=='XNA'].shape
```

```
(0, 46)
```

```
# For Organization column
print('No of XNA values: ', data[data['ORGANIZATION_TYPE']=='XNA'].shape[0])

XNA_count = data[data['ORGANIZATION_TYPE']=='XNA'].shape[0]
per_XNA = round(XNA_count/len(data.index)*100,3)

print('% of XNA Values:',  per_XNA)

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

```
No of XNA values:  11698
% of XNA Values: 17.851
count                      65533
unique                        58
top       Business Entity Type 3
freq                       14455
Name: ORGANIZATION_TYPE, dtype: object
```

```
#check data types of all the columns and change data type
data.head()
```

	SK_ID_CURR	TARGET	NAME_CONTRACT_TYPE	CODE_GENDER	FLAG_OWN_CAR	FLAG_OWN_REALTY	CNT_CHILDREN	AMT_INCOME_TOT/
0	100002	1	Cash loans	M	N	Y	0	20250C
1	100003	0	Cash loans	F	N	N	0	27000C
2	100004	0	Revolving loans	M	Y	Y	0	6750C
3	100006	0	Cash loans	F	N	Y	0	13500C
4	100007	0	Cash loans	M	N	Y	0	12150C

5 rows × 46 columns

```
# Casting variable into numeric in the dataset

numeric_columns=['TARGET','CNT_CHILDREN','AMT_INCOME_TOTAL','AMT_CREDIT','AMT_ANNUITY','REGION_POPULATION_RELATIVE',
                 'DAYS_BIRTH','DAYS_EMPLOYED','DAYS_REGISTRATION','DAYS_ID_PUBLISH','HOUR_APPR_PROCESS_START',
                 'LIVE_REGION_NOT_WORK_REGION', 'REG_CITY_NOT_LIVE_CITY','REG_CITY_NOT_WORK_CITY', 'LIVE_CITY_NOT_WORK_
                'DAYS_LAST_PHONE_CHANGE']

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

	SK_ID_CURR	TARGET	NAME_CONTRACT_TYPE	CODE_GENDER	FLAG_OWN_CAR	FLAG_OWN_REALTY	CNT_CHILDREN	AMT_INCOME_TOT/
0	100002	1	Cash loans	M	N	Y	0	20250C
1	100003	0	Cash loans	F	N	N	0	27000C
2	100004	0	Revolving loans	M	Y	Y	0	6750C
3	100006	0	Cash loans	F	N	Y	0	13500C
4	100007	0	Cash loans	M	N	Y	0	12150C

5 rows × 46 columns

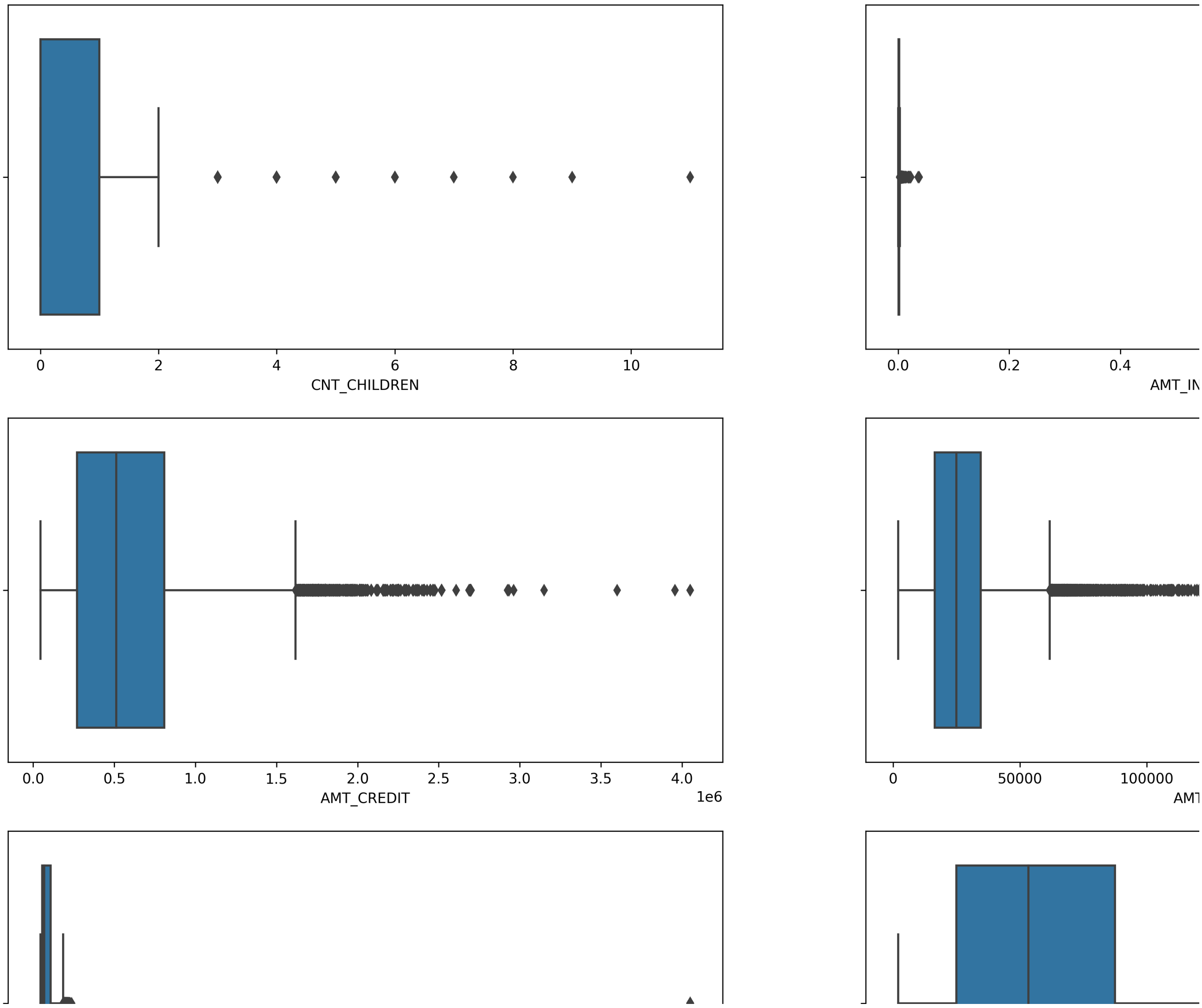
```
# Converting '-ve' values into '+ve' Values
data['DAYS_BIRTH'] = data['DAYS_BIRTH'].abs()
data['DAYS_EMPLOYED'] = data['DAYS_EMPLOYED'].abs()
data['DAYS_REGISTRATION'] = data['DAYS_REGISTRATION'].abs()
data['DAYS_ID_PUBLISH'] = data['DAYS_ID_PUBLISH'].abs()
data['DAYS_LAST_PHONE_CHANGE'] = data['DAYS_LAST_PHONE_CHANGE'].abs()
```

Checking for outliers in numeric variables

```
# describe numeric columns
data[numeric_columns].describe()
```

	TARGET	CNT_CHILDREN	AMT_INCOME_TOTAL	AMT_CREDIT	AMT_ANNUITY	REGION_POPULATION_RELATIVE	DAYS_BIRT
count	65533.000000	65533.000000	6.553300e+04	6.553300e+04	65528.000000	65533.000000	65533.0000C
mean	0.080540	0.419514	1.697608e+05	5.993521e+05	27072.111113	0.020868	16026.83367
std	0.272129	0.724468	4.667589e+05	4.026728e+05	14486.050745	0.013767	4362.11054
min	0.000000	0.000000	2.565000e+04	4.500000e+04	2052.000000	0.000533	7676.0000C
25%	0.000000	0.000000	1.125000e+05	2.700000e+05	16456.500000	0.010006	12390.0000C
50%	0.000000	0.000000	1.440000e+05	5.135310e+05	24903.000000	0.018850	15749.0000C
75%	0.000000	1.000000	2.025000e+05	8.086500e+05	34587.000000	0.028663	19656.0000C
max	1.000000	11.000000	1.170000e+08	4.050000e+06	258025.500000	0.072508	25201.0000C

```
# Box plot for selected columns
features = ['CNT_CHILDREN', 'AMT_INCOME_TOTAL','AMT_CREDIT','AMT_ANNUITY','DAYS_EMPLOYED', 'DAYS_REGISTRATION']

plt.figure(figsize = (20, 15), dpi=300)
for i in enumerate(features):
    plt.subplot(3, 2, i[0]+1)
    sns.boxplot(x = i[1], data = data)
plt.show()
```



The first quartile almost missing for CNT_CHILDREN that means most of the data are present in the first quartile.

There is single high value data point as outlier present in AMT_INCOME_TOTAL and Removal this point will dtrasticaly impact the box plot for further analysis.

The first quartiles is slim compare to third quartile for AMT_CREDIT,AMT_ANNUITY, DAYS_EMPLOYED, DAYS_REGISTRATION. This mean data are skewed towards first quartile.

```
#Creating bins for continous variable categories column 'AMT_INCOME_TOTAL' and 'AMT_CREDIT'
bins = [0,100000,200000,300000,400000,500000,10000000000]
slot = ['<100000', '100000-200000','200000-300000','300000-400000','400000-500000', '500000 and above']

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


bins = [0,100000,200000,300000,400000,500000,600000,700000,800000,900000,10000000000]
slot = ['<100000', '100000-200000','200000-300000','300000-400000','400000-500000', '500000-600000',
        '600000-700000','700000-800000','850000-900000','900000 and above']

data['AMT_CREDIT_RANGE']=pd.cut(data['AMT_CREDIT'],bins,labels=slot)
```

Analysis

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

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


# insights from number of target values

percentage_defaulters= round(100*len(target1_df)/(len(target0_df)+len(target1_df)),2)

percentage_nondefaulters=round(100*len(target0_df)/(len(target0_df)+len(target1_df)),2)

print('Count of target0_df:', len(target0_df))
print('Count of target1_df:', len(target1_df))


print('Percentage of people who paid their loan are: ', percentage_nondefaulters, '%' )
print('Percentage of people who did not paid their loan are: ', percentage_defaulters, '%' )
```

```
Count of target0_df: 60255
Count of target1_df: 5278
Percentage of people who paid their loan are:  91.95 %
Percentage of people who did not paid their loan are:  8.05 %
```

```
# Calculating Imbalance percentage

# Since the majority is target0 and minority is target1

imb_ratio = round(len(target0_df)/len(target1_df),2)

print('Imbalance Ratio:', imb_ratio)
```

```
Imbalance Ratio: 11.42
```

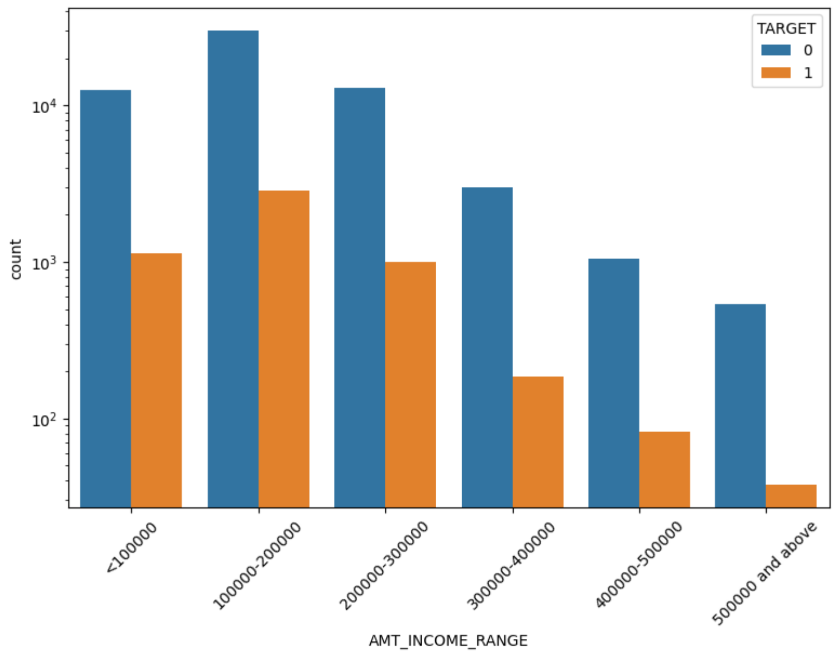
Univariate Analysis

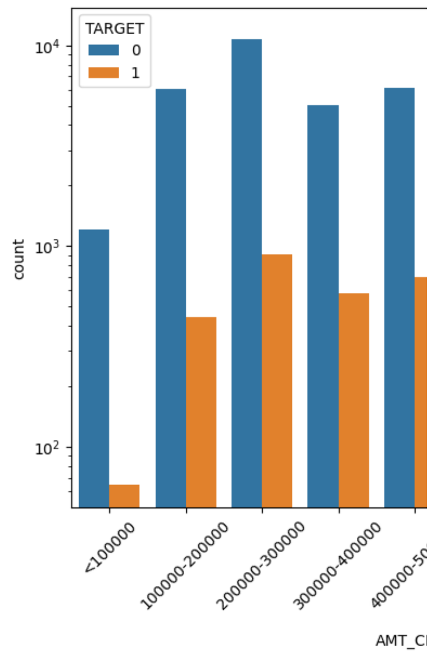
```
# Count plotting in logarithmic scale

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

    sns.set_style('whitegrid')
    sns.set_context('talk')
    plt.rcParams["axes.labelsize"] = 14
    plt.rcParams['axes.titlesize'] = 16
    plt.rcParams['axes.titlepad'] = 14


    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)

    plt.show()
```

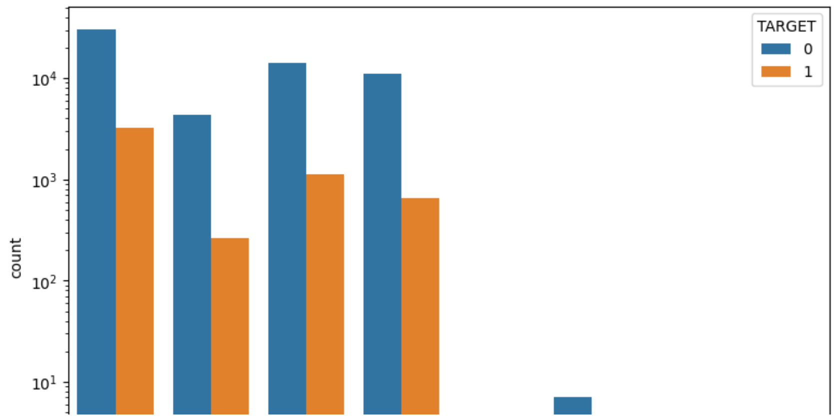
Double-click (or enter) to edit

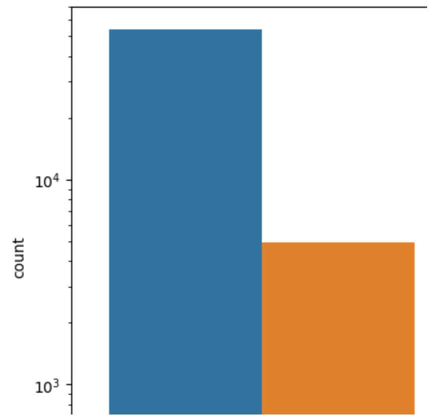
```
# Categoroical Univariate Analysis in logarithmic scale

features = ['AMT_INCOME_RANGE', 'AMT_CREDIT_RANGE','NAME_INCOME_TYPE','NAME_CONTRACT_TYPE']
plt.figure(figsize = (20, 15))

for i in enumerate(features):
    plt.subplot(2, 2, i[0]+1)
    plt.subplots_adjust(hspace=0.5)
    sns.countplot(x = i[1], hue = 'TARGET', data = data)

    plt.rcParams['axes.titlesize'] = 16

    plt.xticks(rotation = 45)
```

```
    plt.yscale('log')
```









Insights: AMT_INCOME_RANGE :

- The people having 100000-200000 are havign higher number of loan and also having higher in defaulter
- The income segment having >500000 are having less defaulter.

AMT_CREDIT_RANGE:

- The people having <100000 loan are less defaulter.
- income having more thatn >100000 are almost equal % of loan defaulter

NAME_INCOME_TYPE:

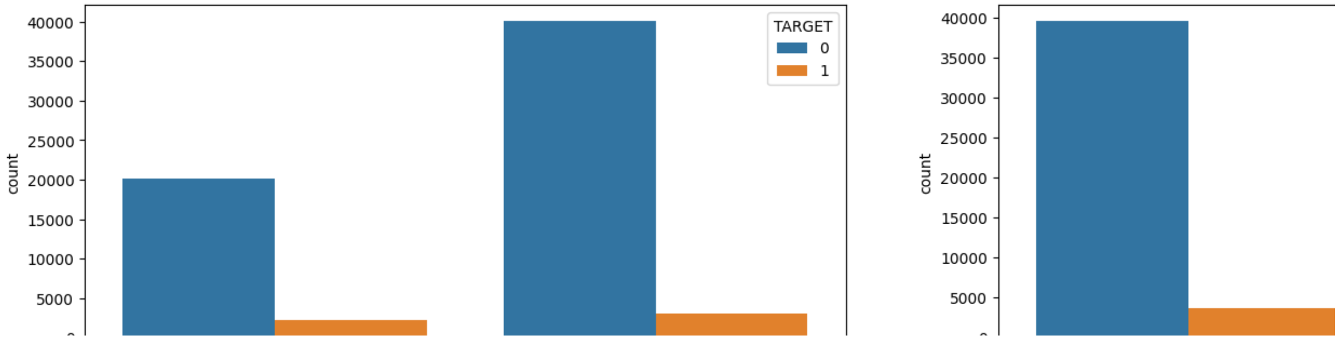
- Student pensioner and business have higher percentage of loan repayment.
- Working, State servent and Commercial associates have higher default percentage.
- Maternity category is significantly higher problem in replayement.

NAME_CONTRACT_TYPE

- For contract type ‘cash loans’ is having higher number of credits than ‘Revolving loans’ contract type.
- From the above graphs we can see that the Revolving loans are small amount compared to Cash loans but the % of non payment for the revolving loans are comapritvely high.

```
# Categoroical Univariate Analysis in Value scale

features = ['CODE_GENDER','FLAG_OWN_CAR']
plt.figure(figsize = (20, 10))

for i in enumerate(features):
    plt.subplot(2, 2, i[0]+1)
```

```
    plt.subplots_adjust(hspace=0.5)
    sns.countplot(x = i[1], hue = 'TARGET', data = data)

    plt.rcParams['axes.titlesize'] = 16
    plt.xticks(rotation = 45)
#     plt.yscale('log')
```



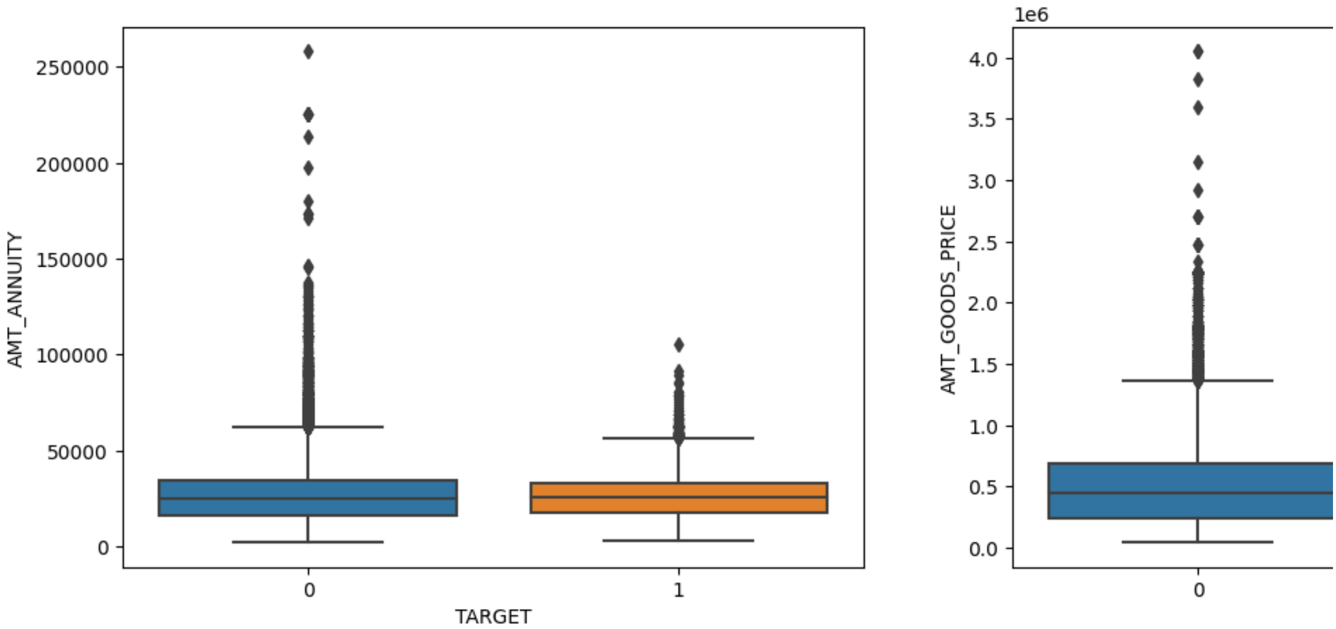
CODE_GENDER:

- The % of defaulters are more in Male than Female

FLAG_OWN_CAR:

- The person owning car is having higher percentage of defaulter.

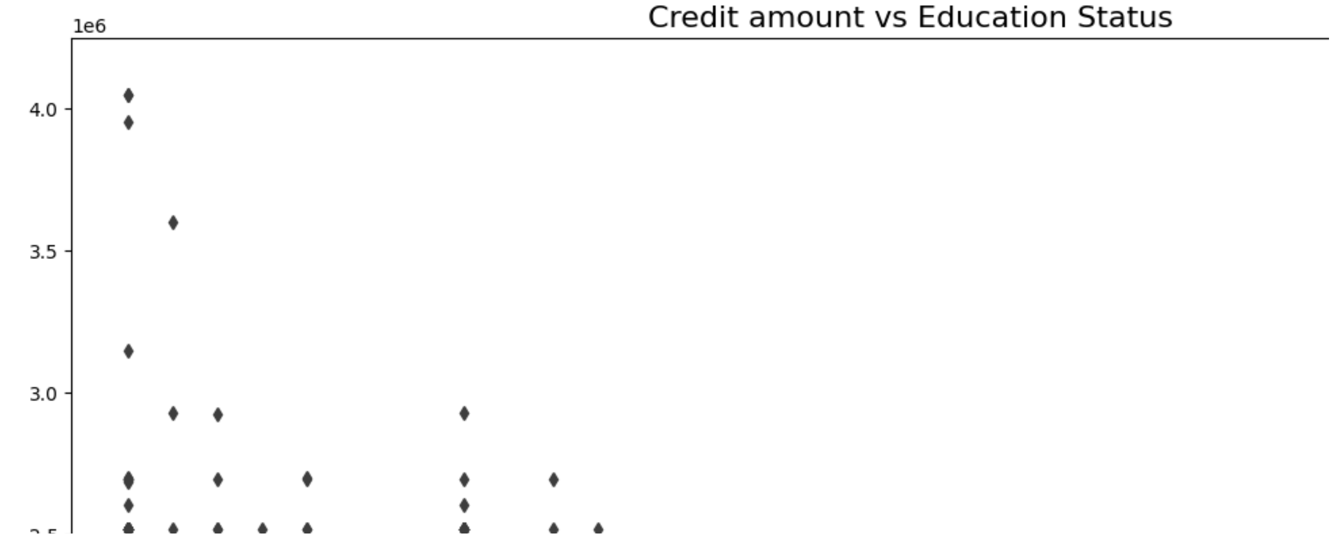
```
# Univariate Analysis for continous variable

features = ['AMT_ANNUITY','AMT_GOODS_PRICE','DAYS_BIRTH','DAYS_EMPLOYED','DAYS_LAST_PHONE_CHANGE','DAYS_ID_PUBLISH']
plt.figure(figsize = (15, 20))

for i in enumerate(features):
    plt.subplot(3, 2, i[0]+1)
    plt.subplots_adjust(hspace=0.5)
    sns.boxplot(x = 'TARGET', y = i[1], data = data)
```



Inference:

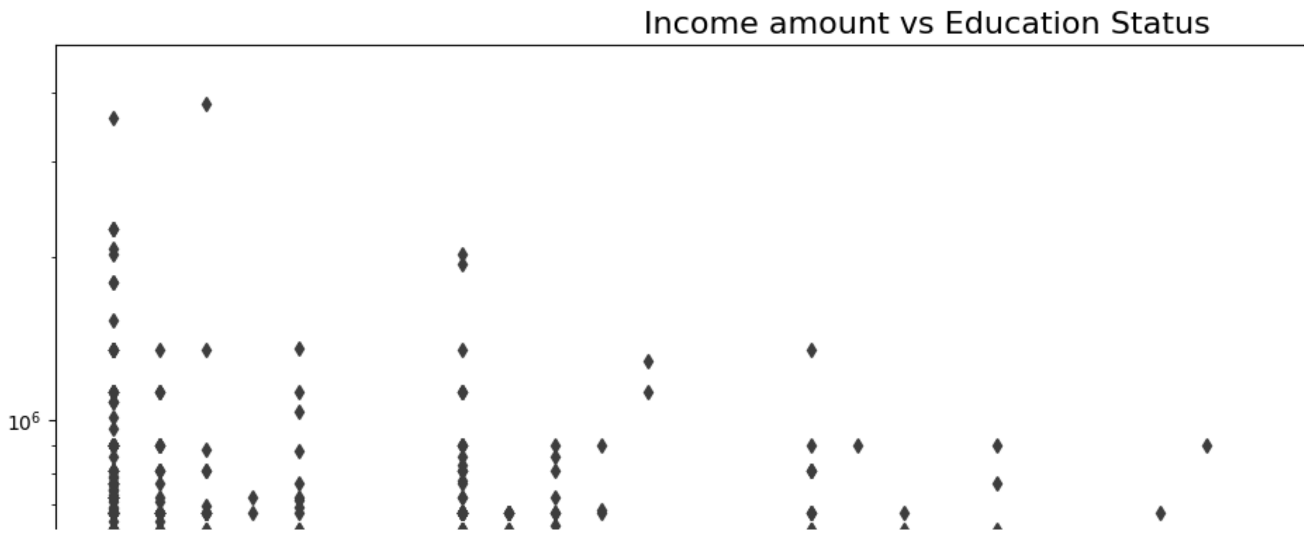
Days_Birth: The people having higher age are having higher probability of repayment. Some outliers are observed in In 'AMT_ANNUITY','AMT_GOODS_PRICE','DAYS_EMPLOYED', DAYS_LAST_PHONE_CHANGE in the dataset. Less outlier observed in Days_Birth and DAYS_ID_PUBLISH 1st quartile is smaller than third quartile in In 'AMT_ANNUITY','AMT_GOODS_PRICE', DAYS_LAST_PHONE_CHANGE. In DAYS_ID_PUBLISH: people changing ID in recent days are relativelty prone to be default. There is single high value data point as outlier present in DAYS_EMPLOYED. Removal this point will drastically impact the box plot for further analysis.

```
#Bivariate for numerical values
#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()
```



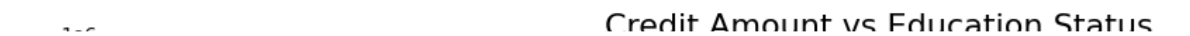
Family status of 'civil marriage', 'marriage' and 'separated' of Academic degree education are having higher number of credits than others. Also, higher education of family status of 'marriage', 'single' and 'civil marriage' are having more outliers. Civil marriage for Academic degree is having most 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()
```



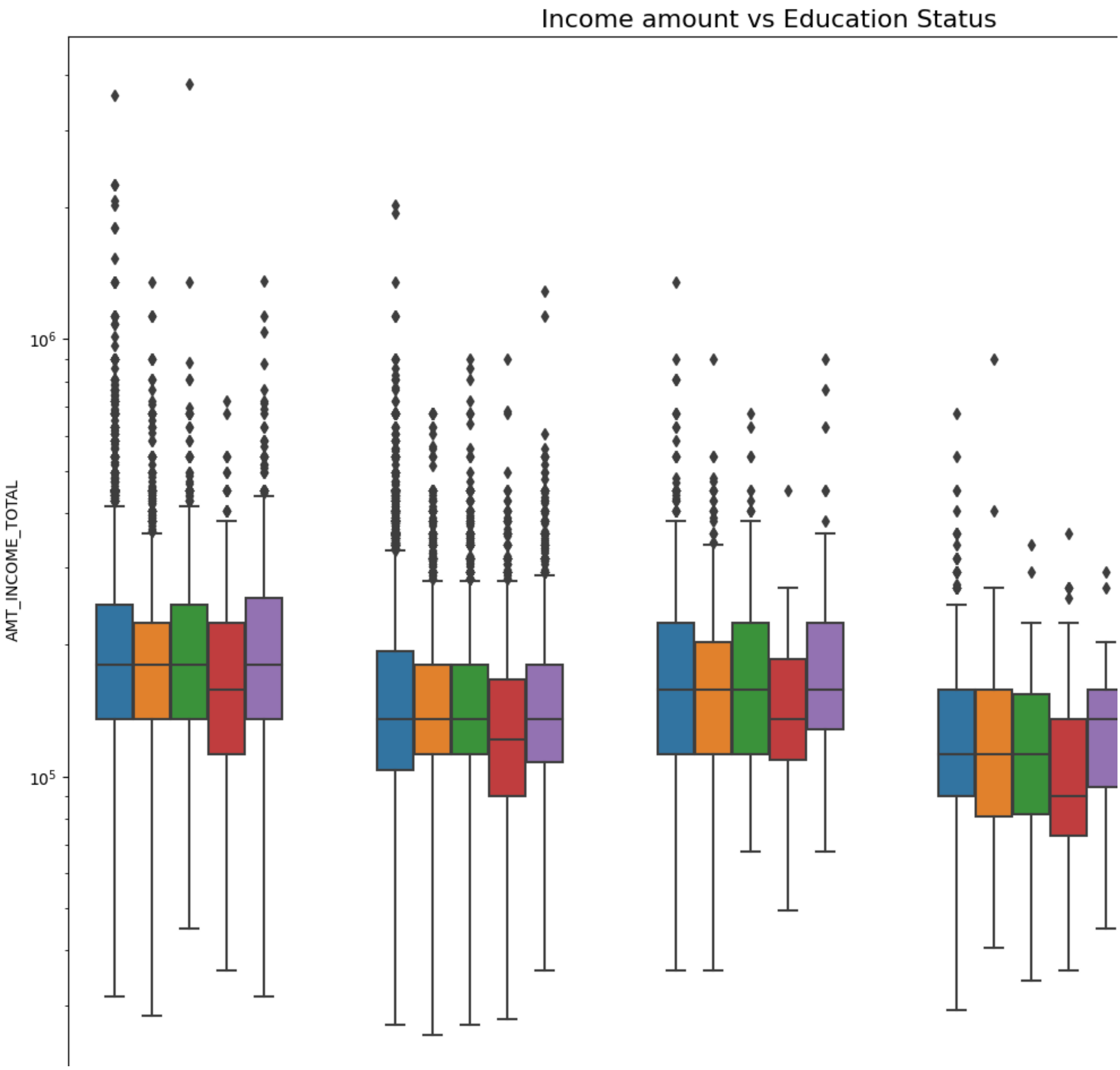
In Education type 'Higher education' the income amount is mostly equal with family status. It does contain many outliers. Less outlier are having for Academic degree but there income amount is little higher that Higher education. Lower secondary of civil marriage family status are have less income amount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

```
#For Target 1
# Box plotting for credit amount

plt.figure(figsize=(15,10))
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()
```



Observations are Quite similar with Target 0 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()
```



There is also have some similarity with Target0, 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.

```
#Correlation
# Top 10 correlated variables: target 0 dataaframe

corr = target0_df.corr()
corrdf = corr.where(np.triu(np.ones(corr.shape), k=1).astype(np.bool))
corrdf = corrdf.unstack().reset_index()
corrdf.columns = ['Var1', 'Var2', 'Correlation']
```

```
corrdf.dropna(subset = ['Correlation'], inplace = True)
corrdf['Correlation'] = round(corrdf['Correlation'], 2)
corrdf['Correlation'] = abs(corrdf['Correlation'])
corrdf.sort_values(by = 'Correlation', ascending = False).head(10)
```

```
<ipython-input-63-227e5fa313af>:4: FutureWarning: The default value of numeric_only in DataFrame.corr is deprecate
  corr = target0_df.corr()
<ipython-input-63-227e5fa313af>:5: DeprecationWarning: `np.bool` is a deprecated alias for the builtin `bool`. To
Deprecated in NumPy 1.20; for more details and guidance: https://numpy.org/devdocs/release/1.20.0-notes.html#depre
  corrdf = corr.where(np.triu(np.ones(corr.shape), k=1).astype(np.bool))
```

	Var1	Var2	Correlation
873	OBS_60_CNT_SOCIAL_CIRCLE	OBS_30_CNT_SOCIAL_CIRCLE	1.00
208	AMT_GOODS_PRICE	AMT_CREDIT	0.99
489	REGION_RATING_CLIENT_W_CITY	REGION_RATING_CLIENT	0.95
410	CNT_FAM_MEMBERS	CNT_CHILDREN	0.88
629	LIVE_REGION_NOT_WORK_REGION	REG_REGION_NOT_WORK_REGION	0.86
908	DEF_60_CNT_SOCIAL_CIRCLE	DEF_30_CNT_SOCIAL_CIRCLE	0.85
734	LIVE_CITY_NOT_WORK_CITY	REG_CITY_NOT_WORK_CITY	0.83
209	AMT_GOODS_PRICE	AMT_ANNUITY	0.78
174	AMT_ANNUITY	AMT_CREDIT	0.77
314	DAYS_EMPLOYED	DAYS_BIRTH	0.62

```
# Top 10 correlated variables: target 1 dataaframe

corr = target1_df.corr()
corrdf = corr.where(np.triu(np.ones(corr.shape), k=1).astype(np.bool))
corrdf = corrdf.unstack().reset_index()
corrdf.columns = ['Var1', 'Var2', 'Correlation']
corrdf.dropna(subset = ['Correlation'], inplace = True)
corrdf['Correlation'] = round(corrdf['Correlation'], 2)
corrdf['Correlation'] = abs(corrdf['Correlation'])
corrdf.sort_values(by = 'Correlation', ascending = False).head(10)
```

```
<ipython-input-64-83c9c380cf9a>:3: FutureWarning: The default value of numeric_only in DataFrame.corr is deprecate
  corr = target1_df.corr()
<ipython-input-64-83c9c380cf9a>:4: DeprecationWarning: `np.bool` is a deprecated alias for the builtin `bool`. To
Deprecated in NumPy 1.20; for more details and guidance: https://numpy.org/devdocs/release/1.20.0-notes.html#depre
  corrdf = corr.where(np.triu(np.ones(corr.shape), k=1).astype(np.bool))
```

	Var1	Var2	Correlation
873	OBS_60_CNT_SOCIAL_CIRCLE	OBS_30_CNT_SOCIAL_CIRCLE	1.00
208	AMT_GOODS_PRICE	AMT_CREDIT	0.98
489	REGION_RATING_CLIENT_W_CITY	REGION_RATING_CLIENT	0.94
410	CNT_FAM_MEMBERS	CNT_CHILDREN	0.89
908	DEF_60_CNT_SOCIAL_CIRCLE	DEF_30_CNT_SOCIAL_CIRCLE	0.88
629	LIVE_REGION_NOT_WORK_REGION	REG_REGION_NOT_WORK_REGION	0.81
734	LIVE_CITY_NOT_WORK_CITY	REG_CITY_NOT_WORK_CITY	0.78
174	AMT_ANNUITY	AMT_CREDIT	0.75
209	AMT_GOODS_PRICE	AMT_ANNUITY	0.75
314	DAYS_EMPLOYED	DAYS_BIRTH	0.59

From the above correlation analysis it is infered that the highest corelation (1.0) is between (OBS_60_CNT_SOCIAL_CIRCLE with OBS_30_CNT_SOCIAL_CIRCLE) and (FLOORSMAX_MEDI with FLOORSMAX_AVG) which is same for both the data set.

Read Previous Application data and merging with application data

```
prev=pd.read_csv(("/content/drive/MyDrive/Trainity Assignments/Trainity Assignment - 6/Dataset/previous_application (1)
```

```
prev.columns
```

```
Index(['SK_ID_PREV', 'SK_ID_CURR', 'NAME_CONTRACT_TYPE', 'AMT_ANNUITY',
       'AMT_APPLICATION', 'AMT_CREDIT', 'AMT_DOWN_PAYMENT', 'AMT_GOODS_PRICE',
       'WEEKDAY_APPR_PROCESS_START', 'HOUR_APPR_PROCESS_START',
       'FLAG_LAST_APPL_PER_CONTRACT', 'NFLAG_LAST_APPL_IN_DAY',
       'RATE_DOWN_PAYMENT', 'RATE_INTEREST_PRIMARY',
       'RATE_INTEREST_PRIVILEGED', 'NAME_CASH_LOAN_PURPOSE',
       'NAME_CONTRACT_STATUS', 'DAYS_DECISION', 'NAME_PAYMENT_TYPE',
       'CODE_REJECT_REASON', 'NAME_TYPE_SUITE', 'NAME_CLIENT_TYPE',
       'NAME_GOODS_CATEGORY', 'NAME_PORTFOLIO', 'NAME_PRODUCT_TYPE',
       'CHANNEL_TYPE', 'SELLERPLACE_AREA', 'NAME_SELLER_INDUSTRY',
       'CNT_PAYMENT', 'NAME_YIELD_GROUP', 'PRODUCT_COMBINATION',
       'DAYS_FIRST_DRAWING', 'DAYS_FIRST_DUE', 'DAYS_LAST_DUE_1ST_VERSION',
       'DAYS_LAST_DUE', 'DAYS_TERMINATION', 'NFLAG_INSURED_ON_APPROVAL'],
      dtype='object')
```

```
# get the type of dataset
prev.dtypes
```

```
SK_ID_PREV                       int64
SK_ID_CURR                       int64
NAME_CONTRACT_TYPE              object
AMT_ANNUITY                    float64
AMT_APPLICATION                float64
AMT_CREDIT                     float64
AMT_DOWN_PAYMENT               float64
AMT_GOODS_PRICE                float64
WEEKDAY_APPR_PROCESS_START      object
HOUR_APPR_PROCESS_START          int64
FLAG_LAST_APPL_PER_CONTRACT     object
NFLAG_LAST_APPL_IN_DAY           int64
RATE_DOWN_PAYMENT              float64
RATE_INTEREST_PRIMARY          float64
RATE_INTEREST_PRIVILEGED       float64
NAME_CASH_LOAN_PURPOSE          object
NAME_CONTRACT_STATUS            object
DAYS_DECISION                    int64
NAME_PAYMENT_TYPE               object
CODE_REJECT_REASON              object
NAME_TYPE_SUITE                 object
NAME_CLIENT_TYPE                object
NAME_GOODS_CATEGORY             object
NAME_PORTFOLIO                  object
NAME_PRODUCT_TYPE               object
CHANNEL_TYPE                    object
SELLERPLACE_AREA                 int64
NAME_SELLER_INDUSTRY            object
CNT_PAYMENT                    float64
NAME_YIELD_GROUP                object
PRODUCT_COMBINATION             object
DAYS_FIRST_DRAWING             float64
DAYS_FIRST_DUE                 float64
DAYS_LAST_DUE_1ST_VERSION      float64
DAYS_LAST_DUE                  float64
DAYS_TERMINATION               float64
NFLAG_INSURED_ON_APPROVAL      float64
dtype: object
```

```
# displaying the informtion of previous application dataset
prev.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1670214 entries, 0 to 1670213
Data columns (total 37 columns):
 #   Column                       Non-Null Count    Dtype  
---  ------                       --------------    -----  
 0   SK_ID_PREV                   1670214 non-null  int64  
 1   SK_ID_CURR                   1670214 non-null  int64  
 2   NAME_CONTRACT_TYPE           1670214 non-null  object 
 3   AMT_ANNUITY                  1297979 non-null  float64
 4   AMT_APPLICATION              1670214 non-null  float64
 5   AMT_CREDIT                   1670213 non-null  float64
 6   AMT_DOWN_PAYMENT             774370 non-null   float64
 7   AMT_GOODS_PRICE              1284699 non-null  float64
 8   WEEKDAY_APPR_PROCESS_START   1670214 non-null  object 
 9   HOUR_APPR_PROCESS_START      1670214 non-null  int64  
 10  FLAG_LAST_APPL_PER_CONTRACT  1670214 non-null  object 
 11  NFLAG_LAST_APPL_IN_DAY       1670214 non-null  int64  
 12  RATE_DOWN_PAYMENT            774370 non-null   float64
 13  RATE_INTEREST_PRIMARY        5951 non-null     float64
 14  RATE_INTEREST_PRIVILEGED     5951 non-null     float64
 15  NAME_CASH_LOAN_PURPOSE       1670214 non-null  object 
```

```
 16  NAME_CONTRACT_STATUS         1670214 non-null  object
 17  DAYS_DECISION                1670214 non-null  int64
 18  NAME_PAYMENT_TYPE            1670214 non-null  object
 19  CODE_REJECT_REASON           1670214 non-null  object
 20  NAME_TYPE_SUITE              849809 non-null   object
 21  NAME_CLIENT_TYPE             1670214 non-null  object
 22  NAME_GOODS_CATEGORY          1670214 non-null  object
 23  NAME_PORTFOLIO               1670214 non-null  object
 24  NAME_PRODUCT_TYPE            1670214 non-null  object
 25  CHANNEL_TYPE                 1670214 non-null  object
 26  SELLERPLACE_AREA             1670214 non-null  int64
 27  NAME_SELLER_INDUSTRY         1670214 non-null  object
 28  CNT_PAYMENT                  1297984 non-null  float64
 29  NAME_YIELD_GROUP             1670214 non-null  object
 30  PRODUCT_COMBINATION          1669868 non-null  object
 31  DAYS_FIRST_DRAWING           997149 non-null   float64
 32  DAYS_FIRST_DUE               997149 non-null   float64
 33  DAYS_LAST_DUE_1ST_VERSION    997149 non-null   float64
 34  DAYS_LAST_DUE                997149 non-null   float64
 35  DAYS_TERMINATION             997149 non-null   float64
 36  NFLAG_INSURED_ON_APPROVAL    997149 non-null   float64
dtypes: float64(15), int64(6), object(16)
memory usage: 471.5+ MB
```

```
# Describing the previous application dataset
prev.describe()
```

	SK_ID_PREV	SK_ID_CURR	AMT_ANNUITY	AMT_APPLICATION	AMT_CREDIT	AMT_DOWN_PAYMENT	AMT_GOODS_PRICE	HOUR_A
count	1.670214e+06	1.670214e+06	1.297979e+06	1.670214e+06	1.670213e+06	7.743700e+05	1.284699e+06	
mean	1.923089e+06	2.783572e+05	1.595512e+04	1.752339e+05	1.961140e+05	6.697402e+03	2.278473e+05	
std	5.325980e+05	1.028148e+05	1.478214e+04	2.927798e+05	3.185746e+05	2.092150e+04	3.153966e+05	
min	1.000001e+06	1.000010e+05	0.000000e+00	0.000000e+00	0.000000e+00	-9.000000e-01	0.000000e+00	
25%	1.461857e+06	1.893290e+05	6.321780e+03	1.872000e+04	2.416050e+04	0.000000e+00	5.084100e+04	
50%	1.923110e+06	2.787145e+05	1.125000e+04	7.104600e+04	8.054100e+04	1.638000e+03	1.123200e+05	
75%	2.384280e+06	3.675140e+05	2.065842e+04	1.803600e+05	2.164185e+05	7.740000e+03	2.340000e+05	
max	2.845382e+06	4.562550e+05	4.180581e+05	6.905160e+06	6.905160e+06	3.060045e+06	6.905160e+06	

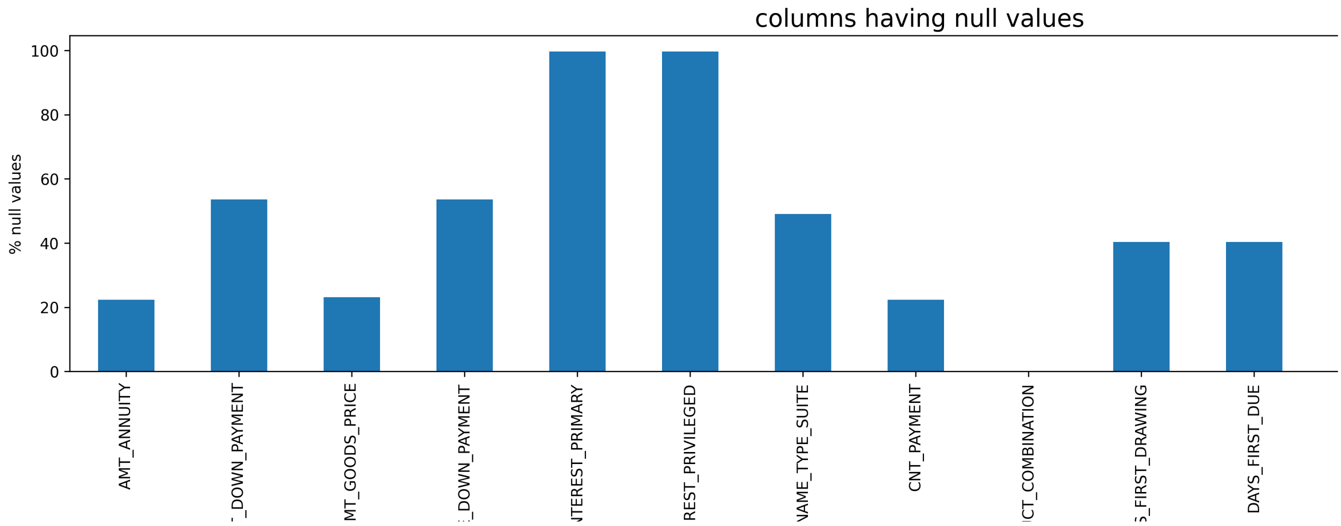
8 rows × 21 columns

```
# Finding percentage of null values columns
NA_col_pre = column_wise_null_percentage(prev)
```

```
# identify columns only with null values
NA_col_pre = NA_col_pre[NA_col_pre>0]
NA_col_pre
```

```
AMT_ANNUITY                  22.29
AMT_DOWN_PAYMENT             53.64
AMT_GOODS_PRICE              23.08
RATE_DOWN_PAYMENT            53.64
RATE_INTEREST_PRIMARY        99.64
RATE_INTEREST_PRIVILEGED     99.64
NAME_TYPE_SUITE              49.12
CNT_PAYMENT                  22.29
PRODUCT_COMBINATION           0.02
DAYS_FIRST_DRAWING           40.30
DAYS_FIRST_DUE               40.30
DAYS_LAST_DUE_1ST_VERSION    40.30
DAYS_LAST_DUE                40.30
DAYS_TERMINATION             40.30
NFLAG_INSURED_ON_APPROVAL    40.30
dtype: float64
```

```
# graphical representation of columns having % null values
plt.figure(figsize= (20,4),dpi=300)
NA_col_pre.plot(kind = 'bar')
plt.title (' columns having null values')
plt.ylabel('% null values')
plt.show()
```




```
# Get the column with null values more than 50%
NA_col_pre = NA_col_pre[NA_col_pre>50]
print("Number of columns having null value more than 50% :", len(NA_col_pre.index))
print(NA_col_pre)
```

```
Number of columns having null value more than 50% : 4
AMT_DOWN_PAYMENT             53.64
RATE_DOWN_PAYMENT            53.64
RATE_INTEREST_PRIMARY        99.64
RATE_INTEREST_PRIVILEGED     99.64
dtype: float64
```

```
# removed 4 columns having null percentage more than 50%.
prev = prev.drop(NA_col_pre.index, axis =1)
prev.shape
```

```
(1670214, 33)
```

```
# Merging the Application dataset with previous appliaction dataset

df_comb = pd.merge(left=data,right=prev,how='inner',on='SK_ID_CURR',suffixes='_x')
df_comb.shape
```

```
<ipython-input-79-bea94fcb8ddd>:3: FutureWarning: Passing 'suffixes' as a <class 'str'>, is not supported and may
  df_comb = pd.merge(left=data,right=prev,how='inner',on='SK_ID_CURR',suffixes='_x')
(300438, 80)
```

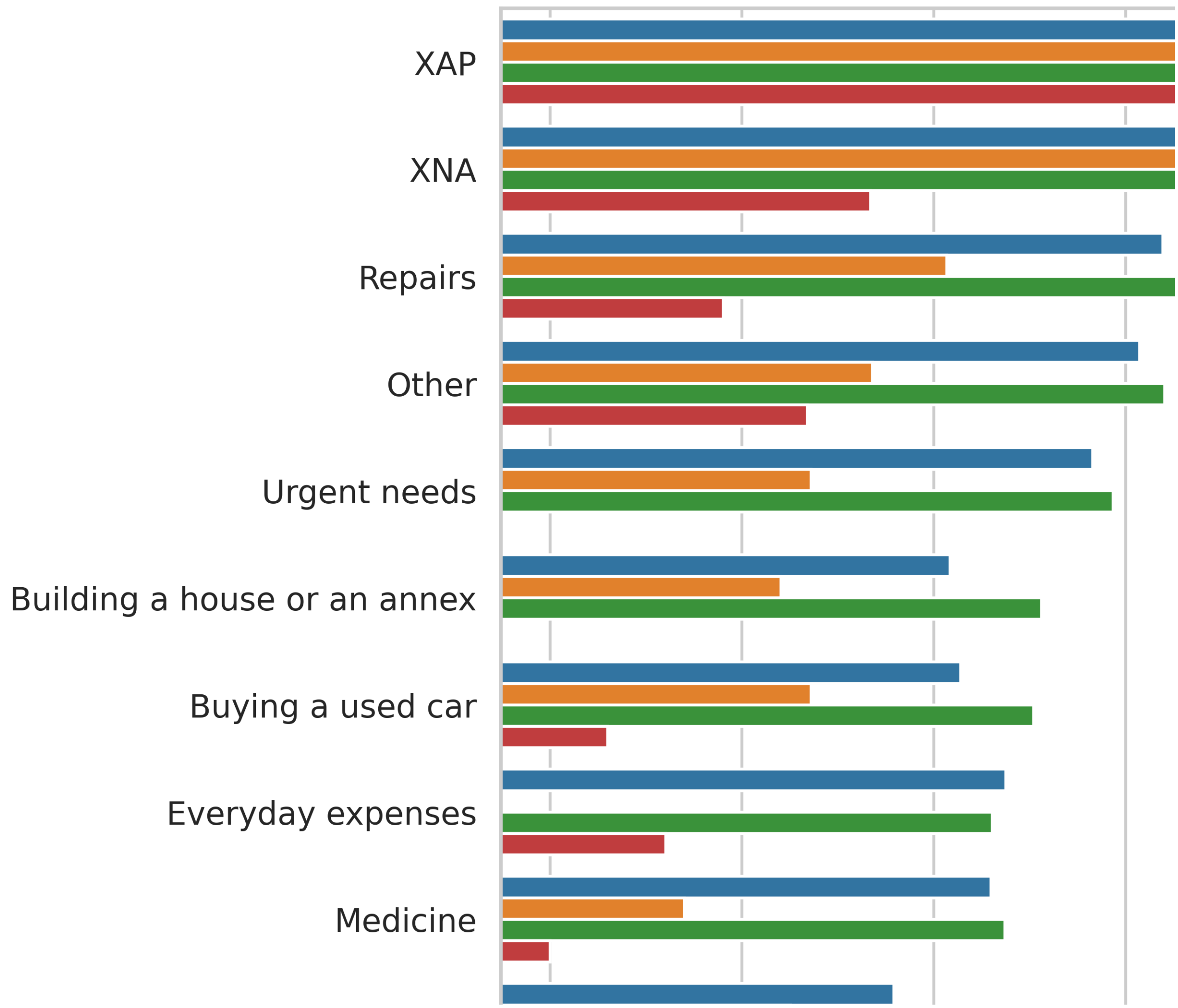
```
df_comb.head()
```

	SK_ID_CURR	TARGET	NAME_CONTRACT_TYPE_	CODE_GENDER	FLAG_OWN_CAR	FLAG_OWN_REALTY	CNT_CHILDREN	AMT_INCOME_TO
0	100002	1	Cash loans	M	N	Y	0	2025(
1	100003	0	Cash loans	F	N	N	0	2700(
2	100003	0	Cash loans	F	N	N	0	2700(
3	100003	0	Cash loans	F	N	N	0	2700(
4	100004	0	Revolving loans	M	Y	Y	0	675(

5 rows × 80 columns

```
# Renaming the column names after merging from combined df

df_comb = df_comb.rename({'NAME_CONTRACT_TYPE_' : 'NAME_CONTRACT_TYPE','AMT_CREDIT_':'AMT_CREDIT','AMT_ANNUITY_':'AMT_A
                          'WEEKDAY_APPR_PROCESS_START_' : 'WEEKDAY_APPR_PROCESS_START',
                          'HOUR_APPR_PROCESS_START_':'HOUR_APPR_PROCESS_START','NAME_CONTRACT_TYPEx':'NAME_CONTRACT_TYPE
                          '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)
```

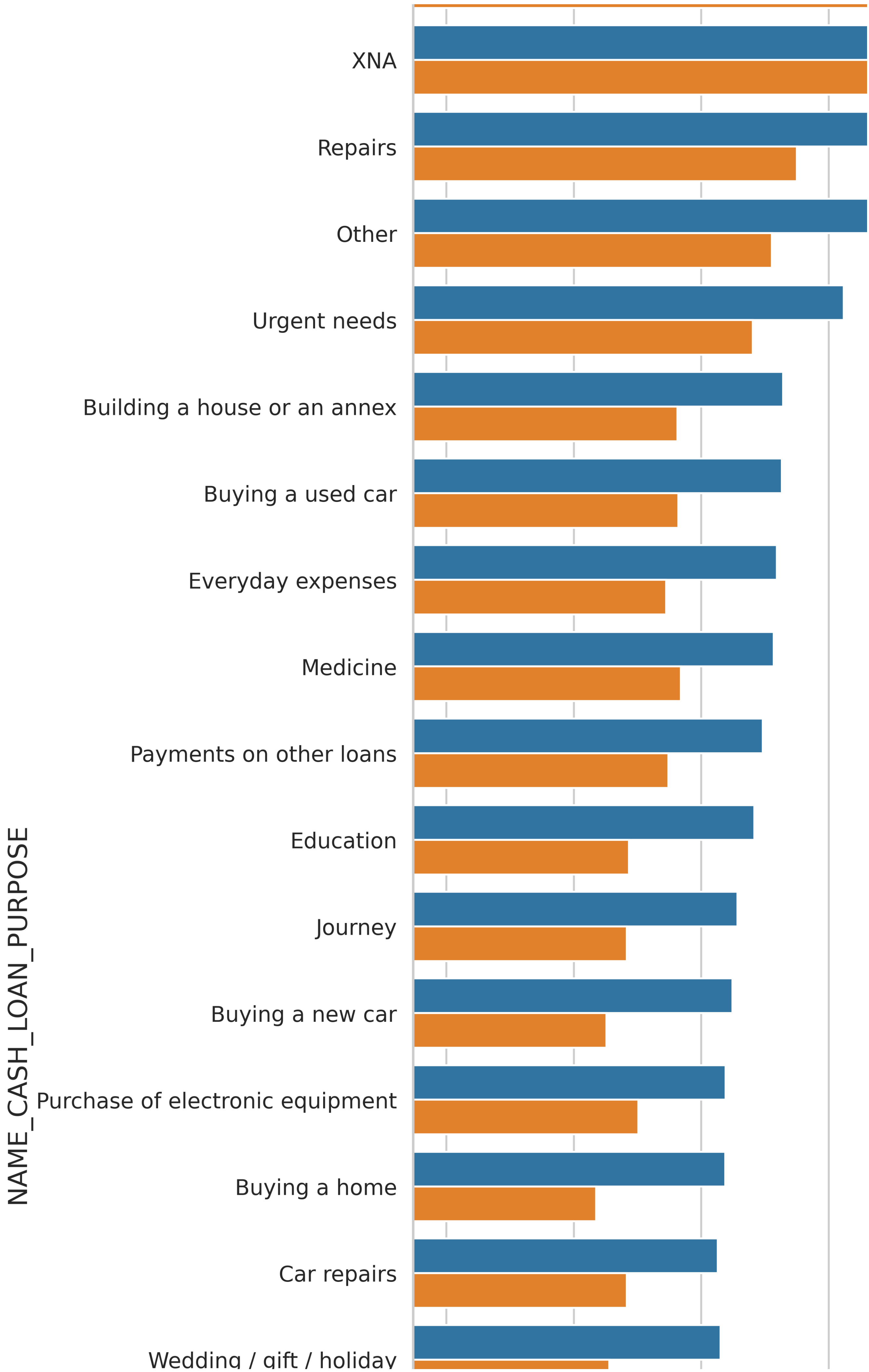
```
# Removing unwanted columns from cmbined df for analysis

df_comb.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=Tr


#Performing Univariate Analysis
# Distribution of contract status in logarithmic scale
# Distribution of contract status in logarithmic scale

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

plt.figure(figsize=(10,25),dpi = 300)
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 = df_comb, y= 'NAME_CASH_LOAN_PURPOSE',
                   order=df_comb['NAME_CASH_LOAN_PURPOSE'].value_counts().index,hue = 'NAME_CONTRACT_STATUS')
```

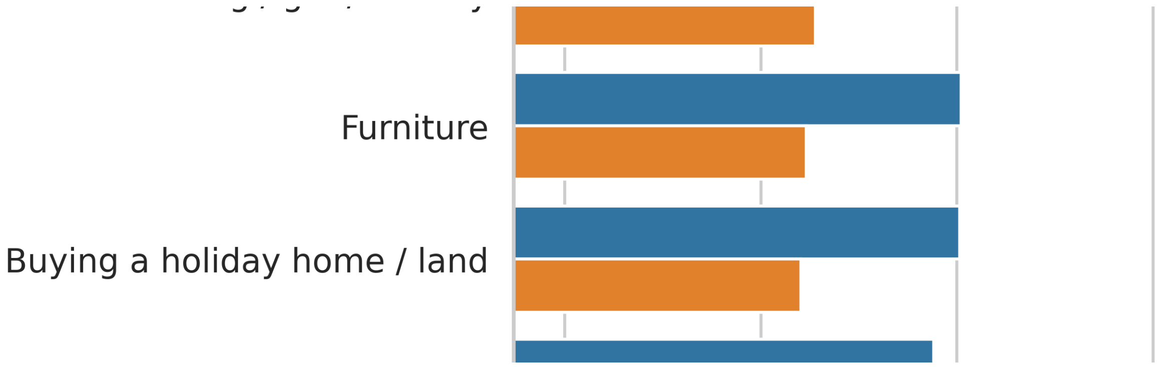


Points to be concluded from above plot:

Most rejection of loans came from purpose 'repairs'. For education purposes we have equal number of approves and rejection 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=(10,30),dpi = 300)
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 = df_comb, y= 'NAME_CASH_LOAN_PURPOSE',
                   order=df_comb['NAME_CASH_LOAN_PURPOSE'].value_counts().index,hue = 'TARGET')
```

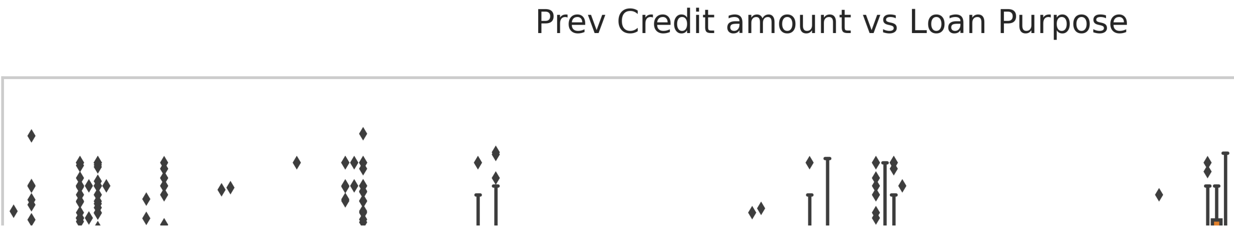

NAME_CASH_LOAN_PURPOSE
XNA
Repairs
Other
Urgent needs
Building a house or an annex
Buying a used car
Everyday expenses
Medicine
Payments on other loans
Education
Journey
Buying a new car
Purchase of electronic equipment
Buying a home
Car repairs
Wedding / gift / holiday



Few points we can conclude from above plot:

Loan purposes with 'Repairs' are facing more difficulites in payment on time. 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.

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

plt.figure(figsize=(20,15),dpi = 300)
plt.xticks(rotation=90)
plt.yscale('log')
sns.boxplot(data =df_comb, 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-

The credit amount of Loan purposes like 'Buying a home','Buying a land','Buying a new car' and'Building a house' is higher. Income type of state servants have a significant amount of credit applied 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=(15,15),dpi = 150)
plt.xticks(rotation=90)
sns.barplot(data =df_comb, y='AMT_CREDIT_PREV',hue='TARGET',x='NAME_HOUSING_TYPE')
plt.title('Prev Credit amount vs Housing type')
plt.show()
```