Bank Loan Case Study

Description:

This case study aims to give you an idea of applying EDA in a real business scenario. In this case study, apart from applying the techniques that you have learnt in the EDA module, you will also develop a basic understanding of risk analytics in banking and financial services and understand how data is used to minimize the risk of losing money while lending to customers.

Approach:

First the understanding of data is important. After that plotting scatter plot and bar plot to understand the data more clearly.

Tech-Stack Used:

Google Colab

Insights:

As a result of this project, I am better able to understand the power of different platforms. For large data sets where the total number of data points is too much, Python is a better choice. This project also taught me how to deal with a lot of data features.

Result:

Importing Libraries

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

import pandas as pd
import numpy as np
import matplotlib.pyplot as plt,seaborn as sns
import math

get_ipython().run_line_magic('matplotlib', 'inline')
pd.set_option('display.max_columns',125)
pd.set_option('display.max_rows',125)
```

```
def count_null_values(df,per=0):
 length = len(df)
 df1 = df.isnull().sum()*100/length
 df2 = df1[df1>=per]
 return df2.sort_values(ascending=False)
```

Reading Input Data

```
application_file_location = "/content/application_data.csv"
df1= pd.read_csv(application_file_location)
df1.head()
```

```
   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
```

Dealing with null values

```
null50 = count_null_values(df1,50)
null50
```

```
COMMONAREA_AVG              69.848764
COMMONAREA_MEDI             69.848764
COMMONAREA_MODE             69.848764
NONLIVINGAPARTMENTS_MEDI    69.415800
NONLIVINGAPARTMENTS_AVG     69.415800
NONLIVINGAPARTMENTS_MODE    69.415800
FONDKAPREMONT_MODE          68.372202
LIVINGAPARTMENTS_MEDI       68.339746
LIVINGAPARTMENTS_AVG        68.339746
LIVINGAPARTMENTS_MODE       68.339746
FLOORSMIN_MODE              67.828153
FLOORSMIN_MEDI              67.828153
FLOORSMIN_AVG               67.828153
YEARS_BUILD_MODE            66.476394
YEARS_BUILD_AVG             66.476394
YEARS_BUILD_MEDI            66.476394
OWN_CAR_AGE                 65.995583
LANDAREA_AVG                59.365610
LANDAREA_MEDI               59.365610
LANDAREA_MODE               59.365610
BASEMENTAREA_MEDI           58.513735
BASEMENTAREA_AVG            58.513735
BASEMENTAREA_MODE           58.513735
EXT_SOURCE_1                56.360290
NONLIVINGAREA_MODE          55.166126
NONLIVINGAREA_MEDI          55.166126
```

```
NONLIVINGAREA_AVG           55.166126
ELEVATORS_MODE              53.280691
ELEVATORS_MEDI              53.280691
ELEVATORS_AVG               53.280691
WALLSMATERIAL_MODE          50.830127
APARTMENTS_MEDI             50.735102
APARTMENTS_MODE             50.735102
APARTMENTS_AVG              50.735102
ENTRANCES_MODE              50.335597
ENTRANCES_AVG               50.335597
ENTRANCES_MEDI              50.335597
LIVINGAREA_MEDI             50.177000
LIVINGAREA_AVG              50.177000
LIVINGAREA_MODE             50.177000
HOUSETYPE_MODE              50.160605
dtype: float64
```

#Drop value with 50% null value

```
df1.drop(null50.index,axis=1,inplace=True)
df1.shape
```

```
(298870, 81)
```

#Check for the null values greater than 15%

```
print('Percentage (%) null values in each column')
null15 = count_null_values(df1,15)
null15
```

```
Percentage (%) null values in each column
```

```
FLOORSMAX_AVG                   49.743032
FLOORSMAX_MODE                  49.743032
FLOORSMAX_MEDI                  49.743032
YEARS_BEGINEXPLUATATION_AVG     48.764011
YEARS_BEGINEXPLUATATION_MODE    48.764011
YEARS_BEGINEXPLUATATION_MEDI    48.764011
TOTALAREA_MODE                  48.254425
EMERGENCYSTATE_MODE             47.381805
OCCUPATION_TYPE                 31.311607
EXT_SOURCE_3                    19.831030
dtype: float64
```

#Remove those columns and drop remaining columns

```
columns_with_null = dict(null15)
del columns_with_null['EXT_SOURCE_3']
del columns_with_null['OCCUPATION_TYPE']
df1.shape
```

```
(298870, 81)
```

Feature selection and remove unnecessary columns

#Treating the columns with the null values

```
null_count = count_null_values(df1)
null_count
```

```
FLOORSMAX_AVG                  49.743032
FLOORSMAX_MODE                 49.743032
FLOORSMAX_MEDI                 49.743032
YEARS_BEGINEXPLUATATION_AVG    48.764011
YEARS_BEGINEXPLUATATION_MODE   48.764011
YEARS_BEGINEXPLUATATION_MEDI   48.764011
TOTALAREA_MODE                 48.254425
EMERGENCYSTATE_MODE            47.381805
OCCUPATION_TYPE                31.311607
EXT_SOURCE_3                   19.831030
AMT_REQ_CREDIT_BUREAU_YEAR     13.504534
AMT_REQ_CREDIT_BUREAU_HOUR     13.504534
AMT_REQ_CREDIT_BUREAU_DAY      13.504534
AMT_REQ_CREDIT_BUREAU_WEEK     13.504534
AMT_REQ_CREDIT_BUREAU_MON      13.504534
AMT_REQ_CREDIT_BUREAU_QRT      13.504534
NAME_TYPE_SUITE                 0.418577
DEF_30_CNT_SOCIAL_CIRCLE        0.332251
OBS_60_CNT_SOCIAL_CIRCLE        0.332251
DEF_60_CNT_SOCIAL_CIRCLE        0.332251
OBS_30_CNT_SOCIAL_CIRCLE        0.332251
EXT_SOURCE_2                    0.213805
AMT_GOODS_PRICE                 0.089671
AMT_ANNUITY                     0.004015
CNT_FAM_MEMBERS                 0.000669
DAYS_LAST_PHONE_CHANGE          0.000669
FLAG_DOCUMENT_12                0.000335
FLAG_DOCUMENT_13                0.000335
FLAG_DOCUMENT_2                 0.000335
FLAG_DOCUMENT_3                 0.000335
FLAG_DOCUMENT_4                 0.000335
FLAG_DOCUMENT_5                 0.000335
FLAG_DOCUMENT_6                 0.000335
FLAG_DOCUMENT_7                 0.000335
FLAG_DOCUMENT_8                 0.000335
FLAG_DOCUMENT_9                 0.000335
FLAG_DOCUMENT_10                0.000335
FLAG_DOCUMENT_11                0.000335
FLAG_DOCUMENT_14                0.000335
FLAG_DOCUMENT_15                0.000335
FLAG_DOCUMENT_16                0.000335
FLAG_DOCUMENT_17                0.000335
FLAG_DOCUMENT_18                0.000335
FLAG_DOCUMENT_19                0.000335
```

```
FLAG_DOCUMENT_20                0.000335
FLAG_DOCUMENT_21                0.000335
FLAG_OWN_REALTY                 0.000000
AMT_INCOME_TOTAL                0.000000
CNT_CHILDREN                    0.000000
CODE_GENDER                     0.000000
NAME_CONTRACT_TYPE              0.000000
FLAG_OWN_CAR                    0.000000
FLAG_EMP_PHONE                  0.000000
AMT_CREDIT                      0.000000
FLAG_WORK_PHONE                 0.000000
FLAG_CONT_MOBILE                0.000000
FLAG_PHONE                      0.000000
FLAG_EMAIL                      0.000000
FLAG_MOBIL                      0.000000
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
TARGET                          0.000000
DAYS_ID_PUBLISH                 0.000000
DAYS_REGISTRATION               0.000000
DAYS_EMPLOYED                   0.000000
DAYS_BIRTH                      0.000000
REGION_POPULATION_RELATIVE      0.000000
NAME_HOUSING_TYPE               0.000000
NAME_FAMILY_STATUS              0.000000
NAME_EDUCATION_TYPE             0.000000
NAME_INCOME_TYPE                0.000000
SK_ID_CURR                      0.000000
dtype: float64
```

#check correlation for the columns EXT_SOURCE_3 and EXT_SOURCE_2 to the targ

et column

```
sns.heatmap(df1[['EXT_SOURCE_3','EXT_SOURCE_2','TARGET']].corr(),annot=True)
```

```
<Axes: >
```


```
df1.drop(['EXT_SOURCE_3','EXT_SOURCE_2'],axis=1,inplace=True)
df1.shape
```

```
(298870, 79)
```

```
#Now there are some columns named flag which contain some true false values
flags = []
for i in df1.columns:
 if 'FLAG' in i:
    flags.append(i)
flags
```

```
['FLAG_OWN_CAR',
 'FLAG_OWN_REALTY',
 'FLAG_MOBIL',
 'FLAG_EMP_PHONE',
 'FLAG_WORK_PHONE',
 'FLAG_CONT_MOBILE',
 'FLAG_PHONE',
 'FLAG_EMAIL',
 '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']
```

#Drop unnecessary flag columns

```
remove_list =
['FLAG_OWN_REALTY','FLAG_OWN_CAR','FLAG_PHONE','FLAG_WORK_PHONE'
]
flags = list(set(flags) - set(remove_list))
# finally remove those columns
df1.drop(flags,axis=1,inplace=True)
# Dataset after removing unnecessary flag values
df1.shape
```

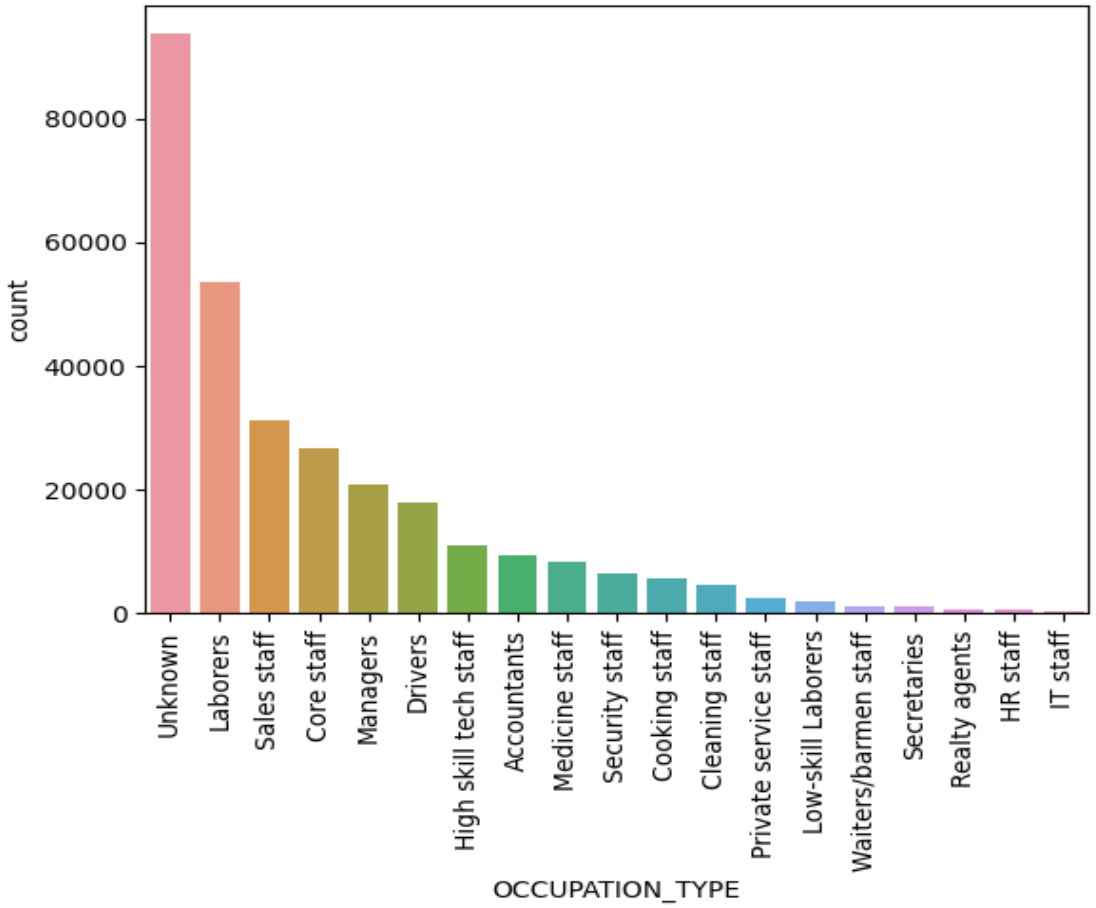
```
(298870, 55)
```

Filling null value

```
df1['OCCUPATION_TYPE'].fillna('Unknown',inplace=True)
sns.countplot(x =df1['OCCUPATION_TYPE'],order =
df1['OCCUPATION_TYPE'].value_counts().index
)
plt.xticks(rotation=90)
```

```
(array([ 0,  1,  2,  3,  4,  5,  6,  7,  8,  9, 10, 11, 12, 13, 14, 15, 16,
        17, 18]),
 [Text(0, 0, 'Unknown'),
  Text(1, 0, 'Laborers'),
  Text(2, 0, 'Sales staff'),
  Text(3, 0, 'Core staff'),
  Text(4, 0, 'Managers'),
  Text(5, 0, 'Drivers'),
  Text(6, 0, 'High skill tech staff'),
  Text(7, 0, 'Accountants'),
  Text(8, 0, 'Medicine staff'),
  Text(9, 0, 'Security staff'),
  Text(10, 0, 'Cooking staff'),
  Text(11, 0, 'Cleaning staff'),
  Text(12, 0, 'Private service staff'),
  Text(13, 0, 'Low-skill Laborers'),
```

```
  Text(14, 0, 'Waiters/barmen staff'),
  Text(15, 0, 'Secretaries'),
  Text(16, 0, 'Realty agents'),
  Text(17, 0, 'HR staff'),
  Text(18, 0, 'IT staff')])
```




```
amt_req = []
for i in df1.columns:
 if "AMT_REQ" in i:
  amt_req.append(i)
amt_req
```

```
['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']
```

```
df1[amt_req].mean()
```

```
AMT_REQ_CREDIT_BUREAU_HOUR    0.006421
AMT_REQ_CREDIT_BUREAU_DAY     0.007052
```

```
AMT_REQ_CREDIT_BUREAU_WEEK    0.034347
AMT_REQ_CREDIT_BUREAU_MON     0.267287
AMT_REQ_CREDIT_BUREAU_QRT     0.265631
AMT_REQ_CREDIT_BUREAU_YEAR    1.900584
dtype: float64
```

```
df1[amt_req].mode()
```

```
   AMT_REQ_CREDIT_BUREAU_HOUR  AMT_REQ_CREDIT_BUREAU_DAY  \
0                         0.0                        0.0

   AMT_REQ_CREDIT_BUREAU_WEEK  AMT_REQ_CREDIT_BUREAU_MON  \
0                         0.0                        0.0

   AMT_REQ_CREDIT_BUREAU_QRT  AMT_REQ_CREDIT_BUREAU_YEAR
0                        0.0                        0.0
```

```
df1[amt_req].median()
```

```
AMT_REQ_CREDIT_BUREAU_HOUR    0.0
AMT_REQ_CREDIT_BUREAU_DAY     0.0
AMT_REQ_CREDIT_BUREAU_WEEK    0.0
AMT_REQ_CREDIT_BUREAU_MON     0.0
AMT_REQ_CREDIT_BUREAU_QRT     0.0
AMT_REQ_CREDIT_BUREAU_YEAR    1.0
dtype: float64
```

```
try1 = df1[amt_req].fillna(df1[amt_req].median())
```

```
df1['NAME_TYPE_SUITE'].fillna('Unknown',inplace=True)
```

```
social_circle = []
for i in df1.columns:
 if 'SOCIAL_CIRCLE' in i:
  social_circle.append(i)
social_circle
```

```
['OBS_30_CNT_SOCIAL_CIRCLE',
 'DEF_30_CNT_SOCIAL_CIRCLE',
 'OBS_60_CNT_SOCIAL_CIRCLE',
 'DEF_60_CNT_SOCIAL_CIRCLE']
```

```
df1[social_circle].mean()
```

```
OBS_30_CNT_SOCIAL_CIRCLE    1.422681
DEF_30_CNT_SOCIAL_CIRCLE    0.143559
OBS_60_CNT_SOCIAL_CIRCLE    1.405678
DEF_60_CNT_SOCIAL_CIRCLE    0.100112
dtype: float64
```

```
df1[social_circle].mode()
```

```
   OBS_30_CNT_SOCIAL_CIRCLE  DEF_30_CNT_SOCIAL_CIRCLE  \
0                       0.0                       0.0

   OBS_60_CNT_SOCIAL_CIRCLE  DEF_60_CNT_SOCIAL_CIRCLE
0                       0.0                       0.0
```

```
df1[social_circle].median()
```

```
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
dtype: float64
```

```
df1[social_circle] = df1[social_circle].fillna(df1[social_circle].median())
```

```
df1['AMT_GOODS_PRICE'].fillna(df1['AMT_GOODS_PRICE'].mean(),inplace=True)
```

```
df1['AMT_ANNUITY'].fillna(df1['AMT_ANNUITY'].mean(),inplace=True)
```

```
df1['CNT_FAM_MEMBERS'].fillna(df1['CNT_FAM_MEMBERS'].median(),inplace=True)
```

```
df1['DAYS_LAST_PHONE_CHANGE'].fillna(df1['DAYS_LAST_PHONE_CHANGE'].median(),i
nplace=True)
```

```
days = []
for i in df1.columns:
 if 'DAYS' in i:
  days.append(i)
days
```

```
['DAYS_BIRTH',
 'DAYS_EMPLOYED',
 'DAYS_REGISTRATION',
 'DAYS_ID_PUBLISH',
 'DAYS_LAST_PHONE_CHANGE']
```

```
df1[days] = abs(df1[days])/365
df1.rename(columns =
{'DAYS_BIRTH':'AGE','DAYS_EMPLOYED':'YEARS_EMPLOYED','DAYS_REGISTRATION':'YEA
RS_REGISTRATION','DAYS_ID_PUBLISH':'YEARS_ID_PUBLISH','DAYS_LAST_PHONE_CHANGE
':'YEARS_LAST_PHONE_CHANGE'},inplace=True)
```

Reading the dataset previous_applications.csv

```
df = pd.read_csv('/content/previous_application.csv')
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 171260 entries, 0 to 171259
Data columns (total 37 columns):
 #   Column                       Non-Null Count   Dtype
---  ------                       --------------   -----
```

```
 0   SK_ID_PREV                  171260 non-null  int64
 1   SK_ID_CURR                  171260 non-null  int64
 2   NAME_CONTRACT_TYPE          171260 non-null  object
 3   AMT_ANNUITY                 134637 non-null  float64
 4   AMT_APPLICATION             171259 non-null  float64
 5   AMT_CREDIT                  171259 non-null  float64
 6   AMT_DOWN_PAYMENT            83469 non-null   float64
 7   AMT_GOODS_PRICE             133673 non-null  float64
 8   WEEKDAY_APPR_PROCESS_START  171259 non-null  object
 9   HOUR_APPR_PROCESS_START     171259 non-null  float64
 10  FLAG_LAST_APPL_PER_CONTRACT 171259 non-null  object
 11  NFLAG_LAST_APPL_IN_DAY      171259 non-null  float64
 12  RATE_DOWN_PAYMENT           83469 non-null   float64
 13  RATE_INTEREST_PRIMARY       605 non-null     float64
 14  RATE_INTEREST_PRIVILEGED    605 non-null     float64
 15  NAME_CASH_LOAN_PURPOSE      171259 non-null  object
 16  NAME_CONTRACT_STATUS        171259 non-null  object
 17  DAYS_DECISION               171259 non-null  float64
 18  NAME_PAYMENT_TYPE           171259 non-null  object
 19  CODE_REJECT_REASON          171259 non-null  object
 20  NAME_TYPE_SUITE             87962 non-null   object
 21  NAME_CLIENT_TYPE            171259 non-null  object
 22  NAME_GOODS_CATEGORY         171259 non-null  object
 23  NAME_PORTFOLIO              171259 non-null  object
 24  NAME_PRODUCT_TYPE           171259 non-null  object
 25  CHANNEL_TYPE                171259 non-null  object
 26  SELLERPLACE_AREA            171259 non-null  float64
 27  NAME_SELLER_INDUSTRY        171259 non-null  object
 28  CNT_PAYMENT                 134636 non-null  float64
 29  NAME_YIELD_GROUP            171259 non-null  object
 30  PRODUCT_COMBINATION         171225 non-null  object
 31  DAYS_FIRST_DRAWING          105098 non-null  float64
 32  DAYS_FIRST_DUE              105098 non-null  float64
 33  DAYS_LAST_DUE_1ST_VERSION   105098 non-null  float64
 34  DAYS_LAST_DUE               105098 non-null  float64
 35  DAYS_TERMINATION            105098 non-null  float64
 36  NFLAG_INSURED_ON_APPROVAL   105098 non-null  float64
dtypes: float64(19), int64(2), object(16)
memory usage: 48.3+ MB
```

```
df.describe()
```

```
         SK_ID_PREV     SK_ID_CURR    AMT_ANNUITY  AMT_APPLICATION  \
count  1.712600e+05  171260.000000  134637.000000     1.712590e+05
mean   1.919741e+06  278719.140967   15532.635304     1.697844e+05
std    5.344304e+05  102855.832468   14522.351767     2.839742e+05
min    1.000001e+06  100006.000000       0.000000     0.000000e+00
25%    1.456136e+06  189766.500000    6169.455000     2.110500e+04
50%    1.918981e+06  279048.000000   10956.150000     7.105500e+04
75%    2.383123e+06  368237.000000   19866.600000     1.800000e+05
```

```
max    2.845377e+06  456254.000000  417927.645000     3.826372e+06

         AMT_CREDIT  AMT_DOWN_PAYMENT  AMT_GOODS_PRICE  \
count  1.712590e+05      8.346900e+04     1.336730e+05
mean   1.895623e+05      6.632274e+03     2.175552e+05
std    3.100716e+05      1.826219e+04     3.048750e+05
min    0.000000e+00      0.000000e+00     0.000000e+00
25%    2.542050e+04      0.000000e+00     4.945500e+04
50%    7.911900e+04      1.660500e+03     1.065555e+05
75%    2.025000e+05      7.731000e+03     2.250000e+05
max    4.104351e+06      1.201500e+06     3.826372e+06
```

Dealing with null values

```
count_null_values(df)
```

```
RATE_INTEREST_PRIVILEGED       99.646736
RATE_INTEREST_PRIMARY          99.646736
RATE_DOWN_PAYMENT              51.261824
AMT_DOWN_PAYMENT               51.261824
NAME_TYPE_SUITE                48.638328
NFLAG_INSURED_ON_APPROVAL      38.632489
DAYS_FIRST_DRAWING             38.632489
DAYS_FIRST_DUE                 38.632489
DAYS_LAST_DUE_1ST_VERSION      38.632489
DAYS_LAST_DUE                  38.632489
DAYS_TERMINATION               38.632489
AMT_GOODS_PRICE                21.947332
CNT_PAYMENT                    21.385029
AMT_ANNUITY                    21.384445
PRODUCT_COMBINATION             0.020437
CHANNEL_TYPE                    0.000584
NAME_PRODUCT_TYPE               0.000584
NAME_YIELD_GROUP                0.000584
SELLERPLACE_AREA                0.000584
NAME_SELLER_INDUSTRY            0.000584
NAME_GOODS_CATEGORY             0.000584
NAME_PORTFOLIO                  0.000584
NAME_PAYMENT_TYPE               0.000584
NAME_CLIENT_TYPE                0.000584
CODE_REJECT_REASON              0.000584
DAYS_DECISION                   0.000584
NAME_CONTRACT_STATUS            0.000584
NAME_CASH_LOAN_PURPOSE          0.000584
NFLAG_LAST_APPL_IN_DAY          0.000584
FLAG_LAST_APPL_PER_CONTRACT     0.000584
HOUR_APPR_PROCESS_START         0.000584
WEEKDAY_APPR_PROCESS_START      0.000584
AMT_CREDIT                      0.000584
```

```
AMT_APPLICATION                0.000584
SK_ID_CURR                     0.000000
NAME_CONTRACT_TYPE             0.000000
SK_ID_PREV                     0.000000
dtype: float64
```

```
#Find the columns with more than 40% of null values
null40 = count_null_values(df,40)
null40
```

```
RATE_INTEREST_PRIMARY       99.646736
RATE_INTEREST_PRIVILEGED    99.646736
AMT_DOWN_PAYMENT            51.261824
RATE_DOWN_PAYMENT           51.261824
NAME_TYPE_SUITE             48.638328
dtype: float64
```

```
#Drop all the values with more than 40% of null values
df.drop(null40.index,axis=1,inplace=True)
df.shape
```

```
(171260, 32)
```

```
#Remove the columns which are unnecessary
df.drop(['WEEKDAY_APPR_PROCESS_START','HOUR_APPR_PROCESS_START','FLAG_LAST_AP
PL_PER_CONTRACT','NFLAG_LAST_APPL_IN_DAY'],axis=1,inplace=True)
df.shape
```

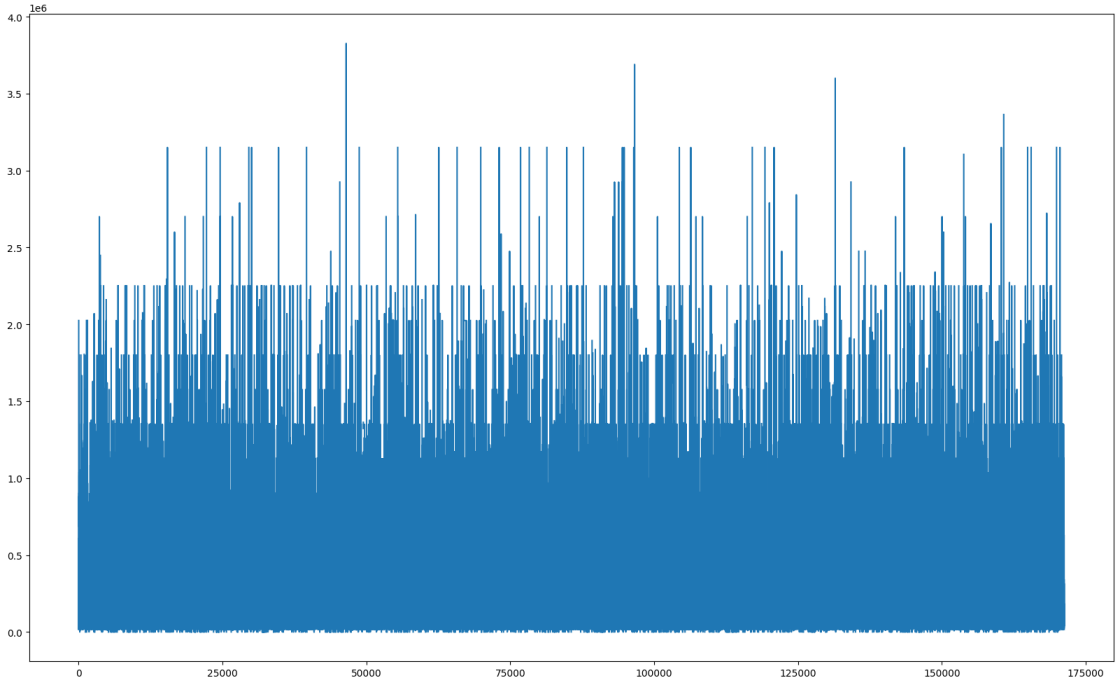
```
(171260, 28)
```

```
#Now find the columns with missing values more than 15%
null15 = count_null_values(df,15)
null15
```

```
DAYS_FIRST_DRAWING           38.632489
DAYS_FIRST_DUE               38.632489
DAYS_LAST_DUE_1ST_VERSION    38.632489
DAYS_LAST_DUE                38.632489
DAYS_TERMINATION             38.632489
NFLAG_INSURED_ON_APPROVAL    38.632489
AMT_GOODS_PRICE              21.947332
CNT_PAYMENT                  21.385029
AMT_ANNUITY                  21.384445
dtype: float64
```

```
plt.figure(figsize=(20,12))
plt.plot(df['AMT_GOODS_PRICE'])
```

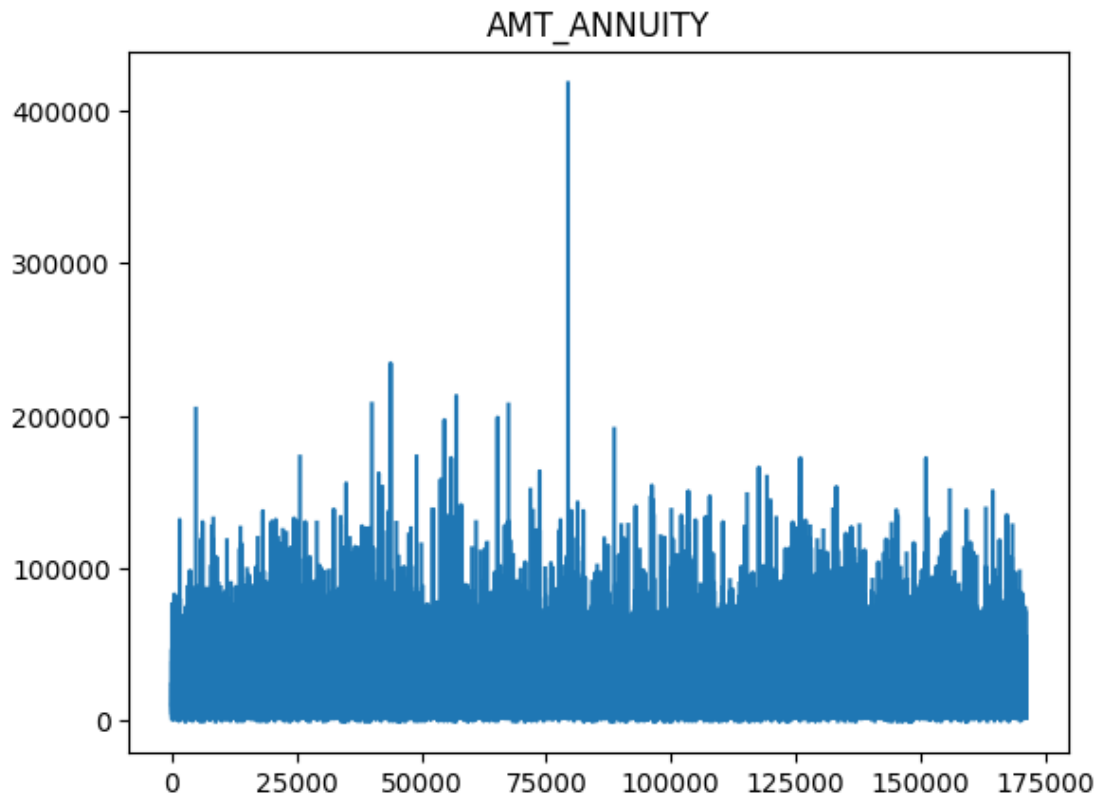
```
[<matplotlib.lines.Line2D at 0x7fce50301460>]
```




```
df['AMT_GOODS_PRICE'].fillna(df['AMT_GOODS_PRICE'].mean(),inplace=True)
```

```
plt.plot(df['AMT_ANNUITY'])
plt.title('AMT_ANNUITY')
```

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

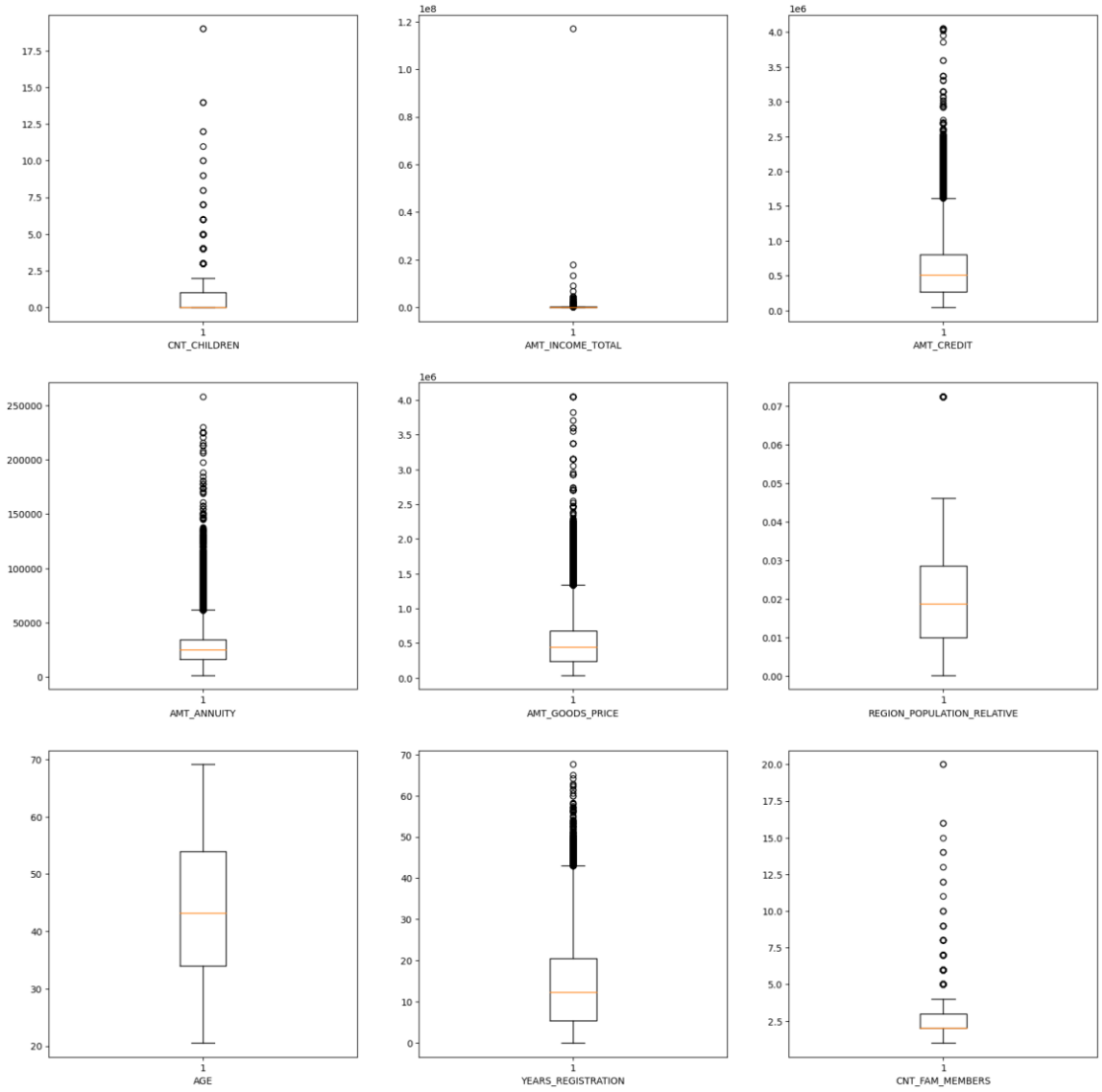



```
df['AMT_ANNUITY'].fillna(df['AMT_ANNUITY'].mean(),inplace=True)

df['CNT_PAYMENT'].fillna(df['CNT_PAYMENT'].median(),inplace=True)
```

Check Outliers

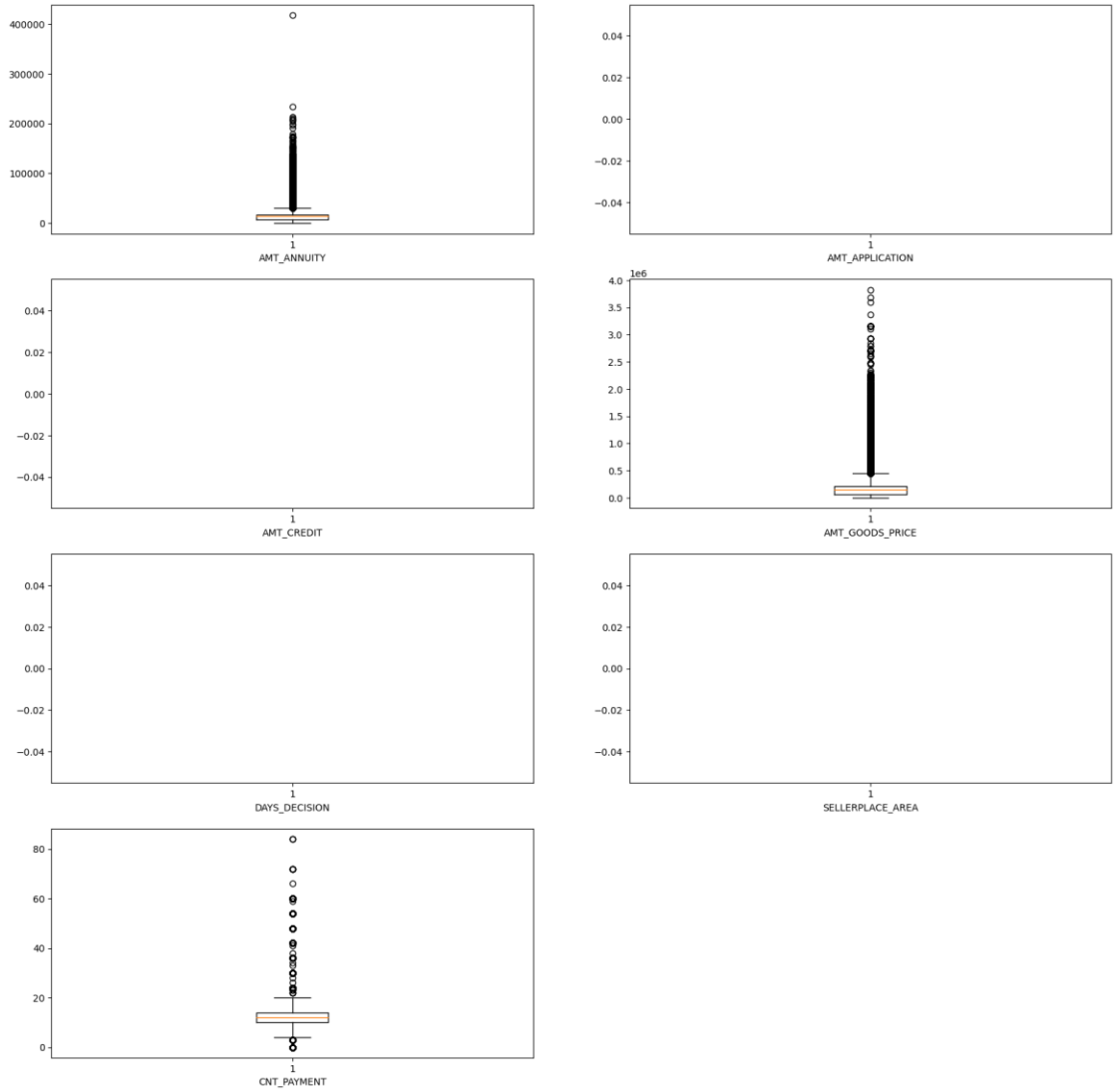
Application_data.csv

```
out_check =
'CNT_CHILDREN,AMT_INCOME_TOTAL,AMT_CREDIT,AMT_ANNUITY,AMT_GOODS_PRICE,REGION_
POPULATION_RELATIVE,AGE,YEARS_REGISTRATION,CNT_FAM_MEMBERS'.split(',')
plt.figure(figsize=(20,20))
#df1.boxplot(column = out_check, grid=False, rot=90, fontsize=15)
for i in range(len(out_check)):
 plt.subplot(3,3,i+1)
 plt.boxplot(df1[out_check[i]])
 plt.xlabel(out_check[i])
```



Previous_application.csv

```
out_check2 =
'AMT_ANNUITY,AMT_APPLICATION,AMT_CREDIT,AMT_GOODS_PRICE,DAYS_DECISION,SELLERP
LACE_AREA,CNT_PAYMENT'.split(',')
plt.figure(figsize=(20,20))
#df1.boxplot(column = out_check, grid=False, rot=90, fontsize=15)
for i in range(len(out_check2)):
 plt.subplot(4,2,i+1)
 plt.boxplot(df[out_check2[i]])
 plt.xlabel(out_check2[i])
```



Data Imbalance

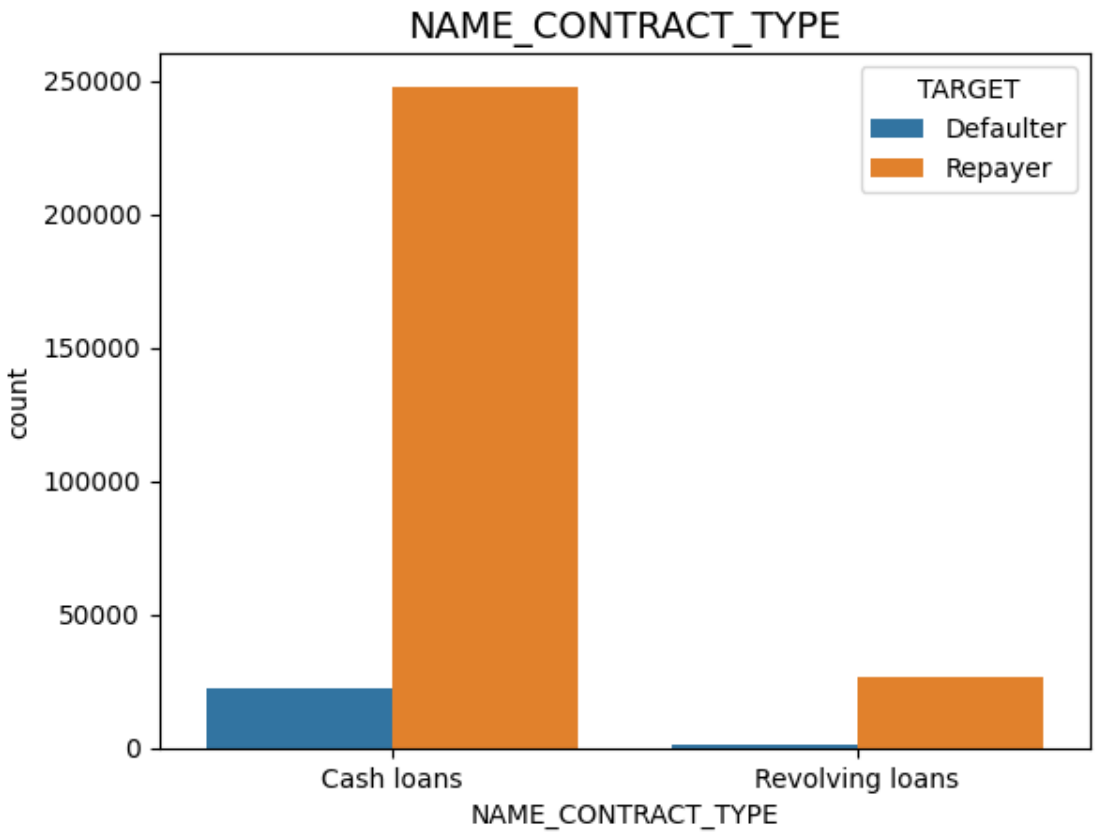
```
df1["TARGET"] = df1["TARGET"].replace({1:"Defaulter",0:"Repayer"})

df1['TARGET'].value_counts()*100/len(df1)
```

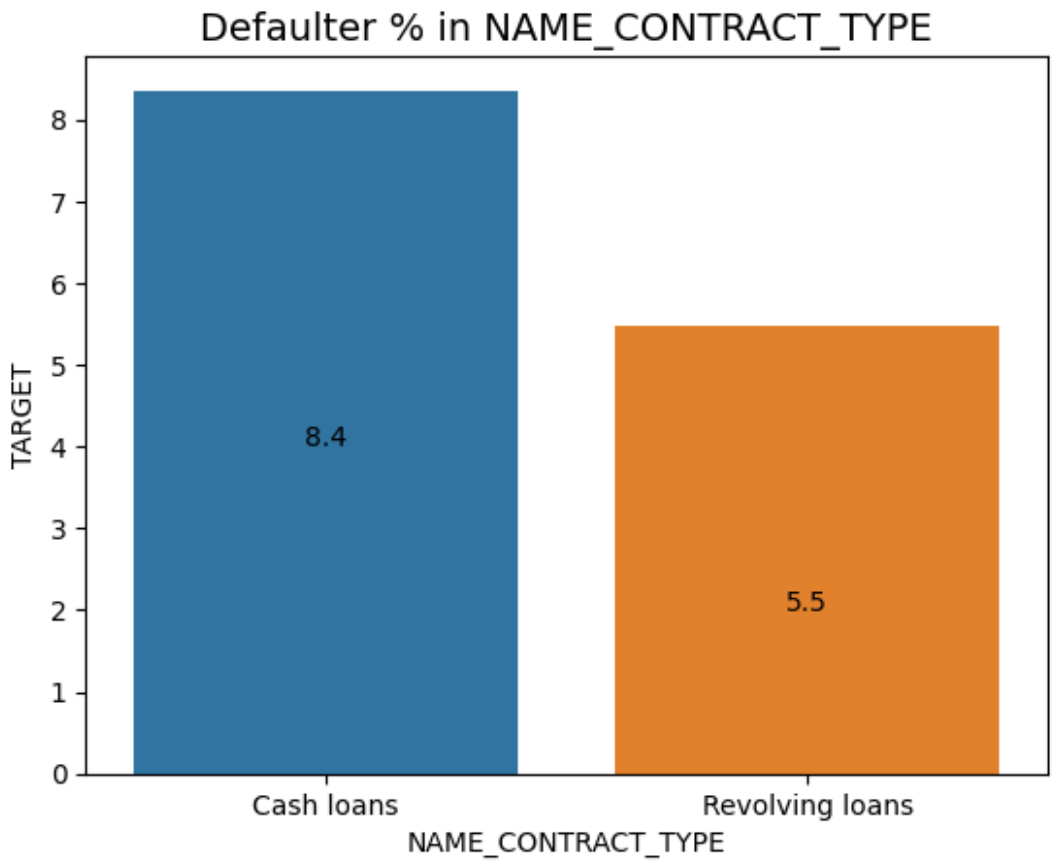
```
Repayer      91.916887
Defaulter     8.083113
Name: TARGET, dtype: float64
```

Univariate Analysis for application_data.csv

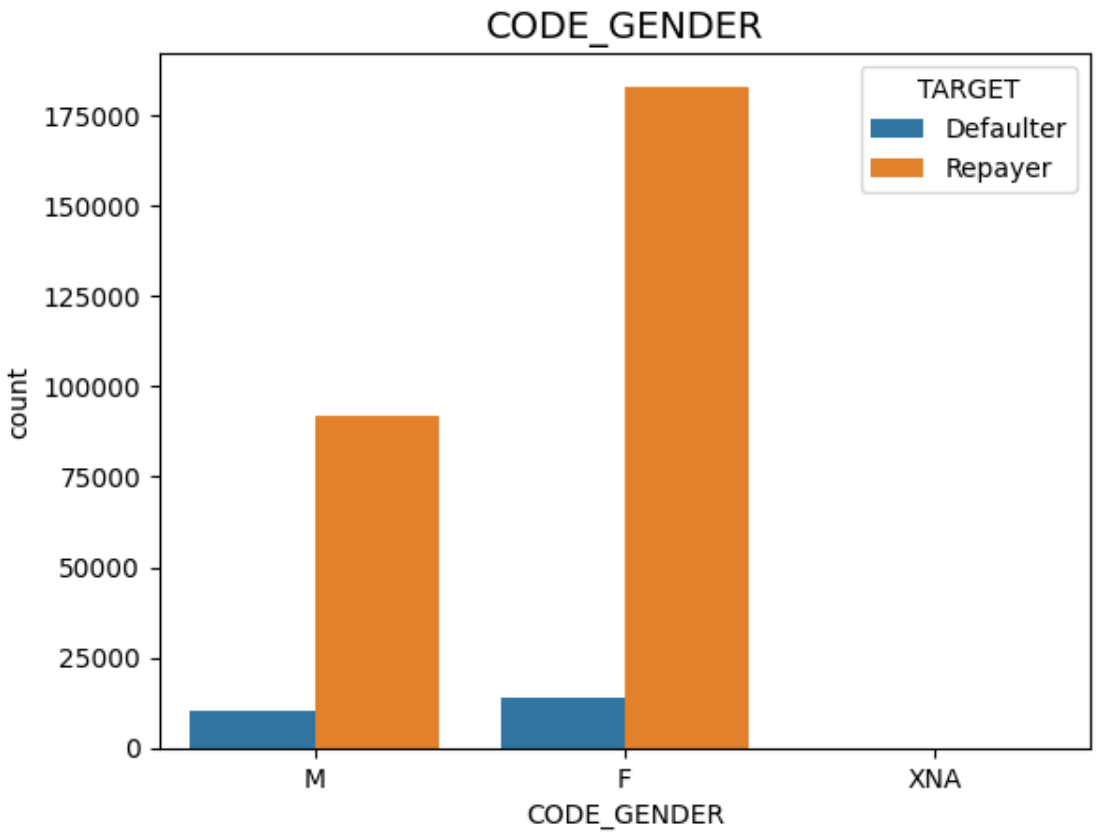
```
def addlabels(x,y):
 for i in range(len(x)):
  plt.text(i, y[i]//2, y[i], ha = 'center')
def univariate(df,data,target):
 col = df[data]
 tar = df[target]
 types = col.dtypes
```

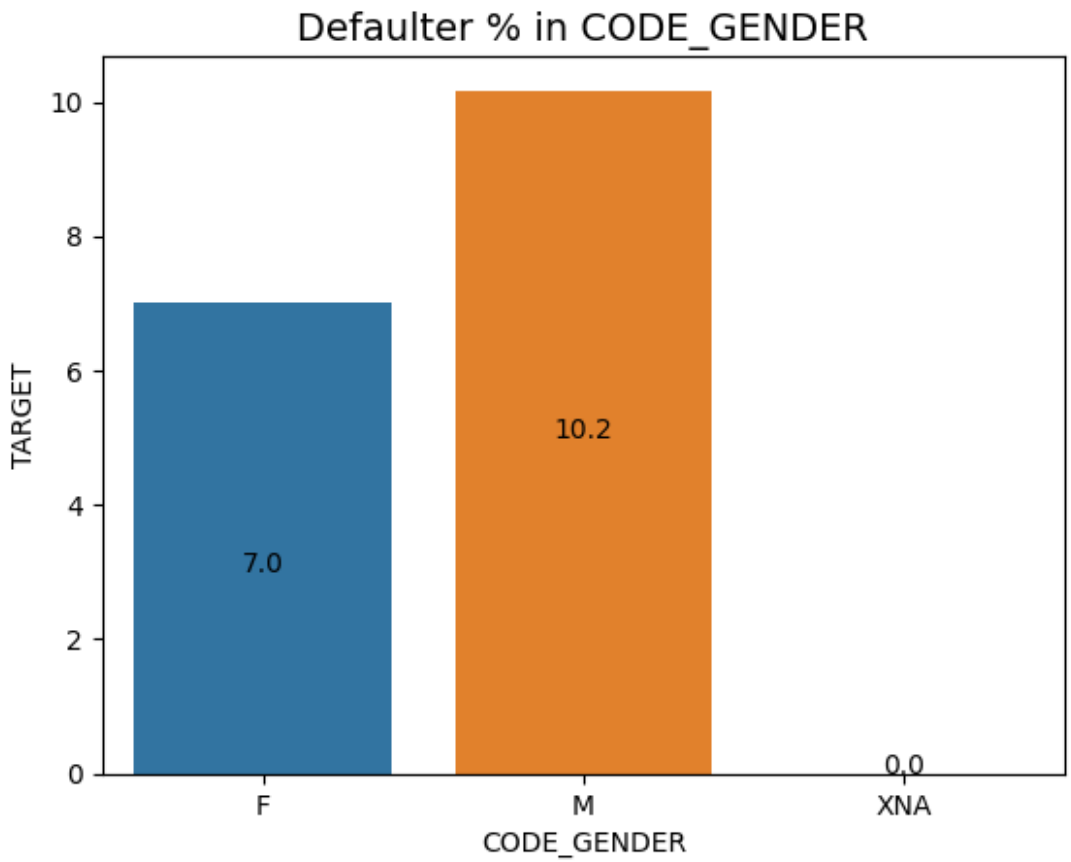
```
 ex = col.value_counts()
 if len(ex)>8:
  plt.figure(figsize = (20,12))
  sns.countplot(x = col, hue = tar)
  plt.xticks(rotation = 90)
  plt.title(data,fontdict={'fontsize': 20})
 elif len(ex)>4:
  plt.figure(figsize = (15,8))
  sns.countplot(x = col, hue = tar)
  plt.xticks(rotation = 45)
  plt.title(data,fontdict={'fontsize': 20})
 else:
  plt.figure()
  sns.countplot(x = col, hue = tar)
  plt.title(data,fontdict={'fontsize': 14})
 plt.xlabel(data)
 pf = df[[data,target]].value_counts().reset_index()
 percent= []
 for i in pf[data].unique():
  try:

percent.append(pf[(pf[data]==i)&(pf[target]=='Defaulter')][0].values[0]*100/(
pf[(pf[data]==i)&(pf[target]=='Defaulter')][0].values[0]+pf[(pf[data]==i)&(pf
[target]=='Repayer')][0].values[0]))
  except:
   percent.append(0)
 if len(percent)>8:
  plt.figure(figsize = (20,12))
  sns.barplot(y = percent, x = pf[data].unique())
  plt.xticks(rotation = 90)
  plt.title('Defaulter % in '+data,fontdict={'fontsize': 20})
 elif len(percent)>4:
  plt.figure(figsize = (15,8))
  sns.barplot(y = percent, x = pf[data].unique())
  plt.xticks(rotation = 45)
  plt.title('Defaulter % in '+data,fontdict={'fontsize': 20})
 else:
  plt.figure()
  sns.barplot(y = percent, x = pf[data].unique())
  plt.title('Defaulter % in '+data,fontdict={'fontsize': 14})
  plt.xlabel(data)
  plt.ylabel(target)
  addlabels(x = pf[data].unique(),y=np.round(percent,1))

univariate(df1,'NAME_CONTRACT_TYPE','TARGET')
```


NAME_CONTRACT_TYPE
TARGET
Defaulter
Repayer
250000
200000
150000
100000
50000
0
count
Cash loans
Revolving loans
NAME_CONTRACT_TYPE

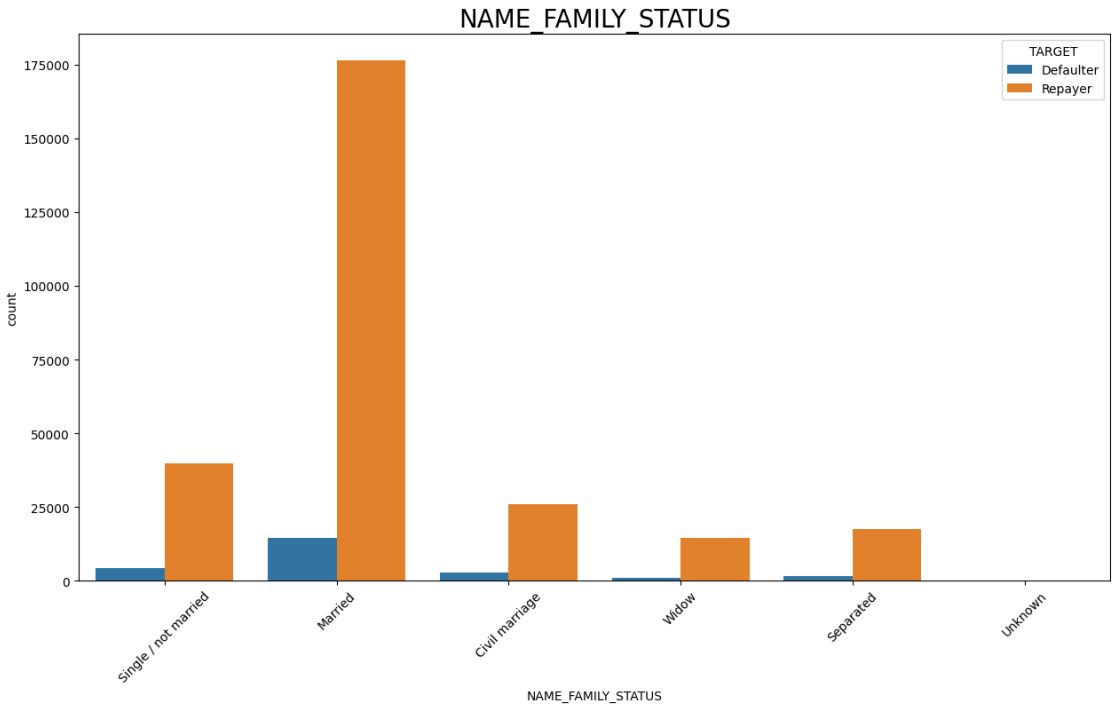


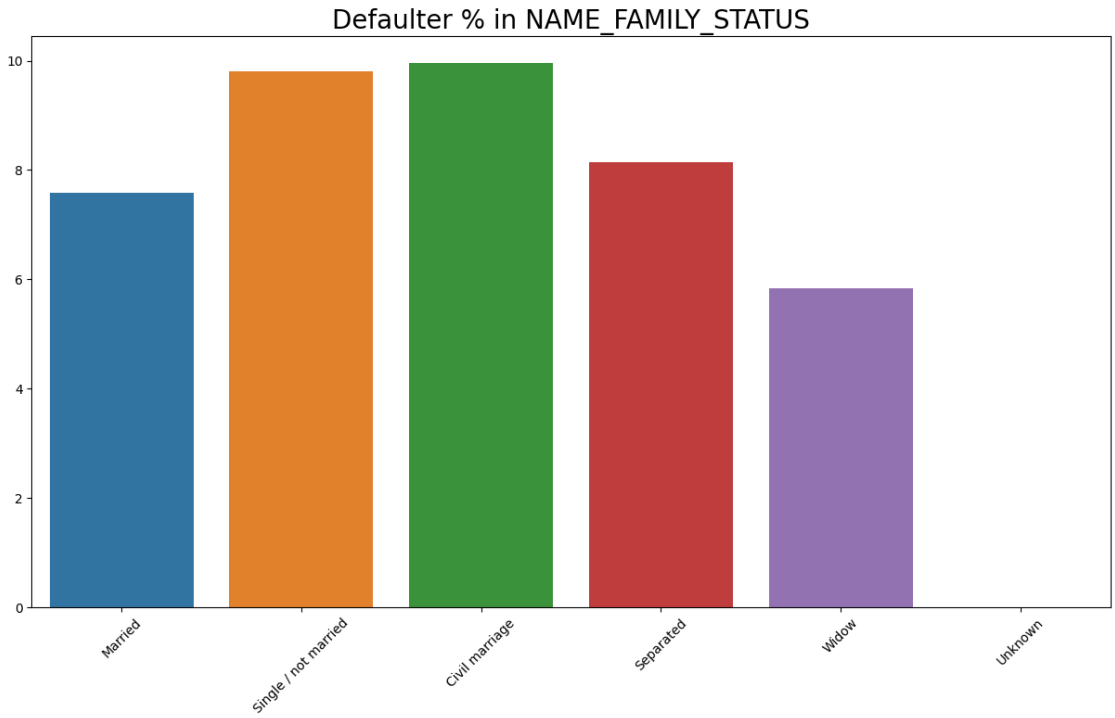

```
univariate(df1,'CODE_GENDER','TARGET')
```


CODE_GENDER
TARGET
Defaulter
Repayer
175000
150000
125000
100000
75000
50000
25000
0
count
M
F
XNA
CODE_GENDER

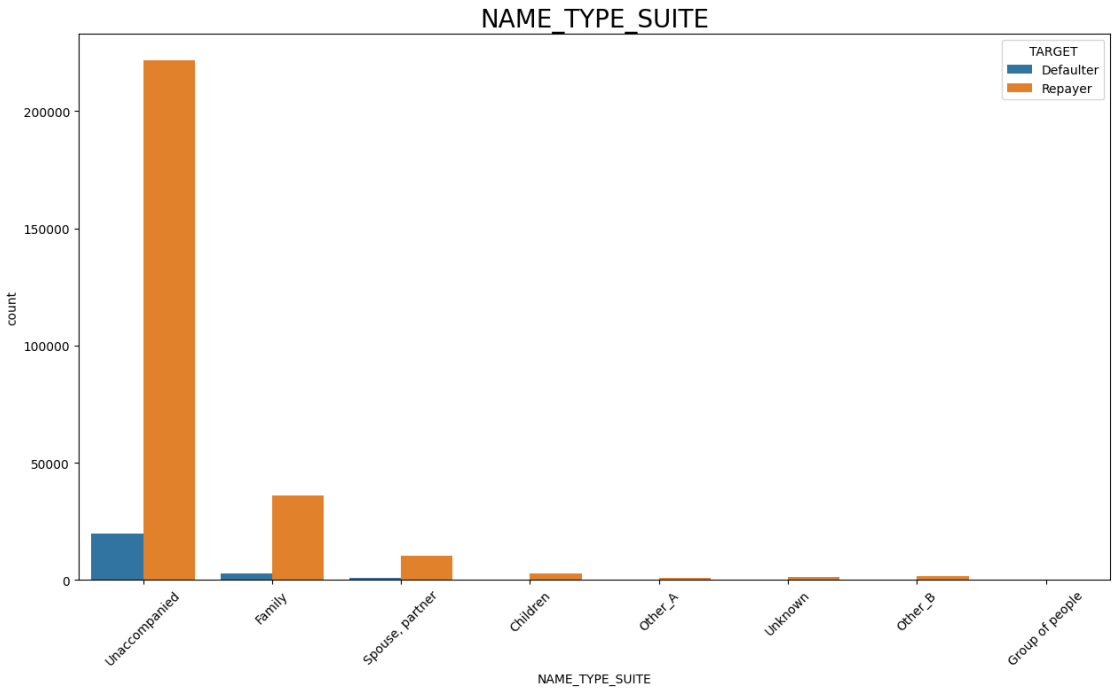


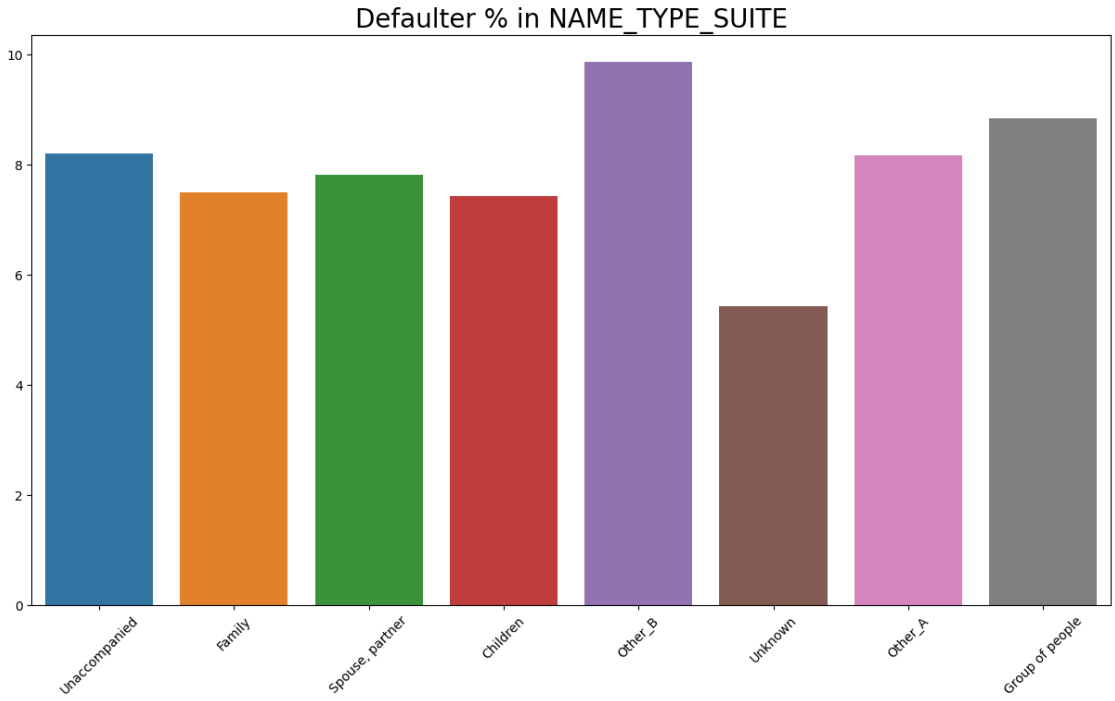

```
univariate(df1,'NAME_FAMILY_STATUS','TARGET')
```



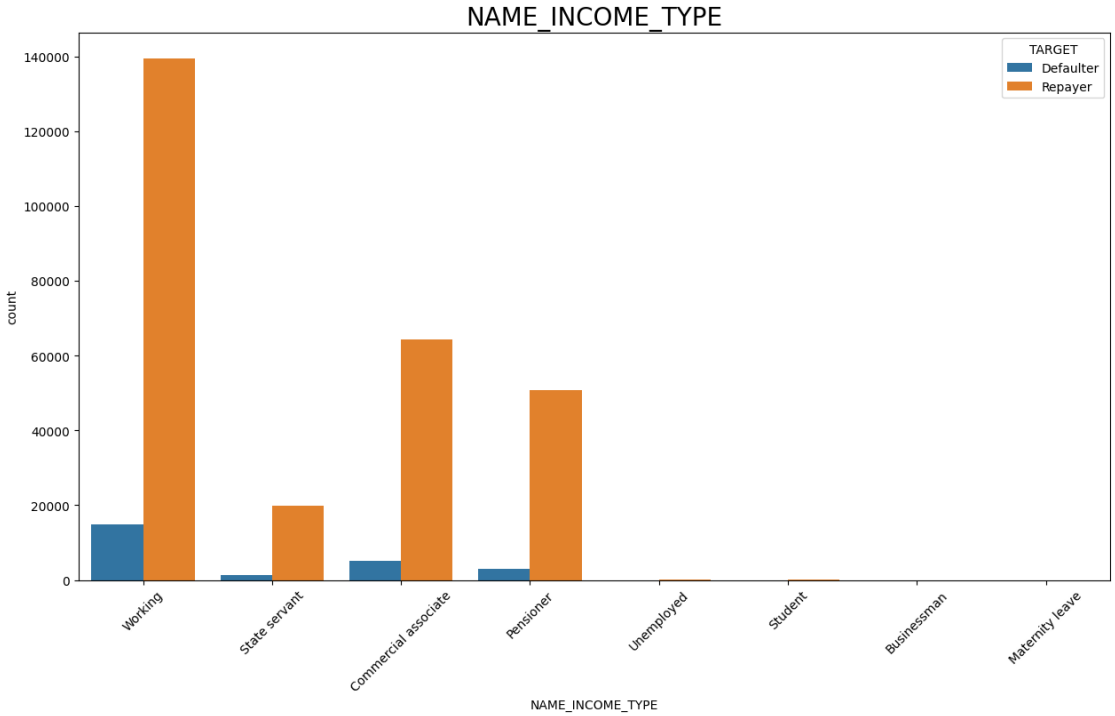


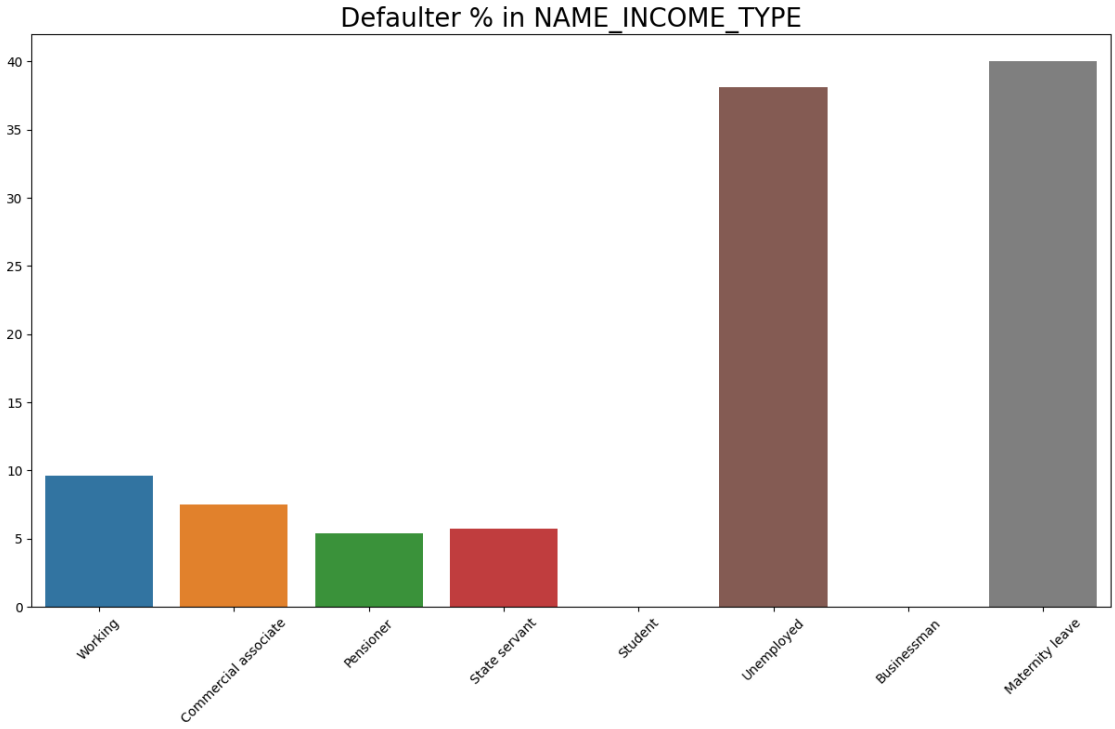

```
univariate(df1,'NAME_TYPE_SUITE','TARGET')
```



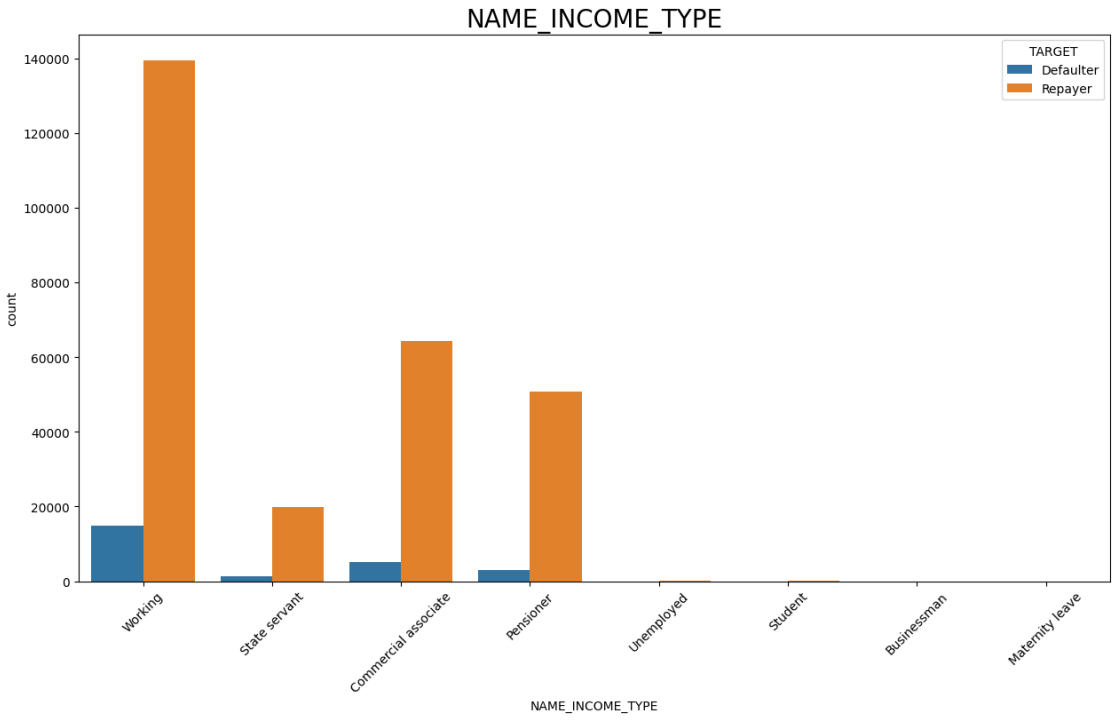


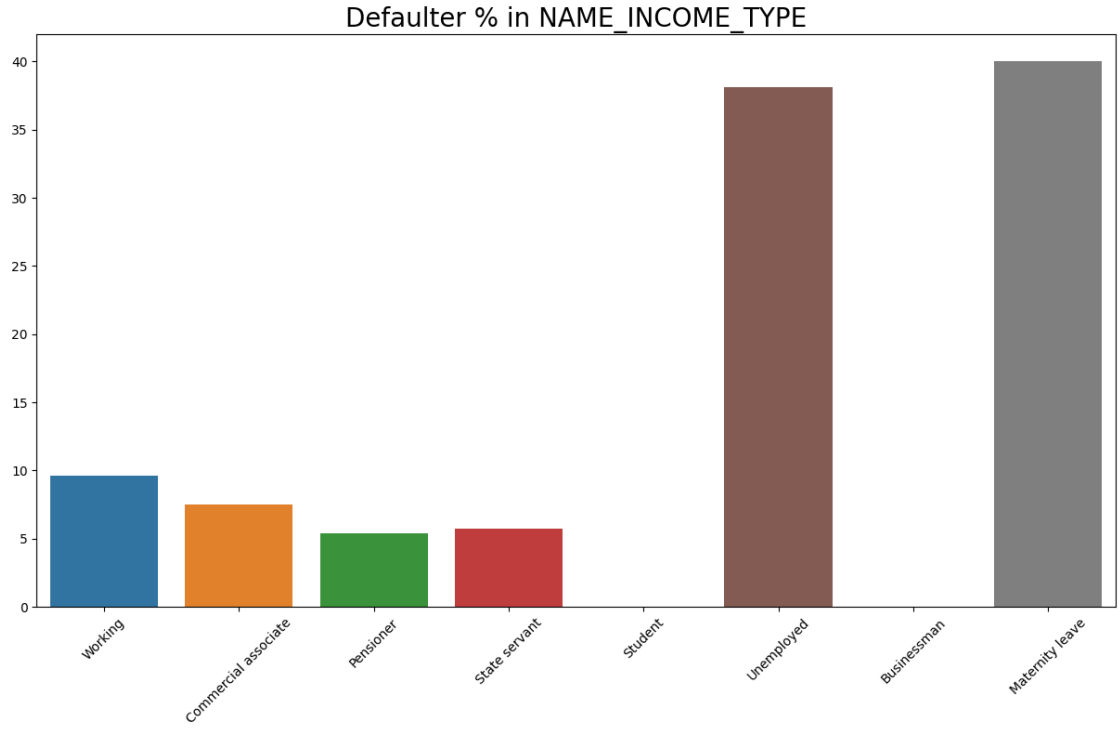

```
univariate(df1,'NAME_INCOME_TYPE','TARGET')
```



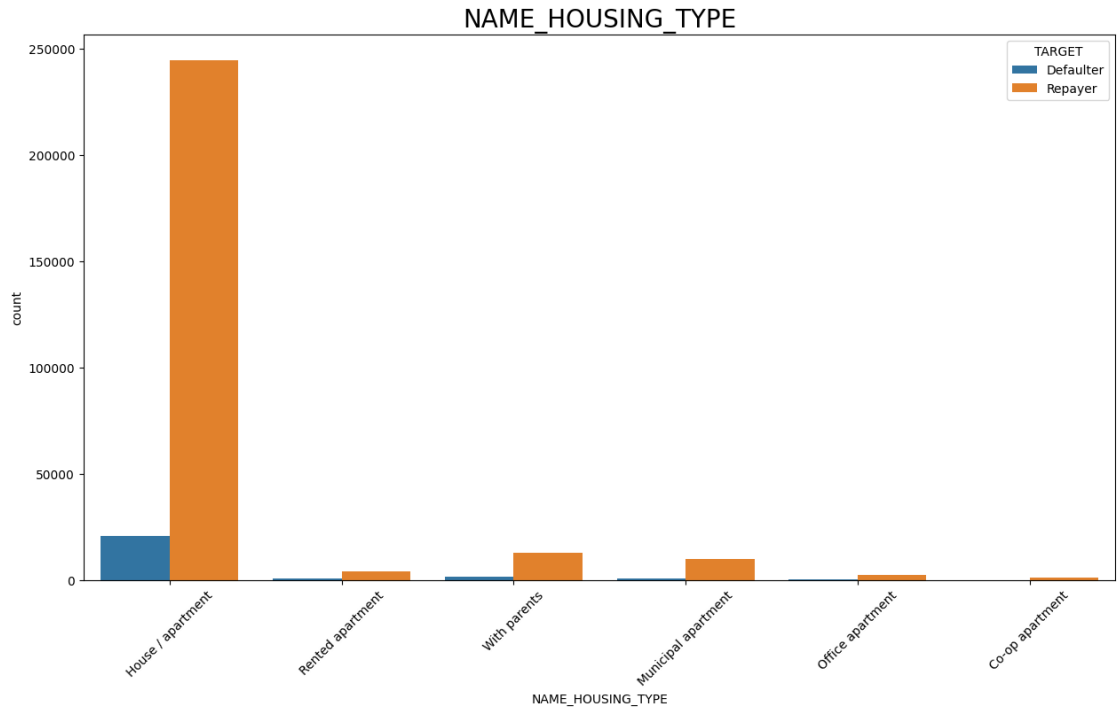


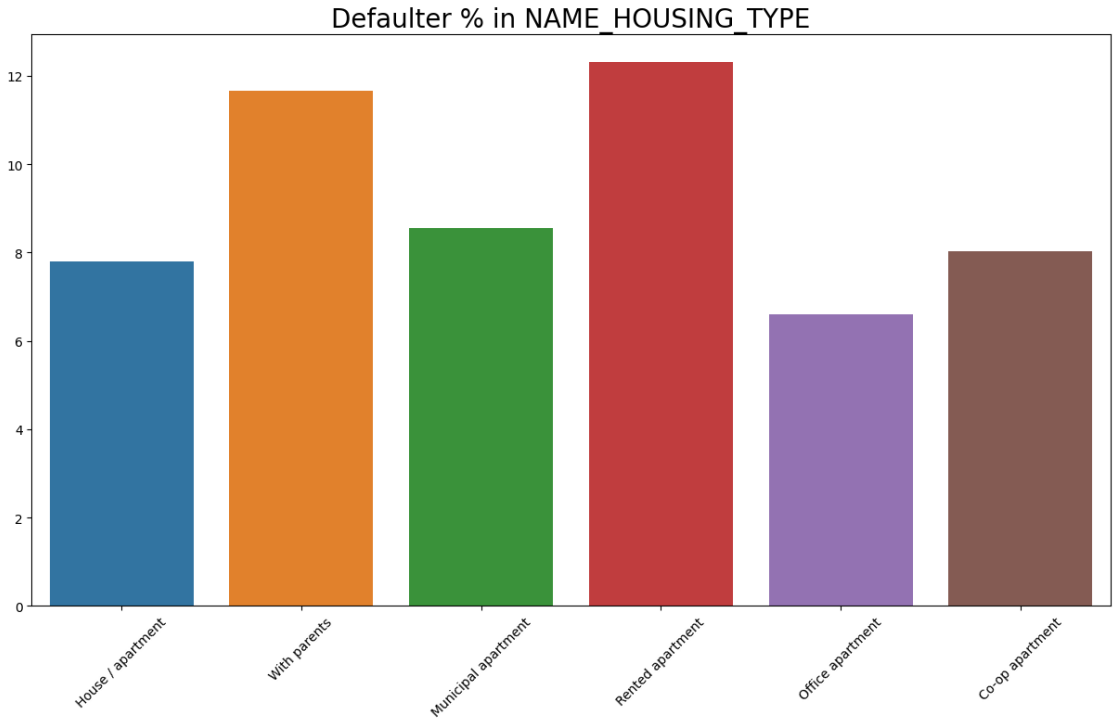

```
univariate(df1,'NAME_INCOME_TYPE','TARGET')
```



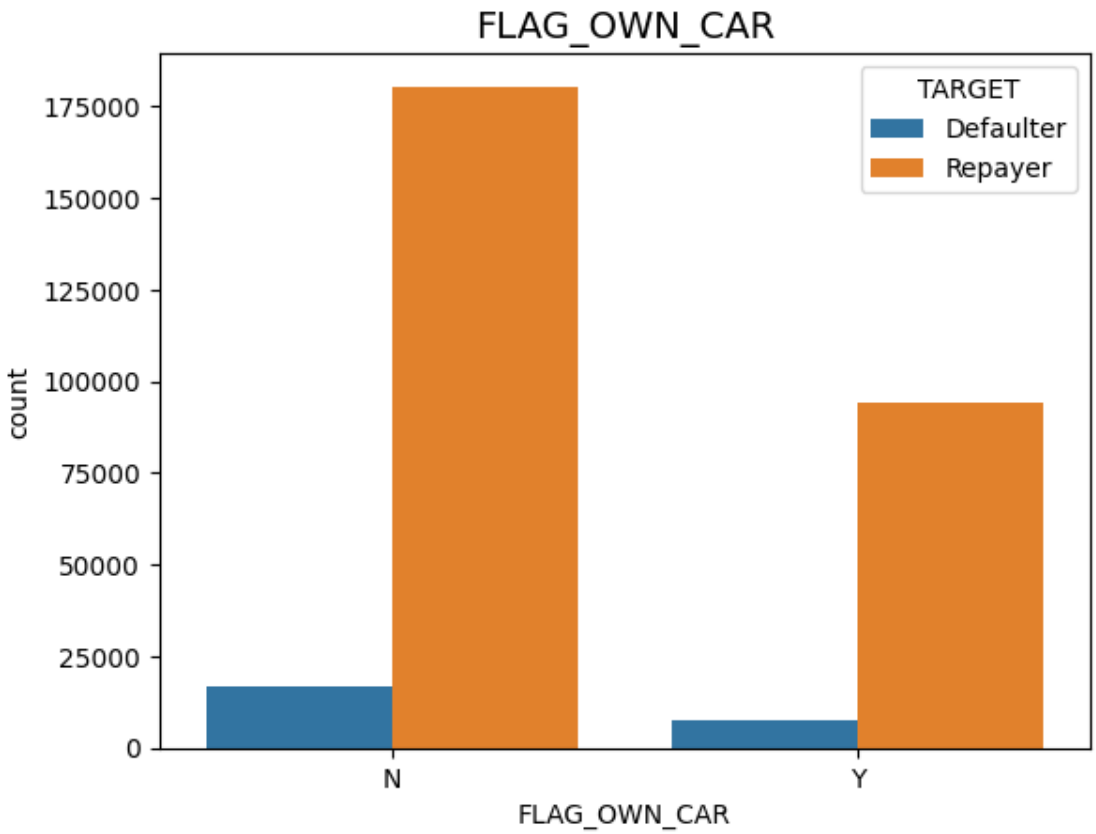


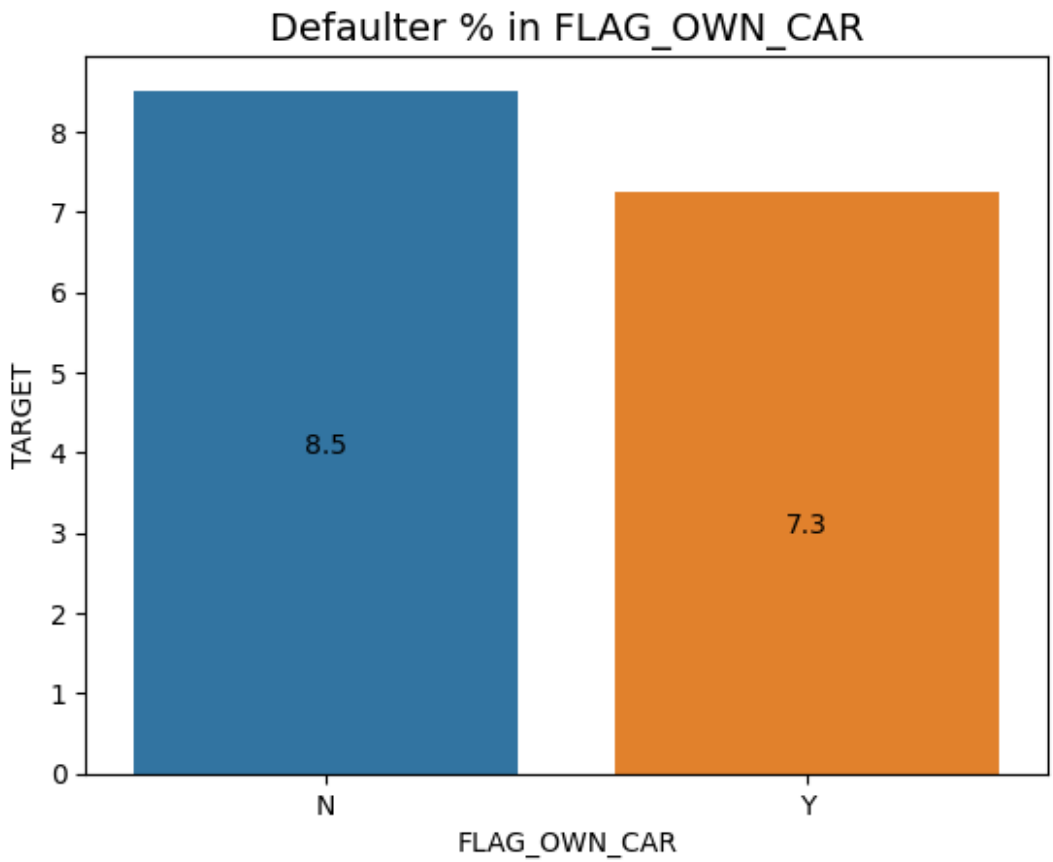

```
univariate(df1,'NAME_HOUSING_TYPE','TARGET')
```



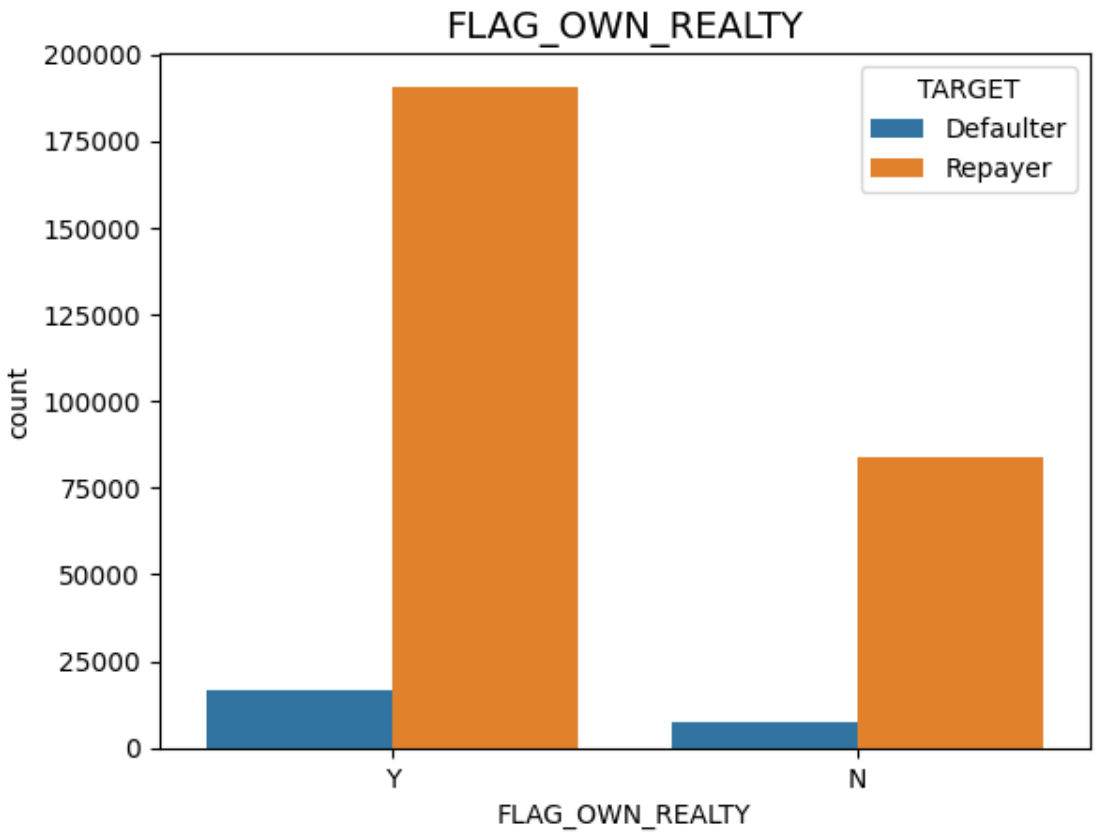


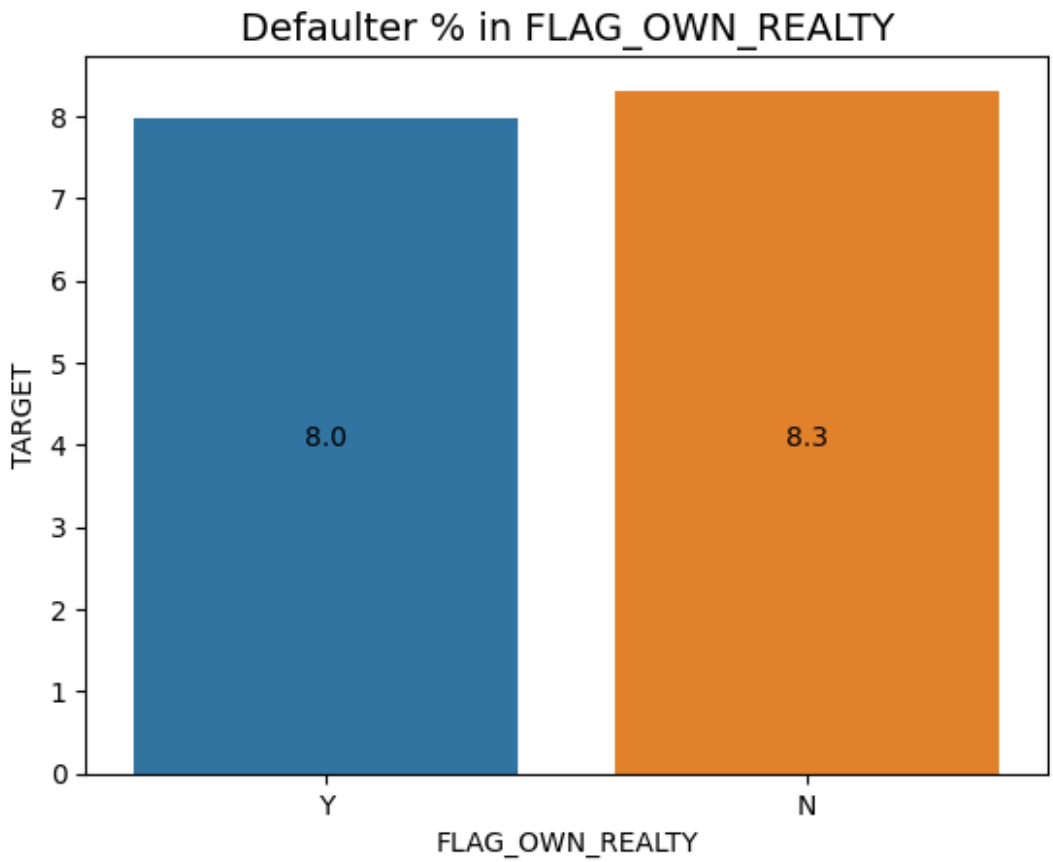

```
univariate(df1,'FLAG_OWN_CAR','TARGET')
```



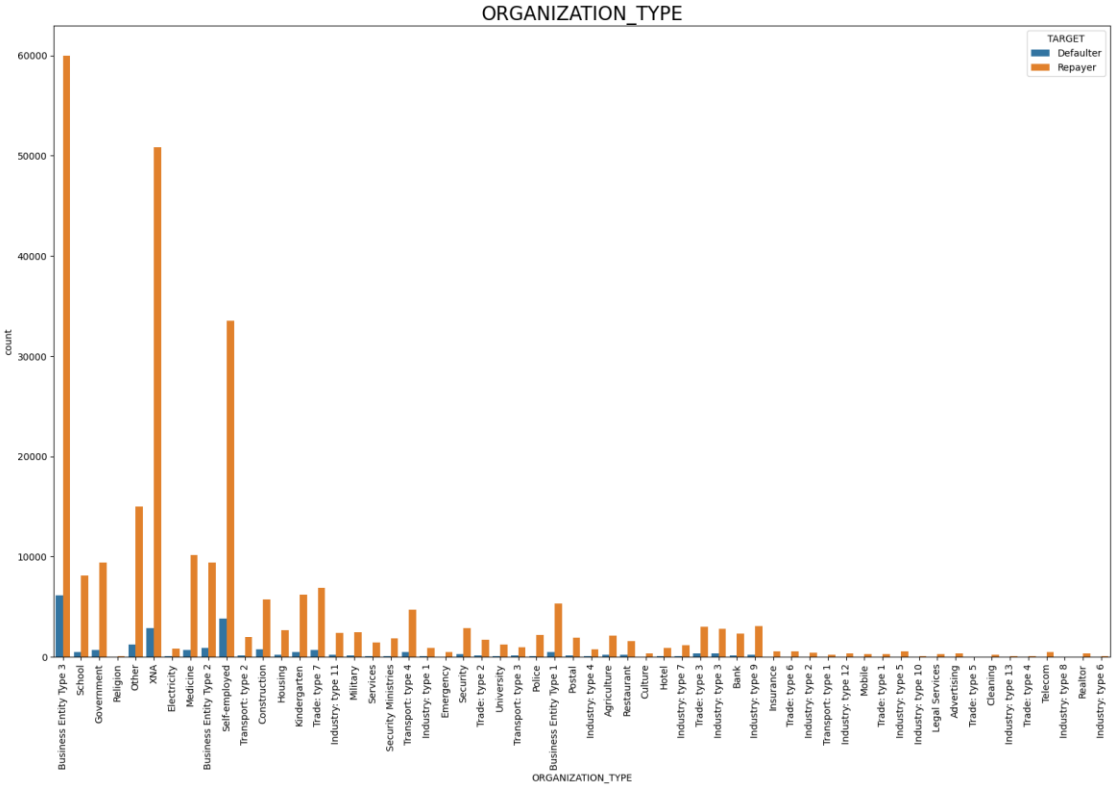


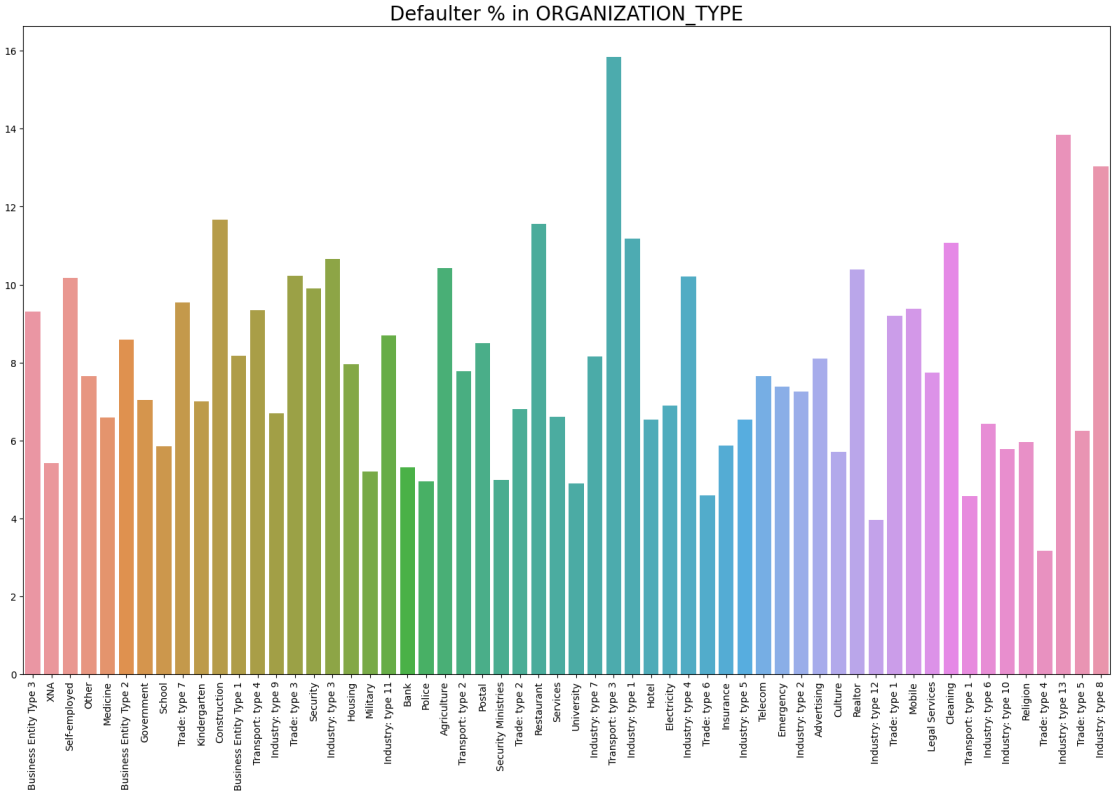

```
univariate(df1,'FLAG_OWN_REALTY','TARGET')
```


FLAG_OWN_REALTY
TARGET
Defaulter
Repayer
count
200000
175000
150000
125000
100000
75000
50000
25000
0
Y
N
FLAG_OWN_REALTY




```
univariate(df1,'ORGANIZATION_TYPE','TARGET')
```


ORGANIZATION_TYPE
TARGET
Defaulter
Repayer
count
ORGANIZATION_TYPE
Business Entity Type 3
School
Government
Religion
Other
XNA
Electricity
Medicine
Business Entity Type 2
Self-employed
Transport: type 2
Construction
Housing
Kindergarten
Trade: type 7
Industry: type 11
Military
Services
Security Ministries
Transport: type 4
Industry: type 1
Emergency
Security
Trade: type 2
University
Transport: type 3
Police
Business Entity Type 1
Postal
Industry: type 4
Agriculture
Restaurant
Culture
Hotel
Industry: type 7
Trade: type 3
Industry: type 3
Bank
Industry: type 9
Insurance
Trade: type 6
Industry: type 2
Transport: type 1
Industry: type 12
Mobile
Trade: type 1
Industry: type 5
Industry: type 10
Legal Services
Advertising
Trade: type 5
Cleaning
Industry: type 13
Trade: type 4
Telecom
Industry: type 8
Realtor
Industry: type 6


Defaulter % in ORGANIZATION_TYPE
Business Entity Type 3
XNA
Self-employed
Other
Medicine
Business Entity Type 2
Government
School
Trade: type 7
Kindergarten
Construction
Business Entity Type 1
Transport: type 4
Industry: type 9
Trade: type 3
Security
Industry: type 3
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
Realtor
Industry: type 12
Trade: type 1
Mobile
Legal Services
Cleaning
Transport: type 1
Industry: type 6
Industry: type 10
Religion
Trade: type 4
Industry: type 13
Trade: type 5
Industry: type 8

#Convert AMT_INCOME_TOTAL to bins

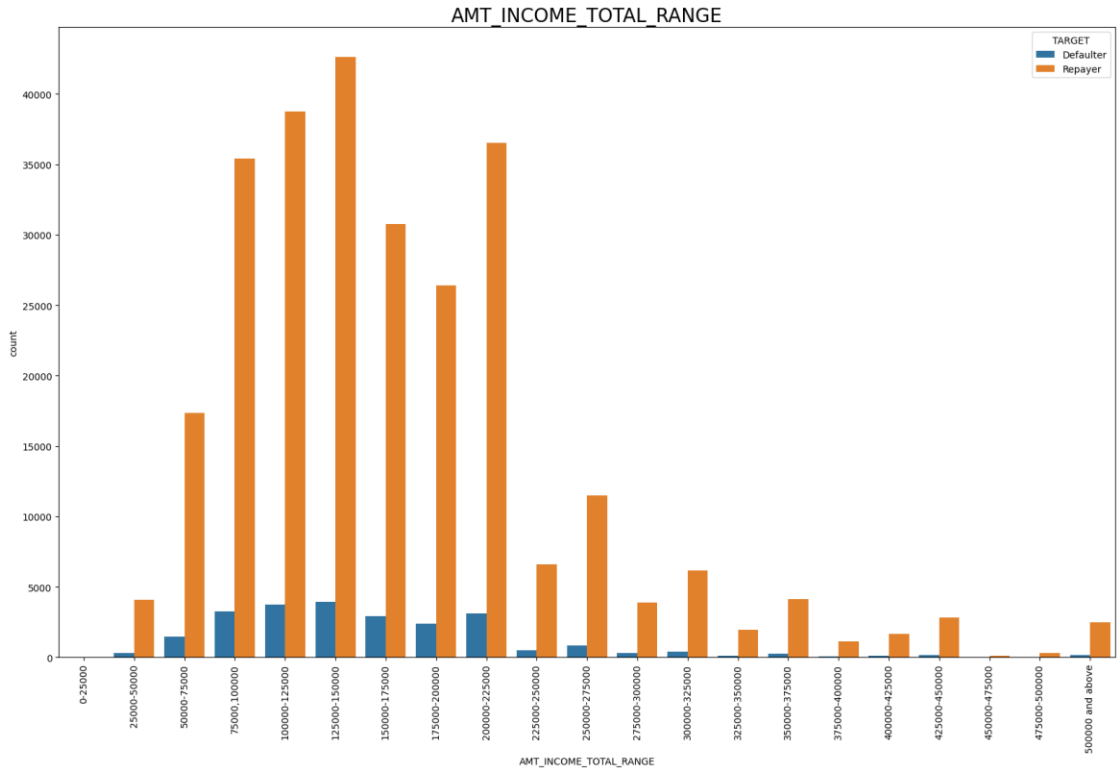
```
incomebins=[0,25000,50000,75000,100000,125000,150000,175000,200000,225000,250000,275000,300000,325000,350000,375000,400000,425000,450000,475000,500000,10000000000]
incomeslots = ['0-25000','25000-50000','50000-75000','75000,100000','100000-125000', '125000-150000', '150000-175000','175000-200000','200000-225000','225000-250000','250000-275000','275000-300000','300000-325000','325000-350000','350000-375000','375000-400000','400000-425000','425000-450000','450000-475000','475000-500000','500000 and above']
df1['AMT_INCOME_TOTAL_RANGE']=pd.cut(df1['AMT_INCOME_TOTAL'],bins=incomebins,labels=incomeslots)
```

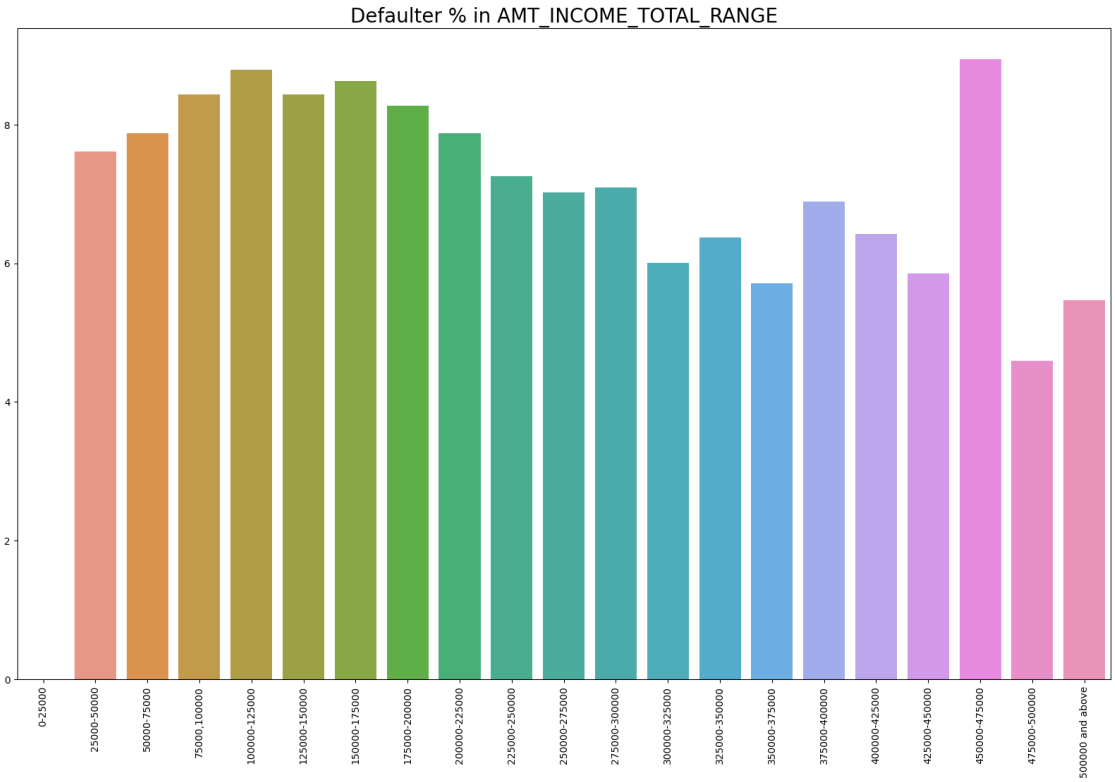
#Convert AMT_CREDIT to bins

```
creditbins = [0,150000,200000,250000,300000,350000,400000,450000,500000,550000,600000,650000,700000,750000,800000,850000,900000,1000000000]
creditslots = ['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']
df1['AMT_CREDIT_RANGE'] = pd.cut(df1.AMT_CREDIT,bins=creditbins,labels=creditslots)
```

#Univariate analysis for AMT_INCOME_TOTAL_RANGE

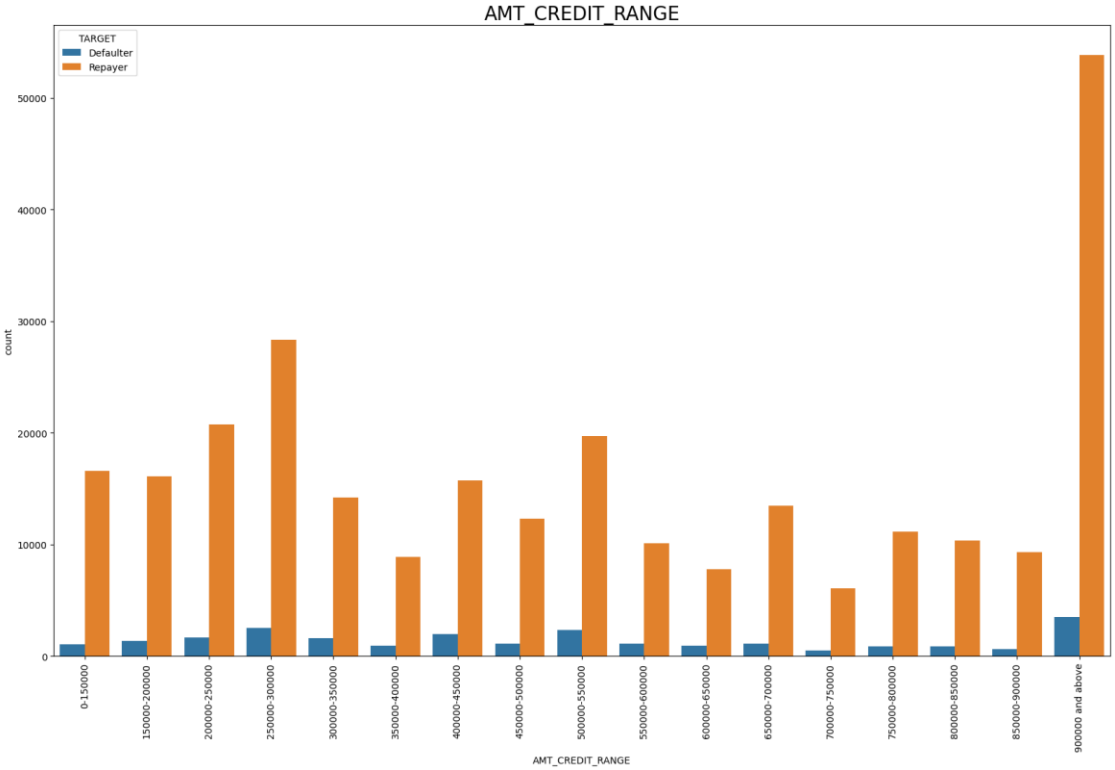
```
univariate(df1,'AMT_INCOME_TOTAL_RANGE','TARGET')
```

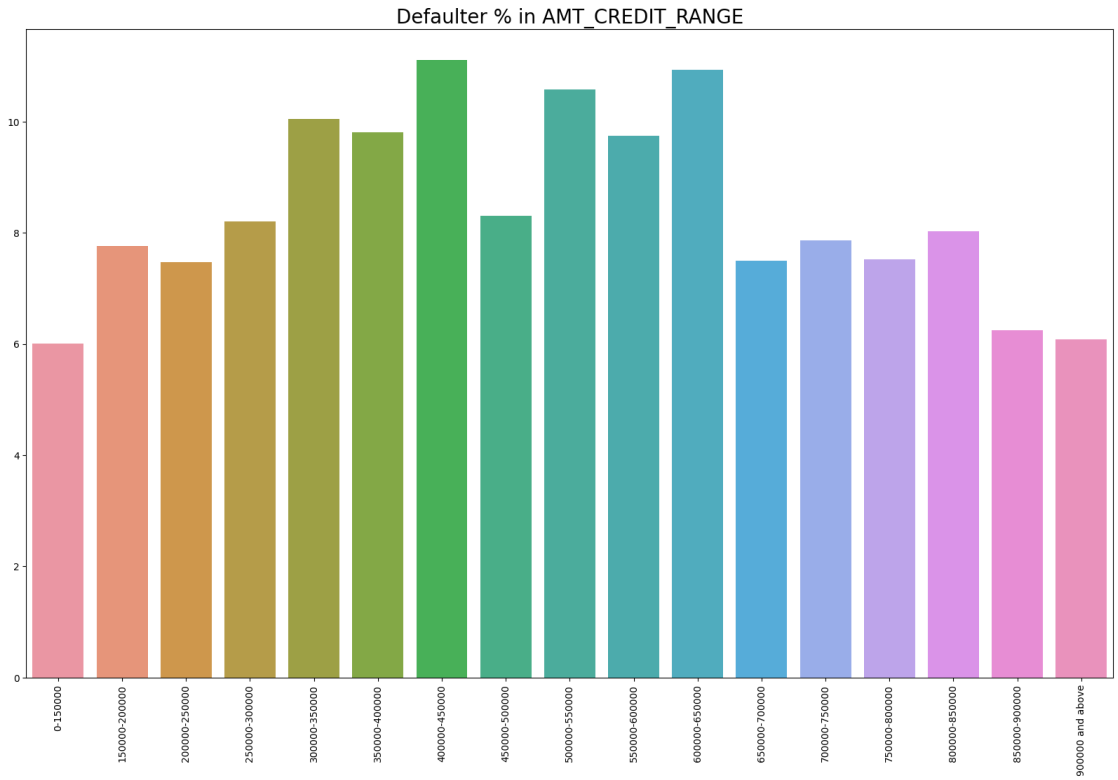




#Univariate analysis for AMT_CREDIT

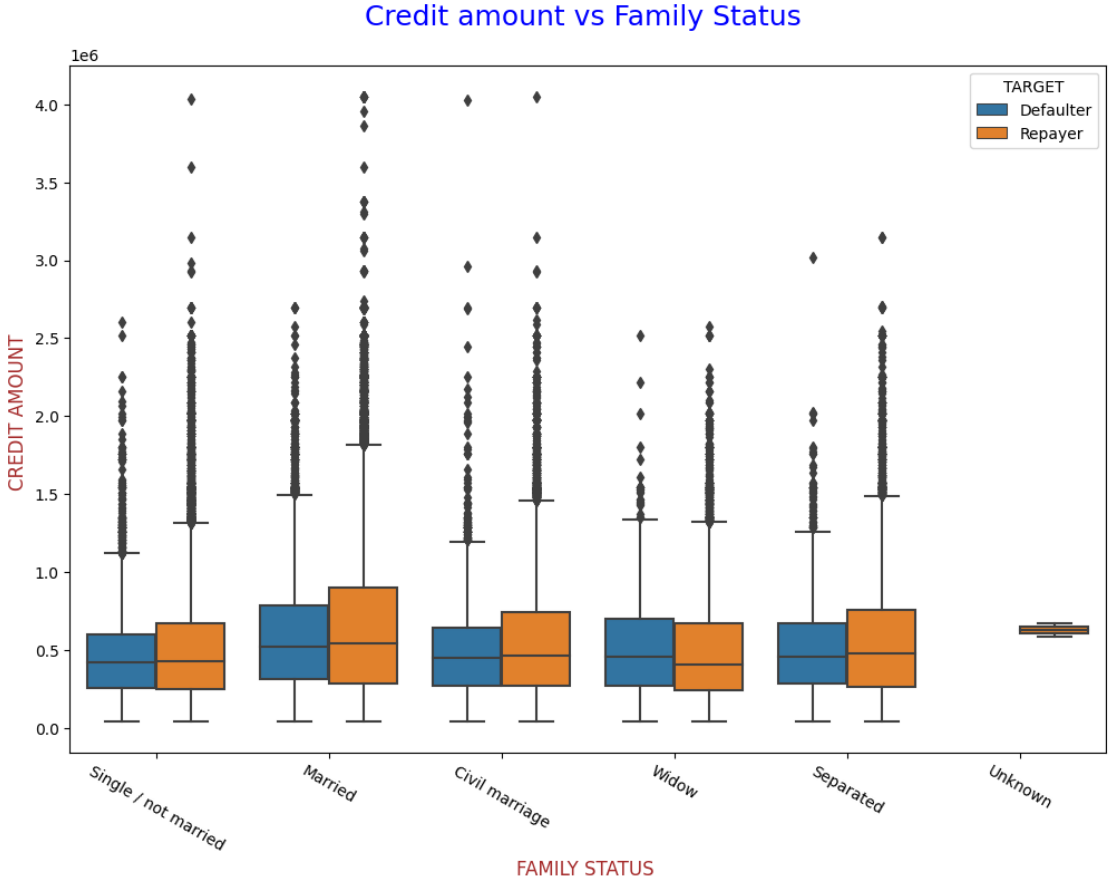
```
univariate(df1,'AMT_CREDIT_RANGE','TARGET')
```



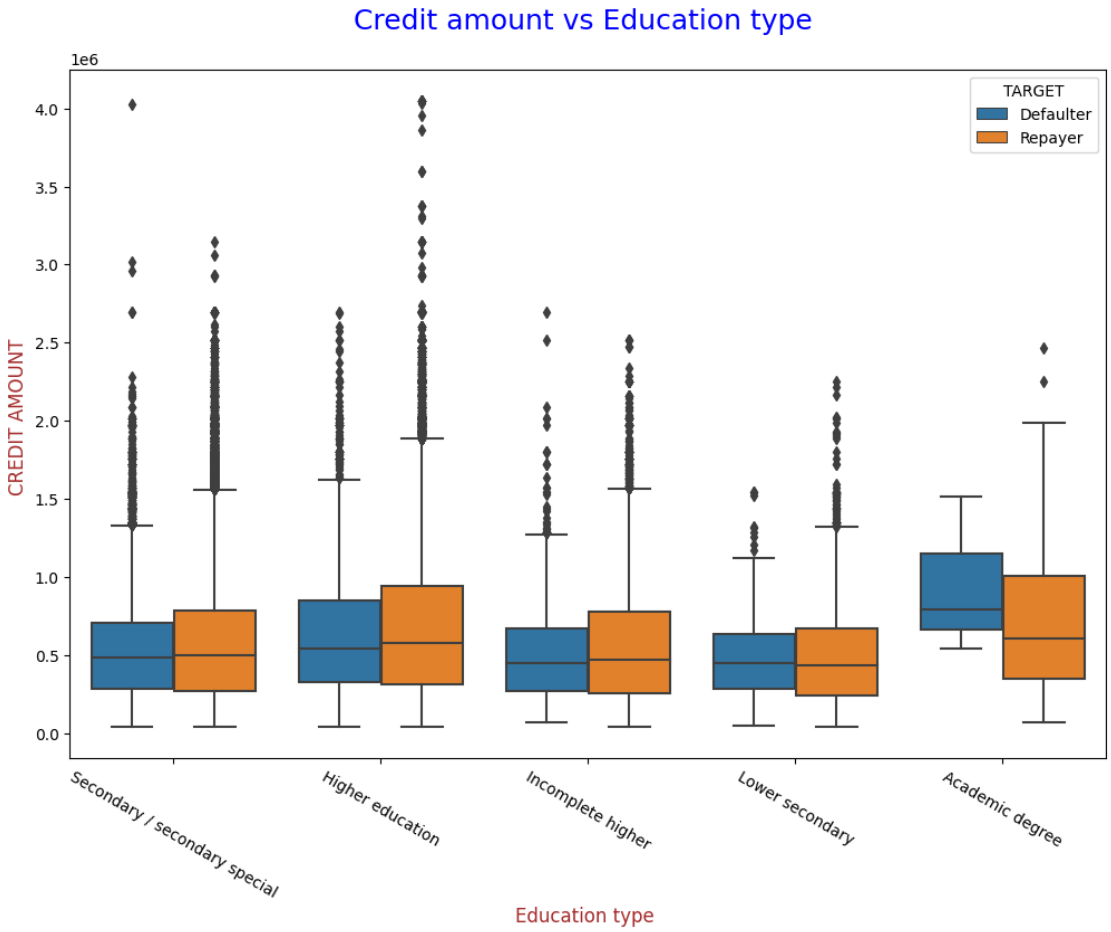


Bivariate analysis for application_data.csv

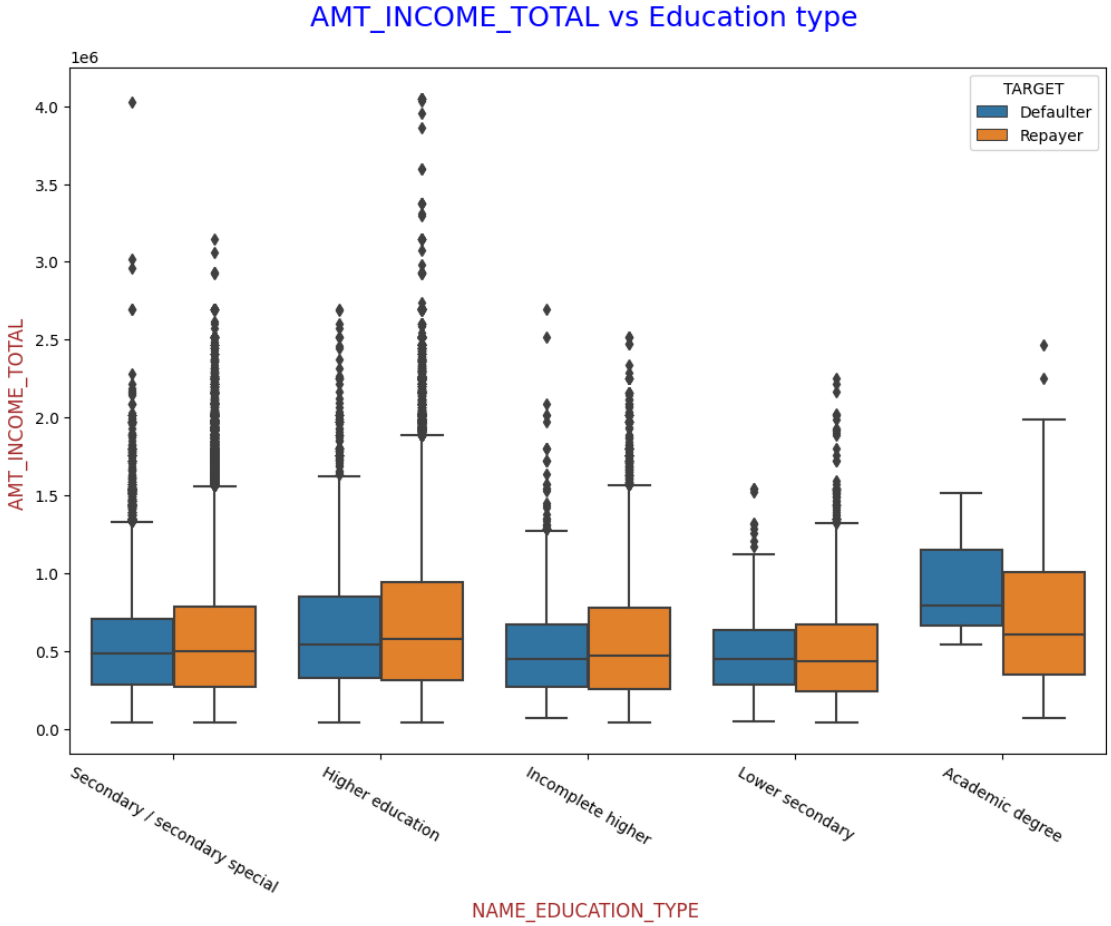
```
plt.figure(figsize=(12,8))
scale_factor=5
sns.boxplot(data=df1,x=df1.NAME_FAMILY_STATUS,y=df1.AMT_CREDIT,hue=df1.TARGET
)
plt.xticks(rotation=-30)
plt.xlabel("FAMILY STATUS ", fontdict={'fontsize': 12, 'fontweight' : 5,
'color' : 'Brown'})
plt.ylabel("CREDIT AMOUNT ", fontdict={'fontsize': 12, 'fontweight' : 5,
'color' : 'Brown'})
plt.title('Credit amount vs Family Status \n',fontdict={'fontsize': 18,
'fontweight' : 10, 'color' : 'Blue'})
plt.show()
```




```
plt.figure(figsize=(12,8))
scale_factor=5
sns.boxplot(data=df1,x=df1.NAME_EDUCATION_TYPE,y=df1.AMT_CREDIT,hue=df1.TARGE
T)
plt.xticks(rotation=-30)
plt.xlabel("Education type ", fontdict={'fontsize': 12, 'fontweight' : 5,
'color' : 'Brown'})
plt.ylabel("CREDIT AMOUNT ", fontdict={'fontsize': 12, 'fontweight' : 5,
'color' : 'Brown'})
plt.title('Credit amount vs Education type \n',fontdict={'fontsize': 18,
'fontweight' : 10, 'color' : 'Blue'})
plt.show()
```

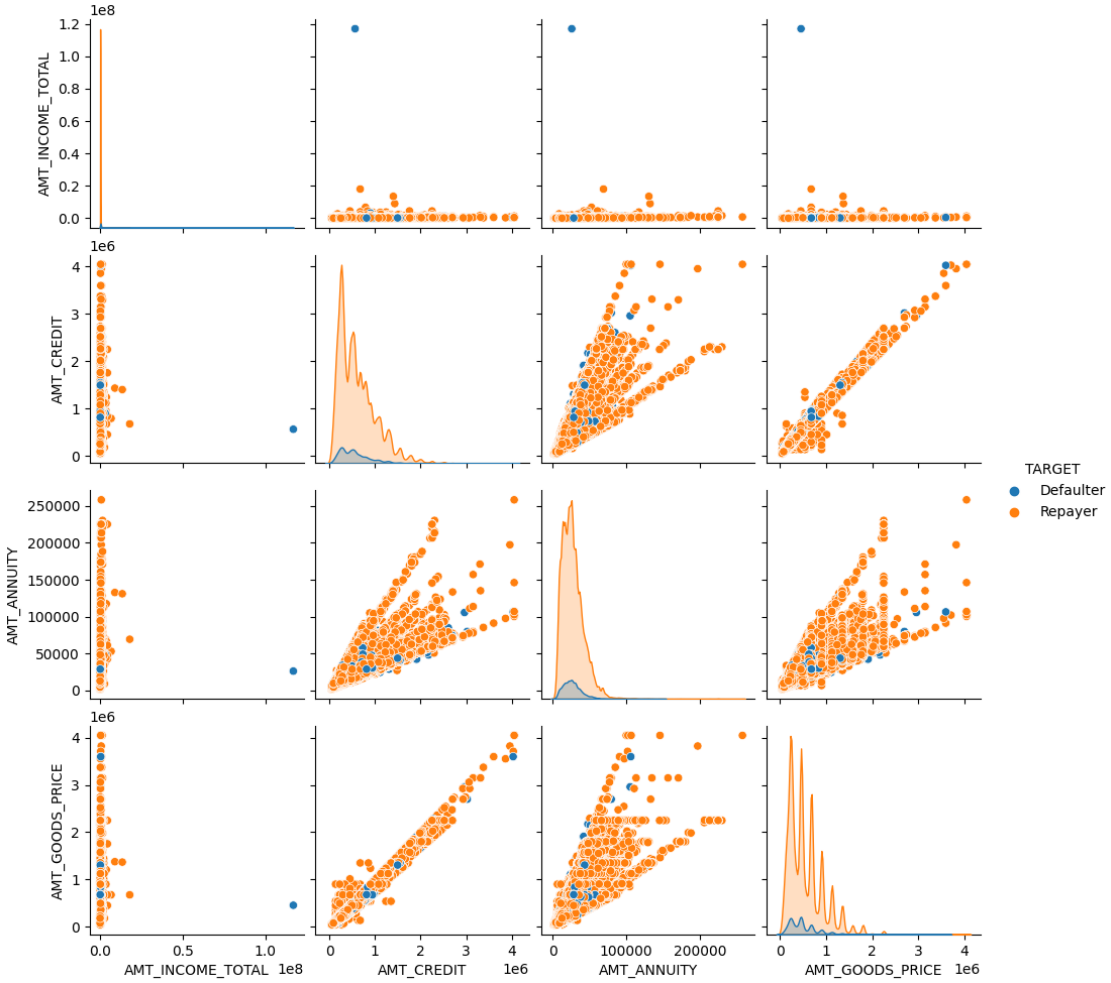



```
plt.figure(figsize=(12,8))
scale_factor=5
sns.boxplot(data=df1,x=df1.NAME_EDUCATION_TYPE,y=df1.AMT_CREDIT,hue=df1.TARGE
T)
plt.xticks(rotation=-30)
plt.xlabel("NAME_EDUCATION_TYPE ", fontdict={'fontsize': 12, 'fontweight' :
5, 'color' : 'Brown'})
plt.ylabel("AMT_INCOME_TOTAL ", fontdict={'fontsize': 12, 'fontweight' : 5,
'color' : 'Brown'})
plt.title('AMT_INCOME_TOTAL vs Education type \n',fontdict={'fontsize': 18,
'fontweight' : 10, 'color' : 'Blue'})
plt.show()
```




```
amount =
df1[['AMT_INCOME_TOTAL','AMT_CREDIT','AMT_ANNUITY','AMT_GOODS_PRICE','TARGET'
]]
sns.pairplot(amount,hue = 'TARGET')
```

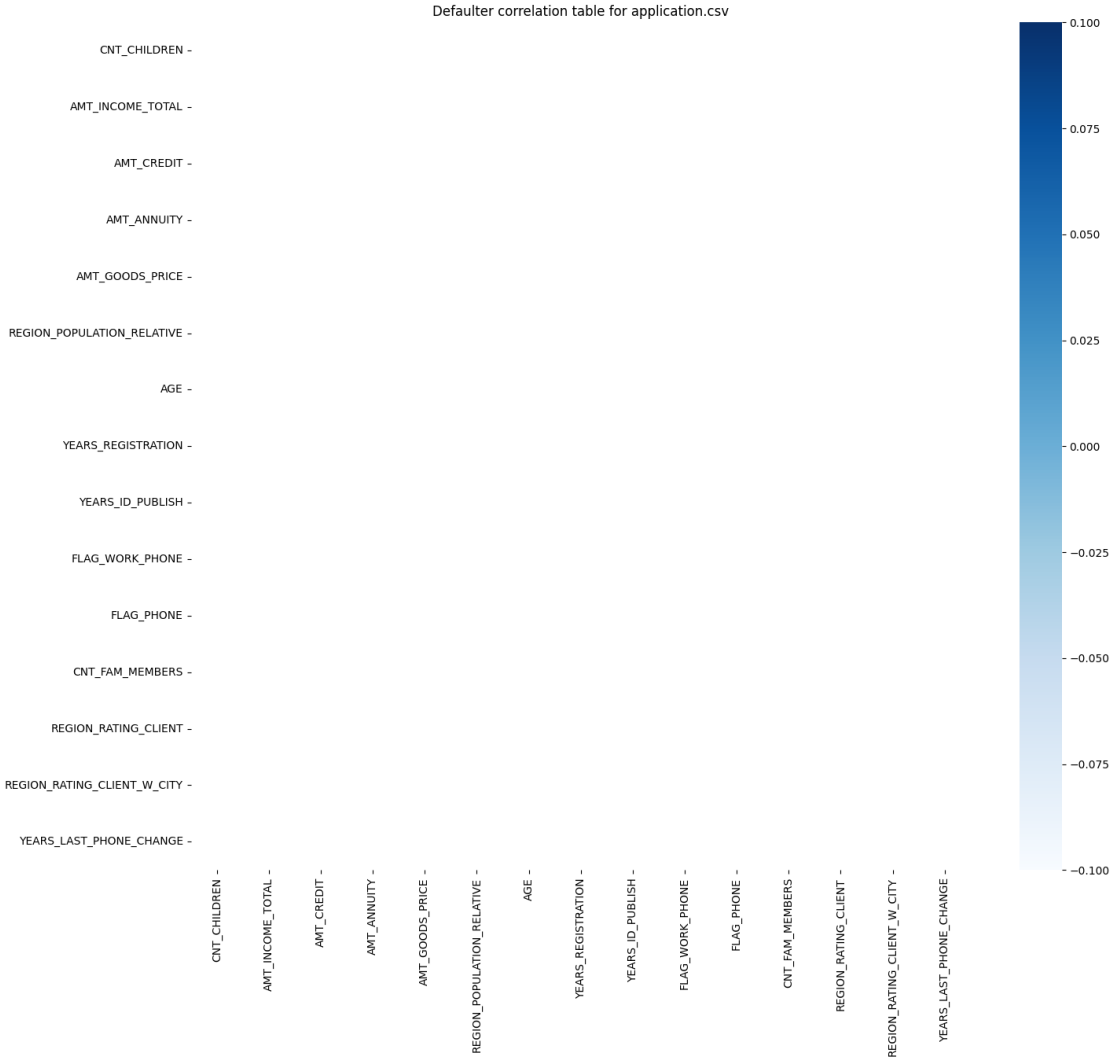
```
<seaborn.axisgrid.PairGrid at 0x7fce4df952b0>
```



Correlation check for the defaulter in application_data.csv

```
defaulter_df = df1[df1['TARGET']==1]

corr2 = defaulter_df[['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', 'AGE','YEARS_REGISTRATION', 'YEARS_ID_PUBLISH',
'FLAG_WORK_PHONE','FLAG_PHONE', 'OCCUPATION_TYPE',
'CNT_FAM_MEMBERS','REGION_RATING_CLIENT',
'REGION_RATING_CLIENT_W_CITY','ORGANIZATION_TYPE','YEARS_LAST_PHONE_CHANGE']]
.corr()
plt.figure(figsize=(16,14))
sns.heatmap(corr2,cmap='Blues',annot=True,linewidth=0.5)
plt.title('Defaulter correlation table for application.csv')
corr2 = corr2.where(np.triu(np.ones(corr2.shape), k=1).astype(bool))
corr_mat = corr2.unstack().sort_values(ascending=False).reset_index()
corr_mat.rename(columns={'level_0':'Var1','level_1':'Var2',0:'Correlation'},i
nplace=True )
print(corr_mat.head(10))
```

	Var1	Var2	Correlation
0	CNT_CHILDREN	CNT_CHILDREN	NaN
1	CNT_CHILDREN	AMT_INCOME_TOTAL	NaN
2	CNT_CHILDREN	AMT_CREDIT	NaN
3	CNT_CHILDREN	AMT_ANNUITY	NaN
4	CNT_CHILDREN	AMT_GOODS_PRICE	NaN
5	CNT_CHILDREN	REGION_POPULATION_RELATIVE	NaN
6	CNT_CHILDREN	AGE	NaN
7	CNT_CHILDREN	YEARS_REGISTRATION	NaN
8	CNT_CHILDREN	YEARS_ID_PUBLISH	NaN
9	CNT_CHILDREN	FLAG_WORK_PHONE	NaN

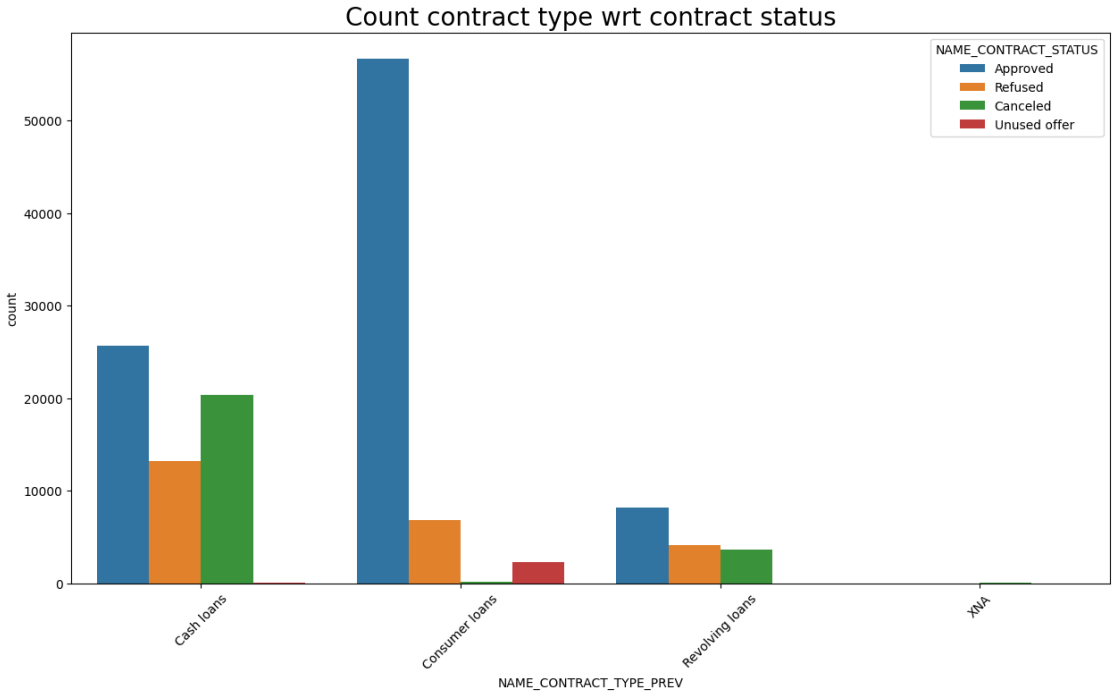


Univariate analysis of merged data frame

```
mergedf = df1.merge(df, on='SK_ID_CURR')

mergedf = mergedf.rename({'NAME_CONTRACT_TYPE_x' :
'NAME_CONTRACT_TYPE','AMT_CREDIT_x':'AMT_CREDIT','AMT_ANNUITY_x':'AMT_ANNUITY
','WEEKDAY_APPR_PROCESS_START_x' :
```

```
'WEEKDAY_APPR_PROCESS_START','AMT_GOODS_PRICE_x':'AMT_GOODS_PRICE','HOUR_APPR
_PROCESS_START_x':'HOUR_APPR_PROCESS_START','NAME_CONTRACT_TYPE_y':'NAME_CONT
RACT_TYPE_PREV','AMT_CREDIT_y':'AMT_CREDIT_PREV','AMT_ANNUITY_y':'AMT_ANNUITY
_PREV','AMT_GOODS_PRICE_y':'AMT_GOODS_PRICE_PREV','WEEKDAY_APPR_PROCESS_START
_y':'WEEKDAY_APPR_PROCESS_START_PREV','HOUR_APPR_PROCESS_START_y':'HOUR_APPR_
PROCESS_START_PREV'}, axis=1)
plt.figure(figsize = (15,8))
sns.countplot(x = mergedf['NAME_CONTRACT_TYPE_PREV'], hue =
mergedf['NAME_CONTRACT_STATUS'])
plt.xticks(rotation = 45)
plt.title('Count contract type wrt contract status',fontdict={'fontsize':
20})
```

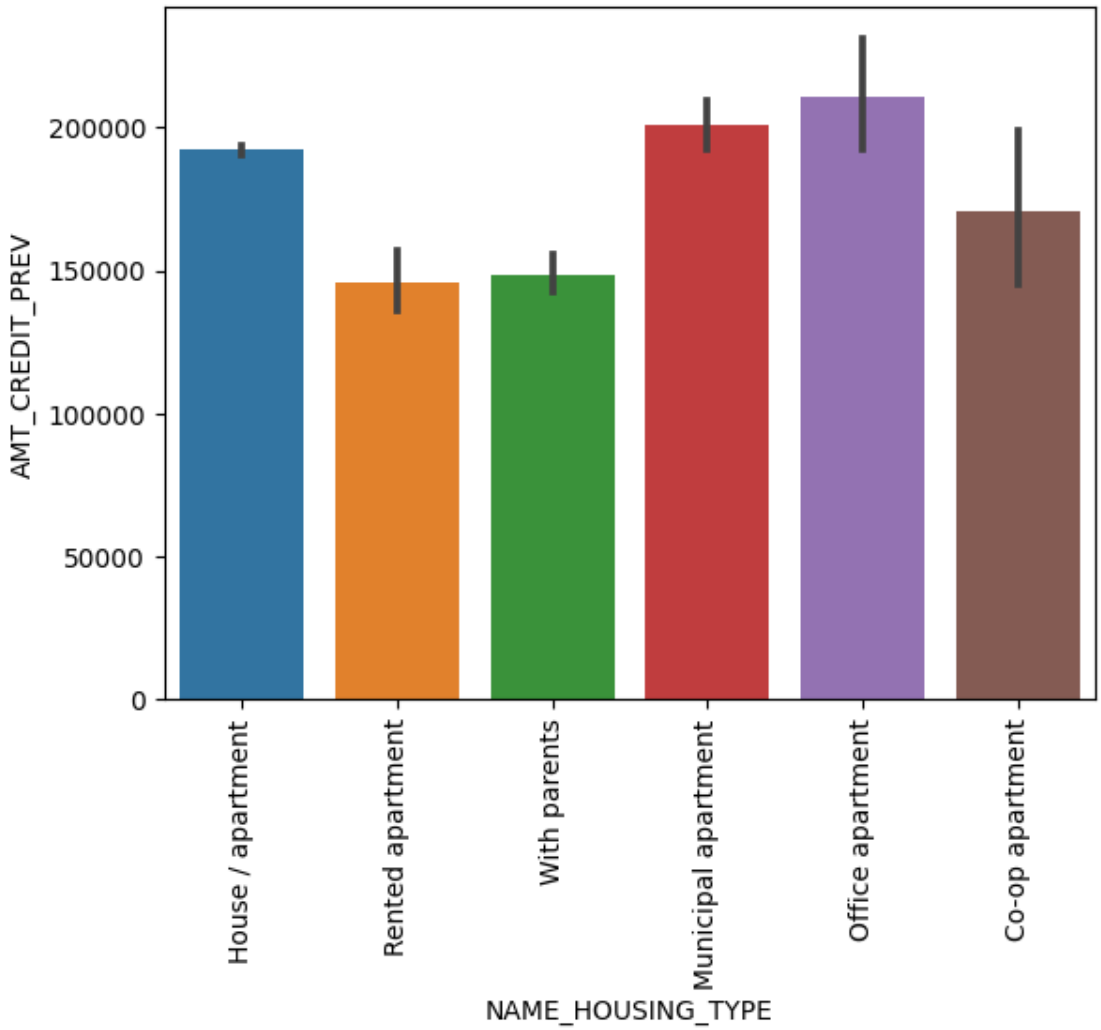
```
Text(0.5, 1.0, 'Count contract type wrt contract status')
```



Bivariate analysis of merged data frame

```
sns.barplot(data=mergedf,x = 'NAME_HOUSING_TYPE',y = 'AMT_CREDIT_PREV' )
plt.xticks(rotation=90)
```

```
(array([0, 1, 2, 3, 4, 5]),
 [Text(0, 0, 'House / apartment'),
  Text(1, 0, 'Rented apartment'),
  Text(2, 0, 'With parents'),
  Text(3, 0, 'Municipal apartment'),
  Text(4, 0, 'Office apartment'),
  Text(5, 0, 'Co-op apartment')])
```

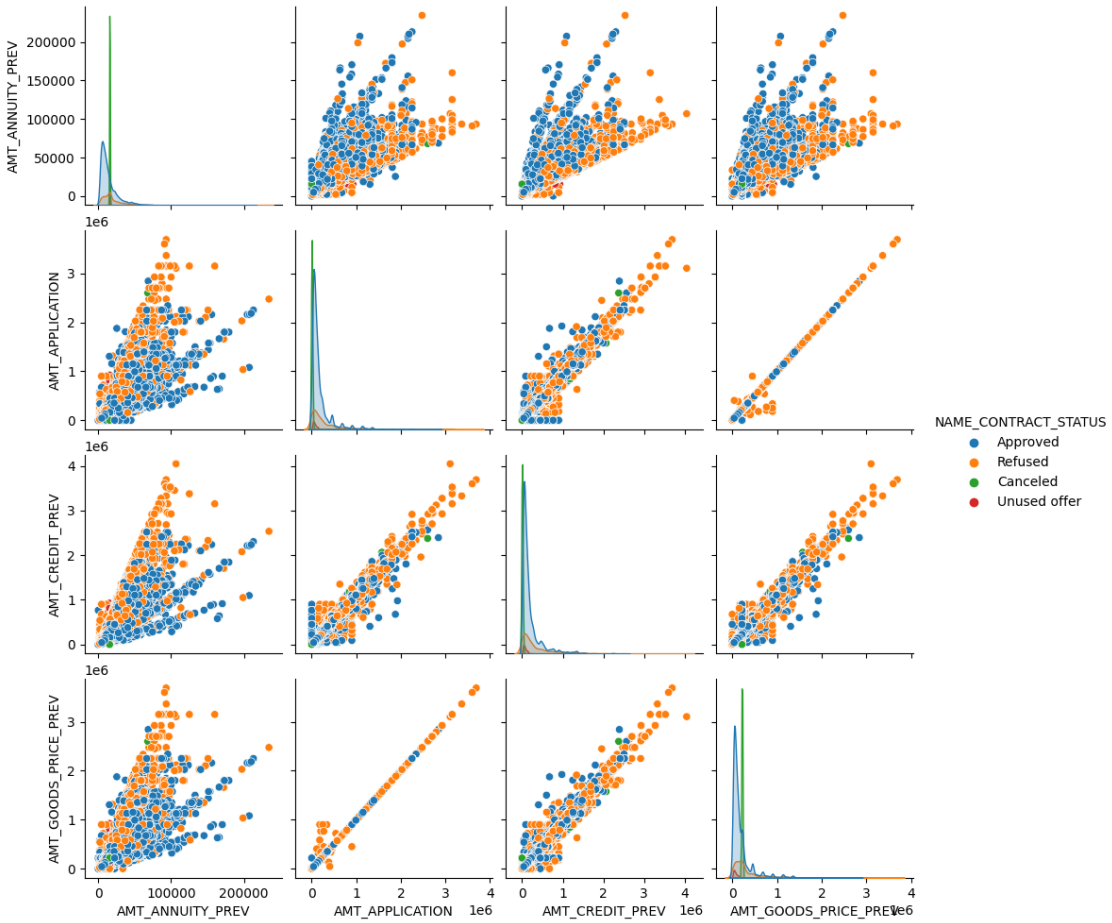


Correlation check for previous_application.csv

```
plt.figure(figsize=(20,14))
amount = mergedf[['AMT_ANNUITY_PREV', 'AMT_APPLICATION',
 'AMT_CREDIT_PREV', 'AMT_GOODS_PRICE_PREV','NAME_CONTRACT_STATUS']]
sns.pairplot(amount,hue = 'NAME_CONTRACT_STATUS')
```

```
<seaborn.axisgrid.PairGrid at 0x7fce4df05040>
```

```
<Figure size 2000x1400 with 0 Axes>
```




```
corr4 = mergedf[['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', 'AGE',
 'YEARS_REGISTRATION', 'YEARS_ID_PUBLISH', 'FLAG_WORK_PHONE',
 'FLAG_PHONE', 'OCCUPATION_TYPE', 'CNT_FAM_MEMBERS',
 'REGION_RATING_CLIENT', 'REGION_RATING_CLIENT_W_CITY',
 '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', 'OBS_30_CNT_SOCIAL_CIRCLE',
 'DEF_30_CNT_SOCIAL_CIRCLE', 'OBS_60_CNT_SOCIAL_CIRCLE',
 'DEF_60_CNT_SOCIAL_CIRCLE', 'YEARS_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',
 'AMT_INCOME_TOTAL_RANGE', 'AMT_CREDIT_RANGE',
 'NAME_CONTRACT_TYPE_PREV', 'AMT_ANNUITY_PREV', 'AMT_APPLICATION',
 'AMT_CREDIT_PREV', 'AMT_GOODS_PRICE_PREV', 'NAME_CASH_LOAN_PURPOSE',
 'NAME_CONTRACT_STATUS', 'DAYS_DECISION', 'NAME_PAYMENT_TYPE',
 'CODE_REJECT_REASON', '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']].corr()

plt.figure(figsize=(35,35))
sns.heatmap(corr4,cmap='Blues',annot=True,linewidth=0.5)
plt.title('Defaulter correlation table for application.csv')
corr5 = corr4.where(np.triu(np.ones(corr4.shape), k=1).astype(bool))
corr_mat = corr5.unstack().sort_values(ascending=False).reset_index()
corr_mat.rename(columns={'level_0':'Var1','level_1':'Var2',0:'Correlation'},i
nplace=True )
print(corr_mat.head(10))
```

	Var1	Var2	Correlation
0	OBS_60_CNT_SOCIAL_CIRCLE	OBS_30_CNT_SOCIAL_CIRCLE	0.998471
1	AMT_GOODS_PRICE	AMT_CREDIT	0.985963
2	AMT_CREDIT_PREV	AMT_APPLICATION	0.975958
3	AMT_GOODS_PRICE_PREV	AMT_APPLICATION	0.949702
4	REGION_RATING_CLIENT_W_CITY	REGION_RATING_CLIENT	0.948084
5	AMT_GOODS_PRICE_PREV	AMT_CREDIT_PREV	0.943099
6	CNT_FAM_MEMBERS	CNT_CHILDREN	0.880690
7	LIVE_REGION_NOT_WORK_REGION	REG_REGION_NOT_WORK_REGION	0.877206
8	DEF_60_CNT_SOCIAL_CIRCLE	DEF_30_CNT_SOCIAL_CIRCLE	0.860852
9	LIVE_CITY_NOT_WORK_CITY	REG_CITY_NOT_WORK_CITY	0.833795